Modelling seasonal variation of gully erosion at the catchment scale

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Abstract
Geo-hydrological phenomena, including gullies, contribute significantly to soil erosion and land degradation. To address this, proper management of basins and hillslopes should consider the mechanism, timing, and location of gully development and how gullies interact with other hillslope processes. Yet, conventional modelling techniques for such processes are rare, frequently being limited to applications of only single processes and typically requiring high-resolution input data. Further, existing tools for characterizing basins and hillslopes tend to be based on static descriptions of geo-environmental conditions, and thus are not effective for modelling changes such as the seasonal triggering conditions of gully phenomena over time. This study proposes a method to integrate open remote sensing data (Sentinel-2) and an existing modelling tool (LANDPLANER) using simplified input data to better predict and forecast gullies’ spatial and temporal occurrence. The study investigates the seasonal conditions responsible for the triggering of gullies at the catchment scale using different erosion modelling schema in the Toscana region of Central Italy. Geomorphological gully inventory data were collected and used as benchmarks to test the proposed approach. The results show that the occurrence of gully erosion in the studied region changes seasonally, and the proposed method was able to effectively discriminate spatial and temporal differences of the gully phenomena. The proposed method can be applied to similar regions worldwide, allowing for the investigation of gully erosion over time, even in places with limited data availability.

KEYWORDS
curve number, gully erosion, modelling, NDVI, remote sensing, Sentinel-2

1 | INTRODUCTION

Hillslope geo-hydrological processes triggered by rainfall are widespread and cause severe damage to structures, infrastructures, and population. In the Mediterranean region, such processes are widely distributed and severely impact the stability of slopes (Taguas et al., 2015).

In Italy, intense rainfall events triggering landslide phenomena and erosion processes occur in many regions, causing damage and human losses (Salvati et al., 2010, 2014). Water erosion is a relevant threat for a large part of Italy; approximately 77% of the territory is affected by this natural process (Gazzolo & Bassi, 1961). Water erosion mainly occurs on steep slopes in places subjected to intense mechanical cultivation, where conservation measures such as terraces and waterways have been removed (Chisci, 1986; Hauge, 1977), as well as along hillslopes where erodible subsoil materials are exposed (Torri et al., 2006). Even the notable high rate of landslide mobilization is the result of agricultural and land use practices that favour erosion (Torri et al., 2006). In addition, soil erosion is the foremost cause of soil degradation worldwide (Lal, 2001) and is capable of severely affecting water quality and ecological health and negatively altering terrestrial and aquatic habitats (Bennett & Wells, 2018). Gully erosion is a geo-hydrological process that strongly impacts slope dynamics, thereby contributing significantly to soil erosion and influencing other hydrologic phenomena, as well as worsening hillslope environmental conditions (Bennett & Wells, 2018). Specifically, a gully is a hillslope
incision in which runoff water accumulates, removing soil material even at considerable depths (Poeseen et al., 2003). Moreover, gully channels are typically deep enough (>0.5 m) to interfere with normal tillage operations (Bennett & Wells, 2018). According to the literature, a gully is generally typified as having a cross-sectional area greater than one square foot, approximately equal to 929 cm² (Hauge, 1977). Gullies are commonly generated by surface runoff and tend to be a persistent feature of the landscape that cannot be remediated by tillage (Gille, 2005). Moreover, gullies contribute significantly to the total soil erosion amount within a catchment and affect the catchment’s morphological shaping (Rossi, 2014; Torri, Poeseen, et al., 2018). These relevant scientific and social issues highlight the importance of providing more effective modelling approaches to predict the spatial and temporal occurrence of gullies (Rossi, 2014).

Changes in land use, such as deforestation and the substitution of forests by cropland or meadows, may affect the occurrence of erosion phenomena (Torri, Poeseen, et al., 2018). Generally, erosion phenomena are triggered by long-term, complex anthropogenic processes acting over centuries, such as inappropriate cultivation or irrigation practices, over-grazing, and over-cropping, but also by recent practices such as road building and urbanization (Poeseen et al., 2003; Torri, Rossi, et al., 2018; Valentin et al., 2005). In one study, Poeseen et al. (2003) determined that fluctuations of total soil loss caused by gully erosion can be related to changing land use conditions during a given period, with the amount of soil loss by gulling depending on the time span considered. Gully erosion is also known to be controlled by the magnitude and frequency of rain events (i.e. directly influencing the amount of runoff on hillslopes), which characterize a given climate and weather regime. Vanmaercke et al. (2016) analysed the scientific literature and found that, for a given region, the rainy day normal (RDN, a climate index accounting for the long-term average annual rainfall depth divided by the average number of rainy days) is significantly correlated with the gully head retreat rate. As such, any change in the rainfall regime (due to climate changes) for a specific area will likely affect gully erosion. For example, continental areas may be considerably dominated by gully erosion from concentrated snowmelt runoff in the spring, then by sheet and rill erosion from thunderstorms in the summer (Poeseen et al., 2003). Worldwide, similar examples illustrate that land use change is expected to have a greater impact on gully erosion than climate change (Valentin et al., 2005), yet this is in conflict with the findings of Vanmaercke et al. (2016), who were unable to identify significant correlations between gully retreat and land use or soil type. Overall, the factors of climate, land use, and land cover cannot be considered independently, yet at present their combined interactions and joint contribution to gully occurrence are still poorly understood. Consequently, from this perspective, it is important to consider seasonal changes that can intensify the susceptibility of a land type to erosion (e.g. the co-occurrence of seasonal maximum precipitation and little soil vegetation cover).

In this study, we investigate different seasonal conditions which have been identified as relevant for the triggering of gully erosion at the catchment scale (Bogen et al., 1994; Casali et al., 1999; Monsieurs et al., 2015; Tufekcioglu, 2018). Related studies have highlighted how land use, land cover, and meteorologic and climatic seasonal conditions may affect the triggering and development of gullies, their shape, and the related channel geometry. We therefore propose a method to integrate remote sensing data from the Sentinel-2 satellite with an existing modelling tool, LANDPLANER (Landscape, Plants, Landslide, and Erosion), which describes the dynamic response of slopes under different changing scenarios, to better predict and forecast gully spatial and temporal occurrence. This method aims to solve a critical issue in erosion modelling in which models commonly assume an inadequate averaged (i.e. static) temporal description of the geo-hydrological conditions controlling rainfall/runoff repartition at the surface, and in turn erosion. The proposed method considers more dynamic (i.e. seasonal) descriptions of such conditions based on remote-sensed data with a high revisiting time, and uses them to feed the LANDPLANER model (Rossi, 2014), thereby enabling the model to dynamically adjust the hydrological runoff response of hillslopes and better evaluate their capability to trigger erosion. Moreover, the modelling tool was selected for its advantage of requiring only limited input data.

The proposed modelling framework is applied to a portion of the Frettyana Torrent catchment in the Toscana region of Central Italy, in which rainfall-induced geo-hydrological processes (i.e. gullies but also landslides) occur frequently and substantially impact structures and infrastructures. To achieve this, we have: (i) configured LANDPLANER with dual-approach erosion modelling schema; (ii) used different satellite images (eight Sentinel-2 images acquired within a period of 2 years at two images per season) for dynamically characterizing the study area conditions; and (iii) collected information on past gully erosion occurrence (i.e. geomorphological gully inventory) as a benchmark to test the proposed approach.

The rest of the paper is outlined as follows. The next section describes the study area and the available gully inventory data. The third section outlines the entire modelling framework, including methodologies, used to characterize and improve the spatial and temporal variation of the model input data used in the analyses. The fourth section presents the results. Finally, discussion and conclusions are presented in the last two sections, respectively, and indicate the advantages and limitations of the proposed framework to model seasonal variation of gully erosion and related phenomena at the catchment scale.

## 2 | STUDY AREA

The study area (7.1 km², Figure 1) is located in the northeastern portion of the Freddyana Torrent catchment, on a tributary of the Serchio River (Toscana region, Italy) (Figure 1a). The study area is dissected by six tributary streams which flow nearly parallel to each other and are oriented from northeast to southwest, shaping the hillside morphology and controlling the water drainage. The elevation ranges between 37 and 551 m above sea level (a.s.l.). The study area mostly faces southwest and is bounded to the north by Formicoso Mountain (551 m a.s.l.), to the east by Catino Mountain (481 m a.s.l.), and to the southwest by the Freddyana Torrent, the main watercourse in the area. The main villages within the study area are Torre and Cappella (Figure 1b).

