

Rockfall impacts on the road network of the Metropolitan Area of Rome: a risk prioritisation framework for decision-makers

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ABSTRACT

Road networks in highly urbanised and geomorphologically complex areas are particularly vulnerable to landslide processes, which may severely affect mobility, emergency response and territorial resilience. In this study, a province-scale framework is proposed to assess rockfall susceptibility, runout and related level of risk affecting the road network of the Metropolitan Area of Rome (Italy).

The methodology integrates machine-learning-based susceptibility modelling, semi-empirical runout simulation and network-oriented impact analysis to derive spatially explicit hazard and indexed-risk scenarios tailored to decision-making needs. Rockfall initiation susceptibility was modelled using a Random Forest classifier trained on an integrated landslide inventory and a set of lithological, morphometric, climatic, seismic and infrastructural predictors. Runout propagation allowed the estimation of impact probability, velocity and kinetic energy on elementary road segments.

Hazard indices were combined with road vulnerability, intrinsic infrastructure value classes and network relevance metrics to produce a hierarchical risk classification of the road network at the provincial scale. Results highlight that high-risk road segments are spatially concentrated rather than uniformly distributed, and that a substantial share of cumulative network risk affects intermediate road classes due to their extensive distribution and functional connectivity role and generally lower protection levels.

The resulting spatial scenarios are conceived as pre-defined operational configurations that can be activated under rainfall-threshold exceedance, supporting impact-based emergency planning, maintenance prioritisation, and strategic risk reduction under constrained financial and institutional conditions.

1. Introduction

The issue of risk prevention and forecasting in relation to geo-hazards become increasingly central in both scientific debate and

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policymaking. Over recent decades, the associated damages have been rising steadily, driven by the amplification of multiple risk components and, in particular, by the growing exposure of populations and infrastructures to hazardous conditions [1–5]. This trend underscores the urgency of developing comprehensive strategies and thus integrating them in urban and metropolitan planning in order to mitigate the impacts of such phenomena, and in particular of rockfalls, one of the most impactful effects for structures and infrastructures [6–8].

Risk mitigation measures can be implemented across different temporal and spatial scales, and can be broadly categorised into structural and non-structural interventions. Structural measures typically involve physical works aimed at reducing hazard intensity or preventing direct impacts, while non-structural measures encompass monitoring, planning, governance [9], and emergency management tools [10].

The design, programming, and implementation of mitigation strategies are closely dependent on the institutional, administrative, and legislative frameworks of individual countries (UNDRR, 2015). In Italy, this institutional landscape is particularly complex. Responsibilities in the field of geo-hazard prevention are distributed among multiple levels of governance: central government, which provides the legal framework; River Basin Authorities, endowed with supra-regional competencies including land-use planning; and the regional administrations, tasked with the practical implementation of national directives. Regions, in turn, may delegate specific responsibilities to provincial/metropolitan and municipal levels [11]. Although coherent in principle, this system often results in fragmented and, at times, inconsistent regulatory frameworks across regions, largely due to the broad autonomy granted to local authorities [12].

Within this institutional setting, the safeguarding and protection of road networks emerges as a matter of strategic importance, particularly with respect to its vulnerability to geo-hydrological hazards. Road infrastructures not only play a vital role in supporting economic and social activities, but also represent a critical element in emergency response and disaster risk reduction, in terms of interconnection system between structures and of accessibility, not only at a municipal level, but rather at a wider territorial scale [13, 14].

The availability of spatially distributed information is therefore essential for effective road network management, particularly for metropolitan authorities responsible for extensive infrastructures under constrained financial and technical resources. Such information supports the prioritisation of inspections, maintenance and medium-term structural interventions, helps identifying segments requiring detailed local investigations, and assists the definition of safer alternative routes during emergencies [15]. An updated spatial data informative system can also strengthen the decision-making process and improve asset management by guiding the allocation of resources towards: (i) targeted mitigation interventions in the most critical locations; (ii) continuous monitoring and early-warning actions across wider high-susceptibility sectors; and (iii) increased awareness among road operators, technical managers, administrators, and exposed communities. In this context, decision-support tools must balance analytical rigour with the practical need to rely on existing institutional datasets that are often heterogeneous in quality, coverage and update frequency.

In this paper, the potential impact of rockfalls on the road network in a highly urbanised area of Italy, like the Metropolitan Area of Rome (hereafter labelled as MAR) has been evaluated.

The MAR territory exactly coincides with the surface of the former Province of Rome, measuring more than 5'300 km² in area and hosting almost 4'300'000 inhabitants. It includes, besides the major city of Rome (surface: 1'287 km²; population: over 2.7 million in 2025), 120 other municipalities, constituting the first Italian provincial dimension in terms of extension and demographic indicators. From 1870 to 2014, the local authority in charge of governing such a wide area was the Province of Rome, whose functions were taken over by the Metropolitan City of Rome Capital (MCRC) in January 2015, after the administrative reorganization of Local Authorities in Italy resulting from Law n. 56 of 2014. The MCRC can boast of a long tradition of care in the knowledge of the territory, functional to the protection of infrastructures and built-up areas, due to the historical competences in road and school building matters, which still characterize it. Since the beginning, the MCRC proved its attention to geological issues and disaster prevention; in modern times, it established with farsightedness a Geological Survey and a Civil Protection Survey in the early '80s [16]. MCRC technical offices daily operate in touch with the territorial context, dealing with technical-administrative problems about land governance and infrastructure management. Such actions are functional to soil protection, environmental conservation, land management and infrastructures safety. Despite the lack of funding and the fragmentation of competences at national and local level, MCRC carried out, on its own initiative, several projects for the prevention of natural and anthropogenic risks, consistently with its duties [16].

