**Introduction**

**Methods**

***Study area***

Map

Description automatically generatedThis 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).

**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 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**

*Rate of forest loss response*

Models revealed that there were no strong effects of the macroeconomic predictors on forest loss between 1993 and 2015 (Figures S2 – S4). 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 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 is not considered definitive.

*New economic land concession response*

There were 287 new ELCs allocated within the study period, with the majority (51%) being designated for rubber production (Table S18). The most valuable crop in terms of commodity price during the study period was rubber, with a mean market price of $1743/ton, followed by rice ($348/ton) and sugar ($282/ton, Table S18). The most valuable crop in terms of producer (farmgate) prices was sugar with a mean price over the study period of $2115/ton, followed by rubber ($317/ton) and corn ($197/ton, Table S18). The largest effect 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 3), 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 3, Figure 2).

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 3, Figure 2). These effects suggest ties between both the development of new industrial-scale concessions and the growth of the agricultural sector, and the injection of foreign wealth into the sector via the purchasing of concessions by international companies. For example, when the agricultural sector’s proportion of national GDP 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 proportion of national GDP increases in a given year by 1% relative to the previous year, the number of new ELCs is predicted to be 6. 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. The one-year time lag of the effect of foreign investment suggests that it takes approximately one year from the time of investment for a company to see the creation of their land concession. 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 3, Figure 2). 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. New concessions inject money into the national economy at various scales, for example at the national level via taxes to the government, and to the local level via employment opportunities and infrastructure development. Thus, as the economy grows, the need for new ELCs diminishes. For example, when GDP per capita in a given year falls by approximately $6 relative to the previous year, the number of new ELCs is predicted to be 8, whereas when the GDP per capita rises in a given year by approximately $60 relative to the previous year, the number of new ELCs predicted is only 3.

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 3). 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). Economic land concessions in Cambodia are predominantly agro-industrial concessions, and therefore the positive relationships between the market price of agricultural commodities and new ELC allocations is not surprising. Rubber and rice are the most valuable market commodities within the variable set, and we can see this reflected in the model; if rubber market prices do not change between years *t* and *t+1* then approximately 4 new ELCs are predicted in year *t+1*, whereas if the price of rubber increases by $1500/ton in year *t*, then approximately 29 new ELCs are predicted in year *t+1*. 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 (Figure 3).

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 3). 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 with no time lag 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). The difference between the number of ELC allocations when the producer price of rubber changes from a decrease of $30/ton (from year *t* to year *t+1*) to no change at all (i.e., the price remains constant) is approximately 3. In contrast, the difference in ELC allocation between no change in price and a positive change of $30/ton is more than 12. 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. 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. Rice production is the dominant agricultural crop in Cambodia and is the second most valuable commodity in terms of market value (Table S18). Yet only 1.7% of ELCs created during the study period were designated for rice production (Table S18), suggesting that rice production and price were not driving forces behind 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 3. 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

**Figure 2. Modelled relationships between economic predictors and the allocation of new economic land concessions in Cambodia between 1993 – 2015. 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.**

A picture containing diagram

Description automatically generated

**Figure 3. Modelled relationships between commodity price predictors and the allocation of new economic land concessions in Cambodia between 1993 – 2015. 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.**

Diagram, engineering drawing

Description automatically generated

**Figure 4. Modelled relationships between producer price predictors and the allocation of new economic land concessions Cambodia between 1993 – 2015. 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.**

**Discussion**

In this study, we have modelled the relationships between macroeconomic and socioeconomic variables and forest loss, forest cover, and the development of new ELCs. We have investigated these relationships at multiple scales using a variety of approaches and have revealed some important relationships from which we can make cautious inferences regarding direct and indirect drivers of forest loss. Furthermore, we have revealed key methodological issues, particularly around scale and model variance, that are likely to be common in these types of analyses, but which often remain unexplored or unreported in the literature.

There were very few significant effects in the macroeconomic analysis 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 unique within Asia because of the civil unrest and war, economic collapse, and subsequent rapid economic revival. 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). Fourth, we only investigated up to two years of time lag between changes in predictor variables and changes in forest cover. It is possible that the effects of macroeconomics on forest cover and LUC operate at a larger temporal scale than considered in this study.

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 economic development of the country was closely linked to the increase in ELCs, which in turn have driven forest loss. There were clear relationships between the size of the agricultural sector, the rates of foreign investment, and the number of new ELCs. 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, 48% were foreign owned (Licadho 2019). Despite real and perceived benefits of attracting foreign investment and expanding the production of cash crops, there are numerous negative effects on local people and the environment. 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 themselves developed agriculture that would have alleviated poverty more effectively than a commercial agricultural enterprise. Furthermore, agro-industrial production of cash crops for international markets leaves the country open to price shocks and other suboptimal market fluctuations (De Schutter 2011).

Changes in new ELC allocation can also be effectively predicted by several key agricultural commodity prices, both on the international market and internally at the farmgate scale. Rubber, sugar, corn, and rice we all important variables in the models, and increases in the market prices of these commodities can predict increases in the allocation of ELCs. Importantly, there were differences in the effects of commodity and producer prices on ELC allocation at different time lags, suggesting 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, 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. Understanding which commodities are driving land conversion, 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 for predicting future forest loss. The Cambodian Prime Minister issued a moratorium on new ELCs in 2012, which drastically reduced (although did not eliminate) ELC allocation. Although this has had a positive effect on forests, rural livelihoods, and indigenous land tenure, it is unclear how long this reprieve will last (Davis et al. 2015), or whether a new mechanism will emerge to replace ELCs. The opaque legal mechanisms and weak institutional frameworks that governed ELCs in the past are likely to continue to hinder the development of sustainable agricultural policies. The relationships between macroeconomics, commodity prices, and industrial-scale agriculture identified in this study are likely replicated across the region, and therefore these results will be of use to researchers and policy makers outside Cambodia.