



Review

Unlocking the Potential of Remote Sensing in Wind Erosion Studies: A Review and Outlook for Future Directions

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Abstract: Remote sensing (RS) has revolutionized field data collection processes and provided timely and spatially consistent acquisition of data on the terrestrial landscape properties. This research paper investigates the relationship between Wind Erosion (WE) and Remote Sensing (RS) techniques. By examining, analyzing, and reviewing recent studies utilizing RS, we underscore the importance of wind erosion research by exploring indicators that influence the detection, evaluation, and modeling of wind erosion. Furthermore, it identifies research gaps particularly in soil erodibility estimation, soil moisture monitoring, and surface roughness assessment using RS. Overall, this research enhances our understanding of WE and RS and offers insights into future research directions. To conduct this study, we employed a two-fold approach. First, we utilized a non-systematic review approach by accessing the Global Applications of Soil Erosion Modelling Tracker (GASEMT) database. Subsequently, we conducted a systematic review of the relevant literature on wind erosion and remote sensing in the core collection of the Web of Science (WoS) database. Additionally, we employed the VOSviewer bibliometric software to generate a cooperative keyword network analysis, facilitating the advancements and identifying emerging areas of WE and RS research. With a non-systematic review, we focused on examining the current state and potential of remote sensing for mapping and analyzing following indicators of wind erosion modelling: (1) soil erodibility; (2) soil moisture; (3) surface roughness; (4) vegetation cover; (5) wind barriers; and (6) wind erosion mapping. Our study highlights the widespread utilization of freely available RS data, such as MODIS and Landsat, for WE modeling. However, we also acknowledge the limitations of high resolution sensors due to their high costs. RS techniques offer an efficient and cost-effective approach for mapping erosion at various scales and call for a more comprehensive and detailed assessment of soil erosion at regional scales. These findings provide valuable guidance for future research endeavors in this domain.

Keywords: advanced remote sensing; wind erosion; wind erosion parameters; wind erosion modelling; non-systematic review; systematic review



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1. Introduction

Wind erosion is a natural soil degradation process [1], often accelerated by human activity [2]. The erosion events caused by wind lead to the depletion of fine particles such as clay and silt [3] and organic matter [4], which can result in decreased soil productivity and degradation of the soil's hydrothermal properties [5]. Wind erosion (WE) predominantly occurs in regions characterized by low precipitation and high evaporation rates, which cover roughly one-third of the global land area and 12% of Europe [6]. Climate change has intensified WE in semi-arid areas by 3.2% from 1980 to 2019 [7]. The United Nations (UN) global soil resources report highlights that a significant proportion of the world's soil is in

suboptimal conditions [8]. Soil erosion, loss of soil carbon, and nutrient imbalance pose significant threats to soil functions.

The process of WE has three phases: (1) initiation of the movement of the soil particles (detachment or deflation), (2) the transportation of the soil particles (suspension, saltation, and surface creep), and (3) the deposition [9,10]. Several models have been developed to simulate the WE [11,12] and estimate the erosion intensity and effectiveness of erosion control strategies [13]. Empirical models are based on observed data and their statistical relationship with analyzed predictors. This approach is simpler, criticized for employing unrealistic assumptions, ignoring heterogeneity of inputs and nonlinear relationships between input parameters [14]. Most empirical models compute soil loss and do not simulate transportation or deposition [11]. Physical models, or process-based models, are based on understanding of the whole process of aeolian transport [15]. The distinction between the models is not always clear, and both approaches could be integrated into one model [2]. Some of the main challenges in aeolian transport modeling have been as identified the fidelity of process representation, up-scaling the presence of heterogeneity, spatial data availability, and large-scale parameter estimation [15].

The management of WE presents a formidable challenge because it involves intricate interplay due to complex interactions among driving forces, pressures, and ecosystem states [16]. Due to the intricate nature of the process, it remains challenging to oversee and measure soil WE on a larger scale [17]. The study of WE involves a range of research techniques, such as laboratory and field measurements, modelling, and the use of remote sensing (RS) technologies. While methods such as wind tunnel testing and direct terrain measurements are commonly employed, they are often constrained by time and environmental factors, and may not fully capture the complex and dynamic spatial and temporal aspects of WE. However, the accuracy of these methods is still being improved [11,18]. In the last two decades, RS [19] and computer technology have made significant progress, with increased technological potential to obtain more relevant data on WE [17]. RS methods are faster than ground methods, can cover large areas, and facilitate repeated monitoring of erosion events or factors affecting the erosion [18,20–22]. The employment of RS technology provides the opportunity to efficiently evaluate soil quality at different scales, with the added benefits of speed and affordability. Nevertheless, the variation in the spectral response of soils at different depths and the disparities in the spatial, spectral, and temporal resolutions of various sensors could necessitate extensive data processing and intricate models [23]. Satellite imagery allows for the quick and timely recording of the presence and intensity of erosion processes, the prediction of their impact on the topography, soils, agricultural land, and landscape systems, and approval of a set of measures to reduce the negative effects on the natural surroundings [24]. The European Space Agency's (ESA) release of the Sentinel 2 sensor, which boasts an average spatial resolution of 10 m and a 5-day revisiting cycle, has made it one of the most widely accessible and practical sources of remote sensing data for soil erosion mapping and modeling, second only to the Landsat series [21]. The new RS systems, including drones and LiDAR, produce the data in higher spatial, temporal, and spectral resolution [18,25]. Additionally, the increasing computer power enables the large-scale application of some detailed approaches used in local scales. Incorporating RS data into WE modeling is anticipated to enhance the accuracy and decrease the level of ambiguity or imprecision present in the model [25,26].

The potential to integrate RS, spatial analysis, geographic information system (GIS), and modelling into WE analyses is still a great challenge. Previous reviews were focused on using RS in erosion or land degradation mapping in general [18,20,22], or were directly focused on WE models [11,12], or the representation of aeolian processes [2,15]. This manuscript reviews the RS approaches used to derive the input parameters for WE models and we analyze the potential of advanced RS methods for improving the quality of main input parameters for WE models.

2. Materials and Methods

To gain a comprehensive understanding of the application of remote sensing (RS) in wind erosion (WE) assessment, we combined a non-systematic and systematic review approach. To conduct the systematic review, the Web of Science (WoS) core collection database was searched for relevant literature on WE and remote sensing. For the non-systematic review, the 'Global Applications of Soil Erosion Modelling Tracker (GASEMT)' database was utilized. This database includes studies published between 1994 and 2018 and is publicly available to users [27]. This review expanded the analysis of the GASEMT database by examining the connection between soil erosion modelling and RS. In this review paper, the impact of six factors that are facilitated in WE studies with the help of RS was evaluated: soil erodibility, soil moisture, surface roughness, vegetation cover, wind barriers, and WE mapping. In each factor, the research and also the future perspectives were examined.

