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Abstract

Given the prospects of low short--term emissions reduction, carbon removals (CDRs) are expected to play an important role in achieving ambitious mitigation targets in future scenarios of integrated assessment models (IAMs), particularly Bioenergy with Carbon Capture and Storage (BECCS). In this paper, we explore the IAMC 1.5℃ database to depict the characteristics of the two main CDR options present in mitigation scenarios: BECCS and afforestation/reforestation. We apply a linear mixed--effect model to capture the specific regional and cross--IAM effects. Results reveal that the distribution of BECCS and afforestation deployment differs across IAMs and regions and, to a second extent, time. BECCS is preferred in the scenarios not for its ability to expand energy use but actually because it appears as an alternative to afforestation, which is associated with a decrease in energy use. However, the regional distribution of CDR deployment does not show a common pattern across scenarios and IAMs. Therefore, a more comprehensive investigation is needed before it can support policy proposals.

KEYWORDS: afforestation, BECCS, IAMs, mitigation scenarios, mixed-effect model, regional analysis

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1. INTRODUCTION

The Paris Agreement has pulled together more than 180 countries to pursue efforts to limit global warming well below 2℃. As a global attempt to develop effective climate change mitigation strategies, those endeavours rely heavily on an ensemble of deep decarbonisation pathways provided by integrated assessment models (IAMs). IAMs are typical analytical tools employed by the scientific community to assess mitigation options related to a given climate target, as well as the feasibility of the technological portfolio.

The most important scientific input of the Paris Agreement was provided by the Intergovernmental Panel on Climate Change (IPCC, 2018). In its most recent report version, land--based mitigation solutions emerge as one of the main cost-effective ways to achieve stringent climate stabilization targets. The land ecosystem can contribute to emissions reductions via avoided deforestation or improved agricultural management (Smith et al., 2013, 2019). Additionally, it has the potential to remove carbon emissions from the atmosphere (Roe et al., 2019). Techniques to deliver Carbon Dioxide Removals (CDR) are known as negative emissions technologies (NET).

Despite the number of CDR approaches increasingly discussed in the literature (Minx et al., 2018), most future mitigation scenarios remain predominantly concentrated on Bioenergy with Carbon Capture and Storage (BECCS) and, to a more limited extent, afforestation/reforestation (Clarke et al., 2014; Harper et al., 2018; Popp et al., 2017; Rogelj et al., 2018; Tavoni & Socolow, 2013) to achieve ambitious mitigation targets. (More recent studies have incorporated other CDR approaches such as Direct Air Capture with Carbon Storage [DACCS; Chen & Tavoni, 2013; Lehtilä & Koljonen, 2018] and soil sequestration [Frank et al., 2017]. On the other hand, ocean--based CDR and removal of non--CO_2 gases have not been accounted for in future mitigation pathways.) Both land--based solutions accumulate carbon in growing biomass through photosynthesis but differ in several aspects. First, the time to achieve forest maturity with afforestation/reforestation is longer compared to the rotation time to harvest bioenergy crops. In fact, forests require several decades for the carbon stock to achieve an equilibrium (Humpenöder et al., 2018). Second, for a given land surface, afforestation is limited to the expansion of forestland, in which there is a maximum carbon amount that can be stocked, whereas bioenergy crops can be grown each year and provide a constant flux of CDR. Finally, contrary to afforestation, BECCS directly reduces the carbon intensity of the energy mix. However, the expansion of BECCS deployment may be limited by trade--offs with food security and biodiversity conservation (Creutzig et al., 2021; Muratori et al., 2016).

The value of bioenergy in the energy system and the value of BECCS in removing carbon emissions are reflected in the relevant role played by BECCS in future mitigation scenarios of IAMs. Carbon removals were considered in IAMs initially for the purpose of hedging on climate risks. On the basis of the precautionary principle, Obersteiner et al. (2001) associated uncertainties on the impacts of increased concentration of emissions in the atmosphere with technological hedge portfolios to support BECCS deployment. In other words, this hedging strategy was used due to the unknown risks of crossing thresholds and provoking irreversible changes in the climate system (tipping points).

Most recent studies using IAMs stress that the faster and more pronounced the decarbonization is, the less substantial the deployment of NETs will be (Hare et al., 2018). In this sense, an insufficiently rapid reduction in emissions leads to higher reliance on CDR, largely from BECCS. This is the case in 1.5℃ scenarios since the overshoot of the carbon budget of this goal must be offset by negative emissions. Ambitious near--term mitigation reduces significantly NET requirements to keep the Paris climate targets within reach but makes even 2℃ unachievable without CDR in Strefler et al. (2018). The reliance on BECCS in 1.5℃ scenarios with limited or no overshoot can be diminished if emissions reductions are driven by low energy demand or low material and Greenhouse Gas (GHG) intensive food consumption in Hilaire et al. (2019). Although not fully eliminating the need for CDR, van Vuuren et al. (2018) point out that these alternatives enable diversifying future mitigation pathways. Mitigation scenarios without any explicit CDR deployment have also been explored in the literature (Eom et al., 2015; Iyer et al., 2015).

The particular case of BECCS deployment involves concerns about the potential feasibility and costs of large-scale implementation (Bauer et al., 2018; Low & Schäfer, 2020). Scaling up BECCS can further exacerbate challenges related to land availability and productivity, food security (food prices), biodiversity and water resources (Rose et al., 2014), as well as the carbon storage capacity (Smith et al., 2016). Although BECCS has the double capacity of contributing to the decarbonization of the energy sector, it is not yet readily available, thereby facing constraints and uncertainties in terms of technology diffusion at the scale necessary to limit global warming by 2100. Yet, BECCS still appears to be privileged over other mitigation strategies in future mitigation scenarios produced by IAMs, including afforestation.

Two papers have tried quantitatively to draw upon the structural elements of IAMs that are influencing the understanding of future mitigation efforts. The analysis of Köberle (2019) found that the model structure and assumptions are determinants in assigning a high value to BECCS. One important driver through which this occurs is the discount rate between 3% and 5% or, additionally, constraints on grid penetration of intermittent renewable sources. Most importantly,

the optimism in relation to the role of BECCS in future mitigation is related to what is not represented in IAMs, such as other land--based solutions or low--carbon innovation in end--use technologies. Based on similar conclusions, Fuhrman et al. (2019) discuss how to better inform climate policy discussions and policymakers.

Differences across model and scenario projections, in particular the approach of land--use sector modelling and respective integration with the energy system, may lead to a wide range of conclusions on the effects of land--based mitigation. The majority of past studies on future mitigation scenarios consider a global coverage (Peters & Geden, 2017), albeit some regional particularities may impact the BECCS effect globally and regionally. The release of the Integrated Assessment Modelling Consortium (IAMC) 1.5℃ scenario explorer (henceforward called IAMC 1.5℃ database; Humpenöder et al., 2018; Huppmann et al., 2018), which combines the outputs from a large sample of IAMs, has enabled comprehensive assessments to be carried out considering these issues. In this paper, we use this database (i) to bring light to their main characteristics in IAMs, particularly regarding deployment potential and their relation with emissions reduction as well as energy use and consumption levels and (ii) to identify whether there is a regional pattern in land--based mitigation deployment, and if so, where reliance on BECCS prevails over afforestation and vice versa. Since implications of land--based mitigation are in general context--specific driven and dependent on factors such as the land--use type or scale of deployment, taking into account regional differences is appropriate when analysing future mitigation pathways. This approach is still under--exploited in the literature of 1.5 and 2℃ scenarios on a quantitative basis.

Our approach applies a linear mixed--effect model to assess the relationship between selected variables and the two land-based mitigation options mostly represented in IAMs, namely BECCS and afforestation, for the 2030–-2100 period. This method allows accounting for the role of IAMs structure in the regional analysis. In summary, the contribution of this paper is twofold: to explore land--based mitigation solutions in the IAMC 1.5℃ database while bringing a regional perspective on the role of BECCS and afforestation. This full--fledged analysis helps us to better understand the basic principles driving the IAMs as well as their main conclusions. Ultimately, it helps to improve the transparency of IAMs and scenarios required for policymaking, as suggested by recent literature (Bistline et al., 2021).

2. METHODS AND DATA

2.1. The IAMC 1.5℃ database

The IAMC 1.5℃ database compiles outputs of several global multi-- region IAMs run in 5-year time-step. It provides more than 170 scenarios from 25 distinct IAMs designed to represent low emissions concentration targets by 2100, and to quantify the impacts of different climate mitigation strategies in a context of societal and technological transformation over the century. The drivers of those changes are consistently defined in the assumptions of IAM models used in the projections. Over the last decades, IAMs have been extensively applied to climate change policy analysis by developing mitigation scenarios. Interactions between socioeconomic and natural processes are modelled through mathematical formulations.

Given that there are significant differences among the structure of models, level of complexity, and assumptions (e.g. on technology constraints: they may reflect both physical and socioeconomic limits, e.g. the inclusion of caps on growth rates, degrees of substitutability of capital and labour or rate of time preference—-discount rate [Köberle, 2019]—-and feedbacks considered [Weyant, 2017]), different IAMs exhibit different pathways for a given climate target, as well a different portfolio of mitigation options. In the case of land management and bioenergy deployment in IAMs, their land--use socioeconomic module is able to capture the competition for land among several possible uses and under a broad range of dynamic factors such as socioeconomic drivers, food demand, productivity increases in crop and livestock systems, or forest area preservation constraints. Potential large differences in the magnitude of mitigation projections can be associated with model inputs along with the manner climate policies are implemented and the wide range of uncertain socioeconomic and technological assumptions behind them. This sensitiveness to the IAMs design can be a source of uncertainty with respect to scenario outcomes.

Each model implements the policy necessary to achieve a climate goal, whether a carbon budget or an emissions reduction target, generally by imposing a global carbon price. Specific assumptions can also be made regarding individual consumption behaviours or the level of energy demand. These mitigation requirements can be related to global mean temperature increase of 1.5 or 2℃ in 2100 or according to levels of radiative forcing (ranging from 1.9 to 4.5 W/m^2). Details on the selected scenarios, the type of climate policy modelled and corresponding mitigation goals are provided in Appendix A. Also, Appendix A points out whether NET is explicitly available, or a carbon price is explicitly represented in the simulations. One key limitation of the IAMs at the database underlying this analysis is the absence of other potential CDR options such as Direct Air capture with carbon Storage (DACCS; Rueda et al., 2021). There is only one exception, and it includes DACCS (see a summary of existing land-based mitigation options in the IAMC 1.5℃ database in Appendix B). The availability of those CDR options is dependent on

the capacity to provide related cost estimations. Seven IAMs models were used to implement the scenarios under investigation, as listed in Figure 1. Further details on model characteristics can be found for AIM/CGE (Fujimori et al., 2017), GCAM (Calvin et al., 2017), IMAGE (Van Vuuren et al., 2017), MESSAGE·GLOBIOM (Fricko et al., 2017), REMIND (Strefler et al., 2018) and REMIND-MAgPIE (Bertram et al., 2018; Kriegler et al., 2017) and WITCH--GLOBIOM (Emmerling et al., 2016).

With a focus on the future prospects of land-based solutions in IAMs, this paper assesses 29 narratives comprising 72 scenarios selected from the IAMC 1.5℃ database version 1.1 (February 7, 2019) as described in Figure 1. We based the selection criteria on the level of mitigation reached in 2100, retaining only the scenarios reaching the most ambitious climate targets (<2℃ or equivalent in W/m^2). The lowest emissions concentration targets can be implemented in IAMs either through the availability of carbon removals or, alternatively, with scenarios in which low energy demand and behaviour change are the key drivers of emissions reductions. Since each narrative is linked with specific model(s), there was no a priori selection of models. Instead, it was derived automatically from the scenario selection. From the 72 scenarios of the 29 narratives under scrutiny, BECCS and afforestation are represented simultaneously in 22 scenarios, whereas BECCS is considered the only land--based option in 31 of them. The total number of scenarios without both BECCS and afforestation is 18 and only one considers afforestation solely. The variable afforestation is not filled in for all models since not all have a land--use module (e.g. Poles EMF33) or a focus on afforestation (such as EMF--33 scenarios).

