Working Paper

The Farmland Biodiversity Score for consistent monitoring of biodiversity based on the measurement of trees on farms

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About the authors

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Abstract

Trees on farms are a critical tool in managing agriculture to support biodiverse landscapes and will play an important part in complementing protected areas as a means of reaching biodiversity targets. A lack of systematic data for the biodiversity in agricultural land means monitoring global targets is difficult. There is an unmet need for repeated, consistent and low cost indicators of agricultural biodiversity, applicable at wide scale and across different landscapes. Here we present the proof of concept for an indicator of the biodiversity value of agricultural landscapes through assessing properties of their trees. Using freely available satellite data products to estimate wooded area, structural diversity and spectral diversity of agricultural lands, landscapes are scored on the biodiversity value. The outputs of which can be mapped at national scales. Qualitative validation shows promising results in four case studies in a variety of agricultural contexts, with the scores reflecting what we expect from photointerpretation of sites across the case study areas. This tool has the potential to be a useful and much needed indicator, and with further development could be a critical metric for the post-2020 agenda for measuring and monitoring agricultural biodiversity.

Executive summary

Effective biodiversity conservation efforts will need to include the agricultural land that covers one-third of global land area. Within forest biomes, trees on farms are an important aspect of how biodiversity can be maintained and enhanced on agricultural land, and will be critical to meeting global biodiversity targets for production landscapes. Trees on farms benefit biodiversity by providing habitat, mitigating external resource pressures (e.g. for timber) and improving connectivity by providing stepping stones and creating a less hostile barrier to movement between large areas of natural land covers.

A lack of systematic data for biodiversity in agricultural land means monitoring global targets is difficult. This unmet need for repeated, consistent and low cost measurements was a likely contributor to the failure of Aichi biodiversity target 7. There is a clear need for indicators of agricultural biodiversity, applicable at wide scale and across different landscapes.

Recent advances in satellite data and geospatial technologies now make it possible to address these challenges and have transformed land monitoring for biodiversity, but to date this has been focussed on forests and natural lands. Here we present the proof of concept for an indicator of the biodiversity value of agricultural landscapes through assessing properties of their trees. The aim is that this indicator will be useful for planners and decision-makers to monitor agricultural land, report on its biodiversity and plan informed conservation strategies. The tool uses freely available satellite data products to estimate wooded area, structural diversity and spectral diversity of agricultural lands, as well as their spatial configuration, and combines them to ascribe a score that can be mapped at national scales. As the current tool is specifically based on measuring the attributes of trees on farms, it is applicable to agricultural lands within forest biomes (i.e. where forests would grow in the absence of human activity). Other tools, or a modified version of the current tool, would be required to measure biodiversity in, for example, rangelands.

Qualitative feedback shows promising results in four case studies in a variety of agricultural contexts, with the mapped scores reflecting what we might expect from photointerpretation of a sample of sites across the case study areas, and the tool is ready for quantitative validation. Further areas for development include improvements in data that can come from forthcoming satellite products, as well as further qualitative validation from those with on-site expertise and potential optimisation of the functional relationships between the remote sensed metrics and biodiversity. This tool has the potential to be a useful and much needed indicator for the post-2020 agenda for measuring and monitoring agricultural biodiversity in forest biomes.

1 Introduction

Globally, conversion of natural land to agriculture is the major cause of land use change and biodiversity loss (IPBES, 2019). Protected areas alone will not be enough to preserve our remaining biodiversity and conservation efforts must also include the agricultural land that covers 30-40% of global land area (IPCC, 2019). These strategies should harness the potential that agroecosystems have to support biodiversity when managed to do so. Reporting on efforts to sustain or improve agricultural biodiversity is hindered by a lack of methods for monitoring it. This paper will outline and present the concept of a new remote sensing based tool for national scale monitoring of biodiversity in agricultural landscapes based on measuring trees on farms.

The Convention on Biological Diversity (CBD) recognised the importance of sustaining biodiversity in agricultural lands by setting a target (target 7) for areas under agriculture to be managed sustainably, ensuring conservation of biodiversity in the Aichi biodiversity targets (2011-2020). Broadly the Aichi targets, including target 7, have failed, with no target being fully met by 2020 (IPBES, 2019; CBD, 2020). This has been partly attributed to the way in which the goals were set, with experts saying the targets were unrealistic and progress too difficult to measure (Green et al., 2019). Sustaining biodiversity on agricultural land is also critical to the sustainable development goals (SDG), with goals to promote sustainable agriculture (SDG2) and to halt biodiversity loss (SDG15). It is therefore critical that an appropriate way of measuring agricultural biodiversity at broad scales is developed if agricultural biodiversity is to be included in future global agendas for sustainability and for these goals to be measured and met, most critically in the forthcoming CBD post-2020 agenda.

Current ways of measuring biodiversity on agricultural land involve time-consuming and costly fieldwork for detailed measurement at the farm scale (Herzog et al., 2013). Field-based methods may require taxonomic expertise, depend on specific fieldwork timing, interviews with farmers on land management and lengthy post-fieldwork sample analysis. This is not appropriate for national or global scale monitoring of targets. Satellite remote sensing has been an established tool for monitoring land cover at large scales for decades, and new technologies and methods are expanding the potential for satellite data. There have been several useful reviews on remote sensing for ecology, conservation and biodiversity (Kerr and Ostrovsky, 2003; Turner et al., 2003; Wang et al., 2010; Anderson, 2018), which show that remote sensing data can collect a variety of useful information about biodiversity at scale with repeat measurements, in a cheap and timely manner. Despite the potential, little effort has been made to develop the appropriate tools to use this data in agricultural landscapes, with much of the focus spent on natural and undisturbed habitat monitoring, or quantifying the damage that agriculture does (Petrou et al., 2015). Applying remote sensing data to the problems of monitoring agricultural biodiversity could offer a solution. While this approach loses individual farm level information, this detail is not necessarily required for national or sub-national target monitoring. Landscape level approaches better serve the aims of target monitoring, and satellite data can facilitate this.

Sustainable approaches to land management show that farms can support biodiversity while remaining productive. Growing research in recent decades has highlighted the link between trees on farms and biodiversity (McNeely & Schroth, 2006). Trees can facilitate greater levels of biodiversity in these agricultural landscapes. Schroth et al. (2004) outline and evidence the three key ways in which these practices boost biodiversity. First is the provision of habitat for species that are able to tolerate certain degrees of disturbance. Trees on farms can provide suitable habitat for plant and animal species that partly rely on forest habitats to survive. Introducing habitat heterogeneity and structural complexity, as well as diverse assemblages of trees onto farms facilitates the integration of some species into these systems. Connecting tree populations across the landscape further promotes species movement, genetic mixing and survival, both within the agricultural land and between large areas of natural habitats. The second is the reduction of pressure on nearby habitats. The hypotheses being that if the needs and resources of the farmer can be met through trees on their farm, they are less likely to exploit trees in external natural habitat patches (Atangana et al., 2014). There is limited research that explicitly tests whether trees on farms reduce the pressure on trees outside farms, with many locally specific factors likely to affect it. Angelsen & Kaimowitz (2004) discuss the circumstances which influence this hypothesis. This includes the farmer's land tenure, capital and labour resources. Lastly is that in mosaic landscapes of agriculture and natural or semi-natural habitat patches, the biodiversity in the non-farmed vegetation parcels is greater where the agricultural land has trees. These landscapes act as buffer zones and provide more permeable connective habitat between other patches. Trees on farms also provide a host of other ecosystem services that reduce biodiversity loss, like supporting soil biodiversity, erosion control and water regulation (Udawatta et al., 2019). Meta-analyses of biodiversity studies have found significantly higher species diversity in agricultural land with trees (Udawatta et al., 2019), with average species richness across all taxa roughly 60% of forest richness and some taxa like mammals and birds having over 90% of the richness found in forests (Bhagwat at al., 2008).

