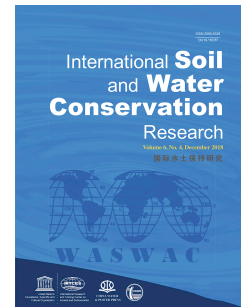


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MEDALUS-R: A revised framework for large-scale spatiotemporal assessment of desertification susceptibility

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Abstract

Desertification remains a persistent environmental challenge in Europe with direct implications for the EU's 2030 sustainability objectives, driven by interacting climatic, biophysical, and human factors. Most existing assessment frameworks, however, rely on static representations, predefined indicator thresholds, or lack an explicit treatment of temporal dynamics and policy-related dimensions. This study introduces MEDALUS-R, a revised, data-driven framework for the spatiotemporal assessment of climate-conditioned desertification susceptibility at the continental scale. MEDALUS-R conceptualizes susceptibility as a continuous spatial property emerging from the interaction of climatic stress, intrinsic land sensitivity, human pressure, and mitigation potential. Using harmonized multi-decadal datasets, objective indicator weighting, and unsupervised parameter optimization, desertification susceptibility is assessed for 37 European countries at 1-km resolution across three consecutive decades spanning 1996–2025. Results indicate that desertification susceptibility across Europe is spatially structured and evolves primarily through gradual intensification within established susceptibility regimes, with higher susceptibility and stronger intensification concentrated in Mediterranean and climatic transition zones. Climatic stress exhibits the strongest spatial association with long-term susceptibility increases, while mitigation-related conditions partially moderate intensification patterns and intrinsic land properties condition regional variability. Sensitivity analysis reveals coherent spatial patterns alongside increasing uncertainty under intensifying conditions, reflecting heightened system responsiveness rather than reduced model robustness. By extending MEDALUS to a multi-temporal, climate-conditioned framework and explicitly incorporating mitigation- and policy-relevant components, MEDALUS-R provides a transparent and adaptable basis for continental-scale monitoring and comparative assessment of desertification susceptibility, supporting soil protection and land degradation neutrality strategies in Europe.

Keywords: Land degradation, Climate adaptation, Land degradation neutrality, EU Soil Monitoring Law, Policy, Sustainability.

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1. Introduction

Land constitutes an integrated terrestrial bioproductive system, composed of soils, vegetation, associated biota, and the ecological and hydrological processes that sustain their structure and function (United Nations Convention to Combat Desertification (UNCCD), 1994)(United Nations Convention to Combat Desertification (UNCCD), 1994)(United Nations Convention to Combat Desertification (UNCCD), 1994). Alteration of this system through land degradation progressively undermines ecological integrity, primary productivity, biodiversity, and ecosystem services, generating cascading impacts across terrestrial environments (IPBS, 2018; Reynolds et al., 2007). In line with its etymological origin in the Latin *dēgradātiō* — denoting a downward progression or loss of status — land degradation generally involves a decline in functional capacity, which may occur gradually or through abrupt threshold-driven state shifts. At the international policy level, land degradation received its first explicit global recognition at the 1977 United Nations Conference on Desertification, reflecting growing awareness of widespread declines in land productivity and ecosystem performance (UNCOD, 1977; United Nations Convention to Combat Desertification (UNCCD), 1994)(UNCOD, 1977; United Nations Convention to Combat Desertification (UNCCD), 1994)(UNCOD, 1977; United Nations Convention to Combat Desertification (UNCCD), 1994). Following its incorporation into Agenda 21, land degradation was formally defined under the United Nations Convention to Combat Desertification (UNCCD) in 1994 as the “*reduction or loss, in arid, semi-arid and dry sub-humid areas, of the biological or economic productivity and complexity of rainfed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from land uses or from a process or combination of processes, including processes arising from human activities and habitation patterns*” (United Nations Convention to Combat Desertification (UNCCD), 1994)(United Nations Convention to Combat Desertification (UNCCD), 1994)(United Nations Convention to Combat Desertification (UNCCD), 1994). While this definition was instrumental in mobilizing political action, its explicit restriction to drylands introduced a lasting conceptual ambiguity between land degradation as a general process and desertification as its specific manifestation within dryland environments. Within the

UNCCD framework (IPCC, 2019), desertification is treated as land degradation occurring in drylands, while degradation processes themselves operate across climatic zones. In this study, desertification susceptibility is analysed within an analytical, modelling-oriented perspective in which climatic conditions define the environmental context of susceptibility, while degradation processes and anthropogenic pressures determine whether and how susceptibility is expressed. This distinction is particularly relevant in Europe, where degradation drivers such as soil erosion, nutrient depletion, and soil organic carbon decline are widespread in humid and temperate regions, including Northern Europe (Afshar et al., 2025), which are not climatically susceptible to desertification. Building on this foundation, the UNCCD has further developed operational frameworks for desertification assessment and monitoring, particularly through the concept of Land Degradation Neutrality (LDN) (UNCCD, 2016) and its associated indicator-based reporting system under Sustainable Development Goal 15.3.1 (UNCCD, 2017). These frameworks rely on harmonized indicators of land productivity, land cover change, and soil organic carbon to enable consistent monitoring and reporting of land degradation trends at national and global scales (UNCCD, 2016, 2017). In this context, spatially explicit susceptibility assessments can support the interpretation of indicator-based results and the spatial prioritization of interventions within LDN monitoring frameworks.

This ambiguity has shaped the development of numerous assessment approaches since the 1990s, including the MEDALUS Project (Mediterranean Desertification and Land Use) (CORDIS, 2024), developed in the context of the Rio process and the early implementation of the UNCCD (Kosmas et al., 1999). MEDALUS and further developments operationalized desertification sensitivity through the Environmental Sensitive Areas (ESA) framework, integrating climate, soil, vegetation, and land management indicators into a composite index. (Kosmas et al., 1999; Právělie et al., 2017; Salvati and Bajocco, 2011). While effective in identifying spatial patterns of desertification sensitivity in Mediterranean environments and widely applied in subsequent studies, its underlying conceptual structure has remained largely unchanged since its development in the late 1990s, reflecting the data and methodological constraints of that period (Kosmas et al., 1999; Právělie et al., 2017; Salvati & Bajocco, 2011).

In this context, while MEDALUS-R builds on the ESAI tradition, it extends beyond a simple data or indicator update through a methodological and operational reorganization of the framework, including the explicit separation of climatic conditioning, intrinsic susceptibility, and anthropogenic modulation, a non-compensatory multiplicative formulation, and a data-driven parameterization strategy. These elements refine how susceptibility is represented and operationalized at large scale. A detailed comparison between MEDALUS and MEDALUS-R is provided in the Supplementary Information (S2. Conceptual advances of MEDALUS-R).

Despite the proliferation of alternative methodologies (Shokri et al., 2025), including LADA (FAO, 2011), and DesertWatch (Pace et al., 2007) no single framework has emerged as a universal standard for land degradation assessment (Karamesouti et al., 2018; Kirkby et al., 2008; Liniger et al., 2017; Sepehr & Zucca, 2012). In parallel, alternative conceptual and methodological approaches have been proposed, including frameworks based on desertification syndromes (Stellmes et al., 2013), convergence of evidence from multiple degradation indicators (Gianoli et al., 2023), and integrated socio-ecological system analysis emphasizing coupled human–environment dynamics (Reynolds et al., 2011). While these approaches provide important advances in representing process complexity and multi-dimensional evidence, they also offer complementary perspectives that can enrich large-scale assessments, particularly when combined with spatially explicit susceptibility frameworks. Nevertheless, MEDALUS remains among the most widely applied approaches for evaluating desertification sensitivity in Europe (European Court of Auditors, 2018), owing to its conceptual simplicity, flexibility, and adaptability to diverse data sources (Ferrara et al., 2020; Salvati et al., 2016). Its robustness is reflected in numerous refinements, including the integration of remote sensing products, updated climate datasets, and alternative weighting schemes (Adesina & Muhammad, 2023; Právělie et al., 2020; Salvati et al., 2011).

However, most existing implementations primarily involve data updates or indicator refinements, while the core conceptual assumptions and aggregation logic of the framework have remained largely unchanged. This is particularly evident in reassessments based on improved climate (aridity) data, which have shown

that earlier estimates, derived using a geospatial method (DISMED) inspired by MEDALUS, substantially underestimated the extent of highly sensitive areas in Europe, revealing rapid expansions of land with high and very high desertification sensitivity within approximately a decade (Právělie et al., 2017).

[illegible]

United Nations Convention to Combat Desertification (UNCCD), 1994)(IPCC, 2019; United Nations Convention to Combat Desertification (UNCCD), 1994).

In this study, we introduce MEDALUS-R, a revised operationalization of the MEDALUS framework designed to assess desertification susceptibility across Europe through a hierarchical and integrative structure. Beyond a data update, MEDALUS-R introduces methodological and structural refinements aimed at improving how MEDALUS-based susceptibility is represented and operationalized at continental scale. Susceptibility is represented as a continuous, climate-conditioned spatial property, while desertification itself remains defined within dryland environments. While remaining conceptual in scope, the framework provides a more explicit organization of climatic, biophysical, and anthropogenic domains. As a result, susceptibility is interpreted as an integrated response to climatic conditions, intrinsic land properties, and anthropogenic modulation, rather than as a direct representation of causal system dynamics. The framework is organized around three interacting domains: (i) climatic conditions, defining the environmental context within which desertification susceptibility is assessed; (ii) natural land susceptibility, reflecting intrinsic soil and vegetation properties that regulate system sensitivity; and (iii) human influence, expressed through the balance between human-induced augmentation (capturing land-use intensity, management practices, and disturbance regimes) and human mitigation potential (representing the capacity of conservation measures, sustainable management, and governance to reduce anthropogenic pressure). By explicitly distinguishing climatic context, intrinsic biophysical sensitivity, and anthropogenic modulation (separating human pressure from mitigation potential), MEDALUS-R enables a coherent assessment of spatial and temporal susceptibility patterns across Europe, while preserving the UNCCD distinction between broader land degradation and desertification within drylands. To address limitations identified in previous implementations, MEDALUS-R adopts a data-driven weighting and parameterization strategy, reducing reliance on subjective assumptions and allowing model structure and weighting to emerge from the underlying data. In this perspective, the framework is consistent with ongoing efforts to improve the transparency and comparability of land degradation assessments and can contribute as a complementary,

spatially explicit tool within the broader context of Land Degradation Neutrality (LDN) monitoring frameworks, without replacing established indicator-based approaches.

2. Material and Methods

2.1. Conceptual Scheme

MEDALUS-R is a climate-conditioned, susceptibility-based framework designed to assess desertification susceptibility as a continuous spatial property across Europe. Building on the original MEDALUS Environmental Sensitive Areas (ESA) framework, the proposed approach explicitly distinguishes between (i) climatic conditioning, (ii) intrinsic biophysical susceptibility, and (iii) anthropogenic modulation, distinguishing climatic conditioning within the susceptibility assessment while retaining the UNCCD definition of desertification as land degradation occurring in drylands.

MEDALUS-R reorganizes the original MEDALUS structure into distinct, non-substitutable domains while retaining a multiplicative composite-index formulation. Desertification susceptibility is represented through four components: Climate Quality Index (CQI), Natural Land Susceptibility (NLS), Human Pressure (HP), and Mitigation Potential (MP). CQI defines the climatic context, NLS represents intrinsic biophysical sensitivity, and the HP/MP ratio represents net anthropogenic modulation by balancing pressure against mitigation capacity. This separation distinguishes intrinsic land sensitivity from anthropogenic pressure and mitigation processes while preserving their interaction within a unified susceptibility framework. The methodological advance therefore lies in the organization, weighting, parameterization, and interpretation of these domains rather than in introducing a fundamentally different mathematical family. Accordingly, desertification susceptibility index (SDI) is defined as:

$$SDI = CQI^{\alpha} \cdot NLS^{\beta} \cdot (HP/MP)^{\gamma}$$

(1)

where α , β , and γ are non-negative scaling exponents regulating the relative contribution of climatic conditions, intrinsic biophysical susceptibility, and anthropogenic modulation, respectively. All component indices are normalized and rescaled to the interval $[1, 2]$ (see Section 2.2, Normalization of Indicators), ensuring strictly positive values and preventing division-by-zero or numerical instability in the multiplicative aggregation.

The multiplicative structure limits compensation among components. Aggregation is performed pixel-wise on a common 1-km grid, with lower-level indices contributing to SDI only through their respective components. The scaling exponents α , β , and γ were not prescribed *a priori*. Instead, they were estimated through an unsupervised, data-driven optimization that balances spatial discrimination, temporal robustness, and stability in the absence of reference degradation data. This strategy avoids subjective parameter tuning and ensures that the relative influence of climatic conditions, intrinsic land susceptibility, and anthropogenic modulation emerges from the spatial and temporal structure of the input data rather than from expert-defined assumptions. In this sense, the resulting parameterization should be interpreted as data-driven rather than process-based. While this approach enables a consistent and stable representation of component interactions at large scale, it does not rely on independent validation against observed degradation processes. This reflects current data limitations at the continental scale and is further discussed among the methodological limitations (Section 4.4). To ensure numerical stability during ratio computation and exponentiation, a small positive constant was applied uniformly to the denominator of the HP/MP term to prevent division by zero and extreme ratios, thereby preserving the relative ordering of susceptibility values while ensuring robust numerical behavior across the full spatial domain.

Components are derived hierarchically from standardized indicators (indicators > indices > components), providing a parsimonious and interpretable structure for continental-scale assessment.

Following component computation, desertification susceptibility was calculated independently for each of the three analysis periods (1996–2005, 2006–2015, and 2016–2025) using identical indicators, normalization bounds, and parameter values, thereby ensuring full temporal comparability.

