# DEFORESTATION IN SOUTH-WEST GHANA (2001-2015)

## DIRECT DRIVERS, THE SIZE OF CLEARINGS, AND EMERGING HOTSPOTS

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*Deforestation in South-West Ghana (2001-2015)*, Direct Drivers, the Size of Clearings, and Emerging Hotspots

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# ABSTRACT

Ghana is among the countries with the highest net deforestation rates worldwide. Open source high resolution satellite imagery is used for forest monitoring to support compliance to REDD+. However, quantitative national-level information on the drivers of deforestation drivers remains generally incomplete or largely absent. This thesis aims to identify important direct drivers of deforestation and their characteristics in South-West Ghana between 2001 and 2015. The follow-up landcover from 2017/2018 serves as a proxy to identify direct drivers. Cocoa was found to be responsible for most deforestation, followed by orchards, low vegetation, rubber and palm. A peak in deforestation in the year 2014 is potentially related to the fact that several media reported an expected cocoa shortage that year. Direct drivers were related to the size of deforested patches to provide insight in the scale of deforestation associated with different drivers. No association was found between the drivers of forest loss and the scale of clearings, which implies that patch size cannot be used to track drivers. Patches below 0.5 ha were responsible for the largest area of deforestation. This provides an indication that smallholder and/or subsistence agriculture are important causes of forest loss in the study area. New hotspots of deforestation in 2015 are identified in order to provide insight as to which emerging drivers are of growing importance. The presence of palm and water in new hotspot areas was particularly high compared to their overall importance. This provides guidance to future conservation efforts.

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At home, Monne, my family, and friends have been a constant source of support, enthusiasm, and patience. I would not do this without you.

The cover art of this thesis was made by Gigi van Grevenbroek, whose work on socially and environmentally relevant themes can be found via gigivangrevenbroek.com.

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# ACRONYMS

UNFCCC The United Nations Framework Convention on Climate Change

REDD+ Reducing Emissions from Deforestation and Degradation, conserving and enhancing forest carbon stocks, and sustainably managing forests

CIAT The Alliance of Biodiversity International and the International Center for Tropical Agriculture

ICCO International Cocoa Organization

OSM OpenStreetMap

# 1 INTRODUCTION

Between 2001 and 2019, a total area of 386 million ha was deforested worldwide, resulting in a 9.7 percent decrease in tree cover [1]. Deforestation and forest degradation have severe adverse ecological and socio-economic effects [2]. Among the ecological effects is the reduction of natural habitat, with potential biodiversity loss as a result [3], [4]. In addition to that, loss of forest contributes to climate change by limiting the uptake of greenhouse gas, and fostering its emission [5], [6]. Socio-economic effects include loss of medicinal plants, shortage of food and water, low agricultural productivity, and unemployment [2].

Ghana is among the countries with the highest net deforestation rates worldwide [7]. At the start of the 1900s, around one-third of Ghana was covered by tropical forest, of which an estimated 78 percent had disappeared by 1989 [8], [9]. More recently, an annual deforestation rate of around 3 percent has been recorded [10]. Agricultural crops such as cocoa, palm, and rubber are important drivers of deforestation in the area [11]–[14]. The industries behind these crops are increasingly concerned about brand equity. The international community is concerned about the loss of globally important biodiversity and ecosystem services, including issues such as threatened species, carbon sequestration and climate regulation. Ghana is one of over 30 countries that has committed to the implementation of policies for Reducing Emissions from Deforestation and Degradation, conserving and enhancing forest carbon stocks, and sustainably managing forests (REDD+) [15]. The REDD+ mechanism was initiated by The United Nations Framework Convention on Climate Change (UNFCCC) and offers financial incentives for developing countries to reduce emissions from deforestation and forest degradation.

Open source high resolution satellite imagery is used to support compliance to REDD+ through forest monitoring. At the global scale, Hansen et al. have published annual quantifications of global forest loss and gain since 2001 based on Landsat imagery [16]. In addition, national governments are developing their own forest monitoring systems [17]. A study on the status of forest monitoring in tropical countries has quantified Ghana's capacity to use remote sensing data and measure forest area change as 'good' [17]. The availability of globally consistent and locally relevant remote sensing imagery allows for large scale identification and quantification of forest loss in a transparent and cost-effective manner [18].

However, quantification of forest loss is not sufficient to understand the drivers of deforestation. Drivers can be either direct (proximate) or indirect (underlying). Proximate drivers are human activities or actions that originate from intended land use and directly result in forest loss [19]. Underlying drivers are social processes and contexts that have an indirect influence on deforestation, e.g. population dynamics or agricultural policies [19]. Insight regarding the drivers of deforestation can complement forest loss monitoring by allowing for more direct targeting of the roots of the problem.

Earlier research on the drivers of tropical deforestation has been done globally [20], [21], as well as specifically in the tropics [19], [22]. However, quantitative national-level information on deforestation drivers remains generally incomplete or largely absent; for many developing countries it is unclear how much deforestation is caused by specific drivers [23]. Quantitative analysis of the drivers of deforestation is fundamental to the development of policies and measures to reduce deforestation [23]. It allows for direct targeting of the supply chains of different crops, thereby helping industries and countries to minimize forest loss. In addition, it can support the development of landscape level approaches, where different supply chains join efforts to halt deforestation and improve ecosystem services in a given landscape.

Remote sensing data is a useful tool for large scale driver analysis. Use of satellite imagery allows for accurate quantification of the importance of different drivers on a national level. At the same time, the high spatial resolution of satellites such as Landsat and Sentinel make their products suitable for detailed regional or local analyses. Furthermore, high-resolution imagery allows for analysis of driver characteristics, such as the typical size of deforested areas. This provides an indication as to whether deforestation is for commercial or subsistence agricultural purposes [22]. Insight in the scale of forest loss associated with different drivers could foster identification of drivers in the future. Furthermore, use of satellite imagery with statistical models can provide insight in spatio-temporal trends of deforestation and its drivers. These trends could not be easily identified on a large scale through fieldwork or by visual inspection of the data [24]. The identification of new clusters of forest loss can provide guidance as to which areas and drivers require further attention for analysis or conservation efforts [24], [25]. This information is of use for conservationists, national governments, as well as agricultural industries which are looking to conserve the forest as well as their image.

## 1.1 RESEARCH OBJECTIVES

This thesis aims to identify the most important direct drivers of deforestation and their characteristics in South-West Ghana between 2001 and 2015. The follow-up landcover from 2017/2018 serves as a proxy to identify direct drivers. Thus, deforestation of an area between 2001 and 2015 is attributed to the landcover that was present in the area in 2017/2018. It is important to note that follow-up landcover can either be the primary motive for forest clearance, or replace forest previously degraded by wood extraction or fire [2]. This distinction is beyond the scope of this research. Therefore, the signification of 'follow-up landcover' and 'driver' is interchangeable in this thesis.

The rest of this thesis addressed the following research objectives:

1. Identify direct drivers of deforestation in South-West Ghana between 2001 and 2015 based on a 10 m resolution landcover classification.

2. Analyse the size of forest clearings in relation to the direct drivers addressed in objective 1 in order to provide insight into the scale of deforestation.

3. Analyse the drivers found in new hotspots of deforestation in 2015 in order to provide insight as to which emerging drivers were of growing in importance.

# 2 DATA AND METHODS

This chapter first introduces the study area, followed by the data and methods.

