Appendix S1

Random forest classification

A random forest classifier is a machine learning algorithm commonly used in remote sensing applications due to its ability to handle high-dimensionality, and high-collinearity data (Belgiu & Drăguţ, 2016; Murray et al., 2018; Sheykhmousa et al., 2020). In essence, a random forest classifier is a combination of simple, binary (i.e. true/false) decision trees that use a randomly selected subsample of training points and covariates to make a prediction (i.e. determine the drivers of forest loss). The combination of these decision trees (i.e. the random forest) often produces more accurate results than any of the individual decision trees (Belgiu & Drăguţ, 2016; VanderPlas, 2016).

To determine the minimum number of decision trees needed, we tested the performance of the classifier using a wide range of individual trees (10-500) and concluded that more than 300 trees did not increase the accuracy of the results. To achieve good spectral separability of the drivers, we tested all the covariates (n=185) as well as several subsets of covariates, including for example, only the medians, only maximum values, only minimum values, only spectral indices. We iteratively tested the values of each covariate against each driver to assess the spectral differences of each driver, thus allowing us to select the spectral bands and indices that better described each driver (**Error! Reference source not found.**). To help discriminate the 'Urban expansion' class, we also used the Global Human Settlement Layers (Pesaresi et al., 2015) available in Google Earth Engine as additional covariates (**Error! Reference source not found.**). After applying the classifier, we post-processed the classified map with a majority filter to remove single, isolated pixels. Lastly, we computed the area of each driver in total, by country, both inside and outside protected areas.

Limitations of the methods used

Some limitations of the study must be acknowledged. Firstly, due to the similarities in their spectral signatures we had to combine different drivers of forest loss into single categories (e.g. human settlements and bare ground; or smallholder agriculture and grazing). For example, oil palm, tea, and cocoa plantations typically exhibit a strong peak in the near-infrared (NIR) region of the spectrum, and lower values in the visible region of the spectrum. While these plantations may be identifiable from high spatial resolution imagery (<3m from Google Earth), they cannot be easily differentiated from Sentinel 2 imagery (10-20m spatial resolution) because they display very similar spectral responses. As a result, we cannot uncouple the contribution of each individual crop to deforestation. Conservation efforts in the region could benefit from a more refined spatio-temporal classification of drivers of forest loss that includes more land cover classes, and how these classes change over time, however, this research is a first step into understanding how land cover is changing in the UGF. In the future, some of these limitations may be overcome with new high resolution (<5m) While limited in the spectral domain, high spatial resolution datasets can be used to unambiguously identify the different drivers of forest loss, to collect data for calibration and validation of models, as well as for Object-Based Image Analysis, to train Convolutional Neural Networks and other machine learning algorithms. For example, Norway's International Climate and

Forests Initiative (NICFI) satellite program (NICFI, 2017) has created twice-yearly mosaics for tropical regions (including West African countries) from 2015 onwards. Users will have to trade off the spectral resolution of Landsat and Sentinel 2 satellites, for the spatial resolution of this dataset. However, these data will certainly benefit conservation efforts throughout the Upper Guinea Forest.

Secondly, some drivers operate at different time scales. For example, oil palm plantations start as bare ground (after forest is cleared) and take several years to reach maturity; during this time, their spectral response will be similar to that of subsistence agriculture. When mature, the spectral response of oil palm plantations is similar to that of a forest and will remain like that for decades, until the mature palm trees die. In contrast, settlement expansion or bare ground can be detected within days or weeks, making these drivers easier to detect and classify from remotely sensed imagery. Since some crop plantations pre-date some Landsat and Sentinel 2 sensors, accurately classifying them remains a challenge using only optical remote sensing and spectroscopic approaches. Drivers of forest loss captured by satellite sensors. for example, forest clearing for subsistence agriculture and grazing activities can, over time, lead to large-scale timber extraction and intensive agriculture, however this is not always the case. The Landsat and Sentinel 2 imagery archives offer few cloud-free images of the study area prior to 2018 to accurately detect if, or when, the drivers of forest loss assessed here are permanent. As a result, the drivers of forest loss were analyzed only for 2019 and not for previous years. Object-based image analysis, high temporal resolution data acquisition, data harmonization, and radar remote sensing can help disaggregate drivers of forest loss over space and time in the UGF.