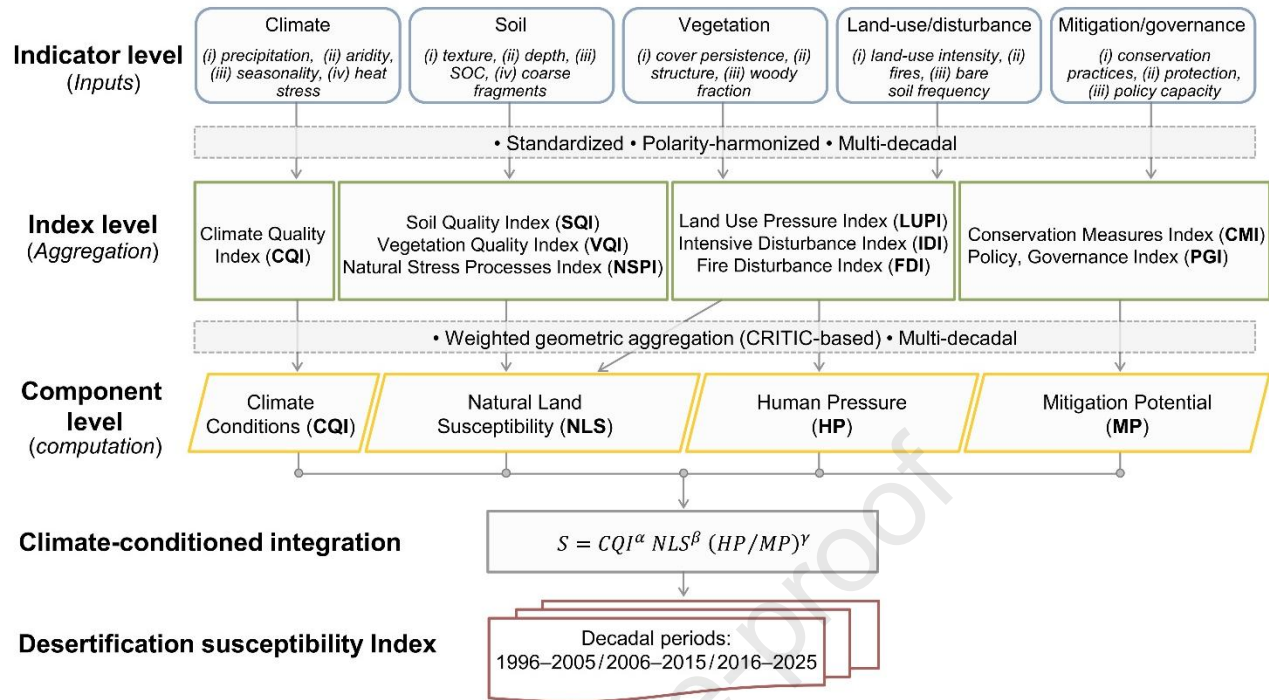


Figure 1. **Conceptual workflow of the MEDALUS-R framework.** The framework integrates harmonized multi-decadal indicators into four non-substitutable susceptibility components: climatic conditions (CQI), natural land susceptibility (NLS), human pressure (HP), and mitigation potential (MP). Indicators are standardized and aggregated hierarchically prior to component construction. Desertification susceptibility is formulated as a climate-conditioned multiplicative interaction among components and computed consistently across three consecutive decadal periods, enabling spatially explicit and temporally comparable assessment at the continental scale.

2.2. Normalization of Indicators

All indicators (third hierarchical level) were standardized prior to aggregation to ensure directional consistency, temporal comparability, and numerical stability across components and decadal periods. Normalization was based on pooled multi-decadal distributions, preventing artificial temporal shifts associated with decade-specific scaling and ensuring that observed changes reflect genuine environmental dynamics rather than methodological artefacts.

Indicator polarity was harmonized so that higher values consistently represent poorer environmental conditions or higher desertification susceptibility. For indicators whose original interpretation implied

improving conditions with increasing values, polarity inversion was applied after normalization to maintain interpretative coherence across the framework. Polarity conventions were defined at the indicator level and applied consistently across all spatial locations and periods.

Indicator normalization was performed using percentile-based min–max scaling. For a given raw indicator X , normalized values X_n were computed as:

$$X_n = \frac{X - P_5}{P_{95} - P_5} \quad (2)$$

where P_5 and P_{95} denote the 5th and 95th percentiles of the indicator's pooled distribution across all decadal periods. Values outside this range were truncated to the $[0, 1]$ interval. The use of the 5th–95th percentile range was intended to limit the influence of extreme values and potential outliers, thereby supporting more robust and stable scaling across spatially heterogeneous conditions and time periods. This approach preserves relative spatial differentiation within the central distribution while reducing the impact of extreme observations.

For indicators requiring polarity inversion, harmonized values X_h were obtained as:

$$X_h = 1 - X_n \quad (3)$$

Because subsequent aggregation relies on multiplicative operations, all harmonized indicators were transformed into an aggregation space bounded away from zero to prevent numerical instability during ratio-based and exponentiated calculations. Aggregation-space values X_a were defined as:

$$X_a = 1 + X_h \quad (4)$$

yielding indicator values in the interval [1, 2]. These transformed indicators constitute the inputs for index construction and component aggregation.

Normalization, polarity harmonization, and aggregation-space transformation were applied independently to each indicator prior to index construction. Normalization bounds, polarity conventions, and aggregation rules were applied identically across all decadal periods (1996–2005, 2006–2015, and 2016–2025), ensuring that temporal differences in indices or components reflect changes in underlying conditions rather than scaling or methodological effects.

2.3. Susceptibility Components

2.3.1. Component structure and indicator weighting

Desertification susceptibility in MEDALUS-R is represented by four non-substitutable components (Climate, Natural Land Susceptibility, Human Pressure, and Mitigation Potential), which serve as complementary proxies for climatic conditioning, intrinsic biophysical sensitivity, anthropogenic pressure, and mitigation capacity, respectively. Each component is computed independently for every decadal period using the standardized indicators defined above, and aggregated using weighted geometric means, a formulation that limits compensatory effects among constituent dimensions.

Objective indicator weighting was performed using the CRITIC (CRiteria Importance Through Intercriteria Correlation) method (Diakoulaki et al., 1995)(Diakoulaki et al., 1995)(Diakoulaki et al., 1995). CRITIC was applied at the indicator level within each index, assigning higher weights to indicators exhibiting both high spatial variability and low redundancy with other indicators. Inter-indicator correlations were evaluated to assess potential redundancy (Supplementary Material S1; Fig. S1 and Table S1) and were generally low to moderate, with no pairwise $|r| > 0.85$. Because CRITIC assigns lower weights to highly correlated variables, this procedure further limits redundancy and potential double-counting within each index. Weights were computed separately for each index using pooled multi-decadal indicator distributions, ensuring temporal consistency and preventing decade-specific bias.

Formally, the CRITIC weight w_j of indicator j is defined as:

$$w_j = \sigma_j \sum_{k=1}^m (1 - \rho_{jk})$$

(5)

where σ_j is the standard deviation of indicator j across the pooled spatial domain, ρ_{jk} denotes the Pearson correlation coefficient between indicators j and k , and m is the total number of indicators within the corresponding index. Weights are subsequently normalized such that $\sum w_j = 1$ prior to aggregation.

2.3.2. Climate

Climate is treated as the primary conditioning domain of susceptibility. Consistent with the UNCCD distinction based on dryland conditions, MEDALUS-R represents climatic constraint continuously across gradients using the Climate Quality Index (CQI), retaining established MEDALUS terminology for comparability.

CQI retains the climatic logic of MEDALUS while limiting redundancy and representing key stress mechanisms (Table 1). Potential evapotranspiration (PET) was not included separately because it is incorporated in the aridity index (AI), which combines precipitation and atmospheric demand. The Precipitation Concentration Index (PCI) captures intra-annual rainfall concentration relevant to runoff, soil moisture, and erosion, while heat-stress frequency (H) replaces mean temperature to better represent threshold-related thermal and evaporative stress.

Climatic variables were derived from the ERA5-Land post-processed reanalysis dataset (Hersbach et al., 2020; Muñoz-Sabater et al., 2021)(Hersbach et al., 2020; Muñoz-Sabater et al., 2021)(Hersbach et al., 2020; Muñoz-Sabater et al., 2021). Monthly aggregates were used for precipitation structure metrics, while daily ERA5-Land data were used to derive mean annual precipitation, aridity conditions, and heat-stress

frequency based on maximum temperature. CQI was computed independently for three consecutive decadal periods (1996–2005, 2006–2015, and 2016–2025).

CQI was computed as the geometric mean of the four climatic indicators:

$$CQI = (P_a \cdot AI_a \cdot PCI_a \cdot H_a)^{1/4}$$

(6)

where P_a , AI_a , PCI_a , and H_a denote aggregation-space values obtained after normalization and directional harmonization (Section 2.2), and $n = 4$ represents the number of indicators included in the index.

AI was defined as the ratio between mean annual precipitation and mean annual potential evapotranspiration (IPCC, 2019; UNEP, 1997)(IPCC, 2019; UNEP, 1997)(IPCC, 2019; UNEP, 1997):

$$AI = \frac{P}{PET}$$

(7)

PCI was computed following (Oliver, 1980)(Oliver, 1980)(Oliver, 1980) as:

$$PCI = 100 \cdot \frac{\sum_{m=1}^{12} p_m^2}{(\sum_{m=1}^{12} p_m)^2}$$

(8)

where p_m denotes monthly precipitation totals.

H was quantified as the proportion of days within each analysis period for which daily maximum air temperature exceeded 35°C, a threshold commonly associated with severe thermal stress in terrestrial systems (IPCC, 2019)(IPCC, 2019)(IPCC, 2019):

$$H = \frac{N_{\text{hot}}}{N_{\text{day}}}$$

298

(9)

299 where N_{hot} denotes the number of days with daily maximum temperature exceeding 35 °C and N_{day} denotes
 300 the total number of valid days in the corresponding period.

301 All climatic indicators were normalized, directionally harmonized, and transformed into aggregation space
 302 following Section 2.2, ensuring that higher CQI values consistently indicate poorer climatic conditions.
 303 CQI acts as the primary climatic conditioning component in the susceptibility framework and directly
 304 contributes to desertification susceptibility through multiplicative aggregation with the remaining
 305 susceptibility components (Eq. 1).

306 Table 1. Structure and indicators of the Climate component (Climate Quality Index, CQI) in the MEDALUS-R
 307 framework. CQI represents the primary climatic conditioning domain of desertification susceptibility and integrates
 308 indicators describing water availability (P), atmospheric demand (AI), rainfall temporal structure (PCI), and thermal
 309 stress (H).

Component	Index	Indicator	Climatic dimension	Role in desertification susceptibility	Data used/source
Climate Quality Index (CQI)	-	Mean annual precipitation (P)	Absolute water supply	Represents long-term moisture availability supporting ecosystem functioning	ERA5-Land reanalysis: daily precipitation aggregated to annual means (Hersbach et al., 2020; Muñoz-Sabater et al., 2021)
		Aridity index (AI)	Supply versus atmospheric demand	Captures climatic moisture constraint relative to potential evapotranspiration	ERA5-Land reanalysis: mean annual precipitation and potential evapotranspiration (Hersbach et al., 2020; Muñoz-Sabater et al., 2021)

		Precipitation Concentration Index (PCI)	Temporal precipitation structure	Describes rainfall concentration and implications for runoff efficiency and soil moisture recharge	ERA5-Land reanalysis: monthly precipitation totals (Hersbach et al., 2020; Muñoz-Sabater et al., 2021)
		Heat-stress frequency (H)	Thermal stress	Represents physiological and evaporative stress associated with extreme temperature conditions	ERA5-Land reanalysis: daily maximum air temperature (Tmax > 35 °C) (Hersbach et al., 2020; Muñoz-Sabater et al., 2021)

2.3.3. Natural Land Susceptibility

Natural Land Susceptibility (NLS) serves as an integrated proxy for the intrinsic biophysical sensitivity of land systems to desertification under given climatic conditions, reflecting long-term soil and vegetation characteristics as well as exposure to climate-driven surface stress processes. These properties integrate the cumulative effects of past land use and disturbance but do not explicitly represent current anthropogenic pressure or management intensity, which are addressed separately within the Human Pressure (HP) and Mitigation Potential (MP) components.

In MEDALUS-R, NLS is quantified through three complementary indices: the Soil Quality Index (SQI), the Vegetation Quality Index (VQI), and the Natural Stress Processes Index (NSPI) (Table 2). SQI captures intrinsic soil constraints affecting water storage and structural stability; VQI represents vegetation persistence, structural development, and functional composition; and NSPI characterizes exposure to climate-driven water and wind erosion processes. Together, these indices describe the inherent sensitivity of land systems prior to anthropogenic modulation.

NLS was obtained by aggregating SQI, VQI, and NSPI using geometric aggregation, following the normalization, directional harmonization, and transformation procedures described in Section 2.2, where $n = 3$ represents the number of components included in the index:

$$NLS = (SQI \cdot VQI \cdot NSPI)^{1/3}$$

(10)

Higher NLS values indicate greater intrinsic biophysical susceptibility to desertification, reflecting unfavorable soil properties, reduced vegetation resilience, and stronger exposure to climate-driven stress processes. NLS was computed independently for each decadal period using identical indicators and aggregation rules, ensuring full temporal comparability.

Table 2. Structure and indicators of the Natural Land Susceptibility (NLS) component in the MEDALUS-R framework. NLS integrates soil properties (SQI), vegetation characteristics (VQI), and exposure to natural stress processes (NSPI) to represent the intrinsic biophysical sensitivity of land systems to desertification under given climatic conditions.