## 2.1 STUDY AREA

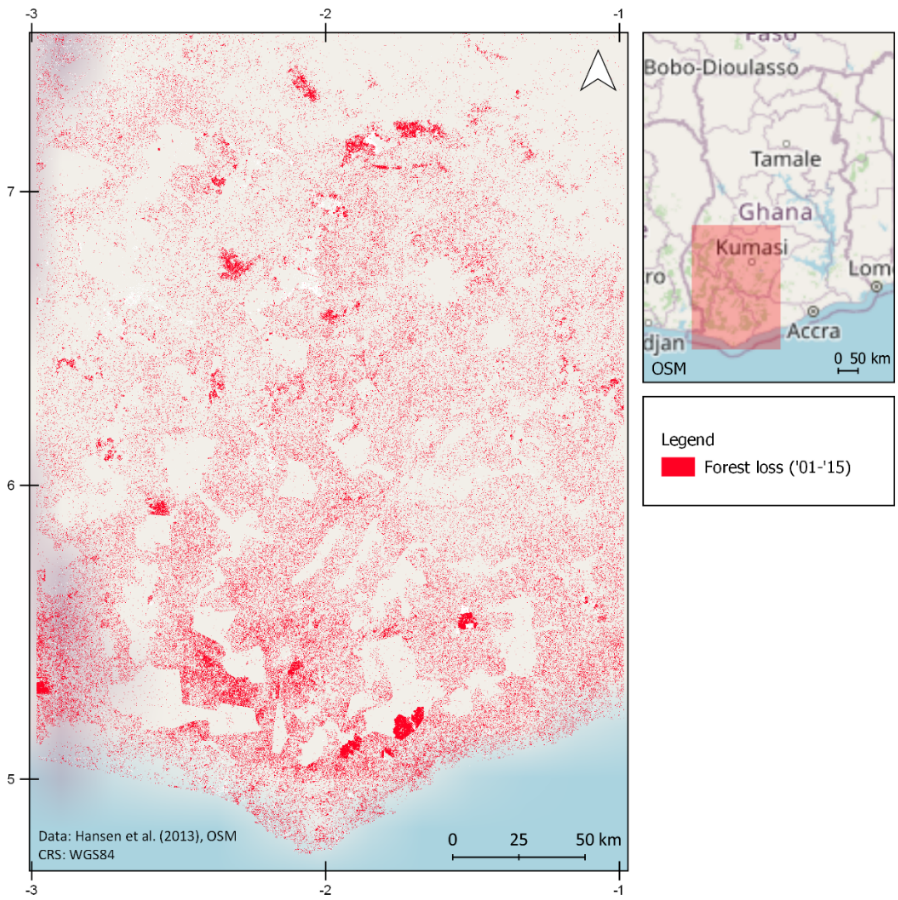


Figure 1: Deforestation in the study area in South-West Ghana between 2001 and 2015.

Ghana's history as one of the countries with the highest forest loss worldwide calls for an analysis of its drivers [7]. The study area of this research is located in South-West Ghana. It encompasses an area of around 67 800 $km^2$, which has been deforested significantly in recent years (Figure 1) [16]. Ghana's tropical forests are located in the south and west, while the central and northern zones are savanna [26]. The area of interest includes protected and deforested areas around Kumasi. The location of the study area was determined by the availability of a landcover classification that includes classes for important drivers of deforestation in the area, such as cocoa, palm, and rubber [11]–[14].

## 2.2 DATA

This section introduces the deforestation data that was used, followed by the data that was used to analyse drivers.

### 2.2.1 *Deforested areas and forest mask*

Deforestation data for the years 2001 until 2015 were obtained in a 30-meter resolution from the Global Forest Change dataset produced by Hansen et al. [16]. The year 2015 was used as a cut-off, because follow-up landcover data was only available for the years 2017/2018. The 2-year gap between 2015 and 2017 was left to ensure a reliable estimation of drivers, as tree crops like cocoa, rubber, and palm take a while to mature [27], [28]. All layers were clipped to the extent of the study area in QGIS 3.12.3. The forest loss layer, indicating the year that a particular patch of forest was lost, served as the basis of the current analysis. Hansen et al. define 'tree cover' as all vegetation above 5 meters in height, which includes both natural forest and plantations [16]. In order to limit the inclusion of non-forest cover, a layer with the percentage tree cover from the same dataset was used to mask out areas with a canopy cover below 30 percent. Applying a relatively high tree cover threshold of 30 percent helps to eliminate less densely planted plantations [29]. The dataset does not include areas that were deforested a second time after reforestation.

### 2.2.2 *Follow-up landcover*

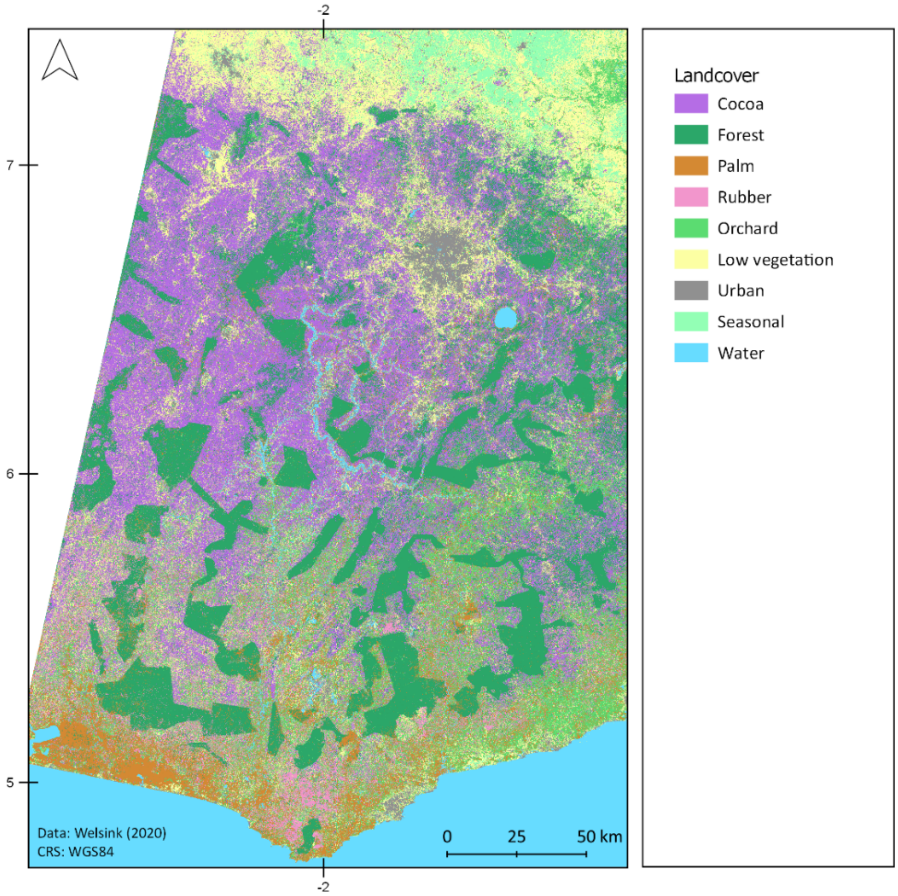


Figure 2: Landcover map used to identify drivers of deforestation between 2001 and 2015. The classification was produced by a Random Forest trained with 800 points per class on Sentinel-1 and Sentinel-2 composites from 2017 and 2018.

The current analysis makes use of a recent 9-class landcover classification of South-West Ghana that was made in collaboration with the The Alliance of Biodiversity International and the International Center for Tropical Agriculture (CIAT) (Figure 2) [30]. The classification was based on Sentinel imagery from the years 2017 and 2018 and is used to established follow-up landcover after deforestation events between 2001 and 2015. It was produced by a Random Forest algorithm trained with 800 points per class on Sentinel-1 and Sentinel-2 composites with a resolution of 10 meters. The classification includes classes for cocoa, rubber, palm, and orchards, which are important known drivers of deforestation in Ghana [11]–[14], [31]. In addition to these classes, seasonal crops are featured, which are planted and harvested annually and therefore have a different temporal signature than the other classes. The classification is completed with classes for low vegetation, urban, and water.

