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Postprint: Research Advances in Satellite Remote Sensing Monitoring and Prediction of Agricultural Drought

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Abstract

Drought constitutes the primary climatic factor impacting agricultural production. Traditional agricultural drought monitoring primarily relies on meteorological and hydrological data. While this approach can yield relatively accurate drought monitoring results at specific observation points, certain limitations persist when monitoring agricultural drought over spatial extents. The rapid advancement of remote sensing technology, particularly the coverage of electromagnetic bands—including visible light, near-infrared, thermal infrared, and microwave—by currently operational satellite sensors, has furnished novel approaches for regional-scale agricultural drought monitoring. The utilization of rich land surface information derived from satellite remote sensing data for agricultural drought monitoring and prediction bears significant research importance. This paper expounds upon the research progress in satellite remote sensing-based agricultural drought monitoring from three perspectives: remote sensing index methods, soil moisture content methods, and crop water requirement methods. Agricultural drought prediction represents a temporal extrapolation based upon drought monitoring. Building upon the synthesis of monitoring progress, this paper further concisely describes the research progress in agricultural drought prediction methodologies, focusing primarily on drought index methods and crop growth model methods.

Full Text

Preamble

Progress of Agricultural Drought Monitoring and Forecasting Using Satellite Remote Sensing

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Abstract: Drought is a major climatic factor affecting agricultural production. Traditional agricultural drought monitoring primarily relies on meteorological and hydrological data, which, while providing relatively accurate point-scale drought monitoring results, still exhibits limitations when monitoring agricultural drought over larger areas. The rapid development of remote sensing technology, particularly the current in-orbit satellite sensors that cover electromagnetic wavelengths from visible, near-infrared, thermal infrared to microwave bands, has provided new means for regional-scale agricultural drought monitoring. Making full use of rich surface information obtained from satellite remote sensing data for agricultural drought monitoring and forecasting holds significant research importance. This paper elaborates on the research progress of satellite remote sensing-based agricultural drought monitoring from three aspects: remote sensing index methods, soil water content methods, and crop water demand methods. Agricultural drought forecasting represents a temporal prediction based on drought monitoring. Building upon the summary of drought monitoring progress, this paper further briefly describes the research progress of agricultural drought forecasting methods, primarily focusing on drought index methods and crop growth model methods. The paper summarizes existing satellite remote sensing-based agricultural drought monitoring methods, identifies their shortcomings, and proposes future prospects. In the future, different remote sensing data sources can be integrated with deep learning methods and crop growth models based on data assimilation approaches to further explore the potential of satellite remote sensing data in dynamic monitoring of agricultural drought, thereby promoting the development of smart agriculture.

Keywords: satellite; remote sensing; agricultural drought; crop growth model; monitoring; forecasting

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Drought is a frequently occurring natural disaster phenomenon. Wilhite and Glantz [?] classified drought into four categories: meteorological drought, hydrological drought, agricultural drought, and socioeconomic drought. Meteorological drought typically represents the degree to which precipitation deviates from normal precipitation over a specific period. Hydrological drought represents the phenomenon where drought periods affect surface or subsurface water resources, thereby impacting human socioeconomic life, and is usually related to meteorological drought, hydrological drought, and agricultural drought.

Agricultural drought, as one of the common agricultural disasters, is mainly manifested by soil moisture being unable to supply the water required for crop growth, affecting crop water absorption and utilization, and subsequently influencing crop yield [?]. Drought stress has varying degrees of impact on various physiological parameters of crops, primarily manifested as inhibiting crop root systems' absorption of water and nutrients, suppressing physiological functions such as photosynthesis and transpiration, and in severe cases, even causing crop wilting and death [?]. Currently, numerous methods have been developed to monitor and characterize agricultural drought, mainly including methods based on ground station measurements of meteorological and hydrological data and methods based on remote sensing data [?]. Ground station measurement data, such as precipitation and temperature, have applicability at local or regional scales that primarily depends on the density and spatial distribution of ground stations, which limits the application of data results at regional scales [?]. With the continuous development of satellite sensors, the capability to obtain large-scale, long-term time series surface monitoring information has gradually improved. Satellite sensors can perceive surface information such as soil, vegetation, and temperature, and incorporating this information into the drought assessment process is an effective method for large-scale agricultural drought monitoring [?, ?].

