

Trying to See the Forest for the Trees: Forest Cover and Economic Activity in Africa

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Paper prepared for the IARIW-TNBS Conference on "Measuring Income, Wealth and Wellbeing in Africa", Arusha, Tanzania November 11-13, 2022

Concurrent Session 6B: Natural Resources

Time: Saturday, November 12, 2022 [10:30 AM -12:00 PM]

Trying to see the forest for the trees: Forest cover and economic activity in Africa

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20 October 2022

Abstract: Africa currently experiences the highest yearly rate of deforestation. As a result, there is debate on the African continent about the causes and consequences of this phenomenon, as well as on the effectiveness of action undertaken to counter this process. This paper contributes to the literature on economic aspects of deforestation in Africa with regard to period of analysis (existing research was limited to 2015), combining econometric and spatial analysis, and introduction of variables not taken into account by previous research. Special attention is paid to participation of African countries in REDD+ program. We demonstrate a negative relationship between economic activity and forest cover using both econometric modeling and spatial analysis. Rising GDP per capita, urbanization, and the occurrence of droughts and floods all contribute to the loss of forest cover. Additionally, the negative correlation between the level of built-up areas and forest areas increased between 2015 and 2019. Conducted research does not allow to conclude that REDD+ program is effective at mitigating deforestation in Africa.

Key words: deforestation, Africa, economic activity, REDD+ **JEL**: Q15, Q23, N57

1. Introduction

Mutual relationships between the natural environment, economy and society are complex and include both virtuous and vicious circles. Forests and forest products play an important role in economies of many countries, especially developing ones. About 20% of rural income comes from forests, and for some countries it is the only source of income (Hogarth et al., 2013). Therefore, many countries experience overharvesting which, especially coupled with a greater demand for arable land, often leads to deforestation.

Deforestation remains one of the major environmental problems all over the world. It is usually discussed in the context of carbon capture and sequestration as well as biodiversity conservation. The importance of forests is well known – they not only provide a home for wildlife but also protect the soil, purify the air, regulate the climate and ensure a stable water supply.

The deforestation process is noticeable on every continent of the world. Crowther et al. (2015) estimated that 15 billion trees are cut each year, and since the inception of mankind, the global number of trees has fallen by about 46%.

Over the past decades, the forest cover in the vast majority of African countries has decreased (Moon & Solomon, 2018). As a matter of fact, during 2010-2020, Africa was the continent experiencing the largest annual rate of net forest loss, equal to 3.9 million hectares per year (FAO, 2020). According to FAO estimates, only Algeria, Tunisia, Eswatini and Cabo Verde observed an opposite trend, while the developments of forest cover in Burundi and Rwanda bear signs of forest transition, which means switching from net forest area loss to net gain. African Wildlife Foundation (2015) counted that Africa is home to 17% of the world's forests. At the same time, 65% of people in Sub-Saharan Africa depend on forests for food or fuel.

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Deforestation is now a significant environmental concern on a global scale, endangering the advantages of forests. Thus, the literature includes several thousand publications that refer to deforestation in their keywords. Contreras-Hermosilla (2000) generalizes all causes of deforestation, calling it unsustainable and uncontrolled exploitation of forests by lumberjacks, miners and rural communities. Sola et al. (2017), when compiling a systematic map, determined that 93 articles about Sub-Saharan countries examined environmental impacts, 60 socio-economic impacts and 27 health impacts. According to their analysis, most articles believe that the direct cause of deforestation research proves that there is no single main reason for this issue. The Dutch sickness and the resource curse are the two unsolved problems in Africa. High resource extraction is also a cause of deforestation, however, the study of this topic needs to be expanded.