Table 1: Map accuracy of the Random Forest landcover classification [30]

| CLASS | PRECISION | RECALL | F1 |
|---|---|---|---|
| Cocoa | 93.5 (93.3, 93.6) | 63.8 (63.6, 63.8) | 75.8 |
| Forest | 74.6 (74.2, 75.1) | 78.1 (78.0, 78.3) | 76.3 |
| Palm | 70.7 (70.3, 71.2) | 55.8 (55.5, 56.1) | 62.4 |
| Orchard | 22.6 (22.2, 23.0) | 85.7 (85.4, 86.0) | 35.8 |
| Low vegetation | 89.0 (88.8, 89.3) | 69.2 (69.1, 69.2) | 77.8 |
| Urban | 82.2 (81.9, 82.6) | 88.1 (87.1, 89.1) | 85.1 |
| Seasonal | 64.3 (63.8, 64.8) | 96.4 (95.9, 96.9) | 77.1 |
| Water | 100.0 (100.0, 100.0) | 100.0 (100.0, 100.0) | 100.0 |

The classification has a moderate overall validation accuracy of 75.6 percent. The classes of rubber, orchard, and seasonal reached a precision below 70 percent. Orchards reached a particularly low precision of only 22.6 percent, which indicates that large areas were wrongly classified as this landcover. (Table 1). Recall fell below 70 percent for the classes of cocoa, palm, and low vegetation, which indicates that a relatively high proportion of these crops was classified as something else. F1 was lower than 70 percent for palm and orchard (which reached only 35.8 percent). To the best of my knowledge, existing classifications do not include separate classes for Ghana's most important (cash) crops and drivers of deforestation. A more elaborate discussion of the landcover classification and its quality can be found in [30].

## 2.3 METHODS

This section starts with the methods for the analysis of direct drivers between 2001 and 2015, followed by the methods to analyse the size of deforested patches in relation to these drivers and the steps taken to perform and assess emerging hotspot analysis. Processing took place in R version 4.0.2. Emerging hotspot analysis was performed in ArcGIS Pro 2.5.1.

### 2.3.1 *Direct drivers between 2001 and 2015*


Figure 3: Workflow for the first research objective.

After masking out deforested areas with a tree cover below 30 percent, the forest loss raster was resampled and aligned (nearest-neighbour) to the landcover raster to ensure that cells overlapped (Figure 3). As a result, the forest loss raster was resampled to a resolution of 10 meters.

Next, the forest loss raster was reclassified to create 1 raster per year with a binary cell value of 0 or 1 that indicated whether it had been deforested in the year in question. The resulting 15 rasters were used to identify the most important deforestation drivers for each year.

The landcover dataset was masked to the deforested areas in each raster, resulting in 15 rasters with the landcover of deforested area of each year. These rasters formed the basis of the calculation of the deforested area that could be attributed to each driver for each year. In addition, they allowed for the calculation of the total deforested area that could be attributed to each driver.

### 2.3.2 *Size of forest clearings in relation to the deforestation driver*


Figure 4: Workflow for the second research objective.

The 15 rasters with the landcover of deforested areas per year were merged in order to calculate the size of forest clearings associated with different drivers (Figure 4). The merged landcover raster was projected to a metric system (ESPG:32630 - WGS 84 - UTM zone 30N) in QGIS in order to be able to calculate area statistics.

One raster was created for each landcover in order to calculate statistics on the (proportional) patch size by driver. A patch in this context consists of consecutive raster cells of deforested area. This also allowed for calculations of the deforested area per patch size for each class, which provides an indication as to whether overall deforestation is is mostly in small or big patches. Bin sizes were 0.5 and 1 ha intervals up to patches of 5 ha. Patches bigger than 5 ha were considered to have a relatively high chance of being commercial plantations. They were placed in a single bin due to their relatively low frequency. It is important to note that very small deforested patches may sometimes result from sensor noise. However, field research found that slash and burn agriculture resulted in land holdings between 0.06 and 0.5 ha [10]. The smallest patches in the analysis are therefore not considered unrealistically small.

### 2.3.3 *Emerging hotspot analysis*

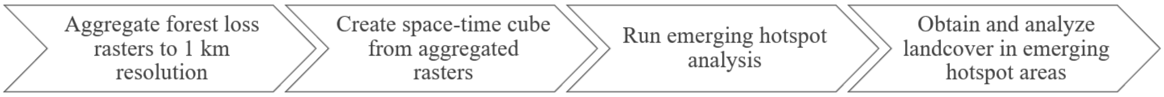


Figure 5: Workflow for the third research objective.

Emerging hotspot analysis in ArcGIS Pro was performed to identify new hotspots of forest loss. A hotspot in this context is an area that exhibits statistically significant clustering of forest loss in the combined spatial and temporal domains [24]. The analysis applies the Getis-Ord Gi-statistic to evaluate the location and the degree of spatial clustering [32], and the Mann-Kendall trend test to evaluate temporal time-series trends [33], [34]. The cluster and trend results from these statistics are used to categorize square bins (in this case 1 by 1 km in size). Emerging hotspot analysis allows for the identification of different types of hot- and coldspots over time, depending on when in the period of interest high or low activity was measured. The currect analysis was limited to new hotspots. A new hotspot is as a statistically significant hotspot (p value $\leqslant 0.05$) in the final time step that has never been a significant hotspot before. This provides insight as to which emerging drivers require attention in upcoming years.

In preparation for the emerging hotspot analysis, the 15 rasters with deforested area per year were aggregated to a resolution of 1 km (Figure 5). The choice for a 1 km resolution was made after empirically testing 1 km and 5 km bins. The 1 km bin preserved a varied distribution of forest loss counts, caught more localized trends, and suited the scale of the analysis. Aggregated cell values were the sum of all deforested cells.

A space-time cube was created from these aggregated rasters in ArcGIS Pro. In the space-time cube, each bin with data represents its own independent time series [24]. The aggregated cells constituted the spatial dimension; the resolution of the time dimension was yearly. The resulting cube served as an input to the emerging hotspot analysis.

The hotspot raster was exported and projected to the metric WGS 84 - UTM zone 30N crs before further analysis. R was used to calculate the absolute, as well as the proportional area per landcover in areas with new hotspots. The proportional area was obtained by dividing the area per class in new hotspots by the total deforested area of that class.

# 3 RESULTS

This section first presents the results from the analysis of direct drivers (objective 1) followed by the analysis of the size of forest clearings (objective 2) and the hotspot analysis (objective 3).

## 3.1 DIRECT DRIVERS BETWEEN 2001 AND 2015

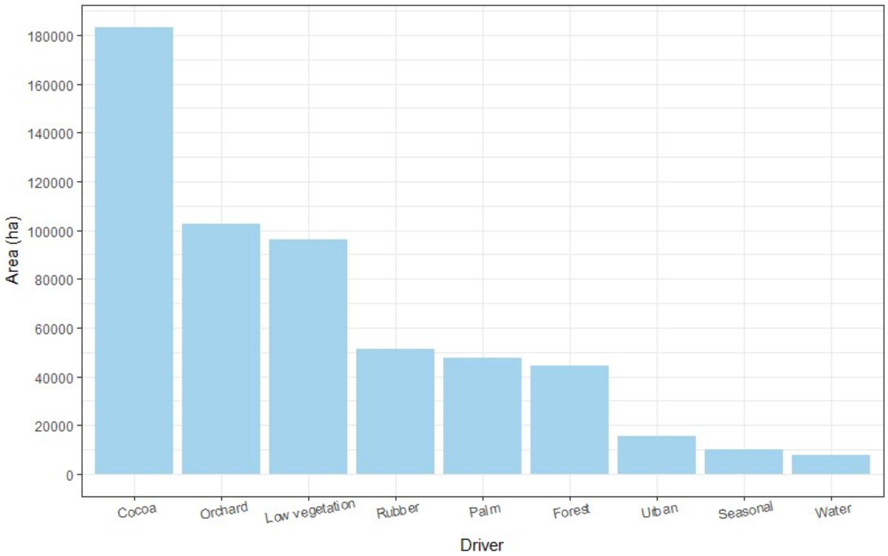


Figure 6: Deforested area (ha) attributed to direct drivers of deforestation between 2001 and 2015.

