

Application of the Mediterranean Desertification And Land Use (MEDALUS) Model for Assessing Desertification Sensitivity: A Review

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Abstract

The Mediterranean Desertification And Land Use (MEDALUS) model, originally developed in 1999, has become one of the most widely adopted models for mapping and assessing desertification sensitivity over the past two decades. The MEDALUS model has gained extensive use in other regions of the world, however, review of the model has not been conducted. The study conducted a systematic review of articles from 1999 to 2024 (25 years) that applied the MEDALUS model. Searches were conducted across Scopus, Web of Science, ScienceDirect, Google Scholar, and supplementary repositories. 73 eligible studies were identified after screening 262 reports. The review evaluated the temporality and geographical distribution of the use of the model, default and modified versions of the model, most used desertification factors and indicators of the model, most used datasets for deriving key indicators, validation approaches, and type of classifying schemes for defining desertification sensitivity. 2018 was the peak of usage of the model having 11 articles. Between 2013 and 2024, 51 articles were published, indicating a considerable growth in the application of the model. The model has been applied in 23 countries, where Egypt (10 articles) and Italy (5 articles) are the most studied countries in the Mediterranean. Most articles are mainly single-year, with limited multi-temporal studies to analyze trends. Rainfall, slope, vegetation indices, and soil texture are the most dominant indicators due to their accessibility. Weighting procedures and sensitivity analysis of indicators, transparent reporting of data sources, and validation of results remain critical issues in the application of the model.

1. Introduction

In 1994, the United Nations defined desertification as “land degradation in arid, semi-arid, and dry sub-humid areas resulting from human activities and climate variations”, including the human effects on climate variation beyond the economic loss [56]. This definition has been widely used and accepted in the literatures of desertification [e.g. 18, 48]. For this study, the definition is upheld and redefined as “land degradation in arid, semi-arid, and dry sub-humid areas caused by the interplay of human activities and climate variations, which leads to irreversible changes in the ecosystem if certain threshold is exceeded”. Desertification sensitivity, also known as Environmentally Sensitive Areas (ESA) is the extent to which a terrestrial environment responds to the adverse effects of environmental and anthropogenic pressures that induce desertification [49].

Several models have been proposed as methods for assessing and mapping desertification sensitivity at different scales with different factors [9, 37, 29, 31, 63]. Some of the prominent models are the Food and Agricultural Organization of the United Nations Environmental Programme, FAO-UNEP [19]; Global Assessment of Human-Induced Soil Degradation, GLASOD [42]; Assessment of Soil Degradation, ASSOD [57]; Mediterranean Desertification Land Use Model, MEDALUS [33] and Land Degradation Assessment in Drylands, LADA [44]. The models that use spatial geo-information tools to combine biophysical factors and especially anthropic factor [9], and flexible for modification are preferred. This makes the MEDALUS model to be of great importance.

The MEDALUS model originated from phases of research programs from 1991 to 1999. The phases are: MEDALUS I and II (before 1996), which focused on establishing field sites, developing process-based models, and early data collection for vegetation, soil, and climate; MEDALUS III (approx. 1996–1999), which aimed to refine the earlier models by combining field data from over 7 sites across the northern Mediterranean [38]; and MEDALUS IV (by 1999), which was led by [33] and is the final phase for refining the methodology, and created the core Environmentally Sensitive Area (ESA) indexing methodology for classifying land into critical, fragile, and sensitive areas using weighted factors (soil, climate, vegetation, and management) [33]. MEDALUS involves multinational research developers [e.g., 33, 34] and was funded by the European Commission [33] to understand, assess, and quantify desertification sensitivity in the Mediterranean [61, 39] using biophysical and socio-economic factors.

The MEDALUS is a multi-factor approach based on both general and local knowledge of environmental processes [60]. The MEDALUS has gained universal adoption because of its ability to be executed in GIS, its flexibility in indicator selection and assignation of weights to indicators [31, 62]. Furthermore, the model has been put to test in some countries in the Mediterranean and has produced good results [34, 7]. In addition, the simplicity and flexibility of the MEDALUS to accept new factors and indicators, with easy implementation led to a widespread use of the MEDALUS in the Mediterranean region [14, 55] as well as outside the Mediterranean region [29, 53, 2], including Africa such as Egypt [e.g., 49], Morocco [e.g., 11], Algeria [e.g., 10] etc.

The field of desertification assessment has recently gained a surge in the application of MEDALUS model across various regions. Despite the widespread and growing adoption of the MEDALUS model, there has been no attempt to conduct a systematic review to critically evaluate its global applications. On previous review on desertification, [6] reviewed soil salinity mapping and monitoring in arid and semi-arid regions using remote sensing technology. The study reviewed indicators for soil salinity, spectral vegetation, remotely sensed images and methods for identifying and mapping soil salinity in arid and semi-arid regions. [48] reviewed the application of remote sensing for desertification studies. The study found out that the Asian continent had more studies using remote sensing to study desertification. Both aforementioned studies did not consider models (mathematical) that have been used for the study of desertification. This creates a significant knowledge gap. It is on this premise that this study aimed to fill this gap by conducting a systematic review to evaluate the temporal evolution and global distribution of studies that applied the model, the original and modified versions of the model, the frequency of usage of indicators and datasets of the model, and the types of Environmentally Sensitive Area (ESA) for defining desertification.

2. Computation of the MEDALUS model

The MEDALUS is a semi-quantitative method, which identifies environmentally sensitive areas (ESAs) by computing Environmentally Sensitive Area Index (ESAI). The ESAI is a composite index, which comprises 4 factors: climate, soil, vegetation, and management. Each parent factor comprises varying indicators (see Table 1). The climate, soil, and vegetation factors address the biophysical condition of the

environment, while the management factor addresses the human activities. To determine the quality of each parent factor, the indicators are weighted between 1 and 2 irrespective of the number of classes in each indicator and based on their significance and range of values of each indicator. Weights of “1” and closer denoted less sensitivity and weights of “2” and closer denoted high sensitivity. Thematic layer for each parent factor was then be quantitatively computed in GIS environment using the geometric mean value of the indicators as shown in Eq. 1 [33].

Table 1
Desertification factors and indicators used in the MEDALUS model [33]

S/N	Factors	Indicators
1	Climate	Aridity, aspect, rainfall distribution
2	Soil	Parent material, soil texture, soil depth, slope gradient, drainage conditions, degree of soil erosion, surface rock fragments
3	Vegetation	Vegetation fire risk, soil erosion protection by vegetation, vegetation for drought resistance, plant cover
4	Management	Intensity of land use, policy on land protection

For clarification, desertification factors are defined as the drivers that trigger desertification. Desertification indicators are defined as parameters that provide synthetic information on threshold levels, status and evolution of relevant physical, chemical, biological, and anthropogenic processes of desertification factors. Desertification indicators are values or variables derived from indices, which provide information about and describe the state of an environment. Think of the desertification factor as the drivers or catalysts of environmental deterioration (say ‘illness’), while the indicators are the signs (say “symptoms”) of the environment undergoing deterioration. In this article, desertification factor is used in lieu of quality index of desertification, and desertification indicator is used in lieu of sub-factor of desertification as used in most literature.

Since the MEDALUS is modifiable, it implies that additional factors besides the four original factors (climate, soil, vegetation, management) and their corresponding indicators can be included in the MEDALUS model. The inclusion of additional factors and indicators also depends on the underlying causation of desertification in a specific region. The source of data for the indicators can be remote sensing and field measurement. Each factor is computed using the expression in Eq. 1.

$$\text{Factor}_i = \sum_i^n [(\text{Index}_i) \times (\text{Index}_{i+1}) \times \dots \times (\text{Index}_{n-i}) \times (\text{Index}_n)]^{1/n}$$

1

Where i represents the index; n is the total number of indices used to compute each factor. Each parent factor will have varying indicators vis-a-vis varying indices.

After computing each thematic layer of factor, the ESAI is computed as the geometric mean value of the factors combined as shown in Eq. 2 [33]:

$$ESA\ Index = \sqrt[n]{Factor_i \times Factor_{i+1} \times \dots \times Factor_{n-i} \times Factor_n}$$

2

Where i is each factor and n is the total number of factors.

While the MEDALUS model has turned out to be an important tool for desertification assessment, it also has specific limitations. These limitations entail the subjectivity of some of the indicators used in the model, the requirement for high-quality data, and the possibility of over-simplification of complex desertification mechanisms. In addition, the MEDALUS model assumes that each index has only a limited capability to influence the resulting value of the ESAI, and only when numerous indicators have a high weight, then an area can be assigned to highly sensitive class [3]. Despite these limitations, the MEDALUS model remains a vital tool for desertification assessment.

