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MODELING FOREST HABITAT DEGRADATION AND THE POTENTIALLY ASSOCIATED OUTBREAK RISK IN EQUATORIAL GUINEA

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Abstract

Countries of the tropical area have been plagued with forest ecosystem degradation to be replaced by a range of anthropic activities such as agricultural expansion, livestock breeding, settlements and extractive activities. Concomitantly, epidemiologists have testified for a rise of Emerging Infectious Diseases (EID) cases in the tropical areas undergoing forest clearance episodes and make the case for their association to forest degradation. In view of the recent literature which strives to demonstrate the mechanisms linking forest ecosystem degradation and land use change to the emergence of infectious diseases, this research has aimed at developing a workflow of analyses to model the risk associated to emerging infectious diseases in a context of forest degradation. After modelling areas of potential pathogen spillover events, it first consisted in highlighting the areas of interface between forest degradation and anthropic activities. The second part of this work produced an index of this infectious risk that combined analyses of the hazardous areas and accessibility to health facilities. The analyses were conducted with ArcGIS and AccessMod software, on the Equatorial Guinea territory using openly available data. Their results enable to locate the areas of interaction between anthropic activities and forest degradation within the country. Moreover, they highlight the areas greatly exposed to a potential epidemiological threat associated with forest habitat degradation due to high proximity to hazardous areas, and the most vulnerable areas to this potential risk due to remoteness from health facilities. Finally, the results show that a significant portion of the population is located in areas with high level of potential infectious risk associated to forest degradation.

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Glossary

Ecotone: transition between two adjacent ecological systems (Despommier, Ellis, and Wilcox 2007; Fonseca 2008; Cain, Bowman, and Hacker 2014).

Spillover: transmission of a pathogen from a reservoir population to a host population (Faust et al. 2018).

Risk: "probability and magnitude of consequences after a hazard" (Turner et al. 2003)

Hazard: "threat to a system […] threats to a system and the consequences they produce (Turner et al. 2003).

Vulnerability: "degree to which a system […] is likely to experience harm due to exposure to a hazard" (Turner et al. 2003).

Background

1. Deforestation, fragmentation, ecotones and edge effects

Over the past decades, deforestation has stroke tropical forests at a drastically increasing pace and scale (Achard 2002) and has been identified as a major driver of global environmental change, significantly affecting climate, biodiversity and nutrient availability (Walsh, Molyneux, and Birley 1993).

Deforestation defined as the "conversion of forest to another land use or the long term reduction of tree canopy cover below the 10% threshold", by the Food and Agriculture Organization of the United Nations (FAO) (2010) participates to forest ecosystem and habitat fragmentation which itself may be referred to as "any process [resulting] in the conversion of formerly continuous forest into patches of forest separated by non-forested lands" (Food and Agriculture Organization of the United Nations (FAO) 2007).
The ecotone is described by Despommier, Ellis, and Wilcox (2007) as a natural or an anthropogenic area of transition between two adjacent ecological systems "where biophysical factors, biological activity and ecological evolutionary processes are concentrated and intensified". Ecotones may be seen as the transition between forest and non-forested habitat (Fonseca 2008; Cain, Bowman, and Hacker 2014), and therefore of the place occurrence of edge effects. These edge effects happen consequently to fragmentation and "contribute to continuing degradation of forest fragments" (Schelhas and Greenberg 1996) and a cause of forest biodiversity reduction (W.F. Laurance and Bierregaard 1997).

2. Health, drivers of emergence, spillover scenarios and mechanisms between hosts

Over the past two decades, the emergence of infectious diseases associated to land use change has received increasing attention (N.L. Gottdenker et al. 2014).

A. Deforestation favors disease transmission

Emerging infectious diseases, that are newly appeared or which incidence or geographic range are rapidly increasing (S.S. Morse 1995), may be due to bacteria, protozoans, fungi or viruses ("Medical Definition of Infectious Disease" 2017) and may be transmitted directly or via vectors (World Health Organization 2017).
Findings in cross-disciplinary research in medicine, ecology and epidemiology have highlighted a rise in Emerging Infectious Diseases cases in the tropical areas undergoing forest clearance episodes or fragmentation (B.A. Wilcox and Ellis 2006). They make the case for the link between infectious disease spillover and ecological systems' structure and organization, and more specifically deforestation and forest fragmentation (N.L. Gottdenker et al. 2014). Anthropogenic ecotones, created by such land use changes, may therefore be seen as areas of interface between intact forests and anthropic activities where ecotonal processes favor pathogen spillover (Despommier, Ellis, and Wilcox 2007).

B. Diseases which emergence was traced back to deforestation and forest fragmentation

Although previous findings in terms of the causality of land use change in infectious disease emergence may be contrasted (D. Valle and Tucker Lima 2014), recent researches highlight recurrent infectious diseases and anthropic activities associated to forest habitat degradation and land use change.

The most documented infectious diseases include zoonoses for instance due to *Escherichia coli bacteria* (T.L. Goldberg 2008), Ebola virus in African countries (J. Olivero et al. 2017; M. Rulli et al. 2017), Henipavirus in Southeast Asia and Africa (Epstein et al. 2014; O. Pernet et al. 2014; Chua 2003), vector borne diseases such as Chagas disease caused by *Trypanosoma cruzi* in Africa (E.N. Vianna et al. 2017), Cutaneous Leishmaniasis caused by *Leishmania* pathogens in Southern American countries (Wolfe N et al. 2000), Buruli ulcers due to *Mycobacterium ulcerans* (Morris et al. 2016) in Oceania, Africa and Latin America (Darie 2003), and varied forms of Malaria caused by *Plasmodium vivax* (N.M. Wayant et al. 2010; Chaves et al. 2018) or *Plasmodium falciparum* (Chaves et al. 2018) vectored by *Anopheles darlingi* mosquitoes (A.Y. Vittor et al. 2009) and which emerged in African, Southeast-Asian and South American countries (B.A. Wilcox and Ellis 2006).

C. Anthropic activities involved

The findings of researches which have intended to identify the drivers of such diseases' emergence point to a range of anthropic activities taking place where forests have been cleared, fragmented or in the fringes of the remaining fragments (N.L. Gottdenker et al. 2014).

Agricultural expansion (T.L. Goldberg 2008; J.A. Patz and Olson 2016), livestock breeding (Goldberg 2008; Pernet et al. 2014), human settlements in fragmented forest margins (M. Rulli et al. 2017; T.L. Goldberg 2008) leading to increased population densities (M. Rulli et al. 2017) and facilitated disease transmission (N.L. Gottdenker et al. 2014) stand as repeatedly identified drivers. Other anthropic activities, such as extractive industries like logging and mining (T.L. Goldberg 2008), road and dam building (J.A. Patz and Olson 2016), irrigation and urbanization (N.L. Gottdenker et al. 2014), as well as bush meat hunting (Wolfe N et al. 2000; O. Pernet et al. 2014; A.K. Wiethoelter et al. 2015) were also identified.

These activities influence the transmission of diseases between wildlife animals and humans but also between wildlife and domestic animals, ultimately affecting human health (Faust et al. 2018). Wildlife-livestock interfaces are critical in disease ecology and may have direct influence on human health (A.K. Wiethoelter et al. 2015). They have already been identified as drivers of Infectious Diseases emergence such as the 1998 outbreak of febrile encephalitis in Peninsular Malaysia due to Hendra virus spread (Chua 2003).

D. Locating the places with greater spillover risk

Different levels of forest habitat degradation have been associated to infectious disease spillover events. On the one hand, Faust et al. (2018) have identified places which have undergone intermediate levels of land conversion as the loci of highest pathogen invasion and probability of individual infection. Some diseases such as Ebola tend to be associated with areas of high

levels of dense forest fragmentation (J. Olivero et al. 2017; M. Rulli et al. 2017) rather than in deforestation hotspots, which are instead more opportune for the development of vectors of diseases like malaria when replaced by secondary growth vegetation such as shrubs and cropland (A.Y. Vittor et al. 2009).
Because they concentrate and intensify biophysical factors, biological activity and ecological evolutionary processes, ecotones, particularly the anthropogenic ones, constitute breeding grounds for disease transmission (Despommier, Ellis, and Wilcox 2007).

E. A diversity of mechanisms

The mechanisms linking the effect of land conversion and pathogen transmission are complex (Burkett-Cadena and Vittor 2018) and may be explained as the "[changes in] the abundance, demography, behavior, movement, immune response and contact between host species and vectors as well as [alteration of] host community" (N.L. Gottdenker et al. 2014). Therefore, pathogen spillover results from a change in ecological conditions followed by increased interactions between species and of the exposure of novel host (K.A Murray and Daszak 2013).

Changing the vector/host/reservoir's ecology

First of all, deforestation and forest fragmentation is likely to alter the vector's, the host's or the pathogen's ecology, niche or community composition (Morris et al. 2016; N.L. Gottdenker et al. 2014) and sometimes result in the loss of reservoir or host species (O. Pernet et al. 2014) or of their composition (M. Rulli et al. 2017), core species predator as a consequence of habitat destruction and which in turn decreases the natural regulation capacity of hosts and reservoirs decreases (E.N. Vianna et al. 2017). Consequently, reservoir and hosts species concentrate in the remaining fragments of forest (T.L. Goldberg 2008) and in ecotones, where they become hyper abundant, resulting in increased pathogenic potential (Despommier, Ellis, and Wilcox 2007), usually where anthropic activities are also taking place.

Creating suitable habitats for vectors

Deforestation and forest fragmentation contribute to creating suitable habitat for vectors which in turn changes their spatial distribution (N.L. Gottdenker et al. 2014) from sylvatic to anthropic biomes (E.N. Vianna et al. 2017) as they search for resources (T.L. Goldberg 2008; Epstein et al. 2014; O. Pernet et al. 2014) due to habitat destruction.
Moreover, Burkett-Cadena and Vittor's (2018) findings highlight how the vectors of human pathogens are more abundant and even favored by deforestation. This may be due to the increase of forest edges preferred for instance by *Anopheles Darlingi* (Chaves et al. 2018), particularly in the aquatic habitat of the interface (Burkett-Cadena and Vittor 2018), to the increase in surface temperatures due to the loss of forest cover (Burkett-Cadena and Vittor 2018; E.N. Vianna et al. 2017) or the proximity of human settlements (A.Y. Vittor et al. 2009) where the vectors finally adapt (Burkett-Cadena and Vittor 2018). Such conditions are likely to create larval breeding sites and increase their biting rate (*ibid*) as shown for one malaria vector *(Anopheles darlingi)* (A.Y. Vittor et al. 2009), and several Chagas disease vectors (*trypanosoma)* (E.N. Vianna et al. 2017).

Increased interspecies contact

Usually, deforestation and fragmentation are followed by activities likely to increase human exposure to pathogens or vectors. As a matter of fact, deforestation and forest fragmentation create interfaces of frequent interspecies contacts and interactions (Wolfe N et al. 2000), that is where humans, domestic animals and wildlife interact and where pathogens that used to be contained in forest ecosystems spillover to anthropic ecosystems (Faust et al. 2018; Despommier, Ellis, and Wilcox 2007). The mechanisms by which deforestation creates conditions where a novel host (with no prior exposure) is exposed to a diverse pool of pathogens (K.A Murray and Daszak 2013) may be exacerbated in areas with high population densities (Jones et al. 2008).

Emerging Infectious diseases associated to land use change pose a significant threat and public health concern in countries of the tropical area, where deforestation dynamics are currently the greatest (Hansen et al. 2013) and where the presence of dense forest biome and humid climate exacerbate the issues aforementioned (Colfer et al. 2006). Besides, Western Africa has been identified as a major hotspot both in terms of Emerging infectious diseases events, with particular threat from zoonotic pathogens from wildlife and vector borne pathogens (Jones et al. 2008), and forest habitat degradation (Global Forest Watch 2018). This particular area therefore constitutes a relevant case study for the issues related to the interactions between health and ecosystem degradation, particularly those triggered by forest loss habitat.

3. Accessibility matters

Accessibility to health care is critical in outbreak control efforts, where inadequate access to services, products or technologies can be responsible for a greater number of cases and deaths as it was for instance the case for Ebola Virus Disease (D.L. Heymann et al. 2015; L.O. Gostin and Friedman 2015).
However, little research has intended to model the exposure to this infectious risk under the angle of travel time to the areas with potential risk of spillover such as used by Ouma et al. (2018) to map the accessibility to emergency facilities in Africa.
Varied tools provided by Geographical Information System (GIS) technologies have been used in some of the research dealing with the infectious risk associated to land use change in order to map hotspots of this risk at different scales (Allen et al. 2017; D. Valle and Tucker Lima 2014) or to visualize the exposure to these areas within buffers (Morris et al. 2016; J. Olivero et al. 2017), that is in terms of distance to the risk area.

4. The concept of risk

Risk, and more precisely environmental risk may be conceptualized as the interaction between hazard, vulnerability and exposure (IPCC 2014). It may be defined as the "probability and magnitude of consequences after a hazard" (Turner et al. 2003). Hazards represent the threats to a system and the possible consequences produced (*ibid*). The interrelated concepts of vulnerability and exposure are social and economic processes (IPCC 2014). As a matter of fact, vulnerability corresponds to "the degree to which a system […] is likely to experience harm due to exposure to a hazard" (Turner et al. 2003).

