# One Belt, Many Roads: Investigating China's Foreign Investment and Land-use Impacts in Southeast Asia

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**Abstract**
Foreign direct investment (FDI) can reshape landscapes in developing countries, but its impact remains unclear. This study examines how China's Belt and Road Initiative (BRI) FDI impacts land-cover and land-use change in Southeast Asia, a key trade partner receiving significant Chinese infrastructure investments. Focusing on areas with BRI investments from 2008 to 2018, we utilize satellite data to analyze land-use changes across Southeast Asia (Cambodia, Laos, Myanmar, Vietnam), particularly urban growth and deforestation. We find that districts that received BRI investment experienced nearly a 5% greater rate of deforestation than the regional average, with a 001% and 0.007% in tree cover associated with a 1% increase in Chinese investment. Districts receiving investments also showed greater increases in cropland and grasslands. While statistical tests indicate the immediate land-cover changes are modest, our findings suggest potential future environmental consequences in Southeast Asia, particularly with ongoing economic development.

**Keywords**
Belt and Road Initiative, Southeast Asia, land-cover change, foreign direct investment

## 1. Introduction

Southeast Asia (SEA) has experienced a surge in cross-border trade and investment, particularly with China. Bilateral trade between China and the Association of Southeast Asian Nations (ASEAN) has more than doubled over the past decade to $722 billion in 2022, accounting for one-fifth of ASEAN's global trade (Wester, 2023). Initiatives like China's Belt and Road Initiative (BRI), introduced in 2013, have led to substantial investments in infrastructure development, including roads, railways, ports, and power plants, in the ASEAN region, accounting for 36 percent of total BRI investment (Yu, 2017). At the same time, these economic investments have local land-use impacts and affect the local environments of recipient countries (Y. Wang et al., 2021). Urban population growth and agricultural product exports, for instance, are found to be associated with tropical deforestation (DeFries et al., 2010) - an example of the interacting forces driving land-use change at local, regional, and global scales (Lambin and Meyfroidt, 2011). Once built, these infrastructure projects could lead to multiple forms of carbon lock-in (Seto et al., 2016). For example, the adoption of technologies and infrastructure that perpetuate fossil fuel use make it more difficult for SEA countries to reach their climate goals; and land-use change due to urbanization could intensify urban heat island impacts within newly built cities, exposing urban residents to heat stress and stroke, as well as other health-related impacts.

Observing and evaluating urban land teleconnections - processes that link land-use and urbanization in multiple and distant locations (Seto et al., 2012) - could shed light on drivers of urban expansion and land-use change in cities in SEA, particularly amongst second-tier cities such as Batam in Indonesia that are expected to experience a 60 percent growth in urban population by 2025 (United Nations, Department of Economic and Social Affairs, Population Division, 2018). How much of this anticipated urban expansion and land-use change in these Southeast Asian countries is driven through foreign flows of investment from China or through urbanization and urban change precipitated by the BRI? And do these urban land teleconnections also include changes in non-urban areas throughout Southeast Asia?

Quantification of the relationship between these investment projects and land-use change patterns in SEA is missing from the current literature. We begin to address this deficit by pulling together multiple data sources and constructing models of investment impacts across SEA districts. Satellite remote sensing data can be used to generate high-resolution land cover classifications to proxy changes in land-use before and after investment projects. Over the span of 2008 to 2018, we employ satellite remote sensing data encompassing Cambodia, Laos, Myanmar, and Vietnam, along with three distinct sets of foreign direct investment data detailing investment totals, project inception years, project sectors, geographical coordinates, and more. This analysis allows us to explore the correlation between China's investments, notably those associated with BRI, and the evolution of urbanization and land-use dynamics across 124 districts, the principal administrative units in these nations. This paper is organized as follows. Section 2 provides a synthesis of the literature for understanding what kinds of land-use change we might expect to observe as a result of FDI. Section 3 describes the data and methods used, where Section 4 describes results, followed by a Discussion and Conclusion in Sections 5 and 6.

## 2. Patterns of land-use change as a result of foreign direct investment (FDI)

*Focus countries in SEA*

Cambodia, Laos, Myanmar and Viet Nam lag behind their neighbors in terms of their economic development, with their combined GDP accounting for just under 15 percent of ASEAN's total nominal GDP (International Monetary Fund, 2024). While their need for development remains great -- the Asian Development Bank estimates that Southeast Asia will need to spend $2.76 trillion on infrastructure through 2030 to sustain economic growth, and predicts an estimated $92 billion annual shortfall in its spending -- country priorities remain distinct (Stratfor, 2017). Due to the relative lack of economic development in Cambodia, Laos and Myanmar, the three countries have been largely dependent on Chinese aid and have provided "unconditional support" for the BRI (Yu, 2017).

In these places, BRI flows are primarily targeted at the development of transportation infrastructure (e.g., rail, motorways, and air connections). FDI specifically linked from China to these four countries in SEA range from $3.1-$8.6 billion USD dating back from the mid-2000s (Table S1). Together, they comprise the China-Indochina Peninsula Economic Corridor (CICPEC), which aims to strengthen China's connections with neighboring ASEAN states, linking it to what is already "one of the more connected transport networks among the developing regions of the world" (Derudder et al., 2018). It aims to connect southern China with major cities in Viet Nam, Laos, Cambodia, Thailand and Singapore through an extensive transportation network of rail, roads and pipelines (Yuen, 2019).

*BRI in SEA*

China is now a leading overseas financier, perhaps best characterized by its BRI (Dreher et al., 2021). China's overseas financing has primarily taken two types: outward direct investment (ODI) and development finance, which is largely funded through two large state-owned policy banks, China Development Bank (CBD) and its Export-Import (EXIM) Bank (Dollar, 2018). However, comprehending China's involvement in overseas development finance is notably complex. Challenges stem from a lack of data transparency, unclear lending criteria, and the ambiguity regarding the identity of the lenders, making it difficult to obtain essential details such as loan amounts, terms, and specific projects financed (Dollar, 2018; Lechner et al., 2020).

What's clear is that most of China's BRI lending in SEA has focused on large-scale infrastructure projects, such as the CICPEC, echoing the initiative's main goal to improve connectivity throughout the region. Beyond transportation infrastructure, the BRI investments in SEA also encompass energy projects, such as 10 Chinese-led fossil fuel power plants (Dayant & Stanhope, 2024). Additionally, there are collaborations between the Chinese government and multinational corporations aimed at setting up economic and trade cooperation zones (Yuen, 2019).

*Patterns of FDI-induced land-use change*

Previous studies that have sought to quantify changes in land-use have identified several anthropogenic drivers, including socio-economic (e.g., GDP and population), proximity to economic centers or transportation infrastructure, and land-use policies (Naikoo et al., 2022), with FDI increasingly becoming a major determinant in shaping landscape dynamics (Piabuo et al., 2023). Specifically within the BRI, scholars contend that further research and critical analysis are required to enhance our understanding of how the BRI has instigated diverse patterns of urbanization across the different geographical landscapes of recipient countries (Andujar et al., 2024).

According to a review of the literature, FDI is influencing several aspects of land dynamics in SEA, including land-use change, urban expansion, and alterations in urban land use:

**1) New urban growth along BRI transportation routes.** Improved transportation has been linked to urban expansion and sprawl, revealed through analysis of Landsat imagery combined with economic data to model rapid urban growth along transportation networks in places such as China (Wei & Ye, 2014). The ability of transportation infrastructure to build or strengthen regional interconnections can also shape urban development (Wei & Ye, 2014). Similar impacts on urban growth are anticipated along these new transportation routes.

**2) New urban growth centers due to special economic development zones.** BRI investments in SEA countries have also targeted the development of special economic development zones (SEZs) or Free Trade Zones, which provide favorable fiscal incentives for investors to establish industrial operations. At the end of 2016, Chinese businesses assisted in establishing around 56 industrial parks and trade cooperation zones in 20 countries along BRI routes, totalling around $18.5 billion USD (UNDP China et al., 2017). In China FDI has been found associated with urban expansion rates due to intensification of urban and agricultural land uses (Seto & Kaufmann, 2003), and that "fast-growth, resource-intensive and export-oriented" development strategies are reflected in changes to the physical landscape (Wei & Ye, 2014). Similar relationships and mechanisms may also be at play across BRI countries. The Laos-China high-speed railway project has helped attract 130 enterprises from nine countries into the Saysettha Development Zone co-developed by China and Laos, generating approximately 8,000 local jobs (Q. Wang, 2024), and potentially acting as a lever for additional growth and development.

**3) Changes in urban land-use types due to urban infill growth.** Urban infill growth (e.g., growth and urban land-cover change that occurs within a city) is often a primary driver of urban growth (Estoque & Murayama, 2015), in, for instance, cities in Viet Nam (Nong et al., 2018). The growing investment from FDI into SEA cities could shape and accelerate urban infill growth. FDI funds a substantial portion of residential and commercial developments in places like China (Seto and Kaufmann, 2003), where county officials also leverage land subsidies to help direct FDI to light industries. FDI can also dramatically shape urban land use. The Cambodian town of Sihanoukville, widely acknowledged as the "poster child" of Sino-Cambodian cooperation and a BRI-led Special Economic Zone (Rana & Ji, 2020), the site of Cambodia's only deep-water port and marks the starting point of a new Chinese-funded expressway to

Phnom Penh. This area has seen a 200 percent increase in tourism and investment, through projects including condos and casinos, that cater largely to tourists, rather than to locals, for whom gambling is illegal (Ellis-Peterson, 2018; Retka, 2018).

4) **Changes in forest and agriculture land cover.** National level studies have suggested that Foreign Investments have an overall negative effect on forest cover (Acheampong & Opoku, 2023; Doytch et al., 2024). Sectoral FDI analysis, suggests that the direction of such effect seems to be dependent on the sector in which the FDI is located as well as the level of development of the receiving country (Doytch et. al 2024). For example, FDI in primary sectors such as agriculture and mining have a worsening effect on forest cover particularly in lower income countries, while service industry FDI appears to have a positive effect. Interestingly FDI in the manufacturing sector seems to also have a negative effect on forest cover potentially through direct land use but also through indirect effects. In the SEA context, China's foreign investment in agriculture has also been identified as often focused on commercial crops with ties to deforestation (Grimsditch, 2017).

## 3. Data and Methods

This section describes the empirical context for our study and our approach to measurement of Chinese investment and our various outcome measures. We use satellite remote sensing data from 2008 to 2018, covering the four SEA countries of Cambodia, Laos, Myanmar, and Viet Nam, combined with three sources of foreign direct investment (FDI) data that include the total amount of the investment, project signed year, project sector, and geological location. We examined the relationship between China's FDI, signified but not limited to the BRI, and urbanization and land-use patterns within 124 districts (the primary administrative divisions), which cover major urban areas within the four SEA countries. Table S2 provides a full list of variable names, sources, and definitions.