Importantly, at Conference of the Parties in 2013 the Reducing Emission from Deforestation and Forest Degradation (REDD+) framework initiative was created to aid in the fight against excessive deforestation. The REDD+ framework developed by the UNFCCC Conference of the Parties serves as a roadmap for activities in the forest sector that reduce emissions from deforestation and forest degradation, as well as for sustainable forest management and the preservation and improvement of forest carbon stocks in developing nations. In 2013, it was decided that REDD+ programs should begin with the development of strategies and action plans, then progress to the implementation of national policies, measures, and programs, and finally to results-driven actions that are fully measured, reported, and verified, allowing countries to seek and obtain performance-based payments (UNFCCC, 2022). Although countries from every continent in the world are involved in the REDD+ program, the African countries are the largest group of countries participating in the program. In Africa, however, there are many challenges related to the implementation of REDD+ programs. These include technological, political and institutional or socio-economic challenges (African Development Bank Group, 2016).

Most of the existing research about deforestation covers specific countries or regions of Africa and is not conclusive with regard to the causes of deforestation. Additionally, almost all researches based on data up to 2015. Therefore, there is a research gap with regard to the period starting from 2015 and assessment of new programs like REDD+. The aim of this article is twofold: 1) to contribute to the existing literature and inspect the relationship between economic activity and deforestation in African countries by? analyzing the latest data until 2019; 2) to assess the effectiveness of the REDD+ program. Both goals are realized in two complementary settings.

Firstly, the article investigates the relationship between GDP per capita, forest products export, REDD+ participation, floods, droughts, urban population growth, forest cover, agriculture, forestry and fishing, forest rent, industry and natural resources rents for the period 2000-2019 (the year 2020 is excluded from the analysis in order to avoid the disruptive effects of the COVID-19 pandemic and due to lack of data for some variables investigated). Secondly, increased data availability allows also to resort to satellite data showing the relationship between the probability of covering the area with forest, trees and shrubs (according to Copernicus Global Land Service, 2022) and maps of built-up areas which are treated as GDP equivalent in the micro scale. Therefore, apart from the scope of analysis, the novelty of the research consists in the datasets and methods applied.

The novelty of the research conducted refers mostly to supplementing traditional econometric methods with GIS methods, as well as introducing shocks that have not been analyzed so far such as droughts, floods, as well as engaging in the REDD+ program.

The research gap was defined as the lack of pan-African analyses for data later than 2015 on the links between economic activity and deforestation.

The remainder of the paper is structured as follows. Section 2 discusses findings of the literature pertaining to the causes of deforestation. Section 3 introduces data and methods applied in empirical research. Section 4 presents results of econometric investigations and map analysis. The final section concludes.

2. Literature review

Deforestation is one of the most regularly analyzed problem related to environmental issues. It is a process of environmental degeneration consisting of the reduction of the forest area (Riberio et al., 2015). World Wildlife Fund (2021) state that deforestation is caused by agriculture, unsustainable forest management, mining, infrastructure projects and increased fire incidence and intensity. Population growth is also considered to be one of the factors contributing to forest degradation. In the case of Africa, the main reasons for deforestation are population growth, subsistence agriculture, forest fires and harvesting of firewood.

The problem of deforestation is more and more often analyzed in connection with the growing environmental awareness of the citizens of the world. The current literature⁴ concerning this subject has over 16 000 publications with keywords such as "land cover" or "deforestation". In connection with Africa, there are about 4 000 publications. These publications can be divided into three main areas. The first is related to geographic and geological issues. These articles mainly contain geological maps and analyze how forest areas change in given regions of the world. They usually do not refer to the socio-economic or political situation. The flagship examples of such literature are Achard et al. (2014), Vijay et al. (2016) and Pearson et al. (2017).

