Operational Mapping and Post-Disaster Hazard Assessment by the Development of a Multiparametric Web App Using Geospatial Technologies and Data: Attica Region 2021 Wildfires (Greece)

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Abstract: The environmental effects of wildfires are a hot issue in current research. This study examines the effects of the 2021 wildfires in the Attica region in Greece based on Earth observation and GIS-based techniques for the development of a web app that includes the derived knowledge. The effects of wildfires were estimated with the use of Sentinel-2 satellite imagery concerning burned area extent and burn severity using a NBR-based method. In addition, the erosion risk was modeled on a pre-fire and post-fire basis with the RUSLE. This study highlights the importance of assessing the effects of wildfires with a holistic approach to produce useful knowledge tools in post-fire impact assessment and restoration.

Keywords: wildfires; geospatial intelligence; web app; operational mapping; burn severity; soil erosion; Attica; RUSLE (revised universal soil loss equation); NBR (normalized burn ratio); remote sensing (rs)

1. Introduction

Greece in the 2021 fire season suffered from one of the greatest ecological disasters caused by wildfires. Especially in the first days of August, an intense prolonged heatwave struck Greece making it the worst that the country faced in almost 34 years. During this period of extreme conditions (27 July to 16 August 2021) in the Greek territory, many wildfires broke out due to the drought that increased wildfire vulnerability. All the means available, from the fire brigade to the local authorities and support from other countries, were used to fight these fires. In addition, evacuations of settlements were performed alongside the use of 112 to send alert messages to citizens, while the Copernicus Emergency Management Service (EMS) was also activated for rapid mapping of the wildfires in most cases [1].

Over the last couple of years, climate change has dramatically affected the Mediterranean region. The vulnerability of this region to drought and rising temperatures has led to severe ecological disasters annually. Specifically, Greece has been dealing with great environmental catastrophic events due to wildfire incidents and remarkably strong heatwaves [2]. The assessment of the wildfires’ effect spatially provides a leading role in the documentation of vulnerable areas in different timescale evaluations [3,4].

Fire incidents constitute a dynamic process in planet Earth alteration affecting the global climate system [5]. Lately, wildfires show an increased occurrence, especially during
the summer months, causing a rise in the overall period of the fire season [6]. The Mediterranean countries have been damaged over the last couple of years, due to extensive fire incidents causing irreversible damage to the environment [7]. Especially, high mountain regions characterized by Mediterranean climates seem to be more vulnerable to wildfire incidents due to the occurrence of high rainfall intensity in sparse vegetation cover areas [8]. Fire impacts on vegetation, soil, atmosphere, and society are dependent on fire characteristics such as severity and size [9]. Particularly, in Mediterranean ecosystems where fires occur in summer, the increased temperatures and evapotranspiration succeeded by the increased precipitation in autumn cause alterations to the ecosystems including increased soil loss [10].

Geospatial intelligence (GEOINT) has as a basic principle, the collection, analysis, and combination of all the available data, both geospatial and satellite imagery for Earth’s geographical area, so as to utilize them in creating useful products in planning, decision making, and emergency response [11]. The integrated use of remote sensing and GIS proved very important in disaster management, with satellite imagery providing a synoptic view, spatiotemporal changes monitoring, and of course sufficient spatial coverage alongside GIS, which enables the utilization of all the geospatial information available. The capabilities of remote sensing for this purpose can be found in their operational use and their damage assessment after a wildfire event [12]. The use of satellite-based remote sensing in wildfires is well-known in the literature. For the mapping of burned areas, plenty of methods have been developed [13] with the use of multispectral data through the decades, including spectral indices among them such as the burn area index (BAI) [14] and normalized burn ratio (NBR) [15]. Additionally, with the use of satellite imagery, not only the burned area but also further information regarding the impact can be retrieved, as in the case of the dNBR [16], where burn severity can also be assessed. In addition, the combination of remote sensing with GIS in the case of wildfires provides a wide range of geospatial information regarding the post-fire period including the mapping of burned areas, soil erosion estimation, and recovery of the ecosystems [17].

Soil erosion caused by land degradation affects both natural and human resources, resulting from insufficient agricultural productivity, and is characterized as one of the most important threats worldwide [18]. Forest fires constitute one of the most critical causes of soil erosion due to their ability to burn large amounts of vegetation cover leading to an increase in runoff and sediment transfer [19,20]. For this purpose, several indices have been developed so as to assess the damage caused by wildfires on soil properties, such as the dNBR (differential NBR), which [8] is calculated based on pre- and post-fire satellite images [21].

Research on soil erosion has been extensively carried out over the past few decades since it is inextricably linked to the world’s most serious environmental problems [8]. There are a wide variety of models that have been developed throughout the years considering soil loss assessment in several regions around the world [22]. The most commonly known models are the Universal Soil Loss Equation [23], its revised version (RUSLE) [24], and the Water Erosion Prediction Project (WEPP) [25]. Those models are used for the estimation of long-term average soil erosion values based on information extracted from rainfall data, soil properties, topography, and land cover management.

A recent study [2] assessed post-fire effects by mapping burned areas and their burn severity and also the soil erosion for an area within the Lokroi Municipality in Central Greece. This study made use of NBR to map the burned areas and to assess the burn severity with the use of Sentinel-2 and Landsat-8 imagery. In addition, to this affected area, the RUSLE was applied to estimate soil erosion. The combined use of these Earth observation and GIS-based methodologies was important before and after the wildfire and led to the identification of the vulnerable areas within the affected region. Another study was conducted [26] regarding the 2021 wildfires in Greece in Attica, Evia, and Peloponnese. In that study, the erosion vulnerability to these areas was evaluated after the fire events with the use of a GIS Boolean logic-based model. The results of the study led
to the erosion risk assessment of these areas, making evident the increased susceptibility to surface runoff erosion. A similar study [27] studied southern Italy’s Basilicata region, following an integrated approach with GIS and remote sensing regarding post-fire erosion risk. The soil fire severity was estimated by the use of Sentinel-2 images while the RUSLE was applied for the modeling of pre-fire and post-fire erosion for the first year after the events. Results of the study revealed the complex relations between fire severity and soil erosion factors while helping with soil loss estimation after the fire events.