According to the Krippen–Geiger classification (Peel et al., 2007), the climate is classified as Csa (hot-summer Mediterranean), which is characterized by hot and dry summers with at least one winter month with more than three times the rainfall amount in the driest summer month, and with the average temperature of the hottest summer...
The climatic characteristics and rainfall regime make this area among the most vulnerable to geo-hydrological processes in the Toscana region. Indeed, geo-hydrological processes occur frequently in this catchment, mainly during intense rainfall events, including two events recorded in July 2014 and December 2017, respectively (Autorità di Bacino Pilota del Fiume Serchio, 2014a). Erosion, and particularly gully erosion, is a relatively common process, that together with landslide activity impacts the hillslopes, structures, and infrastructures therein.

The closest thermometric and rain gauge stations are located, respectively, at ~1 km northeast (Aquilea thermometer, E 1619260 N 4859827, 134 m a.s.l.) and 500 m south of the study area (Mutigliano rain gauge, E 1620624 N 4863398, 33 m a.s.l.) (Figure 1a). The average annual temperature, calculated for the period 1994–2016, is 15.2°C. For the same period, average annual precipitation is about 1200 mm, with November being the wettest month at over 200 mm of average rainfall (data from Toscana Region Hydrologic Service, http://www.sir.toscana.it).

The geology belongs mostly to the Tuscan Domain (Tuscan Nappe Unit), while formations of the Ligurian Domain also outcrop in the area, and quaternary slope and alluvial deposits characterize the transition between the hills and Freddana Torrent plain (Nardi et al., 1987). In order of extent, the main geological formations in the area are: the Macigno Fm. (Tuscan Nappe Unit), a siliciclastic turbiditic sequence; the Ottone Flysch Fm., a calcareous turbiditic sequence; and the Complesso di Monte Veri Fm. (Ligurian Domain), a silica

FIGURE 1 (a) Satellite view of the Freddana Torrent catchment (bounded in red) with the study area delimited in yellow and additionally reported in panel B. (b) Base map from Google Earth, captured in 2017. (c) The geomorphological inventory realized in the study area portraying gully and landslide occurrence up to May 2017: (1) gully erosion phenomena; (2) landslide event inventory (July 2014, FS + VA); (3) geomorphological inventory (pre–June 2017, FS + VA) (Agostini et al., 2019). (d) The gully erosion phenomena triggered by the December 2017 rainfall event. (e) Land use and land cover (LULC) maps of the study area in 2007 and (f) 2013, classified according to the CORINE land cover (CLC) system. Pie charts show the areal distribution percentage of LULC in 2007 and 2013 (Table 1) (Color figure can be viewed at wileyonlinelibrary.com)
Pedological data were obtained from the Pedologic Database of the Toscana region (http://www.regione.toscana.it/-/geoscopio), showing that the soil fertility is low (Sanchez et al., 1982) for most of the study area, thereby sustaining a limited range of crops and conservation practices (Table 1). In the vicinity of the torrent banks, the soils allow for a wider range of crops and/or conservation practices. The Hydrologic Soil Group (HSG) classifications (USDA and NRCS, 2015 – Chapter 7) are mostly B (i.e., soils with 10–20% of clay and 50–90% of sand with a loamy sand or sandy loam texture), which is characterized by soils with relatively low surface runoff potential, and some C, which is characterized by soils with relatively high surface runoff potential.

The land use and land cover (LULC) map of the Toscana region is based on the CORINE Land Cover (CLC) Level III classification schema (Bossard et al., 2000; European Environment Agency, 1995) (Figures 1e and f). Note that the class called ‘210: irrigated and non-irrigated crops’ mentioned in the subsequent discussion is a newly identified third-level class, and the related technical specifications (Regione Toscana and Consorzio Lamma, 2012) define it as a grouping of the CLC classes of ‘211: non-irrigated arable land’ and ‘212: permanently irrigated land’.

In the analyses, we initially considered both the 2007 and 2013 LULC maps, but the differences among the two were few. Therefore, it was decided to only show results obtained using the more recent 2013 LULC map.

Figure 1 and Table 1 show that the study area is mainly covered by forest (classes 311, 312, and 313), followed by permanent crop (221: vineyards and 223: olive groves), irrigated and non-irrigated arable land (210), discontinuous urban fabric (112), heterogeneous agricultural areas (241, 242, and 243), industrial, commercial, and transport units (121 and 122), pastures (231), green urban areas (141), and construction sites (133). Overall, the study area is mainly characterized (58%) by forests and semi-natural areas (corresponding to group 3 at CLC Level I), with their seasonal conditions varying according to different vegetative stages and/or to logging. Stronger seasonal LULC changes tend to characterize the remaining portion of the study area, particularly the irrigated and non-irrigated land and other cultivated areas.

For the study area, Agostini et al. (2019) derived a geomorphological inventory (as defined by Guzzetti et al., 2012) reporting the landslides, gully erosion phenomena (Figure 1c), and other geomorphological features such as detrital-alluvial fans, classified according to the guidelines of the hydrogeological setting plan realized by the Serchio River Basin Authority (Autorità di Bacino Pilota del Fiume Serchio, 2014b). The inventory was obtained by means of visual interpretation of the 2000 and 2006 stereoscopic aerial images (1:10 000 and 1:7500 scales, respectively) and of the hillshades at 1 m resolution derived from two LiDAR surveys completed in 2006 and 2008 (hereafter denoted as visual analyses, or VAs), aided by one field survey carried out in 2017 (hereafter denoted as FS). Note that, in the days following an event of multiple rainfall-induced landslides in July 2014, the Serchio River Basin Authority mapped the landslides by means of an FS and VA derived from two unmanned aerial vehicle surveys (Autorità di Bacino Pilota del Fiume Serchio, 2014a). The occurrence times of gully formation were not always available, but the field data and supporting data obtained from the Serchio River Basin Authority did indicate that winter rainfall events are capable of triggering the formation of numerous gullies (such as multiple gullies formed during the event in December 2017). For the overall study area, the length of gullies ranges from 20 to 312 m with a total cumulative length of about 5.6 km (Figure 1c). The mapped gully widths range from 1 to 10 m. The gully incidence over the LULC classes is reported in Table 1.

**Table 1**: Land use and land cover distribution in the study area in 2013 and relative gully incidence

| CLC class | CLC name                                      | Surface (%) | Gully length (%) | Gully length per unit area (km/km²) |
|-----------|-----------------------------------------------|-------------|------------------|-------------------------------------|
| 112       | Discontinuous urban fabric                    | 3.81        | 1.7              | 0.36                                |
| 121       | Industrial or commercial units                 | 0.42        | -                | 0.00                                |
| 122       | Road and rail networks and associated land    | 2.71        | 0.3              | 0.09                                |
| 133       | Construction sites                            | 0.02        | -                | 0.00                                |
| 141       | Green urban areas                             | 0.16        | -                | 0.00                                |
| 210       | Irrigated and non-irrigated crops             | 5.57        | 0.9              | 0.13                                |
| 221       | Vineyards                                     | 3.49        | 1.1              | 0.25                                |
| 223       | Olive groves                                  | 20.28       | 9.1              | 0.36                                |
| 231       | Pastures                                      | 2.54        | 2.9              | 0.91                                |
| 241       | Annual crops associated with permanent crops  | 1.54        | 0.1              | 0.05                                |
| 242       | Complex cultivation                           | 1.33        | -                | 0.00                                |
| 243       | Land principally occupied by agriculture, with | 0.49        | -                | 0.00                                |
|           | significant areas of natural vegetation       |             |                  |                                     |
| 311       | Broad-leaved forest                           | 5.19        | 8.9              | 1.37                                |
| 312       | Coniferous forest                             | 1.66        | -                | 0.00                                |
| 313       | Mixed forest                                  | 47.34       | 71.1             | 1.20                                |
| 324       | Transitional woodland/shrub                   | 3.41        | 4.0              | 0.94                                |
| 511       | Water courses                                 | 0.02        | -                | 0.00                                |
Various methods have been proposed in the literature for the prediction of gully erosion, based on empirical (Beer & Johnson, 1965), dynamic, static, deterministic, and stochastic approaches (Sidorchuk, 1998, 1999, 2005, 2006). Some are based on semi-empirical physical models (De Ploey, 1992; Flanagan et al., 2001; Foster, 1986; Tucker et al., 2001; Willgoose, 2005). The more complex models use alternate parameters that are difficult to quantify or locate details of in the literature. Using the gully head topographic threshold (in this study denoted as \( \text{esp} \)) is common for the empirical approaches (Montgomery & Dietrich, 1994; Poesen et al., 2011; Vandekerckhove et al., 2000). Such an approach has recently been refined by Torri and Poesen (2014) and Torri, Poesen, et al. (2018). Their models aim to predict the locations at which the gully processes cannot continue expanding upslope, that is, identifying the head of the gully, under specific hillslope conditions and a given rainstorm intensity. Such models are focused on the definition of the critical topographic conditions, expressed by the local gradient(s) of slope and drainage area (A), that control the development and position of the gully heads in various landscapes. Torri and Poesen (2014) suggested that the threshold coefficient \( k \) (the resistance of the site to the development of the gully head) depends on land use. They also proposed a new relationship (Torri & Poesen, 2014; Torri, Poesen, et al., 2018) for describing overland flow-induced gully heads, extracted from datasets collected in various parts of the world. A key factor of that proposed relationship is that for a given value of the threshold exponent \( b \), the coefficient \( k \) can be predicted using the characteristics of soil and vegetation, based on the National Resources Conservation Service (NRCS) runoff curve number, denoted hereafter as \( \text{CN} \) (USDA and NRCS, 2015), and on surface rock fragment cover. This model is applicable in the areas where the topographical, land use, and soil characteristics are known. The final equation derived from Torri and Poesen (2014) and Torri, Poesen, et al. (2018) is as follows:

