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Cost estimation for the monitoring instrumentalization of Landslide Early Warning Systems

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Abstract. Landslides are socio-natural hazards. In Colombia, for example, these are the most frequent hazards. The interplay of climate change and the mostly informal growth of cities in high-hazard areas increases the associated risks. Early warning systems (EWSs) are essential for disaster risk reduction, but the monitoring component is often based on expensive sensor systems. This study aims to develop a cost-effective method for low-cost and easy-to-use EWS instrumentalization in landslide-prone areas identified based on data-driven methods. We exemplify this approach in the landslide-prone city of Medellín, Colombia. We introduce a workflow to enable decision-makers to balance financial costs and the potential to protect exposed populations. To achieve this, we first mapped city-level landslide susceptibility using data on hazard levels, landslide inventories, geological and topographic factors using a random-forest model. We then combine the landslide susceptibility map with a population density map to identify highly exposed areas. Subsequently, a cost function is defined to estimate the cost of EWS-monitoring sensors at the selected sites, using lessons learned from a pilot EWS in Bello Oriente, a neighbourhood in Medellín. Our study estimates that EWS monitoring sensors could be installed in several landslide-prone areas in the city of Medellín with a budget ranging from €5 to €41 per person (roughly COP 23,000 to 209,000), improving the resilience over 190,000 exposed individuals, 81% of whom are located in precarious neighbourhoods; thus, they are a social group of very high vulnerability. We provide recommendations for stakeholders on where to proceed with EWS instrumentalization based on five different cost-effective scenarios. Finally, we discuss the limitations, challenges, and opportunities for the successful implementation of an EWS. This approach enables decision-makers to prioritize EWS deployment to protect exposed populations while balancing the financial costs, particularly for those in precarious neighbourhoods.

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1 Introduction

The lives and livelihoods of billions of people around the world are disrupted by human-induced hazards worsened by climate change. The Intergovernmental Panel on Climate Change (IPCC) of the United Nations has recently reported that climate change is causing more frequent and severe storms, floods, droughts, wildfires, and other extreme weather events (IPPC, 2022). This has global implications and poses several challenges to governments, societies, and science (Marchezini et al., 2018), with some geographic regions being more affected than others. For example, Colombia is one of the most landslide-prone countries in the world. The majority of its population lives in high and very high landslide hazard (Ruiz Peña et al., 2017). This is compounded by a higher frequency of heavy and continuous precipitation, and unplanned urban growth in high-risk areas due to land scarcity (World Bank, 2012), which increases the risk of disasters, particularly for the most vulnerable populations.

As a result of a disaster, or to avoid the impact of an immediate natural hazard, people are sometimes forced to leave their places of residence. Displacement disrupts people's lives, creates unemployment, interrupts education, and reduces access to basic services, among many other things, which may lead to impoverishment and higher vulnerability. Preparedness measures are key to reducing displacement-related risks. These measures improve the risk-knowledge of people at risk of displacement and empower them with informed decision-making and compliance with warnings (UNDRR, 2021). In fact, one of the seven global targets of The Sendai Framework for Disaster Risk Reduction 2015–2030 is to "*Substantially increase the availability of and access to multi-hazard early warning systems and disaster risk information and assessments to people by 2030*" (UN, 2015).

Early warning systems (EWSs) are a major element of disaster risk reduction. They can minimize the loss of lives and economic and social impacts of disasters. Thus, they can be an alternative to relocating exposed populations, especially as this is economically unviable in most regions and often faces strong opposition from residents (Werthmann and Echeverri, 2013). However, beyond its technical implementation and maintenance, the effectiveness of an EWS depends on actively involving at-risk people, improving education and awareness of risks, efficiently disseminating messages and warnings, and ensuring preparedness (World Meteorological Organization, 2018).

Despite being a promising tool when well-integrated and properly managed, EWSs have several challenges, shortcomings, and untapped potentials: The monitoring components of EWSs are often based on expensive high-end sensor systems (e.g., multi-phase GNSS, GB-SAR, and tacheometry), which require highly trained personnel for their operation, and are specifically adapted to the local situation, preventing their transfer to other regions or countries. But there are also low-cost and easy-to-use sensor systems based on, e.g., MEMS tilt inclinometers and acceleration sensors, continuous shear monitor, and piezometers. These geosensors, installed locally in a network, can provide valuable information about the surface and subsurface processes on landslide-prone slopes (Thuro et al., 2014; Uchimura et al., 2015; Singer et al., 2021). Their combination with data analyses and numerical landslide process models (Huggel et al., 2010; Thiebes et al., 2014) has the potential to improve the quality and reliability of hazard warnings and usability, as less manual work is required. An example is the low-cost subsurface monitoring system implemented in the Alps, at Sudelfeld in Bayrischzell, Germany, which operated from 2008-2014 and consisted of cost-efficient ground deformation measures, groundwater level, and precipitation monitoring (Singer and Thuro, 2006; Thuro et al., 2010). In general, the technology and affordability of slope monitoring have improved in recent decades, which now allows for a more widespread application also in low-income countries. Still to date, only a few slopes are being monitored continuously across the globe, some of which are site-specific EWS in Latin America. Publishing on experiences, challenges, and limitations, it is nevertheless rarely done, even less so in English. After all, there is a consensus that implementing EWSs in high-risk areas has not only the potential to reduce losses and damage from landslides worldwide (Grasso, 2014) but also economic benefits. There are estimates of the economic benefits of EWSs, especially in European countries, the United States and Japan (Hallegatte, 2012). For example, in Europe, the annual benefits of EWSs are estimated to be between 470 million and 2.8 billion Euros. Similarly, it has been estimated that the potential benefits in low-income countries, if similar EWSs were available, would reach a cost-benefit ratio between 4 and 35 with co-benefits (Hallegatte, 2012). However, to the authors' knowledge, the estimated cost of the monitoring instrumentalization of local and site-specific EWSs is mostly unknown or unpublished, despite being highly relevant for policy-makers on disaster risk reduction.

The purpose of an EWS is to reduce risk and improve preparedness for hazards in specific locations. Thus, it is imperative to identify hazard-prone areas, the location of people and assets in exposed locations, and their vulnerabilities. In this context, Earth Observation (EO) from in situ or remote sensors plays an important role in early warning, as well as in mapping and monitoring natural hazards (Grasso, 2014; Casagli et al., 2017). EO provides information that can be used, for example, to model the Earth's surface (Geiß et al., 2020), identify populations exposed and vulnerable to different natural hazards (Geiß et al., 2017; Müller et al., 2020; Kühnl et al., 2022), characterize building structural types for seismic risk analyses (Taubenböck et al., 2009; Aravena Pelizari et al., 2021), or develop a global flood monitoring system (Chini and the Global Flood Monitoring team, 2022). EO-derived data capture the shape of the terrain and the natural and built elements on it. Such information can be used to estimate landslide susceptibility at different regions and scales (Cantarino et al., 2019; Palacio Cordoba et al., 2020; Ospina-Gutiérrez and Aristizábal, 2021).

