Carbon sink and methane source: the net role of wetland restoration in CDR portfolio

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Abstract

Carbon Dioxide Removal (CDR) methods are now necessary to mitigate climate change. Wetlands restoration and blue carbon has become of great interest as a Natural-Based Solution (NBS), but previous literature has limited to estimate its potential in isolation. We extended the WITCH Integrated Assessment Model (IAM) to include wetlands restoration as a Carbon Dioxide Removal (CDR) method. Our systematic approach considers the competition with other CDR options, and the potential trade-off between carbon sequestration and methane emissions. We found a potential removal of 0.53–1.04 Gt CO_2/yr by restoring between 57.7 and 81.9 Mha of wetlands by 2100, for carbon taxes peaking at 100–400 (2010 USD), respectively. About half of these potential corresponds to the restoration of coastal wetlands. Wetlands restoration does not shift the CDR portfolio, but allows for additional removals. The sooner restoration efforts are deployed the higher the total removals, even with the same restored area. We found that potential challenges to upscaling include high restoration costs for some wetland types in some regions, and the limit on the amount of restoration that can be done per period. We identified that the contribution to increased global methane emissions is minor, and the potential for co-benefit from restoration, beyond CO_2 removal, are high enough to enable restoration and make wetlands restoration an attractive CDR strategy.

Keywords— wetland restoration, blue carbon, methane, carbon sequestration, natural based solutions

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1 Introduction

Carbon Dioxide Removal (CDR) methods are now necessary to reach Paris Agreement targets (Rogelj et al., 2018; Luderer et al., 2018; Strefler et al., 2018). Several methods have and continue to be studied in terms of its potential, limits to upscaling, cost, and environmental consequences, among others.

Some of these methods are also considered Natural-Based Solutions (NBS) or land-based CDR methods (e.g. afforestation and reforestation)(Griscom et al., 2017). Among these NBS is wetlands restoration.

Wetlands restoration, and in particular blue carbon, has become of great interest as a climate change mitigation strategy (Windham-Myers et al., 2019; Bertolini and da Mosto, 2021; Jiang et al., 2025). Coastal wetlands include mangroves, saltmarshes, and seagrasses, whereas inland wetlands include freshwater marshes, swamps, flooded flats and peatlands. Coastal wetlands per unit area can sequester more carbon than terrestrial forests ecosystems, including tropical rain forests (McLeod et al., 2011; Donato et al., 2011). Moreover, in comparison with other CDR methods, such as DACCS, BECCS, or OAE-with CCS, wetlands restoration does not need transportation or storage infrastructure for the captured carbon, and some studies have found that carbon stored in undisturbed wetlands soils can persist up to several hundreds of years to millennia (Were et al., 2019). Unlike those alternatives, it also requires no additional technological development, suggesting that implementation could being today. Furthermore, wetlands are important ecosystems providing co-benefits for nature. Beyond carbon sequestration, wetlands provide additional ecosystem services such as water purification, biodiversity protection, nitrogen sequestration, coastal protection, fish nurseries, and timber provision (D. P. Costa et al., 2024; Worthington and Spalding, 2018; Conlisk et al., 2022; Zedler and Kercher, 2005; Brander et al., 2024).

Wetlands have estimated carbon stocks of 238 GtC, from which 220 GtC are associated with peatlands, and 18 GtC with coastal wetlands (Goldstein et al., 2020). Higher estimates are described by (Villa and Bernal, 2018) with 400 GtC globally in wetlands in the top 1 m of soil, which is higher than any other biome. In this way, wetlands role in climate change mitigation depends on both conserving existing wetlands to avoid the release of deep stocks of soil organic carbon (Goldstein et al., 2020; Siikamaki et al., 2012) and restoring wetlands with high carbon sequestration rates per year to increase removal.

At the same time, wetlands produce about a third of global methane (CH_4) emissions (Saunois et al., 2025) and are the main natural source of methane (Peng et al., 2022; Nisbet et al., 2023; Kirschke et al., 2013). Moreover, climate change is expected to amplify wetland methane emissions through two key mechanisms: increased biological activity of methane-producing microorganisms due to rising temperatures, and the release of methane from thawing permafrost in polar regions (Moomaw et al., 2018; Chadburn et al., 2017). Considering methane contribution to climate change, it is important to consider both long term CO_2 sequestration and short term CH_4 emissions when assessing the role of wetland restoration for climate change mitigation.

Previous literature has focused on estimating the potential carbon sequestration from wetland restoration. Among these studies (Griscom et al., 2017) has estimated that 0.351 $GtCO_2e$/yr can be sequestered with coastal wetlands restoration (including mangroves, saltmarshes and seagrass) considering a sequestration rate of 12.1 tCO_2e ha-1 yr-1 and a maximum restorable area of 29 Mha. From this, 0.258 $GtCO_2e$/yr comes from restoring mangroves. (Worthington and Spalding, 2018) estimates additional 0.069 Gt of carbon in aboveground biomass and 0.296 Gt of avoided losses of carbon in the top metre of the soil as a result of mangroves restoration. (Jiang et al., 2025) instead have estimated 0.084 (0.075–0.096) $GtCO_2$ removed on the next 40 years by mangroves in China and southeast Asia, considering suitable aquaculture areas for restoration. These studies, while valuable, share a common limitation: estimating potentials in isolation from the broader decarbonization context. These studies have not considered how wetlands restoration competes for investment with other CDR or decarbonization methods, and in most of the cases have omitted wetlands contribution to global methane emissions. Moreover, due to their static approach these cannot inform on limits and challenges to upscaling.

We address these gaps by including wetlands restoration in the WITCH Integrated Assessment Model (IAM) accounting for carbon sequestration, and methane emissions, while also estimating potential co-benefits from ecosystem services. This framework allows us to analyze the role of wetlands restoration in the CDR portfolio by answering the following questions (i) how wetlands restoration competes with other CDR methods?, (ii) what are the limits and challenges to upscaling?, and about optimal restoration strategies in terms of (iii) which types of wetlands to restore?, and (iv) where to restore?.

The paper reads as follows. First, we provide a general description of the WITCH Integrated Assessment Model and the wetlands module developed. Second, we provide the results focusing on each of our research questions. Third, we discuss the robustness of the results with a sensitivity analysis and we conclude with a discussion.

2 Methods

2.1 The WITCH model

The World Induced Technical Change Hybrid (WITCH) (Emmerling et al., 2016), is a process-based global Integrated Assessment Model (IAM) designed to assess climate change mitigation and adaptation policies. It integrates the economy, the energy, land and climate systems, for various regions/coalitions (that range between 12 to 34), to analyze future decarbonization pathways between 2005-2100. The land system is represented using a soft-link with the GLOBIOM model (Havlík et al., 2011; Havlik et al., 2014)(`https://iiasa.github.io/GLOBIOM/`) and the climate model MAGICC (Meinshausen et al., 2020) is used to estimate future climate variables. It uses the SSP scenarios (Riahi et al., 2017) to represent future socio-economic development pathways that include population and GDP projections. It has previously contributed to IPCC assessment and special reports, especially through GWIII. In its core, each of its coalitions solve an intertemporal non-linear optimization problem, to choose technological investment pathways that maximize its welfare, while considering the decisions made by other coalitions. In this sense it is a non-cooperative, simultaneous, open membership game with full information, solved through an iterative algorithm that yields the Nash equilibrium.

The WITCH model covers a broad span of CDR methods including Direct Air Carbon Capture and Utilization (DACCU), Direct Air Carbon Capture and Storage (DACCS), Enhanced Rock Weathering (ERW), Bioenergy with Carbon Capture and Storage (BECCS), Afforestation/Reforestation (AR), Agroforestry, Soil Carbon Sequestration, Biochar, and with the new module described here, wetlands restoration.

More information and detailed documentation on the model can be found in `https://www.witchmodel.org/`.

2.2 The wetlands module

We extended the WITCH model with a wetlands module that represents 5 different wetland types (Swamp, Marsh, Flooded Flat, Mangrove, and Salt Marsh) and includes its land cover, carbon sequestration rates, and methane emissions. The module assumes that existing wetlands areas are conserved and allow for restoration decisions in each region and period of time. Restoration decisions are considered at the WITCH regions spatial resolution and are informed by restoration costs, CO_2 removal, CH_4 emissions and limits to deployment.

CO_2 removal per ha corresponds to the Net Ecosystem Productivity (NEP)[1] from (Taillardat et al., 2020), excluding the effect of methane, which is explicitly represented in the model. CO_2 removals per ha are assumed to be constant through time and regions, but differ per wetland type. We developed a Deep Learning (DL) model that considers temperature, precipitation and wetlands land cover to derive methane emissions. We trained it using monthly CH_4 emissions from WetCharts, monthly ERA5 climate data and GWL_FCS30D land cover data from 2001-2018, at a spatial resolution of 0.5º, and we validated it for 2019. The model estimates monthly mean methane emissions from wetlands and uncertainty (standard deviation) for three SSP-RCP scenarios (See Figure S2). We used these estimations, in conjunction with current wetlands area and literature estimates from (Taillardat et al., 2020), to estimate methane emissions per ha that differ per region, time period and wetland type. The estimations represent increasing methane emissions per ha, due to climate change. For more information on the DL model used see (Rodriguez-Pardo et al., Forthcoming). For the results presented here, we used CH_4 wetlands emissions DL projections under scenario SSP3-RCP7.0. The estimated radiative forcing for the scenarios here considered is between 4-4.5 W/m^2, lower than 7 W/m^2. Therefore, by using estimations with a higher radiative forcing that those of our scenarios, we are considering higher increases in CH_4 emissions for wetlands, being a conservative approach for restored wetlands.

As limits to deployment, we include both a limit on how much area can be restored per period, and a maximum cumulative area that can be restored ($maxW_{w,s}$), of each wetland type w in each spatial unit s. The latter is based on the suitability of a particular location to be a wetland and the current land cover. For this, Potential Natural Vegetation (PNV) maps from (Hengl et al., 2020) at 250 m x 250 m resolution, and current cropland areas from the GLC_FCS30 dataset (Liu et al., 2023) (with associated paper (Zhang et al., 2021)) where used. We chose to use a similar approach to that of (Chapman et al., 2025) using potential natural vegetation. Consider land cover class $j \in J$ and wetland types $w \in wet\_types$

$$maxW_{w,s} = PNV_{w,s} \sum_{j \in J} a_{j,s} T_{j,w} \qquad \forall w \in wet\_types, s \in S \tag{2}$$

$$maxW = PNV \circ (A^T T)^T \tag{3}$$

where $PNV_{w,s}$ is the probability of spatial unit s of being of wetland type w based on physical limits (e.g. potential distribution of land cover, long-term climatic conditions indicators, groundwater and soil conditions, soil lithology), $a_{j,s}$ is the current area of land cover class j in spatial unit s and $T_{j,w}$ is an indicator variable that takes the value of 1 if the transformation from land cover class j to wetland type w is allowed and 0 otherwise. $\circ$ represents the element-wise (hadamard) matrix multiplication. $dim(PNV) = |wet\_types| \times |S|$, A is a matrix with values $a_{j,s}$ and $dim(A) = |J| \times |S|$, T is the logical transition matrix with $dim(T) = |J| \times |wet\_types|$. This results in matrix $maxW$

[1]NEP is defined according to equation 1, as a function of Gross Primary Productivity (GPP) and Ecosystem Respiration (RE). GPP refers to gross assimilation of CO_2 via photosynthesis. When GPP>RE it is considered that there is CO_2 sequestration from the ecosystem.

$$NEP = GPP - RE \tag{1}$$

with $dim(maxW) = |wet\_types| \times |S|$. We assumed that only cropland types can be transformed to wetlands. $a_{j,s}$ comes from GLC_FCS30 dataset (Liu et al., 2023) for year 2022 and not from the land cover variables from the land system in WITCH, and its not updated endogenously in the model. This implies that the upper limits on wetland restoration are not currently considering changes in land cover due to mitigation policy and the opportunity cost of transforming agricultural land. $maxW_{w,s}$ was estimated at a 0.25º resolution and then aggregated to WITCH regions.

For the limit on the restoration per period, we assumed the maximum cumulative restoration $maxW_{w,s}$ divided into the sixteen decision periods of the model.

In the module, restoration costs only represent capital costs (i.e. land acquisition and one-off restoration activities) and differ per region and wetland type. Learning by doing is represented with restoration costs per ha decreasing as cumulative restored area increases with an exogenously defined learning rate of (-0.1). The initial restoration costs are taken from (Taillardat et al., 2020).

For more details on the module, Supplementary section S1 includes the mathematical formulation and assumptions.

2.3 Scenario design

Our scenario analysis is designed to address our specific research questions. The scenarios contain two different dimensions: if wetlands restoration is included or not, and the level of mitigation efforts, represented via an increased carbon tax (See Figure S9). Figure 1 shows which scenarios are compared depending on the research question. When comparing horizontally, for a specific carbon tax, we can assess the effect of including wetland restoration in the CDR portfolio. Instead, when comparing vertically, including wetlands restoration, we can assess how restoration decisions change with increased mitigation efforts, which we use to analyze upscaling. We consider only SSP2 for our analyses.

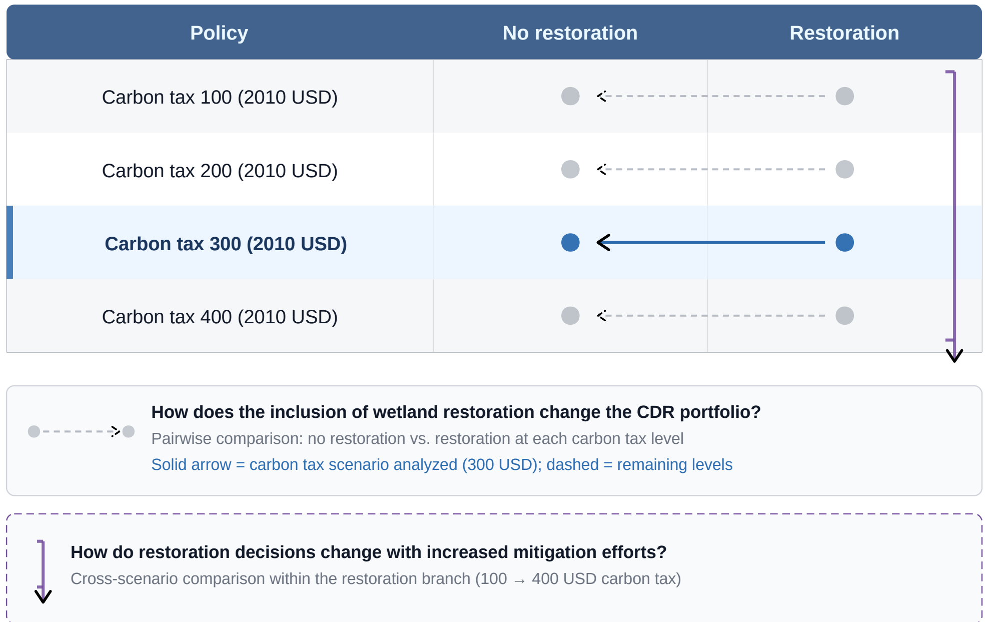
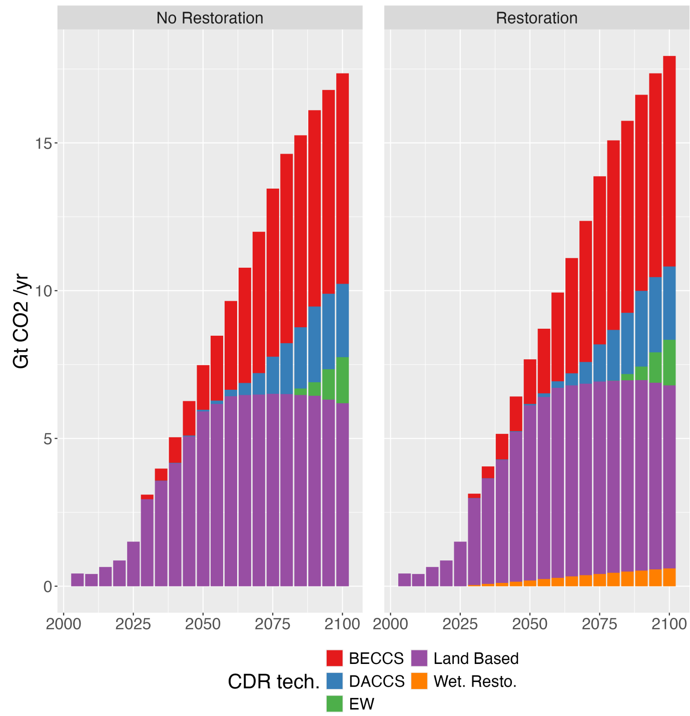


Figure 1: Scenario design. Comparing scenarios with and without restoration allow to assess the competition of wetlands restoration with other CDR methods. Comparing the scenarios with restoration and varying levels of climate change mitigation policy allow to assess upscaling. Carbon tax in (2010 USD/t CO_2e).

