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A case study in the Netherlands

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Application of resistance-capacitance (RC) models to predict soil surface temperature: A case study in the Netherlands

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***Abstract*— Extreme temperatures in urban environments exacerbate thermal discomfort and intensify the Urban Heat Island (UHI) effect, particularly during peak warm periods. Pavements, which constitute a significant portion of urban surfaces, contribute significantly to heat retention, whereas soil and vegetated areas aid in cooling through lower heat storage and higher moisture retention. Accurate forecasting of soil and pavement surface temperatures is critical for developing effective UHI mitigation strategies. This paper explores the application of Resistance-Capacitance (RC) models, a type of grey-box model, for soil surface temperature prediction. Unlike purely physics-based and data-driven models, RC models integrate physical principles with data-driven insights, balancing accuracy and interpretability. The proposed methodology is validated using real-world data from a dike in the Netherlands, where an optimal RC model is identified through an iterative process based on the Akaike Information Criterion (AIC). Results demonstrate that a two-node RC model provides a reliable balance between complexity and predictive accuracy, achieving an R^2 of 0.862 and a mean absolute error (MAE) of 0.675°C. These findings highlight the feasibility of applying RC models for soil temperature prediction while maintaining physical interpretability. Future research could extend this methodology to various soil types and urban surfaces, including pavements, to further enhance predictive capabilities and inform climate-responsive urban design.**

Keywords—surface temperature prediction, RC models, soil, pavement, Urban Heat Island

I. Introduction

A. Context

Extreme temperatures are increasingly prevalent in urban environments, exacerbating thermal discomfort and increasing the risks associated with the Urban Heat Island (UHI) effect, particularly during peak warm periods. The intensity of the UHI effect is closely linked to urban morphology and material properties, with pavements, comprising approximately 30% of urban surfaces, playing a critical role in heat retention and dissipation. However, natural surfaces such as soil and vegetated areas exhibit different thermal behaviours, often contributing to cooling effects due to lower absorption of solar radiation, lower heat storage capacity, higher moisture retention, and evaporative cooling processes.

Pavement surface temperature and the surrounding environment interact dynamically, influencing local microclimates. Due to their high solar radiation absorption and significant heat storage capacity, pavements contribute to elevated ambient temperatures compared to soil or vegetated areas, which can mitigate heat through moisture evaporation and lower thermal conductivity. The occurrence of extreme heat events further intensifies these differences, increasing risks to public health, environmental quality, and economic stability, including higher mortality rates and elevated ground-level ozone formation [1]. Understanding the thermal behaviour of both pavement and soil surfaces is therefore essential for developing strategies to mitigate the UHI phenomenon and improve urban resilience.

B. State of the art

Accurate forecasting of surface temperature is a critical factor in designing and evaluating pavement solutions and their interaction with surrounding soil areas. Soil and pavement surface temperature prediction models can be divided into three categories [2]: physics-based (white box) models, data driven (black box) models and hybrid (grey box) models.

White box models rely on physical laws to characterize soil thermal behaviour. They solve mathematical equations and can show high accuracies if calibrated correctly. However, they require exhaustive information on the physical properties of the modelled soil and are computationally intensive. As an example, the green roof model used by Energy plus [3] requires of tens of parameters such as the Leaf Area Index [4], which is commonly not known. Also, white box models are commonly defined for a particular application while their final use may differ. In the case of the aforementioned model, this was originally developed to determine the ability of soils to support manned and unmanned vehicles and personnel movement in tundra areas for military purposes [5]. Secondly, black-box models rely on statistical or machine learning techniques to establish relationships between input and predicted values. As the term suggests, the relationship between input and output variables is often unclear, making it difficult to build interpretable models. Finally, grey box models are a hybrid approach between physics-based and data driven models. These models use a combination of physical knowledge and information derived from captured data. The physical knowledge is formulated by a set of equations whose parameters are fixed employing measured data. Hybrid models, such as Resistance Capacitance (RC) models, have proven to be a useful approach when modelling key parameters of buildings [6], and envelopes [7] [8]. However, their application for soil temperature prediction is yet to be explored, where more popular approaches are based on physics-based [9] or data driven [10] models.

C. Contribution of this work

This paper presents the methodology to apply a RC model to predict soil temperature. This application of grey box models, to the authors' knowledge, has not yet been made. The proposed methodology is tested and validated with real data from a dike in the Netherlands. Accordingly, this paper is structured as follows. **Section II** illustrates the methodology to identify the optimal RC model for a given dataset. **Section III** describes the case study used for testing. **Section IV** shows the results of applying the proposed methodology on the dataset and presents the model results. Finally, **Section V** summarizes the contribution and significance of this paper, as well as potential directions for further development.

