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Disaster mapping and assessment of Pakistan's 2022 mega‑food based on multi‑source data‑driven approach

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Abstract

Climate change-induced mega-foods have become increasingly frequent worldwide. The rapid mapping and assessment of food disasters pose urgent challenges for developing countries with poor data facilities or databases. In this study, the characteristics of the 2022 mega-food in Pakistan were monitored and analyzed based on multi-resources data. The extent of inundation throughout Pakistan and its impact on farmlands, buildings, and roads were mapped using Synthetic Aperture Radar remote sensing data processing technology. The results showed that a 10-m resolution fooding map could be achieved using the Google Earth Engine platform in a timely manner with reasonable precision. A GIS-based bluespot model was used to evaluate the risk of dam-failure foods. The zone risk distribution map of the dam-failure food was produced with fve risk levels, which contribute to the safety of the key infrastructure for fooding control. The potential infuencing factors of snow melting in northern Pakistan induced by heat waves and disasters was detected using Earth observations and long-record historical data. The study provides data-driven approach options for monitoring food hazards over large areas in emergency using multiavailable data sources, where in situ monitoring is difficult. This study not only provided direct data products and risk maps for mega-fooding control in Pakistan, but also proposed fve aspects of food prevention and control recommendations for this region and its neighborhood areas to cope with food disasters efectively under worsening climate change conditions.

Keywords Mega-food · Disaster risk reduction · Remote sensing monitoring · Risk of dam-failure food · Big data

1 Introduction

Floods are among the most severe disasters, currently accounting for about one-third of all natural hazard events (Cao et al. [2022;](#page-16-0) Wannous and Velasquez [2017\)](#page-18-0). They disrupt lives and livelihoods worldwide (Moreno et al. [2020\)](#page-17-0), destroy agricultural land (Guo et al. [2020](#page-17-1)) and critical infrastructures (Ashizawa et al. [2022\)](#page-16-1), damage economic activities, and cause numerous casualties. According to the United Nations Office for Disaster

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Risk Reduction (UNDRR), the frequency of foods increased considerably from 2000 to 2019 (Kimuli et al. [2021\)](#page-17-2), rising from 1389 to 3254, respectively, and they accounted for 40% of the total number of disasters in 2019 (Tellman et al. 2021; UNDRR [2020\)](#page-18-1). Flood losses are expected to rise due to urbanization and the expansion of impervious surfaces (Gong et al. [2020\)](#page-17-3), as well as global warming and increased extreme weather (Ornes 2018). Winsemius et al. (2016) (2016) (2016) predicted that global absolute losses due to foods could increase up to 20-fold by the end of the century if no countermeasures are taken (Jongman et al. [2012;](#page-17-5) Winsemius et al. [2016](#page-18-2)).

Capturing food data, information, and knowledge efectively is crucial for addressing fooding emergencies, especially in developing countries with limited data facilities or available databases. However, when fooding occurs, transportation and communication infrastructures are prone to paralyzed, making on-site monitoring of the damage difficult. Usually, common approaches in fooding disaster response include hydrological model, meteorological monitoring, remote sensing, and social media mining. Kumari et al. [\(2021](#page-17-6)) applied hydrological models to simulate and predict hydrological processes in watersheds at various scales, but this approach requires extensive parameters support. In addition, the parameters and structure of the model need to be adapted and optimized to the actual situation, which requires a large number of experiments and validation in the target area (Pedram and Paulin [2020\)](#page-17-7). Zheng [\(2020](#page-18-3)) evaluated the risk of the bridge project being washed away by foods using multiple factors such as river sediment changes, river channel evolution, and food peak fow. Li Daihua constructed a runof prediction based on PCA-SHO-SVM and PCA-SHO-BP models (Li [2021](#page-17-8)). These combined models can better realize the prediction of runoff volume, but ignore the lag and error accumulation of the time series of runoff volume, which leads to the increase of error and the decrease of convergence speed. Meteorological observations collect on-site data on the intensity of disasters at fxed locations. Jasper (2002) et al. simulated the spatial distribution of disaster intensity through numerical weather prediction and atmospheric modeling; however, the accuracy of the results of simulations using meteorological models cannot be guaranteed, and the results represent only hydrometeorological considerations. The advantages of remote sensing technology are real-time monitoring, and SAR images provide the possibility for realtime monitoring of food (Li and Demir [2023;](#page-17-9) Hamidi et al. [2023](#page-17-10)). However, the drawbacks of this method are the long time periods required for afected area and the low interactivity between remote sensing products and afected populations (Joyce et al., 2009, Mishra et al., 2022). Social media data can compensate for the real-world monitoring data by analyzing the people response to disaster event whether in physics or emotion; however, shortcomings include biased samples, such as twitter or Chinese Weibo users may not cover the people who do not use smart mobile or related social media APPs (Wu et al. [2020\)](#page-18-4). Historical statistics are also an important source for long-term food hazard prevention and control. Chen et al. [\(2022](#page-16-2)) proposed a real-time correction method for food forecasting using historical food data. With the advent of the Big Data era, an increasing number of data sources (e.g., EM-DAT with the disaster data since 1990) and platforms (e.g., Disaster Risk Reduction Knowledge Service in UNESCO) have been used for food mapping, hazard analysis, and disaster response (DeVries et al. [2020;](#page-16-3) Sadiq et al. [2022](#page-17-11); Wang et al., 2019). The data-driven approach is another potential option for monitoring food hazards over large areas in emergency using multi-available data sources. The application of multisource data fusion for food mapping and assessment can efectively overcome the limitations of individual food monitoring methods and integrate their strengths to form a more objective and comprehensive understanding of foods.

