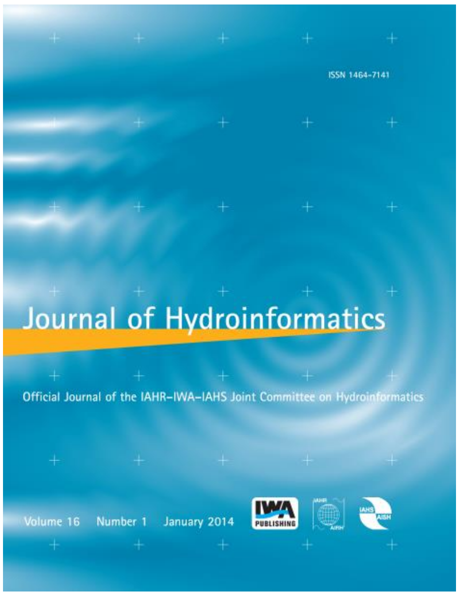
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The SESAMO early warning system for rainfall-triggered landslides

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ABSTRACT

The development of Web-based information systems coupled with advanced monitoring systems could prove to be extremely useful in landslide risk management and mitigation. A new frontier in the field of rainfall-triggered landslides (RTLs) lies in the real-time modelling of the relationship between rainfall and slope stability; this requires an intensive monitoring of some key parameters that could be achieved through the use of modern and often low-cost technologies. This work describes an integrated information system for early warning of RTLs that has been deployed and tested, in a prototypal form, for an Italian pilot site. The core of the proposed system is a wireless sensor network collecting meteorological, hydrological and geotechnical data. Data provided by different sensors and transmitted to a Web-based platform are used by an opportunely designed artificial neural network performing a stability analysis in near real-time or in forecast modality. The system is able to predict whether and when landslides could occur, providing early warnings of potential slope failures. System infrastructure, designed on three interacting levels, encompasses a sensing level, integrating different Web-based sensors, a processing level, using Web standard interoperability services and specifically implemented algorithms, and, finally, a warning level, providing warning information through Web technologies.

Key words | artificial neural network, early warning, integrated information system, MEMS tilt sensor, meteorological micro radar, monitoring system

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INTRODUCTION

Gravitational mass movements include all the processes, from erosion to landslides, that may rapidly modify the morphology of landscape often with destructive effects on human settlements, infrastructures, activities and life. As is widely known, climatic conditions play a crucial role in landslide activation. In particular, heavy precipitation and/or relevantly prolonged rainfall are the most common cause of landslides (Crosta & Frattini 2008). In many cases, mass movements are due to an increasing pore pressure at hydrological boundaries with a subsequent reduction in shear strength. Other causes could be modifications in the slope's geometry as a result of erosion, load due to water saturation, changes of mountains' water level, piping, etc. (Popescu 1994). Both the possible cases of shallow and deep-seated landslides are often referred to as rainfall-triggered landslides (RTLs). The impact of climatic conditions on landslide activation has been widely investigated in the past (e.g., Crozier 1986; Garland & Olivier 1993; Rahardjo *et al.* 1995). Commonly, brief and intense rainfall events typically cause shallow landslides (Cannon & Ellen 1985; Michiue 1985), whereas deeper landslide movements are often triggered by prolonged rainfall of low intensity (Bonnard & Noverraz 2001). Moreover, in certain regions, antecedent conditions may have an influence on the initiation of landslides even more than single heavy events (Kim *et al.* 1992).

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Polemio & Petrucci (2000) reviewed and compared several methodological approaches on the study of RTLs. Such analyses, regarding 234 different countries, showed that Italy provides a relevant sample in terms of widespread predisposition to landslides. Moreover, some recent events have dramatically highlighted the urgent need in Italy of improving the mitigation measures also with more effective strategies for landslides' monitoring and early warning systems (EWSs). Nevertheless, the RTL hazard is not only a specific problem for Italy, but rather a global question, as it is proved by the increasing number of national and international programs and the great economic efforts aimed at a more effective prevention of natural disasters (e.g., Havlik *et al.* 2007; Fernandez-Steeger *et al.* 2009).

An EWS is a non-structural measure for mitigating hazard: it can be thought of as a chain of different information communication systems working together and aimed at the detection, analysis and mitigation of potentially hazardous events. The use of EWSs in landslide management (e.g., Nadim & Intrieri 2011; Thiebes 2012) is rapidly expanding also because they are less expensive than traditional engineered (i.e., structural) mitigation measures that, sometimes, are not even affordable. A new and promising frontier in EWSs for RTL is represented by the combination of hydrological and stability models (e.g. Montgomery & Dietrich 1994; Simoni *et al.* 2008; Capparelli & Tiranti 2010; Arnone *et al.* 2011; Lepore *et al.* 2013). An effective hydrological modelling supporting the evaluation on slope stability and investigating potential landslide triggering factors (e.g., rainfall, soil moisture, antecedent rainfall conditions, etc.) is essential to face and reduce the risk of landslides within a modern and functional EWS, especially where no other mitigation strategies are suitable.

Recent advances in instrumentation have considerably increased the potential for monitoring measures preceding a RTL. At the same time, the development of new and efficient spatial data infrastructures, integrating modern sensor technologies, data storage and retrieval, as well as services for data validation, processing, and warning generation, paves the way to design new EWSs. An example of a modern system has been planned and carried out in Germany within the SLEWS (sensor-based landslide EWS) project, described in Fernandez-Steeger *et al.* (2009).

A similar system for an efficient RTL hazard management, together with a modern real-time monitoring system, represents the basis of the system discussed in this work. In particular, an integrated environmental information platform, able to integrate monitoring services and process multiple heterogeneous spatial information to support stakeholders' decision-making in different fields, is described. The Web-based platform acts as a boundary layer that interfaces external users with the monitoring system.

The entire system has been developed within the Italian research project SESAMO (integrated information system for the acquisition, management and sharing of environmental data aimed at decision-making). The EWS system, specifically designed for shallow landslides triggered by rainfall, has been implemented and tested in a prototypal form; the system has been operative since the end of 2013 and is now monitoring a pilot site characterized by landslide risk.

Some main innovations that refer to the proposed system are synthesized in the following points:

- Use of an advanced monitoring system, arranged by means of different specific and up-to-date sensors: the monitoring system has been designed in order to be flexible, customizable, and built using the most advanced sensors and techniques for sensors fusion. A peculiar and innovative feature of the system is, for instance, the dynamic adjustment of data acquisition timing, which allows for changing the sampling and transmission rate of data to save energy and reduce data. The timing of data acquisition and transmission can be increased automatically, based on rainfall forecast, in situations of interest (e.g., an upcoming relevant rainfall event) or manually by operators.
- Adoption of Web-based technologies for data transmission and managing: data and information transfer, both for input data and output results provided by the system, have been realized using open source Web-based technologies, such as those that are nowadays available from the Open Geospatial Community, and specific protocols. All the heterogeneous sensor data are wireless transmitted to the data sink and converge into a unique information infrastructure (i.e., Web-based platform), where they are stored, processed, displayed and provided to end-users.
- Data retrieved from sensors constitute a first and important source of monitoring information, and are also

processed by specific elaboration modules aimed at the effective blending of information and the implementation of forecasting models for the derivation of warnings. An important data processing module (DPM) of the platform is an artificial neural network (ANN) able to issue specific warnings for landslide over the monitored area. The use of ANNs in studies focused on landslide assessment and prediction is rather common in the literature (e.g., Mayoraz *et al.* 1996; Ermini *et al.* 2005; Doglioni *et al.* 2012; Arnone *et al.* 2014) given their ability to handle a large number of data and learn complex relations between input and output data (Giustolisi & Savic 2006). An innovative aspect of the proposed ANN is related to the adopted training procedure, which uses the physically based and spatially distributed tRIBS-VEGGIE-landslide model (Lepore *et al.* 2013).

After a brief introduction to the SESAMO project, the entire system will be discussed in depth with an accurate description of both the monitoring system and the Web-based information system. Particular attention will be paid to the description of some modules and algorithms adopted in the DPM, such as those used to produce ground corrected radar precipitation maps or the ANN used to evaluate slope stability. Finally, the current status of project and future developments will be discussed, followed by some concluding remarks.

THE SESAMO PROJECT AND THE EARLY WARNING SYSTEM APPLICATION

The SESAMO project involves different scientific and industrial partners with the common objective to create an integrated information system for the acquisition, management and sharing of environmental data and providing environmental services for several applications (http://www.progettosesamo.eu). One of these applications is the development of a modern and efficient EWS for RTLs, which is described in the present work.