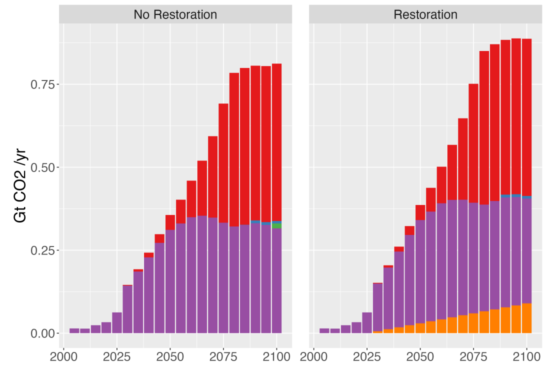
3 Results

3.1 On the introduction of wetlands restoration

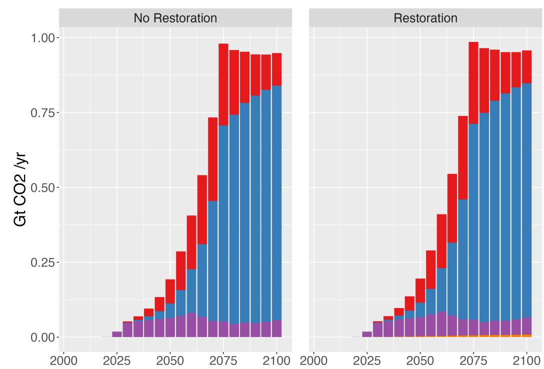
How wetland restoration competes with other CDR Figure 2 shows the CO_2 removed by each of the CDR methods included in the model for each period between 2005-2100 with a carbon tax of 300 (2010 USD). Wetlands restoration does not shift global CDR portfolio, as shown in panel 2a, instead, adding wetlands restoration increase total removal. A reason for this may be the lack of competition of wetlands restoration for resources (e.g. energy, storage, land) with other CDR methods. Moreover, in comparison with the total amount of CO_2 removed, wetlands restoration contribution is small with at most 4% by 2100, with regional variations (see regional CO_2 removal comparison in Figure S10). Contrasted examples for southeast Asia and Canada are highlighted in 2b, 2c showing contributions to total removals of 10% and 1%, respectively.



(a) World



(b) Southeast asia



(c) Canada

Figure 2: **Influence of wetland restoration on CO_2 removals from CDR methods.** Panel a) shows the global CO_2 removals. Panel b) and c) highlight the total CO_2 removals for the WITCH regions Southeast Asia and Canada, respectively. Results come from the scenario "Carbon tax 300". In the charts, in left side, wetland restoration is disabled, while in the right side, it is enabled. Colors represent the CDR methods.

Impacts of wetland restoration on global methane emissions Considering wetlands contribution to global methane emissions, we want to understand the effect of restoration decisions on increased emissions. Figure 3 shows the effect of restoration decisions on global CH_4 emissions. Panel 3a shows the additional methane emissions associated to restored wetlands, which increase with restored area reaching a maximum of 0.017 Mt CH_4/yr globally. The type of restored wetland that contributes the most to these emissions are swamps, followed by marshes. Coastal wetlands have minor contributions in comparison. Panel 3b shows the total CH_4 emissions in the model for the scenario with restoration and without restoration, under a 300 (2010 USD) carbon tax, showing how the additional emissions are small in comparison to the total CH_4 emissions (126.6 Mt/yr) contributing to 0.013% of yearly emissions by 2100. The same results hold on a regional level as can be seen in Figure S15 and S16.

(a) Global CH_4 emissions from restored wetlands

(b) Global total CH_4 emissions

Figure 3: **Wetlands restoration methane emissions**. Panel (a) presents the global CH_4 emissions from restored wetlands by type, expressed in $MtCH_4$/yr, for the scenario "Carbon tax 300". Panel (b) shows the global total CH_4 emissions with and without wetland restoration enabled.

More information on wetlands restoration CO_2 removals and CH_4 emissions per period, region and by wetlands type can be found in Supplementary section S4.1.2.

Competition for resources with other CDR Conceptually, wetlands restoration would compete with other CDR methods for land and investment. Given the assumptions of GLOBIOM, the land use model integrated with WITCH, wetlands restoration could only be competing directly with BECCS and food production for agricultural land. However, as described before, the wetlands module is not connected with the land system module in WITCH, and as a consequence this direct competition for land is not endogenously represented. To acknowledge this, we estimated the opportunity cost per year of transforming the agricultural land required for wetlands restoration. For this, we multiplied the total restored area per region up to 2100 with the land rents (2010 USD/ha) of cropland from (Gurgel et al., 2016). This estimation would represent the amount of revenue that land owners would stop to annually receive when their land is no longer a cropland. Figure S18 shows our estimations by WITCH region. The three regions with largest opportunity cost of changing agricultural land to restored wetlands are China (3,721 million 2010 USD), India (2,218 million 2010 USD) and Southeast Asia (1,743 million 2010 USD). The global opportunity cost per year of agricultural land of 15,387 (million 2010 USD) by 2100 is lower than the annual payment that would be incurred for the emissions sequestered by the restored wetlands of 180,000 (million 2010 USD)[2], suggesting that the opportunity cost of cropland may not be the binding constraint on restoration decisions. However, this is a limitation that could be better addressed in future research.

[2] $0.6\, GtCO_2 \times 10^9 \frac{tCO_2}{GtCO_2} \times 300 \frac{2010USD}{tCO_2} = 180,000$ (million 2010 USD).

3.2 On upscaling

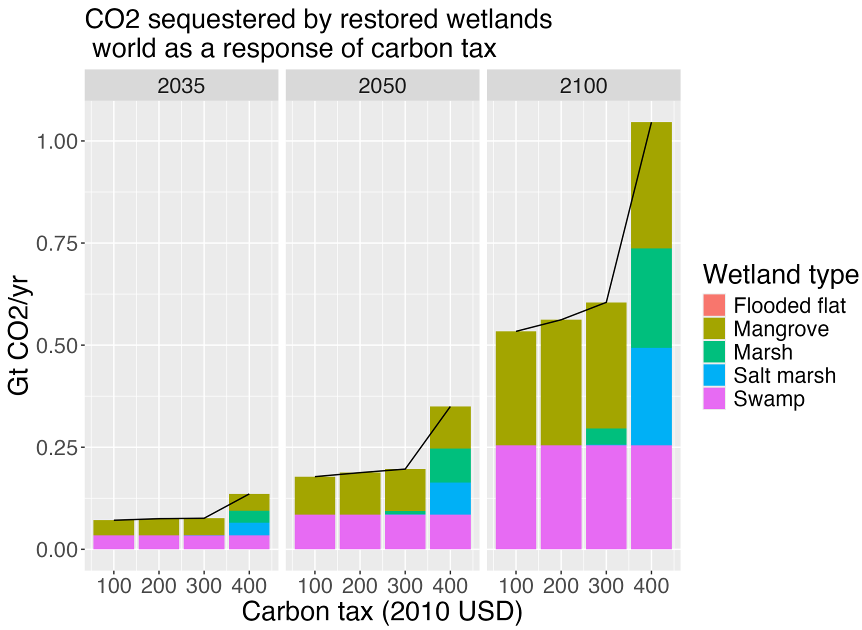


Figure 4: Global removals from wetlands restoration as carbon tax increases by wetland type

CO_2 removal from restored wetlands Figure 4 shows how global carbon removals from wetlands restoration change as carbon tax increases. It can be noted that marshes and salt marshes capture more carbon than swamps (see Figure S1), but they require at least of 300 and 400 (2010 USD) of carbon tax before restoration decisions are made by the model. In contrast, swamps have the lower sequestration rate among all wetland types, but because their restoration cost per ton of CO_2 removed is lower (See Figure S7), they are being restored even with a 100 (2010 USD) carbon tax for all regions and all periods of time. Moreover, mangroves with the highest sequestration rates, lowest restoration cost per ton of CO_2 removed, but less availability, are being restored with all carbon price levels. Both swamps and mangroves are being restored to its full potential in all regions under all carbon tax scenarios, with the exception of *Non-EU Eastern European and Transition Economies* for the 100 (2010 USD) carbon tax (see Fig S19). Flooded flats are not restored under any carbon tax scenario.

Results on a regional level differ as can be seen in Figure S20. For 11 of the 17 regions of the model, the increased carbon tax makes no difference. In these regions, the model restores the maximum area allowed per period for mangroves and swamps, for all levels of carbon tax. Most of mangroves restoration occurs in these regions and no other wetland type, besides these two, is restored. All these regions are in the global south. Lower restoration costs, especially for mangroves, may be one of the main reasons. In contrast, Canada, China, Europe and Japan-Korea regions follow a similar pattern restoring swamps under all carbon tax scenarios and increasing restoration levels, by restoring marshes and salt marshes, at 400(2010 USD) carbon tax. USA has a similar behavior to the previous group, but only restores marshes under a carbon tax of 400(2010 USD). Non-EU Eastern European and Transition countries only restore mangroves with carbon taxes of at least 200 (2010 USD).

In terms of contribution to global removals from wetlands restoration, Southeast Asia, India and, Non-eastern EU countries and transition economies are among the major contributors by 2100 for all carbon tax levels.

Moreover, even when the maximum restoration potential assumed by the wetlands module implementation is of 226 Mha corresponding to a max removal of 3.2 Gt CO_2 per year (See figures S5 and S6), the restoration levels deployed by the model are significantly lower being between 0.53 and 1.04 Gt CO_2/yr for carbon taxes of 100 and 400 (2010 USD), respectively, by 2100. Part of this difference is a consequence of the initial cost per ton of CO_2 removed for wetlands restoration, that vary between 17.49 and 21,195 (2010 USD), in comparison with other methods. For example, DACCS initial costs vary between 3,843 and 6,984 (2010 USD/tCO_2 removed). Methane emissions could also be a limiting factor, especially after exhausting restoration of mangroves and swamps which have the lowest CH_4 emissions.

For coastal wetlands, the model assumes a maximum potential restorable area is of 62 Mha corresponding to 1.6 Gt CO_2 removed per year. These static potentials are higher than those of (0.351 GtCO_2e) estimated by (Griscom et al., 2017), potentially because our estimates are made considering potential natural vegetation (i.e. what can be a wetland) and not only degraded wetlands. By 2100, the model estimates between 0.28 and 0.55 Gt CO_2 removed by coastal wetlands for carbon taxes of 100 and 400 (2010 USD), respectively. In this way, restoration of coastal wetlands correspond to 52% of total removals with wetlands restoration.

Regarding the timing of restoration decisions, since each ha of restored wetland will sequester carbon since the moment of restoration, the model has the incentive to restore as soon as possible to maximize removal. We found that for all wetland types the model restores as much as possible since the first period of time for most regions (see Figure S21). Only for Canada and China there are some delayed restoration starting in 2050. We identified that the per period limit on deployment is always binding for swamps and mangroves, meaning that if the limit is increased, potentially more wetlands will be restored earlier. Restoring earlier imply higher CO_2 removals per yr, increasing total CO_2 removals from wetlands, even if total restored area remains the same.

Upscaling restoration and global methane emissions Our methane emission factors differ per wetland type, region, and time period (See Figure S3). The time period differences reflect how the same ha of wetland will produce more methane as climate change progresses, with increasing temperatures and changing precipitation patterns. In this way, our wetlands module is able not only to capture the fact that wetlands also emit methane, but also the fact that these methane emissions are expected to increase with climate change. Since our model is taxing both CO_2 and CH_4 emissions, our module is able to capture the trade-off between CO_2 removals and CH_4 emissions for restoration decisions. As can be seen in Figure 5 and considering the results described in section 3.1, increased areas due to wetland restoration do not significantly increase global methane emissions with a contribution between 0.01 and 0.07 Mt CH_4 /yr by 2100. For comparison, the total methane emissions for the same scenarios are of 168 and 121 Mt CH_4/yr by 2100. Figure 5 shows the contribution of restored wetlands, for each wetland type, to global methane emissions for three years (2035, 2050 and 2100) with increased levels of carbon tax. The wetland type that produced more methane per unit area is marshes, so it is expected that with restoration of this wetland type with a 400 (2010 USD) carbon tax, this becomes the main contributor to restored wetlands methane emissions. Regional results can be seen in Figure S22.

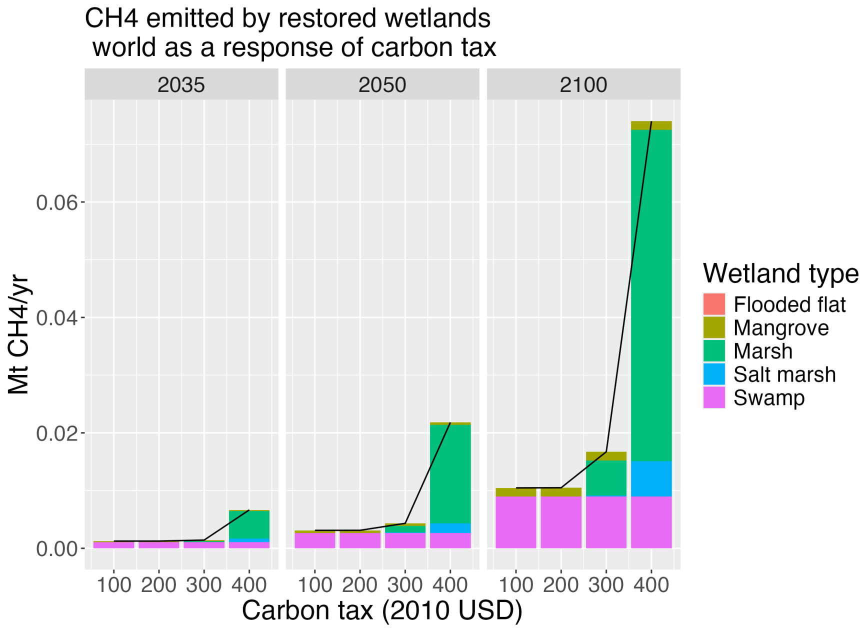
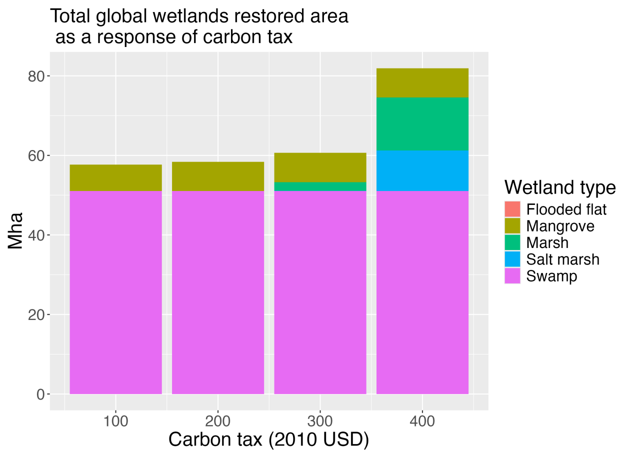


Figure 5: Methane emissions from restored wetlands as carbon tax increases by wetland type

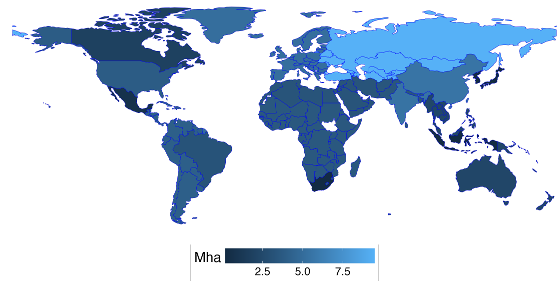
3.3 Which type of wetland and where to restore?