With the rapid development of modern social economy, agricultural management departments require not only accurate real-time monitoring of agricultural drought disasters but also dynamic early warning of agricultural drought. In these aspects, satellite remote sensing can provide excellent data sources. This paper elaborates on the research progress of agricultural drought remote sensing monitoring from three aspects: remote sensing index-based methods, soil water content methods, and crop water demand methods. Agricultural drought forecasting is a temporal prediction based on drought monitoring. Building upon the summary of drought monitoring progress, this paper further briefly describes the research progress of agricultural drought forecasting methods, primarily focusing on drought index methods and crop growth model methods.

2 Research Progress in Agricultural Drought Monitoring Using Remote Sensing

At the regional scale, remote sensing technology-based agricultural drought monitoring methods can comprehensively consider vegetation and soil layer information and are therefore widely applied in agricultural drought monitoring research [?]. The water required for plant growth originates from soil, and soil water deficit directly affects plant growth and development. Therefore, monitoring soil water content through remote sensing can also indirectly perceive the degree of drought occurrence [?, ?]. For agriculture, land surface coverage is mainly bare soil before the growing season, while it is mainly vegetation during the growing season. In this case, the monitoring accuracy of soil moisture under vegetation cover is greatly affected by the vegetation layer, making monitoring more difficult. Therefore, multi-source remote sensing data integration is widely applied in regional-scale soil water content and agricultural drought monitoring [?]. Additionally, the degree of agricultural drought also depends on crop responses to drought stress. This is because different crops have varying degrees of response to drought stress, and the same crop also shows differentiated responses to drought stress at different growth stages [?, ?]. Therefore, taking crop water demand as the starting point, using crop growth models as the carrier, and combining remote sensing ground observation technology to objectively and detailedly describe water stress during crop growth periods is an important research direction in agricultural drought monitoring.

2.1 Remote Sensing Index-Based Agricultural Drought Monitoring

In remote sensing-based agricultural drought monitoring methods, numerous studies have utilized remote sensing drought indices derived from visible and thermal infrared bands to estimate regional-scale drought degrees. For example, the vegetation condition index (VCI) in vegetation drought indices [?] and the temperature condition index (TCI) in temperature drought indices [?]. Based on this, researchers proposed the comprehensive vegetation-temperature drought index—Vegetation Temperature Condition Index (VTCI)—according to the characteristic that the scatter plot of Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) retrieved from remote sensing shows a triangular regional distribution [?], and widely applied it to regional agricultural drought monitoring [?, ?]. Additionally, the shortwave infrared band between visible and thermal infrared is more sensitive to crop leaf water content. Therefore, water stress indices established through the shortwave infrared band are also used to monitor crop drought stress status and evaluate agricultural drought degree, such as the Normalized Difference Water Index (NDWI) [?] and the Shortwave Infrared Water Stress Index (SIWSI) [?]. In longer wavelength electromagnetic spectrum segments, microwave drought indices based on microwave remote sensing are also used for agricultural drought monitoring. For example, Esch et al. [?] proposed the Soil Moisture Index (SMI) for monitoring soil water content in crop-covered areas based on ERS-SAR data, concluding that SMI can better estimate changes in near-surface soil water content.

lists the major remote sensing drought monitoring indices.

2.2 Soil Water Content-Based Agricultural Drought Monitoring

2.2.1 Soil Water Content Retrieval from Visible-Thermal Infrared Data An important approach for agricultural drought remote sensing monitoring is indirect monitoring of soil water content. Before the crop season, land surface coverage is mainly bare soil. In earlier studies on monitoring soil water content, researchers primarily analyzed the correlation between relevant remote sensing drought indices and measured soil water content, and then established linear relationships between them. For example, Ghulam et al. [?] proposed the Perpendicular Drought Index (PDI) based on the spectral space characteristics of vegetation in the red-near-infrared bands, and found that this index has good correlation with surface-measured soil moisture at 0-20 cm soil depth, effectively monitoring drought conditions in bare soil areas. Additionally, thermal infrared remote sensing is widely used for soil water content monitoring. An important method for retrieving soil water content from thermal infrared remote sensing is based on the soil thermal inertia method. Numerous experiments have shown that soil thermal inertia is closely related to soil water content changes. The larger the soil thermal inertia, the smaller the temperature variation amplitude. By monitoring the degree of soil temperature change within a certain time period, the relationship between thermal inertia and soil water content can be quantitatively derived. For the same soil medium, the expression for soil thermal inertia is:

