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Quantifying the biophysical and socioeconomic drivers of changes in forest and agricultural land in South and Southeast Asia

Xiaoming Xu[1] | **Atul K. Jain**[1] | **Katherine V. Calvin**[2]

[1]Department of Atmospheric Sciences, University of Illinois, Urbana, Illinois

[2]Joint Global Change Research Institute, Pacific Northwest National Laboratory, College Park, Maryland

Correspondence
Atul K. Jain and Xiaoming Xu, Department of Atmospheric Sciences, University of Illinois, Urbana, IL.
Emails: jain1@illinois.edu; xuxm@illinois.edu

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Abstract

South and Southeast Asia (SSEA) has been a hotspot for land use and land cover change (LULCC) in the past few decades. The identification and quantification of the drivers of LULCC are crucial for improving our understanding of LULCC trends. So far, the biophysical and socioeconomic drivers of forest change have not been quantified at the regional scale, particularly for SSEA. In this study, we quantify the biophysical and socioeconomic drivers of forest change on a country-by-country basis in SSEA using an integrated quantitative methodology, which systematically accounts for previously published driver information and regional datasets. We synthesize more than 200 publications to identify the drivers of the forest change at different spatial scales in SSEA. Subsequently, we collect spatially explicit proxy data to represent the identified drivers. We quantify the dynamics of forest and agricultural land from 1992 to 2015 using the Climate Change Initiative (CCI) land cover data developed by the European Space Agency (ESA). A geographically weighted regression method is employed to quantify the spatially heterogeneous drivers of forest change. Our results show that socioeconomic drivers are more important than biophysical drivers for the conversion of forest to agricultural land in South Asia and maritime Southeast Asia. In contrast, biophysical drivers are more important than socioeconomic drivers for the conversion of agricultural land to forest in maritime Southeast Asia and less important in South Asia. Both biophysical and socioeconomic drivers contribute approximately equally to both changes in the mainland Southeast Asia region. By quantifying the dynamics of forest and agricultural land and the spatially explicit drivers of their changes in SSEA, this study provides a solid foundation for LULCC modeling and projection.

KEYWORDS
afforestation/reforestation, deforestation, drivers, geographically weighted regression, Johnson's Relative Weight, South and Southeast Asia

1 | INTRODUCTION

Terrestrial ecosystems have been strongly impacted by human activities through changes in land use and land cover (LULCC). Since preindustrial time (ca. 1750) more than 50% of the global land surface has changed (Goldewijk, Beusen, Doelman, & Stehfest, 2017). LULCC impacts the water cycle, the carbon cycle, climate, and greenhouse gas (GHG) emissions (Foley, Defries, & Asner, 2005).

For example, in 2008–2017, annual GHG emissions from land-use change was 1.5 ± 0.7 GtC/yr, accounting for ~13% of the global anthropogenic GHG emissions (Le Quere et al., 2018). Many studies have provided spatially explicit LULCC datasets for quantifying the impact of LULCCs on different fluxes (Goldewijk et al., 2017; Houghton et al., 2012; Meiyappan & Jain, 2012; Ramankutty & Foley, 1999).

In the future, social development and economic opportunities could drive people to further change the land (Lambin et al., 2001). Changes in biophysical conditions, such as climate, soil, and water conditions, may also result in land use change (Mustard, Defries, Fisher, & Moran, 2012). Large uncertainties exist in future LULCC projections (Prestele et al., 2016), partly due to a limited understanding of the spatial variation in socioeconomic and biophysical drivers. Quantifying the socioeconomic and biophysical drivers of LULCC could improve the projections of future land use patterns (Feddema et al., 2005; Meiyappan, Dalton, O'Neill, & Jain, 2014). Some studies have quantified LULCC drivers at different spatial scales. For example, Mon, Mizoue, Htun, Kajisa, and Yoshida (2012) used a logistic regression model to conclude that the deforestation was negatively correlated with elevation and distance to the nearest town in three reserved forests in Myanmar. However, the results of these studies are not evaluated against published case studies. While there are some studies synthesizing published case studies in an effort to generalize LULCC drivers (van Vliet et al., 2016), these studies are typically qualitative rather than quantitative. Very few studies combine quantitative LULCC drivers with information from case studies.

South and Southeast Asia (SSEA) has one of the largest areas of tropical forests (FAO, 2015) and is the most populous region of the world (Cervarich et al., 2016). Although both deforestation and afforestation (or reforestation) processes are observed, the net forest area decreased from 319 million ha in 1990 to 292 million ha in 2015 (FAO, 2015). The drivers of these changes are diverse, including socioeconomic factors, such as the increasing population and economic growth (Lopez & Galinato, 2005; Shehzad, Qamer, Murthy, Abbas, & Bhatta, 2014), and biophysical factors, such as climate change (Islam, Miah, & Inoue, 2016). However, a quantitative spatially explicit analysis of the relationships between the biophysical and socioeconomic drivers and LULCC at the regional scale in SSEA is still lacking.

Therefore, the objective of this study is to quantify the spatially explicit relationships between the biophysical and socioeconomic drivers and LULCC at the regional scale in SSEA. To carry out such analysis for the 16 countries in the SSEA region (Bangladesh, Bhutan, Brunei, Cambodia, India, Indonesia, Laos, Malaysia, Myanmar, Nepal, Pakistan, Philippines, Singapore, Sri Lanka, Thailand, and Vietnam), we synthesized country-specific case studies to identify the major LULCC drivers in SSEA and used a spatially explicit satellite-based LULCC dataset. In this study, we specifically focused on two important LULCC activities, namely from forest to agricultural land and from agricultural land to forest (we use "forest change" to refer specifically to these two changes in this paper). To our knowledge, this study is the first effort to incorporate case study synthesis and quantitative analysis to quantify the biophysical and socioeconomic drivers of forest change in SSEA. The results provide an insight into the complex LULCC processes and could contribute to modeling and projection of LULCC in SSEA. Moreover, this study can serve as a scientific basis for stakeholders to improve land management in SSEA countries.

2 | MATERIALS AND METHODS

Our methodology to quantify the drivers of forest change can be broken down into seven steps: (a) identify the drivers of forest change by analyzing cases studies, (b) collect different biophysical and socioeconomic proxy data to represent the identified drivers of forest change, (c) compile satellite-based LULCC data, (d) identify the concentrated regions of forest change using Getis-Ord Gi* hotspot analysis technique, (e) employ principal component analysis (PCA) to account for multi-collinearity existing in the proxy data, (f) use a Geographically Weighted Regression (GWR) model to build the spatially explicit relationships between the proxy and forest change area, and (g) determine the relative importance of each proxy driver category using the Johnson's relative weight (JRW) method. The Getis-Ord Gi* analysis (step 4) was conducted in ArcMap 10.6 (Redlands, CA, 2017). All other steps were performed in Matlab 2017 (Natick, MA, 2017). For the GWR analysis, we used the Matlab Spatial Econometrics Toolbox (LeSage & Pace, 2009). Each step of the methodology was described in brief in the following sections. A detailed description of the individual steps with a sample calculation can be found in the Supplementary Section Text S1.

