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To measure the deforestation reduced by a policy, we need to compare deforestation rates under a policy with deforestation rates in the absence of policy. Unfortunately the deforestation rate in the absence of a policy, or reference rate, is ex ante difficult to forecast and ex post impossible to observe. This means that reference rates will be set with error and we will not know how large the error will be. The challenging nature of setting reference rates is reflected in the number of proposals for reference rate design. In this paper I show how these proposals ignore forecast error. As a consequence, these proposals have basic structural weaknesses that in- crease the costs of reduced deforestation policy. I propose that a criteria for reference rates is to minimise the cost of forecast error. These ideas are illustrated with a cross country dataset on agricultural expansion. I show that the best forecasting model differs by country and that a country's best forecasting model can be very simple.

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Climate policy, reduced deforestation, forecasting

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The costs of error in setting reference rates for reduced deforestation

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20 August 2014

Abstract

To measure the deforestation reduced by a policy, we need to compare deforestation rates under a policy with deforestation rates in the absence of policy. Unfortunately the deforestation rate in the absence of a policy, or reference rate, is ex ante difficult to forecast and ex post impossible to observe. This means that reference rates will be set with error and we will not know how large the error will be. The challenging nature of setting reference rates is reflected in the number of proposals for reference rate design. In this paper I show how these proposals ignore forecast error. As a consequence, these proposals have basic structural weaknesses that increase the costs of reduced deforestation policy. I propose that a criteria for reference rates is to minimise the cost of forecast error. These ideas are illustrated with a cross country dataset on agricultural expansion. I show that the best forecasting model differs by country and that a country's best forecasting model can be very simple.

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1 Introduction

A policy reduces deforestation when deforestation rates with policy are lower than the rate would have been in the absence of policy. Whilst this assertion is almost trivial, it raises a deep, practical problem for a reduced deforestation policy: what will future deforestation rates be in the absence of a policy to reduce deforestation? The answer to this question is known as a counterfactual. The counterfactual can be used in policy design as a target for the reference rate.[1] The reference rate determines the total compensation payment a country receives (Brown et al. 2007, Angelsen 2008, Sloan et al. 2012). If a country's emissions rate is less than their reference rate, compensation for the difference between the reference rate and emissions rate will be provided. Where the country's emissions from deforestation and forest degradation are greater than the reference rate, no compensation is paid (Eliasch 2008, Angelsen 2008).

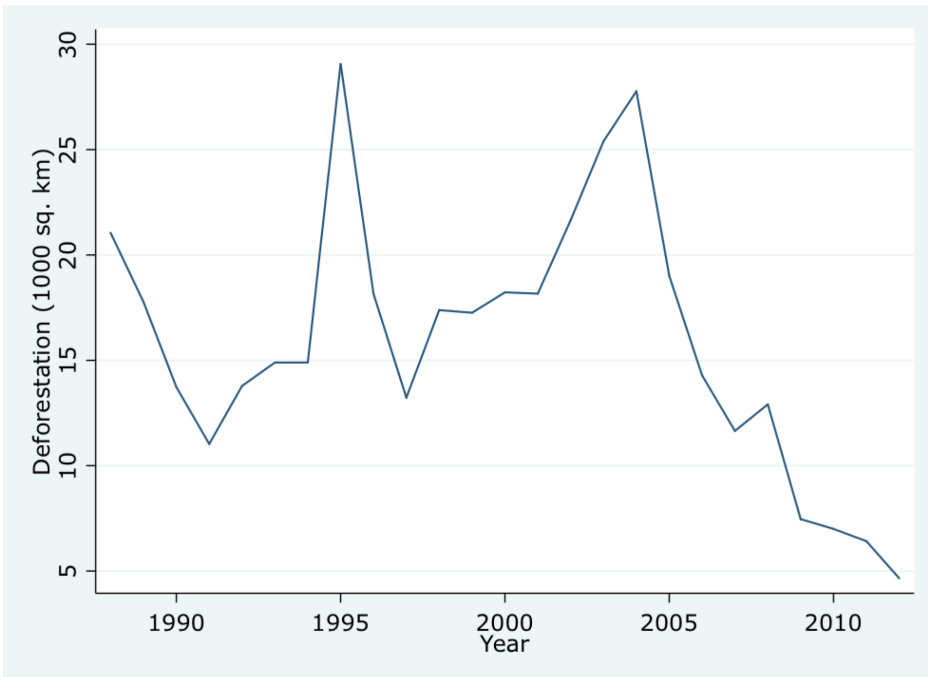
There are two main problems in setting a reference rate. First, the reference rate is a prediction of the counterfactual. Although we have a grasp of the drivers of deforestation (Angelsen and Kaimowitz 1999, Pfaff et al. 2013), predicting future deforestation rates is difficult. Figure 1 shows the variability in deforestation levels over time in the Legal Amazon.[2] Only a remarkably prescient (or lucky) analyst in 1993 could have predicted the following few years' deforestation levels with accuracy. It is almost certain that any reference rate will differ from the counterfactual. The second problem is that we would like to know ex post what would have been the deforestation rate in the absence of a policy. It is well known that the counterfactual is impossible to observe (Holland 1986). For if a policy is implemented, one cannot simultaneously observe what would have occurred in the absence of policy. In short, we are likely to have had *forecast error*,

[1] Otherwise known as a reference level or baseline. I use the term reference rates in this paper as the empirical exercise is in terms of rates

[2] A socio-geographic jurisdiction, containing all of the Brazilian Amazon, and only the Amazon within Brazil.

the difference between the reference rate and the counterfactual, and have no way of knowing how large this forecast error was.

Figure 1: Deforestation in the Legal Amazon. Source: (INPE National Institute of Space Research 2013)



In this paper I discuss this problem. I show how current proposals for setting reference rates do not seek to manage forecast error, leading to errors that are higher than necessary. By focusing on the forecast error, attention is drawn to the asymmetry in forecast error: a given overestimation of deforestation is not the same as a given underestimation. Given this asymmetry, I propose that a criteria for reference rates is to minimise the cost of forecast error. Such a criteria is absent from both the academic and policy discussions surrounding baselines (Griscom et al. 2009, UNFCCC Secretariat 2009, Subsidiary Body for Scientific and Technological Advice (SBSTA) 2011).

