Supporting Information

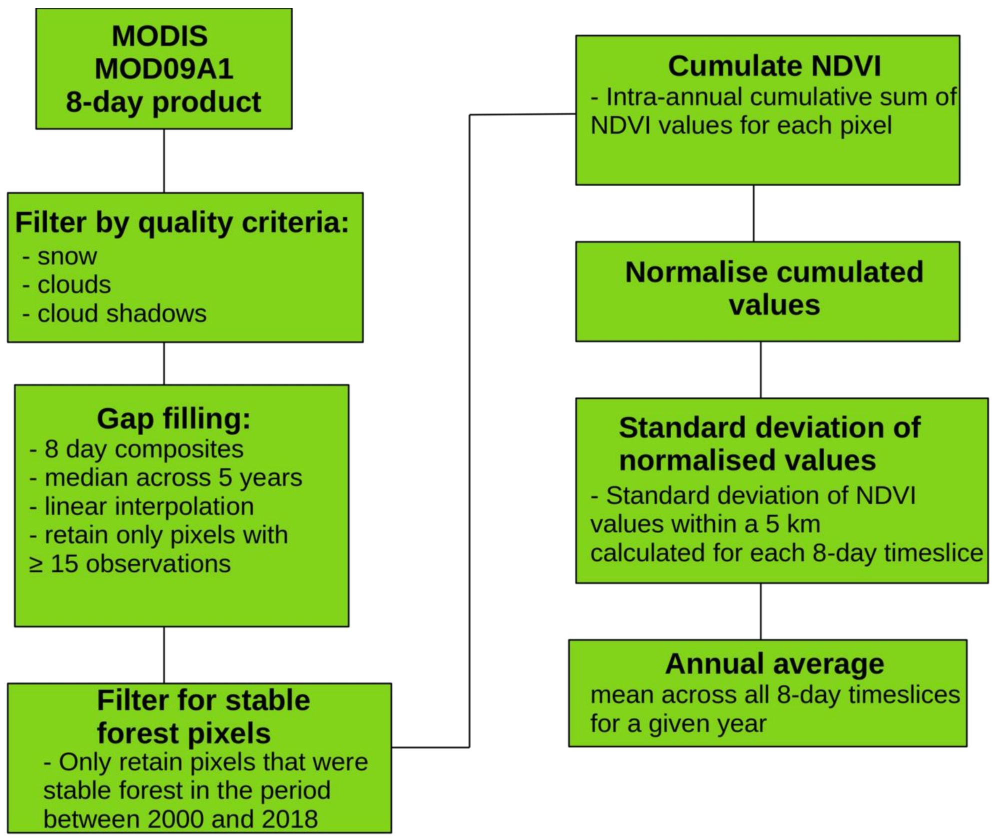

Fig. S1 Workflow adopted for pre-processing the remote sensing data and the calculation of the phenological diversity metric.

Spatial drivers of phenological diversity

Table S1 Predictors used in the analyses aimed at quantifying the spatial drivers of phenological diversity. A full description of the predictors is provided below.

Category	**Full name**	**Units**
Climate	Annual mean temperature	°C
Climate	Aridity	-
Climate	Temperature seasonality	°C
Climate	Precipitation seasonality	mm
Spatial heterogeneity in climatic conditions	sd Annual Mean temperature	°C
Spatial heterogeneity in climatic conditions	sd Annual Precipitation	mm
Spatial heterogeneity in climatic conditions	sd Temperature Seasonality	°C
Spatial heterogeneity in climatic conditions	sd Precipitation Seasonality	mm
Human impact	Human footprint	-
Topography	Topographic heterogeneity	-

Climate features

- We used long-term average data for five climatic variables, including cumulated precipitation , average annual temperature, temperature seasonality, precipitation seasonality, and aridity . The data were retrieved from the CHELSA dataset. These have an original resolution of ~1km. We therefore aggregated them at the same resolution of the phenological diversity dataset (~5km). We calculated the spatial average and standard deviation (spatial heterogeneity) using the values of the pixels falling within each ~5km window, used for calculating phenological diversity. A detailed list of the climatic variables used is reported in Table 1 (Supplementary Information). Data source: https://chelsa-climate.org/

