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Global trends analysis of the main vegetation types throughout the past four decades

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ABSTRACT

In remote sensing studies, the photosynthetically active radiation absorbed by chlorophyll in the green leaves of vegetation canopies is measured using Red and Near-Infra Red bands. The Normalized Difference Vegetation Index (NDVI) is one of the most commonly used vegetation indices that are generally obtained from a calculation of the above mentioned bands; it presents a decent surrogate measures of the physiologically functioning surface greenness level. In this study, the latest version of the GIMMS NDVI data set, between the period of January 1982 and December 2015, were used to classify the global vegetation areas into five main categories (i.e. Agriculture Areas, Boreal Forests, Deciduous Forests, Evergreen and Tropical Forests, and Other Vegetation), using a simple and straight-forward method of classification, surnamed *Global Vegetation Types Classification* (*GVTC*). The total accuracy of the model reached 90.4% with a kappa value of 87.1%.

In each category, a trend analysis has been carried out at both global and continental levels. The objective was to highlight the changes within each category, throughout the past thirty-four years. Results show that Agriculture Areas are increasing worldwide, with a huge upsurge observed since 2011 coinciding with a remarkable decrease in Boreal Forests. Changes in vegetation's classes, between 1982 and 2015, were more pronounceable in continents such as Asia, America and Africa; Europe and Oceania showed limited variations throughout this same period. Following these results, regional policies should be reformed and mitigation plans should be established in order to maintain a sustainable development of the global vegetation lands. The *GVTC* could be implemented with higher spatial resolution imageries for more local-based assessments.

1. Introduction

Our world is changing at fast pace. Most notably, global forest area is declining (Orth & Moore, 1983; Verheyen et al., 2016; Wulder, Butson, & White, 2008), sea level is rising (Gardner, Cogley, Moholdt, Wouters, & Wiese, 2015; Meier & Wahr, 2002; Nicholls & Cazenave, 2010), global warming is increasing (Eide, 2008; Fyfe, Gillett, & Zwiers, 2013) and population worldwide is growing (Cincotta, Engelman, & Anastasion, 2003; Sixsmith, 2013). The availability of remote sensing techniques and satellite imageries made it possible to observe and assess these changes from space in a time- and resource-effective manner (e.g. Cooper, Chen, Fletcher, & Barbee, 2013; Faour & Mhawej, 2014; Kellner & Hubbell, 2017; Kubanek, Nolte, Taubenböck, Wenzel, & Kappas, 2014; Lillesand, Kiefer, & Chipman, 2014).

To describe the physiologically functioning surface greenness level for each picture element and to detect the vegetation trends across the globe, several vegetation indices have been proposed. The most widely used remains the Normalized Difference Vegetation Index (NDVI) (Faour, Mhawej, & Fayad, 2016; Kerr & Ostrovsky, 2003). This index is calculated from the Visible and Near-Infra Red light reflected by vegetation with values ranging from -1.0 to $+1.0$ (Tappan, Tyler, Wehde, & Moore, 1992).

The usage of NDVI in the literature served different purposes: some authors tried to estimate the Fractional Vegetation Covers (FVC), the Leaf Area Index (LAI) and the surface soil moisture content from NDVI (e.g. Carlson & Ripley, 1997; Carlson, Gillies, & Perry, 1994; Jiang et al., 2006; North, 2002; Wu et al., 2014). Others introduced this index in drought studies while detecting changes in vegetation trends (e.g. Faour, Mhawej, & Abou Najem, 2015; Faour, Mhawej, & Fayad, 2016; Gu, BrownVerdin, & Wardlow, 2007; Liu & Kogan, 1996; Mwaniki & Möller, 2015; Peters et al., 2002; Petropoulos, Griffiths, & Kalivas, 2014; Riva, Daliakopoulos, Eckert, Elias, & Liniger, 2017; Shalaby & Tateishi, 2007; Van Hoek, Jia, Zhou, Zheng, & Menenti, 2016). Moreover, the NDVI was used in different discipline, such as forestry and wildfire managements (e.g. Wang, Adiku, Tenhunen, & Granier, 2005; Schrader-Patton, Grulke, & Dressen, 2016; Mhawej, Faour, Abdallah, &

