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GEOSPATIAL MACHINE LEARNING FOR URBAN HEAT ISLAND DETECTION AND FORECASTING

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Abstract: This paper proposes a practical prototype for geospatial machine learning for urban heat island detection and forecasting. The central problem is that urban neighborhoods can experience different thermal conditions because of building density, vegetation and surface material. Treating satellite pixels as independent observations may overstate predictive performance. The proposed working model is designed to test a focused technical contribution rather than make unsupported claims about deployed performance. The implementation uses Python, rasterio, GeoPandas, Random Forest and a traceable evaluation based on open satellite imagery and publicly available weather observations. The study defines reproducible baselines, measurements and limitations so that results can be populated after an actual experiment. The intended outcome is an inspectable system suitable for a computer science and data analytics student research project.

Keywords: remote sensing; urban climate; spatial analysis; working model; empirical evaluation

1. INTRODUCTION

Urban neighborhoods can experience different thermal conditions because of building density, vegetation and surface material. Treating satellite pixels as independent observations may overstate predictive performance. The research objective is to establish whether a carefully instrumented implementation can improve usefulness, reliability or efficiency over a simple baseline. The scope is deliberately bounded to a demonstrable student-scale experiment with explicit input data, prediction or decision outputs and independently verifiable measurements.

2. RESEARCH PROBLEM AND OBJECTIVES

Map neighborhood-scale heat exposure and estimate how land cover relates to observed surface temperature within a selected city. The specific objectives are to define operational inputs, implement a reproducible processing pipeline, expose the outputs through a usable interface, and establish measurable success criteria. A separate baseline is required to show whether the advanced technique offers genuine value in the intended scenario.

Research Questions and Scope

The central research question is whether the proposed geospatial machine learning for urban heat island detection and forecasting working model improves the evidence available for a concrete decision. The first subquestion concerns the quality and completeness of data drawn from open satellite imagery and publicly available weather observations. The second concerns how reliably the method performs under the operating conditions described here: Urban neighborhoods can experience different thermal conditions because of building density, vegetation and surface material. Treating satellite pixels as independent observations may overstate predictive performance. The third concerns whether users can inspect the reasoning behind the output and identify its limitations.

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3. PROPOSED SYSTEM ARCHITECTURE

Assemble satellite land-surface-temperature products, vegetation indices, built-up indicators and available weather records. Reproject into a consistent spatial grid, align dates and train a spatially evaluated random forest to estimate thermal patterns. The proposed architecture separates acquisition, preprocessing, core analysis, persistent storage and presentation. Each stage records configuration versions and errors, allowing the prototype to be restarted and results to be repeated. Input validation must occur before data enters a trained model or decision engine.

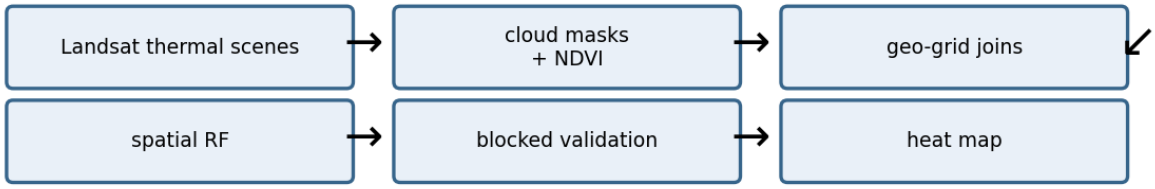


Figure 1. Proposed end-to-end architecture (conceptual working model).

3.1 Module Responsibilities

Module 1 — Landsat thermal scenes: define its accepted input schema, transformation rules, output contract, failure messages and retained provenance. Instrument every stage with timestamped diagnostics so an unexpected result can be traced back to a dataset version or configuration.

Module 2 — cloud masks + NDVI: define its accepted input schema, transformation rules, output contract, failure messages and retained provenance. Instrument every stage with ed diagnostics so an unexpected result can be traced back to a dataset version or configuration.

Module 3 — geo-grid joins: define its accepted input schema, transformation rules, output contract, failure messages and retained provenance. Instrument every stage with timestamped diagnostics so an unexpected result can be traced back to a dataset version or configuration.

Module 4 — spatial RF: define its accepted input schema, transformation rules, output contract, failure messages and retained provenance. Instrument every stage with timestamped diagnostics so an unexpected result can be traced back to a dataset version or configuration.

Module 5 — blocked validation: define its accepted input schema, transformation rules, output contract, failure messages and retained provenance. Instrument every stage with timestamped diagnostics so an unexpected result can be traced back to a dataset version or configuration.

