sciendo

Management Systems in Production Engineering

2025, Volume 33, Issue 3, pp. 388-392

Date of submission of the article to the Editor: 03/2025
Date of acceptance of the article by the Editor: 07/2025

DOI 10.2478/mspe-2025-0037

SPATIO-TEMPORAL KRIGING OF AIR TEMPERATURE FOR EVAPORATION ESTIMATION

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Abstract:
This study focuses on the reconstruction of incomplete and spatially sparse air temperature data for the purpose of estimating evaporation from Lake Most – a large artificial reservoir in the Czech Republic with no natural inflow. The primary objective is to generate daily spatial temperature fields using spatio-temporal kriging and subsequently compute evaporation using a calibrated Hargreaves-Samani (HS) model. We utilize daily data from the years 2020-2022, collected from six low-cost microstations installed around the lake and from a nearby professional meteorological station (Kopisty, operated by the Czech Hydrometeorological Institute). Due to frequent outages, data coverage from the microstations ranges from 5% to 38%. To fill in missing values and estimate temperature over the lake surface, we apply a Gneiting covariance model. All computations are carried out in MATLAB using a in-house implementation. The reconstructed temperature fields exhibit realistic spatial structure and seasonal variability. Based on the interpolated daily mean, maximum, and minimum air temperatures, we compute daily and cumulative evaporation from the lake surface. The results show that even a sparse and unreliable sensor network can yield physically consistent inputs for evaporation estimation when combined with statistical interpolation. The proposed method is readily applicable to other reservoirs under limited measurement conditions and may support hydrological modeling and water balance analysis.

Key words: evaporation, kriging, lake most, temperature, time series

INTRODUCTION

Lake Most was formed as a result of hydric reclamation following the termination of brown coal mining in the Lezaky-Most open-pit mine, located in the northwestern part of the Czech Republic near the city of Most (50°31´N; 13°36´E). After intensive mining activity dating back to the 19th century, the area was left with a vast excavation site exceeding 1,200 hectares. Between 2008 and 2014, the pit was filled using an artificial water supply, creating a reservoir with no natural inflow or outflow, a surface area of over 300 hectares, and a maximum depth of up to 75 meters. Since 2014, the lake level has been stabilized at 199 meters above sea level, and since 2020 the lake has also served recreational purposes [1, 2].

Due to the absence of natural inflow, evaporation plays a key role in the hydrological balance of the lake. It represents the main source of water loss, and accurate estimates are essential for water management and long-term sustainability. While the FAO Penman-Monteith equation [3] is the standard method for estimating potential evapotranspiration, it requires extensive meteorological input. In previous studies, a simplified approach based on a calibrated Hargreaves-Samani (HS) model was proposed. This model relies mainly on temperature data and extraterrestrial radiation and is particularly suitable for situations where comprehensive meteorological data are unavailable [4, 5].

In one of our earlier studies [1], we calibrated the parameters of the HS model to best match the outputs of the Penman-Monteith equation. A six-year dataset from the professional weather station Kopisty was used for calibration, including cross-validation. The result is a calibrated version of the HS model that provides a robust evaporation estimate based solely on temperature inputs.

To acquire temperature data with sufficient spatial and temporal resolution, a network of meteorological micro stations was deployed in 2017 around the lake surface. These low-cost stations measure air temperature, relative humidity, and atmospheric pressure at one-minute intervals. Data are transmitted via radio signal to a central unit and processed using the Grafana system for further analysis [2]. In earlier work, spatial distribution of evaporation was approximated using Thiessen polygons

[1], while current research considers models that account for wind influence and other nonstationary factors [6].
However, data collection from micro stations is not without challenges. Due to their low-cost design and exposure to harsh outdoor conditions, data loss is common and typically caused by power failures, communication breakdowns, or temporary sensor malfunctions. The resulting time series often contain significant gaps, which hinder analysis and reduce the reliability of evaporation estimates. Moreover, the sensor network is relatively sparse and lacks full spatial coverage of the lake and its surroundings.
To address these limitations, we propose a method based on spatio-temporal kriging. Kriging is originally a geostatistical interpolation technique that estimates values at unobserved locations using a model of spatial (and temporal) dependence [7, 8]. It has been widely used in meteorology and hydrology for reconstructing temperature, precipitation, and other climatic variables [9, 10], [11]. For instance, Ghanim and Shexo [11] applied spatio-temporal kriging to interpolate and forecast urban temperatures in Iraq, outperforming dynamic regression-based models. Kriging has also been used for estimating evaporation over lakes such as Kasumigaura in Japan [12], and in Canadian lakes [13], or for modeling evapotranspiration in Pakistan [14] and the Xiangjiang River Basin [15].
Functional and hybrid variants of kriging have been proposed to improve the temporal coherence of predictions. Wiley et al. [16] introduced functional data kriging for evapotranspiration fields, and several recent studies advocate the use of machine learning models in combination with kriging for accurate PET estimation [17, 18]. Additional developments in SPDE-based methods and Bayesian spatio-temporal neural networks illustrate the broad applicability of kriging-like models for temperature and flux estimation [19, 20].
In our study, we employ a full Gneiting-type covariance model with time-space interaction, which allows for a flexible representation of nonstationary dependencies in both space and time [21]. Model parameters are estimated using optimization based on observed data from both the micro stations and the Kopisty station. The kriging implementation is carried out in MATLAB. This approach enables reconstruction of missing temperature values to serve as consistent input for evaporation modeling.