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Adjizian-Gerard, 2016; Mhawej, Faour, & Adjizian-Gerard, 2017), hydrology (Zhao & Chang, 2014; Zhou et al., 2006), agriculture and pedology studies (Chen, De Jeu, LiuVan der Werf, & Dolman, 2014; Epinat, Stein, Steven, de Jong, & Bouma, 2001; Farrar, Nicholson, & Lare, 1994; Houborg & McCabe, 2016).

Various methods, considerations and approaches were proposed to classify and map vegetation classes (Xie, Sha, & Mei, 2008). Historically, these classifications techniques were based on bioclimatic analyses, thus producing climate-vegetation classifications based on simple temperature and water indices (Brovkin, Ganopolski, & Svirezhev, 1997; Running, Loveland, Pierce, Nemani, & Raymond Hunt, 1995). The most well-known examples of these approaches remain Köppen & Geiger (1936) and Holdridge (1947). More recent studies (e.g. Brovkin et al., 1997; Mwaniki & Möller, 2015; Neilson, 1993; Petropoulos et al., 2014; Prentice, Guiot, Huntley, Jolly, & Cheddadi, 1996; Running et al., 1995) have added diverse ecological-based factors (e.g. specific physiological responses to cold tolerance, drought stress, aboveground live biomass and leaf longevity) in relation to the geographic distribution of different vegetation types. Furthermore, other authors have included topographic factors such as altitude and slope (e.g. Carpenter, Gjaja, Gopal, & Woodcock, 1997; Franklin, Connery, & Williams, 1994; Juel, Brian Groom, Svenning, & Ejrnaes, 2015; Mwaniki & Möller, 2015; Sesnie, Gessler, Bryan, & Thessler, 2008) that have the potential to enhance the discrimination between the vegetation classes (Running et al., 1995). Methods used ranged from simple equation (e.g. Brovkin et al., 1997) and simple classification structure (e.g. Lu, Moran, & Batistella, 2003; Running et al., 1995) to more advanced classification methodologies including K-mean (e.g. Burrough, FM van Gaans, & MacMillan, 2000) and ISODATA (Irvin, Ventura, & Slater, 1997) as unsupervised classification and Maximum Likelihood Classification (MLC) (e.g. Hansen, Dubayah, & DeFries, 1996; Rogan, Franklin, & Roberts, 2002) and Decision Tree (DT) (e.g. Chakraborty, Sachdeva, & Joshi, 2016; Lees & Ritman, 1991; Martínez-Verduzco, Guillermo, Mauricio Galeana-Pizaña, & Cruz-Bello, 2012) as supervised classification. Artificial Neural Network (ANN) and fuzzy logic approaches (e.g. Carpenter et al., 1997, 1999), COCKTAIL and TWINSPAN methods (e.g. Tichý, 2002) and the object-based classification (e.g. Aguirre-Gutiérrez, Seijmonsbergen, & Duivenvoorden, 2012; Yu et al., 2006) could also be found in the literature.

Classifying and mapping vegetation areas is pivotal in diverse studies, particularly in terrestrial carbon dioxide and global climate change researches (Xie et al., 2008). Presenting the historical and current state of vegetation cover is equally required to orient vegetation protection and restoration programs as well as being a decision tool in the hand of the policy makers. Still, one major problem faces the vegetation classification studies; it is the lack of clearly defined classes, exacerbated by a significant disagreement among authors on the spatial distribution of each biome classes (Jung, Henkel, Herold, & Churkina, 2006; Townshend, Christopher Justice, Li, Gurney, & McManus, 1991).

