Role of Earth Observation Data in Disaster Response and Recovery: From Science to Capacity Building

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Abstract Risks from natural hazards such as floods, droughts, earthquakes, and landslides are rising due to increasing populations living in more marginal areas and climatic variability, but our ability to provide warnings and mitigation strategies at short, medium, and long timescales is often challenged by the lack of ground observations in the most vulnerable areas. Satellite remote sensing offers unique global observational capabilities that can provide key insight into the multi-faceted topics of disaster hazard and risk assessment, response, and recovery in a way that ground-based systems cannot do alone. From the vantage point of space, satellite platforms can provide estimates of important hazard-related variables, but have varying degrees of accuracies and spatial resolutions. In some cases these data are used to support direct disaster response such as maps showing the spatial extent of the disaster or impact analyses from detecting pre- and post-event changes on the landscape. Examples of such direct support include the disastrous flood events in Malawi in January 2015 and in the southwestern United States in May and June 2015, and the devastating high-magnitude earthquake that hit Nepal in April 2015 (National Planning Commission 2015).

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1 Overview

Timely responses during such disasters are often enabled by data and tools that were developed with data from Earth observing satellites leveraging the rapid dissemination of satellite information. For example, NASA and the Dartmouth Flood Observatory use direct observations of flood water extent from instruments like the moderate resolution imaging spectroradiometer (MODIS) on NASA's Terra and Aqua satellites and these data are available within hours of acquisition. This method complements modeling efforts such as the Global Flood Monitoring System (GFMS, http://flood.umd.edu) that uses near-real-time satellite-based precipitation information to model potential flood inundation, allowing scientists to compare results and ultimately improve their flood estimates. The availability of optical imagery such as from EO-1, Landsat, or commercial imagery from Digital Globe allows for rapid mapping of landslides following a major trigger, such as the Gorkha Earthquake in Nepal in April, 2015. The mapping efforts provided important information to aid in disaster response and recovery efforts.

Looking to the future, the challenge and question is how best to link Earth Observation (EO) imagery and products together to provide more robust hazard assessment and monitoring systems. Ensuring sustainable value and use of the many platforms, data, and tools offered by satellites and the scientific community requires an intimate engagement between the latter and a wide range of stakeholders (Hossain 2015). This issue has become imminent in recent years, as the strong interplay between human activity and nature drives change on almost all continents. There have been success stories that took advantage of the science and observations afforded by satellites to have spectacular societal impacts or provide unprecedented assistance during major disasters.

Despite the gradual development of more mature remote sensing technology and satellite missions for routine environmental monitoring, there is a general lack of capacity building needed in most regions to take fullest advantage of the tremendous influx of satellite environmental data that are and will become available in the near future. In order to unlock the observational capability of satellites to enhance and accelerate societal applications around the world, scientists, stakeholders, and humanitarian and development agencies need to collaborate closer and ensure sustainable synergies. These partnerships and relationships take time to develop and must be nurtured to most effectively transition scientific research to real-world applications. In reality, these collaborations are typically slow and can prove difficult to establish. For disaster assessment and response, there is a wealth of timely data that can significantly contribute to improving rapid hazard response and recovery; however, few communities are able to take full advantage of these remote sensing data and products. Therefore, a goal looking to the future is to collaborate and coordinate information from an ever increasing number of satellite missions and work with the spectrum of users to more effectively convert data and science into actionable products for better decision-making.

This chapter outlines several examples, where the intersection of remote sensing data and science has had a significant impact on applications and decision-making and has been used to assist relief services during disasters. The following sections describe the role Earth Observation (EO) data play in landslide monitoring, earthquake disaster response (using the Nepal 2015 disaster), and in assisting flood relief services in the Lower Zambezi (in collaboration with the United Nations World Food Programme). We recapture these success stories and report current and future prospects as well as challenges.

2 Landslide Hazard Assessment and Monitoring Using Remotely Sensed Data

2.1 Introduction

Mass movements, including debris flows, landslides, mudflows, rockfalls, etc., (herein referred to as landslides) occur in every country on earth and cause thousands of fatalities and significant destruction each year (Petley 2011; Kirschbaum et al. 2015c). Landslides can range in size from a few meters to several kilometers. They occur over a broad range of lithologies, morphologies, hydrologic settings, and climate zones and can be triggered by intense or prolonged rainfall, earthquakes, rapid freezing and thawing of the surface, and anthropogenic activities, among others (Fig. 1). The location, size, and timing of landslide events can be extremely challenging to forecast or evaluate because of the local scales at which they occur and the complex interactions these events have with triggering events.

EO data have played an important role in advancing the mapping and hazard assessment capabilities over local to global scales. However, there remain some limitations to effectively applying these data to landslide mapping, monitoring, and hazard assessment. Building capacity to better utilize EO data for landslide assessment has been developing over the past decade, and significant advancements have been made to better utilize remote sensing data for landslide hazard

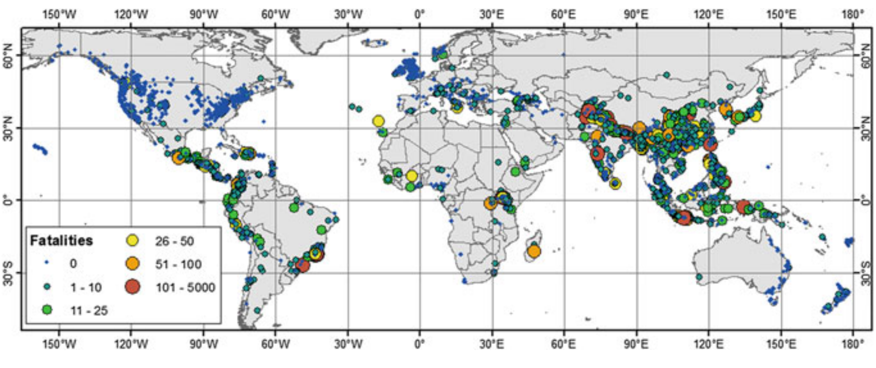

Fig. 1 Global Landslide Catalog (2007–2015) developed at NASA showing number of fatalities for reported events. The Global Landslide Catalog was compiled from media reports, online disaster databases and other sources and contains nearly 7000 events (see Kirschbaum et al. 2010)

assessment. However, there remain some challenges in effectively applying EO data for actionable landslide hazard information. This section provides a few examples of current activities in landslide mapping, monitoring, and hazard assessment and suggests some of the opportunities and challenges of the landslide hazard mapping community in utilizing and building capacity to use EO data.

2.2 Current and Past Approaches

There are many different approaches to landslide hazard assessment and monitoring. One approach to estimating landslide behavior is using a deterministic model to focus on site-specific analysis at a local (hillslope) scale (e.g. Iverson 2000; Baum et al. 2010). In this approach, one needs to account for the way that extreme rainfall interacts with topography, how the water infiltrates the surface and how the subsurface responds to the increased presence of water. These different interactions can vary significantly over one to several meters. The surface and triggering information needed to successfully monitor and assess the hazard is typically obtained from in situ sources (e.g., rain gauges, soil moisture sensors, local high-resolution digital elevation models) and is rarely available from EO data at the resolution needed to conduct the analyses.

Statistical landslide hazard mapping approaches relate potential causal factors (e.g., slope, soil type, distance to drainage, geology) with past local or regional landslide inventories using methods such as logistic regression (e.g. Dai et al. 2004; Ayalew and Yamagishi 2005; Mathew et al. 2009), artificial neural networks (e.g. Ermini et al. 2005; Melchiorre et al. 2008; Pradhan and Lee 2010), or frequency ratio (e.g., Lee and Pradhan 2007; Kirschbaum et al. 2012). These approaches usually produce a static susceptibility map that provides information on the relative or probabilistic potential for landslide activity in a specific area. These studies have ranged from local to global scales and in many cases rely on EO data for homogenous surface inputs.