2.1 | Synthesis of the site level case studies

In this study, we collected 213 publications (including 65 case studies for India synthesized by Meiyappan et al. (2017)) to identify the drivers of forest change at different spatial and temporal scales. We ran an advanced search in all databases available in Web of Science with the query expression "TI = (Drivers OR determinants OR causes OR dynamics) AND TS = (Country name AND land*) AND TS = (crop* OR *forest* OR agricul* OR defor* OR degrad*)" for all 16 SSEA countries. There were in total 565 publications that met the query conditions. By looking through the titles and abstracts, we manually excluded 240 publications that did not mention any LULCC drivers. We carefully read the remaining 325 publications and excluded 112 publications that studied the drivers of LULCC other than forest change. Finally, we determined 213 publications that discussed either qualitatively or quantitatively drivers for forest area gain or forest area loss. We used the criterion "total forest area loss and total forest area gain" rather than the explicit changes from forest to agricultural land and vice versa because very few studies have explicitly investigated the drivers for the latter case (especially the changes from agricultural land to forest).

When analyzing the 213 case studies, we recorded the LULCC type (forest area loss or forest area gain), the study area (the coordinates of the geometric center for the study area at different spatial scale), timespan, and frequency of the drivers mentioned in the publications.

We identified the major drivers by the following method. If the case study stated important drivers, we recorded all of these important drivers mentioned in each publication (some publications discussed multiple drivers). Otherwise, we treated each of the mentioned drivers as major drivers. In order to generalize the drivers, we combined some of the drivers that were closely related. Detailed information is provided in Table 1.

2.2 | Spatial proxy data of the drivers for forest change

After identifying the drivers from the synthesis of case studies, we collected 16 biophysical and 17 socioeconomic proxy datasets to represent these drivers (Table 2). All of these proxies are spatially gridded data, which are used to build the quantitative relationships between the drivers and the forest change. These proxies have different spatial and temporal resolutions (Table 2). We kept the original spatial resolution of each driver. For example, we used

TABLE 1 Generalization of the identified drivers and their corresponding proxy data

Drivers identified from case studies	Collected proxy data	Remarks
• Terrain (topographical conditions)	Terrain index	
• Soil and other environmental conditions	Soil chemical composition, depth, drainage, fertility, and texture	
• Water availability	Distance to waterbodies	
• Climate	Mean, rate of change, and standard deviation of annual precipitation Mean, rate of change, and standard deviation of annual temperature Mean annual potential evapotranspiration	
• Fire	Mean burned area fraction	
• Other natural disaster	Distance to landslide events	
• Population • Labor	Mean and rate of change in urban population density Mean and rate of change in rural population density	The labor amount is directly related to population.
• Urbanization	Mean and rate of change in urban area fraction	
• Migration	Migration	
• Livestock • Grazing	Chicken, Cattle, Sheep, Pig, Goat and Duck counts	Grazing activities are correlated with livestock.
• Accessibility • Transportation • Infrastructure	Market accessibility index	Market accessibility index considers accessibility and infrastructure, particularly the transportation condition.
• Market influence (price) • Economy development • Plantation • Agroforest • Agriculture expansion	GDP per capita	Plantation, agroforest development, and agriculture expansion are related to market and economy. All of them can be reflected by GDP per capita.
• Mining (industry)	Distance to mining facilities	
• Poverty • Income dependency on forest • Livelihood • Benefit	Poverty index	The dependency on forest, livelihood and benefit are all closely related with poverty.
• Shifting agriculture (swidden) • Forest management (policy) • Globalization (international trade) • Fuel wood (logging and charcoal) • Tourism • Culture • Technology • Farm size • Natural regeneration • Education or social awareness • Aquaculture		Spatially explicit proxy data are not available.

0.5° × 0.5° CRU TS climate data, which is relatively coarse compared to the 0.1° × 0.1° resolution of the forest change data. Therefore, when we extracted the climate data values using the coordinates of the 0.1° × 0.1° grids of LULCC data, the 0.1° × 0.1° grids in the same 0.5° × 0.5° grid cell all had the same value. As a result, our analysis may miss some detailed driver information at small scales. However, because the region investigated is much larger than 0.5° × 0.5°, the climate data still have spatial gradients for the GWR analysis.

If the proxy datasets do not change with time (e.g., terrain, soil properties) or are available in the literature for only one time period (e.g., distances to waterbodies, landslide events, and mining facilities, as well as market accessibility index), we use them directly in the quantitative analysis (step 6). If the proxies are time-series data (e.g., burned area fraction, precipitation, temperature, rural and urban population density, and urban area fraction), we use the means and dynamics (rate of change and standard deviation) of them in step 6. Migration data are available at the decadal time scale covering from 1970 to 2000; we used the 1990 to 2000 data as it is closest to our study period in step 6.

2.3 | Land use data

We used the European Space Agency Climate Change Initiative (ESA-CCI) satellite data for land cover dynamics of forest and agricultural land from 1992 to 2015. The original product categorized land cover into 22 classes (level 1) (Defourny, Moreau, & Bontemps, 2017). Our study used the corresponding IPCC classes (Defourny et al., 2017) of agricultural land and forest. We derive the spatial data of the forest change by overlaying the 1992 and 2015 land cover maps from the ESA-CCI data (300 × 300 m resolution). Then we aggregated the forest change maps to 0.1° × 0.1° (~10 km × 10 km) and determined the fractions of the changed area from forest to agricultural land and agricultural land to forest in each 0.1° × 0.1° grid (Figure S1). The 0.1° × 0.1° resolution represents a tradeoff between the finer resolution of the LULCC data (300 m) and the relatively coarser resolution data for biophysical and socioeconomic proxy data (from 0.1° × 0.1° to 0.5° × 0.5°). We also calculated the country-specific areas of these two changes.

The areas changed between 1992 and 2015 due to the conversion of forest to agricultural land and vice versa are 185,468 km^2 and 89,398 km^2 when calculating based on 1992 and 2015 data. On the other hand, the areas changed are 191,277 km^2 and 97,298 km^2 when accumulating the yearly area changes of these two land change activities over the period 1992–2015 (Figure S3). The areas based the former method are 96.96% and 91.88% of the results from the latter method, indicating that forest change data estimated based on 1992 and 2015 years of data are able to capture the major information for this time period.

2.4 | Hotspot analysis

The purpose of the hotspot analysis was to exclude the regions with smaller areas of forest and its change in the driver analysis. The inclusion of such low value regions might dilute the importance of the major drivers. We used the *Getis-Ord Gi** analysis technique to identify the hotspot regions for the changes from forest to agricultural land, and agricultural land to forest. This technique identifies statistically significant spatial clusters of high (hot spots) and low (cold spots) values of changes (Ord & Getis, 1995). A statistically significant hot spot has a greater area of LULCC and is surrounded by other regions with great areas of LULCC. We marked regions with >3 standard deviations (at 99% confidence level) as hotspot regions. We analyzed the hotspot regions in each country at the district level.