The IAMs define different levels of regional aggregation. For the IAMC 1.5℃ database, they have been aggregated into several sub-region categories to make them comparable. The five levels of regional aggregation used in our analysis are described in Table 1: Asia, Latin America, countries of the Middle East and Africa, OECD90+EU member states and candidates and countries from the Reforming Eastern Europe and the Former Soviet Union, hereinafter also referred to as ASIA, IAM, MAF, OECD+EU and REF, respectively.

From more than 500 variables reported and defined in the database, six were selected to compose the analysis, as listed in Table 1. For comparison reasons in the econometric analysis, we also made adjustments in the variables by transforming them into per capita units to eliminate potential population size differences among regions. The mitigation costs are not tested since some IAMs report GOP as exogenous variables, with different implementations of the carbon price, which could be misleading to consider. Despite being also appropriate to account for the

carbon revenue in the analysis, the IAMC 1.5℃ database does not provide information in this respect.

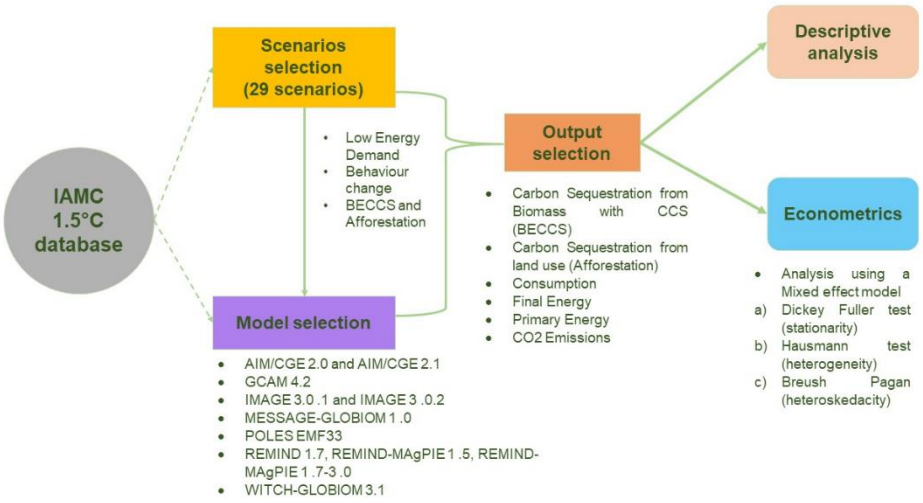


Figure 1 – General approach overview

Table 1 - Definition of regions and variables

Region		Variable	
Acronym	**Definition**	**Acronym**	**Definition**
ASIA	It includes most Asian countries except the Middle East, Japan and Former Soviet Union States.	BECCS	Total carbon dioxide emissions captured from bioenergy use and stored in geological deposits and the deep ocean, in Gt CO2 or Mt CO2 per capita.
LAM	It includes the countries of Latin America and the Caribbean.	AFFOR	Total carbon dioxide sequestered through land-based sinks, in Gt CO2 or Mt CO2 per capita.
MAF	It includes the countries of the Middle East and Africa.	CONS	Total consumption of all goods, by all consumers in a region, in million US$2010 per capita.
OECD+EU	It includes the OECD 90 and EU member states and candidates.	ENE	Total final energy consumption by all end-use sectors such as households, industry or agriculture and all fuels, excluding transmission/distribution losses as well as the energy used by the energy sector, in PJ per capita.
REF	It includes countries from the Reforming Economies of Eastern Europe and the Former Soviet Union.	PRIENE	Total primary energy consumption (direct equivalent) *, in PJ per capita.
		EMI	Total CO2 emissions (not including CCS), in Mt CO2 per capita.

* Primary energy refers to energy in the form found in nature that has not been subjected to any conversion or transformation. For example, coal is a primary energy which becomes secondary energy when converted to synthetic gas.

2.2. BECCS and afforestation in the structure of IAMs

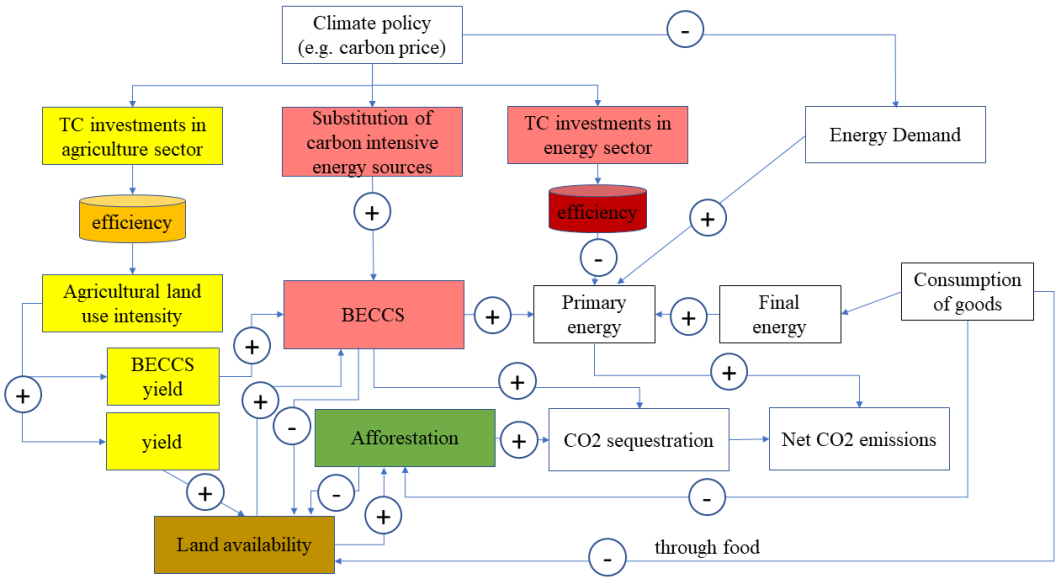
Land-based approaches are key elements of low--carbon future pathways of IAMs. Under a stringent emissions constraint, IAMs deploy mitigation options in different regions and sectors across time to achieve the most cost-effective solution. By integrating the climate, energy and economic systems, IAMs are designed to consider their changes to capture technological change and market conditions. The increasing reliance of IAMs on the deployment of highly land intensive CDR is largely associated with the limited capacity of other sectors to reduce GHG emissions. Most importantly, CDR provides the opportunity to enlarge the available carbon budget for the century by removing a portion of what is emitted from the atmosphere.

The rate of scaling up and the degree of CDR deployment are limited by existing constraints of IAMs, particularly discount rates and land--use assumptions. Köberle (2019) highlights that one important element of the structure of IAMs assigning the high value of CDR is the discount rate. The time path for emission reductions depends critically on the time preference assumption, as a criterion to weight the cost of negative emissions in the future being compared to the cost of deep mitigation today based on this criterion.

Above all, assumptions of technological progress are important drivers of the deployment level and rate of CDR in IAM scenarios. Technological change (TC) responds to economic incentives, which in the climate context is framed as an encouragement for investing in low-carbon technologies compared to other investments. The carbon price is required to induce a move towards a more innovative and clean process in the economic sectors such as the agricultural and energy systems. Despite afforestation being an existing option, whose implementation is relatively cheap, BECCS has the advantage of entailing co-benefits for the energy system.

In the macroeconomic framework of IAMs, investments are directed to energy conversion technologies that convert primary energy carriers into final energy. There is a preference for low-carbon technology within mitigation policies. The optimal energy mix satisfies a cost-minimization objective under a climate mitigation constraint. Bioenergy is considered to be a renewable energy source and therefore, it competes with other energy technologies in the IAMs on the basis of costs. Biophysical constraints on land and water availability as well as costs of biomass feedstock production to be used in the energy system are accounted for either directly through cost-supply curves of different bioenergy carriers (Hoogwijk et al., 2009) or indirectly by dedicated land-use model. Figure 2 depicts in a summary version the rationale for deploying BECCS and afforestation in IAMs. Note that IAMs may diverge in the way the feedback is included.

Figure 2



Simplified representation of the modelling of BECCS and afforestation in IAMs

The performance of BECCS is determined by how much net carbon it is able to capture (carbon efficiency) and how much net energy it produces (energy efficiency; Fajardy et al., 2019). From the carbon efficiency perspective, since carbon emissions are sensitive to increases in land productivity (yield), improving land-use management and agriculture practices could reduce the pressure on crop prices and costs of emissions mitigation. Ultimately, the intensification of land use combined with technological change enables bio-energy production to increase, thereby escalating the potential to produce both low-carbon energy and negative emissions. However, in the presence of a carbon tax applied to terrestrial carbon emissions, forested land may expand

compared to land dedicated to bio-energy crop production (Wise et al., 2009). The availability of BECCS may contribute to the decarbonization of the energy system in a particularly energy-efficient manner but it is surrounded by several uncertainties.

2.3. The linear mixed-effect model approach

In line with the objective of the paper, we used a linear mixed-- effect model approach in which total consumption, final energy, primary energy and emissions were dependent variables and the CDRs (BECCS and afforestation) the explanatory variables in each region. All variables are expressed in per capita units to avoid potential population size differences among regions. A total of eight equations were fitted separately for each couple of dependent and independent variables. The analysis is carried out using the R software (version 3.5.3) under the CRAN GNU license, available as an Open Source.

The general framework of the statistical process unfolds in two stages. Before running the linear mixed-effect models, we looked at the temporal structure of the data. The use of non--stationarity time series may provide spurious estimations, thereby indicating a relationship between two variables which does not exist. In this case, consistent and reliable results may be obtained by converting the data into stationary, that is, by removing the time-trend. The stationary process allows the statistical properties to have constant long-term mean, variance and autocorrelation independent of time. In our analysis, we checked how strongly the dataset is time-dependent by applying the augmented Dickey–Fuller (ADF). This is a widely used method to test the null hypothesis that a unit root is present in an autoregressive model of a given time series and that the process is thus not stationary. Result shows significant non-stationarity in our data. We removed the time-trend by differencing the time series. An additional ADF test was carried out on the differentiated data to check whether the differentiation correctly removed the time-trend. Appendix C exhibits results for stationarity in Tables C1 and C2 for each variable of each region.

The econometric model is used to examine the influence of both BECCS and afforestation on the selected variables over the period analysed. The use of a linear mixed--effect model instead of a classical linear model is important to account for the dependency between data from IAMs, which may induce statistical bias in linear models. In accordance with the literature (Köberle, 2019), we assume the model structure of IAMs plays an important role in assigning values to the variables. Thus, it is appropriate to verify the extent to which their heterogeneity causes any effect on the model response. For taking the group of IAMs into account, we added a random effect term to the fixed effect part of the modelling. Here, the random effect allows for

controlling for the variation between IAMs. The mixed-effect model took the following mathematical form:

$$Y_{ij}\text{reg} = \alpha + \beta X_{ij}\text{reg} + V_{i0} + V_{i1}Z_{ij} + \varepsilon_{ij}$$

where Y_{ij} is the response or dependent variable (CONS, ENE, PRIENE and EMI) for the IAM of the group; α and β are the fixed-effect parameters of the regression model; X_{ij} is the predictor or independent variable (BECCS or AFFOR) for the *j*th observation in the *i*th IAM of the group; the random effect captures the variability across IAMs, in which V_{i0} is the random intercept for the *i*th subject; V_{i1} is the random slope for the *i*th subject; Z_{ij} is term for the *i*th grouping factor (IAM); ε_{ij} is the error term (the vector of unexplained error terms, which is independent and normally distributed with mean vector zero and simple covariance structure) for observation *j* in group *i*; reg is for the region modelled.

The application of the linear mixed-effect model allows subject-specific effects that are unique to a particular group to influence the direction or strength of the relationship between variables. The advantage of its implementation is the possibility of using completely the available information. The variation from one IAM to another is computed within a nested random effect structure where the levels of BECCS and afforestation (being both the fixed and random regressor) are hierarchically subsumed under each IAM level. For each IAM, there are different scenarios under observation, which are correlated within the IAM type but independent between the others. Controlling the variability of the IAMs as a random effect increases the accuracy in the estimation of the variance. As a result, estimations produce random intercepts and slopes for each IAM. The mixed-effect model has been fit for each region separately using the Restricted Maximum Likelihood (REML) method. It makes estimates of variance parameters independent of the estimates for fixed effect. It also provides unbiased estimated coefficients for the random effect in terms of explained variance as opposed to the traditional Maximum Likelihood (ML) estimation technique (further statistical details are available in Gałecki & Burzykowski, 2013; note that different from linear regression models, mixed-effect models are not solved by the least squares method). For modelling the regional effects of BECCS or afforestation according to the IAMC 1.5℃ database, we used the 'lme4 1.1·21' package (Bates et al., 2015) in R.