The second, equally extensive group of publications, is related to social sciences, such as economics and social policy. These articles tackle important issues like the impact of deforestation on economic and social areas or include research on the factors that lead to deforestation. Most often one can come across articles dealing with factor analysis and the relationship between individual indicators or values and the land cover. In Africa, deforestation has a trend starting in pre-colonial times (Mfon et al., 2014). Between years 1500 and 1900 the rainforests were reduced as a result of the demand for wood by colonial governments. Mfon et al. (2014) state that population growth is the leading cause of deforestation. Hussaini (2014) claims the same, emphasizing that population growth has accelerated the process of deforestation. Almost all existing studies show a positive relationship between population growth and deforestation in Africa. Similar conclusions were also reached by Otum et al. (2017), arguing that most of the activities leading to deforestation are human-initiated. The problem of deforestation has significant consequences as it is one of the forces leading to the collapse of our civilization (Bologna & Aquino, 2020).

About two-thirds of Africa's population depends on forest resources and 90% of the population uses firewood and charcoal as energy sources (Ojo et al., 2018). Many researchers have also paid attention to the relationship between GDP per capita and deforestation. Positive relationships between these values have been observed, among others, by Asongu (2011), Chiu (2012), Rudel (2013) or Yalew (2015). Africa is a continent that has been on the path of economic development for many years. However, the increase in economic activity of its inhabitants also contributed to an increase in the demand for wood products or the residence of given areas, which is associated with deforestation. Of all the identified factors influencing deforestation, human activities appear to be most responsible for the loss of forest resources. Deforestation also makes sustainable development almost impossible, especially in developing countries.

Third group of studies are comprehensive studies which include both geographic and economic aspects. Examples are Wu (2011), Rudel (2013) or Jaffé et al. (2021). The authors

⁴ Open access in databases Web of Science, Scopus, EBSCO and Elsevier.

of these publications decided to use and confront not only maps, but also available secondary data on, inter alia, the amount of population, GDP per capita, use of wood products or their export. Rudel (2013) notes the link between population growth and forest degradation. His research shows that deforestation around cities and along transport corridors between cities is more visible. He also highlights that sub-Saharan countries with less dense forests and plenty of dry land unsuitable for agriculture have experienced higher rates of deforestation.

The works by Debel (2014) and Ngwira and Watanabe (2019) are characterized by an interesting point of reference and an unusual approach to the problem. The authors of the research used a survey as a research method. On the basis of their research, they tried to prove whether the population influences the level of deforestation in any way. Interesting conclusions came from the research done by Ngwira and Watanabe (2019) in which questions about land use were asked. They show that the population influences deforestation to a large extent. On the basis of the research conducted by 399 households, they concluded that it is the lack of individual awareness that mainly affects the size and pace of deforestation.

This research is closely linked to the second and the third areas discussed above and supplements the existing literature concerning forest policy evaluation with regard to REDD+ programs. Even though many African countries are involved in REDD+ programs, there are no unambiguous conclusions regarding their effectiveness in the literature. For instance, Gizachew et al. (2017) argue that in Africa, the implementation of these programs is often faced with many obstacles, which means that these programs are implemented slowly or insufficiently. In the same vein, Soliev et. al. (2021) highlight forest-related conflicts in African countries and point out problems related to poor land ownership arrangements, conflicting interests in agriculture, corruption and land grabbing.

3. Data and methods

In econometric modelling of the relationship between economic activity and forest cover the article follows the literature discussed in the previous section. Being guided by the measures of fit of various specifications of the models, this study uses the share of urban population in total population, share of forest product exports and logarithm of GDP per capita in our research.

Variable	Observations	Mean	Std. Dev.	Min	Max	Source of data
Forest cover	1,114	.2911304	.2510279	.0004519	.9324706	FAOstat
Share of urban population in total population	1,125	.4222138	.1795644	.08246	.90092	UNCTADstat
Share of forest product exports in total trade of forest products	1,057	.3757326	.3502865	.000018	.9986392	FAOstat
ln GDPpc	1,085	8.025265	.9829921	6.075522	10.55602	World Bank
REDD+	1,134	.1904762	.39285	0	1	UNFCCC
Flood 2009-2010	1,134	.015873	.1250394	0	1	UNOCHA, 2011
Drought 2011-2012	1,134	.0167549	.1284082	0	1	Haile et al. 2019
Gini coefficient	1,134	.6131695	.0598491	.4879855	.7813728	World Inequality Database
Agriculture, forestry, and fishing (% of GDP)	1,061	20.31285	13.99522	.8926961	79.04236	World Bank
Forest rents (% of GDP)	1,098	5.040416	5.768849	0	40.4083	World Bank
Industry (% of GDP)	1,05	26.0795	13.77264	3.243096	86.66956	World Bank
Total natural resources rents (% of GDP)	1,095	11.98479	12.20867	.0011721	67.88997	World Bank

