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Comment on "The extent of forest in dryland biomes"

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Bastin et al. (Reports, 12 May 2017, p. 635) claim to have discovered 467 million hectares of new dryland forest. We would argue that these additional areas are not completely "new" and that some have been reported before. A second shortcoming is that not all sources of uncertainty are considered; the uncertainty could be much higher than the reported value of 3.5%.

Bastin et al. (1) have discovered "467 million hectares of forest that have never been reported before" in dryland biomes, which "increases current estimates of global forest cover by at least 9%." However, this result depends on the benchmark used for comparison. The authors have used the Food and Agriculture Organization of the United Nations (FAO) Forest Resources Assessment (FRA) Global Remote Sensing Survey 2010, based on Landsat imagery, yet in the paper, the authors agree that this is not an appropriate resolution for mapping dry forests. Instead, they should benchmark against the FAO-FRA, but they state that they were unable to do so; because FAO-FRA "was not based on a global map we could not quantify the extent of dry forest omitted" [supplement of (1)]. However, a global percentage forest cover map consistent with FAO-FRA (2) exists that was missed by the authors. Using this map as a benchmark for comparison, one would reduce the additional 467 Mha of forests (1) to 270 Mha (Table 1). A result similar to (2) (825 Mha of dryland forest) is obtained using the European Space Agency Climate Change Initiative's Land Cover 2015 (3), which is a better benchmark than GlobCover 2009. Almost half of this discrepancy can be found in Africa, where high-quality ground data and statistics are lacking. This deficiency can be attributed to funding, capacity, and accessibility issues, as well as the diverse forest definitions used in different countries.

Furthermore, not all sources of uncertainty have been sufficiently considered:

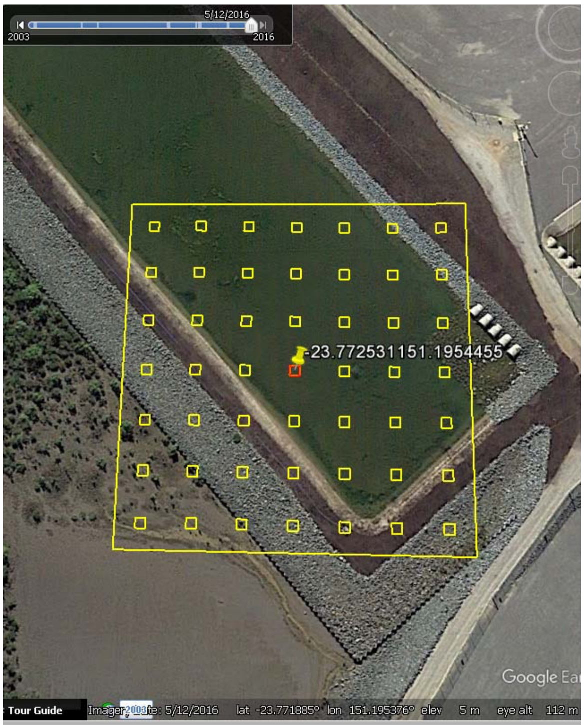
1) The largest source of uncertainty is in the imagery available for interpretation. Bastin et al. (1) have evaluated accuracy using plots from Australia, where the discrepancy is moderate (see Table 1). Australia is fully covered by very high resolution (VHR) imagery, according to our experience, whereas this coverage is much lower in Africa (2, 4). In the reported analysis, 18% of the imagery used for interpretation was not VHR, rendering visual interpretation virtually impossible in the majority of cases (Fig. 1, B and G). Hence, differentiation between trees and shrubs is not possible. For example, large differences in forest cover were found in Tanzania when comparing results derived from Landsat to higher-resolution imagery (5).
2) Most interpretations were undertaken by only one person, so quality assurance through multiple interpretations is not possible. Shown in Fig. 1, A, E, and F, are examples of falsely interpreted images that could have been identified if there were multiple interpretations for each location. Our experience with data collected through Geo-Wiki (www.geo-wiki.org/) is that multiple observations are a critical requirement for quality assurance; for example, in Tanzania the standard deviation between trained operators was around 14% for woody extent (6), and similar results were obtained in Kenya (4), where in 18% of cases, three experts disagreed in a forest/non forest classification.
3) Many images only allow for assignment of a range of tree cover (Fig. 1, B to D).
4) The rule for distinguishing trees from shrubs (i.e., diameter of the crown >3 m if no clear shadow) could lead to an overestimation of for forest because shrub patches can make a bigger common crown (Fig. 1E).
5) The assessment was performed during April to December 2015, when there would have been a lack of VHR imagery for the target year 2015 (Fig. 1, A, G, and H).