The system, whose schematic representation is reported in Figure 1, is constituted by different and interconnected

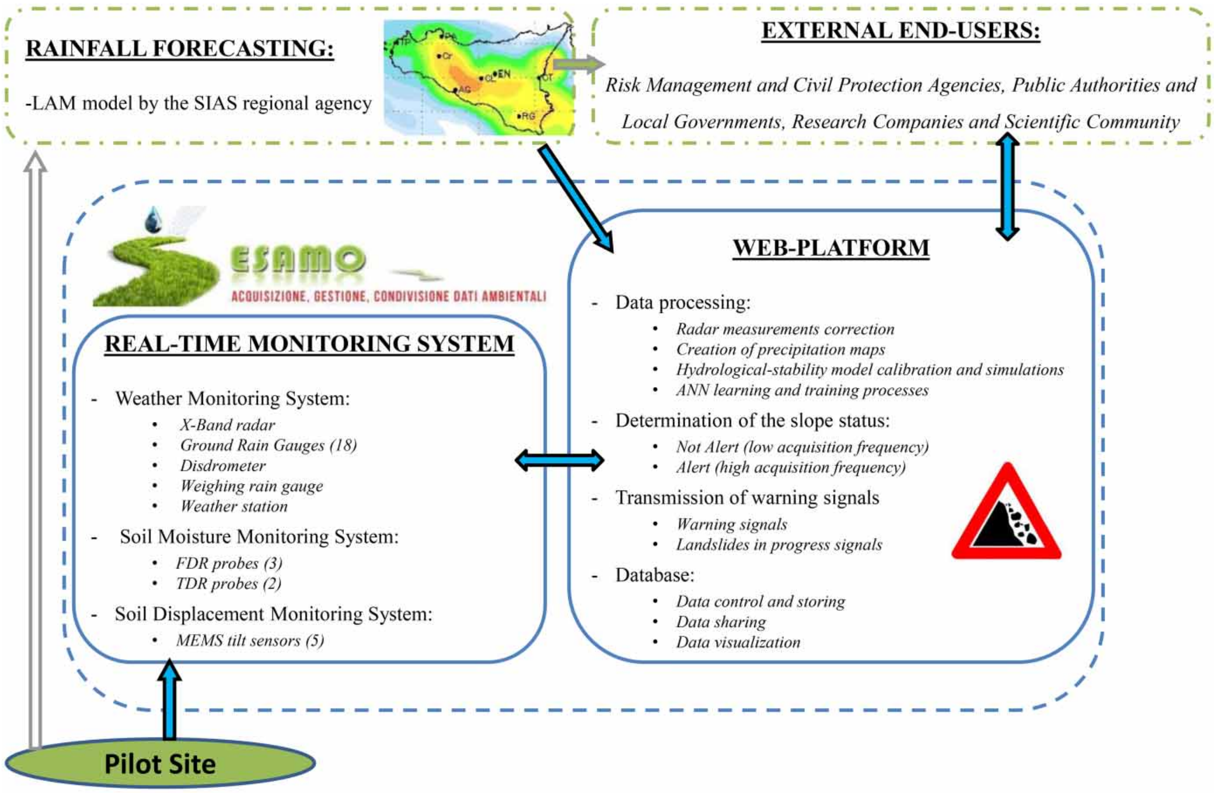

Figure 1 | Schematic representation of the SESAMO EWS for RTLs.

components: the monitoring system, by which heterogeneous real-time data are acquired; the Web-based platform, where data are stored, processed and displayed; the connections with external objects (e.g., other monitoring data providers, the pilot site and the external end-users that are interfaced with SESAMO).

The platform integrates several sub-systems, each one aimed at managing different functions:

- data acquisition, data control and processing, data storage and visualization on the Web platform;
- bilateral communication with the monitoring systems, for data retrieval and for sensors' identification and management;
- hillslope status characterization and generation and transmission of warnings.

The Web-based platform, which can be queried at any time, is able to provide and display all the acquired data and information that could eventually be of interest for researchers, as well as all the local and/or regional agencies and stakeholders involved in hazard assessment and management.

MONITORING SYSTEM

The proposed EWS is supported by an advanced monitoring system involving both the observation of rainfall dynamics in an area of interest and the measurement of several hydrological parameters for a specific potential landslide site identified within the area of interest (i.e., pilot site).

The entire monitoring system can be considered as being constituted by two different subsystems: the weather monitoring system, addressing the retrieving of information related to precipitation dynamics; and the slope monitoring system within the pilot site, regarding soil moisture and soil displacement measurements.

Within the monitoring system two 'conditions' are possible, associated with two different timings of data retrieval by such a system according to two possible configurations: *alert* (data acquisition frequency $= 4\ \mathrm{h}^{-1}$) or *not alert* (data acquisition frequency $= 1\ \mathrm{h}^{-1}$). Thus, all the sensors deployed across the pilot site are able to synchronously vary the acquisition and transmission frequency switching from the low-frequency modality (i.e., *not alert*) to the high-frequency modality (i.e., *alert*), as a function of a signal automatically transmitted to the sensors by the platform.

Weather monitoring system

Given the relevance of the precipitation as the main cause of landslide trigger, an advanced measuring, monitoring and forecasting system has been designed and realized within SESAMO. The forecast/monitoring system consists of different components and provides rainfall forecasts/measurements that feed the hydrological-slope stability model in forecasting/near real-time mode. Moreover, data from the weather module represent, in themselves, a first independent output for potential end-users.

Rainfall forecasts are provided by a limited area model (LAM), which is run by the SIAS regional agency (Servizio Informativo Agrometeorologico Siciliano – Sicilian Agrometeorological Information Service). This LAM is a classical numerical weather prediction model able to provide rainfall amount at hourly time scale with a grid resolution of 7.5 km. The outputs of this model are used to determine the *alert/not alert* condition; in particular, if the 24 hour cumulative rainfall exceeds a given threshold (here prudently set equal to a low value, i.e., 10 mm) the system is set to the *alert* condition and, subsequently, all sensors' data acquisition frequency is increased. In contrast, if forecasted rainfall is lower than the threshold value, the system remains or switches to *non-alert* condition.

The rainfall monitoring system supporting the EWS has been developed by the Department of Civil, Environmental, Aerospace, Materials Engineering (DICAM) of the University of Palermo and covers an area of about 700 km^2 (Figure 2). It consists of a weather micro-radar, a rain gauge network, a weighing rain gauge, a disdrometer and a weather station.

Possibilities of deriving details about the spatio-temporal depiction of rainfall events offered by weather radars, even for local monitoring applications, are increasingly exploited (e.g., Gad & Tsanis 2003; Daliakopoulos & Tsanis 2012; Nielsen *et al.* 2013; Thorndahl & Rasmussen 2013), even if it is worth pointing out that the spatial distribution maps provided by the weather radar are subjected to calibration

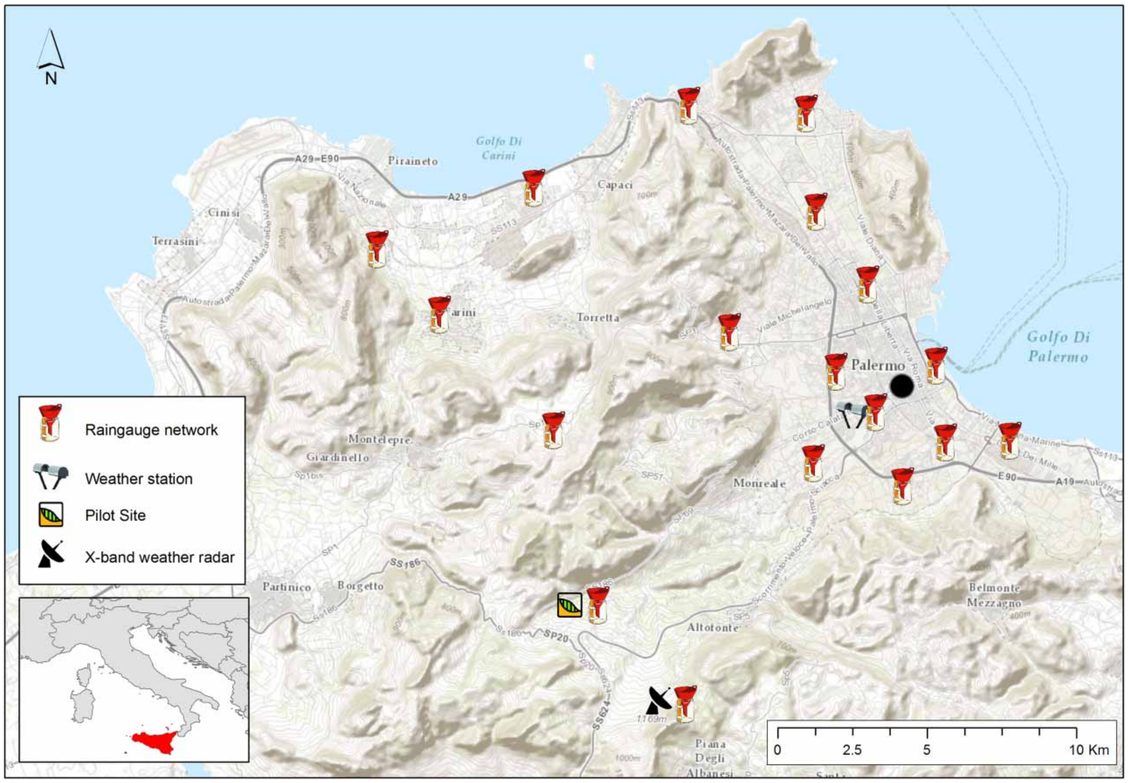

Figure 2 | Study area (Palermo, 38° 05′N–13° 23′E). Localization of the different instruments of the monitoring system covering the pilot site and the entire urban area of Palermo.

and quantitative adjustment based on simultaneous observations from the different rain gauges.

The weather radar used here (Figure 3(a)) is an X-Band mini radar developed by EnviSens Technologies, operating at 9.41 ± 0.03 GHz with a peak power of 10 kW and a maximum range of 30 km. The instrument was installed in the eastern mountains overlooking the urban area of Palermo (Sicily, 38°02′N–13°27′E). A robust procedure that operates the correction for ground clutter values is also provided by EnviSens Technologies and is operationally applied to radar images. The X-band radar is able to produce an image map each minute with a 'virtual' resolution of 60 m. The produced radar maps are transmitted, via GPRS, to SESAMO, where they are opportunely processed.