To identify whether a structural instability in the model could be generating misleading estimations, a Chow Test was applied. (The Chow Test is traditionally used to test for structural change in times series. This application of the F-test requires the sum of the squared errors from the regression of each period under analysis. This means that the break--point where the potential

change in estimations may occur should be specified in advance. Failing to account for breaks might provide poor-quality average relationships.) After detecting a structural break in 2050, we estimated coefficients for the period 2050–2100, both available in Appendix D.

3. RESULTS

Our results first comprise a descriptive analysis of the mean features of BECCS and AFFOR in the IAMC 1.5℃ database. Subsequently, results of the linear mixed-effect model are presented for evaluating the link between BECCS and AFFOR with a selection of variables, considering the variability of IAMs.

3.1. Results of the IAMC 1.5℃ database

Figure 3 exhibits the amount of carbon removal from BECCS and afforestation for the selected scenarios in a global and regional aggregation, respectively. Global requirements for BECCS are projected to increase in the range of 0–4.4 Gt CO2 annually in 2050 and 0.9–12.1 Gt CO2 in 2100. By 2050, the median carbon removal from BECCS is equivalent to that from afforestation (approximately 2–4.7 Gt CO2/year), but with substantial variation among model estimates. In 2100, there is a sharp increase in the median carbon removal from BECCS against a stable range (2.4–5 Gt CO2/year) from afforestation.

Although recent modelling of IAMs features the deployment of BECCS at these large scales, there is considerable scepticism on the likelihood of such upscaling (Peters, 2016). This massive deployment of BECCS would require a large amount of land dedicated to bioenergy crops such as short-rotation coppice and miscanthus. The amount of productive land required for the use of BECCS and afforestation differs depending on the mitigation scenario, region or IAM (see Figure E2 in Appendix E). With a major increase late in the century, the median projection for global land area devoted to energy crops in 2100 is 375 Mha, representing approximately a quarter of the current cropland area. By comparison, the median area of afforestation by 2100 amounts to 33 Mha. The emissions reductions from BECCS and afforestation in each of the five regions of the IAMC database are provided in the lower panel of Figure 3.

Emissions reductions are relative to a baseline scenario without mitigation policies. In Asia, OECD90+EU member states and candidates, as a consequence of differential endowments, the carbon removal potential of BECCS is the largest among the studied regions, as is the land area used for energy crops. Among the geopolitical regions, the Reforming

Economies of Eastern Europe and the Former Soviet Union region is the one where future mitigation potential is the lowest, regardless of the land--based option (a median of 0.3 Gt CO2/year for BECCS and 0.1 Gt CO2/year in 2100). For the case of Latin America, BECCS is expected to be the preferred land--based mitigation option (Tavoni & Socolow, 2013). In our selection of scenarios, the estimated capacity of Latin America to remove carbon ranges in a very similar order for both CDR options in 2100: 0–1.9 Gt CO2 annually for BECCS and 0.5–-1.5 Gt CO2 annually for afforestation in 2100. Despite the relatively low values, this is consistent with Edmonds et al. (2013), where both options dominate the CDR portfolio of Latin America.

Discrepancies in emissions reduction between regions should therefore be carefully interpreted as the regions with the highest emissions in the baseline will tend to have higher levels of mitigation. Figure 3 shows the substantial regional disparities in carbon dioxide removal strategies. The share of afforestation in emissions reductions is higher in Latin America compared to the global situation over the whole period. On the contrary, BECCS has a relatively greater importance in Asia. Latin America is expected to play an important role in helping decarbonize the energy system, as illustrated by its large share of primary energy from biomass. Figure 4 signalises an important contribution of BECCS to the energy system decarbonization in different regions, as it becomes more accessible in future scenarios. The climate policy leads to increases in global bioenergy trade, which Daioglou et al. (2020) project Latin America and the Middle East and Africa to be net exporters of bioenergy by mid-century. The fundamental finding is that the distribution of BECCS and afforestation deployment differs across regions and time, and most importantly, across IAMs. BECCS present a larger standard deviation associated with the estimates compared to afforestation. In other words, BECCS is expected to be adopted on larger scales than afforestation, but the absolute level is uncertain given the discrepancies across models. However, it is cost-effectively available mainly from the middle century onward, when more ambitious mitigation targets (and carbon prices) are expected.

Since regions respond differently to the climate goal, the value of carbon, and therefore the amount of CDR required to achieve the target, is also region-specific (see Figure E3 in Appendix E). The land-use trade-off between BECCS and afforestation plays an important role in determining the level of deployment but also the biomass trade effect Since biomass feedstock can be traded, the related trade profile can influence where each type of CDR is deployed and how. For an increasing value over time, carbon price also varies substantially across IAMs and scenarios. In the short term, afforestation remains the least costly and most easily deployable since forests already store large quantities and are currently available. To the extent to which the carbon storage is limited by land surface over time, the option to produce more negative emissions

is through BECCS deployment. As shown in Figure 5, BECCS appears to be consistently privileged over afforestation in the model architectures in the long run.

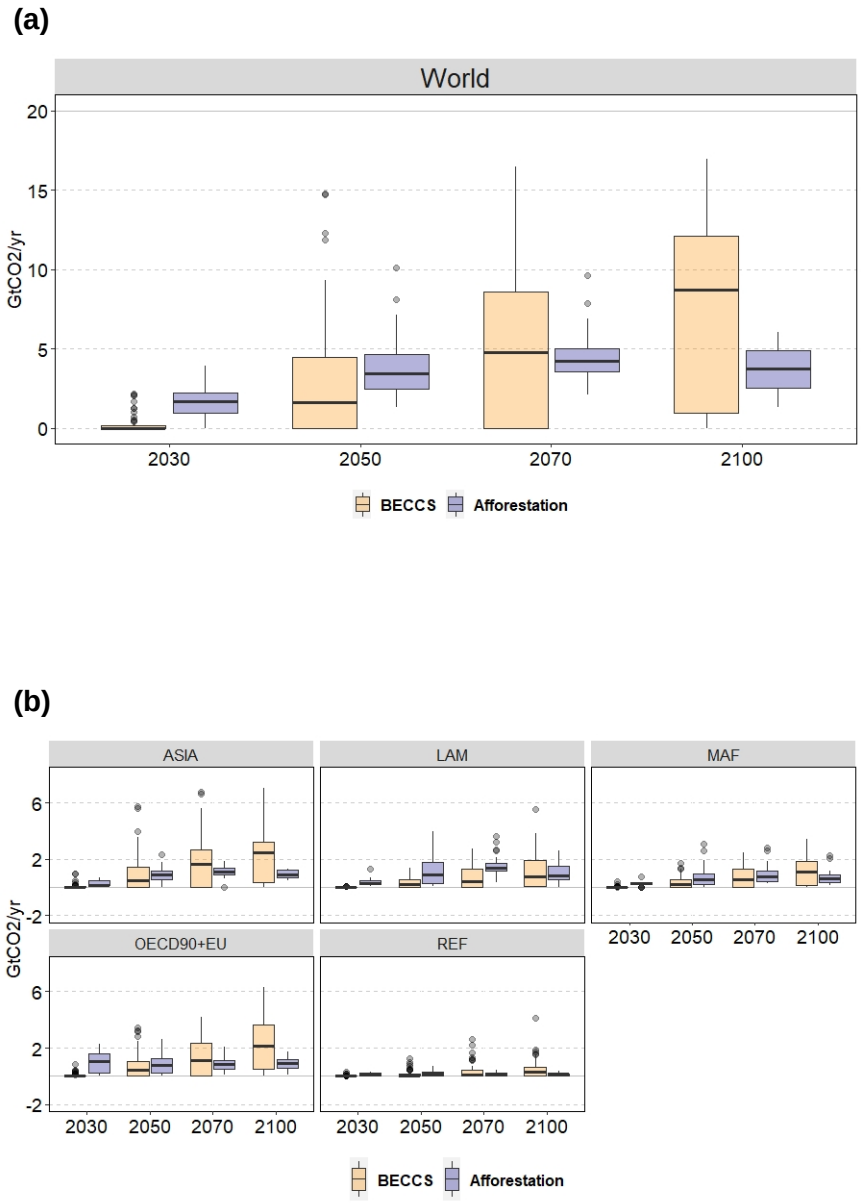


Figure 3 - Global (a) and regional (b) emission reductions from BECCS and afforestation

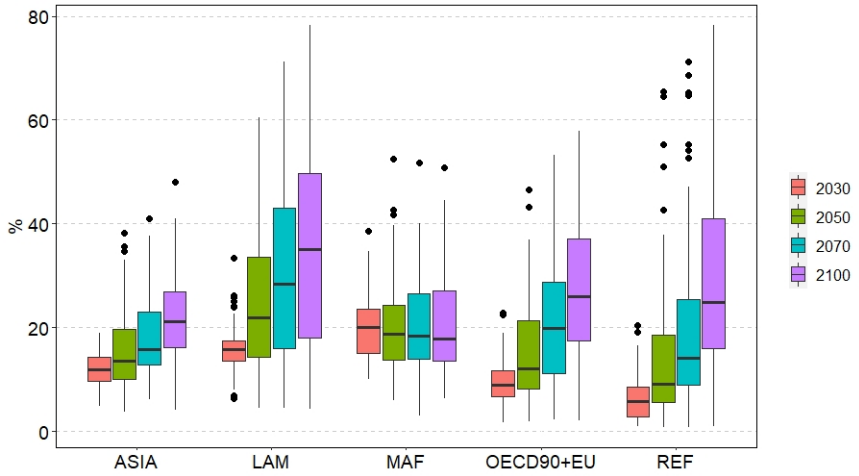


Figure 4 - Share of primary energy consumption of biomass per region. Trade effects are included.

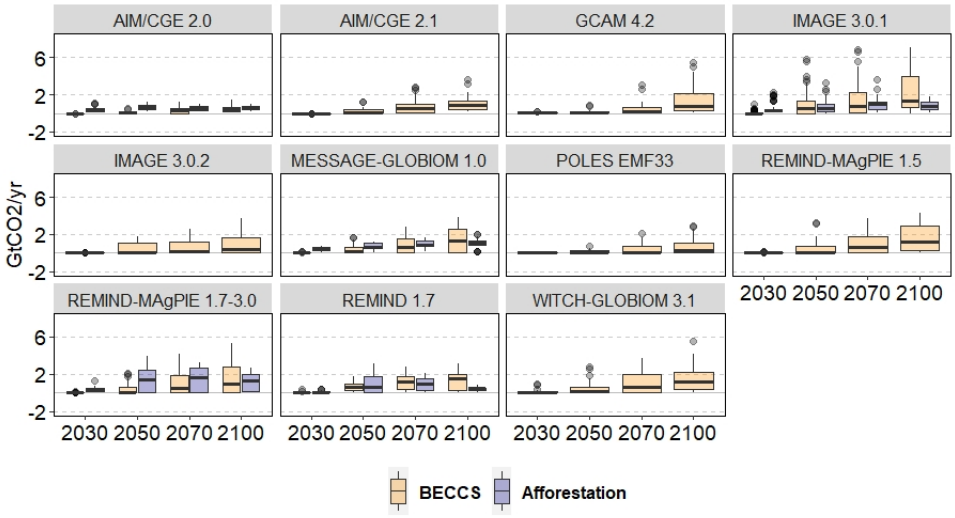


Figure 5 - Emission reductions from BECCS and afforestation in the selected IAMs

3.2. Assessing land-based mitigation in IAMs with linear mixed-effect model

To understand the role of BECCS and afforestation in IAMs, we estimated the effect of both CDRs (in Gt CO2/cap/year) on four IAMs outputs expressed in per capita units: emissions (Gt CO2), primary energy use (PJ), final energy use (PJ) and total consumption (Million US$2010). The estimation is carried out based on a linear mixed-effect model which allows us to control for the dependency between IAM outputs. We present first the specific role of regional CDRs deployment (fixed effect, see Table 2), and then we detail the specific role of IAMs' structure and modelling assumptions for each IAM independently (random effect, see Figure 3). For the confidence interval of estimations, see Table F1 in Appendix F. The estimated coefficients can be

interpreted as the unit change in the selected variable for a unit change in the deployment of BECCS or afforestation. The statistical significance means that we can reject the hypothesis that the dependent variable does not affect the independent one. Statistical significance is based on *p* values. The lower the *p-value*, the larger the confidence is in rejecting the 'no--effect' hypothesis. A large coefficient is not necessarily statistically significant. In this case, it suggests a large confidence interval and an important disagreement among models.