2.5 | Principle component analysis (PCA)

Multi-collinearity is a common problem in land change modeling where one or more explanatory (or proxy) data are dependent on each other. A high degree of multi-collinearity results in high standard errors and spurious coefficient estimates. We employed the PCA method to account for the multi-collinearity. We selected the PCs with cumulative contribution rates (to the total variation of all proxy data) greater than 85% (Deng, Wang, Deng, & Qi, 2008).

2.6 | Geographically weighted regression (GWR)

The GWR model constructs a distinct relationship between each LULCC pixel and concomitant driver proxy data by incorporating pixels falling within a certain bandwidth of the center LULCC pixel (Charlton, Fotheringham, & Brunsdon, 2009). Here we used the adaptive Gaussian kernel to determine the bandwidth, and the local extent to estimate the regression coefficients. The optimal bandwidth size of the kernel was determined by means of comparison of Akaike Information Criterion (AIC) with different bandwidth sizes. We conducted the GWR in the identified hotspot districts of each country.

2.7 | Johnson's relative weight (JRW)

The GWR results can represent the positive or negative impact of each individual proxy driver, as well as its relative magnitude. However, it is difficult to evaluate the combined effects of different driver categories (see the six categories in Table 2). In order to generalize the forest change drivers from different categories, we used the Johnson's Relative Weight (JRW) method to quantify the relative importance of each individual proxy, and then summed up the importance coefficients of all driver categories. The JRW analysis first generates a series of orthogonal variables that are the linear combinations of all original proxy data, and then conducts the regression analysis by using the generated orthogonal variables (this procedure is the same as the PCA analysis in step 5). Then, the Eq. S5 is used to determine the relative importance of the original proxy data (Chao, Zhao, Kupper, & Nylander-French, 2008; Johnson, 2000).

TABLE 2 Proxy variables of the identify drivers

	Category		Proxy variable		Temporal resolution	Spatial resolution	Unit	Source
Biophysical variables	I	Terrain, soil, and water	1.	Terrain	Constant	5′ × 5′ (~10 km × 10 km)	Categorical data into 7 gradient classes	Global Agro-ecological Zones (GAEZ) v3.0 (Fischer, Nachtergaele, & Prieler, 2012)
			2.- 6.	Soil chemical composition, depth, drainage, fertility, and texture				
			7.	Distance to waterbodies		5′ × 5′	km	Calculated from Global Lakes and Wetlands Database (GLWD) level 2 data (Lehner & Doll, 2004)
	II	Climate	8. - 10.	Mean, rate of change, and standard deviation of annual precipitation	Yearly	$0.5^{\circ} \times 0.5^{\circ}$	°C, °C/year	Climatic Research Unit (CRU) TS 4.01
			11. - 13.	Mean, rate of change, and standard deviation of annual temperature			mm, mm/year	
			14.	Mean annual potential evapotranspiration			mm	
	III	Natural disaster	15.	Mean burned area fraction	Yearly (1997–2014)	$0.25^{\circ} \times 0.25^{\circ}$	%	Global Fire Emissions Database 4.1 (Giglio, Randerson, & Werf, 2013)
			16.	Distance to landslide events	Constant	5′ × 5′	km	Calculated from Global Landslide Catalog (Kirschbaum, Adler, Hong, Hill, & Lerner-Lam, 2010)
Socioeconomic variables	IV	Population and urbanization	17. - 18.	Mean and rate of change in urban population density	Yearly	5′ × 5′	inhabitants/km^2, inhabitants/km^2·year	HYDE 3.2 (Klein Goldewijk, Beusen, Doelman, & Stehfest, 2017)
			19. - 20.	Mean and rate of change in rural population density				
			21. - 22.	Mean and rate of change in urban area fraction			%, %/year	
			23.	Migration	Decadal (1970–2000)	$0.5^{\circ} \times 0.5^{\circ}$	Number of migrants/km^2	Global Estimated Net Migration Grids By Decade, v1 (de Sherbinin et al., 2012)
	V	Livestock	24. - 29.	Chicken, Cattle, Sheep, Pig, Goat and Duck counts	Constant	1 km × 1 km	Head/km^2	Gridded Livestock of the World (GLW) version 2 (Robinson et al., 2014)

(Continues)

TABLE 2 (Continued)

Category		Proxy variable	Temporal resolution	Spatial resolution	Unit	Source
VI Economy	30.	Market accessibility index	Constant	1 km × 1 km	-	Verburg, Ellis, and Letourneau (2011)
	31.	GDP per capita	Decadal (1980–2010)	0.5° × 0.5°	USD2005	Global dataset of gridded population and GDP scenarios Murakami and Yamagata (2016)
	32.	Distance to mining facilities	Constant	5′ × 5′	km	Calculated from Mineral Resources On-Line Spatial Data by USGS
	33.	Poverty index	Yearly (1992–2013)	5′ × 5′	-	Calculated from population (HYDE 3.2) (Klein Goldewijk, Beusen, Doelman, & Stehfest, 2017) and Night time light (Version 4 DMSP-OLS Nighttime Lights Time Series) by following the method developed by Ghosh, Anderson, Elvidge, and Sutton (2013)

3 | RESULTS

3.1 | Synthesis of the case study

The case studies regarding the drivers of forest loss and gain are spread across all countries, and have diverse spatial scales, from village to national scale (Figure S5). There are 173 studies (81% of the total collected studies) studying drivers based on field surveys, interviews and literature reviews. Meanwhile, 40 studies (19% of the collected studies) have used quantitative approaches, such as linear regression, logistic regression, system dynamics modeling, and cellular automata modeling to reveal the drivers of LULCC. However, most of these quantitative studies are at smaller spatial scales (village to state and province level) (31 studies). There are only nine quantitative studies at the national scale.

We identify the drivers of forest change from collected case studies (Figure 1 and Table 1). The biophysical drivers include terrain or topographical conditions (e.g., elevation, altitude, and the slope of land), soil conditions (e.g., soil fertility, texture, and moisture), water availability, climate (e.g., temperature, precipitation, and their changes), fire, and other natural disasters (e.g., landslide). The socioeconomic drivers mainly relate to population growth, urbanization, livestock or grazing (e.g., overgrazing), market influence or economy development (e.g., GDP per capita, access to market), plantation or agroforest development, agricultural expansion, mining and industry, accessibility and infrastructure (e.g., transportation, electricity connection), logging and fuelwood, and poverty.

Fire and other natural disasters and terrain are the most frequently mentioned biophysical drivers of forest area loss (deforestation). For example, in India and Indonesia, the two countries with the largest forest area, a majority of studies suggest terrain and fire and other natural disasters as the major biophysical drivers. Our synthesis of site-level case studies also identifies population, plantation, agricultural expansion, accessibility, and infrastructure, as well as fuelwood and logging as the important socioeconomic drivers of deforestation.

There are fewer studies on the drivers of forest area gain (afforestation and reforestation) than on deforestation. Among them, most studies have focused on socioeconomic drivers. The frequently mentioned socioeconomic drivers include accessibility, poverty, economy, and livestock and biophysical drivers include climate and terrain. The major drivers of forest change at different spatial and temporal scales are described in more detail in Supplementary Section Text S2, Figures S6 and S7.

