# Forests can help diminish the number of dengue cases in Costa Rica

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# Forests help diminish dengue cases and outbreaks in Costa Rica

**Matías Piaggio, Eduardo Pacay, Juan Robalino, and Taylor Ricketts**

**Abstract**

Approximately 3.9 billion people are at risk of infection with dengue fever, a group of viruses transmitted by mosquitos.[1,2] In 2019 Central America has suffered a strong dengue epidemic.[3] Costa Rica has almost doubled the number of dengue cases between in the first 24 epidemilogical weeks of 2019 regarding the same period in the previous year.[4] In the Americas, forest cover is thought to diminish anthropogenic habitats for mosquito larvae, as well as increase the presence of their predators.[5,6] Here we estimate the marginal effects of increasing forest cover on dengue prevalence, using econometric models to relate hospital admission records and forest cover maps from 2001 and 2011. We find that increasing the percentage of forest cover significantly decreased both the number of hospital admissions for dengue and the probability of an outbreak. Using the same models, we predict that increasing forest cover by one percentage point would have avoided between 85 to 103 dengue hospital admissions per year. This represents savings between USD 21,500 to 295,000 per year, depending on the severity of dengue cases. Our study shows that forest conservation can be a public health investment that increases welfare both by avoiding sickness and by reducing associated health care expenditures. Understanding the contribution of nature to diminish the risk of disease outbreaks turn even more urgent and important under the COVID-19 global pandemic the world has faced in 2020.[7,8]

**Key words:** dengue, ecosystem services, forest**,** planetary health, conservation, vector-born disease

# Main

Natural habitat protection has been promoted to conserve biodiversity, maintain economic benefits from ecosystems, and encourage the sustainable management and use of nature. [9,10] More recently, interest has grown regarding the impacts that ecosystem change and biodiversity decline will have on human health.[11–16] However, the causal links between nature and health remain poorly understood. These links are often indirect, displaced in space and time, and dependent on a number of modifying forces.[14,15,17] Understanding these complex relationships more fully can support policies that advance nature conservation and human health together.

Dengue Fever is a deadly and growing public health issue in the developing world. Approximately 3.9 billion people are at risk of infection with dengue viruses. [18] In 2019, Central America has suffered one of the worst dengue epidemics in the last times, leaving 50 deaths and more than 177,000 cases between January and July.[3] Dengue is mostly hosted in humans, and transmited by mosquito vectors in the genus *Aedes*. Previous studies indicate that dengue vectors are more abundant in deforested land, like settlements or agriculture.[19–22] However, there exists little evidence on the relationship between forest cover and actual dengue infections in humans. Vanwambeke et al.[20] found that people living closer to forests, or who have spent the day in forest, have a higher probability of infection in Northern Thailand. In contrast, other studies have found lower level of dengue infections in forested areas than in agricultural and urban settings. [23–27] Despite its growing public health importance, the effects of ecosystem change on dengue fever is less well understood than that of other vector borne diseases such as malaria.[28–31]

Forest could help to control dengue viruses through four pathways. First, tropical deforested areas might provide more suitable habitat for mosquito larvae (e.g., standing water, higher temperatures) than intact forests.[6] Second, deforestation is often accompanied by increases in human habitation and agriculture, which could increase host density for mosquitoes and therefore disease transmission.[6,32] Deforestation could also increase the likelihood that wild dengue strains hosted in animals that live in natural areas are transmitted to people, but there is no evidence of such sylvatic dengue virus in the Americas.[6] Third, forest can help to diminish dengue transmission through the 'dilution effect', whereby biodiversity redistributes vector meals to less competent hosts or otherwise reduces mosquito reproduction.[33,34] Finally, forested areas may have larger populations of mosquito predators than urban areas, although this remains a controversial hypothesis. [5,32]

Costa Rica hosts the highest average dengue incidence in Central America between 2005 and 2014 (i.e., 490.8 cases per 100,000 people), and has experienced several recent outbreaks.[35] The number of dengue in the first 24 epidemilogicalweeks of 2019 has almost doubled regarding the same period in 2018.[4] Dengue viruses in Costa Rica are transmitted by the *Aedes aegypti* and (less commonly) *Aedes albopictus* mosquitos.[1,2] *Aedes albopictus* can be abundant in forest patches close to agricultural lands.[36] Costa Rica spent USD 10 million per year on mosquitos control to combat dengue fever.[37,38] The country is also well-known for forest conservation. Roughly half of the country is forested, and roughly a quarter of the continental territory is protected under some management category.[39] The effects of increasing forest cover on dengue fever, however, are not known, making it difficult to understand the potential synergies or trade-offs between these policy efforts.

Here we estimate the marginal effects of increasing forest cover on the number of dengue hospital admissions and the probability of dengue outbreaks in Costa Rica. Our paper is one of the first to examine the relationship between forest cover change and dengue virus infections. To isolate the impacts of forest change, we use two-period panel design and fixed effects models at the district level (n = 473). We isolate forest effects from observable and non observable district features that could be correlated with forest cover and dengue. We also control for time-varying district characteristics, like weather variables and socioeconomic characteristics. As a consequence, our strategy is a highly robust empirical approach to isolate the effect of forest cover on dengue. This is one of the first works to use a robust empirical strategy to quantify the effect of forest cover change in dengue incidende.

# Results

The number of dengue hospital admissions in 2011 varied widely among districts, as did the rate of forest cover change between 2000 and 2011 (Fig. 1). The highest rates of dengue hospital admissions were in rural districts on the eastern and northwestern coasts of Costa Rica (Fig. 1a). Forest cover in Costa Rica increased from 45.5% to 60.2% between 2000 and 2011[40,41] but mostly driven by districts in the northwest, center, and southwest of the country (Fig. 1b). Districts on the Atlantic coast and around the Nicoya Gulf have continued to lose forest. Simply comparing the two maps in Fig.1 suggests a potential correlation between forest cover decline and dengue hospital admissions.

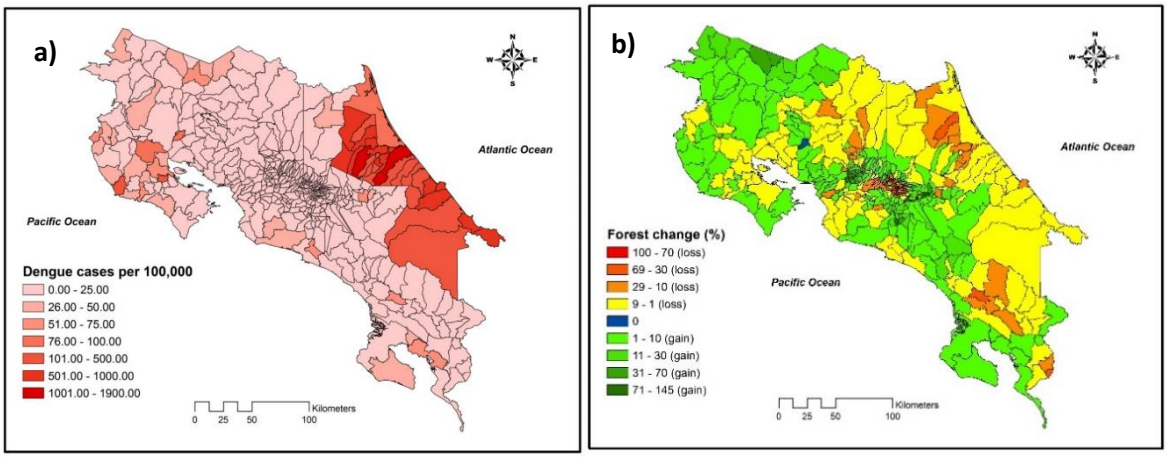


**Figure 1: Geographical distribution of dengue incidence and forest cover change.** Left panel indicates the dengue hospital admissions per 100,000 population per district in 2011. Darker colors indicates districts with higher dengue incidence. Right panel indicates forest change per district between 2000 and 2011. Red to yellow color scale indicates districts where forest diminished, while green scale color indicates districts where forest increased. Source: own elaboration based in Costa Rican Social Security System (CCSS)[42] and Costa Rican Forest Financial Fund (FONAFIFO)[43].

We estimate the effect of forest cover change on dengue hospital admissions and dengue outbreaks (defined as a number of hospital admissions more than one standard deviation above the geometric mean per district).[44] The model specification was set following Eq. (1) and Eq. (2) in *Methods*, using

a two year monthly panel for 2001 and 2011 with district level fixed effects (11,016 observations because of 459 districts in 2 years, and 12 month per year). District level fixed effects allow to interpret the coefficients regarding forest cover as a change in forest cover within each district by comparing the number of cases of a specific district in a specific month in 2001 with the number of cases in the same district in the same month of 2011. We are not comparing the number of dengue cases that take place in two months of the same year in the same district (see *Methods*). In addition, we include socioeconomic control variables, like population size, district population density, % of population in urban areas, and several indicators of socioeconomic level. The socioeconomic controls allow us to isolate the effect of forest cover change in dengue incidence from other determinants, like rural land abandonment, population density, or level of education.

Using our full model (see *Methods*), we find that increased forest cover corresponds to significant declines in both the number of dengue hospital admissions and in dengue outbreaks among districts (Fig. 2). For hospital admissions, this overall relationship holds for every age cohort except children age 0 – 4 years (Fig. 2a; Table S1 – 3). For the probability of dengue outbreaks, the overall relationship only holds for young adults (15 to 34 years old) and adults (35 to 64 years old) (Fig. 2b).

Based on our results, we estimate that increasing the districts' forest cover one percentage point would lead to 85 to 103 fewer hospital admissions per year, as well as 11.1 fewer districts with a dengue outbreaks per year. Xirinachs[45] estimates that an ambulatory dengue case in Costa Rica, in 2014, costs USD 252, considering both direct treatment costs and indirect costs from lost working days. This cost increases to USD 2,881 in cases where hospitalization is needed. Combining these estimates with our model results, we find that increasing Costa Rican forest cover one percentage point can represent savings between USD 21,500 to 295,000 per year, depending on dengue cases severity.

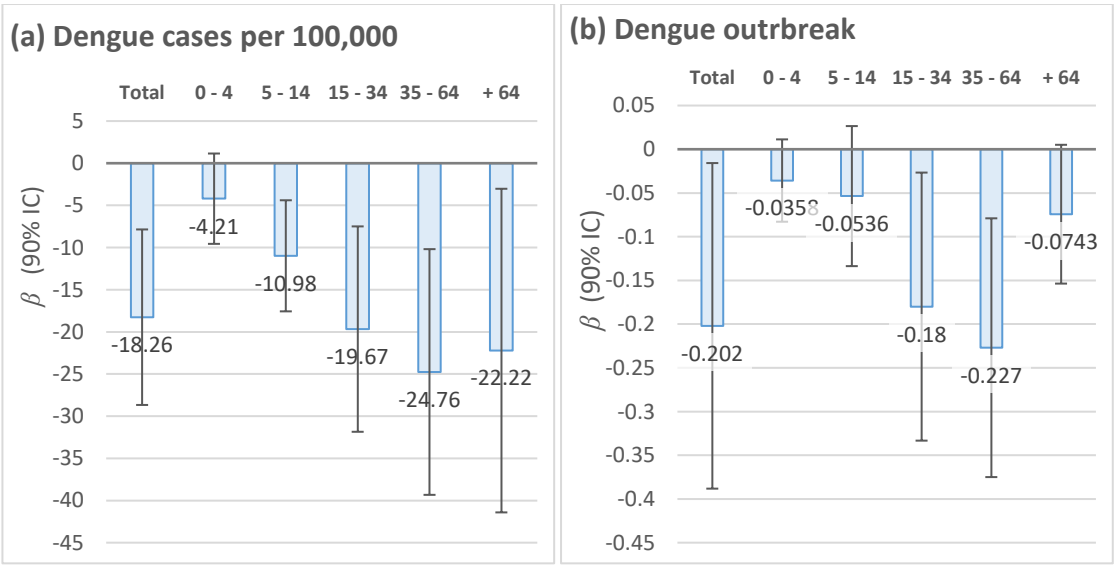


**Figure 2: Effects of a 1% increase in forest cover on dengue incidence and outbreaks (90% confidence intervals).** Estimates are from our full model (Model V), using monthly 2 year panel data from 2000 and 2011. Panel (a) is the model using dengue hospital admissions per 100,000 residents

in each district, month, and year. Panel (b) is the model where the dependent variable equals 1 when there is a dengue outbreak in each district, month, and year. In each panel results are reported for the full sample, as well as for five age cohorts.

To investigate the consistency of these results, we estimate and compare five different model specifications: (1) district fixed effect model without time fixed effects or other controls, controlling only time invariant district characteristics, (2) district and month fixed effects model, controlling district time invariant characteristics and seasonality, (3) district, month, and year fixed effects model, controlling district time invariant characteristics, seasonality, and institutional and economic determinants that has an constant impact between districts, (4) same as #3 but with weather variables, and (5) a model nesting the previous four models including socioeconomic characteristics (the full model reported above). The effect of forest cover remains highly significant and negative for every model, indicating that the estimates are very robust (Table S1, Table S2). Weather variables and socioeconomic variables are also mostly significant.