Table 2 - Effect of BECCS and afforestation (in Gt CO2 sequestered per capita) on selected independent variables (in per capita units)

Region	EMI	PRIENE	ENE	CONS
BECCS				
LAM	1.16***	42.12&**	6.53	69.37
ASIA	1.03***	43.46	21.35	892.71
MAF	1.27***	21.42	31.48	1013.84
REF	3.12	459.85	296.64	59.38
OECD+EU	1.06***	29.18	24.04	699.21
WORLD	1.34***	35.69	19.87	177.16
Afforestation				
LAM	1.21***	16.14***	12.07	275.18
ASIA	2.24***	114.51***	27.29	2980.03
MAF	1.07**	41.55	34.54	7354.66
REF	2.20	444.88	487.02	295.62
OECD+EU	0.26	43.71	15.64	2879.72
WORLD	2.12***	143.13**	68.80	8916.11

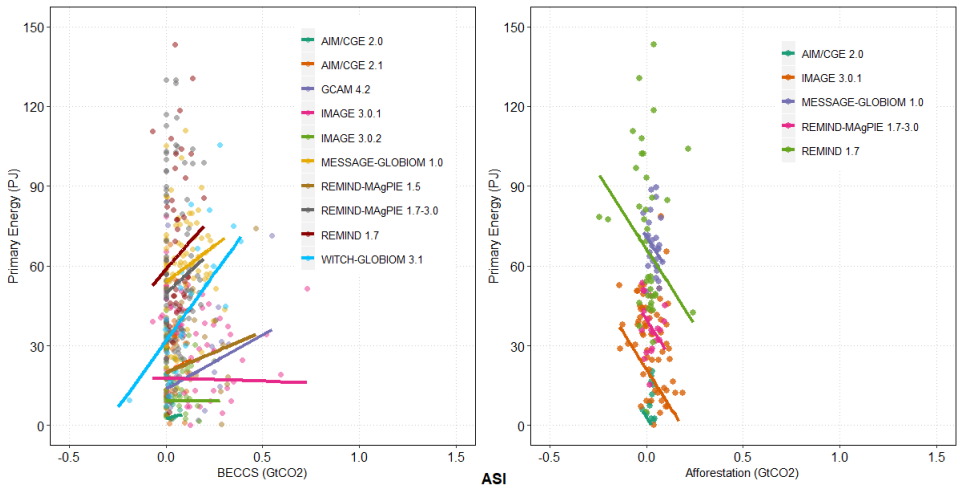
Abbreviations: CONS, total consumption; EMI, emissions; ENE, final energy use; PRIENE, primary energy use.
The asterisk indicates the confidence level: *$p < 0.10$.; **$p < 0.05$.; ***$p < 0.01$.

Our results show a negative relation between emissions and the two CDRs considered at the global and regional levels. The estimated coefficients are significantly different from zero in every region except in the OECD90+EU member states (for afforestation) and Reforming Economies of Eastern Europe (for afforestation and BECCS). Afforestation has a negative effect on primary energy, meaning that an increase in afforestation results in a decrease in primary energy, an effect that is highly significant for two out of five regions considered, as well as at the world level (those estimations are displayed in Figures F1 and F2 of Appendix F). This inverse relationship can be explained by the fact that increased afforestation is more present in scenarios of low energy demand and lifestyle change. In contrast, we did not find any significant relation between BECCS and primary energy in IAMs, except in Latin America. In this region, 1 Gt CO2 removed from the atmosphere with BECCS is associated with an increase in primary energy use by 42 PJ.

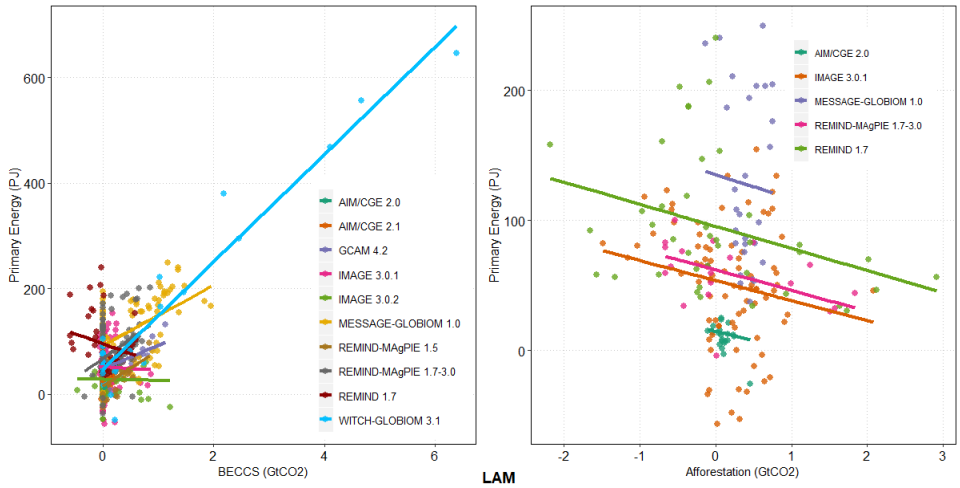
CDRs are characterized by a ramp-up in their deployment, especially for BECCS after 2050. We conducted for this reason a Chow test to evaluate the presence of a possible structural break, that is, a change in the magnitude of the effects of BECCS on the level of energy and emissions before and after 2050. The test is conclusive, which is an indication that the effect of BECCS is mostly concentrated in the period after 2050. The regression coefficients estimated after 2050, as well as their level of significance, do not differ substantially from the values obtained over the entire period (see Appendix D). As previously discussed, Latin America is also the region with the largest projected share of primary energy from biomass, which may explain why we find a significant relation in this region in particular (see Figure E1). Our results fail to provide evidence that the final energy or consumption level is significantly correlated to changes in BECCS or afforestation deployment. Final energy and consumption are likely to be associated with other intrinsic mechanisms in IAMs, such as energy efficiency or demand elasticity. However, we were unable to dig deeper in these directions with the data available in the IAMC 1.5℃ database.

To capture the influence of the model structure, we report the estimated relations between BECCS/afforestation and primary energy for each IAM (see Figure 6; Appendix F displays the estimated coefficient of emissions per IAM for each region, whereas regional estimations per IAM are provided in Appendix G). IAMs agree regarding the role of afforestation on primary energy, which indicates that the role of afforestation in mitigation pathways goes beyond the individual model assumptions on afforestation potentials. There is less agreement for BECCS, depending on the region considered. Models exhibit a positive relationship between BECCS and primary energy for Asia (but IMAGE), OECD90+EU (but REMIND 1.7) and Reforming Economies of Eastern Europe and the Former Soviet Union. This suggests for those regions a systematic increase in primary energy when BECCS deployment increases, however, with uncertainty on the magnitude of this effect. In contrast, there is no agreement for IAM and MAF regions, suggesting a strong variability in the way the different models project those economies. IAMs simulated more consistently a negative response between afforestation and primary energy with, however, a larger range of intercepts. This suggests that the emissions reductions from afforestation occur in a wider range of contexts of energy consumption.

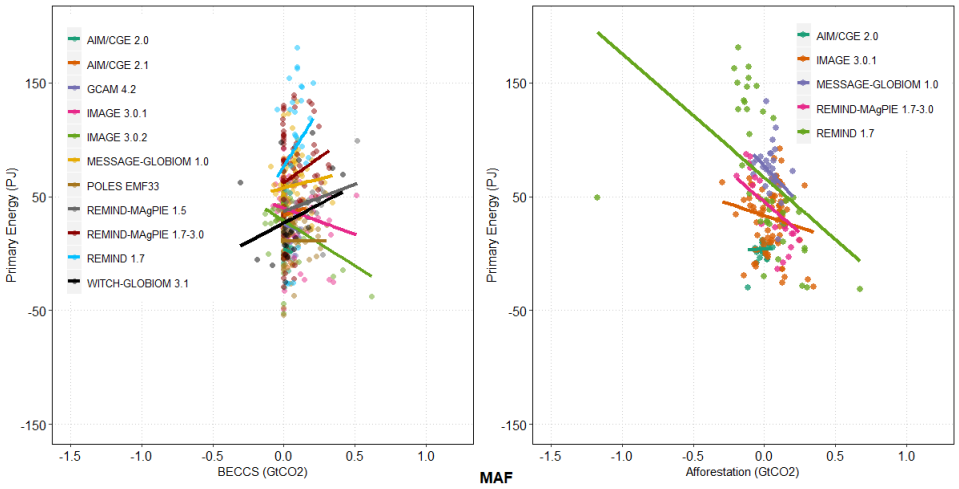
(a)


Primary Energy (PJ)
BECCS (GtCO2)
Afforestation (GtCO2)
AIM/CGE 2.0
AIM/CGE 2.1
GCAM 4.2
IMAGE 3.0.1
IMAGE 3.0.2
MESSAGE-GLOBIOM 1.0
REMIND-MAgPIE 1.5
REMIND-MAgPIE 1.7-3.0
REMIND 1.7
WITCH-GLOBIOM 3.1
ASI

(b)


Primary Energy (PJ)
BECCS (GtCO2)
Afforestation (GtCO2)
AIM/CGE 2.0
AIM/CGE 2.1
GCAM 4.2
IMAGE 3.0.1
IMAGE 3.0.2
MESSAGE-GLOBIOM 1.0
REMIND-MAgPIE 1.5
REMIND-MAgPIE 1.7-3.0
REMIND 1.7
WITCH-GLOBIOM 3.1
LAM

(c)


Primary Energy (PJ)
BECCS (GtCO2)
Afforestation (GtCO2)
AIM/CGE 2.0
AIM/CGE 2.1
GCAM 4.2
IMAGE 3.0.1
IMAGE 3.0.2
MESSAGE-GLOBIOM 1.0
POLES EMF33
REMIND-MAgPIE 1.5
REMIND-MAgPIE 1.7-3.0
REMIND 1.7
WITCH-GLOBIOM 3.1
MAF