3. Method of Systematic Review

A systematic review is defined as a review that uses explicit, systematic methods to collate and synthesize findings of studies that address a clearly formulated question [25]. Put differently, systematic review identifies and evaluates published studies to address specific questions and adheres to a well-defined methodology for searching and selecting studies to review. A systematic review should be duplicable and demonstrate the effects, interventions, and gaps of knowledge about the reviewed studies.

3.1 Identification of studies

This systematic review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [43] to ensure transparency, reproducibility, and completeness in identifying studies that applied the MEDALUS model. The review protocol was not prospectively registered. This is acknowledged as a limitation. However, the eligibility criteria, search strategy, and analysis plan were finalized before the search was conducted and were not modified during the review. The workflow proceeded through identification, screening, eligibility check, and final inclusion of articles. The workflow of the systematic review is presented in Fig. 1.

A comprehensive literature search was conducted for publications available from 1999 to 31st December, 2024. Searches were conducted in two parallel streams: stream 1 entails databases such as Scopus, Web of Science (WoS), ScienceDirect. These databases were selected for their comprehensive coverage of peer-reviewed environmental science, geosciences, and remote sensing literature. Stream 2 entails other sources such as:

1. Google Scholar (first 200 results per search query, following [23] recommendations for Google Scholar searches);
2. ResearchGate (manual search of profiles of key MEDALUS authors);
3. Google web search (targeted search for grey literature: theses, conference proceedings, government reports; first 100 results per query);
4. Backward citation searching: Reference lists of all eligible full-text articles were manually checked;
5. Forward citation searching: Citations of [33] were tracked through Google Scholar to identify additional studies.

Stream 2 search was carried out because of publications that are not indexed in the aforementioned databases. The search strategy used a combination of keywords and Boolean operators. The search was developed iteratively and piloted in Scopus before adaptation to other databases. The main search strings used for each database were:

1. "MEDALUS" OR "Mediterranean Desertification and Land Use" OR "Environmentally Sensitive Area" OR "ESA model" OR "ESAI" AND "desertification" OR "land degradation" OR "sensitivity" OR "susceptibility" OR "vulnerability" OR "severity" OR "risk", must appear in the following fields article title, abstract, keywords.
 2. The articles must be between 1999 and 2024, using all the span of the databases.
 3. Only English language
- iv. Only peer review original/primary research journals were considered.

No additional filters (e.g., document type or subject area) were applied at the search stage to maximize sensitivity. For Google Scholar and Google, the following simplified queries were used: ("MEDALUS model" OR "desertification sensitivity" OR "Environmentally Sensitive Areas" OR "MEDALUS desertification" OR "ESAI" OR "desertification "land degradation". The search identified 262 records, namely: 94 from databases (Scopus: 36; Web of Science: 31; ScienceDirect: 27) and 168 from other methods (Google Scholar: 19; ResearchGate: 23; Google: 111; backward/forward citation searching: 15).

3.2 Screening and eligibility check of reports

All duplicate documents were removed for documents having same study but different download nomenclature. This was achieved by manually opening the documents one at a time to holistically check the title, abstract, and body of the text. 23 duplicates were identified and removed. 239 unique records were then screened by applying a pre-defined framework for eligibility criteria. PEO (Population – Exposure - Outcome) framework for formulating eligibility criteria was used. The PEO defines inclusion and exclusion criteria for reviews [41], it is apposite for methodological reviews. Table 2 shows the eligibility criteria by the PEO framework.

Table 2
PEO framework for the eligibility criteria

S/N	Item	Definition
1	Population (P)	Any geographic area classified as arid, semi-arid, dry sub-humid, or otherwise susceptible to land degradation and desertification.
2	Exposure (E)	Explicit application of the MEDALUS model or its documented variants (e.g., ESA/ESAI methodology as defined by Kosmas <i>et al.</i> , 1999a) for the computation of an ESAI.
3	Outcome (O)	Spatial mapping and/or quantitative assessment of desertification sensitivity, susceptibility, vulnerability, severity, or risk; or identification/classification of Environmentally Sensitive Areas.

In addition, some exclusion criteria that were used are stated below:

1. Publications not in English, even if the abstract was available in English. The rationale is that full-text methodological evaluation requires complete language access.
2. Review papers, editorials, letters, commentaries, book reviews, policy briefs, technical reports, and institutional publications even if they present original empirical MEDALUS applications.
3. Preprints that were subsequently published as peer-reviewed articles (the peer-reviewed version was retained to avoid double-counting).

With the eligibility criteria applied to the 239 unique records, 85 were selected for full-text review. These 85 reports applied the MEDALUS model" OR "desertification sensitivity" OR "Environmentally Sensitive Areas" OR "MEDALUS desertification" OR "ESAI" OR "desertification "land degradation" as the fulcrum or linchpin of the studies. 10 records were excluded for language (Chinese: 6; Arabic: 4). Of the 75 full-text articles assessed for eligibility, 2 were excluded for insufficient methodological detail (one was a conceptual proposal without spatial outputs; one lacked documentation of factors and indicators used). The final review included 73 articles. The objective and systematic review of the 73 articles was guided by the following questions:

1. When has the MEDALUS model been used to study desertification?
2. Where has the MEDALUS model been applied to study desertification?
3. Which studies used the default MEDALUS model?
4. Which studies used the modified MEDALUS model?
5. What are the most frequently used desertification indicators and their sources?
6. What are the validation approaches for the outputs of the model?
7. What are the most used schemes for classifying desertification sensitivity?

The answers to the above questions were extracted from each included article into a spreadsheet. Data extraction was performed independently by three persons to ensure consistency, with disagreements harmonized by a fourth person. Quantitative and qualitative analyses were then performed to identify

trends, patterns, and gaps in the application of the MEDALUS model. The quantitative analysis is presented in charts and tables.

4. Results

4.1 Temporal trends of the use of the MEDALUS model

The first demonstration research on the application of the MEDALUS model was published by [34] in 1999. The study was carried out in the Island of Lesvo, Greece. Since then, its usage has grown considerably. 14 (19.1%) articles were published between 2005 and 2011. A significant 69.9% (51) of the reviewed articles were published between 2013 and 2024. This indicates a significant increase in the application of the MEDALUS model, demonstrating that it has become a more popular tool for assessing desertification sensitivity. The year 2018 marked the peak, with 11 publications (15.1% of the total), followed by 2021 with 10 articles (13.69%). The year 2020 also had a significant number of publications, with 8 articles (10.95%) (see Fig. 2). This trend likely reflects increasing global concern over land degradation, advancements in geospatial technologies, and the proven adaptability of the MEDALUS model.

A critical finding is the overwhelming dominance of single-year assessments. 97% of the reviewed articles (71) used the MEDALUS model for a single year, implying that they typically assess desertification at a single moment in time. Only 2 studies (3%) conducted bi-temporal analysis, namely: [16] investigated desertification in Iran between 1984 and 1997; and [36] investigated desertification in Egypt between 2003 and 2008.

4.2 Geographical distribution of the use of the MEDALUS model

The MEDALUS model has been applied in 23 countries across 5 continents, demonstrating its global reach beyond the Mediterranean. Table 3 shows the continents and countries that applied the model most, while Fig. 3 shows a map where the model has been used most. Egypt and Iran lead with articles with 10 articles each, followed by Algeria and Morocco, with 6 articles each (see Table 3 and Fig. 3). Italy had 5 articles and being a country in the Mediterranean, aligns with the original goal of the MEDALUS model. Iraq, Nigeria, Serbia, and Turkey had 4 articles each, thereby signifying the proneness of these areas to desertification and indicating the extensive use of the MEDALUS model. Countries with 2 articles are Brazil, India, Thailand, and Tunisia. Countries with 1 article are China, Lebanon, Spain, Peru, Sudan, Carbo Verde, Mongolia, and Vietnam respectively. For the continent with the most MEDALUS application, 31 (42.6%) studies were conducted in Africa (North and Sub-Saharan Africa). For example, in the Sahel, 4 studies applied the MEDALUS model in Nigeria and 1 in Sudan. Additionally, a regional study in the Sahel comprises more than a single country (e.g. the Niger-River Basin) and has a single article. Most studies (n = 64) were conducted at the sub-national level. Seven studies (9.6%) were carried out at the national level, and only two (2.7%) were transboundary (Niger-River Basin).

