**Introduction**

Deforestation from human activities is one of the biggest threats to biodiversity around the world (Estoque et al. 2019; Hoang & Kanemoto 2021), and the scale of land use change is such that the global climate is being affected (Jiao et al. 2017). The production and trade in agricultural commodities driven by modern consumption patterns is responsible for the majority of forest loss around the world (Curtis et al. 2018; Pendrill et al. 2019; Hoang & Kanemoto 2021). This is because agricultural production is a fundamental component of many national economies, both for improving food security within countries and for national income generation via international export markets (ref). Growth within agricultural sectors, and other natural resource-based industries, is therefore an important approach for lower income nations where economic development is a priority (Eliste & Zorya 2015; Caravaggio 2020b). Forests have been a casualty of economic growth throughout much of human history (Williams 2003), and little has changed in recent years; between 2005-2013 the expansion of commercial agriculture, plantations, and pastures were responsible for 62% of forest loss across the tropics and subtropics (Pendrill et al. 2019). Therefore, as developing nations strive for economic development, forests and other natural resources are exploited, often with negative consequences for biodiversity, climate change, local livelihoods, and environmental processes and services (ref).

*Economic development and deforestation*

There are several environmental economic theories that link economic development to forest loss, with the environmental Kuznets curve for deforestation (EKCd, Cropper & Griffiths 1994) and Forest Transitions (FT, Mather 1992) being the most studied and debated (Caravaggio 2020a). The ECkd predicts increasing rates of deforestation with increasing economic development until a tipping point is reached, after which further economic development (and associated shifts in the structure of economies) results in decreasing rates of deforestation until net forest loss changes to net forest gain (Bhattarai & Hammig 2004). Similarly, the FT theory predicts decreasing forest cover with increasing economic development, with the rate of forest cover loss accelerating until the tipping point, as described above, is reached, after which loss of forest cover slows. The point at which forest cover begins to increase is termed a forest transition (Lambin & Meyfroidt 2010). Thus, the EKCd and the FT curve are correlated yet inverse. Despite rampant deforestation in much of the tropics (ref), global deforestation rates are decreasing (FAO 2020). Recent studies provide evidence to support the EKCd theory, and suggest a possible move towards a global forest transition (Caravaggio 2020b). Indeed, there are multiple case studies demonstrating how individual countries have undergone forest transitions and are increasing national forest cover, including India (Bhattacharya et al. 2010), Vietnam (Meyfroidt & Lambin 2008), China (He et al. 2014), and South Korea (Youn et al. 2017). Nevertheless, there are still many countries where economic development and global demand for commodities are driving high rates of forest loss, often in some of the most biodiverse regions (Hoang & Kanemoto 2021). In addition to meeting the required economic conditions that precede forest transitions, effective governance relating to land use, forest protection, and agriculture is critical to ensure that forest transitions occur (Riggs et al. 2018). Understanding the relationships between both economic development and the agricultural sector on direct and indirect drivers of forest loss is crucial to develop appropriate policies, identify leverage points, and support effective governance*.*

*SEA and deforestation*

Southeast Asia (SEA) is characterised by complex biogeography and extensive tropical forest cover resulting in exceptional biological diversity, but has one of the highest deforestation rates in the world (Hughes 2017). The loss of SEA’s forests has potentially severe consequences for climate change (Ceddia et al. 2015), ecosystem-based adaptation (Estoque et al. 2019), local people (Poffenberger 2006; Culas 2007; Gaughan et al. 2009; Frewer & Chan 2014), and biodiversity (Hearn et al. 2018; Chapman et al. 2018). The drivers of tropical deforestation vary both by location and by scale, ranging from broader drivers such as population pressure and weak institutions (Geist & Lambin 2002), to proximate causes at a local level such as the expansion of cash crops, agriculture and other food production (Wilcove et al. 2013; Stibig et al. 2014; Imai et al. 2018; Zeng et al. 2018; Estoque et al. 2019), the associated development of roads and infrastructure that facilitate such expansion (Hughes 2018), and civil unrest and war (Kaimowitz & Fauné 2003; Price 2020). Despite the pressure on SEA’s forests, some countries have undergone forest transitions and are seeing net increases in forest cover (Youn et al. 2017). There are legitimate criticisms of the simplicity of traditional metrics of forest transitions; primarily that using the broadest interpretation of ‘forest cover’ ignores forest type or quality resulting in, for example, non-native plantations counting towards net forest gains (Kull 2017). Nevertheless, the reduction in the loss of native forests which are inevitably required to reach a forest transition should be celebrated.

In all Asian case studies of successful forest transition, state intervention has played a role (Youn et al. 2017). Government policies and legal frameworks that disincentivise forest clearance and promote sustainable land use are critical factors in facilitating behaviour change at all levels. Understanding the direct and indirect drivers of forest loss can be challenging as the processes are complex, operate at a variety of scales, and consist of multiple feedback loops and dependencies. Nevertheless, for effective government policies to be developed, researchers must strive to disentangle some of the relationships. As commercial agriculture is one of the most important drivers of forest loss around the world, and because it is a fundamental part of developing economies, it is critical to understand the links between economic development and commodity production, as this will reveal important implications for forest loss in developing countries.