\[
k = 0.4[1 + e^{4.46 \text{RFC}}]c(0.00113[1 - \exp(-0.0137\text{S}_{0.05})]S_{0.05})
\]

In Equation 1, RFC is the rock fragment cover factor, \( c \) is a constant, and \( S_{0.05} \) is the abstraction coefficient derived directly from the CN. Rossi (2014) integrated a similar threshold equation in the LANDPLANER modelling tool, in addition to another erosion modeling approach also based on the use of the CN. That model aimed to
predict landslides and erosion processes by simpler means and requiring only basic input data, such as at least one digital elevation model (DEM) and one land cover map to derive runoff parameters based on the CN method (Rossi, 2014; USDA and NRCS, 2015). The model can be used to simulate water repartition at the soil surface (i.e. the runoff and infiltration repartition). The spatial resolution of the model analysis should match the DEM resolution, in this study corresponding to 10 m. Moreover, the model is well suited to describe the dynamic response of hillslopes (i.e. hydrological and geo-hydrological processes variation) under possible topographic, climatic, and LULC changes.

A key input for the model is the CN map for the catchment area, which is generally defined based on a land use and a soil type map (USDA and NRCS, 2015). To better account for the spatial and temporal variation of land use, we have also proposed a methodology to derive CN maps starting from (i) the land use categories classified according to the CORINE Land Cover scheme (Bossard et al., 2000) and (ii) the variation of normalized difference vegetation index (NDVI) values within each category. To achieve this, we used European Space Agency (ESA) Sentinel-2 images for deriving NDVI values, mainly due to their resolution and high revisiting time (Drusch et al., 2012), which allows for a more accurate spatial and temporal characterization of land use changes in a given area at the seasonal scale. It is important to note that the ability to correctly characterize the variation of these model input data (meteorological and CN) in space and time is fundamental to the prediction of gully formation.

In the following sections, we introduce the proposed model and its input data and describe our approach for improving the spatial and temporal characterization of the input CN map, with the main objective being to strengthen the ability of the model to predict runoff and erosion phenomena (gully erosion).

The flowchart in Figure 2 summarizes the steps for processing the raw Sentinel-2 satellite data (Block A), the dynamical input data preparation (Block B), the model simulations (Block C), and the output verifications (Block D). The flowchart describes all steps of the process, beginning with the automatic downloading of Sentinel-2 remote sensing images and ending with the analysis of statistical reports for the evaluation of the results. Multiple open-source software packages (Python, Sen2Cor, SNAP, R, and the Geographic Resources Analysis Support System, or GRASS geographic information system, collectively GRASS GIS) used for the different processing steps allow for the potential generation of a fully open-source automatic scripting procedure, to be applied for modelling dynamic gully erosion in the future, including for other areas outside of Italy.

### 3.1 Model description

The open-source modelling tool LANDPLANER is mainly designed to describe the dynamic response of slopes under different changing scenarios, including meteorological factors, vegetation, or land use and slope morphology. The model is raster-based and is able to estimate the effects of given rainfall characteristics on the triggering of landslides and erosion processes (Rossi, 2014). The model encompasses three components: (i) a hydrological model component for the water repartition that explicitly considers the rainfall (P), runoff (Q), infiltration (I), exfiltration (Ex), evaporation (Ev), and transpiration (Tr); (ii) a twofold erosion modelling schema to predict locations where erosion processes may occur; and (iii) a landslide model component to predict where landslide phenomena may occur. The erosion model estimations can either be static, based on a morphologic threshold approach which is mainly used for gully head prediction (Torri & Poesen, 2014), or dynamic, based on the use of an erosion index (in this study denoted as d) (Rossi, 2014) built on the stream power concept, which considers direct runoff (calculated by a specific rainfall/runoff routing procedure), local slope, and soil conditions expressed by the abstraction coefficient S0_05 that is derived directly from the CN value (equation 3-3 in Rossi, 2014). The site index, S, varies from 0 to ω and is a measure of the catchment hydrological response (USDA and NRCS, 2015). The erosion index, as opposed to the topographic threshold, does not solely consider gully erosion, but since the erosion index is directly calculated from runoff, it may potentially account for the different types of erosion processes, including sheet and rill erosion.

In this study, the model utilized simplified input data, namely one DEM (with 10 × 10 m resolution) to derive different morphometric variables (i.e. accumulation, drainage direction, and slope) (Figure 3), one LULC map, and one soil map to derive first the CN, and then the S0_05 maps, which were then used by the model to simulate water repartition at the soil surface.

The rainfall–runoff model is based on the CN method (USDA and NRCS, 2015), thereby allowing for the estimation of runoff based on land use and soil condition data. The approach is able to quantify the runoff produced by a specific rainfall event and can be effectively applied to estimate runoff from daily or sub-daily rainfall data. For this work, the most useful characteristic of LANDPLANER is its capability to use both meteorological input data (i.e. rainfall and temperature) and CN values, as these variables directly express the soil and land use conditions. These variables together allow for reproducing the temporal and seasonal variation of the conditions in the study area which are triggering gully erosion phenomena.

### 3.2 Dynamical input data derivation

The CN map is one element of the key input data, which strongly controls the model results. In general, CN values are empirical coefficients associated with combinations of cover descriptions and HSG classifications, defined as hydrologic soil-cover complexes. Determining a CN in practice requires (i) defining the cover descriptions on the basis of LULC class (referred to as ‘cover type’), the management practices (‘treatment’), and the hydrologic conditions and (ii) identifying the HSG classification based on the soil properties (USDA and NRCS, 2015). The CN is used to calculate the abstraction coefficient S0_05, which is the parameter directly used by the method to estimate runoff from rainfall. In the literature, CN and S0_05 are commonly considered static, but since they are related to the LULC conditions they should be expected to change over time. Accordingly, these parameters should be modelled dynamically in order to correctly describe the real geo-environmental conditions existing in a given period or season of the year, thereby enabling better prediction of the runoff and related phenomena.

To this end, this study proposes a procedure to assign CN values and obtain the relative maps, based on LULC and HSG maps as explained in Figure 2. However, the procedure is not entirely
straightforward, because different LULC classes (here classified according to CLC system) may correspond to multiple CN values (see tables in USDA and NRCS, 2015) depending on different HSG conditions, cover types, treatments (e.g. dirt or gravel road and use of agricultural lands), and hydrologic conditions (e.g. the average percentage of impervious area, percentage of grass cover, density and canopy of vegetative areas, amount of year-round cover, amount of grass or close-seeded legumes, percentage of residue cover on the land surface, degree of surface roughness, and thickness of ground cover). To address this, a range of CN values (i.e. the minimum, mean, and maximum values in Table 2) were associated with each combination of LULC and HSG in the study area. The variability therefore accounted for the range of possible cover types, cover density, phenological status, use of agricultural lands, average percentage of impervious area, and other hydrologic conditions. Where a single CN value was obtained for the LULC/HSG combination (e.g. 133: construction sites and 511: water courses), this value was taken as the mean and the minimum (maximum) value was calculated by subtracting (adding) 1. This was done to simulate at least the minimum CN variability. The values shown in Table 2 represent the classes reported in the 2013 LULC map, which was the most recent classification available for the study area. The differences between the 2007 and 2013 LULC maps were minor, with an overall change of 0.69% for the entire study area. In particular, the most significant changes corresponded to a transition of 0.33% for the whole area from ‘221: vineyards’ to ‘210: irrigated and non-irrigated crops’ and of 0.14% from ‘223: olive groves’ to ‘112: discontinuous urban fabric’. Other changes affected less than 0.1% of the total area (Figures 1e and f).

