

This is the peer reviewed version of the following article: Fagan, ME. A lesson unlearned? Underestimating tree cover in drylands biases global restoration maps. Glob Change Biol. 2020; 26: 4679– 4690. <https://doi.org/10.1111/gcb.15187>, which has been published in final form at <https://doi.org/10.1111/gcb.15187>. This article may be used for non-commercial purposes in accordance with Wiley Terms and Conditions for Use of Self-Archived Versions. This article may not be enhanced, enriched or otherwise transformed into a derivative work, without express permission from Wiley or by statutory rights under applicable legislation. Copyright notices must not be removed, obscured or modified. The article must be linked to Wiley's version of record on Wiley Online Library and any embedding, framing or otherwise making available the article or pages thereof by third parties from platforms, services and websites other than Wiley Online Library must be prohibited.

Access to this work was provided by the University of Maryland, Baltimore County (UMBC) ScholarWorks@UMBC digital repository on the Maryland Shared Open Access (MD-SOAR) platform.

Please provide feedback

Please support the ScholarWorks@UMBC repository by emailing scholarworks-group@umbc.edu and telling us what having access to this work means to you and why it's important to you. Thank you.

A lesson unlearned? Underestimating tree cover in drylands biases global restoration maps

Author: M.E. Fagan^{1,*}

Affiliation:

¹Department of Geography and Environmental Systems, University of Maryland Baltimore County, 1000 Hilltop Circle, Baltimore, Maryland 21250, USA.

*Correspondence to: mfagan@umbc.edu.

Abstract: Two recent global maps of tree restoration potential have identified vast regions where tree cover could be increased, ranging from 0.9 to 2.3 billion hectares. Both maps, however, emphasized dryland regions, with arid biomes making up 36-42% of potential restoration area. Drylands biomes have repeatedly been recognized as inappropriate regions for expanding tree cover due to the risks of biodiversity loss, water overconsumption, and fire, so maps that highlight these regions for restoration must sustain careful scrutiny. Here, I show that both recent attempts to map restoration potential in arid regions have been hindered by underlying errors in the global tree cover maps they used. Systematic underestimates of existing sparse tree cover led directly to large overestimates of the potential for tree recovery in drylands. The Atlas of Forest Landscape Restoration Opportunities (Laestadius et al. (2011)) overestimated tree restoration potential across a third of arid biomes by between 7 and 20% (55-166 million hectares). Similarly, Bastin et al. (2019) overestimated tree restoration potential across all arid biomes by 33 to 45% (316-440 million hectares). These inaccuracies limit the utility of this research for policy decisions in drylands and overstate the potential for tree planting to address climate change. Given this long-standing but underappreciated challenge in mapping global tree cover, I propose various ways forward that keep this lesson in mind. To better monitor and restore tree cover, I call for re-interpretation and correction of existing global maps, and for a new focus on quantifying sparse tree cover in drylands and other systems.

Keywords: Forest landscape restoration, savannas, grasslands, desertification, remote sensing, REDD+, global forest change, ecosystem restoration, dry forests, afforestation.

1: Introduction

Drylands make up 41.5% of the global land area (Sorensen 2007) and are home to more than two billion people (UN EMG 2011). Loss of vegetation cover within drylands from anthropogenic degradation is identified as a global restoration challenge (Reynolds et al. 2007), and programs to address “desertification” (i.e., drylands degradation) have attempted to ameliorate human land use pressures in these delicate ecosystems, often by restoring tree cover (FAO 2015). Two recent maps of restoration potential have indicated that extensive areas in dryland biomes could be restored by increasing tree cover (Bastin et al., 2019; Laestadius et al., 2011).

The first map, the Atlas of Forest Landscape Restoration Opportunities (AFLRO), delineated potential forest restoration area by differencing ecoregions with potential forest cover with a map of existing forest cover. The AFLRO identified 23 million square kilometers (2.3 billion ha) with the potential for “forest landscape restoration” (FLR) (Laestadius et al., 2011). Although FLR is a flexible concept that is focused on increasing tree cover, not forest cover *per se*, the AFLRO map was subsequently accused of targeting drylands for replacement by forests (“afforestation”), with 39% of its potential restoration area in dry, historically “grassy” biomes (9 of 23 million km²; Veldman et al. 2013, 2015). In natural grasslands and savannas, dense afforestation and woody encroachment are widespread (Parr et al. 2014; Skowno et al. 2017; Stevens et al. 2017) and have well understood, negative impacts on biodiversity, water supplies,

soil carbon, and fire risk (Veldman et al. 2015b; Honda & Durigan 2016; Stevens et al. 2017; Bond et al. 2019).

To address this criticism, Laestadius et al. (2015b) clarified that the AFRLO was not designed to advocate for afforestation, ecologically-inappropriate tree planting, or the replacement of natural ecosystems. However, the AFLRO was used to inspire many national forest restoration pledges to the global Bonn Challenge, including from arid countries (Laestadius et al. 2015). Given established confusion between degraded forests and natural savannas (Veldman et al. 2015b), a history of intervention to increase tree cover in drylands (Parr et al. 2014), and the lack of formal protection of natural grasslands in comparison to forests (Veldman et al. 2015a; Aleman et al. 2016), there is a real risk that policy makers prioritized grasslands, savannas and natural open-canopy woodlands for increased tree cover (e.g., MINIRENA, 2014).

With a recent restoration analysis by Bastin *et al.* (2019) that also targets drylands for tree planting, this risk has been compounded. Like Laestadius et al. (2011), Bastin *et al.* (2019) produced global maps of tree restoration potential by differencing maps of potential tree cover and existing tree cover. Bastin et al. (2019) report finding “space for at least an additional 0.9 billion ha of canopy cover”, but approximately 42% of their potential restoration area and ~43% of their potential carbon uptake was located in arid biomes. Veldman et al. (2019) critiqued Bastin et al.’s work, stating that it promoted drylands afforestation and arguing that their dryland restoration area is an overestimate that likely arises from relatively high tree cover in protected areas, which would inflate potential tree cover estimates. Bastin et al. (2019b) responded to emphasize that they do not advocate replacement of natural ecosystems and to contend that

drylands protected areas are suitable for estimating potential tree cover because they have ranges of tree cover, fire, and herbivory that are comparable to areas outside. Thus, they argue, their expansive estimates of potential tree restoration in drylands are an indicator of widespread degradation and loss of tree cover outside protected areas.

At first glance, widespread drylands degradation is an intuitive explanation for lower-than-expected tree cover in drylands, given global desertification concerns and the identification by Bastin et al. (2017b) of a massive area of low-density forest cover in global drylands. But there is an alternative hypothesis to explain the expansive area of potential restoration identified in drylands, namely that both restoration maps share core methodological issues that could bias estimates of tree cover (and thus, tree restoration potential) in arid biomes, where tree cover is sparse. To quantify existing tree cover, both studies depend on global forest cover maps derived respectively from MODIS (Laestadius et al. 2011) and Landsat (Bastin et al., 2019) satellite imagery. It is well known that global forest cover maps can underestimate tree cover at low tree densities (Montesano et al. 2009; Sexton et al. 2015; Staver & Hansen 2015; Bastin et al. 2017b), but the impact of these underestimates has rarely been quantified at global scales.

Because of the potential impacts of increasing tree cover in drylands, the methodology of these restoration maps deserves careful scrutiny. As I show below, both map products underestimate existing tree cover in arid biomes, and both calculate potential tree cover with a distinct methodology. Given that their methods simply difference potential and existing tree cover to calculate restoration potential, any missing existing tree cover in drylands creates a “false mirage” of inflated tree restoration potential. A close examination reveals the risks of using

remote sensing products for purposes they were not intended for, and a critical need for improved tree cover maps in arid biomes.

2. Drylands biases in the AFLRO map

Laestadius et al. (2011) (hereafter referred to as “study 1”) estimated the global area that could be brought under forest landscape restoration in three main steps (WRI 2016). First, they used ecoregions to delineate potential forest cover, defining forest using the 10% FAO threshold and thus intentionally including savanna and woodland ecoregions. All areas within selected forested ecoregions were assumed to have potential for restoration (i.e., to be potentially forested). Second, they produced global maps of existing forest cover at a 1 km spatial resolution using MODIS data, using a Vegetation Continuous Fields approach to create three forest classes: woodlands (10-25% cover), open forests (25-49% cover), and closed forests (>49% cover). Finally, they differenced the potential and existing forest cover maps to identify areas that potentially could be restored, with several follow-up steps to eliminate land covers inappropriate for restoration (e.g., urban areas, intensive agriculture, and closed forests).

To determine whether study 1 underestimated existing forest cover in drylands, I assessed its accuracy using an independent, photo-interpreted tree cover dataset generated by Bastin et al. (2017b), the Global Drylands Assessment. This validation dataset estimated tree cover in 1 ha plots at regular intervals over four arid biomes: sub-humid, semi-arid, arid, and hyperarid (Sorensen 2007). After thresholding the validation data at 10% tree cover (the definition of forest in study 1), I used standard confusion matrices to assess the accuracy of the forest and nonforest classes in the study 1 map, in two ways. First, validation plots across the full existing

forest cover map were used (n=85,420); this approach is straightforward but has the disadvantage of including regions unsuitable for restoration (e.g, intact forests). Second, validation plots only in areas with restoration potential were used (deforested areas without agriculture, degraded forests, n=40,126); this method has the advantage of evaluating map accuracy within identified restoration areas, but the disadvantage of only comparing degraded forests with non-forest. In both approaches, if forest cover is underestimated by the study 1 map in dryland biomes, I would expect greater omission of forest than of nonforest, and relatively higher forest omission error in drier biomes.