*Economic land concessions*

Land acquisitions for commercial agriculture have become widespread in recent years, particularly in developing countries that have large areas of undeveloped land and that are striving for private investment to boost economic develop (Kugelman & Levenstein 2012). Such enterprises can improve agricultural productivity, stimulate local economies, and support rural development (Deininger & Byerlee 2011), yet face substantial criticisms for lacking transparent processes, abusing local land rights, and negatively affecting local livelihoods and biodiversity (Deininger & Byerlee 2011; De Schutter 2011; Davis et al. 2015). Cambodia saw an unprecedented surge in private land acquisitions via long-term leases for commercial agriculture, or ‘economic land concessions’ (ELCs), between 2000 and 2012, resulting in over 2 million hectares being leased by 2015 (Davis et al. 2015). Economic land concessions in Cambodia have faced enormous criticism due to widespread accusations of land rights abuses, corruption in the awarding of contracts, and extensive deforestation, even within protected areas (Vrieze & Kuch 2012; Global Witness 2013; Neef et al. 2013; Davis et al. 2015).

*Cambodia*

Cambodia has seen remarkably swift economic growth since the end of civil conflict in in the 1990s (Solcomb 2010), with much of the economic development built upon the growth of the agricultural sector (Eliste & Zorya 2015; Kong et al. 2019). This economic development has brought many benefits, including poverty reduction and food security (World Bank 2014), yet Cambodia’s forests have paid a heavy price for the expansion of the agricultural sector. Forest loss, even within protected areas, has increased as a result of the boom in ELCs (Watson et al. 2014; Davis et al. 2015). To minimise future forest loss and the associated loss of biodiversity, ecosystem services, and local livelihoods, Cambodia needs to reduce deforestation rates and move towards a forest transition by establishing appropriate policies, legal frameworks, and importantly, the governance to effectively implement such mechanisms. Identifying which development pathway Cambodia is on, and the measures that are required to move towards a forest transition, will require a greater understanding of the relationships between economic development, forest loss, and agriculture. There has been some research on drivers of forest loss in Cambodia, for example the direct effect of ELCs (Davis et al. 2015), drivers of deforestation in the north western uplands of the country (Kong et al. 2019), social and political factors influencing forest transition (Riggs et al. 2018), yet there have been no studies that investigate the relationships between macroeconomics, agriculture, and forest loss at the country scale.

In this study, we aim to address this research gap and provide quantitative evidence of relationships between measures of economic development, agricultural commodities, ELCs, and forest loss. For the period 1993 to 2015, we use generalised linear models to 1) model the relationships between the rate of forest loss and macroeconomic, commodity price, and producer price variables, and 2) model the relationships between the allocation of new ELCs and macroeconomic, commodity price, and producer price variables. Our results will provide important data to identify direct and indirect drivers of forest loss in Cambodia, aiding in the identification of leverage points, supporting the development of agricultural and forest policies, and contributing more widely to the forest transition literature for SEA.

**Methods**

*Study area*

This study investigated macroeconomic predictors of forest loss in Cambodia at the national scale between 1993 – 2015. Cambodia is in mainland SEA and is bordered by Laos (NE), Thailand (NW), Vietnam (E), and the Gulf of Thailand (SW) (Figure 1). The country has a surface area of 176,520 km2 (UNCTAD, 2020) and is located at latitudes 10-14° north of the equator and thus has a tropical monsoon climate (McSweeney et al. 2010).

Map

Description automatically generated

**Figure 1. Map of Southeast Asia with Cambodia highlighted in red.**

*Data sources*

National macroeconomic variables were acquired from publicly available sources (Table 1) for the period 1993 – 2015. Data on economic land concessions, protected areas, and elevation (digital elevation model), and shapefiles for the country, provinces, and communes were provided by the Royal Government of Cambodia (via the Wildlife Conservation Society). Forest cover layers were taken from the publicly available European Space Agency Climate Change Initiative (ESACCI) satellite data for the years 1993 – 2015.

*Variable selection*

The response variables were 1) change in forest cover (forest loss) from time *t* to time *t+1* and 2) the number of new economic land concession (ELC) allocations in year *t*. Macroeconomic and control variables were selected based on a combination of previous studies, data availability, and the authors’ knowledge of Cambodia. Macroeconomic variables were selected to create three sets of predictors, each targeting a different driver: economic development (n=8), commodity prices (external market forces, n=8), and producer prices (internal market forces, n=5) (Table S1, Nelson et al. 2006; Ewers 2006; Gong et al. 2013; Kuang et al. 2016; Fan & Ding 2016; Bonilla-Bedoya et al. 2018). Each predictor was hypothesised to be a driver of forest loss (Table S2). Human population density was included as a control variable for the economic set and total forest remaining was included as control variable across all sets, as both were expected to influence forest loss. Both per capita Gross Domestic Product (GDP) and amount of forest remaining were included to reflect the economic development path and the forest scarcity path respectively (Rudel et al. 2005; Lambin & Meyfroidt 2010). After pre-analysis checks for errors and correlation, the resulting variable set contained 20 variables (Table 1).

