The Evaporation Estimation on Lake Most

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INTRODUCTION

Evaporation is one of the main components of the water cycle in nature and it constitutes almost two-thirds of continental precipitation, e.g., (Brutsaert, 2015). However, since evaporation is a complex physical phenomenon, its measurement or calculation procedures are complicated and burdened with a high degree of uncertainty. It is important to note that the fume occurs both from the free water level and from the Earth's surface as well as plants, which leads to the introduction of terms such as evaporation, transpiration, or evapotranspiration.

Additionally, there exist several models for calculating the rate of evaporation, which can be divided into groups according to the provided inputs, e.g., temperature-based, radiation-based, mass-transfer based, and combined methods. Furthermore, within each group, there are many equations, which are widely cited in technical literature. This diversity motivated the Food and Agriculture Organization of the United Nations (FAO) to introduce the standardized approach in the form of the FAO Penman-Monteith equation (see Section 2 for details). Although this equation is considered to be an etalon for calculations, it is a very complicated relationship requiring a lot of input data, which are not always available or measurable in the area of interest. Therefore, many recent papers compare the results of the FAO method with other much simpler methods, which are based on less complicated relationships and computationally less demanding. For example, see (Tabari et al., 2011), (Benzaghta et al., 2012), or (Lang et al., 2017).

In our previous work (Dubovský et al., 2021), we compared several evaporation models providing the meteorological data on Lake Most. We observed that simplified models include always constants used for the approximation and the elimination of required inputs. However, these constants introduced by authors

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concerning their area of interest do not fit on Lake Most. We decided to optimally tune constants concerning results computed by FAO by the calibration process, see (Dlouhá, 2021).

In this paper, we summarize our work and present the comparison with the real-world measurements performed on the Lake Most. Section 2 consists of the description of the Lake Most and the data used in our computations as well as the overview of computational methodology. Section 3 presents the results, which are further discussed in Section 4. Finally, Section 5 concludes the paper.

METHODOLOGY OF RESEARCH

The Lake Most has been created by the hydric recultivation of the Most–Ležáky quarry in the central part of the North Bohemian brown coal basin. It is situated in the North of the Czech Republic near the city of Most (50°310N, 13°360E), see Fig. 1.

