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**Deep Learning Model for Identifying
Ionospheric Electric Field Perturbations
and Seismic Correlation**

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Dedicato,

*Alla bambina di dieci anni che un giorno sognò di diventare una scienziata,
e che non smise mai di credere in quel sogno.*

***Al sogno che ha rifiutato di svanire,
e alla perseveranza che lo ha portato avanti.***

*Alla mia famiglia — il mio Acha, la mia Amma, Veni e Rai —
per il loro amore incondizionato, gli infiniti sacrifici,
e il sostegno costante in ogni passo di questo cammino.*

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Abstract

The quest for dependable earthquake-induced perturbations has driven investigations into the ionosphere. Recent advancements in satellite observations and machine learning offer novel opportunities to investigate these potential correlations via data-driven methodologies.

This thesis examines ionospheric electric field disturbances through the application of deep learning methodologies to global space-based data. The research employs electric field measurements from the DEMETER satellite ICE mission, concentrating on very low frequency (VLF) electric field power spectral density data to examine ionospheric variability on a global scale. A deep learning framework using an LSTM autoencoder is developed to learn the underlying background behavior of the ionosphere and to detect anomalous perturbations in the data. This study utilised an adaptive rolling-window training strategy to address the highly non-stationary characteristics of geophysical datasets, continuously updating the model in response to fluctuating background conditions. This methodological framework integrates deep learning and statistical validation to systematically examine potential correlations between identified ionospheric anomalies and seismic events. The findings indicate that deep learning models can effectively extract significant ionospheric electric field anomalies from extensive satellite datasets and detect statistically significant associations with following earthquakes under the given framework. Additionally, the study attempts a feasibility study on a multi-instrument approach by integrating ground-based ionosonde observations to examine potential coupling between disturbances in the lower and upper ionosphere.

This thesis develops an adaptable and extensible deep learning framework for the detection of ionospheric perturbations from global space-based observations and to study the association with earthquakes. The proposed methodology is intended to be flexible for integration with alternative datasets and signatures supporting ongoing research into lithosphere–ionosphere interactions and enhancing the advancement of data-driven approaches for investigating potential seismo-ionosphere coupling.

Keywords

Ionosphere, Electric field, Earthquake, Deep Learning, Anomaly, LSTM, Autoencoder, DEMETER

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Introduction

Earthquakes remain among the most destructive natural hazards, with a significant impact on human societies, infrastructure, and global economies [1], [2]. Relative motion of tectonic plates along faults leads to the accumulation of strain energy, which is then abruptly released. This energy release generates seismic waves that propagate through the Earth’s crust, resulting in extensive structural damage and significant loss of life [1], [3]. Since earthquakes cannot be prevented, the most effective strategy is to identify robust precursory signals of their occurrence and employ them to implement preventive measures that reduce their consequences.

The search for seismic precursors has long been a central focus of geophysical research. The ionosphere has consistently been regarded as a key environment for detecting such precursor signals. Its importance has risen markedly with the introduction of continuous global observations from satellites such as DEMETER, Swarm, and CSES, together with ground-based GNSS networks and ionosondes, which collectively deliver the comprehensive datasets required for systematic studies of earthquake precursors. Numerous investigations have drawn on these monitoring datasets to explore ionospheric anomalies associated with pre-seismic processes. Early statistical assessments employing ground-based GPS TEC measurements and ionosonde records laid the groundwork for seismo-ionospheric research [4], [5], [6], [7]. Subsequent satellite missions have enabled more systematic studies of seismo-ionospheric signatures. The DEMETER satellite furnished in situ observations of ion density and electromagnetic variations, which have been extensively analysed to detect possible pre-seismic indicators [8], [9]. More recently, the CSES mission has supported in-depth investigations of ionospheric electric field perturbations [10], [11], [12], while the Swarm constellation has facilitated the study of large-scale ionospheric disturbances that may be linked to seismic activity [13], [14], [15]. Concurrently, ground-based VLF/LF radio propagation measurements have yielded statistical indications of disturbances in the lower ionosphere [16], [17]. Extensive GNSS-based analyses, using total electron content (TEC) observations [18], [19], [20], [21], together with GNSS reflectometry and GNSS radio occultation data [22], [23], have further advanced the study of earthquake-related ionospheric anomalies. In addition, multi-instrument strategies that integrate GNSS, CSES, and Swarm observations have enabled more holistic characterisations of such ionospheric disturbances [14], [24]. Recent multi-parameter observational efforts have likewise contributed important insights into lithosphere–atmosphere–ionosphere coupling (LAIC) processes [25], [26].

Recently, many studies have focused on electromagnetic (EM) signals for more understanding of the phenomenon. DEMETER (Detection of Electro-Magnetic Emissions Transmitted from Earthquake Regions) was the first satellite dedicated to monitoring

seismic and volcanic phenomena from space, providing continuous global coverage of the ionosphere [27]. Analyses of DEMETER sensor measurements offer additional evidence for the upward propagation of EM signals, originating near the Earth's surface, into the ionosphere [28], [29]. Nonetheless, the existence of EM precursors remains vigorously debated. Some studies argue that such EM precursors are absent [30]. Much of this controversy stems from the still incomplete understanding of the physical mechanisms driving EM emissions associated with seismic activity, despite a variety of proposed explanations, including atmospheric gravity waves [31], [32], solid-state physics models [33], radon-emission-based mechanisms [34], electric field generation in stressed rocks [35], ULF magnetic field variations [36], and mathematical formulations based on critical dynamics [37]. These discussions are further influenced by the fact that most research falls into two main categories: in-depth analyses of single earthquake events and broad statistical studies of ionospheric conditions prior to earthquakes. Alongside these conceptual issues, there are also practical methodological issues that further hinder progress. Despite decades of research, no single EM signature has consistently emerged as a robust earthquake precursor. One of the possible causes is the methodological constraints in prior studies, such as the use of arbitrary spatial and temporal windows, a strong bias towards near-epicentral data, reliance on hypothesis-driven approaches, and limited global coverage. Frequently, proposed precursor signals are identified through post-hoc analyses of only a small number of major earthquakes, which undermines statistical robustness and reproducibility.

In such a case, the data-driven frameworks can be introduced as a step towards a more robust and comprehensive understanding of this complex relation. The data-driven frameworks that do not depend on predefined hypotheses, and that can generalise across a wide range of tectonic and ionospheric environments, can provide more than merely demonstrating statistical correlations derived from biased data samples [38]. From this standpoint, in-depth time-series analysis of EM signals, aimed at detecting complex temporal patterns plausibly triggered by seismic activity, is particularly crucial. Addressing this gap will require harmonised datasets combined with transparent, data-driven algorithms capable of generalising across diverse tectonic regimes. Rapid advances in artificial intelligence (AI), including deep learning (DL) and generative AI, have recently enabled the solution of problems that were once unfeasible or entirely out of reach. In recent years, researchers have started applying DL techniques to identify anomalous ionospheric signatures that could signal an impending earthquake. Early studies relied on traditional ML methods, particularly support vector machines (SVM) [39], whereas later work incorporated DL models such as convolutional neural networks (CNNs) [40], [41], [42]. While the application of DL to electromagnetic-based precursors is still relatively limited, recent investigations using DEMETER [43], Swarm [44], GNSS [45], and multi-parameter datasets [46] highlight

its increasing effectiveness. As summarised in the work by Zhang et al., DL architectures have progressed from simple feedforward neural networks to more advanced designs such as CNNs, recurrent neural networks (RNNs), and generative adversarial networks (GANs), exhibiting improved ability to detect critical seismic-related perturbations, although issues related to accuracy and interpretability still remain.

In this study, we examine the presence of ionospheric disturbances by developing a deep-learning framework that identifies anomalous patterns in satellite-derived global ionospheric electric-field measurements and assesses their statistical association with worldwide seismic activity. The approach is fully data-driven and exploratory in nature. We further investigate what constitutes an effective temporal strategy for deep learning models operating in a highly non-stationary background environment. The proposed methodology is designed to be adaptable, enabling integration with other datasets and signatures that contribute to ongoing research on lithosphere–ionosphere coupling and support the development of data-driven techniques for probing potential seismic precursors. The contributions of this study are fourfold. First, we introduce a global, anomaly-first strategy that identifies ionospheric disturbances from global ionosphere electric field measurements independently of any earthquake data, enabling a subsequent statistical assessment of their association with seismic events without imposing an a priori causal link. Second, we propose a rolling-window training scheme that iteratively adapts to changing ionospheric conditions and is validated on a primary period (2005–2009) and an independent blind phase (2010), thereby tackling the issue of generalisability in deep learning for this domain. Third, we carry out a systematic exploratory analysis of spatial and temporal labeling choices without assuming any predefined physical coupling mechanism. Fourth, we assess robustness and sensitivity across multiple model configurations and training strategies.

The following sections of this thesis are organized as follows. Chapter 1 explores the theoretical background relevant to possible associations between seismic occurrences and ionospheric disturbances. Moreover, it offers a brief overview of innovative deep learning techniques used to detect unusual patterns within geophysical and ionospheric timeseries datasets. Chapter 2 is dedicated to explaining the vast literature survey and addressing the research gap and problem addressed in this study. Chapter 3 describes the datasets employed in this research. This chapter also clarifies the data preprocessing steps, such as data cleaning, spatial grid creation, time series generation, background correction, and seismic data labelling. Chapter 4 presents the methodological framework formulated for this study. This chapter specifically describes the deep learning architecture implemented for anomaly detection and the statistical approach adopted to assess the relationship between identified ionospheric anomalies and seismic activity. Chapter 5 reports and interprets the model-based results. Chapter 6 presents an additional exploratory study utilizing ground-based ionosonde observations, expanding the

primary analysis through a multi-instrument approach to investigate potential correlations between disturbances in the lower and upper ionosphere. Finally, the “Conclusion and Future Scope ”, summarizes the main findings and also explains the future aspects of the research.

Chapter 1

State of Art

1.1 Ionosphere as a Medium for Seismic Anomalies

As introduced in the thesis Introduction, the search for reliable earthquake-related precursory signals has motivated extensive investigation of the ionosphere as a possible medium for lithospheric signatures. This section discusses recent advancements in this field, highlighting research that investigates ionospheric disturbances as potential precursors to seismic events, while concentrating on the proposed hypotheses underlying this phenomenon and fundamental electric field perturbations.

1.1.1 Ionosphere

The ionosphere is the ionized region of Earth's upper atmosphere. It is a plasma that is embedded in the neutral atmosphere and shaped mainly by gravity, which causes both systems to have horizontal stratification. The neutral atmosphere gives the structure, which is organized vertically by a typical temperature profile. The ionosphere, on the other hand, is structured by the number density of the plasma. Figure 1 shows typical midlatitude profiles of temperature and plasma density. It shows how the thermal structure of the atmosphere and the layering of the ionosphere are related.

The atmospheric temperature profile has evident regions. The temperature drops from the surface at a rate of about 7 K/km through the troposphere. It then rises through the stratosphere because ozone absorbs ultraviolet radiation, reaches a peak at the stratopause near 50 km, and then drops sharply to a low of 130 – 190 K at the mesopause around 90 km due to radiative cooling. In the thermosphere, which is above this height, the temperature rises considerably because high-energy solar photons are absorbed. The temperature can vary significantly, and is often over 1000 K. The atmosphere is relatively uniform in composition below about 100 km because of to a variety of turbulent mixing phenomena. Above the "turbopause," though, various regions start to separate based on their molecular masses. The ionosphere is made up of separate vertical layers that are based on plasma density. This is shown in the right-hand part of Figure 1.1, which shows two profiles: one that is typical of daytime midlatitude conditions and one that is typical of nighttime conditions. During the day, solar extreme ultraviolet (EUV) radiation passes through the exponentially increasing

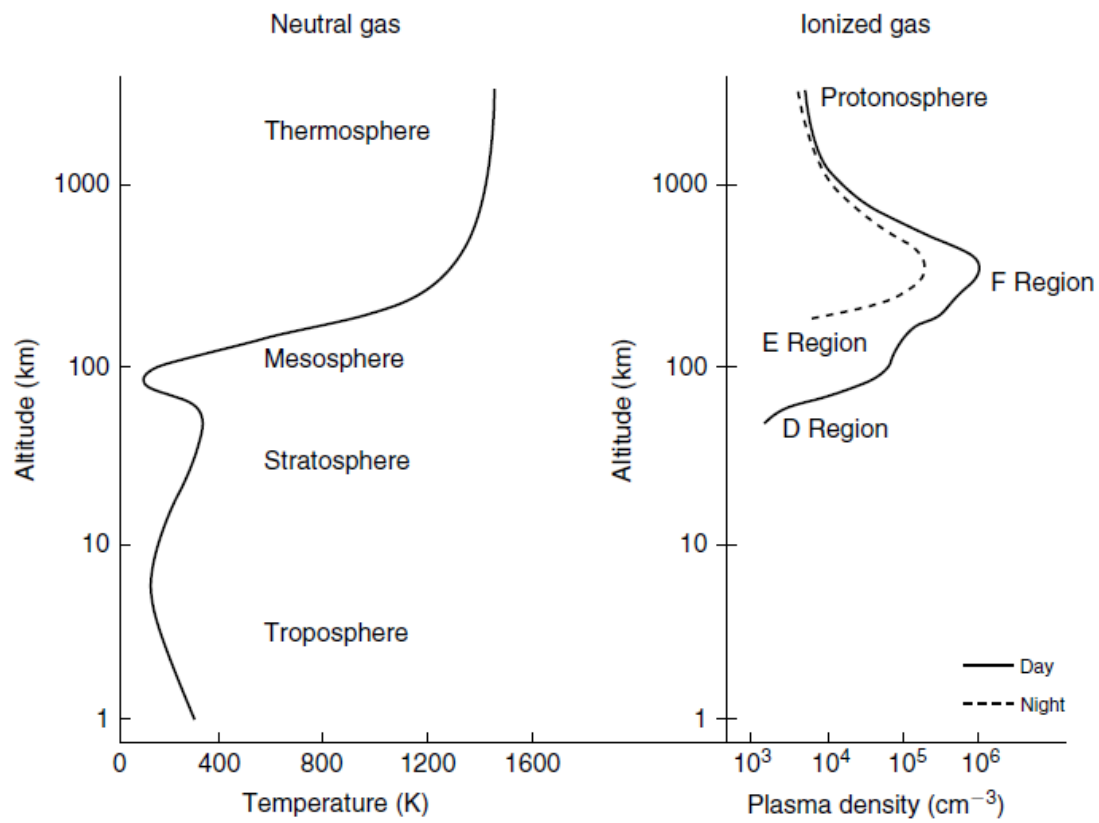


Figure 1.1: Standard profiles of neutral atmospheric temperature and ionospheric plasma density, with the different layers marked. The figure collected from [48]

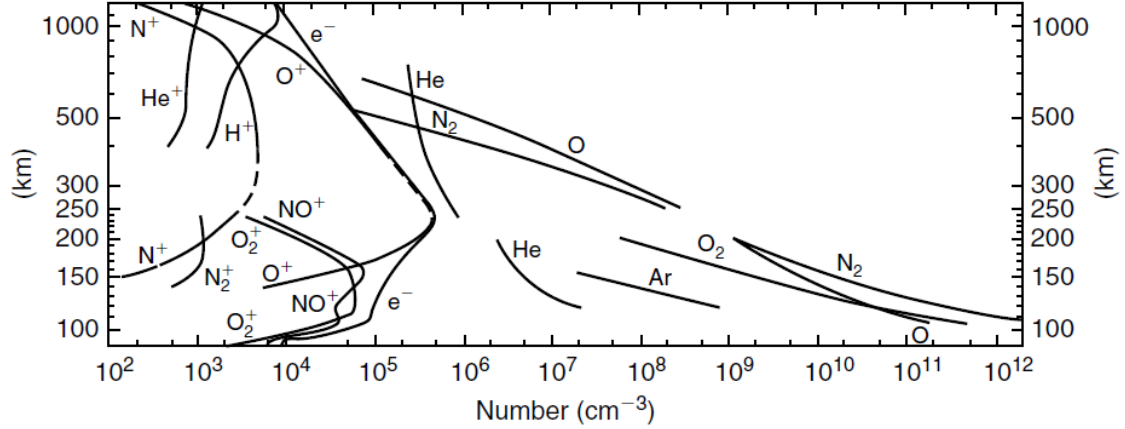


Figure 1.2: Measurements taken by a mass spectrometer over White Sands, New Mexico (32°N, 106°W) during the International Quiet Solar Year (IQSY) show the composition of the atmosphere during the day. The helium distribution comes from observations made at night. The figure collected from [48]. Copyright 1969 by MIT.

neutral atmosphere and is absorbed through photoionization. The basic large-scale vertical layers of ionization are made by the combination of decreasing solar flux with depth, increasing neutral density, and diffusion.

The recombination rate, which is the rate at which ions and electrons combine to make neutral particles, limits this peak density. The recombination rate depends on the types of ions present and how they interact with the neutral gas. The F region is the area between 150 and 500 km above sea level. The F layer has the highest plasma density, which can reach values as high as 10^6 cm^{-3} around noon. The region has an abundance of atomic ions and is the most densely ionized part of the ionosphere. The F region is often split into F_1 and F_2 during the day because of the presence of molecular ions. The E region is the area between 90 and 150 km above sea level. It gets its name from the electric field in radio waves that were first seen in the "Heavyside layer." The D region is where ionization happens below 90 km. Figure 1.2 shows the relationship between neutral and ion composition. It shows experimental data on ion and neutral composition above 100 km. Molecular nitrogen (N_2) and molecular oxygen (O_2) make up most of the neutral composition below and near 100 km. Atomic oxygen (O) levels off at about 120 km, reaching the same level as O_2 . Above about 250 km, atomic oxygen density is higher than both N_2 and O_2 . This trend is caused by solar UV radiation breaking down O_2 molecules, molecular diffusion, and the lack of turbulent mixing above the turbopause. The high amount of atomic oxygen in the neutral composition also appears in the plasma composition. At the peak of plasma density, almost all of the ions are O^+ , which is the same as the high amount of atomic oxygen in the neutral gas. Molecular ions NO^+ and O_2^+ become more important below the peak, and they dominate the plasma below about 150 km. In the E region (90–150

km), molecular ions are the most prominent, and in the F region (150–500 km), atomic O^+ ions are the most common. Above about 600 km, hydrogen ions H^+ become the most common type of ion in a region called the protonosphere. This happens because of charge exchange reactions like $O^+ + H \rightarrow H^+ + O$. Helium ions are quite variable, but at the base of the protonosphere, they form as 50% of all the ions [48].

Looking at the nighttime profile in Figure 1.1, the plasma density near the F peak is lower, but not by nearly as much as the density at lower altitudes. This difference is similar to the change in composition, as shown in Figure 1.2. The density is significantly reduced at night in lower altitude regions where molecular ions are the dominant ion, whereas the O^+ plasma density remains constant throughout the night.

At lower altitudes, the effects of sunrise and sunset are very strong. The F region, on the other hand, stays stable throughout the night. This big difference in how ions behave is because molecular ions recombine with electrons much faster than atomic ions do. The two fast reactions occurring in E-region recombination are dissociative recombination:



At higher altitudes, the dominant process is radiative recombination:



Dissociative recombination happens a lot faster than radiative recombination, which is why molecular ions live for much shorter periods of time than atomic ions. Recombination rapidly diminishes the plasma concentration in the E and D regions when molecular ions' production ceases at night, as they are short-lived. At higher altitudes, however, the O^+ plasma often survive the night at concentrations between 10^4 and 10^5 cm^{-3} . The O^+ ions are actually lost through two-step processes below the F peak. First, charge exchange reactions occur:



followed by the above-mentioned dissociative recombination reactions to finish the recombination process. Also, at night, plasma can flow back into the F region from the plasmasphere, which is a high-altitude region. The long-lived nature of atomic ions also accounts for the many sharp layers of increased plasma density that can be

seen at low altitudes. At this height, meteors drop heavy atomic ions like Fe^+ and Mg^+ that make up these layers. Once they are brought together into sharp layers by plasma transport processes, they stay that way for a long time because they have long recombination lifetimes [48].

Generation of Electric Fields

The different ways that ions and electrons react to the different forces acting on the plasma cause electric fields in the ionosphere. Pressure gradients, gravity, magnetic fields, and neutral atmospheric winds comprise these forces. Ions and electrons don't always move together when these forces act on them because they have different masses and mobilities. It is this discrepancy in motion that generates electric currents within the plasma. The relationship between electric current and charge density is described by the current continuity equation

$$\nabla \cdot \mathbf{J} = -\frac{\partial \rho_c}{\partial t} \quad (1.6)$$

where $\mathbf{J}$ represents the current density and ρ_c is the charge density. If the current has a non-zero divergence, charge begins to accumulate in a region of space. This accumulation of charge produces an electric field according to Poisson's equation

$$\nabla \cdot \mathbf{E} = \frac{\rho_c}{\varepsilon_0} \quad (1.7)$$

where $\mathbf{E}$ is the electric field and ε_0 is the permittivity of free space.

An imbalance in the motion of ions and electrons in the ionosphere can cause the current density to diverge at first. The charge buildup, on the other hand, creates an electric field that quickly changes the plasma's motion so that the current's divergence gets closer to zero. Thus, the electric field works to restore the condition

$$\nabla \cdot \mathbf{J} = 0 \quad (1.8)$$

The charge imbalance required to produce typical ionospheric electric fields is extremely small. For example, an electric field of about 10 mV/m over a spatial scale of 1 km corresponds to a charge density

$$\rho_c = \varepsilon_0 \nabla \cdot \mathbf{E} \quad (1.9)$$

which represents only a few thousand excess charges per cubic meter compared with the total plasma density, which is usually greater than 10^9 m^{-3} . The time required for such an electric field to develop can be estimated using the conductivity relation $\mathbf{J} = \sigma \mathbf{E}$ (Assuming for the moment that σ is uniform and isotropic). Substituting this relation

into the continuity equation leads to the characteristic timescale

$$\tau \approx \frac{\varepsilon_0}{\sigma} \quad (1.10)$$

where σ is the electrical conductivity of the plasma. This timescale around 10^{-6} seconds. This means that electric fields form very quickly when current divergence happens. It is challenging to directly compute the charge density and the consequent electric field from fundamental principles due to the complex forces influencing the ionospheric plasma. Instead, the electric field is usually seen as a variable that changes its magnitude and direction to make sure that the condition $\nabla \cdot \mathbf{J} = 0$ is met.

Numerous mechanisms can generate electric fields in the ionosphere. One important process is the ionospheric dynamo, which moves ionized particles across the Earth's magnetic field using neutral winds. This process is comparable to that of a generator, as it converts the mechanical energy of atmospheric motion into electrical energy. In these situations, the electrical work term works.

$$\mathbf{J} \cdot \mathbf{E} < 0 \quad (1.11)$$

indicating that electrical energy is being produced.

In contrast, electric fields may also originate from external sources, particularly at high latitudes where interactions between the solar wind and the magnetosphere impose electric potentials on the ionosphere. In this situation

$$\mathbf{J} \cdot \mathbf{E} > 0 \quad (1.12)$$

meaning that electrical energy is dissipated within the ionosphere. Joule heating is the process by which this energy is turned into heat. This can have a significant impact on the temperatures and winds in the thermosphere. Strong electric fields can also transfer momentum from ions to neutral particles through ion drag. This makes the ionosphere-magnetosphere system act like an electrodynamic motor.

A property of the ionosphere electric field is that electric fields in the ionosphere can be transmitted over very long distances along the Earth's magnetic field lines due to the extremely high electrical conductivity parallel to the magnetic field. In the ionosphere, The electrical conductivity along the magnetic field direction is much higher than the conductivity that is perpendicular to the field in the ionosphere. This is why the electric potential doesn't change much along magnetic field lines. Consequently, electric fields generated in one area can be "mapped" or transmitted to remote areas of space along the same magnetic field line [48].

As an example, an electric field that forms in the ionosphere at high latitudes can travel along magnetic field lines to the equatorial magnetosphere, which is tens of thousands of kilometers away. Electric fields produced in the solar wind or magnetosphere

can also move down the magnetic field and affect the ionosphere. Measurements taken in the ionosphere and magnetosphere along the same magnetic field line show similar temporal variations in the electric field, although the magnitude changes because magnetic field lines spread out as they extend into space. In addition, the divergence of horizontal currents in the ionosphere can produce field-aligned currents, which flow along magnetic field lines between the ionosphere and the magnetosphere [48].

Magnetosphere-Ionosphere Interaction

So far discussed the basics of the ionosphere, the plasma nature of the ionosphere, and its unique properties have been discussed in this section. Now we need to discuss the interaction of the ionosphere with other layers of the atmosphere. The ionosphere interacts strongly with the magnetosphere, which is the area around Earth where charged particles are controlled by the planet's magnetic field. This creates a protective barrier against the solar wind, which is the primary driver that controls its dynamics. Solar wind-magnetosphere interactions induce a variety of phenomena, such as the generation of energetic particle fluxes, the enhancement of chorus wave activity, and geomagnetic storms [49], [50], [51]. The dynamic conditions of Earth's space environment, which are ultimately caused by solar activity [52], control all of these processes. The strength of these effects is very much affected by how the solar wind interacts with Earth's magnetic field and plasma environment.

The kinetic energy flux that hits the dayside magnetopause is about 10^4 GW. Some of this energy gets into the magnetosphere through reconnection and other processes. Once inside, it is stored, spread out, and eventually dissipated [53]. The energy that comes into the dayside magnetosphere is split up into different paths. A portion of the energy is transferred directly to the high-latitude ionosphere through field-aligned currents, while the remaining portion is transported to the magnetotail for temporary storage in kinetic, thermal plasma, and magnetic field energy. From this tail reservoir, energy is then redistributed through a number of channels: particle injection transmits energy to the ring current, particle precipitation and field-aligned currents send energy to the auroral ionosphere, and some of it re-enters the downstream solar wind without being dissipated in the magnetosphere [53]. The interaction between the magnetosphere and ionosphere is a fundamental and very interesting part of how space near Earth works, but this study doesn't look at this coupling. Instead, we are focusing on the lithosphere-ionosphere coupling, which is still poorly understood and is a very difficult but interesting area of research.

1.1.2 Lithosphere-Ionosphere Coupling

Lithosphere-ionosphere coupling (LIC) refers to the possible transfer of energy, momentum, or electric charge from the solid Earth lithosphere layer to the upper atmosphere and ionosphere, particularly related to tectonic or seismic activity. Observations of ionospheric anomalies date back to investigations following the 1964 Alaska earthquake [54], [55], and since then, ionospheric variations have been increasingly examined as potential earthquake precursors [56]. With the development and understanding of the Global Electric Circuit (GEC), which accounts for the existence of a vertical atmospheric electric field, several studies have suggested that increased atmospheric ionization and changes in conductivity over seismically active areas can alter this vertical electric field, thereby enabling regional atmospheric electrical disturbances to propagate upward into the ionosphere [57], [58], [59], [60], [61]. Over the past several decades, numerous studies have reported perturbations in ionospheric observables hours to several days prior to strong earthquakes (Magnitude ≥ 5). These include variations in electron density, plasma frequency, total electron content (TEC), and electromagnetic emissions in various frequency ranges [7], [10], [12], [20], [25]. With the availability of high-resolution GPS/TEC measurements and satellite-based observations, the number of reported cases has grown substantially [62], [63], [64], [65], [66], [67]. Such observations have motivated the hypothesis that seismic processes in the Earth's lithosphere may cause disturbances that propagate upward through the atmosphere and modify the ionospheric conditions [60], [68], [69], [70]. However, the ionosphere is an intrinsically dynamic and highly variable environment, strongly influenced by solar radiation, geomagnetic activity, and atmospheric waves. This complexity makes it challenging to unambiguously attribute observed ionospheric disturbances to lithospheric sources. As a result, lithosphere-ionosphere coupling remains an open scientific question, requiring careful statistical evaluation and physically consistent interpretation. In this section, the current understanding of lithosphere-ionosphere coupling is reviewed, including the main physical mechanisms proposed in the literature.

Due to the growing interest in understanding the physical mechanism that could possibly connect the lithosphere and ionosphere, a few hypotheses have been proposed based on the primary assumptions. The first one was based on chemical transmission. The hypothesis, grounded in chemical transmission, suggests that radon outflow near the earthquake epicenter (EE) can disrupt atmospheric conductivity, resulting in variations to the atmospheric electric field that subsequently affect the ionospheric plasma density profile [32], [34], [71], [72]. In the second one, the emission of atmospheric acoustic gravity waves (also known as AGWs) is the basis for the theory. More specifically, these oscillations, which are developing around the earthquake epicenter, cause the atmosphere to be perturbed in terms of changes in temperature, pressure, ground

motion, and other components. AGWS can propagate vertically upward, and as a result, they can cause disturbances in the ionosphere [32], [73], [74], [75], [76]. Lastly, there is the phenomenon of electrostatic transmission. The ionospheric ionisation status is altered as a result of "stress-induced positive holes", which are responsible for producing an electrostatic effect in the lithosphere and releasing it in the lower atmosphere [77], [78]. With that being said, there are numerous other aspects of the lithosphere–atmosphere–ionosphere coupling process that cannot be explained at this time. This is due to the fact that there is not enough experimental evidence to support those theories [28], [32], [63], [79]. Combining these concepts, there are two types of proposed models explaining the coupling between the lithosphere and ionosphere. The first one studies the possible coupling mechanism among the lithosphere, atmosphere, and ionosphere, also known as lithosphere–atmosphere–ionosphere coupling (LAIC). In the early version of this model, three major possible channels, the chemical (or electric field) channel, the acoustic gravity wave (AGW) channel, and the electromagnetic (EM) channel, were proposed by Hayakawa. Later, with radon emission as the fundamental source of lithosphere coupling, Pulinetz and Ouzounov proposed a more unified LAIC model [34].

Lithosphere–Atmosphere–Ionosphere Coupling (LAIC)

Of the many short-term earthquake precursors, radon is still the most controversial and is the subject of ongoing academic debate. A significant body of thoroughly documented research presents evidence correlating pre-seismic radon emanation with the earthquake preparation process [81]. Conversely, strict statistical analyses have questioned its reliability, with certain studies determining that radon cannot be substantiated as a reliable precursor [82]. Even with this, the links between radon anomalies and other things, like atmospheric conductivity, cloud formation, surface thermal anomalies, and ionospheric perturbations, have led to a more thorough study of radon's role in lithosphere-atmosphere coupling [83], [84], [85], [86], [87]. A significant advancement has been the discovery of a causal relationship between radon-induced air ionization and the production of surface thermal anomalies. This relationship overcomes the constraints of single-point measurements by facilitating the application of satellite-based thermal imaging to identify radon activity throughout the entire earthquake preparation zone [88]. The well-documented rise in radon emissions preceding significant events, such as the 1995 Kobe earthquake [89], reinforces this correlation.

Thermal Anomalies

In the LAIC mode, the authors state that thermal anomalies, as one of the pre-earthquake anomalies, can be initiated by radon release along active tectonic faults.

The process initiates when stress builds up in the Earth's crust before an earthquake, leading to increased radon emission along active tectonic faults. Radon, upon release into the near-surface atmosphere, undergoes radioactive decay through the emission of alpha particles. High-energy particles collide with air molecules, removing electrons and generating a substantial concentration of ions in the lower atmosphere. This ionization process fundamentally modifies the physical state of the boundary layer. The newly created ions act as efficient nucleation sites for the condensation of water vapor, a process referred to as ion hydration [90]. Under typical atmospheric conditions, water vapor necessitates the presence of surfaces like aerosols for condensation; the ions generated by radon decay serve this purpose even in unsaturated air. When water molecules attach to these ions and condense, they emit latent heat—the identical energy released during cloud formation. The release of latent heat results in a localised temperature rise at the surface, producing the thermal infrared anomalies detected along fault systems. This mechanism is energetically efficient: the energy stored in water vapor, initially obtained from solar heating, is released on a large scale, generating thermal fluxes. The emission of latent heat elevates the ambient air temperature, decreases relative humidity, and induces convective flux upward. As the ion-hydrated clusters rise, they continue to accumulate water molecules, evolving into micron-sized aerosol particles that further augment condensation and heat release at elevated altitudes. This convective transport affects the vertical profile of atmospheric conductivity and generates atmospheric gravity waves that rise. Upon reaching the ionosphere, these disturbances disrupt the surrounding plasma via two principal mechanisms: the altered electric fields from the affected global circuit extend to ionospheric altitudes, while the rising gravity waves transport energy and momentum, resulting in the redistribution of charged particles. The outcome is observable variability in total electron content and plasma density, ionospheric precursors that conclude the coupling sequence initiated by radon emissions from the upcoming earthquake.

Atmospheric Electricity Variations

Another observable anomaly related to seismic event preparation from the atmosphere induced by the random emission as per the LAIC model, is atmospheric electricity variations. The Global Electric Circuit (GEC) is the system of quasi-stationary currents that flows between the positively charged ionosphere and the negatively charged ground. It is mostly driven by global thunderstorm activity [91]. In areas with pleasant conditions, a downward vertical current closes this circuit. The return current density is determined by the atmospheric columnar resistance between the surface and the lower ionosphere, which is about 60 km above the ground. The planetary boundary layer, which is the lowest 2 km of the atmosphere, makes up about 50% of the total

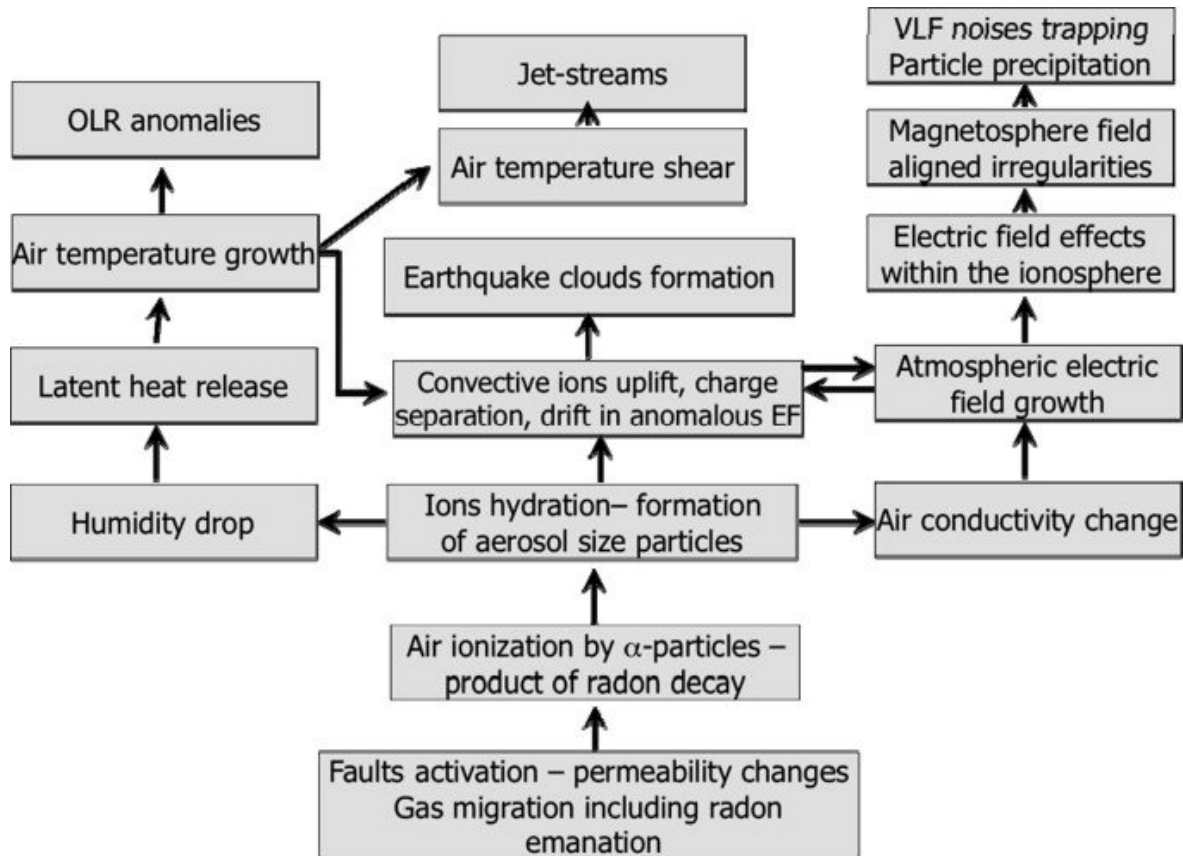


Figure 1.3: Illustrative representation of the Lithosphere-Atmosphere-Ionosphere-Coupling (LAIC) model proposed by Pulinets and Ouzounov, where lithospheric activity triggers radon emission, leading to atmospheric ionization, thermal and electrical changes, and ultimately propagating disturbances into the ionosphere through multiple interconnected channels. Image collected from Pulinets and Ouzounov.

columnar resistance. The first 13 km makes up about 95% of the total columnar resistance [92]. This means that the boundary layer is the main place to control how electric current flows between the ground and the ionosphere. When radon emissions rise before an earthquake, the ionization of air molecules that follows causes the ion concentration to rise at first [93]. As mentioned in the last section, they quickly hydrate by attaching to water vapor molecules and grow into large cluster ions [90]. This growth makes ions much less mobile. Even though the concentration of ions may increase, the effective air conductivity goes down a lot because conductivity depends on both the concentration and mobility of charge carriers. Aerosol-sized ions like these can reduce local air conductivity by hundreds of percent [92]. This drop in conductivity raises the local columnar resistance in the area where the earthquake preparation is taking place, which usually covers several degrees of latitude and longitude, as shown in thermal anomaly images. In the GEC's equivalent electrical circuit, this localized rise in resistance causes the local ionospheric potential to rise relative to the surrounding areas [94]. The ionosphere tries to stay at the same potential as the global mean by moving plasma horizontally through drift processes. Charged particles move from the undisturbed surrounding ionosphere into the area of higher potential to make up for the difference [28]. This redistribution shows up as changes in the concentration of electrons in both the E and F layers and as changes in the total amount of electrons [95]. Two secondary mechanisms help change the electricity. First, the convective motion caused by the release of latent heat from ion hydration makes it possible for electric charges to separate. In the updraft, positive and negative ions move differently, which acts as a convective electric generator and creates an extra electric field in the disturbed volume [96]. Second, charge stratification happens when cluster ions get big enough to make layers of haze or volumetric charge near the surface. The bottom of the layer has a negative charge, and the top has a positive charge. From the ionosphere's point of view, this looks like a positive surface charge, which changes the direction of the natural electric field in the atmosphere over the area that is affected. The three effects that work together to link the radon-induced ionization in the planetary boundary layer to observable changes in the overlying ionosphere are increased columnar resistance modulating ionospheric potential, convective charge separation creating internal fields, and volumetric charge layers changing the boundary condition.

Earthquake Cloud Formation

The LAIC model demonstrates that linear cloud formations, frequently referred to as earthquake clouds, arise from a synthesis of radon-induced ionisation and electrodynamic transport governed by the direction of the anomalous electric field. The model proposes that radon emitted from active tectonic faults ionises the air, and these ions

are conveyed to higher atmospheric layers, where they serve as condensation nuclei for cloud formation [97]. As per the LAIC model, the anomalous electric field generated over the active seismic zone may have positive (directed down) or negative (directed up) directions. The decisive factor influencing cloud formation or dissipation is the direction of the anomalous electric field produced over the seismic zone. When the field reverses direction (pointing upward), positive ions are conveyed into the troposphere, facilitating cloud formation and generating linear structures along fault lines. Conversely, when the field retains its inherent downward orientation, negative ions ascend, recombining with naturally occurring positive ions, resulting in cloud translucence—the clearing of existing cloud cover along tectonic boundaries [98], [99]. The LAIC model integrates cloud formation and dissipation as complementary pre-seismic atmospheric indicators, both caused by radon emission but exhibiting distinct characteristics based on the polarity of the anomalous electric field.

Long Wave Radiation Precursors

The LAIC model discusses that anomalies in outgoing longwave radiation (OLR) incorporate the cumulative thermal effects produced by the earthquake preparation process, extending from the ground surface to the tropopause [100]. These anomalies arise from the sequence of processes outlined: radon-induced ionization results in latent heat release through ion hydration, subsequently heating the lower atmosphere. This thermal energy ascends, and upon reaching the upper atmosphere at an altitude of 10–12 km, it appears as increased infrared emission within the 10–13 μm band, observable by satellites. The duration of these fluctuations generally spans several days to one week prior to the seismic occurrence. The LAIC model also considers the development of anomalous jet streams directed at the forthcoming earthquake epicenter. Rapid, narrow air currents at tropopause altitudes emerge due to the continuous OLR spot, which induces a localized vertical temperature gradient, subsequently producing a horizontal pressure differential [101]. Under typical meteorological conditions, jet streams demonstrate consistent structure and continuity; however, the anomalous jet stream observed prior to earthquakes exhibits distinct behavior: its leading edge remains stationary over the epicentral region for several hours, suggesting that the incoming air mass is diverted vertically into the atmospheric anomaly system generated by the earthquake preparation process, rather than proceeding horizontally. Within the LAIC framework, OLR anomalies and anomalous jet streams are considered as interconnected representations of the same fundamental process—the thermal and dynamic response of the atmosphere to radon-induced ionization and latent heat release in seismically active regions.

Ionosphere-Magnetosphere Fluctuations

The LAIC model discusses that ionospheric fluctuations linked to seismic events result from changes in the global electric circuit due to radon-induced phenomena in the planetary boundary layer, with these effects propagating into the magnetosphere via coupling along geomagnetic field lines [28]. The anomalous electric field produced over the seismic zone alters the ionospheric plasma, and this disturbance is transmitted to the magnetically conjugate region in the opposite hemisphere due to the nearly infinite electrical conductivity along geomagnetic field lines, enabling the electric field to map across hemispheres [102]. This association clarifies the increased intensity of VLF noises detected within the modified magnetospheric tube: extensive irregularities in the ionospheric F-region generate field-aligned irregularities within the magnetospheric tube linked to the affected area, which scatter VLF waves of any origin, limiting them within the tube [103]. The increased VLF emission subsequently elevates the probability of energetic electron precipitation via cyclotron resonance interaction, resulting in anomalous particle fluxes detectable by satellites hours prior to significant earthquakes [34]. The LAIC model notably incorporates the bipolar nature of ionospheric precursors, where anomalies may be either positive or negative in relation to the undisturbed state. This duality originates from the orientation of the anomalous electric field at the ground surface and the associated variations in column air conductivity. During the initial phase of enhanced radon exhalation, air conductivity may rise; however, as ions hydrate and form larger cluster ions, conductivity significantly decreases [94]. An elevation in column air conductivity results in negative electron concentration anomalies in the ionosphere, whereas a reduction in conductivity yields positive anomalies. This mechanism explains observations prior to the Wenchuan earthquake, wherein total electron content deviations transitioned between polarities in the days leading up to the event, with the equatorial anomaly reflecting the overall earthquake preparation process and exhibiting variations at magnetically conjugate points on either side of the magnetic equator [94]. Within the LAIC framework, seismo-ionospheric variations and their magnetospheric extensions are considered as a natural result of radon-induced conductivity variations that modulate the global electric circuit, allowing upward coupling through the ionosphere and along geomagnetic field lines. Figure 1.3 illustrates the representation of the LAIC model proposed. This represents the multiple-channel connection started with the emission of radon gas.

Although many study outcomes aligned with the proposed hypothesis, the absence of experimental evidence regarding the coupling based on radon remains unpopular by the scientific community; researchers continue to seek further validation.

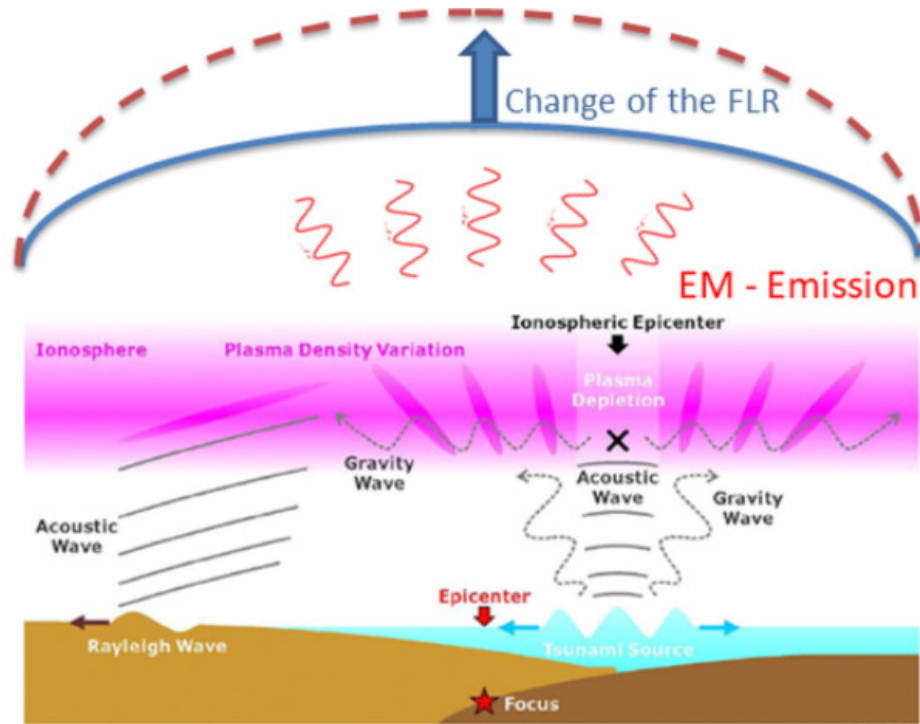


Figure 1.4: The illustration of lithosphere-ionosphere coupling process explained by the MILC model. The figure adapted from the study by Piersanti et al.

Magnetosphere-Ionosphere-Lithosphere coupling (MILC)

Another major channel of the coupling process is Acoustic Gravity Waves (AGW). Numerous studies have provided evidence that atmospheric gravity waves (AGWs) may link the lithosphere to the ionosphere prior to earthquakes. Researchers utilizing VLF/ELF radio signals to investigate the lower ionosphere have detected anomalies preceding and during seismic occurrences, supporting this hypothesis [16], [73], [104], [105]. However, these studies only investigate the ionosphere and fail to explain the coupling between the lithosphere and atmosphere. Korepanov et al. examined surface pressure and magnetic field data to further explore this connection and came to the conclusion that AGWs are a likely coupling mechanism. Nakamura et al. examined the 2004 Niigata-Chuetsu earthquake and discovered that pressure and magnetic fluctuations in the AGW range correlated with ionospheric disturbances. Endo et al. noted that ground motions in the AGW frequency intensified prior to two Japanese earthquakes coinciding with ionospheric disturbances. GPS data from the 2011 Tohoku earthquake demonstrated a direct temporal correlation between crustal motion and variations in VLF/ELF and ultra-low frequency magnetic fields [108], [109], [110], [111]. Collectively, these studies provide increasing evidence that AGWs function as a channel linking the lithosphere, atmosphere, and ionosphere prior to seismic occurrences.

Bringing the evidence together, Piersanti et al. proposed a new hypothesis based

on AGW, termed the Magnetosphere-ionosphere-Lithosphere coupling (MILC) model. The authors explained the MILC model as follows. An AGW is produced around the earthquake epicenter, propagating through the atmosphere. The AGW mechanically interacts with the ionosphere, inducing a localized instability in the plasma distribution via a pressure gradient. This plasma variation induced a "meta-stable" condition in the ionosphere, resulting in a local non-stationary electric current in the E-layer. This subsequently produces an electromagnetic (EM) wave. The interaction of these electromagnetic waves with the magnetospheric field results in a modification of the eigenfrequency of the field line, whose ionospheric footprint is situated above the radial projection of the earthquake epicentre. This image is verified by the following mathematical descriptions. Starting with the fundamental equations of compressible, inviscid flow under a gravity field, in the absence of external forcing. These equations show how mass, momentum, and hydrostatic equilibrium are conserved in a stratified atmosphere. They can be written as

$$\begin{cases} \frac{\partial \rho}{\partial t} + \nabla \cdot (\rho \vec{v}) = 0 \\ \rho \left[\frac{\partial \vec{v}}{\partial t} + (\vec{v} \cdot \nabla) \vec{v} \right] + \nabla p = 0 \\ \nabla p_0 = \rho_0 \vec{g} \\ \rho_0 c_s^2 = \gamma p_0 \end{cases} \quad (1.13)$$

where ρ , p , and $\vec{v}$ represent the atmospheric density, pressure, and velocity, respectively. The parameter c_s denotes the sound speed in the medium, while γ is the adiabatic index.

Using these relations, the propagation of atmospheric gravity waves (AGWs) in a stratified and non-isothermal atmosphere can be derived. Considering an unsteady pressure perturbation p' and assuming adiabatic conditions within a moving reference frame, the equation for the pressure disturbance becomes

$$\frac{\partial^2 p'}{\partial t^2} - c_s^2 \nabla^2 p' + A \cdot p' = 0, \quad (1.14)$$

where

$$A = \frac{\gamma g^2}{c_s}. \quad (1.15)$$

The answer to this equation is a mechanical wave, which is often called a Lamb wave [112], [113]. The dispersion characteristics of this wave are mainly determined by the phase velocity of the surface waves related to the earthquake, represented as v_s . The altitude at which the disturbance is generated and a few seismic parameters, such as the phase velocity of the surface waves ω_s , the peak ground acceleration (PGA), and the strong motion duration of the earthquake, all influence the amplitude of the atmospheric perturbation.

In this context, the pressure gradient produced by an earthquake, represented as $\nabla p'$, serves as an external forcing term in the magnetohydrodynamic (MHD) equations that govern the ionospheric plasma. Taking into account a simplified ionospheric model situated at an altitude of roughly 100 km, where the plasma density diminishes with altitude as z^{-2} , the pressure perturbation can cause fluctuations in the ionospheric plasma density and electric field [114]. When you solve the MHD system for the electric field perturbation $\vec{E}$, you get an electromagnetic wave that travels from the topside ionosphere, usually in the frequency range of 10–700 Hz [114]. At low latitudes ($0^\circ \leq \lambda \leq 30^\circ$), the interaction of electromagnetic wave energy and plasma density fluctuations can alter the eigenfrequency of the local field line resonance (FLR). The resonance frequency of a geomagnetic field line is dependent upon the length of the field line and the distribution of plasma mass density along it [115], [116], [117]. Using the time-of-flight approximation, you can get a first-order estimate of the FLR eigenfrequency f [118].

$$\frac{1}{f} = 2 \int_s \frac{ds}{V_A} \quad (1.16)$$

where V_A is the Alfvén velocity along the magnetic field line and is given by

$$V_A = \frac{B(s)}{\sqrt{\mu_0 \rho(r)}} \quad (1.17)$$

with $B(s)$ showing how strong the magnetic field is along the field line, $\rho(r)$ showing how dense the plasma mass is at geocentric distance r , and μ_0 the magnetic permeability of free space. Changes in the plasma density or the effective field line length can cause the FLR frequency to change. In the MILC framework, these variations are understood as the ionospheric response to the pressure gradients linked to atmospheric gravity waves produced by seismic activity. The entire process by which AGW-based seismic signatures propagate from the lithosphere into the magnetosphere is depicted in the figure 1.4.

In the paper, the authors have verified the theory on the basis of Bayan earthquake; at the same time based on that analysis the authors also stress the shortcomings of this hypothesis. First, the direct link between detected AGWs and seismic activity is not simple. This is because weather systems, synoptic-scale atmospheric circulations, and convective activities around cold fronts can also cause AGWs, especially at middle and low latitudes where earthquakes happen more often. It is also important to be able to tell the difference between changes in ionospheric plasma density caused by internal (seismic) and external (solar) sources. This is because solar activity usually causes vTEC and plasma density irregularities. Third the pre-seismic AGW needs a lot of thought to explain. The authors put forward two hypotheses: either the elevated seismic activity of the Lombok 2018 sequence (four Mw > 6.3 earthquakes within one

month) or the emission of charged gases (e.g., radon) from the Earth's surface. Both are considered credible; however, the absence of local surface gas emission data leads to the denial of the second hypothesis, and the lack of VLF signals, in addition to evident ELF band detection, leaves some questions open for future investigation.

1.1.3 Electric Field Signatures Related to Seismic Events

The investigation of electric field perturbations as possible precursors to seismic events has been a focus of thorough studies for the last twenty years. Numerous studies employing ground-based and satellite measurements have recorded anomalous electric field variations preceding significant earthquakes, offering observational evidence for lithosphere-atmosphere-ionosphere coupling mechanisms. This section looks at important studies that have helped us discover more about seismic-induced ionosphere electric field perturbations phenomena.

Smirnov performed a statistical analysis of the correlation between atmospheric quasi-static electric field variations and seismic activity in the Kamchatka region, utilizing ground-based measurements of the vertical component (E_z) from a network of observation stations. The study examined data from January 1, 1997, to December 31, 2002, identifying 103 instances of anomalous bay-like decreases in the E_z component and documenting 409 earthquakes in the region during this 2,189-day timeframe. The statistical analysis indicated that the most likely bay duration was between 40 and 60 minutes, with a secondary maximum lasting about 160 minutes. The most likely decreases in electric field strength were between minus 100-300 V/m. It was important to note that there was no correlation between either bay duration or field strength decrease and earthquake class or distance to epicenter. This means that the properties of the electric field anomalies do not change with earthquake parameters. The study found that there is a 36% chance that an earthquake will happen 1 to 24 hours after an electric field anomaly. This is a statistical improvement by a factor of 1.9 compared to random expectation (37 observed cases versus 19 expected randomly). This research provides quantitative evidence for pre-seismic perturbations in the atmospheric electric field [119].

Korsunova et al. examined simultaneous measurements of ionospheric parameters and the vertical component of the near-surface atmospheric electric field (E_z) in Kamchatka from 1998 to 2002 for potential coupled earthquake precursors. The research identified cases of unusually elevated sporadic E layer (E_s) activity occurring simultaneously with unusual negative bays in E_z , both occurring more than five days prior to earthquakes with magnitudes ranging from 5.0 to 6.2. We found empirical relationships between the precursor prediction time, the size of the earthquake, and the

distance from the epicenter. These relationships were very similar to those that had already been found for long-term geophysical precursors in the same area. The authors concluded that actual earthquake precursors appear almost simultaneously in both the sporadic E layer and the near-surface electric field when measurements are colocated, and atmospheric electric field anomalies in Kamchatka serve as the earliest indicators of potential seismic hazard, providing significant lead time for short-term forecasting applications [120].

Akhoondzadeh examined ULF electric and magnetic field data from the DEMETER satellite to explore potential seismo-ionospheric anomalies linked to the Mw = 8.1 Samoa earthquake that occurred on 29 September 2009. The research employed electric field measurements from the ICE (Instrument Champ Electrique) experiment and magnetic field data from the satellite's magnetometer, spanning the timeframe from August 1, 2009, to October 11, 2009 (58 days preceding to 11 days following the earthquake). There were distinct shifts in the ULF magnetic components (Bx, By, and Bz) 1 and 3 days before the event. The polarization index calculated from magnetic components showed a clear rise on the same days during both the 10:30 LT and 22:30 LT overpasses. These disturbances were confirmed by simultaneous fluctuations observed in the ULF electric components (Ex, Ey, and Ez) within the geomagnetic coordinate system. The results show that the strongest pre-earthquake anomalies happened 1 to 3 days before the earthquake, complementing the early studies' findings. The author concludes that these results are promising for short-term prediction using ULF magnetic and electric measurements, though further investigation is required to develop accurate regional models discriminating seismic precursors from normal variations [121].

An important review on the ionosphere precursor of earthquake, following the thorough examination of multiple case studies and statistical studies using observations from satellite and ground-based measurements were carried out by Le et al. The authors stated that electric field perturbations are regarded as one of the most significant factors in establishing pre-earthquake ionospheric anomalies. Xu et al. used data from five low-latitude ionosondes before the 2008 Wenchuan Earthquake (Mw=7.9) and found a two-dimensional distribution of the anomalous electric field on May 9, 2008. They found that the F2-region near the epicenter had an unusual increase in the electric field, with a peak value of about 2 mV/m, which is about 10 times the background level, supporting the electric field hypothesis. Following the findings from Klimenko et al., which subsequently employed numerical experiments to imitate the observed variations in Total Electron Content (TEC), concluded that a seismogenic vertical electric field may serve as the primary mechanism for the positive disturbances observed prior to this major mid-latitude earthquake. The review further stated that major changes in the electric field, geomagnetic field, and electron density were found on the day before the Mw8.8 Chile earthquake, using data from the DEMETER satellite [124].

The review concluded the findings from multiple studies conducting statistical analyses showing the regularity of electric field perturbations prior to significant earthquakes. Zhang et al. examined ULF/ELF electric field perturbations captured by the DEMETER satellite prior to 45 earthquakes in Chile with magnitudes ≥ 6.0 , discovering that two-thirds of these occurrences displayed significant ULF/ELF electric field perturbations. Zhang et al. found electrostatic disturbances at ULF and ELF bands before 32 of the 69 strong earthquakes that happened between January 2005 and February 2010. Zhang et al. examined ULF electric field data from the DEMETER satellite for 27 earthquakes in Indonesia and Chile and found that the perturbations ranged from 1.5 to 16 mV/m in the upper ionosphere and were mostly located right over the epicenter area. The authors pointed out that even though satellites can detect quasistatic electric field variations caused by earthquakes, the electric field alone can't fully explain changes in ionospheric plasma. They also said that the model for how an electrostatic field moves from the lithosphere to the ionosphere needs more research. The review concluded that diverse models of the lithosphere-atmosphere-ionosphere coupling system exhibit the shared characteristic that perturbations in the ionospheric electric field constitute the primary cause of pre-earthquake ionospheric anomalies, though with varying mechanisms suggested for the emergence of these disturbances, and proposed the need to validate these models and enhance understanding of earthquake preparation processes with additional direct observations and simultaneous measurements at various altitudes [56].

Potirakis et al. examined the preparatory processes of two major earthquakes in Cephalonia, Greece: the $M_w = 6.0$ event on January 26, 2014, and the $M_w = 5.9$ event on February 3, 2014. The research utilized the method of critical fluctuations (MCF) and natural time (NT) analysis to investigate fracture-induced MHz electromagnetic emissions (EMEs) captured by two telemetric stations situated on Cephalonia and the adjacent island of Zante, in proximity to the epicenters. The analysis showed that the pre-seismic EMEs had signs of critical dynamics in them. Both stations attained a critical state at the same time, a few days before each earthquake. NT analysis confirmed the critical characteristics and showed that the foreshock seismic activity showed critical behavior before both events. The study observed that VLF seismic-ionospheric disturbances documented four days prior to the initial earthquake [129] happened within the same temporal framework as the MHz critical signals, offering supplementary evidence of pre-seismic activity [128]. Following the same methodology, the authors examined critical dynamics in three categories of earthquake-related electromagnetic signals: MHz fracto-electromagnetic emissions (fracto-EME), ultra-low frequency (ULF) magnetic field variations (< 3 Hz), and subionospheric very low frequency (VLF) propagation anomalies. Signatures indicating a transition from a critical state (highly symmetrical) to low symmetry were identified in particular instances

of MHz fracto-EME and ULF variations. The research examined a four-stage model of earthquake dynamics, suggesting that these precursors arise during the spatially extensive initial stage of earthquake preparation and signify complementary expressions of the same generation process as foreshock seismicity [130].

Using CSES-01 satellite data from 2019 to 2021, Recchiuti et al. came up with an approach to find electromagnetic anomalies that are related to earthquakes. The technique used Fast Iterative Filtering (FIF) to make background energy maps in $6^\circ \times 6^\circ$ cells centered on epicenters. Testing on the 14 August 2021 Haitian earthquake (7.2 Mw) showed a clear electric field anomaly at 250 ± 70 Hz that appeared six hours before the event. There was also a perpendicular magnetic anomaly at 190 ± 60 Hz, which showed an electromagnetic wave that fit with the MILC model. The Cretan earthquake on September 27, 2021 (6.0 Mw) happened during a storm, so there were no unusual signs because solar forcing was so strong. The research signifies an important methodological development in identifying earthquake-induced electromagnetic perturbations from inherent ionospheric variability [131].

Most recently, the review carried out by Pulinets and Herrera gives a detailed study of earthquake precursor phenomena from a physical standpoint, integrating decades of research on the lithosphere–atmosphere–ionosphere–magnetosphere coupling system. The authors stressed that understanding the physics of precursor generation is crucial to developing trustworthy short-term earthquake forecasting abilities, criticizing the 1997 seismological consensus that believed short-term forecasting as unattainable [133]. The review follows the Lithosphere-Atmosphere-Ionosphere Coupling (LAIC) model, which says that radon released from active faults ionizes the air and starts a chain reaction of geophysical processes. This ionization changes how well air conducts electricity near the ground and creates more vertical electric fields. These fields can even change direction, with negative bay-like variations. These changes cause major modifications in the ionospheric F-layer (both positive and negative), add more sporadic E-layers at about 120 km above sea level, and change the concentration of electrons in the D-layer, which affects how VLF waves travel. The research defined two theoretical frameworks for modeling ionospheric effects: the generation of near-ground electric field by ionization processes and penetration of this field in the ionosphere, and ionospheric potential variations resulting from alterations in air conductivity for low latitudes. The review also noted some current problems, such as the fact that ion dynamics in the atmospheric boundary layer are not fully modeled and that proposed mechanisms need more experimental validation [132].

In general, there are only a few studies investigating electric field perturbations associated with seismic events when compared to other observables. The available studies have demonstrated some perturbative nature in low-frequency electric field observations from ground- and space-based data, both supporting and contradicting the proposed

hypotheses. However, it must be noted that most studies have been considered as preliminary analytical steps and consistently reference the need for detailed future investigations to confirm these coupling processes, particularly during the preparatory phase of earthquakes. Based on the understanding derived from this review, most studies have followed the standard approach of localized ionosphere-atmosphere search and evaluation, where we miss the global nature of the phenomenon. No study has yet provided a common signature, making it difficult to produce reproducible results. This necessitates the application of widely available global ionospheric information to develop a generalisable understanding of the phenomenon, for which deep learning approaches would be the most suitable methodology, considering the availability of multiple satellite-based global ionosphere observations.

1.2 Deep Learning Approaches for Time-Series Analysis

The development of deep learning in artificial intelligence has improved various tasks, such as image classification and language learning [134], [135], [136], [137]. Recent decades have witnessed significant advancements in AI methodologies, which have been applied across various domains of seismology, including earthquake detection [138], [139], earthquake magnitude prediction [140], classification of seismic signal acceleration [141], the detection and the study of seismo-ionospheric precursors [40], [46], [142], [143]. Their thorough examination, which employed a wide range of methodologies, confirms the possibility of anomalies in ionospheric and atmospheric parameters both prior to and subsequent to the earthquake event, thereby supporting the existing ionosphere-lithosphere coupling hypothesis. Despite the fact that this study employs a diverse set of methods, the model's ability to capture dynamic patterns over time may be restricted by its lack of temporal sequence processing. This is because, when dealing with sequential data like time series, the normal architecture is insufficient to understand the complex temporal relationship within the data.

1.2.1 Recurrent Neural Networks

Recurrent neural networks (RNNs) are a revolutionary architecture that has been developed for capturing such complex relations in sequential data [144], [145]. This model was introduced with the concept of improving the time dependencies or sequential relationships in the data by preserving the past information through hidden nodes [136], [146]. A basic way to describe a hidden node is as follows: if an input neuron receives signals from the environment and an output neuron sends signals back to the environ-

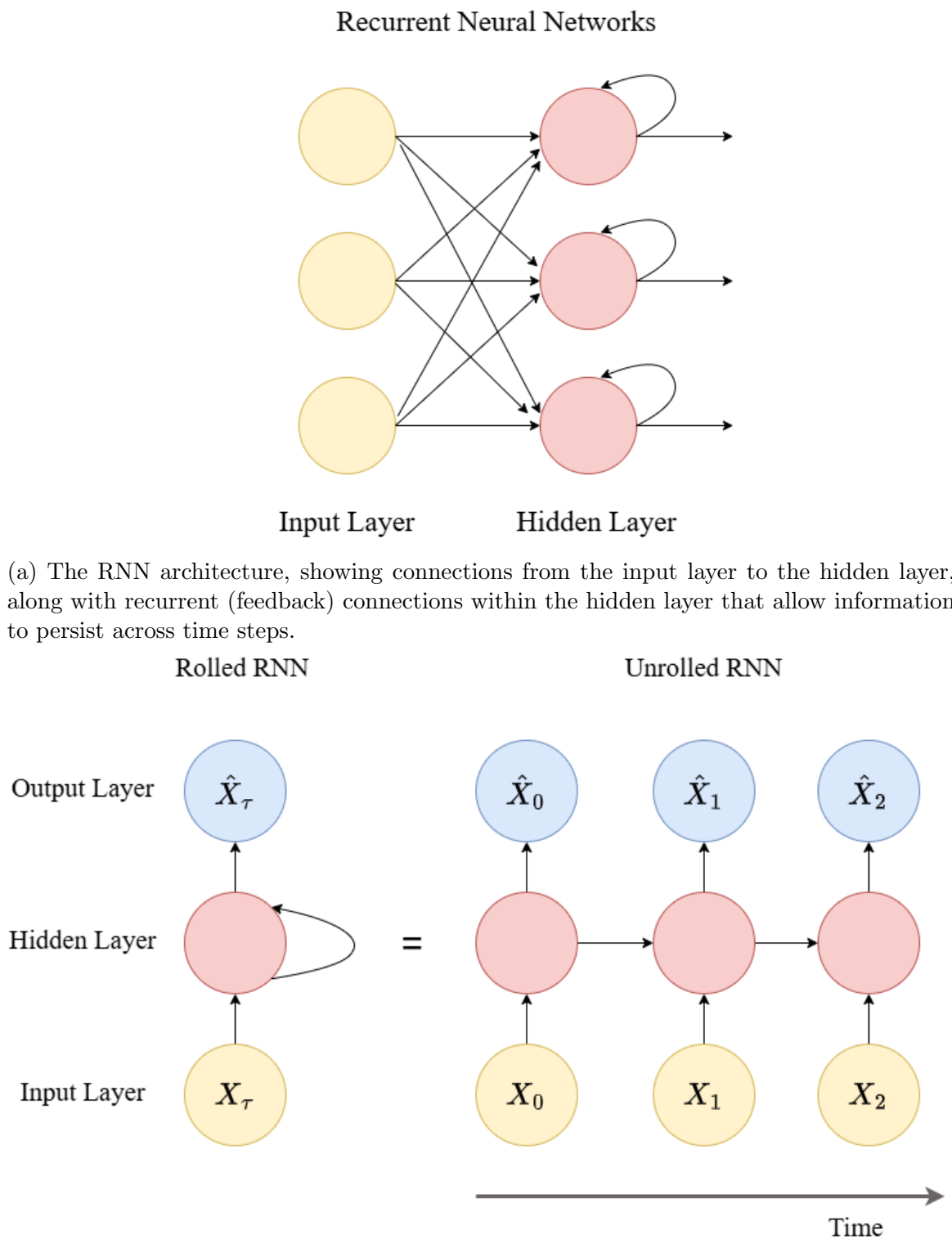


Figure 1.5: The Recurrent Neural Network (RNN) architecture

ment, then any neuron that does not have a direct connection to the environment, but instead connects only to other neurons, is called a hidden neuron. The basic structure of this RNN architecture is shown in the figure 1.5, where figure 1.5a shows the structural representations of the RNN and figure 1.5b represents the temporally unrolled version of the RNN. During training, neural networks with hidden layers learn how to represent the internal state of the input data, which enables the network to generate an output appropriate to the input. In the given architecture, every hidden neuron has its own feedback connection. This keeps track of the previous internal state and will let the model process the current signal along with the information from the earlier timestamp. Meaning, the network will retain past information while processing the new input data. Recurrent neural networks share the same weight parameter across each layer of the network and these weights are still adjusted through Back Propagation Through Time (BPTT) and gradient descent, which allows reinforcement learning. In BPTT, the error signal is propagated backward across multiple time steps. This algorithm takes advantage of the fact that there will be a feedforward neural network with identical behaviour for every RNN over a finite period of time. Backpropagation Through Time trains recurrent neural networks by expanding them over the time dimension, performing forward passes to obtain output, measuring prediction errors, and then propagating those errors backward along the sequence. The gradients computed at each time step are combined to update the shared weights, allowing the network to capture and learn temporal dependencies in sequential data. A more detailed explanation is provided by the authors Staudemeyer and Morris, Werbos, Williams and Zipser, Rumelhart et al. (The mathematical derivation is explained in Appendix B).