*Data processing*

The forest cover response variable was extracted from the ESACCI product by totalling the number of pixels (1 Pixel = 0.09km2) in each year classified as bands 50, 60, 61, 62, 70, 71, 72, 80, 81, 82, 90, and 100 (Table S4). Forest cover data processing was done in QGIS (QGIS Geographic Information System v3.16). The ELC response variable was created by summing the number of new ELC contracts that were dated in each year of the study period, resulting in a count of new ELCs per year. Predictor variables were checked for collinearity, and if two variables in the same set had a correlation coefficient of >0.6 then generally one was removed (Supporting Information). Forest cover was converted to change in forest cover using *forest covert+1 − forest covert*, where *t* represents year *t.* There were no periods of forest gain during the study period, and so the response can be considered as rate of forest loss. All predictors were converted from raw values to change in values using *Xt+1 – Xt,* where *t* represents year *t* (Barrett et al. 2006). The variable *forest remaining* was left as raw values (km2). Cambodia’s first general election and subsequent adoption of a free market economy occurred in 1993, resulting in unreliable GDP-related values for 1993 (Chhair & Ung 2013) and subsequent change values in 1994, and so these years were removed. Predictor variables were not centred or scaled prior to analysis because in this case the value of the intercept, in other words the value of the response *y* when the value of a given predictor *x* is 0 (i.e., there is no change in the predictor from time *t-1* to time *t*) is more meaningful than the value of *y* when the value of *x* is at its mean.

**Table 1. Variables selected for the macroeconomic analysis. Variables range from 1993 – 2015.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Predictor variable** | **Units** | **Resolution** | **Source** | **Details** |
| *Economy* |  |  |  |  |
| GDP per capita | Billions USD | National | World Bank | Constant 2010 rates |
| GDP growth | % | National | World Bank | Annual percentage growth rate of GDP at market prices based on constant local currency |
| Foreign Direct Investment | Millions USD | National | UNCTAD | Inward and outward flows and stock |
| Agricultural sector proportion of GDP | % | National | CNIS | Proportion of national GDP |
| Development flows to agriculture | Millions USD | National | FAO | Donor development investment flows, other official flows, and private donor flows at constant 2016 prices to all agriculture and forestry sub-sectors |
| Development flows to environment | Millions USD | National | FAO | Donor development investment flows, other official flows, and private donor flows at constant 2016 prices to general environment protection |
| *Commodity prices* |  |  |  |  |
| Crop Production | Index | National | FAO | Relative level of the aggregate volume of agricultural production for each year in comparison with the base period 2004-2006 |
| Non-food agricultural production | Index | National | FAO | Relative level of the aggregate volume of non-food agricultural production for each year in comparison with the base period 2004-2006 |
| Forestry production | m3 | National | FAO | Total production values for industrial roundwood, non-coniferous tropical wood, other industrial roundwood, sawlogs and veneer logs (coniferous and non-coniferous), and sawnwood (coniferous and non-coniferous |
| Price of rice | USD/ton | Global | World Bank | Median annual global market price of rice |
| Price of corn | USD/ton | Global | World Bank | Annual global market price of corn |
| Price of rubber | USD/ton | Regional | RASCE | Monthly regional market value of rubber on the Singapore Exchange |
| Price of sugar | USD/ton | Global | World Bank | Annual global market price of sugar |
| *Producer prices* |  |  |  |  |
| Producer price of Rice | USD/ton | National | FAO | Farmgate prices for Cambodian producers |
| Producer price of rubber | USD/ton | National | FAO | Farmgate prices for Cambodian producers |
| Producer price of cassava | USD/ton | National | FAO | Farmgate prices for Cambodian producers |
| Producer price of corn | USD/ton | National | FAO | Farmgate prices for Cambodian producers |
| Producer price of sugar | USD/ton | National | FAO | Farmgate prices for Cambodian producers |
| *Control* |  |  |  |  |
| Population density | pax/km2 | National | FAO | People per km2 |
| Forest remaining | Km2 | National | ESACCI | Raw value of forest remaining |

*Modelling*

This analysis aimed to model the relationships between changes in macroeconomic predictors and 1) the change in forest cover at a national level and 2) the allocation of new ELCs. Models were run for both response variables with each of the three variable sets: economic development, commodity prices, and producer prices. To account for the effect of time, a linear model of the response as a function of time (year) was run and the model residuals were extracted and used as a control predictor in all subsequent models (Crawley 2007). This process minimises the effect of time on changes in the response and reduces temporal autocorrelation. The amount of forest remaining (km2) was also included as a control variable in all models. Modelling was done using Generalised linear models (GLM) and followed an information theoretic approach (Burnham & Anderson 2007). For the models with rate of forest loss as the response both gaussian and gamma distributions were tested, and for the models with ELC allocation a Poisson distribution was used. Resulting models were compared using Akaike’s Information Criterion (AIC). Final rate of forest loss models used gaussian distributions. All predictors in each model set had been selected because of a priori hypotheses (Table S2), and so within each set all combinations of possible models were run and compared using AIC. Models with ∆AIC < 6 were considered to have sufficient support and retained in the final model set. Model averaging was implemented for the final model set, resulting in model-averaged coefficients for all model terms (Burnham & Anderson 2007). Models were run and averaged using the MuMIn package in R (Version 1.43.17, Bartoń 2020). This modelling procedure was repeated for a one-year time lag and two-year time lag as follows:

No time lag:

Where is the response at time , and is predictor variable at time.