The 2022 fash food in Pakistan was the most fatal and severe food disaster in the last decade. In mid-June 2022, Pakistan experienced monsoon climate and extreme heat weather (NASA [2022\)](#page-17-12), and it was thereby subjected to the heaviest precipitation in nearly 30 years, afecting at least two-thirds of the country. Consequent foods afected 45% of the country's agricultural land, causing economic losses of approximately \$10 billion, afecting nearly 33 million people, and resulting in fatal outbreaks of malaria and other diseases (WHO 2022). In response to the 2022 mega-food in Pakistan, this study aimed to rapidly map and assess disasters using multi-source data and related advanced data facilitation. As a result, this study provides not only the direct fooding datasets and related risk maps, but also a reference for emergency responses in developing countries using big data-driven approaches in the Open Science Recommendation era (UNESCO [2021](#page-18-5)).

2 Materials and methods

2.1 Study area

Pakistan is located in the South Asian subcontinent near Arabian Sea in south and Himalaya Mountain in north. The northern region of Pakistan has an undulating terrain and a subtropical climate, which is dry and cold, with perennial snow and glaciers in some regions. The southern part of Pakistan has a tropical climate with hot and humid summers and a long rainy season (Fig. [1\)](#page-3-0) (Beck et al. [2018](#page-16-4)). Owing to its monsoonal climate and topography, Pakistan has experienced several foods throughout its history (Manzoor et al. [2013;](#page-17-13) Shah et al. [2020\)](#page-18-6). In the last 60 years, the country has experienced 19 major food events over a cumulative flood area of more than $594,700 \text{ km}^2$, causing a total direct damage of approximately \$ 30 billion and leading to the loss of 10,668 lives (Shah et al. [2020](#page-18-6)). The heavy precipitation belt in Pakistan is mainly located in the southern part of the border between Sindh and Balochistan, the central part of Balochistan, and the southern and northern tip of Punjab with maximum precipitation of more than 300 mm.

2.2 Data

Multi-source data was used for food monitoring and assessment in Pakistan. Satellite imagery data, land-cover products, and digital elevation models were obtained using the Google Earth Engine platform. Road vector maps were built using OpenStreetMap (OSM). Statistical data on foods in Pakistan from 1950 to 2022 was obtained from the WHO EM-DAT database. Table [1](#page-3-1) lists the specific data sources and their main usage. The precipitation data is retrieved from GloH2O.

2.3 Methods

In this study, multiple sources of available big data was used to monitoring and analysis mega-food in Pakistan, 2022, including the fooding area, potential infuencing factors, and the frequency of foods. The specifc methodology is illustrated in Fig. [2](#page-4-0). First, remote sensing data was used for food monitoring. After detecting the submerged area using Synthetic Aperture Radar (SAR) images, the fooded-area map was overlaid with maps of roads, farmland, and buildings, allowing for a clearer visualization of the damage

Fig. 1 Climatic zoning map of Pakistan

Fig. 2 Data acquisition and methodology

extent. Focusing on the risk of dam-failure foods, a GIS-based bluespot model was used to map and classify the risk of dam-failure foods within 100 km of dams into fve risk levels, thus providing disaster warnings for the area around the dams. As the related driving mechanism of this food is considered to be global climate change and extreme summer heat waves, snowmelt in the northern mountains of Pakistan in 2022 was analyzed using high-resolution Sentinel images and compared with previous years. Finally, historical food events in Pakistan were searched in the EM-DAT database to compare this mega-food with previous mega-foods and gain a comprehensive and visual understanding of the impact of this food in terms of casualties and economic impact.