Working within the existing potentials of satellite remote sensing, this paper presents the proof of concept for a new satellite-based indicator of the biodiversity value of agricultural landscapes through assessing the properties of the woody component from operational remote sensing data products. The farmland biodiversity score (FBS) proposes a starting point to develop upon to appropriately fill the gap that exists in large scale biodiversity monitoring of agricultural landscapes.

2 Methods

The farmland biodiversity score (FBS) assesses the biodiversity value of agricultural landscapes based on the assumption that certain attributes of trees on farms are a good proxy for biodiversity. The score is a composite score from three components: wooded area, structural diversity and spectral diversity, which are then weighted for areas where the positive effects of trees on farms are more pronounced (figure 1). To overcome issues in global land cover products at the pixel scale, we select lands to score by delineating agricultural landscapes, defined as 8 km^2 areas with a defined proportion of cultivated land, based on a land cover product. These agricultural landscapes range from fully transformed cultivated landscapes, to mosaic landscapes with a matrix of cultivated and uncultivated lands. As the score is based on measuring trees, the agricultural landscapes without trees are separated and given a score of 0, while the landscapes with trees proceed to be scored. The assumption is that, while there may be an occasional tree, at the landscape level, there are no trees to deliver their biodiversity value and it cannot be scored. The agricultural landscapes with trees are then scored on three components at a 500 m pixel scale. The wooded area component is a measure of the quantity of trees in the cropland, the structural diversity component measures the variance of tree structures in the cropland, while the spectral diversity component measures the diversity of different spectral signatures of the cropland. Together these components are a measure of the quantity and heterogeneity of trees in the agricultural landscapes. On steep slopes and riparian buffer zones, where trees on farms are more important for biodiversity, the score is weighted to reflect this.

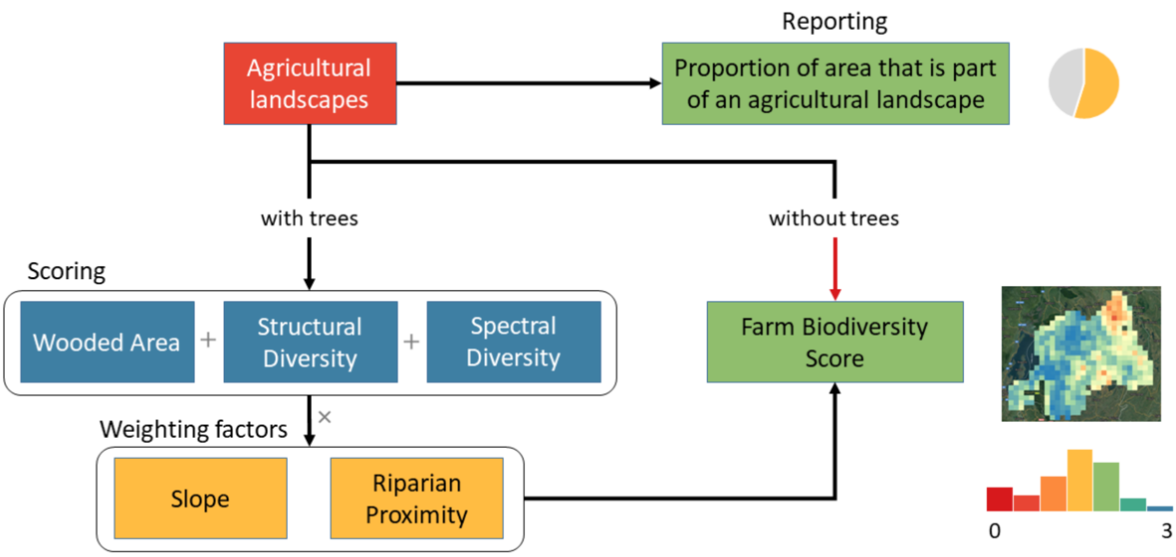

Figure 1. Workflow for the construction and reporting of the wooded farm biodiversity score

The implementation of the FBS is primarily in Google Earth Engine (GEE) a cloud-computing platform for performing geospatial analysis with a large data repository. The spectral diversity layer is calculated in R using the biodivMapR package (Feret & Asner, 2014; Feret & de Boissieu, 2019), and the outputs are imported into GEE for incorporation into the FBS. A GEE app has been created to host the outputs where they can be viewed and interacted. The web app can found at https://blogs.ed.ac.uk/samharrison/fbs/

2.1 Creating the farm biodiversity score

There are three principal components of the FBS, plus two weighting factors; the wooded area (*W*) is the area of the landscape that is covered by woody vegetation; the structural diversity component (*T*) is the diversity of vegetation structure groups, and spectral diversity score (*P*) is the diversity of spectral responses measured by satellite. The sum of these components is then weighted by erosion risk and riparian buffers (*sr*). Each component is scored from 0 to 1 and so scores range from 0 to a maximum of 3.

$$FBS = sr(W + T + P)$$

2.2 Finding the agricultural landscapes

Before scoring the biodiversity, we need to delineate the agricultural landscapes. As land cover products do not classify land use, finding what land is farmed can be difficult. Land cover products classify cultivated pixels and so non-cropped farm pixels like tree cover on farms are not included in the cropland class. Misclassification of cropland is particularly an issue in areas with low cropping density, in crops with similar phenology to natural vegetation (eg savannah), highly fragmented landscapes and in farms with planted or remnants trees around the cropland. The cropland class in the land cover product also includes land covered with temporary crops and fallow. Because the level of omissions of agriculture from crop classifications varies greatly, we delineate agricultural landscapes instead of farms at a pixel scale. These are landscapes (at 8 km^2) where the proportion of cropland, as measured by a land cover product (100 m resolution) meets a given threshold. On the ground, these are landscapes with an agricultural matrix of cultivated and uncultivated lands. The threshold of what proportion of the landscape is cropped to be defined as an agricultural landscape was generously set to be about 3% by default to account for high levels of agricultural area that is not classed as cropland. This threshold can be adjusted for where the farming system may cause fewer pixels to be classified as crop, for example where shade crops and tree crops are prominent. Pasture cannot be delineated from non-grazed grasslands and as such, the FBS is scoring the biodiversity in arable landscapes.

The FBS is based on measuring trees on farms and so agricultural landscapes without trees receive a score of 0. To find these agricultural landscapes without trees, an aboveground woody biomass data product (Globbiomass, described in the data section) is used to map the biomass across the landscapes. A threshold of what landscapes are classed as being without trees is set at 8 t ha^{-1}. As the score is a tree-based measure of agricultural biodiversity, the agricultural landscapes that are below this threshold are given an FBS score of 0. As the biomass product tends to overestimate AGB in low biomass areas, this threshold is not set at a true value but rather is based on how the data product appears to measure ground with very little or no aboveground woody matter.

2.2.1 Wooded Area (*W*)

Wooded area is used in the FBS as a measure of the biodiversity benefits of woody cover. Tree cover in and around farms is important for the diversity of many taxa in agricultural landscapes (Mendoza et l., 2014; Baudron et al., 2019; Socolar et al., 2019). We assume this relationship is broadly linear, where increased woody cover reflects higher biodiversity. In reality, this relationship is far more nuanced by many factors including climate, land management, culture and socioeconomics (McNeely & Schroth, 2006; Steffan-Dewenter et al., 2007; Perfecto & Vandermeer, 2008).