A third approach that focuses on landslide hazard monitoring considers the timing of landslides triggered by rainfall using an archive of previous events. Techniques consider the intensity of rainfall over short to prolonged periods by relating the intensity and duration (I-D) of a storm with previous landslide occurrence. I-D thresholds have been derived statistically and empirically on the global (Caine 1980; Hong et al. 2006; Guzzetti et al. 2008), regional (Dahal and Hasegawa 2008; Brunetti et al. 2010; Saito et al. 2010), and local scales (Larsen and Simon 1993; Saito et al. 2010). Typically, these I-D thresholds utilize in situ networks of rain gauges but some studies have considered the feasibility of applying satellite-based precipitation to estimate thresholds over broader areas (Rossi et al. 2014; Kirschbaum et al. 2015a).

A common theme in all landslide studies is the need for landslide inventories with sufficient information to validate landslide monitoring and hazard assessment systems. Unfortunately, there is a dearth of this information in general and openly available data in particular. Unlike monitoring networks for hurricanes or earthquakes, global systems have not been created to routinely identify the location, timing, and extent of landslide events. Different types of landslide maps can be prepared depending on the purpose of the inventory and extent of the study area. Traditional landslide inventory methods include obtaining a series of aerial photos and conducting field surveys to compile a database of landslides for a particular area over time. Optical remote sensing data has been applied to assess the landslide density, areal extent, and frequency (Petley et al. 2002; Hervas et al. 2003). Other sensors, such as Synthetic Aperture Radar techniques, are being used more often to locally evaluate displacement of landslides and changes over time (Mazzanti 2011). Freely available EO data provide a significant potential capability to this field for improved and more systematic landslide inventory mapping and analysis.

2.3 Application of EO Data in Landslide Studies

The increased availability, accessibility, and resolution of remote sensing data has provided new opportunities to explore issues of landslide mapping, hazard assessment, and monitoring at a range of spatial scales. Table 1 highlights some of the EO datasets that have been utilized for landslide hazard assessment and monitoring from NASA's fleet. Of the surface variables responsible for slope failures, elevation (and its derived products) remains the most important variable in nearly every model for landslide hazard assessment and monitoring. In terms of NASA data, the Shuttle Radar Topography Mission (SRTM, Farr et al. (2007)) has produced data that have now been released at 3-arc s which can be used to derive slope, curvature, aspect, distance to drainage, etc. State variables that provide both the preconditions and triggering conditions for landslides include soil moisture information from the Soil Moisture Active Passive (SMAP) mission and precipitation from GPM. The presence of past burned areas can increase the susceptibility for landslides due to vegetation loss. This data can be obtained from the moderate resolution imaging spectroradiometer (MODIS) both for past burned areas and active fires.

Finally, an important component of all landslide studies is a robust landslide inventory to validate the landslide model or identify previous instability. Optical imagery such as Landsat, EO-1, or ASTER can provide valuable information over the landscape with the advantages of repeat overpasses (Landsat) or the ability to task specific areas (EO-1 and ASTER). High-resolution commercial imagery provides additional information to classify specific landslides on a slope, but can be limited by the availability and cost. Lastly, SAR capabilities have been used to identify elevation changes from repeat overpasses, but the techniques are not yet widely used for larger area landslide inventory mapping.

2.4 Regional Landslide Hazard Assessment and Monitoring in Central America

One of the challenges with utilizing remotely sensed EO data within a landslide hazard assessment or monitoring system is the scale at which the study is

Table 1 Example of some NASA and other EO data and products useful for landslide hazard assessment (acronyms need to be spelled out—SRTM, SMAP, MODIS, GPW V3)

Data type	EO data set	Resolution	Extent	Source
Elevation	*Shuttle Radar Topography Mission (SRTM)*	*30 arc-s (~90 m) and 3-arc s (~30 m)*	*65° N-S*	http://www2.jpl.nasa.gov/srtm/
Forest cover and loss	Global Forest Change 2000–2013	30 m/99.6 %	Global	http://glad.umd.edu/projects/gfm/
Rainfall	*Global Precipitation Measurement (GPM) mission Integrated Multi-satellitE Retrievals for GPM (IMERG)*	*0.1°, 30-min*	*65° N-S*	http://pmm.nasa.gov
Soil moisture	Soil Moisture Active Passive (SMAP)			
Population	*LandScan and Gridded Population of the world, version 3 (GPW V3)*	*1 km*	*Global*	http://web.ornl.gov/sci/landscan/; http://sedac.ciesin.columbia.edu/data/collection/gpw-v3
Active fire and burned areas	Moderate Resolution Imaging Spectroradiometer (MODIS)	1 km	Global	http://modis-fire.umd.edu/

undertaken. Studies are frequently limited to an area where there is sufficient in situ information to fully parameterize the model. We present a case study here for a regional landslide "nowcasting" system that has been developed over Central America utilizing primarily NASA EO data.

2.4.1 Model Description

The Landslide Hazard Assessment for Situational Awareness (LHASA) model was implemented in Central America and the Caribbean by integrating a regional susceptibility map and satellite-based rainfall estimates into a binary decision tree, considering both daily and antecedent rainfall (Kirschbaum et al. 2015a). LHASA produces a pixel-by-pixel nowcast in near-real time at a resolution of 30 arc s to identify areas of moderate and high landslide hazard. The main goal of this system is to provide a set of tools at the regional level to characterize areas of potential landslide hazard that emergency response agencies, other in country groups or international aid organizations can use to improve their situational awareness and focus attention in areas that may need support.

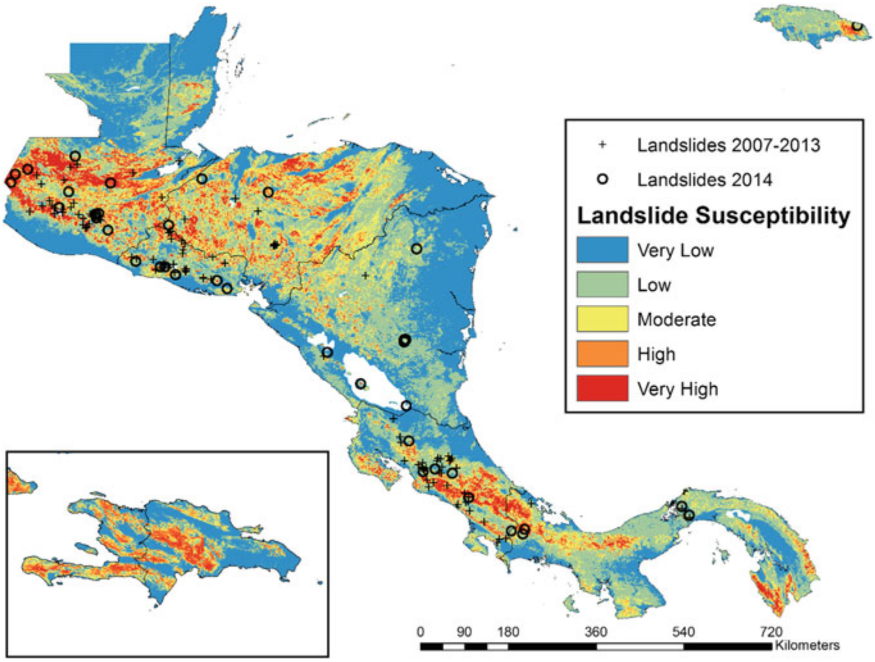

Fig. 2 Landslide susceptibility map for Central America and the Caribbean showing very low to very high susceptibility. *Source* Kirschbaum et al. (2015a)

The landslide susceptibility map going into the LHASA model was developed for Central America and the Caribbean islands by combining three globally available datasets (slope, soil type and road networks) and one regional dataset (fault zones) using a fuzzy overlay methodology (Kirschbaum et al. 2015b). This primarily heuristic model allows for flexibility both in testing a range of different contributing variables as well as incorporating information from landslide inventories that greatly vary in their size, spatiotemporal scope, and collection methods. The resulting susceptibility map provides a relative indication of landslide susceptibility across the over 700,000 km^2 considered at a resolution of 30 arc s (Fig. 2). We tested a range of satellite-derived products including SRTM DEM, forest cover derived from MODIS and AVHRR. After a modified sensitivity analysis, slope, topsoil clay content, presence of roads, and distance to fault zones were included as variables in the susceptibility map.

