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Inferring Vegetation Memory from Remote Sensing Data using novel Climate Reconstruction Products

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by

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Abstract

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List of Abbreviations and Acronyms

H Vegetative Height

N_{mass} Leaf nitrogen content per leaf dry mass

π Period of Oscillation

ρ Damping Ratio

AIC Akaike Information Criterion

AVHRR Advanced Very High Resolution Radiometer

BIEN Botanical Information and Ecology Network

CHELSA Climatologies at High Resolution for the Earth's Land Surface Areas

COMPADRE COMPADRE Plant Matrix Data Base

CRU Climatic Research Unit

DEM Digital Elevation Model

DSSs Decision Support Systems

ECMW European Centre for Medium-range Weather Forecasts

ERA5 European Centre for Medium-range Weather Forecasts ReAnalysis 5

FDD Functional Diversity Dispersion

FDR Functional Diversity Richness

FSC Fast-Slow Continuum

FSC-1 Life History Speed within the Fast-Slow Continuum

FSC-2 Reproductive Strategy within the Fast-Slow Continuum

GBIF Global Biodiversity Information Facility

GIMMS Global Inventory Modelling and Mapping Studies

HWSD Harmonized World Soil Database

iDiv Deutsches Zentrum für integrative Biodiversitätsforschung

LCCSs Land-Cover Classification Systems

LHT Life History Trait

MODIS Moderate-Resolution Imaging Spectroradiometer

NDVI Normalized Difference Vegetation Index

PCA Principal Component Analysis

PFT Plant Functional Trait

Qsoil Soil Moisture

Qsoil1 Soil Moisture (0-7cm)

Qsoil2 Soil Moisture (7-28cm)

Qsoil3 Soil Moisture (28-100cm)

Qsoil4 Soil Moisture (100-255cm)

SPEI Standardized Precipitation Evapotranspiration Index

SPI Standardized Precipitation Index

Tair Air Temperature (0-2m)

TRY TRY Plant Trait Data Base

VI Vegetation Index

1. Introduction

Ecosystems are subject to disturbance regimes which can undergo substantial alterations, especially due to climate change[1]. Widespread bioclimatic impacts which can be attributed to these changes include[2]: (1) increased frequency and intensity of climate extremes[3], (2) increasing temperatures and levels of aridity in dryland regions[4], and (3) shifts in environemntal and ecosystem processes[1,5,6]. This has raised growing concern that future disturbance dynamics will exceed tipping points and cause non-linear shifts in ecosystem state in relation to **attractors**[7] (see table 1.1 for definitions of bold font terms relating to the resilience debate). Such a **regime shift**[8–10] can have a tremendous impact on local as well as global welfare of mankind[11–13]. Therefore, policy makers have made it their mission statement to enforce actions which serve to maintain or boost **resilience**; a biological property which can safeguard against regime shifts. The Aichi biodiversity targets, for example, include the following statement: *"By 2020, ecosystem resilience [...] has been enhanced, [...] thereby contributing to climate change mitigation and adaptation and to combating desertification"* as target 15[14]. Whilst the Aichi targets are set to encompass global action, national policy makers, such as the Australian Government, are recongising the importance of achieving climate resilience as well in stating: *"We achieve climate resilience when short, medium and long-term decision making considers current climate risks and a changing climate"*[15]. Conceiving such strategies and evaluating their respective efficacies requires a thorough understanding of resilience theory and a robust set of tools to measure the resilience of ecosystems.

Generally, resilience can be understood as the capacity of a system to absorb **disturbances** and respond to changing conditions so as to still retain the same function, structure, identity and feedbacks[10,16]. First introduced to biological sciences in 1973 by Holling et al. resilience thinking encompassed two separate characteristics of ecosystems[16]:

1. *Stability* was defined as the ability of a system to return to its original state after a temporary disturbance. The more stable a system, the less it fluctuates in its characteristics and the faster it returns to its initial conditions after a perturbation. Contemporary literature usually refers to this property as **engineering resilience**[6,17,18].

2. *Resilience*, on the other hand, was characterised as the property of a system that allowed it to withstand disturbances without collapsing. The more resilient a system, the higher its chances of persisting under changing conditions. Today this is mostly referred to as **ecological resilience**[19–21].

Within this early context on resilience thinking, a system could be resilient whilst not being very stable and fluctuating in its properties a great deal[16]. Consider Andean grasslands as an example: wildfires lead to immense fluctuations in vegetation cover without making it impossible for the system to recover[22]. As such, resilience thinking often considers large spatial and temporal extents[23] which lend themselves well to remote sensing approaches[24,25].

Assumptions on ecosystem functioning that are made without including resilience thinking may result in particularly dire consequences if the systems in question (also referred to as focal systems[26,27]) are production ecosystems[26,28] (ecosystems which are used by humans for resource allocation).

Simultaneous assessment of components of any given ecosystem is a difficult task that often defies completion[20]. This poses a **major research challenge** of choosing a measure by which to assess resilience and ecosystem components reliably through time and space. Consequently, recent studies have focussed on identifying and quantifying sub-components of ecosystem resilience[29–32]. This is especially the case in remote sensing research where data availability is largely determined through what data repositories are available.

Table 1.1: Basic vocabulary of the ecological stability debate - A few definitions that are key to the understanding of the resilience framework.

Term	Definition
Attractor	A regime towards which a system moves asymptotically [10,12,26,33–36]. Also known as *stable state* [23], *(stable) equilibrium* [18] or *regime* [34].
Disturbance	Any impact that perturbs a systems trajectory from a given attractor [20,34,37–39].
Regime shift	The restructuring of a system from one set of dominant processes and feedbacks governed by one attractor to an alternate set governed by an alternate attractor [26,33,40–42]. Also known as *tipping point* [8] or *bifurcation* [10].
Ecological Resilience	'[...] measures the magnitude of disturbance that can be absorbed before the ecosystem's structure changes' [43]. Also known as *General resilience* [36]. Ecological resilience is a measure of how much a system can be changed until it shifts from one stable state/attractor to another [16,20,21,28,36,43–45].
Engineering Resilience	'[...] measures the speed of recovery after the disturbance' [43]. Also known as *Recovery* [20], *Stability* [16] or *Resiliency* [36]. Engineering resilience is a measure of how fast a system reverts to its pre-change state. It can be measured by assessing the return time [16,20,21,28,34,36,43–45].

Hodgson et al. tackled the problem of resilience compartmentalisation by building a framework for resilience assessments representing resilience as two separate entities: (1) *Resistance* to perturbation and (2) *Recovery* from perturbation [44].

Recovery rates have been used as proxies for resilience metrics in many study settings including (1) palaeoecological research (e.g. by linking recovery rates of tropical ecosystems and disturbances categories [46]), (2) observational studies (e.g. drought-impacts across different temporal and spatial scales [47]), and (3) experimental research (e.g. through applying small-scale disturbances and recording recovery rates [48]).

The *resistance* and *recovery* aspects of the Hodgson et al. framework to resilience can be represented through **ecological stress memory** (also know as 'ecological memory', see table 1.2 for definitions of bold font terms relating to the ecological memory framework). Whilst ecological memory is often understood to be simultaneous with **adaptation to disturbances** resulting in increased biological fitness int eh face of repeated stress events [49], other studies employ **ecological memory as a proxy for recovery rates** [43].

Nyström & Folke reported a direct link between spatial resilience and ecological memory of coral reefs [50]. In forest ecosystems, a positive link between ecological memory and ecosystem resilience has been identified by Johnstone et al [1]. Additional support for this argument stems from remote sensing studies such as De Keersmaecker et al. [43] and Seddon et al. [29] who identified autoregressive coefficients of vegetation properties as proxies of engineering resilience (i.e. recovery rates).

However, even quantifying ecological memory of an entire ecosystem is difficult as ecological memory is a compound metric unifying a multitude of sub-processes [49]. For example, the aforementioned Nyström & Folke recognised legacies, mobile links, and support areas as parts of ecological memory [50] whilst Jonstone et al. propose information and material legacies as the key factors of ecological memory [1]. Hence, ecosystem-scale studies have refocussed their attention on identifying components of ecological stress memory such as **vegetation memory** [1,49].

1.1 Vegetation Memory

Ecological memory (hence also vegetation memory) effects can be understood as the influence of antecedent conditions on ecosystem properties given contemporary disturbance regimes [17,51]. The existence of such temporal effects emphasize the necessity of considering time in ecological frameworks by providing a link between antecedent environmental conditions and plant performance [29,49,52,53]. In fact, there is empirical evidence that past conditions inform contemporary vegetation morphology [49], phenology [17], primary productivity [51,54], species composition [49,55], and carbon cycles [17,53]. Studying vegetation memory sheds light on an important set of ecosystem processes which contain an outstanding potential to make ecosystems resilient in the face of climate change [49].

1.1.1 Terminology

Vegetation memory can - in the broadest of terms - be understood as:

The impacts of antecedent conditions on current vegetation productivity. [17,43,49,51]

In a comprehensive paper, Ogle et al. expanded on this definition by identifying the following three important characteristics to vegetation memory [51]:

1. *Length* - The extent of time through which past conditions significantly affect the current state of vegetation.
2. *Strength* - The magnitude of the effect that past events/conditions have on the current state of vegetation
3. *Temporal Patterns* - The variation in relative impacts of antecedent conditions at different points in time.

Tackling the characteristic of vegetation memory origin, Ogle et al. introduced the notion of **intrinsic** and **extrinsic** memory effects [51] (see table 1.2 and figure 1.4).

Due to the complexity of extrinsic memory components and drivers I find it useful to add another criterion to extrinsic memory characteristics: *Extrinsic Source*. This represents the nature of the antecedent extrinsic conditions that drive current states of vegetation (i.e. the origin/source of the extrinsic memory effect), including (but not limited to): herbivory pressure or climate events.

Table 1.2: Basic vocabulary of the vegetation memory framework - A few definitions that are key to the understanding of vegetation memory and its components.

Term	Definition
Ecological Memory	Ecological memory is synonymous with information and material legacies: adaptations, individuals, and materials that persist after a disturbance and drive the responses to future disturbances [1,50].
Vegetation Memory	Vegetation memory is defined as any response of a single plant or vegetation compounds after following disturbance event that alters the response of the plant/plant community towards future stress events. This includes a modification of interaction with other ecological components [49].
Intrinsic Memory	Intrinsic memory refers to the influence of antecedent conditions of the focal system in determining contemporary conditions of the same system. Also known as *endogenous memory.* [51]
Extrinsic Memory	Extrinsic memory refers to the influence of antecedent conditions of the environment (usually abiotic, climate factors) in determining contemporary conditions of the focal system. Also known as *exogenous memory.* [51]

1.1.2 Ecological Relevance

Vegetation memory is identified as the effect of antecedent conditions on current vegetation patterns [51]. The stronger and longer the memory effect, the more vegetation will be influenced by antecedent anomalies of the ecosystem and abiotic processes thus signalling higher sensitivity to these drivers [43]. A higher sensitivity translates to lower resilience and so:

Vegetation memory has been proposed as a proxy for engineering resilience. [17,56]

Patterns and characteristics of vegetation memory are a vital information criterion for Decision Support Systems (DSSs) aimed at conservation or management efforts due to the inverse relationship between vegetation memory and engineering resilience.

Additionally, vegetation memory is a compound metric which may be driven via a variety of forcing factors [29]. Thus making use of the differentiation of *intrinsic* and *extrinsic* components of vegetation memory by Ogle et al. [51] aids in gaining additional understanding of what local vegetation reacts to.

1.1.3 Quantifying Vegetation Memory

Vegetation memory is influenced by a multitude of processes which range from abiotic characteristics [29,43,53] to biotic system components [1,43]. Comprehensive studies of vegetation response to biotic and abiotic forcing are numerous [17,29,29,46,51,53].

1.1.3.1 Traditional Approaches

Traditional studies of vegetation memory leverage data obtained via extensive sampling campaigns and are thus laborious to carry out. Nevertheless, a multitude of such studies exist which provide a solid foundation for the understanding of ecological memory to date.

Some traditional approaches - like Johnstone et al. [1] - establish theoretical frameworks of vegetation memory (i.e. as material and information legacies) which require empirical assessment through further research.

One such study identified vegetation memory as spectral reddening as a proxy of spatial correlation of ecosystem properties. Increased spatial correlation is regarded as a proxy of high memory and ecosystems approaching regime shifts [57]. Additionally, these largely field-based studies are able to make use of a host of information criteria including but not limited to seed banks, wood thickness, canopy structure, and root depth [58]. Such information is often invaluable as it highlights the functional property of vegetation memory which is often identified through vegetation responses to different disturbances but rarely explained in terms of plant function that enables memory.

Due to limited sampling effort, such traditional studies are - although vitally important for our understanding of vegetation memory pathways - limited in scope. This will often lead to an advanced causal understanding of vegetation memory but only at limited spatial and temporal extents.

1.1.3.2 Remote Sensing Approaches

Remote sensing studies forego tedious field work data collection efforts and rely solely on easily available data. This data may either be obtained via remote sensing methods (i.e. satellite or drone imagery) or be pulled from published data sets from the field.

Using these data sets, remote sensing studies of vegetation memory offer vast improvements in spatial and potentially temporal coverage when compared to traditional approaches. This, in turn, allows for landscape-scale patterns of vegetation memory characteristics to be identified. Unfortunately, to achieve these large spatial extents, one often has to sacrifice patial and temporal resolution. Especially climate data can be unreliable in some regions of the world when field measurements are sparse.

Recent remote sensing studies of vegetation memory have established a multitude of approaches to delineating vegetation memory from a variety of data sets. Examples include the use of:

1. **Correlation coefficients** of different lags of drought indices.

Prominent examples of these approaches (e.g. Vicente-Serrano et al.[59], and Liu et al.[17]), identify vegetation characteristics through time via the Normalized Difference Vegetation Index (NDVI) (aggregated from bi-weekly records to monthly maximum composites). Drought characteristics are usually assessed either via the Standardized Precipitation Evapotranspiration Index (SPEI) or Standardized Precipitation Index (SPI). Additionally, data is assessed for certain quality criteria (e.g. monthly NDVI $< .1$) and standardised. Subsequently, correlation coefficients asses how well NDVI and drought index anomalies co-incide (strength of memory, A in figure 1.1) and at what temporal lag these coefficients are the most relevant (length of memory, B in figure 1.1 and figure 1.2).

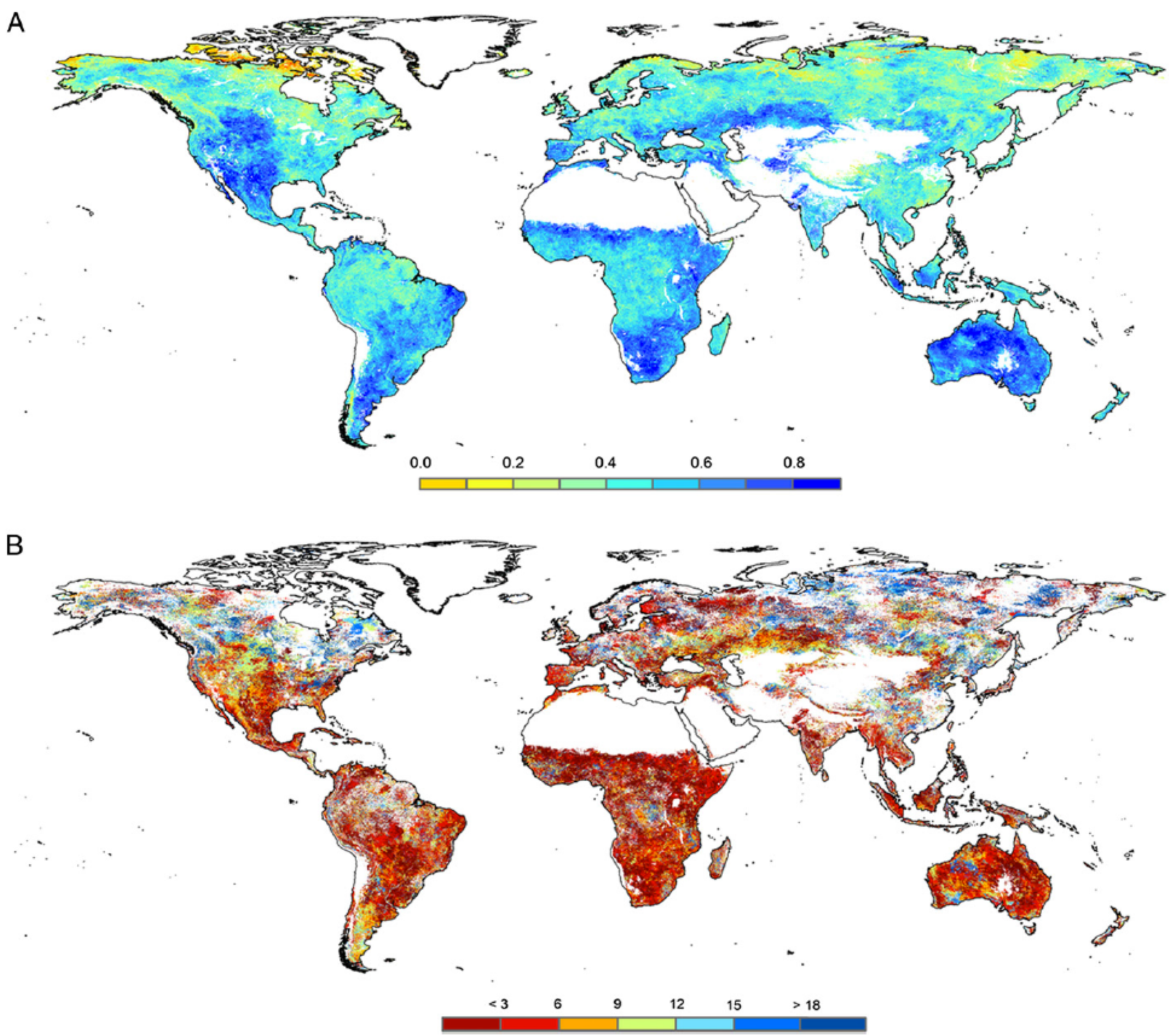


Figure 1.1: Drought Memory Length and Strength - Spatial patterns of drought memory length assessed via correlation coefficients. Figure lifted from Vicente-Serrano et al[59].

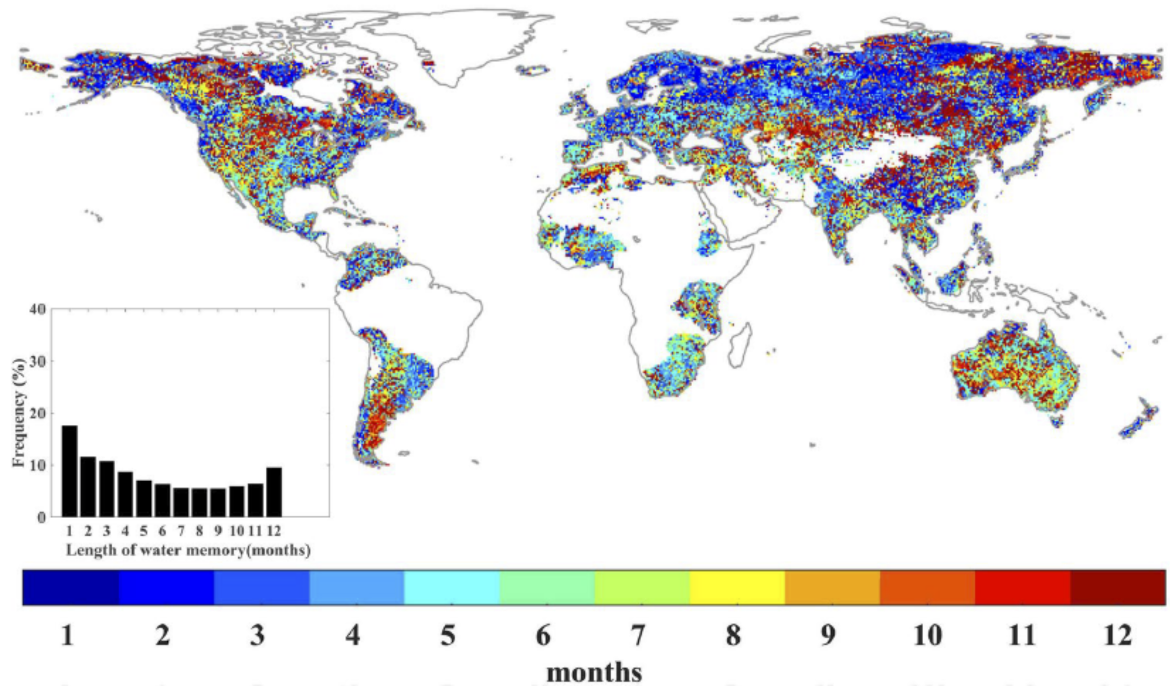


Figure 1.2: Water Memory Length - Spatial patterns of water memory length assessed via correlation coefficients. Figure lifted from Liu et al [17].

2. **Mixed effect models** of antecedent vegetation and climate characteristics and subsequent model selection.

In their 2015 paper, De Keersmaecker et al. introduced a comprehensive vegetation memory modelling approach using NDVI, temperature, and SPEI data in a linear mixed effect model. Again, certain data preparation steps such as removal of low-quality data, calculation of maximum monthly composites of NDVI and subsequent standardisation were carried out. Climate data which did not meet the same spatial resolution as the NDVI data was resampled using the nearest neighbour method. Study results of the **first autoregressive model** (NDVI data regressed via NDVI data a previous time step, also referred to as *intrinsic memory*) are presented in figure 1.3.

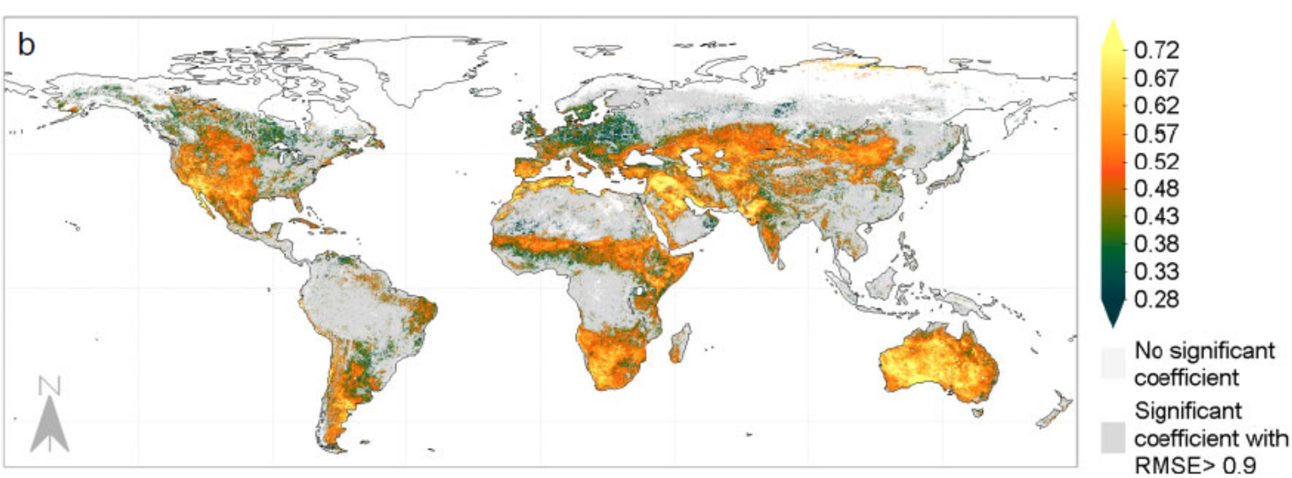


Figure 1.3: Intrinsic Vegetation Memory - Autoregressive coefficients of intrinsic vegetation memory depicting engineering resilience (high memory scores identify low resilience). Figured lifted from De Keersmaecker et al [43].

Seddon et al. [29] delineated autoregressive NDVI patterns very similar to those presented in figure 1.3.

1.1.3.3 Synthesis

Models

Some common modelling practices have emerged from contemporary remote sensing vegetation memory studies:

1. **Intrinsic Memory** is usually identified as the relationship between vegetation properties at time step t a prior time $t-1$ (usually at monthly intervals)[43]. See figure 1.4 for a visual representation.
2. **Extrinsic Memory** is attributed to combinations of temperature, precipitation, and/or drought records[17,43,51,59]. See figure 1.4 for a visual representation.
3. **Model Selection** is used to determine the length of extrinsic memory effects by identifying the time window during which extrinsic forcing holds the most explanatory power of vegetation characteristics[17,43,59].
4. **Anomalies** (i.e. standardised records) of both response and predictor variables are used as these are metrics which can be linked directly to perturbation events[43].

Vegetation memory models can thus usually be summarised as:

$$Y_t = \alpha * Y_{t-1} + \sum_{e=1}^{E} (\beta_e * X_e) \tag{1.1}$$

with Y_t and Y_{t-1} denoting anomalies of vegetation properties at times t and $t-1$ respectively, X_e indexing anomalies of the e'th extrinsic force (out of a total E extrinsic drivers), and α and β representing the **coeffcients** of **intrinsic** and **extrinsic** memory effects respectively. Rerunning such a model with independent, extrinsic inputs (X_e's) at different time lags and subsequent model selection can then be employed to identify the length of the extrinsic vegetation memory related to the e'th extrinsic force.

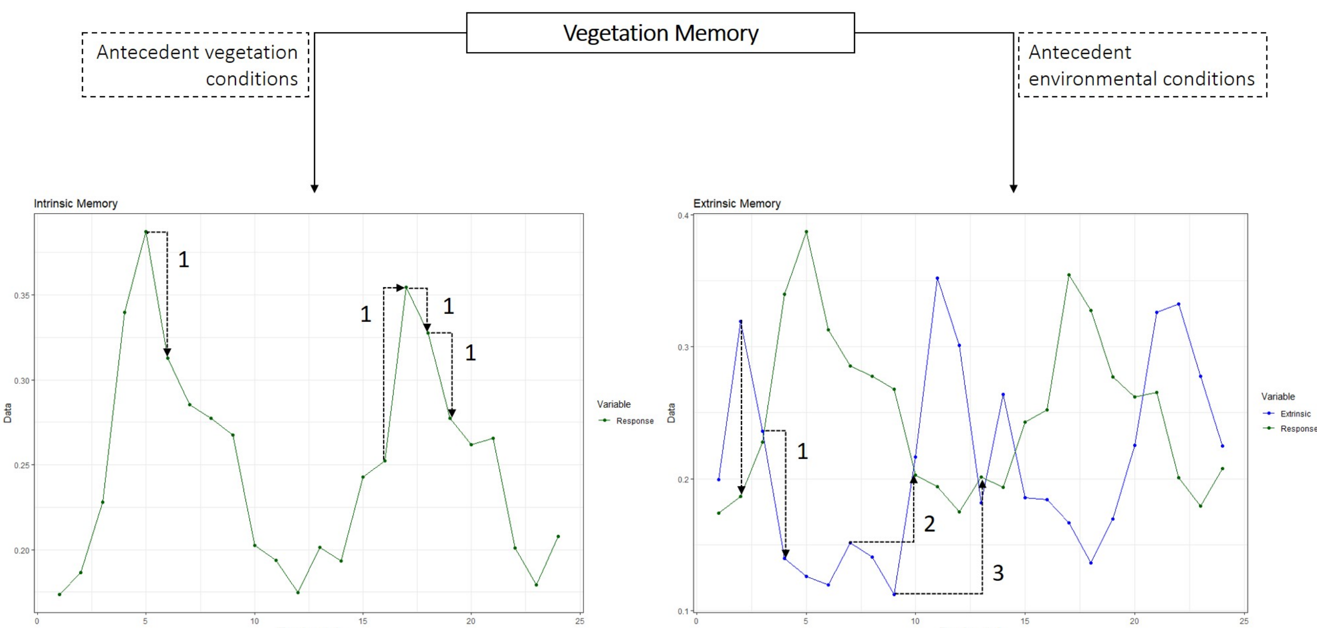


Figure 1.4: Components of Vegetation Memory - Conceptual layout of how intrinsic and extrinsic vegetation memory components can be identified. The concept recognises two important variables: (1) *Response* - contemporary vegetation properties at time t, and (2) *Extrinsic* - antecedent environmental data. Within this framework, vegetation memory - both intrinsic and extrinsic - is identified as the predictability of the response variable through a regression onto itself and extrinsic variables respectively. Regressions of data onto each other are visualised as dashed arrows, lag effects are identified by numbers. Some parts of this figure have been generated via Chunk 37.

Spatial Memory Patterns

Results of the studies above clearly indcate some areas of special interest:

1. *High Memory Coefficients* indicating regions of low resilience can be found largely in *dryland regions* (e.g.: North-East Brazil, Australia, and Spain; figures 1.1 and 1.3).

2. *Trends in Memory Length* signalling a change in causal patterns of memory effects can be found across the Iberian Peninsula, and the contiguous United States of America. See figures 1.1 and 1.2.

Furthermore, all of these regions are characterised by gradients in vegetation memory intensity (figures 1.1 and 1.3). Remote sensing vegetation memory should thus focus on the above listed **dryland regions** characterised by **shifts in memory properties**. Finally, since vegetation memory is largely researched in terms of water limitations and precipitation events, dryland regions are expected to allow for identification of extrinsic memory effects.

Data

Vegetation properties are usually assessed using NDVI data. Additionally, indices of climate metrics are used for the calculation of extrinsic memory components.

Contemporary studies of vegetation memory largely rely on *precipitation* or *drought* data obtained via the SPEI drought index [43,56], and the Climatic Research Unit (CRU) data set [17]. These data sets are *observational* data sets as they are built from observational data often involving simple interpolation methods [60]. Climate science has developed novel data sets which are more advanced than simple observational data sets. Thse are known as climate reanalysis products.

Climate reanalysis data sets are *self-consistent*, *gap-less* (in time and space) and thus **superior** to many observational data sets. One such reanalysis data set is the **European Centre for Medium-range Weather Forecasts ReAnalysis 5 (ERA5)** [61]. The superiority of ERA5 is largely due to:

1. The **volume of observational data** used to create the ERA5 product with data types ranging from satellite data to weather station/independent institute data collection efforts, and station data from a wide variety of data providers [62]. Traditional, observational data sets are often characterised by their individual biases in sampling, and coverage representativeness.

2. Its **sophisticated nature** building upon data assimilation procedures [63], and complex models [64] to shed light on physical processes [65]. As such, ERA5 is currently the *state-of-the-art* climate reanalysis product in climate science and benefits from the developments in data assimilation methodology, understanding of physics of the climate system and their interactions, which have come about in recent decades.

Finally, ERA5 improves on other prominent climate data sets in ecological studies like the aforementioned CRU and SPEI, WorldClim (used by Seddon et al. [29]), or the Climatologies at High Resolution for the Earth's Land Surface Areas (CHELSA) data set [66] in a multitude of ways since it offers:

1. Superior *Temporal Resolution* (superior resolving of climate extremes)

2. Superior *Spatial Resolution* (advanced resolving of local/topographical features)

Therefore, one can reasonably expect to improve on contemporary vegetation memory studies by substituting observational climate data sets with the highly advanced ERA5 data set.

In addition, none of the contemporary vegetation memory studies on landscape-scales include biological ground-truthed data such as the aforementioned indices of functional aspects to plants which traditional approaches can leverage through measures of **Plant Function** and thus aren't posed to identify biological causal pathways of vegetation memory

1.2 Functional Aspects of Vegetation Memory

Contemporary studies identify patterns of vegetation memory but largely forego questions of causal processes to further our understanding of what enables vegetation memory capacities when doing so could enable more refined DSSs. Since vegetation memory acts as a proxy for ecosystem process functioning, I hypothesise that expressions of vegetation memory can be explained through the lens of **functional ecology** since a functional approach to ecosystem processes can potentially explain what functional expressions allow said processes to persist despite perturbations[67–70]. One of the most prominent tools of such studies is the *functional trait framework*. Arguabely, the most important of these frameworks when understanding vegetation processes - such as vegetation memory - is that of **Life History Trait (LHT)** and **Plant Functional Trait (PFT)** frameworks.

1.2.1 Terminology

LHTs and PFTs both capture crucial information of vegetation capabilities to cope with stressors. Despite recording vastly different aspects of plant function in respect to time, they should be regarded as *complementary* due to their demonstrated capabilities in explaining natural phenomena.

1.2.1.1 Life History Traits

LHT frameworks (see table 1.3 for definitions of bold font terms relating to LHTs) assess plant/population characteristics through time thus mirroring the temporal aspect of vegetation memory leading up to, during, and following perutrbations. Since expressions of LHTs explain temporal community processes and may thus be major drivers of ocal vegetation memory expressions. Prominent examples of LHTs include measures relating to (1) **System Turnover**, (2) **Longevity**, (3) **Growth**, and (4) **Reproduction** all of which retain information of how individual biological proceses shape vegetation communities and have been found to explain a majority of variance in plant life history strategies[71].

Table 1.3: Basic vocabulary of Life History Trait frameworks - A few definitions that are key to the understanding of Life History Trait frameworks. Largely influenced by Salguero-Gómez et al[72].

Term	Definition
Life History Traits (LHTs)	LHTs characterise life history processes of populations and thus identifying temporal aspects of their life cycles.
System Turnover	
Generation Time	The time needed to fully replace a population by a new cohort.
Longevity	
Survivorship Curve	Shape of age-specific survivorship curve type.
Age at Sexual Maturity	Time it takes for an average individual of a population to become sexually reproductive.
Growth	
Progressive	Mean probability to advance in life stages.
Retrogressive	Mean probability to regress in life stages.
Reproduction	
Net Reproductive Rate	Mean number of recruits produced by each individual in the population.
Degree of Iteroparity	Spread of reproduction during the lifespan of an individual.
Mature Life Expectancy	Time between age of sexual maturity and life expectancy.

Specifically, I hypothesise for vegetation memory effects to be at least partially driven by:

1. The **Fast-Slow Continuum (FSC)** is a Principal Component Analysis (PCA)-based approach whose two main axes capture over 60% of the variation in plant life history strategies [73] and are largely made up by the LHTs contained in table 1.3 [71]. I hypothesize that expressions of the Fast-Slow Continuum (FSC) will strongly interact with vegetation memory effects due to the holistic nature of the FSC and the temporal nature of both LHTs and vegetation memory effects. The two axes read as follows:
   (a) *Life History Speed within the Fast-Slow Continuum (FSC-1)* explains around 35% of global LHT variation and contrasts species of low generation times, early maturity, and fast growth with species of high generation times, delayed maturity, and slow growth [73]. Fast species rank low on this axis [72].
   (b) *Reproductive Strategy within the Fast-Slow Continuum (FSC-2)* captures approximately 25% of global LHT variation and contrasts species low reproductive output with species that reproduce much, often, and for a long time [73]. Species of low reproductive output rank low on this axis [72].
2. **Reactivity** is a *first time-step* information criterion and a proxy for instantaneous biological responses [74] and may thus be an important criterion in areas of high vegetation memory and thus low engineering resilience.
3. The **Damping Ratio (ρ)** can be regarded as a measure of intrinsic resilience as it indicates how fast transient dynamics of a perturbation event decay; the larger ρ, the faster the population will converge [74].
4. The **Period of Oscillation (π)** is a measure of population life cycles in periodic environments with more rapidly growing populations usually being classified by higher π values [75].

1.2.1.2 Plant Functional Traits

PFT frameworks (see table 1.4 for definitions of bold font terms relating to PFTs) convey information as *snapshots* of reality as their data sets usually do not contain repeated measures of the same individuals over a period of time. These data sets have been linked to evolution [76] and community composition patterns [70,77]. A change in their expression has been found to be correlated with climate change patterns [78] potentially suggesting a causal link between extrinsic vegetation memory and PFT expressions. To classify the way in which PFTs are related to community functions, Nock et al. present the concept of (1) **Effect Traits**, and (2) **Response Traits** [79]. Classifying PFTs according to this framework can profoundly aid the understanding of their influence on spatio-temporal patterns of vegetation performance [41,70]. Effect traits determine how PFTs alter ecosystem processes (predominantely driving post-disturbance recovery) whilst response traits affect how vegetation reacts to perturbations (signifiying resistance potential).

Recent studies suggest that vegetation community functions are governed by integrated phenotypes, which can be regarded as combinations of PFT ranges [79,80] thus calling for a scientific approach focussed on **Functional Diversity Richness (FDR)** which can be identified via an approach in which PFT values of each individual are placed within a multidimensional system with each axis representing the range of values for one specific PFT [81]. Additonally, one may also want to use a measure of evenness which, in a functional biology setting, can be referred to as **Functional Diversity Dispersion (FDD)** which is representative of how evenly dispersed data records are in multidimensional space.

Identifying FDR and FDD requires a lot of indivudal PFT data and so contemporary studies in PFT research have focussed heavily on methods of dimensionality reduction by identifying the PFTs which capture a vast part of the global variation of plant function [77,82]. One such framework has been established in theory by Westoby & Wright in which three important PFT dimensions are recognised: (1) the leaf economic spectrum, (2) the seed size/mass spectrum, and (3) the height of the canopy at maturity [83].

Table 1.4: Basic vocabulary of Plant Functional Trait frameworks - A few definitions that are key to the understanding of Plant Functional Trait frameworks.

Term	Definition
Plant Functional Traits (PFTs)	Plant Functional traits characterise morphological, biochemical, physiological, structural, phenological and/or behavioural aspects of organisms which influence the fitness of said organisms [79].
Effect Traits	These determine a species influence on ecosystem processes [79].
Response Traits	These determine a species ability to colonise a certain habitat and persist despite environmental pressures [79].
Functional Diversity Richness (FDR)	Functional diversity richness measures the range of the PFT spectrum of a given study region/species assembly in multivariate trait space via a multivariate convex hull effectively measuring niche space [81].
Functional Diversity Dispersion (FDD)	Functional diversity dispersion measure the dispersion of PFT values in multivariate trait space with respect to the local functional space centre effectively measuring niche segregation [81].

Using an empirical approach similar to the aforementioned FSC, Díaz et al. identified:

1. *Vegetative height* (H) - an important criterion to accessing light resources
2. *Stem specific density* (SSD) - reflecting a trade-off between growth potential and mortality risk
3. *Leaf area* (LA) - vital consequences for leaf water balance
4. *Leaf mass per area* (LMA) - a proxy for the trade-off between carbon gain and leaf longevity
5. *Leaf nitrogen content per leaf dry mass (N_{mass})* - reflects a trade-off between photosynthetic potential and acquiring nitrogen
6. *Diaspore mass* ($Dmass$) - reflects a trade-off between seedling survival and colonization ability

as the most important PFTs to understanding the global spectrum of plant functioning [82]. Recovery rates of vegetation post-disturbance (i.e. vegetation memory) is influenced by energy and biomass availability. Resource allocation and hence recovery potential using the above six traits is best understood employing H, lMA, and N_{mass} due to their direct link to realising photosynthetic potential. Resistance potential, on the other hand, is influenced heavily by the physical toughness of plant material, presence of storage organs, and many other aspects of plant function captured by PFTs and so SSD, LMA, and N_{mass} are especially promising as drivers of ecosystem resistance.

1.2.2 Ecological Relevance

The diverse range in which measures of plant function can be expressed are representative of the diverse strategies for establishing, growing and reproducing of plants [77]. Hence, understanding how plant functioning enables plants to persist despite (a)biotic forcing (i.e. vegetation memory) is a promising first step to understanding ecosystem-scale responses to climate change. THis is due to the positive effect of biodiversity on ecological stability which has long been recorded [67] and even led to the formulation of prominent concepts like Yacchi's insurance hypothesis which postulates that the loss of a subset of species can be compensated for by the presence of other species given a sufficient overlap in functional aspects of both thus leading to a stabilisation of ecosystem processes [84].

PFTs and LHTs capture information about a variety of ecosystem processes. [85]

Most studies to date have focussed on species diversity [10,11,28]. Some made use of the concept of functional species [21] which presents researchers with a species classification system that is vague at best due to loose definitions of where to draw the lines between functional species. Functional trait biology, which captures the functional diversity of biological systems, is often employed as an improvement to the functional species/type concept [49,52] as it eliminates the necessity of phylogenetic analyses [79] and enables studies to capture intra-specific variation [86–88] thus making landscape-scale studies (such as remote sensing approaches) of vegetation memory patterns possible.

PFTs and LHTs can be captured irrespective of species relationships. [87]

Thus, PFTs and LHTs make for *highly informative* proxies of *ecosystem functioning* which can be recorded across *large spatial and temporal scales* since studies aren't constrained to a handful of species. Additionally, PFTs and represent an improved understanding of functional expressions of plant communities by *expressing information at sub-species level* [86]. Recent research based upon LHT data, for example, has revealed robust trade-off axes in plant [72,73] as well as animal life histories [89,90]. Information about LHTs has been demonstrated to be of use in trying to understand biological responses to temporal phenomena [91] and should thus prove crucial in delineating causal, biological pathways to establishing vegetation memory.

1.2.3 Unifying Information on Plant Functional Traits

PFTs are usually recorded through individual trait campaigns or for single-study purposes. Combining PFT information from these individual data sets can prove challenging due to different measurement practices and understandings of PFTs. A comprehensive handbook on PFT data collection practices by Pérez-Harguindeguy et al. [92] presents an elegant solution to making PFT data sets more comparable. Additionally, PFT data sets have been aggregated into large data bases within online repositories such as:

- The **TRY Plant Trait Data Base (TRY)** [88] is data base of PFT records hosted by the Deutsches Zentrum für integrative Biodiversitätsforschung (iDiv). Its current release (version 4) TRY contains almost seven million PFT records for 1,800 traits with about half of all records being geo-referenced [93].
- The **Botanical Information and Ecology Network (BIEN)** [94] is a repository of global plant diversity, function, and distribution. Its current release (version 4.1) contains over 200 million records at global coverage [95]. See figure 1.5 for an overview of TRY and BIEN data availability.

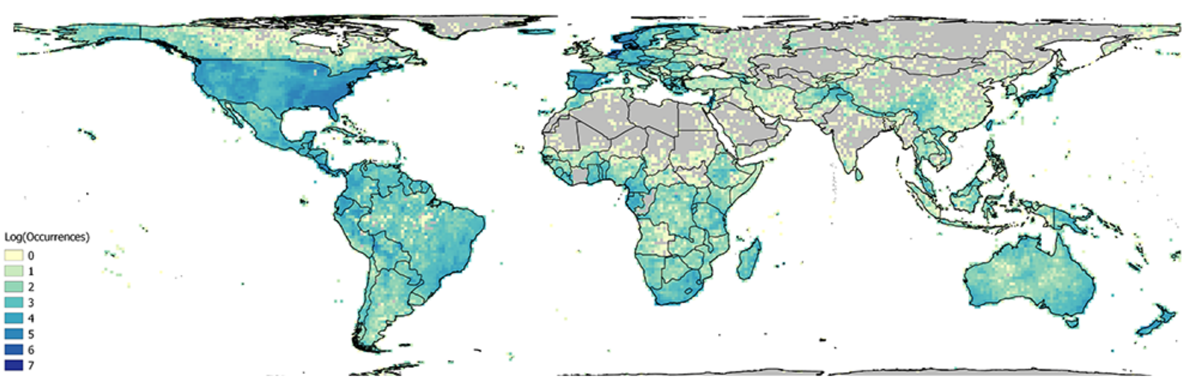


Figure 1.5: BIEN PFT Coverage - Geo-referenced records within version 4.1 of the BIEN data base at logarithmic scale [95].

- The **COMPADRE Plant Matrix Data Base (COMPADRE)** [71] contains LHT, a subclass of PFTs pertaining to life history characteristics (e.g. longevity, reproductive mode, etc.), driven matrix population models which produce important information about community processes through time based on records of different LHTs [72]. In its current release (version 5.0.0) it contains over 7,00 matrix models [96].

Combining information from these data bases should result in a holistic view of global plant function as such an approach would unify PFTs and LHTs to further a spatio-temporal understanding of global plant function.

1.2.4 Putting Plant Function on the Map

Vegetation memory patterns are inherently spatial phenomena [17,43,51,59]. So are patterns of plant functioning [81]. Whilst the above mentioned data bases (TRY, BIEN, and COMPADRE) contain vast amounts of geo-referenced PFT and LHT records, almost no comprehensive, gapless, and internally consistent global products of plant function are available [66,85]. Currently, the most commonly used method for extrapolating PFT records to local/global map products follows the methodology layed out by Ordonez & Svenning [81] which has species-specific PFT means being combined with geo-referenced species occurrences (a conceptual depiction of this can be seen in figure 1.6).

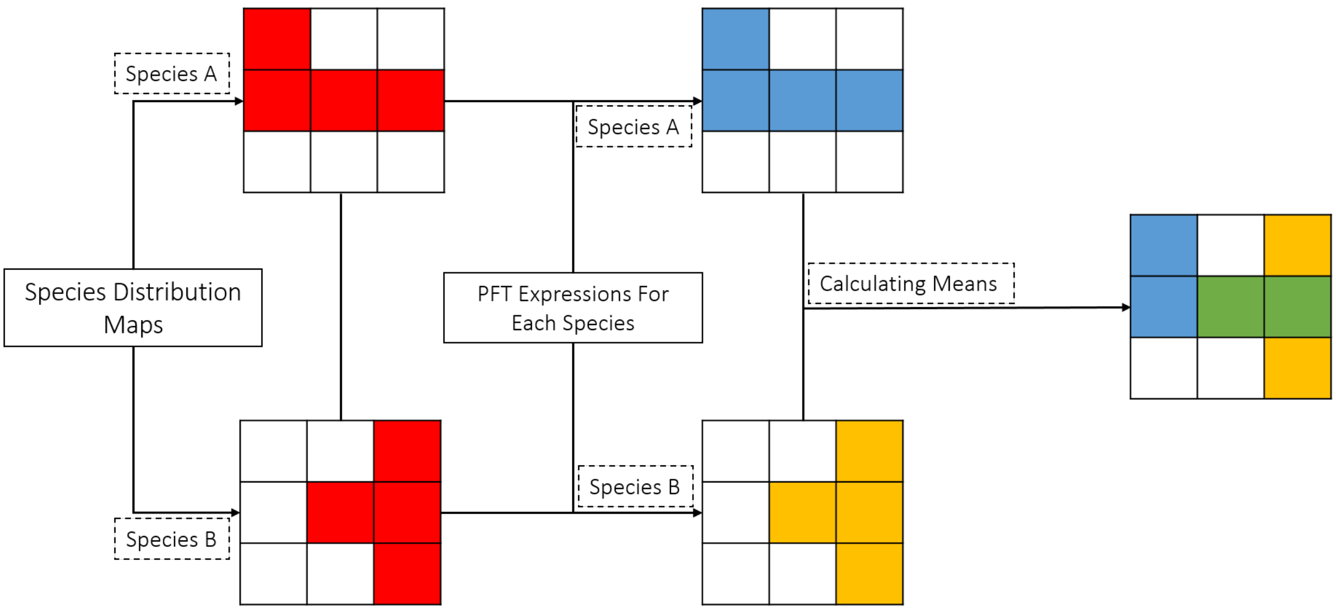


Figure 1.6: Concept of Combining Plant Functional Trait Information with Species-Distribution Maps - Conceptual framework of mapping plant function from PFTs and species distribution maps into gridded map products of mean PFT expressions. Inspired by Ordonez & Svenning [81]. Red cells indicate presence of a species, blue and yellow cells depict the average PFT of species A and B respectively. Green cells represent the average of PFT means of species A and B whilst white cells denote the absence of species and thus PFT data.

Species occurrence data - referred to as **floral data** in the case of plant occurrences - can be obtained via the **Global Biodiversity Information Facility (GBIF)** data base which currently contains over 1 billion geo-referenced occurrence records of species across all kingdoms of life [97].

Unfortunately, this approach is heavily reliant on geo-referenced occurrence records which are subject to sampling bias [98] and renders intra-specific expressions of PFTs virtually non-existent as species are expressed via single mean values for each PFT. Zoological studies have resolved these issues by recording relative abundances of species in addition to occurrence records [99].

Recent approaches in PFT ecology have seen the development of mapping procedures of PFTs according to abiotic conditions through linear models with spatial components [66] and complex Bayesian methods [85]. No such method is available for extrapolating LHT records to broader coverage as these come with an added dimension of time.

Despite the obvious short-commings of this mapping method, including PFT and LHT data to remote sensing vegetation memory studies is a novel approach in itself. This is built around the notion of vegetation memory being driven not only by antecedent conditions but also by functional characteristics of the local vegetation. Making use of the above PFT extrapolation method thus serves as an exploratory analyses of how well it performs when trying to extract causal pathways leading to vegetation memory.

1.3 Thesis Outline

Remote sensing analyses have been the key to identifying vegetation memory patterns through time and space in a multitude of settings [17,43,59]. Refining such approaches will facilitate important knowledge for DSSs on environmental processes in the face of climate change as well as changes in land use by mankind [100]. Considering the direct link between vegetation memory and ecosystem resilience, this will garner an advanced comprehension of resilience and, in turn, enable maintenance and enhancement of ecosystems' resilience thus aiding to stabilize natural systems. It is therefore the **first main goal** (see figure 1.7 for an overview of how I am planning to achieve the research goals layed out here) of this study to:

I. Identify vegetation memory patterns while improving on contemporary approaches.

To do so, I am going to answer the following research questions while focussing on dryland regions and ERA5 data:

1. *Using climate reanalysis data, which variables make up robust vegetation memory metrics?*
2. *How well can we distinguish between intrinsic and extrinsic memory?*

A multitude of recent studies have identified vegetation memory characteristics of a diverse cast of focal ecosystems [17,29,31,49,53,56,101,102]. However, only a few of these have also delineated the ecological processes and causal pathways which have led to the observed patterns of vegetation memory. Achieving an understanding of how functional aspects of vegetation may alter vegetation memory capabilites should serve to bolster our understanding of how resilience comes about and can be maintained. Therefore, the **second main goal** of my thesis is to:

II. Determine how vegetation memory and plant function are linked.

Achieving this goal is possible by answering the following research questions:

1. *Which traits of biological function (PFT and LHT) are related to vegetation memory characteristics?*
2. *What biological traits cause areas to exert intrinsic and extrinsic memory?*

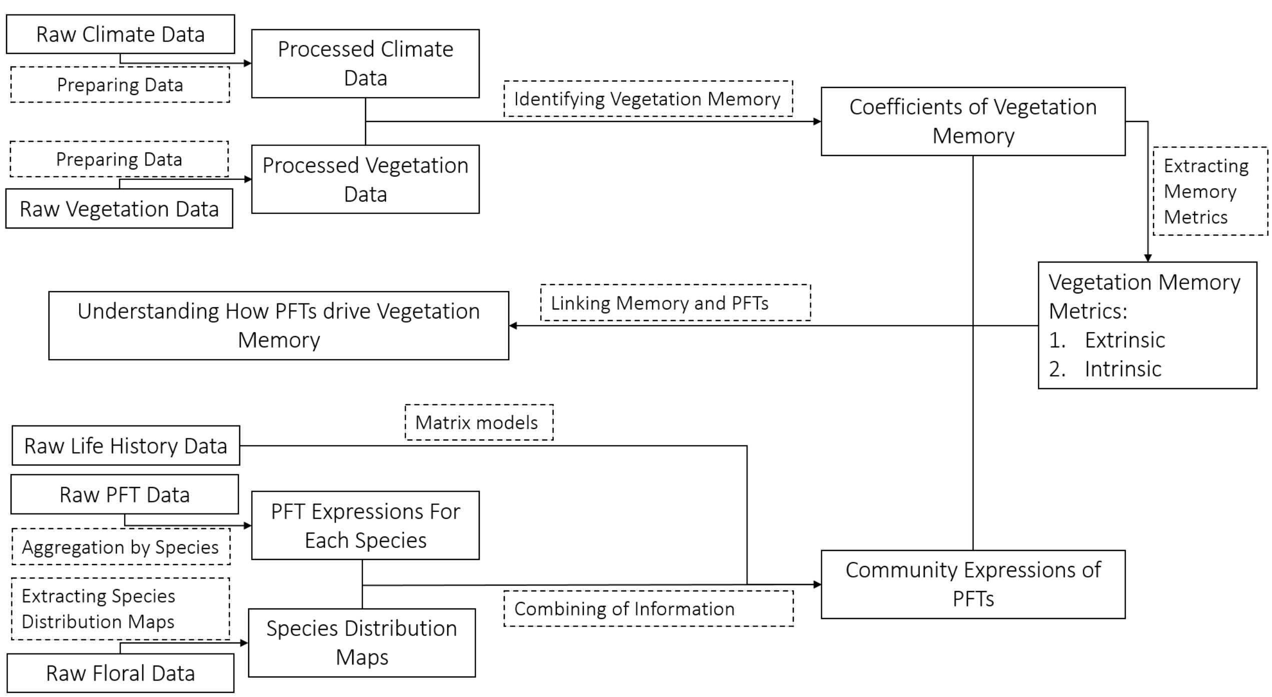


Figure 1.7: Study Outline - Conceptual study flow-chart. Data sets and products are shown in boxes with solid outlines whilst data handling and computational procedures are depicted via dashed-outline boxes.

2. Material & Methods

2.1 Study Regions

The spatial extent of study sites for assessing vegetation memory effects was limited to regions which were (1) suitable for remote sensing studies (i.e. receive satellite coverage year-round), (2) relatively well-sampled in terms of PFTs, LHTs and floral data, and (3) contain large areas classified as **drylands** (as classified via ombrotypes within Rivas-Martínez et al.[103]) which previous studies identified as regions of strong memory effects given autoregressive approaches. Within `R`, limiting to study regions is done using shapefiles (http://www.naturalearthdata.com/downloads/10m-cultural-vectors/) and the `rgdal`[104] package (see Chunk 3).

2.1.1 Iberian Region

The Iberian region - encompassing Portugal, Spain, Andorra and France within this study - has been selected as a study region due to a clear gradient in ombrotypes (see figure 2.1), its high density of TRY PFT and COMPADRE LHT data availability, and previously reportedly clear patterns of vegetation memory effects[43] and vegetation sensitivity[29]. See figures A.4 and A.5 for an overview of Global Inventory Modelling and Mapping Studies (GIMMS) NDVI, ERA5 data, and TRY PFT data (both raw and extrapolated) across the Iberian region.

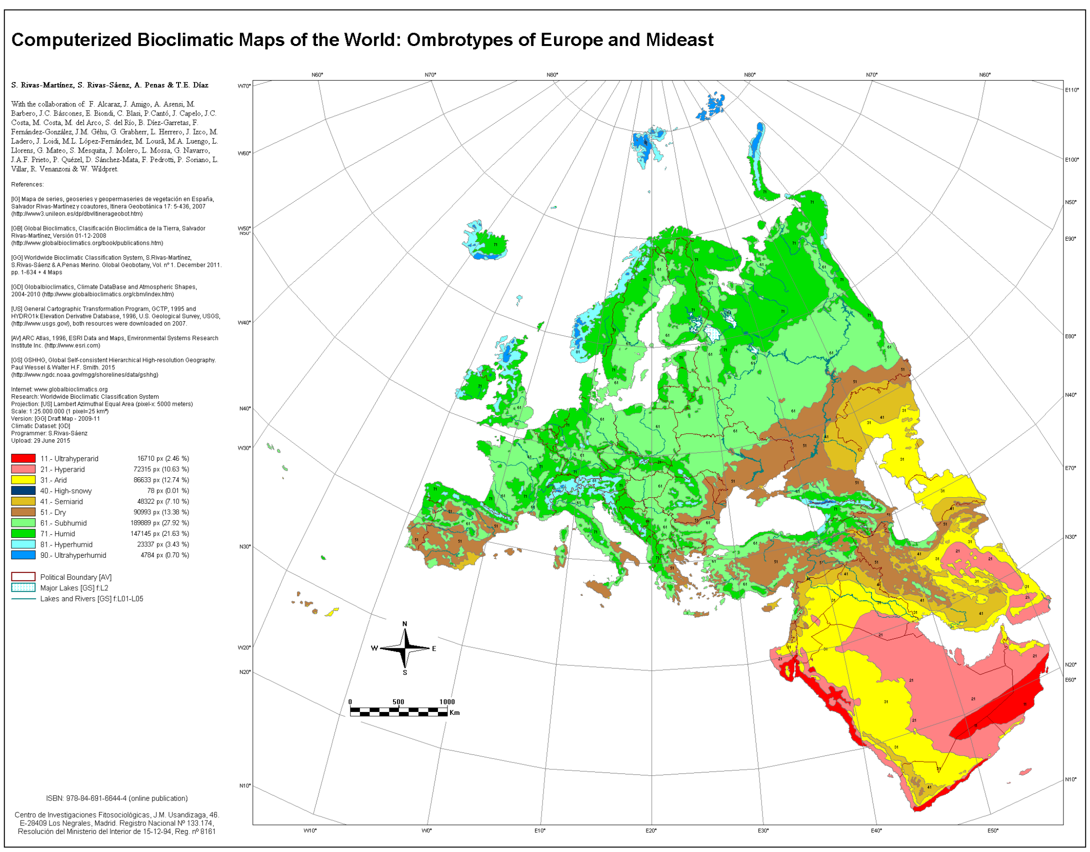


Figure 2.1: European Ombrotpyes - Regions of mean precipitation rates of biological relevance across Europe according to Rivas-Martínez et al.[103] and retrieved via the Worldwide Bioclimatic Classification System[105].

2.1.2 Caatinga, Brazil

The Caatinga in Brazil - a dryland region located within northeastern Brazil - has been selected as a study region due to a predominance in dry ombrotypes and gradients of ombrotypes at its edges (see figure 2.2) as well as previously identified strong vegetation memory effects [43]. Additionally, Seddon et al. identified strong vegetation sensitvity towards water availability across this region [29].

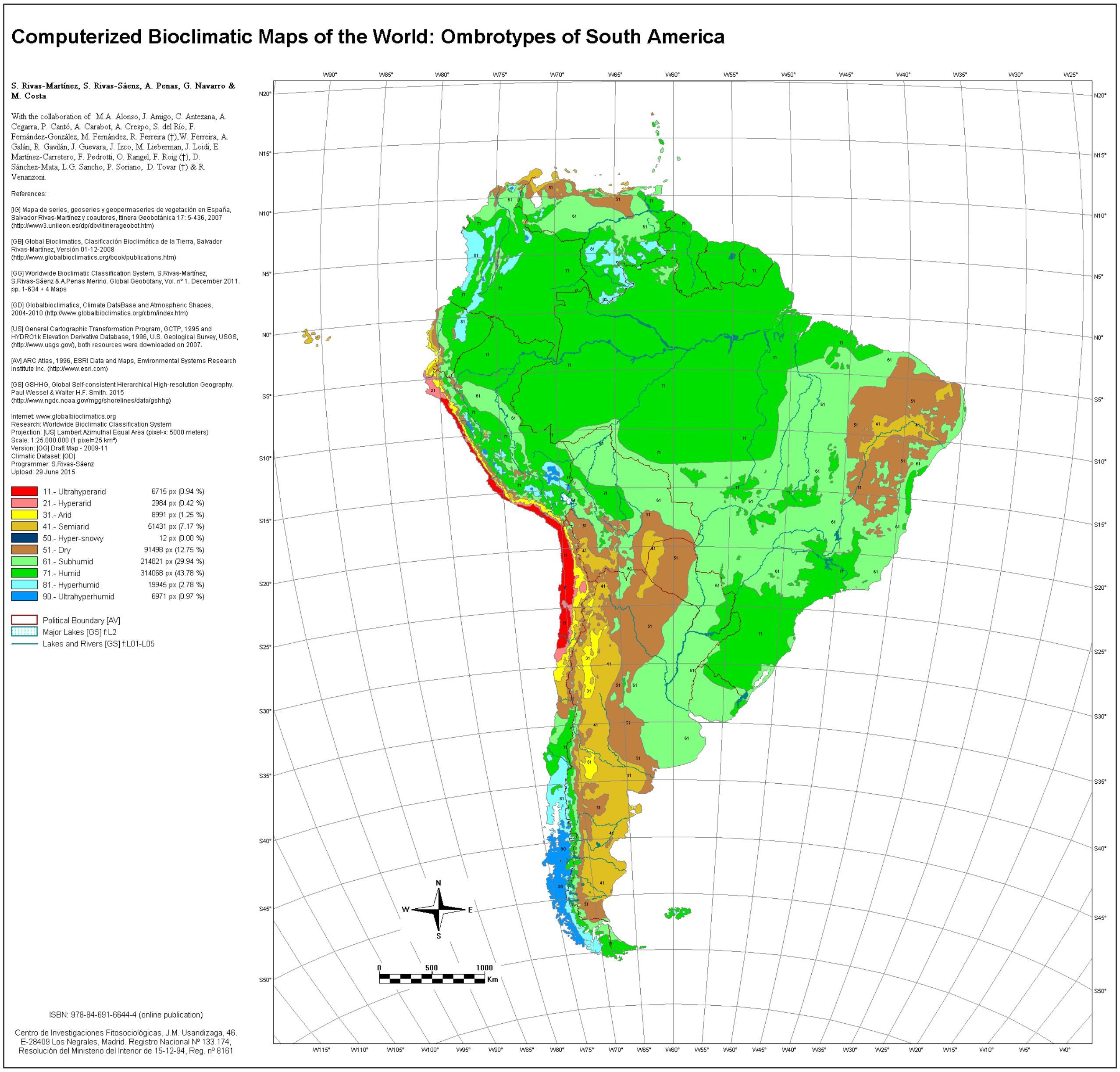


Figure 2.2: South-American Ombrotpyes - Regions of mean precipitation rates of biological relevance across South-America according to Rivas-Martínez et al. [103] and retrieved via the Worldwide Bioclimatic Classification System [106].

See figures A.6 and A.7 for an overview of GIMMS NDVI, ERA5 data, and TRY PFT data (both raw and extrapolated) across the Caatinga.

2.1.3 Australia

Australia has been selected as a study region due to a predominance in dry and even arid ombrotypes as well as gradients of ombrotypes on its eastern coast (see figure 2.3). Previous studies have identified clear patterns of vegetation memory across[43,56], vegetation sensitivity[29], and water memory length and strength[32].

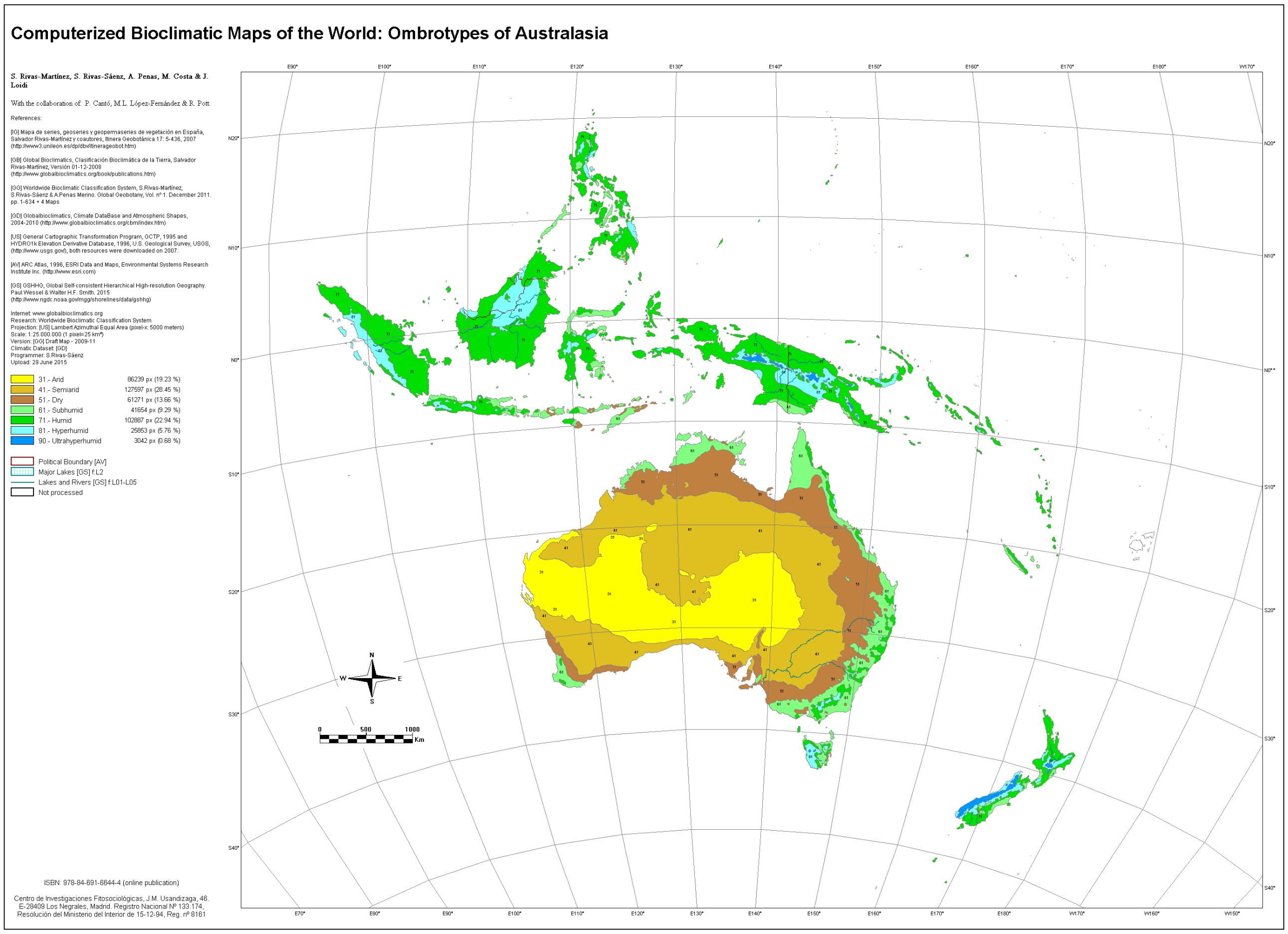


Figure 2.3: Australasian Ombrotpyes - Regions of mean precipitation rates of biological relevance across Australasia according to Rivas-Martínez et al.[103] and retrieved via the Worldwide Bioclimatic Classification System[107].

See figures A.8 and A.9 for an overview of GIMMS NDVI, ERA5 data, and TRY PFT data (both raw and extrapolated) across Australia.

2.2 Identifying Vegetation Memory

2.2.1 Data

2.2.1.1 Vegetation Indices

Patterns of vegetation characteristics - both in time and space - can be assessed readily using remote sensing approaches [29,56,108–112]. A Vegetation Index (VI) is a remote sensing proxy for different vegetation characteristics depending on the choice of VI. VIs have seen various applications in remote sensing including deriving vegetation dynamics on the scale of countries [113–115] or regions [111,116], and analysing resilience of vegetation assemblages to short-term climate anomalies [43]. Biome classifications have undoubtedly been one of the most prominent usages of the VIs [112,117–119] as have applications in agriculture [24,120].

Whilst a vast arsenal of VIs are available to macroecologists (see Cammarano et al. for an overview [111]), one of the main considerations in choosing an appropriate VI is that of **spatial resolution versus length of time series**. As satellite-born sensors receive hardware updates or other improvements - e.g. Advanced Very High Resolution Radiometer (AVHRR) versus Moderate-Resolution Imaging Spectroradiometer (MODIS) sensors - spatial resolution capabilities of VIs increase. However, we can't enhance the resolution of older records of VIs and are thus limited to lower resolution VIs if longer time series are desired. Since vegetation memory is a temporal phenomenon first and foremost, I have prioritised **time series length** over spatial resolution. Within the confines of my thesis, VIs represent the intrinsic characteristics of vegetation systems which will both be used as response and explanatory variables as outlined in figure 1.4.

Normalised Difference Vegetation Index (NDVI)

The NDVI has been selected as a proxy of vegetation characteristics in this study due to (1) its nature as an information criterion of biomass [121] and vegetation cover [111] (indicators of vegetation performance and composition), (2) the availability of a long time series data with global coverage [122], and (3) its demonstrated utility in various ecosystem studies [110] including assessments of vegetation sensitivity and memory [29,43,59]. See table 2.1 for an overview of the core characteristics of the NDVI data set.

Rouse et al. [123] first introduced the NDVI in 1974 and initially coined it 'Vegetation Index'. The NDVI is a composite VI that factors in measurements in the near infra-red wave band (NIR, 0.58-0.68 μm) and the red wave band (RED, 0.75-1.10 μm). These bands belong to the spectrum of light that is absorbed by chlorophyll and thus provide information on green vegetation [124]. The formula for NDVI is as follows [113,124]:

$$NDVI = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{RED}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{RED}}} \tag{2.1}$$

with ρ_{NIR} being the reflection in the NIR band (reflectance from vegetation) and ρ_{RED} being the reflection in the RED band (background/dead biomass reflectance). The NDVI is bound between 0 and 1 with higher values representing denser vegetation. For a more detailed mathematical background on the calculation of NDVI scores see Matsushita et al [125].

Table 2.1: Core Information about NDVI data - Characteristics of the GIMMS NDVI3g data set (v.1).

Characteristic	**Data**
Resolution	$0.083° \times 0.083° \sim 9.27km \times 9.27km$
Time Series	Bi-weekly intervals from January 1982 to December 2015
Source	https://ecocast.arc.nasa.gov/data/pub/gimms/3g.v1/

NDVI data sets are readily available via the GIMMS. For this study the GIMMS3g data set was used (available at https://ecocast.arc.nasa.gov/data/pub/gimms/3g.v1/), which provides AVHRR NDVI data as 15-day maximum-value composites from 1982 to 2015 at $0.083° \times 0.083°$ resolution[126]. The data was processed in `R`, downloaded and compiled into monthly composites using the raster[127] and `gimms` package[128]. See figure 2.4 for a representation of one such global monthly composite. Chunk 8 contains the `R`-code used to process the data.

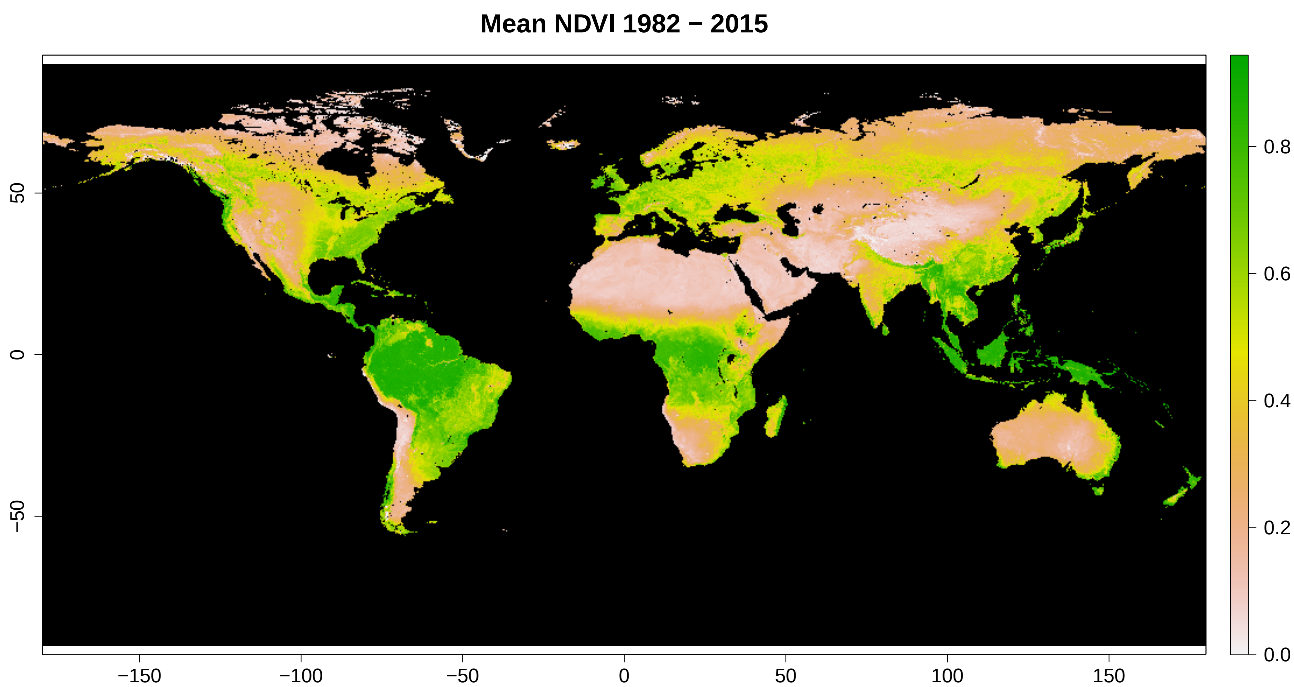


Figure 2.4: Global Representation of the Normalised Difference Vegetation Index (NDVI) - Mean of monthly maximum composite representations of NDVI from January 1982 to December 2015 at global coverage. Higher values of NDVI indicate higher vegetation coverage, plant biomass, and primary production. Figure established via Chunk 14.

2.2.1.2 European Centre for Medium-range Weather Forecasts ReAnalysis 5 (ERA5)

Extrinsic memory effects have largely been understood through processes of drought and water limitation [17,49,52,54,129]. Hence a large number of contemporary studies of vegetation memory have included some form of water availability proxy, through precipitation records [29,53], or drought indices [17,43,56]. Additionally, temperature has been found to be a major driver of drought severity, plant morphology, and vegetation memory effects [29,53,55]. ERA5 data is implemented into my analyses of vegetation memory using two environmental characteristics: (1) Soil Moisture (in four layers), and (2) Air Temperature (as observable at a height of 2m above the ground). See table 2.2 for an overview of core characteristics of the ERA5 data set. See Chunk 4, Chunk 5, and Chunk 6 for the codes used to download ERA5 data from the European Centre for Medium-range Weather Forecasts (ECMW) servers, aggregate data to full time series and fix gridding mismatches to be comparable to GIMMS data.

Table 2.2: Core Information about ERA5 data - Characteristics of the ERA5 data set.

Characteristic	**Data**
Resolution	$\sim 30km \times 30km$
Time Series	Hourly intervals from January 1950 to TODAY
Source	https://apps.ecmwf.int/data-catalogues/era5

Air Temperature recorded in K

Temperature indices have been linked successfully to vegetation sensitivity [29], tree-ring growth [55,130], global primary production [109], as well as severe drought events with possibly devastating consequences to local vegetation [4]. ERA5 recognises several temperature variables (e.g. soil, snow and air temperature) [65]. Within this study, I use Air Temperature (0-2m) (Tair) as contained within the ERA5 data set, due to the demonstrated impact of Tair on different aspects of plant physiology and plant morphology which may manifest in vegetation memory effects. See figure 2.5 for an overview of the ERA5 Tair data.

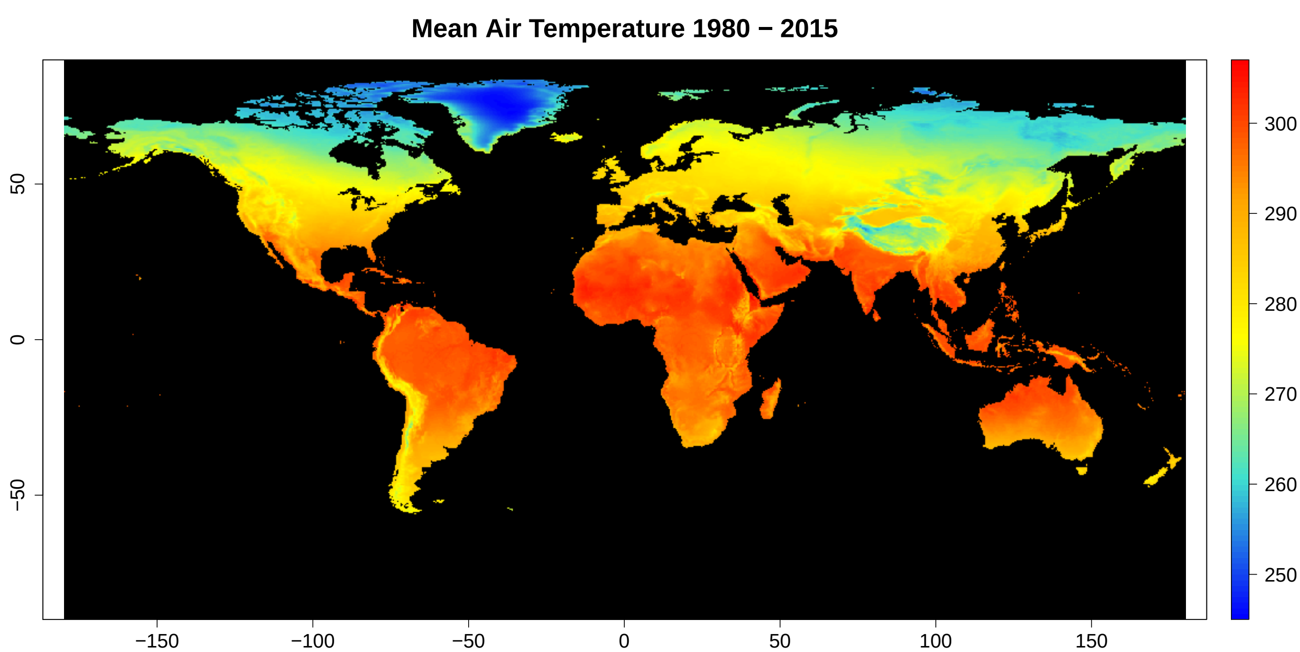


Figure 2.5: Overview of air temperature data - Air temperature data presented in as obtainable via the ERA5 reanalysis product (Tair). Figure established via Chunk 16.

