**Results**

***Macroeconomic analysis***

*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 Sx – Sx). 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 Sx – Sx , Burnham and Anderson, 2007). The largest effects were from two of the control variables (population density, time). The largest effect overall was for population density with a one-year time lag (full averaged coefficient = -632.9, SE = 64.8, Table Sx). The largest effect excluding control variables was for agricultural proportion of GDP (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 Sx, Table Sx) 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 Sx). 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 Sx). 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 Sx). A greater number of effects were revealed in the macroeconomic analysis with new economic land concession allocation as the response. 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 x), 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 X, Figure X).

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 X, Figure X). 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 increases in per capita GDP (one-year time lag rate ratio = 0.985 and two-year time lag rate ratio = 0.974, Table X, Figure X). The reduction in ELC allocation as 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 X). 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 X).

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 X). 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 X, Table X). 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 X). 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 X, Table X). 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 X). 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 X) 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 Sx). Yet only 1.7% of ELCs created during the study period were designated for rice production (Table Sx), 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 X). Cassava is not a particularly valuable crop, yet it was the third most commonly designated crop for new ELCs during the study period (4.9% of new ELCs, Table Sx). It is unclear what is driving the negative relationship between cassava and new ELCs after two years.

***Socioeconomic analysis***

*Commune-level model*

Initial within-set model selection resulted in a final candidate set with 10 models and 13 unique variables (Table Sx). There was a single top model according to AIC (m1), with all other models having delta AIC values of more than 18 (Table Sx). The top model only had one non-control variable - population density (Table 4). The random effects term with the highest variance was Commune (10.45 [SD = 3.23], 60% of the total random effect variance), followed by Province (6.77 [SD = 2.60], 39% of the total random effect variance, Table 4). The variance explained by year at both the commune and province level was low (0.005 [SD = 0.068] and 0.0005 [SD = 0.022] respectively), contributing approximately 1% of the total random effect variance (Table 4). The marginal R2 (fixed effects only) was 0.78 (78%), and the conditional R2 (fixed and random effects) was 1, suggesting that the majority of the model variance was explained by the fixed effects. The largest positive effect was from mean elevation (rate ratio = 2.861, Table 4) which relates to 0.6 forest pixels (0.06 km2) predicted within an “average” commune (i.e., all other fixed and random effects set to their mean) when mean elevation is at the minimum within the country. When the mean elevation is at the maximum found within the country (and all other terms are set to their mean), the number of forest pixels predicted is 13,380 (1,204 km2). This highlights that higher elevation areas of Cambodia are much more likely to be forested than lower elevation areas. The strongest negative effect was from population density (rate ratio = 0.001, Table 4) which relates to approximately 1.5 predicted forest pixels (0.14 km2) at the minimum value of population density found within the country, contrasting with a prediction of effectively zero (2.22 × 10-16) forest pixels at the highest value of population density within the country. All other model terms, excluding the presence of ELCs, had positive effects on forest cover (Table 4). These effects suggest that remote communes (large distances to provincial capitals) that are centrally located within the country (far away from international borders) are predicted to have high forest cover. Interestingly, although the effects are weak, communes that contain ELCs are predicted to have lower forest cover than those without, and communes with protected areas are predicted to have higher forest cover than those without (Table 4).

The results from the final commune-level model must, however, be viewed with extreme caution because model validation revealed some serious underlying issues. As is suggested by the variance associated with the commune-level random effect term, there was extreme variation between communes for all variables (predictors and response, Figure 4). This between-group variance results in the model being unsuitable for generalised (i.e., ‘global’) predictions (Figure 4). Intercept and slope estimates between communes, even within the same province, varied hugely (Figure 5), and this issue was highlighted in diagnostic plots where we see that the assumption of normality of deviations of the conditional means of the random effects (for commune) from the global intercept is violated (Figure Sx). Furthermore, the model residuals displayed heteroskedasticity, with the model predicting particularly poorly for lower values of the response (Figure Sx). Therefore, drawing general inferences about the relationships between forest cover and socioeconomics at the country level using this model is inappropriate.