II. Methodology

RC models integrate data-driven insights with the physical principles governing the modelled system, represented by first-order differential equations. These equations characterize the heat dynamics of the system, which, in this case, corresponds to the soil. Additionally, to enhance the robustness of the models against measurement noise and calibration uncertainties, a stochastic term is incorporated into the system equations.

Fig. 1 shows an example of a RC network of k=4 state variables. The physical model part of this example is described by stochastic differential equations (1)-(4):

$$dT_1 = (-(\frac{1}{C_1R_{12}} + \frac{1}{C_1R_{1a}})T_1 + \frac{1}{C_1R_{12}}T_2 + \frac{1}{C_1R_{1a}}T_a + \frac{G_s}{C_1}\Phi_s)dt + \sigma_1 d\omega_1 \tag{1}$$

$$dT_2 = (\frac{1}{C_2R_{12}}T_1 - (\frac{1}{C_2R_{12}} + \frac{1}{C_2R_{23}})T_2 + \frac{1}{C_2R_{23}}T_3)dt + \sigma_2 d\omega_2 \tag{2}$$

$$dT_3 = (\frac{1}{C_3R_{23}}T_2 - (\frac{1}{C_3R_{23}} + \frac{1}{C_3R_{34}})T_3 + \frac{1}{C_3R_{34}}T_4)dt + \sigma_3 d\omega_3 \tag{3}$$

$$dT_4 = (\frac{1}{C_4R_{34}}T_3 - \frac{1}{C_4R_{34}}T_4)dt + \sigma_4 d\omega_4 \tag{4}$$

where Φ_s [kW/m^2] is the solar irradiation, G_s [m^2] represents the effective soil area, T_a [ºC] is the ambient temperature, $T_s \equiv T_1$ [ºC] is the soil surface temperature, T_i [ºC], with i=2, …, k, is the temperature of state variable i, R_{mn} [ºC/kW] is the thermal resistance between state variables m and n, C_i [kW/ºC] with i=1, …, k is the heat capacity corresponding to state variable i, and $\sigma_i d\omega_i$ is the stochastic term of the equation.

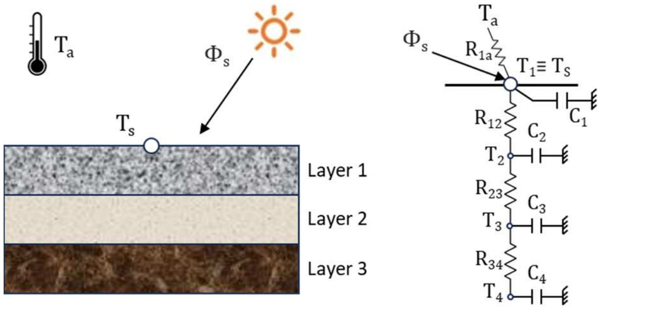

Fig. 1. Simplified representation of a soil (left) and RC network of a model with 4 state variables (right).

The observed data is used to estimate the parameters defined in the previous equations. The data-driven model part of the model is defined as shown in (5):

$$Y_p = T_{sp} + e_p \tag{5}$$

where p is the point in time t_p of a measurement, Y_p [ºC] is the measured surface temperature and e_k the measurement error.

To ensure the physical interpretability of the model, exogenous variables influence only the state variable corresponding to the soil surface temperature, as shown in the example model. Furthermore, all models evaluated during the identifying process will be one-dimensional, i.e., all nodes of the model are connected in series. These constraints guarantee that, for each family of models with k state variables, only a single feasible model exists.

Statistical tests are used to identify the optimal model, defined as the simplest model capable of capturing the key characteristics of a given dataset. When evaluating complex models, information criterion-based methods are often utilized. One of the most widely used criteria for determining the most appropriate model order is the Akaike Information Criterion (AIC) [11]. AIC serves as a comparative metric, meaning it cannot assess a model in isolation but rather in relation to other models. A lower AIC value indicates a more suitable model among the considered alternatives. Equation (6) depicts the formulation of AIC

$$AIC = -2L + 2 \cdot k \tag{6}$$

where L is the log likelihood function of the model evaluated at the maximum likelihood estimate, k is the number of estimated parameters, and n is the number of datapoints.

The proposed methodology to identify the best model is resumed in Fig. 2. The process begins with the calibration of the simplest model, which is initially designated as the best model. Subsequently, models of increasing complexity (with a greater number of state variables) are iteratively calibrated and compared against the current best model. If a newly tested model yields a lower AIC value, it replaces the existing best model, and the process repeats. If the new model does not outperform the current best model, the last identified best model is retained as the final selection.