The analysis showed that between 2001 and 2015, a total area of 558 150 ha of forest was lost. Cocoa was the most prominent driver, covering an area of 183 137 ha (Figure 6). Orchards (102 408 ha) and low vegetation (96320 ha) are second and third in line, followed closely by rubber (51 240 ha), palm (47 565 ha), and forest (44 183 ha). Urban (15 531 ha), seasonal (10 018 ha) and water (7 747 ha) are the least important drivers.

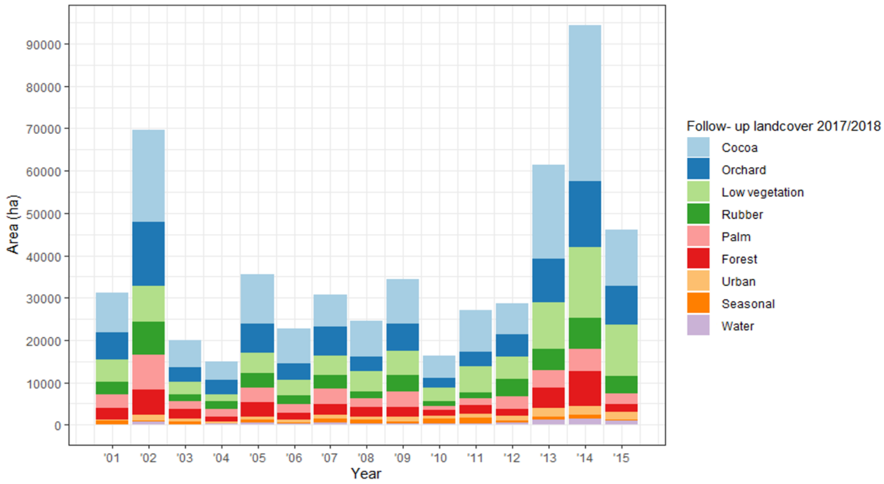


Figure 7: Deforested area (ha) attributed to direct drivers of deforestation between 2001 and 2015 per year.

The importance of drivers remained relatively stable during the study period, although the extent of total deforestation varied (Figure 7). In 2002, a relative peak in deforestation of almost 70 000 ha in total was reached. From 2013 onward, the deforested area per year was never below 46 000, with a peak of almost 95 000 in 2014.

## 3.2 SIZE OF FOREST CLEARINGS IN RELATION TO THE DEFORESTATION DRIVER

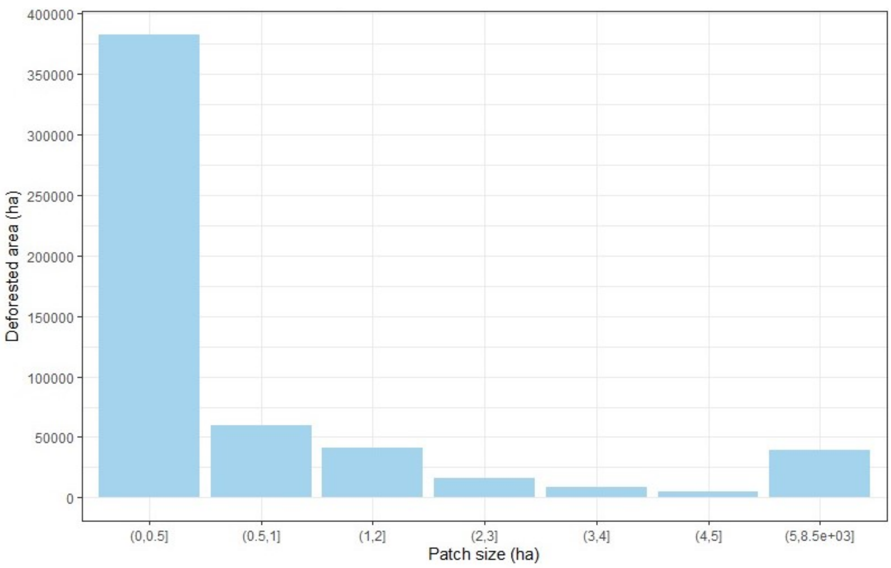


Figure 8: Deforested area per patch size interval. Note, the highest interval includes all patch sizes above 5 ha; the highest patch size is almost 8 500 ha in size.

Despite their small size, patches with an area between 0 and 0.5 ha are responsible for the highest total area of deforestation due to their high frequency of occurrence (Figure 8). In second place are patches with a size between 0.5 and 1 ha, followed by patches between 1 and 2 ha, and patches between 5 and 8 500 ha.

The median patch size of forest clearings does not differ much for different drivers. It falls between 0.02 ha for the classes of orchard, low vegetation, rubber, palm, forest, and seasonal and 0.03 ha for cocoa, urban, and water. The mean patch sizes is higher than the median for all classes, which indicates a positively skewed distribution. The difference between the median and the mean is the largest for cocoa, followed by seasonal, urban, and water.

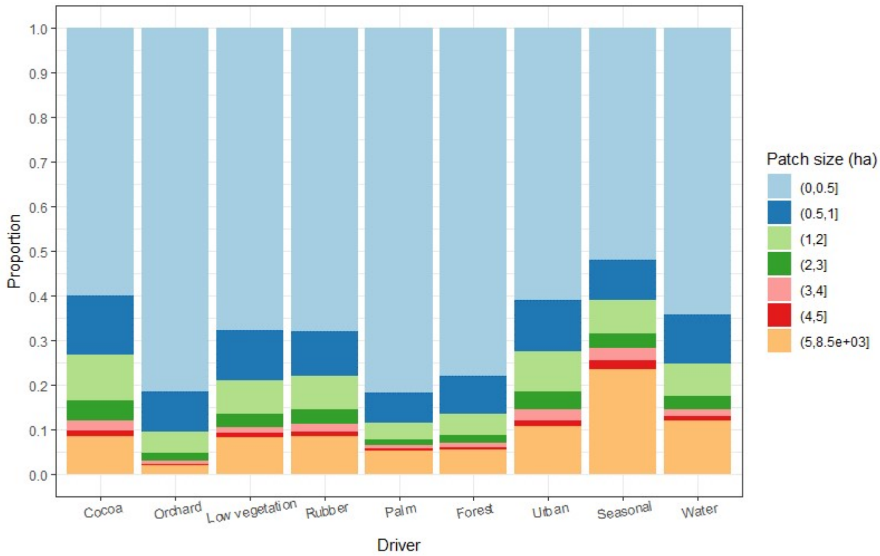


Figure 9: Area proportion of deforestation by patch size per driver. Note, the highest interval includes all patch sizes above 5 ha; the highest patch size is almost 8 500 ha in size.

Further analysis of which patch sizes characterize different drivers shows that the proportion of deforestation by different patch sizes is rather similar for many drivers (Figure 9). Patch sizes below 0.5 ha are responsible for most deforestation for the classes of orchard and palm, followed by forest. Relatively big patch sizes are mostly responsible in the seasonal class, followed by water and urban.