Soil Moisture recorded in $\frac{m^3_{H_2O}}{m^3_{soil}}$

My study uses *Soil Moisture (Qsoil)* as a proxy of local water regimes. Precipitation events are subject to further soil processes such as pore connectivity for precipitation water to be available to plants[131]. Soil moisture should thus serve as a much more direct proxy of local water regimes. Additionally, ERA5 includes four distinct layers in the soil for the calculation of Qsoil indices (see figure 2.6 for an overview): (1) Soil Moisture (0-7cm) (Qsoil1), (2) Soil Moisture (7-28cm) (Qsoil2), (3) Soil Moisture (28-100cm) (Qsoil3), and (4) Soil Moisture (100-255cm) (Qsoil4). Typical drought indices (i.e. SPEI) do not allow for this additional distinction.

Within ERA5, unfrozen ground water (θ) across all four soil layers (k) is defined as:

$$\overline{\theta} = \sum_{k=1}^{4}(R_k * max[f_{liq;k}\theta_k, \theta_{pwp}]) \tag{2.2}$$

with R_k being the root fraction of soil layer k which is a fixed metric according to Land-Cover Classification Systems (LCCSs), and the statement $max[f_{liq;k}\theta_k, \theta_{pwp}]$ calculating the amount of unfrozen soil water in soil layer k. $f_{liq;k}$ is a parametrised function of soil temperature; θ_{pwp} denotes the permanent wilting point according to soil texture. For a more in-depth explanation of how Qsoil is calculated within ERA5, see the IFS Documentation CY45R1 Chapter 4 *Physical Processes*[65].

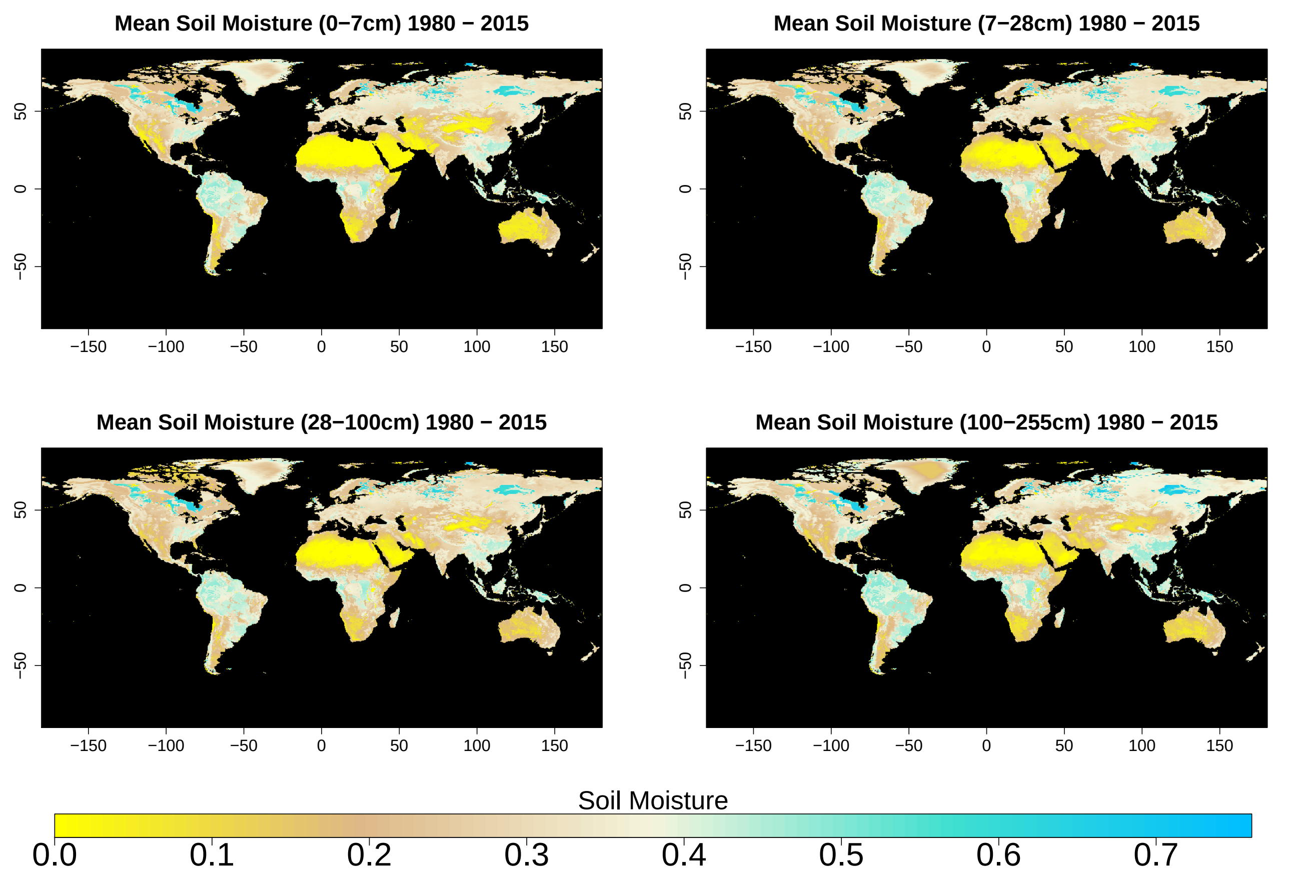


Figure 2.6: Overview of soil moisture data - Soil moisture data presented in layers as obtainable via the ERA5 reanalysis product (Tair, Qsoil1, Qsoil2, Qsoil3, Qsoil4). Figure established via Chunk 15.

2.2.1.3 Digital Elevation Models

Digital Elevation Model (DEM) data preparation as outlined in section 2.2.2.1 To this end, I am using DEM data obtained via the Harmonized World Soil Database (HWSD) which contains different DEM outputs at 3 and 30 arc-second resolution [132,133]. See table 2.3 for an overview of HWSD DEM data characteristics. For an overview of all variables from the HWSD used within this study see table A.2. See figure 2.7 for a global representation of HWSD DEM data and figure A.2 and A.3 for an overview of HWSD slope aspect and incline data respectively as described in table A.2. These haven been rescaled to match GIMMS resolution (see table 2.1).

Table 2.3: Core Information about HWSD data - Characteristics of the HWSD data set.

Characteristic	Data
Resolution	$3arc \times 3arc \sim 31m \times 31m$
Source	http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/ harmonized-world-soil-database-v12/en/

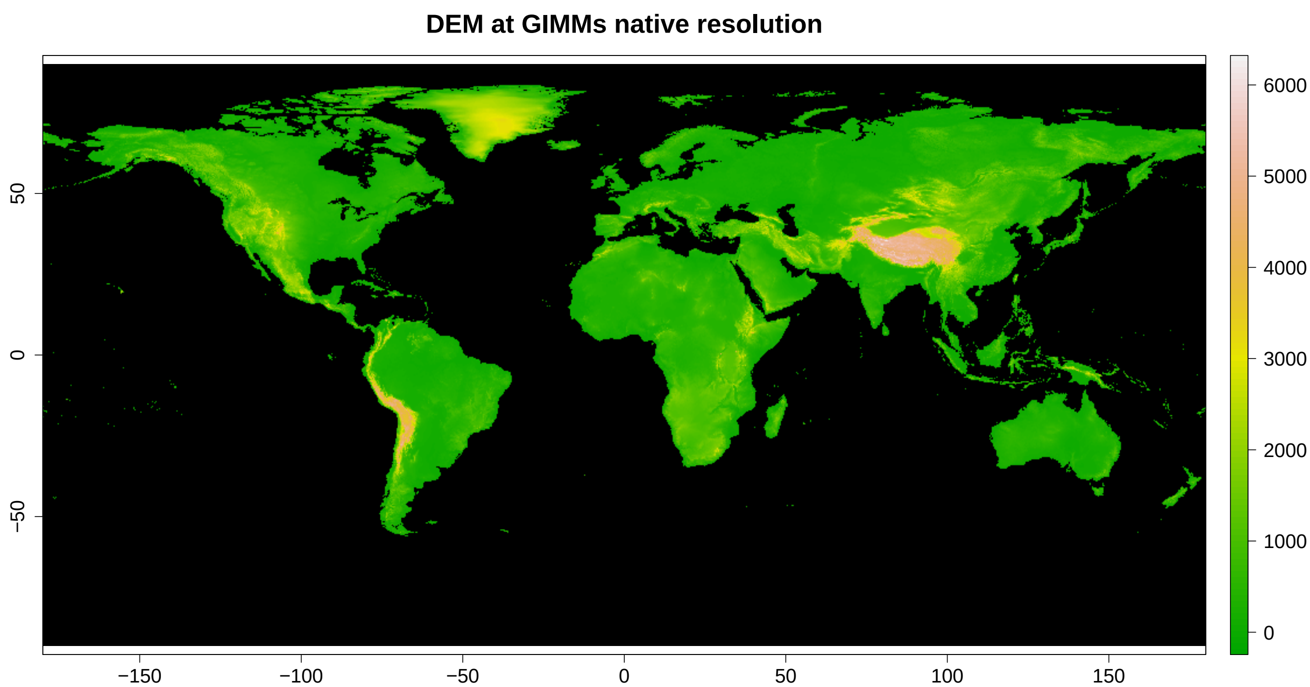


Figure 2.7: DEM elevation data - HWSD elevation data at GIMMS resolution. Figure established via Chunk 17.

2.2.2 Analyses

2.2.2.1 Data Preparation

Monthly Maximum Composites

After retrieving GIMMS NDVI 3g data using the `gimms` package in `R`, bi-weekly NDVI data is aggregated to monthly composites using the *maximum composite* method (see Chunk 8). Doing so is a method for removing data uncertainty due to atmospheric interference which has seen application in recent remote-sensing-based studies of vegetation memory and resilience[17,59,129].

Downscaling

In order to calculate vegetation memory effects (**first research goal**), vegetation data and abiotic data should be represented at the same spatial and temporal resolution. Whilst both NDVI and ERA5 data are available at monthly intervals (after pre-processing as already described), their spatial resolutions differ (e.g. $\sim 9.27km\times \sim 9.27km$, vs. $30km \times 30km$, respectively; see tables 2.1 and 2.2).

There are two ways of remedying this spatial mismatch: (1) aggregating GIMMS data to coarser resolution of ERA5 data, or (2) downscaling of ERA5 data to GIMMS resolution. Whilst aggregating data to coarser resolutions is much easier and less computationally expensive, I have opted to apply **downscaling** to the ERA5 data used within my study so as to retain valuable information within the GIMMS NDVI 3g data set. This will allow more precise vegetation memory identification and result in more biologically relevant patterns of vegetation memory characteristics.

A large host of downscaling methods is available and before choosing any method one has to settle on whether to perform *statistical* or *dynamic* downscaling[60,134]:

1. *Statistical Downscaling* is centred around statistical links between global and local climate patterns[135], comparatively computationally cheap and easily transferable to different study regions but suffers from a strong dependency on the choice of predictors/co-variates[136].
2. *Dynamic Downscaling* is built around regional climate models being implemented into global climate models[135], produces results based on physically consistent processes but computationally expensive[136].

This study is focussed on three study regions (i.e. the Iberian Region, the Caatinga, and Australia) and five ERA5 variables (Tair, Qsoil1, Qsoil2, Qsoil3, and Qsoil4) in monthly intervals from 1981 to 2015. ERA5 data from 1981 is being downscaled to match GIMMS resolution to calculate cumulative lags of memory effect drivers (see section 2.2.2.2). With this, downscaling needs to be performed three times (study regions), for five variables, each with 420 individual time steps (twelve months per year times 35 years). In total, the downscaling process is thus required to be run 6,300 times. Using a computationally expensive method belonging to the group of dynamical downscaling approaches is thus undesireable and I have elected to employ a **statistical downscaling** method to match ERA5 data with GIMMS resolution.

More specifically, I am using **Kriging** - a method that is well-understood and has long been used in non-biological sciences for geostatistical interpolation purposes[137]. Kriging is a two-step process. First, one establishes statistical relationships between data which is to be kriged at its native resolution with covariate data at the same resolution. The second step sees the extrapolation of these relationships using target resolution covariate data. The way in which Kriging improves over other statistical downscaling methods centred around these two steps lies in the fact that the Kriging methodology not only *extrapolates* relationships but *residuals* as well (see figure 2.8 for a visual representation).

Therefore, Kriging within my analyses requires three inputs: (1) ERA5 data at native resolution, (2) HWSD covariates (see table A.2) at ERA5 resolution, and (3) HWSD covariates (see table A.2) at GIMMS resolution to produce sets of ERA5 data at GIMMS resolution. Kriging operations are built around formulae which establish response and predictor relationships. My kriging approaches are specified as follows:

$$Var_{ERA5} = \alpha + \sum_{i=1}^{14}(\beta_i * Cov_{HWSD;i}) \tag{2.3}$$

with Var_{ERA5} identifying any of the five ERA5 variables Tair, Qsoil1, Qsoil2, Qsoil3, or Qsoil4 at any given monthly interval between January 1981 and December 2015. $Cov_{HWSD;i}$ indexes the i^{th} HWSD covariate ranging from elevation and slope aspects to slope incline levels. Due to computational expense the kriging procedure only considers interaction effects between slope incline levels and slope aspects (see Chunk 9).

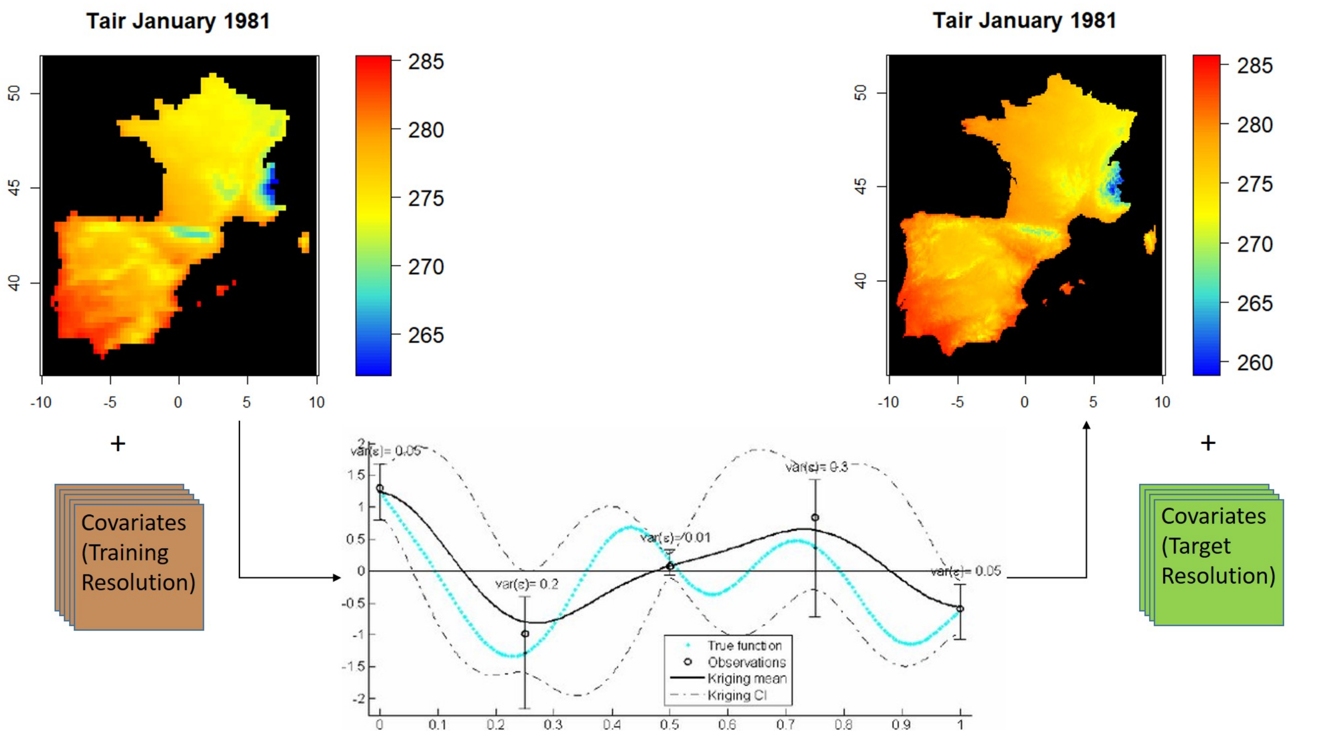


Figure 2.8: Kriging Concept - Statistical downscaling effects of Tair for the time step of January 1981 using HWSD covariate data across the Iberian Region. Diagram source: Le Riche et al., 2012 [138]. Some parts of this figure have been generated via Chunk 37.

For an in-depth mathematical explanation of the Kriging methodology, see Hengl, 2011 [137]. A practical example of its use can be retrieved in Lichtenstern, 2013 [139].

2.2.2.2 Memory Models

1. *Vegetation Memory Coefficients* to identify intrinsic/extrinsic forcing factors answering *research question I.1*.
2. *Model Comparisons* and *Variance Partitioning* to assess relative importance of different factors answering *research question I.1* and *I.2*.

Vegetation Memory Coefficients

The vegetation memory analyses in this study have been informed heavily by DeKeersmaecker et al [43]. Vegetation memory models of this study are built upon the following basic specification:

$$NDVI_t = \beta_{t-1} * NDVI_{[t-1]} + \beta_{Qsoil} * Qsoil_{k;m} + \beta_{Tair} * Tair_t \tag{2.4}$$

with $NDVI_t$ and the Autoregressive NDVI Coefficient ($NDVI_{[t-1]}$) being standardised NDVI anomalies at time step t and $t-1$, respectively; $Qsoil_{k;m}$ denoting Qsoil data at depth level k (translating to Qsoil1- Qsoil4) and cumulative lag of standardised anomalies of lag m, and $Tair_t$ denoting Tair data at time t. See table 2.4 for an interpretation of the model coefficients. The duality of memory effects as *intrinsic* and *extrinsic* as proposed by Ogle et al. [51] is embraced as follows:

1. **Intrinsic Memory** is identified as coefficients of $NDVI_{[t-1]}$ [17,43] (see model formula 2.4).
2. **Extrinsic Memory** are implemented via ERA5 data. See section 2.2.1.2 for the rationale behind the inclusion of the different variables and model formula 2.4 for how they are included in vegetation memory models.
   (a) *Tair* is implemented as an *instantaneous* effect on plant performance.
   (b) *Qsoil1- Qsoil4* effects are implemented as *cumulative lag* effects ranging from instantaneous impacts to lags on annual time windows [59].

Table 2.4: Interpretation of Memory Model Coefficients - Biological Interpretation of Vegetation Memory Coefficients as portrayed in model formula 2.4.

Coefficient	Magnitude	Sign
$\beta_{\mathbf{t-1}}$	Absolute values depict the speed at which systems return to equilibrium/pre-disturbance state. Large absolute values indicate low resilience (i.e. slow return).	*Positive* - NDVI anomalies resemble previous ones. NDVI anomalies gradually diminish over time. *Negative* - NDVI anomalies resemble previous ones, but with the opposite sign. The return to pre-disturbance is characterised through oscillations.
$\beta_{\mathbf{Qsoil}}$	Absolute values depict the resistance to anomalies in Qsoil. Large absolute values indicate low resistance (i.e. strong vegetation responses) to Qsoil anomalies.	*Positive* - Wetter soil conditions than average induce positive NDVI anomalies; drier soil conditions than average induce negative NDVI anomalies. *Negative* - Drier soil conditions than average induce positive NDVI anomalies; wetter soil conditions than average induce negative NDVI anomalies.
$\beta_{\mathbf{Tair}}$	Absolute values depict the resistance to anomalies in air temperature. Large absolute values indicate low resistance (i.e. strong vegetation responses) to air temperature anomalies.	*Positive* - Warmer air temperature than average induces positive NDVI anomalies; colder air temperature than average induces negative NDVI anomalies. *Negative* - Colder air temperature than average induces positive NDVI anomalies; warmer air temperature than average induces negative NDVI anomalies.

Additionally, $\beta_{\mathbf{t-1}}$ is indicative of *intrinsic vegetation memory* [43].

The coefficients of the above drivers of vegetation memory (see table 2.4 and formula 2.4) are identified for each data pixel in the data rasters of the three study regions in four separate models (one for each Qsoil layer). A visual representation of the automated modelling approach used within this study can be seen in figure 2.9. This approach is carried out for each pixel as follows using the code contained within Chunk 10:

1. Data for each variable (NDVI, Tair, Qsoil) is **extracted and detrended** to avoid effects of changing abiotic conditions over long time-series[43] using linear detrending with the pracma package in R.

2. Detrended data is **standardised to Z-Scores** to obtain deviations of monthly means/monthly anomalies for each variable[43]:
$$Anomaly_i = \frac{Detrended_i - \overline{Detrended_{month}}}{SD_{Detrended,month}} \tag{2.5}$$
with i indexing individual, detrended data records. In the case of NDVI, one additionally calculates monthly means of untreated NDVI data across the entire data range. See figure 2.10 for an examplatory overview of NDVI data treatment.

3. Calculation of **lagged effects**:
   (a) $NDVI_{[t-1]}$ is calculated from Z-Score NDVI data.
   (b) Cumulative lags of Qsoil data are established for lags ranging from 0 (instantaneous effects) to annual effects (aggregated over twelve months of detrended Qsoil records) in steps on one month at a time. These lagged effects are subsequently standardised to Z-Scores. See figure 2.11 for an examplatory overview of Qsoil data treatment.
   (c) Tair data is implemented as instantaneous effects and so no lagged effects have to be calculated.

4. Variables in nature are often collinear[85,140]. Failing to address this issue results in masking of information which might influence our understanding of processes in nature significantly[141]. One method of circumventing this issue lies with *PCA*. More specifically, if regression modelling is the target, one may wish to employ **PCA regression** as a three-step process[141] for each of the cumulative Qsoil lags across all four Qsoil layers effectively adding the necessity for a model selection step:
   (a) Z-Score data for NDVI, Tair, and Qsoil are fed to PCA via the vegan package in R. See figure 2.12 for an examplatory overview of data and a PCA result.
   (b) Regression is performed as follows:
$$NDVI_t = \beta_1 * PC_1 + \beta_2 * PC2 + \beta_3 * PC3 \tag{2.6}$$
   with $NDVI_t$ representing NDVI anomalies which have been set to NA (skipped in models) in months for which $Thresholds_i < 0.1$ with $Thresholds_i = \overline{Raw_{NDVI,month}}$[17]. PC_1 through PC_3 and β_1 through β_3 indicate principal components 1 through 3 and coefficients of their effects in the model respectively.
   (c) Model selection is performed to identify the cumulative soil lag which presents the most explanatory power through comparison of model Akaike Information Criterion (AIC) values. The model with the AIC closest to 0 is said to be performing the best[142]. This results in a proxy of Qsoil memory length of local vegetation.
   (d) The regression coefficients β_1 through β_3 can be back-transformed to represent PCA input variable effects (see formula 2.4) using PCA loadings and PCA model coefficients (see figure 2.13).

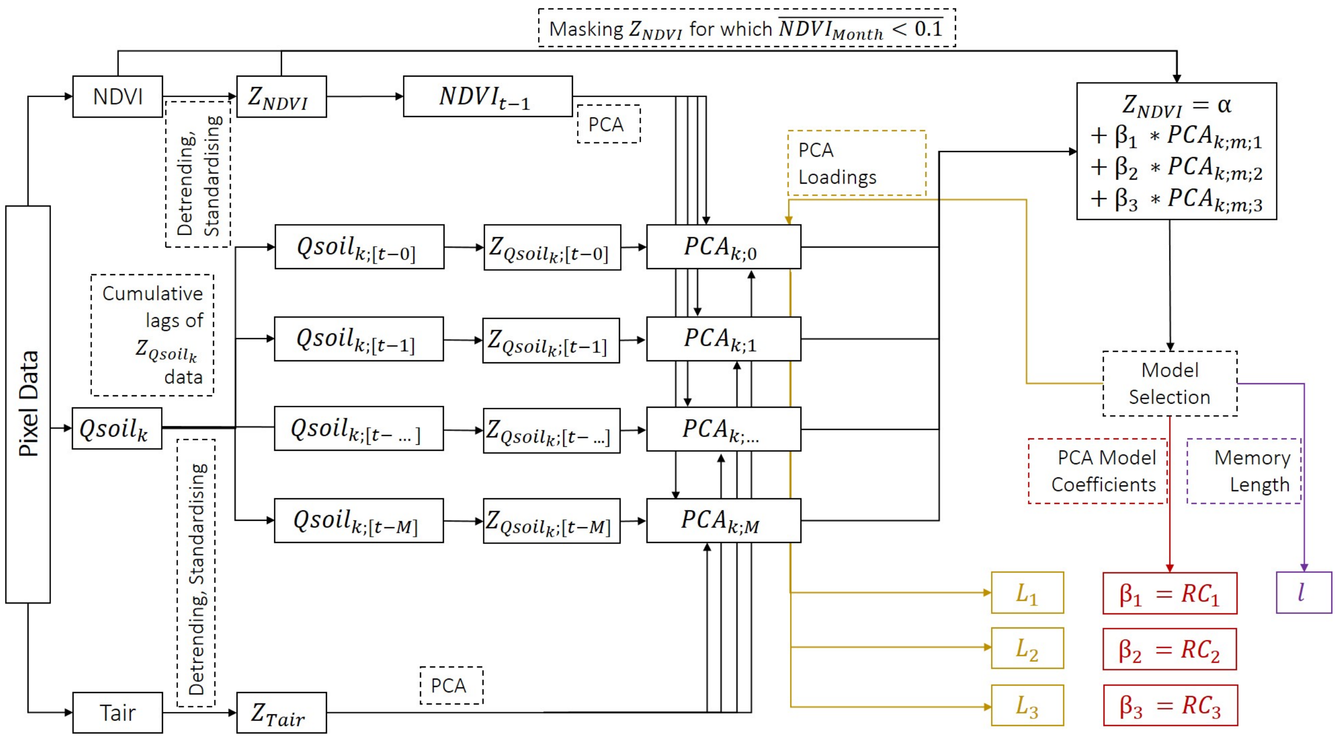
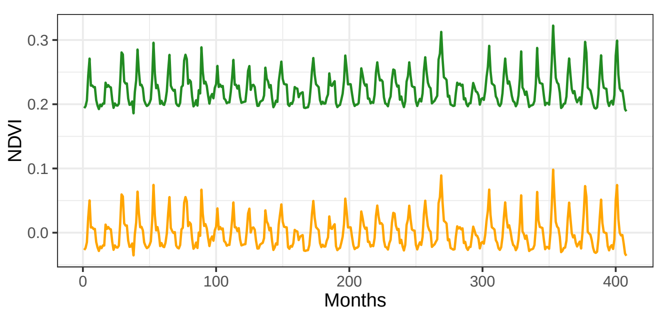
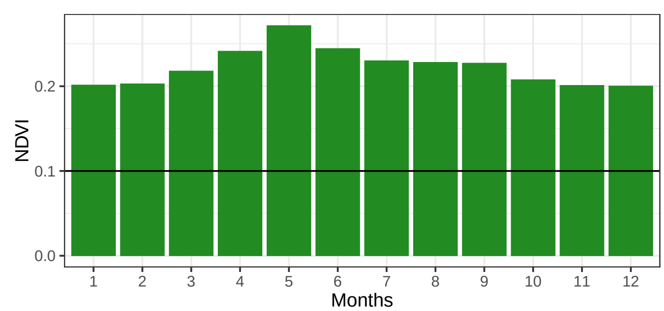


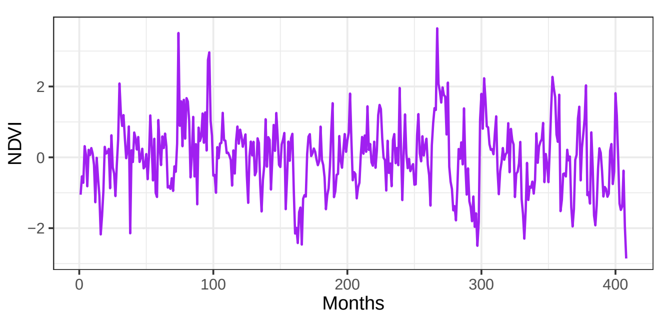
Figure 2.9: Vegetation Memory Model Flowchart - Visual workflow of pixel-wise iterated vegetation memory model. m denotes the currently considered cumulative lag of Qsoil data with M being the maximum cumulative lag. Qsoil layers Qsoil1- Qsoil4 are identified via k. L_1 through L_3 are the loadings of each detrended and standardised variable (NDVI, Tair, and Qsoil) onto the principal components 1 through 3, respectively. PCA model coefficients are identified as β_1 through β_3. l denotes the cumulative Qsoil lag offering the most explanatory power in terms of AIC values of PCA regression models and is thus a proxy for vegetation memory in terms of Qsoil.



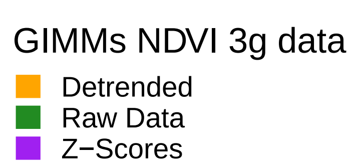
(a) NDVI Time-Series (Untreated and Detrended)



(b) Monthly Means of Untreated NDVI Data with 0.1 Threshold

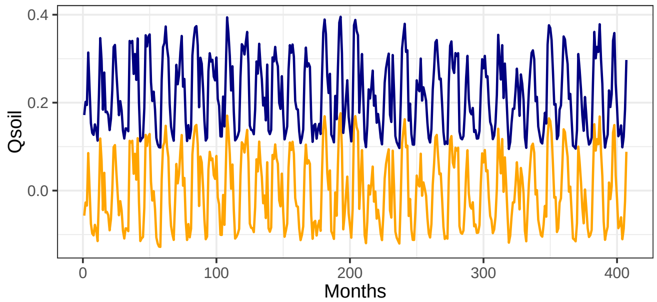


(c) Standardised Detrended NDVI Data (Z-Scores)

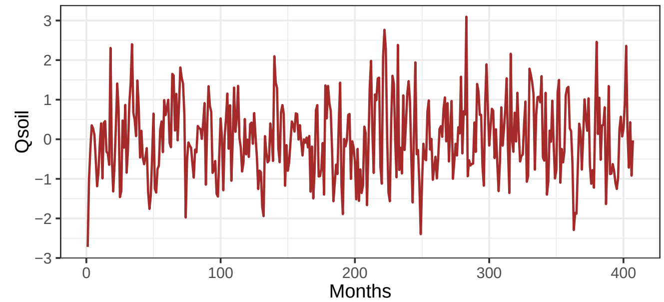


(d) Plotting Colour Reference

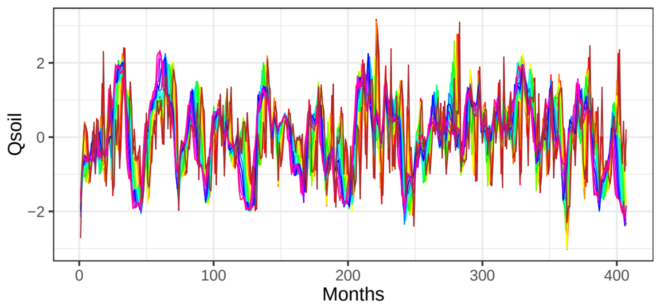
Figure 2.10: Memory Model NDVI Data Treatment - Overview of NDVI data treatment as outlined in figure 2.9 and explained above. The data presented here represents a single pixel in the Iberian dryland region (see figure 2.12). Figure established via Chunk 22.



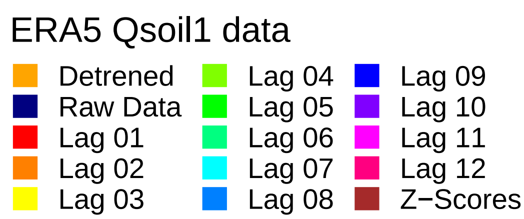
(a) Qsoil1 Time-Series (Untreated and Detrended)



(b) Standardised Detrended Qsoil1 Data (Z-Scores)



(c) Cummulative Qsoil1 Lags



(d) Plotting Colour Reference

Figure 2.11: Memory Model Qsoil Data Treatment - Overview of Qsoil data treatment as outlined in figure 2.9 and explained above. Only Qsoil1 data is represented. The data presented here represents a single pixel in the Iberian dryland region (see figure 2.12). Figure established via Chunk 23.

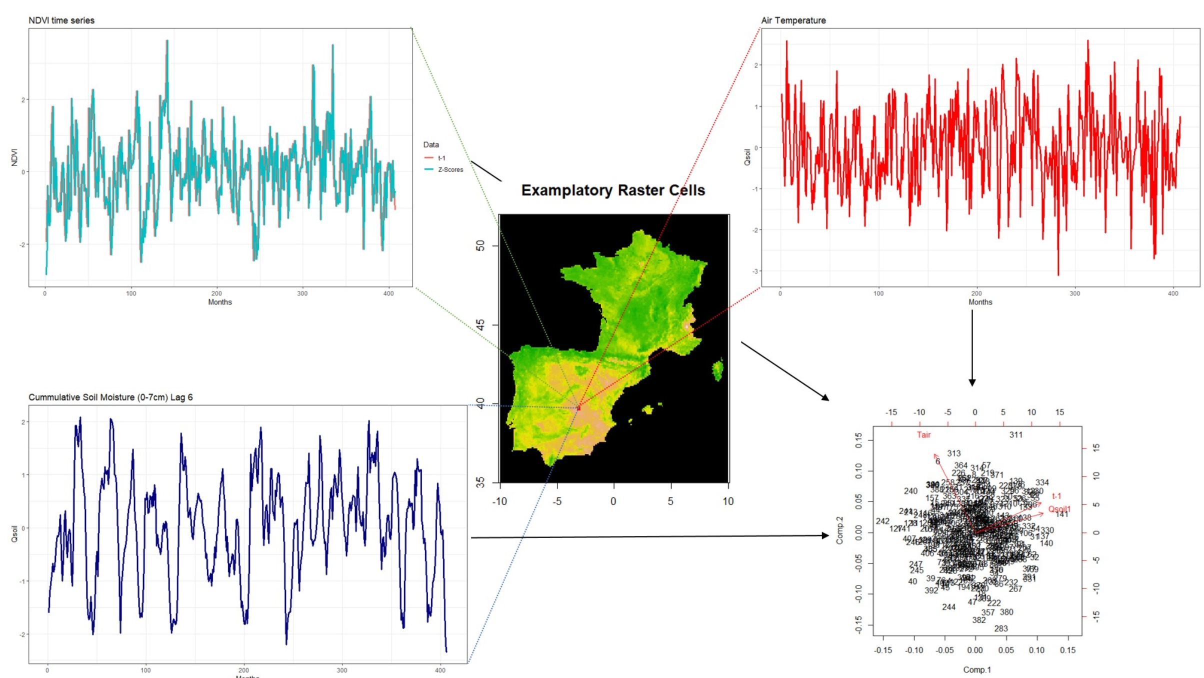


Figure 2.12: Examplatory Vegetation Memory PCA - Overview of Z-Score data for $NDVI_{[t-1]}$, $Qsoil_{1;6}$, and $Tair$ for a single pixel in the dryland region of the Iberian study region (red colouring on NDVI background in central plot) as well as their representation in a PCA. Also pictured: $NDVI_t$ Z-Scores required for PCA regression models (see figure 2.9 and 2.13). Some parts of this figure have been generated via Chunk 37.

Model Formula: $NDVI_t = PC_1 + PC_2 + PC_3$

$NDVI_t$ .... NDVI anomaly at month t
PC_1 .... First principal component
PC_2 .... Second principal component
PC_3 .... Third principal component

	PC1	PC2	PC3
$NDVI_{t-1}$	2.5	-1.14	1.95
$Qsoil_{1;6}$	2.6	-0.73	-2.03
$Tair$	-1.6	-3.00	-0.25
Model Coefficients	**1.77**	**-0.50**	**0.71**

Loadings

$$C_p = \sum_{i=1}^{3} (L_{p;i} * RC_i)$$

C_p .... Coefficient of variable p
i .... Principal component counter
$L_{p;i}$ .... Loading of variable p on principal component i
RC_i .... Model coefficient for principal component i

	PC1	PC2	PC3	Coefficient
$NDVI_{t-1}$	4.41	0.57	1.39	6.4
$Qsoil_{1;6}$	4.57	0.37	-1.45	4.7
$Tair$	-2.79	1.50	-0.18	-1.5

Σ

Figure 2.13: PCA Regression Coefficients - Theoretical back-calculation of regression coefficients from PCA regression coefficients as lined out by Zuur et al [141]. The data presented here (PCA loadings, PCA model coefficients, and final variable coefficients) represents a single pixel in the Iberian dryland region (see figure 2.12).

By following the vegetation memory modelling procedure outlined in figures 2.9 and 2.13 and explained above for each study region one obtains rasters containing the following information for each pixel:

1. **Vegetation Memory Coefficients** as established in formula 2.4 jused to identify meainingful drivers of vegetation memory (*research question I.1*).
2. **Vegetation Memory Length** in regards to Qsoil1, Qsoil2, Qsoil3, and Qsoil4 again being used to answer *research question I.1*.

Model Comparisons

Assessments of differences in relative importance of vegetation memory coefficients in individual models and between models serve to answer the following questions:

1. **Which model variable exerts the greatest influence on vegetation anomalies?** - To answer this question, I am comparing absolute values of variable coefficients across all pixels *within* each *model* individually, separately for each study region. Doing so serves to answer *research question I.1* and *I.2*.
2. **Which Qsoil layer is the most biologically influential?** - The answer to this question can be retrieved by comparing absolute values of Qsoil coefficients for all pixel per model *between* all four *models* for each study region which answers *research question I.1*.

Differences in absolute variable coefficient values within and between models has been assessed using Mann-Whitney-U Test (`wilcox.test(..., paired = FALSE)` in `R`). I have chosen the Mann-Whitney U-Test, since vegetation memory coefficient data cannot be expected to be normal distributed, nor to fall onto symmetrical distributions (hence, one should contrast median values rather than mean values). The code for these assessments can be retrieved in Chunk 10 (`CoeffScaling`).

Although allowing for region-wide generalisations, these assessments of statistical significance can not be used to identify or display spatial patterns of relative memory coefficient importance.

Variance Partitioning

Variance partitioning is a model-driven method of assessing relative importance of vegetation memory model variables. As opposed to Mann-Whitney U model comparisons, variance partitioning can be carried out for each pixel in my study region data rasters individually. This, in turn, results in the identification of patterns of relative model predictor importance.

It was my goal to assess the relative importance of intrinsic and extrinsic vegetation memory components (*research question I.2*). I have identified Qsoil layers to be of special interest in representing extrinsic vegetation memory (see section 3). Therefore, I am assessing the relative information contained in the vegetation memory model predictors $NDVI_{[t-1]}$ (intrinsic memory) and $Qsoil_{k;m}$ (extrinsic soil moisture memory of layer k and cumulative lag m).

Zuur et al. [141] present a method developed by Legendre & Legendre [143] for the purpose of variance partitioning between two explanatory variables. This approach (represented in figure 2.14) is carried out as follows:

1. Apply the full regression model $Z_{NDVI} = NDVI_{t-1} + Qsoil_{k;m}$ and obtain R^2 (the coefficient of determination). This is R^2_{Full} and equal to all explained variance. Unexplained variance can then be calculated as $1 - R^2_{Full}$
2. Obtain R^2 of $Z_{NDVI} = NDVI_{t-1}$. This is $R^2_{NDVI_{t-1}}$ and equal to all variance explained by $NDVI_{[t-1]}$.
3. Obtain R^2 of $Z_{NDVI} = Qsoil_{k;m}$. This is $R^2_{Qsoil_{k;m}}$ and equal to all variance explained by $Qsoil_{k;m}$.

The variance shared between $NDVI_{[t-1]}$ and $Qsoil_{k;m}$ - R^2_{Shared} can then be calculated as:

$$R^2_{Shared} = R^2_{NDVI_{t-1}} + R^2_{Qsoil_{k;m}} - R^2_{Full} \tag{2.7}$$

The pure information contained within $NDVI_{[t-1]}$ (R^2_{t-1}) and $Qsoil_{k;m}$ ($R^2_{k;m}$) can then be calculated as follows:

$$R^2_{t-1} = R^2_{NDVI_{t-1}} - R^2_{Shared} \tag{2.8}$$

$$R^2_{k;m} = R^2_{Qsoil_{k;m}} - R^2_{Shared} \tag{2.9}$$

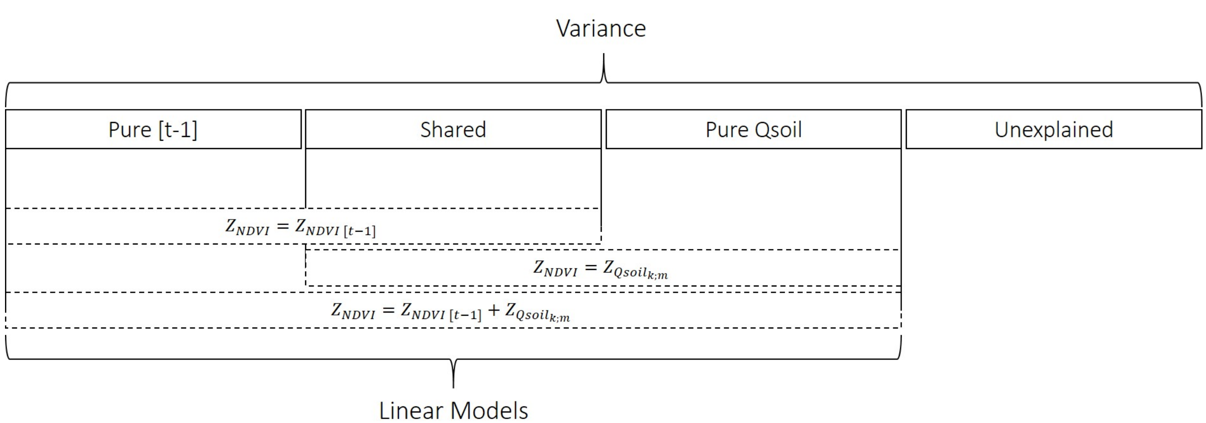


Figure 2.14: Variance Partitioning - Partitioning of variance in pure influence of $NDVI_{[t-1]}$ (Pure $[t-1]$), $Qsoil_{k;m}$ (Pure $Qsoil$, with k identifying the Qsoil layer, and m denoting the cumulative lag of Qsoil data), shared variance between the two (Shared), and residuals (Unexplained). The figure concept has been lifted from Zuur et al. [141] and adjusted to reflect the purpose of this study. Model specifications are contained within dashed boxes.

This form of variance partitioning is carried out for each pixel across all study regions and contained in the vegetation memory model output of Chunk 10 alongside PCA regression models.

2.2.2.3 Vegetation Memory Sensitivity

Following the notion of climate adaptation leading to altered disturbance-responses of local vegetation [49] I am assessing the relationship of vegetation memory characteristics and the mean value of their drivers across the entire time period from 1981 to 2015. This is done using linear regression and useful in answering *research question I.1*.

2.3 Functional Aspects of Vegetation Memory

2.3.1 Data

Contemporary studies of vegetation memory largely describe memory effects in terms of spatial patterns and effect sizes, but forego analyses of plant physiology or morphology to **explain causal pathways** leading to vegetation memory. Expressions of plant morphology and physiology are manifold and so one may wish to enlist multiple different proxies of these biological properties to rationalise vegetation memory effects.

2.3.1.1 COMPADRE

LHT information for plants and animals can be retrieved via COMPADRE; an extensive data base of different species and plot-scale ecosystems at different locations around the Earth [71]. COMPADRE is built around observational data and matrix models [144] which can be used to extract valuable information about temporal processes in biological communities [145,146]. The outputs of COMPADRE matrix models are manifold [73] offering access to a host of biologically relevant proxies of population processes.

For this study, I have selected the following COMPADRE outputs as the most likely to be related to vegetation memory characteristics alongside hypotheses of proposed relationships to vegetation memory:

1. The **Fast-Slow Continuum (FSC)**.
    (a) *FSC-1* - Species of fast life histories exert shorter/weaker vegetation memory.
    (b) *FSC-2* - Species of low reproductive output show longer/stronger vegetation memory.
2. **Reactivity** - Species of higher reactivity exert shorter/weaker vegetation memory.
3. ρ - Species of higher ρ exert shorter/weaker vegetation memory.
4. π - Species of higher π show shorter/weaker vegetation memory.

With COMPADRE, data for almost all variables contained within COMPADRE can be retrieved for all locations contained within the current release of the data base. Sampling effort for LHTs within the COMPADRE scheme can only cover a limited range of geological locations (hence I am not presenting a global data overview). The best sampled for regions on Earth - in terms of COMPADRE sites - are the Iberian Peninsula and the contiguous United States of America. To date, no mapping approach beyond the rasterising of plot-level data of COMPADRE LHTs has been proposed.

2.3.1.2 TRY

Here, I test the relationships between vegetation memory effects and two different PFTs which have been selected because they represent two important plant characteristics/trade-off axes in plant function (1) Vegetative Height, and (2) Leaf nitrogen content per leaf dry mass [82].

Additionally, these two PFTs correspond to two of the three PFT domains (i.e. stems and leaves) layed out in Westoby & Wright's PFT framework [83]. Examining PFTs of multiple aspects of plant function in the face of adverse events is especially important as plant performance levels during and after disturbances often incur responses of all aspects of individual plant functional domains [80].

TRY (and other PFT data bases) suffer from the same limitations as COMPADRE- sampling bias and effort [98]. Certain regions of the earth are well-sampled for PFTs (e.g. the Pyrenees) although these sampling schemes are often limited to plot-level sampling campaigns. This data limitation highlights the potential importance of a mapping approach as lined out in figure 1.6. The TRY data used for my thesis has been obtained via TRY on 07/08/2018.

2.3.1.3 Floral Data

Extrapolating PFT records from species-referenced records to spatial products using species-specific PFT means and species occurence records as layed out by Ordonoez & Svenning[81] (see figure 1.6) may prove to overcome the data limitations of TRY PFT data (see figures **??** and **??**).

Plant species occurence records can be obtained via floral data repositories such as GBIF (see figure 2.15 for a representation of GBIF plant occurence data). Data in GBIF are stored as geo-referenced records of species presence. Generating maps from geo-referenced data points can be achieved by aggregating data points to rasters of a desired extent and resolution (i.e. GIMMS resolution).

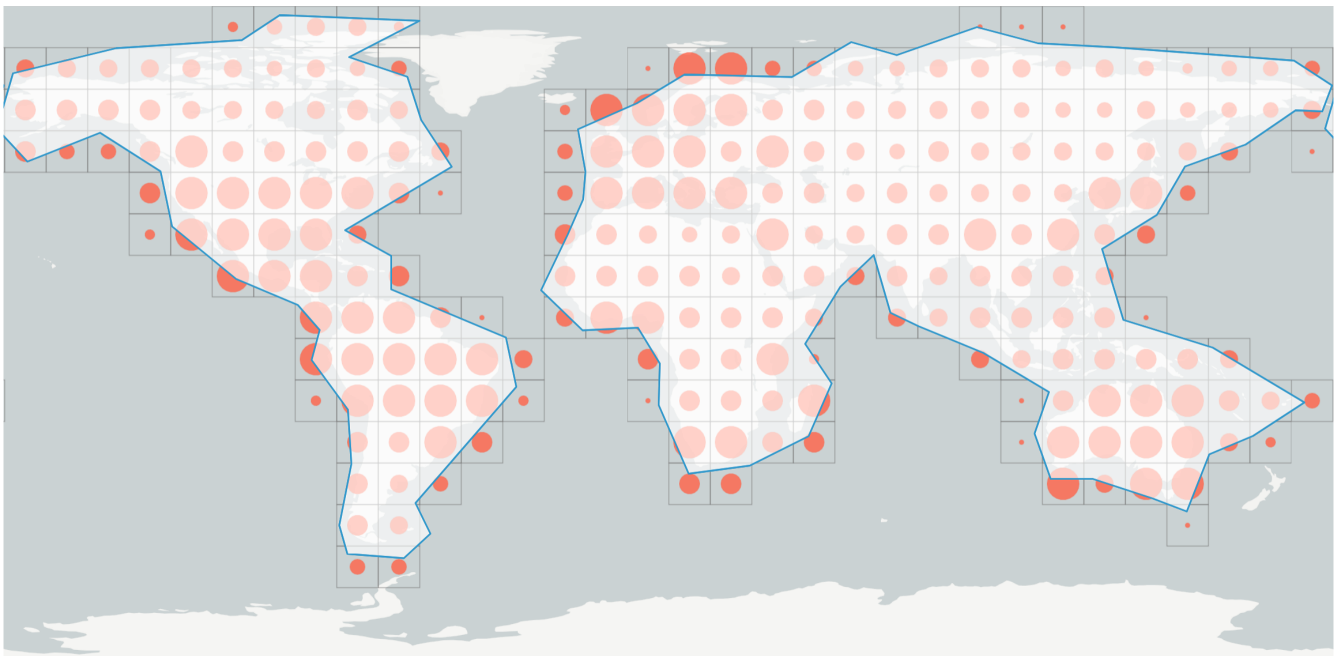


Figure 2.15: GBIF *Plantae* Occurrence Overview - Global representation of occurence records for species within the *plantae* kingdom available via GBIF[97] as of 21/04/19. Figure generated using the GBIF occurence data exploration tool[147] obtaining records from 1982 to 2015 (same as GIMMS data availability). Polygons have been drawn to omit occurence records of marine plantae species. Larger red plotting symbols indicate greater amounts of geo-referenced occurence records.

The floral data used within this study have been obtained for the time period of 1982 to 2015 (the same time span as the data availability for GIMMS NDVI data) via GBIF on 19/04/19 through to 21/04/19.

2.4 Analyses

2.4.1 Life History Traits

LHT data has been obtained via COMPADRE on 28/01/19 in geo-referenced table format and is used to achieve *research goal 2*.

Data Extraction

Target COMPADRE LHTs are extracted using Chunk 12 by aggregating geo-referenced LHT records to rasters of GIMMS resolution using a mean function for each study region.

Models

I use regression models to assess causal links between LHTs expressions (both raw and mean-extrapolated).

2.4.2 Plant Functional Traits

PFT data has been obtained via TRY on 07/08/18 in geo-referenced data table format and is used to achieve *research goal 2*.

Data Extraction

Vegetation memory characteristics are stored as raster data sets to retain spatial patterns of memory coefficients. Therefore, PFT data needs rasterising for comparability. PFT data is extracted and rasterised in two ways:

1. **Raw geo-referenced PFT records**. Geo-referenced TRY data points are aggregated to rasters of GIMMS resolution using a mean function (if multiple PFT records fall onto the same raster cell, the mean value of these is assigned to the cell). This results in rasters of low data-coverage but peer-reviewed data records.

2. **Species-specific mean PFT records**. These are extracted for each species within the TRY data set to enable PFT mapping as depicted in figure 1.6.

Data extraction of PFT records is handled via Chunk 11.

Data Mapping

Data mapping is carried out via Chunk 11 and extrapolates species-specific PFT mean values according to GBIF occurence data (see figure 1.6). Using the approach presented by Ordonez & Svenning [81], I am establishing rasters of mean PFT expressions by:

1. Assigning species-specific mean PFT values to all cells of individual species occurence according to GBIF.

2. Computing the mean PFT value for each cell in the rasters.

3. Removing all cells whose values exceed the upper 95% quantile of mean PFT records in these final mean rasters to remove outliers which may be due to sampling bias. The lower 5% quantile remains unaltered to retain grassland regions which are typical of dryland regions and characterised by low Vegetative Height (H) records.

This results in rasters of high data coverage but at a loss of data reliability.

Models

Like with LHTs, I use regression models to assess causal links between PFT expressions (both raw and mean-extrapolated).

3. Results

3.1 Identifying Vegetation Memory

3.1.1 Vegetation Memory Models

3.1.1.1 Iberian Region

I am only presenting Qsoil1 results here as I have identified Qsoil1 to be most informative Qsoil layer (see figure 3.2 and table 3.2). Results pertaining to Qsoil2, Qsoil3, and Qsoil4 can be found in figures A.10, A.11, and A.12 respectively. Additionally, patterns of $NDVI[t-1]$ and Tair coefficients do not change between different soil layer models and are thus reported on in figure 3.1.

Soil Moisture (0-7cm)

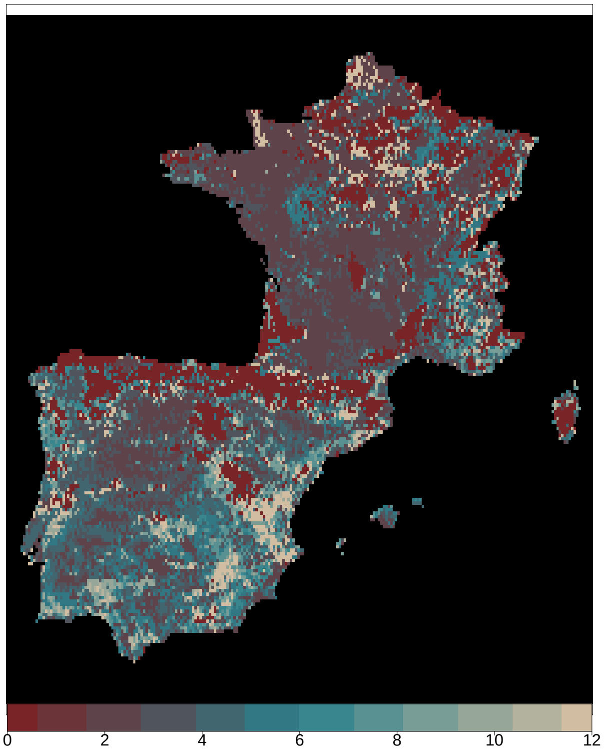
Vegetation memory coefficients of $NDVI_{[t-1]}$ and extrinsic memory (Tair and Qsoil1) across the Iberian region are represented in figure 3.1. Additionally, figure 3.1 depicts Qsoil1 memory length across the Iberian region. The memory patterns are as follows:

1. Qsoil1 memory length (identified as cumulative lags according to AIC values) exhibits low values (short memory) in the region of the Pyrenees with a noticeable shift towards slightly longer memory lengths when moving to dryland regions (particularly across Spain).
2. $NDVI_{[t-1]}$ memory follows the same pattern as presented by De Keersmaecker et al. [43] with strong, positive memory effects in the south of the Iberian region which diminish but remain positive towards the north.
3. Qsoil1 memory is predominantly positive in sign (with a notable exception of the Pyrenees). Especially strong Qsoil1 memory can be observed in the dryland regions of Spain and Portugal.
4. Tair memory falls onto a clear latitudinal gradient with positive memory effects in the north to negative memory effects of almost equal absolute values in the south. Additionally, there seems to be an altitudinal gradient with negative memory effects in the Pyrenees.

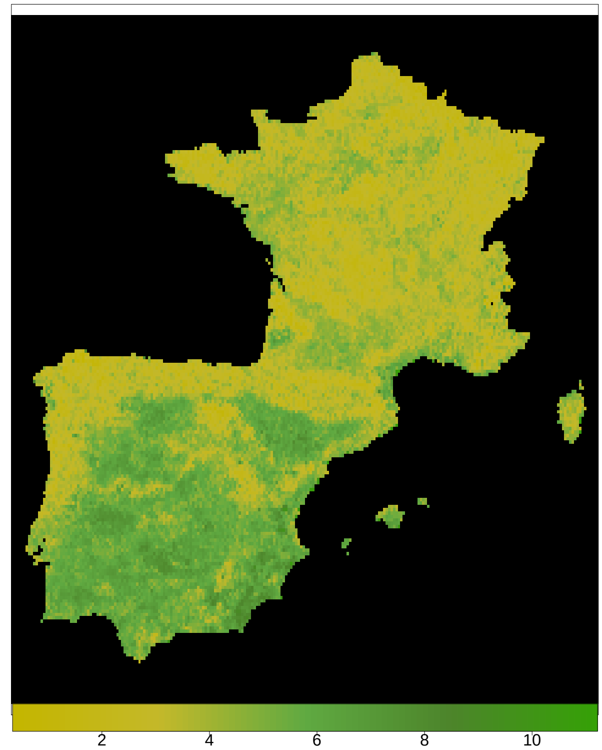
A hierarchy of vegetation memory strength has been established via median values of absolute vegetation memory coefficients. According to this analysis, $NDVI_{[t-1]}$ memory is stronger across the board than Qsoil1 memory which, in turn, is stronger than Tair memory. These differences have been assessed for statistical significance (see table 3.1). Again, only Qsoil1 results are presented here. The hierarchy of median vegetation memory coefficients remains unaltered when considering other Qsoil layers (see tables A.3, A.4, A.5).

Table 3.1: Mann-Whitney U-Test (Iberian Region, Qsoil1 Model) - Rownames represent median values of vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 25.

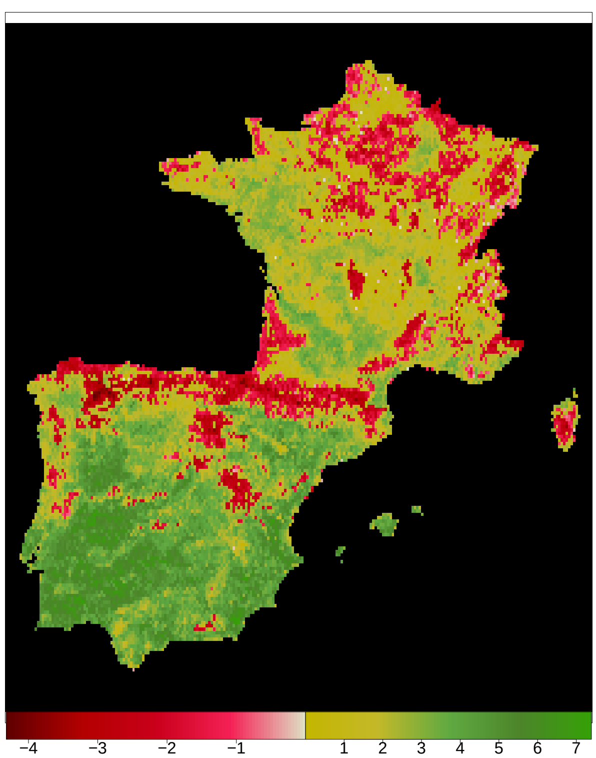
	NDVI [t-1]	Qsoil1	Tair
3.854	NA	2.58e+08	316643639
2.2284	0	NA	248234384
1.1915	0	0.00e+00	NA



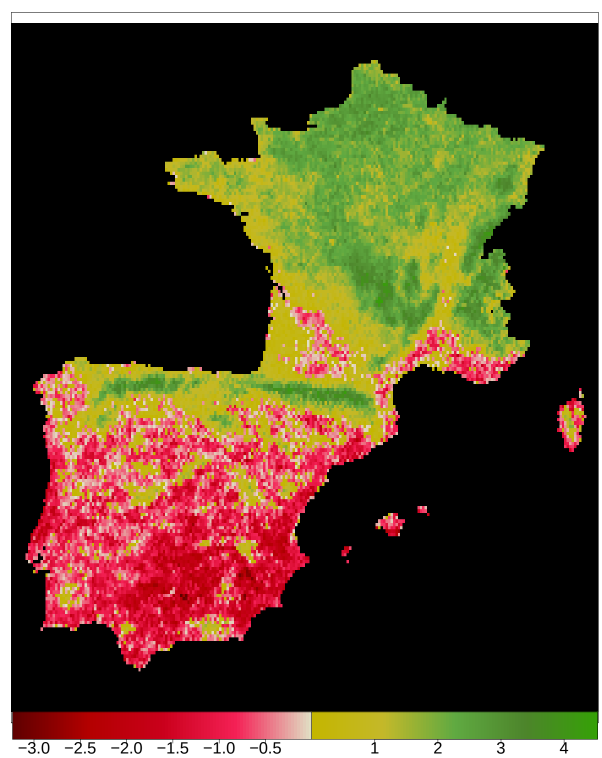
(a) SoilLag



(b) t-1



(c) Qsoil

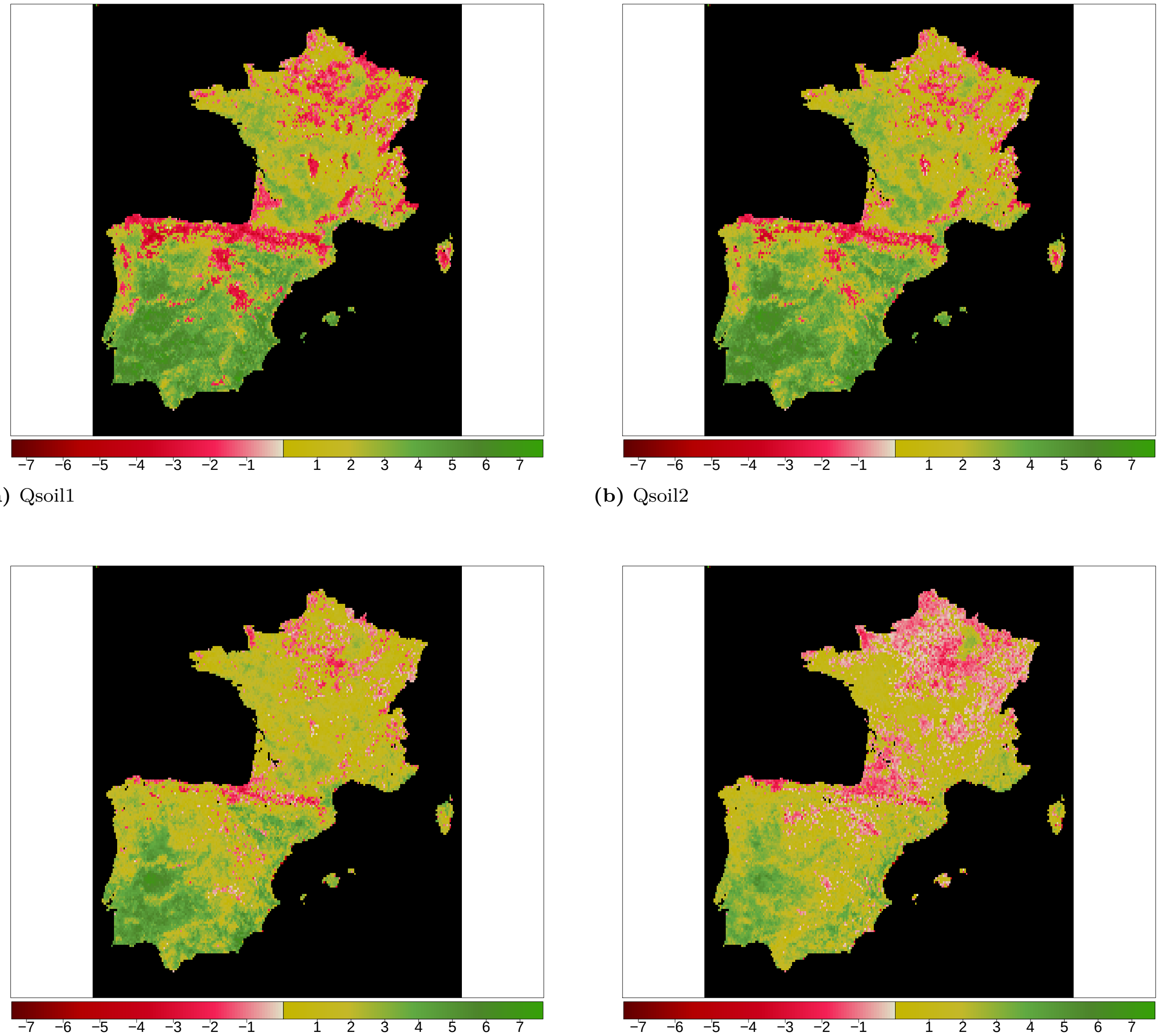


(d) Tair

Figure 3.1: Vegetation Memory Coefficients (Iberian Region; Qsoil1) - Coefficients of vegetation memory obtained via model selection (figure 2.9) and PCA regression (figure 2.13). For an interpretation of these coefficients, see table 2.4. Figure established via Chunk 24.

Soil Layer Comparison

As stated above Qsoil1 has been identified as the most informative Qsoil layer in terms of vegetation memory. This is due to the fact that patterns of Qsoil memory stay consistent across Qsoil layers (see figure 3.2) and Qsoil1 coefficients being larger than coefficients of other Qsoil layers at statistical significance (see table 3.2).



(a) Qsoil1 **(b)** Qsoil2 **(c)** Qsoil3 **(d)** Qsoil4

Figure 3.2: Vegetation Memory Coefficients (Iberian Region, QSoil Layers) - Vegetation memory coefficients of different Qsoil layers. These are also contained in figures 3.1, A.10, A.11, and A.12 and have been scaled to be represented on the same colour axis for comparability. Figure established via Chunk 27.

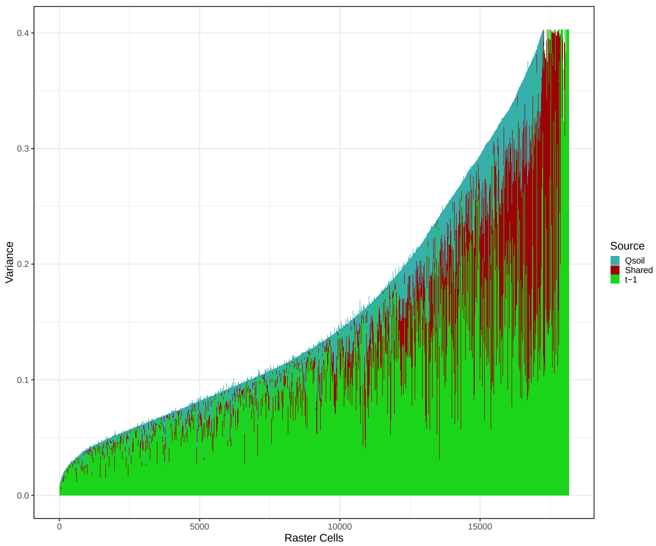
Table 3.2: Mann-Whitney U-Test (Iberian Region, Qsoil Layers) - Rownames represent median values of Qsoil vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 28.

	Qsoil1	Qsoil2	Qsoil3	Qsoil4
2.2284	NA	169919584	201893947	235372117
2.1658	0	NA	195575594	228882554
1.6801	0	0	NA	200374929
1.2293	0	0	0	NA

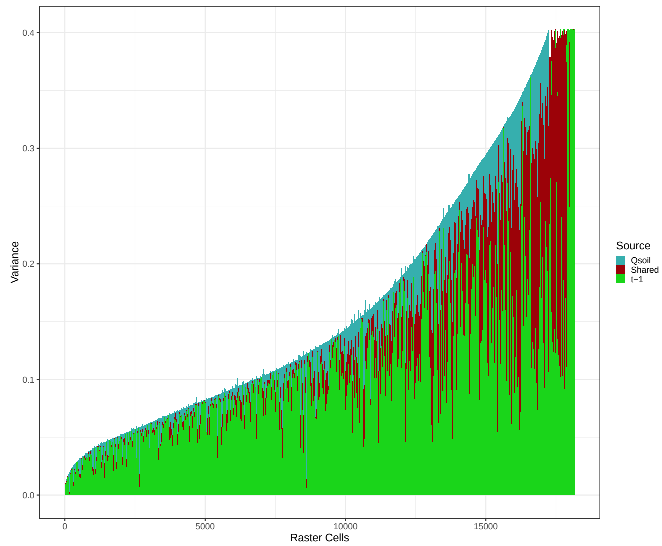
Variance Partitioning

Variance partitioning of $NDVI_{[t-1]}$ and Qsoil has been accessed for all Qsoil layers. These results are presented in figure A.19 and show a clear pattern of $NDVI_{[t-1]}$ explaining an overwhelming majority of NDVI z-scores. Variance explained by Qsoil and variance shared by Qsoil and $NDVI_{[t-1]}$ decrease through the soil layers.

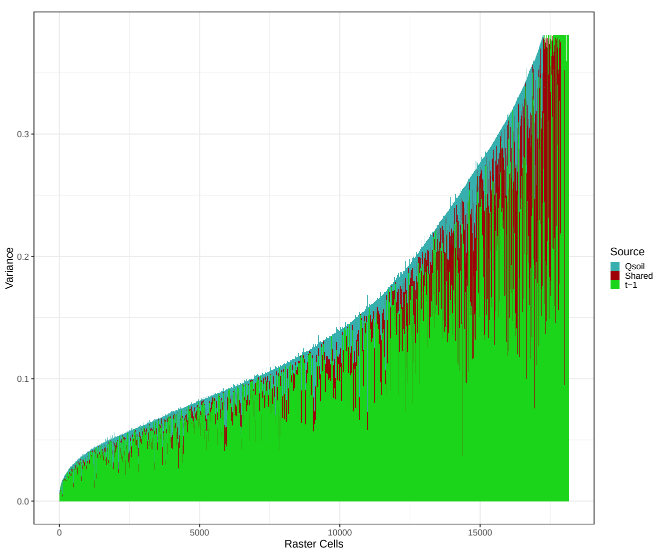
Spatial patterns of explained variance (see figure A.19) reveal that $NDVI_{[t-1]}$ and Qsoil are the most valuable as predictors NDVI across the southern dryland regions of Spain and Portugal.



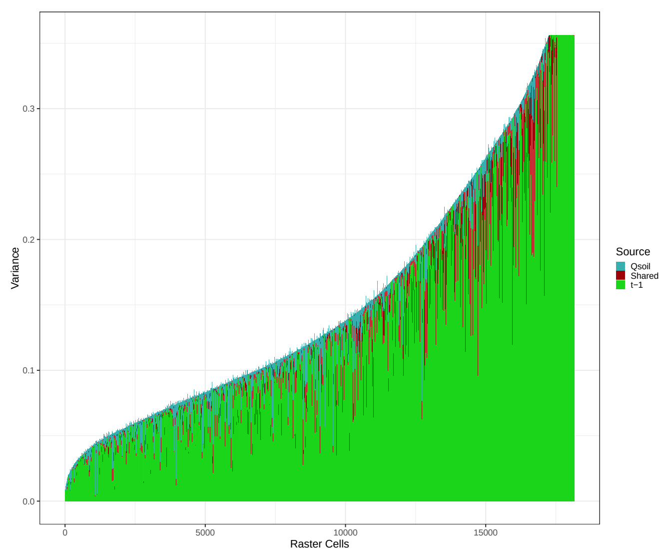
(a) t-1



(b) Shared



(c) Qsoil



(d) t-1

Figure 3.3: Variance Partitioning (Iberian Region; Qsoil1) - Variance of NDVI anomalies explained by (a) full models of intrinsic and extrinsic memory, (b) intrinsic memory, (c) shared variance, and (d) extrinsic memory. A representation of how these were calculated can be retrieved in figure 2.14. Figure established via Chunk 26.

3.1.1.2 Caatinga

I am only presenting Qsoil1 results here as I have identified Qsoil1 to be most informative Qsoil layer (see figure 3.5 and table 3.4). Results pertaining to Qsoil2, Qsoil3, and Qsoil4 can be found in figures A.13, A.14, and A.15 respectively. Additionally, patterns of $NDVI[t-1]$ and Tair coefficients do not change between different soil layer models and are thus reported on in figure 3.4.

Soil Moisture (0-7cm)

Vegetation memory coefficients of $NDVI_{[t-1]}$ and extrinsic memory (Tair and Qsoil1) across the Caatinga are represented in figure 3.4. Additionally, figure 3.4 depicts Qsoil1 memory length across the Iberian region. The memory patterns are as follows:

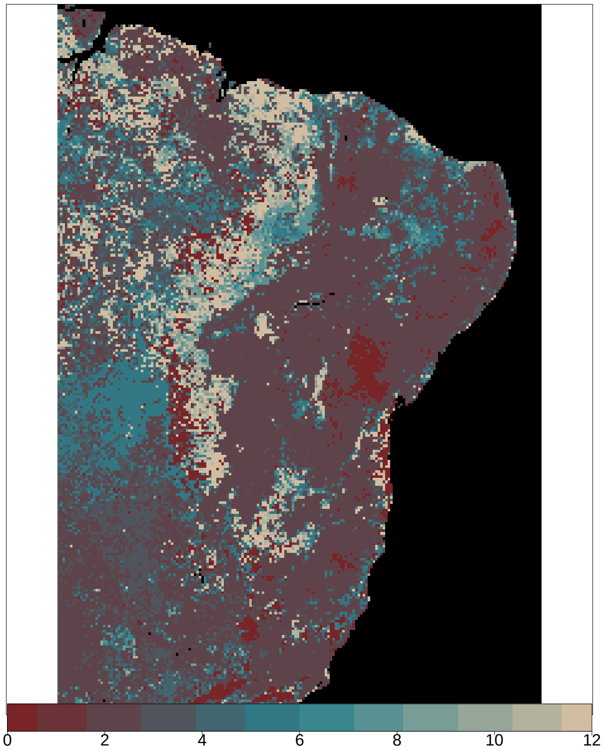
1. Qsoil1 memory length (identified as cumulative lags according to AIC values) exhibits lower values (shorter memory) in the north-eastern dryland regions as well as the south-western tropical regions.
2. $NDVI_{[t-1]}$ memory depicts the same pattern as the vegetation sensitivity index developed by Seddon et al [29] with the north-eastern dryland region being characterised by strong intrinsic memory effects. Notice the negligible coverage of negative $NDVI_{[t-1]}$ memory effects as well as their minute absolute values when compared to positive $NDVI_{[t-1]}$ memory effect values.
3. Qsoil1 memory effects are mostly positive across the entire Caatinga range with the highest absolute values being found in the north-eastern dryland region. Take note that the maximum Qsoil1 memory coefficient is larger than the absolute of the corresponding minimum value. Additionally, there are some changes in Qsoil memory effect sign between Qsoil1 and Qsoil2, and Qsoil3 and Qsoil4 with negative Qsoil effects being identified around the region of Brasilia in the latter two layers.
4. Tair memory patterns follow a pattern that is close to the inverse of the Qsoil1 pattern with large negative values in the north-eastern dryland region. Take note that the absolute of the minimum Tair memory coefficient is larger than the corresponding maximum value.

A hierarchy of vegetation memory strength has been established via median values of absolute vegetation memory coefficients. According to this analysis, $NDVI_{[t-1]}$ memory is stronger across the board than Qsoil1 memory which, in turn, is stronger than Tair memory. These differences have been assessed for statistical significance (see table 3.3).

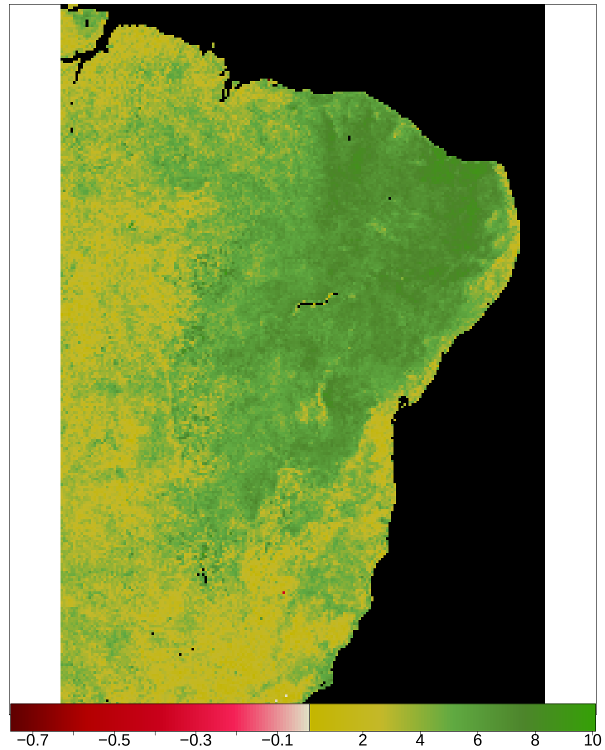
Again, only Qsoil1 results are presented here. The hierarchy of median vegetation memory coefficients remains unaltered when considering other Qsoil layers (see tables A.6, A.7, A.8).

