Remote Sensing Monitoring Approaches

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Meteorological disaster monitoring is an important research direction in remote sensing technology in the field of meteorology, which can serve many meteorological disaster management tasks. The key issues in the remote sensing monitoring of meteorological disasters are monitoring task arrangement and organization, meteorological disaster information extraction, and multi-temporal disaster information change detection. To accurately represent the monitoring tasks, it is necessary to determine the timescale, perform sensor planning, and construct a representation model to monitor information. On this basis, the meteorological disaster information is extracted by remote sensing data-processing approaches. Furthermore, the multi-temporal meteorological disaster information is compared to detect the evolution of meteorological disasters. Due to the highly dynamic nature of meteorological disasters, the process characteristics of meteorological disasters monitoring have attracted more attention. Although many remote sensing approaches were successfully used for meteorological disaster monitoring, there are still gaps in process monitoring. In future, research on sensor planning, information representation models, multi-source data fusion, etc., will provide an important basis and direction to promote meteorological disaster process monitoring.

Keywords: remote sensing monitoring ; extraction

1. Monitoring Task Arrangement and Organization

In the monitoring of meteorological disasters, it is first necessary to reasonably and comprehensively determine the monitoring tasks to clarify the monitoring timescale, carry out sensor planning and construct the conceptual model of monitoring information. The accurate representation of monitoring tasks is the basis and premise of accurately and effectively obtaining disaster information.

1.1. Timescale Determination in Monitoring

As an important branch of geography, the meteorological disaster system has the dual attributes of “natural” and “social”, and it is also “scale” dependent on nature. On the one hand, the dependence is manifested in the significant timescale effect of disaster factors. **Table 1** summarizes the appropriate observation timescale for different meteorological disaster factors [1][2][3]. On the other hand, the dependence is reflected in disaster measurement and monitoring methods, and there are also significant timescale effects [4][5]. For instance, it is necessary to choose remote sensing data with a short cycle for monitoring typhoons with drastic change. Therefore, the timescale is one of the original characteristics of meteorological disasters.

Table 1. Appropriate observation timescale for different meteorological disaster elements.

Scale Classifications	Timescales			Applicable Types of Disaster Elements		
	Extent		Granularity (/y)	Pregnant Environment	Causing Factor	Disaster-Bearing Body
	Time Range(/y)	Timespan(/y)				
Extra-long scale	>100	>1000	100	Solar activity, climate change, landform change	-	Human, economic, environmental, social, and other major categories
		100–1000	10, 50, 100			
Long scale	10–100	50–100	10	Climate change, desertification, soil erosion	-	Human, economic, environmental, social, and other major categories
		10–50	1, 5, 10			

	Timescales			Applicable Types of Disaster Elements		
Scale Classifications	Extent Time Range(/y)	Timespan(/y)	Granularity (/y)	Pregnant Environment	Causing Factor	Disaster-Bearing Body
Meso scale	1–10	5–10	1	Land use, vegetation cover	Drought, precipitation, cold wave	Population (rural population, urban population, etc.), industry (heavy industry, light industry, etc.), agriculture (planting industry, breeding industry, etc.), construction (infrastructure, housing, etc.), transportation (land transport, water transport, etc.) and objects in the primary and secondary classifications in other categories.
		1–5	1 month, 1 year			
Short scale	≤1	1 year	10 days, 1 month, 1 season	-	Rainstorms, typhoons, high temperatures, cold waves, snowfall, hail, and other weather phenomena	Population (rural youth population, urban youth population, etc.), industry (food processing industry, metal manufacturing, etc.), agriculture (corn, wheat, etc.), construction (factory, community, etc.), transportation (railway, aircraft, etc.) and other objects in the primary, secondary, and tertiary classifications in other categories
		1 season	10 days, 1 month			
		10 days	1 day, 1 week			
		1 week	1 day			
		1 day	1 hour, 30 minutes, 1 minute			

With the introduction of the timescale, when conducting meteorological disaster monitoring, the time boundary to be monitored should first be determined according to the time extent, and the disaster monitoring is limited to a certain period [6]. To understand the detailed characteristics of disasters in a certain period, the temporal dynamic characteristics of meteorological disasters can be obtained according to the time granularity [7][8]. Only by selecting a reasonable and appropriate timescale can the effectiveness of and difference in meteorological disaster monitoring be truly identified [9]. In practical applications, the temporal extent and granularity should be considered when selecting a reasonable timescale for meteorological disaster monitoring. It must be noted that there is often more than one applicable scale in scale selection, and multi-scale analysis is often required in the research.