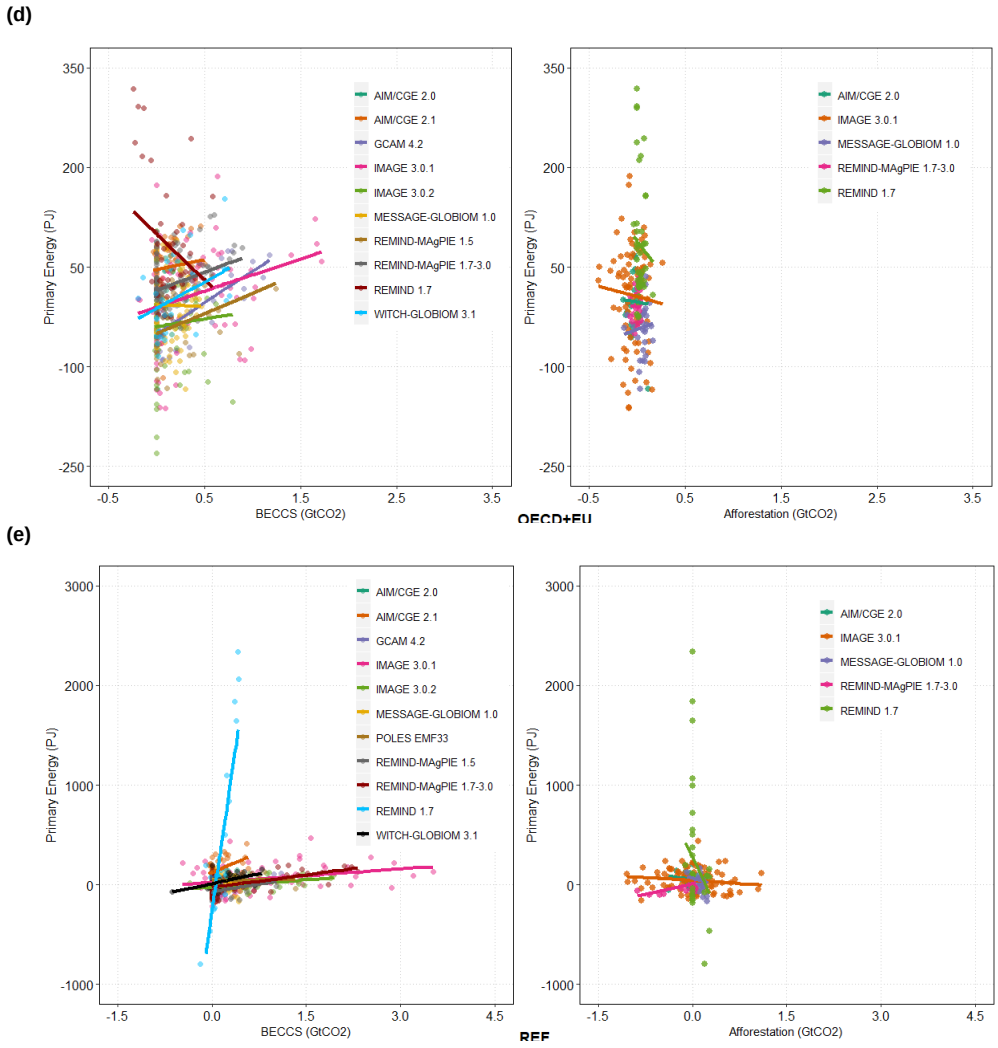


Figure 6 - IAM-specific relations between BECCS and primary energy (left plots) and afforestation and primary energy (right plots) in the five regions of the IAMC database (in per capita units): (a) Asia, (b) Latin America, (c) Middle East and Africa, (d) OECD 90+EU, and (e) Reforming economies of Eastern Europe and the former Soviet Union.

4. DISCUSSION

Land-based mitigation options dominate international climate policy scenarios, as illustrated in the uptake of BECCS and afforestation scenarios into the IAMC 1.5℃ database. Some considerations can be drawn from our cross-IAM assessment. First, both CDR options are

associated with IAMs with significant emissions reduction in most regions. With the promise of future availability, sequestered emissions from BECCS ramp up in the second half of the century while those from afforestation remain stable after 2050. This reflects different assumptions within IAMs regarding the dynamics of carbon flux and the availability of land for each CDR option. In particular, IAMs consider the carbon storage potential of forests to be more limited than that of BECCS since forests stop storing carbon once they reach maturity while BECCS is a flux. Cost estimations of alternative mitigation options in different end uses also differ (Daioglou et al., 2020).

BECCS and afforestation have different effects on the energy system as BECCS generates energy while afforestation does not. On this aspect, our results show that the deployment of BECCS is associated with a greater share of biomass in primary energy in every region considered. However, if we look at the relationship between BECCS and primary energy, this effect is neither clear for every region nor significant at the world scale. This indicates that BECCS is preferred not for its ability to expand energy use but actually because it appears as an alternative to afforestation, which is associated with a decrease in energy use. This is coherent with Creutzig et al. (2021), whose study points out the limitation of BECCS in generating energy compared to other more cost-effective and land-sparing energy solutions, which are not yet reflected in the IAMs scenarios. Most importantly, it suggests that although there is a need to reduce the preference for BECCS, it should be accompanied by a group of strategies such as a broader portfolio of CDRs as well as reduced energy demand or changes in diets.

The availability of other CDRs could also influence the use of BECCS for climate mitigation in the scenarios evaluated. In the lack of other mitigation alternatives or other elements within the IAMs framework, the excessive inclusion of CDR in the modelling appears as a necessary means for achieving stringent mitigation pathways. It also becomes a manner of avoiding other unrealistic scenarios such as those based on extreme demand-side shifts.

According to the scenarios under scrutiny, our results show that there is a larger variance in terms of BECCS deployment compared to afforestation, shedding light on the highly uncertain scale--up of BECCS. In fact, BECCS is implemented later in the century so as to compensate for emissions from earlier periods. In line with Dooley et al. (2018), the high expectation for BECCS appears better explained by individual model assumptions than the narratives (scenarios) since different IAMs display different results for the same variable in the same narrative (e.g., scenarios of the SSP1). This variation in the type of response leads to a mixed conclusion on the functioning of IAMs. Whether characterized by relatively detailed biophysical processes (biophysical--oriented) or by a more detailed description of the economic system (economic-oriented), the modelling pattern can potentially explain the variability since it differs significantly among IAMs.

The availability, economic feasibility and sustainability of energy crops are treated differently in the models and involve constraints that relate to competition for land with other human uses, ecological limits and issues of biomass seasonality and storage (Butnar et al., 2020). The combination of each of these constraints in the modelling assumptions produces a wide range of possible bio-mass potential. Another relevant aspect of the IAM functioning is the land-use representation. Distinctive land--use modules are used for the translation of the narratives into quantitative projections. Each model incorporates the land--use dynamics in the model solution differently, whether by exogenous (AIM/CGE) or endogenous consideration (IMAGE and GCAM).

In view of the future prospects of CDR deployment, Butnar et al. (2020) dive into the transparency of modelling assumptions for BECCS in IAMs. The study finds that all IAMs communicate wider system assumptions and major cost assumptions transparently, but they fail to communicate appropriately modelling details. In this paper, understanding the functioning of IAMs driving the results is also not straightforward. BECCS and afforestation are not represented simultaneously in every IAM. Of the 72 database entries, BECCS is available in 53 (73%) of them, and only 23 (32%) scenarios account for afforestation. It is not obvious whether this is an issue of reporting variables into the database or a matter of modelling representation. Explaining the non--significant relation between BECCS and primary energy, and how this effect does not translate into final energy and consumption is also limited by the lack of details on the modelling of the different IAMs. Other intrinsic mechanisms are potential drivers of this response, such as energy efficiency or demand elasticity. In some IAMs, the integration of bioenergy in the energy system is more challenging (Bauer et al., 2018) due to the carbon tax effect on both the supply and demand side. The effects of a climate policy on the demand side were not investigated, which may contribute to the impacts of BECCS on primary energy, final energy and consumption.

At the regional level, factors such as land availability, quality and accessibility are critical to mitigation potential and may be determinants for regional implementation of BECCS and afforestation. Yet, as indicated by IAMs, future mitigation pathway of each region reflects cost--optimal solutions to achieve both domestic and global demand for CDR. Thus, it occurs where the most suitable production conditions and lowest costs are. Regions with large storage potential have a competitive advantage in implementing CDR (Tavoni & Socolow, 2013). In the case of BECCS, the literature suggests that regions with higher biomass potential such as Latin America or the Middle East and Africa are not necessarily regions with well--characterized carbon storage capacity as OECD90+EU member states and candidates (Fajardy et al., 2019). Hence, large-scale deployment in those regions can be limited, albeit it also depends on the biomass trade effect. On the other hand, the largest share of primary energy from biomass is found in Latin

America, although most other regions, except the Middle East and Africa, face an upward trend as well. According to Daioglou et al. (2020), those two regions integrate the global bioenergy trade chain as net exporters. Hence, to what extent the two land--based options will be produced or traded by one region or another remains uncertain.

Our analysis demonstrates that the observed response of BECCS and afforestation is both IAM-specific and region-specific. The literature to date has mostly concentrated on the impacts of CDR deployment at the global scale. However, the global perspective may fail to provide evidence on where BECCS and afforestation deployment are more feasible. In this paper, we were unable to find strong evidence of regional pattern, and the drivers of regional discrepancies- among IAMs are not obvious. Our analysis is limited by the lack of specificities and scalability of different types of CDR in the IAMs, as argued by Butnar et al. (2020). Since developments of land use are strongly associated with region-and context-specific factors such as institutional and regulatory instruments or type of land, these dimensions should be explicitly represented in the IAMs. An in-depth investigation of the IAM structure is rather imperative for comprehending the dynamics of BECCS and afforestation response as well as mitigation costs projected for the regions. This could disentangle the evolvement of regional land-based mitigation options across time.

5. CONCLUSIONS

This paper investigated the role played by BECCS and afforestation/reforestation on future mitigation scenarios designed by IAMs. These scenarios increasingly rely on the deployment of CDR, from which three patterns of deployment take place, that is, by type of CDR, time horizon and regional. Despite the potential to complement emissions mitigation efforts, this dependence on future large-scale CDR deployment raises questions as to the structure of IAMs that are influencing the feasibility of the resulting mitigation pathways. Our statistical analysis is framed in this context.

According to our cross-IAM assessment, both CDR options are associated with similar regional reductions in carbon emissions. With the promise of future availability, the deployment of BECCS takes place in the second half of the century. An important aspect of BECCS is that it generates energy while afforestation does not. Despite the great share of biomass in primary energy in the regions considered, the effect of BECCS on the energy system is not clear. Most importantly, it fends the preference for BECCS from the argument that it contributes to the expansion of energy use. The conclusion is that BECCS would be more of an alternative to

afforestation, which is extensively included in IAMs as a manner of avoiding other unrealistic scenarios such as those based on extreme demand-side shifts.

This leads to a major conclusion regarding CDR deployment in our analysis: although there is a general agreement across IAMs on the future role these technologies are expected to play, it remains uncertain the extent to which high rates of CDR can be actually delivered and where. This raises concerns about the capacity to limit global warming below 1.5 and 2℃. For the purpose of reducing the dependence on these land--based mitigation options, IAMs should also incorporate a more systematic assessment of CDR portfolios that include other mitigation options and related geophysical constraints. Since demand for CDRs will be heavily conditioned by policies, future research should explore the effects of CDR availability in a cross--model analysis in the context of regional carbon pricing.

The main contribution of this research to the literature is to shed light and disentangle some conclusions about CDR deployment from mitigation scenarios of IAMs. With this study, we remain of the view that policymakers should beware of excessive CDR scenarios of IAMs. Since there has been extensive use of IAMs in the mapping of mitigation options to support decision--making, future investigations should build a deeper link between the results and policy recommendations. This is important as future mitigation scenarios of IAMs are designed to capture different dimensions of reality that are framed in a climate narrative and drive the results. To picture the real-world effects more precisely, taking into account regional particularities is crucial for policy proposals involving land-based mitigation efforts.

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CONFLICT OF INTEREST

There is no financial/personal interest.

DATA AVAILABILITY STATEMENT

Data sharing not applicable as no new data were generated.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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APPENDICES

APPENDIX A

Selected scenarios are distinguished in several aspects. The climate policy can be implemented through a carbon tax in association or not with low concentration targets, low population growth, low energy demand, behaviour change among others, as described in Table A1 below. Those policies are translated into targets, carbon budgets or level of radiative forcing, representing the mitigation goals which is consistent with the 1.5℃ or 2℃ objectives. Scenarios where CDR deployment is explicitly declared were also selected. In some cases, it is specified the amount of CDR available, ranging from 8 GtCO2 to 20 GtCO2 annually. Of the 29 scenarios, however, only 24 have reported results differentiated by region. This regional filter kept them out of the analysis.

