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Less deforestation, more savings, and more health: spillovers from the implementation of national commitments to mitigate climate change by 2050

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1.- Introduction

Between 2001 and 2019, Peru has improved its economic and social performance indicators. The total GDP has multiplied by 2.5 times at an average annual growth rate of 4.61% (INEI, 2021). However, economic growth has been accompanied by three problematic issues. Firstly, a total of 2.6 million hectares of forest cover reduction between 2001 and 2020, reaching a deforestation level of 203 thousand hectares in 2020, which is the highest level in the last 20 years (Dourojeanni et al, 2020; Bastos et al., 2021). Secondly, even two previous malaria control strategies were implemented by the Ministry of Health (the first between October 2005 and September 2010, and the second between 2017 and 2021), once both policies concluded, malaria incidence increases again showing a positive correlation with deforestation. Thirdly, considering that deforestation in the Amazon is the main challenge to be addressed in the fight against climate change, and that people's health is indirectly compromised by climate change (Groves et al., 2020, Benavides et al., 2021) and directly by deforestation (Yasuoka and Levins, 2007; Vittor et al., 2006; Bustíos et al., 2014), increases in greenhouse gas (GHG) emissions from 154 to 205 Mt of CO2 equivalent in 2005 to 2016, respectively (MINAM, 2021), certainly, raises a concern.

Deforestation in the Amazon is the main threat to the country's biodiversity and the main challenge to be addressed in the fight against climate change, since the current state of the Amazon, without the implementation of measures to reverse it, would not only lead to an important advance of deforestation on the forest but that greenhouse gas emissions would increase considerably.

In the Amazonian territory, there are currently 68 million hectares of tropical rain forest; however, this important natural capital is very likely to be affected by the high and growing levels of deforestation. Between 2001 and 2020, 2.6 million hectares were deforested (GEOBOSQUES, 2022), reaching a deforestation level of 203 thousand hectares in 2020, which is the highest level in the last 20 years and represents one hectare lost every 3 minutes. These levels of deforestation raise concerns that the Amazon region is approaching the tipping point (Dourojeanni et al, 2020; Bastos et al, 2021).

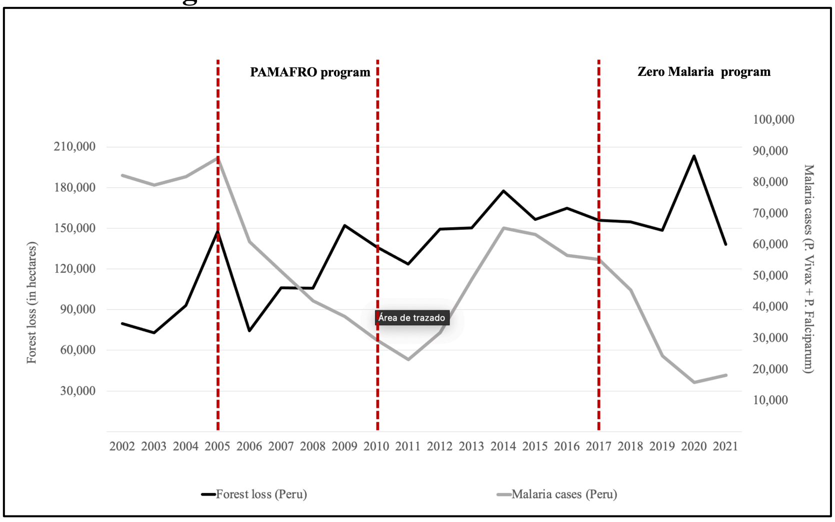
On the other hand, people's health is indirectly compromised by climate change (IDB & Cepal, 2014; Stern et al., 2011; Park, 2011; Lindsay et al., 1998; Manoukis et al., 2011) and directly by deforestation (Yasuoka and Levins, 2007; Vittor et al., 2006; Bustíos et al., 2013). There is empirical evidence that accounts for the causal relationship between deforestation and the incidence of malaria (Garg, 2015) and the spatial behavior of the latter (Desbordes, 2021). Peru had the second highest number of malaria cases in South America behind Brazil in 1999, mainly in the Loreto region, which covers almost a third of the country. Bustíos et al (2014) argued that the change in forest land use towards precarious shifting cultivation has led malaria vectors to seek new breeding sites, dispersing through populated areas where the disease did not exist or was unknown. In fact, the Loreto region has accounted for most malaria cases in the country (Rosas-Aguirre et al., 2015).

Not only due to the large number of incidences during different periods since the 1990s, but also because of the economic burden on the state and the families of the affected communities, this disease is considered a serious public health problem. Between October 2005 and September 2010, Peru received support from the Global Fund - PAMAFRO

Project, which allowed the expansion of comprehensive malaria control strategies in the Peruvian Amazon (Rosas-Aguirre et al., 2015) and drastically reduced the number of cases in Loreto from 54,291 in 2005 to 11,604 in 2010. However, the issue of malaria cases has resurfaced since 2012 and has once again drawn the attention of policymakers (Figure 2). In 2018, there are almost 44,000 cases, of which 96.5% were reported in Loreto. Thus, the Peruvian government has implemented the Zero Malaria Plan 2017-2021, allocating US$25 million to address the large increase in malaria incidence since 2012, mainly in the Amazon region.

Although recent information from MINSA shows that the Zero Malaria Plan had favorable results in reducing the number of malaria cases in the affected areas, as happened with PAMAFRO at the time, from the perspective of a policy decision maker , it is valid to ask whether it is more efficient to allocate economic resources to actions for people affected by malaria or direct efforts towards forest conservation actions that keep the disease vector under control (Figure 1). In this sense, it is pertinent to understand the spatial dynamics of malaria in Peru and its relationship with deforestation and its impact on malaria, giving rise to a negative externality to be mitigated, and thus be able to identify policy measures with a focus on malaria. cost-effective territorial measures that allow dealing with the consequences of climate change.

Figure 1. Forest loss and malaria cases



Source: MINSA, GEOBOSQUES

From the perspective of a policy decision maker, it is valid to ask whether it is more efficient to allocate economic resources to actions for people affected by malaria or direct efforts towards forest conservation actions that keep the disease vector under control. Thus, it is important to understand the spatial dynamics of malaria in Peru and its relationship with deforestation in order to identify potential policies to mitigate a negative externality with a focus on malaria and cost-effective local measures that allow dealing with the consequences of climate change.

Despite most of previous studies have identified a positive relationship between deforestation and malaria cases, causality from deforestation to malaria cases (Berazneva and Byker, 2017 and Garg, 2019), and spatial dependence between forest loss and malaria (Seabra Santos and Almeida, 2018) there is less research in how projecting forest loss – malaria relationship generates health benefits in Peru achieving carbon neutrality by 2050. Thus, the objective of our study is to provide evidence that the path towards carbon neutrality helps to reduce the proliferation of tropical diseases such as malaria, opening the way to the evaluation of other health benefits beyond respiratory diseases. Then, besides using an econometric model we will use the Polysys-Peru model (De La Torre Ugarte et al., 2021).

The structure of this paper is as follows. Sections 2 contains the review of existing literature, section 3 describes the data and analytical strategy, section 4 shows the results obtained, and section 5 shows the conclusions and policy recommendations.

2.- Literature review

In this paper, we investigate the relationship between deforestation and the incidence of malaria. In addition, we use these estimates to quantify the health benefits in Peru of achieving carbon neutrality by 2050, focusing on interventions in AFOLU sector.

The relationship between deforestation and the incidence of malaria has been examined in several previous studies across the world, such as Brazil (Olson et al., 2010; Parente et al., 2012; Saccaro Junior et al., 2015; Mac Donald and Mordecai, 2019), Nigeria (Uneke and Ibeh, 2009), Malaysia (Fornace et al., 2016), Paraguay (Wayant et al., 2010), Perú (Olson et al., 2010), among others.

As a reference, Vittor et al. (2006) have found that that *Anopheles darlingi* biting rate is higher in areas predominantly forested in the Peruvian Amazon, and Vittor (2009) found in the same region that sites with *Anopheles darlingi* had an average of 24.1% forest cover compared with 41.0% for sites without *Anopheles darlingi*. Olson et al. (2010) found that malaria risk increased by 50% in health districts when 4% of the area under study (Mancio Lima County, Brazil) underwent deforestation. Parente et al. (2012) have analyzed both malaria incidence and deforestation rates in four different regions at the State of Pará, eastern Amazon, Brazil, finding that after periods of intense deforestation, malaria incidence rates were high or very high. In Brazil, a similar relationship is found by Saccaro Junior et al. (2015) and Mac Donald and Mordecai (2019), as well, finding the former that for every 1% of deforested area a 23% increase in malaria incidence rates may occur, and the latter that, on average, a 10% increase in deforestation would result in a 2.27% increase in malaria incidence.