Component	Index	Indicator	Biophysical dimension	Role in desertification susceptibility	Data used/source
Natural Land Susceptibility (NLS)	Soil Quality Index (SQI)	Effective fine-earth soil depth (SD_{fe})	Soil volume and water storage	Limits rooting depth and available water capacity	SoilGrids soil depth to bedrock (Hengl et al., 2017); LUCAS topsoil coarse fragment content (Ballabio et al., 2016)
		SOC-to-clay ratio (R_{sc})	Soil structural stability	Mitigates porosity and aggregate stability for resistance to erosion and	SoilGrids 2.0 soil organic carbon (Poggio et al., 2021); LUCAS topsoil clay content (Ballabio et al., 2016)

				root penetration capacity	
	Vegetation Quality Index (VQI)	Plant Cover Persistence (PCP)	Temporal continuity of effective cover	Regulates long-term surface protection against exposure	MODIS Vegetation Continuous Fields (VCF), annual fractional vegetation cover (Hansen et al., 2003; Di Miceli et al., 2022)
		Canopy Structural Capacity (CSC)	Canopy development and biomass	Reflects vegetation ability to buffer climatic stress	MODIS Leaf Area Index (MOD15A2H, Collection 6.1)
		Woody Vegetation Fraction (WVF)	Functional vegetation composition	Indicates permanence, rooting depth, and structural protection	MODIS Vegetation Continuous Fields (VCF): tree and non-tree woody vegetation fractions (Hansen et al., 2003; Di Miceli et al., 2022)
	Natural Stress Processes Index (NSPI)	Rainfall erosivity (WEH)	Water- driven surface stress	Represents climatic forcing of water erosion processes	Pan-European rainfall erosivity dataset (Panagos et al., 2015)
		Wind erosion forcing (WF)	Wind-driven surface stress	Represents exposure to climate-driven	ERA5 reanalysis hourly wind speed (Hersbach et al., 2020); RWEQ-based formulation

				wind erosion processes	
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2.3.3.1. Soil Quality Index

The Soil Quality Index (SQI) serves as a proxy for the intrinsic capacity of soils to resist desertification processes by capturing long-term, inherent soil properties that regulate rooting potential, water storage capacity, soil workability, and physical stability. Variables directly related to climatic forcing, land management, or erosion dynamics are intentionally excluded, as these processes are addressed explicitly in other components of the framework. SQI therefore reflects structural and volumetric soil constraints that condition soil resilience at continental scale.

Given the generally slow and spatially coherent evolution of intrinsic soil properties at continental scale, SQI was treated as quasi time-invariant at the spatial and temporal resolution of the analysis and was applied consistently across all three decadal periods (1996–2005, 2006–2015, and 2016–2025). While some soil attributes, particularly soil organic carbon, may exhibit decadal variability and threshold behavior linked to climatic water balance and soil chemical conditions, representing such dynamics explicitly would require time-resolved, process-based soil datasets that are currently unavailable at the pan-European scale.

SQI integrates two complementary soil dimensions: (i) the effective fine-earth soil volume, which determines the amount of soil available for rooting and water storage, and (ii) the structural condition of the fine-earth matrix, which governs aggregate stability and resistance to physical degradation. These dimensions were combined using a geometric mean to limit compensatory effects, where $n = 2$ represents the number of components included in the index:

$$SQI = (SD_{fe} \cdot R_{sc})^{1/2}$$

(11)

The effective fine-earth soil depth (SD_{fe}) was defined as:

$$SD_{fe} = SD \cdot (1 - RF)$$

(12)

where SD is the soil depth to a restrictive layer or bedrock (Poggio et al., 2021)(Poggio et al., 2021)(Poggio et al., 2021) and RF is the volumetric fraction of coarse fragments (>2 mm) derived from the LUCAS topsoil survey (Ballabio et al., 2016)(Ballabio et al., 2016). For non-EU countries, RF values were obtained using extrapolated estimates provided by ESDAC (Panagos et al., 2022)(Panagos et al., 2022) beyond the EU borders. This formulation ensures that both shallow soils and soils with high rock fragment content are represented as having reduced effective soil volume.

The structural condition of the fine-earth matrix (R_{sc}) was quantified using the ratio of soil organic carbon to clay content:

$$R_{sc} = \frac{SOC}{Clay}$$

(13)

where SOC denotes (Poggio et al., 2021)(Poggio et al., 2021) topsoil organic carbon concentration and $Clay$ represents the clay content of the fine-earth fraction. Also in this case, for non-EU countries, RF values were obtained using extrapolated estimates provided by ESDAC (Panagos et al., 2022)(Panagos et al., 2022) beyond the EU borders. A minimum clay threshold was applied prior to ratio computation to ensure numerical stability.

All SQI components were normalized, directionally harmonized, and aggregated following the procedures described in Section 2.2, ensuring that higher SQI values consistently indicate poorer soil quality and higher intrinsic susceptibility to desertification.

2.3.3.2. *Vegetation Quality Index*

The Vegetation Quality Index (VQI) serves as a proxy for the intrinsic biological capacity of vegetation systems to persist and function under prevailing climatic and environmental conditions. VQI captures vegetation structure, persistence, and functional composition, while excluding variables related to disturbance occurrence, land-use pressure, or management intensity, which are addressed explicitly in other components of the framework.

VQI integrates three complementary vegetation dimensions: Plant Cover Persistence (PCP), Canopy Structural Capacity (CSC), and Woody Vegetation Fraction (WVF). These dimensions were combined using a geometric mean to limit compensatory effects and ensure that low performance in any single dimension proportionally constrains overall vegetation quality, where $n = 3$ represents the number of components included in the index:

$$VQI = (PCP \cdot CSC \cdot WVF)^{1/3} \quad (14)$$

For transparency and interpretability, the spatial distributions of the main component indices (CQI, SQI, and VQI) are provided in the Supplementary Material (Fig. S2).

PCP represents the long-term continuity of effective vegetation cover and was quantified as the fraction of years within each analysis period in which vegetation cover exceeded a minimum effective-cover threshold, derived from MODIS Vegetation Continuous Fields products (Di Miceli et al., 2022; Hansen et al., 2003)(Di Miceli et al., 2022; Hansen et al., 2003).

$$FVC = 1 - \frac{\%Non-Vegetated}{100} \quad (15)$$

Vegetation presence was defined as $FVC \geq 0.30$, and PCP was computed as the proportion of valid annual observations meeting this criterion, consistent with the lower bounds of effective vegetation cover commonly used to distinguish protected from unprotected surfaces in MEDALUS-based desertification sensitivity assessments (e.g., Kosmas et al., 1999; Salvati et al., 2011) Kosmas et al., 1999; Salvati et al., 2011). For the first analysis period (1996–2005), WVF was computed using MODIS data available from 2001–2005 to account for product temporal availability and rescaled for consistency with the other two periods.

CSC represents the ability of vegetation to develop and maintain canopy structure and was quantified using the Leaf Area Index (LAI), a widely used proxy for vegetation structural development and canopy density. It was derived from the MODIS LAI product MOD15A2H (Collection 6.1, Di Miceli et al., 2022) Di Miceli et al., 2022) as the mean LAI within each analysis period after quality filtering, retaining only observations meeting standard MODLAND quality criteria. For the first analysis period (1996–2005), CSC was computed using MODIS data available from 2001–2005.

$$CSC = \overline{LAI}$$

(16)

WVF represents the proportion of perennial woody vegetation and was derived from the MODIS Vegetation Continuous Fields product (Di Miceli et al., 2022; Hansen et al., 2003) (Di Miceli et al., 2022; Hansen et al., 2003) as the mean fraction of tree and non-tree woody vegetation within each analysis period. WVF was computed as the sum of percent tree cover and percent non-tree woody vegetation divided by 100. Also in this case of WVF, for the first analysis period (1996–2005), it was computed using MODIS data available from 2001–2005.

$$WVF = \frac{\%Tree + \%Non-Tree}{100}$$

(17)

All VQI components were normalized, directionally harmonized, and aggregated following the procedures described in Section 2.2, ensuring that higher VQI values consistently indicate poorer vegetation quality and higher intrinsic susceptibility to desertification.

2.3.3.3. *Natural Stress Processes Index*

The Natural Stress Processes Index (NSPI) serves as a proxy for the intrinsic exposure of land systems to climate-driven surface stress processes that predispose soils to degradation, independently of land use, vegetation state, or management practices. In MEDALUS-R, NSPI is formulated as a process-based hazard component, describing the potential intensity of erosion-related stress under prevailing climatic conditions. Soil properties and anthropogenic effects are not incorporated within NSPI itself, as they are represented separately through SQI and the Human Pressure and Mitigation Potential components, respectively. This separation is intended to limit conceptual and statistical overlap among components.

NSPI focuses on the two dominant erosion-related stress pathways operating at continental scale: water-driven erosion hazard (WEH) and wind-driven erosion forcing (WF). These pathways are integrated using a geometric mean to represent combined stress exposure while limiting compensatory effects, where $n = 2$ represents the number of components included in the index:

$$NSPI = (WEH \cdot WF)^{1/2}$$

(18)

WEH was quantified using rainfall erosivity as a proxy for climatic forcing. Following a reduced-form interpretation of the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 2010)(Renard et al., 2010), only the rainfall erosivity factor (R) was retained (Nearing et al., 2017)(Nearing et al., 2017). Soil erodibility was excluded from NSPI to avoid reintroducing intrinsic soil-property effects already represented through SQI within the NLS component. Land-cover and management-related factors were

likewise excluded because these effects are represented separately within the anthropogenic components. Accordingly, water-driven erosion hazard was expressed as:

$$WEH = R$$

(19)

Rainfall erosivity was derived from pan-European datasets developed by Panagos et al. (2015) and represents long-term climatic forcing of water erosion processes, independent of soil and vegetation characteristics.

Wind-driven erosion forcing was quantified using a climatic wind-stress metric adapted from the Revised Wind Erosion Equation (RWEQ) (Fryrear et al., 2001) and derived from hourly ERA5 reanalysis data (Hersbach et al., 2020; Muñoz-Sabater et al., 2021). Hourly wind speed at 10 m height was computed from the zonal and meridional wind components as:

$$U_{10,h} = \sqrt{u_{10,h}^2 + v_{10,h}^2}$$

(20)

Hourly wind speed at 2 m height was subsequently estimated from $U_{10,h}$ using a logarithmic wind profile under neutral atmospheric stability (Garratt, 1994) and a fixed surface roughness length ($z_0 = 0.03$ m), yielding a constant conversion factor applied uniformly across the study domain.

Hourly wind erosion forcing was then computed as:

$$WF_h = U_{2,h} \cdot \max(U_{2,h} - U_t, 0)^2$$

(21)

where U_t denotes the threshold wind speed required to initiate soil particle movement, set to 5 m s^{-1} (Fryrear et al., 2001)(Fryrear et al., 2001) This formulation ensures that only threshold-exceeding wind conditions contribute to erosion forcing, while sub-threshold winds contribute zero by construction.

Hourly wind forcing values were aggregated directly to annual totals by summing WF_h over all valid hourly observations within each calendar year:

$$WF_{year} = \sum_h WF_h \quad (22)$$

For each analysis period, wind-driven erosion forcing was then expressed as the mean of annual total forcing values across all years within the period:

$$WF = \frac{1}{N_{years}} \sum_y WF_{year} \quad (23)$$

where N_{years} denotes the number of years within the corresponding period. This aggregation strategy preserves the influence of short-duration, high-intensity wind events that dominate wind erosion processes, while avoiding attenuation effects associated with daily or monthly averaging.

Hourly wind data were used explicitly to capture threshold exceedance and the non-linear contribution of extreme wind events to erosion forcing, which are not adequately represented by temporally averaged wind speed metrics. The resulting WF metric therefore represents the climatological intensity of wind-driven surface stress, independent of soil properties, vegetation cover, or land management.

All NSPI components were normalized, directionally harmonized, and transformed into aggregation space following the procedures described in Section 2.2, ensuring that higher NSPI values consistently indicate stronger exposure to climate-driven surface stress and higher intrinsic susceptibility to desertification.

2.3.4. Human Pressure

Human Pressure (HP) serves as a proxy for the anthropogenic amplification of desertification susceptibility through land use, management intensity, and recurrent surface disturbances. In MEDALUS-R, HP is explicitly defined as a land-surface pressure domain, distinct from intrinsic biophysical sensitivity (Natural Land Susceptibility) and from climate-driven process exposure (Natural Stress Processes Index). This separation ensures that HP captures how land is used and disturbed, rather than climatic forcing or inherent land properties.

HP is quantified through three complementary parameters: (i) Land Use Pressure Index (LUPI), representing the structural imprint of land cover and land use patterns; (ii) Intensive Disturbance Index (IDI) in cropland, representing management-induced soil exposure; and (iii) Fire Disturbance Index (FDI), representing recurrent fire-related surface disruption, considered here as a proxy for disturbance regimes operating within human-modified systems at the continental scale, given the predominant role of human activity in wildfire occurrence across Europe (San-Miguel-Ayanz et al., 2021)(San-Miguel-Ayanz et al., 2021) (Table 3). These parameters are aggregated using a geometric mean to limit compensatory effects and to ensure that elevated pressure in any single dimension proportionally increases overall human pressure (where $n=3$ represents the number of components included in the index):

$$HP = (LUPI \cdot IDI \cdot FDI)^{1/3}$$

(24)

Table 3. Structure and indicators of the Human Pressure (HP) component in the MEDALUS-R framework. HP quantifies anthropogenic amplification of desertification susceptibility through land-use structure (LUPI) and recurrent surface disturbances (IDI and FDI), explicitly separated from intrinsic biophysical sensitivity and climatic conditioning.

Component	Index	Indicator	Biophysical dimension	Role in desertification susceptibility	Data used/source
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Human Pressure (HP)	Land Use Pressure Index (LUPI)	CORINE land-cover pressure score, $S_{CLC} (period)$	Structural land use	Represents long-term anthropogenic modification of land surface	CORINE Land Cover (CLC) datasets (1990, 2006, 2018; Buttner, 2014),
	Intensity and Disturbance Index (IDI)	Bare soil frequency, B_i	Cropland disturbance	Captures management-induced soil exposure and recurrent surface disturbance	SoilSuite Europe bare-soil frequency composite derived from Sentinel-2 imagery (Heiden et al., 2022; Karlshoefer et al., 2025)
	Fire Recurrence Frequency (FDI)	Fraction of years with burned-area detection, B_y	Fire disturbance	Represents recurrent fire-related surface disruption across land covers	MODIS burned area product MCD64A1, Collection 6.1 (Friedl et al., 2010);

LUPI represents the relative degree of anthropogenic pressure associated with dominant land-cover types. LUPI was derived from the CORINE Land Cover datasets for 1990, 2006, and 2018 (Level-2 classification) (Buttner, 2014) by assigning ordinal pressure scores to each land-cover class based on typical land-use intensity and degree of surface modification. Classes associated with intensive agriculture, artificial surfaces, and infrastructure were assigned higher pressure scores, while broadly natural or semi-natural classes were assigned lower values (Table 4), acknowledging that these may still be subject to management and fragmentation across Europe. The reclassification of CORINE Land Cover Level-2 classes into pressure scores was designed to reflect relative land-use intensity at continental scale, rather than local management practices, thereby ensuring robustness and comparability across regions.