## Discussion

Our findings provide robust empirical evidence that tropical forest conservation can reduce prevalence and outbreaks of a dangerous vector borne disease. Increasing the percentage of forest cover decreases both the number of dengue hospital admissions and the probability of a dengue outbreak. To our knowledge, this is the first study to robustly estimate the effect of forest cover change on dengue virus infections.The effect on hospital admissions is consistent across most age cohorts, while the effect on outbreaks is only significant in adults. Increasing districts' forest cover one percentage point would have reduce annual dengue hospital admissions by 85 to 103 cases, saving USD 21,500-295,000 per year, depending on dengue cases severity.

Differences in forest effects among age cohorts may related to the socio-ecological dynamics of dengue fever. The relationship between forest cover and dengue is absent in young children, but that does not mean that forests help to diminish dengue only in older children, adults and elderly. Hospital admissions tend to be biased toward severe cases, which often result from second infections of denge virus. Cases on young children are more likely to result from first time infections, which are typically less severe.[46] Increasing forest cover appears to diminish the probability of a dengue outbreak only in adults. Adults having fewer opportunities to avoid exposure because of labor commitments outdoors, but forest cover may help to prevent the number of cases from rising to the level of an outbreak.

Forest conservation could be a cost-effective strategy to reduce disease burdens due to dengue fever in Costa Rica. The actual cost per hospital admission is likely to be closer to the upper bound or our estimate because they are typically severe dengue cases. The benefits of increasing forest cover by only 1% (i.e., near USD 295,000) are therefore significant relative to Costa Rica's annual expenditures to control mosquito vectors of dengue fever (USD 10 million).[37,38] Moreover, actual social benefits are likely to far exceed our estimates for two reasons. First, we are only considering a fraction of total dengue cases (i.e., those that are treated at hospitals). Second, forest conservation

is known to supply a range of additional ecosystem services like carbon sequestration, flood control, and freshwater regulation. [47]

Vector-borne diseases are only a problem if people are exposed to the vector.[48,49] While environmental conditions influence the populations and distributions of vector species, individuals can take avoidance behaviors that diminish infection rates, e.g. by applying repellents, spraying insecticides, or avoiding the outdoors during active times for vectors. Other measures like vegetation and water management to avoid vector breeding sites are gaining support.[50,51] As a consequence, forest cover effects may be stronger than we estimate if people decrease their exposure in places where forest cover has decreased and vectors are more abundant. We cannot disentangle these effects in this paper, but we suspect that this partially explains the abscense of forest effects in young children, because of careful avoidance behaviors by parents.

In addition, the relationship between forest cover change and dengue cases is complex, depending also in other land uses and population dynamics. The effect of forest cover change may be interpreted in reference to alternative land uses. This is the case of every study analyzing the effects of land cover and use change. In Costa Rica, the most frequent alternative land uses are agriculture and grasslands. To isolate the effect of forest cover on dengue cases, our results controls for population dynamics through socioeconomic controls. For example, if land abandonment and decreases in subsistence agriculture settelments are correlated with reductions in dengue transmission and increase in forest cover, we can be wrongly attributing the effect to forest cover. By controlling for the share of urban and rural population, we can identify the effect of forest cover while keeping rural population constant.

This paper supplies robust econometric evidence for the links between ecosystem change and public health, but more research is needed to understand the mechanisms behind this relationship. First, we need to better understand how land use is related to ecological dynamics of mosquitos and other disease vectors.[52–55] Second, we need to quantify how individuals' welfare changes as a consequence of dengue transmition risk. These impacts on welfare include not only illness and medical costs, but also the costs of avoidance behaviors.[48,56–58] Third, we need to understand how individual behaviors are a function of perceived risk, and therefore moderate the net effects of land use by reducing exposure when mosquitos are more abundant. A fuller understanding of the mechanisms linking land use change, vector dynamics, transmission risk, avoidance behaviors, and disease incidence would greatly improve our ability to manage dengue fever and other vector borne diseases in more holistic and effective way. It would also help to better align investments in public health and biodiversity conservation, two of the greatests challenges of the coming century. [59]

# Methods

## Empirical strategy

### Marginal effect of forest cover in dengue hospital admissions and outbreaks

We estimate Eq. (1) and Eq. (2) below, to analyze the impact of forest on dengue hospital admissions and outbreaks respectively. To estimate the marginal effect of forest cover on hospital admissions, we run a district level fixed effect model, controlling for unobserved factors that might confound the effect of forest. This is a reduced-form model that accounts for the relationship between dengue transmition risk and the number of people getting ill. The model assumes that population exposure and avoidance behavior keeps constant in time.

(1) $Dengue_{imy} = \alpha + \beta \%forest_{iy} + \boldsymbol{\theta weather_{imy}} + \boldsymbol{\delta socioeconomic_{iy}} + \alpha_i + \varphi_m + \varphi_y + \varepsilon_{imy}$

where:

$Dengue_{imy}$ is dengue incidence per 100,000 population in district *i*, in month *m*, of year *y*.

$\%forest_{iy}$ is and indicator of forest cover. For standardization across districts, we used the share of forest in each district, such that $\%forest_{iy} = F_{iy}/A_i$, where $F$ is the ha. of forest in district $i$ and $A$ is the size of the district.

$\boldsymbol{weather_{imy}}$: is a vector of weather variables, that account for the total rainfall (mm), mean temperature, and the interaction between rainfall and temperature in district *i*, month *m* in year *y*. We include a quadratic term of the weather variables for controlling for a non-linear relationship with dengue incidence. .

$\boldsymbol{socioeconomic_{iy}}$ is a vector of socioeconomic characteristics variables of district *i* in year *y*. These accounts for socioeconomic level, share of people in urban areas, education level, and other socioeconomic characteristics that can be a determinant of dengue incidence. The full list of socioeconomic variables and the descriptive statistics are shown in Table S1 – 1 in Appendix 1 of Supporting Information.

$\alpha_i$, $\varphi_y, \varphi_m$: are fixed effects at the district, month, and year level respectively. $\alpha_i$ controls for time-invariant district characteristics (e.g. area, topography, soils, geology), $\varphi_y$ are district characteristics that varies across years constantly between districts (e.g. national political and economic conditions, national public health system, etc.), and $\varphi_m$ controls for district characteristics that not vary across the same month in different years (e.g., seasonality).

Alternatively, we estimate a linear probability model to analyze how forest cover change impact on the probability of a dengue outbreak (Eq. (2)). This models consider the same assumptions than the described for Eq. (1).

(2) $P(dengue\ outbreak_{imy} = 1) = \alpha + \beta\%forest_{iy} + \boldsymbol{\theta weather_{imy}} + \boldsymbol{\delta socioeconomic_{iy}} + \alpha_i + \varphi_m + \varphi_y + \varepsilon_{imy}$

Where $dengue\ outbreak_{imy}$ is a dummy variable equal 1 if there exists an outbreak in district *i*, month *m*, and year *y*. We define an outbreak if the number of cases is higher than one standard deviation from the geometric mean of the number of dengue hospital admissions per district and per month between 2000 and 2013, following Escudero[44].The rest of the variables are the same than described above.

Fixed effects also allow controlling for any static unobserved covariates that could potentially bias our estimates.[60] In addition, using a two year monthly panel for 2001 and 2011 we can control for several socioeconomic variables at the district level, because national household censuses has been conducted in 2000 and 2011. Table S1 – 1 in Appendix S1 show the descriptive statistics of the variables used in the analysis. We used 2001 as the first year in the analysis, because is the first year for which we have both health and forest cover data. We consider that socioeconomic characteristics of the district in year 2000 are a good proxy for 2001. To test the robustness of our approach, we also estimate a district level fixed effect model using monthly data between 2000 and 2013. The empirical approach and the robustness analysis is described in the *Robustness check* section below. We choose the two year monthly panel for 2001 and 2011 as our main model because we were able to control by many socioeconomic characteristics that are usually related to dengue cases, like population density and access to water.

The model specifications above show that all the variables has a monthly time frequency except forest cover, that has annual variation. There do not exists land cover data on a monthly basis. However, because we are estimating a district level fixed effect, including monthly and annual fixed effect, what we are comparing are the cases of dengue of a particular month, year, and district, with the dengue cases of the same district in the same month and in a different year. Hence, we can explain that changes using a variables that varies annualy.

It is worth to clarify that our model is comparing the number of cases of a specific district in a specific month in 2001 with the number of cases in the same district in the same month of 2011. That is, we are not comparing the numer of dengue cases that take place between months in the same year of a specific district. This is important, because our model takes as constant the share of forest cover in the districts per year. In addition, forest cover is a variable that changes slowly. Fig. 1b shows that forest cover change between 2001 and 2011 in Costa Rica ranges between 1 to 10% for most of the districts. Given that these rates took place in more than a decade, it does look appropriate to assume that forest cover is constant for all the months in the same year. Moreover, this turns less important for our results, given that we are not comparing dengue cases of the same district within the same year.

To explain more clearly, we show in Figure 3 an example of how the empirical strategy works for one hypothetical district. Figure 3 shows the scatter plot between forest cover (%) and dengue incidence for the twelve months in 2001 and 2011 for a hypothetical district. For each year, the forest cover is constant for all the months in the same year. Dengue incidence between the month within a year can be different for many factors, mostly related to weather seasonality.

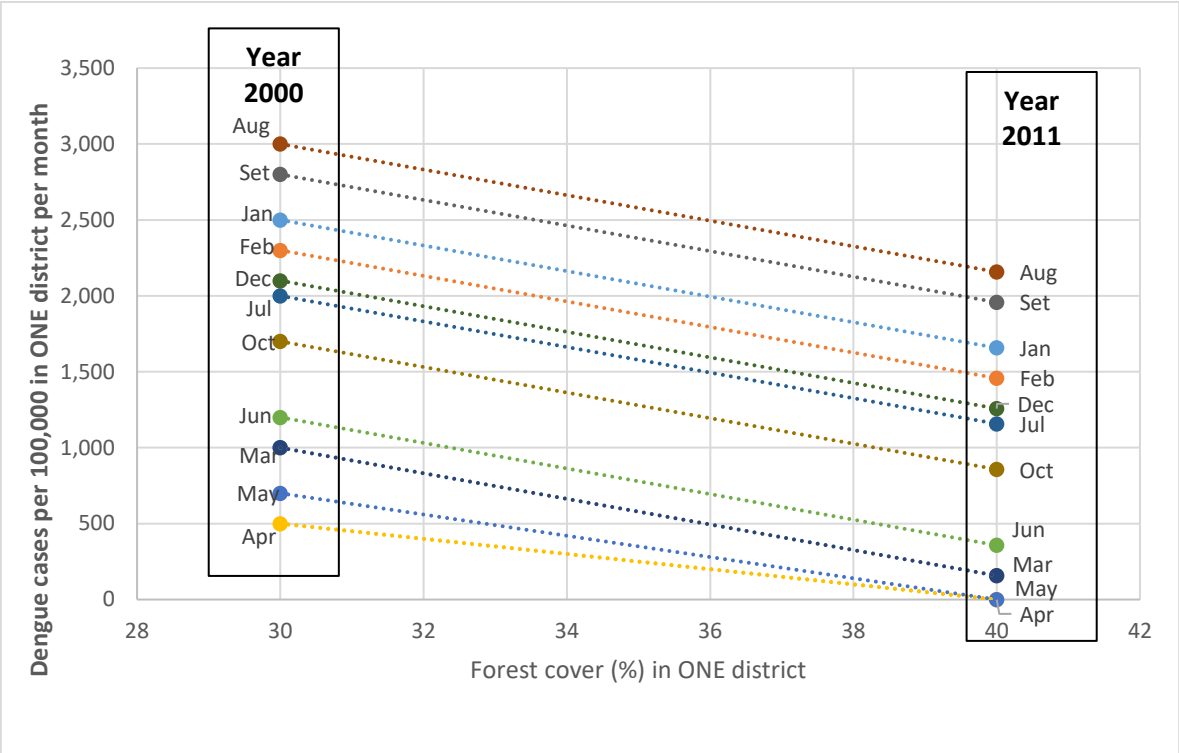


**Figure 3: Hypothetical example of the empirical identification strategy for one district.** Scatter plot shows the dengue incidence per month and forest cover for one hypothetical district in 2000 and 2011. While the number of cases can be different between months in the same year, forest cover is constant within a year.

Our model identifies the change in dengue incidence for the same month of the different years attributed to the annual forest cover change. In practice, we are estimating the average linear relationship of the dotted lines in Figure 3 for 473 districts in Costa Rica between 2001 and 2011. This empirical strategy has been used before by [61] to explain the monthly change in monthly water purification costs, and by [62] to explain the probability of a flood occurrence in a month when forest cover changes. This approach only requires an assumption that the forest cover change between the same month in both years is the same.