Topography

- A measure of topographic complexity was derived from [1]. This measure of topographic complexity is calculated using the Shannon Index with a dataset describing the most common geomorphological forms. Geomorphological forms were originally calculated from a DEM, using a pattern recognition approach that classifies the terrain in terms of the following features: flat, peak or summit, ridge, shoulder, spur, slope, hollow, footslope, valley, and pit or depression. Data source: https://www.earthenv.org/topography

Human footprint

- A measure of human impact was derived from the human footprint dataset [2] The human footprint index is a composite index that quantifies human pressure on the environment. The index has been derived using spatially-explicit data for eight human pressures, including: 1) built environments, 2) population density, 3) electric infrastructure, 4) crop lands, 5) pasture lands, 6) roads, 7) railways, and 8) navigable waterways. The original dataset has an original resolution of ~1km. We therefore aggregated it at the same resolution of the phenological diversity dataset (~5km). Data source: https://wcshumanfootprint.org/

Temporal drivers of phenological diversity

- Annual cumulated precipitation, annual average temperature were retrieved from the TerraClimate dataset, which combines high-spatial resolution climatological normals from the WorldClim dataset with time-varying coarser data from CRU Ts4.0 and the Japanese 55-year Reanalysis (JRA55). We retrived data for period 2000-2020. The dataset, which has a ~4-km spatial resolution, was aggregated at the same resolution of the phenological diversity data. Data source: http://www.climatologylab.org/terraclimate.html.

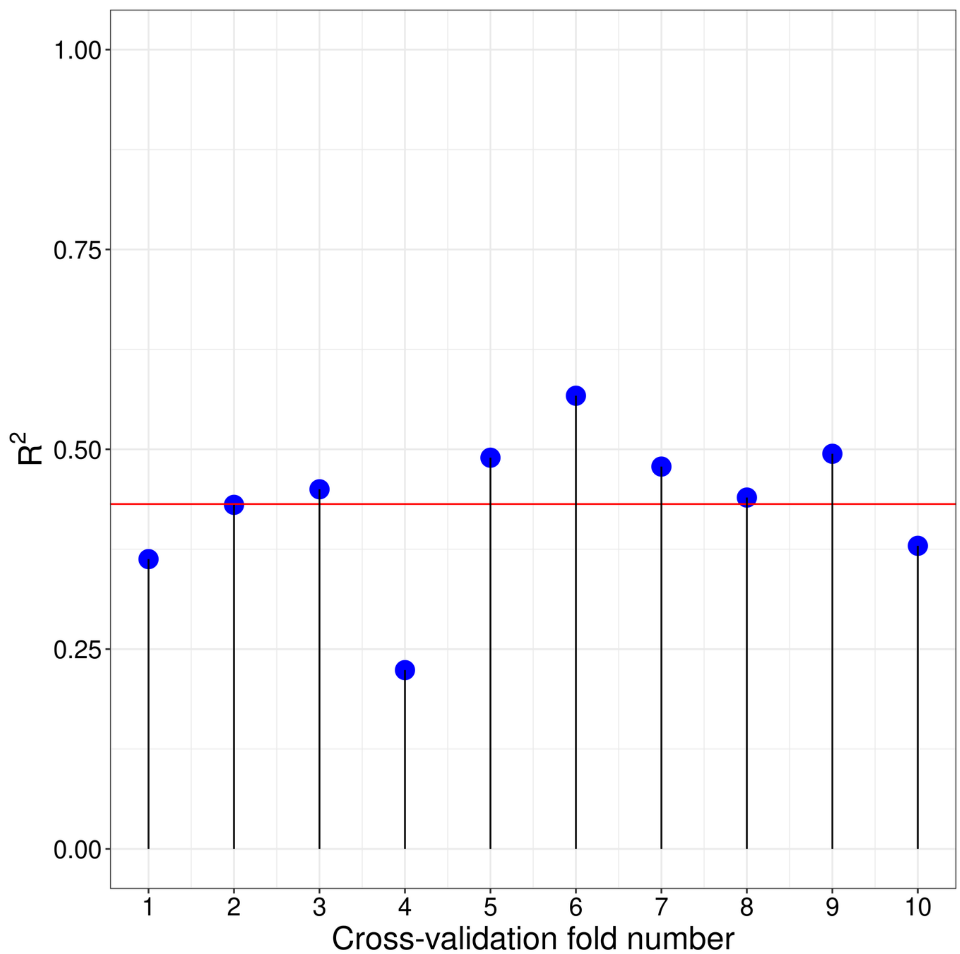

Fig. S2 Results of the block cross-validation exercise, as part of the the Random Forests modelling analysis. The y axis shows the proportion variance explained (R^2) by the model, when tested against a validation subset. The red horizontal line indicates the mean R^2 across all folds.