## 3.3 EMERGING HOTSPOT ANALYSIS

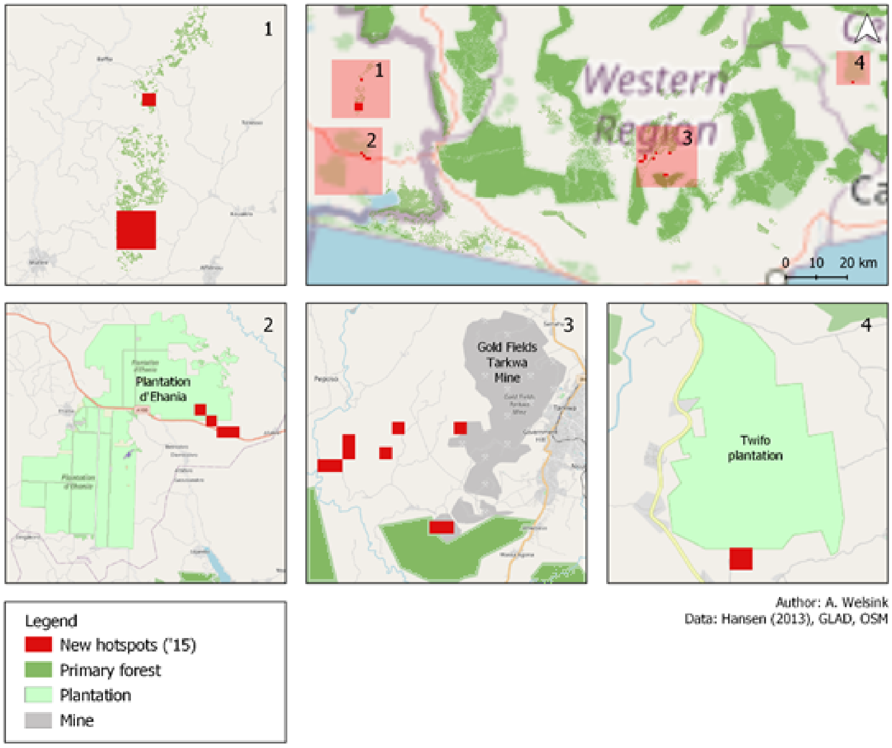


Figure 10: New hotspot areas in the study area in Ghana in 2015, contextualized by the locations of primary forest, existing palm plantations, and open-cast mines (Data source: OSM.

Emerging hotspot analysis provides insight into the location of new hotspots of forest loss and their drivers.New hotspots were exclusively found in the Southern part of the study area (Figure 10). A total of 12 hotspots were found, of which 6 are located relatively close to one another near the town of Tarkwa, where the 'Gold Fields Tarkwa Mine' is located.

In the West, the two Northern hotspots partly cover fragmented primary forest areas along relatively small (dirt) roads that are not captured by the OpenStreetMap (OSM) layer (Figure 10). The area has several (relatively small) existing plantations, including palm and rubber. The more Southern hotspots are located near the large 'Plantation d'Ehania', which reference with data from Hansen et al. confirms was gradually expanded between 2002 and 2015 [16]. A last hotspot is found in the east of the study area, just South of an another existing palm plantation between Twifo Praso and Twifo Hemang, which was expanded between 2003 and 2015.

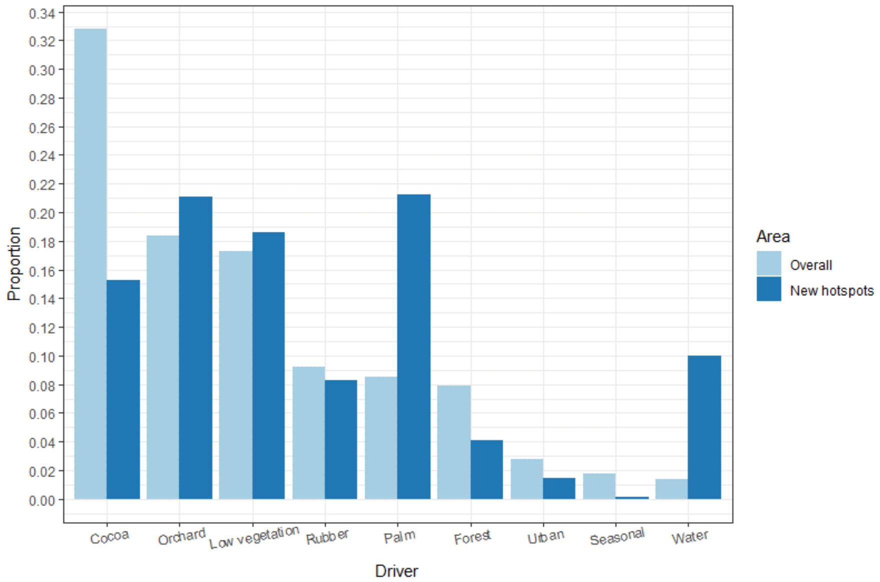


Figure 11: Area proportion of different drivers in all deforested areas and new hotspots.

The overall deforestation in the study area between 2001 and 2015 amounts to 558 150 ha. New deforestation hotspots make up a total area of 974 ha, which is 0.17 percent of the total deforestation. Cocoa constitutes the largest proportion of overall deforestation, followed by orchards and low vegetation (Figure 11). In new hotspots, palm is associated with the largest proportion of deforestation, followed by orchards and low vegetation. The difference between drivers' overall importance and importance in new hotspots is particularly large in the cases of cocoa, palm and water. Cocoa is relatively more important in the overall study area, while palm and water have a relatively high presence in new hotspots.

# 4 DISCUSSION

This section interprets the findings that were presented in the previous section in light of existing research, highlighting the three research objectives one at a time.

## 4.1 DIRECT DRIVERS BETWEEN 2001 AND 2015

The analysis of the most important drivers of forest loss between 2001 and 2015 showed that cocoa was the most prominent driver (Figure 6), which is in line with earlier (localized field) research [11], [12], [35]. Previous research has furthermore pointed to palm and rubber as main agricultural drivers [13], [14]. The current analysis found that although these crops caused 47 565 and 51 240 ha of deforestation respectively, they were surpassed in importance by orchards and low vegetation.

The importance of low vegetation suggests that some deforested areas remained fallow for at least two years (from 2015-2017), or that newly planted crops were still too small to be identified at the time that landcover was classified. This could partly be solved by increasing the time between the year of deforestation and classification. However, the time series of forest loss show that low vegetation makes up a relatively stable proportion of landcover over time (Figure 7). Further research is needed to better understand the use of these areas, which may include for example the maintenance of livestock and/or frequent slash and burn cycles.

The apparent importance of orchards as drivers also requires further verification. Although the production of fruits and nuts is of importance to Ghana's local and national economies, these crops have not been identified as main drivers of deforestation in earlier research [36]. The results from the current analysis provide insight in their potential importance as drivers, but this may partly be explained by their overrepresentation in the landcover map (Table 1). Classification of orchards is challenging due to their dense canopy cover which resembles non-productive trees [37]. Improvement of the classification is desired to obtain a more reliable estimation of the contribution of orchards (and other drivers) to forest loss. The limited quality of the current classification should be taken into account in the interpretation of the results.

The presence of forest as a driver of deforestation is paradoxical, even though it 'only' covered an area of 44 183 ha. The results can be explained by a number of factors, some of which are likely methodological errors. In some areas, conservation efforts may result in forest regrowth after deforestation caused by illegal logging, forest fires, etc. [37]. In addition to that, de- and reforestation cycles may be observed in areas that are planted and logged cyclically to meet the country's demand for timber [38]. However, the presence of forest as a driver will be partly due to inconsistencies between the landcover classification and the forest loss dataset. Importantly, the definitions of forest of the two datasets were not fully in line [16], [30]. The landcover classification was trained with natural forest, while the definition used by Hansen includes all vegetation above 5 meters in height, including both natural forest and plantations [16]. The forest mask of 30 percent canopy cover cannot exclude all plantations, which implies that dense plantations that are cut and replanted will be included in the forest loss layer. Use of a primary forest mask could help to solve this problem, although it implies a loss of information about non-primary forest loss. In addition to that, local discrepancies result from differences in the methods to detect forest and the imagery used (Landsat [16]/Sentinel [30]).

Besides methodological differences between the two datasets, either dataset has its own errors. Clouds will always impact passive optical sensors such as Landsat and Sentinel in areas with persistent cloud cover such as West Africa, which compromises the quality of resulting classifications [39]. Furthermore, the quality of classifications depends on the quality of the training dataset, which was relatively low for the landcover classification Table 1. This classification often confused cocoa plantations and intercrops for natural forests. Such crops with a dense canopy resemble forest, which results in 'deforestation [or reforestation] in disguise' [37]. Once again, this stresses the need to improve the landcover classification. In addition, a distinction should be made between natural forest and production forests with trees planted in a regular pattern.