## Total number in hospital admission and outbreak avoided by increasing forest

We estimate the change in hospital admissions and number of dengue cases using models (5) and (10) in Table S1 – 2 in Annex 1 in Supporting Information, respectively. We computed the fitted number of hospital admissions (dengue outbreak) per district, month, and year, as well as the fitted values when the percentage of forest increases one percentual point of the district area between 2000 and 2013. The difference between these values gives us the decrease in the number of dengue hospital admissions and dengue outbreaks per year as a consequence of increasing forest cover 1 percentual point per district.

## Data

**Hospital admissions:** We compute monthly dengue hospital admissions by district between 2000 and 2013 using the number of monthly hospital admissions, recorded by the *Caja Costarricense de la Seguridad Social* (CCSS)[42]. CCSS has individual records of every hospital admissions following World Health Organization (WHO) International Classification of Diseases (ICD) since 1997. Individual records has information of the four main causes of the hospital admission. However, the only public available information thorugh the CCSS website is data of the first two causes of the hospital admission. Moreover, individual records are reported only at the district level, i.e. public information do not have detail of the hospital or care center within a district where a case has been registered. Given that we are able to have a record of any patient that makes a hospital visit having dengue as one of the first two main causes, we consider that this is a very accurate measure of the dengue incidence. Hospital admissions data may introduce a selection bias if there are people that systematically do not visit a hospital because they have other ways of getting healed [49]. We consider that this is not a source of problem because of two reasons. First, when dengue sympthoms get serious, there is low likelihood that people would not look for a physician. Second, Costa Rica has universal access to health care with broad geographical coverage. Finally, Health Ministry has statistics on the total number of cases available only at county level, recorded by the Health Survaillance Division. When aggregating the hospital admissions of the CCSS at the county level, it shows a correlation of 0.81 with the total number cases recorded by the Health Ministry.

**Socioeconomic data:** We use population at the district level provided by Costa Rican National Institute of Statistic and Censuses (INEC) in census 2000 and 2011 as well as the projections of populations from INEC for the rest of the years[63]. The same data sources are used to compute socioeconomic variables at the district level, like education, access to water, people agglomeration per household, needs satisfied, etc. Table S1- 1 in Appendix 1 in Supporting Information has the full list of socioeconomic characteristics as well as the descriptive statistics.

**Weather data:** Monthly precipitation at the district level has been constructed using Funk et al.[64]. We computed the average of the precipitation values of all pixels contained in each district, in order to obtain the average rainfall in each district. This was done per day, for each month and for each year, for the period 1981-2013. Then to calculate the monthly precipitation, the daily data of each month, year, and district were added.

Monthly average temperature was constructed base in Matsuura and Willmott[65]. Not all the pixels covered all the districts of the country because the layers had a low spatial resolution (0.5 degree by 0.5 degree). To solve this problem, we did a spatial interpolation of the data. We first computed temperatures at sea level using a lapse rate (temperature gradient). Once the temperature data were calculated at sea level, the interpolation of the data was done using Inverse Distance Weights (IDW) method in ArcGis, which generated a layer with smaller pixels for all the districts of the country. Then, the temperature gradient was applied again to the data to determine its temperature at its respective altitude above the sea level. Finally, the average of the values of all the pixels contained in each district was calculated, for all the months and for each year, in order to obtain the average temperature per month.

Matsuura and Willmott[65] is the best data source available regarding temperature to conduct an analysis at the country level. The dataset uses information from weather stations from the Global Historical Climatology Network Monthly (GHCNM). For Costa Rica, GHCNM takes into account eight stations for the whole country. Costa Rica is the country with the second largest number of station per $km^2$ in the GHCNM for the countries in Central America.

**Forest cover data:** In this paper we follow forest cover definition by FONAFIFO[40], including forest, mangroves, wetlands, and moorlands. We measure forest cover using land cover maps elaborated by the REDD+ Program in Costa Rica, and provided by the National Fund for Forest Financing (FONAFIFO). These maps have a 30 m by 30 m resolution following a satellite image interpretation in 12 categories: i) very humid rainforest, ii) humid rainforest, iii) dry forest, iv) mangroves, v) palm forest, vi) annual crops, vii) permanent crops, viii) pastures, ix) urban areas, x) wetlands, xi) moor, and xii) naked soil. Also, categories i) to v) and vii) are split by age cohorts, making a total of 52 categories. The maps are available for 1986, 1992, 1998, 2001, 2008, 2011, and 2013. Land cover categories were aggregated between age cohorts. In this paper, we consider forest as the addition of categories i) to v), and of any age.

## Robustness check

We conduct three additional set of models to check the robustness of our results: i. we estimate the same models using the monthly panel for the whole period between 2000 and 2013 to check the robustness to the number of observations, ii. we estimate our main model and the monthly model in the first set of robustness check by clustering the residuals at a higher geographical level, to check the robustness at potential spatial autocorrelation, and iii. we run the analysis with an alternative land use dataset.

In our main estimate we used only the maps for 2001 and 2011, because 2001 is the first year that we have both, health and land cover data, by the time that we only had socioeconomic data at the district level for 2000 and 2011 from the National Census. Imputing the socioeconomics data at the district level from the census 2000 to the health statistics in 2001, our main model estimates the effect of forest cover change in dengue cases controlling by many socioeconomic characteristics. However, land cover maps are available for 1998, 2001, 2008, 2011 and 2013. To use the health data of the whole period, we estimated the land cover for the years between the dates that maps area available, using linear projections between land cover maps available.

Because of the data linear interpolation, the resulting estimates are subject to measurement error. But if error is random, this produces an 'attenuation bias', i.e. coefficients are biased to zero. Moreover, fixed effects tend to amplify this attenuation bias.[60] A priori, there is no reason to think that this interpolation strategy produces systematic measurement error that induces bias in any particular direction. In the worst of the cases, the interpolation is going to produce conservative estimates of the marginal effect of forest cover on dengue incidence and outbreak probability. This strategy has been used by Vincent et al.[66] and Tan-Soo et al.[62] to estimate the marginal effect of forest cover change in water treatment and flood occurrence in Malaysia respectively.

Table S1 – 4 in Appendix 1 in Supporting Information shows the results for the whole population for the five model specifications. Table S1 – 4 in Appendix 1 in Supporting Information shows the full model specification (Model v.) per age cohort. Different from the main model, in this case specification v. only include population density as a proxy of share of population in urban areas. This is because we do not have annual socioeconomic data at the district level, except of density, that is computed from the INEC annual population projections.

The results show that when controlling by weather variables, increasing the percentage of forest cover is associated with a reduction in both the number of dengue hospital admissions and dengue outbreak of the whole population. However, when looking at the effect by age cohort, increasing forest cover only decreases the number of cases in children between 5 and 14, and young adults between 15 and 34 years old. Different is the effect on dengue outbreak, that is driven by children between 5 and 14 years old and all the adult cohorts.

In general terms, we confirm the results from the main analysis, with slightly differences regarding the age cohorts and seasons. This is expectable, given the adition of several other years that can have different dynamics.


## Aknowledgements

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## Author contributions

Matías Piaggio designed the study, analyzed the data, and wrote the paper; Eduardo Pacay compiled the data and assisted with analysis; Juan Robalino and Taylor Ricketts designed the research and wrote the paper.

## Data availability

All the data used in this research is public available or can be requested to the original data sources. All datasources are listed in the paper.

## Code Availability

All the information needed to reproduce the paper results is detailed in the paper.

# References


1. WHO. WHO | Dengue and severe dengue. *World Health Organization* (2018).
2. Halstead, S. B. Dengue Virus–Mosquito Interactions. *Annu. Rev. Entomol.* **53**, 273–291 (2008).
3. Salinas Maldonado, C. Un brote de dengue pone en alerta a Centroamérica | Sociedad | EL PAÍS. *El País* (2019).
4. Ávalos, Á. Costa Rica casi duplica número de enfermos de dengue en lo que va del año, con respecto al 2018 - La Nación. *La Nación* (2019).
5. Weterings, R., Umponstira, C. & Buckley, H. L. Container-breeding mosquitoes and predator community dynamics along an urban-forest gradient: The effects of habitat type and isolation. *Basic Appl. Ecol.* **15**, 486–495 (2014).
6. Vasilakis, N., Cardosa, J., Hanley, K. A., Holmes, E. C. & Weaver, S. C. Fever from the forest: prospects for the continued emergence of sylvatic dengue virus and its impact on public health. *Nat. Rev. Microbiol.* **9**, 532–541 (2011).
7. Gibb, R. *et al.* Zoonotic host diversity increases in human-dominated ecosystems. *Nature* **584**, 398–402 (2020).
8. Tollefson, J. Why deforestation and extinctions make pandemics more likely. *Nature* **584**, 175–176 (2020).
9. IUCN. IUCN Standard on the Protection of Natural Habitats. International Union for Conservation of Nature. (2015).
10. Mace, G. M. Whose conservation? *Science (80-. ).* **345**, 1558–1560 (2014).
11. MEA. Ecosystems and Human Well-Being. *Ref. Modul. Earth Syst. Environ. Sci.* (2005) doi:http://dx.doi.org/10.1016/B978-0-12-409548-9.09206-X.
12. Pongsiri, M. J. *et al.* Biodiversity Loss Affects Global Disease Ecology. *Bioscience* **59**, 945–954 (2009).
13. Myers, S. S. *et al.* Human health impacts of ecosystem alteration. *Proc. Natl. Acad. Sci. U. S. A.* **110**, 18753–60 (2013).
14. Whitmee, S. *et al.* Safeguarding human health in the Anthropocene epoch: Report of the Rockefeller Foundation-Lancet Commission on planetary health. *Lancet* **386**, 1973–2028 (2015).
15. Patz, J. A. *et al.* Unhealthy landscapes: Policy recommendations on land use change and infectious disease emergence. *Environ. Health Perspect.* (2004) doi:10.1289/ehp.6877.
16. Burkett-Cadena, N. D. & Vittor, A. Y. Deforestation and vector-borne disease: Forest conversion favors important mosquito vectors of human pathogens. *Basic Appl. Ecol.* **26**, 101–110 (2018).
17. Myers, S. S. *et al.* Human health impacts of ecosystem alteration. *Proc. Natl. Acad. Sci. U. S. A.* **110**, 18753–60 (2013).
18. WHO. *Dengue: guidelines for diagnosis, treatment, prevention and control*. www.who.int/neglected_diseases/en (2009).

19. Lourenço-De-Oliveira, R., Castro, M. G., Braks, M. A. H. & Lounibos, L. P. The invasion of urban forest by dengue vectors in Rio de Janeiro. (2004).

20. Vanwambeke, S. O. *et al.* Multi-level analyses of spatial and temporal determinants for dengue infection. *Int. J. Health Geogr.* **5**, 1–16 (2006).

21. Sarfraz, M. S. *et al.* Analyzing the spatio-temporal relationship between dengue vector larval density and land-use using factor analysis and spatial ring mapping. *BMC Public Health* **12**, 1–19 (2012).

22. Weterings, R., Umponstira, C. & Buckley, H. L. Container-breeding mosquitoes and predator community dynamics along an urban-forest gradient: The effects of habitat type and isolation. *Basic Appl. Ecol.* **15**, 486–495 (2014).

23. Troyo, A., Fuller, D. O., Calderón-Arguedas, O., Solano, M. E. & Beier, J. C. Urban structure and dengue incidence in Puntarenas, Costa Rica. *Singap. J. Trop. Geogr.* **30**, 265–282 (2009).

24. Ling, C. Y., Gruebner, O., Krämer, A. & Lakes, T. Spatio-temporal patterns of dengue in Malaysia: Combining address and sub-district level. *Geospat. Health* **9**, 131–140 (2014).

25. Chiu, C. H., Wen, T. H., Chien, L. C. & Yu, H. L. A probabilistic spatial dengue fever risk assessment by a threshold-based-quantile regression method. *PLoS One* **9**, 1–14 (2014).

26. Nakhapakorn, K. & Tripathi, N. An information value based analysis of physical and climatic factors affecting dengue fever and dengue haemorrhagic fever incidence. *Int. J. Health Geogr.* **4**, 13 (2005).

27. Sithiprasasna, R. *et al.* Use of Geographical Information System to Study the Epidemiology of Dengue Haemorrhagic Fever in Thailand. *Dengue Bull.* **21**, 68–72 (1997).

28. Garg, T. *et al.* Ecosystems and Human Health : The Local Benefits of Forest Cover in Indonesia. 1–44.

29. Berazneva, J. & Byker, T. S. Does Forest Loss Increase Human Disease? Evidence from Nigeria. *Am. Econ. Rev. Pap. Proc. 2017* **107**, 516–521 (2017).