In this paper, we are focusing on identifying the historical and current state of five major vegetation classes, without studying their sub-classes. Thus, the extended AVHRR 8-km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data, between the period of January 1982 and December 2015, were used. These imageries correspond to the latest version of the GIMMS NDVI data set. Following a proposed simple classification, surnamed Global Vegetation Types Classification (*GVTC*), global vegetation areas were categorized into five types (i.e. Agriculture Areas, Boreal Forests, Deciduous Forests, Evergreen and Tropical Forests, and Other Vegetation). The terminologies used in this study for the selected classes are as follows: Agriculture Areas include arable land and permanent crops; Boreal Forests are characterized by their location in a circumpolar belt circling the globe, consisting largely of coniferous trees; Deciduous Forests concern trees that characteristically lose their leaves at the end of the growing season; Evergreen and Tropical Forests are characterized by persistent foliage throughout the year; Other Vegetation correspond to abandoned agriculture fields or pasture and do not produce any wood-related products. The proposed vegetation classification system overcomes limitations found in other previous classification approaches such as seasonality, large and continuous training inputs datasets, and salt and pepper effects, among others. The usage of *GVTC* is also aligned with Xie et al. (2008) suggestion to implement a vegetation classification system designed to respond to the objective of the study, where refining or adding classes should be carefully considered for better classification accuracy. Our goal here is to propose a classification procedure that is computationally efficient, producing accurate results which are thoroughly analyzed and discussed. In this context, a trend analysis is produced for each class in the past thirty-four years and for each continent. More precisely, this study aims to answer the following questions: Had the agriculture areas expanded to satisfy the increasing population needs? Had the global warming affected the boreal forests' distribution in the past decades? Did human destroy the tropical forests in that same period and at which extent? Had human policies and interferences affected vegetated areas? Which continents illustrated major vegetation variations and what are the main driving forces behind these changes? Ultimately, is our Earth becoming less green?

2. Materials and methods

2.1. Data background

Tucker et al. (2005) have produced a Normalized Difference Vegetation Index (NDVI) 8-km equal-area dataset, from July 1981 through December 2015, for all continents except Antarctica, using daily daytime Advanced Very High Resolution Radiometer (AVHRR) global area coverage data. They also post-process these data to correct the majority of dropped scan lines, navigation errors, data drop outs, edge-of-orbit composite discontinuities, and other artefacts in the composite NDVI data. The NDVI 8-km and bi-monthly data were processed in the University of Maryland Global Land Cover Facility. The latest version of the GIMMS NDVI data, namely NDVI3g (third generation GIMMS NDVI from AVHRR sensors) can be directly downloaded from *ecocast.arc.nasa.gov*. For further information concerning the processing of the datasets, kindly refer to Tucker et al. (2005). In this study, we focus only on imageries from January 1982 through December 2015, as we intend to work on a yearly basis.

2.2. Proposed classification: the Global Vegetation Types Classification (GVTC)

Remote sensing techniques are used worldwide to classify land cover types (e.g. Aplin, 2004; Green, Dick, & Lackey, 1994; Pagliarella et al., 2016; Yuan, Sawaya, Loeffelholz, & Bauer, 2005), while proposing diverse approaches. Nonetheless, in correspondence to the different wavelengths and sensors used as well as the diverse climatic regions, one land cover type could generate multiple yearly-profiles. Moreover, the lack of one or more satellite imageries per year, caused, for instance, by instrument issues or bad weather conditions, generates a limitation in applying profile-based approaches.

In this study, a simple method surnamed Global Vegetation Types Classification (*GVTC*) that is based on the projection of the NDVI temporal profiles by transforming two dimensional data into only one, was proposed. Accordingly, the above-mentioned problems were solved, most notably distinguishing between major land cover types in different regions of the world and in diverse climate. More precisely, the minimum and maximum yearly NDVI values were retrieved. The amount of change between the minimum and maximum is generally the defining factor in each class. Thus, assumptions were applied on annual basis for each stack of layers containing twenty-four images of global NDVI. Yearly outputs are then classified into six main land cover types (i.e. Agriculture Areas, Boreal Forests, Deciduous Forests, Evergreen and Tropical Forests, Other Vegetation and No Vegetation) as shown in