Table 3.3: Mann-Whitney U-Test (Caatinga, Qsoil1 Model) - Rownames represent median values of vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 25.

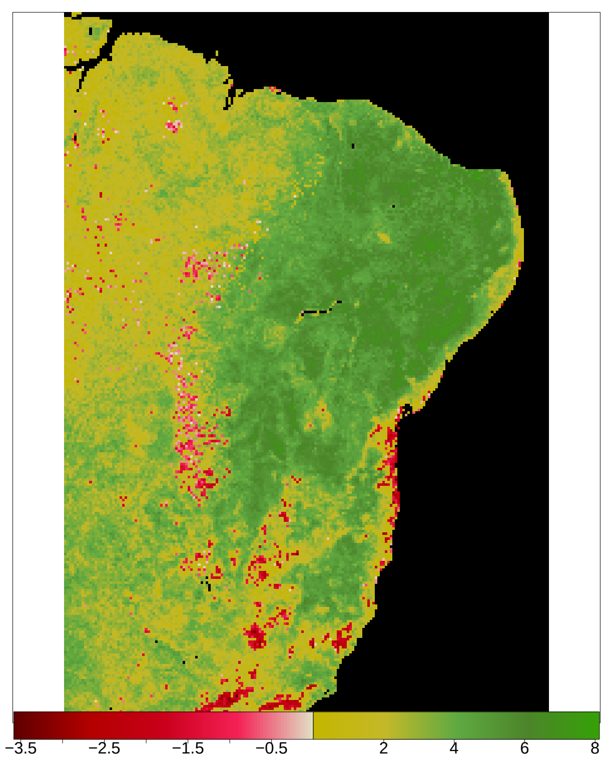
	NDVI [t-1]	Qsoil1	Tair
4.2056	NA	882317448	1.119e+09
3.0887	0	NA	9.731e+08
1.2635	0	0	NA



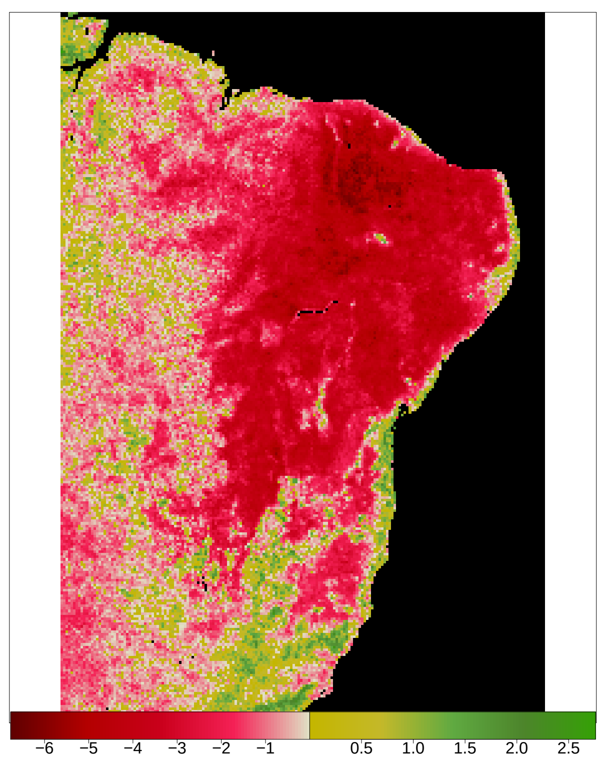
(a) SoilLag



(b) t-1



(c) Qsoil

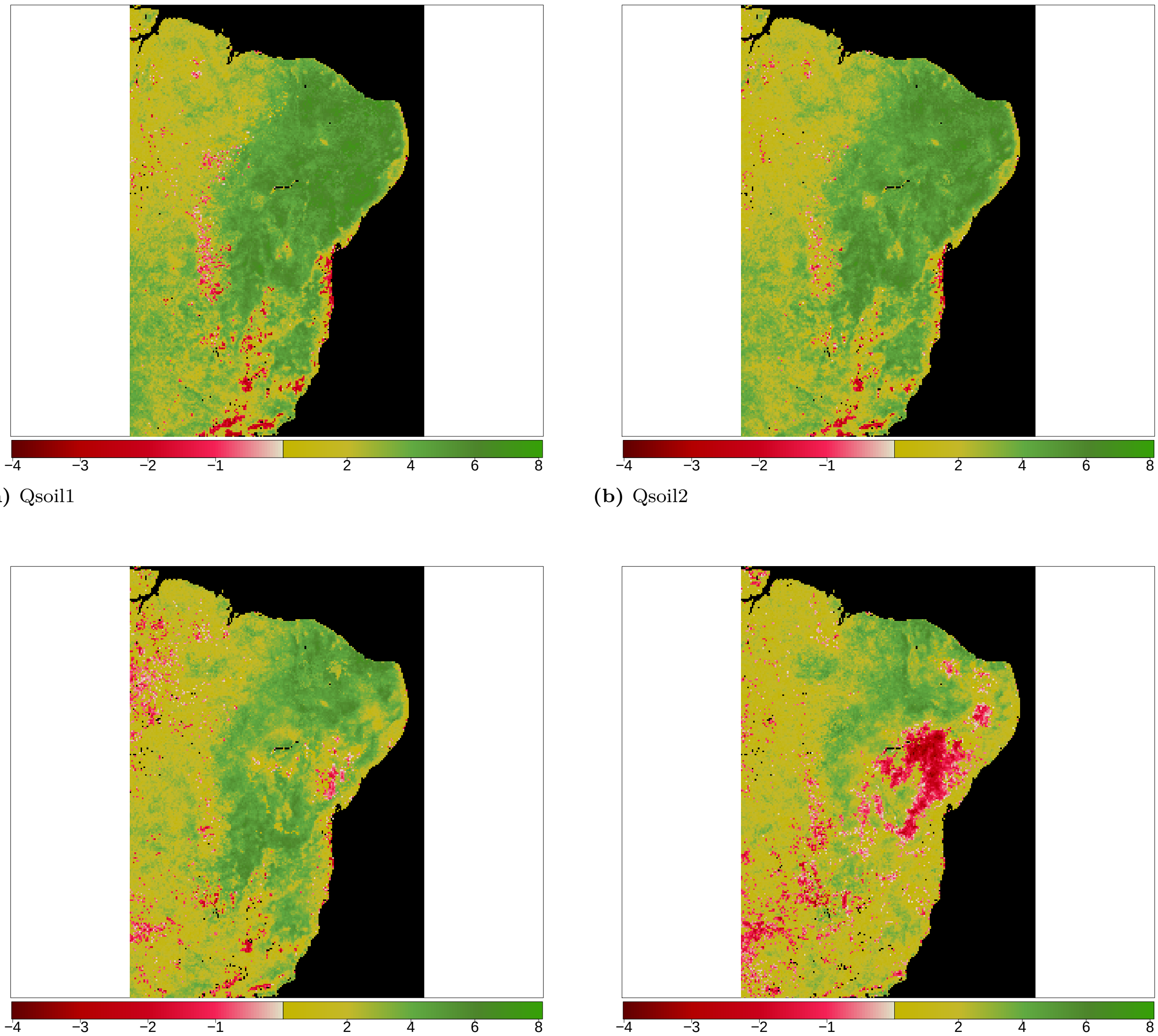


(d) Tair

Figure 3.4: Vegetation Memory Coefficients (Caatinga; Qsoil1) - Coefficients of vegetation memory obtained via model selection (figure 2.9) and PCA regression (figure 2.13). For an interpretation of these coefficients, see table 2.4. Figure established via Chunk 24.

Soil Layer Comparison

As stated above Qsoil1 has been identified as the most informative Qsoil layer in terms of vegetation memory. This is due to the fact that patterns of Qsoil memory stay consistent across Qsoil layers (see figure 3.5) and Qsoil1 coefficients being larger than coefficients of other Qsoil layers at statistical significance (see table 3.4).



(a) Qsoil1 **(b)** Qsoil2 **(c)** Qsoil3 **(d)** Qsoil4

Figure 3.5: Vegetation Memory Coefficients (Caatinga, QSoil Layers) - Vegetation memory coefficients of different Qsoil layers. These are also contained in figures 3.4, A.13, A.14, and A.15 and have been scaled to be represented on the same colour axis for comparability. Figure established via Chunk 27.

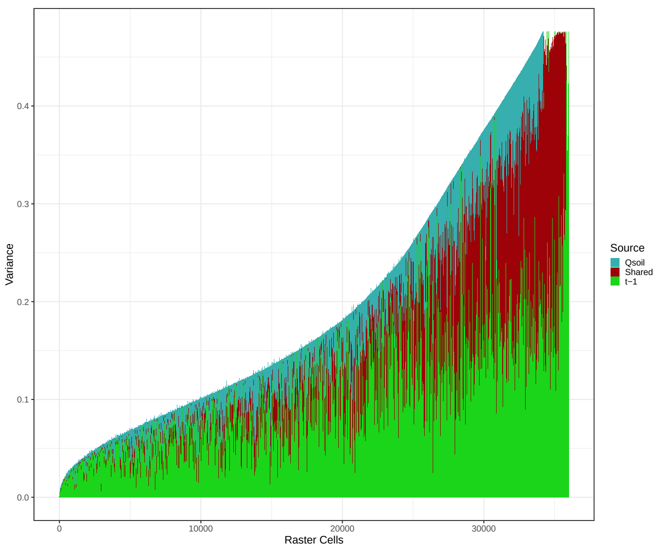
Table 3.4: Mann-Whitney U-Test (Caatinga, Qsoil Layers) - Rownames represent median values of Qsoil vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 28.

	Qsoil1	Qsoil2	Qsoil3	Qsoil4
3.0887	NA	662588655	810071500	963908394
3.0531	0	NA	797671685	954810187
2.3516	0	0	NA	812573884
1.7305	0	0	0	NA

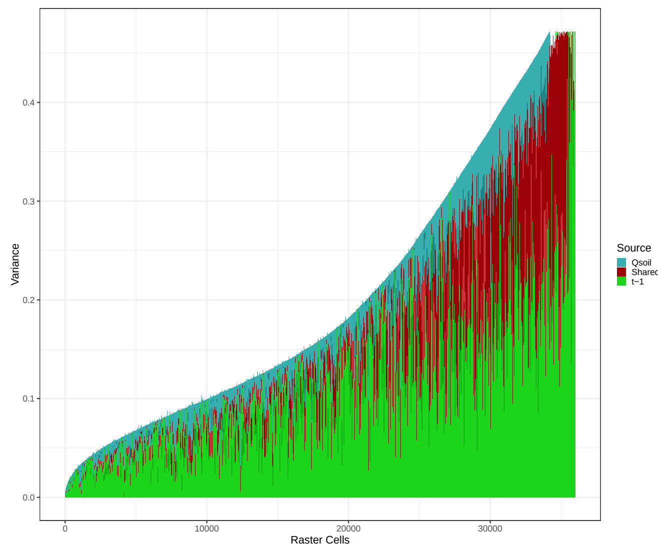
Variance Partitioning

Variance partitioning of $NDVI_{[t-1]}$ and Qsoil has been accessed for all Qsoil layers. These results are presented in figure A.20 and show a clear pattern of $NDVI_{[t-1]}$ explaining an overwhelming majority of NDVI z-scores. Variance explained by Qsoil and variance shared by Qsoil and $NDVI_{[t-1]}$ decrease through the soil layers.

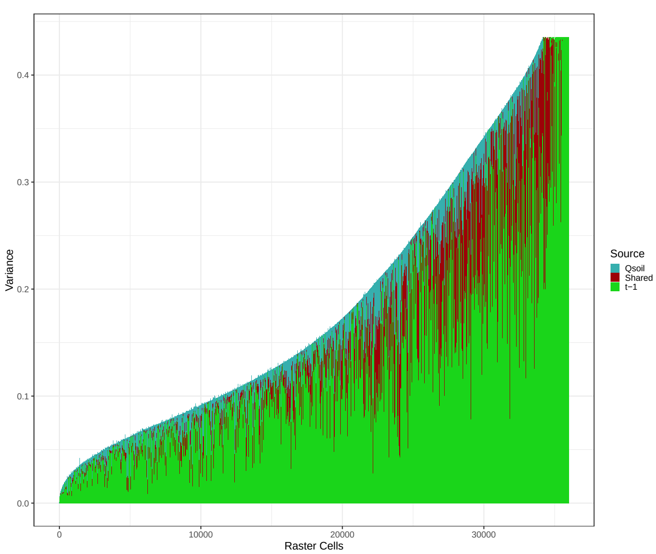
Spatial patterns of explained variance (see figure A.20) reveal that $NDVI_{[t-1]}$ and Qsoil are the most valuable as predictors NDVI across the north-eastern dryland region.



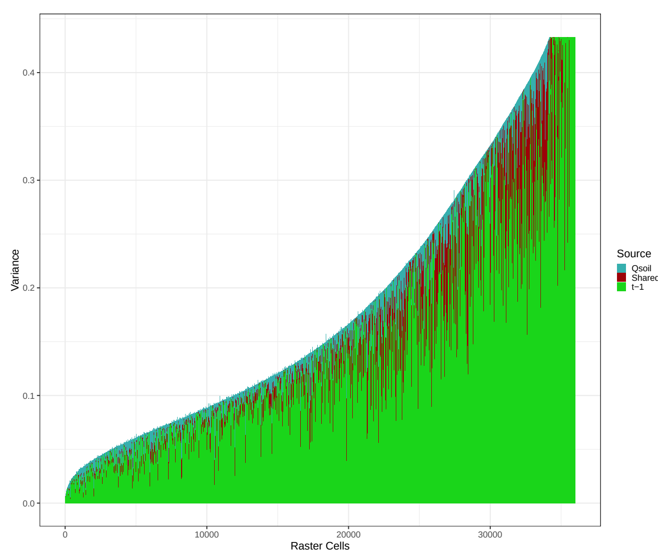
(a) t-1



(b) Shared



(c) Qsoil



(d) t-1

Figure 3.6: Variance Partitioning (Caatinga; Qsoil1) - Variance of NDVI anomalies explained by (a) full models of intrinsic and extrinsic memory, (b) intrinsic memory, (c) shared variance, and (d) extrinsic memory. A representation of how these were calculated can be retrieved in figure 2.14. Figure established via Chunk 26.

3.1.1.3 Australia

Soil Moisture (0-7cm)

I am only presenting Qsoil1 results here as I have identified Qsoil1 to be most informative Qsoil layer (see figure 3.8 and table 3.6). Results pertaining to Qsoil2, Qsoil3, and Qsoil4 can be found in figures A.16, A.17, and A.18 respectively. Additionally, patterns of $NDVI[t-1]$ and Tair coefficients do not change between different soil layer models and are thus reported on in figure 3.7.

Soil Moisture (0-7cm)

Vegetation memory coefficients of $NDVI_{[t-1]}$ and extrinsic memory (Tair and Qsoil1) across Australia are represented in figure 3.7. Additionally, figure 3.7 depicts Qsoil1 memory length across the Iberian region. The memory patterns are as follows:

1. Qsoil1 memory length (identified as cumulative lags according to AIC values) exhibits larger values (longer memory) in the western regions whilst lower memory length indices in the eastern regions of Australia identify shorter memory. Take note that these patterns do not overlap well with the previously identified memory lags of Vicente-Serrano et al.[59], or Liu et al.[17].

2. $NDVI_{[t-1]}$ memory follows the same pattern as presented by De Keersmaecker et al.[43] with strong, positive memory effects all across Australia with stronger $NDVI_{[t-1]}$ memory effects in the Outback and lower effects across the coastlines. Notice the negligible coverage of negative $NDVI_{[t-1]}$ memory effects as well as their minute absolute values when compared to positive $NDVI_{[t-1]}$ memory effect values.

3. Qsoil1 memory effects are mostly positive across the entirety of Australia with the highest values being located in the Outback and negative Qsoil1 memory effects being found on Tasmania, along coastlines and south of the St. George Ranges. Take note that the maximum Qsoil1 memory coefficient is larger than the absolute of the corresponding minimum value. Additionally, there are some changes in Qsoil memory effect sign between Qsoil1 and Qsoil2, and Qsoil3 and Qsoil4 with negative Qsoil effects being identified throughout the entire Outback particularly within the Qsoil4 layer.

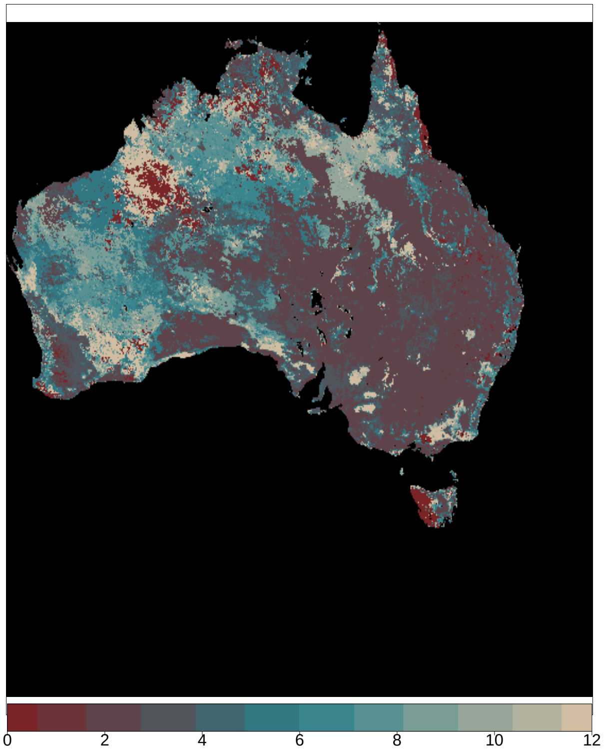
4. Tair memory patterns follow a pattern that is close to the inverse of the Tair pattern with large negative values across all of Australia. Take note that the absolute of the minimum Tair memory coefficient is larger than the corresponding maximum value.

A hierarchy of vegetation memory strength has been established via median values of absolute vegetation memory coefficients. According to this analysis, $NDVI_{[t-1]}$ memory is stronger across the board than Qsoil1 memory which, in turn, is stronger than Tair memory. These differences have been assessed for statistical significance (see table 3.5).

Again, only Qsoil1 results are presented here. The hierarchy of median vegetation memory coefficients remains unaltered when considering other Qsoil layers (see tables A.9, A.10, A.11).

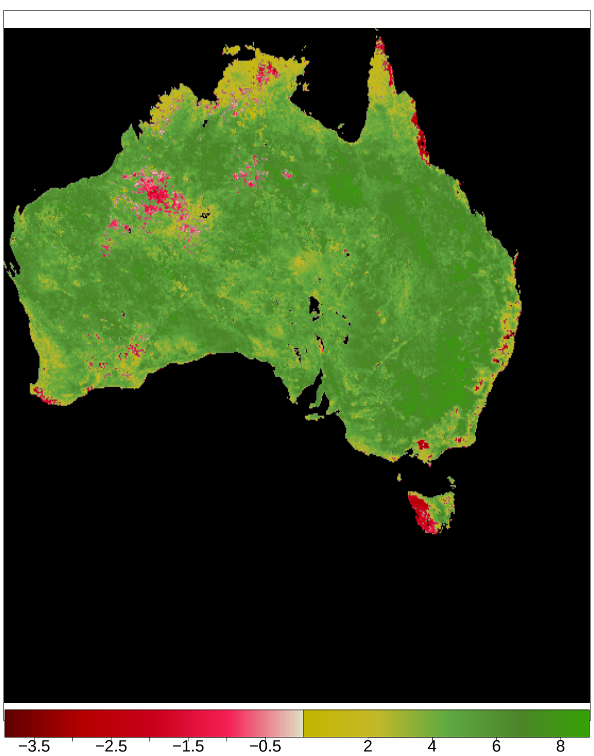
Table 3.5: Mann-Whitney U-Test (Australia, Qsoil1 Model) - Rownames represent median values of vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 25.

	NDVI [t-1]	Qsoil1	Tair
7.4527	NA	8.424e+09	9.680e+09
5.3258	0	NA	8.483e+09
2.8523	0	0.000e+00	NA



(a) SoilLag

(b) t-1



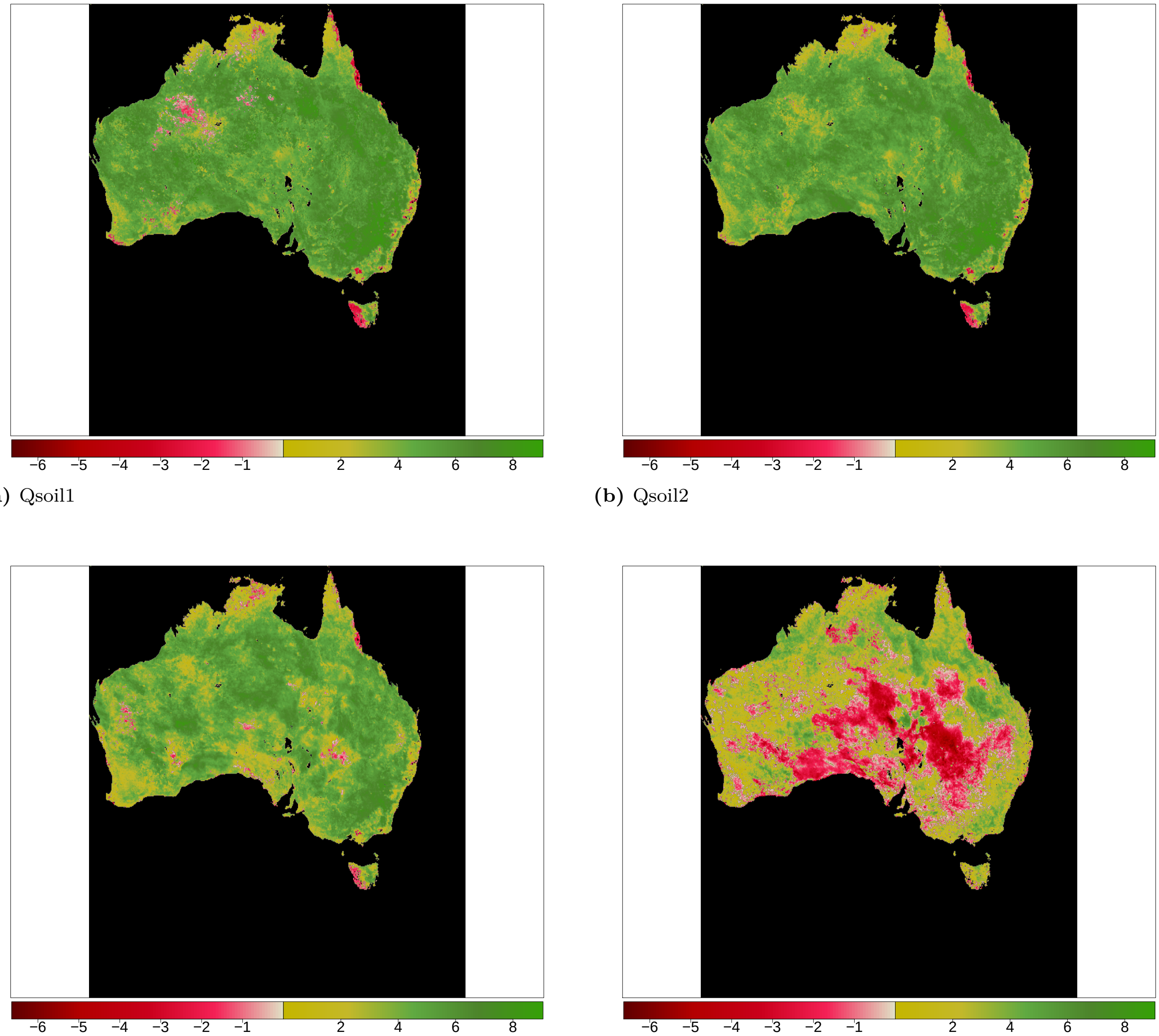
(c) Qsoil

(d) Tair

Figure 3.7: Vegetation Memory Coefficients (Australia; Qsoil1) - Coefficients of vegetation memory obtained via model selection (figure 2.9) and PCA regression (figure 2.13). For an interpretation of these coefficients, see table 2.4. Figure established via Chunk 24.

Soil Layer Comparison

As stated above Qsoil1 has been identified as the most informative Qsoil layer in terms of vegetation memory. This is due to the fact that patterns of Qsoil memory stay consistent across the first three Qsoil layers (see figure 3.8) and Qsoil1 coefficients being larger than coefficients of other Qsoil layers at statistical significance (see table 3.6).



(a) Qsoil1 **(b)** Qsoil2

(c) Qsoil3 **(d)** Qsoil4

Figure 3.8: Vegetation Memory Coefficients (Australia, QSoil Layers) - Vegetation memory coefficients of different Qsoil layers. These are also contained in figures 3.7, A.16, A.17, and A.18 and have been scaled to be represented on the same colour axis for comparability. Figure established via Chunk 27.

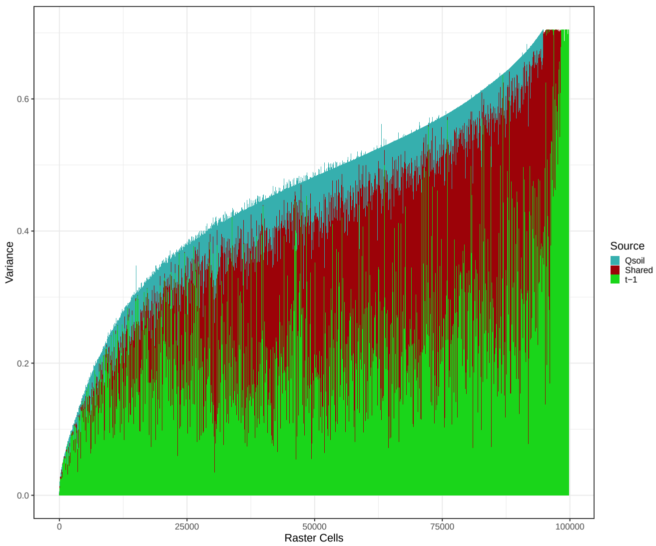
Table 3.6: Mann-Whitney U-Test (Australia, Qsoil Layers) - Rownames represent median values of Qsoil vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 28.

	Qsoil1	Qsoil2	Qsoil3	Qsoil4
5.3258	NA	5.141e+09	6.445e+09	9.032e+09
5.2241	0	NA	6.353e+09	9.135e+09
4.4153	0	0.000e+00	NA	8.428e+09
1.8774	0	0.000e+00	0.000e+00	NA

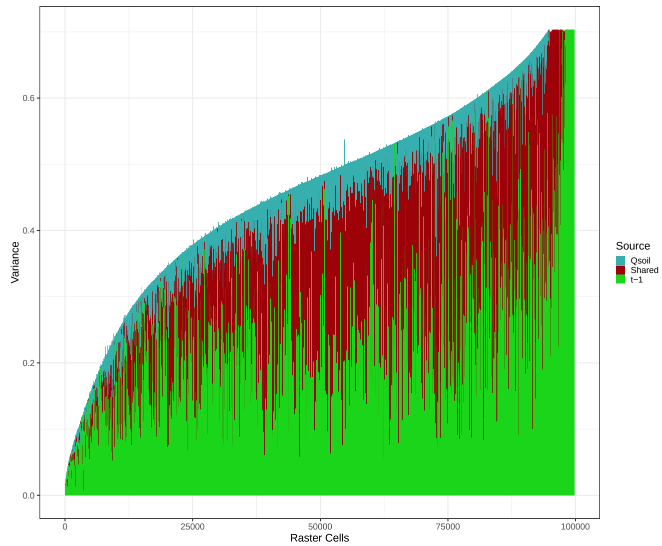
Variance Partitioning

Variance partitioning of $NDVI_{[t-1]}$ and Qsoil has been accessed for all Qsoil layers. These results are presented in figure A.21 and show a clear pattern of $NDVI_{[t-1]}$ explaining an overwhelming majority of NDVI z-scores. Variance explained by Qsoil and variance shared by Qsoil and $NDVI_{[t-1]}$ decrease through the soil layers.

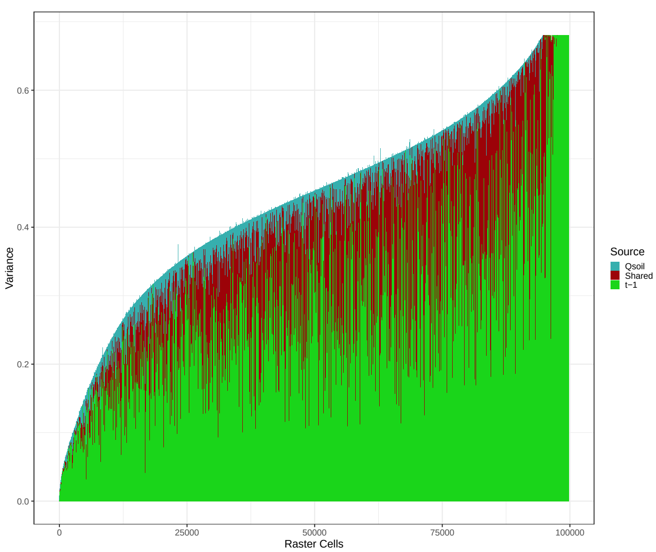
Spatial patterns of explained variance (see figure A.21) reveal that $NDVI_{[t-1]}$ and Qsoil are the most valuable as predictors NDVI across the Outback with patchy distributions.



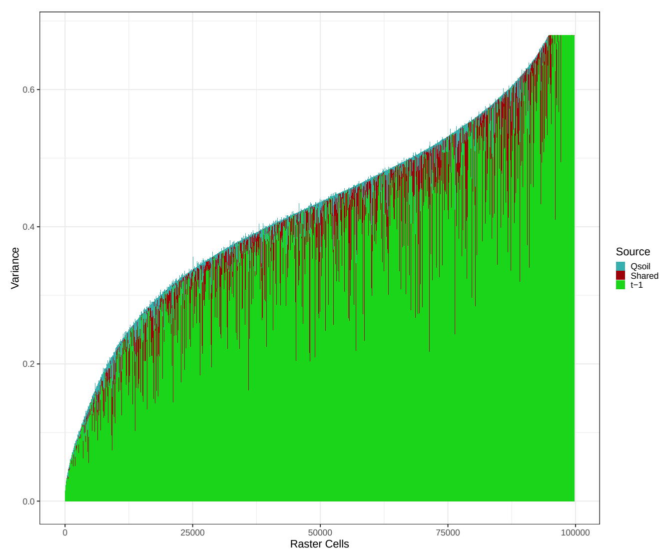
(a) t-1



(b) Shared



(c) Qsoil



(d) t-1

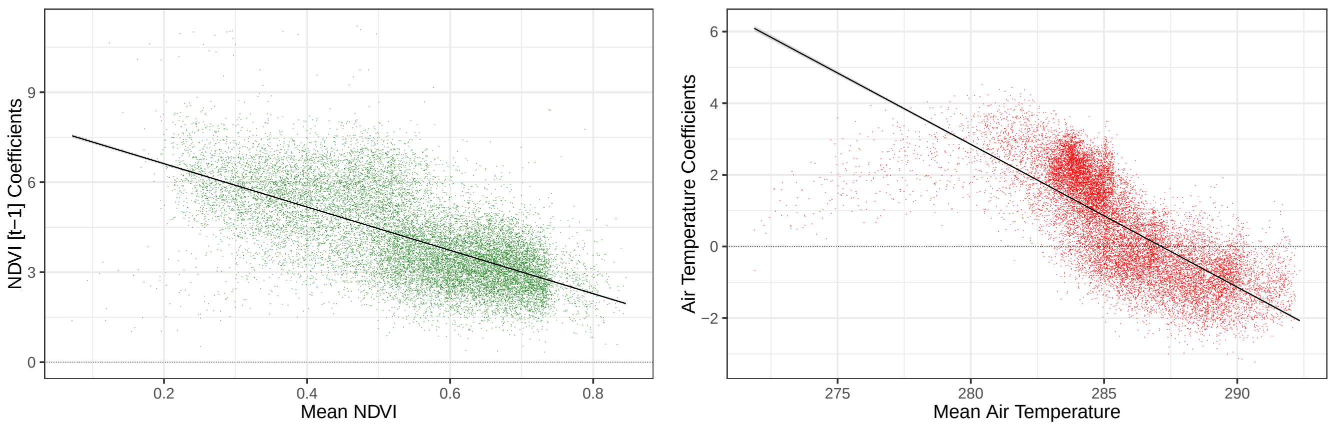
Figure 3.9: Variance Partitioning (Australia; Qsoil1) - Variance of NDVI anomalies explained by (a) full models of intrinsic and extrinsic memory, (b) intrinsic memory, (c) shared variance, and (d) extrinsic memory. A representation of how these were calculated can be retrieved in figure 2.14. Figure established via Chunk 26.

3.1.2 Vegetation Memory Sensitivity

3.1.2.1 Iberian Region

Intrinsic Memory and Air Temperature

Sensitivity relationships of $NDVI_{[t-1]}$ and Tair are depicted alongside raw data in figure 3.10.



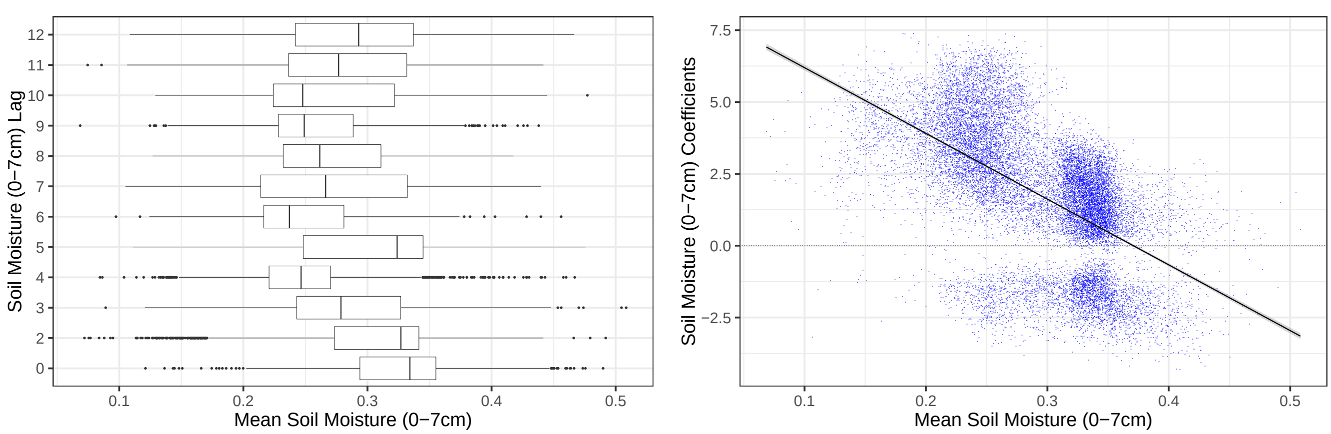
(a) NDVI t-1 **(b)** Tair

Figure 3.10: Vegetation Memory Sensitivity (NDVI t-1 and Tair, Iberian Region) - Vegetation memory coefficients of figure 3.1 plotted against mean intrinsic and extrinsic drivers (see figure A.4). Figure established via Chunk 29.

$NDVI_{[t-1]}$ memory effects across the Iberian region are characterised by an inverse relationship with mean NDVI values ($intercept = 8.0635$; $p_{intercept} = 0$ and $slope = -7.2233$; $p_{slope} = 0$). Tair memory effects across the Iberian region are also characterised by an inverse relationship with mean Tair values ($intercept = 114.4735$; $p_{intercept} = 0$ and $slope = -0.3987$; $p_{slope} = 0$).

Soil Moisture (0-7cm)

Sensitivity relationships of Qsoil1 memory length and Qsoil1 are depicted alongside raw data in figure 3.11.



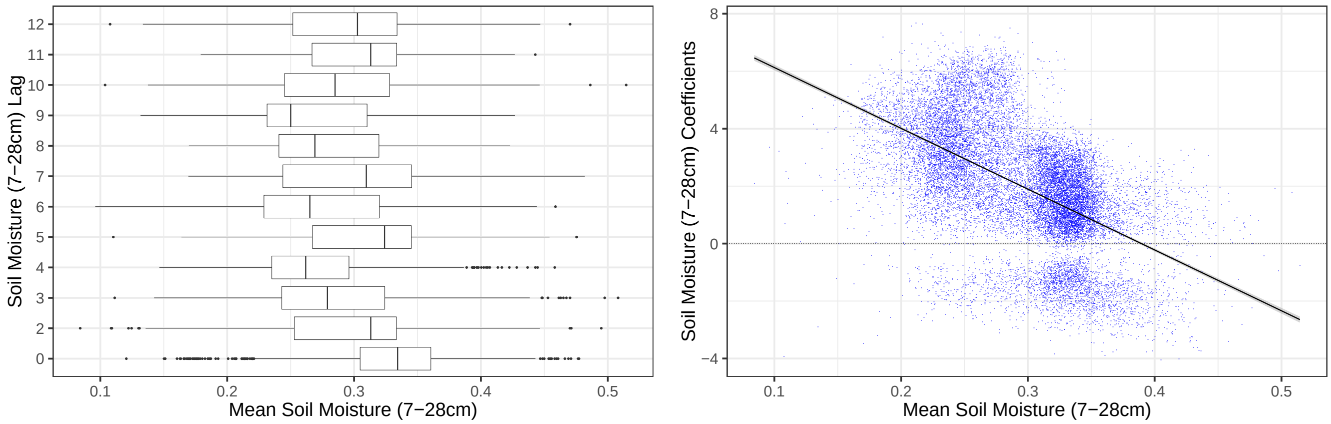
(a) Memory Length (Lag) **(b)** Qsoil

Figure 3.11: Vegetation Memory Sensitivity (Qsoil1, Iberian Region) - Qsoil1 vegetation memory coefficients and Qsoil1 memory length of figure 3.1 plotted against mean Qsoil1 records (see figure A.4). Figure established via Chunk 29.

Qsoil1 memory length across the Iberian region are characterised by an inverse relationship with mean Qsoil1 values ($intercept = 7.8966$; $p_{intercept} = 0$ and $slope = -14.0073$; $p_{slope} = 9.2369 \times 10^{-247}$). Qsoil1 memory effects across the Iberian region are also characterised by an inverse relationship with mean Qsoil1 values ($intercept = 8.4818$; $p_{intercept} = 0$ and $slope = -22.8763$; $p_{slope} = 0$).

Soil Moisture (7-28cm)

Sensitivity relationships of Qsoil2 memory length and Qsoil2 are depicted alongside raw data in figure 3.12.



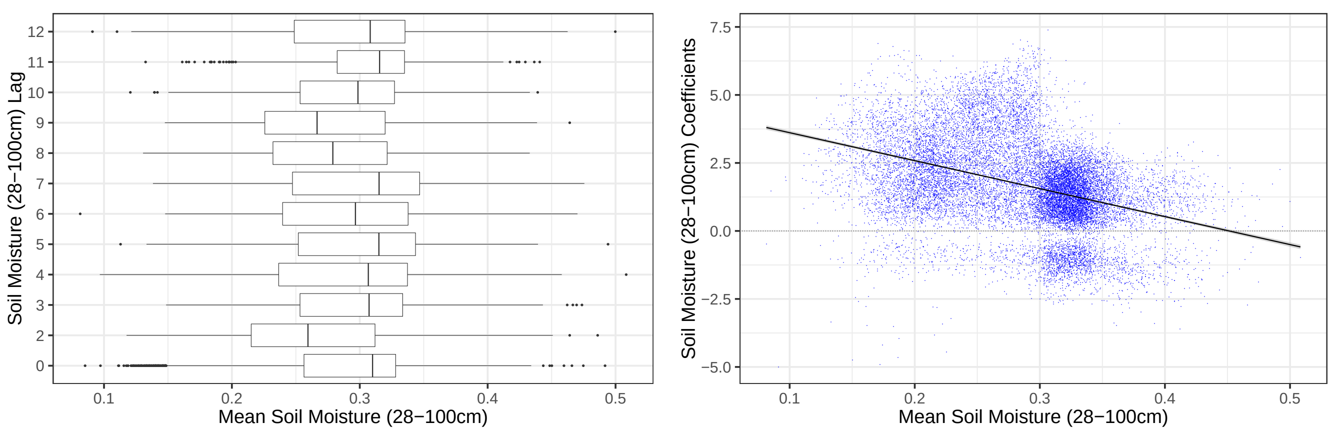
(a) Memory Length (Lag) **(b)** Qsoil

Figure 3.12: Vegetation Memory Sensitivity (Qsoil2, Iberian Region) - Qsoil2 vegetation memory coefficients and Qsoil2 memory length of figure A.10 plotted against mean Qsoil2 records (see figure A.4). Figure established via Chunk 29.

Qsoil2 memory length across the Iberian region are characterised by an inverse relationship with mean Qsoil2 values ($intercept = 5.8551$; $p_{intercept} = 0$ and $slope = -6.5487$; $p_{slope} = 2.504 \times 10^{-44}$). Qsoil2 memory effects across the Iberian region are also characterised by an inverse relationship with mean Qsoil2 values ($intercept = 8.2436$; $p_{intercept} = 0$ and $slope = -21.1656$; $p_{slope} = 0$).

Soil Moisture (28-100cm)

Sensitivity relationships of Qsoil3 memory length and Qsoil3 are depicted alongside raw data in figure 3.13.



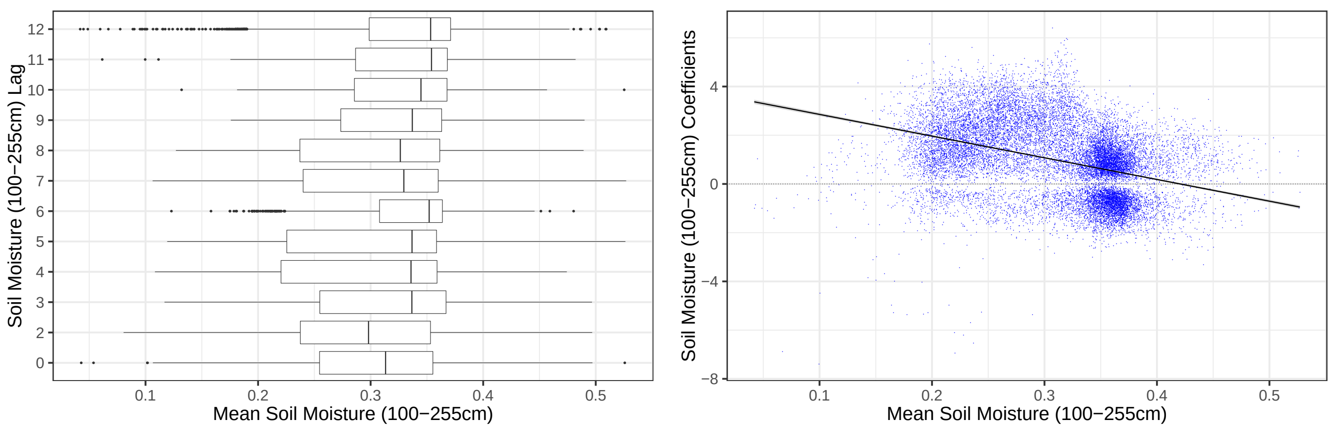
(a) Memory Length (Lag) **(b)** Qsoil

Figure 3.13: Vegetation Memory Sensitivity (Qsoil3, Iberian Region) - Qsoil3 vegetation memory coefficients and Qsoil3 memory length of figure A.11 plotted against mean Qsoil3 records (see figure A.4). Figure established via Chunk 29.

Qsoil3 memory length across the Iberian region are characterised by an positive relationship with mean Qsoil3 values ($intercept = 2.4866$; $p_{intercept} = 1.3572 \times 10^{-64}$ and $slope = 2.7945$; $p_{slope} = 2.1964 \times 10^{-8}$). Qsoil3 memory effects across the Iberian region are characterised by an inverse relationship with mean Qsoil3 values ($intercept = 4.6403$; $p_{intercept} = 0$ and $slope = -10.2822$; $p_{slope} = 0$).

Soil Moisture (100-255cm)

Sensitivity relationships of Qsoil4 memory length and Qsoil4 are depicted alongside raw data in figure 3.14.



(a) Memory Length (Lag) **(b)** Qsoil

Figure 3.14: Vegetation Memory Sensitivity (Qsoil4, Iberian Region) - Qsoil4 vegetation memory coefficients and Qsoil4 memory length of figure A.12 plotted against mean Qsoil1 records (see figure A.4). Figure established via Chunk 29.

Qsoil4 memory length across the Iberian region are characterised by an positive relationship with mean Qsoil4 values ($intercept = 0.6814$; $p_{intercept} = 7.7954 \times 10^{-5}$ and $slope = 11.5433$; $p_{slope} = 9.0016 \times 10^{-100}$). Qsoil4 memory effects across the Iberian region are characterised by an inverse relationship with mean Qsoil4 values ($intercept = 3.7462$; $p_{intercept} = 0$ and $slope = -8.905$; $p_{slope} = 0$).

Summary

Linear regression coefficients of vegetation memory sensitivity relationships across the Iberian region are presented in table 3.7. Almost all vegetation memory coefficients establish themselves in negative correlations with respective mean environmental values. Qsoil memory coefficients are linked more strongly to mean Qsoil data than $NDVI_{[t-1]}$ memory coefficients is to mean NDVI data or Tair memory coefficients and mean Tair data.

Table 3.7: Vegetation Memory Sensitivity (Iberian Region) - Coefficients of linear regressions of vegetation sensitivity across the Iberian Region. Established via Chunk 30.

			Qsoil				**Lag**			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	8.063	114.4735	8.482	8.244	4.64	3.746	7.897	5.855	2.487	0.6814
$p_{Intercept}$	0.000	0.0000	0.000	0.000	0.00	0.000	0.000	0.000	0.000	0.0001
Slope	-7.223	-0.3987	-22.876	-21.166	-10.28	-8.905	-14.007	-6.549	2.795	11.5433
p_{Slope}	0.000	0.0000	0.000	0.000	0.00	0.000	0.000	0.000	0.000	0.0000

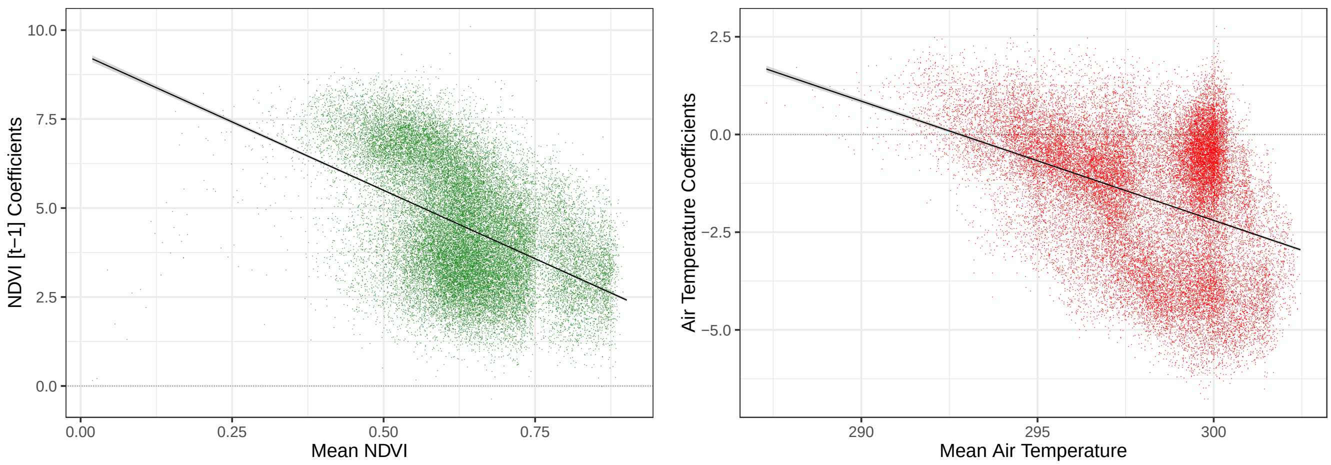
The sensitivity of Qsoil vegetation memory to mean Qsoil layer data diminishes through Qsoil layers (from shallow to deep layers). This effect has been identified as statistically significant according to an Analysis of Variance (ANOVA) at $p = 0$ (established via Chunk 31).

The correlation of Qsoil vegetation memory length to mean Qsoil layer data starts of negative for Qsoil1 and Qsoil2 (diminishing when going from Qsoil1 to Qsoil2) and flips to being positive for Qsoil3 and Qsoil4 (intensifying from Qsoil3 to Qsoil4). This effect has been identified as statistically significant according to an ANOVA at $p = 5.3408 \times 10^{-247}$ (established via Chunk 31).

3.1.2.2 Caatinga

Intrinsic Memory and Air Temperature

Sensitivity relationships of $NDVI_{[t-1]}$ and Tair are depicted alongside raw data in figure 3.15.



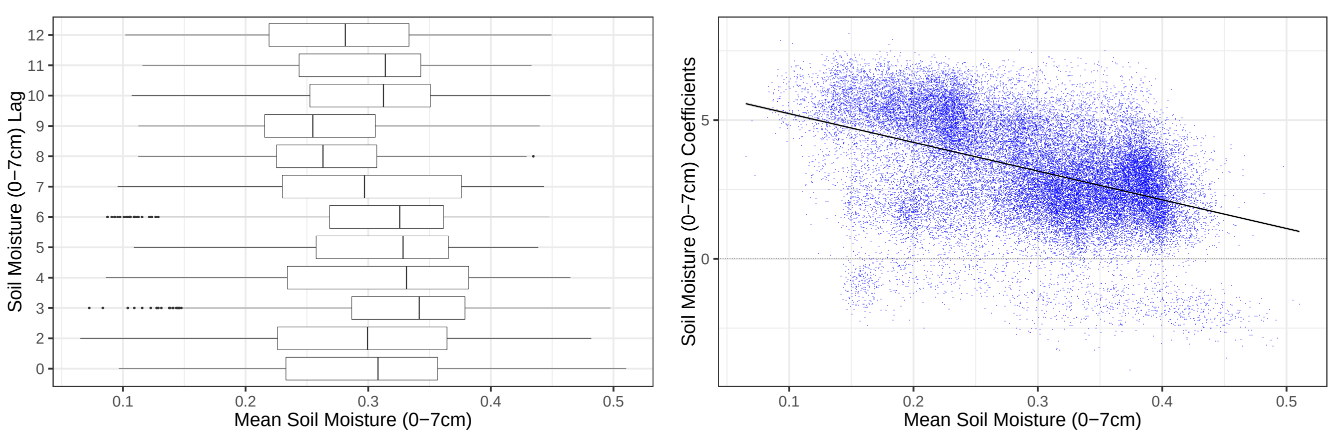
(a) NDVI t-1 **(b)** Tair

Figure 3.15: Vegetation Memory Sensitivity (NDVI t-1 and Tair, Caatinga) - Vegetation memory coefficients of figure 3.4 plotted against mean intrinsic and extrinsic drivers (see figure A.6). Figure established via Chunk 29.

$NDVI_{[t-1]}$ memory effects across the Caatinga are characterised by an inverse relationship with mean NDVI values ($intercept = 9.342$; $p_{intercept} = 0$ and $slope = -7.6875$; $p_{slope} = 0$). Tair memory effects across the Caatinga are also characterised by an inverse relationship with mean Tair values ($intercept = 89.3357$; $p_{intercept} = 0$ and $slope = -0.3051$; $p_{slope} = 0$).

Soil Moisture (0-7cm)

Sensitivity relationships of Qsoil1 memory length and Qsoil1 are depicted alongside raw data in figure 3.16.



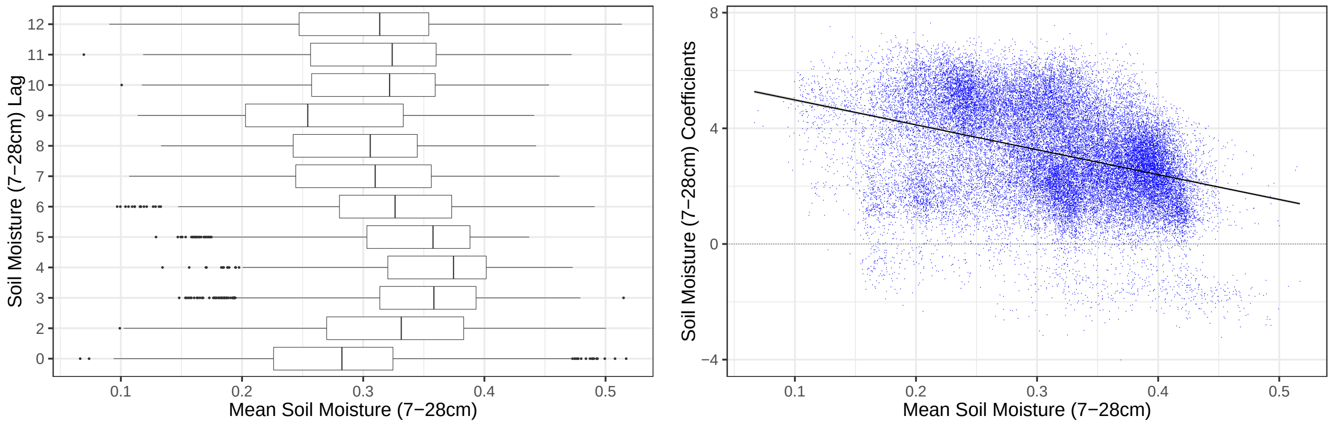
(a) Memory Length (Lag) **(b)** Qsoil

Figure 3.16: Vegetation Memory Sensitivity (Qsoil1, Caatinga) - Qsoil1 vegetation memory coefficients and Qsoil1 memory length of figure 3.4 plotted against mean Qsoil1 records (see figure A.6). Figure established via Chunk 29.

Qsoil1 memory length across the Caatinga are characterised by an inverse relationship with mean Qsoil1 values ($intercept = 4.6348$; $p_{intercept} = 0$ and $slope = -2.5185$; $p_{slope} = 1.8213 \times 10^{-29}$). Qsoil1 memory effects across the Caatinga are also characterised by an inverse relationship with mean Qsoil1 values ($intercept = 6.268$; $p_{intercept} = 0$ and $slope = -10.3546$; $p_{slope} = 0$).

Soil Moisture (7-28cm)

Sensitivity relationships of Qsoil2 memory length and Qsoil2 are depicted alongside raw data in figure 3.17.



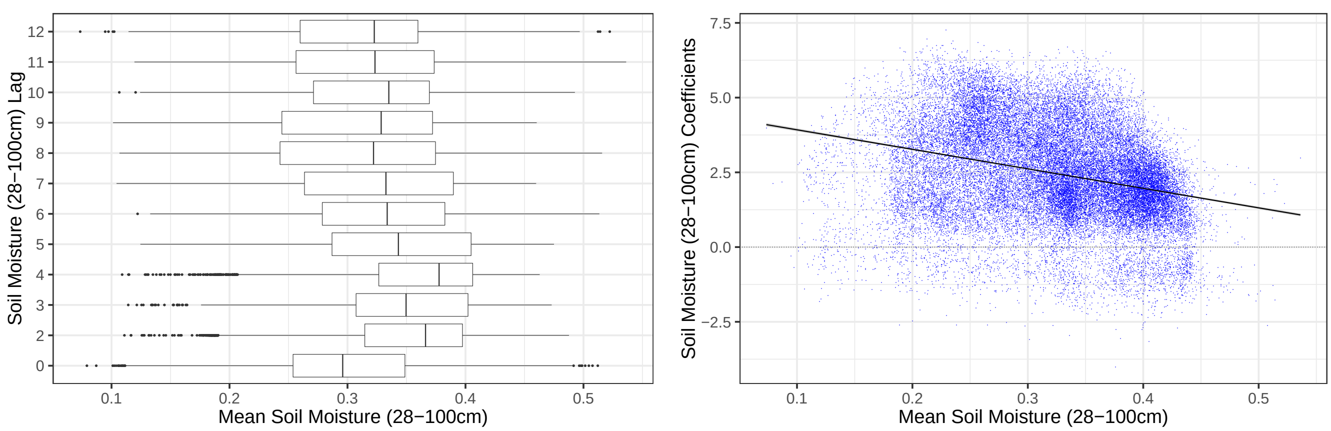
(a) Memory Length (Lag) **(b)** Qsoil

Figure 3.17: Vegetation Memory Sensitivity (Qsoil2, Caatinga) - Qsoil2 vegetation memory coefficients and Qsoil2 memory length of figure A.13 plotted against mean Qsoil2 records (see figure A.6). Figure established via Chunk 29.

Qsoil2 memory length across the Caatinga are characterised by a positive relationship with mean Qsoil2 values ($intercept = 3.7423$; $p_{intercept} = 0$ and $slope = 0.2772$; $p_{slope} = 0.3171$). Qsoil2 memory effects across the Caatinga are characterised by an inverse relationship with mean Qsoil2 values ($intercept = 5.8419$; $p_{intercept} = 0$ and $slope = -8.6058$; $p_{slope} = 0$).

Soil Moisture (28-100cm)

Sensitivity relationships of Qsoil3 memory length and Qsoil3 are depicted alongside raw data in figure 3.18.



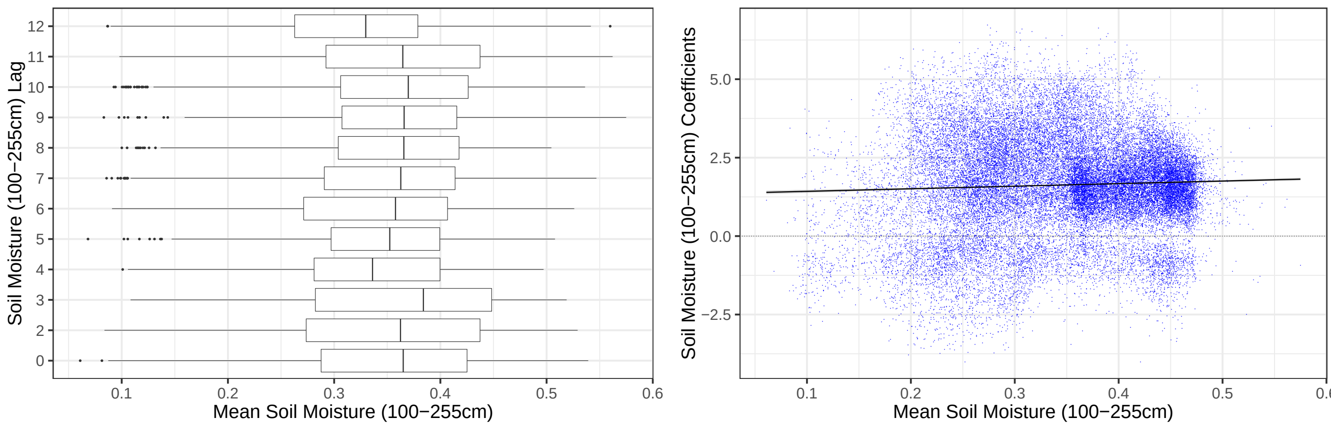
(a) Memory Length (Lag) **(b)** Qsoil

Figure 3.18: Vegetation Memory Sensitivity (Qsoil3, Caatinga) - Qsoil3 vegetation memory coefficients and Qsoil3 memory length of figure A.14 plotted against mean Qsoil3 records (see figure A.6). Figure established via Chunk 29.

Qsoil3 memory length across the Caatinga are characterised by an inverse relationship with mean Qsoil3 values ($intercept = 4.6187$; $p_{intercept} = 0$ and $slope = -0.5314$; $p_{slope} = 0.0966$). Qsoil3 memory effects across the Caatinga are also characterised by an inverse relationship with mean Qsoil3 values ($intercept = 4.5756$; $p_{intercept} = 0$ and $slope = -6.5265$; $p_{slope} = 0$).

Soil Moisture (100-255cm)

Sensitivity relationships of Qsoil4 memory length and Qsoil4 are depicted alongside raw data in figure 3.19.



(a) Memory Length (Lag) **(b)** Qsoil

Figure 3.19: Vegetation Memory Sensitivity (Qsoil4, Caatinga) - Qsoil4 vegetation memory coefficients and Qsoil4 memory length of figure A.15 plotted against mean Qsoil1 records (see figure A.6). Figure established via Chunk 29.

Qsoil4 memory length across the Caatinga are characterised by an inverse relationship with mean Qsoil4 values ($intercept = 5.8634$; $p_{intercept} = 0$ and $slope = -5.1861$; $p_{slope} = 6.3954 \times 10^{-67}$). Qsoil4 memory effects across the Caatinga are characterised by a positive relationship with mean Qsoil4 values ($intercept = 1.3444$; $p_{intercept} = 3.996 \times 10^{-320}$ and $slope = 0.8188$; $p_{slope} = 4.115 \times 10^{-17}$).

Summary

Linear regression coefficients of vegetation memory sensitivity relationships across the Caatinga are presented in table 3.9. Almost all vegetation memory coefficients establish themselves in negative correlations with respective mean environmental values. Qsoil1, Qsoil2, Qsoil3, and $NDVI_{[t-1]}$ are linked especially strongly to environmental mean drivers.

Table 3.8: Vegetation Memory Sensitivity (Caatinga) - Coefficients of linear regressions of vegetation sensitivity across the Iberian Region. Established via Chunk 30.

			Qsoil				Lag			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	9.342	89.3357	6.268	5.842	4.576	1.3444	4.635	3.7423	4.6187	5.863
$p_{Intercept}$	0.000	0.0000	0.000	0.000	0.000	0.0000	0.000	0.0000	0.0000	0.000
Slope	-7.688	-0.3051	-10.355	-8.606	-6.527	0.8188	-2.518	0.2772	-0.5314	-5.186
p_{Slope}	0.000	0.0000	0.000	0.000	0.000	0.0000	0.000	0.3171	0.0966	0.000

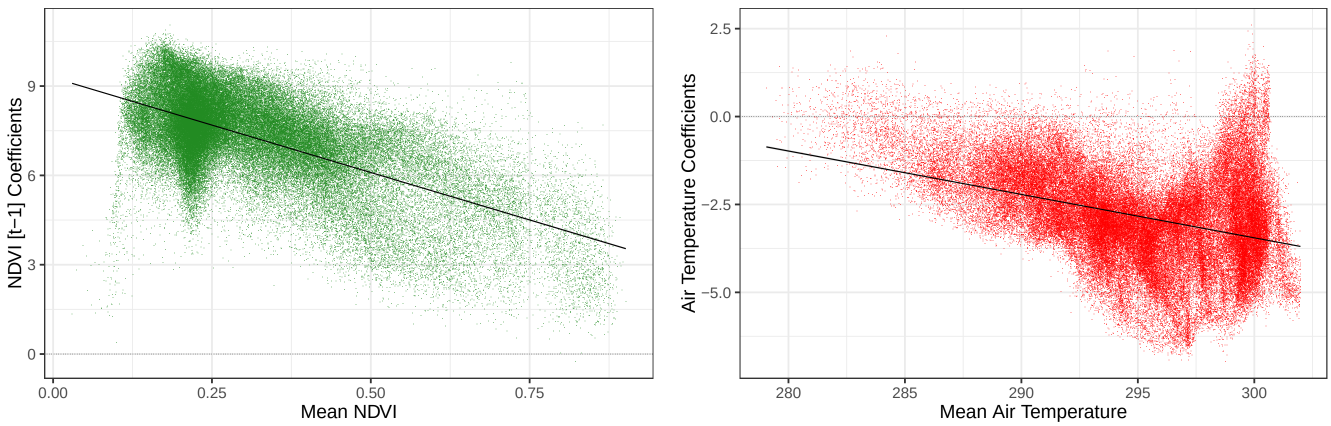
The sensitivity of Qsoil vegetation memory to mean Qsoil layer data fluctuates across the soil layer range whilst diminishing from Qsoil1 to Qsoil2. These differences have been been identified as statistically significant according to an ANOVA at $p = 0$ (established via Chunk 31).

The correlation of Qsoil vegetation memory length to mean Qsoil layer follows no identifiable linear pattern. Differences in linear regressions have been identified as statistically significant according to an ANOVA at $p = 3.8016 \times 10^{-28}$ (established via Chunk 31).

3.1.2.3 Australia

Intrinsic Memory and Air Temperature

Sensitivity relationships of $NDVI_{[t-1]}$ and Tair are depicted alongside raw data in figure 3.20.



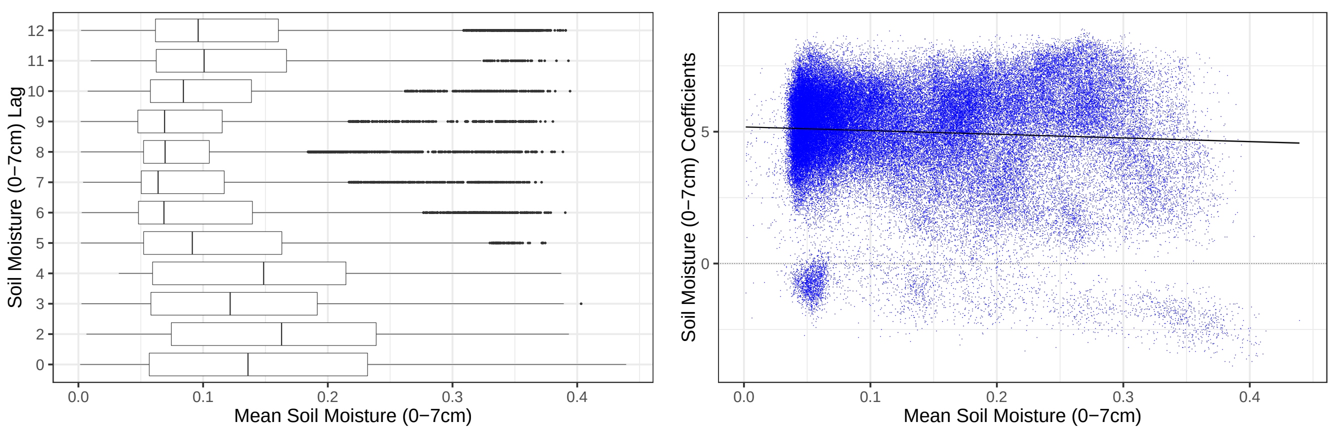
(a) NDVI t-1 **(b)** Tair

Figure 3.20: Vegetation Memory Sensitivity (NDVI t-1 and Tair, Australia) - Vegetation memory coefficients of figure 3.7 plotted against mean intrinsic and extrinsic drivers (see figure A.8). Figure established via Chunk 29.

$NDVI_{[t-1]}$ memory effects across Australia are characterised by an inverse relationship with mean NDVI values ($intercept = 9.2822$; $p_{intercept} = 0$ and $slope = -6.3715$; $p_{slope} = 0$). Tair memory effects across Australia are also characterised by an inverse relationship with mean Tair values ($intercept = 33.5852$; $p_{intercept} = 0$ and $slope = -0.1234$; $p_{slope} = 0$).

Soil Moisture (0-7cm)

Sensitivity relationships of Qsoil1 memory length and Qsoil1 are depicted alongside raw data in figure 3.21.



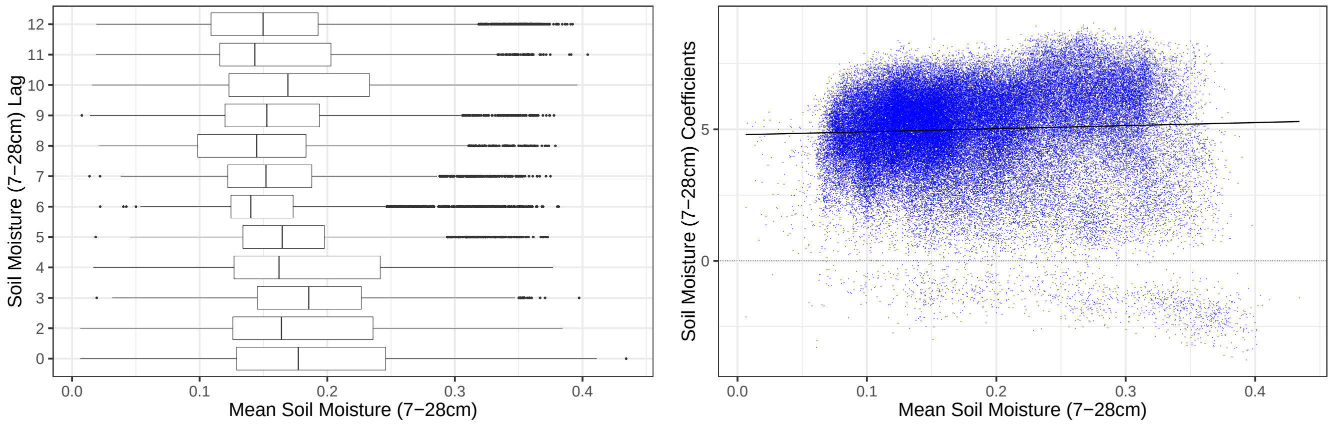
(a) Memory Length (Lag) **(b)** Qsoil

Figure 3.21: Vegetation Memory Sensitivity (Qsoil1, Australia) - Qsoil1 vegetation memory coefficients and Qsoil1 memory length of figure 3.7 plotted against mean Qsoil1 records (see figure A.8). Figure established via Chunk 29.

Qsoil1 memory length across Australia are characterised by an inverse relationship with mean Qsoil1 values ($intercept = 6.1972$; $p_{intercept} = 0$ and $slope = -10.4404$; $p_{slope} = 0$). Qsoil1 memory effects across Australia are also characterised by an inverse relationship with mean Qsoil1 values ($intercept = 5.1809$; $p_{intercept} = 0$ and $slope = -1.393$; $p_{slope} = 8.698 \times 10^{-89}$).

Soil Moisture (7-28cm)

Sensitivity relationships of Qsoil2 memory length and Qsoil2 are depicted alongside raw data in figure 3.22.



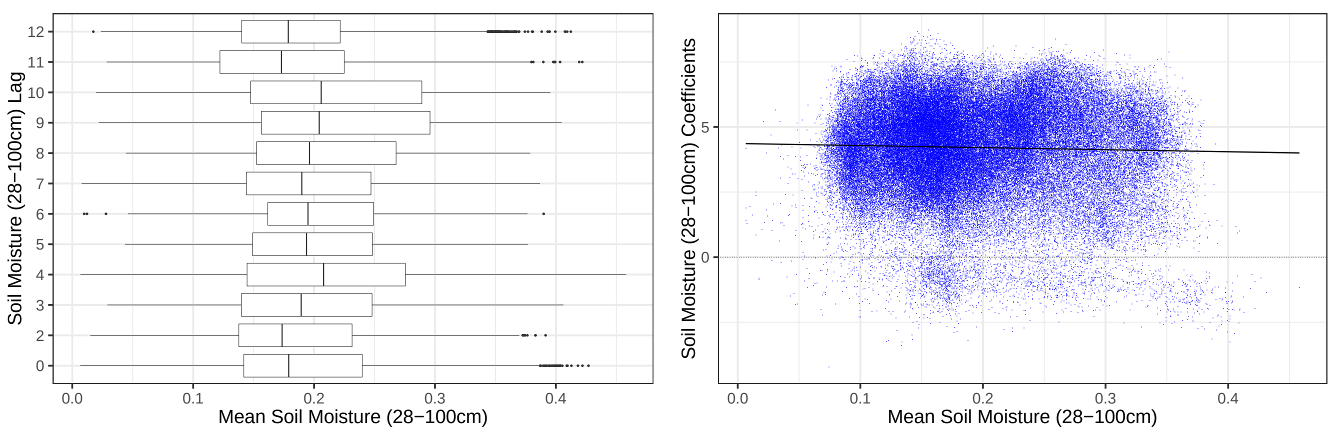
(a) Memory Length (Lag) **(b)** Qsoil

Figure 3.22: Vegetation Memory Sensitivity (Qsoil2, Australia) - Qsoil2 vegetation memory coefficients and Qsoil2 memory length of figure A.16 plotted against mean Qsoil2 records (see figure A.8). Figure established via Chunk 29.

Qsoil2 memory length across Australia are characterised by a negative relationship with mean Qsoil2 values ($intercept = 4.1563$; $p_{intercept} = 0$ and $slope = -5.355$; $p_{slope} = 1.494 \times 10^{-280}$). Qsoil2 memory effects across Australia are characterised by a positive relationship with mean Qsoil2 values ($intercept = 4.7919$; $p_{intercept} = 0$ and $slope = 1.1625$; $p_{slope} = 9.538 \times 10^{-56}$).

Soil Moisture (28-100cm)

Sensitivity relationships of Qsoil3 memory length and Qsoil3 are depicted alongside raw data in figure 3.23.



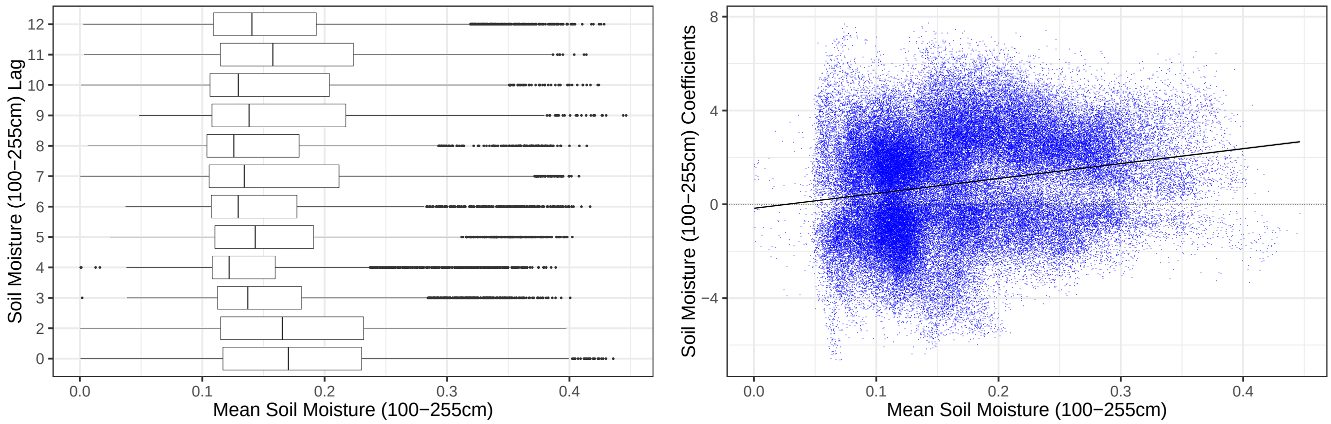
(a) Memory Length (Lag) **(b)** Qsoil

Figure 3.23: Vegetation Memory Sensitivity (Qsoil3, Australia) - Qsoil3 vegetation memory coefficients and Qsoil3 memory length of figure A.17 plotted against mean Qsoil3 records (see figure A.8). Figure established via Chunk 29.

Qsoil3 memory length across Australia are characterised by a positive relationship with mean Qsoil3 values ($intercept = 1.6579$; $p_{intercept} = 0$ and $slope = 0.5925$; $p_{slope} = 1.4295 \times 10^{-4}$). Qsoil3 memory effects across Australia are characterised by an inverse relationship with mean Qsoil3 values ($intercept = 4.3651$; $p_{intercept} = 0$ and $slope = -0.7912$; $p_{slope} = 2.9074 \times 10^{-22}$).

Soil Moisture (100-255cm)

Sensitivity relationships of Qsoil4 memory length and Qsoil4 are depicted alongside raw data in figure 3.24.



(a) Memory Length (Lag)

(b) Qsoil

Figure 3.24: Vegetation Memory Sensitivity (Qsoil4, Australia) - Qsoil4 vegetation memory coefficients and Qsoil4 memory length of figure A.18 plotted against mean Qsoil1 records (see figure A.8). Figure established via Chunk 29.