Based on all the above-mentioned, this study aims at the assessment of the impact that the 2021 fire season wildfires had in the region of Attica, Greece. More analytically, four major wildfires of Schinos, Varympompi, Lavreotiki, and Vilia were mapped in an operational way with the use of Sentinel-2 imagery with the normalized burn ratio spectral index-based approach, thus extracting the burned area extent and assessing the burn severity while Corine Land Cover data was also used to analyze the consequences each fire caused. Furthermore, the soil erosion in the affected areas via the implementation of the revised universal soil loss equation (RUSLE) was assessed to estimate the soil loss and potential high-risk areas. In this way, to meet the purpose of this study effectively to gain geospatial intelligence on the effects of these wildfires, the results of all the applied methodologies were used to develop a web app that constitutes an invaluable tool in post-disaster hazard assessment. The results of the study showed the spatial damage that the wildfires caused in Attica in 2021 and they also demonstrated a significant increase in soil erosion in the affected areas.

2. Wildfires in Attica Region 2021

In the region of Attica, which is located in Central Greece where the capital of Greece, Athens, is, during the 2021 fire season four major wildfires occurred with three of them happening in the above-mentioned August period resulting in extensive damages. To all the four wildfires the Copernicus EMS (Emergency Management Service) was activated with the activations EMSR51O, EMSR527, EMSR540, and EMSR542. Spatially, according to Figure 1, these wildfires were located in western, north-eastern, and south-eastern Attica with the closest to the metropolitan area of Athens being the fire in Varympompi [1,28,29].

![Figure 1. Areas of study.](image_url)

Starting with the May 19th, 2021 wildfire in Schinos that broke out in the evening of that day close to the Schinos settlement in Korinthia. The fire moved from the east to western Attica, reaching to the north of the Kineta settlement during almost five days of activity. Damages were limited to the build-up environment and extended to the forests of the area. The affected area includes the northern slopes of the Geraneia Mountains, which...
includes a Natura 2000 site, and the geomorphological status of the area with high slopes aids the development of floods and other post-fire hazards to the region [28].

The next fire is that of Varympompi, which broke out on the midday of August 3rd, 2021, in the Ano Varympompi area, and lasted for the next few days. More precisely, the northern part of the Attica region was affected from Adames in Kifisia to Ippokrateios, Politia, mainly within the base of Parnitha Mountain. Although the impact included the forest vegetation of the area, an important part of the urban areas of settlements was impacted due to the complexity of the forest and building mixture [1,26].

The wildfire in Lavreotiki started on the morning of August 16th in Markati in the northwest of Lavreotiki. Close-to-settlement areas such as coniferous forests, natural vegetation, and agricultural land were affected by the wildfire. The meteorological conditions made it difficult for the fire brigade to put the fire under control despite the smaller extent than the previously mentioned wildfires [1,26].

Lastly, the wildfire in Vilia also broke out on August 16th at midday a few hours after this in Lavreotiki in Pateras Mountain close to the Vilia settlement. The wildfire was burning an area predominantly consisting of sclerophyllous vegetation and coniferous forests for more than five days with a rapid spread day by day. The above-mentioned conditions in that period led to the devastation of a large area between Vilia and Nea Peramos despite the huge effort and the increased ground and aerial support [1,29].

3. Materials and Methods

3.1. Data and Software

In Table 1, the used datasets are briefly presented. Free and open accessible datasets were selected to be used for each methodological part described in the following subsections.

| Datasets                  | Format          | Resolution Spatial | Source                                      | Purpose/Use                  |
|---------------------------|-----------------|--------------------|---------------------------------------------|------------------------------|
| Sentinel-2 imagery        | Optical Level-2A| 10 m (Used)        | Copernicus Open Access Hub                  | Wildfire Mapping and C Factor|
| Corine Land Cover 2018    | Vector (Polygon)| 2018               | Copernicus Land Monitoring Service          | Wildfire Mapping and P Factor|
| EU-DEM v1.0               | Raster          | 25 m               | Copernicus Land Monitoring Service          | LS Factor                    |
| Meteorological data       | Text            | 2021               | Meteo.gr of the National Observatory of Athens (NOA) | R Factor                    |
| Topsoil physical properties for Europe (based on LUCAS topsoil data) | Raster          | 500 m              | European Soil Data Centre (ESDAC) of Joint Research Centre (JRC) | K Factor                    |
| Topsoil organic carbon (LUCAS) for EU25 | Raster          | 500 m              | European Soil Data Centre (ESDAC) of Joint Research Centre (JRC) | K Factor                    |

1 The used Sentinel-2 acquisitions are presented in detail in Table 2.

For the operational wildfire mapping, optical/multispectral Sentinel-2 mission satellite images of the ESA Copernicus program were utilized which are open and accessible from the Copernicus Open Access Hub [30]. The products used were the atmospherically corrected and scene classified Level-2A Bottom-of-Atmosphere (BOA) [31]. A key characteristic of Sentinel-2 images important in operational purposes is the 5-day interval between satellite acquisitions over an area and their availability on the Copernicus Open Access
Hub a few hours after their acquisition. In Table 2, the full list of Sentinel-2 acquisitions is given for each purpose of this study regarding the mapping of wildfires and the \( C \) factor of the RUSLE. The image selection was redundant to the cloud-free scene availability, taking into consideration the temporal coherence for each purpose.

