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Warming of lowland Polish lakes under future climate change scenarios and consequences for ice cover and mixing dynamics

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ABSTRACT

Study region: The study region comprises 25 lowland Polish lakes in the northern part of the country. The studied lakes provide domestic, industrial and agricultural water supply, and are major attractions for tourism, thus playing a significant role in the Polish economy.
Study focus: The expected impact of future climate change on lake surface water temperature (LSWT) was predicted using the *air2water* model, which relies solely on daily air temperature (AT) as model input. LSWT and AT observations for the period 1987–2016 were used for model calibration and validation. Then, historical (1987–2005) and future (2006–2100) AT time series from nine EURO-CORDEX climate models were used to project future LSWT under emission scenarios RCP4.5 and RCP8.5.
New hydrological insights for the region: The results showed that *air2water* can well reproduce daily LWST with root mean square errors lower than 1 °C on average. The warming trends of both AT and LSWT are expected to be lower than those observed in the past decades (after the 1980s), and ice cover and weak stratification conditions are expected to partially buffer the LSWT response to the high AT warming expected in future winters. However, the overall enduring warming will substantially alter future thermal dynamics, leading to a shortening of ice cover and inverse stratification periods, possibly leading to serious consequences for lake water quality and ecosystem health.

1. Introduction

Water temperature is a key variable controlling many physical and biochemical processes within water bodies, including lentic environments such as ponds and lakes. It controls vertical stratification, thus affecting vertical exchanges of mass and energy (Berger et al., 2010; Butcher et al., 2015; Piccolroaz et al., 2015; Fenocchi et al., 2018), impacts kinetic rates and dissolved oxygen levels

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(Blumberg and Di Toro, 2004; Lofton et al., 2014), and affects ecological processes, such as metabolism and growth of organisms (Lürling et al., 2013). In the past decades, lake surface water temperature (LSWT) in many lakes around the world underwent clear warming trends (e.g., Schneider and Hook, 2010; O'Reilly et al., 2015; Woolway et al., 2017; Lehnherr et al., 2018; Yang et al., 2019; Piccolroaz et al., 2020). A global reconstruction of LSWT during the 20th century highlighted variable mean annual trends across climatic regions, with substantial warming evident after ~1980 and the most responsive lakes to climate change being located in the temperate regions of the Northern Hemisphere (+0.27 °C per decade for these lakes, in response to air temperature (AT) warming of +0.46 °C per decade in the period 1980–2010; Piccolroaz et al., 2020). Warming of lake water temperature is expected to impact the structures and functioning of lake habitats (Verburg et al., 2003; Brucet et al., 2010; Jeppesen et al., 2010; Tunney et al., 2014; Kraemer et al., 2017) in some cases decreasing aquatic ecosystem productivity (O'Reilly et al., 2003) and increasing the expansion of harmful cyanobacteria (Paerl and Paul, 2012; Posch et al., 2012; Mantzouki et al., 2018). Under this scenario, the possible consequences on the ecosystem services of lakes are relevant, primarily concerning future water use for drinking, agricultural and industrial water supply, fisheries management, and recreational activities. Being able to assess the impact of climate warming on lake thermal dynamics can therefore offer a valuable support for designing an efficient and sustainable management of lakes using a long-term view over the coming decades.

Mathematical models can be successfully used to forecast lake water temperature under future climate scenarios. In the past three decades, due to the endeavor of the scientific community, different types of models have been proposed and applied for lake water temperature forecasting. Generally, these models can be divided into two main categories: simple statistical models (Livingstone and Lotter, 1998; Kettle et al., 2004; Czernecki and Ptak, 2018; Zhu et al., 2020a) including artificial neural network models (Sharma et al., 2008; Liu and Chen, 2012), and more complex process-based deterministic models based on laws of physics (Fang and Stefan, 1996; Peeters et al., 2002; Perroud et al., 2009; Martynov et al., 2010; Weinberger and Vetter, 2012; Thiery et al., 2014; Hetherington et al., 2015). Statistical models are simple to implement, however, their accuracies are generally lower compared with other models and their applicability is often restricted to the system and climatic conditions for which they are calibrated. On the other hand,

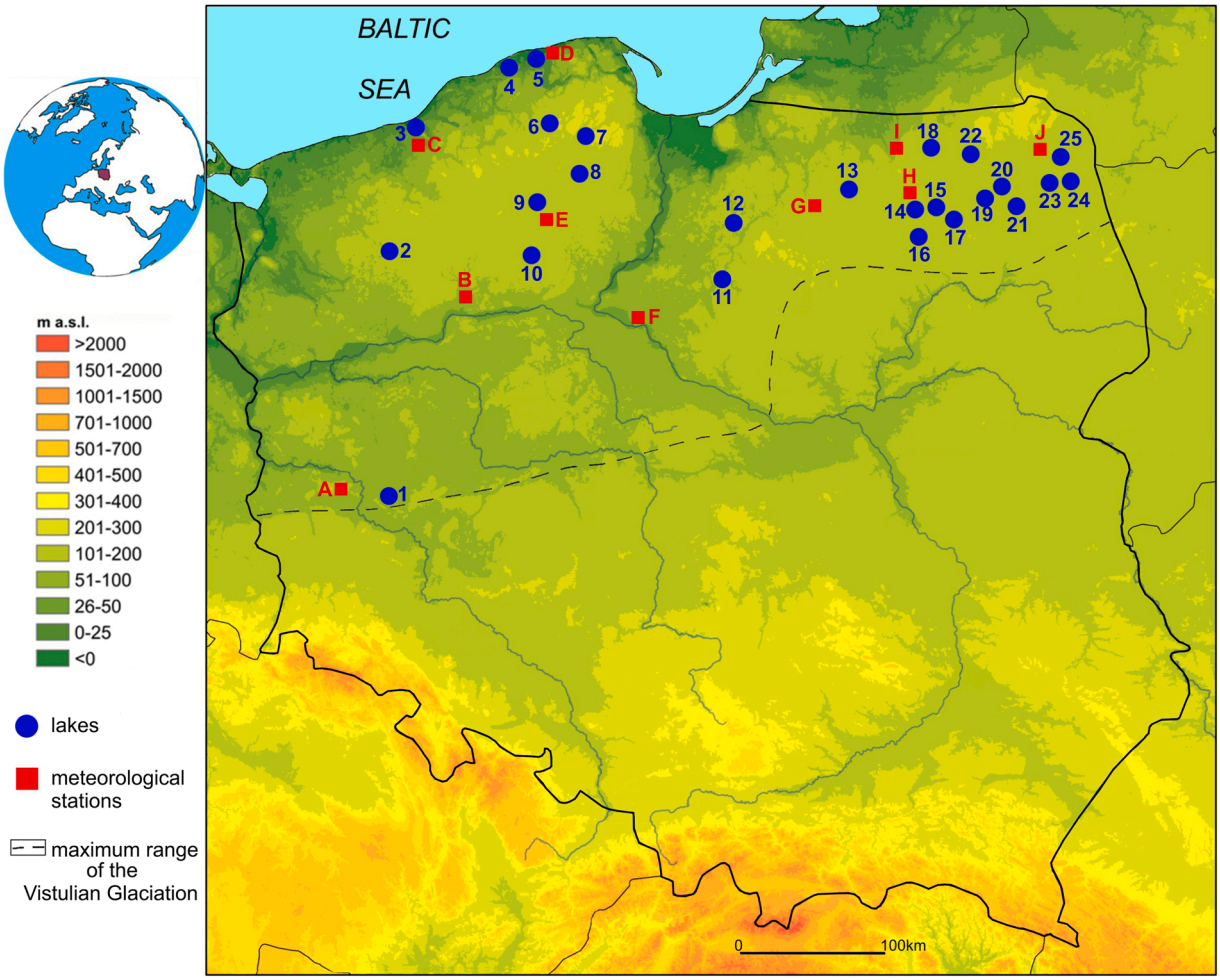

Fig. 1. Location of the studied lakes (blue circles) and of the meteorological stations (red squares) used for model calibration and validation.

process-based deterministic models are accurate and can be more generalizable across different systems, but they are complex and typically need a large number of input data, such as lake morphology, a complete set of meteorological data, inflow and outflow conditions etc., which make them impractical for regions with limited data. A third category of models there exists, which is in between deterministic and statistical models, and that can be referred to as hybrid statistical-physically-based models. These models need few inputs similarly to statistical models, but their mathematical structure accounts for the main physical processes, thus producing more reliable results. A clear example is the hybrid *air2water* model (Piccolroaz et al., 2013; Piccolroaz, 2016), which combines a physical derivation of the key equation with a stochastic calibration of parameters. The model uses only AT as input and has been proven to be a robust tool for lake water temperature prediction (Piccolroaz et al., 2013, 2015; Piccolroaz, 2016; Javaheri et al., 2016; Schmid and Köster, 2016; Flaim et al., 2020; Calamita et al., 2021) and climate change assessment (Wood et al., 2016; Czernecki and Ptak, 2018; Piccolroaz et al., 2018, 2020), also when applied to lakes with different morphological characteristics (Toffolon et al., 2014; Prats and Danis, 2019; Zhu et al., 2020b).

Here, we use the hybrid *air2water* model to investigate how the lowland lakes distributed in the northern part of Poland are expected to respond to future climate change. Previous studies indicated that LSWT in Polish lakes rose significantly in the past decades, based on available observations (Dąbrowski et al., 2004; Wrzesiński et al., 2015; Czernecki and Ptak, 2018; Ptak et al., 2018a, 2018b, 2019a). However, little attention has been payed to investigate the impact of climate change on LWST in these lakes, and only one study is available on the topic (Czernecki and Ptak, 2018), where an empirical-statistical downscaling model was used to assess the impact of global warming on LSWT in 10 Polish lakes. This previous study limited the analysis to the projection of future LSWT, while it did not explore how changing LSWT is expected to affect other lake processes, such as ice-cover formation and mixing regime. In the present study, we extend the analysis to 25 Polish lowland lakes, focusing on evaluating the lakes' thermal sensitivity to climate change across the year through the analysis of long-term trends of different variables and indicators (including temperature anomaly trends, ice-cover duration, and mixing patterns). To this end we consider two future emission scenarios (Representative Concentration Pathways – RCP): the intermediate RCP4.5 and the most severe RCP8.5 scenarios. The results of this study are expected to enrich the existing knowledge concerning lakes' response to ongoing climate change, to be used to inform policymakers and authorities in charge of the management of lakes in Poland, as well as to provide a possible reference for climate change studies in other regions.