With regard to rainfall ground measures, a pre-existing rain gauge network managed by the DICAM has been successively expanded, within the project SESAMO. In particular, the original network was made by nine ISCO

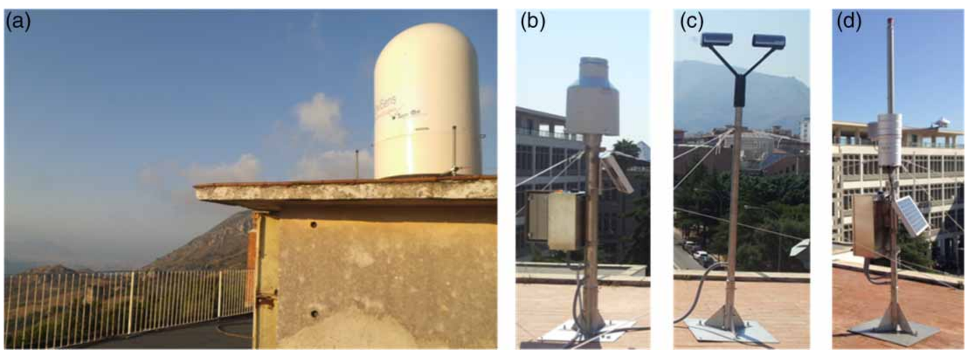

Figure 3 | Meteorological sensors: (a) X-Band radar; (b) weighing rain gauge; (c) disdrometer; (d) weather station.

674 tipping-bucket rain gauges, each one coupled with a data logger to store data. Rainfall, collected with a resolution of 0.1 mm, is first transferred, via GSM, to an ISCO Flowlink® (v. 4.7) database, and then transferred to SESAMO via FTP. This network has been updated with nine more tipping-bucket rain gauges of TECNO PENTA M1 PLUV 1000 series (0.1 mm resolution) which transfer data directly via GPRS to SESAMO.

In addition to the network of tipping-bucket rain gauges, also two benchmark instruments have been installed within the study area (38° 6′18.48″N, 13°20′52.80″E) for the calibration of radar measurements: a weighing rain gauge (OTT – Pluvio2 200) and an optical disdrometer (OTT – Parsivel2) shown in Figures 3(b) and 3(c), respectively. The weighing rain gauge allows high-precision continuous precipitation measurement and is used to check the consistency of the tipping-bucket rain gauge measures. The instrument, which has a collecting area of 200 cm^2, a resolution of 0.1 mm, and is conceived for a precipitation intensity range of 0.05 to 3,000 mm/h, transfers its data via GPRS to SESAMO.

The disdrometer provides the drop size distribution (DSD) that is directly linked to the parameters used to transform radar reflectivity to precipitation estimates. The instrument used here is a laser-based device and is able to calculate the type of precipitation as well as the amount and intensity of precipitation, the visibility in precipitation, the kinetic energy of precipitation and the equivalent radar reflectivity. The latter variable is fundamental for ground comparison at a specific point against radar raw measurements, while the weighing gauge determines high reliable reference values for radar-derived rainfall reconstructions.

Finally, a weather station (Figure 3(d)), which includes different sensors, is used to provide air temperature, relative humidity, air pressure, global solar radiation, wind direction and speed data to the hydrological-stability model.

On-site hydrological and geotechnical monitoring system

The choice of the pilot site has been supported by the regional hydrological system plan PAI (Piano di Assetto Idrogeologico, http://www.sitr.regione.sicilia.it/pai), which provides maps of hydraulic hazard and risk. The criterion used here (i.e., to identify an area with high landslide hazard) led us to the final selection of a hillslope located close to Monreale (Palermo, Italy, 38°05′N–13°23′E; Figure 2), where landslide activation has been observed in the recent past.

The pilot site, with an elevation ranging from 450 to 500 m a.s.l., is shown in Figure 4 by an orthophoto from 2008. In the same figure, a previously activated landslide area, derived from the PAI, is also highlighted. Soil water content and slope displacements are continuously monitored within the pilot area, where one of the rain gauges of the network has also been installed.

Since the soil water content has a key role in triggering landslides, the continuous knowledge of soil moisture at different depths and locations is crucial for monitoring the safety conditions and determining the issue of a warning. Soil moisture observations are used by the system during the preliminary calibration of the hydrological module of the tRIBS-VEGGIE-landslide model and the successive simulation phase by the ANN. More specifically, profiles and values of volumetric soil water content at the surface are measured using three FDR (frequency domain reflectometry) capacitive profile probes and four TDR (time

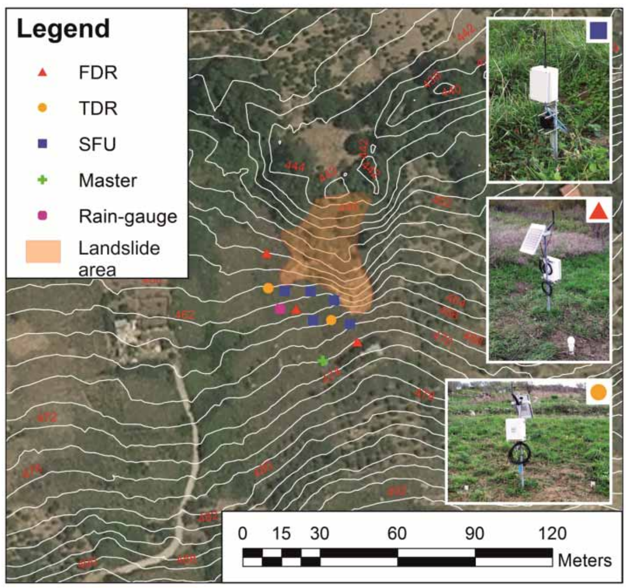

Figure 4 | Pilot site at landslide risk (Palermo, 38° 05′N–13° 23′E). Localization of: soil moisture sensors (FDR and TDR probes); MEMS tilt sensors (SFUs); WSN master; rain-gauge. The previously activated landslide area is also highlighted.

domain reflectometry) probes, and then transmitted, via GPRS, to the SESAMO system. Recorded data are also available for platform users.

Each FDR instrument (Campbell EnviroSCAN) includes four water content sensors that measure soil water at multiple depths (namely 30, 60, 90 and 120 cm below the surface). Around each sensor, the probe creates a high frequency electrical field that extends through the access tube into the soil. The soil water content is then determined from the measurements of electrical capacitance by inversion. Each TDR probe (Campbell CS650) consists of two 30-cm-long stainless steel rods connected to a printed circuit board. This instrument measures propagation time, signal attenuation, and temperature, while volumetric water content, dielectric permittivity and bulk electrical conductivity are then derived by inversion from these raw values. The combined use of the two different sensors types can compensate for some weaknesses of the two methods; e.g., FDR sensors are often sensitive to the soil salinity, especially at low frequencies, and have long periods of stabilization, while TDR sensors are often unreliable in clay soils with a relevant organic matter component.

The real-time slope displacement monitoring is extremely useful for issuing landslide alarms but also in order to verify forecasts of landslide activation, thus minimizing the possibility of issuing false alarms. A new frontier in landslide monitoring is represented by the use of MEMS (micro electro-mechanical sensors) technology for the mass movement sensors such as accelerometers, tilt sensors and inclinometers (Fernandez-Steeger *et al.* 2009). This technology, realized by integration of different small-sized devices and circuits, is nowadays characterized by low production and installation costs. Thus, the use of this technology for landslide sensors allows realization of very dense monitoring networks, with sensors located also at the most inaccessible areas. Moreover, potential economic losses associated with occasional breakage/loss of instruments during landslides could be significantly reduced.

Within the SESAMO project, the mass movements monitoring system has been designed as a series of MEMS-based tilt sensors. Being the monitoring system specific for shallow RTLs, it is possible to assume that landslide events will affect only the superficial layers of the soil and that the kinematics of their movements will be relatively fast. Under such assumptions, a rigid element (e.g., pole) directly rooted into the soil down to the sliding surface, when affected by a landslide, would be subject to a roto-translatory movement. Under this dynamic configuration, the monitoring of tilt angle and the displacement of the pole head become significative and representative for the kinematics state of the monitored portion of soil.

The system has been designed as a network of several functional units (FUs) distributed within the selected monitoring area; each FU is constituted by a MEMS technology-based triaxial inclinometer sensor, fixed on the head of 1-m-long pole, which has to be completely plunged into the soil. The unit is equipped with a module for wireless data transmission, integrated in the MEMS sensor, and is self-powered by a battery. The FUs have been developed and realized by Wisenet (www.wisenetengineering.eu), one of the companies involved in the SESAMO project, despite similar sensors being commercially available. In the selected pilot site, a total number of five slave FUs (SFUs) have been installed close to the previously activated landslide, according to the configuration shown in Figure 4. The system also constitutes a master unit communicating with the remote platform SESAMO through TCP/IP. The master unit and the five SFUs are interconnected through Serial/Ethernet data conversion modules for local communication, forming one of the nodes of a cost-efficient but reliable WSN (wireless sensor network). The master integrates different units (power unit, data processing unit, memory unit and long range transmission-reception unit) and is remotely controlled by the SESAMO platform. The timing of acquisition is communicated from the platform to the master, and then transmitted from the master to the SFUs. Through the master, instantaneous inclination angles are acquired from the different SFUs and transmitted to the Web-platform. Data are finally processed within the SESAMO platform, comparing each value with the immediately previous acquisition to estimate the variation in time of the tilt angle of the pole with respect to the vertical axis and its linear translation; such measurements are compared with opportune threshold values, whose exceeding generates an alarm of *landslide in progress*. To date, such thresholds have been prudently set to a value slightly higher than the maximum sensor background noise measured during a preliminary sensor calibration based on an observation period of one month; the sensors will be calibrated again after a more prolonged period of observation.