These ideas are illustrated through the investigation of agricultural land expansion rates across a sample of tropical countries. With this data I provide evidence that the costs of forecast error are likely to be exacerbated with current proposals for setting a reference rate. Many reference rate proposals rely on extrapolation of recent years' deforestation, imposing a single model of deforestation across participating countries. I show that both of these assumptions lead to higher forecast error: historical rates of agricultural land expansion are a poor predictor of future agricultural land expansion[3] and the most accurate forecast models differ by country. Alternative proposals use more complicated economic models with many variables (Brown et al. 2007, Eliasch 2008, Griscom et al. 2009, Corbera et al. 2010, Sloan et al. 2012). I also show that simple models can outperform more complicated models, running counter to intuition that complicated models generate more accurate forecasts (Pirard and Karsenty 2009).

Whilst not mapping perfectly to deforestation or emissions from deforestation, agricultural land is often used to empirically investigate deforestation.[4] This is because agricultural land expansion is one of the main proximate causes of tropical deforestation (Gibbs et al. 2010, Geist and Lambin 2002, Chomitz et al. 2007). The benefit of using this data is that the forecasts generated are country specific, using a broadly comparable cross country data set.

Forest cover data would be preferred; however, forest cover data is currently measured with considerable error (Angelsen 2008). Tropical deforestation occurs in some of the more remote regions of the planet, and collecting such information is costly. Even from modern satellite technology can it be difficult to distinguish trends in forest cover (Mayaux et al. 2005). Further, measuring how carbon stocks vary across the landscape is also difficult (Grassi et al. 2008). Some proposals are explicitly designed with data quality in mind (Mollicone et al. 2007, Grassi et al. 2008).

Measurement error is only a sufficient condition, and not a necessary condition of incorrectly set reference rates. Also required is that the data be used to predict future

[3] This has been noted previously: "past deforestation is not a very accurate predictor of future deforestation" (Angelsen (2008, p. 472) citing evidence from Haughland (2008)).

[4] For example, Barbier et al. (2005), Arcand et al. (2008)

deforestation. Prediction fundamentally differs from explaining or summarising the past. To *predict* deforestation, a model uses past data to explain future events. To *explain* deforestation, a model uses past data to explain past events.

For example, the relationship between roads and deforestation is investigated using data on the placement of roads and nearby deforestation (Chomitz and Gray 1996, Pfaff 1999, Deng et al. 2011). Explaining deforestation takes the density of roads at a given point in time and investigates the correlation with deforestation at that point in time.[5] Now compare explanation with prediction. Data on roads at a given point in time would be used to predict deforestation in subsequent periods.

The objective with explanation is to construct a model that explains as much of the variation in deforestation through through variation in explanatory variables like road networks. The objective in prediction is to construct a model that reduces the difference between the prediction and realised deforestation, or the forecast error.

Since the objectives across explanatory and predictive models differ, so does the criteria for selecting the best model. As both the explanatory variables and the variable being explained are in the same sample of data, criteria for assessing explanatory models can be termed *in sample criteria* (Auffhammer and Steinhauser 2012). Examples of in sample criteria include information criteria (Akaike or Schwarz), and (adjusted) R^2. On the other hand, as a prediction is outside of the sample used to generate the prediction, the criteria used to assess prediction is termed *out of sample* criteria. Examples of out of sample criteria include the mean squared error and the mean absolute error.

As reference rates are predictions of future emissions from deforestation and forest degradation in the absence of policy, it follows that in selecting models for reference

[5]Throughout this paper, the focus is on accounting for the variation in the dependent variable, and so correlations suffice. Where the identification of causality is the objective, more structure in the model is required.

rates out of sample criteria are relevant.[6]

The limits of the data used in this paper are fully acknowledged. My objective here is not to construct reference emissions rates. My objective is to illustrate the assumptions currently underpinning the setting of reference rates. In illustrating these assumptions, the analysis provides some guidance for the use of data improvements expected to arise over the next decade (United Nations Framework Convention on Climate Change 2009).

The paper proceeds as follows. In the next section various proposals for reference rates, and their shortfalls are discused. How deforestation can be forecasted is explained in section 4. Section 5 presents the data. The results of agricultural land expansion forecasts for a suite of models are presented in section 6.

2 The costs of incorrectly set reference rates

Costs arising from forecast error are inevitable. The costs are large, with one estimate suggesting that depending on the reference rate, Indonesia could stand to gain anywhere from 0 (and not participating in a REDD+[7] policy), to USD 3 billion from participating in a REDD+ policy (Angelsen 2008).

Managing the costs of forecast error is not simply a matter of improving the precision of predicting the counterfactual rate of emissions. The nature of the costs depends on the direction of the error. Where the reference rate of emissions is above counterfactual emissions, two different types of costs emerge. First, compensation for deforestation reductions will exceed the opportunity cost of participation. These additional payments are a windfall to the deforesting nation, are not required to provide an incentive to reduce deforestation and could be used to reduce emissions elsewhere. This leads to

[6] Griscom et al. (2009) use out of sample methods to compare reference rate proposals. Unfortunately, there is only one forecast error per proposal. One can only make limited claims about the performance of reference rates based on a sample size equal to one.

[7] Or Reduced Emissions from Deforestation and forest Degradation

an opportunity cost of foregone deforestation reductions. Further, it is possible that a nation may have its cake and eat it through receiving compensation without deviating from counterfactual emissions rates.

Second, costs also arise when a high reference rate is interpreted as the true counterfactual rate of deforestation. If these permits are traded in global carbon markets, permits are issued for reduced deforestation that did not occur. These permits, often termed 'hot air' (Eliasch 2008, Corbera et al. 2010), no longer represent mitigated carbon and reduce the effectiveness of global climate mitigation efforts. An additional cost is that the lower carbon prices brought about by increased supply may make other genuine emissions reductions projects unviable.

On the other hand, a reference rate could be below the counterfactual level of emissions. Under this scenario the deforesting nation may not be fully compensated for the opportunity costs of reducing deforestation and forest degradation. This missing compensation reduces the value of participation to the deforesting nation, lowering the likelihood of participation.

Further, with other countries receiving compensation for reducing emissions from deforestation and forest degradation, non participation potentially carries an additional cost of carbon leakage. Carbon leakage is the change in emissions that arises due to a policy induced decrease in emissions elsewhere. So not only does a country not reduce emissions with a low reference rate, the country may deforest more than they otherwise would.

Since the costs of forecast error depend on the sign of error, minimising the error will not minimise the overall costs of error. Suppose a forecast overestimating the the future counterfactual will be more costly than an underestimate. That is, hot air is more costly than non participation.[8] This being the case, having a slightly lower reference rate than

[8]Some proposals have been designed to reduce or eliminate the costs of hot air (Grassi et al. 2008,

the best estimate of the counterfactual could lower the expected costs of implementing a REDD+ policy. Minimising the costs of error as an objective, rather than minimising error, is consistent with the broader notion of reducing emissions at least cost.