2.3.1 Flooding water extraction

Optical remote sensing images captured during foods are severely obscured by clouds, causing challenges in obtaining clear surface refectance data. Therefore, SAR images

were used to monitor changes in surface water bodies. There are four polarization methods, namely VH, HV, HH, and VV. Diferent polarization methods have diferent backscattering intensities for diferent ground object signals. VV and VH polarization are diferent polarization methods for radar transmitting and receiving beams. Sentinel-1 satellite images were selected and VV (Vertical Transmit-Vertical Receive) and VH (Vertical Transmit-Horizontal Receive) dual polarizations were used for water index calculation. Threshold value was set using visual discrimination to extract the water bodies. To reduce the misclassifcation of water bodies, an existing land-cover data mask was used to remove areas that were divided into water bodies without foods. Finally, the slope was calculated based on digital elevation model (DEM) data to categorize water bodies that were falsely divided because of mountain shadows. In the process, the regions with slope greater than 5° were removed.

2.3.2 Risk assessment methods for dam‑failure food

We used ArcGIS10.8 software to model bluespots and to map the food risk from dam failure in the basin (ESRI [2022\)](#page-16-5). The bluespot refers to landscape depressions where water can be pooled. The bluespot model uses DEM data to calculate the distribution, depth, and volume of bluespots (Mhina et al. [2021;](#page-17-14) Trepekli et al. [2021\)](#page-18-7). The bluespots are then flled, and when a bluespot is completely flled, the fow will spill over at a so-called pour point, and fow toward other bluespots located at lower elevations, forming fow direction and watershed (Fig. [3\)](#page-5-0).

"Flow" refers to the convergence of fows from multiple rasters onto a single raster image element, which is a spatial extent concept (Thrysøe et al. [2021\)](#page-18-8). The capacity of the bluespots in the basin was positively correlated with the storage capacity and negatively correlated with the fow from the pour point at the same water level. The lower the fow, the lower the risk of dam-failure food. Finally, we combine the bluespot volume and watershed area to calculate the water depth required to fll up the bluespots.

The natural breaks method was used to classify the risk level of dam-failure foods into fve risk levels based on the food depth, namely lower, low, medium, high, and higher risk. The natural breaks method is a commonly used classifcation scheme for thematic mapping in GIS (ESRI [2023\)](#page-16-6). It divides data into several classes based on natural groupings inherent in the data. Classes are formed such that the variability within classes is minimized while the variability between classes is maximized. This enables the method to highlight the overall pattern and structural characteristics of data distribution.

Fig. 3 Working principle of the bluespot model

2.3.3 Ice and snow melting area acquisition method

Floods in southern Pakistan are closely correlated with the water conditions in the highland area in the north, which are characterized by snow and glacial conditions. Thus, snow coverage in the Karakoram Highway (KKH) area refects the water conditions in whole Pakistan with low land. The water body indices of SAR images were constructed using Sentinel-1 SAR satellite images combined with VV and VH polarization and water body distribution data of the KKH region. The fooded regions from May 25, 2022 to June 1, 2022 and from August 22, 2022 to September 4, 2022 were obtained using the threshold method and human–machine interaction interpretation. Due to different times and scenes, there exist overall diferences in the backscatter intensity of images. A single threshold is difficult to define the area of a water body in different situations, thus the threshold of the water body index should be adjusted by virtual interpretation. We used Sentinel-2 images from the GEE platform, land use data, and brightness and Normalized Diference Water Index (NDWI) indices to extract snowpack data for two time periods: January 1, 2022 to April 1, 2022 (on behalf of cold season with snow cover without melting) and June 1, 2022 to September 10, 2022 (on behalf of hot season with snow melting status). This two period snow cover data can make it easy to compare snowmelt conditions in the KKH region in Pakistan.