**Table 2.** List of used Sentinel-2 acquisitions for each area and purpose.

| Area        | Wildfire Start Date | Sentinel-2 Acquisition Date | Relation with the Wildfire Event | Purpose       |
|-------------|---------------------|-----------------------------|----------------------------------|---------------|
| Schinos     | 19 May 2021         | 18 May 2021                 | Pre-event                        | Wildfire Mapping |
| Varympompi  | 3 August 2021       | 29 July 2021, 8 August 2021 | Pre-event, Post-event            |               |
| Lavreotiki  | 16 August 2021      | 13 August 2021, 18 August 2021 | Pre-event, Post-event        |               |
| Vilia       | 16 August 2021      | 29 July 2021, 26 August 2021 | Pre-event, Post-event            |               |
| All the areas | -                  | 10 May 2021, 17 September 021 | Pre-event, Post-event            | C Factor      |

Land cover information for the affected study areas was retrieved with the use of the Corine Land Cover 2018 (CLC 2018) in vector polygon format from vector geodatabase open available from Copernicus Land Monitoring Service [32]. The CLC 2018 is highly accurate (\( \geq 85\% \) accuracy) with a minimum mapping unit (MMU) of 25 hectares and a mapping minimum width (MMW) of 100 m, while it is detailed enough by having 44 land cover classes at its most analytical level-3 [33]. In this study, it was used to map the affected area of the wildfire land cover and for the RUSLE’s \( P \) factor.

Regarding the meteorological data required for the estimation of the \( R \) factor of the RUSLE, these were retrieved from the Meteo.gr of the National Observatory of Athens (NOA) [34]. Data regarding the precipitation for the examined period were obtained from the respective meteorological stations of the Meteo.gr network within and around of each area of study.

The \( EU-DEM \) v1.0 is a digital elevation model (DEM) that was obtained freely from the Copernicus Land Monitoring Service for the application of the RUSLE’s \( LS \) factor. With a resolution of 25 m, it was produced with the fusion of SRTM and ASTER GDEM datasets [35].

The last dataset used refers to the topsoil properties necessary for the \( K \) factor calculation of the RUSLE. This dataset consists of 500 m rasters acquired from the European Soil Data Centre (ESDAC) of the Joint Research Centre (JRC). More specifically, the dataset was derived from the topsoil data collected during the Land Use and Cover Area frame Statistical survey (LUCAS). It includes the content percentage (%) of clay, sand, silt, and the predicted topsoil soil organic carbon content in g C kg\(^{-1}\) [36,37].

The software used includes the free and open ESA STEP SNAP v8.0 remote sensing software for the processing of the satellite images and the commercial GIS suite of ESRI that includes ArcGIS Desktop v.10, ArcGIS Pro v2.8–2.9, and ArcGIS Online with the Web AppBuilder.

### 3.2. Methodology

The methods applied for the purposes of this study are described in the following subsections. In Figure 2, the flowchart presents all the steps followed for each part of the methodology with the mapping of the wildfires presented on the left and the implementation of the RUSLE on the right part. In the middle, the different products are presented with the following addition of them to the web app.
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Figure 2. Methodology flowchart.

3.2.1. Operational Wildfire Mapping

The operational mapping of the previously mentioned wildfires was performed with the use of the Sentinel-2 L2A imagery listed in Table 2. In order to have the most accurate and timely available results, cloud-free images acquired immediately before and after each wildfire event were carefully selected. These images were imported in SNAP and then preprocessed with nearest neighbor resampling of the spectral bands to 10 m resolution and then subset to the area of interest (AOI) extent to enhance processing performance. The next steps included the creation of a cloud and water mask with band maths operations based on the available scene classification from the L2A product and the estimation of the water mask with the normalized difference water index (NDWI) \[38\] and the collocation of the pre-fire and post-fire event imagery followed to merge them into one product.

For this study, for the wildfire mapping, the related spectral indices were applied. More analytically, the normalized burn ratio (NBR) is the used index that utilizes the spectral bands of near-infrared (NIR) in which burned areas present low reflectance and shortwave-infrared (SWIR) in which burned areas show high reflectance for the mapping of burned areas and the assessment of burn severity based on Equation (1). The index has high values where healthy vegetation exists and low values in burned areas and areas with low or no vegetation presence [15,16,39,40].

\[
NBR = \frac{\text{NIR} - \text{SWIR}}{\text{NIR} + \text{SWIR}} \tag{1}
\]

The NBR index was calculated before (pre-fire) and after (post-fire) the fire event and then the difference between the two, the dNBR (Equation (2)), results in a better distinction of the burned areas while the burn severity is also assessed. Burn severity is a term used to express the degree of a wildfire’s impact on an area’s ecosystem. The assessment of burn severity contributes to quantifying the impact of a wildfire and aids restoration attempts and natural disaster management. Based on the dNBR values, the burn severity is classified...
into categories as is shown in Table 3 with the higher values corresponding to higher severity and thus the more severe impact of the wildfire on an area [40–44].

\[
dNBR = \text{PrefireNBR} - \text{PostfireNBR} \tag{2}
\]

After the dNBR estimation, the relativized burn ratio (RBR) was calculated based on Equation (3). This index aids the assessment of burn severity in a diversity of ecosystems and regions by enhancing accuracy. Additionally, it aids the identification of the changes after a fire in areas with low vegetation [45].

\[
RBR = \frac{dNBR}{\text{prefireNBR} + 1.001} \tag{3}
\]

Table 3. Burn severity classification according to dNBR values [16,46].

| dNBR Value * | Burn Severity            |
|--------------|--------------------------|
| 0.100–0.269  | Low severity             |
| 0.270–0.439  | Moderate-low severity    |
| 0.440–0.659  | Moderate-high severity   |
| 0.660–1.300  | High severity            |

*Values ≤ 0.099 represent unburned areas.

The final RBR raster was masked using the above-mentioned cloud and water mask in order to be not only clear from any possible clouds, but also to eliminate existing water surfaces due to their spectral characteristics which make them attributed falsely as burned areas. Results production followed with the masked RBR raster import to the GIS software and its reclassification according to the Table 3 burn severity classes. Conversion to vector polygons, burned area extraction, and clipping of CLC 2018 to the burned area extent were the last steps including the area estimations.