Table 1. Forest cover as a fraction of total country area and its determinants – descriptive statistics

Source: Authors' calculations.

Some other variables discussed by the literature (such as forest fires), turned out to be statistically insignificant. As mentioned earlier, the study also takes into account specific shocks – namely the floods and droughts that took place in many African countries between 2009-2012. Another variable in the model was the participation of countries in REDD+ programs captured by a binary variable equal to 1 since 2013.

In the macroeconomic analysis the study resorts to pooled OLS regression (for illustrative purposes only) and methods appropriate for panel data: static panel model with fixed effects (FE) and dynamic panel model (GMM).

In the spatial analysis, the Copernicus Global Land Service (2022) data for 2015 and 2019 was used, and vector data on the ICPAC (2022) geoportal was presented to illustrate the changes in the forest cover on the African continent⁵. The goal of the analysis was to show the relationship between the forest cover and the GDP per capita expressed by the correlation coefficient calculated on the basis of a square analytical grid of 100mx100m. Therefore, attempts were made to add more detailed information to the data in the system of quasinatural state borders. This approach turned out to be difficult to implement not only due to the size of the maps (each raster contained over 7.6 billion points) but also the lack of data proxying the GDP per capita.

The approximation of maps concerning the state of economic development could be made on the basis of the statistical data subject to interpolation, however, the problem here was the need to determine the centroid of a country and choose the appropriate interpolation method – which strongly influenced the obtained initial data and resulted in the accumulation of errors at the resulting level. The second approach was to use substitutes — maps that are positively and strongly correlated with GDP indicators. Ultimately, a map presenting areas classified as built-up was selected, giving them priority over lighting maps for substantive reasons (night lighting is not always a determinant of prosperity, sometimes it is a necessity, sometimes it is a fashion) and technical reasons (a different methodology of creating maps that may affect the results). On the other hand, built-up maps are directly related to both the location of a country's population and the creation of goods and services.

Finally, the correlation indicators were calculated in the quasi-natural course of the boundaries of the regional level based on data for 6226 spatial units divided into five areas: Eastern, Middle, Northern, Southern and Western Africa. For calculation purposes, the original data (Tree-CoverFraction and BuiltUp-CoverFraction maps) were averaged in the system of vector boundaries of spatial units.

4. Results

Main results of the analysis pertaining to the determinants of the forest cover conducted at the country level are presented in table 2.

Model	(1)	(2)	(3)	(4)	(5)
Method	Pooled OLS	FE	GMM	GMM	GMM
Forest cover t-1			0.943***	1.006***	1.623***
			(0.00463)	(0.0140)	(0.0694)
Forest cover t-2				-0.0338**	-0.648***
				(0.0135)	(0.0696)
Forest cover t-3				````	0.0124
					(0.0147)

Table 2. Determinants of forest cover

 $^{^{5}}$ The raw data shared as a grid (EPSG: 4326) with the ellipsoid WGS 1984 (Terrestrial radius = 6378 km) with a pixel resolution of 1ha was trimmed in QGIS 3.18.3 to the limits of the continent's reach. The study used probability maps saved in the .tiff format to classify a pixel to the coverage described as Tree-CoverFraction and BuiltUp-CoverFraction, both within the range of 0 to 100.