The biomass dataset is used and a threshold is set to define a wooded pixel. If a pixel has a value of >25 t ha $^{-1}$, it is classed as a wooded pixel. The map is resampled to 500 m resolution (25 pixels) where the percentage of wooded pixels within this window is calculated. We then score the 500 m window based on its proportional cover of woody biomass pixels between 0 and 1 for the FBS (table 1). These break values were based on average quintiles from the test sites, and then rounded to a whole number of pixels.

Table 1. Wooded area thresholds and corresponding scores

Wooded pixel count	Wooded area	*W* score
0–4	0–16%	0.2
5–10	16–40%	0.4
11–16	40–64%	0.6
17–21	64–84%	0.8
22–25	84–100%	1.0

2.2.2 Structural diversity (*T*)

There is growing research to show that many species benefit from a greater variety of vegetation structures in agricultural land. Structural complexity creates habitat heterogeneity, boosting diversity for many taxa including birds (Laube et al., 2008; Breitbach et al., 2010; Mulwa et al., 2012) and insects (Thies & Tscharntke 2003; Duelli et al., 1999). While the relationship may not universal (Batary et al 2011; Lee & Martin, 2017), it is widely accepted (Benton et al., 2003; Fahrig et al 2011; Reynolds et al., 2018). The focus here is on compositional structural complexity, rather than configurational aspects of structural heterogeneity.

The biomass product is classed into ordinal groups as a proxy for vegetation structure groups (table 2), and the structural diversity is scored on the variance of these groups within a window of 500m. The biomass map is categorised into groups to make sure the measure of structural complexity is quantifying between-group variance and not the variance within these groups. The scoring for structural diversity is nonlinear based on the assumption that both high and low variance is indicative of low structural diversity and homogenous farming systems. The infographic in figure 2 highlights this relationship. The maximum variance for a set of 25 pixels in ordinal groups 1 to 5 is 4. Therefore, the T score scales variances from 0 to 2 down to 0 to 1, and variances from 2 to 4 inversely from 1 to 0.

Table 2. Biomass thresholds and corresponding structure group

Biomass thresholds (t ha $^{-1}$)	Structure group
0–10	1
10–20	2
20–35	3
35–65	4
65+	5

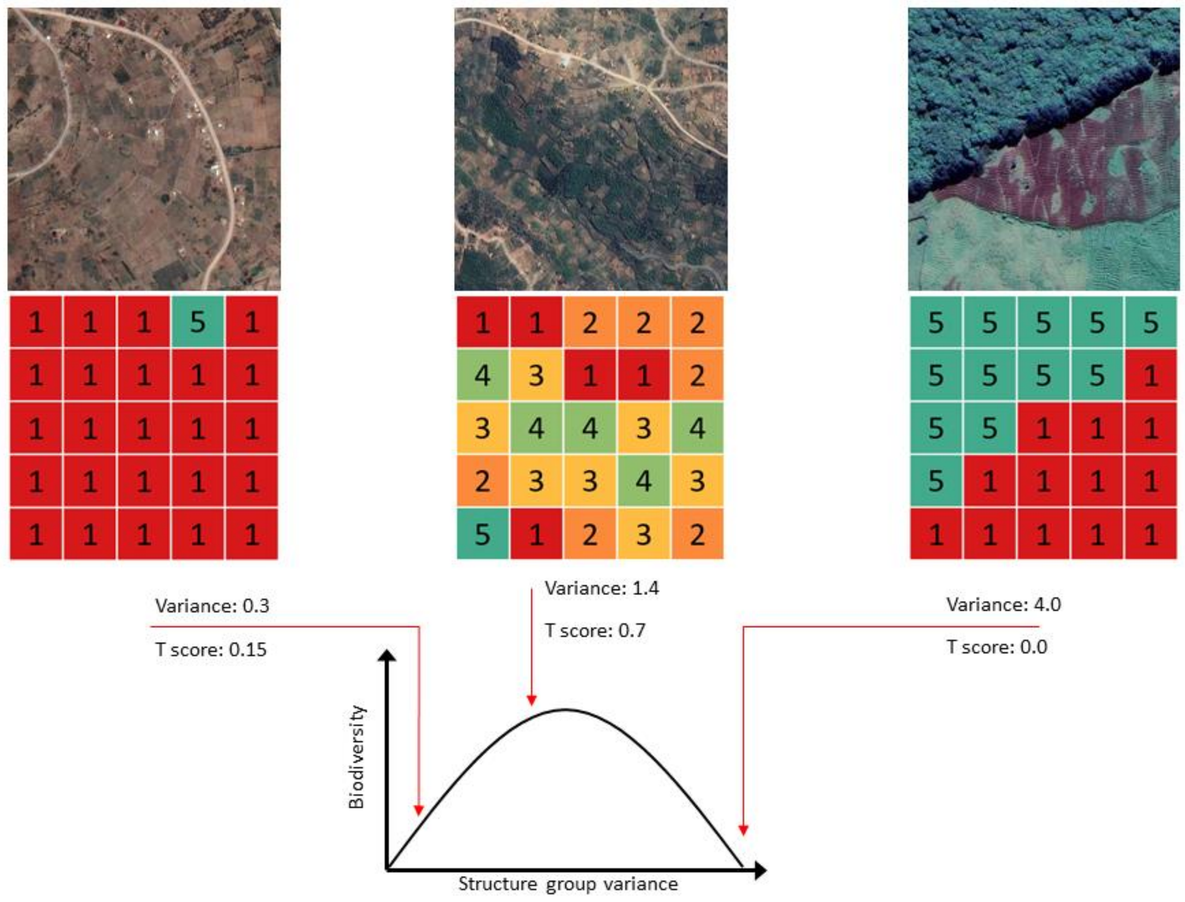

Figure 2. Structural group variance relationship with biodiversity

2.2.3 Spectral diversity (*P*)

Spectral diversity is based on the spectral variance hypothesis (SVH), the idea that spectral heterogeneity across pixels indicates higher niche heterogeneity, resulting in greater biodiversity (Palmer et al., 2000, 2002; Rocchini et al., 2010). The theory has been successfully applied to taxonomic groups including birds (Ozdemir et al.,2018), mammals (Oindo and Skidmore, 2002), and plants (Gould, 2000; Rocchini et al., 2010b; Mapfumo et al., 2016). Most of these studies employ the idea of 'spectral species', where the pixels' spectral response are assumed to characterise a species on the ground and are the subspaces that make up the spectral heterogeneity at a landscape scale. Developing on this idea is the concept of 'spectral communities' when using coarser resolution data, so the spectral response is instead characterising a vegetation community on the ground. The method is based on an unsupervised k-means clustering of pixels to assign them to spectral communities. The Shannon's diversity of these communities is then calculated within a neighbourhood window. Rocchini (et al., 2020) modelled the alpha and beta diversity of Europe using this method with a time series of NDVI data. NDVI uses optical bands that hold importance for understanding vegetation, and using a time series includes information on seasonality and phenology. Following this method, the P score is calculated using the first 3 PCA axes of a time series of NDVI data. Clustering into 200 clusters, models the spectral communities, and the Shannon's index is calculated over a window of 10 x 10 pixels to calculate local alpha diversity. The result is a map at 2.5 km resolution, and the values are scaled to P scores from 0 to 1 using a minimum Shannon's index of 0.5 and a maximum of 3.3. These thresholds were set from the minimum 1st percentile and maximum 99th percentile of the spectral diversity values at all the sites where the FBS was developed and tested.