WEB-BASED PLATFORM

The main objective of the SESAMO platform is to connect and control heterogeneous sensor networks, devices (e.g., mobile phones) and other external data sources (e.g., FTP, local files, etc.) in order to collect and distribute sensors and map data. Such data are also used to feed a set of expandable and configurable software processing modules delivering variegated products, such as maps and decision support information. SESAMO thus allows users to integrate different types of sensors and distribute their data through a single standard protocol, namely SOS (Sensor Observation Service). Some of the platform main activities include data recovery and processing, control and query of the acquisition/transmission timing for the various sensors in the case of alert conditions, the generation of warning/alarm signals, data and information visualization and sharing on behalf of potential end-users. For these reasons the platform must be flexible and generic in order to support different sensorial data deriving from different devices and transmitted by means of different protocols.

The SESAMO platform is based on standard interoperability interfaces and metadata encodings provided by the OGC (Open Geospatial Consortium) Sensor Web Enablement specifications (http://www.ogcnetwork.net/SWE) including, among others:

- Sensor Model Language – SensorML: describing sensors system and processes associated with sensors observations;
- Observation and Measurements – O&M: describing a data model and a schema for encoding observations from sensors;
- Sensor Observation Service – SOS: providing a standard service for accessing sensor observations;
- Sensor Planning Service – SPS: providing a standard service for requesting user-driven tasks to sensor systems.

Other OGC standards used for the development of the SESAMO platform are:

- Web Map Service (WMS) that produces geo-registered map images from one or more distributed geospatial databases that can be displayed in a browser application;
- Web Feature Service (WFS) that enables the creation, modification and transport of geographic information in a vector format through an HTTP protocol and using the XML-based Geography Markup Language (GML);
- Web Coverage Service (WCS) that provides access and processing of geospatial data;
- Web Processing Service (WPS) that defines standard rules for geospatial input and output processing services;
- Catalogue Service for the Web (CSW) that provides a search, navigation and query interface based on resources metadata, particularly those based on other Web services.

Figure 5 shows a schematic representation of the SESAMO information architecture, highlighting the different modules constituting the platform and the main Web-connected components that are singularly described in the following.

Wireless sensor network, *in situ* inspections, and external sources

The WSN is aimed at the realization of an efficient infrastructure for data gathering and transferring from remote sensors to a central gateway server. The WSN makes use of both commercial and proprietary protocols to transfer sensor data, according to sensor specifications. At the lowest level of its communication stack, the WSN relies on 3G and satellite facilities for data transmission. Through this subsystem, data collected by the monitoring system are sent to a central gateway server, which runs the 'Data Import Tool' software application (described below), in order to store and distribute such data to the platform users. The central gateway server can send tasking requests to programmable sensors as well, thus supplying a bi-directional platform for both sensor data gathering and sensor network management. Please refer to the section 'On-site hydrological and geotechnical monitoring system' for a detailed description of all physical components of the WSN. The objective of the ISI (*in situ* inspection) subsystem is to transmit, through mobile devices such as smartphone or tablet, a specific set of information gathered *in situ* to the platform, e.g., media and text information describing either the state of sensors or that of the environment. This information, periodically or exceptionally collected by

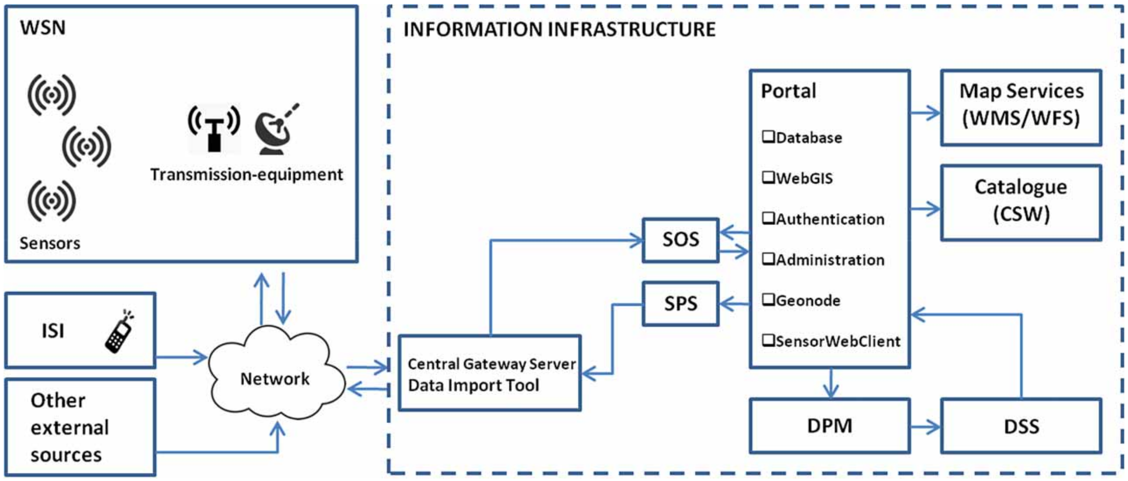

Figure 5 | SESAMO architecture. Schematic representation of modules constituting the platform. ISI, *in situ* inspection; SOS, Sensor Observation Service; SPS, Sensor Planning Service; DPM, data processing module; DSS, decision support system.

expert operators in the field, may support the analysis of results by the other subsystems of the platform and is useful in the decision process to address specific actions.

Finally, the possibility of using external data sources has been considered within the information infrastructure of SESAMO. In particular, such a component has been used for introducing data from the rainfall forecasting model, provided by the local weather agency SIAS. A module of the Data Import Tool has been designed for the 'ingestion' of this data source within SESAMO.

Information infrastructure

Sensor observation service, sensor planning service and data import tool

The SOS standard Web interface allows for storing, retrieving and accessing sensor measurements. The SOS is both used by sensors (via the central gateway) to push observation data into the platform database and by other SESAMO modules to filter and retrieve data for subsequent processing.

The standard Web interface for sensor tasking purposes is the SPS, which is here mainly used with the aim to change the acquisition frequency of a remote sensors subset. Both the SOS and SPS implementation are provided by 52°North Initiative for Geospatial Open Source Software GmbH (http://52north.org/).

Since most of the sensors cannot directly interface with SOS and SPS, a gateway, i.e., the Data Import Tool, has been developed as a plugin that enables the communication with either sensor sockets or specific software protocols, data accessed by means of FTP repositories, external databases, and loading them into the database. The Data Import Tool is also in charge of allowing bi-directional communication between the platform and the sensors, thus enabling sensor tasking. For this purpose, an additional plugin was developed to load tasking requests managed by means of SPS and to send them to the sensors via a proprietary protocol.

Catalogue, map services, data processing module, and decision support system

The catalogue component enables the management of metadata using CSW services. It has been implemented by means of GeoNetwork software (http://geonetwork-opensource.org/) that is based on ISO 19115 Geographic Metadata and ISO 23950 standards. The module allows for both the upload and the search of information from data stored in the SESAMO information infrastructure.

The map services component allows for the management and visualization of distributed geographic information through the standard services WMS, WFS and WCS, implemented by the open source software Geoserver (http://geoserver.org/).

The DPM, based on the OGC WPS service, encapsulates different processes, such as those providing geospatial functionalities and geo-processing. The algorithms of the DPM, such as that for the radar maps ground correction and the ANN, will be described in detail in a specifically dedicated section (Algorithms of the DPM). All the algorithms can be invoked using the WPS. The DPM can retrieve data from SOS, WMS, WFS and the database to supply data to the encapsulated service for processing. Also the WPS implementation is provided by 52°North Initiative for Geospatial Open Source Software GmbH.

The decision support system (DSS) uses modules and algorithms of the subsystem DPM, providing textual or graphical suggestions to expert users supporting the decision process to develop opportune actions. Therefore, from the DSS it is possible to analyse and retrieve an interpretation to algorithms' results.

Portal

The portal represents the interaction and interface layer between the platform, with its services, and the system users. Two typologies of users can access the portal, namely service users and administrators; the portal provides a different user interface for each of them. Administrator users can configure several aspects of the platform; for example, they can create, modify and cancel user accounts or address them to a specific domain. Service users, once logged in, can access several platform tools for map visualizations, data retrieving and downloading, using the implemented sub-models. The application is based on the integration of different open source software such as Geonode, 52°North Sensor WebClient and other proprietary modules such as WebGIS (http://www.webgis.com/). Geonode allows the uploading of spatial data, such as raster and vector maps, in order to distribute them through WMS/WFS according to specific user permissions. Moreover, Geonode updates metadata and configures services for the managing of data using CSW services. The sensor WebClient offers access to measurements retrieved from the SOS. It supplies a map from which the user can select a sensor station, choose a phenomenon and then plot a diagram of data within a time interval. Selected data can also be exported as CSV files for further analysis.

The WebGIS module shows users configured maps containing a selection of layers. The spatial distribution of sensors is available as a derived layer. From the WebGIS module it is also possible to modify sensor acquisition frequencies by means of SPS.

