

Modeling Climate Resilience & Mitigation Potential of Conservation Practices on California Working Lands

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Soil and roots from a Central Coast Rangeland (photo credit: Chelsea Carey, Point Blue), Cover photo: A view of Five Springs Farm riparian restoration (photo credit: Erika Foster, Point Blue)

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Prepared by

Point Blue Conservation Science

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Summary

Point Blue Conservation Science aimed to evaluate the climate impacts of agricultural conservation practices that can enhance resilience to extreme weather events. In California, rangelands make up about 30% of the land area, presenting a unique opportunity to sequester carbon on working landscapes and reduce greenhouse gas emissions (GHG) through management. Despite the growing potential and ongoing initiatives for climate-smart healthy soils in the area, a more thorough and accurate understanding of the climate mitigation impact of conservation practices is needed to better target efforts and maximize effectiveness.

Here we used a process-based ecosystem model (DayCent) to explore the long-term viability of net climate benefits of rangeland restoration in California (https://www.soilcarbonsolutionscenter.com/daycent). The DayCent model underpins commonly used tools to predict climate impacts of agricultural practices, such as the web-based COMET-Planner (http://www.comet-planner.com/); we aimed to test accuracy of this tool in California rangelands. For this report, we leveraged data from 24 paired rangeland sites with conservation practices of either range plantings (perennial grasses) or silvopasture plantings (sparse oaks with ~18% cover). From practice implementation to the year 2100, we ran the DayCent model to project carbon (C) sequestration in soils and woody biomass and emissions from greenhouse gases (GHG): carbon dioxide (CO₂), nitrous oxide (N_2O) and methane (CH₄). The rangeland sites were distributed across three distinct regions in California (San Joaquin Valley, Sacramento Valley, and the Central Coast) and encompassed a gradient that extends from cooler summers in coastal areas to drier summers in the Valley regions. We used field data collected in 2022 to calibrate the model and to project emissions based on two climate models with two future emissions scenarios ("business-as-usual" and "reduced emissions"). Model outputs were then converted to CO₂ equivalents (CO₂-eq) and compared with estimates from the publicly available COMET-Planner as used by the California Healthy Soils Program (https://comet-planner-cdfahsp.com/).

Relative to an 'unplanted' control site dominated by annual grass, the perennial grass range plantings reduced net GHG emissions by 0.35 Mg CO_2 -eq/ha/yr across the 79 year study period (2022 to 2100). Most of these benefits were due to improvements in soil organic carbon (SOC) sequestration, which accrued most quickly at the start of the study and slowed over time. Perennial biomass increased over time and was less variable than annual biomass in changing climate conditions, leading to SOC benefits. Perennial grass rangeland also reduced N₂O emissions, particularly towards the end of the study period when more extreme climate conditions increased N₂O emissions in control plots.

The GHG benefits from silvopasture adoption were much lower, at an average of 0.06 Mg CO_2 -eq/ha/yr across the study period. These benefits were mostly due to C sequestration in woody biomass (particularly at the start of the study), with some benefit also attributed to SOC sequestration and reductions in N₂O emissions. The low climate mitigation potential is likely due to sparse tree densities (~18% cover), used to promote continued grass production for grazing. With silvopasture, we also observed an increase in CH₄, potentially due in part to direct emissions from the trees, which was substantial enough to completely offset SOC and N₂O benefits by 2100 under "business-as-usual" emissions.

While rangeland conservation has important climate benefits over the next century, our results for perennial grass plantings and silvopasture were 66% lower and 93% lower than COMET-Planner estimates, respectively. As a results of this modelling effort, we offer a few recommendations when using tools such as COMET-Planner in regional climate policy:

- 1. Models underpinning these tools should be calibrated using region-specific field data to accurately represent plant communities of interest. Final crop parameters calibrated in this study are available in Table S1 and can be used by others who seek to model perennial grass range and oak communities in California.
- 2. Time-scales of reported GHG estimates should be transparent and tools must include options to reflect *projected* climate conditions to tailor to producer and/or policy goals. We recommend that current COMET-Planner estimates are conservatively not extrapolated beyond 10 years.
- 3. It is imperative for tools to include GHG sources beyond ecosystem C sequestration. For example, silvopasture impacts on CH₄ emissions were substantial and offset C sequestration under business-as-usual emissions.

We will continue these efforts by similarly evaluating the GHG impacts of riparian restoration throughout California. We will also continue to improve DayCent model performance using empirical data collected from Point Blue's Ag-C Monitoring Program, a network of sites tracking conservation practice impact on agricultural lands in the U.S (www.pointblue.org/ag-c). We will communicate our findings to improve understanding of rangeland conservation impacts and enhance the utility of biogeochemical modeling throughout CA rangelands and beyond. We again appreciate the CO₂ Foundation for their generous support which made this work possible.

Introduction

Grazingland conservation practices such as range plantings of perennial grasses and silvopasture are globally acknowledged for the ability to capture and store carbon both aboveground in plants and belowground in soil organic matter (Henry et al., 2024; De Stefano et al., 2018). However, the effects of climate change on carbon stocks and greenhouse gases (GHGs) in rangelands is not well understood (Carey et al. 2020), and the viability of climate change mitigation strategies under future conditions is even less certain (Mayer et al., 2022). Therefore measurement of ecosystem carbon and climate benefits directly from the field, as well as forecasting impacts via ecosystem models is key to understanding current and ongoing impacts of conservation practices.

