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Review

Current Status and Development Trend of Soil Salinity Monitoring Research in China

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Abstract: Soil salinization is a resource and ecological problem that currently exists on a large scale in all countries of the world. This problem is seriously restricting the development of agricultural production, the sustainable use of land resources, and the stability of the ecological environment. Salinized soils in China are characterized by extensive land area, complex saline species, and prominent salinization problems. Therefore, strengthening the management and utilization of salinized soils, monitoring and identifying accurate salinization information, and mastering the degree of regional salinization are important goals that researchers have been trying to explore and overcome. Based on a large amount of soil salinization research, this paper reviews the developmental history of saline soil management research in China, discusses the research progress of soil salinization monitoring, and summarizes the main modeling methods for remote sensing monitoring of saline soils. Additionally, this paper also proposes and analyzes the limitations of China's soil salinity monitoring research and its future development trend, taking into account the real needs and frontier hotspots of the country in related research. This is of great practical significance to comprehensively grasp the current situation of salinization research, further clarify and sort out research ideas of salinization monitoring, enrich the remote sensing monitoring methods of saline soils, and solve practical problems of soil salinization in China.

Keywords: soil salinization; saline soil treatment; remote sensing monitoring; model construction

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1. Introduction

Soil salinization refers to the accumulation of soluble salts in soil caused by certain natural factors such as climate, hydrology, and topography or caused by the combination of destructive human factors and fragile ecological environments, thus leading to the deterioration of soil quality to form saline soils [1]. Soil salinization, as a resource and ecological problem that currently exists on a large scale in all countries of the world, is one of the main types of land desertification and soil degradation [2]. It seriously restricts the production and development of the agricultural industry, the sustainable use of land resources, and the security and stability of the ecological environment. Saline soils are a collective term for all types of soils that are negatively affected by saline components. The unique physicochemical-biological properties of saline soils have a variety of negative impacts. These include reduction in soil fertility and productivity levels, reduction in crop yields and harvests [3,4], waste of agricultural resources, destabilization of the ecological environment, and other secondary hazards [5]. Therefore, strengthening the management and utilization of salinized soils, monitoring and identifying accurate salinization information, and mastering the salinization level of regional arable farmland have been important goals for scientists to research and overcome.

The total area containing saline soils worldwide is currently about 1.1 $\times$ 10^9 hm^2, which is widely distributed in more than a hundred countries and regions around the world, and the global soil salinization level is still showing a rising trend [6]. The total area of saline soils in China has reached 3.69 $\times$ 10^7 hm^2, which is close to 4.88% of the available land area in China [7]. It is mainly distributed in arid and semi-arid regions and coastal areas with arid climate and little rainfall, high soil evaporation, a high groundwater table, and more soluble salts [8–10]. Examples include semi-humid regions such as the Yellow River Basin in North China, the plains in northeast China, and arid and semi-arid regions in northwest China such as Gansu, Ningxia, and Xinjiang. Therefore, study of the spatial distribution and management of soil salinity prevention as well as improvement of monitoring accuracy and early warning capability are gradually becoming a hot spot of concern in the field of saline soil research today.

In order to explore the current research status and current research hotspots of soil salinity monitoring, this paper searched in the China National Knowledge Infrastructure (CNKI) and the Web of Science (WOS) databases using "soil salinity monitoring" as the key search term. CiteSpace software was used to perform keyword co-occurrence analysis on the large number of highly relevant literature datasets obtained from the search (Figures 1 and 2). By extracting the frequency distribution of keywords that express the core content of the literature, a co-word matrix is thus generated based on the keyword matrix. The co-word matrix was visualized as a network to study the development trends and research hotspots in the field of salinity monitoring. The core nodes in the figure can fully reflect the focus and branches of research in the field in recent years. The size of the node represents the frequency of the keyword; the larger the node, the more frequently the keyword appears and the higher the relevance to the topic. Among them, Figure 1 shows the keyword co-occurrence analysis graph based on the relevant research articles in the CNKI database. The analysis shows that the nodal framework consisting of "saline soil", "remote sensing monitoring", "hyperspectral", "arid zone", "multisource remote sensing", and "salinity index" appears more frequently and has stronger correlations among the research articles published in Chinese database. Figure 2 shows a keyword co-occurrence analysis graph based on the relevant international research articles in the WOS database. It can be seen that the nodal framework consisting of "soil salinity", "model", "spatial distribution", "change detection", "prediction", and "remote sensing" appears more frequently and has stronger correlations among the research articles published in international databases. These keywords provide important information for us to analyze the progress of research on soil salinity monitoring in China, and they are the focus of our attention.

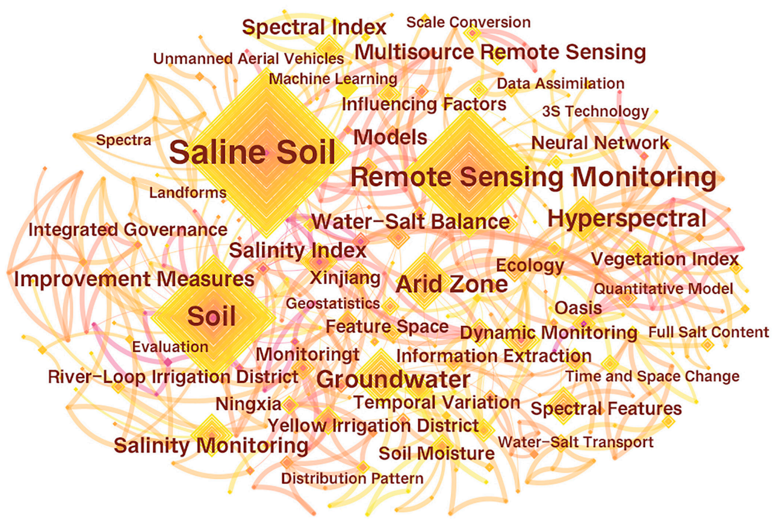

Figure 1. Keyword co-occurrence mapping based on the literature related to soil salinity monitoring in the China National Knowledge Infrastructure (CNKI) database.

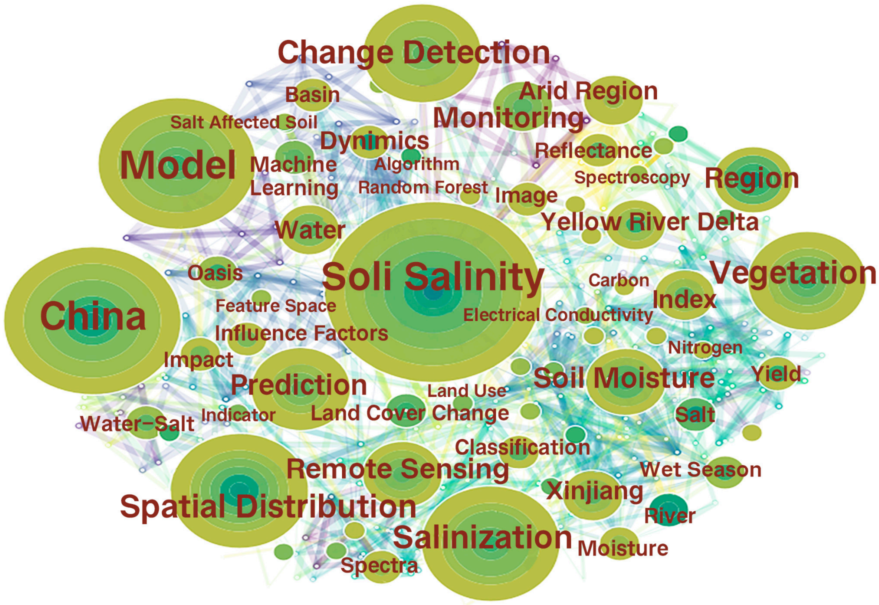

Figure 2. Keyword co-occurrence mapping based on the literature related to soil salinity monitoring in the Web of Science (WOS) database.