Table 3 Geographic distribution of MEDALUS applications

S/N	Continent	Country	Number of studies	%
1	North Africa	Egypt (10), Algeria (6), Morocco (6), Tunisia (2), Sudan (1)	25	34.2
2	Sub-Saharan Africa	Nigeria (4), Cape Verde (1), Niger River Basin (1)	6	8.2
3	Southern Europe (Mediterranean)	Italy (5), Greece (3), Spain (1), Serbia (4)	13	17.8
4	Middle East	Iran (10), Iraq (4), Turkey (4), Lebanon (1)	19	26
5	South/Southeast Asia	India (2), Thailand (2), Vietnam (1)	5	6.8
6	East Asia	China (1), Mongolia (1)	2	2.7
7	South America	Brazil (2), Peru (1)	3	4.1

Europe (17 articles, 23.28%) and the Middle East (14 studies, 19.17%) have a substantial representation. Asia (5 studies, 6.84%) and South America (3 studies, 4.1%) are significantly underrepresented. However, despite their non-Mediterranean climates, countries such as Brazil and Thailand have used the model, demonstrating its global adoption.

4.3 Studies that applied “default” MEDALUS model

In this review, “default” MEDALUS model is the original set of desertification factors (climate, soil, vegetation, and management) and their associated indicators as stated in the [33] handbook. Findings of the articles that applied the “default” MEDALUS are discussed in two folds: (i) at factor-level i.e., the four (4) basic desertification factors irrespective of the exact numbers of indicators used for each factor and (ii) at indicator-level i.e., the exact 16 indicators in the MEDALUS manual.

For the first finding, 38 articles used the four (4) “default” desertification factors for the assessment of desertification sensitivity (see Table 4). This signifies that the core conceptual structure of the MEDALUS remains robust and widely applicable. These 38 articles cut across several countries, with the most prevalent countries being Morocco (5 articles), Egypt (4 articles), and Algeria, Iraq and Italy (3 each). This indicates that many studies employing the “default” model can be found in the Mediterranean and desert-prone areas such as North Africa. Countries like Tunisia, Vietnam, Turkey, Serbia, and Greece each had 2 articles, while Sudan, Nigeria, India, and China only had 1 article each. Figure 4 presents timeline and frequency of the application of the “default” factors of the MEDALUS from 1999 to 2024. 5 articles were published each in 2020, 2021, and 2022, 4 articles each were published in 2018 and 2023 respectively. In addition, 2 articles each were published in 2005, 2015, and 2019.

Table 4
Countries with articles that frequently applied the “default” MEDALUS model

S/N	Country	Number of studies
1	Morocco and Iran	5
2	Egypt	4
3	Algeria and Italy	3
4	Greece, Iran, Serbia, Tunisia, and Turkey	2
5	Brazil, China, India, Iraq, Lebanon, Mongolia, Nigeria, Peru, Spain, Sudan, and Thailand	1

For the second finding, the review looks at whether the exact 16 original indicators for each factor were used. Interestingly, only [33] used the exact 16 “default” indicators as specified in the MEDALUS manual by [33]. However, 7 articles came close to using the “default” indicators of the MEDALUS model. They are [47]; [8]; [26]; [55]; [32]; [22]; and [49]. The articles each used 15 indicators of the MEDALUS model and they are short of a single indicator, which is the degree of soil erosion belonging to the soil factor.

4.4 Studies that used the “modified” MEDALUS model

Modification of the MEDALUS model is defined as any change to the “default” MEDALUS model, including the addition or removal of factors or indicators. The result looks at how researchers have adapted the model by either modifying the basic desertification factors (climate, soil, vegetation, and management) or modifying the indicators associated with these factors. This modification is often done to “align” the MEDALUS model to specific environmental or socio-economic conditions or settings of different study regions. The findings are discussed in two-fold: (i) modification at factor-level i.e., the four (4) basic desertification factors irrespective of the exact numbers of indicators used for each factor; (ii) modification at indicator-level i.e., the 16 varying indicators even if the four (4) basic factors are used.

38 studies (52.1%) retained the four (4) original MEDALUS factors (climate, soil, vegetation, management), while 35 studies (47.9%) introduced modifications at the factor level (see Table 5). 6 articles used the “climate, soil, and vegetation” factors, leaving out management. 5 articles included “erosion and groundwater” to the basic four factors (climate, soil, vegetation, management), expanding the scope of the model. 3 articles each added waterlogging and irrigation factors to the original four factors. Interestingly, still on Table 5, a unique case is the study of [18], who employed soil as the single factor to determine desertification sensitivity. Other combinations such as the addition of physical land, agriculture, geology, technological development, or human to the climate, soil, and vegetation group. In another finding, 3 articles (2 from Iran, 1 from Egypt) used both the default and modified MEDALUS models to compare the results of both models within the same study area.

Table 5
Various modifications of the MEDALUS model at factor-level

S/N	Factor configuration	Count	%
1	Climate (C), Soil (S), Vegetation (V), Management (M)	38	52.1
2	C, S, V only (management excluded)	6	8.2
3	C, S, V, M + Erosion	2	2.7
4	C, S, V, M + erosion + groundwater	5	6.8
5	C, S, V, M + erosion + waterlogging	3	4.1
6	C, S, V, M + irrigation	3	4.1
7	C, S, V, M + social/socio-economic	4	5.5
8	C, S, V, M + water management	2	2.7
9	Other combinations	8	12.3
10	S only (single factor)	1	1.4

The second part of the modification focuses on the 16 original indicators that correspond to the four basic desertification factors. A notable finding is that 62 of the 73 articles modified the original 16 indicators of the MEDALUS model, indicating extensive adaption of the MEDALUS model to local conditions. In fact, if the 7 articles that closely match the original 16 indicators of the MEDALUS model as discussed in section 4.3 were excluded, then 69 articles modified the indicators of the MEDALUS model. This suggests that almost all of the studies were required to modify the indicators to the specific environmental and socioeconomic conditions their study locations. The modification of the indicators can arise because drylands differ in their societal, economic and natural settings [24]. In fact, [20] and [52] suggested that the design of the MEDALUS model should be modified based on the association of the indicators to the local condition of the study area. In addition, the modification of the indicators can also be based on their availability in datasets in respect to the study location, as some locations may lack adequate datasets for certain indicators.

4.5 Most frequently used desertification indicators and their sources

The most used indicators of the climate, soil, vegetation, and management factors are discussed in this section. Table 6 shows the most frequently used desertification indicators for climate factor. Rainfall was found to be used in 51 (69.8%) articles, thereby reflecting its undisputed environmental relevance. However, the diversity of sources (meteorological stations vs. remote sensing) and temporal averaging periods introduces heterogeneity. Station-based measurements offer high temporal resolution and local accuracy but suffer from spatial gaps, particularly in data-sparse regions of Africa and the Middle East. Remote sensing sources (e.g., TRMM) proffer spatial completeness but at coarser resolutions and with

known biases in mountainous and arid terrain [28]; [15]. Notably, eight studies (15.7% of those using rainfall) did not report the data source at all, thereby rendering their results non-reproducible.

The aridity index, used in 48 studies (65.8%), is computed using at least four different mathematical formulae (FAO/UNEP, BGI, UNESCO, De Martonne), each of which defines aridity differently and produces different numerical ranges. The FAO/UNEP and UNESCO indices both compute aridity as the ratio of precipitation to potential evapotranspiration (P/PET) but use different PET estimation methods. The BGI uses a precipitation-temperature relationship with a different functional form. The De Martonne index is another formulation. Aspect was found in 36 (49.3%) articles, aspect affects sun exposure, which in turn impacts soil moisture and vegetation. There is a consistent derivation of aspect from DEM irrespective of the source. Evapo-transpiration was found in 14 (19.1%) articles despite its fundamental role in water balance and aridity (see Table 6). The six different computation methods (Penman-Monteith, Thornthwaite, Turc, remote sensing) yield systematically different values, specifically in arid environments where advection effects are significant. Rainfall erosivity was used in 7 studies, while only 2 studies stated their sources. Other fringe climate indicators were used without stating their sources.