Increasing our understanding of rangeland conservation practice impacts will promote science-based management for carbon storage for soil health, climate mitigation and ecosystem resilience. Here we aim to extend the science describing how these rangelands will respond to climate change and contribute to mitigation effects under different future emissions scenarios. Currently our best estimates using the California Healthy Soils Program web portal COMET-Planner state an annual impact of approximately 1.0 and 0.89 Mg CO₂-eq/ha/yr for perennial grass range planting and silvopasture, respectively. This investigation aims to improve these estimates by projecting climate impacts on 24 rangeland sites throughout California using the DayCent ecosystem model, which underpins the COMET-Planner tool. DayCent incorporates site-specific ecosystem inputs into forecasted estimates, improving accuracy and can also be calibrated to regional conditions using direct in field measurements (Parton et al. 1998). The main research questions were:

- 1. How do future climate changes alter carbon sequestration and GHG emissions from rangelands conservation practices across distinct California regions?
- 2. How do modelled DayCent results compare to COMET-Planner estimates for range planting of perennial grasses and silvopasture oak establishment?

To answer these questions, we modelled the long-term climate effects of perennial grass range plantings and oak silvopasture under four potential future climate scenarios. We evaluated projected ecosystem impacts including biomass production, C sequestration, and GHG flux using two climate "Earth System Models" accessed via the NASA Earth Exchange Global Downscaled Daily Climate Projections database and two representative concentration pathways ("Emissions Reduction" RCP 4.5 and "Business-as-Usual" RCP 8.5) similar to those used by previous scientists for California rangelands (Mayer et al. 2022). Although model implementation is ongoing, this first-ever use of this model within Point Blue partnerships serves as a lasting template for use across rangeland conservation sites in the region and state.

Methods

Empirical data collection

We conducted field sampling across 24 paired rangeland sites (each with one plot unplanted and one plot with a conservation planting; Fig. 1). Our research focused on two conservation practices: 1) range planting, transitioning from annual to perennial grasses; and 2) silvopasture, planting oak trees within rangelands. We selected ranches that have implemented one of these conservation practices within the last 30 years. We then selected unplanted control plots adjacent to the restored site with similar climate, topography, grazing management practices and soil characteristics.

Sites were distributed across three distinct regions in California (San Joaquin Valley, Sacramento Valley, and the Central Coast) and encompassed a gradient that extends from cooler summers in coastal areas to drier summers in the Valley regions. We determined the aridity levels at each site using the Global Aridity Index Database (Trabucco and Zomer, 2018) and classified sites into either wet (sub-humid and humid) or dry (arid and semi-arid) climates.



Figure 1. Map of study sites included in current (perennial grass, oaks) and future (riparian) modeling work across California. Inlet map displays typical distribution of soil samples between conservation planting and unplanted plots.

Empirical data collection encompassed both above and below-ground carbon measurements (Banuelos et al., in prep). We gathered peak herbaceous biomass measurements and clippings from 1.5 m diameter exclosures and assessed woody plant biomass by diameter and height (Foster et al., 2022). We also quantified shrub and perennial grass cover using a line-point intercept, 80-meter perimeter transect (20m x 20m), with the presence or absence of perennial grasses or shrubs evaluated every 5 meters and perennial plants identified to genus. We collected 11 soil samples from 0-30 cm from each conservation planting and unplanted control site and analyzed for bulk density, inorganic and organic soil carbon, pH, and texture.

Estimating GHG benefits over time

DayCent Ecosystem Model

Using the field data as model inputs, we used the DayCent ecosystem model to project total reduction in global warming potential (C sequestration and GHG benefits) through the year 2100. The DayCent model relies on a three-phase approach with sequential scenarios, including a 'spin-up' to establish reasonable historical values for the ecosystem, a 'baseline' management scenario, and then 'future' climate projections (Mayer et al. 2022; Swan et al. 2015; Parton et al. 1998). Input files into the model include site soil texture, historical and current management practices, daily maximum and minimum temperatures (PRISM, 2024) and vegetation productivity. First as the 'spin-up' the model is run for 1,850 years with a cool season perennial grass mixture, a fire return interval of 10 years to reflect Native American burning practices, and a limited grazing regime by native ungulates (Mayer et al. 2022; Van de Water & Safford 2011). The baseline management period consisted of three distinct sub-periods: from 1850-1910 with the transition to annual grassland, yet same fire return interval and low grazing intensity; from 1911 to the year of present-day ownership with fire suppression and intensive continuous grazing through the late winter to mid-spring; and finally from the year of ranch ownership to 2100 with producer-reported management. For the conservation planting plot, perennial vegetation was modeled starting in the year of practice adoption, varying by site.

Model Calibration

Modelled aboveground plant productivity and soil organic matter were compared to values from the literature for the various vegetation types (Potthoff et al. 2005; Mayer et al. 2022; Becchetti 2016.; Higgins et al. 2002) and to the 2022 Point Blue field sampling event for the present-day ecosystem values. We evaluated model fit by calculating the mean difference between modelled and sampled biomass, Pearson's correlation coefficient, and percent bias. Percent bias is a common residual method which estimates systemic bias, or the average likelihood of modeled values to be larger, smaller or similar to observed values (Bennett et al., 2013; Le et al., 2018).