*Study Area and Period*

Administrative boundaries for each district in our study area were obtained from geoBoundaries, an open database of political administrative boundaries (Runfola et al., 2020). We examined investment impacts from 2008 to 2018, which timeframe allowed us to investigate the lagging effects of investment on land cover/land use changes and to establish a comprehensive understanding of urban expansion in SEA countries before they began to receive investment through the BRI.

*Demographic data overview*

For population, we used the district geometries to extract Gridded Population of the World version 4 (CIESIN, 2018), which provided global population and population density at 1 km spatial resolution for every 5 years from 2000 to 2020. For GDP per capita, we utilized gridded GDP global datasets from (Kummu et al., 2018), which is standardized at 5 arc-min resolution from 1990 - 2015. To account for GDP per capita after 2016, we incorporated country level GDP per capita from the Human Development Index published by the World Bank to calculate the annual rate of change of GDP growth for 2016 to 2018 (World Bank, 2023). We applied the rate of change to Kummu et al (2018) to extrapolate GDP per capita for 2016 to 2018 at district level.

*Land cover data overview*

We derived land cover metrics from the MODIS Terra Surface Reflectance Daily Global (MOD09GA.061) and Global Artificial Impervious Area (GAIA). The MODIS data provides daily global surface spectral reflectance at a 500-meter resolution and used to calculate two satellite indices, the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI), for all districts from 2008 to 2018. The NDVI serves as an indicator of vegetation coverage, ranging from -1 to 1, with higher values indicating areas with a higher volume of vegetation, such as forests. On the other hand, the NDBI is an index that measures built-up areas or impervious surfaces, also ranging from -1 to 1. When the NDBI is larger than 0, it signifies the presence of impervious surfaces in the area of interest. As the NDBI value approaches 1, it indicates a higher proportion of impervious surfaces or built-up areas.

The GAIA data offers annual change information on global impervious surface area at a 30m resolution, spanning from 1985 to 2018. We used district boundaries to extract impervious surface data and created four variables for 2008 to 2018 at district level: impervious area at year-end, total yearly impervious area change, percentage of impervious surface area, and percentage of changed area.

We also incorporated categorical Land Cover data derived from the MODIS Land Cover 6.1 product (MCD12Q1.061) which provides global land cover types at yearly intervals at a 500 meter pixel resolution with multiple land cover types available and obtained using supervised learning and additional post-processing that incorporate prior knowledge and ancillary information to further refine specific classes (Friedl & Sulla-Menashe, 2022). We used the Annual International Geosphere-Biosphere Programme (IGBP) classification, which provides 17 land cover types. We merged some classes from these original 17 classes (i.e, Evergreen Needleleaf Forests, Evergreen Broadleaf Forests, Deciduous Needleleaf Forests, Deciduous Broadleaf Forests and Mixed Forests were combined as a singular "Forest" category) to achieve a total of 10 land cover classes. We produced four variables for each land cover type, year, and district in our database: the total area ($m^2$) at the end of the year (EOY), the change in area in $m^2$ throughout year, the percentage value of total area in relation to the total area of district, and the percentage value of changed area in relation to the total area of district. Ultimately our model used the percentage value of total area in relation to the total area of the district as the main variable for analysis.

In addition to the Land Cover data, for data exploration and case studies we used other remote sensing products, such as the Hansen Global Forest Change dataset from (Hansen et al., 2013), which provides information on global forest extent and change with a 30-meter resolution and available from 2000 to 2023; and the ESRI Annual Land Use Land Cover from Impact Observatory with a 10-meter resolution and available from 2017 to 2023.

*Investment data overview*

The foreign direct investment data in this study come from the Geolocated dataset of Chinese overseas development finance (BU data) launched by the Boston University Global Development Policy Center. This dataset harmonizes multiple existing studies on China's overseas development finance from the China Development Bank (CDB) and the Export-Import Bank of China (ExImBank) (Ray et al., 2021). This data includes the project details, including the borrowing entity, lending agency, year of the project being signed, total amount of investment, sector of the project, and the geological footprint of the project spanning from year 2008 to 2019.

We also evaluated AidData's Global Chinese Development Finance Dataset, which offers detailed information of China's overseas investment activities from 2000 to 2017. In contrast to the BU data, Aid data does not provide spatial data for all of the projects, which makes determining whether any impact land-use challenging. While BU data specifically focuses on CDB and ExlmBank, Aid data extends its coverage to encompass a wider scope of Chinese financial institutions, which may include state-owned commercial banks that function as standard commercial entities (Custer et al., 2023). We conducted sensitivity checks utilizing the AID data and found complementarity in the results compared to using the BU data (see Supplementary Information).

To control for DFI from other countries into SEA, we utilized data on the total amount of DFI from 2000 to 2022 from the World Investment Report or DFI published annually by UNCTAD, serves as the authoritative source of information on global foreign direct investment trends at the regional and country levels (UNCTAD, 2022).

*Spatializing investment data*

An essential step in constructing our model to examine the relationship between foreign investment and land cover/land use change is to determine the geographic locations of these investments and the timing of their introduction to local areas. To merge the investment data into the data matrix, we first applied a spatial join to the BRI projects that possess a valid geometry feature, aligning them with the administrative divisions. Then, for each project, we use the year when the project was signed to join the population information for all administrative divisions that overlapped with the project. Finally, to allocate the investment of the project among the intersecting administrative divisions, a population-weighted method was applied to each project. The result produces a panel dataset that provides information on FDI, socioeconomic, and spatial data for each district in our SEA countries.

**Regression Models**

Explanatory models examine the changes in land cover that result from Chinese investment in the five countries contained in our sample. Since our data consist of a panel of city-year observations, we can exploit temporal variation within those cities. The ten-year panel duration also allows us to observe and adjust for trends in our variables over time. As with any non-experimental study, our research design faces the challenge of endogeneity due to unobserved common causes of both the dependent and independent variables. In this case, we are concerned with those unobservable factors that may jointly drive both land-use change and Chinese investment across the sample. For instance, at the district level, local policies and economic shifts may lead Southeast Asian cities to develop vegetated areas themselves. These policy and economic changes may also signal to Chinese investors to invest in their own development in the same district. Isolating the impacts of Chinese investment in SEA districts, therefore, requires removal of confounding influences that drive both SEA district development and the Chinese decision to invest. Our primary regression approach addresses this challenge in three main ways.

Equation 1 below provides our basic model specification. We estimate the impact of Chinese investment, captured by $b_1$. First, we exploit panel variation to include city- and year-level fixed effects as represented by $\alpha_i$ and $\delta_t$, respectively. Second, we adjust our primary estimates for previous years' variation in land-use change. This dynamic panel model structure provides a more conservative estimate of $\beta_1$than what traditional two-way fixed effects specifications can provide. To see why, consider an example of a city that attracts investment in time-period 2 because of visible economic development and resulting land-use change in time-period 1. If outside investors base their investment decisions on prior development trends in the recipient city, then a form of reverse causation can occur, and investment will be endogenous to land cover change. In this way, the earlier period's development is part of the causal explanation of both future development and foreign investment. $\beta_2$ therefore captures the influence of previous changes in vegetation and the built environment and disentangles those influences from the relationship between investment and development.

[Eq. 1]

$$Y_{it} = \alpha_i + \delta_t + \beta_1(X_{it}) + \beta_2(\boldsymbol{Y_{it-1}}) + \beta_3(Z_{it}) + e_{it}$$

$Zit$ is a vector of time-varying controls, including GDP and FDI from countries other than China. These control variables make the model robust to common shocks to both Chinese investment and land cover change. This final addition allows us to remove any additional bias in our estimates that may derive from local economic trends that might signal Chinese investment. $X_{it}$ is calculated as an annual change in the cumulative amount of investment in a city over the study period. To account for the time needed for investment to produce observable changes in land use, we also lag the independent variable such that $\beta_1$ gives the effect of a marginal increase in the prior year's total cumulative investment from Chinese banks.[1]

## 4. Results

*Overall descriptive results*

To analyze the overall land cover changes in Southeast Asia (SEA), we examined data over a 10-year period from 2008 to 2018, encompassing five years before and after 2013, widely regarded as the inception of the Belt and Road Initiative. Table 1 presents the percentage change in major land cover types from 2008 to 2018 based on satellite remote sensing-derived data in each country. We observed deforestation in most countries analyzed; however, each country showed distinct patterns of land cover change. In Cambodia, forest area decreased by 11.01% over the 10-year period, transitioning to other land cover types such as grasslands (6.24%) and savannas (2.58%). These changes, characterized by sparse tree coverage and prevalent grasses, are often the consequence of deforestation for agricultural expansion (Ratnam et al., 2011). The area of cropland and small-scale cropland mixed with natural vegetation increased by 2.24%, indicating that Cambodia experienced the most significant agricultural development compared to the other three SEA countries. Similarly, Laos lost 7.33% of its forest area, transitioning to savannas (4.59%) and grasslands (2.31%). However, no other major changes in land cover type were observed in Laos during this 10-year period.

In both Myanmar and Vietnam, land cover changes were minor during this period, with all seven major land cover types showing less than 1% change. Notably, Vietnam was the only country to show an

[1] We explore models with 2- and 3-year lags in the independent variable, but focus here on the 1-year lag in the interest of space and because the results are consistent across the three different lag options.

increase in forest area (0.64%) and a decrease in cropland and small-scale cropland mixed with natural vegetation (0.71%). Additionally, urban areas in Vietnam increased by 0.16%, which corresponds to 52.38 square kilometers, making it the fastest urbanizing country among the four SEA countries. We note that when comparing changes in land cover, we did not find that the percentage change between districts that received investment and those that did not (with the exception of Cambodia, since every district received investment) were statistically significant (see Table S3).

*District-level land cover changes*

Examining land cover change at the district level, we observe similar overall patterns, but noticeable differences in districts that received investment. Table 2 shows that overall deforestation occurred in most of the SEA area, with districts that received investments experiencing a higher loss of forest cover at 4.82%. These districts receiving investment also saw greater increases in crop and vegetation areas (0.35%), as well as grassland growth (2.47%), compared to the SEA countries evaluated as a whole. However, while the overall districts experienced an 0.28% increase in urban and built-up areas, the districts with BRI investment had only 0.17% growth in these areas. A t-test between the SEA districts with and without Chinese investments identified a statistically significant ($p$-value $< 0.05$) difference in the means of Forest, Grasslands, and Crops with vegetation land cover types, which suggest a relation between this type of land cover and the presence of BRI-related investments.

In Laos, districts that received investment experienced slightly more crop and vegetation area growth by 0.11% compared to the whole country. In Myanmar, districts receiving investment experienced less deforestation compared to the national average. Additionally, these districts had a smaller increase in savannas compared to the rest of the country, but a greater increase in cropland and small-scale cropland mixed with natural vegetation. Moreover, investment districts in Myanmar showed a larger decrease in grasslands compared to the national average. In Vietnam, districts that received investment showed 1.16% more growth in Savannas and 0.36% of Grasslands, as well as a greater decrease in cropland and small-scale cropland mixed with natural vegetation (1.39%) compared to the national average. However, these districts experienced less growth in urban built-up areas by 0.05%.

