ISPRS Journal of Photogrammetry and Remote Sensing 146 (2018) 22–37

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

The impact of dataset selection on land degradation assessment

Arden L. Burrell[a,b,*], Jason P. Evans[a,b], Yi Liu[c]

[a] Climate Change Research Centre, School of Biological, Earth and Environmental Science, University of New South Wales, Australia
[b] ARC Centre of Excellence for Climate Extremes, Australia
[c] School of Geographic Sciences, Nanjing University of Information Science & Technology, Jiangsu 210044, China

ARTICLE INFO

Keywords:
RESTREND
BFAST
Dryland degradation
NDVI
Trend analysis
AVHRR
GIMMS
TSS-RESTREND

ABSTRACT

Accurate quantification of land degradation is a global need, particularly in the world's dryland areas. However, there is a well-documented lack of field data and long-term observational studies for most of these regions. Remotely sensed data offers the only long-term vegetation record that can be used for land degradation assessment at a national, continental or global scale. Both the rainfall and vegetation datasets used for land degradation assessment contain errors and uncertainties, but little work has been done to understand how this may impact results. This study uses the recently developed Time Series Segmented RESidual TREND (TSS-RESTREND) method applied to six rainfall and two vegetation datasets to assess the impact of dataset selection on the estimates of dryland degradation over Australia. Large differences in the data and methods used to produce the precipitation datasets did not significantly impact results with the estimate of average change varying by < 4% and a single dataset being sufficient to capture the direction of change in > 95% of regions. On the other hand, the vegetation dataset selection had a much greater impact. Calibration errors in the Global Inventory Monitoring and Modeling System Version 3 NDVI (GIMMSv3.0g) dataset caused significant errors in the trends over some of Australia's dryland regions. Though identified over Australia, the problematic calibration in the GIMMSv3.0g dataset may have effected dryland NDVI values globally. These errors have been addressed in the updated GIMMSv3.1g which is strongly recommended for use in future studies. Our analysis suggests that using an ensemble composed of multiple runs performed using different datasets allows for the identification of errors that cannot be detected using only a single run or with the data quality flags of the input datasets. A multi-run ensemble made using different input datasets provides more comprehensive quantification of uncertainty and errors in space and time.

1. Introduction

Drylands cover about 41% of the land surface and are characterised by low annual precipitation (Ruppert et al., 2015) and large interannual climate variability (Broich et al., 2014; Khishigbayar et al., 2015) which result in significant natural variation in vegetation productivity (Broich et al., 2014). Dryland degradation poses a serious threat to international food security and has been identified by the United Nations (UN) as an issue of global concern (MEA, 2005). At the 12th Conference of the Parties to the UN Convention to Combat Desertification, nations were called upon to implement plans to reach land degradation neutrality which they defined as *"a state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems"* (Orr et al., 2017).

Despite the importance of dryland degradation monitoring (IPCC, 2017; MEA, 2005), current estimates of the scale of the problem have been described as "highly unreliable and spurious" because they depend heavily on small scale field studies as well as low spatial and temporal resolution expert opinions (Higginbottom and Symeonakis, 2014). Over Australia, which is well studied by global standards, spatial data products provide information about a range of environmental parameters including land cover (Lymburner et al., 2011), vegetation climate zones (BoM, 2012), land use (Australian Bureau of Agricultural and Resource Economics and Sciences, 2015) and soil acidification (State of the Environment 2011 Committee, 2011) (for a full list see Lawley et al. (2016)). None of these products are suitable for change detection or time series analysis, as most are a snapshot of a single point in time or are produced using inconsistent methods (Caccetta et al., 2012) from sparse and infrequent field data (Ludwig et al., 2007). This lack of a long term monitoring program and the problems with existing programs for land degradation detection has been extensively

* Corresponding author at: Climate Change Research Centre, Level 4, Mathews Building, The University of New South Wales, Sydney NSW 2052, Australia.
E-mail address: arden.burrell@unsw.edu.au (A.L. Burrell).

https://doi.org/10.1016/j.isprsjprs.2018.08.017
Received 9 March 2018; Received in revised form 21 August 2018; Accepted 23 August 2018

documented (Day et al., 2007; Eyre et al., 2011; Fisher and Kutt, 2006; Healy et al., 2016; Ludwig et al., 2004; McAlpine et al., 2014; Pickup, 1998). Remotely sensed datasets offer the only viable way to assess dryland degradation at national, continental or global spatial scales, and over multi-decadal time periods.