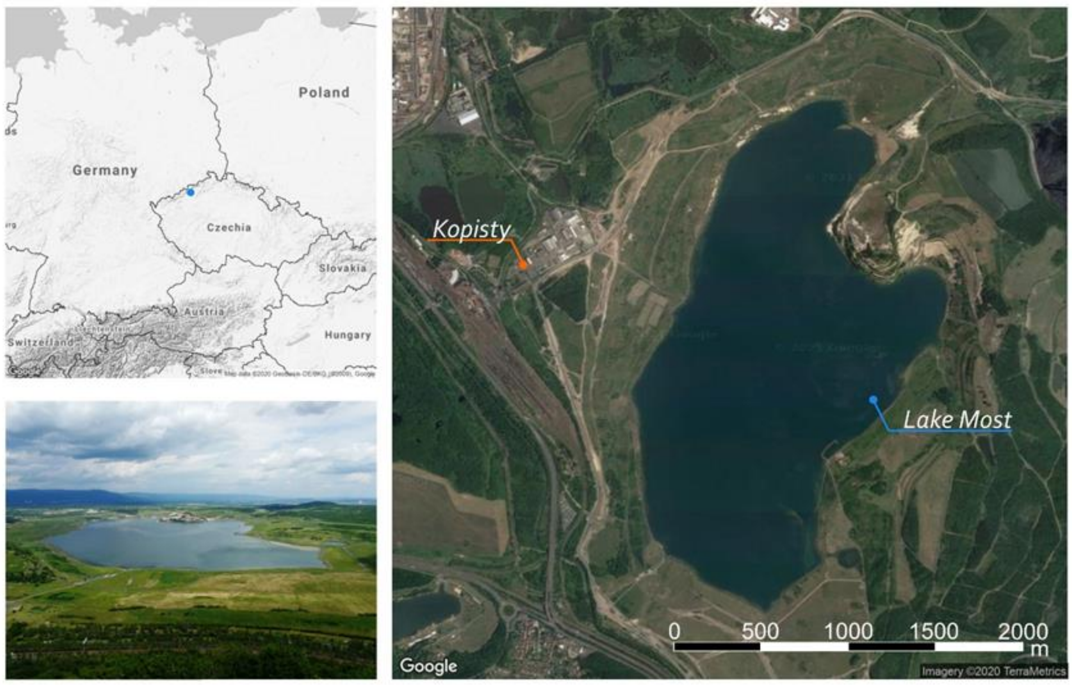

Fig. 1 Lake Most and the surrounding area

Source: Dlouhá et al., 2021

The former mine heavily affected the area of 1254 ha and the pit lake, as a part of its revitalization, was planned to have a surface area of about 300 ha. The lake can be considered as a closed system without natural inflow or outflow since several technical arrangements such as sealing the bottom of the future lake, construction of an underground sealing wall, and strengthening the shoreline have been performed before the flooding. The residual pit of the lake was filled through an artificial feeder during the period from 2008 to 2014 and in the final phase of lake filling, the surface level has risen to the required level of 199 m above sea level. After finishing up the filling process, Lake Most has an actual surface area of 309.4 ha, a coastal line length of 8.9 km, a total water volume of 70.5 million m^3, and a maximum depth of 75 m. The project of the revitalization is secured by the state enterprise Palivový kombinát Ústí (PKU, (pku.cz, 2021)).

The evaporation models used in our analysis require input meteorological data. Luckily, the Kopisty weather station operated by Czech Hydrometeorological Institute (CHMI) is situated approximately 1 km from the lake and the data are recorded at ten-minute intervals. In the comparison to meteorological data from the Czech Republic, the average temperature and precipitation in the area of Lake Most are with the temperature strongly above the average and precipitation strongly below normal precipitation, and with the number of hours of sunshine below the typical value in the Czech Republic (Tolasz, 2017). After the examination of all long-term available data, we can state that the average yearly temperatures and the daily hours of sunshine have an increasing tendency, while the precipitation remains stable.

All of the above-mentioned meteorological data influences the evaporation estimated by the FAO Penman-Monteith equation, see (Allen et al., 1998) and (Jensen and Allen, 2016). To be more specific, the equation is given by

$$E_{FAO} = \frac{0.408\Delta(R_n - G) + \gamma \dfrac{900}{T_a + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34 u_2)}, \tag{1}$$

where:

Δ is the slope of saturation vapour pressure curve [kPa·°C^{-1}],

γ is the psychrometric constant [m·s^{-1}],

u_2 is wind speed [m·s^{-1}],

T_a is the average air temperature [°C],

R_n is the net radiation [kJ·m^{-2}·s^{-1}],

G is the heat flow in the soil [MJ·m^{-2}·day^{-1}],

e_s with e_a is the current water vapour pressure and the mean saturation vapour pressure [kPa], respectively.

These data are provided by Kopisty station.

Although this model is recommended for modelling evaporation, its complexity is the main bottleneck. One must provide all of the input data measurements, which is not always possible; or these historical values are simply not available. Due to this fact, the simplified models introduce constants to neglect the influence of some input quantities. These constants have been obtained by a suitable calibration process. In our case, our future goal is to estimate the evaporation from the planned pit lakes which do not exist right now. They are farther from Kopisty and the meteorological data from Kopisty will be not sufficient. Our goal is the identification of a simplified model which requires the data which can be measured directly on the place, e.g., air temperature, wind speed, and humidity. These values can be used for computing the evaporation using the simplified model.

As an example, let us introduce the Hargreaves-Samani equation proposed in (Hargreaves, 1975) and gradually extended into the final form of (Hargreaves and Samani, 1985). The equation is given by

$$E_{HS} = \frac{0.0023 R_a (T_a + 17.8)\sqrt{T_r}}{\lambda}, \tag{2}$$

where:
T_a is the average air temperature [°C],
T_r is the difference between the maximal and minimal air temperature during the day [°C],
$\lambda = 2.45$ $MJ \cdot m^{-2} \cdot g^{-1}$ is the water specific heat capacity,
R_a is the theoretical extraterestrial radiation [$MJ \cdot m^{-2} \cdot g^{-1}$] computed from the latitude of area and the solar declination determined by the serial number of the day of the year.
In our previous work (Dubovský et al., 2021), we calibrate constants in equation (2) against the values computed by E_{FAO} with respect to Nash-Sutcliffe efficiency (NSE), (Nash and Sutcliffe, 1970). This statistical measure computes the distance between two models providing the value between 0 and 1. If the variance between models is equal to zero, then NSE is equal to one. Conversely, if one model produces a variance equal to the variance of the second one, then it results in an NSE of zero. The index shows how well the scatterplot of the observed and modelled data corresponds to a 1:1 straight line.
We solve the regression optimization problem