This paper reviews the developmental history of saline soil management research in China, discusses the research progress of soil salinity monitoring, and summarizes the main modeling methods for remote sensing monitoring of saline soils. Based on a large amount of domestic and foreign soil salinization research, this paper combines the real needs and frontier hotspots of the country in related research, proposes limitations of soil salinization monitoring research in China, and analyzes the future developmental trend of soil salinization monitoring research in China. This is of great practical significance to comprehensively grasp the current situation of salinization research, further clarify and sort out the research ideas of salinization monitoring, enrich the remote sensing monitoring methods of saline soils, and solve practical problems of soil salinization in China.

2. Research History and Importance of Saline Soil Management in China

As an important actual and potential arable land resource in China, saline soils have strong development and utilization value. Different types of saline soils can be managed and improved in terms of their physicochemical and biological properties by using various types of effective soil improvement tools and other comprehensive measures, thus improving soil quality and productivity levels [11]. Theoretical and technological research on saline soil management in China has been steadily developing. The country attaches great importance to the treatment and utilization of saline soils, policy research, and technological innovation. In the 1950s, the State organized a lot of research on saline resources and mastered the situation of many different regions and different types of saline lands [12–14]. In the 1990s, researchers started to study the regional water and salt movement of saline soils and its regulation and management on the basis of the regional water table, water quality, and a soil water and salt co-forecasting model, and this helped facilitate the improvement of saline soils [15,16]. Thus, during the 20th century, Chinese research in the field of soil salinization focused on research and classification, investigation of causes, and improvement and prevention. Several provinces have conducted focused analyses for regional saline soils [17,18] and have conducted in-depth research while gaining a basic understanding of saline soils, laying the foundation for future monitoring and management of saline soils.

In the 21st century, during the 11th Five-Year Plan, the Chinese Academy of Sciences, together with the relevant domestic forces, organized and implemented the "Research and Demonstration of Supporting Technologies for the Efficient Utilization of Saline Soil in Agriculture", which is a public welfare industry special project for the whole country, and carried out comprehensive research on saline soil management [19,20]. During the 12th Five-Year Plan period, the report of the Chinese Academy of Sciences, "The National Demonstration of Saline Land Management Technology", was received by the national leaders [21–24]. During the 13th Five-Year Plan period, China deployed the national key project of "Typical Fragile Ecological Restoration and Protection Research", which has strongly driven enthusiasm and encouraged researchers to publish related research articles [25–27]. Internationally, the theme of the 8th World Soil Day (WSD) in 2021 is "Preventing Soil Salinization and Improving Soil Productivity" [28]. This theme aims to raise awareness of soils, strengthen national research capacity, and work together to preserve the Earth's environmental carrying capacity. Summarizing the research history of soil salinization management in China since the beginning of the 21st century, it can be seen that during this period, China started to focus on advancing the theory and technology of salinization prevention and control. Comprehensive measures have been applied to manage salinized soils and improve their physicochemical and biological properties. The potential of saline soils as an important arable resource has been fully exploited.

At present, with policy support and implementation of various departments at the national level, research and development of saline soil management and monitoring technology in China has achieved certain results. The research not only covers the direction and content of international saline soil research but also highlights domestic characteristics, with a richer connotation, broader coverage, and more common interdisciplinary association [29]. This further indicates that the nation has recognized the importance and necessity of saline soil treatment to ensure food security and promote ecological stability.

3. Advances in Soil Salinity Monitoring Research

The literature in CNKI and WOS databases was searched based on the similarity of literature keywords. A keyword clustering analysis was performed on the retrieved literature datasets related to soil salinity monitoring (Figures 3 and 4). Keyword clustering analysis is the process of analyzing the set of keywords extracted from the literature into multiple categories consisting of similar objects. There are many different algorithms for clustering analysis, and this study chose Logarithmic Likelihood Ratio (LLR) as the base calculation for the analysis. The labels of each cluster are the key keywords in the co-occurrence network. Based on this, closely related keywords are clustered. The higher the ranking of the cluster number, the more keywords are included in the cluster. Conversely, the more backward the ordinal number, the fewer keywords are contained in that cluster. The modularity value of the clustering metric Q ranges 0–1. The larger the value, the better the clustering effect. Usually, when Q is less than 0.3, it indicates that the literature data set analyzed by this clustering is not well structured. In Figure 3, a value of $Q = 0.8293$ was obtained from cluster analysis of the literature in the CNKI database. In Figure 4, a value of $Q = 0.7128$ was obtained from cluster analysis of the literature in the WOS database. This indicates that the data collected in the Chinese literature database and the international literature database were reliable and the keyword clustering analysis structure was significant.

A total of 16 clustering tags were obtained from the keyword clustering analysis based on the CNKI database (Figure 3). Among the top seven clusters, three of them are related to remote sensing monitoring, namely "quantitative remote sensing", "remote sensing monitoring", and "monitoring models". A total of 10 clustering tags were obtained from the keyword clustering analysis based on the WOS database (Figure 4). Among them, both "machine learning" and "feature space" are specific remote sensing monitoring modeling methods. Based on these methods, the researcher explores the "change detection", "spatial distribution", and "evolution trend" of saline soils in China, making full use of the advanced remote sensing information technology. This demonstrates that to achieve the purpose of saline soil management and utilization on a large scale, it is an important prerequisite to use scientific means to quickly and accurately grasp the information of saline soil distribution and to clarify the spatial and temporal variability characteristics of salinization [30]. With the decades of continuous exploration and practice of soil salinization research in China, there are more and more methods and means of soil salinization monitoring. In summary, they can be divided into two main categories: (1) traditional field investigation and experimental methods and (2) modern remote sensing information technology monitoring methods.

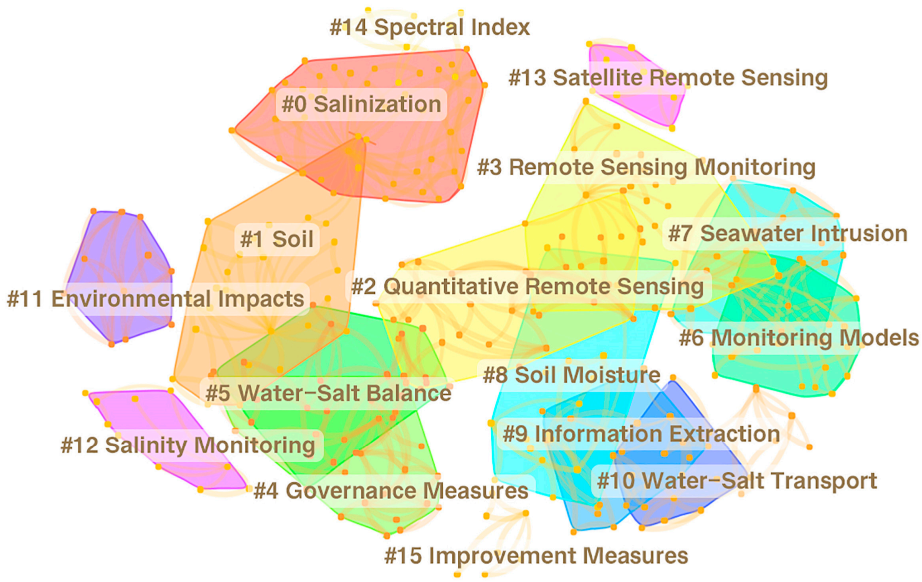

Figure 3. Keyword clustering mapping based on the literature related to soil salinity monitoring in the CNKI database.