There are two common methods for deriving susceptibility maps using EO data: knowledge-driven and data-driven methods. Both methods consist of mathematical predictive models with different advantages and disadvantages. The most common knowledge-driven method is the multicriteria analytical hierarchy process (AHP) developed by Saaty (1980). AHP is based on weights assigned by an expert, which simplifies the decision-making process. AHP uses pairwise comparisons of the weights assigned to individual landslide conditioning factors, indicating their relative importance. The advantages of this method are that it does not require reference data and qualitative and quantitative variables can be used. However, its main disadvantage is that the results depend completely on the assigned weights and factors used. Thus, the method depends on the experience of the user and the potential to identify variables that are important for a special case. In addition, the quantitative factors are transformed into categories based on manually established thresholds, which also affects the final result. The result is a qualitative map with different hazard levels (Günther et al., 2014; Skilodimou et al., 2019), which can only be evaluated if reference data are available. In contrast, several data-driven methods have been used to develop probabilistic susceptibility maps (e.g., logistic regression, discriminant analysis, or random forest). These consist of statistical methods that rely on reference data (e.g., landslide inventories) and independent variables or conditioning factors, (i.e., factors influencing landslide risks), which are used to identify their interconnected relationships with the reference data and predict landslide susceptibility based on the modelled relationships. The main disadvantage of these methods is that they require reference data, which are not always available, inaccurate, or often incomplete or outdated. Regarding the advantages, several conditioning factors can be used and, by means of statistical significance tests, only the important factors can be included in the model. In addition, non-parametric methods, such as random forest, can find nonlinear relationships between the reference data and the conditioning factors, and the normal distribution of the factors is not necessary (Breiman, 2001). Besides, most of the statistical methods can use qualitative and quantitative factors without the need to use thresholds for their categorization. The result is a probability map quantifying landslide susceptibility, which consists of continuous values between zero and one that can be further classified into hazard levels (e.g., Azarafza et al., 2021; Eiras et al., 2021). Previous studies have compared the performance of AHP and statistical methods, and the latter performed better (Erener et al., 2016; Ali et al., 2021; Vojtek et al., 2021). In this context, landslide inventories are essential tools for deriving empirical knowledge and creating and evaluating susceptibility landslide maps using statistical and multi-criteria methods.

According to the Administrative Department for Disaster Risk Management (*Departamento Administrativo de Gestión del Riesgo de Desastres*, DAGRD) in Medellín, between 2004 and 2018 more than 30 thousand potential mass movements, together with events related to flooding and forest fires, were reported in the populated areas of the city (DAGRD, 2018). In response to those risks, on the one hand, the Aburrá valley and the city of Medellín implemented an EWS (*Sistema de Alerta Temprana de Medellín y el Valle de Aburrá*, SIATA) to reduce the impact of these events. SIATA monitors real-time hydrological, meteorological, seismic, and geotechnical variables, to forecast natural and anthropic phenomena and to strengthen risk management in the territory (https://siata.gov.co/sitio_web/).

On the other hand, a unique local, site-specific, and low-cost participatory landslide EWS was implemented in a local community knowns as Bello Oriente by a research project called Inform@Risk (Werthmann et al., 2023). Bello Oriente is a settlement that was originally informally built on one of the eastern slopes of the city with high landslide hazard. The EWS includes a wireless network of sensors based on the Internet of Things (IoT) technologies that monitors movements in the subsurface and their effects on the built infrastructure (e.g. tilting, opening of cracks), groundwater levels, and other parameters that, in combination with weather variables and forecasts, are used to inform people about the level of risk. With this, the system aims to provide exposed people enough time to react in the case of an event and to improve their risk awareness and resilience.

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For the above-mentioned reasons, we selected Medellín, Colombia, as the study area. Using lessons learnt from Bello Oriente and the Infom@Risk project, and assuming that sufficient financial resources are not available on an ad hoc basis for citywide instrumentation with EWSs, we develop a cost function which allows to weigh how much money, on which location(s), and how many people can benefit from an EWS in landslide-prone areas. We propose a cost function based on landslide susceptibility, area, and built-up density to support decision-makers in evaluating the replicability and transferability of the system in other regions based on cost-effectiveness. The objectives of this study are: (1) to identify landslide-prone areas that are suitable for the implementation of EWSs with automatic monitoring sensors; (2) to determine a cost function based on topographic and socioeconomic parameters for the implementation of an EWS; and (3) to provide suggestions for decision-makers on where to start with the implementation of new EWSs based on cost-effectiveness and prioritized areas.

2 Material and methods

In this section the developed workflow for a city-wide cost-effectiveness analysis for an EWS is introduced: First, we introduce the study area and datasets. Second, we explain how the landslide susceptibly map is derived, and how the exposed sites where the installation of an EWS is preferable can be preselected. Third, we calculate physical, social, demographic, and infrastructure parameters for the preselected sites (i.e., in the pool of possible EWS installation) that support the selection of suitable sites (i.e., exposed sites that are suitable for the EWS installation). Lastly, we present the cost function which aims at prioritizing the installation based on cost-effectiveness (Figure 1).

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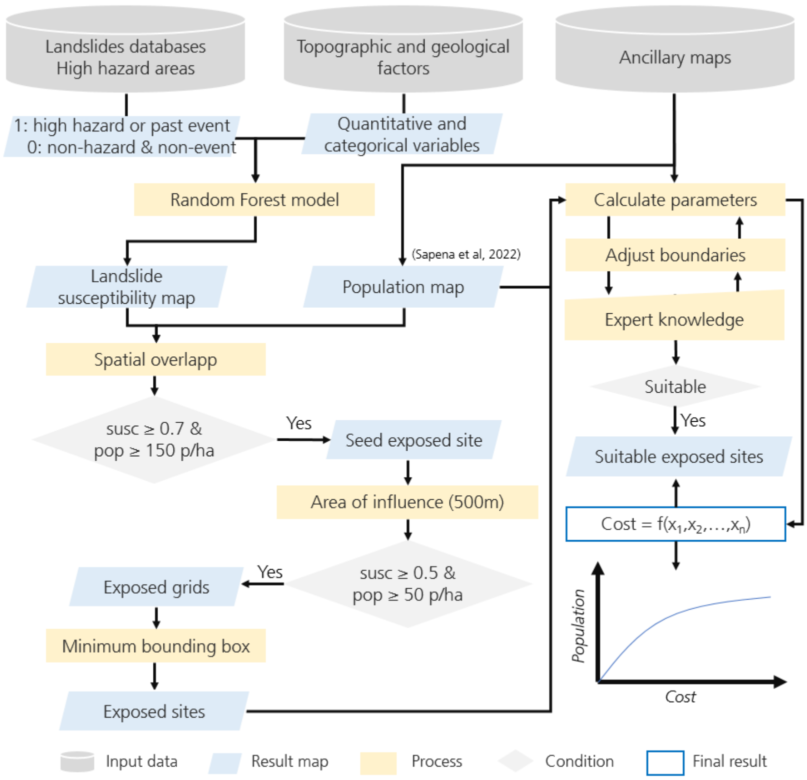

Figure 1. Workflow of the study.

2.1 Study area

This study is conducted in the city of Medellín, Colombia. Medellín is a highly populated city located in the Aburrá valley. It is characterized by a steep topography and a significant landslide risk especially at the eastern slopes of the city, where the prevailing heavily fractured dunite rock is predominant. The dunite is deeply and intensely weathered in tropical conditions due to its high iron content (Thuro et al., 2020). It is covered by colluvium material which was already moved by landslide processes and is now present in a block-in matrix structure with a thickness of between 5 meters to more than 30 meters (Breuninger et al., 2021). This colluvium clearly shows that substantial parts of the slope have been affected by landslides in the past and, because of the still steep topography the hills are prone to landslides.

Besides, a considerable amount of the population are exposed to landslide risks in Medellín, which has been increasing in the last 25 years (Kühnl et al., 2022). The city itself is shaped by different types of urban structural configurations and socioeconomic levels, from high-rise buildings in the business district and the wealthier neighbourhoods to light-weight and low-rise buildings in precarious neighbourhoods. The latter are mostly located in landslide prone areas (Kühnl et al., 2021). These factors cause large inequalities in risk exposure for different social groups.

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2.2 Landslide inventories and hazard map

The long history of landslides in Medellín has resulted in several entities recording landslide events, causalities, and damage to buildings and infrastructure. There are three main databases where people report landslides (i.e., SIMMA, DesInventar and DAGRD).