LUPI captures the structural component of human pressure and was treated as piecewise time-invariant within each analysis period, with pressure scores remaining constant across periods while land-cover maps

vary over time (, reflecting the comparatively slow dynamics of land-cover change at continental scale relative to the decadal aggregation adopted in this study. Formally, LUPi is expressed as:

$$LUPi = s_{CLC} (period)$$

(25)

where $s_{CLC} (period)$ denotes the pressure score assigned to each CORINE land-cover class.

Cropland disturbance was quantified using IDI, derived from bare soil frequency metrics that capture the recurrence of exposed soil surfaces associated with tillage and intensive agricultural management, based on the SoilSuite Europe 5-year Sentinel-2 composite dataset (2018–2022) produced by the German Aerospace Center (DLR) Earth Observation Center (EOC) (Heiden et al., 2022; Karlshoefer et al., 2025). Due to limitations in temporal data coverage, IDI was treated as a spatially explicit but temporally invariant indicator, representing persistent patterns of management-induced disturbance and applied consistently across all analysis periods. Although vegetation cover is also represented within the Vegetation Quality Index (VQI), IDI captures disturbance-driven removal of protective cover rather than intrinsic vegetation persistence, and this partial redundancy is intentional. Under this assumption, IDI captures anthropogenic amplification of desertification susceptibility through repeated soil exposure, independent of climatic forcing and intrinsic soil properties already represented in other components. IDI is defined as:

$$IDI = \frac{1}{N_{obs}} \sum_{i=1}^{N_{obs}} B_i$$

(26)

where B_i is a binary indicator equal to 1 when bare soil is detected in observation i , and N_{obs} is the total number of valid observations within the reference period.

Fire disturbance was quantified using FDI derived from the MODIS burned area product MCD64A1 (Collection 6.1, Friedl et al., 2010). FDI represents the mean annual frequency with which a pixel

experienced at least one fire during a given analysis period, thereby capturing both the spatial distribution and temporal recurrence of fire disturbance across all terrestrial land covers, including forests and rangelands. Only land pixels were considered, with open water bodies excluded using the MODIS land cover product (MCD12Q1, (Friedl et al., 2010)). Within MEDALUS-R, fire is treated as a largely human-induced or human-amplified disturbance pressure acting directly on land surfaces; background climatic conditions and erosion processes are represented separately in CQI and NSPI, respectively.

For each year, burned area presence was first identified as a binary variable, indicating whether any fire occurred within a pixel during that year (burn date > 0). Annual burn presence layers were then averaged over the analysis period to derive FDI at the native MODIS spatial resolution (~500 m). FDI is defined as:

$$FDI = \frac{1}{N_{years}} \sum_{y=1}^{N_{years}} B_y \quad (27)$$

where B_y is a binary indicator equal to 1 if the pixel burned at least once in year y , and 0 otherwise, and N_{years} is the number of years within the corresponding analysis period. Due to MODIS data availability, the earliest period (1996–2005) was constrained to the years 2001–2005 and rescaled accordingly to avoid overweighting. FDI values range from 0 (no fire occurrence during the period) to (potentially) 1 (fire occurrence every year), providing a standardized measure of fire disturbance pressure suitable for integration with other land degradation indicators.

All HP parameters were normalized, directionally harmonized, and transformed into aggregation space following the procedures described in Section 2.2, ensuring that higher HP values consistently indicate stronger anthropogenic pressure and greater amplification of desertification susceptibility.

Table 4. Reclassification of CORINE Land Cover (CLC) Level-2 classes into ordinal land-use pressure scores used to derive the Land Use Pressure Index (LUPI). Higher scores indicate higher anthropogenic pressure.

CLC Level 2 Code	CLC Level 2 Class	Pressure Score (s_{CLC})
11	Urban fabric	0.90
12	Industrial, commercial and transport units	0.95
13	Mine, dump and construction sites	1.00
14	Artificial, non-agricultural vegetated areas	0.75
21	Arable land	0.85
22	Permanent crops	0.90
23	Pastures	0.65
24	Heterogeneous agricultural areas	0.75
31	Forests	0.20
32	Scrub and/or herbaceous vegetation associations	0.30
33	Open spaces with little or no vegetation	0.35
41	Inland wetlands	0.15
42	Coastal wetlands	0.15
51	Inland waters	0.05
52	Marine waters	0.05

559

560 2.3.5. Mitigation Potential

561 Mitigation Potential (MP) serves as a proxy for the capacity of human systems to attenuate desertification
562 susceptibility through the combined effect of implemented conservation practices and institutional
563 governance frameworks. Unlike components describing intrinsic susceptibility or anthropogenic pressure,
564 MP captures the extent to which management actions and regulatory structures moderate the expression of
565 land degradation processes under given climatic conditions. MP is therefore treated as a susceptibility-
566 reducing component within the MEDALUS-R framework.

MP is formulated as the geometric mean of two complementary indices: (i) the Conservation Measures Index (CMI), representing the spatial coverage of land-based mitigation practices, and (ii) the Policy and Governance Index (PGI), representing the institutional context within which such practices operate:

$$MP = (CMI \cdot PGI)^{1/2}$$

(28)

All MP components were processed and aggregated following the common procedures described in Section 2.2. In accordance with the MEDALUS polarity convention, higher MP values indicate lower mitigation capacity and therefore weaker attenuation of desertification susceptibility.

Table 5. Structure and indicators of the Mitigation Potential (MP) component in the MEDALUS-R framework. MP integrates management practices and governance-related mechanisms through two complementary indices, the Conservation Measures Index (CMI) and the Policy and Governance Index (PGI), representing the capacity to attenuate anthropogenic pressure and reduce effective desertification susceptibility.

Component	Index	Indicator	Biophysical dimension	Role in desertification susceptibility	Data used/source
Mitigation Potential (MP)	Conservation Measures Index (CMI)	Cover crops proportion (C_c)	Active soil protection	Represents implementation of management practices reducing soil exposure	Eurostat agri-environmental indicators on cover crops at NUTS-2 level (Eurostat, 2023)
		Conservation tillage proportion (T_c)	Reduced mechanical disturbance	Captures management practices limiting soil structure degradation	Eurostat agri-environmental indicators on reduced/conservation tillage at NUTS-2 level (Eurostat, 2023);

		Natura 2000 coverage (N_{2000})	Institutional spatial protection	Represents legally protected land mitigating degradation risk	Natura 2000 spatial dataset (European Environment Agency, 2023)
	Policy and Governance Index (PGI)	$GAEC_i$ compliance score	Governance and regulation	Represents strength of mandatory land-protection frameworks	National GAEC implementation documents under the EU Common Agricultural Policy (CAP) (Angileri and Loudjani, 2010; Poláková, 2018)

579

580 CMI represents the spatial availability of land-based conservation practices relevant to desertification
 581 mitigation at the regional (NUTS-2) level. CMI focuses on measures that directly influence soil protection
 582 and surface stability, while excluding indicators related to land-use pressure or disturbance intensity, which
 583 are addressed within the Human Pressure component. CMI integrates three indicators using a geometric
 584 mean:

585

$$CMI = (C_c \cdot T_c \cdot N_{2000})^{1/3}$$

586

(29)

587 where C_c is the proportion (%) of agricultural land under cover crops, T_c is the proportion (%) of agricultural
 588 land under reduced or conservation tillage, and N_{2000} is the proportion (%) of land designated as Natura
 589 2000 protected areas. Together, these indicators represent complementary aspects of mitigation capacity,
 590 capturing both active management practices (cover crops and conservation tillage) and institutionalized
 591 spatial protection (protected areas). All indicators were normalized and directionally harmonized such that
 592 higher CMI values correspond to lower coverage of conservation measures and therefore lower mitigation
 593 capacity.

PGI quantifies the strength of mandatory land-protection frameworks at the national level, focusing on the implementation of Good Agricultural and Environmental Condition (GAEC) standards under the EU Common Agricultural Policy (CAP) (Angileri & Loudjani, 2010; Polakova, 2018). PGI is designed to represent institutional mitigation capacity, independent of observed land-use outcomes or management intensity.

A composite governance score was derived for each country through a systematic assessment of GAEC standards (Table 6) as implemented at the Member State level, based on official national GAEC implementation documents issued by competent authorities in accordance with EU CAP regulations (2019, or 2016 for countries that did not provide updated documentation in 2019). These documents describe the legally binding requirements governing soil protection, land management, and environmental safeguards across Member States. For each GAEC standard, national implementation was evaluated along three complementary dimensions: (i) regulatory stringency (degree of obligation and restrictiveness), (ii) thematic scope (range of land uses, soil threats, and spatial contexts covered), and (iii) enforceability (clarity of requirements, monitoring provisions, and presence of sanctions or compliance mechanisms). Each dimension was scored on an ordinal scale ranging from 0 (no effective implementation) to 3 (fully mandatory, comprehensive, and enforceable implementation).

The score assigned to each GAEC standard therefore ranges from 0 to 3, obtained as the sum of the three dimension-specific subscores. With nine GAEC standards considered, the total raw governance score spans an intrinsic range from 0 (no effective GAEC implementation) to 27 (full implementation of all standards with maximum stringency, scope, and enforceability). Each GAEC standard was assigned a continuous score reflecting regulatory stringency, thematic scope, and enforceability. The raw governance score was computed as:

$$PGI_{raw} = \frac{1}{n} \sum_{i=1}^n GAEC_i$$

617 (30)

618 where $GAEC_i$ denotes the score of the i -th GAEC standard and n is the total number of standards considered.

619 Under the adopted scoring scheme, PGI_{raw} is bounded between 0 and 27 (Table S2).

620 Raw governance scores were normalized using a theoretical min–max transformation based on these
 621 intrinsic bounds and directionally inverted to ensure consistency with the normalization and polarity
 622 conventions described in Section 2.2, such that higher values indicate weaker mitigation capacity. The
 623 resulting PGI is a continuous, dimensionless indicator, with lower values indicating stronger governance
 624 capacity and higher values indicating weaker policy protection. This formulation preserves absolute
 625 differences in regulatory stringency across countries and ensures full compatibility with geometric
 626 aggregation within the MEDALUS-R framework.

627 Table 6. General description of Good Agricultural and Environmental Condition (GAEC) standards used for
 628 the construction of the Policy and Governance Index (PGI).

GAEC	Standard title	General description	Relevance to land degradation
GAEC 1	Buffer strips along	Vegetated buffers to reduce runoff and	Limits erosion and sediment
GAEC 2	Water abstraction	Compliance with water use permits	Controls soil moisture stress
GAEC 3	Groundwater protection	Prohibition of harmful discharges	Prevents chemical soil degradation
GAEC 4	Minimum soil cover	Maintenance of soil cover during sensitive	Reduces erosion and surface sealing
GAEC 5	Erosion control	Slope- and site-specific erosion mitigation	Limits topsoil loss
GAEC 6	Soil organic matter	Restrictions on stubble burning and	Preserves soil structure
GAEC 7	Landscape features	Retention of terraces, hedges, and ditches	Reduces erosion pathways
GAEC 8	Non-productive areas	Maintenance of non-productive	Reduces pressure on vulnerable land
GAEC 9	Sensitive land protection	Restrictions on conversion of sensitive	Prevents irreversible degradation

629 2.4. Parameterization of Component Scaling Exponents

630 In the absence of spatially explicit observations of realized desertification outcomes, the scaling exponents

631 α , β , and γ were estimated using an unsupervised, multi-objective optimization framework. The objective

was to identify parameter values that produce susceptibility patterns that are (i) spatially discriminative, (ii) temporally robust, and (iii) stable across consecutive decades. Three complementary objective functions were evaluated: (1) spatial discrimination, quantified as the variance of the logarithm of susceptibility values across the spatial domain; (2) temporal robustness, quantified as the rank correlation of susceptibility values between consecutive decades; and (3) temporal drift, quantified as the absolute change in the median logarithmic susceptibility between decades.

A large ensemble of candidate parameter combinations was sampled within predefined bounds, and only solutions satisfying $\alpha \geq \beta$ and $\alpha \geq \gamma$ were retained. This constraint does not impose climatic dominance a priori, but ensures that climatic context remains explicitly represented in the estimation of desertification susceptibility. In this way, climatic conditions are required to contribute meaningfully to susceptibility patterns while allowing their relative influence to be determined objectively through the optimization procedure.

Pareto-optimal solutions were identified, and the final parameter set was selected as the median-ranked compromise solution across the three objectives, representing a conservative and methodologically neutral balance among discrimination, robustness, and stability. This median-rank selection avoids over-emphasizing any single objective and minimizes sensitivity to sampling variability, thereby providing a robust baseline parameterization for continental-scale assessment.

Let $f_1(\alpha, \beta, \gamma)$, $f_2(\alpha, \beta, \gamma)$, and $f_3(\alpha, \beta, \gamma)$ denote the objective functions representing spatial discrimination, temporal robustness, and temporal drift, respectively. These objectives were evaluated for each candidate parameter combination (α, β, γ) within the Pareto-optimal solution set P . The final parameter set $(\alpha^*, \beta^*, \gamma^*)$ was selected as the median-ranked compromise solution across the three objectives within P :

$$(\alpha^*, \beta^*, \gamma^*) \in P$$

Specifically, the selected parameter combination minimizes the median rank across the three objective functions, thereby yielding a conservative and reproducible parameterization that avoids extreme trade-offs among objectives while preserving interpretability and temporal comparability.