Systematic and Non-Systematic Literature Research

We conducted a bibliographic investigation in September–November 2022 in the WoS database. The query “wind erosion” + “remote sensing” generated 237 research papers, published between 1991 and 2022. We used VOSviewer bibliometric software version 1.6. to draw the cooperative network and keyword co-occurrence map to analyze the research progress and frontier [28].

We used a classical review approach based on non-systematic literature research in databases, SCOPUS, WoS, and Google Scholar. We used search terms such as “Wind erosion modelling, Wind erosion models, Wind erosion mapping, RS, Soil erodibility, Soil moisture, Surface roughness, Vegetation cover, Wind barriers, etc.” to obtain a set of papers focusing on wind erosion modelling and then we searched in the reference literature or used specific queries to obtain additional information.

We restricted our review to those model input parameters that are commonly used in WE models [11,12] and are derived or could be derived with use of RS. These WE models include basic parameters such as soil erodibility, soil moisture, soil roughness, vegetation cover, wind barriers, climate inputs, and other inputs such as threshold velocity, management, and so on. Soil erodibility is used in all the models and is derived from the percentage of sand soil particles and for some models forms additional soil physical parameters. Soil moisture is used directly as an input parameter or is estimated indirectly from the climate parameters. Surface roughness is included in models directly as specific input parameter or indirectly as tillage parameter or soil surface condition parameter. Vegetation or crop cover is directly included in most of the models or is covered in management or surface cover parameters. Wind barriers are related to field length, field geometry and wind speed. Additionally, we reviewed the application of RS methods for WE mapping because the RS is often used for verification of WE models, and in some cases the RS approach could be an alternative to WE models.

Figure 1 shows a flowchart with the results at the different stages of this study taken from the initial WoS search to the final selection of possible papers of interest for this review paper. Even though this was a specific and very stringent search, aimed at excluding unrelated articles from the beginning, the WoS output still generated a relatively large number of 40,127 publications for all six factors (a). As shown in Figure 1a, all the research conducted on the six investigated factors are included in the WoS database with the restriction of “remote sensing”. Following the evaluation of the papers according to the research interest, the cutting point for considering articles for further evaluation depended on the strong and effective relationship to the topic in this step. In this case, 1371 articles were considered for reading their full abstracts by the terms “Wind Erosion” as a restriction for all six evaluated factors (b). Finally, the relevant articles ($n = 207$) which emphasize the relationship of chosen factors with the terms “Wind Erosion” and “Remote Sensing” for more interdisciplinary research were investigated (c).

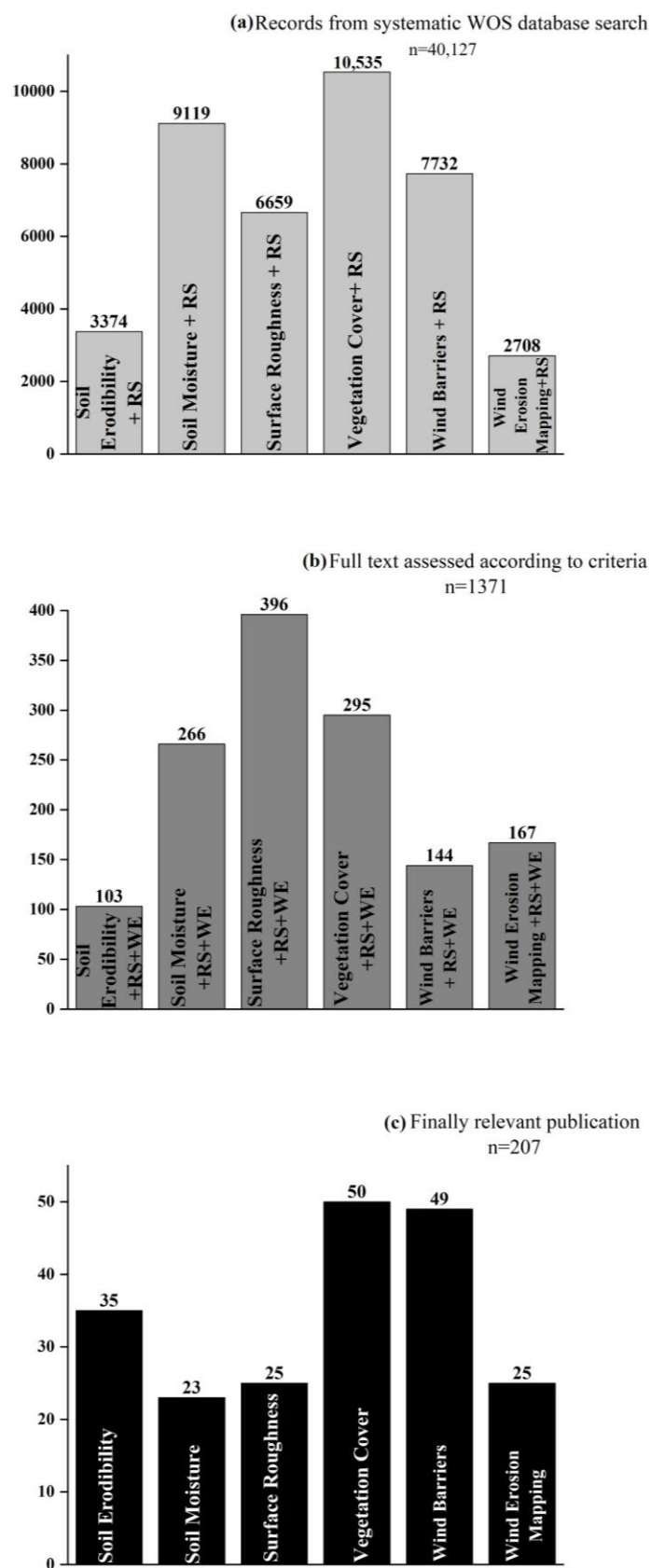


Figure 1. A schematic diagram outlining the process of the literature review according to the WoS database, including overall numbers (a), full text according to criteria (b), and the final count of publications that were deemed applicable (c). WE here is the abbreviation of wind erosion.

Although the climate parameters are crucial for WE modelling, we did not include them in our review, because they are commonly derived from meteorological data and models, and we do not see any potential for RS in this area. In the second phase, we estimated the current and future potential of RS for improving the quality of the input parameters for WE models.

3. Results

3.1. Research Frontiers

In Figure 2, the keyword network analysis map reveals the existence of four groups that represent distinct research areas related to WE and RS. Group 1 is mainly focused on utilizing RS techniques to evaluate land degradation and erosion. This is demonstrated by terms such as “erosion”, “land degradation”, “desertification”, and “impacts”. The terms “China” and “loess plateau” indicate an interest in the dominant interest in land degradation in these regions.