2.2.4 Weighting factor (*sr*)

The weighting factors are used to reflect the changing spatial importance of trees on farms depending on erosion risk and occupancy of riparian buffers in the landscape. As these factors are not aimed at reflecting on-the-ground tree biodiversity patterns, the FBS should be still primarily be composed of the layers above, and the weighting factors will create differences in similar scoring land parcels where the trees may have greater significance.

2.2.4.1 Erosion risk

Slope is used as a simple proxy for erosion risk. Soil erosion can have detrimental effects on soil biodiversity (Pimentel, 2006) and agricultural runoff can severely affect the biodiversity of waterways (Orgiazzi & Panagos, 2018). We make an assumption that steeper slopes are more prone to soil erosion, and therefore are more important landscapes in which to maintain trees and improve FBS. The slope angle is calculated from the SRTM elevation product at a 90 m resolution. The slope map is then refactored into slope classes using the thresholds outlined in table 3.

Table 3. Weighting factor score from slope groups and riparian buffer

Slope (°)	Erosion risk	Weighting factor – inside riparian buffer	Weighting factor – outside riparian buffer
0–8	Light	0.9	0.85
8–12	Moderate	0.95	0.9
12–20	High	1	0.95
>20	Very high	1	1

2.2.4.2 *Riparian buffers*

It is particularly important to promote biodiversity in riparian areas within a landscape. In tropical agricultural landscapes, vegetation in riparian buffers can support more terrestrial biodiversity than surrounding farms. Similarly, riparian buffers are important for healthy waterways (Luke et al., 2019). The ideal width of a riparian buffer to support biodiversity is not uniform. A buffer of 100 m, however, would likely support multiple taxa regardless of agricultural land use or geographic location (Luke et al., 2019). The HydroSHEDS dataset is used to map the riparian zones for the FBS weighting factor (Grill et al., 2019). The resolution of this data means that the river vector lines were only coarsely aligned to the rivers on the ground and the riparian areas were missed using a 100 m buffer. Therefore, a buffer of 500 m meters is used, which is much more likely to catch the majority of the riparian zone, albeit with a degree of inclusion error. A weight score is then assigned to each pixel based on its slope class and whether it in a riparian buffer or not as shown in table 3.

2.3 Reporting

In reporting the FBS, statistics on the proportion of land that is classed as agricultural landscapes will be reported alongside the distribution of FBS scores and maps. The FBS can be applied at regional, national or subnational boundaries and the output maps can be generated weighted or unweighted at the pixel scale (500 m), the landscape scale (8 km) or by administrative boundaries. This flexibility means the tool can be used both for national scale reporting as this is where most targets are set (through National Biodiversity Strategies and Action Plans), but also subnational patterns to manage resources and target intervention.

2.4 Data

The FBS is comprised of analyses of 5 datasets (table 4). The aboveground woody biomass data product is needed to calculate the FBS. Several datasets exist and more products are emerging in the near future. At this proof of concept stage, the 100 m resolution GlobBiomass is arguably the most appropriate dataset to use (Santoro, 2018). This data is a one-off from 2010, so is not operational. Its successor, CCI_biomass has more up-to-date data (2017), but GlobBiomass has the advantage of being better quality, without the erroneous data included in CCI_biomass (poorly geocoded and incidence angle striping from ALOS-2 PALSAR radar data). CCI_biomass aims to continue improving and provide updated biomass information with data additions from future missions (eg the BIOMASS mission), so it may be the most appropriate operational option in the future, but currently, GlobBiomass is a better quality product to use. It is important to note that all biomass products are aimed at modelling forest biomass and usually advise against using the products for analyses outside of these areas. ESA identified some of these data issues, most prominently a bias which generally overestimated in low biomass ranges and underestimated in high biomass areas. The future of biomass products is promising with biomass data from GEDI, NISAR and BIOMASS missions expected within the next few years. Operational biomass products will have improved resolution and hopefully improved accuracy.

Table 4. Datasets used in the FBS

Data	Dataset	Resolution	Purpose
Aboveground biomass	ESA GlobBiomass 2010	100 m	*W* and *T* scores
Land cover	Copernicus Global Land Cover	100 m	Delineating agricultural landscapes
NDVI time series	MODIS Vegetation indices (MOD13Q1)	250 m	*P* score
Elevation	SRTM	90 m	Erosion risk
River network	WWF HydroSHEDS Free-Flowing Rivers Network	-	Riparian buffers

Scoring the FBS first relies on delineating where the farms are. Land cover maps can delineate crop cover from other land cover types. However, for cropland monitoring, comparing different land cover products show dramatic differences. Perez-Hoyos (et al., 2017) looked at several land cover products for cropland monitoring and found little agreement between them, noting some stark differences including GlobCover products estimating global cropland area to be 20% higher than MODIS derived products. When comparing the products to FAO cropland statistics, the product that performed best was not uniform from country to country. Ultimately most land cover products are not reliable, especially for agricultural land, where uncertainties in classification tend to be larger than other classes. The Copernicus Global Land Cover product (CGLS-LC100 2015 Collection 2; Buchhorn et al., 2020) claims higher overall accuracy compared to other popular land cover products, and moderate accuracy for croplands (User's accuracy = 70.2%, Producer's accuracy = 83.9%). This product benefits from being operational and so is updated annually. With moderate accuracy, this is unlikely to pick up small yearly changes, but it may be important where large agricultural expansion is occurring.

A time series of Normalized Difference Vegetation Index (NDVI) from MODIS (MOD13Q1 v006; Didan, 2015) for the year 2019 was used in the FBS to model spectral diversity. This NDVI product is a composite of MODIS images over a 16-day period using the best pixels available. The spatial resolution is low (250m) but benefits from having enough pixels to produce good data in areas or times of high cloud cover. To speed up processing times, the 16-day time series was aggregated to a monthly dataset. This dataset is operational and releases up to date data regularly.

Elevation data is used to calculate slope angle for erosion risk. The SRTM dataset provides a digital elevation model at 90m resolution appropriate for this analysis (Jarvis et al., 2008). River networks needed to be mapped in order to find the riparian areas. The WWF HydroSHEDS Free Flowing Rivers Network (Grill et al., 2019) data was used for these purposes. The river polylines are calculated from a raster dataset at 15 arc-seconds (~500 m at the equator) and as such the river lines have some coarseness.

2.5 Validation

There is a lack of validation data at the scale needed that can be appropriately used to test the scores against. At this stage, the best method to check the performance of the scores is qualitative validation by cross-referencing the FBS output with what we might expect when interpreting high-resolution satellite imagery available on Google Earth. The biomass product used in this proof of concept is from 2010, and so the Google Earth image closest to 2010 was used in the validation. Some of this validation is presented alongside the results below. The FBS was developed and tested in several study sites covering a variety of climates, biomes, policy contexts, farming practices and cultures. These were Chiapas State in Mexico, Honduras, Rwanda, Uganda, Sofala province in Mozambique and West Kalimantan province in Indonesia. The results section will present the output from some of these sites in which the FBS was tested. The sites presented are part of the Trees on Farms for Biodiversity project funded by the International Climate Initiative (IKI) and implemented by World Agroforestry (ICRAF) in partnership with the Centre for International Forestry Research (CIFOR). The project aims to build awareness and understanding of the role trees on farms can play in biodiversity conservation.