One year time lag:

Where is the response at time , and is predictor variable at time.

Two year time lag:

Where is the response at time , and is predictor variable at time.

**Results**

*Forest loss*

During the study period 167,477 km-2 of forest was lost which represented nearly 16% of the total forest cover. The models for changes in the rate of forest loss as a function of macroeconomic predictors produced no strong effects (Figures 2 to 4). For each predictor set there were between 5 and 28 models in the top model set and final coefficients were calculated using full averages (Tables S9 – S17, Burnham and Anderson, 2007). The largest effect was from the control variable population density with a one-year time lag (full averaged coefficient = -632.9, SE = 64.8, Table S10). The largest effect excluding control variables was for agricultural proportion of GDP with a one-year time lag (full averaged coefficient = -14.9, SE = 7.9) suggesting, counterintuitively, that there is a small reduction in the rate of forest loss as the contribution of agriculture to national GDP increases, although this effect is very weak (Figure S2, Table S10) and therefore inference is limited.

*New economic land concessions*

There were 287 new ELCs allocated within the study period, with the majority (51%) being designated for rubber production (Table S18). The largest effect overall was for the economic control variable population density, where there were very strong negative effects across all time lags (rate ratios for one-year lag = 0.012, two-year lag = 0.002, three-year lag = 0.0005, Table 2), indicating that new ELCs do not get allocated in areas of high human population density. The largest overall effect excluding control variables was for changes in agricultural proportion of GDP with no time lag and a one-year time lag (no time lag rate ratio = 1.310, and one-year time lag rate ratio = 1.284, Table 2, Figure 5).

From an economic perspective there were positive relationships between the allocation of new ELCs and increases in the agricultural proportion of GDP and increases in foreign direct investment (one-year time lag rate ratio = 1.004, Table 2, Figure 5). These effects suggest ties between both the development of new ELCs and the growth of the agricultural sector, and the injection of foreign wealth into the sector via the purchasing of concessions by international companies. There was also a positive relationship between new ELC allocation and increases in development flows to the environment sector (no time lag rate ratio = 1.031). This suggests that in the short-term, investments into the environment sector via development funding (predominantly from international donors) does not reduce the number of new ELC allocations. There was a negative relationship between new ELC allocation and positive changes in per capita GDP (one-year time lag rate ratio = 0.985 and two-year time lag rate ratio = 0.974, Table 2, Figure 5). The reduction in ELC allocation as change in per capita GDP increases, over a period of one and two years, potentially suggests that there is a positive economic effect of ELCs.

The largest effect within the commodity set was for the change in market price of rice in the same year as the response (no time lag) with a rate ratio of 1.009 (Table 2). There were further strong positive relationships between the changes in the market price of rubber (no time lag rate ratio = 1.001), the changes in the non-food production index (one-year time lag rate ratio = 1.007), and changes in the market price of sugar (two-year time lag rate ratio = 1.009). There were three negative relationships between ELC allocation and commodity variables, all of which were in the same year as the response (no time lag, Figure 6). There were weak negative effects of changes in the market prices of corn (no time lag rate ratio = 0.997) and sugar (no time lag rate ratio = 0.999). Considering the stronger positive effects of sugar price on ELCs after one- and two-year lags, it is unlikely that the very weak negative effect in the same year as the response is meaningful. The non-food production index had a much stronger negative effect on ELC allocation when there was no time lag (rate ratio = 0.990). The change in direction of the effect of the non-food production index between no time lag and a one-year time lag suggests a complex relationship between the index and ELCs.

The producer price variable set, which reflects the farmgate prices of the commodities, had both positive and negative relationships with ELC allocation (Figure 4, Table 3). The strongest positive relationship was with changes in the producer price of rubber (no time lag rate ratio = 1.035). The effect of positive changes (i.e., net increases) in the price a farmer will get for rubber production can be seen in the predictions of new ELCs (Figure 4). There were also positive relationships between ELC allocation and changes in the producer price of corn (one-year time lag rate ratio = 1.011) and the producer price of rice (two-year time lag rate ratio = 1.013, Figure 4, Table 3). Corn and rice are less valuable in terms of absolute producer prices than sugar and rubber, and this may be reflected in the time lag that exists between positive changes in the prices and increases in new ELCs.