$$\theta^* = \arg\max_{\theta} \left(1 - \frac{\sum_{t=1}^{T} (E_{FAO}\langle t \rangle - E_{HS}^{\theta}\langle t \rangle)^2}{\sum_{t=1}^{T} (E_{FAO}\langle t \rangle - \bar{E}_{FAO})^2} \right), \tag{3}$$

where:
$t = 1, \dots, T$ is the index of the day, $E_{FAO}\langle t \rangle$ is the evaporation estimation computed using equation (1),

$$\bar{E}_{FAO} = \frac{1}{T} \sum_{t=1}^{T} E_{FAO}\langle t \rangle \tag{4}$$

is the mean value, and $E_{HS}^{\theta}\langle t \rangle$ is the estimated value of (2) with unknown parameters $\theta_1, \theta_2 \in \mathbb{R}$ representing the calibrated constants in parametric model given by

$$E_{HS}^{\theta} = \max\left\{0, \frac{\theta_1 R_a (T_a + \theta_2)\sqrt{T_r}}{\lambda}\right\}. \tag{5}$$

We extended model by projection to nonnegative numbers (using the outer max function) to enforce the computation of nonnegative evaporation.
For the calibration, we use the data from years 2014-2019 and to avoid the overfitting of the model, we adopt the K-fold cross-validation methodology (Stone, 1974). Since the objective function of (3) is independent of the order in time, we perform 10 random permutations of the data and we split each permutation into 10 parts - 9 of them is used for the calibration of the model and the remaining part is used for validation. We repeat this permutation 100 times and for each of this permutation we repeat 10 calibration-validation splitting. In

total, we obtain 1000 results of the calibration process, from which we identify the most probable optimal parameters taking the parameters of the model with the mean value of the objective function, see Fig. 2.

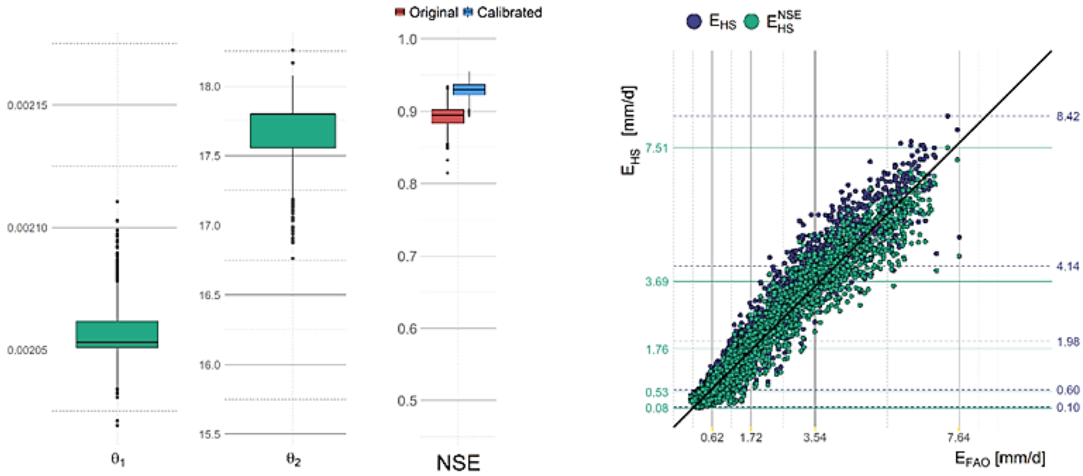

Fig. 2 The calibration of Hargreaves-Samani equation

Source: Dlouhá et al., 2021

In this figure, we present the distribution of optimal parameters with respect to splitting. To be more specific, the optimal calibrated Hargreaves–Samani model is given by

$$E_{HS}^{*} = \max\left\{0, \frac{0.0021 R_a (T_a + 17.5571)\sqrt{T_r}}{\lambda}\right\}. \qquad (6)$$

For more details, please, see (Dlouhá et al., 2021).