30. Chaves, L. S. M., Conn, J. E., López, R. V. M. & Sallum, M. A. M. Abundance of impacted forest patches less than 5 km2 is a key driver of the incidence of malaria in Amazonian Brazil. *Sci. Rep.* **8**, 7077 (2018).

31. Santos, A. S. & Almeida, A. N. The Impact of Deforestation on Malaria Infections in the Brazilian Amazon. *Ecol. Econ.* **154**, 247–256 (2018).

32. Wood, C. L., McInturff, A., Young, H. S., Kim, D. & Lafferty, K. D. Human infectious disease burdens decrease with urbanization but not with biodiversity. *Philos. Trans. R. Soc. B Biol. Sci.* **372**, 20160122 (2017).

33. Keesing, F., Holt, R. D. & Ostfeld, R. S. Effects of species diversity on disease risk. *Ecol. Lett.* **9**, 485–498 (2006).

34. Laporta, G. Z., Prado, P. I. K. L. de, Kraenkel, R. A., Coutinho, R. M. & Sallum, M. A. M. Biodiversity Can Help Prevent Malaria Outbreaks in Tropical Forests. *PLoS Negl. Trop. Dis.* **7**, e2139 (2013).

35. Camacho, K. & Avila, M. L. *Una Visión Comprensiva del Dengue en Centroamérica y República Dominicana: Epidemiología y recomendaciones vacunales Informe final*.

http://www.acencai2018.com/PDF/di/DENGUE_INFORME_FINAL_AHF_16NOV16.pdf (2016).

36. Calderón-Arguedas, Ó. *et al.* Papel potencial de Aedes albopictus Skuse en la transmisión de virus dengue (DENV) en una zona de actividad piñera de Costa Rica. *Rev. Biomédica* 33–41 (2019) doi:10.1371/journal.pone.0157120.

37. Rodríguez, I. Costa Rica ha gastado más de ¢5.000 millones en atender el dengue - La Nación. *La Nación* https://www.nacion.com/el-pais/costa-rica-ha-gastado-mas-de-c-5-000-millones-en-atender-el-dengue/J7K4JU32KBGKFDOALZFZFAPDVQ/story/ (2013).

38. Salud, M. de. *Informe Anual 2017*. http://www.msp.gub.uy (2018).

39. Sánchez-Azofeifa, A. Análisis de la cobertura forestal de Costa Rica entre 1960 y 2013. *AMBIENTICO* **253**, 4–11 (2015).

40. FONAFIFO. *Estrategia Nacional REDD+ Costa Rica: Una iniciativa del Programa de Bosques y Desarrollo Rural*. (2015).

41. Sierra, R., Cambronero, A. & Vega, E. *Patrones y factores de cambio de la cobertura forestal natural de Costa Rica, 1987-2013*. (2016).

42. UNECLAC-CELADE::Redatam Webserver | Statistical Process and Dissemination Tool. https://redatam.ccss.sa.cr/bincri/RpWebEngine.exe/Portal?

43. AGRESTA, DIMAP, Universidad de Costa Rica & Universidad Politécnica de Madrid. *Generating a consistent historical time series of activity data from land use change for the development of Costa Rica's REDD Plus Reference Level*. http://reddcr.go.cr/sites/default/files/centro-de-documentacion/agresta_et_al._2015.b_-_ndice_de_cobertura_como_base_para_estimar_degradaci_n_y_aumento_de_existencias_de_carbono.pdf (2015).

44. Escudero, V. H. Medición de la salud y la enfermedad. *Man. Audit. medica* 17–42 (2003).

45. Xirinachs, Y. Cost-effectiveness analysis of a dengue vaccine in Costa Rica. in *ISPOR 19th Annual Congress - 29 Oct - 2 Nov 2016, Vienna, Austria* 2016 (2016).

46. OhAinle, M. *et al.* Dynamics of dengue disease severity determined by the interplay between viral genetics and serotype-specific immunity. *Sci. Transl. Med.* **3**, 114ra128 (2011).

47. Hassan, R. M., Scholes, R. J., Ash, N. & Millennium Ecosystem Assessment (Program). Condition and Trends Working Group. *Ecosystems and human well-being : current state and trends : findings of the Condition and Trends Working Group of the Millennium Ecosystem Assessment*. (Island Press, 2005).

48. Pattanayak, S. K. & Pfaff, A. Behavior, Environment, and Health in Developing Countries: Evaluation and Valuation. *Annu. Rev. Resour. Econ.* **1**, 183–217 (2009).

49. Zivin, J. G. & Neidell, M. Environment , Health , and Human Capital. *J. Econ. Lit.* **51**, 689–730 (2013).

50. Lindsay, S. W. & Birley, M. Rural Development and Malaria Control in Sub-Saharan Africa. *Ecohealth* **1**, 129–137 (2004).

51. Keiser, J., Singer, B. H. & Utzinger, J. Reducing the burden of malaria in different eco-epidemiological settings with environmental management: a systematic review. *Lancet*

*Infect. Dis.* **5**, 695–708 (2005).

52. Mordecai, E. A. *et al.* Optimal temperature for malaria transmission is dramatically lower than previously predicted. *Ecol. Lett.* **16**, 22–30 (2013).

53. Ali, S. *et al.* Environmental and Social Change Drive the Explosive Emergence of Zika Virus in the Americas. *PLoS Negl. Trop. Dis.* **11**, e0005135 (2017).

54. Beck-Johnson, L. M. *et al.* The Effect of Temperature on Anopheles Mosquito Population Dynamics and the Potential for Malaria Transmission. *PLoS One* **8**, e79276 (2013).

55. Kaewwaen, W. & Bhumiratana, A. Landscape Ecology and Epidemiology of Malaria Associated with Rubber Plantations in Thailand: Integrated Approaches to Malaria Ecotoping. *Interdiscip. Perspect. Infect. Dis.* **2015**, 1–17 (2015).

56. Gersovitz, Mark; Hammer, J. S. Infectious diseases, public policy, and the marriage of economics and epidemiology. *World Bank Res. Obs.* **18**, 129–157 (2003).

57. Over, M., Bakote'e, B., Velayudhan, R., Wilikai, P. & Graves, P. M. *Impregnated nets or DDT residual spraying? Field effectiveness of malaria prevention techniques in Solomon Islands, 1993-1999*. https://www.ncbi.nlm.nih.gov/books/NBK3743/pdf/Bookshelf_NBK3743.pdf (2004).

58. Yasuoka, J. & Levins, R. Impact of deforestation and agricultural development on anopheline ecology and malaria epidemiology. *Am. J. Trop. Med. Hyg.* **76**, 450–60 (2007).

59. United Nations. *Transforming our world: the 2030 Agenda for Sustainable Development Transforming our world: the 2030 Agenda for Sustainable Development Preamble*. http://www.un.org/en/development/desa/population/migration/generalassembly/docs/globalcompact/A_RES_70_1_E.pdf (2015).

60. Wooldridge, J. M. Econometric Analysis of Cross Section and Panel Data. *MIT Press* vol. 58 1096 (2010).

61. Vincent, J. R. *et al.* Valuing Water Purification by Forests: An Analysis of Malaysian Panel Data. *Environ. Resour. Econ.* **64**, 59–80 (2016).

62. Tan-Soo, J.-S., Adnan, N., Ahmad, I., Pattanayak, S. K. & Vincent, J. R. Econometric Evidence on Forest Ecosystem Services: Deforestation and Flooding in Malaysia. *Environ. Resour. Econ.* **63**, 25–44 (2016).

63. INEC. *X Censo Nacional de Población y VI de Vivienda: Resultados Generales*. http://www.inec.go.cr/sites/default/files/documentos/inec_institucional/estadisticas/resultados/repoblaccenso2011-15.pdf.pdf (2011).

64. Funk, C. *et al.* The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Sci. Data* **2**, 150066 (2015).

65. Willmott, C. J. & Matsuura, K. Terrestrial Air Temperature: Gridded Monthly Time Series (1950 - 2014) (V 4.01). http://climate.geog.udel.edu/~climate/html_pages/Global2014/README.GlobalTsT2014.html (2015).

66. Vincent, J. R. *et al.* Accounting for the water purification service of tropical rainforests. 1–35.

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# Forests can help to diminish the number of dengue cases in Costa Rica

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**List of Tables**

## Appendix S1

### Table S1 - 1: Descriptive statistics

| Variable | | Obs | Mean | Std. Dev. | Min | Max | SD | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Overall | Between | Within |
| Dengue | Dengue total: Incidence per 100,000 people | 11016 | 2.18 | 15.24 | 0 | 364.79 | 15.24 | 8.04 | 12.95 |
| | Dengue 0-4: Incidence per 100,000 people | 11016 | 0.60 | 9.76 | 0 | 471.70 | 9.76 | 2.55 | 9.43 |
| | Dengue 5-14: Incidence per 100,000 people | 11016 | 1.23 | 13.41 | 0 | 478.24 | 13.41 | 5.35 | 12.30 |
| | Dengue 15-34: Incidence per 100,000 people | 11016 | 2.54 | 18.41 | 0 | 432.55 | 18.41 | 9.53 | 15.76 |
| | Dengue 35-64: Incidence per 100,000 people | 11016 | 2.86 | 22.13 | 0 | 603.62 | 22.13 | 10.76 | 19.35 |
| | Dengue +64: Incidence per 100,000 people | 11016 | 2.83 | 36.42 | 0 | 1459.85 | 36.42 | 11.50 | 34.56 |
| | Dengue total: outbreak | 11016 | 0.02 | 0.14 | 0 | 1 | 0.14 | 0.05 | 0.13 |
| | Dengue 0-4: Outbreak | 11016 | 0.01 | 0.08 | 0 | 1 | 0.08 | 0.04 | 0.08 |
| | Dengue 5-14: Outbreak | 11016 | 0.02 | 0.13 | 0 | 1 | 0.13 | 0.07 | 0.11 |
| | Dengue 15-34: Outbreak | 11016 | 0.04 | 0.19 | 0 | 1 | 0.19 | 0.11 | 0.15 |
| | Dengue 35 - 64: Outbreak | 11016 | 0.03 | 0.18 | 0 | 1 | 0.18 | 0.10 | 0.15 |
| | Dengue +64: Outbreak | 11016 | 0.01 | 0.11 | 0 | 1 | 0.11 | 0.05 | 0.09 |
| Land cover | % Forest | 11016 | 0.41 | 0.26 | 0.00 | 0.97 | 0.26 | 0.26 | 0.03 |
| | % Agriculture | 11016 | 0.20 | 0.22 | 0.00 | 0.93 | 0.22 | 0.22 | 0.04 |
| | % Wetland | 11016 | 0.002 | 0.02 | 0.00 | 0.49 | 0.02 | 0.02 | 0.00 |
| | % Grassland | 11016 | 0.20 | 0.19 | 0.00 | 0.84 | 0.19 | 0.82 | 0.30 |
| | % Urban | 11016 | 0.15 | 0.28 | 0.00 | 1.00 | 0.28 | 0.28 | 0.01 |
| Weather | Rainfall (monthly mm, log) | 11016 | 199.61 | 165.98 | 0.00 | 986.22 | 165.98 | 62.22 | 153.90 |
| | Temperature (Cº) | 11016 | 22.45 | 2.82 | 15.57 | 30.75 | 2.82 | 2.70 | 0.81 |
| | Rainfall (monthly mm)*Temperature (Cº) | 11016 | 4492.15 | 3827.54 | 0.00 | 26529.06 | 3827.54 | 1673.36 | 3443.23 |
| Socioeconomic | % population urban areas | 11016 | 0.41 | 0.38 | 0.00 | 1.36 | 0.38 | 0.35 | 0.16 |
| | Population density | 11016 | 1237.86 | 2677.98 | 2.18 | 28605.06 | 2677.98 | 2676.02 | 159.60 |
| | % households without access to water | 11016 | 0.04 | 0.08 | 0.00 | 0.86 | 0.08 | 0.07 | 0.03 |
| | % households with more than 4 critical needs | 11016 | 0.48 | 1.25 | 0.00 | 12.70 | 1.25 | 0.97 | 0.80 |
| | % population finished high school | 11016 | 0.43 | 0.19 | 0.03 | 0.93 | 0.19 | 0.17 | 0.07 |
| | % population no health insurance (CCSS) | 11016 | 0.17 | 0.07 | 0.06 | 0.63 | 0.07 | 0.06 | 0.03 |
| | % households hold a car | 11016 | 0.36 | 0.19 | 0.00 | 1.03 | 0.19 | 0.12 | 0.14 |
| | Average nº people per household | 11016 | 3.84 | 0.43 | 2.50 | 5.30 | 0.43 | 0.29 | 0.32 |
| | % households with sewerage system | 11016 | 0.92 | 0.14 | 0.21 | 1.00 | 0.14 | 0.08 | 0.11 |
| | % crowded households | 11016 | 0.07 | 0.05 | 0.00 | 0.40 | 0.05 | 0.04 | 0.02 |