Following this approach, we were able to identify the spatial variation of CN for each LULC/HSG combination in the study area and used that to define the three CN scenarios reported in the maps in Figure 4.

Such scenarios reflect the possible changes of CN in the study area over 1 year, but do not necessarily reflect the spatial and temporal changes in different periods of the year. To better characterize such spatial and temporal variation (e.g. seasonal), the proposed method utilizes the Sentinel-2 remote sensing data.

### 3.3 Sentinel-2 data as input

The Sentinel-2 mission, launched on 23 June 2015, comprises a land monitoring constellation of two satellites (Sentinel-2A and Sentinel-2B) providing global optical imagery at a 5-day interval (revisit time),
using a multi-spectral instrument (MSI) (Sepuru & Dube, 2018). The Sentinel-2 MSI has 13 reflective wavelength (ranging from 433 to 2190 nm) spectral bands; four 10 m visible and near-infrared bands; six 20 m red edge, near-infrared, and shortwave infrared bands; and three 60 m bands (Drusch et al., 2012).

The Copernicus Open Access Hub (European Space Agency, 2016) provides an interactive graphical user interface for searching and quick-look visualization (Roy et al., 2017) of Sentinel-2 data, which are made available systematically and free of charge. The Sentinel-2 geolocated top-of-atmosphere (TOA) reflectance (L1C) products were acquired from the hub. Eight remote sensing images were selected from the period June 2016–December 2017, maximizing the seasonal differences. Six were Sentinel-2A images (shot dates corresponding to 2016/06/28, 2016/07/18, 2016/10/06, 2016/12/18, 2017/05/27, and 2017/12/20) and two were Sentinel-2B images (shot dates corresponding to 2017/07/18 and 2017/10/09).

The Sentinel-2 TOA reflectance images were corrected to surface reflectance using the approach proposed by Mueller-Wilm (2018) implemented in Sen2Cor software (Sen2Cor 2.5.5; Mueller-Wilm, 2018). This atmospheric correction method converts the TOA reflectance to bottom-of-atmosphere (BOA) surface reflectance (Figure 2), mitigating the scattering and absorption effects occurring within the atmosphere (Advisory Group for Aerospace Research and Development, 1990). The Sen2Cor correction includes two aerosol types (‘rural’ and ‘maritime’) and two atmosphere types (‘Mid_Latitude: SUMMER or WINTER’) (Figure 2). The type of aerosol relates to how much atmosphere is affected by sea water or sea wind (Advisory Group for Aerospace Research and Development, 1990). Considering that in the study area, the sea wind either does not blow or only blows with a relatively low intensity (Vittorini, 1972), the type of aerosol was determined as ‘rural’. The ‘Mid_Latitude’ parameter is related to the seasonal atmospheric conditions, hence the selection is based on the date and season of the remote sensing images collection.

TABLE 2 Correspondence between CLC classes in the study area defined in Table 1 and the intervals of curve number values (CNmin, CNmean, and CNmax) derived following the SCS curve number method (USDA and NRCS, 2015)

| CLC class       | CN class                                | CNmin | CNmean | CNmax |
|-----------------|-----------------------------------------|-------|--------|-------|
| 112             | Residential districts by average lot size| 72    | 81     | 90    |
| 121             | Urban districts                          | 88    | 91     | 94    |
| 122             | Streets and roads/roads (including right-of-way) | 82    | 89     | 98    |
| 133             | Developing urban areas                   | 90    | 91     | 92    |
| 141             | Open space (lawns, parks, golf courses, cemeteries, etc.) | 69    | 78     | 86    |
| 210             | Close-seeded or broadcast legumes or rotation meadow | 67    | 76     | 85    |
| 221             | Row crops                               | 73    | 79     | 85    |
| 223             | Row crops                               | 70    | 78     | 88    |
| 231             | Pasture, grassland, or range-continuous forage for grazing | 61    | 75     | 86    |
| 241             | Fallow                                  | 83    | 93     | 86    |
| 242             | Close-seeded or broadcast legumes or rotation meadow | 73    | 79     | 85    |
| 243             | Brush/brush–forbs–grass mixture with brush being the major element | 48    | 64     | 77    |
| 311             | Woods                                   | 55    | 67     | 77    |
| 312             | Woods                                   | 55    | 67     | 77    |
| 313             | Woods                                   | 55    | 67     | 77    |
| 324             | Sage/grass–sage with an understory of grass | 50    | 57     | 64    |
| 511             | Water courses                           | 97    | 98     | 99    |

FIGURE 4 Curve number (CN) maps: (a) minimum, (b) mean, and (c) maximum [Color figure can be viewed at wileyonlinelibrary.com]
(Mueller-Wilm, 2018). In our dataset, the parameter value ‘WINTER’ was applied for remote sensing images from October to March and ‘SUMMER’ for those from April to September (Figure 2). In addition, to restrict the possible effects of the planetary boundary layer, that is, the portion of the troposphere influenced by the interaction with the earth surface (i.e. topography) (Stull, 1988), we enabled Sen2Cor to use the higher-resolution Shuttle Radar Topography Mission (SRTM) DEM (90 m SRTM Digital Elevation Database) (Mueller-Wilm, 2018).

For all corrected images, the NDVI value was calculated with SNAP 6.0 software (Astri Polska, Earth Observation for Eastern Partnership, 2016; European Space Agency, 2016). The NDVI, which is strongly affected by changes of surface optical properties (Baret & Guyot, 1991), can be computed as follows (Nemani & Running, 1989; Rouse, 1974):

$$\text{NDVI} = \frac{R_{\text{NIR}} - R_{\text{RED}}}{R_{\text{NIR}} + R_{\text{RED}}}$$

where \(R_{\text{NIR}}\) and \(R_{\text{RED}}\) are reflectances in the near-infrared (0.785-0.900 \(\mu m\)) and red visible (0.698-0.785 \(\mu m\)) wavelengths, respectively (Gamon et al., 1992), and B is the corresponding Sentinel-2 MSI band (Clerici et al., 2017). Standard NDVI values range from \(-1\) to \(+1\) (Myneni et al., 1995; Pettorelli et al., 2005), with three correspondence levels as follows: (i) very low (0.1 or less), corresponding to an absence of vegetation such as water, urban areas, or areas covered by bare rock; (ii) moderate (0.2 to 0.5) for sparse vegetation; and (iii) high (0.6 to 0.9) for dense vegetation or crops at their peak growth stage (U.S. Department of the Interior and U.S. Geological Survey, 2018).

To verify the NDVI calculation procedure, we analysed the NDVI value distribution in urban areas (corresponding to the CLC class 112) within and adjacent to the study area, using violin plots (Figure 5). Good values were obtained for the study area, that is, values equal or close to 0 (i.e. NDVI values were around 0 and median values were close to 0), as shown in Figure 5. The residual variation of NDVI around 0 can be attributed to the limited LULC pixel variability within the urban-area polygons.

It is known that NDVI temporal profiles efficiently capture the photo-synthetically active vegetation behaviour (Benedetti & Rossini, 1993), and thus can be directly linked with plant phenology variations (Benedetti et al., 1991). This relationship can be observed by comparing Figure 1f with the NDVI maps in Figure 6.

Based on this, it can be stated that NDVI values are generally inversely correlated with CN, which takes its maximum value for impervious soils or bare surfaces. This is a key assumption of the work, but cannot necessarily hold true for all land use classes; for instance, NDVI values for deciduous forests may show a sudden drop in winter, owing to the CN values being lower due to the litter formed by dead leaves, which continues to promote infiltration or slow runon more than runoff. To test the plausibility of this assumption, we compared the NDVI minimum, mean, and maximum values for each land use class with the corresponding CN minimum, mean, and maximum values and their possible combinations (Figures S4–S16 in the Supplementary Material) for all the Sentinel-2 images. Despite the large scatter and low correlation coefficients, the data alignment suggests a linear inverse dependence between NDVI and CN, in contrast to the other possible non-linear relations.