There were two negative relationships between producer price variables and new ELC allocations (Figure 4). Increases in the producer prices of rice and cassava resulted in fewer predicted ELCs in the same year (no time lag rate ratio = 0.976) and two years later (two-year time lag rate ratio = 0.982), respectively. The difference in the direction of the effect of rice producer prices in year *t* and year *t+2* (Figure 4) suggests that there is a complex relationship between rice production and new ELC allocation. The negative relationship between the producer price of cassava and new ELC allocation was strong (two-year time lag rate ratio = 0.982, Figure 4). Cassava is not a valuable crop, yet it was the third most designated crop for new ELCs during the study period (4.9% of new ELCs, Table S18). It is unclear what is driving the negative relationship between cassava and new ELCs after two years.

**Table 2. Parameter coefficients, standard errors, and rate ratios from the top model(s) in the macroeconomic analysis with rate of economic land concession allocation response. Missing values denote predictor variables that were not selected in the top model(s) for that lag period. Coefficients are on the log scale.**

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | ***No time lag*** | | |  | ***1 year time lag*** | | |  | ***2 year time lag*** | | |
| **Variable** | **Coefficient** | **SE** | **Rate ratioa** |  | **Coefficient** | **SE** | **Rate ratioa** |  | **Coefficient** | **SE** | **Rate ratioa** |
| ***Macroeconomic*** |  |  |  |  |  |  |  |  |  |  |  |
| GDP | - | - | - |  | -0.01500 | 0.00340 | 0.985 |  | -0.02600\* | 0.00390 | 0.974 |
| Agricultural proportion of GDP | 0.27000 | 0.07000 | 1.310 |  | 0.25000 | 0.06600 | 1.284 |  | -0.03400\* | 0.07600 | 0.967 |
| Development flows - agriculture | - | - | - |  | - | - | - |  | -0.00005\* | 0.00020 | 1.000 |
| Development flows - environment | 0.03100 | 0.00400 | 1.031 |  | - | - | - |  | -0.00260\* | 0.00450 | 0.997 |
| Foreign direct investment | - | - | - |  | 0.00360 | 0.00050 | 1.004 |  | 0.00040\* | 0.00060 | 1.000 |
| Population density | -4.43000 | 0.85000 | 0.012 |  | -6.09000 | 0.81000 | 0.002 |  | -7.68000\* | 0.95000 | 0.000 |
| Forest remaining | -0.00030 | 0.00004 | 1.000 |  | -0.00004 | 0.00004 | 1.000 |  | 0.00004\* | 0.00005 | 1.000 |
| ***Commodity / production*** |  |  |  |  |  |  |  |  |  |  |  |
| Change in median market price - corn | -0.00330 | 0.005697 | 0.997 |  | 0.00704\* | 0.00647 | 1.007 |  | -0.00365\* | 0.00329 | 0.996 |
| Change in median market price - rice | 0.009324 | 0.00198 | 1.009 |  | -0.00429\* | 0.00272 | 0.996 |  | 0.00004\* | 0.00058 | 1.000 |
| Change in median market price - rubber | 0.001247 | 0.00024 | 1.001 |  | 0.00019\* | 0.00022 | 1.000 |  | -0.00004\* | 0.00009 | 1.000 |
| Change in median market price - sugar | -0.00005 | 0.001931 | 1.00 |  | 0.00708\* | 0.00127 | 1.007 |  | 0.00877\* | 0.00124 | 1.009 |
| Non-food agricultural production index | -0.00995 | 0.00175 | 0.990 |  | 0.00672\* | 0.00264 | 1.007 |  | -0.00149\* | 0.00203 | 0.999 |
| Crop production index | - | - | - |  | 0.00042\* | 0.00144 | 1.000 |  | -0.00328\* | 0.00427 | 0.997 |
| Total production from forestry | - | - | - |  | 0.00000\* | 0.00000 | 1.000 |  | 0.00000\* | 0.00000 | 1.000 |
| Forest remaining | -0.00014 | 0.00002 | 1.000 |  | -0.00017\* | 0.00003 | 1.000 |  | -0.00013\* | 0.00003 | 1.000 |
| ***Producer prices*** |  |  |  |  |  |  |  |  |  |  |  |
| Producer price of corn | 0.00415 | 0.00355 | 1.004 |  | 0.01093\* | 0.00240 | 1.011 |  | 0.00014\* | 0.00081 | 1.000 |
| Producer price of rice | -0.02465 | 0.00436 | 0.976 |  | 0.00452\* | 0.00564 | 1.005 |  | 0.01258\* | 0.00474 | 1.013 |
| Producer price of rubber | 0.03424 | 0.00401 | 1.035 |  | -0.00075\* | 0.00228 | 0.999 |  | -0.00431\* | 0.00467 | 0.996 |
| Producer price of sugar | 0.00004 | 0.00010 | 1.000 |  | 0.00016\* | 0.00018 | 1.000 |  | 0.00000\* | 0.00006 | 1.000 |
| Producer price of cassava | 0.00032 | 0.00123 | 1.000 |  | 0.00006\* | 0.00076 | 1.000 |  | -0.01791\* | 0.00214 | 0.982 |
| Forest remaining | -0.00023 | 0.00002 | 1.000 |  | -0.00015\* | 0.00002 | 1.000 |  | -0.00013\* | 0.00002 | 1.000 |

\* Coefficients derived from full averaging of models within dAIC < 6. In some cases there was a single top model and therefore model averaging was not necessary.