**Table S1 - 2: Estimations result of percentage of forest in dengue hospital admissions per 100,000 and probability of dengue outbreak. Monthly 2 year panel 2000 and 2011**

| | Dengue total population: hospital admissions per 100,000 | | | | | Dengue total population: outbreak | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| % Forest | -15.92*** | -15.92*** | -21.13*** | -19.34*** | -18.26*** | -0.179* | -0.179* | -0.269** | -0.250** | -0.202* |
| *s.e.* | *(5.558)* | *(5.561)* | *(6.412)* | *(6.183)* | *(6.317)* | *(0.102)* | *(0.102)* | *(0.104)* | *(0.103)* | *(0.113)* |
| Rainfall (mm) | | | | -0.0141 | -0.0142 | | | | -0.000115 | -0.000111 |
| *s.e.* | | | | *(0.0210)* | *(0.0209)* | | | | *(0.000266)* | *(0.000265)* |
| Temperature (Cº) | | | | 4.516** | 3.368* | | | | 0.0853*** | 0.0642*** |
| *s.e.* | | | | *(1.873)* | *(1.748)* | | | | *(0.0217)* | *(0.0204)* |
| Hummidity (Rainfall * Tempreature) | | | | -0.00108 | -0.00107 | | | | 2.87e-07 | 5.34e-07 |
| *s.e.* | | | | *(0.00110)* | *(0.00110)* | | | | *(1.20e-05)* | *(1.20e-05)* |
| Rainfall (mm)$^2$ | | | | -2.48e-05 | -2.41e-05 | | | | -2.21e-07 | -2.17e-07 |
| *s.e.* | | | | *(2.27e-05)* | *(2.25e-05)* | | | | *(2.26e-07)* | *(2.24e-07)* |
| Temperature (Cº)$^2$ | | | | -0.0664 | -0.0396 | | | | -0.00153*** | -0.00104** |
| *s.e.* | | | | *(0.0418)* | *(0.0394)* | | | | *(0.000468)* | *(0.000437)* |
| Hummidity (Rainfall * Tempreature)$^2$ | | | | 1.44e-07** | 1.44e-07** | | | | 8.19e-10* | 8.13e-10* |
| *s.e.* | | | | *(6.12e-08)* | *(6.08e-08)* | | | | *(4.91e-10)* | *(4.88e-10)* |
| % population urban areas | | | | | 0.689 | | | | | 0.0235 |
| *s.e.* | | | | | *(1.354)* | | | | | *(0.0195)* |
| ln(density) | | | | | -0.165 | | | | | 0.00701 |
| *s.e.* | | | | | *(4.523)* | | | | | *(0.0561)* |
| % households without access to water | | | | | -24.67** | | | | | -0.286* |
| *s.e.* | | | | | *(11.83)* | | | | | *(0.171)* |
| % households with more than 4 critical n | | | | | 1.198** | | | | | 0.0125 |
| *s.e.* | | | | | *(0.473)* | | | | | *(0.00793)* |
| % population finished high school | | | | | 49.20*** | | | | | 0.576*** |
| *s.e.* | | | | | *(15.77)* | | | | | *(0.196)* |
| % population no health insurance (CCSS) | | | | | -21.24** | | | | | -0.444*** |
| *s.e.* | | | | | *(9.358)* | | | | | *(0.165)* |
| % households hold a car | | | | | -20.11*** | | | | | -0.297*** |
| *s.e.* | | | | | *(5.498)* | | | | | *(0.0819)* |
| Average nº people per household | | | | | 2.473 | | | | | -0.0138 |
| *s.e.* | | | | | *(2.991)* | | | | | *(0.0481)* |
| % households with sewarage system | | | | | 7.378 | | | | | 0.139* |
| *s.e.* | | | | | *(5.496)* | | | | | *(0.0819)* |
| % crowded households | | | | | 10.80 | | | | | 0.197 |
| *s.e.* | | | | | *(24.27)* | | | | | *(0.431)* |
| Constant | 8.729*** | 7.816*** | 8.923*** | -56.60*** | -70.49** | 0.122*** | 0.128*** | 0.147*** | -0.980*** | -0.946** |
| *s.e.* | *(2.287)* | *(2.152)* | *(2.289)* | *(21.32)* | *(30.82)* | *(0.0420)* | *(0.0423)* | *(0.0418)* | *(0.254)* | *(0.419)* |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | No | Yes | Yes | Yes | No | No | Yes | Yes | Yes |
| Month FE | No | Yes | Yes | Yes | Yes | No | Yes | Yes | Yes | Yes |
| Cluster | District | District | District | District | District | District | District | District | District | District |
| Nº obs. | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 |
| Nº groups | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 |
| Min. obs. per group | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 |
| Avg. obs per group | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 |
| Max. obs per group | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 |
| R2 overall | 0.000922 | 0.000267 | 0.000286 | 0.00907 | 0.00517 | 0.00138 | 3.40e-06 | 4.06e-05 | 0.000560 | 0.00172 |
| R2 within | 0.000950 | 0.0189 | 0.0252 | 0.0577 | 0.0704 | 0.000647 | 0.0118 | 0.0220 | 0.0325 | 0.0481 |
| R2 between | 0.00394 | 0.00394 | 0.00394 | 0.000729 | 0.000307 | 0.00472 | 0.00472 | 0.00472 | 0.00305 | 6.35e-06 |

*** p<0.01, ** p<0.05, * p<0.1

**Table S1 - 3: Percentage of forest change and dengue hospital admissions and probability of dengue outbreak by age cohort. Monthly 2-year panel 2000 and 2011.**

| | Dengue : Hospital admissions per 100,000 | | | | | | Dengue : outbreak | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Total (1) | 0 - 4 (2) | 5 - 14 (3) | 15 - 34 (4) | 35 - 64 (5) | +64 (6) | Total (7) | 0 - 4 (8) | 5 - 14 (9) | 15 - 34 (10) | 35 - 64 (11) | +64 (12) |
| % Forest | **-18.26*** ** | **-4.206** | **-10.98*** ** | **-19.67*** ** | **-24.76*** ** | **-22.22*** | **-0.202*** | **-0.0358** | **-0.0536** | **-0.180*** | **-0.227** ** | **-0.0743** |
| *s.e.* | **(6.317)** | **(3.251)** | **(3.995)** | **(7.387)** | **(8.837)** | **(11.64)** | **(0.113)** | **(0.0286)** | **(0.0486)** | **(0.0933)** | **(0.0898)** | **(0.0482)** |
| Rainfall (mm) | -0.0142 | -0.0140 | -0.0289* | -0.000846 | -0.0242 | -0.000596 | -0.000111 | -3.68e-05 | -0.000136 | -0.000119 | 5.91e-05 | -0.000122 |
| *s.e.* | (0.0209) | (0.0115) | (0.0154) | (0.0275) | (0.0292) | (0.0530) | (0.000265) | (0.000113) | (0.000149) | (0.000225) | (0.000217) | (0.000147) |
| Temperature (Cº) | 3.368* | 1.502 | 1.612 | 5.276** | 2.364 | 3.248 | 0.0642*** | 0.0201 | 0.0192* | 0.0799*** | 0.0253 | 0.0221** |
| *s.e.* | (1.748) | (1.101) | (1.737) | (2.354) | (2.321) | (3.747) | (0.0204) | (0.0145) | (0.0110) | (0.0212) | (0.0195) | (0.00958) |
| Hummidity (Rainfall * Temp | -0.00107 | 0.000241 | 0.000229 | -0.00190 | -0.00108 | -0.00261 | 5.34e-07 | -3.64e-06 | -1.83e-06 | -3.16e-06 | -8.69e-06 | -1.54e-07 |
| *s.e.* | (0.00110) | (0.000596) | (0.000691) | (0.00143) | (0.00141) | (0.00261) | (1.20e-05) | (5.41e-06) | (6.66e-06) | (1.09e-05) | (1.04e-05) | (6.64e-06) |
| Rainfall (mm)$^2$ | -2.41e-05 | 1.52e-06 | 4.61e-06 | -4.14e-05 | -2.91e-05 | -2.88e-05 | -2.17e-07 | -5.16e-08 | 7.65e-08 | -7.78e-08 | -2.45e-07 | 1.01e-08 |
| *s.e.* | (2.25e-05) | (9.73e-06) | (1.61e-05) | (2.95e-05) | (3.02e-05) | (6.01e-05) | (2.24e-07) | (1.05e-07) | (1.82e-07) | (1.89e-07) | (1.92e-07) | (1.39e-07) |
| Temperature (Cº)$^2$ | -0.0396 | -0.0236 | -0.0121 | -0.0757 | -0.0108 | -0.0290 | -0.00104** | -0.000335 | -0.000152 | -0.00139*** | -0.000267 | -0.000331 |
| *s.e.* | (0.0394) | (0.0226) | (0.0401) | (0.0532) | (0.0519) | (0.0799) | (0.000437) | (0.000294) | (0.000236) | (0.000431) | (0.000423) | (0.000207) |
| Hummidity (Rainfall * Temp | 1.44e-07** | 1.77e-08 | 4.74e-08 | 1.97e-07** | 1.73e-07** | 2.15e-07 | 8.13e-10* | 3.94e-10 | 3.55e-10 | 6.90e-10 | 8.82e-10** | 3.30e-10 |
| *s.e.* | (6.08e-08) | (2.08e-08) | (3.75e-08) | (7.86e-08) | (7.58e-08) | (1.39e-07) | (4.88e-10) | (2.44e-10) | (3.59e-10) | (4.62e-10) | (4.43e-10) | (2.98e-10) |
| % population urban areas | 0.689 | 0.195 | 0.994 | 0.799 | 0.379 | -0.907 | 0.0235 | 0.000693 | 0.00857 | 0.0231 | 0.0135 | 0.00670 |
| *s.e.* | (1.354) | (1.162) | (0.950) | (1.557) | (2.073) | (2.857) | (0.0195) | (0.00603) | (0.00753) | (0.0156) | (0.0165) | (0.00724) |
| ln(density) | -0.165 | -0.534 | -0.196 | 2.437 | -3.662 | -1.869 | 0.00701 | 0.00338 | 0.0207 | 0.0158 | -0.0397 | 0.0104 |
| *s.e.* | (4.523) | (1.761) | (3.208) | (5.040) | (6.080) | (8.521) | (0.0561) | (0.0157) | (0.0262) | (0.0472) | (0.0448) | (0.0274) |
| % households without acces | -24.67** | -3.633 | -16.85*** | -22.16 | -37.05** | -31.63 | -0.286* | -0.0341 | -0.0721 | -0.177 | -0.209 | -0.0962 |
| *s.e.* | (11.83) | (3.094) | (5.767) | (13.72) | (17.67) | (20.82) | (0.171) | (0.0235) | (0.0816) | (0.167) | (0.149) | (0.0659) |
| % households with more tha | 1.198** | 0.422** | 0.420* | 1.813*** | 1.006 | 0.868 | 0.0125 | 0.00377*** | 0.00400 | 0.0137* | 0.00871 | 0.00500** |
| *s.e.* | (0.473) | (0.170) | (0.245) | (0.573) | (0.868) | (0.815) | (0.00793) | (0.00139) | (0.00467) | (0.00749) | (0.00655) | (0.00226) |
| % population finished high | 49.20*** | 18.37** | 29.41*** | 42.92** | 76.53*** | 88.67** | 0.576*** | 0.155** | 0.219** | 0.405** | 0.640*** | 0.203** |
| *s.e.* | (15.77) | (8.042) | (10.95) | (16.66) | (25.51) | (42.59) | (0.196) | (0.0654) | (0.0874) | (0.158) | (0.187) | (0.102) |
| % population no health insu | -21.24** | 1.283 | -7.339* | -32.61*** | -20.31 | -33.11** | -0.444*** | -0.0191 | -0.198** | -0.431*** | -0.242** | -0.122** |
| *s.e.* | (9.358) | (3.276) | (4.245) | (12.21) | (14.23) | (15.79) | (0.165) | (0.0260) | (0.0769) | (0.148) | (0.119) | (0.0529) |
| % households hold a car | -20.11*** | -7.302** | -10.95*** | -21.41*** | -29.42*** | -13.40 | -0.297*** | -0.0626** | -0.129*** | -0.233*** | -0.294*** | -0.0756** |
| *s.e.* | (5.498) | (3.150) | (3.860) | (6.345) | (8.036) | (11.67) | (0.0819) | (0.0244) | (0.0375) | (0.0671) | (0.0686) | (0.0368) |
| Average nº people per hous | 2.473 | -1.033 | 4.429** | 1.583 | 1.285 | 21.20* | -0.0138 | 0.000381 | 0.0396 | 0.0155 | 0.0159 | 0.0309 |
| *s.e.* | (2.991) | (1.306) | (1.929) | (3.785) | (4.964) | (12.38) | (0.0481) | (0.00928) | (0.0275) | (0.0370) | (0.0417) | (0.0237) |
| % housholds with sewarage | 7.378 | 1.965 | 1.623 | 11.64* | 7.421 | 2.154 | 0.139* | 0.0134 | 0.0669* | 0.139** | 0.129* | 0.0379 |
| *s.e.* | (5.496) | (3.716) | (3.472) | (5.973) | (9.067) | (12.93) | (0.0819) | (0.0171) | (0.0375) | (0.0637) | (0.0688) | (0.0369) |
| % crowded households | 10.80 | -2.201 | -1.529 | -0.441 | 44.97 | -29.84 | 0.197 | -0.0645 | -0.0972 | 0.0792 | 0.300 | 0.00886 |
| *s.e.* | (24.27) | (12.02) | (12.55) | (26.16) | (48.96) | (39.04) | (0.431) | (0.0869) | (0.172) | (0.348) | (0.330) | (0.121) |
| Constant | -70.49** | -18.64 | -48.25** | -102.2*** | -46.58 | -143.4** | -0.946** | -0.317 | -0.637*** | -1.260*** | -0.424 | -0.529** |
| *s.e.* | (30.82) | (18.70) | (19.40) | (38.22) | (43.48) | (66.53) | (0.419) | (0.195) | (0.203) | (0.454) | (0.350) | (0.209) |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | District | District | District | District | District | District | District | District | District | District | District | District |
| Nº obs. | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 |
| Nº groups | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 |
| Min. obs. per group | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 |
| Avg. obs per group | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 |
| Max. obs per group | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 |
| R2 overall | 0.00517 | 0.00174 | 0.00244 | 0.00155 | 0.0128 | 0.00115 | 0.00172 | 0.000880 | 0.000745 | 0.000180 | 0.0174 | 0.000603 |
| R2 within | 0.0704 | 0.00805 | 0.0280 | 0.0671 | 0.0511 | 0.0188 | 0.0481 | 0.0145 | 0.0303 | 0.0463 | 0.0417 | 0.0218 |
| R2 between | 0.000307 | 0.00553 | 0.000334 | 0.000838 | 0.0102 | 0.000135 | 6.35e-06 | 0.000139 | 3.93e-05 | 0.00197 | 0.0216 | 4.12e-07 |