Even though the goal was to capture long-term dependencies, this process appears difficult because of the vanishing or exploding gradient problem [151], [152], [153]. As per BPTT, the error signal itself is computed recursively during backpropagation. This relation indicates that the error at time t depends on the error at the subsequent time step $t+1$. Consider a fully recurrent neural network. During Backpropagation Through Time, this error signal is propagated backward through the network over multiple preceding time steps. Specifically, the error generated at time t is backpropagated for $t - t'$ time steps until it reaches an earlier neuron at time t' , where $t' < t$. As this error moves backward through the network, its magnitude is scaled by the activation derivatives and the connection weights along the way. The backpropagated error is expressed as a product of activation derivatives and connection weights over all time steps between t' and t . Thus, when the error is propagated backward through many time steps, the gradient becomes a product of multiple factors involving the activation derivatives and the corresponding weights. This ultimately gives rise to two possible scenarios. When the magnitude of the product exceeds one over several time steps, the product grows exponentially. In this case, the gradient becomes extremely large, causing unstable

learning behavior and strong oscillations in the weight values. This effect is known as the exploding gradient problem [147], [154]. The other scenario is that as the error is propagated backward through longer time steps, the gradient gradually reduces toward zero. When this happens, earlier neurons of the network receive almost no learning signal, affecting the network's ability to learn long-term dependencies in sequential data. This phenomenon is referred to as the vanishing gradient problem [147], [154]. As a result, the ability of a standard recurrent neural network to learn relationships across long time intervals becomes limited. This limitation is a key motivation for designing more advanced recurrent architectures that can maintain stable gradients throughout training.

1.2.2 Long-Short-Term-Memory Network

The major issue faced by RNNs was the vanishing gradient problem, which made it difficult for these networks to learn long-term dependencies in sequential data, as discussed in the earlier section. As error signals were backpropagated through time, they would either exponentially shrink or explode, preventing the network from retaining information over extended sequences. As a solution to the problem of vanishing gradient, a method of Long-Short-Term-Memory (LSTM) was introduced by Hochreiter and Schmidhuber, Computation. This model embodies a gated system by which it enforces constant error flow within the special cells known as constant error carousels (CECs) [147] (Mathematical explanation is provided in Appendix B). In order to maintain a constant error flow, we need the term of the product of the activation derivative and the weight parameter to be constant. The activation function of the neuron must be linear and must remain constant in time. By keeping activation as an identity function and thus making the self-connection weight as 1, this preservation can be achieved, by which we can ensure that the gradient does not shrink or grow. Thus, short-term memory storage can be achieved for a longer period of time. This cell of self-connection with CEC's backflow is called a memory cell. There will be a bit more explanation needed for the case of connections from other neurons. This is where the gated system of LSTM comes into the picture.

Since there are multiple input connections and since we use the same weight to store or ignore an input, there will arise a problem of conflicting weight update signals. To address this problem, CEC's are extended to connect with input layers and other memory cells using the input and output gates. The input gate (i) applies a sigmoid threshold function, which allows a range of values between $[0,1]$. This means that when the gate is closed, the value goes close to 0 and thereby controls the flow of signal to the memory cell. The currently stored information in the memory cell (the cell state c_τ) is protected from the irrelevant noise by the same input gate. The output gate (o),

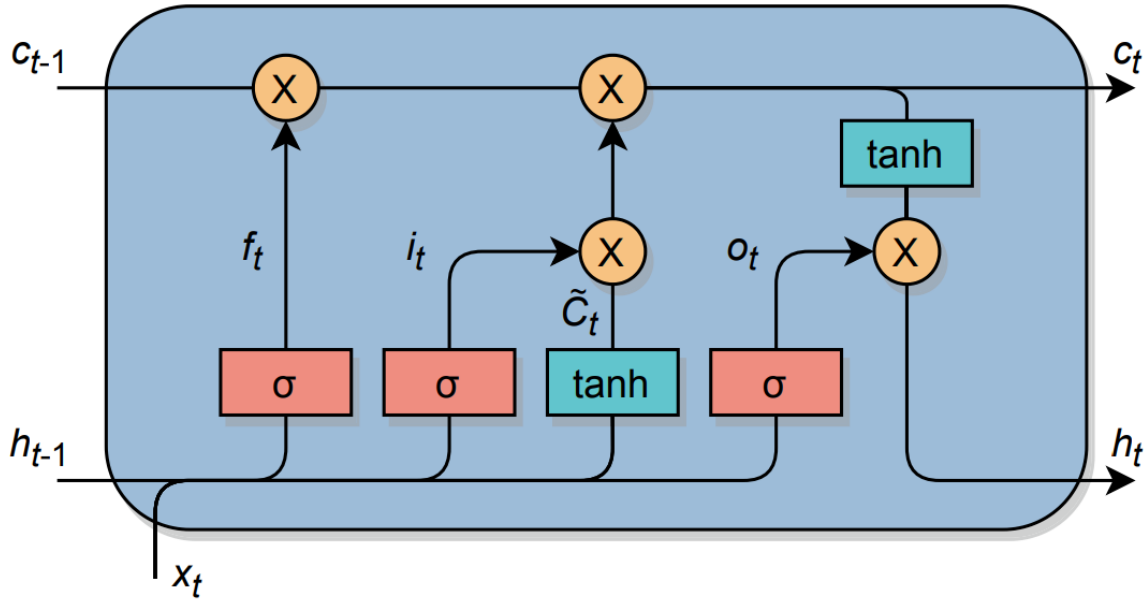


Figure 1.6: The architecture of the LSTM block with its gated system. The image adapted from Thakkar and Chaudhari

on the other hand, helps to control the access to the memory cell content. In general, the basic function of a gated system is to allow or deny the access of constant error flow through CEC [147]. During a continuous input series, the cell state will grow linearly since the weight of self-connection units is set to 1 as a part of CEC. In order to address this issue, Gers et al. introduced a forget gate (f), which learn to reset the cell state. The figure 1.6 illustrates the architecture of a basic LSTM block along with the flow of information within it at time step t . The block receives two inputs: the current input vector x_t and the hidden state from the previous time step h_{t-1} , where state represents the output of the LSTM block at the given timestamp. In addition, the previous cell state c_{t-1} enters the block through the top horizontal path, which represents the memory carried across time steps. The forget gate f_t , computed using a sigmoid activation function, determines how much of the previous cell state should be retained. The input gate i_t decides the amount of new information that can enter the memory cell. At the same time, a candidate memory value $\tilde{c}_t$ is generated using a tanh activation function, representing new information derived from the current input and previous hidden state. The new cell state c_t is then obtained by combining the old memory $f_t \odot c_{t-1}$ with the candidate memory $i_t \odot \tilde{c}_t$, where $\odot$ represents the element-wise multiplication. Finally, the output gate o_t decides how much of the updated cell state should be given as the hidden state of the current time step. The hidden output h_t is produced by applying a tanh activation to the cell state and scaling it by the output gate.

For a given input vector X_t at time t with the previous memory cell state c_{t-1} ,

hidden state h_{t-1} and with the weight W and bias term b , the LSTM block operates as follows.

$$\mathbf{i}_t = \sigma(\mathbf{W}_{xi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1} + \mathbf{b}_i), \quad (1.18)$$

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_{xg}\mathbf{x}_t + \mathbf{W}_{hg}\mathbf{h}_{t-1} + \mathbf{b}_g), \quad (1.19)$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_{xf}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1} + \mathbf{b}_f), \quad (1.20)$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t, \quad (1.21)$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_{xo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1} + \mathbf{b}_o), \quad (1.22)$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t). \quad (1.23)$$

In these equations, $\sigma(\cdot)$ denotes the logistic sigmoid activation function, and $\tanh(\cdot)$ denotes the hyperbolic tangent function. The operator $\odot$ specifies element-wise (Hadamard) multiplication. At time step t , $\mathbf{x}_t$ is the input feature vector, $\mathbf{h}_{t-1}$ is the hidden state from the previous step, and $\mathbf{c}_{t-1}$ is the preceding cell state. The vectors $\mathbf{i}_t$, $\mathbf{f}_t$, and $\mathbf{o}_t$ represent the input, forget, and output gates, respectively, while $\tilde{\mathbf{c}}_t$ denotes the candidate memory. The updated cell state is written as $\mathbf{c}_t$, and the corresponding hidden state as $\mathbf{h}_t$. The weight matrices $\mathbf{W}_{xi}$, $\mathbf{W}_{xf}$, $\mathbf{W}_{xo}$ map the input $\mathbf{x}_t$ to the respective gates, whereas, $\mathbf{W}_{hi}$, $\mathbf{W}_{hf}$, $\mathbf{W}_{ho}$ project the previous hidden state $\mathbf{h}_{t-1}$ to these gates. $\mathbf{W}_{xg}$ and $\mathbf{W}_{hg}$ define the input-to-cell and hidden-to-cell mappings used to compute the candidate cell state. The vectors $\mathbf{b}_i$, $\mathbf{b}_f$, $\mathbf{b}_o$, and $\mathbf{b}_g$ represent the associated bias terms.

This vanilla model can be used in different modes depending on their application domains. Bidirectional LSTMs (BiLSTMs) extend the standard LSTM architecture by enabling the network to learn from both preceding and following context in a sequence [157], [158], [159]. In a BiLSTM, each time step is associated with two LSTM layers: one that processes the sequence from start to end (forward) and another that processes it from end to start (backward). Their outputs are then concatenated, yielding a more informative representation that integrates context from both directions. This design is especially advantageous when the meaning of a word depends heavily on its surrounding context [160].

Stacked LSTMs describe an architecture in which several LSTM layers are placed one above the other. This deeper structure allows the model to capture increasingly complex representations of the input data [161], [162]. In a Stacked LSTM, the output produced by one LSTM layer becomes the input to the subsequent layer. Such a hierarchical arrangement lets the network extract higher-level features in the deeper layers while still modeling temporal dependencies in the earlier ones. Often, the initial layers focus on simpler patterns, whereas the upper layers learn more intricate relationships

within the data [160].

In addition to these, the research community has adopted the combined use of LSTM, depending on the field and purpose. Some well-known examples are CNN-LSTM, LSTM autoencoders, and other hybrid architectures. For example, hybrid LSTM models that combine LSTM with CNNs, ARIMA, and autoencoders have been thoroughly reviewed for use in ionosphere and atmosphere research, focusing on forecasting, monitoring and anomaly detection [163], [164], [165], [166], [167], [168]. These hybrid architectures aim to improve predictive accuracy, combine different data sources, and make computations more efficient by using LSTM's ability to capture long-term dependencies along with the useful features of other algorithms.

Thus, LSTM can be considered as an optimal model when dealing with sequential data. However, at times, depending on the input vector and domain of application, this system becomes harder to train with the increasing computational complexity. Many trials were carried out to improve the current architecture by maintaining the ability to model long-term dependencies. Although this model offers many benefits for analyzing time-series data or sequences, it also comes with several limitations. The internal architecture of LSTMs is complex because they rely on three distinct gates (input, forget, and output) to control information flow. This complex gating mechanism increases the number of trainable parameters and makes the network more difficult to design and fine-tune than simpler alternatives [169]. LSTMs are also computationally demanding and tend to train slowly, since their sequential nature requires each time step to be processed in order, which restricts parallelization [170]. While LSTMs were originally developed to address the vanishing gradient issue in basic RNNs, they do not eliminate it entirely. Some studies indicate that the network weights can still shrink toward zero, which hinders the model from effectively learning relationships between distant events in very long sequences [171]. Along with this, the model maintains a "black box" nature, making it difficult to understand the causal relationships between inputs and outputs [172].

Two of the major improvements in the system to improve the model, considering the limitations, were the introduction of the Gated Recurrent Unit (GRU) and the Attention mechanism. The GRU proposed by Huynh et al. makes the LSTM less complicated by combining the input and forget mechanisms into a smaller design that only needs two gates: the reset gate and the update gate. The reset gate decides how to combine the current input with information that has already been stored, and the update gate decides how much of the previous hidden state should be kept. Because GRU models have fewer parameters and a simpler structure, they often work just as well as LSTMs while being more efficient in terms of computing power, especially when working with smaller datasets or limited computing power [156]. Another form of improvement brought in was the introduction of an attention mechanism [174], [175].

Attention mechanisms give the model a way to give different levels of importance to different parts of an input sequence. Attention doesn't compress the whole sequence into one fixed representation. Instead, it calculates a set of attention weights that show how important each input element is for making the current output. After that, these weights are used to make a weighted sum of the hidden states. This lets the model focus on the most important parts of the sequence when making predictions. Attention mechanisms have been effectively utilized in various sequence modeling tasks, such as machine translation, text summarisation, image captioning [160], and time-series forecasting [174], [175].

LSTM-Based Approaches for Detecting Seismic Precursors

The application of Long Short-Term Memory (LSTM) networks has marked a significant advancement in the detection of seismo-ionospheric precursors, offering distinct advantages over traditional statistical methods and conventional machine learning approaches by effectively capturing temporal dependencies in sequential geophysical data. The studies, like Draz et al., Saqib et al., Şentürk et al., show the application of LSTM in search of ionosphere and atmosphere perturbation induced by the earthquakes.

In a case study of the Mw 7.8 Nepal earthquake that happened on April 25, 2015, Şentürk et al. created a new Multi-Network based Hybrid LSTM model to predict total electron content (TEC) data. This model used LSTM architectures to solve problems with vanishing gradients and uncertainty that simpler recurrent networks couldn't. The model effectively detected substantial negative anomalies around 14 days prior to the event, along with successive positive TEC increases in the four days preceding the mainshock. The authors strongly supported LSTM-based methodologies in seismo-ionospheric research, asserting that the architecture's design for sequential data renders it particularly suitable for TEC time-series short-term forecasting and anomaly detection. They also suggested the future incorporation of additional atmospheric parameters and multi-station data to improve predictive robustness. In a region-specific investigation, Tsai et al. employed deep learning methodologies to identify ionospheric precursors linked to earthquakes of magnitude $M \geq 6.0$ in Taiwan, utilizing hourly Total Electron Content (TEC) data from local GPS networks and contrasting Long Short-Term Memory (LSTM) networks with alternative neural network architectures. The authors discovered that LSTM-based models could detect statistically significant pre-seismic ionospheric anomalies with an overall high accuracy of 78.05%, while effectively filtering out solar and geomagnetic influences. They emphasized that the temporal context provided by LSTM's memory cells was essential for distinguishing true precursors from false positives. By looking at different data sources, like TEC, Outgoing Longwave Radiation (OLR), and atmospheric parameters like Air Pressure

(AP), Relative Humidity (RH), and Air Temperature (AT), Haider et al. looked into atmospheric and ionospheric anomalies related to the 2023 Mw 6.8 Morocco earthquake. They used statistical methods and LSTM-based validation methods. The research validated the existence of persistent pre-seismic anomalies across various atmospheric layers preceding the principal shock. Both statistical and deep learning techniques identified anomalous fluctuations as precursors occurring 8–9 days prior to the earthquake near the epicenter. The authors emphasized that LSTM’s ability to conduct multivariate time-series analysis, coupled with strong statistical methodologies, could be utilized in subsequent research to combine these varied data streams into unifying predictive frameworks, thus improving our understanding of Lithosphere-Atmosphere-Ionosphere-Coupling (LAIC) phenomena. Most recently, Karatay et al. used LSTM-based models to predict IONOLAB-Total Electron Content (TEC) changes one day in advance linking with major earthquakes in Japan and China. They used Global Navigation Satellite Systems (GNSS) data from 19 stations in Japan and China for four major earthquakes: the 2011 Tohoku earthquake (Mw 9.1), the 2008 Iwate-Miyagi Nairiku earthquake (Mw 6.9), the 2008 Sichuan earthquake (Mw 7.9), and the 2010 Yushu earthquake (Mw 6.9). The research confirms the effectiveness of LSTM-based Deep Learning for predicting time series of ionospheric TEC variations, attaining significant forecasting precision across various seismic events. The results confirm LSTM’s forecasting validity without proving causal relationships. The research conducted by Sanjana, Nithya, et al. investigated LSTM networks applied to spatio-temporal datasets for complete earthquake forecasting, integrating both seismic and supplementary geophysical data from various regions. This paper presents a novel approach for earthquake forecasting by the examination of ionospheric indicator signals and atmospheric indices. The study confirmed the effectiveness of LSTM networks in improving earthquake forecasting, particularly in the detection of moderate to high magnitude earthquakes.

1.2.3 Autoencoder

Autoencoders are a neural network architecture for representation learning. The introduction of the concept of autoencoder was given by the Lachter and Bever. In unsupervised machine learning, autoencoders are trained to learn the hidden or unobserved variables in the input data that form the distribution of the input data. The latent space is the collection of these hidden variables for a specific dataset. During training, the autoencoder finds the latent variables that best help it reconstruct the original input accurately. The resulting latent space representation then shows only the most important features in the data. Autoencoder architectures are commonly used in feature extraction tasks, including data compression, image noise reduction, and anomaly detection. Recently, by modifying and updating the theoretical connections

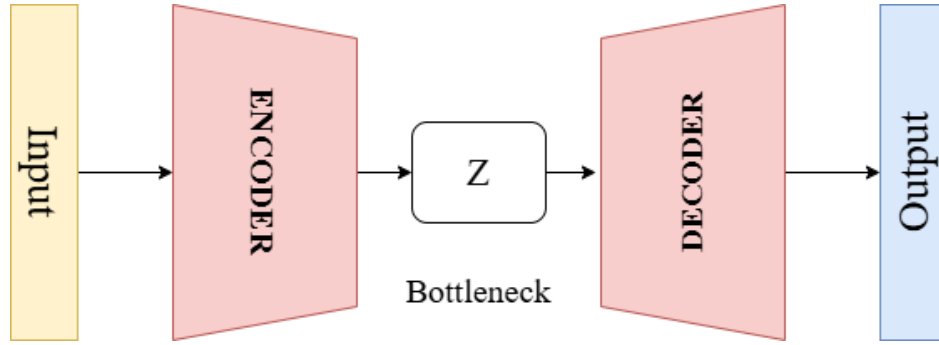


Figure 1.7: The architecture of an autoencoder, where input data is fed to the encoder, which compresses the data into a lower-dimensional state called the latent state (bottleneck), and the decoder finally reconstructs the original input data from the latent representation.

between autoencoders and latent variables, the autoencoder models have emerged at the forefront of generative modeling. Variational autoencoders (VAEs) and adversarial autoencoders (AAEs) are two types of autoencoders that have modified the standard architecture to enable generative applications, such as creating new images or time-series data.

These applications of autoencoders are achieved through its unique architecture, comprising a decoder and an encoder (refer to the figure 1.7). An autoencoder's architecture incorporates a hidden layer z (called the latent layer or bottleneck), which describes a compressed representation of the input data. The encoder component, which transforms the input into a code, mathematically represented as $z = f(X)$, and a decoder, which reconstructs the input from this code, denoted as $X' = g(z)$. If an autoencoder simply learns to perform perfect reconstruction, that is, $g(f(X)) = X$ for all inputs, it offers no practical value. To prevent this, autoencoders are intentionally constrained so that exact copying is not feasible. In contrast, these models are designed to recreate inputs with some approximation, but only for data points similar to those seen during training. By forcing the model to be selective about which input features to keep, it often captures important and useful aspects of the data. In modern autoencoders, these encoder and decoder functions are changed to stochastic mapping $p_{encoder}(z|X)$ and $p_{decoder}(X'|z)$ where X' is the reconstruction of X' [180], [181].

Autoencoders work by feeding input data through an encoder part that compresses the input to a lower dimension of the network before it reaches the decoder. This design means the encoder must find and keep the most important information, which helps recreate the original input accurately. Even with the different modified version of autoencoders, which has different neural network structures to fit various goals and datasets, the basic components are the same. The encoder comprises layers designed to give a compressed representation of the input data through dimensionality reduction. In a standard autoencoder, the hidden layers have fewer neurons than the input layer.

As data goes through these layers, it gets squeezed, which means it is compressed into lesser dimensionality. The bottleneck has the most compressed version of the input. The input layer of the decoder also serves as the output layer of the encoder. A key goal in building and training an autoencoder is to find the fewest important features or dimensions needed to accurately recreate the input. The code, which is the latent space representation formed at this layer, is then sent to the decoder. The decoder has hidden layers, each with an increasing number of neurons. These layers decompress the encoded representation and try to reconstruct the input data. To see how well the autoencoder works, the reconstructed output is compared to the input of the model. The reconstruction error is the difference between the output and the input, revealing the information on how well the model has learned the internal representation of the input data.

In addition to choosing the right neural network architecture, like a CNN, RNN (such as LSTM), transformer, or simple feedforward network, building an autoencoder requires careful consideration of different hyperparameters. The dimensions of the bottleneck determine how much data is compressed. Code size can also serve as a regularisation mechanism; adjusting it helps manage overfitting or underfitting. The depth of an autoencoder is determined by the number of layers in both the encoder and decoder components. A greater depth corresponds to increased model complexity, while a reduced number of layers facilitates quicker processing. Typically, the architecture of autoencoders follows a pattern wherein the neuron count decreases through the encoder layers, reaching its minimum at the bottleneck, and then increases through the decoder layers. The number of neurons is also contingent upon the characteristics of the input data; for instance, an autoencoder designed for processing large images generally requires a larger number of neurons compared to one intended for smaller images. During the training phase, the loss function calculates the reconstruction error by comparing the output with the input. This loss function then does the optimisation of the model's weights by gradient descent during backpropagation. The selection of an appropriate loss function is based on the task for which the autoencoder is designed.

One of the primary applications of unsupervised autoencoders is anomaly detection. By performing representation learning, the model learns the underlying background characteristics of the data when it is trained solely on background samples. After this training phase, if the autoencoder is given anomalous data, it will be unable to reconstruct the input accurately. This leads to a higher reconstruction error. By applying a threshold on this error measure (i.e., the calculated loss), we can decide whether a particular input should be flagged as anomalous or not. Suppose the normal training dataset is given by $X = \{x_1, x_2, \dots, x_n\}$. During training, we learn a model that maps these training samples into a lower-dimensional subspace and then reconstructs them, producing outputs $X' = \{x'_1, x'_2, \dots, x'_n\}$. The encoder phase is to reduce the

dimensionality of the input data X according to Equation 1.24:

$$Z = \sigma(WX + b) \quad (1.24)$$

Here, Z denotes the latent (compressed) representation, σ is the activation function, W is the weight matrix, and b is the bias vector.

Similarly, the decoder stage is trained using Equation 1.25 to reconstruct the data in a space that is comparable to the original input space, but using its own weights, biases, and potentially different activation functions:

$$X' = \sigma'(W'Z + b') \quad (1.25)$$

The main goal of the autoencoder is to reconstruct the inputs by generating output vectors that are as similar as possible to the input data. This is accomplished by minimizing the reconstruction error between input and output [182], [183].

This reconstruction error is typically measured using the Mean Squared Error (MSE), defined as:

$$\mathcal{L} = \frac{1}{n} \sum_{i=1}^n \|x_i - x'_i\|^2 \quad (1.26)$$

where x_i denotes the original input sample and x'_i is the corresponding reconstructed output. So, by thresholding this calculated error, we can easily find the anomalous data:

$$class(x_i) = \begin{cases} normal & L_i < \theta \\ anomalous & L_i > \theta \end{cases} \quad (1.27)$$

[181], [183].

Stochastic gradient descent (SGD) or its more advanced versions, like Adam and RMSprop, are often used to optimize autoencoders. These methods are known to speed up convergence and make training more stable [184]. Choosing the right hyperparameters is very important for how well the training process works. The learning rate controls how much the weights change: a lower learning rate usually leads to stable convergence, but it may take longer to train, while a higher learning rate can make learning less stable. Choosing the right number of epochs, which is how many times the model goes through the whole dataset, is also important to avoid underfitting or overfitting. These factors illustrate the difficulty of finding the right balance when tuning deep learning models for effective anomaly detection. To improve generalization and reduce overfitting, people often use regularization methods like dropout, weight decay, and batch normalisation [185]. During training, dropout randomly turns off some neurons. Weight decay, on the other hand, punishes large weights to encourage simpler representations. Batch normalization makes the training process more stable

by normalizing the activations of each layer [186].

Different types of autoencoders have been made to address specific challenges. The Vanilla Autoencoder (AE) is the basic symmetrical encoder-decoder network that learns to rebuild its input. However, it tends to fit training data too well and has trouble generalizing to new anomalies [187]. The Sparse Autoencoder (SAE) imposes a sparsity constraint that restricts neuron activations, enabling enhanced feature extraction and anomaly detection through the extraction of compact representations [188], [189]. The Denoising Autoencoder (DAE) increases robustness by learning how to rebuild clean inputs from corrupted ones. This makes it especially useful in places where sensor data is often noisy and interfered with [190]. The Contractive Autoencoder (CAE) adds a regularization term that punishes being too sensitive to small changes in input, which makes it less likely to overfit and more robust for industrial monitoring applications [188], [189], [191]. The Stacked Autoencoder (SAE) builds on the standard architecture by stacking multiple encoder and decoder layers. This lets it find subtle anomalies in complex, high-dimensional datasets [192], [193], [194]. The Convolutional Autoencoder (Convolutional AE) substitutes fully connected layers with convolutional and pooling operations to maintain spatial hierarchies, making it highly effective for image-based anomaly detection [187]. The Variational Autoencoder (VAE) uses a probabilistic framework to model the latent space as a Gaussian distribution. This makes it easier to generalize and cuts down on false alarms in anomaly detection [189], [195], [196]. The Recurrent Autoencoder (RAE) uses recurrent neural networks to find patterns in sequential data over time, which makes it a good choice for finding anomalies in time series data [187], [197]. The Adversarial Autoencoder (AAE) uses a generative adversarial framework to make structured latent representations, which improves both the accuracy of reconstruction and the strength of anomaly detection [198]. The Long Short-Term Memory Autoencoder (LSTM-AE) builds on the RAE by using LSTM cells to find long-term dependencies. This makes it great for finding anomalies in real time in dynamic time-series data streams [170], [199]. The Gated Recurrent Unit Autoencoder (GRU-AE) is a more efficient alternative to the LSTM-AE. It uses GRU cells to capture temporal dependencies with fewer parameters and less complexity [200], [201]. The Attention-Based Autoencoder (ABAE) adds attention mechanisms that let the model focus on only the most important features or time steps. This makes it easier to find anomalies in complex time-series data [202]. Finally, the Transformer-Based Autoencoder (TBAE) uses self-attention mechanisms to process sequences at the same time. This helps it find long-range dependencies and makes it more efficient for large-scale anomaly detection tasks [203], [204].

In our research area, the primary use of autoencoders is for anomaly detection. Because the data are time-dependent, most approaches rely on LSTM-based autoencoder architectures. Applying LSTM autoencoders to identify seismic precursors in various

types of geophysical data has emerged as a highly effective technique, with numerous recent studies reporting strong results. The authors Bao et al. looked at electromagnetic signals from the AETA monitoring system set up in the Sichuan–Yunnan area of China. They focused on the Jiuzhaigou earthquake (Mw 7.0) and the Yibin earthquake (Mw 6.0) using data from stations within 200 km of the epicenters. The authors utilized an LSTM Autoencoder trained to learn normal electromagnetic signal patterns, using reconstruction error as an anomaly score. The analysis revealed 2–4% anomalous points (after normalization) half a month before the both preceding earthquakes, providing quantitative evidence that AETA electromagnetic disturbances can be regarded as valid earthquake precursors and with the application of LSTM autoencoder. The authors of Xue et al. used geoelectric field data from several stations in Japan, which is known for having a lot of earthquakes and well-documented seismic electric signals (SES). Their LSTM-Autoencoder architecture used an LSTM encoder to compress input time series into a latent representation and a decoder LSTM to rebuild it. The network was only trained on normal, non-seismic periods. The model was able to find SES even when there was a lot of noise, with detection accuracies over 85%, which demonstrates that it performs better than traditional methods. Abri et al. examined Total Electron Content (TEC) data derived from GPS measurements in two regions: Iquique, Chile, and the Pilbara area of Western Australia. Their hybrid Deep AutoEncoder and Stacked LSTM architecture initially utilized a Deep AutoEncoder for unsupervised feature learning and dimensionality reduction, transforming TEC time-series into a lower-dimensional latent representation, subsequently inputted into a Stacked LSTM network for sequence-to-sequence prediction. The proposed model employs a deep autoencoder and a stacked LSTM architecture to forecast earthquakes based on historical seismic activity. The main goal of this model is to find the link between ionosphere disturbances and earthquakes by using stacked LSTM and deep autoencoder-based models, and got an accuracy of 81% to 84%. In the study by Muhammad and K  lahcı utilized a Long Short-Term Memory (LSTM) based autoencoder to identify anomalies in Total Electron Content (TEC) data captured by GNSS receivers for seismo-ionospheric investigation. They used the LSTM-autoencoder in a semi-supervised way, teaching it to recognize normal TEC behavior during the geomagnetically quiet condition. After training, the model was used to find unusual TEC data that might be linked to seismic activity. The method was tested with TEC data from three GNSS receiver stations in T  rkiye, ANKR, ISTA, and TUBI. It was also checked against results from a previous study of a 7.4 magnitude earthquake in Mexico. In both instances, the model provided valid anomaly detections. The authors discussed on the relationship between the identified anomalies and lithosphere-atmosphere coupling processes, showing the usefulness of AI-based methodologies for investigating ionospheric variations. Collectively, these studies demonstrate that LSTM-Autoencoder architectures offer unique advantages for

seismic precursor detection by combining LSTM’s temporal modeling capabilities with autoencoder’s unsupervised anomaly detection framework, enabling sensitive identification of subtle pre-seismic signals across geoelectric, electromagnetic, and ionospheric data types while effectively filtering out background noise and non-seismic disturbances [207].

We saw through multiple examples that autoencoders have been effectively used as anomaly detectors, but they have limitations when it comes to anomaly detection purposes. Numerous studies concentrate on the unsupervised context, revealing that, contrary to previous assumptions, autoencoders can easily reconstruct any anomalies in the training data, resulting in a non-functional detector [208], [209], [210]. Choosing a threshold is another big problem because finding the best cutoff for reconstruction error usually needs labeled validation data, which is often not available in unsupervised settings [211], [212]. Also, autoencoders can only reconstruct features, so they might miss real physical anomalies that don’t show up as high-level error [213]. The black-box nature of these models makes it even harder to understand why a certain sample was flagged as unusual, which is very important in high-stakes situations.

Considering all the references that served as the baseline study for the application of LSTM-based autoencoder networks for the detection of ionosphere-seismic perturbations, despite the various limitations in LSTM-based models and autoencoder models, we focus our research on developing an LSTM-autoencoder model that uses ionosphere data for seismic precursor detection. First of all, this choice was made because the primary agenda is to detect anomalies in the global ionosphere data, and LSTM autoencoders are used for this purpose in many studies. More specifically, the choice of the such an approach is based on three main reasons. First, the goal of this study is to explore. Instead of trying to figure out right away what the relationship is between ionospheric data and seismic activity, the main goal is to see if there are any statistically significant patterns in the data that can be captured. If these relationships can be supported with a statistical foundation, deeper models may be subsequently developed to further analyze and explain the underlying mechanisms. Second, the present study functions as a preliminary baseline examination. So, a relatively simple architecture was chosen on purpose to test the model’s sensitivity before adding more complex mechanisms like attention-based architectures or advanced feature-focusing strategies. We can better understand how the model works with this specific dataset by starting with a simpler structure. Finally, the time sequences in this study are not very long. The LSTM model is given sequences that last about 34 minutes (duration of a half orbit of Demeter), which is enough to capture the temporal dependencies that are important for this analysis without needing more complex or deeper recurrent architectures. Consequently, an LSTM-autoencoder architecture is deemed suitable for the parameters of the current study.

Chapter 2

The Problem

A number of studies have examined the lithosphere-ionosphere coupling process, progressing from standard case studies that associate seismic events with localized ionospheric perturbations to more advanced machine learning-based methodologies for forecasting these disturbances and associated earthquakes. Looking into a detailed literature survey, the study of seismo-ionospheric phenomena has progressed considerably in the last twenty years. In this section, we look at how studies on lithosphere-ionosphere coupling have changed over time, moving from case-based analyses to statistical investigations and, more recently, to data-driven methods. This development illustrates the increasing endeavor to understand the phenomenon in a more methodical and generalizing manner. We further talk about the main problems with current methods and explain how this work tries to resolve them.

2.1 Case Studies

One of the major forms of seismo-ionospheric research is the event-focused case study. Early examples include the well-studied Wenchuan earthquake (Mw 7.9–8.0, May 12, 2008), where studies using ground-based ionosondes [122], [214], [215] and GPS TEC data [216] reported anomalous foF2 and TEC enhancements in the days preceding the event, providing early evidence for lithosphere-ionosphere coupling. Earth observation satellites revolutionise seismo-ionospheric research by providing global coverage, continuous monitoring, and multi-parameter measurements that ground-based observatories cannot provide. Satellite missions like DEMETER and CSES have made it possible for scientists to study ionospheric disturbances directly above epicentral areas, even in remote ocean areas where ground-based instruments can't reach. These satellites can measure plasma parameters (electron density, ion density, and electron temperature) and electromagnetic fields (electric and magnetic field components across ULF, ELF, and VLF frequency bands) along their orbital paths. With the following few cases, we will see how the space-based observation has helped to advance our understanding of lithosphere-atmosphere-ionosphere coupling mechanisms.

A detailed multiple case study based on DEMETER data was carried out by Thomas et al., which included five major earthquakes (Mw > 6.5): the Molucca Sea, Central Peru, Northern Mariana Islands, Martinique, and New Zealand events. They used DEMETER satellite data from the IAP (Plasma Analyzer) and ISL (Langmuir Probe) experiments. During a 30-day period before and a 10-day period after each

earthquake, they used burst mode data to find the satellite orbits that were closest to each epicenter at a resolution of 20° longitude and 10° latitude. The ionospheric parameters examined included electron density (Ne), electron temperature (Te), and total ion density (Ni). They used a statistical method based on the median and inter-quartile range to set upper and lower limits for finding anomalies in order to separate seismic-induced changes from background noise. They found that 27.8% were caused by geomagnetic activity, while 72.2% happened when geomagnetic conditions were calm and could be linked to seismic activity. They found 8 perturbations for the Molucca Sea earthquake: electron density changes on -25 and -11 days, electron temperature changes on -15 and -9 days (nighttime readings), and total ion density changes on -20 days (nighttime) and -12, -9, and -5 days (morning readings). Of these, 75% were caused by earthquakes. The Central Peru earthquake had four anomalies from morning half-orbit measurements: electron density perturbations on -14 and -5 days and total ion density anomalies on -15 and -5 days. However, 75% of these events happened during geomagnetically active periods, which made it harder to link them to seismic activity. It's worth noting that the DEMETER satellite only had morning measurements for this event. They found 11 anomalies for the Northern Mariana Islands earthquake. One of the most significant was a strong electron density perturbation at -15 days under quiet geomagnetic conditions. They also found electron density anomalies at 0, 2, and 5 days; electron temperature anomalies at -10, -9, -7, -1, and 2 days; and total ion density anomalies at -7 and 0 days, with 36.4% of them being caused by geomagnetic activity. For the earthquake in Martinique, they saw 10 anomalies. These included electron density changes on -30 and -15 days (nighttime) and -15 and 8 days (daytime); electron temperature changes on -30, -15, and -8 days (nighttime) and -18 days (morning); and total ion density changes on -15 days (nighttime) and 8 days (daytime). About 90% of these changes happened when the geomagnetic field was quiet, which strongly supports a link to seismic activity. In the case of the New Zealand earthquake, they found three anomalies: one in electron density at -7 days (morning), one in electron temperature at -15 days, and one in total ion density at -10 days. All of these happened during geomagnetically quiet periods, which means they could have caused the earthquake. Through this study, authors provided evidence that DEMETER IAP and ISL instruments are proficient in detecting seismo-ionospheric anomalies that can help in short-term earthquake prediction. They also suggested the development of more precise regional models of quiet-time ionospheric behavior to enhance the differentiation of seismic precursors from daily variational perturbations.

Another detailed study using DEMETER satellite electric and magnetic field data, employing a novel data analysis tool called ALIF (Adaptive Local Iterative Filtering) combined with multiscale statistical analysis (MSA), were carried out by Bertello et al., for the detailed case study of the April 6, 2009 L'Aquila earthquake ($M_w =$

6.3). They selected satellite orbits that encompassed a $1^\circ \times 1^\circ$ latitude–longitude area, centered on the geographic coordinates of L’Aquila, using the entire DEMETER dataset. To construct a statistical background model, they divided the study area into latitude–longitude cells and averaged the relative energy values. This averaging process considered geomagnetic activity, seismic activity, and local time. They used instantaneous relative energy, kurtosis, and Shannon entropy to look at instrumental background for each cell and averaged relative energy maps to look at environmental background. A signal was considered strange if it was more than 3σ above both backgrounds. Using this method on DEMETER data over L’Aquila, they found an unusual signal at 333 Hz, very low frequency, two days before the earthquake. This was when DEMETER flew directly over L’Aquila. The signal was seen in both electric and magnetic field data, and the relative Poynting vector showed that the wave was moving from the ground to the ionosphere. April 4 was a solar-quiet day with no solar or substorm disturbances. The authors also confirmed that the 333 Hz signal was absent in the adjacent $1^\circ \times 1^\circ$ cells to the north or south of L’Aquila, thereby reinforcing its spatial localization. The research showed the new methodological approach that the coupled use of ALIF and MSA is a strong way to find and get rid of noise in satellite signals, which makes it possible to reliably find pre-seismic electromagnetic anomalies. This study paved the path for the multidisciplinary methodology for differentiating earthquake effects from natural ionospheric dynamics, and proposed that their technique could be utilised for the new missions for real-time background computation and anomaly detection.

Another major case study carried out using DEMETER data to look into electromagnetic perturbation of the Mw 7.8 Northern Sumatra earthquake of the April 6, 2010. Zhima et al. carried out a detailed study to investigate seismic electromagnetic emissions associated with the event. The investigation employed both survey-mode and burst-mode observations from the DEMETER satellite, concentrating on the extremely low frequency (ELF) band, specifically between 300 and 800 Hz. The researchers selected orbits within $\pm 8^\circ$ of the epicenter during the timeframe spanning March 20 to April 10, 2010. To eliminate solar and geomagnetic effects, orbits recorded during periods of disturbed space weather were filtered out. The methodology encompassed three interrelated approaches: (1) an analysis of wave intensity fluctuations along revisiting orbits from August 2009 to May 2010, facilitating a comparison between seismic and quiet periods; (2) the construction of background maps utilizing a same-time seasonal window from 2008 to 2010, which enabled the calculation of perturbation amplitudes; and (3) the application of the Singular Value Decomposition (SVD) method to derive wave propagation parameters from burst-mode waveform data, thereby determining the direction of wave propagation. The findings indicated anomalous increases in wave intensity within the 300–800 Hz range, occurring from 10 to 3 days prior to the main

shock observed along the orbit closest to the epicenter. The SVD analysis showed that some ELF emissions were traveling up from the Earth toward outer space 10 and 6 days before the earthquake. This means that the emissions came from the lithosphere and not from outside sources. The study found that ELF electromagnetic emissions are an effective means to find earthquake precursors, typically appearing days to weeks before the earthquake in the preparation zone. This is a major study that demonstrated the evidence for the possible existence of propagation of seismic induced electromagnetic signature into the ionosphere.

An example of CSES data-based study is the case study of January 2020, Mw 7.7 earthquake on the southern coast of Cuba, conducted by Li et al. They used electric field data, focusing on the ULF frequency band (0–16 Hz) waveform data from the Electric Field Detector (EFD) for the study. They chose ascending orbit data from the seismic zone (about $\pm 18^\circ$ longitude around the epicenter) for the five days before the earthquake and also looked at revisiting orbits over the course of two months. To extract pre-seismic disturbance features, the authors proposed and compared two methods. The SGF + WTA (Savitzky–Golay Filter + Wavelet Time-Frequency Analysis) and EMD + ER (Empirical Mode Decomposition + Energy Ratio). These methods combine traditional small-scale waveform extraction with wavelet time-frequency analysis for feature extraction. The findings indicated that temporally, significant anomalies emerged 13 days prior, with certain orbital perturbations persisting for more than 1 week. spatial disturbances concentrated mainly over the central earthquake zone, with minimal presence in conjugate zone. In the amplitude, the majority of orbital disturbances surpassed the background threshold during the five days preceding the earthquake. Finally, the morphology fluctuations predominantly occurred south of the epicenter, with few instances noted to the north. The study determined that the suggested methods proficiently extract characteristics of electric field signals and offer a novel methodological framework for the analysis of spatial electric field waveform data in seismo-ionospheric research.

A notable example of an attempt to establish a mathematical relationship of Magnetosphere–Ionosphere–Lithosphere Coupling (MILC) model was evaluated with the case study based on August 5, 2018 Bayan earthquake (Mw 6.9) done by Piersanti et al. The authors combined multi-instrument data from atmospheric (ERA5 temperature), ionospheric (vTEC from GNSS, CSES-01 plasma density), and magnetospheric (field line resonance eigenfrequency) observations to analyze both co-seismic and pre-seismic signatures. They found a co-seismic atmospheric gravity wave (AGW) with a vertical wavelength of 7 km, which was followed by a vTEC perturbation with a period of about 97 seconds, about one minute after the earthquake. They also saw a decrease in the magnetospheric FLR eigenfrequency. In the pre-seismic phase (six hours before the earthquake), they saw a similar pattern. This showed that seismic

events can cause AGWs to move upward, change plasma density, and change Alfvén velocity, which in turn changes FLR eigenfrequency. The results were in line with the MILC hypothesis, but the authors admitted that there were certain issues. For example, it was hard to tell the difference between seismogenic AGWs and those caused by weather systems, and it was hard to separate internal (seismic) from external (solar) ionospheric perturbations [32].

The case studies investigated above represent a subset of the broad study examining seismo-ionospheric phenomena linked to significant earthquakes. These studies, encompassing ground-based ionosonde measurements, GPS TEC networks, and satellite missions like DEMETER and CSES, collectively illustrate that ionospheric and electromagnetic perturbations can be detected prior to significant seismic events. Nonetheless, an essential finding is that the characteristics of these precursors are not consistent across earthquakes—timing fluctuates from hours to weeks, spatial extent varies between epicentral and conjugate regions, the polarity of anomalies (positive or negative) is dependent on latitude and local time, and relevant frequency bands span from ULF to VLF depending on the event. This variability highlights a primary challenge: the perturbations are not applicable to all earthquakes. Based on where they are located, geomagnetic latitude, focal depth, and magnitude, the precursors that were seen have different characteristics. This suggests that the classical case study approach alone is not enough to fully understand how seismo-ionospheric coupling works. Numerous additional studies have been conducted beyond those mentioned herein [65], [220], [221]. The prevailing conclusion is that different forms of ionosphere perturbations are a prevalent occurrence preceding significant earthquakes; however, the precise conditions of their occurrence are highly variable. This underscores the necessity for integrated, multidisciplinary, and statistically rigorous frameworks to further this domain.

2.2 Statistical Studies

To verify the presence of seismo-ionospheric precursors, numerous statistical studies have been conducted, examining extensive datasets of earthquakes and ionospheric parameters. Using Superposed Epoch Analysis (SEA) Kon et al. did a statistical study aimed at investigating ionospheric anomalies linked to earthquakes in Japan. The research employed Global Ionospheric Map (GIM) TEC data, normalized as GIM-TEC, covering the period from May 1998 to May 2010, concentrating on earthquakes with a magnitude of $M_w \geq 6.0$ and a focal depth of ≥ 40 km within a 1000 km radius of the study center (37.5°N , 140°E). To ensure statistical robustness, the authors defined an anomaly as TEC values exceeding 2σ of the previous 15-day running standard deviation and validated their results against 10,000 random-SEA iterations. The results

showed that positive GIM-TEC anomalies show up 1 to 5 days before earthquakes, with the biggest ones happening the day before. This finding contradicted earlier statistical analyses performed in Taiwan and China [5], which mainly indicated negative TEC anomalies preceding significant earthquakes. The authors stated that this discrepancy could be related to geomagnetic latitude dependence, indicating that low-latitude areas are affected by the Equatorial Ionospheric Anomaly (EIA), resulting in TEC reductions, whereas mid-latitude regions such as Japan typically display positive TEC enhancements as precursors, suggesting that geographic location significantly influences the observed correlation in statistical studies of seismo-ionospheric precursors.

A notable example is the research by He et al., which employed 7 years of electron density data (Ne) from the Swarm satellite constellation (including Swarm A, B, and C satellites) from 2014 to 2020, together with 527 earthquakes with $M_w \geq 6.0$ that took place worldwide within the same period. The method found disturbances by computing the difference between real orbital electron density observations and a smoothing curve made from each half-orbit of Swarm satellite data. This analysis successfully removed the background ionospheric trend, thereby isolating small-scale, high-frequency fluctuations that may be linked to seismic activity. We used a three-step analysis: first, they looked at the spatial distribution characteristics while removing solar and geomagnetic effects using indices (Kp, Dst, AE, F10.7); second, they compared the changes in disturbances between seismic and non-seismic areas; and finally statistically looked at the number of disturbances before and after earthquakes, all of which were checked against random events. The results showed that some disturbances are indeed linked to seismic activity. For example, disturbances that happen before an earthquake happen more often than those that happen after an earthquake, and they depend on the earthquake's magnitude, focal depth, and location. The study stated that the number of disturbed orbits in most of the 30 days prior to the earthquake is usually higher than that following the earthquake [13]. The authors, however, stress an important point: seismic ionospheric disturbances are extremely weak, making up only about 1% of all disturbances. There are about 300 disturbances in the 30 days before the earthquakes. This means that a disturbance is not always seen before every event. For the 527 earthquakes with $M_w \geq 6.0$, this is about 0.5 disturbances per earthquake [13]. The study concludes that the complexity of ionospheric variability makes it challenging to difficulties in extracting and verify ionospheric phenomena associated with earthquakes. In summary, He et al. state that although a large number of phenomena have been reported, more careful research is needed to confirm the seismic ionospheric phenomena and to understand their coupling mechanisms.

Another example of a statistical study conducted was by Parrot and Li utilizing more than six years of DEMETER satellite data to examine the correlation between ionospheric disturbances and seismic activity. The research utilized two separate sta-

tistical methodologies on various data types. The authors initially created geographic maps of electric-field intensity using histograms and cumulative distribution functions to establish baseline behavior for VLF electric field data. Next, they picked out satellite orbits that passed close to earthquake epicenters in both space and time. They then used superposed epoch analysis to look at how wave intensity changed over time in relation to the earthquake and how far away it was from the epicenter. For ionospheric density data, two statistical methods were used: first, a ratio comparison of electron density recorded 1–30 days before earthquakes against a baseline of 31–75 days before at the same locations, normalized by variance and averaged across all events; second, an automated peak detection algorithm that systematically identified density perturbations across 6.5 years of data, filtered out those associated with geomagnetic activity, and matched remaining perturbations to earthquakes using defined time-distance-magnitude windows, focusing specifically on orbits near epicenter locations. The study examined around 9,000 earthquakes and found that detection rates rose with magnitude with perturbations occurring most often 1–5 days before events. The authors observed a false alarm rate of 22.9% and determined that, despite the presence of statistical correlations, comprehensive earthquake prediction is unattainable due to significant uncertainties and the low signal-to-noise ratio of seismo-ionospheric disturbances.

As per the critical review carried out by Picozza et al. states that one of the most comprehensive statistical studies was carried out by Picozza et al., Němec et al. Using 6.5 years of DEMETER satellite VLF electric field data, they conducted one of the most thorough statistical studies in the field. They aligned thousands of earthquakes in time and space using superposed epoch analysis and discovered a slight but statistically significant drop in electric field intensity at 1.7 kHz, which happened a few hours prior to large-magnitude, shallow (≤ 40 km), nighttime earthquakes with a spatial scale of 350–440 km consistent with the Dobrovolsky radius. The study did, however, identify a number of significant limitations: the statistical significance dropped from 3σ in 2008 to lower levels by 2013 as more data was added; the effect only appears statistically across large datasets, not in individual events; it is restricted to certain conditions (nighttime, shallow depth, mid-to-high latitudes); and, most importantly, the authors themselves notify that, despite the statistical correlation, this cannot support earthquake prediction or association with single events.

Most recently, the work carried out by Zhang et al., which is a thorough statistical study using electric field data from the CSES satellite’s ELF band (19.5–250 Hz) from 2019 to 2021 of 185 global earthquakes with a magnitude of at least 6.0. The study’s methodology entailed the selection of earthquakes according to specific criteria: a magnitude of 6.0 or higher, a depth of less than 40 km, a latitude within $\pm 40^\circ$, and the exclusion of aftershocks. After this, ionospheric data were taken from the area

around the earthquake's epicenter, within 15° to 20° of it. They used data from the same places during a time of low seismic event, specifically 75 to 45 days before each earthquake, to set up background fields. This background was then used to analyze the changes. They used the C-value method to find perturbations by looking at the irregular properties of the electric field's power spectrum. Moreover, superposed epoch analysis was employed to statistically evaluate the spatiotemporal patterns identified in every case. Key findings include that anomalies first appear 15–19 days before earthquakes and peak during the pre-seismic period (4 days before to the day of the earthquake), suggesting a cumulative preparation process; magnitude 7+ earthquakes and marine earthquakes produce stronger and more easily observable anomalies than magnitude 6–7 and land earthquakes, indicating that earthquake characteristics significantly influence ionospheric detectability. The research is constrained by geographical considerations, as earthquakes were exclusively examined in low and middle latitudes to avoid the complexities of higher latitudes.

Using CSES ULF electric field data from 2019 to 2021, Yang et al. did a statistical study of 2,329 earthquakes with $M_w \geq 5.0$. They used EMD-based anomaly detection and Superposed Epoch Analysis to find that ULF disturbances are linked to earthquakes. They mostly happen 11 days before, 2 days before, and on the day of the earthquake, within 200 km of the epicenter. They also found that larger magnitudes and sea earthquakes caused stronger, earlier, and wider anomalies. This study presents a different anomaly detection methodology for studying seismo-ionospheric phenomena and serves as a reference for the utilization of electromagnetic monitoring satellites in earthquake prediction, early warning, and disaster reduction.

In addition to the studies discussed above, a wide range of other statistical analyses have been conducted to improve the understanding of the correlation between seismic activity and ionospheric disturbances, utilizing various datasets and methodological frameworks [5], [17], [226], [227]. These statistical studies, which includes satellite-based observations (SWARM, CSES, DEMETER, GPS-TEC), ground-based observations, and VLF/ULF propagation data, finally demonstrate that ionospheric and atmospheric perturbations are statistically associated with upcoming seismic events. However, the limitations of all of these investigations are consistent, such as regional specificity, the persistent challenge of differentiating seismic signals from solar-geomagnetic noise, a more biased selection of ionospheric data based on earthquakes, and a lack of generalisable findings. These studies provide notable statistical evidence for the possibility of seismo-ionospheric precursors. However, they also indicate that the signals are not strong enough to enable reliable earthquake prediction. This highlights the necessity for ongoing exploration of additional ionospheric parameters, the refinement of methodological frameworks, and a more thorough understanding of the fundamental physical mechanisms.

2.3 Machine Learning–Based Studies

In the preceding two sections, we examined how both case studies and statistical analyses attempted to integrate different methodologies for the automatic detection of ionospheric perturbations. Still, these methods work on the basic idea that we need to first figure out what an anomaly is. In reality, we don't know exactly what seismo-ionospheric anomalies are. We don't have a clear idea of what a precursor looks like in different earthquakes, geographic areas, or geomagnetic conditions. In this case, the rise of machine learning (ML) and deep learning (DL) represents a major change. Instead of using predefined anomaly definitions, these methods learn the underlying connections between input parameters directly from data, without any explicit rule-based definitions. The use ML and DL in seismo-ionospheric research has grown quickly since missions like DEMETER, CSES, and Swarm have made large satellite-based datasets available. In Chapter 1, we looked at some specific examples. Here, we'll go into more detail about a few more studies and look at how researchers have tried to find ionospheric precursors to earthquakes using different machine learning tools.

Lin and Chiou demonstrated an example of using a convolutional neural network for the study of seismo-ionospheric coupling research, where they employed the architecture to study the image-based TEC data. The author used CNN to identify the earthquake precursors through the anomalies in ionospheric data from the TEC images derived from the TEC maps. They used daily TEC images from TEC maps as model inputs. The main goal of this study was to find the precursors of Total Electron Content (TEC) linked to seismic events with a magnitude of $M_w \geq 5.0$. It focused on three different 24-day periods recorded by the Chung-Li Ionosonde station in Taiwan. In the study, they followed targeted analysis of precursors and also employed Butterworth low-pass filtering to get rid of image artefacts. With the combination of this filter and CNN workflow, they were able to find the TEC precursors, one, three, and four days before the big earthquake and two days before the moderate earthquake. The model's dependability was validated by the minimal standard deviation (STD) and mean square error (MSE) values [228].

The study carried out by Akyol et al. proposed a machine learning based technique called EQ-PD for detecting earthquake precursors using the ionosphere TEC data. The study utilised Support Vector Machine (SVM), a traditional machine learning model, to distinguish whether observed spatiotemporal TEC anomalies were related to earthquake precursors or simply background ionospheric changes. The objective of the study was to establish a near-real-time precursor detection system by examining local Total Electron Content (TEC) variations obtained from GPS networks, along with daily geomagnetic indices (Ap, AE, Kp, Dst, and sunspot number) to reflect the state of the ionosphere. The data used in the study were obtained from the EUREF Permanent

GNSS Network (EPN), which monitors a seismically active area in Italy over a period of 2 years and 10 months. The dataset was divided into three separate time periods for training, validation, and testing. It only included earthquakes with magnitudes over 4. The authors utilized the SVM classifier alongside adaptive spatial and spatiotemporal anomaly detection thresholds derived from Pareto distribution and k-means clustering of geomagnetic conditions. The EQ-PD technique successfully identified 17 out of 21 earthquake precursors during validation and 22 out of 24 during testing, although generating 7 and 13 false alarms, respectively. The authors conducted a further evaluation of performance by comparing the results against simulated random guessing scenarios through Matthews Correlation Coefficient (MCC) analysis, thereby validating that the statistical effectiveness of the EQ-PD technique outperformed that of random guessing in all simulated instances. Authors stress on the fact that subsequent research should investigate cost-sensitive supervised learning techniques and draw comparisons with competitive or intelligent guessing methods instead of relying only on random guessing [40].

On the other hand, an exploratory analysis of the application and performance of different ML and DL models in identifying electromagnetic pre-earthquake perturbations using data from the DEMETER satellite was carried out by Xiong et al. The research examined 16 classification algorithms, ultimately determining that LightGBM, a gradient boosting-based technique, was the most effective model for distinguishing earthquake-related electromagnetic anomalies from non-seismic background signals. The objective of the study was to determine whether low-frequency power spectra of electric and magnetic fields could consistently detect pre-earthquake perturbations and to investigate on the most effective spatial and temporal parameters for such detection. The data were chosen from the DEMETER satellite ICE and IMSC sensor observations over six years, from January 2005 to December 2010. They included about 8,760 earthquakes around the world with magnitudes of 5.0 or higher and depths of 40 km or lower. The authors created the dataset by generating an equal number of artificial non-seismic events by sampling time and location outside of spatiotemporal windows around real earthquakes (10 days and 10° in longitude/latitude). Seventeen features derived from logarithmically spaced low-frequency bands (below 3 kHz for electric fields and below 1 kHz for magnetic fields) were used for the model training. The authors found that electromagnetic pre-earthquake perturbations were best classified when using a spatial window defined by Dobrovolsky's formula and a temporal window of a few hours before the main shock, with nighttime data yielding superior performance compared to daytime data. The results show that the electromagnetic signals can be considered as the dominant features for perturbation identification. At the same time, the authors acknowledge that the choice of the geographical region used to simulate the training set of non-seismic data influenced the model's performance,

causing a bias in the data.

An application of complex deep neural network for the study of seismic-induced ionospheric perturbations can be seen in the work of Xiong et al. The study introduced a deep learning model named SeqNetQuake, which integrates Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (Bi-LSTM) networks to detect pre-earthquake ionospheric perturbations utilizing data from the China Seismo-Electromagnetic Satellite (CSES). The study aimed to develop a strong model that could tell the difference between ionospheric anomalies caused by earthquakes and non-seismic background signals and solar-magnetic disturbances. The most innovative idea employed in the study was transfer learning, where it looked into the possibility that transfer learning from the larger DEMETER dataset could help the smaller CSES dataset work better. The data were chosen from measurements taken by the CSES Langmuir Probe (electron density and temperature) between August 2018 and June 2020. This included 2,991 independent earthquakes with magnitudes of 4.8 or higher after removing aftershocks (which are defined as events that happen within $2^\circ \times 2^\circ$ of the epicenter and within 15 days of a main shock). The data also came from the DEMETER satellite (2005–2010), which recorded 8,912 independent earthquakes. The authors generated the dataset by randomly sampling time, latitude, and longitude to make an equal number of non-seismic events. Time points were at least 15 days before or after a real earthquake, and longitude and latitude had to be at least 10° away from the epicenter of a real earthquake. Also, data with a Kp index greater than 3 were put into a third class (label 2) to take into account solar and magnetic activity. This helped the model tell the difference between earthquake-related changes and those caused by geomagnetic storms. The authors found that directly training on CSES data using the SeqNetQuake model with a spatial window defined by Dobrovolsky’s radius and nighttime observations to reduce solar interference resulted in an F1 score of 0.6792 and an MCC of 0.427. When using transfer learning, first training the model on the larger DEMETER dataset and then fine-tuning it on CSES, the performance got a lot better, with a 12% increase in F1 score and a 29% increase in MCC value. SeqNetQuake was one of the model’s best features. It outperformed five other benchmarking classifiers, including a standard CNN, by 64.2% in MCC and about 24.5% in F1 score on an independent test set [229]. The model had many advantages like the advanced deep learning architecture made it easier to extract features from sequential satellite data, and the model was trained on global datasets that covered long periods of time, which made it more generalizable than previous studies with small sample sizes. This study can be considered as the strongest example on how the combination of networks further enhanced by transfer learning allows the identification of pre-earthquake ionospheric perturbations from satellite data.

Most recently, a review paper examined the application of DL models in the in Iono-

spheric Modeling: Progress, Challenges, and Opportunities, where they elaborated on the short-term early warning of major natural disasters. Zhang et al. shows how deep learning is being used more and more to give short-term early warnings of big natural disasters, especially earthquakes, tsunamis, and volcanic eruptions, by looking at ionospheric anomalies. The authors note that deep learning neural networks have shown considerable promise in analyzing ionospheric disturbances triggered by geological activity, successfully classifying signals linked to seismic events by learning the complex relationships that govern geological–ionospheric coupling. The paper cites research using CNNs and LSTMs for the classification of seismic signals, showcasing outstanding classification capabilities [42], [206], [230], and references therein]. The authors stress that deep learning models can find ionospheric anomalies before earthquakes, volcanic eruptions, and tsunamis by combining data from many sources. This makes it possible to monitor anomalies in real time and find them early, which helps with the development of effective early warning systems for geological disasters and speeds up the modernisation of efforts to prevent and reduce disasters [47].

Using deep learning to find ionospheric anomalies caused by earthquakes is a field that is still growing. There are relatively few studies conducted in comparison to the statistical and case study-based evidence previously examined; however, these studies have demonstrated significant advancements in signal detection. But if we look a little closer, we can see that all of the studies we looked at have a similar pattern: they either choose ionospheric conditions around an earthquake that has already happened or generate data based on predefined criteria and create a biased environment for the model to study. This is not an incorrect approach, but it raises major questions concerning the generalizability and practical applicability of these models. In actual operational situations, an early warning system must continually monitor the ionosphere without prior knowledge of an upcoming earthquake, differentiating real precursors from the intricate range of natural ionospheric variations induced by solar activity, geomagnetic storms, and other geophysical phenomena. Future research must therefore prioritise learning based on unbiased, global data to improve the chances that deep learning models learn physically realistic representations rather than random correlations specific to the training data.

2.4 The Problem Statement

Across the body of literature examining the relationship between ionospheric anomalies and seismic activity, most of the studies that have been done so far, on the other hand, use one of two methods. The first category mainly includes large-sample statistical analyses of ionospheric conditions before a list of earthquakes. These analyses often give results that are hard to reproduce or verify across different datasets and regions.

The second group uses case studies that look at specific seismic events and look at ionospheric observations in a limited region around the earthquake’s epicenter. These kinds of methods may show patterns in specific areas, but they don’t give a global perspective and are often strongly dependent on predefined hypotheses. Since the physical mechanisms connecting ionospheric anomalies to seismic activity are not completely understood or widely accepted, considerable uncertainties persist regarding the detection of these potential precursors, their reliable differentiation from background ionospheric variability, and the specific locations or times of their occurrence. Questions about how far they propagate, how they evolve over time, and how they propagate are still mostly unanswered. As a result, the current state of research can be viewed as functioning within a significant knowledge gap. In summary, after years of research, no one signature has been found to consistently work as a precursor. The main reason for this is that the methods used in these studies have some problems, such as using random spatial and temporal windows, having near-epicentral data bias, being based on hypotheses, and limited global coverage. In numerous instances, precursor signatures are derived from post-hoc analyses of a limited number of significant earthquakes, thereby forcing doubt on statistical power and reproducibility. Beyond merely establishing statistical correlations through a biased data sampling methodology, advancements in this domain require data-driven frameworks capable of functioning independently of any established hypotheses and of generalizing across various tectonic and ionospheric conditions [38]. Recent research employing machine learning and deep learning has exhibited significant progress in this field, showcasing significant enhancements in the detection of seismo-ionospheric signals that were previously difficult to identify using traditional methods. However, we identified that data bias, specifically a tendency to train models on previously occurred earthquake events using specially chosen or generated non-seismic samples, remains a crucial limitation that may obstruct the practical implementation of these models in future operational early warning systems. To tackle this issue, this study utilizes a data-driven methodology that employs modern deep learning techniques and utilizes Earth-observation satellite systems that offer global data on ionospheric observables. Our methodology diverges from numerous prior studies by not depending on established physical assumptions or pre-existing hypotheses concerning the expected characteristics of seismic precursors. Instead, the method tries to find anomalies directly in the global space-based ionosphere data and see if there is a statistically significant link between the anomalies found by the model and earthquakes that follows. In addition, this study examines the most effective training strategies for anomaly detection in a highly dynamic and time-varying ionospheric environment, where natural variability and background disturbances present substantial challenges.

In this study, we aim to investigate whether significant ionospheric signatures

potentially linked to seismic activity can be identified through modern data-driven methodologies. The primary aim is to analyze space-based global low-frequency ionospheric electric-field observations and establish whether anomalous behaviors detected demonstrate statistically significant, non-random correlations with seismic events. Due to the existing uncertainties regarding the physical mechanisms that control lithosphere–ionosphere coupling, this study concentrates on creating a statistically robust framework to identify possible ionospheric perturbations that are statistically significantly associated with earthquake occurrence through deep learning methodologies. The research aims to explore the capability of deep learning models to extract significant patterns from highly dynamic ionospheric environments by utilizing space-based global observations and anomaly detection techniques.

Ultimately, this study seeks to establish a preliminary methodological framework for the systematic and data-driven analysis of potential ionospheric disturbances with statistically significant seismic associations. The proposed framework is intended to be adaptable and expandable to incorporate supplementary datasets and observational parameters, allowing for future research endeavours focused on enhancing our understanding of lithosphere–ionosphere interactions while supporting the development of predictive methodologies.

Core Research Question

Can global space-based ionospheric electric-field observations be used to identify statistically significant seismic-related anomalies through data-driven methodologies without relying on predefined physical models?

Main Contributions of This Study

1. A global anomaly-first, adaptable and expandable framework is introduced to identify ionospheric disturbances directly from space-based electric-field observations independently of earthquake catalogues, enabling subsequent statistical evaluation of their association with seismic events without imposing an *a priori* causal assumption.
2. A rolling-window training strategy is proposed to iteratively adapt deep learning models to the highly dynamic ionospheric environment. The framework is validated using both a primary study period (2005–2009) and an independent blind-test phase (2010), thereby addressing model generalisability.
3. A systematic exploratory analysis of spatial and temporal labelling strategies is conducted without assuming predefined lithosphere–ionosphere coupling mechanisms.

4. Robustness and sensitivity analyses are performed across multiple model architectures, configurations, and training methodologies.

Chapter 3

Data and Preprocessing

3.1 Data Description

The study comprised two different sets of data sources, including the space-based ionosphere electric field data and the earthquake catalogue. The following section will describe all the major data sources used in the study.