To provide an indication of potential timing of the landslide activity, TRMM Multi-satellite Precipitation Analysis (TMPA) data was evaluated over its entire archive at the time (2000–2014). An antecedent rainfall index (ARI) was calculated to account for pre-event soil moisture and both daily rainfall and antecedent rainfall percentiles were computed for each $0.25° \times 0.25°$ pixel. Using landslide information obtained from the Global Landslide Catalog (Kirschbaum et al. 2010, 2015c), the study then computed precipitation thresholds based on the occurrence

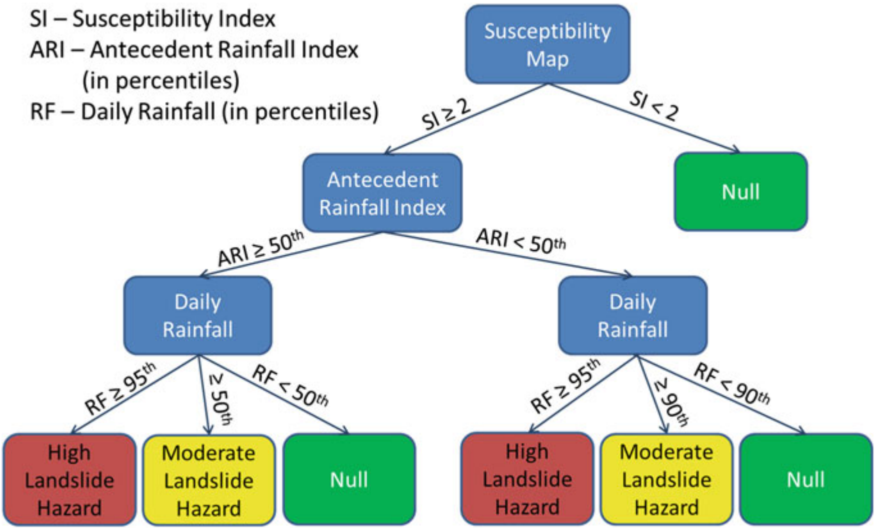

Fig. 3 LHASA Decision tree model. *Source* Kirschbaum et al. (2015a)

of rainfall at the reported landslide locations. A decision tree framework was established to generate moderate hazard, high hazard, or Null nowcasts based on the thresholds for susceptibility, ARI, and daily rainfall (Fig. 3).

The model is updated every day and is currently running in a prototype mode at: http://ojo-streamer.herokuapp.com/meso. This system provides information on all of the input variables (precipitation, susceptibility, and resulting nowcasts), so that individual users can diagnose the conditions at their location of interest as well as see what LHASA generates for potential nowcasts.

2.4.2 Applications and Challenges

The landslide system developed for Central America has a flexible framework that is customizable for other regions with a small level of effort. Currently, this system has been applied in a prototype form in Nepal and Peru. This workflow is also currently being expanded to a global model utilizing a similar approach.

This system provides an overview of potential landslide activity at both regional and soon global perspectives that currently does not exist. By coupling an indication of susceptibility with the intensity of recent rainfall at that pixel, it provides a regional perspective that can provide valuable situational awareness to a range of different end users including the international aid organizations such as the

International Federation of the Red Cross,[1] global disaster centers such as the Pacific Disaster Center,[2] the intelligence and military communities, and others. The framework in which the LHASA system is housed can also allow users to easily extract the underlying data from this model including remotely sensed precipitation, susceptibility, and landslide nowcasts in a variety of different formats.

The challenges in this system lie in the broad regional and global frameworks on which this system was designed. Due to its coarse spatial resolution ($\sim 0.01°$ or approximately 1 km), it has limited applicability for local emergency response groups who may need more detailed, slope-specific information. There is always the potential for increasing the resolution of this product in some areas, however, a major challenge stems from the current resolution of triggering data, namely precipitation, as well as the relative dearth of landslide inventories for model calibration and validation.

2.5 Conclusions

Landslide hazard assessment and monitoring is rarely undertaken at regional or global scales due to the prevailing methodologies that predominately utilize in situ data as well as the techniques that require detailed landslide inventories and triggering data. Of all the limitations of conducting landslide hazard assessment over larger areas and making full use of remotely sensed data, the most challenging element to overcome is the paucity of landslide inventory data beyond site-specific local studies. Optical imagery from EO-1, Landsat imagery can fill a critical need to better identify large landslides. Commercial imagery, such as from DigitalGlobe, provides higher resolution data to map an area. While optical methods are at the mercy of cloudless skies, SAR capabilities can penetrate clouds and allow for detection of changes on a landscape on the order of centimeters. All of these remote sensing capabilities have been used before for landslide detection; however, there is still a need for established, globally acknowledged mapping standards and guidelines to better utilize remote sensing imagery for landslide inventory assessment. Systems such as LHASA demonstrate the feasibility of applying remotely sensed data in a regional or global context to increase awareness, better understand the triggering conditions and ultimately improve response to landslide activity.

[1]www.ifrc.org/.

[2]http://www.pdc.org/.

3 Nepal 2015 Earthquake: Addressing International Development Challenges Through Scientific Networks

3.1 Introduction

Reaping the societal benefits that Earth Observation Systems (EOS) takes concerted efforts on the part of scientists and managers to understand the specific needs of beneficiaries. It also requires a clear understanding of entry points for EOS products and tools in decision-making processes. This not only requires a well-informed user group (potential beneficiaries) but also a group of applied scientists and capacity builders who can translate societal needs into possible data- or application-informed solutions. At the nexus of international development and applied sciences is SERVIR, a joint effort led by the U.S. National Aeronautics and Space Administration (NASA) and the U.S. Agency for International Development (USAID), along with international organizations around the world who have great capacity in connecting challenges posed by environmental, climate change, and disaster management with scientific data and products. A capacity building project, SERVIR strengthens developing countries' abilities to access and apply Earth observation data to manage challenges in the areas of food security, water resources, land use change, and natural disasters.[3]

To do this, SERVIR has created a network of scientists, technologists, trainers, and decision-makers, who collaborate to use Earth observations and geospatial technologies to codevelop solutions to environmental challenges. Foci of SERVIR efforts are in regional hubs, which are international organizations or consortia that have been selected for their history and experience of using GIS and remote sensing for environmental challenges. SERVIR hubs function to apply appropriate science and cutting edge technologies to plug into or become part of existing decision support systems. Active SERVIR regions include Eastern & Southern Africa, led by the Regional Centre for Mapping of Resources for Development (RCMRD; http://www.rcmrd.org/), the Hindu Kush Himalaya region, led by the International Centre for Integrated Mountain Development (ICIMOD; http://www.icimod.org/), and the Lower Mekong region served by a consortium of the Asian Disaster Preparedness Center (ADPC; http://www.adpc.net/), Spatial Informatics Group, Stockholm Environment Institute, and Deltares. USAID regional and bilateral missions play an active role in funding the hubs and articulating the development challenges, while a Science Coordination Office (SCO, previously called a the SERVIR Coordination Office (CO)) at NASA provides scientific and technical backstopping to hubs and manages an Applied Sciences Team (AST). This AST works to address end-user needs in SERVIR regions in direct collaboration with hubs. SERVIR addresses a wide variety of thematic areas, focusing on food security, land cover/land use and ecosystems, water and water-related disasters, and weather and climate.