In this framework, MCRC has promoted since 2005, in cooperation with public research institutes, studies on landslide susceptibility [16] aimed at a preliminary risk evaluation over its large administrative area of interest, first in Italy for exposed elements, numbers of inhabitants, infrastructural and socio-cultural values. In the MAR, several reports of landslide events or scenarios were collected; notably, consistent, area-wide, updated landslide risk studies are available for the urban zone of Rome [17–19], conversely is still lacking for the whole metropolitan area. For this reason, since 2013 the Province of Rome (now MCRC) Geological Survey and the Earth Sciences Department of Sapienza University carried out a landslide susceptibility analysis covering the entire MAR surface [20, 21].

To make a step forward, this article presents a methodological framework specifically designed to evaluate and manage landslide-related risks affecting the road network, focusing on a critical and widespread landslide type: rockfalls. These phenomena are particularly relevant due to the geological and morphological features of the study area, their kinematic characteristics that often produce severe impacts, given the high energy and the intrinsic difficulties in achieving effective early monitoring. Such difficulties arise from the wide extent of susceptible areas and the small, often imperceptible, precursory deformations that precede catastrophic failure in stiff-brittle fractured rock masses.

Spatial component of rockfall hazard evaluation is approached by weighting both initiation susceptibilities and process runout, modelling their kinematics, analysing their maximum runout and fan expansion under different slopes and block geometries [22–25].

In this view, a combination of ML-based susceptibility and semi-empirical GIS-based approaches [26–30] is frequently adopted.

The temporal component of hazard is commonly addressed through the analysis of triggering conditions and recurrence of activating events. In many operational contexts, this is approached through the definition of empirical or physically based thresholds, particularly rainfall intensity–duration relationships, cumulative or antecedent rainfall conditions [31–33]. The exceedance of such thresholds is frequently used in landslide early-warning systems to estimate short-term increases in failure probability, complementing the spatial information provided by susceptibility assessments.

Such approaches aim to address the pressing challenge of equipping decision-makers and competent authorities—national, regional, and local entities—with robust and operationally feasible tools for assessing landslide hazard and related risk scenarios, by integrating existing institutional datasets on landslide phenomena and geo-environmental factors with updated susceptibility analyses based on data-driven techniques [34,35].

Within this perspective, the present study represents a first step in transferring scientific knowledge into operational practice. Within the constraints of the institutional mandate of the MCRC, this study provides a preliminary hierarchical classification of the road network by linking susceptibility and runout assessments with road-network analysis, in order to support long-term preventive planning, maintenance prioritisation, and emergency-oriented risk management strategies [36–38].

2. Geomorphological and land-use framework of metropolitan area of Rome

The study area extends from the Tyrrhenian coastal area of Latium to the internal plain of the Tiber and Aniene rivers, and up to the hills of the Sabatini and Alban Hills volcanic complexes and to the pre-Apennine mountain ranges (respectively Mt. Tiburtini, Simbruini and Mt. Prenestini eastward, and Mt. Lepini southward).

The geomorphological and physiographic framework of the MAR is the expression of the tectonic and geological evolution experienced by the central sector of the Italian peninsula since the Miocene, during the formation of the Apennine chain and the following opening of the Tyrrhenian basin. In the western edge of mountain ranges, carbonatic terms of the Latium-Abruzzi carbonate platform and marly limestone units' facies referred to the pelagic succession outcrop, while in the Roman hilly and coastal plain areas, a Plio-Pleistocene sedimentary complex constituted by both marine and continental deposits (composed of clays, sands and conglomerates deposits) is widely observed.

The outcropping sedimentary formations are interbedded with compositionally and texturally heterogeneous volcanic products, of explosive and effusive acid and basic nature, emitted by both monogenic and polygenic complexes of the Alban Hills and Sabatini