where P is soil thermal inertia, $J/(m^2 \cdot s^1/^2 \cdot K)$; k is soil thermal conductivity coefficient, $J/(m \cdot s \cdot K)$;   is soil density, kg/m^3; c is soil specific heat capacity, $J/(kg \cdot K)$. By establishing a regression model between soil thermal inertia and soil water content, soil moisture conditions in small areas can be indirectly and effectively monitored. The thermal inertia method is suitable for soil water content retrieval in bare soil areas, but has poor retrieval accuracy in vegetation-covered areas. Liu and Zhao [**?**] introduced surface latent heat flux and sensible heat flux into the thermal inertia model in vegetation-covered areas, thereby extending the applicability of the thermal inertia method from bare land to vegetation-covered areas and improving the monitoring accuracy of soil water content. Wu et al. [**?**] proposed an improved apparent thermal inertia calculation model and calculated thermal inertia values under different vegetation cover and different experimental area soil water content conditions based on this model, with results showing that the model has high soil water content monitoring accuracy under low vegetation cover conditions (NDVI $<$ 0.35).

During the crop growing season, vegetation cover is relatively high. At this time, remote sensing drought indices retrieved from visible-thermal infrared remote sensing data are correlated with measured soil water content, and regression models are established between them and applied to soil water content retrieval under crop cover. For example, Sun et al. [**?**] analyzed the correlation between surface soil moisture in the Guanzhong Plain of China and VTCI, with results showing that during the winter wheat growing season, 10-day scale VTCI has significant linear correlation with soil moisture at both 0-10 cm and 0-20 cm soil depths. Although the strong correlation between VTCI and soil moisture enables VTCI to be directly used for soil water content retrieval, as a comprehensive vegetation-temperature drought index, accurately determining the cold and hot boundaries of VTCI in a specific application area is not easy. Yang et al. [**?**] compared soil water content retrieval results based on the TVDI method and the evapotranspiration ratio/potential evapotranspiration ratio method using ASTER data, concluding that although the TVDI method is simple to use and does not require additional meteorological data, regional dry and wet changes can cause errors in determining the dry and wet boundaries of its characteristic space, thereby introducing errors into soil moisture estimation. In contrast, the soil moisture estimation method based on evapotranspiration ratio/potential evapotranspiration ratio can improve the empirical nature of TVDI method estimation to a certain extent and improve the retrieval accuracy of soil water content. To reduce the difficulty of soil water content retrieval caused by the challenges in determining cold and hot boundaries when constructing comprehensive vegetation-temperature drought indices, researchers have taken a different approach, no longer considering the impact of land surface temperature (thermal infrared data) on remote sensing drought monitoring, and directly retrieving soil water content based on visible and near-infrared remote sensing data. For example, Ghulam et al. [?] considered the influence of the vegetation layer and introduced vegetation coverage on the basis of PDI, proposing the Modified Perpendicular Drought Index (MPDI). This index has high correlation with surface-measured soil water content at 0-20 cm soil depth during the middle and late stages of vegetation growth, effectively monitoring drought degree during the crop growing season.