3.2.2. Revised Universal Soil Loss Equation (RUSLE)

The Revised Universal Soil Loss Equation (RUSLE) model provides a widely known and useful tool for soil erosion assessment [2,22,47,48]. Developed in the late 1970s [23], it was formulated so as to conclude a better estimation of the initial parameters defined by the Universal Soil Loss Equation (USLE) [49]. The derived methodology represents the influence of topography, soil properties, meteorological parameters, and land cover on surface and rill erosion [2,47,48]. The average soil loss assessment is enabled by the RUSLE according to the specific study area characteristics [2] and it is based on an empirical equation (Equation (4)), constituting of five factors [24], which can be easily implemented through a GIS framework:

\[
A = R \times K \times LS \times C \times P \tag{4}
\]

where \(A\) is the estimated mean seasonal soil loss (ton h\(^{-1}\) Season\(^{-1}\)), \(R\) represents the rainfall erosivity factor (MJ mm ha\(^{-1}\) h\(^{-1}\) Season\(^{-1}\)), \(K\) is the soil erodibility factor (ton h MJ\(^{-1}\) mm\(^{-1}\)), \(LS\) is the slope length and steepness factor (dimensionless), \(C\) is the cover management factor (dimensionless), and \(P\) represents the conservation practice factor (dimensionless). These factors are of vital meaning in soil erosion assessment, and they should be very carefully estimated in order to lead to highly accurate results (source).

\(R\) factor plays a crucial role in RUSLE modeling since it defines the possibility of erosion risk [49] and it is estimated based on meteorological data from meteorological stations surrounding the study areas as previously mentioned [50]. Using the empirical
formulation (Equation (5)) developed by Loureiro and Couthino [50], monthly rainfall data concerning seasonal time periods of 2021, were used to calculate the $R$ factor:

$$R = \frac{\sum_{i=1}^{12}(7.05 \times r_{10} - 88.92 \times d_{10})}{N}$$

where $R$ represents the rainfall erosivity factor (MJ mm ha$^{-1}$ h$^{-1}$ season$^{-1}$), $N$ is the total months calculated annually, $r_{10}$ is the monthly rainfall exceeding 10 mm, and $d_{10}$ is the number of days when daily rainfall exceeded 10 mm per month. Specifically, rainfall data acquired from each weather station were implemented using a spatial interpolation technique, inverse distance weighting (IDW), so as to define unknown meteorological values within the study areas.

$K$ factor refers to the rainfall impact on soil properties resulting in soil erosion due to sediment penetration, detachment, and transport [23,24,27]. The soil erodibility factor is affected by soil properties such as structure, organic matter, permeability, and soil texture [48]. In this study, the estimation of the $K$ factor was based on Equation (6) developed by Williams and Renard [51]:

$$K = 0.2 + 0.3 \exp \left(0.0256 \times S_a \times \left(1 - \frac{S_{Cl}}{S_i}\right)\right) \times \left(\frac{S_i}{C + S_{Cl}}\right)^{0.3} \times \left(1 - \frac{0.25 + C}{C + \exp(1.72 - 0.95C)}\right) \times (1 - \frac{0.7 + \text{SN}}{\text{SN} + \exp(-5.51 + 22.9 \text{SN})})$$

where $K$ is the soil erodibility factor (ton h MJ$^{-1}$ mm$^{-1}$), $S_a$ represents the percentage of salt, $S_i$ is the percentage of silt, $C$ is the percentage of clay, $S_{Cl}$ stands for $S_{Cl} = 1 - (S_a/100)$. Soil data acquisition was based on datasets provided by the ESDAC database [37]. The resulted $K$ values were implemented on the spatial interpolation method Kriging to produce values covering the total surface of the study areas.

The topographic effect on soil erosion is determined by the impact of the slope length and steepness factor ($LS$ factor) [27]. $LS$ factor constitutes the result of slope length ($L$) and slope steepness ($S$) multiplication. Increased slope steepness values determine increased soil erosion risk due to the increase in the velocity and erosivity of the accumulated runoff [2]. The calculation of the $LS$ factor was based on Equation (7) of Moore and Burch [52]:

$$LS = \left(\frac{U}{L_0}\right)^{m} \times \left\{\sin \left(\frac{\beta \times 0.01745}{S_0}\right)\right\}^{n} \times (m + 1)$$

where $LS$ is the topographic factor, $U$ is the flow accumulation multiplied with the pixel size, $L_0$ is the slope length (22.13 m), $\beta$ is the slope in degrees, $S_0$ is the slope percentage (9%), $m$ is sheet erosion ranging from 0.4 to 0.6, and $n$ is rill erosion ranging from 1 to 1.3. The $LS$ factor was created based on data derived from a digital elevation model (DEM) into a GIS setting. The rill erosion values corresponded to $n = 1.1$ while the sheet erosion values ranged according to the examination area each time. Specifically, for the regions of Schinos, Vilia, and Varympompi, the sheet erosion value was set as $m = 0.45$, whereas for the Keratea region the corresponding value was $m = 0.5$.

$C$ factor demonstrates the cover management factor providing a measure of soil erosion rate as controlled by the cropping and management practices within a region [23,24]. The cover management factor was calculated based on satellite data acquisition corresponding to specific time periods. Specifically, the satellite data consisted of Sentinel-2 images for the regions of Schinos, Vilia, Varympompi, and Keratea, corresponding to time periods before and after the fire. Particularly, through the acquired data, normalized derived vegetation index (NDVI) images were generated to produce the factor’s values based on the formulation (Equation (8)) developed by Durigon et al. [53]:

$$C = \frac{1 - NDVI}{2}$$
The support practice \( P \) factor represents the practices on agricultural land that affect the soil erosion processes [54]. \( P \) factor was estimated based on the Corine Land Cover 2018 dataset. According to Yang et al. [55], all Corine Land Cover classes were assigned the value of 1, except in agricultural regions where the \( P \) factor was given the value of 0.5.

3.2.3. Web App Development

The final processing stage includes the preparation of the results layers to be suitable to be published as web layers on ArcGIS Online. ArcGIS Online is a cloud-based web GIS Software as a Service (SaaS) that is accessible from any device with internet access and which is interactive and enables web map creation among other capabilities. After the publication of the web layers, the web map needed for the web app was created. Finally, the web app in the Web AppBuilder was then developed with the addition of the previously mentioned map, the setting of the user interface (UI), parameters, and widgets [56,57].