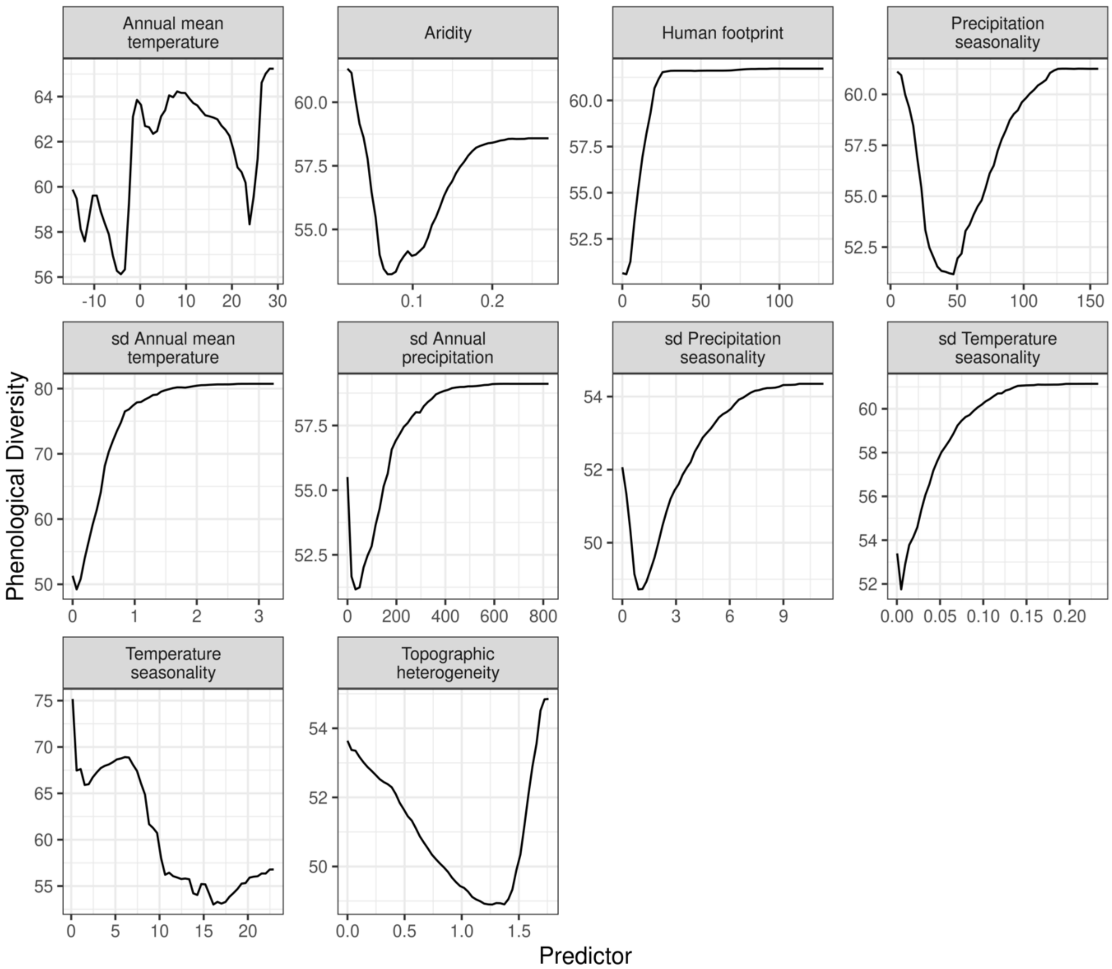

Figure S3. Response functions for spatial random forest models. Partial dependence plots showing the dependence of relative phenological diversity (response variable on the y-axis) on each selected environmental feature (x axis). Values of environmental predictors span the range between the 0.01 and 0.99 percentiles of the actual distributions.