A Rate ratio = exp(coefficient)

Chart

Description automatically generated with medium confidence

**Figure 2. Predicted relationship between rate of forest loss for Cambodia and macroeconomic variables. All y-axes are the amount of forest lost in km2. Points are the observed data, thick lines are model predictions, and faded ribbons are 95% confidence intervals. Row a: Gross Domestic Product (GDP), row b: agricultural sectors contribution (%) to GDP, row c: development flows to the agricultural sector (USD millions), row d: development flows to the environment sector (USD millions), row e: Foreign Direct Investment (USD millions).The left column of plots are the effects on forest cover at time t (i.e. the variable values and forest loss values from the same year), the middle column of plots are the effects at time t+1 (i.e. the effects on forest loss in the subsequent year), and the right column of plots are the effects at time t+2 (i.e. the effects on forest loss two years after the variable values).**

Diagram

Description automatically generated with low confidence

**Figure 3. Predicted relationship between forest loss and commodity variables. All y-axes are the amount of forest lost in km2. Points are the observed data, thick lines are model predictions, and faded ribbons are 95% confidence intervals. Row a: Crop Production Index, row b: Non-food Production Index, row c: median annual market price for rice (USD/t), row d: median annual market price for rubber (USD/t), row e: median annual market price for corn (USD/t), row f: median annual market price for sugar (USD/t), row g: total production from forestry (m3). The left column of plots are the effects on forest cover at time t (i.e. the variable values and forest loss values from the same year), the middle**

Chart, scatter chart

Description automatically generated

**Figure 4. Predicted relationship between forest loss and the producer prices (i.e. farmgate prices) variables. All y-axes are the amount of forest lost in km2. Points are the observed data, thick lines are model predictions, and faded ribbons are 95% confidence intervals. Row a: producer price for rubber (USD/t) row b: producer price for cassava (USD/t), row c: producer price for corn (USD/t), row d: producer price for sugar (USD/t). Left column of plots are the effects on forest cover at time t (i.e. the variable values and forest loss values from the same year), the middle column of plots are the effects at time t+1 (i.e. the effects on forest loss in the subsequent year), and the right column of plots are the effects at time t+2 (i.e. the effects on forest loss two years after the variable values).**

Chart

Description automatically generated

**Figure 5. Modelled relationships between economic predictors and the allocation of new economic land concessions in Cambodia between 1993 – 2015. Points are the observed data, black lines are model predictions, and coloured ribbons are 95% confidence intervals. Top row: no time lag between predictor and response; middle row: 1-year time lag between predictor and response; bottom row: 2-year time lag between predictor and response. Models had Poisson error structures with a log link; points and predictions were back-transformed to the original scale for plotting above.**

A picture containing diagram

Description automatically generated

**Figure 6. Modelled relationships between commodity price predictors and the allocation of new economic land concessions in Cambodia between 1993 – 2015. Points are the observed data, black lines are model predictions, and coloured ribbons are 95% confidence intervals. Top two rows: no time lag between predictor and response; third row: 1-year time lag between predictor and response; bottom row: 2-year time lag between predictor and response. Models had Poisson error structures with a log link; points and predictions were back-transformed to the original scale for plotting above.**

Diagram, engineering drawing

Description automatically generated

**Figure 7. Modelled relationships between producer price predictors and the allocation of new economic land concessions Cambodia between 1993 – 2015. Points are the observed data, black lines are model predictions, and coloured ribbons are 95% confidence intervals. Top row: no time lag between predictor and response; middle row: 1-year time lag between predictor and response; bottom row: 2-year time lag between predictor and response. Models had Poisson error structures with a log link; points and predictions were back-transformed to the original scale for plotting above.**

**Discussion**

In this study, we have modelled the relationships between macroeconomic variables and forest loss and the development of industrial-scale agriculture. We were unable to detect any significant effects of macroeconomic variables on direct forest loss, yet we have revealed some important relationships between macroeconomics and the development of new ELCs, from which we can make inferences regarding indirect drivers of forest loss. Understanding the relationships between economic development and deforestation is critical in countries that are undergoing rapid economic and social development such as Cambodia (Hughes & Un 2011), as it is within these conditions of socioeconomic transition that forest loss is often accelerated (Imai et al. 2018). Knowledge of these relationships can be used to develop land use policies that can guide a country through forest transition periods towards sustainable forestry (Culas 2012).