Share of urban population	0.448***	-0.174***	-0.00649**	-0.00784***	-0.00331*
in total population	(0.0496)	(0.0592)	(0.00276)	(0.00128)	(0.00179)
Share of forest product exports	0.292***	-0.0153	-0.000269	0.000276*	0.000101
in total trade of forest products	(0.0212)	(0.0104)	(0.000339)	(0.000161)	(0.000199)
ln GDPpc	-0.0601***	-0.0120**	-0.00284***	-0.000429**	-0.000249
	(0.00562)	(0.00472)	(0.000364)	(0.000176)	(0.000225)
REDD+	0.0523***	-0.00806**	-0.000213	-0.000212***	-7.68e-05
	(0.0127)	(0.00363)	(0.000167)	(7.88e-05)	(9.79e-05)
Flood 2009-2010	0.0228	-0.00292*	-0.000132	-0.000208**	-0.000137
	(0.0356)	(0.00152)	(0.000218)	(0.000102)	(0.000123)
Drought 2011-2012	0.0181	-0.00364**	-0.000684***	-0.000231*	5.42e-06
	(0.0244)	(0.00181)	(0.000251)	(0.000122)	(0.000150)
Gini coefficient	0.277**	-0.0717	-0.00785**	-0.00326**	-0.00169
	(0.113)	(0.0578)	(0.00326)	(0.00157)	(0.00222)
Agriculture, forestry, and fishing	0.00119	1.24e-05	1.77e-06	1.66e-05**	3.61e-06
(% of GDP)	(0.000873)	(0.000283)	(1.46e-05)	(7.06e-06)	(8.94e-06)
Forest rents (% of GDP)	0.0150***	-0.000420	-9.68e-05***	5.78e-06	8.00e-06
	(0.00189)	(0.000566)	(2.08e-05)	(1.02e-05)	(1.29e-05)
Industry (% of GDP)	0.00488^{***}	-0.000266	-2.98e-05**	1.71e-05***	2.23e-06
	(0.000895)	(0.000203)	(1.18e-05)	(5.81e-06)	(7.51e-06)
Total natural resources rents	-0.00320***	8.21e-05	7.11e-05***	-3.14e-06	1.35e-06
(% of GDP)	(0.000774)	(0.000125)	(1.02e-05)	(5.07e-06)	(6.31e-06)
Constant	0.107	0.524***	0.0463***	0.0147***	0.00742**
	(0.107)	(0.0503)	(0.00416)	(0.00205)	(0.00292)
Observations	924	924	836	799	760
R-squared	0.502	0.529			
Number of countries		53	53	53	53

Source: Authors' calculations.

The most important finding is that there is a strong, statistically significant relationship between the share of urban population and forest cover. In line with model 2, an increase in urban population by 1 p.p. decreases forest cover in a given country almost by 0.2 p.p. The conducted analysis clearly shows how misleading pooled OLS estimations in the analyzed case can be. The estimations in this article also document a negative impact of GDP per capita growth, natural disasters like floods and droughts, income inequalities, and participation in the REDD+ program. Greater share of agriculture in GDP is associated higher proportions of forest cover, but this positive correlation can be associated with the quality of soil in general. Dynamic panel models (3-5) also show a substantial degree of persistence with regard to the forest cover.

The results of the spatial analysis are presented in the Appendix in Figures 1-6.

The Central-Western part of the continent (equatorial forests) has the highest average probability of being classified as a forest cover in the space of individual administrative units, and this probability diminishes with distance from this part. The decline, however, is not the same – the more rapid decline of forest cover to the North and East is also noticeable. The average probability of forest cover occurrence has increased locally in more regions as the trend has moved south (areas in Angola, Zambia). Additionally, there is a rather high probability (over 67.1%) that forests will exist in Liberia, Côte d'Ivoire, or along Madagascar's Eastern coast. Despite this, a sizable portion of Africa is devoid of forest cover (virtually all of the North, with the exception of a few small coastal regions), and a big portion of South-Western Africa is a desert. The situation has not altered dramatically between 2015 and 2019, although an increase in the average probability of classifying a pixel as forest cover has been observed on the scale of the continent, which can be recognized, among others, by the cut-off values for the classes presented in Fig. 1 and 2. At the same time, areas with a greater average probability of classifying pixels as forest areas are declining.