1.2. Sensor Planning in Monitoring

There are three main types of sensor planning solutions: single sensor, multi-sensor in single platform, and multi-sensor in multiple platforms. For the planning of a single sensor, due to the small number of sensors, the data processing steps are relatively simple, and the data specifications between the multi-period data are unified [10]. For instance, Sivanpillai et al. studied rapid flood inundation mapping based on Landsat images [11]. However, due to the single sensor type, fewer types of disaster information can be monitored. When using a multi-sensor in a single platform, it refers to the remote sensing data collected by different sensors on the same platform. For instance, the operational land imager (OLI) data and the thermal infrared sensor (TIRS) data were contained in Landsat-8. Kumar et al. derived the flooded areas from Landsat 8 OLI-TIRS image [12]. Due to the limited number of sensors available on a single platform, it is also relatively easy to obtain information about the available sensor's observation capabilities [13]. When using a multi-sensor on multiple platforms, because of the abundance of available data types, the types of disaster information that can be monitored are more diverse. For instance, Kyriou et al. also studied flood mapping, while the approach used data from active and passive remote sensing sensors such as Sentinel-1 and Landsat-8 [14]. In addition, the potential utility of multi-sensor data fusion for different phases of disaster management: vulnerability assessment, early warning systems, disaster mitigation, response, damage assessment and recovery are delineated [15]. However, the difficulty in using multi-source sensor data will increase to a certain extent, which is mainly reflected in the differences in data specifications (resolution, coordinate system, etc.), the inconsistency of the monitoring period, and the applicability of band fusion.

However, most sensor planning is based on the technical conditions of the sensor itself, which lacks the planning based on the meteorological disaster process monitoring; thus, this kind of planning method would not obtain detailed and specific solutions [16]. For example, it is difficult to directly obtain answers to questions such as “To monitor the status of a certain stage of a meteorological disaster, which combination of sensors is more suitable for current needs?”. Since each type of meteorological disaster has a unique evolutionary process, existing sensor planning methods cannot accommodate the long-term, continuous process monitoring requirements for a single disaster. Researchers are gradually focusing on sensor requirements for different meteorological disasters, analyzing the applicability of sensors according to three aspects: temporal, spatial, and spectral resolution. The existing research results are summarized in **Table 2**.

Table 2. Desired specifications of sensor focusing on meteorological disasters.

Types		Revisit Period (/d)	Spatial Resolution (/m)	Spectral Resolution (/nm)	Spectral Range (/μm)
Drought [17]		2–6	5–1000	2–50	0.76–14.0
Precipitation	Flood [18]	1–2	0.5–30	5–50	0.76–2.5
Typhoon [19]		2–12 h	50–1000	5–50	0.76–2.5
	Snow cover [20]	1–2	5–30	2–50	0.76–2.5
Snow	Sea ice [21]	2–5	30–1000	10–50	0.76–2.5
	Ice slush [22]	2–5	5–30	10–50	0.76–2.5

1.3. Monitoring Information Modeling

In disaster management, the use of multi-period, multi-area, multi-source, and multi-department meteorological disaster monitoring information has gradually become normal. If there is no uniform standard for meteorological disaster information, it will be difficult to share information in disaster management, which is disadvantageous to efficient monitoring and emergency warning [23]. Therefore, the establishment of a reasonable meteorological disaster information representation model is the basic aim of meteorological disaster process monitoring.

The unified management of the distributed sensors and data resources by establishing metadata model specifications has become an important method for disaster information modeling. Considering the universality of the model, it is usually divided into the general metadata model and the dedicated metadata model. General metadata models include Common Alert Protocol (CAP), Emergency Data Exchange Language Distribution Element (EDXL-DE) and EDXL-rm [24]. The dedicated metadata model is specific to specific types of disasters, such as Tsunami Warning Markup Language (TWML) [25][26] and Cyclone Warning Markup Language (CWML) [27], associated with meteorological disasters. However, these specifications are biased towards the service of disaster warning, do not emphasize the importance of disaster monitoring information, and are not fully applicable to the process monitoring needs [28].