2.5. Spatial Harmonization and Resolution

All input layers were harmonized to a common 1 km analysis grid prior to index computation. This intermediate spatial resolution was selected to balance the comparatively coarse resolution of reanalysis-based climatic datasets with the finer spatial detail of soil, vegetation, land-use, disturbance, and mitigation indicators commonly available for Europe.

Spatial resampling was performed using methods appropriate to variable type and physical meaning. Continuous variables were resampled using bilinear interpolation when mapped from coarser to finer resolution and aggregated using arithmetic means when mapped from finer to coarser resolution. Fractional or proportional variables were aggregated by arithmetic mean to preserve their interpretation as area fractions within each grid cell. Categorical land-cover data were first converted to continuous land-use pressure scores and subsequently aggregated by arithmetic mean, thereby avoiding majority-class assumptions.

Climatic indicators derived from ERA5-Land were computed at their native spatial and temporal resolution prior to resampling, ensuring that threshold- and frequency-based metrics accurately reflect underlying temporal dynamics. Resampling of ERA5-Land variables to the 1 km grid does not introduce additional climatic information and should not be interpreted as physical downscaling. The effective spatial resolution of ERA5-Land therefore constrains the spatial detail of climate forcing, and fine-scale variability in the resulting susceptibility patterns reflects heterogeneity in soil, vegetation, land use, disturbance, and mitigation components rather than sub-grid climatic variability. This approach ensures spatial consistency across indices while explicitly avoiding false precision in climate-driven patterns.

3. Results

Desertification susceptibility across Europe was estimated using the MEDALUS-R modelling framework for the territory of 37 European countries, subdivided into approximately 4.97 million grid cells at a final spatial resolution of 1 km. Susceptibility was quantified for three consecutive decadal periods (1996–2005, 2006–2015, and 2016–2025), allowing for a consistent assessment of spatial patterns, temporal evolution, component contributions, and model sensitivity across the European domain.

The modelling outcomes indicate that desertification susceptibility index (SDI) spans a broad numerical range (approximately 0.8 to 12.6), exceeding the conventional 1–2 interval used in the original MEDALUS framework, as a direct consequence of the revised multiplicative formulation (Eq. 1) and the resulting amplification of spatial heterogeneity associated with climatic gradients, intrinsic land characteristics, and human influence. The results presented in the following sections describe (i) the spatial organization of desertification susceptibility across Europe, (ii) its temporal evolution across the analyzed decades, (iii) the relative contribution of the main susceptibility components, and (iv) the sensitivity of susceptibility estimates to model parameterization.

3.1. Spatial patterns of desertification susceptibility

Model-based estimates indicate that desertification susceptibility is spatially heterogeneous across Europe and organized into coherent regional patterns (Figure 2). Across all analyzed decadal periods, susceptibility exhibits pronounced north–south and climatic gradients, with comparatively lower values in northern and north-western Europe and progressively higher values toward southern Europe and climatically transitional regions.

In the baseline period (1996–2005), susceptibility values range from near the lower bound of the index (≈ 0.8) to values exceeding 5 in the most susceptible areas, with a continental median of 2.05 and a 95th percentile of 5.28. The distribution is right-skewed, indicating a predominance of low-to-moderate susceptibility conditions and a comparatively limited upper tail.

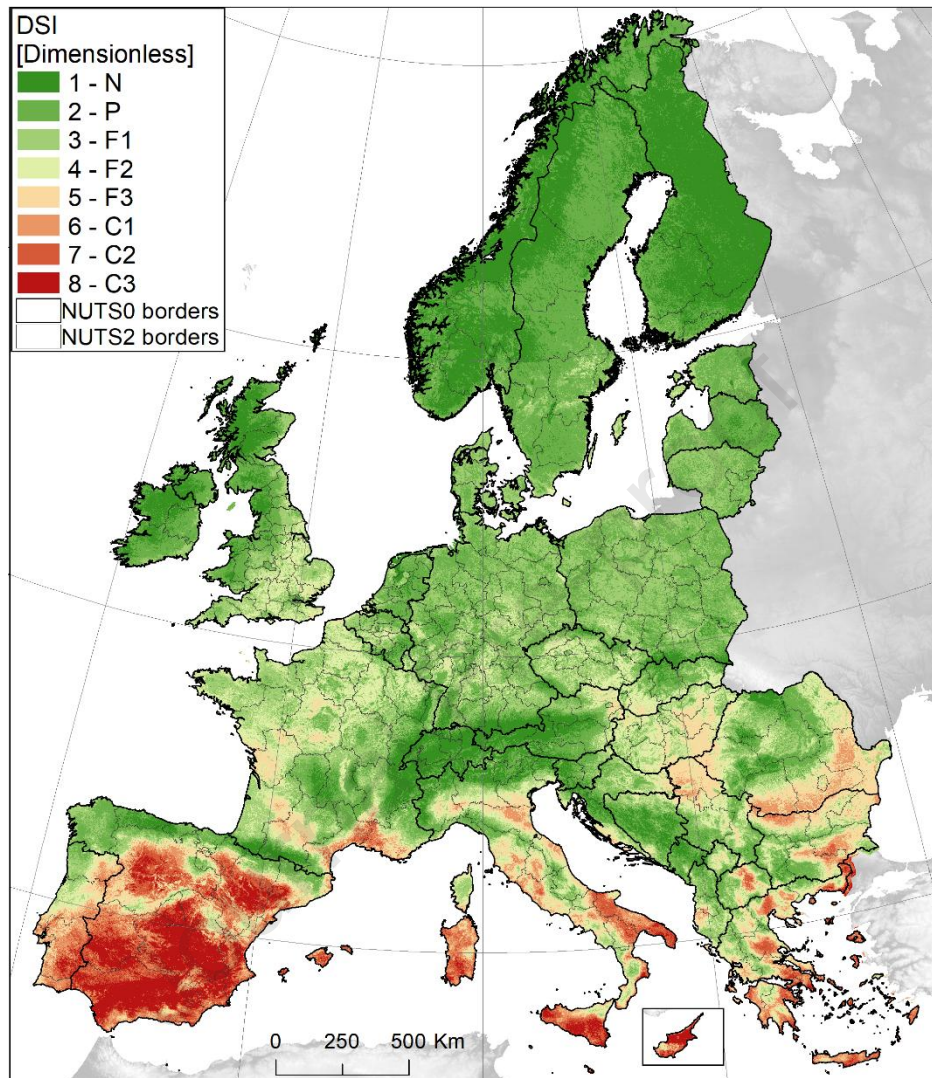
For interpretative purposes, continuous susceptibility values were grouped into eight MEDALUS-consistent classes: Non-affected (N), Potentially affected (P), three Fragile classes (F1–F3), and three Critical classes (C1–C3), using data-driven thresholds (Section 2.4). While most analyses are conducted on continuous values, this classification is used to summarize spatial extent and transitions. Based on this classification, approximately 64% of grid cells fall within the two lowest classes (Non-affected and Potentially affected), which are predominantly distributed across northern Europe, including Boreal and Alpine regions. Intermediate conditions (Fragile classes) account for about 30% of the domain and are widespread across temperate regions and climatic transition zones, while the highest susceptibility classes (Critical classes) collectively represent approximately 6.6% of the domain and are spatially concentrated in southern Europe and other climatically constrained areas, indicating that extreme conditions are spatially limited but clearly present.

At the bioclimatic scale (EEA, 2026) Mediterranean and semi-arid transitional zones consistently exhibited higher median susceptibility values than temperate and northern zones (Table 7). Median values exceeded 2.8 in Mediterranean regions, compared to 1.5–1.7 in Boreal and Alpine zones. Country-level patterns mirrored these gradients, with Cyprus, Greece, and southern Italy exhibiting higher susceptibility, while Sweden, Germany, and Denmark were dominated by lower classes (Table S3).

Table 7. Summary statistics of desertification susceptibility index (SDI) for the principal European biogeographical regions according to the European Environment Agency's delineation of terrestrial biogeographical (EEA, 2026).

Biogeographical region	Mean SDI (2016–2025)	Max SDI	Range SDI	Mean SDI change (%) in 2016–2025 (baseline:	Mean SDI change (%) in 2016–2025 (baseline:
Alpine	1.86	5.57	4.57	14.1	4.7
Boreal	1.93	4.28	3.09	11.8	6.1
Arctic	2.07	2.68	1.32	15.5	2.3
Atlantic	2.49	5.77	4.7	15	8
Continental	2.67	7.56	6.57	19.1	6.2
Pannonian	3.49	5.65	4.11	21.2	4.1
Black Sea	3.61	6.21	4.18	19.4	9.6
Steppic	4.27	5.78	3.63	35.7	12.6
Mediterranean	5.28	12.59	11.37	23.5	12.5

720



721

722 Figure 2. Spatial distribution of desertification susceptibility classes across Europe for three consecutive decadal
 723 periods (1996–2005, 2006–2015, and 2016–2025). Colors represent the eight MEDALUS-consistent susceptibility
 724 classes derived from continuous susceptibility values using data-driven thresholds (Non-affected, Potentially affected,
 725 Fragile F1–F3, and Critical C1–C3; see Section 2.4). Higher class values indicate greater desertification susceptibility.
 726 NUTS-0 (country) and NUTS-2 boundaries are shown for reference.

3.2. Temporal evolution across decadal periods

Model-based estimates indicate a consistent increase in desertification susceptibility across Europe over the three analyzed periods. Median susceptibility rises from 2.05 in 1996–2005 to 2.26 in 2006–2015 ($\approx 10\%$), and further to 2.38 in 2016–2025 ($\approx 5\%$ relative to the previous decade; $\approx 16\%$ relative to the baseline). This upward trend is accompanied by an expansion of the upper tail of the distribution, with the 95th percentile increasing from 5.28 to 6.55, indicating a growing prevalence of high-susceptibility conditions.

Changes in susceptibility, as estimated by the model, are spatially widespread and predominantly positive. Between 1996–2005 and 2006–2015, $\approx 87\%$ of grid cells exhibit increasing susceptibility, with a median change of +0.19. A comparable proportion ($\approx 87\%$) increases between 2006–2015 and 2016–2025, although with a smaller median change (+0.13). Over the full study period, susceptibility increases in $\approx 99\%$ of the European domain, with a cumulative median increase of +0.32 (Figure 3).

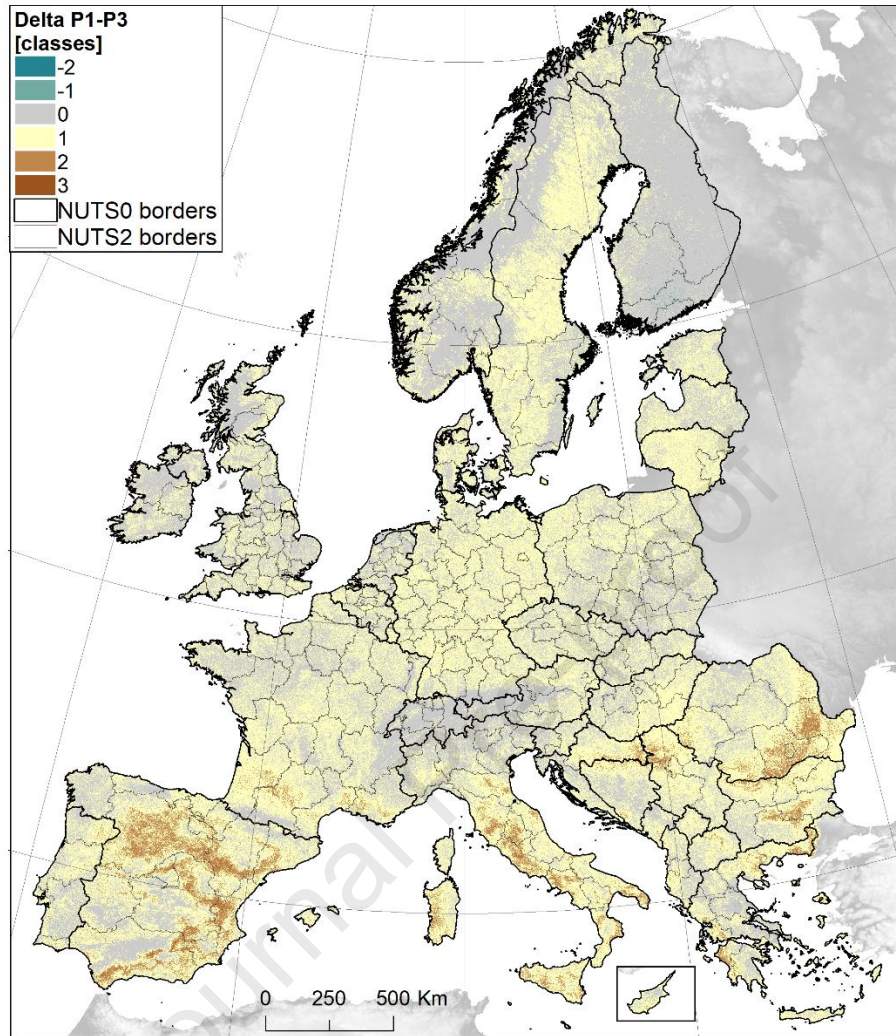


Figure 3. Spatial distribution of changes in desertification susceptibility classes between the first and last decadal periods ($\Delta P1-P3$; 1996–2005 to 2016–2025). Colors represent pixel-wise changes in MEDALUS-consistent susceptibility classes (1–8), where positive values indicate transitions toward higher susceptibility classes, negative values indicate transitions toward lower classes, and zero indicates class stability. The same color scale is used to represent the magnitude and direction of class transitions across the European domain.