*Province-level model*

The province-level models were run to eliminate the commune-level variation and to identify any broader relationships between forest cover and socioeconomics. A candidate set of 19 models was built and an evaluation of AIC selected a single model (m8) as the top model (Table Sx). Model m5 had some support (delta AIC = 5, Table Sx) but was a simpler version of m8 and therefore inferences were drawn from m8 alone. The random effects term with the highest variance was Province (1.18 [SD = 1.08], which constituted XX% of the total random effects variance), followed by year (0.006 [SD = 0.077], which was XX% of the total random effects variance). Sentence about the marginal and conditional R2. Presence of ELCs and presence of PAs had the largest two positive effects relative to their refences levels (no ELCs, no PAs), suggesting that provinces that have those two features are predicted to also have higher forest cover (rate ratios = 1.51 and 1.64 respectively). In provinces where the proportion of males in school and distance to school are both low, higher levels of forest cover are predicted compared with provinces where these variables are high. Furthermore, in provinces where elevation, distance to an international border, and distance to the provincial capital are low, forest cover is predicted to be higher than in provinces where these variables are high. However, all the above effects are very weak (Figures 6 & 7). For example, the difference in the predicted number of forest pixels between a province with a low proportion of males in school and a province with a high proportion (with all other variables set to low), is XX. The difference in the number of predicted forest pixels between a province with low median distances to schools and a province with high median distances (with all other variables set to low), is XX. Presence of PAs had the largest effect on predicted forest pixels. The number of forest pixels predicted for a province with PA presence is XX higher than for a province with no PA presence. The size of the effects in the top model, particularly for the two socioeconomic predictors (proportion of males in school, and distance to school), suggest that these variables have very little power to predict forest cover at the provincial level in Cambodia.

**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.**

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | ***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.

A Rate ratio = exp(coefficient)

Chart

Description automatically generated

**Figure 1. 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 2. 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 3. 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.**

**Table 4. Model outputs and rate ratios from the top models from the socioeconomic analysis. Outputs are for the commune-level analysis and the province-level analysis. Reported coefficients are on the link (log) scale.**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **Variance** | **Std.Dev** | **Coefficient** | | **SE** | **Rate ratio*a*** |
| ***Commune-level final model*** |  |  | |  |  |  |
| *Random effects* |  |  |  | |  |  |
| Commune (intercept) | 10.4500 | 3.2334 | - | | - |  |
| Year/Commune (slope) | 0.0046 | 0.0680 | - | | - |  |
| Province (intercept) | 6.7730 | 2.6025 | - | | - |  |
| Year/Province (slope) | 0.0005 | 0.0220 | - | | - |  |
| *Fixed effects* |  |  |  | |  |  |
| Intercept | - | - | -4.6240 | | 0.5620 |  |
| Population density | - | - | -7.5140 | | 1.1270 | 0.001 |
| Mean elevation | - | - | 1.0510 | | 0.1220 | 2.861 |
| Distance to In'tl border | - | - | 0.5805 | | 0.2036 | 1.787 |
| Distance to Provincial capital | - | - | 0.6929 | | 0.1114 | 2.000 |
| ELC presence | - | - | 0.0000 | | 0.0025 | 0.999 |
| PA presence | - | - | 0.0093 | | 0.0143 | 1.009 |
| ***Province-level final model*** |  |  |  | |  |  |
| *Random effects* |  |  |  | |  |  |
| Province (intercept) | 1.1762 | 1.0845 | - | | - |  |
| Year/Province (slope) | 0.0058 | 0.0765 | - | | - |  |
| *Fixed effects* |  |  | - | | - |  |
| Intercept | - | - | -2.9900 | | 0.4497 |  |
| Males in school (low) | - | - | 0.0051 | | 0.0019 | 1.002 |
| Distance to school (low) | - | - | -0.0174 | | 0.0022 | 1.002 |
| Mean elevation (low) | - | - | -0.0223 | | 0.0024 | 1.002 |
| Distance to border (low) | - | - | 0.0061 | | 0.0019 | 1.002 |
| Distance to Prov capital (low) | - | - | -0.0072 | | 0.0019 | 1.002 |
| Presence of economic concessions (1) | - | - | 1.9974 | | 0.4090 | 1.505 |
| Presence of PAs (1) | - | - | 2.8063 | | 0.4965 | 1.643 |

*a* Rate ratio = exp(coefficient)

Chart, scatter chart

Description automatically generated

**Figure 4. Predicted relationships (red lines) between socioeconomic variables and forest cover in Cambodia between 2007 – 2012 from the top commune-level model. Predictions are ‘global’ i.e., all random effects were set to their mean values, and thus predictions are not for any specific commune. Black dots are the raw data points of each predictor versus forest cover.**

Diagram, shape, arrow

Description automatically generated

**Figure 5. Predicted relationships between population density and forest cover within Cambodian provinces between 2007 – 2012 using the top commune-level model. Faded grey lines are the predictions for each individual commune within each province. Black lines are the mean provincial predictions, which were computed using the 50% quantile from all commune predictions. Plot panels have non-standard y axis ranges.**

A picture containing diagram

Description automatically generated

**Figure 6. Predicted forest cover within each Cambodian province given high and low levels of school attendance (males aged 6 – 24 in school) from the top province-level model. All other variables in the model were set to their reference level (distance to school = low, elevation = low, distance to international border = low, distance to provincial capital = low, economic land concession = yes, protected area = yes).**

A picture containing diagram

Description automatically generated

**Figure 7. Predicted forest cover within each Cambodian province given high and low distances to the nearest school from the top province-level model. All other variables in the model were set to their reference level (school attendance = low, elevation = low, distance to international border = low, distance to provincial capital = low, economic land concession = yes, protected area = yes).**

Socioecon models – report marginal and conditional R2