**Elasticities of Land-Cover responses to Chinese investment**

While the correlative patterns evident in our geospatial analysis indicate substantial land use change, the regressions offer a more conservative picture. These models remove the covariation in financing and land use that is due to confounding factors as well as the signal to invest spurred by earlier land use change. Even with these conservative assumptions in place, several key variable relationships persist. Overall, regression results vary across our suite of land cover outcomes variables considering that the dynamic panel model structure offers a very conservative estimate of these effects since the estimation procedure removes any impacts of investment that are correlated with previous years of land-use change.

To ease interpretation and improve functional form, we convert all variables in our models using the inverse hyperbolic sine (arcsinh) transformation. The resulting coefficient estimates are interpreted as elasticities, or percent changes in the outcome variable that result from a one percent increase in Chinese investment. We present the results of our individual models on 25 distinct land use change variables across Tables S7-S9 and a summary in Figure 2.

Overall, the results show persistent and meaningful, albeit small decreases in vegetation in areas that receive Chinese investment, consistent with potential effects of FDI identified in the literature. We find statistically significant elasticity estimates that indicate that a one percent increase in Chinese investment results in a 0.0012% decrease in medium vegetated area as measured by NDVI and a 0.0011% decrease in tree canopy measures. For our specific land classification indicators measures, we see a 0.007% decrease in tree land cover class (i.e., Dense Vegetation) and a 0.013% increase in Rangeland (i.e., Meadows without treecover) associated with a one percent increase in Chinese investment.

Regarding the effect of Chinese investment on urban area or impervious surfaces, the results of the dynamic panel vary depending on the source, while we observe that a one percent increase in Chinese investment results in a 0.015% increase in non-vegetated area as measured by NDVI, we also see a slight decrease or no meaningful changes when using other land cover classifications products such as the MODIS and ESRI spatial products. Considering the relatively small footprint of urban areas in relation to the district size - the average district contains between 1 to 10% urban areas depending on the land cover product - the relation between both variables might not be properly identified through our model specification. In this sense, while we cannot assert an effect of Chinese investment in urban land cover at the district level from our model alone, we can explore some significant projects that received Chinese investment and gain a deeper understanding of their land change patterns at the hyperlocal level.

*Illustrative case studies*

To illustrate the various types of land-cover change in BRI-investment districts, we present three case studies: 1) the Laos-China RailwayProject, Laos; 2) Pursat-Phnom Korvanh-Veaveng-Thmorda Section of National Road No. 55, Cambodia; and 3) Sihanoukville Special Economic Zone, Cambodia. Further exploration of these case studies, as well as others, can be explored through a web portal we built to support this paper (see Supplementary Information).

1) Laos-China Railway Project

The Laos-China Railway Project is a transnational railway between China and Laos under China's BRI, stretching 924 km in length, with 507 km in China and 417 km in Laos (Xiao et al., 2024). It was initiated in 2016 and completed in 2021. The total cost of the project was $5.9 billion USD and was intended to connect Kunming in Southern China's Yunnan province, which borders Laos, and several SEA countries (AID Data, n.d.-a). It was financed with a 60:40 debt-to-equity ratio, secured through China's Eximbank, and designed for speeds up to 160 km/hour to drastically reduce travel times and enhance trade links across the region (AID Data, n.d.-a).

Examining land-cover change within a 6-km buffer of the Laos-China railway in Laos from 2016 to 2020, we observe a decrease in forest cover 3.91%, with the most notable annual loss occurring between 2018 and 2019 (Figures S1-S2, Table S4). In contrast, grasslands increased by 2.93%, showing substantial growth in the same period. Savannas experienced a modest decline of 0.91%, despite a temporary increase from 2018-19. Croplands and small-scale cropland mixed with natural vegetation saw an increase of 1.83%, particularly in 2019-20. Urban and barren areas remained largely stable, with only minor fluctuations, and wetlands were almost unchanged with a slight increase of 0.02% (Table S4).

These results are largely consistent with Xiao et al. (2024)'s analysis, which saw a 3% increase in deforestation due to the expansion of cropland (8%) and constructed land (38%) in a 10-km buffer along the railway in both China and Laos from 2017.

2) Pursat-Phnom Korvanh-Veaveng-Thmorda Section of National Road No. 55, Cambodia

The National Road No. 55 expansion project spans 182 km from Pursat to the Thmor Da checkpoint on the border with Thailand and was financed as a BRI project with a $129.3 million buyer's credit agreement from China's Eximbank (AID Data, n.d.-b; Xinhua News Agency, 2020). Its aim was to facilitate easier travel from Koh Kong, in Cambodia's west coast, to Phnom Penh, the country's capital. It was completed in March 2020.

Figures S3 and S4 highlight significant land-cover changes in the 6-km buffer area around the road expansion from 2015-2020. Forest areas experienced a notable decline of 7.66%, particularly between 2016 and 2017, reflecting a major reduction in tree cover (Table S5). In contrast, grasslands expanded substantially by 10.74%, especially from 2018 to 2019, indicating a significant shift towards open land use. This transformation suggests increased land clearing or changes in agricultural practices. Savanna regions also decreased by 3.60%, most markedly in 2019-20, signaling a reduction in this type of vegetation. While croplands and areas with mixed natural vegetation saw a slight overall increase of 0.47%, urban built-up areas and barren lands remained relatively stable, showing minimal change.

3) Sihanoukville Special Economic Zone (SSEZ)

The Sihanoukville Special Economic Zone (SSEZ) project was approved in 2006 and supported by a $320 million loan from China's Eximbank in 2010 (AID Data, n.d.-c). It spans 11.13 km², strategically located near key transport hubs and was officially inaugurated on June 13, 2012. By March 2020, it had established 174 factories, focusing initially on textiles and apparel (Inclusive Development International, n.d.). In 2019 it started building a 100 MW coal power plant financed by ICBC Phnom Penh, a local branch of China's ICBC (Inclusive Development International, n.d.).

Compared to the other illustrative case studies, the Sihanoukville Special Economic Zone spans a relatively smaller area. Therefore, we examined it using a higher spatial resolution land cover product from ESRI, although this land cover data has only been available since 2017. Figures S5 and S6 illustrate patterns of land-cover change from 2017 to 2022 in the 6-km buffered area around SSEZ, particularly in the loss of tree cover and growth in urban, built-up area (Table S6). Among these areas, one of the most notable developments is the new residential settlement located to the northwest of the SSEZ, which was classified as forest before 2017. We also observed a spatial shift in crop areas. As shown in Figure S4, the cropland shifted from a more aggregated area southeast of the SSEZ in 2017 to a more sparse area surrounding the SSEZ and the No. 4 National Road to the city in 2022.

## 5. Discussion

Studies have shown that economic globalization has local land-use impacts. Growth in agricultural product exports, for instance, is associated with tropical deforestation (DeFries et al., 2010), an example of the interacting forces driving land-use change at local, regional, and global scales (Lambin &

Meyfroidt, 2011). National and global market forces are also changing smallholder agriculture in SEA, as increasing population density contributes to agricultural intensification (Boserup, 1965). Major overseas investment projects like China’s Belt and Road Initiative BRI have injected billions of dollars of foreign direct investment into SEA countries, with large, yet unknown, impacts on urban expansion and other land-use changes in the region. To shed light on the latter, this study for the first time has quantified, to the authors’ knowledge, the land-use impacts of foreign direct investment in SEA.

We observed several consistent patterns in land-cover change in areas that received BRI investment. Districts receiving BRI investment displayed a significant increase in deforestation compared to the regional average, with nearly a 5% higher rate. This deforestation trend is further supported by the observed land-cover changes, particularly a decline in tree cover. Regression analysis revealed reductions between 0.001% and 0.007% in tree cover, depending on the specific land-cover indicator, associated with a 1% increase in Chinese investment. Examining land cover change at the district level, we observe similar overall patterns, but noticeable differences in districts that received investment. These districts receiving investment also saw greater increases in crop and vegetation areas (0.35%), as well as grassland growth (2.47%), compared to the SEA countries evaluated as a whole. However, while the overall districts experienced an 0.28% increase in urban and built-up areas, the districts with BRI investment had only 0.17% growth in these areas. A t-test between the SEA districts with and without Chinese investments identified a statistically significant ($p$-value $< 0.05$) difference in the means of Forest, Grasslands, and Crops with vegetation land cover types, which suggest a relation between this type of land cover and the presence of BRI-related investments.

This finding is consistent with prior studies that have found SEA’s intact forests and protected areas have been degraded and converted to non-forest land cover and land-use types, including agricultural uses (Estoque & Murayama, 2015; Stibig et al., 2014). (Gibbs et al., 2010) found that a little more than half (55%) of newly converted agricultural land originated from intact forests in the 1980s and 1990s. In SEA, China’s foreign investment in agriculture is frequently linked to commercial cropping practices that are associated with deforestation, as noted by Grimsditch (2012). This finding was further supported in our result in positive increases in flooded vegetated land cover, (0.0098%) in association to BRI investment, as well as the district level difference in mean land cover for small scale cultivation according to the MODIS land cover, although more refined analyses will help to identify the mechanisms in place. BRI-backed transportation projects can also partially explain the loss of forests and trees, aside from increased agricultural expansion. Studies focusing on transportation projects and corridors have highlighted that enhanced connectivity between China and countries like Myanmar, Laos, and Cambodia, facilitated by BRI infrastructure investments, has turned these nations into deforestation hotspots through government-approved land concessions (Lechner et al., 2020).

While overall we expected to see a greater impact of Chinese BRI investment and urban and built-up area expansion, our model was unable to capture a statistically significant effect on urban land cover. This result could be explained by several factors. First, since urban infrastructure (e.g., buildings, roads, etc.,) take time to construct and develop, it is probable that we only captured the early stages of urban development and more significant land-cover changes would be anticipated in the near to medium-term future. Over the past few decades, global built-up area has dramatically increased to 797,076 km$^2$ 1.5 times between 1990, and 2018 (Gong et al., 2020), and it is forecasted that urban land cover will expand by 1.2 million km² by 2030, nearly tripling the size since 2000 (Seto et al, 2014). The pattern of forested land being initially converted to agricultural or croplands aligns with global trends, where agricultural land frequently transitions to urban uses, a shift commonly seen during periods of economic development and population growth (Azadi et al., 2011; Phuc et al., 2014). In Viet Nam, the World Bank estimated that nearly 1 million hectares of farmland was converted to non-agricultural uses between 2001 and 2010 (Phuc et al., 2014). It's also probable that more urban land-cover change, as a result of urban infill development, will occur, as we observed in the case of the Sihanoukville Special Economic Zone, with a more than 6% increase in urban built area.

