Examining the Links between GEF Interventions and an International Pandemic

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I. Introduction & Summary

This synthesis report seeks to explore the research question: *in what ways do GEF operations impact and are impacted by conditions related to an international pandemic?* Recognizing the complexity of this question, rather than seek to answer this question in its entirety, we present a number of case studies and analyses on unstudied or understudied aspects of this relationship. Our findings suggest that:

1. Literature & Past Lessons

    a. Zoonotic disease transmission is exacerbated by human encroachment on natural ecosystems for natural resources. Human economic growth and the over-consumption of resources exploit the human-nature nexus through deforestation practices, land degradation, and depletion of wildlife species.

    b. Deforestation, land degradation, and the exploitation of wildlife species in fresh markets create unnatural conditions for animalistic pathogens to mutate, combine genetic material, and infect humans. Preventative measures are crucial in mitigating public health threats and decreasing the probability of increased emerging infectious diseases.

    c. Through a One-Health approach, it is recommended that regulations on wildlife markets are adopted. By protecting environmental health, the main drivers of zoonotic pathogen transmission will be limited, effectively protecting public health.

2. Satellite Evidence

    a. Within the DRC, vegetation as detected by satellite largely followed similar trends during the COVID pandemic as contrasted to historic trends. No reversal was observed during the pandemic in areas funded by GEF projects.

    b. One exception was identified in the Virunga National Park, in which a larger-than-expected increase in vegetation occurred in the southern region near the onset of the pandemic in late 2019 and early 2020.

3. Controlled Analysis of the Impact of GEF Projects on Health-related Outcomes

    a. We find that improving environmental and socio-economic co-benefits of GEF project implementation may be associated with improved health outcomes.

    b. GEF projects were associated with a 17% reduction in the prevalence of coughs within 10 km of intervention areas, and a 9% reduction in the prevalence of diarrhea.

    c. GEF interventions also demonstrated positive impacts on water accessibility, including the access to source water in dwelling and the presence of water at hand-washing facilities.

    d. All findings were stronger for household clusters closer to GEF interventions.

II. Literature & Past Lessons

Topic	**Key Findings in the Literature**	**Key Recommendations for the GEF**
Relationship between environmental interventions and zoonotic diseases	Human expansion into uninhabited environments drives pathogen reservoirs out of their evolutionary niches and into proximal locations with humans (Oakes, Olson, and Watson 2020). Therefore, Zoonotic disease transmission is exacerbated by human encroachment on natural ecosystems for natural resources (Davidson 2020).	**Adaptation:** GEF Projects designed to mitigate encroachment into natural areas can have health co-benefits by reducing the likelihood of zoonotic disease transmission. Considering these criteria during initial targeting or siting planning could improve these outcomes. **Communication with Partner Agencies:** Ensuring adequate coverage of as many rural communities as possible by cooperating with other agencies would allow all at risk areas to be addressed.
Economic reliance on wildlife industries	Many individuals rely on wet markets for income, food, as well as traditional pharmacological practices (Bridgeman and Lingel 2020). Human economic growth and the over-consumption of resources exploit the human-nature nexus, which causes increasing opportunities for pathogen reservoirs to infect human populations (cf. Beaubien 2020; Maron 2020; Center for Biological Diversity n.d).	**Multi-sectoral approach:** GEF projects that utilize a global, multi-sectoral approach to regulations would effectively address risks across wildlife trade across various industries. **Assessing demand:** Considering the human reliance on wildlife industries, wet market regulatory practices could effectively limit hazardous conditions and black markets.
Sustainable intervention mechanisms	Successful control of zoonotic disease outbreaks requires strong policy implementation framework, well functioning and communicative institutions, research and development, adequate financing, political advocacy, and collaboration across multiple sectors (cf Bhatia 2019; Gorman 2013; United Nations Environment Programme 2020; Pattanayak et al. 2010).	**Supporting capacity:** Future GEF projects with expected socioeconomic or health benefits can measure how their projects strengthen the capacity of at-risk areas to respond to public health crises. Considering finance, cost-and-benefit analyses, as well as implementation framework in project development would shift the dynamics of public health threats. **Long-term investment:** Investing in sustainable environmental technologies, such as intensive agriculture, may be a productive strategy for limiting the consumption of natural resources and the proximity of human populations to zoonoses.

II-A. Introduction

The 21st century has seen an increasing number of virulent outbreaks classified as either epidemics or pandemics. The first pandemic was a strain of coronavirus lasting from 2003 to 2004 originating in the Guangdong Province in China named SARS (SARS-CoV) (Centers for Disease Control and Prevention 2017a). This trend of viral outbreaks continued with Ebola virus in Guinea (2014-2016) and COVID-19 emerging in Wuhan, Hubei Province, China (2019-) (Centers for Disease Control and Prevention 2017b). The common trait among these viral pathogens is that they are all classified as zoonotic, or diseases originating naturally in animals and transmitted to human populations (Center for Disease Control 2017b). The emergence of these events of highly pathogenic diseases highlighted the threat posed by animal populations to humans as well as the relationship between humans and the global environment.

This study aims to examine current medical, epidemiological, and ecological studies on the transmission of infectious zoonotic diseases, specifically data and research on genetic mutations in animal pathogens as a result of human consumption of natural resources. This study offers a comprehensive review of literature on the SARS (2003), Ebola Virus (2014-2016), and the on-going SARS-CoV-2 (2019-) outbreaks to examine how human encroachment on natural resources, such as deforestation and the destruction of ecological biodiversity directly contributes to the widespread transmission of infectious diseases. These sources were used to provide a comprehensive article of all available literature on the subject of zoonotic diseases and the human-nature nexus.

This systematic review explicitly aims to answer the following questions:

1) What is the extent of the Human-Nature nexus and its impact on the spread of zoonotic diseases?

2) What are recommended policies for environmental protection and intervention mechanisms regarding zoonosis?

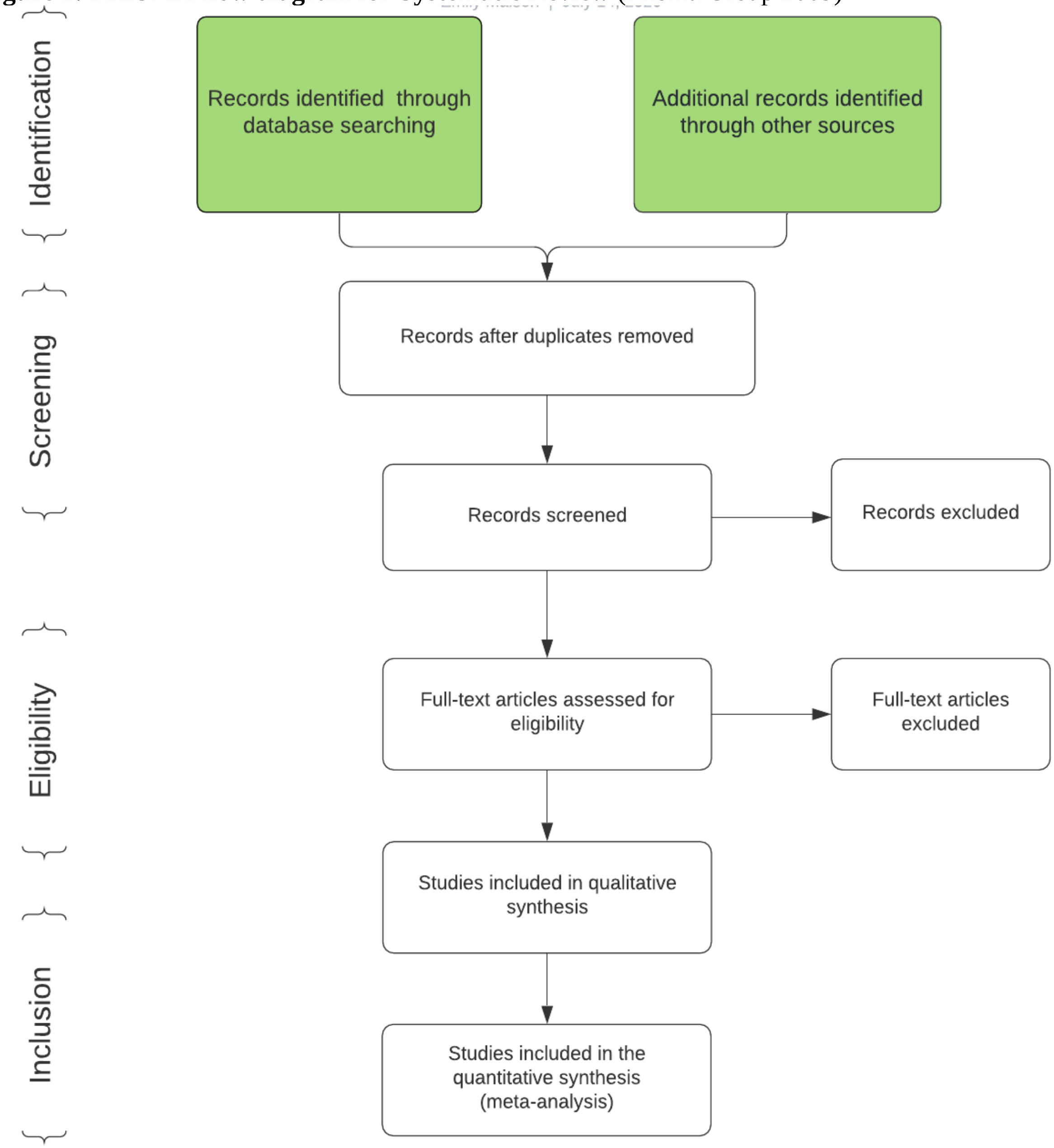
3) Is there any connection between environmental intervention mechanisms and healthcare outcomes?

II-B. Methodology

Research for relevant literature regarding the systematic review of zoonotic disease transmission was first narrowed down to specific disease outbreaks. The SARS, Ebola, and COVID-19 outbreaks were identified as virulent outbreaks during the 21st century that left devastating effects and were considered to originate from animal reservoirs. Using scientific databases, simple google searches, and google scholar, searches were completed using keywords such as “SARS”, “Ebola”, “COVID-19”, “Zoonotic Transmission”, “Zoonotic Transmission”, and so on. Global health websites were first consulted as primary literature on outbreak information, then later searches were made to fill in questions that arose from the available information. In later searches, literature was identified with information regarding origination, epidemiology, and transmission of the above diseases. Comparing the zoonotic origins of the three outbreaks, further research was conducted on transmission and human exacerbation of transmission. Available studies, policy briefs, scientific studies, geospatial and healthcare data, and news articles were aggregated and analyzed for pertinence to the study.

Inclusion and exclusion criteria were developed to narrow down the field of research and the sources included in the systematic review (Prisma Group 2009). Sources identified must relate to zoonotic diseases in some capacity, such as including the specified disease outbreaks, scientific analysis of transmission, and origination. Most literature was determined to be included or excluded on a case by case basis, as some literature regarding suggested environmental regulations did not include the specified keywords. Literature that was identified as instrumental to the analysis of zoonotic disease transmission were included in the study to answer the proposed objectives of the paper. Using the compiled information, further research was conducted on policy suggestions and intervention mechanisms regarding environmental encroachment, transmission of viral pathogens, and disease surveillance. Literature reviewing implementation mechanisms is included as part of the systemic review as it offers critical information on prevention and intervention mechanisms regarding the human-nature nexus.

Figure 1: PRISMA flow diagram for Systematic Review (Prisma Group 2009)



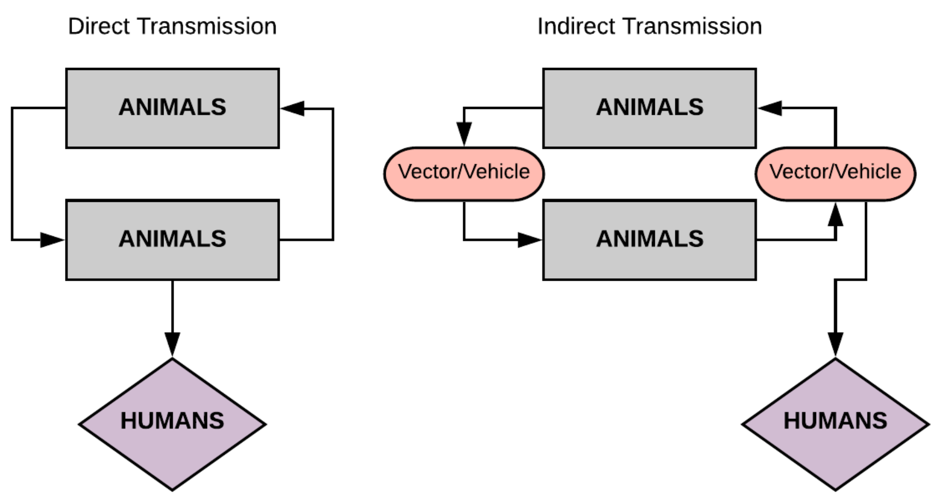
II-C. Literature

A. Zoonotic Diseases

Zoonotic diseases, also known as zoonoses, are diseases that emerge naturally in animal populations and are transmitted to humans (Centers for Disease Control and Prevention 2017b). Over 60% of known infectious diseases in humans are zoonotic, making them the most prevalent classification of disease (Redding et al. 2016). Diseases such as Lyme, Ebola, SARS, COVID-19, and West Nile virus are all attributed to animal hosts (Remmert 2014). Pathogens that result in zoonoses emerge in the form of bacteria, parasites, or viruses in vertebrate animals and circulate naturally in ecosystems (Keesing et al. 2010) . Animals that carry strains of probably zoonotic diseases, such as mammals, birds, and reptiles, are considered to be natural pathogen reservoirs in their respective ecosystems. For an infectious disease to emerge, the pathogen must be able to infect and replicate in human hosts, contact must exist between humans and the pathogen reservoir, and a human urban cycle must be possible (Frutos et al. 2020).