To improve model fit for annual grass, perennial grass, and oak plantings, we adjusted the optimum growth parameters that define potential daily growth, optimum and maximum temperatures for growth, and the shape of the growth temperature curve to best fit observed biomass data. We used 100 randomly selected parameter sets to model each site and calculate model fit parameters, then selected the parameter set with the best model agreement (lowest mean difference, lowest percent bias and highest R²; Fig. S1).

Projecting GHG benefits

After adjusting model parameters to match expected ecosystem carbon, model output was obtained for GHG fluxes (CH₄, N₂O, CO₂), and the difference between the planted and control plot carbon was projected under future climate scenarios. Simulations of future conditions were based on daily climate data from 2023 to 2100 extracted from the CanESM5 (Canadian Centre for Climate Modeling and Analysis) and HadGEM3-ES (Met Office Hadley Centre) Earth system models, as they have been used in previously published California grasslands literature to represent contrasting projections for future precipitation (Mayer et al., 2022). We also used two Representative Concentration Pathway (RCP) 4.5 and 8.5 for 'reduced emissions' and 'business-as-usual' emissions scenarios. We then calculated net global warming potential (GWP) for each site by converting GHG fluxes into CO₂ equivalents (CO₂-eq) and subtracting N₂O and CH₄ emissions from C sequestration in soils and woody biomass. We then calculated net GWP savings as the difference between the treatment and control; higher positive net GWP savings indicate a higher climate-benefit, essentially lower GHG emissions due to the conservation practice.

Data Analysis

Multifactor ANOVAs were performed on model output to explore relative differences due to restoration practices over time. ANOVAs included main effects of treatment (planted vs. control), emissions scenario (RCP 4.5 vs 8.5), climate model (HADGEM3-ES vs. CANESM5), year, and climate type (wet vs. dry) and all interactions first between treatment, year and emissions scenario and then between treatment, year and climate. Site pairs were included as a random effect.

As a coarse initial estimate, we scaled up our findings to estimate the potential climate benefits of silvopasture and perennial planting on rangelands throughout California. We multiplied per-hectare GWP savings for each practice by the area of California rangeland that is dominated by annual grass (7.139 Mha; University of California Agriculture and Natural Resources, 2025), as previously implemented for DayCent modeling of CA rangelands (Mayer et al. 2022). We aim to improve and narrow these estimates by incorporating additional spatial constraints in future reports.

We also compared results to estimates from the COMET-planner web tool generated for the California Department of Agriculture Healthy Soils Program, which is based on the DayCent model without site-specific inputs (<u>http://comet-planner-cdfahsp.com/</u>).

Results & Interpretation

Perennial Grass Range Plantings

Perennial grass range plantings had an annual net climate benefit of 0.35 ± 0.007 Mg CO_2 -eq/ha averaged across all climate types, earth system models, and emissions scenarios, with the majority of these benefits (56%; 0.20 ± 0.005 Mg CO_2 -eq/ha/yr) attributed to SOC sequestration (Fig. 2). These SOC gains were highest at the start of the study and gradually declined over the first 20 years as SOC stock levels reached a new equilibrium. Over time, extreme weather conditions enhanced SOC losses in annual grassland plots, particularly in the business-as-usual emissions scenario (Fig. S2) due to more erratic precipitation patterns and more variable annual biomass production over time (Fig. 3). As a result of SOC loss in annual grassland control sites, relative SOC gains increased towards the end of the study

period but did not increase to initial levels (Fig. 2a). This effect shows that perennial grass plantings continued to protect from SOC loss under future climate conditions compared to annual grassland sites.



Figure 2. Relative perennial grass planting effect on annual change in soil organic carbon (dSOC), N_2O emissions, CH_4 emissions, and net climate benefit (net GWP) over time by emissions scenario and climate. For simple interpretation, positive values represent *GWP savings* due to either increases in C sequestration or decreases in N_2O , CH_4 , and net GWP in perennial grass plots. Panel a) shows annual changes throughout the study period by emissions scenario (RCP 4.5 and RCP 8.5) and climate (wet and dry). Panel b) shows average annual *change* in GWP savings with the conservation practice by emissions scenario across the first 10 years (2022-2032) and across the full study period (2022-2100).



Figure 3. Total above- and belowground biomass production in annual grass control (C - red) plots and perennial grass treatment (T - blue) plots under business-as-usual emissions (RCP8.5) and reduced emissions (RCP4.5) scenarios.

Perennial grass range plantings also reduced N₂O emissions, particularly in wet climates and under the business-as-usual emissions scenario (Fig. 2). In dry sites, N₂O emissions in both treatment and control plots increased over time, but at a similar rate, while wet control sites experienced greater N₂O emissions over time relative to perennial plots (Fig. S3; p < 0.001 for climate-year-treatment interaction; Table S2). Perennial grass planting benefits were also more pronounced over time in the RCP 8.5 emissions scenario (p = 0.040 for climate-year-treatment interaction). We hypothesize broadly that these N₂O differences relate to changes in plant use of soil moisture and nitrogen, as well as increased labile carbon content (Abraha et al. 2018; Hao et al. 2025). There was a near-zero effect on CH₄ emissions due to perennial grass range plantings (Fig. 2).