Regression modeling can help tease apart the land use change implications of Chinese investment projects. Previous studies in the literature (Chandran & Tang, 2013; Piabuo et al., 2023) have not established a clear relationship between FDI and environmental impact in ASEAN countries. However, our study reveals distinct land-cover changes. Specifically, our model isolates landscape changes attributable to Chinese investment, as opposed to temporal and economic trends; however, not all land cover outcomes are sensitive to Chinese investment. We found broad composite indices such as greenness (NDVI) and built-up area (NDBI) do move in predictable ways in response to Chinese financing, but changes in specific land cover types are mostly insignificant after controlling for relevant confounders, with tree canopy, rangeland and flooded vegetation the most responsive to investment shocks. More data are likely necessary to reveal the true impacts of investment on certain types of land cover, since currently available data are just sufficient to construct a panel that affords enough statistical power to capture all relevant relationships. Expansion of these data will allow for more nuanced and stratified models that distinguish more carefully across different types of investment projects.

The implications of land-cover and land-use changes are critical to understand due to their potential to exacerbate climate change and increase carbon emissions, as described by the concept of urban teleconnections (Seto et al., 2011), which argues that the continued growth of urban areas could continue to drive further changes in land-cover, such as deforestation or agricultural expansion. Understanding the negative environmental and climate impacts of the China-SEA relationship only sheds light on part of a more complex geopolitical story. While President Xi Jinping's 2021 declaration of halting overseas financing for coal and other fossil fuel assets abroad marked a significant shift towards renewable investments like hydropower, solar, wind, and bioenergy (Han & Wei, 2022), it overlooks a broader environmental dilemma. Despite this shift, our study shows that Chinese investments drive substantial changes in land use across SEA through infrastructure and industrial projects along major trade corridors. These investments are contributing to an increase in impervious surfaces and the built-up environment, as illustrated in the Sihanoukville Special Economic Zone, which, in turn, exacerbate emissions and have various negative climate impacts. This scenario reveals a complex geopolitical story where actions to reduce direct carbon emissions from energy projects may be offset by indirect effects on land use and associated emissions.

## 6. Conclusion

This study has explored the impact of China's Belt and Road Initiative (BRI) on land cover and land-use change in Southeast Asia, showing how foreign direct investment, especially from China, affects environmental and urban landscapes. The connection between economic development driven by these investments and land-cover changes demonstrates the complex outcomes of globalization on local and regional environments. Since SEA is expected to continue to experience rapid development in the coming decades, understanding which changes in land cover are directly attributable to foreign investments and how these transformations could drive further environmental and climate impacts is essential for devising effective management and development strategies for low or zero-carbon growth (Seto et al, 2021).

## 7. Disclosure Statement

The authors declare no competing interests.

## 8. Data Availability Statement

Data compiled and developed for this paper has been deposited at:

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# Supplementary Information

Table 1. Land cover and impervious surface total area change percent by country from 2008 to 2018

| **Land Cover** | **Cambodia** | **Laos** | **Myanmar** | **Vietnam** |
|---|---|---|---|---|
| Impervious surface | 0.08 | 0.06 | 0.03 | 0.6 |
| Forest | -11.01 | -7.33 | -0.81 | 0.64 |
| Savannas | 2.58 | 4.59 | 0.6 | 0.13 |
| Crops_Vegeation | 2.24 | 0.3 | 0.56 | -0.71 |
| Grasslands | 6.24 | 2.31 | -0.43 | -0.27 |
| Permanent_Wetlands | -0.08 | 0.1 | 0.09 | 0.32 |
| Urban_and_Built_up_Lands | 0.03 | 0.01 | 0.01 | 0.16 |
| Barren | 0 | -0.04 | 0 | -0.28 |

*NDVI (greenness index) and NDBI (built index) variables had less than 0.01 change at the country level and are not included in this table.*

Table 2. Land cover change percentage of districts receiving investment compared to those without investment from 2008 to 2018.

| **Country (districts w. Investment / total districts)** | **Investment** | **Forest** | **Savannas** | **Crops_Vegeation** | **Grasslands** | **Permanent_Wetlands** | **Urban_and_Built_up_Lands** | **Barren** |
|---|---|---|---|---|---|---|---|---|
| All (51/124) | All | -0.95(±5.22) | 1.4(±6.05) | -0.66(±4.19) | -0.01(±4.11) | 0.13(±0.87) | 0.28(±0.96) | -0.18(±0.78) |
| | W/I | -4.82(±7.27) | 1.91(±6.58) | 0.35(±3.72) | 2.47(±5.49) | 0.03(±0.73) | 0.17(±0.77) | -0.08(±0.28) |
| | W/O I | 0.44(±3.32) | 1.22(±5.87) | -1.02(±4.3) | -0.9(±3.05) | 0.16(±0.92) | 0.32(±1.02) | -0.22(±0.89) |
| Cambodia (25/25) | All | -7.09(±8.13) | 0.66(±7.89) | 1.7(±4.31) | 4.71(±7.04) | -0.17(±0.77) | 0.23(±1.09) | -0.01(±0.04) |
| | W/I | -7.09(±8.13) | 0.66(±7.89) | 1.7(±4.31) | 4.71(±7.04) | -0.17(±0.77) | 0.23(±1.09) | -0.01(±0.04) |
| | W/O I | NA | NA | NA | NA | NA | NA | NA |
| Laos (13/18) | All | -7.05(±2.85) | 4.42(±3.89) | 0.38(±0.85) | 2.09(±2.49) | 0.11(±0.12) | 0.02(±0.09) | -0.03(±0.06) |
| | W/I | -6.72(±3.31) | 4.71(±3.92) | 0.49(±0.99) | 1.4(±1.74) | 0.11(±0.13) | 0.03(±0.1) | -0.03(±0.05) |
| | W/O I | -7.9(±0.64) | 3.67(±4.16) | 0.1(±0.19) | 3.88(±3.42) | 0.11(±0.1) | 0(±0) | -0.05(±0.07) |
| Myanmar (4/18) | All | -0.59(±2.37) | 0.84(±2.76) | 0.21(±1.07) | -0.59(±1.07) | 0.14(±0.26) | 0.02(±0.05) | -0.03(±0.11) |
| | W/I | -0.21(±2.06) | 0.2(±1.96) | 0.93(±0.68) | -0.99(±1.45) | 0.13(±0.21) | 0.01(±0.02) | -0.05(±0.17) |
| | W/O I | -0.7(±2.51) | 1.02(±2.98) | 0(±1.08) | -0.47(±0.97) | 0.15(±0.28) | 0.02(±0.05) | -0.03(±0.1) |
| Vietnam (9/63) | All | 0.89(±4.61) | 0.49(±5.51) | -1.93(±4.12) | 0.17(±2.35) | 0.44(±1.33) | 0.34(±0.69) | -0.41(±1.27) |
| | W/I | 0.86(±7.09) | 1.65(±7.07) | -3.32(±2.92) | 0.53(±2.43) | 0.41(±1.14) | 0.29(±0.36) | -0.38(±0.61) |
| | W/O I | 0.9(±4.15) | 0.3(±5.26) | -1.7(±4.26) | 0.11(±2.36) | 0.45(±1.37) | 0.35(±0.73) | -0.42(±1.35) |

Note: Every district in Cambodia received BRI investment.

Figure 1. Comparison of investment in millions USD by district in the four SEA focus countries and percentage of urban change from 2008-2018.

Figure 2. Elasticity estimates for dynamic panel regression models

**One Belt, Many Roads: Investigating China's Foreign Investment and Land-use Impacts in Southeast Asia**
**Supplementary Information**

Data and illustrative case studies can be accessed on our portal: [deleted for anonymous/blind review]

| Countries | Total Quantity of Chinese investments (in Million USD) and number of projects | Total Quantity of BRI related Chinese investments (in Million USD) and number of projects | GDP per capita (current 2022 USD) |
|---|---|---|---|
| Laos | $13,400 (159) | $5,463 (19) | $2,054.40 |
| Viet Nam | $14,191 (64) | $8,692 (13) | $1,149.20 |
| Myanmar | $6,578 (158) | $3,105 (5) | $1,149.2 |
| Cambodia | $8,767 (202) | $4,992 (30) | $1,759.60 |

Table S1. FDI flows from China into SEA countries of interest (Cambodia, Laos, Myanmar and Viet Nam) 2008- 2018. Note: investments are not solely due to BRI. Data source: (AidData's Global Chinese Development Finance Dataset, 2021; Geolocated dataset of Chinese overseas development finance, 2021; The World Bank, 2024 (GDP per capita)). The number of projects may appear higher than the actual count due to double-counting multiple phases of the same project.

Table S2: Description of the variables evaluated in the study for 2008-2018.

| Data Source | Variable Name | Definition |
|---|---|---|
| MODIS Terra Surface Reflectance Daily Global 500m | NDVI | Yearly averaged NDVI for the district |
| | NDBI | Yearly averaged NDBI for the district |
| | NDVI_-1_0.1_pct | Percent of area with NDVI value between value -1~0.1 (non-vegetated area) |
| | NDVI_0.1_0.5_pct | Percent of area with NDVI value between value 0.1~0.5 (low to medium vegetated area) |

| | | |
|---|---|---|
| | NDVI_0.5_1_pct | Percent of area with NDVI value between 0.5~1 (highly vegetated area) |
| | NDBI_-1_0.1_pct | Percent of area with NDBI value between -1~0.1 (non-built-up area) |
| | NDBI_0.1_1_pct | Percent of area with NDBI value between 0.1~1 (-built-up area) |
| Land Cover:<br>MODIS Land Cover Type Yearly Global 500m - Annual International Geosphere-Biosphere Programme (IGBP) classification (2008-2018)<br><br>ESRI 10m Annual Land Use Land Cover (2017-2022) | [land cover class]_eoy | The total area at the end of the year for each land cover type in each district. Unit in $m^2$. |
| | [land cover class]_change | The change in area throughout the year for each land cover type in each district. Unit in $m^2$. |
| | [land cover class]_eoy_prop | Percentage of area at the end of the year for each land cover type in each district. |
| | [land cover class]_change_prop | Percentage change in area throughout the year for each land cover type in each district |
| Global Artificial Impervious Area (GAIA) | imp_area_eoy | The total area of impervious surface at the end of the year in each district. Unit in $m^2$. |
| | imp_area_change | The change in area of impervious surface throughout the year in each district. Unit in $m^2$. |
| | imp_area_eoy_prop | Percentage of area of impervious surface at the end of the yearin each district. |
| | imp_area_change_prop | Percentage change in area of impervious surface throughout the year in each district |
| | avg_rad | Average DNB radiance in each district |

| | | |
|---|---|---|
| VIIRS Nighttime Day/Night Annual Band Composites V2.1 | avg_rad_change | Change in Average DNB radiance in each district |
| Hansen Global Forest Change v1.11 (2000-2023) | tc_area_eoy | The total area of tree canopy at the end of the year in each district. Unit in $m^2$. |
| | tc_area_change | The change in area of tree canopy throughout the year in each district. Unit in $m^2$. |
| | tc_area_eoy_prop | Percentage of area of tree canopy at the end of the yearin each district. |
| | tc_area_change_prop | Percentage change in area of tree canopy throughout the year in each district |
| Gridded Population of the World (GPW), v4. | Interpolated_population | Linear interpolated total of population of the districts from the original data. |
| Gridded global datasets for gross domestic product and Human Development Index over 1990–2015; World Bank | Interpolated_gdp_pc | The GDP per capita 2008-2015 is extracted from the Kummu data by district geometry. 2016-2018 data is extrapolated with the country level GDP per capita data from World Bank. The unit of this data is in US $/per capita. |
| Geolocated dataset of Chinese overseas development finance (BU) | bu_invest | The amount of investment in millions of USD before population weighted calculation from the BU dataset. |
| | Pop_weighted_investment | Population weighted investment in millions of USD from BU dataset |
| | cum_pop_weighted_investment | Accumulated population weighted investment in millions of USD from BU dataset |
| AidData's Global Chinese Development Finance Dataset (Aid) | Aid_invest | The amount of investment in millions of USD before population weighted calculation from the Aid dataset. |

| | | |
|---|---|---|
| | Pop_weighted_aid | Population weighted investment in millions of USD from Aid dataset |
| | cum_pop_weighted_aid | Accumulated population weighted investment in millions of USD from Aid dataset |
| World Investment Report (DFI) | DFI | Total direct foreign investment to the country in millions of USD |