As described in the previous sections, we find that most of the restoration effort is concentrated on restoring swamps and mangroves. Figure 6a shows the total restored area, aggregated by periods and regions, considering each wetland type. Here it can be seen that most restored area is associated with swamps, for which the amount of restoration does not change with the carbon tax, followed by mangroves with minor differences between levels of carbon tax. Restoration of marshes only starts at 300 (2010 USD) and for salt marshes at 400 (2010 USD).

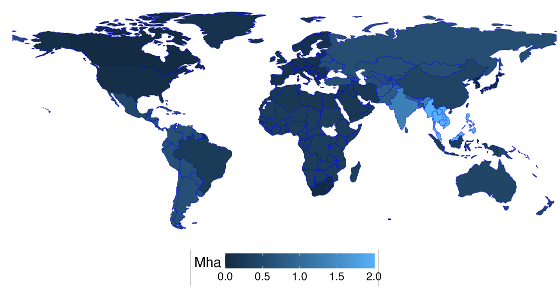
Figures 6b and 6c show the regional distribution of cumulative restored areas for swamps and mangroves for a 300 (2010 USD) carbon tax, which because of the similarities between carbon tax levels is representative of the other carbon tax levels. These maps show how swamps restoration efforts are concentrated in Non-EU Eastern European and Transition countries, while mangroves restoration is concentrated in Southeast Asia and India.



(a) Total Global restored area



(b) Swamps



(c) Mangroves

Figure 6: (a)Total global wetlands restored area by wetland type as a response to carbon tax increase, (b) and (c) show the spatial distribution of restoration for swamps and mangroves, respectively, for a carbon tax of 300 (2010 USD) at a WITCH regions spatial resolution.

3.4 Co-benefits from nature

Beyond CO_2 removal, wetlands provide a broad range of ecosystem services, including nitrogen sequestration, coastal protection, fish nurseries, and water quality regulation (Conlisk et al., 2022; Barbier et al., 2011; Windham-Myers et al., 2019). Consequently restoring wetlands, has the possibility to provide significant co-benefits. We estimated the magnitude of these co-benefits using the total restored areas of each wetland type and the economic valuations for various ecosystems services compiled by Brander et al. (2024) from the Ecosystem Service Valuation Database (ESVD). We excluded the benefit from climate regulation since analyzing this contribution is the central aim of this study. As shown in Figure 7, co-benefits spanning provisioning, regulating, supporting, and cultural services range from 2.046 to 2.804 trillion (2010 USD) for carbon taxes of 100 to 400 (2010 USD), respectively. These figures suggest that non-climate co-benefits alone may be sufficient to enable restoration, reinforcing wetlands as a highly attractive CDR strategy.

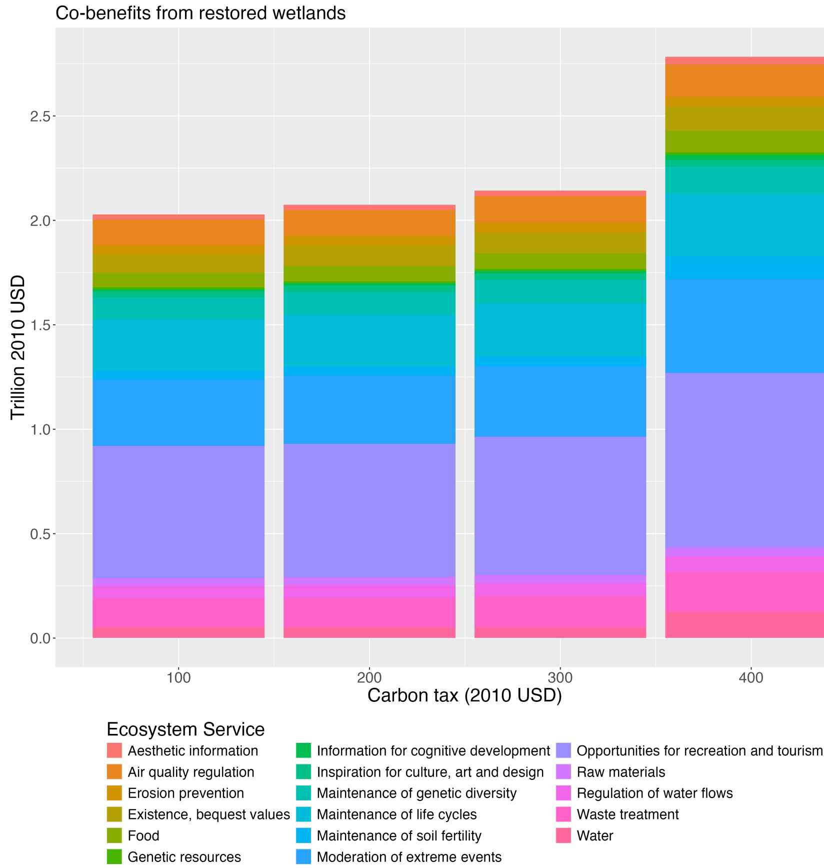


Figure 7: Co-benefits from global wetlands cumulative restored area by 2100 under each level of carbon tax

4 Sensitivity analysis

Considering parametric uncertainty and to understand how robust are our results, we did a sensitivity analysis on: learning rate of restoration costs, the CO_2 sequestration rate for marshes and the initial restoration costs for each wetland type and region. The learning rate was chosen due to the uncertainty of its potential value, not finding any data source or literature providing an estimate. The sequestration rate for marshes was chosen considering the large variation in our data source (See figure S1). Finally, initial wetland restoration costs were considered for its potential effects on which wetland type to restore and its competition with other CDR methods.

Following a similar approach to that of Chiani et al. (2026), we did a Montecarlo analysis varying these 87 parameters (1 learning rate, 1 CO_2 sequestration rate, and 85 initial costs corresponding to the 17 regions and 5 wetland types) according to the distribution and ranges shown in Table S1. We did 1000 runs and used the total restored areas (aggregated for all periods, regions, and wetland types) as our output variable or analysis. We use a regression analysis and Standardized Regression Coefficients (SRC) to rank model sensitivity to each parameter.

We identify that the model is more sensitive to the sequestration rate for marshes, increasing by 17% total restored area in comparison to the baseline (the results for the parameters we are using in the module) when this parameter is increased by 1 standard deviation (i.e. by 9.748 Mt CO_2 per Mha per yr). Initial restoration costs and learning rate have a minor effect increasing at most 3% total restoration area for a decrease in 1 standard deviation in costs or to an increase in 1 standard deviation of the learning rate, respectively. More detailed information on the sensitivity analysis and its results can be found in Supplementary section S5.

We also identified that the upper bound on per period restoration is binding for mangroves and swamps in all period and regions. In consequence, any change to the maximum restoration that can be done per period will affect the presented results. If more restoration per period is allowed, even if the total restored area remains the same, more total CO_2 removal will be done by the end of the century. If less restoration per period is allowed, total restored area will decrease, and in consequence total CO_2 removals.

5 Discussion

With our analysis of wetlands restoration as a CDR technology, that considers the competition with other CDR options, and the trade-off between CO_2 and CH_4 emissions, we analyzed both the effects of including wetlands restoration in the CDR portfolio, and how restoration scales up with increased mitigation efforts.

We found that including wetlands restoration increases total CDR deployment per year and does not shift the CDR portfolio mix. The latter is a result of wetlands restoration only competing for investment resources, and not for storage or energy. For a carbon tax of 300 (2010 USD) global CDR deployment reaches 17.939 Gt CO_2/yr, from which 0.605 Gt CO_2/yr correspond to wetlands restoration, accounting for 4% of total removals. There are some regional differences, for example, wetlands restoration contributing up 10% and 1% of regional CO_2 removals per year for southeast Asia and Canada, respectively.

We also identified that the contribution of increased restoration to global methane emissions is minor, even when considering the increased emissions per ha due to climate change.

When analyzing upscaling of wetlands restoration with increased mitigation efforts, represented by an increasing carbon tax, we identify a potential removal between 0.53 and 1.04 Gt of CO_2 per year by restoring between 57.7 and 81.9 Mha of wetlands by 2100, for carbon taxes of 100 to 400 (2010 USD), respectively. This is about the same amount of emissions of the global aviation sector in 2023 of 0.95 Gt CO_2 (International Energy Agency, 2026). From these, coastal wetlands (mangroves and saltmarshes) contribute about 50% ranging between 0.28 and 0.55 Gt of CO_2 removed, for the same scenarios. The static estimation of (Griscom et al., 2017) of 0.351 Gt CO_2e per year by restoring coastal wetlands is among this range. We found that restoration of salt marshes only starts with carbon taxes of at least 300 (2010 USD), contributing 0.00179 Gt CO_2 removed per year at that level. This contrasts with static estimates, which include 0.0161 Gt CO_2 removed per year from salt marshes without accounting for the carbon price required to trigger their restoration. This could suggest that a way to make salt marshes restoration more competitive, will be to focus on reducing its restoration costs.

About which wetland types to restore, we found that mangroves should be prioritized in regions with potential for restoration due to their high CO_2 sequestration levels, low methane emissions and lower restoration costs per CO_2 removed. Swamps were found to be cost effective with all carbon tax levels, even when they have less CO_2 sequestration rates than the rest of the wetland types, which is compensated by the abundance in potential areas to restore and lower restoration costs. Salt marshes, with also higher sequestration rates and relatively low methane emissions require higher levels of carbon tax to start deployment, due to their higher restoration costs. Freshwater marshes, also require a higher carbon tax, and becomes the major source of methane emissions from wetlands when restored. Flooded flats are not restored under the assessed scenarios, potentially because of their higher restoration costs and low sequestration rates, not being competitive with other wetland types or CDR methods.

In this way, we identified that by including also swamps, marshes and flooded flats, and not only coastal wetlands, the model exploits two pathways for wetlands carbon sequestration: high extent of areas restored and lower sequestration rates (as is the case of swamps), and lower extent with higher sequestration rates (as is the case of mangroves), allowing for an overall larger scales of CO_2 removals from wetlands restoration.

It is important to acknowledge that even when these estimates focus on wetlands restoration as a CDR technology, conservation and rehabilitation of existing wetlands are significantly important. Conservation of current ecosystems is agreed to be a priority for climate mitigation policy, both to avoid releasing the carbon currently stored and for the continuous sequestration from the existing functioning wetlands ecosystems (Goldstein et al., 2020; Taillardat et al., 2020). The world has already lost in average 53.5% of all types of natural wetlands with respect to before 1900 AD, with more loss in inland natural wetlands than coastal wetlands and a progressing rate of loss over the centuries (Davidson, 2014). Donato et al. (2011) estimates that mangroves deforestation is associated with the release of 0.02-0.12 Pg C per year (0.07-0.44 Gt CO_2 per year). In this way, restoration should not be considered instead of conservation, but in addition to it. Similarly, our model analyses the effect of extending wetland areas, when it is also possible to rehabilitate existing degraded wetland ecosystems, an analysis that is out of the scope of this paper.

Furthermore, as with any IAM-based analysis, our approach involves simplifying assumptions that bound the interpretation of results. We exclude peatlands from our analysis. The climate mitigation rationale for peatlands centers on conservation and rehabilitation (rewetting) of degraded areas to prevent release of existing carbon stocks, estimated at $\sim$200 GtC in the top meter of soil (Goldstein et al., 2020; Villa and Bernal, 2018), rather than area expansion. Combined with their relatively low sequestration rates and high methane emissions (Hemes et al., 2018; Taillardat et al., 2020), peatlands are a less suitable target for the type of restoration modeled here, falling outside of the scope of this analysis.

Regarding biophysical considerations, we have simplifying assumptions about where wetlands can be stored, carbon sequestration rates and the storage of removed CO_2 in soils. In our current analysis, we considered those areas that are currently croplands and could be a wetland based on the PNV estimates. PNV estimates indicate that without human intervention, that location could have been a wetland under the current climate conditions. However, this does not explicitly account if the agricultural area was historically a wetland before being converted. This means that the model could potentially be allowing for the analogous to "afforestation" in some locations which may be undesirable for the success of the restoration project and its functioning ecosystem. Better spatial information on what was historically a wetland of each type, could be used to improve this.

We also considered a simplified linear representation of carbon sequestration from wetlands, assuming both: that the sequestration rate of a newly restored wetland is the same as an existing functioning wetland, and that these sequestration rate is constant through time. (Yang et al., 2020) found that carbon sequestration rates may be higher in restored wetlands for some period of time. Moreover, we did not consider different managements, which also affect the sequestration rate (Were et al., 2019).

In our model, we assumed that carbon stored in the soil of restored wetlands remain stored during all the time frame analyzed (up to 2100). Undisturbed coastal wetlands have been found to have carbon stocks that persist up to several hundred of years to millennia (Were et al., 2019; McLeod et al., 2011; Taillardat et al., 2020). However, in the realm of CDR methods it has been classified with a timescale of decades to centuries (Smith et al., 2024; Babiker et al., 2022), which seems to be assigned by extrapolating those of terrestrial ecosystems that store carbon in vegetation or soils (such as forests) with saturation rates, rotation periods and wildfire risks (Chiquier et al., 2022). Still, more understanding is needed on how blue carbon soil stocks respond to disturbances and climate change (Macreadie et al., 2019; Lovelock and Reef, 2020), with some authors already identifying risks from sea level rise to stored carbon in coastal wetlands (Gundersen et al., 2021) and mangrove areas (Hülsen et al., 2025).

Moreover, we are assuming that all restoration projects are successful resulting in functional wetland ecosystems, and we are not considering the time that takes from the initial restoration intervention to the moment the wetland functions as a mature wetland. There is uncertainty about the success of restoration projects (Bayraktarov et al., 2016; Waltham et al., 2020), which can depend on the restoration method, and its location, among others. Understanding the best way, ecologically aligned, to do restoration is essential to maximize success and achieve healthy functional ecosystems (Craft, 2022).

Finally, the competition for land could be a potential challenge or limit to scaling up wetlands restoration. Our simplified post-processing calculation suggests it may not be the most limiting factor, but future research could use an endogenous representation of the connection with the land system to better inform on this. Similarly, because of the spatial resolution used in the analysis, regional aggregations in WITCH, our analysis is limited to provide insights on spatial prioritization of restoration efforts beyond this macro regions. A higher spatial resolution model should be used to better inform local policy and implementation.

Despite these limitations, the modeling framework developed here provides the first dynamic, portfolio-integrated assessment of wetlands restoration as a CDR strategy, and the findings are robust to key parametric uncertainties as shown in the sensitivity analysis.

6 Conclusion

We extended the WITCH IAM to include wetlands restoration as a CDR technology to assess its potential and challenges to upscaling. Our approach considers a broader decarbonization context that includes competition with other CDR methods, carbon sequestration and methane emissions.

We found that wetland restoration is a viable CDR strategy that can remove between 0.53–1.04 $GtCO_2/yr$ by 2100 without displacing other CDR methods, provided carbon taxes reach at least 100–400 (2010) USD/tCO_2, respectively. About half of this removal potential comes from restoring coastal wetlands (mangroves and salt marshes).

We also identified that two potential challenges for upscaling are the limit on the amount of restoration that can be done per period and restoration costs. Our constraint on how much can be restored per period for swamps and mangroves is binding in the majority of the cases. An increased limit will allow for earlier restoration and with it a larger CO_2 removal by the end of the century, even if the total restored area is the same. Restoration costs per ton of CO_2 removed are high, especially for some wetland types (e.g. flooded flats), which are reflected in the wetland types the model prioritizes for restoration. However, the lower costs in various regions of the global south, and the potential to restore mangroves are a good opportunity for removal.