Table 6
Most frequently used climatic indicators and various data sources

Climate indicator	Count (%)	Primary data source	Assessment
Rainfall	51 (69.9)	Meteorological stations (n = 22); RS: TRMM, GPCP, MERRA-2, WorldClim (n = 4); Not reported (n = 8)	15.7% did not report source
Aridity index	48 (65.8)	Mathematical formulae (n = 37): FAO/UNEP (15), BGI (13), UNESCO (7), De Martonne (2); Stations (n = 12); RS: CSI (n = 1)	Multiple incompatible aridity definitions used
Aspect	36 (49.3)	DEM: ASTER/NASA (10), SRTM/USGS (8), DTM (3), Cartosat (1), ALOS PALSAR (1), Field survey (1)	Consistent derivation from DEM
Evapotranspiration	14 (19.2)	Mathematical formulae: Penman-Monteith (6), Thornthwaite (3), Turc (2); RS: CRU, NASA LPDAAC (2); Station (1)	Multiple incompatible methods used
Rainfall erosivity	7 (9.5)	Fournier index (FI) formula (2)	Others did not report source
Wind speed	3 (4.1)	NCEP (1)	Others did not report source
SPEI, bioclimate	2 (2.7) each	Nil	Not stated
Other (temperature, drought index, mobility index, rainfall seasonality)	1 each	Nil	Not stated
<i>NOTE: RS: Remote Sensing, TRMM: Tropical Rainfall Measuring Missions, GPCP: Global Precipitation Climatology Project, MERRA-2: Modern-Era Retrospective analysis for Research and Applications, Version 2, NASA: National Aeronautics Space Administration, FAO/UNEP: Food and Agricultural Organization United Nations Environmental Programme, BGI: Bagnouls-Gaussien aridity Index, UNESCO: United Nations Educational Scientific and Cultural Organization, CSI: Consortium for Spatial Information, DEM: Digital Elevation Model, ASTER: Advanced Spaceborne Thermal Emission and Reflection Radiometer, SRTM: Shuttle Radar Topographic Mission, USGS: United States Geological Survey, DTM: Digital Terrain Model, CRU: Climate Research Unit, LPDAAC: Land Product Data Active Archive Center, NCEP: National Climate.</i>			

For the soil indicators, Table 7 shows the most used desertification indicators for soil factor. Parent material (used in 55 articles, 75.3%) and soil texture (used in 52 articles, 71.2%) are the most used soil indicators. These provide insight into the fundamental composition of the soil, which influences its resilience to erosion and its ability to support vegetation. Soil depth was used in 51 (69.8%) articles and slope gradient was found in 50 (68.4%) articles respectively. Drainage density (38 articles) and rock fragments (30 articles) indicate the structure and permeability of the land, affecting water retention and

the likelihood of erosion. Other indicators such as soil electrical conductivity (13 articles), organic matter (13 articles), and calcium carbonate content (9 articles) were less frequently used but are still relevant, depending on the local soil properties and the focus of the study. These indicators highlight the dynamic properties of soil, which can influence its fertility and vulnerability to degradation.

Table 7
Most frequently used soil indicators and various data sources

Soil indicator	Count (%)	Derivation Method
Parent material	55 (75.3)	Geological/soil maps; field survey; ISRIC; FAO DSMW
Soil texture	52 (71.2)	Laboratory analysis; soil maps; ISRIC
Soil depth	51 (69.9)	Field measurement; soil maps
Slope gradient	50 (68.5)	DEM (SRTM, ASTER); field survey
Drainage density	38 (52.1)	DEM-derived; digitized topographic maps
Rock fragments	30 (41.1)	Field inspection
Soil electrical conductivity	13 (17.8)	Laboratory analysis
Organic matter	13 (17.8)	Laboratory analysis
Calcium carbonate content	9 (12.3)	Laboratory analysis
Soil pH	7 (9.5)	Laboratory analysis
SAR (6), gypsum (5)		Various sources
Chloride, sodium exchange percentage, soil brightness, and soil salinity (3 each)		
Pedology, soil erodibility, soil erosion, soil fertility, soil organic carbon, soil permeability, and soil structure (2 each)		
Aggregate stability, bulk density, carbon to hydrogen, clogging, geomorphology, nitrogen, phosphorous in calcium chloride, potassium, sodicity, soil humus content, topography, water erosion, water table depth (1 each)		
NOTE: ISRIC: <i>International Soil Reference and Information Centre</i> , DSMW: <i>Digital Soil Map of the World</i> .		

Table 8 shows the most used desertification indicators for vegetation factor. Vegetation/plant cover (used in 52 articles) and erosion protection (51 articles) are the most commonly used indicators. Drought resistance (50 articles) and fire risk (40 articles) are also important indicators. Vegetation indicators are overwhelmingly derived from remotely-sensed NDVI and LULC classifications, which are acquired from different sources. Landsat imagery was used in 13 of 22 remote sensing–based vegetation studies, Sentinel-2 was used 5 studies, and MODIS was used in 4 studies. Erosion protection, drought resistance, and fire risk are derived based on land cover and vegetation types. Vegetation

indicators are critical to understanding how vegetation health and coverage affect land degradation, as places with dense vegetation are more resistant to desertification processes.

Table 8
Most frequently used vegetation indicators and various data sources

Vegetation indicator	Count (%)	Data source
Typical Data Source	52 (71.2)	NDVI from Landsat (13), Sentinel-2 (5), MODIS (4); LULC classification
Erosion protection	51 (69.9)	Derived based on land cover type
Drought resistance	50 (68.5)	Derived based on vegetation type
Fire risk	40 (54.8)	Derived based on vegetation type

Table 9 shows the most used desertification indicators for management factor. The management factor refers to human activities that can either prevent or aggravate desertification. Policy enforcement, the most commonly used management indicator, appeared in 31 articles, but only 2 (6.5%) reported how it was measured. Land use intensity, population density, and pasture/livestock grazing intensity (each used in 15 articles) reflect human pressures on the land. Their sources were mostly not reported. Cropland, road density, and old age index were used as fringe indicators and mostly not reported.

Table 9
Most frequently used management indicators and various data sources

Management indicator	Count (%)	Data source
Policy enforcement	31 (42.5)	Source reported: 2 (6.5%); Not reported: 29 (93.5%)
Land use intensity	15 (20.5)	Field inspection (3), aerial photo (1), image classification (1), not reported (10)
Population density	15 (20.5)	Census (3), formula (1), not reported (11)
Pasture/livestock grazing intensity	15 (20.5)	Statistical archive (3), not reported (12)
Other (cropland, road density, old age index)	1–5 each	Mostly not reported

Table 10 presents erosion, waterlogging, groundwater, water management, and run-off factors together with their corresponding indicators. Water and wind erosion indicators are used 6 and 7 articles. SAR and electrical conductivity are used in 5 studies each. Chloride is used 4 articles and water table depth is used in 3 articles respectively. Indicators like chloride, Sodium Adsorption Ratio (SAR), soil pH, and electric conductivity were used as both soil and groundwater indicators, thereby exhibiting their

relevance in multiple contexts and can be found in [2]. The sources of these indicator are mostly not reported. However, water erosion is sourced from the Revised Universal Soil Loss Equation (RUSLE), while SAR and electrical conductivity are sourced from field inspection. These indicators, while used as fringe indicators, demonstrates that local hydrological conditions also play a significant role in desertification.

Table 10
Other factors and indicators that have been used in the reviewed articles

Factor	Indicator	Count (%)	Data source
Erosion	Wind erosion	7 (9.5)	Mathematical model (1), not reported (6)
	Water erosion	6 (8.2)	Mathematical model (2), not reported (4)
	Flood frequency, impervious areas, management quality, management practices	1 each	Not reported
Groundwater	Soil Adsorption Ratio (SAR) and Electrical conductivity	5 (6.8) each	Field inspection (2 each), not reported (3 each)
	Chloride	4 (5.4)	Mostly not reported
	Water table depth	3 (4.1)	
	Total dissolved solids	2 (2.7)	
	Soil pH and water declination	1 each	
Water management	Water use balance, groundwater capacity, irrigation type, irrigation capacity, canal capacity	1 each	
Waterlogging	Waterlogging depth, waterlogging duration, mean water table	1 each	
Run-off	Rain risk and gradient	1 each	
Technological development	Technology development	2 (2.7)	

4.6 Validation approaches used for the ESAI outputs

Remote sensing–derived environmental indicators are inherently indirect and subject to algorithmic, spatial, and scaling uncertainties [51, 59]. As a result, validation against independent or reference data to assess the quality of derived-information from these indicators is essential to ensure the reliability, accuracy, and policy relevance of desertification assessments. Of the 73 articles, only 6 (8.2%) performed any form of validation or accuracy assessment of ESAI outputs. The remaining 67 studies

(91.7%) presented desertification sensitivity maps without any independent validation, thereby treating the ESAI computation as free of uncertainty. The identified validation techniques fall into four major categories: (i) Statistical correlation with soil quality parameters, such as SOM and CEC. 3 out of the 7 articles fall into this category. The studies are [22] and [21], who used SOM as independent variable. [50] used both SOM and CEC as independent variables. (ii) Multivariate regression modelling, such as multi-linear regression and Geographic Weighted Regression (GWR). 2 studies used this approach: [4] and [50]. This approach examines relationships between ESAI values and explanatory environmental variables. (iii) Non-parametric statistical testing, here, only a single study: [12] used Spearman Rank correlation and Kruskal–Wallis ANOVA to validate the final ESAI. The approach statistically compares between ESAI and environmental variables. (iv) Spatial accuracy assessment using independent imagery, only a single study: [58] compared ESAI outputs with high-resolution Google Earth imagery by using binomial probability distribution to test classification accuracy. In general, various approaches have been used to validate the ESAI outputs and thus exist methodological heterogeneity in the validation approaches.