METHODOLOGY OF RESEARCH

Hargreaves-Samani evaporation model

The Hargreaves-Samani (HS) model [4, 5] is a simple empirical method for estimating potential evapotranspiration (ET) based on air temperature and extraterrestrial radiation. Its main advantage lies in its low data requirements and ease of implementation, which makes it particularly suitable for regions lacking full meteorological observations.
The standard form of the model is:

$$E_{HS} = 0.0023 \cdot \frac{R_a}{\lambda} \cdot (T_a + 17.8) \cdot \sqrt{T_r} \tag{1}$$

where:
E_{HS} denotes the potential evapotranspiration in mm/day,
T_α is the mean daily air temperature in °C,
$T_r = T_{max} - T_{min}$ is the temperature range,
R_α is the extraterrestrial radiation in $MJ \cdot m^{-2} \cdot day^{-1}$,
$\lambda = 2.45\ MJ \cdot kg^{-1}$ is the latent heat of vaporization.
To improve the accuracy of ET estimates for Lake Most, the model was calibrated against the reference FAO Penman–Monteith equation [3]. A parameterized form was used:

$$E_{HS}(\theta) = \max\left\{0,\ \theta_1 \cdot \frac{R_a}{\lambda} \cdot (T_a + \theta_2) \cdot T_r^{\theta_3}\right\} \tag{2}$$

where:
$\vartheta = (\vartheta_1, \vartheta_2, \vartheta_3)$ are optimized parameters.
Calibration was performed using cross-validation on data from the Kopisty weather station for the years 2014-2019. The optimal parameters were determined by maximizing the Nash-Sutcliffe efficiency (NSE), resulting in the following calibrated model [22]:

$$E_{HS}^* = \max\left\{0{,}0.002898 \cdot \frac{R_a}{\lambda} \cdot (T_a + 15.19) \cdot T_r^{0.3990}\right\} \tag{3}$$

This calibrated version demonstrated a high agreement with the FAO method, achieving $NSE = 0.923$, $RMSE = 0.465$, $MAE = 0.334$, and a relative bias $PBIAS = 0.72$ when validated on an independent dataset from 2020. For further details see.

Spatio-temporal krigging

To compute evaporation using the Hargreaves-Samani (HS) model, three key daily temperature characteristics are required: the mean temperature T_α, the maximum temperature T_{max}, and the minimum temperature T_{min}. Since the network of micro stations deployed around and directly on Lake Most operates under challenging conditions, measurement outages are frequent, typically caused by power failures or data transmission errors.
To fill in the missing data and spatially smooth the temperature field, we apply spatio-temporal kriging. This approach allows us to reconstruct temperature values at any location and time based on available measurements from other points in space and time. The method is used not only to restore data from malfunctioning micro stations, but also to estimate temperature over the lake surface, where no direct measurements are available.
Our interpolation is based on the Gneiting-type covariance model, which describes the joint dependence on spatial and temporal distance. The model takes the form [21]:

$$C(h,u) = \frac{\sigma^2}{(1+a|u|^{2\alpha})^{\beta}} \cdot \exp\left(-\frac{h^2}{c^2(1+a|u|^{2\alpha})^{\gamma}}\right) \tag{4}$$

where:
h denotes the Euclidean spatial distance between two points,
u is the temporal lag (in days),
σ^2 is the sill (variance),
α is the temporal scaling parameter,
c is the spatial range,
$\alpha = (0, 1]$ controls the smoothness of the temporal dependence,
$\beta = [0, 1]$ governs temporal decay,

γ = [0, 1] represents the degree of space-time interaction. The interpolated temperature value at time t and location x is computed as a weighted average of the available observations:

$$\hat{T}(x,t) = \sum_{i=1}^{n} \lambda_i T(x_i, t_i) \quad (5)$$

where:

λ_i are obtained by solving a linear system based on the covariance matrix among known points and the covariance vector between the known and the prediction point.