3.2 | Forest change

The country-specific and spatial distribution of converting from forest to agricultural land and agricultural land to forest over the time period 1992–2015 is shown in Figure 2 and Figure S4. Malaysia and Philippines experienced large areas of deforestation, as well as afforestation, over 1992–2015. Cambodia and Singapore had more deforestation than afforestation.

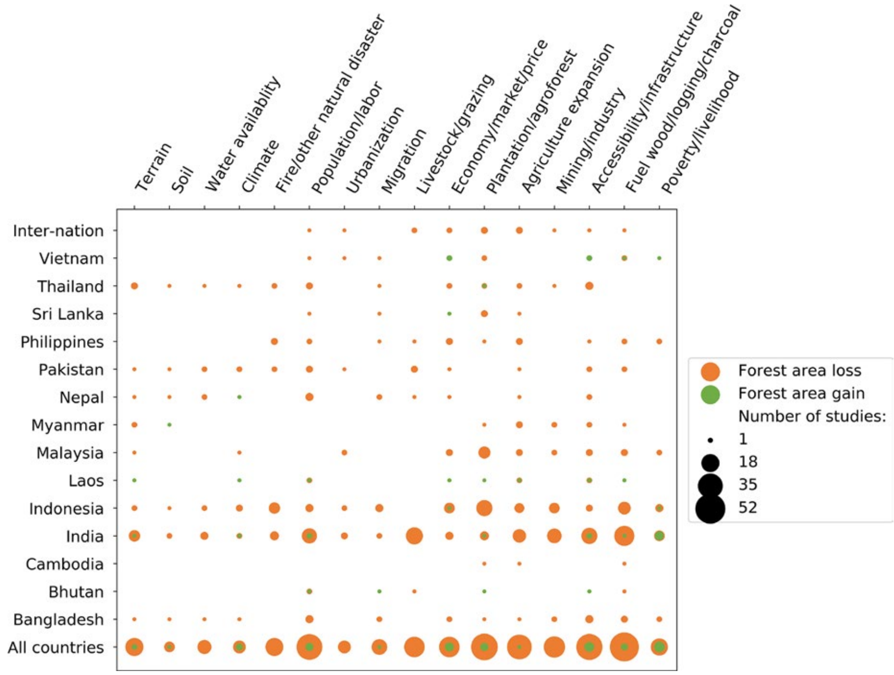

FIGURE 1 Frequency distribution of the major drivers identified from the synthesis of case studies in South and South East Asia (SSEA) countries. The drivers mentioned more than 10 times (sum of the frequencies for both forest area loss and gain) are plotted here. Other identified drivers could be found in Table 1

The conversion from forest to agricultural land and agricultural land to forest co-exist in many regions (Figure S4). The hotspot regions of the two changes over the period 1992–2015 are mainly concentrated in Kalimantan, Sumatra, East India, and the Hindu Kush Himalayan regions (Figure 3).

3.3 | Quantification of the drivers

3.3.1 | Forest to agricultural land

Here, we show national averages of the standardized coefficients with their standard deviations from the GWR analysis (Figure 4). Overall, the impacts of various drivers in different countries are quite heterogeneous. A single driver has different effects on different countries. For example, the distance to waterbodies (variable 7 in Figure4a) can have a positive, negative, or nearly no (~zero values) effect on the change from forest to agricultural land. In general, the distance to waterbodies (variable 7), mean annual precipitation (variable 8), mean burned area fraction (variable 15), goat count (variable 28), and GDP per capita (variable 31) are the important drivers in most countries, but their impacts differ across countries.

In order to generalize the results, we use the relative importance to combine the impacts from different driver categories. Terrain, soil, and water (category I) and livestock (category V) are the most dominant driver categories; they are the most important driver categories in six (i.e., Bhutan, Laos, Malaysia, Myanmar, Nepal, Sri Lanka, and Vietnam) and three countries (i.e., Cambodia, India, and Indonesia) respectively (Figure 5a). On the other hand, natural disasters (category III) have the least impacts in most countries (11 countries).

The importance of biophysical drivers is relatively lower (the importance of socioeconomic drivers is higher) in some South Asian countries such as Bangladesh, Nepal, and Pakistan and maritime Southeast Asian countries Philippines and Indonesia, mainly because of lower JRWs of the terrain, soil, and water (I) and higher JRWs of the urbanization and population (IV) and economy (VI). Socioeconomic and biophysical drivers have approximately equal importance in some countries in Mainland Southeast Asia, such as Malaysia, Laos, Thailand, and Vietnam (Figure 5a).

3.3.2 | Agricultural land to forest

For the conversion from agricultural land to forest, mean burned area fraction (variable 15), migration (variable 23), and poverty index (variable 33) are the most important drivers in most countries (Figure 4b). Migration (variable 23) has a strong negative effect on this change (standardized coefficient <-0.4) in India, but smaller (mostly positive) effects in other countries. Similarly, pig count (variable 27) has a strongly positive effect on this change in India (standardized coefficient >0.4). These two drivers are the most important for changes from agricultural land to forest in India. We observe smaller impacts of these drivers (small absolute value of the standardized coefficients) on the change from agricultural land to forest than the change from forest to agricultural land. Some variables have nearly negligible impacts in most countries, such as rate of change of annual precipitation, standard deviation of annual temperature, chicken count, and market accessibility index (variables 9, 13, 24, and 30).

Terrain, soil, and water (category I) is the most important driver category in five countries (Bhutan, Cambodia, Indonesia, Laos, and Sri Lanka), while livestock (category V) is the most important category in four countries (i.e., Brunei, India, Myanmar, and Nepal) (Figure 5b). For example, the relative importance of terrain, soil, and water condition (I) in Indonesia is as high as 40.36%, highlighting the importance of the favorable environmental conditions for forest regrowth.