Despite the large amount of error derived from comparing 1 ha scale validation data to a 1 km pixel product, the results were clear. In the full existing forest cover map, omission errors for forest (35%) slightly exceeded those for nonforest (29%) across all arid biomes (Figure 1, Table 1A). Forest omission error (30%) was comparable to nonforest (33%) in the least arid subhumid biome, but greater than nonforest error in the semi-arid biome (45% vs. 26%) and slightly higher in the arid biome (41% vs. 38%) (Table S1). Similarly, in the restoration potential area, forest omission errors across all arid biomes were markedly higher (66%) and exceeded those for nonforest (17%) (Figure 1, Table 1B). Forest omission error in the restoration area was lowest in the least arid subhumid biome (56%), and highest in the semi-arid (79%) and arid biomes (64%) (Table S2).

Although the validation data were not established to assess the accuracy of the existing forest map, we can use them to calculate a corrected forest cover area that accounts for omission and commission errors (Olofsson et al. 2013), and difference the corrected forest area with the area

of forest cover in the original study 1 map. Following this method, I roughly estimate that these widespread omission errors decreased intact forest cover in drylands by between 55 and 166 million hectares (Table 1C). Because potential forest cover was simply differenced with existing forest cover across those regions, study 1 likely overestimated drylands restoration potential by a similar magnitude—between 7% and 20% of its global drylands total of 828 million hectares.

3. Drylands biases in the Bastin et al. map

Bastin *et al.* (2019) (hereafter referred to as “study 2”) estimate the global area that could be increased in tree cover (i.e., area with the potential for restoration) by first predicting maximum potential tree cover using reference forest cover plots and several global environmental layers (climate, soil, and topography). Then, they differenced the potential tree cover with a map of current tree cover—the Hansen Global Forest Cover map (HGFC) (Hansen et al. 2013). Although study 2 summarizes its results in area units (canopy cover), these are derived from percent tree cover estimates at each pixel. As an example, if a location had a maximum potential tree cover of 30% and HGFC tree cover of 10%, study 2 would estimate restoration potential at 20%. If the actual tree cover at that location was 20%, the HGFC tree cover underestimate of 10% would lead to 2× the estimated restoration potential. The potential bias in drylands can thus be evaluated by examining deviations between known and predicted percent tree cover.

To test whether study 2 overestimated restoration potential in drylands, I calculated the difference between reference tree cover plot measurements (Bastin et al. 2017b) and HGFC tree cover estimates (Hansen et al. 2013) (Figures 2, 3). Following the methods of study 2, I then summed canopy cover differences at each plot for each of the four arid biomes (Table 2A). To

make biome-level estimates of bias, I divided plot canopy cover differences by the plot area, and used the resulting percent plot-level bias to estimate the total bias in canopy cover area in each arid biome (Table 2B). If HGFC estimates of restoration potential are unbiased in dryland biomes, I would expect differences between photo-interpreted tree cover and HGFC tree cover to be centered on zero.

Instead, the percent differences in tree cover between HGFC estimates and plot measurements are non-zero across all arid biomes (Figure 3; $p < 0.0001$; linear regression). This simple re-analysis indicates the HGFC map underestimates tree cover by an average of 5.9% across arid biomes (range of 0.5-8.8%; Table 2). By subtraction, this indicates study 2 overestimated tree restoration potential in drylands. Due to the vast area of drylands biomes, a small underestimate in percent tree cover converts to a large canopy cover area bias; I estimate ~315 Mha of canopy cover area were mis-identified as potential tree restoration potential (Figure 4, Table 2B). This error represents a third of the gross total restoration potential in drylands (973 Mha) identified by study 2, and an area slightly larger than the nation of India.

Because total carbon stocks partly depend on canopy area estimates, the restoration potential for carbon is also potentially overestimated in drylands by as much as 91.7 gigatons carbon (Bastin et al., 2017b; Bastin et al., 2019). However, it is difficult to quantify the exact degree to which global tree restoration potential was inflated. Their maximum potential tree cover map is an interpolated surface derived from machine learning and has not been made available to other researchers for analysis. Actual error could be higher. For example, the data show that the HGFC map occasionally over-predicts tree cover in drylands (Figures 3, 4), often in specific

regions. In study 2, if HGFC predictions exceeded potential tree cover, they were set to zero restoration potential. If we assume that all HGFC over-predictions that exceed actual tree cover will also exceed potential tree cover, they should thus be set to zero. Under this assumption the mean percent overestimate in tree cover would be higher, and study 2 would overestimate tree restoration potential in drylands by as much as 440 Mha canopy cover (by 45% of the current total: Table 2).

In a prior paper, Bastin *et al.* (2017b) used a similar approach to demonstrate that the HGFC map underestimated tree cover by ~427 million hectares (Mha) in dryland ecosystems (Figure 5). These two analyses differ in how they treat tree cover, and are not directly comparable. However the re-analysis presented here agrees with Bastin *et al.* (2017b), indicating that study 2 (Bastin *et al.* 2019b) overestimated tree restoration potential in drylands by a similar magnitude.

Globally, drylands figure prominently as areas of tree restoration potential in Africa and North and South America (Figure 5). Identified areas with tree restoration potential (910.7 Mha) appear to mainly include pastures and dryland ecosystems, likely because mesic areas with row crop agriculture were excluded from consideration. In study 2, excluding agriculture lowered the potential restoration area in drylands by ~61%; this implies that, after accounting for agriculture, overestimating restoration potential in drylands might lower global tree restoration potential by 119-173 Mha (13-19%).

4. Causes of mis-estimates

It should be emphasized that neither study 1 or study 2 advocate targeting drylands for inappropriate restoration, and both recognize the negative consequences of inappropriate restoration in drylands (Laestadius et al. 2015b; Bastin et al. 2019a). Nonetheless, each map emphasized arid biomes as restoration opportunities for similar methodological reasons. In the case of study 1, they used MODIS data to estimate tree cover at a global scale, and recent work has shown that MODIS products can have challenges in predicting very low tree cover (e.g., Staver & Hansen, 2015). In the case of study 2, their methodological error was using the Hansen et al. (2013) data to estimate existing tree cover in drylands. Bastin et al. (2017b) extensively documented that Hansen et al. (2013) underestimated “forest” cover (i.e., >10% tree cover) in drylands. Hojas-Gascon et al. (2015) observed a similar HGFC underestimate at intermediate tree cover (20-80%) in Tanzania. More recently, Cunningham et al. (2019) found that the HGFC product begins to dramatically underestimate tree cover below approximately 2270 mm of mean annual precipitation (e.g., tropical dry forest). In this study, I show that the HGFC product underestimates tree cover even at very low cover in hyperarid systems (Figure 3), and that this bias in drylands has a large cumulative effect on global canopy cover estimates.

Both of the re-analyses analyses of study 1 and 2 presented here assume that the Global Drylands Assessment validation data is relatively unbiased in drylands. The validation data, because it is derived from high-resolution satellite imagery, potentially could have difficulty separating tree cover from shrub cover (Schepaschenko et al. 2017). However, although it is not error-free, the Global Drylands Assessment dataset has been shown to be relatively unbiased at a global scale and used conservative criteria (shadows, canopies ≥ 3 m in diameter) to separate tree from shrub cover (Bastin et al. 2017a, 2017b). Furthermore, most of the restoration area highlighted by

study 1 has a tree canopy height ≥ 5 m (Figure S1; Los et al. 2012), which meets the 5 m tree height definition used by the AFLRO forest map and the HGFC (Hansen et al. 2013; P. Potapov, *pers. comm.*). In the case of study 2, it used a similar photo-interpretation plot methodology to create training data for its predictions of potential tree cover. Any significant confusion between tree and shrub cover in the potential tree cover data set would inflate predicted potential forest cover, and thus bias estimates of restoration potential upwards as well.