Overall, GHG benefits were only 35% and 32% of the COMET-Planner estimates in business-as-usual and reduced emissions scenarios, respectively (p=0.011 for year-treatment-RCP interaction; Fig. 2). Since GWP benefits declined over time (Fig. 2), we compared annual relative GWP in the first 10 years of the study and throughout the study period and found that annual climate benefits were increased to 48% under business-as-usual emissions and 45% of COMET-Planner estimates in the reduced emissions scenario. Over time, climate benefits were increasingly attributed to N_2O reductions (24% in the first 10 years and 39% by 2100; Fig. 2).

Silvopasture

Overall, silvopasture had fewer climate benefits than perennial grass plantings (Fig. 4). Relative SOC accrual averaged 0.10 Mg CO₂-eq/ha/yr and was not significantly different between treatment and control sites (p=0.183; Table S2). Low SOC sequestration is likely because tree plantings in the study sites were sparse to allow for on-going grazing and only covered $18 \pm 6\%$ of the plot area. SOC accrual in both control and treatment plots generally declined over time, particularly under business-as-usual emissions, and both plots experienced a decline in SOC by the end of the study period (Fig. S3). We expect this decline in SOC relates to the slower rate of biomass accumulation leading to lower additional organic inputs from leaf litter and roots into the soil (Joslin et al. 1987; Dahlgren et al. 1997; Alberti et al, 2015).

Carbon sequestration in woody biomass was on average $0.035 \pm 0.003 \text{ Mg CO}_2$ -eq/ha/yr throughout the study period (Fig. 4) and was significantly higher in wet climates (p<0.001). Carbon sequestration due to tree growth was highest at the start of the study when trees were younger and accumulating biomass at a faster rate (Fig. 4).



Figure 4. Relative silvopasture effect on annual change in soil organic carbon (dSOC), N_2O emissions, CH_4 emissions, and net climate benefit (net GWP). Positive values represent GWP savings due to either increases in C sequestration or decreases in N_2O , CH_4 , and net GWP in silvopasture plots. Panel a) shows annual changes throughout the study period by emissions scenario (RCP 4.5 and RCP 8.5) and climate (wet and dry). Panel b) shows average annual change by emissions scenario across the first 10 years (2022-2032) and across the full study period (2022-2100).

While silvopasture had no significant impacts on N_2O emissions (p=0.60; Table S2; Fig. S4), CH_4 emissions were substantially higher in silvopasture plots throughout the study period and, under business-as-usual emissions, completely offset C sequestration by the end of the study period (Fig. 4). Trees contain microbes involved in CH_4 production, which can be more active in areas with higher precipitation (Moisan et al., 2024), evidenced by higher relative CH_4 emissions in wet climates (Fig. 5). Direct CH_4 emissions also can pass from the soil through the plants and leak into the atmosphere (Covey et al. 2018).



Figure 5. Annual CH₄ flux over time for both treatment (silvopasture) and paired control sites by emissions scenario and climate type.

Taken together, annual net climate benefits over the entire study period were only 0.05 and 0.06 Mg CO_2 -eq ha-1 yr⁻¹ under business-as-usual and reduced emissions, respectively (Fig. 4). Under business-as-usual emissions, these benefits were eventually offset by increased N₂O and CH₄ emissions and declining SOC levels (Fig. 4), as the initial rapid growth period of the oaks ended and competition for resources expanded (Tyler et al. 2006). Averages over the first 10 years were substantially higher (0.10 Mg CO₂-eq under business-as-usual emissions and 0.08 Mg CO₂-eq under reduced emissions) due to greater C sequestration in woody biomass, but still substantially lower than the 0.89 Mg CO₂-eq/ha/yr estimated by COMET-Planner.

It is important to note that COMET-Planner does not take into account CH_4 emissions for this practice, which was significantly greater under tree production and fully negates the C sequestration benefits by the year 2100 under business-as-usual emissions scenarios. However, even without CH_4 emissions considered, the combined effect of N₂O and C sequestration resulted in an annual climate benefit of 0.18 Mg CO₂-eq/ha/yr, still only 20% of COMET-Planner estimates. This may be because tree planting densities in our study sites may be lower than are assumed in COMET-Planner. "Silvopasture" is defined by the NRCS as at least 10% coverage of woody species, and while our average tree coverage was 18%, some sites were below this threshold due to poor tree establishment or to maintain grass production for grazing.

Estimating statewide mitigation potential

As a rough initial estimate, we scaled up our results to all rangelands in California dominated by annual grasses (7.139 Mha; University of California Agriculture and Natural Resources, 2025), resulting in the average annual net climate benefit through 2100 of 2.5 MMT CO₂-eq year⁻¹ for perennial grass plantings and 0.4 MMT CO₂-eq year⁻¹ for silvopasture (Table 1). Near-term (2022-2032) benefits are greater at 3.4 MMT CO₂-eq year⁻¹ for perennial grass planting and 0.6 MMT CO₂-eq year⁻¹ for silvopasture adoption.