Compared with visible and thermal infrared spectral bands, the electromagnetic waves emitted by synthetic aperture radar satellites are more sensitive to surface water content changes. Before the crop season, the correlation between radar backscatter information and ground-measured soil water content can be analyzed, and soil water content in bare soil areas can be retrieved based on empirical models. On this basis, soil water content estimation based on machine learning methods has been widely studied [?]. Additionally, some methods based on semi-empirical models and physical models have also been widely studied and used for soil water content retrieval in bare soil areas, achieving relatively ideal results [?, ?]. However, during the crop growing season, monitoring soil water content in crop-planted areas with vegetation cover is more difficult due to the mixed influence of radar signals by both soil and crop canopy layers. To solve this problem, researchers have improved soil water content retrieval accuracy by introducing radar scattering models to eliminate vegetation layer interference with radar signals. Vegetation scattering models represented by the Michigan Microwave Canopy Scattering Model (MIMICS) have been widely used in soil water content retrieval research and have achieved relatively ideal results [?, ?]. However, because the MIMICS model characterizes the vegetation layer in detail, its model structure is relatively complex and is generally only suitable for soil water content retrieval under tall vegetation cover [?]. For crops, the vegetation layer is generally relatively low with simple internal structure, so soil water content retrieval can be based on simplified vegetation contribution models. On this basis, the Water Cloud Model (WCM) was proposed, which simplifies the complex radar scattering effects between the vegetation layer and soil layer, assumes the vegetation layer is a uniform medium, and defines a parameter to describe vegetation layer characteristics [?]. Therefore, this model is suitable for soil water content retrieval under crop cover. Currently, in research on soil water content retrieval based on WCM, studies combining radar satellite data with optical satellite data are predominant [?, ?]. Optical satellite data are generally used to retrieve vegetation layer characteristic parameters described in WCM. Considering that optical remote sensing data are susceptible to cloudy weather, resulting in unstable availability during crop growth periods, Han et al. [?] combined WCM with a Simple Algorithm For Yield estimate (SAFY) model, used Leaf Area Index (LAI) retrieved from Sentinel-2 satellite data as a state variable of the SAFY model, and simulated the daily variation of vegetation description parameters (LAI) in WCM during the winter wheat growth period, effectively solving the problem that vegetation description parameters in WCM cannot accurately describe surface vegetation status during radar satellite overpass due to poor optical data availability, thereby improving soil water content retrieval accuracy.

lists the major models for soil moisture retrieval from microwave remote sensing.

2.2.2 Soil Water Content Retrieval from Microwave Data Soil moisture changes affect soil dielectric constant, which in turn changes microwave emissivity, thereby altering the brightness temperature recorded by passive microwave sensors. Therefore, surface brightness temperature recorded by passive microwave remote sensing can be used to monitor soil thermal radiation and indirectly monitor soil water content. That is, the relationship between brightness temperature and soil dielectric constant is first established through radiative transfer models, and then the relationship between soil dielectric constant and soil water content is established through dielectric mixing models, finally achieving soil water content retrieval [**?**]. The t-w model proposed by Mo et al. [**?**] is the basis for most radiative transfer models. This is a zero-order radiative transfer model containing two parameters: Vegetation Optical Depth (VOD) and single scattering albedo. For soil water content retrieval under vegetation cover, a key step is effectively estimating VOD parameters. Research has found that VOD can be estimated by establishing an empirical linear relationship between vegetation water content and VOD [**?**]. Therefore, using visible-near-infrared remote sensing data to retrieve vegetation indices related to vegetation water content can indirectly achieve VOD estimation. Additionally, some studies have attempted to establish regression models between brightness temperature data and soil moisture using comprehensive multi-factor data to retrieve surface soil water content [**?**]. With the rapid development and wide application of passive microwave sensors, using multi-frequency, multi-angle dual-polarization brightness temperature data can reduce model uncertainty compared with previous single-sensor data for soil water content retrieval. Passive microwave sensors generally have larger swath widths than active microwave sensors, making them suitable for global or regional-scale soil moisture monitoring. lists the major soil moisture content products based on microwave remote sensing. Among them, there are more soil moisture content products based on passive microwave remote sensing data. After combining passive microwave remote sensing data with active microwave remote sensing data, the spatial resolution of retrieved soil moisture content products can be improved from about 30 km to about 3 km.

2.3 Crop Water Demand-Based Agricultural Drought Monitoring

2.3.1 Agricultural Drought Monitoring Based on Crop Canopy Water Content Monitoring crop water demand changes can effectively reflect current agricultural drought degree. The direct means of monitoring crop water demand is monitoring crop canopy water content. The simplest method is to retrieve vegetation water content by establishing regression models between relevant spectral indices and vegetation canopy water content [?]. For example, Gao [?] established a remote sensing estimation model for vegetation canopy water based on NDWI and achieved good results. With the wide application of machine learning algorithms, researchers have improved vegetation water content retrieval accuracy by directly establishing regression models between multiple spectral bands and vegetation water content [?]. Crop water stress causes changes in canopy temperature, so monitoring crop canopy water content changes by combining visible-thermal infrared data is important for assessing agricultural drought degree. Gerhards et al. [?] provided a detailed summary of crop water stress monitoring based on multispectral/hyperspectral thermal infrared remote sensing. Additionally, microwave data have been gradually applied to vegetation water content retrieval research. Some studies have attempted to retrieve crop canopy water content by combining optical and microwave remote sensing data [?]. Compared with canopy water content retrieval methods based on statistical models, crop water monitoring methods based on radiative transfer models are more mechanistic. Commonly used radiative transfer models in previous studies include the PROSPECT (The Leaf Optical Properties Spectra) leaf model, SAIL (Scattering by Arbitrarily Inclined Leaves) canopy model, and the PROSPECT+SAIL coupled leaf-canopy model. Wu et al. [?] coupled the leaf radiative transfer model—PROSPECT model and canopy radiative transfer model—SAIL model, and used vegetation index NDWI as the optimization comparison object to retrieve vegetation water content, effectively improving vegetation water content retrieval accuracy. With the wide application of hyperspectral satellite data, researchers have combined radiative transfer models with hyperspectral data to further improve crop water content retrieval accuracy [?, ?].