Qsoil4 memory length across Australia are characterised by an inverse relationship with mean Qsoil4 values ($intercept = 5.9721$; $p_{intercept} = 0$ and $slope = -8.3884$; $p_{slope} = 2.7441 \times 10^{-308}$). Qsoil4 memory effects across Australia are characterised by a positive relationship with mean Qsoil4 values ($intercept = -0.17$; $p_{intercept} = 5.8333 \times 10^{-21}$ and $slope = 6.3562$; $p_{slope} = 0$).

Summary

Linear regression coefficients of vegetation memory sensitivity relationships across Australia are presented in table 3.9. Almost all vegetation memory coefficients establish themselves in negative correlations with respective mean environmental values. Qsoil1 memory length, Qsoil4 (in a positive relationship), and $NDVI_{[t-1]}$ are linked especially strongly to environmental mean drivers.

Table 3.9: Vegetation Memory Sensitivity (Australia) - Coefficients of linear regressions of vegetation sensitivity across the Iberian Region. Established via Chunk 30.

			Qsoil				**Lag**			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	9.282	33.5852	5.181	4.792	4.3651	-0.170	6.197	4.156	1.6579	5.972
$p_{Intercept}$	0.000	0.0000	0.000	0.000	0.0000	0.000	0.000	0.000	0.0000	0.000
Slope	-6.372	-0.1234	-1.393	1.163	-0.7912	6.356	-10.440	-5.355	0.5925	-8.388
p_{Slope}	0.000	0.0000	0.000	0.000	0.0000	0.000	0.000	0.000	0.0001	0.000

The sensitivity of Qsoil vegetation memory to mean Qsoil layer data fluctuates across the soil layer range with Qsoil4 coefficients' relation to mean Qsoil drivers being strong and positive. These differences have been been identified as statistically significant according to an ANOVA at $p = 3.639 \times 10^{-79}$ (established via Chunk 31).

The correlation of Qsoil vegetation memory length to mean Qsoil layer follows no identifiable linear pattern. Differences in linear regressions have been identified as statistically significant according to an ANOVA at $p = 0$ (established via Chunk 31).

3.1.3 Summary

3.1.3.1 Vegetation Memory Models

Across all three study regions, the **Qsoil1** layer has been **identified as the most informative** of all the Qsoil layers.

Some persistent vegetation memory patterns have emerged across all three study regions:

1. **Qsoil1 memory length** (identified as cumulative lags according to AIC values) exhibits **shorter** values **in drylands** when compared to adjacent non-dryland regions.

2. $NDVI_{[t-1]}$ **memory** follows the same pattern as identified in previous studies [29,43] with **strong and positive** memory effects **across dryland regions**.

3. **Qsoil1 memory** effects are **strong and positive across dryland regions**.

4. **Tair memory** patterns are usually **strong and negative in dryland regions**.

Additionally, model coefficient comparison via Mann-Whitney U-Tests revealed that $NDVI_{[t-1]}$ is a larger memory component than Qsoil coefficients which, in turn, are larger components that Tair.

Variance partitioning of $NDVI_{[t-1]}$ and Qsoil identified a **subsiding effect of Qsoil effects through soil layers**. Overall, $NDVI_{[t-1]}$ **explains more variance in NDVI z-scores than Qsoil data** or variance shared by $NDVI_{[t-1]}$ or Qsoil data.

3.1.3.2 Vegetation Memory Sensitivity

In terms of vegetation memory sensitivity:

1. $NDVI_{[t-1]}$ memory coefficients are **strongly negatively correlated** to mean NDVI records.

2. **Tair** memory coefficients are **weakly negatively correlated** to mean Tair records.

3. **Qsoil** memory coefficients are **overwhelmingly correlated strongly negatively** to mean Qsoil records.

4. **Qsoil memory length** is **largely correlated negatively** with mean Qsoil records. Noticeable exceptions include Qsoil3 and Qsoil4 across the Iberian region.

With the exception of Qsoil4 across Australia, **Qsoil vegetation memory sensitivity decreases as soil layers become deeper**.

Strong correlations of Qsoil memory length and mean Qsoil records is usually found in **Qsoil1** and **Qsoil4**.

3.2 Functional Aspects of Vegetation Memory

3.2.1 Life History Traits

3.2.1.1 Iberian Region

Fast-Slow Continuum

Relationships of vegetation memory coefficients and FSC-1 records across the Iberian region are represented in figure 3.25. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.10.

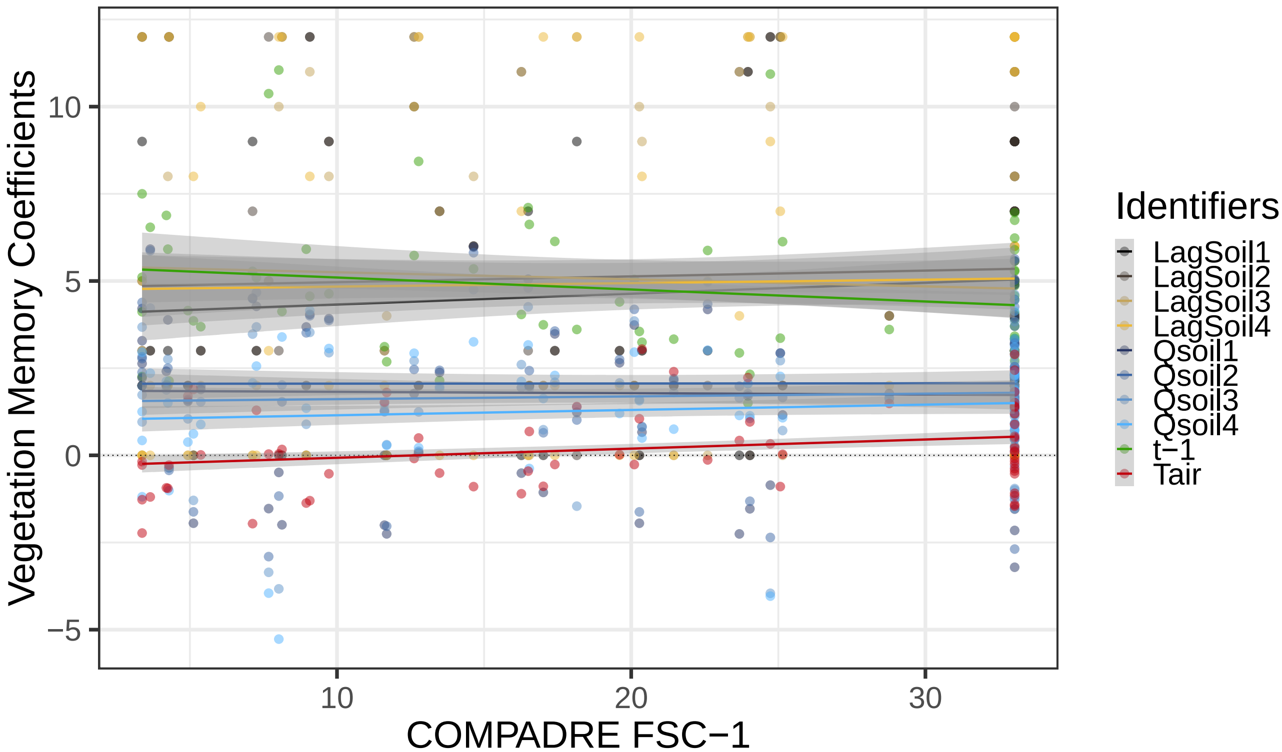


Figure 3.25: COMPADRE FSC-1 and Vegetation Memory (Iberian Region) - Linear regression coefficients of COMPADRE FSC-1 and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of FSC-1 and vegetation memory coefficients across the Iberian region are built on 67 data points each. Whilst most intercepts of these regressions are statistically significant, only the regression slope of Tair memory coefficients and FSC-1 is statistically significant but minute in nature.

Table 3.10: COMPADRE FSC-1 and Vegetation Memory (Iberian Region) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				Lag			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	5.4434	-0.3326	1.8599	2.0514	1.5327	0.9971	4.0145	4.8008	5.4526	4.7394
$p_{Intercept}$	0.0000	0.2618	0.0024	0.0002	0.0019	0.0249	0.0001	0.0000	0.0000	0.0003
Slope	-0.0344	0.0262	-0.0038	0.0004	0.0079	0.0152	0.0311	0.0166	-0.0202	0.0100
p_{Slope}	0.1180	0.0438	0.8810	0.9847	0.7036	0.4226	0.4680	0.7186	0.6972	0.8544

Relationships of vegetation memory coefficients and FSC-2 records across the Iberian region are represented in figure 3.26. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.11.

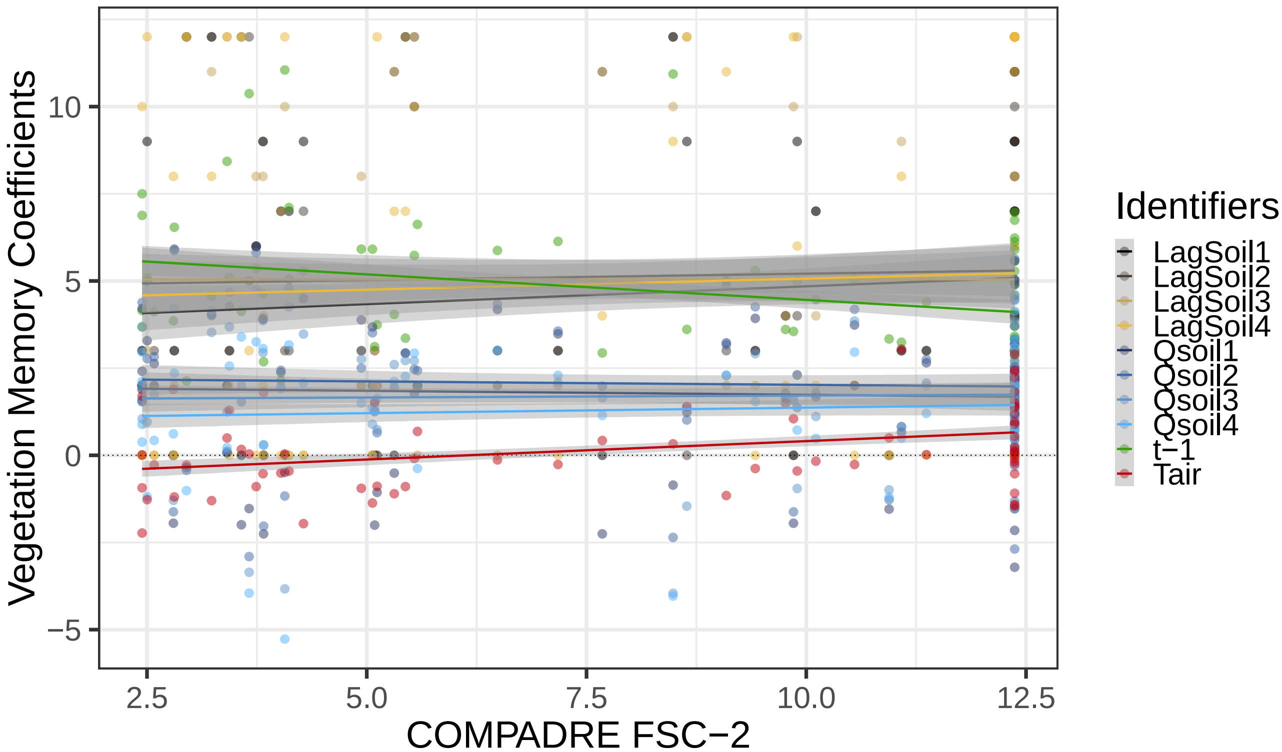


Figure 3.26: COMPADRE FSC-2 and Vegetation Memory (Iberian Region) - Linear regression coefficients of COMPADRE FSC-2 and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of FSC-2 and vegetation memory coefficients across the Iberian region are built on 67 data points each. Whilst all intercepts of these regressions are statistically significant, only the regression slopes of $NDVI_{[t-1]}$ and Tair memory coefficients and FSC-2. $NDVI_{[t-1]}$ memory decreases with increasing FSC-2 records. Tair memory increases with increasing FSC-2 records.

Table 3.11: COMPADRE FSC-2 and Vegetation Memory (Iberian Region) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				**Lag**			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	5.9207	-0.6467	1.9640	2.2173	1.6021	1.0501	3.8272	4.8370	5.0392	4.4284
$p_{Intercept}$	0.0000	0.0425	0.0035	0.0003	0.0031	0.0319	0.0007	0.0001	0.0003	0.0019
Slope	-0.1463	0.1053	-0.0227	-0.0196	0.0111	0.0317	0.1019	0.0372	0.0007	0.0640
p_{Slope}	0.0179	0.0038	0.7559	0.7625	0.8499	0.5572	0.4035	0.7760	0.9962	0.6787

Period of Oscillation (π)

Relationships of vegetation memory coefficients and π records across the Iberian region are represented in figure 3.27. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.12.

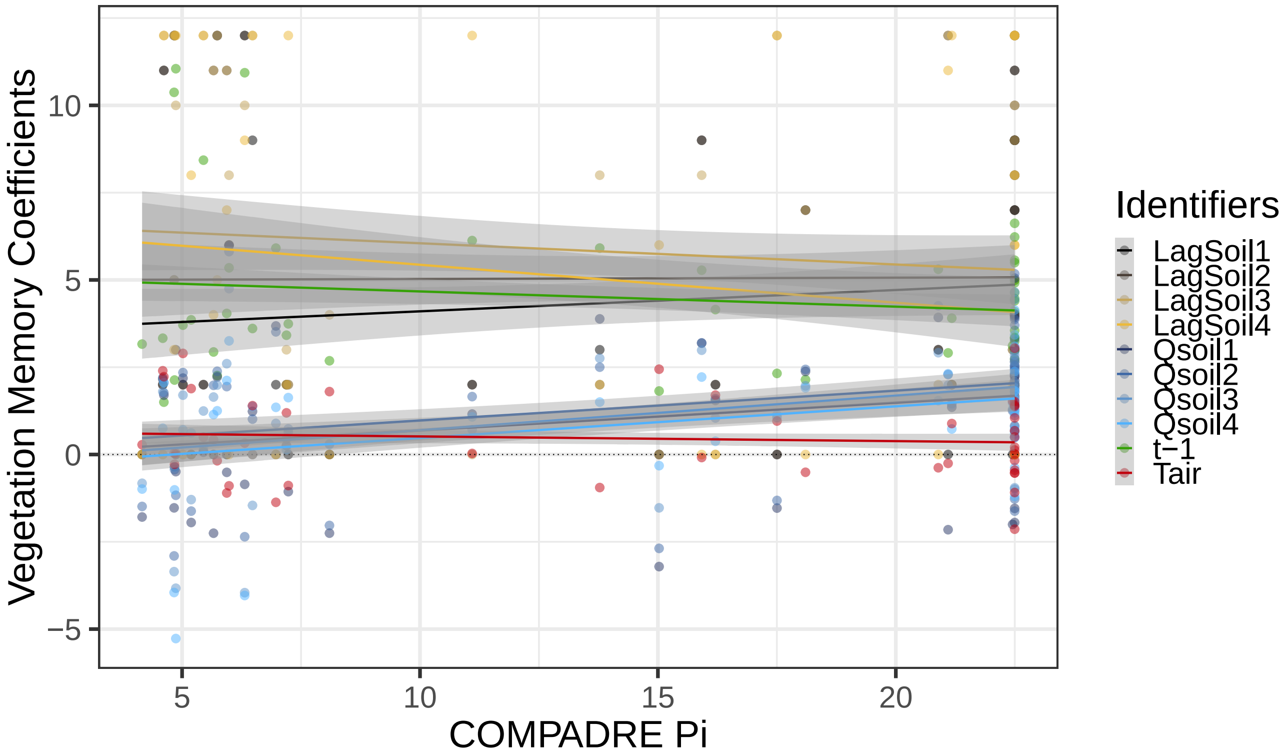


Figure 3.27: COMPADRE Period of Oscillation and Vegetation Memory (Iberian Region) - Linear regression coefficients of COMPADRE Period of Oscillation and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of π and vegetation memory coefficients across the Iberian region are built on 46 data points each. Only intercepts of Qsoil memory length and $NDVI_{[t-1]}$ regressions are statistically significant. Regression slopes, on the other hand, are only significant for Qsoil2, Qsoil3, and Qsoil4.

Table 3.12: COMPADRE Pi and Vegetation Memory (Iberian Region) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				**Lag**			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	5.1059	0.6520	-0.1074	0.1157	-0.2936	-0.4345	3.4905	4.9891	6.6589	6.5217
$p_{Intercept}$	0.0000	0.0875	0.8773	0.8530	0.6072	0.4175	0.0113	0.0009	0.0001	0.0001
Slope	-0.0435	-0.0134	0.0796	0.0856	0.0989	0.0907	0.0610	0.0038	-0.0608	-0.1087
p_{Slope}	0.3069	0.5598	0.0669	0.0294	0.0066	0.0078	0.4540	0.9650	0.5098	0.2462

Damping Ratio (ρ)

Relationships of vegetation memory coefficients and ρ records across the Iberian region are represented in figure 3.28. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.13.

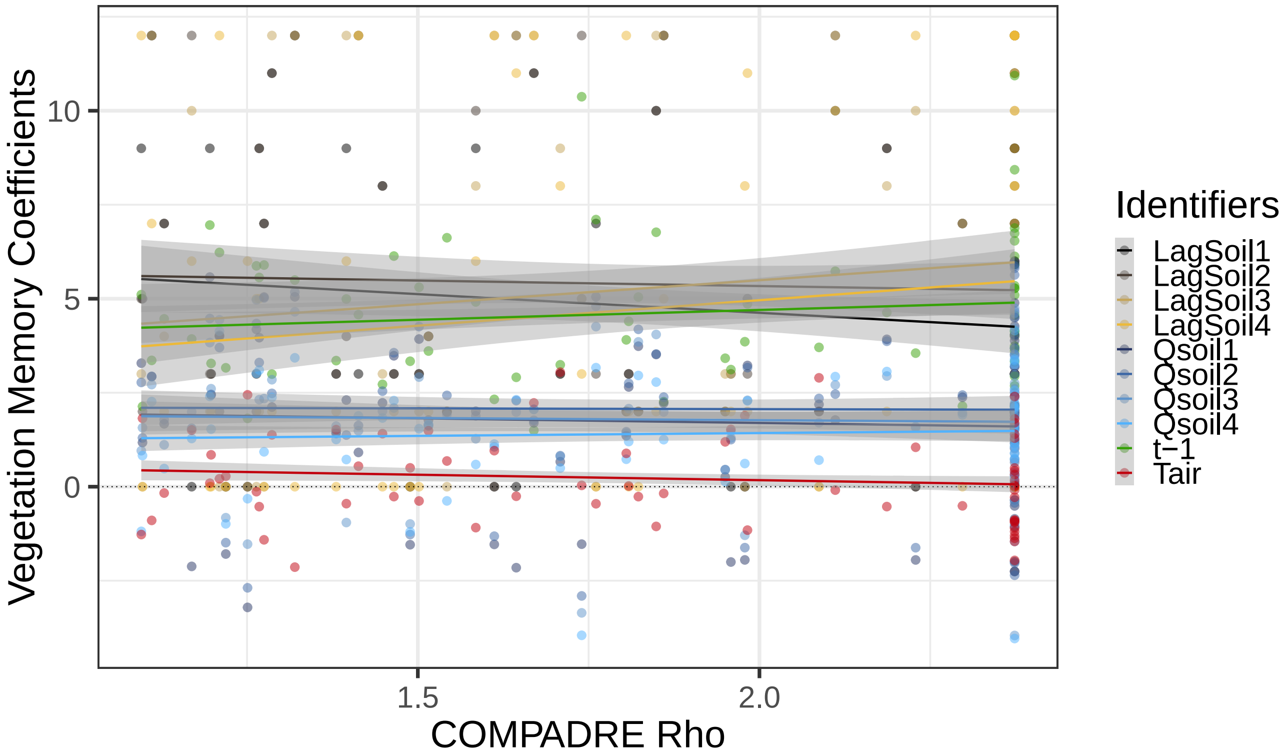


Figure 3.28: COMPADRE Damping Ratio and Vegetation Memory (Iberian Region) - Linear regression coefficients of COMPADRE Damping Ratio and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of ρ and vegetation memory coefficients across the Iberian region are built on 68 data points each. Intercepts of $NDVI_{[t-1]}$, Qsoil1, Qsoil2, Qsoil3, Qsoil1 memory length, and Qsoil2 memory length are statistically significant. Regression slopes, on the other hand, are not statistically significant for any of the regressions.

Table 3.13: COMPADRE Rho and Vegetation Memory (Iberian Region) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				**Lag**			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	3.6586	0.7530	2.1915	2.1433	1.9998	1.1250	6.6103	5.9246	2.9362	2.2494
$p_{Intercept}$	0.0001	0.2105	0.0707	0.0425	0.0285	0.1473	0.0014	0.0078	0.2189	0.3506
Slope	0.5212	-0.2896	-0.2479	-0.0404	-0.1152	0.1510	-0.9922	-0.2939	1.2779	1.3552
p_{Slope}	0.2784	0.3580	0.6937	0.9411	0.8069	0.7090	0.3456	0.7964	0.3076	0.2850

Reactivity

Relationships of vegetation memory coefficients and reactivity records across the Iberian region are represented in figure 3.29. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.14.

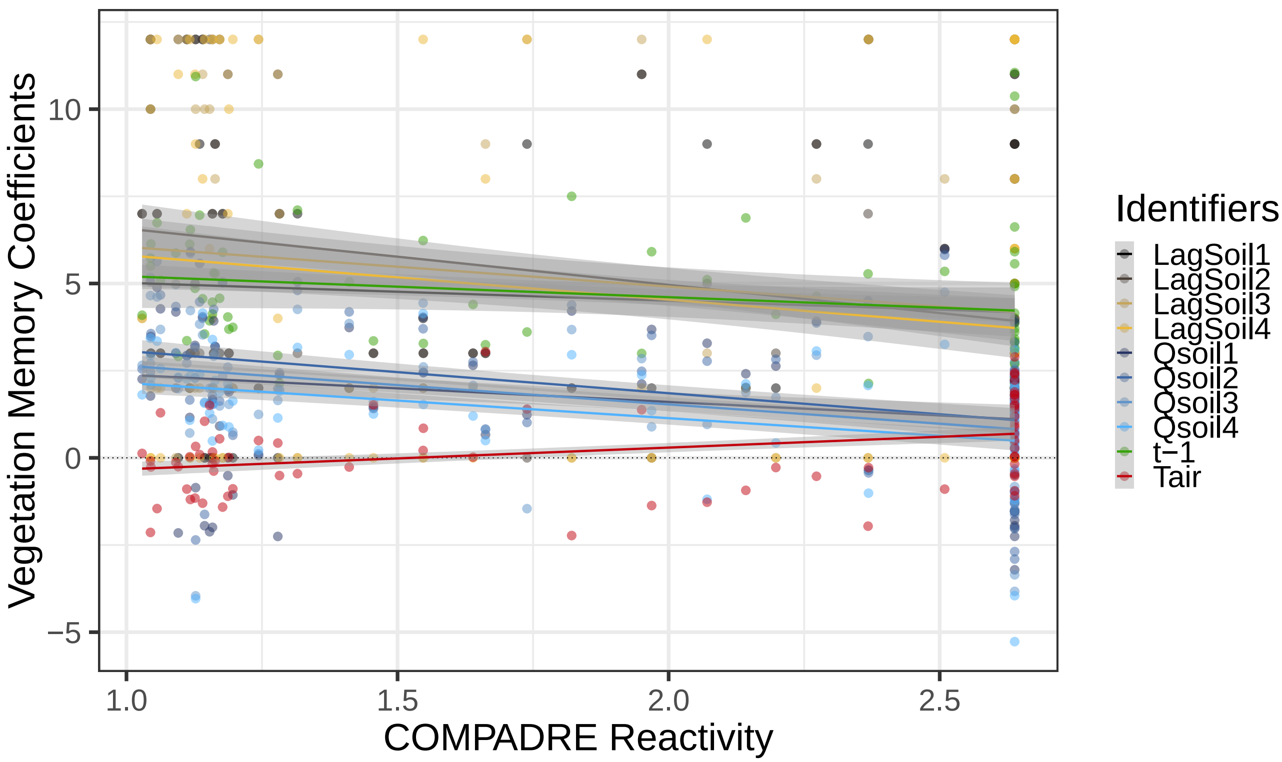


Figure 3.29: COMPADRE Reactivity and Vegetation Memory (Iberian Region) - Linear regression coefficients of COMPADRE Reactivity and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of reactivity and vegetation memory coefficients across the Iberian region are built on 71 data points each. Whilst COMPADRE reactivity is not linked statistically significantly to Qsoil memory lengths, relationships of all other vegetation memory coefficients and COMPADRE reactivity are.

$NDVI_{[t-1]}$ and Qsoil memory effects decrease with increasing COMPADRE reactivity. This effect diminishes throughout the Qsoil layers but stays statistically significant. Tair memory effects increase with increasing COMPADRE reactivity.

Table 3.14: COMPADRE Reactivity and Vegetation Memory (Iberian Region) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				Lag			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	5.8096	-0.9483	3.1582	4.2720	3.7464	3.1565	5.5325	8.1863	7.1894	7.0815
$p_{Intercept}$	0.0000	0.0186	0.0002	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0001
Slope	-0.6010	0.6209	-0.7768	-1.2092	-1.1071	-1.0093	-0.5127	-1.6133	-1.1391	-1.2722
p_{Slope}	0.0845	0.0029	0.0639	0.0007	0.0006	0.0006	0.4679	0.0307	0.1754	0.1414

3.2.1.2 Caatinga

Fast-Slow Continuum

Relationships of vegetation memory coefficients and FSC-1 records across the Caatinga are represented in figure 3.30. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.15.

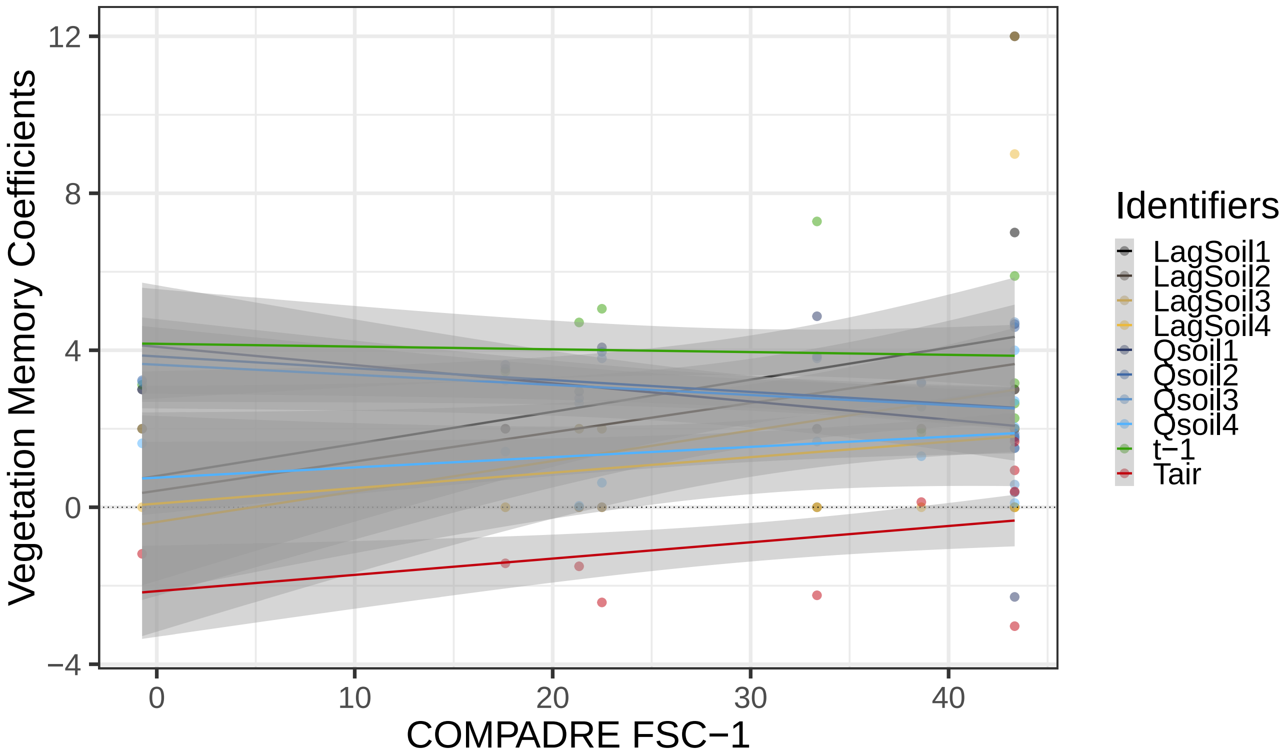


Figure 3.30: COMPADRE FSC-1 and Vegetation Memory (Caatinga) - Linear regression coefficients of COMPADRE FSC-1 and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of FSC-1 and vegetation memory coefficients across the Caatinga are built on 10 data points each. Almost all linear regressions coefficients are not statistically significant.

Table 3.15: COMPADRE FSC-1 and Vegetation Memory (Caatinga) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				Lag			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	4.1648	-2.1384	4.0874	3.8430	3.6320	0.7532	0.7962	0.4203	-0.3762	0.0924
$p_{Intercept}$	0.0163	0.0988	0.0296	0.0034	0.0046	0.4270	0.7700	0.8773	0.8947	0.9676
Slope	-0.0070	0.0415	-0.0464	-0.0302	-0.0257	0.0262	0.0818	0.0745	0.0776	0.0395
p_{Slope}	0.8672	0.2559	0.3407	0.3092	0.3801	0.3553	0.3250	0.3684	0.3692	0.5621

Relationships of vegetation memory coefficients and FSC-2 records across the Caatinga are represented in figure 3.31. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.16.

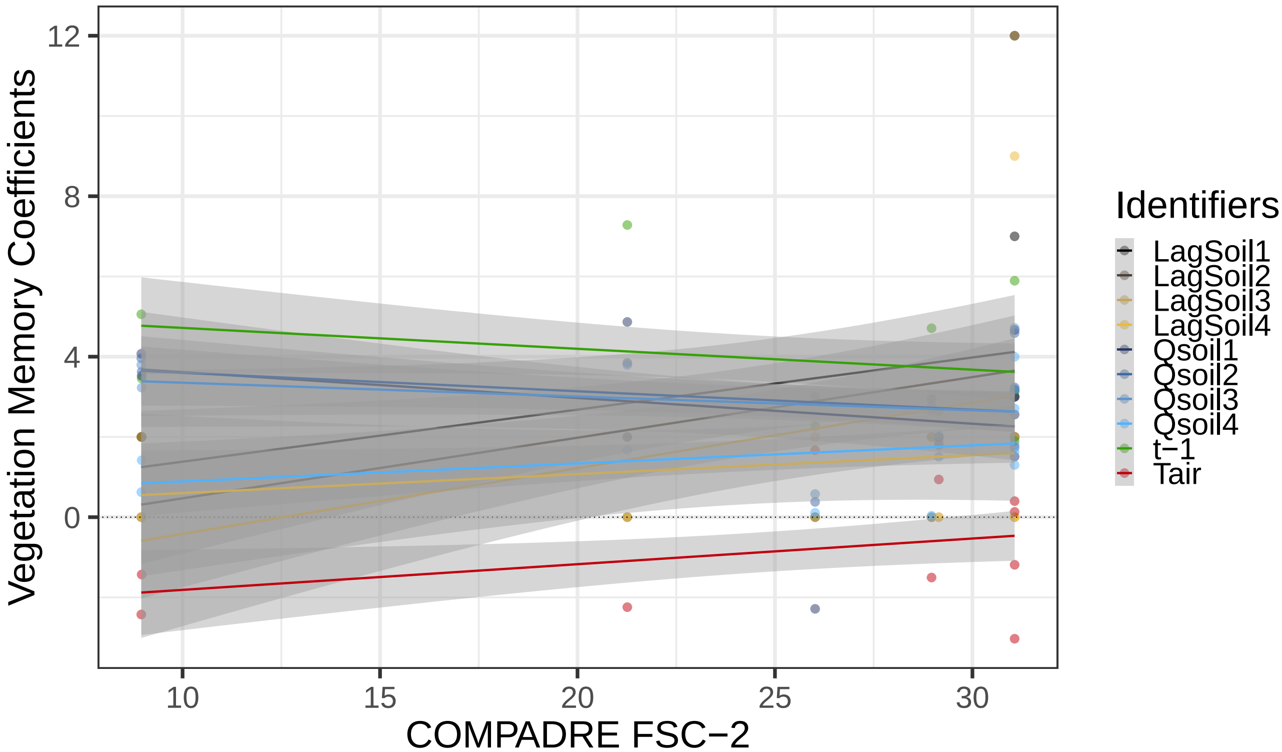


Figure 3.31: COMPADRE FSC-2 and Vegetation Memory (Caatinga) - Linear regression coefficients of COMPADRE FSC-2 and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of FSC-2 and vegetation memory coefficients across the Caatinga are built on 10 data points each. Almost all linear regressions coefficients are not statistically significant.

Table 3.16: COMPADRE FSC-2 and Vegetation Memory (Caatinga) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				**Lag**			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	5.2385	-2.4521	4.2578	4.0574	3.6954	0.4395	0.0839	-1.0409	-2.0526	0.1273
$p_{Intercept}$	0.0167	0.1459	0.0734	0.0115	0.0181	0.7182	0.9813	0.7649	0.5726	0.9662
Slope	-0.0521	0.0640	-0.0643	-0.0460	-0.0344	0.0450	0.1299	0.1511	0.1637	0.0474
p_{Slope}	0.4558	0.3036	0.4396	0.3624	0.4920	0.3460	0.3568	0.2740	0.2547	0.6821

Period of Oscillation (π)

Relationships of vegetation memory coefficients and π records across the Caatinga are represented in figure 3.32. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.17.

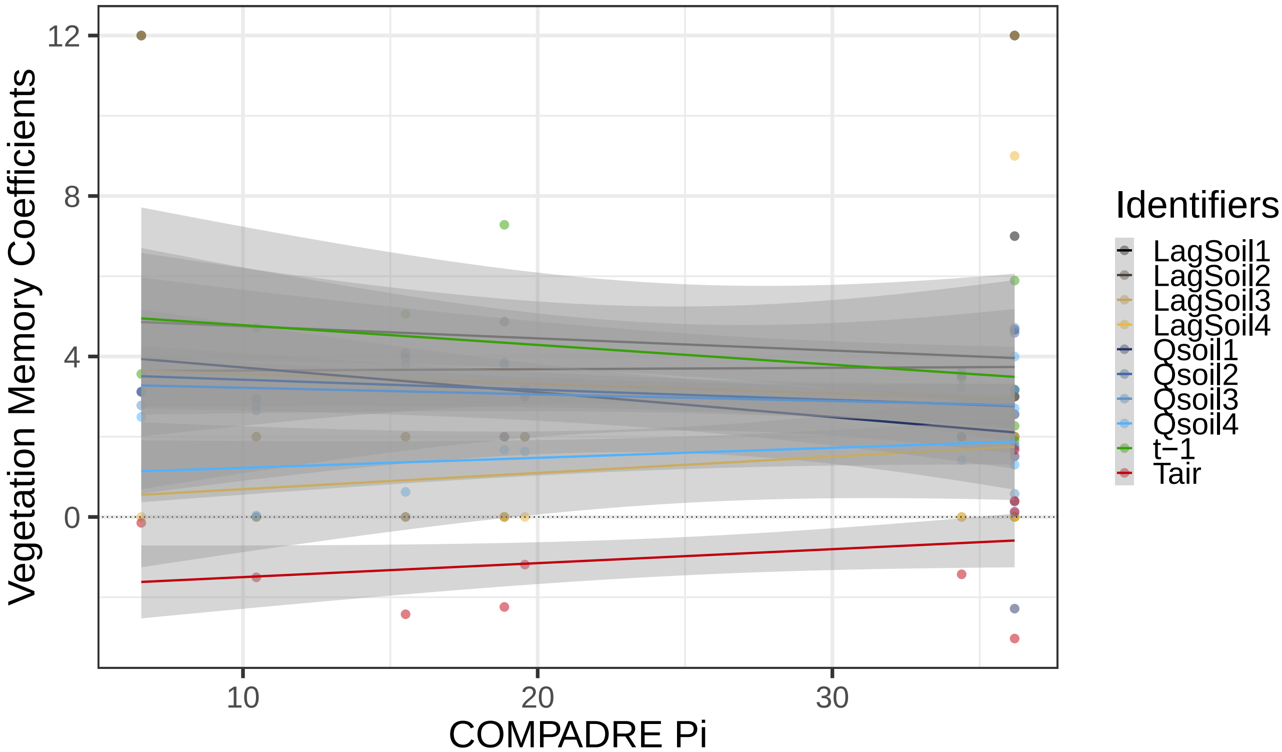


Figure 3.32: COMPADRE Period of Oscillation and Vegetation Memory (Caatinga) - Linear regression coefficients of COMPADRE Period of Oscillation and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of π and vegetation memory coefficients across the Caatinga are built on 10 data points each. Again, almost all linear regressions coefficients are not statistically significant.

Table 3.17: COMPADRE Pi and Vegetation Memory (Caatinga) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				Lag			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	5.2706	-1.8476	4.3434	3.6723	3.3870	0.9755	5.0573	3.6142	3.8016	0.2882
$p_{Intercept}$	0.0032	0.1420	0.0226	0.0047	0.0059	0.3402	0.1940	0.3547	0.3491	0.9015
Slope	-0.0491	0.0348	-0.0618	-0.0251	-0.0166	0.0249	-0.0303	0.0034	-0.0241	0.0405
p_{Slope}	0.3188	0.4233	0.3030	0.4872	0.6308	0.4965	0.8214	0.9802	0.8670	0.6354

Damping Ratio (ρ)

Relationships of vegetation memory coefficients and ρ records across the Caatinga are represented in figure 3.33. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.18.

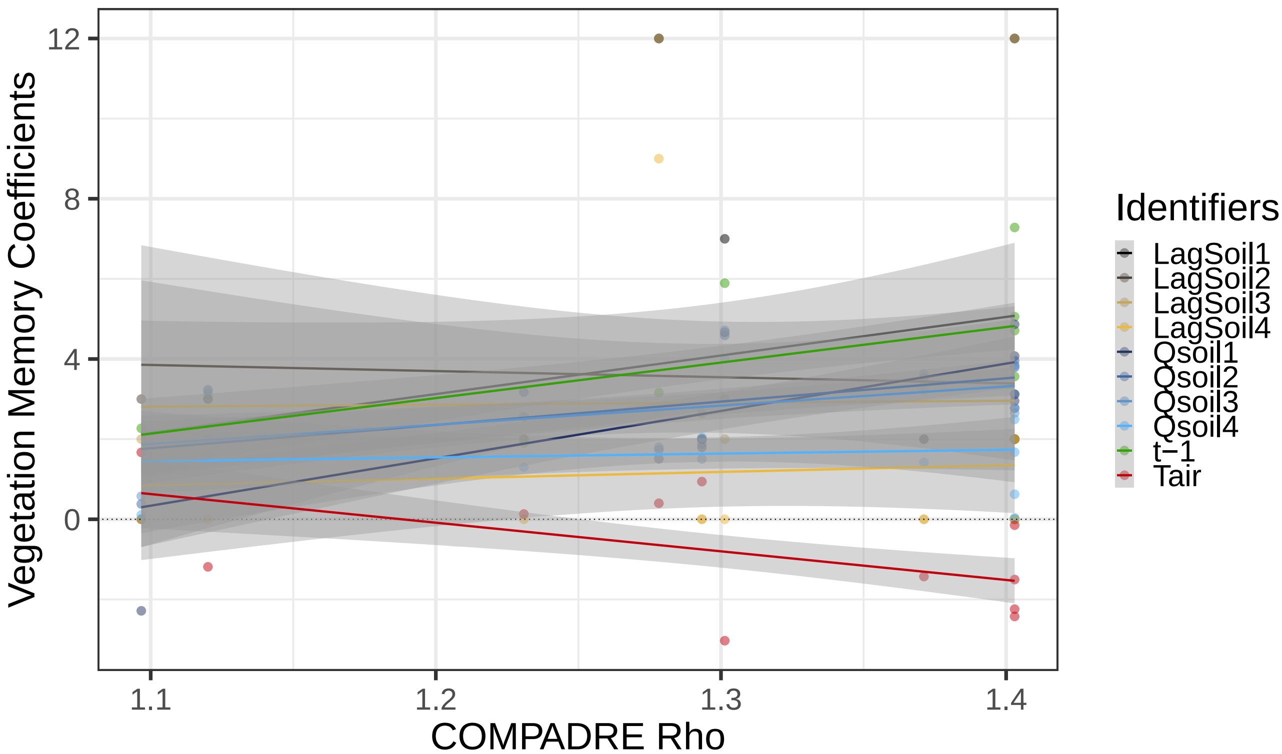


Figure 3.33: COMPADRE Damping Ratio and Vegetation Memory (Caatinga) - Linear regression coefficients of COMPADRE Damping Ratio and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of ρ and vegetation memory coefficients across the Caatinga are built on 11 data points each. Once more, almost all linear regressions coefficients are not statistically significant.

Table 3.18: COMPADRE Rho and Vegetation Memory (Caatinga) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				**Lag**			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	-7.6188	8.4896	-12.6646	-4.6329	-3.3823	0.4037	-8.428	5.5330	2.2728	-0.9941
$p_{Intercept}$	0.1667	0.1181	0.0497	0.2635	0.4232	0.9306	0.609	0.7492	0.9010	0.9264
Slope	8.8695	-7.1458	11.8215	5.8229	4.7843	0.9503	9.627	-1.5285	0.4894	1.6733
p_{Slope}	0.0482	0.0903	0.0221	0.0822	0.1559	0.7895	0.450	0.9080	0.9721	0.8394

Reactivity

Relationships of vegetation memory coefficients and reactivity records across the Caatinga are represented in figure 3.34. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.19.

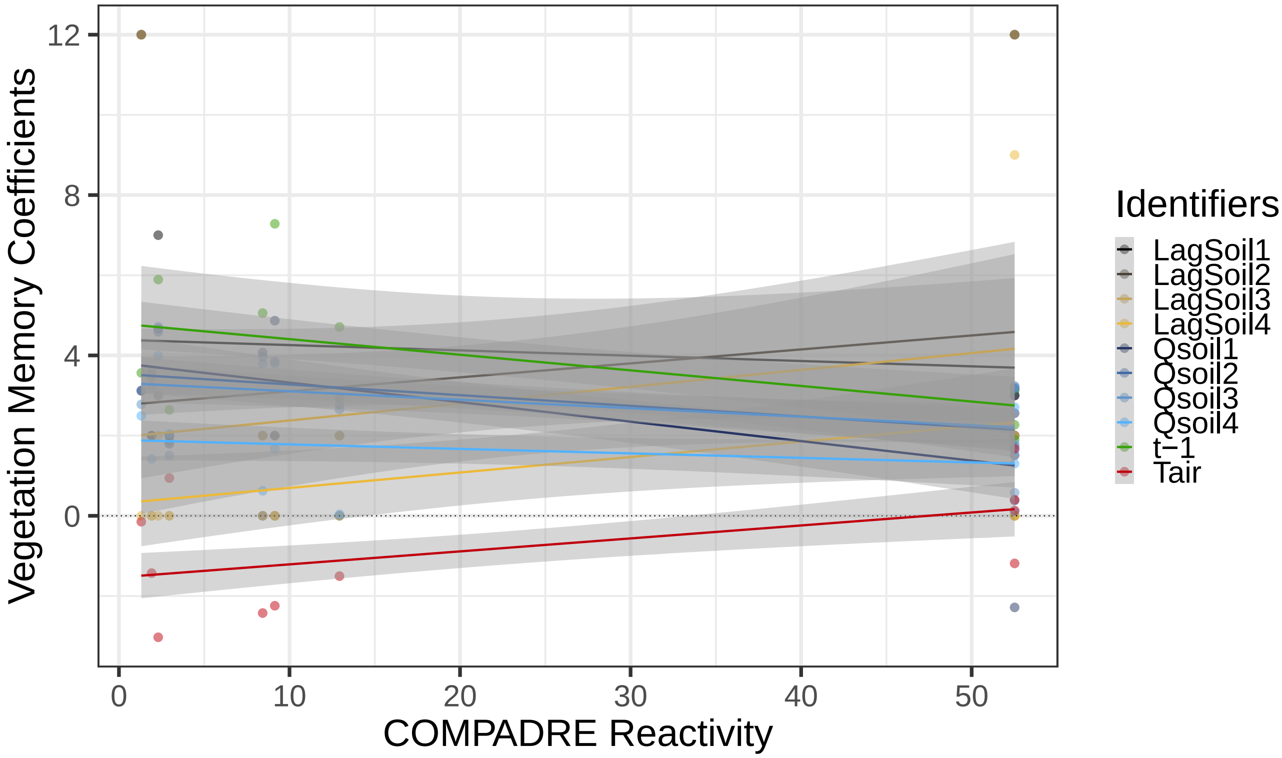


Figure 3.34: COMPADRE Reactivity and Vegetation Memory (Caatinga) - Linear regression coefficients of COMPADRE Reactivity and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of reactivity and vegetation memory coefficients across the Caatinga are built on 11 data points each. Again, my analyses did not identify statistically significant relationships between COMPADRE reactivity and vegetation memory coefficients.

Table 3.19: COMPADRE Reactivity and Vegetation Memory (Caatinga) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				**Lag**			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	4.7957	-1.5349	3.8087	3.5421	3.3172	1.8933	4.3909	2.7570	1.9571	0.3092
$p_{Intercept}$	0.0000	0.0260	0.0004	0.0000	0.0001	0.0048	0.0460	0.1824	0.3546	0.7928
Slope	-0.0389	0.0324	-0.0486	-0.0266	-0.0211	-0.0112	-0.0132	0.0348	0.0420	0.0385
p_{Slope}	0.0694	0.1047	0.0543	0.0920	0.1853	0.4974	0.8274	0.5717	0.5172	0.3061

3.2.1.3 Australia

Fast-Slow Continuum

Relationships of vegetation memory coefficients and FSC-1 records across Australia are represented in figure 3.35. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.20.

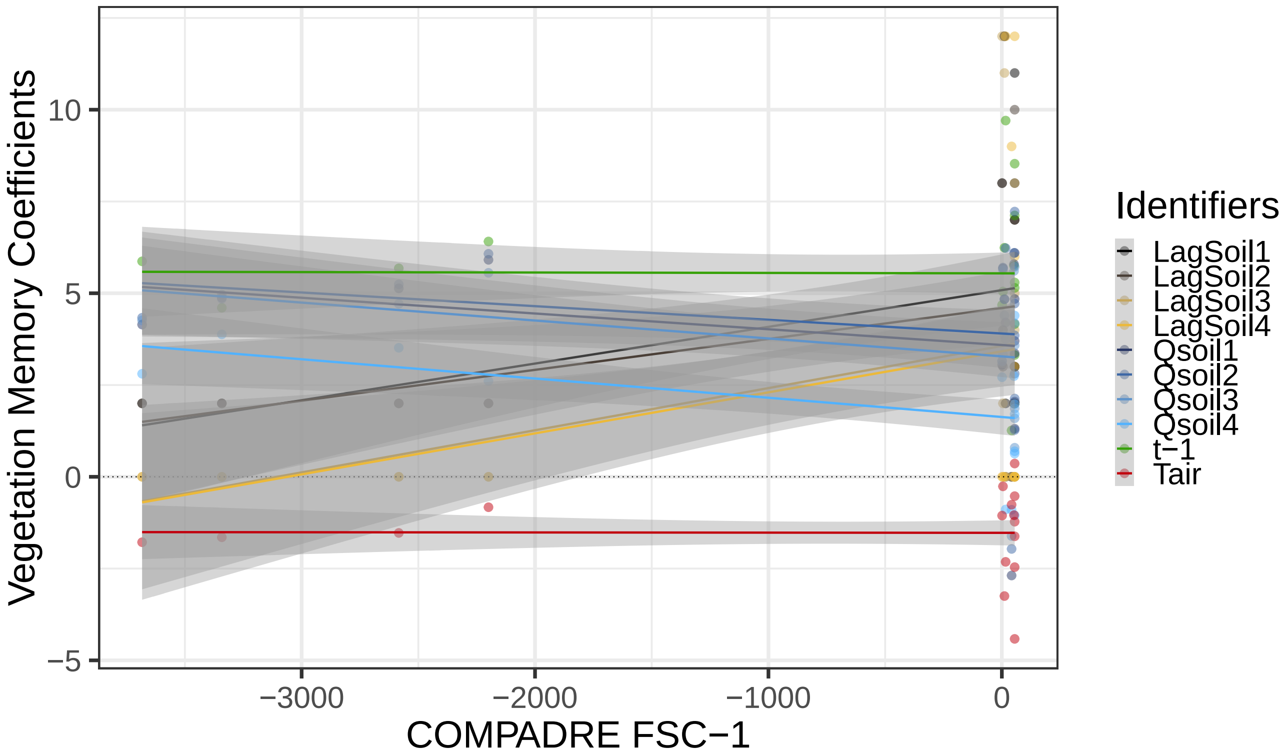


Figure 3.35: COMPADRE FSC-1 and Vegetation Memory (Australia) - Linear regression coefficients of COMPADRE FSC-1 and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of FSC-1 and vegetation memory coefficients across Australia are built on 16 data points each. Whilst all intercepts of these regressions are statistically significant, none of the regression slopes are.

Table 3.20: COMPADRE FSC-1 and Vegetation Memory (Australia) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				**Lag**			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	5.5424	-1.5262	3.5898	3.9032	3.2799	1.6290	5.0844	4.5973	3.5648	3.4176
$p_{Intercept}$	0.0000	0.0006	0.0001	0.0000	0.0000	0.0046	0.0001	0.0004	0.0068	0.0156
Slope	0.0000	0.0000	-0.0004	-0.0004	-0.0005	-0.0005	0.0010	0.0008	0.0012	0.0011
p_{Slope}	0.9767	0.9822	0.3233	0.4071	0.2166	0.1251	0.1492	0.2279	0.1459	0.1969

Relationships of vegetation memory coefficients and FSC-2 records across Australia are represented in figure 3.36. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.21.

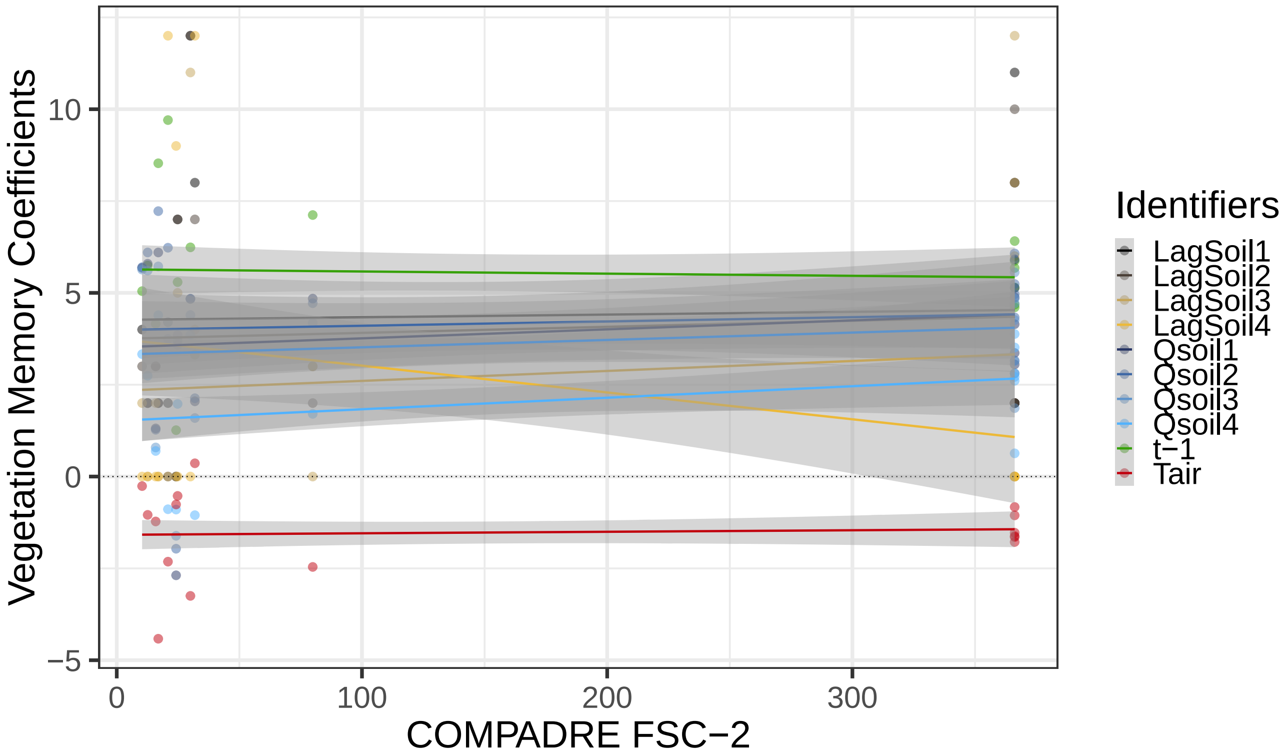


Figure 3.36: COMPADRE FSC-2 and Vegetation Memory (Australia) - Linear regression coefficients of COMPADRE FSC-2 and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of FSC-2 and vegetation memory coefficients across Australia are built on 16 data points each. Whilst almost all intercepts of these regressions are statistically significant, none of the regression slopes are.

Table 3.21: COMPADRE FSC-2 and Vegetation Memory (Australia) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				**Lag**			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	5.6412	-1.5861	3.5168	3.9873	3.3179	1.5181	4.2607	3.7464	2.3326	3.7500
$p_{Intercept}$	0.0000	0.0019	0.0005	0.0002	0.0004	0.0257	0.0051	0.0108	0.1315	0.0281
Slope	-0.0006	0.0004	0.0024	0.0012	0.0020	0.0031	0.0007	0.0016	0.0027	-0.0073
p_{Slope}	0.8504	0.8255	0.4874	0.7489	0.5375	0.2641	0.8982	0.7751	0.6808	0.2997

Period of Oscillation (π)

Relationships of vegetation memory coefficients and π records across Australia are represented in figure 3.37. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.22.

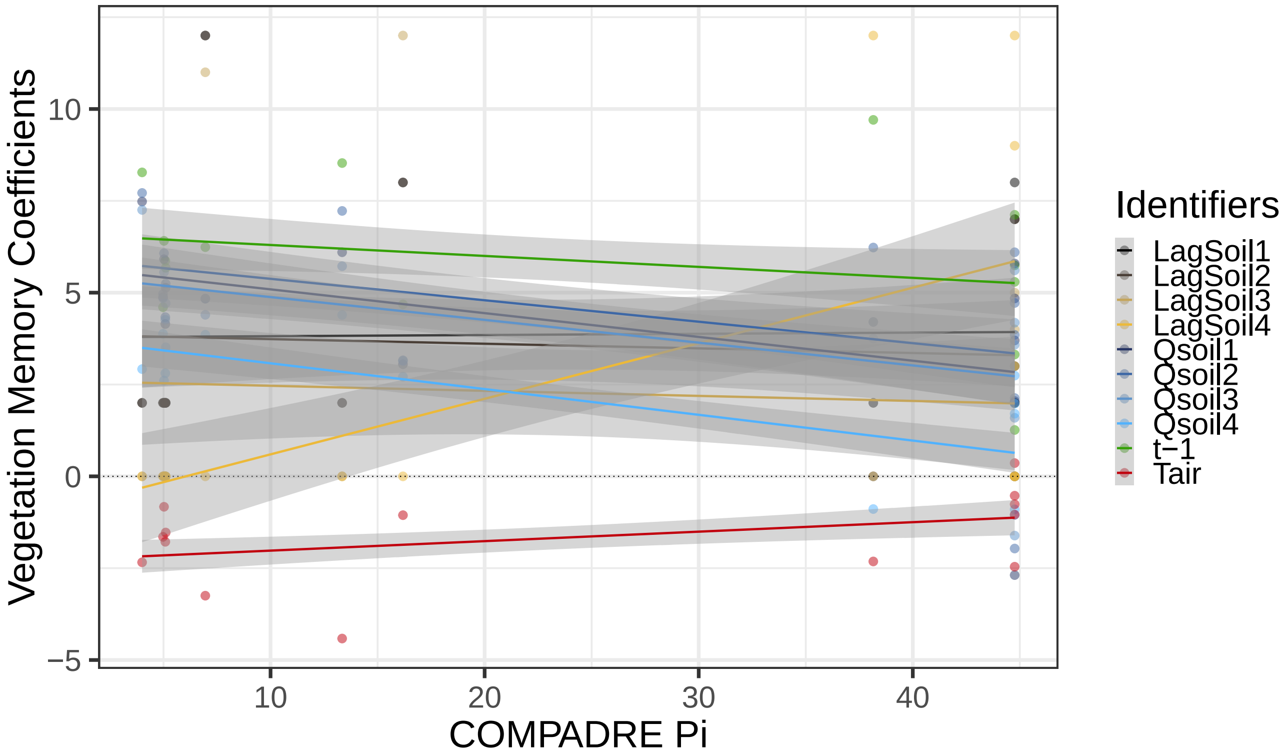


Figure 3.37: COMPADRE Period of Oscillation and Vegetation Memory (Australia) - Linear regression coefficients of COMPADRE Period of Oscillation and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of π and vegetation memory coefficients across Australia are built on 14 data points each. Again, almost all intercepts of these regressions are statistically significant. However, only some linear regression slopes pertaining mostly to Qsoil memory effects and memory lengths are statistically significant.

Table 3.22: COMPADRE Pi and Vegetation Memory (Australia) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				**Lag**			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	6.5963	-2.2802	5.7378	5.9607	5.5000	3.7786	3.7824	3.8621	2.6027	-0.9142
$p_{Intercept}$	0.0000	0.0007	0.0000	0.0000	0.0000	0.0000	0.0305	0.0298	0.1947	0.5931
Slope	-0.0298	0.0258	-0.0648	-0.0584	-0.0620	-0.0701	0.0032	-0.0126	-0.0138	0.1513
p_{Slope}	0.3676	0.1560	0.0640	0.1013	0.0399	0.0035	0.9517	0.8171	0.8347	0.0205

Damping Ratio (ρ)

Relationships of vegetation memory coefficients and ρ records across Australia are represented in figure 3.38. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.23.

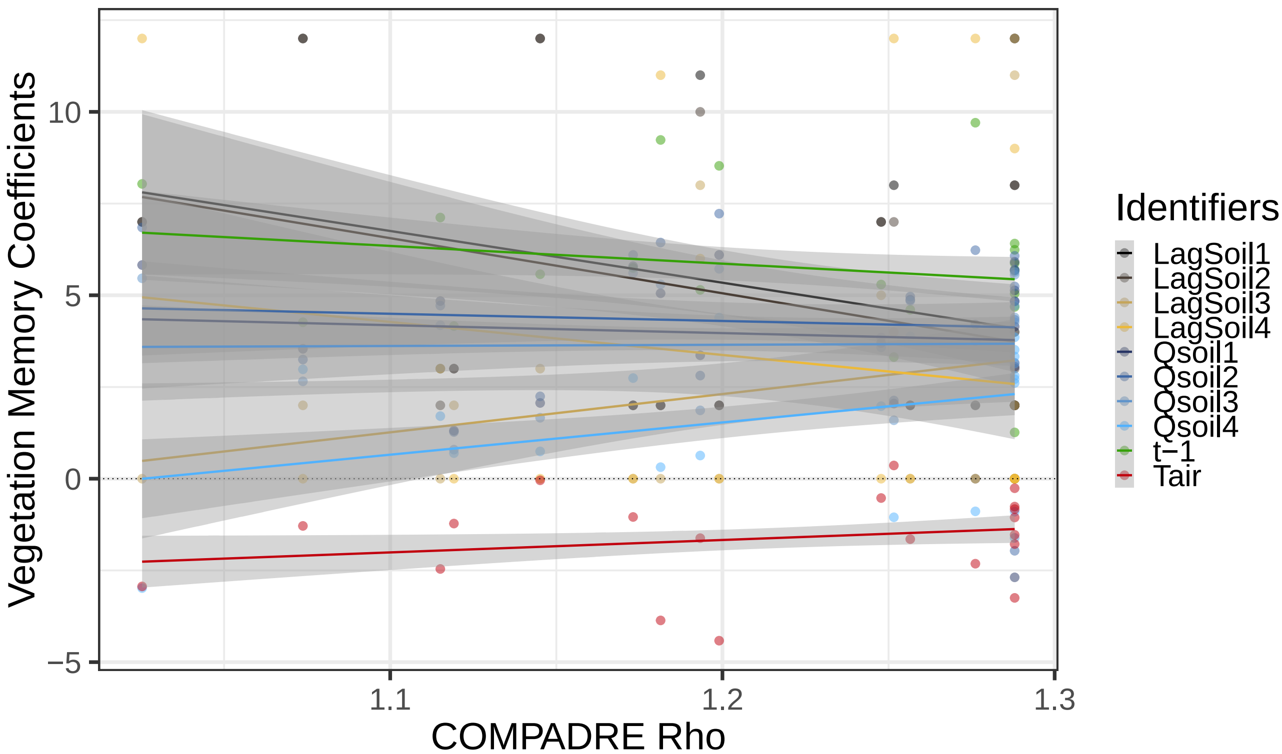


Figure 3.38: COMPADRE Damping Ratio and Vegetation Memory (Australia) - Linear regression coefficients of COMPADRE Damping Ratio and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of ρ and vegetation memory coefficients across Australia are built on 20 data points each. None of the delineated linear regression coefficients are statistically significant.

Table 3.23: COMPADRE Rho and Vegetation Memory (Australia) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

			Qsoil				**Lag**			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	11.6623	-5.7314	6.5573	6.6552	3.2565	-9.0182	22.2656	23.0814	-10.2155	14.1757
$p_{Intercept}$	0.1083	0.1975	0.3783	0.4044	0.6413	0.1831	0.1186	0.1091	0.4356	0.4177
Slope	-4.8337	3.3840	-2.1568	-1.9629	0.3283	8.7932	-14.1026	-15.0220	10.4359	-9.0023
p_{Slope}	0.4055	0.3493	0.7220	0.7629	0.9543	0.1179	0.2228	0.1987	0.3349	0.5298

Reactivity

Relationships of vegetation memory coefficients and reactivity records across Australia are represented in figure 3.39. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.24.

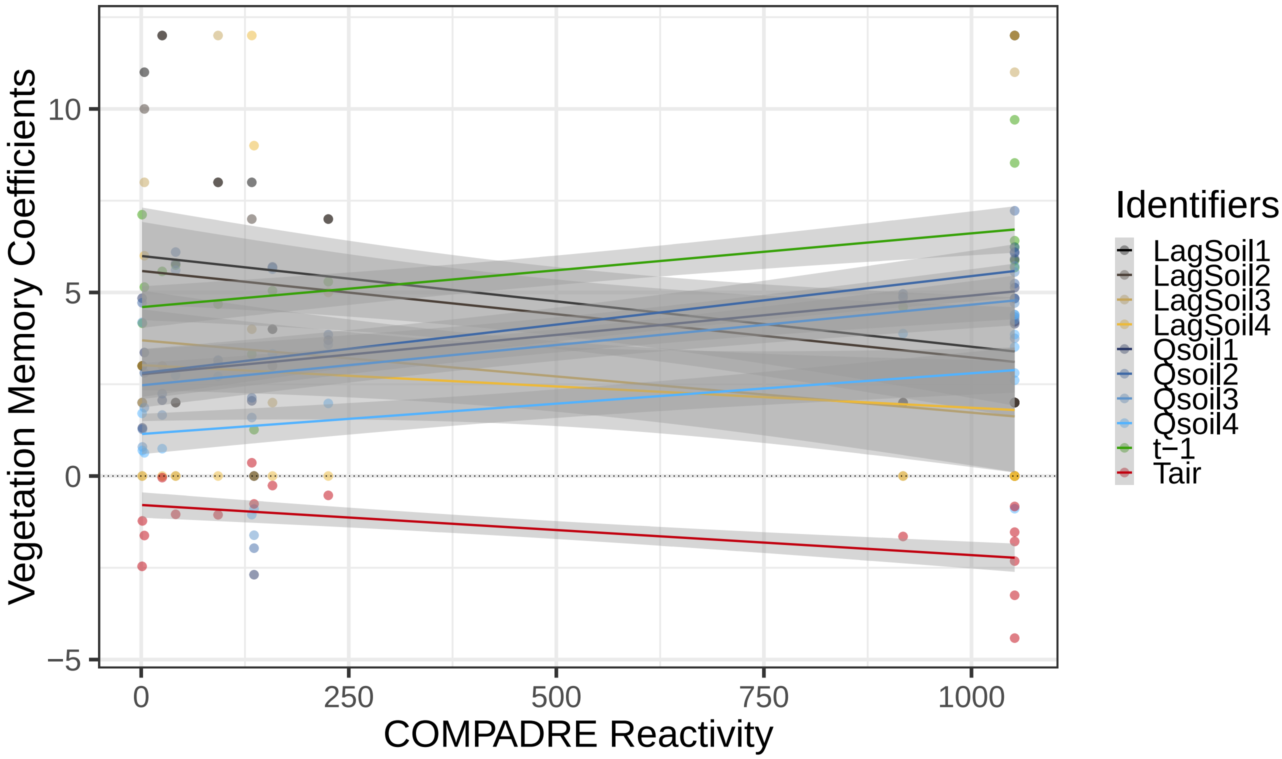


Figure 3.39: COMPADRE Reactivity and Vegetation Memory (Australia) - Linear regression coefficients of COMPADRE Reactivity and vegetation memory coefficients. Figure established via Chunk 32.

Linear relationships of reactivity and vegetation memory coefficients across Australia are built on 17 data points each. My analyses identified statistically significant relationships for all vegetation memory coefficients but Qsoil memory lengths with positive relationships between $NDVI_{[t-1]}$ as well as Qsoil memory effects and COMPADRE reactivity. With the exception of Tair, all of these relationships are positive correlations.

Table 3.24: COMPADRE Reactivity and Vegetation Memory (Australia) - Linear regression coefficients of COMPADRE data and vegetation memory coefficients. Established via Chunk 33.

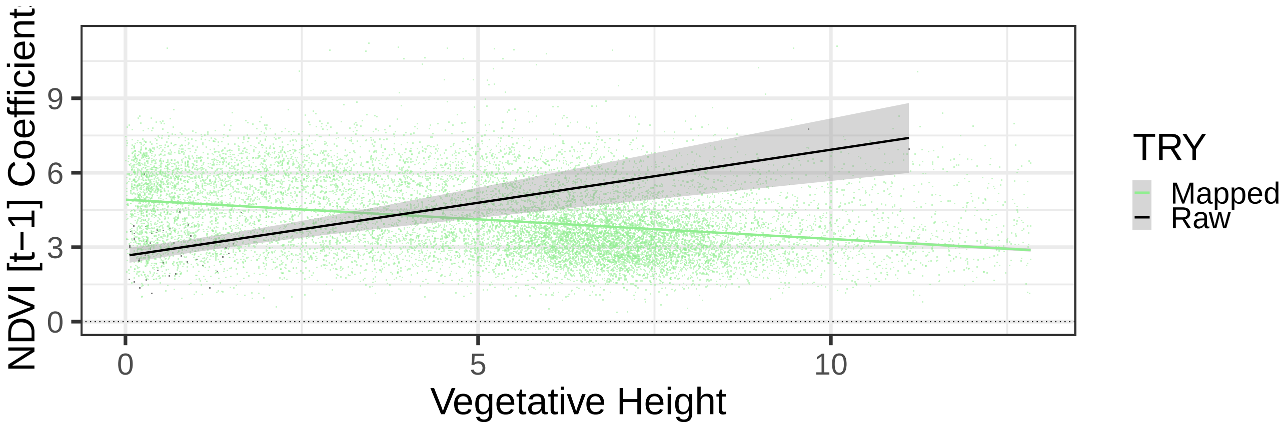
			Qsoil				**Lag**			
	t-1	Tair	1	2	3	4	1	2	3	4
Intercept	4.5999	-0.7890	2.7709	2.8030	2.4710	1.1432	5.9946	5.5867	3.6980	3.0208
$p_{Intercept}$	0.0000	0.0400	0.0011	0.0007	0.0011	0.0585	0.0004	0.0009	0.0171	0.0700
Slope	0.0020	-0.0014	0.0022	0.0026	0.0022	0.0017	-0.0025	-0.0024	-0.0020	-0.0012
p_{Slope}	0.0335	0.0200	0.0546	0.0176	0.0308	0.0659	0.2367	0.2642	0.3544	0.6229

3.2.2 Plant Functional Traits

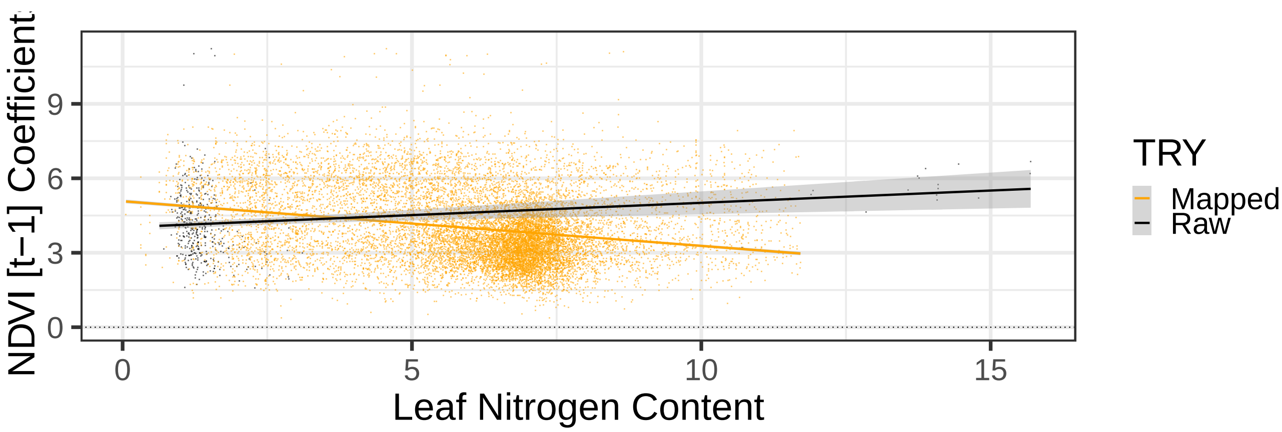
3.2.2.1 Iberian Region

Intrinsic Memory

Relationships of $NDVI_{[t-1]}$ vegetation memory coefficients and H, and N_{mass} records across the Iberian region are represented in figure 3.40. These relationships have been assessed through linear regressions.



(a) Height



(b) Nitrogen

Figure 3.40: PFTs and Intrinsic Memory (Iberian Region) - Intrinsic Memory (NDVI t-1, figure 3.1) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.5). Figure established via Chunk 34.

H is correlated with $NDVI_{[t-1]}$ memory effects as:

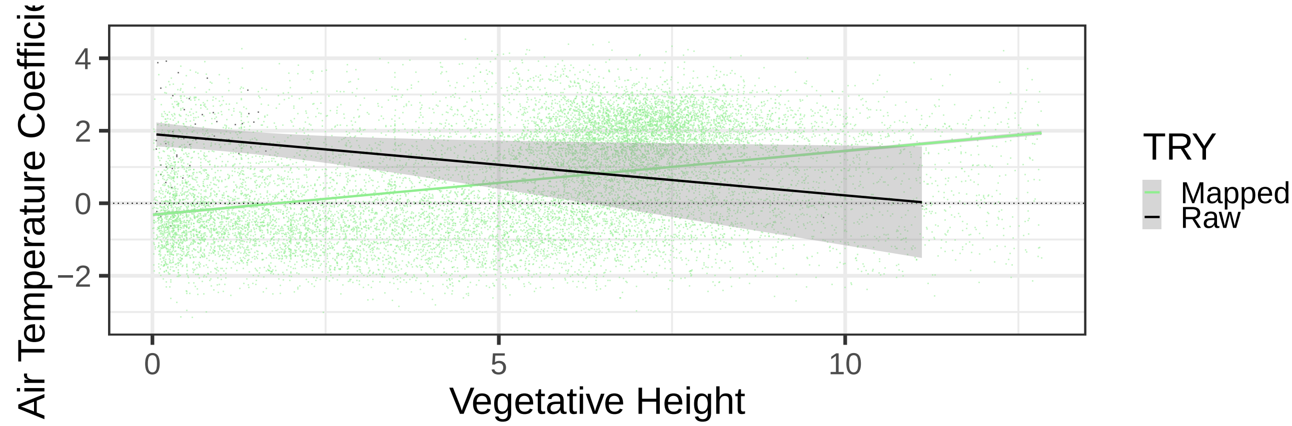
1. $Intercept = 2.6515$ ($p_{Intercept} = 3.7857 \times 10^{-22}$); $Slope = 0.4277$ ($p_{Slope} = 9.8097 \times 10^{-8}$) for untreated, geo-referenced data
2. $Intercept = 4.9137$ ($p_{Intercept} = 0$); $Slope = -0.1582$ ($p_{Slope} = 0$) for mapped mean trait data

N_{mass} is correlated with $NDVI_{[t-1]}$ memory effects as:

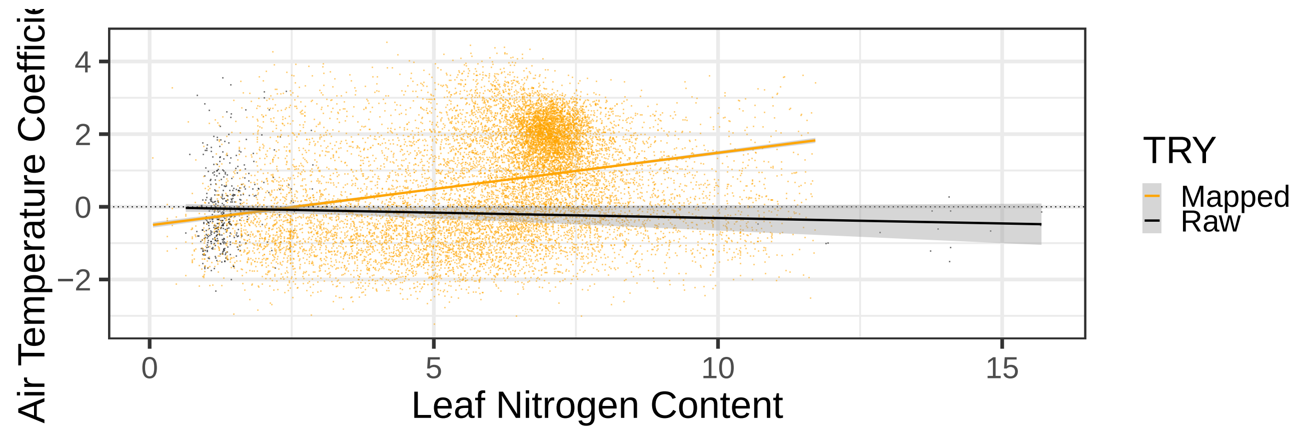
1. $Intercept = 4.0231$ ($p_{Intercept} = 6.2519 \times 10^{-176}$); $Slope = 0.0989$ ($p_{Slope} = 3.5129 \times 10^{-4}$) for untreated, geo-referenced data
2. $Intercept = 5.0768$ ($p_{Intercept} = 0$); $Slope = -0.1799$ ($p_{Slope} = 6.1229 \times 10^{-184}$) for mapped mean trait data

Air Temperature

Relationships of Tair vegetation memory coefficients and H, and N_{mass} records across the Iberian region are represented in figure 3.41. These relationships have been assessed through linear regressions.



(a) Height



(b) Nitrogen

Figure 3.41: PFTs and Tair Memory (Iberian Region) - Tair Memory (figure 3.1) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.5). Figure established via Chunk 34.