One of the unfortunate qualifications of zoonotic diseases is that they are generally unpredictable. Although emerging infectious diseases in global history tend to mimic each other, there is currently no way to predict emerging diseases - instead, it has historically been an accidental process (Ries 2020). The emergence of an infectious disease from animals to humans is a very low probability event resulting from the stochastic conjunction of independent low probability events (Frutos et al. 2020). Features that characterize previous zoonoses are not necessarily consistent with other outbreaks, thus making the events difficult to hypothesize.

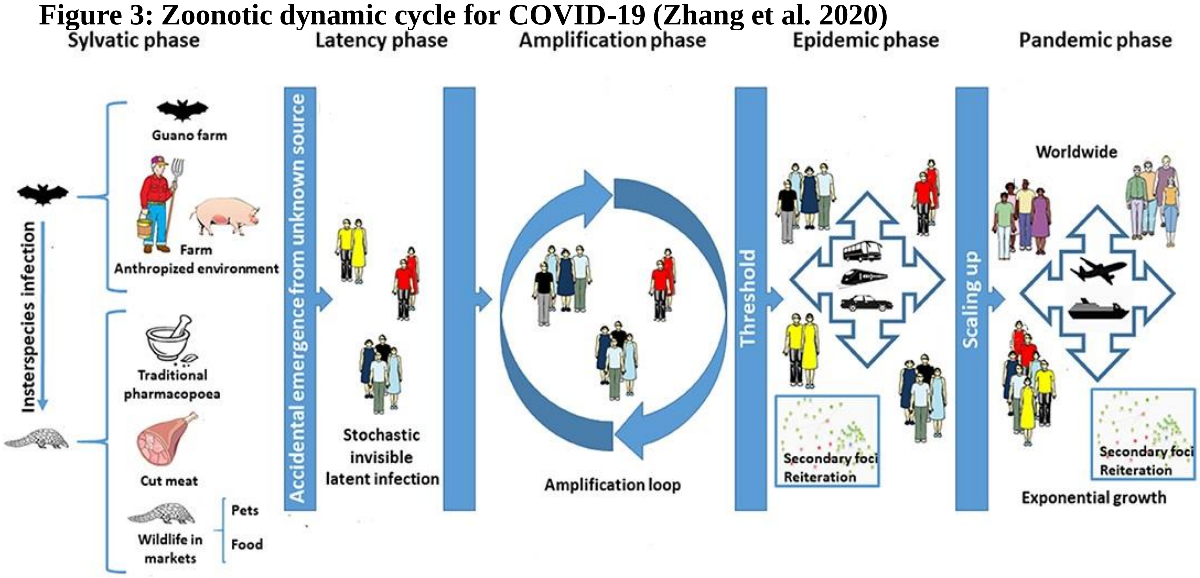
Figure 2: Type of Transmission of Zoonoses (Patz et al. 2002)



The three infectious diseases focused on in this article, SARS, Ebola and COVID-19, are all classified as zoonotic diseases that emerged in different contexts with different epidemiologies. SARS and COVID-19 are both strains of *Coronavirus,* a family of RNA viruses that usually cause mild to moderate upper-respiratory infections (Liu 2020). *Coronaviruses* are zoonotic as they are susceptible to mutation and recombination of RNA to infect human hosts (Liu 2020). SARS and COVID-19 genetic codes have been traced to similar strains of *coronaviruses* in pangolins, civet cats, and bats (Zhang et al. 2020). Scientists have concluded that genetic mutations in pathogens caused by wildlife trade markets are the most likely cause of SARS and COVID-19 (Contini et al. 2020). However, Ebola is attributed to bats leaving deforested areas in Guinea and infecting villages there (Olivero et al. 2017). All three listed viral diseases are classified as zoonotic due to their origination in animal genetic code, however their epidemiology varies. Studying each infectious disease can help determine similarities, such as their cyclical nature and transmission patterns. It is important to understand and analyze the emergence and nature of zoonotic outbreaks in order to help eradicate future threats (cf, Contini et al. 2020; Klasko 2020; Oakes 2020) .

Looking at Figure 3, we can see a simple dynamic zoonotic cycle of SARS-COV-2 (COVID-19) through animal hosts to pandemic-scale infectious diseases (Zhang et al. 2020). An unidentified animal virus originally circulated within its own species before the sylvatic phase of infection (Frutos et al. 2020). However, with human involvement in animal ecosystems, the unknown animal pathogen was transmitted during the Sylvatic phase through human-nature relations. The initial source of contact is unknown, but probable sources of the infection include Guano and anthropomorphized farming, traditional pharmacology, and consumption of animals (Zhang et al). In the Latency phase, the unknown pathogen was transmitted to humans and an invisible stochastic infection circulated in Wuhan, China (Hurewitz 2020). An amplification loop created between human to human transmission moved the infectious disease from the latency phase to an epidemic phase (Greenfield 2020). International mobility and global international trade exponentially increased the number of cases from an epidemic to a pandemic (Karesh et al. 2005).

Figure 3: Zoonotic dynamic cycle for COVID-19 (Zhang et al. 2020)



Although the conditions and classifications evident for COVID-19 do not emerge in other zoonotic diseases, such as SARS and Ebola, the dynamic cycle is nonetheless an important figure for understanding the exponential spread of zoonotic diseases (cf, Zhang et al. 2020; Greenfield 2020) . The cycle displays the emergence of zoonoses in animal populations that is transmitted to humans in one of many possible ways due to the interconnectedness of human-animal interaction (United Nations Environment Programme and International Livestock Research Institute 2020).

Environmental Causes

Zoonoses are transmitted from animals to humans through multiple pathways. Environmental conditions affect the transmission of zoonotic diseases by affecting the ecosystems of natural pathogen reservoirs (Centers for Disease Control and Prevention 2017b). Land degradation, deforestation, destruction of natural habitats, overexploitation of wildlife, and decreasing biodiversity caused by human activities have fundamentally created more opportunities for the spread of infectious diseases (Newburger 2020). Human economic growth, consumption of wildlife, and need for expansion are at the cost of environmental destruction and concomitant transmission of Zoonoses (Contini et al. 2020). Zoonotic diseases are fundamentally an environmental crisis as it indicates human expansion into natural ecosystems and increased interactions with nature (cf, Contini et al. 2020; Newburger 2020; Davidson 2020).

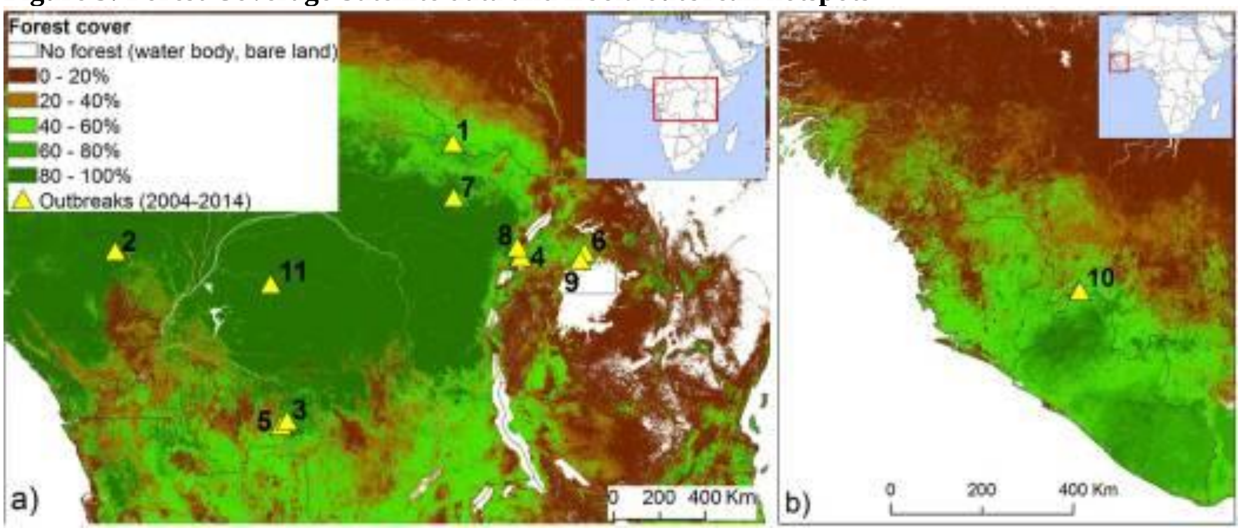
Deforestation and Land Degradation

Human encroachment on natural environments exacerbates the spread of infectious zoonotic diseases. Our actions have significantly impacted more than three quarters of the Earth's land surface, destroyed more than 85% of wetlands, and dedicated more than 33% of land and 75% of freshwater to agriculture (Settele et al. 2020). Deforestation and land degradation as a result of human economic expansion into uninhabited environments drives pathogen reservoirs out of their evolutionary niches and into proximal locations with humans (Oakes, Olson, and Watson 2020). Scientists believe there are approximately 1.7 million unidentified zoonotic diseases that exist naturally in birds and mammals, however these diseases have not spread to humans as of yet because they aren't proximal to humans (Settele et al. 2020). However, future pandemics are expected to occur more frequently as human economic dominance requires a vast amount of natural resources (Davidson 2020). Deforestation effectively eliminates the natural ecosystems of animals that naturally harbor infectious zoonotic diseases, causing species to flee to other areas for habitation (Nunez 2019). Anthropomorphized environments can provide an acceptable habitat for a large range of species that may be displaced, thus allowing pathogen reservoirs to be in proximity to human beings (Afelt, Frutos, and Devaux 2018)[1]. Unnatural connections and relationships that form between pathogen reservoirs and human populations create conditions for infectious diseases to emerge (Watts 2020).

Zoonotic environmental infectious disease outbreaks are exacerbated by the encroachment of human populations on natural environments (Mitchell 2020). In a study conducted by Allen et al, four types of environmental infectious disease events (i.e. increased distribution, incidence, virulence, or other factors) were regressed as a function of human population density, latitude, rainfall, and wildlife species density. The result of the regression showed a statistically significant relationship between origins of zoonotic disease outbreaks and areas with higher population densities and biological diversity. Zoonotic infectious disease risk was concluded to be elevated in forested areas that were experiencing land-usage changes by human encroachment (Allen et al. 2020).

Satellite evidence suggests that one viral zoonotic pathogen outbreak caused by deforestation is the Ebola virus (Rulli et al. 2017). Ebola is a haemorrhagic fever which often causes fatal illness in primates and humans. The 2014-2016 Ebola outbreak was caused by a young child being exposed to bats in New Guinea (World Health Organization 2020a). A study conducted by Rulli, Santini, Hayman, and D'Odorico (2017), satellite derived land cover data was matched in New Guinea to recent outbreak hotspots and patterns of land usage. In the 2014 outbreak year, the average forest cover in the surroundings of these eleven centers of the first infection (25-50km radius) was significantly greater than the average cover across the region (p value of 0.0052). The forest fragmentation, expressed in a compound fragmentation index, showed that fragmentation - on average - increases closer to outbreak centers. This provides evidence that, due to trends of deforestation, natural Ebola reservoirs were forced into human villages, which in turn caused an increased transmission rate. Once the pathogen had been transmitted to humans, Ebola spread due to crowded urban areas, increased mobilization, conflicts between traditional practices, and weak health care systems (Olivero et al. 2017).

Figure 3: Forest Coverage Satellite data and Ebola outbreak hotspots



Source: Rulli et al. (2017)

Deforestation and land degradation additionally causes the depletion of biodiverse ecosystems, which makes it increasingly difficult for environmental factors to naturally halt the transmission of pathogens to external areas (Mitchell 2020). Decrease of biodiversity reduces the ability of ecological niches to provide a sustainable ecosystem, thus increasing the probability of disease transmission. For example, looking at malaria, if forests are destroyed then the animals that normally consume mosquitoes will seek habitats in other areas or decrease in population, thus decreasing the threat to mosquitoes (MacDonald and Mordecai 2019). With no natural predators of mosquitoes, there are no environmental conditions to control mosquito populations thus increasing the probability of mosquito-borne diseases (Keesing et al. 2010).

Wildlife Industries

The global economy is dependent on natural resources for production and diverse commodities. The demand for diverse commodities and the increasing human population leads to the overconsumption of natural resources (Karesh et al. 2005). Besides land encroachment, wildlife industries are a prime example of human monetization of wild animals and their habitats. Wildlife industries commodifies wild animals for traditional medicinal practices and food (Lynteris and Fearnley 2020). Global demand for animals and their products as well as the lack of regulation in wildlife markets creates conditions for Zoonoses to emerge and renders the world susceptible to future pandemics (Center for Biological Diversity n.d.).

Wet markets are the main source of food and income for many people all over the world. Wet markets are similar to farmer's markets as they are typically large collections of open stalls selling fresh seafood, wild meat, and other sources of food (Bridgeman and Lingel 2020). These markets sell and slaughter common domesticated animals, such as chickens and goats, however there are recorded instances of live species such as beavers and porcupines being slaughtered on site (Beaubien 2020). Many wildlife and wet markets are slightly regulated, but the conditions among stalls are not. The name "wet" comes from wet floors due to water being sprayed over produce, animal carcasses kept on ice, and the blood of slaughtered animals (Bridgeman and Lingel 2020). Animals in wet markets are kept in dirty, cramped conditions with other animals, causing hazardous conditions and extreme stress (cf, Beaubien 2020; Bridgeman and Lingel 2020; Lynteris and Fearnley 2020).

Some wildlife industries specialize in the trade of protected species, creating a black market for wild animals. Black markets have limited traceability and unregulated health practices, which can increase the spread of animal illnesses (Maron 2020). Buying, selling, and slaughtering wild animals for consumption increases the probability of infection from zoonotic pathogens (Hurewitz 2020).

Zoonoses are transmitted when animal pathogen reservoirs are in close proximity to humans. Wildlife markets exponentially increase animal-human interaction because of the diversity of species that are in contact with each other and humans under hazardous conditions (Webster 2004). Hunters, middle marketers, and consumers experience some type of contact as each animal is traded (Karesh et al. 2005). Wild mammals, birds, and reptiles flow daily through trading centers, where they are in contact with persons and with dozens of other species before they are shipped to other markets, sold locally, or even freed and sent back into the wild (Beaubien 2020). The increased diversity of species and contact between humans increases the transmission of diseases as well as the probability of future outbreaks (Sape 2020).