2. Materials and methods

2.1. Study area and available data

As a result of the impact of the last glaciation (approximately 12,000 years ago), the majority of lakes are distributed in the northern part of Poland (Fig. 1), where a transitional climate dominates. Moderate marine climate characterizes the western part, and it gradually transitions into a continental climate towards the east.

In the present study, 25 lowland Polish lakes were studied (Fig. 1). These lakes play a significant role in various aspects of economic development in Poland, as they provide domestic, industrial and agricultural water supply, and are major attractions for tourism. The

Table 1
Morphometric characteristics of the studied lakes (Choiński, 2006).

Lake No.	Lake name	Depth (m)		Area (km^2)	Altitude (masl)	Volume (10^6 m^3)	Meteorological station
		mean	max				
1	Sławskie	5.2	12.3	8.23	56.9	42.66	Zielona Góra (A)
2	Lubie	11.6	46.2	14.88	95.5	169.88	Piła (B)
3	Jamno	1.4	3.9	22.32	0.1	31.53	Koszalin (C)
4	Gardno	1.3	2.6	23.38	0.3	30.95	Łeba (D)
5	Łebsko	1.6	6.3	70.20	0.3	117.52	Łeba
6	Jasień	8.3	32.2	5.75	112.7	26.10	Chojnice (E)
7	Raduńskie Górne	15.5	43	3.63	161.6	60.16	Chojnice
8	Wdzydze	15.5	69.5	14.17	134	220.80	Chojnice
9	Charzykowskie	9.8	30.5	13.36	120	134.53	Chojnice
10	Sępoleńskie	4.8	10.9	1.58	112.8	7.50	Chojnice
11	Bachotek	7.2	24.3	2.15	70.8	15.39	Toruń (F)
12	Jeziorak	4.1	12.9	31.53	99.2	141.59	Olsztyn (G)
13	Dadaj	12	39.8	9.75	122.5	120.78	Olsztyn
14	Mikołajskie	11.2	25.9	4.24	115.7	55.74	Mikołajki (H)
15	Śniardwy	5.8	23.4	114.88	115.7	660.21	Mikołajki
16	Nidzkie	6.2	23.7	17.5	117.9	113.87	Mikołajki
17	Roś	8.1	31.8	18.09	114.4	152.92	Mikołajki
18	Mamry	9.8	43.8	98.51	115.8	1003.37	Kętrzyn (I)
19	Ełckie	15	55.8	3.85	119.9	57.42	Mikołajki
20	Selmęt Wielki	7.8	21.9	12.08	120.7	9.96	Mikołajki
21	Rajgrodzkie	9.4	52	14.99	118.5	142.62	Suwałki (J)
22	Litygajno	6	16.4	1.55	132.8	9.76	Suwałki
23	Białe Augustowskie	8.7	30.0	4.53	122.2	41.72	Suwałki
24	Studzienicze	8.7	30.5	2.44	123.4	22.07	Suwałki
25	Wigry	15.4	74.2	21.15	131.9	336.73	Suwałki

main morphological characteristics of the study lakes are summarized in Table 1, which shows that the considered lakes span relatively different morphological ranges: the mean water depth ranges from 1.3 m to 15.5 m, and the lake area varies between 1.545 km^2 and 114.88 km^2.

Daily LSWT and AT data were used for these lakes. Daily LSWT is measured at a water depth of 0.4 m below water surface (or ice cover when present) at 7 or 8 a.m. local time by the Institute of Meteorology and Water Management–National Research Institute. Water temperature was measured at the shore by means of well-scoop thermometers. For each lake, daily AT data were obtained from the nearest meteorological station (Fig. 1 and Table 1). For 21 lakes, observed data were available for 30 years (1987–2016), while for the other four lakes, including Sławskie, Lubie, Roś and Wigry, observed data were available for 28 years (1987–2014).

Finally, data on the duration of the ice cover period for all lakes (except for Lake Bachotek) were provided in reference to earlier studies (Choiński et al., 2015; Wrzesiński et al., 2015; Ptak et al., 2019b,2020) based on monitoring of ice phenomena conducted by the Institute of Meteorology and Water Management – National Research Institute. Ice cover start and end dates are defined as the first and last dates when the lake is completely ice-covered.

2.2. Air2water model

The *air2water* model is a parsimonious model for LSWT prediction, which uses only AT as external forcing (Piccolroaz et al., 2013; Piccolroaz, 2016). Due to its simplicity and high accuracy, it has been widely used for LSWT predictions in many lakes worldwide (Toffolon et al., 2014; Piccolroaz et al., 2015, 2018, 2020; Javaheri et al., 2016; Schmid and Köster, 2016; Czernecki and Ptak, 2018; Prats and Danis, 2019; Flaim et al., 2020; Piccolroaz et al., 2020; Zhu et al., 2020b; Calamita et al., 2021). When tested using different AT datasets (in-situ, gridded, and modeling data), the model has been shown to produce consistent LSWT projections irrespective of the AT dataset used to drive the model (Piccolroaz et al., 2018). In fact, *air2water* is a data-driven model where the value of the calibrating parameters are derived from observations. This makes the model highly versatile and its successful use possible even when using coarse gridded datasets with resolution larger than 0.5°–1° (Piccolroaz et al., 2018).

The *air2water* model is based on the volume-integrated heat balance of the surface mixed layer of the lake. Through simple linearization of the heat flux terms using Taylor expansion (Piccolroaz et al., 2013), and using AT as a proxy for the integrated effect of the relevant processes and fluxes (Livingstone and Padisák, 2007), the volume-integrated heat balance equation reduces to a simple ordinary differential equation depending on AT, LSWT and a number of parameters summarizing the main climatic and thermo-physical properties of the lake (Piccolroaz et al., 2013; Piccolroaz, 2016). In this study we used the 6-parameter version of the model, which recently has been successfully applied by Piccolroaz et al. (2020) in a global reconstruction of twentieth century LSWT. This global application showed good performance for lakes located in snow and polar climate regions, thus motivating the use of this version of the model for the present climate change study. The *air2water* model in its 6-parameter version reads as follows:

$$\frac{dT_w}{dt} = \frac{1}{\delta}\left[a_1 + a_2 T_a - a_3 T_w + a_5 cos\left(2\pi\left(\frac{t}{t_y} - a_6\right)\right)\right] \tag{1}$$

$$\delta = \begin{cases} \exp\left(-\frac{T_w - T_h}{a_4}\right) \text{ for} T_w \geq T_h \\ 1 \text{ for} T_w < T_h \end{cases} \tag{2}$$

where t is time (expressed in days), t_y is the duration of the year (in days), T_w is LSWT, T_a is AT, T_h is a reference value for the deep lake temperature, δ is a dimensionless term representing the ratio between the volume of the surface lake layer and a reference volume, and a_1–a_6 are model parameters resulting from linearization of the heat flux terms (see Piccolroaz et al., 2013 and Piccolroaz, 2016 for details). The dimensionless depth δ is a time-varying term that quantifies thermal stratification through the difference between surface and deep water temperatures. According to the empirical relationship in Eq. (2), δ ranges from 0 to 1, with values decreasing for increasing temperature difference (i.e., thermal stratification) and δ approaching 1 when the lake is well mixed (i.e., when $T_w = T_h$). The value of T_h is fixed to 4 °C for dimictic lakes (i.e., lakes that mix completely twice each year), and to the minimum or maximum annual LSWT for warm and cold monomictic lakes (i.e., lakes that mix completely once each year), respectively. The inclusion of lake stratification through δ is the key term that distinguishes *air2water* from traditional statistical models and that has been proven to be crucial to satisfactorily predict LSWT dynamics.

Eq. (1) was solved with a daily time step, using the Crank-Nicolson method, and considering a lower bound of LSWT at 0 °C. The model parameters were calibrated using the Particle Swarm Optimization (PSO) algorithm (see Kennedy and Eberhart, 1995), using the observed LSWT data to infer the parameters' value. The PSO is an evolutionary, self-adaptive search optimization technique inspired by animal social behavior. This method is based on an iterative procedure that explores the hyperspace of parameters to converge to the set of parameters that minimizes the error between simulated and observed data (in this case LSWT). Detailed descriptions of the *air2water* model can be found in Piccolroaz et al. (2013) and Piccolroaz (2016).

The model was calibrated for each lake, using daily AT data measured at the nearest meteorological station (Fig. 1 and Table 1) as model input and observed LSWT as reference time series for computing model performance. Model performance was evaluated using the following three metrics, according to other water temperature prediction studies (e.g., Piccolroaz et al., 2018; Graf et al., 2019; Zhu et al., 2020b): Nash-Sutcliffe efficiency coefficient (NSE), the root mean square error (RMSE), and the mean absolute error (MAE).

$$NSE = 1 - \frac{\sum_{i=1}^{N}(T_M(i) - T_O(i))^2}{\sum_{i=1}^{N}\left(T_O(i) - \overline{T}_O\right)^2}. \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(T_M(i) - T_O(i))^2} \tag{4}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|T_M(i) - T_O(i)| \tag{5}$$

where N is the number of samples (i.e., daily averages), $T_O(i)$ and $T_M(i)$ are the observed and modeled daily water temperature values at time i, and $\overline{T}_O$ is the average value of T_O.

Model calibration and validation was performed using the historical AT and LSWT observational dataset (1987–2016). The available times series were divided into two subsets: 2/3 of the time series for model calibration, and the remaining 1/3 for model validation. The above metrics of model performance were evaluated for each lake and for both calibration and validation periods separately. A shorter validation period was preferred in favor of a more robust calibration of model parameters because the validity of *air2water* has already been demonstrated in several previous applications. In this regard, we refer to Piccolroaz (2016) for details about the model performance with different ratios between the number of data in calibration and validation. Model validation years were sampled every third year of the time series, thus allowing to evenly distribute calibration and validation years over the study period. In this way, possible long-term warming trends are included in the model calibration, making the optimization of the model parameters more robust.