Though our simulated climate benefits were lower than COMET-Planner estimates, at the regional scale, rangeland restoration can potentially contribute to near-term climate mitigation goals with careful evaluation of suitable sites and widespread practice adoption. California's net neutrality goal requires emissions to be reduced by an additional 129.3 MMT CO_2 -eq year⁻¹ beyond previous targets (Di Vittorio et al., 2024), and our results suggest that widespread perennial range plantings could contribute to approximately 2.6% of these required reductions in the near-term. Our estimated mitigation potential is a fraction of the total mitigation potential of rangeland statewide when other conservation practices suitable for various habitat types are considered. Other restoration practices such as compost amendments and riparian restoration, among others, have been shown to have significant climate benefits that can be applied to a variety of rangeland ecosystems (Grauver et al. 2019; Mayer et al. 2022; Di Vittorio et al. 2024).

Table 1. Annual climate benefit of perennial range planting and silvopasture if applied to all rangeland in California dominated by annual grasses. Estimates are presented for near-term (2022-2032) and long-term (2022-2100) climate benefits and by emissions scenario.

Restoration Practice	Timescale	Area rangeland	Business-as-usual emissions (RCP 8.5)	Reduced emissions (RCP 4.5)
		Mha	Climate benefit MMT CO ₂ -eq year ⁻¹	Climate benefit MMT CO ₂ -eq year ⁻¹
Perennial	2022-2032	7.139	3.532	3.369
planting	2022-2100	7.139	2.624	2.406
Silvopasture	2022-2032	7.139	0.724	0.583
	2022-2100	7.139	0.387	0.462

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Supplementary Materials



Figure S1. Model fit as compared to empirical biomass collected from 24 study sites in 2022 for aboveground annual and perennial grassland biomass and woody biomass from oak plantings.



Figure S2. Annual changes in SOC stock over time for both treatment (planted perennial grass) and paired control sites by emissions scenario and climate type.



Figure S3. Annual changes in SOC stock over time for both treatment (silvopasture) and paired control sites by emissions scenario and climate type.



Figure S4. Annual N_2O flux over time for both treatment (silvopasture) and paired control sites by emissions scenario and climate type.

Table S1. Calibrated crop parameters representing California annual (ANGR) and perennial (PGIN) grassland communities and oak trees (OAK) for use in DayCent crop.100 and tree.100 files, modified from Mayer et al. 2022

Crop.100) File	Tree.100 File				
Parameter	ANGR	PGIN	Parameter	OAK		
PRDX(1)	1.9	2.0	DECID	1		
PPDF(1)	20.0	23.0	PRDX(2)	2.5		
PPDF(2)	40.0	47.0	PPDF(1)	20		
	25	25		20		
	2.5	2.5		1		
	2.5	1.5		1		
BIOFLG	1	1	PPDF(4)	3.5		
BIOK5	600.0	650.0	CERFOR(1,1,1)	20		
PLTMRF	1.0	1.0	CERFOR(1,1,2)	300		
FULCAN	100.0	100.0	CERFOR(1,1,3)	300		
FRTCINDX	2	1	CERFOR(1,2,1)	35		
FRTC(1)	0.5	0.6	CERFOR(1.2.2)	250		
FRTC(2)	01	02	CEREOR(123)	250		
FRTC(3)	90.0	108.0	CEREOR(131)	80		
	0.2	0.0		1100		
	0.3	0.8	CENFON(1,3,2)	1100		
	0.3	0.2	CERFUR(1,3,3)	1100		
CFRICN(I)	0.7	0.7	CERFOR(1,4,1)	140		
CFRICN(2)	0.4	0.4	CERFOR(1,4,2)	4000		
CFRTCW(1)	0.25	0.75	CERFOR(1,4,3)	4000		
CFRTCW(2)	0.3	0.45	CERFOR(1,5,1)	83		
BIOMAX	200.0	280.0	CERFOR(1,5,2)	4000		
PRAMN(1.1)	25.0	35.0	CERFOR(1.5.3)	4000		
PRAMN(2,1)	390.0	390.0	CEREOR(161)	24		
PRAMN(3.1)	340.0	90.0	CEREOR(1.6.2)			
DDAMN(1.2)	540.0 60.0	60.0		0		
F RAIVIN(1,2)	200.0	200.0		10		
PRAMIN(2,2)	390.0	390.0	CERFUR(2,1,1)	40		
PRAMN(3,2)	340.0	100.0	CERFOR(2,1,2)	300		
PRAMX(1,1)	30.0	35.0	CERFOR(2,1,3)	300		
PRAMX(2,1)	440.0	440.0	CERFOR(2,2,1)	50		
PRAMX(3,1)	440.0	100.0	CERFOR(2,2,2	250		
)			
PRAMX(1,2)	80.0	95.0	CERFOR(2,2,3	250		
)			
PRAMX(2,2)	440.0	440.0	CERFOR(2,3,1)	99		
PRAMX(3.2)	440.0	100.0	CERFOR(2.3.2	1100		
)			
PRBMN(1.1)	40.0	50.0	CEREOR(2.3.3	1100		
		0010)			
PRBMN(21)	390.0	390.0	, CEREOR(2.4.1)	140		
PRBMN(2,1)	340.0	100.0	CEREOR(2, 4, 2)	4000		
	540.0	100.0		4000		
	0.0	0.0		4000		
FILDIVIIN(1,2)	0.0	0.0	CENFON(2,4,5	4000		
	0.0	0.0		500		
F RDIVIN(2,2)	0.0	0.0		4000		
PRBININ(3,2)	0.0	0.0	CERFUR(2,5,2	4000		
)			
PRBMX(1,1)	50.0	55.0	CERFOR(2,5,3	4000		
)			
PRBMX(2,1)	420.0	420.0	CERFOR(2,6,1)	62		
PRBMX(3,1)	420.0	100.0	CERFOR(2,6,2	0		
)			
PRBMX(1,2)	0.0	0.0	CERFOR(2,6,3	0		
)			
PRBMX(2,2)	0.0	0.0	CERFOR(3,1,1)	40		
· · ·						