4. Results

4.1. Burned Areas and Burn Severity

The total burned area of the four wildfires in Attica during the 2021 fire season reached 243.98 km\(^2\) making evident the large extent of damage caused to the region. As Figure 3 presents, the wildfire in Vilia burned the largest area reaching almost 96 km\(^2\), followed by Varympompi with 78.95 km\(^2\), Schinos with 64.05 km\(^2\), and Lavreotiki that has a burned an area of 5 km\(^2\).

![Figure 3](image_url)

**Figure 3.** Burn Severity of 2021 Attica region wildfires: (a) Schinos; (b) Varympompi; (c) Vilia; (d) Lavreotiki. The burned area classification based on burn severity is illustrated including the percentage of the burned area total of each area per class.
Analyzing the burn severity of these wildfires, generally the impact was severe enough with the moderate-high severity accounting for 53.69% or 131 km$^2$ out of the total burned area with the moderate-low (28.36%) and low (17.8%) following, while high severity covers 0.14%. More specifically, considering each area based on Figure 3, it is evident that the moderate-high severity characterizes all the burned areas except Lavreotiki, where lower severity levels prevail, whereas in Schinos a mostly close-to-equal distribution is observed among burn severity levels. It should be noted that in the cases of Varympompi and Vilia, the percentages of burn severity levels coverage in each case follow an almost identical pattern in the moderate severity levels percentage.

Regarding the affected land cover based on CLC 2018 as presented in Figure 4 and Table 4, the total numbers show that the third CLC category which includes forests, shrubs, and/or herbaceous vegetation is heavily impacted by the wildfires covering 82.71% or 201.8 km$^2$ of the total burned area, thus highlighting the ecological disaster in the region.

To put it another way, coniferous forests (72.48 km$^2$), sclerophyllous vegetation (52.47 km$^2$), transitional woodland-shrub (46.13 km$^2$), and mixed forests (24.73 km$^2$) comprised the most affected land cover. In Schinos, the burned area consisted of 62.80% of coniferous forests, in Varympompi transitional woodland-shrubs and mixed forests took up 46.60%, although it should be mentioned that a significant part of the artificial surfaces category was impacted in the region reaching 9.56% of the total burned area, including discontinuous urban fabric.

Continuing with Lavreotiki, coniferous forests, natural grasslands, and sclerophyllous vegetation accounted for 64.44% of the total burned area, and lastly, in Vilia sclerophyllous vegetation was 49.21% of the burned area.

![Figure 4. Burned land cover of Attica region wildfires based on Corine Land Cover 2018: (a) Schinos; (b) Varympompi; (c) Vilia; (d) Lavreotiki. The third level of Corine Land Cover 2018 was utilized and clipped to each burned area to assess the affected land cover.](image-url)
Table 4. Burned land cover of Attica region wildfires based on Corine Land Cover 2018 (% of the burned area total of each area per land cover category).

| CLC 2018                                                                 | Schinos | Varympompi | Lavreotiki | Vilia |
|---------------------------------------------------------------------------|---------|------------|------------|-------|
| 111: Continuous urban fabric                                              | 0.02%   | 0.47%      |            |       |
| 112: Discontinuous urban fabric                                           | 0.42%   | 7.96%      | 0.47%      |       |
| 121: Industrial or commercial units                                       | 0.29%   |            |            |       |
| 122: Road and rail networks and associated land                           | 0.36%   |            |            |       |
| 123: Airports                                                             | 0.31%   |            |            |       |
| 131: Mineral extraction sites                                             | 0.00%   |            |            |       |
| 142: Sport and leisure facilities                                         | 0.63%   |            |            |       |
| 211: Non-irrigated arable land                                            | 5.47%   |            |            | 1.29% |
| 223: Olive groves                                                         | 0.16%   |            |            |       |
| 231: Pastures                                                             | 0.23%   |            |            | 0.19% |
| 242: Complex cultivation patterns                                         | 2.42%   | 10.76%     | 8.21%      | 0.76% |
| 243: Land principally occupied by agriculture, with significant areas of natural vegetation | 10.58%  | 9.87%      | 13.06%     | 1.45% |
| 311: Broad-leaved forest                                                 | 4.33%   |            |            |       |
| 312: Coniferous forest                                                    | 62.79%  | 15.41%     | 23.18%     | 19.73%|
| 313: Mixed forest                                                         | 0.01%   | 22.11%     |            | 7.58% |
| 321: Natural grasslands                                                   |         |            | 20.92%     | 1.52% |
| 323: Sclerophyllous vegetation                                            | 3.04%   | 2.88%      | 20.35%     | 49.21%|
| 324: Transitional woodland-shrub                                          | 14.77%  | 24.49%     | 13.81%     | 17.34%|
| 333: Sparsely vegetated areas                                            | 0.16%   |            |            | 0.21% |
| 334: Burnt areas (Previous wildfire)                                      |         |            |            | 0.65% |
| 411: Inland marshes                                                      | 0.32%   |            |            |       |
| 512: Water bodies (Coast)                                                 | 0.02%   |            |            |       |
| 523: Sea and ocean (Coast)                                                | 0.18%   |            |            |       |

The correlation between burn severity and land cover led to useful findings. More analytically, transitional woodland-shrubs were the main land cover category characterized by high severity along with broad-leaved forests. Moderate-high severity existed mostly in coniferous forests (41 km²), sclerophyllous vegetation (30.96 km²), and transitional woodland-shrub (28.65 km²). In Vilia, 28.49 km² of sclerophyllous vegetation belonged to this burn severity level as well as 19.3 km² of coniferous forests in Schinos, 12.31 km² of mixed forest in Varympompi, and 0.79 in Lavreotiki accordingly. Regarding moderate-low severity, this was found in coniferous forests (18 km²), sclerophyllous vegetation (15.57 km²), and transitional woodland-shrubs (11.5 km²). In each area, the following prevailed: the sclerophyllous vegetation of Vilia (13.5 km²), coniferous forests of Schinos (10.27 km²), transitional woodland-shrubs of Varympompi (4.26 km²), and sclerophyllous vegetation of Lavreotiki (0.6 km²). Lastly, low severity is primarily met in coniferous forests (13.4 km²) and it mainly characterizes coniferous forests in Schinos (10.9 km²), sclerophyllous vegetation in Vilia (5.14 km²), and complex cultivation patterns in Varympompi (2.99 km²) and Lavreotiki (0.17 km²).