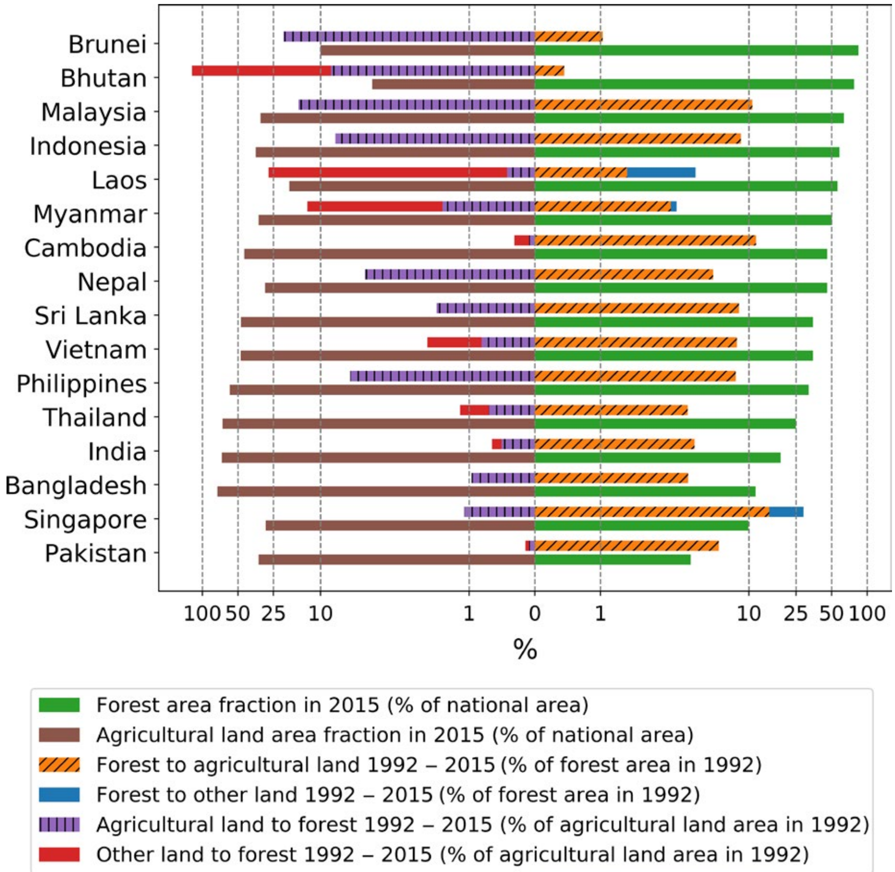

FIGURE 2 Estimated changes from forest to agricultural land (right) and agricultural land to forest (left) over 1992–2015 based on the European Space Agency Climate Change Initiative land cover product (Defourny et al., 2017)

Natural disasters (category III) has the least influence in most countries (11 countries).

For changes from agricultural land to forest, biophysical drivers are less important than socioeconomic drivers in Bangladesh, Bhutan, India, Pakistan, and Nepal (Figure 5b). The importance of biophysical and socioeconomic drivers are approximately equal in most mainland Southeast Asia countries, including Cambodia, Malaysia, Myanmar, Philippines, and Thailand. The importance of climate (II) is higher in maritime Southeast Asia such as Indonesia and Philippines. Indonesia has the highest JRW for biophysical drivers, mainly due to terrain, soil, and water (I), while Philippines has the greatest JRW of climate (II) among all countries.

4 | DISCUSSION

4.1 | Results comparison

Here we use a quantitative study of LULCC drivers in India (Meiyappan et al., 2017) to validate our results. The India study compiled >200 socioeconomic variables in ~630,000 villages (~2 km × 2 km on average) to identify the drivers of LULCC (including forest area losses and gains). The study used a "fractional" binomial logit model and synthesized case studies to evaluate the results. The "fractional" binomial logit model generates similar results as our GWR analysis, by using regression coefficients to indicate the influence of different drivers (both studies used the same *z*-score standardization for all driver variables). Here, we include the 65 case studies compiled in Meiyappan et al. (2017) to identify the drivers of forest change. This will not directly affect our quantitative driver analysis because our 33 biophysical and socioeconomic proxy data are collected regardless of the frequencies of the drivers mentioned in the literature. In addition, we did not use the village level socioeconomic dataset compiled in the India study, as we did not have the same level of information in other countries. Therefore, our quantitative driver analysis (Figures 4 and 5) is independent from Meiyappan et al. (2017), and the results of the two studies are comparable.

We compared the drivers for the forest to agricultural land of this study with the drivers for forest area loss in India (1995–2005) (Meiyappan et al., 2017). Most of the driver proxies at the country scale used in this study do not directly match the drivers used in Meiyappan et al. (2017). Instead, we have compared the effect of the drivers in this study with the drivers with closely related proxy variables in Meiyappan et al. (2017).

In our results, mean annual precipitation has a positive impact, meaning an increase in mean annual precipitation causes more forest to be converted to agricultural land. The Meiyappan et al. (2017) study used precipitation of wettest month or quarter rather than mean annual precipitation, but also found a positive impact on forest loss, suggesting that forests are more likely to be converted to cropland with increases in precipitation.

In our study, the market accessibility index has a negative impact on the change from forest to agricultural land. The negative impact

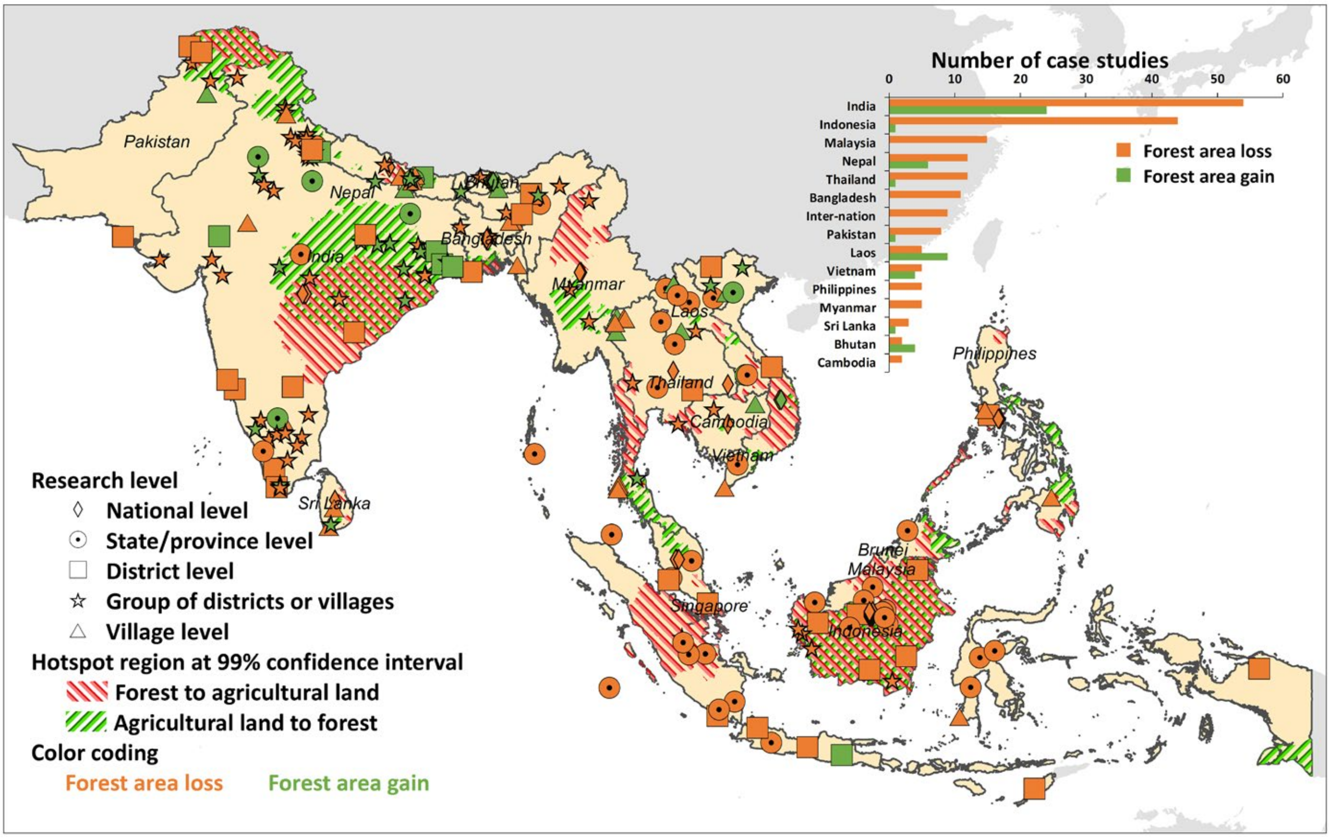

FIGURE 3 Spatial distribution of case studies and hotspot regions land use and land cover change (LULCC) drivers. The locations and research levels of the case studies, as well as the number of case studies, are extracted from the 213 publications listed in Tables S1 and S2, as well as Tables S10 and S11 in Meiyappan et al., 2017. The hotspot regions at 99% confidence interval are recognized from the Hotspot analysis with the Getis-Ord Gi* values ≥3

is mainly because forests in the region that are difficult to reach are unlikely to be converted to cropland. The Indian study uses a "very steep (>50%) slope" (of the land) as an indicator of accessibility, and finds a negative relationship, which matches with this study.