[3] https://www.servirglobal.net/.

Given its position to accelerate applications of EO data in decision-making contexts in many regions of the world, SERVIR has been leveraged in many cases to provide technical input into emergency mapping and disaster response support, often in the form of rapid satellite image acquisition and interpretation (Boccardo 2013). Some of the earliest and strongest demands for information have come from fire mapping needs (Lewis 2009). Applications and customizations of satellite-based fire information are often taken up very quickly by environmental management and disaster management communities, likely for two reasons: first, the high applicability and accessibility of the Fire Information for Resource Management System (FIRMS) (Davies et al. 2009) and MODIS active fire products (Giglio 2010; Justice et al. 2011), and second, a close understanding of the challenges that forest and fire managers face. To further facilitate design and operationalization of such systems, applications have been cofunded and codeveloped between SERVIR hubs and with government ministries and departments themselves. Summaries and examples of disaster response support provided in Mesoamerica, Eastern and Southern Africa, and the Hindu Kush Himalaya can be found in Bajracharya et al. (2014), Flores Cordova et al. (2012), Gurung et al. (2014), Graves et al. (2005), Hardin et al. (2005), Macharia et al. (2010) and Wang et al. (2011). Throughout the communication and collaboration that occurs during needs assessments, product development, and iterations thereof, a vibrant network of scientists, technologists, managers, trainers, development professionals, and decision-makers, have been formed. The remainder of this section focuses on the description on one of the many subnetworks that we argue allowed for a successful integration of Earth observations into disaster response support.

3.2 Role of Earth Observations in the 2015 Nepal Earthquake Facilitated by SERVIR Network

The 25 April 2015 magnitude 7.8 earthquake and aftershocks (including the 12 May 2015 magnitude 7.3 aftershock) in Nepal led to over 9000 deaths, widespread damage to buildings and infrastructure, over 4000 landslides, avalanches, and other economic ramifications (National Planning Commission 2015; Kargel et al. 2016). Immediately following the earthquake, ICIMOD and the participants in the SERVIR network came into play to provide EOS-derived products to inform decision-makers the extent and magnitude of the impact, particularly around the state of geohazards (ICIMOD 2015).

Before the earthquake, though, a preexisting network of science data product providers and end users existed (Fig. 4). During the earthquake, ICIMOD and the NASA/SERVIR Coordination Office leveraged the preexisting network to connect ICIMOD and government agencies in Nepal with an even broader network of science data product providers (Fig. 5). Some 40 volunteer landslide mappers in the U.S., organized by the University of Arizona, NASA, and USGS; and another 40 or so volunteer mappers in Nepal, organized by ICIMOD, were able to put EOS

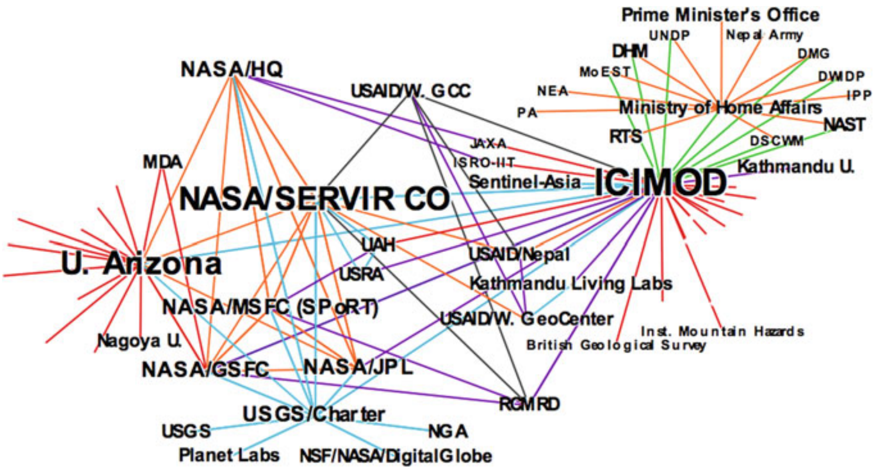

Fig. 4 Network connections before earthquake response (prior to April 2015). *Orange* Disaster response coordination, *Purple* Science/technical collaboration, *Gray* Project management connection, *Blue* Imaging needs communicated and images provided, *Red* Landslide mapping, *Green* Value-added products demanded and provided

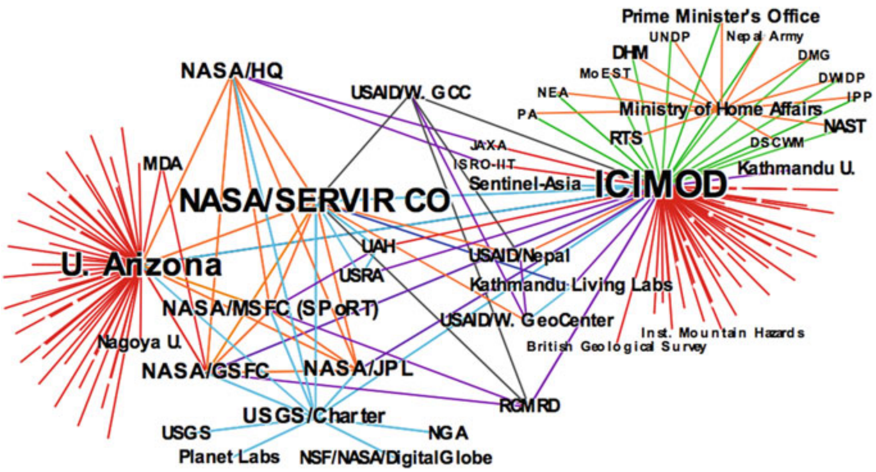

Fig. 5 Network connections during earthquake response (April–June 2015). The demand for situational awareness that satellite images and their analysis provide mushroomed during the earthquake response. The surge in landslide mapping efforts (*red*) produced information and products that were readily transferred through a previously existing network, allowing them to reach government and nongovernment end users in Nepal

products to immediate use by plugging into this strong network that ICIMOD and SERVIR had developed over the previous 5 years. The main audiences for value-added products were the Ministry of Home Affairs, Prime Minister's Office, and numerous other government agencies in Nepal. USAID offices in Washington, D.C., and in Nepal provided crucial funding and project management support, while the NASA/SERVIR CO connected Earth science data users in Nepal to a vast network of Earth scientists within NASA and outward through its affiliates.

Figures 4 and 5 depict lenses of NASA/SERVIR and ICIMOD for the event response. It is important to note that there were even more collaborators with ICIMOD from other countries, more connections between Nepal and the US, more connections between ICIMOD and other Nepal agencies, and more connections between International Charter and international space agencies, than depicted here.

What is the lesson learned here? When it comes to reaping benefits of EO data around the world, networks are not formed overnight. Meaningful responses to disasters rely on existing networks of scientific and technical collaboration, as presented in this brief case study. As of late October 2015, 5760 ad hoc products and 5840 images have been contributed to the USGS Hazard Data Distribution System, the US's platform for organizing and disseminating its contributions to the Charter (USGS 2015). The absorption and use of such a volume of products and satellite images require significant capacity to translate these intermediate outputs into actionable information.

3.3 Conclusions

Much is left to be done toward standardization for international disaster response (McCann and Cordi 2011), but certainly a strong history of collaboration and vibrant network of collaborators eases the connections between how Earth observations can play a role in meeting the demands during disaster response. Even though the network analysis presented is from specific project and organizational lenses, it is telling to see how many "connections" there were before the crisis. Also, many more connections were made during the crisis, but it is difficult to know whether the same quantity and quality of connections could have been made during the crisis response had there not been the previous network connectivity. Without such prior connections and capacities, we hypothesize that there would not have been as effective a response from the EO side.