3 Existing reference rate proposals

In this section, existing reference rate proposals are discussed. Attention is drawn to two reasons why the costs of forecast error are exacerbated with current proposals.[9]

Table 1 summarises the structure of baselines for various REDD+ policy proposals. The selction is based on the summaries Griscom et al. (2009) and Busch et al. (2009), with additional proposals included. The majority of these reference rely on historical reference rates to set their emissions targets.

Table 1: The structure of various reference rate proposals.

Proposal	Baseline structure
Santilli et al. (2005)	Historical average
Mollicone et al. (2007)	Historical average, higher than historical for historically low deforestation countries.
Strassburg et al. (2009)	Weighted combination of global and national historical rates
Woods Hold Research Center (2008)	Historical average, with payments withheld for stocks
Terrestrial Carbon Group (2008)	Constant rate = 1/50th carbon stocks
Joanneum Research (2006)	Corridors based on historical averages
Grassi et al. (2008)	Baselines constructed using historical averages
Herold et al. (2012)	Forecasting without forecast errors
Combes-Motel et al. (2009)	Compensate efforts rather than reduced deforestation
Pirard and Karsenty (2009)	Compensate efforts rather than reduced deforestation

Combes-Motel et al. 2009).

[9]For a model based approach to comparing baselines, see the recent working paper by Pana and Gheyssens (2013).

Santilli et al. (2005) offered the concept of 'compensated reductions' for a RED policy,[10] which is based on the Certified Emissions Reductions in the Clean Development Mechanism.[11] The reference rate was set to the historical rate of deforestation over some time period, "[a]ny historical average since the 1970s ... would be adequate" (Santilli et al. 2005, p. 270). The authors do not express any concern over the accuracy of the reference rate, nor the costs of a mistaken reference rate. "The principle in all cases is to set baselines in terms of historic deforestation or destruction of carbon stocks and create incentives for progressive reductions, or avoiding future increases." (Santilli et al. 2005, p. 270).

Mollicone et al. (2007) noted that one limitation of the use of historical reference rates as a determinant of baselines is that nations with low historical deforestation rates will receive little incentive to join a reduced deforestation mechanism. A global baseline of deforestation is used as a reference rate for countries with historically low emissions rates. This has the potential benefit of reducing carbon leakage. The authors focus on the accuracy of the data to construct reference rates. As for the accuracy of the model for setting reference rates, the authors state "[a]n optimal technical solution to set baselines would be to use historical average figures during the time period from 1990 to 2005" (p.477).

Terrestrial Carbon Group (2008) take another route, assuming that all economically, politically and not yet protected forests would be cleared over the next 50 years. Each year, 1/50$^{\text{th}}$ of these forests would be available for clearing, or traded as reduced emissions. With this proposal, one still needs to estimate what would be economically viable.

[10] RED, or Reducing Emissions from Deforestation. A precursor to current Reduced Emissions from Deforestation and forest Degradation (REDD+) discussions.

[11] Commonly known by their acronyms, CER and CDM

One way to do this would be to assume that all forests will be cleared except for those that are exceptionally costly to clear, or currently protected. This extreme would be an upper bound on feasible deforestation. The authors acknowledge the risk of hot air that "get[ting] it wrong" would create (p. 4).

Strassburg et al. (2009) note both that a global reference rate provides weak incentives to any particular country and that the Terrestrial Carbon Group proposal would violate additionality, the condition that emissions reductions should be additional to what the national would have undertaken anyway, and generate hot air. Strassburg et al. proposed that a country's reference rate be a weighted average of national and global emissions rates.[12] This proposal caps the global reference rate as equal to the sum of national levels. That is, countries with high deforestation will have a reference rate lower than the historical average. Again, the proposal uses historical emissions to estimate the reference rates.

Woods Hold Research Center (2008) argue that the proposals based on global rates have weaker 'economic rationale' (p. 2). Woods Hold Research Center proposed an alternative means of accommodating for countries with low deforestation rates. In this proposal, emissions reductions are effectively taxed. The revenue collected is distributed to countries based on the area of forests in the country. There is no mention of how national baselines are set, but the global baseline used to calculated dividends would be constructed using historical emissions rates.

Joanneum Research (2006) explicitly mention the variability of deforestation rates and the costs they impose. To account for the inevitable variability in deforestation rates,

[12] The global reference rate is used to generate the "expected emissions" for a country. This is the fraction of all forest carbon stock in developing countries emitted per year.

a corridor reference rate is proposed. Here, countries with deforestation rates below a threshold are credited, countries with deforestation rates above a second threshold receive no compensation (or a debit against future deforestation) and countries with deforestation rates between these thresholds receive discounted payments. This proposal; however, will only perform well to the extent that these thresholds are accurately set. The authors suggest that the "establishment of a reference rate should be informed by data on historical emissions, emission trends over time, and should also take into account external parameters".[13]

Grassi et al. (2008) recognise the uncertainty over data and prediction. Based on UNFCCC guidelines the authors seek to minimise the possibility of hot air through application of the 'conservativeness' principle. This is a combination of not overestimating the baseline and not underestimating deforestation during the policy's life. The baseline is the historical emissions minus the a margin of error based on confidence intervals.

Herold et al. (2012) provide a practical framework through which forecasting can be implemented. Owing to implementation difficulties, forecasting baselines is expected to occur in later phases of REDD+. The authors correctly understand the role of forecasting, and develop a (single) model of forecast deforestation in Brazil. The statistics for forecast accuracy appear to be based upon in sample criteria rather than out of sample criteria.

Combes-Motel et al. (2009) eschew baselines for avoided deforestation in favour of 'compensated successful efforts.' The idea is to reward efforts instead of baselines, since accurate baselines are difficult to establish. The authors are concerned about the risk of hot air and resolve this risk by removing REDD+ from carbon markets. By doing so, a large source of funds for reduced deforestation programs is lost (Tacconi 2009). **Pirard**

[13] No page numbers given in the document.

and Karsenty (2009) also favour the compensation of efforts over avoided deforestation. They have a good discussion of the costs of using baselines, but do not have a discussion of the costs of their approach.

3.1 Weaknesses of these reference rate proposals

There are two main weaknesses of these proposals that I wish to draw attention to. First, reference rates are often based on past deforestation rather than the prediction of future deforestation. Second, reference rates typically impose a single model of deforestation over all countries.

Many of the reference rates in table 1 use historical rates of deforestation. The corridor approach still requires a baseline to set the upper and lower bounds, in which historical emissions rates are proposed.[14] The historical rate of deforestation accurately summarises past deforestation; however, a reference rate is set based on future, counterfactual deforestation rates.