In the Indian study, the availability of power supply for domestic purpose is negatively associated with forest loss; our study suggests that urban area fraction has a negative impact on forest loss. If we assume that urban areas in India have a higher availability of power supply for domestic purpose, the results from the two studies are similar.

Our results suggest that the area of forest converted to agricultural land is greater in regions that are close to mining facilities (negative impact from the distance to mining facilities), while in Meiyappan et al. (2017) the occupation (building/mining materials) has a positive impact. It is highly possible that in the regions close to mining facilities (lower value of the distance to mining facility), more people work for the mining industry and the occupation in mining is higher. Therefore, these two drivers have opposite impacts but the same interpretation.

The distance to waterbodies in our study has a positive impact on the change from forest to agricultural land, and the proportion of cropland irrigated has a negative impact on forest area loss in the Indian study. The regions near to waterbodies (lower value of the distance to waterbodies) have better irrigation conditions for cropland and greater proportions of cropland irrigated; this can promote crop yield and therefore reduce the pressure on adjoining forests (Meiyappan et al., 2017). Therefore, the area of forest converted to agricultural land is smaller in such regions. The two studies match with each other in this dimension.

The above discussion shows that our results on the drivers for the conversion from forest to agricultural land in India are similar to a previous national scale study in India (Meiyappan et al., 2017).

4.2 | Drivers for LULCC

4.2.1 | Forest to agricultural land

Terrain (variable 1 in Figure 4a) has a positive impact on the conversion from forest to agricultural land in India, which is different from other countries. This is mainly because the hotspot regions of this change in India concentrate in the Orissa and Chhattisgarh states in center-east of the country (Figure 3), where forest, as well as its changes, are mainly located in higher and steeper regions. This region also has the largest area of shifting cultivation in India (Singh, Purohit, & Bhaduri, 2016). Shifting cultivation mainly occurs in high and steep regions; therefore, we can observe more forest area loss in regions with high terrain index values.

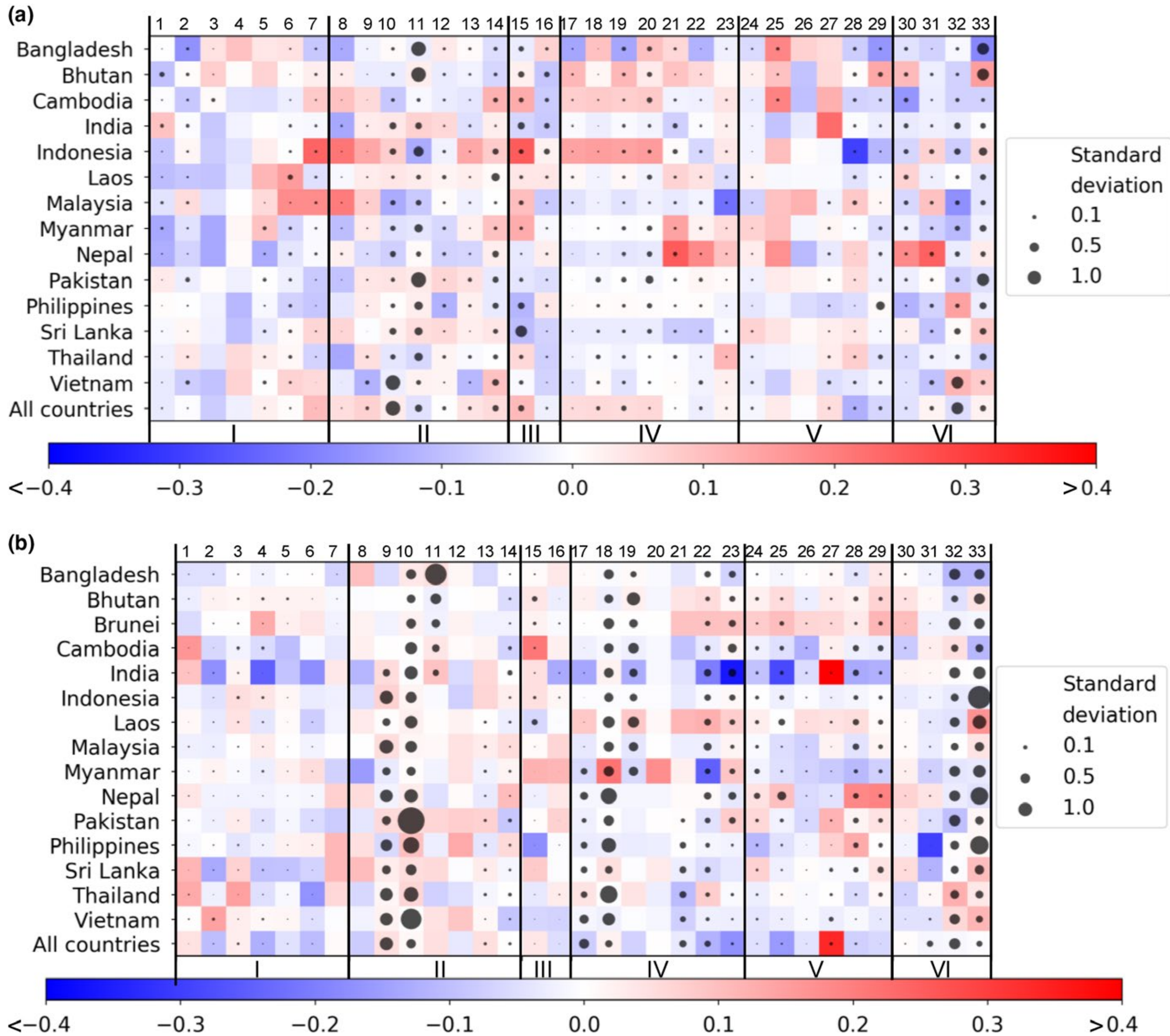

FIGURE 4 The national average of standardized coefficients of each driver in different countries for the conversions (a) from forest to agricultural land, and (b) from agricultural land to forest. The standardized coefficient refers to a number of standard deviations change in LULCCs, per standard deviation change in diving factors. The description of variables 1–33 and categories I–VI list could be found in Table 2. The size of the black dot indicated the standard deviation of the standardized coefficient in each country

Unlike most of the countries analyzed, most soil variables (variable 2–6 in Figure 4a) have positive influences in Bangladesh. The hotspot regions of change from forest to agricultural land in Bangladesh are concentrated in the southwest coastal regions (Figure 3). Our previous work in Bangladesh has shown that the forest in this region was mainly mangrove forest, and agricultural land is mainly used for aquaculture (fish or shrimp ponds). Therefore, the changes from forest to agricultural land are mainly mangrove to aquaculture in these regions (Uddin, Hoque, & Abdullah, 2014). Although satisfactory pond bottom soil conditions favor aquaculture production (Salam, Khatun, & Ali, 2005), our results indicate that soil conditions do not directly motivate changes from mangrove forest to aquaculture. In Bangladesh, the mean urban and rural population densities (variable 17–19 in Figure 4a) have negative impacts on this change, which is also different from most other countries. This may be because regions with higher population have more urban land, which crowds out other land types such as forest; therefore, there is less forest area that can be converted to agricultural land (Shehzad et al., 2014).