5. Equatorial Guinea

Equatorial Guinea is a West African country with a population reaching 1.3 million inhabitants in 2017 (Trading Economics 2018) and which economy mainly relies on oil extraction (African Development Bank, Organisation for Economic Co-operation and Development, and Development Centre 2003). In 2014, 98% of the country was still covered with tropical rainforest, and therefore constitutes one of the biodiversity conservation targets of IUCN's West and Central Africa (WCPA) programs. Over the 2004-2014 decade, the country has faced a yearly rate of degradation of 0.9% and of deforestation of 0.1%, mainly for timber exportation towards Asia and Europe and agricultural expansion (Central African Forest Initiative n.d.). The government has however committed to implementing REDD+ strategy to address the drivers of deforestation and forest degradation (*ibid*).

Although infectious disease emergence associated to land use change has not specifically been studied, the country was identified as a potential risk area for yellow fever (F.M. Shearer et al. 2018), Ebola and Marburg fever epidemic and outbreak and reservoir (Pigott et al. 2017, 2014), and harbors environment suitability for Zika virus (J. P. Messina et al. 2016).

For the reasons mentioned above, and the fact that it is a relatively small country, Equatorial Guinea was thought to be a very good candidate to achieve the two main research aims of our study;

Research Goal

(1) Mapping the areas of interface between forest degradation and anthropic activities, as they can be potential areas of spillover occurrence, (2) Identifying the areas where the population would be most vulnerable to the potential risk of Emerging Infectious Disease associated to forest habitat degradation by incorporating realistic measures of both proximity to potential hazardous areas and accessibility (or lack thereof) to emergency facilities.

Answering Allen et al.'s (2014) call for an analysis of the spatial distribution of interfaces associated with potential spillover risk and for interdisciplinary and ambitious approach to foster pandemic control, this research aims at producing a complete workflow based on high resolution openly available data, to support decision making in land use planning and public health surveillance.

Data

1. Equatorial Guinea

A mask was created to define the extent of the Equatorial Guinean territory and was used to clip out all other data sets. The country boundaries were downloaded from the GADM website (GADM 2018).

2. Deforestation

Deforestation data for years 2010-2014 and 2001-2005 was obtained from the dataset provided by the University of Maryland (Hansen et al. 2013) available from the Global Forest Watch portal (http://data.globalforestwatch.org). This raster data locates the deforested pixel and indicates the year of deforestation at a 30m resolution.

3. Landcover

The land cover raster was obtained from the Copernicus Global Land Service (Jacobs and Smets 2017). This 100m resolution raster file provides information about the different categories of land cover in Equatorial Guinea: evergreen broadleaf closed and open forest, deciduous broadleaf closed and open forest, herbaceous wetland, temporary and permanent water bodies, herbaceous wetland, urban areas, shrubs, herbaceous vegetation, cropland and open sea areas. Cropland data used in the analyses described here below were extracted from this dataset.

4. Population

The 2015 adjusted population raster dataset (100m) was obtained for Equatorial Guinea on the WorldPop website, modelled with peer-reviewed statistical methods "to transform and disaggregate population counts at administrative unit levels to 100x100m grid square level, exploiting relationships with spatial covariate layers from satellites and other sources" (Worldpop 2013). The adjusted to UN estimates population count map indicator was used.

5. Settlements

The shape point file of "populated places (settlements)" was retrieved from the humanitarian data exchange website from the United Nations office for Coordination of Human Affairs (OCHA) (National Geospatial-Intelligence Agency (NGA) 2011). This dataset includes information about the location and name of the 2049 settlements.

6. Livestock

Livestock raster datasets (1000m) for the year 2006 were obtained from the Geo Wiki portal (T. Robinson and Conchedda 2014a, 2014c, 2014b) for cattle, goat and sheep densities, and were combined together.

7. Logging concessions

The point shapefile dataset of the logging concessions (Equatorial Guinea Ministry of Agriculture and Forests and The World Resource Institute 2013) was downloaded from the Global Forest Watch portal (http://data.globalforestwatch.org/datasets) and includes information about the company holding the concession, the date of exploitation, the localization, the area and the state of exploitation.

8. Waterways

The line shapefile dataset of waterways in Equatorial Guinea was downloaded from the humanitarian data exchange website from the United Nations office for Coordination of Human Affairs (OCHA) (Open Street Map 2018b)and contained information about river features.

9. Hospitals

The 2017 hospital shape point file for Equatorial Guinea was obtained from (Ouma et al. 2018), and contained 18 public facilities "targeted at a broad range of emergency or referral care to the general population" *(ibid)*.

10.Roads

The road shape files were obtained from Open Street Map website (Open Street Map 2018a) and from (Ouma et al. 2018) for Equatorial Guinea, and were merged together. It includes information about the type of roads of the feature line dataset.

11. Digital Elevation Model (DEM)

The 30m DEM tiles for Equatorial Guinea were downloaded from the USGS website (https://earthexplorer.usgs.gov/), combined together, and clipped on the mask for Equatorial Guinea.

Methods

The detailed processes of the developed workflow can be found in appendix 1.

1. Areas with greater potential for spillover events occurrence

In order to translate the land use change associated with greater spillover risk described by the literature, the beginning of this workflow has worked on modelling forest habitat degradation through the identification of deforested and fragmented areas.

A. Deforested areas

The Global Forest Watch provides fine resolution (30m), locally relevant records of forest change since 2000, from Earth observation satellite data (Hansen et al. 2013). The "Global forest cover loss 2000-2014" dataset maps deforestation considered as "a stand replacement disturbance or a change from a forest to non-forest state" (*ibid*).

Forest loss data were extracted from this dataset for the periods 2001-2005 and 2010-2014.

A part of this work has aimed at mapping the interface between the areas of forest degradation and anthropic activities. Therefore, the periods of study of these interface need to precede the dates (2006 and 2015) of the available data of proxies for anthropic activities (human and livestock population, land cover, settlements, etc…), as described hereafter.
Deforestation was analyzed over a period of five years (2001-2005 and 2010-2014) in order to reflect the array of possible ecological and epidemiological mechanisms described in the literature depending on the infectious disease studied; 4 years for malaria in (N.M. Wayant et al. 2010), 5 years for malaria in (K.M. Fornace et al. 2016), within the same year as deforestation for Ebola in (J. Olivero et al. 2017; M. Rulli et al. 2017).

Another subset of deforestation events was extracted for the period 2001-2014 in order to compare them with logging concessions data which also range across this timeline.

Binary masks of deforestation were created by assigning a common value to all the deforested pixels. These masks were resampled using a majority technique in order to match the resolution of the proxies for anthropic activities; 925.18m for the livestock densities and 92.52 for all the other layers. These resolutions were chosen to match the population and the livestock layers'. The majority technique of resampling was chosen because it minimized the pixel loss between the original and the final resolutions.
All these processes were executed using ArcGIS 10.3 (http://desktop.arcgis.com/en/).

B. Ecotones and areas of transitional fragmentation

In order to enhance areas with frequent interactions and interspecies contact, the second process consisted in modeling anthropic ecotones (Despommier, Ellis, and Wilcox 2007), in other words forest margins, with areas of transitional fragmentation, as described as "areas of intermediate level of habitat loss" in (Faust et al. 2018).
These landscape elements were processed with the Guidos toolbox (P. Vogt and Riitters 2017), a publicly available software which enables creating maps of image pattern and object attributes from a reclassified land cover. The software was used to conduct a Morphological Segmentation of binary Patterns (MSPA) (P. Soille and Vogt 2009) and a fragmentation analysis (P. Vogt and Riitters 2017).
The MSPA processing first consisted in identifying areas of interspecies contact, which correspond to forest margins; forest islet, loop and branch, bridge, perforation and edges such as described in Figure 1. Faust et al.'s (2018) methodology considered the area within 200m on each side of the forest edge. This was reflected by setting up the edge width to 5 pixels, in order to span equally on both sides of the originally 1-pixel wide forest edge.

Edge widths were set up to 5 pixels (500m on our map) to reflect

The fragmentation analysis developed in Vogt and Riitters (2017) consisted in identifying the different levels of fragmentation of an area based on spatial density of forest cover. The smallest observation window available (7x7 pixels) was used in order to get a localized assessment of the fragmentation and best reflect the creation of interspecies contact at the finest scale. The analysis was conducted on a recoded land cover layer (4 bytes) to indicate foreground,

background and non-fragmenting background pixels. This process enabled to assess the fragmentation level of the country and extract the areas with transitional levels of fragmentation (between 40 and 60%).
Both the MSPA and the FAD processing were based on the 2015 land cover layer.

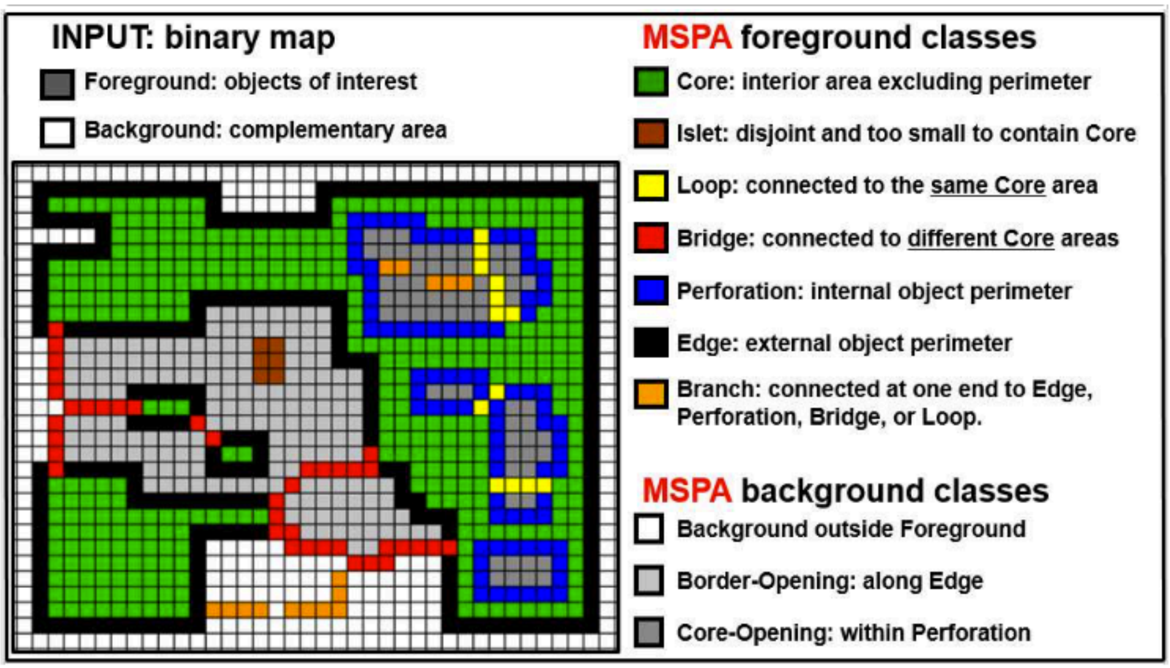

Figure 1: MSPA: Overview of the various foreground and background MSPA, extracted from Vogt (2018)

2. Areas of interfaces: hazardous areas and anthropic activities

Interface between each risk defined area (deforested or anthropic-ecotones) and anthropic activities were modelled in ArcGIS 10.3 (http://desktop.arcgis.com/en/) using zonal statistics coverage tools and raster calculations. They aimed to highlight areas that maximize interactions between deforestation or fragmentation and anthropic activities. All these analyses were conducted with the 2000-2014 deforestation areas except for the livestock data for which the 2001-2005 deforestation areas were used since the data relative to these densities were only available for 2006. Prior to the interface analyses, the proxy layers had been resampled to match the population density layer's, using the nearest neighbor technique.

3. Exposure to hazardous areas

This part consisted in realistically modelling the hazardous areas with potential spillover risk by considering time of travel through conducting a cost distance analysis and zonal statistics in ArcGIS 10.3 (http://desktop.arcgis.com/en/) and get a realistic extent of accessibility to these hazardous areas. The task consisted in three successive steps; the creation of a cost raster in AccessMod, the cost-distance analysis and the exposure.

A. Creation of a cost raster

A merged land cover comprising the land cover layer, the road network, the hydrographic network (rivers and water bodies) was created in AccessMod ver.5 (Ray and Ebener 2008, https://www.accessmod.org). The software enabled to attribute priorities between road types and the other elements of the landscape and to correct topological errors (removing artefacts). The produced merged land cover was exported in Arcmap in order to assign to each pixel value, the time needed to cross the cell, depending on the speed of travel through the different elements of the landscape.

Table 1 below describes the travel scenario that was applied to the cost raster.