Table 1. Area of forest in the world's drylands (Mha)

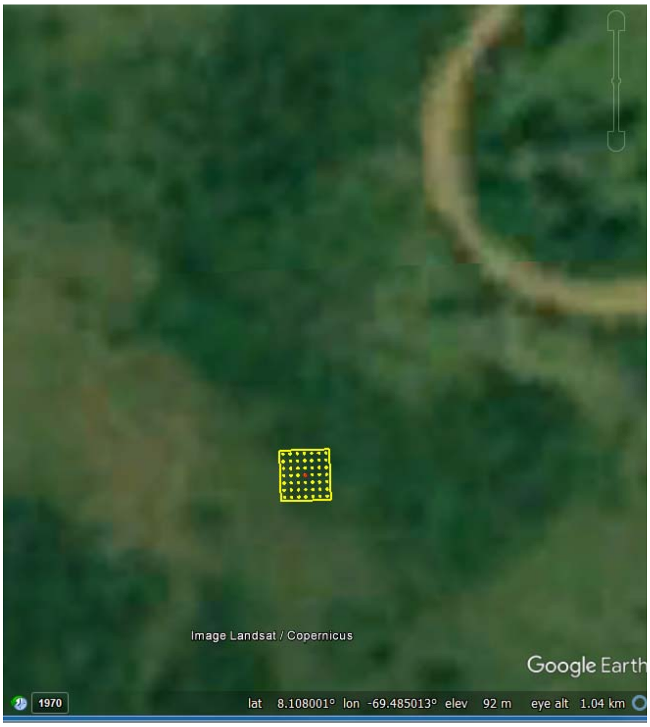
Continent	Dryland assessment (*1*)	Global forest map calibrated with FAO-FRA (*2*)	Difference
Africa	286	167	119
Asia	213	183	30
Europe	63	57	6
North America	204	142	63
Oceania	114	81	33
South America	197	179	18
Dryland total	1079	809	270

To account for these additional sources of uncertainty, we reestimated, using Collect Earth, a randomly selected sample of 370 pixels [data S1 of (1)], which covered all continents, the dryland category, and a range of tree cover percentages. We observed a 14% discrepancy in the forest/nonforest classification (instead of the 3.5% reported in the article for Australia only), with RMSE of 24% for tree cover estimation (instead of 8.32%). During the visual interpretation, we assigned the most probable tree cover percentage and a possible range. The average range of tree cover was ±38%, where around 15% of images with trees could not be definitively interpreted as forest or nonforest.

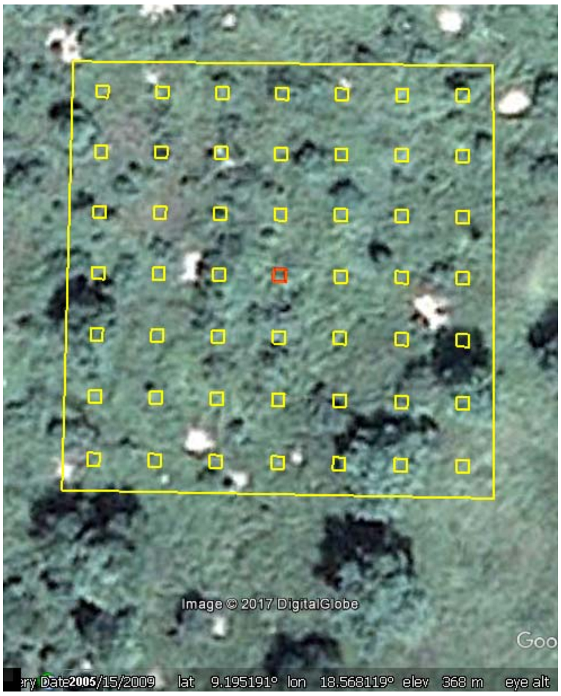
The Global Drylands Assessment (1) represents a considerable advance in the systematic assessment of forest extent. Some uncertainties could be mitigated if more than one person estimated each plot so that additional quality controls could be implemented. The ability to specify the range of tree cover in addition to the most probable value would also allow for fuzzy estimation of percentage tree cover. For now, these results should be treated with care. Overestimation of forest area can lead to increasing pressure on existing forest resources.