Most of the aforementioned studies have identified a positive relationship between deforestation and malaria cases, while only Berazneva and Byker (2017) and Garg (2019) identified the causality from deforestation to malaria cases. Both studies also tested the effects of deforestation on other diseases and found no significant effect, which implies that the effect of deforestation is specific to malaria. Specifically, Berazneva and Byker (2017) investigated the dynamic impact of forest loss on malaria in Nigeria finding that a loss of 1% of forest cover in the previous year leads to a two percentage points increase in malaria incidence. In Indonesia, Garg (2019) provides causal evidence finding that a 1% decline in primary forest cover loss increases by 10% the incidence of malaria, and that the effect is strongest in villages near forest (but persists to a lesser extent in more distant villages). Furthermore, as in Garg (2014), the author found also that deforestation has no discernible effect on the incidence of other diseases such as measles, diarrhea, and respiratory infections.

Besides deforestation other covariates may also contribute to malaria incidence. Malaria is driven by a complex set of economic, socio economic and ecological factors. Regarding economic activities, in mining and logging camps, and in new farming settlements typically malaria occurs (Confalonieri et al., 2014). There is also evidence that the construction of large collection of surface waters such as dams (Quiroz and Motta-Veiga, 2012; Kaiser et al., 2005) or irrigation systems (Pattanayak and Pfaff, 2009; Yasuoka and Levins, 2007) work as potential pathways through forest loss can increase malaria incidence.

About socio economic factors, malaria is related to mobility of humans making them both infected and suceptible to the difficult logistics for the provision of health care service in remote communities (Gil et al., 2007). This interaction is seen in informal gold mining sites (Barbieri et al., 2005; Barbieri and Sawyer, 2007). Oppositely, urbanization due to demographic changes, better-quality "mosquito-proof" housing will, and better access to health care will lead decreased malaria transmission (De Silva and Marshall, 2012; Escobedo, 2010; Willicox and Ellis, 2006). In addition, in areas completely deforested and replaced by pasture malaria cases become rare (Castro et al., 2006).

As part of ecological factors, a positive association between climatic and hydrological factors and malaria incidence has been found especially with river level and precipitation (Bazurko et al., 2011), as well with higher ground temperatures (Kweka et al., 2016), amount and duration of sunlight, and puddle formation (Gottwatt, 2013; Wolfarth, 2011; Pattanayak and Pfaff, 2009, Yasuoka and Levins, 2007; Magris et al., 2007; Bautista et al., 2006). Furthermore, changing landscapes can influence microclimatic conditions (e.g., temperature, evapotranspiration, and surface run-off) all key determining mosquito abundance and survivorship (Patz and Olson, 2006).

Even previous studies suggest the existence of a positive correlation between deforestation and the incidence of malaria although this relationship could be fed back or affected by other variables (economic, socioeconomics and ecological factors), only some papers have addressed the potential issues of endogeneity (Garg, 2019; Garg, 2014; Berazneva and Byker, 2017) in order to estimate causal impact of forest loss on malarian transmission. Nevertheless, besides Santos and Almeida (2018) for Brazil, the literature addressing spatial dependence between forest loss and malaria -as incidence of malaria in one particular location could be spread to the nearby areas and infect humans- is still scarce.

Thus, we provide in this study insights of the relationship between deforestation and malaria cases in Peruvian Amazon given the rising concern of public health related to natural resource degradation. Specifically, we aim to enhance the estimation of deforestation's influence on malaria case incorporating spatial dependence among the variables of interest. Recent empirical works on the determinants of life expectancy in developing countries state that frequent omission of spatial dependence is troublesome, from an economic and econometric perspective, because local outbreaks of many infectious diseases are characterized by rapid spatial propagation (Desbordes, 2021).

On the other side, despite the paucity of studies on forest loss in Peru, significant efforts were made to forecast its evolution through 2035 using trends and linear regressions based on the deforestation pattern of previous years. Limacho (2015) and PCNB (2016) estimate the main drivers of deforestation (cropland, grasslands, timber production, and forest fires, among others) as they want to reach better decision policies. MINAM et al. (2018) predicted trends for each forest use category because the objective was to establish and validate the NDCs. Seminario et al. (2017) incorporated land-use change and forestry production modules into the T21-Peru model for the purpose of simulating the Peruvian economy by 2035. This system dynamics model take into account the interactions and feedbacks between the agriculture (by natural region and two crop groups), forestry (Amazon), manufacturing, mining, and services sectors. The exchange of capital, labor, and land between sectors limited agriculture's profitability and, consequently, its growth. The demand for cropland in the rainforest was primarily influenced by agricultural profits and population growth. Profits in agriculture depended on capital elasticity and production, which was simulated by a Cobb-Douglas function that included capital, employment, and land. Nevertheless, T21-Peru examined the other forest loss drivers as fixed coefficients, grouped 16 forest categories into five categories, projected GHG emissions with an average coefficient per hectare lost, and did not account for price changes. The roles of secondary forests, forest burning, and fallow lands were omitted.

Multivariate regressions based on linear, spatial, and panel data models are utilized in international research on forest loss drivers. These studies share variables such as crop consumption (local production, imports), local population (growth, density, urban or rural status), ground and river roads (accessibility, length, density, pavement status), market distance, institutional/financial variables (amount of infrastructure credit, presence of development projects, number of local banks, social aid), geophysical variables (nitrogen in soils, soil moisture, annual precipitation), and area of natural protected areas. Some studies attribute deforestation to the lack of recognition of the forest's value, which is represented by income and profit variables. These studies examine agriculture, livestock, and forestry variables such as prices (exports, imports, local market, inputs), government subsidies (agriculture, technology, equipment), soil quality, average household income (agriculture, livestock, forestry, off-farm, share), household (size, number of years in location), association status, livestock heads, and debt amount (Hargrave & Kis-Katos, 2013; Araujo, Combes & Feres, 2014; Garrett et al., 2017). Intriguingly, the direction and magnitude of the effect of income on deforestation vary widely: in some cases, it is negative (Pfaff, 1999; Araujo, Combes & Feres, 2014; Ferretti-Gallon & Busch, 2014; Garrett et al., 2017) and in others, it is positive (Geist & Lambin, 2002). These differences may reflect an increase in productivity per hectare (intensification) in the agricultural sector (Foley et al, 2005). La Rosa (2016) highlights in Peru variables such as proximity (to deforested areas, natural protected areas, roads, and urban areas), sector GDP (agriculture, manufacture), cropland size, productivity (agriculture, timber), indigenous population size, employment by sector and region, and elevation.

Finally, achieving net-zero emissions is necessary to limit global warming to well below 2 °C and toward 1.5 °C, as stipulated by the Paris Agreement. More than 50 countries have set goals to achieve net-zero emissions, typically by 2050, and the majority are working towards similar objectives. To reach these objectives, the electricity, transportation, agriculture, land-use, buildings, industry, and waste-management sectors must undergo transformations (Fazekas, Bataille & Vogt-Schilb, 2022). Despite the fact that solutions exist to transition to a carbon-neutral economy, including technological and behavioral changes that are frequently accompanied by economic, social, or development benefits, many obstacles impede their adoption (Fazekas, Bataille & Vogt-Schilb, 2022).

The transformations of decarbonization can come with local benefits, such as lower energy costs owing to record-cheap renewable energy, operating savings due to electromobility, the benefits of avoided air pollution to health, reduced time wasted in traffic congestion, better health outcomes linked to physical exercise, reduced accidents, healthier diets, better industrial and agricultural productivity, and ecosystem services including biodiversity preservation, provision of fresh water, and attraction of tourism (Groves et al., 2020; IDB & MINAM, 2021, Benavides et al., 2021; Vogt-Schilb, 2021; Fazekas, Bataille & Vogt-Schilb, 2022).

The contribution of decarbonization to health enhancements has focused on the advantages of improved air quality, as phasing out fossil fuels offers health benefits from cleaner air, water, and soil. There is a estimation about health cost of coal, oil, gas and its deaths generated (Markandya and Wilkinson, 2007) and water available tith power generation can be reduced by up to 95% if 100% of the world's energy comes from renewable sources (Lohrmann et al., 2019). In addition, cleaner air (indoor and outdoor) reduces the risk of cardiorespiratory disease, which is a health benefit associated with the electrification (IEA, 2016; Anenberg et al., 2019; RMI, 2020).

The development of this study contributes to the generation of evidence that the path towards carbon neutrality helps to reduce the proliferation of tropical diseases such as malaria, opening the way to the evaluation of other health benefits beyond respiratory diseases.

3.- Data and methodology

3.1.- Econometric models

3.1.1.- Fixed effects model

The main objective of this study is to investigate the relationship between a district's level of deforestation and its malaria incidence. For it, given panel data as input, this relationship of interest can be rewritten empirically as the following:

$$Malaria_{it} = f(Deforestation_{it}, \beta) \dots (1)$$

where $Malaria_{it}$ resembles the number of registered cases of malaria and it's a function of $Deforestation_{it}$, which represents the deforested area in district i in year t. In turn, β explicates the effect that $Deforestation_{it}$ exerts on $Malaria_{it}$. Though, for our empirical setting to capture forest loss's impact on malaria incidence, several other influences must be considered, including both the observed and unobserved. Furthermore, this first relation can be expressed in the context of a panel data fixed effects model:

$$Malaria_{it} = Deforestation_{it}\beta + \boldsymbol{X}_{it}\boldsymbol{\gamma} + \mu_i + \varepsilon_{it} \dots (2)$$

In equation (2), we yet again assume a linear structure for the relationship of interest and add the presence of a several control variables for district i which are represented by $\boldsymbol{X}_{it}$. This may control for several other covariates which influence malaria incidence in districts i in year t such as: climatological factors, socioeconomic and healthcare variables, and some controls. Thus, the effects of this set of observed control variables will be represented by the vector $\boldsymbol{\gamma}$. μ_i controls for the unobserved heterogeneity of each cross-section unit. ε_{it} represents the idiosyncratic deviations of the model for district i in year t.