The speed on major and minor arterial, primary and secondary roads were drawn from (Ouma et al. 2018). The other speeds were inspired from (World Health Organization 2013) and (World Road Transport Organisation 2018). Considering an average walking speed of 5km/h for an average adult, each landscape element was assigned a scaled down average walking speed, depending on the relative difficulty to walk through it. Waterways and permanent water bodies were considered as barriers to travelling (unless a road crosses over) and were assigned a NoData value by Accessmod in order to translate infinite costs of travel.

Table 1: Travel scenario

Element	**Speed (km/h)**	**Mode of transportation**	**Time to travel across the 92.52m cell (min)**
Road types			
Tertiary road	20	Motorized	0.2776
Major arterial	60	Motorized	0.0925
Minor arterial	60	Motorized	0.0925
Primary highway	80	Motorized	0.0694
Secondary road	70	Motorized	0.0793
Motorway	100	Motorized	0.0555
Landscape elements (from the 2015 land cover)			
Shrubs	4	Foot	1.3878
Herbaceous vegetation	5	Foot	1.1102
Cropland	4	Foot	1.3878
Urban	5	Foot	1.1102
Permanent water bodies	0	None	Infinite
Temporary water bodies	3	Foot	1.8504
Herbaceous wetland	3	Foot	1.8504

Evergreen broadleaf closed forest	2	Foot	2.7755
Deciduous broadleaf closed forest	2	Foot	2.7755
Evergreen broadleaf open forest	4	Foot	1.3878
Deciduous broadleaf open forest	4	Foot	1.3878

B. Cost distance assessment

This step consisted in conducting a cost distance analysis in ArcGIS 10.3 (http://desktop.arcgis.com/en/) on the hazardous areas, considering the cost of travelling across the landscape to the edge of the hazardous areas.
This was performed both on the deforested and the ecotone layers. The results of this analysis were two travel time maps were the value on each pixel indicates the travel time to the edge of the nearest hazardous area.

C. Population exposure assessment

This step consisted in summing (with the zonal statistics tool) the population within each class of cost distance in order to assess the proportion of the population located in, close or remotely from the hazardous areas.

4. Accessibility analysis to hospitals

The vulnerability of the population to the infectious risk was translated with an accessibility analysis to the nearest hospital facilities. It was conducted in AccessMod ver. 5 (Ray and Ebener 2008, http://accessmod.org) and consisted in assessing the accessibility of the population at risk to the hospital facilities on the whole territory. Similarly to the cost distance analysis to surface areas performed in ArcGIS (http://desktop.arcgis.com/en/) as described in the previous section, the accessibility analysis in AccessMod consisted in translating the spatial distribution of travel time across the landscape and to the nearest hospital facilities, in order to model their accessibility for the population. This AccessMod tool uses the merged land cover produced and described in the previous section, the vector points layer of hospital facilities and the travelling scenario described in Table 1. The analysis may either be anisotropic (reflects the influence of slope on travel time) or isotropic (ignores it). In this analysis, the travel time was computed over the whole territory and without considering the effect of slope in order to enable the comparison with the analysis conducted in Arcmap, which couldn't take it into account similarly.
The result of this analysis produced a raster map of the travel time to the 18 hospital facilities which was classified into 6 categories of travel time and intersected with the settlements layer to give a visual representation of their proximity to the nearest hospitals as a function of travel time.

5. Representing the level of risk through heat maps

The final step of the workflow consisted in creating an index of the infectious disease risk associated with forest habitat degradation based on the cost distance and the accessibility analyses described here before.

The values of accessibility to hospitals were inverted so that the direction of their variation would match those of the cost distance to hazardous areas maps; a decrease in the index translates into an increase of the risk.

Then, cost distance raster values and the inverted accessibility raster values were normalized according to the methodology developed by European Commission, Organisation for Economic Co-operation and Development, and SourceOECD (Online service) (2008).

$$Normalized\ index = \frac{x - x_{min}}{x - x_{max}}$$

This simple normalization enables to bring the information on the cost distance to hazardous areas and the accessibility to hospitals to a comparable range and to combine them together.

However, inverting the values of accessibility led to creating an index with very small values (almost all beneath 1) which impairs the effect of accessibility to hospitals to be reflected in the final EID risk index, when combined to the values of cost distance to hazard areas. The normalized values of accessibility were therefore multiplied by a factor of 10 in order to offset the effect induced by the inversion.

Finally, the normalized rasters were summed together and represented in a heat map classified in 5 categories of risk (with the smallest values expressing the highest EID risk) with a geometrical interval in order to appreciate small variations of risk throughout the landscape.

A final zonal statistics was carried out to sum the population in each of the risk category and appreciate the distribution of the population within these categories.

Results

1. Hazardous areas modelling

1. Deforestation

Forest loss events from 2001 to 2005 and from 2010 to 2014 can be observed in Figure 2 and 3 respectively. In the first period, the deforestation covered about 2.5% of the territory, contra 7.5% in the 2010-2014 period, which highlights an intensification of deforestation dynamics between the two periods of time. The distribution of these events enhances areas of concentrated anthropic activities in urban areas and the construction of roads between them.

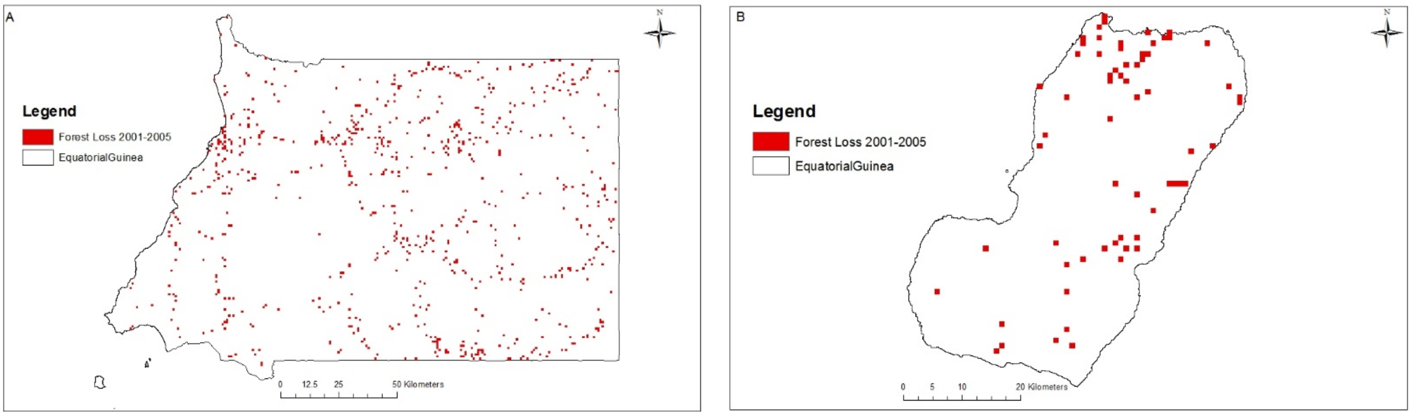

Figure 2: Forest loss events (deforestation) between 2001 and 2005, in (A) the mainland region of Equatorial Guinea, (B) in Bioko island, with a 925.18m resolution.

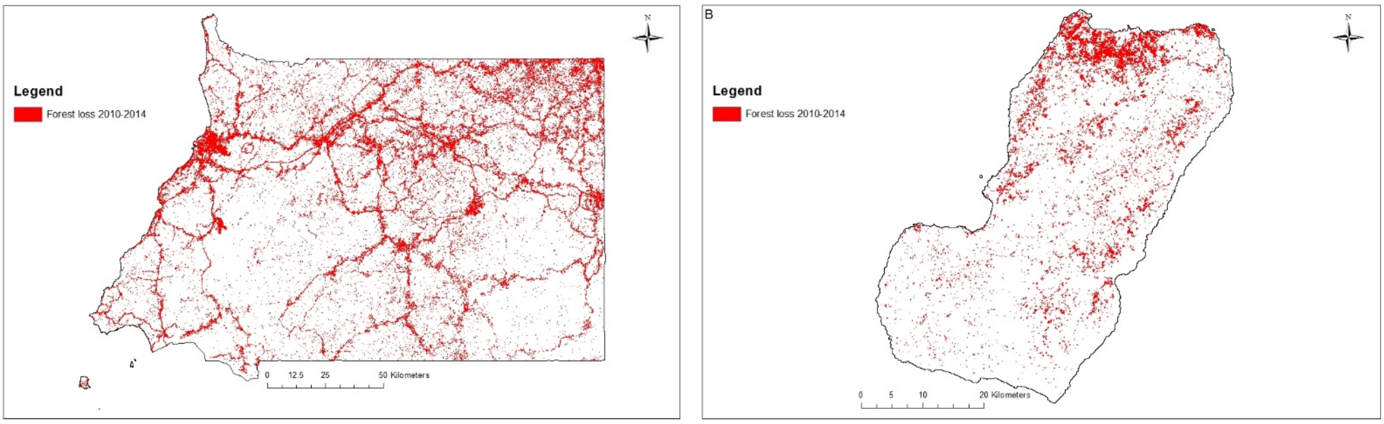

Figure 3: Map of forest loss events (deforestation) between 2010 and 2014, in (A) the mainland region of Equatorial Guinea, (B) in Bioko island, with a 92.52m resolution.

2. Ecotones

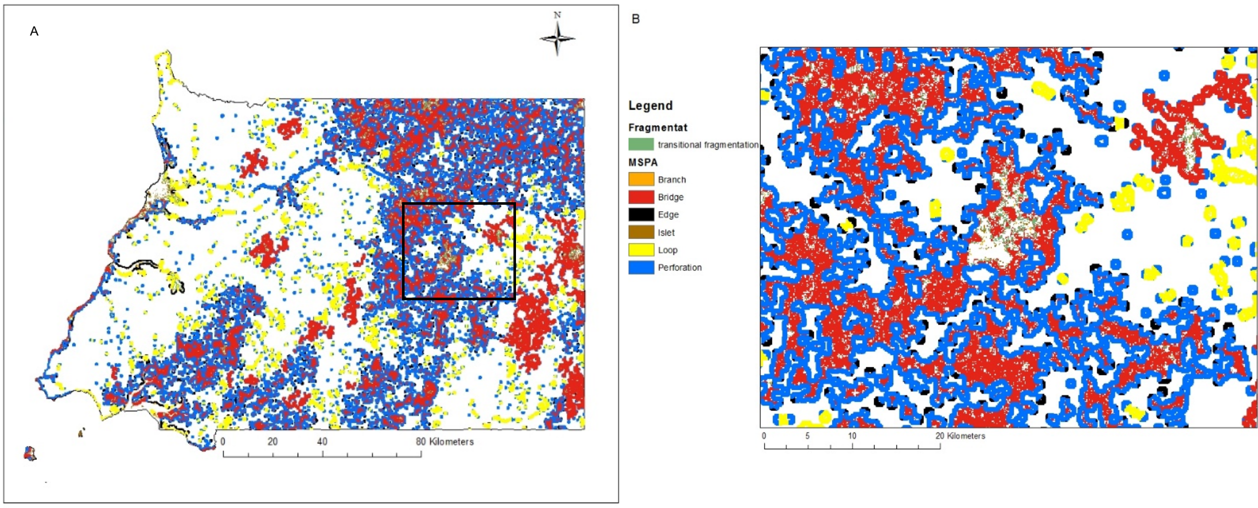

Figure 4:Mapping of ecotones, composed of transitional areas of fragmentation (between 40 and 60%) and forest margin elements identified by the MSPA analysis considering 500m forest edges, based on the 2015 land cover, in (A) Equatorial Guinea mainland, (B) the city of Djibloho, where anthropic activities are concentrated.

Figure 4 enables to visualize a possible way of modelling the areas of increased inter-species interactions. According to this model, these areas covered about 60% of the country in 2015 and were mainly represented by perforations, bridges and loops. Forest fragmentation and resulting areas of increased interspecies contact are spread out over the country, which leads to some overlaps with the deforested areas of 2010-2014. Most perforation areas and bridges are located in the Northeastern part of the country, the center and the Southwestern part.

2. Interfaces

1. Population density

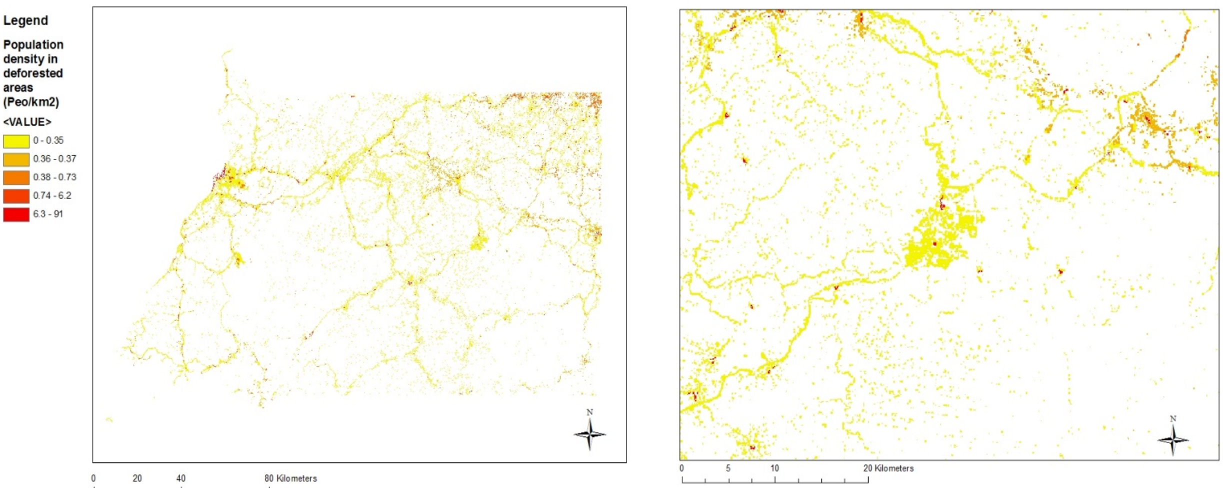

Figure 5: Population density in areas deforested between 2010 and 2014, in Equatorial Guinea mainland (left), the city of Djibloho (left).