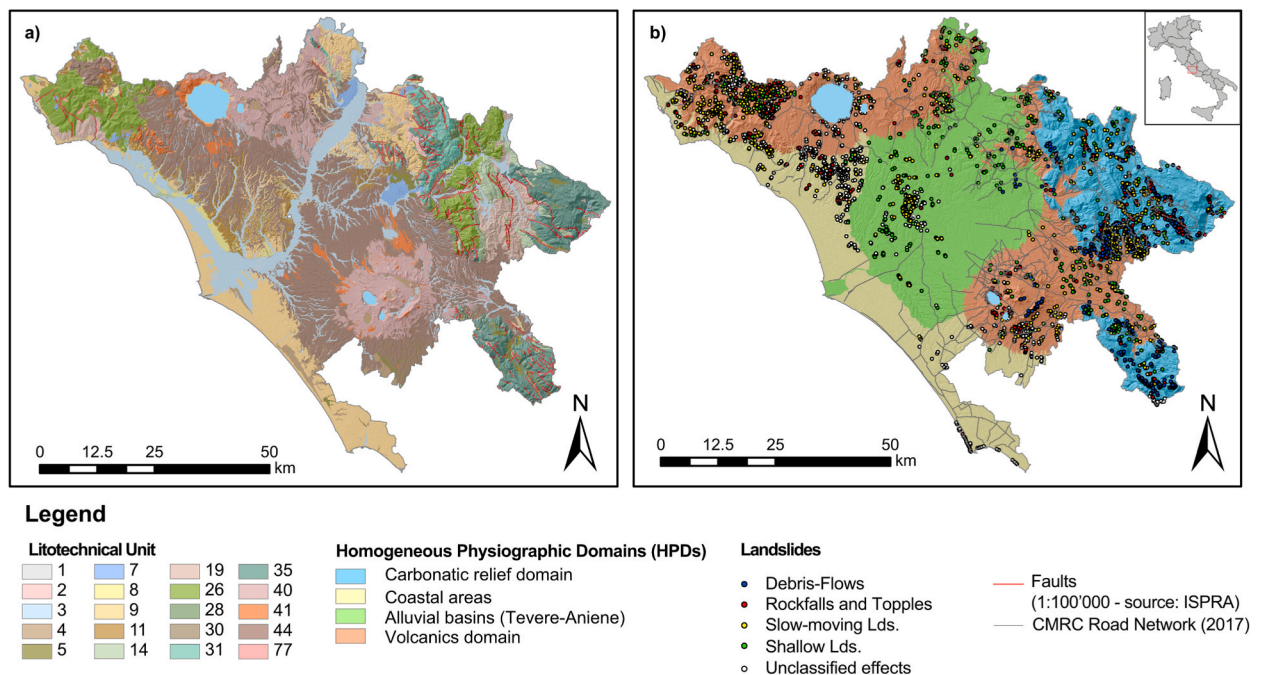


Fig. 1. Lithotechnical units of the MAR area (a). The location of landslide effects available in the catalogues and MCRC road network, and the distinction in physiographic domains are shown (b). Detailed road network graph is reported in Fig. 4. Codes associated to lithotechnical units: anthropic deposits (1), slope breccia and cemented alluvial deposits (2), pebbly and sandy alluvial deposits (3), silty and clayey marsh deposits (4), eluvium and colluvium deposits with residual soil (5), travertines (7), conglomerates and cemented gravels (8), sandstones and arenaceous deposits, locally cemented (9), clays and silty-clay deposits (11), marls, marly limestones and calcarenites (14), pelitic and arenaceous flysch (19), stratified and marly limestones (26), marly clays (30), stratified limestones (31), massive limestones (35), lithoid tuffs and phreatomagmatic units (40), massive lavas (41), stratified tuffs, and pyroclastic deposits (44), landslide and detritic deposits (77).

volcanic district. In the north-western sector, corresponding to the Tolfa Mountains, older deposits of the *Flysch della Tolfa* crop out. They refer to the External Ligurian Unit and represents the uppermost nappe of the tectonic stack in the innermost sector of the Central Apennines.

The wide variability of the outcropping lithologies in the articulated geomorphology is well reflected in the typology of landslide processes active in the area (Fig. 1), represented by rockfalls, rock block slides and topples terms, to shallow landslides or roto-translational slides.

In detail, four macro-groups of landslide mechanisms can be identified:

- slow-type landslides (namely, earth/debris roto-translational slides and earth flows);
- shallow landslides (i.e. soil slip, solifluction, slow shallow movements);
- rockfalls (comprising pure fall mechanism, rock-block slides, and topples);
- debris-flows (including both debris-flows and concentrated streamflow).

The frequency landslide distribution in the four macro-categories markedly reflects the areal extension and nature of the outcropping litotechnical units (Figs. 1 and 2).

Rockfall mechanism represents 18% of the total effects database (Fig. 2a), while debris flow populated it out of the 13% (Fig. 2b). Rockfalls are diffusely recorded where massive and stratified limestone and tuffs outcrop, homogeneously distributed in the whole study area (Fig. 1).

Rapid flow landslides mechanisms, instead, are primarily involved in carbonatic units and flysch units, where relevant debris covers are developed, therefore concentrated in the eastern border of the MAR territory (Fig. 1).

The largest part of the landslide catalogue is represented by slow-type landslides (40%) and shallow landslides (28%), which, in the