Additionally, throughout the filling of the lake, the operational data were monitored. These data contain the achieved altitude of the lake level, its area, the perimeter of

the shore-line, and the volume of refilled water. We define E_{lake} determined from the simplified balance equation, where we neglect other influences, such as ground and underground tributary or runoff. The equation is given by

$$E_{lake} = precipitation + artificial\ inflow - level\ change. \qquad (7)$$

From 2014, when the filling of the lake has been finished, the water losses and consequent decrease of the water surface level have been observed and the water had to be refilled. Keeping the water level stable is one of the key components of hydric reclamation planning in the region and provides the securitization of long-term sustainability. Table 1 summarizes the data of precipitation (meteorological data from Kopisty), artificial inflow (the amount of refilled water measured by supplier), and the change of water level (which has been continuously daily measured using the measuring device installed on Lake Most). For the purposes of further processing, only the conversion from m^3 to the height of the water column in mm is achieved by dividing purchased volume by the lake area 309.4 ha.

Table 1 The summary of operation data obtained on Lake Most

Year	Precipitation	Artificial inflow	Level change	E_{lake}
2014	501	1616	1310	807
2015	482	390	10	861
2016	525	228	-60	813
2017	512	355	40	827
2018	357	541	10	888
2019	493	320	10	803
2020	414	311	-90	815

In 2014 the lake was still in massive filling phase, which raised the water level by 1310mm. This process consequently caused the change of the lake surface area, the length of the bank line, and hence gradual saturation of the newly flooded surface.

RESULTS

We compare evaporation computed by E_{FAO} using equation (1), original Hargreaves-Samani equation E_{HS} (2), and calibrated Hargreaves-Samani equation E_{HS}^{*} (6) with the simplified balance equation E_{lake} (7). Please, see Fig. 3. where we present annual evaporation. For the demonstration of the modelling properties of the monthly evaporation, we present the results computed for year 2018 in Fig. 4.

