A PROTOTYPE EARTH OBSERVATION-BASED FRAMEWORK FOR SIMULATING URBAN INTERVENTION EFFECTS ON LAND SURFACE TEMPERATURE

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ABSTRACT:

The surface urban heat island phenomenon poses critical challenges for climate-resilient urban planning, due to its well-known negative impact on thermal comfort and increased health risks during heatwave events. This work presents a prototype Earth Observation-based framework for the simulation of Land Surface Temperature (LST) to support scenario-driven assessment of urban transformations. The framework integrates Landsat 8/9 LST observations from 2015 to 2024 with Sentinel-2 reflectance data, used to derive surface material fractions through spectral unmixing, together with a set of Urban Canopy Parameters including sky view factor, building height, tree canopy height and soil imperviousness. These inputs form a comprehensive set of predictor layers that describe urban morphology and surface materials, and which can be modified in typical urban planning or retrofitting interventions. Random Forest regression models are trained to predict seasonal average LST from the predictor variables. The Metropolitan City of Milan is used as a case study. A Python module is designed to allow users to delineate intervention areas and adjust predictor layers to generate what-if scenarios that mimic real urban interventions. The summer model achieves the best performance, with a mean absolute error lower than 2 K, and the accuracy assessment shows good agreement with Landsat observations ($R^2 > 0.74$) and moderate agreement with ECOSTRESS data ($R^2 > 0.63$). An example application illustrates the potential of the framework for the analysis of urban heat mitigation strategies and its future integration into operational urban digital twin systems.

1. INTRODUCTION

The Surface Urban Heat Island (SUHI) phenomenon describes how urban areas often record substantially higher Land Surface Temperature (LST) than their rural surroundings. This temperature increase can affect thermal comfort and exacerbate health risks, particularly during heatwaves, by amplifying heat stress exposure for urban dwellers and city users (Ebi et al., 2021). Unlike the Urban Heat Island (UHI), which refers to the near-surface air temperature difference between urban and rural areas and is strongly influenced by local meteorological factors, SUHI patterns primarily emerge as a direct result of urbanisation, which alters both morphological characteristics and surface material properties, thereby changing heat accumulation in cities (Shao et al., 2023). Although the correlation between LST and surface air temperature (one of the most common thermal comfort indicators) is not always linear, LST remains a reasonable proxy for capturing spatial and seasonal variations in air temperature (Muse et al., 2024). Moreover, LST can be systematically observed through widely available Earth Observation (EO) thermal imagery, such as Landsat, enabling consistent and spatially extensive monitoring of urban thermal patterns at the city scale. By contrast, air temperature data rely on ground sensor networks, which typically have scattered spatial coverage, limiting the ability to monitor UHI dynamics across entire metropolitan areas. With this in mind, this work aims to develop a prototype urban digital twin application for the analysis and simulation of urban thermal dynamics, driven by surface material characteristics and urban morphological features.

The proposed simulation framework integrates thermal EO data and surface material fractions (from the spectral unmixing of multispectral imagery) with Urban Canopy Parameters (UCP), such as sky view factor, building height, soil imperviousness, and tree canopy height, to train a machine-learning model predicting how urban transformations (e.g., new construction, retrofitting, or greening) may affect LST (Li et al., 2020). The selected predictors layers represent a comprehensive set of urban features associated with the SUHI effect, for which LST variation is a direct physical observable (Mokarram et al., 2024). The workflow includes a dedicated module for the preparation of simulation layers, where the user is allowed to delineate planned intervention areas and specify the type of change to be applied. This allows for the generation of "what-if" urban transformation scenarios and the analysis of triggered impacts on LST patterns. The framework is designed for integration into urban digital twin platforms, supporting scenario-based urban planning through EO-driven simulations.

The activities have been carried out within the project Smart Urban Resilience Enhancement (SURE), funded by the European Space Agency (ESA) and led by the e-GEOS company (https://www.e-geos.it). The prototype's requirements were defined through continuous dialogue with key public and private stakeholders, including the Metropolitan City of Milan (Northern Italy), which serves as the case study for the development and testing of the proposed LST simulation model. The accuracy of the predicted LST maps, generated using actual predictor layer values, was evaluated against both ECOSTRESS thermal data (https://ecostress.jpl.nasa.gov) and air temperature sensor observations. Finally, examples of LST simulated maps, produced by altering predictor values to explore hypothetical what-if scenarios, are presented and discussed.