DEMETER ICE Electric Field Data

The Detection of Electro-Magnetic Emissions Transmitted from Earthquake Regions (DEMETER) mission is the first scientific implementation of the CNES Myriade microsatellite program [231], [232]. DEMETER was launched successfully in late June 2004 from the Baikonur Cosmodrome using a Russian DNEPR launch vehicle [233]. The total duration of the mission was from 2004 June to March 2011. The spacecraft was initially injected into a nearly circular, Sun-synchronous polar orbit at an altitude of about 710km, with an inclination close to 98°. In December 2005, the orbit was lowered to roughly 660 km to prolong the mission’s operational lifetime and enhance the scientific output. Due to its Sun-synchronous orbit, DEMETER repeatedly sampled the ionosphere at nearly constant local times, acquiring data near 10:30 local time on the dayside and 22:30 local time on the nightside [234], [235]. The satellite performed about 14 revolutions per day, with successive equatorial crossings separated by roughly 2860 km in longitude, which corresponds to a revisit interval of about 16 days at low latitudes [229], [232].

The main scientific goal of the DEMETER mission was to detect and characterise ionospheric disturbances generated by natural geophysical phenomena, particularly earthquakes, but also volcanic eruptions and tsunamis. A further objective was to track electromagnetic anomalies associated with human-made activities. Through systematic and global observations, worldwide measurements from space, DEMETER was intended to complement ground-based and other satellite observations, which are still limited in both spatial and temporal coverage [27], [231].

It comprised five specialized instruments: the Instrument Champ Électrique (ICE), intended to measure electric field fluctuations across a wide frequency spectrum [236]; the Instrument Magnétique Search Coil (IMSC), dedicated to magnetic field observations [237]; the Instrument Analyseur de Plasma (IAP), which determined key ionospheric plasma parameters [238]; the Instrument Détecteur de Particules (IDP), focused



Figure 3.1: The Demeter satellite boom configuration. Adapted from [231]

on detecting energetic particles [239]; and the Instrument Sonde de Langmuir (ISL), consisting of two Langmuir probes for in situ plasma diagnostics [240]. Collectively, these instruments provided coordinated observations of electric and magnetic fields, particle populations, and plasma characteristics. The effect of electromagnetic disturbances induced by the satellite on the sensors is avoided by setting the IMSC captor at the end of a 1.9m long boom, while the ICE captor is at the extremity of four booms, each 4m long. This boom configuration can be referred to in Figure 3.1 [231]. The sensor configuration of the satellite can be referred to from the figure 3.2. Table 3.1 lists the measured parameters of the mission.

Operational observations were confined to invariant geomagnetic latitudes between -65° and $+65^\circ$, providing broad coverage of the Earth's most seismically active zones. The onboard data processing system of the DEMETER mission functions in two primary modes: a survey mode, which continuously records low-bit-rate data along the entire orbit, and a burst mode, which acquires high-bit-rate data when flying over seismically active regions. As shown in figure 3.3, the areas where burst mode is activated are highlighted in grey on the global map. In survey mode, the telemetry volume is about 950 MB per day, whereas in burst mode it crosses 1 Gbit per day. For the wave experiment, burst mode operation includes recording waveforms of three electric field

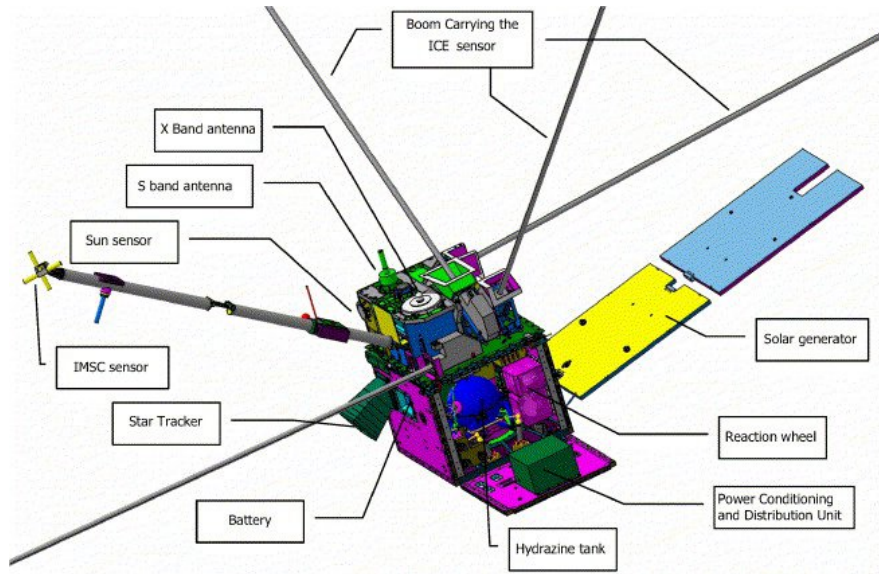


Figure 3.2: The layout of the Demeter satellite and its sensor configuration. (Cussac et al.)

Table 3.1: Demeter scientific mission: list of the measured parameters.(Cussac et al.)

Parameter	Value
Frequency range, B	10 Hz - 17 kHz
Frequency range, E	DC - 3.5 MHz
Sensitivity B	$2 \times 10^{-5} \text{ nT Hz}^{-1/2}$ at 1 kHz
Sensitivity E	$0.2 \mu\text{V m}^{-1} \text{ Hz}^{-1/2}$ at 500 kHz
Particles: electrons	30 keV - 10 MeV
Ionic density	$5 \times 10^2 - 5 \times 10^6 \text{ ions/cm}^3$
Ionic temperature	1000 - 5000 K
Ionic composition	$\text{H}^+, \text{He}^+, \text{O}^+, \text{NO}^+$
Electron density	$10^2 - 5 \times 10^6 \text{ cm}^{-3}$
Electron temperature	500 - 3000 K

components up to 15 Hz, waveforms of all six electromagnetic field components up to 1 kHz, and waveforms of both electric and magnetic components up to 17 kHz. It also stores the spectrum of a single electric component up to 3.5 MHz, together with snapshots of the corresponding waveform up to 3.5 MHz. In survey mode, the data set consists of waveforms of three electric components up to 15 Hz, spectra of both electric and magnetic components up to 17 kHz, the spectrum of one electric component up to 3.5 MHz, and the outputs of a neural network designed to identify whistlers and sferics [27]. This, together with the mission's extended duration and stable orbit, made DEMETER particularly well-suited for statistical studies of potential seismo-ionospheric coupling [218], [242]. In this framework, DEMETER was designed as a research-based mission rather than a practical earthquake forecasting tool. Its primary objective was to record the electromagnetic perturbations of Earth's geophysical processes and to enhance knowledge of the coupling mechanisms linking the solid Earth

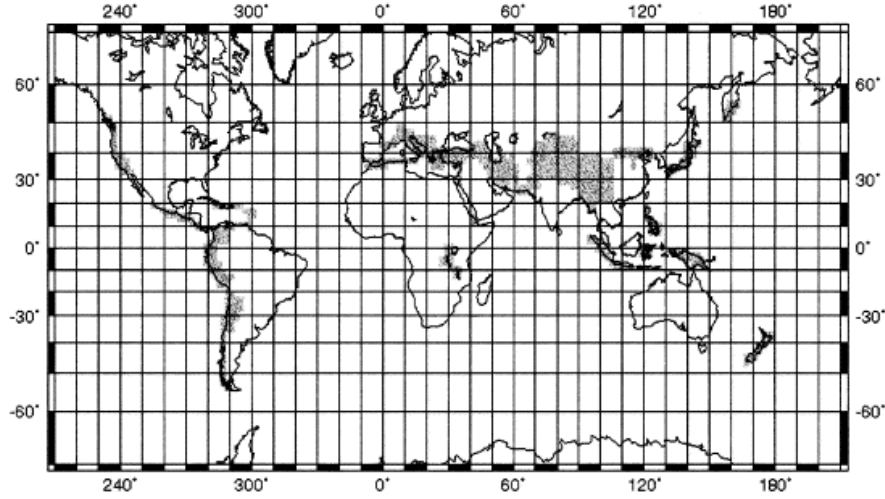


Figure 3.3: The image shows the seismic zone as grey dots, indicating where the satellite's burst mode was activated (adapted from [27]).

with its surrounding fluid layers, such as the atmosphere and ionosphere. The mission's distinctive blend of continuous global coverage, multiple complementary instruments, and extended operational lifetime has established DEMETER as a foundational dataset for later data-driven and statistical investigations of ionospheric disturbances associated with seismic events. In our study, we use the ionospheric electric field measurements provided by the ICE sensor. The ICE experiment onboard the DEMETER satellite was developed to characterise the Earth's electric field environment, with a particular focus on ionospheric perturbations associated with seismic events, thunderstorms, and both natural and anthropogenic wave emissions. The instrument is composed of four spherical electric field probes (E1–E4). These are arranged in the spacecraft coordinate system such that E1 and E2 are approximately aligned with the satellite's Y-axis, while E3 and E4 are oriented at 45° relative to the X-axis (nadir direction) on either side of the orbital XZ plane. This configuration enables nearly orthogonal sampling of the electric field vector (see Figure 3.4).

ICE functions as a double-probe system, measuring potential differences between pairs of sensors (primarily $E12 \approx Y$ -axis, $E34 \approx Z$ -axis, and $ER \approx$ radial), from which the three components of the DC and High Frequency (HF) electric field are determined. In survey mode, it continuously acquires low bit-rate data such as DC/ULF waveforms, ELF and VLF power spectra, HF spectra, and performs neural-network-based identification of whistlers and sferics for global-scale monitoring. In Burst mode, it delivers high bit-rate, detailed observations over selected regions by recording full waveforms in the DC/ULF, ELF, VLF, and HF ranges, together with high-resolution power spectra. Overall, ICE spans a wide frequency range from DC up to about 3.5 MHz, covering DC/ULF (0–15 Hz), ELF (15 Hz–1 kHz), VLF (15 Hz–17 kHz), and HF (10 kHz–3.175 MHz), thereby enabling multi-scale investigations of ionospheric electric field variability

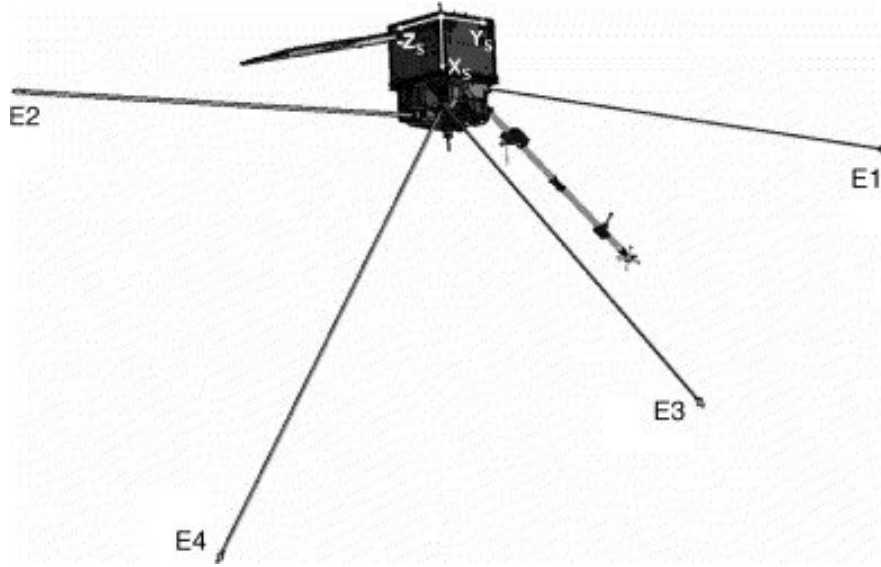


Figure 3.4: The ICE sensor coordinate alignment on the Demeter satellite (Adapted from [236]).

[236].

In this work, we have used the very low frequency (VLF) power spectral density data (APID 1132). The measurements are delivered as binary .DAT files, with each file corresponding to a one half-orbit. The files follow the naming pattern:

"DMT_N1_<apid>_<nnnnn>_<start_date>_<end_date>.DAT",

where "<apid>" is the data product identifier (1132 for the VLF electric field spectra), "<nnnnn>" is the file sequence number (the orbit number, with the final digit indicating the direction: 0 for descending/daytime orbits and 1 for ascending/nighttime orbits), and "<start_date>" and "<end_date>" are the timestamps of the first and last samples, formatted as "yyyymmdd_hhmmss".

The Level-1 data files are structured with a fixed temporal format consisting of four consecutive blocks. Block 1, the general header, stores information on the orbit time and orbit type. Block 2 provides orbital and geomagnetic parameters, including geocentric latitude and longitude, satellite altitude, local time, magnetic coordinates, invariant latitude, magnetic local time, and magnetic field quantities derived from models. Block 3 contains attitude information, expressed as transformation matrices between the spacecraft, geographic, and geomagnetic coordinate frames. Block 4 holds the experiment data, i.e., the ICE VLF power spectra analysed in this study.

For the APID 1132 product, the experiment data block starts by specifying the chosen electric field component (E_{12}) together with the spectral configuration. The spectral information is then stored as arrays of power values. Each spectrum contains $N_{bf} = 1024$ frequency bins, and spectra are produced at a temporal resolution of 2.048s, so that one complete power spectrum is recorded every 2.048 s. A sequence of N_b successive spectra is grouped into a single block, giving a total block duration of $N_b \times$

Power spectrum of 1 component of the electric field in the VLF range					
Filename: <i>DMT N1 1132 <nnnnns> <start_date> <end_date>.DAT</i>					
Field number	Type	Array dim.	Size (bytes)	Unit	Description
Data header					
1	A21	1	21		Data type: "VLF ELECTRIC SPECTRUM"
2	I*1	32	32		House-Keepings and Status (see DR1)
3	A9	1	9		Data coordinate system: "Sensor "
4	A3	1	3		Component name: "Eij", i, j are the sensor numbers
5	A16	1	16		Data unit: " $\log(\mu V^2/m^2/Hz)$ "
6	I*1	1	1		Number of consecutive spectra (Nb): 2 or 8 (1)
7	I*2	1	2		Number of spectrum frequencies (Nbf): 1024 or 256
8	R*4	1	4	s	Total time duration of Nb spectra: 16.384, 4.096 or 1.024 s
9	R*4	1	4	Hz	Frequency resolution: 19.53125 or 78.125
10	R*4	2	8	Hz	Frequency range: [19.53125 or 78.125 - 20000].
11	I*2	7	14		UT time of the first spectrum as: year, month, day, hour, minute, second, millisecond (2)
Power spectrum data					
12	R*4	Nbf	Nbf*4	$\log(\mu V^2/m^2/Hz)$	Power array of the first spectrum
...	...	...	...	...	
12 + (Nb-1)	R*4	Nbf	Nbf*4	$\log(\mu V^2/m^2/Hz)$	Power array of the Nb th spectrum

Figure 3.5: The data description of VLF spectrum density data provided by the DEMETER mission team. (adapted from DEMETER Data product description)

2.048s (here: 4.096s for $N_b = 2$). The spectral resolution is 19.53125 Hz. The spectral values are given as logarithmic power spectral densities in units of $\log(\mu V^2 m^{-2} Hz^{-1})$, and each spectrum is tagged with an exact timestamp corresponding to the time of its first frequency bin. Refer to the figure 3.5 for the specifications of block 4 details.

Seismic Data

The second dataset used in this study to examine seismic correlations is a global earthquake catalogue spanning the six-year interval from 2005 to 2010. The earthquake catalogue was downloaded from the ANSS Comprehensive Earthquake Catalogue (Com-Cat), curated by the United States Geological Survey [243], which offers worldwide hypocentral coordinates and moment magnitude (M_w) estimates for seismic events recorded since the early twentieth century. For this analysis, only earthquakes with a magnitude of $M_w \geq 5$ were selected. All earthquakes meeting this threshold within the specified time window were retained. Consequently, the dataset contains roughly 12,000 earthquakes distributed globally across all of the Earth's tectonic settings.

Table 3.2: Quality-control filters applied to orbit files from the Demeter ICE VLF data. (Reproduced from [244])

Step	Number of half orbit files (ICE)
Total orbit data available	57 839
Glitched orbit files removed	726
Missing or incomplete orbit files removed	1 655
Orbits outside 2005 Jan–2010 Dec removed	2 906
Final set of full-quality orbit files	52 552

3.2 Data Cleaning and Filtering

Comprehensive data preprocessing was undertaken to ensure consistency, including the exclusion of the initial and final mission years (2004, 2011) due to known calibration and operational anomalies, and the removal of all incomplete orbits to preserve data integrity between day and night sets. After these quality controls, the resulting dataset comprises 26,276 orbits, yielding 52,552 half-orbit spectrograms suitable for further analysis. To ensure a homogeneous ionospheric baseline and to avoid noisy VLF signatures that typify nightside passes, we confined our study to the 26,276 daytime ($\approx 10:30$ LT) DEMETER orbits, whose electric-field spectra are markedly quieter, thereby providing a cleaner framework for anomaly detection. Summary of data after every filtration is given in the following table [3.2](#)

3.3 Spatial Gridding and Time Series Construction

Raw data from satellite platforms, especially VLF power spectral density (PSD) measurements of the ionospheric electromagnetic observations, are complex and impacted by many sources, such as those from the magnetosphere (e.g., banded VLF emissions [245] and quasi-periodic wave emissions [246]) and from ionospheric plasma irregularities [247]. It is hard to use this spectral data directly to find small signals that might come from the lithosphere, even if it has a lot of information. When you measure spectral power across a wide range of frequencies, you frequently get a lot of background noise, natural variations, and short bursts of high energy. The unexpected very low frequency (VLF) radio events recorded by the satellite DEMETER are detailed in the study by Parrot et al. These can obscure faint but crucial geophysical patterns.

To tackle these challenges, a spatially organized method is applied. The Earth’s surface is divided into set geographic cells with a grid. This means that electric field

spectral signatures recorded at regular periods can be linked to specific locations. This allows to generate time series for each area and examine how signals vary over time, regardless of the satellites' movement or their coverage of the area. Grouping PSD data by location helps the identification of region-specific noise characteristics and recurring patterns, such as seasonal changes, geomagnetic effects, or differences by latitude, both of which are critical for filtering out persistent but non-relevant signals.

To facilitate spatial referencing, the Earth’s surface was partitioned into a regular grid with spatial resolution of $20^\circ \times 20^\circ$ in both latitude and longitude (Figure 3.6). Each grid cell is assigned a numerical label, ordered sequentially from the southernmost to the northernmost regions (G1, G2, ...). Each cell in this grid serves as a spatial unit for aggregating and analysing the electric field data recorded during each satellite overpass. During each orbit, the satellite traverses multiple grid cells, with data segmentation performed at two-minute intervals. At each interval, the maximum overlapping grid cell is identified, and all associated measurements are attributed to it. This ensures each grid cell’s time series is not biased by partial coverage and reflects consistent spatial domains over the dataset period.

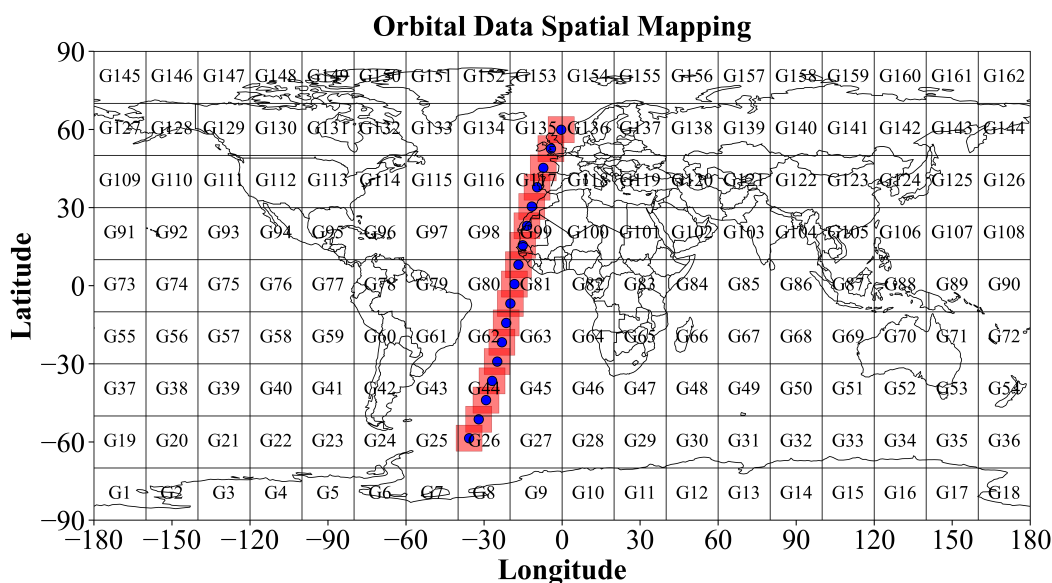


Figure 3.6: The figure illustrates the path of day orbit 027640. The blue dots represent the orbit’s position at every 2-minute interval, where spectral features are calculated within the area of the red squares. (Reproduced from [244])

Quantifying ionospheric variability requires characterizing the statistical properties of the electric field’s spectral power. To ensure robustness and capture both regular and rare geophysical behaviours, 11 logarithmically spaced spectral bands in the very low frequency (VLF) range below 3 kHz were selected from the ICE instrument’s power spectral density measurements [43]. These span the extremely low frequency (ELF, 3–3000 Hz), capturing phenomena attributable to both background processes and possible seismo-ionospheric electromagnetic anomalies.

The table below outlines the frequency bands used in this study. Each band is defined based on a multiplication of the ICE instrument’s base resolution $f_0 = 19.53$ Hz. The selected bands progressively span from tens of Hz to over 3 kHz, ensuring sensitivity across different electromagnetic phenomena in the ionosphere [43].

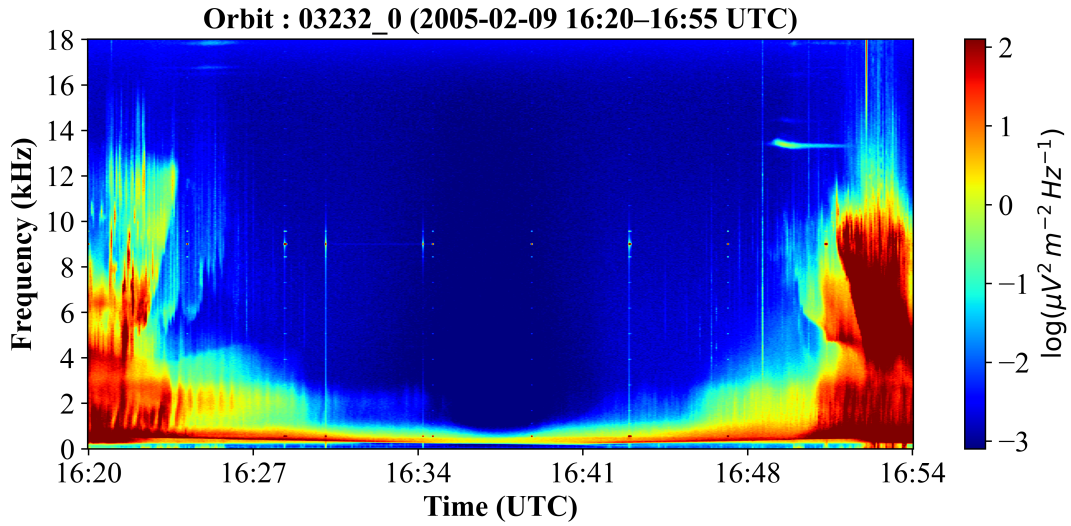
Table 3.3: Frequency bands derived from ICE measurements (Reproduced from [244])

Code	Frequency Bands ($f_0 = 19.53$ Hz)	Numeric Range (Hz)
FB1	$(1-2) \times f_0$	19.53 – 39.06
FB2	$(15-19) \times f_0$	292.95 – 371.07
FB3	$(19-24) \times f_0$	371.07 – 468.72
FB4	$(24-31) \times f_0$	468.72 – 605.43
FB5	$(31-39) \times f_0$	605.43 – 761.67
FB6	$(39-49) \times f_0$	761.67 – 956.97
FB7	$(49-61) \times f_0$	956.97 – 1,191.33
FB8	$(61-77) \times f_0$	1,191.33 – 1,503.81
FB9	$(77-97) \times f_0$	1,503.81 – 1,894.41
FB10	$(97-122) \times f_0$	1,894.41 – 2,382.66
FB11	$(122-154) \times f_0$	2,382.66 – 3,008.2

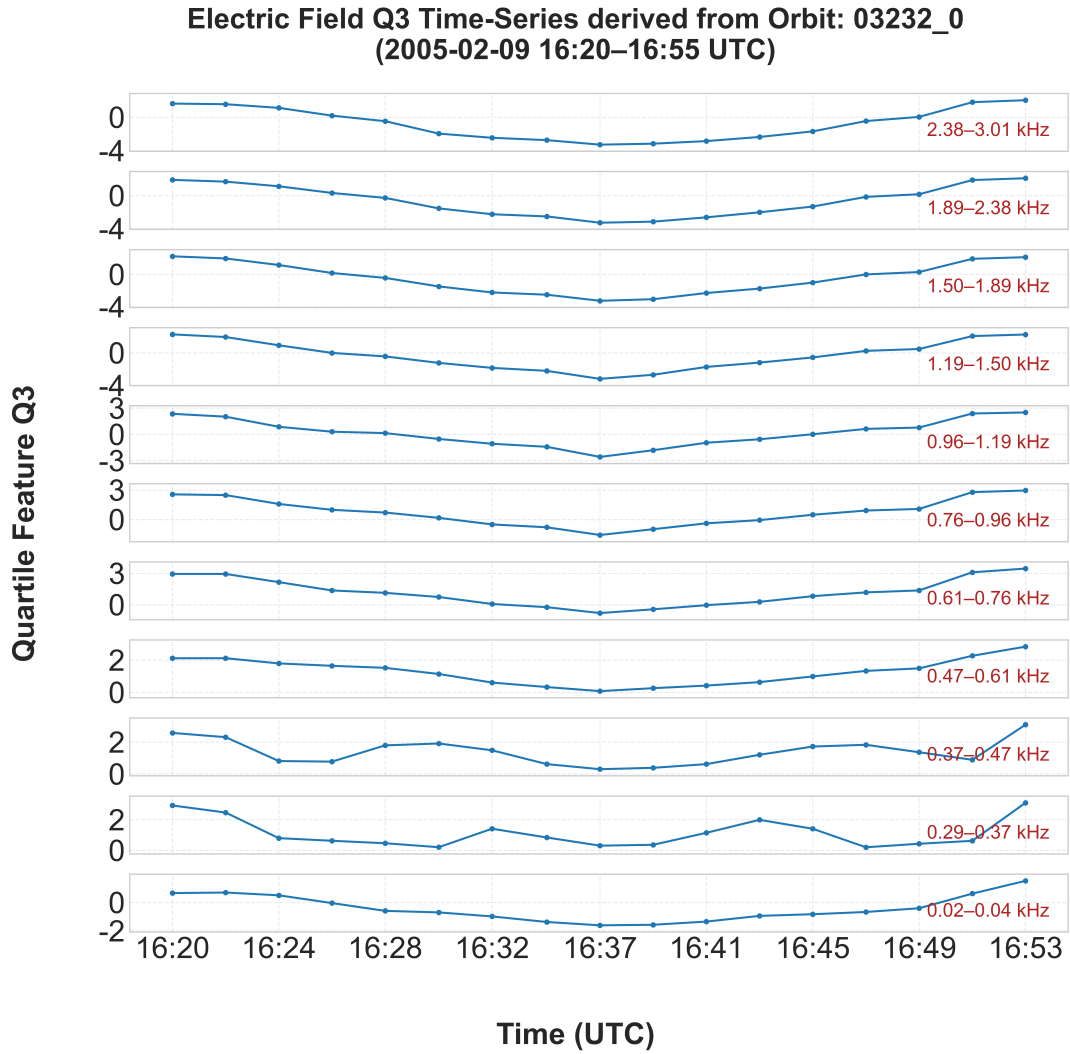
For each 2-minute interval for a specific spatial range or $10^\circ \times 10^\circ$ degree square around the orbital footprint, empirical quantiles such as Q1 (lower quartile), Q2 (median), and Q3 (upper quartile) are calculated for the data within each frequency band. This multi-quantile extraction strategy accounts for understanding the overall behaviour distributions of physical measurements in the ionosphere, improving resilience to outliers and enhancing the possibility of anomaly detection [14], [249].

Figure 3.7 illustrates an example of converting PSD data into time-series data. Figure 3.7a represents the PSD plot of orbit 03232, which is a day orbit. The converted timeseries is illustrated in the figure 3.7b, a single orbit, lasting approximately 34 minutes and covering a frequency range of 3 kHz, is transformed into 11 discrete time series corresponding to the 11 selected frequency bands, each containing 17 data points.

These calculated features are then assigned to the grid cell that exhibits the greatest spatial overlap with the corresponding spectrogram interval. As a result, each grid cell aggregates a set of temporal records. Over the study period from 2005 to 2010, this procedure produced extensive multi-frequency time series data for 162 grid cells worldwide. Polar grid cells, consistent with DEMETER’s invariant latitude constraints, are largely unpopulated, which is a common limitation in satellite remote sensing caused by orbital restrictions. To maintain the quality and comparability of these gridded time series, additional filtering was carried out to exclude cells and intervals that were insufficiently sampled in both space and time (consequently, only grid cell G19–G144 was retained for the analysis). A representative illustration of the gridding and temporal feature construction is provided in figure 3.8, which demonstrates the



(a) Electric field PSD of a daytime orbit with the frequency ranging from 19.3 Hz to 18 kHz. The total duration of a half orbit is about 34 minutes.



(b) Derived electric field Q3 time series for 11 frequency bands, resampled every 2 minutes, yielding 17 points per band.

Figure 3.7: (a) PSD and (b) derived timeseries data below 3 kHz Comparison of DEMETER electric-field measurements for orbit 03232.0.

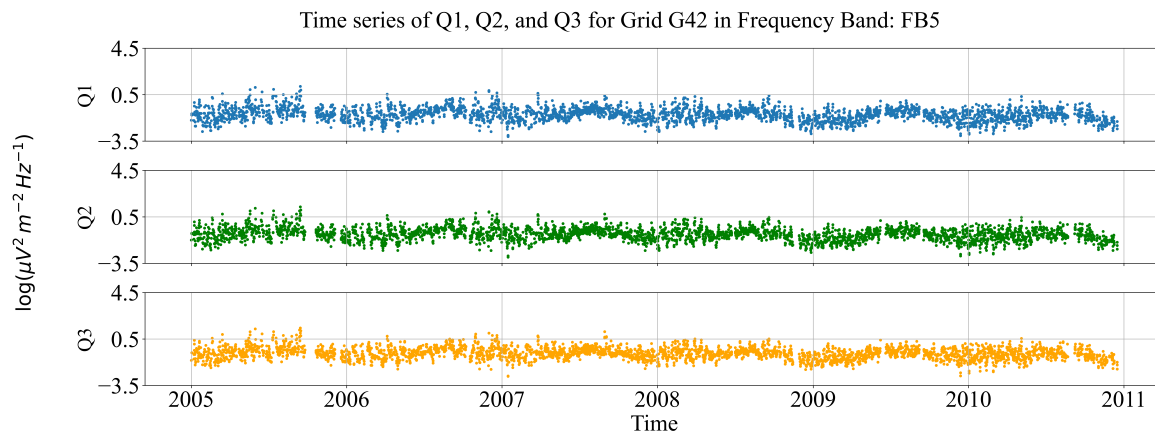


Figure 3.8: Temporal variation of the quantile feature Q3 over a six-year period for a specific grid cell (G42) for frequency band FB5.

six-year temporal evolution of the quantile features in a specific grid cell for frequency band FB5 as a practical example.

The outlined grid-based approach, which involves regular spatial partitioning, strong quantile-based feature extraction, and meticulous temporal aggregation, establishes a reliable basis for future ionospheric anomaly detection research. Although this study employs a global framework, the term “global” here denotes the lack of region-specific preselection (for instance, targeting particular seismic zones) rather than a homogeneous spatial coverage of the entire planet. The DEMETER satellite offers quasi-global sampling in longitude, but its observations are restricted by fixed invariant latitudes. Consequently, high-latitude and polar regions are entirely missing from the dataset, and the resulting analysis mainly characterises ionospheric dynamics at low and mid latitudes. A grid-based scheme is used to arrange the spectral measurements spatially, converting them into geographically referenced time series. Each grid cell corresponds to a specific geographic area within which local ionospheric variability can be examined. This methodology enables the generation of spatially resolved time series that retain geographic context and support region-dependent background removal and trend determination. In total, 162 grid cells are distributed worldwide, with each half-orbit crossing roughly 145 of them. Grids lying poleward of $\pm 65^\circ$ geomagnetic latitude remain mostly unoccupied, consistent with DEMETER’s invariant orbital limitations. Accordingly, the findings should be viewed as geographically distributed yet spatially non-uniform, reflecting the actual observational footprint of the DEMETER daytime orbits.

3.4 Exploratory Data Analysis

To examine the statistical relationships among the extracted quantile features, a Pearson correlation analysis was carried out for the Q1, Q2, and Q3 time series. The purpose of this analysis was to quantify the linear dependence among the quantiles and to determine whether they convey overlapping or complementary information for subsequent modelling. Specifically, the correlation analysis helps to decide whether all quantile features should be included together or if a reduced feature set would be sufficient without significant loss of information.

The Pearson correlation coefficient between two variables $Q1$ and $Q2$ is defined as

$$r_{Q12} = \frac{\sum(Q1 - m_{Q1})(Q2 - m_{Q2})}{\sqrt{\sum(Q1 - m_{Q1})^2 \sum(Q2 - m_{Q2})^2}}, \quad (3.1)$$

where m_{Q1} and m_{Q2} denote the mean values of the vectors $Q1$ and $Q2$, respectively [250], [251].

Correlation Matrices (Q1, Q2, Q3) Across FB1–FB11 for Grid G95

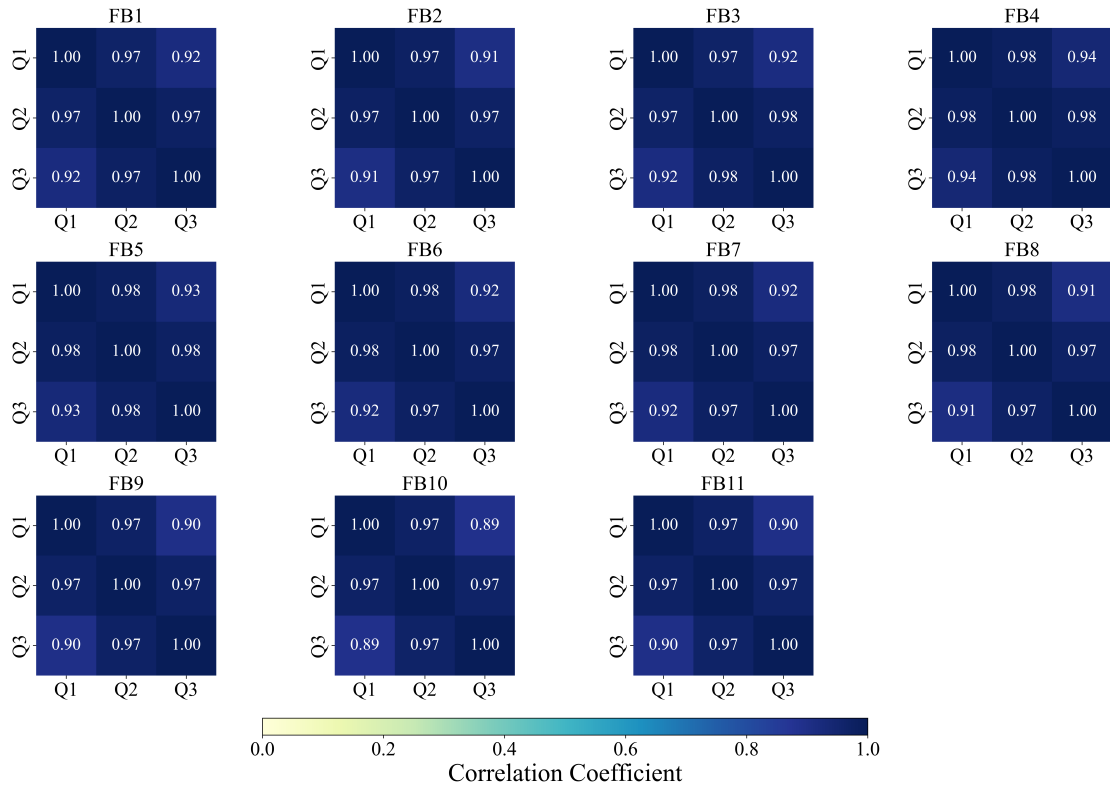


Figure 3.9: Pearson correlation matrix of the quantile features Q1, Q2, and Q3 across the 11 frequency bands for grid G95 representing low latitude location. The colourbar plots the maximum and minimum possible coefficient range.

Figures 3.9 and 3.10 present the Pearson correlation matrices for the three quantile-based features Q1, Q2, and Q3 across all 11 frequency bands (FB1–FB11), for the

low-latitude grid G95 and the mid-to-high latitude grid G114, respectively. Across both grids and all frequency bands, the correlations between the quantiles are consistently strong, with coefficients always above 0.82 and usually exceeding 0.90. This reveals a strong linear dependence among Q1, Q2, and Q3, implying that these three quantiles describe very similar characteristics of the underlying ionospheric power distribution. Across both grids, the strongest correlations typically occur between Q2 and Q3, followed by Q1–Q2, whereas Q1–Q3 tends to be slightly lower yet still very high. This correlation pattern persists over the entire frequency spectrum, indicating that the relationships among the quantile features are largely unaffected by frequency band or geographic region. The uniformly strong correlations observed across all bands and in both latitude ranges suggest substantial redundancy among the quantile-based features. Consequently, to avoid unnecessary feature duplication while preserving a reliable characterisation of the data distribution, Q3 was chosen as the final feature for further analysis, as it offers a statistically robust and physically interpretable measure of ionospheric background variability and anomalous disturbances.

Correlation Matrices (Q1, Q2, Q3) Across FB1–FB11 for Grid G114

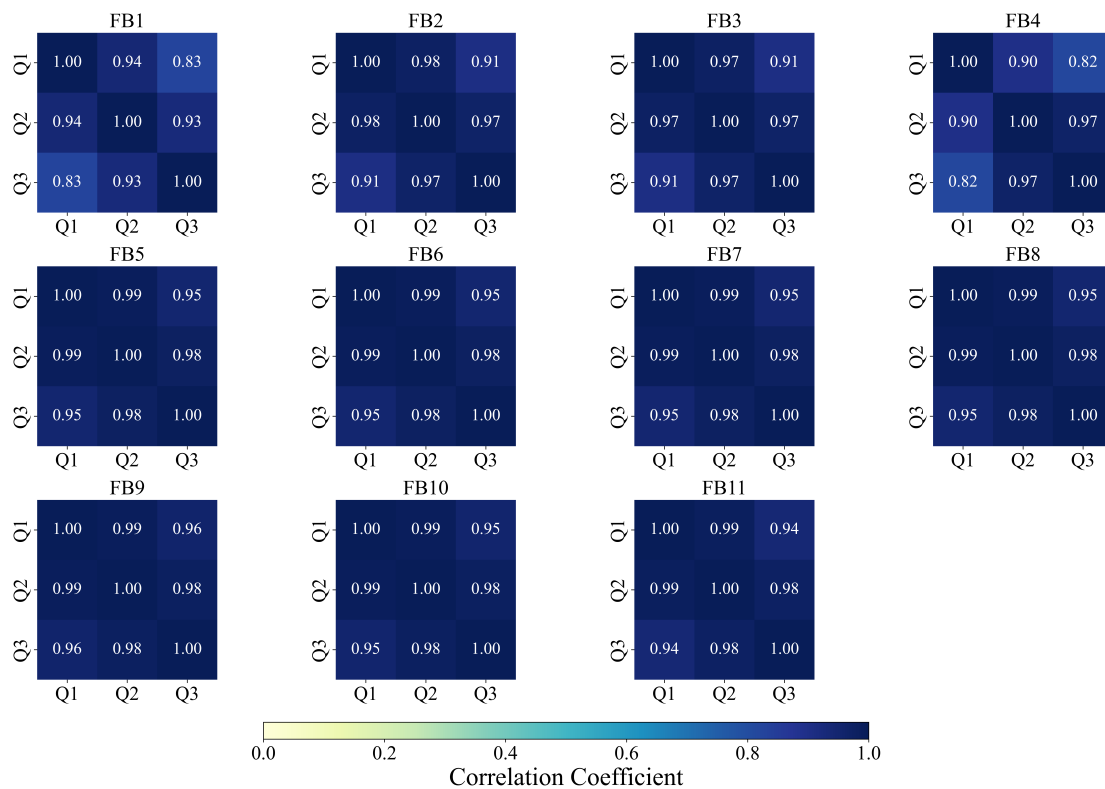


Figure 3.10: Pearson correlation matrix of the quantile features Q1, Q2, and Q3 across the 11 frequency bands for grid G114 representing the mid-high latitude location. The colourbar plots the maximum and minimum possible coefficient range.

After performing the correlation analysis and visually examining the Q3 dataset across grid locations and frequency bands, we observed recurring patterns in the data

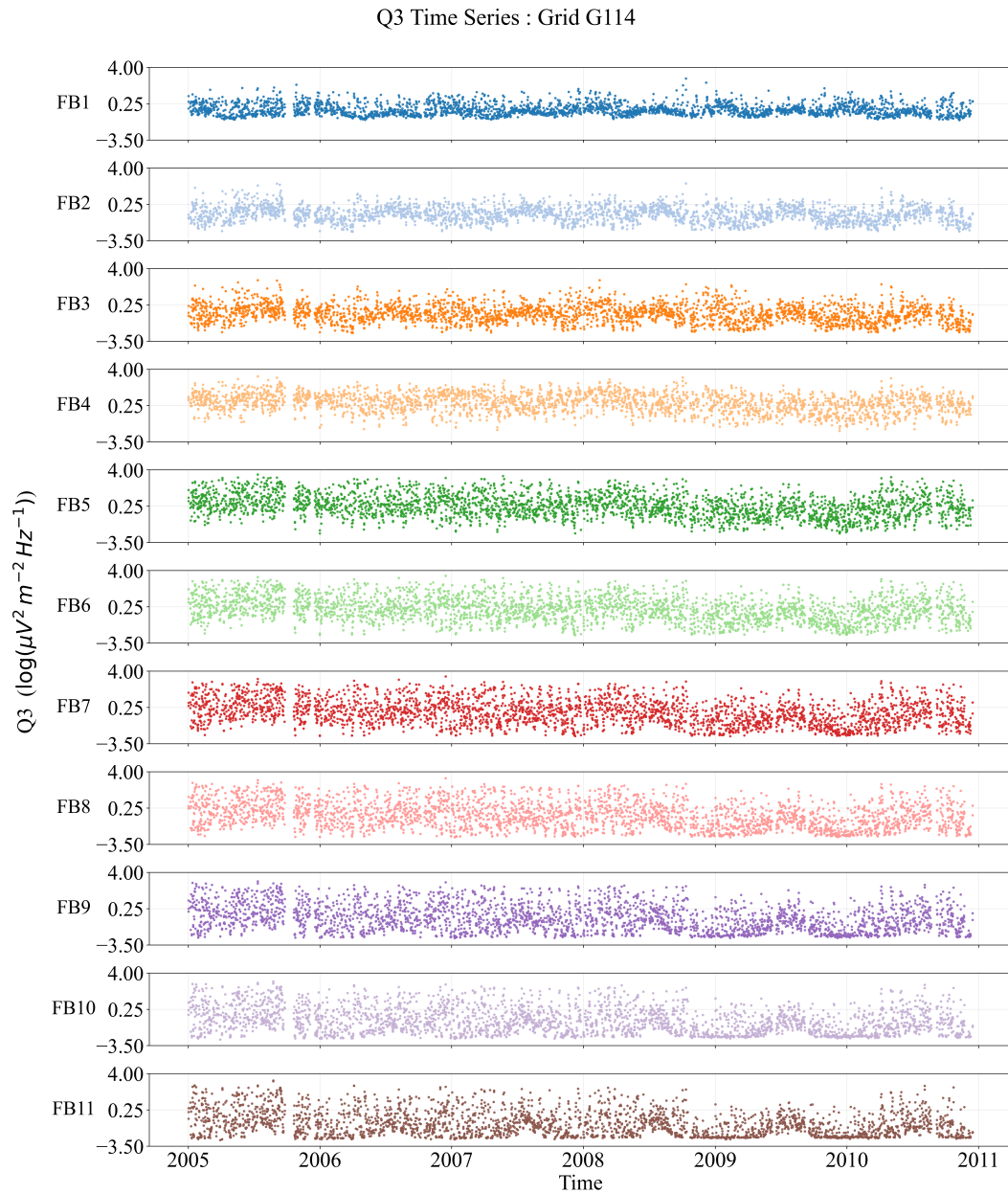


Figure 3.11: Temporal variation of the quantile feature Q3 over six years for a specific grid cell G114 representing mid-latitude to high-latitude geographic locations across the 11 frequency bands.

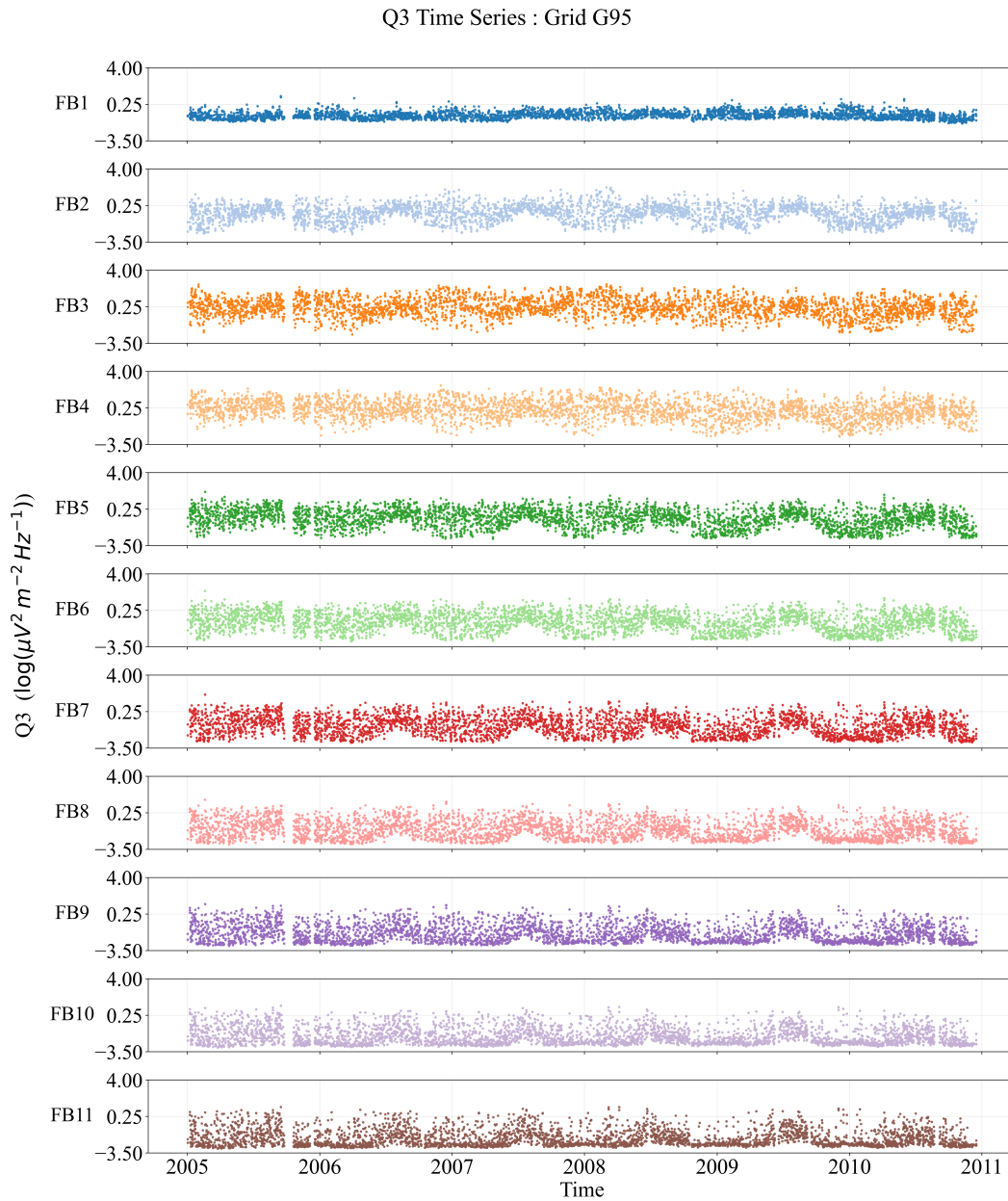


Figure 3.12: Temporal variation of the quantile feature Q3 over six years for a specific grid cell G95 representing low-latitude geographic locations across the 11 frequency bands.

that are specific to certain geographic areas and frequency ranges. An example of the gridding and temporal feature construction is shown in Figure 3.11, which presents the six-year evolution of the quantile feature Q3 within grid cell G114, characteristic of mid- to high-latitude locations, across 11 frequency bands. Figure 3.12 similarly depicts the six-year temporal evolution of the Q3 for a representative low-latitude grid cell (G95) over the same 11 frequency bands. In all panels, the horizontal axis represents time (in years) and the vertical axis shows the corresponding Q3 values; the axis limits are kept fixed for all grids to enable straightforward visual comparison. A brief data gap near the end of 2005 is visible in every frequency band, corresponding to a period of missing observations. The time series exhibits clear seasonal modulation and intrinsic feature variability, with a marked quasi-sinusoidal pattern characterised by recurring peaks around mid-year. This seasonal signature offers confirmation that the extracted Q3 feature is physically relevant, as it reproduces the well-known seasonal behavior of the ionosphere documented in earlier research. This behavior is primarily controlled by solar extreme ultraviolet radiation [252], thermospheric circulation [253], and large-scale atmospheric coupling processes, including tidal forcing [253], [254] and external forcing from solar and geomagnetic activity [255], [256], [257].

The spread of the data shows a clear dependence on frequency, generally increasing toward higher frequency bands, which points to greater variability and heightened sensitivity in the upper VLF range. Temporal changes in dispersion are also evident, for example, certain bands, such as FB11, show a gradual reduction in spread over the six-year interval. Comparatively, the overall Q3 levels are consistently higher in the mid to high latitude grid G114 than in the low-latitude grid G96, whereas G96 displays systematically lower dispersion across most bands. This reduced variability in G96 makes the seasonal patterns more pronounced, underscoring the role of latitude in controlling both the amplitude and stability of ionospheric electromagnetic fluctuations. These behaviours vary from grid to grid according to their geographic location. Consequently, it is necessary to perform detailed, grid and frequency band specific background corrections in order to characterise and learn the underlying background behaviour more accurately and to make the data appropriate for anomaly detection.

3.5 Background Correction

The background correction process constitutes a fundamental preprocessing step in this study, aimed at removing long-term and periodic variations from the raw time series data. The objective is to isolate short-term fluctuations that are more relevant for anomaly detection and model training. In many satellite ionospheric and geophysical datasets, the observed signal is often influenced by predictable components such as seasonal effects, orbital cycles, or gradual instrumental drifts. If not accounted for,

these systematic variations can mask the smaller but meaningful deviations that may indicate significant events. The background correction, therefore, seeks to model and eliminate these deterministic patterns, leaving a residual signal that reflects genuine physical changes. The discrete time series from each grid cell exhibits a long-term seasonal sinusoidal pattern and trend, as illustrated in Figure 3.8. Upon meticulous examination, each grid cell has demonstrated that geographical location, specifically the transition from lower to higher latitudes, significantly impacts the nature of data. To address this seasonality and trend, the background behaviour of the data is represented by a function that combines a linear and a sinusoidal component. The linear term models the slow, monotonic trends over time, while the sinusoidal term captures the repeating periodic variations inherent in the system. The general form of the background function can be expressed as

$$f(t) = a + bt + c \sin \left(\frac{2\pi t}{d} + e \right) \quad (3.2)$$

where a denotes the constant offset representing the mean background level, b is the coefficient of the linear trend accounting for slow drifts, c represents the amplitude of the periodic component, d defines the period of the cycle which is fixed as 1 year, and e is the phase shift. This formulation provides a balance between simplicity and flexibility, enabling the function to reproduce both steady and oscillatory behaviour commonly observed in time-dependent datasets.

A resampling process is used to deal with the inconsistencies and high-frequency changes in the original time series before fitting the background model. The data is resampled into equal time intervals (for example, 30-day windows) to calculate a representative statistical feature. When resampling, the mean value is calculated within a 90% confidence range of the resampled data, which makes sure that outliers are not included in the background estimation. This helps prevent anomalous points from biasing the background model, which is crucial for the subsequent anomaly detection process. This resampling stage helps reduce short-term and random noise, making sure that the fitting process picks up on the broader background in the data instead of just spikes or irregular disruptions. Moreover, by reducing the temporal resolution, background fitting can be easily achieved, and it also minimizes the influence of missing or unevenly spaced observations, facilitating a more reliable estimation of the long-term background behavior, which in turn supports the Model's anomaly detection.

The parameters of the function a, b, c, d , and e are estimated using a non-linear least squares optimization method. The fitting process minimises the discrepancy between the observed data and the modelled values according to the following chi-

square function:

$$\chi^2 = \sum_{i=1}^N \frac{(Y_i - f(t_i))^2}{\sigma_i^2} \quad (3.3)$$

where Y_i represents the observed value at time t_i , $f(t_i)$ is the corresponding fitted value from the background function, σ_i denotes the measurement uncertainty or standard deviation for each observation (calculated over resampled interval), and N is the total number of data points [258], [259]. The chi-square value quantifies how well the fitted curve represents the observed data, taking into account the variability in measurement precision.

To evaluate the goodness of fit, the reduced chi-square statistic, χ_ν^2 , is used and defined as [259]

$$\chi_\nu^2 = \frac{\chi^2}{\nu} = \frac{1}{N - p} \sum_{i=1}^N \frac{(Y_i - f(t_i))^2}{\sigma_i^2} \quad (3.4)$$

The p is the number of parameters in the model, and $\nu = N - p$ is the number of degrees of freedom. The reduced chi-square provides a normalized measure of the fit quality, allowing for comparison across different datasets. A value of χ_ν^2 close to unity generally indicates a good fit, implying that the model reproduces the data within the limits of observational uncertainty. Significantly greater values suggest underfitting or unmodeled variability, while values much smaller than one may indicate overfitting error estimates [259].

Once the parameters of the background function are determined, the function is fitted to the entire dataset using the estimated coefficients. Then the fitted curve is subtracted from the original dataset to produce the background-corrected residuals. The residual at each time point t is computed as

$$X(t) = Y(t) - f(t) \quad (3.5)$$

where $X(t)$ represents the background-corrected value and $Y(t)$ is the original observation. This background and residual separation is a standard step in timeseries preprocessing and is particularly useful for isolating anomalous deviations from the underlying trend, which can then be analysed using anomaly detection methods [260]. These residuals reflect the deviations of the observed signal from its expected background level, effectively isolating the short-term variations and potential anomalies of interest.

The outcome of the background correction process is a clean, detrended, and deseasonalised dataset that captures the true variability of the system. The localized grid specific fitting technique guarantees that the background representation precisely reflects spatially changing patterns and preserves local homogeneity within each grid cell.

This technique improves the sensitivity of future anomaly identification by offering a more accurate and relevant assessment of the background behavior for each grid location. The incorporation of the reduced chi-square evaluation provides a quantitative measure of fitting performance, allowing for ongoing verification of model adequacy. Overall, this method ensures that subsequent modeling and anomaly detection processes operate on a well-corrected and physically meaningful dataset, free from the influence of predictable long-term or periodic variations.

3.6 Seismic Labelling

In our study, the data labelling scheme is not given a priori. Still, it must be derived from physical and geophysical considerations, in particular from the spatio-temporal relationships between satellite orbital data (footprints) and earthquake occurrences. The way this “possible classing” of the dataset is defined has a direct impact on what the model will learn as “seismic” versus “non-seismic” behaviour, and therefore must be formulated explicitly.

To start with, the input of the model, which is a sampled sequence of fixed duration, is to be chosen. For our study, we focus on two consecutive daytime orbit pairs as a single input or a sequence. To construct labels, we consider a set of spatial and temporal windows defined with respect to the defined sequence. For each overpass and corresponding measurement segment, we specify a geographic neighbourhood around the satellite track and a temporal interval after the observation time. In this work, we focus on correlations with earthquakes occurring after the time of observation; therefore, all temporal windows are defined in the future relative to the satellite pass. Earthquake catalogues are then queried within these windows. If at least one earthquake satisfying predefined magnitude criteria falls inside the chosen spatio-temporal window, the associated satellite data segment can be assigned to a “potentially seismic-related” class; otherwise, it can be treated as belonging to a “background” or “non-seismic” class. It should be noted that, depending on the selected spatial and temporal association windows, the same earthquake may label more than one consecutive sequence as seismic. Such dependencies cannot be completely avoided within the present framework. In the training setting considered here, the training phase is initially adjusted to focus on the non-seismic category: only those samples with no recorded seismic activity in the corresponding window are used as clean background examples. These constitute the labeled class “0” subset representing “normal” conditions, while the remaining data, which may include both ambiguous and potentially seismic-related cases, are labeled class “1”.

From the point of view of earthquake forecasting and post hoc co-matching, the selection of spatial and temporal windows is not a purely technical detail but a central

Table 3.4: Spatial window definitions used for seismic/non-seismic classification (TW - 48 hours fixed).

Criteria Name	Spatial Window Description
SW05x05_TW48	$05^\circ \times 05^\circ$ square centered along passes footprint
SW10x10_TW48	$10^\circ \times 10^\circ$ square centered along passes footprint
SW20x20_TW48	$20^\circ \times 20^\circ$ square centered along passes footprint
SW22x22_TW48	$22^\circ \times 22^\circ$ square centered along passes footprint
SW23x20_TW48	$23^\circ \times 20^\circ$ rectangular centered along passes footprint

modelling assumption. The window size directly determines which events are treated as “associated”, narrow windows lower the likelihood of false matches but can overlook long-lead or spatially offset precursors, while wider windows raise the detection rate at the expense of capturing more unrelated variability. Different studies adopt different lead times (from minutes to several days) and spatial extents (from a few hundred kilometres to regional scales) when associating geophysical or ionospheric anomalies with seismic events. Satellite-based studies of seismo-ionospheric anomalies typically explore ranges from a few days up to several weeks around the mainshock and spatial radii of a few hundred to roughly 1,500 km, precisely because detection statistics and precursor times are highly sensitive to these parameters [261], [262], [263]. Similar considerations arise in purely seismological and machine-learning approaches, where spatio-temporal windows determine how earthquakes are clustered and how predictive patterns are extracted from catalogues [264], [265]. This diversity reflects both the complexity of the lithosphere–atmosphere–ionosphere coupling mechanisms and the existing lack of consensus concerning the typical range at which earthquake-related perturbations are most likely to appear. Instead, window definitions are often motivated by empirical discoveries, theoretical models, or practical considerations such as satellite orbit shape and data coverage. To date, there is no universally accepted temporal or spatial criterion that systematically isolates earthquake-related signals from other sources of variability. Consequently, any labeling strategy, such as the one adopted in this work, must be presented as a methodological choice rather than an established standard. We have used a set of spatial–temporal window configurations for the preliminary part of the study. The spatial windows (SW) tested are $5^\circ \times 5^\circ$, $10^\circ \times 10^\circ$, $20^\circ \times 20^\circ$, $22^\circ \times 22^\circ$, and $23^\circ \times 20^\circ$ polygons along the footprint. In the first part of the modelling, these different spatial windows and a fixed temporal window of 48 hours are used for seismic association. Table 3.4 provides the naming convention and a detailed description of each spatial window. An example of an input of two consecutive daytime orbit data and its spatial window marking for seismic search is illustrated in the figure 3.13

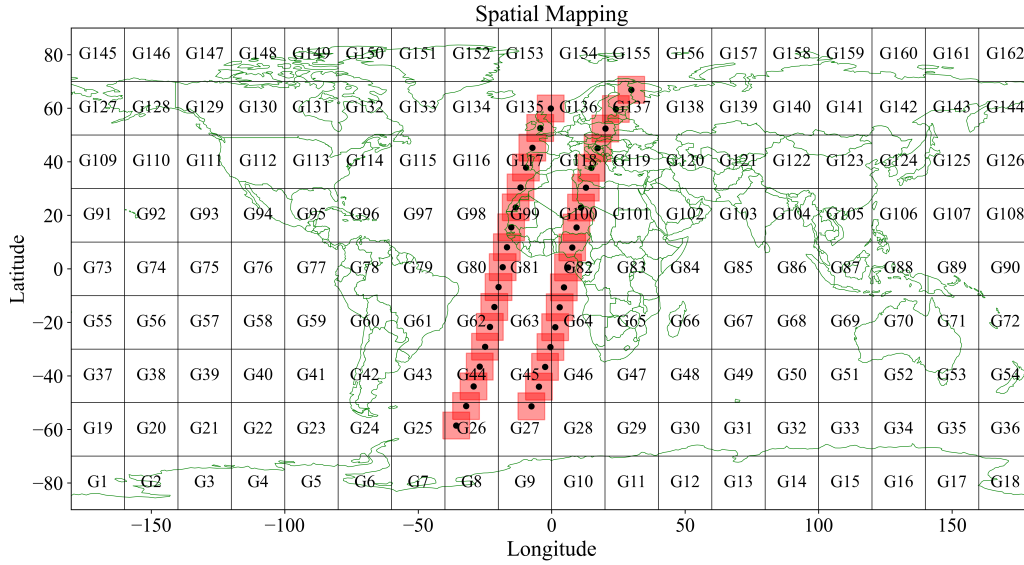


Figure 3.13: A representative example of spatial width "SW10x10". $10^\circ \times 10^\circ$ spatial coverage relative to the satellite footprint.

After identifying the best-performing spatial-window category under the above-specified criteria, we perform a time-window analysis using several temporal windows (TW) of 6, 12, 24, and 48 hours following sequence. Each combination of SW-TW is treated as a separate criterion and is trained and evaluated with the same deep-learning pipeline. The final reference criterion is selecting the best choice of SW-TW combination, based on statistical screening results from the model outcome for detailed analysis. This two-stage screening procedure is intended to determine which way of partitioning the data, defined by the chosen spatial and temporal window, yields the most reliably learnable representation of nominal ionospheric behaviour across different models, rather than to optimise any particular post-hoc correlation metric. The spatial and temporal window is therefore not just a statistical hyperparameter; it dictates how individual orbits are assigned to seismic or non-seismic classes and thus directly shapes the composition of the training set. A tighter spatial window leads to fewer orbits being tagged as seismic, leaving a larger pool of non-seismic samples for learning the background behaviour. Conversely, a broader window increases the number of samples marked as seismic, which in turn reduces the amount of data available for training. Each spatial-temporal choice hence defines a distinct model trained on a uniquely composed dataset. Because there is no established agreement in the literature on the characteristic spatial and temporal scales of pre-seismic ionospheric disturbances, a systematic survey of a physically motivated range of configurations is the most appropriate methodological strategy. The criterion selected during the primary training and analysis phase is then carried over unchanged to the blind phase, enabling independent temporal validation of this choice using data that were completely excluded from the

selection process.

Chapter 4

Methodology

4.1 Rolling Window Implementation

The rolling window model training and validation approach is a framework designed to analyse time-dependent data while maintaining temporal consistency and adaptability. The conventional way of splitting the data into a fixed training and validation period will fail to account for the temporal continuity of the data, potentially leading to biased performance estimates. This cannot be considered a temporally adaptive approach in which the model is restricted to learn from a fixed set of data alone. Instead of training a model only once in the entire dataset, our method divides the data into overlapping “windows”, where each window includes a defined training and validation segment. In this study, each window comprises twelve months of training data followed by three months of validation data. After each iteration, the window shifts forward by three months, and the entire process is repeated. Figure 4.1 shows a schematic overview of the proposed strategy. A single row corresponds to the entire study period within the selected time frame, with each box indicating a 3-month segment. Each rolling window spans 15 months and is divided into training and validation segments, depicted by blue and orange boxes, respectively. At each iteration, the window advances by 3 months to the next position. Windows are indexed starting from 0, such that (w_0) , (w_1) , and so forth up to (w_{19}) represent a total of 20 windows over the full duration. Across all windows, the training segments overlap by 9 months, whereas the validation segments are non-overlapping and independent. Within each window, the training segment is used exclusively to train the model, while the validation segment is reserved for an independent assessment of anomaly detection performance. Crucially, all reported performance measures are based solely on the anomaly detection outcomes obtained over the complete 3-month validation segment of each window. In effect, this full validation segment plays the role of an independent test set in the standard sense: it consists of data on which the model has never been trained, that has not been used for hyperparameter tuning, and on which all performance metrics are ultimately computed.

The 20 windows are further partitioned into two analysis stages. The first, or primary stage consists of windows w_0 through w_{15} , whose validation segments cover the years 2006–2009. This constitutes the main modeling phase, during which the model is repeatedly trained on each window’s training segment and then evaluated on its corresponding validation segment. This stage is used for the primary statistical

analysis and for selecting the best-performing detection criteria (see section 3.6) based on performance on the validation data. The second, blind analysis phase includes windows w_{16} to w_{19} , whose validation segments span January–December 2010. In this blind phase, the rolling training procedure continues: for each blind window, the model is retrained on the associated training segment to track changes in the ionospheric background, but the validation data used for performance assessment are entirely new and were never involved at any point during the primary phase, neither in training, nor validation, nor criterion selection. The independence of the blind phase is thus guaranteed in three distinct ways. First, within each blind window, the validation segment used for anomaly detection and statistical evaluation is disjoint from the training data of that window. Second, none of the four 2010 validation segments appear in any training or evaluation step of the primary phase, which ends at w_{15} with validation data only up to December 2009. Third, the choice of the best performing spatio-temporal detection criterion and the model architecture is fully determined from the primary phase before any 2010 data are accessed in any form.

Consequently, the blind phase analysis demonstrates the generalizability and real-world utility of the rolling-window training framework when data extend beyond the initial study period, mimicking an operational setting in which the model is continually updated to reflect recent ionospheric background conditions and then evaluated on the subsequent, previously unseen interval.

Before the modelling phase begins, the data undergo a background correction process aimed at removing slow-varying trends and periodic fluctuations that may interrupt the detection of meaningful anomalies by the model. This correction step is crucial because environmental or instrumental data often contain cyclical patterns that are not of interest for specific anomaly analysis.