There are two types of methods used to assess ecosystem changes in dryland regions; those that analyse changes in the seasonal phenology of vegetation, and those that look for changes in the relationship between vegetation and climate variables such as precipitation (Burrell et al., 2017; Higginbottom and Symeonakis, 2014). The most widely used method to assess changes in vegetation phenology with respect to time is the Breaks For Additive Seasonal and Trend (BFAST) (Verbesselt et al., 2010a, 2010b). BFAST decomposes the vegetation phenology signal present in remotely sensed Vegetation Index (VI) time series data into its seasonal, trend, and remainder components. This allows the method to detect abrupt changes in both the trend and seasonal components of the vegetation phenology (Kuenzer et al., 2015). In ecosystems with low interannual climatic variability, the vegetation phenology is relatively stable. This means that breakpoints detected in the phenology cycle using BFAST can be attributed to ecosystem disturbances (Hutchinson et al., 2015; Verbesselt et al., 2010a, 2010b). In regions with high interannual climate variability, drought and flood years can cause significant natural changes in the phenological cycle. This makes the separation of natural variability from environmental change problematic (Burrell et al., 2017; Fensholt et al., 2015; Kuenzer et al., 2015; Watts and Laffan, 2014).

The second approach to dryland degradation analysis is to look at changes in the relationship between climate variables and a VI such as the Normalized Difference Vegetation Index (NDVI), which is a measure of vegetation greenness and a proxy for ecosystem productivity. The most widely used method based on this relationship is the Residual Trend (RESTREND) method proposed by Evans and Geerken (2004). RESTREND works by first performing an Ordinary Least Squares (OLS) linear regression between annual peak NDVI and the relevant climate variables (Reeves et al., 2015; Wang et al., 2012a; Wessels et al., 2007). RESTREND is able to estimate the change in ecosystem productivity that is not caused by interannual climatic variability (Evans and Geerken, 2004; Wessels et al., 2007, 2012). Which climate variables are used in RESTREND analysis varies regionally. In Australia and Africa, where water is the primary limiting factor (Broich et al., 2014; Guan et al., 2014; Zhang et al., 2018), a vegetation-precipitation relationship (VPR) is calculated (Burrell et al., 2017; Evans and Geerken, 2004; Wessels et al., 2012). In cold drylands like Mongolia, temperature also plays a major role and, as such, is included as an additional climate variable (Keenan and Riley, 2018; Liu et al., 2013). A trend analysis is then performed on the VPR residuals, with a negative trend indicating land degradation (Andela et al., 2013; Li et al., 2012). An example of a RESTREND analysis is included in supplementary material.

Two of the three key assumption of the RESTREND method are that there is a statistically significant VPR, and that this VPR remains comparable for the entirety of the time series (Burrell et al., 2017; Wessels et al., 2012). This means that in regions where a degradational process is introduced or removed, leading to rapid ecosystem change, RESTREND can fail to detect the change (Wessels et al., 2012). The third assumption is that any trend in the residuals remains monotonic for the entire time series. In a previous study of dryland degradation over Australia, Burrell et al. (2017) found that at least one of the key assumptions of the RESTREND method was violated in approximately 15% of pixels. In areas with documented examples of rapid ecosystem change, RESTREND analysis alone was unable to capture the extent of the changes. Similar problems with RESTREND were found in a study over Kyrgyzstan (Eddy et al., 2017).