The challenge of tree cover underestimates at low tree cover is common to several similar global tree cover products, including the LVCF tree cover product (Sexton et al. 2015) and MODIS VCF (Staver & Hansen 2015; Tang et al. 2019). Tang et al. (2019) found that the MODIS VCF product underestimated tree cover by 5.6% in shrublands and savannas, very close to the 5.9% bias observed in this study for the HGFC product. This particular challenge likely arises from multiple causes (Sexton et al. 2015; Cunningham et al. 2019; Smith et al. 2019). First, it may be caused by intra- and interannual variability in tree and herbaceous phenology in response to rainfall, which can lead to variable estimates of cover over time (Smith et al. 2019). Second, it could be caused by the weak vegetation signal at low cover in soil-dominated regions (Smith et al. 2019), or the strong signal of herbaceous vegetation as tree cover grows sparse (Naidoo et al. 2016). Third, a lack of good training datasets for regions with sparse tree cover (particularly in Africa; Schepaschenko et al., 2017) could contribute to poor accuracy. Fourth, it may arise from the shorter stature of trees in arid and hyperarid systems (i.e., less than a 5-meter tree height definition), although both the HGFC and MODIS VCF products are sensitive to tree and shrub cover at shorter heights (Hansen et al. 2013; Tang et al. 2019). Finally, underestimates of tree cover may result from the net effect of the compositing algorithms that create cloud-free annual

images needed to estimate tree cover. Currently, both the LVCF and HGFC products use cloud-free imagery composites, often from the dry season, to map global forest cover (Hansen et al. 2013; Feng et al. 2016). This likely results in low estimates of forest cover since in arid and semiarid biomes, the most cloud-free time of year is the driest time, when green plants do not photosynthesize strongly and/or shed their leaves (Anyamba & Tucker 2005; Yang et al. 2014).

5. Ways forward: creating corrected estimates

If current global forest cover maps have issues estimating existing tree cover and restoration potential in dry biomes, then what are possible solutions? First, there are alternative maps of global forest cover and biomass that use microwave (SAR) data instead of MODIS and Landsat optical data (Shimada et al. 2014; Martone et al. 2018; Zhang et al. 2019). Because they can penetrate cloud cover and potentially map wet season tree cover, SAR-derived maps could be more accurate in drylands and are a promising approach. However, given the sensitivity of SAR sensors to soil moisture and leaf mass, drylands variability in rainfall and phenology present a challenge that requires optimization to local seasonality (e.g., Bouvet et al., 2018; Brandt et al., 2018). Although regional studies have indicated that fractional tree cover can be accurately mapped using SAR (Naidoo et al. 2016; Baumann et al. 2018; Brandt et al. 2018a; Wessels et al. 2019), its accuracy relative to other global land cover maps remains to be determined.

Second, current forest maps could be used more conservatively. One policy relevant solution could be to simply not support tree-based restoration in drylands biomes, or below a certain level of rainfall, and to encourage researchers to omit these areas from tree restoration potential maps (e.g., Veldman et al., 2019). However, this solution would fail to identify wooded habitats in

dryland regions in need of restoration, such as riparian forests, hill slopes, or agroforests.

Alternatively, estimates of tree restoration potential in drylands could make more conservative area estimates by using a higher threshold for identifying potential tree restoration (e.g., more than +5.9% between existing and potential cover). Identifying levels of bias in tree cover estimates across discrete regions (this paper) or across continuous measurements of rainfall (e.g., Cunningham et al. 2019) could limit the false-positive identification of potential restoration in drylands.

Third, corrected versions of global forest cover maps could be generated by statistical re-analysis of existing maps. It is challenging to properly address directional errors in global models, but the hydrological literature contains a number of examples of global model calibration using validation data (Beck et al. 2017). In this case, instead of simply using flawed maps of existing tree cover, study 2 could have corrected existing tree cover using a statistical model that included plot-level differences in tree cover estimates as a co-variate. For example, LiDAR measurements of tree height have been successfully extended across landscapes by integrating known reference height estimates with continuous raster data on tree cover and environmental variables (Babcock et al. 2015; Baccini et al. 2017). In the study 2 paper, the improvement from such an approach would be partial at best, as 49% of tree cover in drylands was underestimated as 0% tree cover by the HGFC map (Table 3). These pixels are indistinguishable from naturally bare areas, and any attempt to increase tree cover in bare areas would result in large commission errors. However, the remaining 51% of drylands tree cover that was underestimated could be corrected through statistical means, as described above (i.e., it has >0% estimated tree cover that could be increased).

Regardless of how researchers attempt to correct maps of restoration potential in arid biomes in the future, this analysis has underlined that current global products are limited in their ability to map sparse tree cover. Therefore, over nearly half the earth's surface, caution should be exercised in their use. Beyond dryland systems, low tree cover is common in boreal, agricultural and urban systems. For example, monitoring sparse tree cover at high latitudes is one major focus of the current NASA ABoVE aerial campaign (Miller et al. 2019). How well existing satellite sensors can monitor global changes in sparse tree cover over time is an open question. At a coarse scale, vegetation optical depth derived from passive microwave sensors has tracked global shifts in dryland tree cover (Poulter et al. 2014; Tian et al. 2017; Brandt et al. 2018b), and overlap between MISR optical imagery (stereogrammetry) has been used to map tree cover (Chopping et al. 2008). At a fine scale, high-resolution sensors can detect scattered trees using a variety of methods (Greenberg et al. 2005; Zeidler et al. 2012; Brandt et al. 2018a), but such approaches suffer from high cost, intense computing demands, small individual image extents, and attendant challenges with capturing wet-season phenology. The increasing global coverage of high-resolution imagery is enabling hybrid approaches to monitor changes in low tree cover systems, in which tree cover datasets derived from spatially-extensive, high-resolution data are used to train moderate resolution optical and/or SAR data (Montesano et al. 2016; Brandt et al. 2018a). Future innovations may include wall-to-wall maps of tree cover at high resolution enabled by cloud computing (Seiferling et al. 2017; Neigh et al. 2019).

6. Conclusions

The need for innovation in monitoring sparse tree cover systems over time is urgent and pressing, given rapid global changes. Tree cover in dryland systems is shifting in response to changes in fire frequency (Abatzoglou & Williams 2016; Andela et al. 2017; Stevens et al. 2017), droughts (Allen et al. 2010) and fuelwood harvesting (Sedano et al. 2016), with long-term consequences for rural livelihoods and ecosystem services (Ahlström et al. 2015; FAO 2015). At high latitudes, sparse tree and shrub cover is increasing in response to climate change (Myers-Smith et al. 2011). And for both natural and agricultural tree cover, massive investments in habitat restoration and tree planting are presenting new monitoring challenges (Brandt et al. 2018a; Dave et al. 2019).

Despite this urgency, and because of it, researchers should be careful to avoid using global remote sensing products for purposes they were not intended, especially when their flaws are known. Both studies examined here (Laestadius et al. 2011; Bastin et al. 2019b) overstated the potential area available for tree restoration in drylands, with potential policy impacts on Bonn Challenge commitments from arid countries (e.g., Laestadius et al. 2015a). Although this does not obviate the core conclusions of these studies, their work suggests that tree cover can play a larger role in counteracting land degradation and greenhouse gas emissions than is feasible. Increasing tree cover, especially in humid regions, has the potential to address climate change by sequestering large amounts of carbon (Griscom et al. 2017). Three-quarters of Nationally Determined Contributions to the Paris Agreement include restoration goals (IUCN 2017), and policy makers rely on the best available science to forecast potential carbon sequestration from restoration activities.

Because of their ecological and economic fragility (UN EMG 2011; Buisson et al. 2019), tree-based restoration in drylands needs to proceed with a careful focus on ecosystem integrity and targeted benefits. For example, because of the slow growth rate of trees in arid biomes (Poorter et al. 2016), their relatively low carbon stock per hectare (Grace et al. 2006; Pan et al. 2011), and the risk of fire (Veldman et al. 2015b), drylands are not ideal locations for tree-based restoration to sequester carbon. However, in many arid landscapes, targeted interventions to increase or maintain tree cover can markedly improve human well-being (Djouidi et al. 2015; McKinnon et al. 2016).

Although this study found that existing global studies overestimate the tree restoration potential in drylands, it is clear that much land remains in need of restoration in these regions. Degraded drylands with depressed tree cover are relatively common, especially in sub-Saharan Africa where charcoal harvesting is the main source of household energy (Iiyama et al. 2014; Sedano et al. 2016; Brandt et al. 2018a; Osborne et al. 2018). On the other hand, the core goal of the two studies analyzed here (identifying where tree cover could be increased) may not apply to all dryland ecosystems. Ecological restoration in some dryland ecosystems involves re-establishing fire regimes and decreasing grazing pressure, which may lower tree cover (Buisson et al. 2019). Restoring trees appropriately to arid landscapes can benefit biodiversity conservation, water quality, and human well-being, but proposing restoration in any landscape needs to be done thoughtfully and with realistic expectations.

