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LANDSLIDE RISK MANAGEMENT IN AREAS AFFECTED BY WILDFIRES OR FLOODS: A COMPREHENSIVE FRAMEWORK INTEGRATING GIS, REMOTE SENSING TECHNIQUES, AND REGIONAL CLIMATE MODELS

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Abstract

Over the past few decades, numerous studies and technical surveys have documented a significant number of landslides activated in areas that had recently been affected by wildfires or floods, thereby suggesting a potential link between landslides and these phenomena. With the climate crisis exacerbating the intensity and frequency of wildfires and floods, understanding this link has nowadays become even more crucial and requires further exploration. This study proceeds along this path and establishes a comprehensive framework for rapidly evaluating the effect of a wildfire or a flood on the local landslide mechanism, as well as for effectively managing landslide hazards in the affected area. The proposed framework incorporates advanced Geographical Information System (GIS) tools, remote sensing techniques, and state of the art regional climate models, to assess landslide hazard and risk from wildfires and floods on the impacted area, as well as to offer vital tools for landslide management. Consequently, it provides a comprehensive and thorough assessment of the impact of these catastrophic phenomena on affected areas. Remote sensing and GIS techniques offer a cost-effective solution, as these methods, contrary to traditional in-situ methods, can be easily and rapidly applied even on large and complex areas. The integration of regional climate models also ensures the long-term viability of the proposed approach, as it takes under consideration the impacts of the climate crisis. As a result, the proposed framework contributes to scientists' ongoing efforts in understanding the dynamic *character of the landslides phenomenon that evolves and interacts with other natural disasters. Simultaneously, the results of the proposed methodology can effectively contribute to the local stakeholders' efforts to promptly assess the relative impact and make informed decisions regarding the required mitigation measures. Wildfires that ravaged the Chania regional unit in western Crete, Greece, in 2021, are selected as a case study to highlight the applicability and effectiveness of the proposed framework.*

***Keywords**: Landslides, Geographical Information System (GIS), Remote Sensing, Regional Climate Models, Multi-Criteria Decision Analysis (MCDA), Landslide Susceptibility Assessment.*

Περίληψη

Τις τελευταίες δεκαετίες, πολυάριθμες μελέτες και τεχνικές έρευνες έχουν καταγράψει ένα σημαντικό αριθμό κατολισθήσεων που ενεργοποιήθηκαν σε περιοχές οι οποίες είχαν πρόσφατα πληγεί από πυρκαγιές ή πλημμύρες, υποδηλώνοντας μια πιθανή σύνδεση μεταξύ των κατολισθήσεων και αυτών των φαινομένων. Με την κλιματική κρίση να επιδεινώνει την ένταση και τη συχνότητα των πυρκαγιών και των πλημμυρών, η κατανόηση αυτής της σύνδεσης, έχει γίνει στις μέρες μας ακόμη πιο κρίσιμη και απαιτεί περαιτέρω διερεύνηση. Αυτή η μελέτη διερευνά αυτή τη σύνδεση και δημιουργεί ένα ολοκληρωμένο πλαίσιο για την ταχεία αξιολόγηση της επίδρασης μιας πυρκαγιάς ή μιας πλημμύρας στον τοπικό μηχανισμό κατολισθήσεων, καθώς και για την αποτελεσματική διαχείριση των κινδύνων κατολισθήσεων στην πληγείσα περιοχή. Το προτεινόμενο πλαίσιο ενσωματώνει προηγμένες τεχνικές Γεωγραφικών Συστημάτων Πληροφοριών (GIS) - τηλεπισκόπησης καθώς και τελευταίας τεχνολογίας περιοχικών κλιματικών μοντέλων, για την αξιολόγηση του κινδύνου κατολισθήσεων και του αντίστοιχου ρίσκου που προκαλείται έπειτα από την εκδήλωση πυρκαγιών ή πλημμυρών σε μια περιοχή, ενώ παράλληλα προσφέρει και τα κατάλληλα εργαλεία για την αποτελεσματική τους διαχείριση. Κατά συνέπεια, παρέχει μια ολοκληρωμένη και ενδελεχή αξιολόγηση των επιπτώσεων αυτών των καταστροφικών φαινομένων στις πληγείσες περιοχές. Οι τεχνικές τηλεπισκόπησης και GIS προσφέρουν μια οικονομική και αποδοτική λύση, καθώς αυτές οι μέθοδοι, σε αντίθεση με τις παραδοσιακές επιτόπου μεθόδους, μπορούν να εφαρμοστούν εύκολα και γρήγορα ακόμη και σε μεγάλες και πολύπλοκες περιοχές. Η ενσωμάτωση περιφερειακών κλιματικών μοντέλων διασφαλίζει επίσης τη μακροπρόθεσμη βιωσιμότητα της προτεινόμενης προσέγγισης, καθώς λαμβάνει υπόψη τις επιπτώσεις της κλιματικής κρίσης. Ως αποτέλεσμα, το προτεινόμενο πλαίσιο συμβάλλει στις συνεχείς προσπάθειες των επιστημόνων για την κατανόηση του φαινομένου των κατολισθήσεων ως ένα δυναμικό

φαινόμενο που εξελίσσεται και αλληλοεπιδρά με άλλες φυσικές καταστροφές. Ταυτόχρονα, εξοπλίζει τους τοπικούς φορείς διοίκησης με τα απαραίτητα εργαλεία για την έγκαιρη αξιολόγηση του σχετικού αντίκτυπου και τη λήψη τεκμηριωμένων αποφάσεων σχετικά με τα απαιτούμενα μέτρα μετριασμού. Οι πυρκαγιές που έπληξαν την περιφερειακή ενότητα των Χανίων στη δυτική Κρήτη, Ελλάδα το 2021, επιλέγονται ως μελέτη εφαρμογής για την ανάδειξη της εφαρμοσιμότητας και αποτελεσματικότητας του προτεινόμενου πλαισίου.

Λέξεις Κλειδιά: Κατολισθήσεις, Γεωγραφικά Συστήματα Πληροφοριών (GIS), Τηλεπισκόπηση, Περιοχικά Κλιματικά Μοντέλα, Πολυκριτηριακές Μέθοδοι Ανάλυσης, Εκτίμηση Κατολισθητικής Επιδεκτικότητας.

1. Introduction

Landslides pose nowadays a significant threat to human health and safety, as they result in numerous fatalities every year (Froude and Petley, 2018) and cause the disruption or destruction of critical infrastructure systems, such as dams, bridges, and roads (Papoutsis et al., 2020; Valkaniotis et al., 2022). Historically, entire villages, such as the "Paleo Micro Chorio" in Greece in 1963 (Psomiadis et al., 2020a), or even small towns, such as the "Santa Maria Tlahuitoltepec" in Mexico in 2010 (Soares et al., 2011), have been nearly wiped off the map because of intense landslides. Due to the climate crisis, the frequency and severity of landslides are expected to increase in many regions worldwide (Lin et al., 2022), thereby exposing higher numbers of people to landslide risk (Gariano and Guzzetti, 2016). Landslides are considered one of the most critical natural hazards, and the scientific community is actively pursuing the development of methods for their prompt identification and mitigation. However, their complex nature and the variation in factors that influence their activation over time and from region to region, make their study a quite difficult and challenging process (van Westen et al., 2006).

Over the past few decades, numerous research studies and technical surveys have pointed at a potential link between landslides and wildfires or floods (Culler et al., 2023; Palmer, 2022; Sprague-Wheeler, 2003; Swanson, 1979), as an increased number of landslides has been observed in the years following either an extended wildfire or flood (Duncombe, 2018; Rengers et al., 2020; Sarro et al., 2021). For instance, in the years following the devastating wildfires of 2007 in the Ilia regional unit, located in the north-west Peloponnese, Greece, more than 120 landslides were recorded in the fire-affected areas (Lainas et al., 2016). Similarly, after the flood events in the northern and eastern parts of Bosnia and Herzegovina in 2014, several thousand landslides were also documented (Djuric et al., 2015). Nevertheless, it is worth noting that some other studies have provided different results, as they reported that the occurrence of wildfires or floods in certain cases was not accordingly followed by an increased number of landslides in those areas (Campbell, 1975; Rengers et al., 2020). Thus, it is crucial to develop a framework to evaluate whether the local landslide mechanism of an area which was affected by wildfires or floods has been also impacted and, if so, to determine the extent of this impact.

The main objective of this study is to provide a methodological framework that would allow stakeholders to better evaluate whether an area affected by wildfires or floods is expected to experience an increased number of landslides in the aftermath of such calamities. If this turns out to be the case, this framework can also then provide the necessary tools for a functional and effective management of landslide risk. Hence, it must possess specific characteristics. Firstly, it must include methodologies that can be rapidly applied, even across extended and complex areas. Secondly, considering the dynamic nature of landslides, the whole process may require regular updates, which means that the entire framework should be based on low or no-cost methodologies and open access or publicly available data. Thus, conventional methods, such as the installation of piezometers or inclinometers, are not suitable for the rapid and cost-effective monitoring of landslides over large areas (van Westen et al., 2006). On the contrary, remote sensing techniques combined with geographical information systems (GIS) tools can offer swift application, even across extensive and complex regions, while being cost-effective and requiring minimal resources. Furthermore, to ensure the longevity of the entire approach, it is crucial to take into account the impact of the climate crisis, which can be accomplished by incorporating the application of regional climate models (RCM) into the proposed framework. Finally, the applicability of the proposed framework is tested by using the 2021 wildfires in the Chania regional unit, Greece, as a case study to evaluate their impact on the local landslides' activation mechanisms.

2. Data and methods

The designed framework must be cost-effective, easily, and rapidly applicable, use minimum resources, be based on open access or publicly available data, and take into consideration the effects of the climate crisis. This study proposes a framework that is based on the previously mentioned specifications, summarised graphically in Figure S1 (see supplementary material). An outline of its components is shown in Figure 1 and, as it can be observed, the framework is divided into three main sections.

The first section focuses on the examination of the characteristics of the Area of Interest (AOI), which were used as inputs into the framework, and the methods for their processing. The data used during this study, along with the respective sources, are detailed in Supplementary Material Table S1, while their processing methods in Table S2. Most of the data used in the proposed framework are open access or publicly available. Open access data is freely available for anyone to use and share, while publicly available data, while freely accessible, may retain some limitations on its use, distribution, or modification (Tedersoo et al., 2021).

The second section of the framework includes the outcomes that this approach is expected to provide. For the AOI, these are the “Landslide Inventory Mapping”, the “Landslide Susceptibility Assessment”, the “Hazard Assessment”, the “Risk Assessment”, and the “Landslides Management” tools. The third and final section analyses how the above outcomes can be employed across the different phases of a comprehensive and thorough landslide management plan, i.e., the mitigation, preparedness, response, and recovery phases.

The individual methods applied in each section are thoroughly analysed in the following paragraphs. It should be noted, however, that the proposed framework does not introduce new methods. Instead, it integrates a range of existing ones, which operate and interact with each other in a multifaceted manner, thereby leveraging the knowledge generated and provided by various scientific research studies. Subsequently, the proposed framework is applied to evaluate the impact of wildfires that ravaged the Greek regional unit of Chania in Grete, in 2021. Thus, the effectiveness of the proposed framework is evaluated, and significant results and conclusions emerge.