To address these problems, Burrell et al. (2017) proposed the Time Series Segmented Residual Trends (TSS-RESTREND) method. TSS-RESTREND is an extended version of RESTREND incorporating a modified version of the BFAST method to look for rapid ecosystem changes that violate the key assumptions that underpin a standard RESTREND (Burrell et al., 2017; Wessels et al., 2012). If a significant breakpoint is found in either the VPR or the VPR-Residuals, TSS-RESTREND uses multivariate regression with an additional variable to account for the breakpoint. When applied to Australia, TSS-RESTREND, was able to improve the detection of degraded areas compared to RESTREND alone as well as to accurately detect both the timing and the direction of change in two regions with known histories of degradation (Burrell et al., 2017).

One of the main advantages of automated analysis of remotely sensed data using methods like TSS-RESTREND, RESTREND or BFAST, is that the analysis is easy to replicate. This is particularly true for methods like TSS-RESTREND and BFAST, where the methods are available as R packages that can be freely downloaded and implemented (http://cran.rproject.org/package=bfast and (https://cran.r-project.org/package=TSS.RESTREND). This facilitates the direct comparison of different studies over different timescales and regions which allows for the discussion of global dryland trends (Higginbottom and Symeonakis, 2014). Inherent in the intercomparison of studies is the assumption that any changes in vegetation and precipitation are larger than the noise present in the datasets used to capture them (Verbesselt et al., 2010b). That is, the signal to noise ratio is high enough that it is possible to separate real variations in the vegetation from those caused by the systematic errors and uncertainties in the datasets (Scheftic et al., 2014; Verbesselt et al., 2010b).

A study by Ibrahim et al. (2015) in the Sub-Saharan region of West Africa over the time period 1982–2012, found that using datasets with different signal-to-noise ratios can have a substantial impact on the results. The results of a RESTREND analysis between GIMMSv3.0g and CRU3 were compared with one performed between GIMMSv3.0g and the Soil Moisture Index produced by the Climate Prediction Centre. It was found that the estimated vegetation trends differed across the entire study area with RESTREND applied to a soil moisture dataset detecting land degradation with greater consistency than the rainfall/NDVI RESTREND. In addition, two other studies have examined the impact of vegetation datasets on RESTREND analysis by comparing NDVI to Enhanced Vegetation Index (EVI) (John et al., 2015) and the passive microwave based Vegetation Optical Depth (VOD) (Andela et al., 2013) over a common time period. All three studies found that dataset selection significantly impacted results, but because the datasets tested were not measuring the same things, it is impossible to know how much of the difference is caused by errors in the datasets.

Climate controlled dryland vegetation trend analysis depends on two datasets: a vegetation dataset (usually NDVI) and a climate dataset (Wessels et al., 2007). The only globally consistent NDVI datasets with more than 20 years temporal coverage are derived from NOAA Advanced Very High Resolution Radiometer (AVHRR) data (Yengoh et al., 2015). Two versions of the AVHRR derived Global Inventory for Mapping and Modelling Studies (GIMMS) dataset (Pinzon and Tucker, 2014) are used in this study (GIMMSv3.0g and GIMMSv3.1g). GIMMS NDVI is derived from multiple sensors and there are documented inconsistencies across sensor transitions (see Section 2.2 for details). Climate variability in dryland regions is often linked to multidecadal climate processes like the El Niño–Southern Oscillation (ENSO) (Broich et al., 2014) which operate on multiannual through multidecadal cycles. This gives the GIMMS datasets a large advantage over shorter temporal and higher spatial resolution products like those derived from MODIS (Moderate Resolution Imaging Spectroradiometer). This is one of the main reasons it remains in widespread use today in both vegetation assessment (Fensholt et al., 2009; Fensholt and Proud, 2012), as well as in the testing and validation of land surface climate models (Anav et al., 2013; Zhu et al., 2016).

Unlike vegetation datasets, there exists a range of global and national precipitation datasets that have been created using different data. These datasets differ in spatial and temporal resolutions, data sources, spatial coverage, temporal latency and design objective (Beck et al.,