Model-derived class-based transitions reflect these continuous changes of desertification susceptibility. Between the first two decades, $\approx 34\%$ of grid cells transition toward higher susceptibility classes, $\approx 65\%$ remain stable, and $\approx 1.0\%$ shift toward lower classes. Upward transitions are mainly concentrated in southern Europe and climatic transition zones, while northern Europe exhibits higher class persistence. Between 2006–2015 and 2016–2025, upward transitions affect $\approx 28\%$ of the domain, persistence increases

to $\approx 70\%$, and downward transitions remain limited (1.5%). During this latter interval, transitions from intermediate to higher susceptibility classes become relatively more frequent, particularly in Mediterranean Europe, south-eastern Europe, and continental climatic transition zones. At the European scale, this intensification is reflected by a measurable shift in susceptibility states, with $\approx 6\%$ of the domain newly entering Fragile classes (F1–F3) and $\approx 3\%$ transitioning into Critical classes (C1–C3). These changes are disproportionately concentrated in southern and south-eastern European countries, including Bulgaria (4.8% of national territory affected by strong class increases), Spain (3.2%), Italy (1.3%), Portugal (0.7%), and Greece (0.6%), highlighting a spatially coherent pattern of intensification in regions already characterized by moderate vulnerability.

When considering dominant long-term trajectories over the full study period (1996–2025), $\approx 69\%$ of the European domain exhibits stable susceptibility conditions, predominantly across northern and north-western Europe, including Scandinavia, the British Isles, northern Germany, and Poland. In contrast, $\approx 20\%$ of the domain follows a stepwise increasing trajectory across both decadal transitions, spatially concentrated in southern Europe and climatic transition zones, particularly in Mediterranean Europe and south-eastern Europe. Areas characterized by persistently high susceptibility throughout all periods account for an additional 3.1% of the domain and are mainly clustered in Mediterranean and semi-arid regions, while 7.6% of grid cells follow mixed or non-monotonic trajectories without clear regional clustering (Figure 4).

As a complementary climatic diagnostic, temporal changes in the AI-defined dryland domain were also examined. The area classified as dryland according to $AI < 0.65$ increased from 453,554 km² (9.1% of the valid domain) in 1996–2005 to 532,485 km² (10.7%) in 2016–2025, corresponding to a net increase of 78,931 km². Between the first and last periods, 85,660 km² shifted into dryland conditions, whereas 6,729 km² shifted out. In parallel, AI decreased across 71% of the study domain, with a median ΔAI of -0.055 , indicating that changes in climatic aridity were spatially more widespread than areas crossing the $AI = 0.65$ threshold (Fig. S3).

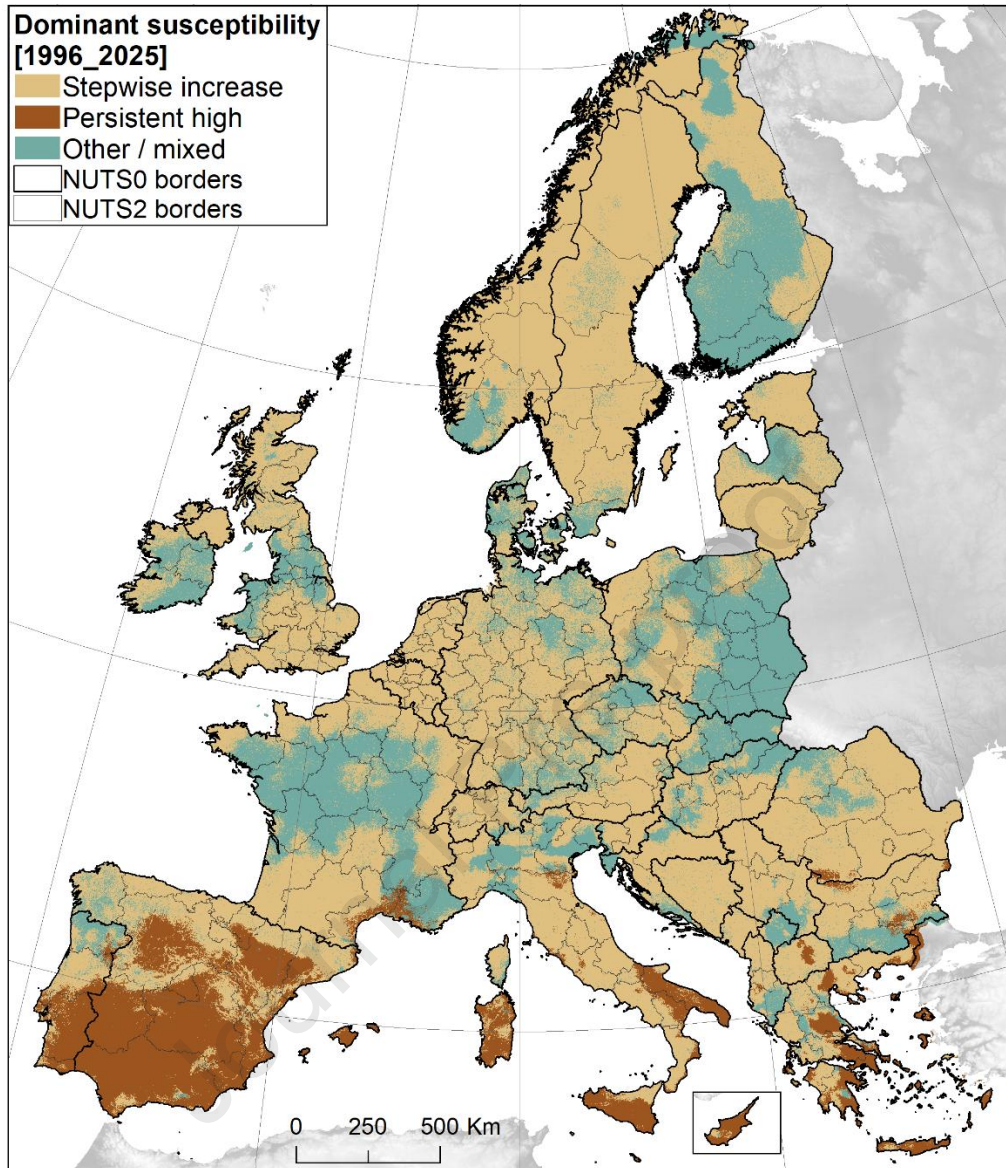


Figure 4. Dominant susceptibility trajectories (1996–2025). Spatial distribution of dominant temporal trajectories of desertification susceptibility derived from three consecutive decadal periods. Pixels are classified into Stepwise increase, Persistent high, and Other/mixed trajectories, highlighting the geographical concentration of long-term susceptibility intensification across southern Europe and climatic transition zones.

3.3. Contribution of susceptibility components

Model-based desertification susceptibility emerges from interacting climatic, intrinsic land, human pressure, and mitigation-related components (Figure 5). Pixel-wise dominance analysis shows that mitigation-related

factors are the largest relative component in $\approx 59\%$ of the domain, climatic susceptibility in 39%, and intrinsic land susceptibility in 1.8%, reflecting relative modulation rather than single-driver control.

Climatic susceptibility dominates southern Europe and climatic transition zones, defined as regions between humid temperate and semi-arid Mediterranean climates, including the Mediterranean Basin, Iberian interior, southern France, Italy, Greece, and south-eastern Europe. These regions largely overlap with areas experiencing monotonic or persistent increases ($\approx 24\%$ of Europe), indicating a strong spatial association between climatic susceptibility and long-term intensification patterns.

Intrinsic land susceptibility contributes to elevated baseline susceptibility in Mediterranean lowlands, semi-arid interiors, and erosion-prone transition areas. Human pressure acts as an amplifier in intensively managed regions of southern and eastern Europe. In contrast, mitigation-related factors dominate northern and north-western Europe, including Scandinavia and the British Isles, supporting persistent low susceptibility and high stability.

The individual components showed distinct temporal trajectories across the three study periods (Table 8). CQI increased modestly at continental scale, whereas NLS showed a small overall decline and HP remained comparatively stable. MP exhibited the largest temporal shift, decreasing markedly between the first and last periods. These results indicate that the temporal evolution of overall susceptibility reflects contrasting component-specific changes rather than a uniform shift across all model domains.

Table 8. Temporal evolution of the four main MEDALUS-R components across the three decadal periods. Mean component values are reported for 1996–2005, 2006–2015, and 2016–2025, together with the mean pixel-wise change between the first and last periods and the proportions of the modeled domain showing increasing or decreasing values. Higher CQI, NLS, and HP values indicate less favorable conditions, while MP follows the polarity convention adopted in the framework.

Component	Mean 1996–2005	Mean 2006–2015	Mean 2016–2025	Mean Δ P1–P3	Increasing (%)	Decreasing (%)	Unchanged (%)
CQI	1.319	1.324	1.339	0.02	56.9	42.4	0.7
NLS	1.291	1.287	1.283	−0.008	21.9	77	1.1
HP	1.336	1.334	1.333	−0.002	10.3	10.5	79.2
MP	1.82	1.529	1.362	−0.458	<0.1	>99.9	<0.1

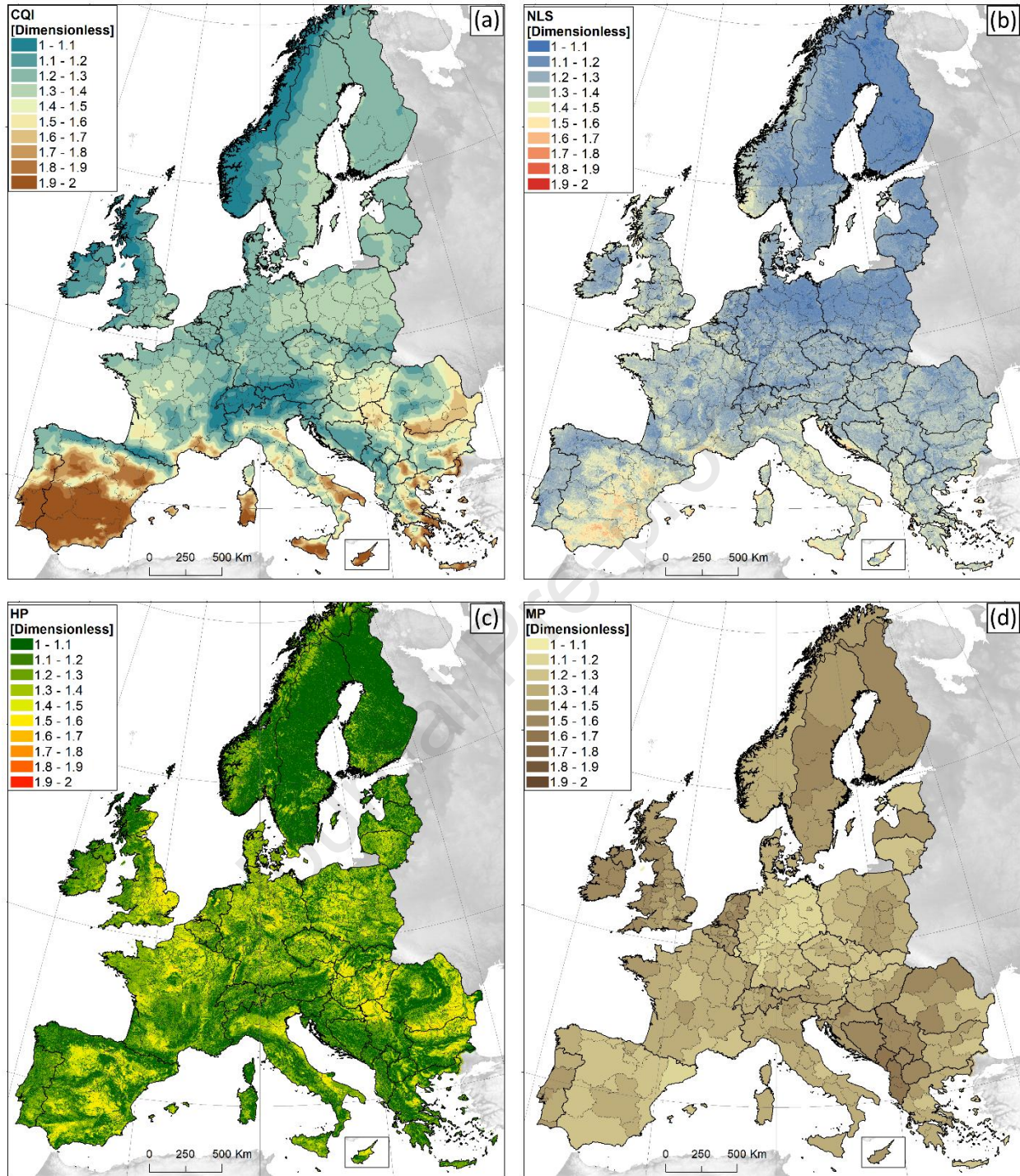


Figure 5. Spatial distribution of the four main components of the MEDALUS-R framework across Europe: (a) Climate Quality Index (CQI), (b) representing climatic conditioning; Natural Land Susceptibility (NLS), representing intrinsic biophysical sensitivity; (c) Human Pressure (HP), representing anthropogenic disturbance and land-use pressure; and (d) Mitigation Potential (MP), representing the capacity of management practices and governance to attenuate

desertification susceptibility. All components are shown for the same reference period (2016–2025) and mapped at 1-km spatial resolution. Higher values indicate poorer conditions (higher susceptibility or lower mitigation capacity).

3.4. Sensitivity analysis of parameterization

Sensitivity analysis based on the ensemble of Pareto-optimal parameterizations indicates that the main spatial patterns of susceptibility are robust, while the magnitude of uncertainty increases under more adverse conditions. In this context, sensitivity is evaluated within an ensemble-based framework, where variability across Pareto-optimal parameterizations reflects the response of model outputs to parameter choices, rather than from one-at-a-time perturbations of individual inputs. Agreement with the baseline classification is highest in 1996–2005 (median 0.90; $\approx 63\%$ of the domain ≥ 0.8), decreasing to 0.80 in 2006–2015 and 0.20 in 2016–2025.