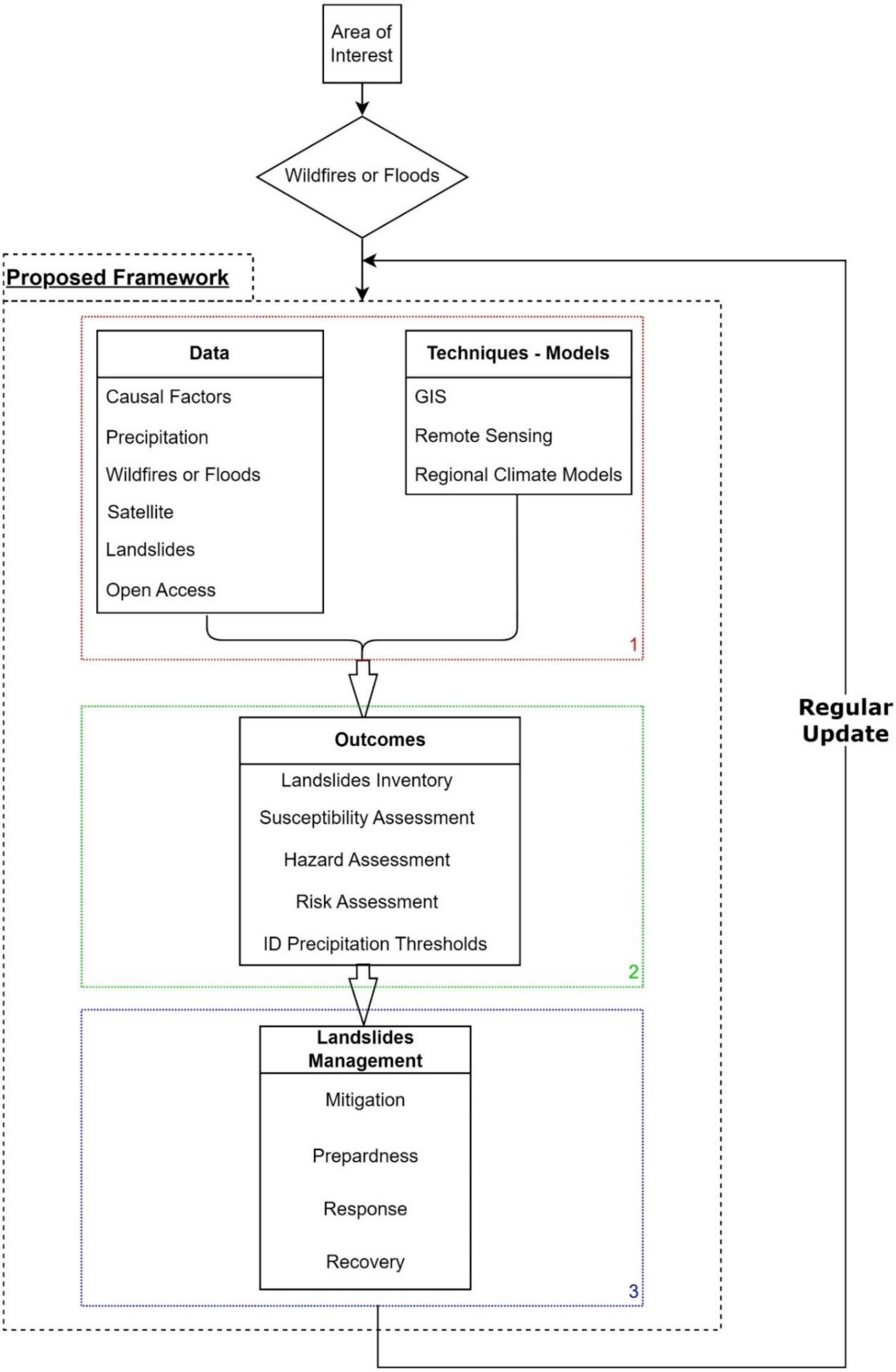

Fig. 1: Graphical Representation of the Proposed Framework

2.1 Identification of the Most Critical, Local, Landslide Causal Factors

Every region has its own unique characteristics that shape its landscape and affect its landslide susceptibility. Therefore, it is essential, as an initial step in establishing the framework, to identify and determine the spatial characteristics of the AOI that can potentially impact the occurrence of landslides. This step is significant as these factors provide an initial understanding of the functioning of the local landslide mechanism before the onset of wildfires or floods. In this regard, the application of Multi-Criteria Decision Analysis (MCDA) can be a valuable tool in identifying the most critical causal factors in the AOI and subsequently, in evaluating their relative contribution/weight to the activation of the local landslide mechanism (Psomiadis et al., 2020b). For instance, Nefros et al. (2023b) identified precipitation, lithology, slopes' angle, slopes' aspect, distance from roads, distance from rivers, land use / land cover and relative relief as the most critical causal factors for the South Pilio region in Central Greece and used analytical hierarchy process (AHP), a MCDA method, in a GIS environment, to form the relative landslide susceptibility map. Useful information about the MCDA methods used in past scientific research studies conducted in regions near the examined area, and their findings, can be also extracted from the publicly available global database GEOLAND (Nefros and Loupasakis, 2022). In this study, we show via examples how further details concerning potential causal factors, along with their suggested potential values-weights, can be extracted by using GEOLAND along with other publicly available databases (e.g., using GEOLAND in combination with the active faults of Greece database Ganas et al., 2013) to subsequently determine the values of the "distance from active faults" causal factor).

2.2 Analysing Precipitation Data

Precipitation plays a significant role in most of the processes included in the proposed framework. For instance, precipitation time series can be used to evaluate:

a. The mean annual precipitation (MAP), which is one of the most common landslide causal factors according to Nefros and Loupasakis (2022) and is therefore used during the formation of the landslides' susceptibility maps.

b. The precipitation intensity (usually calculated per day or per hour), for assessing the activation precipitation thresholds for landslides, both before and after the occurrence of wildfires or floods.

c. The bias corrected projected values of the precipitation for the following decades, through the use of regional climate models (RCM).

Precipitation is a prevalent factor in triggering landslides worldwide (Polemio and Petrucci, 2000), and is especially prominent in Greece (Koukis et al., 1997). Nowadays, precipitation data is collected by various sources, but not all of these databases are publicly available. This study focuses on the meteorological databases with publicly available precipitation datasets, such as the *Meteo* platform (Lagouvardos et al., 2017) and the *Hydroscope Project* (Sakellariou et al., 1994). However, the density of the meteorological stations, the time span, and the completeness of the data can vary significantly, necessitating the verification of data reliability (Nefros et al., 2023b). A comprehensive list of potential meteorological databases is provided in Table S1.

2.3 Assessing the Extent, Frequency and the Severity of the Impact of Wildfires or Floods

The occurrence of catastrophic events, such as wildfires or floods in the AOI, does not necessarily mean that the landslide hazard has also increased. Therefore, after such events in the AOI it is crucial to rapidly determine the damage made to the local vegetation, as this can have negative implications on soil cohesion. Through the proposed framework, this damage is evaluated through the following three steps: delineation, frequency, and severity.

The first step, delineation, concerns the assessment of the spatial characteristics of these catastrophic events. It can be accomplished in a GIS environment by using satellite images to calculate indexes, such as the normalized difference vegetation index (NDVI) (Reszka and Fuentes, 2015), for the assessment of the burned areas, as well as the normalized difference water index (NDWI) (Khalifeh et al., 2019) for the assessment of the flooded areas. Alternatively, publicly available platforms such as the European Forest Fire Information System (EFFIS) (Llorens et al., 2021) and the European Flood Awareness System (EFAS) (Smith et al., 2016) can be used, as they provide direct information about the affected areas. The second step, the evaluation of frequency, includes the identification of the occurrence of such catastrophic events in the AOI in the past. In many cases the recurrence of these events can cause critical disturbance to the local vegetation (Moghli et al., 2022) and can therefore subsequently also affect the landslide susceptibility of the AOI. The spatial frequency of these catastrophic events can be evaluated by comparing the previously mentioned indexes NDVI and NDWI, derived by past and current satellite images. Alternatively, they can be evaluated by using publicly available databases that directly provide such information, like the Apostolakis et al. (2021) and the Diakakis (2014) databases. The third step concerns the evaluation of the severity of the impact of these catastrophic events on the local vegetation. Usually, after a high intensity wildfire, the extensive damage caused to the trunks and foliage of the trees gradually leads to their roots' decomposition and the erosion of the soil. If the prevailing factors in this area (such as the slope's angle) favour the appearance of landslides, the frequency of landslides is going to increase (Calcaterra et al., 2007). However, after the occurrence of some wildfires, the vegetation roots can survive for a period that usually spans from one to six years, after which they start to decompose, and it is only then that we witness an increase in the number of landslide events (Meyer et al., 2001; Sprague-Wheeler, 2003). In some other cases, the impact of the catastrophic events on the vegetation is not irreparable, and the vegetation can remain alive and can progressively be restored after a few years (Pereira et al., 2016). In these cases, soil coherence is preserved during the whole period, thereby leading to insignificant changes to landslide occurrence. Hence, the evaluation of the severity of the wildfires and their impact on the local vegetation can provide critical insights.

The severity of a wildfire can be evaluated either through the NDVI change (before and after the wildfire), or similar indexes (such as the Differenced Normalized Burn Ratio (DNBR), the Relativized Burn Ratio (RBR) (De Simone et al., 2020), and the Burned Vegetation Index (BVI) (Kovács, 2019). Besides the assessment of severity, these indexes can also provide vital information concerning the changes caused to the forest structure and moisture (Cocke et al., 2005). Publicly available databases, such as the Coordination of Information on the Environment (CORINE), can provide additional information about the pre-existing land use/land cover in the AOI, such as the type of vegetation before the wildfire events.

2.4 Using Satellite Images for identifying new landslides and monitoring existing ones.

Besides the assessment of the previously mentioned indexes in order to evaluate the damage made by catastrophic events like wildfires or floods, satellite images can be also used to identify new landslides and monitor existing ones. This can be very critical as these landslides can provide direct evidence about the situation of the AOI following the catastrophic events. Thus, they can be used both for updating the landslide susceptibility assessment of the AOI and for the evaluation of the efficacy of the previously applied susceptibility methods. Furthermore, Persistent Scatterer Interferometry (PSI) can provide advantages to scientists, especially in difficult-to-access or extended areas, where the application of traditional methods is not a cost-effective solution. The process for identifying new landslides and the monitoring of existing ones, by using remote sensing techniques, is thoroughly analysed in Nefros et al., (2023a). In this study, the parallelized persistent scatterers interferometry (P-PSI) technique, developed by BEYOND (*the Operational Unit Center for Earth Observation Research and Satellite Remote Sensing of the Institute of Astronomy and Astrophysics, Space Applications and Remote Sensing of the National Observatory of Athens*) was used, along with open access or publicly available data, for the swift identification and monitoring of 235 new landslides.

2.5 Forming a Landslide Inventory

Forming a comprehensive landslides inventory is a critical step in our proposed framework, as it is needed for the application of the MCDA methods. Specifically, it is needed both for assessing the factors that caused the landslides, as well as for evaluating the effectiveness of the method. An example worth noting is Nefros et al., (2023b), where a local landslide inventory was formed by using pre-existing inventories provided by the Hellenic Survey of Geology and Mineral Exploration (HSGME), remote sensing techniques, field surveys and open access or publicly available data. A full list of publicly available databases concerning landslides, is included in Supplementary Material Table S1.

2.6 Using Other Open Access or Publicly Available Data

As previously noted, open access or publicly available data play a vital role when it comes to the effective application of our proposed framework, as they contribute to determining the areas affected by wildfires or floods, identifying new landslides and, as a result, the forming of a comprehensive landslide inventory. However, their use is not only limited to these sectors, as they can also contribute to the verification of the effectiveness of each of the measures applied by the stakeholders. In Greece, open access and publicly available data can be obtained by European organizations (such as the European Environment Agency), by Ministries (such as through the geoportal of the Ministry of the Environment and Energy), by public services (such as the Hellenic Statistical Authority and the Hellenic Survey of Geology and Mineral Exploration - HSGME), by regional administrations (such as the Regional Administration of Crete) or by institutes (such as the Institute of Astronomy and Astrophysics, Space Applications and Remote Sensing of the National Observatory of Athens). A full list of the sources of all the data used during this study is provided in Table S1.

3. Results

As mentioned earlier, our proposed framework aims to provide a comprehensive evaluation of the potential danger for landslides in an area affected by wildfires or floods, as well as aid in the identification of the requisite measures for their effective management. In this direction, and following the requirements illustrated in Figure 1, the methods included in the proposed framework are designed with a twofold objective. First, to allow for the rapid conduct of a landslide hazard and risk assessment of the AOI right after a wildfire or flood and, second to aid in the subsequent monitoring of ongoing landslides in the most critical subregions of the AOI. As a result, impacted AOI stakeholders are placed in a good position to effectively apply focused and effective measures to address the dangers that have arisen following wildfires or floods. As a case study, the proposed framework is applied to examine how the occurrence of the 2021 wildfires in the Chania Regional Unit, in western Crete Island, Greece, have affected the local landslide mechanism. The current study shows that the proposed framework can effectively combine the previously mentioned GIS-remote sensing techniques with regional climate models to provide a complete landslides' hazard and risk assessment for the AOI. Finally, it shows how local stakeholders can leverage the results provided by the framework and use its outputs to put in place a complete and effective landslides management plan for each of the four phases involved, i.e., the mitigation, preparedness, response, and recovery phases.

3.1 Creating a Landslide Inventory Map

By using the GEOLAND open access platform (Nefros and Loupasakis, 2022) alongside landslide data provided by the Hellenic Survey of Geology and Mineral Exploration (HSGME), an initial landslides inventory for the AOI was created. Subsequently, the initial inventory was enriched with the new landslides that were identified using the P-PSI method, and a complete landslides inventory was therefore created. Figure 2 illustrates the relative landslides inventory map (LIM) which was formed for the AOI and shows the complete landslides inventory. A LIM can be very helpful for a researcher as it illustrates "where do which landslides occur" (Günther, 2007), and represents one the simplest qualitative approaches for conducting an initial landslide hazard assessment of the AOI (Pardeshi et al., 2013). In Figure 2, the red triangles represent the landslide events that have been recorded in the AOI. Therefore, based on the principle that “in many landscapes, landslides tend to occur where they have occurred in the past” (Malamud et al., 2004), the LIM provides stakeholders with clear and direct indications of the potential location of future landslides within the AOI.

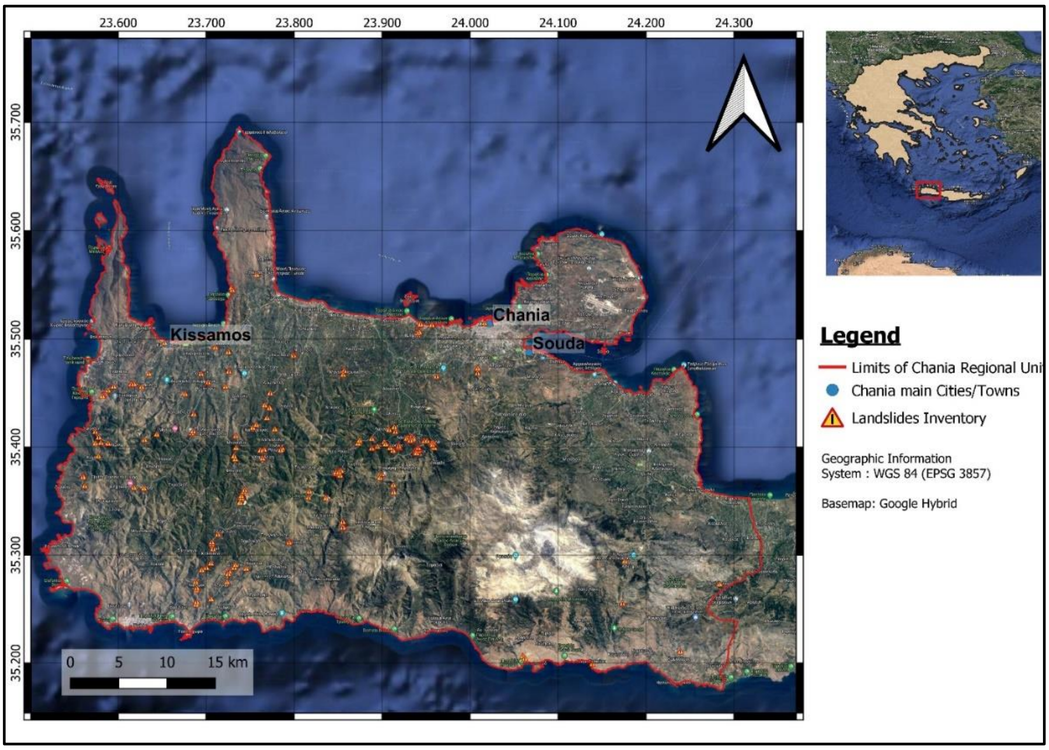

Fig. 2: Landslides Inventory Map for the Chania Regional Unit, Greece.