4.2. Soil Erosion Risk

Regarding the soil erosion risk derived from the use of the RUSLE concerning the time periods before and after the fire incidents in the Attica region in 2021, the spatial distribution of soil loss is presented in the following Figures 5–8. Due to the assessed areas’ heterogeneity of characteristics, the soil loss results in ton/ha/season were converted into a universal classification based on each area as presented in Table 5. More analytically, the 5 classes (from very low to very high erosion risk) were specified on an equal interval for each case estimated from the standard deviation average of soil loss before and after the fire events. In this way, a comparable classification, taking into consideration each area’s
soil loss results, was constructed which enables the identification of the change concerning erosion risk in pre-fire and post-fire results.

Figure 5. Erosion Risk according to RUSLE soil loss for Schinos burned area: (a) before the fire; (b) after the fire. The erosion risk as classified is presented including the percentage of the burned area total of each area per class.
Figure 5. Erosion Risk according to RUSLE soil loss for Schinos burned area: (a) before the fire; (b) after the fire. The erosion risk as classified is presented including the percentage of the burned area total of each area per class.

Figure 6. Erosion Risk according to RUSLE soil loss for Varympompi burned area: (a) before the fire; (b) after the fire. The erosion risk as classified is presented including the percentage of the burned area total of each area per class.

Figure 7. Erosion risk according to RUSLE soil loss for Lavreotiki burned area: (a) before the fire; (b) after the fire. The erosion risk as classified is presented including the percentage of the burned area total of each area per class.
Figure 7. Erosion risk according to RUSLE soil loss for Lavreotiki burned area: (a) before the fire; (b) after the fire. The erosion risk as classified is presented including the percentage of the burned area total of each area per class.

Figure 8. Erosion risk according to RUSLE soil loss for Vilia burned area: (a) before the fire; (b) after the fire. The erosion risk as classified is presented including the percentage of the burned area total of each area per class.

Table 5. Erosion risk classification for RUSLE soil loss (ton/ha/season), presenting each class for each area.

| Erosion Risk | Schinos | Varympompi | Lavreotiki | Vilia       |
|--------------|---------|------------|------------|-------------|
| Very Low     | 0.00–122.44 | 0.00–235.67 | 0.00–42.60 | 0.00–1957.77 |
| Low          | 122.44–244.88 | 235.67–471.34 | 42.60–85.20 | 1957.77–3915.54 |
| Moderate     | 244.88–367.32 | 471.34–707.01 | 85.20–127.80 | 3915.54–5873.31 |
| High         | 367.32–489.76 | 707.01–942.68 | 127.80–170.40 | 5873.31–7831.08 |
| Very High    | >489.76     | >942.68    | >170.40    | >7831.08    |

Soil loss results, in general, show a clear differentiation between the pre-fire and post-fire states in all four areas. More specifically, the pre-fire state is characterized by very low soil erosion risk, which is predominant in all cases. Regarding the post-fire soil erosion risk, it was clearly increased in the four areas of interest. Very low soil erosion risk was reduced to 45.76% whereas the low and moderate soil erosion risk constitutes a combined 40.12% of the burned areas. Moreover, the rest areas are characterized by high and very high soil erosion risk values of almost 7% each. It has to be mentioned that the results of the RUSLE cover a slightly reduced area than the original burned areas due to the slope estimation in the LS factor.

To begin with, the analysis of Schinos burned areas (Figure 5). Figure 5a illustrates that the area has a very low soil erosion risk. In the post-fire state (Figure 5b) the increased soil erosion risk is evident in the area with a reduction of very low to almost 50% area coverage with a main concentration in an axis from the north to the southeastern parts of the region. To analyze more, the western part of the area is characterized by concentrations of moderate...
to very high erosion risk as well as the southern part with an important concentration on the east–west axis. Moderate (13.04% or 7.43 km$^2$) and low (26.19% or 14.92 km$^2$) are distributed over the area covering a total large extent. A further analysis associated with the burn severity shows that moderate-high severity prevails in all erosion risk classes while considering that land cover coniferous forests are the most affected.

Regarding the burned areas of Varympompi in Figure 6a, the area in the pre-event soil erosion risk was very low. Analyzing the post-fire soil erosion risk as of Figure 6b, very low erosion risk covered 52.37% of the area, especially in the southern and eastern parts. Low erosion risk was distributed over the area characterizing 23.94% of it alongside moderate (11.71% or 8.14 km$^2$). The higher erosion risk categories took up the rest, almost 12% of the area, with very high erosion risk covering important parts to the west in the Partnitha Mountain base and around the Afidnes area in the north-central to northern parts. The distribution of erosion risk based on burn severity followed the same trends proportionally as the predominant moderate-high severity category. Assessing erosion risk with land cover, very low erosion risk characterized mostly transitional woodland-shrubs and low mixed forests alongside moderate, and high while very high was mainly spread within mixed and coniferous forests and transitional woodland-shrubs.

Proceeding to Lavreotiki, the pre-fire state as in previous cases showed a very low soil erosion risk (Figure 7a). In Figure 7b, the post-fire erosion risk presented an increase with very low and low erosion risk taking up 77.63% or 3.38 km$^2$ of the area. In the rest of the area, the moderate risk was sparsely distributed (11.90%) while the almost equal coverage of high and very high erosion risk was mainly located in the north-northeastern part of the region. Concerning the burn severity, the erosion risk followed a distribution based on moderate-low severity which covered the larger area. From the CLC 2018 perspective, the very low and low erosion risk was found primarily in coniferous forests and sclerophyllous vegetation while moderate, high, and very high was found in natural grasslands.