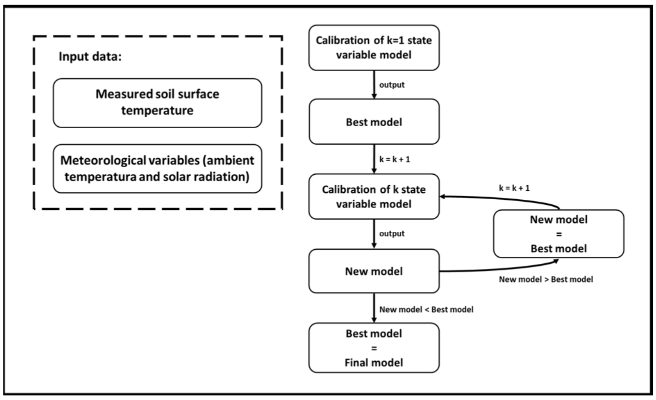

Fig. 2. Optimal RC model identifying process.

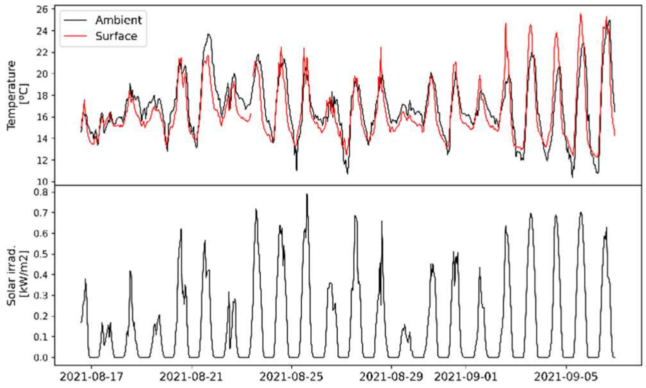

Fig. 3. Time-series plot of ambient and soil surface temperature (top), and time-series plot solar irradiation (bottom).

III. Case study

The dataset used to validate the proposed methodology is obtained from previous works [12]. The modelled soil corresponds to a section of 5 x 18 m of a dike located in Flood Proof Holland [13]. The measurement period is 20 days, corresponding to summer period (from 2021/08/17 to 2021/09/06). Measured data consists of surface temperature and meteorological variables (ambient temperature, solar irradiation, and wind). Soil surface temperature was obtained with a thermal camera Flir A35 and a frequency of 30 minutes. Meteorological data was obtained from a weather station located in Rotterdam airport, with a frequency of 60 minutes. Fig. 3 depicts that soil surface temperature shows a strong correlation with both ambient temperature and solar global horizontal irradiation.

IV. Results and dicussion

The methodology outlined in **Section II** is applied on the case study described in **Section III**. The most complex model evaluated during the process consists of k = 3 nodes. To assess model accuracy, two additional error metrics are computed alongside the AIC value: the coefficient of determination (R^2) and the mean absolute error (MAE). MAE (7) quantifies the difference between predicted and measured values. On the other hand, R^2 (8) quantifies the proportion of variance in the observed data that is explained by the model. A higher R^2 value indicates that the predicted values closely align with the actual measurements. Both metrics are widely adopted metrics for evaluating model performance [14][15][16].

$$\boldsymbol{MAE} = \frac{\mathbf{1}}{\boldsymbol{n}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} |\boldsymbol{y_i} - \hat{\boldsymbol{y}}_{\boldsymbol{i}}| \tag{7}$$

$$\mathbf{R^2} = \mathbf{1} - \frac{\sum_{i=1}^{n}(\boldsymbol{y_i} - \hat{\boldsymbol{y}}_{\boldsymbol{i}})^2}{\sum_{i=1}^{n}(\boldsymbol{y_i} - \bar{\boldsymbol{y}})^2} \tag{8}$$

Fig. 4 illustrates the morphology of the three models evaluated during the process, while TABLE I. presents their descriptions and corresponding metrics. The error metrics for all three models are nearly identical, indicating similar predictive performance. The primary distinction among the models lies in their complexity, as reflected in the AIC values. Although the three-node model exhibits slightly higher accuracy than the two-node model, the added complexity does not justify its selection. Plots of actual soil temperature, and output and residuals for the optimal model can be seen in Fig. 5.

The k = 2 nodes model shows a notable accuracy, with a MAE of 0.675 ºC and an R^2 value of 0.862. In addition, a detailed analysis of Fig. 5 reveals that although the residuals occasionally exceed ± 2 ºC, this phenomenon does not lead to an increase in the maximum temperatures of the modelled soil time window surrounding the prediction. From the perspective of UHI where key indicators are often associated with the maximum temperature reached by the modelled soil or pavement, this represents a valuable characteristic of the model.