3.2 Landslides Susceptibility Assessment

Landslide susceptibility (LS), according to Chalkias et al., (2014), is the propensity of soil or rocks to produce a landslide. To evaluate the LS of the AOI, the aforementioned analytical hierarchy process (AHP) was employed. Firstly, relative research studies conducted in the area of interest, such as Kouli et al. (2014), Psomiadis et al. (2020b) and Nefros et al. (2023b), were studied. Experts identified the “mean annual precipitation” (F1), the “slopes angle” (F2), the “slopes aspect” (F3), the lithology (F4), the “relative relief” (F5), the “distance from streams” (F6), the “normalized difference vegetation index” (NDVI) (F7), and the “distance from roads” (F8), as the most critical causal factors. Their values were determined by using open access or publicly available data, as per the proposed framework.

Specifically, the mean annual precipitation was assessed using the precipitation time series from 21 meteorological stations, offering publicly available data, as recommended by Nefros et al., (2023b). A comprehensive list of these stations is provided in Table S3. The slopes angle, aspect and relative relief were calculated using GIS and a high resolution (12.5 m *12.5 m) Digital Elevation Model (DEM), acquired by ALOS/PALSAR according to Xiong et al. (2017). Distance from streams and distance from roads were calculated using GIS techniques and open-access data from *openstreetmap*, according to Table S1. The lithological data was acquired by using the publicly available data provided by the geoportal of the administration of the Chania regional unit (Table S1) and the Hellenic Survey of Geology and Mineral Exploration (HSGME). NDVI was assessed using Sentinel-2 images, thresholds suggested by Arabameri et al. (2019) and the following equation:

$$NDVI = \frac{NIR-RED}{NIR+RED} \qquad (1)$$

The corresponding maps that were created for each causal factor are illustrated in Figures 3 to 10. The subclasses of each causal factor are presented in Table S3.

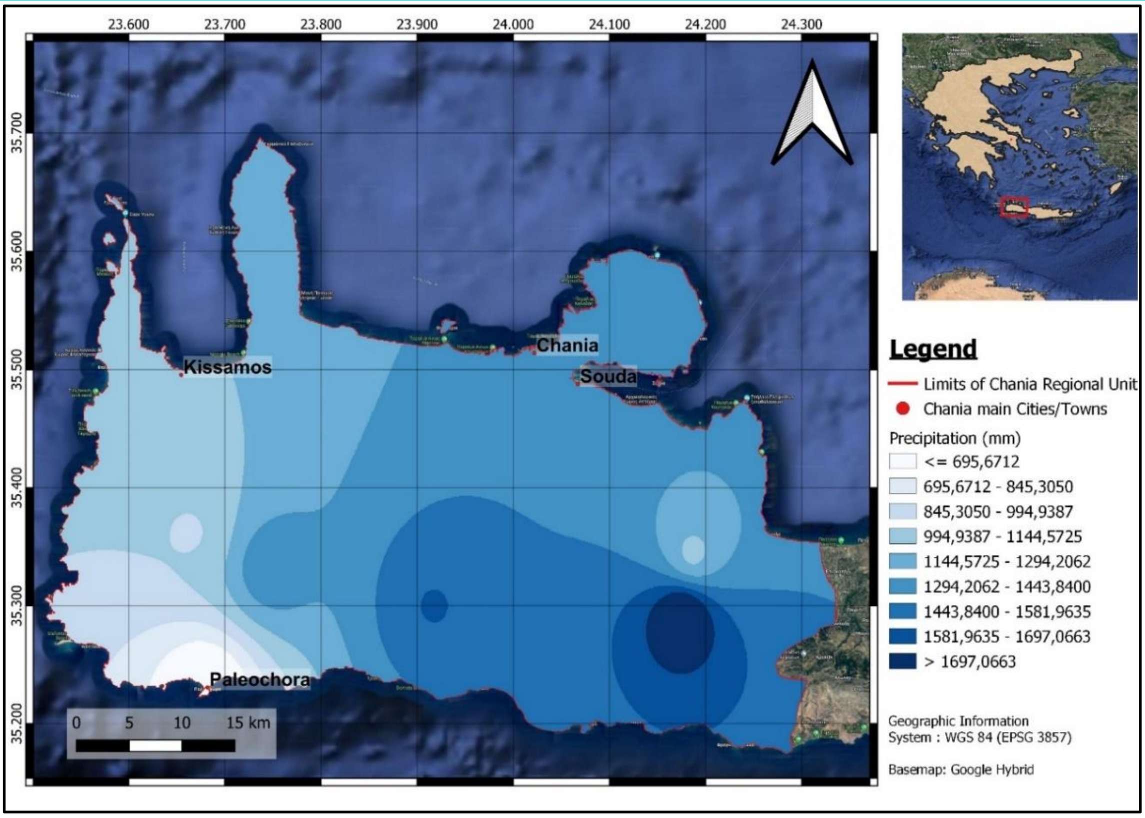

Fig. 3: Landslides Causal Factor Mean Annual Precipitation, for the Chania Regional Unit.

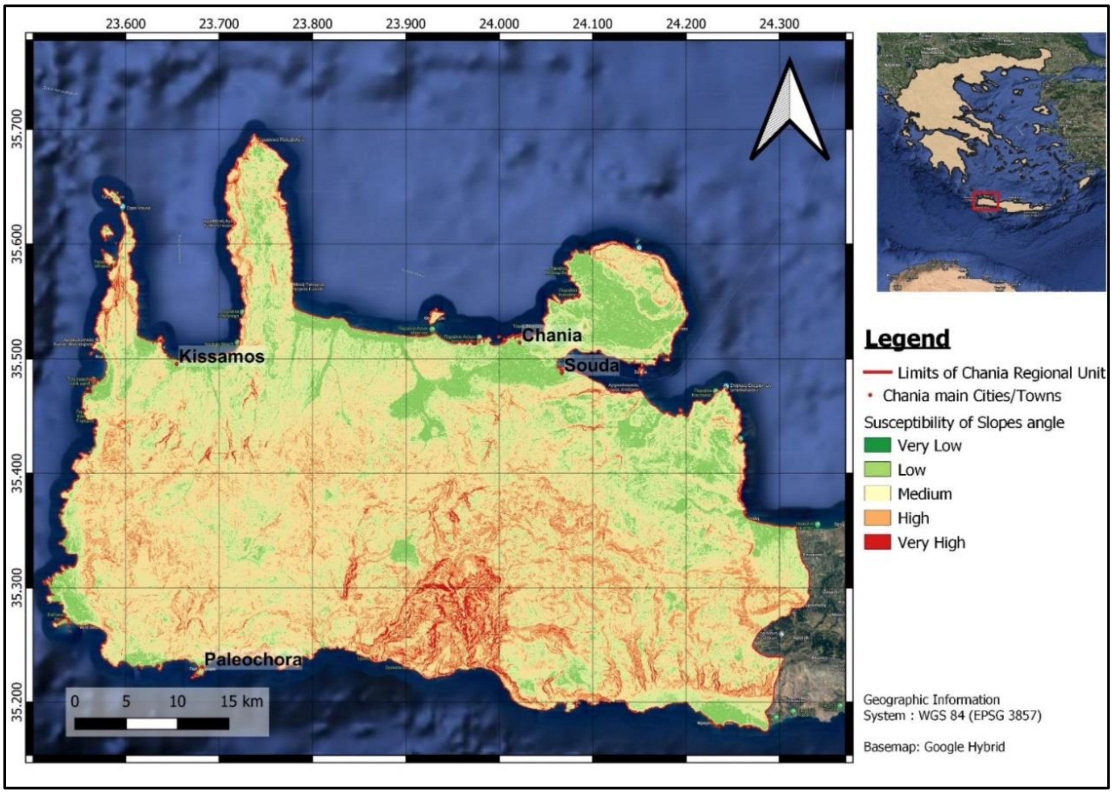

Fig. 4: Landslides Causal Factor Slopes Angle, for the Chania Regional Unit.

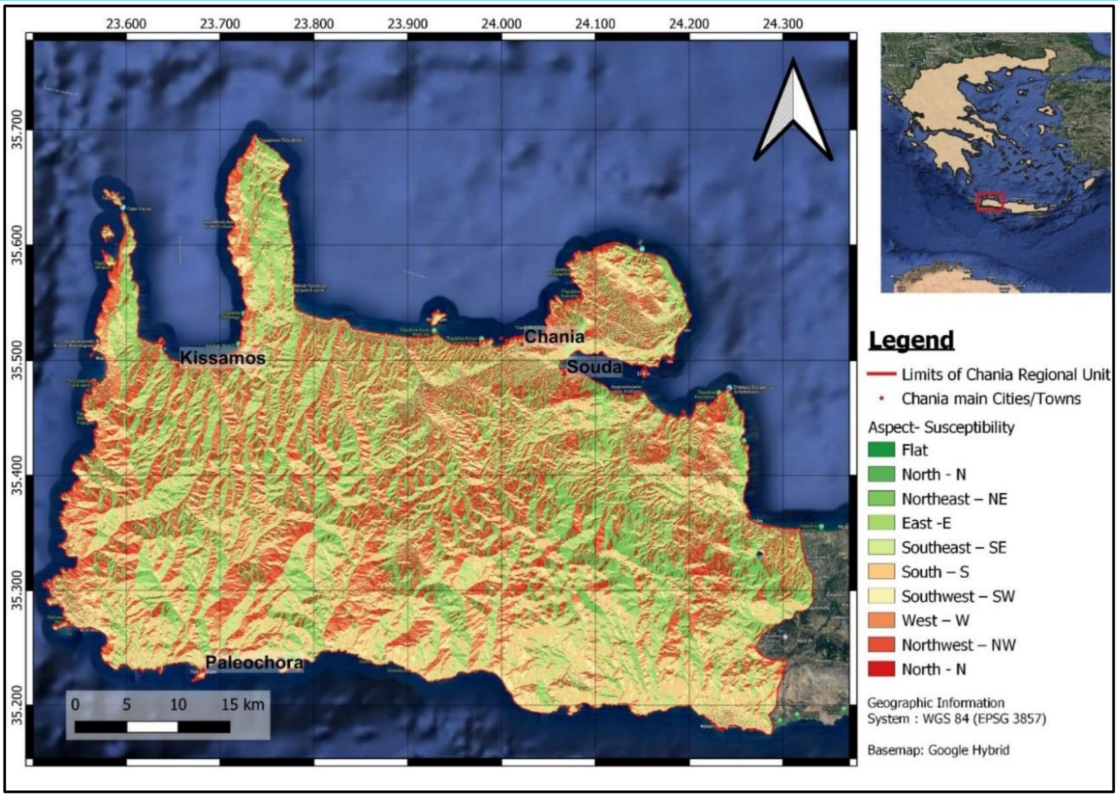

Fig. 5: Landslides Causal Factor Slopes Aspect, for the Chania Regional Unit.

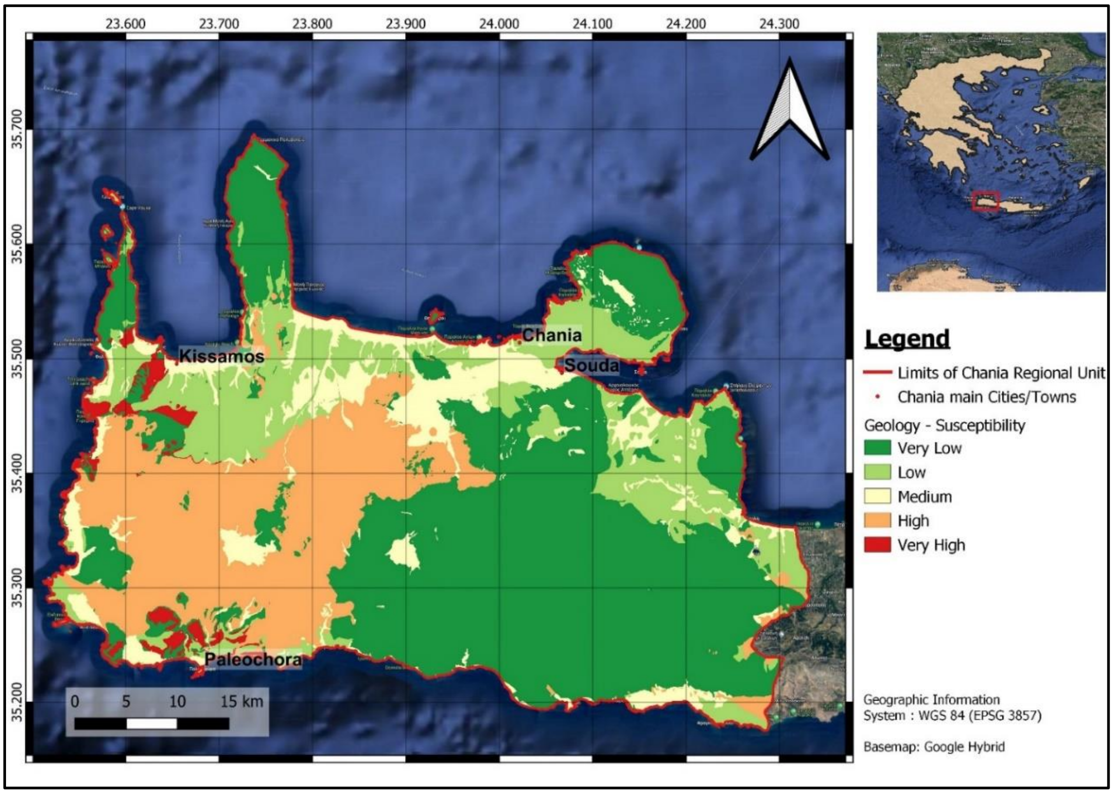

Fig. 6: Landslides Causal Factor Lithology, for the Chania Regional Unit.