References and Notes:

Abatzoglou, J.T. & Williams, A.P. (2016). Impact of anthropogenic climate change on wildfire

- across western US forests. *Proc. Natl. Acad. Sci.*, 113, 11770 LP – 11775.
- Ahlström, A., Raupach, M.R., Schurgers, G., Smith, B., Arneth, A., Jung, M., Reichstein, M., Canadell, J.G., Friedlingstein, P. & Jain, A.K. (2015). The dominant role of semi-arid ecosystems in the trend and variability of the land CO₂ sink. *Science* (80-.), 348, 895–899.
- Aleman, J.C., Blarquez, O. & Staver, C.A. (2016). Land-use change outweighs projected effects of changing rainfall on tree cover in sub-Saharan Africa. *Glob. Chang. Biol.*, 22, 3013–3025.
- Allen, C.D., Macalady, A.K., Chenchouni, H., Bachelet, D., McDowell, N., Vennetier, M., Kitzberger, T., Rigling, A., Breshears, D.D., Hogg, E.H. (Ted), Gonzalez, P., Fensham, R., Zhang, Z., Castro, J., Demidova, N., Lim, J.-H., Allard, G., Running, S.W., Semerci, A. & Cobb, N. (2010). A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. *For. Ecol. Manage.*, 259, 660–684.
- Andela, N., Morton, D.C., Giglio, L., Chen, Y., van der Werf, G.R., Kasibhatla, P.S., DeFries, R.S., Collatz, G.J., Hantson, S., Kloster, S., Bachelet, D., Forrest, M., Lasslop, G., Li, F., Mangeon, S., Melton, J.R., Yue, C. & Randerson, J.T. (2017). A human-driven decline in global burned area. *Science* (80-.), 356, 1356 LP – 1362.
- Anyamba, A. & Tucker, C.J. (2005). Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981–2003. *J. Arid Environ.*, 63, 596–614.
- Babcock, C., Finley, A.O., Bradford, J.B., Kolka, R., Birdsey, R. & Ryan, M.G. (2015). LiDAR based prediction of forest biomass using hierarchical models with spatially varying coefficients. *Remote Sens. Environ.*, 169, 113–127.
- Baccini, A., Walker, W., Carvalho, L., Farina, M., Sulla-Menashe, D. & Houghton, R.A. (2017). Tropical forests are a net carbon source based on aboveground measurements of gain and

loss. *Science* (80-.), 358, 230 LP – 234.

Bastin, J.-F., Mollicone, D., Grainger, A., Sparrow, B., Picard, N., Lowe, A. & Castro, R.

(2017a). Response to Comment on “The extent of forest in dryland biomes.” *Science* (80-.), 358, eaao2070.

Bastin, J.F., Berrahmouni, N., Grainger, A., Maniatis, D., Mollicone, D., Moore, R., Patriarca, C., Picard, N., Sparrow, B., Abraham, E.M., Aloui, K., Atesoglu, A., Attore, F., Bassüllü, Ç., Bey, A., Garzuglia, M., García-Montero, L.G., Groot, N., Guerin, G., Laestadius, L., Lowe, A.J., Mamane, B., Marchi, G., Patterson, P., Rezende, M., Ricci, S., Salcedo, I., Diaz, A.S.-P., Stolle, F., Surappaeva, V. & Castro, R. (2017b). The extent of forest in dryland biomes. *Science* (80-.), 356, 635–638.

Bastin, J.F., Finegold, Y., Garcia, C., Gellie, N., Lowe, A., Mollicone, D., Rezende, M., Routh, D., Sacande, M., Sparrow, B., Zohner, C.M. & Crowther, T.W. (2019a). Response to Comments on “The global tree restoration potential.” *Science* (80-.), 366, eaay8108.

Bastin, J.F., Finegold, Y., Garcia, C., Mollicone, D., Rezende, M., Routh, D., Zohner, C.M. & Crowther, T.W. (2019b). The global tree restoration potential. *Science* (80-.), 365, 76–79.

Baumann, M., Levers, C., Macchi, L., Bluhm, H., Waske, B., Gasparri, N.I. & Kuemmerle, T. (2018). Mapping continuous fields of tree and shrub cover across the Gran Chaco using Landsat 8 and Sentinel-1 data. *Remote Sens. Environ.*, 216, 201–211.

Beck, H.E., van Dijk, A.I.J.M., de Roo, A., Dutra, E., Fink, G., Orth, R. & Schellekens, J. (2017). Global evaluation of runoff from 10 state-of-the-art hydrological models. *Hydrol. Earth Syst. Sci.*, 21, 2881–2903.

Bond, W.J., Stevens, N., Midgley, G.F. & Lehmann, C.E.R. (2019). The Trouble with Trees: Afforestation Plans for Africa. *Trends Ecol. Evol.*, 34, 963–965.

- Bouvet, A., Mermoz, S., Le Toan, T., Villard, L., Mathieu, R., Naidoo, L. & Asner, G.P. (2018).
An above-ground biomass map of African savannahs and woodlands at 25m resolution
derived from ALOS PALSAR. *Remote Sens. Environ.*, 206, 156–173.
- Brandt, M., Rasmussen, K., Hiernaux, P., Herrmann, S., Tucker, C.J., Tong, X., Tian, F., Mertz,
O., Kergoat, L., Mbow, C., David, J.L., Melocik, K.A., Dendoncker, M., Vincke, C. &
Fensholt, R. (2018a). Reduction of tree cover in West African woodlands and promotion in
semi-arid farmlands. *Nat. Geosci.*, 11, 328–333.
- Brandt, M., Wigneron, J.-P., Chave, J., Tagesson, T., Penuelas, J., Ciais, P., Rasmussen, K.,
Tian, F., Mbow, C., Al-Yaari, A., Rodriguez-Fernandez, N., Schurgers, G., Zhang, W.,
Chang, J., Kerr, Y., Verger, A., Tucker, C., Mialon, A., Rasmussen, L.V., Fan, L. &
Fensholt, R. (2018b). Satellite passive microwaves reveal recent climate-induced carbon
losses in African drylands. *Nat. Ecol. Evol.*, 2, 827–835.
- Buisson, E., Le Stradic, S., Silveira, F.A.O., Durigan, G., Overbeck, G.E., Fidelis, A., Fernandes,
G.W., Bond, W.J., Hermann, J.-M., Mahy, G., Alvarado, S.T., Zaloumis, N.P. & Veldman,
J.W. (2019). Resilience and restoration of tropical and subtropical grasslands, savannas, and
grassy woodlands. *Biol. Rev.*, 94, 590–609.
- Chopping, M., Moisen, G.G., Su, L., Laliberte, A., Rango, A., Martonchik, J. V. & Peters,
D.P.C. (2008). Large area mapping of southwestern forest crown cover, canopy height, and
biomass using the NASA Multiangle Imaging Spectro-Radiometer. *Remote Sens. Environ.*,
112, 2051–2063.
- Cunningham, D., Cunningham, P. & Fagan, M.E. (2019). Identifying biases in global tree cover
products: a case study in Costa Rica. *Forests*, 1–37.
- Dave, R., Saint-Laurent, C., Murray, L., Antunes Daldegan, G., Brouwer, R., de Mattos

- Scaramuzza, C.A., Raes, L., Simonit, S., Catapan, M., García Contreras, G., Ndoli, A., Karangwa, C., Perera, N., Hingorani, S. & Pearson, T. (2019). *Second Bonn Challenge progress report. Application of the Barometer in 2018*. Gland, Switzerland.
- Djouidi, H., Vergles, E., Blackie, R.R., Koame, C.K. & Gautier, D. (2015). Dry forests, livelihoods and poverty alleviation: understanding current trends. *Int. For. Rev.*, 17, 54–69.
- FAO. (2015). *Global guidelines for the restoration of degraded forests and landscapes in drylands: building resilience and benefiting livelihoods*, by Berrahmouni, N., Regato, P. & Parfondry, M. *Forestry Paper No. 175*. Rome.
- Feng, M., Sexton, J.O., Huang, C., Anand, A., Channan, S., Song, X.-P., Song, D.-X., Kim, D.-H., Noojipady, P. & Townshend, J.R. (2016). Earth science data records of global forest cover and change: Assessment of accuracy in 1990, 2000, and 2005 epochs. *Remote Sens. Environ.*, 184, 73–85.
- Grace, J., José, J.S., Meir, P., Miranda, H.S. & Montes, R.A. (2006). Productivity and carbon fluxes of tropical savannas. *J. Biogeogr.*, 33, 387–400.
- Greenberg, J.A., Dobrowski, S.Z. & Ustin, S.L. (2005). Shadow allometry: Estimating tree structural parameters using hyperspatial image analysis. *Remote Sens. Environ.*, 97, 15–25.
- Griscom, B.W., Adams, J., Ellis, P.W., Houghton, R.A., Lomax, G., Miteva, D.A., Schlesinger, W.H., Shoch, D., Siikamäki, J. V., Smith, P., Woodbury, P., Zganjar, C., Blackman, A., Campari, J., Conant, R.T., Delgado, C., Elias, P., Gopalakrishna, T., Hamsik, M.R., Herrero, M., Kiesecker, J., Landis, E., Laestadius, L., Leavitt, S.M., Minnemeyer, S., Polasky, S., Potapov, P., Putz, F.E., Sanderman, J., Silvius, M., Wollenberg, E. & Fargione, J. (2017). Natural climate solutions. *Proc. Natl. Acad. Sci.*, 114, 11645–11650.
- Hansen, M.C., Potapov, P. V, Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau,