The important aspect of the background correction in this study is its iterative nature. In contrast to the standard practice of fitting the background function only once with a fixed reference period, the background information is gradually updated as the analysis proceeds through successive rolling windows. For each rolling window, the background curve is fitted using all available data from the beginning of the study (January 1, 2005) to the start of the corresponding validation period. This ensures that each new fit incorporates the cumulative understanding from previous time intervals, thus allowing the model to continuously enhance its understanding of the long-term background behaviour. In the first window, the fitting process uses only the data from the initial twelve-month training period. For the subsequent windows, the fitting dataset expands to include all data up to the start of the current validation period. Thus, each rolling window extends the background information by three months to account for the period associated with the validation data of the preceding window. This fitting approach allows the model to adapt to slow temporal variations

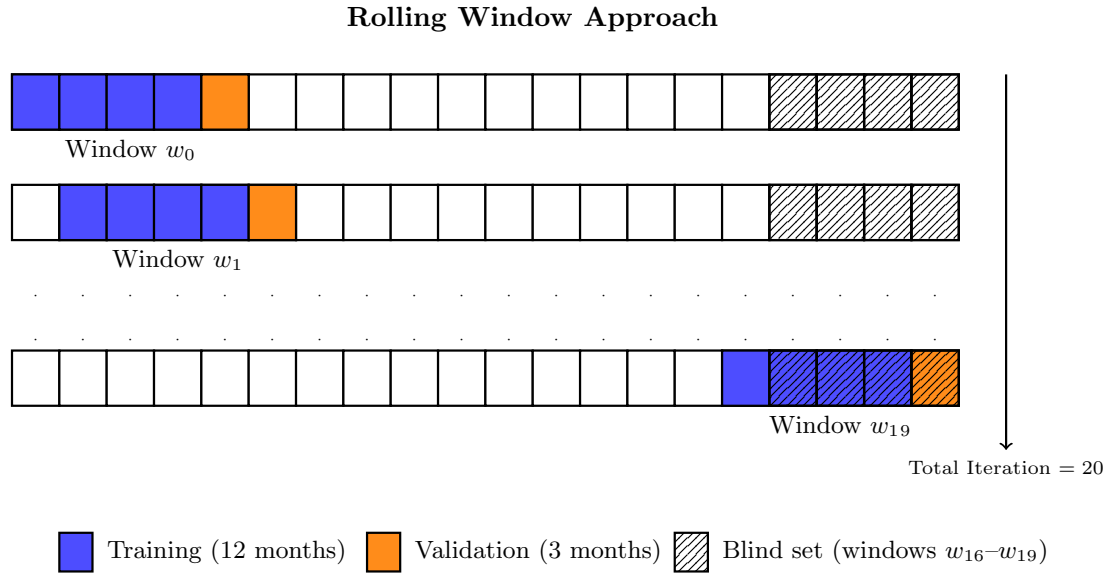


Figure 4.1: Schematic representation of the rolling-window strategy: Each box represents a 3-month period, and each window has 15 months in total (12 months for training and 3 months for validation) and shifts forward in 3-month increments. Training segments are overlapped, and validation segments are independent. A total of 20 such windows were indexed, starting from 0, for the duration of 6 years. Windows 16–19 are set aside for blind phase analysis, which includes four validation segments from 2010. Adapted from [244]

and evolving data characteristics, ensuring that the background correction remains accurate and stable over extended periods. The iterative improvement also enhances continuity between consecutive windows, reducing discontinuities or abrupt shifts that might otherwise arise from independent fitting operations.

One notable aspect of the background correction procedure is that it is carried out using grid-based, spatially segmented frequency band-specific data. Each grid cell represents 11 discrete datasets (of selected frequency band) covering a six-year period, within which the rolling-window approach is independently applied. For each grid cell with 11 frequency-based features, a background-corrected dataset is generated by sequentially updating the background information in accordance with the expanding time window. This design allows the correction process to account for local temporal dynamics while maintaining spatial independence between grid cells. As a result, the method produces a series of background-corrected datasets for all rolling windows across the eleven input features, corresponding to the Q3 data derived from the eleven frequency bands considered in the study. As detailed in section 3.5, the background correction relies on the function defined in Equation 3.2. This formulation integrates both linear and periodic components, enabling it to capture long-term trends as well as recurring seasonal patterns inherent in the data. The inclusion of the sinusoidal term provides flexibility for representing cyclic fluctuations, while the linear term accounts

for slow, monotonic changes over time. Together, these components allow the fitted background to evolve smoothly, accurately reflecting the natural variability observed within the five-year record for each grid cell. Section 3.5 outlines the resampling procedure applied to decrease the number of data points and enhance the fitting accuracy. Because the background information spans at least twelve months, two resampling intervals were examined: one every 15 days and another every 30 days.

To evaluate the fitting performance across all grids and rolling windows, the *reduced chi-square* (χ_{red}^2 equation 3.4) values were computed for each feature under both resampling intervals. A comparative assessment of these results indicated that the 30-day resampling interval provided the most consistent and reliable fitting performance. In particular, the majority of features exhibited comparatively lower and more uniformly distributed χ_{red}^2 values with the 30-day scheme, suggesting a better overall model fit.

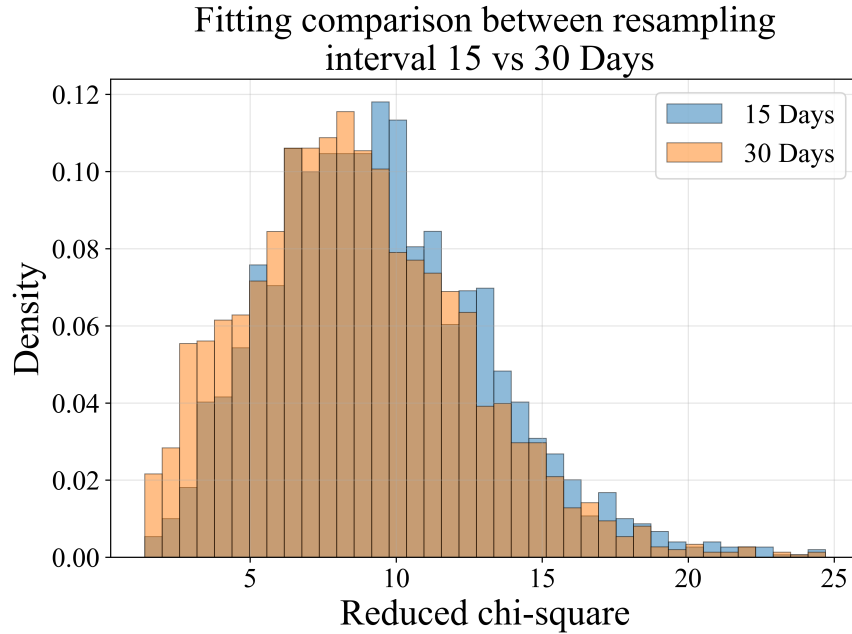


Figure 4.2: Density distributions of the reduced chi-square (χ_{red}^2) values across all the windows and for all the grids, comparing two resampling intervals of 15 days (blue) and 30 days (orange). The distributions were obtained by aggregating the results from all rolling windows and grid cells. The 30-day resampling interval exhibits a narrower and slightly left-shifted distribution, indicating a more stable and generally better model fit across grids.

To further illustrate this observation, Figure 4.2 presents the density distributions of the reduced chi-square values for both the 15-day and 30-day resampled datasets. The reduced chi-square values are predominantly between 5 and 15, with a tail toward higher values, indicating that the model captures the overall trend of the data while some variability remains unaccounted for. Yet, it is evident that the 30-day resampling interval yields more consistent fitting results compared to the 15-day interval. The density curve for the 30-day data is concentrated toward lower χ_{red}^2 values, suggesting

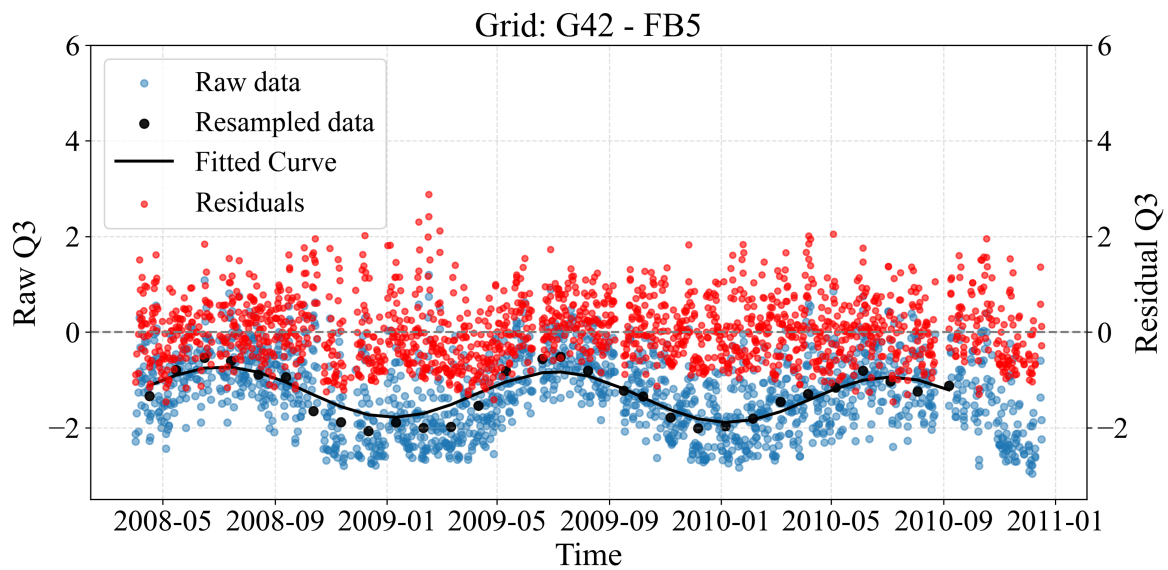


Figure 4.3: Temporal evolution of the Q3 quartile feature for grid cell G42 in frequency band FB5. An extended time span (April 2008 to January 2011) is displayed to make the annual periodic pattern clearly visible, although the background correction itself is applied only within the window w_{19} . Blue dots represent the original measurements, black dots indicate the 30-day resampled background estimates, and the black curve depicts the fitted background model, which combines a linear trend with an annual sinusoidal term and is obtained excluding the validation segment of w_{19} . Red dots show the background-corrected residuals (right axis), with the dashed grey line indicating zero. The residuals cluster around zero, demonstrating that the main trend and periodic components have been effectively removed, while large positive deviations are intentionally retained as candidate anomalous signals.

improved fitting stability and reduced variability across the rolling windows, features, and grid cells. In contrast, the 15-day resampling produces a broader spread with a longer upper tail, implying that more frequent sampling may introduce additional noise and minor irregularities in the fitting process. Overall, the 30-day resampling interval strikes a better balance between temporal resolution and fitting reliability, making it the more suitable choice for subsequent background-correction analysis. An illustrative example of the background performed on the grid "G42", window W_{19} , and feature FB5 is presented in the Figure 4.3. To provide enough temporal context for the periodic pattern to be clearly seen, the figure shows an extended interval covering windows w_{13} through w_{19} (April 2008 to January 2011). The blue scatter points correspond to the raw Q3 observations, the black dots indicate the 30-day resampled values, and the black curve represents the fitted background model. The sinusoidal character of this fitted curve is clearly evident across the extended time span, illustrating that the background model adequately captures the recurring annual cycle present in the ionospheric electric field data.

In line with the rolling-window training scheme, the background estimation and curve fitting for w_{19} are carried out without using the validation portion (October 2010 to January 2011). The residuals (red scatter), plotted against the right axis with the dashed grey line indicating zero, are computed by subtracting the fitted background from the raw measurements over the entire window. The fitted background explicitly consists of a linear trend plus an annual periodic term. The inferred linear slope is about -0.107 per year, which is small compared with the short-term fluctuations and therefore does not dominate visually. In contrast, the oscillations due to the annual component are now visually identifiable in the plot. The residuals, shown on the right axis, cluster around zero (mean ≈ 0.08), indicating that subtracting the background effectively removes the main trend and periodic structure. The evident asymmetry in the residual distribution, with some points showing large positive deviations, is an intentional outcome of the background estimation design: by excluding extreme values during resampling, genuine anomalous departures are deliberately retained in the residuals rather than being incorporated into the background. This ensures that potentially strong ionospheric disturbances are preserved during preprocessing, yielding an anomaly-sensitive input for the subsequent deep learning-based detection stage. Once the correction has been performed for all individual grids, the outputs are concatenated to reconstruct a time series covering the full spatial domain for the whole period of study. This ensures that both spatial and temporal consistencies are preserved across the dataset. The sequences sampled from this dataset are fed as input to the deep learning model. The model training, anomaly detection, and further analysis follow the same methodology, where, for each iteration, the windows used for training and validation are progressively shifted. In each step, training is carried out on the non-

seismic portion of the training dataset segment, while validation is performed on the corresponding validation segment. Anomaly detection and seismic analysis were also carried out individually for each window following the proposed framework. A detailed description of this procedure is provided in the following section. Overall, this strategy creates a futuristic, temporally adaptive, and continuously evolving modeling framework that is able to sustain stable performance over long time spans. Through repeated cycles of retraining, recalibration, and validation, the rolling-window scheme offers an effective mechanism for monitoring and identifying anomalies that may be associated with major events, such as seismic activity. By integrating adaptive background correction, robust scaling, and iterative validation, it keeps the model focused on true deviations from normal behavior, while reducing false alarms caused by systematic or long-term trends.

4.2 Model: LSTM Autoencoder

Detecting seismic-induced ionospheric electric field anomalies within a highly non-stationary and strongly varying ionospheric environment is a complex and challenging task. The difficulty is further increased by the fact that physical signatures of such perturbations have no clear definitions and are embedded within background fluctuations driven by solar-driven and other atmospheric phenomena. So, distinguishing weak seismic-related signals from a dominant ionospheric background remains a major methodological challenge.

To address these challenges and to take advantage of the availability of long-term continuous satellite observations, this study employed a data-driven deep learning approach. Rather than relying on predefined physical thresholds or anomaly templates, the model is designed to learn the intrinsic nature of normal ionospheric electric field behaviour directly from the data. This strategy is well-suited for the study of such an environment with strong temporal variability.

Specifically, this study employs an unsupervised learning framework based on a combination of an LSTM network and an autoencoder architecture. The advantages of this combined approach for unsupervised and semi-supervised anomaly detection have been widely discussed in the literature by Wei et al., Provotar et al., Nguyen et al., Homayouni et al., Maleki et al. and Park et al. The proposed model consists of an autoencoder component stacked with LSTM layers. Such an LSTM autoencoder trained exclusively on nominal data can effectively be employed for anomaly detection in multivariate time-series datasets [271]. This formulation allows the model to be trained on nominal data, in our case, the non-seismic class of data, and thereby learn the intrinsic background nature of data. The use of an LSTM-based architecture is motivated by the sequential nature of satellite observations and the need for understanding the time-

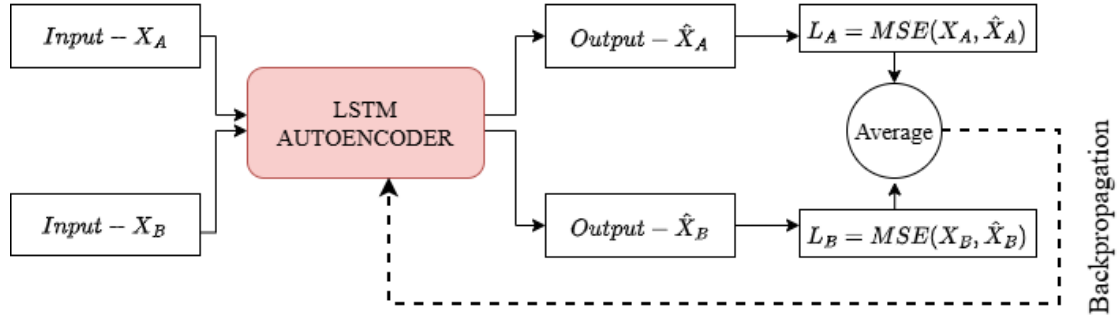


Figure 4.4: The illustration of the proposed LSTM Autoencoder network. The encoder and the decoder are composed of stacked LSTM layers. The two inputs represent the paired half-orbit sequence input sample, where each half-orbit is fed to the network independently. Once the decoder reconstructs both input sequences independently, the loss is calculated using the mean squared error (MSE). While backpropagating, the averaged loss from both inputs is used (adapted from [244]).

varying nature of ionospheric electric field data. At the same time, the autoencoder architecture enables the model to learn a compact, compressed representation of the ionospheric electric field background state.

Figure 4.4 illustrates the workflow of the proposed network. The architecture is composed of three main components: an encoder network that compresses the input sequence, a latent representation that serves as an information bottleneck, and a decoder that reconstructs the original sequence from the latent representation. The unidirectional LSTM encoder network is responsible for transforming the input series into a compressed latent representation. It is composed of two stacked LSTM layers, enabling the extraction of temporal features, followed by a linear layer to project the output to a latent dimension. The latent representation is kept as two-dimensional, providing a low-dimensional representation of the entire input sequence. This is fed as input to a unidirectional LSTM decoder after expanding the latent vector z across the temporal dimension. The decoder learns to generate a time-dependent reconstruction, which is later on fed to a linear layer to produce the reconstructed feature vector with the same dimensionality as the input vector.

4.2.1 Input to the Network

Having introduced the overall structure of the LSTM autoencoder, we now describe the model components in greater detail, beginning with the definition of the input representation provided to the encoder. As per the proposed strategy of the iterative rolling window, each temporal window is treated as an independent training and validation set. Within a given window, the satellite data are sampled to construct model inputs based on consecutive daytime half-orbit pairs. Returning to the idea of rolling windows, each

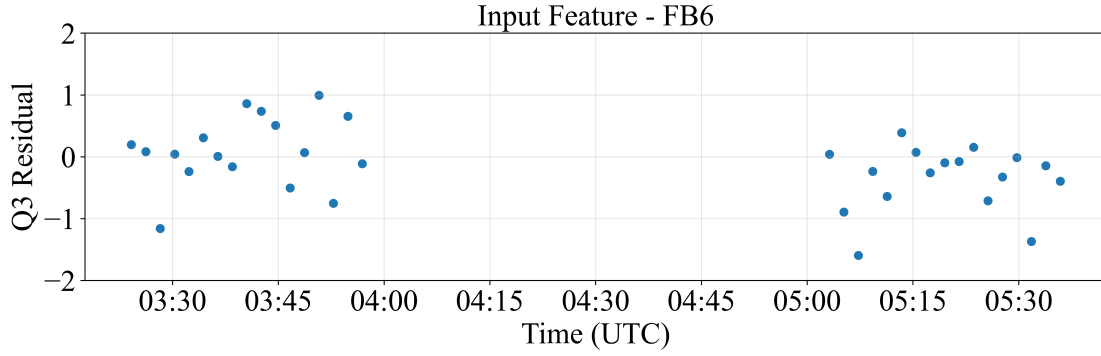


Figure 4.5: The figure represents an example of an input sample of two daytime half-orbit pairs. The Y-axis represents the background-corrected residuals of Q3 values for the frequency band FB6. Each is composed of 17 data points representing 17 timestamps. The gap between the two half-orbits represents the duration of a nighttime orbit pass, which we have ignored for the study.

window is treated as an independent training segment. For a given window, the data is sampled so that two consecutive daytime half-orbits form a single input sequence set to the model. From a physical standpoint, each DEMETER half-orbit corresponds to an uninterrupted latitudinal cross-section, offering insight into the ionospheric conditions along the satellite’s trajectory. Employing two successive daytime half-orbits enables the models to capture a wider temporal evolution of the ionosphere, while still preserving a consistent sampling in local time. This approach is somewhat tricky because, during training, the model only sees one half-orbit of fixed length at a time. However, two half-orbits are processed in parallel, and backpropagation is performed using the average loss computed over both half-orbits. We experimented with concatenating two full orbits directly, but in practice, the joining points often correspond to geographically distinct ionospheric systems. This can introduce artefacts at the concatenation boundary, causing the loss to be dominated by these artificial transitions and degrading the quality of anomaly detection. Figure 4.5 illustrates the time-series data for a single input set to the model. There are 2 sets of 17 data points each, representing 34 minutes of daytime half-orbits sampled every 2 minutes. The gap between the two sets of points corresponds to the nighttime half-orbits, which are excluded from the study. Because LSTM models require meaningful temporal sequences, and the missing nighttime segments would effectively be constant gaps, omitting them does not negatively impact the analysis. Furthermore, not all half-orbits are exactly 34 minutes long, some are slightly longer and others shorter, so we trimmed them to enforce a fixed sequence length. We also excluded certain orbits from sequence construction when large gaps occurred due to multiple missing orbits. Formally, each input sample can be expressed as

$$\mathbf{X}^{(k)} = \left\{ \mathbf{x}_1^{(k)}, \mathbf{x}_2^{(k)}, \dots, \mathbf{x}_T^{(k)} \right\}, \quad \mathbf{x}_t \in \mathbb{R}^F, \quad (4.1)$$

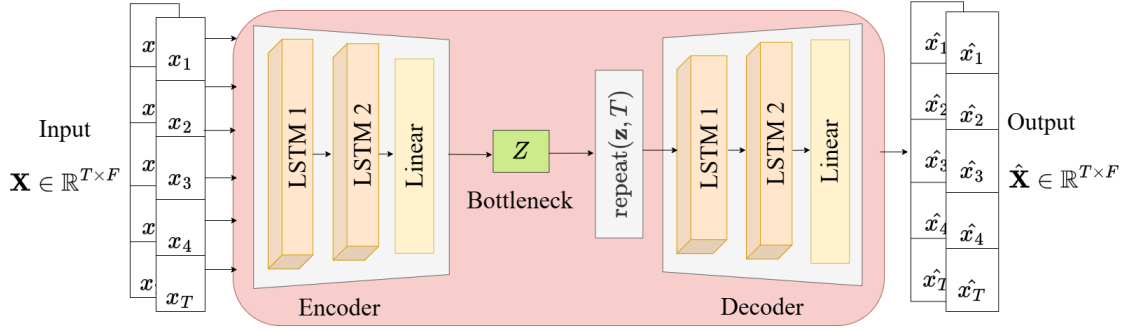


Figure 4.6: Schematic illustration of the LSTM autoencoder architecture. An input time series consisting of input features F and timestamp T is fed to the encoder stacked with LSTM layers. The output of the encoder is the latent vector of dimension L . To enable sequence reconstruction, the latent vector is replicated across the temporal dimension before entering the decoder. The reconstructed sequence is compared to the input using an MSE loss (adapted from [244])

where $\mathbf{x}_t$ denotes the feature vector at time step t ($T = 17$) belonging to 11 features ($F = 11$) derived from the lower frequency bands of the spectrum and $k \in \{a, b\}$ denotes the two consecutive daytime half-orbit segments. The model processes batches of such sequences, preserving the temporal ordering of the observations. The choice of using half-orbit sequences as input samples results in a physically meaningful segmentation of the satellite data, maintaining continuity along the orbit while limiting the sequence length to a scale suitable for efficient recurrent modelling. This sequential structure is necessary, as continuously evolving ionospheric processes can't be represented by the shuffled samples. By providing the encoder with such an input structure, the model can learn a stable, interpretable representation of typical pole-to-pole ionospheric electric field behaviour.

4.2.2 Encoder: Forward Pass

As shown in Figure 4.6, the encoder consists of two stacked LSTM layers followed by a linear layer. The input to the encoder is defined as in equation 4.1. The five main hyperparameters we consider are the batch size S , the input size F (the total number of features), the hidden size H (the dimensionality of the LSTM internal state), the number of LSTM layers N and the latent dimension L . For a given batch size S , the input tensor is given by

$$\mathbf{X} \in \mathbb{R}^{S \times T \times F} \quad (4.2)$$

As explained in the section 1.2.2, LSTM incorporate gated mechanism. All LSTM layers initialize with zero hidden and cell states: $\mathbf{h}_0^{(l)} = \mathbf{0}, \mathbf{c}_0^{(l)} = \mathbf{0} \in \mathbb{R}^{1 \times B \times H}$ for each

layer 1. The Layer 1 processes each timestep $\mathbf{x}[:, t, :] \in \mathbb{R}^{S \times 11}$:

$$\mathbf{i}_t = \sigma(\mathbf{W}_{xi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1} + \mathbf{b}_i), \quad (4.3)$$

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_{xg}\mathbf{x}_t + \mathbf{W}_{hg}\mathbf{h}_{t-1} + \mathbf{b}_g), \quad (4.4)$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_{xf}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1} + \mathbf{b}_f), \quad (4.5)$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t, \quad (4.6)$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_{xo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1} + \mathbf{b}_o), \quad (4.7)$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t). \quad (4.8)$$

In these equations, $\sigma(\cdot)$ denotes the logistic sigmoid activation function, and $\tanh(\cdot)$ denotes the hyperbolic tangent function. The operator $\odot$ specifies element-wise (Hadamard) multiplication. At time step t , $\mathbf{x}_t$ is the input feature vector, $\mathbf{h}_{t-1}$ is the hidden state from the previous step, and $\mathbf{c}_{t-1}$ is the preceding cell state. The vectors $\mathbf{i}_t$, $\mathbf{f}_t$, and $\mathbf{o}_t$ represent the input, forget, and output gates, respectively, while $\tilde{\mathbf{c}}_t$ denotes the candidate memory. The updated cell state is written as $\mathbf{c}_t$, and the corresponding hidden state as $\mathbf{h}_t$. The weight matrices $\mathbf{W}_{xi}$, $\mathbf{W}_{xf}$, $\mathbf{W}_{xo}$ map the input $\mathbf{x}_t$ to the respective gates, whereas $\mathbf{W}_{hi}$, $\mathbf{W}_{hf}$, $\mathbf{W}_{ho}$ project the previous hidden state $\mathbf{h}_{t-1}$ to these gates. $\mathbf{W}_{xg}$ and $\mathbf{W}_{hg}$ define the input-to-cell and hidden-to-cell mappings used to compute the candidate cell state. The vectors $\mathbf{b}_i$, $\mathbf{b}_f$, $\mathbf{b}_o$, and $\mathbf{b}_g$ represent the associated bias terms [272], [273], [274].

Once the first layer processes the first input timestamp, it computes gates, updates $\mathbf{c}_1$ and outputs $\mathbf{h}_1$ of shape (S, H) . This $\mathbf{h}_1$ is stored in $Output_l$. After the processing of each timestamp, each $\mathbf{h}_t$ appended to $Output_l$ yielding a vector of dimension (S, T, H) . Layer 2 receives the complete layer 1 hidden sequence as input (input size = hidden size). Layer 2 undergoes the same process as for layer 1. Finally, layer 2 is provided with 3 outputs.

- $Output_2 : (S, T, H)$ - All timesteps hidden state of LSTM layer 2.
- $\mathbf{h}_n : (N, S, H)$ - the final hidden state $\mathbf{h}_{17}^{(l)}$ from each LSTM layer.
- $\mathbf{c}_n : (N, S, H)$ - the final cell state from each layers.

In our architecture, the final hidden state of layer 2 ($\mathbf{h}_{17}^{(2)}$) (S, H) is used as input to the following fully connected layer:

$$\mathbf{z}^{(k)} = \mathbf{h}_{17}^{(2)} \mathbf{W}_e + \mathbf{b}_e, \quad \mathbf{z}^{(k)} \in \mathbb{R}^{S \times L} \quad (4.9)$$

where $\mathbf{W}_e$ and $\mathbf{b}_e$ represents associated weight and bias and $\mathbf{z}^{(k)}$ the compressed latent representation. The final hidden state of the top LSTM layer is produced once the entire input sequence has been processed. This vector encodes the aggregated

temporal information of the whole sequence and functions as a compact summary of its evolving dynamics. Since the LSTM updates its memory at every time step using both the current input and the previous hidden state, it implicitly retains information from all earlier steps, with their contributions weighted according to their learned importance during training. Here we have fixed the latent dimension to be two ($L = 2$), thereby compressing all 187 input features ($T \times F = 17 \times 11$) into a 2-dimensional vector ($S, 2$). The stacked LSTM layers will enable hierarchical feature learning. The lower layer (layer 1) focuses on short-term variation in the sequences, while higher layers (layer 2) progressively encode long-term temporal dependencies.

4.2.3 Latent Space Representation

The latent space plays a central role in the autoencoder architecture. By constraining the dimensionality of $\mathbf{z}$ (refer to equation 4.9), the model is forced to retain only the most informative features of the input sequence; it acts as the information bottleneck. The dimensionality of the latent space is chosen to be significantly smaller than the decoder hidden state, providing an effective compressed state. From a physical perspective, in this bottleneck, the latest vector can be interpreted as the compact representation of the background ionospheric electric field state over a duration reflecting the temporal trends and recurrent patterns.

4.2.4 Decoder: Forward Pass

The decoder also follows the same structure as the encoder and is implemented by 2 stacked LSTM layers followed by the fully connected layer that projects back into the original feature space. Unlike the encoder, the decoder don't process the full input sequence, but the decoder is fed by the latent vector that is expanded along the temporal dimension, where every timestep receives identical 2D latent code $\mathbf{z}$, making the final vector

$$\mathbf{z}' = \text{repeat}(\mathbf{z}, T) \in \mathbb{R}^{S \times T \times L} \quad (4.10)$$

This sequence is then fed to the decoder, which learns to generate time-dependent reconstruction by internally modelling the temporal dependencies based on the latent representation. The decoder also processes each timestamp of the sequence as the encoder, and finally provides the outputs the same as the encoder layer 2. The output $Output_2$ from the 2nd LSTM layer of the decoder is fed to the fully connected layer with output dimension same as the input dimension to produce a reconstructed feature vector:

$$\hat{\mathbf{x}} = \mathbf{h}_{17}^{(2)} \mathbf{W}_o + \mathbf{b}_o \quad (4.11)$$

where $\mathbf{h}_{17}^{(2)}$ represents the final hidden state of the second LSTM layer of the decoder and $\mathbf{W}_o$, $\mathbf{b}_o$, respectively, the weight and bias of the output linear layer. The resulting output reconstructed sequence of a given input sequence $\mathbf{X}^{(k)}$ is thus given as,

$$\hat{\mathbf{X}}^{(k)} = \left\{ \hat{\mathbf{x}}_1^{(k)}, \hat{\mathbf{x}}_2^{(k)}, \dots, \hat{\mathbf{x}}_T^{(k)} \right\}, \quad \hat{\mathbf{x}}_t^{(k)} \in \mathbb{R}^F, \quad (4.12)$$

4.2.5 Model Training

In technical terms, training aims to minimize the error between the model's predictions and the true targets. In our setting, this corresponds to minimizing the difference between the reconstructed data and the original input data. This minimization is achieved via backpropagation, where the errors are propagated backwards through the network using the chain rule of calculus to compute gradients, which are then used to iteratively update the weights and biases. This process allows the model to reduce error and thereby learn complex patterns in the data effectively. In our case, backpropagation proceeds backward through both the decoder and the encoder networks. For recurrent layers, gradient computation is performed using Backpropagation Through Time (BPTT) (for more details, refer to Appendix B), which unrolls the network across the entire sequence length of $T = 17$. As we train over multiple epochs, this procedure continues until the loss stabilizes on both the training and validation sets [148], [275], [276]. A well-trained model typically shows the loss for both training and validation starting at a relatively high value, then decreasing (often approximately exponentially) before flattening out as it converges. In this study, the model is trained using non-seismic labelled data taken from the training segments of each window defined in the rolling-window scheme. As described earlier, the data is split into two half-orbit sequence pairs (X^a and X^b). These sequences are independently fed into the network. For each sequence, the input and corresponding output are compared to compute the reconstruction loss. The loss function employed is the Mean Squared Error (MSE) [146]. The reconstruction errors obtained from both sequences are then averaged to obtain the overall reconstruction loss, which is used during backpropagation to optimise the network weights (see Figure 4.4). Training is carried out with a batch size of $S = 8$ and a learning rate of $lr = 10^{-3}$, using the Adam optimisation algorithm [277]. The maximum number of training epochs is set to 1500, with early stopping employed to terminate training when no further improvement in validation performance is observed, thereby reducing the risk of overfitting. Data were normalised using a standard scaler that was fitted exclusively on the training set. The deep learning models were developed in Python (version 3.11) with PyTorch (version 2.1). Table 4.1 summarises the LSTM autoencoder architecture along with the main training hyperparameters employed in this work.

Table 4.1: Summary of the LSTM autoencoder architecture and training hyperparameters. Adapted from [244]

Parameter	Value
Input features	11
Sequence length	17 time steps
Encoder	Two LSTM layers, one linear layer
Decoder	Two LSTM layers, one linear layer
Hidden units	{8, 12, 18, 32, 64}
Latent dimension	2
Optimizer	Adam
Learning rate	10^{-3}
Batch size	8
Epochs	1500
Early stopping patience	100 epochs
Loss function	Mean squared error (MSE)

We trained multiple versions of the LSTM autoencoder with different hidden sizes H , while keeping all other hyperparameters fixed. A key characteristic of this training setup is the rolling-window strategy. Each window consists of a 12-month training set and a 3-month validation set. For every epoch, the non-seismic labeled nominal data from both the training and validation sets are used to promote learning and generalization of the model. During the training of each model, we implemented two training modes: (i) weight-updating models and (ii) weight re-initializing models. In the weight-updating mode, the trained weights from the previous window serve as the initial weights for training in the subsequent window, thereby propagating learned information across successive windows. In the weight re-initializing mode, the weights are reinitialized before training in each new window, enforcing independent learning for each iteration. Each model is named chronologically to reflect its training configuration. Table 4.2 lists the models trained under 2 modes and the corresponding hidden sizes H used for each category. In this naming convention, weight-updating models are labeled with capital letters, and weight re-initializing models are also denoted by capital letters preceded by the common prefix "In-". Model training follows a two-

Table 4.2: LSTM autoencoder models and training modes. Adapted from [244]

Model group	Hidden sizes
Updating models {A, B, C, D, E}	8, 12, 18, 32, 64 units
Re-initializing models {In-A, In-B, In-C, In-D, In-E}	8, 12, 18, 32, 64 units

stage procedure within each window, designed to strictly separate model learning from performance assessment at every step. In the first stage, the model is trained solely on the non-seismic portion of the 12-month training interval. Any orbits identified

as seismic according to the selected spatio-temporal criterion are completely excluded from the training set, so the model learns only the nominal background behaviour of the ionospheric electric field. The model’s ability to generalise is then evaluated on the non-seismic subset of the 3-month validation interval, using the model’s evaluation mode. This step checks whether the model has captured the nominal ionospheric background without overfitting to the specific training window, by relying on data it has not seen during training. In the second stage, after training is finalised, the model is run on the entire 3-month validation interval, now including both seismic and non-seismic periods. Anomaly detection results are derived from this full validation dataset. Because the model was trained exclusively on non-seismic data from the training interval, the complete validation segment, containing both seismic and non-seismic data, represents truly unseen data for anomaly detection. This procedure is repeated for all 20 rolling windows (under 2 phases of analysis), ensuring that in each iteration, the anomaly detection performance is evaluated on data that has never been used during training.

4.3 Anomaly Detection

After training the model network exclusively on non-seismic half-orbit data pairs, the reconstruction error can be treated as the main criterion for distinguishing ordinary background ionospheric electric field dynamics from seismic disturbances. Consequently, the anomaly detection framework relies on an analysis of the “reconstruction error” [266], [278], [279]. During training, the model learns the recurring patterns characteristic of the non-seismic class of data, enabling it to reconstruct inputs that follow similar patterns with high accuracy. When we then feed the model with data belonging to the seismic category, any inherent differences between the two categories will be reflected in the reconstruction error, since this error quantifies the deviation of the output sequence from the input sequence. Because the model is not familiar with the patterns present in the seismic data, it will tend to produce a larger reconstruction error for such inputs. By applying a threshold derived from the reconstruction loss on the training data, we can flag any sequence whose reconstruction error exceeds this threshold as an anomalous sequence according to the model.

4.3.1 Reconstruction Error Computation

For each input sequence $\mathbf{X}^{(k)} \in \mathbb{R}^{T \times F}$ ($T = 17$, $F = 11$), the model produces reconstructed output $\hat{\mathbf{X}}^{(k)} \in \mathbb{R}^{T \times F}$ through the latent bottleneck ($L = 2$). The reconstruction error for a half-orbit sequence in the input sample $\epsilon^{(k)}$ is computed as the mean

squared error across all temporal and feature dimensions:

$$\mathcal{L}_{(k)} = \frac{1}{T \times F} \sum_{t=1}^T \sum_{f=1}^F \left(X_{t,f}^{(k)} - \hat{X}_{t,f}^{(k)} \right)^2 \quad (4.13)$$

This scalar error $\mathcal{L}_{(k)}$ represents how well the 187-dimensional input sequence is reconstructed through the 2-dimensional bottleneck. The nominal (non-seismic) sequences are low in $\mathcal{L}_{(k)}$ as they are the data used during training. Seismic sequences containing signatures absent from training data exhibit higher reconstruction errors due to poor latent encoding. Since we have 2 half-orbit sequences as a single input sample, the final error will be the average of both errors.

$$\mathcal{L} = \frac{1}{2} (\mathcal{L}_a + \mathcal{L}_b). \quad (4.14)$$

This aggregate error provides a balanced measure of how well the model is able to reconstruct both half-orbit sequences simultaneously. The contribution from each of the sequences is weighed equally, so there won't be any domination of a single sequence in the distribution. This is important because the model is forced to learn from daytime ionospheric conditions at two closely located, different geographic locations.

4.3.2 Anomaly Threshold: 98th Percentile Baseline

The anomaly threshold τ is established using the error distribution of training data. Given the rolling window training strategy, each time window w_i produces an independently trained model M_{w_i} and thus a corresponding window-specific threshold τ_{w_i} . Specifically, τ_{w_i} is defined as the 98th percentile of the empirical distribution of reconstruction errors computed on the training dataset of each rolling window:

$$\tau_{w_i} = \text{quantile}(\mathcal{L}_{\text{training}}, 0.98) \quad (4.15)$$

where $\mathcal{L}_{\text{training}}$ represents the training dataset reconstruction error for the given rolling windows. This approach of training data-based threshold choice comes from the idea that the training dataset represents the known period of information to the model. This percentile-based thresholding ensures that only the top 2% of reconstruction errors corresponding to the most extreme outliers of the error distribution in each window are classified as potential anomalies, maintaining sensitivity to true seismic events. An input sample $\mathbf{X}$ from a window w_i is labelled as anomalous if its reconstruction error $\mathcal{L}$ exceeds the threshold τ_{w_i} :

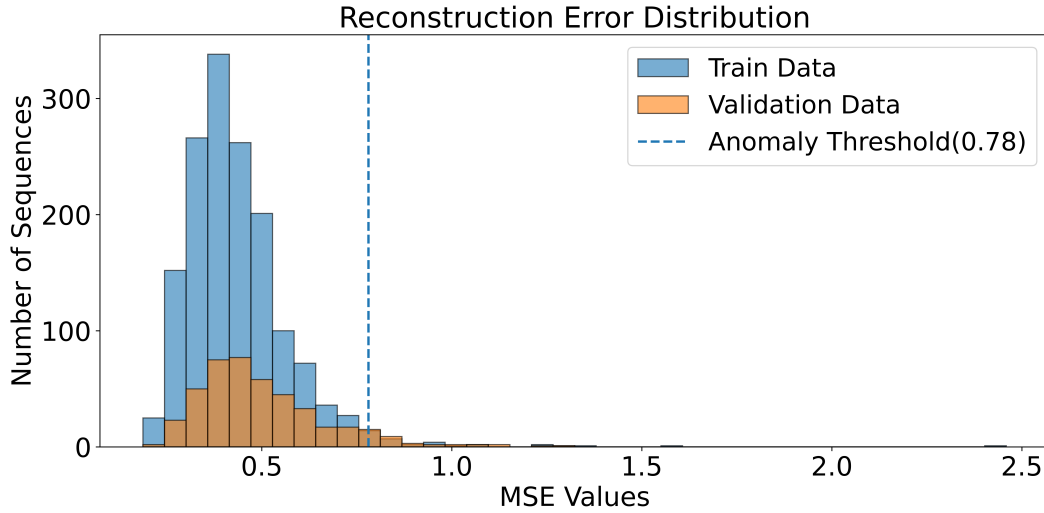


Figure 4.7: Reconstruction error (MSE) distribution for the training and validation sets in rolling window w_1 . The 98th percentile of the training set (blue vertical line) is used as the anomaly threshold. The X-axis denotes the reconstruction error calculated, and the Y-axis represents the number of sequences.

$$X = \begin{cases} 1 & \text{if } \mathcal{L} > \tau_{w_i} \\ 0 & \text{otherwise} \end{cases} \quad (4.16)$$

For both the training and validation datasets, anomalies are identified using a threshold derived from the training data. Figure 4.7 shows representative reconstruction error distributions for the training and validation sets for a window w_1 of a reference model (trained for the preliminary analysis for the period 2005-2009), with the anomaly threshold indicated by a vertical blue line. The y-axis represents the number of sequences (input samples), and the x-axis represents the values of the computed reconstruction error. By giving a very strict threshold, we make sure only the most extreme outliers in both training and validation are labelled as anomalies. At the same time, the range of reconstruction errors computed for each window differs, indicating variations in the complexity and variability of the underlying data. These differences reveal how well the model has captured the dominant patterns within each window: narrower error distributions are associated with more stable background behaviour, whereas broader distributions point to greater variability or more intricate dynamics, which would be largely overlooked when using standard data segmentation and training strategies. A complete set of error distributions for all rolling temporal windows is presented in Appendix C.2.

4.4 Evaluation Framework

The trained model, therefore, flags certain sequences in both the validation and training sets as anomalies based on reconstruction error analysis. Let the number of detected anomalies for a given data window be n_{w_i} . The true positives are those detected anomalies that fall into the seismically labelled category under the chosen spatial and temporal constraints. These true positives are expressed as a percentage called the seismic anomaly ratio, ρ_{w_i} . The associated uncertainty is computed using the binomial error:

$$\sigma_{\rho_{w_i}} = \sqrt{\frac{\rho_{w_i}(1 - \rho_{w_i})}{n_{w_i}}} \quad (4.17)$$

4.4.1 Random Sampling Baseline Test

To assess whether our findings could arise purely by chance, we require a baseline for comparison, which we derive from a random sampling test distribution. For this, we use the entire available dataset spanning six years. We randomly select 200 input sequences (each sequence corresponding to two daytime orbits) and then determine how many of these sequences are classified as seismic. Typically, this is done by checking whether at least one earthquake occurs within the specified spatial range and within a temporal window starting from the end time of the sequence. In our approach, we introduce temporal randomisation. For a sequence defined over the interval $[t_o, t_T]$, where t_T denotes the final timestamp of the sequence. Instead of using the sequence end time as the reference, we randomly choose a datetime (t_R) within 5–30 days after the orbit end time and then search for earthquakes.

$$t_R \sim \mathcal{U}(t_T + 5 \text{ days}, t_T + 30 \text{ days}), \quad (4.18)$$

This ensures that both the location and timing relative to the orbit are effectively random. We repeat this sampling procedure 1000 times to obtain a distribution of seismic anomaly ratios, which we treat as the random reference distribution. The median of this distribution ($Q2_{RST}$) is used as the random baseline. The 0.3–99.7 percentile range, corresponding to a 3-sigma interval, is also used in the analysis and is denoted as 0.3–99.7%*RST*.

4.4.2 Performance Metrics

To evaluate the model performance across all windows, we introduced a cumulative metric in the form of the meta-analytic score. The score is obtained by averaging the

Zscore values Z_{w_i} computed for each rolling window. The Z_{w_i} itself is designed to quantify the strength of the deviation from the defined random baseline. This means it measures how much the observed seismic anomaly rate produced by the model differs from what would be expected if seismic anomaly occurrence purely happened by chance. Larger values of Z_{w_i} therefore indicate a stronger and more statistically meaningful deviation from the randomness, whereas the values close to zero indicate behaviour consistent with the baseline. For each rolling window, the Z_{w_i} is computed using the seismic-anomaly ratio and the uncertainty associated with it. This normalization ensures that windows with fewer anomalies are not over-interpreted and that variability due to sampling fluctuations is explicitly taken into account.

$$Z_{w_i} = \frac{\rho_{w_i} - Q2_{RST}}{\sigma_{\rho_{w_i}}}. \quad (4.19)$$

By averaging the resulting values across all windows, the meta-analytic score reflects both how large and how consistently the model departs from what would be expected at random. The summary score is defined as the Z-factor.

$$z_f = \frac{1}{W} \sum_{i=1}^W Z_{w_i}, \quad (4.20)$$

where W represents the total number of rolling windows used for the calculation. For weight-updating models, for the preliminary analysis (model trained over data from 2005-2009: w_0 - w_{15}), W will be kept 15, as we ignore the first window for the calculation since the models begin with randomly initialised parameters for the first window. This yields a single, interpretable measure of overall performance that indicates whether the model systematically shows an elevated rate of seismic-associated anomalies throughout the entire study, rather than producing random window-specific signals.

Although the statistical meta-analytic score used here does not constitute a strict implementation of Stouffer's meta-analysis in its true form, it is nevertheless interpreted within the same conceptual framework of meta-analysis [280], [281]. In both cases, the main focus is to combine information from multiple, partially independent tests in order to assess whether there is a consistent deviation from a null hypothesis when the outcome is considered collectively.

$$z = \frac{\sum_{i=1}^W Z_{w_i}}{\sqrt{W}}, \quad (4.21)$$

In classical Stouffer's method, the individuals *Zscore* Z_{w_i} are combined into a cumulative statistic as shown in equation 4.21. This calculated z is then compared against the

critical threshold $z \geq 2$ in direct analogy with conventional *Zscore* hypothesis testing.

$$z_f > \frac{z}{\sqrt{W}}. \quad (4.22)$$

Within the context of the present study, we adopt a closely related interpretation. Under the formulation of our Z-factor, the Stouffer-type significance condition can be expressed by equation 4.22. For example, for primary phase analysis ($W=15$), the $Zscore \geq 3$ can be represented as a critical threshold $z \geq 3$ corresponds to $z_f \geq 0.77$ whereas for the blind phase with $W=4$, $z_f \geq 1.5$. Models that satisfy this criterion are therefore interpreted as exhibiting a statistically significant association between detected anomalies and seismic events when evaluated over the full temporal window of the study. Importantly, this strategy prioritizes consistency over time rather than focusing on isolated periods of high significance, making it better suited to the inherently non-stationary character of the underlying geophysical system. By subsequently comparing how many models satisfy this cumulative significance requirement under different spatio-temporal labelling definitions, we can determine which criterion produces the most robust and consistently high-performing results. This chosen definition is then used in the subsequent sections of the study for in-depth analysis and interpretation.

Along with this analysis, we compute the average seismic anomaly ratio across all rolling windows, together with its associated uncertainty. This average measure is expressed as

$$\bar{\rho} = \frac{1}{W} \sum_{i=1}^W \rho_{w_i} \quad (4.23)$$

where $\bar{\rho}$ denotes the mean seismic anomaly ratio across windows. It is the arithmetic mean of the window-wise ratios ρ_{w_i} . The uncertainty associated is obtained by propagating the individual binomial uncertainties $\sigma_{\rho_{w_i}}$ associated with each window, and is given by

$$\varepsilon = \frac{1}{W} \sqrt{\sum_{i=1}^W \sigma_{\rho_{w_i}}^2} \quad (4.24)$$

Taken together, the values $\bar{\rho} \pm \varepsilon$ offer a concise and interpretable summary of the average strength and reliability of the seismic anomaly association across the entire time span considered in the rolling-window analysis.

4.4.3 Lead-Time Analysis

To investigate the temporal relationship between the detected ionosphere seismic-associated anomalies and matched seismic events, we introduced the lead time analysis. Let a sequence be defined over the interval $[t_o, t_T]$, where t_T denotes the final times-

tamp of the sequence. For each of such sequence, a seismic search range is defined that extends forward in time from t_T to $t_T + TW$, where TW is the chosen temporal window duration. Let t_{eq} represent the occurrence time of the first earthquake whose epicenter falls within the predefined spatial window and time lies within the temporal window defined. Then the anomaly-earthquake lead time Δt is then defined as

$$\Delta t = t_{eq} - t_T. \quad (4.25)$$

This quantity represents the time interval between the end of the ionospheric observation sequence that the model labels as anomalous and the occurrence of the first corresponding seismic event.

To describe the behaviour expected purely by chance, the same lead-time analysis is applied to randomly chosen sequences from the full dataset after randomising the end time t_T in the same way as in the random sampling test. A total of 100 sequences were sampled from each rolling window, giving 1600 sequences in total for constructing the random lead-time distribution. This procedure produces a reference distribution of Δt values that reflects chance temporal associations between arbitrary sequences and earthquakes. An equivalent analysis is then performed for the sequences flagged as anomalous by the models trained using the selected optimal seismic-association criteria. The analysis is performed using the primary phase analysis data period, covering the first 16 windows. By comparing the lead-time distributions obtained for anomalous versus random sequences, we can evaluate whether the detected anomalies tend to precede earthquakes more consistently than would be anticipated from random temporal coincidence.

4.4.4 Threshold Sensitivity Test

As of now, we have adopted and fixed 98% as the anomaly threshold. This corresponds to a very conservative outlier window designed to identify only the most extreme deviations from the model-learned background. This decision was made in advance, independently of any seismic association findings, as a conservative operating point that strikes a balance between two competing risks: (i) thresholds that are too low increase the anomaly rate and may misclassify normal ionospheric variability as anomalous, potentially inflating the apparent seismic association; and (ii) thresholds close to the 99th percentile yield too few detections, reducing statistical power and increasing uncertainty in the Z-factor estimates. Because this threshold directly determines the anomaly rate and thus influences the seismic association results, questions naturally arise regarding how sensitive the model is to this choice. Without exploring alternative thresholds or demonstrating robustness, one might reasonably worry that the conclu-

sions could depend strongly on the specific threshold used. Although we ensured that the threshold was selected *a priori* and not tuned to maximise the observed seismic association, thereby limiting bias from multiple testing or “look-elsewhere” effects, we recognise that a thorough sensitivity assessment of the threshold choice is necessary. To address this, we performed a threshold sensitivity analysis to test the robustness of our results across a range of percentile values. This procedure verifies that the detected seismic associations are not artifacts of one particular threshold but instead remain stable under reasonable variations of this parameter. Specifically, we varied the anomaly threshold between the 95th and 99th percentiles. The evaluation was based on Z-factor values computed across all model training configurations, with particular emphasis on the primary phase training setup (training data from 2005 to 2009) under the 2 training strategies. All Z-factor estimates were obtained from performance metrics on the validation dataset.

To facilitate reproducibility, detailed information regarding the DEMETER dataset, preprocessing pipeline, model architecture, training configuration, anomaly-threshold definition, and software environment is provided in Appendix [A](#).

Chapter 5

Results and Discussion

5.1 The Best-Performing Criteria

In the results section of this study, we adopt a structured evaluation approach, beginning with model training on datasets constructed according to specific spatio-temporal criteria selected for seismic association. The first step consists of dividing the data into seismic and non-seismic classes using a fixed temporal window of 48 hours and several spatial criteria. Table 5.1 lists the chosen seismic spatial windows (SW) combined with the fixed temporal window (TW) and reports the corresponding average fraction of seismic data over all rolling windows. The window criterion directly affects the classification of sequences into seismic and non-seismic categories, thereby changing the composition of the training dataset and the resulting model behaviour. Each SW-TW configuration, therefore, corresponds to a distinct modelling scenario rather than a simple parameter tuning step. The initial results focus on model training and performance assessment based on these datasets. At this stage, the models are trained, as described in the previous section, solely on non-seismic data taken from the training windows. Subsequently, we examine the reconstruction errors and compute the seismic anomaly ratio for each rolling window during both the training and validation phases. For the final evaluation, however, we rely exclusively on the validation period, since it represents a non-overlapping, independent time interval that the model has never seen during training. Using this validation dataset, we then calculate the Z -factor (see Equation 3.2), which measures how much the model-derived seismic anomaly ratio (ρ_{w_i}) across all windows departs from the random baseline.

Table 5.2 summarises the Z -factor values computed for all configurations of SW with a fixed TW for the models trained in the primary phase analysis. The significance

Table 5.1: Average percentage of seismic-class data available across all rolling windows for different spatial and fixed temporal window combinations

Spatial Window	Temporal Window (TW)	Average seismic-class data (%)
$05^\circ \times 05^\circ$	48 h	11.5
$10^\circ \times 10^\circ$	48 h	29.5
$20^\circ \times 20^\circ$	48 h	52
$23^\circ \times 20^\circ$	48 h	55.5
$22^\circ \times 22^\circ$	48 h	55

Table 5.2: Z-factor values for each trained model under different spatial-window configurations at TW48.

Criterion	A	B	C	D	E	In-A	In-B	In-C	In-D	In-E
SW05×05	0.32	-0.01	0.24	0.12	0.62	0.02	0.26	0.33	0.31	0.13
SW10×10	0.66	0.52	0.43	0.90	0.71	0.43	0.45	0.58	0.84	0.73
SW20×20	0.62	0.95	1.17	1.11	0.69	0.68	0.76	0.58	0.51	0.93
SW22×22	0.58	0.93	1.04	0.77	1.27	0.78	0.94	0.71	1.14	0.93
SW23×20	0.48	0.69	0.92	1.11	0.89	0.71	1.12	0.66	1.03	1.08

Table 5.3: Average percentage of seismic-class data available across all rolling windows for fixed spatial and different temporal window combinations.

Spatial Window	Temporal Window (TW)	Average seismic-class data (%)
22° × 22°	6 h	13
22° × 22°	12 h	22
22° × 22°	24 h	36
22° × 22°	48 h	55

threshold used here is $Zscore = 3$ ($Z_f = 0.77$ refer to calculation 4.22), and any value higher than this quantity is highlighted in the table. Figure 5.1 shows how many models that exceed the statistical threshold corresponding to a $Zscore > 3$ for each spatial criterion. The y-axis indicates the number of models that fulfill the statistical requirement, and the x-axis specifies the spatial window (SW) selection. The $5^\circ \times 5^\circ$ spatial window does not satisfy the $Zscore$ criterion for any model, whereas all other spatial windows have at least two models that satisfy it. Among these, the $22^\circ \times 22^\circ$ spatial window performs best, with 7 out of 10 models exceeding the $Zscore$ threshold of 3. Because this spatial configuration outperforms the remaining criteria, we fix the spatial window $22^\circ \times 22^\circ$ for the subsequent analysis, which focuses on determining the best-performing temporal range. It is important to note that further widening of the spatial window is intentionally avoided for two reasons. First, at this scale, the second sequence already begins to overlap spatially with the area used for the first sequence. Second, increasing the spatial extent beyond this value markedly raises the fraction of seismic-class samples. Beyond this point, seismic events can no longer be treated as rare occurrences, which undermines the fundamental assumption of the LSTM autoencoder trained on predominantly non-seismic data. Therefore, extending the spatial range beyond this limit is no longer suitable for the intended anomaly-detection framework.

Now that we have identified the best-performing spatial range, we experimented with a series of temporal windows ranging from 6 to 48 hours, as summarized in Table 5.3. Table 5.4 summarises the Z-factor values computed for all configurations of TW with a fixed SW for the models trained in the primary phase analysis. The significance

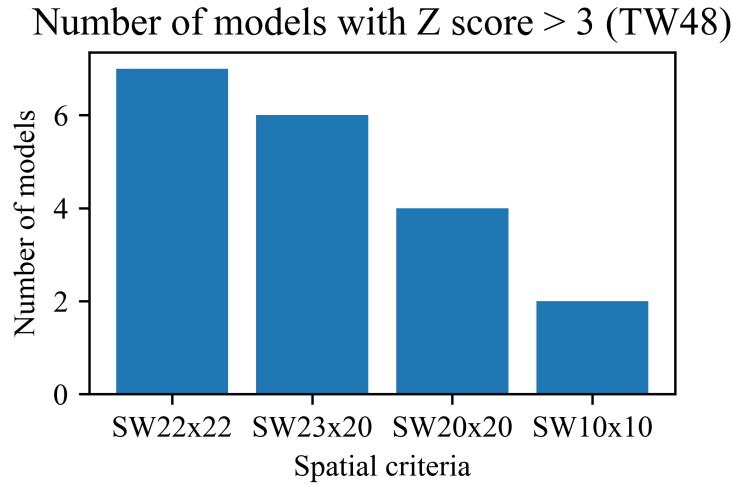


Figure 5.1: Statistics of models exceeding the significance threshold ($Z_{score} > 3$) for each spatial window configuration. The SW22x22 window yields more models with statistical performance.

Table 5.4: Z-factor values for each trained model under different Temporal-window configurations at SW22x22

Criterion	A	B	C	D	E	In-A	In-B	In-C	In-D	In-E
TW6	0.16	0.07	-0.21	0.51	0.14	0.13	0.15	-0.02	0.33	0.43
TW12	0.58	0.51	0.44	0.59	0.63	0.43	0.10	0.33	0.37	0.47
TW24	0.97	1.07	0.90	0.75	0.72	0.59	0.77	0.55	0.88	0.63
TW48	0.58	0.93	1.04	0.77	1.27	0.78	0.94	0.71	1.14	0.93

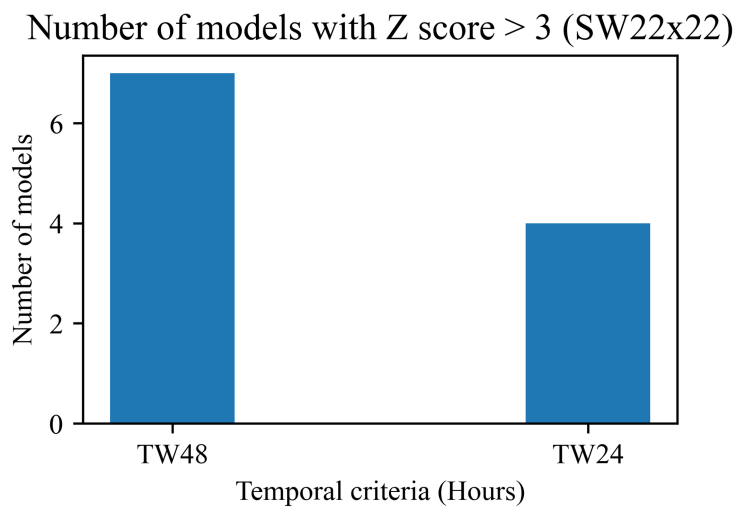


Figure 5.2: Statistics of models exceeding the significance threshold ($Z_{score} > 3$) for each temporal window configuration. The "TW48" window yields more models with statistical performance.

threshold used here is $Zscore = 3$ ($Z_f = 0.77$ refer to equation 4.22), and any value higher than this quantity is written in bold in the table. The outcomes of the Z -factor analysis for the different TW configurations are presented in Figure 5.2. Under the same selection criterion of $Zscore > 3$, most of the shorter temporal windows, specifically "TW6" and "TW12", fail to meet the threshold, whereas "TW48" continues to yield the best performance.

Therefore, based on a systematic, statistically grounded screening procedure, where multiple SW and TW configurations are evaluated over five years of data using 5 independent model architectures and two training strategies, we select the spatio-temporal window "SW22x22_TW48" as the best performing criterion for the seismic association study under the chosen dataset and conditions. All subsequent analyses will be based on models trained on datasets prepared according to this criterion. A detailed evaluation of this criterion and the corresponding models is provided in the following sections. Figure 5.3 presents the statistics of seismic and non-seismic two-half-orbit pair sequences across the 20 training-validation windows for the chosen configuration "SW22x22_TW48". Under this spatio-temporal window setup, each rolling window segment includes a sufficient number of both seismic and non-seismic samples to enable robust model training while maintaining a balanced class distribution and avoiding statistical bias.

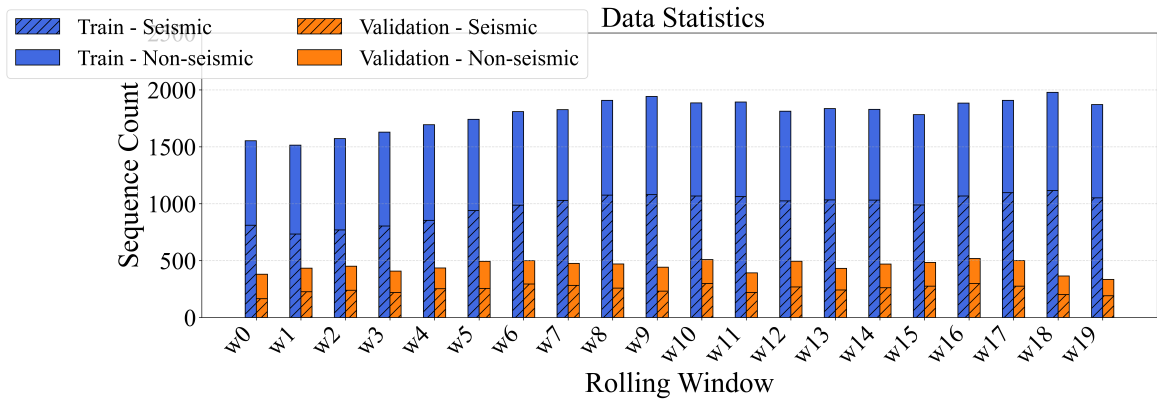


Figure 5.3: Distribution of seismic and non-seismic data samples across rolling windows under the selected configuration "SW22x22_TW48". The y-axis represents the number (count) of sequences (two daytime half-orbit pairs), and the x-axis represents the windows. The bars show the number of sequences used for training (blue) and validation (orange), further categorised as seismic (hatched) and non-seismic subsets.

5.2 Primary Phase Analysis

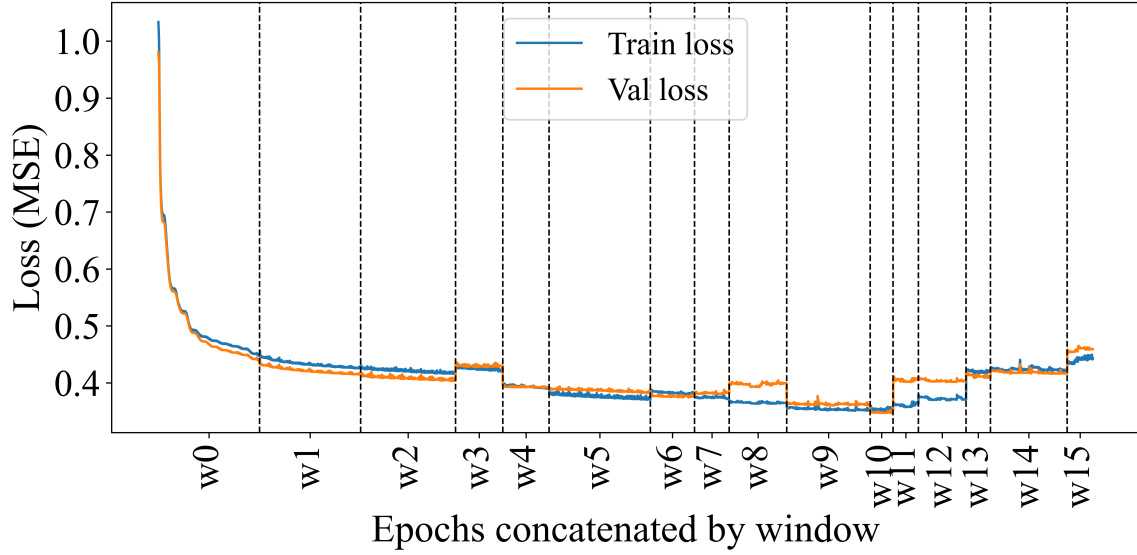
5.2.1 Model Training Outcomes

The models were trained in two distinct operational modes using the first 16 rolling windows (w_0 – w_{15}). The initial evaluation stage relies on the training loss curves, where each model is trained using non-seismic samples drawn from the training segments and, simultaneously, evaluated on non-seismic samples from the validation segment. The loss function used is the mean squared error (MSE), as defined in Section 4.3.2.

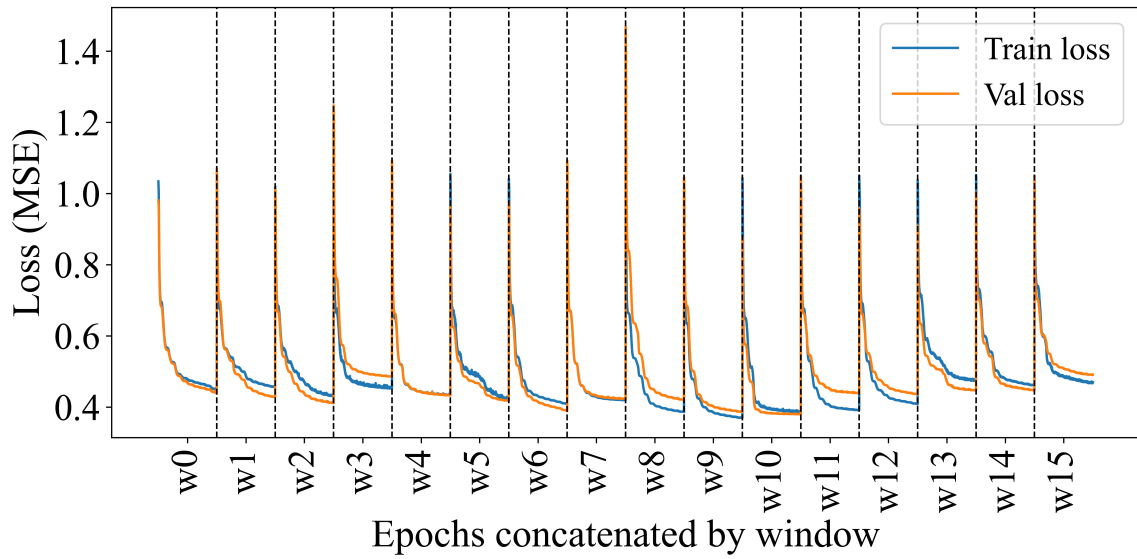
From the loss curves, we analyse how the loss value changes over epochs and how the optimization behaviour changes as training advances through successive rolling windows. Typically, a sharp initial drop followed by a gradual flattening indicates that the model is learning a stable representation of the background (non-seismic) signal and is moving towards convergence. This characteristic training behaviour is well documented in the deep-learning literature, where a decreasing training loss reflects a better fit to the training data, whereas the validation loss serves as a measure of generalisation and a warning signal for potential overfitting when it begins to diverge from the training curve [282], [283].

Figure 5.4 presents the loss curves for two models trained under two different operational modes. Figure 5.4a shows models A trained in the weight-updating mode, where model parameters are propagated and updated across rolling windows. Figure 5.4b shows models In-A trained in the weight re-initialization mode, in which parameters are reset at the start of each window and training starts from scratch. In each subplot, the y -axis denotes the MSE loss, while the x -axis represents training epochs, grouped by rolling windows. For clarity, the loss curves from consecutive windows are concatenated, enabling the overall training process across the dataset to be viewed as one continuous sequence. This visualisation emphasises how training dynamics change under non-stationary conditions and how the selected retraining strategy affects convergence behaviour over time.