The analyses showed that about 19.3% of the 2015 population of Equatorial Guinea was located in areas which had undergone deforestation in the previous 5 years, and 40.55% was located in ecotones in 2015. Places where the highest population densities in deforested areas can be found correspond to the cities of Bata, Evinayong, Ebebiyin, Mongomo and the capital of Malabo or their surroundings.

Within ecotones, densities are the highest in the Northeastern part of the country, close to the borders with Cameroon and Gaboon, particularly around the city of Anisoc. Areas of highest densities range from 6.3 to 91 people per square kilometer. Detailed results of this interface can be found in Appendix 2.

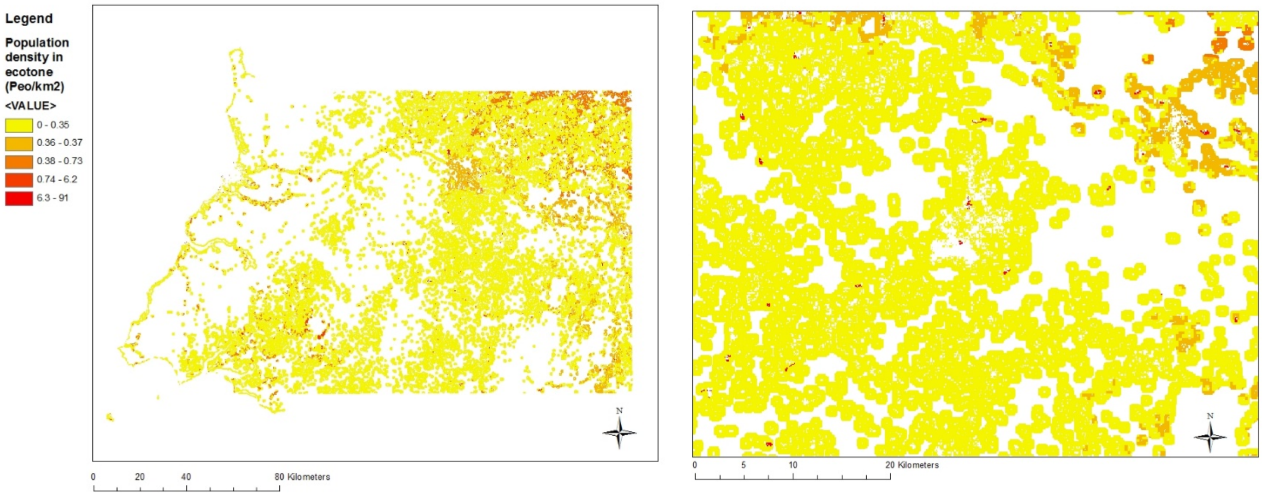

Figure 6: Population density in ecotones (2015), in Equatorial Guinea mainland (left) and in Djibloho (right)

2. Settlements

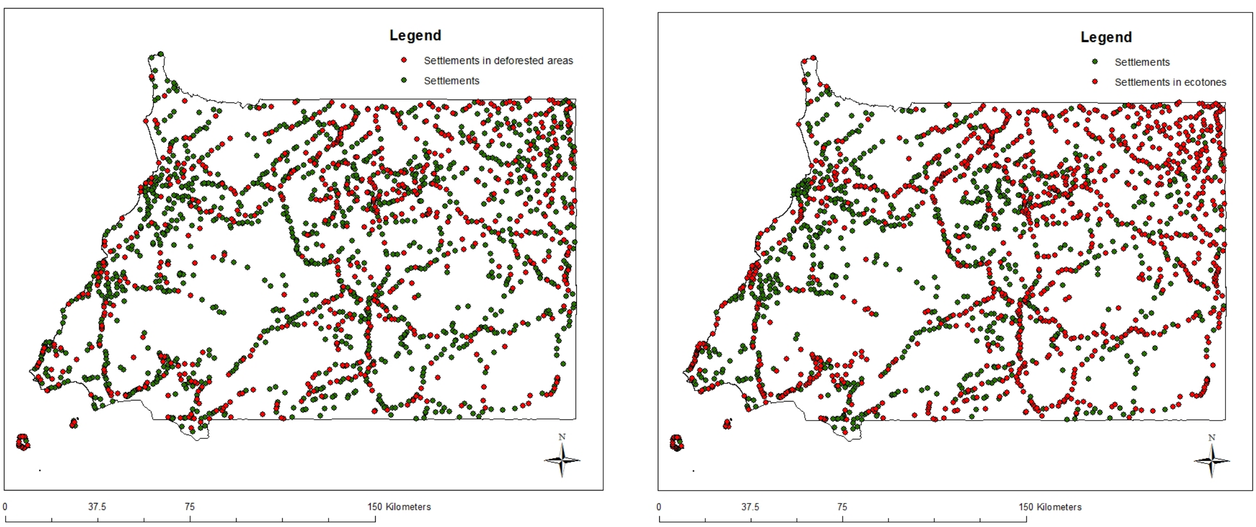

Figure 7: Settlements in mainland Equatorial Guinea (green), in areas deforested between 2010 and 2014 (red, right) and in ecotones (red, left)

The analyses conducted on the settlement layer suggested that 76.6% of the 2049 settlements were located within deforested areas and 77.25% were located in ecotones. They seem to be concentrated around urban areas and along the main roads. These high rates illustrate the phenomenon of human encroachment and dwelling in forest fringes following deforestation events. Please refer to appendix 3 for the detailed results of this interface analysis.

3. Cropland

17.9% of the 2015-cropland areas were located on lands deforested in the previous 5 years and 43.1% of these croplands were located in ecotones which emphasizes their proximity to the forest matrix and the potential for pathogen spillover, due to the creation of favorable habitats and to increased human exposure. These croplands are usually located close to areas with greater human population density. When croplands are not overlapping ecotones, they are usually circled by them. Please refer to appendix 4 for the detailed results of this interface analysis.

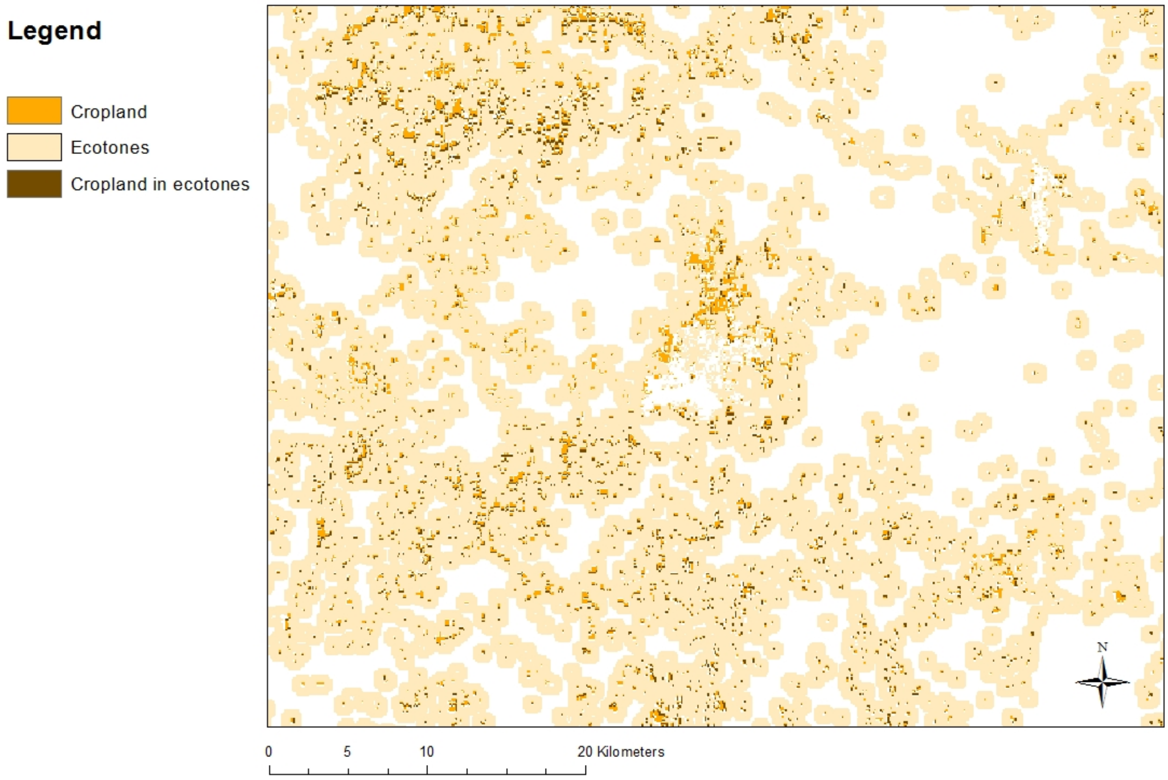

Figure 8: Zoom on cropland, ecotones and their overlap, in Djibloho city.

4. Landcover and deforested areas

Table 2: Distribution of deforestation events of 2010-2014 within the landcover categories of 2015

Landcover class	% of deforestation
shrubs	0.03
herbaceous vegetation	4.98
cropland	4.61
urban	3.38
permanent water bodies	0.01
temporary water bodies	0.01
herbaceous wetland	0.01
evergreen broadleaf closed forest	64.89
deciduous broadleaf closed forest	3.66
evergreen broadleaf open forest	14.06
deciduous broadleaf open forest	4.25
open sea	0.11

The statistics performed on the deforested areas in the different land cover classes highlight that most of these events are located on land classified as "closed forest" in the 2015 land cover, which enhance discrepancy between the two datasets used. Otherwise, this analysis enables to identify the anthropic activities that were carried out in 2015 on deforested areas, such as livestock breeding on herbaceous vegetation, agriculture on cropland and urban expansion in urban areas. Deforestation in open forests can be interpreted as exploitation of forest (timber and non-timber products) and settlements.

5. Livestock breeding

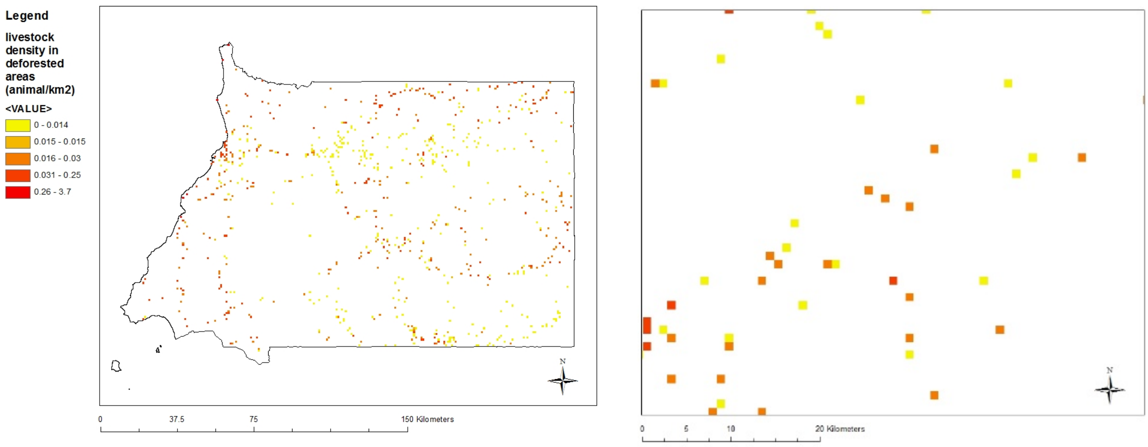

Figure 9: Livestock breeding densities (2006) in areas deforested between 2001 and 2005, mainland Equatorial Guinea (left) and Djibloho city (right).

Livestock densities are much lower in deforested areas than in ecotone areas. Whereas the highest livestock densities range between 0.26 and 3.7 animals per square kilometer in deforested areas, they reach between 28 and 170 animals per square kilometer in ecotones.

There are also less animals located in deforested areas since 52.34% of the 2006 livestock densities were located in ecotones in 2015, whereas only 1.4% of this livestock was located in areas deforested between 2001 and 2005.

The higher densities can be found along the coast, in the northern and southern part of the country. Variation in small densities displayed in Figure 9 also highlight the presence of livestock located along some of the roads. Please refer to appendix 5 for detailed figures.