Table S4. T-test results comparing changes in land cover in districts receiving and not receiving investment.

| LC_type | Difference | Mean_WO_BU | Mean_W_BU | statistic | p.value | parameter | conf.low | conf.high |
|---|---|---|---|---|---|---|---|---|
| Barren | -0.1 | -0.2 | -0.1 | -1.7 | 0.1 | 197.1 | -0.3 | 0.0 |
| Crops and vegetation | -1.4 | -1.0 | 0.4 | -2.2 | 0.0 | 105.3 | -2.6 | -0.1 |
| Forest | 5.3 | 0.4 | -4.8 | 5.1 | 0.0 | 59.9 | 3.2 | 7.3 |
| Grasslands | -3.4 | -0.9 | 2.5 | -4.2 | 0.0 | 63.9 | -5.0 | -1.8 |
| Permanent Wetlands | 0.1 | 0.2 | 0.0 | 1.0 | 0.3 | 114.7 | -0.1 | 0.4 |
| Savannas | -0.7 | 1.2 | 1.9 | -0.7 | 0.5 | 83.4 | -2.7 | 1.4 |
| Urban and Built-up | 0.2 | 0.3 | 0.2 | 1.2 | 0.2 | 121.6 | -0.1 | 0.4 |

Welch's two-sided t-tests, which do not assume equal population variances, as a way of comparing differences in mean percentage change in various land-cover types across all four SEA countries evaluated in the study.

Table S4. Annual and total land cover change of project Laos-China Railway, Laos from 2016-2020

| Land Cover Change % | 2016-17 | 2017-18 | 2018-19 | 2019-20 | 2016-20 |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| **Forests** | 0.66 | -0.29 | -2.28 | -2.00 | -3.91 |
| **Savannas** | -0.74 | -0.27 | 0.77 | -0.67 | -0.91 |
| **Grasslands** | -0.60 | 0.70 | 1.84 | 1.00 | 2.93 |
| **Wetlands** | 0.04 | 0.01 | -0.02 | 0.00 | 0.02 |
| **Croplands / Natural Vegetation** | 0.65 | -0.16 | -0.32 | 1.65 | 1.83 |
| **Urban Built Up** | 0.00 | 0.00 | 0.02 | 0.04 | 0.07 |
| **Barren** | 0.00 | 0.00 | 0.00 | -0.01 | -0.01 |

Table S5. Annual and total land cover change of project National Road No. 55, Cambodia from 2015-2020

| Land Cover Change % | 2015-16 | 2016-17 | 2017-18 | 2018-19 | 2019-20 | 2015-20 |
|---|---|---|---|---|---|---|
| **Forests** | -0.85 | -3.62 | -1.23 | -1.67 | -0.29 | -7.66 |
| **Savannas** | -0.48 | 2.16 | 1.31 | -3.49 | -3.09 | -3.60 |
| **Grasslands** | 1.19 | 1.85 | 0.01 | 5.0 | 2.74 | 10.74 |
| **Wetlands** | 0 | 0 | 0.01 | -0.01 | -0.01 | -0.01 |
| **Croplands / Natural Vegetation** | 0.1 | -0.39 | -0.08 | 0.22 | 0.61 | 0.47 |
| **Urban Built Up** | 0 | 0 | 0 | 0 | 0.01 | 0.01 |
| **Barren** | 0 | 0 | 0 | 0 | 0 | 0 |

Table S6. Annual and total land cover change (ESRI) of Sihanoukville Special Economic Zone, Cambodia from 2017-2022

| Land Cover Change % | 2017-18 | 2018-19 | 2019-20 | 2020-21 | 2021-22 | 2017-22 |
|---|---|---|---|---|---|---|
| **Trees** | -2.27 | -7.95 | -5.01 | -0.79 | 2.95 | -13.06 |
| **Built Area** | 0.51 | 1.74 | 2.71 | 2.17 | -0.28 | 6.84 |
| **Rangeland** | 1.07 | 8.58 | 2.61 | -2.63 | -4.95 | 4.69 |
| **Bare Ground** | 0.54 | 0.99 | 0.71 | 0.84 | -0.91 | 2.18 |
| **Flooded Vegetation** | -1.26 | -0.82 | -0.39 | -0.09 | 0.54 | -2.01 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Water** | 0.3 | 0.18 | 0.04 | 0.54 | 0.04 | 1.13 |
| **Crops** | 1.09 | -2.7 | -0.69 | -0.06 | 2.61 | 0.25 |

Table S7. Estimates of effects of Chinese FDI on Land use Indices

| VARIABLES | (1) Non-vegetated % | (2) Medium Vegetation % | (3) High Vegetation % | (4) Built up area % | (5) GAIA Impervious % | (6) Tree Canopy |
|---|---|---|---|---|---|---|
| | | | | | | -0.00109** |
| Chinese foreign investment (population weighted) | 0.0150** | -0.00121** | 0.00153 | 0.00875 | 0.0007 | (0.000449) |
| | (0.00662) | (0.000496) | (0.0106) | (0.00699) | (0.00065) | -0.00167 |
| GDP per capita | 0.0691*** | -0.00559*** | -0.0382 | -0.0243 | 0.00967 *** | (0.00317) |
| | (0.0222) | (0.00168) | (0.0256) | (0.0158) | (0.00967) | -0.00165* |
| Direct foreign investment (Non-Chinese) | -0.00216 | 0.00191 | -0.0187 | -0.0623*** | 0.00193 | (0.000967) |
| | (0.00989) | (0.00130) | (0.0191) | (0.0200) | (0.00147) | 0.0573 |
| Constant | | | | | | (0.0699) |
| | -0.977** | 2.191*** | 0.975** | 1.040*** | 1.01557*** | |
| | (0.385) | (0.295) | (0.407) | (0.348) | (0.00464) | 1,240 |
| Observations | | | | | | 124 |
| Number of city_id | 1,240 | 1,240 | 1,240 | 1,240 | 1,240 | Yes |
| City FE | 124 | 124 | 124 | 124 | 124 | -0.00109** |

*Notes*: Regression type—district/city and year fixed effects dynamic panel model (Eq. 1). Restrict counterfactual sample to districts with any Chinese investment from 2008-2018 (intensive margin). Functional form for all variables is inverse hyperbolic sine (arcsinh), yielding elasticity estimates for all coefficients. Robust standard errors in parentheses and clustered at district level. *** p<0.01, ** p<0.05, *p<0.1; two-tailed tests for all variables.

Table S8. Estimates of effects of Chinese FDI on Land Cover Classes (MODIS)

| VARIABLES | (1) Forests | (2) Savannah | (3) Cropland | (4) Grassland | (5) Wetlands | (6) Urban Built-up | (7) Barren | (8) Water |
|---|---|---|---|---|---|---|---|---|
| Chinese foreign investment (population weighted) | -0.000649 | -0.00184 | -0.000108 | -0.000725 | -0.00105 | 0.000128 | 0.000849 | -0.000547 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (0.00121) | (0.00139) | (0.000668) | (0.00141) | (0.000746) | (0.000144) | (0.00115) | (0.000336) |
| GDP per capita | 0.0195*** | -0.00180 | -0.00569 | -0.00845 | 0.000509 | 0.000844 | 0.00612 | -0.00304* |
| | (0.00604) | (0.00496) | (0.00466) | (0.00528) | (0.00367) | (0.000888) | (0.00374) | (0.00175) |
| Direct foreign investment (non-Chinese) | 0.00416 | 0.00295 | -0.00508** | 0.00254 | (0.00221) | (0.000380) | (0.00276) | (0.00105) |
| | (0.00298) | (0.00334) | (0.00243) | (0.00426) | -0.00535 | -0.00393 | -0.0879 | 0.0542** |
| Constant | -0.439*** | 0.119 | 0.113 | 0.0804 | (0.0529) | (0.0142) | (0.0555) | (0.0275) |
| | (0.111) | (0.0868) | (0.0688) | (0.0743) | (0.00221) | (0.000380) | (0.00276) | (0.00105) |
| | | | | | | | | |
| Observations | 1,240 | 1,240 | 1,240 | 1,240 | 1,240 | 1,240 | 1,240 | 1,240 |
| Number of city_id | 124 | 124 | 124 | 124 | 124 | 124 | 124 | 124 |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: Regression type—district/city and year fixed effects dynamic panel model (Eq. 1). Restrict counterfactual sample to districts with any Chinese investment from 2008-2018 (intensive margin). Functional form for all variables is inverse hyperbolic sine (arcsinh), yielding elasticity estimates for all coefficients. Standard errors in parentheses and clustered at district level. *** p<0.01, ** p<0.05, *p<0.1; two-tailed tests for all variables.

Table S9. Estimates of effects of Chinese FDI on Land Cover Classes (ESRI)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | Water | Trees | Flooded Vegetation | Crops | Bare Ground | Rangeland | Urban/ Built Env. |
| | 0.000617 | -0.00685* | 0.00981** | 0.00377 | 0.00178 | 0.0132*** | -0.00612 |
| Chinese foreign investment (population weighted) | (0.00373) | (0.00405) | (0.00398) | (0.00416) | (0.00120) | (0.00503) | (0.00316) |
| | 0.0808*** | -0.0904*** | 0.0222** | 0.111*** | 0.0115*** | -0.0892*** | 0.1102*** |
| GDP per capita | (0.0157) | (0.0155) | (0.0109) | (0.0168) | (0.00263) | (0.0130) | (0.00658) |
| | -0.0261** | 0.0398*** | -0.0213*** | -0.0503*** | -0.00505*** | 0.0180** | -0.0238*** |
| Direct foreign investment (non-Chinese) | (0.0105) | (0.0105) | (0.00755) | (0.0116) | (0.00166) | (0.00893) | (0.0068) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Constant | 0.577*** (0.213) | 1.284*** (0.207) | -0.222 (0.144) | 1.745*** (0.263) | -0.167*** (0.0392) | 1.434*** (0.191) | -0.890*** (0.00353) |
| Observations | 1,240 | 1,240 | 1,240 | 1,240 | 1,240 | 1,240 | 1,240 |
| Number of city_id | 124 | 124 | 124 | 124 | 124 | 124 | 124 |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: Regression type—district/city and year fixed effects dynamic panel model (Eq. 1). Restrict counterfactual sample to districts with any Chinese investment from 2008-2018 (intensive margin). Functional form for all variables is inverse hyperbolic sine (arcsinh), yielding elasticity estimates for all coefficients. Standard errors in parentheses and clustered at district level. *** p<0.01, ** p<0.05, *p<0.1; two-tailed tests for all variables.