The knowledge representation method can provide semantic integration among people, heterogeneous systems, and people-to-systems. The following related techniques are gradually being introduced to disaster information modeling: 1) Ontology. Ontology is helpful in expressing the concept of disaster and eliminating semantic heterogeneity. After the foundation of standardized geographic ontology proposed by Kolas et al. [29], more specific geospatial ontologies have been established in disaster management, such as MDO, DOLCE+DnS, etc. [30][31]; 2) Knowledge graph. The knowledge graph can describe various entities and their complex relationships and is good at expressing various entities or events existing in the real world. The graph frameworks for natural disaster monitoring and assessment have been established and are currently used to represent information on typhoons, landslides, and their secondary disasters [32].

In summary, the existing disaster information models rarely consider the spatio-temporal factor; most of them record spatio-temporal information as common attributes [33]. A meteorological disaster system is a typical kind of structure and process, which is inherently bound to time and space. Disaster monitoring information is closely related to the disaster evolution process. It is necessary to consider the time and space characteristics in the disaster monitoring information model to support the further formal description and in-depth analysis of disaster monitoring information according to the spatio-temporal framework.

2. Meteorological Disaster Information Extraction

2.1. Information Extraction of Pregnant Environment

The pregnant environment is the natural and human environment that causes disasters. The monitoring of the pregnant environment, mostly before the disaster occurs, and the monitoring results can help to evaluate the disaster risk and predict the disaster. For meteorological disasters, monitoring the pregnant environment is mainly carried out by the extraction of surface environmental information from the lithosphere to the atmosphere. There is a lot of information regarding the pregnant environment, such as altitude, slope, river, road, formation lithology, fault zone, etc., which can be divided into two categories: surface parameters and land cover.

Extraction of Surface Parameters

The methods of extracting surface parameters using remote sensing methods mainly include the empirical model method and the physical model method. The empirical model method is mainly implemented by establishing an empirical regression model between remote sensing observation signals and surface parameters [34]. To improve the precision of information extraction, the empirical model is constructed in the following two ways: (1) constructing the empirical model using the remote sensing data after the topographic correction; (2) direct use of topographic data (such as altitude, slope, aspect) to participate in the construction of empirical models [35]. However, the empirical model method is not strong in terms of spatio-temporal extension, and its applicability is often limited by time and space [36][37]. This is because the empirical model is based on a large number of remote sensing data characteristics and the corresponding statistical results of ground realities. The difference in weather and insolation at different times affects the characteristics of remote sensing data. The difference in land type in different spaces affects the statistical results of ground realities. Therefore, the empirical model built under a specific space-time is not suitable for a large-scale extension.

The main strategies for retrieving surface parameters based on physical models are as follows: (1) on the basis of considering the influence of local terrain on the imaging geometry, the surface parameters are extracted using a physical model that is suitable for a flat surface [38]; (2) on the basis of considering the spatial heterogeneity of the surface space, appropriately adjust the value range of the driving data of the existing flat physical model to make it more in line with the actual situation of the surface [39]; (3) develop physical models for specific terrain; this will also be the direction in which a great breakthrough may be made in the inversion modeling of special terrain surface parameters [40][41].

Extraction of Land Cover Information

To improve the accuracy of remote sensing extraction of land cover information, it is necessary to involve as much multi-source and multi-temporal remote sensing information and existing knowledge as possible, and also to develop scientific methods to effectively fuse heterogeneous information and eliminate redundancy [42][43]. A variety of methods have been developed to integrate multi-source information and can be summarized by the following three aspects: (1) based on the remote sensing image characteristics, such as spectral characteristics, shape characteristics, texture characteristics, and context characteristics, introduce the current mature artificial intelligence algorithms or mathematical methods, such as a decision tree model [44], Markov chain model [45], convolutional neural network model [46], etc., to develop a classification algorithm; (2) develop new classification algorithms to effectively coordinate multi-source and multi-temporal remote sensing data [47][48]; (3) introduce various thematic information and relevant geoscience knowledge into the research on land-cover classification with multi-source and heterogeneous information [49][50].