First, SIMMA (*Sistema de Información de Movimientos en Masa*) is a national landslide inventory managed by the Colombian Geological Survey (*Servicio Geológico Colombiano*) (SIMMA, 2022). For the city of Medellín 13 landslide events with precise coordinates occurred between 1985 and 2013.

Secondly, DesInventar is an international Disaster Information Management System that helps to analyse disaster trends and their impacts (DesInventar, 2022). It includes information on space, time, type of event, causes, sources, as well as direct and indirect effects. In this study, we consulted the 'Medellín Área Metropolitana' database managed by the Universidad Nacional de Colombia with registers from the year 1880 to 2022. We found 21 landslides with precise coordinates in the municipality of Medellín from 2018 to 2022.

The third landslide inventory is managed by DAGRD. Occurred or foreseen landslides are registered by DAGRD based on emergency calls from citizens. This information is later evaluated by a technician from DAGRD. The department provided us with data for the period 2004 to 2018, which contains more than 30,200 reports of potential mass movements with their coordinates. The vast majority of the reports are located in the urban areas of the city, disregarding events in rural regions.

Beyond these databases on landslides, remote sensing data and techniques have proven suitable for landslide detection and mapping (Guzzetti et al., 2012), especially when inventories lack the spatial accuracy of the events. Consequently, we combine for our approach the three inventories, and we complement the information with landslide locations in the urban-rural border and rural areas that we detect using remote sensing data. We use multi-temporal Landsat-7, Landsat-8 and Sentinel-2 imagery and apply change detection methods of vegetation indices in tentative areas based on landslides news articles. We follow the assumption that major changes in indices on steep slopes are related to significant variations in the soil surface or removal of vegetation and might be caused by landslides (Mondini et al., 2011). We identify 8 landslides between 2008 and 2019.

The city of Medellín not only has an unprecedented number of mass movements inventories, but also the latest Master Plan from 2014 (*Plan de ordenamiento territorial*, POT 2014) includes the zoning of landslide hazards (Alcaldía de Medellín, 2014a). The hazard map is the result of the combined analysis of information available for the municipality, such as the hazard map from the POT 2006, a probabilistic hazard map from the Universidad Nacional, the DAGRD landslide inventory (up to the year 2014), complemented by heuristic processes, field work and expert knowledge from DAGRD and the Administrative Department of Planning (*Departamento Administrativo de Planeación*, DAP) technicians. We use the mass movements inventories and the hazard map from the POT 2014 as reference data for modelling landslide susceptibility. We assume all

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available reports are landslides, due to the lack of specifications about the type and considering that most mass movements in Medellín are landslides. These data are used to train and evaluate the model as further explained in section 2.4.

2.3 Factors influencing landslide risk

For modelling landslide susceptibility, we use topographic, geological, and precipitation factors, and to support the selection of suitable locations for the installation of EWSs, we rely on socio-demographic factors. Our database consists of the official cartography from open data platforms of the city of Medellín and the metropolitan area of the Aburrá valley (*Área Metropolitana Valle de Aburrá*, AMVA), such as 'GeoMedellín' (https://geomedellin-m-medellin.opendata.arcgis.com/) and 'Datos Abiertos del AMVA' (https://datosabiertos.metropol.gov.co/). Besides, we use precipitation data from SIATA, OpenStreetMaps data to complement existing cartography, and ancillary maps from previous studies.

Regarding the topography, we derive several factors from contour lines. We use contour lines of different scales for urban (1:2,000) and rural areas (1:5,000) to generate a Triangular Irregular Network (TIN) surface. From this TIN the altitude is interpolated to create a Digital Elevation Model (DEM) with a spatial resolution of 5 meters. This the DEM is then used to derive several topography-related factors such as slope, aspect, which indicates the downhill direction of the slope, and curvature, which shows the shape or curvature of the slope (Figure 2). Additionally, the DEM is used to model water flows and derive the stream network, stream order, landslide travel paths, and angle of reach of landslides (α, also known as 'fahrböschung angle'), which shows the possible mobility of a landslide (Hungr et al., 2005). The stream network is extracted by setting a threshold of 500 pixels of water accumulation (i.e., water from at least 12,500 m² flows into the streams, assuming no water loss). We tested several thresholds, both higher and lower, and 500 pixels proved to be the most appropriate compared to the POT drainage system, as it depends on the spatial resolution. The Strahler method (Tarboton et al., 1991) is used to classify the streams into numeric orders, differentiating between main streams as the major tributaries (order from 7 to 5), and other streams as the outermost tributaries (order from 4 to 1). Two Euclidean distance maps are created to measure the distance of a given pixel to the main streams and the other streams (Figure 2). Finally, the travel path and angle of reach of a landslide are used as support in the selection of exposed sites to identify unpopulated areas in which landslides can be triggered and whose runout can reach into the inhabited area.

With regard to the geology, geomorphology and geotechnics of the study area, we collect data from 'Datos Abiertos del AMVA'. We use three maps with categorical information on the geologic units, the geomorphologic units, and the geotechnical zoning. The surface geology is a relevant factor because it informs about the physical nature of the materials, their properties and mechanical strength characteristics. Geomorphology shows the stability, slope, and shape of the landscape, while geotechnics provide information on the type of soil (Universidad Nacional de Colombia, 2009) (Figure 2).

Precipitation is an important triggering factor for landslides. Within the mountainous study area, the average yearly precipitation varies considerably due to local luv and lee effects. Thus, we use precipitation data from the meteorological stations of SIATA (https://siata.gov.co/descarga_siata/index.php/index2/estaciones/). We download precipitation measurements from 215 stations in the Aburrá valley for 2021. We calculate the accumulated precipitation over the year per station and interpolate the station values to calculate a continuous map of accumulated precipitation with a spatial resolution of 5 meters. We use the *Ordinary Kriging* and the *optimized smoothed* method, which provided a *root mean square error* of 506 mm (Figure 2).

When it comes to decisive factors for the suitability and prioritization of possible locations for implementing an EWS, we use socio-demographic and infrastructure variables. First, we use a high resolution population map with the estimated number of people per building and grid of 100 meters (Sapena et al., 2022). The population counts are used for identifying exposed sites with high-density population and high landslide susceptibility. The calculated population and building density for these sites is combined with data on the vulnerability of people based on the precarious conditions of the built-up areas (Kühnl et al., 2021). This joint analysis allows us to prioritize exposed areas with higher vulnerability to disastrous events. Second, we employ data on the road infrastructure, which is a relevant factor for the installation of sensors in the EWS. We complemented the official road network cartography in 'GeoMedellín' with additional roads from OpenStreetMap (downloaded in 2022, openstreetmap.org) (Figure 2).