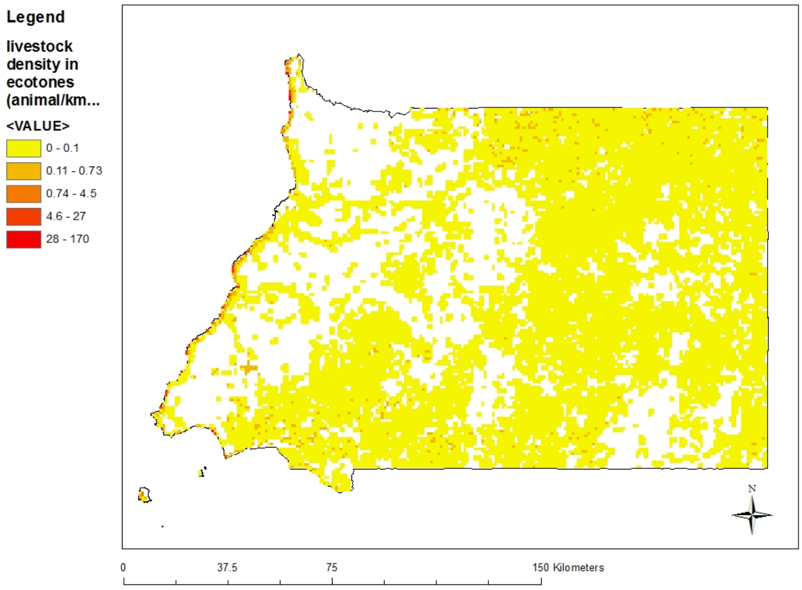

Figure 10: Livestock breeding densities (2006) in the areas considered as ecotones in 2015.

6. Logging concessions

The interface between deforestation and logging concessions was studied between 2001 and 2014, and enables to located places of potential spillover risk due to wood extraction.

The results of this analysis highlight that deforestation in Equatorial Guinea is not solely carried out in logging concessions. As a matter of fact, the analysis enabled to highlight that only a small portion of deforestation can be attributed to logging activities since it was assessed that 84.8% of the deforestation between 2001 and 2014 had been carried out outside logging concessions.

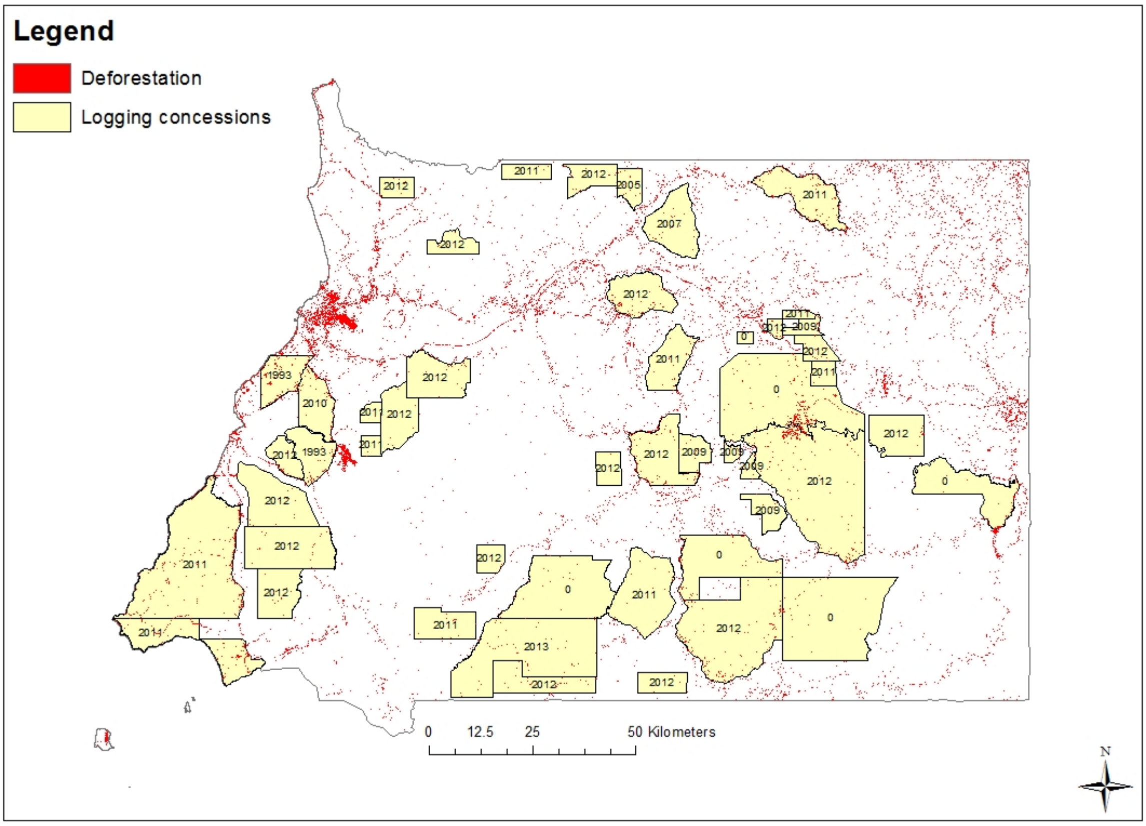

Figure 10: Deforestation events between 2001 and 2014 and location of logging concessions and the year the permit was granted. Missing permit years are indicated with a 0.

3. Exposure to hazardous areas

The cost distance analysis, based on the travel time to deforested areas and ecotones, as displayed in Figure 12 and 13, highlight that in 2015, most of the country was located within less than two hours of travel from an area deforested between 2010 and 2014 or from an ecotone. Only a very little portion of the country is remote from these deforested and fragmented areas.

Such proximity to deforested areas and ecotones result in the majority of the population being located within or very close to them (within less than an hour of travel), as displayed in Figure 13.

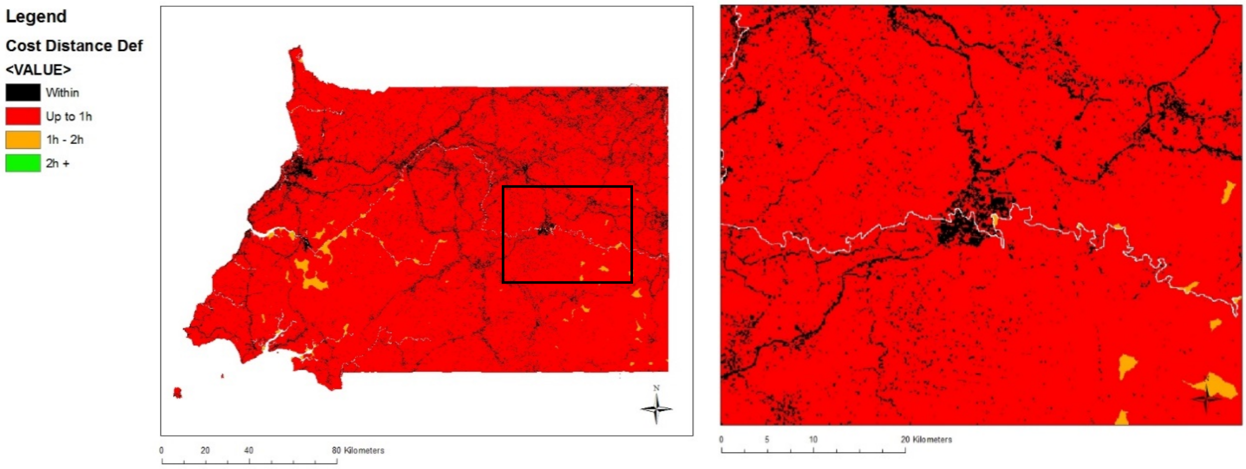

Figure 11: Cost distance map to deforested areas, mainland Equatorial Guinea (left) and zoom on Djibloho (right).

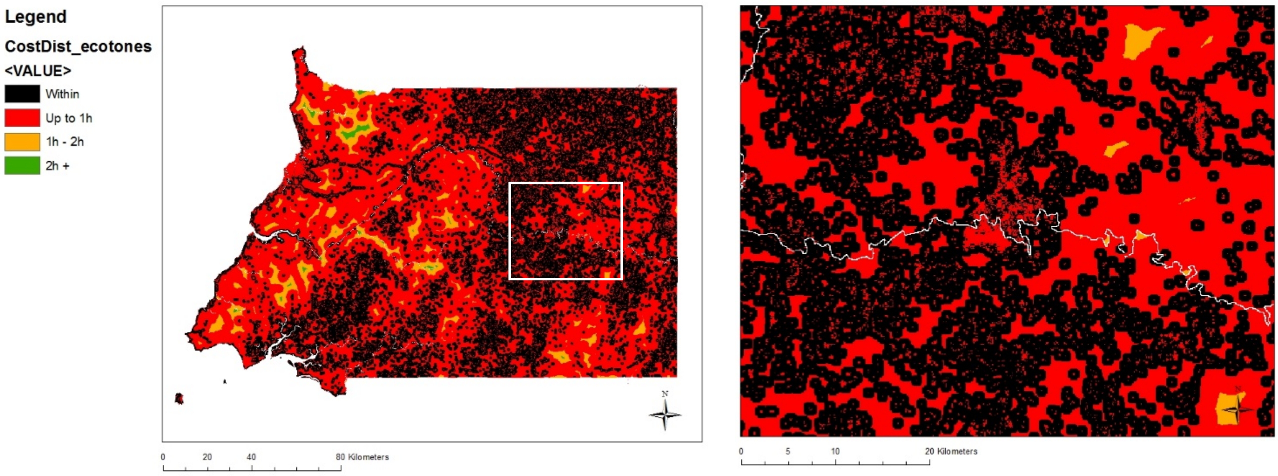

Figure 12: Cost distance map to ecotones, mainland Equatorial Guinea (left) and zoom on Djibloho (right).

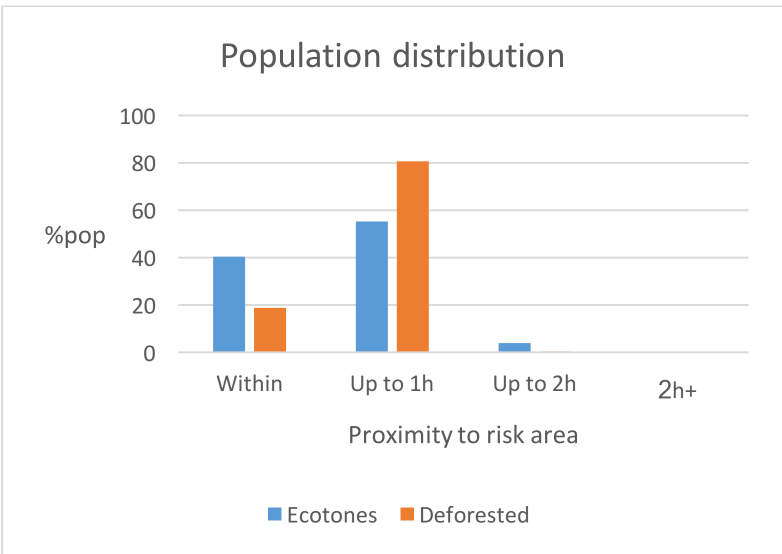

Figure 13: Distribution of the population (%) in the categories of cost-distance to ecotones and deforested areas.

4. Translating population vulnerability to infectious risk through the accessibility to hospitals

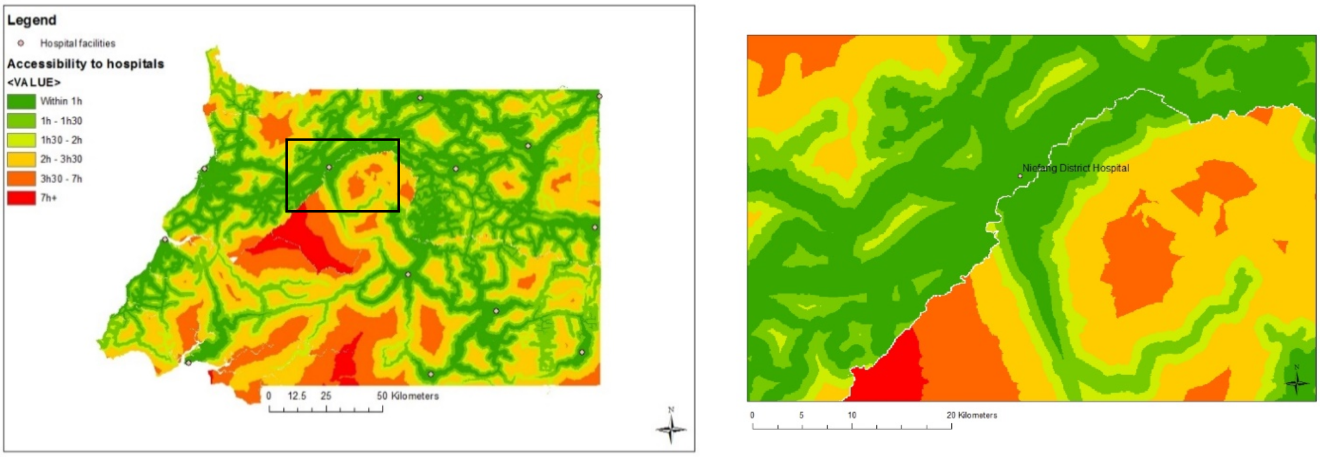

Figure 14: Accessibility to hospitals over the whole country displays a maximum travel time of 13h36 (left). Zoom on Niefang District Hospital (right).