In Uganda, approximately half of the land is used for agriculture, most of this is smallholder farms growing food crops and cash crops. While farming is predominantly subsistence agriculture, there are areas of largescale agriculture which mainly focus on sugarcane, palm oil and rice. Most of the biodiversity loss in Uganda is related to expansion of smallholder farming into forested areas, with conversion also occurring in savannah grasslands for maize and wetlands for rice.

Rwanda is a small and densely populated country, with agricultural land that is estimated to be over two-thirds of the nation's total land area. In recent decades, cropland expansion has precipitated losses in forest and grassland cover of 65% and 32% respectively (1990-2016) with resultant losses in biodiversity. Roughly a third of farmers own less than 0.2 ha of land and the agricultural mosaic is largely smallholder farms with some largescale farms growing export crops like tea.

The rainforests in Indonesia are some of the most biodiverse in the world, containing 10% of the world's known plant species, 12% of mammal species and 17% of all known bird species. The biodiversity of these forests are under threat from the fragmentation of habitats from agricultural expansion, primarily driven by expansion of oil palm, of which more than 50% occurred at the expense of natural forests between 1990 and 2005.

Forests cover almost half of the land area in Honduras, but are under threat from agricultural expansion which is estimated to be driving 80% of deforestation in the country. In terms of area, cattle ranching is by far the most extensive agricultural practice in Honduras and is the main driver of this forest loss, now covering nearly a quarter of the country's land area. Alongside this, grain cultivation in rotation and shade coffee are also widely farmed in the forest biomes of Honduras.

3 Results

This section will present the results from sites involved in the Trees on Farm project. The outputs can be viewed and interacted with in a Google Earth Engine app found at https://blogs.ed.ac.uk/samharrison/fbs/. A selection of these maps is shown in the results section here, with a more comprehensive list of maps available to view in the Earth Engine app.

3.1 Uganda

In Uganda, 78.8% of the country was part of an agricultural landscape, almost all of which had trees. Figure 3 shows the unweighted FBS at the pixel scale for Uganda. The highest scoring areas in Uganda appear to be across a central belt of the country, with the cropland here generally scoring around 2. The scores get patchier in the north where farms with some of the poorest scores are punctuated by areas of higher scoring agricultural landscapes. There are a small number of landscapes that were classed as unwooded with a score of zero. Scores were also high on areas of the east and west borders of the country, where farms are located on the slopes of mountains or mountain ranges.

As the approach we have taken includes all land within an agricultural landscape, at the pixel level there will be lots of non-cultivated land included in the analysis. Northeast Uganda is generally drier and much more sparsely cultivated than the south, so the proportion of non-cultivated land in these landscapes may be higher. Adjusting the crop threshold for what is considered an agricultural landscape may reduce some of these inclusions, but at the risk of losing agricultural landscapes elsewhere.

It is hard to validate these maps at scale, but from qualitative validation, the scoring seems to be reflecting what we might expect from the satellite images. Figure 4 shows a selection of high resolution images and their respective scores. These images, alongside further qualitative validation in this method, show that the FBS scores are generally reflecting what we might expect from the satellite images. The low scoring farm (fig. 4a) has no woody cover (W score: 0) with little structural diversity (T score: 0.12), and while the spectral diversity (P score: 0.48) may pick up fields at different planting stages, it is not enough to give the area a high score. Figure 4b shows greater woody cover (W score: 0.4) but little diversity in its structure (T score: 0.22), with the spectral variance (P score: 0.57) accounting for half the overall score. The high scoring landscape (fig. 4c) has greater woody cover with a W score of 1 and more diversity in structure with a variety of tree densities (T score: 0.83, P score: 0.77).