The lack of regulation in wet markets as well as the consumption of wildlife creates conditions for new zoonotic pathogens to emerge (cf, Webster 2004; Sape 2020; Maron 2020; Degnarian 2020) . When animals are contained in unhealthy environments and stressed, animals infected with diseases can urinate, defecate, and excrete other biofluids in essentially the same areas where they are killed (Maron 2020). Their meat is then taken by customers, allowing disease contamination with humans. Additionally, when under duress, animals release cortisol in their bodies which inhibits their immune system response, making them more susceptible to infections (Maron 2020). The conditions of wet markets represses animal immune-inflammatory responses and allows pathogens to proliferate (Degnarian 2020). The pathogens they harbor can intermingle and exchange genetic material (Degnarian 2020). Additionally, pathogens that occur naturally in these wild species can intermingle with others and swap genetic code under duress (Maron 2020). This poses an unknown and predictable threat to public health as these mutations can create further variable pathogens that can make them more susceptible to human contraction, especially with consuming animal products (Hurewitz 2020).

Currently, the world has seen two viral disease outbreaks that have emerged specifically from wet markets: SARS (2002) and COVID-19 (2019). SARS, or severe acute respiratory syndrome, is classified as a type of coronavirus found in animals that causes fever, body aches, and other mild respiratory symptoms (Centers for Disease Control and Prevention 2017a). The outbreak was first documented in Guangdong, China in 2003 when atypical pneumonia was found in people. The outbreak lasted approximately six months with 8,098 people infected worldwide and 774 deaths (Ries 2020). Using contact tracing methods as well as genome cataloging, the SARS coronavirus strain was traced to origins in animals sold at wet markets (Webster 2004).

In one study, Chinese scientists used nasal and fecal swabs from 25 different species in the markets found that civet cats carried coronavirus isolates that were 99.8% homologous to the human SARS coronavirus (Hu et al. 2017). In another study, scientists from the Chinese Academy of Sciences in Wuhan spent years studying and cataloging coronaviruses in horseshoe bats in a single cave (Guan et al. 2003). Using genome analysis, the new identified coronavirus strains were shown to have the same evolutionary ancestors as the SARS coronavirus strain (Guan et al. 2003). Scientists concluded that genetic recombination between raccoon civets and horseshoe bats most probably produced the evolution of the strain that caused the SARS outbreak. Infected bats and uninfected civets came in contact at a market, the virus was transmitted to civets and then multiplied and mutated until the virus infected humans (cf, Guan et al. 2003; Hu et al. 2017; University of California Berkeley 2006) .

COVID-19 is the most recent outbreak of coronaviruses. COVID-19, also known as SARS-CoV-2, originated in Wuhan, Hubei province of China (National Institute of Allergy and Infectious Diseases n.d.). As COVID spread across China and later other countries, the WHO declared the outbreak a pandemic. COVID-19 is a strain of the SARS-CoV virus that manifests in the lower lungs causing a range of respiratory symptoms such as coughing, shortness of breath, muscle aches, and in some cases, death (Virginia Department of Health 2020). At the time of this writing, COVID-19 had spread to 140 countries with a confirmed case count of 15 million and 618,000 deaths (Johns Hopkins University of Medicine nd). However, at this time the pandemic is still on-going and thus these estimates are subject to change.

While unverified, the source of the COVID-19 outbreak is believed to be the Huanan Seafood Wholesale market (Maron 2020). The Huanan market is a wet market with open-air stalls of fresh seafood, meat, fruit, and live animals. In investigating the origin and epidemiology of COVID-19, scientists cataloged the coronaviruses genome in humans and compared it to the genome in animal coronaviruses (Wong et al. 2020). The nucleic acid sequence most resembled horseshoe bats, but suggested an intermediary host as well. Using contact tracing methods, the original infected patients were all traced back to the Huanan Seafood market where horseshoe bats and civet cats were being sold (Andersen et al. 2020).

Table 1: Epidemiological, Clinical, and Biological Characteristics of SARS, EBOLA, and COVID-19.

Characteristics	SARS-CoV (SARS)	EBOLA	SARS-CoV-2 (COVID-19)
Distribution	Pandemic	Epidemic	Pandemic
Origin	Guangdong Province, South China	Southeastern Guinea	Wuhan, Hubei Province, China
Natural Reservoir	Bat	Bat	Bat
Intermediary Host	Palm-civet	Monkeys, apes, and pigs	Not verified. Most likely Pangolins, civet cats, and others.

Transmission	Human to Human; respiratory	Human to Human; contact with bodily fluids	Human to Human; respiratory
Main Symptoms	Influenza like: fever, cough, chills, respiratory distress	Fever, aches, pains, gastrointestinal symptoms, unexplained hemorrhaging	Influenza like: fever, dry cough, headache, myalgia malaise, shortness of breath
Lethal disease	Acute Respiratory Distress Syndrome (ARDS)	Dehydration as a result of diarrhea	Severe pneumonia
Vulnerable Populations	Elderly and persons w/ pre-existing conditions	Elderly, persons w/ pre-existing condition, children	Elderly and persons w/ pre-existing conditions
R0*	2.0-5.0	1.5-1.9	1.4-5.5

Source: Author's aggregation of data from literature sources (Contini et al. 2020)
*R0 is a factor of transmission that is used to indicate how many people will be infected as a result of one individual with the disease. For example, with a R0 of 2.0, a person with SARS will be expected to infect approximately 2 other people (Ives and Bozzuto 2020).

B. Intervention Mechanisms

Emerging infectious diseases are a major public health problem, which requires an interdisciplinary and holistic approach for identification, prevention, and management. The environment impacts more than 80% of major infectious diseases - diseases which cost the United Healthcare system approximately $4.2 trillion USD per year due to 2.6 billion cases per year (National Environmental Health Partnership Council 2016). Environmental health mechanisms work to prevent and control diseases, injuries, and disabilities related to the human-nature nexus. The United Nations environment program suggests implementing a "One health" approach to public health concerns. The concept of "One Health" recognizes that the environment and human health are fundamentally connected (United Nations Environment Programme 2020). One Health is a validated, integrated and holistic approach to public health interventions that is being advocated by WHO, the FAO, and the World Organization for Animal Health (OIE) for combating health threats through human-animal-plant-environment interface (Mackenzie and Jeggo 2019). The policy concept focuses on consequences, responses, and actions at the animal-human-ecosystem interface to implement a multi-sectoral and interdisciplinary approach to optimal health (Bhatia 2019). Policy implementation, political advocacy, program development, research sharing, institutional collaboration, and active participation is necessary to bring change in the narrative around the human nature nexus (Gorman 2013).

In the report, "Preventing a Future Pandemic" (2020), the United Nations environment program evaluates the complexity and severity of zoonoses. Because of the wide impact of zoonoses, the responsibility for the prevention and control of zoonotic pathogens falls across several different sectors. Successful control of zoonotic disease outbreaks requires strong policy implementation frameworks, well functioning and communicative institutions, adequate financing, and many other mechanisms. The current disease prevention framework is severely fragmented, as competitions for public health resources can sometimes render funds for infectious disease control inadequate. The United Nations recommends multiple policy approaches to implementing a concrete, effective "One-health" economy (United Nations Environment Programme 2020). Raising awareness and fostering understanding at all levels in society would help catalyze further policy interventions and research on zoonotic diseases. Across many different sectors, there is a need for improving cost-benefit analyses for investment strategies as well as strengthening environmental support for the WHO, expanding scientific inquiry and research, effective tracing and monitoring practices, economic and health incentives, land and wildlife protection, as well as strengthening the capacity of countries to respond to public health threats (Pattanayak et al. 2010). This multi-sectoral, holistic approach would allow zoonotic disease transmission to be addressed at every level in society and thus effectively monitoring, controlling, and tracing emerging infectious diseases.

A current example of the One-Health framework is the Ugandan “One-Health Strategic Plan” implemented from 2018-2022. Uganda has faced shifting dynamics of health threats due to expanding populations, economic development, human migration, and land usage (Republic of Uganda Ministry of Health 2019). Uganda’s changing environment required a multi-sectoral approach to public health. The Government of Uganda implemented a One Health approach to addressing zoonoses and other biological threats. The strategic plan includes interventions in educational, political, and healthcare sectors as well as in wildlife markets. Public health officials work to monitor food markets by inspecting livestock for pathogens, monitoring the destruction of contaminated meat, and implementing healthy market practices. Zoonotic outbreaks were monitored and investigated in terms of patient cases, disease vectors, and contact tracing. By involving public health officials in all sectors related to food safety and health, public health practices became widespread. As of 2020, the One Health programme in Uganda has already significantly reduced sickness and deaths caused by zoonoses, such as Ebola (United Nations Environment Programme 2020).

The most frequent environmental health interventions include deforestation and land degradation prevention mechanisms. Preventing human encroachment on natural environments will protect the natural biomes of pathogen reservoirs, preserve biodiversity, and limit the proximity of humans to animals (Settele et al. 2020). Deforestation and land degradation are primarily motivated by economic incentives for expansion and global population growth (Davidson 2020). By countering the monetary and opportunity costs of land usage, successful policy mechanisms can limit deforestation and land degradation (Mueller et al. 2013). For example, multiple different land regulation tactics were used in Bolivia to successfully combat the depletion and degradation of rainforests (Mueller et al. 2012). Property rights and land usage regulations were clarified by the federal government and penalties incurred for unregulated usage of land. By adopting high fees for regulated deforestation and high fees for illegal deforestations, profitability from land manipulation was decreased and negative incentives were produced in illegal deforestation.

REDD+, or Reducing Emissions from Deforestation and Forest Degradation, is a mitigation tactic created by the Food and Agriculture Organization of the United Nations aiming at encouraging developing countries to mitigate climate change (World Health Organization 2020b). REDD+ advocates for various policy mechanisms, specifically incentives and compensations to reduce deforestation through payments for environmental services (Forest Carbon Partnership 2020). These policies include supporting intensive agriculture, reducing agricultural rent, and backing technological innovation. Reducing agricultural rent raises the effective cost of agricultural labor, making more attractive opportunities off farms and decreasing the incentive for land degradation (Angelsen 2010). Supporting intensive agriculture and technological innovation put an emphasis on intensive production inputs rather than land usage (See Table 2), thus removing labor from deforestation sectors. REDD+ policies are advantageous in environmental interventions as they efficiently target the root of deforestation and degradation and compensate those who are most affected by forest conservation (c.f., Angelsen 2010). Although there are other policies that target deforestation and land degradation, REDD+ policies are favorable because they address a variety of issues that developing countries face in policy implementation[1] (Angelson 2010). REDD+ strategies are attractive mechanisms for developing countries to limit environmental impacts, thus effectively decreasing the probable threat of zoonotic outbreaks (cf, Angelsen 2010; World Health Organization 2020b; Forest Carbon Partnership 2020, Mueller et al. 2013).

[1] Although there are other deforestation policies, REDD+ policies encompass a wide range of economic, environmental, socio-economic, and socio-political issues. Environmental policies that target deforestation tend to fall under the guidelines of REDD+supported policies although they may not be officially advocated (cf, Angelsen 2010; World Health Organization 2020b; Mueller et al. 2013).

In addition to combatting the public health threat exacerbated from land encroachment, the prevention and control of foodborne diseases and zoonoses in markets have become major public health concerns requiring immediate attention (World Health Organization 2006). Wet markets are the source of both SARS and COVID-19 as they perpetrate an environment where the proliferation of pathogens is imminent. In an open letter to the Director General of the World Health Organization, over 250 environmental organizations signed a petition to implement regulations on wet markets immediately (Sape 2020). The letter sustains that "any policies and practices that sustain the wildlife trade carry a huge and unpredictable public health risk that could lead to future outbreaks and pandemics of zoonotic diseases" (Sape 2020). The organizations recommend that nations implement a federal ban on live wildlife markets, exclude wild animals in the WHO's definition of traditional medicine, assist governments and lead a coordinated response on public health education, as well as encouraging other sources of protein for consumers of wild animals.

Table 2: Policies to reduce deforestation (Angelsen 2010)

Policy	Effectiveness of forest conservation	Direct costs of policy (efficiency)	Effect on inequality or poverty
1. Reduce (extensive) agriculture rent			
Depress agricultural prices	High	Negative	Negative
Create off-farm opportunities	High	Medium – high	Neutral – positive
Support intensive agricultural sector	Moderate – high	High	Uncertain
Selectively support extensive agriculture	Uncertain – moderate	High	Positive
Ignore extensive road building	High	Negative	Negative
Secure property rights	Uncertain	Medium	Uncertain
2. Increase forest rent and its capture			
Higher prices for forest products	Moderate	Low	Positive – uncertain
CFM – capture local public goods	Moderate	Low – medium	Positive
PES – capture global public goods	Potentially high	Medium – high	Uncertain – positive
3. Protected areas	Moderate – high	Medium	Uncertain
4. Cross cutting policies			
Good governance	Low – moderate direct effects	Low or even negative	Positive
Decentralisation	Low – moderate direct effects	Low – medium	Positive

Although some public health officials argue for the closure of wet markets, it is apparent that perseverance of traditional medicinal practices would lead to black markets that are impossible to regulate (Lynteris and Fearnley 2020). An alternative to the closure of wet markets is to implement strong scientific regulation at wet markets in regards to traditional medicinal practices. Governments would consult basic principles of good agricultural practices (GAP) and hygienic practices from the Codex General Principles for Food Hygiene to improve market safety (World Health Organization 2006). Because wet markets encompass various sectors, it is recommended that a multisectoral team consisting of experts in nutrition, epidemiology, agriculture, toxicology, health sciences, and waste management should consult on a health food market project (Frutos et al. 2020). Further recommendations include opening traditional pharmacopeia shops under government regulation, required validation of products by wildlife health professionals, contact traceability protocols, and subsidized products to prevent black market incentives (cf, Frutos et al. 2020; National Environmental Health Partnership Council 2016).