We identified that swamps and mangroves are restored with all carbon tax levels, but marshes and salt marshes require at least a carbon tax of 300 (2010 USD) to be considered. In particular, passing from a 300 to a 400 (2010 USD) carbon tax could increase total removals by 0.44 Gt CO_2/yr in 2100, almost doubling total removals by wetlands restoration. The latter due to the restoration of salt marshes, the second wetland type with higher CO_2 sequestration rates. Consequently, reducing salt marshes restoration cost is a practical approach that could support upscaling. Moreover, wetlands restoration should start as soon as possible, especially for mangroves and swamps to maximize removal up to the end of the century.

Moreover, when upscaling wetlands restoration, not only the benefits (CO_2 sequestered) increase, but also the drawbacks (CH_4 emissions and competition for land). However, we found that CH_4 emissions from wetlands restoration remain small in comparison to total CH_4 emissions, even under the higher carbon tax scenario. This is in part explained by the modeling considering the trade-off between these two greenhouse gas emissions when determining which wetland type to restore and where.

With our sensitivity analysis we identified that our results are robust to changes in the learning rate and initial wetland restoration costs. However, total restored areas could be sensitive to marshes sequestration rate with increased wetland restoration at higher sequestration rates.

The importance of wetlands goes beyond its potential for removing carbon from the atmosphere. Wetlands also provide other ecosystem services and are important for biodiversity protection. Our analysis suggests that even without endogenously accounting for these co-benefits from nature, its potential as a CDR technology is enough reason to prioritize efforts in restoration. Moreover, our simplified post-processing analysis suggests that the restored wetlands area in our scenarios could generate additional benefits, from the provision of ecosystem services, between 2.046 to 2.804 Trillion (2010 USD) for carbon taxes of 100 to 400 (2010 USD), respectively. If compared with our postprocessing opportunity cost for land, we can see how the estimated co-benefits from wetlands restoration significantly exceed the cost, re-affirming the importance of this strategy.

An endogenous consideration of these benefits could incentivize more restoration decisions in the model representing a promising direction for future research. In this way, wetlands restoration could be analyzed in IAMs under a broader perspective, which could include its role, not only for climate change mitigation, but also climate change adaptation, for example due to coastal protection. This approach could be an example of how we can use IAMs to analyze integrated solutions for nature and biodiversity, and climate change, a direction that allows us to endorse synergies and avoid trade offs (Pörtner et al., 2023). Specifically, restoration efforts here considered for its potential for CO_2 removal, could also be aligned with the Ramsar Convention on Wetlands goals (Ramsar Convention on wetlands, 2025) and the Global Biodiversity Framework (GBF) (CBD, 2022).

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Supplementary Information

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S1 Wetlands module -Mathematical Formulation

The mathematical formulation was designed to be used with various levels of spatial resolution. However, for the results presented here the spatial resolution used was WITCH regions, therefore set $N = S$.

S1.1 Sets

From WITCH model:

- T: set of periods indexed in t .
- N: set of economic regions indexed in n.

Editing existing sets:

- e: set of emission-related entities indexed in e. Adding elements: {co2_afolu_wetl, ch4_afolu_wetl, ch4_biogenic, ch4_biogenic_wetl}

Additional sets:

- S: set of spatial units indexed in s.
- $natS$: set of sources of natural capital indexed in a.
- map_natCap: Set that maps the tree of the different sources of natural capital.
- $map\_spatialUnit_{s,n}$: Mapping between the spatial unit s defined and the region n.
- all_wet_types: set of all wetland types in (Zhang et al., 2024) dataset. Indexed in v.
- wet_types: set of wetland types represented in the WITCH model indexed in w. Subset of all_wet_types.

S1.2 Parameters

In blue data sources

$c_{s,w}$:	Initial wetland restoration cost per ha of wetland type w for spatial unit s. [T\$/(ha yr)]	(Taillardat et al., 2020; Bayraktarov et al., 2016; Zeng et al., 2021)
$cL_{s,w,t}$:	Wetland restoration cost per ha of wetland type w for spatial unit s in period t, including learning. [T\$/(ha yr)]	Using $c_{w,s}$ and learning function.
$emiCO2_{w,s}$:	Net CO_2 emissions/sequestration per ha of wetland of type w for each spatial unit s per year. The Net Ecosystem Productivity (NEP). [TonC $ha^{-1}yr^{-1}$] (The flux).	(Taillardat et al., 2020), (D. P. Costa et al., 2024)
$emiCH4\_lit_{w,s}$:	CH_4 per ha of wetland of type w for each spatial unit s per year. From the literature. [TonC $ha^{-1}yr^{-1}$] (The flux).	(Taillardat et al., 2020)
$emiCH4\_DL_{s,t}$:	CH_4 world annual emissions aggregated among all wetland types in spatial unit s and time period t. Available for SSP1-RCP2.6, SSP3-RCP3.7 and SSP5-RCP8.5 scenarios. Derived from ML model [Ton CH_4/yr].	(Rodriguez-Pardo et al., Forthcoming)
$emiCH4_{w,s,t}$:	CH_4 emissions per ha of wetland type w for each spatial unit s per year for period t. [TonC $ha^{-1}yr^{-1}$] (The flux)	Using $emiCH4\_DL_{s,t}$, $emiCH4\_lit_{w,s}$ and $wArea_{w,s,t}$.
$maxW_{w,s}$:	Upper bound in the amount of ha of wetland of type w that can be restored in spatial unit s based on physical limits (e.g. potential distribution of land cover, long-term climatic conditions indicators, groundwater and soil conditions, soil lithology). [ha]	Based on (Chapman et al., 2025; Hengl et al., 2020).
$wArea_{v,s,t}$:	Wetland area of type v in spatial unit s from data sets for calibration for $t \in \{1,2,3,4\}$. [ha] 3	GWL_FCS30 dataset-(Zhang et al., 2024)
$baseline\_emiCH4\_wetl_n$:	Baseline CH_4 emissions per year [GTC/yr] in region n. Used to calculate Δ (additional emissions).	Using $emiCH4\_DL_{s,t}$.
$baseline\_area\_wetl_{w,s}$:	Baseline area [ha] of each wetland type w in each spatial unit s. Used to calculate total restored area for annual sequestration.	Using $wArea_{v,s,t}$
$restProArea_{w,*}$:	Information on wetlands restoration projects area [ha]. Includes both mean and percentile 75.	(Taillardat et al., 2020)
$adj\_ub\_rest\_pro_{w,s,t}$:	Adjustment factor to determine the amount of restoration projects that can be done in each spatial unit s, in each period t, of each wetland type. [No unit, $\in \mathbb{R}^+$]	Defined by user
$cropland2022_n$:	Cropland land cover area in 2022 [ha].	(Zhang et al., 2021)

S1.3 Decision variables

$x_{w,s,t}$: amount of area of wetland of type w to restore in spatial unit s in period t [ha].

Auxiliary variables:

$area_{w,s,t}$: wetland area of type w in spatial unit s in period t ("the stock") [ha].

$Q\_WET\_S_{s,t}$: Amount of CO_2 stored in wetlands in spatial unit s in period t [TonC].

$Q\_WET_{t,n}$: Amount of CO_2 stored in wetlands in period t and region n [GTonC].

$CUM\_Q\_WET_{t,n}$: Cumulative quantity of additional CO_2 stored in wetlands in period t and r

$Q\_EMI\_WET_{e,t,n}$: Emissions-related quantities of e [GtCe/yr] for wetlands in region n and pe

S1.4 Constraints

Consider the sets $S_n = \{s : s \text{ is inside region } n\}$ as the sets denoting the connection between the spatial units s and WITCH regions n.

S1.4.1 Restoration costs

- Affect mitigation costs

$$COST\_EMI('co2\_afolu\_wetl', t, n) = \sum_{w,s \in S_n} cL_{w,s,t} x_{w,s,t} \qquad \forall t \in T, n \in N \tag{S1}$$

where, $cL_{w,s,t} = max(c_{s,w}/100, c_{s,w}(area_{w,s,t} - baseline\_area\_wetl_{w,s} + 1)^{-0.1})$ to represent how restoration cost decreases with increased cumulative restoration.

S1.4.2 Wetland areas

- Bounds on wetland restored area based on physical limits.

$$\sum_{t \in T} x_{w,s,t} \leq maxW_{w,s} \qquad \forall w \in wet\_types, s \in S \tag{S2}$$

- Per period bound on restoration

$$x_{w,s,t} \leq \begin{cases} maxW_{w,s}/16 & \text{if } t > 4 \\ 0 & \text{if } t \leq 4 \end{cases} \tag{S3}$$

- Ensure total restoration does not exceed current cropland. Used because of the construction of $maxW$ using the same PNV map for most wetland types.

$$\sum_{w,s \in S_n, t} x_{w,s,t} \leq cropland2022_n \qquad \forall n \in N \tag{S4}$$

- Define initial area of wetlands

$$area_{w,s,t} = wArea_{w,s,t} \quad \forall w \in wet\_types, s \in S, t \in \{1, 2, 3, 4\} \tag{S5}$$

- Area balance constraint. Not yet considering reductions in wetland area due to transformations to other land use types (e.g. urban development) $\implies$ Assumes preserve existing.

$$area_{w,s,t+1} = area_{w,s,t} + x_{w,s,t+1} \qquad \forall w \in wet\_types, s \in S, t > 4 \tag{S6}$$

S1.4.3 Wetland emissions

- Define carbon storage per spatial unit that will be stored in period t. Here we only consider restored wetlands sequestration. We don't consider sequestration of existing natural wetlands because this is the equilibrium status (already indirectly included in existing emissions), we consider only the changes/deviations from equilibrium. This assumes wetland area of each type w is monotonically increasing through time.

$$Q\_WET\_S_{s,t} = \sum_{w \in wet\_types} (area_{w,s,t} - baseline\_area\_wetl_{w,s}) emiCO2_{w,s} \qquad \forall s \in S, t \in T \tag{S7}$$

$$Q\_WET_{t,n} = \sum_{s \in S_n} Q\_WET\_S_{s,t} \qquad \forall t \in T, n \in N \tag{S8}$$

- Define cumulative carbon storage in wetlands

$$CUM\_Q\_WET_{t,n} = \begin{cases} 0 & \text{if } t \leq 4 \\ CUM\_Q\_WET_{t-1,n} + Q\_WET_{t,n} & \text{if } t > 4 \end{cases} \qquad \forall t \in T, n \in N \tag{S9}$$

- Estimate anthropogenic CH_4 emissions- those of restored wetlands.

$$Q\_EMI\_WET('ch4\_afolu\_wetl', t, n) = \sum_{w, s \in S_n} (area_{w,s,t} - baseline\_area\_wetl_{w,s}) emiCH4_{w,s,t} \qquad \forall t \in T, n \in \tag{S10}$$

- Estimate biogenic CH_4 emissions- those from increasing CH_4 emission factors due to climate change in both existing and restored wetlands.

$$Q\_EMI\_WET('ch4\_biogenic\_wetl', t, n) = \sum_{w, s \in S_n} baseline\_area\_wetl_{w,s} emiCH4_{w,s,t} \qquad \forall t \in T, n \in N \tag{S11}$$

- Associate wetland emissions

$$Q\_EMI('co2\_afolu\_wet', t, n) = -Q\_WET_{t,n} \qquad \forall t \in T, n \in N \tag{S12}$$

$$Q\_EMI('ch4\_afolu\_wetl', t, n) = Q\_EMI\_WET('ch4\_afolu\_wetl', t, n) \qquad \forall t \in T, n \in N \tag{S13}$$

$$Q\_EMI('ch4\_biogenic\_wetl', t, n) = Q\_EMI\_WET('ch4\_biogenic\_wetl', t, n) - baseline\_emiCH4\_wetl_n \tag{S14}$$

With the subtraction of baseline CH_4 emissions, for each wetland type w we consider only additional emissions due to increased $emiCH4_{w,s,t}$ in a time period or increased area due to restoration.

S1.4.4 Decision variables characteristics

- Variables types

$$x_{w,s,t} \in \mathbb{R}^+ \qquad \forall w \in wet\_types, s \in S, t \in T \tag{S15}$$
$$area_{w,s,t} \in \mathbb{R}^+ \qquad \forall w \in wet\_types, s \in S, t \in T \tag{S16}$$
$$Q\_WET\_S_{s,t} \in \mathbb{R}^+ \qquad \forall s \in S, t \in T \tag{S17}$$
$$Q\_WET_{t,n} \in \mathbb{R}^+ \qquad \forall t \in T, n \in N \tag{S18}$$
$$CUM\_Q\_WET\_S_{t,n} \in \mathbb{R}^+ \qquad \forall t \in T, n \in N \tag{S19}$$
$$Q\_EMI\_WET_{e,t,n} \in \mathbb{R} \qquad \forall e \in e, t \in T, n \in N \tag{S20}$$

S2 Data sources

S2.1 CO_2 sequestration by wetlands

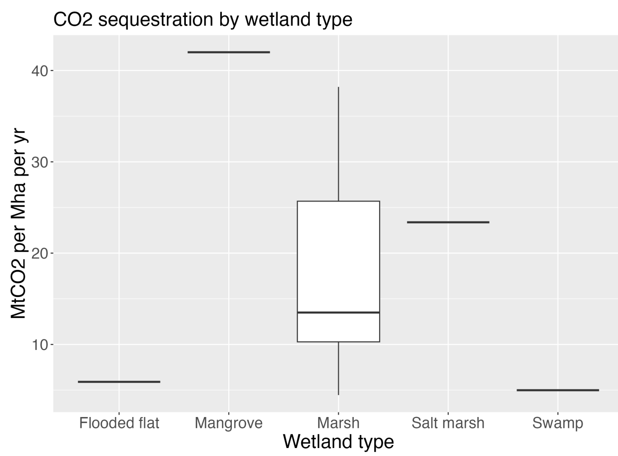


Figure S1: CO_2 sequestration rates (NEP) based on (Taillardat et al., 2020) for each wetland type.

S2.2 Projections of methane emissions from wetlands

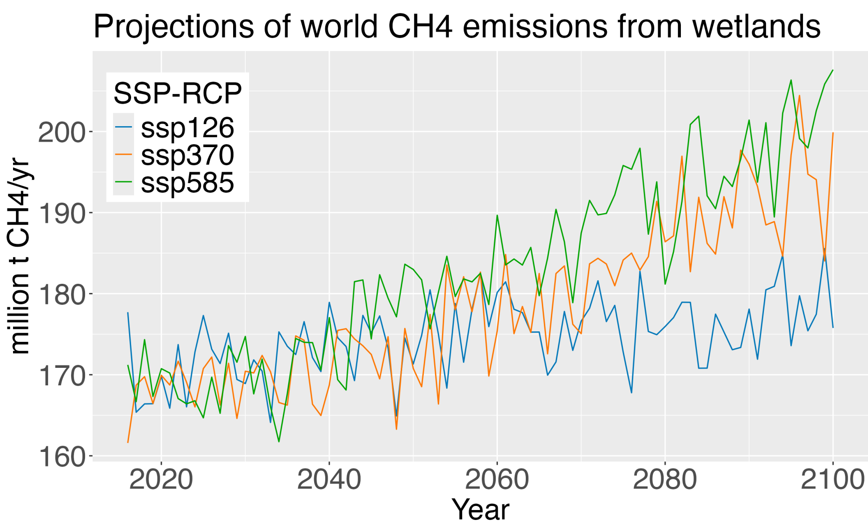


Figure S2: Global projections of CH_4 emissions for wetlands under three different SSP-RCP scenarios from our Deep Learning (DL) model.

