March 11th, 2025

**Science of Remote Sensing**

Dear Editors-in-Chief Dr. Peter Atkinson, Dr. Shunlin Liang and Dr. Randolph H. Wynne,

On behalf of our co-authors, we are pleased to submit our original manuscript, “**Mapping rooftop materials across diverse urban landscapes using high-resolution satellite imagery and convolutional neural networks**” for your consideration under Science of Remote Sensing.

Building materials and their spatial distribution greatly influence the outcomes of human-made and natural disasters in urban and peri-urban areas. The choice of materials affects the resilience and durability of structures against hazards like fires, floods, hurricanes, tornadoes, and earthquakes. With urban expansion into risk-prone areas, it is crucial to analyze urban building materials to improve exposure assessments, emergency planning, and community preparedness. Rooftops are an important feature of buildings that can be observed from space, offering an opportunity for extensive mapping with remote sensing data. Previous efforts to map rooftop materials at the roofprint level across large areas have been hindered by a lack of operational training data, high-resolution satellite imagery, or models that can be generalized for classification across cities with distinct urban patterns.

In this study, we apply a Convolutional Neural Network (CNN) model alongside high-resolution multispectral imagery from PlanetLabs to classify ten rooftop materials in Washington, D.C., and Denver, Colorado, United States. To tackle the challenges of consistent training data, we combine geospatial vector data of “building roofprints” with real estate-derived characteristics, enabling the creation of labeled image data from broadly available imagery. Our results indicate that our CNN-based pipeline is an effective tool for mapping rooftop materials in built environments with varying urbanization patterns. The F1 scores for the most common roof material classes range from 0.56 to 0.95. In Washington, D.C., the CNN model outperformed a traditional pixel-based machine learning classifier by 15%, and in Denver, Colorado, by 17%, based on weighted F1 scores across all classes. **Our research advances the mapping of urban materials and offers a scalable open-source pipeline that can enhance risk and exposure mapping, emergency management, and community preparedness in the continental U.S. and beyond.**

**We** **believe** **that our** **manuscript** **aligns with** **the** **Aims** **and** **Scope** **of** **the** **Science** **of** **Remote** **Sensing** **journal.** **It** **makes** **an** **original** **contribution** **to Earth** **Data** **Science** **and** **Machine** **Learning,** **specifically in** **urban** **mapping** **and** **hazard** **risk** **reduction.** We confirm that our manuscript is not currently under consideration by, nor has it been published in any other journal. We appreciate your handling our manuscript and hope it can be considered for review in the Science of Remote Sensing.

Sincerely,

A close-up of a signature

AI-generated content may be incorrect.

Maxwell Cook

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