The accessibility map in Figure 14, based on the travel time to the nearest hospital facility over the whole country enables to visualize the areas where the population would be most vulnerable to a health hazard due to limited access to health care. There are 18 facilities in Equatorial Guinea located in urban areas, usually on the main road network. Overlapping the result of this analysis on the settlements data (Figure 15) enables to visualize that a majority of these are located within one hour from the nearest hospital, but that a few of them stand very remote from health facilities and would be more vulnerable to the EID risk. These are notably located within Monte Alen National Park and in the Southern part of the country.

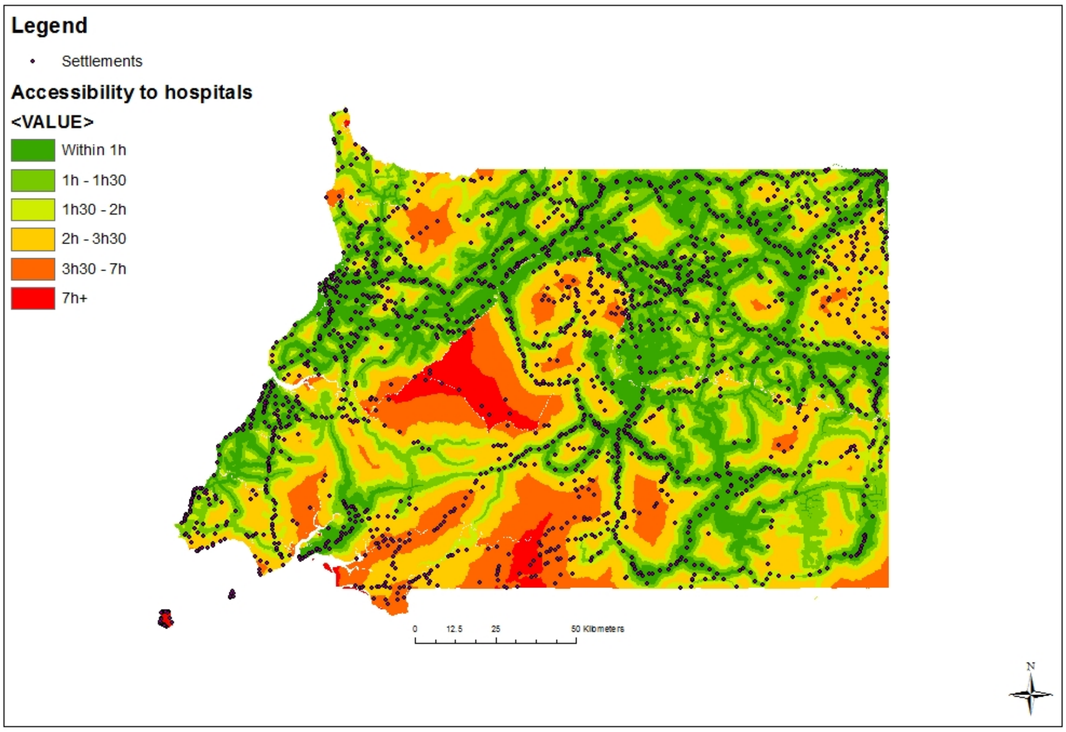

Figure 15:Overlap between accessibility to hospitals and settlements

5. Infectious risk associated to forest habitat degradation and lack of accessibility to hospital facilities.

Combining hazard information relative to deforestation and ecotones to the vulnerability analysis has enabled to locate "hotspots" of infectious risk related to forest habitat degradation. Such hotspots are defined to be located in and close to hazardous areas where the accessibility to health facilities is low. In other word, we modelled the risk associated to Emerging infectious disease (EID) as the combination of proximity to areas of greater interspecies contact due to forest habitat degradation, and the lack of accessibility to hospitals.

These heatmaps enable to combine the information of hazardous areas and their proximity with the accessibility to health facilities. The resulting maps (Figure 16 and 17) highlight (in red) the areas most at risk due to great proximity to deforested areas or ecotones and limited access to hospitals. Several areas of deforestation and ecotones are identified at greater risk associated with deforestation; the city of Djibloho for instance, as displayed in Figure 17, the Northeastern part of the country close to Cameroon, and the areas located along the motorway, and other smaller road axes.The areas associated with greater risk due to ecotone presence are especially located in the Southwestern and northeastern part on the country.

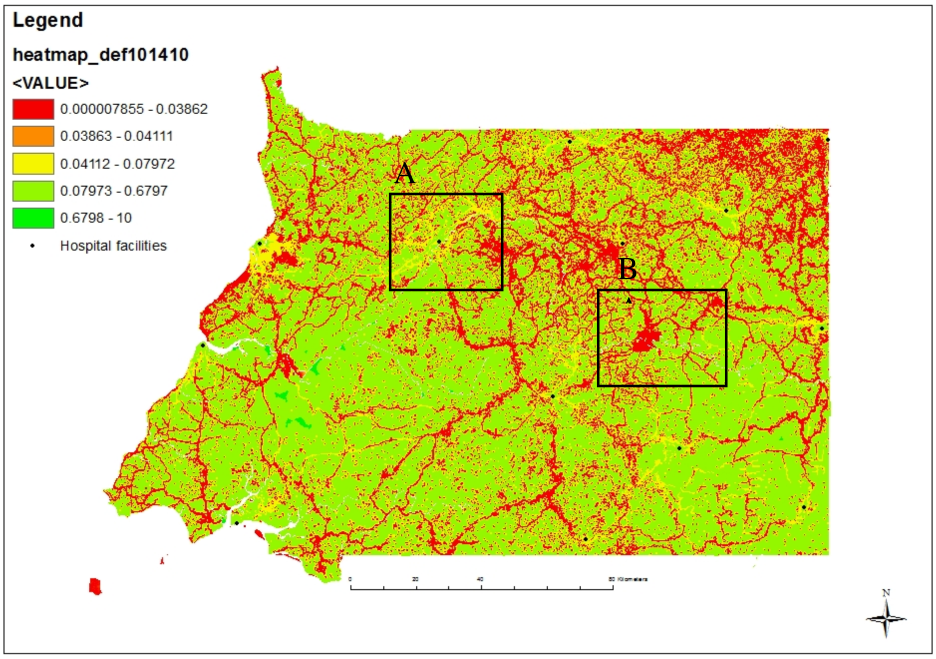

Figure 17: EID risk based on the cost distance to deforested areas and the accessibility to hospitals (factored by 10).

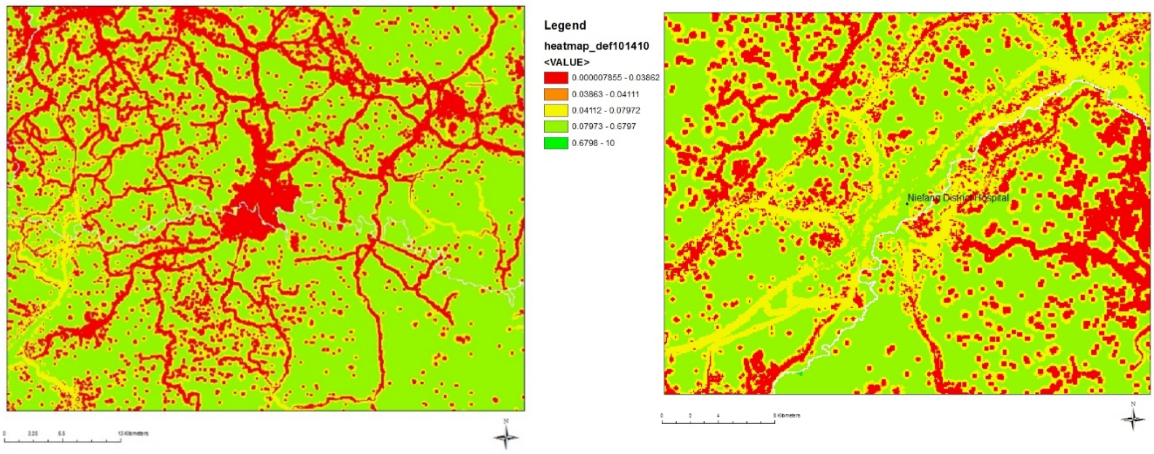

Figure 16: EID risk, zoom on Djobloho city (B, left) and Niefang city (A, right). These two maps enable to picture how the EID risk in a region close to a hazardous area is mitigated by the presence of a hospital (in Niefang).

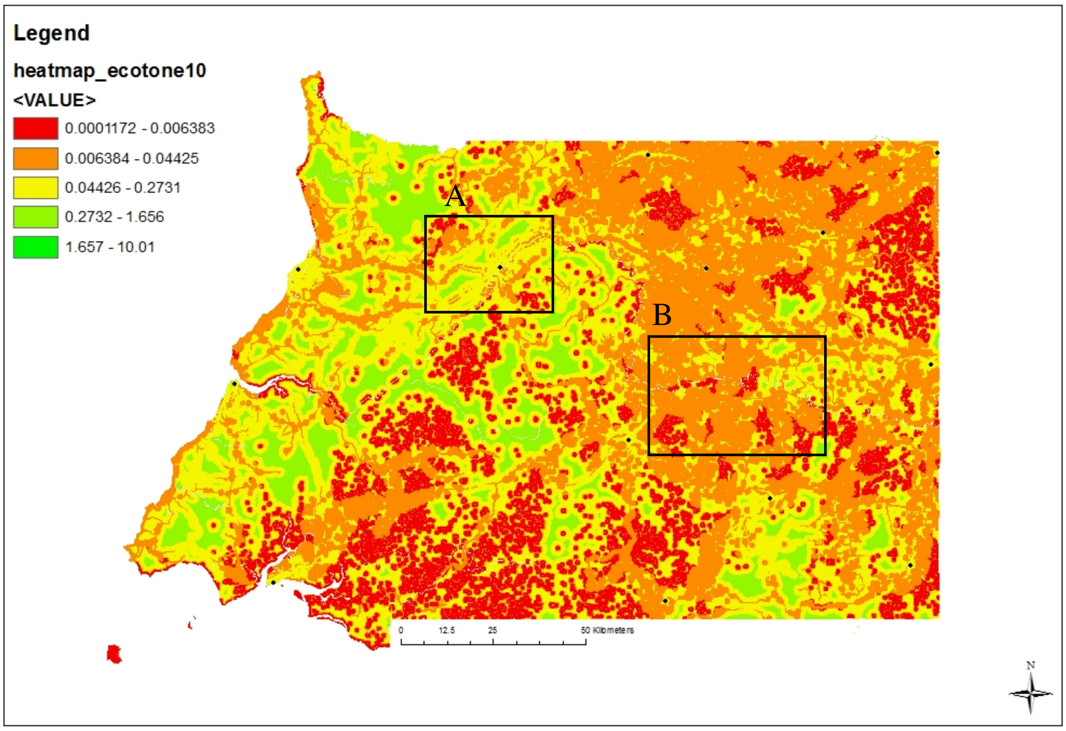

Figure 19: EID risk distribution based on the cost distance to ecotones and the accessibility to hospitals

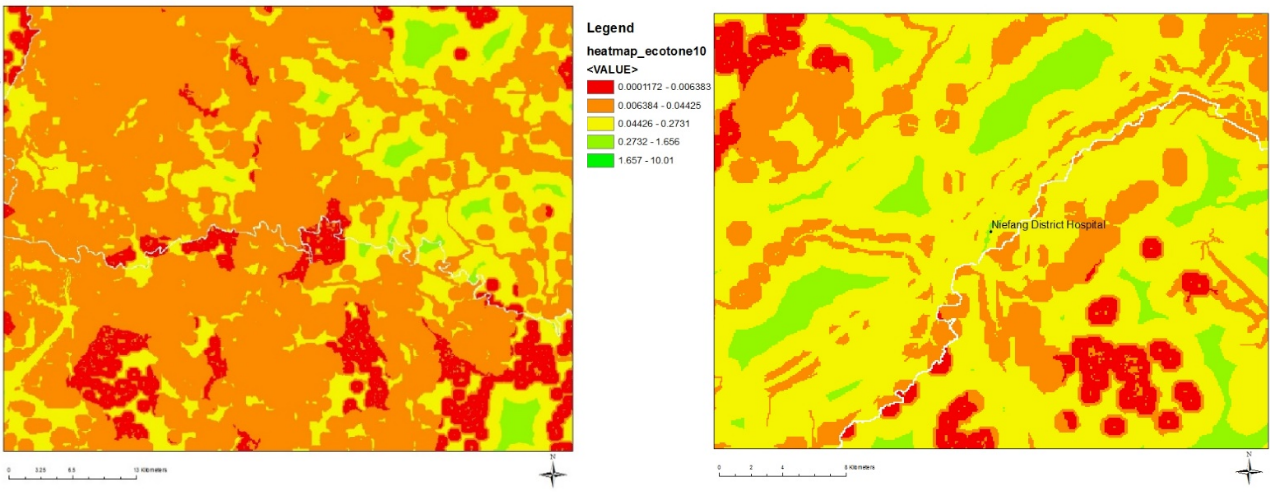

Figure 18: EID risk distribution, zoom on Djobloho city (left, B) and Niefang city (right, A).