II-D. Literature Synopsis

Ebola, SARS, and COVID-19 are prime examples of the prevalence of emerging zoonotic diseases caused - at least in part - due to overconsumption of natural resources (cf, Degnarain 2020). In a review of the current literature regarding zoonotic diseases, most scientists accept that human encroachment on natural environments creates conditions for zoonotic disease to transmit to human populations (Mitchell 2020). The current literature asserts that forest degradation, land degradation, loss of biodiversity, and wildlife markets create the unnatural conditions needed for the spread of animalistic pathogens. Although it is equally important to improve healthcare systems, surveillance, and contact traceability, environmental interventions are essential to mitigating future public health threats due to the presence of zoonotic diseases as a result of the human-nature nexus (World Health Organization 2006). It is of the utmost importance that nations begin implementing environmental protection mechanisms for mitigating future infectious disease threats (Davidson 2020).

Human encroachment on natural environments exacerbates the spread of infectious zoonotic diseases (Mitchell 2020). As a result of agricultural development, deforestation and land degradation drive pathogen reservoirs out of their evolutionary niches, thus increasing the proximity of zoonotic diseases to human beings (Watts 2020). Deforestation causes depletion of biodiverse ecosystems, which makes it more difficult for environmental factors to naturally halt the transmission of pathogens to external areas (Belden 2010). The global economy is dependent on natural resources for production and diverse commodities, yielding devastating impacts on the environment from overconsumption. Wildlife markets in China are an additional example of human overconsumption of natural resources as the industry monetizes wild animals for traditional medicinal practices and delicacies (Sape 2020). The lack of regulation in wet markets as well as the consumption of wildlife creates conditions for new zoonotic pathogens to emerge, such as the SARS (2003) and COVID-19 (2019) outbreaks. Wet markets force animals into close proximity with one another, creating opportunities for viral pathogens to mutate genetic code that make them more transmissible to humans (Bi 2020; Maron 2020). Policies that sustain the wildlife trade industry and promote land degradation are an unpredictable public health risk that will likely lead to future outbreaks and pandemics of zoonotic diseases (Sape 2020).

If these trends of encroachment continue, we can expect to see increasing amounts of new diseases emerge in human populations that are not equipped to handle them (Newburger 2020). In order to prevent future outbreaks, measures must be taken to protect environmental health, such as decreasing deforestation and regulating wildlife markets through REDD+ policies, or the “One-Health” approaches supported by the U.N. (Davidson 2020; Afelt, Frutos, and Devaux 2018). In addition, regulations are also needed in wildlife markets to eradicate public health threats that arise from the commoditization of wild animals (Oakes, Olson, and Watson 2020). The current literature suggests scientific approaches to traditional medicinal practices and state-owned traditional pharmaceutical shops to open as a way to recognize the importance of wildlife in traditional medical practices (Frutos et al. 2020). Scientists and government agencies should collaborate to implement feasible REDD+ reorganizations in wildlife markets such as quality checks, improved technological processes, contact traceability between sales, and other safety mechanisms (United Nations Environment Programme 2020). Adopting a “One-Health” mindset regarding public health and introducing environmental protection policies may also be a productive strategy for mitigating public health threats (cf, Oakes, Olson, and Watson 2020; Davidson 2020; United Nations Environment Programme).

III. Satellite Evidence on Vegetation During pre and during COVID

In this section, we seek to utilize satellite imagery to evaluate the impact of the COVID-19 pandemic on areas where Global Environment Facility (GEF) land degradation and biodiversity projects have been implemented.

III-A. Background, Data & Methods

To examine vegetation in the era of COVID-19, this study used the Breaks For Additive Season and Trend (BFAST) approach to detect abrupt changes within MODIS Normalized Difference Vegetation Index (NDVI) time series models [1]. This approach contrasts past seasonal trends in forest cover with contemporary trends to establish “breaks” - i.e., if there were unusually high or low levels of vegetation. BFAST was specifically applied to protected areas the GEF has had an active presence within. Then, the NDVI time series models were compared to MODIS Enhanced Vegetation Index (EVI) BFAST time series models.

The MODIS product MOD13Q1, which generates satellite data every 16 days at a spatial resolution of 250 m, is composed of two primary vegetation layers: NDVI and the Enhanced Vegetation Index (EVI) [2]. NDVI values provide a proxy measurement for vegetation health and biomass by calculating the difference between near-infrared and red light (wavelengths that are particularly sensitive to the differences between dense and sparse vegetation). NDVI ranges from +1.0 to -1.0. High NDVI values of approximately 0.6 to 0.8 indicate dense, healthy vegetation while low values of 0.2 to 0.5 correspond to sparse vegetation or senescing crops [3]. The EVI layer makes up for some limitations of the NDVI layer by having improved sensitivity in high biomass regions and minimized canopy-soil variations [4]. It corrects for atmospheric haze and is not as saturated as NDVI for satellite imagery showing rainforests, heavily vegetated areas, and regions with large amounts of chlorophyll. EVI also has a value range of -1 to 1 where healthy vegetation is typically between 0.2 and 0.8 [5].

In this study, the specific regions of forest that were examined focused on legally protected areas that have received GEF assistance within the demarcated areas being defined by the World Database on Protected Areas (WDPA) [6]. For each protected area, the BFAST monitor was applied on a 16-day MODIS NDVI/EVI satellite image time series over a period stretching from 2010 to August 2020. The stable history period from the beginning of 2010 lasted until the start of the monitoring period in January 2019. During the monitoring period, it was determined whether the observations within the monitoring period fitted to the preprocessed continuation of the regression model in the stable history period. If the observations in the monitoring period did not conform to the stable regression model, the estimated time of break was specified.

The BFAST monitoring period began in the year 2019 to allow monitoring to occur for one year to better detect breaks in the year 2020–the year of COVID-19’s intensified spread. As countries began paying greater attention to lockdown restrictions and the global economic slowdown, illegal logging, mining, and forest clearing operated with decreased regulation. The detection of breakpoints in 2020 that indicate deforestation in the form of decreased NDVI or deforestation mitigation efforts as increased NDVI tell whether the forest health initiatives of GEF projects were undone or preserved in the era of COVID-19. Breaks detected in the NDVI time series models were compared to breaks in time series representing EVI. NDVI and EVI images are also included with the time series for each protected area.

III-B. Study Area - Democratic Republic of the Congo Forest Ecology

After the Amazon rainforest, the Congo Basin tropical rainforest, which spans across Cameroon, the Central African Republic, the Democratic Republic of the Congo (DRC), Equatorial Guinea, Gabon, and the Republic of the Congo, is the second largest collection of humid tropical forests in the world [8]. About 60% of the Congo Basin stretches across the DRC, making the country a focal point for REDD+ (reduced emissions from deforestation and forest degradation) policy [9]. Agricultural expansion through shifting cultivation, which is propagated by illegal logging, is considered the largest cause of deforestation in the country [10]. Forest loss is further exacerbated by the DRC's poverty, declining food production, low food exports and imports, and a population more than twice the population of the five other countries in the Congo Basin– underlying conditions known to lead to mismanaged logging [11].

In March 2020, the World Wide Fund for Nature (WWF) reported a record amount of tree cover loss in Indonesia, the DRC, and Brazil. Indonesia lost 130,000 hectares of forest, which made it the hardest-hit country in the world that month. The DRC and Brazil followed by losing 100,000 and 95,000 hectares of rainforest, respectively [12]. Because of the DRC's placement within the world's second largest massif of humid tropical forests, and, consequently, the prevalence of GEF land degradation and biodiversity projects in the area within the past decades, the DRC was chosen as the focal country of this study.

Additionally, in the three months after the first identified case of coronavirus in the DRC on March 10, 2020, COVID-19 gradually spread to more than 4,500 people across 11 of the country's provinces. The number of confirmed cases was likely an underestimate due to the lack of available testing [13]. And, as the DRC combatted the outbreak of COVID-19, it also began tackling the eleventh outbreak of the Ebola virus snce 1976, which was declared on June 1, 2020, following the discovery of a cluster of cases in the provincial capital of Mbandka, a city with almost half a million residents [14]. This Ebola outbreak is the second-worst in history with 3,453 cases and 2,273 deaths in the same month it was declared [15].
The intensity of the spread of COVID-19 has been further exacerbated by the simultaneous outbreak of Ebola and smaller scale outbreaks of measles, malaria, and monkeypox, as well as disinformation spread in larger cities calling coronavirus a "disease of the rich" or a punishment from God to the LGBT community [16]. As of September 25, 2020, the country had 10,578 persons infected with coronavirus [17]. Out of 54 countries on the African continent, the DRC has the 17th most cases in late September 2020 [18]. The DRC's role as a deforestation and COVID-19 hotspot made it an ideal country for this analysis.

Sample areas of 33 km x 37 km were used to represent each WDPA, with a centerpoint defined by the centroid of each protected area. Within the DRC, three GEF projects that combat deforestation in protected areas were identified for analysis using the BFAST approach:

1) Democratic Republic of Congo Conservation Trust Fund,
2) CBSP Forest and Nature Conservation Project, and

3) CBSP Catalyzing Sustainable Forest Management in the Lake Tele-Lake Tumba (LTLT) Transboundary Wetland Landscape.

In addition, a small number of WDPAs in which the GEF did not undertake activities were selected, and BFAST analysis was run in those locations as a control group.

Title	Implementation Start	Implementation Completion
Democratic Republic of Congo Conservation Trust Fund	October 2013	N/A
CBSP Forest and Nature Conservation Project	May 2009	May 2014
CBSP Catalyzing Sustainable Forest Management in the Lake Tele-Lake Tumba (LTLT) Transboundary Wetland Landscape	January 2010	December 2014

Table 1. Overview of select GEF interventions in DRC protected areas.

III-C. Results of Satellite Analysis

Democratic Republic of Congo Conservation Trust Fund & CBSP Forest and Nature Conservation Project

This analysis explored two overlapping funding initiatives the GEF engaged with, in 2009 and 2013. In 2009, GEF activities sought to preserve the ecological integrity of protected areas if the DRC government lacked the institutional capacity to prioritize conservation. The economic mismanagement of Zairean President Mobutu Sese Seko between 1965 and 1997, as well as the the First Congo War from 1996-1997, heightened growing pressures from poaching and habitat fragmentation that a post-conflict government would potentially be unable to regulate. The GEF project focused on maintenance of the protected areas network and each park's biodiversity assets after the war in three pilot protected areas: the Maiko National Park, the Garamba National Park, and the Virunga National Park.

In 2013, GEF-conducted activities in the Democratic Republic of Congo (DRC) were augmented by the establishment of a Conservation Trust Fund (CTF). The CTF sought to help preserve the biodiversity of DRC protected areas and ensure a declining rate of deforestation. The operationalization of the fund–and concomitant reinforced conservation of protected areas–took place as a part of the Democratic Republic of Congo Conservation Trust Fund project. The management of targeted protected areas occurred under the Congolese Institute for Nature Conservation (ICCN), which selected the Garamba National Park, the Kahuzi-Biega National Park, and the Salonga National Park as the National Parks to receive CTF funding in the first round of capitalization. The GEF-financed activities also reinforced conservation in the Virunga National Park and the Maiko National Park.

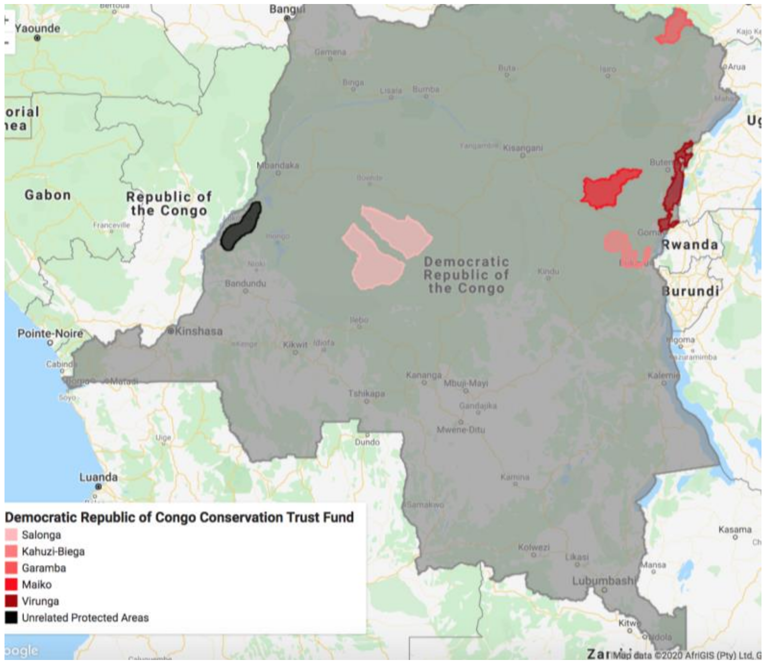
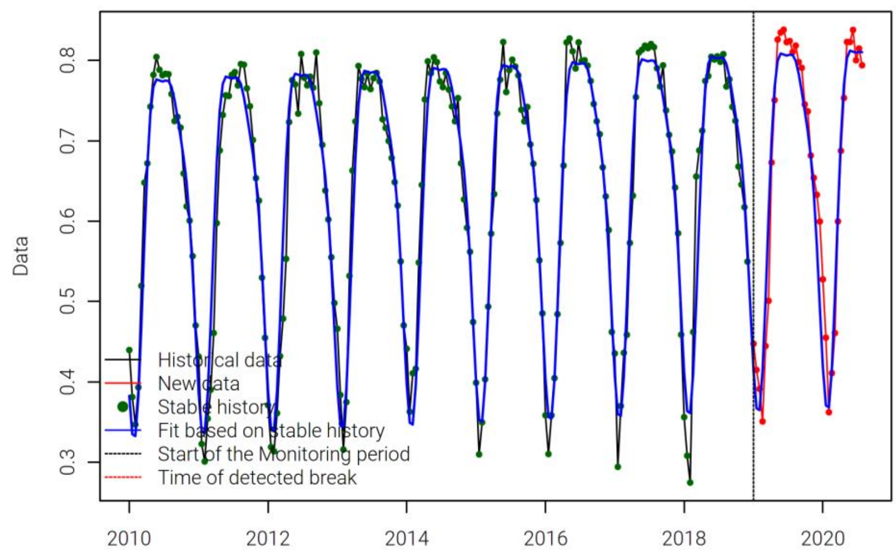


Figure III.1. Protected areas associated with the Democratic Republic of Congo Conservation Trust Fund project and CBSP Forest and Nature Conservation Project

Each of these six implementation regions were independently assessed using the BFAST approach to detect if there was a break in vegetative data on or around the time of the COVID pandemic; we focus on a period from 2019 until mid-2020; by starting our monitoring period in 2019, we produce a more conservative test than if we were to start in 2020.