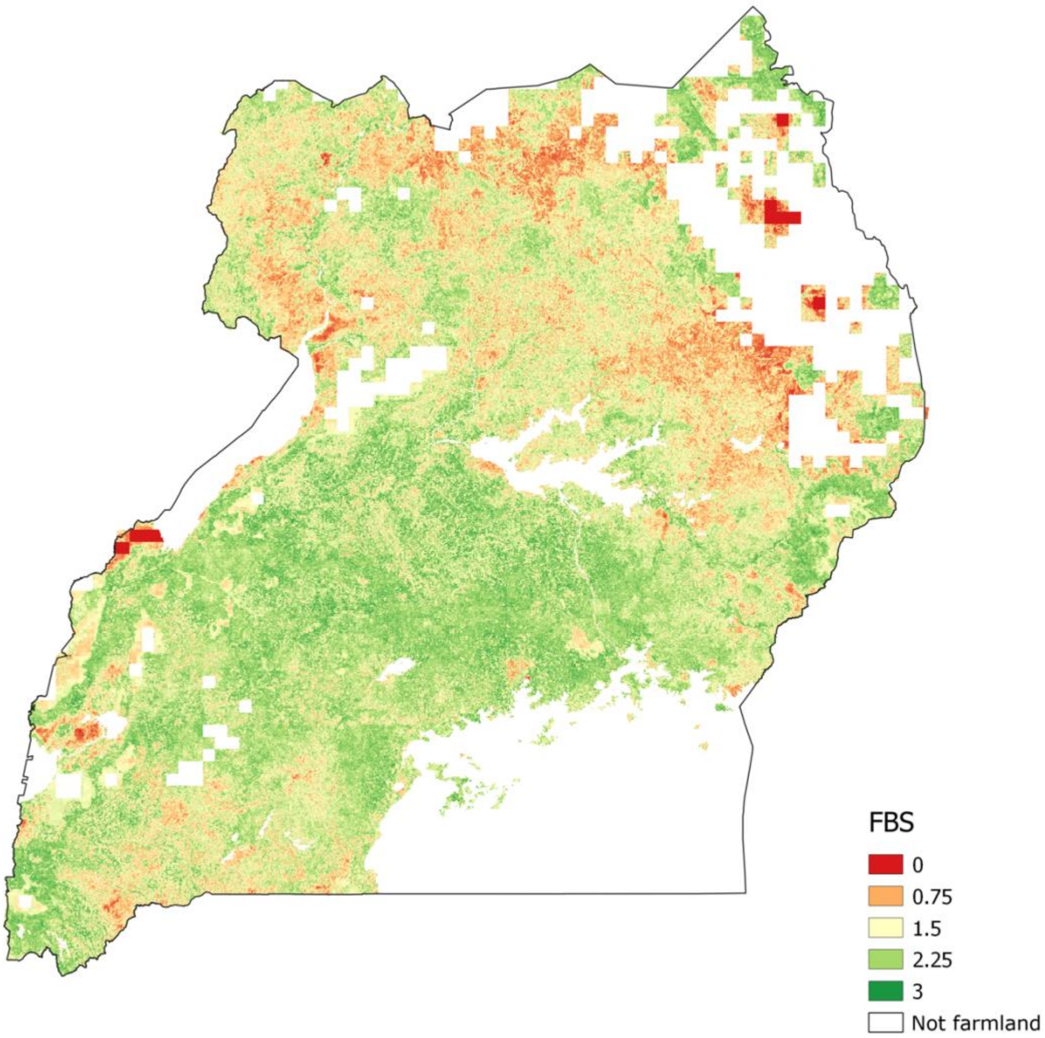

Figure 3. Unweighted FBS values for Uganda

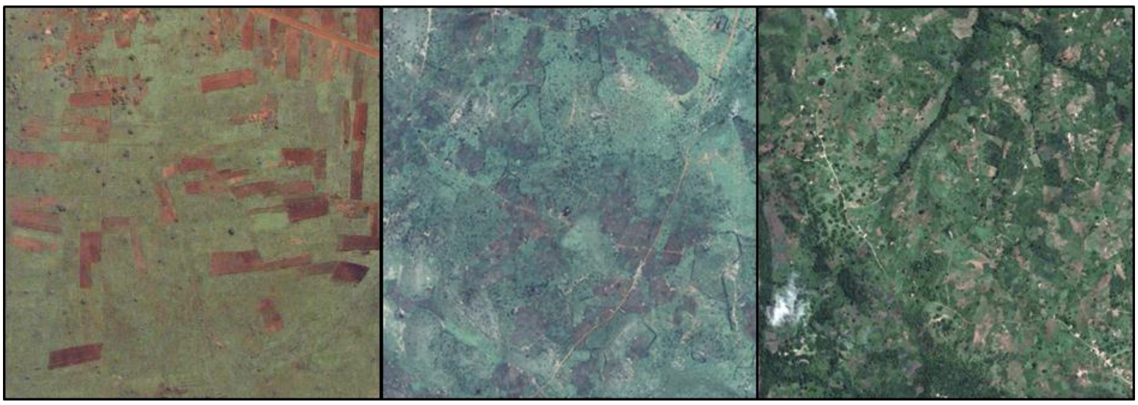

Figure 4. a. Low (0.6), b. medium (1.2) and c. high (2.6) scoring agriculture in Uganda

3.2 Rwanda

Almost all landscapes in Rwanda are agricultural landscapes with only 9% of the lands area not part of these landscapes. None of the agricultural landscapes were without trees at the landscape level. Figure 5 shows the national pattern having an east-west divide with higher FBS landscapes in the west. The administrative boundary map shows that there is an appreciable difference in the mean FBS between the highest district (Gakenke, 2.2) and lowest (Nyagatare, 1.2); this was the greatest difference between 2nd administrative units across all the study areas.

Validation here showed similar outcomes as for Uganda with the scores reflecting what we would expect when interpreting the high resolution images. A sample of these images is shown in figure 6. The high scoring landscape shows greater woody cover and variability in structure among small fields, while the lowest scoring landscapes, mostly located in the driest region of the country, had little woody cover, mostly as part of boundaries for large fields.

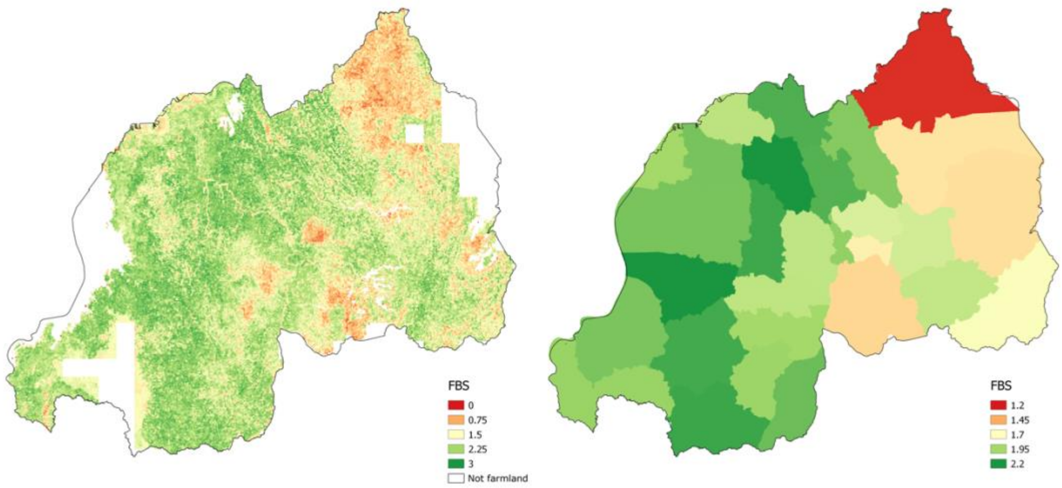

Figure 5. Weighted FBS values for Rwanda at pixel scale and administrative boundary aggregated

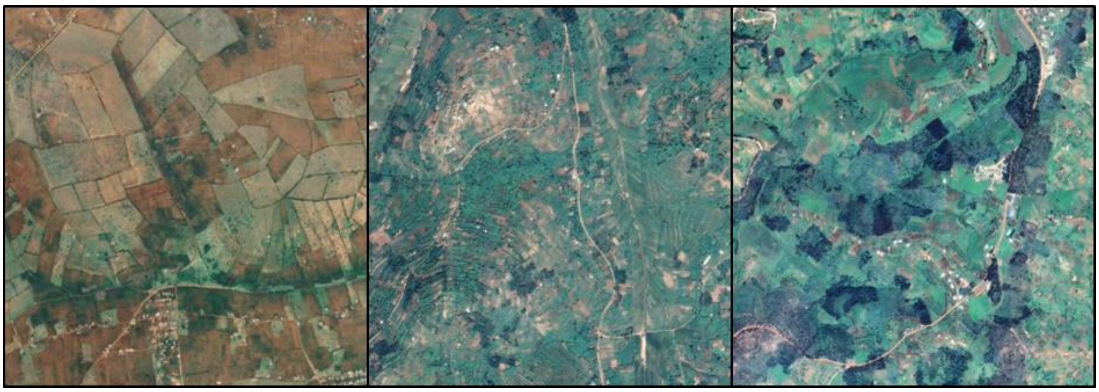

Figure 6. a. Low (0.7), b. medium (1.4) and c. high (2.5) scoring agriculture in Rwanda

3.3 Honduras

Almost all of the agricultural landscapes in Honduras were landscapes with trees, and made up 81% of the land area. Figure 7 shows the FBS aggregated at the landscape scale. In contrast to Uganda and Rwanda, there does not appear to be a dominant national pattern in score distribution, instead, the scores are generally more even and the spread of values is smaller, with fewer values at the extreme ends. When aggregating to the 2nd administrative boundary, the mean values ranged from 1.5 to 1.9, which highlights the much tighter spread.

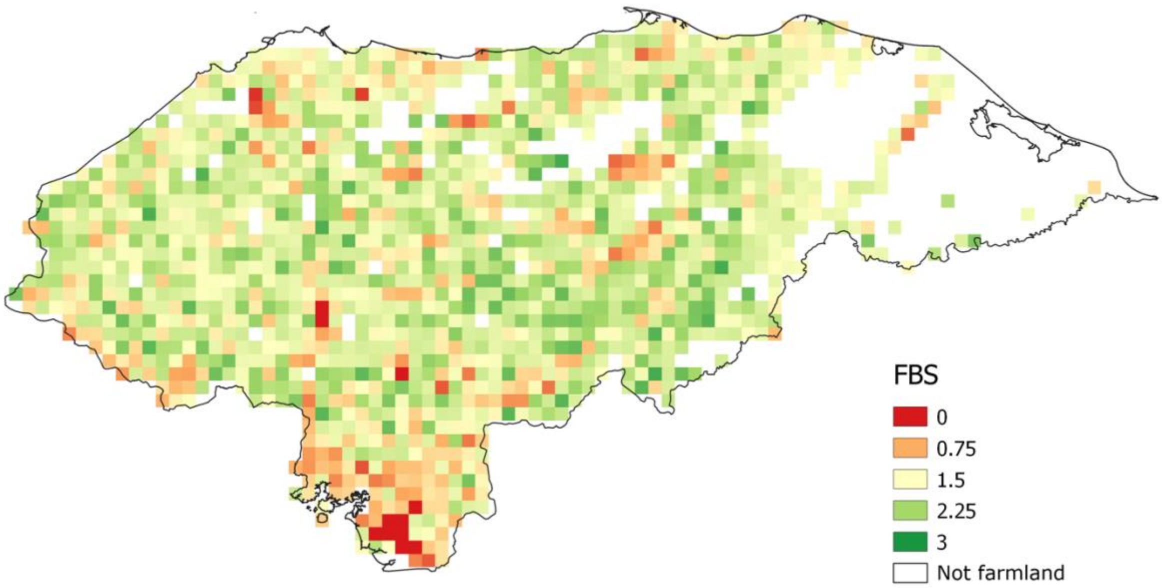

Figure 7. Weighted FBS values at the landscape level for Honduras

The non-wooded agricultural landscapes that scored zero in the south of Honduras are areas dominated by large-scale commercial agriculture with few or no trees. Elsewhere in the country, the zero-scoring landscapes are those located in and around large towns and cities.