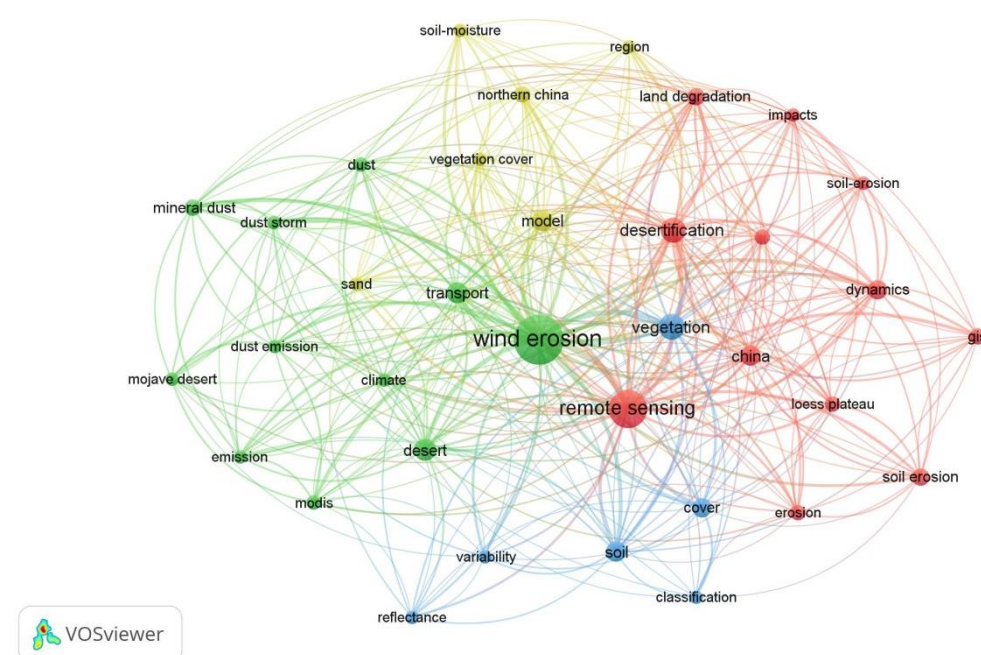


Figure 2. Keyword network analysis.

Groups are identified by color (Group 1—red; 2—green; 3—blue and 4—yellow). The size of the labels and circles in the figure is directly proportional to the frequency of occurrences. The lines connecting the terms indicate significant connections, with the thickness of the lines representing the strength of the association. Additionally, the distance between the terms in the figure also reflects the strength of the association.

The Group 2 research fronts are focused on the effect of WE on dust emission, as indicated by the link to terms “emission”, “dust”, and “desert” with terms of “modis” and “transport”. The time-series MODIS data are utilized for the purpose of identifying the erodibility of landscapes and mapping the hazard of WE during different seasons [29]. Group 3 pertains to the use of RS classification of vegetation cover as a crucial input for WE modeling. This is evident from the presence of terms such as “cover”, “variability”, “reflectance”, and “classification”. Group 3’s position on the network map suggests that it has a stronger association and greater connectivity with Group 1. On the other hand, Group 4 is focused on WE modeling and has a regional scope, as indicated by the frequent occurrence of terms such as “model” and “region”. The application of RS for analyzing the inputs such as “vegetation cover”, “soil moisture”, and “sand” for erosion models is visible here as well. The frequent use of the term “dust” and “desert” shows the increasing importance of desertification. The co-occurrence groups highlight two distinct trends:

- The majority of studies in the field of WE and RS are completed on a regional scale;
- The research emphasizes more variable and effective factors in the process of erosion. The frequent use of terms such as “vegetation” and “climate change” shows this trend.

3.2. Remote Sensors and Indicators Used in Wind Erosion Modelling

Recent soil survey data, such as the LUCAS topsoil and RS data, have made large-scale soil erosion modeling more feasible. LUCAS Soil, which is an extensive and recurring topsoil survey conducted every three years across the European Union, is an example of such data [30]. The development of dynamic indexes and proxies for soil coverage will be facilitated by the increased availability of surveyed data and the utilization of RS data (MODIS, Landsat) and Copernicus products [31]. Landsat, with its collection of images dating back to the Landsat Multispectral Scanner (MSS) to the Landsat Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) is home to the oldest archive of imagery from various sensors. With a spatial resolution of 30 m, it continues to be one of the most utilized satellite images in WE modeling, as shown in Figure 3. Additionally, the Shuttle Radar Topography Mission (SRTM) data, derived from synthetic aperture radar (SAR) imagery, remain a critical source of data for erosion assessment. Other sensors, such as ASTER, Sentinel, and SPOT, among others, offer lower or medium spatial resolution.

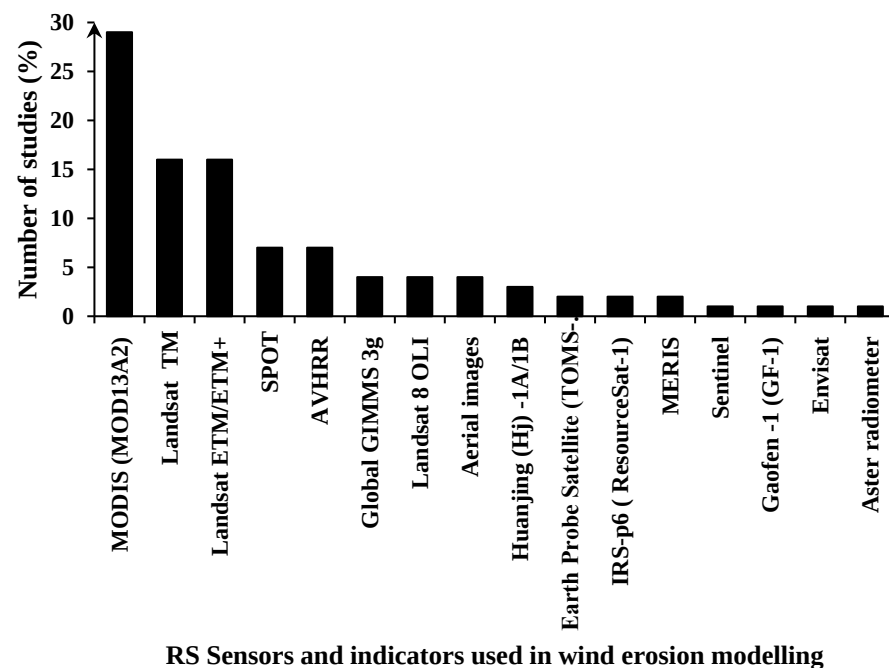


Figure 3. The percentage of global studies that employed various RS sensors and indicators for estimating WE parameters. (Note: this Figure was generated from the GASEMT database).