PRBMX(3,2)	0.0	0.0	CERFOR(3,1,2)	300
	0.02	0.02	CERFUR(3,1,3)	300
FLIGNI(2,1)	0.0012	0.0012	CERFOR(3,2,1)	50
FLIGNI(1,2)	0.26	0.26	CERFOR(3,2,2)	250
FLIGNI(2,2)	-0.001	-0.001	CERFOR(3,2,3	250
	5	5		00
FLIGNI(1,3)	0.26	0.26		80
FLIGNI(2,3)	-0.001	-0.001	CERFOR(3,3,2)	1100
HIMAX	0.00	0.00	CERFOR(3,3,3	1100
HIWSE	0.0	0.0	, CEREOR(3.4.1)	140
HIMON(1)	0.0	2.0	CERFOR(3.4.2	4000
)	
HIMON(2)	0.0	1.0	CERFOR(3,4,3	4000
	05	0.0		<u>00</u>
	0.5	0.0		4000
EFRGRIN(2)	0.5	0.0	CERFUR(5,5,2	4000
EFRGRN(3)	0.5	0.0	, CERFOR(3,5,3	4000
	0.04	0.15		25
VLUSSP	0.04	0.15	CERFOR(3,6,1)	25
FSDETH(1)	0.2	0.2	CERFOR(3,6,2	0
FSDETH(2)	0.7	0.7) CERFOR(3,6,3	0
	0.2	0.2		00
	150.0	160.0		0.5
	130.0	100.0		0.4
	0.2	0.2		0.4
	0.05	0.05		0.54
	0.05	0.05		0.4
	0.14	0.14	FUFRAU(3,1)	0.09
	2.0	2.0		0.15
	0.3	0.0	FCFRAC(5,1)	0.02
CRPRTF(2)	0.0	0.0	FCFRAC(6,1)	0
CRPRIF(3)	0.0	0.0	FCFRAC(1,2)	0.34
MRTFRAC	0.05	0.05	FCFRAC(2,2)	0.4
SNFXMX(1)	0.0	0.0	FCFRAC(3,2)	0.09
DEL13C	27.0	27.0	FCFRAC(4,2)	0.33
CO2IPR(1)	1.1	1.3	FCFRAC(5,2)	0.08
CO2ITR(1)	0.65	0.77	FCFRAC(6,2)	0.17
CO2ICE(1,1,1)	1.3	1.0	TFRTCN(1)	0.18
CO2ICE(1,1,2)	1.0	1.0	TFRTCN(2)	0.05
CO2ICE(1,1,3)	1.0	1.0	TFRTCW(1)	0.18
CO2ICE(1,2,1)	1.3	1.3	TFRTCW(2)	0.05
CO2ICE(1,2,2)	1.0	1.0	FNFTIM	2
CO2ICE(1,2,3)	1.0	1.0	FNGDDL(1)	2400
CO2IRS(1)	1.0	1.0	FNGDDL(2)	7
CKMRSPMX(1)	0.1	0.1	FNGDDL(3)	35
CKMRSPMX(2)	0.15	0.15	LEAFDR(1)	0
CKMRSPMX(3)	0.05	0.05	LEAFDR(2)	Õ
CMRSPNPP(1)	0.0	0.0	LEAFDR(3)	Õ
CMRSPNPP(2)	0.0	0.0	I FAFDR(4)	Õ
CMRSPNPP(3)	1 25	1 25	LEAFDR(5)	ñ
CMRSPNPP(A)	10	10		0
CMRSPNPP(5)	4.0	40	$I F \Delta F D R(7)$	0 6
CMRSPNIPP(A)	4.0 1 K	 1 5		0.0 0 A
CGRESP(1)	1.5	0.23		0.0
	0.20	0.20		0.0