2.3.2 Agricultural Drought Monitoring Based on Crop Growth Models During the growing season, crops affected by drought stress will have their physiological functions inhibited, leading to changes in physiological parameters, which is the theoretical basis for remote sensing technology to monitor agricultural drought. The degree of water stress on crop growth varies across relatively large regions, and crops show different growth statuses when subjected to different degrees of drought stress at different growth stages [?]. At the same growth stage, crop growth status also differs under different degrees of drought stress. When conducting regional-scale agricultural drought monitoring, remote sensing data-derived drought indices are limited by spatiotemporal conditions and generally have low temporal resolution. However, crops will show water-deficit physiological reactions in a relatively short time after water deficit occurs. Therefore, these indices may not reflect yield losses caused by water deficiency during critical growth stages. Drought indices based on crop water demand and soil water supply at daily time steps can describe the impact of drought stress on crop growth in more detail. When assessing the impact of water deficit on plant growth, crop growth models can capture the response between crop physiology and water depletion, and can consider the impact of drought stress on leaf growth processes. Therefore, compared with using remote sensing drought indices alone, combining crop growth models with remote sensing data for agricultural drought stress monitoring will be more advantageous. Generally, process-based crop growth models combine crop characteristics, soil characteristics, and environmental conditions to simulate crop growth and yield formation, and can be widely applied in different regions and growing seasons [?]. For example, compared with VTCI at four main growth stages, 10-day scale VTCI has strong correlation with soil water content and can more comprehensively and accurately reflect drought changes during the main growth stages of crops [?]. Therefore, 10-day scale VTCI can be used as a variable to retrieve soil moisture and combined with crop growth models through indirect methods, i.e., first establishing a linear relationship between VTCI and a certain intermediate variable of the model (such as soil water content), and then running the model with the help of this intermediate variable. For example, Xie et al. [?] used 10-day scale VTCI retrieved from Landsat satellite data to linearly estimate soil water content, and used the estimated soil water content and LAI retrieved from Landsat satellite data as observations in the CERES-Wheat model assimilation process, assimilating LAI and soil water content during the main growth stages of winter wheat, thereby improving drought stress simulation accuracy. Although indirect methods initially solved the problem of combining remote sensing drought monitoring results with crop growth models, they easily introduce external errors and are relatively crude when considering the temporal scale heterogeneity problem between remote sensing drought monitoring results and crop growth models.

Numerous studies have improved agricultural drought dynamic monitoring levels by combining remote sensing data with crop growth models based on data assimilation algorithms for agricultural drought monitoring [?]. Although some classical crop growth models (such as DSSAT and WOFOST models) have strong mechanistic structures and can describe crop growth processes in detail and dynamically simulate changes in relevant stress factors affecting crop growth [?], their application in solving regional-scale drought monitoring problems with satellite remote sensing data is limited to some extent. This is mainly because such complex models require numerous input data, including detailed agrometeorological data, variety data, and field management data, which are difficult to obtain at regional scales, making it difficult for the models to combine with remote sensing data for large-scale agricultural drought monitoring.