There is some notion of prediction in some of these proposals, but they are implemented in an ad hoc manner. For instance, the inclusion of global deforestation rates into the reference rate for a country is partly to control carbon leakage. Here, the authors are aware that past rates of deforestation will not predict the future well and adjust reference rates accordingly. Contrary to the argument in Woods Hold Research Center (2008), there is a strong economic rationale (leakage) for this adjustment. Unfortunately proposals as a rule do not focus on prediction.

A second problem with current proposals for reference rates is the imposition of a uniform deforestation model across countries. It is true that in these proposals, each

[14] Terrestrial Carbon Group (2008) requires an estimation of economic viability. A linear allocation of deforestation over fifty years bears no relation to counterfactual emissions (for example, see figure 1). Alternatively, the reference rate would be an upper bound of possible deforestation and thus, be higher than is necessary, generating hot air.

country will have a difference reference rate. This is because the model is parameterised according to country characteristics. For instance, a higher historical deforestation rate will result in a higher reference rate under most of these proposals. However, for all of these proposals, the model of the reference rate is common across countries.

For such reference rate to be accurate, the processes of deforestation and forest degradation need to be equivalent across countries. There is little reason to assume that deforestation processes are the same across countries. A great deal of research highlights how the determinants of deforestation are dependent on the local context (Angelsen and Kaimowitz 1999, Chomitz et al. 2007, Pfaff et al. 2013).[15] Further, it is well accepted that processes will differ by country for even the most basic of macroeconomic variables (Lütkepohl and Krätzig 2004). Where countries have different processes of forest use, a model that estimates the reference rate accurately in one country is unlikely to be suited to estimate a reference rate in another country. Assuming an incorrect model generates error in setting reference rates, which raises the costs of implementing a reduced deforestation policy.

4 Method

In this section I discuss the forecasting procedure employed in this paper. I begin with a discussion of the general framework, followed by the criteria for model fit.

Country level forecasts are estimated for the 16 countries with a UN-REDD National Programme.[16] Because it is the largest source of emissions from land use, land use

[15] I am not suggesting that uniform models provide no insights. Models have their role in both clarifying and improving our understanding of the world. Whether these models have superior predictive power is an empirical question. Here, I raise this empirical question by entertaining the possibility that country specific forecasts of deforestation may perform better than global models.

[16] The full list of countries are: Bolivia, Brazil, Cambodia, Democratic Republic of the Congo (DRC), Ecuador, Indonesia, Nigeria, Panama, Papua New Guinea, Paraguay, the Philippines, Republic of Congo, Solomon Islands, Sri Lanka, Tanzania, Vietnam and Zambia.

change and forestry (FAOSTAT 2013), I also include Brazil.

The sample of countries is small, but sufficient to make the empirical application's argument. I focus on these 17 countries because first, they all are participating in the developing REDD+ policy. Second, some of the most important countries in terms of deforestation are included, like Indonesia and Brazil; if the argument holds for these countries, then the argument holds for any REDD+ policy. Third, I only need a handful of countries and models to show the heterogeneity in agricultural land expansion process across countries. Indeed, the results are more striking because of the relatively small number of countries and the small number of models employed.

4.1 General model

I use a flexible framework that allows different countries to have different forecasting models. The most general model used to estimate agricultural land expansion for country i, τ periods away from time t is (1). Agricultural land in a country is best characterised as a unit root process (see table 3), so the dependent variable $d_{i,t+\tau}$ will be the rate of agricultural land expansion.

$$d_{i,t+\tau} = \alpha_i + \sum_{s=0}^{k_i} \rho_{i,s} d_{i,t-s} + \theta_i \sum_{j=1}^{N} w_{ij} d_{j,t} + \sum_{r=0}^{\ell_i} \boldsymbol{\beta}_{r,i} \mathbf{x_{i,t-r}} + \epsilon_{i,t+\tau} \tag{1}$$

Where $d_{i,t-s}$ is the rate of agricultural land expansion for region i at time $t-s$ and $\mathbf{x_{i,t-r}}$ is a vector of lagged covariates at time $t-r$. I have N other countries' lagged agricultural land expansion rates in this general framework $d_{j,t}$. I am allowing the opportunity for a country's rate of agricultural land expansion to be predicted by a neighbouring country's rate. This claim seems plausible, given the discussion concerning carbon leakage from reduced deforestation projects (Wunder 2009, Murray et al. 2004, Meyfroidt and Lambin 2009). Further, it has been shown that using spatial lags, in addition to temporal lags improves forecast performance in other contexts (Giacomini and Granger 2004, Auffhammer and Steinhauser 2007). Spatial lags are weighted by coefficients w_{ij}, which are assumed to be known in advance. Overall, 92 different models are estimated for each country.

4.2 Model fit criteria

Equation 1 can be used to generate many different models by changing the combination of right hand side variables. The combinations used are presented in appendix A. To establish which model predicts the future the 'best', out of sample criteria are required. Out of sample criteria are based on the forecast error, or the difference between the predicted agricultural land expansion rate and the realised agricultural land expansion rate. I use the mean squared error (MSE).[17] Finally, since the costs of setting reference rates too high are qualitatively different from setting reference rates too low, I also develop criteria that account for the direction of error.

To generate these statistics I first need a sample of forecast errors for country i. The procedure to obtain a sample of forecast errors is algorithm 1. First, I choose a forecast length τ and a starting year t. The model generates a forecast $\hat{d}_{i,t+\tau}$. Then t is increased by one and another forecast obtained. The procedure is repeated until the final year in the dataset $t + \tau = T$, generating a sequence of agricultural land expansion rate estimates. After τ periods, the actual land expansion rate $d_{i,t+\tau}$ is realised and a *forecast error*, $e_{i,t+\tau} = \hat{d}_{i,t+\tau} - d_{i,t+\tau}$ can be obtained. This forecast error is obtained for all $T - t - \tau + 1$ forecasts. In this paper $T = 2009, t = 2000$ and $\tau = 1$.

[17]In prior versions of this paper, two additional criteria were used: mean absolute error (MAE), and the mean Canberra error (MCE), based on the Canberra distance (Lance and Williams 1966, 1967). The criteria are useful under different assumptions concerning the marginal costs of error. Where the marginal costs of error are proportional to the size of the error, the MAE is useful. Where the marginal costs of error increase in the size of the error, the MSE is more relevant. The MCE would be useful in the case where the marginal costs of error are greater when agricultural land expansion rates are low. Outside of the differences in interpretation, focusing on the MSE does not change the paper's results.