Table A1 – Description of selected scenarios

Scenario	Type of climate policy	Target (°C)	Budget (GtCO2)	Forcing in 2100 (W/m^2)	CDR availability	Carbon tax in 2020 ($US/tCO2)
CEMICS-1.5-CDR8	LCT and CDR	1.5	X	2.0	8 GtCO2	X
CEMICS-1.5-CDR20	LCT and CDR	1.5	X	2.0	20 GtCO2	X
CEMICS-2.0-CDR20	LCT and CDR	2.0	X	2.6	20 GtCO2	X
CEMICS-2.0-CDR8	LCT and CDR	2.0	X	2.6	8 GtCO2	X
EMC_lowEI_100$	LCT and CDR	X	X	X	X	100$ and increase 5% per year afterwards
EMC_lowEI_30$	LCT and CDR	X	X	X	X	30$ and increase 5% per year afterwards
EMC_Def_100$	FTA and Ctax	X	X	X	X	100$ and increase 5% per year afterwards
EMC_Def_30$	FTA and Ctax	X	X	X	X	30$ and increase 5% per year afterwards
IMA15-Def	LCT and Ctax	X	X	1.9	X	X
IMA15-Eff	TEME	X	X	X	X	X
IMA15-LiStCh	BC	X	X	X	X	X
IMA15-Pop	LPG	X	X	X	X	X
IMA15-RenElec	LCE	X	X	X	X	X
IMA15-TOT	TEME,BC, LPG, LCE, Ctax	X	X	X	X	X
SMP_1p5C_lifesty	LCB, LED, BC	X	400	X	X	X
SMP_2C_lifesty	LCB, LED, BC	X	1000	X	X	X
SSP1-19	LCT	X	X	1.9	X	X
SSP1-26	LCT	X	X	2.6	X	X
SSP1-34	LCT	X	X	3.4	X	X
SSP1-45	LCT	X	X	4.5	X	X
LowEnergyDemand	LED	1.5	X	X	X	X
EMF33_Med2C_full	LCB, CDR	X	1600	X	BECCS, CFH	X
EMF33_Med2C_nobeccs	LCB, CDR	X	1600	X	CFH	X
EMF33_tax$_{hi}$_full	Ctax and CDR	X	X	X	BECCS, CFH	30$ and increase at 5% per year afterwards
EMF33_tax_hi_none	Ctax	X	X	X	X	30$ and increase at 5% per year afterwards
EMF33_tax_lo_full	Ctax and CDR	X	X	X	BECCS, CFH	20$ and increase at 3% per year afterwards
EMF33_tax_lo_none	Ctax	X	X	X	X	20$ and increase at 3% per year afterwards
EMF33_WB2C_full	LCB, CDR	X	1000	X	BECCS, CFH	X
EMF33_WB2C_nobeccs	LCB, CDR	X	1000	X	BECCS, CFH	X

LCT = low concentration target, FTA = full technology availability, Ctax = carbon tax,
TEME = technologies for energy and material efficiency, BC = behaviour change,
LPG = low population growth, LCE = low carbon energy, LCB = low concentration target
LED = low energy demand, CDR = carbon dioxide removal, CFH = cellulosic fuels, hydrogen

APPENDIX B

The IAMC 1.5℃ database presents an ensemble of quantitative model-based climate mitigation pathways underlying socioeconomic, development energy system and land use change. Those aspects vary across both IAMs and scenarios, which is also the case for land-based mitigation options. For scenarios, Table B1 shows that carbon sequestration from Afforestation and BECCS are the most represented options, and jointly. Exceptions include EMC and SSP5 scenarios, with the use of BECCS only. LED is the only scenario in which there is a focus on mitigation using Afforestation. On the other hand, other types of CDR are yet to be explored in the modelling framework.

Table B1 - Land-based mitigation options in the IAMC 1.5℃ database

Scenarios	Afforestation	BECCS	Others
ADVANCE	Yes	Yes	X
CD-LINKS	X	X	X
CEDS	X	X	X
CEMICS	Yes	Yes	Yes(DACCS)
EMC	X	Yes	X
EMF	Yes	Yes	X
IMA	Yes	Yes	X
LED	Yes	X	X
PEP	Yes	Yes	X
SKY	Yes	Yes	X
SMP	Yes	Yes	X
SSP1-5,19	Yes	Yes	X
SSP1	Yes	Yes	X
SSP2	Yes	Yes	
SSP3	Yes	Yes	X
SSP4	Yes	Yes	X
SSP5	X	Yes	X

APPENDIX C

The ADF test was used to evaluate the existence of stationarity in the modelling data. In addition to testing stationarity in the variables, we tested the mixed effect models for cointegration by applying the ADF on their residuals, in this case. Results indicate stationarity and cointegration if the significance level is achieved, as observed by the p-value. Another option is to compare the statistical test with the critical values of 99%, 95% or 90%. The number of observations

determines the critical value of the Dickey-Fuller table (Fuller, 2009). Since there are more than 500 in the modelling data, at 1%, 5% and 10%, the critical values are -3.96, -3.41 and -3.13, respectively. Tables C1 and C2 show the statistic test and level of significance. In all cases, we rejected the unit root hypothesis and concluded that the differenced series is stationary.

Table C1 – Augmented Dickey-Fuller test: Type 3 (with drift and trend)

Region	BECCS	AFFOR	CONS	ENE	PRIENE	EMI
lag 0						
ASIA	-12.64***	-15.17***	-5.59***	-13.02***	-13.77***	-13.98***
LAM	8.83***	-13.59***	-8.00***	-12.94***	-13.52	-15.22***
MAF	-13.10***	-13.33***	-9.88***	-12.73***	-12.78**	-15.76***
OECD+EU	-11.19***	-9.98***	-10.05***	-13.70***	-12.46***	-14.30***
REF	-8.82***	-12.22***	-5.54***	-10.61***	-10.77***	-12.7***
lag 1						
ASIA	-11.16***	-8.6***	-4.86***	-11.82***	-11.64***	-14.17***
LAM	-10.36***	-12.32***	-7.70***	-13.08***	-13.36***	-15.22***
MAF	-13.81***	-12.24***	-9.97***	-11.88***	-11.22***	-15.09***
OECD+EU	-12.76***	-7.67***	-10.38***	-12.37***	-11.00***	-13.05***
REF	-10.90***	-14.93***	-5.14***	-17.44***	-14.67***	-14.44***

Table C2 – Augmented Dickey-Fuller test on residuals (cointegration): Type 3 (with drift and trend)

Region	CONS		ENE		PRIENE		EMI	
	BECCS	AFFOR	BECCS	AFFOR	BECCS	AFFOR	BECCS	AFFOR
lag 0								
ASIA	-10.99***	-10.20***	-15.69***	-8.14***	-15.80***	-10.25***	15.70***	-9.15***
LAM	12/50***	-7.66***	-14.50***	-7.20***	-13.80***	-7.76***	-19.2***	-10.07***
MAF	-12.87***	-8.42***	-16.10***	-9.22***	-16.40***	-10.58***	-18.3***	-9.02***
OECD+EU	-11.60***	-6.85***	-15.40***	-9.18***	-14.40***	-9.51***	-16.40***	-8.40***
REF	-8.40***	-8.86***	-14.90***	-6.23***	-16.96***	-6.38***	-16.40***	-7.29***
lag 1								
ASIA	-11.43***	-5.93***	-14.65***	-9.05***	-14.10***	-8.29***	-15.80***	-9.70***
LAM	-14.10***	-8.61***	-14.40***	-9.05***	-14.1	-8.41***	-17.30***	-9.44***
MAF	-14.51***	-9.19***	-15.60***	-8.47***	-15.1***	-8.04***	-17.10***	-8.27
OECD+EU	-12.60***	-7.43***	-14.80***	-8.99***	-13.21***	-8.03***	-15.00***	-8.90***
REF	-8.90***	-8.51***	-16.5***	-9.60***	-15.88***	-8.86***	-16.90***	-7.15***

APPENDIX D

The use of Chow test is useful in this analysis to determine whether there is a change in the relation between CDR deployment and selected variables after 2050. The test returns results of F statistics and the p-value. In Table D1, the calculated F-value exceeds the F-critical value (1.96) and we reject the hypothesis that there is no difference between both time periods at 95\% confidence level, reinforced by statistically significant p-values (lower than 0.001). For primary energy consumption in Asia, OECD+EU and Reforming Economies, however, the year of 2050 does not indicate a change in the parameters. Table D2 presents the separate estimations of the coefficients for 2050-2100, whose significance remains unchanged.

Table D1 – Chow test for structural break in 2050

Region	EMI		PRIENE	
	F value	P value	F value	P value
BECCS				
LAM	71.82	0.00	32.47	0.00
ASIA	227.90	0.00	55.56	0.00
MAF	56.76	0.00	7.88	0.00
REF	106.03	0.00	13.36	0.00
OECD+EU	55.48	0.00	33.88	0.00
Afforestation				
ASIA	16.33	0.00	2.63	0.07
LAM	9.94	0.00	9.33	0.00
MAF	20.78	0.00	5.20	0.01
OECD+EU	0.27	0.76	1.38	0.25
REF	2.44	0.09	1.90	0.15

Table D2 – Coefficient estimations for the 2050-2100 period (in *per capita* units)

Region	EMI (MtCO2)	PRIENE (GtCO2/PJ)	ENE (GtCO2/PJ)	CONS (MtCO2/MillionUS$2010)
BECCS				
ASIA	-1.11 **	34.64	-17.99	1134.92
LAM	-1.26 ***	48.58 ***	-3.11	-24.50
MAF	-1.48 **	34.43	-25.21	1612.38
OECD+EU	-1.08 ***	16.56	-29.76	-191.63
REF	-3.23	433.81	285.92	52.31
Afforestation				
ASIA	-2.61 **	-81.19 **	-40.11	719.06
LAM	-1.05 **	-17.38 *	-11.34 *	-424.26
MAF	-1.21 ***	-23.97	-25.65	-3421.55
OECD+EU	-0.65	-203.38	-197.74	-23649.13
REF	1.57	-465.38	-450.05	1004.80

APPENDIX E

This section complements the descriptive analysis with two types of information obtained from the 1.5℃ database: i) land coverage at different dimensions and ii) regional carbon prices in IAMs. Figure E1 displays the distribution of data on global and regional land coverage differentiated between energy crops and forest whereas Figure E2 shows the amount of productive land categorised by IAMs. The figures allow us to understand the variability or spread of the data set.

For example, data on land covered by energy crops is more spread in comparison to that dedicated for forests in most regions. We can also observe that some IAMs do not estimate land coverage of forests, or at least, do not report this variable. In IAMs, future mitigation pathways involving both BECCS and Afforestation are linked to a carbon price, which is region-specific. According to Figure E3, IAMs project the carbon prices to increase over the century with Asia and OECD90+EU facing the largest mitigation costs. The price dynamic is directly reflected in the results.