In two most populous countries in SSEA, India and Indonesia, livestock (variables 24 to 29) is the most dominant driver category, while population and urbanization is the least important driver category (Figure 5a). Our results agree with the conclusion of a meta-analysis by Rudel, Defries, Asner, and Laurance (2009) that, in recent years, well-capitalized ranchers, farmers, and loggers producing for consumers in distant markets have become more prominent in tropical

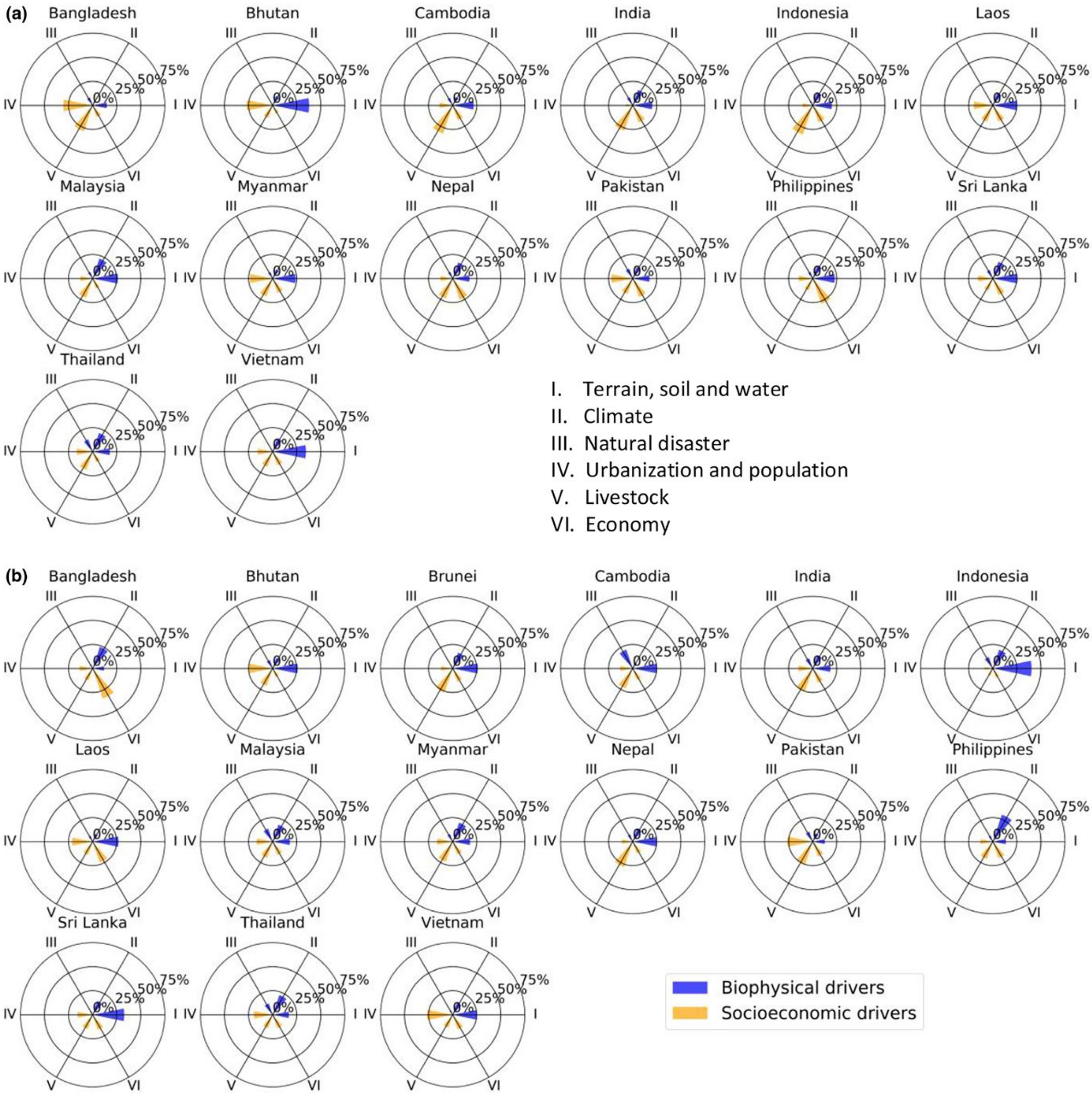

FIGURE 5 The relative importance of different drivers for the conversions (a) from forest to agricultural land and (b) from agricultural land to forest in SSEA countries

forests, and this globalization has weakened the historically strong relationship between local population growth and forest cover.

In some countries, biophysical drivers are more important. For example, in Bhutan, the conversion from forest to agricultural land has been controlled mainly by biophysical drivers rather than socioeconomic drivers, especially terrain, soil, and water conditions. Bhutan has a traditional culture of protecting forest (Bruggeman, Meyfroidt, & Lambin, 2016), and local residences avoid affecting forest when developing their social economy. Biophysical conditions, therefore, have a greater impact.

4.2.2 | Agricultural land to forest

Climate conditions (temperature and precipitation) are mostly positively or neutrally associated with the change from agricultural land to forest, indicating that wetter and warmer conditions with higher variations are favorable for forest regrowth. However, the higher standard deviations of the standardized coefficients in all countries indicate that the impacts of temperature variations and mean temperature are highly heterogeneous (Figure 4b). In the tropical forest, wetter (when mean annual precipitation is less than 2,445 mm) and warmer conditions are beneficial for tree productivity (Schuur, 2003). Therefore, precipitation and temperature have positive impacts. We observe negative impacts of mean annual precipitation in India and Myanmar (variable 8 in Figure 4b), showing that this change mainly takes place in relatively drier regions in these two countries.

Population and urbanization usually have smaller impacts, except in India, Laos, and Myanmar. In India, lower population and less urbanized regions favor reforestation and afforestation (Mon et al., 2012). On the contrary, we observe mostly positive impacts from population and urbanization variables in Laos. Phompila, Lewis, Ostendorf, and Clarke (2017) suggest that population increases can simultaneously lead to an increase in forest and expansion in forest clearance in different locations of Laos.