Algorithm 1 Obtaining a sample of forecast errors $(e_{i,t+s})_{s=\tau}^{T-t-\tau+1}$

Require: Choose a forecast length, τ
Require: Choose a starting period to forecast from, t
while $t + \tau \leq T$ **do**
Estimate model using data from the first time period to time t
Obtain forecast of agricultural land expansion $\hat{d}_{i,t+\tau}$
Obtain error of forecast $e_{i,t+\tau} = \hat{d}_{i,t+\tau} - d_{i,t+\tau}$
Set $t = t + 1$
end while

Let $(e_{t+s})_{s=\tau}^{T-t-\tau+1}$ be a sequence of forecast errors, which are converted to the MSE via (2).

$$MSE = (T - t - \tau + 1)^{-1} \Sigma_{s=\tau}^{T-t-\tau+1} e_{t+s}^2 \tag{2}$$

Because the MSE squares errors, the values of the statistic are not so easy to interpret. The benefit of the MSE is that the statistic punishes higher error terms more greatly. That is, a forecast error of two percent has an MSE equal to $0.02^2 = 0.0004$. This is more than twice is costly than an MSE of one percent $0.01^2 = 0.0001$. To compare various models, I use the relative mean squared forecast error ($RMSE$). The $RMSE$ for a model is calculated by dividing the model's MSE for a given model by the benchmark model's MSE. In this paper, the benchmark model will be the first order autoregressive lag model.

$$d_{i,t+1} = \alpha_i + \rho_i d_{i,t} + \epsilon_{i,t+1} \tag{3}$$

These criteria are useful for minimising the forecast error. With additional information about the costs of error, one can do better. For instance, suppose that the threat of non participation and carbon leakage has lower costs than hot air.[18] Then, setting a

[18]This is inline with the proposals by Grassi et al. (2008) and Combes-Motel et al. (2009).

reference rate too high is more costly than setting a reference rate too low. With this information, reference rates can be improved by using criteria that assess both the direction and the size of the error.

The MSE cannot assess the direction of error since, in squaring error terms, the MSE treats over and underestimtes equivalently. As a first step to establishing the costs of forecast error, I introduce additional criteria that assess the direction of error. I define a *positive* error where the forecast is higher than the realised value, and a *negative* error where the forecast is less than the realised value. Thus, deforesting nations are better off and hot air occurs under positive errors, whilst deforesting nations incur costs and have an incentive not to participate under negative errors.

In equation 4, I define the mean positive error (MPE), and the mean negative error (MNE). Additionally, I take the mean error (ME), which is just the weighted sum of errors over all forecasts. The ME establishes whether a model forecasts an overestimate or an underestimate on average.

$$MPE = n_P^{-1} \Sigma_{s=1}^{n_P} e_{t+s} \mathbb{1}\{e_{t+s} \geq 0\} \tag{4a}$$

$$MNE = n_N^{-1} \Sigma_{s=1}^{n_N} e_{t+s} (1 - \mathbb{1}\{e_{t+s} \geq 0\}) \tag{4b}$$

$$ME = n^{-1} \Sigma_{s=1}^{n} e_{t+s} \tag{4c}$$

Where $\mathbb{1}\{e_{t+s} \geq 0\}$ = 1 where the forecast of agricultural land expansion is higher than the realisation and $\mathbb{1}\{e_{t+s} \geq 0\}$ = 0 otherwise. The number of years where the forecast is greater than the realised expansion rate is n_P and n_N is the number of years where the forecast is below the realised expansion rate.

5 Data

In this section, I discuss the data used in the analysis, discuss its validity in use for investigating deforestation and present a preliminary diagnostic test.

The data used comes from the World Bank development indicators (The World Bank 2013). This is a cross country panel of all nations, and for reasons of parsimony, I focus on three variables in particular: agricultural land, income and population. Agricultural land is in square kilometres, income is gross domestic product in constant local currency units, and population is straightforward. The maximum length time series used in this analysis runs from 1980–2009.

There are two chief concerns with the data. First, since the data is collected from different national agencies, the data quality will vary from country to country. Second, agricultural land expansion is only a proxy of deforestation. An alternative dataset is the UN Food and Agriculture Organisation's (FAO) forest inventory dataset. There are two main problems with this dataset. First, as with the agricultural land area data, quality varies across countries. Additionally there is also a concern over the quality of pre 2000 data. Pre 2000 observations are constructed through models of deforestation where observations are missing (Rudel and Roper 1997, Grainger 2008). Second, there are only three years worth of post 2000 data.[19] Using average deforestation rates from three years of levels data leaves only one error estimate.

5.1 Data summary

Summary statistics for agricultural land area for each country investigated are presented in table 2. There is substantial variation in the size of agricultural landholdings across countries. Brazil, Nigeria and Indonesia are the largest areas in terms of landholdings.

[19]Specifically the years 2000, 2005 and 2010.

Table 2: Summary statistics for agricultural land area in thousands of square kilometres. 'C.Var.' is the coefficient of variation, which is equal to the standard deviation divided by the mean.

Country	Mean	Std. Dev.	C.Var.
Bolivia	360.2	10.7	0.030
Brazil	2526.8	169.9	0.067
Cambodia	44.1	9.8	0.222
Congo, Dem. Rep.	257.7	1.6	0.006
Ecuador	76.0	4.1	0.053
Indonesia	447.8	51.8	0.116
Nigeria	728.8	23.1	0.032
Panama	21.3	1.2	0.057
Papua New Guinea	9.5	1.3	0.136
Paraguay	180.0	24.1	0.134
Philippines	112.2	3.8	0.034
Congo, Rep.	105.4	0.1	0.001
Solomon Islands	0.7	0.1	0.137
Sri Lanka	23.8	0.9	0.039
Tanzania	344.2	12.5	0.036
Vietnam	81.6	15.0	0.184
Zambia	216.4	12.6	0.058

Accordingly, thee countries have the largest variation in landholdings over time. Another sense of the variation adjusts for the size of landholdings. For instance, a 1 km^2 increase from 10 km^2 of agricultural land is in proportional terms larger than a 2 km^2 increase from a base of 1000 km^2. After accounting for average agricultural land area through the coefficient of variation, we see that some smaller nations have relatively large variation in landholdings. In particular, Cambodia and Vietnam have large variation in agricultural land over time.

There are two consequences of greater variability in agricultural land expansion rates. First, predicting future rates of agricultural land expansion is potentially more difficult with higher variability. Second, where the costs of forecast error are positively related to the error, then countries with greater variation in the data may have greater costs of error. Overall, variability in agricultural land expansion rates differs by orders of magnitudes across countries. This means that both forecast error and the costs of error are likely to vary across countries.