ALGORITHMS OF THE DATA PROCESSING MODULE

The DPM includes different sub-modules, each one containing opportune algorithms, which are directly or indirectly necessary for the generation of the different products by the system. In particular, the DPM is essentially based on three sub-modules as shown in the sections below: the first sub-module is aimed at the calibration of the radar base equations; the second sub-module operates the ground radar maps correction, taking into account all the point measurements arising from the tipping-bucket sensor network; finally, the third sub-module constitutes the ANN, a data-driven model, used to investigate the slope stability.

Radar base equations' calibration

In order to build a reliable and accurate system for the rainfall monitoring, weather sensor data have to be exploited by means of different operational modules and algorithms forming a specific sub-system of the DPM aimed at the radar base equations' calibration and rainfall radar maps' corrections. The general structure considered for this system is provided in Figure 6, where the input data measurements obtained by different sensors, the application modules and their outputs are represented and linked in a functional scheme.

The base equations for the radar are here referred to as radar equation and Z-R equation. The first links the radar raw measurements to a physical quantity, called radar reflectivity Z, which is related to the rainfall rate R. The Z-R equation represents the functional relationship between these two variables. Both the equations can be calibrated using the reference Z and R values provided by the disdrometer and derived from the DSD. While the radar equation is calibrated comparing the radar raw data and the disdrometer reflectivity, the Z-R relationship is calibrated on the base of the values of Z and R as retrieved from the

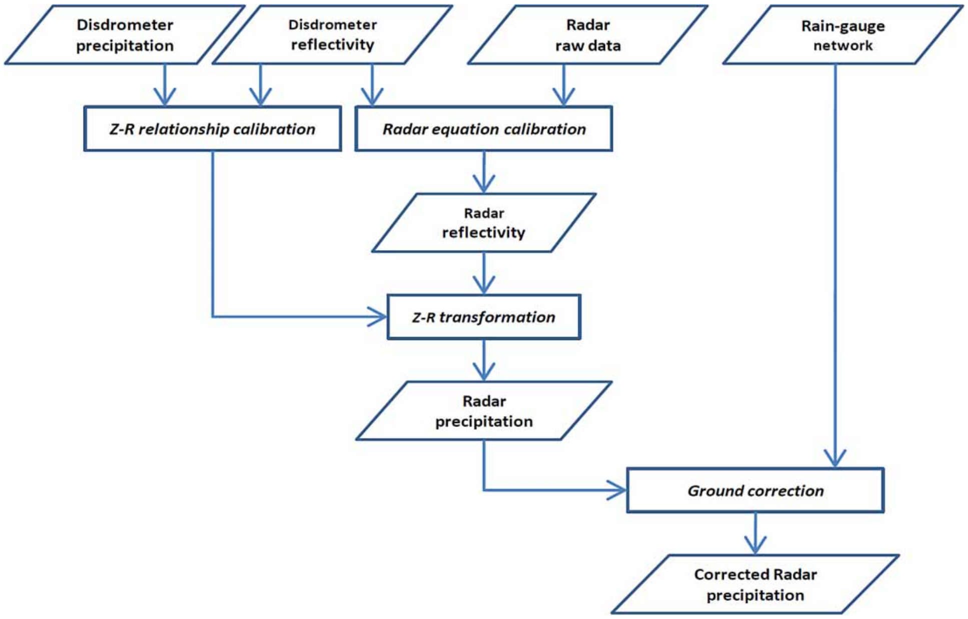

Figure 6 | Schematic representation of the system for precipitation measurement and radar maps ground correction.

disdrometer. Finally, radar estimates are constrained to ground point measurements with a correction procedure based on rain gauges measurements.

Radar data are preliminarily corrected for ground clutter and partial beam interceptions with an algorithm based on clear sky conditions developed by EnviSens Technologies and distributed with the device (Allegretti *et al.* 2012).

The calibration of the radar equation consists of an adjustment of the value of a constant resuming all the physical and device losses. In particular, the calibration is carried out computing the RMSE (root mean square error) value between the radar reflectivity measured by disdrometer and those obtained from radar raw data and the radar equation for values of the constant ranging between 90 and 100 dBZ (i.e., a range where the value of the constant is expected for the specific device), and selecting the value corresponding to the minimum RMSE. For a reference event, this procedure has led to an increment of the default value provided by developers for this constant (i.e., 91.4 dBZ) of about 5% (i.e., 96.4 dBZ).

A simple and efficient form for the Z-R equation is the well-known Marshall & Palmer (1948) equation:

$$Z = a \cdot R^b \qquad (1)$$

The parameters a and b of this equation are often derived from the literature, where the characterization of their values can be found accordingly with the weather event typology (e.g., Joss & Waldvogel 1969, 1970). Since the disdrometer provides direct measurements of Z and R based on the *DSD*, it is possible to design an appropriate calibration module for the Z-R equation parameters' calibration. From the analysis of the performance associated with various couples of parameters a and b, in terms of RMSE between the direct disdrometer R values and R estimated from the values of disdrometer Z, an optimal couple of parameters, corresponding to the minimum RMSE, has been detected. Such a procedure is summarized, for a reference event that occurred on 2nd March 2014 (in Figure 7), where all the values of RMSE obtained for different continuous ranges of a and b are displayed, and the optimal values are also highlighted. This analysis has been repeated for the events registered within a one-year-long disdrometer record set allowing for the characterization of Z-R relation parameters for the study area. Results of this characterization can be summarized by deriving the median values of parameters ($a = 279.5$, $b = 1.71$); these values are slightly different from the literature values often adopted (e.g., $a = 200$, $b = 1.6$) reported by Marshall &

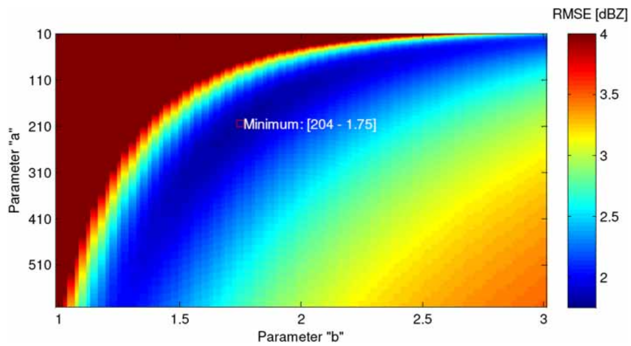

Figure 7 | Calibration of Equation (1) parameters *a* and *b*.

Palmer (1948) and Marshall *et al.* (1955). These constant values are used as default values by the system when the real-time calibration cannot be accomplished.

Radar maps' ground correction

Rain gauge measurements are usually considered as reference values for quantitative applications, and then achieving the congruence between radar estimates and rain gauges measurements is assumed as a target for the precipitation monitoring system. With this aim, here we adopt a ground correction algorithm based on the spatial gauge-radar adjustment technique proposed by Koistinen & Puhakka (1981).

The method is based on the estimate of a multiplicative correction map given by two components: a regression radial corrective field and a local residual component weighted with distances between pixel radar value and available rain gauges. The accuracy of this procedure is clearly related to the density and spatial distribution of the ground rain gauge stations. For this reason the original tipping-bucket sensor network has been doubled in the number of instruments and one of the rain gauges has been placed within the pilot site.

The comparison between some measures from rain gauges and corresponding radar point estimates, considering a 15-minute cumulated precipitation, has shown a good level of agreement in terms of mean values and correlation. Some inconsistencies can be related to different factors such as the different nature of the physical variables measured by rain gauges and radar, the different elevations at the sites (i.e., rain gauges) where the correction is performed (whose effect could be exacerbated by the presence of wind), other issues related to the not perfect coincidence between the rain gauge and the corresponding radar-pixel value, etc.

In Figure 8, an example of the application of the ground correction procedure described above is reported with regard to a reference event and considering a 15-minute accumulated map. From the observation of original and corrected radar maps, it can be observed that the procedure succeeds on applying a spatial distributed correction to the entire map and modifying some spatial features according

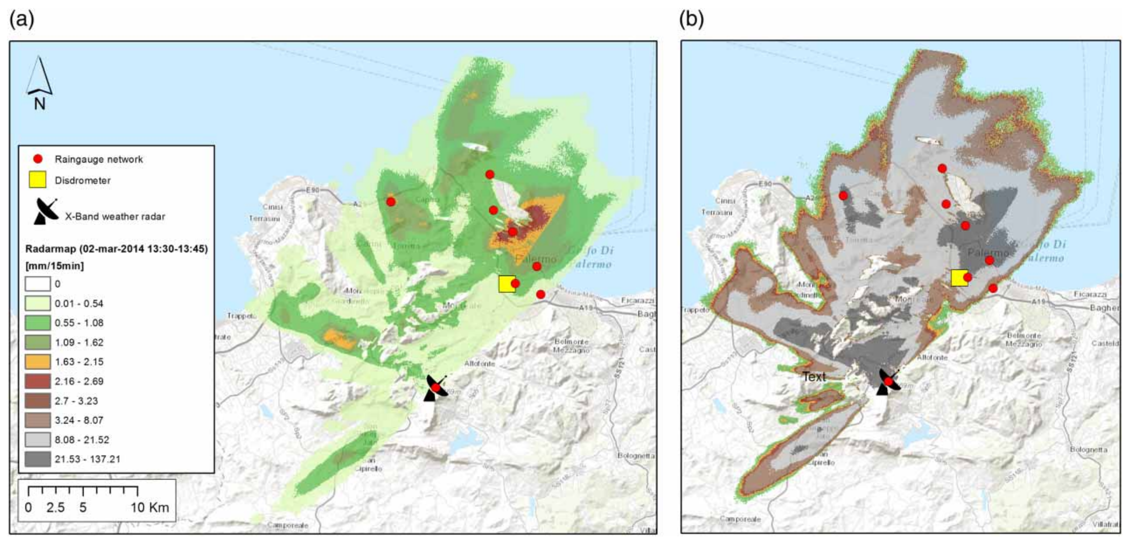

Figure 8 | (a) Radar raw estimate and (b) corrected precipitation maps.

to rain gauge values. The generation of accurate rainfall maps is one of the expected products of the SESAMO Web platform and, for this purpose, it is possible, for an interested user, to download corrected radar maps deriving from this sub-module (such as that represented in Figure 8(b)) for any rainfall event.