Figure III.2.1 BFAST results of the Garamba National Park NDVI time series with no detected breaks.

The Garamba National Park did not illustrate any breaks in the time series, with the seasonal patterns in 2019 and 2020 being very similar to historic patterns. As seen in the time series shown in Figure III.2.1, NDVI peaks between May and June and reaches its lowest values in



February. This seasonal pattern continued into 2020. This was the same finding as in the EVI case.

The Kahuzi-Biega National Park NDVI time series experienced no breaks in 2020 (Figure III.3.1). Despite a 0.236 decline in NDVI between January 1, 2020, and January 17, 2020, the sudden drop was not as severe as drops in 2019, such as the -0.427 change between October 16, 2019, and November 1, 2019. Therefore, the decrease in January 2020 was not enough to detect a break in the time series. Additionally, NDVI values were at historically high levels from March 2020 to July 2020. The values ranged from 0.83 to 0.84; NDVI levels only managed to reach a high of 0.815 on March 22, 2019. The EVI time series experienced no breaks in 2020, as well.

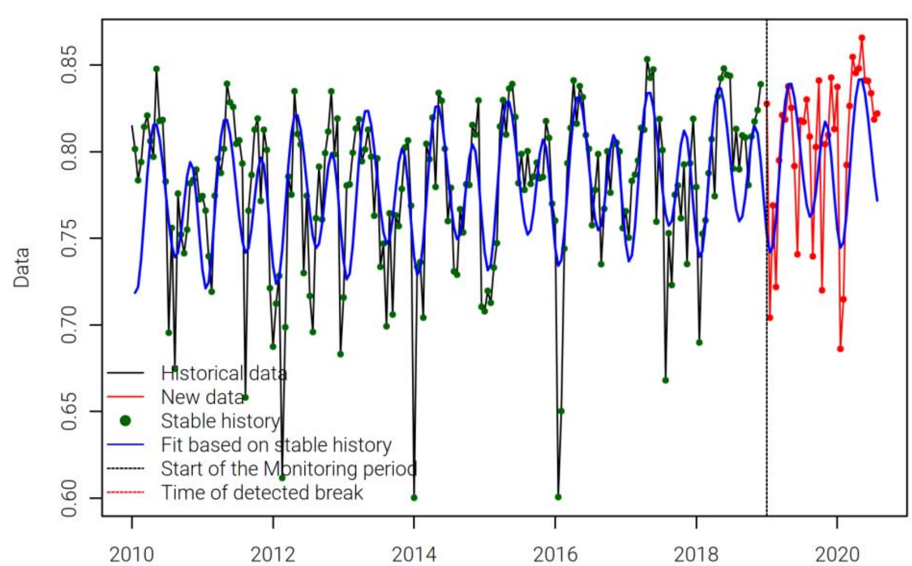


Figure III.3.1 BFAST results of the Kahuzi-Biega National Park NDVI time series with no detected breaks.

The Salonga National Park saw few dramatic changes in NDVI except for a 0.115 decrease between May 25 and June 10 and a 0.112 decrease between August 29 and September 3. Both sudden declines in NDVI were followed by gradual increases that spanned one month and two months, respectively, and the restoration of fairly high NDVI values of 0.79 on average. Neither the NDVI time series shown in Figure III.4.1 nor the EVI time series illustrate breaks in 2020.

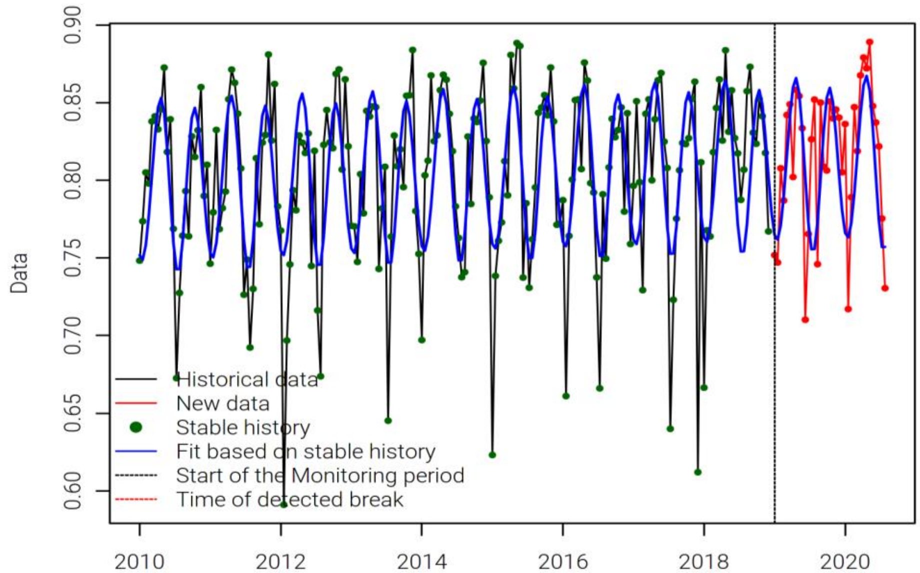


Figure III.4.1 BFAST results of the Salonga National Park NDVI time series with no detected breaks.

In the case of **the Virunga National Park**, we focus on the southern half, as the centroid-based approach to representing national parks is not suitable for the park's geometry due to a natural corridor between two larger protected areas (Figure III-5.1).

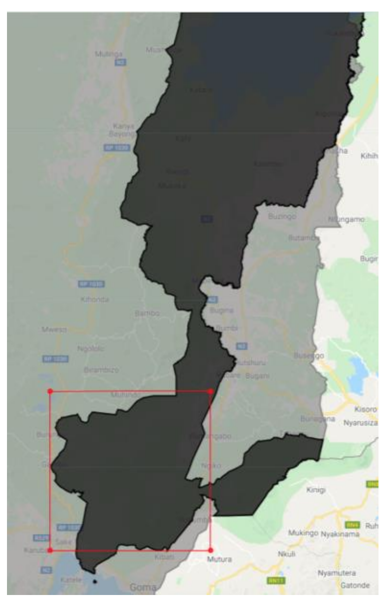


Figure III-5.1 The subset taken for Virunga National Park shown as a red box.

The Virunga National Park NDVI time series (Figure III-5.2) detected a break on November 1, 2019. Between 16-day periods, the park's NDVI experienced the most dramatic drop starting on November 1 as it declined by 0.131 from 0.552 to 0.421. The only other NDVI change of a similar magnitude occurred between October 16, 2019, and November 1, 2019, as NDVI increased by 0.149. By December 3, 2019, the park's NDVI recovered to 0.548–a value just 0.004 less than the value at the beginning of November. A break was also detected in the EVI time series for the protected area (Figure 5.6) on January 17, 2020. Between January 1, 2020, and January 17, 2020, EVI dropped by 0.038. Figure III-5.4 shows the spatial pattern of NDVI over the time period when the break in NDVI was captured.

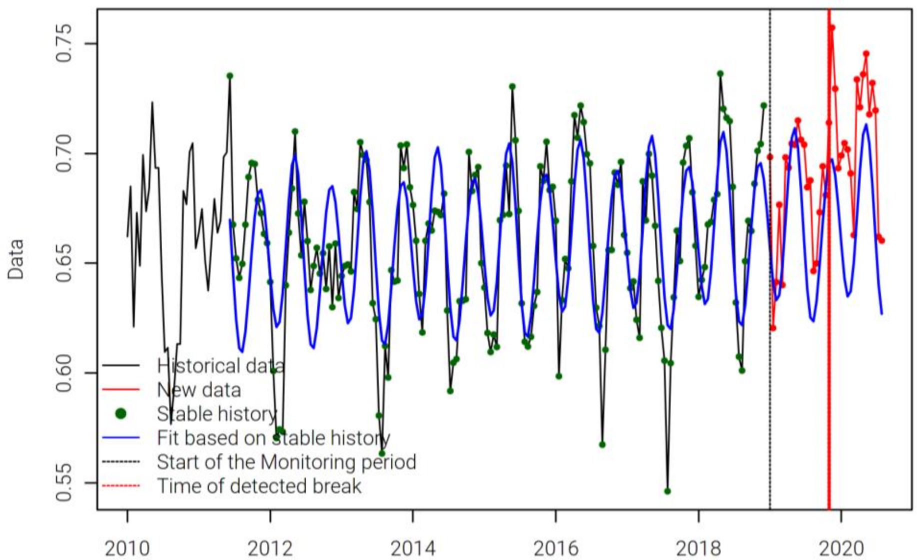


Figure III-5.2 BFAST results of the Virunga National Park NDVI time series with a break detected on November 1, 2019.

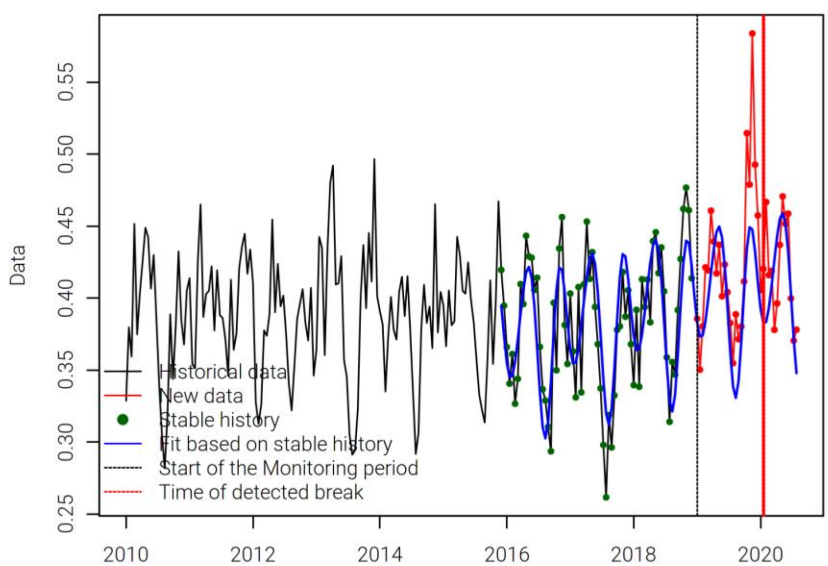


Figure III-5.3 BFAST results of the Virunga National Park EVI time series with a break detected on January 17, 2020.

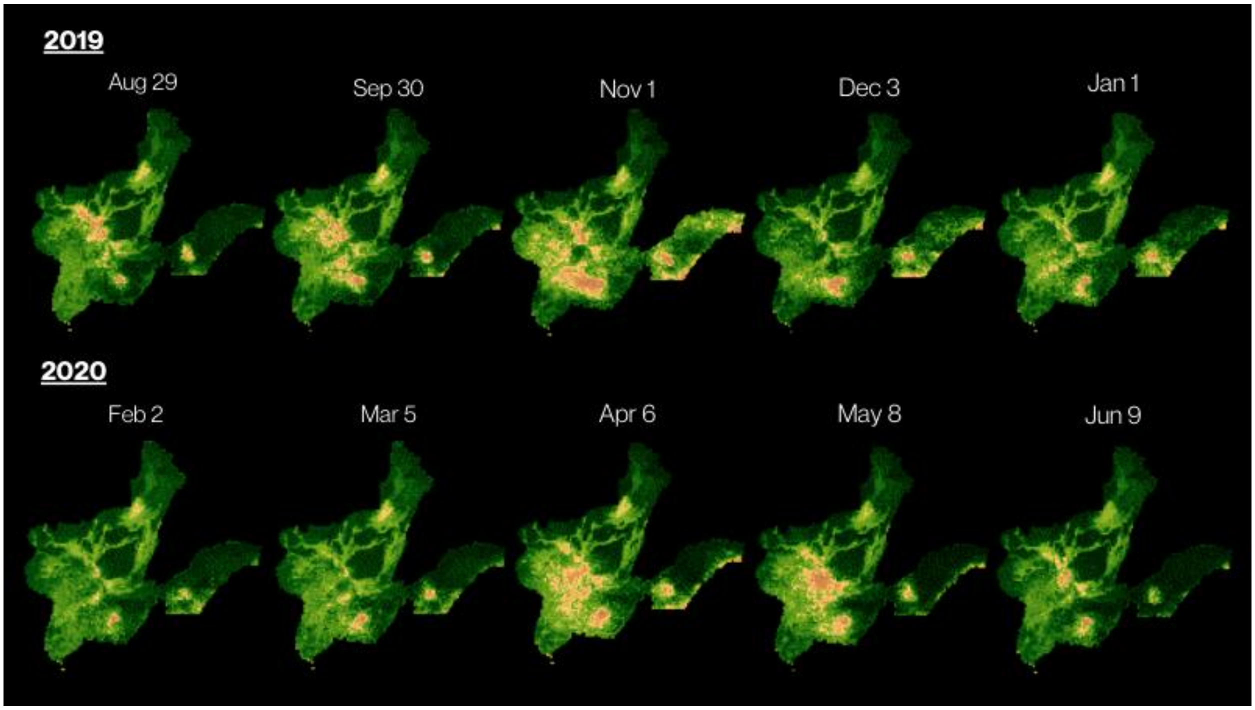


Figure III-5.4 Time series of mean NDVI for serial 16-day MODIS composites spanning August 29, 2019 to January 1, 2020 and February 2, 2020 to June 9, 2020.