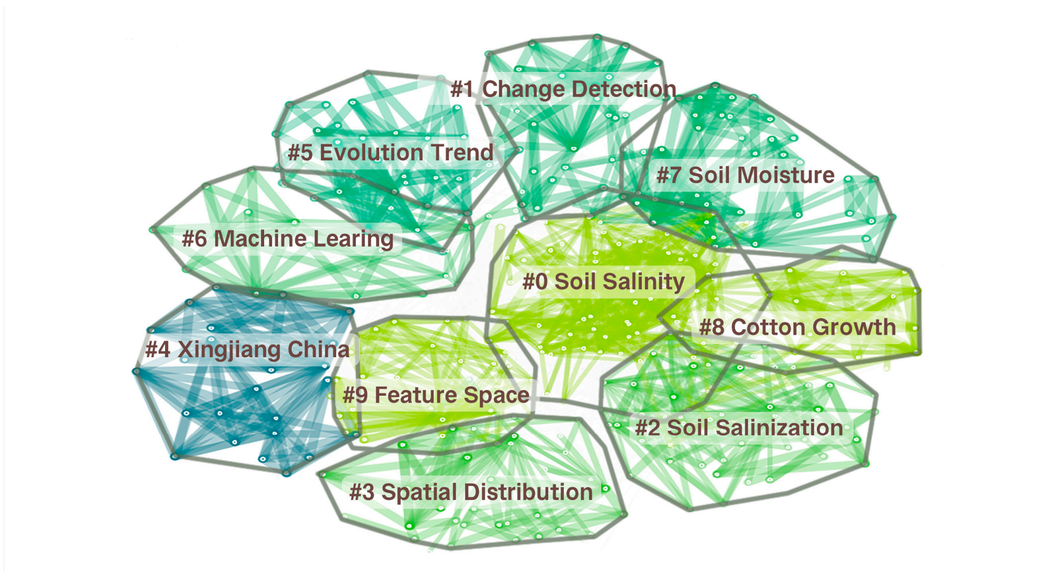

Figure 4. Keyword clustering mapping based on the literature related to soil salinity monitoring in the WOS database.

3.1. Field Investigations and Experiments

The field survey is to select test areas in the field where salinity characterization exists and to obtain visual information on soil salinity from soil samples to provide an accurate and reliable data source for the study. During the sampling process, the soil sample points should be evenly distributed throughout the work area. The sample points should also be divided into typical sampling areas containing four different landscapes, vegetation cover, soil types, etc. that are more representative. For soil samples collected at different depths, soil conductivity can be measured using the EM38 Geodetic Conductivity Probe [31]. The content of each ion in the soil can also be detected, and the corresponding total soil salt content can be calculated [32]. We can also use dry weight and wet weight to determine soil water content as well as soil evapotranspiration [33], and we can use a portable spectrometer to obtain spectral curve data from different sampling points [34]. In this way, we can achieve the purpose of extracting information on soil salinization.

The field survey method of collecting soil samples in the field and then analyzing them has become a basic monitoring tool for accurate information on soil salinization [35]. Kai Deng et al. [36] established a linear mixed model based on the linear relationship between magnetic susceptibility apparent conductivity and actual measured soil salinity to assess the spatial distribution of salinity in the soil profile. Wenping Xie et al. [37] constructed a multiple regression model between magnetic susceptibility geodetic conductivity and soil multiple regression models between geodetic conductivity and soil salinity to quantitatively assess the spatial and temporal evolution of soil salinity in the estuary over the past decade. Yasenjiang Kahaer et al. [38] performed indoor hyperspectral measurements and conductivity measurements on soil samples obtained from fieldwork and established a hyperspectral estimation model of soil conductivity after screening parameters. Finally, effective monitoring of soil salinity was achieved.

By analyzing the results of scientists' investigations, we can find that field surveys and experimental methods can extract saline soil information very precisely. However, this method is mainly based on manual point-by-point examination, which is less efficient and difficult to obtain the salinity variation characteristics of large areas at a macroscopic scale [39–41]. Especially in the study area where the vegetation cover is complex and the natural environment is harsh, the number of monitoring stations is not sufficient, and the difficulty of field investigation is increased. All these problems render the traditional monitoring method of field surveys insufficient to meet research needs [42,43].

3.2. Remote Sensing Information Technology Monitoring

Among the many soil physicochemical parameters, soil salinity content is the primary parameter for measuring salinization. The higher the soil salinity, the higher the risk of soil salinization. When the accumulation of salts in the soil exceeds a certain level, it leads to weakening of the bond between soil particles, loosening of soil structure, reduction of soil fertility, and even directly affects the survival of vegetation [2,44]. At the same time, there is a close relationship between soil conductivity and soil salinity. Soil conductivity is a measure of the ability of ions in the soil to conduct electricity, and it reflects the amount of dissolved ions in the soil, including salt ions and other dissolved substances. Similar to soil salinity, conductivity can be an important factor in measuring salinity [45,46]. Moisture in the soil can also largely reflect the salinity of the soil. Salt moves with water, and soil salts are prone to shift with changes in moisture. Under strong evaporation, salts in groundwater and deep soil rise to the surface along soil capillaries and accumulate, resulting in salinization of regional soils [47–49]. Additionally, the heavy metal content in soil also interacts with soil salinization and constrains it. Some heavy metal elements, such as cadmium and lead, can affect the growth of soil microorganisms and form insoluble complexes when combined with salts. They can reduce the activity of salts in the soil, thus affecting the process of conversion and circulation of salts in the soil and aggravating the degree of soil salinization [50,51].

Different levels of soil salinity, water content, and some heavy metals can be distinguished by using the different spectral reflectance of remote sensing images for different features. The multidimensional combination of different bands in spectral images can also construct a variety of model indices that can monitor soil salinization. Therefore, the use of remote sensing to track physicochemical parameters such as soil salinity, conductivity, water content, and heavy metals can all be effective in monitoring saline soils. In recent years, remote sensing information technology has been innovating, and the spectral resolution and spatial resolution of remote sensing images have been increasing. Efficient, convenient, and large-scale means of monitoring soil salinity have been rapidly developed. The method of monitoring salinity based on remote sensing images is gradually becoming common and is rapidly developing into an important tool for studies such as soil salinity information extraction, monitoring, and forecasting [52–54].