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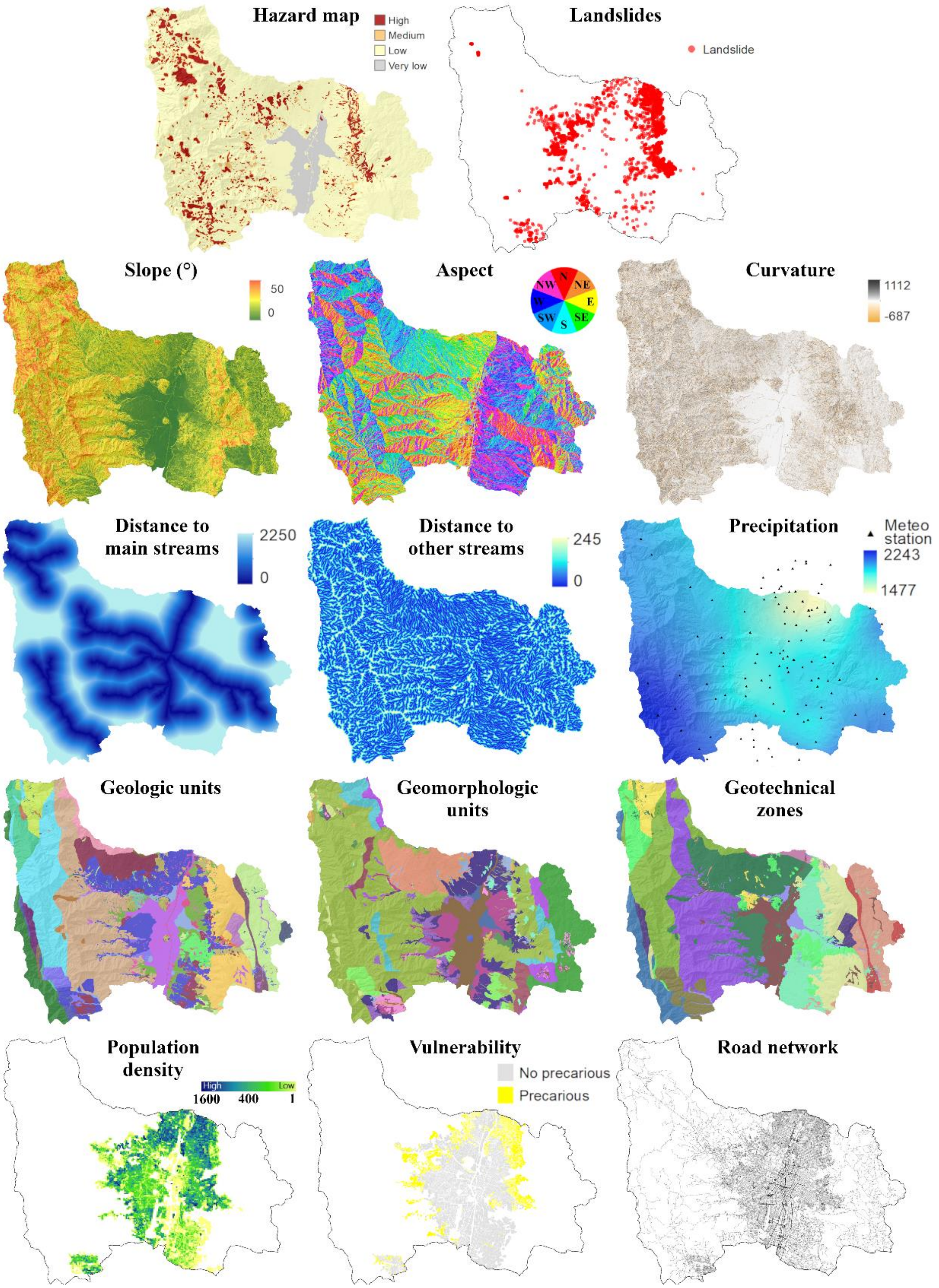

235 **Figure 2. Dependent variables in the model (hazard map and landslide events), independent variables or conditioning factors (topographic, geological, and precipitation), and ancillary data (socio-demographic and infrastructure).**

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2.4 Mapping landslide prone areas

In this study, we use baseline data on recent landslide events and an official hazard map for training a statistical model to predict the probability of landslide events based on several conditioning factors, which we refer to as landslide susceptibility. Hence, we leverage the best hazard map available at the city level, which includes local expert knowledge, and additionally, we feed the model with new data not included in the previous version (i.e., all landslides from SIMMA and RS, and landslides after 2015 from DesInventar and DAGRD). We create a set of sampling points within high-hazard zones (5,000 points), recorded landslide events (2,800 points) and non-hazardous areas, including medium, low or very low hazard zones (8,000 points). For each point, we add a numeric attribute with the dependent variable: high-hazard (1) and non-hazard (0), and the value of all conditioning factors explained in section 2.3 representing the independent variables in the model. Then, we split the sampling set into training (70%) and testing (30%) data. We use the non-parametric Random Forest (RF) algorithm (Breiman, 2001) with 100 trees, 3 variables at each split and 5 terminal nodes. The susceptibility map is calculated with the training data. The result is the probability of a pixel being high-hazard (1), which is calculated as the proportion of votes in the ensemble of trees. The testing data that did not participate in training the model is used for evaluating the model. We use the remaining testing set to measure the accuracy statistics.

2.5 Selection of exposed areas

We assign a zero susceptibility level to areas with slope equal to or lower than 10° in the resulting landslide susceptibility map, since these slopes are not considered hazardous for the specific case of Medellín (Alcaldía de Medellín, 2014b). Afterwards, we calculate the average susceptibility per 100-meter grid cell and combine the result with the population density per grid in order to select the exposed areas. For that, we focus on the urbanized area of Medellín, since it is the area with the most exposed elements and, we do not have population data for rural areas. We apply an iterative process as can be seen in Figure 1. First, we identify seeds of exposed sites with both, high susceptibility (≥ 0.7) and high population density (≥150 people/ha). If two or more seeds are contiguous or within 100 meters, the centroid is used as a seed. Second, we use the seeds as starting points and look in an area of influence of 500 meters, which is set to keep a similar size as the reference EWS in Bello Oriente, for pixels with medium to high susceptibility (≥ 0.5) and medium to high population density (≥50 people/ha). Hence, we identify all the surrounding pixels around the seeds that are also susceptible to landslides and populated. Third, we calculate the minimum bounding box for each cluster of pixels to automatically define a preselected exposed site. Fourth, we adapt the shape of the preselected sites based on the urban structure, topography, travel path and angle of reach of a landslide. Finally, we calculate the area, mean susceptibility, total population, population density, vulnerable population, built-up and road density, number of buildings, mean slope, main orientation of the slope, and open areas for the preselected sites, which are then used by experts to inspect and select the suitable exposed sites based on the requirements of the EWS and previous experience in Bello Oriente.

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2.6 Developing a cost function

To estimate the costs of the monitoring instrumentalization of EWSs in suitable sites, we use the recently implemented EWS in Bello Oriente as a reference regarding the required manpower (working hours for the construction and installation of the sensor system), the required sensor density and types, as well as the cost of the individual sensors. The EWS in Bello Oriente covers an area of 39 hectares with a total population of 4,600 residents, from which 1,800 settle in a high-hazard zone of landslides. The EWS utilizes a novel wireless geosensor network based on IoT technologies (e.g., LoRa® wireless data communication and MEMS sensors) and 1,100 meters of Continuous Shear Monitor (Thuro et al., 2010) measurement cable and extensometers to monitor subsurface movements and the near-surface groundwater levels as basis for the generation of warnings. As the exact location of future landslides cannot be predicted based on the geological investigations, an area wide coverage with high spatial and temporal density of observation is required. The wireless geosensor network in Bello Oriente thus consists of 111 sensor nodes, of which about 45 monitor subsurface deformation and groundwater levels (Inform@Risk Subsurface Measurement Nodes) and 70 detect movement of existing built infrastructure (Inform@Risk Infrastructure Nodes). The spacing of sensors is adjusted based on the level of landslide risk, with high-risk areas having approximately 8 sensors per hectare and areas with no risk having no sensors. The sensor nodes are developed as open source and can be reproduced using the published PCB schematics, 3D printing models, and building instructions (Gamperl et al., 2023). Details about the measurement system are described in Gamperl et al., (2021) and Singer et al., (2021) and on the Inform@Risk Wiki (www.informatrisk.com).