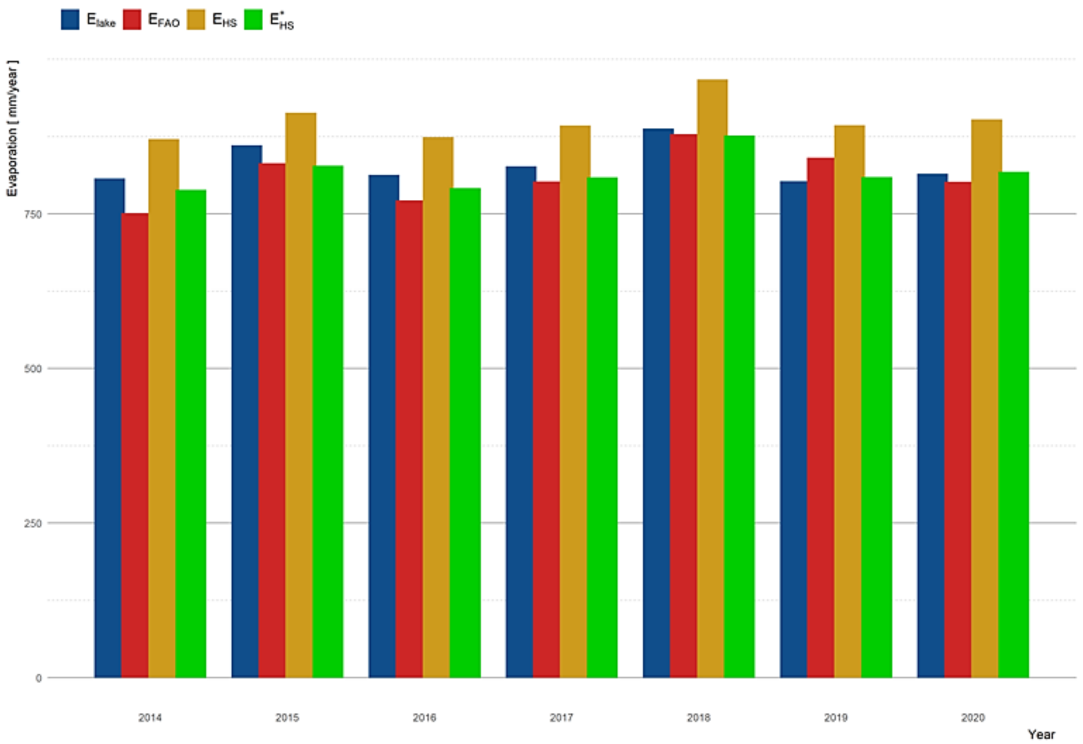

Fig. 3 The annual evaporation estimated by models presented in the paper

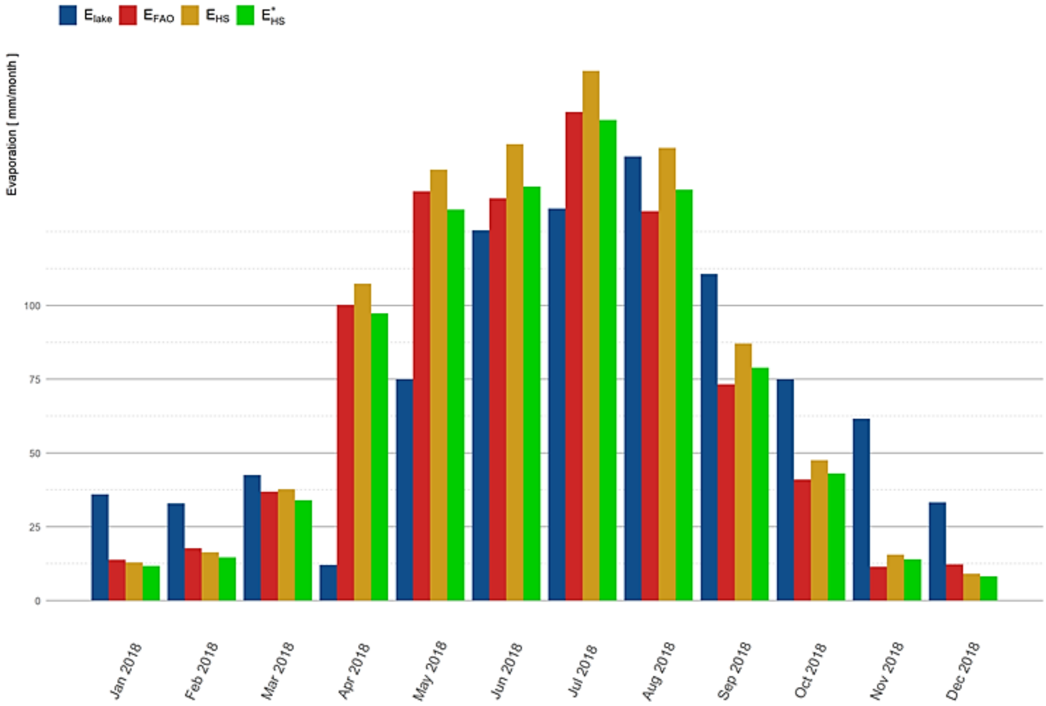

Fig. 4 The monthly evaporation in year 2018 estimated using models presented in the paper

The evolution of water surface level is presented in Fig. 5.