As illustrated in Figure 3, the number of indicators and RS sensors used through the WE evaluation in this systematic review is very variable. Different usage of RS data is based on its cost. Acquiring most of these images comes with a low cost or is entirely free in some cases. Additionally, high spatial resolution sensors such as IKONOS, GeoEye, and QuickBird can be utilized to evaluate erosion factors. Nonetheless, their usage in erosion assessment over large areas is often limited due to the high costs associated with acquiring them [32]. The MODIS data series was the most applied image during this study (Figure 4). Among these studies, the utilization of freely available Landsat images is frequently observed, followed by images from Google Earth.

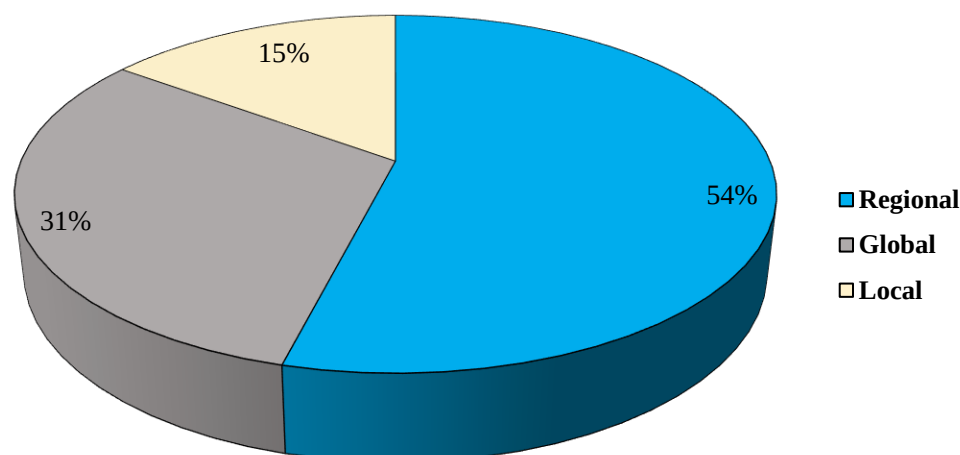


Figure 4. The percentage of studies carried out globally that utilized remote sensing to estimate WE parameters across varying spatial scales of application. (Note: this Figure was generated from the GASEMT database).

Although other soil erosion models can be expensive and time-consuming, RS techniques can map erosion more efficiently and affordably with less expert data, time, and cost in local, global, regional, and plot applications (Figure 4). Until 2018, efforts to quantify and map the extent of soil erosion have been primarily focused on local-scale applications, despite many attempts [21].

As illustrated in Figure 4, with the advancement in RS knowledge, a more comprehensive and detailed assessment of the spatial distribution and magnitude of soil erosion at regional scales is required, along with the development of sustainable management and effective rehabilitation strategies. The occurrence of the term “region” in conjunction with the term “model” suggests a focus on using models at the regional scale.

3.3. Wind Erosion Factors and RS

3.3.1. Soil Erodibility

Current State and Research Gaps

Erodibility, a crucial factor for predicting WE [33–35], refers to a soil’s susceptibility to erosion under specific meteorological conditions, or the efficiency of soil erosion on a surface given certain meteorological forcing. The interaction of fine soil particles (silt, clay, and sand) and organic carbon typically determines erodibility and is associated with factors such as soil structure, organic content, surface roughness, and soil texture [36]. However, measuring erodibility can be challenging due to these multiple factors. The influence of soil surface conditions based on soil type is often overlooked as a source of variation in characterizing soil surface erodibility and in using RS for soil assessment [37]. The computation of soil erodibility has been approached differently in various studies [38]. Ref. [39] calculated the wind erodibility of European soils by using a multiple regression equation based on soil texture and chemical properties, while Ref. [40] used soil organic carbon and soil particle size distribution to calculate erodibility in Inner Mongolia, China. However, soil erodibility equations typically require specific physical soil properties that may not be widely available. In the United States, the wind erodibility index (WEI) is available through the USDA Web Soil Survey geographic database [41]. Conducting long-term erosion plot studies is necessary to obtain direct measurements of soil erodibility. Most of the earlier studies [42–45] have been limited only to experimental study areas. Ref. [46] analyzed the soil erodibility of soil moisture, gravel cover, and surface roughness in combination with Landsat8 data to evaluate the direct impact on soil erodibility. Close-range photogrammetry was used to generate a gravel percentage map and the ASTER digital topographic model was used to analyze surface roughness. Ref. [47] highlighted the potential of directional and multi-angular soil reflectance to enhance the knowledge of

erodibility and to detect and quantify soil erosion. In addition, the authors suggested that utilizing ground-based radiometers, as well as current and upcoming versions of angular sensors mounted on aerial and satellite platforms, and multi-angular spectral reflectance holds promise for remotely assessing and computing soil surface characteristics, thereby offering a comprehensive framework. Bi-directional soil spectral reflectance models [48,49] have the potential to establish a framework for integrating the analysis of soil surface erodibility and potentially measuring WE. Ref. [50] employed Landsat MSS and AVIRIS imagery to illustrate the movement of sand from deserted agricultural areas.

Future Directions

Remote sensing is a valuable and economical means of obtaining data for mapping and modeling soil properties, soil resources, and their temporal and spatial variations [47,51–54]. Utilizing Visible, Near Infrared, and Shortwave Infrared sensors, it is possible to calibrate site-specific datasets that depict the correlation between spatiotemporal and quantitative variations in soil information across extensive regions [53]. Ref. [55] estimated soil erodibility by the support vector regression method on Landsat-8 images with relative percent deviation equals 2.01.

The presence of vegetation, crop residues, or clouds can hinder the accuracy of soil property predictions, which is why extracting spectral information solely from bare soil pixels may yield successful results [56]. Ref. [57] stated that a single satellite image provides only 0.5% of valid bare soil pixels, which is inadequate for soil mapping. To address this, new methods of bare soil detection, especially from Landsat and Sentinel images, are being employed. Ref. [58] used the MID-Infrared profile of four images to identify bare soil pixels and established a correlation between the amount of clay content and these pixels to generate a soil clay content map. Refs. [59,60] used a fusion technique, which increased the exposed soil coverage from 36% (single image) to 75%. Meanwhile, Ref. [61] utilized a five-year compilation of Landsat TM imagery and the Barest Soil Composite Image (BSCI) technique to achieve 90% in soil mapping. In a similar attempt, Ref. [62] integrated the reflectance and spectral parameters obtained from Sentinel-2 images with a wider range of spectral and non-spectral covariates to forecast topsoil clay content. Ref. [63] also proved that multi-temporal images performed better in predicting soil properties, then single-date images. The Soil Composite Mapping Processor (SCMaP) was devised by [64] to surmount the obstacle of insufficient soil exposure and to map soil properties in Germany. Further research advancement and improvement is expected as high signal-to-noise ratio spectrometers on space-borne imagery become available, along with the PRISMA, such as EnMAP [65], HISUI [66], SHALOM [67], HySpex [68], and the Sentinel-10/CHIME [69].