It is important to emphasize that we currently only include the implementation of the wireless geosensor network in the cost function. The costs regarding the risk evaluation, social interventions, dissemination, continuous maintenance, and social work are not included. The CSM-EXT measurement system was excluded, because it was found to be very complex and costly to install in a densely populated area. Consequently, its usability for widespread installation is limited and whether its implementation is a viable and cost-effective alternative to the wireless sensor network has to be assessed based on a detailed survey on-site. The costs of the social work are also highly site specific and depend on many factors as e.g., whether the municipality decides to do a risk assessment on the site, whether the community welcomes such an installation of an EWS, or whether NGOs working with the community on site can share their knowledge and aid in setting up the system. Additionally, depending on the risk awareness and the social structure of the community, the amount and type of social work can vary tremendously. Based on the experience of the Inform@Risk project however, the cost for the initial social implementation of the EWS (mainly cost for social workers who accompany and explain the installation works, produce and distribute information leaflets, and conduct training workshops and emergency drills) can be expected to be at least the same as for the implementation of the technical system.

In the following, we explain the variables considered in the cost function. The cost for the different elements of the Inform@Risk sensor system have been determined based on the required working time for production and installation, the

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required 3D printing time, and the material costs (i.e., electronics, sensors, cables, connectors, and accessories). For the working time, in this study we consider an hourly rate of €15, which correlates to the approximate hourly cost (including all insurances and benefits) of a geotechnician in Colombia. The 3D printing time was assigned with a cost of €3/hour which includes the estimated cost for the filament, power, maintenance and investment cost for the 3D printer distributed over the estimated machines life span of 10,000 operating hours. The material costs include all components required to build and install the system. The costs are calculated without VAT. A detailed list of the required materials as well as working instructions for construction and installation of the sensor system are provided on the Inform@Risk Wiki.

Subsequently, we use a density of 8 sensors per hectare for the highest susceptibility level of 1, which gives a very dense grid of sensors. This density is scaled down based on the susceptibility (i.e., a susceptibility of 0.5 results in 4 sensors/ha). Afterwards, the built-up density determines the type of sensors that are installed. In highly urbanized areas more infrastructure sensors are preferred, while in less urbanized areas more subsurface sensors are considered. Therefore, we multiply the sensor density by the total area to obtain the number of sensors per site, subsequently we multiply the number of sensors by the built-up density to calculate the amount of infrastructure sensors, the remaining ones are the subsurface sensors. Regarding the gateways, we assume that at least one gateway per 25 ha is necessary. However, we suggest to have at least two gateways as a redundancy factor, in order to have a backup in case one of them fails. This is a conservative assumption since that many gateways will generally not be needed. Previous tests for the city of Medellín showed that using 2 to 4 gateways in the city centre could provide enough transmission reach to supply the whole eastern slope of Medellín. The cost for the three different sensor systems is shown in Table 1.

Table 1. Cost for the different monitoring sensor systems.

System	3D Printing time and cost (€3/h)	Working time and cost (€15/h)	Material cost	Total cost
Inform@Risk Infrastructure Node	4.4h €13.2	1.5h – 1.75h €22.5	€215	€250
Inform@Risk Subsurface Node	40.7h €122.1	3.75h €56.25	€355	€535
Gateway	-	8h €120	€2,100	€2,220

The cost function is calculated following Eq. (1):

$$COST = \mathrm{S} \times 8 \times \mathrm{A} \times (B_{DENS} \times €250 + (1 - B_{DENS}) \times €535) + \mathrm{G} \times €2{,}220, \quad (1)$$

where $\mathrm{G} = \begin{cases} A \leq 25\ ha = 1 \\ A > 25\ ha\ \&\ A \leq 50\ ha = 2, \\ A > 50\ ha = 3 \end{cases}$

$COST$ is the cost estimation of the monitoring instruments from an EWS in an AOI, S is the landslide susceptibility, A is the area of the AOI in ha, and B_{DENS} is the built-up density in the AOI.

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On the basis of the results of the cost function, we develop alternative cost-effectiveness scenarios to support decision-making with where to start with the implementation of new EWSs. The scenarios we evaluate are: prioritizing (1) the total EWS cost; (2) the cost per person; (3) the total population (exposed and vulnerable); (4) the landslide susceptibility; and (5) the combination of the aforementioned scenarios (1-4). Priority is given to the lowest costs in (1) and (2) and to the highest population and susceptibility in (3) and (4). For the combination of cost-effectiveness scenarios (5), we normalized the values with the min-max scale, where 1 is the highest priority and 0 the lowest. The normalized values are mapped and plotted on a graph that can be used to support decision-making.

3 Results

3.1 Susceptibility map, exposed and suitable sites for landslide EWSs

We mapped the landslide susceptibility with a measured overall accuracy of 75.26% (Figure 3A). The sensitivity and specificity of the produced map were 80% and 71%, respectively. The sensitivity is the percentage of the high-hazard (1) class predicted correctly, and the specificity is the percentage of the non-hazard (0) class predicted correctly. These metrics suggest that our model tends to slightly overestimate landslide susceptibility. Despite the discrete values in the reference data, the susceptibility map is a probability map with continuous values ranging between 0 and 1 (a detail can be seen in Figure 3B). Therefore, the accuracy is measured by considering probabilities higher or equal to 0.5 as high-hazard (1), and probabilities lower than 0.5 as non-hazard (0), disregarding any degree in the susceptibility map for the validation metrics.

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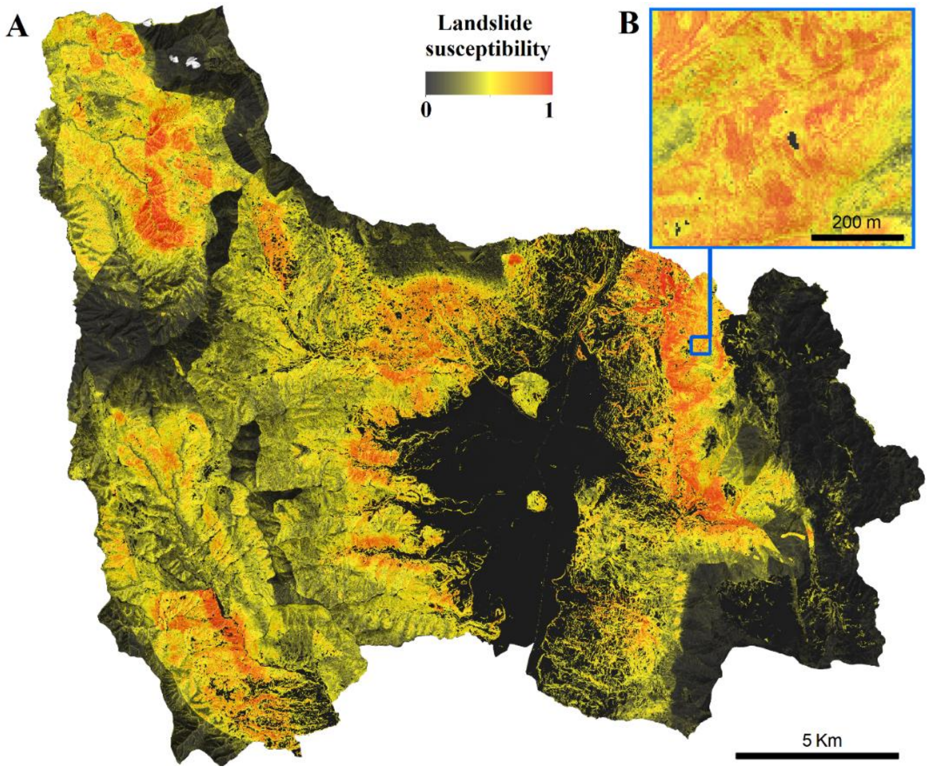

Figure 3. (A) Landslide susceptibility map (after filtering slopes equal or lower than 10°), and (B) detail in Bello Oriente neighbourhood.

