RELATING SENTINEL-1 TIME-SERIES TO BOREAL FOREST ATTRIBUTES USING CONVOLUTIONAL AUTOENCODERS

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ABSTRACT

The analysis of C-band SAR backscatter time-series over boreal forests can provide tools for a variety of forestry-related applications, such as the estimation of biophysical attributes (Antropov & Rauste & Häme & Praks, 2017) or the assessment of the soil freeze/thaw status (Rignot & Way, 1994). Such studies examined the correlation between temporal profiles and biophysical attributes of boreal forests and found that backscatter seasonal variations were mostly attributed to changes in ground conditions (Rignot et al., 1994). The recent availability of temporally dense Sentinel-1 C-band data further opens up the estimation of forest biophysical attributes or cover types from SAR time-series. However, such applications over large areas of Canada's boreal forests pose challenges including massive processing requirements of such dense time-series which convey noisy or redundant information. Furthermore, specific challenges for sparsely inventoried northern boreal forests of Canada include the lack of forest information required to train parametric models or supervised classifiers. For that matter, SAR time-series representation of lower dimensionality derived from unsupervised deep learning algorithms are sought after as input to non-parametric modelling of forest attributes or unsupervised classification of forest types.

An example of such deep learning methodology are Autoencoders (Kramer, 1991), which can project data onto a space of lower dimension. An Autoencoder network consists of two blocks, an encoder and a decoder. The encoder projects the input data of high dimension, onto a space of lower dimension, the so-called ''embeddings''. The decoder then reconstructs the original data from this lower dimensional representation. This reconstruction task acts as the training objective of the network.

Di Martino et al. (2022) demonstrated the capabilities of C-Band SAR dual-polarized (VV, VH) Sentinel-1 (S-1) time-series to discriminate agricultural crop classes through the unsupervised K-Means clustering of S-1 embeddings derived from a Convolutional Autoencoders (CAE) algorithm. As an extension to other vegetation types, the objectives of this study were to assess the capacity of CAE embeddings from S-1 time-series to i) discriminate classes of boreal forests and ii) relate to forest attributes.

For this purpose, we selected a boreal study site of around 1,500 km^2 near the town of Hay River in Northwest Territories (NWT), Canada. This study site, part of the Multisource Vegetation Inventory (MVI) project (Castilla et al. 2022), is dominated by upland coniferous forests (black spruce), treed and non-treed wetlands, water bodies and burned areas. Two datasets were obtained from the MVI project: i) a 2007 land cover map we updated to year 2020 and ii) 39 400-m^2 forest inventory (FI) ground plots with a suite of plot-level forest structural attributes derived from tree-level measurements (Castilla et al. 2022). For our analysis, we retained stand height (StH, m), quadratic mean diameter (QMD, cm) and aboveground biomass (AGB, t/ha).

We exported from Google Earth Engine platform around 15 million of S-1 time-series across the study area each made of 111 dual-polarized acquisitions in descending mode, between May 2017 and December 2020. We projected the S-1 time-series onto a space of embeddings of lower dimension (n = 3) using the CAE algorithm. We mapped the 3D sub-space of the normalized CAE embeddings onto an RGB color space for visual analysis. We analyzed the Pearson's correlation coefficient r between the CAE embeddings and the forest structural attributes. Finally, we clustered the CAE embeddings using unsupervised K-Means classifier providing eight clusters across the study area. Correlations and clusters were analyzed based on MVI land cover map and FI plots.

For the eight CAE-based clusters, a first forest cluster included 33 of 39 FI plots with AGB, QMD and StH mean values of 143.3 t/ha, 18.9 cm and 21.3 m, respectively. This cluster corresponded to well-stocked conifer forest stands with taller and larger trees. A second forest cluster included 6 of 39 FI plots with AGB, QMD, StH mean values of 49.9 t/ha, 10.3 cm and 12.1 m, respectively. Compared to the first, this second cluster corresponded to less stocked conifer forest stands with significantly smaller and shorter trees. Additional results showed that specific CAE embeddings were significantly correlated to the three structural attributes with r values ranging from 0.58 to 0.61. These preliminary results indicates that CAE embeddings correlate to forest attributes and their unsupervised classification can discriminate broad forest classes. More fundamentally, soil and forest biophysical attributes of boreal forests are known to play a significant role in the temporal behavior of SAR time-series. Further investigations of such complex roles are required and could be supported by our approach as the autoencoder architecture and output embeddings picked up some of the effects of biophysical attributes on the SAR temporal behavior.

On-going work includes refined parametrization of our CAE-based approach (SAR time-series post-processing, number of embeddings, clustering…) and extension to other NWT FI plots to further assess the capacity of CAE embeddings from S-1 time-series to relate to forest attributes and to classify cover types of boreal forests.

Keywords— Autoencoder, Boreal Forest, Clustering, Deep Learning, SAR, Sentinel-1, Time-Series

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