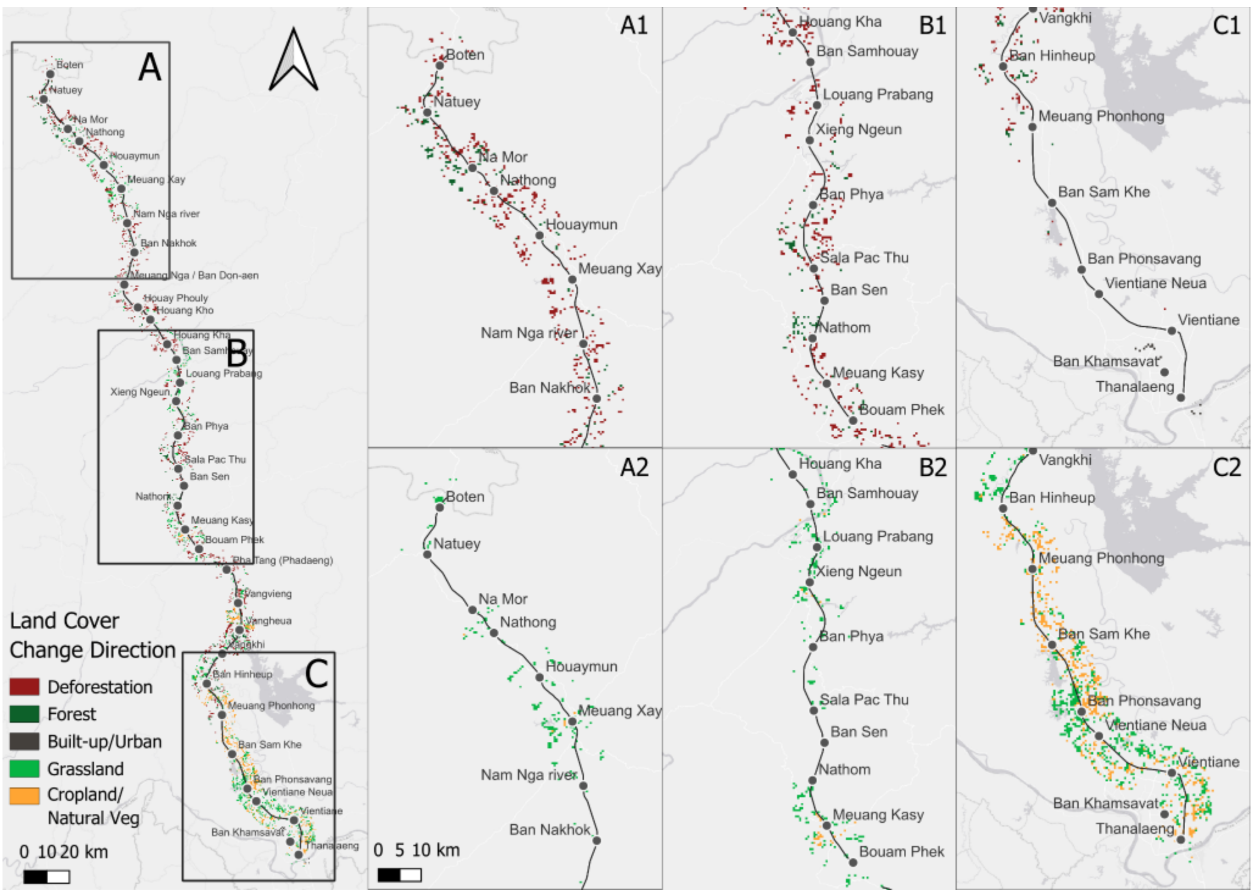


Figure S1. Land cover change detection of 6 km buffered area of Laos-China Railway, Laos from 2016-2020

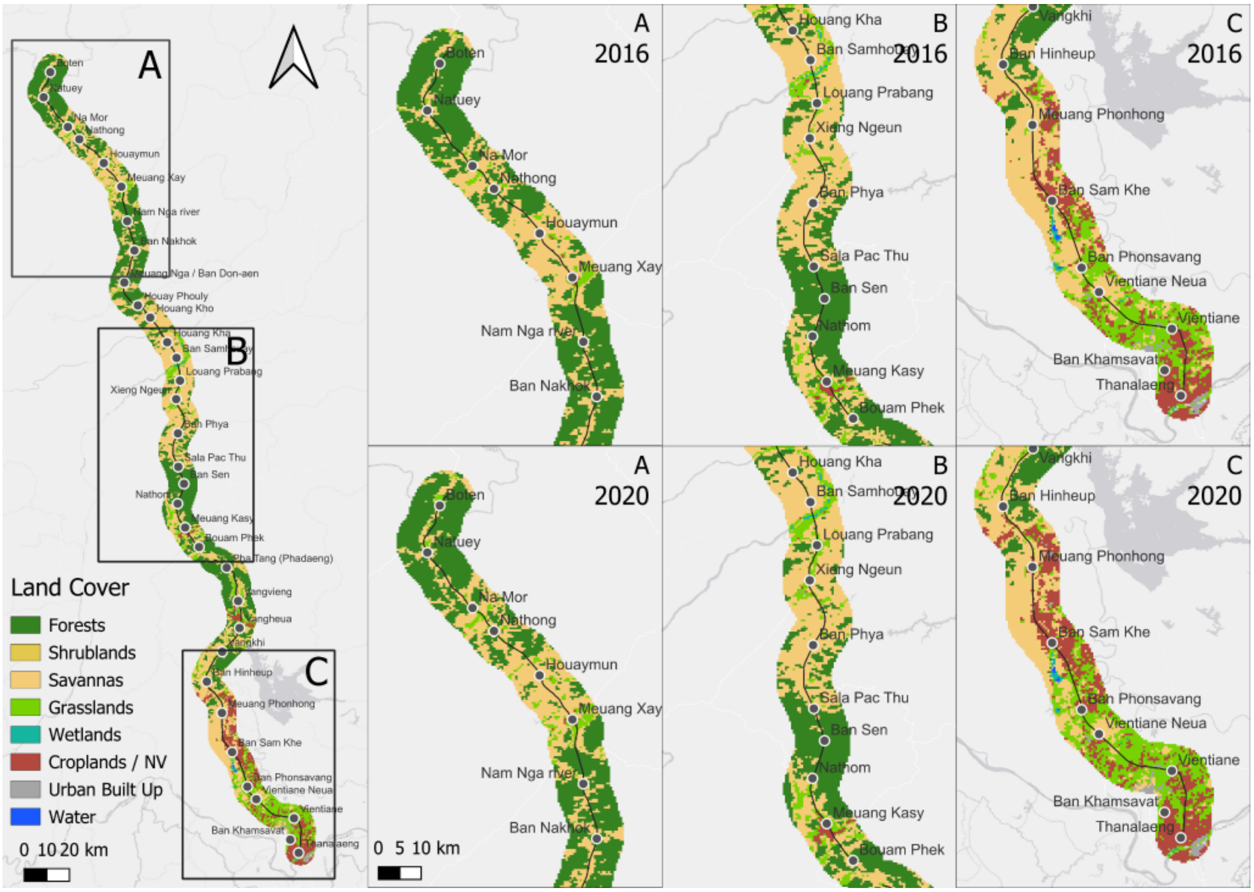


Figure S2. Land cover comparison of 6 km-buffered area of Laos-China Railway in Laos from 2016 vs. 2020.

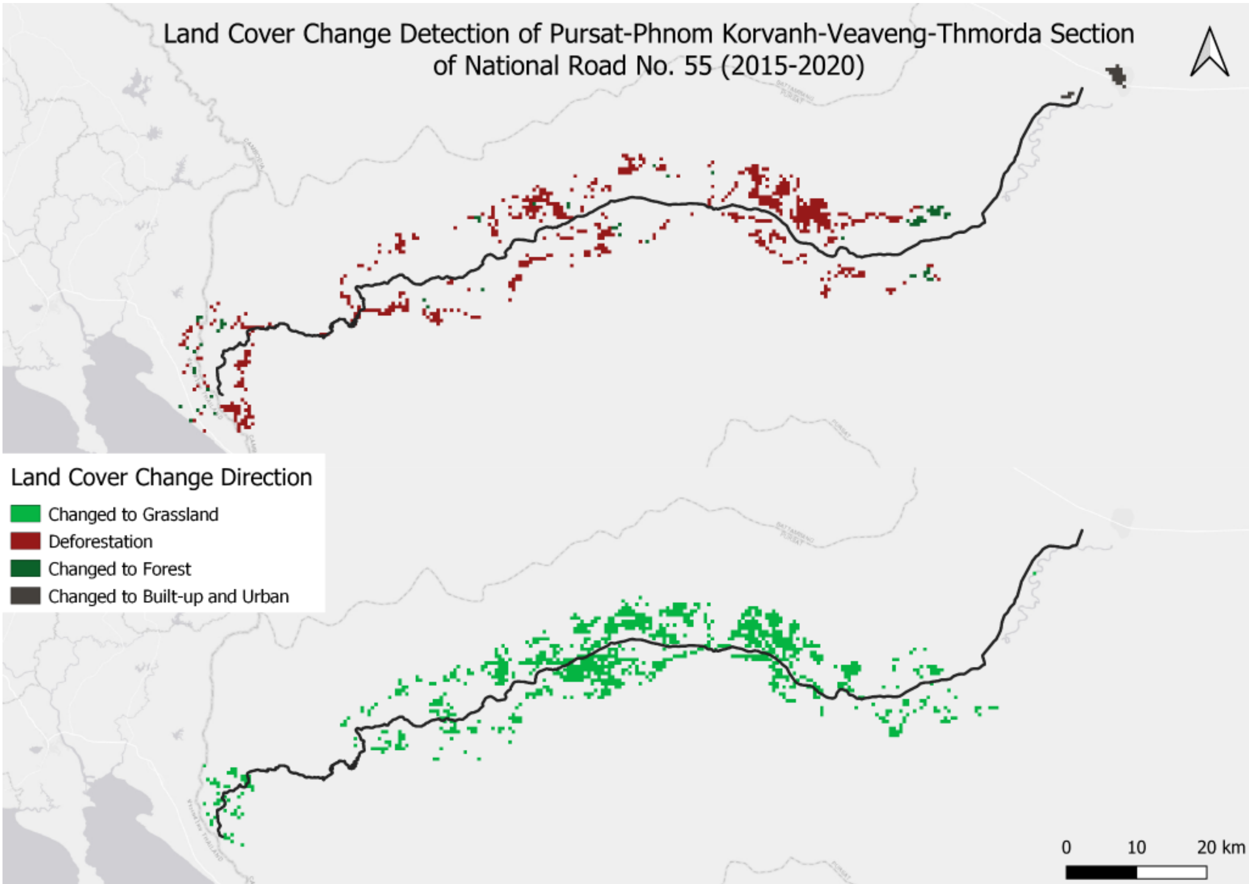


Figure S3. Land cover change detection of 6 km buffered area of National Road No. 55, Cambodia from 2015- 2020