As shown in Figure 5.4, vertical dashed lines mark the change between windows, where the training data curve duration differs due to the application of early stopping, a criterion used to stop training once the model begins to overfit. Consequently, each point on the curves represents the reconstruction error at a particular epoch within a specific window. In the weight-updating models, the parameters are updated across rolling windows. This results in a sharp decrease in loss during the initial training window (w_0), followed by gradual evolution of both training and validation losses (mostly flat) across subsequent windows. The absence of loss spikes at window boundaries indicates that the model retains information learnt from earlier windows and requires only adaptation when fed with new data. The close-lying training and validation losses



(a) Weight Updating Mode



(b) Weight Re-initialization Mode

Figure 5.4: Training loss curves for models trained under two operational modes using the first 16 rolling windows (w_0 – w_{15}): (a) Model A - Weight Updating Mode and (b) Model In-A - Weight Re-initialization Mode. Loss curves are concatenated across consecutive windows to show how training evolves over time.

further suggest stable convergence and limited overfitting, despite the non-stationary nature of the ionospheric background. Small increases and decreases in the loss curve are observed across certain rolling windows, even though the overall trend remains stable. These local fluctuations show the differences in the intrinsic characteristics of the data within each window. As the ionospheric background is non-stationary, consecutive windows may exhibit varying levels of variability or transient structures. Consequently, when a new window is introduced, the model although retaining knowledge from previous windows, may temporarily experience increased reconstruction error before adapting to the updated data distribution. Such behaviour indicates that certain windows are more challenging to learn than others. Importantly, these loss variations do not indicate instability or overfitting; rather, they highlight the model’s sensitivity to evolving background conditions and its capacity to adapt while preserving previously learnt representations.

In the weight re-initialization mode, the learning exhibits a different behaviour. The loss begins at comparatively high levels at the start of each rolling window, indicating both the re-initialization of model parameters and intrinsic differences in the data. A distinctive learning curve is created across windows, nevertheless, as the model quickly relearns the predominant background patterns within each window. This approach typically involves lengthier training stages inside individual windows than the weight-updating mode, making it possible to monitor the convergence behaviour more clearly. The model can reliably learn the background structure from scratch, even in spite of variable data conditions indicated by the consistent convergence throughout each window. Moreover, the variation in the initial loss differs across windows provides insight into the intrinsic complexity of different temporal segments, with higher starting losses corresponding to windows that are more challenging to learn. While this approach leads to lesser temporal continuity across windows, it offers a clearer view of short-period window-specific learning capabilities and convergence properties. Overall, the comparison highlights that the choice of training strategy helps explain how the model’s adaptation and convergence occur when modelling long-term, non-stationary geophysical time series.

5.2.2 Anomaly Detection Results

Once the model is trained, anomaly detection is performed through reconstruction error analysis. Here, the reconstruction error distribution is used to determine the threshold for anomaly detection, as described in Section 4.3.2. Based on the chosen threshold from training segments of each window, any sequence whose error exceeds this threshold is labelled as anomalous. These anomalous sequences are then cross-checked against the earthquake catalogue within the corresponding spatial and temporal window to

establish earthquake associations. In this way, we obtain the seismic-anomaly ratio per window (ρ_{w_i}). This ratio indicates the fraction of model-detected anomalies that have a seismic association under the defined SW-TW criteria. It should be noted that the binomial uncertainties associated with the seismic-anomaly ratios assume independence among detections within each validation window. Since a single earthquake may occasionally be associated with more than one flagged anomalous sequence within the same window. Figure 5.5 shows the seismic-anomaly ratio as a function of the rolling windows (w0–w15). Blue and orange markers correspond to the training and validation results, respectively, with error bars indicating their binomial uncertainties. The solid horizontal red line represents the Random Sampling Test median baseline ($Q2_{RST}$) (refer to the RST distribution in section C.1), and the dotted horizontal lines indicate its 0.3–99.7 RST percentile range. The results in the figure 5.5a are obtained from model A trained in the weight-updating mode, whereas those in 5.5b are from mode In-A trained in the weight re-initialization mode. Across all rolling windows, most seismic anomaly ratios are above the random median, indicating that detected ionospheric anomalies tend to cluster near earthquakes under the specified SW-TW criteria more often than would be expected by chance. In several windows, both training and validation ratios reach or surpass the 99.7% random bound, corresponding to deviations at the 3σ level. For most models, this pattern appears consistently across different dataset windows, suggesting that the association is not driven by a single favourable period but remains stable under varying background conditions. The error bars on the validation ratios are much larger than those for training, reflecting the smaller number of detected anomalies in validation compared with training. Although the training results show smaller uncertainties because they are based on a larger number of detected anomalies, the validation results offer a more informative measure of model performance, as the validation windows were excluded from model tuning. Consequently, the seismic-anomaly ratios obtained on the validation set constitute an out-of-sample evaluation of whether the identified ionospheric disturbances generalize to previously unseen time periods, rather than merely capturing the model’s fit to the training data. Even though the statistical uncertainties are larger for the validation set, several windows still lie above the random baseline and, in some instances, approach or surpass the 99.7% RST threshold, suggesting that the observed seismic associations are not confined to the training intervals alone. There are a few windows where the model performance is notably poor consistently, like w_2 . In these windows, the average seismic anomaly ratio falls below the random range, undercutting the lower bound of the random distribution. This behaviour suggests that, for these specific temporal segments, the detected ionospheric anomalies are not only uncorrelated with seismic activity but may exhibit an apparent anti-correlation with earthquake occurrence rate. This may correspond to distinct background conditions, although the specific physi-

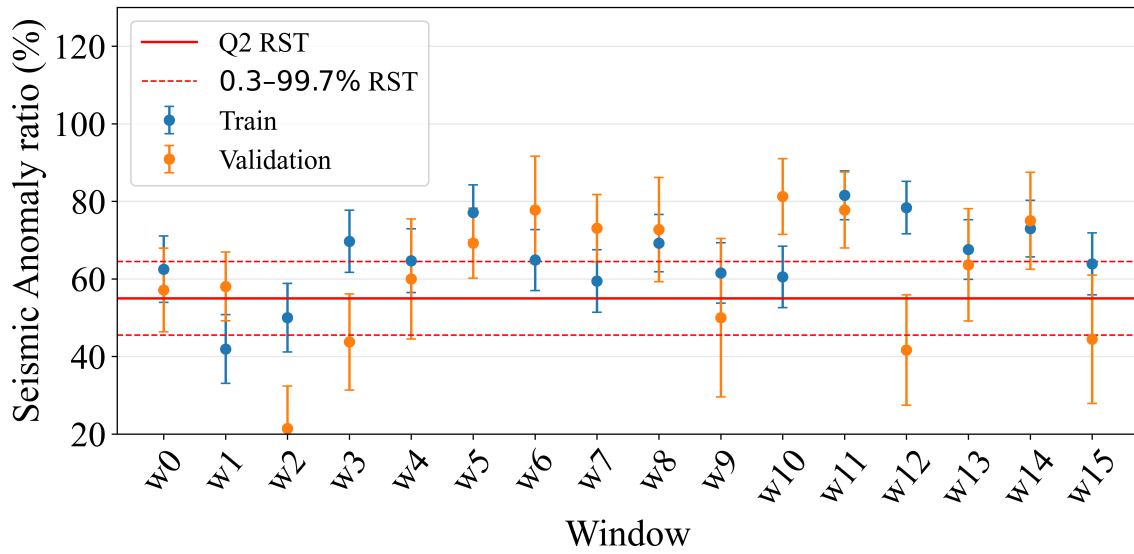
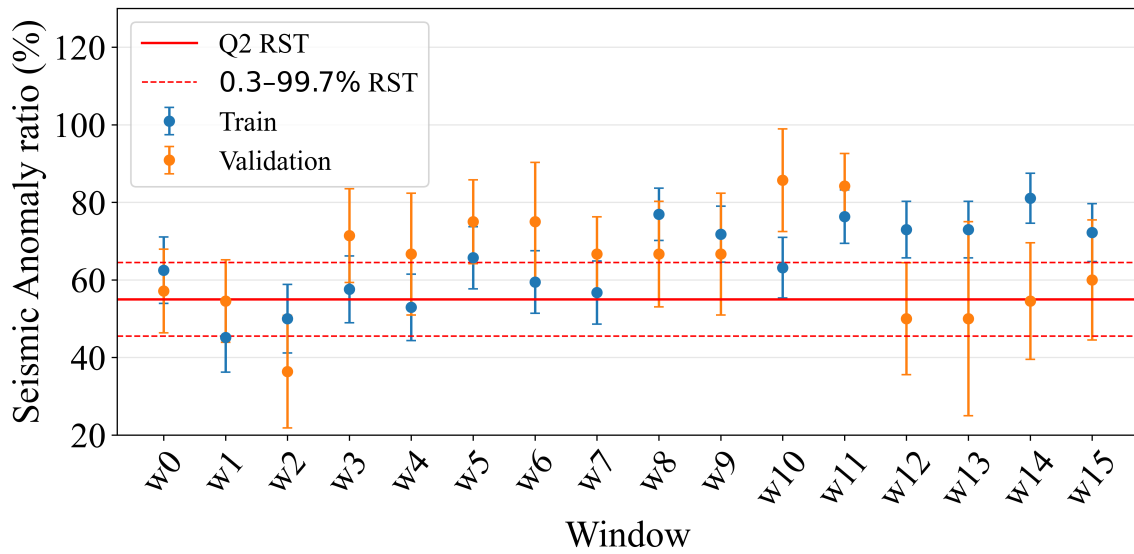
(a) **Weight Updating Mode**(b) **Weight Re-initialization Mode**

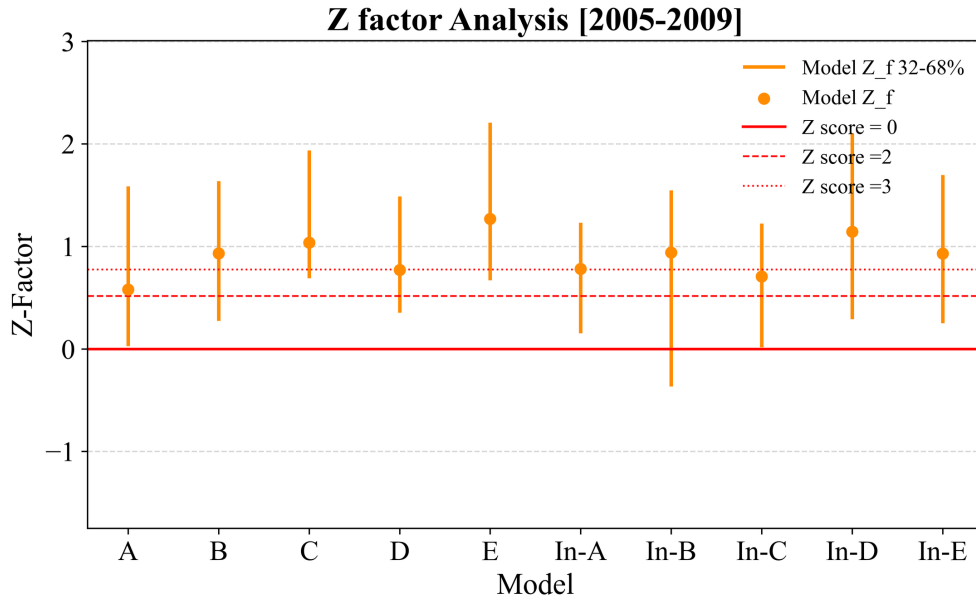
Figure 5.5: Seismic anomaly ratio as a function of rolling windows (w_0 – w_{15}). Blue and orange markers represent training and validation results, respectively, with error bars representing their corresponding binomial uncertainties. The horizontal red lines indicate the Random sampling test median (Q2 RST baselines) and dotted horizontal lines, its 0.3-99.7 percentile range (refer to the RST distribution in section C.1). Results are for the model trained under (a) Model A - Weight Updating Mode and (b) Model In-A – Weight Re-initialization Mode.

cal or statistical factors driving this behaviour cannot be perfectly identified from the present analysis. However, there is no strong, systematic, generalisable pattern in the ratios across models that could be identified.

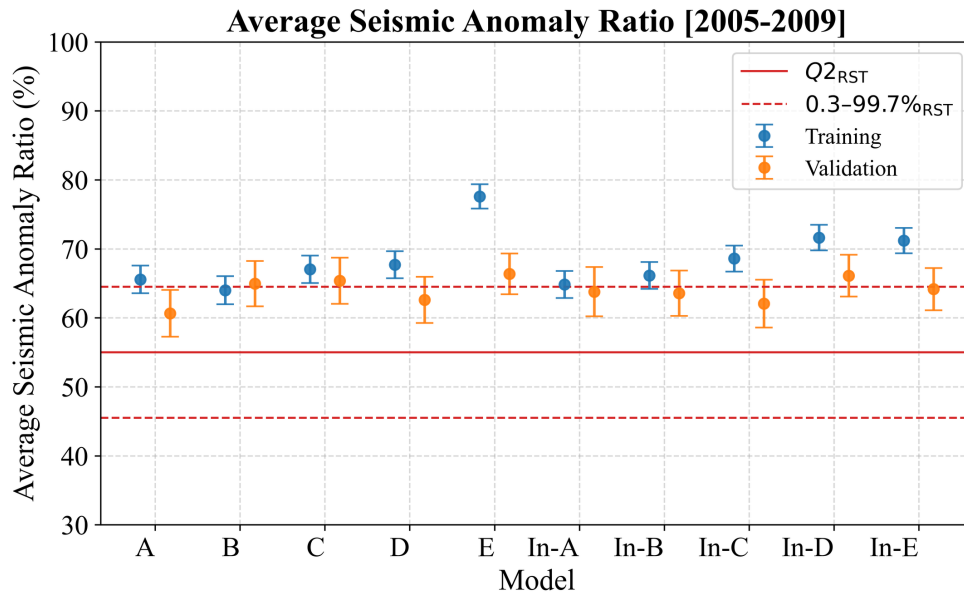
A comparison of the two training strategies shows that both weight updating and weight re-initialization produce seismic anomaly ratios that remain broadly comparable across rolling windows. For each method, the training and validation ratios fluctuate over time, but no clear, systematic pattern emerges along the window sequence. Although some windows display differences in dispersion, these variations do not form a consistent trend that would justify declaring one strategy to be identified as uniformly superior. Likewise, when contrasting the different model configurations (refer to section C.3), no single model systematically outperforms the others over the full temporal range. Performance changes from window to window and differs between training and validation segments, which prevents a robust, ranking-based assessment of the models using this evaluation alone. At this point, choosing a single “best” model would be premature, and such a choice would risk over-interpreting window-specific variations instead of reflecting stable, generalisable behaviour. Importantly, for all strategies and models, the seismic anomaly ratios tend to remain above the random baseline, suggesting that the detected association does not rely exclusively on a particular training procedure or model architecture.

Within the current evaluation framework, it is difficult to draw firm conclusions about relative model performance across the different rolling windows. Each window corresponds to a unique ionospheric interval, with its own background conditions, geomagnetic activity levels, and noise characteristics. Consequently, shifts in seismic anomaly ratios from one window to another may primarily reflect changes in the ionospheric environment rather than genuine differences in model skill. This issue is particularly relevant when focusing on the validation segments, which do not overlap between windows and thus probe distinct, temporally independent data segments. As a result, straightforward, window-by-window comparisons of model performance risk are misleading, since they merge the effects of model behavior with window-specific environmental variability. A more suitable evaluation would aggregate performance in a consistent manner across windows, allowing the extraction of broader trends or long-term behavior while explicitly accounting for the non-stationary nature of the ionosphere. Such a framework would provide a more reliable basis for comparing different models and training strategies than relying on isolated statistics from individual windows.

With this objective, we introduce an aggregate performance statistic called Z-factor analysis 4.4.2. For each window, we compute the deviation of the seismic anomaly ratio with respect to the random baseline, and then average the result $Zscore$ across all windows to obtain the overall deviation of the model’s ratio over the validation data. A



(a) Z-factor across models for the chosen criteria. The Z-factor is computed based on the seismic-anomaly ratio from the validation segment of rolling windows. The x-axis denoted the models, and the y-axis denoted the z-factor values. The horizontal lines indicate standard significance levels ($Z_{score} = 0, 2, 3$, refer to equation 4.22). Most models have $Z > 2$, signifying statistically significant performance under this arrangement.



(b) Comparison of the average seismic anomaly ratio and its corresponding uncertainty during training and validation among models for the specified criterion. The x-axis denoted the models, and the y-axis denoted the seismic anomaly ratio in percentage values. Blue and orange markers indicate training and validation ratios, respectively. All models have ratios beyond the random baseline median ($Q2_{RST}$), with several exceeding the 99.7% random confidence level ($0.3-99.7\%_{RST}$), signifying a statistically robust anomaly-earthquake correlation.

Figure 5.6: Model-based comparison of (a) Z-factor statistics and (b) average seismic-anomaly ratios for the statistically selected spatial-temporal setting, evaluated over the first 16 rolling-window segments (2005-2009).

detailed examination of the Z-factor and the mean seismic anomaly ratio across the 16 rolling windows for two trained models as a representative example is shown in Figure 5.6. Figure 5.6a summarises the Z-factor statistics derived from the seismic-anomaly ratios on the validation segment of each window, along with the corresponding 32–68 percentile range, for all ten LSTM-autoencoder variants. Reference $Zscore$ levels (0, 2, 3) are also indicated using horizontal red lines (refer to equation 4.22). Across models, the findings consistently indicate a strong, statistically significant deviation from the random baseline, with seven out of ten models exceeding the $Zscore = 3$ threshold, commonly interpreted as strong statistical evidence. This pattern confirms that the ionospheric electric-field anomalies identified by the models coincide with earthquake occurrence more frequently within the selected spatial and temporal bounds than expected by chance. Notably, both the weight-updating and re-initialising model families attain similarly competitive Z-factors, indicating that the rolling-window framework is robust to different optimisation strategies and thereby strengthening the stability and reliability of the overall methodological approach.

Figure 5.6b supports this conclusion by illustrating the average seismic-anomaly ratio calculated over the training and validation segments for the same set of models. The average seismic-anomaly ratio is the arithmetic mean of the window-wise ratio ρ_{w_i} across all the rolling windows. Its uncertainty is propagated in quadrature (refer to equation 4.24). The blue markers show the training datasets, while the orange markers show the validation segment. This chart shows that the findings are consistent across models and between the training and validation phases. In almost all modes, the training and validation ratios are much higher than the $Q2_{RST}$ baseline (solid red line) and often equal to or greater than 99.7% RST (refer to the RST distribution in section C.1). This indicates the model generalises effectively to unseen data beyond the training phase. Also, the validation ratios stay mostly the same and are closer to their training counterparts, which means that there is no significant overfitting. These results imply that the selected $22^\circ \times 22^\circ$ geographical frame and the 48-hour temporal window provide more consistent correlations between model-detected ionospheric anomalies and seismic occurrences than random chance of occurrence.

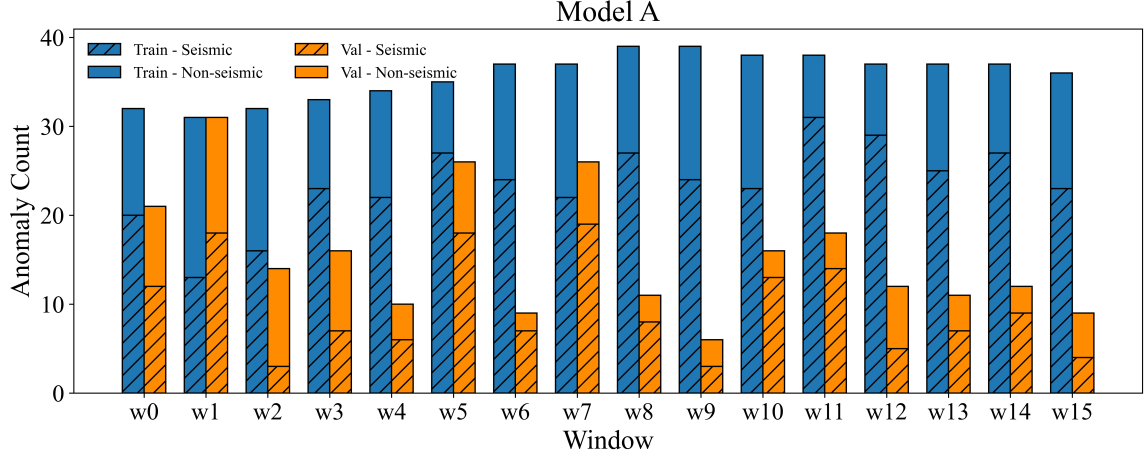
As a result, it is hard to find a single model or training approach that always does better than the others based on the combined assessment of the Z-factor and the mean seismic anomaly ratio across different models. The findings indicate that the identified association is invariant across all model configurations and is unaffected by any specific architecture or training methodology. The lack of a dominant model suggests that the detected signal cannot be ascribed to finely tuned hyperparameters or a particular network configuration. It implies that the underlying relationship remains consistent across several modelling alternatives. This further supports the idea that the differences from the random baseline show a real statistical trend at this space-time

scale, not just a result of a specific model design.

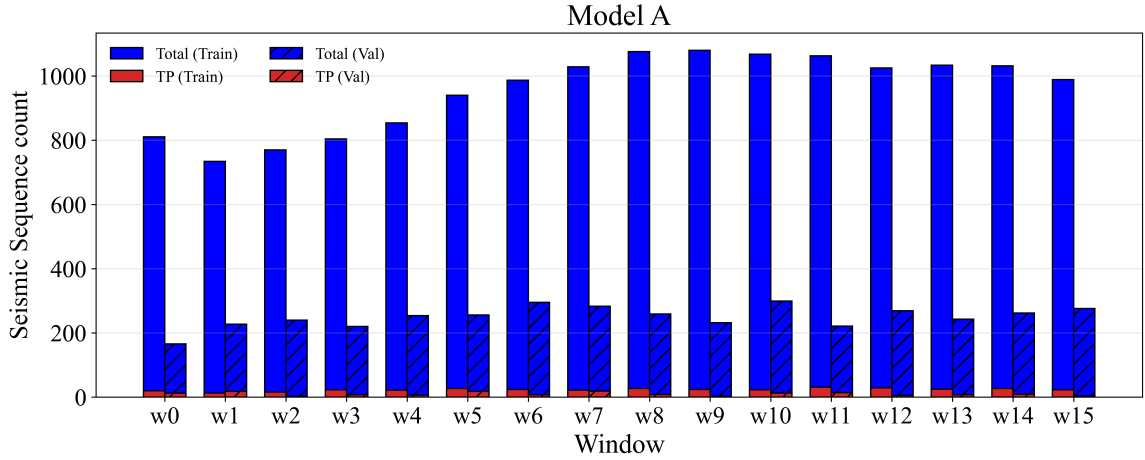
5.2.3 Precision Vs Recall

In deep learning-based classification and anomaly detection frameworks, a key criterion for assessing model performance is its ability to properly balance true positives and false positives, where true positives correspond to correct predictions and false positives correspond to incorrect predictions [284], [285], [286]. Figures 5.7 and 5.8 illustrate the precision and recall computed for each rolling window for Model A trained under the weight-updating mode and Model In-A under the weight re-initialization mode, respectively. Precision is technically equivalent to the seismic-anomaly ratio itself, as it quantifies the fraction of detected anomalies that are actually seismic in nature. Recall, on the other hand, is defined as the ratio of the total number of seismic sequences correctly tagged as anomalies to the total number of seismic sequences. For the precision plots (Figures 5.7a and 5.8a), the x-axis represents the rolling windows from w_0 to w_{15} , while the y-axis denotes the count of anomalous sequences. The total number of anomalies detected in the training and validation datasets is shown using blue and orange bars, respectively, where the hatched portion represents the seismic component of the total anomalies in each window (i.e., the true positive counts). In the training data, a degree of continuity or a gradual trend can be observed in the anomaly counts. This behaviour can be attributed to the overlapping nature of the rolling windows, where nine months of each window overlap with the preceding one. In contrast, no clear or regular pattern is observed in the validation segment, either in the total anomaly counts or in their seismic component, as none of the validation segments overlap for any windows. Under the overall evaluation, and when averaging across all windows and model configurations, also consistent with the average seismic anomaly ratio (see Figure 5.6b), on average, the proposed framework flags approximately 15 anomalous sequences in the validation set. Of these, roughly $\approx 65\%$ correspond to true positives, meaning that the identified sequences are followed by at least one earthquake within the specified spatiotemporal window. In other words, on average, around 10 out of 15 model-identified anomalous sequences are followed by an earthquake with magnitude ≥ 5 compared to approximately 55% expected from the random empirical baseline (refer to the RST distribution in section C.1). Put differently, on average, roughly 10 of the 15 anomalous sequences flagged by the models occur within the spatiotemporal window of an earthquake, a proportion that consistently exceeds what would be expected by random chance.

For the recall plots (Figures 5.7b and 5.8b), the x-axis again represents the rolling windows from w_0 to w_{15} , while the y-axis denotes the count of seismic sequences. Each blue bar represents the total number of seismic sequences within the full duration

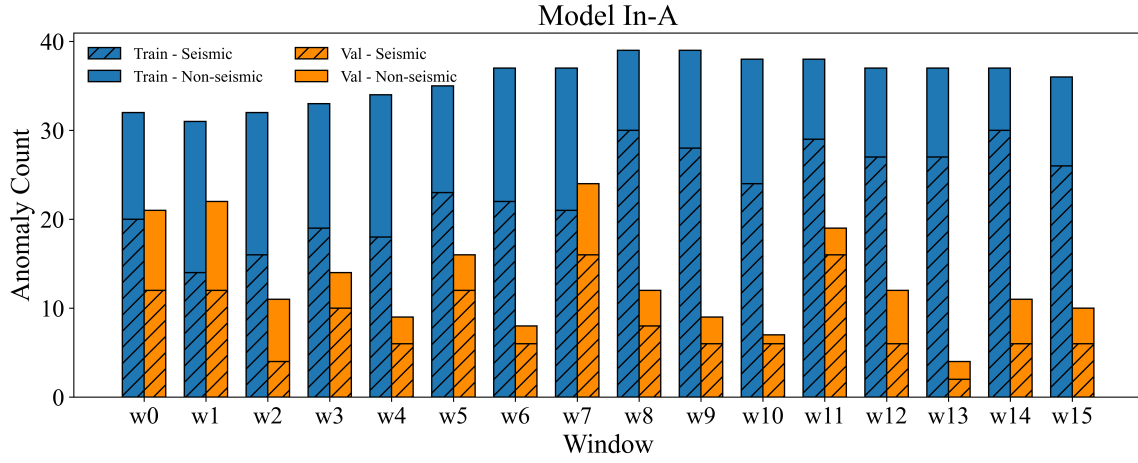


(a) Precision plotted as the barplot for the model A trained under the weight updating mode for each window from w_0 to w_{15} . The x-axis represents the windows, and the y-axis denotes the anomaly count, where blue and orange bars represent the training and validation dataset anomalies, respectively. The hatched segment represents the seismic part of the total anomalous sequences.

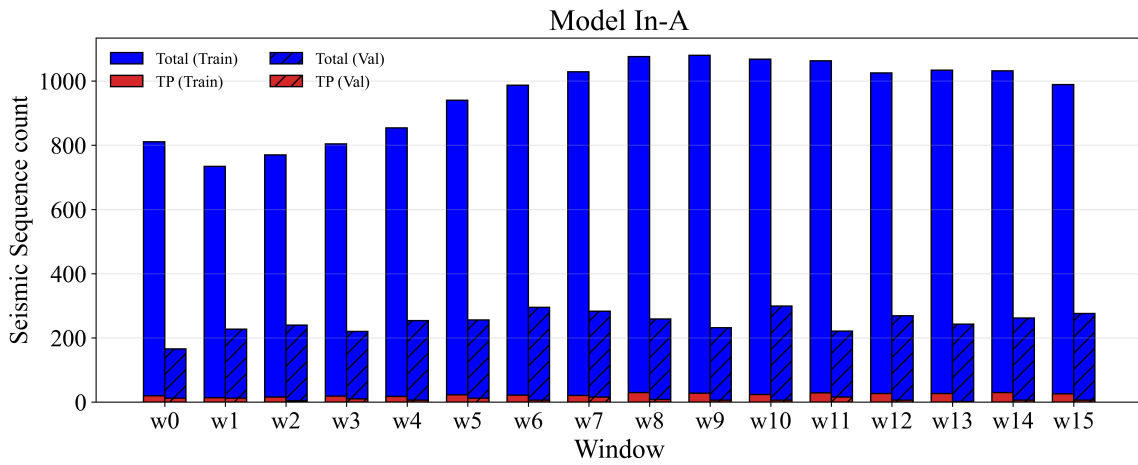


(b) Recall plotted as the bar plot for the model A trained under the weight updating mode for each window from w_0 to w_{15} . The x-axis represents the windows, and the y-axis denotes the seismic sequence count, where blue bars represent the training and validation (hatched) total seismic sequences. The red overlaying bars represent the count of detected seismic sequences.

Figure 5.7: (a) Precision and (b) recall for Model A trained in weight updating mode for the first 16 rolling windows w_0 to w_{15} .



(a) Precision plotted as the bar plot for the model In-A trained under the weight re-initialising mode for each window from w_0 to w_{15} . The x-axis represents the windows, and y axis denoted the anomaly count, where blue and orange bars represent the training and validation dataset anomalies, respectively. The hatched segment represents the seismic part of the total anomalous sequences.



(b) Recall is plotted as the bar plot for the model In-A trained under the weight re-initialising mode for each window from w_0 to w_{15} . The x-axis represents the windows, and the y-axis denotes the seismic sequence count, where blue bars represent the training and validation (hatched) total seismic sequences. The red overlaying bars represent the count of detected seismic sequences.

Figure 5.8: (a) Precision and (b) recall for Model In-A trained in weight re-initialising mode for the first 16 rolling windows w_0 to w_{15} .

of the training (unhatched) and validation (hatched) segments, whereas the lower red portion indicates the number of seismic sequences detected as anomalous by the model. The recall, which quantifies the proportion of all seismic sequences correctly detected as anomalies, remains relatively low, with an average value of approximately 4.3% across all windows in the validation segment. This low recall is expected and denotes the anomaly detection strategy adopted in this study, which applies a high anomaly detection threshold and retains only the most extreme outliers as anomalies. These results further indicate the possibility that only a small fraction of all seismic sequences are associated with ionospheric electric-field disturbances that are sufficiently strong to be detected by the model.

The observed combination of relatively high precision ($\approx 65\%$) and low recall ($\approx 4.3\%$) indicates that the framework operates as a highly conservative anomaly detector. In practical terms, approximately two-thirds of the detected anomalies are associated with at least one earthquake within the adopted spatial and temporal association window, while approximately one-third are not associated with a subsequent earthquake and therefore constitute false positives under the present evaluation framework. It should also be noted that anomalies classified as false positives in the present framework are not necessarily physically meaningless. Such anomalies may arise from ionospheric variability driven by solar-terrestrial interactions, atmospheric coupling processes, instrumental effects, or other geophysical phenomena not explicitly considered in the seismic association analysis. Furthermore, some anomalies may be related to seismic processes that fall outside the adopted association criteria, for example, earthquakes occurring beyond the selected spatial window, outside the forecasting time interval, or below the chosen magnitude threshold. Consequently, the term 'false positive' should be interpreted within the context of the adopted evaluation framework rather than as definitive evidence of a non-seismic origin.

Furthermore, the practical interpretation of the reported precision, in particular the $\approx 10\%$ excess should be considered in light of the relatively broad association criteria employed in this study. Because an anomaly is considered a true positive whenever at least one earthquake occurs within a $22^\circ \times 22^\circ$ region and within 48 h of the anomaly, the reported precision does not imply precise earthquake localisation or short-term forecasting capability. Instead, it demonstrates that the detected anomalies occur before earthquakes more frequently than expected by chance. Therefore, the principal contribution of the framework is scientific rather than operational: it provides statistical evidence that a subset of extreme ionospheric electric-field anomalies is associated with subsequent seismic activity, while further refinement would be required before any practical forecasting application could be considered.

This study prioritises precision over recall, as the primary objective is not to identify all seismic sequences but to conduct a data-driven deep learning analysis for the detec-

tion of rare, extreme ionospheric low-frequency electric field anomalies and to evaluate their statistical association with subsequent seismic activity. Due to the nature of this problem and the highly turbulent nature of the ionosphere, concentrating on recall would provide a significant number of false positives, which, in practical terms and considering the point of view of future development of early warning systems, are more unfavourable than missed occurrences. Consequently, the framework is intentionally constructed for detecting just the most significant anomalies from the observed background behaviour of daytime low-frequency ionospheric electric field data.

5.3 Blind Phase Analysis

To evaluate the genuine generalisation ability and adaptability of the proposed framework on entirely unseen data, a dedicated blind-phase analysis was conducted using observations from 2010 (the blind set). This blind-phase stage corresponds to the last four rolling windows, labelled w_{16} – w_{19} . Consistent with the rolling-window scheme, the training portions for these windows still include overlapping samples from earlier years, while the validation portions are strictly non-overlapping and consist exclusively of 2010 data. The blind windows are trained using the same rolling-window setup as in the primary phase. Each blind window trains on the latest 12 months of data, which naturally includes data from earlier years (e.g., 2009). As the blind phase advances, the validation set from the previous blind window is incorporated into the training set of the subsequent blind window, reflecting the overlapping structure of a rolling-window scheme. None of the 2010 validation segments were used for either training or evaluation in the primary phase, guaranteeing that all blind-phase performance metrics are based on data the model had not seen before. This design again guarantees an unbiased assessment of model performance on unseen data. It has to be noted that all the evaluations are based on the model's outcome from the validation data alone.

For the weight-updating models, the network parameters learned up to window w_{15} , the final window used in the 2005–2009 analysis, were reloaded and served as the initial weights for training in the blind-phase, thereby preserving the cumulative learning acquired in the previous period. In contrast, the re-initialised models were trained from scratch with randomly initialised parameters, using the same training procedure as in the Primary phase analysis. As before, this constitutes a follow-up analysis on models trained with data segmented using a $22^\circ \times 22^\circ$ spatial window and a 48-hour temporal window.

The training dynamics of the models under both operational modes during the blind-phase are presented in Figure 5.9. In Figure 5.9(a), corresponding to the weight-updating mode, the training and validation loss behaviour reflects the cumulative learning process inherent to the weight-updating strategy. The training loss shows a gradual

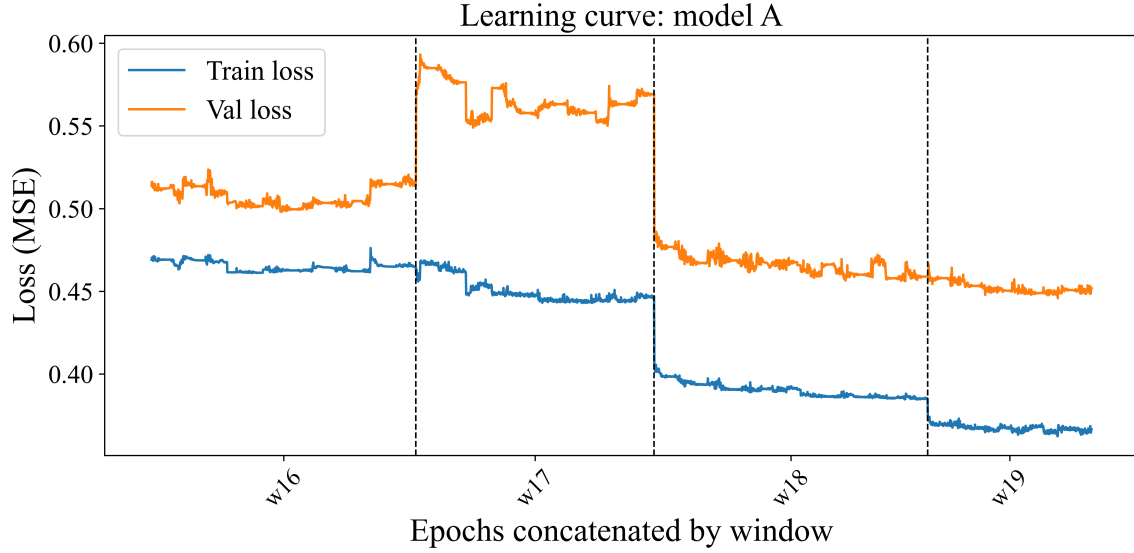
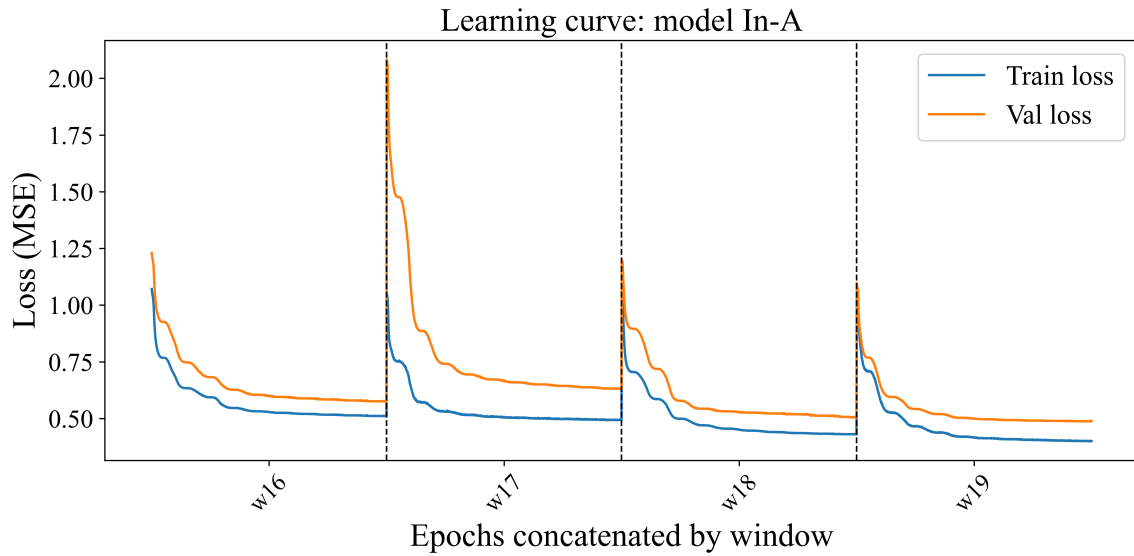
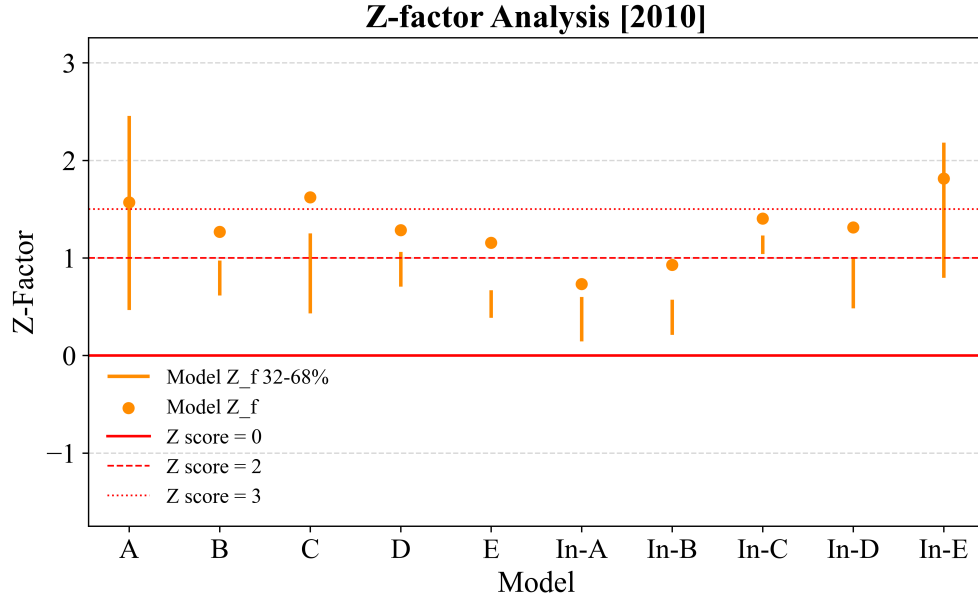
(a) **Weight Updating Mode**(b) **Weight Re-initialization Mode**

Figure 5.9: Training loss curves for models trained under two operational modes using the last 4 rolling windows (w_{16} – w_{19}) for blind phase analysis: (a) Model A - Weight Updating Mode and (b) Model In-A - Weight Re-initialisation Mode. Loss curves are concatenated across consecutive windows to show how training evolves over time.

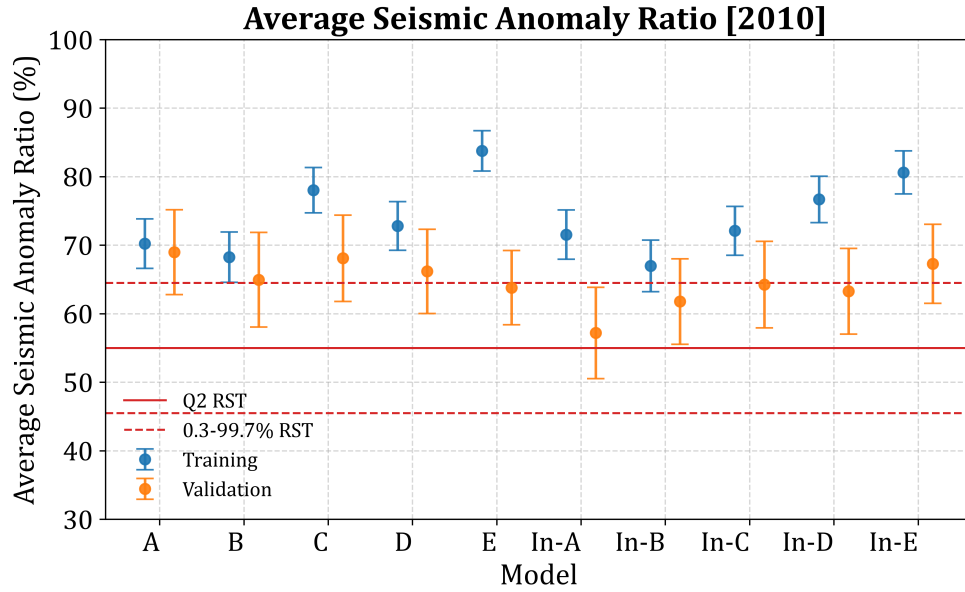
and consistent decrease across successive windows (w_{16} – w_{19}), indicating that the model progressively refines its internal representation as additional data becomes available. The absence of sharp resets at window boundaries highlights the continuity of learned parameters across windows. The validation loss follows a broadly similar trend but exhibits a noticeable increase at the beginning of window w_{17} , after which it stabilises and gradually decreases in subsequent windows. This temporary rise suggests a shift in the data distribution or increased variability during this interval, requiring the model to readjust before achieving improved generalisation. Overall, the convergence of both training and validation losses across later windows indicates stable learning and no strong evidence of overfitting, with the gap between the two remaining relatively consistent. In contrast, Figure 5.9(b), representing the weight re-initialisation mode, shows distinct loss spikes at the beginning of each window, followed by rapid convergence within each segment. These abrupt increases correspond to the reinitialisation of model parameters, after which the network independently relearns the underlying data structure for each window. The comparatively higher variation observed in window w_{17} may indicate increased variability in the underlying data during this period. This is reflected in the loss behaviour, suggesting that the model requires additional adaptation to represent the more complex patterns within this window. Despite these differences in convergence behaviour, both approaches demonstrate stable optimisation within each window, highlighting the contrasting yet complementary learning dynamics of cumulative adaptation versus independent retraining.

Figure 5.10a presents the Z-factor statistics for each model over the blind-phase windows. Horizontal red lines indicate $Zscore$ levels of 0, 2, and 3 (refer to equation 4.22). These Z-factors are computed from the seismic-anomaly ratios using only the validation segments of the blind-phase windows. While the Z-factor values are generally lower than those obtained for the 2005–2009 interval, most models still display positive scores, with many reaching or exceeding the $Zscore = 2$ threshold and a few exceeding the $Zscore = 3$ level. In aggregate, both training strategies produce similar Z-factor performance, though the weight-updating models tend to achieve slightly higher scores, likely due to the advantage of their longer accumulated training history. The close agreement between the two optimisation strategies during the blind-phase supports the robustness of the rolling-window learning framework and suggests that the observed seismic-anomaly relationship is not an artefact of a specific training procedure or time period.

Figure 5.10b presents the corresponding average seismic-anomaly ratios for the blind-phase windows. Across the different model variants, the validation ratios remain consistently high, generally between 60–70%. These values are substantially above the random baseline $Q2_{RST}$ and frequently exceed the 99.7% RST threshold (refer to the RST distribution in section C.1). Figure 5.11 summarises the primary and blind



(a) Z-factor across models for the chosen criteria. The Z-factor is computed based on the seismic-anomaly ratio from the validation segment of rolling windows. The x-axis denoted the models, and the y-axis denoted the Z-factor values. The horizontal lines indicate standard significance levels ($Z_{score} = 0, 2, 3$, refer to equation 4.22). Most models have $Z > 2$, signifying statistically significant performance under this arrangement.



(b) Comparison of the average seismic anomaly ratio and its corresponding uncertainty during training and validation among models for the specified criterion. The x-axis denoted the models, and the y-axis denoted the seismic anomaly ratio in percentage values. Blue and orange markers indicate training and validation ratios, respectively. All models have ratios beyond the random baseline median ($Q2_{RST}$), with several exceeding the 99.7% random confidence level (0.3-99.7% RST), signifying a statistically robust anomaly-earthquake correlation.

Figure 5.10: Model-based comparison of (a) Z-factor statistics and (b) average seismic-anomaly ratios for the statistically selected spatial-temporal setting, evaluated over the blind phase rolling-window segments (2010).

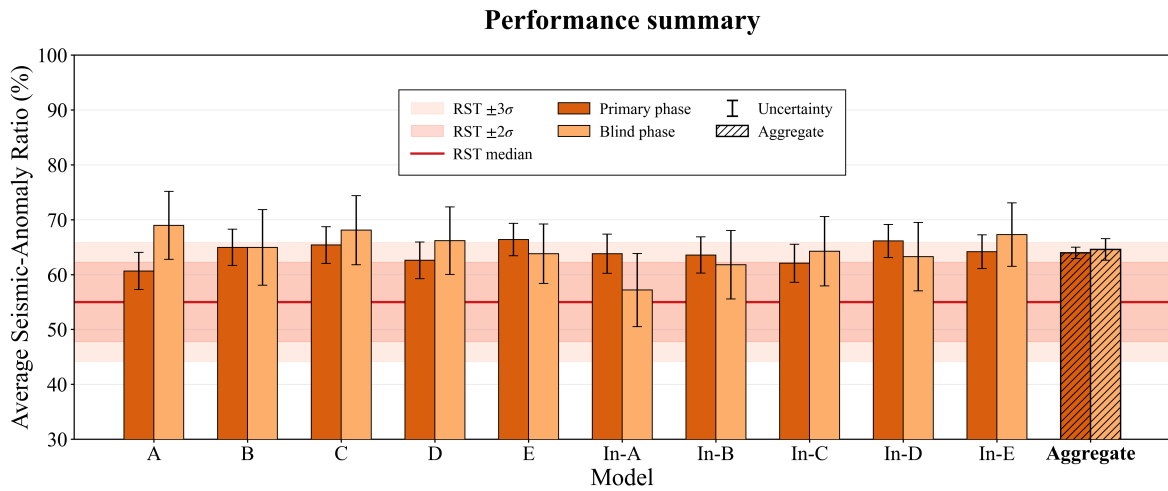


Figure 5.11: Consolidated summary of the anomaly-earthquake association rate computed from validation data segment for the selected criteria SW22x22_TW48. The x-axis lists the evaluated model configurations, including the weight-updating models A - E, the re-initialised models In-A - In-E, and the aggregate result. The y-axis shows the average seismic-anomaly ratio in percentage. Bars show the observed association rate for each model during the primary and blind phases, with error bars indicating the associated uncertainty propagated in quadrature. The aggregate (bars with hatches) represents the average performance across all models. The horizontal reference line marks the random median expectation, while the shaded region represents the $\pm 2\sigma$, $\pm 3\sigma$ range of RST, where σ is the standard deviation computed as the square root of the variance of the random ratios.

phase analysis outcome, for each model and in aggregate, the average seismic-anomaly association rate computed from validation segments, its uncertainty, and its deviation from the empirical random baseline for the selected SW22x22_TW48 criterion. The figure shows that most of the models trained with both the primary-phase (orange) and blind-phase (yellow) results remain consistently above the random expectation with a deviation of roughly $2-3\sigma$ from the random baseline. The aggregate (bars with hatches) represents the average performance across all models, and for both primary and blind phase, the observed association rates (approximately 65%) correspond to deviations of roughly $2-3\sigma$ from the random baseline, indicating a persistent positive statistical association between detected anomalies and subsequent earthquakes in the given framework.

Overall, the blind-phase results reinforce the conclusions drawn from the initial sixteen rolling windows covering 2005–2009. These results imply that the anomalies detected by the models are statistically more likely to coincide with earthquakes than would be expected under a random association in the given framework. The similar performance of the weight-updating and re-initialised model families further indicates that the findings are not tied to a particular optimisation strategy but instead arise from a robust and reproducible learning process intrinsic to the adopted LSTM autoencoder architecture. A further advantage of the proposed methodology is its temporal stability that consistent behaviour is observed for both the primary phase period and the independent blind-phase year, demonstrating that the model behaviour is not because of any specific dataset or time interval. Accordingly, the performance observed in both phases can be attributed to the combined influence of the LSTM architecture, the adaptive rolling-window training strategy, and the statistically chosen spatio-temporal window configuration.

It should be noted that the anomaly scores reported in this study are derived from reconstruction errors aggregated across all eleven frequency bands and the full sequence duration. Consequently, although the framework can identify statistically anomalous sequences, the detected anomalies cannot presently be attributed to a specific frequency band, orbital segment, or physical wave mode. Therefore, the current results should be interpreted primarily as evidence of statistically unusual ionospheric behaviour rather than as identification of a particular physical mechanism responsible for the observed perturbations.

5.4 Solar Events Dependencies

Solar activity plays a dominant role in shaping the ionospheric environment and is a primary source of large-scale ionospheric variability. This naturally raises the question of whether the anomalies identified by the proposed model could be primarily

driven by variations in solar activity, rather than reflecting a possible lithosphere-ionosphere coupling associated with seismic processes. To examine this possibility, an auxiliary analysis was conducted using international sunspot number data obtained from the World Data Center SILSO, Royal Observatory of Belgium, Brussels. Figure 5.12 shows the temporal evolution of the daily sunspot number during the study period. Solar activity is higher at the beginning of the interval, around 2005, and progressively decreases toward a minimum near 2009, corresponding to the declining phase of solar cycle 23, after which a gradual increase is observed. Among the available solar indices, the sunspot number provides the most reliable long-term proxy for solar-cycle evolution and its cumulative influence on the ionosphere [287]. While geomagnetic indices such as Kp, Dst, and AE are commonly used to characterise short-term space-weather disturbances, the focus here is on assessing potential long-term modulation effects.

The primary objective of this study is to evaluate whether anomalies detected by a data-driven deep-learning framework exhibit a statistically significant association with earthquakes when compared against an empirical random baseline. To support this goal, the methodology incorporates an iterative background correction applied at the grid-cell level, which removes dominant seasonal and long-term components of the ionospheric signal that are largely associated with solar activity. As a result, the model operates on residual variability rather than on large-scale periodic structures. Furthermore, anomaly thresholds are defined within rolling training windows, allowing them to adapt continuously to evolving ionospheric conditions across both geomagnetically quiet and disturbed periods. Consequently, no explicit exclusion of storm-time intervals or conditioning on geomagnetic indices is applied. Such selective filtering could restrict the analysis to a narrow subset of background regimes and introduce bias by training the model exclusively under artificially quiet conditions. By retaining the full spectrum of natural variability, the framework enables the model to learn a realistic, time-evolving background state. At the same time, the random-shift baseline ensures that the statistical association between detected anomalies and earthquakes is evaluated against chance coincidence under comparable space-weather conditions.

Within this framework, the sunspot number is used solely as an auxiliary diagnostic to verify that the detected anomaly rates do not trivially track the long-term solar cycle. The absence of a systematic relationship between quarterly mean sunspot activity and anomaly occurrence suggests that the detected anomalies are not dominated by large-scale solar-cycle modulation. This addresses a key concern relevant to the windowed and long-term nature of the present analysis. Notably, several previous studies explicitly removed periods of elevated solar activity during pre-processing [39], [41], [288]. In contrast, the approach adopted here intentionally follows a black-box philosophy, training the deep-learning model directly on global low-frequency ionospheric electric-field measurements without applying solar-activity corrections, allowing the

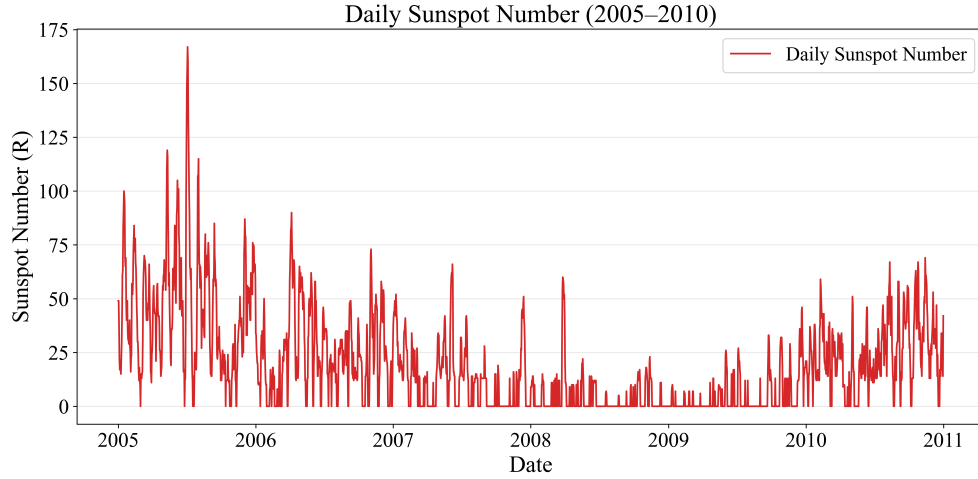
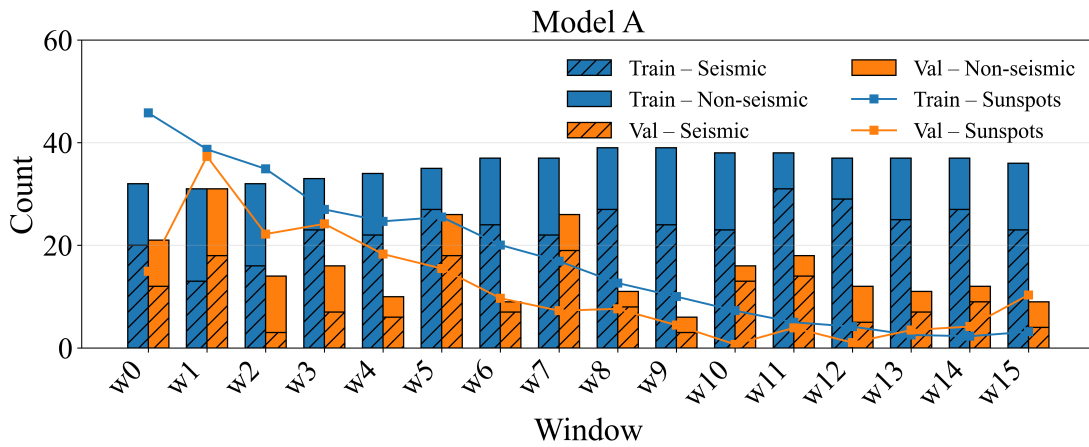


Figure 5.12: temporal evolution of the daily sunspot number during the study period. Solar activity is higher at the beginning of the interval, around 2005, and progressively decreases toward a minimum near 2009, corresponding to the declining phase of solar cycle 23, after which a gradual increase is observed.

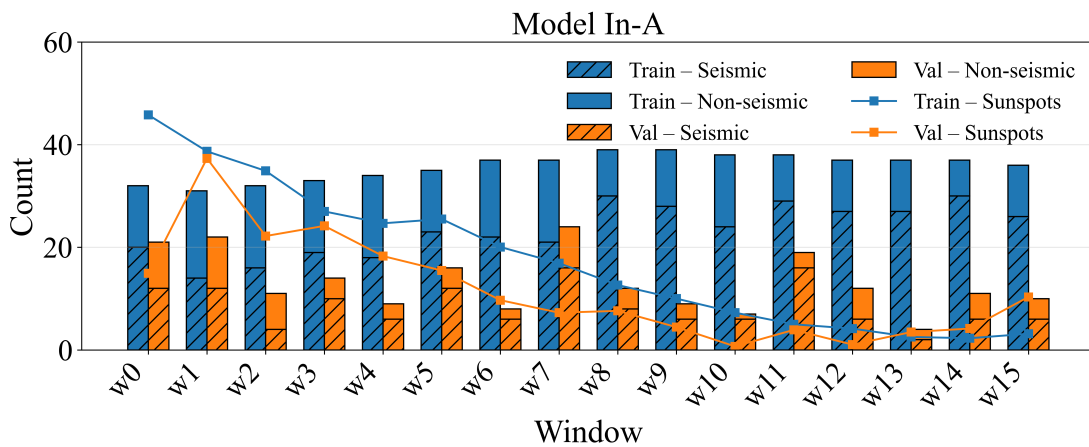
network to autonomously learn characteristic background behaviour.

As a post hoc verification, the relationship between detected anomalies and solar activity was explicitly examined. The total number of anomalies identified within each rolling window, for both training and validation segments between 2005 and 2009, was compared with the mean sunspot number over the same temporal windows. Figure 5.13a and Figure 5.13b illustrate this comparison using Model A and Model In-A as a representative example for weight updating and weight re-initialising modes of training, respectively. The bar plot shows the number of detected anomalies per window, distinguishing between seismic and non-seismic cases via hatched segments, while the line plot depicts the corresponding mean sunspot number.

The findings indicate a clear reduction in solar activity throughout the research period, aligning with the declining phase of solar cycle 23. Visual inspection shows no apparent correspondence between anomaly counts and mean sunspot number; while solar activity decreases steadily, anomaly detections fluctuate independently without exhibiting a correlated trend. These observations indicate that the anomaly detections are not driven by solar activity, nor do they appear to be influenced by long-term solar-cycle variations. This indicates that further solar-activity filtering is unnecessary when implementing the suggested framework on low-frequency ionospheric electric-field data, hence reinforcing the robustness of the deep-learning methodology employed in this study. Although the present analysis reduces the influence of large-scale background variability through adaptive background correction, it does not explicitly filter or condition on geomagnetic activity indicators such as Kp, Dst, or AE. Explicit geomagnetic screening therefore, represents an important future extension for improving the physical interpretation of the detected anomalies and further assessing the contri-



(a) An example illustration of model A showing window-based anomaly statistics together with solar activity (y-axis) for the study period of 2005-2009. The bar plots represent the precision of the model anomaly detection, separated into seismic (hatched) and non-seismic components for both training (blue) and validation (orange) segments. The overlying line plots (y-axis) show the corresponding mean sunspot number within each window, representing solar activity.



(b) An example illustration of model In-A shows window-based anomaly statistics together with solar activity (y-axis) for the study period of 2005-2009. The bar plots represent the precision of the model anomaly detection, separated into seismic (hatched) and non-seismic components for both training (blue) and validation (orange) segments. The overlying line plots (y-axis) show the corresponding mean sunspot number within each window, representing solar activity.

Figure 5.13: An anomaly-sunspot correlation check was carried out for Model A trained in (a) weight updating and Model In-A trained in (b) weight Re-initialising mode for the first 16 rolling windows w_0 to w_{15} .

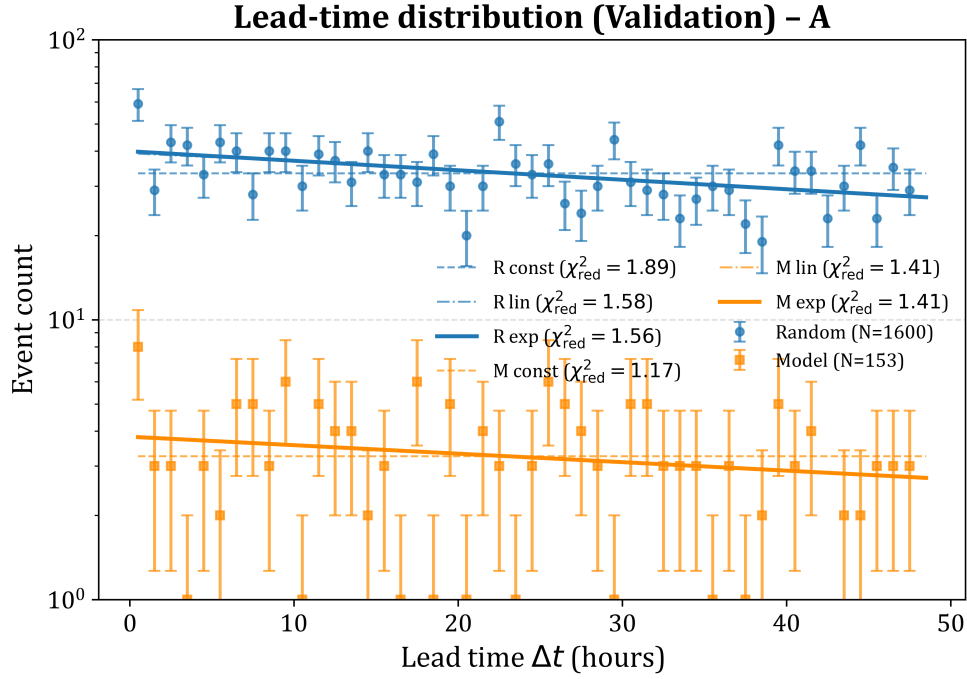
bution of space-weather-related effects.

5.5 Lead-Time Analysis

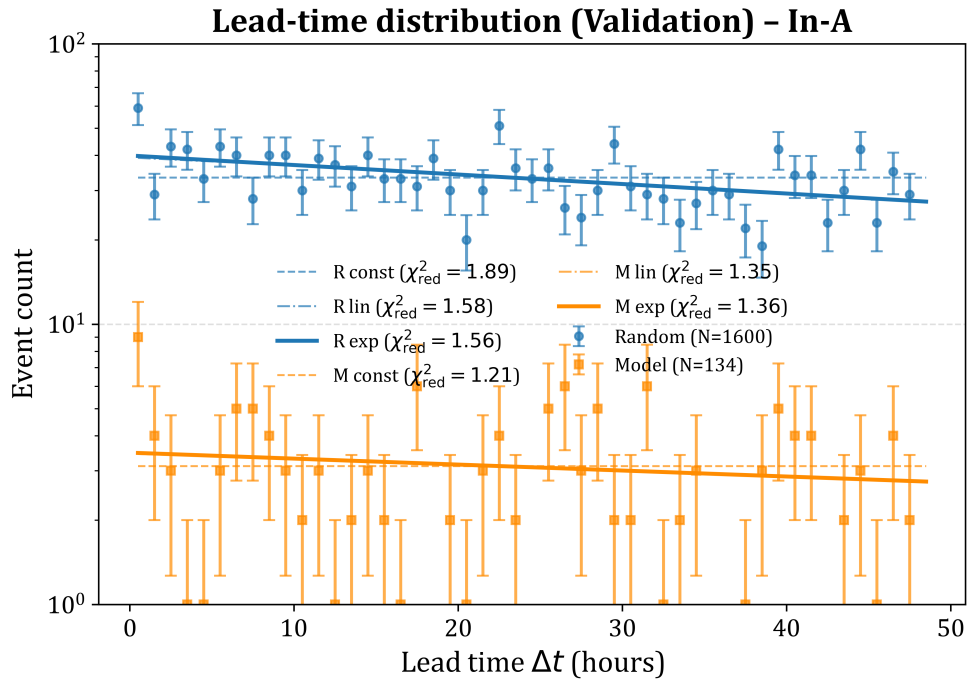
As discussed in the validation methodology, a lead-time analysis was carried out to investigate further the temporal relationship between the ionospheric anomalies detected by the model and the occurrence of the first associated earthquakes. The objective of this analysis was to examine how the time difference between the end of an anomalous ionospheric sequence and the occurrence of the first associated earthquake is distributed, and whether this distribution differs from what would be expected purely by chance. For this purpose, the anomaly-earthquake lead time was computed for each anomalous sequence identified by the model within the chosen spatial and the 48-hour temporal range from all the rolling windows. The same procedure was applied to randomly selected sequences, but along with randomised anomaly time to construct a reference distribution representing random temporal associations (refer to section 4.4.3). The resulting lead-time values were then grouped into bins, which provide a direct visual representation of how frequently earthquakes occur at different time delays following an anomaly.

Figure 5.14 shows the resulting lead-time distributions for Model A and Model In-A, corresponding to the two different training strategies (weight updating and weight re-initialisation), together with the corresponding random baseline. In both figures, the vertical axis is shown on a logarithmic scale. The error bars associated with each bin represent the statistical uncertainty of the event counts and are estimated assuming Poisson statistics, where the uncertainty is given by the square root of the number of events in each bin. The error bars are asymmetric about the data points because Poisson uncertainties are defined in linear count space, and when displayed on a logarithmic axis, these visually enlarge at low counts but remain statistically consistent.

To characterise the overall trend of the lead-time distributions, three simple functional forms were fitted to the binned data, a constant function, a linear function, and an exponential function. These fits were applied independently to the random baseline and to the model derived distributions for the validation data. For the constant model, the lead-time distribution is assumed to be uniform across the temporal window. The fitted constant level is obtained as the arithmetic mean of the binned lead time counts after excluding bins with zero values. The predicted distribution is made by assigning this constant value to all bins. For the linear model, we defined a first-order relationship between the event counts and lead time. The model parameters, such as the slope and intercept (a_l, b_l) , are estimated using ordinary least-squares regression. For the exponential model, the lead time distribution is described using an exponential decay function of the form $y = a \times \exp(-bx)$. The amplitude a is initialised using



(a) Lead time analysis of a representative example of weight updating mode training, model "A".



(b) Lead time analysis of a representative example of weight re-initialising mode training, model "In-A".