The time series analysis of deforestation showed a number of years with particularly high forest loss, with the highest peak in 2014 (Figure 7). No one driver stood out particularly in that year, which complicates the search for an explanation of this apparent increase in deforestation. However, it is clear that cocoa was the primary driver, and a tentative explanation for an increase in forest loss for cocoa production in the year 2014 is available. Two years earlier, in 2012, large chocolate manufacturers such as Barry Callebaut and Mars expressed concerns about future cocoa shortages [40]. Media picked this up two years later, reporting on the expectation that the world would be running out of chocolate [41]–[43]. The International Cocoa Organization (ICCO) issued a statement in which it explained that no extreme shortages were expected [44]. Nevertheless, the idea that there would be a cocoa shortage may have induced increased deforestation activity. Newly cleared forest areas produce up to 25 percent higher yields than replanted areas, and clearing a new forest area costs about half the effort of replanting an existing plantation [45]. Areas that were deforested in response to the expected cocoa shortage may sometimes eventually have been planted by crops other than cocoa (perhaps after consideration of the statement by the ICCO). The expected cocoa shortages and resulting economic opportunities may thus also partly explain relatively high forest loss in areas that were eventually planted by crops other than cocoa. More research is needed to verify this theory and understand the cause-and-effect relationships involved.

## 4.2 SIZE OF FOREST CLEARINGS IN RELATION TO THE DEFORESTATION DRIVER

The analysis of patch size in relation to different drivers showed that patches below 0.5 ha were responsible for the largest total deforested area (Figure 8). Small patches are associated with smallholder or subsistence agriculture, while bigger patches provide an indication of commercial plantations [22]. In 2016, smallholder farms had an average size of just over 2 ha [46]. Contrary to expectations, the mean patch size was similar for all classes, far below 2 ha. This is surprising as some drivers (palm, rubber) were expected to be associated with large scale plantations, while others (cocoa, seasonal) were expected to be grown by smallholders relatively often [47]. The low variation in patch size by driver suggests that small scale deforestation was most common for all drivers. The fact that there was no clear association between the driver of forest loss and the scale of deforestation implies that patch size cannot be used as a guide to pinpoint drivers.

The apparent importance of subsistence agriculture over commercial plantations is in line with previous research, which states that agricultural commercialization in Ghana has been largely small-holder based in Ghana, as opposed to other African countries [48]. In spite of several large-scale international land acquisitions, smallholders still constituted 90 to 95 percent of the farms in the previous decade [49], [50]. Continuous small-scale deforestation in spite of forest management efforts may be partly explained by the fact that 80 percent of Ghana's land is held under customary land tenure, which complicates forest management structure and conservation reinforcement [48]. Field research is needed to verify the importance of subsistence agriculture over commercial plantations for different drivers, as patch size will not always suffice to make this distinction.

## 4.3 emerging hotspot analysis

The identification of drivers in new hotspots provides guidance as to which upcoming drivers deserve further attention for the purpose of conservation [24], [25]. Cocoa was highly represented in hotspots areas, but passed by palm as the most prominent driver, in spite of its overall importance from 2001 to 2015. Palm and water were highly presented in new hotspot areas in 2015 compared to their overall importance from 2001 to 2015. The presence of palm can be explained by the development of palm plantations over the years. The 'Plantation d'Ehania' and the 'Twifo' plantation were both expanded from 2002/2003 until 2015. These large commercial plantations were expanded relatively quickly, which makes their appearance in new hotspots more likely. The prevalence of water in new hotspots can be explained by the practice of open-cast mining. The water areas in new hotspots were found near the 'Gold Fields Tarkwa Mine'. Open-cast mines like the 'Tarkwa' mine are generally filled with water and will therefore often be classified as such. Verification with satellite imagery verified that this was the case here as well. The Ghanaian mining industry is an important driver of deforestation. Companies with permits for surface mining have cleared large tracts of forests [9], [51]. Besides commercial legal mining, illegal artisanal mining practices, which result in severe soil erosion, are deeply rooted in the local culture and supported by traditional leaders [52], [53]. Future classifications for the purpose of driver analysis should include a separate class for open-cast mines.

# 5 CONCLUSION

This thesis has analysed direct drivers of deforestation and their characteristics in South-West Ghana between 2001 and 2015. Drivers were identified as follow-up landcover after deforestation based on a 9-class landcover classification of the year 2017/2018. Cocoa was found to be responsible for most deforestation, in line with earlier research [11], [12], [35]. Orchards were found to be the second most prominent driver, followed by low vegetation. Rubber and palm, which are traditionally considered important drivers of deforestation in other geographies, came 4th and 5th [13], [14]. Further analysis is needed to validate these findings.

The analysis showed a peak in deforestation in the year 2014. A tentative explanation for the high forest loss in that year relates to the fact that several media reported an expected cocoa shortage that year [41]–[43]. This may have led people to clear land for cocoa production. The fact that the proportion of cocoa driven deforestation was not much higher than in other years suggests that newly cleared forest was eventually partly used for other crops when it became clear that cocoa shortage was overstated [44]. Further research is needed to verify this hypothesis.

The second objective of this thesis was to analyse the size of forest clearings in relation to their driver. No association was found between the drivers of forest loss and the scale of clearings, which implies that patch size cannot be used to track drivers. Patches below 0.5 ha were responsible for the largest area of deforestation. This provides an indication that smallholder and/or subsistence agriculture are important causes of forest loss in the study area. Forest monitoring should not overlook such small scale deforestation, as its total impact on forest loss has proven bigger than that of large plantations.

Thirdly, emerging hotspots of deforestation in 2015 were analysed. Palm and water were particularly important in new hotspot areas, compared to their overall importance. Cocoa was relatively unimportant, due to its high presence as a driver in earlier years. The emergence of palm in hotspot areas was explained by the expansion of existing plantations. Water was found in an open gold mine; a separate class for mines should be included in future versions of the landcover map. These emerging hotspots can guide monitoring activities by providing a statistical tool to identify new hotspots of deforestation and their associated drivers.

The analyses in this thesis have demonstrated the potential use of remote sensing for the analysis of deforestation drivers. Analysis of satellite imagery can complement fieldwork by allowing for objective analyses of drivers and associated trends over large areas at a relatively low cost [11].

# BIBLIOGRAPHY


[1] G. F. Watch, *Global Deforestation Rates & Statistics by Country | GFW*, en, 2020. [Online]. Available: https://www.globalforestwatch.org/dashboards/global (visited on 08/11/2020).

[2] J. Teye, "Deforestation in Ghana," *Acta Geographica-Trondheim*, vol. A, no. 10, 2005.

[3] A. H. Mas and T. V. Dietsch, "Linking Shade Coffee Certification to Biodiversity Conservation: Butterflies and Birds in Chiapas, Mexico," en, *Ecological Applications*, vol. 14, no. 3, pp. 642–654, 2004, ISSN: 1939-5582. DOI: 10.1890/02-5225.

[4] J. E. Tondoh, F. N. Kouamé, A. Martinez Guéi, B. Sey, A. Wowo Koné, and N. Gnessougou, "Ecological changes induced by full-sun cocoa farming in Côte d'Ivoire," *Global Ecology and Conservation*, vol. 3, pp. 575–595, Jan. 2015, ISSN: 2351-9894. DOI: 10.1016/j.gecco.2015.02.007.