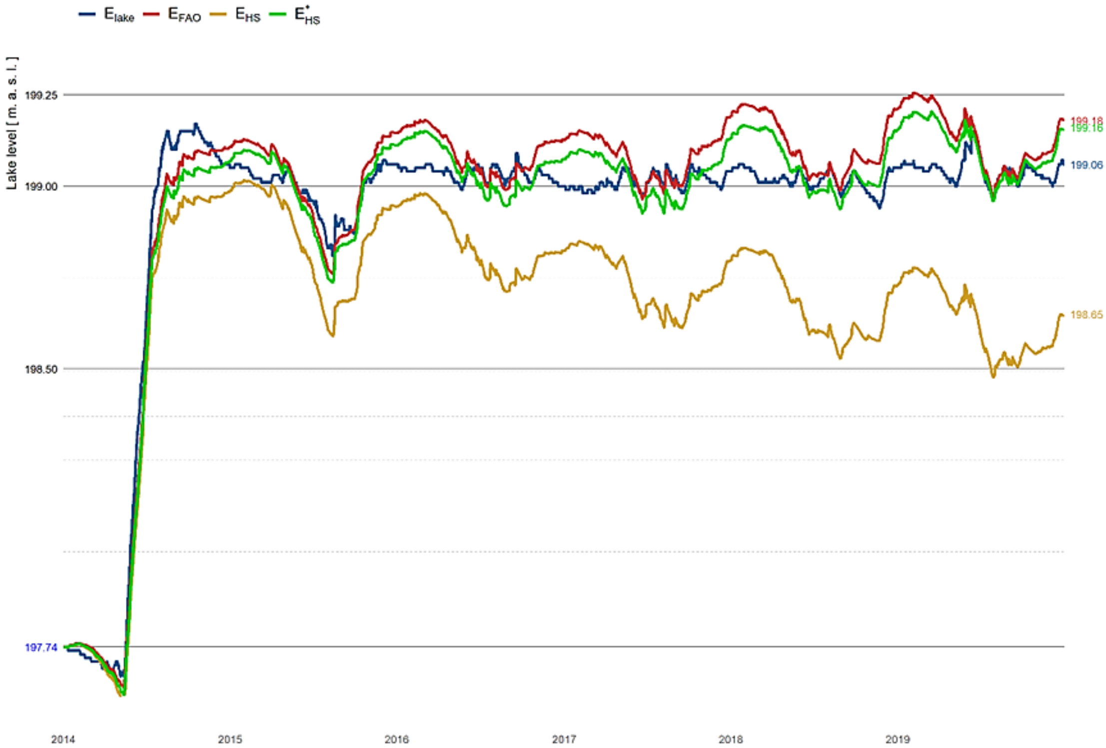

Fig. 5 The change of water level estimated by models discussed in the paper compared against real measurements on Lake Most

In the case of models for the evaporation computation, we recursively add the precipitation (measured in Kopisty), add the amount of refilled artificial water,

and substract the theoretical evaporation starting at real operational water level at the beginning of year 2014, i.e., 197.74 m. Therefore, the water level modelled by E_{FAO},E_{HS}, and E_{HS}^{*} in Fig. 5 can be considered as cumulative sum. These values are compared against operational water level measured every day.
In Fig. 6, we repeat the same process, however, in this case we start from the initial state at the beginning of the year and estimate the water level.

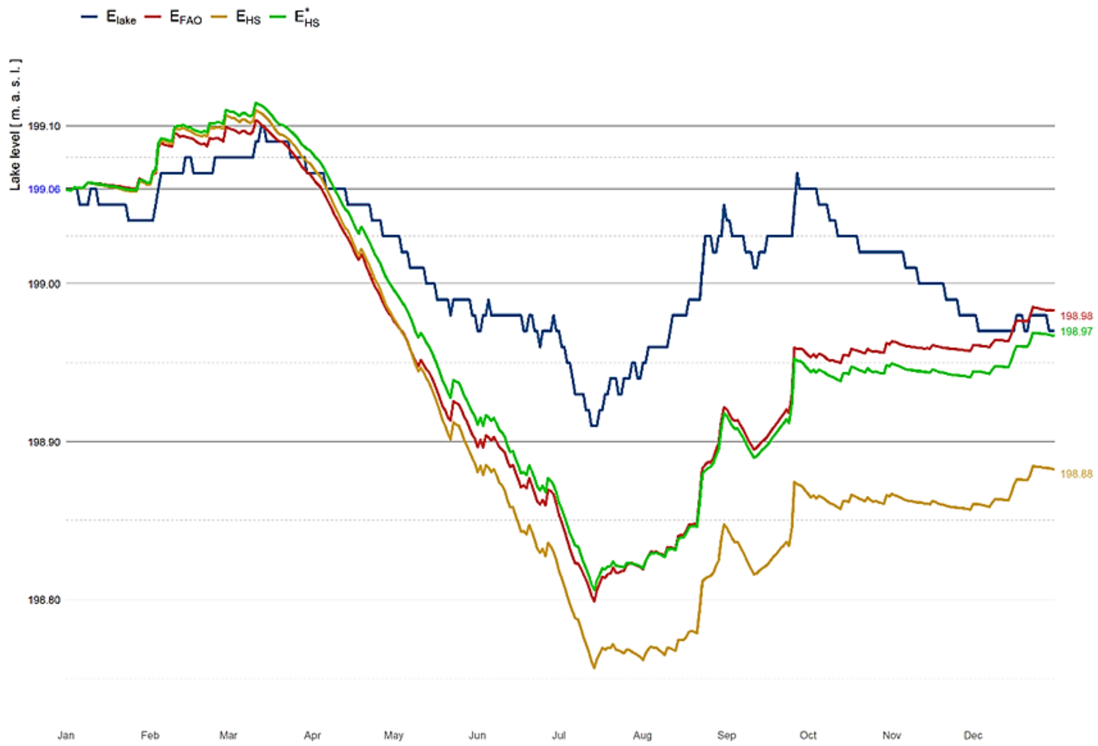

Fig. 6 The change of water level estimated by models discussed in the paper compared against real measurements on Lake Most during year 2020

