**Methods**

***Study area***

This study investigated macroeconomic and socioeconomic predictors of forest cover and loss in Cambodia at two different spatial resolutions over two time periods. The macroeconomic analysis was at the national scale between 1993 – 2015, and the socioeconomic analysis was at the scale of a) the commune, and b) the province between 2007 – 2012. Cambodia is in mainland SEA and is bordered by Laos (NE), Thailand (NW), Vietnam (E), and the Gulf of Thailand (SW) (Figure x). 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).

***Variable selection***

The response variables for the macroeconomic analysis were 1) change in forest cover from time *t* to time *t+1* and the number of new economic land concession (ELC) allocations in year *t*. The response variable for the socioeconomic analysis was forest cover area. Both forest cover response variables were produced from the same data source (see “Data sources” below). Macroeconomic, socioeconomic, and control variables for both sets of analysis 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=10), commodity prices (external market forces, n=8), and producer prices (internal market forces, n=5) (Nelson et al. 2006; Ewers 2006; Gong et al. 2013; Kuang et al. 2016; Fan & Ding 2016; Bonilla-Bedoya et al. 2018). 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).

Socioeconomic variables were selected to create 8 variable sets reflecting different aspects of socioeconomic status and development (Luck et al. 2009; Ty et al. 2012; Kristensen et al. 2016; Bonilla-Bedoya et al. 2018). The variable sets were population demographics (n=8), education (n=4), employment (n=5), economic security (n=2), access to services (n=4), social justice (n=2), migration (n=2), and control variables (n=6). Control variables were included to account for the effects of environmental and other human factors including economic land concessions (Abdullah & Nakagoshi 2007; Davis et al. 2015), protected areas (Bonilla-Bedoya et al. 2018), elevation (Ty et al. 2012), and distance to human infrastructure (Ty et al. 2012). A habitat control variable was excluded because the response variable (forest cover) was extracted from a land cover layer and represented a specific type of habitat, resulting in non-independence between the response and habitat.

***Data sources***

National macroeconomic variables were acquired from publicly available sources (Table 1) for the period 1993 – 2015. Fine-scale socioeconomic variables were extracted from the Cambodian Commune Database for the years 2007 – 2012 (Table 2) which are available from Open Development Cambodia ([www.opendevelopmentcambodia.net](http://www.opendevelopmentcambodia.net)). 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 European Space Agency Climate Change Initiative (ESACCI) satellite data for the years 1993 – 2015.

***Data processing***

The forest cover variable (response) for both analyses 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 Sx). For the macroeconomic analysis, the total forest cover for the whole country was used, and for the socioeconomic analysis the forest cover layer was further stratified into forest cover per commune and province. Forest cover data processing was done in QGIS (QGIS Geographic Information System v3.16). For both analyses, 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).

*Macroeconomic analysis*

Forest cover was converted to change in forest cover using *forest covert+1 − forest covert*, where *t* represents year *t.* 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 were removed. To simplify interpretation, predictor variables were not centred or scaled prior to change calculations or modelling.

*Socioeconomic analysis*

Data from the Commune Database were at the resolution of individual village, and so the selected variables (Table 2) were aggregated to the commune and province level after error checking and cleaning (Supporting Information). Some variables were converted from raw values to proportional data to account for large differences in commune and province size and human population (Table 2). Data were checked for errors and inconsistencies in R (Supporting Information, R Core Team, version 4.0).

***Modelling***

*Macroeconomic models*

This analysis aimed to model the relationships between changes in macroeconomic predictors and 1) the rate of forest loss at a national level and 2) the allocation of new ELCs, both for the time period 1993 – 2015. 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. 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). Both gaussian and gamma distributions were tested and resulting models were compared using Akaike’s Information Criterion (AIC). Final models used gaussian distributions. All predictors in each model set had been selected because of a priori hypotheses (Table Sx), 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). 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.

*Socioeconomic models*

This analysis aimed to model the relationships between forest cover and socioeconomic variables within communes between 2007 – 2012. The results of initial commune-level modelling prompted further aggregation of the data to the province-level and models were built to investigate the relationships between forest cover and socioeconomic variables within provinces for the same time period.

*Commune-level models*

Generalised linear mixed models (GLMM) were used with commune nested within province as random intercept terms to account for repeat measurements and the hierarchical data structure, and year as a random slope term to account for temporal autocorrelation (Zuur et al. 2009). The natural logarithm of commune area (km2) was used as an offset term in all models to account for large variation in commune size. Due to the large number of available predictor variables, maximal within-set models were run first for each of the 8 variable sets (Table Sx), and variables with very weak, or no effect were dropped. This process resulted in a final set of 13 variables which were included in a global model. Global model complexity was reduced stepwise by removing the variable with the weakest effect at each step until all remaining variables were either significant based on approximate p values or had a large coefficient. The complexity of mixed models makes the assessment of term significance challenging, and so effect sizes were assessed via predictions and plotting before removal to ensure no significant effects were missed. The resulting final model fit was assessed via diagnostic plots (residuals versus fitted, quantile-quantile of random effects, Supporting Information, Harrison et al (2018)). Marginal (fixed effects only) and conditional (fixed and random effects) R2 values were calculated based on Nakagawa & Schielzeth (2017) using the R package ‘MuMIn’ (Bartoń 2017). To investigate the variation in effects between provinces, predictions were made for each variable within each commune and the 50% quantile from all commune-level predictions in each province was extracted as the provincial mean prediction, with the 2.5 and 97.5% quantiles extracted as ‘variation intervals’.

*Province-level models*

The same GLMM model formulation was used for the province-level models except that commune was removed from the random effects structure. Based on provincial-level histograms of predictor variables, 14 predictors were converted to categorical variables by splitting the data by the mean, resulting in “high” and “low” values (Table 2) and maximal within-set models were run.

***Cluster analysis***

Agglomerative clustering was conducted to create a typology for provinces based on the socioeconomic variables used in the analysis above. Several agglomerative clustering approaches were assessed and compared using cophenetic correlation and Gower distance metrics, and the appropriate number of clusters (k) was selected using the matrix correlation statistics (Borcard et al. 2018).