2.3.4 Historical food range extraction

Based on historical statistical disaster data in the EM-DAT database, we selected catastrophe events with high death tolls and large afected populations (Table [2\)](#page-6-0). Based on the time period of the events, multi-source remote sensing images were collected for water body extraction, namely Sentinel-1, Sentinel-2, Landsat-5, Landsat-7, and Landsat-8, during the relevant time period of the food events. The quality assessment (QA) band information is stored in binary format, with each binary bit representing a diferent meaning, and the $7th$ bit comprised water information. Bitwise is an operation that performs a single bit operation. Therefore, bitwise operations in the QA band are typically used to extract specifc quality indicators and masks, such as water and clouds

Id	Year	Total deaths	Number of affected persons	Sources of remote sensing images
1	2022	1400	33,012,700	Sentinel-1
\overline{c}	2010	1985	20,359,496	Landsat-5 and Landsat-7
3	2011	509	5,400,755	Landsat-5
$\overline{4}$	2012	480	5,049,364	Landsat-5 and Landsat-7
5	2014	255	2,530,673	Landsat-8
6	2015	238	1,572,423	Sentinel-2
7	2020	410	1,550,170	Sentinel-1
8	2013	234	1,497,725	Landsat-8

Table 2 Data of flood occurrence period

3 Results

3.1 Flood distribution in emergency

Sentinel synthetic image data were used to extract waterbodies during three periods: before, during, and after the disaster. The revisit period of Sentinel-1 satellite is 6 days, making it difficult to achieve quasi real-time flood monitoring. Therefore, the time periods selected in this study are full coverage data before, during, and after the disaster as short intervals as possible. The three periods of this food event were selected from May 25 to June 6, 2022, August 25 to September 03, 2022, and September 04 to 16, 2022. The water extraction results are shown in Fig. [4](#page-7-0). Blue represents the water before the food from May 25, 2022 to June 6, 2022. According to statistics, the water area of Pakistan increased from 19,849.24 to 35,940.19 km^2 from August 25 to September 3, 2022, representing an increase of 81.1%. The province with the largest increase in water area was Sindh, increasing from 8,214.26 to 20,912.29 km^2 (i.e., increase of 157.7%). After the disaster, the water area of the Sindh Province accounted for 58.2% of the total water area of Pakistan. From September 4 to 16, the food began to subside, and the water area of Pakistan reduced to $32,980.25 \text{ km}^2$ (i.e., a decrease of 8.23%). The water area of Sindh reduced from 20,912.29 to 16,966.14 km^2 (i.e., a decrease of 18.87%).

3.2 Damage caused by fooding (buildings, farmland, and roads)

We obtained the base map data of buildings in Pakistan from Microsoft/Global ML Building Footprints, a vector map of building distribution extracted from Bing Maps. The food coverage was extracted using the synthetic Sentinel-1 images of Pakistan from August 23 to September 3, 2022, and then, it was overlaid to obtain the food-afected buildings (Fig. [5](#page-8-0)a). In total, 211,200 buildings were afected by foods throughout Pakistan, covering an area of 76.53 km^2 . The Khyber Pakhtunkhwa province was the most affected, damaging a total of 67,500 buildings. The number of afected buildings in the Punjab and Sindh

Fig. 4 Flood distribution range in Pakistan: **a** August 25 to September 3, 2022; **b** September 4 to September 16, 2022. *Blue* areas represent water before the food in May 25–June 6, 2022; *red* areas represent inundated areas after fooding occurred

Fig. 5 Damage caused by fooding: **a** fooded buildings; **b** fooded farmland; and **c** fooded roads (*red lines*)

provinces was 63,400 and 50,500, respectively. The monitoring results of the afected farmland (Fig. [5](#page-8-0)b) show that foods inundated 25,514,700 ha of farmland across the country, with Sindh being the most severely afected, with 1,467,200 ha of farmland being afected. The monitoring results of road damage combined with the OSM data are shown in Fig. [5c](#page-8-0). As of September 3, 55,970 roads (including major roads, urban roads, and township roads) were affected by floods in Pakistan, with a total length of 6,953.83 km. Among the provinces, the roads in Sindh were the most severely afected, with a total length of 3,352.18 km of afected roads, followed by Punjab and Baluchistan provinces, with total lengths of 1,581.84 and 1,390.34 km, respectively.