DISCUSSION

From the results presented in the previous section, we can state that the evaporation in the area of Lake Most can be modelled and estimated by several evaporation models. In the case of E_{FAO}, which is a model recommended by the Food and Agriculture Organization of the United Nations, the main bottleneck is the high requirement on the input data. In our case, we are using the meteorological data measured in near Kopisty meteostation, however, we are afraid that if the distance between the area of the interest and data measuring station were larger, the data would not be sufficient to provide the correct estimation. This is the reason, why we are considering simplified models, namely Hargreaves-Samani equation E_{HS}. This model requires only the air temperature, which can be relatively cheaply measured in any area of interest. Additionally, if we provide the correct prediction of the temperature to our model, we will be able to consequently predict the evaporation. In the case of E_{FAO} and the prediction, we would have to predict a much larger number of input values and the error in prediction will be influenced by the error of prediction of these

input values. Since the lake does not have any natural inflow, these predictions are crucial for PKU for the preparation of the budget for the next year. In this case, the predictions presented in form of annual evaporation (like in Fig. 3) are the key material for the estimation of the water which must be purchased in the following year. The more specific time of refilling can be chosen with respect to monthly evaporation (like in Fig. 4) and the amount of available water in refilling sources and, consequently, the price of water. In the case of E_{HS}, the only information necessary for the prediction of water level is the precipitation and the actual state, see Fig. 6. In this figure, we used the exact values of temperature but only because of the comparison to real measured data. Please, notice that the model has been calibrated on the data from years 2014-2019, but the figure presents the estimation for the year 2020.
Additionally, the presented results demonstrate the capability of the calibration process. The Hargreaves-Samani equation with original coefficients is overestimating the evaporation, see Fig. 3 and Fig. 4, and after the calibration process against the FAO equation, the estimation is improved to fit values produced by FAO model. We are using the analysis on Lake Most to find the best-simplified evaporation model with only small requirements on input data for the area of interest. Since the meteorological station Kopisty (the professional meteorological station operated by CHMI) is only one kilometre from the lake, we think that this distance is sufficient for the input data to the FAO equation. Even if we would be able to measure the data directly next to the lake, the diameter of the lake is larger than one kilometre, therefore we suppose that the distance of Kopisty does not have a large impact on the estimated evaporation.

CONCLUSION

Although the evaporation estimations play crucial role in the planning of hydric reclamation of former coal quarries, they could be inaccurate due to the complexity of evaporation as a physical process but also because of inaccuracy of the physical/meteorological inputs. It is not possible to build professional meteostation near every single lake, therefore, the analysis of the influence and the requirement of the input data type are still the actual research scope.
In this paper, we compared the real measured data with theoretical evaporation estimations computed by FAO model recommended by Food and Agriculture Organization of the United Nations and Hargreaves-Samani equation, which requires only the measurement of temperature. Additionally, we demonstrate the capability of our calibration approach to tune the coefficients in Hargreaves-Samani equation to produce better estimations. The results show that if we calibrate the coefficients of simplified model to the specific area, then we are able to produce better evaporation estimations on the area.
Our future goal is to estimate the evaporation from the pit lakes near Lake Most which do not exist right now. They are farther from Kopisty and therefore, in this case, the meteorological data from Kopisty will be not sufficient even for Hargreaves-Samani equation. However, we suppose that the calibrated model

on the Lake Most will be suitable if we provide the measurements of the temperature directly in the place of new lakes. These measurements are relatively cheap to obtain. The presence of Kopisty station near the Lake Most allows to analyse these simplified models.

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Abstract: After finishing the mining process, the best way to deal with the residual of open-cut coal mines in the north-western region of the Czech Republic has been proposed to be hydric recultivation. The area of our study is the first artificial Lake Most (formerly known as Ležáky-Most coal quarry) finished in 2014 and opened to the public in 2020 for recreational purposes. Since the lake is a closed system without natural inflow and outflow, the prediction of evaporation plays a crucial role in the securitization of long-term sustainability based on the capability of keeping the stable level of a dimension of the final water level. In this paper, we use the historical data consisting of the altitude of the lake level, its area, the perimeter of the shoreline, and especially the volume of refilled water. These data are compared against the computational methods; namely, the Penman-Monteith Equation and Hargreaves-Samani model calibrated by the method proposed in our previous work.

Keywords: evaporation, hydric recultivation, calibration, modelling