4.7 Most used schemes for classifying desertification sensitivity

The scheme for classifying desertification sensitivity as captured in the manual of the MEDALUS model are as follows: Critical (C3), critical (C2), critical (C1), fragile (F3), fragile (F2), fragile (F1), potential, Not threatened. The scheme is way of defining the degree of criticality and fragility of a region to desertification sensitivity based on the computation of the ESAI. For clarification, “critical categories” (C3, C2, C1) indicate areas with the highest sensitivity, while the “fragile categories” (F3, F2, F1), indicate regions at a moderate risk of degradation. The “potential category” reflects regions that could become vulnerable to desertification, and “not threatened” signifies that a region shows no signs of desertification sensitivity. In the review, six (6) distinct classification schemes were identified for categorizing ESAI output into desertification sensitivity classes (see Table 11). Only 34 articles used the original eight-class scheme. The remaining 53.4% used simplified or alternative classifications, ranging from three to five classes and different class names. Of the 34 articles that used the original eight-class scheme, only 6 studies are from the Mediterranean, 10 studies are from North-Africa, and 4 studies are from the Middle-east (4 in Iran, 1 in Iraq). The five-class scheme appears to be a more abridged version of the eight-class scheme, which is appropriate for studies that may focus on wider regional assessments without the need for highly detailed categories like C1, C2, or F1, F2, and F3.

Despite these variations of the classification schemes, the basic classification system stays consistent with the overall purpose of assessing desertification threat, and the class that are used frequently reflects the goal of the study and the local environmental setting.

Table 11
Most used schemes for classifying desertification sensitivity

Scheme	Class name	Count (%)
Eight-class (MEDALUS manual)	Critical (C3, C2, C1), Fragile (F3, F2, F1), Potential, non-affected areas (N)	34 (46.6)
Five-class	Critical, fragile, moderately fragile, potentially sensitive, slightly sensitive	10 (13.7)
Four-class (Version A)	Low, moderate, high, very high	9 (12.3)
Four-class (Version B)	Low, moderately, sensitive, very sensitive	6 (8.2)
Four-class (Version C)	Potentially affected areas, moderately fragile areas, highly fragile areas, and highly critical areas	6 (8.2)
Three-class	Low, moderate, high	10 (10.9)

6. Discussion

The temporal analysis reveals a clear growth trajectory in the adoption of the MEDALUS model. There are noticeable increases in desertification studies in specific years, possibly due to increasing land degradation and desertification challenges in the usability and robustness of the MEDALUS model. The growth in the application of the model between 2005–2012 and the surge in application of the model between 2013–2024 could be driven by the improved access to free satellite imagery (e.g. Landsat archive); increasing GIS capacity in developing countries and growing international attention to desertification under the United Nations Convention to Combat Desertification (UNCCD) and the adoption of Sustainable Development Goal 15.3 on Land Degradation Neutrality in 2015.

Despite this growth, the near-total dominance of single-year applications (97%) represents a major methodological limitation. Only two studies [16] and [36] conducted bi-temporal analyses. Because MEDALUS aggregates multiple drivers into a single composite index, static application risks misrepresenting degradation dynamics. A critically sensitive area may be recovering, while a moderately sensitive area may be actively degrading. This is a limitation of single-year assessments. Multi-temporal studies would enable change detection, attribution of sensitivity changes to specific drivers (climate trends versus land use change), and evaluation of whether policy interventions have reduced sensitivity over time.

The MEDALUS model has been applied across 23 countries spanning Africa, Europe, the Middle East, Asia, and South America, demonstrating its global reach beyond the Mediterranean for which it was originally designed. Africa accounts for the highest application (46.6%), driven primarily by North African countries (Egypt, Algeria, Morocco) bordering the Sahara. The high representation of North African and Middle Eastern countries is expected given their extensive arid lands. Iran, as the most studied non-

Mediterranean country (10 studies), underscores the model's adaptability to arid regions outside the Mediterranean and the urgency of desertification assessment in the Middle East. Europe's substantial contribution (23.3%) reflects the historical connection to the European Commission, which funded the original MEDALUS research programs.

Three critical observations emerge from the geographic analysis. First, several major dryland regions with severe desertification challenges remain entirely unrepresented, namely: Central Asia (Kazakhstan, Uzbekistan, Turkmenistan), East Africa (Kenya, Tanzania, Ethiopia), the Horn of Africa (Somalia), Australia, and southern Africa (Namibia, Botswana). Whether the model is transferable to these contexts remains empirically untested. Second, the predominance of sub-national applications limits the ability to draw regional or continental conclusions about desertification patterns. Only two studies applied MEDALUS at regional or transboundary scales, thereby constraining regional-scale assessment and inference. The exclusion of non-English publications likely underrepresents East Asian and Arabic literature, particularly from China, where desertification research is extensive. This introduces language bias and limits global generalization. Third, the exclusion of non-English publications introduces a language bias that may under-represent methodological innovations from China and Arabic-speaking regions where desertification research is active, thereby limiting the global generalizability of the findings of the review.

At the factor level, the geographic distribution of the applications of the default model extends beyond the Mediterranean to non-Mediterranean regions including Brazil, India, and Mongolia, thereby reinforcing the model's cross-regional adaptability. Countries that applied the default model tend to share similar arid or semi-arid environmental settings, suggesting that the original four-factor structure resonates in regions with comparable desertification drivers. At the indicator level, application of the default model was remarkably low. Only one study [34] used all 16 original indicators exactly as specified in the MEDALUS model. Seven additional studies came close, each omitting only the soil erosion indicator. The remaining studies modified the indicator set. The consistent omission of soil erosion, which is the most commonly excluded original indicator can be attributed to methodological constraints rather than environmental irrelevance. However, quantifying soil erosion requires field measurement or estimation using data-intensive models (e.g., RUSLE, EUROSEM). This pattern, in which data convenience rather than environmental relevance drives indicator selection, recurs throughout the review and a bias in the MEDALUS.

The modification of the default model at factor level ranges from the removal of management factor to the addition of erosion, groundwater, waterlogging, irrigation, socioeconomic, and water management factors in various combinations. These modifications demonstrate context-specific adaptation; for example, the addition of waterlogging and groundwater factors (which are not captured in the MEDALUS manual) reflects the importance of hydrological processes in regions such as the Nile Delta and southern Iran. The single-factor application by [18], using soil alone, represents an extreme case of model reduction that may be justified when a single driver is demonstrably dominant. The modification also buttresses the flexibility of the model.

However, the scientific basis for most modifications is poorly documented. Only 12 of 35 modified studies explicitly justified their modifications with reference to local environmental conditions or literature. The remaining 23 introduced changes without stated rationale, raising the possibility that modifications could be driven by data availability (what data the researchers could obtain) rather than scientific reasoning (what factors actually drive desertification in that region). The three studies that compared default and modified models within the same study area (concentrated in Iran and Egypt) collectively suggest that modifications incorporating region-specific factors such as groundwater can improve the assessment. However, this evidence is too sparse and context-specific to support generalized conclusions, since none of these studies reported quantitative accuracy metrics (e.g., overall accuracy or kappa coefficient against ground truth), relying instead on qualitative judgment.

For the modification of the default model at indicator level, the near-universal modification of indicators challenges the conceptual identity of the MEDALUS model. This has practical implications: for instance, when two studies both claim to apply "MEDALUS" but use different factors, indicators, weights, data sources, and classification thresholds, the comparability of their resulting ESAI outputs is inherently limited. This tension between local adaptability and cross-study comparability is the central methodological challenge facing the MEDALUS framework and underscores the urgent need for standardized guidelines governing indicator selection, weighting justification, and modification documentation.

Rainfall, aridity, and aspect constitute the dominant climate indicators, consistently used together across studies, thereby reflecting their interrelated roles in water availability, which is the primary climatic driver of desertification. Fringe indicators such as temperature, drought index, wind speed, and rainfall erosivity, which are not specified in the MEDALUS manual, were used infrequently and in specific contexts, thereby reflecting adaptation to local environmental challenges. Two critical inconsistencies emerge in climatic indicator sourcing. First, rainfall, though widely used, is inconsistently sourced. Station-based measurements offer localized accuracy but suffer from spatial gaps, particularly in data-sparse regions of Africa and the Middle East. The non-reporting of rainfall data sources by 15.7% of studies renders their results non-reproducible.