In recent years, compared with complex crop models, some crop growth models with relatively simple structures that can simulate crop drought stress status have been proposed, making regional-scale agricultural drought remote sensing monitoring possible. Representative models include the AquaCrop model [?] and SAFY-WB model [?]. Currently, these two models have attracted increasing attention from researchers and have good application prospects in regional-scale research, particularly in remote sensing data assimilation. AquaCrop is a water-driven model that can accurately describe the relationship between yield and water requirement of major herbaceous crops under different water stress conditions. The model simulates crop transpiration and uses Normalized Crop Water Productivity (NCWP), whose introduction enables AquaCrop to be applied at different locations and growing seasons. The SAFY-WB model is composed of the SAFY model [?] combined with the FAO water balance model [?]. In the original SAFY model, the parameter factor used to measure the degree of drought stress on crops was a fixed value, but in reality, the drought stress on crops during the growing season is closely related to agricultural drought degree. During the crop growing season, agricultural drought often varies. Therefore, the SAFY-WB model can effectively simulate the dynamic changes of drought stress during crop growth by introducing dynamic water stress coefficients. Additionally, Silvestro et al. [?] analyzed the sensitivity of AquaCrop and SAFY-WB models in simulating winter wheat yield under drought stress conditions and found that at the regional scale, AquaCrop performed better in simulating crop growth under different water-deficit environments than SAFY-WB, but had stricter parameter calibration requirements than SAFY-WB.

3 Research Progress in Agricultural Drought Forecasting

There are two methods for forecasting agricultural drought based on satellite remote sensing. One method is to simulate future agricultural drought conditions through drought spatiotemporal prediction models based on drought monitoring. The other method is to improve the water stress module of crop growth models, construct crop drought monitoring models, use remote sensing observations as intermediate variables for assimilating drought stress, and combine them with short-, medium-, and long-term meteorological data for agricultural drought forecasting.

3.1 Drought Index-Based Agricultural Drought Forecasting

Forecasting agricultural drought based on remote sensing drought indices has important research value. Such research mainly uses time series remote sensing drought indices as input data and forecasts drought changes in future time periods based on time series analysis methods. For example, Han et al. [?] used the Auto Regressive Integrated Moving Average (ARIMA) model to analyze and model VTCI spatiotemporal sequences and conduct drought analysis and forecasting during the winter wheat growing season, with results showing that 1-2 step predictions based on this model could better predict regional drought changes. Li et al. [?] applied the Seasonal Auto Regressive Integrated Moving Average (SARIMA) model to model and forecast VTCI during the summer maize growing season, with results showing that the ARIMA model had higher

VTCI prediction accuracy than the SARIMA model, and VTCI 1-3 step predictions based on the ARIMA model showed stable accuracy performance across multiple years.

Historical drought data exhibit big data characteristics, and artificial intelligence algorithms can effectively mine data features from historical years to further improve drought forecasting accuracy. In recent years, researchers have begun conducting drought forecasting based on neural networks and deep learning methods, achieving good results [?, ?]. With the rapid development of remote sensing technology, remote sensing-derived surface drought indices themselves already possess spatial big data characteristics. Moreover, with the combined use of multi-satellite sensors, remote sensing drought indices also have increasingly high temporal dimensions. Currently, there are still few studies on agricultural drought forecasting based on machine learning algorithms for remote sensing drought indices, which will be a future research hotspot.

3.2 Crop Growth Model-Based Agricultural Drought Forecasting

The ultimate goal of agricultural drought forecasting is to predict the degree of impact of drought on crop growth. From this perspective, crop growth model-based agricultural drought forecasting methods have important research value. Crop growth models are driven by meteorological data. By introducing meteorological forecast data for a future period, they can effectively simulate crop growth status in future time periods and forecast crop drought stress status. Additionally, combining crop growth simulation with agricultural drought monitoring can improve the water stress module of crop growth models to achieve agricultural drought monitoring and early warning [?]. For example, Wu et al. [?] used the weather generator LarsWG5.5 to simulate future meteorological data and input it into a calibrated crop growth model to predict winter wheat yield under climate change conditions and assess yield reduction risks. Remote sensing observations can timely reflect the instantaneous state of the surface and effectively monitor agricultural drought degree. For the above drought forecasting models, introducing relevant remote sensing observations can further improve model prediction capabilities. Therefore, using medium- and long-term meteorological data provided by meteorological, water conservancy, and agricultural and rural departments as input data for these models, and applying data assimilation technology to couple remote sensing observations (such as soil moisture) with model simulation values, can effectively improve the agricultural drought forecasting capability of models [?, ?]. For example, Wang et al. [?] used regional farmland water information obtained from the AMSR-E sensor as an intermediate variable in the model based on the improved ARID CROP model to predict the dynamic changes of agricultural drought, with results showing that introducing remote sensing observation information into the improved crop growth model can effectively improve the prediction capability of winter wheat growth and development and regional agricultural drought forecasting.