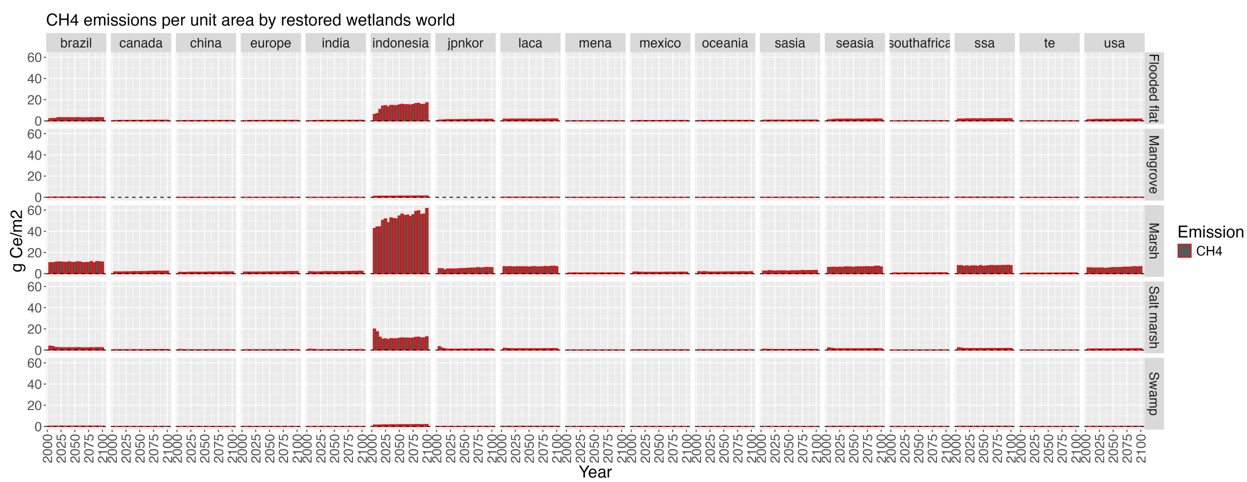
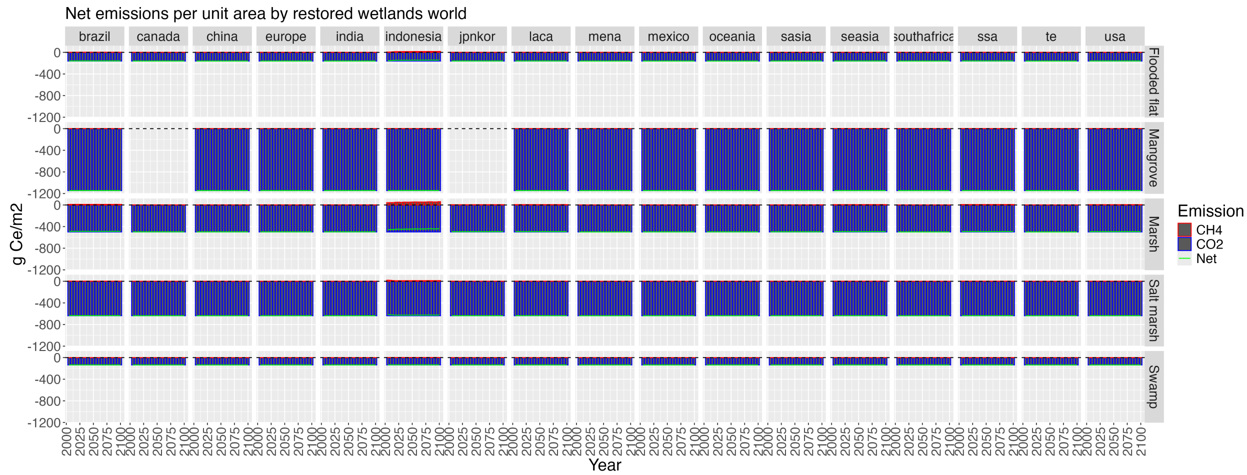


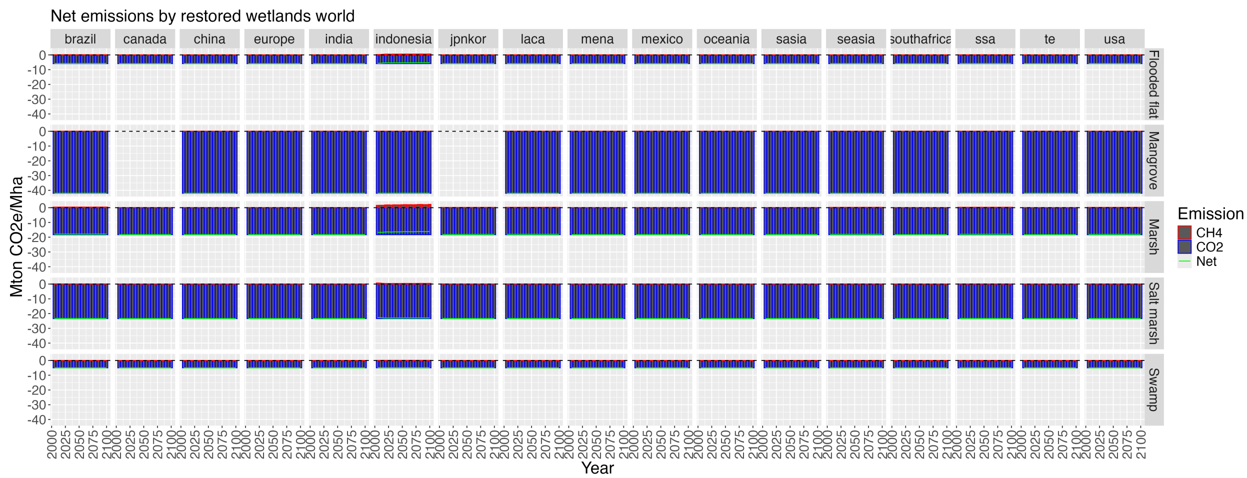
Figure S3: Methane emissions per unit area for each wetland type, period and region. These emission factors were derived from the Deep Learning projections considering current wetlands area, their spatial location and emission factors from literature.

S2.3 Net emissions per unit area

Considering methane GWP for 100 years.



(a) gCe/m2



(b) $MtCO_2e/Mha$

Figure S4: Net emissions per unit area considering both CO_2 sequestration and CH_4 emissions considering a GWP of 100 years for methane. There is no emission factors associated to mangroves in Canada and Japan/Korea because of the lack of existing mangroves in these regions.

S2.4 Maximum restorable area per region and wetland type

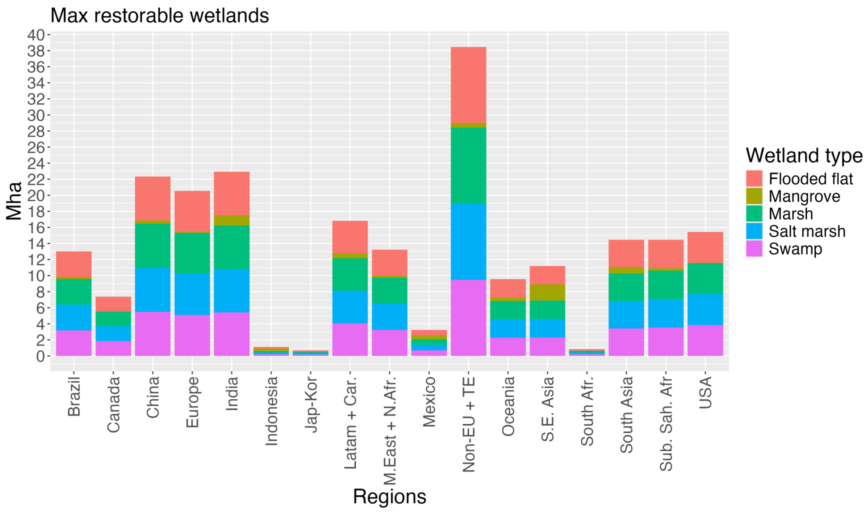


Figure S5: Max restorable area per region and wetland type

S2.5 CO_2 sequestration potential per region and wetland type

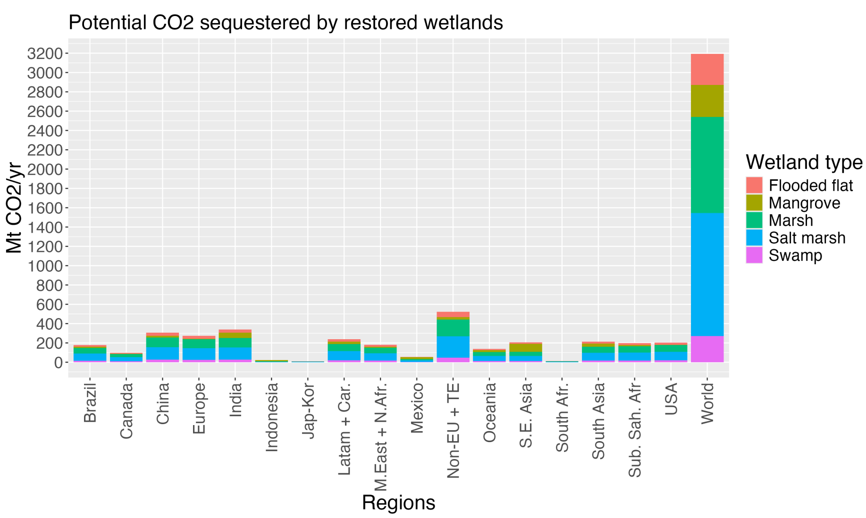


Figure S6: CO_2 sequestration potential per region and wetland type

For mangroves, global potential is around 368.7 Mt CO_2/yr if restoring maximum restorable area.

S2.6 Restoration costs

Restoration costs per ton of CO_2 removed These are the initial starting costs which are decreases by learning.

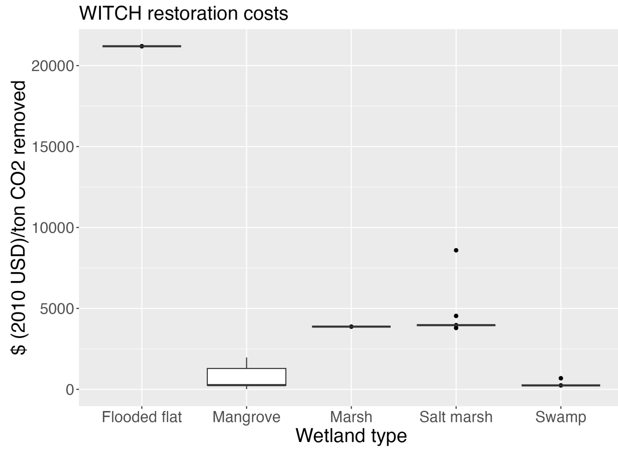


Figure S7: Initial restoration costs per ton of CO_2 removed in WITCH for each wetland type. Variation comes from the 17 regions.

Restoration costs per ha for each region and wetland type The figure shows the regional differences on the assumptions on the initial restoration cost of each wetland type.

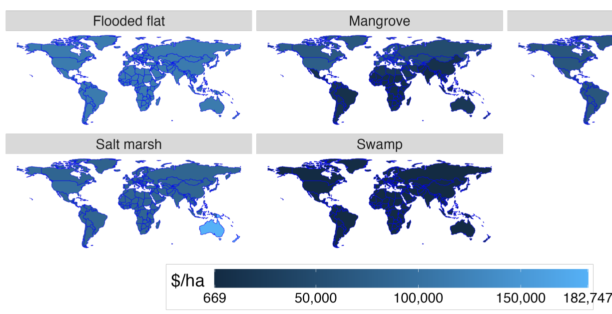


Figure S8: Initial wetlands restoration costs for each region and wetland type

S3 Carbon tax pathways

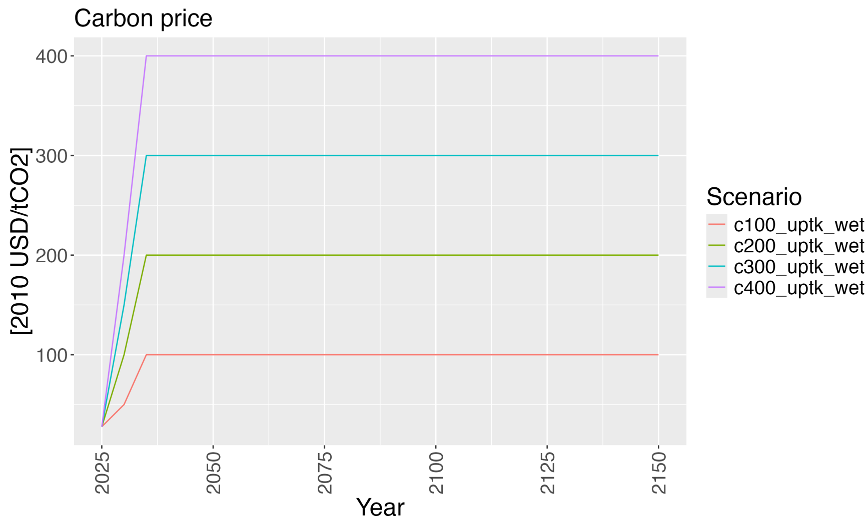


Figure S9: Carbon tax pathways

S4 Additional results

S4.1 For scenario comparison between restoration and no restoration

S4.1.1 CDR portfolio

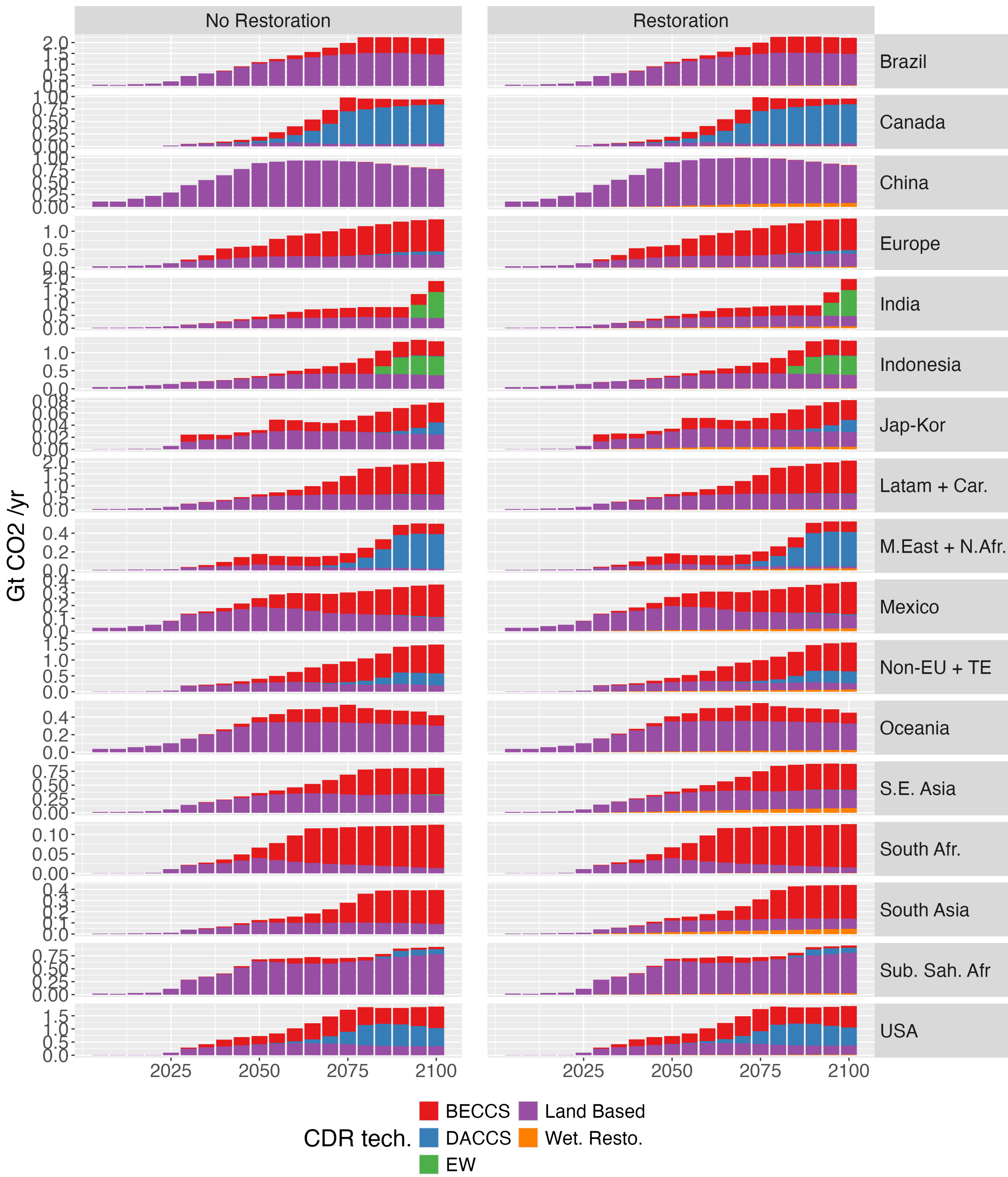


Figure S10: CDR portfolio for scenario "Carbon tax 300" with and without wetlands restoration for all WITCH regions

S4.1.2 Emissions of wetlands

In this section we deepen on the wetlands associated emissions for the scenario with restoration and a 300 (2010 US) carbon tax.

