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Deep learning for 250m Resolution Annual Land Cover Mapping from 2010 to 2024 in Canada Using MODIS Time-Series Data

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Abstract:

Monitoring land cover changes is vital for understanding the impacts of climate change and supporting effective environmental management. Canada, as a northern region, faces significant challenges due to rapid land cover changes influenced by climatic shifts and anthropogenic activities. While Natural Resources Canada (NRCan) provides high-resolution (30m) land cover maps every five years, the process is labor-intensive, and the temporal resolution is insufficient for tracking annual changes. Moreover, the 250m annual Canadian land cover maps are limited to the years of 2001 to 2011 (Pouliot et al. 2014). This research addresses these gaps by proposing a novel deep learning-based framework for generating annual land cover maps from year 2010 to 2024 at 250m resolution across Canada. We use MODIS MOD13Q1 vegetation indices time-series data and NRCan's 30m maps from year 2010, 2015 and 2020 as ground truth.

The first contribution is a new time-series change detection approach. Using MODIS MOD13Q1 data from 2010 to 2024, we construct time-series data for each 250m pixel across Canada (Latifovic et al. 2017). A supervised deep learning model, trained using NRCan's 30m maps from 2010, 2015, and 2020, is employed to detect changes. Unlike traditional unsupervised thresholding methods, which rely on fixed criteria in the original data space, this model leverages the non-linear feature space of the training data to adaptively determine change criteria. This approach significantly reduces omission and commission errors, improving the reliability of detected changes in dynamic environments.

The second innovation is the development of geographically dependent transition matrices. These matrices estimate the likelihood of land cover transitions within the ecozones of Canada, which tend to have different local geographic and climatic conditions. Comparing with a single transition matrix for entire Canada, these geographically dependent matrices may better accommodate the spatial heterogeneity/non-stationary nature of land cover change. Caused by the unique local climatology and geography patterns of Canada. We calculate region-specific transition probabilities by analyzing the 30m maps of 2010, 2015 and 2020. This geographic specificity enables more accurate modeling of land cover dynamics, accommodating the spatial variability inherent in a diverse landscape like Canada. These location-specific transition probabilities significantly enhance the robustness of the detection process.

The third contribution is an improved classification model to better classify the detected pixels. Once changes are detected, a deep learning architecture is used to classify the changed pixels into appropriate land cover categories. We developed a new spatial-temporal residual neural network (ST-ResNet, see Figure 1 for its architecture) to better capture the subtle differences among different classes for enhanced classification accuracy. Instead of training one model on NRCan's 30m maps in year 2010, 2015, and 2020, we train three models for each year to better accommodate the temporal variations of land class signatures. Figure 2 indicates that the model can generate large-scale land cover maps that are consistent with the "ground-truth" map. This model outperforms traditional machine learning methods, such as Random Forest, and other deep learning architectures. The classification accuracy is substantially improved, enabling precise mapping of diverse land cover types, even in challenging areas.

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Together, these advancements create a robust pipeline for generating annual 250m land cover maps for Canada from 2010 to 2024. Preliminary results demonstrate the effectiveness of this framework in detecting and classifying land cover changes across various regions and time periods. The integration of MODIS MOD13Q1 time-series data with NRCan's 30m maps as ground truth ensures a high degree of accuracy and reliability. The outcomes of this research will have significant implications for environmental monitoring and climate change studies.

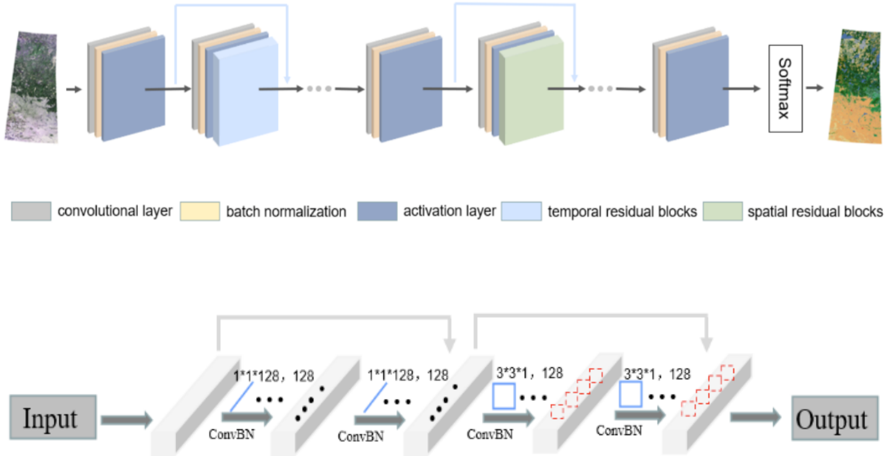

Figure 1: The architecture of the proposed spatial-temporal residual network

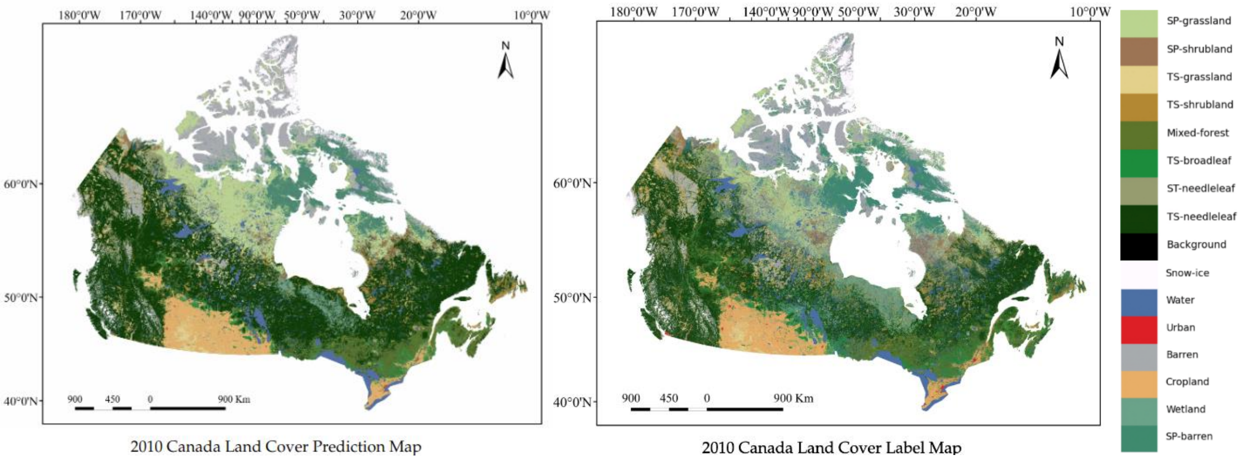

Figure 2: The visual comparison of predicted map and "ground-truth" map. They look very consistent.

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