Uncertainty magnitude, quantified as the ensemble standard deviation (*SD*), increases consistently over time (Figure 6). Median *SD* values rise from 0.071 in 1996–2005 to 0.084 in 2006–2015 and 0.095 in 2016–2025, while the 95th percentile increases from approximately 0.60 to 0.96. Higher uncertainty values are spatially concentrated in southern Europe, particularly in Mediterranean regions, south-eastern Europe, and Mediterranean–temperate transition zones, whereas northern and north-western Europe exhibit consistently lower uncertainty.

The reference baseline corresponds to the selected optimal parameterization, against which agreement metrics and ensemble variability are evaluated. Importantly, increasing uncertainty does not indicate reduced model reliability. Instead, it reflects heightened sensitivity of susceptibility estimates under intensified conditions, where a larger proportion of grid cells approach class thresholds and small parameter differences lead to larger variability in modeled outcomes. The persistence of coherent spatial patterns across parameterizations supports the robustness of the main results, while highlighting regions where susceptibility outcomes are most responsive to parameter choices.

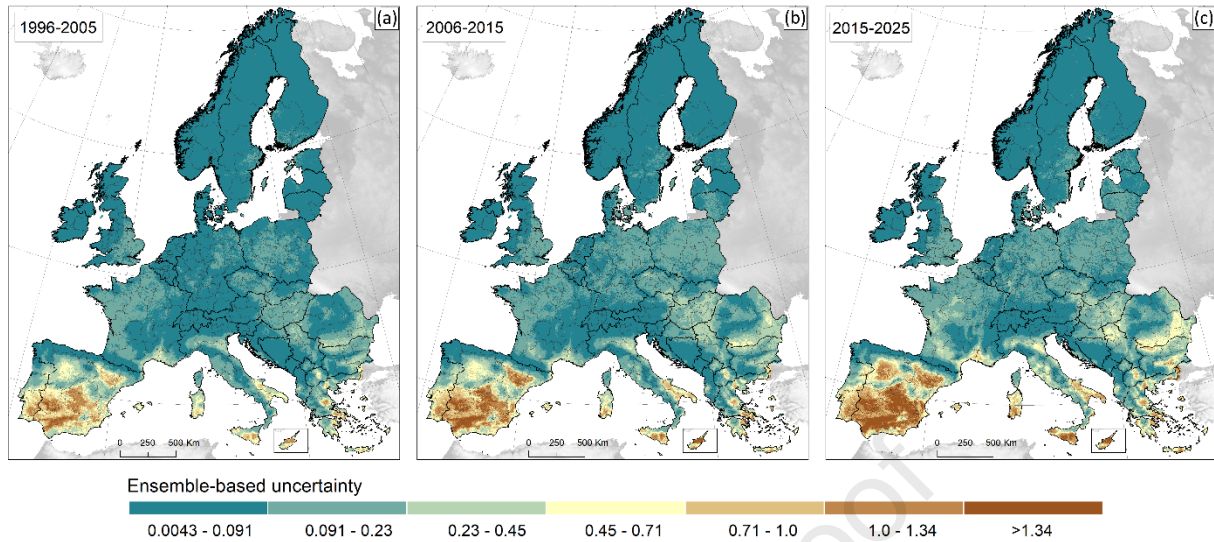


Figure 6. Spatial distribution of ensemble-based uncertainty in desertification susceptibility across Europe. Maps show the standard deviation (SD) of susceptibility values (dimensionless) derived from the ensemble of Pareto-optimal parameterizations for the three analyzed decadal periods, (a) 1996–2005, (b) 2006–2015, and (c) 2016–2025. Higher values indicate greater sensitivity of susceptibility estimates to parameter choices. The same color scale is applied across panels to facilitate comparison of uncertainty magnitude and its spatial evolution over time.

4. Discussions

4.1. Spatial and temporal patterns of desertification susceptibility across Europe

The modelling results consistently suggest that the estimated desertification susceptibility across Europe is structured into coherent and persistent large-scale patterns, rather than exhibiting predominantly spatially fragmented behavior. At the continental scale, susceptibility exhibits an overall north–south gradient, with generally lower levels across northern and north-western Europe and progressively higher levels toward southern Europe and Mediterranean–temperate transition zones. This general spatial organization is broadly consistent with patterns reported in previous local, regional, and pan-European desertification and land-degradation assessments, which have identified Mediterranean environments as structurally more sensitive due to the combined influence of climatic seasonality, recurrent drought exposure, and long-term water

stress (Kosmas et al., 1999; Právělie et al., 2017; Rubio & Bochet, 1998; Salvati & Zitti, 2008). European-scale assessments related to desertification and land degradation have been developed using heterogeneous methodological approaches, including MEDALUS/DISMED-based sensitivity mapping (Právělie et al., 2017; Salvia et al., 2019), climate-based desertification-risk projections (Spinoni et al., 2015), convergence-of-evidence approaches (Cherlet et al., 2018; Gianoli et al., 2023), syndrome-based analyses (Stellmes et al., 2013), integrated socio-ecological frameworks (Reynolds et al., 2011), and indicator-based assessments of land degradation and desertification in drylands (Schillaci et al., 2026). However, these approaches address different assessment constructs, ranging from susceptibility and climatic risk to broader land degradation or observed degradation within drylands, and are therefore not directly comparable numerically or spatially. Among the available multi-country assessments explicitly mapping desertification sensitivity, the DISMED-derived studies remain the closest methodological reference for comparison with MEDALUS-R. In both cases, the analyses are restricted to Mediterranean and climatic transition regions of Europe, which are explicitly modelled and reported (Právělie et al., 2017; Salvia et al., 2019). While focusing on only part of Europe makes the comparison between MEDALUS-R and classical MEDALUS applications meaningful, it also renders such comparisons inherently partial. Nonetheless, several notable differences emerge, including smoother spatial transitions, reduced fragmentation, and finer spatial detail in the MEDALUS-R results. More importantly, MEDALUS-R appears able to identify areas exhibiting relevant susceptibility to desertification that are not highlighted by classical MEDALUS applications. These include, for example, the Gulf of Lion in France, Sardinia, large sectors of southern Italy, the Greek mainland and islands, Cyprus, central and northern sectors of Italy, as well as parts of the Pannonian region and major lowlands of Romania. In addition, a further contribution of the proposed MEDALUS-R framework lies in its ability to extend the assessment beyond administrative and climatic boundaries considered in previous exercises, including northern European regions. Although these areas do not exhibit clear desertification susceptibility, they still display spatially coherent patterns of land sensitivity that warrant attention and monitoring, particularly in the context of recent record-breaking warming across Europe (Dong & Sutton, 2025).

Within this overarching gradient, the results suggest a functional subdivision of Europe into three main susceptibility regimes that is useful for interpretation. Northern and north-western Europe is characterized by comparatively low susceptibility and high temporal stability, central and eastern Europe exhibits predominantly intermediate susceptibility with pronounced spatial heterogeneity, and southern Europe, including Mediterranean and semi-arid transitional areas, shows higher and more spatially clustered susceptibility levels. Similar regional contrasts have been documented in earlier MEDALUS-based applications and ESAI mapping efforts, suggesting that these spatial configurations are largely associated with enduring climatic and biophysical constraints rather than short-term or localized fluctuations (Cherlet et al., 2018; Ferrara et al., 2020; Právělie et al., 2017). However, the present results indicate that these broad susceptibility regimes persist coherently across multiple decades when assessed within a climate-conditioned, data-driven framework, and that their internal dynamics tend to be characterized by gradual intensification, an aspect that was conceptually inferable but could not be resolved by earlier static or single-period assessments.

From a temporal perspective, the analysis reveals a clear and consistent trend of increasing desertification susceptibility from the first (1996–2005) to the most recent (2016–2025) period, primarily expressed through upward transitions between susceptibility classes rather than through large-scale spatial reorganization. Across Europe, upward class transitions consistently outnumber downward transitions, while areas exhibiting improvement remain negligible in extent. The persistence of these spatial patterns suggests that desertification susceptibility across Europe tends to evolve primarily through gradual intensification within established susceptibility regimes, rather than through a redistribution of susceptible areas. This intensification is reflected by a net expansion of Fragile and Critical classes between successive periods, particularly during the most recent decade, while regions with low baseline susceptibility largely remain stable.

By extending traditional static assessments to a multi-temporal perspective, this work provides new elements that support the interpretation that desertification susceptibility in Europe primarily evolves along

899 persistent long-term trajectories, with gradual intensification dominating over abrupt spatial shifts at the
 900 continental scale. This interpretation is consistent with earlier European assessments suggesting that
 901 desertification processes typically reflect sustained climatic pressure and persistent land-use pathways,
 902 while advancing existing knowledge by quantitatively documenting the temporal coherence and
 903 progressive intensification of susceptibility patterns across multiple decades using a harmonized framework
 904 (Právělie, 2016; Salvati et al., 2011; Spinoni et al., 2018)(Právělie, 2016; Salvati et al., 2011; Spinoni et al.,
 905 2018)(Právělie, 2016; Salvati et al., 2011; Spinoni et al., 2018)(Právělie, 2016; Salvati et al., 2011; Spinoni
 906 et al., 2018).

907 The spatial persistence and gradual intensification of susceptibility prompt consideration of which
 908 components most strongly contribute to observed changes over time. While the multi-temporal framework
 909 captures how susceptibility evolves across Europe, interpreting these patterns requires disentangling the
 910 relative roles of climatic stress, intrinsic land sensitivity, and human pressure. The observed temporal trends
 911 indicate that changes in susceptibility are primarily driven by climatic intensification, while intrinsic land
 912 sensitivity largely governs the spatial distribution of susceptible areas and human pressure acts as a local
 913 amplifying factor. Mitigation potential exhibits spatial variability and localized improvements, but its
 914 overall buffering effect remains insufficient to counterbalance the dominant climatic signal at the
 915 continental scale. This assessment (Section 4.2) is particularly important given that several indicators were
 916 intentionally held constant due to the limited availability of harmonized temporal data.

917 4.2. Drivers of susceptibility: climatic stress, land sensitivity, and human pressure

918 The component-based analysis suggests that the increase of desertification susceptibility across Europe is
 919 most strongly associated with climatic stress ($r = 0.654$, $p < 0.001$), whereas intrinsic land sensitivity and
 920 human pressure show weaker, more context-dependent associations ($r \approx 0.13$ and $r \approx 0.09$, respectively).
 921 Spatial analysis of long-term susceptibility changes between the baseline period (1996–2005) and the most
 922 recent period (2016–2025) indicates that climatic susceptibility is most closely aligned with areas

923 experiencing the largest increases, covering approximately 497,480 km² (i.e., the upper decile of change
924 across a total modeled land area of about 4,974,784 km²). At the continental scale, this relationship supports
925 a robust association between increasing susceptibility and pre-existing climatic constraints. These
926 relationships between susceptibility components and long-term change are illustrated by the pixel-wise
927 scatter plots in Figure 7, which highlight contrasts in the strength and direction of associations.

928 This signal is further supported by contrasts between areas experiencing strong and weak susceptibility
929 change. Grid cells in the upper decile of susceptibility increase, covering approximately 497,000 km²,
930 exhibit markedly higher climatic susceptibility than areas with minimal change. In these strongly
931 intensifying areas, median climatic susceptibility reaches approximately 1.90, compared to about 1.40 in
932 the lower decile, corresponding to an increase of roughly 36%. These areas are predominantly located in
933 southern Europe, Mediterranean regions, and climatic transition zones, which together account for most
934 high-change locations identified in this study. This spatial concentration of susceptibility intensification in
935 climatically constrained regions is consistent with independent European-scale evidence of increasing
936 climatic stress. Figure 6 further illustrates this pattern, showing a clear positive relationship between
937 climatic susceptibility and susceptibility change.

938 Mitigation-related factors show an opposing association with susceptibility change, acting as a moderating
939 influence. The explicit separation between human pressure and mitigation potential allows anthropogenic
940 influence to be interpreted as a balance between degradation drivers and response capacity, providing
941 additional insight compared to previous formulations in which these aspects were combined into a single
942 dimension. At the continental scale, mitigation indicators are moderately negatively correlated with long-
943 term susceptibility increases ($r \approx -0.37$, $p < 0.001$). Areas experiencing the strongest susceptibility
944 intensification (upper decile), covering roughly 0.5 million km², are characterized by lower mitigation-
945 related values, with a median of approximately 1.36, compared to 1.72 in areas with minimal change,
946 corresponding to a reduction of about 21%. Spatially, these low-mitigation, high-intensification areas are
947 concentrated mainly in southern and south-eastern Europe, including parts of the Mediterranean basin and

continental transition zones, whereas higher mitigation-related values and lower susceptibility increases are more common in northern and north-western Europe. This pattern is illustrated in Figure 6 by a clear negative relationship, highlighting the role of mitigation-related conditions in dampening climate-driven susceptibility intensification rather than acting as a primary control.

Intrinsic land susceptibility shows a weaker but positive association with long-term susceptibility change, with a modest spatial correlation ($r \approx 0.13$, $p < 0.001$). Areas of strong intensification exhibit median intrinsic susceptibility values of approximately 1.20, compared to 1.06 in areas with limited change, corresponding to an increase of about 13.5%. As illustrated in Figure 6, the relationship displays a broad spread at lower intrinsic susceptibility values and a narrower range at higher values, indicating that intrinsic land properties condition the range of possible susceptibility responses rather than directly controlling change magnitude. This pattern suggests that unfavorable soil, vegetation, and topographic conditions influence where intensification is more pronounced, although their role remains secondary to climatic stress at the continental scale.

In contrast, human pressure shows the weakest association with temporal changes in susceptibility ($r \approx 0.09$, $p < 0.01$), with only marginal differences between areas of high and low change. Grid cells in the upper decile of susceptibility increase exhibit human pressure values differing by less than 5% from those in the lower decile. This limited relationship is reflected in Figure 6 as a diffuse scatter with no clear trend, supporting the interpretation that human pressure plays a minor role in explaining decadal susceptibility change within the present modelling framework. This reduced explanatory power should be interpreted in light of the modelling design, as several pressure-related indicators were intentionally held constant due to the lack of harmonized temporal datasets at the continental scale. Consequently, human pressure appears to contribute more strongly to baseline susceptibility patterns than to the temporal intensification captured in this analysis.