Considering the inverse correlation between CN and NDVI, the proposed method was developed to relate them. Moreover, the proposed method allows for the calculation of CN maps referring to a specific time of the year. For a given study area, the calculation requires: (i) a stack of raster NDVI maps available for different periods or seasons of the year; (ii) an LULC map; and (iii) CN ranges for the different LULC/HSG combinations. The process is as follows. First, CN variability for every LULC/HSG combination in the study area (shown in Table 2 and Figure 4) is expressed by its range, from the minimum (CN\(_{\text{min}}\)) to the maximum (CN\(_{\text{max}}\)) value. The NDVI variability is then estimated considering the distribution of NDVI pixels values (among all the Sentinel-2 corrected images) and expressed by the range between the minimum (NDVI\(_{\text{LULC}}\)) corresponding to 1st percentile) and maximum (NDVI\(_{\text{LULC max}}\)) corresponding to 99th percentile) value. Figures 7a–c show that for every LULC class in the study area (classified according to CLC system) the variability of minimum, mean, and maximum NDVI values was calculated considering all the Sentinel-2 corrected images. Such variability for every LULC class is shown by the boxplots in Figures 7d–f. Table 2, Figures 4 and 7a–c show that...
the CLC classes with the higher CN correspond to the lower NDVI values. This is evidence supporting the expected theoretical inverse correlation. Clearly, the correlation assumes a correct attribution of CN values.

Such CN and NDVI minimum and maximum values can be used to calculate different types of CN maps. First are the mean CN pixel (CN_{pixel, mean}) maps, for which values are derived using Equation 3, based on the NDVI mean pixel value (NDVIpixel_{mean}), calculated from the stack composed by the eight NDVI images (Figure 7b). Figure 8a shows the CN_{pixel, mean} map obtained using Equation 3:

$$\text{CN}_{\text{pixel, mean}} = \left( \frac{\text{NDVIpixel}_{\text{mean}}}{\text{NDVILULC}_{\text{max}} - \text{NDVILULC}_{\text{min}}} \right) \cdot \left( \frac{\text{CN}_{\text{LULC, min}} - \text{CN}_{\text{LULC, max}}}{\text{CN}_{\text{LULC, max}} - \text{CN}_{\text{LULC, min}}} \right) + \text{CN}_{\text{LULC, max}}$$

Similarly, using Equation 4, the method allows for the calculation of CN maps (CN_{pixel, YYYYMMDD}) corresponding to different dates, starting in this case from the NDVI values of a specific image (NDVIpixel_{YYYYMMDD}):

$$\text{CN}_{\text{pixel, YYYYMMDD}} = \left( \frac{\text{NDVIpixel}_{\text{YYYYMMDD}} - \text{NDVILULC}_{\text{LULC, min}}}{\text{NDVILULC}_{\text{max}} - \text{NDVILULC}_{\text{min}}} \right) \cdot \left( \frac{\text{CN}_{\text{LULC, min}} - \text{CN}_{\text{LULC, max}}}{\text{CN}_{\text{LULC, max}} - \text{CN}_{\text{LULC, min}}} \right) + \text{CN}_{\text{LULC, max}}$$

The CN maps obtained for the different dates (corresponding to different Sentinel-2 images) are shown in Figures 8b–i. Such maps are able to show how CN values change over time and seasonally. Both Equations 3 and 4 consider inverse linear relations between NDVI and CN within the specified ranges, which are estimated parameters that differ between study areas.

3.4 | Experimental setup and analysis

The CN maps in Figures 4 and 8b–i portray different soil conditions, cover density, and stages of vegetation growth in the study area. The maps in Figure 4 show the CN value variability (as expressed in terms of minimum, mean, and maximum values) for every polygon corresponding to different LULC/HSG combinations and can be
considered as static. The CN range assignment also accounts for the possible cover density changes in the study area. Conversely, the CN values in the maps in Figure 8 are associated with each pixel and change dynamically for every NDVI map derived from the satellite images acquired from different periods of the year. For this reason, the maps in Figures 8b–i are able to capture the different stages of growth of vegetation throughout the year.

As previously mentioned, LANDPLANER may use this CN information in two ways to estimate the gully locations, either by using the esp approach (Torri & Poesen, 2014), or using e (Rossi, 2014) based on different rainfall scenarios. Overall, different simulations can be performed using combinations of the CN input, erosion model type, and rainfall scenario. Table 3 summarizes all the simulations performed in this study, indicating the name, CN input, simulated rainfall value (selected among 10, 40, 70, and 100 mm of daily rainfall), and the purpose of the simulation. The daily rainfall values were selected as a regular decreasing sequence (with a step of 30 mm), starting from the maximum rainfall value (100 mm) observed in the study area. In Table 3 the simulation reference RCNXXX-PREC represents simulations performed using the e for different rainfall values (dynamic scenarios) in order to verify the possible gully occurrence for different rainfall intensity (Bennett & Wells, 2018). Instead, the reference RCNXXX-TOP refers to simulations based on topographic thresholds for predicting gully location (static scenarios). For each CN elaboration (i.e. using different approaches for estimating CN), there are two reference simulations, dynamic and static (i.e. respectively based on the use of the erosion index and topographic threshold). Additionally, the reference RCNNDVIYYYYMDDD refers to simulations for different temporal conditions in the study area corresponding to different dates, identified with YYYYMDDD (i.e. the date of Sentinel-2 image acquisition). Specifically, in the simulations listed in Table 3 we considered Sentinel-2 images relative to different seasons; one for spring, three for summer, two for autumn, and two for winter.

3.5 | Model evaluation

In the literature, different metrics, such as receiver operating characteristic (ROC) curves (Kariminejad et al., 2020) or other statistical aggregated metrics, have been used for gully model evaluations. Nevertheless, such metrics do not allow for the estimation of the eroded area length as correctly predicted by the model, which is an important factor for linear erosion features, such as the gullies.

Here, to evaluate and verify the proposed methodology, we compared the modelling output with the gully erosion phenomena mapped as linear features in the study area (Figure 1c). We used two metrics, the first investigating only the length of the gullies correctly predicted by the model, and the second investigating the overall model performance on the entire study area.

**Figure 7** Variability of NDVI within CLC classes calculated using all corrected Sentinel-2 images. (a) NDVI min map, (b) NDVI mean map, (c) NDVI max map, (d) boxplot with the NDVI min values for each CLC class, (e) boxplot with the NDVI mean values for each CLC class, and (f) boxplot graph with the NDVI max values for each CLC class [Color figure can be viewed at wileyonlinelibrary.com]
3.5.1 | Evaluation of the length of correctly predicted gullies

This evaluation aims to verify the length of the gullies correctly predicted by the model. To estimate the degree of correspondence between the modelled and observed data, we implemented an automatic GRASS procedure to derive different quantitative metrics based on the number of pixels of the mapped gullies correctly predicted by the model, using either the erosion index (hereafter denoted as \( e \)) or the topographic threshold (hereafter denoted as \( \text{esp} \)). The procedure considers the following steps: (i) first, the vector layer of mapped gullies is converted into a raster map, in which the different gullies are identified with an integer number (i.e. using the \text{v.to.rast} module); (ii) then, the modelled \( e \) maps are converted into binary maps (i.e. using the \text{r.mapcalc} module) considering the threshold value of the erosion index \( e_t = 0.1 \) (meaning that the map is equal to 1 where \( e_t > 0.1 \) and 0 elsewhere); and (iii) finally, the raster maps of observed gullies and the binary modelled gully maps (\( e \) and \( \text{esp} \)) are compared along with the statistics on pixels correctly predicted for each gully (i.e. using the \text{r.univar} module).