A keyword timeline analysis was performed on the literature datasets related to soil salinity monitoring from 1981 to 2022 and 2002 to 2022 retrieved from the CNKI and the WOS databases, respectively (Figures 5 and 6). The keywords in the figure are spread out in the clusters they belong to according to the chronological order in which they appear in the corresponding years, showing the development of keywords in each cluster. The size of the keyword node represents the frequency of the keyword occurrence, and the warm and cold colors of the node periphery represent the emergence and the duration of the keyword. The larger the keyword node, the warmer the color of the edge of the node, the more frequently the hotspot appears, and the longer it lasts. Conversely, the smaller the node, the cooler the color of the node edge, the less frequently the hotspot appears, and the shorter the duration of the hotspot. The analysis of the development of soil salinity monitoring showed that in the mid-1990s, results for "dynamic monitoring" clustering began to appear in the Chinese literature database, and attention was focused on "remote sensing monitoring" (Figure 5). In the 21st century, "machine learning" and "feature space" methods for monitoring "soil salinity" and "soil moisture" have begun to appear in the international literature database (Figure 6). While a large number of studies on soil salinity monitoring based on remote sensing have gradually emerged, keyword nodes such as "remote sensing technology", "hyperspectral", "radar remote sensing", "feature space", "inversion models", "random forest", "classification", and "index" have also begun to appear in other clusters one after another. There are a large number of keyword links between them, both within and across clusters. These remote sensing monitoring-related research terms link the whole clustering trend and become important research hotspots in domestic and international literature databases.

Based on data analysis and processing of multiple remote sensing images, Yanhua Li et al. [55] established a soil salinity monitoring index model using Landsat-TM multispectral remote sensing image data to invert and estimate soil salinity in the Weigan River-Kuche River basin. Also using field collection samples and Landsat8 image data, Mingkuan Wang et al. [56] collected soil samples in the key study area in the Yellow River Delta region in the field and acquired simultaneous phase Landsat8 image data. They constructed multiple models for remote sensing inversion of soil salinity and inversion of the spatial distribution of soil salinity in the study area based on the optimal model. The results showed that the relationship between reflectance of remote sensing images and soil salinity content is not purely linear, and the constructed salt estimation model can better simulate the relationship between soil salinity and spectral data. Yanling Li et al. [39] established a machine learning and statistical regression model based on the fusion of multispectral and hyperspectral images, which significantly improved the accuracy of salt inversion. Similarly, Wumuti Aishanjiang et al. [57] matched field-measured hyperspectral data with WorldView-2 remote sensing images to improve the prediction accuracy and mapping accuracy of soil salinity. The quantitative inversion model developed in this paper considering vegetation and moisture does not require complex parameters. To a certain extent, it meets the needs of salinity monitoring in arid and semi-arid regions. This can promote further applications of high-spatial-resolution satellites such as WorldView-2 in salinity monitoring. In the meantime, some scientists have also used radar remote sensing data combined with soil moisture and pH factors to achieve predictive inversion of soil salinity. In terms of the variability and correlation used to reveal soil properties, M. Samiee et al. [58] used geostatistical methods to simulate the spatial correlation of soil salinity, and the results were used to predict the spatial distribution of soil properties by spatial interpolation methods. In addition, more and more kinds of remote sensing images have been applied to salinity monitoring. For example, Junying Chen et al. [59] used unmanned aerial vehicle (UAV) aerial imagery and high-resolution remote sensing imagery to construct a salinity inversion model and used an improved scale conversion method to achieve soil salinity monitoring at the ascending scale. Predictive inversion of soil salinity was achieved by using radar remote sensing data combined with soil moisture and pH factors by Zaytungul Yakup et al. [60]. The monitoring model developed in this paper does not need to consider complex dielectric constants. This can meet the needs of soil salinity monitoring to a certain extent and promotes the application of Phased Array type L-band Synthetic Aperture Radar data in soil salinity monitoring. Yumei Li et al. [61] focused on the current status of the application of lidar three-dimensional remote sensing observation technology in the three-dimensional dynamic monitoring of various natural resources. The paper provides a comprehensive analysis of the potential and limitations of lidar applications in natural resource surveys. These authors are also considering how to combine multi-source, multi-scale, and multi-platform remote sensing data with artificial intelligence. The goal is to build an integrated "sky-air-ground" natural resources survey and monitoring technology system. This is the developmental direction of future methods for three-dimensional dynamic monitoring of natural resources.

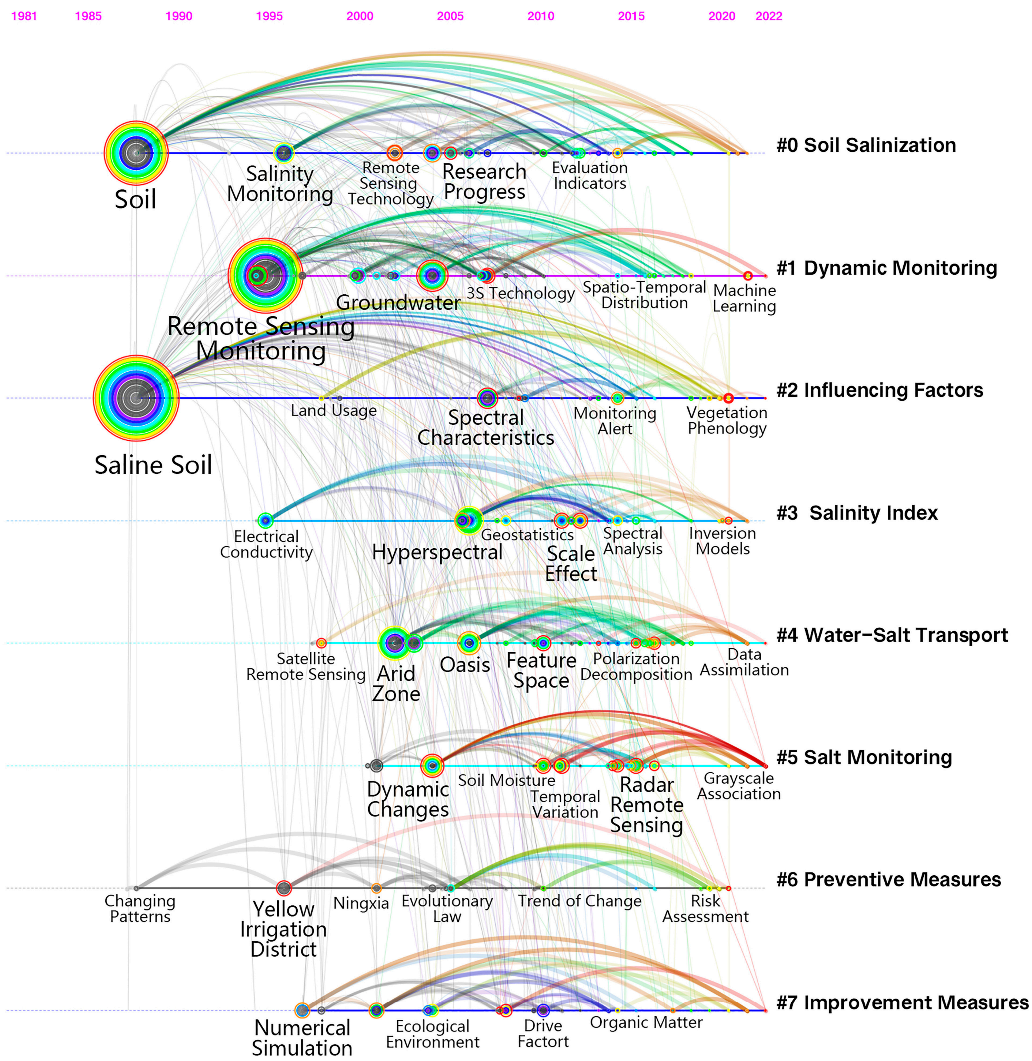

Figure 5. Keyword timeline mapping based on the literature related to soil salinity monitoring in the CNKI database from 1981 to 2022.