In the case of the soil modelled in this study, discrepancies between the predicted and observed surface temperatures may be attributed to factors not accounted for in the model, such as soil's capacity to retain moisture. These unmodelled parameters influence the thermal properties of the soil, leading to a slight decoupling between the actual and predicted values. This effect becomes more evident when the model's results are examined over a shorter time frame, as illustrated in Fig. 6. In the peak highlighted by the first marker, the measured soil surface temperature coincides with local maximum in both ambient temperature and solar irradiation, whereas the predicted temperature reaches its peak with a slight delay. Conversely, in the second marked peak, the predicted surface temperature aligns with the local maximum of ambient temperature and solar irradiation, but the observed maximum surface temperature occurs earlier.

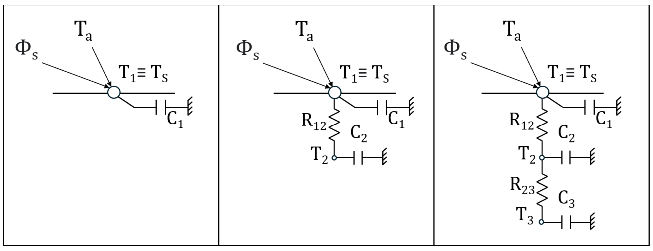

Fig. 4. Representation of RC network of a model with 1 node (left), 2 nodes (middle), and 3 nodes (right).

TABLE I. Evaluation metrics of all evaluated RC models

K	Nº OF PARAMETERS	R^2	MAE [ºC]	AIC
1 node	3	0.8632	0.6712	989.51
2 node	5	0.8626	0.6749	982.04
3 node	7	0.8627	0.6744	987.18

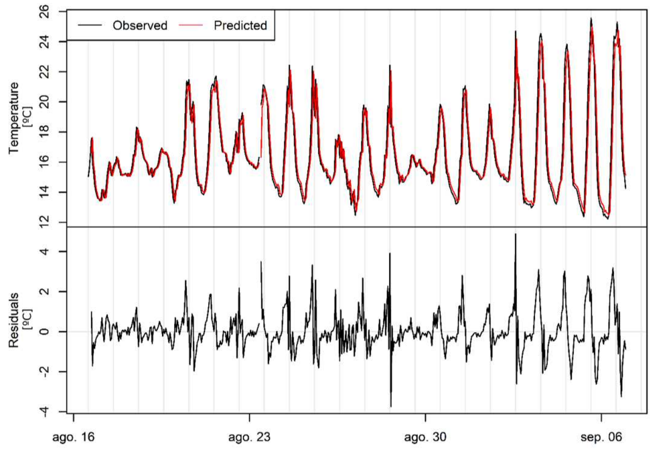

Fig. 5. Time-series plots of observed and predicted soil surface temperature of the optimal model (top), and the residuals for the model (bottom).

V. Conclusions

This paper presents a methodology for applying RC models to predict soil surface temperature. The proposed approach is validated by identifying the optimal model for predicting the soil surface temperature of a dike in the Netherlands. The accuracy of the identified model ($R^2 = 0.862$ and MAE = 0.675 ºC) demonstrates the feasibility of using grey-box models for soil surface temperature prediction.

This study has been conducted while preserving the physical interpretability of the evaluated models by imposing morphological constraints. Future research could explore the performance of models identified without these restrictions. Additionally, the proposed methodology could be applied to soils and surfaces composed of different materials, such as pavements, to evaluate how the RC modelling approach performs in relation to the thermal and physical properties of the modelled materials.

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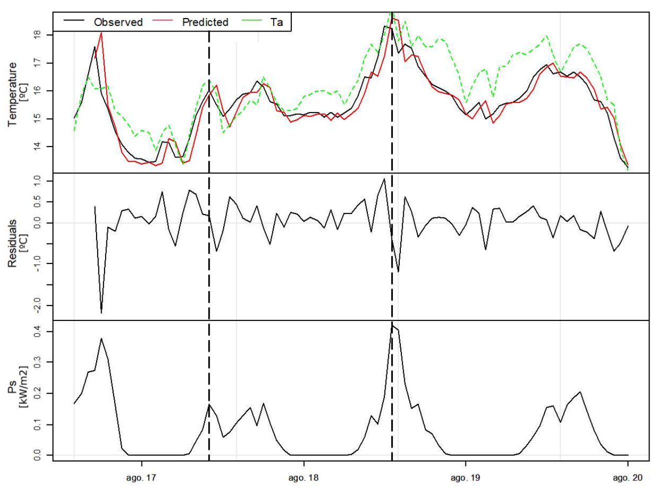

Fig. 6. Time-series plots of ambient temperature, and observed and predicted (k = 2 nodes model) soil surface temperature (top), residuals of the model (middle), and solar irradiation (bottom).