CO_2 emissions/removals for a 300 (2010 USD) carbon tax Figure S11 shows how wetlands' restoration contribution to CO_2 emissions reduction vary per region, with most regions showing negligible differences, and others such as south and southeast asia showing the major differences.

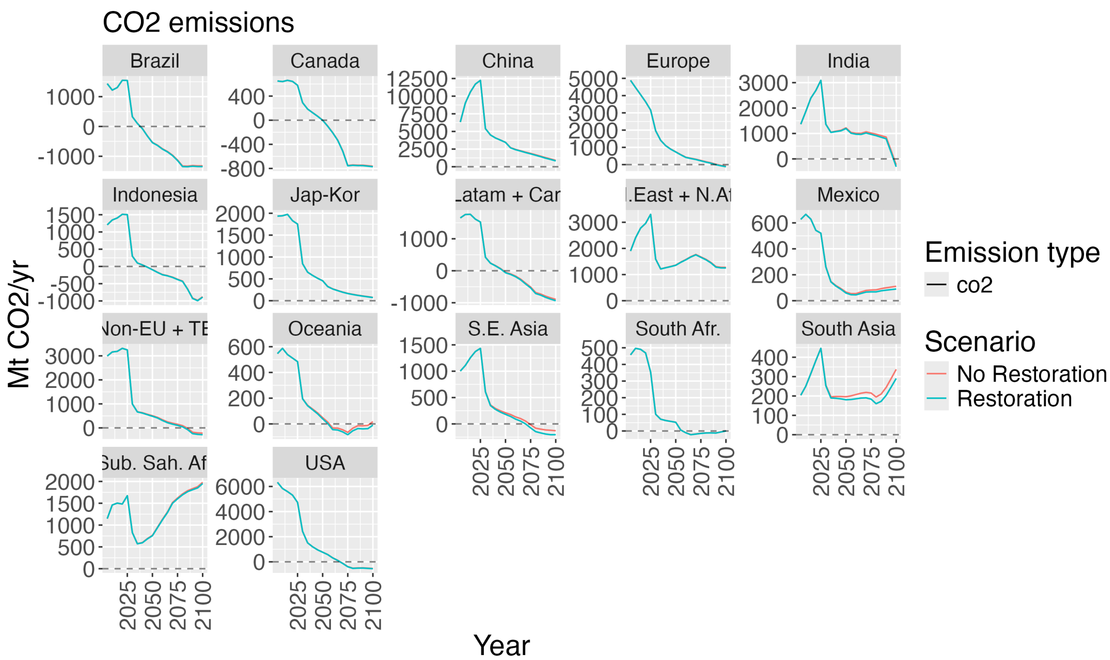


Figure S11: Total CO_2 emissions per year for each WITCH region

Figure S12 shows the pathways of CO_2 removals from wetlands. The linear pathway reflects model assumptions and selection of restoration areas per wetland type per period. All additional (restored) ha of wetland sequester carbon, so as cumulative restored areas increase, so does CO_2 removals per year. It can also be noted in this figure that there is removal from wetlands in all regions of the world, reflecting an incentive to do restoration efforts globally.

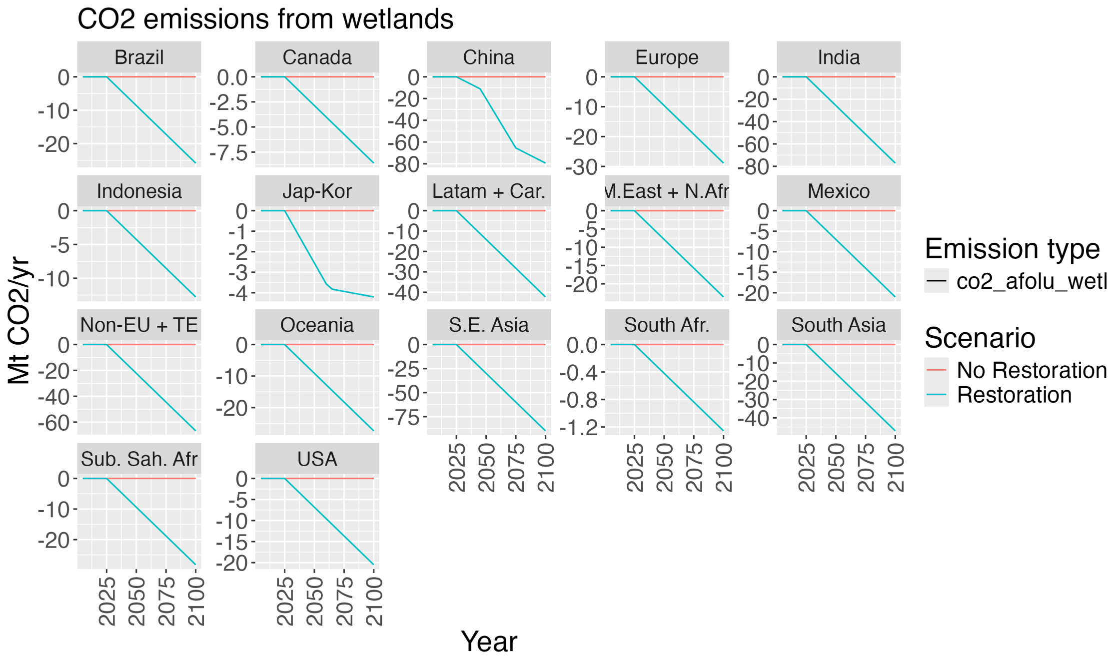


Figure S12: Total CO_2 emissions per year, from wetlands, for each WITCH region

Figure S13 shows which wetland types are contributing more to wetlands global removals. It shows that major reductions come from swamps, followed by mangroves. However, the reason behind the contribution differs with swamps having more reductions because of more areas being restored worldwide with lower sequestration rates versus mangroves with significantly higher sequestration rates, but lower restored areas. The same results are shown for each WITCH region in Figure S14 where it can be seen how regions such as India, Latin America and Caribbean, Mexico, Oceania, south Asia and southeast asia contribution to global removals is mainly through mangroves restoration. In contrast, the regions such as Canada, Europe and the USA are relying on Swamps restoration.

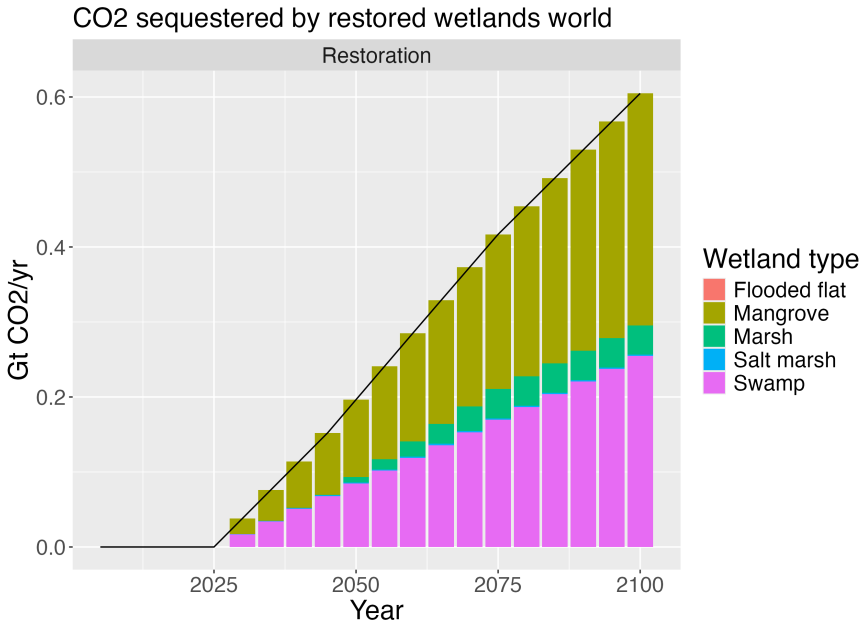


Figure S13: Global CO_2 emissions per year, from wetlands, per wetland type

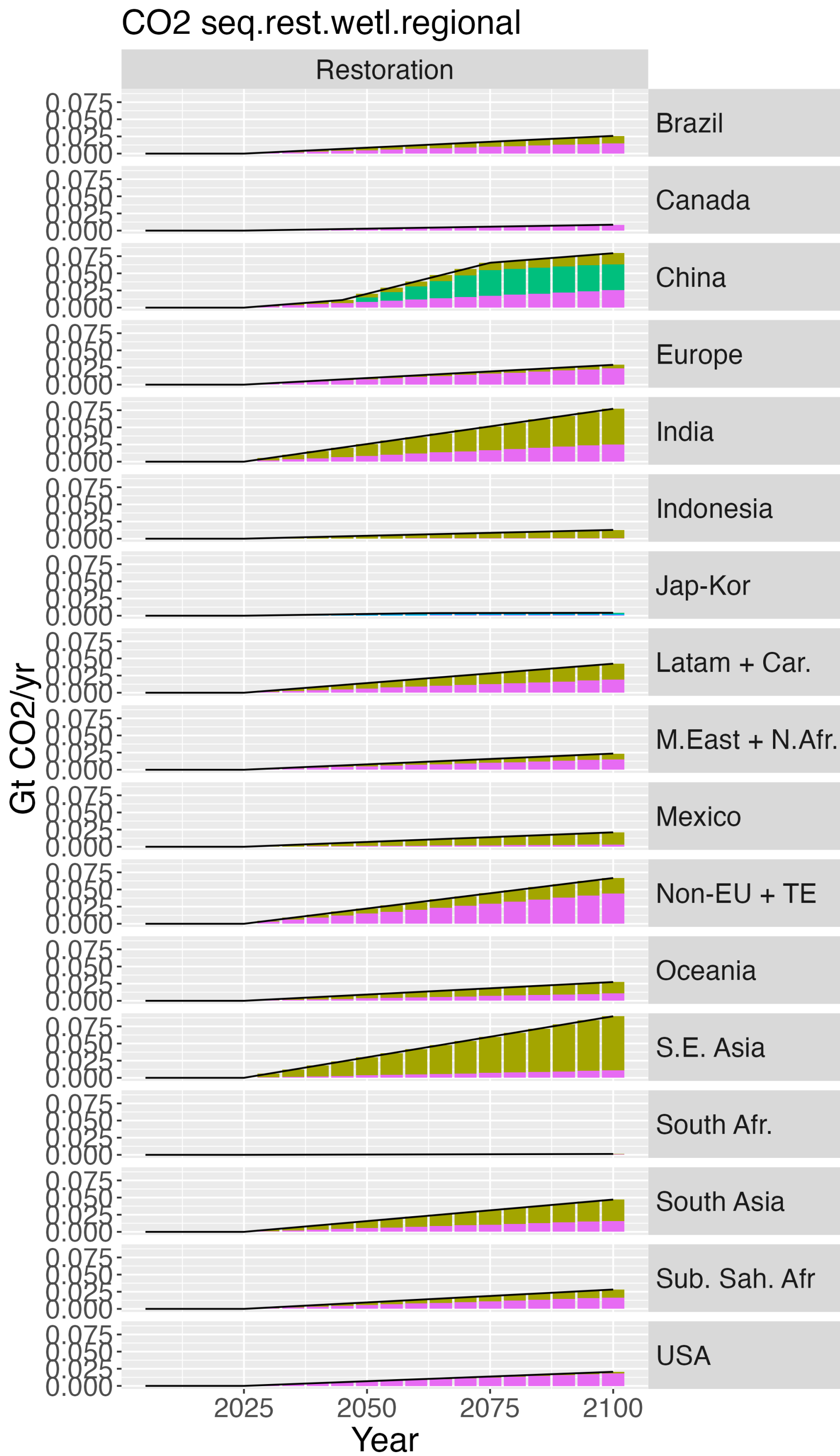


Figure S14: CO_2 emissions per year, from wetlands, per wetland type for each WITCH region

CH_4 emissions for a 300 (2010 USD) carbon tax The figure shows all CH_4 emissions in the model for each region, comparing scenarios with and without wetlands restoration.

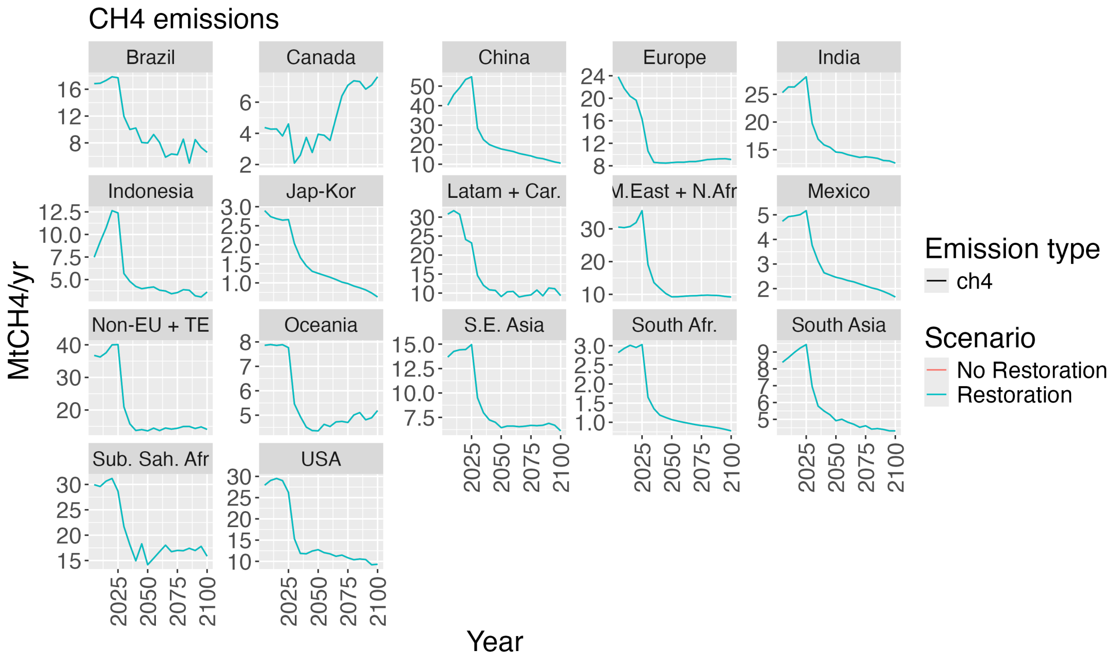


Figure S15: Total CH_4 emissions per year for each WITCH region. In addition to other sources of methane in WITCH, these methane emissions include both the additional emissions from existing wetlands due to climate change (i.e. increased temperature and precipitation), and the emissions from restored wetlands.