Table 3 shows there is strong evidence that the growth rates of agricultural landholdings do not follow a unit root process for any country investigated.[20] The null that the growth rate of agricultural land expansion follows a unit root process can be rejected at the one percent level for all countries except for Ecuador. For Ecuador, the null can be rejected at the five percent level. On the other hand, the null that the log of agricultural land follows a unit root process cannot be rejected for most countries. For comparability, I will use growth rates of agricultural landholdings for all countries in the rest of the paper.

Checking for unit roots also provides evidence against the use of historical reference rates. The historical deforestation rate as a baseline is equivalent to saying that past deforestation predicts future deforestation. A unit root in levels, see (5), says that future deforestation is past deforestation plus an error term. That is, past deforestation is our best prediction of future deforestation. As such, rejection of the unit root without a constant provides some evidence against the use of historical deforestation rates as baselines.

$$\Delta\ell_{i,t+1} = \Delta\ell_{i,t} + \Delta e_{i,t+1} \tag{5}$$

[20]Unit root processes are highly persistent, which means that shocks to a variable (for instance, a large one off expansion of agricultural land) have very long lasting effects. These persistent processes invalidate standard asymptotic theory that is used for inference, and suggesting spurious relationships between variables.

Table 3: Results of Augmented Dickey-Fuller tests on agricultural land expansion. The null hypothesis is that the variable contains a unit root, and the alternative is that the variable was generated by a stationary process.

	Growth		Levels					
Country	Constant	No Constant	No Constant		Constant		Trend	
			AR(1)	AR(2)	AR(1)	AR(2)	AR(1)	AR(2)
Bolivia	***	***						
Brazil	***	***			***	***	**	*
Cambodia	***	***						
Congo, Dem. Rep.	***	***						
Ecuador	***	**						
Indonesia	***	***						
Nigeria	***	***						
Panama	***	***						
Papua New Guinea	***	***						
Paraguay	***	***						
Philippines	***	***						
Congo, Rep.	***	***			**	*		
Solomon Islands	***	***						
Sri Lanka	***	***			***		***	
Tanzania	***	***			*			
Vietnam	***	***						
Zambia	***	***						

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6 Results

The section first presents the best perfoming model for each country, followed by an investigation into the direction of error.

6.1 Best performing model

The best performing models for each country are presented in table 4. In this table are the empirical exercise's main arguments. First, that the best forecast model differs by country. Given that the number of models is small,[21] this heterogeneity in best performing models is striking. There is strong evidence that a global model will not generate the most accurate reference rates at the country level. Second, table 4 shows that alternative models improves upon historical averages as forecasts. The historical average is not in the top three forecasts for any country investigated.

There is no single models that performs best across the sample. The humble autoregressive of order one model (3) performs best for the Solomon Islands, the Republic of Congo and Zambia. More general autoregressive lag models perform best in two countries. Using agricultural expansion rates from neighbouring countries results in the best forecasts in Bolivia and Cambodia. Forecasted variables result in the best forecasts of agricultural expansion in two countries. The Environmental Kuznets Curve generates in the best forecasts in three countries and general auto regressive distributed lag models perform best in five countries.

Table 5 shows the heterogeneity in the forecast error rates across countries. Since the deforestation forecast error is likely to differ across countries, so to will confidence about reduced deforestation permits issued in different countries. For instance, Brazil's

[21] 92 models are estimated. For an example of the thousands of possible combinations of forecasting models that can arise from a general model such as (1), see Auffhammer and Steinhauser (2012) who develop 27,216 models from two general models.

forecasts have lower mean squared error than Sri Lanka's. Permits issued for emissions reductions in Brazil are more likely to represent actual emissions reductions than permits issued in Sri Lanka.

Where emissions permits are not believed to represent actual emissions reductions, participants in carbon markets may discount reduced deforestation permits. If permits are not distinguished by country, then some credible permits may be discounted by association with less credible permits. On the other hand, distinguishing permits by country might result in some countries receiving the lion's share of REDD+ funds.

It is possible that the models in table 4 may be selected based on chance. That is, the improvements in forecast error do not reflect the ability of the model to capture the underlying deforestation process. Such a – very real – possibility does not invalidate the paper's thesis. First, there are formal techniques to investigate 'data snooping' (White 2000, Hansen 2005). Second, the possibility of chance guiding model selection reminds us of the impossibility of certainty in setting reference rates. Awareness of this impossibility directs attention away from a search for the perfectly accurate forecast into a conversation about managing this error.

6.2 The direction of errors in the best performing models.

The paper's final investigation looks at the direction of error with each country's best performing model. Recall that asymmetric costs of an incorrect reference rate are likely: a higher reference rate generates hot air and windfall benefits to the deforesting country; a lower reference rate may lead to non participation. As argued above, a reasonable objective for reference rate may be to minimise the expected cost of errors. I present some simple statistics to illustrate this phenomenon.

The results are found in table 6, where I have multiplied the errors by 100. There is much heterogeneity in the results, with ten countries having a negative average error and seven having a positive average error. Cambodia and Papua New Guinea both would have benefited from these reference rates, with seven out of nine years yielding positive forecast errors. Vietnam gains the most from such a baseline over the period investigated; the corollary is that most of the hot air would also come from Vietnam.

It is difficult to see Sri Lanka or the Democratic Republic of the Congo agreeing to such a baseline. Sri Lanka loses on average, with the reference rate underestimating agricultural expansion by 1.2 percent each year on average. This is driven by some years of high agricultural expansion, so in some years Sri Lanka would gain from the reference rate. On the other hand, the Democratic Republic of the Congo's reference rate underestimates agricultural expansion every year. This consistent underestimating of the reference rate occurs even though the reference rate is the second most accurate reference rate (see table 5). This final result shows the value of modified directional error measures: if underestimated forecast errors are more costly than overestimated forecasts, a less accurate measure in mean squared error terms may be preferred.

7 Conclusion

Estimating reference rates is a challenge for the implementation of reduced deforestation policy. Where the reference rate is set incorrectly, costs arise. By not focusing on out of sample criteria, current reference rates systematically add to these costs. In this paper, I highlight how current proposals for reference rates can exacerbate the costs of setting reference rates.

First, proposals set reference rates without predicting future deforestation. Second, current proposals employ one global model of deforestation that is parameterised according to national deforestation rates. These weaknesses will result in costs of implementation even if we perfectly understood past deforestation. These weaknesses are illustrated using agricultural land expansion rates across a sample of tropical nations over 1980—2009.