On both maps, the presence of the Niefang hospital, surrounded by road infrastructure is a good example of the mitigation of the risk associated with the hazardous areas. The areas with the most reduced risk combine intact forest fragments and accessibility to hospital facilities and are located on the eastern part of the country. However, the map of EID risk associated with ecotones displays risk areas that stretch further than the ones associated with deforestation although the deforestation map highlight concentrated areas of very high risk. As a matter of fact, the zonal statistic sum over these different categories of risk and the population layer highlight that the areas associated with greater risk due to ecotones comprise the majority of the population (40% at least).

Summing the population density in these different categories of risk enable to assess the population exposed to the risk of infectious diseases associated to forest habitat degradation. The results highlight that about 30% of the population is located within areas with a high level of risk associated to deforestation and about 50% in areas associated to forest degradation (ecotones). They represent the most vulnerable population to the Emerging infectious disease risk as defined by this approach and could consequently be targeted by monitoring and surveillance program. Please refer to appendices 6 and 7 for detailed figures.

Discussion

1. Contribution

A. Health

Responding to Allen et al. (2014) call for the design of ambitious approaches to risk prediction, these modelling efforts strive to give a spatial illustration of the mechanisms of pathogen spillover due to land use change mainly described in Faust et al. (2018).
This cross-disciplinary research intends to draw attention on the Emerging risk of infectious diseases associated to forest habitat degradation and land use change. Such risk was modeled through the combination of hazardous areas and the accessibility to health care facilities. This model implies that this infectious risk is likely to be mitigated through improvements in health monitoring and infrastructures and/or through the conservation of forest habitat ecosystems.
While such approach is not designed to identify hotspot of emergence of specific diseases nor to demonstrate the relationship between environmental degradation and disease emergence, it nonetheless draws attention on potential areas of pathogen spillover into the population and therefore candidates for index case mapping. Identification systems of exposed areas and populations need to be improved, coupled with the improvements in surveillance and monitoring (K.M. Fornace et al. 2016), which is what this research has striven to participate to, along with supporting the implementation of adequate public health interventions to mitigate this risk. The methodology used to design these models aims to support outbreak monitoring, surveillance and the implementation of early warning systems
This research exemplifies that high resolution maps to support health monitoring can be created with open data that could be analyzed with open access software. Such granular analysis aims to support upstream measures decision making and helps to target accurate responses to potential infectious disease risks.

B. Forest management, biodiversity and health

This work is enshrined in the research momentum which strives to link ecosystem and biodiversity conservation to health issues. It is grounded in the assertion of disease emergence regulation by intact primary forests as a valuable ecosystem services (B.A. Wilcox and Ellis 2006).

Such advances in research are supported by the momentum for sustainable forest management in Equatorial Guinea (Martin et al. 2013) and commitments to the international initiative for Reducing Emissions from Deforestation and Forest Degradation (REDD+) commitments (Central African Forest Initiative n.d.).

2. Methodology and findings relevance

A. Modelling hazardous areas

Considering the limited understanding stated out by Murray and Daszak (2013) on epidemiological factors of emergence of infectious diseases related to land use change and the complex mechanisms that link them, hazardous areas were modelled in two different ways and then analyzed separately in order to best reflect the spectrum of environmental conditions of forest habitat degradation which can be associated to infectious disease emergence, pointed out by recent epidemiological research (Faust et al. 2018; Despommier, Ellis, and Wilcox 2007; B.A. Wilcox and Ellis 2006; N.L. Gottdenker et al. 2014).

While deforestation mapping highlights specific, more localized areas likely to create favorable conditions for pathogen adaptation and transmission, ecotone modelling displays areas of interspecies contact that are more spread out on the territory.

While deforestation mapping intends to model and point out areas of concentrated forest disturbance and removal, ecotones displays areas of interaction between the remaining fragments or forest core and the anthropic matrix.

A study on the factors of emergence for a specific disease is likely to filter these areas according to the type of forest cover (J. Olivero et al. 2017), to the forest patch size (Chaves et al. 2018), tree crown cover density over time (K.M. Fornace et al. 2016) for instance.

B. Areas of interface

Modelling areas of interface between hazardous areas and different anthropic activities enables to understand what the activities undertaken in hazardous areas that can potentially increase human exposure to infectious risks are and where they are located. They allow to point out hotspots of greater exposure where surveillance should be targeted.

Urban expansion and settlements in recently deforested areas should especially be subject to increased monitoring, as a significant part of the population is located within areas which have undergone forest clearance and areas of increased interspecies contact. The mapping of the settlements located in hazardous areas can support decision making for the implementation of monitoring sites.

In Equatorial Guinea, agriculture is one of the activities which greatly contribute to increased exposure to pathogens and was modelled through cropland. The results suggested that in Equatorial Guinea, agriculture is particularly exposed activity to the infectious risk especially due to overlap and proximity with hazardous areas. On the other hand, interactions of forest habitat loss and livestock breeding interactions seem less interrelated in Equatorial Guinea at the time of the study, than in countries of South Eastern Asia such as Malaysia for instance (Chua 2003). As a matter of fact, results showed that only a fraction of the 2006 livestock densities were located in previously deforested areas and that these densities were rather low.

However, these results are likely to differ in another period of time and should be compared against an analysis of more recent data. To support this hypothesis, results show that about half of the 2006 livestock were located in areas considered as ecotone in 2015. Assuming that livestock farming has remained in the same areas as in 2006, and has expanded, these are located in hazardous areas and should receive increased attention and surveillance.

In terms of methodological limitations, the interface analysis between the land cover classes and the deforestation events has highlighted a discrepancy in the forest cover assessment between the two datasets since most forest loss events were located within closed forest pixels. This could be explained by the different primary resolutions of the datasets used (about 30m for the gross forest loss datasets and 100m for the land cover), with pixels in the land cover data set not capturing finer grain deforestation.

These analyses were limited by data availability and could be completed by including other factors pointed by epidemiological studies such as mammal biodiversity (Allen et al. 2017), extractive industries (Allen et al. 2014), bush meat hunting (Wolfe N et al. 2000), or irrigation activities (N.L. Gottdenker et al. 2014). Moreover, the logging extraction data only gave a general idea of the areas were wood extraction could be carried out but there are no open data available to identify the impacts associated to logging extraction. Moreover, the inclusion of more recent and finer scale data on livestock breeding would also contribute to completing the model. Environmental and climatic variables such as included by (E.N. Vianna et al. 2017; D. Valle and Tucker Lima 2014) could contribute to refining these analyses.

C. Exposure to hazardous areas

Whereas a classic approach to modelling accessibility would be based on assessing the distance to deforested areas and ecotones, the analyses conducted in this research have used travel time based on different transportation means as the proxy for accessibility. As the country's road infrastructures develop, the scenario used can be adapted to reflect the new conditions of travelling.

Almost the whole country is located within 1 hour of travel to deforested areas and ecotones which can be explained both by the large area covered by deforestation and ecotones and by the small surface area of the country. Moreover, deforestation patches are often located on or along the main arterial roads. Comparing the analysis of the cost distance maps against population density demonstrates that most of the population is located within 1 hour of travel from deforested areas or ecotones, and that at least 40% of the population could be subject to increased monitoring and attention for being located within the hazardous areas.

Such mapping highlights the extent to which the population of a country can be impacted by forest habitat degradation. Although deforestation is concentrated in specific areas of the country, the surface of the country and the road infrastructure network result in a great exposure of the population to hazardous areas.

D. Accessibility to hospitals

Infectious disease risk is intertwined and likely to be exacerbated by economic and social factors such as the access to adequate public health infrastructures (B.A. Wilcox and Ellis

2006). In this regard, the approach developed in this research has taken into consideration the accessibility to medical infrastructure as a component of the infectious risk associated with forest degradation. The accessibility analysis has therefore enabled to identify areas where the transmission and the spread of infectious diseases in remote settlements would be difficult to monitor first of all and costly to cure secondly.

Another way to model the population's vulnerability could therefore be based on population densities, access to sanitation, or an in depth analysis of one of the interfaces studied in the first section.

E. Heat maps and the risk of infectious Emerging disease associated to forest habitat degradation

Comparing the exposure to hazardous areas against the accessibility to hospitals has enabled to point out areas where the population would encounter a greater risk of infectious disease emergence and outbreaks. The produced heat maps give a broad idea of potential hotspots for Emerging infectious risk associated to forest habitat degradation and enable to identify vulnerable areas where new infrastructures should be implemented or where existing ones could become monitoring centers. The highlighted vulnerable areas constitute good candidates for increased surveillance.

These maps also highlight the areas that could benefit from the construction of new infrastructures, such as in the Southern and the Northwestern parts of the country. Moreover, it enhances that some existing facilities such as Anisok District hospital, could become monitoring centers due to their proximity to both types of hazardous areas, to their good accessibility for the surrounding area, and for being located in high risk areas. This could also be the case of Nsoc Nsomo District hospital.

These results could also be interpreted through thresholds of risk defined accordingly to the epidemiological specificities of different diseases and these analyzes should also be refined considering environmental and epidemiological factors more accurately, depending on each specific infectious disease. Moreover, these results should be filtered according to the capacity of the facilities to diagnose and treat Emerging Infectious Diseases.

Computing the population located in the areas considered at highest risk enables to emphasize the need to develop appropriate measures to monitor the potential infectious risk, since a significant portion of the population seems to be affected.

The index developed by this approach was intended to associate the data of hazardous areas with the data of accessibility in the simplest manner as possible. Ultimately, the created heat maps highlight that a significant portion of the population is located in regions very vulnerable to infectious risk associated to land use change and which also are poorest in terms of heath infrastructures. The mapping of risk areas also highlights how road infrastructures that imply greater and easier mobility across the territory, also contribute to increased infectious risk associated to forest habitat degradation. Such heat maps could be more nuanced if created for territories with more heterogeneous results of cost distance analysis to hazardous areas.

The final result obtained with this methodology is intended to be very general and simple. It could be complexified by including and weighting other factors of exacerbation of the

infectious disease risk such as the increase in population densities, the access to potable water and sanitation (B.A. Wilcox and Ellis 2006).
However, as the methodology showed, the inversion of the accessibility data has led to creating an index of values too small to be directly compared against the values of hazardous areas. The factor 10 by which the accessibility values were consequently multiplied has led to the creation of an index with an extreme value of 10. Improvement of this methodology should focus on finding a way to combine both information without having to weigh them and should perhaps extract outliers from the analysis.

3. The way forward

Little research has been made on the epidemiological context of Equatorial Guinea associated to anthropic environmental change and the drivers of disease emergence linked to them, this research therefore aims to constitute a stepping stone for future studies on the subject in this area. The methodology developed in the course of this research aimed at producing general results to locate areas with greater potential risk associated to forest habitat degradation and could be replicated on countries or regions with larger surface areas. Possible improvements include adapting it to a specific disease and including the factors of emergence accordingly. Moreover, existing epidemiological studies on the factors of emergence of specific Emerging infectious diseases such as conducted in (Chaves et al. 2018; K.M. Fornace et al. 2016; T.L. Goldberg 2008; J. Olivero et al. 2017; O. Pernet et al. 2014; M. Rulli et al. 2017; D. Valle and Tucker Lima 2014; E.N. Vianna et al. 2017; A.Y. Vittor et al. 2009) for instance, could be completed with an accessibility analysis to hospital facilities by using the same approach.
The robustness of the methodology developed in this research could be tested against by comparing the identification of hotspots of specific Emerging infectious diseases with the hotspots highlighted in the results of this research.
The model's sensitivity should be tested by comparing the final results after having increased or decreased the travel times (Table 1) through the different elements of the landscape. Such approach implies that any change in the road and bridge infrastructures will affect the accessibility results and should therefore be reflected.

Finally, both the cost distance and the accessibility analyses were isotropic. This limitation should be overcome to produce more accurate results, especially in countries with great elevation differences that would significantly influence the distribution of travel time.

Conclusion

This research has built on existing literature on the mechanisms of infectious disease emergence associated to tropical forest degradation in order to model the areas of Equatorial Guinea associated with this potential risk and the population exposed to it. Mapping this risk has consisted in modelling areas of potential interspecies contact through two different approaches (deforestation and ecotones) and to assess the cost distance to these areas based on the time to travel to their edges, which represented the hazard of Emerging infectious diseases. The vulnerability was assessed through an accessibility analysis to the nearest hospital facilities over the whole Guinea Equatorial territory. Other results include the interfaces between hazardous

areas and anthropic activities, where interspecies contact is likely to be maximized, and assessment of the population densities in the hazardous and the risk areas.
The result of this analysis point to areas where the population could be exposed to a risk of infectious Emerging disease and provide a basis for decision making with respect to monitoring and surveillance that can support and complement specific epidemiological studies.