The artificial neural network (ANN)

The evaluation of the hillslope conditions, in both *near real-time* and *forecasting* modalities, is carried out by using an ANN, specifically designed and trained to predict the stability conditions as a function of meteorological variables. The stability conditions are provided by the ANN in terms of a stability index (SI) which is modelled using a continuous scale ranging from 0 (stable) to 1 (unstable).

The type of used ANN, schematically depicted in Figure 9, is a feed-forward multi layer perceptron (MLP) network, which is one of the most adopted ANNs for landslide susceptibility applications (e.g., Lee *et al.* 2004; Caniani *et al.* 2008; Melchiorre *et al.* 2008; Pradhan & Lee 2009). Network design and training properties were chosen following Arnone *et al.* (2014).

The ANN was built up considering the following variables: (1) event duration, (2) cumulated rainfall depth, (3) maximum intensity, (4) initial soil moisture, and, finally, (5) the corresponding stability condition in terms of SI. The input layer consists of four neurons corresponding to the first four mentioned input variables; the output layer consist of one neuron that provides two possible stability conditions, *landslide* (1) or *no-landslide* (0); while, in the hidden layer, eight neurons are set (Figure 9). Numerical computing was carried out through the software Matlab (MathWorks).

The training phase of the network, i.e., the 'learning' process of the relationship cause–effect between input and output variables, requires a training data set that consists of sets of input variables, representing different conditions and events, for which the stability conditions (output) are known. In order to create a reliable training data set and since the ANN requires a large data set in which both input forcings and output conditions are present in sufficient ratio, a physically based and spatially distributed model, the tRIBS-VEGGIE-landslide (Lepore *et al.* 2013), is used as a simulator of natural hydrological-stability processes. Variations of the stability conditions in time and space as a function of rainfall and soil moisture forcings are thus estimated to generate an appropriate data set for training and testing the ANN. The algorithm used for the training is the GDM (gradient descend with momentum), that is one of the back-propagation algorithms most suitable to manage a large amount of data.

The tRIBS-VEGGIE-landslide belongs to the widely used category of hydrological-stability models able to estimate the stability conditions at distributed scale in terms

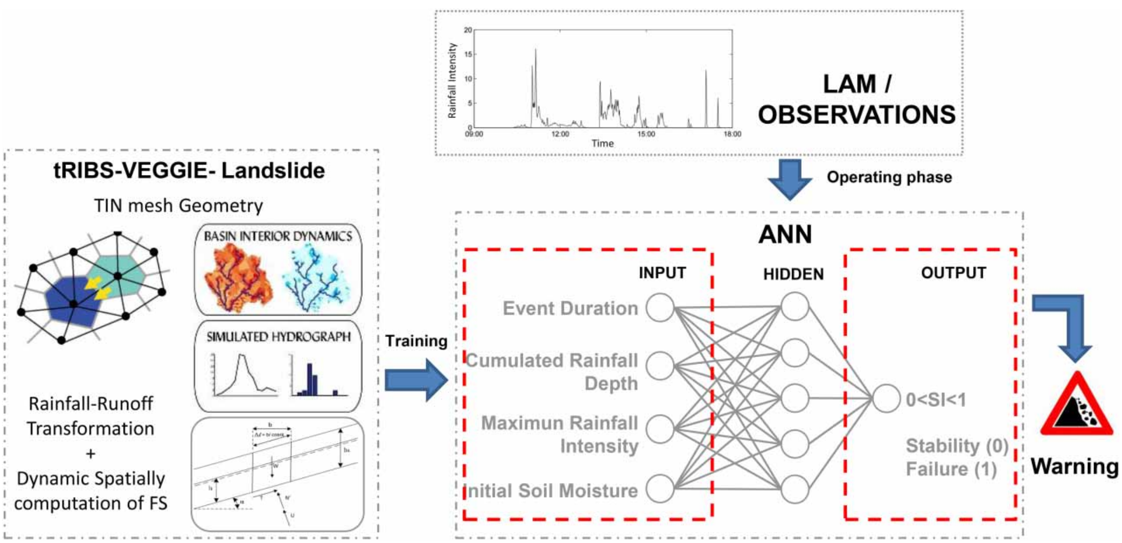

Figure 9 | Schematic representation of the artificial neural network (ANN). TIN, triangulated irregular network; SI, stability index; LAM, limited area model.

of a factor of safety (FS), defined as the ratio between destabilizing and stabilizing forces acting on a supposed failure surface; the FS can therefore be higher (stability condition) or lower (instability) than one. Such types of models are based on numerical approaches and require various types of information both distributed and not, such as: topography (e.g., digital elevation model, DEM), land use, type of soil, soil and land parameters, climatic parameters.

The soil moisture dynamics are simulated by means of an ecohydrological module that takes into account the main hydrological processes at the catchment scale (i.e., evaporation, infiltration, interception, etc.) as well as biochemical and biophysical processes of plants interacting with the soil and the atmosphere. In particular, for a given computational cell, the model provides the soil moisture time profile with the resolution of the 1D Richards equation, also taking into account the effects of plant roots' uptake. The FS time profiles are calculated using the infinite slope equation for saturated and unsaturated soils (Lepore *et al.* 2013):

$$FS = \frac{c'}{\gamma_s z_n \sin\alpha} + \frac{\tan\phi}{\tan\alpha} + \frac{\gamma_w \psi_b}{\gamma_s z_n} \cdot \left(\frac{\theta - \theta_r}{\theta_s - \theta_r}\right)^{1-1/\lambda} \cdot \frac{\tan\phi}{\sin\alpha}, \quad (2)$$

where c' and ϕ are geotechnical parameters of the soil (cohesion and friction angle, respectively), γ_s and γ_w are the specific weights of soil and water, respectively, z_n is the thickness of the soil measured along the normal to the direction of the slope, α is the angle of the sliding plane, ψ_b, λ, θ_r, and θ_s are hydrological parameters of the retention curve of the soil (i.e., height of capillary rise, index of pore-size distribution, content and residual water saturation, respectively), and θ represents the water content at the time in which FS is computed. The model does not require assumptions about the depth of the sliding plane (and thus the thickness of the soil involved in the landslide); FS is calculated at different soil layers, which correspond to the vertical mesh used to evaluate the soil moisture profile. Hence, the sliding surface of the computational cell is allocated to the depth where the minimum FS value is achieved.

The complexity of the physically based hydrological-stability model and the associated high computational cost justify the choice of using the ANN to simulate the numerical model during the operative phases, which allows the system to reduce the computation time and maintains the efficiency in the evaluation of hillslope conditions.

ANN training and validation procedures

The ANN is associated with a given hillslope, which has to be previously characterized geometrically, hydrologically and geotechnically. The adopted procedure to train the ANN encompasses three different procedural steps: calibration of the tRIBS-VEGGIE-landslide model for the pilot site; generation of a sufficiently long synthetic rainfall events series; assessment of the stability conditions, *landslide* (1) or *no-landslide* (0), as a function of the different external forcings (rainfall and soil moisture).

The tRIBS-VEGGIE-landslide model was first calibrated on the hydrological component at the pilot site considering a time window from mid-January, 2014, to mid-June, 2014. Rainfall data necessary for calibrating the model were collected from the rain gauge installed within the study site, assumed as uniformly distributed over the entire hillslope. Geotechnical soil parameters were assessed through an appropriate survey campaign at the pilot site; in particular, given the small area of the study site, only two soil samples were taken, representative of the upper and the lower parts of the hillslope, respectively. Both the samples showed that the dominant soil type is a clayey soil with a higher percentage of silt (42%) in the upper part of the hillslope as compared to the lower part of the hillslope (28%) and low percentages of sand and rock fragments in the surface layer (Table 1). The hillslope was assumed to be divided into two homogeneous parts (i.e., the upper and the lower) with spatially uniform soil and land use characteristics. The initial soil hydraulic parameter values were inferred from soil data, such as soil texture data and bulk density, by means of Rosetta (Schaapp *et al.* 2001), a computer program that translates basic soil data into hydraulic properties through pedotransfer functions. Measurements provided by FDR and TDR probes were subsequently used to calibrate some of these parameters on the basis of the soil moisture profiles and performing an accurate tuning of the hydrological parameters that can be also defined at various depths. Soil and hydraulic properties

Table 1 | Model parameters and characteristics of the pilot site

Characteristic	Initial values: Upstream	Initial values: Downstream	Source	Final values: Upstream	Final values: Downstream
Clay [%]	51	59	S	–	–
Silt [%]	42	28	S	–	–
Sand [%]	7	12	S	–	–
Rock fragments [%]	–	1	S	–	–
Bulk density [g/cm^3]	1.556	1.539	S	–	–
Soil moisture at saturation [cm^3/cm^3]	0.506	0.499	R	0.460	0.450
Residual soil moisture [cm^3/cm^3]	0.104	0.100	R	0.235	0.225
Saturated hydraulic conduct [mm/hr]	1.386	2.128	R	0.750	

R = from Rosetta (Schapp *et al.* 2001); S = from survey.

of the study site derived for both the upper and lower parts are reported in Table 1.