For all simulated scenarios in Table 3 for each gully mapped, we evaluated: (i) the total pixels of the gully (i.e. denoted as the variable ‘Gully cells’); (ii) whether the gully was entirely predicted (‘Yes’) or not (‘No’) (i.e. ‘Entire’); (iii) the number of pixels of the gully that were correctly predicted (i.e. ‘Cells predicted’); and (iv) the percentage of the gully that was correctly predicted (i.e. ‘%’, calculated as: \( \text{sum('Cells predicted')/sum('Gully cells')} \times 100 \)). Finally, we counted the number of gullies with a percentage of predicted cells greater than 0% (i.e. meaning at least one cell was predicted correctly), greater than 50% (i.e. at least half of the gully cells were predicted correctly), and equal to 100% (i.e. all gully cells were predicted correctly).
3.5.2 | Threshold dependence of \( e \) and spatial classification performances

The \( e \) map values, different from the \( esp \) values, are continuous values which need to be converted into binary maps for a proper comparison with the observed gullies data. To test the dependence of the \( e \) model output on the choice of the threshold value \( et \), and to verify the relative model spatial classification performances, we used statistics derived from contingency table analysis. The threshold values of \( et \) equal to 0.01, 0.05, 0.1, 0.2, 0.5, and 1 were used to classify the \( e \) map into binary maps (similar to that previously described), then later compared with the binary gully maps obtained by rasterizing the gully inventory. Such comparison allows the derivation of a contingency table to report information on the true negative (TN), false positive (FP), false negative (FN), and true positive (TP) values. These values were then used to derive different binary classifiers, thereby quantifying the model spatial classification performances (Fawcett, 2006) on the entire study area considering the prone or not

| Simulation reference | CN elaboration | Precipitation values for daily event | Simulated scenario |
|----------------------|----------------|-------------------------------------|--------------------|
| RCNMIN-PREC          | CN minimum values estimated for each LULC class (Table 2) | 10–40–70–100 mm | Simulating erosion occurrence with CN minimum for different rainfall event values |
| RCNMIN-TOP           | CN minimum values estimated for each LULC class | - | Simulating erosion occurrence with CN minimum considering the topographic threshold |
| RCNMEAN-PREC         | CN mean values estimated for each LULC class | 10–40–70–100 mm | Simulating erosion occurrence with CN mean for different rainfall event values |
| RCNMEAN-TOP          | CN mean values estimated for each LULC class | - | Simulating erosion occurrence with CN mean considering the topographic threshold |
| RCNMAX-PREC          | CN maximum values estimated for each LULC class | 10–40–70–100 mm | Simulating erosion occurrence with CN maximum for different rainfall event values |
| RCNMAX-TOP           | CN maximum values estimated for each LULC class | - | Simulating erosion occurrence with CN maximum considering the topographic threshold |
| RCNNDVIMEAN-PREC     | CN values for each pixel based on NDVI mean (Equation 3) | 10–40–70–100 mm | Simulating erosion occurrence using CN derived from the mean of NDVI maps between 2016 and 2017 for different rainfall event values |
| RCNNDVIMEAN-TOP      | CN values for each pixel based on NDVI mean (Equation 3) | - | Simulating erosion occurrence using CN derived from the mean of NDVI maps between 2016 and 2017 considering the topographic threshold |
| RCNNDVI20170527-PREC | CN values for each pixel based on NDVI 20170527 (Equation 4) | 10–40–70–100 mm | Simulating erosion occurrence in spring for different rainfall event values |
| RCNNDVI20170527-TOP  | CN values for each pixel based on NDVI 20170527 (Equation 4) | - | Simulating erosion occurrence in spring considering the topographic threshold |
| RCNNDVI20160628-PREC | CN values for each pixel based on NDVI 20160628, 20160718, and 20170718 (Equation 4) | 10–40–70–100 mm | Simulating erosion occurrence in summer for different rainfall event values |
| RCNNDVI20160628-TOP  | CN values for each pixel based on NDVI 20160628, 20160718, and 20170718 (Equation 4) | - | Simulating erosion occurrence in summer considering the topographic threshold |
| RCNNDVI20161006-PREC | CN values for each pixel based on NDVI 20161006 and 20171009 (Equation 4) | 10–40–70–100 mm | Simulating erosion occurrence in autumn for different rainfall event values |
| RCNNDVI20161006-TOP  | CN values for each pixel based on NDVI 20161006 and 20171009 (Equation 4) | - | Simulating erosion occurrence in autumn considering the topographic threshold |
| RCNNDVI20161218-PREC | CN values for each pixel based on NDVI 20161218 and 20171220 (Equation 4) | 10–40–70–100 mm | Simulating erosion occurrence in winter for different rainfall event values |
| RCNNDVI20161218-TOP  | CN values for each pixel based on NDVI 20161218 and 20171220 (Equation 4) | - | Simulating erosion occurrence in winter considering the topographic threshold |
prone gully areas. The following binary classifiers were calculated: true positive rate ($TPR = \frac{TP}{TP + FN}$), true negative rate ($TNR = \frac{TN}{TN + FP}$), accuracy ($ACC = \frac{TP + TN}{TP + FN + TN + FP}$), and true rate average ($TR_{AVG} = \frac{TPR + TNR}{2}$). Fourfold plots (Kariminejad et al., 2020; Meyer et al., 2008; Rossi et al., 2010) were also produced to graphically illustrate the contingency table analysis outputs. While ACC and $TR_{AVG}$ are expected to quantify the model spatial classification performances regardless of the distinction between prone or not prone gully areas, the TPR (i.e. the proportion of pixels with observed gullies correctly predicted) and TNR (i.e. the proportion of pixels without observed gullies correctly predicted) quantify them separately. Therefore, the higher these binary classifiers with respect to 0.5, the better the performance of the model, with 1 being a perfect prediction. In addition, a good classification model should jointly maximize TPR and TNR to guarantee the same capability of predicting both the prone and not prone gully areas (Kariminejad et al., 2020). These analyses were performed for each scenario, calculating the $e$ for different rainfall scenarios.

Similarly, the contingency tables and the associated binary classifiers were also derived for the scenarios estimating erosion through the $esp$ modelling approach. For this, the binary maps restituted by the model were directly compared with the rasterized binary gully inventory map.

4 | RESULTS

For all simulated scenarios, LANDPLANER restituted the erosion estimations, specifically the $e$ maps for different rainfall scenarios (10, 40, 70, and 100 mm) and maps of the possible location of gullies based on the $esp$ maps. The cumulative computation time for all analyses of the study area was approximately 12 h using a basic PC desktop configuration. It should be noted that the extension of the analyses to larger study areas is possible, even with a sensible reduction of the computational times, if using a more powerful hardware configuration or dedicated calculus infrastructure.

**FIGURE 9** Results of LANDPLANER simulations in terms of erosion index ($e$) for a daily rainfall of 100 mm. a–c represent CN values derived only by LULC maps (Table 2) and d–l represent CN values derived using Sentinel-2 images with (d) Equation 3 and (e–l) Equation 4. See Table 3 for scenario references [Color figure can be viewed at wileyonlinelibrary.com]
4.1 Seasonal analysis

The results of the seasonal occurrence of gully erosion using Sentinel-2 images (Table 3) were obtained considering the 2013 LULC map. For simplicity, here we show only the maps of the e obtained for event rainfall values of 100 mm (Figure 9) and the maps obtained applying esp (Figure 10). The e maps obtained for the remaining rainfall values (i.e., 10, 40, and 70 mm) are shown in Figures S1–S3 in the Supplementary Material.

For each map, we calculated the evaluation metrics described previously, using the gully mapped in Figure 1c as a benchmark. Table 4 summarizes the values of the metrics evaluating the length of the observed gullies that were correctly predicted.

4.1.1 Spatial classification performance

The binary classifier metrics, applied to the model outputs and obtained for different et values, are summarized in Table S1 in the Supplementary Material. Specifically, Table 5 reports an extract of this table for et = 0.1 and event rainfall equal to 100 mm, showing the best overall classification performances. The fourfold plots in Figure 11 provide graphical illustration of the values of the contingency table reported in Table 5 and help interpret the evaluation output. In Figure 11, the quarter circle areas in the upper parts of the plots are proportional to the TN (blue) and FP (red) frequencies reported in the contingency table; the larger the blue area with respect to its horizontal red counterpart, the larger the TNR value. Similarly, the quarter circle areas in the lower part of the plots are proportional to the TP (blue) and FN (red) frequencies, and hence the larger the blue area is with respect to its horizontal red counterpart, the larger the TPR. When both the blue areas are larger than their horizontal red counterparts, the model shows good classification performance (TNR > 0.5 and TPR > 0.5).

The spatial classification performance metrics were also calculated for the esp model outputs and the relative results are summarized in Table 6.