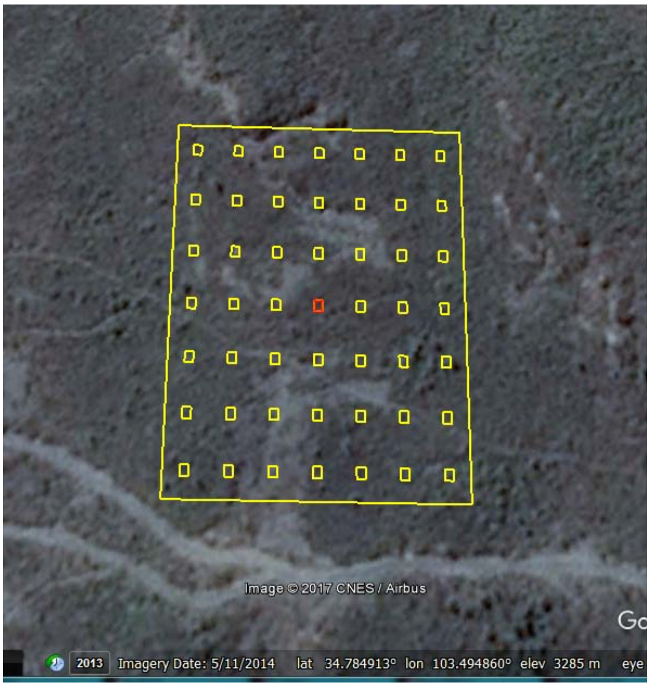
A – classified as "Forest", 55 % of tree cover (ID 6770, -23.772531, 151.1954455)



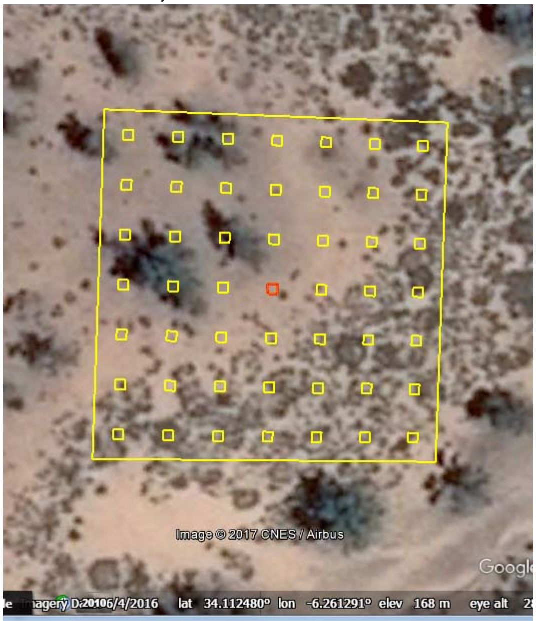
B – "Forest", 65% (ID 38252, 8.105318325, -69.48468723.)



C – “Forest”, 25% (ID 144189, 9.195183, 18.56817692)



D – “Forest”, 65% (ID 21442, 34.78514337, 103.4949039)



E – “Forest “35% (ID 129732, lat 34.11231, lon - 6.26125753)

F – “Forest” 25% (ID 128579, lat 34.698524, lon 0.278477738)