3.3 Risk zoning for dam‑failure food

Ever-expanding foods have caused the collapse of several dams in Pakistan, and the secondary damage caused by dam-failure foods has huge risk damaged the lives and properties of the Pakistani population. To obtain an early indicator of the risk of dam-failure foods in watersheds near other dams, we analyzed the elevation and bluespot distribu-tion maps of Pakistan (Fig. [6](#page-8-1)a), and divided the risk into five levels (Fig. 6b). Comprehensive statistics showed that in Pakistan, higher-risk areas covered 3,251 km², high-risk areas covered 8,246.58 km², medium-risk areas covered 14,327.96 km², low-risk areas covered 19,471.94 km², and lower-risk areas covered 7,418.35 km². As shown in Fig. [6](#page-8-1)a

Fig. 6 Risk of dam-failure food: **a** distribution of bluespots; **b** risk level of dam-failure food

and b, the northern mountainous areas and the estuary of the Indus River in Pakistan in south were dominated by high- and higher-risk areas, respectively, whereas the eastern plains of Pakistan in the Panjab and Sindh provinces were dominated by low- and lowerrisk areas, respectively. According to the data, in the Sindh province, dams were mainly located in Hyderabad and Karachi, where the higher-risk of dam-failure food was dominant, covering an area of 571.36 km². The northern part of Sindh province was dominated by medium- and low-risk, with areas of 3,710.11 and 5,655.08 km², respectively. A larger area of lower-risk was located in Sukkur City in the northeast of the province, covering an area of $3,293.72 \text{ km}^2$. In Punjab province, the high- and higher-risk areas of dam-failure food were located near the dams in the southwest and north of the province, with areas of 4,896.56 and 1,299.62 km^2 , respectively; the watersheds near other dams were mainly medium- and low-risk areas, covering 9,259.28 and 12,432.69 km², respectively; and lower-risk areas were sporadically distributed over 2,894.28 km². Baluchistan province had fewer dams, but they were all predominantly high- and higher-risk areas of 545.41 and 493.59 km2 , respectively. Khyber Pakhtunkhwa, Federally Administered Tribal Areas, and Azad Kashmir were predominantly high-risk with areas of 438.84, 139.47, and 59.45 km^2 , respectively.

Approximately half of the dams in Pakistan are afected by fooding, mainly in the Sindh, Baluchistan, and Punjab provinces. In this context, there is a need to strengthen the protection of dams in Hyderabad and Karachi in the Sindh province, as most of these regions are at a higher-risk of dam-failure foods. Furthermore, in the Punjab province, monitoring of food-afected dams in Faisalabad, Lahore, and Gujranwala should also be strengthened. In Baluchistan, the situation of dams afected by foods in southwest Makran needs to be closely monitored, and most of the area is at a higher-risk. In addition, most areas of Lasbela, in the southeast of the province, are at a higher-risk and will be afected by dam-failure foods from Karachi. Eforts should be made to strengthen the protection of the dams in Karachi, as well as enhancing early warning monitoring and food prevention measures.

3.4 Historical food data extraction

The foods that occurred in the eight periods listed in Table [2](#page-6-0) were extracted, and the map of food frequency in Pakistan from 2010 to 2022 was obtained by adding the time sequence (Fig. [7](#page-10-0)). According to a frequency analysis of extraordinary floods over the years, foods in Pakistan have primarily occurred in the lower reaches of the Indus River Basin. The border between Balochistan and Sindh is disaster-prone.

4 Discussion

4.1 Potential capability in the seasonal food map estimation

Seasonal fooding is a global challenge, with staggering impacts and losses in developing countries. The lack of adequate data infrastructure and decision support systems makes it difficult to quickly translate data into flooding maps and disaster reduction knowledge that are easier for the public and policy makers understanding. This study was conducted to obtain a clear map of food hazard distribution by using multi-source remote sensing data and historical hazard information simultaneously during sudden mega-foods in Pakistan