Larger commercial farms are more common in Honduras than in Rwanda and Uganda, where agricultural land is mostly smallholdings. Using satellite images to validate the FBS performance in Honduras picks up how the score fares in these landscapes. Some of the lowest scoring landscapes are in areas where woody cover may be high, but the large scale growing of tree crops means there is little structural or spectral variation. For example, figure 8a shows large scale tree cropping in northern Honduras, perhaps of oil palm, which has an FBS of 1.0, with a W score of 0.60, T score of 0.26 and P score of 0.14. The higher scoring image (figure 8b) shows a lower intensity mixed system with good woody cover (W score: 1) and a variety of structures and mix of agricultural land uses (T score: 0.74, P score: 0.86) combining for an overall score of 2.6.

Figure 8. a. A low scoring tree crop plantation, and b. a higher scoring low intensity system in Honduras

3.4 West Kalimantan

The least farmed of the study sites was West Kalimantan, with 60% of the land being part of an agricultural landscape, all of which have trees. The agriculture here is predominantly large scale oil palm plantation, which poses an interesting test for the FBS. Much of this is not classed as cropland as perennial woody crops are instead classed as forest/shrub in the land cover product. As such the crop threshold was set to its lowest possible value (a single 100 m pixel within the 8km landscape) in order to make sure as much of the agricultural land was analysed. Perhaps due to the dominance of one land use type, the FBS score for West Kalimantan in relatively uniform with little spread of values as shown in figure 9. When aggregated to regencies, the range of means was small, from 1.4 to 1.7, showing the homogeneity of the scores.

This site is the most difficult to validate as persistent cloud cover means clear images for the years around 2010 are rare. The landscapes with the highest scores were those where the largescale palm plantations were yet to reach, or in the early stages of clearance (figure 10a). The type of oil palm plantation that is now widespread in the region scores around 1, figure 10b shows a plantation landscape that scored 0.7.

The poor performance of the land cover product in West Kalimantan did mean that the score failed to pick up some areas of agriculture in the province, particularly small scale farms in a forest-farm mosaic landscape. This is likely to reduce the overall scores for West Kalimantan and these mosaic landscapes would score much higher than the large plantations. Setting the crop threshold to the lowest possible value helped to pick up more agricultural landscapes, but there were still areas that were not delineated and thus not scored.

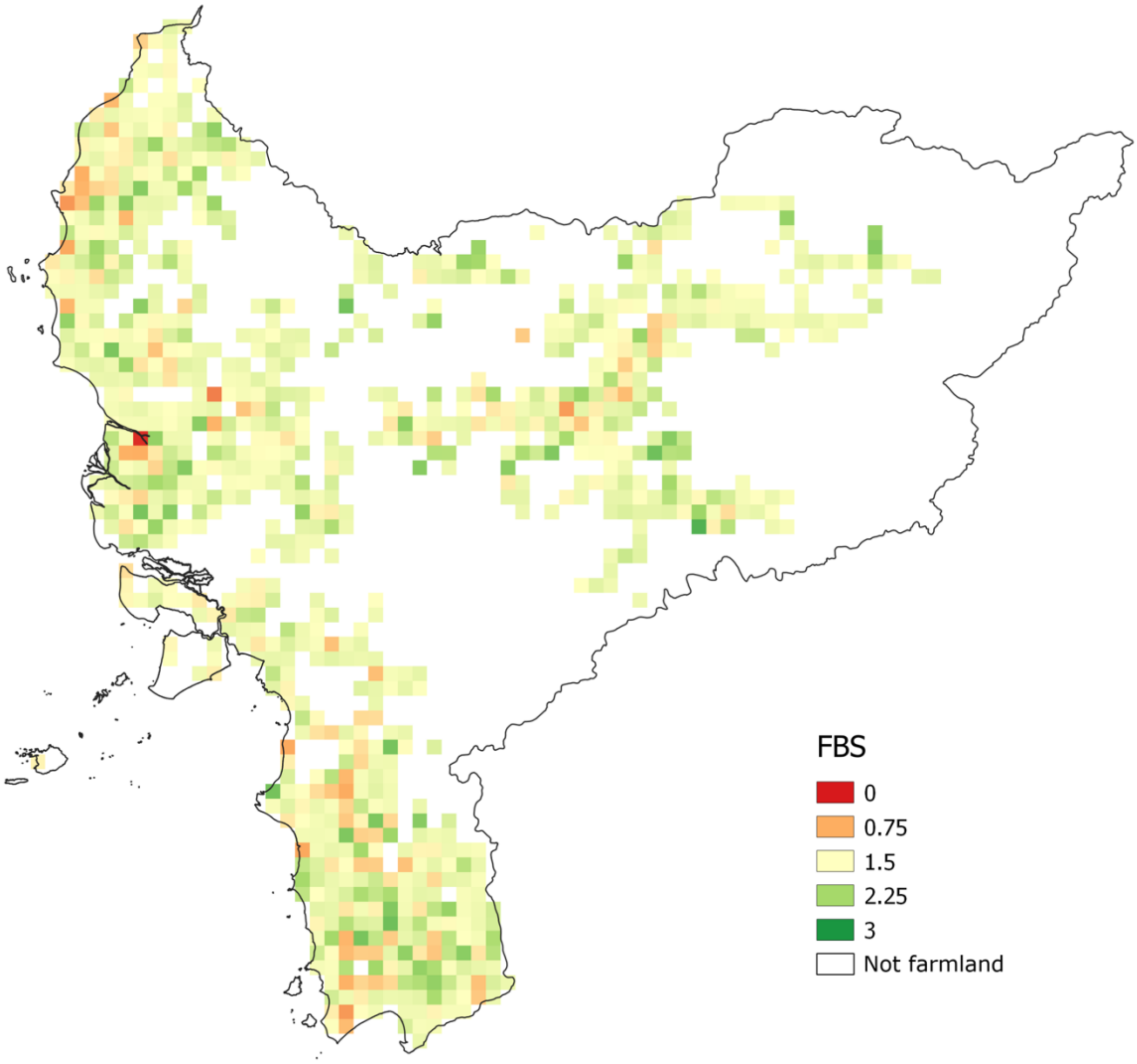

Figure 9. Weighted FBS values at the landscape level for West Kalimantan, Indonesia

Figure 10. a. A high scoring landscape (2.6), possibly in clearance and b. a low scoring (0.7) high intensity oil palm plantation in West Kalimantan

4 Next steps

This paper has shown the proof of concept for a remote sensing based approach to estimating farm biodiversity. The FBS shows encouraging potential, but the following section will outline the avenues for improvement to the FBS.