In our implementation, we do not impose any additional unbiasedness constraint-thus, we adopt the formulation, where the mean is assumed to be zero (or constant).

The kriging computation is implemented in MATLAB. For each temperature component (T_{α}, T_{max}, T_{min}), we perform independent interpolation, either on a regular spatial grid or at specific locations with missing observations. As input, we use data from functioning micro stations, supplemented by the professional weather station at Kopisty, which provides reference measurements unaffected by the lake microclimate.

The interpolated values then serve as input for evaporation estimation using the calibrated HS model.

RESULTS

For this study and the subsequent interpolation of the temperature field, we used daily data from the years 2020-2022 obtained from an automated network of micro stations located around Lake Most and from the professional meteorological station Kopisty (operated by the Czech Hydrometeorological Institute, ČHMÚ). The micro stations measure air temperature at one-minute intervals. For the purposes of evaporation estimation, these readings were aggregated into daily mean, maximum, and minimum temperatures.

The network includes six micro stations with identifiers jm15, jm25, jm31, jm41, jm45, and jm51. Their spatial distribution is shown in Figure 3. Although all stations were operational during the observation period, the quality and continuity of the data were affected by various technical failures.

The percentage of available daily data for each station over the 2020-2022 period is summarized in Table 1.

Table 1
Percentage coverage of daily temperature data from micro stations in the years 2020-2022

jm15	jm25	jm31	jm41	jm45	jm51
5.11%	29.93%	27.28%	33.39%	6.39%	37.50%

The values presented indicate that none of the micro stations provided a complete data record over the three-year period. This highlights the need for spatio-temporal kriging, which enables the reconstruction of missing values and the generation of a spatially continuous temperature field.

Figure 1 compares the completeness of the daily temperature time series between the professional station Kopisty and the micro station jm51.

While the Kopisty station delivers a complete series without interruptions, the micro station exhibits numerous gaps, including extended periods without any measurements.

Based on the described approach, we applied spatio-temporal kriging to the daily temperature data from 2020-2022 with the goal of reconstructing missing observations from micro stations. For each day, we interpolated three temperature variables (T_{α}, T_{max}, T_{min}) at a set of locations where measurements were unavailable.

The parameters of the Gneiting covariance model $\vartheta = (\sigma^2, a, c, \alpha, \beta, \gamma)$, were selected once based on a reasonable fit to the structure of the available data. These parameters remained fixed and were used to interpolate all three temperature characteristics regardless of the specific day or location. The interpolation was implemented in MATLAB using fully vectorized computation of distance and covariance matrices.

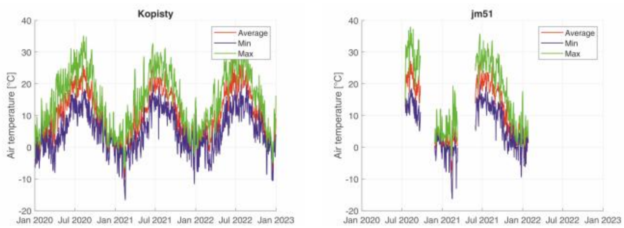

Fig. 1 Comparison of temporal coverage of daily temperature data from the Kopisty station (left) and the micro station jm51 (right) during the period 2020-2022. While the professional station provides an complete time series, the microstation exhibits significant data gaps

Figure 2 shows the result of interpolating the daily mean temperature at micro station jm51. The kriged time series maintains continuity even during periods with missing original data, while smoothly connecting to the observed values. This approach enables the generation of consistent inputs for evaporation modeling, even at stations with substantial data gaps.

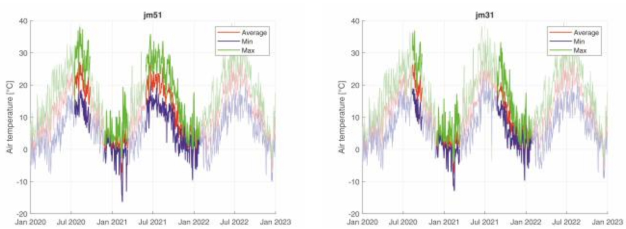

Fig. 2 Results of spatio-temporal kriging for temperature at micro stations jm51 (left) and jm31 (right) during the period 2020-2022. Dark points indicate the original available measurements, while light curves represent the kriged estimates. The interpolation clearly fills in missing data smoothly and connects consistently to the existing observations

Spatio-temporal kriging not only enables the reconstruction of missing values at sensor locations, but also allows temperature to be estimated at locations without any direct measurements. This is particularly valuable in the case of the water surface of Lake Most, where no micro stations are installed directly above the lake. By combining spatial and temporal dependencies, kriging provides an estimated temperature field over the entire area of interest.