*Direct forest loss*

There were very few significant effects from the models with forest loss as the response variable. Some of the predictor variables have been shown to correlate with LUC in other studies, such as GDP (Ewers 2006; Gong et al. 2013; Kuang et al. 2016; Fan & Ding 2016), the contribution of economic sectors to national GDP (Gong et al. 2013), human population growth and density (Fan & Ding 2016; Bonilla-Bedoya et al. 2018), and agricultural output (Fan & Ding 2016). There are several possible explanations for the lack of effects in this study. First, previous studies have been at different scales to this study, such as global (e.g., Ewers, 2006), or sub-national (e.g., Gong et al., 2013), and therefore the drivers which are operating at those scales may be different to the drivers operating at the national scale in Cambodia. Second, Cambodia’s economy is a rare example of civil unrest and war resulting in economic collapse, followed by subsequent rapid economic revival (other Asian examples include Japan and Vietnam, see Hamada & Kasuya 1992 and Riedel & Turley 1999). This may render comparison of macroeconomic drivers of forest loss and LUC with other Asian countries ineffective. For example, Cambodia’s economy is in its infancy relative to many other countries in the region, and therefore forest loss during the study period may have been driven more by local drivers such as poverty, insecure land tenure, and land speculation by migrants, rather than national-level economics. Third, we did not include predictor variables covering institutional factors, land rights or tenure, or environmental policies, which have been shown to be important (Culas 2007). Finally, we only investigated up to two years of time lag between changes in predictor variables and changes in forest cover. It is possible that changes in certain macroeconomics take longer than two years to have a significant effect on forest cover. For example, the “trickle down” effect of foreign investment, whereby the local economies of the host nation see increased productivity and profitability which in turn may drive land use change and forest loss at the local scale, is smaller and more fragile than usually assumed (Jensen 2006). Therefore, if there is an indirect effect of foreign investment on forest loss, it may take several years for this effect to trickle down to forests at local levels.

*New ELCs*

In contrast, the macroeconomic variables were effective at predicting the allocation of new ELCs. Although ELCs do not guarantee deforestation (indeed not all ELCs are awarded on forested land), the deforestation rates within ELCs are up to 105% higher than comparable areas with no ELCs (Davis et al. 2015). There has also been widespread allocation of ELCs within forested community land and protected areas, resulting in the loss of important forest habitat, rural livelihoods, and indigenous land rights (Global Witness 2013; Watson et al. 2014). Therefore, ELCs themselves can be considered direct drivers of forest loss, rendering the macroeconomic predictors indirect drivers. Our results have demonstrated that during the study period, the national economy and economic development of the country, including increases in foreign investment, changes in the structure of national GDP, and fluctuations in agricultural commodity prices, were closely linked to the increase in ELCs, which in turn have been shown to drive forest loss (Davis et al. 2015; Watson et al. 2014).

*Economics*

There were clear relationships between the size of the agricultural sector, the rates of foreign investment, and the number of new ELCs. When the agricultural sector’s contribution to national GDP increases, so do the predicted number of new ELCs. For example, when the agricultural sector’s GDP proportion decreases by 3% in a given year relative to the previous year, the number of new ELCs allocated that year is predicted to be approximately 2, whereas when the sector’s GDP proportion increases in a given year by 1% relative to the previous year, the number of new ELCs is predicted to be 6. Likewise, when foreign investment into the country increases, so do the predicted number of new ELCs. For example, when the amount of foreign investment decreases by approximately $10 million relative to the previous year, the number of new ELCs one year later is predicted to be 3. Conversely, when foreign investment in a given year increases by approximately $300 million relative to the previous year, then one year later the number of new ELCs is predicted to be 10. Although our results do not describe causation, it is clear that there are important relationships between foreign investment, agriculture, and the development of new ELCs. Cambodia is likely to continue prioritising growth within the agricultural sector (Eliste & Zorya 2015), and neoliberal economic policies will continue to encourage foreign investment (Hughes & Un 2011; Green 2020; Phillips & Davy 2021). Therefore, it is likely that the development of industrial-scale commercial agriculture will continue. The process of awarding ELC contracts in Cambodia has been criticised for lacking transparency and for corruption (Vrieze & Kuch 2012; Neef et al. 2013), and so it is not always possible to identify who owns a particular concession. Nevertheless, of those identified (80% are identifiable), 48% were foreign owned (Licadho 2019). Despite real and perceived benefits of attracting foreign investment and promoting the expansion of cash crops (Li et al. 2018; Taylor et al. 2019), there are numerous negative effects on local people and the environment (Curtis et al. 2018; Zaehringer et al. 2020). Development of potential agricultural land by investors comes with opportunity costs for local people, who otherwise may have had access to the land, water, and other resources, and could have developed agriculture themselves that would have alleviated poverty more effectively than an externally owned commercial agricultural enterprise.