H is correlated with Tair memory effects as:

1. $Intercept = 1.9078$ ($p_{Intercept} = 3.2011 \times 10^{-15}$); $Slope = -0.1691$ ($p_{Slope} = 0.0276$) for untreated, geo-referenced data

2. $Intercept = -0.317$ ($p_{Intercept} = 1.237 \times 10^{-43}$); $Slope = 0.1761$ ($p_{Slope} = 0$) for mapped mean trait data

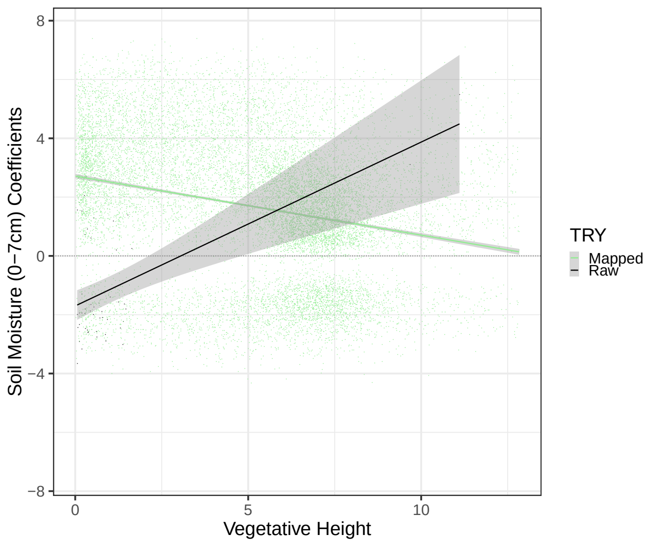
N_{mass} is correlated with Tair memory effects as:

1. $Intercept = -0.0113$ ($p_{Intercept} = 0.855$); $Slope = -0.0298$ ($p_{Slope} = 0.1482$) for untreated, geo-referenced data

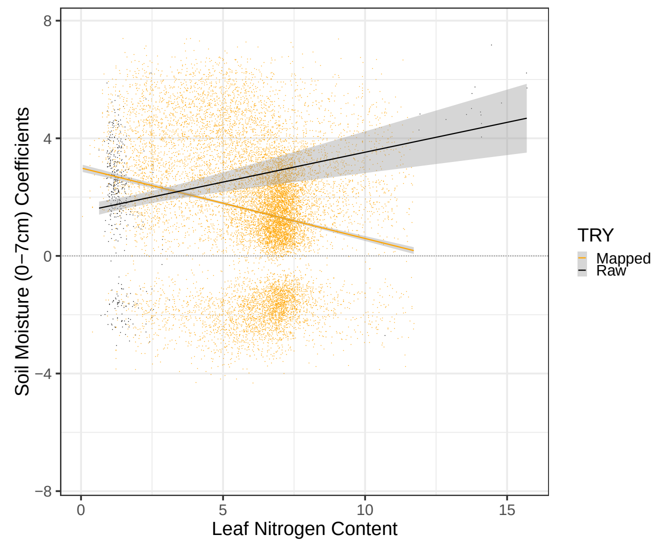
2. $Intercept = -0.5085$ ($p_{Intercept} = 2.2801 \times 10^{-39}$); $Slope = 0.1994$ ($p_{Slope} = 7.94 \times 10^{-232}$) for mapped mean trait data

Soil Moisture (0-7cm)

Relationships of Qsoil1 vegetation memory length, and coefficients and H, and N_{mass} records across the Iberian region are represented in figure 3.42. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.25.



(a) Height



(b) Nitrogen

Figure 3.42: PFTs and Qsoil1 Memory (Iberian Region) - Qsoil1 Memory (figure 3.1) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.5). Figure established via Chunk 34.

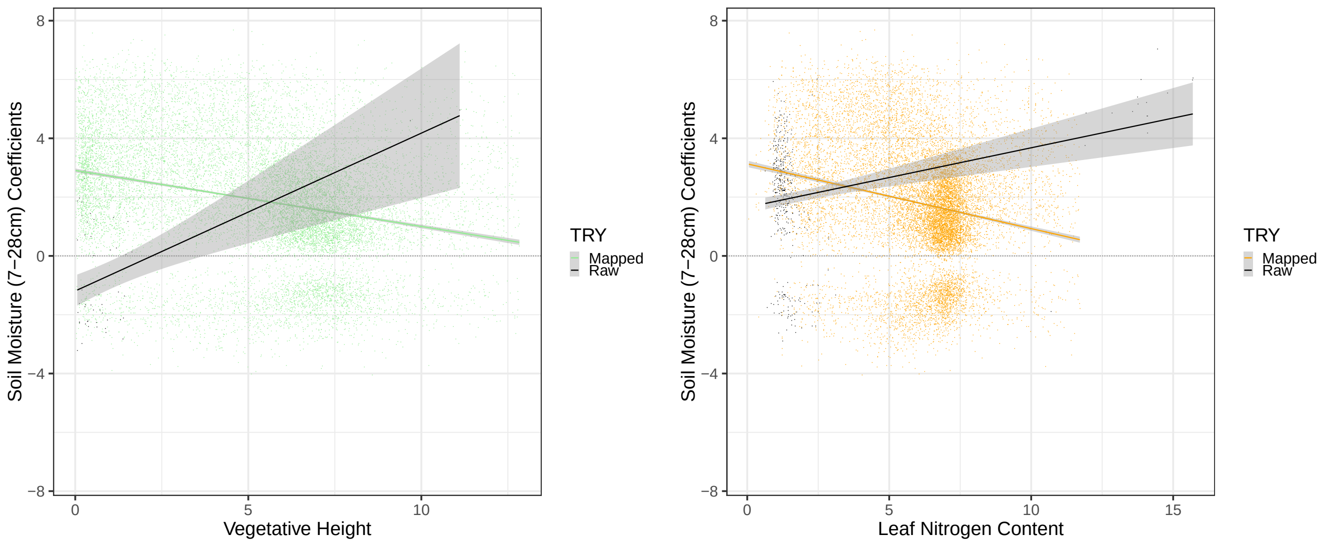
My analyses identified statistically significant relationships for all Qsoil1 related vegetation memory coefficients. Whilst geo-referenced data records of H and N_{mass} establish themselves in positive correlations with Qsoil1 memory effects and Qsoil1 memory length in the case of H, mapped mean trait values of H and N_{mass} are correlated negatively to Qsoil1 related vegetation memory coefficients.

Table 3.25: PFTs and Qsoil1 Memory (Iberian Region) - Coefficients of linear regressions of Qsoil1 memory coefficients against PFT data (vegetative height H, and leaf nitrogen mass Nmass) both as raw geo-referenced data (R), and extended maps of species-specific trait means (M). Established via Chunk 35.

	Qsoil				**Lag**			
	H		Nmass		H		Nmass	
	R	M	R	M	R	M	R	M
Intercept	-1.7021	2.7139	1.4959	2.9909	2.3419	4.2748	5.3394	4.8624
$p_{Intercept}$	0.0000	0.0000	0.0000	0.0000	0.0008	0.0000	0.0000	0.0000
Slope	0.5574	-0.2007	0.2031	-0.2398	0.1256	-0.0851	-0.2027	-0.1781
p_{Slope}	0.0000	0.0000	0.0000	0.0000	0.6681	0.0000	0.0127	0.0000

Soil Moisture (7-28cm)

Relationships of Qsoil2 vegetation memory length, and coefficients and H, and N_{mass} records across the Iberian region are represented in figure 3.43. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.26.



(a) Height

(b) Nitrogen

Figure 3.43: PFTs and Qsoil2 Memory (Iberian Region) - Qsoil2 Memory (figure A.10) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.5). Figure established via Chunk 34.

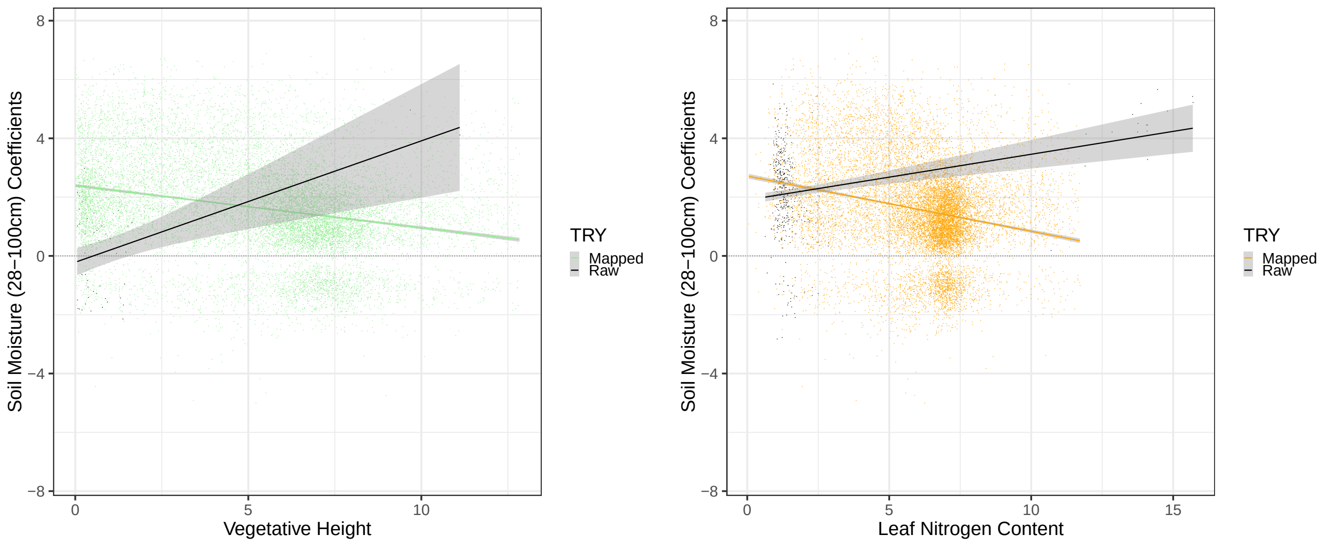
My analyses identified statistically significant relationships for all Qsoil2 related vegetation memory coefficients with the exception of H and Qsoil2 memory length. Whilst geo-referenced data records of H and N_{mass} establish themselves in positive correlations with Qsoil2 memory effects, mapped mean trait values of H and N_{mass} are correlated negatively to Qsoil2 related vegetation memory coefficients. Qsoil2 memory length is correlated negatively to both H and N_{mass}.

Table 3.26: PFTs and Qsoil2 Memory (Iberian Region) - Coefficients of linear regressions of Qsoil2 memory coefficients against PFT data (vegetative height H, and leaf nitrogen mass Nmass) both as raw geo-referenced data (R), and extended maps of species-specific trait means (M). Established via Chunk 35.

	Qsoil				**Lag**			
	H		Nmass		H		Nmass	
	R	M	R	M	R	M	R	M
Intercept	-1.1921	2.9064	1.6543	3.1314	3.4366	4.0972	5.4557	4.6986
$p_{Intercept}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Slope	0.5368	-0.1904	0.2023	-0.2202	-0.2691	-0.0178	-0.2357	-0.1106
p_{Slope}	0.0000	0.0000	0.0000	0.0000	0.3846	0.0685	0.0041	0.0000

Soil Moisture (28-100cm)

Relationships of Qsoil3 vegetation memory length, and coefficients and H, and N_{mass} records across the Iberian region are represented in figure 3.44. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.27.



(a) Height

(b) Nitrogen

Figure 3.44: PFTs and Qsoil3 Memory (Iberian Region) - Qsoil3 Memory (figure A.11) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.5). Figure established via Chunk 34.

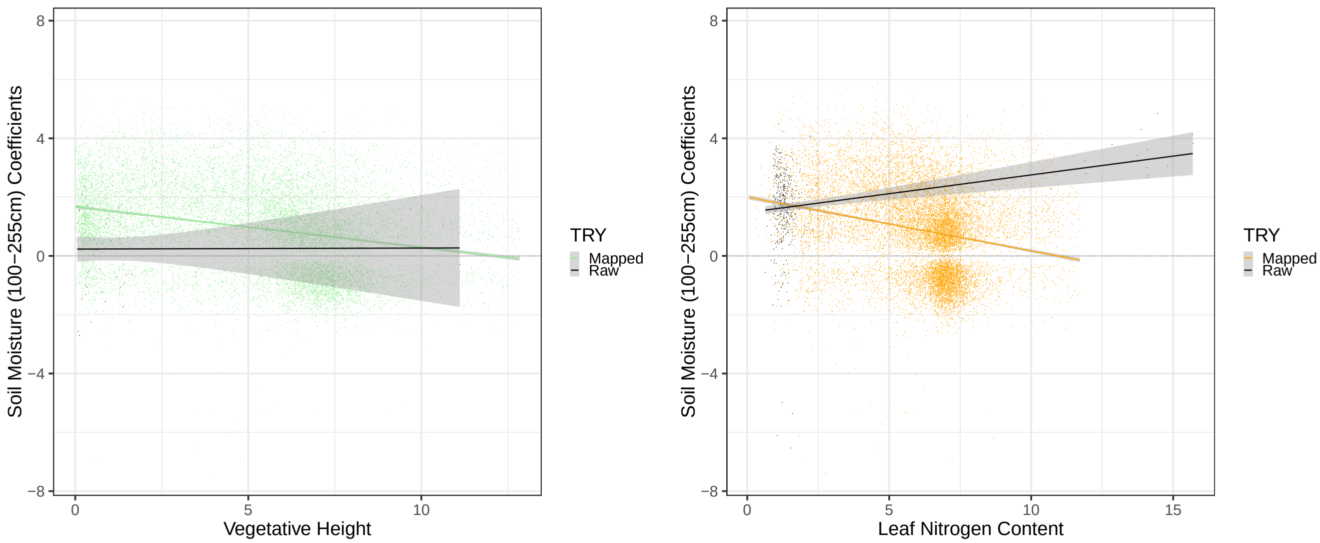
Linear regression analyses identified statistically significant relationships for all Qsoil3 related vegetation memory coefficients with the exception of H and Qsoil3 memory length. Whilst geo-referenced data records of H and N_{mass} establish themselves in positive correlations with Qsoil3 memory effects, mapped mean trait values of H and N_{mass} are correlated negatively to Qsoil3 related vegetation memory coefficients. Qsoil3 memory length is correlated negatively to both H and N_{mass}.

Table 3.27: PFTs and Qsoil3 Memory (Iberian Region) - Coefficients of linear regressions of Qsoil3 memory coefficients against PFT data (vegetative height H, and leaf nitrogen mass Nmass) both as raw geo-referenced data (R), and extended maps of species-specific trait means (M). Established via Chunk 35.

	Qsoil				**Lag**			
	H		Nmass		H		Nmass	
	R	M	R	M	R	M	R	M
Intercept	-0.2154	2.3935	1.9010	2.7168	5.9910	3.4241	4.8415	4.0994
$p_{Intercept}$	0.3608	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Slope	0.4128	-0.1436	0.1556	-0.1878	-0.7147	0.0024	-0.2447	-0.1009
p_{Slope}	0.0003	0.0000	0.0000	0.0000	0.0377	0.8365	0.0053	0.0000

Soil Moisture (100-255cm)

Relationships of Qsoil4 vegetation memory length, and coefficients and H, and N_{mass} records across the Iberian region are represented in figure 3.45. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.28.



(a) Height **(b)** Nitrogen

Figure 3.45: PFTs and Qsoil4 Memory (Iberian Region) - Qsoil4 Memory (figure A.12) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.5). Figure established via Chunk 34.

Linear regression analyses identified statistically significant relationships for all Qsoil4 related vegetation memory coefficients with the exception of geo-referenced H and Qsoil3 memory effects, and memory length as well as geo-referenced N_{mass} and Qsoil4 memory lengths. Whilst geo-referenced data records of H and N_{mass} establish themselves in positive correlations with Qsoil4 related memory coefficients, mapped mean trait values of H and N_{mass} are correlated negatively to Qsoil4 related vegetation memory coefficients.

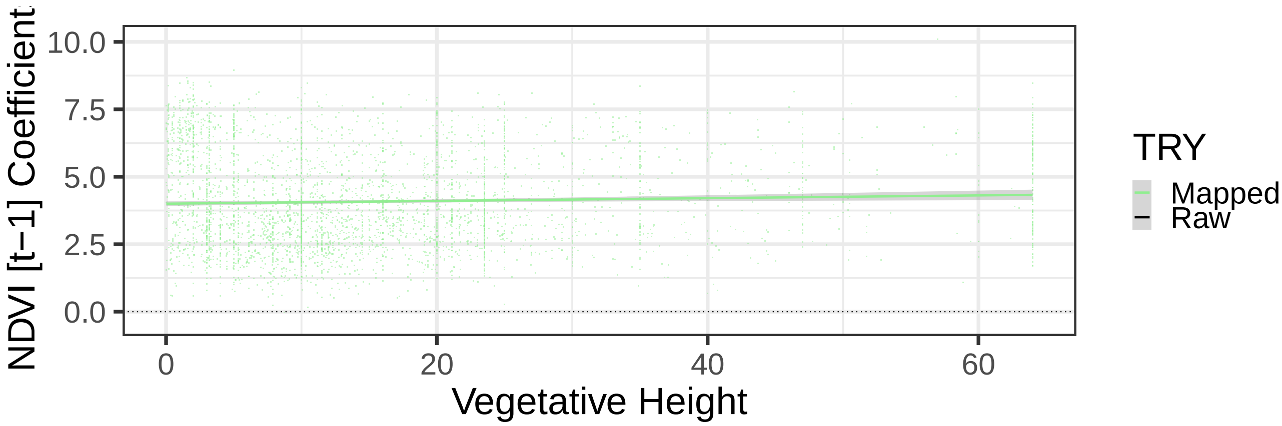
Table 3.28: PFTs and Qsoil4 Memory (Iberian Region) - Coefficients of linear regressions of Qsoil4 memory coefficients against PFT data (vegetative height H, and leaf nitrogen mass Nmass) both as raw geo-referenced data (R), and extended maps of species-specific trait means (M). Established via Chunk 35.

	Qsoil				**Lag**			
	H		Nmass		H		Nmass	
	R	M	R	M	R	M	R	M
Intercept	0.2325	1.6693	1.4763	2.0007	7.5845	3.2405	3.3523	3.0346
$p_{Intercept}$	0.2893	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Slope	0.0035	-0.1376	0.1278	-0.1828	-0.0932	0.2163	-0.1955	0.2369
p_{Slope}	0.9716	0.0000	0.0000	0.0000	0.7838	0.0000	0.0241	0.0000

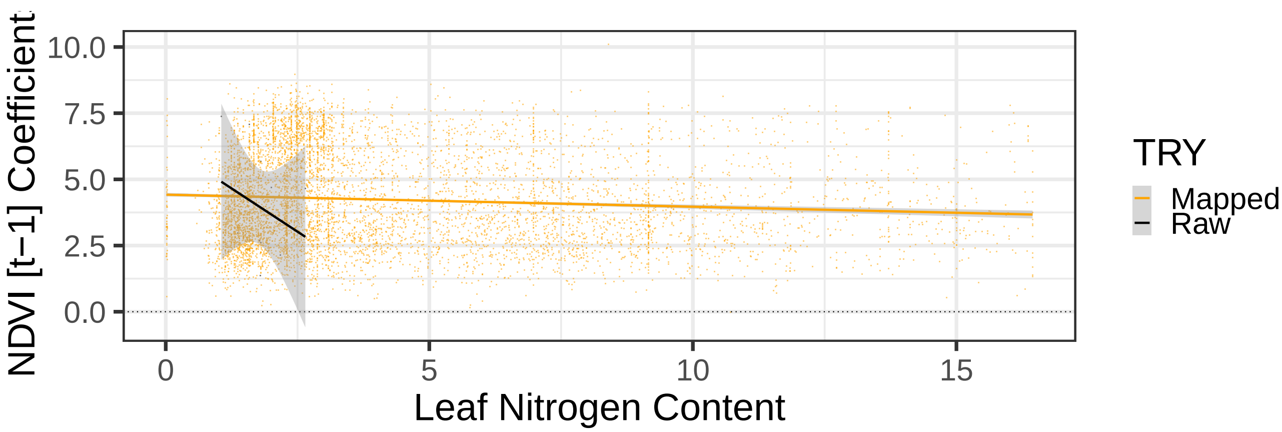
3.2.2.2 Caatinga

Intrinsic Memory

Relationships of $NDVI_{[t-1]}$ vegetation memory coefficients and H, and N_{mass} records across the Caatinga are represented in figure 3.46. These relationships have been assessed through linear regressions.



(a) Height



(b) Nitrogen

Figure 3.46: PFTs and Intrinsic Memory (Caatinga) - Intrinsic Memory (NDVI t-1, figure 3.4) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.7). Figure established via Chunk 34.

Correlations of H with $NDVI_{[t-1]}$ memory effects are as follows:

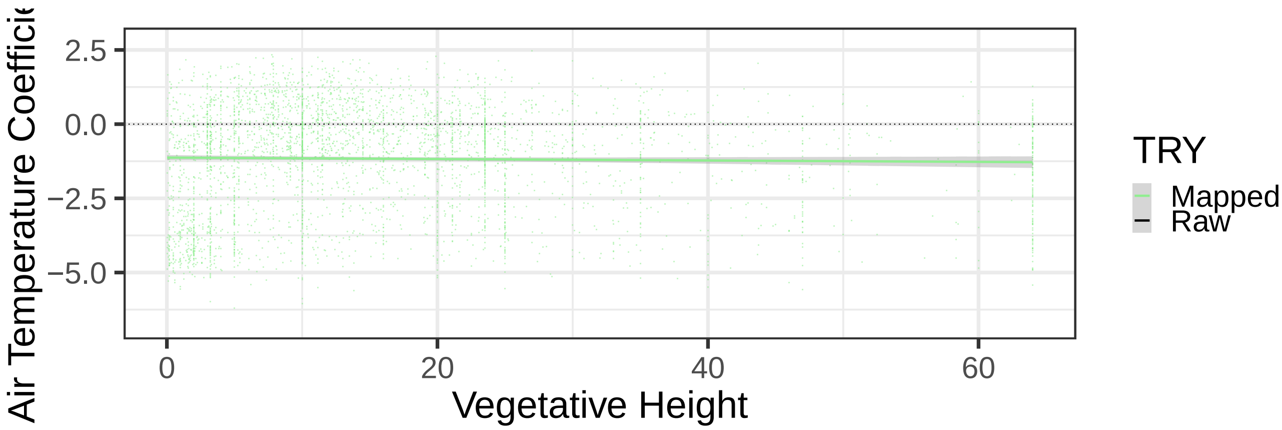
1. Cannot be calculated for untreated, geo-referenced data due to a lack of data.
2. $Intercept = 4.0028$ ($p_{Intercept} = 0$); $Slope = 0.0051$ ($p_{Slope} = 0.01$) for mapped mean trait data

N_{mass} is correlated with $NDVI_{[t-1]}$ memory effects as:

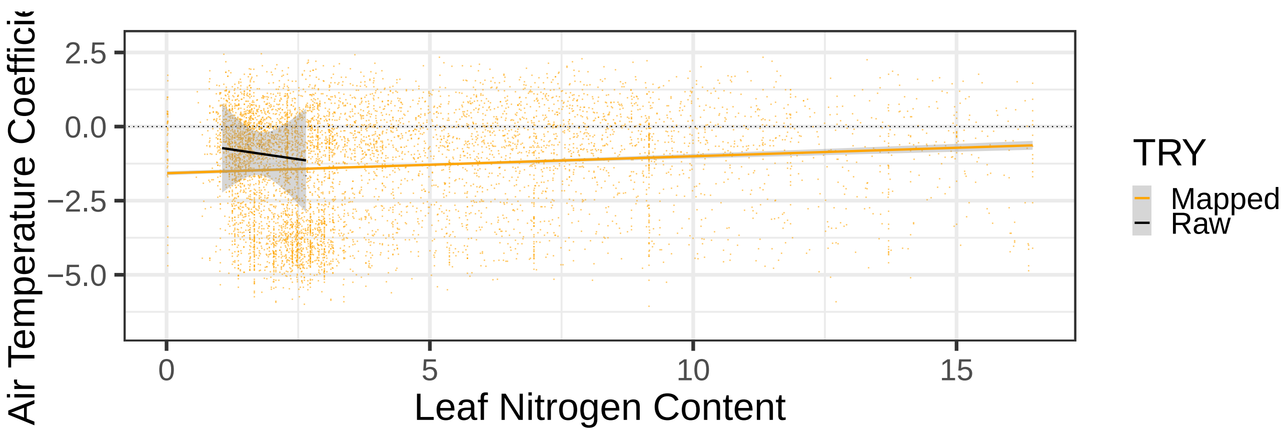
1. $Intercept = 6.2885$ ($p_{Intercept} = 0.0564$); $Slope = -1.306$ ($p_{Slope} = 0.4293$) for untreated, geo-referenced data
2. $Intercept = 4.4226$ ($p_{Intercept} = 0$); $Slope = -0.0456$ ($p_{Slope} = 6.7904 \times 10^{-14}$) for mapped mean trait data

Air Temperature

Relationships of Tair vegetation memory coefficients and H, and N_{mass} records across the Caatinga are represented in figure 3.47. These relationships have been assessed through linear regressions.



(a) Height



(b) Nitrogen

Figure 3.47: PFTs and Tair Memory (Caatinga) - Tair Memory (figure 3.4) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.7). Figure established via Chunk 34.

Correlations of H with Tair memory effects are as follows:

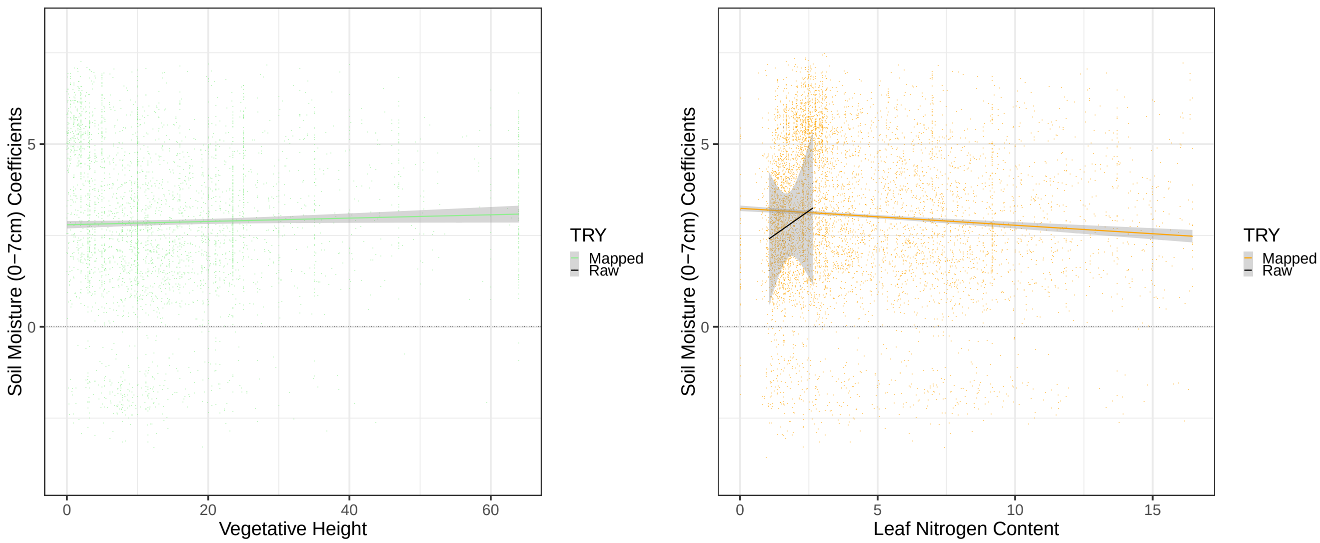
1. Cannot be calculated for untreated, geo-referenced data due to a lack of data.
2. $Intercept = -1.128$ ($p_{Intercept} = 1.3981 \times 10^{-133}$); $Slope = -0.0024$ ($p_{Slope} = 0.2332$) for mapped mean trait data

N_{mass} is correlated with Tair memory effects as:

1. $Intercept = -0.452$ ($p_{Intercept} = 0.7649$); $Slope = -0.2604$ ($p_{Slope} = 0.7537$) for untreated, geo-referenced data
2. $Intercept = -1.5734$ ($p_{Intercept} = 0$); $Slope = 0.0572$ ($p_{Slope} = 1.0603 \times 10^{-20}$) for mapped mean trait data

Soil Moisture (0-7cm)

Relationships of Qsoil1 vegetation memory length, and coefficients and H, and N_{mass} records across the Caatinga are represented in figure 3.48. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.29.



(a) Height

(b) Nitrogen

Figure 3.48: PFTs and Qsoil1 Memory (Caatinga) - Qsoil1 Memory (figure 3.4) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.7). Figure established via Chunk 34.

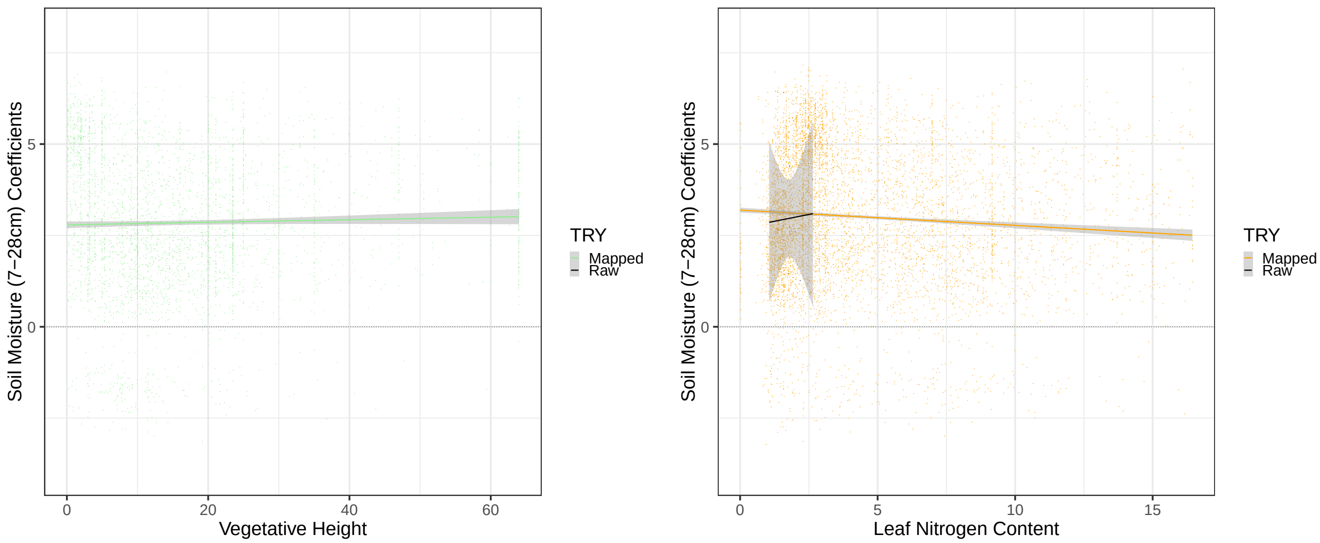
Linear regression identified statistically significant relationships for Qsoil1 related vegetation memory coefficients and species-specific mapped trait means of H and N_{mass}. All identified significant relationships are weak. No untreated, geo-referenced H data is available across the Caatinga.

Table 3.29: PFTs and Qsoil1 Memory (Caatinga) - Coefficients of linear regressions of Qsoil1 memory coefficients against PFT data (vegetative height H, and leaf nitrogen mass Nmass) both as raw geo-referenced data (R), and extended maps of species-specific trait means (M). Established via Chunk 35.

	Qsoil				**Lag**			
	H		Nmass		H		Nmass	
	R	M	R	M	R	M	R	M
Intercept	NA	2.7918	1.8503	3.2419	NA	3.1386	1.5191	3.6321
$p_{Intercept}$	NA	0.0000	0.3248	0.0000	NA	0.0000	0.2751	0.0000
Slope	NA	0.0046	0.5288	-0.0463	NA	0.0162	0.5776	-0.0346
p_{Slope}	NA	0.0545	0.6009	0.0000	NA	0.0000	0.4417	0.0009

Soil Moisture (7-28cm)

Relationships of Qsoil2 vegetation memory length, and coefficients and H, and N_{mass} records across the Caatinga are represented in figure 3.49. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.30.



(a) Height **(b)** Nitrogen

Figure 3.49: PFTs and Qsoil2 Memory (Caatinga) - Qsoil2 Memory (figure A.13) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.7). Figure established via Chunk 34.

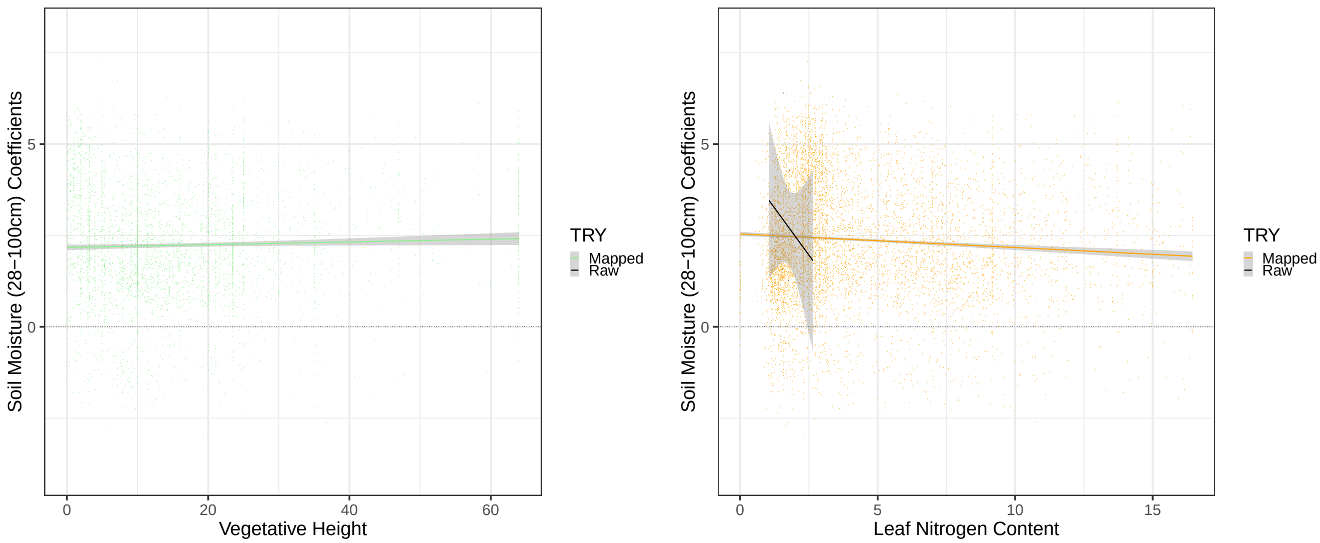
Linear regression identified statistically significant relationships for Qsoil2 related vegetation memory coefficients and species-specific mapped trait means of H and N_{mass} with the exception of H and Qsoil2 memory effects. All identified significant relationships are weak. No untreated, geo-referenced H data is available across the Caatinga.

Table 3.30: PFTs and Qsoil2 Memory (Caatinga) - Coefficients of linear regressions of Qsoil2 memory coefficients against PFT data (vegetative height H, and leaf nitrogen mass Nmass) both as raw geo-referenced data (R), and extended maps of species-specific trait means (M). Established via Chunk 35.

	Qsoil				**Lag**			
	H		Nmass		H		Nmass	
	R	M	R	M	R	M	R	M
Intercept	NA	2.7901	2.7025	3.1926	NA	2.8584	0.8132	3.3645
$p_{Intercept}$	NA	0.0000	0.2389	0.0000	NA	0.0000	0.6372	0.0000
Slope	NA	0.0035	0.1486	-0.0417	NA	0.0177	0.9237	-0.0290
p_{Slope}	NA	0.1003	0.9023	0.0000	NA	0.0000	0.3390	0.0127

Soil Moisture (28-100cm)

Relationships of Qsoil3 vegetation memory length, and coefficients and H, and N_{mass} records across the Caatinga are represented in figure 3.50. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.31.



(a) Height **(b)** Nitrogen

Figure 3.50: PFTs and Qsoil3 Memory (Caatinga) - Qsoil3 Memory (figure A.14) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.7). Figure established via Chunk 34.

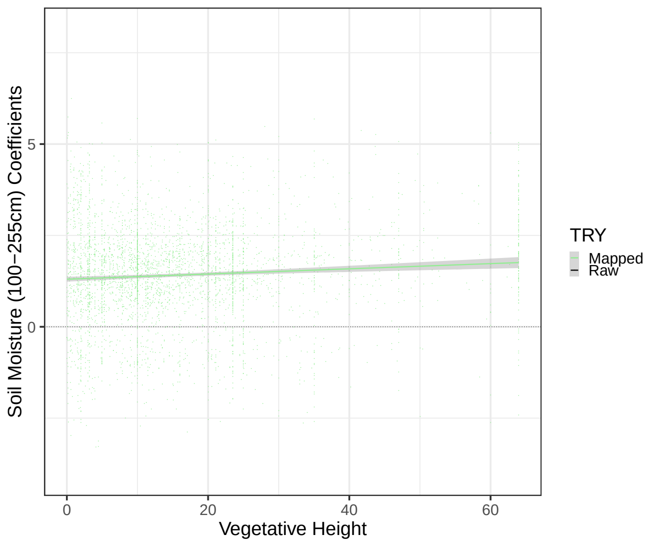
Linear regression identified statistically significant relationships for Qsoil3 related vegetation memory coefficients and species-specific mapped trait means of H and N_{mass} with the exception of N_{mass} and Qsoil3 memory length. All identified significant relationships are weak. No untreated, geo-referenced H data is available across the Caatinga.

Table 3.31: PFTs and Qsoil3 Memory (Caatinga) - Coefficients of linear regressions of Qsoil3 memory coefficients against PFT data (vegetative height H, and leaf nitrogen mass Nmass) both as raw geo-referenced data (R), and extended maps of species-specific trait means (M). Established via Chunk 35.

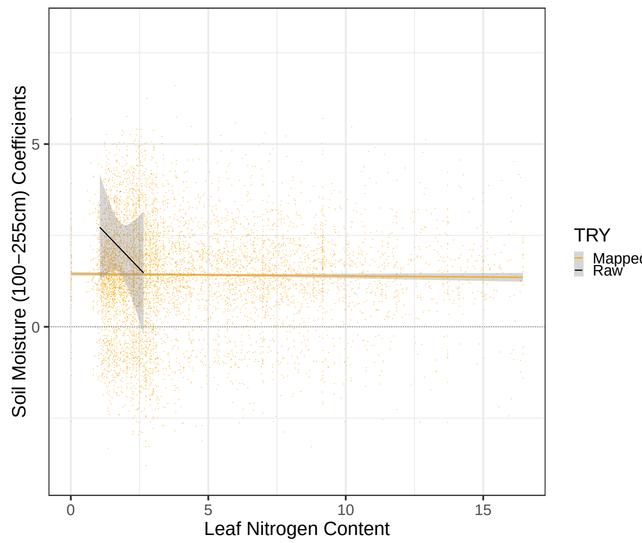
	Qsoil				**Lag**			
	H		Nmass		H		Nmass	
	R	M	R	M	R	M	R	M
Intercept	NA	2.1721	4.5450	2.5410	NA	3.4985	-0.1001	3.8130
$p_{Intercept}$	NA	0.0000	0.0567	0.0000	NA	0.0000	0.9818	0.0000
Slope	NA	0.0038	-1.0329	-0.0371	NA	0.0142	1.1307	-0.0243
p_{Slope}	NA	0.0359	0.3894	0.0000	NA	0.0021	0.6407	0.0789

Soil Moisture (100-255cm)

Relationships of Qsoil4 vegetation memory length, and coefficients and H, and N_{mass} records across the Caatinga are represented in figure 3.51. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.32.



(a) Height



(b) Nitrogen

Figure 3.51: PFTs and Qsoil4 Memory (Caatinga) - Qsoil4 Memory (figure A.15) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.7). Figure established via Chunk 34.

With the exception of mapped H and Qsoil4 memory effects as well as mapped N_{mass} and Qsoil4 memory length, linear regression analyses identified no statistically significant relationships for Qsoil4 related vegetation memory coefficients H and N_{mass}. All identified significant relationships are weak. No untreated, geo-referenced H data is available across the Caatinga.

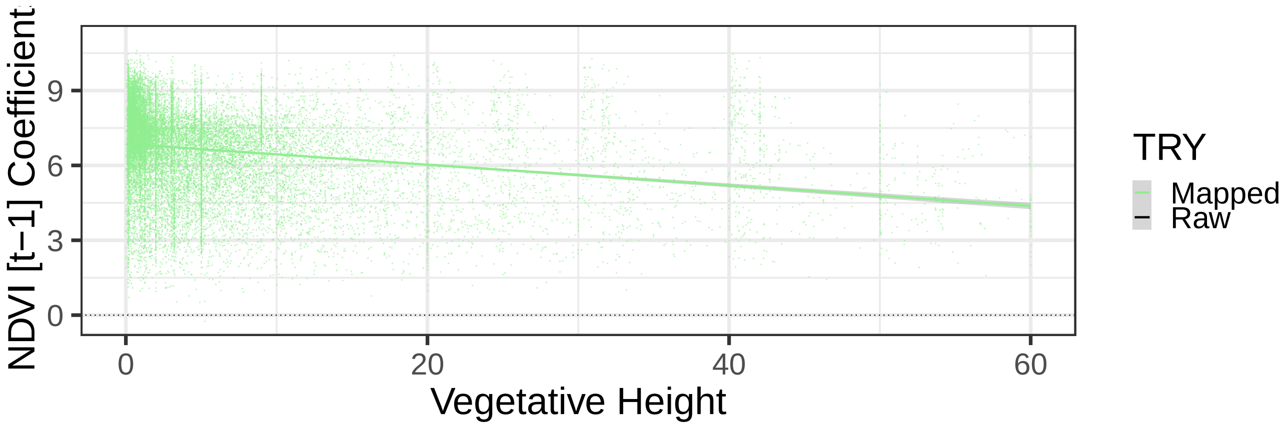
Table 3.32: PFTs and Qsoil4 Memory (Caatinga) - Coefficients of linear regressions of Qsoil4 memory coefficients against PFT data (vegetative height H, and leaf nitrogen mass Nmass) both as raw geo-referenced data (R), and extended maps of species-specific trait means (M). Established via Chunk 35.

	Qsoil				**Lag**			
	H		Nmass		H		Nmass	
	R	M	R	M	R	M	R	M
Intercept	NA	1.3021	3.5510	1.4494	NA	3.5553	0.7752	3.6638
$p_{Intercept}$	NA	0.0000	0.0334	0.0000	NA	0.0000	0.8855	0.0000
Slope	NA	0.0071	-0.7844	-0.0058	NA	-0.0059	0.4335	-0.0353
p_{Slope}	NA	0.0000	0.3392	0.2374	NA	0.2479	0.8834	0.0253

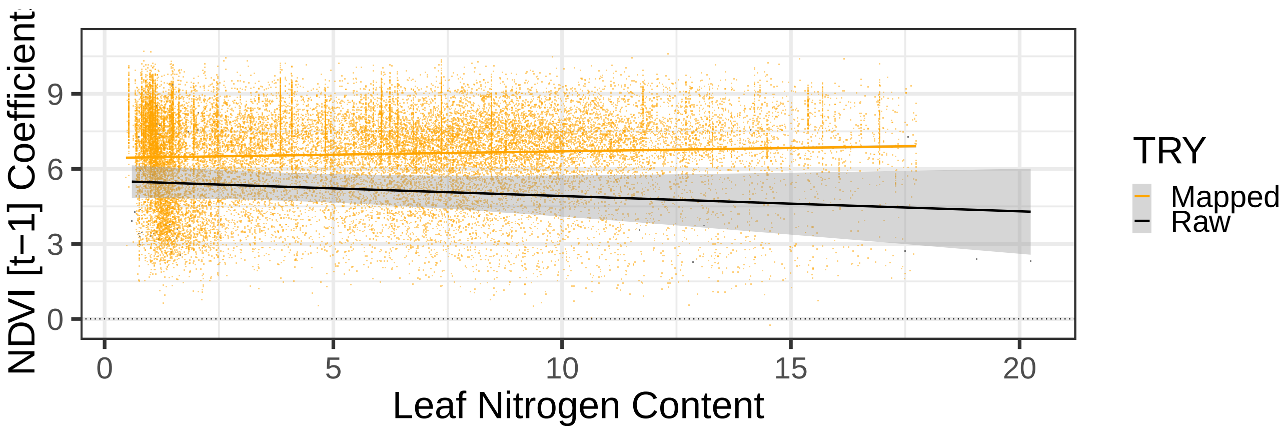
3.2.2.3 Australia

Intrinsic Memory

Relationships of $NDVI_{[t-1]}$ vegetation memory coefficients and H, and N_{mass} records across Australia are represented in figure 3.52. These relationships have been assessed through linear regressions.



(a) Height



(b) Nitrogen

Figure 3.52: PFTs and Intrinsic Memory (Australia) - Intrinsic Memory (NDVI t-1, figure 3.7) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.9). Figure established via Chunk 34.

Correlations of H with $NDVI_{[t-1]}$ memory effects are as follows:

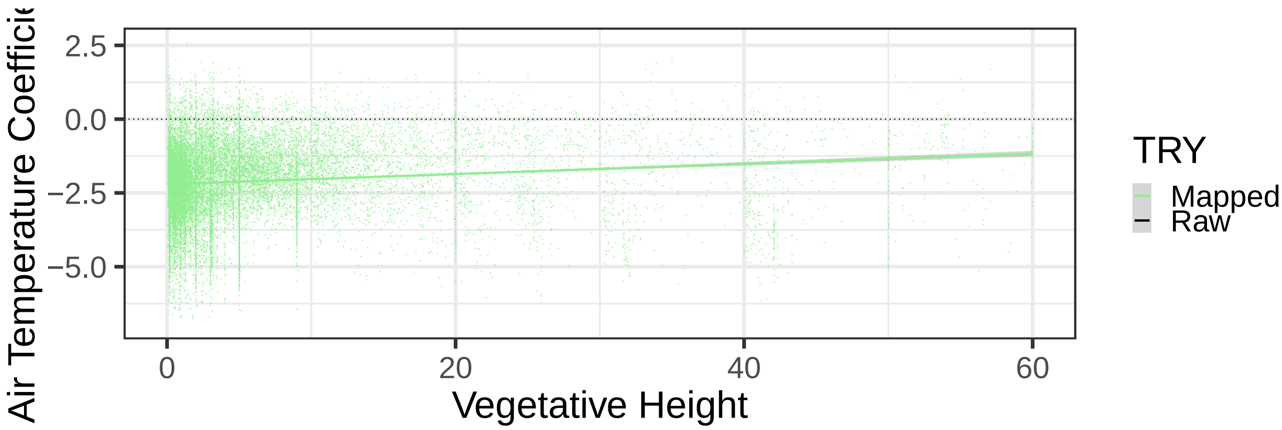
1. Cannot be calculated for untreated, geo-referenced data due to a lack of data.
2. $Intercept = 6.8559$ ($p_{Intercept} = 0$); $Slope = -0.0414$ ($p_{Slope} = 2.5162 \times 10^{-263}$) for mapped mean trait data

N_{mass} is correlated with $NDVI_{[t-1]}$ memory effects as:

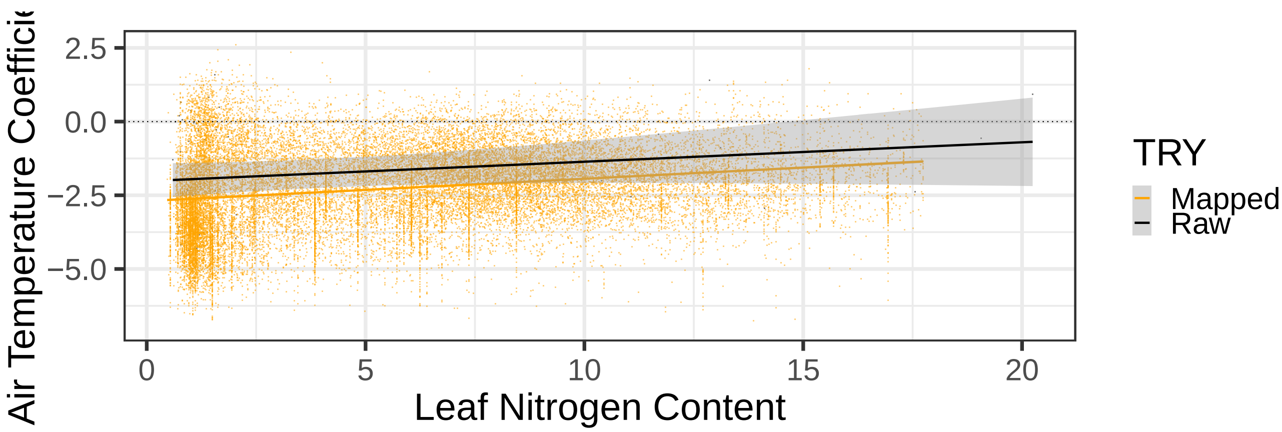
1. $Intercept = 5.5265$ ($p_{Intercept} = 6.1469 \times 10^{-22}$); $Slope = -0.0612$ ($p_{Slope} = 0.2239$) for untreated, geo-referenced data
2. $Intercept = 6.434$ ($p_{Intercept} = 0$); $Slope = 0.0268$ ($p_{Slope} = 2.2178 \times 10^{-27}$) for mapped mean trait data

Air Temperature

Relationships of Tair vegetation memory coefficients and H, and N_{mass} records across Australia are represented in figure 3.53. These relationships have been assessed through linear regressions.



(a) Height



(b) Nitrogen

Figure 3.53: PFTs and Tair Memory (Australia) - Tair Memory (figure 3.7) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.9). Figure established via Chunk 34.

Correlations of H with Tair memory effects are as follows:

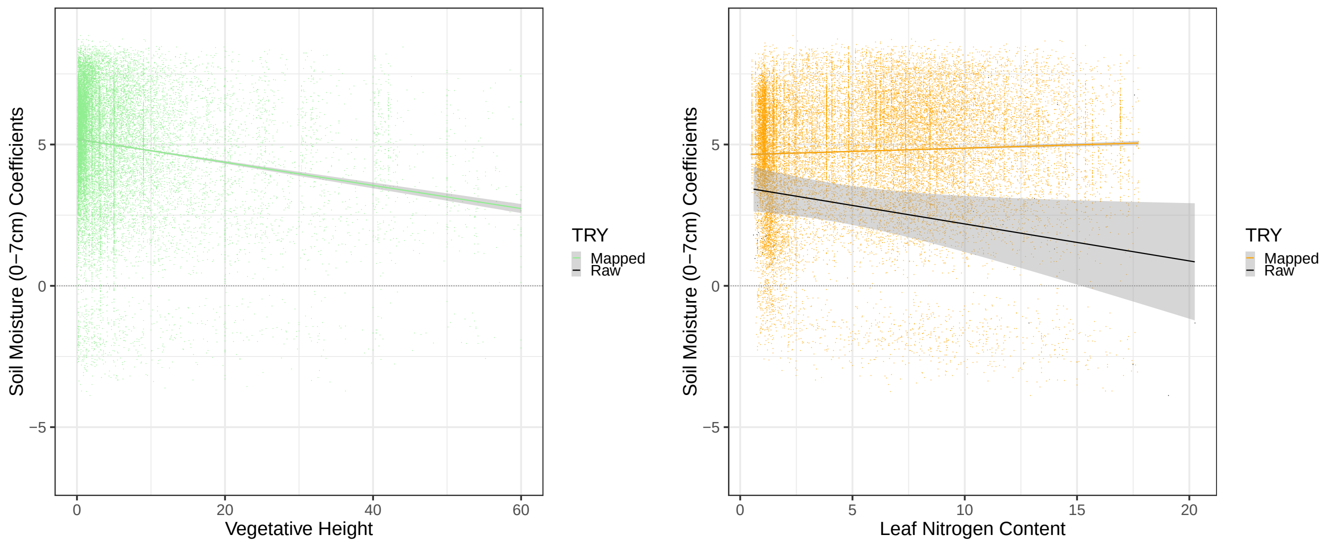
1. Cannot be calculated for untreated, geo-referenced data due to a lack of data.
2. $Intercept = -2.2053$ ($p_{Intercept} = 0$); $Slope = 0.0173$ ($p_{Slope} = 2.7281 \times 10^{-79}$) for mapped mean trait data

N_{mass} is correlated with Tair memory effects as:

1. $Intercept = -2.0208$ ($p_{Intercept} = 1.108 \times 10^{-8}$); $Slope = 0.0659$ ($p_{Slope} = 0.1343$) for untreated, geo-referenced data
2. $Intercept = -2.6959$ ($p_{Intercept} = 0$); $Slope = 0.0757$ ($p_{Slope} = 0$) for mapped mean trait data

Soil Moisture (0-7cm)

Relationships of Qsoil1 vegetation memory length, and coefficients and H, and N_{mass} records across Australia are represented in figure 3.54. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.33.



(a) Height **(b)** Nitrogen

Figure 3.54: PFTs and Qsoil1 Memory (Australia) - Qsoil1 Memory (figure 3.7) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.9). Figure established via Chunk 34.

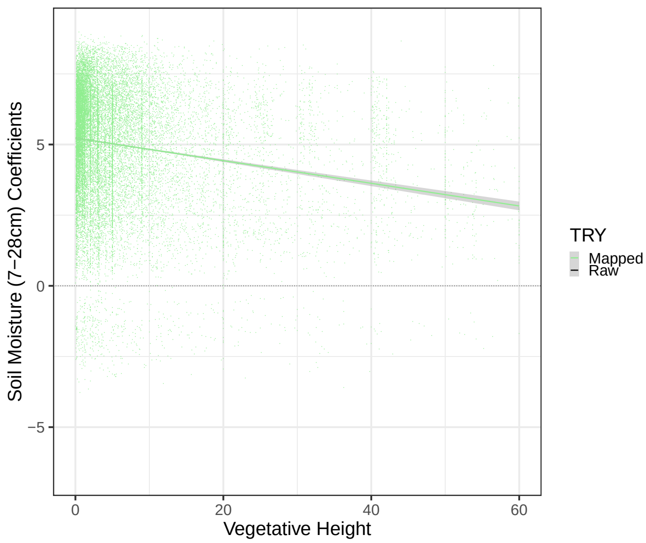
Linear regression identified statistically significant relationships for Qsoil1 related vegetation memory coefficients and species-specific mapped trait means of H and N_{mass}. All identified significant relationships are weak. No untreated, geo-referenced H data is available across Australia.

Table 3.33: PFTs and Qsoil1 Memory (Australia) - Coefficients of linear regressions of Qsoil1 memory coefficients against PFT data (vegetative height H, and leaf nitrogen mass Nmass) both as raw geo-referenced data (R), and extended maps of species-specific trait means (M). Established via Chunk 35.

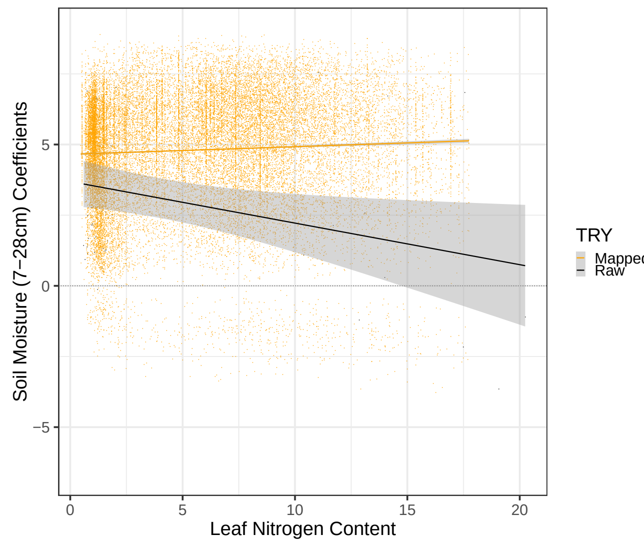
	Qsoil				**Lag**			
	H		Nmass		H		Nmass	
	R	M	R	M	R	M	R	M
Intercept	NA	5.1889	3.4980	4.6391	NA	3.676	4.9904	4.5844
$p_{Intercept}$	NA	0.0000	0.0000	0.0000	NA	0.000	0.0000	0.0000
Slope	NA	-0.0409	-0.1308	0.0233	NA	0.010	-0.1857	-0.0827
p_{Slope}	NA	0.0000	0.0334	0.0000	NA	0.000	0.0180	0.0000

Soil Moisture (7-28cm)

Relationships of Qsoil2 vegetation memory length, and coefficients and H, and N_{mass} records across Australia are represented in figure 3.55. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.34.



(a) Height



(b) Nitrogen

Figure 3.55: PFTs and Qsoil2 Memory (Australia) - Qsoil2 Memory (figure A.16) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.9). Figure established via Chunk 34.

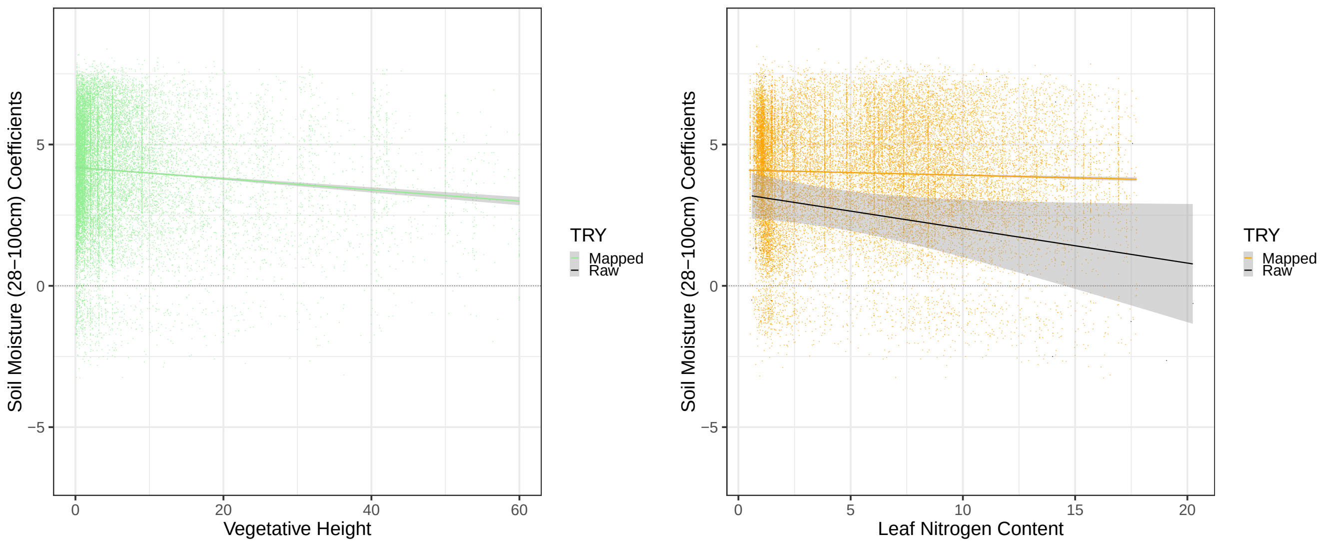
Linear regression identified statistically significant relationships for Qsoil2 related vegetation memory coefficients and species-specific mapped trait means of H and N_{mass}. All identified significant relationships are weak. No untreated, geo-referenced H data is available across Australia.

Table 3.34: PFTs and Qsoil2 Memory (Australia) - Coefficients of linear regressions of Qsoil2 memory coefficients against PFT data (vegetative height H, and leaf nitrogen mass Nmass) both as raw geo-referenced data (R), and extended maps of species-specific trait means (M). Established via Chunk 35.

	Qsoil				**Lag**			
	H		Nmass		H		Nmass	
	R	M	R	M	R	M	R	M
Intercept	NA	5.229	3.6902	4.6535	NA	2.7922	3.3841	3.3365
$p_{Intercept}$	NA	0.000	0.0000	0.0000	NA	0.0000	0.0000	0.0000
Slope	NA	-0.040	-0.1471	0.0269	NA	0.0235	-0.1116	-0.0313
p_{Slope}	NA	0.000	0.0217	0.0000	NA	0.0000	0.0719	0.0000

Soil Moisture (28-100cm)

Relationships of Qsoil3 vegetation memory length, and coefficients and H, and N_{mass} records across Australia are represented in figure 3.56. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.35.



(a) Height **(b)** Nitrogen

Figure 3.56: PFTs and Qsoil3 Memory (Australia) - Qsoil3 Memory (figure A.17) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.9). Figure established via Chunk 34.

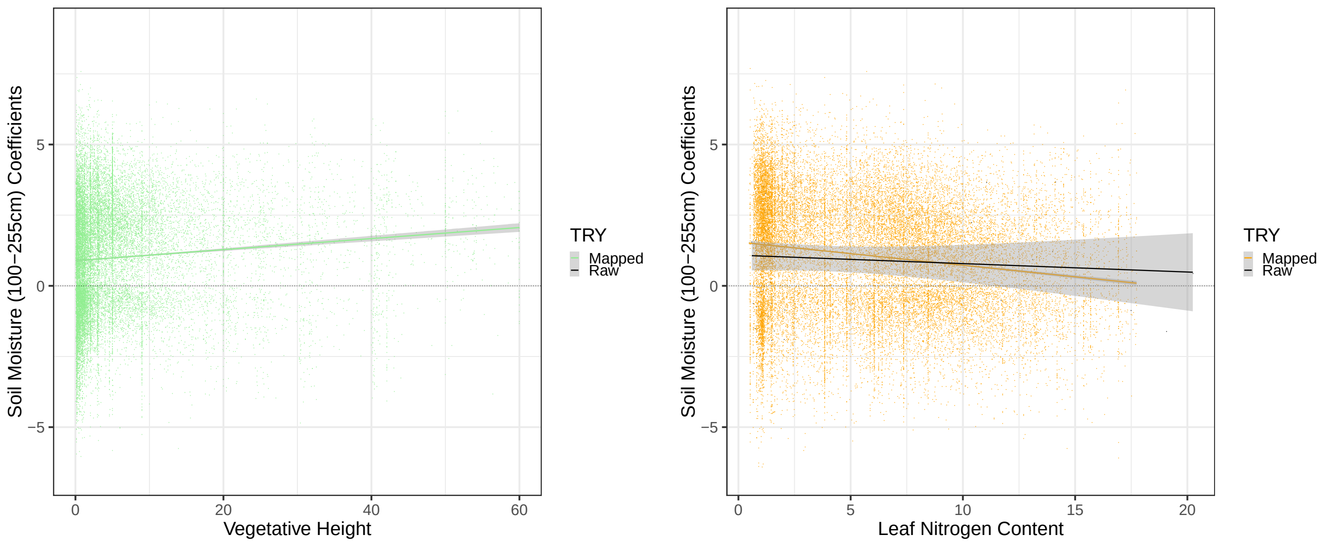
Linear regression identified statistically significant relationships for Qsoil3 related vegetation memory coefficients and species-specific mapped trait means of H and N_{mass}. All identified significant relationships are weak. No untreated, geo-referenced H data is available across Australia.

Table 3.35: PFTs and Qsoil3 Memory (Australia) - Coefficients of linear regressions of Qsoil3 memory coefficients against PFT data (vegetative height H, and leaf nitrogen mass Nmass) both as raw geo-referenced data (R), and extended maps of species-specific trait means (M). Established via Chunk 35.

	Qsoil				**Lag**			
	H		Nmass		H		Nmass	
	R	M	R	M	R	M	R	M
Intercept	NA	4.1881	3.2561	4.1002	NA	1.556	2.1163	2.2773
$p_{Intercept}$	NA	0.0000	0.0000	0.0000	NA	0.000	0.0003	0.0000
Slope	NA	-0.0199	-0.1225	-0.0185	NA	0.038	0.0316	-0.0427
p_{Slope}	NA	0.0000	0.0505	0.0000	NA	0.000	0.6937	0.0000

Soil Moisture (100-255cm)

Relationships of Qsoil4 vegetation memory length, and coefficients and H, and N_{mass} records across Australia are represented in figure 3.57. These relationships have been assessed through linear regressions, the coefficients of which are depicted in table 3.36.



(a) Height **(b)** Nitrogen

Figure 3.57: PFTs and Qsoil4 Memory (Australia) - Qsoil4 Memory (figure A.18) plotted against expressions of (a) H, and (b) N_{mass} both via geo-referenced TRY records and mapped species-specific trait means (figure A.9). Figure established via Chunk 34.

Linear regression identified statistically significant relationships for Qsoil4 related vegetation memory coefficients and species-specific mapped trait means of H and N_{mass}. All identified significant relationships - with the exception of N_{mass} and Qsoil4 memory length - are weak. No untreated, geo-referenced H data is available across Australia.

Table 3.36: PFTs and Qsoil4 Memory (Australia) - Coefficients of linear regressions of Qsoil4 memory coefficients against PFT data (vegetative height H, and leaf nitrogen mass Nmass) both as raw geo-referenced data (R), and extended maps of species-specific trait means (M). Established via Chunk 35.

	Qsoil				**Lag**			
	H		Nmass		H		Nmass	
	R	M	R	M	R	M	R	M
Intercept	NA	0.8896	1.0847	1.5502	NA	4.6977	3.7408	3.4594
$p_{Intercept}$	NA	0.0000	0.0002	0.0000	NA	0.0000	0.0001	0.0000
Slope	NA	0.0195	-0.0298	-0.0821	NA	-0.0401	0.0846	0.1644
p_{Slope}	NA	0.0000	0.4588	0.0000	NA	0.0000	0.5063	0.0000

3.2.3 Summary

3.2.3.1 Life History Traits

Linear regressions of COMPADRE data against vegetation memory coefficients have proven **largely inconclusive**, especially due to low spatial COMPADRE data coverage **across the Caatinga and Australia**.

Making use of the much higher spatial coverage of COMPADRE data across the **Iberian region**, COMPADRE **reactivity** emerged as an **important factor in explaining vegetation memory patterns**:

1. $NDVI_{[t-1]}$ memory strength decreases as reactivity increases.
2. Tair memory strength increases as reactivity increases.
3. Qsoil memory strength decreases as reactivity increases.

Overall, **vegetation memory strength decreases** as **reactivity increases**.

3.2.3.2 Plant Functional Traits

Analyses of the relationships of PFT expressions and vegetation memory characteristics (summaries of which are provided in tables A.12, A.13 , A.14, A.15, A.16, and A.17) revealed that:

1. **Geo-referenced PFT records cannot be linked to vegetation memory characteristics** in a statistically significant way across all three study regions.
2. **Mapped species-specific PFT means can be linked to patterns of vegetation memory** characteristics across all three study regions. However, these **relationships are weak**.
3. There is a **mismatch between geo-referenced PFT records and mapped species-specific trait means** in that relationships of the two towards the same vegetation memory characteristics often follow positive and negative relationships, respectively.

Overall, **PFTs cannot be linked to vegetation memory characteristics in a meaningful way** via linear regressions.

4. Discussion

4.1 Vegetation Memory

4.2 Life History Traits

4.3 Plant Functional Traits

5. Conclusion

Outlook

1. Soil moisture-driven drought indices[148]?
2. Use BIEN data

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Appendix

A.1 Project Requirements

Following these steps ensures full reproducibility of the entire analysis. Alternatively, codes can be retrieved via https://github.com/ErikKusch/M.Sc.Thesis.

With the exception of python, bash, and matlab scripts to obtain ERA5 data, have been carried out in `R`[149] using the functionality contained within the base installation as well as the packages outlined in table A.1. Chunk 1 contains the `R` commands used to install all packages needed to reproduce the analyses of this study from a base installation of `R`. Data sources and methods of data retrieval are stated for each data set individually. All codes needed to reproduce the analysis at the core of this thesis have been included to this document in section A.3. Note that the computation can be sped up by altering the `Cores` argument to enable parallel processing via the `foreach` and `doparallel`[150] packages.

A.1.1 `R` Requirements

A.1.1.1 `R` Packages

Table A.1: R Packages - Packages which need to be loaded into R to fully reproduce the analyses within this study.

Package	Version	Use
automap[151]	1.0-14	Statistical Downscaling of ERA5 5 data
doParallel[150]	1.0.14	Paralell processing
foreach[152]	1.4.4	Paralell processing
gameofthrones[153]	1.0.0	Data visualisation
ggplot2[154]	3.1.0	Data visualisation
gimms[128]	1.1.1	Downloading GIMMs NDVI3g data
ncdf4[155]	1.16.1	Namespace for NetCDF files
pracma[156]	2.2.2	Detrending time series
raster[127]	2.8-19	Rasterising NetCDF data
rgbif[157]	1.2.0	Downloading floral occurence data
rgdal[104]	1.4-2	Loading and using shapefiles
sp[158]	1.3-1	Converting point data to rasterised data
vegan[159]	2.5-4	PCA approach for model building
xlsx[160]	0.6.1	Export of numeric results

Chunk 1: Installing and loading of R packages needed to reproduce the analyses of this study.

```r
install.load.package <- function(x) {
    if (!require(x, character.only = TRUE))
        install.packages(x, repos = "http://cran.us.r-project.org")
    require(x, character.only = TRUE)
}
package_vec <- c("automap", "doParallel", "foreach", "gameofthrones", "ggplot2",
    "gimms", "gridExtra", "ndcf4", "pracma", "raster", "rgbif", "rgdal", "sp", "vegan",
    "xlsx")
sapply(package_vec, install.load.package)
```

A.1.1.2 Project Directories

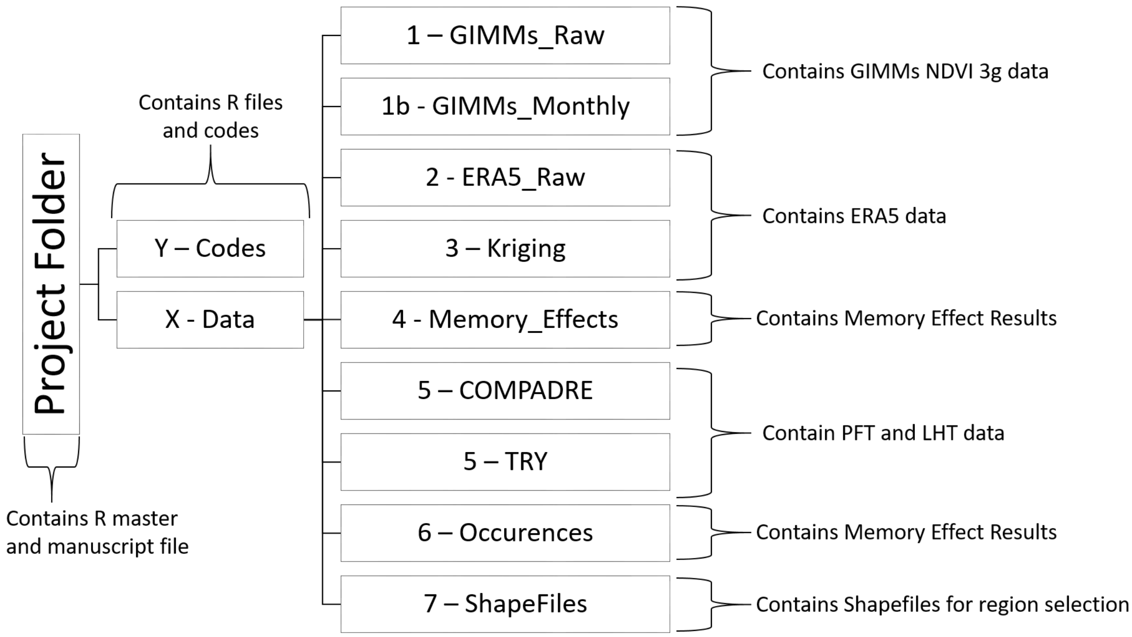

Figure A.1: Working Directories - An overview of working directories established/required by Chunk 2.