Second, aridity is computed using at least four incompatible mathematical formulae, each defining aridity differently and producing different numerical ranges. A given location may be classified as "arid" under one index and "semi-arid" under another. Yet all studies apply the same MEDALUS weight thresholds (1–2) regardless of which formula was used, meaning that identical ESAI weights for aridity represent different physical conditions across studies. This compromises cross-study comparability. The problem is exemplified by [30], who computed aridity as the ratio of annual precipitation to mean annual temperature: a formulation not equivalent to any standard aridity index. Such ad hoc expression, when applied without recalibration of weight thresholds, introduce systematic bias into the ESAI computation.

The FAO-56 Penman-Monteith method is considered the most physically rigorous approach for estimating reference evapotranspiration because it integrates both energy balance and aerodynamic

components, incorporating radiation, temperature, humidity, and wind speed variables [5]. Yet it was used in fewer than half of the evapotranspiration studies (6 of 14), with the remaining studies employing simpler methods (Thornthwaite, Turc) that are known to produce systematically different values, particularly in arid environments. This methodological heterogeneity introduces further inconsistency into the computation of the climatic factor.

The six most frequently used soil indicators (parent material, soil texture, soil depth, slope, drainage density, rock fragments) share a critical characteristic: they are relatively static geological properties derivable from existing maps, global databases (ISRIC, FAO DSMW), or DEMs without requiring field visits. These databases may be decades old and mapped at coarse scales (e.g., 1:5,000,000 for FAO DSMW), yet their accuracy at the local scales at which most MEDALUS studies operate is rarely questioned. Dynamic soil properties with strong relevance to active desertification processes such as organic carbon (in 2 studies), soil moisture, biological activity, and aggregate stability (1 study each) are substantially under-represented. This under-representation is driven by data scarcity (these properties require costly field sampling and laboratory analysis) rather than environmental irrelevance. The consequence is that the soil indicators in most MEDALUS applications reflects the static geological inheritance of the landscape rather than its current degradation trajectory. This is a significant conceptual limitation rarely acknowledged by the studies themselves

While slope is computationally straightforward to derive from DEM, its role in desertification is context-dependent. For example, steep slopes promote water erosion but may also support orographic rainfall and cooler microclimates, while flat terrain may promote waterlogging and salinization in some contexts but facilitate erosion in others. The uniform weight assignment (1 for gentle slopes, 2 for steep slopes) does not capture this contextual variability. Soil erosion, despite being specified in the original MEDALUS manual, is omitted in approximately 90% of studies due to the data-intensive nature of its quantification. This is another instance of data convenience prevailing over environmental relevance.

The reliance on NDVI introduces well-documented limitations: saturation in dense vegetation, sensitivity to soil background reflectance in sparse canopies (a critical issue in arid environments), and seasonal variability. For areas with sparse vegetation cover, the Soil Adjusted Vegetation Index (SAVI; [27]) and Modified Soil Adjusted Vegetation Index (MSAVI; [45]) reduce soil background effects and are more appropriate, yet no study in the review employed them. A deeper methodological concern is that the original MEDALUS vegetation indicators (erosion protection, drought resistance, fire risk, plant cover) are defined qualitatively based on vegetation community type (e.g., "mixed Mediterranean macchia" = low fire risk) in the MEDALUS manual. Most studies approximate these qualitative assessments through NDVI, but the correspondence between NDVI values and the original MEDALUS vegetation classes has never been formally validated. This represents an unexamined assumption at the core of most MEDALUS vegetation factor computations.

Usage of Landsat dominance reflects its free accessibility, global coverage, and long temporal record, rather than its suitability because it is coarse resolution compare to Sentinel-2 (10m cell size of few

bands). This finding that Landsat data dominates in the derivation vegetation indicators corroborates the observation of [48] that Landsat is predominant in desertification studies. Sentinel-2 and MODIS were less frequently used despite offering higher spatial resolution (for Sentinel-2) or higher temporal resolution (for MODIS). This pattern further reinforces the conclusion that data accessibility, rather than “fitness-for-purpose”, drives methodological choices in MEDALUS applications.

The management factor exhibits the most severe problem of data transparency of any factor. Policy enforcement is the most frequently used management indicator, which underlines the importance of governance and regulatory frameworks in controlling land use and desertification, is reported without a documented data source in 93.5% of studies. The majority of the studies that used land intensity, population density, and pasture grazing intensity did not specify their data sources. In the original MEDALUS manual, these indicators are scored on the 1–2 scale based on expert judgment of local land management: a process that is inherently subjective and non-reproducible. If management indicators are being assigned through undisclosed expert judgment without systematic data derivation, then the management factor in most MEDALUS applications is effectively an unvalidated expert opinion rather than an empirical assessment. Given that the management factor carries equal weight in the ESAI computation as the biophysical factors, this opacity could undermine the scientific credibility of the composite index. The near-total absence of documented data sources for management indicators represents the most critical reporting backdrop identified in this review.

Three overarching patterns characterize indicator selection across all factors. First, each study selected indicators based on some combination of: (i) association with desertification processes; (ii) frequency and success of usage in prior studies; and (iii) availability in accessible datasets. The third criterion, data availability, appears to be the dominant driver, as evidenced by the systematic under-representation of data-intensive indicators (soil erosion, dynamic soil properties, evapotranspiration) and over-representation of easily accessible indicators (DEM-derived slope, NDVI, global soil database properties). Second, desertification is inherently location-specific, meaning that a uniform approach to indicator selection is neither realistic nor desirable. Third, and most critically, the overwhelming majority of studies (except [17] and [1]) did not calibrate weights using statistical methods or conduct sensitivity analysis to test the influence of weighting variations on ESAI outputs. Improving the objectivity and transparency of weighting procedures is essential for strengthening the scientific credibility of MEDALUS applications.

The validation of ESAI values with SOM and CEC using statistical correlation is based on the assumption that higher desertification sensitivity should correspond to lower soil fertility and organic matter. SOM is a widely recognized indicator of soil health and degradation status [35]; and CEC of a soil represents the total amount of exchangeable cations that the soil can adsorb and the capacity of the soil to hold on to these cations [50]. A statistically significant negative correlation between ESAI and SOM/CEC would therefore lend credibility to the sensitivity classification [50]. This approach is quite robust and enables quantitative assessment of the model consistency. For this approach to be rigorous, the validation variable (SOM, CEC) must not simultaneously serve as an input indicator. The validation of ESAI using

the GWR is noteworthy because it accounts for spatial non-stationarity: the fact that desertification drivers and their relative importance vary across space, thereby GWR tests a fundamental assumption of the MEDALUS model since desertification is not uniform or constant across an area; it differs from location to location even within the same area. These approaches enhance understanding of model structure but primarily test internal statistical coherence.

The Spearman Rank correlation and Kruskal–Wallis ANOVA test whether statistically significant differences existed among environmental variables across ESA classes. This approach goes beyond simple bivariate correlation by testing whether the categorical ESA classification (critical, fragile, potential, not threatened) discriminates meaningfully among field-measured environmental conditions [13]. The spatial accuracy assessment entails generating random points on the ESAI output and compared classifications with high-resolution Google Earth imagery using a binomial probability distribution function. This approach most closely resembles conventional accuracy assessment methods in remote sensing [12] and uses genuinely independent reference data. However, visual interpretation of desertification sensitivity from imagery is inherently subjective, and temporal mismatch between the ESAI assessment period and the Google Earth imagery acquisition date may introduce error.

While the MEDALUS has been widely adopted, majority of the studies do not explicitly perform validation, this represents a methodological limitation in the literature rather than a justification for omission. Without empirical validation, ESAI outputs remain largely model-driven representations rather than independently validated assessments. The lack of validation constrains confidence in the utility of the model for evidence-based policy decisions. For the few studies that validated, there exist inconsistencies the validation approaches. The approaches therefore methodological heterogeneity in the validation of desertification sensitivity, thereby limiting the reproducibility and comparability of ESAI outputs across studies.

Alternative schemes for classifying desertification sensitivity have been used in MEDALUS studies. These alternative schemes represent different ESAI threshold levels that are rarely reported explicitly in studies. This heterogeneity in classification schemes makes it impossible to compare sensitivity maps across studies. A region classified as "fragile (F2)" under the eight-class scheme might be classified as "moderate" under a three-class scheme or "sensitive" under a four-class scheme, with different policy implications. For instance, if Egypt (classified using eight classes) and Nigeria (classified using four classes) both report that "most of the study area is critically sensitive," these statements are not comparable because the underlying ESAI threshold for "critical" is defined differently.