2.3. Future climate data

Historical (1987–2005) and projected (2006–2100) AT data relative to the intermediate RCP4.5 and high RCP8.5 emission scenarios were obtained from the Coordinated Regional climate Downscaling Experiment CORDEX (www.cordex.org), an international coordinated effort under the auspices of the World Climate Research Programme. Specifically, CORDEX provides a collection of high-resolution regional climate simulations for different domains around the world, by dynamically downscaling the outputs of General Circulation Models (GCMs) using Regional Climate Models (RCMs). Regional downscaling plays an important role for the accurate assessment of local impacts and effective definition of regional adaptation plans. Indeed, while GCMs provide projections of how the climate may change in the future at the global scale, RCMs use these projections to provide information with greater detail and on smaller spatial scales.

In the present study, simulations for the European domain (EURO-CORDEX, https://euro-cordex.net/) at the spatial resolution of 0.44 degree (EUR-44, ~50 km) were downloaded from the Earth System Grid Federation (ESGF) node hosted by the German Climate Computing Centre (DKRZ, https://esgf-data.dkrz.de/projects/esgf-dkrz/). The EURO-CORDEX ensemble available for the emission scenarios and periods considered in this study consists of the nine different GCM-RCM combinations summarized in Table 2, that is all the available combinations relative to ensemble r1i1p1 and downscaling realization v1. Other emission scenarios were not considered since these would have drastically reduced the number of GCM-RCM combinations contemporaneously available for all the emission scenarios.

Despite the high grid resolution of the EUR-44 CORDEX product, possible biases remain due to epistemic and parametric errors, which suggests the need to further adjust RCMs outputs (Christensen et al., 2008). Notwithstanding, previous studies demonstrated good performance of CORDEX products for limnological applications (Mailhot et al., 2019; Shatwell et al., 2019; Musie et al., 2020) and for climate change studies in Poland (Romanowicz et al., 2016; Mezghani et al., 2017; Piniewski et al., 2017). In order to account for the possible under-representation of AT from the climate models, the "change factor method" (Diaz-Nieto and Wilby, 2005; Minville et al., 2008) was used to downscale the future AT scenarios. This downscaling method allows for adjusting future projections of a climate variable for which *in situ* observations are available during a historical period (h) by simply adding projected changes in such climate variable relative to the same baseline period, h, to the historical *in situ* observed climatological year. Hence, for each lake

Table 2
List of the CORDEX EUR-44 ensemble of simulations used in the present study.

Model Combination ID	GCM Institute	GCM	RCM Institute	RCM
1	CNRM-CERFACS	CNRM-CM5	CNRM	ALADIN53
2	CNRM-CERFACS	CNRM-CM5	HMS	ALADIN52
3	CNRM-CERFACS	CNRM-CM5	RMIB-UGent	ALARO-0
4	CNRM-CERFACS	CNRM-CM5	SMHI	RCA4
5	ICHEC	EC-EARTH	KNMI	RACMO22E
6	IPSL	IPSL-CM5A-MR	IPSL	INERIS-WRF331F
7	MPI-M	MPI-ESM-LR	CLMcom	CCLM4-8-17
8	MPI-M	MPI-ESM-LR	MPI	CSC-REMO2009
9	MPI-M	MPI-ESM-LR	SMHI	RCA4

and for the generic climate model and emission scenario, we extracted the modeled AT ($T_{a,mod}$) from the grid cell containing the barycenter of that lake and we computed the adjusted AT time series in the year y (T_a^y) as follows:

$$T_a^y = \overline{T}_a^h + \left(T_{a,mod}^y - \overline{T}_{a,mod}^h\right) \tag{6}$$

where $T_{a,mod}^y$ is the predicted daily AT time series in the year y for the given climate model and emission scenario, and $\overline{T}_a^h$ and $\overline{T}_{a,mod}^h$ are the observed (i.e., at the nearest meteorological station to the lake, see Table 1) and modeled climatological mean annual cycles (on daily basis) for the same historical period h, respectively. In the present case, y spans the period 2006–2100 (i.e., when climate models' projections are available), and the reference historical period h is 1987–2005 (i.e., the period covered by both observed and historical climate models' outputs). We note that, by construction, this approach is fully consistent with running the future climate scenarios using the model parameter values obtained for each lake from calibrating the model with the historical AT data measured at the corresponding meteorological station (see Table 1).

The expected long-term variations of AT and lakes' thermal behavior were analyzed in terms of anomalies, a standard and consolidated practice in climate change studies (e.g., Luterbacher et al., 2004; Hansen et al., 2012). While the international standard is to use a baseline period of 30 years for calculating anomalies, due to data limitation and for the sake of consistency the anomalies were evaluated comparing *air2water* projections under future scenarios with *air2water* simulations obtained using AT from climate models historical runs (i.e., 1987–2005), without loss of generality. Anomalies were calculated for each lake separately and to emphasize the inter-lake variability of LSWT expected for Polish lakes in the next century, the temperature anomalies were averaged across the different GCM-RCM combinations (multi-model average) while keeping the variability among the lakes. This choice was motivated by the wish to provide a combined and synthesized overview of the results, making it easily accessible also to policymakers and a non-scientific audience. For the sake of completeness, the full modeling outputs (file air2water_results.7z) and the future annual and seasonal trends of AT and LSWT for all the GCM-RCM combinations (Tables S1-S5) are available in the Supplementary Material.

3. Results

3.1. Model performance for the historical period

Table 3 summarizes the optimal values of the model parameters (a_1-a_6) along with the metrics of model performance (which we recall were calculated based on daily LSWT values) for each lake separately. In the calibration period, NSE values varied between 0.958 and 0.993 among the 25 lakes, with an average value of 0.982; RMSE values varied between 0.78 °C and 1.50 °C with an average value of 0.99 °C; MAE values varied between 0.62 °C and 1.12 °C with an average value of 0.76 °C. In the validation period, NSE values

Table 3
Estimated parameters, the root mean square error (RMSE), the mean absolute error (MAE) and Nash-Sutcliffe efficiency coefficient (NSE) for model calibration and validation.

Lake No.	Parameters						Calibration			Validation		
	a_1 (°C d^{-1})	a_2 (d^{-1})	a_3 (d^{-1})	a_4 (°C)	a_5 (°C d^{-1})	a_6 (-)	NSE	RMSE (°C)	MAE (°C)	NSE	RMSE (°C)	MAE (°C)
1	0.310	0.051	0.070	18.696	0.255	0.516	0.989	0.777	0.617	0.991	0.712	0.551
2	0.203	0.034	0.050	15.917	0.181	0.507	0.977	1.066	0.875	0.976	1.129	0.862
3	0.154	0.082	0.093	18.455	0.221	0.466	0.963	1.343	1.008	0.967	1.268	0.956
4	0.365	0.168	0.197	13.943	0.494	0.482	0.968	1.229	0.924	0.967	1.257	0.946
5	0.874	0.247	0.314	15.450	0.944	0.500	0.970	1.189	0.928	0.973	1.146	0.899
6	0.138	0.037	0.042	14.603	0.089	0.477	0.958	1.502	1.122	0.952	1.594	1.173
7	0.125	0.028	0.037	8.233	0.083	0.524	0.981	0.919	0.714	0.983	0.867	0.677
8	0.106	0.025	0.030	8.231	0.068	0.507	0.983	0.906	0.681	0.984	0.877	0.680
9	0.148	0.035	0.043	9.951	0.110	0.524	0.993	0.996	0.764	0.992	1.098	0.785
10	0.219	0.041	0.052	13.284	0.165	0.498	0.988	0.834	0.635	0.985	0.922	0.688
11	0.196	0.044	0.054	13.377	0.174	0.510	0.987	0.883	0.672	0.987	0.886	0.683
12	0.203	0.054	0.062	20.093	0.194	0.474	0.978	1.169	0.877	0.977	1.210	0.933
13	0.108	0.033	0.037	9.270	0.089	0.500	0.980	1.063	0.810	0.980	1.067	0.809
14	0.140	0.037	0.045	10.248	0.116	0.560	0.988	0.834	0.623	0.988	0.818	0.627
15	0.346	0.131	0.149	14.374	0.372	0.490	0.987	0.879	0.685	0.986	0.919	0.719
16	0.220	0.055	0.068	15.483	0.217	0.510	0.988	0.851	0.641	0.990	0.798	0.601
17	0.239	0.066	0.083	18.648	0.262	0.503	0.982	1.003	0.724	0.988	0.863	0.659
18	0.113	0.042	0.049	10.943	0.120	0.508	0.985	0.903	0.657	0.986	0.883	0.672
19	0.149	0.033	0.041	8.964	0.123	0.505	0.988	0.845	0.659	0.988	0.841	0.658
20	0.131	0.037	0.044	10.328	0.106	0.489	0.988	0.818	0.641	0.989	0.789	0.625
21	0.159	0.028	0.036	9.686	0.134	0.502	0.974	1.272	0.828	0.983	1.015	0.785
22	0.162	0.042	0.049	13.016	0.133	0.501	0.988	0.852	0.655	0.988	0.854	0.676
23	0.135	0.041	0.045	11.292	0.102	0.489	0.987	0.888	0.689	0.987	0.874	0.716
24	0.146	0.042	0.047	10.598	0.110	0.494	0.986	0.900	0.697	0.987	0.882	0.717
25	0.161	0.037	0.043	9.407	0.109	0.526	0.984	0.954	0.740	0.982	1.048	0.825

ranged from 0.952 to 0.992 (average value: 0.982); RMSE values ranged from 0.71 °C to 1.59 °C (average value: 0.99 °C); MAE values ranged from 0.55 °C to 1.17 °C (average value: 0.76 °C). In both the model calibration and validation periods, NSE values for all the lakes were close to unity and in any case larger than 0.950, indicating high performance of the *air2water* model (i.e., small residual variance compared to the observed data variance). In addition, both RMSE and MAE were lower than 1.00 °C on average and did not show meaningful differences between calibration and validation periods, indicating robust identification of model parameters and overall good accuracy of the predicted LSWT values.