Livestock variables play important roles in this change in India. The cattle count has a negative impact (variable 25 in Figure 4b). Given that cattle is common agricultural labor in India (Basu, 2011), we can infer that the regions with lower cattle count have less cultivating activities and human disturbance. Agricultural land in regions with less human disturbance is more likely to be converted to forest; thus we observe a negative impact from cattle count.

In Bangladesh, socioeconomic drivers are more important than biophysical drivers, especially the economy category, particularly in the southern coastal regions of Bangladesh where aquaculture ponds are concentrated. Aquaculture has higher profits (Ali, 2006), the changes from aquaculture to forest (mangrove) could have large impacts on the economy. Therefore, we note greater importance of the economy on land conversions in Bangladesh. We also find that climate is important because of its impacts on aquaculture (Huq, Huge, Boon, & Gain, 2015).

4.3 | Implications

Our results have several practical implications. First, both biophysical and socioeconomic drivers strongly influence the inter-change between forest and agricultural land. However, our synthesis of case studies indicates that there are more studies discussing socioeconomic drivers than biophysical drivers (Figure 1 and Figure S5). Our results emphasize the importance of the biophysical drivers, especially for the change from agricultural land to forest. When opting to afforest and reforest, decision-makers should consider the local terrain, soil, water, climate conditions, as well as the impacts of natural disasters.

Second, the spatially explicit results show the high heterogeneity and complexity of the drivers of forest change. To understand deforestation, afforestation, and reforestation, one has to first get a thorough understanding of local conditions from both biophysical and socioeconomic aspects. We have reported and discussed the dominant drivers for 16 countries with large differences in socioeconomic conditions. The results improve our understanding of the key factors influencing deforestation, afforestation, and reforestation in each country. For example, livestock (category V) is the most dominant driver category for India and Indonesia for the conversion from forest to agricultural land. Meanwhile, for the changes from agricultural land to forest, livestock variables (category V) play important roles in this change in India, but terrain, soil, and water conditions are more important in Indonesia (category I). Both deforestation and afforestation (reforestation) are strongly impacted by livestock in India, suggesting local stakeholders could influence deforestation, afforestation, or reforestation through changes in livestock or grazing activities. In Indonesia, similar strategies may be effective in preventing deforestation. Meanwhile, terrain, soil, and water conditions are more critical for afforestation and reforestation in Indonesia.

Finally, the detailed drivers of forest change can be incorporated into land use downscaling models such as spatial dynamic allocation model to improve their projections (Meiyappan et al., 2014). Improvement of land use downscaling models can help bridge scales between human and earth systems, providing better LULCC projections in the future. In addition, these detailed drivers can also be incorporated in economic models estimating future LULCC, like GCAM (Wise, Dooley, Luckow, Calvin, & Kyle, 2014). Models like GCAM typically rely on profit to determine LULCC, but this study has shown that many other factors are important for driving these changes. Such integration is challenging in many aspects, such as the uncertainties of the spatially explicit driver datasets are high, the lack of future datasets, and the non-linear relationships between these drivers and other socioeconomic processes. To overcome these challenges, we could use the historical results (such as this study) as references for the future projection, adopt socioeconomic scenarios (such as the Shared Socioeconomic Pathways [SSPs]) to generate consistent biophysical and socioeconomic variables, and further study the relationships between LULCC drivers and different socioeconomic processes.

4.4 | Uncertainties and limitations

This study quantifies the biophysical and socioeconomic drivers of changes from forest to agricultural land and agricultural land to forest in SSEA for the first time. However, there are some caveats and limitations in this study.

First, although we have collected the spatially explicit proxy data to represent the important drivers identified from case studies, however, there are still some important drivers we do not have proxy data for, such as shifting cultivation (swidden), fuelwood (logging and charcoal), globalization (international trade), and forest management (policy), which are either difficult to quantify or lacking reliable gridded data. These drivers could have large impacts on either the change from forest to agricultural land or from agricultural land to forest. For example, shifting cultivation has large impacts on both changes (Bruun, Neergaard, Lawrence, & Ziegler, 2009); globalization (international trade) is linked to deforestation (Lopez & Galinato, 2005). The absence of the proxy data for these drivers may influence our results. However, the current availability of data does not allow us to include them; thus, we leave their incorporation to future studies.

Second, we should note that spatial and temporal inconsistencies existed between spatial proxy data and LULCC data (Table 2). These will introduce uncertainties in the driver analysis. Additionally, we have collected the proxy data for the drivers from global datasets rather than regional datasets. Some of the global datasets have not been calibrated against regional data in SSEA countries, which may have a relatively lower quality in our study area and thus influence quantitative driver results. We use these global datasets for several reasons. First, global datasets cover the entire study area. Regional datasets covering the entire SSEA are relatively rare. Second, our GWR analysis needs gridded driver proxy data to match with the gridded forest change data. Regional datasets are usually based on geopolitical units that may introduce additional uncertainties. Finally, the data used are from the best available global datasets in literature and are consistent at both spatial and temporal scales. This means that these datasets in different countries and time periods are comparable. In contrast, some regional datasets may not be consistent in spatial or temporal scale due to the different data sources and data quality. Therefore, while there are still inconsistencies and missing details in our datasets, our quantitative analysis is robust at the country scale in SSEA region.

Third, as mentioned in the "Synthesis of the Site Level Case Studies" section, we assume that the synthesized drivers of forest area loss and gain represent the drivers of the specific changes from forest to agricultural land and vice versa. This assumption may introduce noise and additional uncertainties into the driver synthesis, because the drivers of other LULCC activities (except for the interchanges between forest and agricultural land) are included and counted indiscriminately (since we also assume all mentioned drivers in case studies are equally important unless specified). However, the impacts of these assumptions on our quantitative driver results are limited, because these assumptions only influence the frequencies of different drivers (Figure 1), but are not directly related to the spatial proxies, which are collected regardless the frequencies of the drivers mentioned in the literature. Therefore, we believe the collected case studies represent the drivers of the changes from forest to agricultural land and vice versa.

Lastly, a country-by-country validation will further reinforce our findings. However, the quantitative studies at country level in SSEA are rare (nine studies), and the driver proxies used in these studies greatly differ. In this case, we have validated our result by comparing to a quantitative study in India and found a good match between two studies, strengthening our results.

By synthesizing the local-scale driver information of forest change and using quantitative models, this study provides insight into the complexity of LULCC processes. Unlike previous studies, which focus on socioeconomic drivers, this study highlights the importance of both biophysical and socioeconomic drivers. Generally, socioeconomic development increases food and land demands, driving people to convert forest to agricultural land if biophysical conditions are favorable. Agricultural land with less favorable biophysical conditions may be abandoned for tree regrowth or converted to forest plantations; reduced human disturbance and livestock pressure results in more forest regrowth. These driving processes vary across regions and countries, emphasizing the needs for region- and country-specific strategies for deforestation and afforestation. The biophysical and socioeconomic drivers identified can help to improve the accuracy of the LULCC modeling and projections that are important inputs to earth system models.

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ORCID

Xiaoming Xu https://orcid.org/0000-0003-1405-8089
Atul K. Jain https://orcid.org/0000-0002-4051-3228
Katherine V. Calvin https://orcid.org/0000-0003-2191-4189

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