7. Conclusion

The systematic review demonstrates the growing importance and adaptability of the MEDALUS model in assessing desertification sensitivity across diverse geographic and climatic regions from 1999 to 2024. Originally developed for the Mediterranean, the core problem addressed was the need to understand the adaptability of the model and its modification across diverse global arid and semi-arid environments.

There has been growing importance of MEDALUS model with 2018 marking the peak of usage of the model. Africa (particularly Egypt, Iran, and Algeria) accounts for the highest usage. The review highlights that while a majority of studies adhere to the default factors (climate, soil, vegetation, management), modifications are frequent to suit local environmental settings. A striking finding is the overwhelming dominance of single-year assessments (97% of studies), with limited (2 studies) multi-temporal analyses to analyze trends over time. Most used indicators include rainfall, aridity, soil texture, vegetation cover, and policy enforcement. They are heavily influenced by data availability rather than solely environmental relevance. The review revealed that various sources of data were used for deriving the indicators and remote sensing-based datasets are the predominant sources of data. The default eight-class scheme for classifying desertification sensitivity was mostly used, though variations of classification schemes were found in studies.

A critical issue across the reviewed articles is the widespread reliance on subjective weighting of indicators. Majority of studies did not calibrate weights using statistical methods; and did not conduct sensitivity analysis to test the influence of weighting variations on ESAI outputs. The flexibility of the model is a key strength, which suits local environmental settings, but it introduces significant subjectivity in indicator selection and weighting. The lack of standardization of threshold levels of indicators also challenges the model as a consistent scientific methodology. Moreover, the near-absence of multi-temporal studies means that policymakers and land managers are making decisions based on a static picture of a dynamic problem, which could potentially lead to ineffective or misdirected interventions. The review confirms the versatility of the model across varied geographical and climatic zones. The review also agrees with literature that remote sensing is the most used techniques for desertification studies. The review provides clear guidance for researchers and practitioners on the application of the MEDALUS model in desertification assessment. It contributes to the existing body of knowledge by shifting the focus from the structure of the model (the factors and indicators) to its execution (the weighting and thresholding). The review is however limited by the exclusion of non-English publications, potentially under-representing methodological insights from Chinese and Arab regions.

Future studies should move beyond single-year analysis to conduct time-series analysis to monitor the rate of change in sensitivity over decades. There is need for statistically calibrated weighting procedures and sensitivity analysis to test the influence of weighting variations on ESAI outputs. Researchers should endeavor to report transparent documentation of data sources, particularly for management indicators to maximize the replicability and reliability of their findings. Local station/ground-truth data should be used for cross-validation of indicators where necessary and external data should be used to empirically validate results. To enhance the application efficiency of the model, the scientific community should focus on developing the MEDALUS model into a suite of easily deployable and executable computer programs. These will ensure scientific credibility of the output produced by the model. By addressing these gaps and building on its strengths, the MEDALUS model can continue to serve as a critical tool for sustainable land management and combating desertification globally. This review has provided a holistic evaluation of the applications of the MEDALUS model, identified areas for improvement, and offered actionable recommendations to maximize its potential.

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Data availability

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Figures

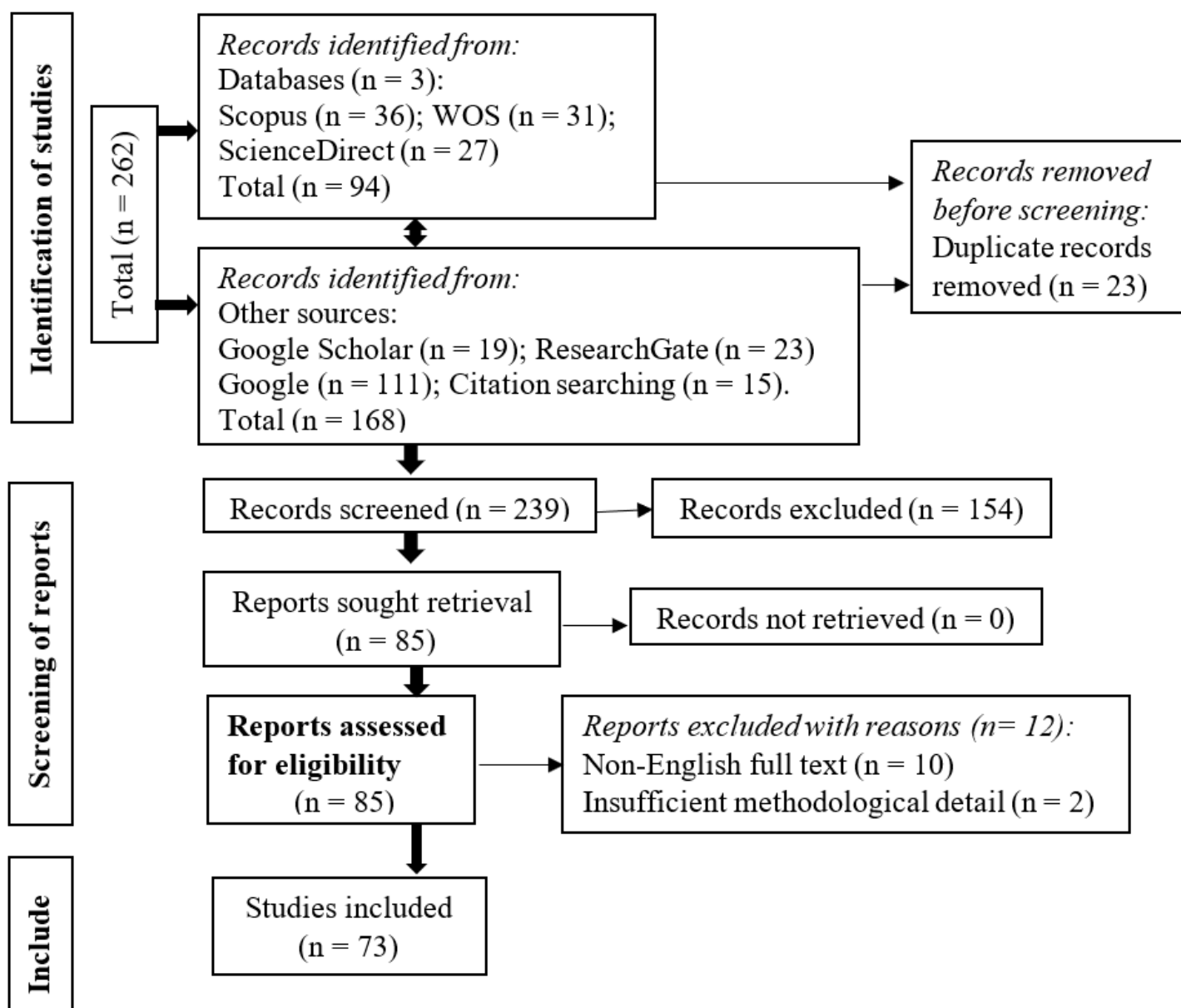


Figure 1

Methodology workflow diagram of the review illustrating the literature search and screening process. Adapted from PRISMA 2020 guidelines for systematic reviews