The **Maiko National Park** experienced intense bouts of deforestation in February, May, June, and October of 2019. NDVI decreased by 0.271 between February 2 and February 18, 0.332 between May 9 and June 10, and 0.348 between September 14 and October 16. But, these periods of land degradation were followed by remarkably quick recoveries. NDVI increased by 0.328 between February 18 and March 6, 0.36 between June 10 and June 26, and 0.353 between October 16 and November 1. No breaks were detected in the Maiko National Park NDVI time series (Figure III-6.1) in the year 2020 despite a drop in NDVI between May 24, 2020, and June 15, 2020, of 0.229. The sudden drop in NDVI in the summer months of 2020 is small compared to decreases in NDVI the year prior. Also, the lowest NDVI value in 2020 of 0.635 on June 15 is 0.22 greater than the lowest recorded NDVI of 2019, which was 0.415 on October 16. Between 2010 and 2019, the national park has experienced a dramatic drop in NDVI between June and July, possibly indicating a seasonal pattern of low vegetation density in the summer months. The drop in deforestation detected between May 8, 2020, and June 15, 2020, may correlate with season patterns as opposed to unregulated deforestation activities in the era of COVID-19. Nevertheless, NDVI from January 1, 2020, and May 8, 2020, have reached historically high levels above 0.8. NDVI in 2019 was between 0.65 and just below 0.8 on average in 2019. Similarly, no breaks were detected in the EVI time series.

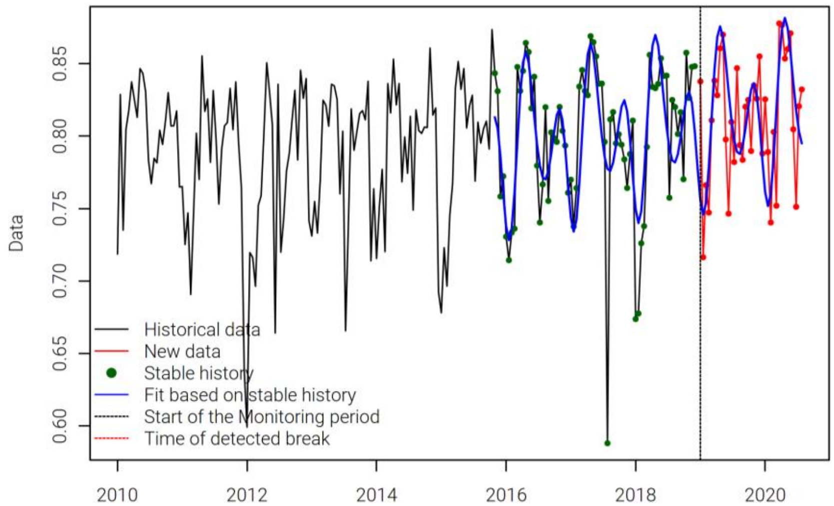


Figure III-6.1 BFAST results of the Maiko National Park NDVI time series with no detected breaks.

CBSP-Catalyzing Sustainable Forest Management in the Lake Tele-Lake Tumba (LTLT) Transboundary Wetland Landscape (2012)

The 2012 GEF project focused on preserving the LTLT landscape, which is the world's largest swamp forest and the world's second-largest wetland area. 30% of the landscape is dry forest, and 60% of the region is swamp and floodable forests. To analyze the effects of COVID-19 on the project, a time series was generated for the Tumba-Lediima National Park, which is the WDPA within the LTLT landscape.

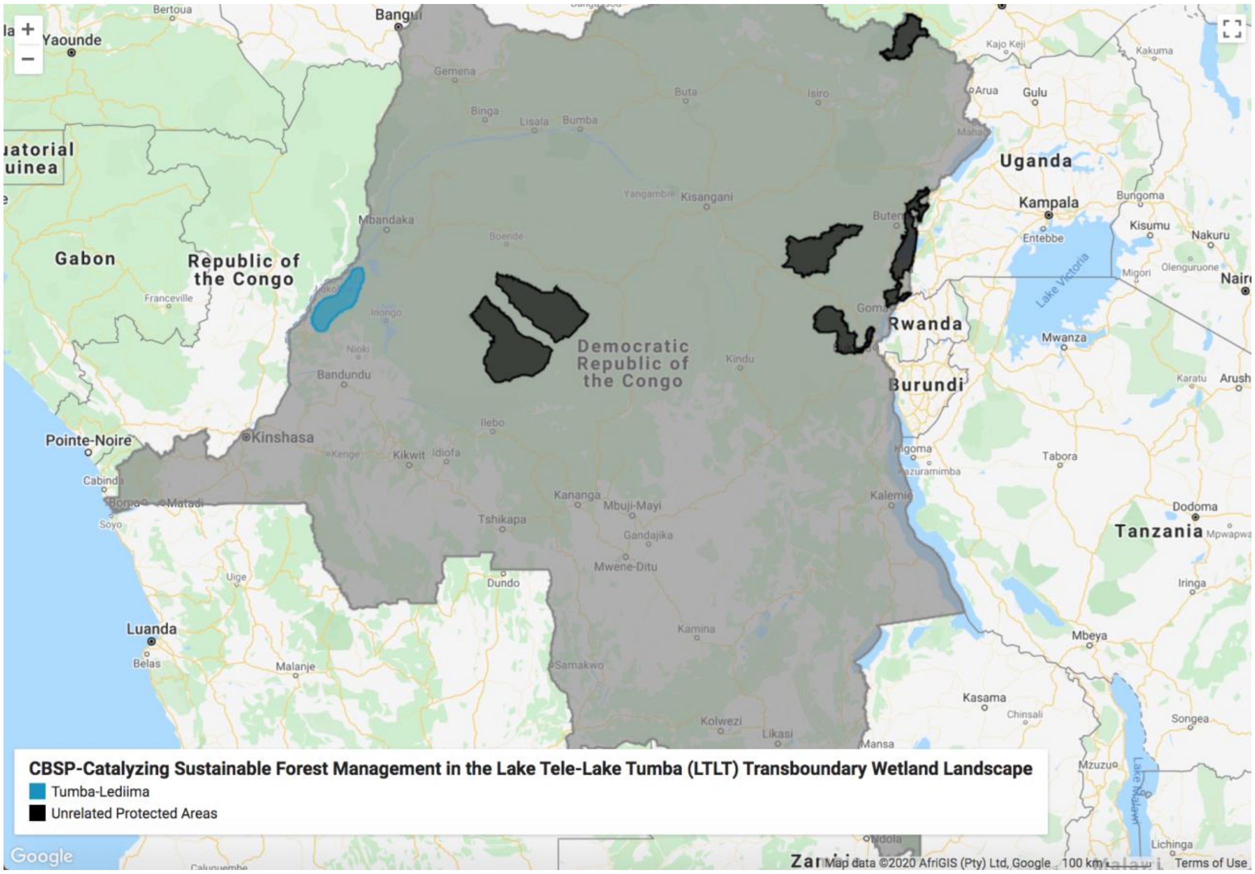


Figure 7. Protected areas associated with the CBSP-Catalyzing Sustainable Forest Management in the Lake Tele-Lake Tumba (LTLT) Transboundary Wetland Landscape project.

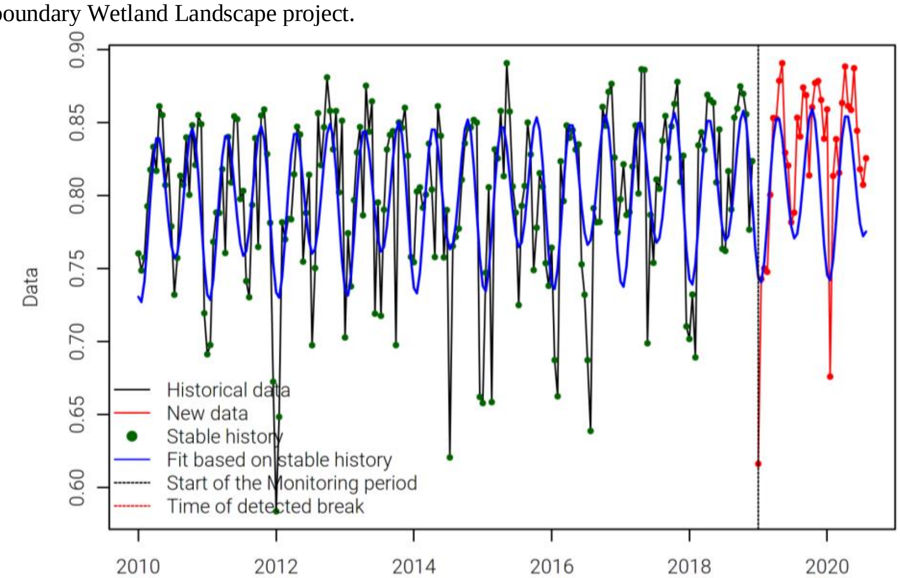


Figure 8.1 BFAST results of the Tumba-Lediima National Park NDVI time series with no detected breaks.

There were no detected breaks in the **Tumba-Lediima** time series (Figure 8.1). In 2019, the national park experienced some dramatic changes in NDVI, such as a 0.182 decrease between December 19, 2018, and January 1, a 0.135 decrease between February 2 and February 18, as well as a 0.143 decrease between May 9 and June 10. But, these drops follow a seasonal trend of

NDVI variability. Predictably, NDVI decreased by 0.162 between January 1, 2020, and January 17, 2020. Surprisingly, NDVI experienced a steady increase afterward and remained stable up until the last recorded value on June 25. Perhaps fewer visitations to and activities within the park amidst worldwide lockdowns allowed for high NDVI values starting in February 2020. No breaks were detected for the park's EVI times series.

Control Areas

Six non-GEF protected areas in the DRC were chosen as control areas for better interpretation of the results from the six GEF protected areas in the DRC that were chosen. These six protected areas were the Sankuru Nature Reserve, the Lomako-Yokokala Nature Reserve, Abumonbazi Nature Reserve, the Bombo Lumene Hunting Reserve, the Maika-Penge Hunting Reserve, and the Rubi-Tele Hunting Reserve. These areas were selected to identify if any nation-wide trends could be responsible for any breaks detected. Using the same procedure as detailed above, a BFAST analysis was performed for each control; no breaks were found in any case.

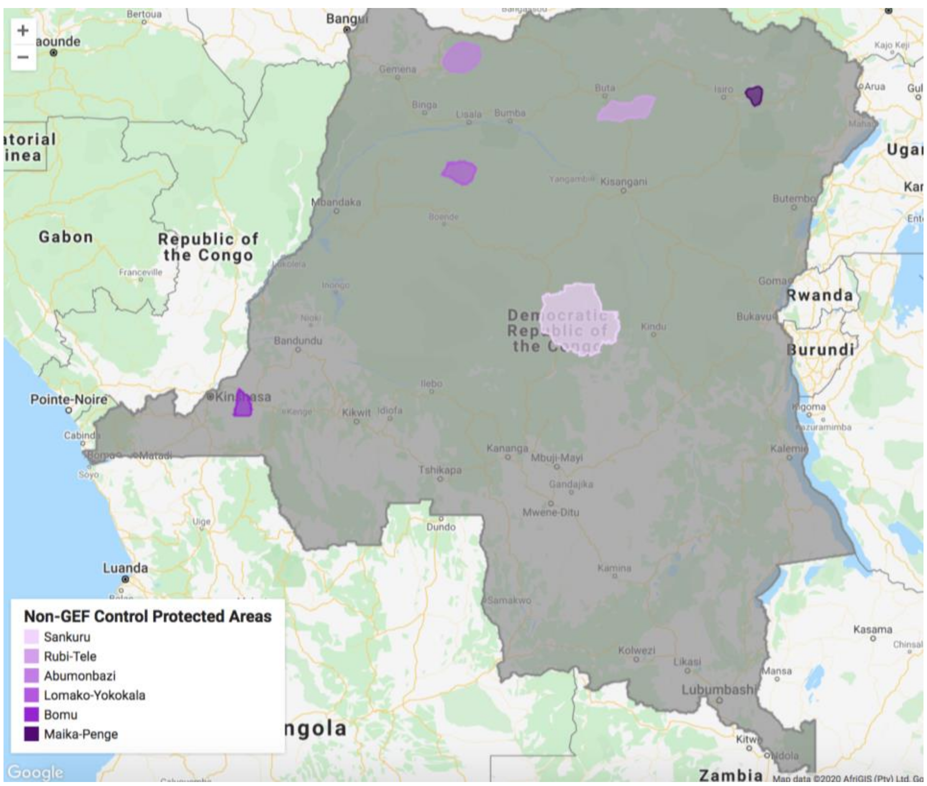
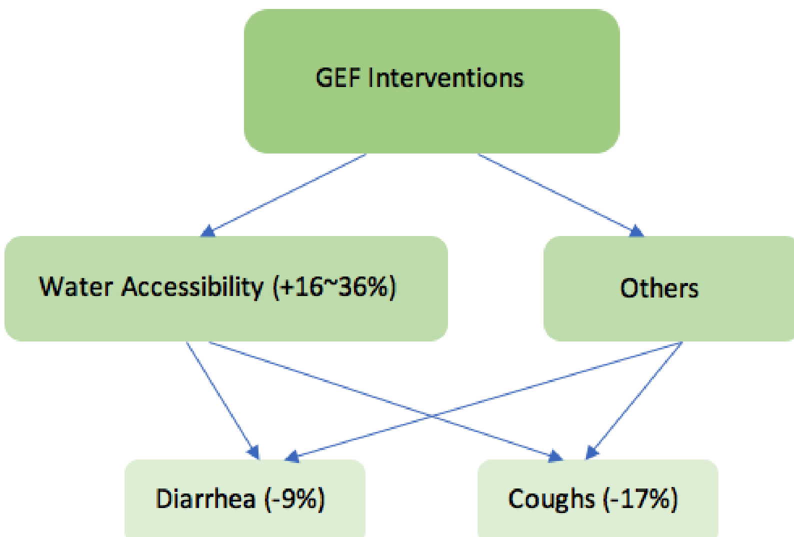


Figure 9. Map of non-GEF control areas.