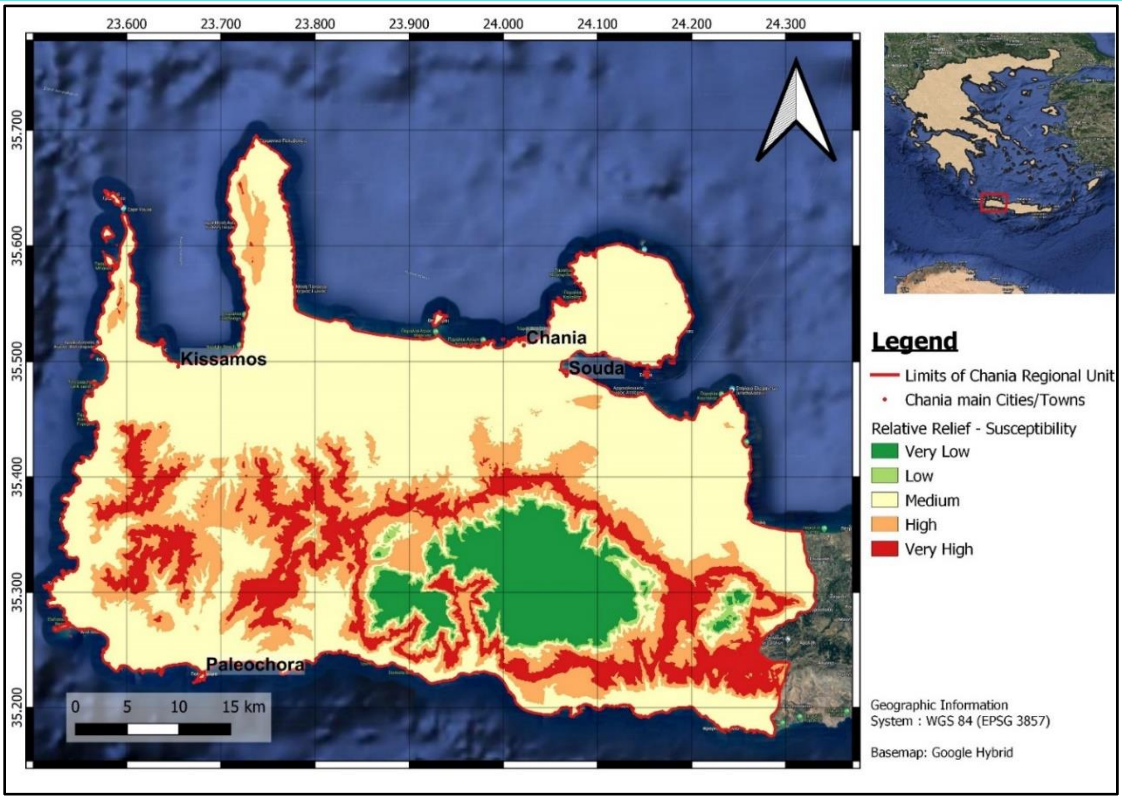

Fig. 7: Landslides Causal Factor Relative Relief, for the Chania Regional Unit.

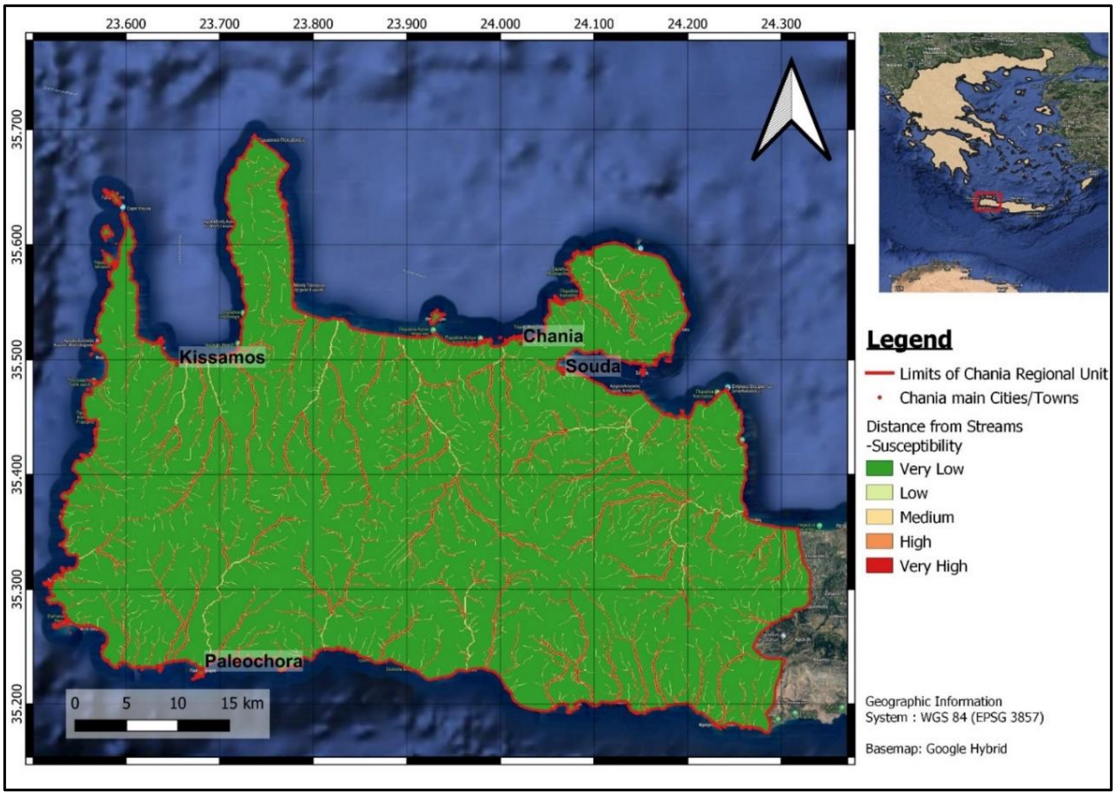

Fig. 8: Landslides Causal Factor Distance from Streams, for the Chania Regional Unit.

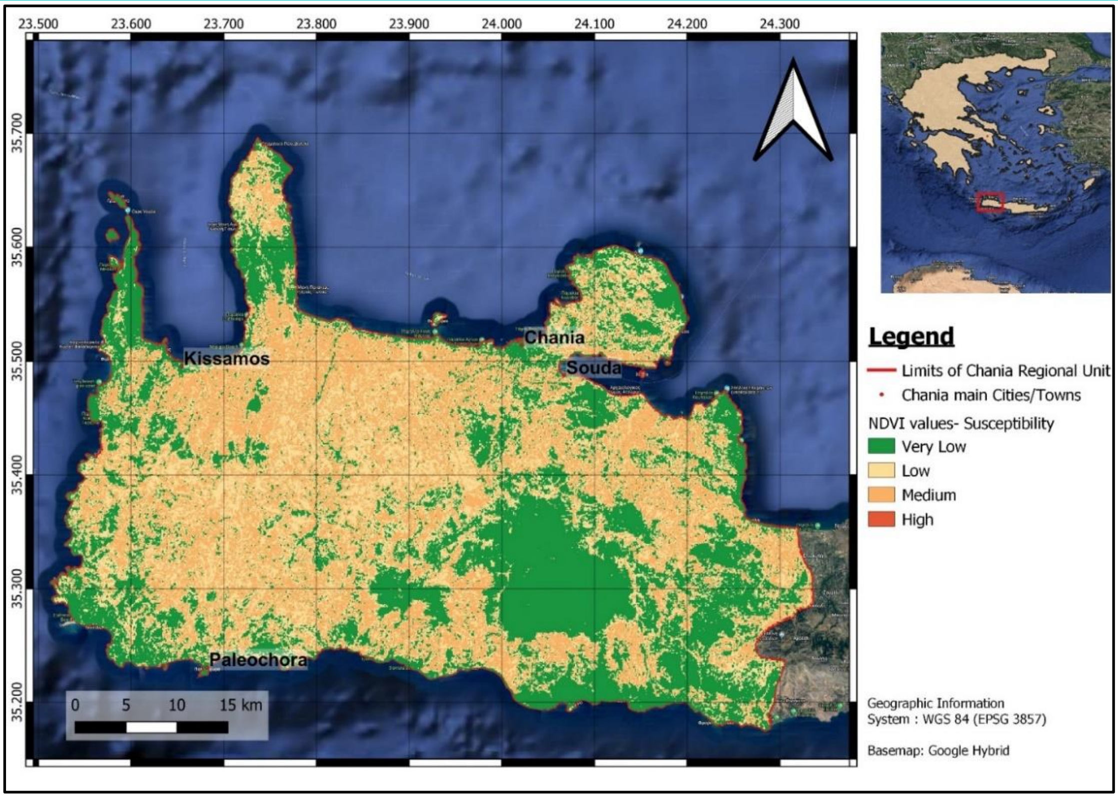

Fig. 9: Landslides Causal Factor NDVI, for the Chania Regional Unit.

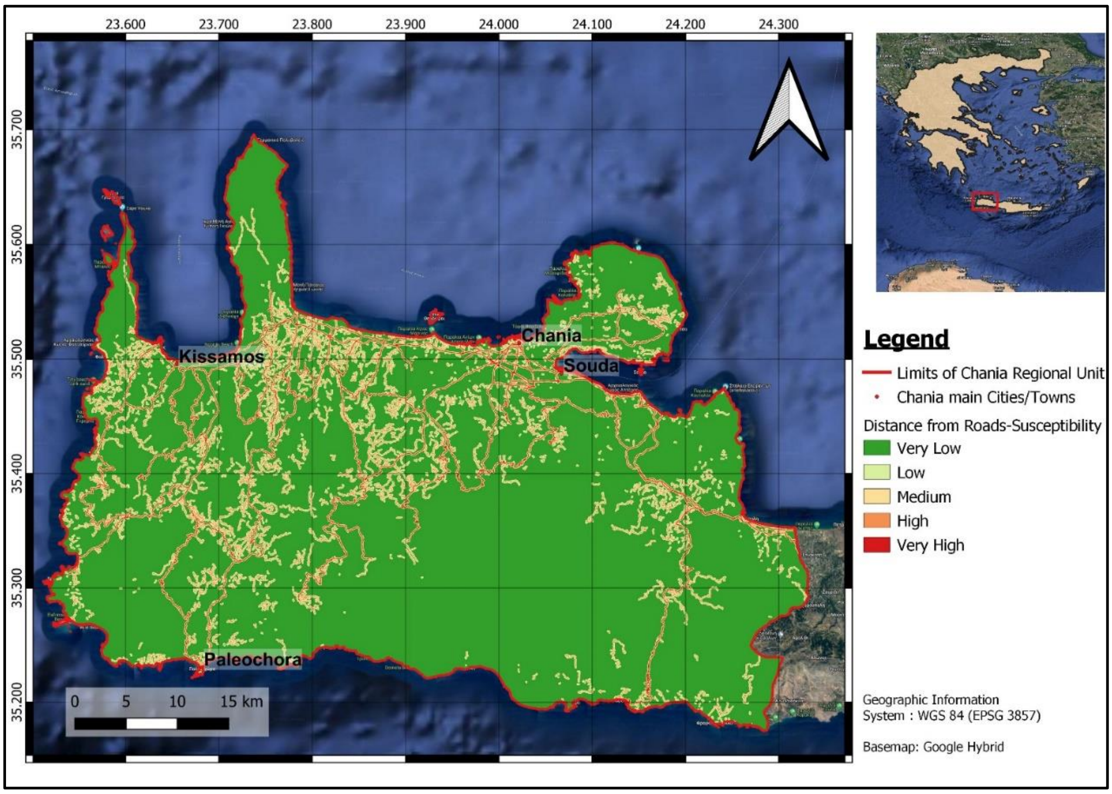

Fig. 10: Landslides Causal Factor Distance from Roads, for the Chania Regional Unit.

Subsequently, as presented in Tables 1 and 2, the relative weights-contribution of each factor were evaluated by experts using a pair wise matrix. The relationship between each pair of causal factors was assessed by using Table S4.

Table 1. Causal Factors Pair Wise Matrix.

Causal Factors	F1	F2	F3	F4	F5	F6	F7	F8
F1	1.00	1.00	4.00	1.00	4.00	2.00	3.00	2.00
F2	1.00	1.00	2.00	0.50	2.00	1.00	2.00	1.00
F3	0.25	0.50	1.00	0.25	3.00	0.50	1.00	0.50
F4	1.00	2.00	4.00	1.00	3.00	1.00	1.00	1.00
F5	0.25	0.50	0.33	0.33	1.00	0.50	1.00	2.00
F6	0.50	1.00	2.00	1.00	2.00	1.00	1.00	1.00
F7	0.33	0.50	1.00	1.00	1.00	1.00	1.00	1.00
F8	0.50	1.00	2.00	1.00	0.50	1.00	1.00	1.00
Total	4.83	7.50	16.33	6.08	16.50	8.00	11.00	9.50

Table 2. Causal Factors Weights Assessment.