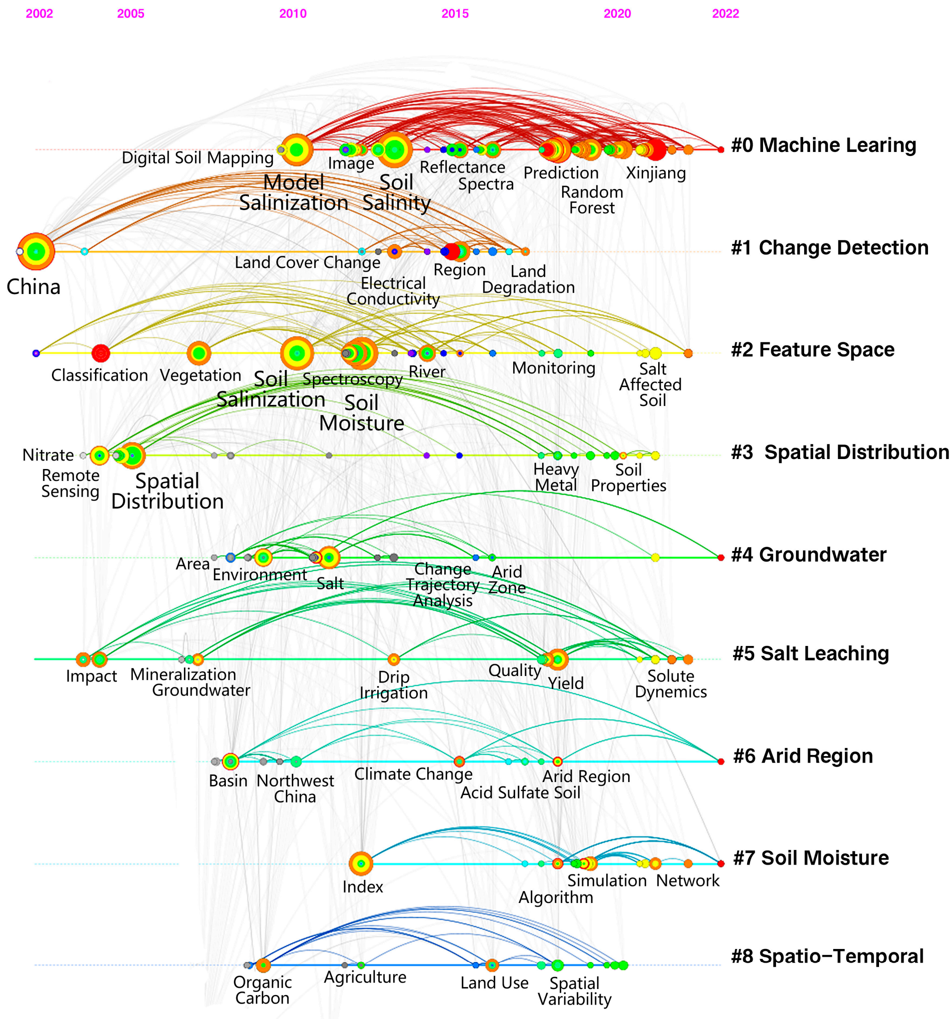

Figure 6. Keyword timeline mapping based on the literature related to soil salinity monitoring in the WOS database from 2002 to 2022.

New theories and technologies in image processing [62,63], machine learning [64], remote sensing monitoring [65], and other research fields are gradually developing and innovating. By summarizing a large number of domestic and foreign researchers' studies in recent years, it is clear that research using satellite remote sensing data to extract salinity information by classification or soil salinity inversion by multiple spectral indices has further deepened [66,67]. At the same time, more researchers are also focusing on the application of integration between different observation elements, different scales, and different data. We try to improve the accuracy of inversion of soil salinization information in terms of classification algorithms and model construction. This will provide reliable information for the development of saline soil management, ecological maintenance, and sustainable agricultural development in China.

4. Main Modeling Approaches for Soil Salinity Remote Sensing Monitoring

In recent years, countless domestic and international researchers have created many additional soil salinity monitoring techniques by tirelessly decoding an enormous amount of sensing image data. Keyword burst detection analysis was performed in CiteSpace software using the retrieved literature dataset related to soil salinity monitoring from 1981 to 2022 obtained by searching in the CNKI and the WOS databases (Figure 7). This analysis can be used to detect large changes in the number of citations of keywords in the literature during a certain time period. Thus, it helps to obtain the latest information on the frontiers of research in the field. The keyword burst detection mapping shows that since the information extraction and dynamic monitoring of salinized soil, many researchers have started to focus on the construction of models for soil salinization information by remote sensing. For example, "classification" appeared in 2012, "feature space" appeared in 2013, "quantitative models" appeared in 2015, "neural networks" and "random forest" appeared in 2016, "methods plsr" appeared in 2018, and "model", "machine learning", and "monitoring models" appeared in 2020. Among the 35 main keywords obtained from the analysis, a variety of keywords related to remote sensing monitoring modeling studies have begun to appear frequently in the last decade. These modeling studies are updated quickly and span a long period of time, and all of them have gradually achieved valuable research results while broadening the methods of soil salinity monitoring. This indicates that modeling studies have become a hot method in remote sensing monitoring of soil salinity.

Figure 7. Keyword burst detection mapping based on the literature related to soil salinity monitoring from 1981 to 2022 in the CNKI and WOS databases. Note: In the Figure, the blue lines correspond to the year in which the keywords first started to appear; the red lines correspond to the year in which the keywords started and ended as research frontiers.

The core method of quantitative assessment of soil salinity using remote sensing data is to explore the correlation between the content of relevant salinity indicators and remote sensing data [68]. Among them, salinity indexes can be obtained by bringing soil samples collected from field surveys back to the laboratory and performing measurement experiments for analysis. Pre-processed remote sensing image data are rich in spectral information of features, which are contained in the reflectance of different wavelength bands of remote sensing data. The spectral information contained in a single band is limited. Therefore, after extracting the spectral reflectance of the bands of the remotely sensed image, a combination operation between different bands can be performed. These indices are usually a priori formulas derived from existing studies (Tables 1 and 2).

Table 1. Salinity indexes and related calculation formulas.