3.3.2. Soil Moisture

Current State and Research Gaps

The presence of soil moisture is a significant contributor to the cohesion of soil particles and acts as a mitigating factor for wind erosion [16]. Soil erodibility reaches its peak when the soil is completely dehydrated. However, as the soil moisture content increases beyond this limit, there is a noticeable reduction in erodibility. Erodibility rapidly increases with the soil moisture content [70]. Precisely monitoring and estimating the spatial and temporal changes in soil moisture is of great significance [71]. Estimating soil moisture becomes more challenging in regions with dense vegetation or snow cover, as well as areas with intricate topography [72]. Soil moisture content in correlation with the number of erosive days could predict some mitigation effect for some areas [39].

The production of dust is connected to the annual diversity in plant cover resulting from the variation in soil moisture [50]. Traditional techniques of restoration and reclamation necessitate surface disturbance and rely on adequate moisture to avoid erosion, making them vulnerable to significant erosion risk in the absence of wet conditions [16]. Several machine learning algorithms have been utilized for extracting water bodies and shorelines from remote sensing images, including neural networks, convolutional neural networks,

artificial neural networks, support vector machines, naive Bayes, random forest, gradient boosted machine, recursive partitioning and regression trees, and constraint energy minimizations [73]. Individual spot measurements do not capture high spatial and temporal variability [74,75] and therefore are not suitable for regional and global research [71,76].

Future Directions

The investigation of soil moisture RS commenced during the mid-1970s, after the satellite expansion [71]. Optical and thermal infrared sensors, along with active microwave RS techniques, can be utilized to measure the soil moisture content in the near-surface soil [77]. Several soil moisture estimation outputs have been created via microwave RS, such as SMOS [78], AMSR-E [79], and SMAP [80]. Ref. [81] applied the Landsat and SPOT images for SWI to identify the WE risk in the farming region in Hungary. The driest area (SWI < 6%) exposed WE to a wider scope. Ref. [46] utilized the NDMI and WETNESS spectral index as indicators for estimating soil moisture, enabling the identification of sources for sand and dust storms using RS analysis. Ref. [82] used Sentinel-1 and Landsat-7 data to assess SMC in Egypt and achieved the result with R² reaching 0.83. Ref. [83] exhibited the capability of estimating soil moisture by integrating on-site soil moisture measurements and MODIS land parameters (LST and NDVI) to generate daily soil moisture products at a resolution of 1 km. The utilization of the presently accessible MODIS time-series products for soil moisture and wind speed can be concurrently employed to detect landscape erodibility and to delineate the seasonal variations of WE hazard [29].

The latest progress in RS have exhibited the capability of quantifying the spatial differences in surface soil moisture across diverse topographic and land cover conditions [84,85]. Unfortunately, there is presently no dataset or model that can accurately determine the deep soil moisture content at a high resolution [76]. In addition, there is no comprehensive map of soil moisture along with its changes during the growing season, land cover, microbial population, etc. Establishing soil moisture prediction methods and combining them with artificial intelligence can help us to solve this problem in the future. Ref. [86] predicted soil surface moisture through the implementation of polarimetric decomposition in tandem with quantile regression forests (QRF). Ref. [87] applied Radial RBFNN and a PCA model to achieve an accurate prediction of farmland moisture. They also developed a range of intelligent prediction techniques for soil moisture content, which significantly enhance the level of agricultural intelligence. The emergence of UAV platforms has now offered an economical approach to measure the soil moisture content on a large scale [76]. Ref. [88] demonstrated that the derived GNSS soil moisture estimates can complement the current global soil moisture databases and offer more frequent retrievals at a resolution of 9 km.

To improve future soil moisture retrieval algorithms, it would be advantageous to integrate spaceborne measurements from multiple sensors, physically based model predictions, and in situ observations in a synergistic manner. Additionally, research should focus on developing approaches for mapping soil moisture in areas with dense vegetation [71].

3.3.3. Surface Roughness

Current State and Research Gaps

Surface roughness refers to the way surfaces are expressed in terms of topography, including features on horizontal and vertical scales ranging from millimeters to a few hundred meters [29]. Precise understanding of surface roughness and its influence on wind speed is crucial for various fields, including climate modeling, wind power meteorology, agriculture, and erosion hazard assessment [89]. Nearly flat surfaces with loose sand-sized particles, lacking any shelter or cover objects, are particularly sensitive to WE [90].

Surface roughness can be considered a direct input parameter or indirectly estimated through soil moisture or vegetation biomass in WE modeling [91,92]. It can be utilized as a WE predictor by determining the potential for soil particle retention, emission, and saltation [93]. However, the measurement accuracy of surface roughness is constrained by the measurement method, instruments used, and data pre-processing [94]. Surface

roughness can be measured using contact or non-contact methods. Contact methods include the grid plate and profiler methods, while non-contact methods include laser profiler, stereophotography, pencil-beam radiometer, and LiDAR [95,96]. Achieving the required measurement accuracy is challenging due to limitations such as large spatial sampling intervals, short sampling segments, temporal variability, and inconvenient operation. However, TLS as a non-contact device [97] can furnish spatial data of high resolution (in mm), depicting surface alterations over time [98]. Other surface properties can be derived from the strength of the reflected signal. The best machine learning approaches for surface roughness estimation consist of both classical machine learning algorithms such as random forest, neural network and support vector machine and artificial neural network (ANN), as well as deep learning algorithms including multilayer perceptron (MLP) and deep belief network (DBN) [99].

Future Directions

RS has proven to be a fast and efficient way to provide high-resolution spatial data over large areas which can be utilized to derive surface roughness parameters. The roughness of a surface can be inferred by analyzing the reflectance of the surface from various angles of illumination and the sensor view, which is characterized by the BRDF [49]. Refs. [100,101] developed correlations between radar backscatter cross sections and surface roughness obtained from wind velocity profile data [102]. Ref. [103] estimated the surface roughness with 92.0% accuracy by using the image features and the combination of IPSO and SVR. Ref. [104] used electromagnetic radiation, particularly low-frequency microwaves, to characterize surface roughness. The limitation of satellite images is the ability to estimate the soil surface characteristics only in areas not covered by vegetation [105].