*** p<0.01, ** p<0.05, * p<0.1

**Table S1 - 4: Estimations result of percentage of forest in dengue incidence and probability of dengue outbreak. Monthly panel 2000 – 2013.**

| | Dengue total population: Hospital admissions per 100,000 | | | | | Dengue total population: outbreak | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** | **(10)** |
| % Forest | 6.572 | 6.572 | -10.04* | -9.778* | -9.281* | 0.107 | 0.107 | -0.227*** | -0.228*** | -0.219*** |
| *s.e.* | (4.662) | (4.662) | (5.175) | (5.132) | (5.161) | (0.0795) | (0.0795) | (0.0808) | (0.0805) | (0.0811) |
| Rainfall (mm) | | | | -0.104*** | -0.104*** | | | | -0.000350** | -0.000349** |
| *s.e.* | | | | (0.0192) | (0.0192) | | | | (0.000142) | (0.000142) |
| Temperature (Cº) | | | | 7.160*** | 7.146*** | | | | 0.0475*** | 0.0473*** |
| *s.e.* | | | | (1.911) | (1.898) | | | | (0.0164) | (0.0162) |
| Hummidity (Rainfall * Tempreature) | | | | 0.00397*** | 0.00397*** | | | | 1.37e-05** | 1.37e-05** |
| *s.e.* | | | | (0.000794) | (0.000795) | | | | (6.14e-06) | (6.14e-06) |
| Rainfall (mm)$^2$ | | | | 6.31e-05*** | 6.30e-05*** | | | | 2.40e-07* | 2.38e-07* |
| *s.e.* | | | | (1.56e-05) | (1.56e-05) | | | | (1.28e-07) | (1.28e-07) |
| Temperature (Cº)$^2$ | | | | -0.193*** | -0.192*** | | | | -0.00147*** | -0.00145*** |
| *s.e.* | | | | (0.0482) | (0.0478) | | | | (0.000366) | (0.000360) |
| Hummidity (Rainfall * Tempreature)$^2$ | | | | -8.95e-08*** | -8.94e-08*** | | | | -3.66e-10 | -3.63e-10 |
| *s.e.* | | | | (2.74e-08) | (2.75e-08) | | | | (2.24e-10) | (2.24e-10) |
| ln(density) | | | | | 6.893** | | | | | 0.120** |
| *s.e.* | | | | | (2.970) | | | | | (0.0513) |
| Constant | 1.414 | -0.155 | 3.051 | -59.77*** | -94.64*** | 0.0398 | 0.0254 | 0.0942*** | -0.235 | -0.843** |
| *s.e.* | (1.918) | (1.945) | (2.118) | (18.89) | (25.96) | (0.0327) | (0.0327) | (0.0332) | (0.187) | (0.342) |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | No | Yes | Yes | Yes | No | No | Yes | Yes | Yes |
| Month FE | No | Yes | Yes | Yes | Yes | No | Yes | Yes | Yes | Yes |
| Cluster | District | District | District | District | District | District | District | District | District | District |
| Nº obs. | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 |
| Nº groups | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 |
| Min. obs. per group | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| Avg. obs per group | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| Max. obs per group | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| R2 overall | 0.00181 | 0.0111 | 0.0132 | 0.000372 | 0.00288 | 0.000671 | 0.00947 | 0.0228 | 0.00475 | 0.000557 |
| R2 within | 4.27e-05 | 0.0109 | 0.0295 | 0.0343 | 0.0346 | 0.000100 | 0.0143 | 0.0629 | 0.0658 | 0.0665 |
| R2 between | 0.0178 | 0.0178 | 0.0178 | 0.200 | 0.0977 | 0.00370 | 0.00370 | 0.00370 | 0.0565 | 0.0310 |

*** p<0.01, ** p<0.05, * p<0.1

**Table S1 - 5: Percentage of forest change and dengue hospital admissions and probability of dengue outbreak by age cohort. Monthly panel 2000 – 2013**

| | Dengue : Hospital admissions per 100,000 people | | | | | | Dengue : outbreak | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Total | 0 - 4 | 5 - 14 | 15 - 34 | 35 - 64 | +64 | Total | 0 - 4 | 5 - 14 | 15 - 34 | 35 - 64 | +64 |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| % Forest | -9.281* | -2.717 | -5.850** | -12.74** | -6.816 | -12.66 | -0.219*** | -0.0201 | -0.0793** | -0.171*** | -0.134** | -0.0658* |
| *s.e.* | (5.161) | (1.809) | (2.732) | (6.038) | (6.905) | (9.737) | (0.0811) | (0.0171) | (0.0369) | (0.0656) | (0.0657) | (0.0340) |
| Rainfall (mm) | -0.104*** | -0.0210*** | -0.0391*** | -0.123*** | -0.141*** | -0.189*** | -0.000349** | -0.000141* | -0.000289*** | -0.000326*** | -0.000454*** | -0.000359*** |
| *s.e.* | (0.0192) | (0.00750) | (0.0109) | (0.0255) | (0.0279) | (0.0356) | (0.000142) | (7.83e-05) | (9.15e-05) | (0.000120) | (0.000146) | (0.000108) |
| Temperature (Cº) | 7.146*** | 0.899 | 4.050*** | 9.081*** | 7.717*** | 10.64*** | 0.0473*** | 0.00489 | 0.0199** | 0.0563*** | 0.0362*** | 0.0210** |
| *s.e.* | (1.898) | (0.610) | (1.136) | (2.502) | (2.257) | (3.811) | (0.0162) | (0.00514) | (0.00946) | (0.0137) | (0.0119) | (0.00858) |
| Hummidity (Rainfall * Tempreature) | 0.00397*** | 0.000830** | 0.00152*** | 0.00469*** | 0.00528*** | 0.00728*** | 1.37e-05** | 5.03e-06 | 1.06e-05*** | 1.06e-05** | 1.50e-05** | 1.31e-05*** |
| *s.e.* | (0.000795) | (0.000338) | (0.000477) | (0.00109) | (0.00110) | (0.00148) | (6.14e-06) | (3.21e-06) | (3.78e-06) | (5.30e-06) | (6.21e-06) | (4.59e-06) |
| Rainfall $(mm)^2$ | 6.30e-05*** | 1.37e-05** | 2.04e-05** | 7.14e-05*** | 9.27e-05*** | 0.000117*** | 2.38e-07* | 6.25e-08 | 1.75e-07** | 2.28e-07** | 3.14e-07** | 1.91e-07** |
| *s.e.* | (1.56e-05) | (6.41e-06) | (8.77e-06) | (2.08e-05) | (2.59e-05) | (2.93e-05) | (1.28e-07) | (8.27e-08) | (8.04e-08) | (1.01e-07) | (1.46e-07) | (8.85e-08) |
| Temperature $(Cº)^2$ | -0.192*** | -0.0255* | -0.106*** | -0.244*** | -0.207*** | -0.293*** | -0.00145*** | -0.000135 | -0.000551** | -0.00150*** | -0.00104*** | -0.000576*** |
| *s.e.* | (0.0478) | (0.0138) | (0.0281) | (0.0624) | (0.0566) | (0.0934) | (0.000360) | (0.000122) | (0.000224) | (0.000312) | (0.000282) | (0.000205) |
| Hummidity $(Rainfall * Tempreature)^2$ | -8.94e-08*** | -2.12e-08** | -2.87e-08* | -1.00e-07** | -1.28e-07*** | -1.83e-07*** | -3.63e-10 | -5.84e-11 | -2.15e-10 | -2.71e-10 | -3.14e-10 | -2.64e-10* |
| *s.e.* | (2.75e-08) | (1.07e-08) | (1.67e-08) | (3.98e-08) | (4.08e-08) | (4.86e-08) | (2.24e-10) | (1.31e-10) | (1.36e-10) | (1.84e-10) | (2.60e-10) | (1.58e-10) |
| ln(density) | 6.893** | 1.460 | 4.288** | 8.729** | 6.820* | 12.91** | 0.120** | 0.0183** | 0.0606*** | 0.109*** | 0.0819** | 0.0501** |
| *s.e.* | (2.970) | (1.160) | (1.925) | (3.594) | (3.547) | (5.615) | (0.0513) | (0.00905) | (0.0207) | (0.0405) | (0.0376) | (0.0208) |
| Constant | -94.64*** | -13.69 | -56.46*** | -119.6*** | -100.6*** | -150.7*** | -0.843** | -0.126* | -0.444*** | -0.976*** | -0.647*** | -0.409*** |
| *s.e.* | (25.96) | (10.31) | (15.84) | (33.56) | (30.19) | (54.62) | (0.342) | (0.0743) | (0.137) | (0.272) | (0.234) | (0.146) |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | District | District | District | District | District | District | District | District | District | District | District | District |
| Nº obs. | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 |
| Nº groups | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 |
| Min. obs. per group | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| Avg. obs per group | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| Max. obs per group | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| R2 overall | 0.00288 | 0.000211 | 0.00123 | 0.00276 | 0.00181 | 0.00115 | 0.000557 | 4.62e-05 | 0.000334 | 0.00165 | 0.000654 | 0.000294 |
| R2 within | 0.0346 | 0.00425 | 0.0132 | 0.0293 | 0.0279 | 0.0132 | 0.0665 | 0.00647 | 0.0197 | 0.0479 | 0.0458 | 0.0234 |
| R2 between | 0.0977 | 0.0493 | 0.0660 | 0.103 | 0.0984 | 0.0800 | 0.0310 | 0.00453 | 0.0101 | 0.0306 | 0.0253 | 0.0137 |