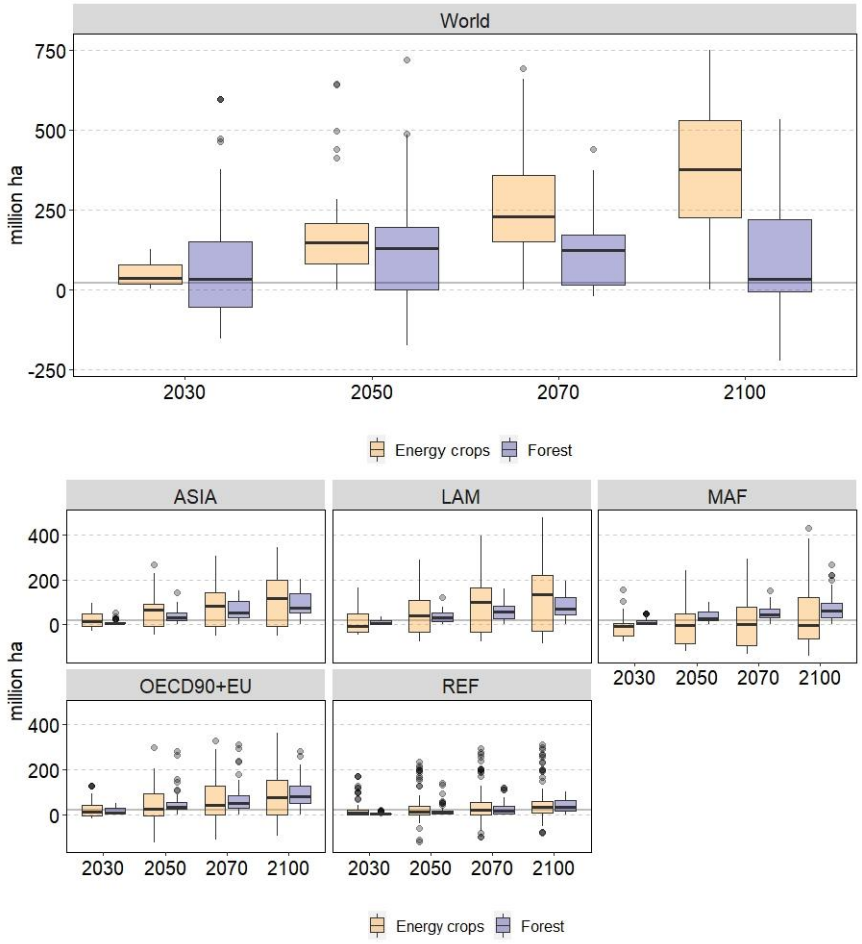


Figure E1 - Global and regional land coverage

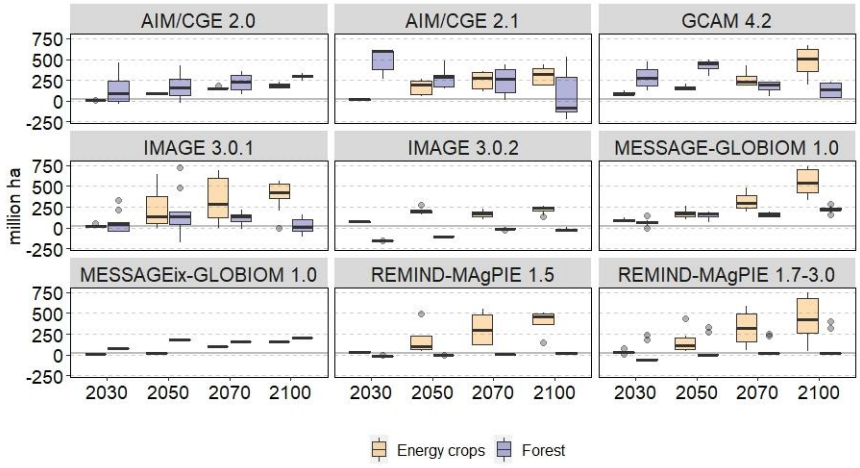


Figure E2 - Land coverage in the IAMs

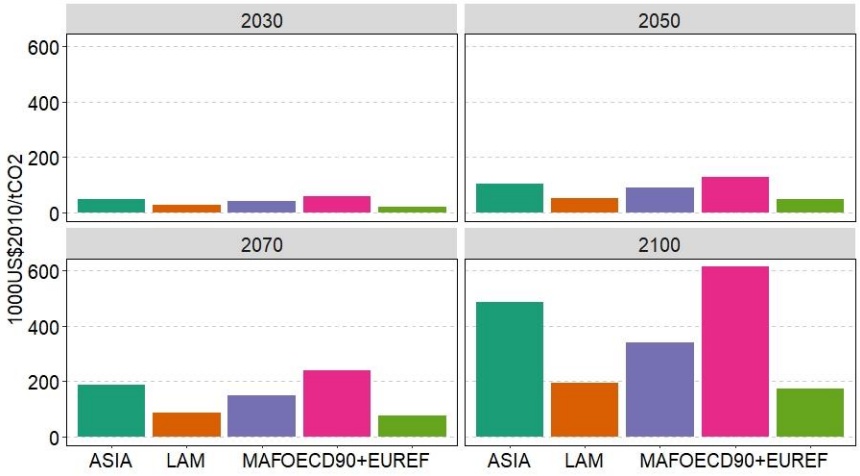


Figure E3 - Regional carbon prices in the IAMs

APPENDIX F

This section helps better visualise the results from the linear mixed effect model. In Figure 1 and Figure 2 the relationship between BECCS and Afforestation with emissions and primary energy is displayed for each of the regions. Considering potential uncertainties of the estimations, we calculated the range of plausible values in which coefficients are likely to fall between. This confidence interval sets probability limits of 2.5% and 97.5%, as described in Table F1. As part of the random effect, Figure F3 reports the independent coefficient estimations of emissions per IAM in each region.

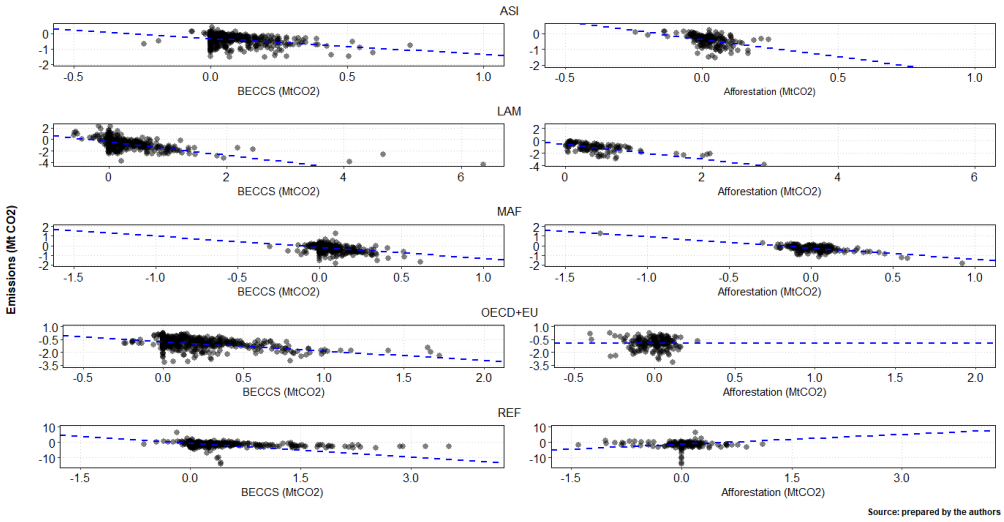


Figure F1 – Changes in emissions per region

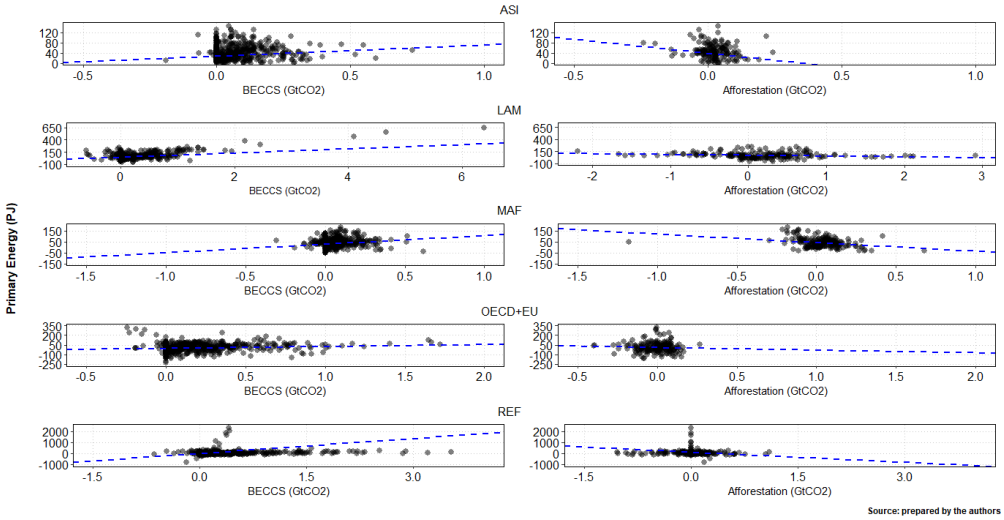
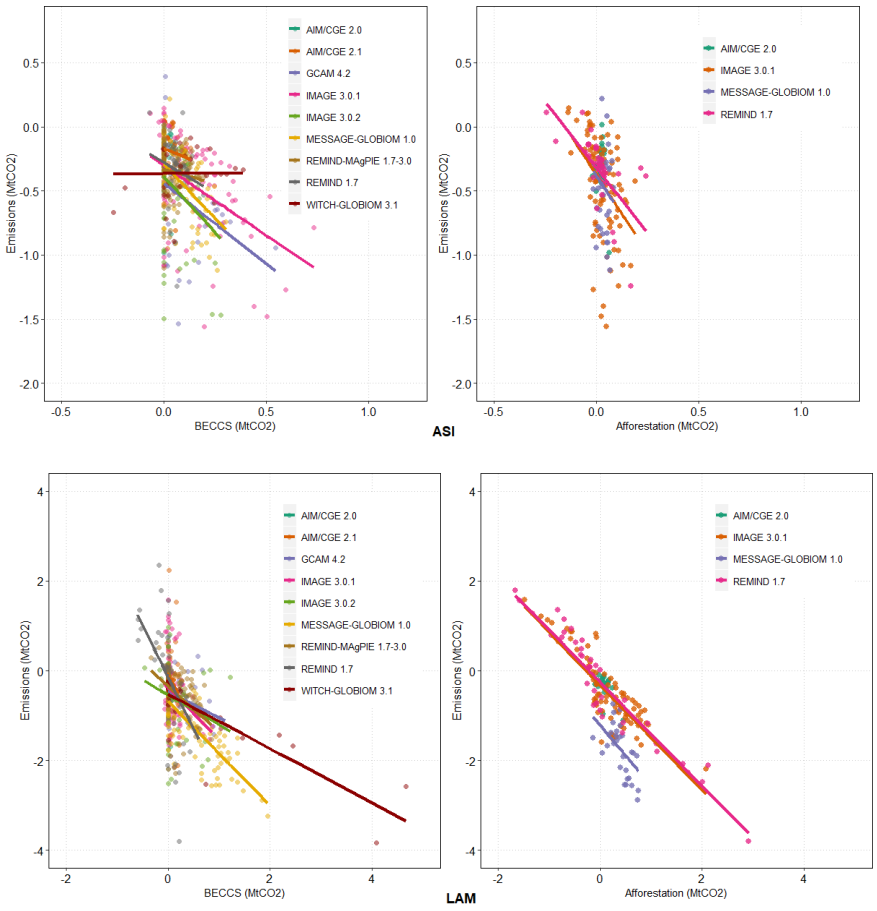


Figure F2 – Changes in primary energy per region

Table F1 - Confidence interval from coefficient estimation

Region	EMI		PRIENE		ENE		CONS	
	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%
BECCS								
LAM	-1.7	-0.7	8.5	75.2	-34.4	18.3	-1146.5	1316.7
ASIA	-1.6	-0.4	1.2	87.8	-47.6	2061.9	-3663.4	5678.7
MAF	-1.8	-0.7	-46.1	85.2	-61.2	0.8	-4172.1	2073.4
REF	-7.0	0.6	-293.8	1194.3	-283.4	847.2	-1212.5	1300.8
OECD+EU	-1.4	-0.7	-27.8	76.1	-63.8	10.5	-4356.8	2507.2
Afforestation								
LAM	-1.3	-1.1	-26.8	-5.8	-21.8	-0.8	-998.6	1316.7
ASIA	-3.1	-1.4	-195.7	-41.2	-75.6	16.6	-8623.2	2061.9
MAF	-1.4	-0.7	-93.6	10.6	-68.5	2.2	-21410.8	6749.8
REF	-4.9	9.9	-1258.0	375.4	-1241.3	266.5	-751.0	1185.7
OECD+EU	-1.6	0.9	-238.3	141.6	-88.6	133.7	-3582.3	9557.0