Although progress has been made in utilizing RS to account for the effects of surface roughness on WE, there are still significant constraints with the methodology and parameterization. For instance, Ref. [104] evaluated the precision and accuracy of LiDAR-based estimations of these parameters in comparison with manual pin-profilers. Their experiments showed that, while the surface RMS can be estimated precisely and accurately from LiDAR data, the correlation length estimates were not as reliable.

The accuracy of LiDAR technologies is constantly improving. Nowadays, the LiDAR reaches relative vertical accuracy in the order of, say, a few centimeters or even millimeters when using UAVs or terrestrial laser scanners [92,106]. Therefore, the constraining factors for surface roughness parameters do not reside in the precision or fidelity of the input data, but rather in the ability to capture the fluctuations in surface roughness due to shifts in vegetation cover, soil moisture levels, or tillage techniques. Accomplishing this necessitates coordinating data acquisition with these occurrences, which can be a time-consuming and an expensive undertaking, and may also be unfeasible for large-scale modeling efforts.

3.3.4. Vegetation Cover

Current State and Research Gaps

Vegetation reduces WE as follows: 1. safeguards the soil from erosive influences by enveloping a portion of its surface; 2. diminishes the velocity of the wind near the ground; 3. traps the soil particles [107]. Vegetation represents mainly standing live and dead biomass (e.g., crops in various development stages) and standing or flat litter (e.g., crop residues). The impact of vegetation on soil erodibility is contingent upon various factors such as the extent of vegetation cover, height, and spatial distribution or arrangement within a landscape [108]. The establishment of vegetation cover and development of windbreaks are the most common erosion control measures [18].

The impact of vegetation on WE in drylands has been primarily studied through wind tunnel experiments, windbreak studies, and field trials [107]. The degree of vegetation's influence on WE is determined by the amount, height, and distribution of vegetation in the landscape. During different seasons, the state of vegetation cover undergoes changes, which in turn affects its ability to mitigate wind erosion. The impact of seasonality on

vegetation cover relates to the growth and development stages of crops or plant species. In some regions, vegetation cover may decrease during dry seasons or winter, leading to reduced erosion control capacity. Conversely, during the rainy seasons or periods of active growth, the vegetation cover tends to increase, providing greater protection against erosion. The extent of vegetation cover is often represented as the ratio of the surface area covered by plants [109]. If the vegetation cover is below 20%, it has a minimal impact on reducing wind velocity, while erosion is essentially halted if the vegetation cover exceeds 60% [110]. Therefore, understanding the seasonality of vegetation cover is crucial for assessing its effectiveness in erosion control throughout the year. The review focusing on erosion monitoring [111] identified Landsat, SPOT, and MODIS data as the most-used RS systems for state-based monitoring of ground cover and identified the products most suitable for erosion monitoring [112–114]. For the WE modelling, the information about vegetation cover, its annual dynamics, and crop residues are important. Vegetation cover for the European scale model [115] was estimated from the Leaf Area Index derived from ENVISAT/MERIS satellite images. For the European WE model (WEELS), the Land Use data were gathered from existing maps, farmers files, agricultural statistics, or the land use dataset was estimated through modeling techniques in case of unavailability [36]. In [116]’s study on the East Africa region, the vegetation cover fraction was obtained from GCLS SPOT/PROBA-V images at a resolution of 1 km. For the East Africa region, Ref. [116] used a fraction of vegetation cover derived from GCLS SPOT/PROBA-V images at 1 km resolution. For the regional studies, the data from MODIS with a resolution of 250 m or 1 km [117–119] or Landsat with a resolution of 30 m [120,121] are often used. The pre-processed data products from Copernicus Global Land Services are also used [122]. For the historical analyses of the vegetation cover development, the MODIS data were combined with 8 km spatial resolution AVHRR [40,123,124] or the Landsat data were used [125].

Vegetation cover is often derived from the Normalised Difference Vegetation Index [126] using a dimidiate pixel model [127] or a specific regression model is developed [122]. From the range of vegetation indexes the Average Maximum Modified Soil Adjusted Vegetation Index was also used [120,128]. A classical RS classification approach was also used for the vegetation cover estimation [125]. In small experimental areas, the vegetation cover could be visually mapped in the field [129], using the line transect method [130] or a pin-type profile meter [131]. The impact of vegetation cover can be disregarded when examining the potential for WE [132], or in the case where the erosion events are expected at a time when there is no vegetation cover in the field [133]. Support Vector Regression and Random Forests are two popular classic machine learning algorithms, and have been widely used in regression and classification of vegetation-related studies [134].

Future Directions

RS has emerged as an effective tool to monitor and analyze vegetation to effectively incorporate seasonality and cover patterns over space and time [135]. Recent advancements in image-based techniques [136] and high-resolution RS [137–139] have enabled rapid and large-scale quantification of plant characteristics such as height, width, and porosity. These data can be utilized to quantify the dynamics of vegetation cover throughout different seasons and improve erosion modeling. RS has also facilitated the refinement of physical and spectral characteristics connected to vegetation cover and surface morphological structures [140–142], particularly by incorporating spatial patterns of vegetation [143,144]. Additionally, RS approaches hold great promise for quickly obtaining tillage information on individual fields over large areas [145]. Estimation of lateral cover with RS represents a great challenge. Depending on the scale of studies, authors use different approximations of lateral cover, based on empirical relations with fractional vegetation cover [146], LAI, or more recently, based on functional relationship with normalized and rescaled albedo resulting in so-called albedo-derived lateral cover [147]. Aerial drones (unmanned aerial vehicles (UAVs)) can be used for low-elevation surveys to collect vegetation transect measurements quickly and inexpensively [148]. Terrestrial laser scanning (TLS) with high

resolution can detect small changes in height around partially vegetated erodible surfaces, aiding in the identification of erosional and depositional regions with high accuracy [107]. High spatial resolution RS allows for the direct imaging of individual plants that are at least the size of the ground resolution of the RS image. This capability enables the effective use of geostatistical methods for describing plant distribution [149]. RS data are becoming increasingly useful for modelling spatial and temporal variability in vegetation [150]. Recent advances in image-based techniques [136] and high-resolution RS [137–139] allow for the rapid quantification of plant characteristics such as height, width, and porosity over relatively large scales. RS approaches also offer a promising option for rapidly collecting tillage information on individual fields over large areas [145].