The core independent variable including in $\boldsymbol{X}_{it}$ is forest loss (in hectares) 1 year ago (lagged forest loss), following Berazneva and Byker (2017) and Jung (2015). Using this lagged variable has a twofold purposes: it allows us, firstly, to consider the dynamic impact of forest loss on malaria, which suggest a temporary ecological disturbance consistent with findings in the tropical medicine literature (Berazneva and Byker, 2017). Secondly, the temporal-lagged deforestation variable can prevent the potential endogeneity concern associated with the consequence of omitted variables and/or potential bidirectional causal relationship (MacDonald and Mordecai, 2019) or reverse feedback from malaria to deforestation (Garg, 2019). Thus, we estimate the following equation:

$$Malaria_{it} = Deforestation_{it-1}\beta + \boldsymbol{X}_{it}\boldsymbol{\gamma} + \mu_i + \varepsilon_{it} \dots (3)$$

3.1.2.- Spatial dependence estimation

In this paper, we employ spatial econometrics to identify the spatial spillover effect of local deforestation on other regions (districts). Previous literatures have indicated that the relationship between deforestation and malaria, as well as other controls may have a spatial correlation of malaria contagions through space (Seabra Santos and Almeida, 2018; Olson et al., 2010; Hahn et al., 2014). In addition, since Anopheles darlingi has a radius locomotion up to 7 – 12 km away from its breeding source (Kauffman and Briegel, 2004; Charlwood and Alecrim, 1989), a disturbance such as deforestation may thus lead to a higher (or lower) incidence of the mosquitoes in neighboring districts (Seabra Santos and Almeida, 2018). A conventional ordinary least squared (OLS) model assuming independent relationship across observations will provide biased and inconsistent estimates if the independence assumption is invalid (Le Sage and Pace, 2009). Thus, to prevent the potential issues of spatial dependence and obtain an unbiased estimation, we insert the spatial components in the next equation:

$$\begin{aligned} Malaria_{it} = {} & \rho W Malaria_{it} + \beta_1 Deforestation_{it-1} \\ & + \varphi_1 W Deforestation_{it-1} + \varphi_j \boldsymbol{W}\boldsymbol{X}_{it} + \mu_i + \xi_t + \lambda W u_{it} + \varepsilon_{it} \dots (4) \end{aligned}$$

where ρ is the spatial lag coefficient, φ is the spatial lag coefficient of the covariates, and λ is the spatial error coefficient. The matrix of spatial weights, W, used to perform the spatial lag are a Binary Contiguity Matrix (Binary), a Row Standardized Contiguity Matrix (Raw Standardized) and a Hybrid of and Inverse Distance and Contiguity Matrix (Hybrid), which were estimated following a queen structure (which considers adjacency in knots and sides) for testing the malaria-deforestation relationship. The first one was based plainly on the earlier definition. The second one divides the elements of row of the matrix by the total of the number of neighbors, which is useful in spatial regressions since it sets to introduce geographical effects at their mean where applied. In turn, the third one is the result of multiplying each element *ij* of the Binary Matrix to the inverse of the distance between spatial units *i* and *j*.

In the literature on malaria infection, no theory is found that supports which spatial parameters should be used (Seabra Santos and Almeida, 2018). According to Elhorst (2014), if $\rho = 0$, we will have the spatial Durbin error model (SDEM); if $\varphi = 0$, we will have the Kelejian-Prucha (SAC) model; and if $\lambda = 0$, we will have the spatial Durbin model (SDM). We also have the case of two spatial coefficients being nonsignificant: if $\rho = 0$ and $\varphi = 0$, we estimate the spatial error model (SEM); if $\varphi = 0$ and $\lambda = 0$, we obtain spatial lag model (SAR); and, finally, if $\rho = 0$ and $\lambda = 0$, we find the spatial lag of X (SLX). However, if $\rho = 0$, $\varphi = 0$ and $\lambda = 0$, we estimate a panel model, in this case, of fixed effects, as we explained before. As it will be explained later, after performing some tests, we find that the Spatial Durbin Error error model (SDEM) is the most appropriate.

3.1.3.- Data and variables

We use a yearly data for 442 districts located in 6 regions-departments of the Peruvian Amazon (Amazonas, Cajamarca, Huánuco, Loreto, San Martín, and Ucayali) from 2001 to 2020. This were selected conveniently given that these regions report the highest levels of cumulated deforestation in the last decade.

Data for this study came from multiple sources. First, the number of malaria cases come from administrative records (at the district, province, and region level) of the National Center for Epidemiology, Disease Prevention and Control of the Ministry of Health (MINSA). The same source provides information regarding the total health and sanitation expenditure by the Central Government, as well as the number of public health care facilities by level of care. GeoBosques, a forest cover changes monitoring platform at the Ministry of Environment (MINAM), provides forest loss information[1]. Finally, socioeconomic (and economic) data (average years of education, and GDP in agriculture and mining), rurality condition and climatological measures (temperature, precipitation, evapotransmiration) came from the National Institute of Statistics (INEI), the Presidency of the Council of Ministers' report on rural municipalities, and the National Service of Meteorology and Hydrology of Peru (SENHAMI), respectively. Finally, a control variable indicating the implementation of both malaria control programs (PAMAFRO and Plan Malaria Cero) was considered. Descriptive statistics for selected variables are summarized in Table 1.

Table 1. Summary of variables (2001 – 2020)

Variables*	N	Mean	SD	Min	Max
Malaria	6,581	128.05	652.96	.00	16,369.00
Deforestation	5,640	337.64	693.82	.00	7,770.69
Temperature	9,724	20.22	5.05	9.44	28.18
Precipitation	9,724	109.88	59.54	1.54	453.81
Evapotranspiration	9,724	112.14	22.66	64.76	150.40
Population density	9,438	44.89	108.74	.07	1,693.57
Rurality condition	9,724	.77	.42	.00	1.00
Average years of education	8,840	8.27	.54	7.12	9.67
GDP - agriculture	8,840	905,199.72	363,054.42	191,338.00	1,703,992.00

[1] The detection of the forest cover loss areas was carried out using a method called DSU, which is based on a Linear Model of Spectral Mixture (MLME) that assumes that the spectral response of a pixel is the linear combination of the materials that are shaped in the pixel. DSU uses the pixels of forest and forest loss, it assumes that when the cover of a forest is lost due to anthropogenic or natural causes, the result is a pixel of bare soil, the mixture of soil with dry vegetation or deforestation residues such as logs, which can also be next to standing forests. More specific information available in: https://geobosques.minam.gob.pe/geobosque/descargas_geobosque/perdida/documentos/Protocolo_Metodologico_Deteccion_Perdida_de_Bosque.pdf?Wed%20Oct%2020%202021%2012:18:27%20GMT-0500%20(hora%20est%C3%A1ndar%20de%20Per%C3%BA)

Variables*	N	Mean	SD	Min	Max
GDP - mining	8,840	1,047,761.80	1,215,242.57	45.00	3,789,024.00
Malaria control program	9,724	.19	.39	.00	1.00
Expenditure on healthcare	9,724	255,400,000.00	202,894,583.30	19,475,805.00	924,400,000.00
Public health care facilities I-1	8,129	9.23	44.44	.00	505.00
Public health care facilities I-2	8,129	5.84	38.87	.00	447.00
Public health care facilities I-3	8,129	8.05	58.44	.00	664.00
Public health care facilities I-4	8,129	.32	1.56	.00	18.00

(*) Cases of malaria - Vivax, Falciparum or Malariae of year *t* in district *i*; Forest loss in the district (in hectares) of year *t* in district *i*; Mean temperature (in C°) of year *t* in district *i*; Mean precipitation (in mm/month) of year t in district *i*; Mean evapotranspiration (in mm/day) of year *t* in district *i*. Estimated population density of year *t* of the district *i*. Rurality indicator (1 if rural) of district *i*. Average years of education of population older than 15 years old of year *t* in region *j*. Total GDP of Agriculture, Livestock, Hunting and Forestry (in thousands of PEN) of year *t* in region *j*; Total GDP of Extraction of Oil, Gas and Minerals (in thousands of PEN) of year *t* in region *j*; Indicator of enrollment in malaria program (1 if district *i* have been treated in programs PAMAFRO between years 2005 and 2010 or PLAN MALARIA CERO 2017 and 2020). Total public expenditure in healthcare of year *t* in region *j*. Public health care facilities in the district (Level of care I-1) of year *t* in district *i*; Public health care facilities in the district (Level of care I-2) of year *t* in district *i*; Public health care facilities in the district (Level of care I-3) of year *t* in district *i*; Public health care facilities in the district (Level of care I-4) of year *t* in district *i*.