Chunk 2: Identifing and generating the folder structure used within the computational steps. A visual overview is presented in A.1.

```
mainDir <- getwd() # extract the project folder location
# WORKING DIRECTORY FOR CODES
Dir.Codes <- paste(mainDir, "/Y - Codes", sep="")
# WORKING DIRECTORY FOR DATA
Dir.Data <- paste(mainDir, "/X - Data", sep="")
# WORKING DIRECTORY FOR RAW GIMMS DATA
Dir.Gimms <- paste(Dir.Data, "/1 - GIMMs_Raw", sep="")
if(!dir.exists(Dir.Gimms)){dir.create(Dir.Gimms)}
# WORKING DIRECTORY FOR PROCESSED GIMMS DATA
Dir.Gimms.Monthly <- paste(Dir.Data, "/1b - GIMMs_Monthly", sep="")
if(!dir.exists(Dir.Gimms.Monthly)){dir.create(Dir.Gimms.Monthly)}
# WORKING DIRECTORY FOR RAW ERA5 DATA
Dir.ERA <- paste(Dir.Data, "/2 - ERA5_Raw", sep="")
# WORKING DIRECTORY FOR PROCESSED ERA5 DATA
Dir.ERA.Monthly <- paste(Dir.Data, "/2b - ERA5_Monthly", sep="")
if(!dir.exists(Dir.ERA.Monthly)){dir.create(Dir.ERA.Monthly)}
# WORKING DIRECTORY FOR KRIGING COVARIATES
Dir.KrigCov <- paste(Dir.Data, "/3 - Kriging", sep="")
# WORKING DIRECTORY FOR MEMORY EFFECT DATA
Dir.Memory <- paste(Dir.Data, "/4 - Memory_Effects", sep="")
# WORKING DIRECTORY FOR COMPADRE DATA
Dir.Compadre <- paste(Dir.Data, "/5 - COMPADRE", sep="")
# WORKING DIRECTORY FOR TRY PFT DATA
if(!dir.exists(Dir.Memory)){dir.create(Dir.Memory)}
Dir.TRY <- paste(Dir.Data, "/5 - TRY", sep="")
# WORKING DIRECTORY FOR OCCURENCE DATA
Dir.OCCs <- paste(Dir.Data, "/6 - Occurences", sep="")
if(!dir.exists(Dir.OCCs)){dir.create(Dir.OCCs)}
# WORKING DIRECTORY FOR SHAPEFILES (contains masking file for water bodies)
Dir.Mask <- paste(Dir.Data, "/7 - ShapeFiles", sep="")
```

A.1.1.3 R Functions for Region Selection and Raster Names

Chunk 3: User-defined functions used to optimise further functions of this analysis when (1) Limitting to study regions (RegionSelection), and (2) assigning names to model rasters (Fun__NamesRas).

```r
### RegionSelection [Region, RegionFile, Extent] (selecting region and extent from
### shapefiles)
RegionSelection <- function(Region, RegionFile, Extent) {
  ## loading shapefiles
  Shapes <- readOGR(Dir.Mask, "ne_50m_admin_0_countries", verbose = FALSE)
  ## selecting region from shapefile run global analysis read user-defined extent
  ## (if applicable)
  if (Region == "Global") {
    if (is.null(Extent)) {
      area <- extent(-180, 180, -90, 90)
    } else {
      area <- Extent
    }
    location <- 1:length(Shapes) # selecting all countries contained within the shapefile
  } else {
    Where <- Region # countries to consider
    location <- NA # position vector in shapefile list
    for (i in 1:length(Where)) {
      # select region from Shapefiles
      location[i] <- which(as.vector(Shapes$NAME) == Where[i])
    }
    if (is.null(Extent)) {
      # read user-defined extent (if applicable)
      area <- extent(Shapes[location, ])
    } else {
      area <- Extent
    }
  }
  if (is.null(RegionFile)) {
    # if no file name has been specified
    RegionFile <- toString(Region) # take name of region
  }
  # returning parameters
  return(list(area, location, RegionFile))
}

### Fun_NamesRas [raster, ClimVar, ClimVar2]
# (assigning layer names to model rasters) ----
Fun_NamesRas <- function(raster, ClimVar, ClimVar2, rasiter = 1){
  names(raster) <- c(paste("Most informative", ClimVar[[rasiter]],"lag", sep=" "),
                     "Model AICs", "Model p-value", "Antecedent NDVI (c_NDVI)",
                     paste("Antecedent" , ClimVar[[rasiter]], "(c_clim)", sep=" "),
                     paste("Antecedent" , ClimVar2[[rasiter]], "(c_clim2)", sep=" "),
                     "Explained Variance", "Variance (NDVI)", "Variance (Shared)",
                     paste("Variance (" , ClimVar[[rasiter]], ")", sep=""))
  return(raster)} # Fun_NamesRas end
```

A.1.2 ERA5 Data

A.1.2.1 Obtaining ERA5 Data

Chunk 4: Obtaining ERA5 data from the ECMW servers. Substitute the date statement to download the full data set. Python script.

```
import cdsapi

c = cdsapi.Client()
c.retrieve('reanalysis-era5-complete', {    # do not change this!
    'class'   : 'ea',
    'expver'  : '1',
    'stream'  : 'moda',
    'type'    : 'an',
    'param'   : '39.128/40.128/41.128/42.128/167.128',
    'levtype' : 'sfc',
    'date'    : '19800101/19800201/19800301/19800401/19800501/19800601/19800701/19800801/19800901/19801001/19801101/
19801201/19810101/19810201/19810301/19810401/19810501/19810601/19810701/19810801/19810901/19811001/19811101/
19811201/19820101/19820201/19820301/19820401/19820501/19820601/19820701/19820801/19820901/19821001/19821101/
19821201/19830101/19830201/19830301/19830401/19830501/19830601/19830701/19830801/19830901/19831001/19831101/
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19861201/19870101/19870201/19870301/19870401/19870501/19870601/19870701/19870801/19870901/19871001/19871101/
19871201/19880101/19880201/19880301/19880401/19880501/19880601/19880701/19880801/19880901/19881001/19881101/
19881201/19890101/19890201/19890301/19890401/19890501/19890601/19890701/19890801/19890901/19891001/19891101/19891201',
    'decade'  : '1980',
}, 'All_1980s.grib')
```

A.1.2.2 Pre-Processing ERA5 Data

Chunk 5: Processing ERA5 data from local downloads to merge by time step. Bash script.

```
#!/bin/bash

. /opt/.profiles/cdo.bash

# Convert files to netcdf format
cdo -f nc setgridtype,regular 'All_1980s.grib' 'All_1980s.nc'
cdo -f nc setgridtype,regular 'All_1990s.grib' 'All_1990s.nc'
cdo -f nc setgridtype,regular 'All_2000s.grib' 'All_2000s.nc'
cdo -f nc setgridtype,regular 'All_2010s.grib' 'All_2010s.nc'

# Change variable names to identifiable ones
cdo chname,var167,Tair,var39,Qsoil1,var40,Qsoil2,var41,Qsoil3,var42,Qsoil4 'All_1980s.nc' 'All_1980s_renamed.nc'
cdo chname,var167,Tair,var39,Qsoil1,var40,Qsoil2,var41,Qsoil3,var42,Qsoil4 'All_1990s.nc' 'All_1990s_renamed.nc'
cdo chname,var167,Tair,var39,Qsoil1,var40,Qsoil2,var41,Qsoil3,var42,Qsoil4 'All_2000s.nc' 'All_2000s_renamed.nc'
cdo chname,var167,Tair,var39,Qsoil1,var40,Qsoil2,var41,Qsoil3,var42,Qsoil4 'All_2010s.nc' 'All_2010s_renamed.nc'

# Merge the files over time
cdo -r mergetime `ls *'_renamed.nc'` 'All_variables_1980_2016.nc'

# Cleanup
rm *renamed.nc
```

Chunk 6: Regridding ERA5 data to fit GIMMS and HWSD extents. Matlab script.

```
clear
clc
fn              = 'All_variables_1980_2016.nc';
```

```
ncin            = netcdf.open(fn,'NC_NOWRITE');
lon_orig        = double(netcdf.getVar(ncin,0));
lat             = double(netcdf.getVar(ncin,1));
time            = double(netcdf.getVar(ncin,4));
Tair_orig(:,:,:)   = double(netcdf.getVar(ncin,8));
Qsoil1_orig(:,:,:) = double(squeeze(netcdf.getVar(ncin,5)));
Qsoil1_orig(:,:,:) = double(squeeze(netcdf.getVar(ncin,5)));
Qsoil1_orig(:,:,:) = double(squeeze(netcdf.getVar(ncin,5)));
Qsoil1_orig(:,:,:) = double(squeeze(netcdf.getVar(ncin,5)));
netcdf.close(ncin)

lon_orig(lon_orig>180)=lon_orig(lon_orig>180)-360; % Convert longitude to the -180 to 180 reference

% Re-organise by longitude
[lon,I]   = sort(lon_orig);
Qsoil1 = Qsoil1_orig(I,:,:);
Qsoil2 = Qsoil2_orig(I,:,:);
Qsoil3 = Qsoil3_orig(I,:,:);
Qsoil4 = Qsoil4_orig(I,:,:);
Tair   = Tair_orig(I,:,:);

clear Qsoil1_orig Qsoil2_orig Qsoil3_orig Qsoil4_orig Tair_orig

%%
for ivar = 1:5
    if ivar==1; var = Qsoil1; VarName='Qsoil1'; end
    if ivar==2; var = Qsoil2; VarName='Qsoil2'; end
    if ivar==3; var = Qsoil3; VarName='Qsoil3'; end
    if ivar==4; var = Qsoil4; VarName='Qsoil4'; end
    if ivar==5; var = Tair;   VarName='Tair';   end

    fn = [Variables{ivar},'_TrainingResolution.nc'];
    [lon_dim,lat_dim,tim_dim] = size(Tair);
    ncout = netcdf.create(fn,'CLOBBER');
    lonID = netcdf.defDim(ncout,'lon',lon_dim);
    latID = netcdf.defDim(ncout,'lat',lat_dim);
    timID = netcdf.defDim(ncout,'time',tim_dim);
    varid1  = netcdf.defVar(ncout,'lon',      'nc_float',[lonID]); %#ok<*NBRAK>
    varid2  = netcdf.defVar(ncout,'lat',      'nc_float',[latID]);
    varid3  = netcdf.defVar(ncout,'time',     'nc_float',[timID]);
    varid5  = netcdf.defVar(ncout,VarName,    'nc_float',[lonID,latID,timID]);
    % Put the attributes for the lon dimension
    netcdf.putAtt(ncout,varid1,'units','degrees_east');
    netcdf.putAtt(ncout,varid1,'standard_name','longitude');
    % Put the attributes for the lat dimension
    netcdf.putAtt(ncout,varid2,'units','degrees_north');
    netcdf.putAtt(ncout,varid2,'standard_name','latitude');
    % Put the attributes for the Time
    netcdf.putAtt(ncout,varid3,'units','hours since 2008-01-01 06:00:00');
    netcdf.putAtt(ncout,varid3,'calendar','proleptic_gregorian');
    netcdf.putAtt(ncout,varid3,'standard_name','time');
    netcdf.endDef(ncout)
    netcdf.putVar(ncout,varid1, lon)
    netcdf.putVar(ncout,varid2, lat)
    netcdf.putVar(ncout,varid3, time)
    netcdf.putVar(ncout,varid5, var)
    netcdf.close(ncout)
end
```

A.2 Data

A.2.1 HWSD Data

Table A.2: HWSD Variables and Explanations - HWSD variables used within this study and their explanations. Slope aspects and inclines are recorded as number of 3 arc-second cells falling into 5 minute cells

HWSD Variable	Explanation
Elevation	Altitude in metres as measured from sea-level
Slope_aspect_N	$(0°; 45°]$; $(315°; 360°]$
Slope_aspect_E	$(45°; 135°]$
Slope_aspect_S	$(135°; 225°]$
Slope_aspect_W	$(225°; 315°]$
Slope_aspect_U	Slope undefined or slope incline is less than 2%
Slopes1	$0\% \leq$ incline $\leq 0.5\%$
Slopes2	$0.5\% \leq$ incline $\leq 2\%$
Slopes3	$2\% \leq$ incline $\leq 5\%$
Slopes4	$5\% \leq$ incline $\leq 10\%$
Slopes5	$10\% \leq$ incline $\leq 15\%$
Slopes6	$15\% \leq$ incline $\leq 30\%$
Slopes7	$30\% \leq$ incline $\leq 45\%$
Slopes8	Incline $> 45\%$

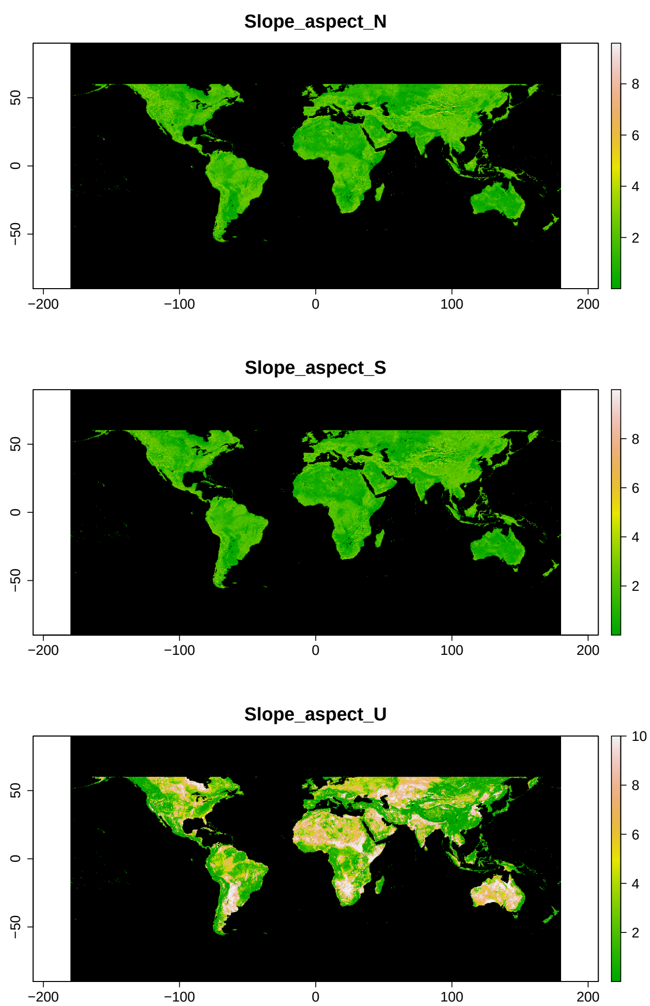


Figure A.2: HWSD slope aspect data - HWSD data at GIMMS resolution divided by 1000 for displaying. Figure established via Chunk 18.

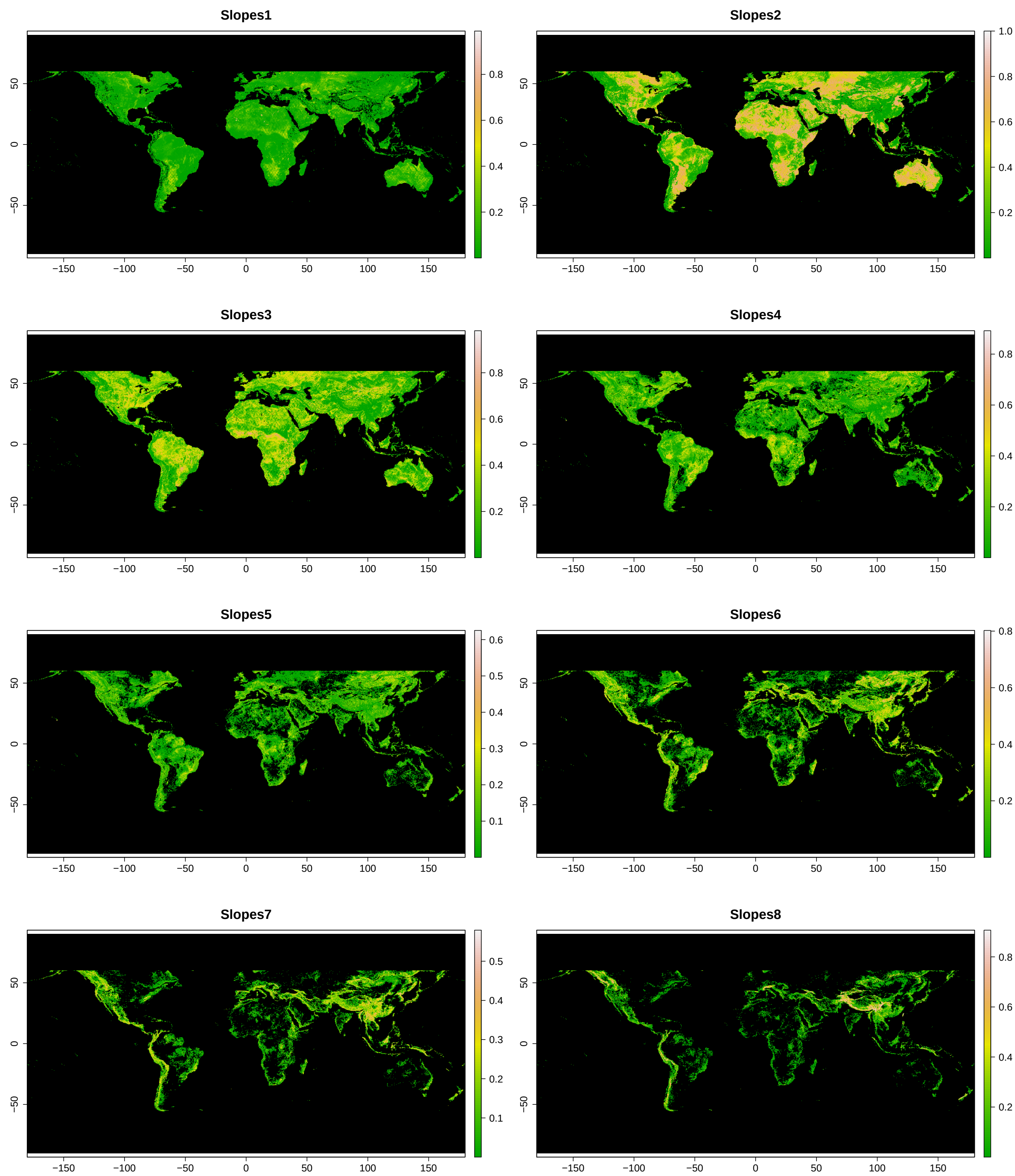


Figure A.3: HWSD slope incline data - HWSD data at GIMMS resolution. Data has been divided by 1000 for displaying. Figure established via Chunk 19.

A.2.2 Study Regions

A.2.2.1 Iberian Region

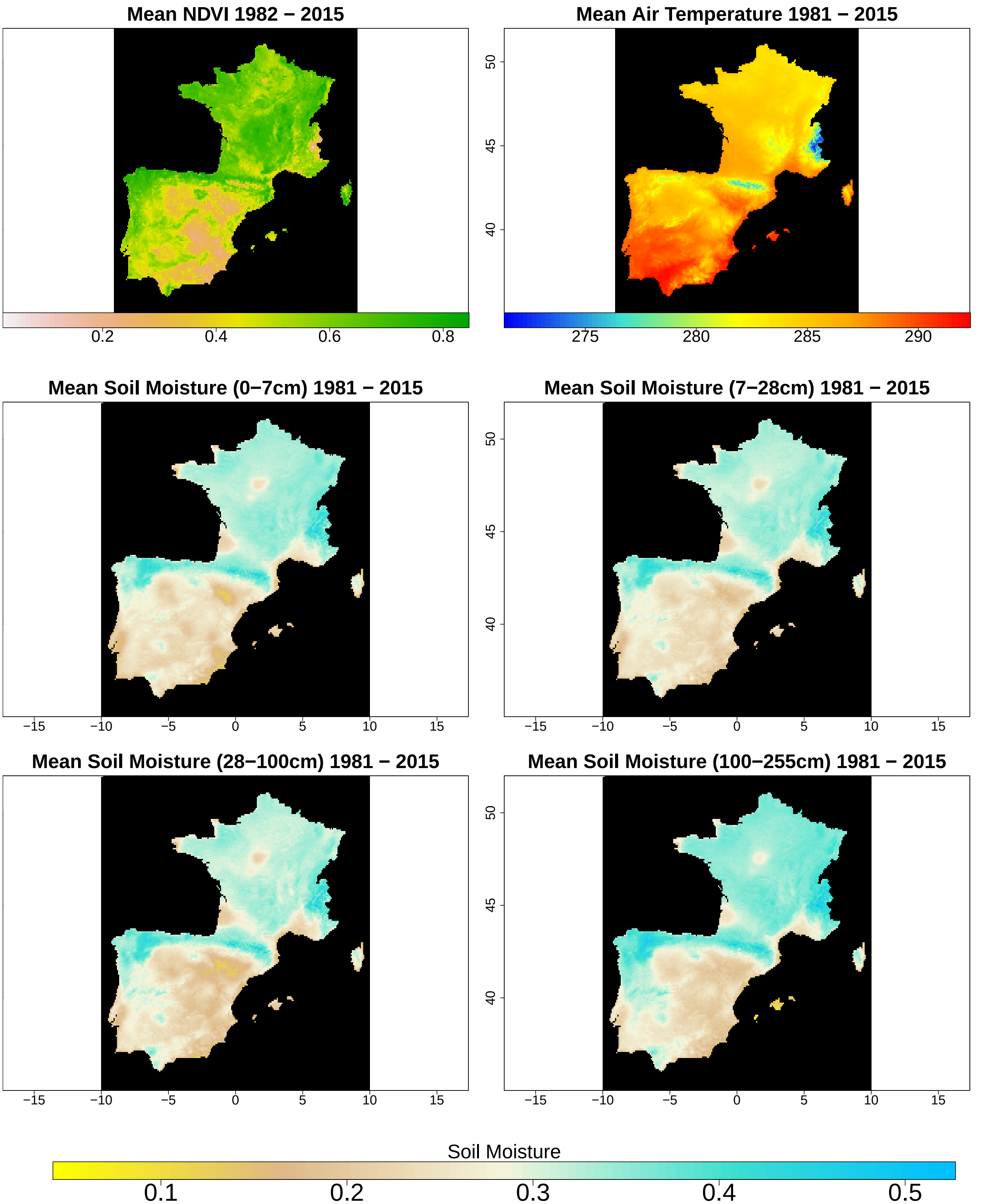


Figure A.4: Data Overview (Iberian Region) - Data required for identificiation of vegetation memory: (1) GIMMS NDVI 3g; and (2) ERA5: Tair, Qsoil1, Qsoil2, Qsoil3, Qsoil4. Figure established via Chunk 20.

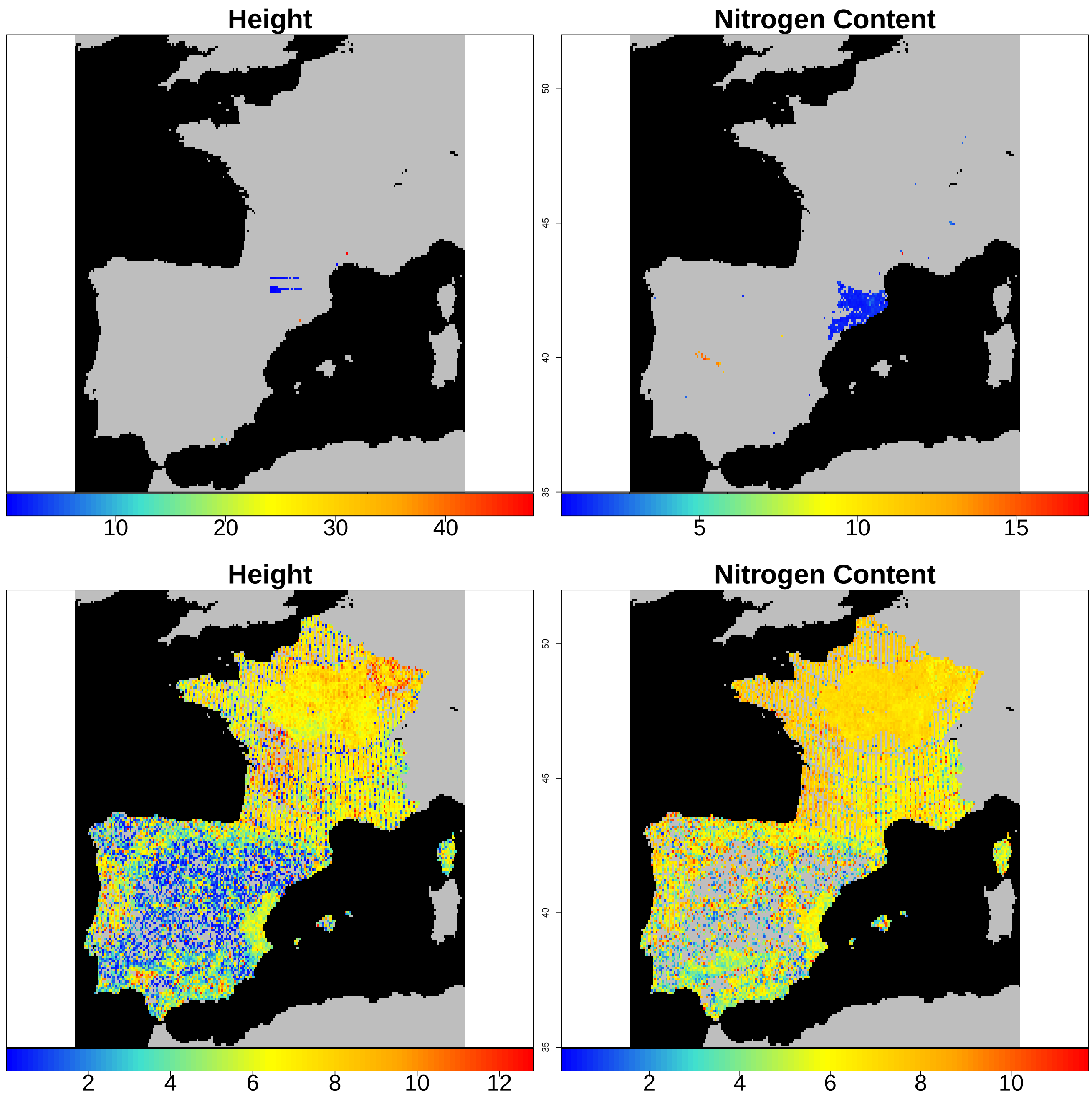


Figure A.5: TRY Data (Iberian Region) - TRY PFT data across the Iberian Region: (1) Geo-referenced records (upper row), and (2) Extrapolated species-specific mean PFT records (lower row). Figure established via Chunk 21.

A.2.2.2 Caatinga, Brazil

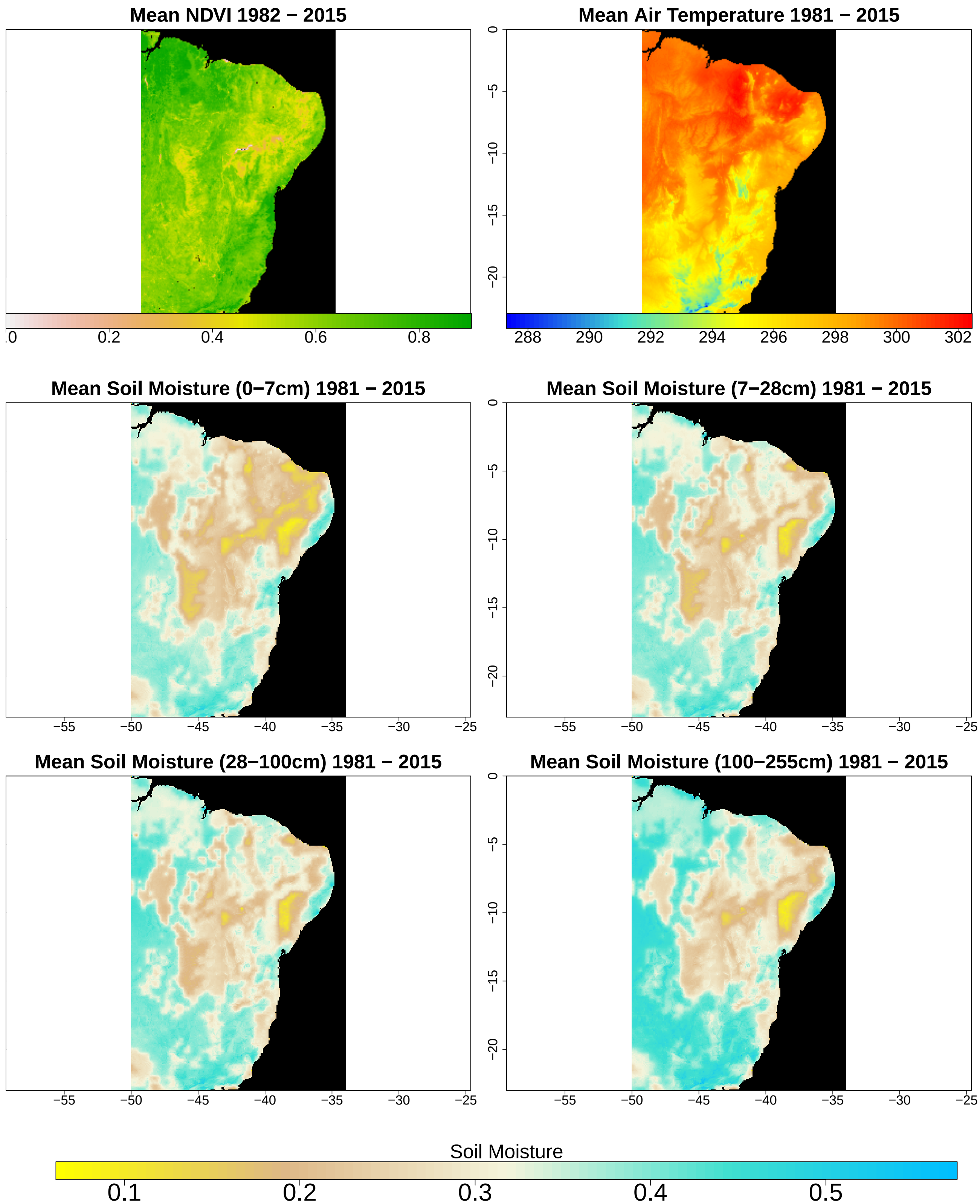


Figure A.6: Data Overview (Caatinga, Brazil) - Data required for identificiation of vegetation memory: (1) GIMMS NDVI 3g; and (2) ERA5: Tair, Qsoil1, Qsoil2, Qsoil3, Qsoil4. Figure established via Chunk 20.

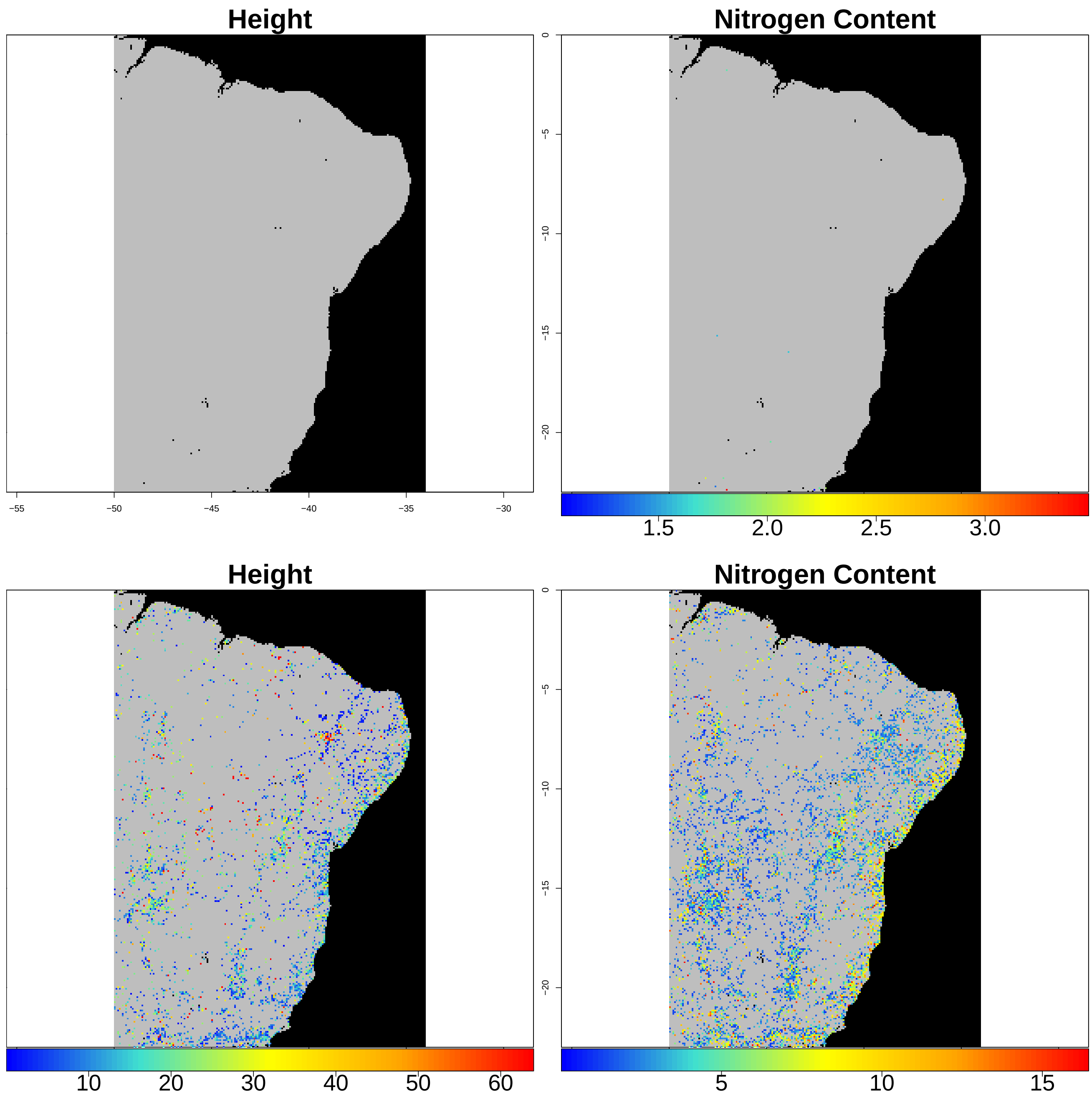


Figure A.7: TRY Data (Caatinga, Brazil) - TRY PFT data across Caatinga, Brazil: (1) Geo-referenced records (upper row), and (2) Extrapolated sepcies-specific mean PFT records (lower row). Figure established via Chunk 21.

A.2.2.3 Australia

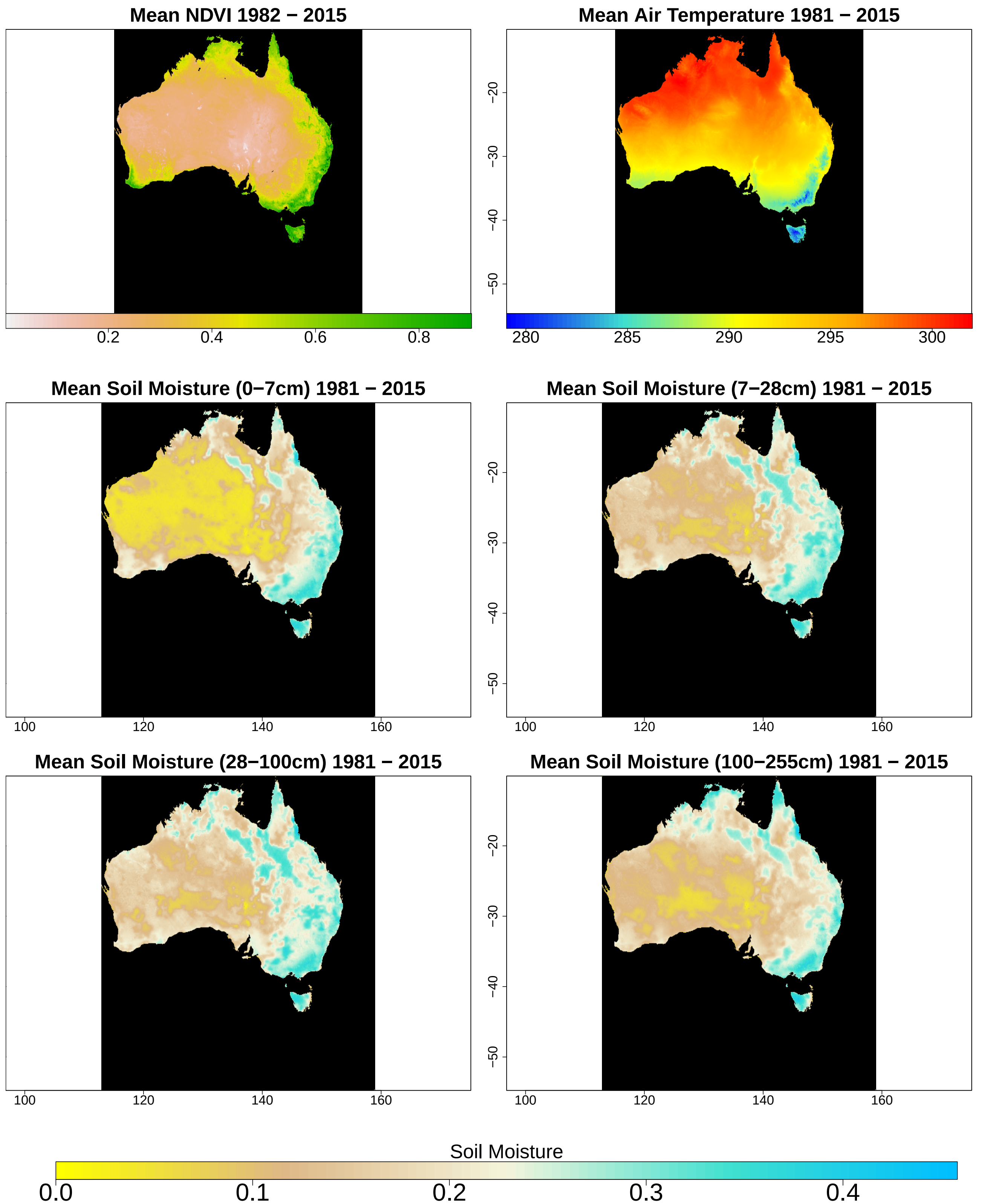


Figure A.8: Data Overview (Australia) - Data required for identificiation of vegetation memory: (1) GIMMS NDVI 3g; and (2) ERA5: Tair, Qsoil1, Qsoil2, Qsoil3, Qsoil4. Figure established via Chunk 20.

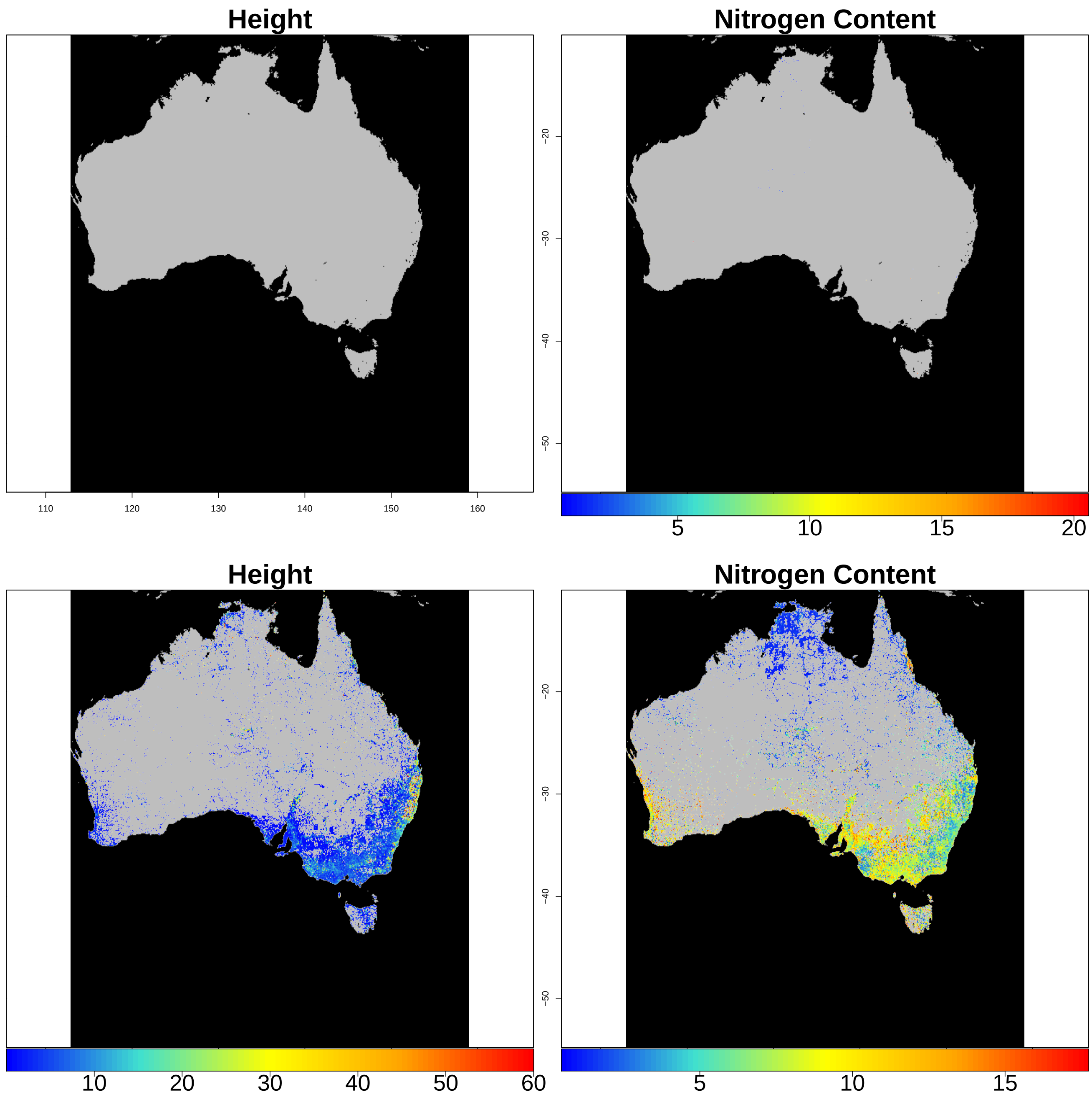


Figure A.9: TRY Data (Australia) - TRY PFT data across Australia: (1) Geo-referenced records (upper row), and (2) Extrapolated species-specific mean PFT records (lower row). Figure established via Chunk 21.

A.3 R Analyses Codes

A.3.1 Master File

Chunk 7: Running the entire analysis once data has been allocated to directories. S0a_Packages.R can be found in Chunk 1, S0b_Directories.R is located in Chunk 2 whilst S0c_Functions.R is contained in Chunk 3. S1_GIMMs.R, S2_ERA5.R, S3_VegetationMemory.R, S4_PFTs.R, and S4_COMPADRE.R are included in Chunk 8, Chunk 9, Chunk 10, Chunk 11, and Chunk 12, respectively.

```
rm(list = ls()) # clearing environment
####--------------- PACKAGES ----
source("Y - Codes/S0a_Packages.R") # loading packages
####--------------- DIRECTORIES ----
source("Y - Codes/S0b_Directories.R") # setting directories
####--------------- FUNCTIONS ----
source("Y - Codes/S0c_Functions.R") # Loading miscellaneous functions
####--------------- VARIABLE VECTORS ----
ModVars <- c("Tair", "Qsoil1", "Qsoil2", "Qsoil3", "Qsoil4")
ClimVars = list("Qsoil1_mean", "Qsoil2_mean", "Qsoil3_mean", "Qsoil4_mean")
ClimVars2 = list("Tair_mean", "Tair_mean", "Tair_mean", "Tair_mean")
###---------------- FUNCTIONS --------------------------------------------------------
####--------------- Fun_Vegetation [Regions, RegionFiles, Extents, From, To, Lags, Cores]
# (selecting and preparing data, and calculating vegetation memory) ----
Fun_Vegetation <- function(Regions, RegionFiles, Extents, From, To, Lags, Cores) {
  FromY <- (From - ceiling(1/12 * max(Lags))) # Figuring out real start year after factoring in lags
  ##### GIMMs NDVI -----
  print("+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
  print("HANDLING GIMMs NDVI DATA")
  print("+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
  setwd(mainDir)
  source(paste(Dir.Codes, "S1_GIMMs.R", sep="/"))
  # Download NDVI data for full years (from, to), turn it into monthly composite
  # rasters checking if all files are already there and not running this function
  # if they are
  froms <- c(1982, 1986, 1991, 1996, 2001, 2006, 2011)
  tos <- c(1985, 1990, 1995, 2000, 2005, 2010, 2015)
  for(RasGimms in 1:length(tos)){
    if(file.exists(paste(Dir.Gimms.Monthly, "/GlobalNDVI_", froms[RasGimms], tos[RasGimms], ".nc", sep=""))){
      print(paste("Global NDVI raster from", froms[RasGimms], "to", tos[RasGimms], "has already been established."))
      next()
    }else{
      RasterGIMMs(from = froms[RasGimms], to = tos[RasGimms])
    }
  }
  # Load composite NDVI data and limit to extent of a study region saving the
  # resulting data
  for (CombineRun in 1:length(Regions)) {
    # Checking if this particular data has been produced already
    if (file.exists(paste(Dir.Gimms.Monthly, "/NDVI_", RegionFiles[[CombineRun]],
                          ".nc", sep = ""))) {
      print(paste("NDVI raster stack already cropped for: ", RegionFiles[[CombineRun]],
                  sep = ""))
      (next)()
    }
    CombineCDFs(Region = Regions[[CombineRun]], RegionFile = RegionFiles[[CombineRun]],
                Extent = Extents[[CombineRun]])
  } # CombineCDFs
  ##### ERA5 -----
  print("+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
```

```
print("HANDLING ERA5 DATA")
print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
setwd(mainDir)
source(paste(Dir.Codes, "S2_ERA5.R", sep="/"))
# kriging ERA5 variable data across study regions for selected time period
# parallel
if (Cores > 1) {
  cl <- makeCluster(Cores) # Assuming X node cluster
  registerDoParallel(cl) # Register cores
  for (KrigRegion in 1:length(Regions)) {
    # looping over regions
    print("##################################################")
    print(paste("Kriging ERA5 ", toString(ModVars), " data from across ",
                RegionFiles[[KrigRegion]], sep = ""))
    foreach(Krigrun = 1:length(ModVars)) %dopar% {
      # looping over variables
      source(paste("Y - Codes", "S0a_Packages.R", sep="/")) # load packages to each core
      source(paste("Y - Codes", "S0b_Directories.R", sep="/")) # set packages for each core
      source(paste(Dir.Codes, "S0c_Functions.R", sep="/")) # Loading miscellaneous functions
      source(paste(Dir.Codes, "S2_ERA5.R", sep="/")) # source function for each core
      ModVars <- c("Tair", "Qsoil1", "Qsoil2", "Qsoil3", "Qsoil4")
      # Checking if this particular data has been kriged already
      if (!file.exists(paste(Dir.ERA.Monthly, "/", ModVars[[Krigrun]],
                             "_mean_", RegionFiles[[KrigRegion]], "_", 1, FromY, "_", 12, To,
                             ".nc", sep = "")))
      {
        sapply(package_vec, install.load.package)
        RasterEra5(Variable = ModVars[[Krigrun]], Region = Regions[[KrigRegion]],
                   RegionFile = RegionFiles[[KrigRegion]], Extent = Extents[[KrigRegion]],
                   FromY = FromY, FromM = 1, ToY = To, ToM = 12, Temporary = "Keep")
      } # check if already kriged
    } # parallel run
  } # Region-loop
  stopCluster(cl) # stop cluster
} else {
  # non-parallel looping over regions looping over variables Checking if this
  # particular data has been kriged already
  for (KrigRegion in 1:length(Regions)) {
    for (Krigrun in 1:length(ModVars)) {
      if (file.exists(paste(Dir.ERA.Monthly, "/", ModVars[[Krigrun]], "_mean_",
                            RegionFiles[[KrigRegion]], "_", 1, FromY, "_", 12, To, ".nc", sep = ""))) {
        print(paste(ModVars[[Krigrun]], " data already kriged for: ", RegionFiles[[KrigRegion]],
                    sep = ""))
        (next)()
      }
      RasterEra5(Variable = ModVars[[Krigrun]], Region = Regions[[KrigRegion]],
                 RegionFile = RegionFiles[[KrigRegion]], Extent = Extents[[KrigRegion]],
                 FromY = FromY, FromM = 1, ToY = To, ToM = 12, Temporary = "Keep")
    } # Variable-loop
  } # region-loop
} # RasterEra5 function
##### VEGETATION MEMORY -----
print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
print("IDENTIFYING VEGETATION MEMORY")
print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
setwd(mainDir)
source(paste(Dir.Codes, "S3_VegetationMemory.R", sep="/"))
# Calculating vegetation memory
```

```
  `%nin%` = Negate(`%in%`) # create a 'not in' statement
  if (Cores > 1) {
    # parallel
    cl <- makeCluster(Cores) # Assuming X node cluster
    registerDoParallel(cl) # registering cores
    for (MemReg in 1:length(Regions)) {
      # looping over regions
      print("#################################################")
      print(paste("Calculating vegetation memory according to ", toString(ModVars),
                  " across ", RegionFiles[[MemReg]], sep = ""))
      foreach(Memrun = 2:length(ModVars)) %dopar% {
        # looping over variables
        source(paste("Y - Codes", "S0a_Packages.R", sep="/")) # load packages to each core
        source(paste("Y - Codes", "S0b_Directories.R", sep="/")) # register directories with each core
        source(paste(Dir.Codes, "S0c_Functions.R", sep="/")) # Loading miscellaneous functions
        source(paste(Dir.Codes, "S3_VegetationMemory.R", sep="/")) # source functions for each core
        ModVars <- c("Tair", "Qsoil1", "Qsoil2", "Qsoil3", "Qsoil4")
        # check if already computed
        if (paste(RegionFiles[[MemReg]], "_Tair_mean-", ModVars[Memrun],
                  "_mean", paste(Lags, collapse = "_"), "_", FromY, "-", To, ".nc",
                  sep = "") %nin% list.files(Dir.Memory)) {
          VegMem(ClimVar = paste(ModVars[Memrun], "_mean", sep = ""), ClimVar2 = "Tair_mean",
                 Region = RegionFiles[[MemReg]], Cumlags = Lags, FromY = FromY,
                 ToY = To)
        }
      } # parallel loop
    } # region-loop
    stopCluster(cl) # stop cluster
  } else {
    # non-parallel looping over regions looping over coefficients of soil layers
    # check if already computed
    for (MemReg in 1:length(Regions)) {
      for (Memrun in 2:length(ModVars)) {
        if (paste(RegionFiles[[MemReg]], "_Tair_mean-", ModVars[Memrun],
                  "_mean", paste(Lags, collapse = "_"), "_", FromY, "-", To, ".nc",
                  sep = "") %nin% list.files(Dir.Memory)) {
          VegMem(ClimVar = paste(ModVars[Memrun], "_mean", sep = ""), ClimVar2 = "Tair_mean",
                 Region = RegionFiles[[MemReg]], Cumlags = Lags, FromY = FromY,
                 ToY = To)
        } else {
          print(paste("Vegetation memory already computed for", ModVars[Memrun],
                      " across:", RegionFiles[[MemReg]], sep = " "))
        }
      } # memory-loop
    } # region-loop
  } # VegMem function
  # scaling coefficients per region to be represented on fixed scales looping over
  # regions
  for (MemReg in 1:length(Regions)) {
    CoeffScaling(ClimVar = ClimVars, ClimVar2 = ClimVars2, Region = list(RegionFiles[[MemReg]],
                                                                          RegionFiles[[MemReg]],
                                                                          RegionFiles[[MemReg]],
                                                                          RegionFiles[[MemReg]]),
                 Cumlags = list(Lags, Lags, Lags, Lags), FromY = FromY, ToY = To, UAbs = TRUE)
  } # CoeffScaling function
} # Fun_Vegetation
####--------------- Fun_PFTs [Regions, RegionFiles, Extents, From, To, Occ]
# (aggregating PFT data, downloading species occurences, building PFT rasters)
```

```r
# ----
Fun_PFTs <- function(Regions, RegionFiles, Extents, From, To, Occ) {
  source(paste(Dir.Codes, "S4_PFTs.R", sep="/"))
  print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
  print("CALCULATING SPECIES SPECIFIC-TRAIT MEANS")
  print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
  # calculating species-specific trait means
  if (!file.exists(paste(Dir.TRY, "/SpeciesTraits.RData", sep = ""))) {
    PFTs() # species-specific trait means
  } else {
    print("Species-specific trait means already calculated")
  }
  print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
  print("OBTAINING SPECIES OCCURENCE RECORDS FROM GBIF")
  print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
  # figuring out ISO3166 codes for selected regions
  ISO3166_df <- read.csv(paste(Dir.Mask, "/ISO3166.csv", sep = "")) # read ISO3166 country code list
  CountCodes <- ISO3166_df$ISO.3166.ALPHA.2[which(ISO3166_df$Country %in% unlist(Regions))]
  CountCodes <- toString(CountCodes)
  CountCodes <- gsub(pattern = ", ", replacement = ";", x = CountCodes)
  # Download occurence files from GBIF
  if (Occ == "Download") {
    GbifStat <- NULL
    # species occurences
    Attempt <- 0
    while (is.null(GbifStat) || GbifStat != "Done") {
      if (Attempt > 0) {
        print("Encountered an error and starting the downloading of GBIF occurence data again.
              This is usually due to issues with the GBIF server connection and you don't have
              to worry as long as your internet connection is stable.")
      }
      Attempt <- Attempt + 1
      try(GbifStat <- DistMaps(Species = "All", Years = From:To, CountCodes = CountCodes))
      }
    } else {
      print("Occurence data will not be downloaded according to function call.")
    }
  # generate mean rasters of PFTs across specifiec regions looping over regions
  for (CompReg in 1:length(Regions)) {
    if (!file.exists(paste(Dir.TRY, "/TRY-", RegionFiles[[CompReg]], ".nc", sep = ""))) {
      PFTRasters(Region = Regions[[CompReg]], RegionFile = RegionFiles[[CompReg]],
                 Extent = Extents[[CompReg]], CountCodes = CountCodes)
    } else {
      print(paste("TRY data already aggregated to mean raster for region ",
                  RegionFiles[[CompReg]], sep = ""))
    }
  } # region-loop
} # Fun_PFTs
####--------------- Fun_Compadre [Variables, Regions, RegionFiles, Extents]
# (selecting and preparing data, and making COMPADRE data into rasters) ----
Fun_COMPADRE <- function(Variables, Regions, RegionFiles, Extents) {
  print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
  print("COMPADRE ANALYSES")
  print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
  source(paste(Dir.Codes, "S4_COMPADRE.R", sep="/"))
  # Build rasters of compadre variables across study regions looping over Compadre
  # variables looping over regions
  for (CompVar in 1:length(Variables)) {
```

```
    for (CompReg in 1:length(Regions)) {
      if (!file.exists(paste(Dir.Compadre, "/", Variables[[CompVar]], "/",
                             Variables[[CompVar]], "_", RegionFile = RegionFiles[[CompReg]], ".nc",
                             sep = ""))) {
        RasterCOMPADRE(Variable = Variables[[CompVar]], Region = Regions[[CompReg]],
                       RegionFile = RegionFiles[[CompReg]], Extent = Extents[[CompReg]])
      } else {
        print(paste(Variables[[CompVar]], " already rasterised across ",
                    RegionFiles[[CompReg]], sep = ""))
      }
    } # region-loop
  } # CompVar-loop
} # Fun_Compadre
####--------------- FUNCTION CALLS ----
Fun_Vegetation(Regions = list(c("Portugal", "Spain", "France", "Andorra"), "Brazil", "Australia"),
               RegionFiles = list("Iberian Region", "Caatinga", "Australia"),
               Extents = list(extent(-10,10,35,52), extent(-50,-34,-23,0), NULL),
               From = 1982, To = 2015, Lags = 0:12, Cores = 5)

Fun_PFTs(Regions = list(c("Portugal", "Spain", "France", "Andorra"), "Brazil", "Australia"),
         RegionFiles = list("Iberian Region", "Caatinga", "Australia"),
         Extents = list(extent(-10,10,35,52), extent(-50,-34,-23,0), NULL),
         From = 1982, To = 2015, Occ = "Download")

Fun_COMPADRE(Variables = list("Reactivity", "Rho", "Pi", "FastSlow"),
             Regions = list(c("Portugal", "Spain", "France", "Andorra"), "Brazil", "Australia"),
             RegionFiles = list("Iberian Region", "Caatinga", "Australia"),
             Extents = list(extent(-10,10,35,52), extent(-50,-34,-23,0), NULL))
```

A.3.2 Vegetation Memory

A.3.2.1 GIMMs Data

Chunk 8: Downloading GIMMs NDVI3g data, establishing rasters of monthly composites (RasterGIMMs), and creating NDVI raster stacks for each study region (CombineCDFs).

```r
setwd(Dir.Gimms)
gimms_files <- updateInventory
####--------------- RasterGIMMs [from, to] ----
RasterGIMMs <- function(from, to){
  print("##################################################")
  print(paste("Rasterising GIMMs NDVI data from ", from, " to ", to, sep=""))
  setwd(Dir.Gimms) # set working directory to base GIMMs folder
  # PREPARING DATA----
  invisible(capture.output(gimms_files <- downloadGimms(x = as.Date(paste(from,"-01-01",sep="")), # start date
                                                        y = as.Date(paste(to,"-12-31",sep="")), # end date
                                                        dsn = Dir.Gimms))) # where to store the files
  gimms_raster <- rasterizeGimms(x = gimms_files, remove_header = TRUE) # rasterising
  indices <- monthlyIndices(gimms_files) # extract month indices from file list (should be two of each)
  gimms_raster_mvc <- monthlyComposite(gimms_raster, indices = indices) # create composites according to indices
  # Fix NDVI misbehaviours
  gimms_raster_mvc[gimms_raster_mvc<0] <- 0 # set threshold for barren land (NDVI<0)
  gimms_raster_mvc[gimms_raster_mvc>1] <- 1 # set threshold for saturated NDVI (NDVI > 1)
  # Indices
  Years <- rep(seq(from, to, 1), each = 12) # The year corresponding to each month in the stack
  names(gimms_raster_mvc) <- paste(month.abb, Years, sep = "") # create names for rasters
  # SAVING DATA----
  writeRaster(gimms_raster_mvc, paste(Dir.Gimms.Monthly, "/GlobalNDVI_", from, to, sep=""),
              overwrite=TRUE, format="CDF", varname="GIMMsNDVI")
  setwd(mainDir)}# end of RasterGIMMS-function
####--------------- CombineCDFS [Region, RegionFile, Extent] ----
CombineCDFs <- function(Region, RegionFile, Extent){
  print("##################################################")
  print(paste("Producing cropped GIMMs NDVI raster stacks for ", RegionFile, sep=""))
  # SELECTING FILES----
  files <- list.files(Dir.Gimms.Monthly)
  files.pos <- grep("GlobalNDVI", files)
  # REGION SELECTION----
  Shapes <- readOGR(Dir.Mask,'ne_50m_admin_0_countries', verbose = FALSE)
  RegObj <- RegionSelection(Region = Region, RegionFile = RegionFile, Extent = Extent)
  area <- RegObj[[1]]
  location <- RegObj[[2]]
  RegionFile <- RegObj[[3]]
  # LOADING, CROPPING AND MASKING----
  setwd(Dir.Gimms.Monthly)
  ras <- list()
  for(i in 1:length(files.pos)){
    rasinter <- brick(files[files.pos[i]]) # load i-th ndvi file
    rasinter <- crop(rasinter, area) # cropping to extent
    rasinter <- mask(rasinter, Shapes[location,]) # masking via Shapefile
    ras[[i]] <- rasinter # save masked ndvi to list
  }
  ras <- brick(ras) # create one big regional ndvi raster
  # SAVING DATA----
  writeRaster(ras, paste(Dir.Gimms.Monthly, "/NDVI_", RegionFile, sep=""),
              overwrite=TRUE, format="CDF", varname="NDVI",
              longname= paste("Monthly NDVI means across ", Region, sep=""))
  setwd(mainDir)} # CombineCDFs
```

A.3.2.2 ERA5

Chunk 9: Kriging ERA5 data from ERA5 to GIMMS resolution using HWSD covariates (table A.2) (RasterEra5).

```
###---------------- PREAMBLE ---------------------------------------------------------
Variables_vec <- c("Tair_mean", "Qsoil1_mean", "Qsoil2_mean", "Qsoil3_mean", "Qsoil4_mean")
VariablesNames_vec <- c("Air Temperature", "Soil Moisture (0-7cm)", "Soil Moisture (7-28cm)",
                        "Soil Moisture (28-100cm)", "Soil Moisture (100-255cm)")
Covariates_vec <- c("Slopes1", "Slopes2", "Slopes3", "Slopes4", "Slopes5", "Slopes6", "Slopes7", "Slopes8",
                    "Slope_aspect_N", "Slope_aspect_E", "Slope_aspect_S", "Slope_aspect_W", "Slope_aspect_U",
                    "Elevation")
Variables_vec <- c("Tair_mean", "Qsoil1_mean", "Qsoil2_mean", "Qsoil3_mean", "Qsoil4_mean")
VariablesNames_vec <- c("Air Temperature", "Soil Moisture (0-7cm)", "Soil Moisture (7-28cm)",
                        "Soil Moisture (28-100cm)", "Soil Moisture (100-200cm)")
Covariates_vec <- c("Slopes1", "Slopes2", "Slopes3", "Slopes4", "Slopes5", "Slopes6", "Slopes7", "Slopes8",
                    "Slope_aspect_N", "Slope_aspect_E", "Slope_aspect_S", "Slope_aspect_W", "Slope_aspect_U",
                    "Elevation")
####--------------- RasterEra5 [Variable, Region, FromY, FromM, ToY, ToM, Temporary]
# (selecting data, downscaling, exporting rasters) ----
RasterEra5 <- function(Variable, Region, RegionFile, Extent, FromY, FromM, ToY, ToM, Temporary){
  VarPos <- which(Variables_vec == paste(Variable, "mean", sep="_")) # position for indexing of variable
  YearVec <- rep(1980:2015, each = 12) # Year vector to indicate months for time frame selection
  # CONSOLE MESSAGE----
  print("##################################################")
  print(paste("Kriging ERA5 ", VariablesNames_vec[VarPos], " data from ", FromM, "/", FromY, " to ", ToM, "/", ToY,
              " across ", RegionFile, sep=""))
  # FORMULAE VECTORS----
  Krig_formula <- "ERA5 ~ Slopes1+Slopes2+Slopes3+Slopes4+Slopes5+Slopes6+Slopes7+Slopes8+Slope_aspect_N+
  Slope_aspect_E+Slope_aspect_S+Slope_aspect_W+Slope_aspect_U+Elevation+
  Slopes1:Slope_aspect_N+Slopes2:Slope_aspect_N+Slopes3:Slope_aspect_N+
  Slopes4:Slope_aspect_N+Slopes5:Slope_aspect_N+Slopes6:Slope_aspect_N+
  Slopes7:Slope_aspect_N+Slopes8:Slope_aspect_N+Slopes1:Slope_aspect_S+
  Slopes2:Slope_aspect_S+Slopes3:Slope_aspect_S+Slopes4:Slope_aspect_S+
  Slopes5:Slope_aspect_S+Slopes6:Slope_aspect_S+Slopes7:Slope_aspect_S+
  Slopes8:Slope_aspect_S"
  # LOAD DATA----
  ## Era5 data
  FirstMonth <- which(YearVec == FromY)[FromM] # first month to consider
  LastMonth <- which(YearVec == ToY)[ToM] # last month to consider
  ras <- list() # create empty list for era5 raster data
  Montquence <- FirstMonth:LastMonth
  ras <- brick(paste(Dir.ERA, "/", Variable ,"_TrainingResolution.nc", sep="")) # loading data
  ras <- ras[[Montquence]] # limitting to sought-after months
  extent(ras) <- c(-180,180,-90,90) # fix extent
  ## Covariates for Kriging
  Cov_coarse <- list() # create empty list
  for(c in 1:length(Covariates_vec)){ # cycle through all covariates and load the data
    Cov_coarse[[c]] <- raster(paste(Dir.KrigCov, "/Co-variates_TrainingResolution.nc", sep=""),
                              varname = Covariates_vec[c])}
  Cov_coarse <- brick(Cov_coarse) # make coarse covariate data into one big brick
  extent(Cov_coarse) <- c(-180,180,-90,90) # fix extent
  Cov_fine <- list() # create empty list
  for(c in 1:length(Covariates_vec)){ # cycle through all covariates and load the data
    Cov_fine[[c]] <- raster(paste(Dir.KrigCov, "/Co-variates_NativeResolution.nc", sep=""),
                            varname = Covariates_vec[c])}
  Cov_fine <- brick(Cov_fine) # make fine covariate data into one big brick
  # REGION SELECTION----
  Shapes <- readOGR(Dir.Mask,'ne_50m_admin_0_countries', verbose = FALSE)
  RegObj <- RegionSelection(Region = Region, RegionFile = RegionFile, Extent = Extent)
```

```
area <- RegObj[[1]]
location <- RegObj[[2]]
RegionFile <- RegObj[[3]]
# CROPPING AND MASKING----
## Era5 cropping and masking
ras <- crop(ras, area) # cropping to extent
ras <- mask(ras, Shapes[location,]) # masking via Shapefile
## Coarse covariate cropping and masking
Cov_coarse <- crop(Cov_coarse, area) # cropping to extent
Cov_coarse <- mask(Cov_coarse, Shapes[location,]) # masking via Shapefile
## Fine covariate cropping and masking
Cov_fine <- crop(Cov_fine, area) # cropping to extent
Cov_fine <- mask(Cov_fine, Shapes[location,]) # masking via Shapefile
# KRIGING----
Months1 <- (ToY-FromY-1)*12 # how many months to cover just by years
Months2 <- abs(ToM-FromM+1) # how many months to cover only taking months of time frame into account
FullMonths <- Months1+Months2 # total count of months that are covered
if(FromY == ToY){# if range doesn't exceed a calendar year
  Years <- rep(YearVec[FirstMonth], Months2) }else{
  FromLeft <- 12-FromM+1 # months left in starting year
  ToCovered <- ToM # months to be covered in final year
  Years1 <- rep(FromY, FromLeft)
  Years2 <- rep(ToY, ToCovered)
  if(ToY-FromY > 1){
    Years3 <- rep((FromY+1):(ToY-1), each = 12) # months in full years
    Years <- c(Years1, Years3, Years2) }else{
    Years <- c(Years1, Years2)}}
Months <- rep(c(1:12), length = length(Years))
Names <- paste(month.abb, Years, sep="") # combination of month names and years
## Preparing Kriging
Dir.Temp <- paste(Dir.ERA.Monthly,"/Temp_",Variable,"_",RegionFile, sep="")
dir.create(Dir.Temp)
TempNames <- paste(rep(YearVec),
                   rep(c("01","02","03","04","05","06","07","08","09","10","11","12")),sep="_")
# figuring out where to begin with the names
if(FromM < 10){
  TempStart <- which(TempNames == paste(FromY,"_0",FromM, sep="")) }else{
  TempStart <- which(TempNames == paste(FromY,"_",FromM, sep=""))}
# figuring out where to stop with the names
if(ToM < 10){
  TempStop <- which(TempNames == paste(ToY,"_0",ToM, sep="")) }else{
  TempStop <- which(TempNames == paste(ToY,"_",ToM, sep=""))}
TempNames <- TempNames[TempStart:TempStop]
Ras_Krig <- list()
### Actual Kriging
counter <- 0
for(i in 1:length(names(ras))){
  if(paste(TempNames[i], ".nc", sep="") %in% list.files(Dir.Temp)){ # check if this file has already been produced
    print(paste(TempNames[i], "already kriged", sep=" "))
    Ras_Krig[[i]] <- raster(paste(Dir.Temp, "/", TempNames[i], ".nc", sep=""))
    next()}
  counter <- counter + 1
  T_Begin <- Sys.time()
  RasterX <- ras[[i]]# extracting raster from Era5 stack
  # Base and Covariate Coarse Data
  Origin <- as.data.frame(RasterX, xy = TRUE)
  Origin <- na.omit(Origin)
  for(c in 1:length(Covariates_vec)){
```

```
    Cov_coarse[[c]][!is.na(RasterX) & is.na(Cov_coarse[[c]])] <- 0 # 0 cells where no info
    Cov_coarse[[c]][is.na(RasterX)] <- NA # ensure same NAs
    Covariate <- as.data.frame(Cov_coarse[[c]], xy = TRUE)
    Covariate <- na.omit(Covariate)
    Origin <- cbind(Origin, Covariate[,3])}
  colnames(Origin) <- c("x","y", "ERA5", Covariates_vec)
  # checking data availability
  for(it_check in 1:length(colnames(Origin))){
    if(length(which(Origin[,it_check] != 0)) < 2){
      stop(paste("The native resolution data does not support kriging using the formula you have specified
                 because ", colnames(Origin)[it_check], " does not contain enough data records for kriging
                 to be performed across the region you have specified (", Region, ").", " You can resolve
                 this issue by either removing the interaction effects containing this variable from the
                 formula or choosing a bigger study region.", sep=""))}}
  OriginK <- Origin
  gridded(OriginK) <- ~x+y
  # CROPPING TARGET
  Cov_fine[[1]][which(is.na(as.vector(Cov_fine[[1]])))] <- 0
  Cov_fine[[1]] <- mask(Cov_fine[[1]], Shapes[location,])
  Target <- as.data.frame(Cov_fine[[1]], xy = TRUE)
  for(c in 2:length(Covariates_vec)){
    Cov_fine[[c]][which(is.na(as.vector(Cov_fine[[c]])))] <- 0
    Cov_fine[[c]] <- mask(Cov_fine[[c]], Shapes[location,])
    Covariate <- as.data.frame(Cov_fine[[c]], xy = TRUE)
    Target <- cbind(Target, Covariate[,3])}
  colnames(Target) <- c("x","y", Covariates_vec)
  TargetK <- Target
  gridded(TargetK) <- ~x+y
  # KRIGING
  invisible(capture.output(
    kriging_result <- autoKrige(
      as.formula(Krig_formula),OriginK, TargetK, verbose = FALSE)))
  Krig_ras <- raster(kriging_result$krige_output)
  Ras_Krig[[i]] <- Krig_ras
  # writing the raster
  writeRaster(Krig_ras, filename = paste(Dir.Temp,"/",TempNames[i],sep=""), overwrite=TRUE, format="CDF")
  if(counter == 1){
    T_End <- Sys.time()
    Duration <- as.numeric(T_End)-as.numeric(T_Begin)
    print(paste("Calculating monthly ERA5 ", VariablesNames_vec[VarPos], " rasters from ", FromM, "/", FromY,
                " to ", ToM, "/", ToY, " across ", RegionFile, " should finish around: ",
                as.POSIXlt(T_Begin + Duration*(length(names(ras))-i), tz = Sys.timezone(location=TRUE)), sep=""))
    pb <- txtProgressBar(min = 0, max = length(names(ras)), style = 3)}
  setTxtProgressBar(pb, i)} # kriging loop
# COMBINING KRIGED ENSEMBLES FROM MEMORY----
Ras_Krig <- brick(Ras_Krig)
ras <- Ras_Krig
# ELIMINATE KRIGING ARTIFACTS OF SOIL MOISTURE BY BOUNDING
if(Variable == "Qsoil1" | Variable == "Qsoil2" | Variable == "Qsoil3" | Variable == "Qsoil4"){
  values(ras)[which(values(ras) < 0)] <- 0}
# SAVING DATA----
setwd(Dir.ERA.Monthly)
writeRaster(ras, paste(Variable, "_mean_", RegionFile, "_", FromM, FromY, "_", ToM, ToY, sep=""),
            overwrite=TRUE, format="CDF", varname=Variable,
            longname= paste(Variables_vec[VarPos], " mean for years ", FromM, "/",FromY, " to ", ToM,"/",ToY,
                            " across ", Region, sep=""))
if(Temporary == "Delete"){unlink(Dir.Temp, recursive = TRUE)}
setwd(mainDir)}# end of RasterEra5 function
```