3.3.5. Living Wind Barriers

Current State and Research Gaps

The windbreaks have various functions in landscapes. Beside the soil protection against wind and water erosion, they positively affect the microclimate, plant productivity [150,151], soil properties [152–154], biodiversity, and also serve other purposes such as protecting buildings, offering thermal comfort to livestock, reducing snow and sand accumulation, and mitigating wind impacts on the transportation infrastructure [155]. Therefore, the effect of windbreaks is evaluated from different perspectives [156,157]. The WE model incorporates three aspects of wind barriers: (1) wind barriers' height; (2) optical porosity; (3) wind barriers' width. The wind barriers' height affects the shelter length [158]. For the erosion modelling purpose, the height is measured by altimeter [159] or from vertical images of the windbreak [132], or is estimated from the average height of windbreak types [160]. Ref. [161] estimated the average tree height of windbreaks from first principal component of GF-1 Multi-Spectral high resolution satellite image. Porosity refers to the proportion of open space to the occupied space of tree stems, branches, twigs, and leaves. It impacts the degree of wind speed reduction and shelter effect of windbreaks [162]. Since measuring aerodynamic porosity is challenging, optical porosity is used as an alternative. Optical porosity is calculated as the ratio of white pixels to the total pixels in digitized black and white pictures taken at a distance of 30 m from the windbreak [163]. These images are processed using software such as ImageTool 3.0 or GIMP 2.10.34 [132,159,164,165]. In RS-based windbreak studies, it is common to assume an approximate shape for the simulated trees. However, this approach often results in notable discrepancies between the simulated and actual results. Ref. [166] employed TLS to obtain parameters used in a quantitative structural model (AdQSM) to reconstruct the tree structure and restore the wind field environment using the computational fluid dynamics software PHOENICS-2022. The findings suggest that TLS can effectively retrieve windbreak parameters and quantify porosity, thereby substantially improving the credibility of windbreak impact investigations in windbreak forests. The wind barriers' width is related to barrier porosity [161,165], but also has a specific effect on wind velocity [167]. Using 10 m SPOT5 images is applicable for windbreaks' width measurement; however, errors may arise when the windbreak is presented on both sides of the road, in the case of sparse or young windbreaks [168]. Aerial images were analyzed using object-oriented image analysis to map the windbreaks [169–171], but also for the automatic extraction of wind barriers' width [172]. The wind barriers are neglected in regional scale models [17,35,39,116,122,173], because such a dataset does not exist for large areas. In most of the local studies, the effect of wind barriers is modelled in the direction of prevailing winds [159,165] or as a Euclidean distance from the nearest windbreak [161]. The most innovative methodology is to calculate the wind reduction for all wind directions and to weight them according to the average occurrence of erosive winds [132]. A unique method is to estimate the shelter area from lateral cover and shadows derived from the multitemporal MODIS albedo images [147].

Future Directions

For the large-scale studies, where wind barrier mapping is not possible, the existing satellite land cover products could be used. The Copernicus Land Monitoring Service provides a GIS layer of High Resolution Layer Small Woody Features, that were mapped from very-high spatial resolution imagery [174] and are available for EEA collaborating countries. The forest areas are included in High Resolution Layer Forest [175], derived from Sentinel 2 images, that also includes information about tree cover, the type of dominant leaves, and the category of the forest.

Remote sensing data obtained from satellites, which are usually calibrated with LiDAR measurements, are commonly utilized to evaluate the height of tree canopies at varying spatial scales and resolutions. For example, MODIS images, trained by Geoscience Laser Altimeter System (GLAS), were utilized to generate a global map of canopy height in 500 m resolution [176]. Landsat images and GLAS were used to produce woody vegetation structure maps with 30 m resolution [177]. Sentinel-2 images and the canopy height model were used to produce a country-wide map of vegetation height in Switzerland in resolution 10 m ("Country-wide high-resolution vegetation height mapping with Sentinel-2", 2019). The Radar images are applicable for tree height estimation as well [178].

The LiDAR scanner is used in forestry research to measure tree height over more than two decades [179]. Current research includes an estimation of canopy base height and bulk density for fire modelling [180], for detection of the sub-canopy structure [181], and mapping of the urban ecological network [182].

The use of existing satellite products such as Copernicus High Resolution Layer Small Woody Features could improve the large scale models, where the effect of wind barriers is neglected [122,183]. The disadvantage is that this dataset does not provide information about windbreak height or porosity and is available only for EEA contributing countries. Satellite images were tested for wind barriers' mapping [168], rough estimation of sheltered areas [147], and for estimation of the wind barriers width, height, and porosity [161] or gaps [184]. The 10 m resolution images are applicable, however better results would be obtained with more detailed images as was shown from aerial images [169–171]. LiDAR was proven as a precise tool for tree height mapping and also as a source of training data for satellite-based tree height estimations. The feature of wind barriers mapping is in application of LiDAR data, very high resolution multispectral satellite images, or in fusion of different RS approaches [185,186].

3.3.6. Wind Erosion Mapping

Current State and Research Gaps

RS approach is used more often for deriving the inputs for WE models, than for mapping the eroded areas. The sole effect of WE is hard to recognize from RS images; therefore, the compound effect with water erosion [187], tillage erosion [188], or land degradation in general [20,21] is mapped.

Monitoring of agricultural soil degradation by RS was reviewed by the authors of [21] and they identified two RS approaches for mapping the WE: (1) mapping direct indicators such as surface lowering or changes in surface roughness; and (2) mapping indirect indicators based on WE relationship with changes in vegetation cover. One illustration of the initial approach involves utilizing radar remote sensing to delineate the patterns of wind-induced land deterioration in the northeast Patagonian region [189]. A second approach could be illustrated by a study that used ASTER images to obtain a WE risk map for Inner Mongolia from the basis of the land use classes, and vegetation height [190].

Ref. [187] summarized the contribution of RS to mapping land depletion in Latin America and Caribbean. The most-used WE indicators were sand dunes, however various surface erosion features such as wind streaks, desert pavements, paleo-aeolian sand features, sand encroachments, blowouts, and changes in vegetation cover were used as well.

Machine learning models commonly employed for wind erosion mapping in various environmental research areas encompass decision tree models, linear equation models,

particle swarm optimization-adaptive network-based fuzzy inference system, genetic algorithms, support vector regression, artificial neural networks, hybrid models, random forest, Wang and Mendel's method, partial least square regression, principal component regression, Cubist, Bayesian additive regression trees, radial basis function, extreme gradient boosting, and regression tree analysis [188].

Future Directions

Detecting the traces of WE from RS images remains challenging. Ref. [20] describes some obstacles in mapping the land degradation at a regional scale: (1) the relationship between RS indicators and soil properties is complex and not straightforward and (2) obtaining data on subsurface soil properties can be challenging. An additional challenge is to distinguish the indicators of WE from other types of land degradation. To direct future research, the community will benefit from multi-temporal and multi-spectral data such as Landsat or Sentinel 2 series [21]. In addition, combining different mapping approaches from several RS platforms [17], using new LiDAR technics detection in changes soil surface [20] or drone-based RS [25] are opportunities in the mapping of WE for future studies. The new very-high resolution satellite systems such as Venus (Israel Space Agency and National Center for Space Studies, France) [191], Gaofen (China) [192], or Planet Satellites [193] bring more detailed images. The spatial and temporal resolution will also increase for upcoming hyperspectral missions such as Copernicus Chime (ESA) [194], HysIS (Indian Space Research Organisation), EnMAP (Environmental Monitoring and Analysis Program) [195], radar mission Copernicus Rose-L [196] and CIMR (ESA) [197], SCATSAT-1 [198], and NovaSAR-01 (CSIRO Centre for Earth Observation) [199].