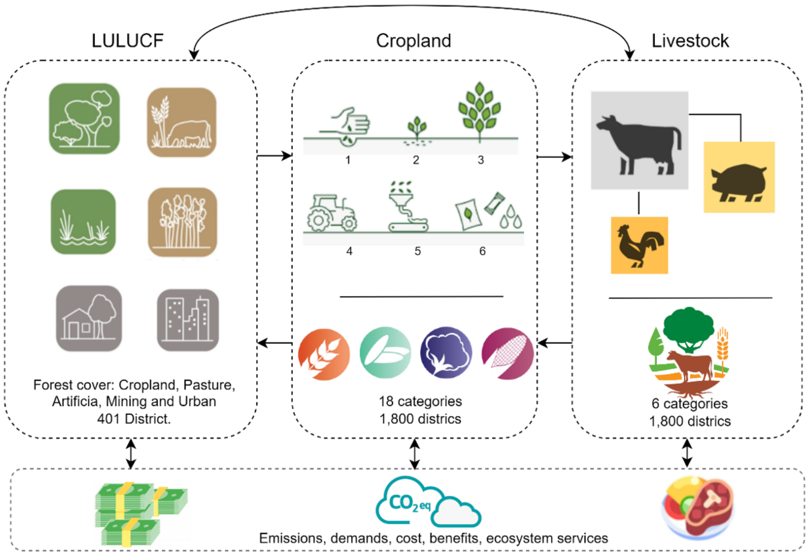
3.2.- Modeling the deforestation dynamic

3.2.1.- POLYSYS-Peru Model

POLYSYS-Peru integrates the agricultural, forestry and land use sectors into a single model, which allows capturing the relationship between these activities and land use change. This model has been calibrated based on the INGEI 2016 and considers the management of primary and secondary forest soil inventories, as well as the relationship of these forests with the causes of deforestation, loss of soil productivity, expansion of agriculture and livestock, mining, forest fires and urban expansion (De La Torre Ugarte et al, 2021; MINAM, 2021).

The POLYSYS-Peru integrated model considers the competition for land use between crops and pastures, especially in the Amazon region, where deforestation becomes a response to agricultural and livestock pressures. Based on these variables, the model, through supply and demand, can determine prices, quantities produced and demanded, operating costs, income and investments, as well as environmental impacts such as emissions and ecosystem services from a base year. Land use is at the heart of the interaction. Crops and pastures compete for land use according to their profitability per hectare. In the Amazon region, this competition for land affects the forest landscape, as deforestation becomes a response to agricultural and livestock pressures. It is important to note that the greatest pressure from agricultural and livestock activities on the forest comes from small producers who do not have the resources to maintain soil productivity, so they resort to deforestation to replace the loss of productivity.

Figure 2. Diagram of the AFOLU integrated model



3.2.1.1.- Study area

The model considered 1791 districts distributed in seven regions (North Coast, Central Coast, South Coast, South Coast, North Highlands, Central Highlands, South Highlands, and Amazon), the agricultural sector includes 16 crop categories: alfalfa, corn, legumes, tubers, fruits and vegetables for domestic consumption and export, cocoa, hard yellow corn, sugar cane, rice, cotton, grains and cereals, coffee, and pastures. The livestock sector has also been divided in the same way as the agricultural sector but has been categorized into six types of livestock species: cattle, pigs, poultry, sheep, goats and auquenidos; considering the district distribution offered by the IV CENAGRO of the livestock sector. The Interaction between the agricultural sector and the Land Use, Land Use Change and Forestry (LULUCF) sector, or landscape management, is only considered in the Amazon, because the POLYSYS-Peru model only considers Amazonian tropical forests.

In the POLYSYS model, systems of simultaneous equations are established where the unknowns represent variations in endogenous variables that are solved in response to changes in the exogenous variables of the model. The result represents the market in equilibrium and the generated path functions as a baseline. At this point, the generation of scenarios implies that the equilibrium is affected exogenously by disturbances, and the results are stored as the results of the policies to be analyzed, generating alternative paths to the equilibrium one. Among the possible scenarios are the incorporation of rice cultivation due to intermittent droughts and an increase in pork consumption to replace meat consumption.

On the consumption side, the model considers price, cross-price and income elasticities, which represent the preferences of the population. Thus, the proportional changes in the exogenous variables determine the cumulative effect of the changes in the package of exogenous variables for each scenario, including variations in the consumption variables of the different goods.

3.2.1.2.- Data

Databases with detailed information on the performance of the Peruvian agricultural and livestock sector, and which are simultaneously reliable, are scarce. The best options are those government databases (estimates) published by different public institutions, especially the Ministry of Agriculture and the Ministry of Environment. These databases tend to be, to a large extent, approximations. POLYSYS Peru uses fundamentally four different data sources: SIEA, ENA, CENAGRO and Inforcarbon.

The Agricultural Information and Statistics System (SIEA) presents information compiled by the Peruvian Ministry of Agriculture and available to the public. The Anuario Estadístico de Producción Agrícola Boletines Anuales (midagri.gob.pe) contains data series on prices, production, yields and harvested area for each department and for each crop in the country, from 2016 to 2021. The Statistical Yearbook of Livestock and Poultry Production contains data series on prices, production, yield and population for each department and for the main livestock species in the country, from 2016 to 2021. The data contained in SIEA are an approximation of real values and there may be possible important differences with reality. It can be found at the following link: Home (midagri.gob.pe). On the other hand, MIDAGRI provided disaggregated information for the agricultural sector at the district level on the same variables, which are consistent with the departmental and national values presented by SIEA.

The National Agrarian Survey (ENA) is a survey with data available by year from 2014 to 2019. This survey is conducted by the National Institute of Statistics and Informatics. ENA includes information by year on agricultural costs: pesticides, seeds, and fertilizers. ENA data are collected annually, therefore, investment data are not available for long periods of time. In this sense, ENA data represent current expenditures associated with the agricultural sector. ENA data can be downloaded from the following link: http://iinei.inei.gob.pe/microdatos/.

The CENAGRO is a census of the Peruvian agricultural sector and the most reliable source of data available, it was applied by the National Institute of Statistics and Informatics in 2012. On the other hand, CENAGRO lacks cost data, which is essential for the POLYSYS simulation model. It can be downloaded at the following link: http://iinei.inei.gob.pe/microdatos/. A quick exploration of the main results of the IV CENAGRO can be seen in the following link IV Censo Nacional Agropecuario 2012 - Cuadros Estadísticos (inei.gob.pe). For the livestock sector, the livestock population by species at the district level is obtained and projected using departmental values provided by the SIEA.

Inforcarbono is a methodology for calculating emissions from each crop and from the livestock sector. It is a consolidated spreadsheet where different factors are applied to different variables for each sector. This methodology allows to obtain linearity in the emission calculations, so it will be easier to incorporate them in the POLYSYS simulation.

3.2.1.3.- Variables

Thirty-two variables are considered in the agriculture sector and eleven in the livestock sector. On the agriculture side the variables are Land, Yields, Costs, Prices, Demand, Yield variation rate, Cost increase, Variation of total land comprising the increase or decrease of land allocated to each crop category, per capita consumption, Calories per capita, Agricultural production, Net present value, International market results in production and International market results in value. Likewise, the variables on emissions related to this sector are Aggregate emissions factor, Flooded rice field emissions factor, Harvest residue emissions factor, Synthetic fertilizer emissions factor, Fixative emissions factor, Residue burning emissions factor, Indirect fertilizer emissions factor, Aggregate total emissions, Total flooded rice field emissions, Total harvest residue emissions, Total synthetic fertilizer emissions, Total fixative emissions, Total residue burning emissions and Total indirect fertilizer emissions. On the livestock side, the following variables are considered: Heads of cattle, increase in the number of heads, Cost, Saca (supply or slaughter), Consumption, Emissions, Prices, Pastures, Factors explaining prices, Factors explaining costs and Live load.

3.2.1.4.- Main components in the agricultural sector

Agricultural supply

The logic of the farmer-producer is to maximize the profit from the income obtained (price multiplied by yield of the crop category) per hectare minus the cost of agricultural production of the crop category per hectare. A more realistic situation is that the farmer has a certain amount of agricultural area which he must distribute among crops and this distribution will be made based on which crop will be the most profitable; therefore, the agricultural area initially allocated to a crop may be less or more depending on the market situation.

The dynamics of profitability per hectare between crops and pastures has an impact on deforestation, since the farmer's logic as a producer is to obtain the maximum possible profit by distributing the agricultural area among crops, allocating more hectares of agricultural area to the most profitable crops. In short, farmers optimize profit.

Agricultural demand

In the POLYSYS model, demand takes a more passive position in the sense that instead of generating a different demand for each period, a single national demand is used which adapts, over time, to supply conditions. Changes in the quantity demanded for a crop will depend on the sensitivity of consumers to changes in the price of the crop or its substitute.