CGRESP(2) CGRESP(3) NO3PREF(1) CLAYPG	0.23 0.23 0.5 6.0	0.23 0.23 0.5 6.0	LEAFDR(10) LEAFDR(11) LEAFDR(12) BTOLAI	0.6 0 0 0.012
CMIX	0.25	0.25	KLAI	1000
TMPGERM	10.0	10.0	LAITOP	-0.47
DDBASE	1500.0	1500.0	MAXLAI 3.5	10
TMPKILL	7.0	7.0	MAXLDR	1
BASETEMP	10	10	FORRTF(1)	0.45
BASETEMP(2)	30	30	FORRTF(2)	0
MNDDHRV	100	100	FORRTF(3)	0
MXDDHRV	200	200	SAPK	1500
	120.0	120.0		0 21
	0.5	0.5		0.21
	0.12	0.12		0.22
WSCOFF(2)	15	9.0	WDLIG(4)	0.25
NPP2CS(1)	10	1.0	WDLIG(5)	0.3
FMAX	1.0	15	WDLIG(6)	0.25
SFAVAIL(1)	0.9	0.9	WOODDR(1)	0.99
AMAX(1)	50	50	WOODDR(2)	0.8
AMAXFRAC(1)	0.75	0.75	WOODDR(3)	0.00 3
AMAXSCALAR1(1)	1	1	WOODDR(4)	0.00 2
AMAXSCALAR2(1)	1	1	WOODDR(5)	0.00 22
AMAXSCALAR3(1)	1	1	WOODDR(6)	0.18
AMAXSCALAR4(1)	1	1	WOODDR(7)	0.39 5
ATTENUATION(1)	0.579 99	0.579 99	WRDSRFC	0.14
BASEFOLRESPFRAC(1)	0.1	0.1	WMRTFRAC	0.05
CFRACLEAF(1)	0.45	0.45	SNFXMX(2)	0
DVPDEXP(1)	-0.48	-0.48	DEL13C	0
DVPDSLOPE(1)	2.457	2.457	CO2IPR(2)	1.25
GROWTHDAYSI(I)	1	1	CO2ITR(2)	0.75
	25	25 CE	CO2ICE(2,1,1)	1.25
	65 105	65 105	CO2ICE(2,1,2)	1
	105	17.29	CO2ICE(2,1,3)	1 25
	270	270	CO2ICE(2,2,1)	1.2.5
PSNTMIN(1)	4	4	CO2ICE(2,2,2)	1
PSNTOPT(1)	24	24	CO2IRS(2)	1
			BASFC2	1
			BASFCT	400
			SITPOT	0.3
			MAXNP	13
			FKMRSPMX(1)	0.20 5
			FKMRSPMX(2	0.28
			FKMRŚPMX(3)	0.00 45
			FKMRŚPMX(4)	0.00 45
			FKMRSPMX(5)	0.00 7

) FMRSPLAI(1) 0 FMRSPLAI(2) 0 FMRSPLAI(3) 0.75 FMRSPLAI(3) 0.75 FMRSPLAI(4) 1 FMRSPLAI(5) 2 FMRSPLAI(6) 2 FMRSPLAI(7) 2 FGRESP(1) 0.233 FGRESP(2) 0.233 FGRESP(2) 0.233 FGRESP(3) 0.233 FGRESP(4) 0.233 FGRESP(5) 0.233 FGRESP(5) 0.233 FGRESP(6) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.233 NO3PREF(2) 0.5 TLAYPG 8 TMIX 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1	FKMRSPMX(6	0.26
FMRSPLAI(1) 0 FMRSPLAI(2) 0 FMRSPLAI(3) 0.75 FMRSPLAI(3) 0.75 FMRSPLAI(4) 1 FMRSPLAI(5) 2 FMRSPLAI(6) 2 FMRSPLAI(7) 2 FGRESP(1) 0.233 FGRESP(2) 0.233 FGRESP(3) 0.233 FGRESP(4) 0.233 FGRESP(5) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.222 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1 <td>)</td> <td></td>)	
FMRSPLAI(2) 0 FMRSPLAI(3) 0.75 FMRSPLAI(4) 1 FMRSPLAI(5) 2 FMRSPLAI(6) 2 FMRSPLAI(7) 2 FGRESP(1) 0.233 FGRESP(2) 0.233 FGRESP(3) 0.233 FGRESP(4) 0.233 FGRESP(5) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1 <td>FMRSPLAI(1)</td> <td>0</td>	FMRSPLAI(1)	0
FMRSPLAI(3) 0.75 FMRSPLAI(4) 1 FMRSPLAI(5) 2 FMRSPLAI(6) 2 FMRSPLAI(7) 2 FGRESP(1) 0.233 FGRESP(2) 0.233 FGRESP(3) 0.233 FGRESP(4) 0.233 FGRESP(5) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1 </td <td>FMRSPLAI(2)</td> <td>0</td>	FMRSPLAI(2)	0
FMRSPLAI(4) 1 FMRSPLAI(5) 2 FMRSPLAI(6) 2 FMRSPLAI(7) 2 FGRESP(1) 0.233 FGRESP(2) 0.233 FGRESP(3) 0.233 FGRESP(4) 0.233 FGRESP(5) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.233 FGRESP(7) 0.233 NO3PREF(2) 0.5 TLAYPG 8 TMIX 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1	FMRSPLAI(3)	0.75
FMRSPLAI(5) 2 FMRSPLAI(6) 2 FMRSPLAI(7) 2 FGRESP(1) 0.233 FGRESP(2) 0.233 FGRESP(3) 0.233 FGRESP(4) 0.233 FGRESP(5) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12	FMRSPLAI(4)	1
FMRSPLAI(6) 2 FMRSPLAI(7) 2 FGRESP(1) 0.233 FGRESP(2) 0.233 FGRESP(3) 0.233 FGRESP(4) 0.233 FGRESP(5) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.233 FGRESP(7) 0.233 FGRESP(7) 0.233 NO3PREF(2) 0.5 TLAYPG 8 TMIX 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1	FMRSPLAI(5)	2
FMRSPLAI(7) 2 FGRESP(1) 0.233 FGRESP(2) 0.233 FGRESP(3) 0.233 FGRESP(4) 0.233 FGRESP(5) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.233 FGRESP(7) 0.233 FGRESP(7) 0.233 NO3PREF(2) 0.5 TLAYPG 8 TMIX 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1	FMRSPLAI(6)	2
FGRESP(1) 0.233 FGRESP(2) 0.233 FGRESP(3) 0.233 FGRESP(4) 0.233 FGRESP(5) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.233 NO3PREF(2) 0.5 TLAYPG 8 TMIX 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1	FMRSPLAI(7)	2
FGRESP(2) 0.233 FGRESP(3) 0.233 FGRESP(4) 0.233 FGRESP(5) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.233 NO3PREF(2) 0.5 TLAYPG 8 TMIX 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1	FGRESP(1)	0.233
FGRESP(3) 0.233 FGRESP(4) 0.233 FGRESP(5) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.233 NO3PREF(2) 0.5 TLAYPG 8 TMIX 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1	FGRESP(2)	0.233
FGRESP(4) 0.233 FGRESP(5) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.233 NO3PREF(2) 0.5 TLAYPG 8 TMIX 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1	FGRESP(3)	0.233
FGRESP(5) 0.233 FGRESP(6) 0.233 FGRESP(7) 0.233 NO3PREF(2) 0.5 TLAYPG 8 TMIX 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1	FGRESP(4)	0.233
FGRESP(6) 0.233 FGRESP(7) 0.233 NO3PREF(2) 0.5 TLAYPG 8 TMIX 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1	FGRESP(5)	0.233
FGRESP(7) 0.233 NO3PREF(2) 0.5 TLAYPG 8 TMIX 0.22 TMPLFF 7 TMPLFS 10 FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1	FGRESP(6)	0.233
NO3PREF(2)0.5TLAYPG8TMIX0.22TMPLFF7TMPLFS10FURGDYS120FLSGRES1TMXTUR0.12NPP2CS1	FGRESP(7)	0.233
TLAYPG8TMIX0.22TMPLFF7TMPLFS10FURGDYS120FLSGRES1TMXTUR0.12NPP2CS1	NO3PREF(2)	0.5
TMIX0.22TMPLFF7TMPLFS10FURGDYS120FLSGRES1TMXTUR0.12NPP2CS1	TLAYPG	8
TMPLFF7TMPLFS10FURGDYS120FLSGRES1TMXTUR0.12NPP2CS1	TMIX	0.22
TMPLFS10FURGDYS120FLSGRES1TMXTUR0.12NPP2CS1	TMPLFF	7
FURGDYS 120 FLSGRES 1 TMXTUR 0.12 NPP2CS 1	TMPLFS	10
FLSGRES 1 TMXTUR 0.12 NPP2CS 1	FURGDYS	120
TMXTUR 0.12 NPP2CS 1	FLSGRES	1
NPP2CS 1	TMXTUR	0.12
	NPP2CS	1