Module 6 — heat map: define its accepted input schema, transformation rules, output contract, failure messages and retained provenance. Instrument every stage with timestamped diagnostics so an unexpected result can be traced back to a dataset version or configuration.

3.2 Data Integrity and Design Controls

Separate raw inputs from transformed records; keep validation, model fitting and final reporting as distinct operations. Reject incomplete records rather than silently substituting values. Sensitive records and personal identifiers should be excluded unless specifically required and approved.

4. WORKING MODEL IMPLEMENTATION

Implementation components: Python, rasterio, GeoPandas, Random Forest. The demonstration data source is Open satellite imagery and publicly available weather observations. The working sequence begins with importing or streaming representative observations, then applying domain-appropriate cleaning and transformations. Model or rule outputs are saved with timestamps, configuration settings and enough provenance for review. The interface should offer at least one realistic example, one difficult example and one failure-mode demonstration. The implementation should capture runtime, data volume, model settings and reproducibility seeds where applicable.

4.1 Prototype Demonstration Scenario

Operational example: Map neighborhood-scale heat exposure and estimate how land cover relates to observed surface temperature within a selected city. The initial input is retained separately from transformed records so a reviewer can reproduce the decision. The processing logic follows this specific procedure: Assemble satellite land-surface-temperature products, vegetation indices, built-up indicators and available weather records. Reproject into a consistent spatial grid, align dates and train a spatially evaluated random forest to estimate thermal patterns. An operator sees both the

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recommended output and its source evidence. This makes the prototype inspectable instead of presenting a prediction as an unexplained result.

4.2 Testing and Reproducibility

Implementation verification: Assemble satellite land-surface-temperature products, vegetation indices, built-up indicators and available weather records. Reproject into a consistent spatial grid, align dates and train a spatially evaluated random forest to estimate thermal patterns. Create a unit test for accepted inputs, a negative test for malformed input and a boundary test for rare or extreme values. Capture the configuration of each run so unexpected behavior can be traced to the dataset version, selected method or processing step. A visible error state is preferable to a confident but unsupported answer.

4.3 Build and Validation Steps

Step 1. Fix datasets, source rights and input formats. In the demonstration, preserve the associated input ID and expected behavior so the test can be rerun and inspected.
Step 2. Run independent preprocessing and schema-validation unit tests. In the demonstration, preserve the associated input ID and expected behavior so the test can be rerun and inspected.
Step 3. Implement a baseline, then the advanced technique under the same resource constraints. In the demonstration, preserve the associated input ID and expected behavior so the test can be rerun and inspected.
Step 4. Record configuration seeds, library versions, hardware and dataset hash. In the demonstration, preserve the associated input ID and expected behavior so the test can be rerun and inspected.
Step 5. Expose detailed error states, human review and an exportable audit report. In the demonstration, preserve the associated input ID and expected behavior so the test can be rerun and inspected.
Step 6. Run edge cases such as missing inputs, noisy records and distribution shift. In the demonstration, preserve the associated input ID and expected behavior so the test can be rerun and inspected.

4.4 Runtime and Quality Checks

Capture CPU and memory consumption, throughput, rejected-record count, and median/p95 inference time where appropriate. Identify one realistic scenario, one boundary scenario and one misleading or adversarial scenario. Compare saved outputs with an independently curated label or trusted reference before declaring a working-model success.

5. EXPERIMENTAL DESIGN AND EVALUATION

Validate with geographic holdout blocks and independent observation dates. Report mean absolute temperature error, spatial residual clustering and uncertainty across vegetation and built-density groups. Run a controlled study on a held-out evaluation partition or a set of documented scenarios. Record baseline and proposed-system results using identical inputs, disclose training and testing boundaries, and present confidence intervals where the sample size permits. Any future results table should be filled from measured runs only; numerical values are intentionally not supplied in this draft.

5.1 Measurement Procedure

Evaluation protocol: Validate with geographic holdout blocks and independent observation dates. Report mean absolute temperature error, spatial residual clustering and uncertainty across vegetation and built-density groups. Report how the comparator was chosen and keep input records and resource limits equivalent across competing methods. Inspect examples of incorrect predictions, not only aggregate performance. If the dataset is small, repeat the experiment with multiple documented partitions and quantify uncertainty. Leave all outcome cells empty until the student has run the actual working model.

5.2 Numerical Illustrative Results — Synthetic Only

Table 1 presents a hypothetical controlled comparison to demonstrate the intended results layout. These figures were constructed for illustration, not generated from benchmark execution. Metric units are listed separately; cross-metric magnitudes must not be compared as if they share a scale.