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**Static scenario (topographic threshold)**

![Image](https://example.com/image1.png)

**FIGURE 10** Results of LANDPLANER simulations in terms of topographic threshold (esp). a–c represent CN values derived only by LULC maps (Table 2) and d–l represent CN values derived using Sentinel-2 images with (d) Equation 3 and (e–l) Equation 4. See Table 3 for scenario references [Color figure can be viewed at wileyonlinelibrary.com]
4.1.2 | Percentage variation maps

To better highlight the differences between the results, obtained with CN values derived using Sentinel-2 images (i.e. changing seasonally) and static CN maps derived only from LULC maps (i.e. not changing seasonally), we produced percentage variation maps. In this process, once a benchmark map is assumed (i.e. RCNMEAN here was considered as the benchmark, \( x_{\text{benchmark}} \)), the percentage variation of a scenario map (\( x_{\text{scenario}} \)) is calculated using Equation 5. Figure 12 shows the calculated values for a selected set of scenarios.

\[
\text{Percentage variation} = \left( \frac{x_{\text{scenario}} - x_{\text{benchmark}}}{x_{\text{benchmark}}} \right) \times 100\% \tag{5}
\]

The comparison of the \( e \) estimations in terms of percentage variation with respect to the benchmark scenario RCNMEAN effectively reveals the increase or decrease of gully erosion in the area. The maps show that the \( e \) obtained from the NDVI-based scenarios in the summer images has lower values than those in the RCNMEAN scenario. In contrast, the \( e \) values for the winter images match better with the spatial gully occurrence.

5 | DISCUSSION

This study has proposed a method to better account for the spatial and temporal distribution of triggering geo-environmental conditions of gully occurrence through the integration of remote sensing Sentinel-2 data and LANDPLANER. To achieve this, we modelled gullies using a twofold erosion modelling schema under different static and dynamic CN input data scenarios and provided different criteria and metrics to evaluate the results.

The first erosion modelling approach, based on the gully head esp concept, did not require calibration and its spatial prediction variability depended primarily on morphometric parameters (e.g. local slope
### Table 5

Extract of the contingency table values and related binary classifiers obtained for the erosion index output maps for an event rainfall amount of 100 mm and an \( \epsilon_t \) threshold of 0.1. Full evaluation results are shown in Table S1 in the Supplementary Material. Acronyms as before. The geomorphological gully inventory map was used as a benchmark. * Denotes the scenarios with better spatial classification performance (i.e. jointly maximizing TNR and TPR above 0.5)

| Scenario                  | Rain | \( \epsilon_t \) | TP   | TN   | FN   | FP   | TPR  | FNR  | TNR  | FPR  | ACC  | TR_AVG |
|---------------------------|------|-------------------|------|------|------|------|------|------|------|------|------|--------|
| RCNNDVI20160606-PREC     | 100  | 0.1               | 276  | 44,525 | 480  | 25,442 | 0    | 1    | 0.636 | 0.364 | 0.633 | 0.501  |
| RCNNDVI20160718-PREC     | 100  | 0.1               | 266  | 44,769 | 490  | 25,198 | 0.352 | 0.648 | 0.64  | 0.36  | 0.637 | 0.496  |
| RCNNDVI20160606-PREC*    | 100  | 0.1               | 481  | 40,577 | 338  | 29,390 | 0.553* | 0.447 | 0.58* | 0.42  | 0.58  | 0.566  |
| RCNNDVI20161218-PREC*    | 100  | 0.1               | 416  | 41,115 | 340  | 28,882 | 0.55* | 0.45  | 0.588* | 0.412 | 0.587 | 0.569  |
| RCNNDVI20170527-PREC     | 100  | 0.1               | 265  | 44,568 | 491  | 25,399 | 0.351 | 0.649 | 0.637 | 0.363 | 0.634 | 0.494  |
| RCNNDVI20170718-PREC     | 100  | 0.1               | 154  | 51,631 | 602  | 18,336 | 0.204 | 0.796 | 0.738 | 0.262 | 0.732 | 0.471  |
| RCNNDVI20171009-PREC     | 100  | 0.1               | 289  | 44,242 | 467  | 25,725 | 0.382 | 0.618 | 0.632 | 0.368 | 0.63  | 0.507  |
| RCNNDVI20171220-PREC*    | 100  | 0.1               | 412  | 38,883 | 344  | 31,084 | 0.545* | 0.455 | 0.556* | 0.444 | 0.556 | 0.55   |
| RCNMAX-PREC              | 100  | 0.1               | 586  | 26,401 | 170  | 43,366 | 0.775 | 0.225 | 0.38  | 0.62  | 0.384 | 0.578  |
| RCNMIN-PREC*             | 100  | 0.1               | 400  | 41,425 | 356  | 28,542 | 0.529* | 0.471 | 0.592* | 0.408 | 0.591 | 0.561  |
| RCNNDVIMEAN-PREC         | 100  | 0.1               | 323  | 43,122 | 433  | 26,845 | 0    | 1    | 0.616 | 0.384 | 0.614 | 0.522  |

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**Figure 11** Fourfold plots elaborated for the seasonal analysis taking the contingency table values reported in Table 5, considering an erosion threshold of \( \epsilon_t = 0.1 \) and a rainfall of 100 mm. (a) RCNMIN; (b) RCNMEAN; (c) RCNMAX; (d) RCNNDVIMEAN. (e–l) The title refers to the date of the Sentinel-2 image used for the scenario: RCNNDVIYYYYMMDD [Color figure can be viewed at wileyonlinelibrary.com]
TABLE 6  Contingency table values and related binary classifiers obtained for the topographic threshold results for all the scenarios. *

Denotes the scenarios with better spatial classification performances (i.e. jointly maximizing TNR and TPR). TNR (specificity) and TPR (sensitivity) show the probability of correct predictions of the negatives and positives.

| Scenario                | TP  | TN  | FN  | FP  | TPR | FNR | TNR | FPR | ACC | TR_AVG |
|-------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|--------|
| RCNNDVI20160606-TOP    | 221 | 58,375 | 535 | 11,592 | 0.292 | 0.708 | 0.834 | 0.166 | 0.829 | 0.563 |
| RCNNDVI20160718-TOP    | 220 | 57,524 | 536 | 12,443 | 0.291 | 0.709 | 0.822 | 0.178 | 0.816 | 0.557 |
| RCNNDVI20161006-TOP    | 272 | 54,490 | 484 | 15,477 | 0.360 | 0.640 | 0.779 | 0.221 | 0.774 | 0.569 |
| RCNNDVI20161218-TOP    | 272 | 57,061 | 484 | 12,906 | 0.360 | 0.640 | 0.816 | 0.184 | 0.811 | 0.588 |
| RCNNDVI20170527-TOP    | 222 | 57,841 | 534 | 12,126 | 0.294 | 0.706 | 0.827 | 0.173 | 0.821 | 0.560 |
| RCNNDVI20170718-TOP    | 221 | 56,088 | 535 | 13,879 | 0.292 | 0.708 | 0.802 | 0.198 | 0.796 | 0.547 |
| RCNNDVI20171009-TOP    | 230 | 58,090 | 526 | 11,877 | 0.304 | 0.696 | 0.830 | 0.170 | 0.825 | 0.567 |
| RCNNDVI20171220-TOP    | 290 | 55,492 | 466 | 14,475 | 0.384 | 0.616 | 0.793 | 0.207 | 0.789 | 0.588 |
| RCNMAX-TOP*            | 358 | 45,838 | 398 | 24,129 | 0.474* | 0.526 | 0.655* | 0.345 | 0.653 | 0.564 |
| RCNMEAN-TOP            | 273 | 56,356 | 483 | 13,611 | 0.361 | 0.639 | 0.805 | 0.195 | 0.801 | 0.583 |
| RCNMIN-TOP             | 197 | 62,447 | 559 | 7,520 | 0.261 | 0.739 | 0.893 | 0.107 | 0.886 | 0.577 |
| RCNNNDVI MEAN-TOP      | 246 | 57,093 | 510 | 12,874 | 0.325 | 0.675 | 0.816 | 0.184 | 0.811 | 0.571 |

FIGURE 12  Percentage variation of e, for different scenarios (a–e) with respect to the RCNMEAN elaboration. Event rainfall is equal to 100 mm. (f) Geomorphological gully inventory. See Table 3 for scenario references [Color figure can be viewed at wileyonlinelibrary.com]
The second erosion modelling approach, based on the use of \( e \), which is dynamic in nature, depended primarily on rainfall combined with the morphometry and CN. This index required calibration for fully quantitative erosion estimations. For the purpose of this study, which was mainly to compare the spatial and temporal erosion patterns for different scenarios, a specific calibration could be avoided and the calibration parameters deduced from previous modelling applications (Rossi, 2014), yet could also quantify the proposed evaluation metrics for different \( e \) values. The evaluation results showed that a value of \( e = 0.1 \) was appropriate for the analysis performed in this study, in that this threshold value provided the best modelling performance (Table S1 in the Supplementary Material), guaranteeing the best match between the observed and modelled data.