Table S2. Results of analysis of variance (ANOVA) on annual biomass production, change in soil organic carbon (dSOC), nitrous oxide emissions (N_2O), methane emissions (CH₄) and net global warming potential (GWP) in perennial plantings and silvopasture plots. *P*-values are presented for main and interactive effects of climate model (mod; CanESM5 vs. HadGEM3-ES), treatment (trt; planted vs. unplanted), year, emissions scenario (rcp; RCP4.5 vs. RCP8.5) and climate (wet vs. dry). Site pair was included as a random effect. P-values significant at alpha = 0.05 are presented in bold.

		Perennial	Range Pl	antings		Silvopasture				
Source of Variation	Herbaceous Biomass	dS O C	N ₂ O	CH₄	GWP	Woody Biomass	dSOC	N ₂ O	CH₄	GWP
mod	<0.001	<0. 00 1	0.0 01	<0.001	<0.001	0.375	0.074	0.049	<0.001	0.080
trt	<0.001	<0. 00 1	<0. 00 1	0.613	0.021	NA	0.183	0.600	0.064	0.001
year	<0.001	<0. 00 1	<0. 00 1	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
rcp	0.010	<0. 00 1	<0. 00 1	<0.001	<0.001	0.969	<0.001	<0.001	<0.001	<0.001
climate	<0.001	<0. 00 1	<0. 00 1	0.898	<0.001	<0.001	0.002	0.790	0.777	0.387
trt:year	<0.001	<0. 00 1	<0. 00 1	0.780	0.087	NA	0.241	0.709	<0.001	0.002
trt:rcp	<0.001	0.0 12	0.0 43	0.001	0.012	NA	0.419	0.491	0.032	0.270

year:rcp	0.010	<0. 00 1	<0. 00 1	<0.001	<0.001	0.969	<0.001	<0.001	<0.001	<0.001
trt:climate	0.121	0.0 12	<0. 00 1	0.657	0.982	NA	0.564	0.721	0.394	0.238
year:climate	<0.001	<0. 00 1	<0. 00 1	0.236	<0.001	<0.001	0.003	0.199	0.685	0.764
trt:year:rcp	<0.001	0.0 11	0.0 40	0.001	0.011	NA	0.416	0.490	0.030	0.267
trt:year:clim ate	0.159	0.0 14	<0. 00 1	0.649	0.889	NA	0.559	0.775	0.086	0.239