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Examining the Reliability Gap: Insights into Forest Canopy Height Using Evidential Deep Learning

Lucas Kugler, Christine Wessollek, and Matthias Forkel
Technische Universität Dresden, Photogrammetrie und Fernerkundung, Environmental Remote Sensing , Germany
(lucas.kugler@tu-dresden.de)

Estimating forest canopy height is a crucial aspect in quantifying forest biomass, carbon stocks, monitoring forest degradation, and succession or restoration initiatives. Operational forest structure monitoring on a large scale involves various satellite sensors and datasets as well as large geographical variations. Challenges remain in obtaining uniformly representative ground truth data across diverse areas, phenology phases and forest types. Recently deep learning models are more frequently used to map forest canopy height at large scales by e.g., using sample observations from space-borne LiDAR sensors as training data. Training deep learning models rely on large amounts of data but are often trained on limited source domain data that is confined to cover the above-mentioned aspects. However, during testing, models may encounter out-of-distribution samples, leading to unexpected model behaviour and predictions. This vulnerability reduces the reliability of deterministic Deep Learning architectures, and finally, reliance on predictions without confidence indicators can result in misleading scientific conclusions or potentially under-informed policy decisions. Due to the varying ways of data processing, differences in forest canopy height products emerge, and hence product inter-comparison is often difficult and debatable. Existing products often do not provide any information about the confidence of their predictions.
To address this lack of confidence, we employ evidential deep Learning, adapting non-Bayesian architectures to estimate forest height and associated evidence. This approach aims to capture both aleatoric and epistemic uncertainties in areas with different forest structures investigating study areas , by incorporating evidential priors into the Gaussian likelihood function. Our method involves training a myriad of deep learning architectures including a basic CNN and Residual neuronal nets for regression to infer the hyperparameters of the evidential distribution.

Alongside other current studies, Sentinel-2 and Sentinel-1 satellite imagery serve as predictors for forest canopy height, with reference data obtained from the Global Ecosystem Dynamics Investigation (GEDI) LiDAR instrument on the International Space Station. The research explores the effects of distributional data shifts on canopy height predictions and identifies footprint samples where prediction uncertainty increases, representing different forest structures.
The application of evidential deep learning could extend far beyond this study, potentially benefiting various tasks in estimating biophysical parameters from remote sensing.