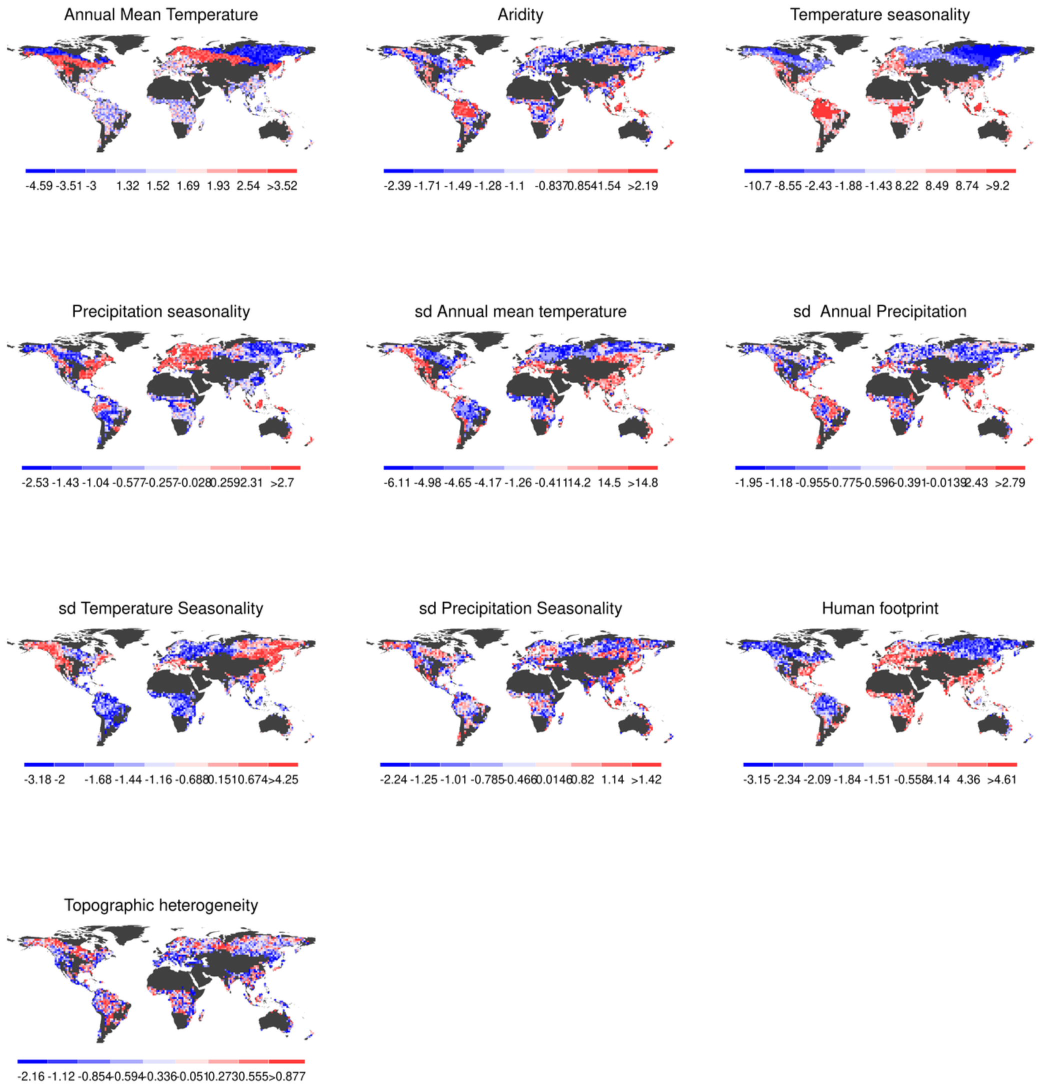

***Fig.* S4** Local response maps, calculated using the local interpretable model-agnostic explanation (LIME). This methodology aims to explain how a complex black-box model creates a prediction for a given instance. This is achieved by fitting a local surrogate model (a simple model) that approximates the behaviour of a complex model for a limited area of the of space defined by the predictor variables.