The results of the model performance are graphically summarized in Fig. 2, which shows the heat map-scatter plot between observed and simulated daily LSWT in the calibration and validation periods for all the lakes together. All the points are well aligned along the 1:1 line, with low dispersion as indicated by the heat map (color), and with absence of any visible bias depending on LWST. Only a minor systematic deviation is recognizable for lower LSWT (i.e., lower than about 2 °C), where the model slightly underestimates observations.

3.2. Long-term trends and lakes' thermal sensitivity to climate change

Lake surface water temperatures in the future scenarios were projected using the calibrated *air2water* model for each lake. In this section, we provide an analysis of the results in terms of mean annual and seasonal AT and LSWT trends, and we use the model's output to characterize lakes' thermal sensitivity to climate change. Table S1 summarizes the warming rates (°C per decade) of the projected mean annual AT and LSWT for each lake under the two scenarios (RCP4.5 and RCP8.5), while the seasonal warming rates for spring, summer, autumn and winter AT and LSWT for each lake are listed in Tables S2-S5. Seasons were defined as follows: JFM – January-February-March (Winter), AMJ – April-May-June (Spring), JAS – July-August-September (Summer), OND – October-November-December (Autumn). As commented above, in the following analysis we averaged the AT and LSWT trends from the nine GCM-RCM combinations obtaining a representative and compact overview of the expected long-term trends, while the trends for each lake and climate model are available in Tables S1-S5 and the raw modeling outputs are made accessible in the Supplementary Material (file air2water_results.7z).

Annual average (Table S1): For the scenario RCP4.5, with the warming rates of AT varying between 0.11 °C per decade and 0.32 °C per decade (average value: 0.21 °C per decade), LSWT is expected to warm by 0.15 °C per decade (range: 0.06–0.24 °C per decade). For the scenario RCP8.5, with the warming rates of AT varying between 0.33 °C per decade and 0.56 °C per decade (average value: 0.44 °C per decade), LSWT is expected to warm by 0.34 °C per decade (range: 0.22–0.45 °C per decade).

JFM (Table S2): For the scenario RCP4.5, with the warming rates of ATs varying between 0.16 °C per decade and 0.47 °C per decade (average value: 0.29 °C per decade), LSWT is expected to warm by 0.15 °C per decade (range: 0.07–0.26 °C per decade). For the scenario RCP8.5, with the warming rates of ATs varying between 0.34 °C per decade and 0.86 °C per decade (average value: 0.54 °C per decade), LSWT is expected to warm by 0.35 °C per decade (range: 0.23–0.52 °C per decade).

AMJ (Table S3): For the scenario RCP4.5, with the warming rates of ATs varying between 0.09 °C per decade and 0.45 °C per decade (average value: 0.22 °C per decade), LSWT is expected to warm by 0.21 °C per decade (range: 0.09–0.45 °C per decade). For the scenario RCP8.5, with the warming rates of ATs varying between 0.20 °C per decade and 0.72 °C per decade (average value: 0.36 °C per decade), LSWT is expected to warm by 0.36 °C per decade (range: 0.17–0.72 °C per decade).

JAS (Table S4): For the scenario RCP4.5, with the warming rates of ATs varying between 0.04 °C per decade and 0.35 °C per decade (average value: 0.14 °C per decade), LSWT is expected to warm by 0.12 °C per decade (range: 0.03–0.31 °C per decade). For the scenario RCP8.5, with the warming rates of ATs varying between 0.24 °C per decade and 0.63 °C per decade (average value: 0.42 °C

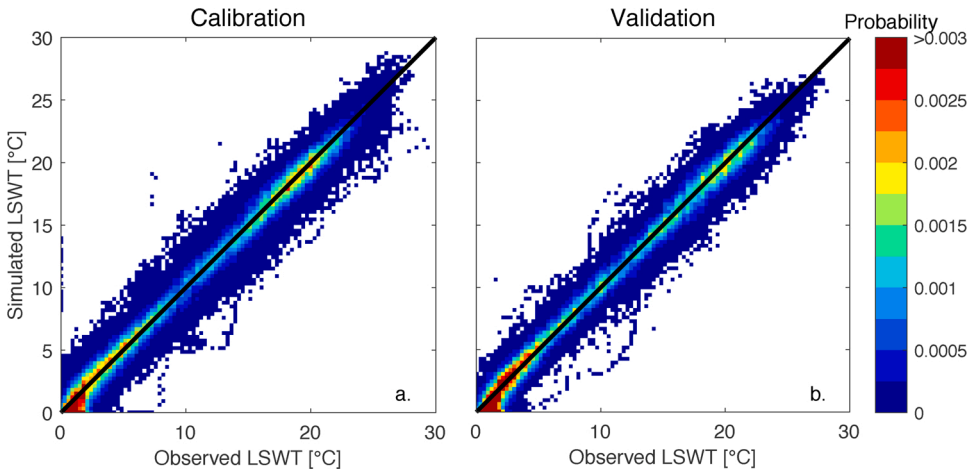

Fig. 2. Heat map-scatter plot between observed and simulated daily lake surface water temperature (LSWT) in (a) calibration and (b) validation periods for all lakes. The color indicated the density probability (i.e., number of points falling in each cell, divided by the total number of points). The black line is the 1:1 line.

per decade), LSWT is expected to warm by 0.34 °C per decade (range: 0.18–0.54 °C per decade).

OND (Table S5): For the scenario RCP4.5, with the warming rates of ATs varying between 0.07 °C per decade and 0.27 °C per decade (average value: 0.18 °C per decade), LSWT is expected to warm by 0.11 °C per decade (range: 0.04–0.18 °C per decade). For the scenario RCP8.5, with the warming rates of ATs varying between 0.35 °C per decade and 0.58 °C per decade (average value: 0.44 °C per decade), LSWT is expected to warm by 0.30 °C per decade (range: 0.21–0.39 °C per decade).

Overall, the projected warming rates of LSWT are lower than those of AT for the mean annual and the four seasons (Tables S1-S5) although in spring LSWT in some lakes is projected to warm at similar or higher rates than AT (Table S3). For both scenarios (RCP4.5 and RCP8.5), the highest warming rates of LSWT are obtained in spring (AMJ) followed by winter (JFM), while the seasons with the lowest LSWT warming rates are summer (JAS) and fall (OND).

Boxplots summarizing AT and LSWT long-term trends at monthly scale for all lakes are presented in Fig. 3 (panels a, b, d, and e). The analysis of the single months confirms the seasonal long-term LSWT trends discussed above. The shape of the monthly AT warming rates between the two emission scenarios is overall similar, except that in the RCP4.5 scenario the minimum AT warming trend is expected in August while in the RCP8.5 scenario in May. The effect on the resulting LSWT trends is the absence of a second warming peak in late summer under the RCP4.5 scenario, which on the contrary is expected under the RCP8.5 scenario. More important, the intra-annual distribution of monthly LSWT warming rates is substantially different compared to that of the driving AT warming rates (Fig. 3 panels b and c vs panels a and b). This is primarily motivated by the seasonality of lakes' stratification that determines lakes' thermal inertia and hence, together with ice dynamics, shapes the LSWT response to changes in AT (Piccolroaz et al., 2015; Zhong et al., 2016; Shatwell et al., 2019). In particular, while AT in winter months (from January to March) shows the highest warming