2. MATERIALS AND METHODS

The development of the LST simulation model considered multi-source geospatial datasets spanning 10 years (2015–2024) for the

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Metropolitan City of Milan. LST from Landsat 8/9 (https://www.usgs.gov/landsat-missions/landsat-collection-2-surface-temperature) was derived from 76 cloud-free daytime acquisitions. Surface material fractions were derived from Sentinel-2 imagery (30 acquisitions within ±3 days of Landsat LST dates) through regression-based spectral unmixing (Okujeni et al., 2016). The resulting fractions represent the proportional abundance of key urban surface materials within each pixel, including: asphalt/concrete, shingle, metal, bare soil/sand, low vegetation/grass, tall vegetation, and water. UCP layers, considered instead as time-invariant in the model development, were derived from the Milan digital surface model and building geodatabase, as well as from global tree canopy height and soil imperviousness maps (Vavassori et al., 2024). UCP layer values were normalised to [0–1] range to match the scale of surface material fractions for model training.

The LST simulation model is based on a Random Forest regression (see Figure 1). Training data combine time-invariant layers with time-variant LST and surface material fraction observations, aggregated over three seasonal periods: summer (June-September), winter (December-March), and intermediate. Sampling was restricted to stable areas identified using multitemporal soil consumption maps (https://www.isprambiente.gov.it/en/databases/data-base-collection/soil-and-territory/use-of-soil) to exclude zones affected by relevant changes between the years 2015 and 2024.

A stratified sampling scheme, based on seasonal Local Climate Zone (LCZ) maps (Stewart & Oke, 2012; Xi et al., 2024), derived from Sentinel-2 imagery following a procedure previously published by the authors (Vavassori et al., 2024), was applied to ensure balanced coverage and representation of different urban textures in the model training phase.

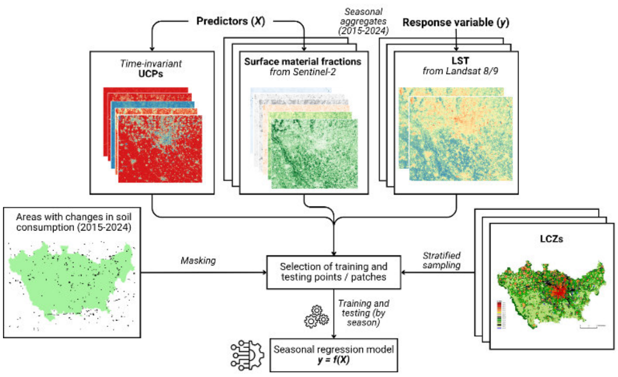

Figure 1. Schematic of the LST model implementation workflow

The trained seasonal LST models are used to simulate LST responses by varying input predictor layers to represent planned or hypothetical urban transformations. The workflow includes a simulation module (Python notebook) that modifies input raster layers using user-defined vector masks to outline transformation areas and specify changes to predictor layers. Two main approaches are supported: value replacement masking and percentage adjustment masking, allowing for exploratory what-if scenarios testing. Additional details on this module are reported in Section 4.

The draft Python source code used to implement the entire simulation framework is openly available on GitHub (https://github.com/gisgeolab/SURE).

3. RESULTS AND MODEL ASSESSMENT

The LST simulation model was optimised and validated through a series of tuning and accuracy assessments combining cross-validation, grid search, and independent comparisons. Model accuracy was evaluated using approximately 1,000 randomly sampled points located outside the training areas. Considered accuracy metrics included the Pearson's correlation coefficient (r), the coefficient of determination (R^2), the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE) and the Mean Bias Error (MBE). The final seasonal models achieved satisfactory accuracy, with the summer model performing best against LST Landsat observations used for testing (r = 0.86, R^2 = 0.74, MAE = 1.67 K, RMSE = 2.18 K, MBE ~ 0). Validation against ECOSTRESS observations revealed instead a moderate agreement (r = 0.80, R^2 = 0.64), with higher errors (MAE = 3.03 K; RMSE = 3.59 K) and a negative bias (MBE = −2.89 K), suggesting that ECOSTRESS LST values are systematically lower than the simulated ones (see Figure 2).

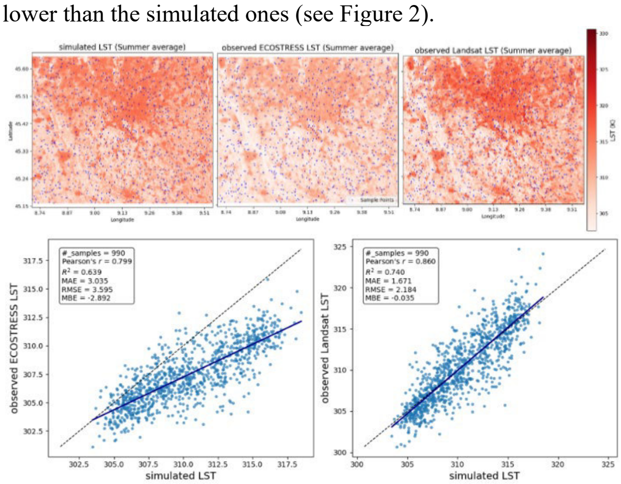

Figure 2. Summary of agreement statistics between simulated and observed LST values. Upper panels: Spatial distributions of average summer LST [K] for simulated data, ECOSTRESS and Landsat observations with random sampling locations shown as blue dots. Lower panels: Scatterplots comparing the sampled simulated LST with ECOSTRESS and Landsat observations, including regression lines (dark blue), 1:1 reference lines (black dashed) and agreement metrics