No universal forecasting model for setting reference rates arises in this analysis. Rather, the conclusion drawn is that each country has its own process of agricultural land expansion. I acknowledge that deforestation and agricultural land expansion do not map one to one; however, the results indicate that the use of a single model to set baselines across countries may raise the costs of implementing REDD+ policy. This result will become import when data allows more countries to set baselines with forecasting methods (Herold et al. 2012).

There will be costs to allowing country specific reference rates. First, this may open a window for strategic behaviour in setting reference rates. Some countries might have more capacity to obtain more generous reference rates through bargaining power alone. A counter arguement is that open data could be used to prevent such behaviour.

I acknowledge data limitations, and note the chief focus used in this paper is in highlighting that the importance of forecast error. Awareness of and focusing on this error in setting reference rates can be used to understand the costs and benefits of different reference rate proposals. Where the costs of measurement error are sufficiently high, then uniformly applied, historical averages could be justified. Importantly, this justification rests on solid economic grounds: lowering the costs of setting baselines. Further, the criteria suggests that the timing of transitions between phases, as in (Herold et al. 2012), comes down to benefits and costs of trasitioning from one reference rate design to another.

The REDD+ literature to date has intuitively grasped the notion about the costs of error. For instance, with proposals mitigating the possibility of carbon leakage or hot air into the design of reference rates. I suggest that the costs of error in various reference rate proposals be made explicit and used as a criteria for setting baselines. Naturally, investigating the costs of error is a worthy topic of future research. Focusing on the costs of error can provide a rationale for non-forecasted baselines in the short term, can provide guidance on when to transition to using more data intensive techniques and can also exploit the improvements in data quality expected in the long term.

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A Forecasting models

In this section, the focus will typically be on one-step ahead forecasts. That is, forecasting next year's agricultural land growth. The models are all specific versions of (1).

Benchmark model: univariate AR(1) estimates The AR(1) model, also shown in (3), will be the benchmark used to compare other models.

$$d_{i,t+1} = \rho_{i,0} + \rho_{i,1} d_{i,t} + \epsilon_{i,t+1}$$

Historical averages Historical averages are computed by taking the average deforestation rate over 1990–2000 for any period $s \in \{2001, \ldots, 2009\}$

$$d_{i,s} = \frac{1}{10} \sum_{t=1990}^{2000} d_{i,t}$$

Univariate AR(p) estimates The univariate AR(p) models have up to four lags of agricultural expansion rates as predictors. This is sufficient for macroeconomic variables (Lütkepohl and Krätzig 2004).

$$d_{i,t+1} = \rho_{i,0} + \sum_{p=1}^{P} \rho_{i,s} d_{i,t+1-p} + \epsilon_{i,t+1} \tag{6}$$

Multivariate estimates Thus far I have only focused on agricultural land expansion; however, we know more about the process of deforestation. In particular, population and national income are commonly thought to explain deforestation (Angelsen and Kaimowitz 1999, Van and Azomahou 2007). This additional information on the process of deforestation could be used to improve forecasts. National income is the Gross Domestic Product in constant local currency units. The forecasts are generated using versions of (7), where n is the population growth rate and g is the GDP growth rate.

$$d_{i,t+1} = \alpha_i + \sum_{p=0}^{P} \rho_{i,p} d_{i,t-p} + \sum_{q=1}^{Q} \beta_{i,q}^{GDP} g_{i,t+1-q} + \sum_{r=1}^{R} \beta_{i,r}^{Pop} n_{i,t+1-r} + \epsilon_{i,t+1} \tag{7}$$

Forecasted explanatory variables It is possible that models based on in sample criteria actually perform very well as forecasts. In this section, I use basic explanatory models deforestation as predictors.

I choose two basic models. First I estimate a basic model using two commonly used explanatory variables: population and income. The second is the Environmental Kuznets Curve. The models for the forecasts without a lagged dependent variable are in (8). To convert these models into forecasts of agricultural land expansion, I obtain forecasts of explanatory variables.

$$d_{i,t+1} = \beta_0 + \beta_1 \hat{g}_{i,t+1} + \beta_2 \hat{n}_{i,t+1} + \epsilon_{i,t+1} \tag{8a}$$

$$d_{i,t+1} = \beta_0 + \beta_1 \hat{g}_{i,t+1} + \beta_2 \hat{g}^2_{i,t+1} + \epsilon_{i,t+1} \tag{8b}$$

Where $\hat{g}_{i,t+1}$ is forecasted GDP growth for country i at time $t+1$ and $\hat{n}_{i,t+1}$ is the forecast of population growth for country i at time $t+1$. The forecasted data is taken from the IMF World Economic Outlook reports (International Monetary Fund 2009). There are multiple editions of the World Economic Outlook reports each year, which provide estimates of the following years' national income and population. I take estimated income from the September report each year. There are missing observations for some countries (there are no forecasts for either the Republic of the Congo or the Democratic Republic of the Congo) and some countries' forecasts begin only in 2003. For cross country comparability, I forecast from 2003–2009.

Lagged Environmental Kuznets Curve I also investigate a lagged version of the Environmental Kuznets Curve.

$$d_{i,t+1} = \beta_0 + \beta_1 g_{i,t} + \beta_2 g^2_{i,t} + \epsilon_{i,t+1} \tag{9}$$

Spatial estimates Previous authors have shown how forecasts can be improved by using spatial models (Giacomini and Granger 2004, Auffhammer and Steinhauser 2007, Auffhammer and Carson 2008). In this section, I use agricultural land expansion rates from neighbouring countries as predictors of a country's agricultural land expansion rate.

The basic model is in (10), where w_{ij} is a weight determining how much of a neighbour country j is to country i. Although I am only forecasting agricultural land expansion rates for a handful of countries, j can be any of the 224 currently existing countries, not just for those I forecast agricultural land expansion..

$$d_{i,t+1} = \theta_{i,0} + \rho_{i,1} d_{i,t} + \theta_{i,2} \sum_{j=1}^{224} w_{ij} \ell_{j,t} + \epsilon_{i,t+1} \tag{10}$$

The data for the weighting matrix comes from Mayer and Zignago (2011). The data is in the form of a 224×224 matrix, with elements equal to 0 if the row country does not share a border with the column country. The cell equals 1 if the row country shares a border with the column country (see table 7).