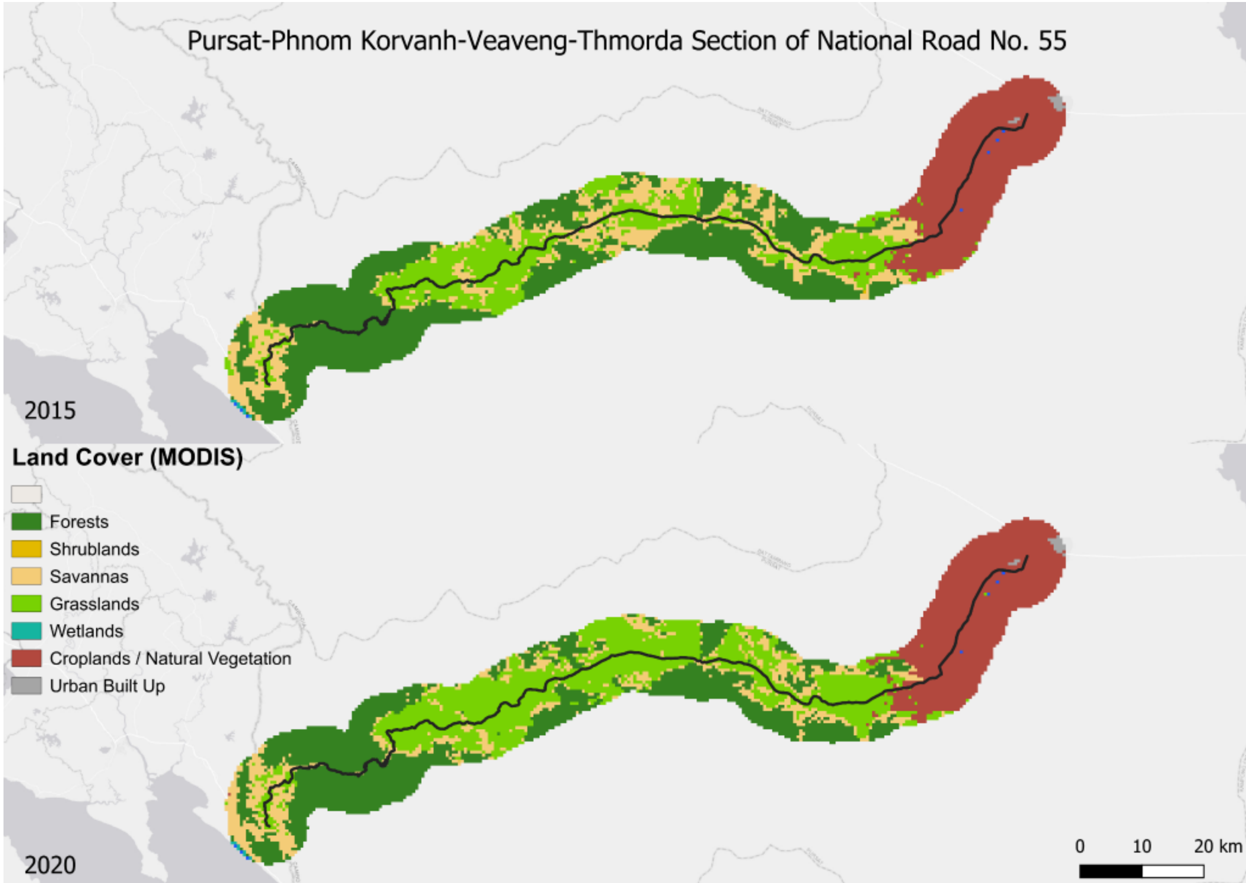

Figure S4. Land cover comparison of 6 km buffered area of National Road No. 55, Cambodia on 2015 v.s. 2020

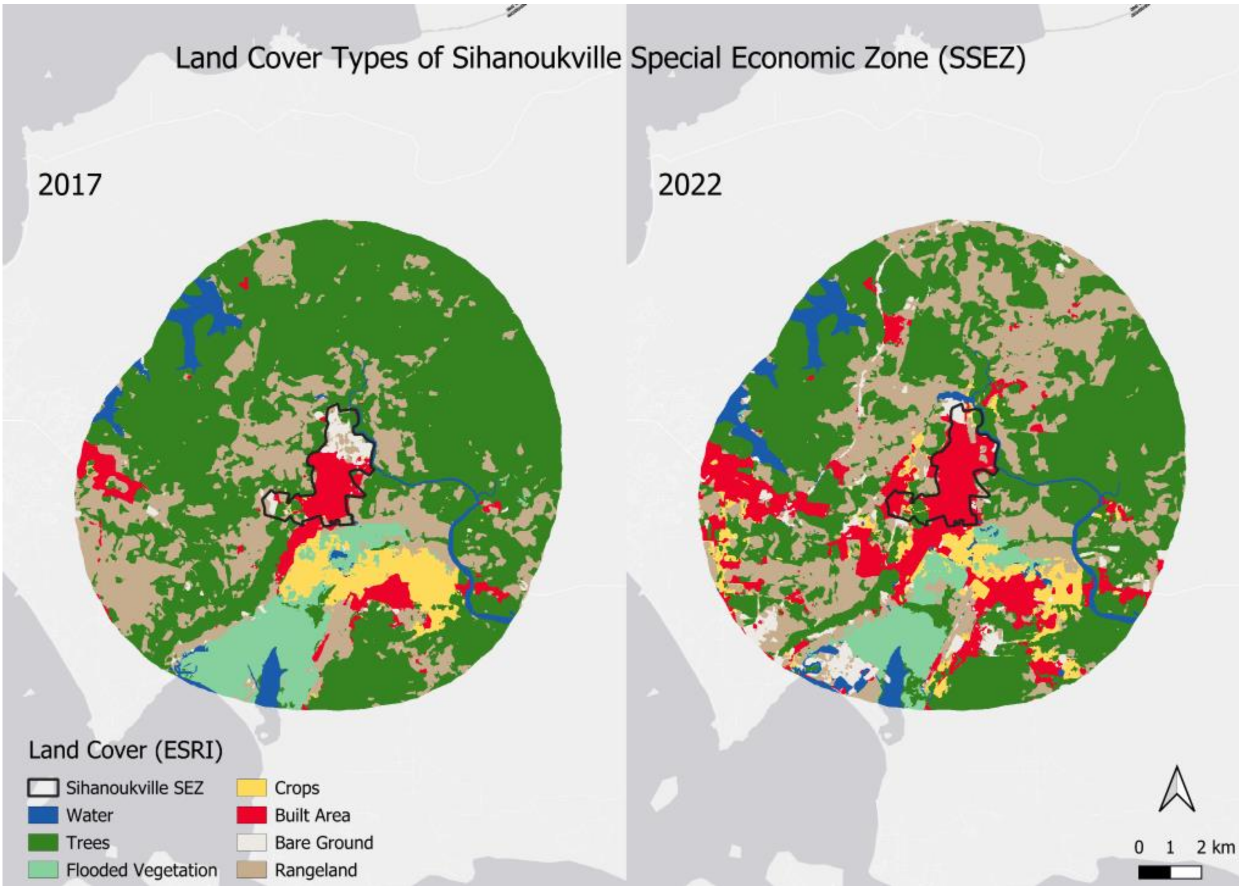


Figure S5. Land cover (ESRI) comparison of 6 km buffered area of Sihanoukville Special Economic Zone, Cambodia in 2017 vs. 2022.

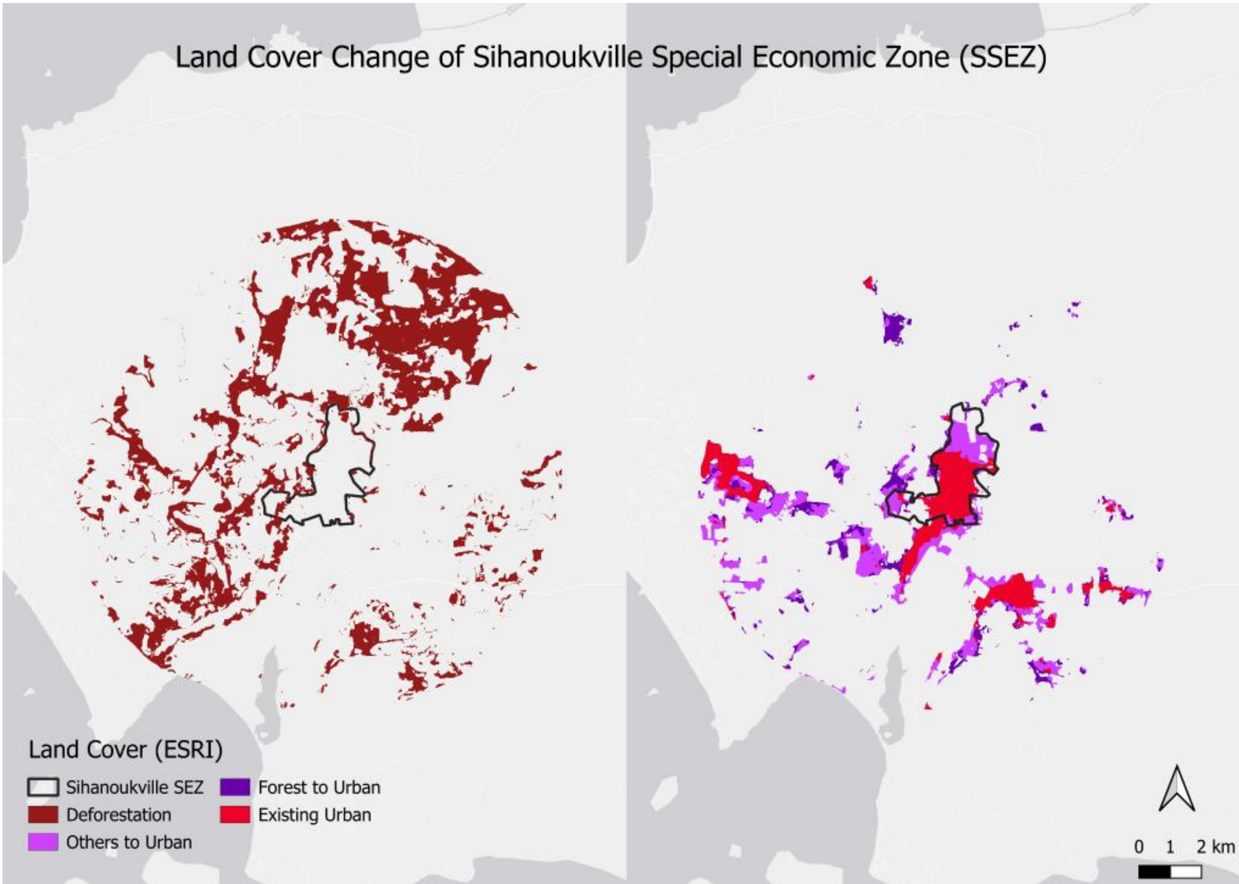

Figure S6. Land cover change detection (ESRI) of 6 km buffered area of Sihanoukville Special Economic Zone, Cambodia in 2017 vs. 2022.