4 Mapping and Predicting Flood Hazard in the Lower Zambezi for the Humanitarian Aid Sector

4.1 The Situation

The Zambezi River is the fourth largest river in Africa and is an important source for biodiversity, agriculture and hydroelectric power. The river flows into the Indian Ocean and through eight countries (Zambia, Angola, Namibia, Botswana,

Table 2 Flood data for all countries in the ZRB over the last 20 years

Year	Occurrences	Total deaths	Affected	Injured	Homeless	Total affected	Total damage in ° 000
1995	*5*	*24*	*5350*	*0*	*23300*	*28650*	*0*
1997	4	118	808028	0	2104	810132	0
1998	*5*	*101*	*1,319,600*	*0*	*0*	*1,319,600*	*20,789*
1999	2	23	72,000	0	0	72,000	12,400
2000	*11*	*955*	*4,913,776*	*28*	*108,800*	*5,022,604*	*508,100*
2001	9	218	1,945,904	5	200	1,946,109	46,300
2002	*5*	*26*	*397,540*	*0*	*500*	*398,040*	*0*
2003	12	73	565,500	3	12,825	578,328	200,000
2004	*7*	*30*	*558,345*	*13*	*1,700*	*560,058*	*0*
2005	6	18	53,373	12	63,500	116,885	0
2006	*7*	*13*	*2,300*	*28*	*37,725*	*40,053*	*8,490*
2007	16	209	2,223,362	0	12,159	2,235,521	171,000
2008	*7*	*151*	*188,780*	*15*	*1,942*	*190,737*	*0*
2009	10	223	1,246,395	0	5,065	1,251,460	0
2010	*8*	*38*	*261,185*	*31*	*78,875*	*340,091*	*0*
2011	16	290	798,491	201	6,876	805,568	12,000
2012	*4*	*14*	*91,385*	*0*	*0*	*91,385*	*0*
2013	8	285	380,120	76	0	380,196	30,000
2014	*9*	*50*	*145,555*	*2*	*20,000*	*165,557*	*20,000*
2015	5	432	768,881	645	595	770,121	0
Total	*156*	*3,291*	*16,745,870*	*1,059*	*376,166*	*17,123,095*	*1,029,079*

Note that a value of 0 may denote data not available. *Source* EMDAT http://www.emdat.be/advanced_search/index.html

Zimbabwe, Mozambique, Malawi, and Tanzania) in the southeast of the continent. Some of the most important wetlands in Africa are linked to the Zambezi River, while agricultural production is governed by the variability in river storage and flows. The basin encompasses humid, arid, and semiarid regions, with the flow regime being controlled by seasonal rainfall that causes the area to be seasonally flooded. Estimates of population within the Zambezi River Basin (ZRB) range from 30 to 40 million people, the majority of whom live in rural areas.[4] Very frequently, almost every year, moderate to high-magnitude floods put millions of people and their livelihoods at risk (Table 2). Over the past two decades, large floods have affected an estimated 17 million people (see Table 2) and led to significant crop damages with persisting consequences.

[4]World Bank: http://siteresources.worldbank.org/INTAFRICA/Resources/Zambezi_MSIOA_-_Vol_1_-_Summary_Report.pdf; WWF: http://wwf.panda.org/about_our_earth/about_freshwater/rivers/zambezi/.

The countries within the ZRB and in particular the downstream country of Mozambique with its vast delta area, suffer from weak infrastructure and resources and thus lack the foundational data required to establish effective flood management, mitigation, and relief services plans, let alone an operative flood forecasting system. Despite some local flood forecasting efforts in the ZRB, according to the World Meteorological Organization (WMO) there is currently no integrated flood warning system in the basin, primarily due to poor communication facilities and limited exchange of information and data in real time (WMO 2009). Furthermore, flow and water level measurement stations are exiguous in most countries in the region.

This general lack of information regarding the most serious and regular natural hazard in the region exacerbates the challenges faced by humanitarian emergency response to flood events. The United Nations World Food Programme (WFP) is the food aid arm of the UN and one of the largest providers of disaster assistance to the region. In addition to rapid emergency food aid, WFP also provides additional logistics and emergency telecommunications assistance to organizations that are part of the overall flood response. Reliable maps showing the extent of rivers and floodplain inundation as well as associated effects on critical infrastructure provide maximum situational awareness in support of preparedness, response, and recovery activities.

Ideally, these types of situational or logistics operational planning maps (Fig. 6) should be delivered in near-real time to WFP field officers on the ground. At present, the only consistently and freely available flood maps delivered in near-real time are provided by a unique global flood monitoring system funded by NASA using daily images from the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard NASA's Terra spacecraft (as illustrated in Fig. 7). With composite MODIS images, NASA produces cloud-free maps showing the precise locations of flooded areas where there may be concomitant (and significant) population displacement. NASA also makes the raw GIS data available for download enabling overlay of the MODIS analysis on operational planning maps. These maps are used by WFP staff to pinpoint the worst-hit areas. With the new composite images, there is a dramatic increase in mapping accuracy as well as a daily timeline of the progression or recession of the flood waters. Observations of floodplain inundation over time allow disaster relief agencies like WFP to identify serious flood events and allocate resources and direct operations accordingly.

The challenge faced by both the humanitarian aid sector and the scientific community is twofold: (1) the data received by the flood response teams need to be actionable information (timely, clear, simple to understand and compatible with standard mapping software such as ESRI) and (2) should not provide a deterministic, but a probable range of floodplain inundation variables (volume, area, depths), preferably with long lead times, in the form of a simple early warning system. This would allow humanitarian aid agencies such as WFP to more effectively allocate and preposition resources that would ensure the most efficient aid distribution and emergency response. Also, it would allow local and national authorities in the region to ensure sustainable management in the areas of food security and water