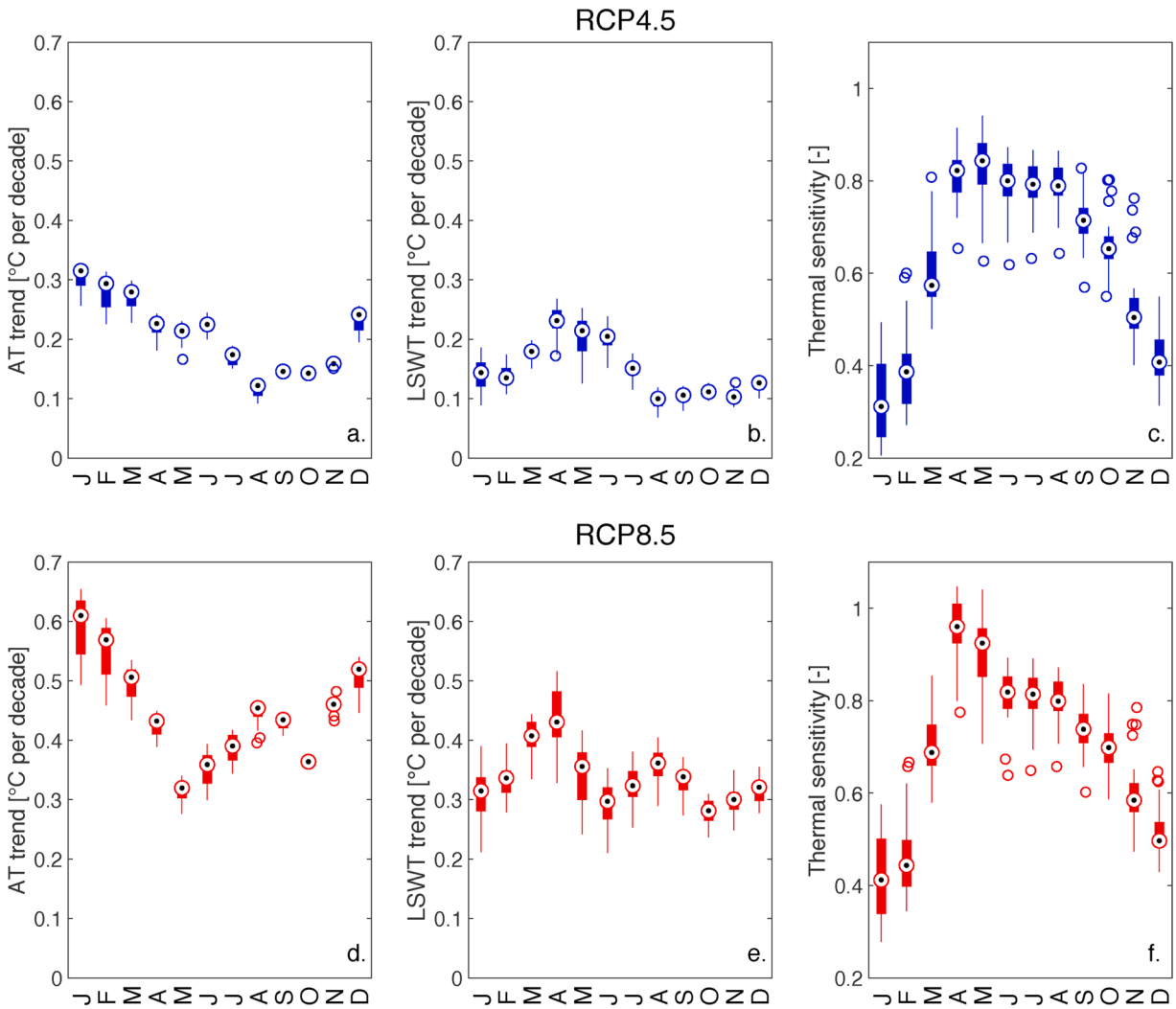

Fig. 3. Boxplots of (a), (d) air temperature (AT) trends, (b), (e) lake surface water temperature (LSWT) trends, and (c), (f) lakes' thermal sensitivity at monthly scale. Thermal sensitivity is defined as the slope of the regression line (without intercept) between LSWT and AT monthly anomalies. Subplots (a)-(c) are relative to scenario RCP4.5, and subplots (d)-(f) to scenario RCP8.5.

trends, a contextual marked LSWT response is not evident as a consequence of the weak stratification hence large thermal inertia and insulating effect of the ice cover when present (see also Fig. 8 and the Discussion section). The combination of these two factors makes the lakes less thermally sensitive in this period of the year.

According to Piccolroaz et al. (2020), lake thermal sensitivity to changes in AT was evaluated for each lake as the slope of the regression line (without intercept) between LSWT and AT monthly anomalies (evaluated relative to the reference period 1987–2005), and is shown in Fig. 3c and f. This metric summarizes the reactivity of LSWT to changes in AT and clearly indicates low thermal sensitivity (resiliency, values <0.6) of lakes in winter (JFM) and autumn (OND), compared to a larger thermal sensitivity (values ~ 0.8) in spring and summer.

The time series of AT and LSWT mean annual anomalies relative to the reference period 1987–2005 are presented in Fig. 4, for both the RCP4.5 and RCP8.5 scenarios. The AT warming predicted for the next century is expected to be followed by a contextual progressive warming of LSWT, although LSWT is expected to warm less than AT in both scenarios (the LSWT long-term trends being 72 % and 76 % of the AT long-term trends under scenarios RCP4.5 and RCP8.5, respectively).

3.3. The impact of climate change on LSWT extremes, mixing regime, and ice cover

In this section, the projected LSWT are analyzed to gather insights into how lakes' thermal dynamics are expected to be impacted by future warming.

For each lake, we identified the 50th, 90th, and 99th percentiles of LSWT during the reference period 1987–2005 and evaluated how the number of days in a year with LSWT above these reference thresholds is expected to change in the future. The first percentile is the median of annual LSWT, thus is the value of LSWT that has been exceeded half of the time during the reference period, while statistical thresholds ranging from 90th to 99th percentiles are typically used to define extreme conditions (McPhillips et al., 2018). The expected anomalies' trends averaged across lakes are shown in Figs. 5 and 6 for the 50th and 99th percentiles, respectively (for the sake of conciseness, the results for the 90th percentile are not shown but only commented below). While the LSWT values associated to the two percentiles are lake dependent (Figs. 5a and 6 a), the future trends are coherent: the variability (i.e., confidence band) across lakes is relatively small and a progressive increase of the number of days with LSWT above these thresholds is evident. For both

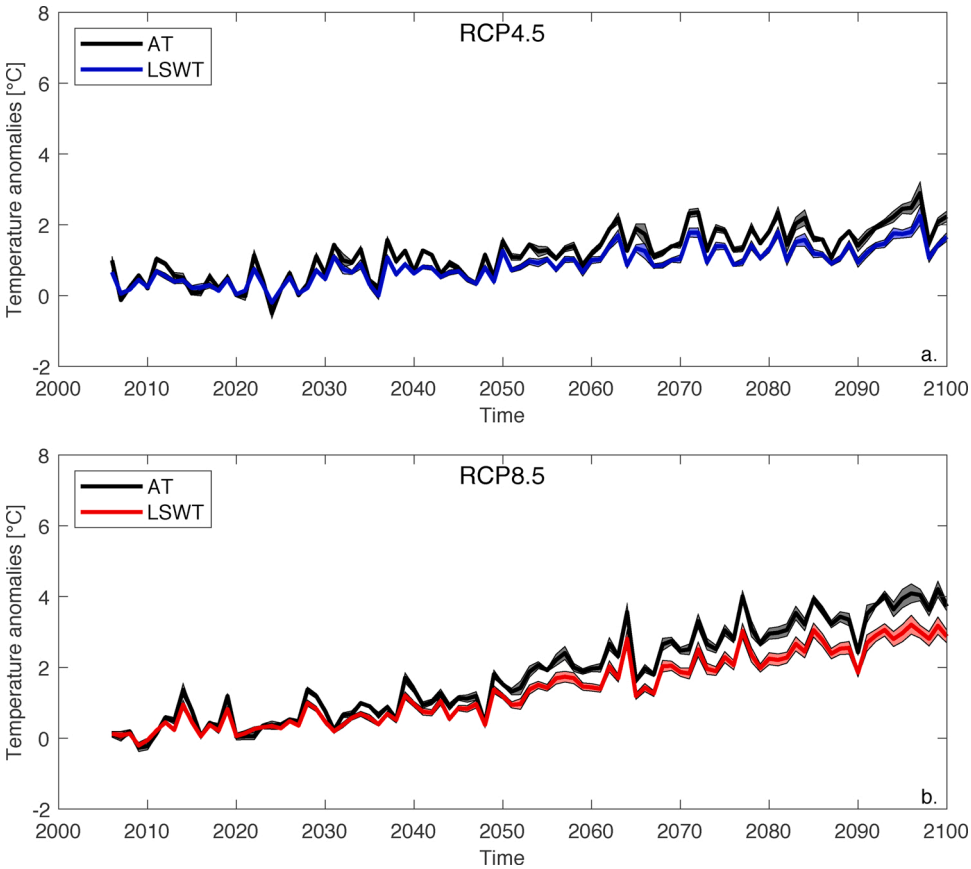

Fig. 4. Time series of air temperature (AT) and lake surface water temperature (LSWT) mean annual anomalies during the 21st century: (a) scenario RCP4.5, (b) scenario RCP8.5. Anomalies are relative to the reference period 1987-2005. The confidence band indicates the standard deviation of anomalies among the studied lakes.

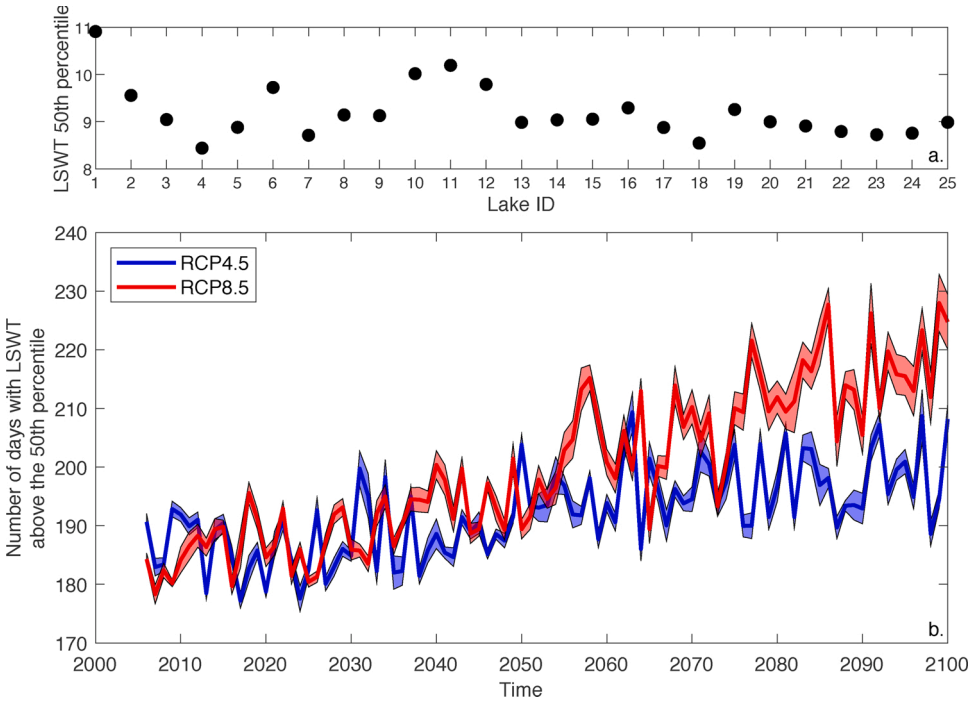

Fig. 5. Number of days with lake surface water temperature (LSWT) above the 50th percentile value of the historical period (1987-2005): (a) LSWT 50th percentile for each lake, (b) number of days with LSWT above the 50th percentile during the 21st century. The confidence band indicates the standard deviation of anomalies among the studied lakes.