In recent years, with the acceleration of global urbanization, a great deal of infrastructure construction has rapidly changed land cover in a few decades or less [51]. The impact of urbanization on the changing pregnant environment, and even the occurrence of meteorological disasters, has gradually become one of the focuses of pregnant environment monitoring. Urbanization and urban consumption produce large amounts of greenhouse gases, which upset the balance of the earth’s ecosystem. This is a direct driver of climate change, contributing to global warming and to the deterioration of the pregnant environment in the ecosystem. Monitoring the pregnant environment under urbanization by remote sensing is an important reference to assess the risk of meteorological disasters [52]. For instance, Waghwala et al. assessed flood risk based on the satellite image of Resources-1, then they proposed that a change from a low to a high urbanization pattern is the main driver for increasing flood risk [53] (**Figure 1**).

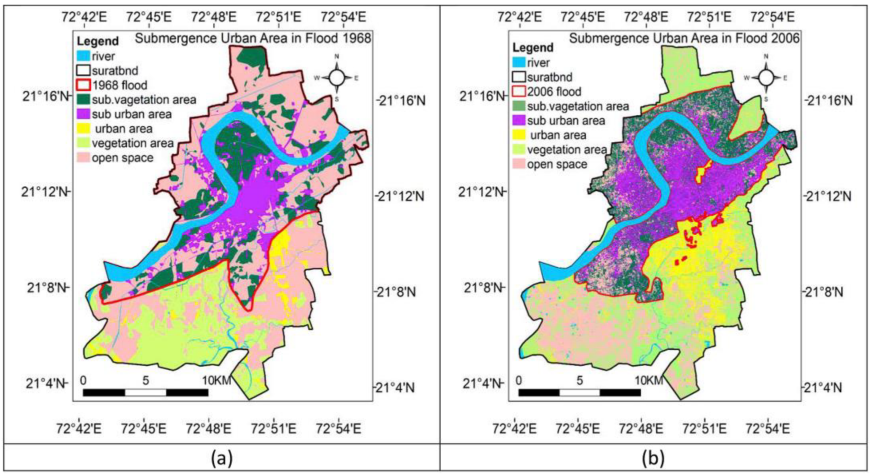

Figure 1. (**a**) Urban flood risk area of year 1968; (**b**) Urban flood risk area of year 2006 [53].

2.2. Information Extraction of Causing Factor

The cause of meteorological disasters is the weather phenomena that may cause disasters. The characteristic parameters of meteorological disasters can reflect the genetic characteristics, structural characteristics, and development process characteristics of disasters and are an important basis for the monitoring and evaluation of the causes. The monitoring of causes based on disaster-characteristic parameters focuses on the type of characteristic parameter on the one hand and on the method of extraction used for each characteristic parameter on the other hand. The extraction of information regarding the causes of different meteorological disasters is discussed in the following parts.

Drought

In principle, remote sensing approaches to drought monitoring can be divided into two categories: 1) the change in soil moisture can cause changes of soil spectral characteristics; 2) the change in plant physiological processes caused by drought can change the spectral properties of leaves and significantly affect the spectral properties of plant canopy. Sensors for drought remote sensing include a visible light band, near-infrared band, thermal infrared band, microwave band, etc. The common approaches include the soil thermal inertia method, soil moisture inversion method, vegetation index method, surface temperature method, and composite index method (**Table 3**).

Table 3. Information extraction of drought.

Type	Index/Method	Description
Soil thermal inertia	**Apparent thermal inertia (ATI) [54]**	**The higher the soil moisture content, the greater the soil thermal inertia, resulting in a small temperature difference between day and night.**
Soil moisture	**Microwave-based soil moisture retrieval [55]**	**The dielectric properties of liquid water are obviously different from those of dry soil.**
Vegetation index	**Vegetation condition index (VCI) [56]**	**Drought reduced the absorption of soil nutrients by vegetation and limited the growth of vegetation, resulting in changes in vegetation index.**
	Anomaly vegetation index (AVI) [57]	
	Vegetation health index (VHI) [58]	
Surface temperature	**Temperature condition index (TCI) [59]**	**Drought means that the soil water supply decreases, the surface temperature increases, the vegetation cover area will appear and the vegetation canopy temperature increases.**
	Normalized difference temperature index (NDTI) [60]	
Composite index	**Temperature vegetation drought index (TVDI) [61]**	**Considering the relationship between "vegetation index + land surface temperature" and drought. Due to the diversity of indexes, the inversion of these indexes usually depends on multi-source remote sensing data (Figure 3).**
	Synthesized drought index (SDI) [62]	
	Optimized meteorological drought index (OMDI) and optimized vegetation drought index (OVDI) [63]	

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