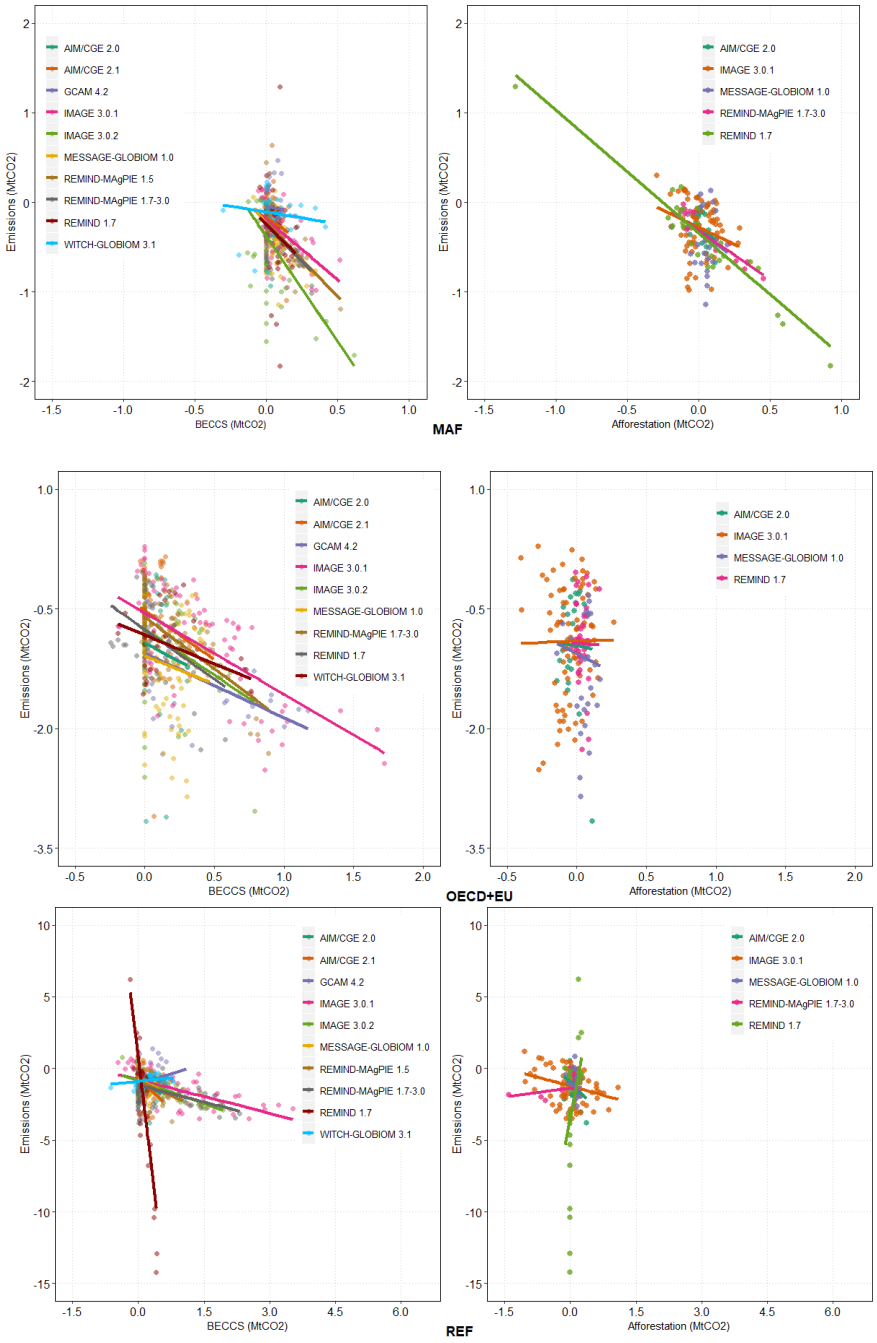


Figure F3 - Changes in emissions per IAM

APPENDIX G

This section details the estimated coefficients of each IAM in each region, which correspond to the random effect. The tables distinguish results for BECCS and Afforestation separately, evidencing the number of IAMs in which they are included. They highlight the influence of IAM differences in determining the relationship between the analysed variables, as observed by the wide range of estimated coefficients. The variability of IAM is confirmed by the calculation of

variance, particularly for primary energy.

Table G1 – Estimated coefficient per IAM for ASIA

Region	EMI (MtCO2)	PRIENE (GtCO2/PJ)	ENE (GtCO2/PJ)	CONS (MtCO2/MillionUS$2010)
BECCS				
AIM/CGE 2.0	-0.79	17.91	-7.69	398.78
AIM/CGE 2.1	-0.63	40.19	-6.87	-1930.33
GCAM 4.2	-1.25	40.82	-21.94	—-
IMAGE 3.0.1	-1.09	-1.97	-27.73	-716.62
IMAGE 3.0.2	-1.75	0.90	-26.22	1115.20
MESSAGE-GLOBIOM 1.0	-1.70	54.41	-50.70	12046.76
POLES EMF33	—-	—-	—-	—-
REMIND-MAgPIE 1.5	-1.74	31.12	-26.71	—-
REMIND-MAgPIE 1.7-3.0	-0.44	66.21	-40.18	-617.26
REMIND 1.7	-0.95	83.84	-31.52	-2253.99
WITCH-GLOBIOM 3.1	0.01	101.13	26.03	-900.89
Afforestation				
AIM/CGE 2.0	-2.08	-115.23	-15.52	-1757.55
AIM/CGE 2.1	—-	—-	—-	—-
GCAM 4.2	—-	—-	—-	—-
IMAGE 3.0.1	-2.45	-114.88	-23.22	-3539.66
IMAGE 3.0.2	—-	—-	—-	—-
MESSAGE-GLOBIOM 1.0	-2.48	-113.90	-39.29	-10255.41
POLES EMF33	—-	—-	—-	—-
REMIND-MAgPIE 1.5	—-	—-	—-	—-
REMIND-MAgPIE 1.7-3.0	-2.12	-114.52	-24.80	261.95
REMIND 1.7	-2.05	-113.99	-33.64	390.50
WITCH-GLOBIOM 3.1	—-	—-	—-	—-

Table G2 - Estimated coefficient per IAM for LAM

Region	EMI (MtCO2)	PRIENE (GtCO2/PJ)	ENE (GtCO2/PJ)	CONS (MtCO2/MillionUS$2010)
BECCS				
AIM/CGE 2.0	-1.22	59.78	17.88	225.99
AIM/CGE 2.1	-1.89	60.09	13.18	-1470.22
GCAM 4.2	-0.57	43.81	-13.48	—-
IMAGE 3.0.1	-1.16	-5.88	-36.46	861.81
IMAGE 3.0.2	-0.66	-1.41	2.47	810.15
MESSAGE-GLOBIOM 1.0	-1.16	57.53	10.77	2641.60
POLES EMF33	—-	—-	—-	—-
REMIND-MAgPIE 1.5	-0.97	69.43	-3.20	—-
REMIND-MAgPIE 1.7-3.0	-1.02	73.64	9.23	-1100.66
REMIND 1.7	-2.32	-37.74	-91.85	-1354.98
WITCH-GLOBIOM 3.1	-0.60	101.98	26.17	-58.71
Afforestation				
AIM/CGE 2.0	-1.16	-14.12	-0.88	-365.00
AIM/CGE 2.1	—-	—-	—-	—-
GCAM 4.2	—-	—-	—-	—-
IMAGE 3.0.1	-1.17	-15.49	-8.44	-235.45
IMAGE 3.0.2	—-	—-	—-	—-
MESSAGE-GLOBIOM 1.0	-1.36	-18.36	-20.35	567.94
POLES EMF33	—-	—-	—-	—-
REMIND-MAgPIE 1.5	—-	—-	—-	—-
REMIND-MAgPIE 1.7-3.0	-1.20	-15.78	-8.76	-656.58
REMIND 1.7	-1.16	-16.96	-21.94	-686.82
WITCH-GLOBIOM 3.1	—-	—-	—-	—-

Table G3 - Estimated coefficient per IAM for MAF

Region	EMI (MtCO2)	PRIENE (GtCO2/PJ)	ENE (GtCO2/PJ)	CONS (MtCO2/MillionUS$2010)
BECCS				
AIM/CGE 2.0	-1.34	-62.50	-32.43	-1040.83
AIM/CGE 2.1	-1.12	43.19	-26.62	-801.38
GCAM 4.2	-0.27	-52.66	-42.96	—-
IMAGE 3.0.1	-1.34	-45.72	-67.85	-1289.93
IMAGE 3.0.2	-2.34	-78.81	-56.10	-1120.86
MESSAGE-GLOBIOM 1.0	-1.73	31.62	-40.34	-1661.34
POLES EMF33	-0.67	-0.22	-19.52	—-
REMIND-MAgPIE 1.5	-1.68	46.63	-23.61	—-
REMIND-MAgPIE 1.7-3.0	-1.60	88.33	-21.35	-630.81
REMIND 1.7	-1.57	200.10	-5.99	-605.11
WITCH-GLOBIOM 3.1	-0.26	65.68	-9.47	-960.47
Afforestation				
AIM/CGE 2.0	-0.95	21.09	6.60	-6502.29
AIM/CGE 2.1	—-	—-	—-	—-
GCAM 4.2	—-	—-	—-	—-
IMAGE 3.0.1	-0.76	-20.47	-27.93	2569.41
IMAGE 3.0.2	—-	—-	—-	—-
MESSAGE-GLOBIOM 1.0	-1.19	-68.17	-59.13	-32139.38
POLES EMF33	—-	—-	—-	—-
REMIND-MAgPIE 1.5	—-	—-	—-	—-
REMIND-MAgPIE 1.7-3.0	-1.10	-47.82	-29.97	-576.74
REMIND 1.7	-1.37	-92.40	-62.26	-124.31
WITCH-GLOBIOM 3.1	—-	—-	—-	—-

Table G4 - Estimated coefficient per IAM for OECD+EU

Region	EMI (MtCO2)	PRIENE (GtCO2/PJ)	ENE (GtCO2/PJ)	CONS (MtCO2/MillionUS$2010)
BECCS				
AIM/CGE 2.0	-0.90	42.45	-21.00	-777.48
AIM/CGE 2.1	-1.23	31.52	-12.49	-1174.48
GCAM 4.2	-0.81	94.70	11.73	—-
IMAGE 3.0.1	-1.02	48.52	5.18	284.53
IMAGE 3.0.2	-1.15	22.95	-34.36	-324.26
MESSAGE-GLOBIOM 1.0	-0.70	-3.96	-5.60	2609.46
POLES EMF33	—-	—-	—-	—-
REMIND-MAgPIE 1.5	-1.57	60.68	-25.64	—-
REMIND-MAgPIE 1.7-3.0	-1.30	54.36	-20.91	3322.65
REMIND 1.7	-1.24	-139.23	-147.25	-8153.66
WITCH-GLOBIOM 3.1	-0.72	79.79	9.90	-1380.41
Afforestation				
AIM/CGE 2.0	-0.32	-24.51	15.72	2873.45
AIM/CGE 2.1	—-	—-	—-	—-
GCAM 4.2	—-	—-	—-	—-
IMAGE 3.0.1	0.06	-39.78	16.04	2523.13
IMAGE 3.0.2	—-	—-	—-	—-
MESSAGE-GLOBIOM 1.0	-0.92	53.11	23.22	3250.07
POLES EMF33	—-	—-	—-	—-
REMIND-MAgPIE 1.5	—-	—-	—-	—-
REMIND-MAgPIE 1.7-3.0	0.00	-10.94	19.08	2931.59
REMIND 1.7	-0.11	-196.40	4.14	2820.36
WITCH-GLOBIOM 3.1	—-	—-	—-	—-

Table G5 - Estimated coefficient per IAM for REF

Region	EMI (MtCO2)	PRIENE (GtCO2/PJ)	ENE (GtCO2/PJ)	CONS (MtCO2/MillionUS$2010)
BECCS				
AIM/CGE 2.0	-1.49	54.62	57.63	-815.76
AIM/CGE 2.1	-2.86	264.52	105.50	-899.71
GCAM 4.2	1.01	100.43	4.16	—-
IMAGE 3.0.1	-0.78	45.14	4.12	-220.56
IMAGE 3.0.2	-1.07	49.89	-8.55	54.05
MESSAGE-GLOBIOM 1.0	-1.39	-105.85	0.85	3959.25
POLES EMF33	-0.89	7.85	-17.42	—-
REMIND-MAgPIE 1.5	-1.36	99.92	-83.95	—-
REMIND-MAgPIE 1.7-3.0	-0.79	84.43	-4.84	144.29
REMIND 1.7	-25.02	4324.47	3151.28	-1130.28
WITCH-GLOBIOM 3.1	0.32	132.96	54.27	-616.27
Afforestation				
AIM/CGE 2.0	-3.00	-209.12	-257.31	888.79
AIM/CGE 2.1	—-	—-	—-	—-
GCAM 4.2	—-	—-	—-	—-
IMAGE 3.0.1	-0.84	-53.38	-33.51	163.93
IMAGE 3.0.2	—-	—-	—-	—-
MESSAGE-GLOBIOM 1.0	-1.68	-138.26	-226.14	-1297.89
POLES EMF33	—-	—-	—-	—-
REMIND-MAgPIE 1.5	—-	—-	—-	—-
REMIND-MAgPIE 1.7-3.0	0.38	155.44	20.05	744.40
REMIND 1.7	16.12	-1979.08	-1938.20	978.89
WITCH-GLOBIOM 3.1	—-	—-	—-	—-

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