Equilibrium

When supply and demand converge it is because the farmer-producer has decided to allocate land and at the same time will be allocating how much he will produce which is equivalent to how much will be demanded and consumed.

3.2.1.5.- Main components in the livestock sector

The livestock sector models the six livestock species compartment. The simulation of the livestock sector is carried out considering a logistic function that allows simulating a general trend of the district's livestock population. However, given that the value of the population in this sector is affected by other variables, mainly of an economic nature, shocks of these variables are incorporated; for example, meat production will depend mainly on the population growth of the livestock species, which in turn will depend on the demand for meat consumption. It is worth mentioning that the agricultural sector generates the necessary outputs for the livestock sector.

3.2.1.6.- Main components in the forestry sector

The USCUSS sector module consists of a soil stock inventory management of primary forest, secondary forest, agricultural land, pasture, mining land, human settlements and roads, and other lands. This means that sources of forest deforestation reduce the forest stock but increase the stocks of other lands. However, satellite information does not clearly differentiate deforestation due to logging (timber and fuelwood) and any residual is apportioned to agricultural and livestock land. The following diagram illustrates the relationship between flows and stocks.

The LULUCF model addresses deforestation by estimating the causes of deforestation for each of the 5 categories considered: Croplands, Pastures, Mining Lands, Settlements and Other Lands. In the case of crops, the following are considered as explanatory variables: agricultural income, forestry income, total paved roads and rural population. In the case of pasture, forest income, annual increase in head of cattle, total paved and unpaved roads, and an efficiency factor related to time, which allows controlling the trend improvements in the sector related to a higher animal load per hectare, have been considered. In the case of settlement, paved roads have been considered as the main explanatory variable, together with a constant component. In the case of mining, the projection of the international price of gold has been considered as the main explanatory variable. Finally, for deforestation by other lands, the average deforestation of previous years has been considered.

A malaria module is included in LULUCF, it calculates the malaria cases level generated by deforestation using spatial econometric estimates of malaria and deforestation. Malaria cases are forecasted based on the estimated malaria deforestation elasticity, considering the indirect and direct effects of deforestation on malaria. Also, it provides the economic cost of malaria-related expenses, this estimate considers that a case of malaria generates between 10 to 20 days of lost work therefore it estimated of the minimum and maximum of cost due malaria, a minimum salary of 1,025 soles (close to 269 USD) and a work month that includes 20 days.

3.2.2.- Savings in health care costs due to stopping deforestation

3.2.2.1.- Background

Peru faces climate change by formulating adaptation and mitigation goals expressed in the Nationally Determined Contributions. The Nationally Determined Contributions (NDCs) assumed as a country and society are framed in the Paris Agreement on climate change, which was ratified by Peru on July 22, 2016. This is presented as a Peruvian response to climate change and is framed together with the commitment of the international community to address its impacts and reduce greenhouse gas emissions thus limiting the increase in the average temperature of the planet well below 2 °C. The mitigation target has the ambition to achieve a 40% reduction of GHG emissions compared to a BAU scenario by 2030.

To achieve this objective, Peru is committed to achieving carbon neutrality by 2050. for this purpose, it is necessary the implementation of mitigation measures in LULUCF comprises combined actions for which enabling conditions are required (forest management and granting of rights, improved governance, institutionalism and monitoring and control) and are based on best production practices aimed at increasing productivity and area under these ves practices.

3.2.2.2.- Methodology

The process to analyze the impacts of the of the interventions in reducing deforestation and consequently in reducing malaria, starts by generating two scenarios in POLYSYS, first a baseline scenario (BAU) and then a scenario with interventions are estimated, DDP. For the BAU scenario, deforestation increases according to its trend evolution for the main causes: agriculture, based on the historical trend and growth of the sector; mining, based on international gold price projections; infrastructure, based on the growth of the road network expansion; and urbanization, based on the growth of the rural population in the region. Deforestation rates according to territorial forest categories remain constant throughout the 2020-50 period.

For the DDP scenario, based on MINAM (2021), the following transformations have been simulated in:

- Reduction of primary forest deforestation driven by the allocation of forest rights and by investments for conservation, recovery and increased productivity of agricultural soils in the Amazon through the introduction of agroforestry systems (coffee and cocoa), the implementation of a logistical support platform for agricultural development and the development of silvopastoral systems that together allow reducing the pressure of agriculture on the forest. In addition, agroforestry and silvopastoral systems contribute to carbon sequestration and increase crop productivity under agroforestry systems. In no case does the allocation of rights contemplate concessions in the primary forest for the development of forestry plantations.

- Encouragement to take advantage of forest resources through the promotion of concessions under sustainable forest management and forest plantations for commercialization.

- Significant promotion of investments in plantations for restoration purposes that in no case considers the development of forest plantations in the primary forest.

In the agriculture sector, the following transformations are considered following transformations:

- Recovery and management of natural pastures and high Andean and Amazonian pastures, which results in an increase in efficiency of the livestock and reduces emissions per kilo of beef.

- Development of silvopastoral systems in the Amazon region, resulting in Amazon, which results in greater cattle efficiency, reducing emissions per kilo of beef produced in the Sierra region. efficiency, reducing emissions per kilo of beef produced in the Sierra region. emissions per kilo of beef produced in the Amazon region. in the Amazon region, and additionally contributes to carbon sequestration. contributes to carbon sequestration.

- Use of agricultural residues through the production of organic fertilizers organic fertilizers to replace inorganic fertilizers inorganic fertilizers, mainly for fruit, cereal, grain and rice crops. and grains, and rice.

- Adoption of the intermittent drying system for rice crops on the rice crops on the coast to replace the traditional traditional system of rice cultivation; this rice cultivation system; this helps reduce emissions and emissions and increases crop productivity. crop productivity.

An additional transformative element is the promotion of changes in the food diet, namely:

- On the carbohydrate side, it is driving a transition from rice consumption to the consumption of tubers, cereals and consumption of tubers, cereals and grains, and legumes, while maintaining a similar level of calorie similar level of calorie consumption. This contributes to reduce the pressure of rice crop expansion and redirects and redirects demand towards lower-emission crops. crops that generate lower emissions.

- On the meat consumption side, a transition away from beef consumption is encouraged. a transition from beef consumption to pork consumption to pork consumption, thus maintaining the trend growth of the the trend growth of meat consumption is maintained, but with a meat consumption, but with a greater share of pork pork consumption, but with a higher share of pork pork in relation to beef. This contributes to reduce the pressure of deforestation by livestock expansion into the forest, and redirects demand and redirects demand towards lower-emission consumption with lower emissions.

Considering the estimated level of deforestation, the malaria level forecast for each of the scenarios is obtained based on the evolution of deforestation. For this purpose, the number of malaria cases in 2020 is taken as a starting point, and thereafter it is calculated, with the rate of change of deforestation and the estimated elasticity that relates deforestation to malaria cases, the level of malaria cases forecasted.
For the estimation of the cost of malaria cases, a minimum and maximum is estimated based on the period that a malaria case can last. It is estimated the cost in lost work days, so it is considered the minimum wage, currently at 1,025 (269 dollars) with an exchange rate of 3.8, as well as a month with 20 working days (between 10 and 20 days).

The savings in health costs are calculated by comparing the costs between the two scenarios, business as usual and the decarbonization scenarios. For this purpose, the total cost increase is estimated year by year and the total accumulated cost to 2050 is calculated. A cost per case is constant in period, so this estimate are expressed in 2020 constant dollars.

4.- Results

4.1.- Malaria and deforestation relationship

4.1.1.- Fixed effects estimation

We estimated equation (3). A quadratic term is added for the variable of interest intending to identify nonlinear effects of deforestation over malaria incidence. We applied a logarithmic transformation for all continuous variables. Table 2 presents first evidence about the sign and significance of the covariates. Remarkably, the incidence in malaria is shown to be associated consistently with a positive and statistically significant coefficient starting from column 8 onwards. In summary, the results show that an increase in past deforestation is correlated directly with an increase in next year's malaria incidence. But this impact appears to be penalized as its quadratic term's coefficient is statistically significant though negative and with lower magnitude.