Fig. 7 Flood frequency in Pakistan from 2010 to 2022 (*Blue* represents perennial water, and *red* represents fooded area. The darker the *red* color, the higher the frequency of foods occurring in the area)

in summer of 2022. The all-weather feature of radar data, the high-resolution feature of Sentinel satellite data, the global open infrastructure data, and the availability of global historical disaster statistics were fully utilized in the study, making possible rapid disaster mapping and assessment driven by multiple sources of data. These mapping and evaluation results were quickly published and shared based on the platforms of the Disaster Risk Reduction Knowledge Service in the International Engineering Science and Technology Knowledge Center Auspices of UNESCO [\(https://drr.ikcest.org\)](https://drr.ikcest.org) and the Data Sharing Platform of China-Pakistan Earth Science Research Center (<http://www.cpjrc.net/>) providing information and knowledge support for disaster emergency relief and post-disaster rebuilt. The released data based on this study includes Sentinel-1, Sentinel-2 remote sensing imagery in Pakistan, Pakistan food-afected roads, farmland and buildings dataset, Pakistan dam-failure inundation risk dataset, Pakistan food distribution dataset, etc. This web sharing model of rapid mapping results is proved to be very efective in this disaster reduction event. After releasing the datasets on the website, they are accessed by 3148 users in 2022 and the number of data downloads was 282.45GB. In the future, we hope that more remote sensing data, infrastructure data, socioeconomic data, and historical disaster data can be opened and shared, and more open data infrastructure or knowledge platform can be accessed to improving the food response capacity of developing countries.

4.2 Flood infuencing factors and social impacts in Pakistan

4.2.1 Flood infuencing factors of the 2022 mega‑food

The direct cause of the 2022 foods was possibly the impact of the tropical depression, which is also related to abnormal atmospheric circulation over the Qinghai–Tibet Pla-teau (Ren et al. [2022;](#page-17-15) Chao et al. [2023\)](#page-16-7). Compared with a single event, a compound extreme weather event indicates that multiple climate conditions markedly change simultaneously, rapidly exceeding the limits that human and natural systems can sustain, thereby increasing the risk of catastrophic consequences (Zscheischler et al., 2020). The foods in Pakistan severely afected the south and it has close relationship with the northern high mountainous regions. Therefore, by comparing the snowmelt area with those in previous years, we explored some infuence factors of the snowmelt water supply in the KKH mountain area. Using the Sentinel-1 SAR image water body index, the water body distribution data of the KKH region before and during the food was obtained using the threshold method and human–machine interaction interpretation. The water body area of the region increased from $1,030.87 \text{ km}^2$ to $1,460.78 \text{ km}^2$, representing an increase of 41.7% during the food. Using Sentinel-2 images, snow data from January 1 to April 1, 2022 and from June 1 to September 10, 2022 was extracted combined with land use data. The snow ablation data from June, 2022 was obtained by masking in Fig. [8](#page-11-0)a, with area of 595,911.29 km². Meanwhile, snowmelt data for the same period in 2021 (Fig. [8](#page-11-0)b) was extracted with area of $526,272.70 \text{ km}^2$. The snow ablation area in 2022 increased by $69,638.59 \text{ km}^2$ compared with that in 2021. The added snow melting water fowed into south of Pakistan overlaid the mega-fooding in the summer of 2022.

The above comparison of alpine snowmelt data for 2021 and 2020 reveals that there may be a considerable positive correlation between the increase in the melting of alpine snow and the fooding in summer. A comparison of the temperatures of Pakistan released by the World Meteorological Organization with those of previous years reveals that extreme high temperatures were observed in Pakistan in 2022. Through previous studies (Meehl and Orser [1999](#page-17-16); Leiserowitz et al. [2005](#page-17-17)), high-temperature heat waves lead to higher temperatures in the alpine regions and the increased temperatures lead to faster snow melt in the northern mountains (Mallapaty [2022\)](#page-17-18). In a previous experiment by Immerzeel et al. in [2009,](#page-17-19) it was also confrmed that the increase in the area of water bodies in the Indus Basin was closely related to the melting of alpine snowpack due to climate warming. However, the quantitative relationship of precipitation and snowmelt for their contribution to the season fooding in Pakistan can be further analyzed in the future.