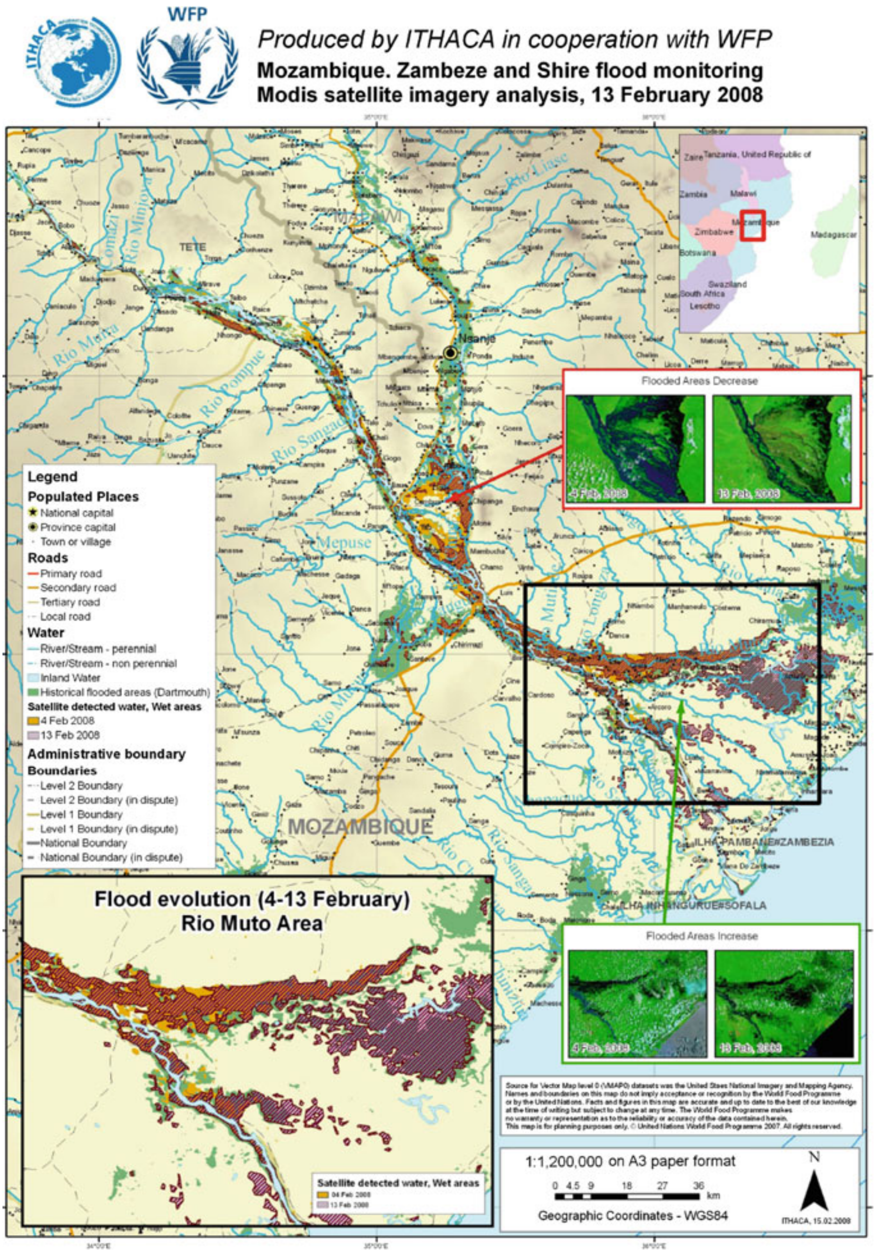

Fig. 6 Example of a map sent to field response teams in the humanitarian aid sector, in this case by WFP. This map shows flood evolution in the Lower Zambezi based on MODIS satellite imagery for the event in February 2008. The map was produced by the Information Technology for Humanitarian Assistance, Cooperation and Action (ITHACA) Institute in Turin, Italy. ITHACA is one of the top-level academic institutions who are enabling WFP to take advantage of recent advances in remote sensing technology. With this type of help, WFP has rapid access to satellite imagery analysis of disaster areas. The detailed maps help guide and inform its humanitarian operations

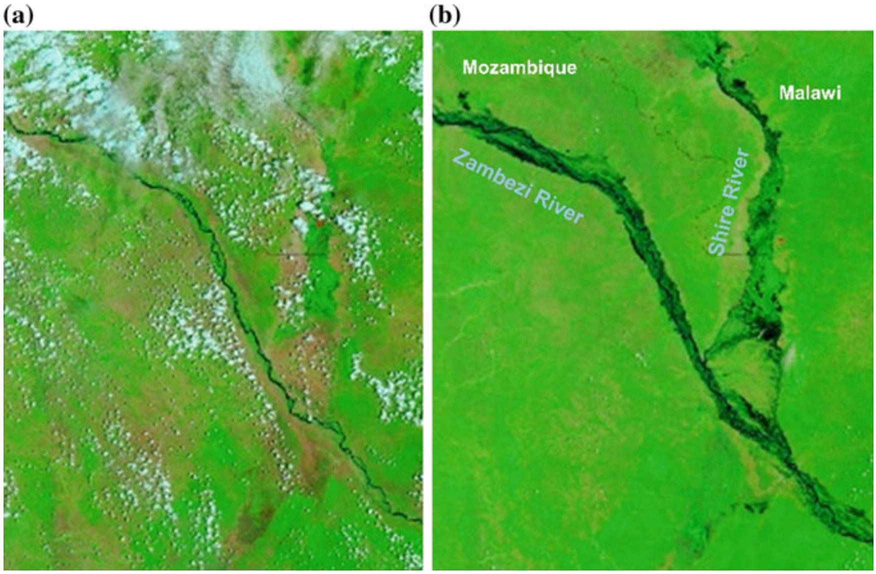

Fig. 7 Inundation surrounds the Zambezi River in the image in **b**, captured by the MODIS on February 10, 2007. Mozambique was experiencing its worst floods in 6 years when the Zambezi overtopped its banks in January and February 2007, reported the United Nations Office for the Coordination of Humanitarian Affairs (OCHA). As of February 12, 2007, an estimated 29 people had died and 60,000 had been evacuated from the riverbanks. These images show the lower Zambezi where it meets the Shire River flowing south from Malawi, one of the most severely affected regions in Mozambique. The image in **b** provides a remarkably cloud-free view of the floods, while the image in **a**, taken on December 31, 2006, shows the region before the rain started in January. Images such as these are provided by the MODIS Rapid Response Team and the Dartmouth Flood Observatory (http://floodobservatory.colorado.edu) on a daily basis (© NASA Earth Observatory)

supply. Most importantly, it would provide the potentially affected communities time to prepare accordingly.

4.2 The Challenge

4.2.1 The Scientific World: Thriving to Do It Right

With flood frequency likely to increase as a result of altered precipitation patterns triggered by climate change, there is a growing demand for more data and, at the same time, improved flood inundation modeling. This is essential for the development of more reliable flood forecasting systems over large scales that account for errors and inconsistencies in both observations and modeling. It is clear that there is an ever increasing abundance of forecast models and data that predict the magnitude, frequency, and impacts of extreme weather events, such as floods. Recent and ongoing advances in Numerical Weather System (NWS) model development (ECMWF models, NOAA NCEP models, and WRF models) can provide forecasts of rainfall fields and even streamflow at a high spatial resolution that can deliver accurate information at the appropriate regional and basin scale for hydrology.

However, predicting flood inundation in 2-D in near-real time and particularly with long lead times (i.e. 10 + days) as required by flood relief services is still a major challenge and only a couple of flood inundation models are actually capable of delivering data at (local) scales appropriate for flood disaster management and emergency response, let alone in near-real time. Over the last few decades, there have been major advances in the fields of remote sensing, numerical weather prediction, and flood inundation modeling (Pappenberger et al. 2005). At the same time, there are currently attempts to roll out models on a continental to global scale (Thielen et al. 2009; Alfieri et al. 2013; Pappenberger et al. 2012; Paiva et al. 2011, 2013; Winsemius et al. 2013). In this context, see in particular Sampson et al. (2015) for an illustration of the type of 2-D flood hazard model used in Schumann et al. (2013) for flood inundation forecasting in the Lower Zambezi.

These models, with a few exceptions, predict at a point discharge level with relatively little attention to accuracy at the appropriate inundation model grid scale. Typical grid resolutions of continental or global scale models dealing with flood inundation processes are in the order of a few tens of square kilometers (Yamazaki et al. 2011; Pappenberger et al. 2012), which is often too coarse to resolve inundation pattern details necessary to understand associated local risks. The type of hydrodynamic model presented by Paiva et al. (2013) in an Amazon River case study moves certainly in the right direction in terms of large-scale hydrology and in-channel hydrodynamics but it employs a simple fill operation for the floodplain with prediction of storage volume only. Since the model lacks floodplain hydraulics, it cannot reproduce inundation area dynamically. In addition to these shortcomings, most models employed in flood forecasting and mapping use simple flow routing schemes that only account for the kinematic force term in hydrodynamics but ignore diffusion and backwater effects.

Consequently, during many major flood events particularly in coastal areas, such as Cyclone Eline associated with the devastating floods in Mozambique in 2000 or the Hurricane Sandy and Katrina events in the U.S., commonly used flood models are inadequate. This is worsened by the fact that oftentimes downstream coastal-ocean boundaries in inland inundation models are not represented correctly or missing altogether. The main reason for this is not because such estuary models do not exist but rather that accurate representation of boundary conditions is needed at very high spatial resolution. Advances in computing only made this possible very recently. In addition, there is a gap between the coastal and riverine scientific communities as these two fields employ computer models that, despite solving very similar hydrodynamic equations, require different forcing and input data.