Table 2. Panel data fixed effects regression

Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ln_ldeforestacion: Lagged Log Forest loss in the district (hectares)	-0.0421**	0.0662	0.0695	0.0696	0.0737	0.0810*	0.0790	0.166***	0.177***	0.205***	0.207***
	(0.0201)	(0.0480)	(0.0478)	(0.0477)	(0.0476)	(0.0487)	(0.0487)	(0.0469)	(0.0474)	(0.0469)	(0.0459)
ln_ldeforestacion2: Lagged Log Forest loss in the district (hectares) ^ 2		-0.0173**	-0.0174**	-0.0171*	-0.0174**	-0.0193**	-0.0189**	-0.0219***	-0.0233***	-0.0274***	-0.0275***
		(0.00872)	(0.00873)	(0.00874)	(0.00874)	(0.00881)	(0.00882)	(0.00827)	(0.00829)	(0.00817)	(0.00805)
ln_temp: Log of mean Temperature (C°)			-0.890***	-1.317***	-1.133***	-1.149***	-1.014***	-1.425***	-0.882***	-0.316	-0.327
			(0.273)	(0.308)	(0.305)	(0.312)	(0.293)	(0.301)	(0.289)	(0.312)	(0.313)
ln_prec: Log of mean Precipitation (mm/month)				-0.345***	-0.348***	-0.352***	-0.362***	-0.110**	-0.0325	-0.0539	-0.0523
				(0.0590)	(0.0592)	(0.0601)	(0.0609)	(0.0482)	(0.0472)	(0.0470)	(0.0464)
ln_evapotrans: Log of mean Evapotranspiration (mm/day)					-0.742*	-0.876**	-1.290***	3.129***	2.589***	2.251***	2.252***
					(0.402)	(0.408)	(0.411)	(0.530)	(0.541)	(0.550)	(0.550)
c.ln_density#c.rural_pcm: Interaction of ln_density and rural condition						-0.217	-0.242	-0.257	-0.149	-0.114	-0.124
						(0.224)	(0.226)	(0.227)	(0.231)	(0.230)	(0.231)
programa: District treated in programs against malaria							0.0739**	-0.0710**	-0.0170	-0.0230	-0.0258
							(0.0330)	(0.0345)	(0.0357)	(0.0356)	(0.0346)
ln_p_salud: Log of National expenditure on health services by region j								-0.337***	-0.0979**	-0.190***	-0.178***
								(0.0305)	(0.0448)	(0.0407)	(0.0459)
ln_pbi2: Log of GDP Agriculture region j									-0.649***	-0.126	-0.109
									(0.116)	(0.119)	(0.132)
ln_pbi7: Log of GDP Extracting - mining in region j										-0.0985***	-0.0980***
										(0.0254)	(0.0256)
ln_educacion: Log of Average years of education in region j											-0.347
											(0.711)
Constant	0.977***	0.934***	3.622***	6.479***	9.424***	10.61***	12.24***	-2.159	2.431	-1.859	-1.497
	(0.0497)	(0.0430)	(0.842)	(1.105)	(2.108)	(2.217)	(2.364)	(2.101)	(2.379)	(2.282)	(2.422)
N	8,840	8,840	8,840	8,840	8,840	8,580	8,580	8,580	8,580	8,580	8,580
R-squared	0.002	0.005	0.005	0.009	0.010	0.012	0.013	0.098	0.110	0.122	0.122
Number of _ID	442	442	442	442	442	429	429	429	429	429	429
Year FE	No	No	No	No	No	No	No	No	No	No	No
Period:	2001-2020	2001-2020	2001-2020	2001-2020	2001-2020	2001-2020	2001-2020	2001-2020	2001-2020	2001-2020	2001-2020

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4.1.2.- Spatial estimations

It is necessary to continue addressing the risk of misspecifications, especially considering other non-observable influences on the malaria incidence. Particularly, the presence of spatial dependance between neighbor districts. To explore this, three types of contiguity matrices were estimated using geographical data provided by the MINAM's GeoBosques plataform.

Firstly, we applied the most widely used spatial autocorrelation method to test if variables of different regions are correlated or present independence. The Moran's Index test or Moran's I test states as null hypothesis that errors in an estimation such as the latter are *iid*. When rejected, it brings evidence that neighbor regions variables may be correlated. In table 3, we present our Moran's I test statistics and respective p-values according to the structure set by the matrices used for years 2001 to 2020.

Table 3. Moran's I test statistics and p-values

	Queen - Binary		Queen - Row Standarized		Hybrid (Queen * ID)	
	z-stat	p-val	z-stat	p-val	z-stat	p-val
2001	21.217	0.000	20.014	0.000	15.037	0.000
2002	23.344	0.000	22.428	0.000	17.355	0.000
2003	23.493	0.000	21.54	0.000	16.544	0.000
2004	23.479	0.000	22.514	0.000	17.055	0.000
2005	23.479	0.000	22.557	0.000	16.934	0.000
2006	25.308	0.000	24.492	0.000	17.615	0.000
2007	26.113	0.000	26.23	0.000	17.619	0.000
2008	26.579	0.000	26.35	0.000	16.972	0.000
2009	26.579	0.000	26.35	0.000	16.972	0.000
2010	25.768	0.000	25.43	0.000	16.525	0.000
2011	25.667	0.000	25.581	0.000	17.389	0.000
2012	28.328	0.000	28.481	0.000	18.645	0.000
2013	29.21	0.000	29.308	0.000	18.675	0.000
2014	29.093	0.000	29.388	0.000	17.979	0.000
2015	28.129	0.000	29.033	0.000	17.23	0.000
2016	27.848	0.000	28.843	0.000	17.066	0.000
2017	27.526	0.000	28.808	0.000	16.78	0.000
2018	26.931	0.000	28.275	0.000	16.372	0.000
2019	25.564	0.000	26.827	0.000	15.28	0.000
2020	24.174	0.000	25.058	0.000	13.342	0.000

Results show that for every year and for every W matrix structure the test rejects its null hypothesis, suggesting that in every year the estimation presents spatial interdependence among districts. Therefore, for the estimation to be consistent, a spatial model that accounts for the non-observed indirect spatial effects other districts exert between each other is needed.

Although, spatial dependence is evidenced by the test, it is not clear if the issue relies on spatial autocorrelation from the same dependent variable, meaning malaria rates are interdependent or "spatially lagged" between districts, or if key covariates of other districts, like deforestation, are spatially lagged between each other, making in the example other districts deforestation agent on one's malaria rates. Even less is clear if neither are the case and the errors are those which are correlated spatially between districts. Knowing that for each case there are specific spatial models which address each specific dependence issue, we applied two tests for model selection using the three W spatial matrix.

The first one consisted in a robust Lagrange multiplier test for spatial autocorrelation between both dependent variables and errors. Specifically, it tests the significance of coefficients of a modified model which introduces both a spatial autocorrelation term in the main structure – on the dependent variable - and the error structure. Thus, if there was spatial lagged dependence, it would be evidenced by its coefficient failing the null hypothesis. The table 4 shows the results of this first test.

Table 4. Robust Lagrange Multiplier Tests

Queen - Binary		Queen - Row Standarized		Hybrid	
I. Spatial lag		I. Spatial lag		I. Spatial lag	
Ha:	Spatial lag dependence	Ha:	Spatial lag dependence	Ha:	Spatial lag dependence
LM	13.509	LM	1.1795	LM	2.6712
df	1	df	1	df	1
p-value	0.000	p-value	0.2775	p-value	0.1022
II. Spatial error		II. Spatial error		II. Spatial error	
Ha	Spatial error dependance	Ha	Spatial error dependance	Ha	Spatial error dependance
LM	24.526	LM	72.475	LM	40.382
df	1	df	1	df	1
p-value	0.000	p-value	0.000	p-value	0.000

In general, this test shows strong evidence, across all three W matrix, that this estimation presents spatially lagged errors terms in the error structure. On the other hand, it is just for the case of the Binary matrix, that actual spatial autocorrelation is hinted.

To complement these results more directly, a secondary test was conducted which compares six predefined modifications of the current model being then tested by computing a Bayesian nonparametric method denominated Posterior Probability assigned at each specification. This test simulates an Ordinary Least Square model and 5 spatial regression models: Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), Spatial Durbin Model (SDM), Spatial Durbin Error Model (SDEM), Spatial Lag of X (SLX). The selection process consists in selecting the model which offers higher posterior probability. Table 5 shows the results of these computations by matrices.

Table 5. Bayesian posterior probability

Queen - Binary					
OLS	**SAR**	**SDM**	**SEM**	**SDEM**	**SLX**
0.00000	0.00000	0.84408	0.00000	0.15592	0.00000
Queen - Row Standardized					
OLS	**SAR**	**SDM**	**SEM**	**SDEM**	**SLX**
0.00000	0.00000	0.97229	0.00000	0.02771	0.00000
Hybrid					
OLS	**SAR**	**SDM**	**SEM**	**SDEM**	**SLX**
0.0000	0.0000	0.9607	0.0000	0.0393	0.0000

These results show for each matrix that the highest posterior probability in each case is associated with a SDM model and secondly to a SDEM model, leaving the other specification with extremely low estimates. This results alone evidence that spatial dependence may be coming from spatially lagged covariates, and in a minor way from the error structure. This would mean that not only deforestation in a given district may be influencing the same district's malaria rate but, that it may respond to the deforestation occurred in nearby districts. Since the previous parametric test strongly evidenced the lack of spatial lag dependence in favor of spatially dependent errors, and these computations generally suggest the inclusion of a lagged covariates, the spatial model to be selected will be the Spatial Durbin Error Model (SDEM), since it integrates both components into the spatial estimation.

Table 6 shows the main results of the SDEM estimations per each matrix. After considering spatial spillover effects of the covariates and the errors, coefficients associated to deforestation keep being positive and statistically significant. This means that higher rates of deforestation may lead to increases in registered malaria cases, significantly on the same district that is being deforested and more importantly, as noted by the magnitude of the coefficients, on those adjacent. Furthermore, this effect of the forest loss is also penalized as the quadratic term is also statistically significant and negative. Similar conclusion is evidenced by all three matrices.