- D., Stehman, S. V, Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O. & Townshend, J.R.G. (2013). High-resolution global maps of 21st-century forest cover change. *Science* (80-.), 342, 850–3.
- Hojas-Gascon, L., Cerutti, P.O., Eva, H., Nasi, R. & Martius, C. (2015). *Monitoring deforestation and forest degradation in the context of REDD+: Lessons from Tanzania*. CIFOR.
- Honda, E.A. & Durigan, G. (2016). Woody encroachment and its consequences on hydrological processes in the savannah. *Philos. Trans. R. Soc. B Biol. Sci.*, 371, 20150313.
- Iiyama, M., Neufeldt, H., Dobie, P., Njenga, M., Ndegwa, G. & Jamnadass, R. (2014). The potential of agroforestry in the provision of sustainable woodfuel in sub-Saharan Africa. *Curr. Opin. Environ. Sustain.*, 6, 138–147.
- IUCN. (2017). *The Bonn Challenge and the Paris Agreement: How can forest landscape restoration advance Nationally Determined Contributions? (Forest Brief 21)*. Gland, Switzerland.
- Laestadius, L., Buckingham, K., Maginnis, S. & Saint-Laurent, C. (2015a). Before Bonn and beyond: the history and future of forest landscape restoration. *Unasylva*, 66, 11–18.
- Laestadius, L., Maginnis, S., Minnemeyer, S., Potapov, P. V, Reyter, K. & Saint-Laurent, C. (2015b). Sparing grasslands: Map misinterpreted. *Science* (80-.), 347, 1210 LP – 1211.
- Laestadius, L., Maginnis, S., Minnemeyer, S., Potapov, P., Saint-Laurent, C. & Sizer, N. (2011). Mapping opportunities for forest landscape restoration. *Unasylva*, 62, 47–48.
- Los, S.O., Rosette, J.A.B., Kljun, N., North, P.R.J., Chasmer, L., Suárez, J.C., Hopkinson, C., Hill, R.A., van Gorsel, E., Mahoney, C. & Berni, J.A.J. (2012). Vegetation height and cover fraction between 60° S and 60° N from ICESat GLAS data. *Geosci. Model Dev.*, 5, 413–

432.

- Martone, M., Rizzoli, P., Wecklich, C., González, C., Bueso-Bello, J.-L., Valdo, P., Schulze, D., Zink, M., Krieger, G. & Moreira, A. (2018). The global forest/non-forest map from TanDEM-X interferometric SAR data. *Remote Sens. Environ.*, 205, 352–373.
- McKinnon, M.C., Cheng, S.H., Dupre, S., Edmond, J., Garside, R., Glew, L., Holland, M.B., Levine, E., Masuda, Y.J. & Miller, D.C. (2016). What are the effects of nature conservation on human well-being? A systematic map of empirical evidence from developing countries. *Environ. Evid.*, 5, 1.
- Miller, C.E., Griffith, P.C., Goetz, S.J., Hoy, E.E., Pinto, N., McCubbin, I.B., Thorpe, A.K., Hofton, M., Hodkinson, D., Hansen, C., Woods, J., Larson, E., Kasischke, E.S. & Margolis, H.A. (2019). An overview of ABoVE airborne campaign data acquisitions and science opportunities. *Environ. Res. Lett.*, 14, 80201.
- MINIRENA. (2014). *Forest Landscape Restoration Opportunity Assessment for Rwanda*. Nairobi, Kenya.
- Montesano, M.P., Neigh, S.R.C., Sexton, J., Feng, M., Channan, S., Ranson, J.K. & Townshend, R.J. (2016). Calibration and Validation of Landsat Tree Cover in the Taiga–Tundra Ecotone. *Remote Sens.* .
- Montesano, P.M., Nelson, R., Sun, G., Margolis, H., Kerber, A. & Ranson, K.J. (2009). MODIS tree cover validation for the circumpolar taiga–tundra transition zone. *Remote Sens. Environ.*, 113, 2130–2141.
- Myers-Smith, I.H., Forbes, B.C., Wilmking, M., Hallinger, M., Lantz, T., Blok, D., Tape, K.D., Macias-Fauria, M., Sass-Klaassen, U., Lévesque, E., Boudreau, S., Ropars, P., Hermanutz, L., Trant, A., Collier, L.S., Weijers, S., Rozema, J., Rayback, S.A., Schmidt, N.M.,

- Schaepman-Strub, G., Wipf, S., Rixen, C., Ménard, C.B., Venn, S., Goetz, S., Andreu-Hayles, L., Elmendorf, S., Ravolainen, V., Welker, J., Grogan, P., Epstein, H.E. & Hik, D.S. (2011). Shrub expansion in tundra ecosystems: dynamics, impacts and research priorities. *Environ. Res. Lett.*, 6, 45509.
- Naidoo, L., Mathieu, R., Main, R., Wessels, K. & Asner, G.P. (2016). L-band Synthetic Aperture Radar imagery performs better than optical datasets at retrieving woody fractional cover in deciduous, dry savannahs. *Int. J. Appl. Earth Obs. Geoinf.*, 52, 54–64.
- Neigh, C.S.R., Carroll, M.L., Montesano, P.M., Slayback, D.A., Wooten, M.R., Lyapustin, A.I., Shean, D.E., Alexandrov, O., Macander, M.J. & Tucker, C.J. (2019). An API for Spaceborne Sub-Meter Resolution Products for Earth Science. In: *IGARSS 2019-2019 IEEE Int. Geosci. Remote Sens. Symp.* IEEE, pp. 5397–5400.
- Olofsson, P., Foody, G.M., Stehman, S. V & Woodcock, C.E. (2013). Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sens. Environ.*, 129, 122–131.
- Osborne, C.P., Charles-Dominique, T., Stevens, N., Bond, W.J., Midgley, G. & Lehmann, C.E.R. (2018). Human impacts in African savannas are mediated by plant functional traits. *New Phytol.*, 220, 10–24.
- Pan, Y., Birdsey, R.A., Fang, J., Houghton, R., Kauppi, P.E., Kurz, W.A., Phillips, O.L., Shvidenko, A., Lewis, S.L. & Canadell, J.G. (2011). A large and persistent carbon sink in the world's forests. *Science (80-.)*, 333, 988–993.
- Parr, C.L., Lehmann, C.E.R., Bond, W.J., Hoffmann, W.A. & Andersen, A.N. (2014). Tropical grassy biomes: misunderstood, neglected, and under threat. *Trends Ecol. Evol.*, 29, 205–213.

Poorter, L., Bongers, F., Aide, T.M., Almeyda Zambrano, A.M., Balvanera, P., Becknell, J.M.,
Boukili, V., Brancalion, P.H.S., Broadbent, E.N., Chazdon, R.L., Craven, D., de Almeida-
Cortez, J.S., Cabral, G.A.L., de Jong, B.H.J., Denslow, J.S., Dent, D.H., DeWalt, S.J.,
Dupuy, J.M., Durán, S.M., Espírito-Santo, M.M., Fandino, M.C., César, R.G., Hall, J.S.,
Hernandez-Stefanoni, J.L., Jakovac, C.C., Junqueira, A.B., Kennard, D., Letcher, S.G.,
Licona, J.-C., Lohbeck, M., Marín-Spiotta, E., Martínez-Ramos, M., Massoca, P., Meave,
J.A., Mesquita, R., Mora, F., Muñoz, R., Muscarella, R., Nunes, Y.R.F., Ochoa-Gaona, S.,
de Oliveira, A.A., Orihuela-Belmonte, E., Peña-Claros, M., Pérez-García, E.A., Piotto, D.,
Powers, J.S., Rodríguez-Velázquez, J., Romero-Pérez, I.E., Ruíz, J., Saldarriaga, J.G.,
Sanchez-Azofeifa, A., Schwartz, N.B., Steininger, M.K., Swenson, N.G., Toledo, M.,
Uriarte, M., van Breugel, M., van der Wal, H., Veloso, M.D.M., Vester, H.F.M., Vicentini,
A., Vieira, I.C.G., Bentos, T.V., Williamson, G.B. & Rozendaal, D.M.A. (2016). Biomass
resilience of Neotropical secondary forests. *Nature*, 530, 211–214.

Poulter, B., Frank, D., Ciais, P., Myneni, R.B., Andela, N., Bi, J., Broquet, G., Canadell, J.G.,
Chevallier, F. & Liu, Y.Y. (2014). Contribution of semi-arid ecosystems to interannual
variability of the global carbon cycle. *Nature*, 509, 600.

Reynolds, J.F., Smith, D.M.S., Lambin, E.F., Turner, B.L., Mortimore, M., Batterbury, S.P.J.,
Downing, T.E., Dowlatabadi, H., Fernández, R.J., Herrick, J.E., Huber-Sannwald, E., Jiang,
H., Leemans, R., Lynam, T., Maestre, F.T., Ayarza, M. & Walker, B. (2007). Global
Desertification: Building a Science for Dryland Development. *Science* (80-.), 316, 847 LP
– 851.

Schepaschenko, D., Fritz, S., See, L., Laso Bayas, J.C., Lesiv, M., Kraxner, F. & Obersteiner, M.
(2017). Comment on “The extent of forest in dryland biomes.” *Science* (80-.), 358,

554 eaao0166.

555 Sedano, F., Silva, J.A., Machoco, R., Meque, C.H., Siteo, A., Ribeiro, N., Anderson, K., Ombe,
556 Z.A., Baule, S.H. & Tucker, C.J. (2016). The impact of charcoal production on forest
557 degradation: a case study in Tete, Mozambique. *Environ. Res. Lett.*, 11, 94020.

558 Seiferling, I., Naik, N., Ratti, C. & Proulx, R. (2017). Green streets – Quantifying and mapping
559 urban trees with street-level imagery and computer vision. *Landsc. Urban Plan.*, 165, 93–
560 101.