In an attempt to overcome some of the challenges noted, Schumann et al. (2013) built a first large-scale flood inundation forecasting model for data-poor regions and

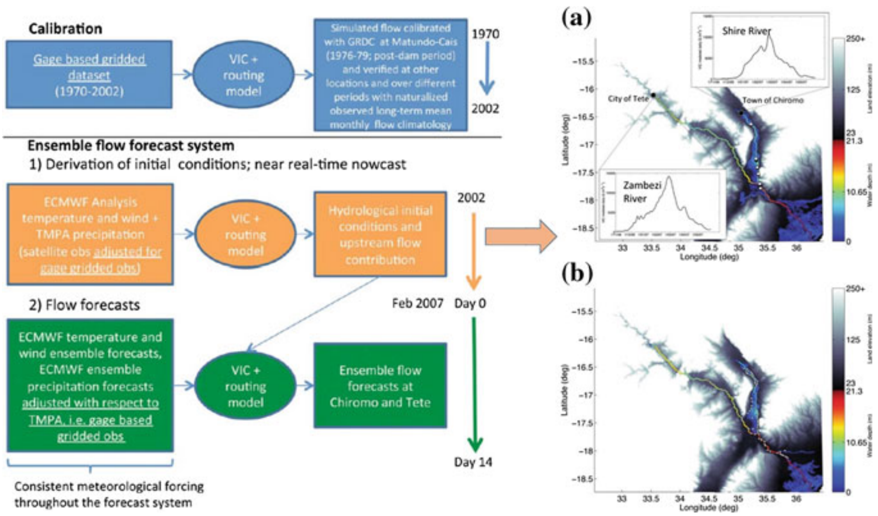

Fig. 8 Schematic of the calibration of the VIC hydrology model and the setup of the forecast flow generation (*left panel*). Illustration of the LISFLOOD-FP flood simulation (1 km resolution) at the time of the (**a**) ICESat-1 overpass and (**b**) Landsat overpass in February 2007, using the VIC baseline hydrographs shown. ICESat-1 water level locations and Landsat flood edge points are also shown. The *color shading* represents flooded area and water depths in m (*right panel*). Modified from Schumann et al. (2013)

tested it on the Lower Zambezi basin. In their application, the Variable Infiltration Capacity (VIC) hydrology model (Liang et al. 1994) is forced with medium-range weather forecast reanalysis data to provide flow at entry points to a flood model. The flood model applied is the computationally efficient 2-D hydrodynamic model, LISFLOOD-FP (Bates et al. 2010), complemented with a subgrid channel formulation (Neal et al. 2012) to generate flood inundation variables for the Lower Zambezi basin. Their forecast system (Fig. 8) showed good performance levels in both in-channel water levels during the calibration phase (18 cm in error) and flooded area predictions during the validation phase (86 % fit compared to a Landsat image of the 2007 event).

4.2.2 The Decision-Making World: Delivering Actionable Information

It is clear that there is an ever increasing abundance of extreme event data, from all kinds of models and observational systems, as well as other types of geospatial data sets available to describe and quantify the processes, magnitude, frequency, and impacts from extreme weather and climate change, such as floods. The scientific community is working to provide an enormous volume of valuable geospatial datasets to the public that can deliver information at various temporal and spatial resolutions spanning the entire natural process of an extreme event. This information can be in the form of event reanalysis, probabilistic forecast or scenario projections.

However, this wealth of information is completely under-utilized by emergency response teams, due to a number of reasons, most of which relate to its relative novelty: (1) limited time and personnel capacity to understand, extract, process, and handle new types of geospatial datasets; (2) limited near-real-time data accessibility, bandwidth, and sharing capacity; (3) incompatibility between user platforms and geospatial data formats; (4) data availability may be simply unknown and/or data latency may be inadequate; and (5) limited understanding by scientists and engineers about end user information product and timing needs; and (6) limited feedback from end users as to the usefulness and accuracy of the information when the data is actually made available.

In order to address this frequently encountered mismatch between data availability and end-user needs, geospatial data layers of extreme event prediction relevant to stakeholders should be delivered in an easily accessible format, through a user friendly web-based interface such as one that could be provided by Google, Inc., Amazon.com, Inc. or Environmental Systems Research Institute, Inc. (Esri) for instance.

4.3 Meeting Midway

4.3.1 Innovation

Flood prediction is a major component of any integrated flood management plan, which in turn constitutes an essential part of efficient water resources prediction and management. The Global Flood Working Group (GFWG), a consortium of top scientists and decision-makers concerned with flooding, has identified the need for better flood forecasting up to 30-days lead time as one of their primary objectives and scientific pillars, especially in data-poor regions. A possible way forward may be to develop a simple and robust satellite-assisted operational early warning system that can be used to predict with a long lead time (>30 days) a possible range of anomalous flood water conditions that can manifest themselves in the form of inundation area, volume, and depth above the mean condition. In order to achieve optimal use of such a system for emergency flood relief services, the modeling framework proposed for the Lower Zambezi area in collaboration with the humanitarian aid sector (WFP) and through space agency funding support (NASA, 13-THP13-0042) needs to address the following aspects, which makes it unique and quite different from existing (flood) early warning systems:

- Establishing a very long term record of forecast flood inundation that can be queried using observed antecedent and present satellite soil moisture data (e.g. from satellite missions such as ESA's SMOS or NASA's SMAP) as well as forecast rainfall data or forecast flows, or indeed any relevant near-real time observed or gauged flood variables for that matter. In fact, one may decide to use data assimilation techniques, such as presented by Neal et al. (2009) for example, to augment the model (forecast) accuracies. Figure 4 (Pillar 1) schematizes one possible modeling framework.

- This flood inundation early warning system or 'dynamic library' can be applied without the need to run models and provides not a deterministic but a probable range of flood inundation with long lead times.
- The proposed system computes actual floodplain flow processes by solving the shallow water equation, using LISFLOOD-FP after Bates et al. (2010) and Neal et al. (2012), and outputs actual flood inundation at high spatial resolution (1 km). Moreover, it is tuned towards a specific high-risk region and the decision-making needs of one of the largest humanitarian organizations (WFP), which is to look at possible flood inundation projections and not only in-channel flow predictions. This is important since floodwaters exiting the channel will spread across the terrain and inundate the floodplain where the risk and hazard then inevitably become localized. Note that most existing regional to global so-called flood (forecasting) models are often hydrologic models and simulate in-channel flow only, and oftentimes with only relatively basic water flow algorithms.
- Easily transitional to end user and flexible for a wide range of water-related issues. The proposed system is tailored specifically towards easy implementation in a variety of decision-making operations.

This is the first time such a system is presented for the ZRB and potentially operated. Currently, neither any operational flood early warning systems nor flood forecasting model dynamically computes inundation patterns at acceptable resolutions across floodplains in data-poor regions. Furthermore, given that many flood model runs are performed a priori using a wide range of possible flows, many inundation scenarios can easily be uploaded to a server made accessible to humanitarian agencies as well as the scientific community. This allows data queries to be performed easily and files to be downloaded as needed. Also, such a system would be straightforward to scale up to a global level (following for example a model setup similar to that described in Sampson et al. 2015) to address other flood prone hotspots which require almost yearly attention by emergency responders (Fig. 9).