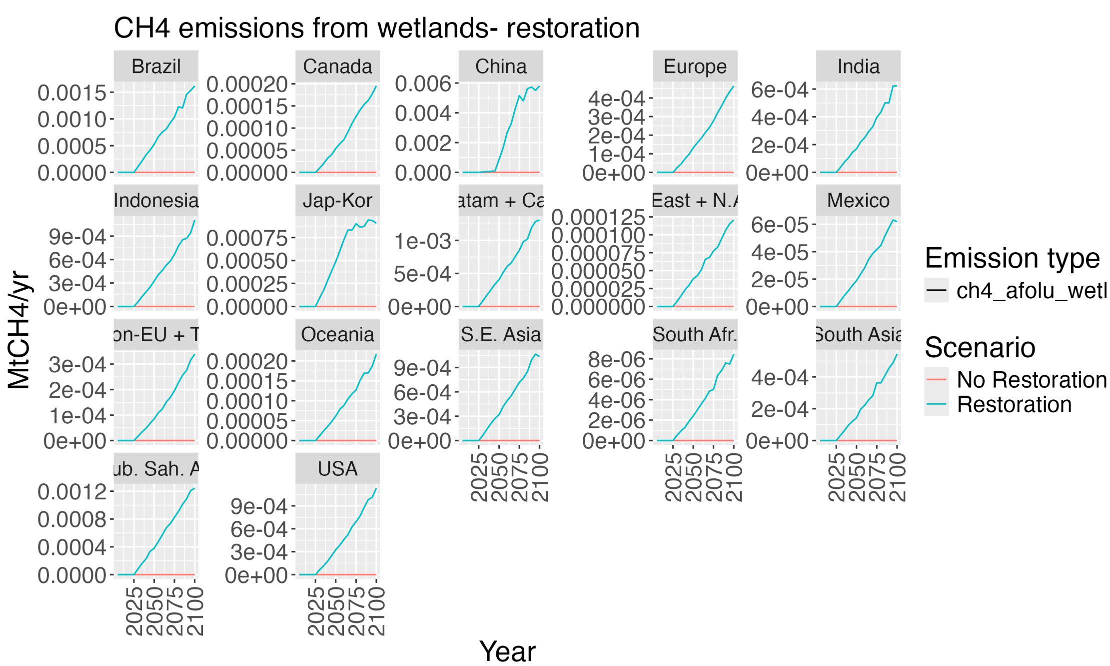


Figure S16: CH_4 emissions associated with restored wetlands

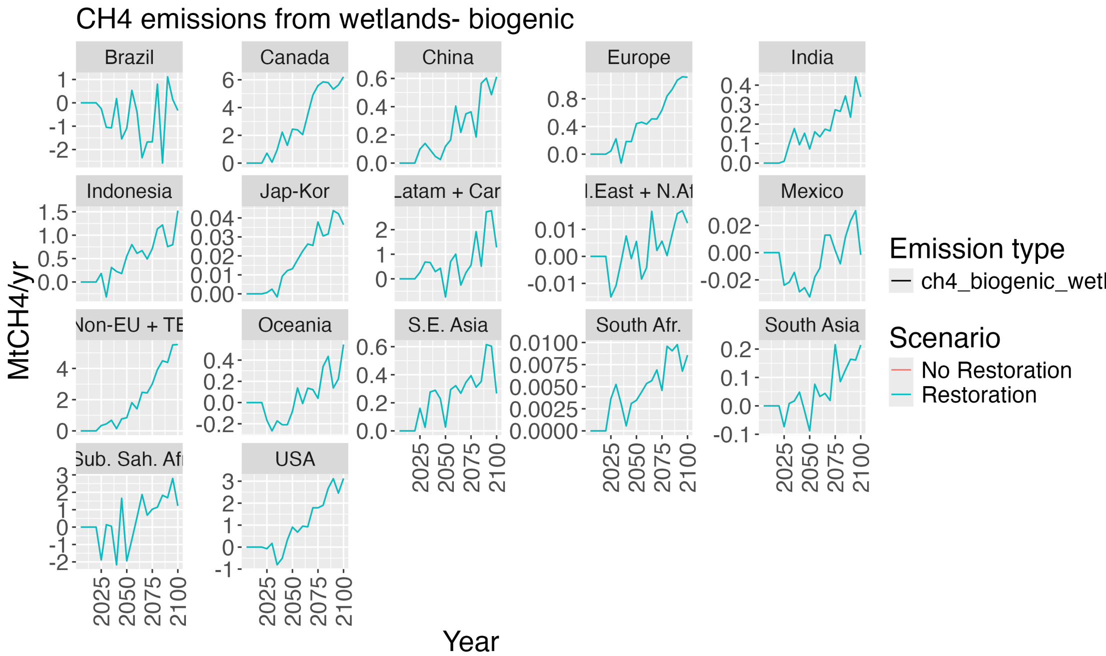


Figure S17: Additional CH_4 emissions associated with current wetlands due to climate change (increased temperature and changing precipitation patterns).

Opportunity cost of agricultural land transformation The figure shows the estimates opportunity costs due to the transformation of agricultural land for mangroves. The width of the bar represents the magnitude of the cropland rent, the height of the bar represent the transformed area (for wetlands restoration), and the area represent the magnitude of the opportunity cost for each region.

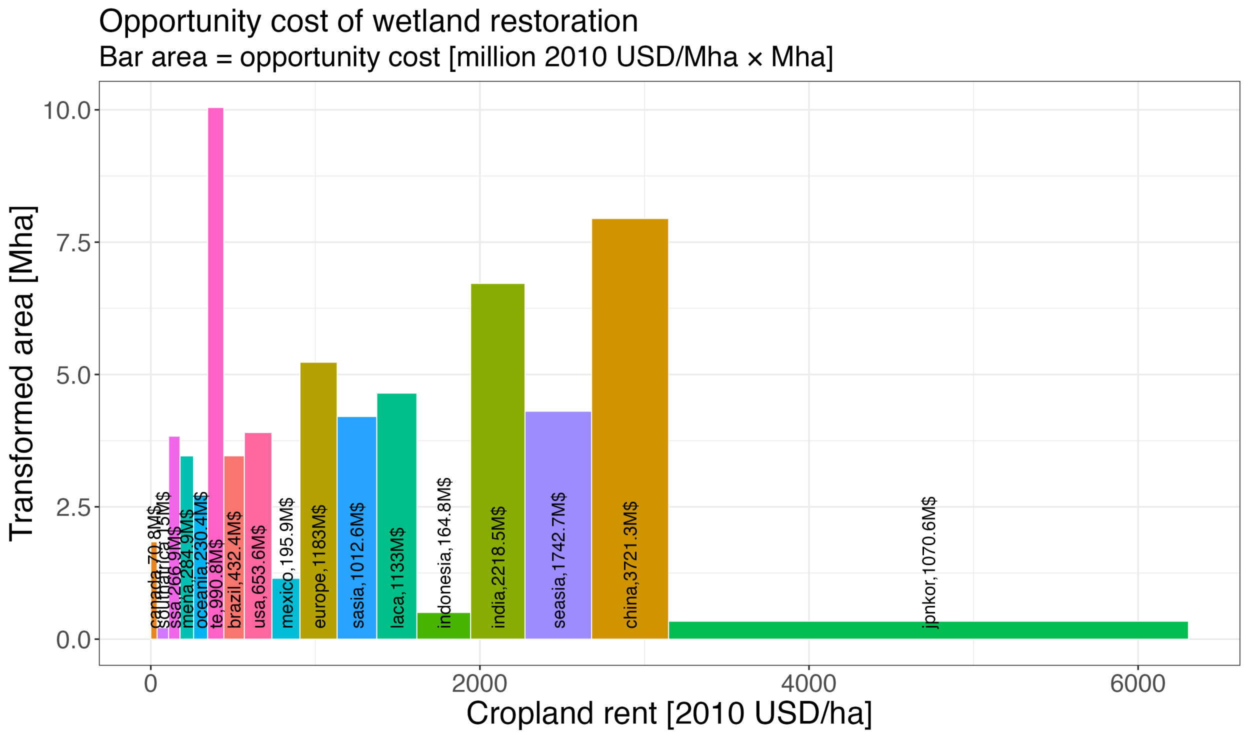


Figure S18: Opportunity cost of agricultural land transformation. Using land rents for cropland from (Gurgel et al., 2016)

S4.2 For increasing carbon tax

S4.2.1 Restoration decisions vs maximum potential

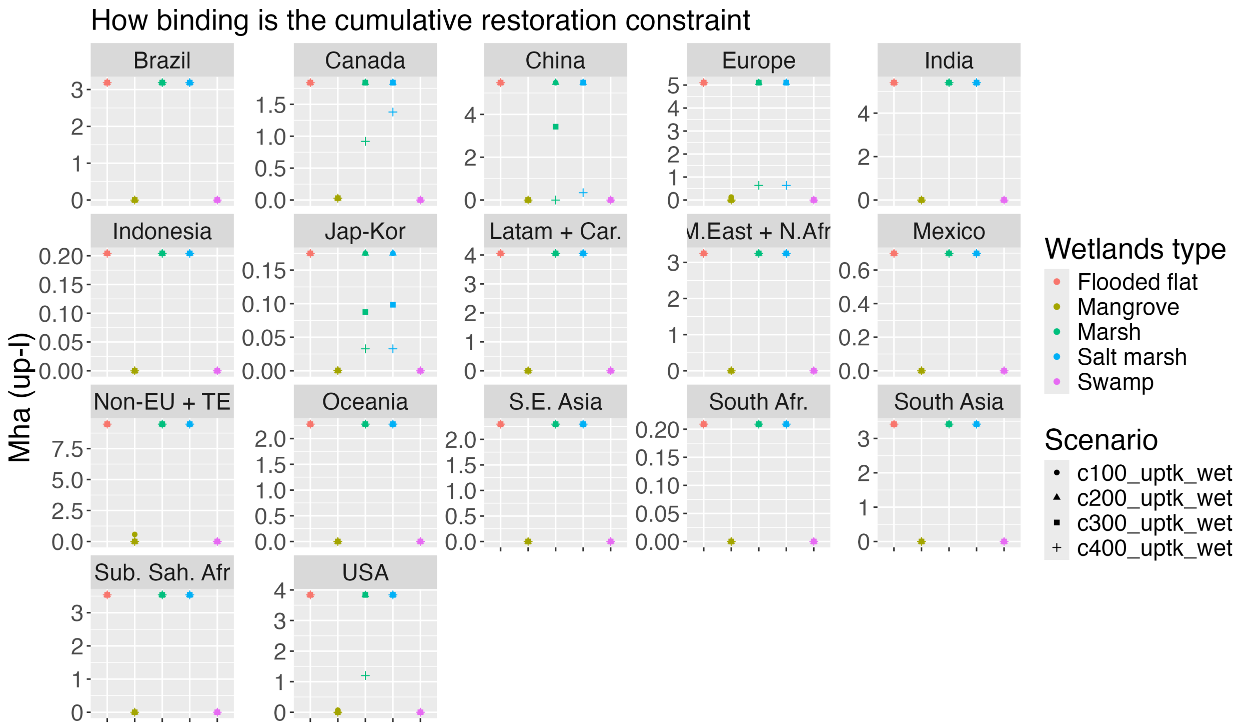


Figure S19: How binding is the constraint on maximum cumulative restoration. In other words, how close are cumulative restoration decisions to the maximum potential. A value of 0 means that the maximum potential area is being restored. A value > 0 means that cumulative restored area is less than the maximum potential.

S4.2.2 Regional removals as carbon tax increases

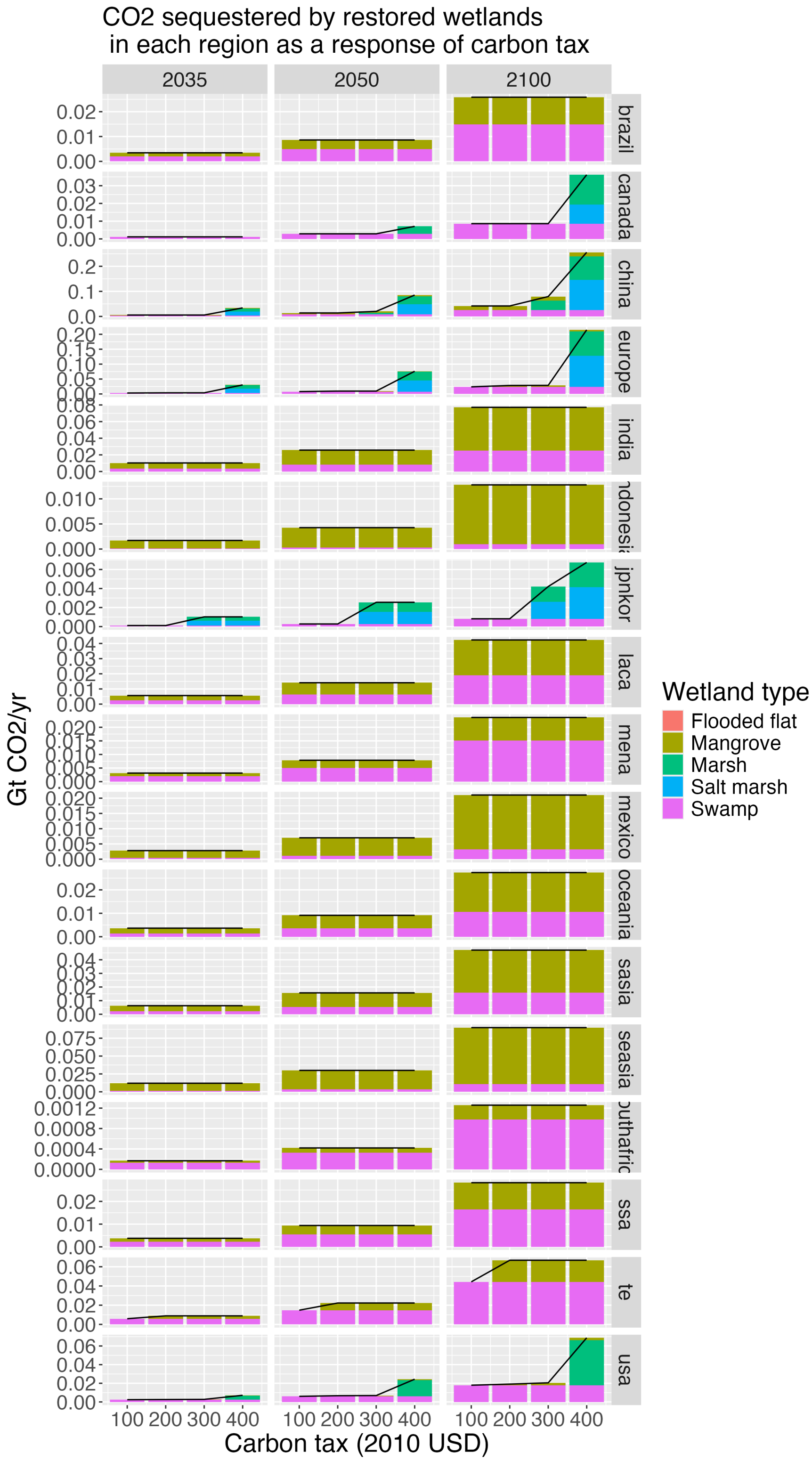


Figure S20: Regional removals from wetlands restoration as carbon tax increases by wetland type

S4.2.3 Restoration area decisions as carbon tax increases

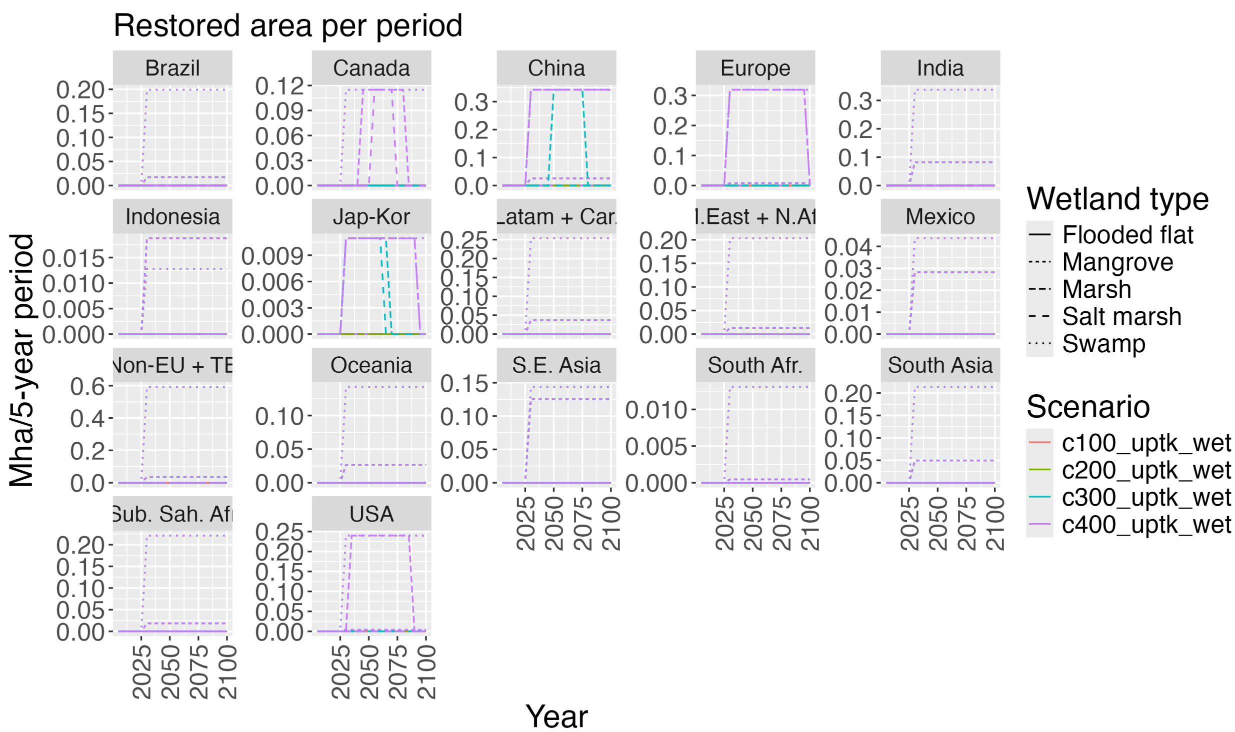


Figure S21: Decision on area to be restored for each wetland type, WITCH region, period and carbon tax mitigation scenario.