[5] J. Mascaro, G. P. Asner, D. E. Knapp, T. Kennedy-Bowdoin, R. E. Martin, C. Anderson, M. Higgins, and K. D. Chadwick, "A Tale of Two "Forests": Random Forest Machine Learning Aids Tropical Forest Carbon Mapping," en, *PLoS ONE*, vol. 9, no. 1, B. Bond-Lamberty, Ed., e85993, Jan. 2014, ISSN: 1932-6203. DOI: 10.1371/journal.pone.0085993.

[6] F. Ruf, G. Schroth, and K. Doffangui, "Climate change, cocoa migrations and deforestation in West Africa: What does the past tell us about the future?" en, *Sustainability Science*, vol. 10, no. 1, pp. 101–111, Jan. 2015, ISSN: 1862-4057. DOI: 10.1007/s11625-014-0282-4.

[7] FAO, *Global forest resources assessment 2015*. en. Rome: Food and Agriculture Organization of the United Nations, 2015, OCLC: 964529974, ISBN: 978-92-5-108826-5.

[8] W. Hawthorne, "The flora and vegetation of Ghana's forests," Forestry Department, Accra, Ghana, Tech. Rep., 1989, pp. 8–14.

[9] M. Hirons, "Mining in Ghana's forests: Cross-sectoral linkages and the prospects for REDD," English, *International Development Planning Review; Liverpool*, vol. 35, no. 3, pp. 283–302, 2013, Num Pages: 20 Place: Liverpool, United Kingdom, Liverpool Publisher: Liverpool University Press, ISSN: 14746743. DOI: 10.3828/idpr.2013.18.

[10] M. Appiah, D. Blay, L. Damnyag, F. K. Dwomoh, A. Pappinen, and O. Luukkanen, "Dependence on forest resources and tropical deforestation in Ghana," en, *Environment, Development and Sustainability*, vol. 11, no. 3, pp. 471–487, Jun. 2009, ISSN: 1573-2975. DOI: 10.1007/s10668-007-9125-0.

[11] B. DeVries, J. Verbesselt, L. Kooistra, and M. Herold, "Robust monitoring of small-scale forest disturbances in a tropical montane forest using Landsat time series," *Remote Sensing of Environment*, vol. 161, pp. 107–121, May 2015, ISSN: 0034-4257. DOI: 10.1016/j.rse.2015.02.012.

[12] A. Kroeger, H. Bakhtary, F. Haupt, and C. Streck, *Eliminating Deforestation from the Cocoa Supply Chain*, en. World Bank, Mar. 2017. DOI: 10.1596/26549.

[13] K. Asubonteng, K. Pfeffer, M. Ros-Tonen, J. Verbesselt, and I. Baud, "Effects of Tree-crop Farming on Land-cover Transitions in a Mosaic Landscape in the Eastern Region of Ghana," en, *Environmental Management*, vol. 62, no. 3, pp. 529–547, Sep. 2018, ISSN: 0364-152X, 1432-1009. DOI: 10.1007/s00267-018-1060-3.

[14] T. Chiti, E. Grieco, L. Perugini, A. Rey, and R. Valentini, "Effect of the replacement of tropical forests with tree plantations on soil organic carbon levels in the Jomoro district, Ghana," en, *Plant and Soil*, vol. 375, no. 1-2, pp. 47–59, Feb. 2014, ISSN: 0032-079X, 1573-5036. DOI: 10.1007/s11104-013-1928-1.

[15] R. M. Ochieng, I. J. Visseren-Hamakers, and K. S. Nketiah, "Interaction between the FLEGT-VPA and REDD+ in Ghana: Recommendations for interaction management," en, *Forest Policy and Economics*, Emerging Forest Regimes, vol. 32, pp. 32–39, Jul. 2013, ISSN: 1389-9341. DOI: 10.1016/j.forpol.2012.07.003.

[16] M. Hansen, P. Potapov, R. Moore, *et al.*, "High-resolution global maps of 21st-century forest cover change," *Science*, no. 342, pp. 850–853, 2013.

[17] E. Romijn, C. B. Lantican, M. Herold, E. Lindquist, R. Ochieng, A. Wijaya, D. Murdiyarso, and L. Verchot, "Assessing change in national forest monitoring capacities of 99 tropical countries," en, *Forest Ecology and Management*, Changes in Global Forest Resources from 1990 to 2015, vol. 352, pp. 109–123, Sep. 2015, ISSN: 0378-1127. DOI: 10.1016/j.foreco.2015.06.003.

[18] R. DeFries, F. Achard, S. Brown, M. Herold, D. Murdiyarso, B. Schlamadinger, and C. d. Souza, "Reducing greenhouse gas emissions from deforestation in developing countries: Considerations for monitoring and measuring," en-US, Global Terrestrial Observing System (GTOS), Tech. Rep. 46, 2006.

[19] H. Geist and E. Lambin, "Proximate causes and underlying driving forces of tropical deforestation," *BioScience*, no. 52, 2002.

[20] R. S. DeFries, T. Rudel, M. Uriarte, and M. Hansen, "Deforestation driven by urban population growth and agricultural trade in the twenty-first century," en, *Nature Geoscience*, vol. 3, no. 3, pp. 178–181, Mar. 2010, Number: 3 Publisher: Nature Publishing Group, ISSN: 1752-0908. DOI: 10.1038/ngeo756.

[21] K. Rademaekers, L. Eichler, J. Berg, M. Obersteiner, and P. Havlik, "Study on the evolution of some deforestation drivers and their potential impacts on the costs of an avoiding deforestation scheme.," ECORYS and IIASA, Rotterdam, Netherlands, Tech. Rep., 2010.

[22] V. de Sy, "Remote sensing of land use and carbon losses following tropical deforestation," en, ISBN: 9789462578036, PhD thesis, Wageningen University, Wageningen, Jun. 2016. DOI: 10.18174/380263.

[23] N. Hosonuma, M. Herold, V. D. Sy, R. S. D. Fries, M. Brockhaus, L. Verchot, A. Angelsen, and E. Romijn, "An assessment of deforestation and forest degradation drivers in developing countries," en, *Environmental Research Letters*, vol. 7, no. 4, p. 044 009, Oct. 2012, Publisher: IOP Publishing, ISSN: 1748-9326. DOI: 10.1088/1748-9326/7/4/044009.

[24] N. L. Harris, E. Goldman, C. Gabris, *et al.*, "Using spatial statistics to identify emerging hot spots of forest loss," en, *Environmental Research Letters*, vol. 12, no. 2, p. 024 012, Feb. 2017, Publisher: IOP Publishing, ISSN: 1748-9326. DOI: 10.1088/1748-9326/aa5a2f.

[25] A. Etter, C. Mcalpine, S. Phinn, D. Pullar, and H. Possingham, "Characterizing a tropical deforestation wave: A dynamic spatial analysis of a deforestation hotspot in the Colombian Amazon," en, *Global Change Biology*, vol. 12, no. 8, pp. 1409–1420, 2006, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1365-2486.2006.01168.x, ISSN: 1365-2486. DOI: 10.1111/j.1365-2486.2006.01168.x.

[26] J. Förster, "The Potential of Reducing Emissions from Deforestation and Degradation (REDD) in Western Ghana," en, PhD thesis, University of Bayreuth, Bayreuth, Germany, Aug. 2009.

[27] A. Ismail and M. Mamat, "The optimal age of oil palm replanting," *Oil Palm Industry Economic Journal*, vol. 2, no. 1, pp. 11–18, 2002.

[28] V. H. L. Rodrigo, C. M. Stirling, Z. Teklehaimanot, and A. Nugawela, "Intercropping with banana to improve fractional interception and radiation-use efficiency of immature rubber plantations," en, *Field Crops Research*, vol. 69, no. 3, pp. 237–249, Mar. 2001, ISSN: 0378-4290. DOI: 10.1016/S0378-4290(00)00147-7.

[29] S. S. Saatchi, N. L. Harris, S. Brown, *et al.*, "Benchmark map of forest carbon stocks in tropical regions across three continents," en, *Proceedings of the National Academy of Sciences*, vol. 108, no. 24, pp. 9899–9904, Jun. 2011, ISSN: 0027-8424, 1091-6490. DOI: 10.1073/pnas.1019576108.