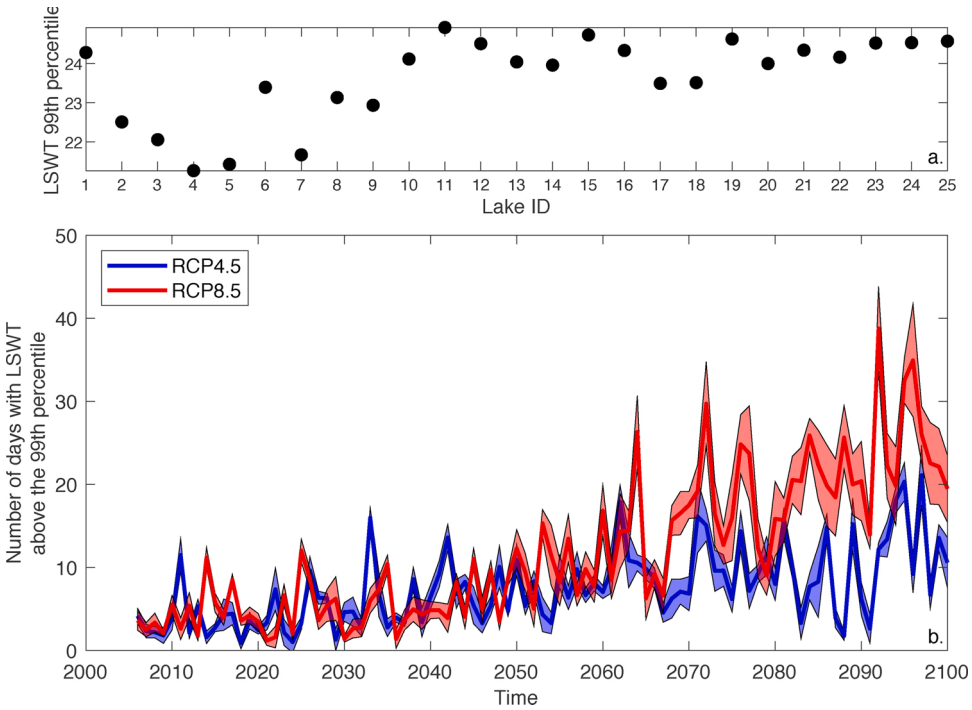

Fig. 6. Number of days with lake surface water temperature (LSWT) above the 99th percentile value of the historical period (1987-2005): (a) LSWT 99th percentile for each lake, (b) number of days with LSWT above the 99th percentile during the 21st century. The confidence band indicates the standard deviation of anomalies among the studied lakes.

percentiles, the expected trends are comparable between the two scenarios until around 2050, while afterwards the RCP8.5 scenario is characterized by faster trends, according to the stronger AT warming in the second half of the century relative to the RCP4.5 scenario (see e.g., Fig. 4). As a consequence, in the last decade of the century we expect that under the RCP4.5 scenario the number of days per year with LSWT warmer than the current median value will increase by 17 ± 2 days (i.e.,+9 ± 1%), versus an increase of 35 ± 5 days (i.e., +19 ± 2%) under the RCP8.5 scenario (Fig. 5). More relevant for the aquatic ecosystem and from a water resources perspective, the number of days per year with LSWT warmer than what nowadays can be defined an extreme event (i.e., the 99th percentile), is expected to increase by 9 ± 1 days (i.e., +235 ± 41 %) and 21 ± 4 days (i.e., +582 ± 98 %) under the RCP4.5 and RCP8.5 scenarios, respectively. When considering the number of days above the 90th percentile of LSWT during the reference period, they are expected to increase by 25 ± 3 days (i.e., +67 ± 8%) and 48 ± 4 days (i.e., +130 ± 8%) respectively under the RCP4.5 and RCP8.5 scenarios by the end of the century.

All the lakes considered in the analysis are dimictic, meaning that LSWT crosses the temperature of maximum density equal to about 4 °C (at atmospheric pressure) two times per year, in spring when lakes stratify, and in fall when they mix before inverse stratification in winter. Accordingly, we defined the winter inverse stratification period as the period when LSWT is colder than 4 °C (McCormick, 1990), and evaluated how the number of days characterized by inverse stratification conditions will change in the future. The anomalies relative to past (1987–2005) conditions when inverse stratification was 121 ± 5 days per year, on average, are shown in Fig. 7. For both scenarios, the number of days with LSWT below 4 °C present clear decreasing trends, indicating a progressive shortening of the inverse stratification period, hence a contextual lengthening of summer stratification. On average, winter inverse stratification is expected to be 37 ± 4 days (i.e., -31 ± 4%) and 64 ± 10 days (i.e., -53 ± 11 %) shorter in the last decade of the 21st century relative to current conditions, under the RCP4.5 and RCP8.5 scenarios respectively.

Finally, results allowed for the projection of how the number of annual ice-covered days will change in the future. Here, the number of ice cover days were defined as the days with LSWT < 1.5 °C (to account for both the fact that LSWT in winter was measured below ice and for model limitations in simulating the ice cover, further hampered by the use of AT from historical climate models' runs), which provided a RMSE between simulated and observed ice cover duration of 13 days during the reference historical period 1987–2005. The comparison between observed and modelled ice cover duration is provided in Fig. 8, which also shows the projected future trends for the decades 2040–2050 and 2090–2100. While under current conditions all lakes are ice-covered in winter, under the RCP4.5 scenario the ice cover period will reduce by 22 ± 2 % by middle of the century and by 60 ± 12 % by the end of the century, with a long-term trend of -3.7 ± 1 days per decade. The projected shortening of the ice cover period is more severe under the RCP8.5 scenario, with the number of ice cover days reducing by 36 ± 7% by middle of the century and by 86 ± 7 % by the end of the century, with a long-term trend of -6.7 ± 1 days per decade that is expected to significantly shorten the ice-cover period in most of the lakes by the end of the century (10 ± 7 days per year in the last decade of the 21st century, to be compared to 68 ± 16 days per year under reference conditions).

4. Discussion

4.1. Model performance and limitations

The only input data required by the *air2water* model is AT, assumed as reasonable proxy for the overall external forcing (Livingstone and Padisák, 2007). Although this is certainly a simplification, the model explicitly includes the effect of the thermal inertia and of the stratification of the lake (through the dependence on LSWT in Eq. 1 and the well-mixed layer thickness defined in Eq. 2,

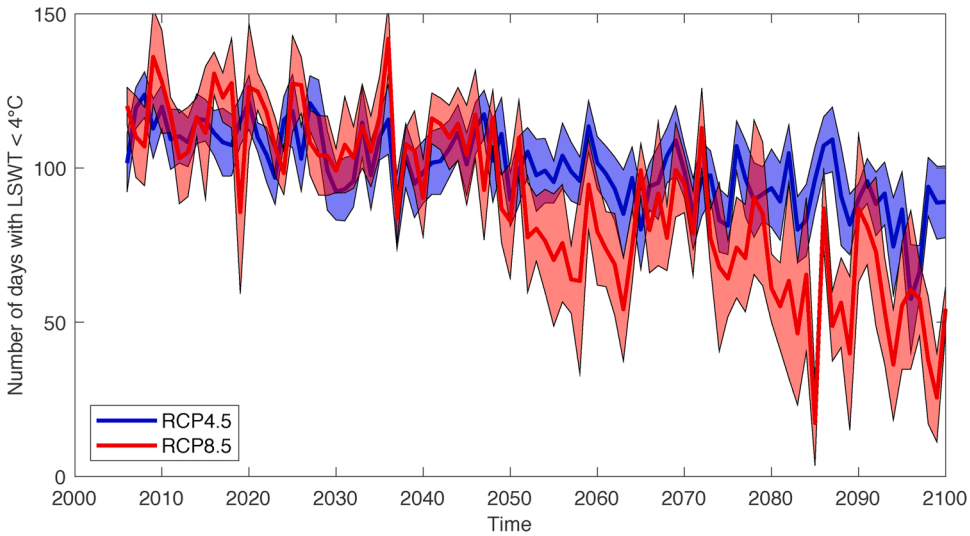

Fig. 7. Number of days with lake surface water temperature (LSWT) below 4 °C, during the 21st century.

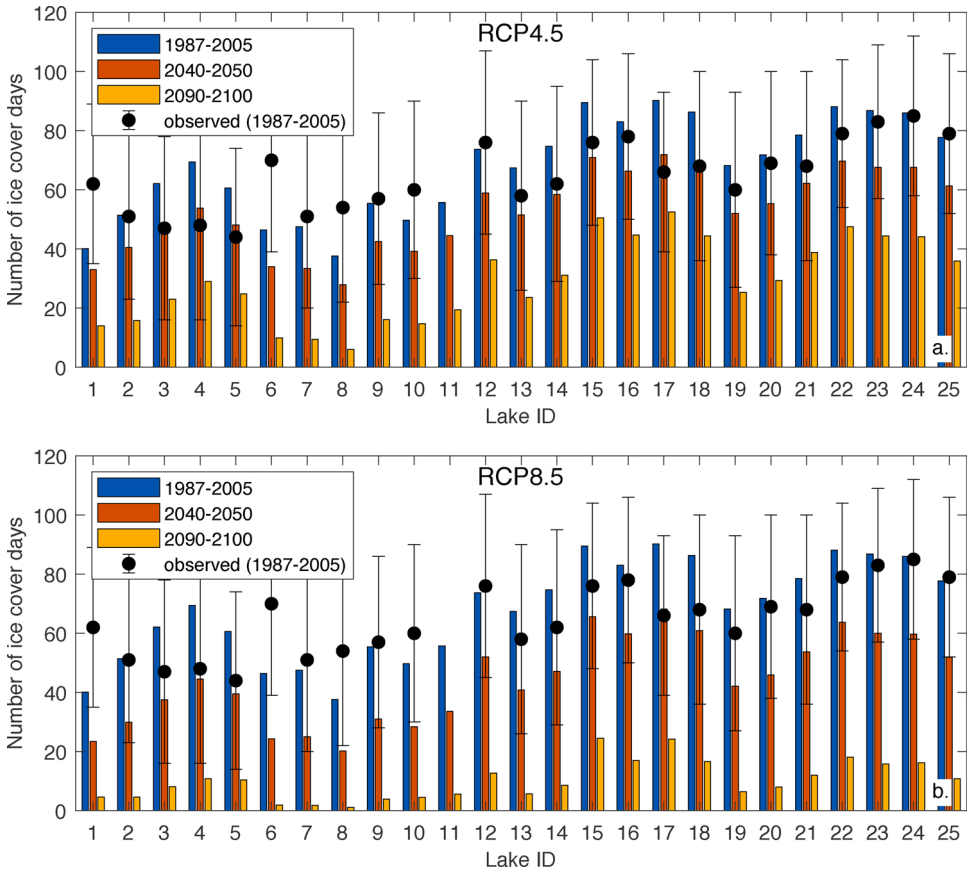

Fig. 8. Future trends in the number of ice cover days: (a) scenario RCP4.5, (b) scenario RCP8.5. The number of observed ice cover days for the historical period 1987-2005 are also shown in terms of mean ± standard deviation.

respectively). In addition, the contributions to the heat budget that are not directly dependent on AT and LSWT (such as solar radiation, wind speed, air humidity, etc.) are at least partially summarized by the sinusoidal term in Eq. 1. In this way, the *air2water* model shares the same simplicity and parsimony of statistical models, but its physically based derivation ensures high performance, comparable to that of more complex deterministic models (Toffolon et al., 2014; Piccolroaz, 2016). Indeed, the good performance and reliable predictions found in previous applications of the *air2water* model have also been confirmed in the present study, where we obtained daily RMSE and MAE lower than 1 °C on average both in calibration and in validation.