Figure 5.14: Model-based comparison of lead time analysis (a) weight updating and (b) weight re-initialising model. The plot shows the lead time distributions on a logarithmic y-axis, with blue markers representing the random baseline (R) and yellow markers representing the model-based validation results (M), plotted as a function of lead time in hours on the x-axis, the horizontal dotted line indicates the constant function fit, the dashed line with markers represents the linear fit, and the solid curve corresponds to the exponential fit, with the reduced chi-square values and total data points available for the distribution

the first positive bin count, while the decay constant b is initialised as the inverse of the lead time range. The parameters are then estimated using constrained nonlinear least squares optimisation. The goodness of fit was evaluated using the reduced chi-square statistic, which accounts for both the uncertainties and the number of free parameters (refer to equation 3.4). For the random baseline, the exponential and linear models yield comparable reduced chi-square values, consistent with the expectation that random temporal associations approximately follow an exponential waiting time behaviour over a limited time range. In contrast, the distributions obtained from the model-detected anomalies exhibit systematically lower reduced chi-square values and do not follow the same decay pattern as the random reference. In both cases, the linear and exponential fits nearly coincide across the lead-time range, suggesting that the data do not allow a clear distinction between these two functional forms.

Table 5.5 summarises the fitted parameters and reduced chi-square values obtained for the random baseline and the model-based validation results for both Model A and Model In-A. The random baseline exhibits relatively high event counts because of the higher number of available samples and shows a clear decrease with lead time, as reflected by the negative linear slope and the exponential decay. In contrast, both model configurations yield substantially lower count levels due to the lack of higher data statistics and much weaker dependence on lead time, with near to zero linear slopes and flatter exponential behaviour. Once parameter uncertainties are accounted for, the linear and exponential fits become statistically indistinguishable across all three cases — sharing compatible intercepts, slopes, and reduced chi-square values. Notably, for the random baseline the linear and exponential fits yield a lower reduced chi-square than the constant fit, consistent with the known exponential waiting-time behaviour expected from random temporal associations; whereas for the model-derived distributions, the constant fit performs comparably or better. While this difference is not yet statistically significant given the limited event counts, it suggests that extending the analysis to larger datasets or longer temporal windows could provide the statistical power needed to exploit the lead-time distribution as an additional discriminator between genuine precursory signals and random coincidence. The similarity of the fitted parameters and reduced chi-square values between models further suggests that the observed behaviour is robust and not sensitive to the specific training strategy. Given the relatively small number of events, the existing data do not support a reliable discrimination between these two functional forms. Overall, the comparison shows that the anomalies identified by the model follow a temporal pattern distinct from random coincidence, but the available data statistics do not permit the determination of a single preferred functional form for the decay. In other words, while the model derived lead time distributions differ markedly from those expected by chance, the precise mathematical form of the decay cannot be uniquely resolved within the present analytical

framework.

Table 5.5: Lead-time distribution fit parameters for the random baseline (R) and model validation results (M). Uncertainties correspond to standard errors of the fitted parameters.

Function	Parameter	Random (R)	Model A (M)	Model In-A (M)
Constant	C	33.33 ± 1.15	3.255 ± 0.242	3.116 ± 0.269
	χ^2_{red}	1.89	1.17	1.21
Linear	a_l	-0.249 ± 0.076	-0.022 ± 0.018	-0.014 ± 0.019
	b_l	39.299 ± 2.098	3.783 ± 0.479	3.451 ± 0.520
	χ^2_{red}	1.58	1.41	1.35
Exponential	a	39.958 ± 2.283	3.821 ± 0.519	3.481 ± 0.549
	b	0.0078 ± 0.0023	0.0070 ± 0.0054	0.0049 ± 0.0062
	χ^2_{red}	1.56	1.41	1.36

5.6 Threshold Sensitivity Analysis

To evaluate how sensitive the model performance is to the choice of anomaly threshold, we performed a threshold sensitivity analysis for thresholds between the 95th and 99th percentiles and examined how the Z-factor score changes for all models across different training strategies using the primary phase model training (2005-2009). The calculations rely exclusively on the model's outcomes based on the validation data. For each threshold, we computed the Z-factor and its corresponding 32–68% uncertainty interval, using the same methodology as in the main text. Figure 5.15 presents the Z-factor as a function of threshold percentile for all ten models. Across the 95th–98th percentile range, Z-factor values remain consistently above $Zscore = 2$ (refer to equation 4.22) for most models and frequently exceed $Zscore = 3$, indicating that the association signal is robust with respect to the threshold choice. The decline observed at the 99th percentile is consistent with the expected reduction in the number of detected anomalies at very high thresholds, which increases statistical uncertainty and lowers the power to detect an association, rather than reflecting any genuine weakening of the ionosphere–seismicity relationship.

For Model In-B, the Z-factor is undefined at the 99th percentile because in one window only a single anomaly was detected, leading to $\sigma_{\rho_{w_i}} = 0$ and thus an infinite $Zscore$ for that window. This appears in the figure as the absence of a central marker. The 32–68% uncertainty band is therefore derived from the remaining finite Z_i values. Obtaining statistically significant results at the 98th percentile, where fewer anomalies are detected than at lower thresholds, constitutes a more conservative test and therefore strengthens the conclusions of the main analysis. Furthermore, because the 98th

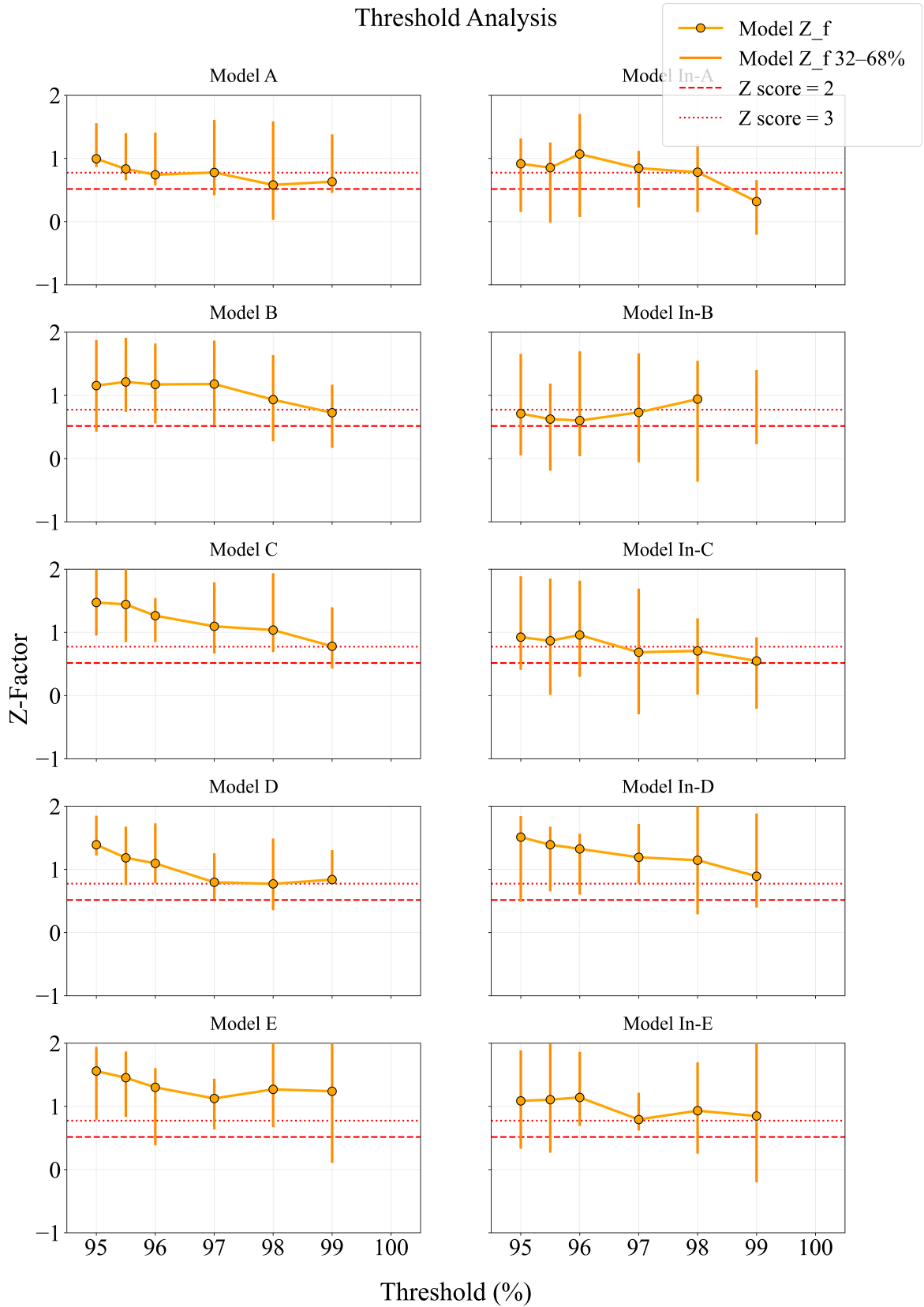


Figure 5.15: Threshold sensitivity analysis of the Z-factor across all ten models (Weight updating Models A - E, left column; weight re-initialising models In-A - In-E, right column). Each panel shows the Z-factor (dark orange circles) and its 32-68% uncertainty interval represented by vertical bars (light orange) as a function of the anomaly detection threshold, varied from the 95th to the 99th percentile of the training reconstruction error distribution. Horizontal dashed and dotted red lines indicate $Z_{score} = 2$ and $Z_{score} = 3$ (for calculation, refer to equation 4.22) respectively.

percentile threshold was chosen prior to computing any seismic association statistics, the analysis does not gain from implicit optimization over multiple threshold values. It is also important to note that the blind analysis provides an additional validation: using an independent time period, the choice of the 98th percentile threshold remains appropriate, and the models still perform well under this setting.

Chapter 6

Multi-Instrumental Approach - Feasibility Study

This study was carried out during a six-month research period abroad as part of the PhD programme. The main purpose of this period was to gain exposure to a new scientific environment and to explore how the existing work could be extended using additional approaches. We proposed to extend the current thesis work by examining whether a multi-instrument approach, along with a broader set of parameter searches, could improve our understanding of the relationship between ionospheric anomalies and seismic events, supported by a statistical analysis.

In recent years, many studies have used Digisonde data to investigate possible seismic-induced ionospheric anomalies. Several works have reported variations in the F2 region, particularly changes in the peak electron density ($NmF2$), as well as enhancements or depressions in the critical frequency of the F2 layer (f_oF2) during the pre-earthquake period [289], [290]. In addition, a number of studies have evaluated the presence of travelling ionospheric disturbances (TIDs; wave-like plasma-density perturbations). These disturbances appear in a variety of morphological forms, including split or “Y-forking” traces [291], “W”- and “Z”- shaped ionogram structures associated with seismic and infrasonic wave activity [292], [293], cusp-like distortions and multilayer stratifications [294], as well as double-peaking and small-scale irregularity features observed in disturbed ionospheric conditions [295], [296]. Furthermore, several case studies of major earthquakes have reported the formation of sporadic E layers (Es; transient dense ionisation layers in the E region) [297], [298] and their dynamic behaviour, along with the presence of Spread-F signatures, meaning diffuse or broadened F-region ionogram traces [296], as possible ionospheric responses to seismic activity [299], [300]. There have also been attempts to combine satellite-based and ground-based observations for the same major events, as discussed by Wojciech et al. and Pulinets et al. These studies emphasised that integrating multiple observational techniques, together with a clear understanding of the underlying physical mechanisms, is essential for developing a reliable approach toward earthquake-related ionospheric monitoring.

The objective of this work was to integrate both space-based and ground-based instruments to detect irregularities in the topside and bottomside ionosphere, with a focus on the identification of possible statistically significant seismic influence. This work began as a continuation of the main thesis study, where a deep learning model

was developed using global ionospheric electric field data to detect anomalies in the topside ionosphere. From this model, we identified strong outlier events in the global electric field dataset, representing possible topside irregularities. However, the physical mechanism describing how such irregularities may propagate, possibly from the bottomside to the topside ionosphere, remains unclear. The objective was to investigate bottomside ionospheric irregularities during periods when the model had already identified topside anomalies, and to assess the statistical significance of their association with earthquakes.

It must be emphasised at the outset that this chapter represents a feasibility study rather than a confirmatory investigation. The number of spatially and temporally coincident satellite-ionosonde events satisfying geomagnetic criteria was reduced to very few usable cases, which is insufficient for any statistical inference regarding bottomside–topside ionospheric coupling. The results presented here should therefore be interpreted as a preliminary exploration of methodology and data compatibility, not as evidence for or against seismo-ionospheric coupling.

6.1 Overview of Ionosonde Measurements

An ionosonde is a ground-based high-frequency radar instrument made to measure the vertical structure of the ionosphere. It provides measurements of the electron density distribution as a function of altitude by transmitting radio pulses directly upward and recording the returned echoes of the signals (refer [PITHIA-NRF](#)). Digisondes are the digital updated version of ionosondes with the same working principle. The basic principle relies on the interaction between radio waves and the ionospheric plasma. When a radio wave travels through the ionosphere, its electric field interacts with free electrons and forces them to oscillate. Because the ionosphere behaves as a plasma, these electrons have a natural oscillation frequency, called the plasma frequency, which depends on the local electron density. This characteristic frequency determines how radio waves propagate in the medium.

The plasma frequency is expressed as

$$\omega_p = 2\pi f_p = \sqrt{\frac{Ne^2}{\varepsilon_0 m_e}}, \quad (6.1)$$

where N is the electron density, e is the electron charge, ε_0 is the permittivity of free space, and m_e is the electron mass. The corresponding refractive index of the ionosphere, in its simplest form, is

$$\mu_p = \sqrt{1 - \frac{\omega_p^2}{\omega^2}}, \quad (6.2)$$

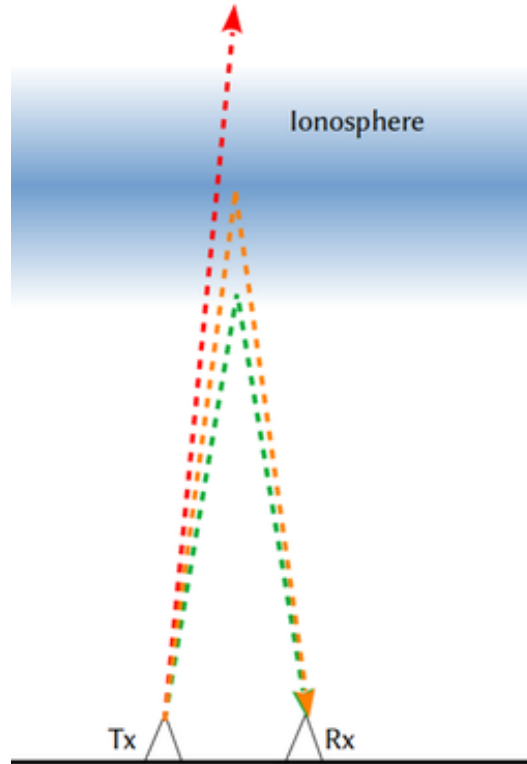


Figure 6.1: Illustration of the ionosonde radar system working principle. The different coloured rays represent radio signals of different frequencies: green is the lowest, orange is higher, and red is the highest. Tx and Rx represent the transmitter and receiver units of the system. Image collected from the [PITHIA-NRF](#)

where ω is the angular frequency of the transmitted radio wave. When ω approaches ω_p , reflection or strong refraction can occur[302], [303], [304]. Meaning, when the radio wave travels upward, it is reflected at the altitude where its frequency matches the local plasma frequency of the ionospheric electrons. Since the plasma frequency depends directly on the electron density in plasma, the point of reflection corresponds to a specific electron concentration. By measuring the time delay between transmission and reception of the radio signal, the virtual reflection height can be estimated. Using the known relation between plasma frequency and electron density, the electron density at that altitude can then be calculated.

To construct a vertical profile, the ionosonde performs regular frequency sweeps over a defined range, typically from about 0.5 MHz up to 20 MHz. This process is also called sounding, and on average, sounding extends up to 90 seconds. Each transmitted frequency is reflected at a different height, depending on the local electron density. Lower frequencies are reflected in regions of lower electron density, generally at lower altitudes. As the transmission frequency increases, the reflection point shifts upward toward regions of higher electron density. The highest frequency that can still be reflected corresponds to the peak electron density in a given ionospheric layer and is

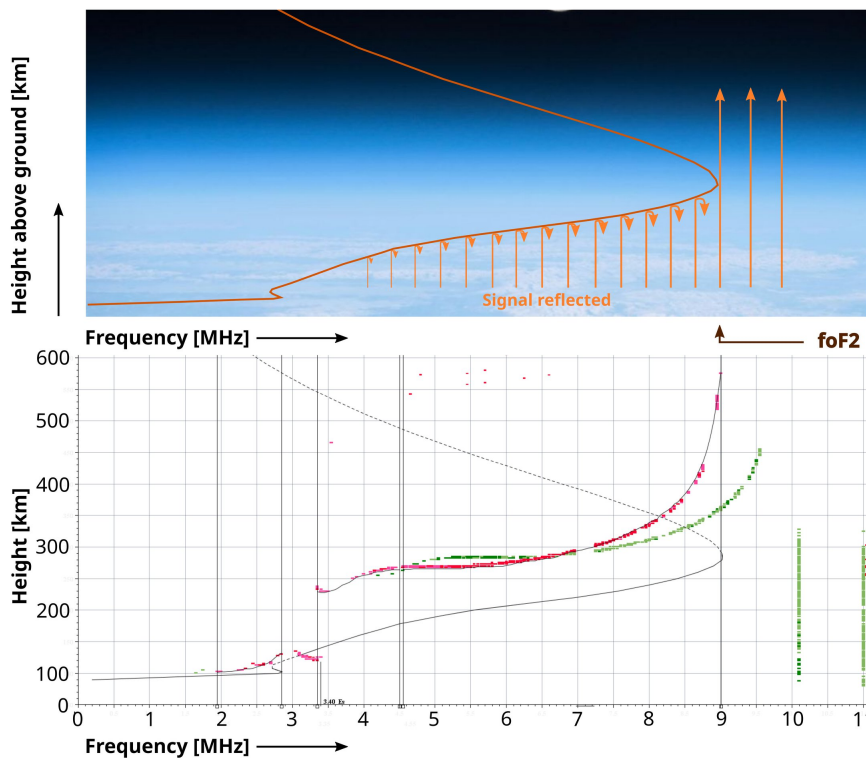
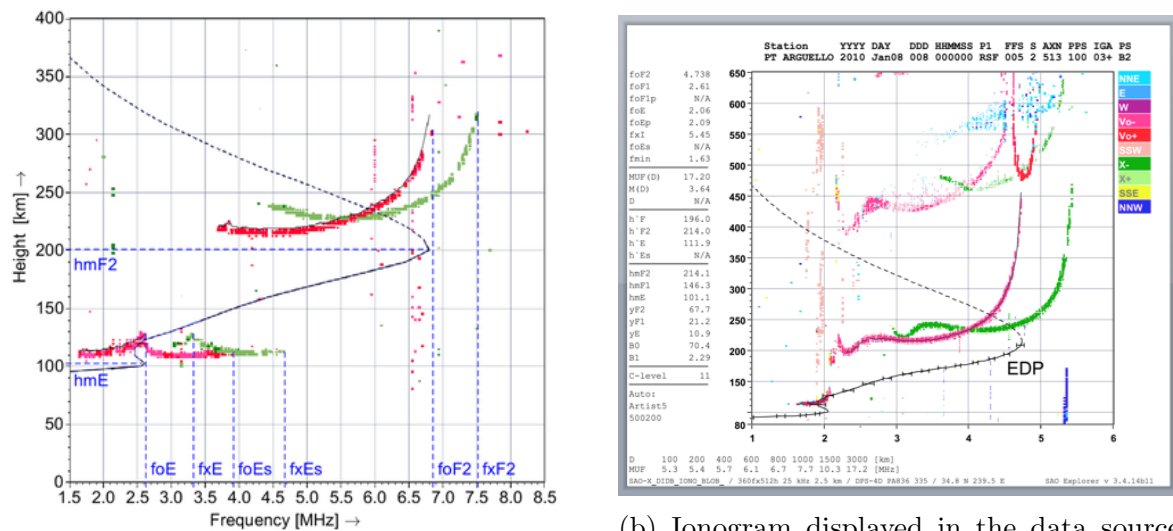


Figure 6.2: The illustration of the ionospheric sounding process (upper plot) and ionogram sample showing estimation of critical frequency (foF2) of the F2 layer (lower plot). The x-axis of the ionogram represents the frequency sweeping in MHz, and the y-axis the altitude in km. Image collected from [T-FORS](#).



(a) Example of a standard ionogram. Image collected from [PITHIA-NRF](#).

(b) Ionogram displayed in the data source (DIGIBASE) interface. image corrected from [GIRO](#).

Figure 6.3: (a) and (b) show two representations of ionogram data.

known as the critical frequency. If the transmitted frequency exceeds the maximum plasma frequency present in the ionosphere, the radio wave is no longer reflected and instead propagates through the ionosphere into space. Figure 6.1 illustrates the working principle of an ionosonde. Signals of different frequencies, from the lowest (green) to higher frequencies (orange), are reflected at different altitudes, while those with frequencies above the critical limit (red) propagate into space without reflection. Tx and Rx represent the transmitter and receiver units of the system. Through this frequency-sweeping method, the ionosonde generates an ionogram, which represents the apparent reflection height as a function of frequency and allows detailed analysis of ionospheric layer structure. Figure 6.2 illustrates the formation of an ionogram by the sounding at multiple frequencies. Top plot represents the ionosphere and how the radio wave at different frequencies is being reflected, and how the estimation of the critical frequency of the layer is estimated (orange arrows represent the radio signal sent by the ionosphere radars). The bottom plot is an example of an ionogram with the ordinary and extraordinary reflections plotted and an estimation of the frequency and virtual height of each layer of the ionosphere. The vertical black line shows where exactly the E and F layers are marked with respect to the illustrated ionosphere formation in the top plot. Figure 6.3 illustrates 2 examples of ionograms with a better picture of understanding. Figure 6.3a illustrates first example of an ionogram. The x-axis represents the frequency range in MHz, and the y-axis represents the height in km. The red and green structures, called traces, show the reflections from the ionosphere. Due to the birefractive nature of the ionosphere, two types of reflections are observed: the ordinary and extraordinary modes, represented by the red and green traces, respectively. The black curve is generated by a computer program and represents the plasma frequency as a function of the true altitude. This height is slightly lower than the one directly indicated by the ionogram traces because radio waves travel slightly slower in the ionosphere than in free space. Therefore, a correction is applied to estimate the actual height. The blue lines indicate important ionospheric parameters that are determined automatically. The parameter hmF2 shows the altitude where the electron density reaches its maximum value in the F2 layer, while hmE represents a local maximum in the E layer. The parameters foF2 and fxF2 correspond to the critical frequencies of the F2 layer for the ordinary and extraordinary wave modes. Similarly, foE, fxE, foEs, and fxEs represent the critical frequencies for the normal E layer and the sporadic E layer. At hmF2, the electron density reaches its peak and then decreases with increasing altitude. The ionosonde can measure the ionosphere only up to this maximum height. The dashed black curve above this peak is not directly measured but is estimated using a model.

Figure 6.3b shows the ionogram displayed in the data source interface for the station PT ARGUELLO for the sounding at 2010-01-08 00:00 UT, which carries a bit more

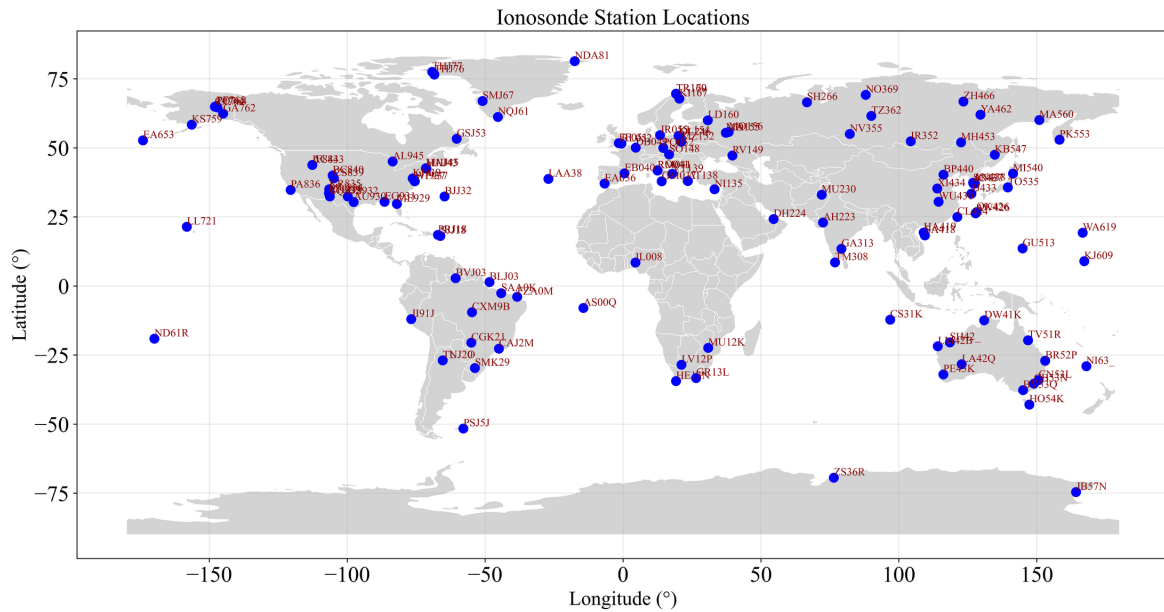


Figure 6.4: The location of all available diagnoses around the globe and their station ID.

information to interpret the ionogram. On the left side, several parameters derived from the ionogram are listed. At the top, information about the station and observation time is provided. On the right side, multiple colour bars can be seen, representing wave polarization, angle of arrival, and Doppler frequency (for example, NNE means North-North-East) and a table of Maximum Usable Frequencies calculated for a number of preset path distances (bottom) [305], [306] (refer [GIRO](#) for more information).

The ARTIST software automatically analyzes the ionogram and calculates the vertical electron density profile (EDP) in real time. The thin black curves represent the ordinary (O-mode) traces identified by the ARTIST algorithm. The thicker black curve, shown with uncertainty bars, corresponds to the calculated bottomside electron density profile. The same software also automatically extracts ionospheric parameters from the ionogram. At present, 49 scaled ionospheric parameters are defined. However, the most commonly used parameters include the layer critical frequencies, such as f_oF2 , f_oF1 , f_oE , and f_oEs , where the prefix “fo” denotes the ordinary-wave critical frequency of the corresponding ionospheric layer. The corresponding minimum virtual heights are denoted $h'F2$, $h'F$, $h'E$, and $h'Es$, where the prime indicates the apparent or virtual reflection height measured from the ionogram. Irregularity-related parameters include the average range-spread indices QF and QE for the F and E regions, respectively, and the frequency-spread indices FF and FE for the F and E regions, respectively. [305], [306], [307] (for more details refer [PITHIA-NRF](#)).

In total, there are 127 ionosondes around the globe (see figure 6.4). Since the ionosonde only sees the ionosphere right vertically above the station, collective data from all the ionosondes across the globe will be needed for understanding the global

ionospheric nature. But there are some limitations. Each station operates in its own way, with different time resolutions and observation schedules, so the data are not uniform across locations. Since ARTIST is not fully developed, with evidence of ionograms which have been incorrectly scaled, some records require manual scaling [308], [309].

Now that we know about the ionosondes, their operation, and also the basic information on how to understand ionograms, the next step is to understand the typical and atypical variations in the ionograms. The ionogram has its basic nature depending on the geographic location, where each latitude has its specific nature of ionospheric plasma properties. There has been no detailed research that states and studies elaborately all 127 stations and their properties. But there are some typical properties which depend on the diurnal nature of the ionosphere and solar influence. Beyond that, there are some unusual responses due to the coupling between the lithosphere or magnetosphere and the ionosphere. The main mechanism behind the ionisation in the ionospheric plasma is photoionisation, a process by which an electron is removed from the atom or molecule. During the absence of the sun, recombination happens where the free electron is captured by a positive ion. These two processes determine the extension of ionisation in the ionosphere, which in turn results in the different ionosphere layer formation in nighttime and daytime. Accordingly, from lower to higher plasma density, we distinguish ionosphere layers D, E, F1 and F2. During daytime, E and D, along with F1 and F2, will be visible, whereas during nighttime, due to very low ionisation and electron density, the E and D regions disappear and the F region persists [310], [311], [312]. This diurnal effect will be visible in ionograms. The daytime and nighttime ionograms are evidently distinguishable. Figure 6.5 illustrates typical daytime and nighttime ionograms. The presence of different ionospheric layers, the E, F1, and F2 visible in the daytime, whereas the nighttime has only F layers present. The foF2 parameters are also marked on the plot, where, during the day, it is higher, representing higher ionisation. On the other hand, seasonal and solar cycle changes can also be visible in the ionogram. The local window and summer result in variation in the level of the ionising radiation availability. Furthermore, the 11-year solar cycle, with the variation of the number of sunspots, active regions, and coronal heating, will result in the variation of ionisation. The effective results can be seen in the foF2 parameter. Figure 6.6 illustrates a comparison of daytime and nighttime ionograms during the higher and lower solar activity. From the ionograms, it's evident that the values of critical frequency are higher during higher solar activity compared to the low ones at daytime and nighttime.

Some of the major bottomside ionosphere irregular structures visible in the ionograms are the sporadic E layer (Es), spread-F, and travelling ionospheric disturbances. The sporadic E layer is a dense layer of charged particles in a high range around 90-150

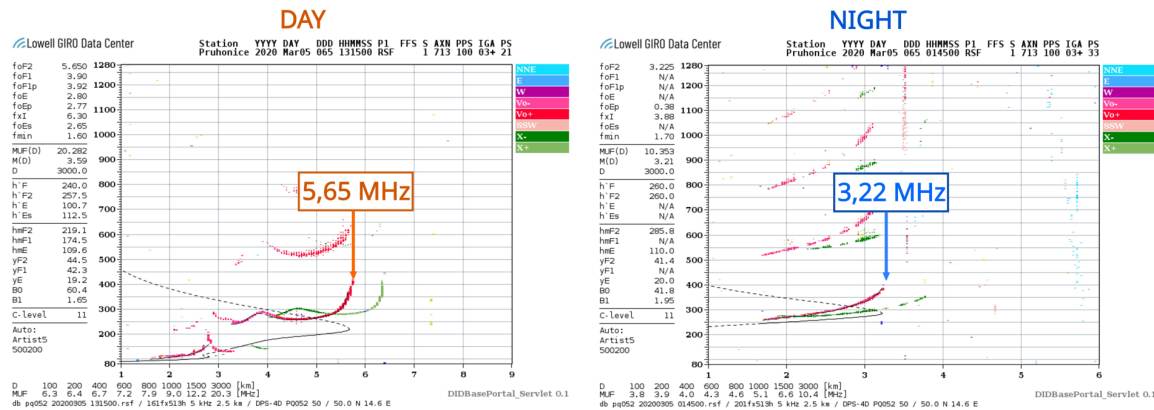


Figure 6.5: An example of typical daytime (left) and nighttime (right) ionograms. The presence of different ionospheric layers, the E, F1, and F2 visible in the daytime, whereas the nighttime has only F layers present. The foF2 parameters are also marked on the plot, where during the day, it is higher, representing higher ionisation. Image collected from T-FORS.

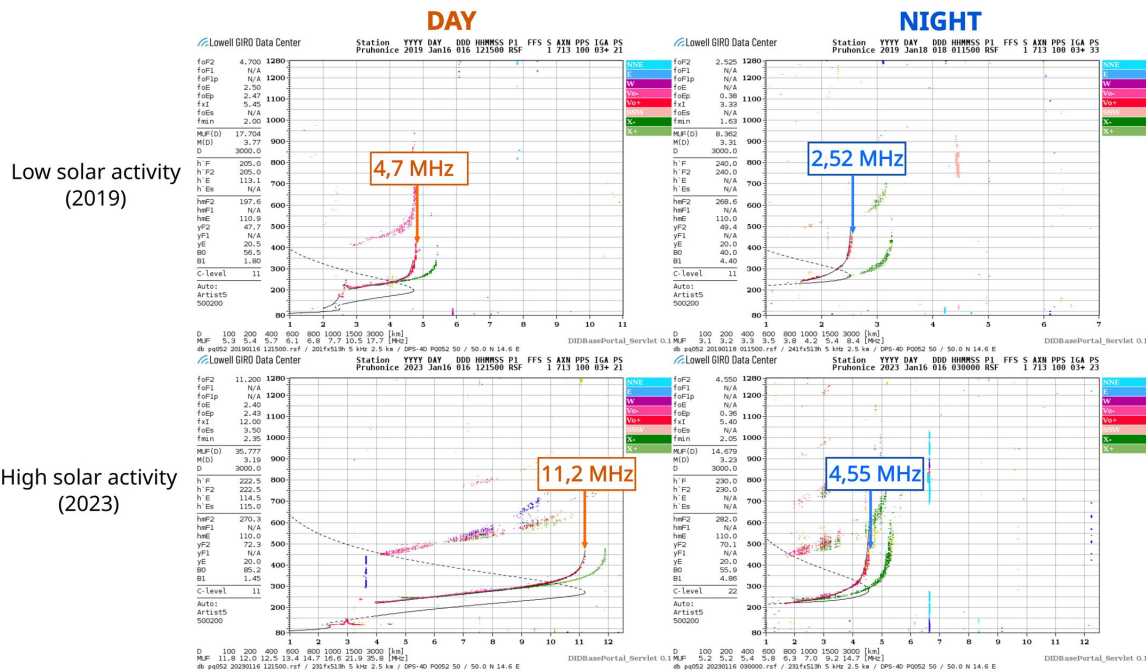


Figure 6.6: Ionograms comparing the recording during higher (bottom) and lower (top) solar activity around local noon (left) and midnight (right). Image collected from T-FORS.

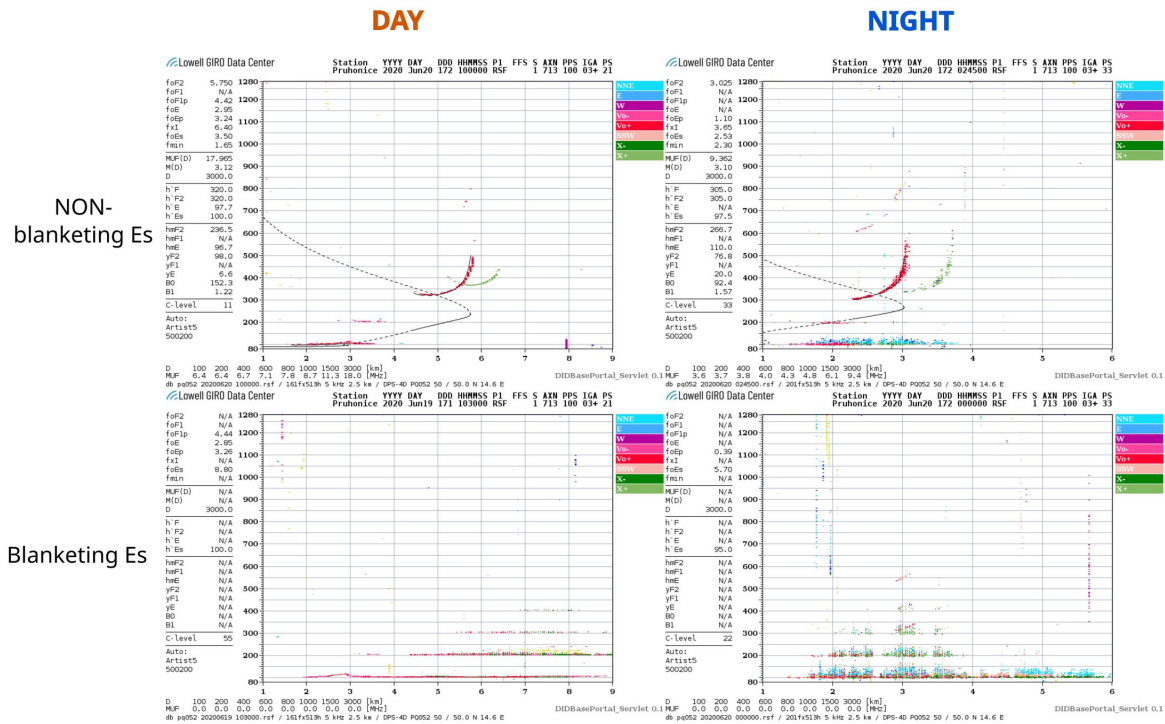


Figure 6.7: An example illustration of ionograms with a non-blanketing (top) and blanketing (bottom) Es layer during daytime (left) and nighttime (right). Image collected from T-FORS.

km[313], [314], [315]. Wind shear is considered the most common cause of this formation [316], [317]. There are multiple sources for the wind shear, namely atmospheric gravity waves, tides, and planetary waves [318], [319], [320], [321]. In mid-latitudes, Es layers show a strong diurnal variation [315], [322]. In some cases the Es layer occurs in such a way that it obscures the overlaying layers; such Es layers are called 'blanketing'. Figure 6.7 illustrates example ionograms with a non-blanketing (top) and blanketing (bottom) Es layer during daytime (left) and nighttime (right). During the daytime, Es layers are less dense than at night. At the same time, the presence of blanketing Es has obscured the F layers. If present, the critical frequency (foEs) and minimum virtual height (h'Es) of this layer will be automatically scaled and calibrated by the ARTIST software and will be available. Another important visible irregularity is Spread F, where typical clean narrow traces of layers become more spread and diffused. This indicates the presence of plasma instability in that region, which eventually results in the multi-directional scattering of radio waves [323]. In equatorial, low-latitude region, there are caused by Rayleigh-Taylor (RT) instability. This is a gravitational instability that usually occurs after sunset [324], [325]. The pre-reversal enhancement (PRE) (temporary surge in the eastward electric current and vertical plasma drift) results in the lifting of the F-region to a higher altitude, resulting in a density gradient [326], [327], [328]. This unstable system causes the formation of a plasma bubble, a pocket of low-density plasma. Thus, in most of the ionograms in the equatorial region, the formation of

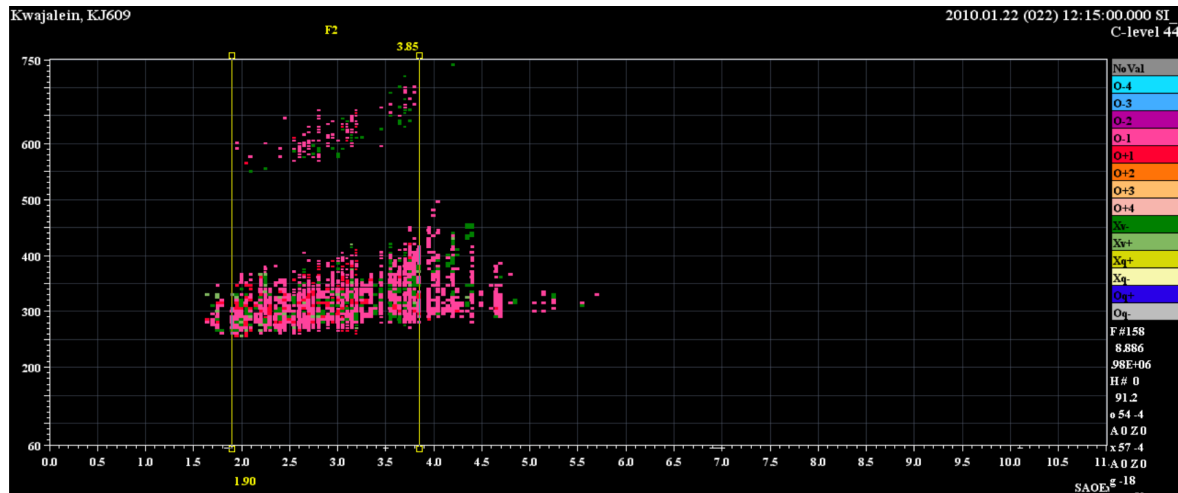


Figure 6.8: An example illustration of ionograms with strong range and frequency spread F.

plasma bubbles and spread F is very common at midnight. In mid-latitude regions, this is caused by the electrodynamic instability due to the interaction between the electric field, neutral window, and gravity, known as Perkins instability [329], [330]. This instability is also triggered by external factors, most importantly, atmospheric gravity waves [329], [331]. There are two types of spread F: range spread F, indicating the echoes are coming from different heights, and frequency spread F, where a trace across a range of different frequencies at a fixed height can be seen [332]. The parameters of frequency spread (FF and FE) and average range spread (QF, QE) in the F layer and E layer are calibrated from the ionogram. Figure 6.8 shows an example of ionograms with strong range and frequency spread F.

Most importantly, Traveling Ionospheric Disturbance (TIDs). They are the manifestation of acoustic gravity waves in the ionosphere, which are plasma density fluctuations that move through the ionosphere as waves at a wide range of speeds and frequencies. These fluctuations result in the energy and momentum between different parts of the upper atmosphere [333], [334]. Usually, there are three types of these things based on how long they last and how fast they move. LSTIDs, or large-scale TIDs, have horizontal propagation speeds of 300 m/s to 1000 m/s, horizontal wavelengths of more than 1000 km (1000–3000 km), and periods of 30 minutes to 3 hours. Medium-scale TIDs (MSTIDs) move horizontally at speeds of 100 m/s to 300 m/s, have horizontal wavelengths of several hundred km, and last from 15 to 60 minutes. People have also seen small-scale TIDs with wavelengths of less than 300 km. MSTIDs are the ones mostly linked to ionospheric coupling with the lower atmosphere [333], [334], [335]. These disturbances appear in a variety of morphological forms, including split or “Y-forking” traces [291], “W”- and “Z”-shaped ionogram structures associated with seismic and infrasonic wave activity [292], [293], cusp-like distortions and multilayer

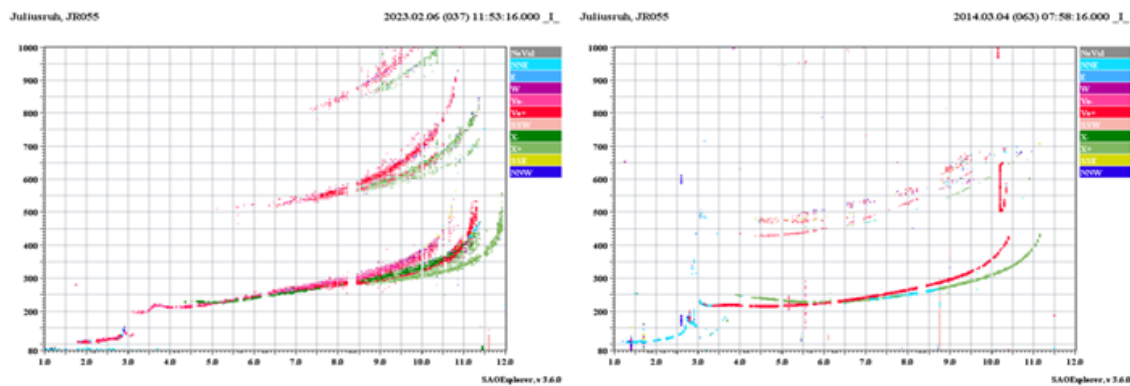
stratifications [294], as well as double-peaking and small-scale irregularity features observed in disturbed ionospheric conditions [295], [296]. Figure 6.9 illustrates different types of TID signature responses in the ionogram.

6.2 Seismic-Induced Irregularities in the Ionogram

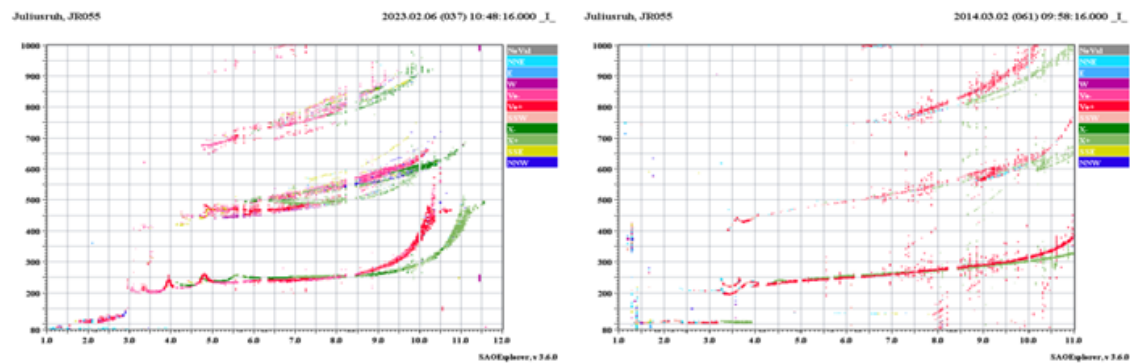
In the previous section, various categories of ionogram irregularities were examined. Nonetheless, a seismic origin can only be confirmed after excluding other dominant factors, such as geomagnetic storms, substorms, and climatological or local geographic effects specific to the station. Numerous studies have carried out detailed analyses of particular ionospheric irregularities that repeatedly appear in ionograms across different geographic regions and can be associated with seismic activity.

One of the key diagnostic parameters is the abnormal change in the critical frequency foF2 (both increases and decreases). Before earthquakes, foF2 typically departs from its quiet-day monthly median by more than the $\pm 25\%$ confidence range within roughly 5 days of the event [5]. These foF2 disturbances are important because the seismogenic electric field can be intensified through enhanced $E \times B$ drift, thereby affecting the Equatorial Ionization Anomaly (EIA) fountain mechanism at both low and mid-latitudes [336], [337]. A comprehensive statistical analysis of 184 earthquakes with magnitudes $M \geq 6.0$ in Taiwan revealed that pre-seismic foF2 anomalies at low-latitude stations were predominantly negative, with lead times of 1–5 days [5]. Ahmed et al. reported both positive and negative foF2 deviations at low-latitude ionosonde stations in Pakistan prior to earthquakes with $M > 5.0$. Negative deviations exceeding the lower confidence limit occurred before an Mw 5.1 event, and positive anomalies were detected within 10 days preceding an Mw 7.5 earthquake. Similarly, Dabas et al. documented unusual foF2 perturbations 1–25 days before and 2–3 days after the main shock for 11 earthquakes across the Indian subcontinent. Additionally, Ondoh reported increases in foEs a few days prior to two major Japanese earthquakes under geomagnetically and solar quiet conditions. For mid-latitude regions, Karaboga et al. analyzed ionosonde observations from five Japanese stations (1980–2008) and identified statistically significant foF2 anomalies using interquartile range techniques, with the largest deviations occurring 1–3 days before earthquakes of $Mw \geq 6.5$. Comparable behaviors were also found by Perrone et al. at Italian mid-latitude stations for earthquakes with $Mw \geq 5.5$.

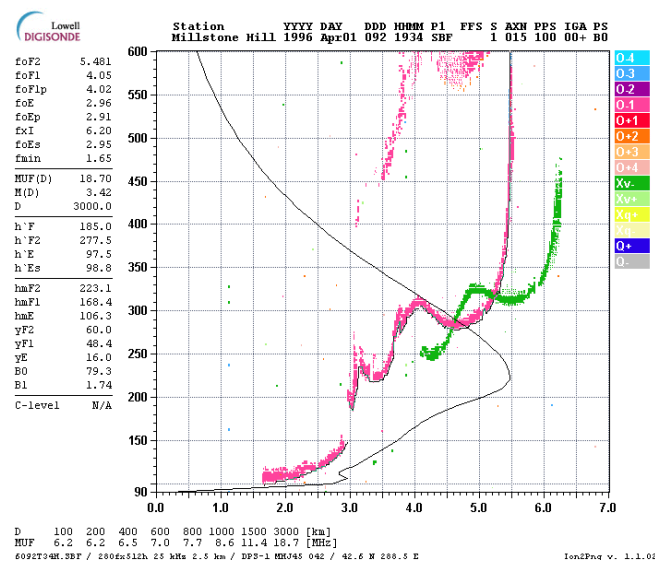
Another important class of irregularities is Traveling Ionospheric Disturbances (TIDs). In a study on Rayleigh wave signatures in ionograms induced by strong earthquakes, Maruyama et al. analyzed 43 earthquakes of magnitude ≥ 8.0 using ionograms from



(a) Image collected from T-FORS



(b) Image collected from T-FORS



(c) Image Collected from HAARP

Figure 6.9: (a) Y/U-forked F traces in the near of foF2 (b) Multi-cusp signatures in the F trace, (c) W-shaped F traces.

five Japanese stations (1957–2011). They identified distortions characterized by multiple cusp signatures (MCSs), with detections limited to epicentral distances less than ~ 6000 km. A study conducted in 2020 on eleven earthquakes (magnitude < 4) near New Delhi reported distortions in ionogram traces in the form of Y-shaped forking, observed primarily on the precursor day and after the earthquake. Similar Y-forked traces were also detected at Ahmedabad (23°N , 72°E , 15°N dip) and Trivandrum (8.5°N , 76.9°E , 0.5°N dip). These features are interpreted as signatures of TIDs [291]. Likewise, Liu and Sun observed seismo-TID signatures at low-latitude East Asian stations during the 2011 Tohoku earthquake, with a delay of approximately 4 minutes after the event.

At low latitudes, day-to-day variability in sporadic E (Es) is strongly influenced by equatorial electrojet dynamics, which complicates the identification of Es anomalies associated with seismic activity. Nevertheless, anomalous foEs enhancements exceeding 8 MHz were detected two days before the M 7.2 Hyogo-ken Nanbu earthquake (January 17, 1995) at mid-latitude Japanese ionosonde stations, including Shigaraki (120 km from the epicenter) and Kokubunji (500 km from the epicenter). These stations, all within 500 km of the epicenter, are located in regions where intense radon emission was reported, with near-surface radon levels reaching 100 times the background, and where convective “seismic cloud” activity was observed at altitudes of 680–2000 m. Ondoh (2004) proposed a mechanism connecting these phenomena via a radon-induced electrostatic process: radon ions released from faults are transported upward by convection, leading to charged ice crystals. Subsequent lightning discharges generate transient electric fields in the lower ionosphere that can surpass breakdown thresholds, producing electron heating and enhanced ionization of E-region neutrals (90–120 km). This leads to the formation of dense Es layers, which manifest as localized foEs anomalies over the epicentral area [85]. Additional mid-latitude investigations show that foEs may increase by about 50–110% roughly 2–4 days prior to earthquakes [342].

Another atypical irregularity is the deviation in Spread-F occurrence from its normal background behavior. Under typical conditions, Spread-F events are less frequent at mid-latitudes than at low latitudes [343]. Liperovskaya documented a reduction in Spread-F occurrence probability one to two weeks before earthquakes at mid-latitude Japanese stations. In contrast, Gurram et al. reported at a low-latitude equatorial station that, on an earthquake day, equatorial Spread-F irregularities exhibited markedly smaller spatial scales, indicating that earthquake-related electric fields may have modified their structuring and temporal evolution. Furthermore, mid-latitude ionosonde analyses suggest that the Spread-F index can rise by about 16–83% approximately 3–5 days preceding earthquakes [342].

Seismo-ionospheric anomalies display clear latitude-dependent behaviors that are controlled by background electrodynamics. At low latitudes, these anomalies are chiefly

linked to alterations of the Equatorial Ionization Anomaly (EIA) triggered by seismogenic electric fields. They primarily appear as significant deviations in foF2 (both enhancements and depletions), changes in the intensity of the $E \times B$ plasma drift, and the presence of traveling ionospheric disturbances (TIDs), including characteristic Y-shaped traces and multiple cusp patterns. Nonetheless, reliably detecting sporadic E (Es) anomalies at low latitudes is difficult, as they are strongly modulated by the highly variable equatorial electrojet.

By comparison, mid-latitude regions exhibit clearer and more statistically robust signatures in both foF2 and foEs. These signatures include unusual increases in the sporadic E critical frequency (foEs), disturbances in the occurrence of Spread-F, and a more distinct presence of traveling ionospheric disturbances (TIDs). The comparatively steady ionospheric background at mid-latitudes makes it easier to identify perturbations triggered by seismic activity. While many such signatures occur in both latitude ranges, how clearly they can be distinguished is highly dependent on the prevailing ionospheric state, which may either mask or enhance the detected anomalies.

6.3 Data Sources and Preprocessing

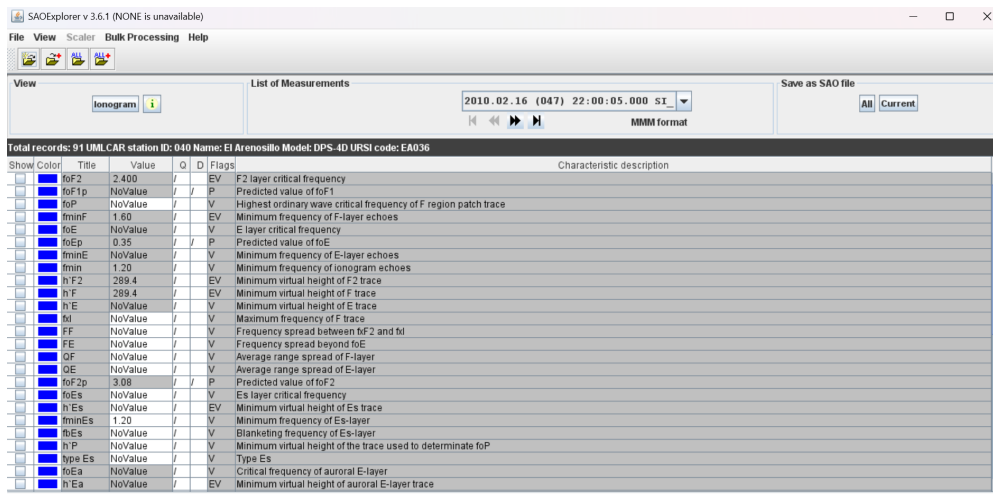
The ionogram data analysed in this study were obtained from the Digital Ionogram Database (DIDBase) and accessed through the SAO Explorer software (Version 3.6.3) with a precision of 1 – 50 kHz for frequencies and 1 – 10 km for heights, depending on the sounding parameters selected by each station operator. DIDBase is an online archive that provides autoscaled ionosonde measurements collected from a global network of ground-based Digisonde stations. The database supplies ionograms together with derived ionospheric parameters in Standard Archiving Output (SAO) format, facilitating the archiving and exchange of reduced data of individual ionograms, enabling the retrieval of soundings corresponding to specific times and geographic locations (refer [PITHIA-NRF](#)) [306], [307]. The SAO format was originally developed to store Digisonde ionograms scaled using the autoscaling software ARTIST. The scaled ionospheric parameters can be obtained automatically using this software. They can also be entered manually if needed. Most of the reported values represent either frequency (in MHz) or height (in km). The values are written in the format F8.3 (DDDD.DDD), which gives a precision of 1 kHz for frequencies and 1 meter for heights. In general, the accuracy of these stored values corresponds to one ionogram pixel, meaning one frequency step or one height increment. At present, 49 scaled ionospheric parameters are defined. For any parameter that is not available for a given ionogram, a default “no reading” value must be used [307]. DIDBase is not an open-access database and requires authorized credentials for access. Figure 6.10a illustrates an example of the database interface displaying the available autoscaled parameters. The example corresponds to the sta-

tion "El Arenosillo" (station ID EA036) for the date and time 2010-02-16 22:00:05 UT. Since this station operates with a sounding interval of 15 minutes, ionogram data are available at 15-minute intervals for the selected duration. Figure 6.10b shows the ionogram recorded at the same station and time. In this interval, manual scaling can be done. For that, the bound (which is visible as yellow lines making the range of the F layer) can be moved to the correct scaling and further to calibrate the parameters. As described in the previous section, a single ionogram represents a sounding with an average duration of approximately 90 seconds, covering a range of transmitted frequencies expressed in MHz. From DIDBase, the ionograms and their associated parameters can be downloaded in SAO format, from which a processing code was developed to extract the required ionospheric feature parameters for further analysis.

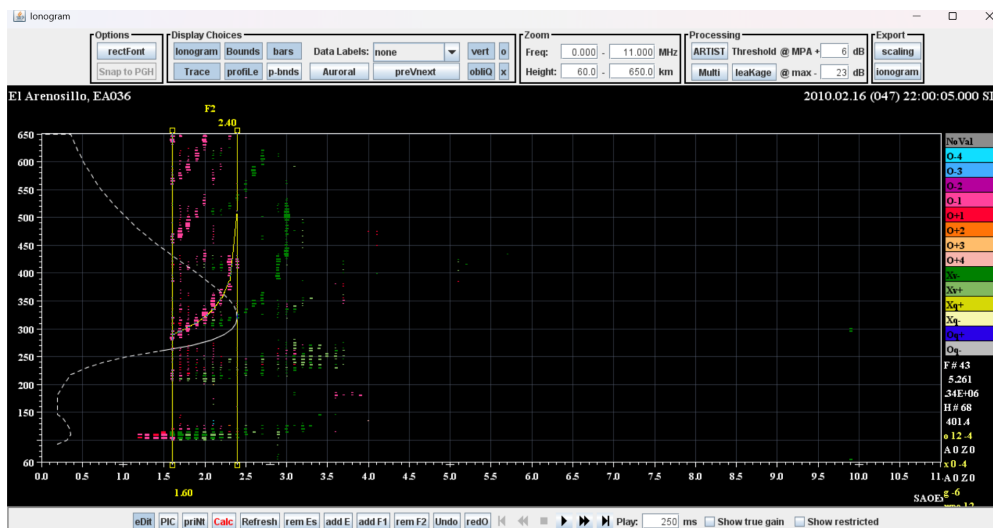
Since this study represents an extension of the earlier model-based analysis, only the data corresponding to the blind set year 2010 were considered. We first examined the availability of operational Digisonde stations during 2010. To focus the analysis on equatorial and mid-latitude regions, a latitude restriction between -30° and 40° was applied. This choice helped avoid complications related to the South Atlantic Anomaly and ensured coverage of major seismic regions. Out of 127 ionosonde stations worldwide, 67 were located within this latitude range. Among them, only 23 stations were operational and provided usable data during 2010. The approach adopted here was to use the models trained under the blind test year (2010) and extract the anomalies identified within their validation segments. These anomalies are interpreted as representations of topside ionospheric electric field disturbances detected by the deep learning framework.

Spatial Coincidence Search Between Satellite Passes and Ionosonde Soundings

The first step of the procedure was to examine the spatial coincidence between anomalous satellite sequences (each corresponding to two consecutive daytime half-orbits) and the ionosonde stations. To define spatial range, the zenith angle of the Digisonde and the orbital altitude of the DEMETER satellite were considered. Based on these parameters, a spatial range around each station was calculated, within which a satellite pass could be regarded as being in the effective vicinity of the ionosonde. Figure 6.11 presents a schematic illustration of the selected spatial range used. In the figure, the y-axis represents altitude in kilometres, while the x-axis denotes horizontal distance on the Earth's surface. During 2010, the DEMETER satellite altitude was approximately 660 km. Using this value and the zenith angle, the corresponding ground-projected base radius was calculated to be approximately 553.8 km, which is close to 5° in geographic



(a)



(b)

Figure 6.10: (a) shows the SAO Explorer interface displaying the autoscaled ionospheric parameters for the selected ionogram recorded at El Arenosillo (station ID 040) on 16 February 2010 at 22:00 UT. The table lists the extracted parameters derived from the ionogram. These values are automatically generated by the ARTIST scaling software and provide a quantitative representation of the ionospheric conditions at the time of sounding. (b) Ionogram recorded at El Arenosillo (EA036) on 16 February 2010 at 22:00 UT (Local time = UT + 1 hr). The horizontal axis represents frequency (MHz), and the vertical axis represents virtual height (km). Overall, the ionogram indicates relatively stable nighttime ionospheric conditions.

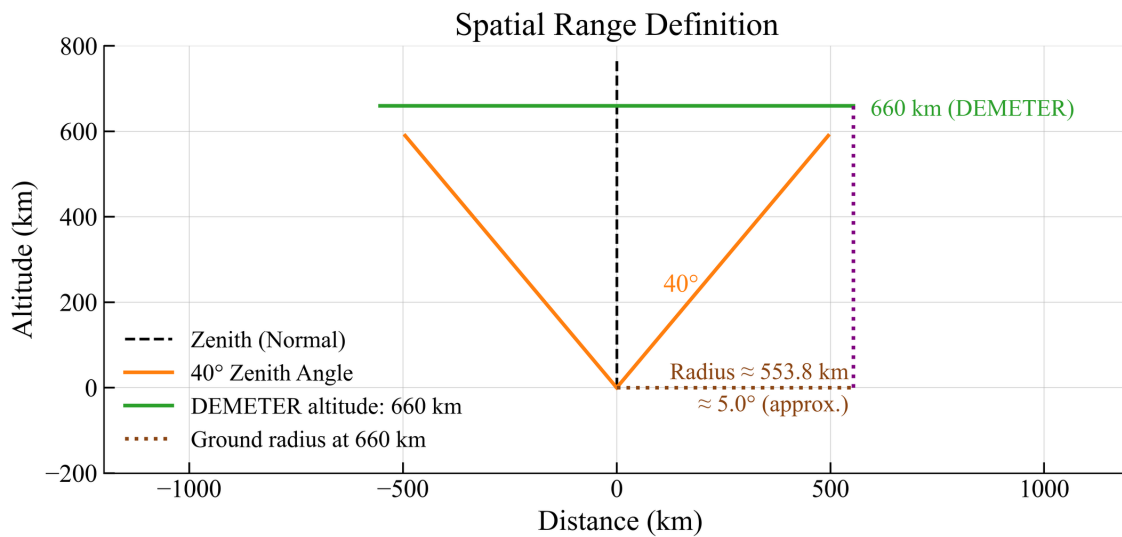


Figure 6.11: Geometrical definition of the spatial range considered around the Digisonde station. The satellite altitude is approximately 660 km (green line). A 40° zenith angle defines the lateral extent of the observation cone (orange lines), corresponding to a ground-projected radius of approximately 554 km (around 5° in latitude/longitude). The dashed vertical line represents the zenith (normal) direction. This geometry defines the spatial window used for satellite–station coincidence analysis.

terms. A fixed kilometre-based unit was adopted to ensure consistency across different latitudes and to account for spherical geometry effects between equatorial and higher latitude regions. Figure 6.12 shows the locations of the selected Digisonde stations operating in 2010, together with the spatial ranges considered for the satellite-ground coincidence search.

On recalling the results from the blind data analysis from all the models trained, we had 4 windows of validation data, which are non-overlapping with a span of 3 months covering the whole of 2010. Table 6.1 provides the statistics of anomaly sequences detected in each window by the 10 models trained under two different modes. The number of anomalies identified by each model differs, depending on the model’s ability to learn from the training data. Furthermore, when comparing the detected sequences across all windows, there are common sequences that multiple models consistently label as anomalies. Finally, in total there were 106 unique anomalous sequences across all 4 windows studies. From this point, we carried out this analysis by checking if these

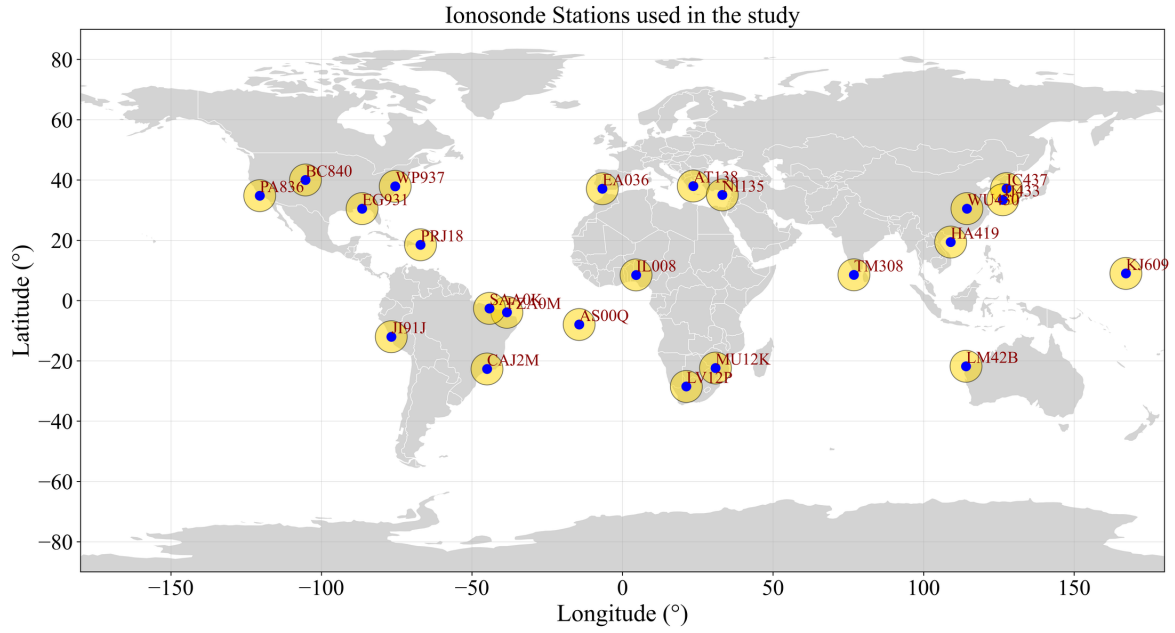


Figure 6.12: The geographic locations of the stations available for this study (in the year 2010 and under the specified latitudinal restriction), together with their spatial range used for satellite coincidence searches (Yellow circle).

Table 6.1: Number of detected anomalous sequences in the validation set (Window 16-19) for each model in the blind year analysis.

Model	W16	W17	W18	W19
A	15	33	9	13
B	21	32	6	12
C	13	44	8	17
D	15	41	9	15
E	30	46	10	22
In-A	21	43	6	13
In-B	20	33	10	12
In-C	26	44	7	13
In-D	18	47	9	12
In-E	20	50	11	12

anomalous orbital sequences are passing or crossing the desired spatial area around the selected list of ionosonde stations. We also collected the record of the entry and exit times of the orbitals over the spatial range of all the stations. Accordingly, all 23 stations that were operated in the year 2010, which are located in the selected latitudinal geographical region, were mapped to the list of spatially coincident ionosondes. The figure 6.13 illustrates the statistics of the number of anomaly sequences that have passed over the vicinity spatial range of each station operated in 2010. The x-axis denotes the station name, and the y-axis represents the number of times the anomalous orbital sequences passed over the respective stations. All 106 anomalous orbital passes intersected the spatial coverage of all 23 Digisonde stations, yielding a total of 163 spatial coincidence events. In a number of cases, individual orbital passes overlapped with the spatial ranges of more than one station.