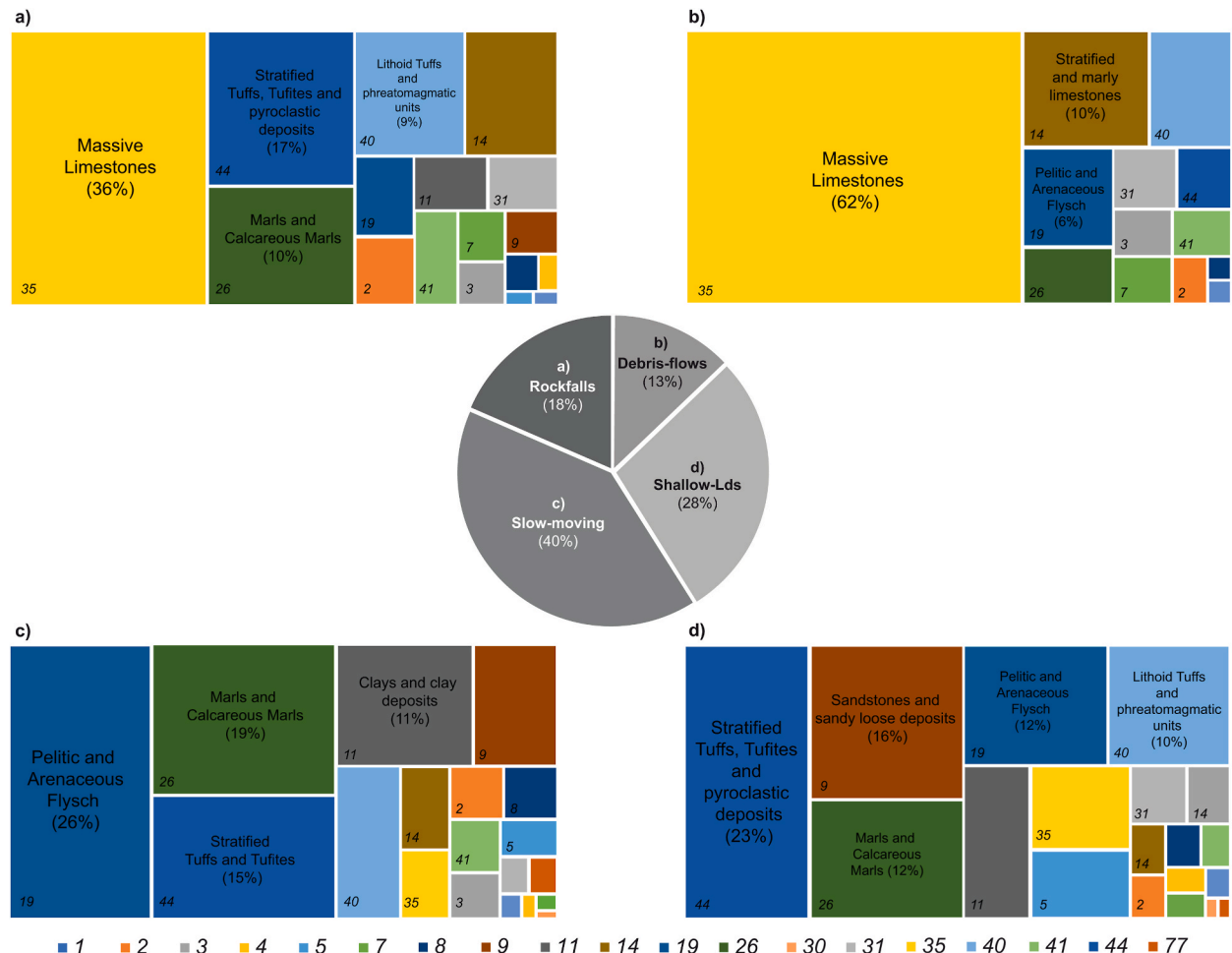


Fig. 2. Percentage distribution of main landslide mechanism (a-rockfall; b-debris-flows; c-slow-moving; d-shallow-landslides) in the study area and relative distribution of the outcropping litotechnical units in the landslide area. For litotechnical units' codes (bottom left corner of every box) and related description refer to caption of Fig. 1.

first case, dominantly involved pelitic and arenaceous flysch (26%), stratified limestones and marly limestones (19%) and stratified tuff sequences and pyroclastic deposits (15%; Fig. 2c), while in the latter, pyroclastic flow deposits, sandstone and sandy loose deposits, with Marls and calcareous marls constitute about 50% of the shallow events (Fig. 2d).

As premises, in the study we focused on rockfall triggering and spreading, analysing an ensemble scenario, suitable for risk management and for definition of intervention priorities in MCRC, the stakeholder in charge of infrastructure management, soil protection and risk prevention studies along roadways.

The occurrence of landslides in the MAR results from the combined influence of natural predisposing factors and anthropic pressures, whose interaction intensifies geo-hydrological risk. Among natural triggers, intense and prolonged rainfall constitutes the principal driver of slope instability, as the rapid rise in pore-water pressure and localised seepage processes frequently promote rock mass failure (Fig. 3b).

In addition, seismic triggering, although less frequent than rainfall-induced events in Rome, poses a considerable hazard. Earthquake-triggered failures are typically characterised by minor but spatially distributed effects, with the potential to obstruct transport networks and thus hampering emergency response operations (Martino et al., 2017). While historically the most severe earthquake-induced landslides have occurred in the Province of Rieti, evidence of past earthquake-induced failures are reported in the area in the Italian Catalogue of Earthquake-induced ground failure (CEDIT; [40,41]). Susceptibility analyses and the proximity of eastern sectors of MCRC to major seismogenic sources — including the Colli Albani volcanic district and the Salto Lake–Ovindoli–Barrea fault system [42] — demonstrate that the MAR cannot be considered immune to such phenomena (Fig. 3a).

Anthropogenic factors further amplify slope instability. Urban expansion and associated earthworks, such as road cuts, frequently alter slope geometry and induce mechanical disequilibria that predispose hillslopes to failure. In peri-urban environments, not adequately controlled forestry practices can reduce root cohesion, enhance surface runoff, and diminish the natural capacity of vegetation to retain shallow debris and rockfall material.

These slope failures frequently involved the Rome urban area interacting with the socio-economic activities, posing relevant risk conditions and an impact on human lives.