A high probability of classifying an area as built-up is much more concentrated, especially in capital areas (e.g. Accra in Ghana, Lome in Togo, Pretoria in South Africa or Khartoum in Sudan) or in areas rich in water (e.g. Nile valley and delta). What is also worth noting is the relatively heavily built-up area between Cameroon and the Mali, and a slightly less built-up strip along the great African lakes, from South Sudan to Zimbabwe. In contrast to forest areas, the average probability of classifying an area as a built-up area declines in the quartile system, as evidenced by the lower initial values of the middle ranges of values shown in Figs. 3 and 4. Quartiles presenting changes in the average level of qualifying an area to be classified as forest show that the greatest changes in this aspect occurred in the subtropical belt between the Chad Basin and the Congo Basin, as well as in large areas between Southern Africa, with the exception of the South-Western part of the Kalahari Basin. However, these changes are not uniform. Relatively large areas to the South and North-East of the Congo Basin experienced a rise in probability (on a scale of 1.83 to 17.02%), whereas big areas to the North and South-East of this basin have a fall in the average probability level (from 0.23 to 21.53%). In the coastal strip between Nigeria and Cameroon, as well as between Uganda and Tanzania, the probability of classifying a pixel as a forest cover has decreased (see Fig. 5).

Changes in the cover classified as built-up areas are not as pronounced in case of forest cover. Over the years 2015-2019 the greatest changes in the probability of classification were observed in the belt between Egypt and Lesotho: the area located directly next to Cairo, the Aswan area, then a large area between Kampala in Uganda, Lilongwe and Blantyre in Malawi, the area between Lusaka in Zambia and Harare in Zimbabwe, to Pretoria and Johannesburg in South Africa. The Gulf of Guinea belt, the area between Dakar in Senegal and Bissau in Guinea-Bissau, and the area around Marrakech in Morocco are the last areas of reasonably vigorous urban growth (see Fig. 6).

In order to offer a synthetic overview of these results, Table 3 presents correlation coefficients calculated for mean probability of classification of an area as built-up and mean probability of classification of an area as tree-covered for African countries clustered in five regions.

Region	Number of countries	2015	2019
Eastern Africa	17	-0.247	-0.258
Middle Africa	9	-0.114	-0.117
Northern Africa	7	-0.161	-0.189
Southern Africa	5	-0.059	-0.081
Western Africa	16	-0.166	-0.176

Table 3. Correlation coefficients between mean probability of classification of an area as built-up and mean probability of classification of an area as tree-covered – African regions

Source: Authors' calculations.

The Pearson coefficient demonstrates a negative correlation between the average probabilities of classifying a pixel as a forest or built-up area, which is consistent with expectations. At the same time, however, the scale of correlation varies spatially, ranging from -0.059 in Southern Africa to -0.247 in Eastern Africa. It is noteworthy that in absolute terms these values grew in 2019 and ranged between -0.081 and -0.258. This indicates that positive changes in economic development in the East of the continent occur more frequently at the expense of a forest gust than in other parts of Africa. The relatively rapid deforestation process for industrialization also covers locations North of the Sahara, where afforestation is minimal otherwise. Acceleration of deforestation processes occurs in West Africa as well, however, in these regions we are dealing with both an increase in forest cover and its loss, so the assessment cannot be straightforward. This fact is also influenced by demographic processes, which forces specific land use patterns – for instance, Nigeria's more inhabited areas have a greater impact on the loss in tree cover than Burkina Faso's relatively less populated areas.

Due to the focus on the effectiveness of REDD+ programs, Table 4 includes a similar comparison for the REDD+ program participating and non-participating countries.