It is worth noting by the national expenditure's coefficient that direct increases in care and action by the government appears to be statistically effective in counteracting the illness in one given district yet it faces the indirect nature of the effects of deforestation on malaria rates.

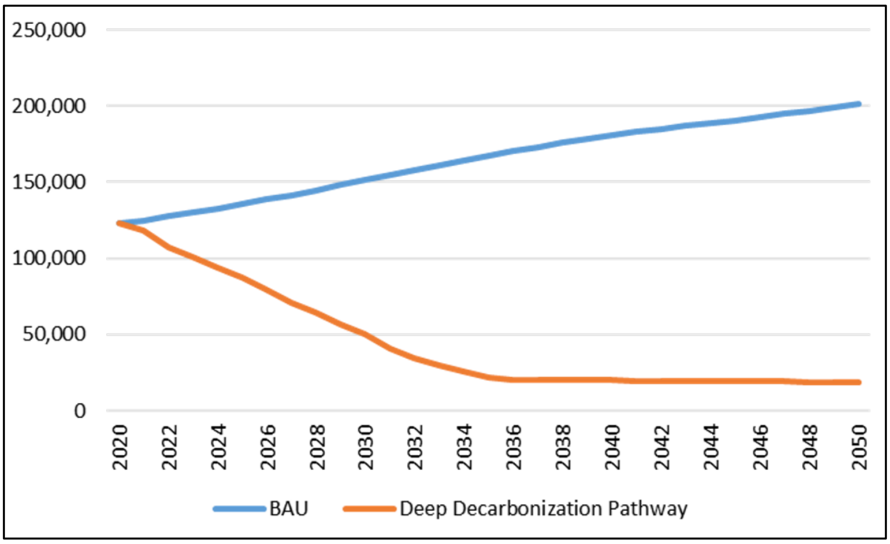
Table 6. Spatial Durbin error model estimation

	SDEM - Queen Binary			SDEM - Queen Row Standarized			SDEM - Hybrid		
Var.	Direct Effects	(Indirect) Spillover Effects	Total effects	Direct Effects	(Indirect) Spillover Effects	Total effects	Direct Effects	(Indirect) Spillover Effects	Total effects
ln_ldeforestacion: Lagged Log Forest loss in the district (hectares)	0.0833***	0.0403***	0.1236***	0.0748**	0.2236***	0.2984***	0.1379***	2.2718***	2.4096***
	(0.0301)	(0.0105)	(0.0303)	(0.0328)	(0.0538)	(0.0547)	(0.0351)	(0.4956)	(0.4755)
ln_ldeforestacion2: Lagged Log Forest loss in the district (hectares) ^ 2	-0.0069*	-0.007***	-0.0139***	-0.0099**	-0.0328***	-0.0427***	-0.0069	-0.5227***	-0.5296***
	(0.004)	(0.0015)	(0.0042)	(0.0041)	(0.0076)	(0.0082)	(0.0046)	(0.0804)	(0.078)
ln_temp: Log of mean Temperature (C°)	0.045	-0.0064	0.0385	-1.6986	1.497	-0.2016	1.8578	-19.0108	-17.153
	(1.2136)	(0.2749)	(1.0471)	(2.6743)	(2.7986)	(1.0076)	(1.4072)	(11.7675)	(10.5029)
ln_prec: Log of mean Precipitation (mm/month)	-0.0256	-0.0038	-0.0295	0.2626	-0.3228	-0.0601	-0.0727	0.3658	0.2931
	(0.1036)	(0.0276)	(0.0886)	(0.1911)	(0.228)	(0.107)	(0.122)	(1.2186)	(1.1123)
ln_evapotrans: Log of mean Evapotranspiration (mm/day)	2.2925*	-0.0088	2.2837**	3.9146	-1.9571	1.9575*	5.9986***	-33.1416***	-27.143**
	(1.2778)	(0.2798)	(1.102)	(3.6522)	(3.7251)	(1.0486)	(1.4311)	(12.4817)	(11.1905)
c.ln_density#c.rural_pcm: Interaction of ln_density and rural condition	0.0551	-0.1106***	-0.0555	0.0341	-0.4975**	-0.4634*	0.1325	-9.5193***	-9.3868***
	(0.0886)	(0.0424)	(0.1073)	(0.0918)	(0.2152)	(0.2523)	(0.0957)	(1.7844)	(1.7742)
programa: District treated in programs against malaria	0.136**	-0.0219*	0.1141**	0.1557	-0.1572	-0.0015	0.2107***	-2.4979***	-2.2871***
	(0.0581)	(0.0125)	(0.0503)	(0.1205)	(0.1292)	(0.048)	(0.0636)	(0.6412)	(0.5842)
ln_p_salud: Log of National expenditure on health services by region j	-0.2804***	0.0232	-0.2572***	-0.4074***	0.283*	-0.1243**	-0.1675**	-0.4137	-0.5812
	(0.0651)	(0.0149)	(0.0567)	(0.1568)	(0.1669)	(0.057)	(0.0771)	(0.7233)	(0.6545)
ln_pbi2: Log of GDP Agriculture region j	1.6375*	-0.4141**	1.2234	10.9619***	-12.2225***	-1.2606	-2.0139*	11.6049	9.591
	(0.8817)	(0.201)	(0.7754)	(1.4816)	(1.631)	(0.8041)	(1.0598)	(9.8774)	(8.9468)
ln_pbi7: Log of GDP Extracting - mining in region j	0.6595***	-0.1383***	0.5212***	0.896***	-0.9146***	-0.0186	-0.2004	1.5109	1.3105
	(0.1646)	(0.039)	(0.142)	(0.2724)	(0.3076)	(0.1505)	(0.1913)	(1.8202)	(1.6526)
ln_educacion: Log of Average years of education in region j	-0.2294***	0.0236***	-0.2058***	-0.226***	0.1191***	-0.1069***	-0.1497***	0.5043**	0.3546*
	(0.019)	(0.0044)	(0.0166)	(0.0285)	(0.0328)	(0.0173)	(0.0224)	(0.2111)	(0.1914)
N		8580			8580			8580	
Number of _ID		429			429			429	
Period		2001-2020			2001-2020			2001-2020	

4.2.- The deforestation dynamic

Interventions in the forestry sector can succeeded in reversing the increasing trend of deforestation (Figure 3); the annual deforestation rate by 2050 falls from 200,000 to 20,000 hectare annually. This is mainly because incentives to deforestation are addressed, forest productivity is boosted, value is given to standing forest, productive activity is promoted, property rights are strengthened, and the forest is protected from deforestation.

Figure 3. Forecast of yearly deforestation (in hectares) by scenario



The reduction of deforestation reduces forest emissions (Figure 4), as well as the promotion of plantations and agroforestry systems contribute to carbon sequestration, as can be seen, transforming the forest into a carbon sink, going from 244 Mt emitted to the sector sequesters 38 Mt in 2050.