S4.2.4 Methane emissions per region due to restored wetlands

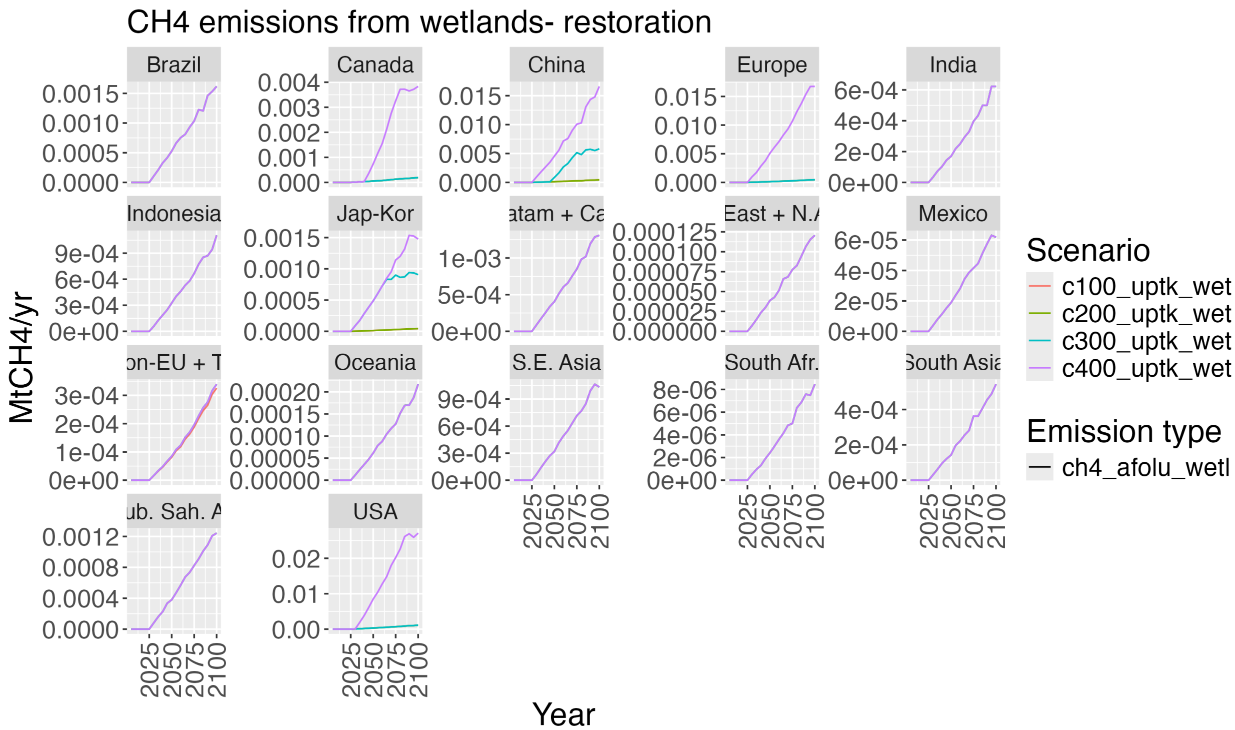


Figure S22: Methane emissions due to restored wetlands. Total methane emissions for the same scenarios vary around 1 Mt CH_4/yr for South Africa and 20 Mt CH_4/yr for China, India and Sub Saharan Africa.

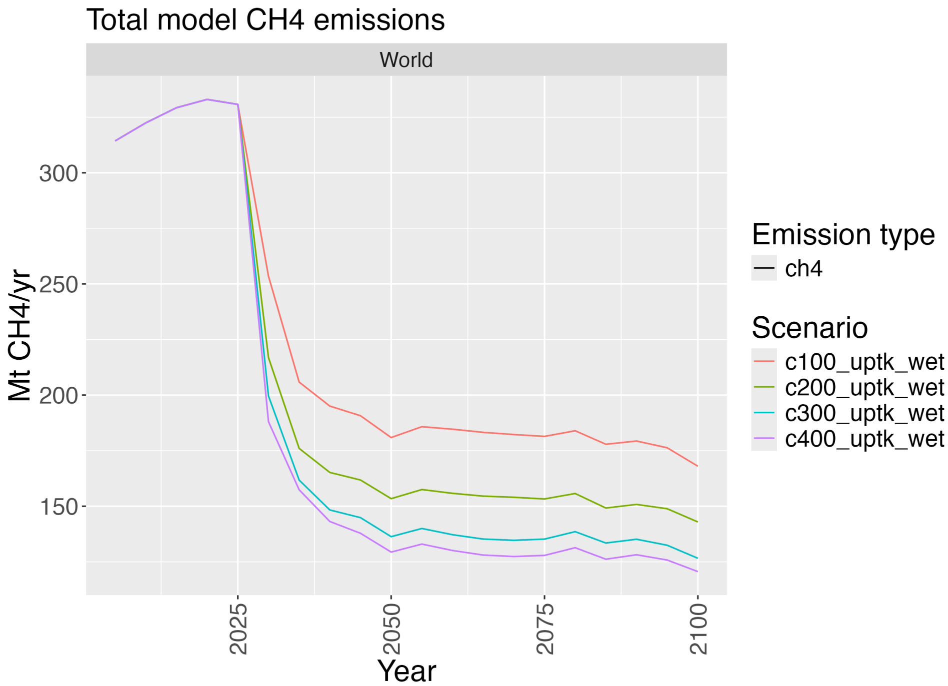


Figure S23: Total global CH_4 emission for carbon tax scenarios

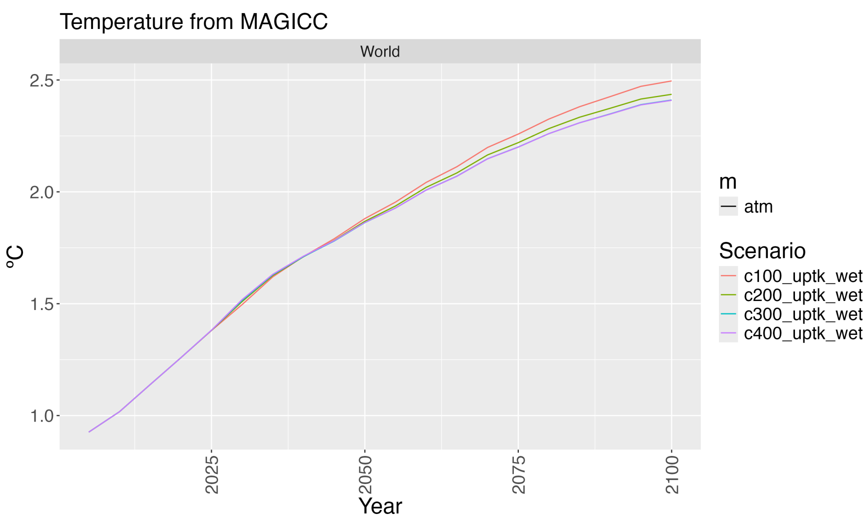


Figure S24: Temperature pathways for our carbon tax scenarios with wetlands restoration

S5 Sensitivity Analysis

Considering parametric uncertainty, and to understand the robustness of the results, we did a sensitivity analysis on the following parameters: learning rate for restoration cost, how much sequestered CO_2 per Mha for marshes $emiCO2_{marsh}$, and the initial restoration cost c_{n,wet_types} for each region and wetland type. We applied the sensitivity analysis to the scenario with restoration and a carbon tax of 300 (2010 USD). Table S1 shows the distributions and values assign for the sensitivity exercise. We did 1000 runs with each run containing a realization of the different parameters according to the distributions chosen.

Parameter [Unit]	Distribution	Baseline value
learning rate [Unitless]	Uniform(0.06,0.6)	0.1
$emiCO2_{marsh}$ [MtCO2 per Mha per yr]	Uniform(4.455, 38.207)	18.3
c_{n,wet_types} [T$ per Mha per yr]	Uniform(1/2 * baseline, 2* baseline)	See Figure S8

Table S1: Parameters, distributions and its values for sensitivity analysis

To analyze the model sensitivity, we chose the total amount of restored area (aggregated for all periods, regions and wetland types) as the output variable of interest. Increased restored areas is the decision variable of the module, and more restored areas imply more carbon sequestration from wetlands, more methane emissions, and more opportunity cost of land.

S5.1 On restored areas

To test the impact of each individual parameter on the output variable Y, we used the following multiple linear regression:

$$Y = \beta X + \epsilon \tag{S21}$$

where Y is the global restored area in all periods and of all wetland types, $X = [\mathbf{1}, x_1, x_2, ..., x_{87}]$ where x_1 is the learning rate, x_2 is $emiCO2_{marsh}$ and x_3 to x_{87} correspond to the initial restoration cost c_{n,wet_types} for $n = 17$ and $wet\_types = 5$. To assess the sensitivity of the model to each parameter, we consider if the associated β_i was significant and to be able to rank the impact we use the Standardized Regression Coefficients (SRC) so we can compare given the inputs have different units of measurement. Then our sensitivity index S_i is

$$S_i = |SRC_i| = \left|\hat{\beta}_i \frac{\sigma_{x_i}}{\sigma_Y}\right| \tag{S22}$$

These SRC_i are interpreted as the change in Y in standard deviations per one standard deviation increase in x_i.

Our regression analysis resulted in an $R^2 = 0.8446$ and an adjusted $R^2 = 0.8298$, which we considered good for the purpose of the sensitivity analysis. We identified 27 parameters with a significant $\hat{\beta}_i$ with a level of significance $\alpha = 0.05$. From those, the top five[4] in terms of our sensitivity index are shown in Table S2.

[4]The rest of the parameters are not shown because they have similar or smaller impact in total restored areas.

	Parameter	SRC	$\lvert SRC \rvert$	SRC^2
1	emiCO2.182	0.84	0.84	0.70
2	wetlRest_cost_ha_te.182	-0.15	0.15	0.02
3	wetlRest_cost_ha_te.186	-0.15	0.15	0.02
4	wetlRest_cost_ha_china.186	-0.14	0.14	0.02
5	wetlRest_cost_ha_europe.186	-0.10	0.10	0.01
6	wetlRest_cost_ha_india.182	-0.10	0.10	0.01
7	wetl_learn_rate	0.08	0.08	0.01

Table S2: Sensitivity indexes from multiple linear regression

We can see that, from the parameters assessed, the model is more sensitive to changing values in the sequestration rate for marshes. Specifically, a change in one standard deviation in this parameter (i.e. in 9.748 Mt CO_2 per Mha per yr) would result in an increase in total restored area of $0.84 \times \sigma_Y = 11.16$ Mha. Considering the value of Y for the baseline scenario (that described in section 3.1) of 60.63 Mha of restored wetlands, a change of 11.16 Mha will correspond to aproximately 18% more Mha restored. As can be seen in Figure S25 it is expected that most of the increase in restored areas is of Marshes.

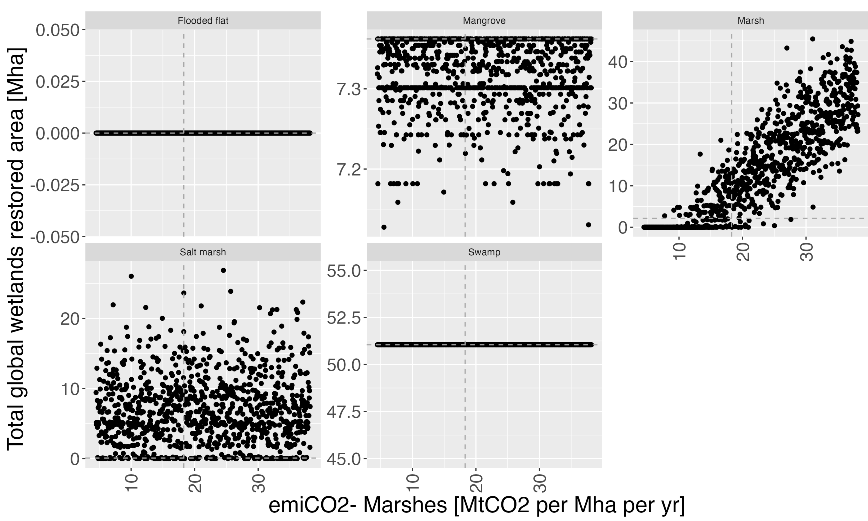


Figure S25: Total restored areas with varying values of marshes sequestration factor, by wetland type. The horizontal gray dashed line indicates the value for the baseline run (the scenario with a 300 (2010 USD) carbon tax) of total restored areas. The vertical dash line indicates the baseline value for the parameter.

In contrast, specific initial costs for a wetland type and region, even when statistically significant imply a small change in Y. For example, decreasing by one standard deviation the initial cost to restore marshes in Non EU countries and transition countries by 0.028 T$ per Mha per yr is associated with an increase in total restored areas of 2.053 Mha, an increase in 3.4% in total restored areas.

To test if the initial restoration costs as a whole are significant to explain total restoration areas variability, i.e. if the model is sensitive to initial restoration costs, we did a partial F-test of the betas associated to the 85 restoration costs. With a significance $\alpha = 0.05$ and a p-value of

2.2e-16, we reject the null hypothesis, and therefore the model is statistically sensitive to the initial restoration costs as a group.

To compare how sensitive is the model to initial restoration costs in comparison to emiCO2 for marshes, we use SRC_i^2 interpretation as the proportion of variance explained by that parameter. With it, we can estimate a group $SRC^2_{wetlRest\_cost} = \sum_{i \in costs\,parameters} SRC_i^2 = 0.14$ that compared to the 0.7 for emiCO2.182 indicates that the model is more sensible to the sequestration rate for marshes that for the initial costs of restoration as a group.

In conclusion, the model is more sensitive to the sequestration rate for marshes, that explains about 70% of the variability of the total restored areas from the Montecarlo ensemble, followed by initial restoration costs and the learning rate. However, the expected change in total restoration areas due to initial restoration costs and learning rate can be considered to be small (with maximum a 3% increase in total restored areas w.r.t. baseline) indicating our results are robust to changes in these two parameters considering the ranges evaluated. Differences in total restored areas due to changes in the sequestration rates of marshes could be important (with a change of 17% more restored areas w.r.t. baseline), which is expected since CO_2 sequestration is the main driver of wetlands restoration in the current modeling exercise.

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