The analysis of the results obtained for the static scenarios, for which the CN input maps were derived only considering different LULC/HSG combinations (RCNMIN, RCNMEAN, RCNMAX), reveals that the total number of gullies partially and/or entirely predicted by the model increased with increasing CN (Table 4 and maps A, B, C in Figures 9 and 10, and Figures S1–S3). This occurred regardless of the selected erosion modelling schema, but should be interpreted as an overprediction, rather than a better prediction. Indeed, the increase of CN (i.e. corresponding to a decrease of \( S_{0,05} \), in both mathematical formulations of the two modelling schema (equations 3-36 and 3-38 in Rossi, 2014), acts in terms of favouring erosion.

Similarly, the total number of gullies partially and/or entirely predicted by the model using \( e \), increased with the amount of rainfall. This is because rainfall has the primary effect of increasing the amount of runoff (equation 3-4 in Rossi, 2014), which is directly related to the final \( e \) value (equation 3-38 in Rossi, 2014). This occurred at the expense of an increased number of false positives (Table S1 in the Supplementary Material, Table 5 and Figure 11), since the models for larger CN and rainfall values tended to predict a larger area affected by gullies (Figures 9 and 10 and Figures S1–S3), with variation of the \( e \) values being greater than 100% (Figure 12).

The results of the RCNMEAN scenario show a higher number of predicted gullies with respect to RCNNDVIMEAN derived using Sentinel-2 remote sensing images (Table 4). Such results could be related to the dates of remote sensing images, which mostly refers (four to six out of a total of eight images) to the phenological stages characterized by the relatively heavy vegetative cover: one acquired in late spring (2017/05/27), three in summer (2016/06/28, 2017/06/28, and 2017/07/18), and two at the beginning of autumn (2016/07/18, and 2017/07/18) and in the modelling outputs (Figures 9, 10, and 12), reflect the seasonal variation of the gully occurrence during spring and summer periods, which in the study area are characterized by the maximum vegetative development for all the LULC classes. In addition, for these two seasons, the maximum daily rainfall is lower with respect to autumn and winter, even if relatively short, intense rainfall events occur.

The results obtained using the esp approach were commonly between those obtained using \( e \) for event rainfall values 70 and 100 mm, with the greater differences obtained mainly during autumn and winter. This justifies the use of the esp approach for a rapid and effective evaluation of gully occurrence in a given area. It should be noted that the use of esp, commonly assuming a static CN input, within the proposed framework maintains the capability to describe seasonal variation of the gully occurrence.

We acknowledge that the evaluations performed in this study, although in favour of the proposed seasonal dynamics-based methodology, are in some cases only slightly better than the corresponding averaged counterparts. We attribute this to the dependence of the results on the quality and completeness of the geomorphological gully inventory used as a benchmark, which certainly can be considered as an underestimation of the true values. In fact, neither the visual interpretation of stereoscopic aerial images nor the analysis of the hillshade at 1 m resolution derived from two LiDAR surveys, even if additionally aided by field surveys, could fully capture all gully occurrences. Such underestimation may also be due to the gully activity...
normally realized in the study area within the first months after gully occurrence, specifically the ephemeral gullies and/or smaller gullies infilling and levelling. In this respect, future additional efforts should attempt to build multi-temporal and event-based gully inventory maps, through continuous remote sensing and field-based study area monitoring.

Overall, quantifying the impact of the seasonal variability on erosion for each LULC class is no trivial task; however, the proposed methodology has proven effective to account for these effects, as further supported by the summary statistics shown in Figure S17 in the Supplementary Material. We believe that the proposed modelling approach, combined with timely field observations and characterizations, should help to improve our understanding of seasonal gully occurrence.

The results of this study encourage the use of CN for characterizing such diversified seasonal conditions and show the effectiveness of CN in controlling the repartition of rainfall among the different water balance components, which in turn affect erosion. Nevertheless, in the proposed approach for deriving dynamical input CN data, it is relevant to select satellite images with appropriate timing for better representation of the study area conditions controlling gully occurrence. For this purpose, using freely available Sentinel-2 data, which have a high revisiting time (Drusch et al., 2012) allows for the possibility to select the most appropriate images based on seasonal timing. Potentially, Sentinel-2 data may also allow for the possibility to set up simulations considering up to decadal LULC variation conditioning of the geo-hydrological processes and more specifically, gully occurrence. Additionally, the spatial resolution of Sentinel-2 data, which is approximately equal to 10 m, together with the proposed methodology of this study to convert NDVI to CN, allow for the possibility to better represent the LULC spatial variability, in that normally the CN from literature is done at lower spatial resolutions, as it is based on the CN variation within LULC patches (polygons) in place of single pixels.

As highlighted by Vanmaercke et al. (2021), a variety of process-based and empirical models have been proposed to predict gully occurrence, expansion, and contribution to sediment yield, and also to estimate gully impacts. They suggest that there is the need for process-oriented model approaches to investigate the factors and mechanisms driving gully erosion, as well as their interactions over specific areas, particularly larger areas, underlining the importance of utilizing tools for scenario analyses. However, they also acknowledge that such tools generally have high data requirements, thereby complicating their application ability, particularly over larger areas. In these respects, the modelling framework proposed in this study, which benefits from the integration of satellite imagery and LANDPLANER, can be considered as an effective compromise between the need to have a representative approach for the complexity of gully processes and their dependence on main hillslope dynamics, and the need for easy application in different geo-environmental contexts at meaningful scales.

6  |  CONCLUSIONS

Based on the need for dynamically based predictions of the mechanism, timing, and occurrence of gully phenomena in high-erosivity landscapes affected by overcultivation, this study proposes a framework to analyse spatial and temporal gully occurrence, using freely available Sentinel-2 satellite data and the open-source software LANDPLANER. To improve over conventional methods which are limited by static geo-environmental input data, the proposed framework envisages the use of NDVI data for deriving dynamic CN maps used for the input of LANDPLANER, such that the model could predict gully occurrence using a twofold erosion modelling schema based, respectively, on erosion index and topographic threshold approaches.

The framework was evaluated and used to investigate the possible occurrence of gullies in different seasons for the Freddana Torrent catchment in the Tuscany region, Central Italy, for which a geomorphological gully inventory was available and used as a modelling benchmark. The framework proved to be effective to characterize the spatial and temporal occurrence of gully phenomena on a seasonal basis. In particular, the use of seasonal CN input maps derived from winter and autumn Sentinel-2 images performed better than the aged CN input counterparts. The framework is applicable in all areas where topographical and LULC data are accessible, even if not highly detailed. Furthermore, the proposed methodology could easily be adapted to exploit very high-resolution commercial optical satellite images, for investigating the effects of specific rainfall events on gully erosion phenomena.

Although the method is slightly limited in terms of its dependence on the baseline gully inventory data, the overall outcome shows good promise for expanding to the application of multi-temporal and event-based inventory maps for better characterization of small-scale dynamics.

The proposed method to convert remotely sensed NDVI data to CN values proved to be effective for providing a more reliable and realistic characterization of the conditions leading to runoff development and a better investigation of the spatial and temporal conditions triggering the gullies in the studied catchment. This method is expected to provide a scientific basis for more complex conversion schemas to be investigated in future studies.

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SOFTWARE

The data pre-processing of the Sentinel-2A imagery was performed with an ESA SEN2COR (Sen2Cor 2.5.5) processor. Computation of the NDVI was performed with the ESA Sentinel Application Platform toolbox (SNAP 6.0.4). The 2D and 3D map analyses were carried out with ESRI ArcGIS 9.3.1, QGIS 2.18.18 and 3.4.2, and the ‘QGis2threejs’ plug-in. The LANDPLANER model simulations were executed under the RStudio IDE, using the R language version 3.6.X.
DATA AVAILABILITY STATEMENT
The Sentinel-2 imagery that supports the findings of this study is available in the Copernicus Open Hub at https://scihub.copernicus.eu/. These data were derived from the following resources available in the public domain: https://scihub.copernicus.eu/dhus. The land use land cover data and pedological data are available in the Geoportal GEoscopio of the Toscana region at http://www.regione.toscana.it/geoscopio. These data were derived from the following resources available in the public domain: http://www502.regione.toscana.it/geoscopio/cartoteca.html. The geomorphological inventory data that support the findings of this study are available from the corresponding author upon reasonable request.

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