The second and third operational steps of the training procedure are aimed at creating, through the tRIBS-VEGGIE-landslide model, a training data set for the ANN representative of different possible scenarios. In particular, at the second step, a 100-year-long hourly rainfall series has been generated using the stochastic weather generator AWE-GEN (Fatichi *et al.* 2011). The synthetic rainfall time series has been used, at the third step, to force the calibrated hydrological-stability model, which provides, as outcome, the corresponding time series of FS.

Starting from the generated weather forcing time series, it has been possible to extract about 15,000 rainfall events and to characterize them in terms of duration, intensity and total precipitation. For each of these events also the initial soil moisture and the minimum value of FS have been derived and recorded.

Starting from the tRIBS input forcing and model output, the final data set, consisting of five vectors (i.e., event duration, rainfall depth, maximum intensity, initial soil moisture, stability condition) has been obtained and then used to train the ANN. Figure 10 shows an extraction of the whole time series. Each event is characterized by rain duration (Figure 10(a)), rain depth (Figure 10(b)) and maximum rain intensity (Figure 10(c)). The tRIBS-VEGGIE-landslide provides the initial soil moisture prior of each event and computes the resulting FS. In particular, Figure 10(d) shows the mean value in depth of the initial soil moisture profile. The output values of FS were then reclassified in terms of SI in order to assume either value 0 (i.e., not failure condition for FS $>$ 1) or 1 (failure for FS $\leq$ 1) (Figure 10(e)). The figure highlights the importance of considering the soil moisture condition prior to each event, whose effect can be more significant than the maximum rainfall intensity or total rainfall depth. In fact, most of the failure cases occur at very high initial mean soil moisture. Among all the analysed rainfall events, 136 resulted associated with a failure event in tRIBS-VEGGIE-landslide, corresponding to about 1% of the total number of rainfall events.

The ANN developed here is site-specific and for any area different from the pilot site described (e.g., different geometry and hydrological and mechanical properties), the ANN has to be trained again.

An essential component in evaluating reliability of geomorphic models is validation against observed data. Given the absence of a historically consistent database of observed landslide events, in order to validate the ANN, a comparison between the two used models (tRIBS-VEGGIE-landslide vs. ANN) has been performed under a new climate scenario generated by the AWE-GEN. This new scenario is represented by a synthetic, 25-year-long hourly rainfall series and contains about 3,500 rainfall events.

Following the same procedure used for the training phase, the time series has been used to force the calibrated tRIBS-VEGGIE-landslide model and thus obtain the data set to validate the ANN. Based on this new simulation, the tRIBS-VEGGIE-landslide returned 27 landslide events.

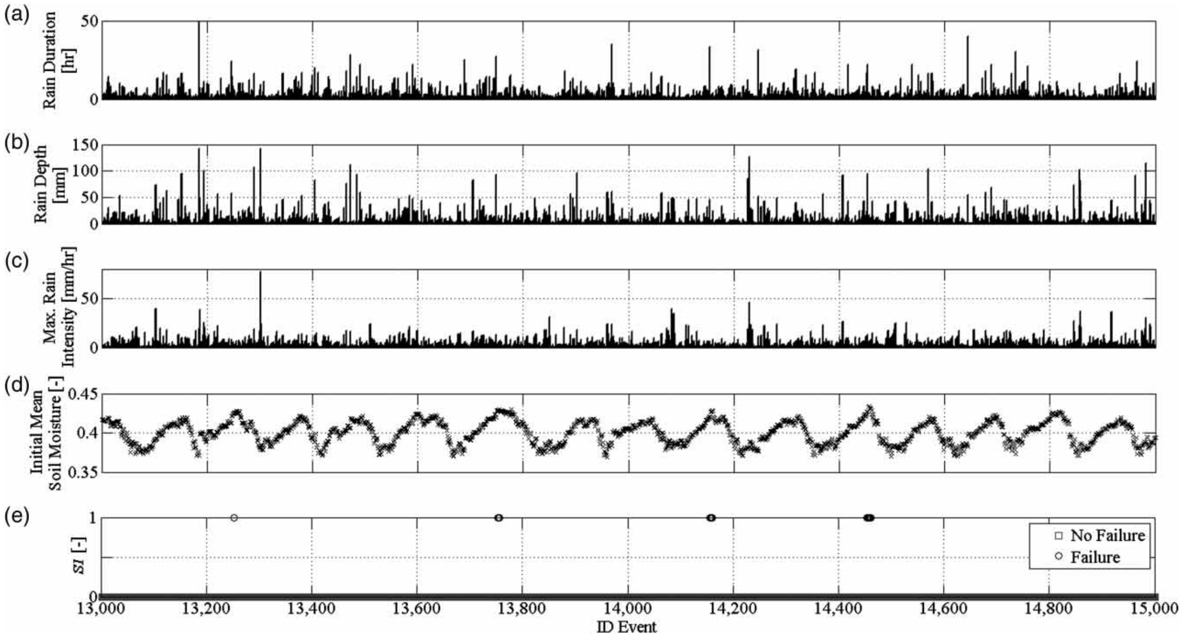

Figure 10 | Extract from the training data set for the ANN. Series relative to the last 2,000 events (of a total of 15,000) are shown. Duration, depth and maximum intensity of the synthetic precipitation series, used to force the tRIBS-VEGGIE-landslide model, are shown in the three upper panels ((a), (b), (c), respectively). Initial mean (in depth) soil moisture and corresponding stability condition, obtained as model outputs, are shown in the two lower panels ((d), (e), respectively).

The ANN outputs were relevantly consistent with those obtained by the tRIBS-VEGGIE-landslide model for the test period, since the ANN was able to predict correctly about 93% of *no landslide* events and about 95% of *landslide* events, with about 7% of *false alarm* and about 5% of *missed detection*.

Operating ANN

Once all the design, training and classification steps of the MLP are defined, the network is able to provide, running in an efficient way within SESAMO, the stability conditions in terms of SI ($0 \leq \mathrm{SI} \leq 1$) induced by the *near real-time* (through the immediately previous sensors acquisitions) or *forecasted* (through the LAM outputs) meteorological conditions. The network has been implemented into the DPM with an executable object managed by both the system and users by means of an interfaced WPS.

The ANN outputs thus lead to the issuance of *warning signals* by SESAMO in the case of hillslope instability, i.e., when SI overcomes a cutoff value that can be defined by the decision-maker. In order to minimize the generation of false alarms, which is a common problem in many traditional EWSs, the evaluation of the hillslope stability, in *forecasting* mode, is carried out using the first 24 hours of the LAM projections. In fact, it is widely recognized that quantitative precipitation forecast is less reliable as the time span increases. Thus, in order not to propagate the uncertainty arising from weather model into the stability model, we preferred to limit the warning time, nevertheless ensuring the issuance of adequate (i.e., daily) advance warning.

DISCUSSION

The proposed EWS still has to be considered as in a prototypal form, even if most of the key elements have been fully developed and are already operative, such as the monitoring system and the platform modules for data acquisition and processing, and for the management of the visualization/sharing/downloading processes of the different platform products (data tables, graphs, radar precipitation maps, etc.).

The platform is already able to generate accurate precipitation maps, thus producing one of the expected user delivered products of the system. The above-described prototypal procedures for the radar and the Z-R equations' calibration and for the precipitation map ground correction, refer to an ensemble of applications developed for the joint use of only some of the available different sensors. In order to obtain more robust parameters accounting for the effects of rainfall event features on the Z-R equation, the application for a selected set of events will also be required. Moreover, a further module will be shortly added for the comparison of weighing gauge and tipping-bucket rain gauges, in order to perform the calibration of the latter.

To date, the system has been running only for a few months (excluding the preliminary set-up period), which is obviously a short time with respect to the possibility of determining the dynamic evolution of a complex hydrological process such as RTLs. During such a brief and relatively dry observation period, no critical rainfall event producing instability conditions for the pilot site has occurred. The correct functionality of the SESAMO system has been tested and verified from both a hydrological and informatics point of view as a whole system and for the different components of the system.

The monitoring system is correctly recording weather, soil moisture and soil displacement data. The data transfer system has been checked from an informatics point of view and no issues have been detected. Each single sub-component of the Web-based platform has been tested, verifying that data are correctly stored and/or processed (correction and delivery of radar maps) and used to determine slope stability by the ANN component. The platform correctly receives external weather data, namely those provided by the LAM of the SIAS regional agency, and is proved to be able to switch the timing of data acquisition/transmission (*alert* or *not alert* configuration) depending on the 24-hour cumulative rainfall forecasts. The platform has been also proved to be able to transmit warning signals to external end-users.

During the monitoring period, although the system has switched from the *not alert* to the *alert* configuration almost 30 times up to now, the ANN has never issued warnings and, coherently, no slope movements have been detected by the tilt sensors network over the pilot site. The non-issuance of false alarms can be considered as a positive proof of the system functioning as a whole, even if some false alarms could be expected as a consequence of ANN performances shown in the section 'ANN training and validation procedures'; unfortunately the lack of detected historical landslides precludes the possibility of a rigorous and complete validation of the system in addition to the validation model vs. model shown in that same section.