Causal Factors	F1	F2	F3	F4	F5	F6	F7	F8	Total		**Weight**	Consistency	Final Weight
F1	0.21	0.13	0.24	0.16	0.24	0.25	0.27	0.21	1.73		**0.216**	8.70	**10**
F2	0.21	0.13	0.12	0.08	0.12	0.13	0.18	0.11	1.08		**0.135**	8.60	**6**
F3	0.05	0.07	0.06	0.04	0.18	0.06	0.09	0.05	0.61		**0.076**	8.94	**3**
F4	0.21	0.27	0.24	0.16	0.18	0.13	0.09	0.11	1.39		**0.173**	8.76	**8**
F5	0.05	0.07	0.02	0.05	0.06	0.06	0.09	0.21	0.62		**0.077**	8.46	**3**
F6	0.10	0.13	0.12	0.16	0.12	0.13	0.09	0.11	0.97		**0.121**	8.66	**5**
F7	0.07	0.07	0.06	0.16	0.06	0.13	0.09	0.11	0.74		**0.093**	8.49	**4**
F8	0.10	0.13	0.12	0.16	0.03	0.13	0.09	0.11	0.88		**0.109**	8.50	**5**
Total	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00			CI	0.09	
											RI	1.41	
											CR	**0.06**	
											Check CR<0.1	**OK**	

AHP was applied accordingly for the evaluation of the weights of the individual subclasses within each causal factor. The detailed outcomes are presented in Table 3.

Table 3. Landslide weight rating adopted in this study for the causal factors' subclasses.

Causal Factor Code	Layers	Subclasses	Weight	Relative Susceptibility Ranking
F1	Mean Annual Precipitation	>1600mm	10	Very High
		1400—1600 mm	9	High
		1200—1400 mm	8	High
		1000—1200 mm	7	Medium
		800—1000 mm	5	Low
		<800mm	3	Very Low
F2	Slope Angle	>45°	10	Very High
		31-45°	9	High
		16-30°	8	Medium
		6-15°	3	Low
		0-5°	1	Very Low
F3	Slope Aspect	Flat	0	Very Low
		North - N (0° – 22.5°)	9	High
		Northeast – NE (22.5° – 67.5°)	6	Medium
		East -E (67.5° – 112.5°)	4	Low
		Southeast – SE (112.5° – 157.5°)	2	Low
		South – S (157.5° – 202.5°)	4	Low
		Southwest – SW (202.5 ° -247.5°)	6	Medium
		West – W (247.5° – 292.5°)	9	High
		Northwest – NW (292.5° – 337.5°)	10	Very High
		North - N (337.5° – 360°)	9	High
F4	Geology	Loose quaternary deposits (Alluvial deposits, Slope debris and fans, Torrent terraces)	8	Medium
		Neogene (reefal Limestones, Pantanassa formation)	7	Low
		Limestones – Marbles (Platy limestones, Limestones and dolomites, Carbonate undivided layers)	6	Very Low
		Flysch	10	Very High
		Schists and Ophiolites (phyllites, quartzites, shales, schists)	9	High
F5	Relative Relief	>1401 m	2	Very Low
		1301—1400 m	4	Low
		1201—1300 m	6	Medium
		1101—1200 m	7	Medium
		10011100 m	8	High
		901—1000 m	9	High
		801—900 m	10	Very High
		701—800m	9	High
		601—700 m	8	High
		501—600m	7	Medium
		< 500m	6	Medium

F6	Stream Network	a. Class 1 (Buffer)		
		< 10m	7	High
		10-20m	5	Medium
		> 20m	0	Very Low
		b. Class 2 (Buffer)		
		< 20m	8	High
		20-50m	6	Medium
		> 50m	0	Very Low
		c. Class 3 (Buffer)		
		< 50m	10	Very High
		50-100m	7	High
		> 100m	0	Very Low
		d. Class 4 (Buffer)		
		< 20m	7	High
		20-50m	5	Medium
		> 50m	0	Very Low
		e. Class 5 (Buffer)		
		< 10m	4	Low
		10—20m	2	Low
		> 20m	0	Very Low
F7	NDVI	< 0,15	10	High
		0,15-0,3	8	Medium
		0,3-0,43	6	Low
		> 0,43	4	Very Low
F8	Distance from Road Network	a. Category 1 (Motorway, trunk, primary, secondary roads)		
		Surfaced (Buffer)		
		< 20m	10	Very High
		20—50m	8	High
		50—100m	6	Medium
		> 100m	0	Very Low
		b. Category 2 (Track grade 1, track grade2, service roads)		
		Surfaced (Buffer)		
		< 20m	7	High
		20—50m	5	Low
		50—100m	3	Low
		> 100m	0	Very Low
		c. Category 3 (Tertiary, residential, living streets, service, footway, track grade3, track grade4, pedestrian, path, bridleway roads	0	Very Low

To form the relative LS map, these factors were inserted in a GIS environment, and the landslide susceptibility index (LSI) was calculated for every pixel of the AOI, according to the following equation:

LSI= 10*precipitation+ 6*“slopes angle” + 3* aspect + 8* lithology +3* “relative relief” + 5*“distance from streams” + 4*NDVI + 5* “distance from roads (2)

Figure 11 illustrates the LSM for the AOI that was produced as a result. The Consistency Ratio (CR) is an index used to assess the appropriateness of judgements made by the experts and when it exceeds 0.1, the judgements need re-examination (Saaty, 1987). According to the methodology suggested by Saaty (1987), to assess the CR the following equations are used:

$$CR = \frac{CI}{RI} \qquad (3)$$

- where CI is the Consistency Index:

$$CI = \frac{\lambda max - n}{n-1} \qquad (4)$$

- λmax is the maximum eigenvalue,
- n is the number of the causal factors, and
- RI is the Random Index, evaluated by the Table S5.

Table 2 presents the assessment of the Consistency Index (CI), Random Index (RI), and Consistency Ratio (CR) index. Since the CR is less than 0.1, the experts’ judgements are deemed acceptable. A more detailed analysis of the AHP method is provided by Nefros et al., (2023b).

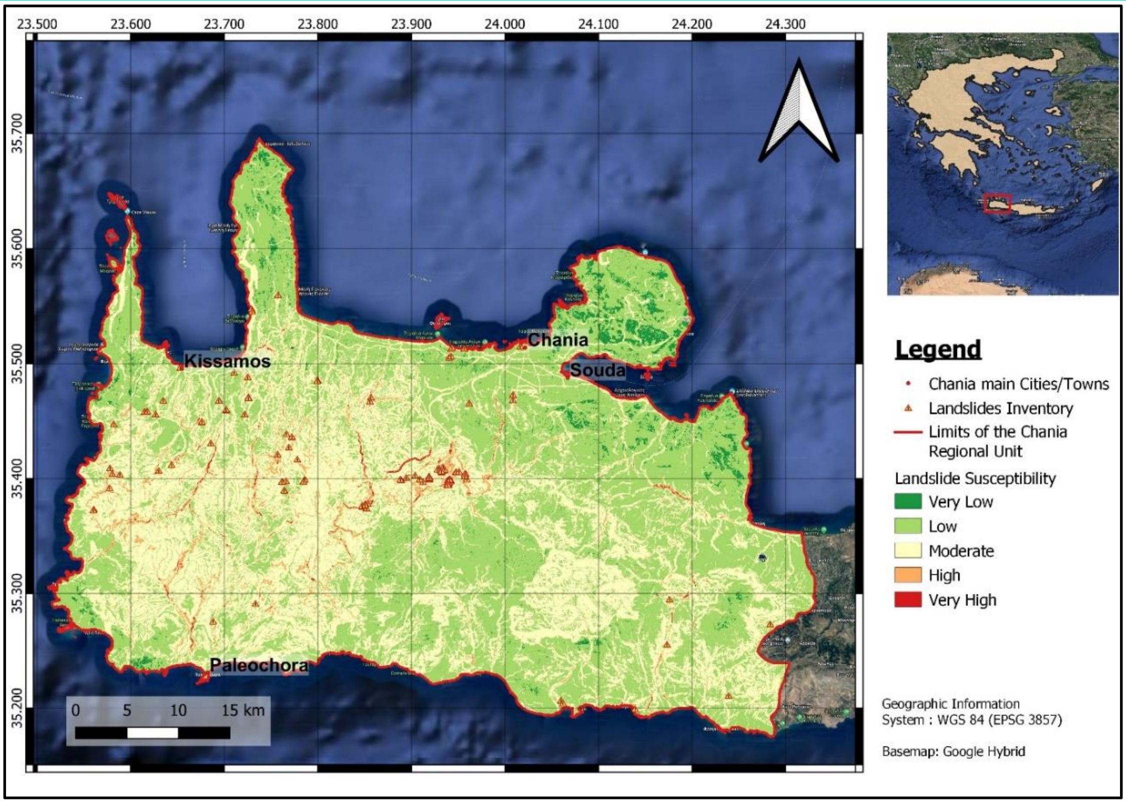

Fig. 11: Landslides Susceptibility Map for the Chania Regional Unit, Greece.

As it is illustrated in Figure 11, the majority of landslides occurred in regions classified as high and very high susceptibility, with only a small proportion occurring outside these susceptibility classes. As shown in Figure 12, the Receiver Operating Characteristics (ROC) curve was generated, and the calculated Area Under Curve was 81,9%, indicating a highly satisfactory level of the method's effectiveness.

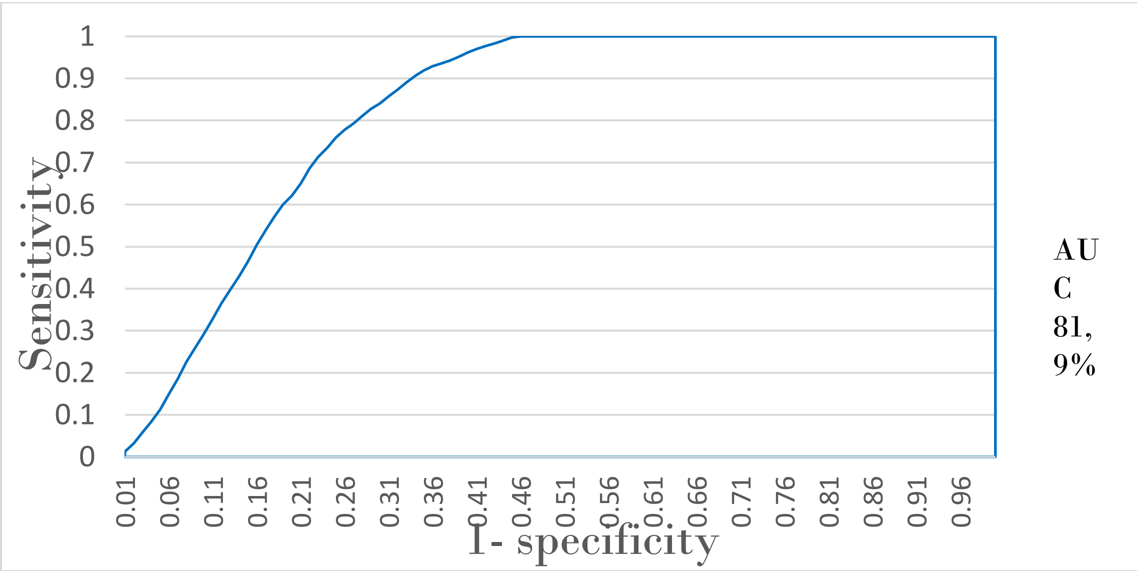

Fig. 12: Area Under the Curve for evaluating the efficacy of the applied method.

3.3 Landslides Hazard Assessment

According to Varnes (1984) a natural hazard assessment includes the evaluation of the probability of the occurrence of a potentially damaging phenomenon in a given area within a specified period of time. In the current case study, the natural hazards which are assessed are landslides following the occurrence of the 2021 wildfires in the Chania regional unit. Currently, there is no universally acceptable methodology for evaluating the landslide hazard (Pardeshi et al., 2013). For the purposes of this study the landslide hazard model suggested by Guzzetti (2005) has been followed, according to which the landslide hazard assessment of an area is evaluated by using the following equation:

$$H_L = S * P_N * P_C \quad (5)$$

where H_L represents the Landslide Hazard, S the landslide susceptibility, PN the Landslides occurrence in an established period t, and PC the conditional probability of landslide damage to the population.

According to equation (5), in order to evaluate the HL change, due to the occurrence of a wildfire or flood in the AOI, the following elements must be determined:

a. The landslide susceptibility (S) for that subregion affected by the wildfires or floods. Among the landslide causal factors evaluated in paragraph 3.2 for the AOI, only the NDVI (F7) is expected to change due to the occurrence of the examined hazard (wildfire). Considering that the NDVI weight to the evaluation of the landslide susceptibility (S), as illustrated in Table 2, is 0.092 (9.2% of the total), and a significant portion of the examined subregions featured sparse and light vegetation before the wildfire, the relative change in S is also expected to be relatively small. However, it is necessary to determine the boundaries of this subregion (affected by a wildfire or flood event), in order to reduce the extent of the examined area, and consequently to simplify and accelerate the calculation process.

b. The landslides occurrence (PN) in the affected area. To assess the change of this index, a landslide inventory must be established before and after the occurrence of the examined hazard. To rapidly form a complete landslides inventory after a wildfire or flood, the P-PSI technique is used, as described in Nefros et al., (2023a).

c. The conditional probability of the landslide damage to the population (PC), presented by the potential fatalities caused by the examined hazard. This index is assessed by evaluating the landscape of the examined region along with the distance from local cities/towns/villages and their population.

The wildfire events that occurred in 2021 were selected as a case study, to show the applicability and the potentiality of the proposed framework. These events were selected as the most significant and recent ones, as according to (Operational Unit Center for Earth Observation Research and Satellite Remote Sensing BEYOND of the Institute of Astronomy and Astrophysics, 2023), no significant wildfire event was recorded in 2022. Therefore, the landslide susceptibility map illustrated in Figure 11 was cropped to match the limits of the wildfires of 2021. Then, in a GIS environment, it was spatially multiplied as per equation (5) with the PN represented by the landslides' raster image derived by the P-PSI method and the PC, which was evaluated according to the region's landscape and its distance from the local town of Paleochora. This process is analysed in the following paragraphs.