Fig. 8 Karakoram Highway (KKH) snow melt for **a** 2021 and **b** 2022

4.2.2 Social impacts of the 2022 mega‑food

The 2022 mega-food in Pakistan was the worst national fooding since 2010, which caused severe human and economic losses. These foods have caused widespread fooding of houses, cropland, and roads in Pakistan. Statistics show that cropland was the main type of land affected by floods in Pakistan. The 2022 floods affected over $23,000 \text{ km}^2$ cropland areas, which are the most severely affected since 2010 (Table [3\)](#page-12-0). The proportion of built-up areas and cropland submerged by foods in Pakistan in 2020 and 2022 has signifcantly increased compared with other years (Fig. [9\)](#page-12-1). According to the Atlantic Council, total agricultural losses in Pakistan amounted to \$3.18 billion, with \$1.63 billion in Sindh and \$1.04 billion in Baluchistan. Livestock losses amounted to \$291 million, of which \$125 million was lost in Baluchistan and \$109 million in Sindh. This damage results in a severe deterioration in agricultural production and living conditions, including soil erosion and nutrient loss, resulting in infertile land, the severe sanding of arable land, and a reduction or even elimination of crop yields. Pakistan, the world's ffth-largest cotton producer (Azam and Shafque [2017\)](#page-16-8), saw approximately 45% of its cotton production destroyed, amassing \$3 billion on importing raw materials for its textile industry. According to PARC (Pakistan Agricultural Research Council) Islamabad and ICIMOD (International Centre for Integrated Mountain Development), in the worst-hit province of Sindh, economic losses reached \$1.3 billion for rice, cotton, and sugar cane crops, and \$374 million for tomatoes, onions, and chilies.

Local vegetable prices for onions and tomatoes increased tenfold compared with their usual prices, whereas livestock economic losses amounted to \$13 million (Bhutto 2023). Simultaneously, transport networks and communication facilities were severely damaged (Imran et al. [2023\)](#page-17-20), causing challenges in distributing relief supplies in a timely manner.

The foods directly resulted in large economic losses, a lack of basic livelihood protection in afected areas, several disaster victims, and a decline in the living standards of those living in the afected areas. This loss disrupted the established social order, triggered epidemics of infectious diseases, increased security pressure, and afected all aspects of societal and social stability. Furthermore, atmospheric pollutants, industrial wastewater, domestic sewage, and other ground pollutants transported by heavy rainfall converge into food waters, containing numerous germs and toxic and harmful substances. As a result, drinking water safety could not be guaranteed, thereby severely endangering the lives and health of the Pakistani people.

The statistical data of food disasters in Pakistan from 1950 to 2022 was obtained from the World Health Organization EM-DAT database and was used to analyze the food season, the number of deaths, and afected individuals. With relation to the number of deaths, the most fatal years were 1950, 2010, 2022, 1992, and 1998, with over 1,000 deaths (Fig. [10a](#page-13-0)). Among these years, the 1950 food had the highest number of deaths (nearly 3,000). As of September 15, 2022, this food had killed 1,481 people in Pakistan. In terms of the number of individuals afected, 2022 and 2010 had the highest numbers, with over 33 and 20 million people affected, respectively (Fig. [10](#page-13-0)b).

Fig. 10 Historical distribution of individuals affected by floods in Pakistan: **a** mortality; **b** affected population

4.3 Suggestions in response to mega‑fooding events

Combined with extreme climate compound events, such as monsoon anomalies, high temperatures, and heat waves, as well as historical food hazard statistics and analysis, fve aspects of food prevention and control recommendations were derived for local and neighborhood regions (like India, Nepal, Bangladesh, etc.):