An example of data visualization by the SESAMO platform is shown in Figure 11. More specifically, the main view for sensor query is shown in Figure 11(a), while a view for time series visualization is shown in Figure 11(b). Each sensor can be selected within a dedicated graphical tool and its location is visualized in a map (Figure 11(a)). One or more time series can be selected for visualization (left panel of Figure 11(b)) and the relative plots are displayed in a dedicated panel on the right panel of Figure 11(b). In the example shown in Figure 11(b), relative to a 12-day-long period (i.e., from 20 January to 31 January 2014), the top plot on the right shows rainfall forecasted by the LAM; in particular, the bars refer to 1 hour rainfall depth (mm/h), the solid line refers to the 24 hour cumulative rainfall (mm/day) while the dashed line shows the rainfall threshold (i.e., 10 mm/day) fixed to switch the system from the configuration *not alert* to *alert* and vice versa. The middle plot shows the rainfall intensity (mm/h) arising from the ground-corrected radar precipitation maps (pixel covering the pilot site). The bottom plot refers to the average relative soil moisture.

Forecasts provided by the SIAS were very close to the measured rainfall over the entire period represented in the figure. Three sub-periods with 24 hour cumulative rainfall forecasts above the fixed threshold can be seen in Figure 11(b). During such periods the system has operated accordingly to the high-frequency (4 h^{-1}) modality (i.e., *alert*), and this can be highlighted observing the denser traces relative to the measured rainfall and soil moisture. Soil moisture profile is hydrologically consistent with precipitation measurements for the selected period. Similar time series for other kinds of data and for different periods could be selected and visualized, such as tilt sensors data or the SI computed by the ANN (not shown here because not informative – horizontal line with values equal to 0).

Despite the applicability of the proposed system in an operational way being encouraging according to the obtained

(a) (b)

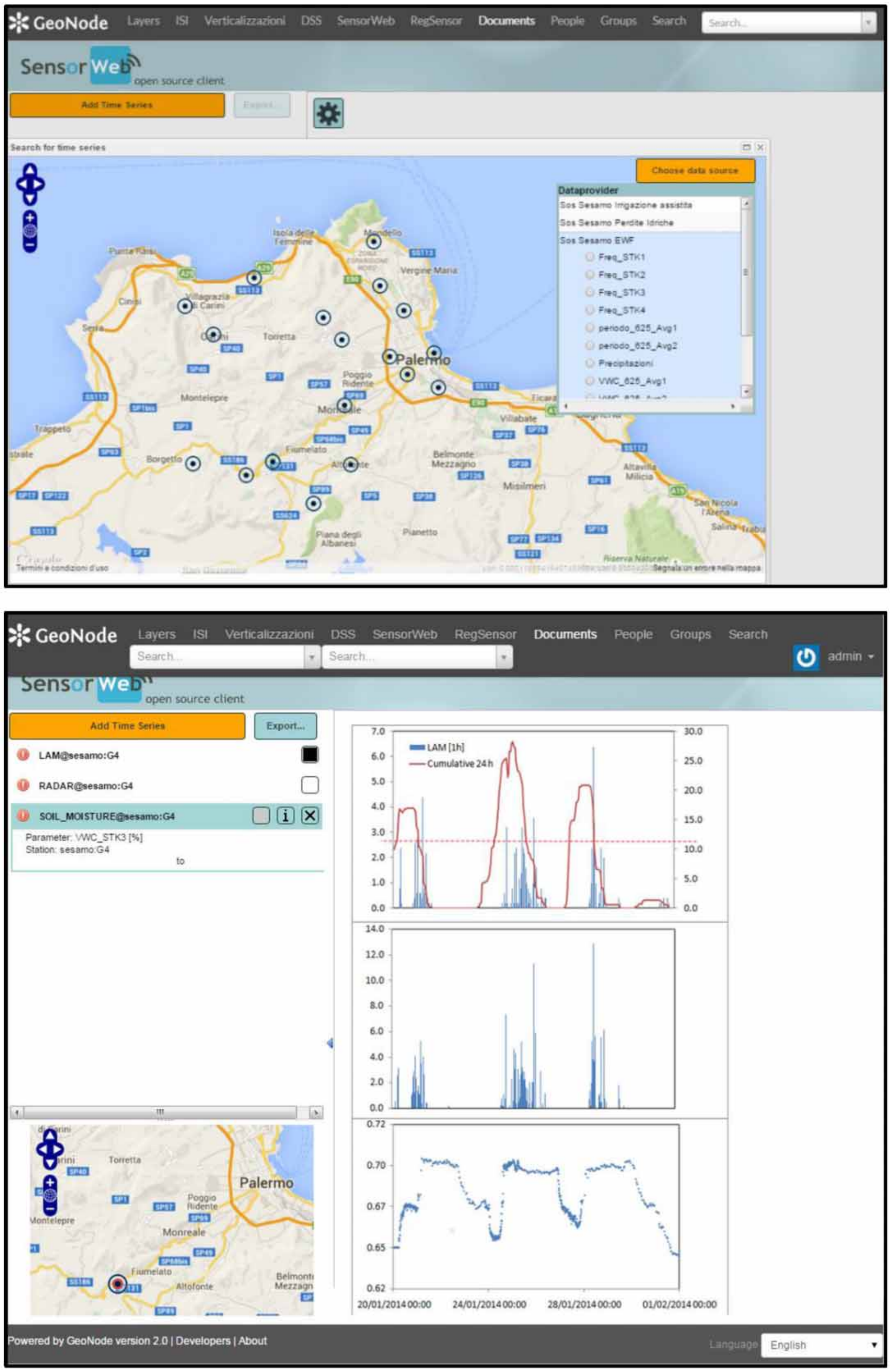

Figure 11 | Example of data visualization by the SESAMO platform: (a) main view for sensors query; (b) three different time series for the same 12-day-long period (from 20 January to 31 January 2014) have been selected (on the left) and visualized (on the right). The top-right panel refers to the 1 hour rainfall (bars, mm/h) and the 24 hour cumulative rainfall (solid line, mm/day) forecasts (from the LAM of the SIAS regional agency) for the pilot site. Middle panel on the right refers to the measured rainfall for the pilot site (data from radar after data processing). Bottom-right panel shows the average relative soil moisture measured within the pilot site.

preliminary analyses, the effective functionality of system capabilities to provide reliable warnings relative to RTLs should be verified in a longer period of application. This future objective, beyond the scope of the present work, is currently under investigation in order to test the ability of the system in correctly issuing landslide warning before the event itself and minimizing the number of false alarms.

CONCLUSIONS

Rainfall is the most common triggering cause of landslides and the monitoring of some key variables is essential to predict the behaviour of RTLs. Given the urgent need for efficacious systems for the mitigation of the effects due to RTLs, we have described a modern and accurate EWS supported by an extremely advanced weather monitoring system and a relatively low-cost sensor network displaced over a monitored slope.

The entire SESAMO system has been developed within an integrated information system framework, based on Web services and following OGC standards. The SESAMO EWS is a real-time integrated system whose efficacy is substantially based on the rapid availability of different data, arising from different sensors and able to indicate up-to-date and reliable hazardous scenarios for the monitoring area.

Recent improvements and new technologies applied to rainfall and slope displacement monitoring instruments could provide important information to identify not only the occurrence but also the specific locations of potential landslides during intense or prolonged rainfall events. For this reason, particular emphasis has been placed in this study on the description of the complex precipitation monitoring system developed for the urban area of Palermo (Italy). Accurate and timely knowledge of precipitation is a key aspect for warning systems. Traditional ways of measuring and predicting precipitation are often based on local rain gauges, which have a very limited spatial representativeness. Inclusion of weather radar, as for the system presented here, provides precipitation estimates that are more representative over large areas and can be used to better predict the distribution of slope failures within a given area.

Another substantial advance from current to next-generation technical systems for RTL early warning is represented by the use of ANNs for the analysis of susceptibility to landslide. The SESAMO-ANN is developed using the hydrological outcome of a recent, physically based and spatially distributed model (i.e., the tRIBS-VEGGIE-landslide). It is able to predict the FS of the monitored site to a reasonable level, using short-term field monitoring data and continuous weather predictions as inputs.

The SESAMO information infrastructure has been designed as a system that ensures accessibility of different information sources performing suitable interpretation and homogenization operations. Following OGC standards, different Web services (i.e., WMS, WFS, WCS and WPS) have been adopted for the distribution and the representation of map information, raster data and vector data. The modelling languages for the communication of sensors data and geographical information are provided by the XML grammars provided respectively by the SensorML (Sensor Markup Language) and the GML (Geography Markup Language).

Although an efficient EWS should be designed in relation to the peculiarities of the area to be monitored, this research provides a general framework and the first input for designing a modern EWS. In fact, the proposed system tracks a new and interesting path in the field of landslide risk management, laying the foundations for a multidisciplinary approach and future cross-sectorial advances that could further improve the general performances of future EWSs.

Gaining real experiences with new prototypal EWSs is crucial to develop confidence and reducing scepticism on such systems, testing innovations. The system, presented here at a prototypal stage, integrates appropriate procedures for the detection of potential instability phenomena triggered by rainfall and, consequently, could provide, in the future, an effective support in decision-making for all those authorities in charge of civil protection.

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