To select the exposed sites for the possible implementation of landslide EWSs considering the risk factors, we combined the landslide susceptibility, and the vulnerable and exposed elements. We identified 44 seeds (Figure 4, A and B), which were used to find susceptible and populated areas around them to delineate the boundaries of the sites. Then, we calculated the socio-demographic and topographic factors used to select or discard sites based on their suitability. We discarded 16 sites based on their non-suitability for the implementation of a node-based EWS based on experts' recommendations (Figure 4C). The most frequent reason was the high building density, with limited open space for installing subsurface sensors and where only infrastructure nodes would have been possible, limiting the monitoring capabilities of the EWS. Additionally, some of the reminder 28 pre-selected sites were split into smaller areas or reshaped based on the topography, built-up density, and road network to delineate the extension of the suitable exposed sites (Figure 4D).

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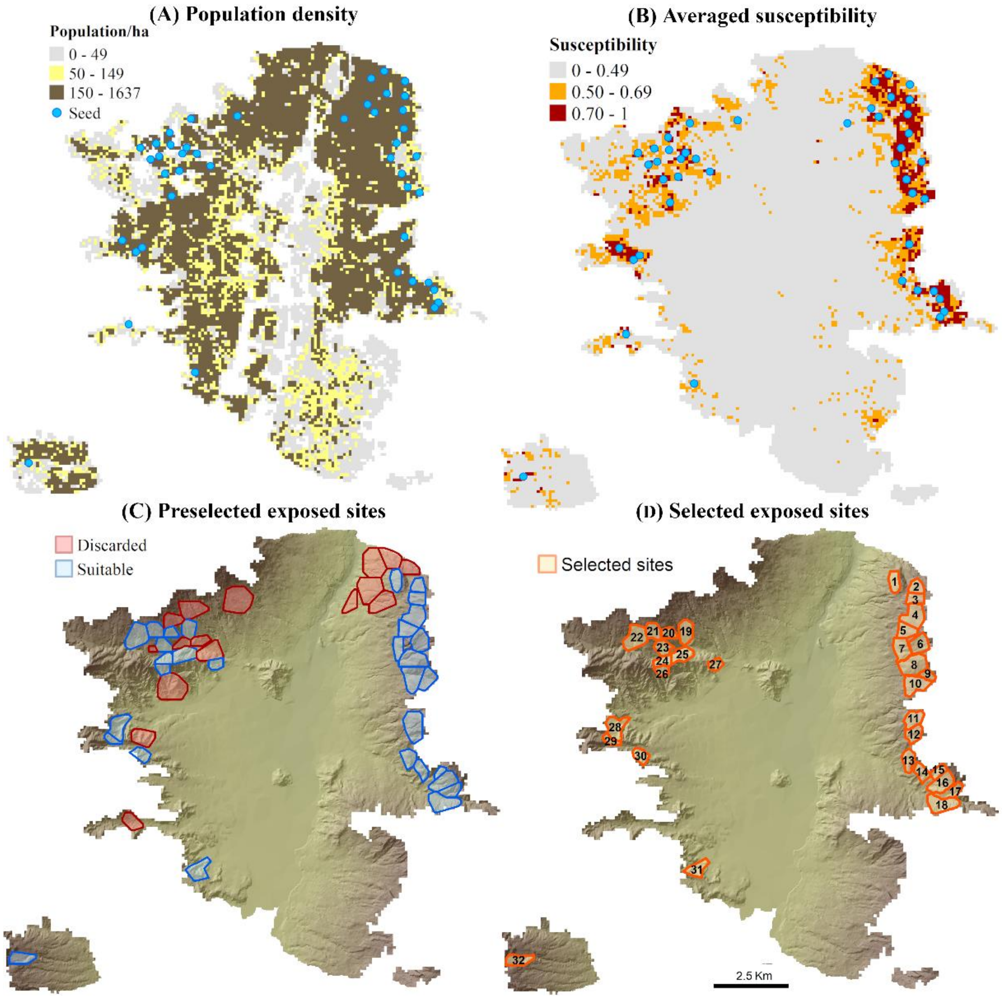

Figure 4. Identification of seeds based on (A) high populated and (B) susceptible grids. (C) Automatic delineation of exposed sites by means of seeds' areas of influence and preselection of suitable sites with. (D) Suitable exposed sites after the manual delineation of their boundaries.

The manual delineation resulted in 32 preferred sites suitable for the installation of landslide node-based EWSs (Figure 4D). For these sites, socio-demographic and topographic factors, which are used in the cost estimation function, were calculated (Table S1). Most of the sites are located in the north-eastern part of Medellín, but also in the east and west due to higher population densities and high landslide hazards (see Figure 2 and Figure 4). The sites have an average extension of 27 hectares, with an average built-up density of 20%, and an average population density of 224 people per hectare (p/ha) (Table S1). Whereas the most densely populated site, located in *Área de expansion Pajarito* (site 21), has 512 p/ha and a low built-up density, since it corresponds to an expansion area in the city with high-rise buildings in the west side of the valley and where no vulnerable population was identified. On average, the sites have around 34% of open land, which is relevant for the installation of the subsurface sensors. Regarding the slope, the mean slope of the selected sites is 24°, with a minimum slope

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of 15° in the west and a maximum of 35° in the east. In terms of landslide susceptibility, the average is 0.68, while the minimum susceptibility for selected sites is 0.51 and the maximum is 0.85.

3.3 Cost estimation for the instrumentalization of landslide EWSs

Relying on the landslide susceptibility map and the factors calculated in Table S1, we estimated the costs for the installation of the monitoring sensors for EWSs in the selected sites according to Eq. (1). To facilitate decision-making on where the city could begin installing the next EWS, we evaluated several cost-effectiveness scenarios that not only focus on monetary efficiency, but also consider other priorities such as the number of exposed and vulnerable people and landslide susceptibility, providing a more complete picture of site characteristics. Hence, we consider five priority scenarios: prioritizing the total EWS cost, cost per person, total exposed population within the site, of which vulnerable, landslide susceptibility, and their combination.

Figure 5A informs about the amount of people potentially supplied with an EWS as a function of the economic resources required by means of representing the overall costs of the system against the total population per site. The priority is represented based on the combined scenario with a grey gradient, the darker, the higher the priority. The cost of the systems ranged from €26,000 (≈ COP 132 Million, Colombian pesos, with a conversion rate of COP 5,040 per € at the time of writing) to €157,000 (≈ COP 789 Million). With regards to the cost per person (p.p.), we estimated a price between €5 to €41 p.p. (≈ COP 23,000 to 204,000 p.p.). Therefore, if the purpose is, for instance, to start with the most affordable system (i.e., prioritizing EWS cost), the EWS in *El Corazón* (site 29) located in the western slope of the city, is the cheapest (Figure 5A); however, it covers less population than other sites with similar costs. In this sense, the EWS in *El Pesebre* (site 27) is the second cheapest and covers more than twice the exposed population in site 29, although most of them are not vulnerable.

To showcase the potential of the proposed cost function, we have simulated a case scenario where the city of Medellín has a budget of COP 2,000,000,000 (≈ €397,000) to invest in the monitoring instrumentalization of landslide EWSs. We suggest several sites where the city might start implementing the systems based on different cost-effectiveness priorities. Figure 5B shows the sites' locations where EWSs could be instrumentalized with this budget according to the different scenarios (i.e., overall cost, cost p.p., exposed and vulnerable population, landslide susceptibility, and the aforementioned scenarios combined) using the values from Table S1. The colour of the sites represents the prioritization according to the scenario. Sites with more than one colour are prioritized in various scenarios. The table in Figure 5B shows: the total number of EWSs that could be instrumentalized with the given budget per priority scenario, the total cost, average cost per person, the total number of exposed and vulnerable people, and the average susceptibility.