The results evidenced absence of any systematic bias between simulated and observed LSWT, except for a slight model underestimation around the lowest values of LSWT in winter (Fig. 2). In this respect, it should be noted that the observed LSWT only rarely approaches 0 °C due to sampling 0.4 m below ice cover in winter, while a lower bound at 0 °C was used in the *air2water* model in absence of any better estimate from the available data. Notwithstanding, the overall model performance is high and the lack of precise information on the timing of ice cover from the available LSWT observations (since measurements are taken 0.4 m below ice cover) did not preclude from identifying the duration of the ice cover period with reasonable accuracy (Fig. 8). Indeed, the RMSE is 13 days, corresponding to ∼19 % of the mean ice cover duration across lakes under current conditions, and smaller than the corresponding average standard deviation equal to 30 days. While the error in the duration of the ice cover period could have been reduced by considering lake-specific LSWT thresholds, for the sake of simplicity we preferred to consider a fixed 1.5 °C threshold (larger than 0 °C for the reason discussed above) for all lakes, which still provided estimated ice cover duration always within the confidence band of observations. In addition, the use of a fixed threshold allowed to identify an interesting clustering between lakes in the eastern and western part of Poland. The performance for lakes in the eastern zone (IDs 12–25; average RMSE ∼9 days) is higher than for lakes in the western side of Poland (IDs 1–10; average RMSE ∼17 days). The evident division into two zones reflects the features of transitional climate in the analyzed region. According to Woś (2010), the western part is under the influence of marine (warmer and more humid) climate, and the eastern part is dominated by continental (dry and colder) climate. The ice cover is therefore more dynamic and less persistent in the western region, hampering its precise prediction in the lakes located in this part of the country. This pattern is confirmed by the decrease in ice cover thickness and increase in ice cover duration observed when moving from East to West (Choiński et al., 2015), thus further explaining the higher RMSE values found in the western side of Poland.

Despite the overall good performance and reasonable model errors obtained in the present application of the *air2water* model, still the results are inevitably affected by some uncertainties and limitations. The absence of a physically based ice module in the *air2water*

model is certainly the first main limitation of the present application. A dedicated ice module is currently under development, and will be available soon. Second, the use of only one lake model limits the representation of plausible future lake temperature scenarios and may bias the results due to the unavoidable epistemic uncertainty. Expanding the present LSWT projections by using an ensemble of deterministic lake models is certainly advisable in a further development of the present study. In this regard, we do not advise the use of purely statistical models as they are deemed controversial in climate change applications (Piccolroaz et al., 2018, 2020). Finally, here we averaged the results obtained by applying the *air2water* model with AT from nine different GCM-RCM combinations. The drawbacks of considering multi-model averages have been commented in recent literature (Knutti et al., 2010; Madsen et al., 2017), and this may bias some analyses aimed at investigating the variability of extreme values. However, multi-model averages are still largely used in the literature (e.g., Knutti and Sedláček, 2013) and in reports by the Intergovernmental Panel on Climate Change (IPCC), IPCC (Stocker et al., 2013), as they have the advantage of providing a combined and synthesized overview of the results accessible also to a non-scientific audience. While here we preferred to push on the easy accessibility of the results to a larger audience, we suggest that further research efforts should be spent on properly quantifying the uncertainty stemming from the use of multiple climate and lake models. In this regard, Tables S1-S5 suggest that the variance of AT and LSWT future trends across the nine GCM-RCM combinations may be relevant. For example, when the mean annual trends are concerned (Table S1), the coefficient of variation (i.e., the ratio of the standard deviation to the mean) relative to the nine GCM-RCM combinations averaged across the 25 lakes is 27 % and 29 % for AT and LSWT respectively under the RCP4.5 scenario, and it is 16 % and 17 % for AT and LSWT respectively under the RCP8.5 scenario. These averaged values increase to a maximum of 47 % for AT and 46 % for LSWT when summer trends are considered under the RCP4.5 scenario, with peaks up to 59 % for AT in some lakes (Table S4). In general, inter-model variability increases moving from lakes located in the western (warmer and more humid) zone to lakes located in the eastern (colder and dry) zone of Poland (Tables S1-S5).

4.2. Future trends and lakes' thermal sensitivity

Lakes' thermal sensitivity to changes in AT has been found to be highly variable throughout the year, with spring and summer months being the most responsive to changes in AT (Fig. 3), confirming previous studies based on historical observations in other lakes (Winslow et al., 2017; Woolway et al., 2017; Toffolon et al., 2020). In particular, we found thermal sensitivity values equal to ~0.70 for annual means and between ~0.70−0.90 in spring and summer, coherently with studies of lake surface heat budgets (Schmid et al., 2014). On the other hand, lower thermal sensitivity (values <0.6) has been found for winter and autumn due to the weaker/absent thermal stratification (thus higher thermal inertia) and insulating effect of the ice cover (when present). We recall that the concept of lake thermal sensitivity used here is an indicator of the sensitivity of LSWT to changes in AT and should not be confused with a measure of the ratio between LSWT and AT long-term warming trends. In this regard, previous studies of other lakes around the world (Austin and Colman, 2008; O'Reilly et al., 2015; Piccolroaz et al., 2015) and in Europe (Woolway et al., 2017) found that LSWT warming can be faster than that of AT especially in summer and for deep and cold lakes (O'Reilly et al., 2015; Woolway and Merchant, 2017). Different explanations have been proposed for this amplified response of LSWT to AT including changes in the timing of lake stratification (Austin and Colman, 2007; Piccolroaz et al., 2015; Zhong et al., 2016), changes in large-scale climatic forcing such as solar radiation (Fink et al., 2014), variation of lake clarity (Rose et al., 2016), timing and duration of the ice cover (Austin and Colman, 2007; O'Reilly et al., 2016), but also the methodological approach and averaged indicators used in the data analysis (Toffolon et al., 2020).

The results of the present study showed that LSWT will warm at lower rates than AT in the future in all the investigated lakes and under both scenarios (warming at 72 % and 76 % than AT on average for RCP4.5 and RCP8.5, respectively; Fig. 4), coherently with previous modeling studies in other lakes (e.g., Butcher et al., 2015; Czernecki and Ptak, 2018; Shatwell et al., 2019). The projected

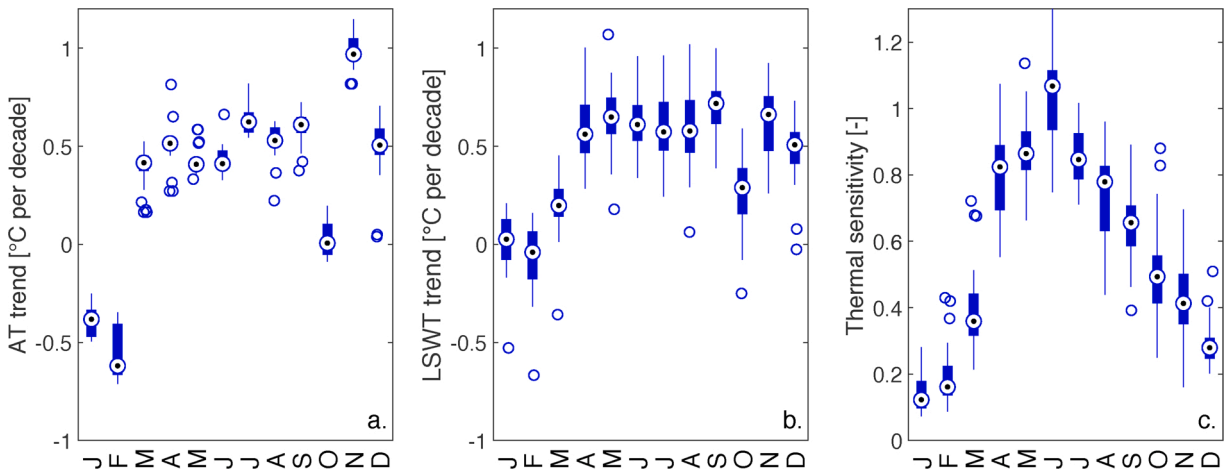

Fig. 9. Boxplots of (a) air temperature (AT) trends, (b) lake surface water temperature (LSWT) trends, and (c) lakes' thermal sensitivity at monthly scale relative to observed data in the period 1987-2016.

warming trends at both monthly and annual time scales throughout the 21st century are in agreement with projections for some lakes in north-eastern Germany, obtained using the lake model FLake under the RCP4.5 scenario (Shatwell et al., 2019). Specifically, in both cases the modeling projections suggest that the study lakes will warm predominantly in spring and winter (determining a shortening of inverse stratification and ice cover periods), and to a lower extent in summer and autumn, as a consequence of the seasonal pattern of AT trends expected in the future (Fig. 3). The results are coherent also with previous estimates obtained for some of the study lakes by Czernecki and Ptak (2018) using an empirical-statistical model for LSWT, which projected similar annual LSWT trends and lower warming rates of LSWT compared to AT. However, when looking at the seasonal pattern of the expected warming rates, the results by Czernecki and Ptak (2018) do not agree with what shown in the present study (and in Shatwell et al., 2019 for the contiguous German lakes). The reason is likely attributable to the coarser resolution of GCMs projections used in that previous study (ranging between 0.5° and 4°, then linearly interpolated at 0.25°), which is expected to introduce larger inaccuracies especially in the regions at the border between sea and land where most of the study lakes are located.