*** p<0.01, ** p<0.05, * p<0.1

**Table S1 - 6: Percentage of forest change and dengue hospital admissions and probability of dengue outbreak by age cohort. Monthly 2-year panel 2000 and 2011, residuals clustered at the county level (robustness check)**

| VARIABLES | Dengue : Hospital admissions per 100,000 | | | | | | Dengue : outbreak | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Total | 0 - 4 | 5 - 14 | 15 - 34 | 35 - 64 | +64 | Total | 0 - 4 | 5 - 14 | 15 - 34 | 35 - 64 | +64 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| % Forest | **-18.26**** | **-4.206** | **-10.98**** | **-19.67**** | **-24.76**** | **-22.22** | **-0.162**** | **-0.0358** | **-0.0536** | **-0.180** | **-0.227**** | **-0.0743** |
| s.e. | **(7.339)** | **(3.871)** | **(4.760)** | **(7.809)** | **(10.83)** | **(14.63)** | **(0.0696)** | **(0.0363)** | **(0.0465)** | **(0.105)** | **(0.105)** | **(0.0578)** |
| *Rainfall (mm)* | -0.0142 | -0.0140 | -0.0289* | -0.000846 | -0.0242 | -0.000596 | 0.000208 | -3.68e-05 | -0.000136 | -0.000119 | 5.91e-05 | -0.000122 |
| s.e. | (0.0243) | (0.0139) | (0.0148) | (0.0334) | (0.0333) | (0.0544) | (0.000234) | (0.000125) | (0.000199) | (0.000171) | (0.000197) | (0.000120) |
| *Temperature (Cº)* | 3.368 | 1.502 | 1.612 | 5.276* | 2.364 | 3.248 | 0.0593*** | 0.0201 | 0.0192** | 0.0799*** | 0.0253 | 0.0221** |
| s.e. | (2.005) | (1.332) | (2.157) | (2.736) | (1.934) | (3.048) | (0.0206) | (0.0190) | (0.00880) | (0.0240) | (0.0210) | (0.0102) |
| *Hummidity (Rainfall * Tempreature)* | -0.00107 | 0.000241 | 0.000229 | -0.00190 | -0.00108 | -0.00261 | -1.25e-05 | -3.64e-06 | -1.83e-06 | -3.16e-06 | -8.69e-06 | -1.54e-07 |
| s.e. | (0.00157) | (0.000644) | (0.000817) | (0.00210) | (0.00199) | (0.00327) | (1.22e-05) | (5.84e-06) | (1.00e-05) | (1.05e-05) | (1.21e-05) | (6.31e-06) |
| *Rainfall (mm)* $^2$ | -2.41e-05 | 1.52e-06 | 4.61e-06 | -4.14e-05 | -2.91e-05 | -2.88e-05 | -3.95e-07 | -5.16e-08 | 7.65e-08 | -7.78e-08 | -2.45e-07 | 1.01e-08 |
| s.e. | (3.29e-05) | (1.21e-05) | (2.04e-05) | (4.64e-05) | (4.05e-05) | (6.03e-05) | (2.82e-07) | (1.46e-07) | (2.94e-07) | (1.66e-07) | (1.75e-07) | (1.21e-07) |
| *Temperature (Cº)* $^2$ | -0.0396 | -0.0236 | -0.0121 | -0.0757 | -0.0108 | -0.0290 | -0.00109** | -0.000335 | -0.000152 | -0.00139*** | -0.000267 | -0.000331 |
| s.e. | (0.0447) | (0.0261) | (0.0482) | (0.0586) | (0.0472) | (0.0638) | (0.000414) | (0.000387) | (0.000197) | (0.000459) | (0.000409) | (0.000212) |
| *Hummidity (Rainfall * Tempreature)* $^2$ | 1.44e-07 | 1.77e-08 | 4.74e-08 | 1.97e-07 | 1.73e-07 | 2.15e-07 | 1.14e-09 | 3.94e-10 | 3.55e-10 | 6.90e-10 | 8.82e-10 | 3.30e-10 |
| s.e. | (9.97e-08) | (2.82e-08) | (5.56e-08) | (1.34e-07) | (1.19e-07) | (1.79e-07) | (7.21e-10) | (3.49e-10) | (6.29e-10) | (5.11e-10) | (5.34e-10) | (3.29e-10) |
| *% population urban areas* | 0.689 | 0.195 | 0.994 | 0.799 | 0.379 | -0.907 | 0.0137 | 0.000693 | 0.00857 | 0.0231 | 0.0135 | 0.00670 |
| s.e. | (1.129) | (0.806) | (0.787) | (1.586) | (1.680) | (2.909) | (0.00938) | (0.00468) | (0.00782) | (0.0179) | (0.0121) | (0.00772) |
| *ln(density)* | -0.165 | -0.534 | -0.196 | 2.437 | -3.662 | -1.869 | 0.00848 | 0.00338 | 0.0207 | 0.0158 | -0.0397 | 0.0104 |
| s.e. | (5.143) | (1.214) | (3.718) | (5.994) | (6.342) | (9.203) | (0.0390) | (0.0163) | (0.0238) | (0.0428) | (0.0400) | (0.0272) |
| *% households without access to water* | -24.67 | -3.633 | -16.85** | -22.16 | -37.05* | -31.63 | -0.199 | -0.0341 | -0.0721 | -0.177 | -0.209 | -0.0962 |
| s.e. | (14.49) | (3.401) | (6.263) | (17.16) | (21.01) | (25.13) | (0.126) | (0.0286) | (0.0890) | (0.197) | (0.174) | (0.0902) |
| *% households with more than 4 critical need* | 1.198 | 0.422** | 0.420 | 1.813* | 1.006 | 0.868 | 0.00660 | 0.00377*** | 0.00400 | 0.0137 | 0.00871 | 0.00500 |
| s.e. | (0.746) | (0.179) | (0.325) | (0.874) | (1.185) | (0.918) | (0.00863) | (0.00122) | (0.00620) | (0.0119) | (0.0111) | (0.00305) |
| *% population finished high school* | 49.20** | 18.37** | 29.41* | 42.92* | 76.53** | 88.67* | 0.426** | 0.155* | 0.219** | 0.405* | 0.640*** | 0.203 |
| s.e. | (22.91) | (8.476) | (15.92) | (22.49) | (32.30) | (47.13) | (0.183) | (0.0820) | (0.0981) | (0.207) | (0.216) | (0.121) |
| *% population no health insurance (CCSS)* | -21.24** | 1.283 | -7.339* | -32.61** | -20.31 | -33.11** | -0.318** | -0.0191 | -0.198*** | -0.431** | -0.242* | -0.122** |
| s.e. | (9.496) | (2.868) | (3.763) | (13.82) | (12.89) | (12.78) | (0.112) | (0.0280) | (0.0514) | (0.156) | (0.127) | (0.0465) |
| *% households hold a car* | -20.11*** | -7.302** | -10.95** | -21.41*** | -29.42*** | -13.40 | -0.214*** | -0.0626** | -0.129*** | -0.233*** | -0.294*** | -0.0756* |
| s.e. | (6.246) | (3.275) | (3.926) | (6.214) | (9.391) | (14.48) | (0.0600) | (0.0280) | (0.0441) | (0.0750) | (0.0849) | (0.0415) |
| *Average nº people per household* | 2.473 | -1.033 | 4.429* | 1.583 | 1.285 | 21.20 | 0.0119 | 0.000381 | 0.0396 | 0.0155 | 0.0159 | 0.0309 |
| s.e. | (2.646) | (0.905) | (2.158) | (3.135) | (4.718) | (13.72) | (0.0299) | (0.00903) | (0.0271) | (0.0335) | (0.0378) | (0.0279) |
| *% housholds with sewarage system* | 7.378 | 1.965 | 1.623 | 11.64** | 7.421 | 2.154 | 0.0532 | 0.0134 | 0.0669** | 0.139*** | 0.129** | 0.0379 |
| s.e. | (4.337) | (3.229) | (2.261) | (4.175) | (7.738) | (15.78) | (0.0538) | (0.0122) | (0.0267) | (0.0450) | (0.0590) | (0.0462) |
| *% crowded households* | 10.80 | -2.201 | -1.529 | -0.441 | 44.97 | -29.84 | 0.00259 | -0.0645 | -0.0972 | 0.0792 | 0.300 | 0.00886 |
| s.e. | (26.31) | (6.279) | (8.501) | (29.37) | (49.41) | (43.12) | (0.312) | (0.0601) | (0.188) | (0.361) | (0.435) | (0.131) |
| *Constant* | -70.49** | -18.64 | -48.25* | -102.2** | -46.58 | -143.4* | -0.860** | -0.317 | -0.637*** | -1.260** | -0.424 | -0.529** |
| s.e. | (30.81) | (15.82) | (24.60) | (42.39) | (39.66) | (80.14) | (0.331) | (0.218) | (0.212) | (0.465) | (0.407) | (0.246) |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | County | County | County | County | County | County | County | County | County | County | County | County |
| NB: obs. | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 | 11016 |
| NB: groups | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 |
| Min. obs. per group | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 |
| Avg. obs per group | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 |
| Max. obs per group | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 |
| R2 overall | 0.00517 | 0.00174 | 0.00244 | 0.00155 | 0.0128 | 0.00115 | 0.00156 | 0.000880 | 0.000745 | 0.000180 | 0.0174 | 0.000603 |
| R2 within | 0.0704 | 0.00805 | 0.0280 | 0.0671 | 0.0511 | 0.0188 | 0.0439 | 0.0145 | 0.0303 | 0.0463 | 0.0417 | 0.0218 |
| R2 between | 0.000307 | 0.00553 | 0.000334 | 0.000838 | 0.0102 | 0.000135 | 0.000181 | 0.000139 | 3.93e-05 | 0.00197 | 0.0216 | 4.12e-07 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table S1 - 7: Percentage of forest change and dengue hospital admissions and probability of dengue outbreak by age cohort. Monthly panel 2000 – 2013, residuals clustered at the county level (robustness check)**

| | Dengue : Hospital admissions per 100,000 people | | | | | | Dengue : outbreak | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Total | 0 - 4 | 5 - 14 | 15 - 34 | 35 - 64 | +64 | Total | 0 - 4 | 5 - 14 | 15 - 34 | 35 - 64 | +64 |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| % Forest | -9.281 | -2.717 | -5.850* | -12.74 | -6.816 | -12.66 | -0.164* | -0.0201 | -0.0793* | -0.171 | -0.134 | -0.0658 |
| *s.e.* | (8.316) | (1.950) | (3.066) | (9.715) | (11.03) | (14.18) | (0.0881) | (0.0234) | (0.0457) | (0.100) | (0.0998) | (0.0512) |
| Rainfall (mm) | -0.104*** | -0.0210 | -0.0391** | -0.123** | -0.141*** | -0.189*** | -3.45e-05 | -0.000141 | -0.000289* | -0.000326* | -0.000454*** | -0.000359* |
| *s.e.* | (0.0348) | (0.0124) | (0.0173) | (0.0440) | (0.0414) | (0.0633) | (0.000103) | (0.000115) | (0.000153) | (0.000176) | (0.000151) | (0.000183) |
| Temperature (Cº) | 7.146** | 0.899* | 4.050** | 9.081** | 7.717** | 10.64* | 0.0236* | 0.00489 | 0.0199** | 0.0563** | 0.0362* | 0.0210* |
| *s.e.* | (3.119) | (0.463) | (1.511) | (4.258) | (3.430) | (5.166) | (0.0120) | (0.00575) | (0.00883) | (0.0220) | (0.0180) | (0.0107) |
| Hummidity (Rainfall * Tempreature) | 0.00397** | 0.000830 | 0.00152** | 0.00469** | 0.00528*** | 0.00728*** | 1.93e-06 | 5.03e-06 | 1.06e-05 | 1.06e-05 | 1.50e-05** | 1.31e-05 |
| *s.e.* | (0.00143) | (0.000555) | (0.000724) | (0.00182) | (0.00167) | (0.00254) | (4.65e-06) | (4.99e-06) | (6.29e-06) | (7.65e-06) | (6.40e-06) | (7.84e-06) |
| Rainfall $(mm)^2$ | 6.30e-05** | 1.37e-05 | 2.04e-05 | 7.14e-05** | 9.27e-05*** | 0.000117** | 8.72e-08 | 6.25e-08 | 1.75e-07 | 2.28e-07* | 3.14e-07** | 1.91e-07 |
| *s.e.* | (2.24e-05) | (1.05e-05) | (1.25e-05) | (2.92e-05) | (2.88e-05) | (4.47e-05) | (9.46e-08) | (1.11e-07) | (1.10e-07) | (1.20e-07) | (1.11e-07) | (1.33e-07) |
| Temperature $(Cº)^2$ | -0.192** | -0.0255** | -0.106** | -0.244** | -0.207** | -0.293** | -0.000733** | -0.000135 | -0.000551** | -0.00150*** | -0.00104** | -0.000576** |
| *s.e.* | (0.0790) | (0.0100) | (0.0378) | (0.107) | (0.0875) | (0.131) | (0.000258) | (0.000140) | (0.000205) | (0.000481) | (0.000385) | (0.000261) |
| Hummidity $(Rainfall * Tempreature)^2$ | -8.94e-08** | -2.12e-08 | -2.87e-08 | -1.00e-07* | -1.28e-07** | -1.83e-07** | -1.49e-10 | -5.84e-11 | -2.15e-10 | -2.71e-10 | -3.14e-10* | -2.64e-10 |
| *s.e.* | (3.88e-08) | (1.94e-08) | (2.37e-08) | (5.19e-08) | (4.57e-08) | (7.33e-08) | (1.76e-10) | (1.93e-10) | (2.08e-10) | (2.20e-10) | (1.77e-10) | (2.36e-10) |
| ln(density) | 6.893* | 1.460 | 4.288* | 8.729** | 6.820 | 12.91** | 0.0347* | 0.0183* | 0.0606*** | 0.109** | 0.0819* | 0.0501*** |
| *s.e.* | (3.309) | (1.258) | (2.166) | (3.953) | (3.948) | (5.828) | (0.0195) | (0.00938) | (0.0174) | (0.0410) | (0.0401) | (0.0171) |
| Constant | -94.64** | -13.69** | -56.46*** | -119.6** | -100.6** | -150.7** | -0.268 | -0.126* | -0.444*** | -0.976** | -0.647** | -0.409*** |
| *s.e.* | (35.73) | (5.937) | (16.39) | (49.05) | (37.67) | (63.30) | (0.170) | (0.0670) | (0.127) | (0.363) | (0.292) | (0.109) |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | County | County | County | County | County | County | County | County | County | County | County | County |
| Nº obs. | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 | 77112 |
| Nº groups | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 | 459 |
| Min. obs. per group | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| Avg. obs per group | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| Max. obs per group | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| R2 overall | 0.00288 | 0.000211 | 0.00123 | 0.00276 | 0.00181 | 0.00115 | 0.00149 | 4.62e-05 | 0.000334 | 0.00165 | 0.000654 | 0.000294 |
| R2 within | 0.0346 | 0.00425 | 0.0132 | 0.0293 | 0.0279 | 0.0132 | 0.0396 | 0.00647 | 0.0197 | 0.0479 | 0.0458 | 0.0234 |
| R2 between | 0.0977 | 0.0493 | 0.0660 | 0.103 | 0.0984 | 0.0800 | 0.0163 | 0.00453 | 0.0101 | 0.0306 | 0.0253 | 0.0137 |