*Commodity and producer prices*

Changes in new ELC allocation can be effectively predicted by several key agricultural commodity prices, both on the international market and internally at the scale of the individual producer. Rubber, sugar, corn, and rice we all important variables in the models, and increases in the market prices and producer prices of these commodities can predict increases in the allocation of ELCs. Economic land concessions in Cambodia are predominantly agro-industrial concessions, and therefore the positive relationships between the price of agricultural commodities and new ELC allocations is not surprising. Rubber and rice are the most valuable market commodities within the variable set (Table Sx), and we can see this reflected in the model; if international rubber prices increase by $1500/ton, the model predicts an additional 29 new ELCs the following year, compared with an additional 4 if rubber prices do not change. Likewise, when the producer price of rubber decreases in value, very few new ELCs are predicted in the following year, but when prices increase by for example, $30/ton, in the following year 12 new ELCs are predicted. This suggests that producers are highly influenced by sale prices of commodities, particularly of high value products such as rubber, and that they will act quickly when there is the potential for financial gain. Similarly, if there is no change in the market price of rice between two given years, then approximately 5 new ELCs are predicted. If the market value increases by $300/ton then in year *t+1* approximately 80 new ELCs are predicted. Interestingly the effect of changes in sugar price were weak when there was no time lag, but the effect was stronger when both a one-year and two-year time lag were introduced.

The differences in the effects of commodity and producer prices on ELC allocation at different time lags is interesting, as it suggests that either investors will delay investing in a new crop for up to two years after the prices increase, or that the process of purchasing land and establishing an ELC venture can in some cases be a slow process. International market forces are known to drive LUC in Cambodia (Grogan et al. 2019), and globally, land conversion for commodity production is the single largest driver of deforestation (Curtis et al. 2018). Grogan et al (2015) provide an empirical example of how the international market price of rubber can drive deforestation in frontier areas of Cambodia and Vietnam. Our study reinforces this link between commodity and producer prices of key agricultural products and development activities which reduce forest cover.

*Conclusions*

Cambodia’s post-war economic recovery has been remarkably swift, boasting growth rates greater than any other Asian country excluding China (Solcomb 2010). On one hand this has benefited the Cambodian people through poverty reduction and improved access to services (World Bank 2014), yet on the other hand much of this economic growth has been built upon natural resource exploitation (Davis et al. 2015; Eliste & Zorya 2015) which has had negative effects on protected areas, forests, and local people (Vrieze & Kuch 2012; Global Witness 2013; Watson et al. 2014). Economic land concessions have proved a popular mechanism with which to direct foreign investment, expand industrial-scale commercial agriculture, and boost economic activity, yet have also been a key driver in deforestation. High rates of deforestation, in the context of Cambodia’s economic status and the rural population’s reliance on natural resources (Nguyen et al. 2015), suggests that the country is on the increasing deforestation trajectory of the EKCd (Bhattarai & Hammig 2004), whereby national economic development is improved at the expense of forest cover (Stern 2004). To eliminate forest loss, and begin moving towards possible afforestation, Cambodia will need to experience a forest transition.

Perhaps the most relevant case study to compare with Cambodia is that of its neighbour Vietnam, which underwent a forest transition in the 1990s, and over the next two decades national forest cover increased (Meyfroidt & Lambin 2008). Vietnam’s forest transition was driven by a combination of factors including land scarcity due to increasing human populations, reductions in hillside cultivation owing to land degradation and land use policies, increased productivity in existing agricultural lands, government policies that promoted smallholder forestry, increased demand for timber, and a scarcity of forest products that provided incentives for reforestation (Meyfroidt & Lambin 2008). Recent studies have highlighted Cambodia’s readiness for a forest transition; all of the necessary econometric milestones have been reached including robust government policies and legal frameworks, the promotion and expansion of tourism, integration into global markets for capital, commodities, and labour, and prevalent international conservation ideologies, yet deforestation rates are not decreasing (Riggs et al. 2018). Case studies of other Asian countries that have gone through forest transitions, including Vietnam, have highlighted the need for at least one element of effective governance (Clement et al. 2009; Bhattacharya et al. 2010; He et al. 2014). Governance failures at all levels in Cambodia are likely hindering progress towards more sustainable forest management and ultimately a forest transition (Milne & Mahanty 2015; Riggs et al. 2018).

Understanding which macroeconomic factors and agricultural commodities are driving land conversion via ELCs, the strength of the effects, the time lags, and the legal and institutional mechanisms that facilitate the link between prices and forest loss, is critical both for predicting future forest loss and identifying the appropriate institutional levels to target policy interventions. The opaque legal mechanisms and weak institutional frameworks that govern ELCs, natural resource management, and forest governance in Cambodia are likely to continue to hinder the development of sustainable forest and agricultural policies in the short term (Milne & Mahanty 2015). Industrial-scale agriculture in low income countries such as Cambodia are often criticised for failing to alleviate poverty or contribute to rural development, and often come with huge opportunity costs for local people, who would likely benefit more if they were given access to the land (De Schutter 2011). Furthermore, agro-industrial production of cash crops for international markets leaves the country open to price shocks and other suboptimal market fluctuations. Nevertheless, the agricultural sector is still a fundamental part of the national economy and labour force, and further agricultural development that embodies sustainability, increased productivity through improved technology, and value-addition via further processing rather than land expansion, can continue to contribute to national development and poverty alleviation without the need for further deforestation (Eliste & Zorya 2015).