Figure 3 shows the spatial distribution of daily evaporation from the surface of Lake Most, computed using the calibrated Hargreaves-Samani model for 27 August 2021.

The input for the calculation consisted of daily mean, maximum, and minimum temperatures obtained through spatio-temporal kriging. The resulting field captures the variability of evaporation across the domain, including over the lake surface, where no measurements are available.

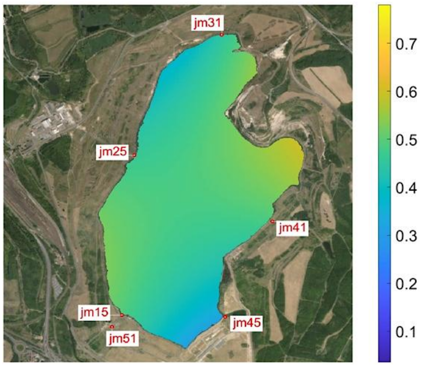

Fig. 3 Spatial distribution of daily evaporation (in mm/day) computed using the Hargreaves-Samani model for 27 August 2021. The input temperature values were obtained through spatio-temporal kriging. The color scale represents evaporation intensity, and the locations of the micro stations are marked with red dots

The highest evaporation values are observed in the northeastern part of the lake, which corresponds to the spatial distribution of temperature and the exposure of the area. This result demonstrates the practical use of kriged temperature fields as inputs for spatially distributed evaporation estimation.

DISCUSSION

The results show that spatio-temporal kriging based on the Gneiting covariance model is a suitable tool for reconstructing daily temperature characteristics from incomplete or spatially sparse datasets. The method is capable of smoothly filling in missing values and producing a spatially continuous temperature field that can subsequently be used to estimate evaporation with simple temperature-based models such as Hargreaves-Samani.

The main advantage of the proposed approach is its flexibility and low data preprocessing requirements – the interpolation is performed directly on the available measurements, without the need for a stationary network or prior imputation. Using a single set of parameters for all days and all temperature variables proved sufficient for practical applications. The resulting interpolated fields show realistic spatial structure and smoothly align with existing measurements.

In addition to filling gaps at sensor locations, the kriged temperature fields enable evaporation to be computed not only at specific points, but also spatially integrated over the entire lake surface. This improves the accuracy of evaporation estimates in cases where area-wide measurements are unavailable and overcomes limitations associated with using a single reference station.

However, several limitations must be acknowledged. In this study, no quantitative validation of interpolation accuracy was performed, such as cross-validation on withheld data. Moreover, the covariance model was applied uniformly over the entire period, although temporal structures (e.g., seasonal variability) may require different parameterizations. Future work should therefore consider seasonally adjusted or conditional calibration of the model.

From a practical perspective, the method can be further used not only for gap-filling, but also for spatial extrapolation of temperature into areas without sensor coverage, including the lake surface. This output is essential for realistic evaporation modeling, which depends on local temperature conditions.

CONCLUSION

In this study, we presented an approach for processing incomplete temperature data from the Lake Most region using spatio-temporal kriging. We demonstrated that, even in the presence of significant measurement gaps from micro stations, a properly selected covariance model enables the reconstruction of smooth and realistic temperature fields in both time and space.

The kriging method was applied to daily mean, maximum, and minimum temperatures, which served as input for evaporation estimation using a calibrated Hargreaves-Samani model. The results show that consistent input data can be obtained not only at individual locations (e.g., to fill gaps at malfunctioning stations), but also through spatial interpolation over the lake surface.

The method is fully implemented in MATLAB and is computationally efficient, making it suitable for application to larger datasets. In future work, we plan to assess the prediction accuracy through validation experiments and consider extending the approach to additional meteorological variables, such as humidity or wind speed. We also intend to use the interpolated temperatures for spatially resolved evaporation calculations, including seasonal analyses and integration into the lake's water balance assessment.

ACKNOWLEDGEMENTS

The authors would like to express thanks to The Institute of Atmospheric Physics CAS for the provided meteorological data from their measuring station Kopisty. This contribution was made possible thanks to the funding provided by our Department of Mathematics at FAST, VSB-TUO.

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