For this reason, a complete review of the population and distribution in the slope failure catalogues, a homogeneous evaluation of predisposing factors controlling the occurrence of landslides, as well as the quantification of the impact of rockfalls on the road network, is mandatory to provide adequate instruments in support of decision-making for risk assessment and management.

In this sense, susceptibility analysis and rockfall propagation modelling were best tuned and validated to assess the impact on the whole road network. Susceptibility- and risk-based scenarios were reconstructed by calculating and combining Hazard Indexes, Intrinsic exposure value and relevance of elementary roads in the whole network, providing a classification of risk along the main road corridors of Rome.

Exposed elements are mainly represented by road network, with more than 75% of the total represented by Urban Roads, and more than 16% of Major (Provincial or Municipal roads) (Fig. 4).

Out of a total network length of 8,036,588 km, public management accounts for 41.3% of the network, including ANAS (national public road authority), ASTRAL (regional public infrastructure company), and MCRC. The provincial roads consist of about 2000 km of

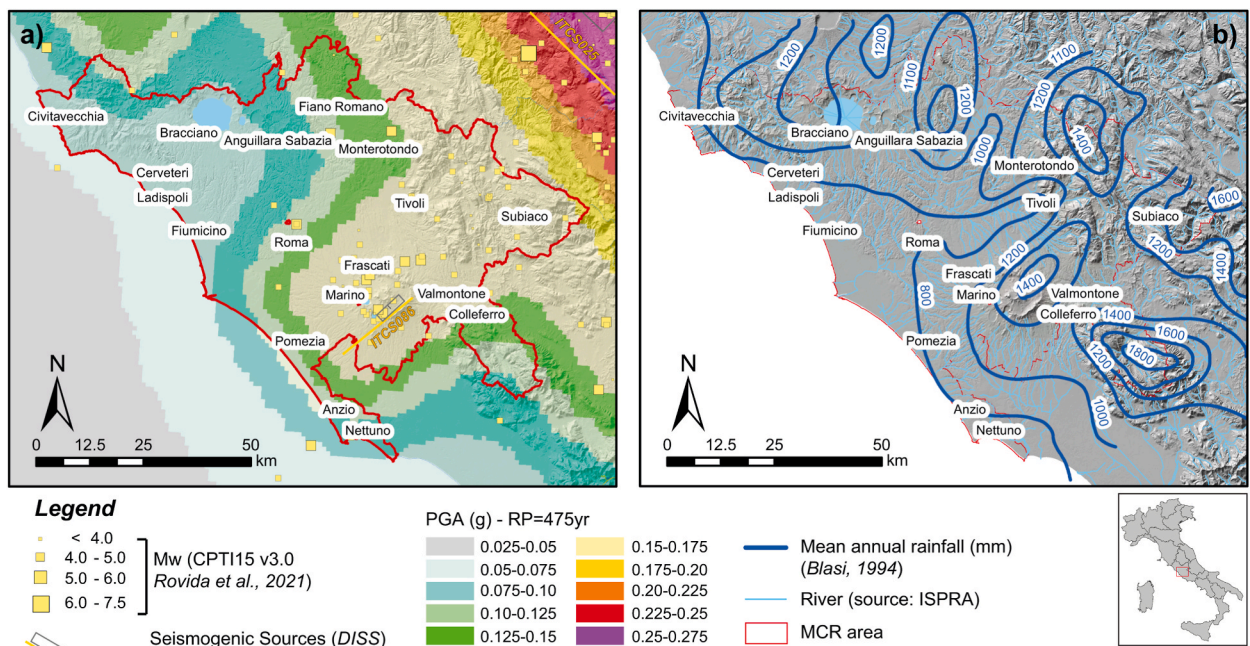


Fig. 3. Extension of the MAR with respect to a) seismic hazard map and seismogenic sources and b) mean annual rainfalls [39].