561 Sexton, J.O., Noojipady, P., Song, X.-P., Feng, M., Song, D.-X., Kim, D.-H., Anand, A., Huang,
562 C., Channan, S., Pimm, S.L. & Townshend, J.R. (2015). Conservation policy and the
563 measurement of forests. *Nat. Clim. Chang.*

564 Shimada, M., Itoh, T., Motooka, T., Watanabe, M., Shiraishi, T., Thapa, R. & Lucas, R. (2014).
565 New global forest/non-forest maps from ALOS PALSAR data (2007–2010). *Remote Sens.*
566 *Environ.*, 155, 13–31.

567 Skowno, A.L., Thompson, M.W., Hiestermann, J., Ripley, B., West, A.G. & Bond, W.J. (2017).
568 Woodland expansion in South African grassy biomes based on satellite observations (1990–
569 2013): general patterns and potential drivers. *Glob. Chang. Biol.*, 23, 2358–2369.

570 Smith, W.K., Dannenberg, M.P., Yan, D., Herrmann, S., Barnes, M.L., Barron-Gafford, G.A.,
571 Biederman, J.A., Ferrenberg, S., Fox, A.M., Hudson, A., Knowles, J.F., MacBean, N.,
572 Moore, D.J.P., Nagler, P.L., Reed, S.C., Rutherford, W.A., Scott, R.L., Wang, X. & Yang,
573 J. (2019). Remote sensing of dryland ecosystem structure and function: Progress,
574 challenges, and opportunities. *Remote Sens. Environ.*, 233, 111401.

575 Sorensen, L. (2007). *A Spatial Analysis Approach to the Global Delineation of Dryland Areas of*
576 *Relevance to the CBD Programme of Work on Dry and Sub-Humid Lands*. Cambridge, UK.

- Staver, A.C. & Hansen, M.C. (2015). Analysis of stable states in global savannas: is the CART pulling the horse? – a comment. *Glob. Ecol. Biogeogr.*, 24, 985–987.
- Stevens, N., Lehmann, C.E.R., Murphy, B.P. & Durigan, G. (2017). Savanna woody encroachment is widespread across three continents. *Glob. Chang. Biol.*, 23, 235–244.
- Tang, H., Armston, J., Hancock, S., Marselis, S., Goetz, S. & Dubayah, R. (2019). Characterizing global forest canopy cover distribution using spaceborne lidar. *Remote Sens. Environ.*, 231, 111262.
- Tian, F., Brandt, M., Liu, Y.Y., Rasmussen, K. & Fensholt, R. (2017). Mapping gains and losses in woody vegetation across global tropical drylands. *Glob. Chang. Biol.*, 23, 1748–1760.
- UN EMG. (2011). *Global drylands: a UN system-wide response*. Geneva, Switzerland.
- Veldman, J.W., Aleman, J.C., Alvarado, S.T., Anderson, T.M., Archibald, S., Bond, W.J., Boutton, T.W., Buchmann, N., Buisson, E., Canadell, J.G., Dechoum, M. de S., Diaz-Toribio, M.H., Durigan, G., Ewel, J.J., Fernandes, G.W., Fidelis, A., Fleischman, F., Good, S.P., Griffith, D.M., Hermann, J.-M., Hoffmann, W.A., Le Stradic, S., Lehmann, C.E.R., Mahy, G., Nerlekar, A.N., Nippert, J.B., Noss, R.F., Osborne, C.P., Overbeck, G.E., Parr, C.L., Pausas, J.G., Pennington, R.T., Perring, M.P., Putz, F.E., Ratnam, J., Sankaran, M., Schmidt, I.B., Schmitt, C.B., Silveira, F.A.O., Staver, A.C., Stevens, N., Still, C.J., Strömberg, C.A.E., Temperton, V.M., Varner, J.M. & Zaloumis, N.P. (2019). Comment on “The global tree restoration potential.” *Science* (80-.), 366, eaay7976.
- Veldman, J.W., Buisson, E., Durigan, G., Fernandes, G.W., Le Stradic, S., Mahy, G., Negreiros, D., Overbeck, G.E., Veldman, R.G., Zaloumis, N.P., Putz, F.E. & Bond, W.J. (2015a). Toward an old-growth concept for grasslands, savannas, and woodlands. *Front. Ecol. Environ.*, 13, 154–162.

- Veldman, J.W., Overbeck, G.E., Negreiros, D., Mahy, G., Le Stradic, S., Fernandes, G.W., Durigan, G., Buisson, E., Putz, F.E. & Bond, W.J. (2015b). Where Tree Planting and Forest Expansion are Bad for Biodiversity and Ecosystem Services. *Bioscience*, 65, 1011–1018.
- Wessels, K., Mathieu, R., Knox, N., Main, R., Naidoo, L. & Steenkamp, K. (2019). Mapping and Monitoring Fractional Woody Vegetation Cover in the Arid Savannas of Namibia Using LiDAR Training Data, Machine Learning, and ALOS PALSAR Data. *Remote Sens.* .
- WRI. (2016). Atlas of Forest Landscape Restoration Opportunities Data Information [WWW Document]. URL <https://www.wri.org/resources/maps/atlas-forest-and-landscape-restoration-opportunities/data-info>
- Yang, Y., Long, D., Guan, H., Scanlon, B.R., Simmons, C.T., Jiang, L. & Xu, X. (2014). GRACE satellite observed hydrological controls on interannual and seasonal variability in surface greenness over mainland Australia. *J. Geophys. Res. Biogeosciences*, 119, 2245–2260.
- Zeidler, J., Wegmann, M. & Dech, S. (2012). Spatio-temporal robustness of fractional cover upscaling: a case study in semi-arid Savannah's of Namibia and Western Zambia. In: *Earth Resour. Environ. Remote Sensing/GIS Appl. III*. International Society for Optics and Photonics, p. 85380S.
- Zhang, Y., Liang, S. & Yang, L. (2019). A Review of Regional and Global Gridded Forest Biomass Datasets. *Remote Sens.* .

Acknowledgments: K.D. Holl, J. Leighton Reid, R.A. Zahawi, K. Reytar, P. Potapov, and R.S. DeFries provided valuable commentary on previous versions of this paper. **Funding:** None declared; **Author contributions:** MEF is responsible for the conceptualization, data analysis, and writing; **Competing interests:** Author declares no competing interests; **Data and materials**

availability: All data is available in the main text or the supplementary materials of Bastin et al.
(Bastin et al. 2017b, 2019b), or at the WRI AFLRO website (WRI 2016).

Table 1: Accuracy assessment of the Atlas of Forest and Landscape Restoration Opportunities (AFLRO). Tables 1A and 1B show confusion matrices calculated using the drylands validation data, following an area correction method (Olofsson et al. 2013) where reference plot counts are shown as area-weighted frequencies. From this, the producer’s accuracy (100-Omission Error) and user’s accuracy (100-Commission Error) are calculated. Table 1A shows the accuracy of the full map area, while Table 1B shows the accuracy of the restoration area. Table 1C shows how estimates of the AFLRO forest area shift after taking into account map error; note that the corrected full map forest area was adjusted for degraded forest proportion, to conservatively exclude forest area that can be restored.

Table 1A: Full Map Area (n=85,420)

		Reference		Total	User Acc.	Com. Error
		Nonforest	Forest			
Map	Nonforest	0.35	0.18	0.53	65.7	34.3
	Forest	0.14	0.33	0.47	69.5	30.5
	Total	0.49	0.51	1		
	Prod. Acc.	70.6	64.5	Overall	67.5	
	Om. Error	29.4	35.5			

Table 1B: Restoration Area Only (n=40,126)

		Reference		Total	User Acc.	Com. Error
		Nonforest	Forest			
Map	Nonforest	0.46	0.29	0.76	61.4	38.6
	Forest	0.09	0.15	0.24	62.1	37.9
	Total	0.56	0.44	1		
	Prod. Acc.	83.4	34.1	Overall Acc.	61.6	
	Om. Error	16.6	65.9			

Table 1C: Corrected Forest Area Estimates

Accuracy Assessment	Original Map Forest Area (km²)	Corrected Map Forest Area (km²)	Difference (C-O) Area (km²)	Degraded forest correction (0.78 *Difference) (km²)	Final estimate of bias (Mha)
Full Map	9,116,538	9,821,829	705,291	549,405	54.9
Restoration Area	2,014,975	3,669,678	1,654,703	--	165.5

Table 2A-B: The impact on canopy cover estimates in drylands biomes of a potential underestimate of tree cover by the Hansen et al. (2013) product. In the low-end bias estimate, reference plot and Hansen tree cover (TC) estimates are differenced, and then summed across plots before multiplication by the plot area (0.49 ha) to convert to canopy cover (ha). In the high-end bias estimate, reference plot and Hansen tree cover are differenced and summed in the same manner, but Hansen tree cover is not allowed to exceed photo-interpreted tree cover (setting negative differences to 0).