Salinity Index	Calculation Formula	Note	Reference
Salinity Index (SI)	$\sqrt{B \times R}$	B is the blue band R is the red band	[69]
Salinity Index 1 (SI1)	$\sqrt{G \times R}$	G is the green band R is the red band	[70]
Salinity Index 2 (SI2)	$\sqrt{G^2 + R^2 + NIR^2}$	G is the green band R is the red band NIR is the near infrared band	[71]
Salinity Index 7 (SI7)	$\frac{NIR \times R}{G}$	NIR is the near infrared band R is the red band G is the green band	[72]
Salinity Index-T (SI-T)	$\frac{R}{NIR} \times 100$	R is the red band NIR is the near infrared band	[73]
Salinity Index (S)	$\frac{R}{NIR}$	R is the red band NIR is the near infrared band	[74]
Salinity Index (S1)	$\frac{B}{R}$	B is the blue band R is the red band	[74]
Salinity Index (S2)	$\frac{B-R}{B+R}$	B is the blue band R is the red band	[74]
Salinity Index (S3)	$\frac{G \times R}{B}$	G is the green band R is the red band B is the blue band	[74]
Salinity Index (S5)	$\frac{B \times R}{G}$	B is the blue band R is the red band G is the green band	[74]
Brightness Index (BI)	$\sqrt{R^2 + NIR^2}$	R is the red band NIR is the near infrared band	[75]
Brightness Index (BRI)	$\sqrt{G^2 + R^2}$	G is the green band R is the red band	[76]
Intensity Index 1 (Int1)	$\frac{G+R}{2}$	G is the green band R is the red band	[77]
Intensity Index 2 (Int2)	$\frac{G+R+NIR}{2}$	G is the green band R is the red band NIR is the near infrared band	[77]
Salinity Ratio Index (SRI)	$(R - NIR) \times (G + NIR)$	R is the red band NIR is the near infrared band G is the green band	[78]
Normalized Difference Salinity Index (NDSI)	$\frac{R-NIR}{R+NIR}$	R is the red band NIR is the near infrared band	[79]
Normalized Difference Water Index (NDWI)	$\frac{G-NIR}{G+NIR}$	G is the green band NIR is the near infrared band	[79]
Canopy Response Salinity Index (CRSI)	$\sqrt{\frac{(NIR \times R)-(G \times B)}{(NIR \times R)+(G \times B)}}$	NIR is the near infrared band R is the red band G is the green band B is the blue band	[80]
Clay Index (CLEX)	$\frac{SWIR1}{SWIR2}$	SWIR1 and SWIR2 are the short-wave infrared bands	[81]
Carbonate Index (CAEX)	$\frac{R}{G}$	R is the red band G is the green band	[82]

Table 2. Vegetation indexes and related calculation formulas.

Vegetation Index	Calculation Formula	Note	Reference
Ratio Vegetation Index (RVI)	$\frac{NIR}{R}$	NIR is the near infrared band R is the red band	[83]
Enhanced Ratio Vegetation Index (ERVI)	$\frac{NIR+SWIR2}{R}$	NIR is the near infrared band SWIR2 is the short-wave infrared band R is the red band	[83]
Green Ratio Vegetation Index (GRVI)	$\frac{NIR}{G}$	NIR is the near infrared band G is the green band	[84]
Difference Vegetation Index (DVI)	$NIR - R$	NIR is the near infrared band R is the red band	[85]
Enhanced Difference Vegetation Index (EDVI)	$NIR + SWIR1 - R$	NIR is the near infrared band SWIR1 is the short-wave infrared band R is the red band	[86]
Renormalized Difference Vegetation Index (RDVI)	$\frac{NIR-R}{\sqrt{NIR+R}}$	NIR is the near infrared band R is the red band	[87]
Generalized Difference Vegetation Index (GDVI)	$\frac{NIR^2-R^2}{NIR^2+R^2}$	NIR is the near infrared band R is the red band	[88]
Normalized Difference Vegetation Index (NDVI)	$\frac{NIR-R}{NIR+R}$	NIR is the near infrared band R is the red band	[89]
Green Normalized Difference Vegetation Index (GNDVI)	$\frac{NIR-G}{NIR+G}$	NIR is the near infrared band G is the green band	[90]
Extended Normalized Difference Vegetation Index (ENDVI)	$\frac{NIR+SWIR2-R}{NIR+SWIR2+R}$	NIR is the near infrared band SWIR2 is the short-wave infrared band R is the red band	[91]
Enhanced Vegetation Index (EVI)	$2.5 \times \frac{NIR-R}{NIR+6R-7.5B+1}$	NIR is the near infrared band R is the red band B is the blue band	[92]
Two Band Enhanced Vegetation Index (EVI2)	$2.5 \times \frac{NIR-R}{NIR+2.4R+1}$	NIR is the near infrared band R is the red band	[93]
Chlorophyll Index Green (CIgreen)	$\frac{NIR}{G} - 1$	NIR is the near infrared band G is the green band	[94]
Simple Ratio Index (SRI)	$\frac{NIR}{R}$	NIR is the near infrared band R is the red band	[95]
Nonlinear Vegetation Index (NLI)	$\frac{NIR^2-R}{NIR^2+R}$	NIR is the near infrared band R is the red band	[96]
Modified Nonlinear Vegetation Index (MNLI)	$\frac{1.5(NIR^2-R)}{NIR^2+R+0.5}$	NIR is the near infrared band R is the red band	[96]
Modified Simple Ratio (MSR)	$\frac{NIR-B}{R+B}$	NIR is the near infrared band B is the blue band R is the red band	[97]
Triangular Vegetation Index (TVI)	$0.5[120(NIR - G) - 200(R - G)]$	NIR is the near infrared band G is the green band R is the red band	[98]
Modified Triangular Vegetation Index (MTVI)	$1.2[1.2(NIR - G) - 200(R - G)]$	NIR is the near infrared band G is the green band R is the red band	[99]
Soil-Adjusted Vegetation Index (SAVI)	$\frac{(1+L)(NIR-R)}{NIR+R+L}$	L is the soil adjustment coefficient, which is generally close to 0.5 NIR is the near infrared band R is the red band	[100]
Green Soil-Adjusted Vegetation Index (GSAVI)	$(1 + L)\frac{NIR-G}{NIR+G+L}$	NIR is the near infrared band G is the green band L is the soil adjustment coefficient, which is generally close to 0.5	[101]
Optimization Soil-Adjusted Vegetation Index (OSAVI)	$\frac{NIR-R}{NIR+R+0.16}$	NIR is the near infrared band R is the red band	[102]
Green Optimization Soil-Adjusted Vegetation Index (GOSAVI)	$\frac{NIR-G}{NIR+G+0.16}$	NIR is the near infrared band G is the green band	[103]
Composite Spectral Response Index (COSRI)	$\frac{B+G}{R+NIR} \times \frac{NIR-R}{NIR+R}$	B is the blue band G is the green band NIR is the near infrared band R is the red band	[104]
Visible Atmospherically Resistant Index (VARI)	$\frac{G-R}{G+R-B}$	G is the green band R is the red band B is the blue band	[105]
Atmospherically Resistant Vegetation Index (ARVI)	$\frac{NIR-(2R-B)}{NIR+(2R+B)}$	NIR is the near infrared band R is the red band B is the blue band	[106]

A remote sensing monitoring model was constructed with the aim of establishing the relationship between soil salinity content and the abovementioned modeling factors. Therefore, the research hotspot of remote sensing monitoring of soil salinity mainly lies in the construction of an efficient and reliable remote sensing monitoring model [107,108]. Various models are used to extract salinity information mainly by remote sensing technology to obtain more accurate inversion results and to assess the regional soil salinity distribution. Among them, the most commonly used remote sensing models for salinity monitoring mainly include the following.

4.1. Partial Least Squares Regression

Partial least squares regression (PLSR) is a new multivariate statistical data analysis algorithm that combines the advantages of multiple stepwise linear regression models, principal component models, and simple linear regression models in one [109,110]. Partial least squares regression implements a combination of simplified data, structural regression modeling, and the analysis of correlations between two groups of variables. It also implements cross-validity validation of component extraction in the calculation process, reorganization and screening of information in the variable system, and selection of several new components with the best systematic explanatory power for regression modeling. This provides a great convenience for statistical analysis of multivariate data [111]. Therefore, partial least squares regression, which can automatically filter variables based on correlation and ensure model stability, has been widely used in recent years to model spectral data and achieve high-accuracy predictions.