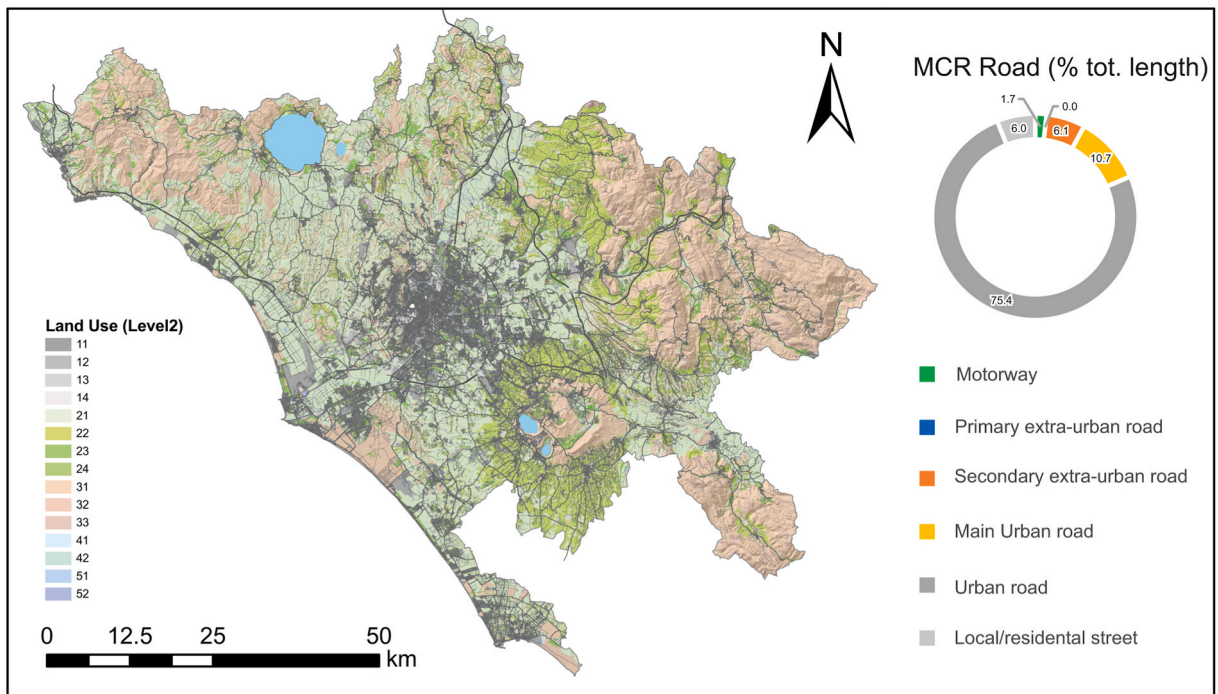


Fig. 4. Road Network graphs and Land Use classes according to Corine Land Cover Map at Level 2. Classes refer to the standard definition of CLC and range in the area, from 11 to 52. The percentage distribution of road type in the territory of the MAR is reported.

length managed and maintained by the MCRC technical offices, supported by the Metropolitan Geological Department. Private concessionaires manage 6.1% of the motorway network, namely ASPI – Autostrade per l'Italia, SAT, Concessionari del Tirreno, and Strada dei Parchi. The remaining 52.6% (4,223,611 km) is attributed to unknown or unspecified management operators and classified as “UNK”.

To quantify the associated risk, the road network's intrinsic value, its vulnerability to rockfall events, and the relevance of elementary portions of the network in the traffic system (centrality and connectivity) have to be defined.

In summary, the historical analysis of landslides occurrence in the MAR shows that inventoried events are mostly of low intensity and small dimensions, but with high frequency. Such a pattern often compromises the communication system, due to the capillary structure of the provincial road network, significantly crossing critical areas. In many cases, the predisposing causes are the construction features of the routes, mainly built in the '50s of 20th century, enlarging or modifying former minor inter-municipal roads. Frequently, hydraulic systems are absent or insufficient to ensure proper drainage, and upper and lower slopes lack retaining structures. Moreover, local circumstances in the surroundings or on the overlying escarpments - as runoffs, discharges of water, unstable vegetation, etc. - trigger the onset of gravitational movements in the mountain and hilly slopes or flooding in lowland areas. On the other hand, large-scale landslides affecting the entire slope are limited in the MAR; MCRC Geological Department selected some of such critical sites for pilot projects of geotechnical monitoring [16].

3. Materials and methods

3.1. Rockfall susceptibility analysis and rockfall propagation modelling

Large-scale studies aimed at zoning and managing the territory for informative and/or advisory purposes require the definition of scenarios based on the consideration of landslide intensity and quantification of susceptibility and recurrence. These tasks were in the first instance achieved by joining susceptibility statistical analyses and simplified semi-empirical runout modelling methods, which are able to return spatial hazard levels respectively for landslide trigger and runout. The study was performed in two subsequent steps: in the first instance, a susceptibility analysis was carried out to point areas prone to failure for different landslide types. Then, scenarios of spreading and run-out of rapid rockfalls were reconstructed by means of the distributed semi-empirical model Flow-R 2.0.9 Pro (CERI License) [30].

Prior to the analysis phases, in the first stage, we firstly collected and reviewed the available input datasets (i.e., landslide catalogues and other relevant geo-thematic information). A systematic review of available landslide catalogues was performed, merging the IFFI (Italian Landslide Inventory) and the PAI (i.e. hydrogeological risks regulatory plan) catalogues referred to the area, with the local effects database in the Rome municipality [17,43,44]. A total of 293 rockfall effects have been identified.

In addition to rockfall catalogue, 15 of the most important and more frequently considered predisposing variables or proxies were

acquired [45]. These variables and parameters are:

- Litotechnical Units;
- Primary and derived morphometric variables, such as:
 - Elevation;
 - Slope;
 - Aspect;
 - Curvature (Total, Planar, Profile);
 - Topographic Position Index (TPI, 100-300 and 1000m; [46]);
 - Topographic Wetness Index (TWI; [47]);
 - Stream Power Index (SPI; [48]);
- Land Use (Corine Land Cover and Lazio Region Land Use Map DGR n.953/2000);
- Distance to River;
- Distance to Fault;
- Distance to Road.
- Peak ground acceleration (PGA) from Seismic Hazard Map for a Return Period of 475 yrs and assumed as proxy of historical seismicity and slope damaging
- Mean Annual Rainfall (100m resolution from Voronoi of stations with 10-year record)

The latter covariates are here not intended to represent direct triggering variables, but rather static regional proxies of long-term preparatory conditions influencing rockfall susceptibility (e.g., weathering, hydro-climatic stress). The assessment of slope failure susceptibility was carried out according to different methods, based on data availability in terms of quantity (relevant for statistical analyses) and quality (e.g., landslides mapped as points vs. polygons) of the inventoried landslides.