3.3.1 Evaluation of the Extent of the Affected Area

As a first step, the subregions of the area which were affected by the wildfires or floods must be delineated to accelerate the calculation process. Therefore, the *FireHub* publicly available platform, provided by BEYOND NOA, was used. This platform presents a diachronic inventory of forest fires in Greece. The forest fires that occurred in the Chania regional unit (AOI) from 1984 to 2022, were digitize and inserted in GIS.

Figures 13 and 14 illustrate with red colour the two regions of the AOI (Chania regional unit), which were affected by the wildfires of 2021. The first one is located north of the Paleochora town and the second one is situated to the east of it. As shown in Figure 14, besides the wildfires of 2021, region 2 was also affected by wildfires in 1987. Due to the significant time gap between these two wildfire events (1987 and 2021), the influence of the first one is considered to be insignificant, as it exceeds the threshold of 20 years suggested by Moghli et al. (2022), for considering it as a recurrence.

By using GIS, it was calculated that the 2021 wildfires in the first subregion affected an area of almost 255.000 m^2, while in the second subregion the area affected covers almost 985.000 m^2. Obviously, the extent of the second subregion is significantly greater than that of the first subregion. Subsequently, and as a second step, the changes in NDVI before and after the wildfire events were evaluated and are illustrated in Figure 15. Figure S3 illustrates the differenced NDVI (dNDVI), resulted due to the 2021 wildfires. As seen in Figures 15 and S3, the NDVI change in subregion 2 was significantly higher compared to that of subregion 1, showing the relative impact of two wildfires to the local ecosystem

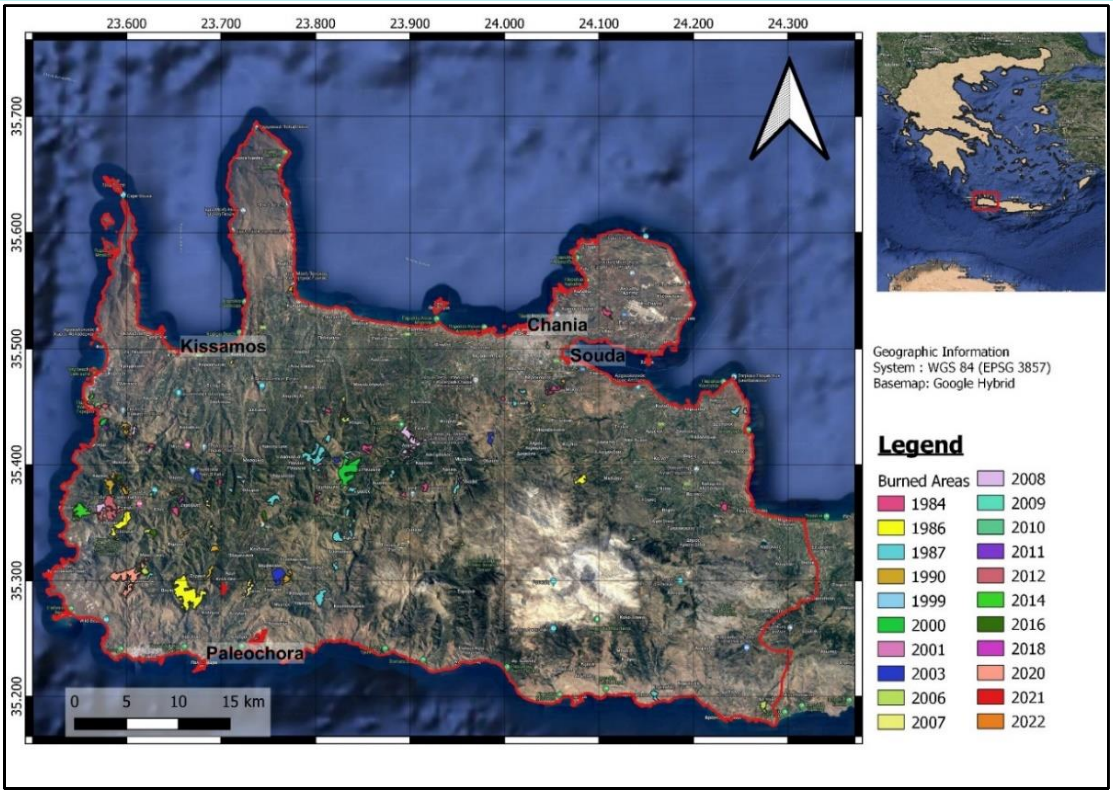

Fig. 13: Mapping the Burned Areas by Year, in Chania Regional Unit.

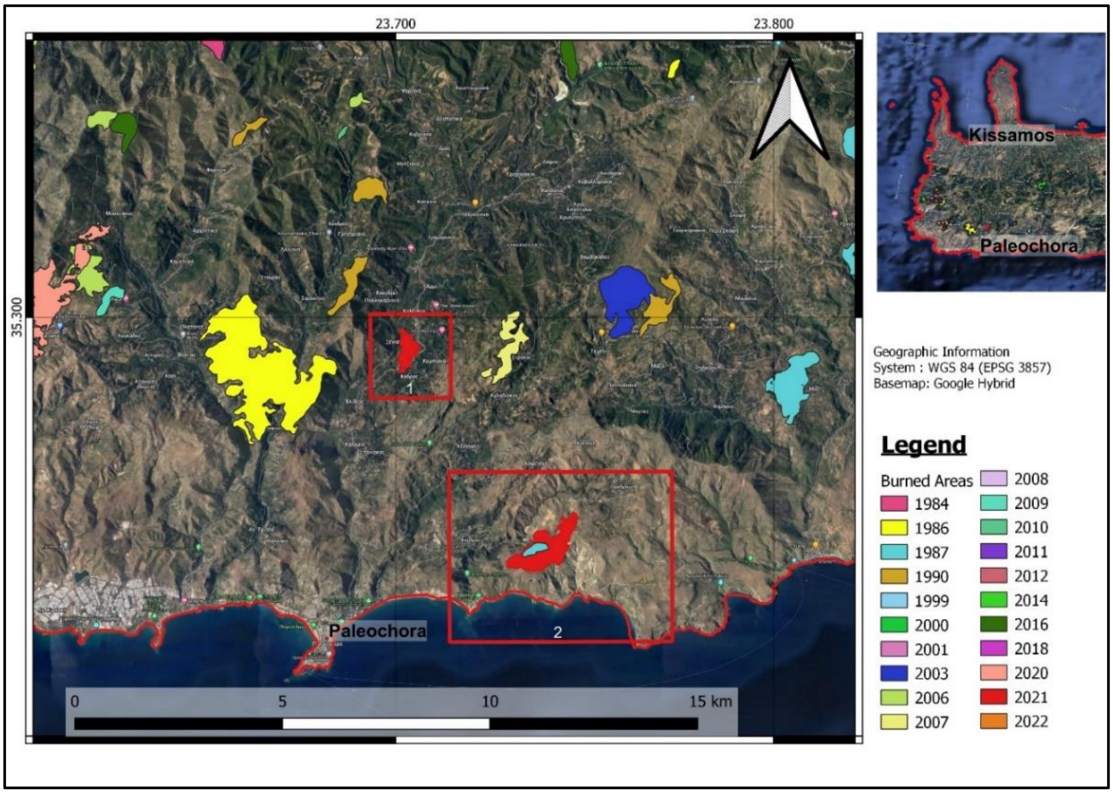

Fig. 14: Detail of the 2021 Burned Areas, in Chania Regional Unit.

Hence, the wildfire that affected subregion 2 was more severe than the one that affected subregion 1. Moreover, considering that NDVI is one of the causal factors used in the LSI assessment (equation 1), this change is expected to relatively affect landslide susceptibility, and subsequently the landslide hazard to the AOI. A new Landslide Susceptibility map, which considers the AOI after the wildfires of 2021, was generated for subregions 1 and 2 (see Figure 16).

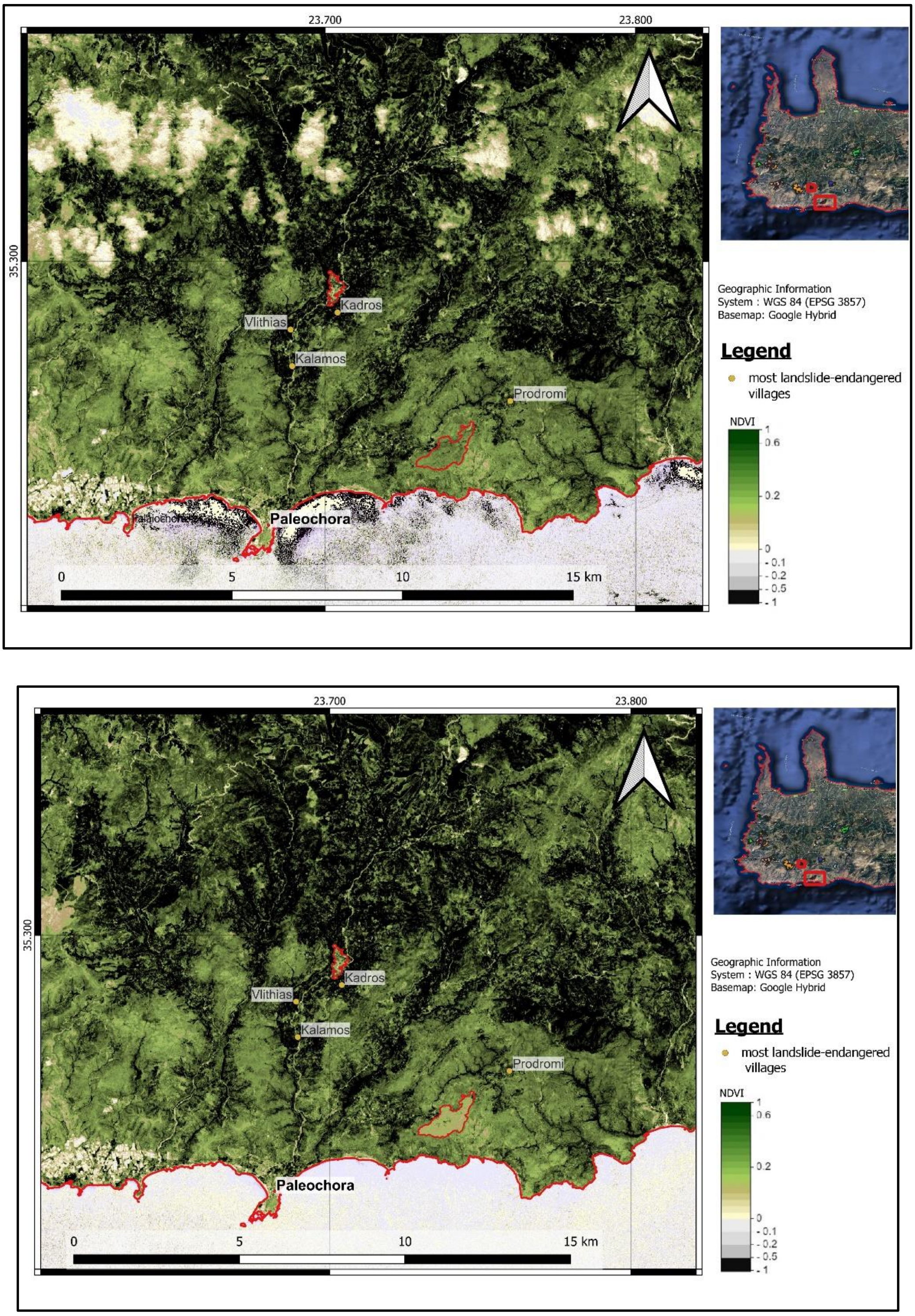

Fig. 15: Evaluating NDVI for the 2021 burned subregion 1 and subregion 2 before (a) and after (b) the wildfires.

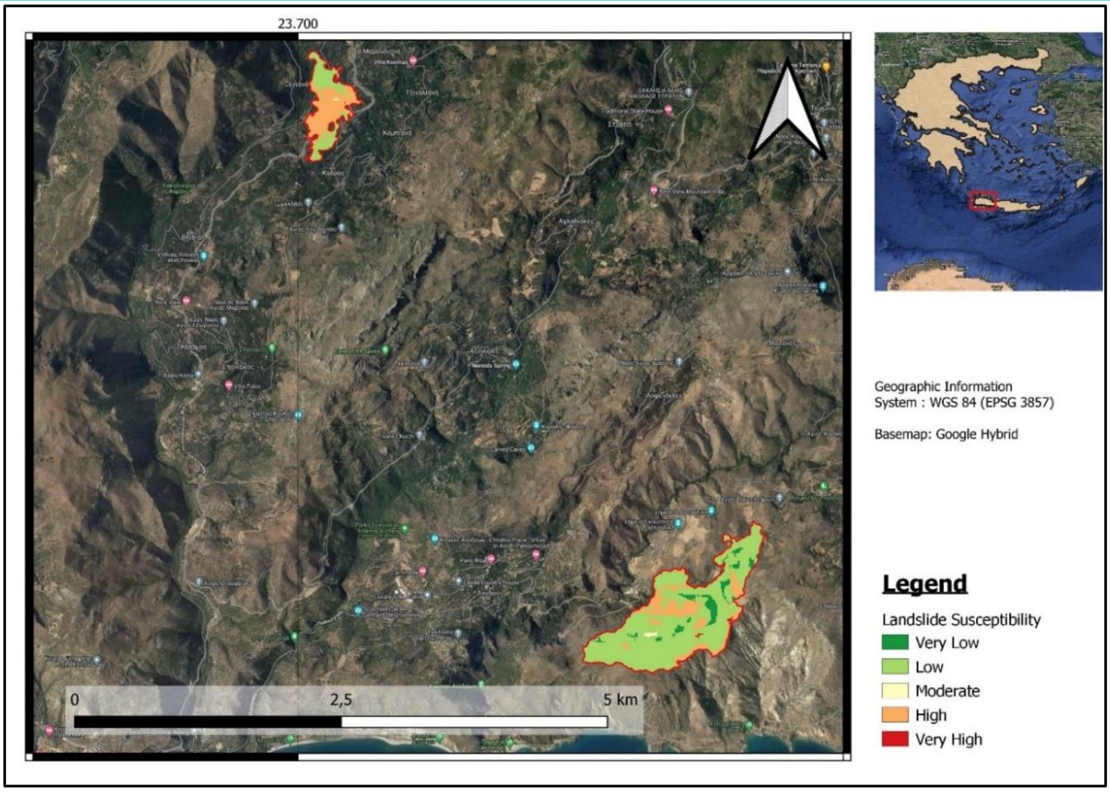

Fig. 16: Landslide Susceptibility Assessment for the 2021 burned subregions 1 and 2.