Viscarra Rossel et al. [112] showed that the partial least squares regression method has better soil nutrient prediction capability. This method allows modeling when the number of sample points is smaller than the number of variables and provides excellent processing and analysis capabilities for complex problems. Numerous researchers have also used this model to invert soil organic matter and to filter the most important organic matter content variables from spectral data [113], resulting in better robustness of the established models. For example, Yumiti Maiming et al. [114] set the independent variable as the original spectral reflectance and the dependent variable as the soil organic matter content to construct an estimation model based on methods such as partial least squares regression. It was shown that the inverse logarithmic first-order differential transformation could help to improve the accuracy of the partial least squares regression estimation model.

4.2. Support Vector Machines

Support vector machines (SVM) are a method that better implements the idea of structural risk minimization. It can better solve practical problems such as small samples, nonlinearity, and high-dimensional data. It can be extended to other machine learning problems such as function fitting [115]. Support vector machines are a kind of machine learning method based on statistical theory, which has a strong mathematical foundation and is intuitive, stable, accurate, and efficient. Compared with traditional statistical methods, it has the advantages of strong functional expression, good generalization ability, and high learning efficiency. It is widely used in the fields of soil salinity information extraction because it is easy to combine with multiple sources of information and has relatively high accuracy [116]. However, at the same time, support vector machines are also too sensitive to the selection of parameters and functions and have shortcomings in solving multi-classification problems [117].

Using the spectral information of Landsat ETM+ images, Fei Zhang et al. [118] found that the support vector machines regression method based on texture features had an improved effect on the monitoring accuracy of soil salinity information. Similarly, Yiliyas Jiang [119] referred to the salinity classification system and used support vector machines to determine the optimal parameters, thus obtaining more accurate soil salinity classification information. In addition, Xi Wang et al. [120] selected support vector machines as a modeling method for machine learning based on the small sample size and practical situation of the study and performed remote sensing inversion of salinized soil organic matter.

4.3. BP Neural Network

BP neural network (BPNN) is a multilayer feedforward neural network trained according to the error back-propagation algorithm. It mainly contains two processes: forward propagation of signals and backward propagation of errors. BP neural networks can identify nonlinear relationships between input and output data sets in complex systems without constructing mathematical equations. It can eliminate the influence of specific values to a certain extent, has strong self-learning ability, strong adaptability, and anti-interference ability, and it is widely used by researchers in the inversion monitoring of salinity [121].

Wenzhe Feng et al. [122] simultaneously introduced BP neural network, support vector machines, and extreme learning machines to build a soil salinity monitoring model so as to improve the monitoring accuracy of soil salinity by satellite remote sensing. Among them, a three-layer BP neural network was used to build a soil salinity dynamics model according to the principle of relatively small error in training results. The results showed that the BP neural network model based on multi-source remote sensing images is more accurate. Xueli Feng et al. [123] found that the stability and prediction accuracy of the BP neural network model combining the second-order derivatives of spectral feature bands, radar backscattering characteristics, and combined surface roughness were higher than the rest of the models. This shows that the BP neural network model combined with multi-source remote sensing data can quickly and accurately monitor the distribution of soil salinization, which provides important guidance for the prevention and control of soil degradation.

4.4. Random Forest

Random forest (RF) is a new classification and prediction model that uses multiple decision trees for training and prediction of samples. The model randomly selects the training sample set with split attribute set, which is a combination of multiple decision trees and is less sensitive to outliers [124]. This gives random forest models high noise immunity and nonlinear mining ability, and the distribution of data does not need to conform to any assumptions, which performs well in the randomization training phase of samples and variables. Random forest models have been increasingly used for classification and regression in recent years because of their high accuracy in predicting results, the importance of computable variables, and the ability to model complex interactions among a large number of predictor variables [125,126].

Jie Hu [127] compared partial least squares regression and random forest regression methods using hyperspectral first-order differentiation, broad-band spectral indices, and narrow-band spectral indices as independent variables. The results showed that the random forest regression model could better predict soil salinity using spectral data, and the model for the bare soil area had the highest prediction accuracy compared to the model for the other sample areas. Meanwhile, in order to monitor the spatial variability of soil salinity as accurately as possible on a large scale, Lina Meng [128] used ordinary kriging, geographically weighted regression, and a random forest model combined with several environmental auxiliary variables to map the distribution of surface soil salinity in the study area. The results show that the random forest model has the highest prediction accuracy among the various prediction methods, indicating that the model is effective in quantitatively estimating soil salinity at the regional scale.

4.5. Feature Space

The modeling method based on the spectral feature space can also be applied to construct a soil remote sensing monitoring model [129]. The distance to a certain feature point in the two-dimensional or three-dimensional feature space of soil salinization covariates can reflect different degrees of salinity and determine the change trend between different covariates. We can analyze the scattered spatial map with practical experience so that we can use spatial characteristic covariates of the scattered map to build the corresponding model [130]. Among them, two-dimensional feature space can clearly express the distribution pattern of factors affecting the soil salinization process. For example, the two-dimensional scatter diagram between vegetation and soil salinity has been elaborated and discussed by domestic and foreign researchers. In view of the future development path of soil salinity monitoring, two-dimensional feature space can no longer satisfy the analysis and display of multiple factors involved in salinization at the same time. With the development of remote sensing technology, the emergence of three-dimensional technology can help promote the development of soil salinity feature space research to three-dimensional or multi-dimensional space.

On the one hand, in the study of two-dimensional feature space application, Jianli Ding et al. [131] constructed a two-dimensional feature space based on a modified soil-adjusted vegetation index and moisture index to derive a remote sensing monitoring index model for soil salinization. The results showed that the two-dimensional feature space correlated well with the soil surface salinity of the oasis in the arid zone. Fei Wang et al. [132] constructed a quantitative relationship between surface-based feature vectors and the occurrence of the salinization process. It was found that the feature space model could invert the soil salinity distribution of the delta oasis in the study area more accurately. In addition, Lingling Bian et al. [133] quantitatively explored the patterns between soil salinity and surface biophysical parameters and also constructed a soil salinity eigenspace model. The results showed that the salinity index and albedo characteristic spatial model has a strong predictive ability and is most suitable for the inversion of salinization in coastal areas.

On the other hand, the use of three-dimensional feature spaces is increasingly developed. The relationship between soil salinization, albedo, and the modified type of soil adjusting the vegetation index was used by Juan Feng et al. to construct the feature space [134] The monitoring model constructed by surface albedo and soil-adjusted vegetation index was found to have a high correlation with soil salinity, which can better quantify and monitor the degree of soil salinization in the study area. Not only that, XuePing Ha et al. [135] used the relationship between salinity index, surface albedo, and soil salinity based on three-dimensional feature space to efficiently and accurately extract salinization information of the oasis in the study area.

5. Discussion

The extraction of soil salinization information by remote sensing monitoring technology has recently become a hot spot in the field of remote sensing research. Many researchers domestic and abroad are gradually developing new technical means and research methods to expand research in the field of high-precision monitoring of regional soil salinization.

Various models including those summarized above have been widely used for remote sensing monitoring of soil salinity. Many of these improved and optimized mathematical models have been continuously applied to the study of the spatial distribution of soil salinity (Table 3). In addition, the back trajectory model can be used to track the trajectory of saline sands and salt dusts. The vertical distribution characteristics of sands and dusts in the atmosphere are detected by using satellite remote sensing data or UAV remote sensing data combined with the back trajectory model for the purpose of monitoring the time-series trajectory of saline soils [136,137]. Many of these models, which have achieved high accuracy, provide a favorable basis for spatial and temporal analysis and prediction of regional salinization. At the same time, however, this paper argues that there are still some shortcomings in the current research on soil salinity monitoring in China that need to be further discussed and addressed by researchers.