A.3.2.3 Calculation of Vegetation Memory

Chunk 10: Computing vegetation memory for study regions as specified by lags, time frame, and variables to be considered (VegMem), scaling rasters of vegetation memory to be on the same scale for each study region (CoeffScaling).

```
Variables_vec <- c("Tair_mean", "Qsoil1_mean", "Qsoil2_mean", "Qsoil3_mean", "Qsoil4_mean")
VariablesNames_vec <- c("Air Temperature", "Soil Moisture (0-7cm)", "Soil Moisture (7-28cm)",
                        "Soil Moisture (28-100cm)", "Soil Moisture (100-200cm)")
####--------------- VegMem [ClimVar, Region, Cumlags, FromY, ToY]
# (selecting data, calculating vegetation memory according to specified lags, exporting rasters) ----
VegMem <- function(ClimVar, ClimVar2, Region, Cumlags, FromY, ToY){
  print("#################################################")
  print(paste("Identifying vegetation memory effects of NDVI based on antecedent NDVI and ",
              VariablesNames_vec[which(Variables_vec == ClimVar2)], " (immediate effects) and ",
              VariablesNames_vec[which(Variables_vec == ClimVar)], " at lags: ", toString(Cumlags)," across ",
              Region, sep=""))
  # LOAD DATA----
  ## NDVI/GIMMs
  NDVI_ras <- brick(paste(Dir.Gimms.Monthly,"/NDVI_", Region,".nc", sep=""))
  ## ERA5
  Clim <- list.files(Dir.ERA.Monthly)[grep(pattern = ClimVar, list.files(Dir.ERA.Monthly))]
  Clim <- Clim[grep(pattern = Region, Clim)] # files in target region
  Clim <- Clim[grep(pattern = FromY, Clim)] # files with correct start date
  Clim <- Clim[grep(pattern = ToY, Clim)] # files with correct end date
  Clim_mean_ras <- brick(paste(Dir.ERA.Monthly, "/", Clim, sep="")) # rasterise
  Clim2 <- list.files(Dir.ERA.Monthly)[grep(pattern = ClimVar2, list.files(Dir.ERA.Monthly))]
  Clim2 <- Clim2[grep(pattern = Region, Clim2)]
  Clim2 <- Clim2[grep(pattern = FromY, Clim2)]
  Clim2 <- Clim2[grep(pattern = ToY, Clim2)]
  Clim2_mean_ras <- brick(paste(Dir.ERA.Monthly, "/", Clim2, sep=""))
  # PREPARE DATA----
  ## Limit NDVI data to ERA5 time frame
  NDVIYears <- rep(1982:2015, each = 12) # Year vector to indicate months for time frame selection
  NDVITo <- max(which(NDVIYears %in% ToY))
  if(min(which(NDVIYears %in% FromY)) == Inf){
    NDVIFrom <- 1 }else{ NDVIFrom <- min(which(NDVIYears %in% FromY))}
  NDVI_ras <- NDVI_ras[[NDVIFrom:NDVITo]] # NDVI data is limitted
  ## Identify data positions
  # establish a mean raster (this sets every cell to NA where any NA is within the time series)
  NATest_ras <- mean(NDVI_ras)
  NATest_vec <- values(NATest_ras) # set values as vector
  Data_Pos <- which(!is.na(NATest_vec)) # select non-NA positions (these are the ones we should build models on)
  # PREPARE RASTERS----
  ModelEval_ras <- NDVI_ras[[1:10]] # select six raster layers
  # put names on the layers to tell us what they contain later
  ModelEval_ras <- Fun_NamesRas(raster = ModelEval_ras, ClimVar = ClimVar, ClimVar2 = ClimVar2)
  # MODELS----
  for(pixel in Data_Pos){ # loop non-NA pixels
    T_Begin <- Sys.time() # note time when calculation is started (needed for estimation of remaining time)
    ## DATA ----
    ### NDVI stuff -----
    NDVI_vecraw <- as.vector(NDVI_ras[pixel]) # eytract data
    NDVI_vecdet <- detrend(NDVI_vecraw, tt = 'linear') # linear detrending
    # create NDVI data frame
    NDVI_df <- data.frame(Month = rep(1:12, length(NDVI_vecraw)/12), NDVI_raw = NDVI_vecraw, NDVI_de = NDVI_vecdet)
    ## calculate anomalies (Z-scores) and monthly means
    NDVI_df <- transform(NDVI_df, NDVI_Anomalies = ave(NDVI_de, Month, FUN=scale),
                         NDVI_Threshold = ave(NDVI_raw, Month, FUN=function(t) mean(t, na.rm=TRUE)))
    NDVI_df <- NDVI_df[nrow(NDVI_df):1,] # reverse order to read "present to past"
```

```
NDVI_anom <- c(NDVI_df$NDVI_Anomalies, rep(NA, max(Cumlags))) # extract anomalies, adding cumlag NAs
ThreshPos <- which(NDVI_df$NDVI_Threshold < 0.1) # positions which should be excluded
if(length(ThreshPos) == length(NDVI_vecraw)){ # if all months should be masked due to NDVImean < 0.1
  # set all in model raster layers to NA for this pixel
  ModelEval_ras[pixel] <- as.numeric(rep(NA, dim(ModelEval_ras)[3]))
  next()}
# calculate lag 1
NDVI_Lag1 <- c(NDVI_anom[-1], NA) # adding one NA for month preceeding data range of NDVI itself
### Climate stuff -----
#### ClimVar ------
Clim_vec <- as.vector(Clim_mean_ras[pixel]) # extract raw data for pixel (instantenous predictor)
Clim_vec <- detrend(Clim_vec, tt = 'linear') # linear detrending
Clim_vec <- Clim_vec[nrow(Clim_vec):1,] # reverse order to read "present to past"
# calculate cumulative climate indices (antecedent predictor)
Clim_cum <- rep(NA, length(Cumlags))
Clim_cum <- as.list(Cumlags)
position <- 1
for(lag in Cumlags){
  for(i in 1:(length(Clim_vec)-lag)){
    Clim_cum[[position]] <- c(Clim_cum[[position]], sum(Clim_vec[i:(i+lag)]))}
  Clim_cum[[position]] <- Clim_cum[[position]][-1] # removing initial NA
  # adding enough NAs to bring it up to full length
  Clim_cum[[position]] <- c(Clim_cum[[position]], rep(NA , length(Clim_vec)-length(Clim_cum[[position]])))
  position <- position+1}
# make data frame of climate stuff
Clim_df <- as.data.frame(Clim_cum) # make list into data frame
Clim_df <- cbind(rep(12:1, length(Clim_vec)/12), Clim_vec, Clim_df) # append month index and raw data
colnames(Clim_df) <- c("Month", "Clim_raw", paste(rep("ClimCum_",length(Cumlags)),Cumlags, sep="")) # column names
# calculate anomalies
for(anomaly in 2:length(Clim_df)){# cycle through all the columns of the climate data frame except the month column
  Clim_iter <- with(Clim_df, cbind(Month, Clim_df[,anomaly])) # extract necessary data
  colnames(Clim_iter) <- c("Month", "AnomalyCalc") # set column names
  Clim_iter <- transform(Clim_iter, # calculate anomaly for each month
                       AnomalyCalc = ave(AnomalyCalc, Month, FUN=scale))
  # save to original data frame
  Clim_df[,anomaly] <- Clim_iter$AnomalyCalc}
#### ClimVar2 ------
Clim2_vec <- as.vector(Clim2_mean_ras[pixel]) # extract raw data for pixel (instantenous predictor)
Clim2_vec <- detrend(Clim2_vec, tt = 'linear') # linear detrending
Clim2_df <- data.frame(Month = rep(1:12, length(Clim2_vec)/12), Clim2_raw = Clim2_vec)
# calculate anomalies
Clim2_df <- transform(Clim2_df,
                    Clim2_Anomalies = ave(Clim2_raw, Month, FUN=scale))
Clim2_df <- Clim2_df[nrow(Clim2_df):1,] # reverse order to read "present to past"
Clim2_anom <- Clim2_df$Clim2_Anomalies
### Combining all the data -----
ModData_df <- cbind(NDVI_anom[1:length(Clim2_anom)], NDVI_Lag1[1:length(Clim2_anom)], Clim_df, Clim2_anom)
if(length(ThreshPos) > 0){ # set threshold months to NA if necessary
  ModData_df$NDVI_anom[ThreshPos] <- NA}
ModData_df <- na.omit(ModData_df) # get rid of NA rows
## MODELS ----
### Establishing models----
# list to save Model objects
Mods_ls <- as.list(rep(NA, length(Cumlags))) # List of models
ps <- rep(NA, length(Cumlags)) # p-values
coeffst1 <- rep(NA, length(Cumlags)) # coefficients of NDVI-1
coeffsC <- rep(NA, length(Cumlags)) # coefficients of ClimVar
coeffsC2 <- rep(NA, length(Cumlags)) # coefficients of ClimVar2
```

```
# itterate over all climate lags
counter <- 0 # create a counter variable
for(ModelIter in Cumlags){ # go through all possible cumulative lags
  ## PCA of our variables
  pca_mat <- matrix(cbind(ModData_df$NDVI_Lag1,ModData_df[, counter+4], ModData_df$Clim2_anom),
                    ncol = 3, byrow = FALSE, dimnames = list(1:length(ModData_df$NDVI_Lag1),
                                                            c("t-1", ClimVar, ClimVar2))) # pca matrix
  pca <- rda(pca_mat) # running pca
  ## Extracting PC axes
  pc1 <- summary(pca)[["sites"]][,1]
  pc2 <- summary(pca)[["sites"]][,2]
  pc3 <- summary(pca)[["sites"]][,3]
  ## Building models
  Mod0 <- lm(ModData_df$NDVI_anom ~ 1) # null model
  Mod <- lm(ModData_df$NDVI_anom ~ pc1 + pc2 + pc3) # full model
  loadings <- summary(pca)[["species"]] # extract loadings
  coefficients <- Mod$coefficients[2:(dim(summary(pca)[["sites"]])[2]+1)] # extract coefficients
  ## Make coefficients representative by multiplying them with the loadings
  t1newCof <- loadings[1,] * coefficients
  CnewCof <- loadings[2,] * coefficients
  C2newCof <- loadings[3,] * coefficients
  ## Saving information to vectors
  coeffst1[counter+1] <- sum(t1newCof) # NDVI-1
  coeffsC[counter + 1] <- sum(CnewCof) # ClimVar
  coeffsC2[counter + 1] <- sum(C2newCof) # ClimVar2
  if(anova(Mod0, Mod)$RSS[1] > anova(Mod0, Mod)$RSS[2]){ # only save p value if model is an imporvement
    ps[counter+1] <- anova(Mod0, Mod)$'Pr(>F)'[2]
  }else{ # if model is not an improvement over null, set p to 1
    ps[counter+1] <- 1}
  Mods_ls[[counter+1]] <- Mod # save model to list of models
  counter <- counter + 1 }
### Selecting best model -----
AICs <- sapply(X = Mods_ls, FUN = AIC) # calculate AICs for each model
Best <- which(abs(AICs) == min(abs(AICs), na.rm = TRUE))[1] # best model, if same value present use first
c_NDVI <- coeffst1[Best] # ndvi coefficient
c_Clim <- coeffsC[Best] # climate coefficient
c_Clim2 <- coeffsC2[Best] # p-value of climate coefficient
p_Mod <- ps[Best] # p-value is set to p-value of best model
AICMod <- AICs[Best] # AIC is set to best AIC
Bestlag <- Cumlags[Best] # this is the lag at which best model was observed
## EXPLAINED VARIANCE----
colnames(ModData_df)[c(1:2)] <- c("NDVI_anom", "NDVI_Lag1")
# Legendre & Legendre
Explainedvar <- lm(data = ModData_df,
                   NDVI_anom ~ NDVI_Lag1 + ModData_df[,Best+5])
Explainedvar <- summary(Explainedvar)[["r.squared"]]
VarTotalNDVI <- lm(data = ModData_df,
                   NDVI_anom ~ NDVI_Lag1)
VarTotalNDVI <- summary(VarTotalNDVI)[["r.squared"]]
VarTotalQsoil <- lm(data = ModData_df,
                    NDVI_anom ~ ModData_df[,Best+5])
VarTotalQsoil <- summary(VarTotalQsoil)[["r.squared"]]
VarShared <- VarTotalQsoil + VarTotalNDVI - Explainedvar
VarNDVI <- VarTotalNDVI - VarShared
VarQsoil <- VarTotalQsoil - VarShared
## WRITING INFORMATION TO RASTERS----
ModelEval_ras[pixel] <- as.numeric(c((Bestlag), AICMod, p_Mod, c_NDVI, c_Clim, c_Clim2, Explainedvar,
                                     VarNDVI, VarShared, VarQsoil)) # saving model information to raster
```

```
    ## Updating progress bar----
    if(pixel == Data_Pos[1]){ # if we are currently on the first pixel
      T_End <- Sys.time() # note end time
      Duration <- as.numeric(T_End)-as.numeric(T_Begin) # calculate the time it took to establish and select models
      ## Put an estimator up on the console that tells the user when to expect the program to finish its current run
      print(paste("Calculating Vegetation Memory effects across ", Region, " should finish around: ",
                  as.POSIXlt(T_Begin + Duration*length(Data_Pos), tz = Sys.timezone(location=FALSE)), sep=""))
      ## Update progress bar
      pb <- txtProgressBar(min = 0, max = length(Data_Pos), style = 3)
      pbi <- 0}
    pbi <- pbi + 1 ## Update progress bar
    setTxtProgressBar(pb, pbi)} # end of pixel loop
  ### Save raster -----
  writeRaster(ModelEval_ras, filename = paste(Dir.Memory,"/", Region, "_", ClimVar2, "-", ClimVar,
                                              paste(Cumlags, collapse="_"),"_",FromY,"-", ToY, ".nc",sep=""),
              overwrite=TRUE, format="CDF")
  setwd(mainDir)}# end of VegMem function

####--------------- CoeffScaling [ClimVar, ClimVar2, Region, Cumlags, FromY, ToY, UAbs]
# (loading previously saved rasters and making visualisation of model coefficients better) ----
CoeffScaling <- function(ClimVar, ClimVar2, Region, Cumlags, FromY, ToY, UAbs){
  print("#####################################################")
  print(paste("Producing composites of vegetation memory effects across ", unique(Region), sep=""))
  # PREPARATIONS ----
  Rasters <- ClimVar
  minmaxNDVIn <- rep(NA, length(ClimVar)*2)
  minmaxNDVIs <- rep(NA, length(ClimVar)*2)
  minmaxCVn <- rep(NA, length(ClimVar)*2)
  minmaxCVs <- rep(NA, length(ClimVar)*2)
  minmaxCV2n <- rep(NA, length(ClimVar)*2)
  minmaxCV2s <- rep(NA, length(ClimVar)*2)
  minmaxPos <- 1
  # LOADING DATA ----
  for(rasiter in 1:length(ClimVar)){ # cycle through specified vegetation memory rasters
    # load raster
    Alter_ras <- brick(paste(Dir.Memory,"/", Region[[rasiter]], "_", ClimVar2[[rasiter]], "-", ClimVar[[rasiter]],
                             paste(Cumlags[[rasiter]], collapse="_"),"_",FromY,"-", ToY, ".nc",sep=""))
    Alter_ras <- Fun_NamesRas(raster = Alter_ras, ClimVar = ClimVar, ClimVar2 = ClimVar2, rasiter = rasiter)
    # PREPARING DATA ----
    P_ras <- Alter_ras$Model.p.value # extract p-value layer
    C_clim <- Alter_ras[[5]] # extract ClimVar coefficients
    C_climNon <- C_clim
    C_climNon[which(values(P_ras) < 0.05)] <- NA # set everything that significant to NA
    C_climSig <- C_clim
    C_climSig[which(values(P_ras) >= 0.05)] <- NA # set everything that's not significant to NA
    C_clim2 <- Alter_ras[[6]] # extract ClimVar2 coefficients
    C_climNon2 <- C_clim2
    C_climNon2[which(values(P_ras) < 0.05)] <- NA # set everything that significant to NA
    C_climSig2 <- C_clim2
    C_climSig2[which(values(P_ras) >= 0.05)] <- NA # set everything that's not significant to NA
    C_NDVI <- Alter_ras$Antecedent.NDVI..c_NDVI. # extract NDVI-1 coefficients
    C_NDVINon <- C_NDVI
    C_NDVINon[which(values(P_ras) < 0.05)] <- NA # set everything that significant to NA
    C_NDVISig <- C_NDVI
    C_NDVISig[which(values(P_ras) >= 0.05)] <- NA # set everything that's not significant to NA
    C_Lags <- Alter_ras[[1]] # extract Lags coefficients
    C_LagsNon <- C_Lags
    C_LagsNon[which(values(P_ras) < 0.05)] <- NA # set everything that significant to NA
```

```
    C_LagsSig <- C_Lags
    C_LagsSig[which(values(P_ras) >= 0.05)] <- NA # set everything that's not significant to NA
    # SAVING PARAMETERS ----
    Rasters[[rasiter]] <- list(C_NDVINon, C_NDVISig, C_climNon, C_climSig,
                               C_climNon2, C_climSig2, C_LagsNon, C_LagsSig)
    ## Identify maximum values of each coefficient raster
    minmaxNDVIn[minmaxPos] <- max(values(C_NDVINon), na.rm = TRUE)
    minmaxNDVIs[minmaxPos] <-max(values(C_NDVISig), na.rm = TRUE)
    minmaxCVn[minmaxPos] <- max(values(C_climNon), na.rm = TRUE)
    minmaxCVs[minmaxPos] <- max(values(C_climSig), na.rm = TRUE)
    minmaxCV2n[minmaxPos] <- max(values(C_climNon2), na.rm = TRUE)
    minmaxCV2s[minmaxPos] <- max(values(C_climSig2), na.rm = TRUE)
    minmaxPos <- minmaxPos + 1 # +1 to counter in vector
    ## Identify minimum values of each coefficient raster
    minmaxNDVIn[minmaxPos] <- min(values(C_NDVINon), na.rm = TRUE)
    minmaxNDVIs[minmaxPos] <-min(values(C_NDVISig), na.rm = TRUE)
    minmaxCVn[minmaxPos] <- min(values(C_climNon), na.rm = TRUE)
    minmaxCVs[minmaxPos] <- min(values(C_climSig), na.rm = TRUE)
    minmaxCV2n[minmaxPos] <- min(values(C_climNon2), na.rm = TRUE)
    minmaxCV2s[minmaxPos] <- min(values(C_climSig2), na.rm = TRUE)
    minmaxPos <- minmaxPos + 1 # +1 to counter in vector
  } # end of loop cycling through specified vegetation memory rasters
  # MANN-WHITNEY U ----
  ## setting up directory
  Dir.Memory.Reg <- paste(Dir.Memory,"/",unique(Region),"-",FromY,"_",ToY, sep="")
  dir.create(Dir.Memory.Reg)
  ## cleaning directory o potential earlier runs
  if(paste("U-Variables_Abs",UAbs,".xlsx",sep="") %in% list.files(Dir.Memory.Reg)){
    file.remove(paste(Dir.Memory.Reg,"/U-Variables_Abs",UAbs,".xlsx",sep=""))}
  # Establish matrices and vectors for naming
  UModMat <- matrix(rep(NA, length(Rasters)^2), nrow=length(Rasters)) # for saving U outputs
  UVariables <- c("NDVI t-1", "Qsoil", "Tair", "Lags") # for naming purposes
  UMedians <- matrix(rep(NA, length(Rasters)^2), nrow=length(Rasters)) # for saving variable value medians
  dimnames(UMedians) <- list(c(1:4), UVariables) # set names
  # variable-wise comparison
  for(UVar in 1:length(Rasters)){ # loop over all variables
    for(UTest in 1:(length(Rasters)-1)){ # loop over the model layers
      UTest2 <- UTest + 1 # create seperate counter for variable with which to compare
      while(UTest2 <= length(Rasters)){ # cycle so long as second counter does not exceed range of specified models
        if(UAbs == TRUE){ # if absolute values should be used
          Test1 <- abs(values(Rasters[[UTest]][[UVar * 2]])) # data extraction
          Test2 <- abs(values(Rasters[[UTest2]][[UVar * 2]])) # data extraction
        }else{ # if absolute values are not desired
          Test1 <- values(Rasters[[UTest]][[UVar * 2]])
          Test2 <- values(Rasters[[UTest2]][[UVar * 2]])}
        test <- wilcox.test(Test1, Test2, paired = FALSE) # WHitney-U Test
        UModMat[UTest, UTest2] <- test$statistic # Extract test statistic
        UModMat[UTest2, UTest] <- test$p.value # Extract p-value
        Med1 <- median(Test1, na.rm=TRUE) # extract median
        Med2 <- median(Test2, na.rm=TRUE) # extract median
        UMedians[UTest,UVar] <- Med1 # write median of first object
        if(UTest2 == length(Rasters)){ # only write median of last variable
          UMedians[UTest2,UVar] <- Med2}# if statement
        UTest2 <- UTest2 + 1 } # while statement
    } # for UTest statement
    # saving output
    write.xlsx(UModMat, sheetName = UVariables[UVar],
               file = paste(Dir.Memory.Reg,"/U-Variables_Abs",UAbs,".xlsx",sep=""), append = TRUE)
```

```r
} # for UVar statement
write.xlsx(UMedians, sheetName = "Variable medians", # saving output
           file = paste(Dir.Memory.Reg,"/U-Variables_Abs",UAbs,".xlsx",sep=""), append = TRUE)
UModelMat <- matrix(rep(NA,3^2),nrow=3) # matrix for model-internal comparisons
dimnames(UModelMat) <- list(UVariables[1:3], UVariables[1:3]) # set names
# model-wise comparison
for(UTest in 1:(length(Rasters))){
  if(UAbs == TRUE){ # if absolute values should be used
    ND <- abs(values(Rasters[[UTest]][[2]]))
    QS <- abs(values(Rasters[[UTest]][[4]]))
    TA <- abs(values(Rasters[[UTest]][[6]]))
  }else{ # if absolute values are not desired
    ND <- values(Rasters[[UTest]][[2]])
    QS <- values(Rasters[[UTest]][[4]])
    TA <- values(Rasters[[UTest]][[6]])}
  UModelMat[2,1] <- wilcox.test(ND, QS, paired = FALSE)$p.value # WHitney-U Test
  UModelMat[3,2] <- wilcox.test(QS, TA, paired = FALSE)$p.value # WHitney-U Test
  UModelMat[3,1] <- wilcox.test(ND, TA, paired = FALSE)$p.value # WHitney-U Test
  UModelMat[1,2] <- wilcox.test(ND, QS, paired = FALSE)$statistic # WHitney-U Test
  UModelMat[2,3] <- wilcox.test(QS, TA, paired = FALSE)$statistic # WHitney-U Test
  UModelMat[1,3] <- wilcox.test(ND, TA, paired = FALSE)$statistic # WHitney-U Test
  write.xlsx(UModelMat, sheetName = paste("Model", UTest, sep=" "), # saving output
             file = paste(Dir.Memory.Reg,"/U-Variables_Abs",UAbs,".xlsx",sep=""), append = TRUE)
} # for UTest statement
# SAVING DATA FOR LATER PLOTTING ----
for(iterplot in 1:length(ClimVar)){ # cycle through all specified vegetation memory raster for plotting
  ## lags -----
  Lag_ras <- brick(paste(Dir.Memory,"/", Region[[iterplot]], "_", ClimVar2[[iterplot]], "-", ClimVar[[iterplot]],
                         paste(Cumlags[[iterplot]], collapse="_"),"_",FromY,"-", ToY, ".nc",sep=""))
  ## NDVI[t-1] -----
  Rasters[[iterplot]][[1]][1] <- max(minmaxNDVIn)
  Rasters[[iterplot]][[1]][2] <- min(minmaxNDVIn)
  Rasters[[iterplot]][[2]][3] <- max(minmaxNDVIs)
  Rasters[[iterplot]][[2]][4] <- min(minmaxNDVIs)
  ### ClimVar -----
  Rasters[[iterplot]][[3]][1] <- max(minmaxCVn)
  Rasters[[iterplot]][[3]][2] <- min(minmaxCVn)
  Rasters[[iterplot]][[4]][3] <- max(minmaxCVs)
  Rasters[[iterplot]][[4]][4] <- min(minmaxCVs)
  ### ClimVar2 -----
  Rasters[[iterplot]][[5]][1] <- max(minmaxCV2n)
  Rasters[[iterplot]][[5]][2] <- min(minmaxCV2n)
  Rasters[[iterplot]][[6]][3] <- max(minmaxCV2s)
  Rasters[[iterplot]][[6]][4] <- min(minmaxCV2s)
  ### sighnifciant coefficient rasters (already with max/min dots)
  Save_ras <- brick(Lag_ras[[1]], # Lags
                    Rasters[[iterplot]][[2]], # NDVI
                    Rasters[[iterplot]][[4]], # climvar
                    Rasters[[iterplot]][[6]]) # climvar2
  ### Saving significant effects -----
  writeRaster(Save_ras, filename = paste(Dir.Memory.Reg ,"/", ClimVar[[iterplot]], "_", ClimVar2[[iterplot]],
                                         paste(Cumlags[[iterplot]], collapse="_"), "Plots.nc",sep=""),
              overwrite=TRUE, format="CDF")} # plotting loop
setwd(mainDir)} # CoeffScaling end
```

A.3.3 Plant Functional Traits

Chunk 11: Calculating species-specific PFT means (PFTs), creating distribution maps from floral occurence data obtained from GBIF (DistMaps), and combine occurence maps with species trait means (PFTRasters).

```
####--------------- PFTs []
# (loading data, building species-specific trait means and saving the result) ----
PFTs <- function(){
  # LOADING DATA ----
  ## NDVI (reference raster) ---
  NDVI_ras <- brick(paste(Dir.Gimms.Monthly,"/GlobalNDVI_20112015.nc", sep=""))
  ref_ras <- NDVI_ras[[6]]
  ref_ras[which(values(ref_ras) > -1)] <- 8888 # identify land pixels
  ## Master PFT data from TRY
  PFT_Master <- read.table(file = paste(Dir.TRY, "/4704.txt", sep=""), stringsAsFactors = FALSE, fill = TRUE,
                           sep="\t", header = TRUE)
  ## Extracting necessary data to handle smaller data frame
  PFTs_df <- data.frame(Species = PFT_Master$SpeciesName, ObsID = PFT_Master$ObservationID,
                        Variable = PFT_Master$DataName, Value = PFT_Master$OrigValueStr, Unit = PFT_Master$UnitName)
  ## fixing factor to numeric
  as.numeric.factor <- function(x) {as.numeric(levels(x))[x]}
  PFTs_df$Value <- as.numeric.factor(PFTs_df$Value)
  # CALCULATING SPECIES-SPECIFIC MEAN TRAIT VALUES ----
  ## Preparations for calculations
  Species <- unique(PFTs_df$Species) # all species to consider
  FullSpec_df <- data.frame(Species = NA, Nmass = NA, Height = NA)
  ## Calculations
  for(Iter in 1:length(Species)){ # loop over all species that need consideration
    T_Begin <- Sys.time() # read start time (needed for expected finishing time)
    ### Nitrogen mean
    Nitro <- which(PFTs_df$Species == Species[Iter] & # positions of nitrogen rows for species
                   PFTs_df$Variable == "Leaf nitrogen content per dry mass (Nmass)")
    Mean_Nitro <- mean(PFTs_df$Value[Nitro], na.rm = TRUE) # mean
    ### Height mean
    Height <- which(PFTs_df$Species == Species[Iter] & # positions of height rows for species
                    PFTs_df$Variable == "Plant height vegetative")
    Mean_Height <- mean(PFTs_df$Value[Height], na.rm = TRUE) # mean
    ### Combining data into a data frame
    Spec_df <- data.frame(Species = Species[Iter], Nmass = Mean_Nitro, Height = Mean_Height)
    FullSpec_df <- rbind(FullSpec_df, Spec_df)
    ### Updating progress bar
    if(Iter == 1){ # estimate on finishing time on first loop
      T_End <- Sys.time() # read end time
      Duration <- as.numeric(T_End)-as.numeric(T_Begin) # duration between date points
      ### Output to console
      print(paste("Calculating species-specific trait mean values should finish around ",
                  as.POSIXlt(T_Begin + Duration*length(Species), tz = Sys.timezone(location=TRUE)), sep=""))
      ### Removing empty initial row
      FullSpec_df <- FullSpec_df[-1,]}# end of estimator if-statement
    pb <- txtProgressBar(min = 0, max = length(Species), style = 3) # Setting up a progress bar
    setTxtProgressBar(pb, Iter)}# end of species-specific mean trait value calculation for-loop
  FullNA <- which(is.na(FullSpec_df$Nmass) & is.na(FullSpec_df$Height)) # identifying species where both means are NA
  CorrectedSpec_df <- FullSpec_df[-FullNA,] # removing full NA species records
  # Save the species-specific and NA-freed data
  save(CorrectedSpec_df, file = paste(Dir.TRY, "/SpeciesTraits.RData", sep=""))
  setwd(mainDir)

  # BUILDING RASTERS FROM RAW TRAIT MEASURES ----
  ## create empty data frame and filling it
```

```
  Locs_df <- data.frame(H = NA, Nmass = NA, Lat = NA, Lon = NA)
  `%nin%` = Negate(`%in%`) # create a 'not in' statement
  ## eliminate observations with less than three records (these can't have enough data)
  IDs <- PFTs_df$ObsID
  exclude <- names(table(IDs))[which(table(IDs) < 3)]
  IDs <- unique(IDs)[which(as.character(unique(IDs)) %nin% exclude)]
  ## loop over all observations with enough data
  for(i in 1:length(IDs)){
    T_Begin <- Sys.time() # read start time (needed for expected finishing time)
    Iter_df <- PFTs_df[which(PFTs_df$ObsID == IDs[i]),] # extract all data for current observation
    ## data extraction
    Nmass <- Iter_df$Value[which(Iter_df$Variable == "Leaf nitrogen content per dry mass (Nmass)")]
    if(length(Nmass) == 0){Nmass <- NA}
    H <- Iter_df$Value[which(Iter_df$Variable == "Plant height vegetative")]
    if(length(H) == 0){H <- NA}
    Lat <- as.numeric(Iter_df$Value[which(Iter_df$Variable == "Latitude")])
    Lon <- as.numeric(Iter_df$Value[which(Iter_df$Variable == "Longitude")])
    Locs_df <- rbind(Locs_df, c(H, Nmass, Lat, Lon)) # bin data
    ## Updating progress bar
    if(i == 1){ # estimate on finishing time on first loop
      T_End <- Sys.time() # read end time
      Duration <- as.numeric(T_End)-as.numeric(T_Begin) # duration between date points
      ### Output to console
      print(paste("Extracting raw geo-referenced data should finish around ",
                  as.POSIXlt(T_Begin + Duration*length(IDs), tz = Sys.timezone(location=TRUE)), sep=""))
      ### Removing empty initial row
      Locs_df <- Locs_df[-1,]
      pb <- txtProgressBar(min = 0, max = length(IDs), style = 3)}
    setTxtProgressBar(pb, i)
  } # obvservation loop
  ## converting to spatial points objects
  H_df <- na.omit(Locs_df[which(!is.na(Locs_df$H)),-2])
  H_pts <- data.frame(y = H_df$Lat, x = H_df$Lon, z = H_df$H)
  H_pts <- na.omit(H_pts)
  coordinates(H_pts) = ~x+y # convert x and y to coordinates
  Nmass_df <- na.omit(Locs_df[which(!is.na(Locs_df$Nmass)),-1])
  Nmass_pts <- data.frame(y = Nmass_df$Lat, x = Nmass_df$Lon, z = Nmass_df$Nmass)
  Nmass_pts <- na.omit(Nmass_pts)
  coordinates(Nmass_pts) = ~x+y # convert x and y to coordinates
  ## rasterising
  rast <- raster(ext=extent(ref_ras), resolution=res(ref_ras)) # create raster to be filled
  H_rasOut <- rasterize(x = H_pts, y = rast, field = H_pts$z, fun = mean) # rasterize irregular points
  Nmass_rasOut <- rasterize(x = Nmass_pts, y = rast, field = Nmass_pts$z, fun = mean) # rasterize irregular points
  Means_ras <- brick(H_rasOut, Nmass_rasOut)
  ## saving data
  writeRaster(x=Means_ras, filename = paste(Dir.TRY,"/RawTRY-Global", sep=""),overwrite=TRUE, format="CDF")
}# end of PFTs-function

####--------------- DistMaps [Species, Extent, Years, CountCodes]
# (Obtaining occurence data via GBIF, rasterising, saving the raster, limitting to a region) ----
DistMaps <- function(Species, Years, CountCodes){
  print("##################################################")
  print(paste("Downloading occurence data of species: ", Species, " across: ", CountCodes, sep=""))
  # LOADING SPECIES DATA FRAME ----
  load(paste(Dir.TRY, "/SpeciesTraits.RData", sep="")) # load data frame 'CorrectedSpec_df'
  if(Species == "All"){ # selecting all species contained in 'CorrectedSpec_df'
    Species <- sort(CorrectedSpec_df$Species)
    Species <- Species[-which(Species == "-")] # remove this error of a species name
```

```r
    SP <- "All"
  }else{
    SP <- "Dummy" # only used if single species is targeted
  }
  # GLOBAL REFERENCE DATA (needed for rasterising and masking) ----
  ## NDVI (reference raster) ---
  NDVI_ras <- brick(paste(Dir.Gimms.Monthly,"/GlobalNDVI_20112015.nc", sep=""))
  ref_ras <- NDVI_ras[[6]]
  ref_ras[which(values(ref_ras) > -1)] <- 8888 # identify land pixels
  # IDENTIFYING GBIF KEY(S) ----
  # if data is already present and all species are sought-after
  if("SpeciesGBIFKeys.rda" %in% list.files(path=Dir.TRY) & SP == "All"){
    print("Loading species-specific GBIF keys from local storage") # output to console
    load(paste(Dir.TRY, "/SpeciesGBIFKeys.rda", sep=""))
  }else{
    ## Preparations ---
    Key_vec <- NA # create empty vector for gbif key(s)
    Species_Pres <- NA # create empty vector for all species which we have occurence records for
    print("Identifying species-specific GBIF keys from GBIF repository") # output to console
    pb <- txtProgressBar(min = 0, max = length(Species), style = 3) # Setting up a progress bar
    for(Iter in 1:length(Species)){ # cycle through all species specified
      key <- name_suggest(q=Species[Iter], rank='species')$key[1] # pull gbif key
      Key_vec <- c(Key_vec, key) # append key to key vector
      if(!is.null(key)){ # if we have occurence data in the gbif records
        Species_Pres <- c(Species_Pres, Species[Iter]) # append species to species vector
      }
      setTxtProgressBar(pb, Iter)}
    ## Fixing vectors
    Key_vec <- Key_vec[-1] # Removing empty initial element
    Species_Pres <- Species_Pres[-1] # removing empty initial element
    # Save the species-specific and NA-freed data
    if(SP == "All"){ # if we want all species, we might as well save the names and key objects for later saving of time
      save(list = c("Species_Pres", "Key_vec"), file = paste(Dir.TRY, "/SpeciesGBIFKeys.rda", sep=""))}} # GBIF keys
  # OCCURENCE DATA ----
  ## Preparation
  print("Downloading species-specific occurence records from GBIF") # output to console
  pb <- txtProgressBar(min = 0, max = length(Species_Pres), style = 3) # Setting up a progress bar
  ## If an error occured previously
  if("Breakage.txt" %in% list.files(path = mainDir)){ # this file is only present if the run finished prematurely
    OccIter <- read.table(paste(mainDir, "/Breakage.txt", sep=""))[1,1] # position at which it failed previously - 1
  }else{
    OccIter <- 0 # set to 0 if it didn't fail previously
  }
  if(OccIter > 1){ # if previous run (OccIter) failed at the second step or later
    Start <- OccIter + 1 # start from where it failed, OccIter is the last one that got done
  }else{ # if it failed at the first one
    Start <- 1 # start at the first species
  }
  for(OccIter in Start:length(Key_vec)){ # cycling through all species to obtain occurence data
    # if species name cannot be put into a file name due to special characters, this excludes 61 species records
    if(grepl('[^[:alnum:]. .).(.-]', Species_Pres[OccIter]) == TRUE){
      next()}
    if(paste(Species_Pres[OccIter], "_", CountCodes, ".rda", sep="") %in% list.files(path=Dir.OCCs)){
    }else{ # data not present locally yet
      ## Downloading Data
      key <- Key_vec[OccIter] # select GBIF key
      Gbif <- occ_data(key, limit=200000, hasCoordinate = TRUE, year = Years,
                       hasGeospatialIssue = FALSE, country = CountCodes) # download data
```

```
      ## Dealing with separate data frames of years
      BaseOcc <- rep(NA, 3) # create empty vector
      BaseOcc_df <- t(as.data.frame(BaseOcc)) # make empty vector into empty data frame
      colnames(BaseOcc_df) <- c("decimalLatitude", "decimalLongitude", "year") # set column names
      for(i in 1:length(Years)){
        # create a data frame of latitude and longitude records of currently iterated year
        GbifFrame <- data.frame(decimalLatitude = Gbif[[i]]$data$decimalLatitude,
                                decimalLongitude = Gbif[[i]]$data$decimalLongitude,
                                year = rep(Years[i], length(Gbif[[i]]$data$decimalLatitude)))
        BaseOcc_df <- rbind(BaseOcc_df, GbifFrame)}
      ## Sanity check
      if(dim(BaseOcc_df)[1] == 1){ # if there is no occurence data
        next()}
      BaseOcc_df <- BaseOcc_df[-1,] # remove initial NA row
      ## Saving data frame
      save(BaseOcc_df, file = paste(Dir.OCCs,"/", Species_Pres[[OccIter]], "_", CountCodes,".rda",sep=""))}
    setTxtProgressBar(pb, OccIter) # pdate progress bar
    # save current iteration number to disk (used for jumping right back in if errors occur)
    write.table(OccIter, file = paste(mainDir, "/Breakage.txt", sep=""))
  }# occurence data loop
  file.remove(paste(mainDir, "/Breakage.txt", sep=""))
  setwd(mainDir)
  GbifStat <- "Done"
  return(GbifStat)
}# end of Mapping function

####--------------- PFTRasters [Region, Extent, RegionFile, CountCodes]
# (loading data, building species-specific trait mean rasters for study regions) ----
PFTRasters <- function(Region, Extent, RegionFile, CountCodes){
  print("##################################################")
  print(paste("Building mean trait rasters across ", RegionFile,sep=""))
  load(paste(Dir.TRY, "/SpeciesTraits.RData", sep="")) # load data
  RawTry_ras <- brick(paste(Dir.TRY,"/RawTRY-Global.nc", sep=""))
  # GLOBAL REFERENCE DATA (needed for rasterising and masking) ----
  ## NDVI (reference raster) ---
  NDVI_ras <- brick(paste(Dir.Gimms.Monthly,"/GlobalNDVI_20112015.nc", sep=""))
  ref_ras <- NDVI_ras[[6]]
  ref_ras[which(values(ref_ras) > -1)] <- 8888 # identify land pixels
  # REGION SELECTION----
  Shapes <- readOGR(Dir.Mask,'ne_50m_admin_0_countries', verbose = FALSE)
  RegObj <- RegionSelection(Region = Region, RegionFile = RegionFile, Extent = Extent)
  area <- RegObj[[1]]
  location <- RegObj[[2]]
  RegionFile <- RegObj[[3]]
  # CROPPING AND MASKING ----
  ## Reference cropping and masking
  ref_rasC <- crop(ref_ras, area) # cropping to extent
  ref_rasF <- mask(ref_rasC, Shapes[location,]) # masking via Shapefile
  # RAW TRY DATA ----
  RawTry_rasC <- crop(RawTry_ras, area) # cropping to extent
  RawTry_rasF <- mask(RawTry_rasC, Shapes[location,]) # masking via Shapefile
  writeRaster(x=RawTry_rasF, filename = paste(Dir.TRY,"/RawTRY-",RegionFile, sep=""),overwrite=TRUE, format="CDF")
  # CALCULATING MEAN RASTERS WITH DISTRIBUTION MAPS ----
  # create empty mean raster
  BaseMeans <- ref_rasF
  values(BaseMeans)[!is.na(values(BaseMeans))] <- 0
  # build brick for mean calculations
  BaseMeans <- brick(BaseMeans, BaseMeans, BaseMeans, BaseMeans)
```

```r
  names(BaseMeans) <- c("Height", "NMass", "HCount", "NCount")
  # progress bar
  pb <- txtProgressBar(min = 0, max = length(list.files(Dir.OCCs)), style = 3) #
  # looping over all .rda occurence files previously downloaded
  for(OccRast in 1:length(list.files(Dir.OCCs))){
    # OCCURENCE ----
    load(paste(Dir.OCCs, "/", list.files(Dir.OCCs)[OccRast], sep=""))
    ## Converting to SpatialPoints
    pts <- data.frame(y = BaseOcc_df$decimalLatitude, x = BaseOcc_df$decimalLongitude,
                      z = rep(1, length(BaseOcc_df$decimalLongitude)))
    pts <- na.omit(pts) # remove NA rows
    coordinates(pts) = ~x+y # convert x and y to coordinates
    # RASTERISING ----
    # create raster to be filled
    rast <- raster(ext=extent(ref_ras), resolution=res(ref_ras))
    # rasterize irregular points
    # we use a mean function here to regularly grid the irregular input points
    rasOut<-rasterize(x = pts, y = rast, field = pts$z, fun = max)
    ## Occurence cropping and masking
    rasC <- crop(rasOut, area) # cropping to extent
    rasF <- mask(rasC, Shapes[location,]) # masking via Shapefile
    # TRAIT MEANS ----
    # loading data of currently iterated on species
    Grep <- list.files(Dir.OCCs)[OccRast]
    Grep <- gsub(x = Grep, pattern = CountCodes, replacement = "")
    Grep <- gsub(x = Grep, pattern = "_.rda", replacement = "")

    NMass <- CorrectedSpec_df$Nmass[which(CorrectedSpec_df$Species == Grep)]
    Height <- CorrectedSpec_df$Height[which(CorrectedSpec_df$Species == Grep)]
    # BUILDING MAP
    Identifier <- which(!is.na(values(rasF)))
    if(length(NMass) != 0){
      if(!is.nan(NMass)){ # add current species-NMass to raster layer and bump up count by 1
        values(BaseMeans$NMass)[Identifier] <- values(BaseMeans$NMass)[Identifier] + NMass
        values(BaseMeans$NCount)[Identifier] <- values(BaseMeans$NCount)[Identifier] + 1}}
    if(length(Height) != 0){
      if(!is.nan(Height)){ # add current species-Height to raster layer and bump up count by 1
        values(BaseMeans$Height)[Identifier] <- values(BaseMeans$Height)[Identifier] + Height
        values(BaseMeans$HCount)[Identifier] <- values(BaseMeans$HCount)[Identifier] + 1}}
    setTxtProgressBar(pb, OccRast) # update progress bar
  } # OccRast-loop
  # CALCULATE MEANS ----
  TestHeight <- BaseMeans$Height/BaseMeans$HCount
  values(TestHeight)[which(values(TestHeight) > quantile(values(TestHeight), .95, na.rm = TRUE))] <- NA
  TestNMass <- BaseMeans$NMass/BaseMeans$NCount
  values(TestNMass)[which(values(TestNMass) > quantile(values(TestNMass), .95, na.rm = TRUE))] <- NA
  Means_ras <- brick(TestHeight, TestNMass)
  # SAVING DATA ----
  writeRaster(x=Means_ras, filename = paste(Dir.TRY,"/TRY-",RegionFile, sep=""),overwrite=TRUE, format="CDF")
}# PFTRasters
```

A.3.4 COMPADRE

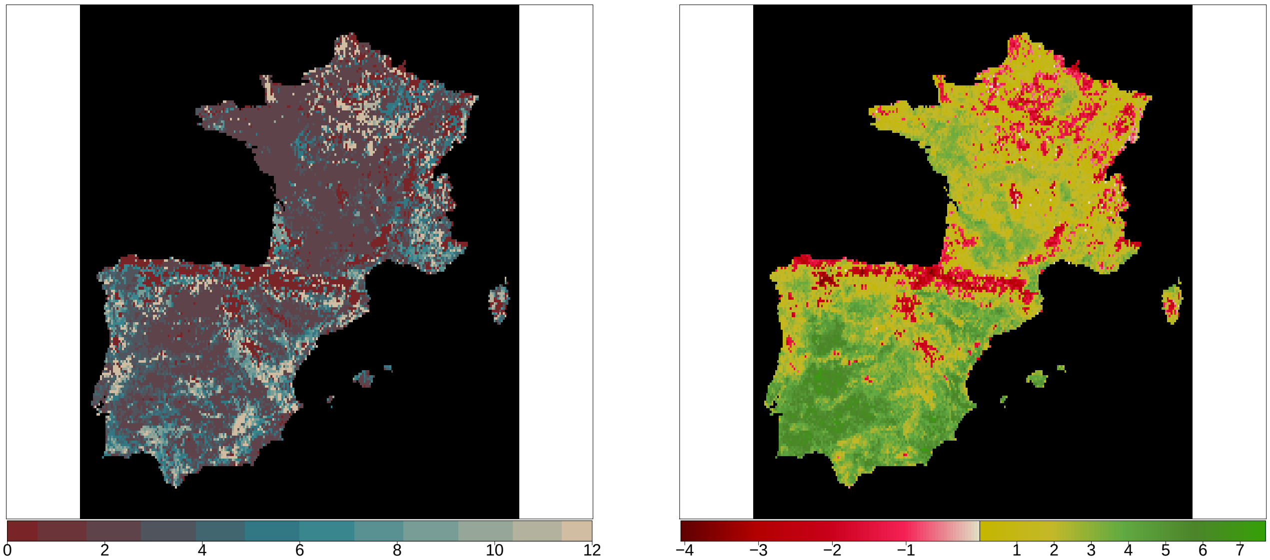
Chunk 12: Extracting and rasterising COMPADRE data from COMPADRE data base for each study region (RasterCOMPADRE).

```
####--------------- RasterCOMPADRE [Variable, Region, RegionFile, Extent]
# (Selecting specified COMPADRE data, rasterising, saving the raster, limitting to a region) ----
RasterCOMPADRE <- function(Variable, Region, RegionFile, Extent){
  print("#################################################")
  print(paste("Rasterising COMPADRE ", Variable, " across ", RegionFile, sep=""))
  # LOADING DATA ----
  Compadre_df <- read.csv(paste(Dir.Compadre, "/allCOMPADREOutput.csv", sep="")) # load data frame
  NDVI_ras <- brick(paste(Dir.Gimms.Monthly,"/GlobalNDVI_20112015.nc", sep="")) # reference raster
  ref_ras <- NDVI_ras[[6]] # select only one years data
  ref_ras[which(values(ref_ras) > -1)] <- 8888 # select only land pixels and set them to -8888
  # REGION SELECTION----
  Shapes <- readOGR(Dir.Mask,'ne_50m_admin_0_countries', verbose = FALSE)
  RegObj <- RegionSelection(Region = Region, RegionFile = RegionFile, Extent = Extent)
  area <- RegObj[[1]]
  location <- RegObj[[2]]
  RegionFile <- RegObj[[3]]
  # DATA MANIPULATION ----
  if(Variable == "FastSlow"){ # analysis of PCA axes
    FSVars <- c("GenT", "H", "La", "GrowSSD", "ShriSSD", "RepSSD", "S", "R0", "Lmean")
    VariableCol <- match(FSVars, colnames(Compadre_df))
    FSLoads <- list(c(.87,.53,.7,-.8,.04,-.81,-.25,-.03,.12), # PCA 1 according to Salguero-Gomez, 2017
                    c(.15,.27,.28,-.05,-.79,.32,.65,.7,.26)) # PCA 2 according to Salguero-Gomez, 2017
    pts <- na.omit(data.frame(y = Compadre_df$Lat, x = Compadre_df$Lon, z = Compadre_df[,VariableCol]))
    PCA1_df <- t(t(pts[,-1:-2]) * FSLoads[[1]]) # multiplying by first axis loadings
    PCA1_df <- rowSums(PCA1_df) # build sums for single index along PCA 1
    PCA1_df <- cbind(pts[,1:2], PCA1_df) # binding with coordinates
    coordinates(PCA1_df) = ~x+y # convert x and y to coordinates
    PCA2_df <- t(t(pts[,-1:-2]) * FSLoads[[2]]) # multiplying by second axis loadings
    PCA2_df <- rowSums(PCA2_df) # build sums for single index along PCA 2
    PCA2_df <- cbind(pts[,1:2], PCA2_df) # binding with coordinates
    coordinates(PCA2_df) = ~x+y # convert x and y to coordinates
    ## Rasterizing ----
    rast <- raster(ext=extent(ref_ras), resolution=res(ref_ras)) # create raster to be filled
    rasOut1 <-rasterize(x = PCA1_df, y = rast, field = PCA1_df$PCA1_df, fun = mean) # rasterize irregular points
    rasOut2 <-rasterize(x = PCA2_df, y = rast, field = PCA2_df$PCA2_df, fun = mean) # rasterize irregular points
    rasOut <- brick(rasOut1, rasOut2)
    names(rasOut) <- c("FS PCA1", "FS PCA2")
  }else{ # single variable desired
    VariableCol <- which(colnames(Compadre_df) == Variable) # figure out the position of the desired Variable
    pts <- na.omit(data.frame(y = Compadre_df$Lat, x = Compadre_df$Lon, z = Compadre_df[,VariableCol]))
    coordinates(pts) = ~x+y # convert x and y to coordinates
    rast <- raster(ext=extent(ref_ras), resolution=res(ref_ras)) # create raster to be filled
    rasOut<-rasterize(x = pts, y = rast, field = pts$z, fun = mean) # rasterize irregular points
  }
    # CROPPING AND MASKING ----
    rasC <- crop(rasOut, area) ## Occurence cropping and masking
    rasF <- mask(rasC, Shapes[location,]) # masking via Shapefile
    # DATA EXPORT ----
    Dir.Temp.Compadre <- paste(Dir.Compadre, Variable, sep="/")
    dir.create(Dir.Temp.Compadre)
    values(rasF)[which(values(rasF) == Inf)] <- NA # get rid off Inf values (when dealing with Rho)
    invisible(writeRaster(rasF, filename = paste(Dir.Temp.Compadre, "/",Variable,"_",RegionFile,sep=""),
                          overwrite=TRUE, format="CDF"))
}# end of RasterCOMPADRE
```

A.4 Results

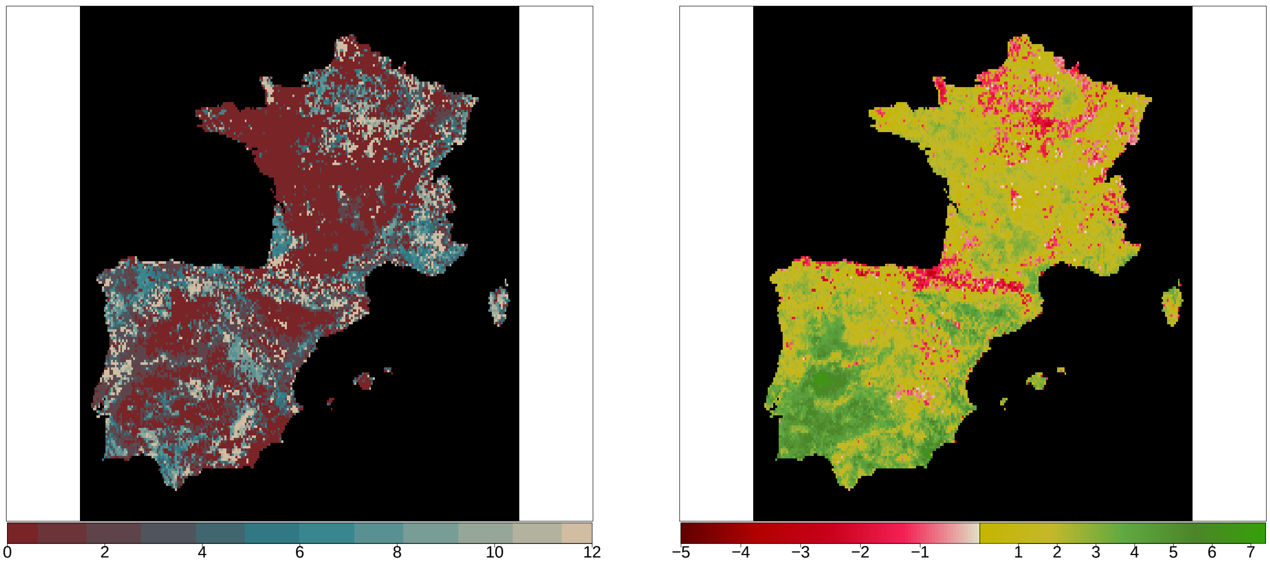
A.4.1 Vegetation Memory Models

A.4.1.1 Iberian Region



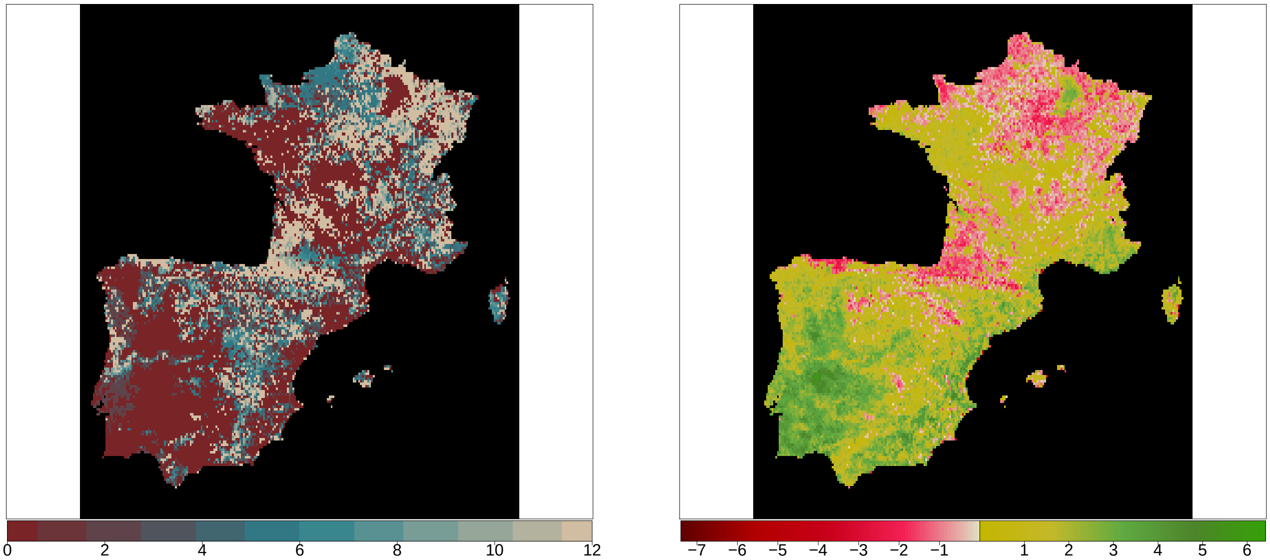
(a) SoilLag **(b)** Qsoil

Figure A.10: Vegetation Memory Coefficients (Iberian Region; Qsoil2) - Coefficients of vegetation memory obtained via model selection (figure 2.9) and PCA regression (figure 2.13). For an interpretation of these coefficients, see table 2.4. Figure established via Chunk 24.



(a) SoilLag **(b)** Qsoil

Figure A.11: Vegetation Memory Coefficients (Iberian Region; Qsoil3) - Coefficients of vegetation memory obtained via model selection (figure 2.9) and PCA regression (figure 2.13). For an interpretation of these coefficients, see table 2.4. Figure established via Chunk 24.



(a) SoilLag **(b)** Qsoil

Figure A.12: Vegetation Memory Coefficients (Iberian Region; Qsoil4) - Coefficients of vegetation memory obtained via model selection (figure 2.9) and PCA regression (figure 2.13). For an interpretation of these coefficients, see table 2.4. Figure established via Chunk 24.

Table A.3: Mann-Whitney U-Test (Iberian Region, Qsoil2 Model) - Rownames represent median values of vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 25.

	NDVI [t-1]	Qsoil2	Tair
3.8554	NA	259724355	316424407
2.1658	0	NA	241657391
1.1946	0	0	NA

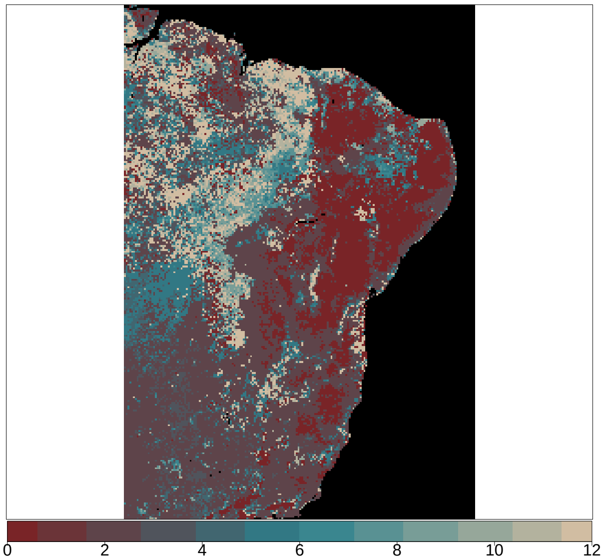
Table A.4: Mann-Whitney U-Test (Iberian Region, Qsoil3 Model) - Rownames represent median values of vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 25.

	NDVI [t-1]	Qsoil3	Tair
3.8629	NA	285161401	316091617
1.6801	0	NA	213476555
1.1994	0	0	NA

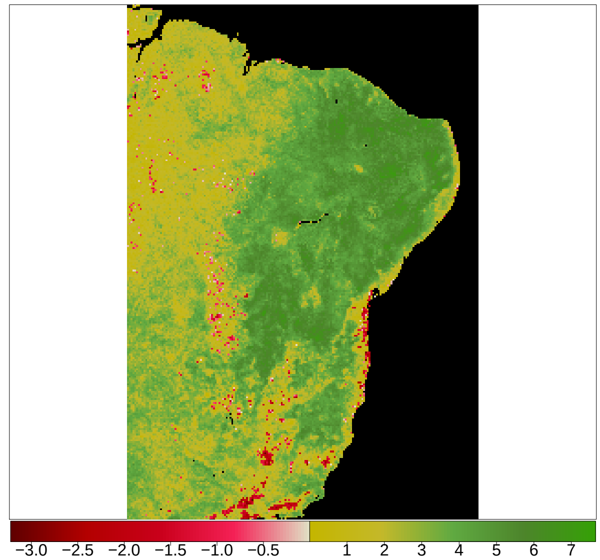
Table A.5: Mann-Whitney U-Test (Iberian Region, Qsoil4 Model) - Rownames represent median values of vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 25.

	NDVI [t-1]	Qsoil4	Tair
3.852	NA	306106900	3.16e+08
1.2293	0	NA	1.80e+08
1.1907	0	0	NA

A.4.1.2 Caatinga

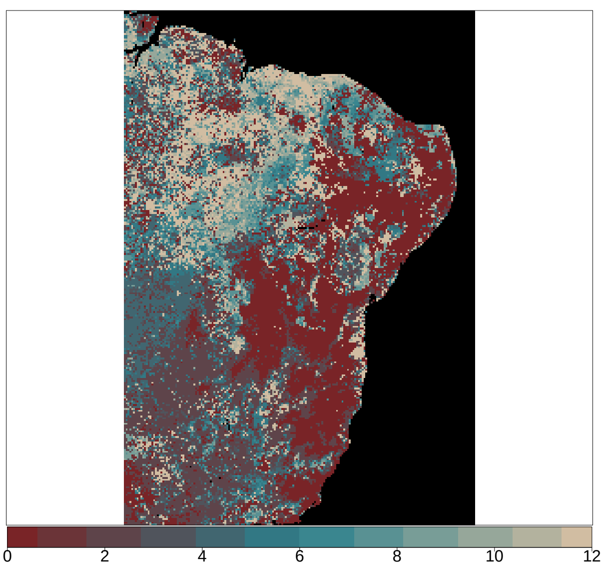


(a) SoilLag

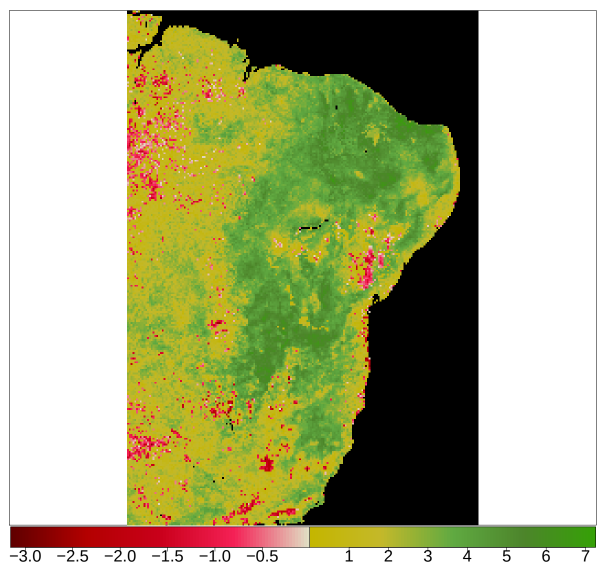


(b) Qsoil

Figure A.13: Vegetation Memory Coefficients (Caatinga; Qsoil2) - Coefficients of vegetation memory obtained via model selection (figure 2.9) and PCA regression (figure 2.13). For an interpretation of these coefficients, see table 2.4. Figure established via Chunk 24.

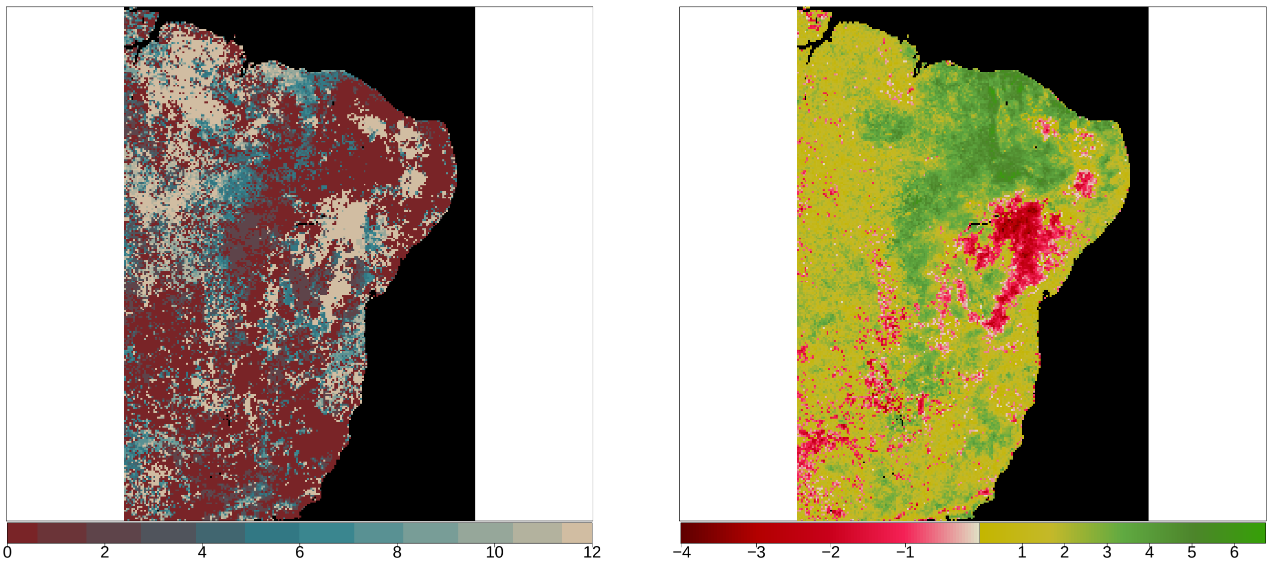


(a) SoilLag



(b) Qsoil

Figure A.14: Vegetation Memory Coefficients (Caatinga; Qsoil3) - Coefficients of vegetation memory obtained via model selection (figure 2.9) and PCA regression (figure 2.13). For an interpretation of these coefficients, see table 2.4. Figure established via Chunk 24.



(a) SoilLag **(b)** Qsoil

Figure A.15: Vegetation Memory Coefficients (Caatinga; Qsoil4) - Coefficients of vegetation memory obtained via model selection (figure 2.9) and PCA regression (figure 2.13). For an interpretation of these coefficients, see table 2.4. Figure established via Chunk 24.

Table A.6: Mann-Whitney U-Test (Caatinga, Qsoil2 Model) - Rownames represent median values of vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 25.

	NDVI [t-1]	Qsoil2	Tair
4.2049	NA	899172763	1.12e+09
3.0531	0	NA	9.65e+08
1.2642	0	0	NA

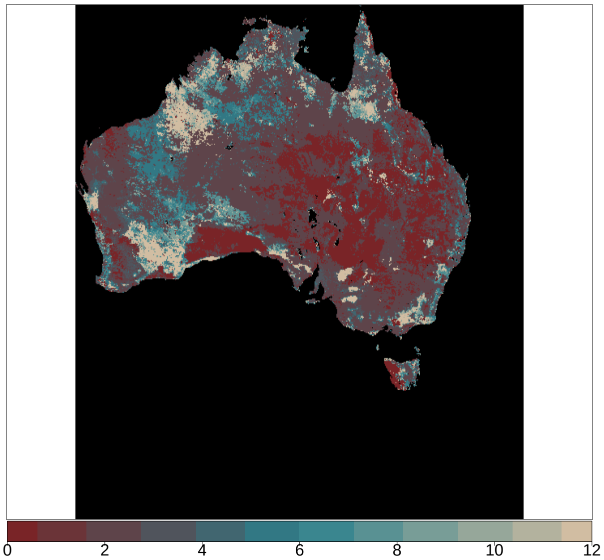
Table A.7: Mann-Whitney U-Test (Caatinga, Qsoil3 Model) - Rownames represent median values of vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 25.

	NDVI [t-1]	Qsoil3	Tair
4.207	NA	1.028e+09	1.116e+09
2.3516	0	NA	8.525e+08
1.2683	0	0.000e+00	NA

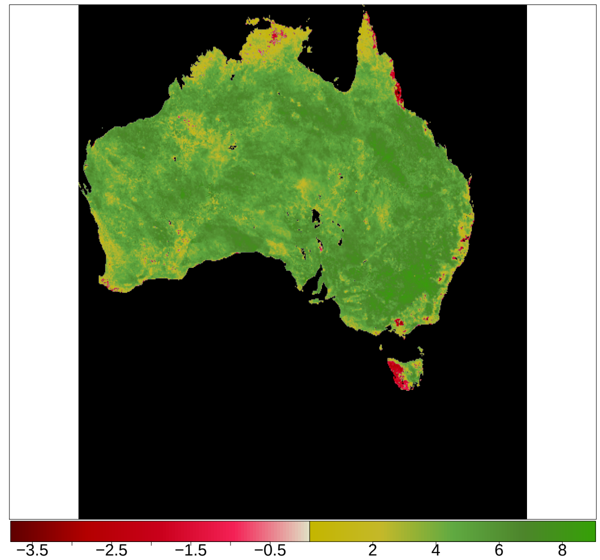
Table A.8: Mann-Whitney U-Test (Caatinga, Qsoil4 Model) - Rownames represent median values of vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 25.

	NDVI [t-1]	Qsoil4	Tair
4.2082	NA	1.152e+09	1.116e+09
1.7305	0	NA	7.298e+08
1.2681	0	0.000e+00	NA

A.4.1.3 Australia

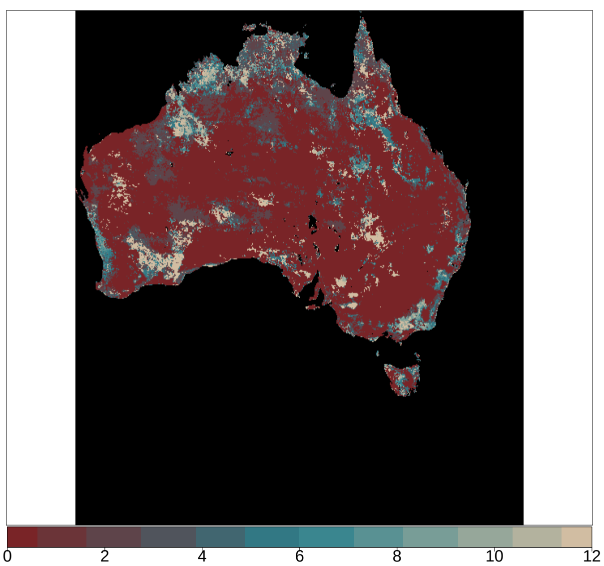


(a) SoilLag

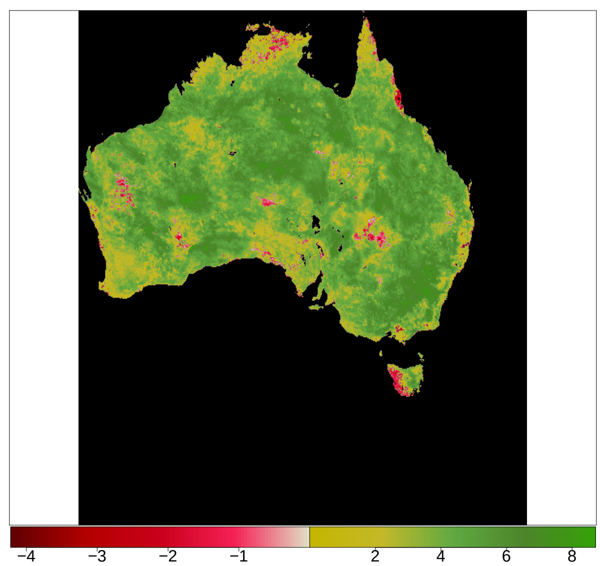


(b) Qsoil

Figure A.16: Vegetation Memory Coefficients (Australia; Qsoil2) - Coefficients of vegetation memory obtained via model selection (figure 2.9) and PCA regression (figure 2.13). For an interpretation of these coefficients, see table 2.4. Figure established via Chunk 24.

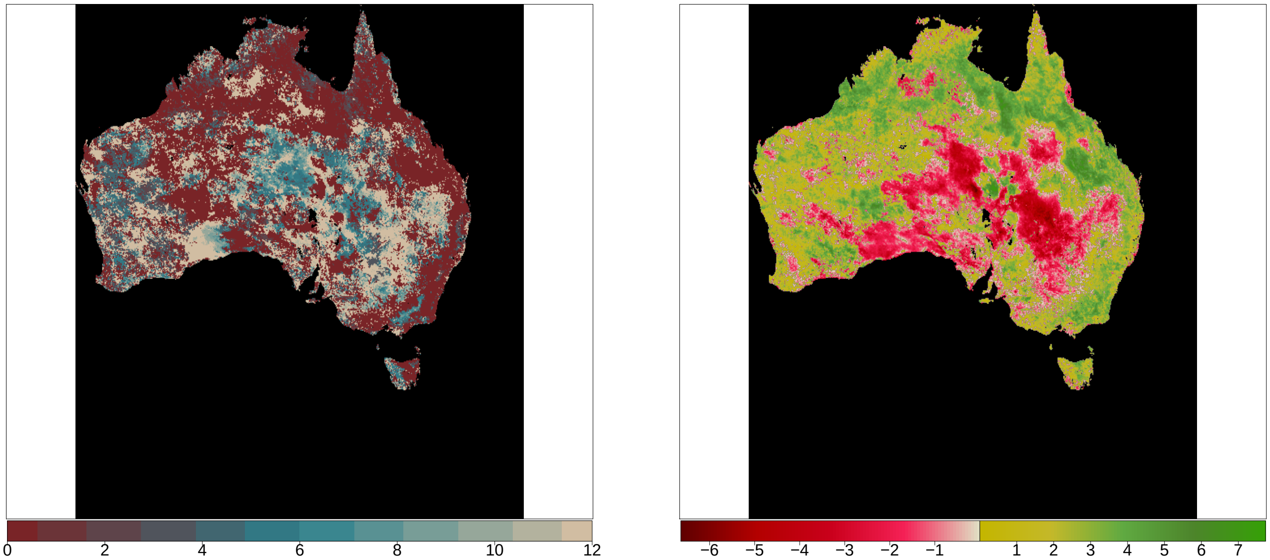


(a) SoilLag



(b) Qsoil

Figure A.17: Vegetation Memory Coefficients (Australia; Qsoil3) - Coefficients of vegetation memory obtained via model selection (figure 2.9) and PCA regression (figure 2.13). For an interpretation of these coefficients, see table 2.4. Figure established via Chunk 24.



(a) SoilLag **(b)** Qsoil

Figure A.18: Vegetation Memory Coefficients (Australia; Qsoil4) - Coefficients of vegetation memory obtained via model selection (figure 2.9) and PCA regression (figure 2.13). For an interpretation of these coefficients, see table 2.4. Figure established via Chunk 24.

Table A.9: Mann-Whitney U-Test (Australia, Qsoil2 Model) - Rownames represent median values of vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 25.

	NDVI [t-1]	Qsoil2	Tair
7.452	NA	8.541e+09	9.680e+09
5.2241	0	NA	8.556e+09
2.8518	0	0.000e+00	NA

Table A.10: Mann-Whitney U-Test (Australia, Qsoil3 Model) - Rownames represent median values of vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 25.

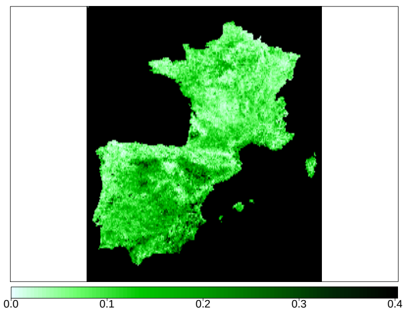
	NDVI [t-1]	Qsoil3	Tair
7.4543	NA	9.064e+09	9.678e+09
4.4153	0	NA	7.490e+09
2.8534	0	0.000e+00	NA

Table A.11: Mann-Whitney U-Test (Australia, Qsoil4 Model) - Rownames represent median values of vegetation memory coefficients contained in column names. U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells. p-values belonging to these U-values are represented in the lower-lefthand block of cells. Established via Chunk 25.

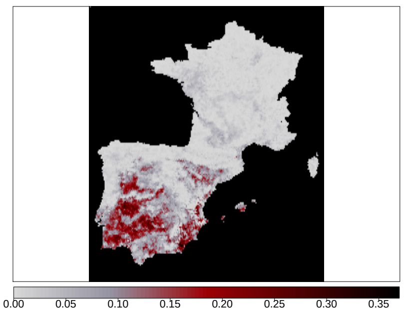
	NDVI [t-1]	Qsoil4	Tair
7.469	NA	9.797e+09	9.674e+09
1.8774	0	NA	3.235e+09
2.8601	0	0.000e+00	NA

A.4.2 Variance Partitioning

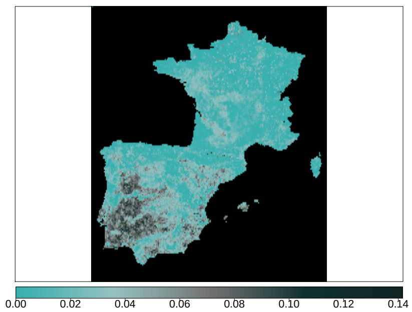
A.4.2.1 Iberian Region



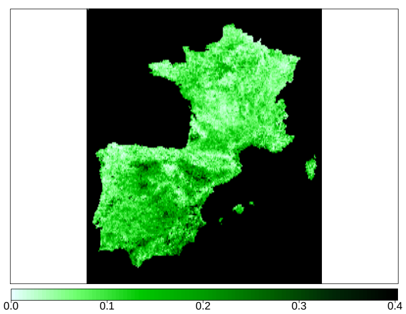
(a) Total



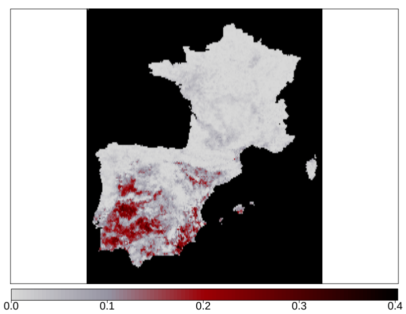
(b) t-1



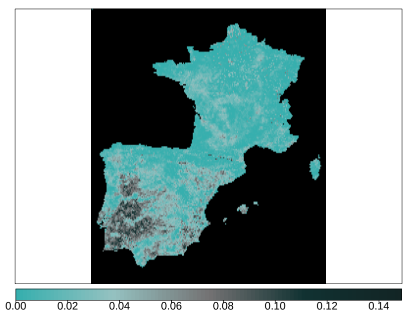
(c) Shared



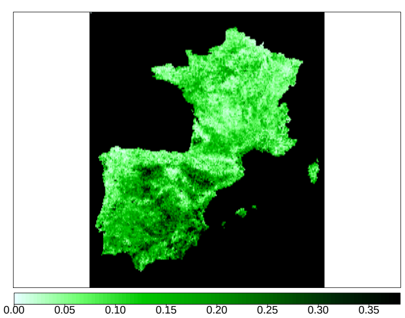
(d) Qsoil



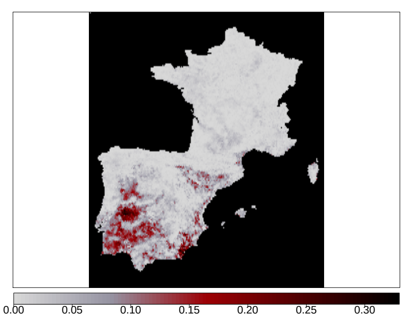
(e) Total



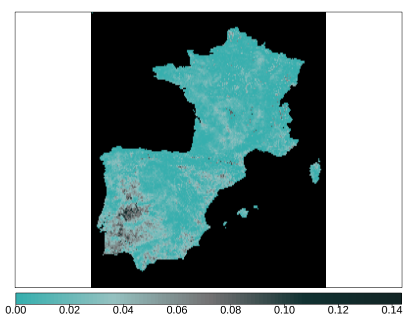
(f) t-1



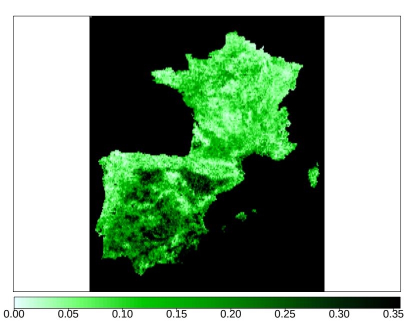
(g) Shared



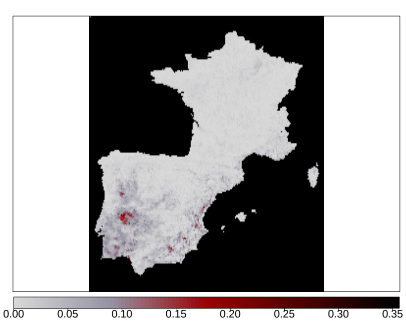
(h) Qsoil



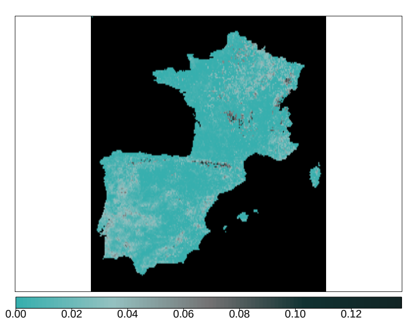
(i) Total



(j) t-1



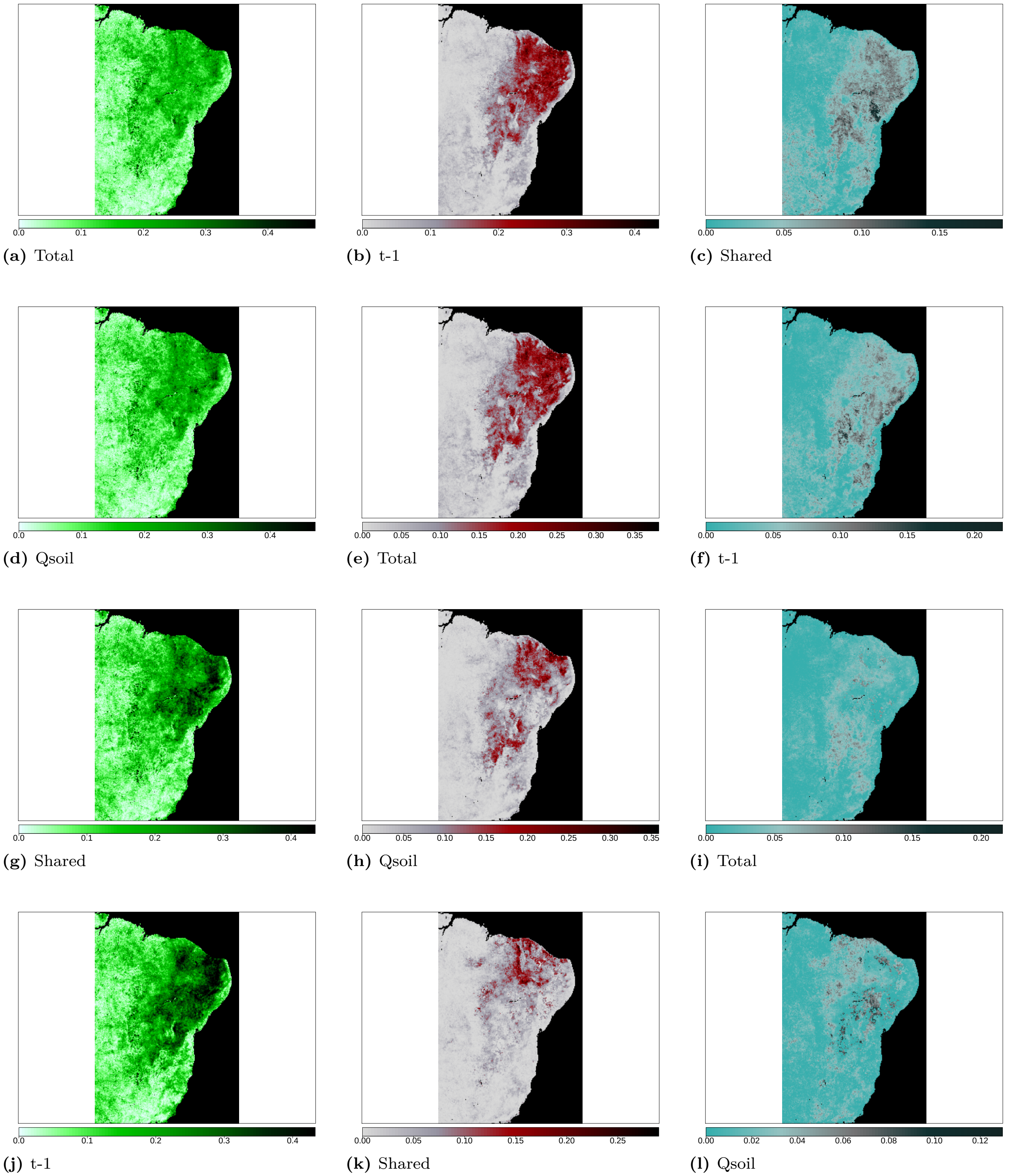
(k) Shared



(l) Qsoil

Figure A.19: Variance Partitioning (Iberian Region) - Variance of NDVI anomalies explained by (a,d,g,j) full models of intrinsic and extrinsic memory, (b,e,h,k) intrinsic memory, (c,f,i,l) shared variance, and (d) extrinsic memory across soil layers Qsoil1 to Qsoil4. A representation of how these were calculated can be retrieved in figure 2.14. Figure established via Chunk 26.