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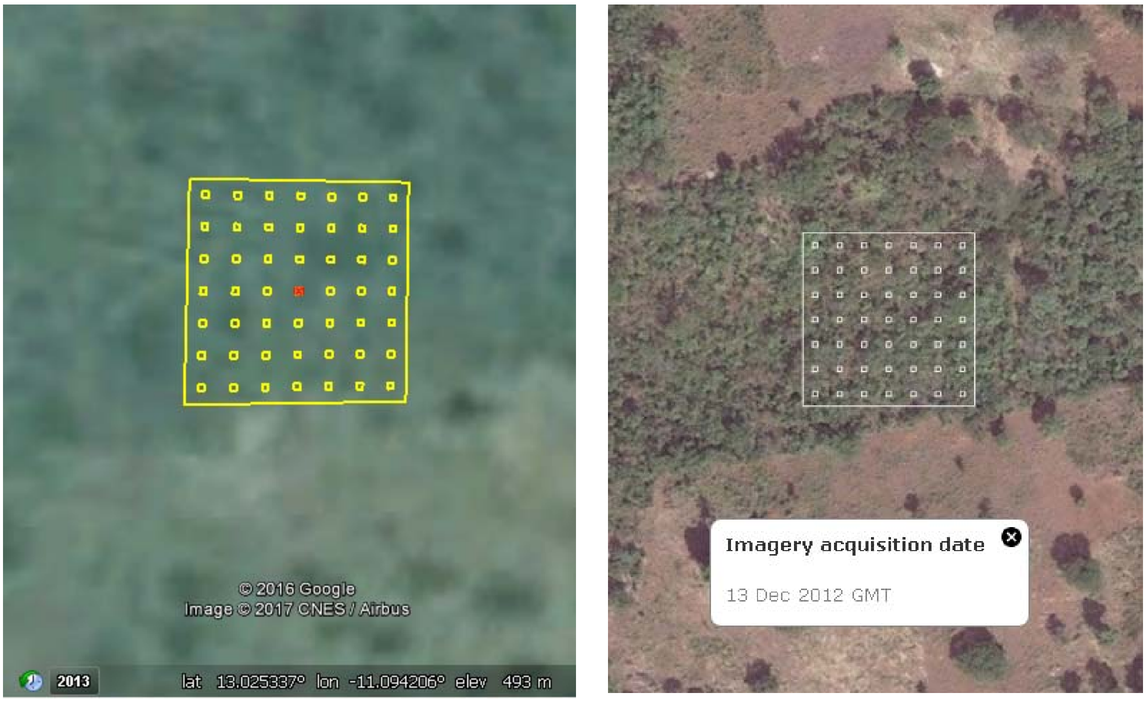
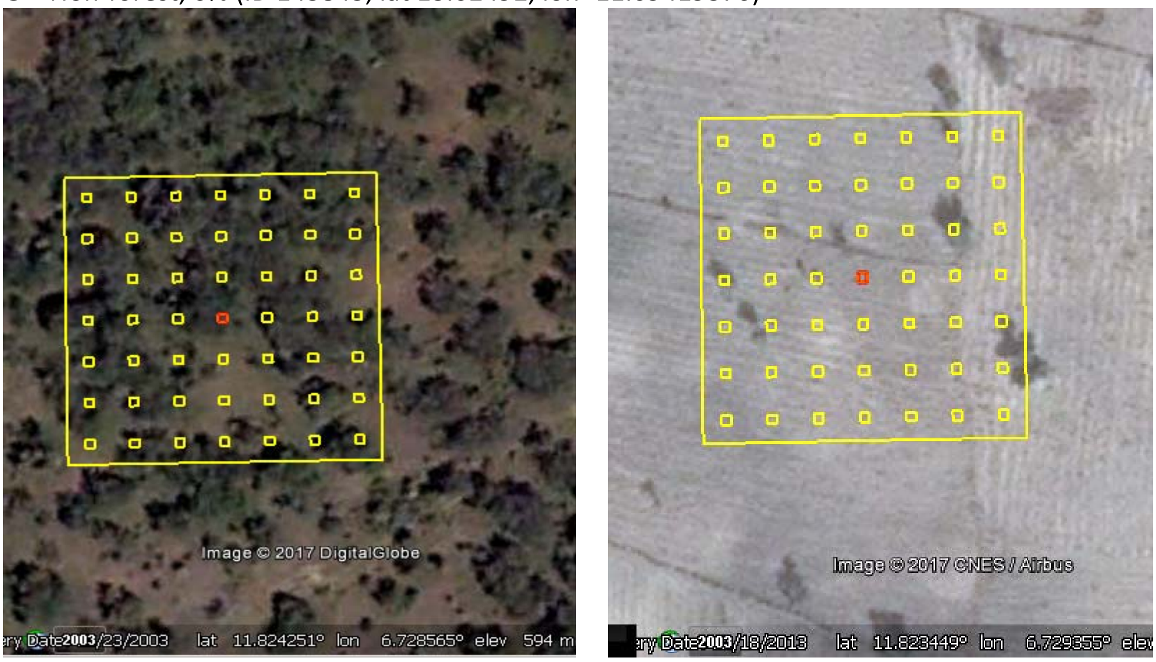


G – Non-forest, 0% (ID 143843, lat 13.02492, lon -11.09419376)



H – "Forest", 95% (ID 143864, lat 11.824136, lon 6.728381478)

Fig. 1. Selected examples illustrating that Bastin et al.'s efforts in classifying forest are incorrect or uncertain. (A) Classified as "Forest," 55% tree cover (ID 6770, lat –23.772531, lon 151.195446). A water pool was classified as forest because the VHR image (2016) was not available at the time of assessment. (B) "Forest," 65% (ID 38252, lat 8.105318, lon –69.484687). This medium-resolution image from the 1970s was classified as forest, but it is unclear whether this was or has remained forest. (C) "Forest," 25% (ID 144189, lat 9.195183, lon 18.568177). There is evidence for a few big trees, but background can be formed by either trees or shrubs, so a wide range of tree cover can be assigned. (D) "Forest," 65% (ID 21442, lat 34.785143, lon 103.494904). No evidence of forest is present at all, and a wide range of tree cover can be assigned in these cases. (E) "Forest," 35% (ID 129732, lat 34.11231, lon –6.261258). Apparently the groups of shrubs have been classified as trees. (F) "Forest," 25% (ID 128579, lat 34.698524, lon 0.278478). Tree cover should be 8 to 10%, and cropland >20% should not be classified as forest. (G) "Nonforest," 0% trees (ID 143843, lat 13.02492, lon –11.094194). Forest can be seen only in the VHR image (right panel). (H) "Forest," 95% (ID 143864, lat 11.824136, lon 6.728381). Land cover change between 2003 (left panel) and 2013 (right panel) is apparent.

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