Table 3. Multiple modeling approaches for remote sensing to monitor soil salinity.

Authors	Monitoring Model	Reference
Jie Wang et al.	Multiple Linear Regression (MLR)	[138]
Jianwen Wang et al.	Multiple Stepwise Linear Regression (MSLR)	[139]
Yasenjiang Kahaer et al.	Nonlinear Regression (NR)	[140]
Haifeng Wang et al.	Quadratic Polynomial Regression (QPR)	[141]
Elia Scudiero et al.	Ordinary Least Square (OLS)	[142]
Shengmin Peng et al.	Partial Least Squares Regression (PLSR)	[143]
Lornbardo et al.	Quantile Regression (QR)	[144]
Pingping Jia et al.	Poisson Regression (PR)	[145]
Richard H. Anderson et al.	Ridge Regression (RR)	[146]
Glen Fox et al.	Principal Component Regression (PCR)	[147]
Yan Shen et al.	Stepwise Regression (SR)	[148]
Haorui Chen et al.	Multiple Mixed Regression (MMR)	[149]
Ayetiguli Sidike et al.	Stepwise Multiple Regression (SMR)	[150]
Nurmemet Erkin et al.	Multiple Adaptive Regression Spline (MARS)	[151]
Akshar Tripathi et al.	Decision Tree Algorithm (DTA)	[152]
Yinyin Wang et al.	Random Forest (RF)	[153]
Jinjie Wang et al.	Classification and Regression Tree (CART)	[154]
Xiaoyan Guan et al.	Support Vector Machine (SVM)	[115]
Xiaoping Wang et al.	Grid Search Support Vector Machine (GSSVM)	[155]
Utpal Barman et al.	Differential Evolutionary Support Vector Machine (DESVM)	[156]
Zheng Wang et al.	Particle Swarm Optimization Support Vector Machine (PSOSVM)	[157]
Zhongyi Qu et al.	BP Neural Network (BPNN)	[158]
Christina Corbane et al.	Convolutional Neural Network (CNN)	[159]
Sedaghat A. et al.	Artificial Neural Network (ANN)	[160]
Dawei Hu et al.	BP Artificial Neural Network (BPANN)	[161]
Xiaoping Wang et al.	Bootstrap-BP Neural Network (Bootstrap-BPNN)	[162]
Gopal Ramdas Mahajan et al.	Ordinary Krieger (OK)	[163]
Jialin Zhang et al.	Universal Kriging (UK)	[164]

Table 3. *Cont.*

Authors	Monitoring Model	Reference
Eldeiry A. A. et al.	Modified Residual Kriging (MRK)	[165]
Ku Wang et al.	Residual Universal Kriging (RUK)	[166]
Ting Du et al.	Two-Dimensional Feature Space (2DFS)	[167]
Bing Guo et al.	Three-Dimensional Feature Space (3DFS)	[168]
Yueru Wu et al.	Dobson Model (DM)	[169]
Ya Liu et al.	Structural Equation Model (SEM)	[170]
Purandara B. K. et al.	Solute Transport Model (STM)	[171]
Suchithra M. S. et al.	Extreme Learning Machine (ELM)	[172]
Ya Liu et al.	Spectral Index Regression (SIR)	[173]
Elia Scudiero et al.	Spatial Autoregressive Model (SAM)	[174]
Zhen Li et al.	Geographically Weighted Regression (GWR)	[175]

First of all, the most important shortcoming is that the universal applicability of monitoring models needs to be further improved. Saline soil resources in China are distributed in different climatic zones, and there are large differences in soil types, water and heat conditions, and planting methods. Therefore, the physical and chemical properties of soils in the current study area, temporal and climatic conditions, relevant environmental factors, and model application preferences considered by researchers in constructing monitoring models can lead to a generally low applicability of the optimal models derived from the final experiments. However, this can invert the soil salinization information of the current study area with high accuracy. Nevertheless, it is difficult for it to be applied to other seasons in the same study area or to other study areas with different environmental states.

Secondly, sometimes there are more types and a greater abundance of salt-tolerant vegetation cover in the study area. The soil salinity monitoring model constructed in the study area needs to be adjusted because of the large differences in spectral characteristics between different vegetation types and bare soil. Therefore, the model can be applied to areas with different vegetation growth stages and areas with different arable, grassland, and woodland coverage to eliminate the influence of vegetation on monitoring results as much as possible. This not only increases the difficulty of designing and executing the distribution of soil sampling points during fieldwork but also incorporates more variables into the construction of the model. This will lead to a decrease in the accuracy of monitoring models to invert salinity. Therefore, how to construct a salinity monitoring model that can efficiently and accurately reflect the salinity of vegetation cover areas will be a major problem to be faced in this field in the future.

6. Research Perspectives on Soil Salinity Monitoring in China

A synthesis of previous studies carried out on soil salinization shows that most monitoring methods are based on the spectral response characteristics of salinized soils. Researchers have combined the spectral information obtained from different remote sensing data with non-remote sensing parameters to establish inverse models for regional soil salinity monitoring. However, due to the high correlation between water and salt in soil salinization, salt moves with water, and soil salinity is easily shifted with changes in moisture. In the monitoring of salinity, not only the salt but also the water will be considered to further develop water–salt synergistic monitoring so as to achieve the purpose of high monitoring accuracy and effective monitoring.

For the scale studies of salinized soils, researchers have mostly conducted a single scale or chosen the administrative district as the scale indicator for analysis. Some results have been obtained for soil salinity monitoring at different scales, such as field and regional scales. However, the correlation between different scales and their transformation have been less studied. Various reasons, such as surface heterogeneity, complexity of the salinization process, and significant variability in the dominant factors affecting the spatial variability of soil salinity at different scales [176], can lead to large differences in the autocorrelation of the same variable at different scales. There are limitations in studying salinization at a single scale.

The variability of soil salinity shows obvious scale effects with spatial scales. If the analysis is performed only at large scales, it may cause the spatial structural features at small scales to be obscured, making it difficult to analyze the structural features of soil spatial variability in depth. Soil salinity research based on multi-scale methods as well as scale-transformation methods can solve this problem well, which will provide new research ideas for soil salinity monitoring.

7. Conclusions

The proper management of saline soil resources in China is related to national food security and ecological stability. The leaders of the Party and the State attach great importance to the management and utilization of saline soils. As an important land resource in China, saline soils of different types, vast areas, and great potential provide unique research conditions for our researchers. Efficient and accurate monitoring of salinization information along with the management and development of unused saline soils provides more room for development to expand the country's arable land resources and expand the path of agricultural development.

With the continuous progress of remote sensing technology, research on soil salinization information extraction methods has developed over a long period. In order to obtain more accurate inversion data to characterize the interrelationship between soil salinity status and its influencing factors, the construction of remote sensing monitoring models has gradually become a research hotspot in the field of soil salinity monitoring. In future research, the exploration of soil salinization information extraction will become more extensive, will generate more data, and will be more accurate in judgment [176]. In general, according to current scientific needs and national demands, soil salinization research in China will play an important role for national food security [177], arable land security [178], saline land improvement [179], land use protection [180], ecology, and sustainable agricultural development. In the face of today's increasingly serious soil salinization situation, it is important to seek more efficient, reliable, accurate, and economical soil salinization monitoring technologies.

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