In the last area, Vilia, the soil erosion risk is presented in Figure 8. During the pre-fire period, the area was at very low erosion risk (Figure 8a). The post-fire erosion risk was higher in all the previously mentioned areas as of Figure 8b. Starting with the very low erosion risk it only covered 38.57% of the Vilia burned area followed by the low with 27.63%. To continue with the moderate severity which was dispersed all over the area it encompassed 16.29% or 14.73 km$^2$ of it. An important part covered the high (9.36%) together with very high (8.14%) soil erosion risk with the area’s topography playing a key role in their spatial distribution located mainly in large parts in the central part of it. As already seen in the previous areas, the same pattern regarding burn severity was followed with the predominant moderate-high severity in this case covering the larger part of each risk category. Lastly, sclerophyllous vegetation, as of land cover, in every soil erosion risk class, was the major affected land cover.

4.3. Web App

The web app is presented in Figure 9 and it includes all the above-mentioned results layers. Within the user interface, the various widgets are visible including map navigation ones and information, legend, layer list, and basemap selection. Others include location retrieval, search, drawing, sharing, measuring, and swiping between layers while coordinates can also be retrieved and converted. The web app is easily accessible from any device through the link: https://learn-students.maps.arcgis.com/apps/webappviewer/index.html?id=b55b1a2c8f464d28b18182809c590a33, accessed on 2 May 2022.
Figure 9. Screenshot of the developed web app. The user interface is shown with the web map of the affected areas and the widgets.

5. Discussion

This study achieved the target of assessing the impact of the wildfires that struck the Attica region in 2021 by combining remote sensing and GIS techniques and free open available datasets. The methods used led to the production of results which helped in understanding the effects of the four examined wildfires. The operational wildfire mapping with the use of Sentinel-2 optical imagery with the application of NBR was effective in mapping the burned areas and assessing their burn severity on a near-real-time basis and with a very good spatial resolution. The later soil erosion risk modeling derived from the RUSLE was sufficient enough to trace the soil loss before and after the wildfire events and understand the risk that each area faces after them. The highlight of this study is the addition of all these products to the web app developed for this purpose thus enabling the getting of an inclusive geospatial intelligence of the post-fire situation.

As mentioned above, the wildfires of 2021 constitute one of the greatest disasters Greece has faced. The analysis that has been implemented in this manuscript was related to the wildfires that broke out in the Attica region. Specifically, the study areas consisted of the wildfire incidents that broke out in Varympompi, Schinos, Vilia, and Lavreotiki. Those regions had been extensively affected by the fires with the burned areas varying from 5 km² to 96 km². The burn severity demonstrated some very interesting patterns spatially, predominated by moderate-high burn severity values in all regions, except Lavreotiki, where moderate-low severity values presented high frequency as well. Based on the results, the fires affected mostly forestry area consisting of broad-leaved, sclerophyllous, and mixed vegetation.

Wildfire incidents usually lead to post-catastrophic events such as the soil erosion phenomenon. In this study, advanced erosion modeling was applied to the above-mentioned regions in Attica in order to estimate the erosion risk resulting from the wildfire incidents. Particularly, RUSLE modeling was implemented so as to calculate the soil loss rates considering the study area. According to the results, erosion mapping after the wildfire incidents seemed to present high soil loss values in comparison to their pre-fire state. Post-fire mapping displayed very high erosion values according to RUSLE modeling in all four areas of interest.

Analyzing the results of the burned areas, moderate-high severity characterized the burned areas which were also found in large concentrations in all of them except Lavreotiki.
Within the boundaries of the affected areas, it could be observed that low severity values were present. Assessing the severity through the land cover, areas with moderate-high severity belong to the forest category of CLC 2018 thus making evident the ecological disaster but also the role of fuel that those areas constituted. The burned agricultural areas had moderate-low severity while the discontinuous urban fabric such as in Varympompi was characterized by mixed burn severity values. Another remark should be made about the terrain that affects the burned areas. More specifically, in most of the valley bottoms or higher altitudes, low severity values were found, or they were unburned due to their characteristics (e.g., low or no vegetation).

We will proceed to the erosion risk analysis over the burned areas in which the soil loss and thus the erosion risk increased to a large extent, pinpointing areas that may face excessive soil loss in the future. The analysis of the factors has revealed the significant influence of topography on the erosion risk based on the LS factor, which makes clear the higher values of soil loss to the hydrographic network. Considering the K factor’s influence, which is a factor that does not take into consideration the post-fire state, it showed some interesting patterns in Varympompi, where moderate to high values corresponded to high erosion risk. However, due to the fact that soil properties hardly ever face significant alterations over the years, the K factor is considered to contribute effectively in soil erosion assessment offering reliable results. With regards to the P factor, it did not play an important role in the model’s results, making it evident that it is not taken into consideration in many studies [58]. The NDVI-based C factor before and after the wildfires clearly showed a homogenous increase within the affected areas contributing to the soil loss increase. In the last factor considered, the R factor, there was a moderate correlation with the erosion risk which in some cases was related to increased soil loss.

Some comparisons can be made between burn severity and land cover with the erosion risk. In Schinos, higher erosion risk was found in coniferous forests, transitional woodland-shrubs, and mainly in areas of higher burn severity values. Passing to Varympompi, higher erosion risk values were located in the burned forest areas. It is worth mentioning that in the discontinuous urban fabric, in the north of the area, the risk was also high, presenting a trend of higher soil loss to the higher burn severity areas. In Lavreotiki, there was not a clear correlation between burn severity and erosion risk while the significant concentrations in high and moderate soil erosion risk were found in sclerophyllous vegetation and natural grasslands. Lastly, the soil erosion risk was higher in forest areas within the Vilia burned area and areas of moderate-high values.