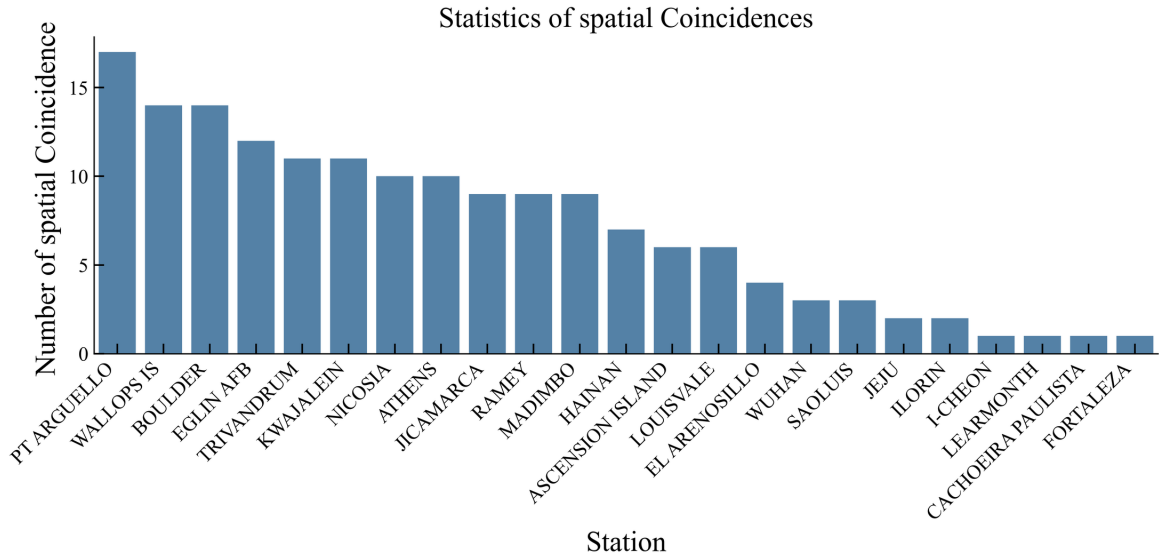


Figure 6.13: Distribution of spatially coincident stations across the set of anomalies detected by all models trained on the blind dataset.

Temporal Coincidence Search Between Satellite Passes and Ionosonde Soundings

From there, the next step is to find the temporal coincidence of the anomalous orbits and ionosonde soundings. For that, we defined a temporal window with respect to the total sounding time of ionosondes (90 seconds). The idea is to minimise the temporal ambiguity and ensure that the compared measurements represent approximately the same ionospheric state. By applying both the spatial and temporal constraints, we ensure that identified satellite-ground connections are physically meaningful. Each Digisonde sounding represents an ionogram recorded over a finite time interval. Let

- t_s denote the starting time of the ionosonde sounding,
- $t_s + 90$ s denote the end of the sounding interval.

Thus, the Digisonde sounding period is defined as:

$$[t_s, t_s + 90 \text{ s}].$$

The satellite presence within the spatial region of interest is described by:

- t_e - time at which the satellite enters the defined spatial range,
- t_x - time at which the satellite exits the spatial range.

Hence, the satellite observation interval is:

$$[t_e, t_x].$$

Temporal coincidence is defined based on the overlap between these two time intervals. The simultaneous observation duration T_o is computed as

$$T_o = \max(0, t_x - \max(t_s, t_e)).$$

This formulation ensures that:

- The overlap begins at the later of the two starting times (t_s or t_e).
- The overlap extends up to the satellite exit time t_x covering the spatial range.
- If no temporal intersection exists, the overlap duration is zero.

The $\max(0, \cdot)$ term prevents negative overlap values in cases where the intervals do not intersect. The constraint applied here is,

$$t_e \leq t_s + 90 \text{ s}.$$

This ensures that the satellite enters the spatial region during or immediately after the ionosonde sounding starts but definitely before the end of the sounding. Depending on the relative positions of the two intervals, several cases arise:

1. The satellite pass begins before the sounding and exits during the sounding.
2. The satellite enters during the sounding and exits afterward.
3. The satellite completely spans the sounding interval.

4. The satellite interval partially overlaps at the end of the sounding.
5. No overlap exists between the two intervals.

In all cases, the same mathematical formulation for T_o is applied. A positive value of T_o indicates a valid temporal coincidence, whereas $T_o = 0$ implies no simultaneous observation. Fundamentally, the overlap duration T_o represents the time interval during which both the satellite and the ionosonde are observing the ionosphere within the same spatial region. Under the defined temporal coincidence criterion, five unique coincidence events were identified. In these cases, anomalous orbital passes detected by the model passed over the defined spatial coverage areas of three different Digisonde stations at the time of sounding. The resulting overlap durations ranged from approximately 0.6 seconds to a maximum of about 120 seconds. Table 6.2 provides the list of ionosonde soundings that are spatially and temporally coincident with the anomalous orbital data. Regarding the topside ionosphere, since we started with the anoma-

Table 6.2: The list satellite-ionosonde temporal and spatial coincidences and corresponding overlap duration (T_o in seconds).

Station Name	Sounding Timestamp (UTC)	T_o (S)
EL ARENOSILLO	2010-03-27 10:30:05	103.918
JICAMARCA	2010-11-11 14:30:00	29.856
KWAJALEIN	2010-03-02 22:35:00	60.636
KWAJALEIN	2010-05-03 22:40:00	120.692
KWAJALEIN	2010-10-22 22:22:00	0.613

lous orbitals data detected by the model, we are sure about the abnormal behavior visibility. Now, to understand if we have bottomside anomalies or irregularities, we need to evaluate the ionograms. In the initial phase of the study, we assessed the sensitivity of the model anomaly detection to solar activity. However, this does not imply that the model never identifies any anomalies induced by the solar storms. In this instance, examining both the upper and lower parts of the ionosphere requires the removal of any disturbed day events, as ionograms are highly sensitive to these effects. We assessed the two principal geomagnetic indices during the period of ionogram soundings: the Disturbed Storm Time index (Dst), and the auroral electrojet index (AE). The geomagnetic AE indices are obtained from the World Data Center (WDC) for Geomagnetism, Kyoto, presented in IAGA-2002 format with a one-hour data interval[346]. The Dst index data were obtained from the Geomagnetic Observatory Niemegk, GFZ German Research Centre for Geosciences, Potsdam, Germany. All geomagnetic data were utilised to understand the background geomagnetic conditions throughout the analysis period. Figure 6.14 illustrates the variation of the hourly Dst index, starting a window of 3 days before the target day of sounding to one day after

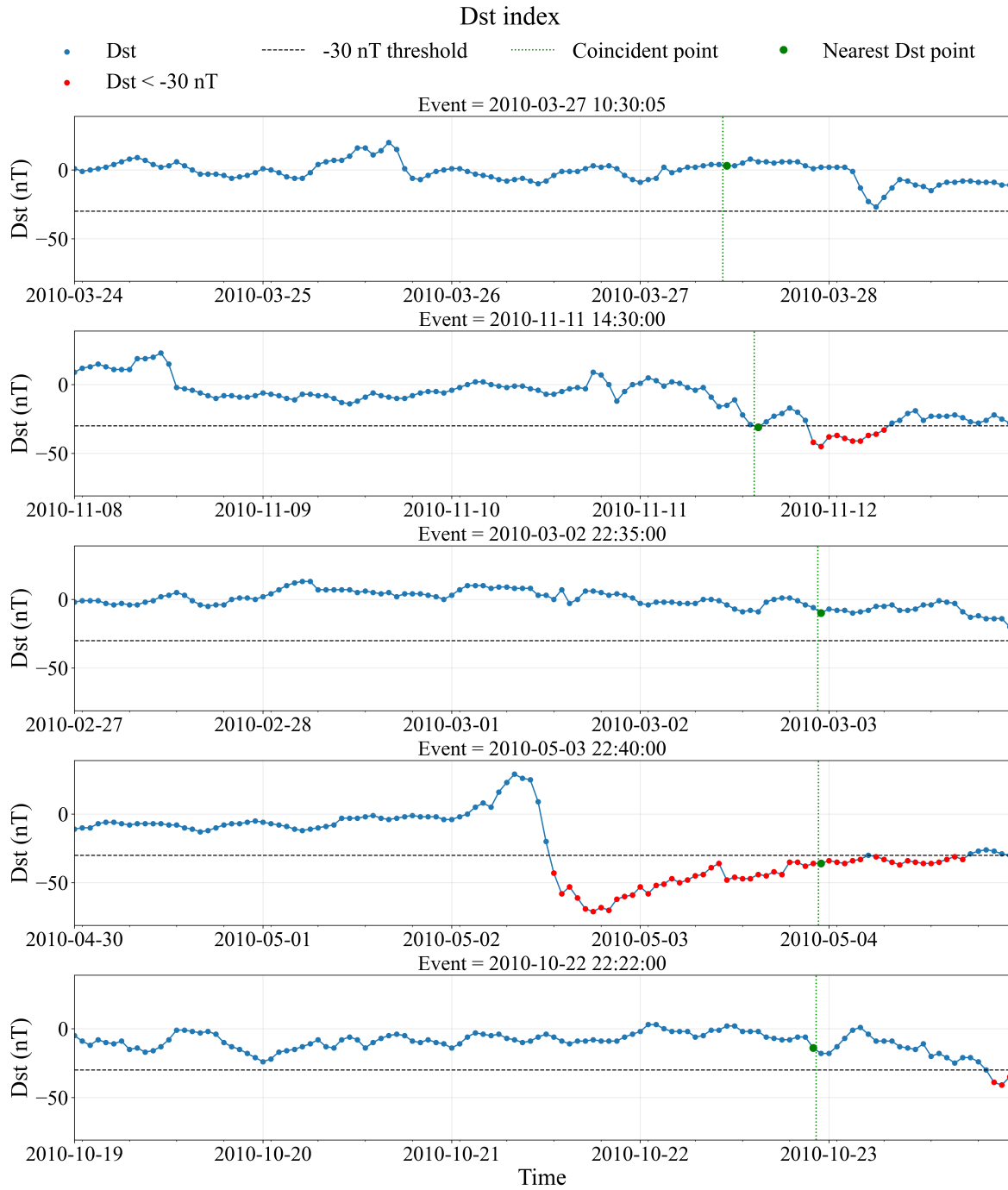


Figure 6.14: Dst index for a time window of 3 days before and 1 day after the day of sounding (for all 5 sounding data). The black dashed horizontal lines indicate commonly used disturbance thresholds ($\text{Dst} = -30 \text{ nT}$). The point of coincidence is marked by a vertical green dotted line and the nearest Dst point is marked by green dotted marker point.

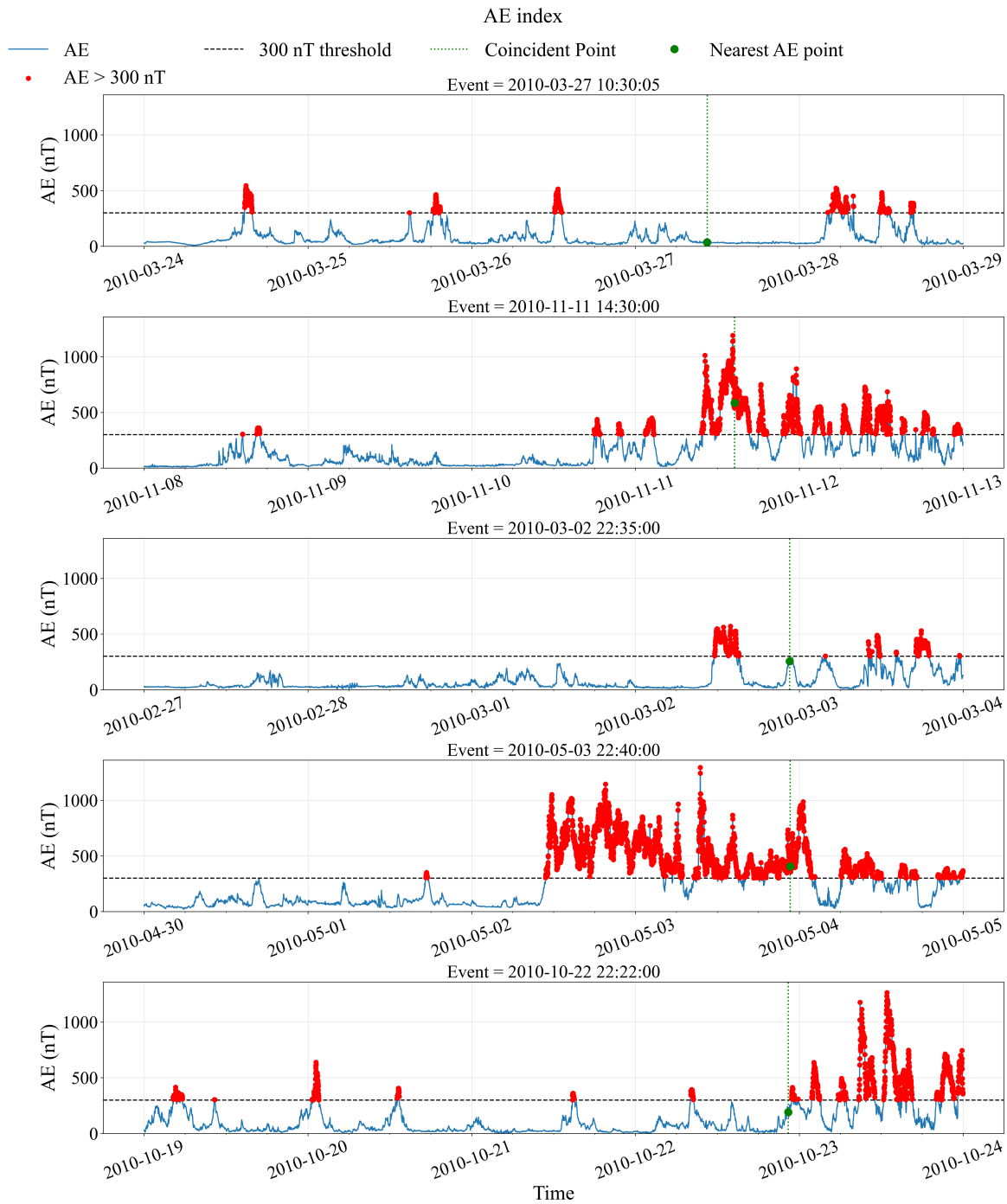


Figure 6.15: AE index for a time window of 3 days before and 1 day after the day of sounding (for all 5 soundings data). The black dashed horizontal lines indicate commonly used disturbance thresholds ($AE = 300$ nT). The point of coincidence is marked by a vertical green dotted line and the nearest AE point is marked by green dotted marker point.

the date of soundings for the five finalised events. The time period is to account for the time-delayed effect of the storm. The Y-axis represents the Dst index in its corresponding units, and the X-axis represents the datetime. The dotted line denotes the threshold employed (-30 nT) in the study to differentiate between quiet and disturbed days [347]. Figure 6.15 illustrates the variation of the AE index, starting a window of 3 days before the target day of sounding to one day after the date of soundings for the five finalised events. The Y-axis represents the AE index in its corresponding units, and the X-axis represents the datetime. The dotted line denotes the threshold employed (300 nT) in the study to differentiate between quiet and disturbed days [348]. Based on the detailed analysis of the Dst index, it is evident that a moderate geomagnetic storm occurred on the coincidence day of 2010-05-03; therefore, this day must be excluded from further evaluation. On 2010-11-11, following the coincidence, a week-long storm occurred, which can be disregarded since we are concerned only with the point of coincidence, and the effect of storms in the recovery phase is not applicable here. When analysing the AE index plot, we can see that on the days 2010-11-11 and 2010-05-03, there was a very intense intensification of the AE index right before and during the coincidence. Such sharp intensifications signal the onset of CIR/HSS-driven storms or associated HILDCAA events, where sustained auroral electrojet activity, often represented by peaks well above quiet levels, pumps energy from high-speed solar wind streams into the magnetosphere-ionosphere system through continuous magnetic reconnection and Alfvénic fluctuations. This surge enhances Joule heating and particle precipitation in the auroral oval, promptly generating gravity waves and Prompt Penetration Electric Fields (PPEFs) that propagate equatorward, immediately disturbing high-latitude ionograms with spread-F traces, range ambiguities, and rapid h'F fluctuations as plasma densities bubble chaotically under intensified $E \times B$ drifts [349]. During the prolonged recovery phase, Disturbance Dynamo Electric Fields (DDEFs) emerge from storm-altered thermospheric winds, driving poleward EIA expansion and periodic traveling ionospheric disturbances (TIDs) that reach low and midlatitudes, manifesting in ionograms as sustained F-layer uplifts, oscillatory foF2 variations, and multiple trace wiggles, especially evident when auroral forcing sustains electrojet vigor without full quiet-time recovery [350], [351]. Thus, these AE spikes foreshadow a cascade from high-latitude electrodynamic chaos to distant latitudinal coupling, visibly transforming ionograms from crisp quiet-time reflections into distorted, scintillation-prone signatures across hemispheres [352], [353]. Thus, these coincidental events have to be avoided from further evaluations. On the days 2010-03-27 and 2010-10-22, the AE index shows a short-term enhancement several hours before the coincidence time and an intensification that is close to the threshold, indicating a weak substorm. This suggests that its effects likely do not persist for more than about 3 hours, which makes these cases suitable for further evaluation. For the date 2010-03-02, there is a strong

intensification of about 700 nT, reaching a moderate substorm level roughly 6 hours before the coincidence. Since the corresponding station is Kwajalein, which is a low-latitude station, the expected effects should be observable in less than 4 hours. As the coincidence time is still more than 6 hours away, we can still include this event in our analysis.

6.4 Anomalies in Bottomside Ionosphere

The next stage of the analysis focused on examining the selected ionograms for the presence of irregularities. A systematic three-step procedure was followed to ensure a consistent and reliable evaluation. Although the spatial and temporal coincidence criteria are defined using a 553 km radial distance around each ionosonde station and the corresponding satellite entry and exit times within this radius during the sounding time, the DEMETER anomalies are identified based on sequence, not at individual time samples. Each anomalous input sequence corresponds to two consecutive daytime half-orbits and gives a wide spatial region (on the order of $\sim 22^\circ$ in longitude, with extensive latitudinal coverage along the orbit). As a result, the deep learning model flags an orbit segment as anomalous but does not provide the specific position or time within the sequence at which the disturbance is strongest.

For this reason, the coincidence criteria are used to establish that the satellite pass and the ionosonde sounding are observing approximately the same ionospheric volume within a physically meaningful overlap window. To account for the propagatory nature of irregularities, ionograms within a ± 12 hours interval around each selected sounding were examined. This step was intended to determine whether any observed irregular features showed temporal continuity, propagation, or repetition over time, depending on the geographic location. By analysing neighbouring soundings within this time window, it becomes possible to distinguish isolated features from patterns that evolve or persist for a long period.

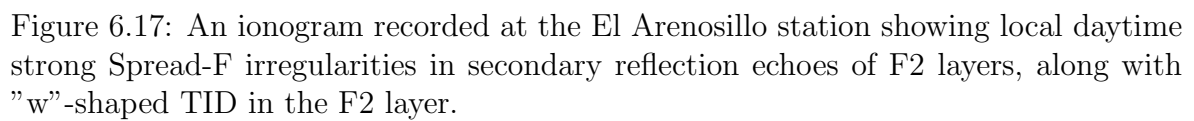
Second, each ionogram was visually inspected to identify clear and recognisable irregular structures. Particular attention was given to the presence of sporadic E layers, spread-F signatures, and travelling ionospheric disturbances (TIDs). These features are commonly associated with disturbed ionospheric conditions. In cases where other potential drivers, such as latitudinal conditions, geomagnetic activity, or climatological effects, can be reasonably excluded, these irregularities may be considered as possible signatures associated with seismic events. This manual examination is also necessary to locate any TIDs, as they cannot be distinguished from any observable parameters derived from ionograms. Finally, the statistical evaluation where the monthly median behaviour of the ionosonde parameters along with inter-quartile range (Q1-Q3) was analysed by considering all available soundings for the corresponding month. The de-

rived features, such as the critical frequencies and minimum virtual heights of the F2 layers (f_oF2 , $h'F2$), as well as the sporadic E parameters (f_oEs , $h'Es$). In addition, spread-related indicators such as QF, QE, FF, and FE were examined to assess the presence of range and frequency spreading in both the F and E regions. Altogether, this provides a background reference against which individual ionograms can be compared. Since the ionosphere varies with geographic location, computing the monthly median and Q1-Q3 range of the ionosonde features at the exact sounding time provides a representative background state for that station. This helps identify whether certain irregularities are continuously present throughout the month, possibly due to the station's latitudinal position or other location-specific factors. By evaluating whether the selected sounding statistically deviates from the typical monthly pattern, it becomes possible to assess whether the observed features represent genuine irregularities or fall within the normal background nature of the station. As mentioned before, there are no specific features that can indicate TID presence; the manual evaluation is mandatory for detecting the presence of TIDs.

EL ARENOSILLO

Starting with the first sounding data for the El Arenosillo station at 10:30:05 on 2010-03-27. In order to understand the local ionospheric condition of the station, we need to study a bit about the station location. El Arenosillo is a coastal ionosonde station situated in southwestern Spain. The station functions under the Instituto Nacional de Técnica Aeroespacial (INTA) and is equipped with a Digisonde system for the continuous observation of ionospheric conditions every 15 minutes. It is located at approximately 37.1°N latitude and 6.7°W longitude, indicating a mid-latitude position in the European region. Since the date of sounding is in the summer period, the local time will be UT + 2 hours. Therefore, we will be looking at an ionogram representing the bottomside ionosphere over a mid-latitude region in the summertime, around noon time 12.30. By analysing the ionograms over a continuous 24-hour interval, the temporal variation of the ionosphere from 00:30 UT on 2010-03-27 to 00:30 UT on 2010-03-28 can be assessed. The station soundings happen every 15 minutes, which leaves us with around 96 ionograms to manually evaluate.

On evaluating the ionograms, we found certain irregularities present mainly in the daytime hours. The sounding at 8.00 UT showed the presence of sporadic E layers with critical frequency f_oEs around 4 MHz at $h'Es$ 110 km. In addition, a spread is observed in the secondary reflections of the F2 layer when compared to the ordinary (O) trace. This suggests fluctuations in the F2 region of the ionosphere. Since the time difference between successive reflections from the F2 layer occurs within a few milliseconds, a noticeable difference in the trace structure indicates that variations in



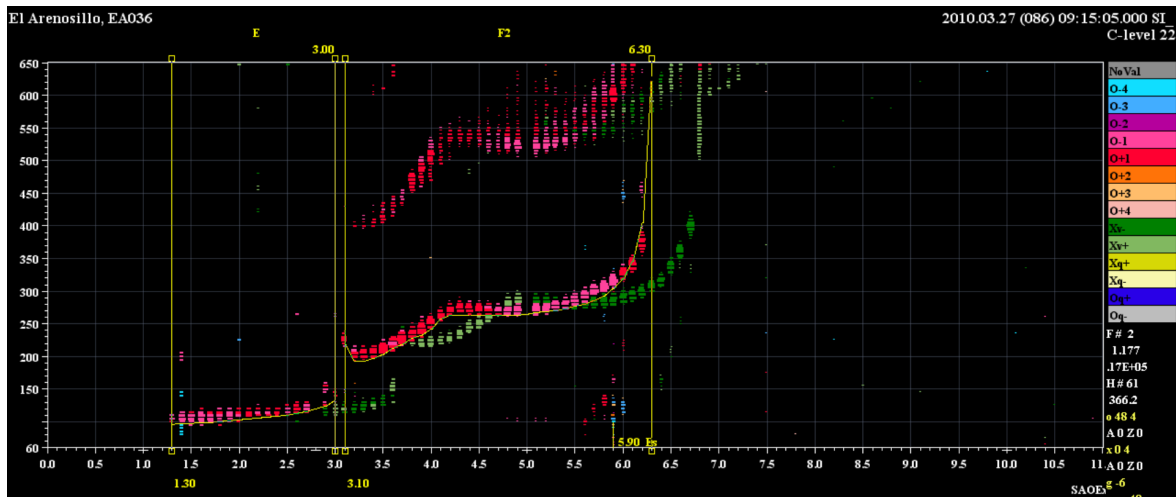


Figure 6.18: Ionogram recorded at the El Arenosillo station showing local daytime Spread-F irregularities in secondary reflection echoes of F2 layers, along with "w" shaped TID in F2 layer and weak spread in Es layer with high critical frequency

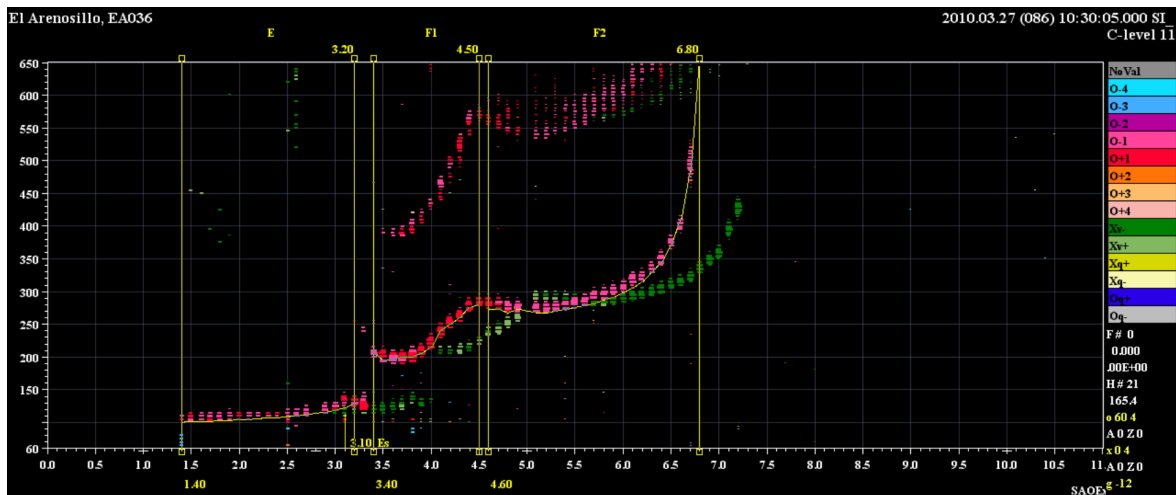


Figure 6.19: The coincident Ionogram recorded at the El Arenosillo station showing local daytime with the presence of the Es layer.

the ionosphere are occurring during that short interval. Such differences in the reflected signal pattern, therefore, point to changes in the state of the F2 layer.

Figure 6.16 illustrates the ionogram at 8.00 UT. As explained in the section 6.1, the ionogram represents signal traces reflected from the ionosphere in the frequency vs altitude frame. The red traces represent ordinary traces, and the green the extraordinary traces. Starting at 110 km, we can see the E layer, and towards the end of it, we can see the beginning of the F layer. Around 2.6 MHz to 4 MHz, at the same altitude as the E layer, a nonblanketing Es layer can be seen. At 8:30 UT, the ionogram indicates the absence of the Es layer, revealing a visible wavy structure at the foF2 point for the F2 layer, accompanied by an obvious spread and a wave-like pattern in the secondary reflection of the F2 layer, which readily indicates the presence of TID behaviour (refer

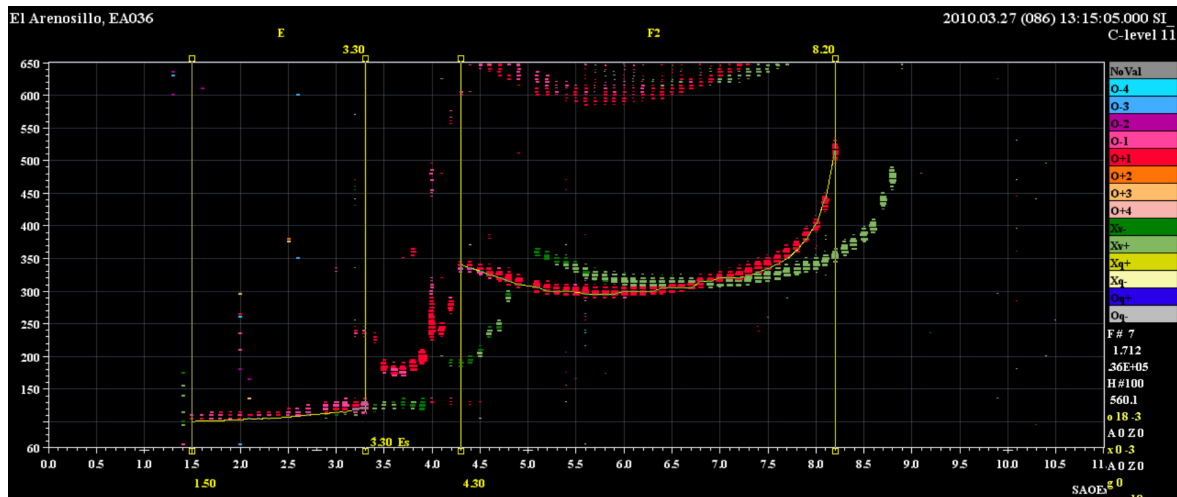


Figure 6.20: Ionogram recorded at the El Arenosillo station showing local daytime with "Y"-shaped fork-like TID in F1 layer and weak spread in Es layer.

to figure 6.17). Figure 6.18 represents the ionogram at 09:15 UT. Here, the TID has disappeared, although the spread in the secondary reflections of the F layer persists. Interestingly, the Es layer has formed at a higher frequency level, with $f_oE_s = 5.9$ MHz, which later disappeared. This is a notable feature, as the Es layer forms and vanishes abruptly. Figure 6.19 represents the ionogram at the point of coincidence. Here, a small Es layer formation is visible. The other anomalies observed in the previous ionogram have disappeared at this time. Later, upon analyzing the afternoon ionograms, we found a fork-like TID structure in the F1 layer trace, along with an extended Es layer. Figure 6.20 shows the ionogram at 13:15 UT, where TID formation is observed in the F1 layer. This feature disappeared immediately in the next sounding, representing the highly volatile nature of the ionogram and suggesting the propagation of ionospheric anomalies. Figure 6.21 represents the ionogram around the dusk time. Multiple reflections of E layers along with mild spread; also, there is another trace with spread present around 700 km virtual height, which is quite unusual. Finally, under the analysis of the ionograms over the 24-hour duration, we identified multiple irregular structures, mostly unrelated to solar terminator effects (sunrise and sunset) or typical nighttime spread-F conditions. This suggests that the bottomside ionosphere was disturbed during the period when the topside ionosphere exhibited anomalies.

However, it should be noted that the ARTIST software autoscaling is not always fully reliable. On closer inspection, an O-trace of the Es layer can be seen extending up to $f_oE_s = 4.5$ MHz. Although not very strong, the software failed to mark it. At the same time, the F1 layer clearly exists between the F2 and E layers, but it is not marked in most of the ionograms. This highlights the necessity of manual visual inspection and scaling in the analysis.

Now we examine the monthly median plots for the El Arenosillo station for March.

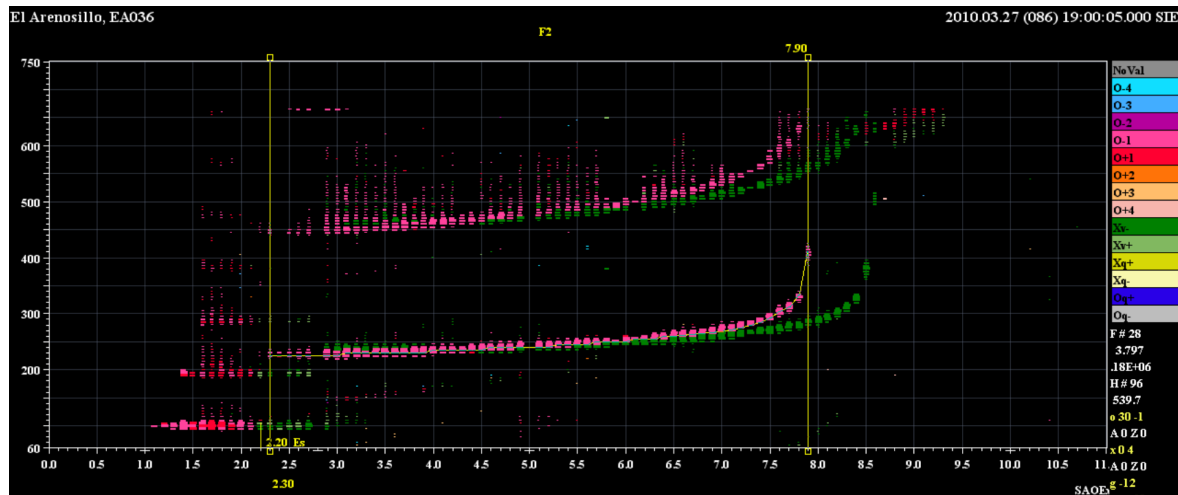


Figure 6.21: Ionogram recorded at the El Arenosillo station showing local nighttime wavey structure formation in secondary reflection echoes of F2 layers, along with the E layer with multiple reflections.

Figure 6.22 shows the diurnal variation of the ionospheric parameters in the ionosphere above the station during this month. The x-axis represents the sounding times, while the y-axis shows the corresponding ionospheric parameters. The monthly median is shown by blue dots, while the orange and green lines indicate the corresponding Q3 and Q1 limits. The light-blue shaded area represents the interquartile range of the data. The coincidence points are highlighted with a dark red marker: when a coincidence value lies outside the interquartile range, it is marked with a star; otherwise, it is shown as a filled circle. Dark blue and pink points represent data within 12 hours before and after a coincident point that falls outside the interquartile range, indicating anomalous behavior.

From the foF2 curve, we observe relatively high values between about 06:45 UT and 20:00 UT. The peak electron density in the F2 layer, which determines foF2, is governed by the intensity of solar ionizing radiation. This, in turn, varies with local time (solar zenith angle), season, latitude/longitude, and the phase of the solar cycle [354], [355], [356], [357], [358]. Consequently, the increase of foF2 starting around 06:45 UT, corresponding to local sunrise, and its maintenance at elevated levels until roughly 20:00 UT are expected, as it is supported by photoionization during daytime. After this interval, foF2 decreases to lower values, consistent with reduced ion production and enhanced electron recombination. Considering h'F2, the minimum virtual height of the F2 trace, we note that it can be identified in the ionograms as moving from higher to lower altitudes around local sunrise, then increasing toward local noon, decreasing again around local sunset, and finally reaching its maximum close to midnight. This pattern is consistent with known physical processes: during nighttime, in the absence of solar extreme ultraviolet (EUV) radiation, ion production effectively ceases and recombination dominates, especially at lower altitudes. As a result, electron density in

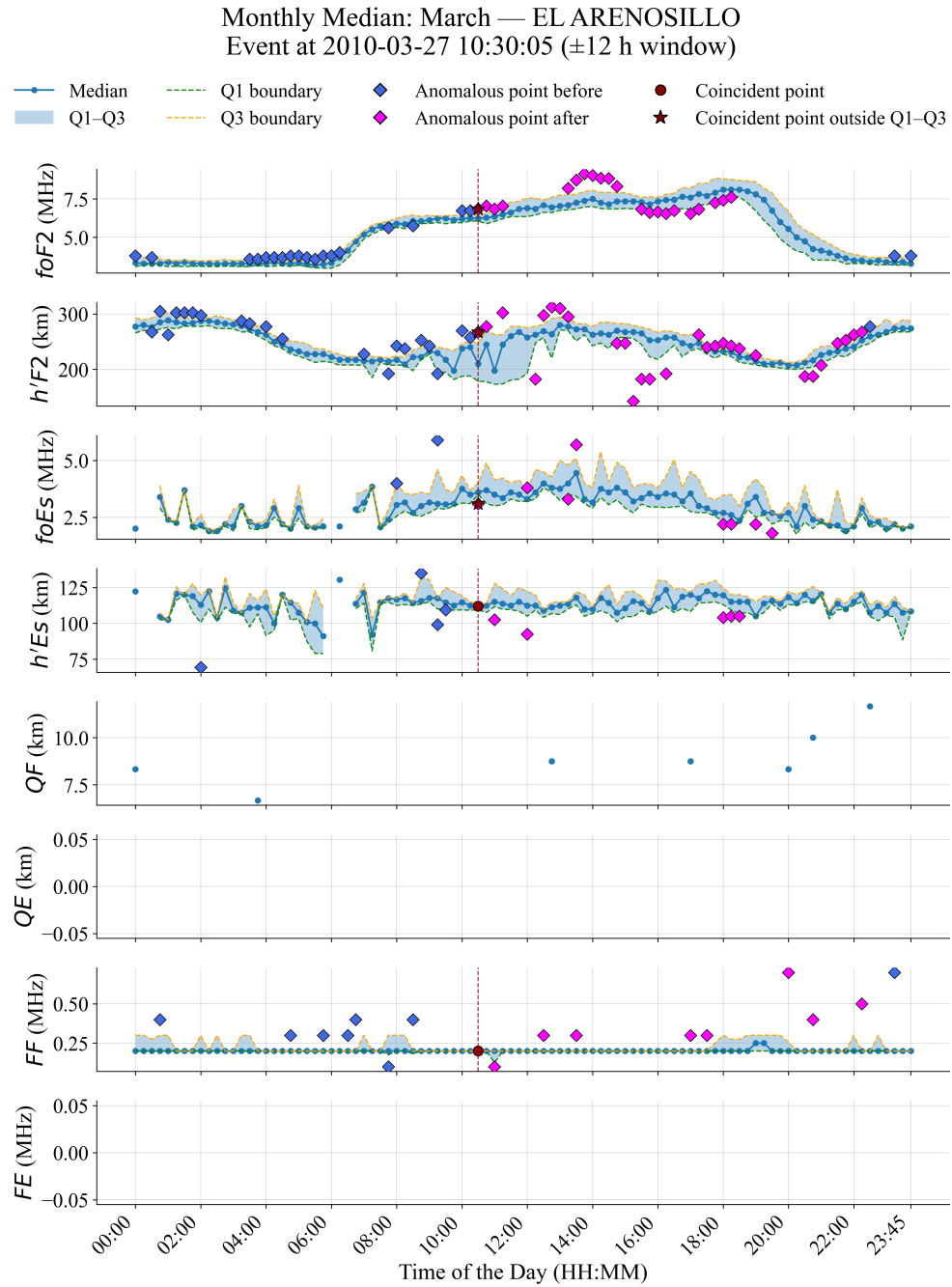


Figure 6.22: Monthly median of derived features, such as the critical frequencies and virtual heights of the F2 layers ($foF2$, $h'F2$), as well as the sporadic E parameters ($foEs$, $h'Es$) and spread-related indicators such as QF, QE, FF, and FE for all the operational sounding times of a day during the month of March of 2010 for El Arenosillo. Monthly median representations mitigate the effects of possible autoscaling errors in individual ionograms. The x-axis represents the sounding timestamps, and the y-axis denotes the derived features with their respective units. The monthly median is shown by blue dots, while the orange and green lines indicate the corresponding Q3 and Q1 limits. The light-blue shaded area represents the interquartile range of the data. The coincidence points are highlighted with a dark red marker: when a coincidence value lies outside the interquartile range, it is marked with a star; otherwise, it is shown as a filled circle. Dark blue and pink points represent data within 12 hours before and after a coincident point that falls outside the interquartile range, indicating anomalous behavior.

the bottomside F region decreases more rapidly, shifting the effective reflection level upward and producing relatively high h'F2 values [359], [360]. After sunrise, renewed solar ionization enhances electron density at lower altitudes, compressing the F2 layer and lowering the reflection height. As daytime heating continues, thermospheric expansion and diffusion lift the plasma to higher altitudes, leading to a gradual increase in h'F2 toward midday and afternoon. Around sunset, as solar production drops, ambipolar diffusion initially reduces h'F2, followed by a rise driven by recombination processes [311], [359], [360]. Further, this shows that there are repeated formations of the Es layer with a critical frequency around 2-3 MHz and a virtual altitude of 110 km, which is common in mid-latitude ionosphere, which increases in summer [361]. It is widely accepted that wind shear is the physical mechanism behind it [316], [361], [362], [363], [364]. The feature commonly appears between 09:30 UT and 14:00 UT, after which it disappears and reappears for a shorter interval from 17:00 to 18:30 UT during March. The mean range spread of the diffuse E-layer trace is not a typical characteristic for this month, as indicated by QE having no values over the entire period. In contrast, the presence of QF at different timestamps indicates that the monthly median exhibits range spread at those times, although the available data are too limited to reliably determine the interquartile range. Moreover, the median frequency spread of the F layer is approximately 0.2 MHz throughout, except at 19:00 and 19:15 UT.

Ionogram analysis reveals the occurrence of sporadic E (Es) layer formations at the coincidence point. A statistical comparison with the monthly median shows that the virtual height (hEs) lies within the interquartile range, implying no substantial departure from normal background conditions. However, the critical frequency of the Es layer (foEs) displays a significant deviation from the monthly median and falls below the first quartile (Q1), indicating anomalously reduced values, which can be considered as an atypical irregularity that can be related to seismic events in mid-latitudinal ionograms [342]. Additional variations are observed in the F2 layer, particularly in foF2, with consistent patterns identified in two soundings taken immediately before and after the coincidence event. This indicates that the anomalous conditions persisted for roughly 1.5 hours. This supports the evidence provided by previous studies which showed pre-seismic irregularities with F2 critical frequency deviating more than 25 percentile range of the data [5]. A more extensive statistical assessment over a ± 12 -hour window reveals that several data points before the coincidence, as well as many after it, show pronounced departures from the monthly median. These deviations are characterized primarily by a substantial reduction in F2 layer virtual height (h'F2) accompanied by a marked increase in frequency-related parameters. Such deviations demonstrate that the observed irregularities cannot be explained by normal ionospheric variability for that month. It should also be emphasized that reflection spread cannot be reliably quantified using only monthly median plots. In addition, traveling ionospheric distur-

bances (TIDs) fork-shaped are identified in both the F1 and F2 layers, particularly in secondary reflections which supports the findings by the study carried out by Bhardwaj et al. The one-hour period surrounding the coincidence event is marked by distinctly atypical ionospheric behavior. Notably, these anomalies occur under relatively quiet geomagnetic conditions. Although an enhanced auroral electrojet (AE) index of about 300 nT was recorded between 12:00 and 14:00 UT on the preceding day, its effects are unlikely to persist 12 hours later. Thus, the detected disturbances cannot be attributed to earlier geomagnetic activity. Collectively, the results strongly support the presence of irregular, anomalous structures in the bottomside ionosphere during the coincidence interval.

KWAJALEIN

Kwajalein is a low-latitude ionosonde station located in the central Pacific Ocean on Kwajalein Atoll, Republic of the Marshall Islands. The station has the Digisonde system that provides continuous ionospheric observations at regular intervals, typically every 5 minutes. It is situated at approximately 8.7°N latitude and 167°E longitude, representing a near-equatorial location in the Pacific Ocean. The local time at Kwajalein is UT + 12 hours.

The final two coincident ionograms are from this station. The first coincident ionogram is on 2010-03-02 at 22:35:00 UT. Thus, we will be looking at the 24-hour window for irregularity search from 10:35 UT 2010-03-02 to 10:35 UT 2010-03-03. Starting with the first irregular observation in the ionogram from the sounding at 11:20 UT on 2010-03-02 (see Figure 6.23), which corresponds to local midnight (11:20 PM) over a low-latitude region. In this ionogram, a noticeable spread in the Es layer is visible, a strong spread formation in the F2 layer and bubble-like formation is also visible. This behavior is consistently observed in the ionograms up to midnight (until 13:30 UT). However, this type of Spread F in the equatorial region during solar minimum, occurring in the midnight to post-midnight hours, is commonly referred to as post-midnight equatorial F region irregularities. The study by Li et al. shows that Spread F is usually initiated during the pre-midnight hours and lasts for several hours into the post-midnight period, driven by gravity wave perturbations. Previous studies have reported that post-sunset equatorial ionospheric electrodynamics give rise to nighttime ionospheric irregularities (plasma density fluctuations), such as Equatorial Spread F (ESF) and Equatorial Plasma Bubbles (EPBs), in the vicinity of the magnetic equator. Kelley, Kelley et al. and Adebisin et al. have proposed and examined the theoretical framework underlying the physical mechanisms that seed EPBs and other irregularities. The Rayleigh–Taylor (RT) instability is widely regarded as the primary mechanism responsible for these structures and is driven by the pre-reversal enhancement (PRE)

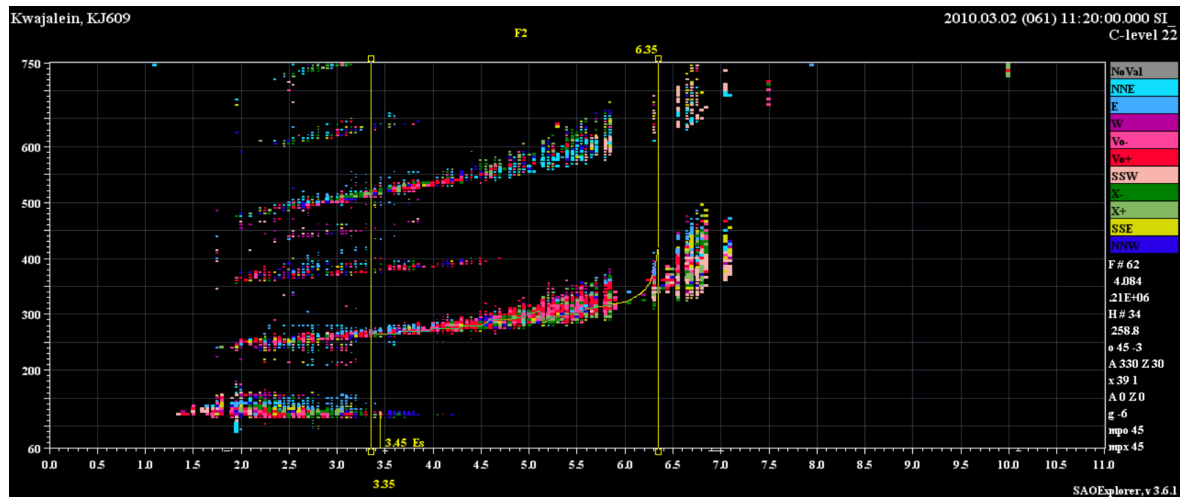


Figure 6.23: Local nighttime ionogram from the Kwajalein station illustrating Spread-F signatures and bubble-like plasma irregularities in the F-region along with multiple reflections of the E layer. The ionogram is showing the interference of multiple oblique echos.

of the zonal electric field [369], [370], [371], [372]. Therefore, although this is indeed an irregularity, it cannot be classified as anomalous relative to the general background behavior of the ionosphere over the station. Furthermore, the ionograms appear to be more disturbed by multiple interferences from oblique signals of unknown origin, and this feature is present in almost all the night ionograms. Figure 6.24 shows the ionogram at 20:00 UT, where a strong spread Es layer with multiple reflections is visible, while the F2 layer appears normal. Finally, Figure 6.25 presents the ionogram at the point of coincidence. Unfortunately, no data are available from 20:00 UT on 2010-03-02 to 04:30 UT on 2010-03-03, most likely due to some technical error associated with the station.

Figure 6.26 shows the monthly median of features in March 2010 for Kwajalein station. The foF2 shows a similar diurnal trend, with the highest values during the daytime (local time) and the lowest during the nighttime. During daytime, foF2 starts rising around the sunrise (18:00 UT) and reaches the maximum at sunset time (6:00-7:00 UT - 10 MHz). During the nighttime, the value slowly decreases and reaches the minimum around the pre-sunrise hours (17:30 - 18:00 UT - 0 MHz). As mentioned before, after the sunrise, the electron production increases as solar ionization begins. After sunset for the equatorial region, the recombination happens slowly, and thus the equatorial ionosphere remains dense, resulting in the gradual decrease in value during the night hours [373], [374], [375], [376]. For h'F2, higher values are typically observed during the daytime (320 km). As the presunset period approaches (around 03:30 UT), a noticeable decrease occurs. Shortly after sunset (beyond approximately 04:30 UT), the layer height begins to rise gradually, forming a small peak before almost stabilizing for a period (between 230-260 km). A more distinct increase is then observed

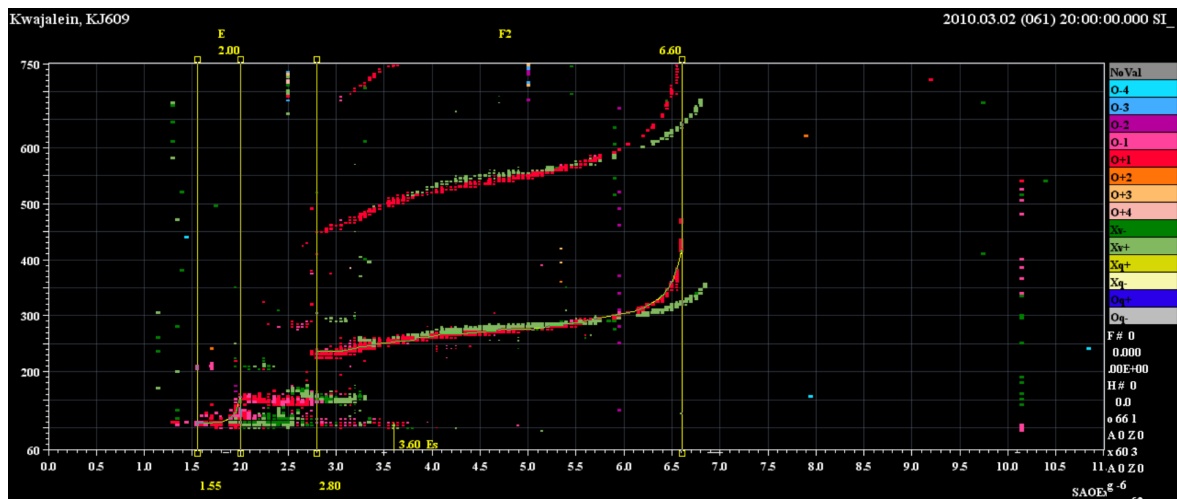


Figure 6.24: Local daytime ionogram from the Kwajalein station illustrating spread in the E layer and presence of Es layer.

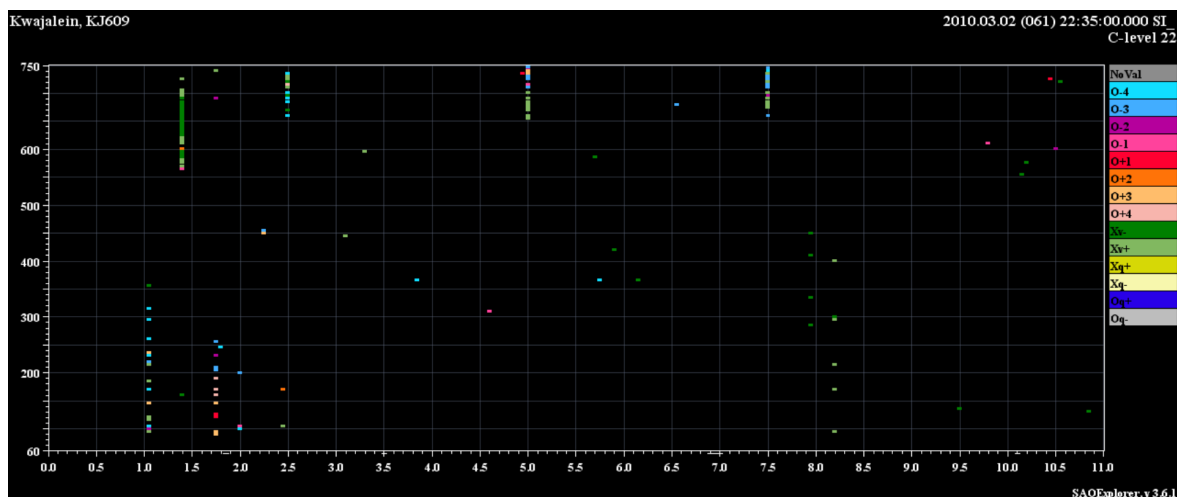


Figure 6.25: The coincident ionogram sounding of Kwajalein station with no data availability.

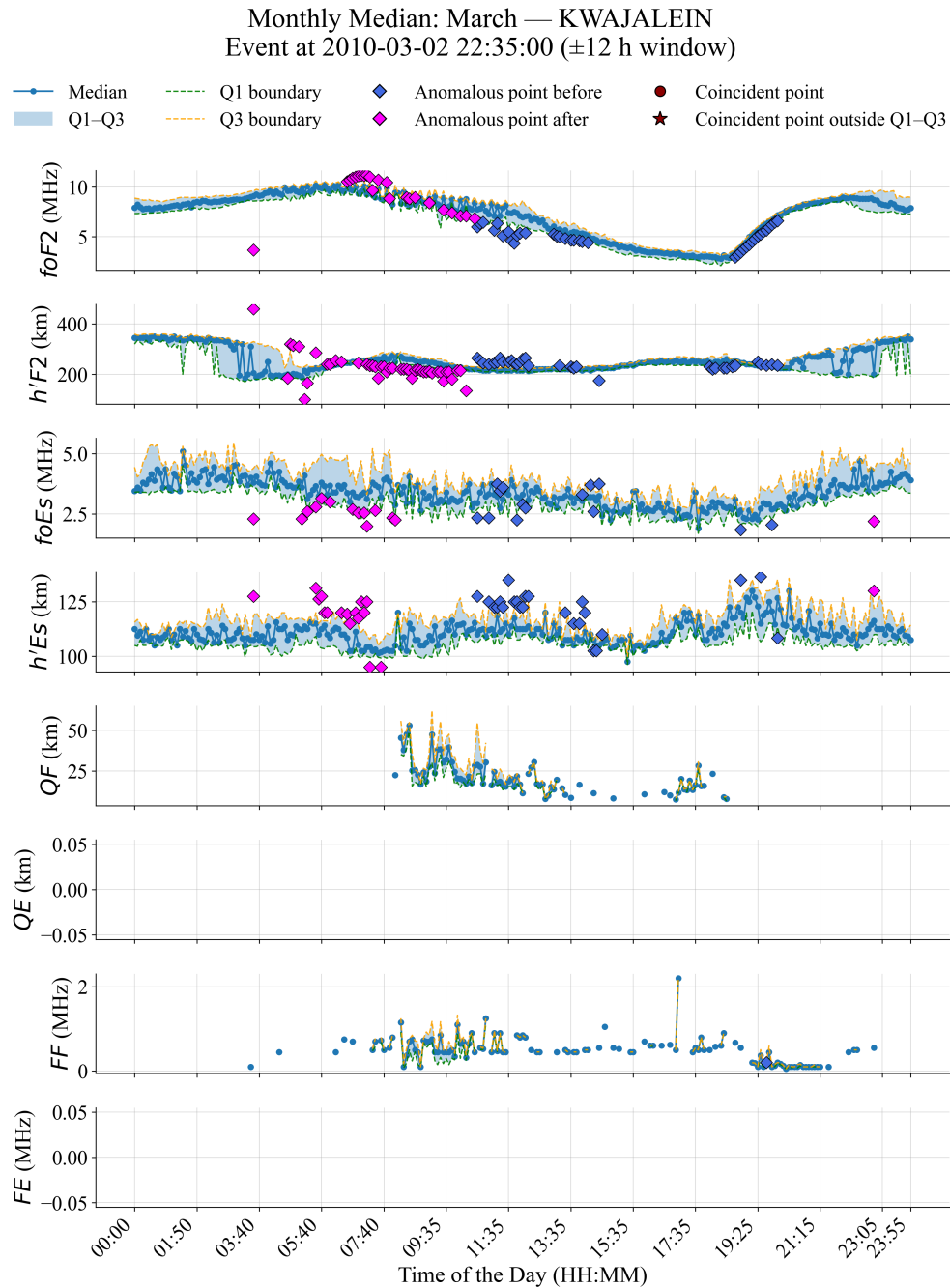


Figure 6.26: Monthly median of derived features, such as the critical frequencies and virtual heights of the F2 layers ($foF2$, $h'F2$), as well as the sporadic E parameters ($foEs$, $h'Es$) and spread-related indicators such as QF, QE, FF, and FE for all the operational sounding times of a day during the month of March of 2010 for Kwajalein. The x-axis represents the sounding timestamps, and the y-axis denotes the derived features with their respective units. The monthly median is shown by blue dots, while the orange and green lines indicate the corresponding Q3 and Q1 limits. The light-blue shaded area represents the interquartile range of the data. The coincidence points is absent in this case. Dark blue and pink points represent data within 12 hours before and after a coincident point that falls outside the interquartile range, indicating anomalous behavior.

during the post-sunrise hours. The highest values of h'F2 generally occur around local noon and the early afternoon. Such diurnal behavior is characteristic of low-latitude or equatorial stations and has been documented in equatorial ionospheric studies Ehinlafa et al., Ehinlafa et al., EOS and ASO.

Previous studies by Adebessin et al., Bai et al., Ambili et al. and Ehinlafa et al. have shown that nighttime increases in the ionospheric electron density gradient are often accompanied by a corresponding rise in h'F2. This enhancement is primarily associated with vertical plasma drift during the post-sunset period, when recombination losses are relatively weak. In addition, atmospheric gravity waves and irregular neutral wind patterns have been identified as contributing factors that can further amplify nighttime electron density gradients and elevate the F-layer height. The observed nighttime increase in h'F2 reflects reduced recombination rates and the upward redistribution of plasma. Moreover, upward plasma drift following sunset can lead to rapid changes in electron density distribution, producing the post-sunset height peak commonly observed in the equatorial ionosphere [378]. The formation of Es is recurrent, with the critical frequency varying between 2-3.5 MHz and mostly at a virtual height of around 100 km. The sporadic E layers are more frequent during the daytime and are also present during the midnight duration (11:00-13:00 UT) [382]. The similar pattern of h'Es and foEs is found in the study carried out by Prasad et al., where Es layers are found frequently during the daytime and midnight hours in the low-latitudinal region. The equatorial type sporadic E layer (Esq) is characterized by a diffuse and non-blanketing Es. These are formed by the gradient drift plasma instability in the equatorial electrojet (EEJ) current.[322], [362], [384], [385]. Further under the analysis of QE and FE features, it is visible that the spread in range and frequency of E layers is not very common in the month for Kwajalein, whereas during the local nighttime, there is a range and frequency spread seen in the F layer.

When examining the statistical distribution of the data in the monthly median plot, we notice that the coincidence point is absent because, as previously mentioned, the ionogram data are not available for that time interval. However, within a ± 12 -hour window around where the coincidence point would be, we can still observe greater deviations from the interquartile range of the data. When comparing with the AE index data during those hours, we can relate that the found clustering of deviation from the interquartile range is actually due to the presence of week substorm. Nevertheless, based on our manual inspection for irregularities and the lack of the coincident ionogram, this event is not suitable for further analysis, since we cannot reliably confirm the presence of an atypical irregularity in the hours surrounding the coincidence.

The final coincident ionogram is also from the Kwajalein station, corresponding to the sounding on 2010-10-22 at 22:22:00. It should be noted that the sounding interval was changed from every 5 minutes to every 7 minutes, so for this month the available

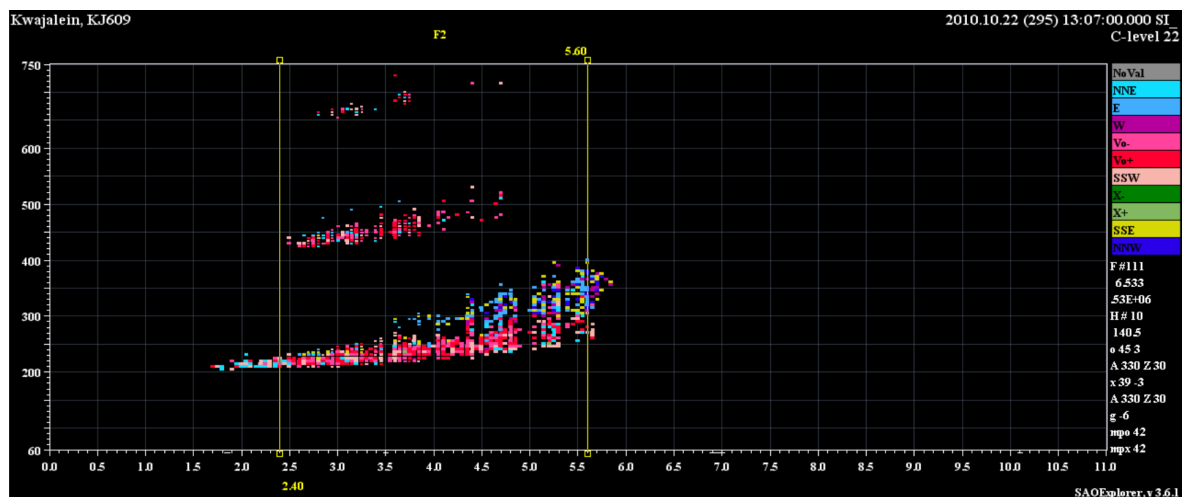


Figure 6.27: Local nighttime ionogram from the Kwajalein station illustrating Spread-F signatures and bubble-like plasma irregularities in the F-region with multiple oblique interferences (the different colours in the trace).

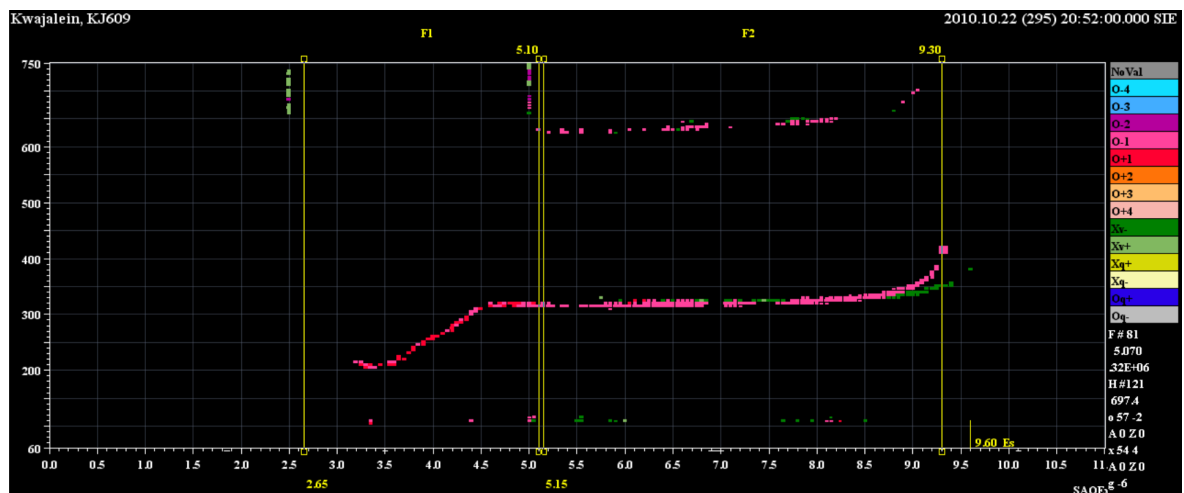


Figure 6.28: Local daytime ionogram from the Kwajalein station illustrating a very weak Es layer with high critical frequency.

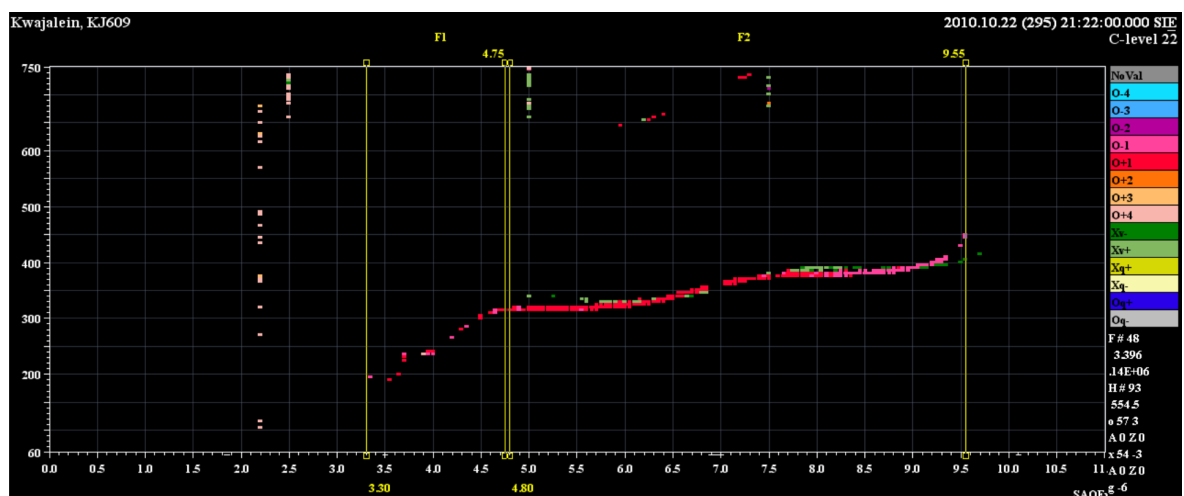


Figure 6.29: Local daytime ionogram from the Kwajalein station illustrating a wavy "w"-type TID formation in the F1 layer.

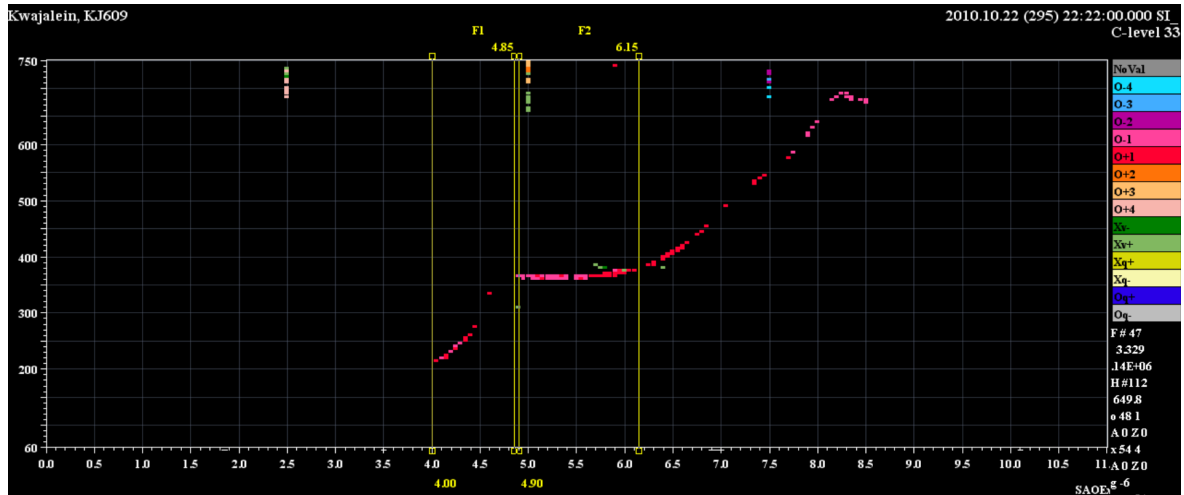


Figure 6.30: The coincident ionogram at local daytime from the Kwajalein station illustrating a wavy TID formation in the F2 layer at 680km.

ionogram data are now at 7-minute resolution. During local nighttime, it is observed that the F layer exhibits strong spread, and bubble formations are present along with multiple oblique traces, indicating nighttime ionospheric irregularities (plasma density fluctuations) such as Equatorial Spread F (ESF) or Equatorial Plasma Bubbles (EPBs) over the magnetic equator, similar to the previous case (see Figure 6.27). Figure 6.28 shows the ionogram for the sounding at 20:52 UT, where a sudden appearance of a weak Es layer is seen with a critical frequency of about 8.3 MHz. In this instance, the autoscaling performed by the ARTIST software does not provide a reliable identification. This Es layer behaves dynamically: in the subsequent ionogram, its critical frequency drops to 2.5 MHz, which is an anomalous behaviour indicating rapid changes in ionospheric conditions. Furthermore, the ionogram at 21:22 UT (see Figure 6.29) shows the presence of TIDs, with a characteristic W-shaped pattern in the F1 and F2 layers. These TIDs continue to be visible in the ionograms up to 22:45 UT. Finally, Figure 6.30 presents the coincident ionogram, in which TIDs are clearly seen at higher frequencies and greater altitudes, also illustrating their propagation.