Table 2A:

Biome	Plot count <i>n</i>	Plot area (ha) <i>Plot Count*0.49</i>	Summed plot-level canopy cover bias, low est. (ha) <i>sum(Plot TC - Hansen TC)*0.49</i>	Summed plot-level canopy cover bias, high est. (ha) <i>sum(Plot TC - Hansen TC)*0.49</i>	Canopy cover percent over- estimate (low) <i>Plot canopy cover overestimate/Plot area*100</i>	Canopy cover percent over- estimate (high) <i>Plot canopy cover overestimate/Plot area*100</i>
Hyperarid	19,056	9337.4	44.9	47.1	0.5	0.5
Arid	45,322	22207.8	519.6	541.8	2.3	2.4
Semiarid	93,661	45893.9	3197.3	4187.4	7.0	9.1
Dry Subh.	55,754	27319.5	2405.5	3925.7	8.8	14.4
Total	21,3793	104758.6	6167.2	8701.9	5.9	8.3

Table 2B:

Biome	Biome area (Mha)	Canopy cover percent over- estimate (low) <i>(Plot canopy cover overestimate /Plot area)</i>	Canopy cover percent over- estimate (high) <i>(Plot canopy cover overestimate /Plot area)</i>	Low biome overestimate, canopy cover <i>(% canopy cover overestimate *Biome area) (Mha)</i>	High biome overestimate, canopy cover <i>(% canopy cover overestimate *Biome area) (Mha)</i>
Hyperarid	978	0.5	0.5	4.7	4.9
Arid	1566	2.3	2.4	36.6	38.2
Semiarid	2263	7.0	9.1	157.7	206.5
Dry Subh.	1326	8.8	14.4	116.8	190.5
Total	6132	5.9	8.3	315.8	440.1

Table 3: Distribution of errors in the HGFC product relative to the Hansen tree cover values, by proportion of sample. Reference plot tree cover values were differenced with predicted HGFC tree cover to calculate bias, and then binned into three categories: HGFC underestimate (bias>0), equal (bias=0), and HGFC overestimate (bias<0). For each category, the number of plots with predicted HGFC tree cover is shown (along with the percent of plots). Predicted HGFC tree cover has two categories: 0% tree cover, and greater than 0%. In plots with underestimated tree cover, the majority (60%) have 0% predicted tree cover.

Bias (Plot TC - Hansen TC)	Plot Count	<i>Hansen TC = 0%</i>	<i>Hansen TC > 0%</i>
>0% (Hansen < Plot)	69,102	<i>34,066 (49%)</i>	<i>35,036 (51%)</i>
0% (Hansen = Plot)	114,607	<i>114,510 (99.9%)</i>	<i>97 (0.01%)</i>
<0% (Hansen > Plot)	30,084	<i>0 (0%)</i>	<i>30,084 (100%)</i>

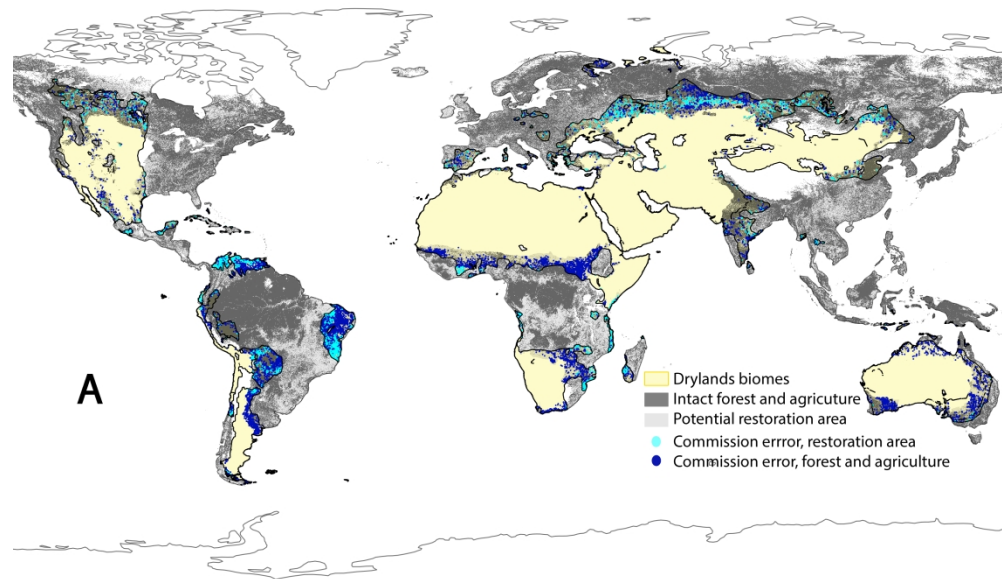


Figure 1: Spatial distribution of error in the AFLRO existing tree cover map across arid biomes. In this map, differences between photo-interpreted reference plots (thesholded at $\geq 10\%$ tree cover) and the AFLRO map of existing forest cover are plotted across the drylands biomes analyzed by Bastin et al. (2017). To evaluate the AFLRO forest/nonforest classification in the area of overlap, map commission errors (A) and omission errors (B) are shown for the forest class. Dark plots are not suitable for restoration in the AFLRO map (forests and agriculture); bright plots are potential restoration locations.

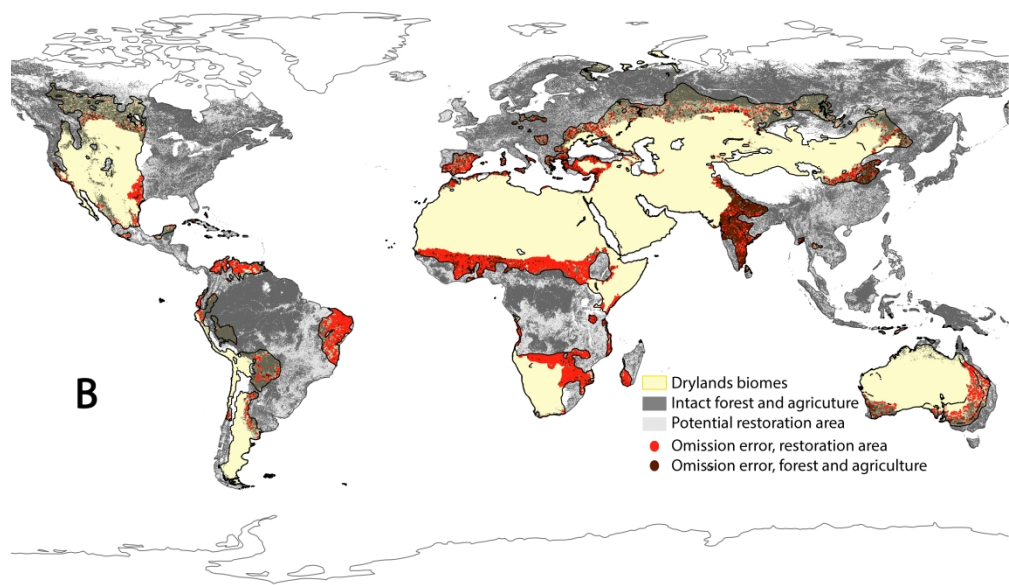


Figure 1: Spatial distribution of error in the AFLRO existing tree cover map across arid biomes. In this map, differences between photo-interpreted reference plots (thesholded at $\geq 10\%$ tree cover) and the AFLRO map of existing forest cover are plotted across the drylands biomes analyzed by Bastin et al. (2017). To evaluate the AFLRO forest/nonforest classification in the area of overlap, map commission errors (A) and omission errors (B) are shown for the forest class. Dark plots are not suitable for restoration in the AFLRO map (forests and agriculture); bright plots are potential restoration locations.

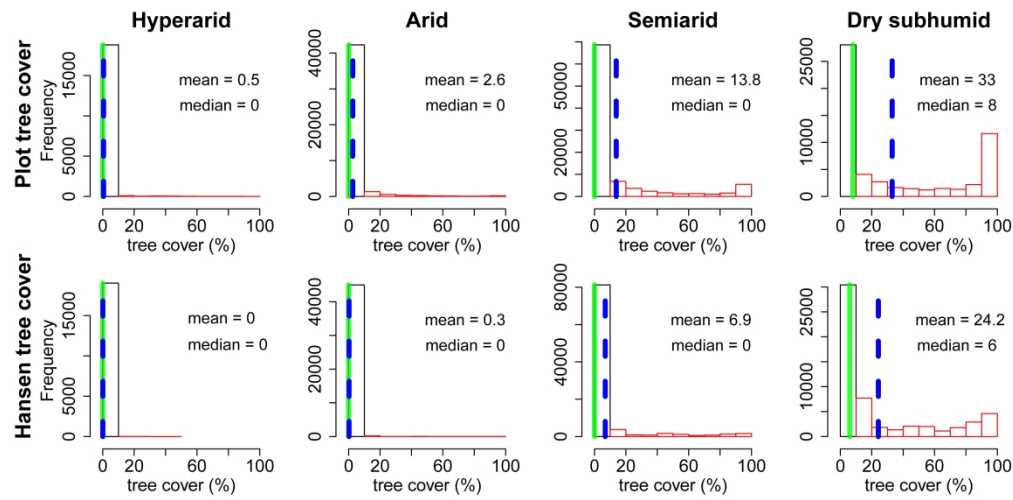


Figure 2: Comparing photo-interpreted and HGFC tree cover estimates used by Bastin et al. (1). Shown are the distributions of plot-level estimates from reference, photo-interpreted tree cover (top row) and HGFC tree cover (bottom row), in drylands biomes sampled by Bastin et al. (5) ($n=213,700$). The vertical blue dashed line represents the mean of each distribution and the green line represents the median of each distribution, while the red histograms indicate tree cover $>0\%$.