Lately, RUSLE modeling has been applied to several studies in the Mediterranean region regarding post-fire assessment [2,26,27,47]. Tselka et al. [2] implemented RUSLE modeling in Central Greece so as to detect spatial correlations regarding the erosion risk after a fire event. Results of this study demonstrated as well that there was a rise in soil loss values immediately after the fire incident. The outputs of this study were also formed mostly based on the LS factor, while there was also a correlation between factors R and C and the outputs which could be attributed to the total length of the study area. Another interesting study is the one of Polykretis et al. [47], in which RUSLE modeling was applied in Crete, Greece in order to evaluate the factor’s influence in soil erosion mapping. The outputs showed that the R and C factors seemed to affect mostly the erosion risk assessment. In addition to our study, the LS factor was characterized as a static factor regarding its effect on soil loss mapping. Similarities were also detected in a study published by Evelpidou et al. [26] regarding the erosion risk after the wildfires that broke out in Greece in 2021. Results also demonstrated a significant increase in soil loss after the fire incidents using a Boolean logic-based model. Comparable patterns to our study have been also demonstrated in research carried out by Lanorte et al. [27], in which soil erosion risk was assessed after wildfire events in a southern Italy region. In this research, soil erosion risk is significantly increased after the fire, complying with the spatial patterns of our results.
At this point, the empirical part of the study is evaluated. In the mapping of burned areas, satellite image availability plays an important role operationally. Sentinel-2 has a very good temporal resolution but all the optical sensors can be severely affected by cloud and smoke cover over an area of interest thus limiting the burned area mapping capabilities which is a factor that affected the image selection of this study. Although, despite the fact that the 10 m resolution of Sentinel-2 is sufficient, the availability of higher resolution datasets could enhance the mapping’s detail. Proceeding to the burn severity, it is important that it is assessed also by field surveys to validate the results derived from the satellite imagery. An issue faced through the use of NBR is the misclassification of unburned areas as burned ones. This is caused by areas having similar spectral properties in the used spectral bands. In addition to the use of masks to minimize these effects, a manual selection of the burned consulting the post-fire Sentinel-2 natural and false-color images was also performed to maximize the accuracy.

Continuing with the empirical part, generally, the datasets proved adequate to meet this study’s purposes. The land cover retrieved from the CLC 2018 dataset gave a clear view of the affected burned areas and proved to be sufficient in in $P$ factor estimation. However, a more detailed dataset such as Urban Atlas 2018 could further improve them. With regards to the used DEM, a high-resolution DEM like that of Hellenic Cadastre with a 5 m resolution [2] would have given higher detail in the RUSLE as well as a closer resolution to the burned areas. In this context, the difference in resolution between the 10 m of burn severity and the 25 m selected based on DEM of RUSLE soil loss creates a difference in detail. Considering the total extent of all four wildfires, a higher resolution could have caused processing volume-related problems. The meteorological dataset concerning rainfall data for the creation of $R$ factor was based on a dense network of stations for the examined time periods. In general, dense point networks provide better outcomes in the implementation of spatial interpolation techniques. Soil-related datasets and, more specifically, the topsoil ones from ESDAC used in this study, led to the $K$ factor estimation but their resolution is very low (500 m) thus degrading detail. In addition, quality of the ESDAC raster datasets in combination with their low resolution made it necessary to apply the kriging spatial interpolation technique in order to improve both quality and resolution.

Finally, considering the RUSLE implementation, the $C$ factor, which is based on NDVI, proved very useful in the RUSLE estimation before and after a wildfire event. However, it might present some issues in regards to distinguishing between burned and non-burned areas. Alternatively, for the $K$ factor, the soil erodibility dataset by ESDAC would have been also suitable to be used instead of the previously mentioned ESDAC datasets as a ready-to-use solution. The RUSLE modeling validation could have included fieldwork after the fire event. Classification of the soil loss to create soil erosion risk categories was challenging and the final selection was performed after tests with other existing classification methods. The web app is maintained and updated through the ESRI’s ArcGIS Online services while content updates can also be conducted if more products are added or by updating existing ones. In addition, any update to the UI or widgets can be conducted by taking into consideration end-users’ feedback and when new or updated features are provided by ESRI.

6. Conclusions

Taking into consideration the future work and potential based on this study, some remarks are presented. The use of higher resolution datasets could further improve the wildfire impact assessment detail and accuracy, such as high-resolution satellite imagery, DEM, more analytical land cover, and better soil properties datasets in terms of sampling and resolution. Improvements of the utilized methods and comparisons with other related ones could be a step forward in accuracy and validation assessment. Other steps may include a rethinking of the RUSLE erosion risk modeling approach concept based on the literature and a detailed analysis between burn severity and RUSLE erosion risk could aid in finding spatial relations between them [2]. A key future step is the conduction of in
situ surveys for the validation of the results derived with the above-mentioned methods regarding burn severity [59] and soil loss. Finally, this work could also be expanded by considering more parameters and it could also be implemented in a similar way for future wildfire events constituting an important tool that not only permits post-fire impact assessment but also creates a useful archive for future studies and decision-making.

To sum up, the findings of this study helped in gaining geospatial intelligence over the effects that the 2021 wildfires had in the Attica region. Results regarding burn severity, land cover, and erosion risk, combined in a usable web app, could give a significant advantage to impact assessment research along with the decision making and planning over natural hazards management by stakeholders over the restoration procedures as well as the needed measures in vulnerable areas. In other words, the knowledge that this tool encompasses could help in pinpointing problematic areas and making all the needed post-fire actions more focused and effective. In the region of Attica, the results of this study based on the four studied wildfires showed that in 2021, a large part of the region was burned severely losing important parts of natural ecosystems and these areas are at an increased risk of soil erosion. This situation highlights the need for immediate action that should be taken in those areas by the stakeholders. Lastly, this study, with the presented innovative workflow and holistic approach, tried to highlight the importance of assessing the effects of a wildfire event with the use of Earth observation and GIS-based techniques using a cloud-based platform, in an attempt to share and disseminate the knowledge gained about the impacts on the affected environment.

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