From Figure 16, it emerges that while great parts of subregion 1 are moderately landslide susceptible, significant changes, as compared with pre-fire susceptibility, were not observed. On the other hand, a small part of subregion 2 has slightly changed its landslide susceptibility from low and moderate, to high and very high.

3.3.2 Evaluation of the Landslides Occurrence (PN) of the Affected Area

As shown by Nefros et al., (2023a), the P-PSI technique can be rapidly applied after a wildfire to identify new landslides. Therefore, the P-PSI technique was applied by using satellite images before and after the wildfire events of 2021, and the initial landslides inventory was enriched with the newly identified landslides. Figure 17 illustrates the velocities of the resulting Persistent Scatterers for the AOI. Significantly more Persistent Scatterers (PS), and with greater velocities, were identified in subregion 2, which suggests a greater landslide activity in that subregion following the wildfire.

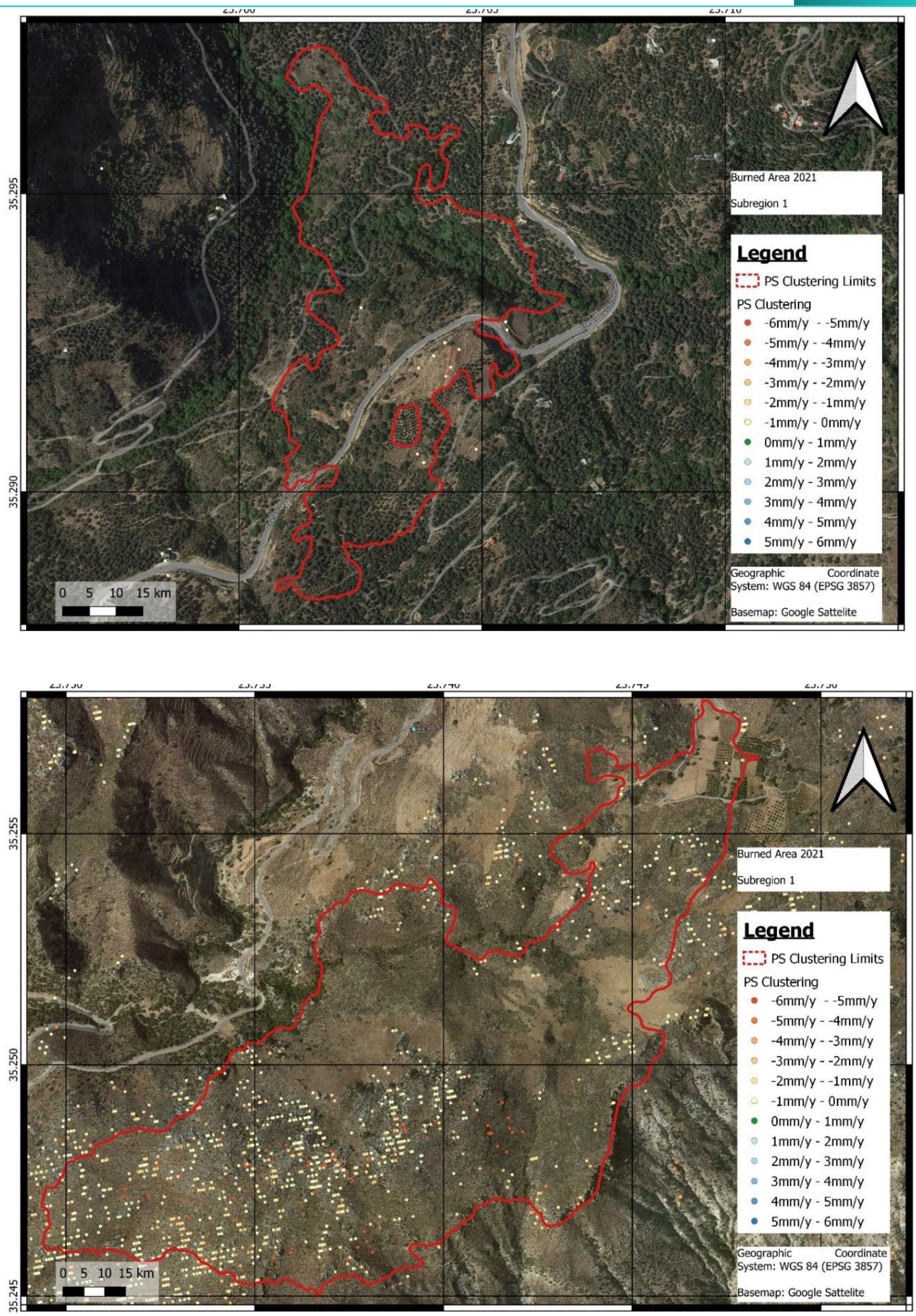

Fig. 17: Applying P-PSI technique for the 2021 burned subregion 1 (a) and subregion 2 (b).

3.3.3 Conditional probability of the landslide damage to the population (P_C)

The conditional probability of landslide damage to the population (PC) was assessed by considering that potential landslides activated in subregions 1 and 2 can affect the local population living in neighbouring residential areas or using the neighbouring road network. Using GIS techniques and the digital elevation model of the AOI, we found that the landslides identified in subregion 1 could affect the villages of Kadros, Vlithias, and Kalamos. Accordingly, we found that the landslides identified in subregion 2 could affect the village of Prodromi and part of the coastal road located east of the Paleochora town. Subsequently, Pc was evaluated by using the diagram shown in Figure S2, as suggested by Guzzetti (2005). It was found that Pc was the same for both subregions (10-0,01).

By calculating the factors S, PN, and PC and entering them into equation (5), the landslide hazard was evaluated for every pixel of the AOI. Figure 18 illustrates the landslides hazard assessment for both subregions 1 and 2, which were affected by the 2021 wildfires in the AOI. The results indicate that subregion 2 faces a significantly higher hazard compared to subregion 1, even though the two subregions share similar geomorphological characteristics due to their proximity.

It is important to note that numerous landslides were recorded in subregion 2 following the wildfires of 2021. A characteristic example is the rather intense landslide event which was activated in February 2022, and which resulted in traffic disruption on the coastal road east of Paleochora, a road section which is quite frequently used by locals and tourists (zarpanews, 2022). On the other hand, only a few landslides were identified in subregion 1.

3.4 Landslides Risk Assessment

According to (Günther, 2007), the landslide risk in an area is expressed by the following equation:

$$R = H \times V \qquad (6)$$

Where R stands for risk, H for hazard and V for vulnerability.

The risk evaluated using equation (6) is spatially illustrated in risk landslides maps. Risk landslides maps differ from the hazard ones as they aim to identify "what consequences do landslides have" (Günther, 2007). This information is essential as it will reveal the most vulnerable areas. These areas face the most potential socio-economic impact and are therefore the areas where the stakeholders must focus their attention and efforts. At the same time, the information gained through this process can contribute to a cost- damage prediction procedure.

This is very important for stakeholders, as it can help them determine whether the evaluated risk is acceptable, or whether concerted efforts should be undertaken to reduce the risk of landslides occurring in the AOI. Consequently, the low cost and swift applicability of the proposed framework are of crucial importance, as they allow a tactical re-evaluation of the cost-damage prediction procedure and the potential acceptable risk. Abrahams et al., (2017) suggests the formation of risk maps by superimposing the landslide hazard maps on vulnerability maps, which evaluate vulnerability considering the population density, the built environment, and critical infrastructures. However, this methodology is mostly a qualitative approach and is exposed to potentially biased conclusions, as the selection of each factor depends on criteria that are arbitrarily selected by experts to define vulnerability.

Moreover, the landscape of the broader area must be considered, so as to evaluate the residential areas and the parts of the road network that could be affected by potential landslides. The analytical hierarchy process (AHP) can be applied to evaluate the vulnerability of a region by applying quality criteria, such as the density of the population and the concentrations of vulnerable social groups (such as elderly and infants), along with construction criteria, such as the age of the buildings. However, its application requires the participation of many experts in order to avoid the potential for biased conclusions. At the same time, programs such as STONE used by Guzzetti (2005) can be used to evaluate the rock fall trajectories. Thus, the potential damage (fatalities and destruction of critical infrastructure) can be evaluated.

Accordingly, for the AOI, the AHP method was used to define the most critical factors which affect this vulnerability (e.g., population of villages/cities/towns, local road networks, bridges, industries that can be affected according to the terrain), along with their weight, based on socio-economic criteria. For instance, in population criteria, buildings where disabled people, elderly or infants are usually gathering, receive a bigger weight compared with simple buildings. The assessment of these factors' weight is analysed in Tables S6 and S7. Subsequently they were combined in a GIS environment and by using equation (6) the risk for the two subregions was evaluated. As shown in Figure 19, the evaluated risk for subregion 2 is higher than the one for subregion 1. However, between subregions 1 and 2, the difference in landslide risk is smaller than the difference in landslide hazard.

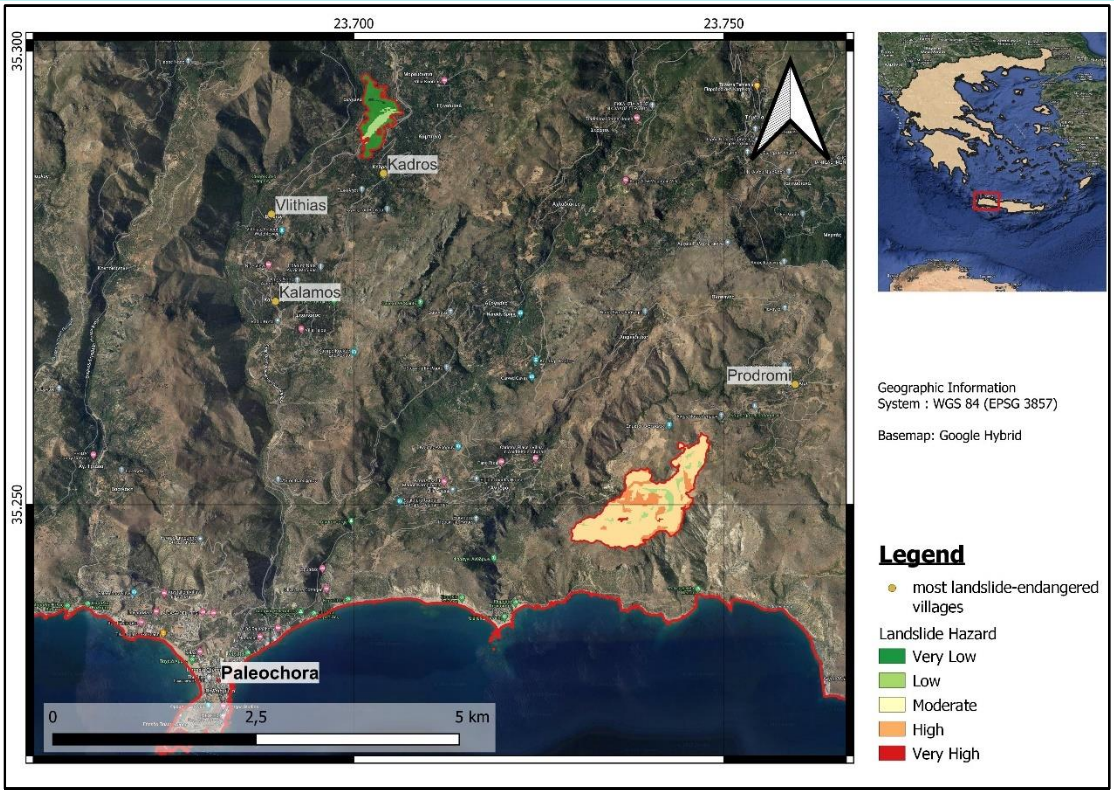

Fig. 18: Hazard Assessment for subregions 1 and 2, burned in 2021.