The multivariate logistic regression approach (LR) was used for slow-type and shallow landslides as well as rockfalls [26,49], while the integration of quantitative (Frequency Ratio, FR; [50]) and heuristic (morphology-based) approaches has been used for debris-flows. This different approach was adopted because of the reduced statistical significance of debris flow databases that have not guaranteed reliable performance.

Statistical methods are to-date procedures capable of providing objective and reliable results in landslides susceptibility assessment for regional-scale purposes [51], and one of the most adopted in virtue of the great reproducibility of the obtained results [49,52].

Machine learning algorithms have been increasingly applied to landslide and rockfall susceptibility mapping, with the Random Forest (RF) classifier emerging as one of the most widely adopted approaches [45], and here adopted for the target of the research.

RF is an ensemble learning method based on the aggregation of multiple decision trees, each constructed using a random subset of predictor variables and training data. By combining the outcomes of many trees, the algorithm reduces variance and improves predictive accuracy compared to single classifiers [53]. In the context of rockfall susceptibility analysis, RF is particularly advantageous because it can: i) handle nonlinear relationships between conditioning factors (e.g., slope gradient, lithology, land cover, PGA); ii) manage directly both continuous and categorical variables; iii) provide measures of feature importance, allowing researchers to identify the most influential predictor.

The RF model adopted in this study was selected based on previous comparative applications in the same study context, where it showed better performance than traditional statistical approaches such as bivariate Frequency Ratio and multivariate Logistic Regression ([20], 2019; [54]). Consequently, the method is now considered a robust and explainable tool for regional-scale hazard mapping and decision support in civil protection and land-use planning.

To maximize the predictive capabilities of the statistical models, filtering possible noise in the available predisposing variables information resulting by a gross mapping of landslide source-area and transport-accumulation zone, a morphologically-based criterion for selection of source areas was adopted: for each type of landslide starting from the identification points of the landslide available in the catalogue, represented by the highest point along with the landslide crown, by means of geospatial analysis, detachment areas of landslide events were derived, intersecting the perimeter polygons of the landslide areas (where available) and a circular buffer around it. In this way, the portions of the slope where conditions as similar as those controlling the landslide triggering have been derived, inferring the real conditions predisposing the instability. For initiation areas a buffer with a diameter of 20 m has been adopted, defining within it some unstable points proportionate to guarantee a minimum spacing of 10 m, corresponding to the double of the resolution of the adopted terrain model (DTM).

In the model training workflow, a fundamental step in the assessment of the spatial proneness of the territory to triggering landslides is the reliable definition of stable areas, where to train the statistical model in non-landslide areas. With this objective, starting from the distribution of landslides in the MAR, basing on landslide density analysis within a regular grid of 1 km², stable points were defined in cold spots, maintaining a random distribution that guarantees a minimum distance of 20 m each other and a precautionary minimum distance of 250 m from the closest landslide, preserving a ratio between 30-70% and 40-60% of unstable and stable points, respectively. To verify the predictive performance of the derived susceptibility models, the datasets were *a priori* divided into training, validation and test groups, with the latter in a proportion of up to 20%. The susceptibility function was trained and tested on 10 K-fold random partitions of the dataset to estimate the accuracy of the predictive model and avoid selection bias.

Predictive performances were validated by reconstructing Receiver Operating Characteristic (ROC) curves of the classifier, respectively calculated as the composition of True Positive and False Positive Rates, and the resulting Area Under Curve (AUC). Additional metrics like F1 score have been calculated.

The overall workflow has been divided in three stage: a first training and calibration stages, devoted to train RF susceptibility model and derive runout modelling parameters, ii) a worst-case scenario of rockfall initiation and spreading in the MAR; iii) risk assessment on the MAR road network, by weighing exposure and vulnerability of elementary segments of the network (Fig. 5).

Firstly, the input parameters have been calibrated by back analysing some selected cases in each homogeneous physiographic domain. Runout zones resulting from the spreading were simulated, and maximum runout probability was calibrated and optimally tuned using the boundary of documented past events (landslide polygons) and aerial/satellite photographs (Fig. 6).

As regards rockfall hazard evaluation, modelling has been completed by spreading and run-out scenarios through Flow-R 2.0.9 using simplified travel-angle quantification and energy limitations [30].

For the large-scale purpose of the study, in propagation modelling, we tuned on and adopted the reference values for runout proposed by Oppikofer et al. [55] and Horton et al. [30] for fragmental rockfalls (up to a few m^3 in volume). In particular, given the average size of the rockfall process, a friction algorithm with a reach angle of 32° and a maximum velocity of 30 m/s, and a lateral spreading Holmgren [56] modified direction algorithm with exponent $x = 1$ and height modification $dh = 1$ m has been adopted, with a Gamma (2000) persistence algorithm.

Starting from the susceptibility map, in the maximum class of initiation susceptibility, potential source areas have been extracted by delineating clumps of pixels above 95% of the frequency distribution.

Source areas were later extracted from raster cells of susceptibility greater than predefined thresholds and filtered considering their spatial significance.