4.3.2 The Way Forward

The Current Situation

In order to respond most efficiently to flood events in the region, WFP needs a reliable long lead-time forecast of high-resolution floodplain inundation for its decision-making process. At WFP, most of the advanced remote sensing information is processed/managed at HQ level in Rome, Italy. Data and maps are made

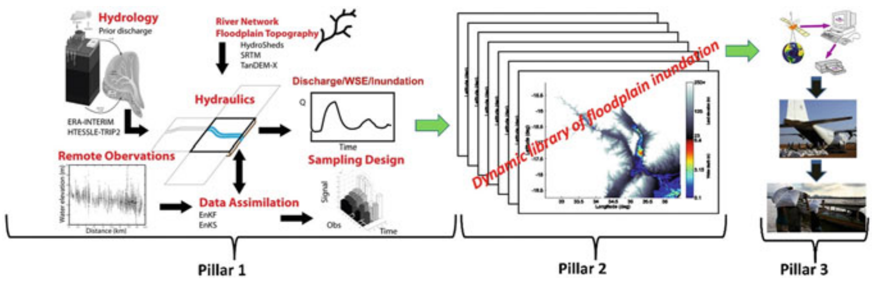

Fig. 9 Schematic of the flood inundation forecasting system proposed for the flood prone regions in the Lower Zambezi basin. Pillar 1 (personal communication, Neal (2014)) presents one possible modeling framework that can be adopted. Pillar 2 illustrates the 'dynamic' library that will be the output of the modeling in Pillar 1. This library of possible flood inundation scenarios can then be queried by decision-makers at WFP in our case (Pillar 3)

available to field offices in order to help with strategic planning for the humanitarian response. Since computer resources are fairly limited at both HQ and field level, the WFP relies at the moment heavily on support from both the remote sensing community and the weather forecast community, primarily in the form of NRT flood mapping from MODIS, real-time satellite precipitation as well as rainfall forecasts and the GDACS Global Flood Detection System (Version 2) (GDACS GFDS) run by the EC-JRC in collaboration with the UN and Dartmouth Flood Observatory (DFO). However, none of these systems provide forecast on floodplain inundation despite it being such valuable information. The main reason for this is that the types of 2-D hydrodynamic models (i.e. flood models) needed to simulate floodplain inundation at high enough spatial resolutions (at least 1 km grids) cannot currently be run within an operational forecast mode since these models typically have a high computational burden and require very accurate topographic boundary conditions.

A New Approach: Combining Global Flood Model Layers with Satellite Data for Decision-Makers

Facilitating Satellite Data Use for Decision-Makers: The 'Early Bird Catches the Worm'

The NASA Early Adopter Programs (see the chapter on Early Adopter for more details on page 231) are designed to provide specific support to so-called 'Early Adopters' in prelaunch applied research to facilitate feedback on NASA mission products (e.g. SMAP, http://smap.jpl.nasa.gov/science/early-adopters) *pre-launch*, and accelerate the use of products *post-launch*. Working with WFP as a SMAP early adopter, Schumann et al. (2014) started to look into simplifying model output delivery, extending forecast lead time and augmenting performance. As outlined earlier, in this particular setup, they used ECMWF archived forecast rainfall to compute flows that generate daily inundation patterns over a period of about 10 years using the coupled VIC-LISFLOOD-FP forecast model. These simulations allow generating a library of flood model outputs (inundated area, floodplain water volume), essentially from a long time series of rainfall data. They then used this library to correlate and log-regress ECMWF rainfall, satellite soil moisture, and model output floodplain inundation volume. Subsequently, the regression model is applied as a predictor for flood inundation variables and conditions. Using both forecast rainfall and soil moisture conditions to predict flood inundation volume has much higher skill than using rainfall as a sole predictor (correlation of 0.88 vs. 0.49). In the Mozambique test case, their regression model had a relative bias of 17 %, with a relative error in predicting the 2007 flood event of 33 %. In other words, based on rainfall forecasts and satellite soil moisture observations that WFP would have access to, a simple regression can be queried to predict a range of plausible floodplain inundation volume and area contained in the library, with a long lead time. This 'dynamic library' could be extended and hosted by the JRC-UN GDACS GFDS platform, which WFP can easily access and is already familiar with.

Enabling Free and Seamless Data Access with High-End Web-Based Data Analysis Platforms

Current efforts can be augmented by including satellite and other observed or modeled data layers from national agency data centers into web-based data analysis platforms (e.g. Google Earth Engine) thereby enhancing deliverables that plan to make satellite-based flood maps and global flood model simulations easily accessible through such online platforms. Multiple data layers, such as for instance rainfall products from the Global Precipitation Measurement (GPM) mission or soil moisture fields, can be handled to feed in seamlessly with the already planned data layers, i.e., flood hazard data from DFO and maps from a global high-resolution flood hazard model (Fig. 10). The result would be a multilayer flood event hazard chain ranging from a flood driver layer (i.e., precipitation from the GPM mission) through flood onset layers (soil moisture products) to flood event hazard layers (from NRT MODIS combined with global flood model maps). In addition to making all this available on the platforms such as provided by Google, Inc., one could envisage employing new ICT technologies to deliver these layers seamlessly and tailored to targeted, more local, stakeholders. New mature geospatial technologies can leverage current data system capabilities such as provided by NASA's ECHO, NSIDC and EOSDIS (Worldview) for example, and allow interoperability between multiple interactive map viewers on both mobile and traditional computing platforms. These solutions are now sustainable and extensible thereby increasing the efficiency for decision-makers and enabling new users to benefit from Earth science data.

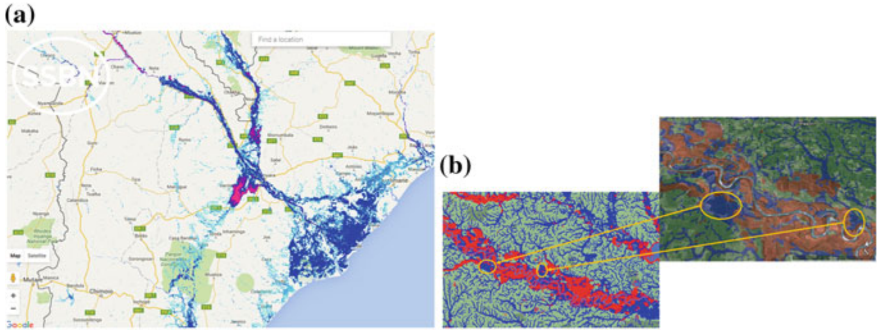

Fig. 10 Illustration of one example of new and innovative solutions/approaches. **a** High-resolution map layers of global flood hazard from 1:100 year return period flow based on the LISFLOOD-FP model (© University of Bristol/SSBN Ltd) made freely available on Google's visualization platform for noncommercial use. Here the area of the Lower Zambezi is shown with flood depth ranging from 1 m (*light blue*) to 5 m (*pink*). **b** MODIS near-real-time flood map (© DFO) of a river near the northern border of Texas during the devastating floods in May/June 2015 (in *red*) overlain on the 1:100 year flood hazard layer from the global flood model shown in **a** (in *blue*). Note that combining satellite observations and models allows to overcome commonly encountered limitations in real-time flood mapping, such as obstruction by cloud and/or forest cover as depicted in the image in the *top panel* in **b**

5 Outlook

The case studies reported in this chapter illustrate great potential and possible ways forward on how the scientific community can engage with the stakeholder community to address most urgent issues, locally, regionally, and globally using EO data. Such connections could allow meaningful discussion that has up to now been largely uncoordinated, oftentimes only taking place on a voluntary effort basis. Such connections are however necessary to globalize and accelerate societal applications that utilize satellite data. This need is further reinforced by the fact that although societal benefits from satellite observations share a number of common features, what works for one region may not necessarily work for another region, even when the problems are similar.

It is clear that the satellite technology and science communities must engage with the stakeholder community to discuss what is possible and most urgently needed. These communities must determine priorities in order to scale up the data and efforts most efficiently in order to benefit societal applications in the best possible way (Hossain 2015). In anticipation of even more data and applications from Earth observing satellites, the Earth science community should engage into identifying key applications alongside key scientific issues. Using these key applications as a guide, the Earth science community needs to establish strong connections with regional stakeholder communities from all around the world, allowing for more rapid dissemination and discovery of EO data at the local level.

Currently, the scientific community has varying perspectives on how these technologies and activities should be pursued in the coming years for the benefit of decision-making and societies in general. Since it will undoubtedly take time and effort to reach consensus, communities should begin to build stronger collaborations and engage to address the challenges that lie ahead.

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