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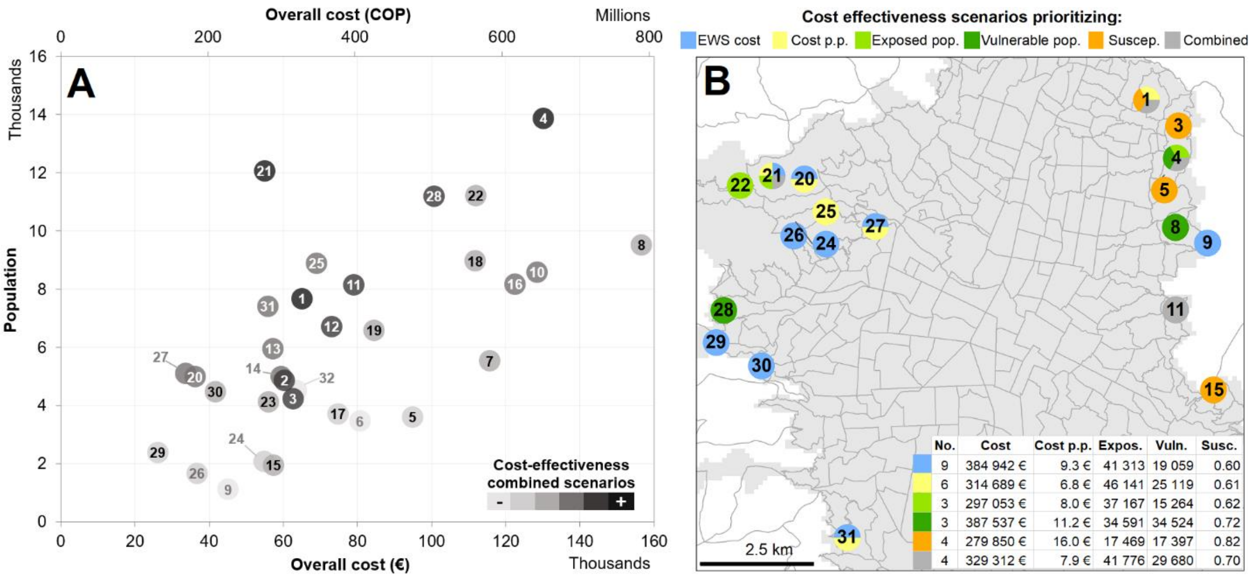

No.	Cost	Cost p.p.	Expos.	Vuln.	Susc.
9	384 942 €	9.3 €	41 313	19 059	0.60
6	314 689 €	6.8 €	46 141	25 119	0.61
3	297 053 €	8.0 €	37 167	15 264	0.62
3	387 537 €	11.2 €	34 591	34 524	0.72
4	279 850 €	16.0 €	17 469	17 397	0.82
4	329 312 €	7.9 €	41 776	29 680	0.70

Figure 5. (A) Overall costs of the monitoring system installation of a site-specific EWS versus the number of people for each site. The label number represents the site ID, while the grey tone represents the priority per site based on the cost-effectiveness of the combined scenario. Cost is given in Euros (€) and Colombian pesos (COP). (B) Based on the priority, the map shows the sites where EWSs could be instrumentalized with a budget of COP 2,000 Million. Values are summarized in a table with: the number of EWS, total cost, cost per person, people exposed, people vulnerable and susceptibility.

With the same budget, the city could (1) instrumentalize nine EWS if the total cost is to be minimized. Most of them are located in the western slopes, covering 41,000 people, of which 19,000 are considered vulnerable, and the average landslide susceptibility is around 0.6. However, if (2) all priorities are considered four EWSs could be installed, with a lower average cost per person, mainly in the eastern slope, but also one in the western part of the city. In this scenario, the number of people exposed is also 41,000, but of which almost 30,000 are vulnerable, and the sites have a higher susceptibility. For instance, a site of high relevance based for a few scenarios is located on the north-eastern slope of Medellín, between the south of *Carpinelo* and north of *Maria Cano-carambolas* (site 4), with almost 14,000 vulnerable people living in precarious settlements with a high mean landslide susceptibility (0.74). The estimated cost p.p. here is €9.4 (COP 47,000), meaning that with approximately €130,000 (COP 656 Million) the system could cover a high share of exposed and at the same time vulnerable people. Likewise, the EWS in *Santo Domingo el Savio 1* (site 1) located in the north-eastern slope of the city, is the most effective one in terms of cost per person, susceptibility, and combined priorities; however, if the intention is to cover the maximum amount of population exposed is not the most suitable one. In that case, the EWS in *Área de expansion de Pajarito* (site 21), in the western slopes, covers more exposed people, the cost per person is the most effective, and the total price of the system is lower than in site 1, but the landslide susceptibility is lower and thus the probability of a landslide. On the other hand, the EWS in *El Corazón* (site 29) would be the most affordable EWS with a low cost per person, yet it has the lowest susceptibility and less people exposed, which might diminish its eligibility. Similarly, the most expensive EWS in *La Cruz*

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(site 8), in the north-eastern slope, has a reasonable cost per person, and the number of people exposed and the landslide susceptibility are considerably high.

Figure S1 displays the 32 sites from higher to lower priority where a site-specific EWS could be installed. Figure S1 shows the accumulated value of five priorities (the exposed population is split by vulnerability); hence, all priorities can be jointly evaluated. Therefore, the higher the combined value in Figure S1, the higher is the priority of various cost-effectiveness scenarios simultaneously. This graphic representation enables decision-makers to locate the ideal site for the implementation of the next EWS, depending on different priorities such as available funds (as was previously done in Figure 5B) or exposed population.

Furthermore, Figure 6 represents the developed cost function after prioritizing the installation of EWSs based on the different cost-effective scenarios. If the city has funds to implement EWSs in the 32 proposed suitable sites, a total of €2.4 Million (≈COP 12,100 Million) would be necessary to cover the 200,000 people exposed. The trend lines (Figure 6) show the amount of people covered by EWSs depending on the available funds and the priority scenario. Prioritizing the cost p.p. is the most effective in terms of budget and people covered; however, as seen in Figure S1 it disregards landslide susceptibility and the total amount of people exposed. In that sense, the combined scenario has a similar trend and accounts for all factors, thus we recommend if possible, using the combined scenario for prioritizing the installation of new EWSs. As an example, we showed the priority of site 4 for all cost-effectiveness scenarios. With these scenarios, a conscious and informed policy decision can be made - why to install an EWS where.

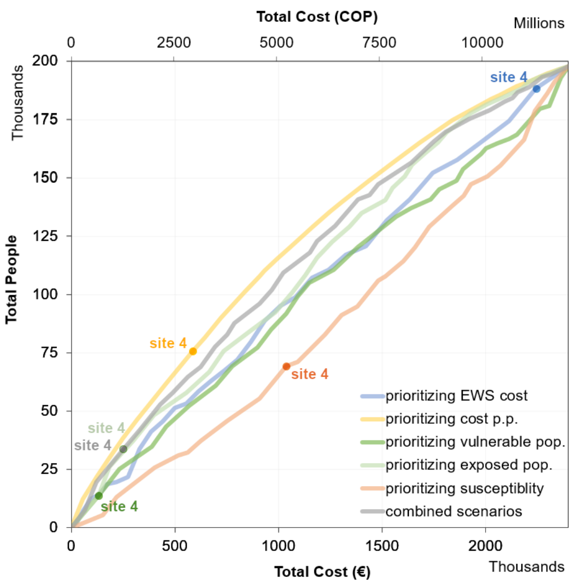

Figure 6. Cost function based on different cost-effectiveness scenarios and their combination. It informs about the number of people than can be covered with available funds based on the preferred priority. Site 4 is highlighted to illustrate the priority of the site according to the cost-effectiveness scenario considered.