Table 7: Sub matrix of the spatial matrix. Data: Mayer and Zignago (2011)

	Brazil	Paraguay	Papua New Guinea
Brazil		1	0
Paraguay	1		0
Papua New Guinea	0	0	

A limitation of this data is that only land boundaries are recognised. Countries that share an off shore border, for instance Papua New Guinea and the Solomon Islands, are not deemed neighbours. A consequence of this tight definition is that islands are not deemed to share contiguous boundaries with any country. As such, spatial forecasts for the Philippines, Solomon Islands or Sri Lanka cannot be estimated.

It would be possible to manually alter the weighting matrix, but for two reasons I choose not to. First, it rapidly becomes ambiguous which countries share an off shore border. For instance, a border between Papua New Guinea and the Solomon Islands seems reasonable, but how to treat Sri Lanka and Indonesia remains unclear. I err on the side of clarity in this exposition. Second, I do not presuppose that these forecasts will be the best available for each country. As such, I leave more detailed spatial weighting matrices for future work.

Table 4: Best performing forecasts by country. $RMSFE$ is the mean squared error relative to the AR(1) model.

Country	Model one	RMSFE one	Model two	RMSFE two	Model three	RMSFE three
Bolivia	Spatial + AR(3)	.008	X(1,4,0)	.009	X(1,1,0)	.01
Brazil	X(4,1,1)	.009	AR(2)	.01	X(1,1,1)	.01
Cambodia	Spatial + AR(3)	.006	Spatial + AR(2)	.008	Spatial + AR(1)	.009
Congo, Dem. Rep.	$\hat{X}$	.003	$\hat{X} + AR(1)$	.003	X(2,1,0)	.005
Ecuador	EKC	.006	X(1,1,1)	.009	X(1,3,1)	.009
Indonesia	X(1,2,0)	.01	X(1,1,0)	.01	X(1,2,0)	.01
Nigeria	X(1,4,1)	.009	X(1,4,1)	.009	AR(2)	.01
Panama	$\hat{X} + AR(1)$	.002	$\hat{X} + AR(1)$	.002	$E\hat{K}C + AR(1)$	.003
Papua New Guinea	AR(3)	.01	AR(3)	.01	AR(4)	.01
Paraguay	$\hat{X} + AR(1)$	.002	$\hat{X}$	.003	$E\hat{K}C + AR(1)$	.003
Philippines	$E\hat{K}C + AR(1)$	.007	EKC	.008	X(1,2,0)	.009
Congo, Rep.	AR(1)	.007	$\hat{X} + AR(1)$	.007	$E\hat{K}C + AR(1)$	.01
Solomon Islands	AR(1)	.011	AR(2)	.012	X(1,1,0)	.012
Sri Lanka	X(3,1,4)	.006	X(3,2,4)	.006	X(3,3,4)	.007
Tanzania	X(1,3,1)	.009	X(1,3,0)	.009	X(1,3,1)	.009
Vietnam	$E\hat{K}C + AR(1)$	.003	$E\hat{K}C + AR(1)$	.003	$\hat{X}$	.005
Zambia	AR(1)	.01	AR(3)	.01	X(1,1,0)	.011

Key: AR(1) use first order autoregression, see (3)

AR(p) use univariate autoregressive models, see (6)

X(p, q, r), use p, q, r lags of agricultural land expansion, GDP and population growth. See (7)

$\hat{\mathbf{X}}(1)$ use projected multivariate regression. See (8a)

EK̂C use projected Environmental Kuznets Curve. See (8b)

EKC use Environmental Kuznets Curve. See (9)

Spatial uses spatial regression methods. See (10)

Table 5: Best performing forecasts by country. $MSFE$ is the mean squared error.

Country	Model	MSFE
Bolivia	Spatial + AR(3)	.00559
Brazil	X(4,1,1)	.00239
Cambodia	Spatial + AR(3)	.00801
Congo, Dem. Rep.	$\hat{X}$	.00005
Ecuador	EKC	.0465
Indonesia	X(1,2,0)	.08838
Nigeria	X(1,4,1)	.03125
Panama	$\hat{X} + AR(1)$	.00113
Papua New Guinea	AR(3)	.18738
Paraguay	$\hat{X} + AR(1)$	.00811
Philippines	$E\hat{K}C + AR(1)$	.00668
Congo, Rep.	AR(1)	1.00e-05
Solomon Islands	AR(1)	.05995
Sri Lanka	X(3,1,4)	.15964
Tanzania	X(1,3,1)	.01702
Vietnam	$E\hat{K}C + AR(1)$	.01922
Zambia	AR(1)	.00486

Key: AR(1) use first order autoregression, see (3)

AR(p) use univariate autoregressive models, see (6)

X(p, q, r), use p, q, r lags of agricultural land expansion, GDP and population growth. See (7)

$\hat{\mathbf{X}}(1)$ use projected multivariate regression. See (8a)

EK̂C use projected Environmental Kuznets Curve. See (8b)

EKC use Environmental Kuznets Curve. See (9)

Spatial uses spatial regression methods. See (10)

Table 6: Directional forecast errors as for best performing forecasts as per table 4. *MFE* is the mean forecast error. *MPFE* is the mean positive forecast error, the average error across years where the forecast is greater than realised agricultural land expansion rate. *MNFE* is the mean negative error, the average error across years where the forecast is less than realised agricultural land expansion rate. Columns three and five are respectively the number of years where the best performing forecast is greater than or less than the realised value. See equation 4 for details.

Country	MFE	MPFE	$\sum \mathbb{1}\{e_{t+s} \geq 0\}$	MNFE	$\sum \mathbb{1}\{e_{t+s} < 0\}$
Bolivia	0.127 76	0.516 76	6	0.650 24	3
Brazil	0.1562	0.606 61	4	0.204 13	5
Cambodia	0.499 56	0.773 73	7	0.460 04	2
Congo, Dem. Rep.	−0.063 19		0	0.063 19	2
Ecuador	0.270 44	1.6652	4	1.589 24	3
Indonesia	−0.435 06	2.510 01	3	1.9076	6
Nigeria	0.025 84	1.485 06	4	1.141 53	5
Panama	−0.223 12	0.242 44	1	0.300 71	6
Papua New Guinea	−0.776 72	0.855 18	7	6.488 37	2
Paraguay	−0.0098	0.878 58	3	0.676 09	4
Philippines	−0.4715	0.852 14	1	0.692 11	6
Congo, Rep.	−0.015 04	0.004 79	4	0.0309	5
Solomon Islands	−0.770 93	1.2772	4	2.409 44	5
Sri Lanka	−1.287 93	1.689 21	4	3.669 64	5
Tanzania	−0.416 85	0.371 27	5	1.402 01	4
Vietnam	0.911 86	1.451 27	5	0.436 66	2
Zambia	0.257 22	0.662 95	6	0.554 24	3