When comparing the future warming trends (Fig. 3) with those observed in the recent period for which LSWT observations are available (1987–2016; Fig. 9), interesting considerations can be drawn. The mean annual LSWT warming rate expected under scenario RCP4.5 (0.15 °C per decade) will be lower than what observed in the period 1987–2016 (0.44 °C per decade), according to a milder warming of AT expected for this scenario (0.21 °C per decade) compared to past AT observations (0.34 °C per decade). Higher LSWT warming (0.34 °C per decade) is expected under the RCP8.5 scenario due to larger AT warming (0.44 °C per decade), but still the projected LSWT warming trend is expected to be lower than that observed in recent decades. The large warming observed in 1987–2016 is coherent with the substantial LSWT warming occurred since the 1980s worldwide (Piccolroaz et al., 2020), including Europe (Woolway et al., 2017), as a consequence of an abrupt shift in the climate. During this period, the observed LSWT trend was larger than that of AT, consistently with what observed in similar studies (Woolway et al., 2017; Czernecki and Ptak, 2018). This condition is not expected in the future, primarily because of a seasonal shift in the AT warming patterns relative to past conditions. Indeed, the largest AT warming is expected in the winter months (both scenarios, particularly in January and February; Fig. 3a and d), compared to past conditions when it was occurring during the rest of the year (Fig. 9a). The future AT warming is therefore not expected to be followed by an equally intense LSWT warming, since in the winter period the insulating effect of the ice cover and the large thermal inertia due to weak stratification reduce lakes thermal sensitivity (Figs. 3c and f and 9 c) and hence inhibit the LSWT response to warming AT (Fig. 3b and e). In general, the different pattern of future AT warming trends compared to past conditions (Fig. 3a and d vs Fig. 3a) is expected to alter the seasonal pattern of lakes' thermal sensitivity (Fig. 3c, f vs Fig. 9c) through changing stratification and ice cover timing and duration. For example, under the RCP8.5 scenario, the substantial shortening of the ice cover and inverse stratification periods (Figs. 7 and 8), is expected to progressively increase the lakes' thermal sensitivity in the winter period (Fig. 3f). Related to this, the projected shortening of the ice cover duration under the RCP8.5 scenario (6.7 ± 1 days per decade) is expected to be larger than that observed in the period 1961–2010 by Choiński et al. (2015) and quantified in 5.6 days per decade.

Finally, while under both scenarios no lakes are projected to undergo a regime shift from dimictic to warm monomictic (i.e., lakes mixing once per year; Fig. 7), under the more severe RCP8.5 scenario the projected halving of the number of days with LSWT staying below 4 °C relative to reference conditions suggests that this scenario may lead to serious consequences for the water quality and ecosystem health of these lakes.

4.3. Implications for management and conservation plans

The generally warmer LSWT and shortening of inverse stratification and ice cover periods projected under both scenarios are likely to have serious consequences for the aquatic life and water quality of the analyzed lakes, jeopardizing their ecological health and use as water resources (Tilzer and Goldman, 1978; Coloso et al., 2011; Leach et al., 2018). As an example, water temperature changes in the future may affect many fish species, especially with respect to their spatio-temporal distribution patterns (Pandit et al., 2017) and with particular concern for cold-water habitats (Williams et al., 2015). This is particularly true in light of the projected tendency of climate change towards shorter ice cover periods (Fig. 8) and intensification of high LSWT values (Fig. 6) in the future. These aspects should be carefully considered in medium- to long-term management and conservation plans of these lowland Polish lakes, as ignoring the rate of climatic change could result in ineffective restoration plans (Lin et al., 2017). Being able to design effective management and conservation plans is particularly relevant for the study lakes, given their strategic importance in many areas of the economy in northern Poland (tourism, agriculture, industry). In this regard, the results of the present study are expected to provide an useful support for local policymakers and authorities in charge of the management of these lakes in compliance with the water quality objectives set by the EU Water Framework Directive (2000/60/EC). Besides presenting an overview of the expected impact of climate change on LSWT, ice cover, and mixing dynamics for several lowland lakes in Poland, the present analysis is also aimed at being used as a reference for identifying the most vulnerable lakes where detailed studies should be focused. Similarly, the availability of climate change projections of lakes' thermal evolution are expected to be useful for prioritizing the numerous local level restoration projects aimed at preserving and improving the water quality of these lakes (Łopata et al., 2013; Gołdyn et al., 2014; Dondajewska et al., 2018; Kowalczewska-Madura et al., 2018; Grochowska et al., 2019), supporting the continuity of lake restoration programs in the future years, and helping to revise the undertaken and planned lake management projects in order to make them more effective. Finally, the outcome of the present study is also expected to be useful for ongoing governmental programmes (among others the plan of counteracting effects of droughts) aimed at facing the ongoing and forecasted water deficit. This is expected to become an increasing problem in Poland, where the country's water resources per inhabitant are among the lowest in Europe (Nowak and Ptak, 2018). One of the strategies to address this problem is the damming of existent lakes, reducing the outflows and increasing the available water resource. While this operation, if realized, is expected to further affect the lakes' thermal and mixing dynamics, knowing the expected impact of climate change on the

existing lakes is a fundamental pre-requisite for designing any future management plan going in this direction.

5. Conclusions

In this study, the *air2water* model was employed to forecast LSWT in 25 lowland lakes in Poland, under two future emission scenarios: RCP4.5 and RCP8.5. Projected AT time series from nine different GCM-RCM combinations provided by EUR-44 CORDEX (spatial resolution 0.44°) were used as model input to evaluate the impact of climate change on LSWT, ice cover, and mixing patterns. The analysis of results in terms of future (2006–2100) anomalies and long-term trends compared to past (1987–2005) conditions lead to the following conclusions:

(1) The *air2water* model performed well for LSWT forecasting for all the lakes, with average values of NSE, RMSE and MAE are 0.982, 0.99 °C and 0.76 °C in model calibration and validation. No systematic biases were introduced by the model, expect for a slight underestimation at low (i.e., close to 0 °C) temperatures, which however is attributable to the fact that in winter water temperature measurements are taken 0.4 m below the ice cover, hence are always slightly warmer than 0 °C (used as lower LSWT threshold in the model).
(2) The warming trends of both AT and LSWT projected under the future scenarios are expected to be lower than those observed in past decades (1987–2016), and with a different timing throughout the year as a result of different AT and, in turn, thermal stratification patterns. Particularly, AT is expected to warm the most in the winter period, while in the past decades the larger warming occurred during the rest of the year.
(3) Seasonal and monthly analysis showed that LSWT is expected to warm slower than AT throughout the 21st century (i.e., LSWT long-term trends being 72 % and 76 % than the corresponding AT trends for scenarios RCP4.5 and RCP8.5, respectively). The mean annual LSWT is expected to warm up to 0.15 °C per decade and 0.34 °C per decade under scenarios RCP4.5 and RCP8.5, respectively, on average across all lakes. In both cases, spring (AMJ) will be the season with the highest LSWT warming (0.21 °C per decade and 0.36 °C per decade, for the two scenarios respectively), while fall (OND) will be the season with the lower warming trend (0.11 °C per decade and 0.30 °C per decade, for the two scenarios respectively).
(4) The AT warming expected in winter months will contribute to shortening the inverse stratification and ice cover periods, particularly under the RCP8.5 scenario that, if realized, could seriously threaten lakes' mixing regime and the existence of the ice cover period. With AT warming projected for this scenario, inverse stratification is expected to reduce by 53 ± 11 % (64 ± 10 days) and the ice cover period by 86 ± 7% (6.7 ± 1 days per decade), by the end of the 21st century on average. For the milder RCP4.5 scenarios, the expected shortening of inverse stratification is quantified in 31 ± 4 % (37 ± 4 days) and that of the ice cover period in 60 ± 12 % (3.7 ± 1 days per decade), by the end of the 21st century on average.
(5) The low thermal sensitivity of lakes in winter due to the insulating effect of the ice cover and large thermal inertia associated with weak stratification conditions is expected to partially buffer the LSWT response to AT warming.
(6) All lakes are expected to undergo significant warming especially in the high range of LSWT, with a substantial increase in the number of days with LSWT above thresholds that nowadays can be defined as extreme events (i.e., 90th and 99th percentile). For example, the number of days per year with LSWT above the 99th percentile calculated for the reference period, are expected to increase by 9 ± 1 days (i.e., $+235 \pm 41$ %) and 21 ± 4 days (i.e., $+582 \pm 98$ %) under the RCP4.5 and RCP8.5 scenarios, respectively.

Though the *air2water* model performed well, it does not explicitly account for the effects of external forcing other than AT (such as solar radiation, wind speed, and air humidity). We therefore suggest that, as a further step, some efforts should be spent in validating the lakes' thermal dynamics projections presented here, complementing the present future projections with results from more sophisticated deterministic models. Notwithstanding, the results presented in this study provide useful insights about the future thermal dynamics of lowland lakes in Poland, which are expected to be beneficial for policymakers and authorities in charge of the management of lakes in Poland and possibly in other countries with similar lacustrine systems and climatic conditions.

CRediT authorship contribution statement

Sebastiano Piccolroaz: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration. **Senlin Zhu:** Funding acquisition, Conceptualization, Writing - review & editing. **Mariusz Ptak:** Data curation, Writing - review & editing. **Mariusz Sojka:** Data curation, Writing - review & editing. **Xinzhong Du:** Writing - review & editing.

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A. Supplementary data

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