Figure 4. Net emissions of AFOLU sector by scenario

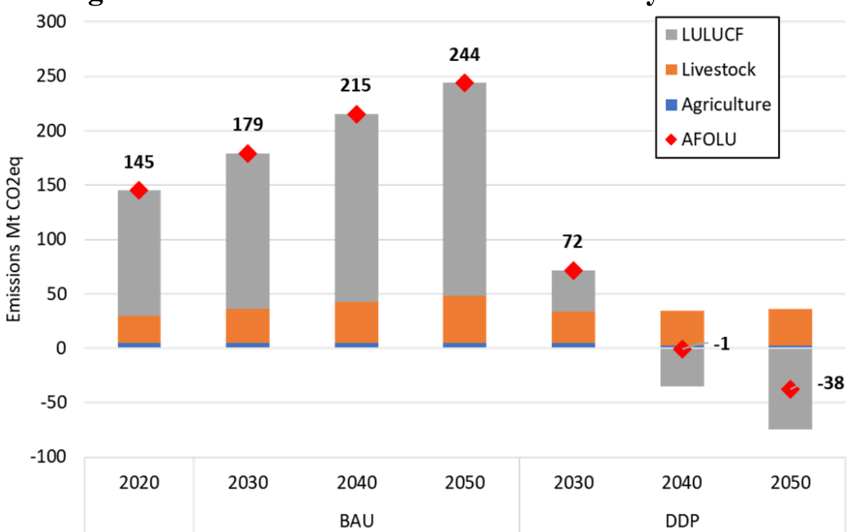


Figure 5. Evolution of malaria cases due to deforestation

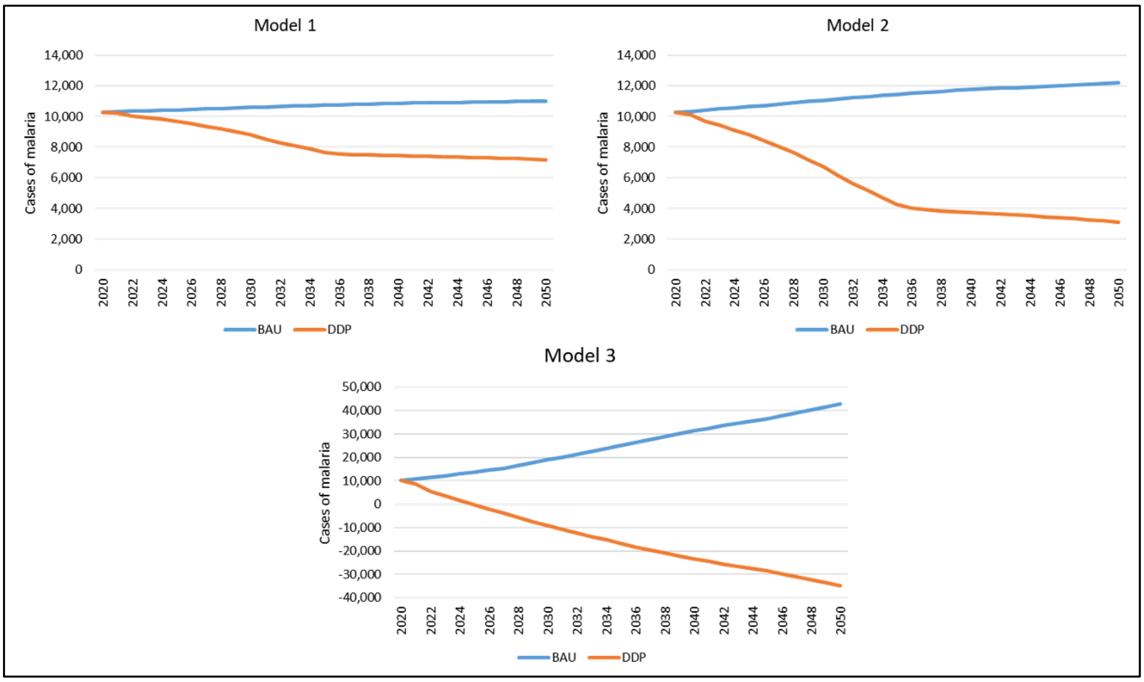
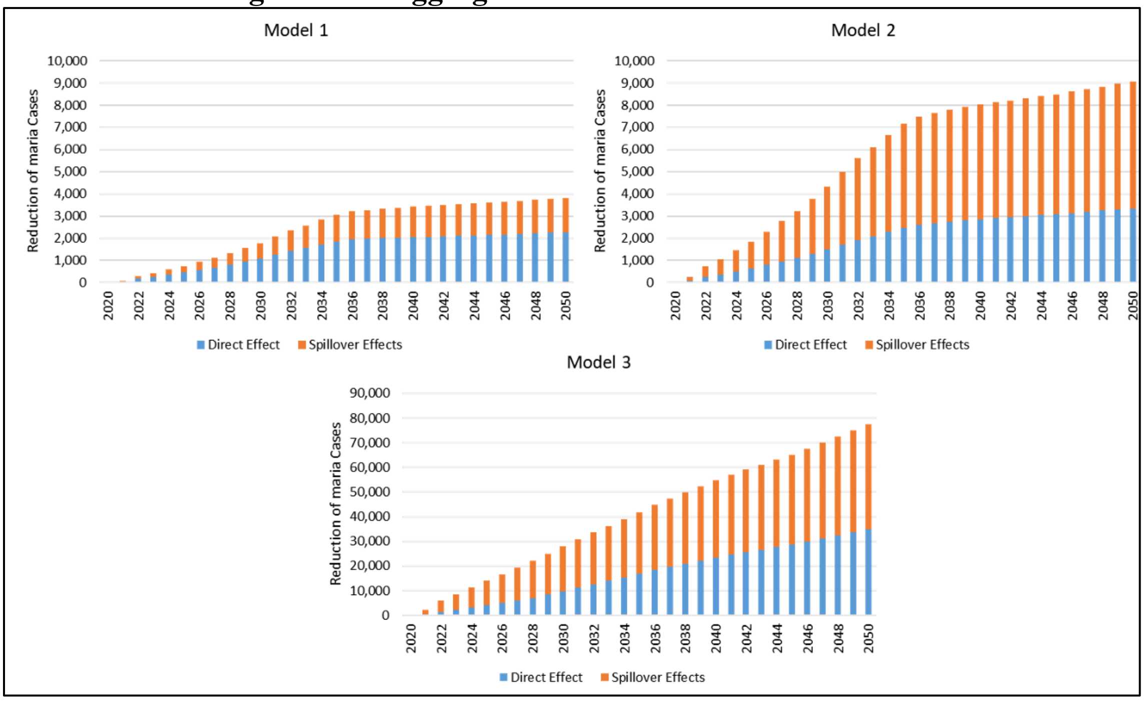


Figure 6. Disaggregation of malaria cases evolution

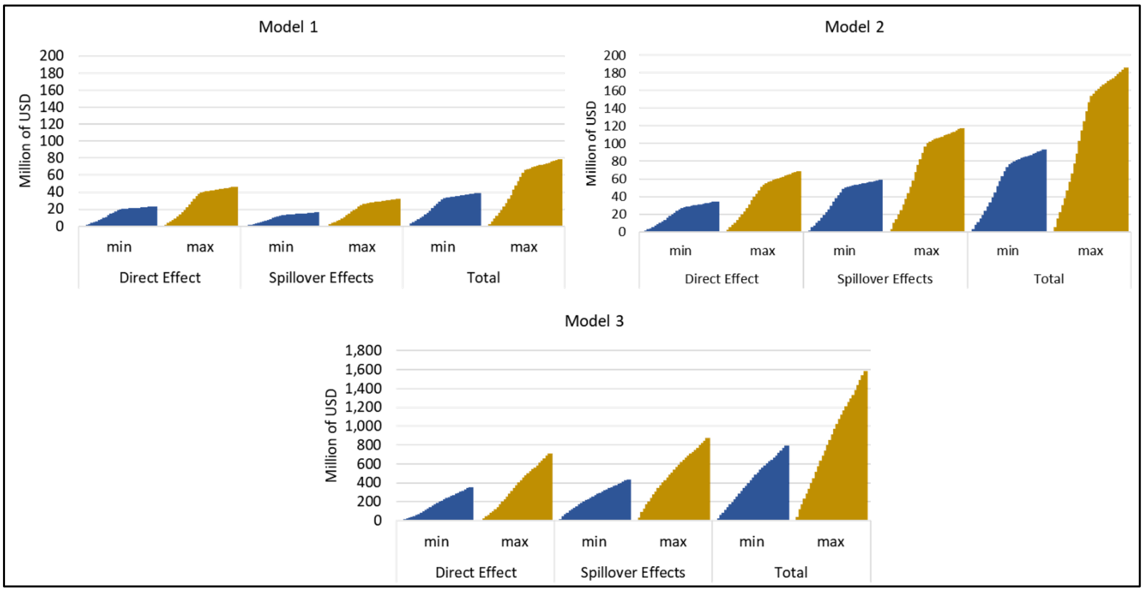


This reduction in the advance of deforestation impacts the evolution of malaria cases that occur, reduced from 11,500 to 7,000 cases in 2050 following model 1; and from 12,000 to 3,000 cases according to model 2 and from 41,000 to negative case according to model 3 (Figure 5). Consequently, the interventions can generate savings in health expenditures. This reduction in the advance of deforestation impacts the level of malaria cases that occur, from 8,000 to 200 cases in 2050 following model 1; and from 17,000 to 1900 cases according to model 2 (Figure 6). Consequently, the interventions can generate savings in health expenditures. As can be seen, according to the econometric approach, the contribution of spillover can be even greater than the direct effect, so it is important to consider what happens in neighboring districts (Figure 7).

Table 7. Overall cumulative saving health due to stopping deforestation

		Model 1	Model 2	Model 3
Overall saving health (million USD)	min	39.2	92.9	794
	max	78.4	185.7	1,588

Figure 7. Disaggregation of costs



5.- Conclusions

In this study, we find evidence that forest loss in the Peruvian Amazon increases malaria contagions not only in local districts but also in the neighbor districts. After disaggregating the direct effects and spillover effects of deforestation on malaria cases, our results support the existence of a relationship between deforestation and malaria in the Peruvian Amazon that transcends beyond a local area.

Our findings address a gap in the literature which was more focused in the correlational and causality issue, except Seabra Santos and Almeida (2018) who had some similar findings than ours for the Brazilian Amazon. Certainly, there are other economic, socio-economic and ecological factors besides forest loss that has direct and/or spillover effects on malaria cases, such as health facilities, education, rural population density, and precipitation. Our findings show that indirect or spillover and total effects are larger under the one-dimensional W contiguity matrix but more conservative with a restricted W hybrid spatial matrix.

The reduction in the advance of deforestation impacts the evolution of malaria cases that occur, reduced from 11,500 to 7,000 cases in 2050 following model 1; and from 12,000 to 3,000 cases according to model 2 and from 41,000 to negative case according to model 3. Consequently, the interventions can generate savings in health expenditures.

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