*Robustness checks*

| VARIABLES | (1)<br>ln_ndvi_1_01_pct | (2)<br>ln_ndvi_01_05_pct | (3)<br>ln_ndvi_05_1_pct | (4)<br>ln_ndbi_01_1_pct | (5)<br>ln_gaia_mean |
|---|---|---|---|---|---|
| ln_cum_pop_weighted_investment = L, | 0.0829** | -0.00157** | -0.0239 | 0.0214 | 0.00212** |
| | (0.0364) | (0.000610) | (0.0307) | (0.0202) | (0.000837) |
| ln_ndvi_1_01_pct = L, | 0.376*** | | | | |
| | (0.0690) | | | | |
| ln_ndvi_01_05_pct = L, | | 0.615*** | | | |
| | | (0.0534) | | | |
| ln_ndvi_05_1_pct = L, | | | 0.124*** | | |
| | | | (0.0378) | | |

| | | | | | |
|---|---|---|---|---|---|
| ln_ndbi_01_1_pct = L, | | | | 0.692***<br>(0.0466) | |
| ln_gaia_mean = L, | | | | | 0.815***<br>(0.0137) |
| Constant | -0.410*** | 1.765*** | -0.129* | -0.176*** | 0.00310** |
| | (0.116) | (0.246) | (0.0727) | (0.0631) | (0.00133) |
| Observations | 2,010 | 2,010 | 2,010 | 2,010 | 2,010 |
| Number of city_id | 201 | 201 | 201 | 201 | 201 |
| City FE | Yes | Yes | Yes | Yes | Yes |

BU1

BU 2

| VARIABLES | (1)<br>ln_ndvi_1_01_pct | (2)<br>ln_ndvi_01_05_pct | (3)<br>ln_ndvi_05_1_pct | (4)<br>ln_ndbi_01_1_pct | (5)<br>ln_gaia_mean |
|---|---|---|---|---|---|
| ln_cum_pop_weighted_investment = L, | 0.0661** | -0.00155*** | -0.0187 | 0.00973 | 0.00205** |
| | (0.0258) | (0.000585) | (0.0302) | (0.0130) | (0.000834) |
| interpolated_gdp_pc = L, | 1.40e-10***<br>(0) | -0*<br>(0) | 6.83e-11***<br>(0) | -0<br>(0) | -0***<br>(0) |
| ln_ndvi_1_01_pct = L, | 0.590***<br>(0.0652) | | | | |
| ln_ndvi_01_05_pct = L, | | 0.637***<br>(0.0499) | | | |
| ln_ndvi_05_1_pct = L, | | | 0.140***<br>(0.0374) | | |
| ln_ndbi_01_1_pct = L, | | | | 0.805***<br>(0.0278) | |
| ln_gaia_mean = L, | | | | | 0.816***<br>(0.0138) |
| Constant | -0.296*** | 1.668*** | -0.149** | -0.193*** | 0.00368*** |
| | (0.113) | (0.229) | (0.0734) | (0.0587) | (0.00138) |
| Observations | 2,010 | 2,010 | 2,010 | 2,010 | 2,010 |
| Number of city_id | 201 | 201 | 201 | 201 | 201 |
| City FE | Yes | Yes | Yes | Yes | Yes |

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

AID 1

| VARIABLES | (1) ln_ndvi_1_01_pct | (2) ln_ndvi_01_05_pct | (3) ln_ndvi_05_1_pct | (4) ln_ndbi_01_1_pct | (5) ln_gaia_mean |
|---|---|---|---|---|---|
| ln_cum_pop_weighted_aid | 0.0617* | -0.000570 | -0.0312* | 0.0156 | 0.00284*** |
| | (0.0347) | (0.000466) | (0.0184) | (0.0177) | (0.000857) |
| ln_ndvi_1_01_pct = L, | 0.325*** | | | | |
| | (0.0674) | | | | |
| ln_ndvi_01_05_pct = L, | | 0.615*** | | | |
| | | (0.0538) | | | |
| ln_ndvi_05_1_pct = L, | | | 0.122*** | | |
| | | | (0.0382) | | |
| ln_ndbi_01_1_pct = L, | | | | 0.708*** | |
| | | | | (0.0395) | |
| ln_gaia_mean = L, | | | | | 0.819*** |
| | | | | | (0.0143) |
| Constant | -0.474*** | 1.768*** | -0.322*** | -0.338*** | -0.0395*** |
| | (0.122) | (0.248) | (0.0905) | (0.0727) | (0.00814) |
| Observations | 2,010 | 2,010 | 2,010 | 2,010 | 2,010 |
| Number of city_id | 201 | 201 | 201 | 201 | 201 |
| City FE | Yes | Yes | Yes | Yes | Yes |

AID 2

| VARIABLES | (1) ln_ndvi_1_01_pct | (2) ln_ndvi_01_05_pct | (3) ln_ndvi_05_1_pct | (4) ln_ndbi_01_1_pct | (5) ln_gaia_mean |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| ln_cum_pop_weighted_aid | 0.0484** | -0.000546 | -0.0268 | 0.00631 | 0.00281*** |
| | (0.0218) | (0.000423) | (0.0177) | (0.0119) | (0.000838) |
| interpolated_gdp_pc | 1.26e-10*** | -0 | 6.77e-11*** | -0 | -0*** |
| | (0) | (0) | (0) | (0) | (0) |
| ln_ndvi_1_01_pct = L, | 0.592*** | | | | |
| | (0.0647) | | | | |
| ln_ndvi_01_05_pct = L, | | 0.643*** | | | |
| | | (0.0486) | | | |
| ln_ndvi_05_1_pct = L, | | | 0.142*** | | |
| | | | (0.0375) | | |
| ln_ndbi_01_1_pct = L, | | | | 0.808*** | |
| | | | | (0.0248) | |
| ln_gaia_mean = L, | | | | | 0.819*** |
| | | | | | (0.0144) |
| Constant | -0.315*** | 1.637*** | -0.341*** | -0.192*** | -0.0387*** |
| | (0.116) | (0.223) | (0.0919) | (0.0587) | (0.00829) |
| | | | | | |
| Observations | 2,010 | 2,010 | 2,010 | 2,010 | 2,010 |
| Number of city_id | 201 | 201 | 201 | 201 | 201 |
| City FE | Yes | Yes | Yes | Yes | Yes |

BU Sensitivity Check

| VARIABLES | (1) ln_ndvi_1_01_pct | (2) ln_ndvi_01_05_pct | (3) ln_ndvi_05_1_pct | (4) ln_ndbi_01_1_pct | (5) ln_gaia_mean |
|---|---|---|---|---|---|
| ln_cum_pop_weighted_investment | 0.127*** | -0.00133** | -0.0346 | -0.00787 | -0.00155 |
| | (0.0372) | (0.000546) | (0.0397) | (0.0257) | (0.00180) |
| interpolated_gdp_pc | 1.58e-10*** | -0* | 6.16e-11*** | -0 | -0** |
| | (0) | (0) | (0) | (0) | (0) |
| ln_ndvi_1_01_pct = L, | 0.549*** | | | | |
| | (0.0696) | | | | |
| ln_ndvi_01_05_pct = L, | | 0.592*** | | | |
| | | (0.0683) | | | |

| | | | | | |
|---|---|---|---|---|---|
| ln_ndvi_05_1_pct = L, | | | 0.135*** | | |
| | | | (0.0397) | | |
| ln_ndbi_01_1_pct = L, | | | | 0.792*** | |
| | | | | (0.0267) | |
| ln_gaia_mean = L, | | | | | 0.801*** |
| | | | | | (0.0166) |
| Constant | -0.460*** | 1.873*** | -0.129 | -0.184*** | 0.00762*** |
| | (0.133) | (0.314) | (0.0801) | (0.0659) | (0.00186) |
| Observations | 1,941 | 1,941 | 1,941 | 1,941 | 1,941 |
| Number of city_id | 201 | 201 | 201 | 201 | 201 |
| City FE | Yes | Yes | Yes | Yes | Yes |

AID Sensitivity Check

| VARIABLES | (1) ln_ndvi_1_01_pct | (2) ln_ndvi_01_05_pct | (3) ln_ndvi_05_1_pct | (4) ln_ndbi_01_1_pct | (5) ln_gaia_mean |
|---|---|---|---|---|---|
| ln_cum_pop_weighted_aid | 0.0543* | -0.000286 | -0.0487** | -0.0198 | 0.00172 |
| | (0.0286) | (0.000472) | (0.0234) | (0.0193) | (0.00154) |
| interpolated_gdp_pc | 1.38e-10*** | -0 | 6.59e-11*** | -0 | -0*** |
| | (0) | (0) | (0) | (0) | (0) |
| ln_ndvi_1_01_pct = L, | 0.555*** | | | | |
| | (0.0678) | | | | |
| ln_ndvi_01_05_pct = L, | | 0.598*** | | | |
| | | (0.0659) | | | |
| ln_ndvi_05_1_pct = L, | | | 0.131*** | | |
| | | | (0.0378) | | |
| ln_ndbi_01_1_pct = L, | | | | 0.758*** | |
| | | | | (0.0302) | |
| ln_gaia_mean = L, | | | | | 0.806*** |
| | | | | | (0.0176) |

| | | | | | |
|---|---|---|---|---|---|
| Constant | -0.558*** | 1.855*** | -0.288*** | 0.419*** | 0.0712*** |
| | (0.0974) | (0.302) | (0.0892) | (0.0643) | (0.00492) |
| | | | | | |
| Observations | 1,941 | 1,941 | 1,941 | 1,941 | 1,941 |
| Number of city_id | 201 | 201 | 201 | 201 | 201 |
| City FE | Yes | Yes | Yes | Yes | Yes |

[1] We also consider models that lag the cumulative investment measure by two and three years. The results are in line with findings presented in this manuscript and do not add substantial new information. We feature the one-year lag for brevity and to maintain the largest possible sample size given that additional lagging reduces the available number of city-year observations. Additional results with longer lags for the independent variables are available on request.