The comparatively lower agreement observed with ECOSTRESS observations may be associated with differences in temporal representativeness, given the shorter period available to derive ECOSTRESS-based reference LST (2019–2024), as well as with systematically different acquisition times relative to Landsat observations. In particular, Landsat acquires around 10:00 AM GMT over the Milan area, whereas ECOSTRESS observations are collected at variable times of day due to its non-sun-synchronous orbit. To mitigate the impact of these temporal discrepancies, only ECOSTRESS acquisitions falling within a central daytime window (09:00–12:00 GMT) were considered in the analysis.

Finally, regression analyses against ground-based air temperature (averaging period: 2015-2024), retrieved from the local regional environmental protection agency (ARPA) network, confirmed physically plausible relationships, with higher LST values corresponding to higher air temperatures in compact and mid-rise building areas, and cooler conditions in vegetated or open areas (see Figure 3). While a positive relationship is observed, LST values tend to be consistently higher than air temperature, especially in compact built LCZ classes. This behaviour reflects the different physical nature of the two variables: LST responds directly to radiative forcing and surface material properties, while air temperature also responds to local atmospheric processes. Consistent with previous studies, these differences are amplified during warm conditions and in built environments, where the LST–air temperature discrepancy is typically larger and associated with a higher spatial variability (Naserikia et al., 2024). This comparison should nevertheless be interpreted with caution, given the limited number of available ground stations in the study area. Despite these residual ambiguities, the LST model effectively captures overall urban thermal variability and shows promising potential for scenario-based simulations.

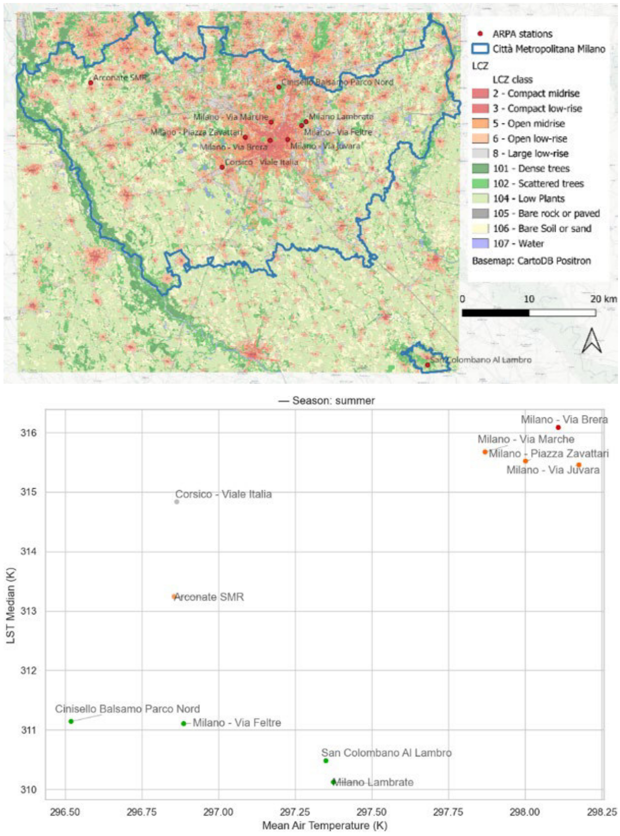

Figure 3. Comparison between simulated LST and ground-based air temperature observations for the Metropolitan City of Milan. Upper panel: Spatial distribution of air temperature monitoring stations over the LCZ map of Milan. Lower panel: Scatter plot of observed mean air temperature at ARPA station locations versus median simulated LST computed within a 200 m buffer from each station; point colours indicate the dominant LCZ class within the buffer

4. DEMONSTRATIVE FRAMEWORK APPLICATION

As a demonstrative application of the proposed framework, a what-if simulation was prepared considering an urban park in Milan to assess the potential cooling effect induced by a hypothetical urban forestation intervention. The experiment simulates an increase in tall vegetation fraction and tree canopy height, combined with a proportional reduction of grass and bare soil fractions (see Figure 4).

The simulation was implemented using the input layer simulator module, which enables controlled modification of input predictor layers through raster algebra operations driven by polygonal vector masks. Within the selected area of intervention, predictor values can be altered either by percentage-based adjustments or by direct value replacement, allowing the emulation of planned or hypothetical changes in urban texture.