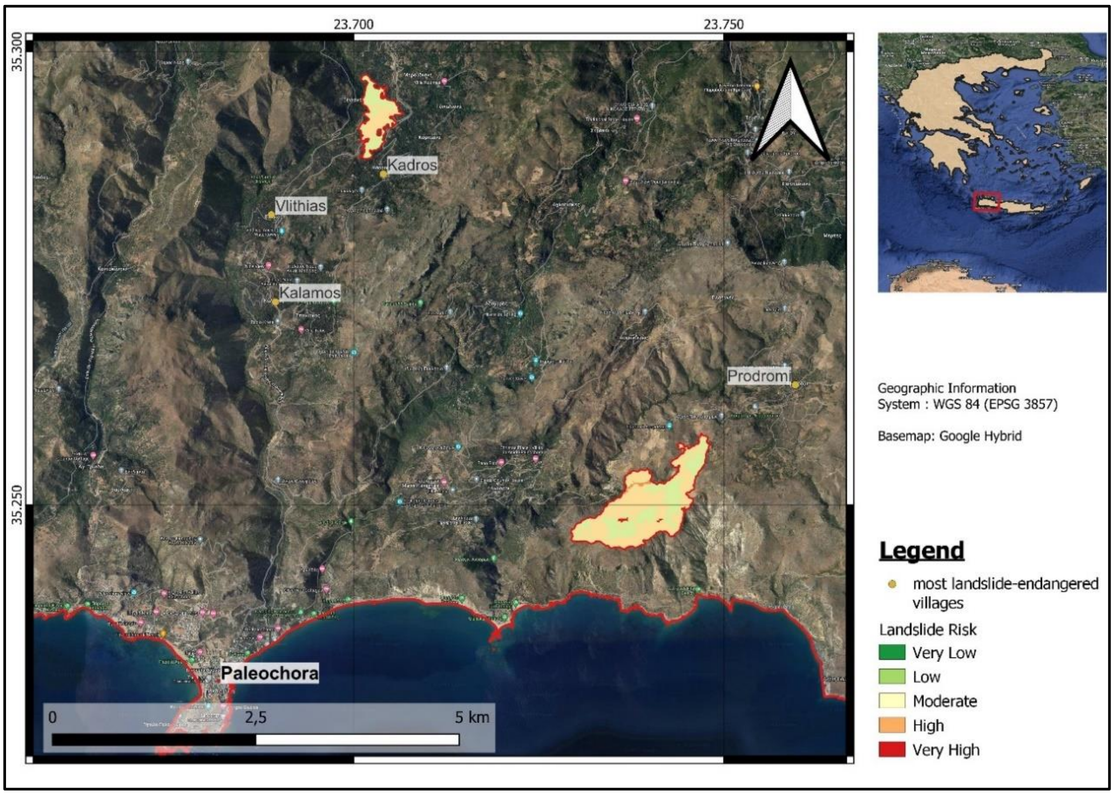

Fig. 19: Risk Assessment for the 2021 burned subregions 1 and 2.

3.5 Evaluation of the ID Precipitation Thresholds

Considering that precipitation is by far the most common landslides activation factor in Greece (Koukis et al., 1997), it is critical to evaluate the landslides' precipitation activation thresholds. Following the methodology analysed in Nefros et al., (2022), and by using the landslides inventory and the precipitation time-series of a local dense network of meteorological stations (step 1 of the proposed framework), the Intensity Duration (ID) precipitation thresholds for different regions in the Chania regional unit were evaluated and are synoptically presented in Table 4. In these thresholds, "I" represents the intensity of the rainfall triggering landslides (mm/h), and "D" corresponds to the relevant duration of this rainfall (hours).

Table 4. Landslides Precipitation Activation ID Thresholds for most critical regions in Chania Regional Unit, Greece.

Region	Alikianos	Askifou	Kandanos	Stalos	Strovles
Threshold (ID)	$I = 12.9*D^{-0.6}$	$I = 19.8*D^{-0.5}$	$I = 10.8*D^{-0.6}$	$I = 6.5*D^{-0.7}$	$I = 7.6*D^{-0.7}$

These precipitation thresholds can be compared to the precipitation measurements recorded by the local meteorological stations, in a near real time basis, to evaluate the potential activation of landslides in the AOI. Based on this comparison, besides the activation status of the landslides, useful conclusions can also be extracted about their spatial distribution and severity. Therefore, the proposed framework can be rather useful in providing an early warning system.

Moreover, these conclusions can be combined with the landslide risk maps, produced in the previous steps, to identify potential high socio-economic damages to the AOI due to the activated landslides. Thus, preventive measures can be applied on time by the stakeholders, while at the same time, search and rescue prioritization maps that minimize the socio-economic damage can also be produced.

3.5.1 Reduction of the ID Precipitation Thresholds due to a wildfire or flood

A devastating phenomenon, such as a wildfire or flood, can cause important changes to the local vegetation and the terrain conditions of the AOI, thereby affecting the ID precipitation thresholds. However, the swift evaluation of the updated thresholds is a rather difficult process, as it requires the existence of a landslides inventory that has been updated with the landslides that occurred after the devastating phenomenon. As already shown in section 3.1, the proposed framework can exceed this limitation, as it can produce an up-to-date landslides inventory by using open access data and the P-PSI technique. A characteristic example is analysed in Nefros et al., (2022), where a wildfire that occurred in Northern Peloponnese, Greece caused a 13% reduction to the local ID precipitation thresholds. Hence, as the proposed framework can be used to rapidly evaluate the updated precipitation thresholds, it can be rather useful during the preparation phase in areas affected by wildfires or floods.

3.5.2 Applying Regional Climate Models

Regional climate models (RCMs) can be used to evaluate the impact of the climate crisis on the occurrence of landslides. As shown in Nefros et al., (2023b), RCMs can indicate the subregions within an area where the ID precipitation thresholds are expected to be exceeded more frequently in the following decades. Thus, by using the proposed framework stakeholders can identify the subregions where landslides are projected to occur more frequently and with greater intensity due to the climate crisis. This knowledge is vital in the context of the preparedness phase, as it can allow stakeholders to put in place the necessary preventive measures.

Following this methodology, the projected changes to the local precipitation thresholds of the AOI were evaluated for two representative concentration pathways (RCP 4.5 and RCP 8.5) emission scenarios. The most significant changes for the AOI (Chania regional unit), were observed in the Kandanos and Strovles subregions. Table 5 summarises these changes.

Table 5. Changes in local Precipitation ID Thresholds in Chania Regional Unit, Greece.

Projected Changes for the 2031-2060 period		
RCP Emission Scenarios	**Subregions**	
	Kandanos	**Strovles**
RCP4.5	135%	17%
RCP8.5	139%	38%

4. Discussion

4.1 Contributing to a Comprehensive Landslides Management

As mentioned earlier, the results of the proposed methodology could constitute an effective tool for risk reduction. Thus, it can contribute to the stakeholders' efforts for an effective and comprehensive landslides management. According to Mansourian et al., (2006), a complete landslides management plan must include the following phases: mitigation, preparedness, response, and recovery.

4.1.1 Mitigation Phase

During the mitigation phase, stakeholders must prevent or reduce the impact of the landslides on the AOI in the long term. The results of the proposed methodology can significantly contribute to the accomplishment of this requirement, as it can allow stakeholders to:

a. Identify the most susceptible zones of the AOI by using the susceptibility maps. Determining these zones can help stakeholders specify the type and the location of the necessary preventive measures (e.g., retaining walls).

b. Evaluate the impact of a wildfire or flood event to the local landslide occurrence. Thus, stakeholders can make informed decisions (e.g., determine if a reforestation project after a wildfire, or the reinforcement of bridge piers after a flood, are required).

c. Identify the most vulnerable areas in the AOI, by using the results of the risk assessment tool generated following the application of the framework. Thus, stakeholders will be able to reduce the socio-economical damage of a potential landslide (e.g., by deciding the relocation of a school from an area with a high landslide hazard to a safer one).

4.1.2 Preparedness Phase

The preparedness phase focuses on ensuring that the civil protection mechanism is well-prepared to act effectively in the case of a landslide event. The results of the proposed methodology can significantly contribute to this direction, as it can allow the authorities to:

a. Determine which subregions are expected to be mostly affected, what severity these landslides are expected to have, and which subregions are the most vulnerable ones. This information can be evaluated by using the precipitation data gathered as part of the first step of applying the proposed framework and by evaluating the ID precipitation activation thresholds.

b. Evaluate these thresholds' reduction due to a wildfire or flood event.

c. Via the results of the regional climate models, evaluate how climate change is expected to affect the precipitation trends in the AOI, and consequently the landslide mechanism.

4.1.3 Response Phase

During extreme precipitation events, numerous landslides can be simultaneously activated in the AOI, injuring, or even killing people, causing the entrapment of others, and damaging critical infrastructures (such as bridges and parts of the local road network). A characteristic example is that of the "Oceanis" storm, as named by the NOA, which occurred in February 2019 in Crete Island, and caused acute landslide problems that greatly affected the local society (see (Nefros et al., 2023b) for a detailed analysis). For the response phase of the landslides management plan to be effective, civil protection authorities must be equipped with the appropriate tools and resources that will enable them to react rapidly in the event of a landslide (or even a series of landslide events), and effectively address their impact. The results of the proposed methodology can significantly contribute to this direction.

As shown in Figure 17, by using the P-PSI technique (Nefros et al., 2023a) as part of the proposed framework, new landslides in the AOI can be rapidly identified and the ongoing ones can be monitored. Compared to traditional in situ techniques, P-PSI, as a remote sensing technique, can be rapidly applied even over extended and complicated landscapes, and can monitor even a great number of landslides (Nefros et al., 2023a). Moreover, the standardization and the parallelization of the process achieved by using the P-PSI technique reduce further by a factor of five the required time for its application, and increase considerably its effectiveness, as it minimizes human intervention to the calculation process. Furthermore, P-PSI (Nefros et al., 2023a) or other remote sensing techniques can be also used, along with open access data, to rapidly evaluate the condition of the local road network and determine safe evacuation routes for civilians. Hence, the results of the proposed methodology, can provide the necessary time for civil protection authorities to evacuate safely the local population from the endangered regions. Thus, it contributes significantly to the response phase of the landslide management plan.

4.1.4 Recovery Phase

During the recovery phase, stakeholders must promptly restore the affected area to help citizens return to normalcy. These actions include the demolishing or repairing of damaged infrastructure, as well as the building of new ones. The proposed framework contributes to this effort as it enables:

a. Quick decision making.

b. The monitoring of the stability of the most critical infrastructure.

c. The identification of the safest areas for the construction of new infrastructure in the AOI.

After a landslide has occurred in an area that was impacted by wildfires or floods, quick decisions should be made by stakeholders to prevent the activation of new landslides which can (further) affect critical infrastructure. For instance, by using the results of the P-PSI method, the stability of these infrastructures can be regularly assessed, and quick decisions can then be made about the necessity of any stabilization measures. Moreover, the proposed framework contributes to the longevity of the new constructions, as it evaluates the projected impact of the climate crisis on the AOI. This is achieved as the updated landslides' activation precipitation thresholds are evaluated and compared to the precipitation projections for the following decades, which have been evaluated using regional climate models. Therefore, this facilitates the formulation of long-term and effective planning, as it allows for building new infrastructure in the safer areas of the AOI.

4.2 Forming a Unified Platform and Disseminate the Knowledge Gained

For the proposed framework to be functional and achieve the effective dissemination of knowledge gained to citizens, it must be available through a unified platform. Nowadays, web applications, such as geoportals, can contribute to landslides management, as they can effectively present spatial data derived from different sources. The use of real time web platforms and user-friendly applications is very significant, as they can also benefit from crowdsourcing techniques, such as gathering information concerning natural disasters directly from citizens located in the field. Thus, the results of GIS and Remote Sensing techniques that are derived from the proposed framework can be made available via a single platform, so as to disperse the knowledge gained to citizens, while at the same time provide all the necessary information to the relevant stakeholders for effectively managing the area affected by the natural disasters. Through this framework, civil protection agencies have a variety of different and effective tools at their disposal, as well as a standardized process that can guide them through each step.

The proposed methodology allows for efficiently managing landslide events by civil protection stakeholders, as it integrates individual processes into a common frame. For instance, a civil protection servant, can relatively easily identify a high-risk area using only the landslide risk map resulting from the proposed methodology. This facilitates prompt and direct implementation of necessary measures, such as reinforcing the slope's stability or relocating a facility. Moreover, it can contribute to the long-term urban planning of a regional unit, as stakeholders by using the resulted landslide susceptibility and hazard maps, can identify and the select the relatively safe regions for development. However, the comprehensive application of the proposed framework and the establishment of the required web application/geoportal still requires basic knowledge of remote sensing, GIS, geology, and hydrogeology principles. These principles, in most of the cases, may not be possessed by civil protection servants. For instance, the framework relies on the use of PS and P-PSI techniques which use Sentinel-1 satellite images, which in turn require the basic knowledge of INSAR (Interferometry Synthetic Aperture Radar). Thus, while the framework allows for the standardization of various individual processes, a further full automatization of the whole framework would be significantly beneficial as part of a future research study.

5. Conclusions

Due to climate change, wildfires and floods are expected to be more frequent and more intense in the following years, leading to the occurrence of more landslides. The framework proposed by this study combines novel and effective GIS and remote sensing techniques with regional climate models in order to evaluate the impact of wildfires or floods on the stability of an AOI.

Our framework was applied to two subregions of the Chania regional unit, in Crete Island, Greece, which were affected by wildfires in 2021, in order to evaluate the impact of wildfires on the local landslide activation. The wildfires affected the two subregions in different ways, even though as neighbouring regions they share similar geomorphological characteristics. Firstly, a complete landslides inventory map was created by leveraging the ability of the P-PSI technique to promptly identify new landslides and effectively monitor slow-moving ones. Additionally, by assessing the landslides susceptibility and hazard within this framework, and by using GIS and remote sensing techniques, it was proven that the hazard in the second subregion was significantly higher compared to the first one. Landslide risk was also found to be higher in the second region. However, in this case the difference between the two was considerably smaller. The integration of open access or publicly available data renders the proposed framework a cost-effective solution which can be rapidly applied even on complex or extended landscapes. Additionally, the use of regional climate models enables the longevity of the approach, as it allows for evaluating the projection of the precipitation in the following decades. The combined use of precipitation projections, along with the regular update of the precipitation activation thresholds in the burned areas, enables the evaluation of the impact of the climate crisis.

Finally, the results of the proposed methodology can be a valuable tool for stakeholders as it can contribute to all the phases of a complete landslides management plan. Based on the findings of this framework, stakeholders can make informed decisions regarding the implementation of the appropriate measures that are needed in the mitigation, preparedness, response, and recovery phases of an effective landslides management plan.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflict of interest regarding this publication.

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Supplementary Material

This article contains as supportive material three Figures (Figures S1, S2 and S3) and seven Tables (Table S1 - S7).

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