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4 Discussion

In this paper, we developed a workflow for the localization of exposed areas susceptible to landslides, and a cost-effectiveness function for the installation of an EWS to assist in prioritization in support of decision-making.

We proved that it is possible to map landslide susceptibility fairly accurate based on remotely sensed data and ancillary datasets using a data-driven method, which does not require prior knowledge about the interplay between conditioning factors. Besides, using a non-parametric random forest model allowed us to use a wide range of conditioning factors and to find non-linear relationships in the data despite the lack of normal distribution of the factors. As a result, we produced an updated landslide susceptibility map complementing the official hazard map of the city from 2014 with new mass movement instances from landslide inventories.

We demonstrated that estimating the price to instrumentalize the monitoring component of EWSs can be transparently done in a public manner, which – to our knowledge – has never been reported before. This new information is useful for decision-makers in disaster risk reduction, where EWSs are a key element (UN, 2015). The proposed automatic monitoring system was designed to be highly modular, scalable, and customizable so that it follows overall goals for community-based EWSs (Gumiran et al., 2019). This allowed us not only to perform this transferability study in an area-wide manner for an entire city based on the experiences of EWS installation in one neighbourhood, but also it has the potential to be transferred easily to other sites worldwide with similar characteristics (e.g., mountainous and densely populated areas in Asia). Additionally, since it is based on the open LoRa® standard, it can potentially benefit from already existing infrastructure (i.e., gateways with a cost of €2,200 each), which eases the transferability within a city and reduces costs when scaling up the systems.

We also showcased how different cost-effectiveness scenarios impact the overall cost and the amount of exposed and vulnerable population when investing a given budget, and how it could be optimized. The combination of a very detailed warning system on site with city-wide information about susceptibility and population creates unique opportunities for researchers and decision-makers. The analysis shows at a glance where a landslide EWS can be the most cost-effective.

We successfully localized and suggested more than thirty areas in Medellín where a low-cost and site-specific EWS based on a network of geo-sensors could be implemented to protect thousands of lives, and most importantly, we estimated the price to instrumentalize the monitoring component of an EWS in each location. With this, a conscious, informed, and transparent policy decision can be supported - where to install an EWS under limited available financial funds.

However, challenges remain: Regarding the landslide susceptibility map, we obtained a good accuracy despite evaluating the probability map with a dichotomous variable, i.e., hazard or non-hazard. The generalization into a dichotomous value influenced the measured overall accuracy, since there is a high frequency of values ranging between 0.4 and 0.6, that are either evaluated as high-hazard or non-hazard. We found that the majority of the misclassifications in the accuracy analysis corresponded to the medium hazard class, which is considered non-hazard. Yet, we also found low hazard areas with medium-

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high susceptibility values, as well as high-hazard areas with low susceptibility values. This could be attributed to the use of two different sources as reference data for training a model, which can sometimes lead to contradictions, particularly considering that the DAGRD inventory includes community reports that may not always pertain to landslides. For instance, medium or low hazard zones in the POT2014 with similar conditioning factors than areas with recent landslides in the inventories, as well as recent landslides recorded in medium or low hazard zones, are expected to have high susceptibility levels in our model, which would be identified as an error in the validation. Therefore, it is important to highlight that data-driven methods depend on the quality and veracity of the reference data, as well as on the conceptual approach. In our case, on the one hand, the landslide inventories consist of events noticed by people and thus are mostly located in urban areas, which might introduce a biased higher frequency of landslides in urbanized regions. However, since we focus on the installation of an EWS in urban areas, the potential bias of higher susceptibility in urban areas than in rural areas introduced by the inventories are not critical in this study. Besides, all historic landslides in Medellin have a strong anthropic triggering factor, so it is logical to have a higher density of events in the urban areas. On the other hand, we expect the official hazard map being of high quality since it was evaluated and improved by experts; however, we found that a high share of landslides between 2014 and 2021 were reported in low hazard areas according to the hazard map of 2014, which could also be related to mass movements reported by citizens that are not necessarily landslides. Another factor that could potentially affect the results is the increase in population along the urban-rural border since the official hazard map was created. Given the significant influence of anthropogenic factors on landslides in Medellín, this may account for the differences between our landslide susceptibility map and the official landslide hazard map.

Regarding the selection of suitable locations for the installation of EWSs, we followed an iterative process using seeds of high susceptibly and exposure, and manually set thresholds. The thresholds were set to find the highest exposed areas (by means of using the population density and susceptibility), and to limit the number of seeds to a reasonable amount to start with. We limited the size of the sites based on the previous experience from Bello Oriente. This might affect the outlines of the sites and thus the selected suitable sites. It is important to note that the proposed thresholds and sizes are adapted to the context of the city of Medellín, therefore, they should be adjusted in different regions.

The cost estimation is subject to uncertainties in the cost function and its underlying data as well. The proposed system has only been implemented once, in Bello Oriente, and the cost and density of sensors are based on the experiences at this site. Varying parameters like a less steep terrain or a more densely populated area can cause unknown changes in the cost function. Yet, with every additional sensor system that is installed, factors in the cost function such as the sensor density can be adapted and will become more reliable. Moreover, part of the cost depends on the local circumstances as well as the amount and training of the available personnel. While the uncertainties in the absolute costs are expected to be quite high, the relative cost differences between multiple sites can still be evaluated with our proposed cost function. Therefore, the proposed approach can be used to identify prioritized areas within the city to begin with the installation of new landslide EWSs based on cost-effectiveness.

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While the EWS in Bello Oriente was initially developed as a prototype by a research project from the academia and private companies, its implementation also involved other key stakeholders such as the government, local civil society organizations and the local community. The participation of these diverse actors proved crucial in overcoming various challenges, including issues related to social conflict, insufficient risk awareness, limited political commitment, changes of local government, limited resources, inadequate territorial planning, etc (Werthmann, 2023).

Considering the complexity of implementing an EWS, it is important to emphasise that the estimated costs presented in this study only consider the installation of the monitoring instruments. Thus, the cost for the maintenance of the system, which involves a large number of working hours and instruments, as well as the protection elements for the instruments, are left aside. Other costs not included in our results are the warning elements, the safety signs installed for the emergency routes and meeting points, along with the social work with the community and all the other sectors involved in the EWS (i.e. government, local civil society organizations, etc.). The success of the EWS relies on social work since risk awareness and trust in the system define the willingness to participate in the process and also the willingness to react in case of a warning. This is also essential for ensuring the sustainability of the EWS even after the monitoring instruments have been installed.

5 Conclusions

The Sendai Framework for Disaster Risk Reduction 2015-2030 emphasizes the importance of implementing multi-hazard ESWs to mitigate disaster risks and prevent loss of lives. This is particularly crucial in countries like Colombia, where a significant proportion of the population is exposed to landslide hazards and high vulnerability prevails.

Drawing on the experience of the EWS installed in Medellín as part of the Inform@risk project, this study identified 32 highly exposed areas in the city of Medellín that are suitable for the installation of a highly modular, scalable, and customizable EWSs. We estimated that the city would need between €5 to €41 per inhabitant to implement the monitoring component of EWSs, depending on the characteristics of the sites. We presented an approach for prioritizing the selection of exposed sites based on different cost-effective scenarios, budget, landslide susceptibility, the total population exposed, territorial planning agenda, etc. The results of this study are intended to guide decision-makers and support disaster risk reduction measures not only in Medellín, Colombia but also in other regions facing similar challenges.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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