Metric	Baseline	Proposed (synthetic)
Temperature MAE (°C)	3.4	2.2
RMSE (°C)	4.5	3.0
Hotspot omission (%)	24	14

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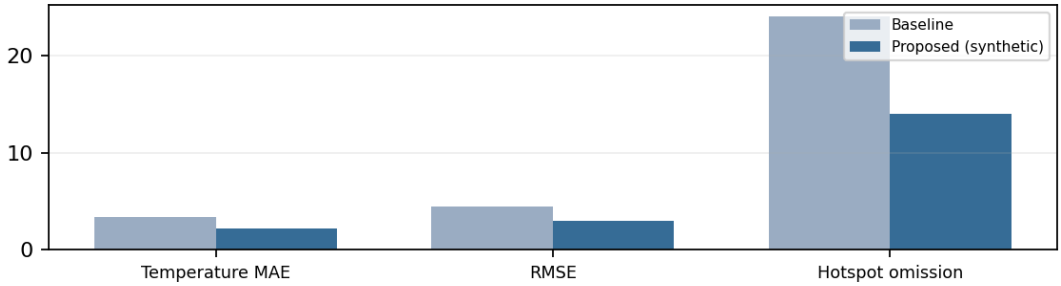


Figure 2. Baseline versus proposed values, based exclusively on synthetic scenario assumptions.

5.3 Interpretation

Synthetic spatial-block illustrations suggest a lower temperature error with multi-feature learning. Surface temperature cannot be equated to personal heat exposure.

A valid experiment must hold the testing data constant across comparators, report sample counts and uncertainty, and avoid leakage between training, development and evaluation sets. Improvements must be interpreted with their runtime, fairness, privacy and maintenance costs.

6. RISK, ETHICS AND LIMITATIONS

Land surface temperature is not identical to near-surface air temperature or personal heat exposure. Cloud contamination and acquisition time affect inference; explain these differences in every map. Additional limitations include dataset representativeness, changing deployment conditions and the narrow scale of a classroom prototype. Decisions with safety, employment, health or legal consequences require qualified human oversight. Clearly document data access permission and reproducibility constraints.

6.1 Threats to Validity

Failure investigation: Land surface temperature is not identical to near-surface air temperature or personal heat exposure. Cloud contamination and acquisition time affect inference; explain these differences in every map. Include a case where the advanced method underperforms a simple baseline and explain the probable reason. Discuss whether the failure comes from noisy inputs, label ambiguity, unrepresentative data, operational constraints or algorithm design. Record what changed after corrective action rather than omitting unfavorable observations.

6.2 Operational Safeguards

Before demonstrating this project, check access rights for the intended dataset (Open satellite imagery and publicly available weather observations), avoid identifying individuals in screenshots, and preserve data provenance. Because the prototype uses Python, raster Io, Geoplanids, Random Forest, record tool and library versions. Explain which decisions remain with human operators and how they can challenge or override an incorrect recommendation.

6.3 Ablation and Failure-Mode Plan

Baseline audit. Replay identical inputs with simple rules or a non-learning heuristic. Record both favorable and unfavorable outcomes in the final experiment log.

Feature ablation. Remove one feature group at a time to quantify what drives the proposed improvement. Record both favorable and unfavorable outcomes in the final experiment log.

Distribution shift. Evaluate a later period, unseen source or changed acquisition conditions. Record both favorable and unfavorable outcomes in the final experiment log.

Error inspection. Manually inspect false alarms and missed cases, recording plausible causes. Record both favorable and unfavorable outcomes in the final experiment log.

Resource analysis. Evaluate batch size, memory, latency and storage alongside the headline accuracy. Record both favorable and unfavorable outcomes in the final experiment log.

Human review. Require confirmation for consequential decisions, with a clear override and correction pathway. Record both favorable and unfavorable outcomes in the final experiment log.

6.4 Responsible Reporting

Do not state that the system was deployed, trained on proprietary records, or experimentally validated until supporting data and execution logs exist. Make every numerical chart caption identify whether it is measured, reproduced from a

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cited publication, or synthetic. Data access permissions and reproducibility constraints should be documented with the eventual released implementation.

7. CONCLUSION AND FUTURE WORK

This study specifies a testable geospatial machine learning for urban heat island detection and forecasting prototype built around a distinct data problem, implementation pipeline and evaluation protocol. Its value will depend on measured performance against the stated baseline, usability of the demonstration and transparent discussion of failure cases. Future development can extend the experiment to larger datasets, additional locations or groups, and monitoring under changed operating conditions without exaggerating the current prototype's readiness.

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