S1. LPJ-GUESS Model Modifications, Experimental Setup and Forcing Data

We used LPJ-GUESS version 4.1.1 (Nord et al., 2021) for our simulations. To ensure reproducibility, we provide a list of modifications made to the model, which are also documented in our GitHub repository: https://github.com/natel-c/lpjg-modif-emulator

- **Modification 1:** Implemented an eXtended NetCDF input (cfxinput.h/cpp).
- **Modification 2:** Added output for annual climate data.
- **Modification 3:** Introduced a parameter to apply a fixed nitrogen deposition across simulations (fixed_ndep and fixed_ndep_year).
- **Modification 4:** Enabled the output of spin-up period results (if_spinup_outputs).
- **Modification 5:** Added spinup_clear2_year parameter to control stand-replacing disturbances.

Experimental Setup

For the LPJ-GUESS simulations, the following settings were applied:

- Fire model: Disabled.
- Nitrogen deposition: Held constant at 2015 levels, following Lamarque et al. (2013).
- Disturbance interval: Default LPJ-GUESS setting of 100 years.
- Replicate number of patches: 50.
- Vegetation type: Potential natural vegetation only, to simplify ecosystem carbon responses and isolate climate-driven impacts.

Each simulation began with a 500-year spin-up to stabilize carbon pools, using the 1901 atmospheric CO_2 concentration and repeating, detrended 1901–1930 climate data. Following the spin-up, a stand-replacing disturbance (via spinup_clear2_year) simulated a clear-cut, removing all vegetation and exposing soil. Vegetation residues were left on-site, contributing to litter and soil carbon pools. Post-disturbance, natural vegetation regrew under historical (1850–2014) and future (2015–2100) conditions. Land-use changes were not incorporated.

Forcing Data

The simulations used both historical (1850–2014) and future (2015–2100) climate data. Future runs began from the end state of the historical period.

- Climate Data: Bias-corrected CMIP6 data from the ISIMIP 3b project (Lange, 2019) was used, including five Earth System Models (ESMs) to cover climate sensitivity variations: IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, GFDL-ESM4, and UKESM1-0-LL. Simulations included four Representative Concentration Pathways (RCPs): RCP2.6, RCP4.5, RCP7.0, and RCP8.5.
- Nitrogen Deposition: Set at 2015 levels based on Lamarque et al. (2013) data.
- Atmospheric CO_2 Concentrations: Aligned with observed CO_2 mixing ratios for each RCP scenario.

Table S1. Random forests hyperparameters, showing the values tested during the hyperparameter grid search and the best values for each task (Carbon stocks: C stocks and Carbon fluxes: C fluxes).

Hyperparameter	Description	Values	Best value (C stocks | C fluxes)
n_estimators	Number of trees in the random forest	350, 500, 600, 700, 1000	1000 | 1000
max_samples	The number of samples to draw from data to train each decision tree	0.2, 0.4, 0.6, 0.8, 1.0	0.2 | 0.2
max_features	Number of features to consider when looking for the best split	0.2, 0.4, 0.6, 0.8, 1.0	0.8 | 0.8
max_depth	Maximum depth of the decision tree	200, 1000, 2000	200 | 200
min_samples_split	Minimum number of samples required to split an internal node	10, 20, 250, 400	250 | 250

Table S2. Neural network hyperparameters, showing the values tested during the hyperparameter grid search and the best values for each task (Carbon stocks: C stocks and Carbon fluxes: C fluxes).

Hyperparameter	Name	Description	Values	Best value (C stocks | C fluxes
learning_rate	Learning rate	Controls the step size at each iteration while moving toward a minimum of the loss function.	0.001, 0.01, 0.1	0.001 | 0.001
layers	Number of layers	Defines the depth of the neural network. Each layer encapsulates a state (weights) and some computation.	1, 2, 3	2 | 2
neurons	Number of neurons	The basic computational units in a neural network layer. More neurons can capture more complex patterns.	32, 64, 128	64 | 128
activation_function	Activation function	Introduces non-linearity into the network, allowing it to learn complex patterns.	'relu', 'tanh'	‘tanh’ | ‘relu’
dropout_rate	Dropout rate	A regularization technique to prevent overfitting. Determines the proportion of neurons randomly set to zero during training.	0, 0.2, 0.5	0.2 | 0.2
batch_size	Batch size	Determines the number of samples processed before the model is updated. Affects training speed and stability.	32, 64, 128	32 | 128