Taken together, the component-based evidence indicates that recent estimated intensification of desertification susceptibility across Europe is driven primarily by climatic stress, with intrinsic land

sensitivity conditioning regional responses and mitigation-related factors partially moderating susceptibility growth. Human pressure contributes more clearly to baseline susceptibility patterns than to temporal intensification within the present framework, reflecting both its spatial heterogeneity and limitations in harmonized temporal data availability. Overall, climatic stress shows the strongest alignment with long-term susceptibility increases, while mitigation-related conditions dampen intensification and intrinsic land properties mainly influence variability rather than directly driving change.

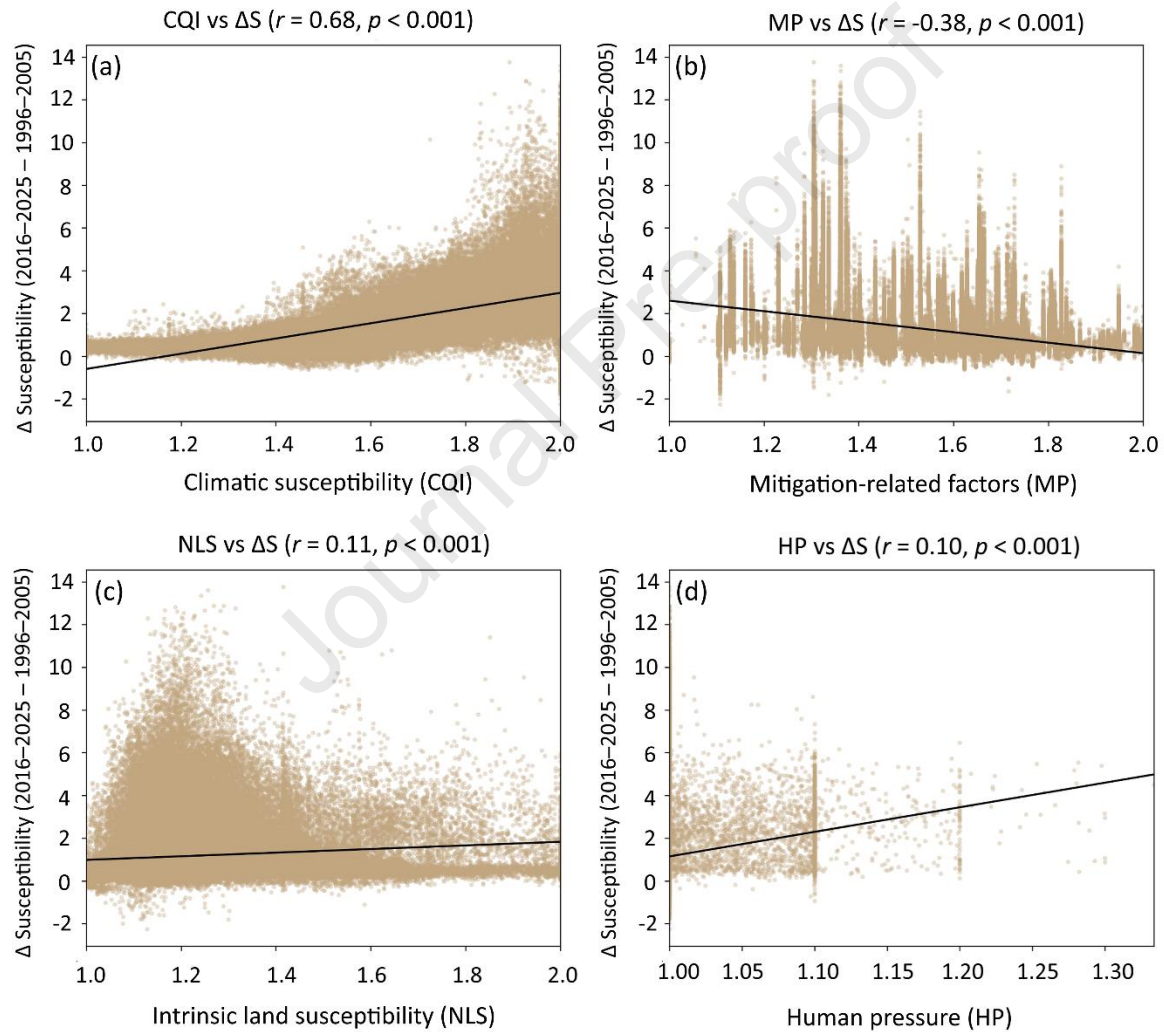


Figure 7. Relationships between susceptibility components and long-term changes in desertification susceptibility across Europe. Scatter plots show pixel-wise relationships between modeled susceptibility change (1996–2005 to 2016–2025) and the main components: (a) climatic susceptibility (CQI), (b) mitigation-related factors (MP), (c)

intrinsic land susceptibility (NLS), and (d) human pressure (HP). Linear models are used as a first-order approximation to summarize dominant trends and enhance comparability across components, rather than to represent underlying non-linear processes. Accordingly, these relationships should be interpreted as descriptive patterns rather than process-based or predictive models.

4.3. Interpretation of susceptibility trajectories and uncertainty

The dominant susceptibility trajectories across Europe suggest that desertification risk primarily evolves through gradual, cumulative change, while acknowledging that such gradual forcing may still give rise to localized or threshold-driven shifts rather than large-scale abrupt spatial reorganization. Stable trajectories are most prevalent in northern and north-western Europe, where favorable climatic conditions and higher mitigation capacity coincide with low baseline susceptibility. Stepwise increasing trajectories occur more frequently in Mediterranean regions, south-eastern Europe, and climatic transition zones, indicating that intensification generally reinforces existing regional gradients rather than creating entirely new hotspots.

The identification of these temporal patterns is partly influenced by the methodological framework, including the time-invariant nature of some indicators, which may moderate the expression of short-term dynamics. These modeled trajectories should be interpreted as probabilistic representations of evolving susceptibility, not deterministic predictions. Their consistency across parameterizations reflects aggregated tendencies arising from interacting drivers and indicates directional coherence rather than fixed pathways.

Ensemble uncertainty increases over time in a manner consistent with heightened system sensitivity under intensifying conditions. Median ensemble standard deviation rises from approximately 0.07 in 1996–2005 to about 0.10 in 2016–2025, while the upper uncertainty tail nearly doubles (95th percentile from ≈ 0.60 to ≈ 0.96). As susceptibility approaches class thresholds, small parameter differences can produce larger variability, especially in already stressed environments. Accordingly, uncertainty hotspots tend to overlap with regions undergoing rapid climatic intensification and structural vulnerability, highlighting areas where future trajectories may be more contingent on management and policy interventions.

4.4. Implications, limitations, and perspectives for future research

Implications for science and policy. The adoption of a multi-temporal, harmonized framework for assessing desertification susceptibility offers added value for examining long-term land degradation dynamics at the continental scale. By enabling consistent comparisons across successive decades, MEDALUS-R facilitates the identification of gradual trends and evolving susceptibility trajectories, beyond short-term variability. This temporal perspective is particularly relevant in Mediterranean and climatic transition regions, where cumulative climatic and anthropogenic pressures are likely to contribute to progressive susceptibility intensification.

From a policy perspective, the framework may complement established indicator-based approaches by supporting EU-level screening, comparative assessment, and spatial prioritization for soil protection and land degradation neutrality, rather than prescribing specific interventions. In this sense, MEDALUS-R responds to gaps highlighted by the (European Court of Auditors, 2018)(European Court of Auditors, 2018)(European Court of Auditors, 2018), which emphasized the limited availability of harmonized and temporally consistent tools for assessing desertification risk across Member States. The inclusion of mitigation- and policy-related components represents a step toward greater policy relevance, although further refinement is needed. While applied here in an *ex-post* assessment context, the framework could also support exploratory scenario-based sensitivity analyses as improved management and policy data become available. Overall, MEDALUS-R revises rather than replaces MEDALUS, improving interpretability and reducing reliance on heuristic assumptions through data-driven weighting and parameterization, while retaining flexibility as improved datasets become available.

Key methodological and data limitations. Consistent with its data-driven structure, several limitations should be considered when interpreting the results. First, desertification susceptibility is inherently scale-dependent, and continental-scale outputs should not be interpreted as substitutes for local or site-specific assessments. While MEDALUS-R is designed to capture broad spatial gradients and long-term trends across Europe, it does not resolve fine-scale processes such as field-level management practices, irrigation

decisions, or short-term extreme events. This trade-off between spatial coverage and local detail is common to European-scale assessments. Second, the datasets integrated into the framework differ in spatial resolution, thematic detail, and data origin. Several climatic indicators are derived from relatively coarse reanalysis products (e.g., ERA5-Land at ~9 km resolution), which are appropriate at continental scale but require spatial resampling (using bilinear interpolation, suitable for continuous variables). Such procedures may introduce localized smoothing effects and do not inherently improve spatial accuracy. In addition, some remote sensing datasets are not fully available for the earliest period (1996–2000), which may introduce additional uncertainty in baseline estimates. However, this limitation is not expected to introduce systematic bias in the spatial patterns or temporal trends identified, as the framework is primarily driven by consistent climatic gradients and structurally stable indicators across periods. Third, a subset of susceptibility indicators was intentionally held constant over time due to the lack of harmonized temporal data at the European scale, particularly for management- and policy-related variables (e.g., PGI, Natura 2000 coverage, SQI, and rainfall erosivity). These indicators address mitigation capacity but are currently implemented at aggregated administrative levels (NUTS2 or national), which may underrepresent local variability. Data access constraints, especially for Eurostat microdata and non-EU countries, further limit their spatial and temporal refinement, leading to the use of EU-27 median values as proxies. Fourth, the analysis does not validate modeled susceptibility changes against observed degradation outcomes (e.g., erosion rates or productivity loss), reflecting both data limitations and the conceptual distinction between susceptibility and realized degradation. In particular, spatially explicit and harmonized data on additional degradation processes such as soil compaction, sealing, or sub-surface structural degradation, which are relevant components of human pressure, are currently unavailable at the continental scale and therefore could not be incorporated. Fifth, an additional limitation concerns the absence of explicit indicators representing water resource overexploitation, which is a key driver of desertification, particularly in southern Mediterranean regions. In the present framework, this dimension is not explicitly represented due to the lack of harmonized and spatially consistent datasets on groundwater abstraction and irrigation pressure at the pan-European scale. As a result, the current implementation may not fully capture the

contribution of anthropogenic water stress to susceptibility patterns, and the integration of such indicators represents an important priority for future developments. Despite this constraint, susceptibility mapping remains valuable as an early-warning and risk-screening tool. Sixth, the Policy and Governance Index (PGI) attempts to quantify soil conservation commitments across EU Member States, but governance and policy effectiveness are inherently complex and would ideally require transdisciplinary analysis. Within the present geoscience-oriented scope, PGI relies on simplified, aggregated information and therefore remains an important target for future refinement. Finally, as with most large-scale frameworks, each index simplifies complex socio-environmental processes, and indicator selection and aggregation may influence component contributions. Nevertheless, MEDALUS-R addresses key limitations of earlier approaches by avoiding arbitrary thresholds and fixed weights, instead relying on empirically derived parameterizations and sensitivity analysis to enhance transparency and robustness.

Interpretation limits. The results represent model-based estimates of relative susceptibility and should be interpreted as probabilistic indications of sensitivity rather than as direct observations of degradation or deterministic forecasts. The identified trends describe changes in the likelihood and spatial organization of susceptibility, rather than causal attribution or realized impacts. As with other composite index approaches, the framework does not explicitly represent causal mechanisms linking drivers and processes. The objective of the framework is not to disentangle causal pathways or attribute outcomes to individual indicators, but rather to identify spatial patterns of susceptibility emerging from the interaction of multiple drivers. Accordingly, the results represent integrated responses reflecting the combined influence of climatic, biophysical, and anthropogenic factors, rather than the effect of isolated components. As such, the results should be interpreted as indicative representations of susceptibility rather than direct measurements of degradation dynamics. In this context, human pressure contributes more clearly to baseline susceptibility patterns than to modeled temporal intensification, reflecting both its spatial heterogeneity and current data constraints.

Perspectives for future research. Future work could enhance the framework by integrating spatially explicit, time-resolved management and policy datasets, potentially through coordinated efforts led by institutions such as the European Soil Observatory or within the Soil Health Monitoring Law, thereby strengthening the policy dimension represented by the PGI. In this context, further investigation could also be pursued at pilot sites of the EU-funded MONALISA project, providing opportunities to test and refine the approach using high-resolution field data and stakeholder-driven management scenarios. Coupling MEDALUS-R with observed degradation indicators, national datasets, and scenario-based climate projections could further improve interpretability and policy relevance. Extending the framework beyond Europe using globally harmonized datasets also appears to be a promising direction for comparative desertification assessments.

5. Conclusions

This study introduces MEDALUS-R, a revised, data-driven framework for spatiotemporal assessment of climate-conditioned desertification susceptibility at the continental scale. Results suggest that susceptibility is spatially structured and generally intensifies gradually, particularly where climatic constraints are stronger and mitigation capacity is lower. By incorporating mitigation- and policy-related components and data-driven parameterization, MEDALUS-R supports temporally comparable assessments across regions and decades, with potential for ex-post evaluation and ex-ante scenario exploration as improved data become available. The framework should be interpreted as a complementary large-scale screening tool rather than a substitute for established monitoring systems or indicator-based approaches. Further development will depend on more spatially explicit management and policy data, while targeted field observations remain essential for calibration and evaluation against local degradation processes.

Results indicate a clear increase in desertification susceptibility across Europe from the late 1990s to the most recent decade, expressed mainly through upward transitions to higher susceptibility classes. Climatic

intensification dominates this trend; intrinsic land sensitivity structures spatial patterns, human pressure acts as a secondary amplifier, and localized mitigation improvements do not offset the continental-scale climatic signal.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

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on behalf of all authors