4 Outstanding Issues and Future Prospects

Although current research on agricultural drought monitoring and forecasting based on satellite remote sensing data has made numerous breakthroughs in many aspects, there are still some issues that need to be addressed in related fields:

(1) Combining multiple remote sensing drought monitoring indices can improve the monitoring errors of single drought indices. Currently, there are not many composite indices that comprehensively consider drought indices at different crop growth stages, and there is also a lack of indices related to crop mechanisms. Therefore, it is necessary to combine multiple indices, consider drought stress impact factors from mechanistic principles, and develop comprehensive indices to improve drought monitoring accuracy.

(2) Remote sensing drought monitoring indices retrieved from medium spatial resolution remote sensing data have been widely studied and proven effective in characterizing regional drought degree. In recent years, with the launch of high spatial resolution remote sensing satellites, researchers have explored fusing medium and high spatial resolution remote sensing data to obtain downscaled time series remote sensing drought monitoring indices when acquiring time series higher spatial resolution remote sensing drought monitoring indices. They have also attempted to integrate data from multiple homogeneous remote sensing data sources to obtain time series remote sensing drought monitoring indices. However, current research on fusing heterogeneous remote sensing data for drought monitoring indices is still relatively limited, and related methods are still preliminary. In the future, deep learning technology can be explored to deeply mine feature information among heterogeneous remote sensing data, construct relevant drought monitoring indices, and establish agricultural drought dynamic monitoring systems to promote the development of smart agriculture.

(3) Drought monitoring methods that fuse multi-source remote sensing data can better characterize the comprehensive drought status of vegetation and soil layers, thereby obtaining relatively ideal agricultural drought monitoring results. Against this background, the spatiotemporal consistency problem between different data sources needs further consideration. For example, in previous studies, the retrieval of soil water content based on WCM combined with optical and radar images has been studied and analyzed in detail. However, in a relatively large study area, especially in southern China, optical images are susceptible to cloudy weather most of the time, and data source availability is not very high, limiting the application of remote sensing data. In this case, timely and effective determination of vegetation description parameters of WCM is very important, requiring researchers to consider the impact of differences in acquisition dates between different types of remote sensing data sources on drought

monitoring results. Currently, there are not many studies on this aspect. In the future, this problem can be addressed by exploring the use of remote sensing data sources from the same system. For example, the Sentinel series satellites carry payloads covering microwave-visible-thermal infrared bands, with each data source having similar spatial and temporal resolutions, high synergy among data sources, and global observation capabilities. Therefore, deep learning methods can be explored to obtain complementary information among broader data sources to obtain high spatial and temporal resolution remote sensing drought monitoring results.

(4) As an important environmental factor, agricultural drought has a significant impact on crop growth. When using data assimilation methods to combine it with crop growth models for crop yield estimation, most existing studies adopt indirect methods. To reduce the introduction of external errors and simultaneously consider the temporal scale heterogeneity problem between remote sensing drought monitoring results and crop growth models, future research can explore direct methods to combine drought monitoring results with crop growth models. By introducing deep learning methods to synchronize the temporal scales of time series drought monitoring results and crop growth models, and more scientifically considering the staged and differentiated effects of water stress on crop growth according to the physiological characteristics of crops at various growth stages, the accuracy of dynamic drought monitoring using crop growth models can be improved.

The rapid development of satellite remote sensing technology has deepened research on agricultural drought monitoring using satellite data and gradually promoted the marketization of agricultural drought monitoring based on satellite remote sensing data. This paper focused on agricultural drought monitoring using satellite remote sensing, elaborated on its research progress, and briefly described the research progress of agricultural drought forecasting based on satellite remote sensing. Currently, domestic remote sensing satellite data have exhibited big data characteristics, and artificial intelligence-based information automatic acquisition and interpretation technology will enable remote sensing data to be more widely and effectively applied in agricultural drought monitoring. Meanwhile, for massive remote sensing data sources, combining deep learning technology with crop growth models and based on data assimilation concepts to deeply explore the potential of satellite remote sensing in dynamic monitoring of agricultural drought can further promote the development of smart agriculture.

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