Foremost is the need for validation. A search for appropriate datasets has yielded little in the way of comparative biodiversity metrics for agricultural land across nations. Subnational datasets are also scarce, with few countries having available data. There are some datasets like the Pan-European Common Bird Monitoring Scheme (PECBMS), which collates bird diversity data from most European countries' national bird surveys, many of which sample birds in agricultural lands. Efforts have been made in recent years to set up common bird monitoring schemes in Africa (Wotton et al., 2020) for both inside and outside protected areas. A comparable multinational dataset is likely to be an unrealistic request, but a deeper search may return a set of useable datasets like the PECBMS to test with the FBS. A more realistic approach to improve the method through validation is to gather further qualitative feedback from those with on-the-ground experience and knowledge of agricultural biodiversity across a large scale.

A useful facet of a monitoring tool is the ability to map not just spatial patterns but temporal changes too. In further development and testing of the tool, the detection of FBS change over time should be assessed by looking at areas of known change in intensification or intervention to see how the FBS measures this.

4.1 Potential additional modules

Additional components could be included as optional for specific uses or planning purposes. Landscape connectivity, for example, is an important aspect of biodiversity in agricultural areas, facilitating movement and genetic mixing across landscapes and between intact habitats. Producing useful and informative maps of connectivity in agricultural landscapes requires significant research and modelling efforts that are outwith the scope of this study. Research into developing informative connectivity data layers for agricultural land is ongoing, and these could optionally be included in the FBS when available.

4.2 Parameter / threshold fine-tuning

The FBS is based on many assumptions on a variety of window sizes, thresholds, classes and cluster parameters. Performing some sensitivity analysis on this could help improve the model and our understanding of the importance of some of these parameters. For biomass thresholds, an idea for more informed thresholds could be based on potential biomass from climate and elevation data. The empirical data on potential biomass from climate alone is scant, with a few datasets on potential biomass for some biomes using sophisticated models (Exbrayat et al., 2017). A more thorough literature review on this could help make a more informed threshold choice based on potential biomass by biome or climate. This would reduce any potential bias towards higher biomass ecoregions.

Improvements to the structural diversity layer should be carefully thought through. The variance around the structural classes is currently used to measure structural diversity. While this seems to work well in many cases, it may not always be the best measure. Certain configurations of biomass data within the window can lead to good structural variance scores while having a relatively homogenous structure. Some further testing and time to develop a more appropriate measures of structural diversity is needed to improve this. The biomass class thresholds should be tested in more locations as the current classes may be biased toward wetter biomes. More classes for low biomass pixels could help to reduce this bias as an alternative to the potential biomass approach mentioned above.

The output of spectral variance analysis is currently at 2.5 km, from a 10-pixel window of 250 m data. This may be too large a pixel size to pick up some homogenous farms where the surrounding landscape is spectrally diverse. To reduce the scale of the spectral diversity, finer resolution input data will be needed. NDVI data at a smaller spatial resolution exists but lacks the temporal resolution or the 16-day 'best pixel' data quality that MODIS has. As with much of the data used, there is a compromise to be made. Higher resolution data is also likely to result in longer computing time and a greater computer power requirement. Large scale spectral variability analysis is a new method, and any subsequent literature may help shed light on the sensitivity of some of the parameters like window size or number of clusters.

4.3 Weighting

Improvements to the weighting factors should include sensitivity analysis. At the moment, the score can be reduced by a fifth if the land is not sloping and not riparian. Exploring how there parameters alter wider scale scoring and patterns could help adjust these factors accordingly. Slope is currently used as a proxy for erosion risk. Much more sophisticated erosion models exist and this simple proxy could be elaborated to include some of the detail included in erosion models. For example, the commonly used and adapted USLE model uses a slope-length factor instead of the slope angle alone (Wischmeier & Smith, 1978). Including the upslope length along with the slope in the weighting would make it a more accurate reflection of erosion risk. Other erosion risk factor that could be included are soil type and climate.

With a focus on the biomass product, there may be a bias towards wetter biomes as farms in drier climates may struggle to grow the size or abundance of trees in wetter forest biomes. If further testing shows this is the case, a weighting by biome or ecoregion could help balance out this bias. An ecoregion weighting could also be used to account for the rarity of ecosystems, i.e. trees on farms in rare wooded biomes may have more importance than in more abundant biomes.

4.4 Data improvements

The FBS could be improved when newer, up-to-date and/or operational biomass datasets become available. The GlobBiomass dataset used here compromises recency for better quality data, as such the qualitative validation can be tricky where there have been significant changes in the past decade. An up to date biomass product could provide a more up-to-date FBS, but with poorer quality data, the score may be affected. As and when new data becomes available, this can be incorporated into the FBS for operational and recent biomass data, for example, GEDI, NISAR and BIOMASS mission data is expected to be operationally released in the next few years (Dubayah et al., 2020; Duncanson et al., 2020; Quegan et al., 2019). For any new biomass dataset used, the thresholds that are applied to the biomass data should be reconsidered and tested in a range of landscapes, as each dataset will perform differently in these landscapes.

Similarly, recently released GEDI data has also been used to produce a global forest height map (Potapov et al., 2020). This could be explored as a dataset for structural diversity scoring instead of biomass. This dataset is currently at a prototype stage with known data issues but will be updated and refined over time. Although the data should still be applicable outside of forests, it has been designed for forest height mapping and not tree height in general.

As mentioned above, an alternative dataset for the spectral analysis could improve the spectral variance layer. Sentinel-2 data may offer a solution and could be used to generate a time series of vegetation index at the resolution needed, but data quality control will be needed to make sure the images are cloud-free.

Land cover products continue to be an issue. In drier biomes overestimation of agricultural landscapes is likely as natural vegetation here is confused with cropland. In forest biomes underestimation of these landscapes is likely, as wooded farms in a mosaic of forest remnants are confused with forest classes. A possible solution to this would be to use locally specific land cover maps where possible. These may be made by government agencies, NGO's or researchers with ground data to have tailored a land cover or land use map to the specific area. However, these are not always available or willingly shared.

4.5 Make it operational

After further development of the FBS, it would be made more useful if it were reworked into an operational web tool, app or dashboard for planners or land managers to view and interact with the outputs. This may also allow the user to tweak the parameters of the FBS based on their own assumptions of the land in which they are applying the tool.

The FBS is currently modelled in Google Earth Engine, with the spectral variance layer being calculated in R using the biodivMapR package. Calculating the spectral variance layer requires computing power which may not be accessible to all potential users. Making the model operational could require this spectral variance analysis to be rewritten into a cloud computing platform with links into Google Earth Engine, which could be possible with Google Colab. If the operational biomass layers are not available through Google Earth Engine, this platform could be used to get data and make it available for analysis in Earth Engine.

5 Conclusion

Recent advances in remote sensing data and technologies are creating new opportunities for the conservation of biodiversity. The ability to use and analyse recent data means we can map the current state of environments and observe changes going forward. The application of these technologies in an accessible tool needs to be fully realised in agricultural biodiversity if we are to gauge our progress towards global agricultural biodiversity targets set in the post-2020 agenda. While there are aspects of farm biodiversity this does not account for, like inputs, livestock grazing and other management practices, the FBS indicator presented here is a promising proof of concept. With further testing and development, the indicator could be an invaluable tool for decision-makers. It could provide relevant information to a range of users on the spatial patterns and temporal changes of trees on farms and their contribution to agricultural biodiversity.

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