IV. Impact of GEF Interventions on Health Outcomes

IV-A. Summary

The study presented here aims to quantify the association between GEF interventions and local health conditions of children under five years in Kenya, focusing on health measures including the prevalence of diarrhea and coughs. We test the hypothesis that improving environmental and socio-economic cobenefits of GEF project implementations may result in improved health outcomes. Our study found localized associations in both variables tested, with a 17% reduction in the prevalence of coughs within 10 km from the intervention areas and a 9% reduction in the prevalence of diarrhea was found within a distance smaller than 3 km. Besides the direct measure of health outcomes, GEF interventions also demonstrated positive impacts on water accessibility, including the access to source water in dwelling and the presence of water at hand-washing facilities. All the impacts above are stronger for clusters closer to GEF interventions. However, the estimated impacts on the health metrics were observed when the intermediate outcomes were controlled, meaning that GEF projects may also have influenced the metrics tested through other, still untested causal pathways.



IV-B. Data Description and Methods

This analysis uses the health survey dataset from Kenya DHS 2014, which contains 1594 survey clusters - each cluster representing 19-25 households. The focal areas of the GEF projects analyzed include biodiversity, land degradation, climate change, and sustainable forest management. Only projects started to be implemented before 2014 are considered for this analysis. The data is mapped in Figure 1(a) and Figure 1(b) with the prevalence of diarrhea and the prevalence of coughs respectively.

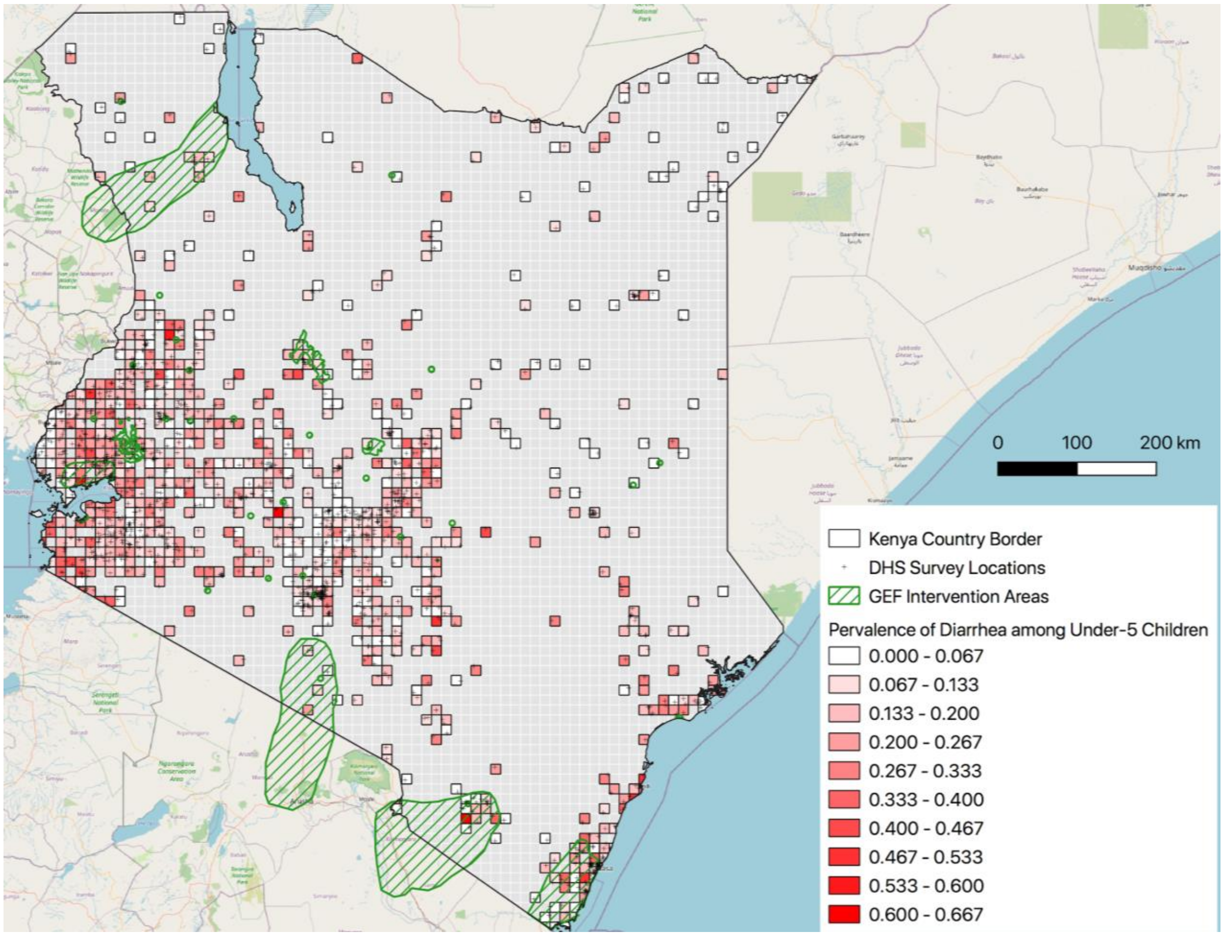


Figure 1 (a). Geographic distribution of households analyzed in this study, superimposed on GEF projects. Coloring indicates prevalence of diarrhea among under-5 children.

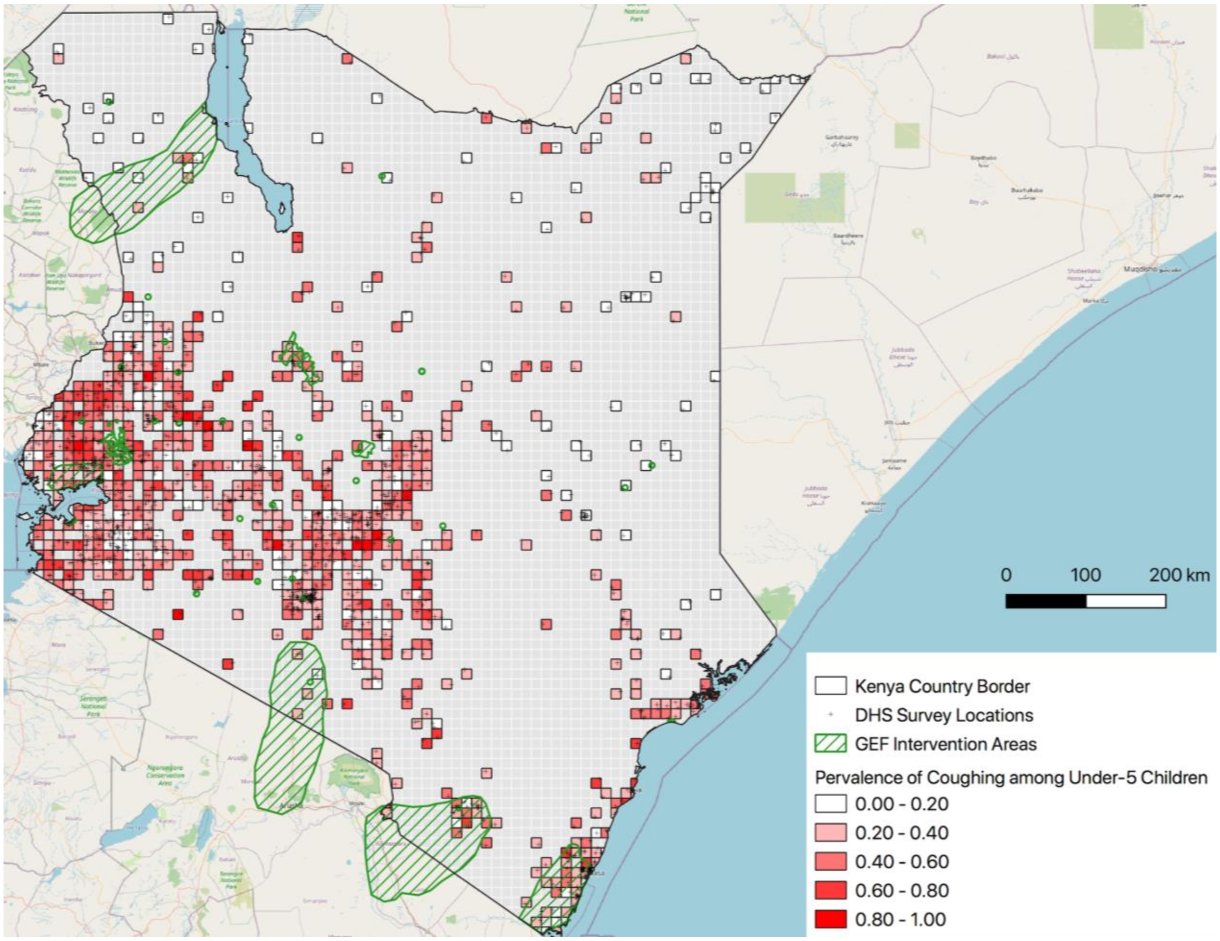


Figure 1 (b) Geographic distribution of households analyzed in this study, superimposed on GEF projects. Coloring indicates prevalence of coughing among under-5 children.

To quantify the association between GEF interventions and children's health conditions, a quasi-experimental geospatial interpolation (QGI) method is used on Kenya's DHS data. The QGI method needs three parameters: the sample density, the upper distance bound and the maximum matching difference. The QGI method uses a propensity-matching approach to pair treated and controlled survey clusters based on covariates. A treated cluster (i.e., a cluster close to a GEF project) and a controlled cluster (i.e., a cluster far from any GEF project) were paired if the difference in their propensity scores was smaller than the maximum matching difference. Then the outcome measures were contrasted within each pair to get an estimated impact, across all observations. This process was performed iteratively by increasing the radius of treated areas until it reaches the upper distance bound. The increase of radius in each iteration is determined by the sample density. When the estimation was obtained for each iteration, the relationship between distance and the estimated association is modeled through a third-degree polynomial. More details on the QGI approach can be found in (Runfola et al. 2019).

IV-C. Results: Diarrhea

Previous research conducted by WHO has found that diarrheal diseases could be attributable to risk factors such as drinking water (34%), sanitation (19%), and hygiene (20%). Since there were GEF projects that directly sought to influence water access and quality, we were interested in studying the impact of GEF projects on improving the sources of drinking water and the accessibility of water for sanitation and hygiene. We also investigated potential impacts from GEF on the diarrhea prevalence among children under five years.

Relevant to drinking water, sanitation, and hygiene, three outcome variables are identified: the average quality of source water for drinking, the presence of water at handwashing facilities, and the accessibility to source water in dwelling. Through the QGI method, GEF interventions demonstrated significant impacts on the percentage of households with the accessibility to source water in dwelling and the presence of water at handwashing facilities. The results showed consistency across robustness tests (see Appendix II (c), (d)). Note that measures on children's counts on these two variables indicated a positive insignificant trend.

In addition to the impacts on selected risk factors, we estimated GEF's impacts on diarrhea prevalence. The prevalence was defined as the percentage of children having diarrhea within the past two weeks of their interviews. The QGI method measured the pure impact of GEF interventions on diarrhea prevalence by controlling variables in Table IV-1 (with a maximum matching difference of 0.3) . The results are illustrated in Figure 2, where the x-axis is the distance between a survey location and its nearest project location and the y-axis is the estimated impact of GEF interventions on the percentage of children having diarrhea. We found that the prevalence of diarrhea was around 9% lower on average for survey locations closer than 3 km from GEF intervention areas, compared with the prevalence at survey locations 33 km away[2]. The impacts were significant at distances smaller than 3 km. Since GEF interventions also demonstrated impacts on a few control variables, the impacts on diarrhea prevalence might be underestimated and there were other causal pathways not yet been tested.

Because of the uncertainties regarding the sample density and the maximum matching difference, robustness tests were performed for sample densities ranging from 30*2 to 30*16 and maximum matching differences ranging from 0.1 to 0.75. Across these tests, the directionality of relationships observed remained consistent for all of the analysis mentioned above, though the magnitude of these relationships and the statistically significant distance intervals varied. Detailed test results can be seen in Appendix II (a), (b), and (d).

[2] This upper-distance threshold is arbitrary; as such, robustness tests are conducted and included in the appendix.

Outcome Variable	**Min**	**Median**	**Max**	**Resolution**	**Source**
Percentage of children having diarrhea in the past two weeks	0.00	0.13	1.00	Household	Demographic and Health Surveys (DHS)
Control Variable	**Min**	**Median**	**Max**	**Resolution**	**Source**
Percentage of children having water source at home	0.00	0.18	1.00	Household	Demographic and Health Surveys (DHS)
Percentage of children having electricity at home	0.00	0.06	1.00	Household	Demographic and Health Surveys (DHS)
Percentage of children having water at hand-washing facility	0.00	1.00	1.00	Household	Demographic and Health Surveys (DHS)
Average quality of source water for drinking	0.00	1.25	2.00	Household	Demographic and Health Surveys (DHS)
Average quality of toilet facility	0.00	1.00	2.00	Household	Demographic and Health Surveys (DHS)
Average quality of roof material	0.71	1.00	2.00	Household	Demographic and Health Surveys (DHS)
Wealth index	0.00	1.75	4.00	Household	Demographic and Health Surveys (DHS)
Percentage of children living with household members who wash their hands with soap	0.00	1.00	1.00	Household	Demographic and Health Surveys (DHS)
Average education level of mothers	0.00	1.28	3.00	Household	Demographic and Health Surveys (DHS)
Percentage of children living in households where water is purified before drinking	0.00	0.41	1.00	Household	Demographic and Health Surveys (DHS)
Aridity (2000)	3.30	27.92	72.70	55 km	Climate Research Unit
Mean temperature (2000)	14.18	21.35	30.10	55 km	Climate Research Unit
EVI (2000)	309.00	3388.70	5438.00	5 km	Climate Hazards Group
Annual precipitation (2000)	20.96	104.64	177.50	55 km	Climate Research Unit
Population (2015)	0.00	43206.14	645457.00	1 km	Global Human Settlement Layer (GHSL)
Nighttime luminosity (2015)	0.00	0.06	51.23	0.5 km	National Centers for Environmental Information
Travel time to population centers (2000)	0.00	31.04	652.82	1 km	Malaria Atlas Project
Proximity to water (2017)	0.00	52194.29	438089.30	1 m	Global Self-consistent, Hierarchical, High-resolution Geography Database(GSHHG)
Land surface temperature (2000)	12.60	23.36	38.41	6 km	MODIS

Table IV-1. Datasets used in this analysis.