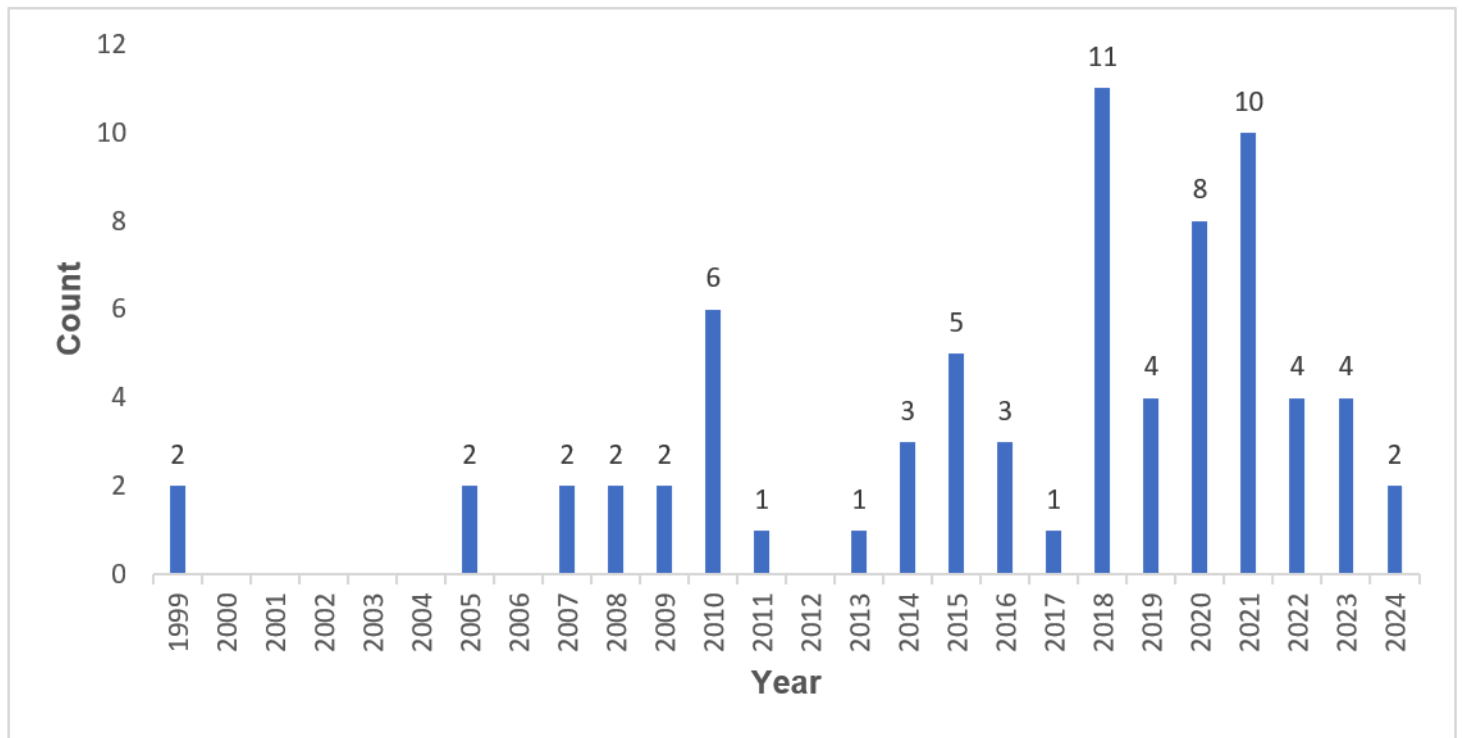


Figure 2

Timeline and frequency of the application of the MEDALUS model from 1999 to 2024

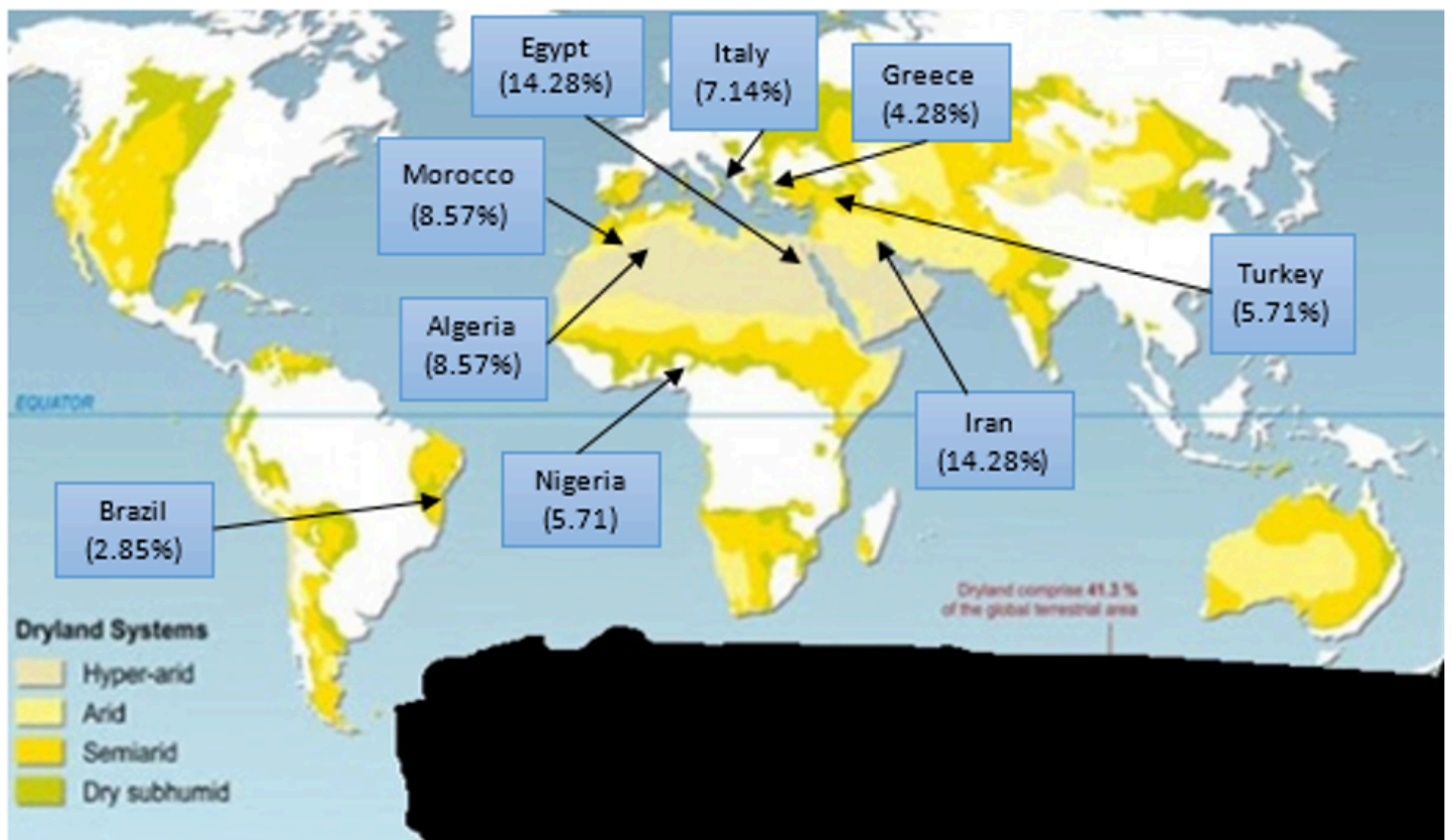


Figure 3

World map showing the geographical distribution of countries where the MEDALUS model has been applied. Source: [40]

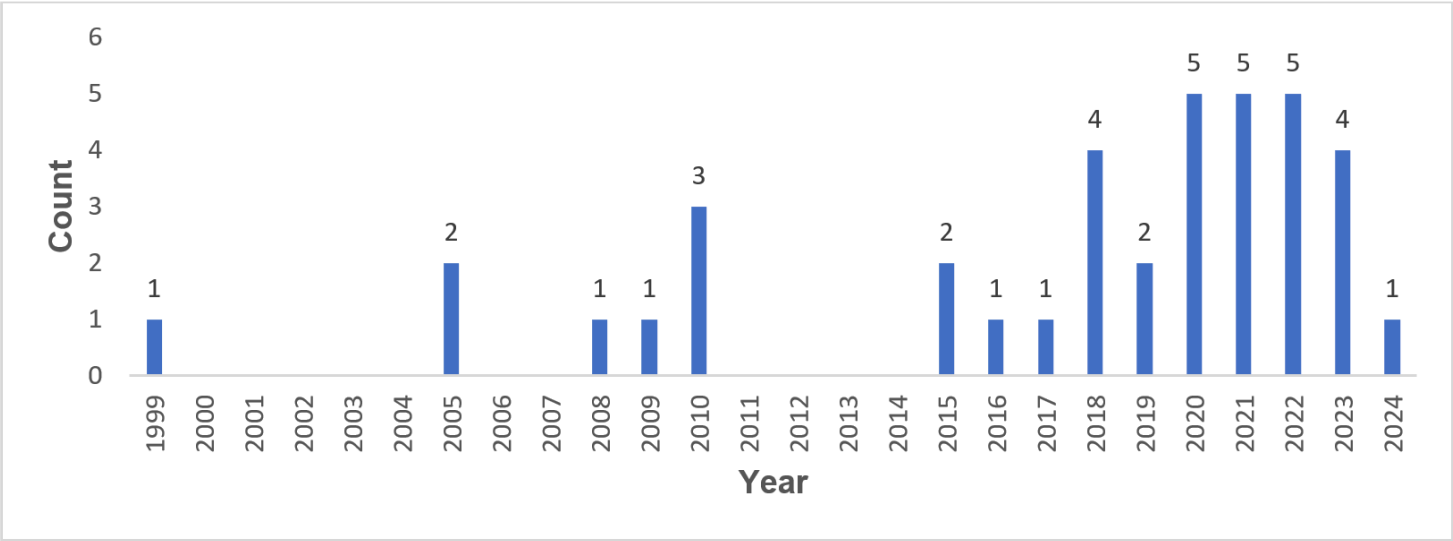


Figure 4

Timeline and frequency of the application of the “default” MEDALUS model from 1999 to 2024