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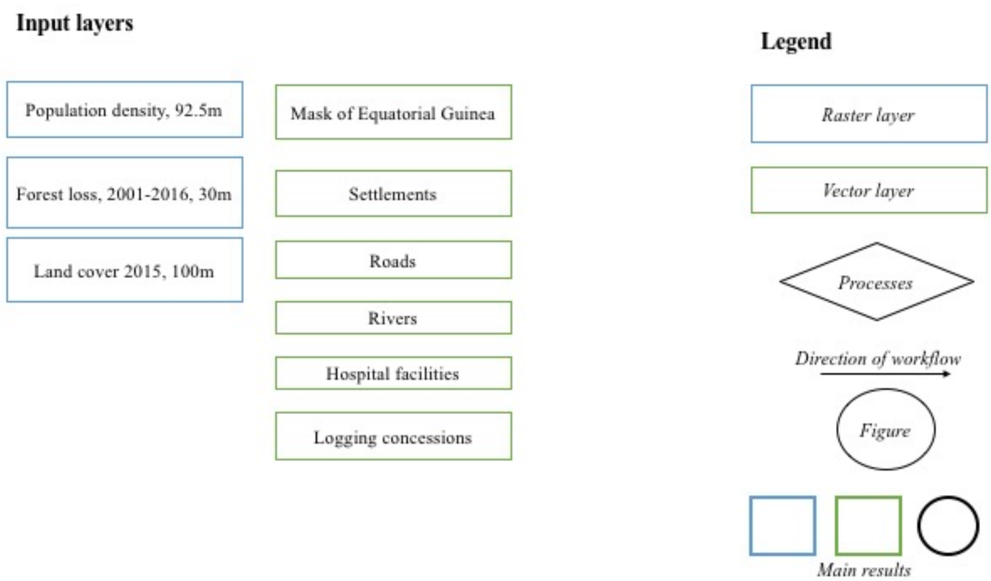
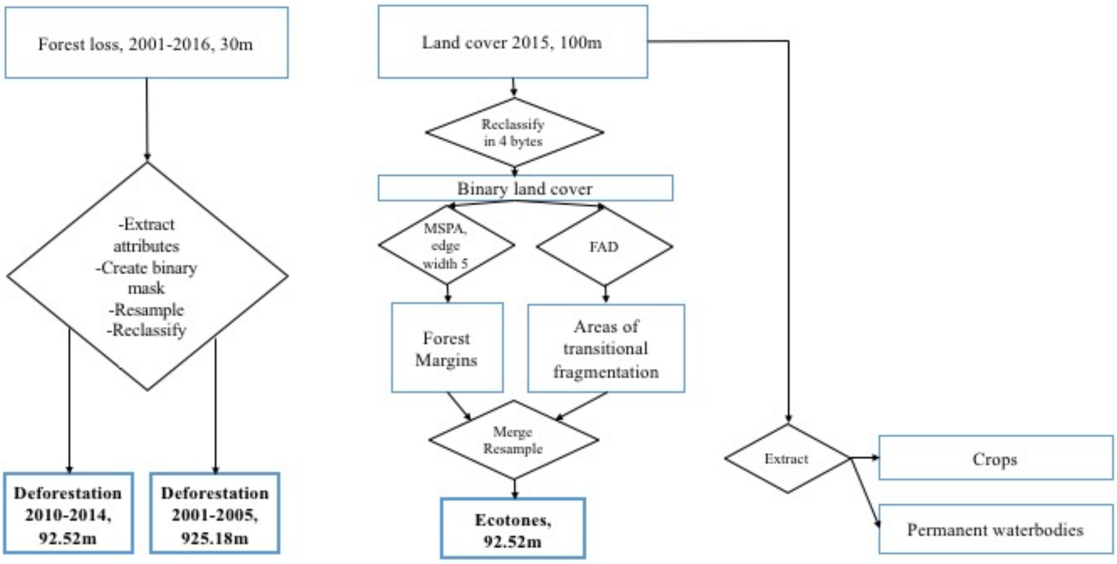
Appendices

1. Appendix 1: Processes workflow

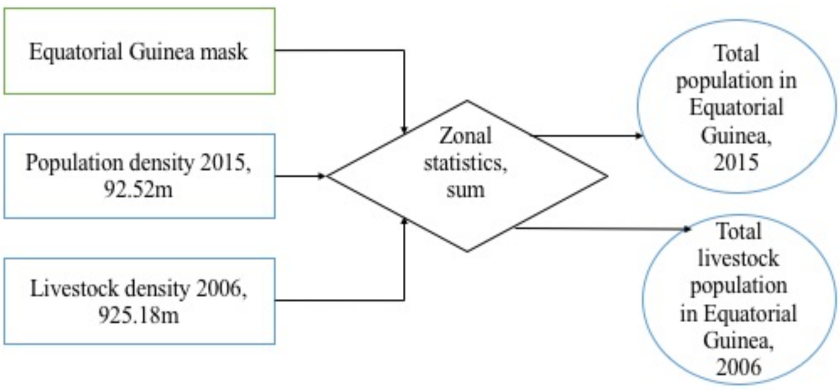
All analyses were processed in ArcGIS (http://desktop.arcgis.com/en/), unless if indicated otherwise (AccessMod ver.5, https://www.accessmod.org).



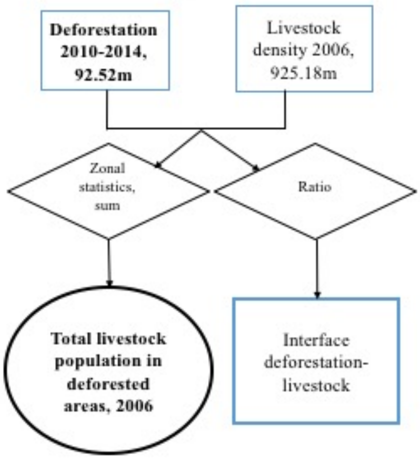
Input preparation (1)



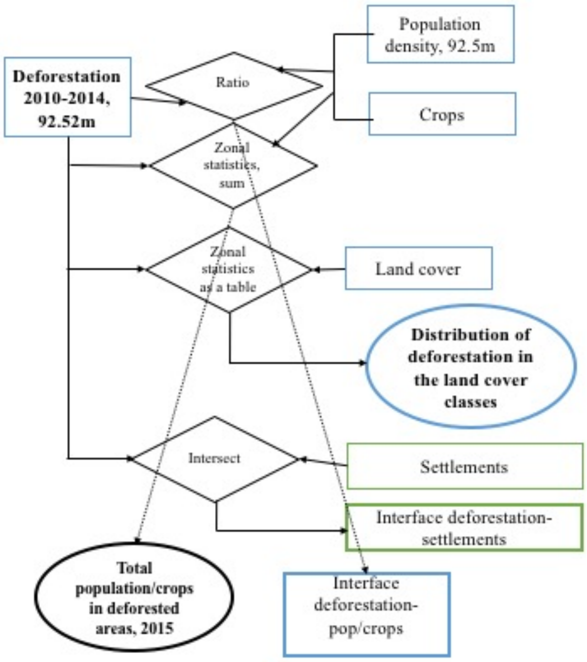
Input preparation (2)



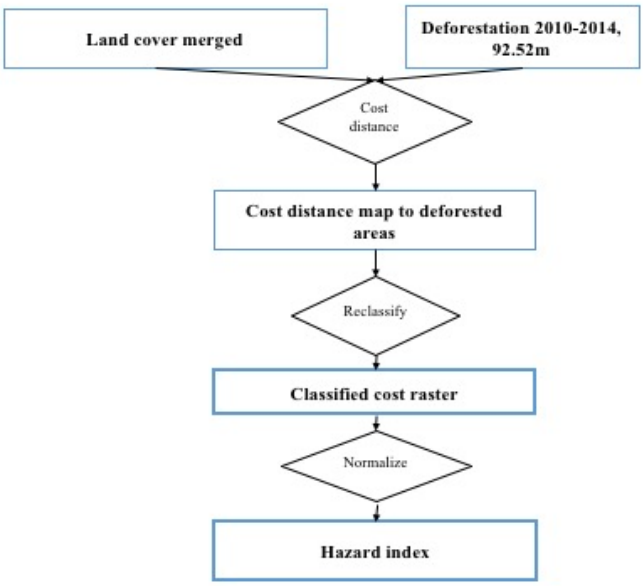
Interface analyses



Same processes with the ecotone layer

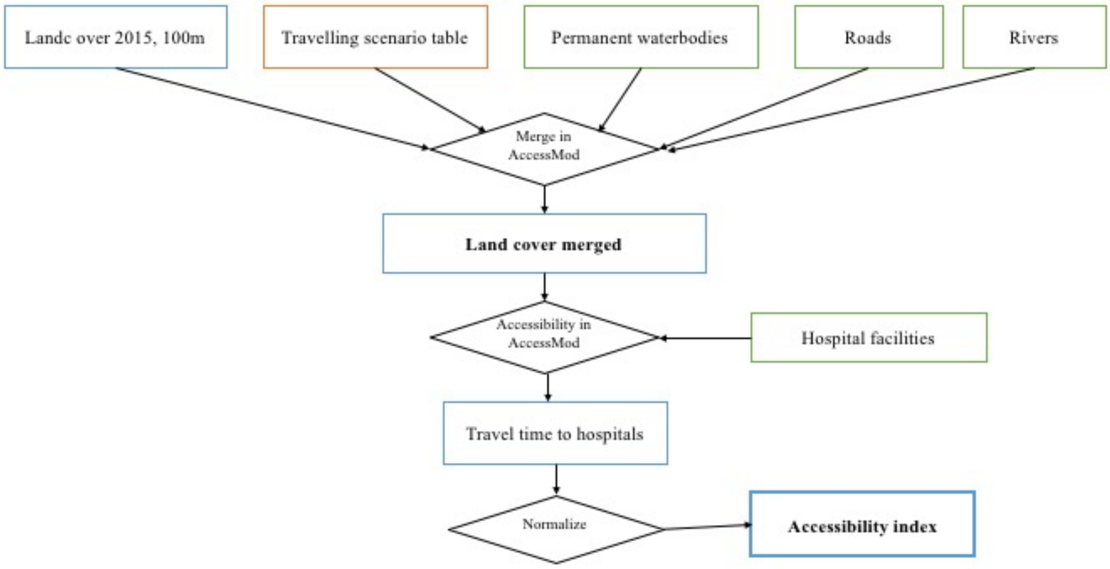


Cost distance analysis to hazardous areas

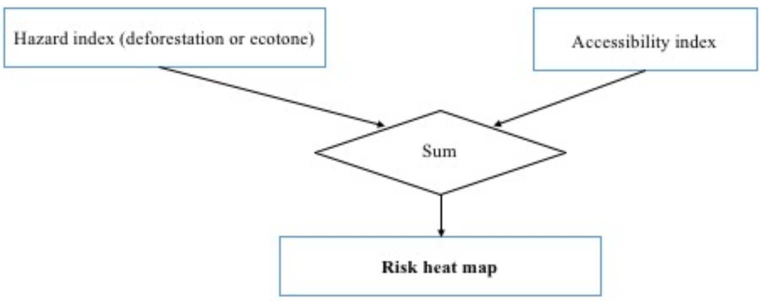


Same processes with the ecotone layer

Cost distance analysis to hospitals



Risk modelling



2. Appendix 2: Interface between hazardous areas and the population distribution

Layer	Summed population	%
Equatorial Guinea	769’142	100
Deforestation (2010-14)	148’581	19.32
Ecotones	322’935	40.5

3. Appendix 3: Interface between hazardous areas and settlements

Layer	Summed population	%
Equatorial Guinea	2049	100
Deforestation (2010-14)	1569	76.57
Ecotones	1583	77.25

4. Appendix 4: Interface between hazardous areas and cropland

Layer	Summed population	%
Equatorial Guinea	2’419’040	100
Deforestation (2010-14)	432’360	17.87
Ecotones	1’042’288	43.09

5. Appendix 5: Interface between hazardous areas and livestock

Layer	Summed population	%
Equatorial Guinea	3967.4	100
Deforestation (2010-14)	55.7308	1.4
Ecotones	2076.67	52.34

6. Appendix 6: Distribution of the population in risk areas associated to deforestation

Risk category	Index Range	% of pop in deforested
1 (highest)	0.000007855 - 0.03862	29.41
2	0.03863 - 0.04111	1.83
3	0.04112 - 0.07972	28.61
4	0.07973 - 0.6797	39.90
5 (lowest)	0.6798 - 10	0.25

7. Appendix 7: Distribution of the population in risk areas associated to ecotones

Risk category	**Index range**	**% of pop in ecotones**
1 (highest)	0.0001172 - 0.006383	10.45
2	0.006384 - 0.04425	39.53
3	0.04426 - 0.2731	41.51
4	0.2732 - 1.656	8.48
5 (lowest)	1.657 - 10.01	0.04