References

[1] E. E. Ikechukwu, 'The Effects of Road and Other Pavement Materials on Urban Heat Island (A Case Study of Port Harcourt City)', *Journal of Environmental Protection*, vol. 6, no. 4, Art. no. 4, Mar. 2015, doi: 10.4236/jep.2015.64033.

[2] J. Drgoňa *et al.*, 'All you need to know about model predictive control for buildings', *Annual Reviews in Control*, vol. 50, pp. 190–232, Jan. 2020, doi: 10.1016/j.arcontrol.2020.09.001.

[3] 'EnergyPlus Version 24.1 Documents'. Accessed: Jul. 18, 2024. [Online]. Available: https://bigladdersoftware.com/epx/docs/24-1/

[4] D. J. Sailor, 'A green roof model for building energy simulation programs', *Energy and Buildings*, vol. 40, no. 8, pp. 1466–1478, Jan. 2008, doi: 10.1016/j.enbuild.2008.02.001.

[5] 'FASST Vegetation Models'. Accessed: Feb. 20, 2025. [Online]. Available: https://apps.dtic.mil/sti/citations/ADA428989

[6] P. Bacher and H. Madsen, 'Identifying suitable models for the heat dynamics of buildings', *Energy and Buildings*, vol. 43, no. 7, pp. 1511–1522, Jul. 2011, doi: 10.1016/j.enbuild.2011.02.005.

[7] B. Arregi, R. Garay-Martinez, and J. C. Ramos, 'Estimation of thermal resistance and capacitance of a concrete wall from *in situ* measurements: A comparison of steady-state and dynamic models', *Energy and Buildings*, vol. 296, p. 113393, Oct. 2023, doi: 10.1016/j.enbuild.2023.113393.

[8] P. Biddulph *et al.*, 'Inferring the thermal resistance and effective thermal mass of a wall using frequent temperature and heat flux measurements', *Energy and Buildings*, vol. 78, pp. 10–16, Aug. 2014, doi: 10.1016/j.enbuild.2014.04.004.

[9] A. Glodeanu, I. G. Pérez, and N. P. Cerezo, 'Optimization at microscale level of climate-informed decision-making processes regarding human thermal comfort', *Journal of Urban Management*, Dec. 2024, doi: 10.1016/j.jum.2024.11.010.

[10] S. E. Tabrizi *et al.*, 'Hourly road pavement surface temperature forecasting using deep learning models', *Journal of Hydrology*, vol. 603, p. 126877, Dec. 2021, doi: 10.1016/j.jhydrol.2021.126877.

[11] J. E. Cavanaugh and A. A. Neath, 'The Akaike information criterion: Background, derivation, properties, application, interpretation, and refinements', *WIREs Computational Statistics*, vol. 11, no. 3, p. e1460, 2019, doi: 10.1002/wics.1460.

[12] 'Crack Detection for Dikes using Distributed Temperature Sensing', 2022, Accessed: Feb. 17, 2025. [Online]. Available: https://resolver.tudelft.nl/uuid:61999eab-1630-43b2-9b49-b2691d630e4e

[13] nembroers, 'Flood Proof Holland', VPdelta. Accessed: Jul. 23, 2024. [Online]. Available: https://vpdelta.tudelftcampus.nl/flood-proof-holland/

[14] I. Lopez-Villamor, O. Eguiarte, B. Arregi, R. Garay-Martinez, and A. Garrido-Marijuan, 'Time of the week AutoRegressive eXogenous (TOW-ARX) model to predict thermal consumption in a large commercial mall', *Energy Conversion and Management: X*, vol. 24, p. 100777, Oct. 2024, doi: 10.1016/j.ecmx.2024.100777.

[15] L. Chen, B. Basu, and D. McCabe, 'Fractional order models for system identification of thermal dynamics of buildings', *Energy and Buildings*, vol. 133, pp. 381–388, Dec. 2016, doi: 10.1016/j.enbuild.2016.09.006.

[16] J. Song, L. Zhang, G. Xue, Y. Ma, S. Gao, and Q. Jiang, 'Predicting hourly heating load in a district heating system based on a hybrid CNN-LSTM model', *Energy and Buildings*, vol. 243, p. 110998, Jul. 2021, doi: 10.1016/j.enbuild.2021.110998.