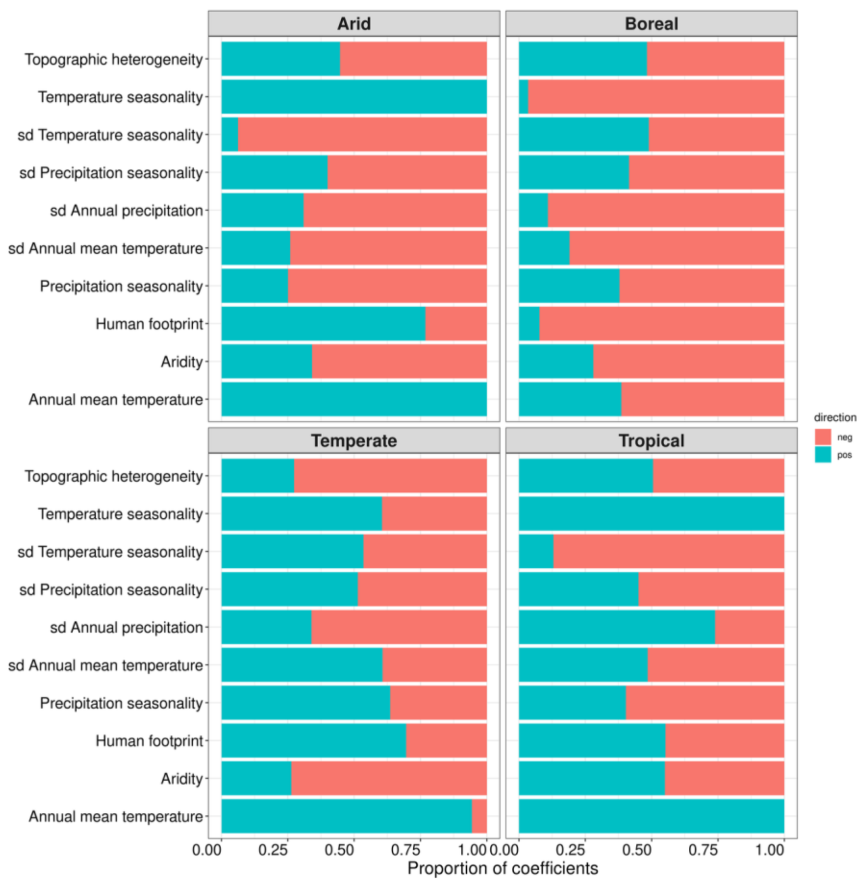

Fig. S5 Biome-level proportion of positive and negative effects, as quantified using the Local Interpretable Model-agnostic Explanations (LIME) analysis (see Supplementary Fig. 4 and Methods).

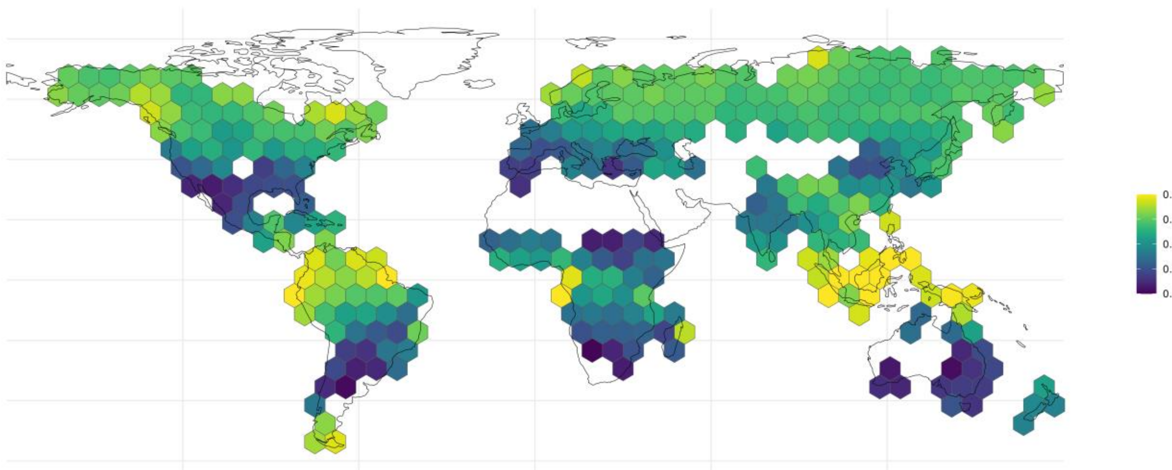

Fig. S6 Spatial distribution of the average proportion of gap-filled observations in 8-day MODIS data, using either linear interpolation or 5-year mean NDVI values. The proportion of gap-filled observations was calculated annually for the phenological diversity time-series dataset, and the map illustrates the average for three specific years: 2003, 2011, and 2020.

References

1. Amatulli, G. *et al.*. A suite of global, cross-scale topographic variables for environmental and biodiversity modeling. *Scientific Data* **5**, 180040 (2018).

2. Venter, O. *et al.*. Global terrestrial Human Footprint maps for 1993 and 2009.. *Sci Data* **3**, 160067 (2016).