[30] A.-J. Welsink, *Comparing Classification of Ghana's Complex Agroforestry Land Cover by a Random Forest and a Convolutional Neural Network with a Small Training Set*, English, Mar. 2020.

[31] V. Vijay, S. L. Pimm, C. N. Jenkins, and S. J. Smith, "The Impacts of Oil Palm on Recent Deforestation and Biodiversity Loss," en, *PLOS ONE*, vol. 11, no. 7, M. Anand, Ed., e0159668, Jul. 2016, ISSN: 1932-6203. DOI: 10.1371/journal.pone.0159668.

[32] J. K. Ord and A. Getis, "Local Spatial Autocorrelation Statistics: Distributional Issues and an Application," en, *Geographical Analysis*, vol. 27, no. 4, pp. 286–306, 1995, ISSN: 1538-4632. DOI: 10.1111/j.1538-4632.1995.tb00912.x.

[33] M. Kendall and J. Gibbons, *Rank Correlation Methods*. London: Griffin, 1990.

[34] H. B. Mann, "Nonparametric Tests Against Trend," *Econometrica*, vol. 13, no. 3, pp. 245–259, 1945, Publisher: [Wiley, Econometric Society], ISSN: 0012-9682. DOI: 10.2307/1907187.

[35] R Bymolt, A Laven, and M Tyszler, "Demystifying the Cocoa Sector in Ghana and Côte d'Ivoire," en, The Royal Tropical Institute, Amsterdam, Tech. Rep., 2018.

[36] M. Pouliot, T. Treue, B. D. Obiri, and B. Ouedraogo, "Deforestation and the Limited Contribution of Forests to Rural Livelihoods in West Africa: Evidence from Burkina Faso and Ghana," en, *AMBIO*, vol. 41, no. 7, pp. 738–750, Nov. 2012, ISSN: 1654-7209. DOI: 10.1007/s13280-012-0292-3.

[37] E. O. Acheampong, C. J. Macgregor, S. Sloan, and J. Sayer, "Deforestation is driven by agricultural expansion in Ghana's forest reserves," en, *Scientific African*, vol. 5, e00146, Sep. 2019, ISSN: 2468-2276. DOI: 10.1016/j.sciaf.2019.e00146.

[38] K. A. Oduro, G. M. J. Mohren, M. Peña-Claros, B. Kyereh, and B. Arts, "Tracing forest resource development in Ghana through forest transition pathways," en, *Land Use Policy*, vol. 48, pp. 63–72, Nov. 2015, ISSN: 0264-8377. DOI: 10.1016/j.landusepol.2015.05.020.

[39] M. C. Hansen, A. Krylov, A. Tyukavina, P. V. Potapov, S. Turubanova, B. Zutta, S. Ifo, B. Margono, F. Stolle, and R. Moore, "Humid tropical forest disturbance alerts using Landsat data," en, *Environmental Research Letters*, vol. 11, no. 3, p. 034 008, Mar. 2016, ISSN: 1748-9326. DOI: 10.1088/1748-9326/11/3/034008.

[Online]. Available: https://doi.org/10.1088%2F1748-9326%2F11%2F3%2F034008 (visited on 07/16/2019).

[40] R. Pendrous, *Mars urges action on cocoa to beat shortage*, en-GB, Library Catalog: www.foodmanufacture.co.uk, 2012. [Online]. Available: https://www.foodmanufacture.co.uk/Article/2012/06/13/Mars-Chocolate-warns-action-on-cocoa-needed-to-beat-shortage (visited on 08/03/2020).

[41] R. A. Ferdman, "The world's biggest chocolate-maker says we're running out of chocolate," en-US, *Washington Post*, Nov. 2014, ISSN: 0190-8286. [Online]. Available: https://www.washingtonpost.com/news/wonk/wp/2014/11/15/the-worlds-biggest-chocolate-maker-says-were-running-out-of-chocolate/ (visited on 08/03/2020).

[42] T. Ford, J. Vit, N. Rupert, T. Branigan, and E. Saner, "The cocoa crisis: Why the world's stash of chocolate is melting away," en, *the Guardian*, Nov. 2014, Library Catalog: www.theguardian.com Section: Food. [Online]. Available: http://www.theguardian.com/lifeandstyle/2014/nov/21/cocoa-crisis-world-chocolate-stash-melting-away (visited on 08/03/2020).

[43] R. Moss, "The World Is Running Out Of Chocolate, This Is Not A Drill," en, *The Huffington Post UK*, Nov. 2014, Library Catalog: www.huffingtonpost.co.uk Section: Life.

[44] I. C. Organization, *ICCO Statement on Reports of a Cocoa Supply Deficit in 2020*, International Cocoa Organization, 2014.

[45] R. A. Rice and R. Greenberg, "Cacao Cultivation and the Conservation of Biological Diversity," *AMBIO: A Journal of the Human Environment*, vol. 29, no. 3, pp. 167–173, May 2000, ISSN: 0044-7447, 1654-7209. DOI: 10.1579/0044-7447-29.3.167.

[46] M. Kansanga, P. Andersen, D. Kpienbaareh, S. Mason-Renton, K. Atuoye, Y. Sano, R. Antabe, and I. Luginaah, "Traditional agriculture in transition: Examining the impacts of agricultural modernization on smallholder farming in Ghana under the new Green Revolution," *International Journal of Sustainable Development & World Ecology*, vol. 26, no. 1, pp. 11–24, Jan. 2019, ISSN: 1350-4509. DOI: 10.1080/13504509.2018.1491429.

[47] G. C. Schoneveld and L. German, "Translating Legal Rights into Tenure Security: Lessons from the New Commercial Pressures on Land in Ghana," *The Journal of Development Studies*, vol. 50, no. 2, pp. 187–203, Feb. 2014, ISSN: 0022-0388. DOI: 10.1080/00220388.2013.858129.

[48] J. A. Yaro, J. K. Teye, and G. D. Torvikey, "Agricultural commercialisation models, agrarian dynamics and local development in Ghana," en, *The Journal of Peasant Studies*, vol. 44, no. 3, pp. 538–

554, May 2017, ISSN: 0306-6150, 1743-9361. DOI: 10.1080/03066150.2016.1259222.

[49] J. Chamberlin, "It's Small World After All: Defining Smallholder Agriculture in Ghana," en, *International Food Policy Research Institute*, IFPRI Discussion Paper, no. 00823, 2008.

[50] K. Lanz, J.-D. Gerber, and T. Haller, "Land Grabbing, the State and Chiefs: The Politics of Extending Commercial Agriculture in Ghana," en, *Development and Change*, vol. 49, no. 6, pp. 1526–1552, 2018, ISSN: 1467-7660. DOI: 10.1111/dech.12429.

[51] C. P. Hansen, J. F. Lund, and T. Treue, "Neither Fast, Nor Easy: He Prospect of Reduced Emissions from Deforestation and Degradation (REDD) in Ghana," *International Forestry Review*, vol. 11, no. 4, pp. 439–455, Dec. 2009, Publisher: Commonwealth Forestry Association, ISSN: 1465-5489, 2053-7778. DOI: 10.1505/ifor.11.4.439.

[52] S. M. Banchirigah, "Challenges with eradicating illegal mining in Ghana: A perspective from the grassroots," en, *Resources Policy*, vol. 33, no. 1, pp. 29–38, Mar. 2008, ISSN: 0301-4207. DOI: 10.1016/j.resourpol.2007.11.001.

[53] J. M. Kusimi, "Assessing land use and land cover change in the Wassa West District of Ghana using remote sensing," en, *GeoJournal*, vol. 71, no. 4, pp. 249–259, Apr. 2008, ISSN: 0343-2521, 1572-9893. DOI: 10.1007/s10708-008-9172-6.