A.4.2.2 Caatinga



(a) Total **(b)** t-1 **(c)** Shared

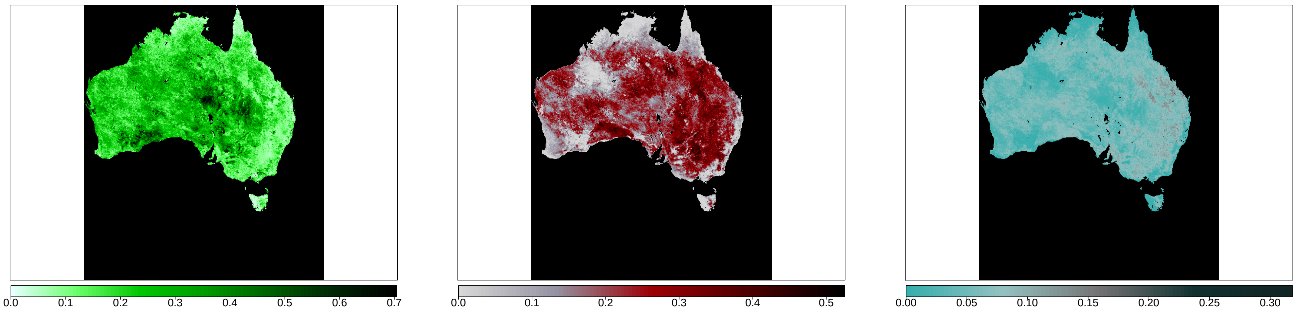
(d) Qsoil **(e)** Total **(f)** t-1

(g) Shared **(h)** Qsoil **(i)** Total

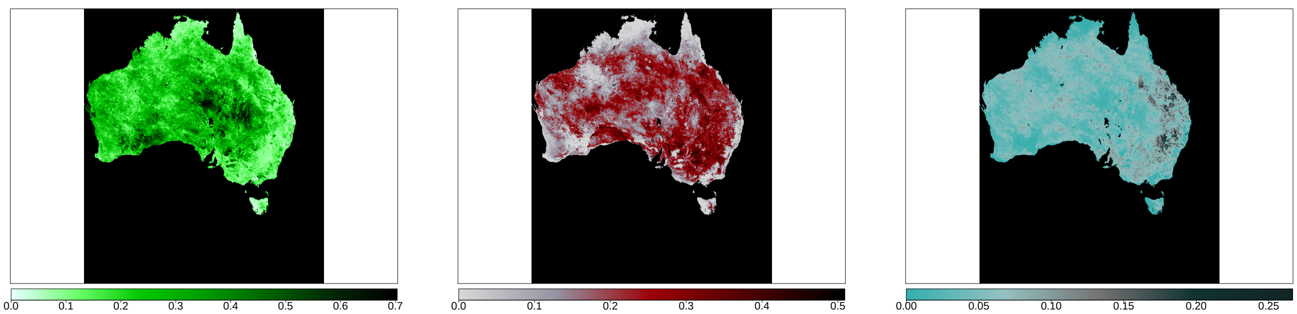
(j) t-1 **(k)** Shared **(l)** Qsoil

Figure A.20: Variance Partitioning (Caatinga) - Variance of NDVI anomalies explained by (a,d,g,j) full models of intrinsic and extrinsic memory, (b,e,h,k) intrinsic memory, (c,f,i,l) shared variance, and (d) extrinsic memory across soil layers Qsoil1 to Qsoil4. A representation of how these were calculated can be retrieved in figure 2.14. Figure established via Chunk 26.

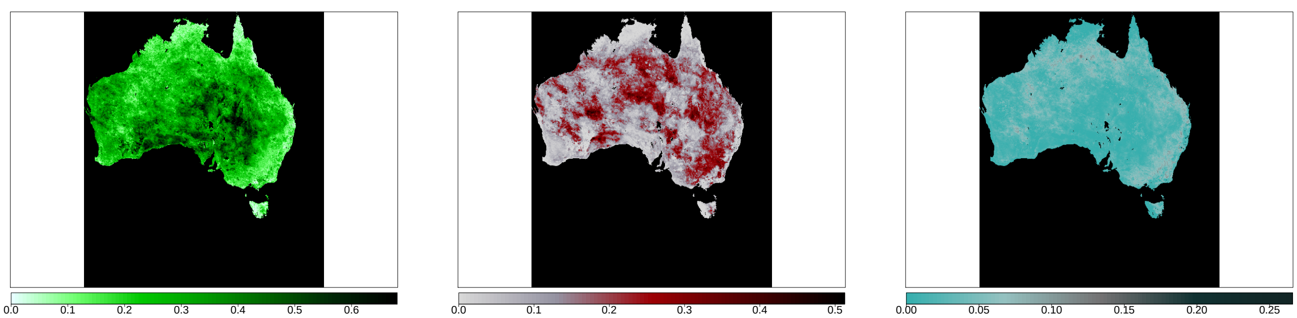
A.4.2.3 Australia



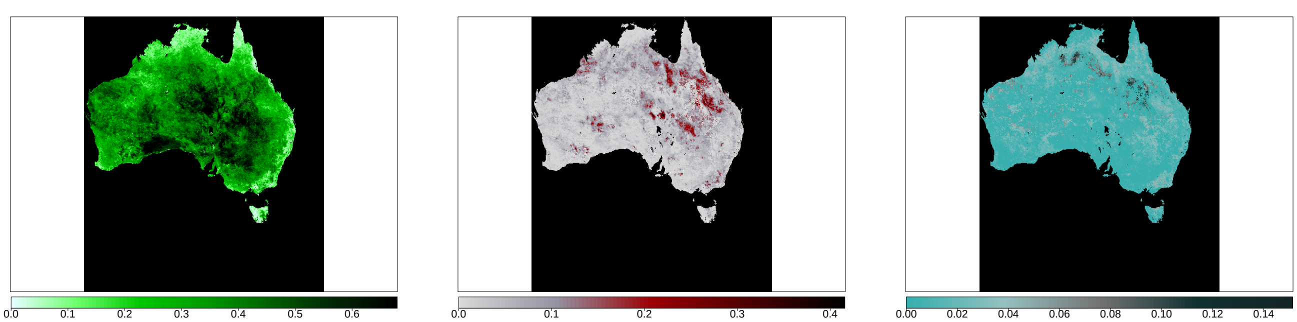
(a) Total **(b)** t-1 **(c)** Shared



(d) Qsoil **(e)** Total **(f)** t-1



(g) Shared **(h)** Qsoil **(i)** Total



(j) t-1 **(k)** Shared **(l)** Qsoil

Figure A.21: Variance Partitioning (Australia) - Variance of NDVI anomalies explained by (a,d,g,j) full models of intrinsic and extrinsic memory, (b,e,h,k) intrinsic memory, (c,f,i,l) shared variance, and (d) extrinsic memory across soil layers Qsoil1 to Qsoil4. A representation of how these were calculated can be retrieved in figure 2.14. Figure established via Chunk 26.

A.4.3 Functional Aspects of Vegetation Memory

A.4.3.1 Iberian Region

Table A.12: Geo-referenced PFTs and Vegetation Memory (Iberian Region) - Linear regression coefficients of vegetative height (H) and leaf nitrogen mass (Nmass) against vegetation memory coefficients. Established via Chunk 36.

	t-1		*Tair*		**Qsoil** *1*		*2*		*3*		*4*	
	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}
Intercept	2.65	4.0	1.91	-0.01	-1.70	1.5	-1.19	1.6	-0.22	1.90	0.23	1.48
$p_{Intercept}$	0.00	0.0	0.00	0.85	0.00	0.0	0.00	0.0	0.36	0.00	0.29	0.00
Slope	0.43	0.1	-0.17	-0.03	0.56	0.2	0.54	0.2	0.41	0.16	0.00	0.13
p_{Slope}	0.00	0.0	0.03	0.15	0.00	0.0	0.00	0.0	0.00	0.00	0.97	0.00

Table A.13: Mapped species-specific mean PFTs and Vegetation Memory (Iberian Region) - Linear regression coefficients of vegetative height (H) and leaf nitrogen mass (Nmass) against vegetation memory coefficients. Established via Chunk 36.

	t-1		*Tair*		**Qsoil** *1*		*2*		*3*		*4*	
	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}
Intercept	4.91	5.08	-0.32	-0.51	2.7	2.99	2.91	3.13	2.39	2.72	1.67	2.00
$p_{Intercept}$	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Slope	-0.16	-0.18	0.18	0.20	-0.2	-0.24	-0.19	-0.22	-0.14	-0.19	-0.14	-0.18
p_{Slope}	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00

A.4.3.2 Caatinga

Table A.14: Geo-referenced PFTs and Vegetation Memory (Caatinga) - Linear regression coefficients of vegetative height (H) and leaf nitrogen mass (Nmass) against vegetation memory coefficients. Established via Chunk 36.

	t-1		*Tair*		**Qsoil** *1*		*2*		*3*		*4*	
	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}
Intercept	NA	6.29	NA	-0.45	NA	1.85	NA	2.70	NA	4.55	NA	3.55
$p_{Intercept}$	NA	0.06	NA	0.76	NA	0.32	NA	0.24	NA	0.06	NA	0.03
Slope	NA	-1.31	NA	-0.26	NA	0.53	NA	0.15	NA	-1.03	NA	-0.78
p_{Slope}	NA	0.43	NA	0.75	NA	0.60	NA	0.90	NA	0.39	NA	0.34

Table A.15: Mapped species-specific mean PFTs and Vegetation Memory (Caatinga) - Linear regression coefficients of vegetative height (H) and leaf nitrogen mass (Nmass) against vegetation memory coefficients. Established via Chunk 36.

	t-1		*Tair*		**Qsoil** *1*		*2*		*3*		*4*	
	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}
Intercept	4.00	4.42	-1.13	-1.57	2.79	3.24	2.8	3.19	2.17	2.54	1.30	1.45
$p_{Intercept}$	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00
Slope	0.01	-0.05	0.00	0.06	0.00	-0.05	0.0	-0.04	0.00	-0.04	0.01	-0.01
p_{Slope}	0.01	0.00	0.23	0.00	0.05	0.00	0.1	0.00	0.04	0.00	0.00	0.24

A.4.3.3 Australia

Table A.16: Geo-referenced PFTs and Vegetation Memory (Australia) - Linear regression coefficients of vegetative height (H) and leaf nitrogen mass (Nmass) against vegetation memory coefficients. Established via Chunk 36.

					Qsoil							
	t-1		*Tair*		*1*		*2*		*3*		*4*	
	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}
Intercept	NA	5.53	NA	-2.02	NA	3.50	NA	3.69	NA	3.26	NA	1.08
$p_{Intercept}$	NA	0.00	NA	0.00	NA	0.00	NA	0.00	NA	0.00	NA	0.00
Slope	NA	-0.06	NA	0.07	NA	-0.13	NA	-0.15	NA	-0.12	NA	-0.03
p_{Slope}	NA	0.22	NA	0.13	NA	0.03	NA	0.02	NA	0.05	NA	0.46

Table A.17: Mapped species-specific mean PFTs and Vegetation Memory (Australia) - Linear regression coefficients of vegetative height (H) and leaf nitrogen mass (Nmass) against vegetation memory coefficients. Established via Chunk 36.

					Qsoil							
	t-1		*Tair*		*1*		*2*		*3*		*4*	
	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}	H	N_{mass}
Intercept	6.86	6.43	-2.21	-2.70	5.19	4.64	5.23	4.65	4.19	4.10	0.89	1.55
$p_{Intercept}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Slope	-0.04	0.03	0.02	0.08	-0.04	0.02	-0.04	0.03	-0.02	-0.02	0.02	-0.08
p_{Slope}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

A.5 R Data Visualisation Codes

A.5.1 Preamble

Chunk 13: Preamble needed for processing the following chunks within this manuscript.

```
source("S0a_Packages.R")  # loading packages
source("S0b_Directories.R")  # setting directories
source("S0c_Functions.R")  # Loading miscellaneous functions
col.NDVI <- rev(terrain.colors(100))
col.qsoil <- colorRampPalette(c("yellow", "burlywood", "beige", "turquoise", "deepskyblue"))(100)
col.tair <- colorRampPalette(c("blue", "turquoise", "yellow", "orange", "red"))(100)
SR_cols <- list(col.NDVI, col.tair, col.qsoil, col.qsoil, col.qsoil, col.qsoil)
SR_Titles <- list("NDVI", "Air Temperature", "Soil Moisture (0-7cm)", "Soil Moisture (7-28cm)",
    "Soil Moisture (28-100cm)", "Soil Moisture (100-255cm)")
setwd(Dir.KrigCov)
Elevation <- raster(list.files()[2], varname = "Elevation")
ElevationF <- raster(list.files()[1], varname = "Elevation")
```

A.5.2 Data Overview

A.5.2.1 NDVI

Chunk 14: Plotting global NDVI mean for the time frame of 1982 - 2015.

```
setwd(Dir.Gimms.Monthly)
NDVIMean_ras <- mean(brick(list.files()[1:7]), na.rm = TRUE)
plot(NDVIMean_ras, colNA = "black", main = "Mean NDVI 1982 - 2015", cex.main = 2,
    legend.width = 1.5, legend.shrink = 1, axis.args = list(cex.axis = 1.5), cex.axis = 1.5)
```

A.5.2.2 ERA5

Chunk 15: Two by two plotting of global soil moisture indices across four different soil layers all on the same scale.

```
Variable <- c("Qsoil1", "Qsoil2", "Qsoil3", "Qsoil4")
colour = col.qsoil
par(mfrow = c(2,2))
setwd(Dir.ERA)
Era_list <- list(NA, NA, NA, NA)
for(i in 1:4){
  Era5ras <- mean(brick(list.files()[grep(pattern = Variable[i], list.files())]), na.rm = TRUE)
  values(Era5ras)[which(is.na(values(Elevation)))] <- NA
  Era_list[[i]] <- Era5ras
}
Era5ras <- brick(Era_list)
Era5ras[1] <- max(Era5ras)@data@max
for(i in 1:4){
  plot(Era5ras[[i]], colNA = "black", main = paste("Mean", SR_Titles[i+2], "1980 - 2015"),
       cex.main = 2, legend.width = 1.5, legend.shrink=1,
       axis.args=list(cex.axis=1.5), cex.axis = 1.5, col = colour, legend = FALSE)
}
```

Chunk 16: Plotting mean air temperature from 1982 - 2015 globally.

```
Variable <- c("Tair")
colour = col.tair
setwd(Dir.ERA)
Era5ras <- mean(brick(list.files()[grep(pattern = Variable, list.files())]), na.rm = TRUE)
values(Era5ras)[which(is.na(values(Elevation)))] <- NA
plot(Era5ras, colNA = "black", main = paste("Mean", SR_Titles[2], "1980 - 2015"),
     cex.main = 2, legend.width = 1.5, legend.shrink=1,
     axis.args=list(cex.axis=1.5), cex.axis = 1.5, col = colour, legend = TRUE)
```

A.5.2.3 HWSD

Chunk 17: Plotting HWSD elevation data.

```
plot(ElevationF, colNA = "black", cex.main = 2, legend.width = 1.5, legend.shrink = 1,
    axis.args = list(cex.axis = 1.5), cex.axis = 1.5, legend = TRUE, col = terrain.colors(100),
    main = "DEM at GIMMs native resolution")
```

Chunk 18: Loading HWSD data and plotting HWSD slope incline data.

```
Covariates_vec <- c("Slopes1", "Slopes2", "Slopes3", "Slopes4", "Slopes5", "Slopes6", "Slopes7", "Slopes8",
                    "Slope_aspect_N", "Slope_aspect_E", "Slope_aspect_S", "Slope_aspect_W", "Slope_aspect_U",
                    "Elevation")
Cov_fine <- list() # create empty list
for(c in 1:length(Covariates_vec)){ # cycle through all covariates and load the data
      Cov_fine[[c]] <- raster(paste(Dir.KrigCov, "/Co-variates_NativeResolution.nc", sep=""),
                              varname = Covariates_vec[c])
      }
Cov_fine <- brick(Cov_fine) # make fine covariate data into one big brick

for(i in 1:13){
values(Cov_fine[[i]]) <- values(Cov_fine[[i]])/1000
}
par(mfrow = c(3,2))
for(i in 9:13){
  plot(Cov_fine[[i]], colNA = "black", cex.main = 2, legend.width = 1.5, legend.shrink=1,
       axis.args=list(cex.axis=1.5), cex.axis = 1.5, legend = TRUE, col = terrain.colors(100),
       main = Covariates_vec[[i]])
}
```

Chunk 19: Plotting HWSD slope aspect data

```
par(mfrow = c(4, 2))
for (i in 1:8) {
    plot(Cov_fine[[i]]/10, colNA = "black", cex.main = 2, legend.width = 1.5, legend.shrink = 1,
        axis.args = list(cex.axis = 1.5), cex.axis = 1.5, legend = TRUE, col = terrain.colors(100),
        main = Covariates_vec[[i]])
}
```

A.5.2.4 Study Regions

Chunk 20: Function for plotting data overviews in three-by-two plots for study regions.

```
col.NDVI <- rev(terrain.colors(100))
col.qsoil <- colorRampPalette(c("yellow", "burlywood", "beige", "turquoise", "deepskyblue"))(100)
col.tair <- colorRampPalette(c("blue", "turquoise", "yellow", "orange", "red"))(100)
SR_cols <- list(col.NDVI, col.tair, col.qsoil, col.qsoil, col.qsoil, col.qsoil)
SRData <- function(Region) {
    ### LOADING DATA ----
    setwd(Dir.Gimms.Monthly)
    SR_NDVI <- mean(brick(list.files()[grep(pattern = Region, list.files())]), na.rm = TRUE)
    setwd(Dir.ERA.Monthly)
    SR_Qsoil1 <- mean(brick(list.files()[grep(pattern = paste("Qsoil1_mean_", Region,
        sep = ""), list.files())]), na.rm = TRUE)
    SR_Qsoil2 <- mean(brick(list.files()[grep(pattern = paste("Qsoil2_mean_", Region,
        sep = ""), list.files())]), na.rm = TRUE)
    SR_Qsoil3 <- mean(brick(list.files()[grep(pattern = paste("Qsoil3_mean_", Region,
        sep = ""), list.files())]), na.rm = TRUE)
    SR_Qsoil4 <- mean(brick(list.files()[grep(pattern = paste("Qsoil4_mean_", Region,
        sep = ""), list.files())]), na.rm = TRUE)
    SR_Tair <- mean(brick(list.files()[grep(pattern = paste("Tair_mean_", Region,
        sep = ""), list.files())]), na.rm = TRUE)
    ### FIXING VALUES ----
    QsoilStack <- stack(SR_Qsoil1, SR_Qsoil2, SR_Qsoil3, SR_Qsoil4)
    SR_Qsoil1[1:2] <- c(min(QsoilStack, na.rm = TRUE)@data@min, max(QsoilStack, na.rm = TRUE)@data@max)
    SR_Qsoil2[1:2] <- c(min(QsoilStack, na.rm = TRUE)@data@min, max(QsoilStack, na.rm = TRUE)@data@max)
    SR_Qsoil3[1:2] <- c(min(QsoilStack, na.rm = TRUE)@data@min, max(QsoilStack, na.rm = TRUE)@data@max)
    SR_Qsoil4[1:2] <- c(min(QsoilStack, na.rm = TRUE)@data@min, max(QsoilStack, na.rm = TRUE)@data@max)
    ### PLOTTING ----
    Plot_Stack <- stack(SR_NDVI, SR_Tair, SR_Qsoil1, SR_Qsoil2, SR_Qsoil3, SR_Qsoil4)
    par(mfrow = c(3, 2), mai = c(1, 0, 0.5, 0))
    for (i in 1:length(SR_cols)) {
        if (i == 1) {
            plot(Plot_Stack[[i]], colNA = "black", main = paste("Mean", SR_Titles[[i]],
                "1982 - 2015"), cex.main = 3, legend.width = 3, legend.shrink = 1,
                axis.args = list(cex.axis = 2.5), cex.axis = 2, col = SR_cols[[i]],
                axes = TRUE, legend = FALSE)
        } else {
            plot(Plot_Stack[[i]], colNA = "black", main = paste("Mean", SR_Titles[[i]],
                "1981 - 2015"), cex.main = 3, legend.width = 3, legend.shrink = 1,
                axis.args = list(cex.axis = 2.5), cex.axis = 2, col = SR_cols[[i]],
                axes = TRUE, legend = FALSE)
        }
        if (i <= 2) {
            plot(Plot_Stack[[i]], legend.only = TRUE, smallplot = c(0, 0.93, 0.12,
                0.16), horizontal = TRUE, axis.args = list(cex.axis = 2.5), col = SR_cols[[i]])
        }
        if (i == 2) {
            par(mai = c(0.5, 0, 0.5, 0))
        }
    }
    return(SR_Qsoil4)
}
```

Chunk 21: Function for plotting TRY data overviews in two-by-two plots for study regions.

```
col.tair <- colorRampPalette(c("blue", "turquoise", "yellow", "orange", "red"))(100)
TRYRegions <- function(Region) {
    ### LOADING DATA ----
    setwd(Dir.Gimms.Monthly)
    Back_ras <- mean(brick(list.files()[1:7]), na.rm = TRUE)  # background raster for later plots
    values(Back_ras)[which(!is.na(values(Back_ras)))] <- 8888
    Titles <- c("Height", "Nitrogen Content")
    ### PLOTTING ----
    par(mfrow = c(2, 2), mai = c(1, 0, 0.5, 0))
    setwd(Dir.TRY)
    Plot_ras <- brick(list.files(Dir.TRY)[grep(pattern = Region, list.files(Dir.TRY))][1])  # Raw file
    Plot1_ras <- brick(list.files(Dir.TRY)[grep(pattern = Region, list.files(Dir.TRY))][2])  # Distrib file
    Back_ras1 <- crop(Back_ras, extent(Plot_ras))
    Back_ras1 <- stack(Back_ras1, Back_ras1)
    names(Back_ras1) <- c("Height", "Nitrogen")
    for (i in 1:2) {
        plot(Back_ras1[[i]], colNA = "black", main = Titles[i], cex.main = 3, legend = FALSE,
            col = "grey")
        plot(Plot_ras[[i]], add = TRUE, legend = FALSE, col = col.tair, axes = TRUE)
        plot(Plot_ras[[i]], legend.only = TRUE, smallplot = c(0, 0.95, 0.075, 0.115),
            horizontal = TRUE, axis.args = list(cex.axis = 2.5), col = col.tair)
    }
    for (i in 1:2) {
        plot(Back_ras1[[i]], colNA = "black", main = Titles[i], cex.main = 3, legend = FALSE,
            col = "grey")
        plot(Plot1_ras[[i]], add = TRUE, legend = FALSE, col = col.tair, axes = TRUE)
        plot(Plot1_ras[[i]], legend.only = TRUE, smallplot = c(0, 0.95, 0.075, 0.115),
            horizontal = TRUE, axis.args = list(cex.axis = 2.5), col = col.tair)
    }
}
```

A.5.3 Vegetation Memory Models

Chunk 22: Plotting NDVI data treatment in two-by-two plots.

```
## load data
IbRas <- grep(list.files(Dir.Gimms.Monthly), pattern = "Iberian Region")
IBNDVI <- brick(paste(Dir.Gimms.Monthly, list.files(Dir.Gimms.Monthly)[IbRas],
    sep = "/"))
## extract data
NDVI_vecraw <- as.vector(IBNDVI[35363])
NDVI_vecdet <- detrend(NDVI_vecraw, tt = "linear")  # linear detrending
NDVI_df <- data.frame(Month = rep(1:12, length(NDVI_vecraw)/12),
    NDVI_raw = NDVI_vecraw, NDVI_de = NDVI_vecdet)  # create NDVI data frame
## calculate anomalies (Z-scores) and monthly means
NDVI_df <- transform(NDVI_df, NDVI_Anomalies = ave(NDVI_de,
    Month, FUN = scale), NDVI_Threshold = ave(NDVI_raw,
    Month, FUN = function(t) mean(t, na.rm = TRUE)))
## plotting data frame
NDVIplot_df <- data.frame(NDVI = c(NDVI_vecraw, NDVI_vecdet,
    NDVI_df$NDVI_Anomalies, NDVI_df$NDVI_Threshold[1:12]),
    Ident = c(rep("Raw Data", length(NDVI_vecraw)),
        rep("Detrended", length(NDVI_vecraw)), rep("Z-Scores",
            length(NDVI_vecraw)), rep("Monthly Means",
            12)), Months = c(rep(1:length(NDVI_vecraw),
        3), 1:12))
## raw and detrended
ggplot(NDVIplot_df[1:(length(NDVI_vecraw) * 2), ],
    aes(x = Months, y = NDVI, col = Ident)) + geom_line(size = 2) +
    theme_bw(base_size = 35) + theme(legend.position = "none") +
    scale_color_manual(values = c("orange", "forestgreen"))
## monthly means
ggplot(NDVIplot_df[(length(NDVI_vecraw) * 3 + 1):(dim(NDVIplot_df)[1]),
    ], aes(x = as.factor(Months), y = NDVI, col = Ident)) +
    geom_bar(stat = "identity", fill = "forestgreen") +
    theme_bw(base_size = 35) + theme(legend.position = "none") +
    scale_color_manual(values = c("forestgreen")) +
    xlab("Months") + geom_hline(aes(yintercept = 0.1),
    size = 1.5)
## z-scores
ggplot(NDVIplot_df[(length(NDVI_vecraw) * 2 + 1):(length(NDVI_vecraw) *
    3), ], aes(x = Months, y = NDVI, col = Ident)) +
    geom_line(size = 2) + theme_bw(base_size = 35) +
    theme(legend.position = "none") + scale_color_manual(values = c("purple"))
## legend
leg <- ggplot(NDVIplot_df[1:(length(NDVI_vecraw) *
    3), ], aes(x = Months, y = NDVI, col = Ident)) +
    geom_line(size = 2) + scale_color_manual(values = c("orange",
    "forestgreen", "purple")) + theme_bw(base_size = 65) +
    guides(colour = guide_legend(override.aes = list(size = 20))) +
    labs(col = "GIMMs NDVI 3g data")
legend <- cowplot::get_legend(leg)
grid.newpage()
grid.draw(legend)
```

Chunk 23: Plotting Qsoil 1 data treatment in two-by-two plots.

```
setwd(Dir.ERA.Monthly)
Qsoil <- brick(list.files()[grep(list.files(), pattern = "Iberian Region_11981_122015.nc")[1]])
load(paste(Dir.Data, "ModData_df.RData", sep = "/"))  # model data for pixel 35363
Clim <- as.vector(Qsoil[35363])[1:dim(ModData_df)[1]]
Clim_vec <- detrend(Clim, tt = "linear")  # linear detrending
## raw and detrended
plot1_df <- with(ModData_df, data.frame(Months = rep(1:dim(ModData_df)[1],
    2), Qsoil = c(Clim, Clim_vec), Ident = rep(c("Raw Data",
    "Detrened"), each = dim(ModData_df)[1])))
ggplot(plot1_df, aes(x = Months, y = Qsoil, col = Ident)) +
    geom_line(size = 2) + theme_bw(base_size = 35) +
    theme(legend.position = "none") + scale_color_manual(values = c("orange",
    "navyblue"))
## raw and detrended
plot2_df <- with(ModData_df, data.frame(Months = rep(1:dim(ModData_df)[1],
    1), Qsoil = c(Clim_raw), Ident = rep(c("Z-Scores"),
    each = dim(ModData_df)[1])))
ggplot(plot2_df, aes(x = Months, y = Qsoil, col = Ident)) +
    geom_line(size = 2) + theme_bw(base_size = 35) +
    theme(legend.position = "none") + scale_color_manual(values = c("brown"))
## Cummulative soil moisture lags
plot3_df <- with(ModData_df, data.frame(Months = rep(1:dim(ModData_df)[1],
    13), Qsoil = c(ClimCum_0, ClimCum_1, ClimCum_2,
    ClimCum_3, ClimCum_4, ClimCum_5, ClimCum_6, ClimCum_7,
    ClimCum_8, ClimCum_9, ClimCum_10, ClimCum_11, ClimCum_12),
    Ident = as.factor(rep(c("Z-Scores", "Lag 01", "Lag 02",
        "Lag 03", "Lag 04", "Lag 05", "Lag 06", "Lag 07",
        "Lag 08", "Lag 09", "Lag 10", "Lag 11", "Lag 12"),
        each = dim(ModData_df)[1]))))
ggplot(plot3_df, aes(x = Months, y = Qsoil, col = Ident)) +
    geom_line(size = 1) + theme_bw(base_size = 35) +
    theme(legend.position = "none") + scale_color_manual(values = c(rainbow(12),
    "brown"))
## legend
Qsoilplot_df <- rbind(plot1_df, plot3_df)
leg <- ggplot(Qsoilplot_df, aes(x = Months, y = Qsoil,
    col = Ident)) + geom_line(size = 2) + scale_color_manual(values = c("orange",
    "navyblue", rainbow(12), "brown")) + theme_bw(base_size = 65) +
    guides(colour = guide_legend(ncol = 3, override.aes = list(size = 20))) +
    labs(col = "ERA5 Qsoil1 data")
legend <- cowplot::get_legend(leg)
grid.newpage()
grid.draw(legend)
```

A.5.4 Results

A.5.4.1 Memory Models

Chunk 24: Plotting vegetation memory model outputs.

```
ModelRes <- function(Region, SoilLayer) {
    col.signeg <- got(n = 100, alpha = 1, begin = 0, end = 1, direction = -1, option = "targaryen2")
    col.sigpos <- got(n = 100, alpha = 1, begin = 0, end = 1, direction = -1, option = "tyrell")
    col.nonsig <- colorRampPalette(c("grey"))(1)
    col.lags <- got(n = 12, alpha = 1, begin = 0, end = 1, direction = 1, option = "daenerys")
    smallplotxpos <- c(0.5, 0.93, 0.03, 0.065)  # where to put colour scales
    smallplotxneg <- c(0.05, 0.5, 0.03, 0.065)  # where to put colour scales
    Files <- list.files(Dir.Memory)[grep(list.files(Dir.Memory), pattern = Region)]
    Files <- Files[grep(Files, pattern = ".nc")]
    plot_ras <- brick(paste(Dir.Memory, Files[SoilLayer], sep = "/"))
    plot(plot_ras[[1]], col = col.lags, colNA = "black", legend = FALSE, axes = FALSE)
    plot(plot_ras[[1]], legend.only = TRUE, col = col.lags, smallplot = c(0.05, 0.93,
        0.03, 0.065), horizontal = TRUE, axis.args = list(cex.axis = 2.5))
    if (SoilLayer == 1) {
        RasLay <- 4:6
    } else {
        RasLay <- c(5)
    }
    for (Plot in RasLay) {
        Neg_ras <- plot_ras[[Plot]]
        Neg_ras[which(values(Neg_ras) >= 0)] <- NA
        Pos_ras <- plot_ras[[Plot]]
        Pos_ras[which(values(Pos_ras) < 0)] <- NA
        plot(Neg_ras, col = col.signeg, colNA = "black", legend = FALSE, axes = FALSE)
        if (Plot == 4 & Region == "Iberian Region") {
            plot(Pos_ras, col = col.sigpos, colNA = "black", legend = FALSE, axes = FALSE,
                add = TRUE)
        } else {
            plot(Pos_ras, col = col.sigpos, legend = FALSE, axes = FALSE, add = TRUE)
        }
        plot(Neg_ras, legend.only = TRUE, col = col.signeg, colNA = "black", smallplot = smallplotxneg,
            horizontal = TRUE, axis.args = list(cex.axis = 2.5))
        if (Plot == 4 & Region == "Iberian Region") {
            plot(Pos_ras, legend.only = TRUE, col = col.sigpos, smallplot = c(0.05,
                0.93, 0.03, 0.065), horizontal = TRUE, axis.args = list(cex.axis = 2.5))
        } else {
            plot(Pos_ras, legend.only = TRUE, col = col.sigpos, smallplot = smallplotxpos,
                horizontal = TRUE, axis.args = list(cex.axis = 2.5))
        }
    }
}
```

Chunk 25: Loading U-Test results of model coefficients and displaying as a table.

```
Ures <- function(Region, SoilLayer) {
    Dir.Reg <- paste(Dir.Memory, "/", Region, "-1981_2015", sep = "")
    Files <- list.files(Dir.Reg)[grep(list.files(Dir.Reg), pattern = ".xlsx")]
    Utab <- read.xlsx(file = paste(Dir.Reg, Files, sep = "/"), sheetName = paste("Model",
        SoilLayer))
    Medians <- read.xlsx(file = paste(Dir.Reg, Files, sep = "/"), sheetName = "Variable medians")[SoilLayer,
        ]
    Medians <- as.vector(Medians[1, c(2:4)])
    Utab <- Utab[, -1]
    colnames(Utab) <- c("NDVI [t-1]", paste("Qsoil", SoilLayer, sep = ""), "Tair")
```

```
    rownames(Utab) <- c(round(Medians, 4))
    Utab <- round(Utab, 4)
    Short <- paste("Mann-Whitney U-Test (", Region, ", Qsoil", SoilLayer, " Model)",
        sep = "")
    Long <- paste("Rownames represent median values of vegetation memory coefficients contained in column names.
              U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells.
              $p$-values belonging to these $U$-values are represented in the lower-lefthand block of cells.
              Established via \\ref{rUresChunk}.")
    kab <- kable(Utab, booktabs = TRUE, caption = paste("\\textbf{", Short, " -} ",
        Long, sep = ""), caption.short = Short, escape = FALSE, format = "latex")
    kab <- kable_styling(kab, latex_options = c("hold_position"))
    print(kab)
}
```

A.5.4.2 Variance Partitioning

Chunk 26: Plotting variance partitioning results.

```
VarParRes <- function(Region, SoilLayer, Plot = 1) {
    col.varpar1 <- got(n = 100, alpha = 1, begin = 0, end = 1, direction = -1, option = "wildfire")
    col.varpar2 <- got(n = 100, alpha = 1, begin = 0, end = 1, direction = -1, option = "targaryen")
    col.varpar3 <- got(n = 100, alpha = 1, begin = 0, end = 1, direction = -1, option = "jon_snow")
    col.list <- list(col.varpar1, col.varpar2, col.varpar3)
    Files <- list.files(Dir.Memory)[grep(list.files(Dir.Memory), pattern = Region)]
    Files <- Files[grep(Files, pattern = ".nc")]
    Alter_ras <- brick(paste(Dir.Memory, Files[SoilLayer], sep = "/"))[[7:10]]
    Alter_ras[2] <- 0
    values(Alter_ras)[which(values(Alter_ras) < 0)] <- 0
    cells <- order(values(Alter_ras[[1]]))
    plot_df <- data.frame(Variance = NA, Cell = NA, Source = NA)
    Idents <- c(NA, "t-1", "Shared", "Qsoil")
    for (i in 1:4) {
        Alter_ras[[i]][which(values(Alter_ras[[i]]) > quantile(values(Alter_ras[[1]]),
            0.95, na.rm = TRUE))] <- quantile(values(Alter_ras[[1]]), 0.95, na.rm = TRUE)
        if (i > 1) {
            plot_df1 <- data.frame(Variance = values(Alter_ras[[i]])[cells], Cell = 1:length(cells),
                Source = rep(Idents[i], length(cells)))
            plot_df <- rbind(plot_df, plot_df1)
        }
    }
    plot_df <- na.omit(plot_df)
    p <- ggplot(data = plot_df, aes(y = Variance, x = Cell, fill = Source)) + geom_bar(stat = "identity") +
        ylim(0, quantile(values(Alter_ras[[1]]), 0.95, na.rm = TRUE)) + theme_bw(base_size = 20) +
        xlab("Raster Cells") + scale_fill_manual(values = c(col.list[[3]][1], col.list[[2]][50],
        col.list[[1]][30]))
    if (Plot == 1) {
        print(p)
    } else {
        for (i in 2:4) {
            col.varpar <- col.list[[i - 1]]
            plot(Alter_ras[[i]], col = col.varpar, colNA = "black", legend = FALSE,
                axes = FALSE)
            plot(Alter_ras[[i]], legend.only = TRUE, col = col.varpar, smallplot = c(0.05,
                0.93, 0.03, 0.065), horizontal = TRUE, axis.args = list(cex.axis = 2.5))
        }
    }
}
```

A.5.4.3 Soil Layer Comparison

Chunk 27: Comparing soil layer memory coefficients.

```
SoilLayersRes <- function(Region) {
    col.signeg <- got(n = 100, alpha = 1, begin = 0, end = 1, direction = -1, option = "targaryen2")
    col.sigpos <- got(n = 100, alpha = 1, begin = 0, end = 1, direction = -1, option = "tyrell")
    col.nonsig <- colorRampPalette(c("grey"))(1)
    smallplotxpos <- c(0.5, 0.93, 0.03, 0.065)  # where to put colour scales
    smallplotxneg <- c(0.05, 0.5, 0.03, 0.065)  # where to put colour scales
    Dir.Reg <- paste(Dir.Memory, "/", Region, "-1981_2015", sep = "")
    Files <- list.files(Dir.Reg)[grep(list.files(Dir.Reg), pattern = ".nc")]
    SoilLayer <- 1
    Alter_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[3]]
    for (SoilLayer in 2:4) {
        Add_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[3]]
        Alter_ras <- stack(Alter_ras, Add_ras)
    }
    for (Plot in 1:4) {
        Neg_ras <- Alter_ras[[Plot]]
        Neg_ras[which(values(Neg_ras) >= 0)] <- NA
        Pos_ras <- Alter_ras[[Plot]]
        Pos_ras[which(values(Pos_ras) < 0)] <- NA
        plot(Neg_ras, col = col.signeg, colNA = "black", legend = FALSE, axes = FALSE)
        plot(Pos_ras, col = col.sigpos, legend = FALSE, axes = FALSE, add = TRUE)
        plot(Neg_ras, legend.only = TRUE, col = col.signeg, colNA = "black", smallplot = smallplotxneg,
            horizontal = TRUE, axis.args = list(cex.axis = 2.5))
        plot(Pos_ras, legend.only = TRUE, col = col.sigpos, smallplot = smallplotxpos,
            horizontal = TRUE, axis.args = list(cex.axis = 2.5))
    }
}
```

Chunk 28: Loading U-Test results of soil layer comparison and displaying as a table.

```
UQsoilres <- function(Region) {
    Dir.Reg <- paste(Dir.Memory, "/", Region, "-1981_2015", sep = "")
    Files <- list.files(Dir.Reg)[grep(list.files(Dir.Reg), pattern = ".xlsx")]
    Utab <- read.xlsx(file = paste(Dir.Reg, Files, sep = "/"), sheetName = "Qsoil")
    Medians <- read.xlsx(file = paste(Dir.Reg, Files, sep = "/"), sheetName = "Variable medians")[,
        3]
    Utab <- Utab[, -1]
    colnames(Utab) <- paste("Qsoil", c(1:4), sep = "")
    rownames(Utab) <- c(round(Medians, 4))
    Utab <- round(Utab, 4)
    Short <- paste("Mann-Whitney U-Test (", Region, ", Qsoil Layers)", sep = "")
    Long <- paste("Rownames represent median values of Qsoil vegetation memory coefficients contained in column names.
             U-Test statistics of vegetation memory coefficient values are contained within the upper-righthand cells.
             $p$-values belonging to these $U$-values are represented in the lower-lefthand block of cells.
             Established via \\ref{rUQsoilRes}.")
    kab <- kable(Utab, booktabs = TRUE, caption = paste("\\textbf{", Short, " -} ",
        Long, sep = ""), caption.short = Short, escape = FALSE, format = "latex")
    kab <- kable_styling(kab, latex_options = c("hold_position"))
    print(kab)
}
```

A.5.4.4 Vegetation Memory Sensitivity

Chunk 29: Vegetation sensitivity plots.

```
PatcausRes <- function(Region, SoilLayer, SoilOnly) {
    Dir.Reg <- paste(Dir.Memory, "/", Region, "-1981_2015", sep = "")
    Files <- list.files(Dir.Reg)[grep(list.files(Dir.Reg), pattern = ".nc")]
    Alter_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))
    Files <- list.files(Dir.ERA.Monthly)[grep(list.files(Dir.ERA.Monthly), pattern = Region)]
    Files <- Files[grep(Files, pattern = ".nc")]
    EQsoil <- Files[grep(Files, pattern = "Qsoil")]
    EQsoil <- brick(paste(Dir.ERA.Monthly, EQsoil[SoilLayer], sep = "/"))
    EQsoil <- values(mean(EQsoil))
    ETair <- Files[grep(Files, pattern = "Tair")]
    ETair <- brick(paste(Dir.ERA.Monthly, ETair, sep = "/"))
    ETair <- values(mean(ETair))
    ENDVI <- list.files(Dir.Gimms.Monthly)[grep(list.files(Dir.Gimms.Monthly), pattern = Region)]
    ENDVI <- brick(paste(Dir.Gimms.Monthly, ENDVI, sep = "/"))
    ENDVI <- values(mean(ENDVI))
    plot_df <- data.frame(Memory = values(Alter_ras[[1]]), NDVI = values(Alter_ras[[2]]),
        Qsoil = values(Alter_ras[[3]]), Tair = values(Alter_ras[[4]]), ENDVI = ENDVI,
        EQsoil = EQsoil, ETair = ETair)
    plot_df <- na.omit(plot_df)
    QsoilTitle <- c("(0-7cm)", "(7-28cm)", "(28-100cm)", "(100-255cm)")
    Output <- as.list(rep(NA, 8))
    if (SoilOnly == TRUE) {
        plotm <- ggplot(plot_df, aes(x = as.factor(Memory), y = EQsoil)) + geom_boxplot() +
            theme_bw(base_size = 35) + ylab(paste("Mean Soil Moisture", QsoilTitle[SoilLayer])) +
            xlab(paste("Soil Moisture", QsoilTitle[SoilLayer], "Lag")) + coord_flip()
        print(plotm)
        Output[[1]] <- summary(lm(Memory ~ EQsoil, data = plot_df))[["coefficients"]][1,
            1]
        Output[[2]] <- summary(lm(Memory ~ EQsoil, data = plot_df))[["coefficients"]][1,
            4]
        Output[[3]] <- summary(lm(Memory ~ EQsoil, data = plot_df))[["coefficients"]][2,
            1]
        Output[[4]] <- summary(lm(Memory ~ EQsoil, data = plot_df))[["coefficients"]][2,
            4]
        plotq <- ggplot(plot_df, aes(x = EQsoil, y = Qsoil)) + geom_point(shape = ".",
            alpha = 0.5, col = "blue", size = 3.5) + theme_bw(base_size = 35) + xlab(paste("Mean Soil Moisture",
            QsoilTitle[SoilLayer])) + ylab(paste("Soil Moisture", QsoilTitle[SoilLayer],
            "Coefficients")) + stat_smooth(method = "lm", col = "black", level = 0.95) +
            geom_hline(yintercept = 0, linetype = "dotted")
        print(plotq)
        Output[[5]] <- summary(lm(Qsoil ~ EQsoil, data = plot_df))[["coefficients"]][1,
            1]
        Output[[6]] <- summary(lm(Qsoil ~ EQsoil, data = plot_df))[["coefficients"]][1,
            4]
        Output[[7]] <- summary(lm(Qsoil ~ EQsoil, data = plot_df))[["coefficients"]][2,
            1]
        Output[[8]] <- summary(lm(Qsoil ~ EQsoil, data = plot_df))[["coefficients"]][2,
            4]
    } else {
        plotN <- ggplot(plot_df, aes(x = ENDVI, y = NDVI)) + geom_point(shape = ".",
            alpha = 0.5, col = "forestgreen", size = 3.5) + theme_bw(base_size = 35) +
            xlab("Mean NDVI") + ylab("NDVI [t-1] Coefficients") + stat_smooth(method = "lm",
            col = "black", level = 0.95) + geom_hline(yintercept = 0, linetype = "dotted")
        print(plotN)
        Output[[1]] <- summary(lm(NDVI ~ ENDVI, data = plot_df))[["coefficients"]][1,
```

```
            1]
        Output[[2]] <- summary(lm(NDVI ~ ENDVI, data = plot_df))[["coefficients"]][1,
            4]
        Output[[3]] <- summary(lm(NDVI ~ ENDVI, data = plot_df))[["coefficients"]][2,
            1]
        Output[[4]] <- summary(lm(NDVI ~ ENDVI, data = plot_df))[["coefficients"]][2,
            4]
        plotT <- ggplot(plot_df, aes(x = ETair, y = Tair)) + geom_point(shape = ".",
            alpha = 0.5, col = "red", size = 3.5) + theme_bw(base_size = 35) + xlab("Mean Air Temperature") +
            ylab("Air Temperature Coefficients") + stat_smooth(method = "lm", col = "black",
            level = 0.95) + geom_hline(yintercept = 0, linetype = "dotted")
        print(plotT)
        Output[[5]] <- summary(lm(Tair ~ ETair, data = plot_df))[["coefficients"]][1,
            1]
        Output[[6]] <- summary(lm(Tair ~ ETair, data = plot_df))[["coefficients"]][1,
            4]
        Output[[7]] <- summary(lm(Tair ~ ETair, data = plot_df))[["coefficients"]][2,
            1]
        Output[[8]] <- summary(lm(Tair ~ ETair, data = plot_df))[["coefficients"]][2,
            4]
    }
    return(Output)
}
```

Chunk 30: Linear regression coefficients of vegetation memory sensitivity.

```
PatCauseTab <- function(ModelCoeffs, Region) {
    # using Outputs of PatcauseRes for ModelCoeffs argument
    tabout <- data.frame(Column = ModelCoeffs[1:4])
    starts <- seq(1, length(ModelCoeffs), by = 4)
    for (i in 2:(length(ModelCoeffs)/4)) {
        tabout <- cbind(tabout, ModelCoeffs[starts[i]:(starts[i] + 3)])
    }
    colnames(tabout) <- c("t-1", "Tair", "1", "2", "3", "4", "1", "2", "3", "4")
    rownames(tabout) <- c("Intercept", "$p_{Intercept}$", "Slope", "$p_{Slope}$")
    Short <- paste("Vegetation Memory Sensitivity (", Region, ")", sep = "")
    Long <- paste("Coefficients of linear regressions of vegetation sensitivity across the Iberian Region.
             Established via \\ref{rPatcaustab}.",
        sep = "")
    kab <- kable(tabout, booktabs = TRUE, caption = paste("\\textbf{", Short, " -} ",
        Long, sep = ""), caption.short = Short, escape = FALSE, format = "latex")
    kab <- add_header_above(kable_input = kab, header = c(` ` = 3, Qsoil = 4, Lag = 4),
        bold = TRUE, align = "c")
    kab <- kable_styling(kab, latex_options = c("hold_position"))
    print(kab)
}
```

Chunk 31: ANOVAs of Qsoil layer and Memory length models.

```
PatCausAnova <- function(Region) {
    ## LOADING
    Dir.Reg <- paste(Dir.Memory, "/", Region, "-1981_2015", sep = "")
    Files <- list.files(Dir.Reg)[grep(list.files(Dir.Reg), pattern = ".nc")]
    SoilLayer <- 1
    Alter_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[1]]
    for (SoilLayer in 2:4) {
        Add_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[1]]
        Alter_ras <- stack(Alter_ras, Add_ras)
    }
    Memory <- Alter_ras
```

```r
    SoilLayer <- 1
    Alter_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[3]]
    for (SoilLayer in 2:4) {
        Add_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[3]]
        Alter_ras <- stack(Alter_ras, Add_ras)
    }
    Qsoil <- Alter_ras
    Files <- list.files(Dir.ERA.Monthly)[grep(list.files(Dir.ERA.Monthly), pattern = Region)]
    Files <- Files[grep(Files, pattern = ".nc")]
    EQsoil <- Files[grep(Files, pattern = "Qsoil")]
    SoilLayer <- 1
    Alter_ras <- mean(brick(paste(Dir.ERA.Monthly, EQsoil[SoilLayer], sep = "/")))
    for (SoilLayer in 2:4) {
        Add_ras <- mean(brick(paste(Dir.ERA.Monthly, EQsoil[SoilLayer], sep = "/")))
        Alter_ras <- stack(Alter_ras, Add_ras)
    }
    EQsoil <- Alter_ras
    ## DATA
    anova_df <- data.frame(EQsoil1 = values(EQsoil[[1]]), EQsoil2 = values(EQsoil[[2]]),
        EQsoil3 = values(EQsoil[[3]]), EQsoil4 = values(EQsoil[[4]]), Qsoil1 = values(Qsoil[[1]]),
        Qsoil2 = values(Qsoil[[2]]), Qsoil3 = values(Qsoil[[3]]), Qsoil4 = values(Qsoil[[4]]),
        Memory1 = values(Memory[[1]]), Memory2 = values(Memory[[2]]), Memory3 = values(Memory[[3]]),
        Memory4 = values(Memory[[4]]))
    anova_df <- na.omit(anova_df)
    ## ANOVA Memory
    Mod1 <- lm(Memory1 ~ EQsoil1, data = anova_df)
    Mod2 <- lm(Memory2 ~ EQsoil2, data = anova_df)
    Mod3 <- lm(Memory3 ~ EQsoil3, data = anova_df)
    Mod4 <- lm(Memory4 ~ EQsoil4, data = anova_df)
    AnMem <- anova(Mod1, Mod2, Mod3, Mod4)
    ### Qsoil
    Mod1 <- lm(Qsoil1 ~ EQsoil1, data = anova_df)
    Mod2 <- lm(Qsoil2 ~ EQsoil2, data = anova_df)
    Mod3 <- lm(Qsoil3 ~ EQsoil3, data = anova_df)
    Mod4 <- lm(Qsoil4 ~ EQsoil4, data = anova_df)
    AnQsoil <- anova(Mod1, Mod2, Mod3, Mod4)
    return(list(AnMem, AnQsoil))
}
```

A.5.5 Plant Function

A.5.5.1 Life History Traits

Chunk 32: Plotting COMPADRE data against vegetation memory coefficients.

```
Comres <- function(Region, Variable) {
    col.tair <- got(n = 1, alpha = 1, begin = 0, end = 1, direction = -1, option = "tully")
    col.ndvi <- got(n = 1, alpha = 1, begin = 0, end = 1, direction = 1, option = "tyrell")
    col.qsoil <- got(n = 4, alpha = 1, begin = 0, end = 1, direction = 1, option = "white_walkers")
    col.mem <- got(n = 4, alpha = 1, begin = 0, end = 1, direction = 1, option = "greyjoy")
    VarHold <- Variable
    if (Variable == "FSC-1" | Variable == "FSC-2") {
        Variable <- "FastSlow"
    }
    ## Memory Data Memory
    Dir.Reg <- paste(Dir.Memory, "/", Region, "-1981_2015", sep = "")
    Files <- list.files(Dir.Reg)[grep(list.files(Dir.Reg), pattern = ".nc")]
    SoilLayer <- 1
    Memory_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[1]]
    for (SoilLayer in 2:4) {
        Add_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[1]]
        Memory_ras <- stack(Memory_ras, Add_ras)
    }
    # t-1
    Dir.Reg <- paste(Dir.Memory, "/", Region, "-1981_2015", sep = "")
    Files <- list.files(Dir.Reg)[grep(list.files(Dir.Reg), pattern = ".nc")]
    SoilLayer <- 1
    NDVI_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[2]]
    # Qsoil
    Dir.Reg <- paste(Dir.Memory, "/", Region, "-1981_2015", sep = "")
    Files <- list.files(Dir.Reg)[grep(list.files(Dir.Reg), pattern = ".nc")]
    SoilLayer <- 1
    Qsoil_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[3]]
    for (SoilLayer in 2:4) {
        Add_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[3]]
        Qsoil_ras <- stack(Qsoil_ras, Add_ras)
    }
    # Tair
    Dir.Reg <- paste(Dir.Memory, "/", Region, "-1981_2015", sep = "")
    Files <- list.files(Dir.Reg)[grep(list.files(Dir.Reg), pattern = ".nc")]
    SoilLayer <- 1
    Tair_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[4]]
    ## COMPADRE data
    Dir.Comp <- paste(Dir.Compadre, Variable, sep = "/")
    Compad_ras <- list.files(Dir.Comp)[grep(list.files(Dir.Comp), pattern = Region)]
    if (VarHold != "FSC-2") {
        Compad_ras <- raster(paste(Dir.Comp, Compad_ras, sep = "/"))[[1]]
    } else {
        Compad_ras <- brick(paste(Dir.Comp, Compad_ras, sep = "/"))[[2]]
    }
    values(Compad_ras)[which(values(Compad_ras) > quantile(values(Compad_ras), 0.66,
        na.rm = TRUE))] <- quantile(values(Compad_ras), 0.66, na.rm = TRUE)
    if (VarHold == "FSC-1" | VarHold == "FSC-2") {
        values(Compad_ras)[which(values(Compad_ras) < quantile(values(Compad_ras),
            0.05, na.rm = TRUE))] <- quantile(values(Compad_ras), 0.05, na.rm = TRUE)
    }
    plot_df <- data.frame(Data = c(values(Memory_ras[[1]]), values(Memory_ras[[2]]),
        values(Memory_ras[[3]]), values(Memory_ras[[4]]), values(NDVI_ras), values(Qsoil_ras[[1]]),
```

```
        values(Qsoil_ras[[2]]), values(Qsoil_ras[[3]]), values(Qsoil_ras[[4]]), values(Tair_ras)),
        Identifiers = rep(c("LagSoil1", "LagSoil2", "LagSoil3", "LagSoil4", "t-1",
            "Qsoil1", "Qsoil2", "Qsoil3", "Qsoil4", "Tair"), each = length(values(Memory_ras[[1]]))),
        Compadre = rep(values(Compad_ras), 10))
    Variable <- VarHold
    plot_df <- na.omit(plot_df)
    Output <- as.list(rep(NA, 10))
    plot <- ggplot(data = plot_df, aes(x = Compadre, y = Data, col = Identifiers)) +
        geom_point(alpha = 0.5, size = 3.5) + theme_bw(base_size = 35) + xlab(paste("COMPADRE",
        Variable)) + ylab("Vegetation Memory Coefficients") + geom_hline(yintercept = 0,
        linetype = "dotted") + stat_smooth(method = "lm", level = 0.66) + scale_color_manual(values = c(col.mem,
        col.qsoil, col.ndvi, col.tair))
    print(plot)
    Idents <- c("t-1", "Tair", paste("Qsoil", 1:4, sep = ""), paste("LagSoil", 1:4,
        sep = ""))
    for (i in 0:(length(Idents) - 1)) {
        Output[[(4 * i + 1)]] <- summary(lm(Data ~ Compadre, data = plot_df[which(plot_df$Identifiers ==
            Idents[(i + 1)]), ]))[["coefficients"]][1, 1]
        Output[[(4 * i + 2)]] <- summary(lm(Data ~ Compadre, data = plot_df[which(plot_df$Identifiers ==
            Idents[(i + 1)]), ]))[["coefficients"]][1, 4]
        Output[[(4 * i + 3)]] <- summary(lm(Data ~ Compadre, data = plot_df[which(plot_df$Identifiers ==
            Idents[(i + 1)]), ]))[["coefficients"]][2, 1]
        Output[[(4 * i + 4)]] <- summary(lm(Data ~ Compadre, data = plot_df[which(plot_df$Identifiers ==
            Idents[(i + 1)]), ]))[["coefficients"]][2, 4]
    }
    return(list(leg, Output, dim(plot_df)[1]/10))
}
```

Chunk 33: Linear regression coefficients of COMPADRE data and vegetation memory coeffcients.

```
CompadTab <- function(Region, ModelCoeffs, Variable) {
    tabout <- data.frame(Column = ModelCoeffs[1:4])
    starts <- seq(1, length(ModelCoeffs), by = 4)
    for (i in 2:(length(ModelCoeffs)/4)) {
        tabout <- cbind(tabout, ModelCoeffs[starts[i]:(starts[i] + 3)])
    }
    rownames(tabout) <- c("Intercept", "$p_{Intercept}$", "Slope", "$p_{Slope}$")
    tabout <- round(tabout, 5)
    colnames(tabout) <- c("t-1", "Tair", 1:4, 1:4)
    Short <- paste("COMPADRE ", Variable, " and Vegetation Memory (", Region, ")",
        sep = "")
    Long <- paste("Linear regression coefficients of COMPADRE data and vegetation memory coefficients.
            Established via \\ref{rCOMPADTab}.",
        sep = "")
    kab <- kable(tabout, booktabs = TRUE, caption = paste("\\textbf{", Short, " -} ",
        Long, sep = ""), caption.short = Short, escape = FALSE, format = "latex")
    kab <- add_header_above(kable_input = kab, header = c(` ` = 3, Qsoil = 4, Lag = 4),
        bold = TRUE, align = "c")
    kab <- kable_styling(kab, latex_options = c("hold_position"))
    print(kab)
}
```

A.5.5.2 Plant Functional Traits

Chunk 34: Plotting TRY data against vegetation memory coefficients.

```
Tryres <- function(Region, SoilLayer, Variable) {
    Dir.Reg <- paste(Dir.Memory, "/", Region, "-1981_2015", sep = "")
    Variable_vec <- c("t-1", "Qsoil", "Tair")
    LocVar <- which(Variable_vec == Variable) + 1
    TryFiles <- list.files(Dir.TRY)[grep(list.files(Dir.TRY), pattern = Region)]
    TryRaw <- brick(paste(Dir.TRY, TryFiles[1], sep = "/"))
    values(TryRaw)[which(values(TryRaw) > quantile(values(TryRaw), 0.99, na.rm = TRUE))] <- NA
    TryDis <- brick(paste(Dir.TRY, TryFiles[2], sep = "/"))
    Files <- list.files(Dir.Reg)[grep(list.files(Dir.Reg), pattern = ".nc")]
    Alter_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[LocVar]]
    Memory_ras <- brick(paste(Dir.Reg, Files[SoilLayer], sep = "/"))[[1]]
    data_df <- data.frame(Height = c(values(TryRaw[[1]]), values(TryDis[[1]])), Nitrogen = c(values(TryRaw[[2]]),
        values(TryDis[[2]])), Qsoil = c(values(Alter_ras), values(Alter_ras)), Memory = c(values(Memory_ras),
        values(Memory_ras)), TRY = c(rep("Raw", length(values(Alter_ras))), rep("Mapped",
        length(values(Alter_ras)))))

    VarTitle <- c("NDVI [t-1] Coefficients", "Qsoil", "Air Temperature Coefficients")[(LocVar -
        1)]
    if (LocVar == 3) {
        VarTitle <- c("Soil Moisture (0-7cm) Coefficients", "Soil Moisture (7-28cm) Coefficients",
            "Soil Moisture (28-100cm) Coefficients", "Soil Moisture (100-255cm) Coefficients")[SoilLayer]
    }
    if (Variable != "Qsoil") {
        Output <- as.list(rep(NA, 16))
    } else {
        Output <- as.list(rep(NA, 32))
    }
    p1 <- ggplot(data_df, aes(x = Height, y = Qsoil, col = TRY)) + geom_point(shape = ".",
        alpha = 0.5, size = 3.5) + theme_bw(base_size = 35) + xlab("Vegetative Height") +
        ylab(VarTitle) + geom_hline(yintercept = 0, linetype = "dotted") + stat_smooth(method = "lm") +
        scale_color_manual(values = c("lightgreen", "black"))
    print(p1)
    if (length(which(!is.na(data_df$Height[which(data_df$TRY == "Raw")]))) < 2) {
        Output[[1]] <- NA
        Output[[2]] <- NA
        Output[[3]] <- NA
        Output[[4]] <- NA
    } else {
        Output[[1]] <- summary(lm(Qsoil ~ Height, data = data_df[which(data_df$TRY ==
            "Raw"), ]))[["coefficients"]][1, 1]
        Output[[2]] <- summary(lm(Qsoil ~ Height, data = data_df[which(data_df$TRY ==
            "Raw"), ]))[["coefficients"]][1, 4]
        Output[[3]] <- summary(lm(Qsoil ~ Height, data = data_df[which(data_df$TRY ==
            "Raw"), ]))[["coefficients"]][2, 1]
        Output[[4]] <- summary(lm(Qsoil ~ Height, data = data_df[which(data_df$TRY ==
            "Raw"), ]))[["coefficients"]][2, 4]
    }
    Output[[5]] <- summary(lm(Qsoil ~ Height, data = data_df[which(data_df$TRY ==
        "Mapped"), ]))[["coefficients"]][1, 1]
    Output[[6]] <- summary(lm(Qsoil ~ Height, data = data_df[which(data_df$TRY ==
        "Mapped"), ]))[["coefficients"]][1, 4]
    Output[[7]] <- summary(lm(Qsoil ~ Height, data = data_df[which(data_df$TRY ==
        "Mapped"), ]))[["coefficients"]][2, 1]
    Output[[8]] <- summary(lm(Qsoil ~ Height, data = data_df[which(data_df$TRY ==
        "Mapped"), ]))[["coefficients"]][2, 4]
```

```r
p2 <- ggplot(data_df, aes(x = Nitrogen, y = Qsoil, col = TRY)) + geom_point(shape = ".",
    alpha = 0.5, size = 3.5) + theme_bw(base_size = 35) + xlab("Leaf Nitrogen Content") +
    ylab(VarTitle) + geom_hline(yintercept = 0, linetype = "dotted") + stat_smooth(method = "lm") +
    scale_color_manual(values = c("orange", "black"))
print(p2)
Output[[9]] <- summary(lm(Qsoil ~ Nitrogen, data = data_df[which(data_df$TRY ==
    "Raw"), ]))[["coefficients"]][1, 1]
Output[[10]] <- summary(lm(Qsoil ~ Nitrogen, data = data_df[which(data_df$TRY ==
    "Raw"), ]))[["coefficients"]][1, 4]
Output[[11]] <- summary(lm(Qsoil ~ Nitrogen, data = data_df[which(data_df$TRY ==
    "Raw"), ]))[["coefficients"]][2, 1]
Output[[12]] <- summary(lm(Qsoil ~ Nitrogen, data = data_df[which(data_df$TRY ==
    "Raw"), ]))[["coefficients"]][2, 4]
Output[[13]] <- summary(lm(Qsoil ~ Nitrogen, data = data_df[which(data_df$TRY ==
    "Mapped"), ]))[["coefficients"]][1, 1]
Output[[14]] <- summary(lm(Qsoil ~ Nitrogen, data = data_df[which(data_df$TRY ==
    "Mapped"), ]))[["coefficients"]][1, 4]
Output[[15]] <- summary(lm(Qsoil ~ Nitrogen, data = data_df[which(data_df$TRY ==
    "Mapped"), ]))[["coefficients"]][2, 1]
Output[[16]] <- summary(lm(Qsoil ~ Nitrogen, data = data_df[which(data_df$TRY ==
    "Mapped"), ]))[["coefficients"]][2, 4]
if (Variable == "Qsoil") {
    if (length(which(!is.na(data_df$Height[which(data_df$TRY == "Raw")]))) <
        2) {
        Output[[17]] <- NA
        Output[[18]] <- NA
        Output[[19]] <- NA
        Output[[20]] <- NA
    } else {
        Output[[17]] <- summary(lm(Memory ~ Height, data = data_df[which(data_df$TRY ==
            "Raw"), ]))[["coefficients"]][1, 1]
        Output[[18]] <- summary(lm(Memory ~ Height, data = data_df[which(data_df$TRY ==
            "Raw"), ]))[["coefficients"]][1, 4]
        Output[[19]] <- summary(lm(Memory ~ Height, data = data_df[which(data_df$TRY ==
            "Raw"), ]))[["coefficients"]][2, 1]
        Output[[20]] <- summary(lm(Memory ~ Height, data = data_df[which(data_df$TRY ==
            "Raw"), ]))[["coefficients"]][2, 4]
    }
    Output[[21]] <- summary(lm(Memory ~ Height, data = data_df[which(data_df$TRY ==
        "Mapped"), ]))[["coefficients"]][1, 1]
    Output[[22]] <- summary(lm(Memory ~ Height, data = data_df[which(data_df$TRY ==
        "Mapped"), ]))[["coefficients"]][1, 4]
    Output[[23]] <- summary(lm(Memory ~ Height, data = data_df[which(data_df$TRY ==
        "Mapped"), ]))[["coefficients"]][2, 1]
    Output[[24]] <- summary(lm(Memory ~ Height, data = data_df[which(data_df$TRY ==
        "Mapped"), ]))[["coefficients"]][2, 4]
    Output[[25]] <- summary(lm(Memory ~ Nitrogen, data = data_df[which(data_df$TRY ==
        "Raw"), ]))[["coefficients"]][1, 1]
    Output[[26]] <- summary(lm(Memory ~ Nitrogen, data = data_df[which(data_df$TRY ==
        "Raw"), ]))[["coefficients"]][1, 4]
    Output[[27]] <- summary(lm(Memory ~ Nitrogen, data = data_df[which(data_df$TRY ==
        "Raw"), ]))[["coefficients"]][2, 1]
    Output[[28]] <- summary(lm(Memory ~ Nitrogen, data = data_df[which(data_df$TRY ==
        "Raw"), ]))[["coefficients"]][2, 4]
    Output[[29]] <- summary(lm(Memory ~ Nitrogen, data = data_df[which(data_df$TRY ==
        "Mapped"), ]))[["coefficients"]][1, 1]
    Output[[30]] <- summary(lm(Memory ~ Nitrogen, data = data_df[which(data_df$TRY ==
        "Mapped"), ]))[["coefficients"]][1, 4]
```

```r
        Output[[31]] <- summary(lm(Memory ~ Nitrogen, data = data_df[which(data_df$TRY ==
            "Mapped"), ]))[["coefficients"]][2, 1]
        Output[[32]] <- summary(lm(Memory ~ Nitrogen, data = data_df[which(data_df$TRY ==
            "Mapped"), ]))[["coefficients"]][2, 4]
    }
    return(Output)
}
```

Chunk 35: Linear regression coefficients of TRY data and vegetation memory coeffcients.

```r
TryTab <- function(ModelCoeffs, SoilLayer, Region) {
    ModelCoeffs <- unlist(ModelCoeffs)
    tabout <- data.frame(Column = ModelCoeffs[1:4])
    starts <- seq(1, length(ModelCoeffs), by = 4)
    for (i in 2:(length(ModelCoeffs)/4)) {
        tabout <- cbind(tabout, ModelCoeffs[starts[i]:(starts[i] + 3)])
    }
    colnames(tabout) <- rep(c("R", "M"), 4)
    rownames(tabout) <- c("Intercept", "$p_{Intercept}$", "Slope", "$p_{Slope}$")
    Short <- paste("PFTs and Qsoil", SoilLayer, " Memory (", Region, ")", sep = "")
    Long <- paste("Coefficients of linear regressions of Qsoil", SoilLayer, " memory coefficients against PFT data
              (vegetative height H, and leaf nitrogen mass Nmass) both as raw geo-referenced data (R),
              and extended maps of species-specific trait means (M).
              Established via \\ref{rTRYresTab}.",
        sep = "")
    kab <- kable(tabout, booktabs = TRUE, caption = paste("\\textbf{", Short, " -} ",
        Long, sep = ""), caption.short = Short, escape = FALSE, format = "latex")
    kab <- add_header_above(kable_input = kab, header = c(` ` = 1, H = 2, Nmass = 2,
        H = 2, Nmass = 2), italic = FALSE, align = "c")
    kab <- add_header_above(kable_input = kab, header = c(` ` = 1, Qsoil = 4, Lag = 4),
        bold = TRUE, align = "c")
    kab <- kable_styling(kab, latex_options = c("hold_position"))
    print(kab)
}
```

Chunk 36: Overview of linear regression coefficients of TRY data and vegetation memory coeffcients.

```r
PFTTab <- function(ModelCoeffs, Region, Data) {
    # Outputs of Tryres to ModelCOeffs
    tabout <- data.frame(Column = ModelCoeffs[1:4])
    starts <- seq(1, length(ModelCoeffs), by = 4)
    for (i in 2:(length(ModelCoeffs)/4)) {
        tabout <- cbind(tabout, ModelCoeffs[starts[i]:(starts[i] + 3)])
    }
    colnames(tabout) <- rep(c("H", "$N_{mass}$"), 6)
    rownames(tabout) <- c("Intercept", "$p_{Intercept}$", "Slope", "$p_{Slope}$")
    Short <- paste(Data, " PFTs and Vegetation Memory (", Region, ")", sep = "")
    Long <- paste("Linear regression coefficients of vegetative height (H) and leaf nitrogen mass (Nmass) against
              vegetation memory coefficients.
              Established via \\ref{rPFTTab}.",
        sep = "")
    kab <- kable(tabout, booktabs = TRUE, caption = paste("\\textbf{", Short, " -} ",
        Long, sep = ""), caption.short = Short, escape = FALSE, format = "latex")
    kab <- add_header_above(kable_input = kab, header = c(` ` = 1, `t-1` = 2, Tair = 2,
        `1` = 2, `2` = 2, `3` = 2, `4` = 2), italic = TRUE, align = "c")
    kab <- add_header_above(kable_input = kab, header = c(` ` = 5, Qsoil = 8), bold = TRUE,
        align = "c")
    kab <- kable_styling(kab, latex_options = c("hold_position"))
    print(kab)
}
```

A.5.6 Miscellaneous Figures

Chunk 37: Producing miscellaneous figures used for flow charts and scheme overviews.

```r
rm(list = ls())  # clearing environment
####--------------- PACKAGES ----
source("Y - Codes/S0a_Packages.R")  # loading packages
####--------------- DIRECTORIES ----
source("Y - Codes/S0b_Directories.R")  # setting directories
####--------------- FUNCTIONS ----
source("Y - Codes/S0c_Functions.R")  # Loading miscellaneous functions

## MEMORY COMPONENT SCHEMATIC -----
cell <- 34881
RegionFile <- "Iberian Region"
From <- 1982
To <- 2015
Lags <- 0:12
Yearvec <- rep(c(1982:2015), each = 12)
Time <- paste("1", (From - 1), "_12", To, sep = "")
DetVars <- c("NDVI", "Qsoil1", "Qsoil2", "Qsoil3", "Qsoil4", "Tair")
Dir.Memory.Reg <- paste(Dir.Memory, "/", RegionFile, "-", From - ceiling(1/12 * max(Lags)),
    "_", To, sep = "")
# Era5
Environment <- list.files(Dir.ERA.Monthly)
EnvRegion <- Environment[grep(RegionFile, Environment)]
EnvRegion <- EnvRegion[grep(Time, EnvRegion)]
setwd(Dir.ERA.Monthly)
Qsoil1 <- brick(EnvRegion[1])
Qsoil2 <- brick(EnvRegion[2])
Qsoil3 <- brick(EnvRegion[3])
Qsoil4 <- brick(EnvRegion[4])
Tair <- brick(EnvRegion[5])
# NDVI
Vegetation <- list.files(Dir.Gimms.Monthly)
VegRegion <- Vegetation[grep(RegionFile, Vegetation)]
setwd(Dir.Gimms.Monthly)
NDVI <- brick(VegRegion[1])
NDVI <- NDVI[[c(as.numeric(min(which(Yearvec == From)):max(which(Yearvec == To))))]]
setwd(mainDir)
# Memory
Memory <- list.files(Dir.Memory)
Memory <- Memory[grep(RegionFile, Memory)]
Memory <- Memory[grep(paste(From - ceiling(1/12 * max(Lags)), To, sep = "-"), Memory)]
## Plotting Frames
cells <- adjacent(NDVI, cells = cell, directions = 8, include = TRUE)
cells <- cells[10:18]
NDVI_vec <- as.numeric(apply(NDVI[cells], 2, mean))
NDVI_df <- data.frame(NDVI = c(as.numeric(NDVI_vec)))
NDVI_df <- transform(NDVI_df, DeNDVI = c(detrend(NDVI, tt = "linear")))
Data_df <- data.frame(Qsoil1 = as.numeric(apply(Qsoil1[cells], 2, mean)), Qsoil2 = as.numeric(apply(Qsoil2[cells],
    2, mean)), Qsoil3 = as.numeric(apply(Qsoil3[cells], 2, mean)), Qsoil4 = as.numeric(apply(Qsoil4[cells],
    2, mean)), Tair = as.numeric(apply(Tair[cells], 2, mean)))
# Data Manipulation
Data_df <- transform(Data_df, NDVI = c(NDVI_df$NDVI, rep(NA, 12)), DeNDVI = c(NDVI_df$DeNDVI,
    rep(NA, 12)), DeQsoil1 = detrend(Qsoil1, tt = "linear"), DeQsoil2 = detrend(Qsoil2,
    tt = "linear"), DeQsoil3 = detrend(Qsoil3, tt = "linear"), DeQsoil4 = detrend(Qsoil4,
    tt = "linear"), DeTair = detrend(Tair, tt = "linear"))  # linear detrending)
Data_df <- as.data.frame(cbind(Data_df[, 6], Data_df[, c(1:5, 7:12)]))
```

```r
colnames(Data_df)[1] <- "NDVI"
Data_df$Qsoil1 <- c(Data_df$Qsoil1[c(-1, -2)], NA, NA)
Data_df1 <- Data_df[1:24, ]
## Intrinsic
Intrinsic_df <- data.frame(Data = Data_df1$NDVI, Variable = rep("Response", dim(Data_df1)[1]),
    Time = rep(1:dim(Data_df1)[1], 1))
ggplot(data = Intrinsic_df, aes(x = Time, y = Data, color = Variable)) + geom_line() +
    theme_bw() + geom_point() + scale_colour_manual(values = c("darkgreen")) + ggtitle("Intrinsic Memory") +
    xlab("Time [months]")
## Extrinsic
Extrinsic_df <- data.frame(Data = c(Data_df1$NDVI, Data_df1$Qsoil1), Variable = c(rep("Response",
    dim(Data_df1)[1]), rep("Extrinsic", dim(Data_df1)[1])), Time = rep(1:dim(Data_df1)[1],
    2))
ggplot(data = Extrinsic_df, aes(x = Time, y = Data, color = Variable)) + geom_line() +
    theme_bw() + geom_point() + scale_colour_manual(values = c("blue", "darkgreen")) +
    ggtitle("Extrinsic Memory") + xlab("Time [months]")

## KRIGING SCHEMATIC ----- data
setwd(Dir.ERA.Monthly)
tairf <- brick(list.files()[15])
setwd(Dir.ERA)
tairr <- brick(list.files()[5])
# cropping
Shapes <- readOGR(Dir.Mask, "ne_50m_admin_0_countries", verbose = FALSE)
RegObj <- RegionSelection(Region = c("Portugal", "Spain", "France", "Andorra"), RegionFile = "Iberian Region",
    Extent = extent(-10, 10, 35, 52))
area <- RegObj[[1]]
location <- RegObj[[2]]
RegionFile <- RegObj[[3]]
rasinter <- crop(tairr, area)  # cropping to extent
tairr <- mask(rasinter, Shapes[location, ])  # masking
# plotting
col.tair <- colorRampPalette(c("blue", "turquoise", "yellow", "orange", "red"))(100)
plot(tairr[[1]], colNA = "black", main = paste("Tair January 1981"), cex.main = 1.5,
    legend.width = 2, legend.shrink = 1, axis.args = list(cex.axis = 1.5), cex.axis = 1,
    col = col.tair, axes = TRUE, legend = TRUE)
plot(tairf[[1]], colNA = "black", main = paste("Tair January 1981"), cex.main = 1.5,
    legend.width = 2, legend.shrink = 1, axis.args = list(cex.axis = 1.5), cex.axis = 1,
    col = col.tair, axes = TRUE, legend = TRUE)

## MODEL SCHEMATIC -----
load(paste(Dir.Data, "ModData_df.RData", sep = "/"))  # model data for pixel 35363 in Iberian rasters
## location plot
IbRas <- mean(brick(paste(Dir.Gimms.Monthly, list.files(Dir.Gimms.Monthly)[10], sep = "/")))
cells <- adjacent(IbRas, cells = 35363, directions = 8, include = TRUE)
cells <- cells[10:18]
Cellras <- IbRas
values(Cellras)[cells] <- 8888
values(Cellras)[which(values(Cellras) != 8888)] <- NA
plot(IbRas, colNA = "black", main = "Examplatory Raster Cells", cex.main = 1.5, legend = FALSE,
    legend.width = 1, legend.shrink = 1, axis.args = list(cex.axis = 1), cex.axis = 1)
plot(Cellras, col = "red", add = TRUE, legend = FALSE, axis.args = list(cex.axis = 1),
    cex.axis = 1)
## NDVI series
plot_df <- data.frame(Months = rep(1:dim(ModData_df)[1], 2), NDVI = c(ModData_df$`NDVI_anom[1:length(Clim2_anom)]`,
    ModData_df$`NDVI_Lag1[1:length(Clim2_anom)]`), Data = c(rep("Z-Scores", dim(ModData_df)[1]),
    rep("t-1", dim(ModData_df)[1])))
ggplot(plot_df, aes(x = Months, y = NDVI, col = Data)) + geom_line(size = 1.2) +
```

```r
    theme_bw() + labs(title = "NDVI time series")
## Cummulative soil moisture lags
plot_df <- with(ModData_df, data.frame(Months = rep(1:dim(ModData_df)[1], 1), Qsoil = c(ClimCum_6)))
ggplot(plot_df, aes(x = Months, y = Qsoil)) + geom_line(col = "navyblue", size = 1.2) +
    theme_bw() + labs(title = "Cummulative Soil Moisture (0-7cm) Lag 6")
## Tair
plot_df <- with(ModData_df, data.frame(Months = rep(1:dim(ModData_df)[1], 1), Qsoil = Clim2_anom))
ggplot(plot_df, aes(x = Months, y = Qsoil)) + geom_line(col = "red", size = 1.2) +
    theme_bw() + labs(title = "Air Temperature")
## PCA
biplot(princomp(pca_mat))
```

A.6 Declaration Of Authorship

I, Erik Kusch, hereby declare that this thesis and the work presented in it is entirely my own. Where I have consulted the work of others, this is always clearly stated.

Erik Kusch

____
Signature

____
Date