Table 4. Correlation coefficients between mean probability of classification of an area as built-up and mean probability of classification of an area as tree-covered - REDD+ and nonREDD+ involved countries

Group of countries	Number of countries	2015	2019
nonREDD+	- 27	-0.096	-0.100
REDD+	27	-0.280	-0.290

Source: Authors' calculations.

In this case, the Pearson coefficient is also negative. In absolute terms both among REDD+ and nonREDD+ countries, this correlation increased in 2019. A greater negative correlation is observed for the REDD+ countries.

Both dimensions of this analysis confirm a negative impact of GDP pe capita and increased urban population on forest cover. We also show that participation in REDD+ program does not contribute to an increase in the forest cover among participating countries. Negative coefficients for participation in this program can be treated as a sign of ineffectiveness, however, without counterfactual analysis it is difficult to assess whether without the program the percentage of forest cover of REDD+ countries would be greater.

5. Discussion and conclusions

The increasing deforestation in African countries is a conspicuous trend. The findings of this study, together with projections of an expanding African population, lead to rather pessimistic projections. Furthermore, the study demonstrated that one of the primary causes of deforestation is population growth, which is supported by research from Mfon et al. (2014), Hussaini (2014), and Otum et al (2017). In this article's research, it was also proven that there is a strong link between GDP per capita growth and deforestation, demonstrating that GDP per capita growth leads to increased deforestation. Researchers such as Asongu (2011), Chiu (2012), and Rudel (2013) published related findings.

Based on the map analysis, it can be concluded that deforestation continued in Africa between 2015 and 2019. When the correlation between built-up areas (GDP per capita equivalent) and forest areas is examined, it is clear that the relationship is inverse — the larger the built-up area, the lower the level of forest cover. There are noticeable differences in this correlation over time and across different areas of Africa. In 2019, all correlations have decreased when compared to 2015. The largest of the large-scale correlations occurs in East Africa, owing to, among other things, the reliance on biomass fuels.

Regarding the second goal of research, connected with effectiveness of the REDD+ program, the effectiveness or ineffectiveness of these programs cannot be determined unequivocally based on this research. The increased negative correlation between the growth of built-up areas and forest areas can only be interpreted as an indication that the implemented programs are ineffective. However, it should be noted that if these countries did not participate in programs supporting sustainable deforestation, the level of deforestation could worsen even further. Extensive research should be conducted to precisely define it (e.g. by creating case studies of individual countries). To preserve biodiversity and save the lives of many species, as well as people, effective programs supporting environmental protections should be elaborated. At the same time, it is necessary to conduct research in the near future in order to determine how trends change, especially since the world may now be facing a raw materials crisis.

Conducted analysis was confined to the period of 2000-2019. The outbreak of the COVID-19 pandemic has brought forest protection to a new meaning, as it has been proven that deforestation contributes to an increased risk of pandemic zoonoses (Brancalion et al., 2020). Over the first weeks following the implementation of confinement measures to reduce the spread of COVID-19 disease, deforestation increased by 63% in America and Asia-Pacific, and by as much as 136% in Africa (Brancalion et al., 2020). According to the latest reports from the World Resource Institute (2021) the highest forest loss from 2020 to 2021 in Africa was noticed in Democratic Republic of the Congo (499,059 hectares). Therefore, future analyses should focus on short-run and long-run implications of the outbreak of COVID-19 on the forest cover in Africa.

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Appendix Figure 1. Tree cover fraction in 2015 (mean of classification probability)



Figure 2. Tree cover fraction in 2019 (mean of classification probability)





Figure 3. Built-up cover fraction in 2015 (mean of classification probability)

Figure 4. Built-up cover fraction in 2019 (mean of classification probability)



Figure 5. Change in the mean probability of classification of area as tree-covered (2015-2019)



Figure 6. Change in the mean probability of classification of area as built-up (2015-2019)