From the analysis of the October monthly median parameters for Kwajalein, it is evident that the overall trend is similar to that in March (see figure 6.31). The peak critical frequency of foF2 remains nearly unchanged, whereas the virtual height appears to have increased. Another difference is seen in the Es-layer critical frequency, whose values are slightly lower than those in March. At the coincidence time, the most important feature is a decrease in foF2, which falls well below the interquartile range (below Q1), indicating a statistically significant deviation of more than 25 percentiles in the F2-layer electron density relative to the monthly background nature, which is a typical seismic-related perturbation as per the statistical studies carried out by Liu et al. When examined in a short temporal window around the event (within almost 2

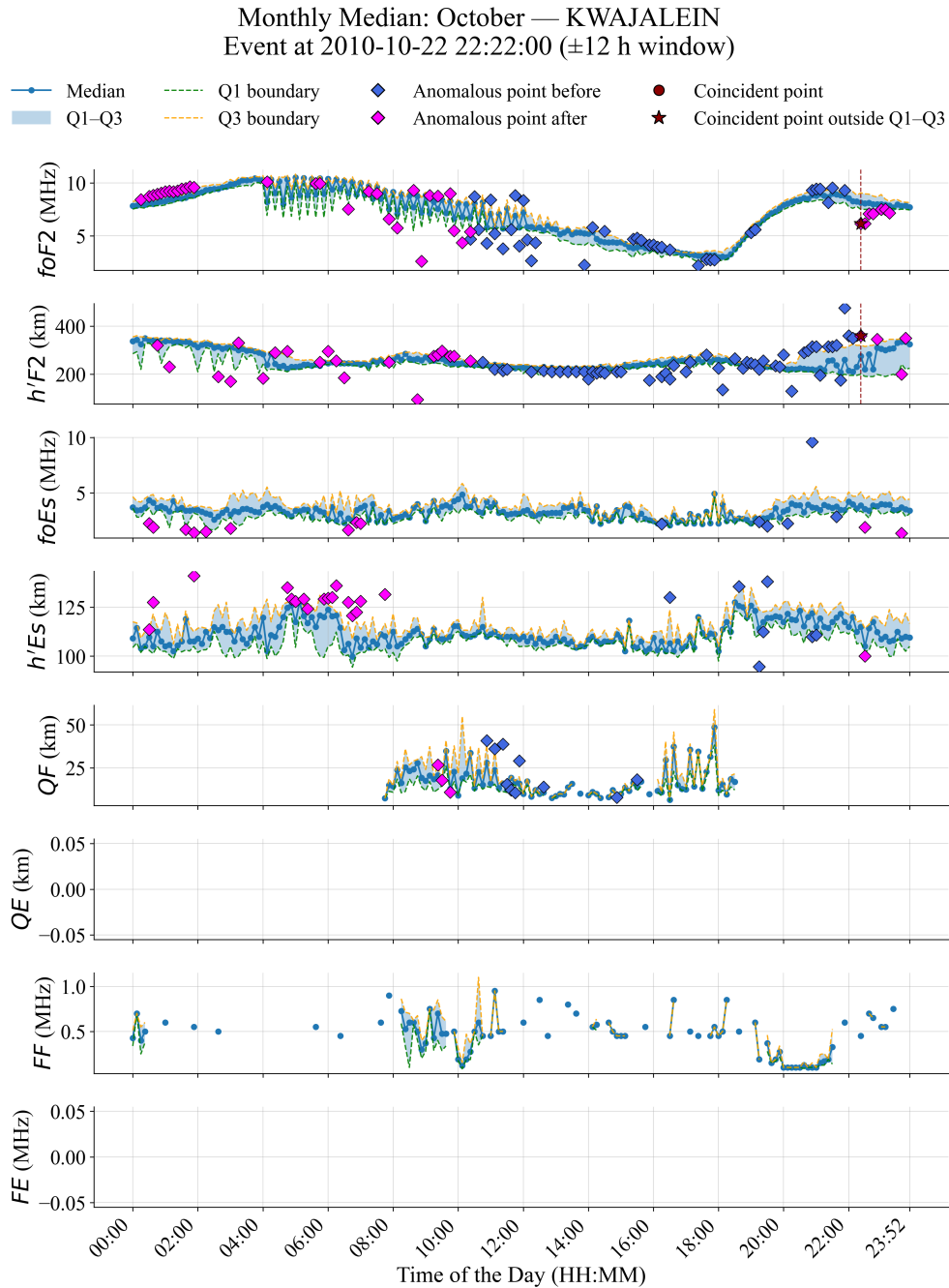


Figure 6.31: Monthly median of derived features, such as the critical frequencies and virtual heights of the F2 layers ($foF2$, $h'F2$), as well as the sporadic E parameters ($foEs$, $h'Es$) and spread-related indicators such as QF, QE, FF, and FE for all the operational sounding times of a day during the month of October of 2010 for Kwajalein. The x-axis represents the sounding timestamps, and the y-axis denotes the derived features with their respective units. The monthly median is shown by blue dots, while the orange and green lines indicate the corresponding Q3 and Q1 limits. The light-blue shaded area represents the interquartile range of the data. The coincidence points are highlighted with a dark red marker: when a coincidence value lies outside the interquartile range, it is marked with a star; otherwise, it is shown as a filled circle. Dark blue and pink points represent data within 12 hours before and after a coincident point that falls outside the interquartile range, indicating anomalous behavior.

hours before and after), foF2 does not behave as an isolated outlier; instead, it shows a clustered pattern deviation suggesting a sustained disturbance rather than random variability. A similar structured behavior is observed in hF2, which shows a positive deviation from the median, indicating an uplift or restructuring of the F-region during this interval. In contrast, hEs does not show a coincident value, but in the post-event period, there is a clear clustering of elevated values, many of which exceed the upper interquartile bound, pointing to enhanced Es layer heights following the event. Additionally, the spread-F-related parameters exhibit increased spread and clustering, indicating enhanced irregularities in the F-layer. AE data show high-intensity auroral activity (with values exceeding 300 nT and reaching much higher levels) after the event. Such elevated AE values are well known to be associated with substorm activity, which can generate traveling ionospheric disturbances (TIDs) and perturb the low-latitude ionosphere through electrodynamic coupling. Therefore, the clustered deviations in foF2, hF2, and hEs, along with increased spread-F in the post-coincidence 12-hour duration, can be reasonably linked to the enhanced auroral activity, indicating that the observed irregularities are not purely local or random but are driven by disturbed geomagnetic conditions associated with substorm dynamics. Yet the deviation of features in the interval between 16.00-23.59 UT can be considered as irregularities with other drivers than storms or normal ionospheric behaviour, and thus can be considered as atypical anomalous behaviour.

6.5 Earthquake-Anomaly Association

After completing the irregularity analysis of the coincident ionograms, only two valid coincidence cases remained for further investigation: El Arenosillo (2010-03-07 10:30:05 UT) and Kwajalein (2010-10-22 22:22:00 UT). The next step was to examine whether any significant earthquakes occurred near these stations within a defined spatial and temporal range.

For this purpose, we searched for earthquakes occurring within a ± 30 -day temporal window around each satellite sounding time. This window allows us to examine possible pre-seismic, co-seismic, and post-seismic anomaly propagation. Several previous studies have investigated different temporal windows for detecting earthquake-related anomalies in ionospheric parameters. Most commonly, time intervals of 5–10 days before and after an earthquake have been analysed. However, evidence of related disturbances has also been reported for longer intervals of up to 20 days, and in some cases extending to about 40 days for very large magnitude earthquakes [340], [386], [387], [388], [389], [390], [391]. Based on these findings, we selected a 30-day window as a balanced and physically reasonable choice to investigate potential earthquake-related anomalies. Within this time frame, earthquakes were examined under two spatial

criteria:

1. A spatial window of 553 km radius around the ionosonde station. This corresponds to the primary spatial range previously used for checking satellite–station coincidence.
2. The Dobrovolsky radius is calculated for each earthquake in order to determine whether the ionosonde station falls within the potential preparation zone of the earthquake epicentre [392]. The effective radial distance is provided by the function, $R = 10^{0.43M}$, where M is the magnitude of the earthquake. This range of choice is supported by multiple studies conducted in the field [28], [393], [394], [395]

The results of the analysis are as follows:

1. Under the first spatial criterion, an earthquake of magnitude 6.3 was identified at the location (36.9, -3.54), approximately 289 km from El Arenosillo. This event occurred 15 days (371.7 hours) after the sounding time.
2. Based on the Dobrovolsky radius calculation, the same earthquake was found to include the El Arenosillo station within its estimated preparation zone.

No additional earthquake events meeting the specified spatial and temporal criteria were found for the two examined cases. This limits the possibility of performing any meaningful statistical analysis or conducting a comparative case study at this stage. With such a small number of coincidence events, the dataset does not provide a sufficient basis for drawing reliable statistical inferences. Given the present limitations in event counts and data coverage, it is not feasible to conduct a statistical or physically comprehensive case study within the scope of this work. For this reason, the study is intentionally concluded at this stage. A detailed event-based investigation, including multi-parameter physical validation and mechanism analysis, would require a dedicated and carefully formulated follow-up study. At this point, the results are therefore restricted to reporting the observed irregularities in the coincidences ionograms under the defined criteria. Future research, supported by a larger dataset and extended observational evidence, may revisit these cases in greater depth. In this sense, the present work should be considered as a baseline step that opens the way for further exploration of possible seismic-induced irregularity propagation between the topside and bottomside ionosphere using combined satellite and ionosonde measurements.

6.6 Summary

This study was carried out during a six-month research period abroad as part of the PhD program. The main purpose of this period was to gain exposure to a new scientific

environment related to my core research and to explore how the existing work could be extended using additional approaches. We proposed to extend the current thesis work by examining whether a multi-instrument framework and a broader parameter search could improve our understanding of the relationship between ionospheric anomalies and seismic events, supported by a statistical analysis.

The objective of this work was to integrate both space-based and ground-based instruments to detect irregularities in the topside and bottomside ionosphere, with a focus on the identification of possible statistically significant seismic association. This work began as a continuation of the main thesis study, where a deep learning model was developed using global ionospheric electric field data to detect anomalies in the topside ionosphere. From this model, we identified strong outlier events in the global electric field dataset, representing possible topside irregularities. However, the physical mechanism describing how such irregularities may propagate, possibly from the bottomside to the topside ionosphere, remains unclear. To explore this aspect, ionogram data were included in the study. The aim was to check for bottomside ionospheric irregularities at times when the model had already detected topside anomalies.

For this purpose, we searched for spatial and temporal coincidences between model-detected anomalous satellite observations and ionosonde station measurements. The analysis focused on the year 2010, which corresponds to a period of low solar activity and was also used as a blind phase analysis for the model establishment. Ionosonde stations located between -30° and 40° latitude were selected. This choice helped avoid complications related to the South Atlantic Anomaly and ensured coverage of major seismic regions. We looked for satellite orbital entry to the defined 553 km radius around the station during the sounding duration of 90 seconds. Due to the lack of continuous ionosonde sounding and the variation in sounding intervals among stations, only a small number of cases showed spatial and temporal coincidence between anomalous satellite passes and available ionograms. Additionally, storm-disturbed days were excluded because ionograms are highly sensitive to solar and geomagnetic activity. This further reduced the number of usable cases. During manual inspection of the ionograms, some records were found to contain incomplete or insufficient scaling, which reduced the final dataset to only two suitable cases. The two cases, recorded at the stations El Arenosillo and Kwajalein at two different sounding times, showed clear atypical irregularities under the manual search of irregularities from the ionograms, as well as the statistical study carried out by using the monthly median of derived features. When searching for earthquakes within the defined spatial and temporal range, only one event was identified. This earthquake occurred 15 days after the sounding at the station El Arenosillo and satisfied the predefined criteria. However, since the study aimed to look for statistically sound results, such a limited number of cases did not allow further statistical analysis or comparative evaluation.

A detailed physical study of the detected case could be carried out in the future, but this currently falls beyond the scope of the current work. Given the current data limitations, the study is concluded at this stage. The present work, therefore, can be considered as a baseline step. It highlights both the potential and the practical challenges of combining satellite and ionosonde measurements to study possible irregularity propagation between the topside and bottomside ionosphere in relation to seismic activity.

Conclusions and Future Scope

In this study, we have developed and evaluated a strong adaptive data-driven methodological framework for detecting the time-transient perturbations in the space-based global low-frequency ionospheric electric field observations that have a statistically significant association with earthquakes. This study was motivated by the idea of the application of deep learning in the field of lithosphere-ionosphere coupling research, which operates in a fully data-driven form without relying on any predefined physical models. The major objective was to develop a systematic methodological approach for processing the satellite observations on a global scale rather than focusing on individual events over localised regions. By combining an adaptive training method, strong statistical analysis, and meta-analysis, this study aims to provide a statistically validated and reproducible methodology framework for detecting significant levels of ionospheric electric field perturbations associated with the following seismic events.

The first step of the study was to construct spatially mapped time series from the spectral electric-field data. A grid-based approach was adopted to extract features at a temporal resolution of 2 minutes from all daytime satellite orbits. A discrete time series of a quartile feature (Q3) for the 11 frequency bands was generated for each grid cell. The main methodological framework used in this work is a rolling-window approach, in which both background correction and model training are performed in an iterative manner. The dataset was divided into a sequence of shorter temporal windows, where each window covers a fixed-duration interval of 15 months, within which the data are further separated into a training segment and a validation segment. In this study, each training segment spans 12 months, followed by a non-overlapping validation segment of 3 months. The temporal windows are then advanced using a rolling strategy, so that consecutive training periods partially overlap, while the corresponding validation periods remain independent and non-overlapping. To address long-term trends and slow variations in the data, background correction was carried out using simple curve-fitting techniques, applied separately to each grid cell and frequency band, considering their distinct geographical characteristics, following the rolling window, where all available past data up to the current validation period are used to study the background. This enables the framework to adapt continuously to evolving ionospheric conditions as the analysis progresses in time, thereby reducing long-term variability while preserving short-term transient behaviour. In order to study the temporally evolving characteristics of the ionospheric electric field observations and for anomaly detection, we employed an LSTM autoencoder architecture as the main model in this study. Training was performed using only the non-seismic labelled class of data under the rolling-window scheme, enabling the model to adapt to evolving changes in the data continuously, ensuring a reliable evaluation of its performance across different

time periods. A single input sample to the model is defined as a sequence composed of two consecutive daytime orbits. However, each half-orbit was fed into the model separately, and optimisation was conducted using the average loss computed over both input sequences. With the application of both weight-updating and re-initialization modes of training, we were also able to examine whether the model's performance is sensitive to the specific training strategy. To validate the significance of the result from these, we introduced the random sampling test (RST) as the null hypothesis in this framework. The RST directly tests whether the observed association disappears under temporal randomisation and also quantifies the positive deviation of the association from the random chance.

A core methodological point of this work is the exploration of multiple spatial (SW) and temporal (TW) windows for defining the seismic association. This step is crucial and is treated as a key modelling decision because there is no universally accepted definition of a space-time window for seismic-ionospheric coupling. The selection of SW and TW directly controls what part of the dataset is labelled as “non-seismic” and used for training. The SW-TW choice does not only affect the final statistical evaluation; it also determines the composition of the training data and, consequently, the background ionospheric behaviour learned by the model. Therefore, this represents a fundamental modelling assumption that cannot be avoided. Importantly, the final choice of SW and TW is not made on a single positive output, but we conduct a statistically based filtering in which different SW and TW configurations are tested over five years of data, using five model architectures and two different training strategies. A given criterion is considered best performing only if a large number of models repeatedly exceed an applied significance threshold. The selected SW 22×22 and TW48 criterion should therefore be viewed as criteria empirically identified as best performing within the tested framework rather than as a physically established universal propagation scale for lithosphere-ionosphere coupling. The persistence of statistically significant performance on the blind dataset provides evidence that the selected criterion generalises to unseen data and is not solely dependent on the specific temporal interval used during criterion selection. Overall, the exploration of SW and TW is a necessary methodological approach, supported by statistical testing across different model architectures and training strategies, and strengthened through validation on an independent blind dataset. Under the meta-analysis carried out with the selected $22^\circ \times 22^\circ$ SW and 48-hour TW criterion, anomalous sequences detected by all the models, averaged across all the windows, are followed by earthquakes significantly more often than expected from a random chance of occurrence, with deviations mostly in the $2 - 3\sigma$ range. Averaged across the evaluated models and temporal windows, approximately 65% of the model-detected anomalous sequences are followed by at least one earthquake of magnitude $M \geq 5$ within the defined spatio-temporal window, where the random expected range is

around 55%. The consistency of these results across the independent primary phase and the blind-phase period suggests that the framework captures a temporally stable pattern rather than a model-specific or period-specific effect.

It is important to clarify the statistical assumptions underlying this evaluation. The statistical measures reported in this study should be interpreted within the context of the adopted framework. Although consecutive rolling windows may share part of their training data, all anomaly detection results used for the final seismic-association analysis are computed exclusively on the validation segments, which are temporally non-overlapping. The seismic-anomaly ratio is evaluated independently within each validation segment of the windows. The corresponding binomial uncertainty is also computed separately for each window. When average seismic-anomaly ratios or Z-factor-based scores are computed across windows, only these independent validation-window outcomes are combined, and the associated uncertainties are propagated in quadrature. At the same time, complete independence among all detected seismic sequences within a window cannot be strictly guaranteed, because the same earthquake may label more than one consecutive sequence as seismic under the selected spatial and temporal association criteria. Such dependencies cannot be fully avoided in the present framework, particularly when relatively broad spatial and temporal windows are considered. Consequently, the reported deviations above the RST expectation should be interpreted as evidence of robust excess association within the assumptions of this framework.

Another important choice of this study is the absence of data filtering based on geomagnetic indices such as Kp, Dst, or AE. Instead, the framework used a background correction removing large-scale ionospheric structure (seasonal and long-term components mostly associated with solar activity) at the grid-cell level, thereby allowing the model to operate on short-term variability rather than on the dominant periodic background. Filtering out storm-time intervals will restrict the model from learning from biased background conditions. By not biasing the data with just the quiet background, the model is trained to adapt to both quiet and disturbed ionospheric conditions naturally. Further, the auxiliary analysis using sunspot number shows that anomaly rates from each window do not closely track the long-term solar-cycle variability, suggesting that the detected anomalies are not primarily controlled by solar-cycle modulation. However, sunspot number alone cannot exclude the influence of short-duration geomagnetic disturbances, since episodic space-weather events may occur independently of the long-term solar-cycle trend. Explicit geomagnetic screening therefore, represents an important future extension for improving the physical interpretation of the detected anomalies and further assessing the contribution of space-weather-related effects. Similarly, in our study, the earthquake catalogue declustering is intentionally not applied. The objective of this study is to evaluate anomaly and earthquake as-

sociation in its natural statistical form using only a commonly adopted magnitude threshold of $M \geq 5$. The random baseline is constructed using the same earthquake catalogue, ensuring that if there is a clustering effect, it is present in both the real and randomised cases. Therefore, it cannot be claimed that the statistically significant deviation that we see from the random statistics is due to this clustering, but it does not completely eliminate its influence on the underlying association statistics. Consequently, future work should investigate the sensitivity of the results to catalogue declustering procedures. Furthermore, raising the magnitude threshold would substantially reduce the number of available events, leading to a significant loss of statistics. Thus, the adopted approach provides a balanced and less biased setting for evaluating the statistical association of the model-detected ionosphere anomalies and earthquakes. In addition, from the perspective of understanding physical phenomena, the present study does not distinguish between shallow and deep earthquakes, nor between continental and oceanic events. These factors may influence the efficiency of any potential lithosphere–ionosphere coupling mechanism and therefore could affect the observed association statistics. A systematic investigation of focal depth, tectonic setting, and alternative magnitude thresholds represents an important direction for future work.

Furthermore, this study prioritises precision over recall. The aim is not to develop an operational earthquake forecasting system, but to investigate whether extreme ionospheric electric-field anomalies occur before earthquakes more frequently than expected by chance. Consequently, the framework is intentionally conservative and employs a high anomaly threshold, resulting in the detection of only a small subset of seismic-labelled sequences. While this strategy yields relatively low recall, it reduces the number of candidate anomalies requiring interpretation and enables a clearer assessment of their statistical association with subsequent seismic activity. The resulting high-precision, low-recall behaviour indicates that the framework is more suitable for anomaly-first scientific investigation than for operational earthquake early-warning applications. In practical terms, the observed (≈ 10) percentage point excess over the random baseline means that model-detected anomalies are associated with subsequent earthquakes more often than expected by chance under the adopted RST framework. However, this statistical excess should not be interpreted as operational predictive power. The limited statistical sample prevents a robust identification of the underlying decay behaviour in the model distributions under the lead-time analysis carried out. Finally, under the threshold sensitivity analysis, we found that the Z-factor score remains higher than or stable across thresholds between the 95th and 99th percentiles, with consistent Z-factor trends. This indicates that the results are robust and not driven by a specific choice of anomaly threshold.

Lastly, we conducted an exploratory analysis to evaluate the feasibility of integrating multi-instrument observations and machine learning techniques for the investigation

of the propagative nature of ionospheric irregularities between the top and bottom layers of the ionosphere in relation to seismic activity. We specifically looked for ionosonde sounding data that spatially and temporally aligned with anomalies identified by the LSTM-based model in satellite observations, aiming at finding corresponding signatures in the bottomside ionosphere. Even though the method seemed promising, the small number of coincident and high-quality observations made it impossible to draw any statistically strong conclusions. Nonetheless, this study underscores significant practical challenges and constitutes a preliminary step, establishing a foundation for future searches with more extensive datasets and enhanced data accessibility.

Taken together, this work underscores the potential of entirely data-driven deep learning methodologies to enhance the understanding of lithosphere-ionosphere coupling in a systematic and unbiased manner. This study's importance lies in its methodological shift, moving away from traditional event-specific, hypothesis-driven analyses toward a comprehensive, globally oriented framework grounded in statistical rigour. The significance of this study is not just in the results, but also in establishing a generalisable method that can work in various types of geophysical situations. By focusing on adaptive learning, statistical null testing, and meta-analysis, the framework provides a foundation for future studies trying to detect ionospheric anomalies statistically associated with subsequent earthquakes using satellite observations.

Looking into the scope for improvement in this study, it is noted that anomalies are defined only based on reconstruction errors produced by an LSTM autoencoder, by averaging over eleven frequency bands and time steps. As a result, individual anomalies cannot directly point out the specific frequency bands or visually interpretable spectral signatures; anomalies cannot presently be localised to a specific orbital segment, frequency band, physical wave mode, or coupling mechanism. The anomaly score, therefore, does not correspond to feature-level variations that can be physically explained. However, as the current study focuses on the statistical behaviour and generalisability of the deep learning-based anomaly detector rather than the physical interpretation of individual anomalous events, this limitation represents a natural direction for future development. Along with that, we acknowledge the fact that more advanced deep learning frameworks for the analysis of time series have been developed in recent years, but we have used the LSTM version. However, this choice was intentional, as this work represents an initial step and began as a trial move towards the application of deep learning in related fields. Moreover, for the study of short-duration datasets such as orbital data, a basic LSTM network is sufficient. In addition, the current choice of feature selection relies on a simple statistical representation of input signals prior to model ingestion. While computationally efficient and suitable for an initial investigation, this approach may limit the model's ability to capture more intrinsic temporal and spectral structures present in the data. Future work could therefore explore

more advanced deep-learning-based feature extraction techniques, such as CNN-based spectral encoders for learning localised frequency-domain structures across different bands, or tokenisation strategies that segment signals into meaningful patches and enable the application of transformer-based models. Beyond improving detection performance, these approaches could substantially enhance physical interpretability. For example, band-wise reconstruction-error analysis could identify which frequency bands contribute most strongly to a detected anomaly, while feature-attribution techniques could quantify the relative importance of individual input features. Similarly, attention mechanisms within transformer architectures may help identify the temporal regions of an orbital sequence that are most influential for anomaly detection. Such information would allow future studies to connect detected anomalies to specific spectral signatures, temporal segments, and potentially relevant physical processes. Consequently, advanced architectures incorporating CNNs, attention mechanisms, and transformer-based representations may not only improve anomaly localisation but also provide a more physically interpretable understanding of the observed ionospheric perturbations.

In conclusion, this study offers a statistically sound framework for identifying potential ionospheric disturbances that are statistically significantly associated with the following seismic events using modern data-driven techniques. It establishes a flexible and adaptable structure applicable to different datasets and observational signatures, thereby laying the groundwork for the future exploration of potential lithosphere–ionosphere coupling processes. Because the framework is naturally adaptable and flexible to accommodate and update the temporal variations, it can be improved for use with new datasets and ionospheric signatures, like magnetic field measurements or atmospheric indicators. This will let the framework learn more about different types of data and signatures. Applying the methodology to more recent missions like CSES and the Swarm constellation will improve the reliability of the statistics and make it easier to further evaluate observed statistical associations between anomalies and earthquakes that were found. As discussed earlier, we can also make the current model better by incorporating more advanced neural network designs, such as hybrid CNN–LSTM or transformer-based architectures. This will help us better capture spatio-temporal patterns in ionospheric observations and extract important features from them more easily.

Appendices

Appendix A

Reproducibility Summary

This appendix consolidates all information required to reproduce the analyses presented in this thesis. It is organised into 7 tables covering (A.1) the DEMETER dataset and access, (A.2) data sampling and preprocessing, (A.3) model architecture, (A.4) training hyperparameters and rolling-window strategy, (A.5) anomaly-detection thresholds, (A.6) Ionosonde-study data source, and (A.7) software environment and code availability.

Table A.1: DEMETER dataset description and data-access information.

Item	Detail
Satellite mission	DEMETER (Detection of Electro-Magnetic Emissions Transmitted from Earthquake Regions), CNES
Instrument	ICE (Instrument Champ Électrique), electric field experiment measuring VLF electromagnetic wave spectra
Data product	L1 calibrated electric field spectral measurements (survey mode), frequency-domain power spectral densities derived from ICE observations
Product version	CDPP archived DEMETER-ICE calibrated products (version as distributed by the CDPP archive: Level-1)
Time coverage used	2005-01-01 to 2010-12-31
Orbit selection	Day-side half-orbits only; DEMETER altitude approximately 660–715 km; consecutive half-orbits paired when temporal separation was ≤ 2 h
Local-time window	Day-side observations only (local time approximately 10:30 LT descending orbit)
Geographic coverage	Global coverage
Frequency range	19.53 Hz – 20 kHz
Seismic source	USGS earthquake catalogue Access https://earthquake.usgs.gov ; earthquakes with magnitude $M_w \geq 5.0$
Sunspot Data source	World Data Center SILSO, Royal Observatory of Belgium, Brussels https://www.sidc.be/SILSO/home
Exclusion criteria	Incomplete orbit pairs, sequences containing fewer than 17 valid samples per half-orbit, boundary samples excluded from frequency-band scoring, and missing-data segments preventing sequence construction
<i>Data availability - DEMETER</i>	
Archive	CDPP Plasma Physics Data Centre, https://cdpp-archive.cnes.fr/user/cdpp/modules/1778
Access type	Publicly available; free registration required

Table A.2: Data sampling and preprocessing pipeline.

Step	Detail
Raw sampling rate	ICE electric-field spectra sampled every 2.048 s in survey mode
Resampling	Spectral measurements were aggregated into 2-min samples within each geographic cell
Input features	11 frequency-band channels derived from DEMETER ICE electric-field observations below 3 kHz
Feature list	Frequency-band features FB1–FB11: 19.53–39.06 Hz, 39.06–78.13 Hz, 78.13–156.25 Hz, 156.25–312.50 Hz, 312.50–625.00 Hz, 625.00–937.50 Hz, 937.50–1250.00 Hz, 1250.00–1562.50 Hz, 1562.50–1875.00 Hz, 1875.00–2382.66 Hz, and 2382.66–3008.20 Hz
Sequence (model input)	Consecutive valid daytime half-orbit pairs (Gap between sequences $\leq$ is 2 hr). 34 time steps per input sequence, constructed by pairing two consecutive 17-sample day-side half-orbits
Normalisation method	Seasonal background correction was applied per frequency band and geographic cell. Model inputs were normalised using statistics computed from the training split.

Table A.3: LSTM autoencoder architecture used in this study. Adapted from [244].

Component	Specification
Model type	LSTM autoencoder
Input dimension	11 features $\times$ 34 time steps
<i>Encoder</i>	
LSTM layers	2 stacked LSTM layers
Hidden units	{8, 12, 18, 32, 64} per LSTM layer
Linear layer	Fully connected layer mapping encoder output to latent representation
Latent dimension	2
<i>Decoder</i>	
Latent expansion	Latent vector repeated across all time steps prior to decoding
LSTM layers	2 stacked LSTM layers
Linear (output) layer	Fully connected layer projecting decoder outputs to feature space
Output dimension	11 features $\times$ 34 time steps

Table A.4: Training hyperparameters, rolling-window configuration, and reproducibility controls. Adapted from [244].

Parameter	Value
<i>Optimisation</i>	
Optimizer	Adam
Learning rate	1×10^{-3}
Batch size	8
Maximum epochs	1500
Early-stopping patience	100 epochs
Loss function	Mean squared error (MSE) reconstruction loss
<i>Rolling-window strategy</i>	
Training window length	12 months
Validation window length	3 months
Window step / stride	3 months; validation segments are non-overlapping
Total number of windows	20 rolling windows over the DEMETER analysis period
<i>Training modes</i>	
Weight-updating models	Model weights from window t were used to initialise training for window $t+1$; models A, B, C, D, and E used hidden sizes $H = \{8, 12, 18, 32, 64\}$
Weight-reinitialising models	Model weights were randomly reinitialised before training each rolling window; models In-A, In-B, In-C, In-D, and In-E used hidden sizes $H = \{8, 12, 18, 32, 64\}$
<i>Reproducibility controls</i>	
NumPy seed	201894
PyTorch seed	201894

Table A.5: Anomaly scoring and threshold definitions.

Item	Detail
Anomaly score	Sequence reconstruction error computed as the mean squared error (MSE) between the input sequence and the autoencoder reconstruction, averaged over all features and time steps
Threshold computation	Empirical percentile threshold derived from the training reconstruction-error distribution; the primary threshold corresponded to the 98th percentile
Threshold update policy	Threshold recomputed independently for each rolling window using the corresponding training data
Decision rule	A sequence was classified as anomalous if its reconstruction error exceeded the selected percentile threshold
Evaluation metrics	Percentage of detected anomalies associated with at least one earthquake within the predefined spatial and temporal criteria. Results were compared against a random baseline and evaluated separately for each rolling window and forecasting horizon
<i>Baseline comparison</i>	
Baseline type	Random anomaly-selection baseline generated by repeatedly drawing 200 random sequences from all windows and calculating the seismicity ratio.
Number of baseline iterations	1000 iterations
Significance criterion	Observed seismic-anomaly ratio compared with the median and 0.3–99.7 percentile envelope of the random baseline distribution; results exceeding the upper envelope were considered statistically significant

Table A.6: Data sources used in the multi-instrument feasibility study.

Data used	Source / availability
Ionosonde data	Digital Ionogram Database (DIDBase), accessed using SAO Explorer. Access requires authorised credentials.
SAO ionosonde parameters	Standard Archiving Output (SAO) files from DIDBase. Parameters are autoscaled using ARTIST and may require manual verification. The extracted parameters include f_oF2 , $h'F2$, f_oEs , $h'Es$, QF, QE, FF, and FE.
Ionogram images	Ionograms downloaded or visually inspected through SAO Explorer/DIDBase for the selected station-time intervals.
Ionosonde station list	Operational Digisonde stations available in 2010, restricted to the latitude range -30° to 40° .
Dst index	Geomagnetic Observatory Niemegk, GFZ German Research Centre for Geosciences, Potsdam, Germany.
AE index	World Data Center for Geomagnetism, Kyoto. Data were used in IAGA-2002 format with one-hour resolution.

Table A.7: Software environment and code availability.

Item	Detail
<i>Computing environment</i>	
Operating system	Linux-based high-performance computing environment (FBK DICLUB cluster)
Hardware	GPU-accelerated training on HPC resources.
<i>Core dependencies</i>	
Python	Python 3.11
PyTorch	PyTorch deep-learning framework
NumPy	NumPy numerical computing library
pandas	pandas data-analysis library
scikit-learn	scikit-learn machine-learning utilities and preprocessing tools
matplotlib	matplotlib visualisation library
<i>Additional libraries</i>	
Scientific computing	SciPy, GeoPandas, Shapely, Seaborn, and custom Python modules developed for DEMETER data processing.
<i>Code availability</i>	
Repository	Research code was developed in Python and executed on institutional computing resources. The code is not publicly available at the time of submission due to ongoing project development and data-management considerations
Access requests	Requests for access to the research code may be directed to the corresponding author and supervisors

Appendix B

Back Propagation Through Time

The most common form of weight optimisation of the RNN is Back Propagation Through Time (BPTT), where the error signal is propagated backward across multiple time steps. This algorithm takes advantage of the fact that there will be a feedforward neural network with identical behaviour for every RNN over a finite period of time. Figure B.1 shows a fully recurrent neural network with only two neuron layers (see figure (a)) and its corresponding unfolded version over time with a separated layer for each of the time steps (see figure (b)). In the figure (a), at given timestamp 1, the two neurons (c_1 and c_2) are labelled as $c_{1,1}$ and $c_{2,1}$. These are connected in 2 ways: self-connection with corresponding weight $w_{1,1}$ (neuron 1 feeds back to itself) and $w_{2,2}$ (neuron 2 feeds back to itself), and cross-connection with weight associated $w_{1,2}$ (neuron 1 sending information to 2) and $w_{2,1}$ (neuron 2 sends information to neuron 1). Since every unit can influence itself and other units over time, this network is called fully recurrent. The figure (b) is the temporally unfolded network where feedback loops in one block are stretched across time steps $(1, 2, \dots, t-1, t)$, while all layers share the same weight. At each time step, the state of a neuron is updated based on the outputs of neurons from the previous time step. For example, the neuron $c_{1,2}$ at time step 2 depends on the previous states $c_{1,1}$ and $c_{2,1}$. The influence of $c_{1,1}$ is controlled by the weight $w_{1,1}$, while the influence of $c_{2,1}$ is determined by the weight $w_{2,1}$. Similarly, the neuron $c_{2,2}$ at time step 2 depends on the previous states $c_{2,1}$ and $c_{1,1}$. In this case, $w_{2,2}$ determines how strongly the neuron remembers its own previous state, and $w_{1,2}$ determines how much the other neuron affects it. To understand how backpropagation through time works, we need to examine it more closely. Let τ denote discrete time steps, where $\tau = 1, 2, 3, \dots, t$. The training interval from an initial time t' to a final time t defines the temporal window over which learning is carried out.

Let N denote the set of all units in the network. Each unit in the network is indexed by variables such as u, v, l , and k , where $u, v, l, k \in N$. The input units form a subset denoted by I , while the set of non-input units is denoted by U . Non-input units include both hidden units and output units. The set of output units is represented by O . The activation (output) of a unit u at time τ is represented by $y_u(\tau)$. The weighted input to a unit is denoted by $z_u(\tau)$. The weight connecting unit v to unit u is represented by $W_{u,v}$. The input signal transmitted from unit v to unit u at time τ is denoted by $X_{u,v}(\tau)$. In addition, each unit has an activation function f_u that transforms the weighted input into the output of the neuron. For training, the network produces outputs that are compared with desired target values with respect to the input. The

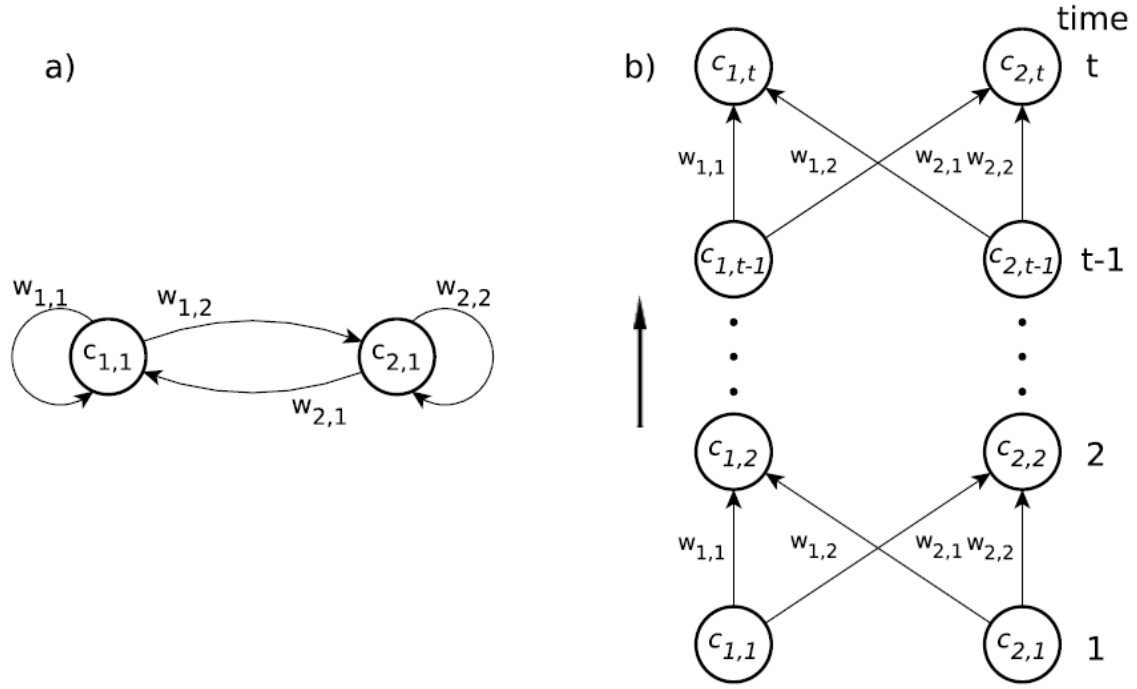


Figure B.1: a) A simple fully recurrent neural network with 2 neurone layers with self-feedback connections. Two neurones are named as c_1 and c_2 . b) depicts the temporally unfolded version of the same network, where for each timestamp, we get a feedforward network. Corrected from the work of Staudemeyer and Morris

target output for unit u at time τ is represented by $d_u(\tau)$. The difference between the predicted output and the target value produces an error or the loss term, which is later used to adjust the network weights during learning.

For a non-input unit u , the output of it at time τ is defined as

$$y_u(\tau) = f_u(z_u(\tau)) \quad (\text{B.1})$$

where $y_u(\tau)$ represents the output of the unit, $z_u(\tau)$ is the weighted input to the unit, and f_u denotes a differentiable activation function. The weighted input to a neuron is obtained by combining all incoming signals. For unit u at time $\tau + 1$, this can be written as

$$z_u(\tau + 1) = \sum_l W_{u,l} X_{l,u}(\tau + 1) \quad (\text{B.2})$$

where the input of the neuron is represented as the sum of all incoming signals multiplied by their corresponding weights. This expression can be expressed in the expanded form as:

$$z_u(\tau + 1) = \sum_v W_{u,v} y_v(\tau) + \sum_i W_{u,i} y_i(\tau + 1) \quad (\text{B.3})$$

where l is an index used to sum over all neurons connected to neuron u , representing every predecessor neuron that sends a signal to u . The first term corresponds to recur-

rent connections that transmit information from hidden units (represented by v) at the previous time step τ . The second term corresponds to external inputs (represented by i) provided at the current time step. During training, the network output is compared with target values. The total error accumulated over the sequence between t' and t is defined as

$$E_{total}(t', t) = \sum_{\tau=t'}^t E(\tau) \quad (\text{B.4})$$

where $E(\tau)$ represents the error at time τ . The error function used is squared error:

$$E(\tau) = \frac{1}{2} \sum_{u \in U} (e_u(\tau))^2 \quad (\text{B.5})$$

The error term for unit u is defined as

$$e_u(\tau) = \begin{cases} d_u(\tau) - y_u(\tau), & u \in T(\tau) \\ 0, & \text{otherwise} \end{cases} \quad (\text{B.6})$$

where $d_u(\tau)$ denotes the desired target output and $T(\tau)$ is the set of non-input units, where at time τ the outputs of the unit $u \in T(\tau)$ should match with some target value.

To compute gradients for learning, an error term is defined for each non-input unit. This measures how the error changes with respect to the weighted input of the neuron:

$$\vartheta_u(\tau) = \frac{\partial E(\tau)}{\partial z_u(\tau)} \quad (\text{B.7})$$

For the final time step, the error signal becomes

$$\vartheta_u(\tau) = f'_u(z_u(\tau)) e_u(\tau) \quad (\text{B.8})$$

where $f'_u(z_u(\tau))$ represents the derivative of the activation function of neuron u , evaluated at time τ . This term tells us how responsible the neuron output is to changes in its input. If the neuron is a sensitive point, this derivative will be large; else, it will be small.

For earlier time steps, the error signal depends on the error signals of units at the next time step:

$$\vartheta_u(\tau) = f'_u(z_u(\tau)) \sum_k W_{k,u} \vartheta_k(\tau + 1) \quad (\text{B.9})$$

This means, at earlier timestamps, the neuron may not have the direct output error; instead, its contribution to the total error can be computed from the derivative of the current neuron and the weighted sum of future timestamp error signals. This relationship allows error signals to propagate backward across time steps in the unfolded

network.

The goal of learning is to adjust each weight $W_{u,v}$ in order to minimize the total sequence error E_{total} . Therefore, we compute the gradient of the total error with respect to the weight. Since the total error is defined as a sum over time steps, the derivative can be written as

$$\frac{\partial E_{total}}{\partial W_{u,v}} = \frac{\partial}{\partial W_{u,v}} \left(\sum_{\tau=t'}^t E(\tau) \right) = \sum_{\tau=t'}^t \frac{\partial E(\tau)}{\partial W_{u,v}} \quad (\text{B.10})$$

since we know that

$$E(\tau) = E(y_u(\tau)) = E(f_u(z_u(\tau))) = E(f_u(z_u(W_{u,v}))) \quad (\text{B.11})$$

The error at each time step depends on the weight through the weighted input $z_u(\tau)$. Applying the chain rule gives

$$\frac{\partial E(\tau)}{\partial W_{u,v}} = \frac{\partial E(\tau)}{\partial z_u(\tau)} \frac{\partial z_u(\tau)}{\partial W_{u,v}} \quad (\text{B.12})$$

Using the definition of the error signal

$$\vartheta_u(\tau) = \frac{\partial E(\tau)}{\partial z_u(\tau)} \quad (\text{B.13})$$

The expression becomes

$$\frac{\partial E(\tau)}{\partial W_{u,v}} = \vartheta_u(\tau) \frac{\partial z_u(\tau)}{\partial W_{u,v}} \quad (\text{B.14})$$

The weighted input $z_u(\tau)$ is a linear combination of inputs and weights, therefore

$$z_u(\tau) = \sum_l W_{u,l} X_{l,u}(\tau) \quad (\text{B.15})$$

Taking the derivative with respect to $W_{u,v}$ yields

$$\frac{\partial z_u(\tau)}{\partial W_{u,v}} = X_{u,v}(\tau) \quad (\text{B.16})$$

Substituting this result gives

$$\frac{\partial E(\tau)}{\partial W_{u,v}} = \vartheta_u(\tau) X_{u,v}(\tau) \quad (\text{B.17})$$

Finally, summing over all time steps results in the gradient of the total error:

$$\frac{\partial E_{total}}{\partial W_{u,v}} = \sum_{\tau=t'}^t \vartheta_u(\tau) X_{u,v}(\tau) \quad (\text{B.18})$$

The weight update is then performed using gradient descent:

$$\Delta W_{u,v} = -\eta \frac{\partial E_{total}}{\partial W_{u,v}} \quad (\text{B.19})$$

where η is the learning rate controlling the step size of the update.

Backpropagation Through Time trains recurrent neural networks by expanding them over the time dimension, performing forward passes to obtain output, measuring prediction errors, and then propagating those errors backward along the sequence. The gradients computed at each time step are combined to update the shared weights, allowing the network to capture and learn temporal dependencies in sequential data. A more detailed explanation is provided by the authors Staudemeyer and Morris, Werbos, Williams and Zipser, Rumelhart et al. Despite the fact that the goal was to capture long-term dependencies, this process appears difficult because of the vanishing or exploding gradient problem [151], [152], [153].

From equation B.9, we see that the error signal itself is computed recursively during backpropagation. This relation indicates that the error at time τ depends on the error at the subsequent time step $\tau + 1$.

Consider a fully recurrent neural network with a set of non-input units denoted by U . Let an output neuron $o \in O$ produce an error signal at time step τ . During Backpropagation Through Time, this error signal is propagated backward through the network over multiple preceding time steps. Specifically, the error generated at time t is backpropagated for $t - t'$ time steps until it reaches an earlier neuron v at time t' , where $t' < t$.

As this error moves backward through the network, its magnitude is scaled by the activation derivatives and the connection weights along the way. This cumulative scaling can be described by the following factor:

$$\frac{\partial \vartheta_v(t')}{\partial \vartheta_o(t)} = \begin{cases} f'_v(z_v(t')) W_{o,v}, & \text{if } t - t' = 1, \\ f'_v(z_v(t')) \left(\sum_{u \in U} \frac{\partial \vartheta_u(t'+1)}{\partial \vartheta_o(t)} W_{u,v} \right), & \text{if } t - t' > 1. \end{cases} \quad (\text{B.20})$$

The first case corresponds to the situation where the error is propagated backward by a single time step. Here, the scaling factor depends directly on the derivative of the activation function at v and the weight of the connection between o and v . In the second case, where the error travels across multiple time steps, the propagation becomes recursive because the error at time t' now depends on the error signals at later time steps.

To make this recursive dependency more clearly, the recurrent network is unfolded in time. Let u_τ denote a non-input neuron at time τ in one of the time-unrolled layers of the network, with $t' \leq \tau \leq t$. By assigning $u_t = v$ and $u_{t'} = o$, the backward

propagation of the error signal can be written in the following expanded form:

$$\frac{\partial \vartheta_v(t')}{\partial \vartheta_o(t)} = \sum_{u_{t'} \in U} \cdots \sum_{u_{t-1} \in U} \left(\prod_{\tau=t'+1}^t f'_{u_\tau}(z_{u_\tau}(t - \tau + t')) W_{u_\tau, u_{\tau-1}} \right). \quad (\text{B.21})$$

This expression shows that the backpropagated error is expressed as a product of activation derivatives and connection weights over all time steps between t' and t . Thus, when the error is propagated backward through many time steps, the gradient becomes a product of multiple factors involving the activation derivatives and the corresponding weights.

This ultimately gives rise to two possible scenarios. When the magnitude of the product

$$|f'_{u_\tau}(z_{u_\tau}) W_{u_\tau, u_{\tau-1}}| \quad (\text{B.22})$$

exceeds one over several time steps, the product grows exponentially. In this case, the gradient becomes extremely large, causing unstable learning behavior and strong oscillations in the weight values. This effect is known as the exploding gradient problem [147], [154].

On the other hand, if

$$|f'_{u_\tau}(z_{u_\tau}) W_{u_\tau, u_{\tau-1}}| < 1, \quad (\text{B.23})$$

the product decreases at every time step. As the error is propagated backward through more longer time steps, the gradient gradually reduces toward zero. When this happens, earlier neurons of the network receive almost no learning signal, affecting the network's ability to learn long-term dependencies in sequential data. This phenomenon is referred to as the vanishing gradient problem [147], [154]. As a result, the ability of a standard recurrent neural network to learn relationships across long time intervals becomes limited. This limitation is a key motivation for designing more advanced recurrent architectures that can maintain stable gradients throughout training.

Constant Error Carousels (CECs)

As a solution to the problem of vanishing gradient, a method of Long-Short-Term-Memory (LSTM) was introduced by Hochreiter and Schmidhuber, Computation. This model embodies a gated system by which it enforces constant error flow within the special cells known as constant error carousels (CECs) [147]. Let's say, for a single neuron u , with a single connection to itself, the error flow at a timestamp τ in the

BPTT is derived from equation B.9

$$\vartheta_u(\tau) = f'_u(z_u(\tau))W_{u,u}\vartheta_u(\tau + 1) \quad (\text{B.24})$$

In order to maintain a constant error flow, we need the term of the product of the activation derivative and weight parameter to be constant; that is:

$$f'_u(z_u(\tau))W_{u,u} = 1.0 \quad (\text{B.25})$$

which can be written as,

$$f'_u(z_u(\tau)) = \frac{1}{W_{u,u}} \quad (\text{B.26})$$

Upon integration, this will be:

$$f_u(z_u(\tau)) = \frac{z_u(\tau)}{W_{u,u}} \quad (\text{B.27})$$

This means that the activation function of the neuron u must be linear and must remain constant in time. If the output of a given neuron at time τ is given by $y_u(\tau)$, then when applying the above concept:

$$y_u(\tau + 1) = f_u(z_u(\tau + 1)) = f_u(y_u(\tau)W_{u,u}) = y_u(\tau) \quad (\text{B.28})$$

By keeping f_u as an identity function and thus making $W_{u,u}$ as 1, this preservation can be achieved, by which we can ensure that the gradient does not shrink or grow.

Appendix C

Additional Results

C.1 Random Sampling Test - SW22x22_TW48

The figure C.1 represents the histogram that shows the null/reference distribution of seismic association ratios generated by the random sampling test described in section 4.4.1, for a sliding window of $SW = 22$ and a temporal window of $TW = 48$ h. Each of the 1000 iterations draws 200 random input sequences from the full six-year dataset and evaluates seismic association against a randomised reference time (rather than the true sequence end time), so the resulting ratios reflect chance-level association rather than any real seismo-ionospheric coupling. The distribution is roughly symmetric and median around $Q2_RST = 0.55$ and 0.3–99.7 percentile interval $[0.45, 0.65]$. The ratios have to be converted to percentages for the study comparison.

C.2 Error Distribution Analysis

As explained in section 4.3.2, the anomaly detection is carried out under the reconstruction error analysis. The same section showed an illustrative example of how the distribution looks for a given window and also explained how the distribution varies according to the model’s capability to learn the data in each window. Here I would like to share more plots for a better understanding of the error distribution of the trained model under the preliminary analysis. Figure C.2 and C.3 show representative reconstruction error distributions for the training and validation sets for all 16 windows of a reference model (trained for the preliminary analysis for the period 2005–2009), with the anomaly threshold indicated by a vertical blue line. The y-axis represents the number of sequences (input samples), and the x-axis represents the values of the computed reconstruction error. From these plots, we observe that for most windows, the training and validation error distributions are very similar, leading to only the most extreme outliers in both training and validation being labelled as anomalies. At the same time, the range of reconstruction errors computed for each window differs, indicating variations in the complexity and variability of the underlying data. These differences reveal how well the model has captured the dominant patterns within each window: narrower error distributions are associated with more stable background behaviour, whereas broader distributions point to greater variability or more intricate dynamics, which would be largely overlooked when using standard data segmentation

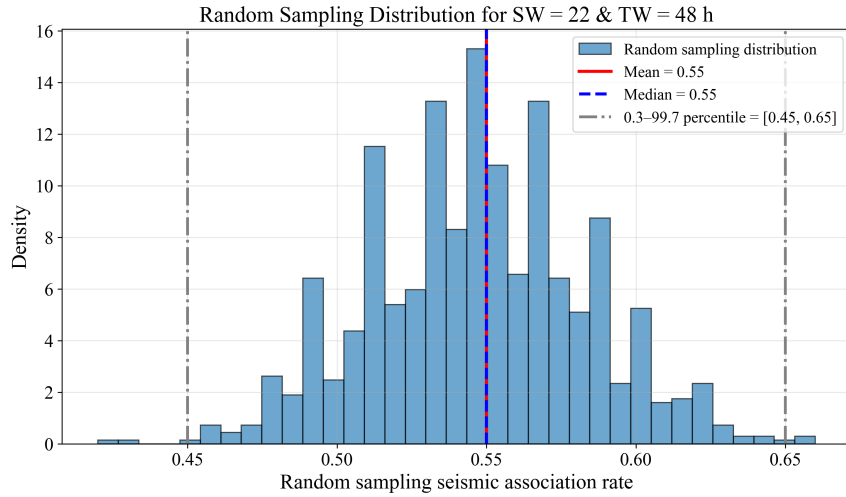


Figure C.1: Random sampling test (RST) distribution of seismic association rates for $SW = 22$ and $TW = 48$ h, obtained from 1000 iterations of the temporally randomised sampling procedure. The distribution is centered at $Q2_{RST} = 0.55$ (median, blue dashed) with a mean of 0.55 (red), and the grey dash-dot lines mark the 0.3–99.7 percentile interval.

and training strategies.

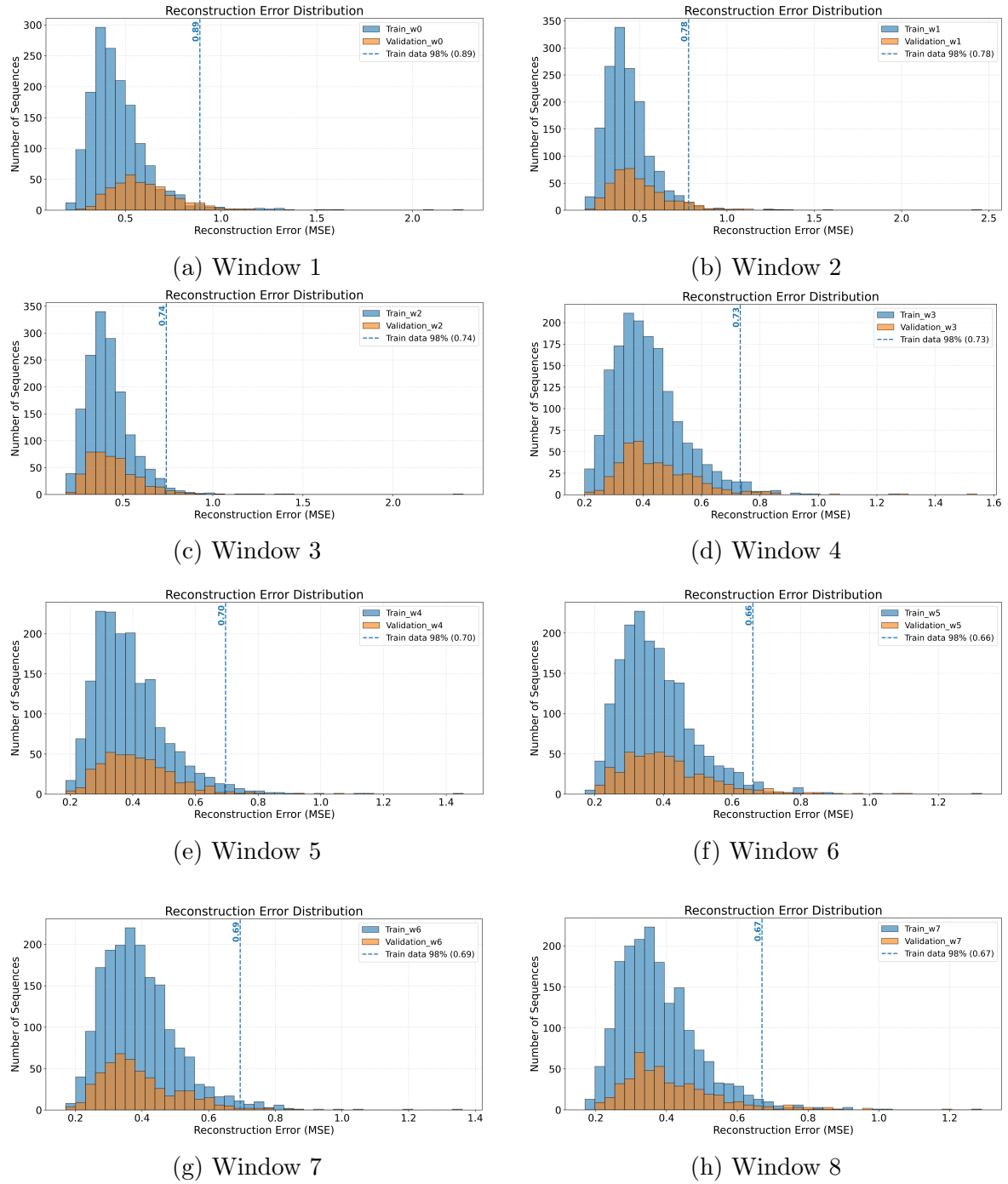


Figure C.2: The error distribution of training and validation data for rolling temporal windows (1-8). In the figure, the anomaly threshold is marked by a blue vertical line, representing the 98th percentile value of the training data distribution. The indexing of the windows started with 0.

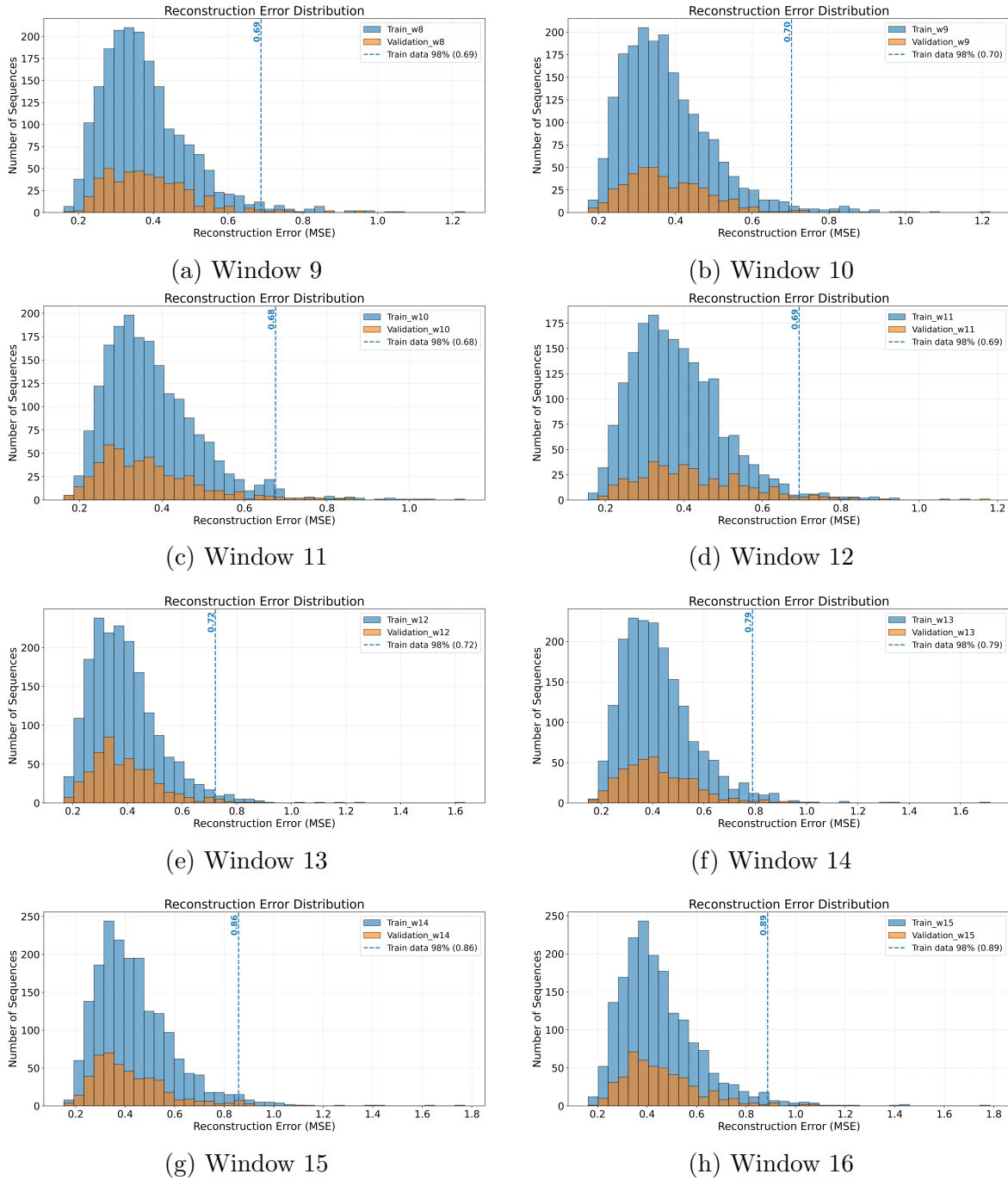


Figure C.3: The error distribution of training and validation data for rolling temporal windows (9-16). In the figure, the anomaly threshold is marked by a blue vertical line, representing the 98th percentile value of the training data distribution. The indexing of the windows started with 0.

C.3 Seismic-Anomaly Ratio

This section provides the seismic anomaly ratio relative to RST for every model trained across all window sizes. Figure C.4 shows the seismic-anomaly ratio as a function of the rolling windows (w0–w15). Blue and orange markers correspond to the training and validation results, respectively, with error bars indicating their binomial uncertainties. The solid horizontal red line represents the Random Sampling Test median baseline ($Q2_{RST}$), and the dotted horizontal lines indicate its 0.3–99.7 percentile range. The results in the left column are obtained from models trained in the weight-updating mode, whereas those in the right column are from models trained in the weight re-initialization mode. Across all models and rolling windows, most seismic anomaly ratios are above the random median, indicating that detected ionospheric anomalies tend to cluster near earthquakes more often than would be expected by chance. In several windows, both training and validation ratios reach or surpass the 99.7% random bound, corresponding to deviations at the 3σ level. For most models, this pattern appears consistently across different dataset windows, suggesting that the association is not driven by a single favorable period but remains stable under varying background conditions. There are a few windows where the model performance is notably poor consistently, like w_2 , and w_{12} . In these windows, the seismic anomaly ratio falls below the random range, undercutting the lower bound of the random distribution. This behaviour suggests that, for these specific temporal segments, the detected ionospheric anomalies are not only uncorrelated with seismic activity but may exhibit an apparent anti-correlation with earthquake occurrence. This may correspond to distinct background conditions, although the specific physical or statistical factors driving this behaviour cannot be perfectly identified from the present analysis. However, there is no strong, systematic, generalisable pattern in the ratios across models that could be identified.

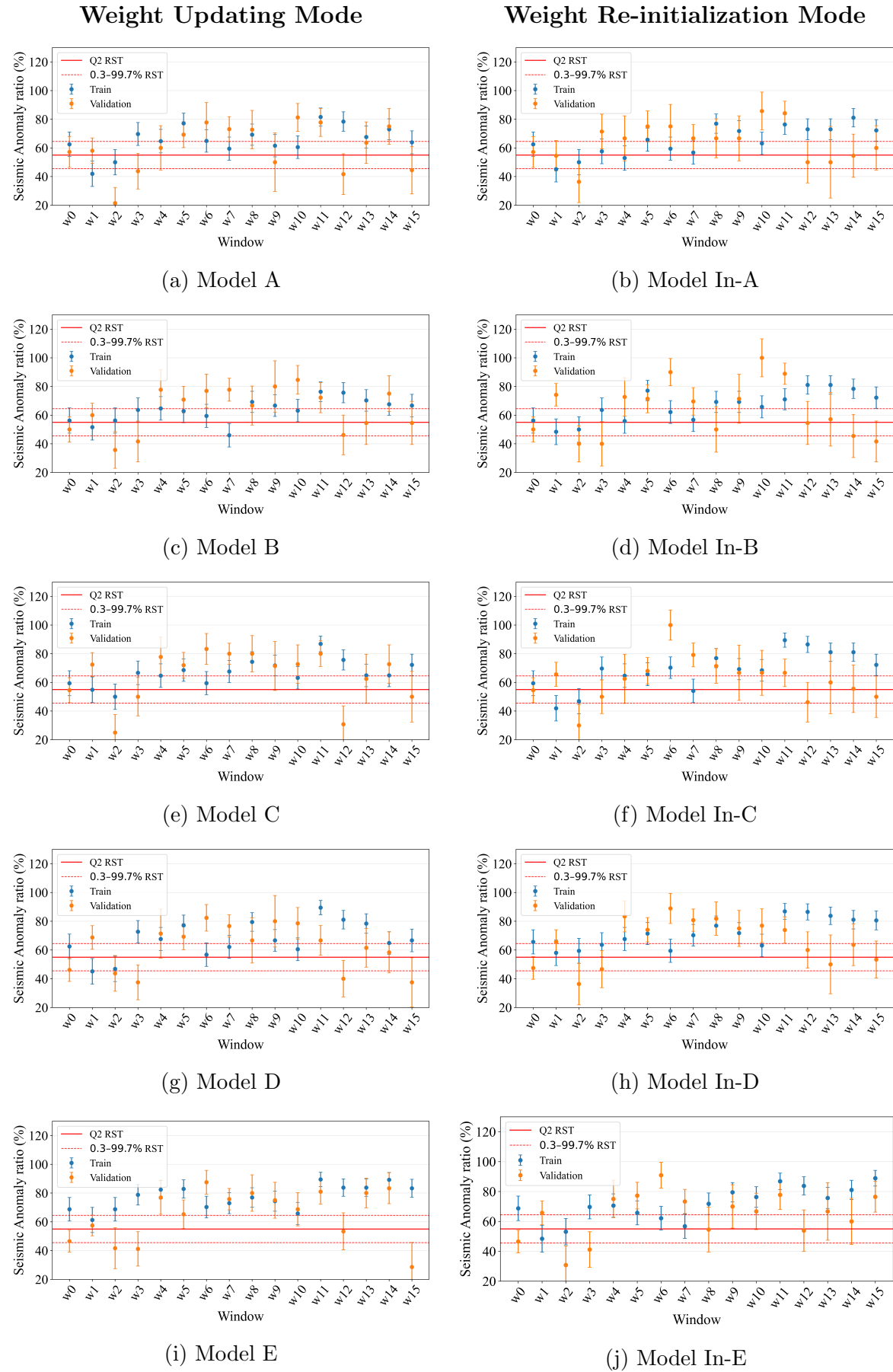


Figure C.4: Seismic anomaly ratio as a function of rolling windows (w_0 – w_{15}). Blue and orange markers represent training and validation results, respectively, with error bars representing their corresponding binomial uncertainties. The horizontal red lines indicate the Random sampling test median($Q2_{RST}$ baselines) and dotted horizontal lines, its 0.3-99.7 percentile range.

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