The resulting simulated predictor layers were subsequently used as input to the trained LST model to generate a scenario-based LST map, which was compared against the baseline condition. The results show a reduction in LST within the intervention area, consistent with the expected cooling effect of increased tree canopy cover and, in turn, suggest the capability of the model to provide physically consistent outcomes.

The source code and test data used in this example are available in a dedicated branch of the GitHub project repository (https://github.com/gisgeolab/SURE/tree/layers_simulator). The modular structure and rule-based layer manipulation make the approach particularly suitable for integration within urban digital twin environments, where alternative planning scenarios can be rapidly tested and evaluated under consistent modelling assumptions.

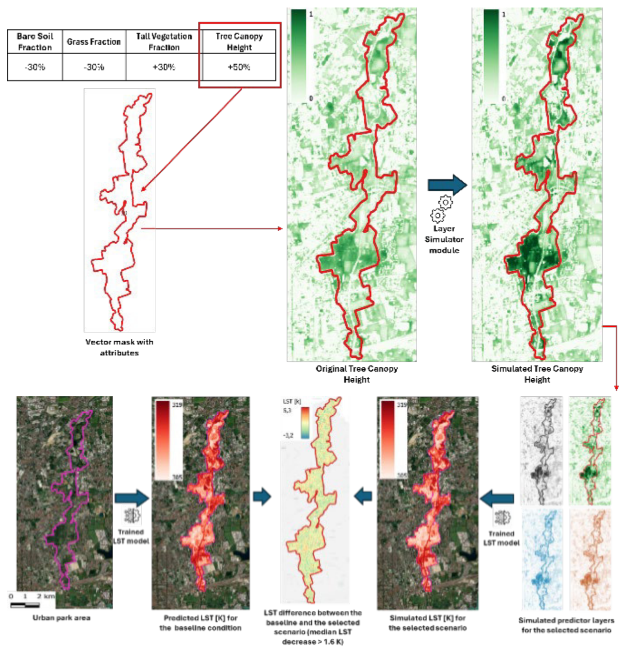

Figure 4. Schematic of what-if simulation workflow for an urban park in Milan. Upper panels: Modification of input predictor layers using the layer simulator module to increase tall vegetation fraction and tree canopy height while reducing grass and bare soil fractions. Lower panels: Baseline and scenario-based LST maps generated using the trained LST model, together with the corresponding LST difference, illustrating the cooling effect of the hypothetical urban forestation intervention

5. CONCLUSIONS AND OUTLOOK

The proposed framework demonstrates how EO-based modelling can support urban heat risk analysis through LST simulation, by empowering urban planners to assess the impact of greening, material, and morphological interventions on LST without requiring advanced technical expertise. As most of the considered input predictors and LST satellite observations are widely available globally, the approach is readily transferable across different urban contexts worldwide.

Despite these advantages, several limitations currently constrain full operational deployment. In particular, the simplified representation of urban thermal processes, driven mainly by surface properties and urban morphology, lacks an explicit treatment of meteorological forcing. This choice reflects the necessary trade-off between model complexity and usability that is required to support urban digital twin applications by non-expert users, but it also limits very accurate simulations of fine-scale and short-term thermal dynamics. In addition, the reliance on medium-resolution, multi-source Earth Observation datasets with heterogeneous spatial and temporal characteristics may introduce spatial aggregation artefacts and limit robust validation and uncertainty quantification. Implementation and validation on additional real-world scenario testing are foreseen in subsequent phases of this work.

Future developments will consider the integration of higher-resolution thermal observations from upcoming missions such as the Copernicus Land Surface Temperature Monitoring (LSTM), alongside high-resolution multispectral and hyperspectral optical data from missions such as PRISMA and the Italian IRIDE constellation. The combined availability of spatially and temporally resolved thermal and optical data is expected to support the extension of the framework toward finer-scale urban applications. The availability of such data is key to modelling intra-urban thermal variability and short-term heat dynamics in heterogeneous urban environments. From a modelling perspective, while the framework builds on established EO workflows, further advances are needed to improve simulation capabilities and to strengthen the linkage between LST modelling and urban heat-risk assessments. In this context, recent advances in artificial intelligence modelling provide opportunities to extend the relatively simple regression-based approach adopted in this prototype toward more advanced predictive models. However, their application to urban heat modelling will require careful validation and interpretability to ensure suitability for decision-support applications.

Ultimately, the framework can serve as a prototype component for future urban digital twins, where its modular, EO-driven architecture could be embedded within broader digital ecosystems to enable near-real-time urban heat monitoring, data assimilation, and dynamic scenario testing. Beyond data and modelling developments, future work will also address the design and integration of user-friendly dashboards and interfaces that will allow a broader range of users, including planners and decision-makers, to effectively access, interpret, and interact with simulation outputs.

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