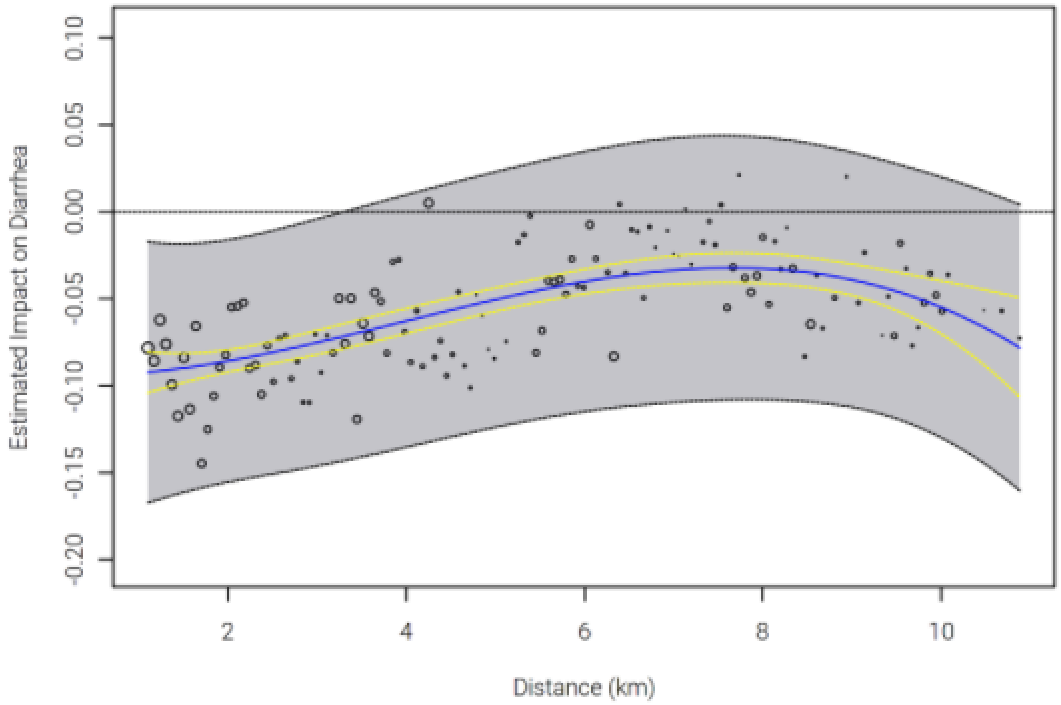


Figure IV-2. Estimated impact of GEF projects on Diarrhea prevalence in under-5 children, over distance.

IV-D: Results: Lower Respiratory Infections

Previous studies conducted by the World Health Organization (WHO) have shown that environmental factors, including household air pollution from the use of solid fuels for cooking, can contribute to more than 50% of lower respiratory infections among children under five years in low- and middle-income countries. Inadequate hand hygiene and ambient air pollution are also considered risk factors of lower respiratory infections. As a primary or secondary outcome of many GEF projects is water quality and quantity as well as clean energy, we anticipate these projects might improve children's hand hygiene by improving their accessibility to water and reduce household air pollution by reducing the use of solid fuels like wood.

To estimate potential impacts on lower respiratory infections, we chose the prevalence of coughing among children under five years as an outcome measure. The pure impacts of GEF projects were estimated through the QGI model with the control variables listed in Table 3. The maximum matching difference was set to 0.2. Figure 3 illustrates the fitted regression line for the estimated impact of GEF projects on the prevalence of coughing. The impacts were significant for distances smaller than 10 km. Compared with clusters not proximate to GEF projects, communities within 10km of GEF interventions have estimated prevalence of coughing 17% less, on average. As shown in the appendix, we also find that the GEF has influence on two control variables potentially associated with coughing - accessibility to water and handwashing facilities.

The result was robust in terms of the direction of the relationship, despite the small variations in magnitude. Similar to the study of diarrhea prevalence, the impacts on the prevalence of coughing might be underrated as GEF projects also influenced some control variables (e.g. the accessibility to water), and GEF projects impacted the prevalence of coughing in other ways that we could not capture.

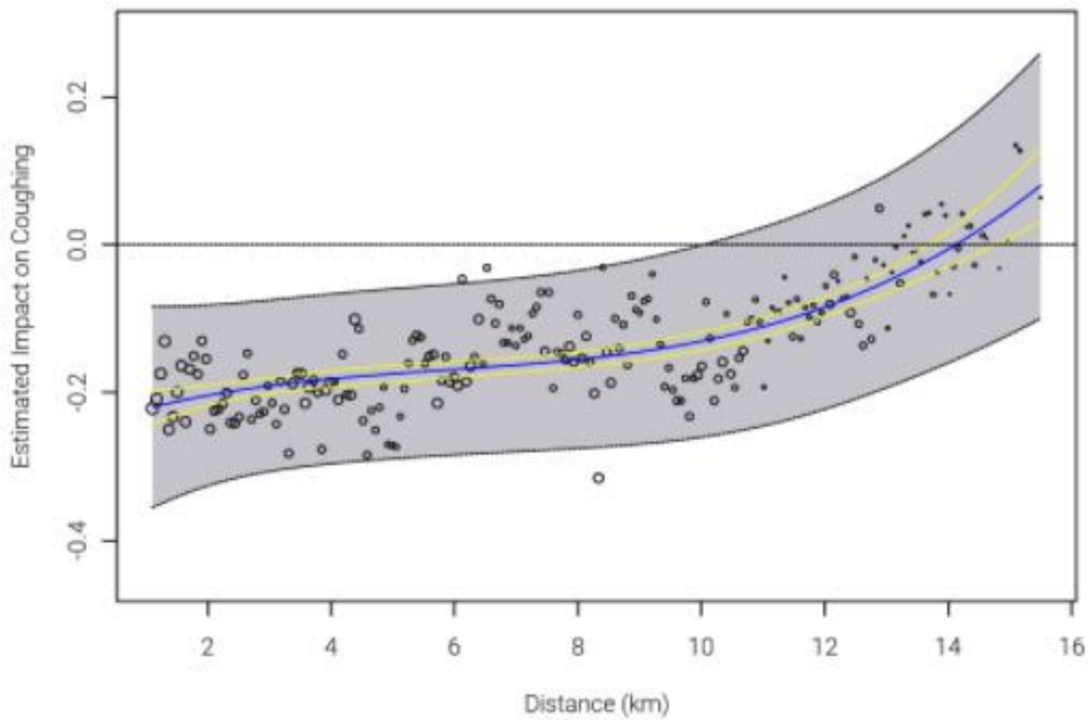


Figure IV-3. Impact of GEF projects on coughing prevalence in under-5 children.

Outcome Variable	**Min**	**Median**	**Max**	**Resolution**	**Source**
Percentage of children having coughs in the past two weeks	0.00	0.35	1.00	Household	Demographic and Health Surveys (DHS)
Control Variable	**Min**	**Median**	**Max**	**Resolution**	**Source**
Percentage of children having water source at home	0.00	0.18	1.00	Household	Demographic and Health Surveys (DHS)
Percentage of children having electricity at home	0.00	0.06	1.00	Household	Demographic and Health Surveys (DHS)
Percentage of children having water at hand-washing facility	0.00	1.00	1.00	Household	Demographic and Health Surveys (DHS)
Average quality of roof material	0.71	1.00	2.00	Household	Demographic and Health Surveys (DHS)
Wealth index	0.00	1.75	4.00	Household	Demographic and Health Surveys (DHS)

Percentage of children living in a household where a separated room is used as kitchen	0.00	0.25	1.00	Household	Demographic and Health Surveys (DHS)
Average number of household members sharing one sleeping room	1.00	3.55	10.00	Household	Demographic and Health Surveys (DHS)
Average frequency of household members smoking at home	0.00	0.00	4.00	Household	Demographic and Health Surveys (DHS)
Percentage of children living in households where solid fuel is used for cooking	0.00	1.00	1.00	Household	Demographic and Health Surveys (DHS)
Average education level of mothers	0.00	1.28	3.00	Household	Demographic and Health Surveys (DHS)
Percentage of children living in households where water is purified before drinking	0.00	0.41	1.00	Household	Demographic and Health Surveys (DHS)
Aridity (2000)	3.30	27.92	72.70	55 km	Climate Research Unit
Mean temperature (2000)	14.18	21.35	30.10	55 km	Climate Research Unit
EVI (2000)	309.00	3388.70	5438.00	5 km	Climate Hazards Group
Annual precipitation (2000)	20.96	104.64	177.50	55 km	Climate Research Unit
Population (2015)	0.00	43206.14	645457.00	1 km	Global Human Settlement Layer (GHSL)
Nighttime luminosity (2015)	0.00	0.06	51.23	0.5 km	National Centers for Environmental Information
Travel time to population centers (2015)	0.00	31.04	652.82	1 km	Malaria Atlas Project
Proximity to water (2017)	0.00	52194.29	438089.30	1 m	Global Self-consistent, Hierarchical, High-resolution Geography Database(GSHHG)
Land surface temperature (2015)	12.60	23.36	38.41	6 km	MODIS

Table 2

IV-E. Limitations

There are a number of limitations of this study, including inaccurate distance measures, seasonal biases and the mismatch in time of some covariates. In this study, distances were calculated as the distances between survey clusters and the boundaries of GEF interventions. Since our dataset only contained polygons for SFM project boundaries, we created 3 km buffers to represent intervention areas for those projects with point locations only. This representation may not precisely reflect the intervention areas. Moreover, for privacy concerns, the locations of survey clusters are randomly displaced up to 2 km for urban areas and up to 5 km for rural areas, which also introduces inaccuracies in the distance measure. Besides the distance and outcome measures, the data for some of the geographical characteristics (see Table 1) of the survey locations was from 2015, which was one year after our year of study.

While the results of our robustness tests suggest that the directionality of our findings is accurate, there are a number of limitations to the conclusions we can draw. First, we can not be sure if the impacts on the prevalence of diarrhea and coughing were localized to areas proximate to GEF projects, as the significant distance range varied for different sample densities. This is also influenced by the distribution of the distances, as there are fewer clusters farther away from GEF locations - i.e., it is harder to detect statistical significance due to a smaller N as distances increase. Second, the estimated impacts on the health metrics were observed when the intermediate outcomes (e.g. water accessibility) were controlled, meaning that GEF projects may influence the metrics through other pathways that have not yet been recognized or accounted for in this analysis.

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Appendix I: QGI Result for Intermediate Outcomes

outcome	mean	significant distance interval	Control Variables	sample density	maximum matching difference	upper distance bound
percentage of households accessible to water at hand-washing facilities	36%	1-4 km	1. Wealth index 2. Month of Interview 3. Aridity (2000) 4. Mean Temperature (2000) 5. EVI (2000) 6. Annual Precipitation (2000) 7. Nighttime luminosity (2015) 8. Travel time to population centers (2015) 9. Proximity to water (2017) 10.Land surface temperature (2015)	30*16	0.2	0.4
percentage of households having water source in dwelling	16%	1-3 km		30*16	0.2	0.3
average water quality	Not significant					
percentage of households using solid fuels for cooking	Not significant					

Appendix II: Robustness Test Results

Outcome	Sample Density	Maximum Matching Difference	Mean	Significant Distance Interval
percentage of children experienced coughing in the past two weeks	30*16	0.3	-17%	1-10 km
	30*8	0.3	-16%	1-9 km
	30*4	0.3	-17%	1-6 km
	30*2	0.3	-22%	2-4 km
	30*16	0.1	NaN	NaN
	30*16	0.2	-18%	1-10 km
	30*16	0.4	-17%	1-10 km
	30*16	0.5	-17%	1-9 km
	30*16	0.6	-21%	1-9 km
	30*16	0.75	NaN	NaN

(a)

Outcome	Sample Density	Maximum Matching Difference	Mean	Significant Distance Interval
percentage of children having water source in dwelling	30*16	0.2	16%	1-3 km
	30*8	0.2	14%	1-4 km
	30*4	0.2	15%	2-5 km
	30*2	0.2	16%	3-6 km
	30*16	0.1	16%	1-3 km
	30*16	0.3	16%	1-2 km
	30*16	0.4	16%	1-2 km
	30*16	0.5	15%	1-2 km
	30*16	0.6	16%	1-2 km
	30*16	0.75	16%	1-2 km

(b)

Outcome	Sample density	Maximum Matching Difference	Mean	Significant Distance Interval
children's accessibility to water at handwashing facilities	30*16	0.2	36%	1-4 km
	30*8	0.2	38%	1-3 km
	30*4	0.2	NaN	NaN
	30*2	0.2	NaN	NaN
	30*16	0.1	NaN	NaN
	30*16	0.3	36%	1-4 km
	30*16	0.4	38%	1-3 km
	30*16	0.5	38%	1-3 km
	30*16	0.6	39%	1-3 km
	30*16	0.75	40%	1-2 km

(c)

Outcome	Sample density	Maximum Matching Difference	Mean	Significant Distance Interval
	30*16	0.3	-9%	0-3 km
	30*8	0.3	-8%	0-3 km
	30*4	0.3	-9%	0-3 km
	30*2	0.3	NaN	NaN
	30*16	0.1	NaN	NaN
	30*16	0.2	-10%	1-2 km
	30*16	0.4	-9%	0-3 km
	30*16	0.5	-9%	0-3 km
	30*16	0.6	-8%	0-4 km
diarrhea	30*16	0.75	-9%	0-3 km

(d)