IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium | 979-8-3503-2010-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/IGARSS52108.2023.10283354

FORESTMAP: MAPPING FOREST ATTRIBUTES ACROSS THE GLOBE - FIRST CASE STUDY

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ABSTRACT

This paper presents the project ForestMap – a project aiming to develop and distribute new methods, which provide the benefits of accurate forest maps to a global audience. Using the recent developments in remote sensing, machine learning, and Artificial Intelligence (AI) the goal is to export the Scandinavian success stories to a wide range of stakeholders in the world.

Index Terms— Forest, map, global, machine learning, Artificial Intelligence

1. INTRODUCTION

Forests provide countless values to people and society, both in developing as in developed countries. For the developed countries the main value has been from wood and products from wood. In many developing countries the forest is still seen as a common right of access, supplying firewood, food and building material. Today, new societal values are provided by the forests, important to human well-being [1,2]. Presumably the most important value of the forests is that they have been identified to have a major role in global climate change, where deforestation, afforestation and new strategies to actively increase carbon sequestration, are very important processes. Moreover, the forests are critical habitats for biodiversity and there is increasing evidence that biodiversity contributes to forest ecosystem functioning and the provision of ecosystem services [3]. However, there is very little global discussion on how improved management of productive forests could contribute to mitigation of climate change and enrichment of biodiversity. A fundamental need from forest stakeholders is data about the forest state and change in terms of biomass, tree species composition, and forest cover. However, depending on the stakeholder, the need of data, required accuracy, willingness to pay and need of decision support is very much variating.

2. FOREST MAPS

Information summarizing the forest state for specific target areas, such as at the global, national, regional or forest estate level, as well as geographical maps showing the spatial distribution of the forest information are very valuable for sustainable management. Examples of these maps are the global maps of biomass and biomass change provided by the Global Forest Watch [4], and the biomass maps produced from radar data [5]. The latter maps comprise estimates of forest biomass for the years 2010, 2017 and 2018, and are derived from a combination of remote sensing data sources, depending on the year, from the Copernicus Sentinel-1 mission, Envisat's ASAR instrument and JAXA's Advanced Land Observing Satellite (ALOS-1 and ALOS-2), along with additional information from other Earth Observation sources. Furthermore, examples at national scale are the Basemap of precision forest maps of the USA produced by SilviaTerra in cooperation with Microsoft (www.silviaterra.com), and the national forest maps produced in Sweden [6] and Finland [7] using remote sensing data in combination with field measurements. In the last decades, airborne laser scanning (ALS) has been successfully used for large-area forest mapping in the Nordic countries [8]. In the case of Sweden, the Swedish National Land Survey (Lantmäteriet) made an ALS mapping of all forested land during the period 2009 to 2016. The primary aim of the scanning was to produce a new national elevation model with high accuracy, to aid scenario analyses of climate change induced effects, although the laser data were also made publicly available at low cost. The Swedish Forest Agency and the Swedish University of Agricultural Sciences (SLU) were commissioned by the government to do a nationwide forest map using the ALS data from Lantmäteriet [9]. These maps were produced using the area-based method [10] using sample plot data from the Swedish National Forest Inventory (NFI) [11] as the reference data. The predicted variables were stem

volume, above-ground tree biomass, basal area, mean tree height and mean stem diameter. Additional map products such as soil wetness maps and slope maps were also derived from the ALS data. These maps have found wide-spread use in the forestry sector for management planning, environmental monitoring, and at authorities like e.g., the Swedish Forest Agency and the County Boards. The use of open data from the Swedish Forest Map could potentially lead to more work opportunities, new entrepreneurships, innovations, and a healthy competition within the forestry sector, since the maps provide accurate and up-to-date information about the forest resources that are available to everyone, including small enterprises and private owners. The benefit provided by the first national ALS raised sufficient interest in the society and the private sector to jointly provide fundings for continuously repeated ALS campaigns.

3. FORESTMAP – FIRST CASE STUDY

The first case study of the project ForestMap - a project aiming to develop and distribute new methods, which provide the benefits of accurate forest maps to a global audience – will be presented. Using the recent developments in remote sensing, machine learning, and Artificial Intelligence (AI) [e.g., 12-17], the goal is to export the Scandinavian success stories to a wide range of stakeholders in the world. Previously, the most limiting resource in remote sensing-based mapping of forest has been availability of data and especially reference data in the form of surveyed field plots. Today, there are many more open sources of remote sensing data available to everyone, and the fields of machine learning and AI provide new tools to develop mapping models using existing data sets and then re-use the models in other areas using only very little new reference data from the new target area. The ForestMap project will perform this task, by developing general AI models trained on existing Scandinavian data which can be fine-tuned to use at other forested areas. Here, a neural network (NN) mapping forest attributes from airborne laser scanning data using field surveyed plots as reference data has been trained, closely mimicking the today very successfully utilized linear regression-based method to produce national maps of forest attributes in Sweden. We present the first case study of the ForestMap project, where the NN trained on Swedish data was applied and evaluated on data from another European country. This was performed by fine-tuning the trained model using transfer learning with a small amount of local survey data.

4. ACKNOWLEDGMENTS

Project ForestMap is supported under the umbrella of ERA-NET Cofund ForestValue by Swedish Governmental Agency for Innovation Systems, Swedish Energy Agency, The Swedish Research Council for Environment, Agricultural Sciences and Spatial Planning, Academy of Finland, and the Scientific and Technological Research Council of Turkey. ForestValue has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 773324.

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