- 1. An awareness of the risks and impacts of food disasters should be improved to address the increasing frequency and intensity of extreme rainfall events and regional fooding due to global warming and El Niño, among other climate factors. The impact of heavy rainfall and fooding can be severe, as seen in recent disasters, with some countries and regions facing extreme fooding challenges, including the 2018 extraordinarily heavy rainfall disaster in Japan that killed 225 people (Hiroshige et al. [2019\)](#page-17-21), leaving 13 missing, and forcing over 8 million to evacuate to surrounding areas, as well as the 2021 fooding event in Germany, which resulted in over 130 casualties (Alexander and Simone [2021\)](#page-16-9), the 2021 heavy rainfall in Tennessee, USA, which caused 25 deaths, destroyed hundreds of houses and dozens of factories, and afected 700 families, and the 2022 Australian storm, which caused 22 deaths and economic losses of nearly A\$1.5 billion. As the impact of heavy rainfall and fooding becomes increasingly alarming, all departments have the responsibility of raising awareness regarding disaster risk prevention and addressing the dangers and impacts of food disasters.
- 2. The fexible application of big data and data platforms to improve food hazard monitoring, early warning, and rapid response capabilities should be enhanced. The integrated use of various types of big data, including remote sensing big data (Bai et al. [2021\)](#page-16-10), monitoring big data (Kikuko et al. [2021\)](#page-17-22), statistics (Guo et al., 2023), social media big data (Huang et al. [2018](#page-17-23)), and literature big data (Zhang et al., 2023), will enable timely disaster early warning. This warning, in turn, will allow departments to take prompt and appropriate emergency response measures, considerably reducing the damage caused by flooding.
- 3. Governments must continuously monitor the dynamics of areas fooded by dam failures to safeguard critical infrastructure. The monitoring of food-induced destruction in a particular area should be prioritized to provide early warning to areas that have not yet breached the dam, as well as scientifcally deploying rescue measures to reduce disaster risks and losses. In the post-disaster recovery phase, emphasis should be placed on enhancing the construction and protection of relevant infrastructure in areas that have historically been severely afected to improve their ability to withstand disaster risks. Numerous studies have demonstrated that disasters are strongly related to the environmental vulnerability of the afected region, and that vulnerability is rooted in a lack of capacity and resources to cope with disasters, which includes a range of issues, such as poor infrastructure, social marginalization, and inequality (O'Keefe et al. 1976). Thus, it is imperative that governments enhance their disaster-response capacities and actively build the necessary facilities to respond to disasters.
- 4. Investigating the logic underlying the diferent causes of compound food hazards and their various factors is needed to strengthen the analysis of compound hazards due to weather events, as these causes can difer signifcantly. For example, in the case of foods in Pakistan, monsoon anomalies play a major role, and exploring their underlying causes can offer valuable insights. Similarly, for snowmelt in mountainous regions, examining the causes of high temperatures and heat waves can provide a better understanding of the

issue. In addition, investigating the connections between these deep-seated causes, particularly from a global perspective, is benefcial to understand the relationship between food hazards and climate change. Based on these evaluations, comprehensive food control policies should be initiated for mega-fooding management in these regions.

5. Improving disaster response and handling capabilities is crucial. Taking Pakistan as an example, in the analysis presented in this study, historical disasters in the country have posed substantial threats to the lives and national property of the population on several occasions. Pakistan contributes to only 1% of the global greenhouse gas emissions but is ranked as the eighth most vulnerable country to extreme weather in the world (Kreft and Eckstein [2013;](#page-17-24) Schilling et al. [2013](#page-17-25)). Owing to its monsoon climate (Ullah et al. [2021](#page-18-9)) and limited resources (Khan et al. [2019\)](#page-17-26), Pakistan is highly vulnerable to foods, which are exacerbated by snow and ice melt caused by extremely hot weather. Additionally, the country's fragile disaster-bearing environment (Ashraf and Rustam [2020](#page-16-11)) further contributes to its susceptibility to such disasters. It is crucial to improve their national capacity to cope with foods in the future, including glacial fooding, fash foods, and plains fooding (Aslam Muhammad [2018\)](#page-16-12).

4.4 Future work

There are still some limitations in this study. The available remote sensing data here is Sentinel-1 data, but its revisit period is not daily. Therefore, it is necessary to conduct integrated observation and data fusion of multi-source remote sensing images to improve the real-time images and food coverage extraction in the target area. Remote sensing imagery can only perform food coverage monitoring but cannot simulation and prediction of food processes. Therefore, multiple hydrological models need to be used and compared to select the best hydrological model to analyze the process of this major food in Pakistan. We only counted the buildings and road afected by the foods from a macro perspective, but do not evaluate their damages details. In the future, it is a very important work to combine multiple sources of big data (such as media data, drone image data, and statistical data) to monitor and evaluate the specifc damages of the construction and infrastructures.

5 Conclusions

In order to improve emergency disaster reduction capabilities, this study utilized multisource data to monitor, analyze, and assess mega-foods in Pakistan in 2022. SAR imagery based on the GEE platform was used to enable the rapid monitoring of food coverage in Pakistan, combined with the underlying OSM data, which provided statistics on the major land types afected. Next, further analysis on the severity of food impacts in each province of Pakistan was conducted. Simultaneously, the GIS-based bluespot model approach was utilized to map and analyze the risk level of dam-failure foods and the location distribution of diferent risk zones, which has positive implications for strengthening disaster prevention infrastructure. In addition, by combining Earth observations with long-term recorded historical data, we detected the infuence factor of heat waves that lead to snowmelt in northern Pakistan and their hazardous impacts. Based on the lessons learned from this study, fve recommendations have been made for related regions to address climate change and food disasters.

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Declarations

Confict of interest The authors declare that they have no confict of interest.

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