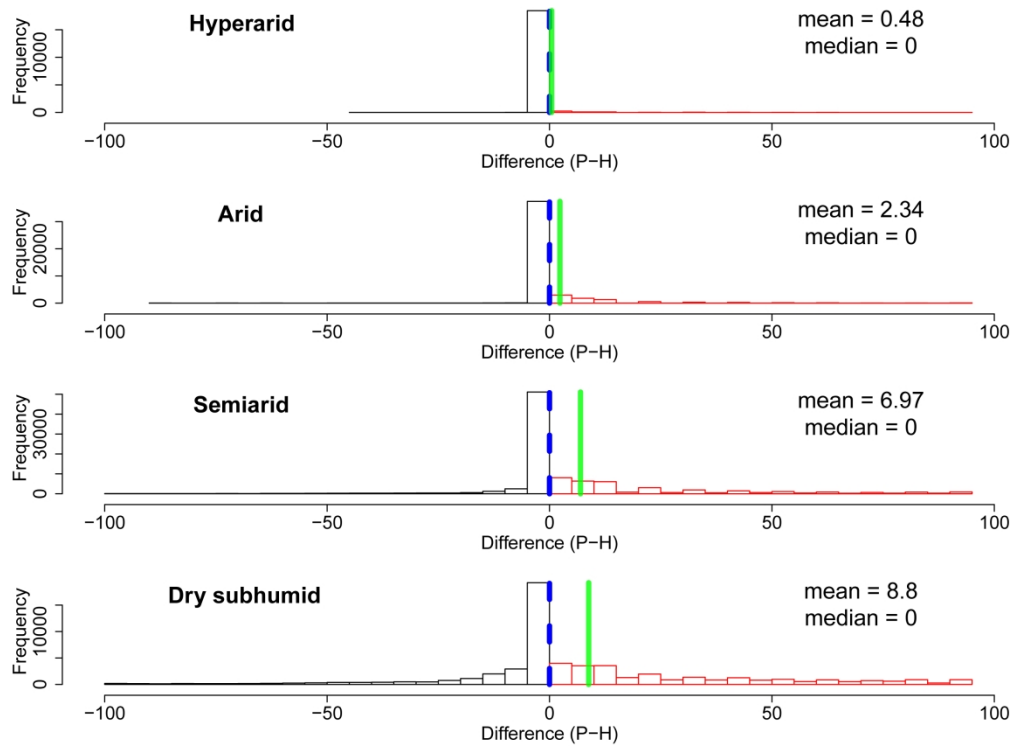


Figure 3: Dryland biome bias in HGFC tree cover estimates used by Bastin et al. (1). Shown are the distributions of plot-level differences between reference, photo-interpreted tree cover (P) and HGFC tree cover estimates (H), in drylands biomes sampled by Bastin et al. (5) (n=213,700). The vertical blue dashed line represents the median of each distribution and the green line represents the mean of each distribution, while the red histograms indicate tree cover >0%. Plot measurements of tree cover are significantly greater than the HGFC tree cover estimates across all dryland biomes ($p<0.0001$).

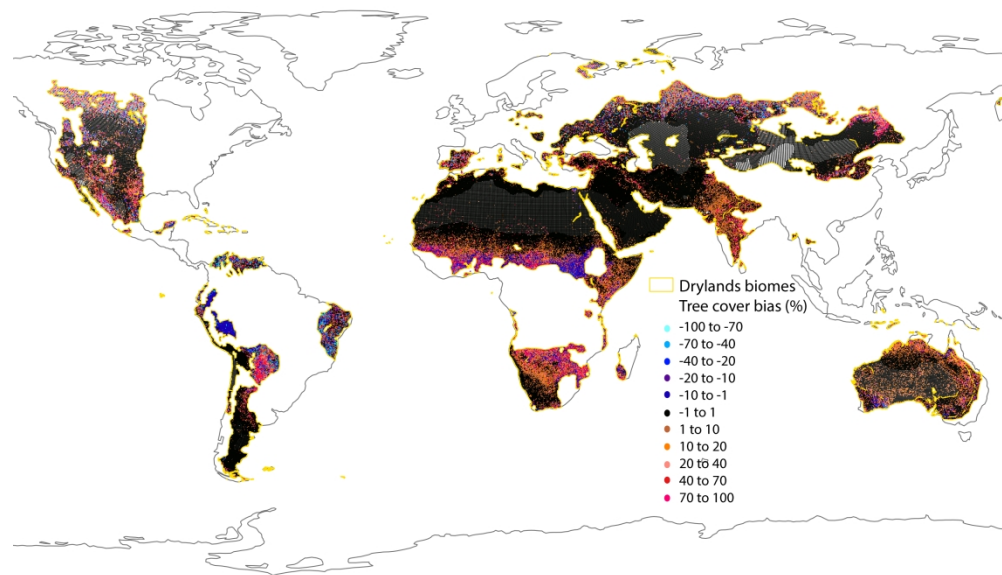


Figure 4: Spatial distribution of bias in existing tree cover maps across arid biomes. In this map, the difference between photo-interpreted plots and HGFC estimates of percent tree cover are plotted across the four drylands biomes analyzed by Bastin et al. (2017). Blue points (negative numbers) indicate plots where the HGFC overestimated tree cover, while reddish points (positive numbers) indicate plots where the HGFC underestimated tree cover. The density of the plots at the global scale gives rise to the appearance of solid regions of color.

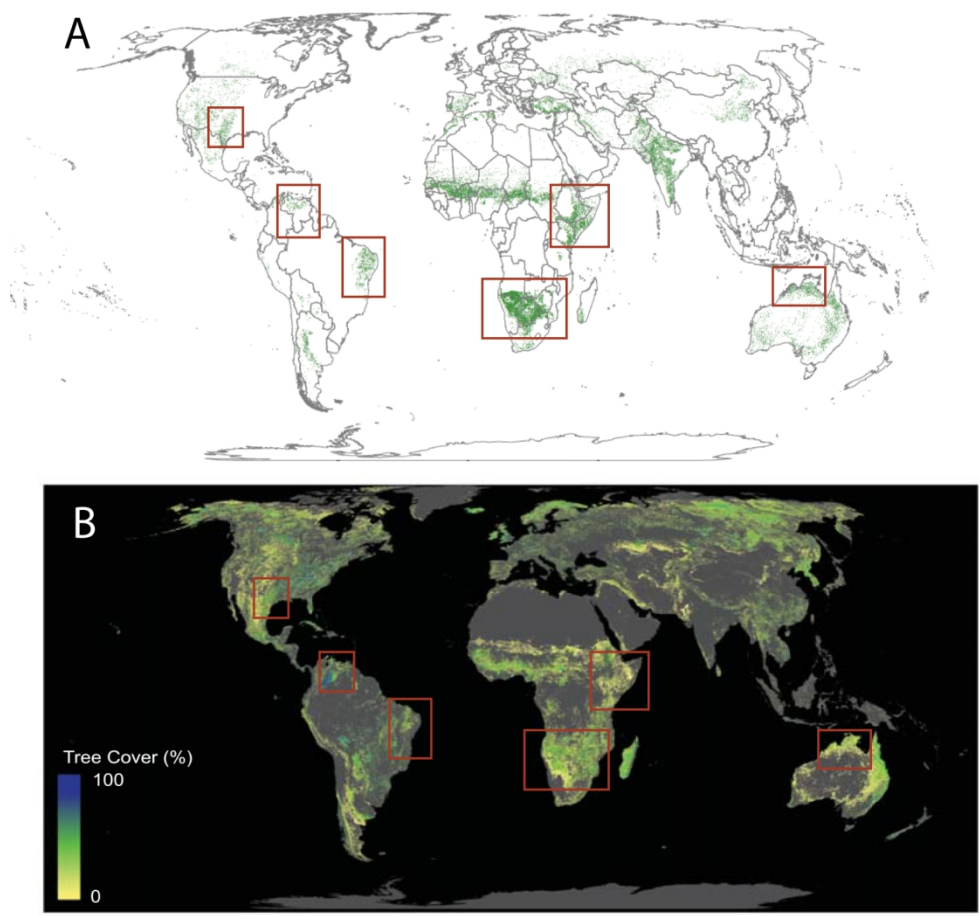


Figure 5: Examples of dryland systems identified for restoration by Bastin et al. (2019b). Panel A is reprinted from Bastin et al. (2017b), showing numerous plots (in green) where the HGFC product underpredicted tree cover. Panel B is reprinted from Bastin et al. (2019b). Red boxes in both panels highlight locations where extensive tree restoration potential coincides with HGFC underpredictions.

Black and white figures for print version (zip file can be downloaded here):

https://drive.google.com/file/d/1F9XZUHGb1HXyfyiMzP2F1_cOE4lehaOM/view?usp=sharing