*** p<0.01, ** p<0.05, * p<0.1

# Figures

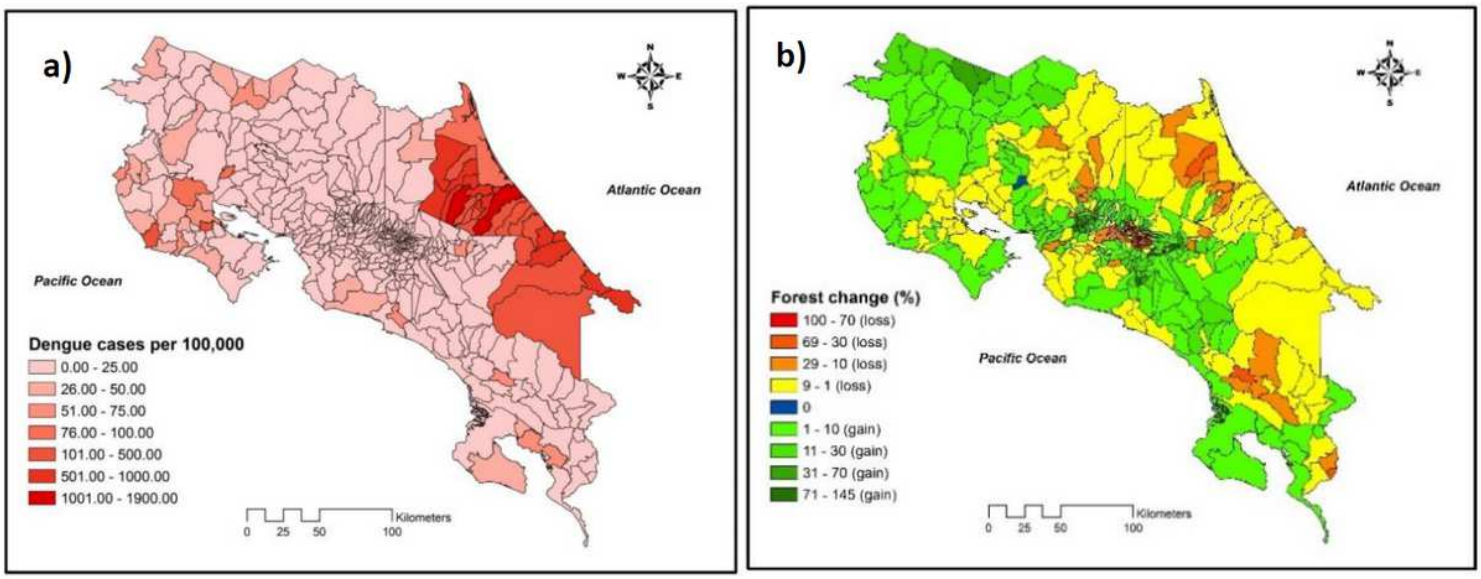


**Figure 1**

Geographical distribution of dengue incidence and forest cover change. Left panel indicates the dengue hospital admissions per 100,000 population per district in 2011. Darker colors indicates districts with higher dengue incidence. Right panel indicates forest change per district between 2000 and 2011. Red to yellow color scale indicates districts where forest diminished, while green scale color indicates districts where forest increased. Source: own elaboration based in Costa Rican Social Security System (CCSS)42 and Costa Rican Forest Financial Fund (FONAFIFO)43.

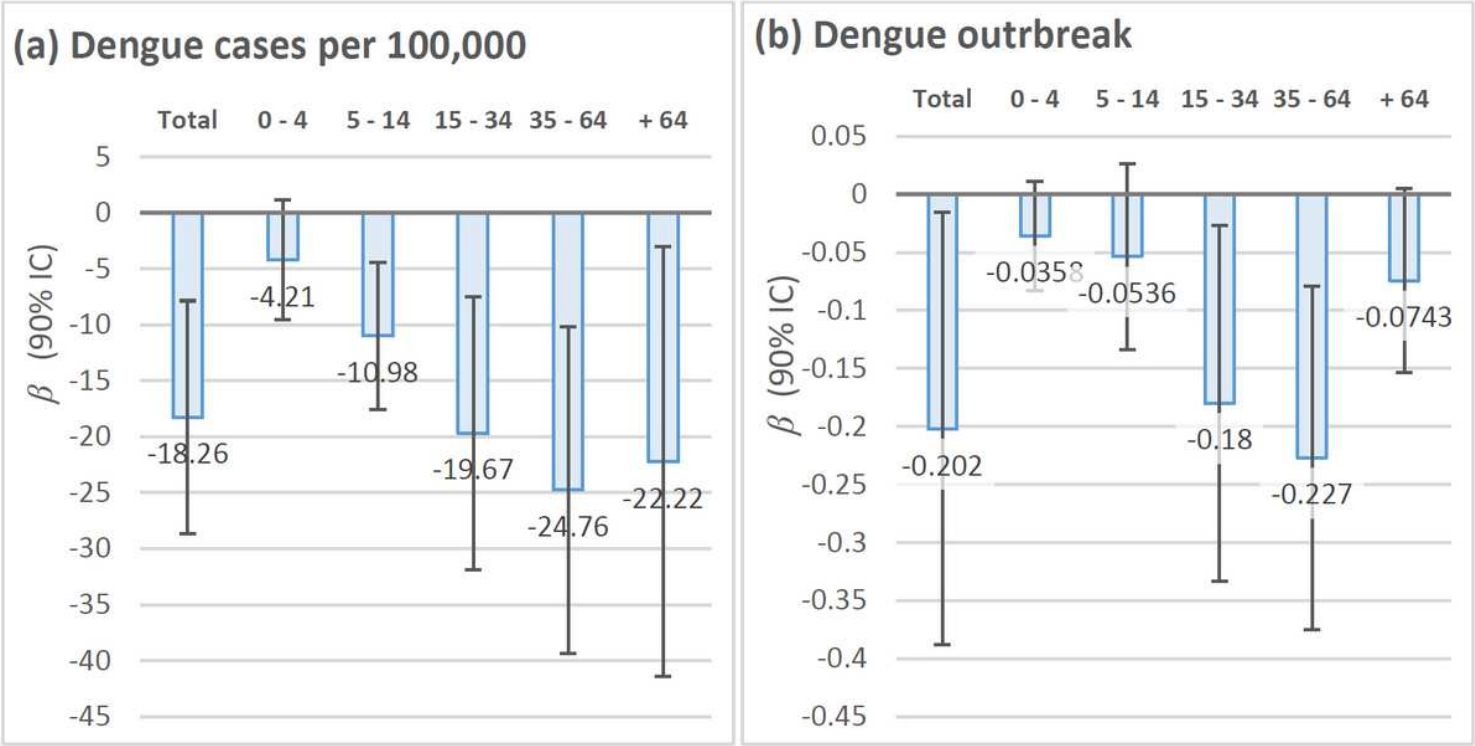

**Figure 2**

Effects of a 1% increase in forest cover on dengue incidence and outbreaks (90% confidence intervals). Estimates are from our full model (Model V), using monthly 2 year panel data from 2000 and 2011. Panel (a) is the model using dengue hospital admissions per 100,000 residents in each district, month, and year. Panel (b) is the model where the dependent variable equals 1 when there is a dengue outbreak in each district, month, and year. In each panel results are reported for the full sample, as well as for five age cohorts.

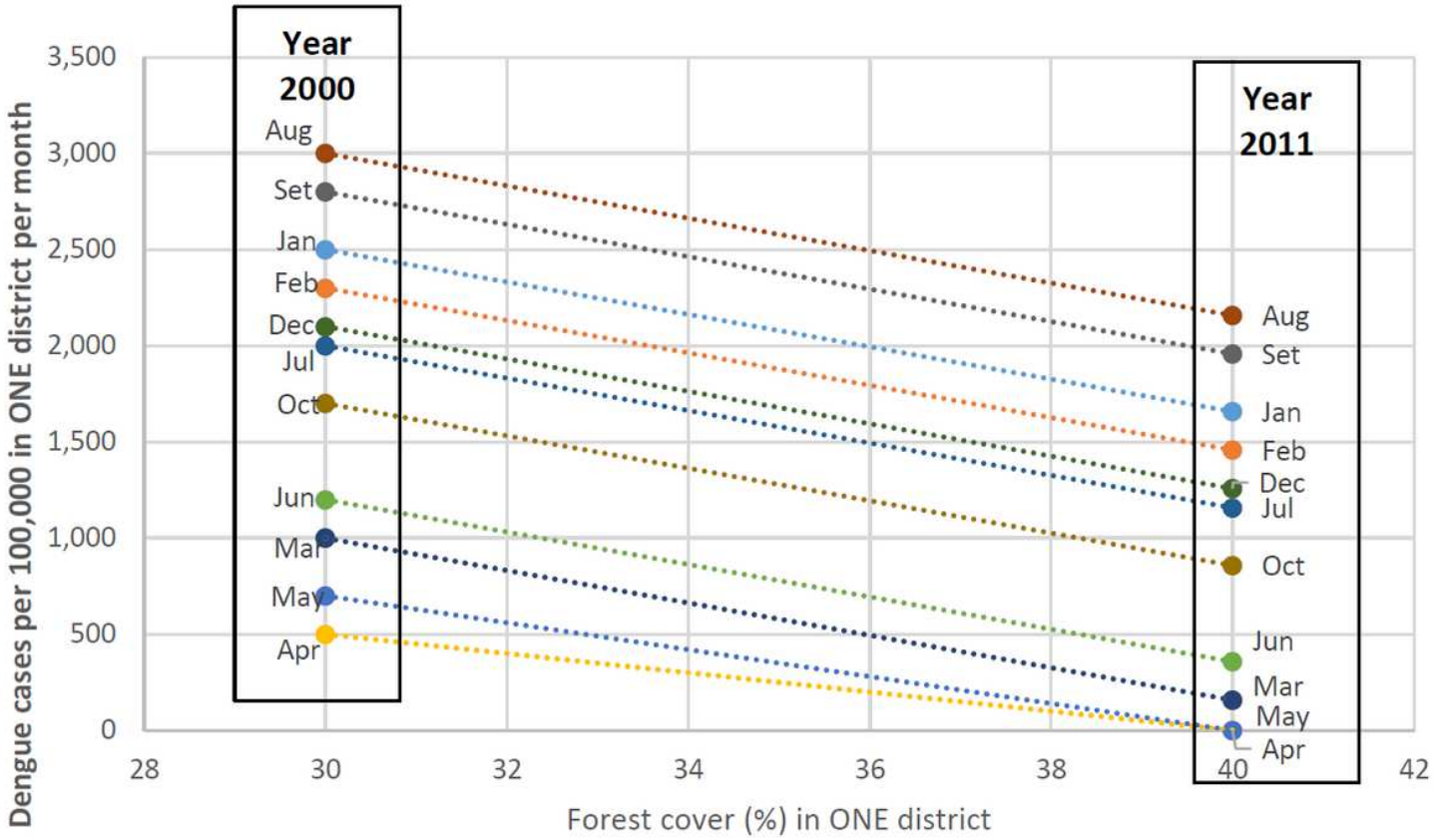


**Figure 3**

Hypothetical example of the empirical identification strategy for one district. Scatter plot shows the dengue incidence per month and forest cover for one hypothetical district in 2000 and 2011. While the number of cases can be different between months in the same year, forest cover is constant within a year.