Landsat 8 has improved spectral and radiometric characteristics that make it suitable for mapping soil erosion at both regional and local scales [200,201]. While the previous Landsat TM series had higher spectral resolution with seven bands (including two mid IR bands) that were more appropriate for degraded landscapes, the SPOT series satellites provide a higher spatial resolution with sensors called High Resolution Visible (HRV) and High Resolution Visible and Infrared (HRVIR), which can detect reflected radiance in three bands at a spatial resolution of 20 m and have been shown to be better at differentiating eroded regions than Landsat TM observations [21]. The cost-effectiveness of the high resolution IKONOS sensor compared to lower resolution air photographs is not significant [202]. SPOT 5 has a lower cost compared to IKONOS and QuickBird, and has been employed in numerous research works [203]; however, the limited spectral resolution of SPOT 5 hinders its potential in mapping soil erosion as it results in restricted spectral observations. The Sentinel 2 sensors, developed by the ESA, have an average spatial resolution of 10 m and a 5-day repeated coverage, making them the most probable and advantageous choices for soil erosion mapping after Landsat data, particularly in developing countries in which the obtaining of high-resolution sensors can be challenging. Sentinel 2 has exhibited its usefulness in the mapping of vegetation [204,205] and water resources' mapping [21].

4. Discussion

Much of WE research uses RS to predict, monitor, and track wind erosion events and assess their impacts, but also as a source of input data for WE modelling, which is third of the challenges of aeolian transport modelling identified by [15]. WE models and RS systems are still under development. New, more detailed datasets are available from RS and other systems, enabling the development of erosion models, which could work with new and different input factors.

The main challenges for mapping soil erodibility is its complexity and spatial and temporal variation together with the fact that spectral information on soil properties could be extracted from bare soil pixels only. The analysis of multitemporal satellite images improves the coverage and quality of the analyses. Additional advancement is expected from forthcoming space-borne imagery spectrometers such as EnMAP, HISUI, SHALOM, HySpex2, and the Sentinel-10/CHIME. Similar challenges occur in soil moisture mapping.

Soil moisture is important in many fields; therefore, the research is more advanced here and soil moisture products and techniques based on modelling or on radar or optical remote sensing are developed. Surface roughness is mapped using radar images; however, it seems that the LiDAR and UAV systems are becoming more suitable due to their increased availability and accuracy. Due to the variations caused by changes in vegetation cover, soil moisture, or tillage practices, the mapping of surface roughness is still challenging. Vegetation mapping is a wide topic; therefore, many remote sensing approaches and products have already been developed. The challenge for WE modelling remains the mapping of lateral cover. The windbreaks are mapped from high resolution satellite images or drones that have become more available in the last decade. Various techniques and products have been developed for woody vegetation mapping. The challenge for WE modelling is the mapping of tree height and porosity. This will be possible with the application of LiDAR, very high-resolution multispectral satellite images, or in fusion of different RS approaches. Direct mapping of WE traces with remote sensing remains challenging, the advances could be reached by multiple use of available systems such as LiDAR, SPOT, HRV, and HRVIR.

Future Research Needs

When evaluating different parameters that affected the WE modelling and could be advanced by RS, several concepts are apparent that could serve as guidance for future research. Some recommendations include:

- EnMAP, HISUI, SHALOM, HySpex2, and the Sentinel-10/CHIME could help to remotely mapping soil erodibility [65–67,69,206];
- GNSS and UAV platforms now provide an economical method for evaluating soil moisture content on a broad level [76,88];
- With the advancement of aerial LIDAR and UAVs, surface roughness measurement has been developed, but the possibility of capturing the variations in surface roughness due to the changes in vegetation cover, soil moisture, or tillage practices is still a big challenge [107];
- Recent advancements in image-based techniques now allow for the rapid and large-scale quantification of vegetation cover [136] and high-resolution RS [137–139];
- The feature of wind barriers mapping is in the application of LiDAR data, very high-resolution multispectral satellite images, or in fusion of different RS approaches [185,186];
- All the mentioned satellites and sensors, especially LiDAR, SPOT, HRV, and HRVIR are helpful in advancing the goal of WE mapping with RS, but unfortunately, a large-scale comprehensive map of WE has not yet been prepared [20,21,25];
- The data obtained from remote sensors primarily focus on surface features mapping, and direct linkage to soil erosion may require the use of inference methods [207]. However, it is important to note that remote sensing data encompass a wide range of information beyond surface features. For instance, atmospheric dust is extensively monitored using remote sensing techniques;
- High resolution data (SPOT-5 and QuickBird) show potential to offer accurate data for soil erosion mapping; however, the acquisition cost of some sensors such as IKONOS and QuickBird can be prohibitive for the large-scale mapping of soil erosion [21].

5. Conclusions

The issue of global warming presents a complex challenge for the world. While certain areas may experience increased vulnerability to WE [102,208,209], it is also important to acknowledge that other regions might witness a reduction in vulnerability [210]. Although numerous researchers have investigated various aspects of water erosion modelling, the implementation of advanced RS techniques in WE modelling has not received much scrutiny. This study presents an outline of the advancements in RS applications for WE modelling across different time periods and spatial scales. The systematic review results showed that most countries have not considered WE as a serious threat yet, and certain

countries have more studies in this field, but the number of studies in the whole world is progressing, and this shows the growing importance of the challenge of WE. It is obvious that bibliometric studies offer only a transient snapshot of a particular research area. The non-systematic review results showed that while RS applications were used to quantify factors in WE, the focus was primarily on small-scale projects. Hence, measuring spatial variability requires a more detailed and widespread effort. The use of RS utilities to monitor WE is largely unattainable in developing countries, which affects WE studies. Hence, the latest sensors such as the Sentinel 2 and Landsat 8 series are currently in high demand because of their enhanced spatial, spectral, radiometric, and temporal resolutions, along with their affordability. High resolution data especially LiDAR, SPOT, HRV, and HRVIR are very helpful for WE mapping. Monitoring of the effective factors in WE has become easier with the help of RS tools, but the possibility of capturing the variations due to the changes in vegetation cover, soil moisture, or tillage practices remains a big challenge.

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