Thirdly, here we assume that all intact forests are used by pygmy hippopotami, however these animals are known to remain close to water sources and avoid mountainous terrain (Bogui et al., 2016; Eshuis et al., 2011; Ouattara et al., 2018). Further work on the conservation of this species must contemplate wetland, rivers, and swamp distribution to better account for the drivers that directly affect pygmy hippopotami and their distribution. Lastly, clouds are prevalent in the UGF, and the Hansen et al., (2013) dataset, has a limited number of observations of this region (Wulder et al., 2016). When combined, high cloud prevalence and low image availability, increase the misclassification of forest loss and standing forest. To overcome this limitation, we used Sentinel 2 data which provides a higher number of observations for each site, thus increasing the probability of cloud-free pixels. We also found examples where standing forest had been classified as 'loss', and areas where cleared forest was not classified as 'loss' by the Hansen (2013) dataset. These misclassifications may be related to (1) the low number of usable observations for the region, (2) the definition of 'forest', and (3) the similarities in the spectral signatures of forests and crops such as oil palm, cocoa and forestry plantations. Despite these limitations, the Hansen (2013) dataset is the most comprehensive and accurate dataset of forest loss to date. With this in mind, and after the results from the independent accuracy assessment we are confident that our results provide insights into the forest loss dynamics in the Upper Guinea Forest.

Lastly, we found areas of forest loss that followed the boundaries of some protected areas but from several hundreds of meters withing the protected areas which may have resulted in commission and omission errors in our analysis. This could be due to errors in the boundaries reported by UNEP-WCMC & IUCN (2020), or by people deliberately leaving buffer areas to camouflage illegal activities inside the protected areas. We did not modify the boundaries of any protected areas and these causes should be further investigated.

References:

Barnes E. M., Clarke T. R., Richards S. E., Colaizzi P. D., Haberland J., Kostrzewski M., Waller P., Choi C., Riley E. & Thompson T. (2000) Coincident detection of crop water stress, nitrogen status and canopy density using ground based multispectral data. In: *Proceedings of the Fifth International Conference on Precision Agriculture, Bloomington, MN, USA*

Belgiu M. & Drăguţ L. (2016) Random forest in remote sensing: A review of applications and future directions. *ISPRS journal of photogrammetry and remote sensing* **114:** 24–31

Daughtry C. S. T., Walthall C. L., Kim M. S., de Colstoun E. B. & McMurtrey J. E. (2000) Estimating Corn Leaf Chlorophyll Concentration from Leaf and Canopy Reflectance [WWW document]. *Remote Sensing of Environment* **74:** 229–239 URL https://www.sciencedirect.com/science/article/pii/S0034425700001139

Descals A., Wich S., Meijaard E., Gaveau D. L. A., Peedell S. & Szantoi Z. (2021) High-resolution global map of smallholder and industrial closed-canopy oil palm plantations. *Earth System Science Data* **13:** 1211–1231

European Spatial Agency (2015) *Sentinel-2 User Handbook*.

Gao B. (1996) NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space [WWW document]. *Remote Sensing of Environment* **58:** 257–266 URL https://www.sciencedirect.com/science/article/pii/S0034425796000673

Gitelson A. A., Kaufman Y. J., Stark R. & Rundquist D. (2002) Novel algorithms for remote estimation of vegetation fraction [WWW document]. *Remote Sensing of Environment* **80:** 76–87 URL https://www.sciencedirect.com/science/article/pii/S0034425701002899

McFeeters S. K. (1996) The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International journal of remote sensing* **17:** 1425–1432

Murray N. J., Keith D. A., Simpson D., Wilshire J. H. & Lucas R. M. (2018) Remap: An online remote sensing application for land cover classification and monitoring [WWW document]. *Methods in Ecology and Evolution* **9:** 2019–2027 URL https://doi.org/10.1111/2041-210X.13043

Pesaresi M., Ehrlich D., Florczyk A., Freire S., Julea A., Kemper T., Soille P. & Syrris V. (2015) *GHS-BUILT R2015B - GHS built-up grid, derived from Landsat, multitemporal (1975, 1990, 2000, 2014)* [WWW document]. URL http://data.europa.eu/89h/jrc-ghsl-ghs_built_ldsmt_globe_r2015b

Rikimaru A., Roy P. S. & Miyatake S. (2002) Tropical forest cover density mapping. *Tropical ecology* **43:** 39–47

Rock B. N., Vogelmann J. E., Williams D. L., Vogelmann A. F. & Hoshizaki T. (1986) Remote Detection of Forest Damage: Plant responses to stress may have spectral "signatures" that could be used to map, monitor, and measure forest damage. *Bioscience* **36:** 439–445

Sheykhmousa M., Mahdianpari M., Ghanbari H., Mohammadimanesh F., Ghamisi P. & Homayouni S. (2020) Support vector machine vs. random forest for remote sensing image classification: A meta-analysis and systematic review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*

Tucker C. J. (1979) Red and photographic infrared linear combinations for monitoring vegetation. *Remote sensing of Environment* **8:** 127–150

VanderPlas J. (2016) *Python data science handbook: Essential tools for working with data*. ' O'Reilly Media, Inc.'

UNEP-WCMC and IUCN (2021) Protected Planet Report 2020. UNEP-WCMC and IUCN: Cambridge UK; Gland, Switzerland.