Once calculated, propagation allowed for detailing and quantifying the overall runout extension and kinetic parameters of the

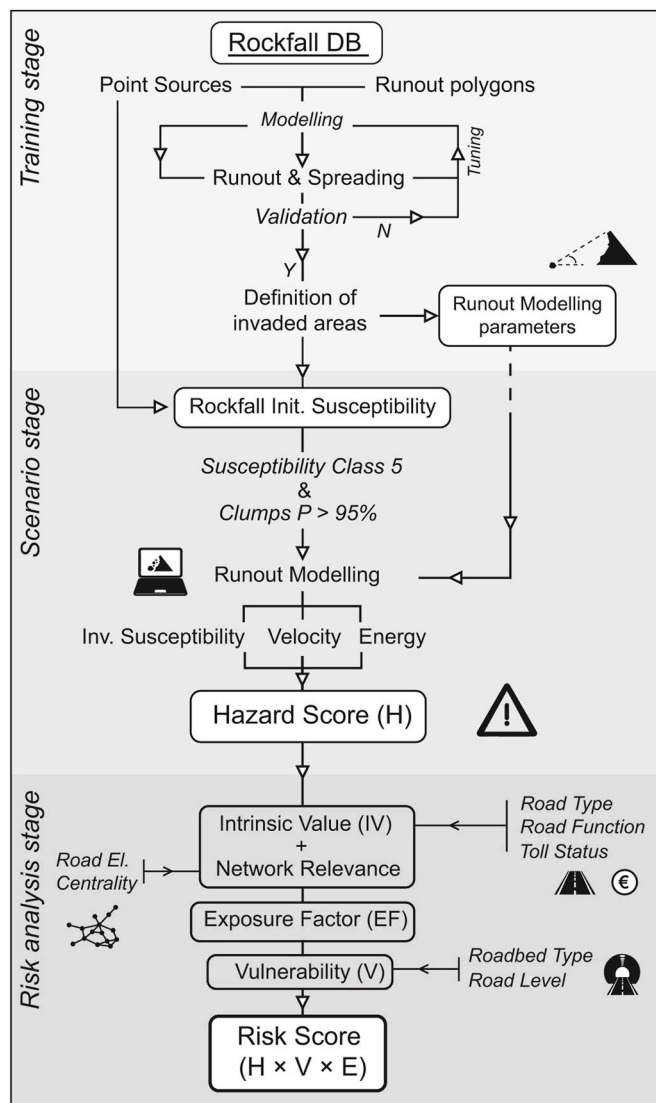


Fig. 5. Methodological workflow adopted in this study.

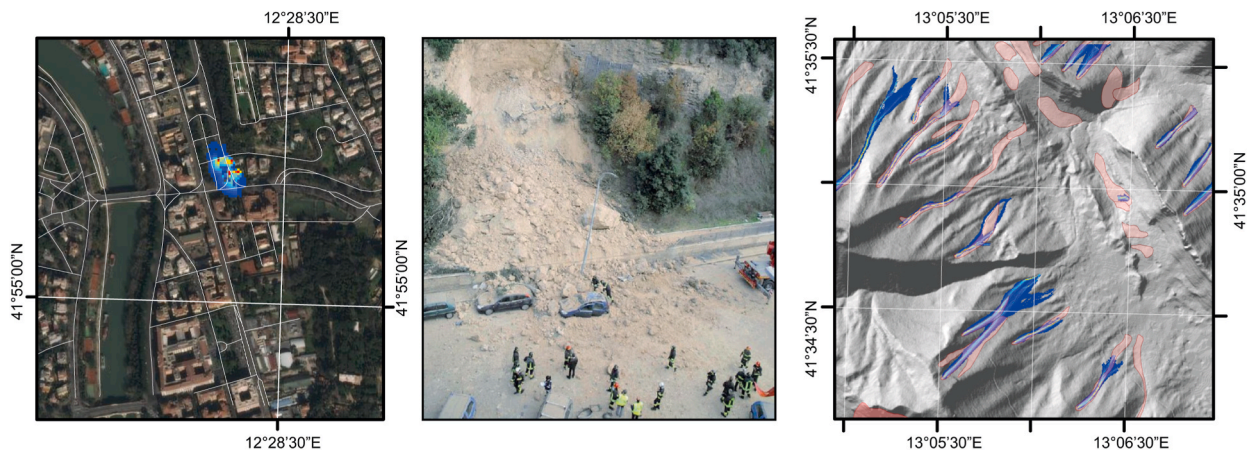


Fig. 6. Calibration of travel parameters through spatial overlay between modelling propagation areas (left) with respect to historical images (centre) or landslide polygons available in the database (right).

invaded area detached from susceptible source areas.

Concerning landslide effects available in the catalogue where cartographic assessment or a qualitative estimation of the maximum runout is lacking, the parent slope portions, as identified from Slope Units (SUs) delineations [57], have been classified as areas of attention. These areas should be interpreted as indicative screening zones of potential criticality, where evidence of rockfall events is recognised but with inaccurate geolocation, or not sufficiently robust for quantitative modelling. As such, they are not included in the quantitative risk assessment but highlight areas where further investigation or monitoring may be warranted.

Based on this procedure, potential rockfall scenarios were simulated, modelling propagation from Clumps belonging to the highest Susceptibility level, with a percentile in the clumps greater than the 95th, allowing a quantitative weight of the impact on elementary segments of the road network (Fig. 5).

3.2. Definition of hazard indices

The hazard assessment integrates three key parameters derived from rockfall runout modelling to characterize the potential impact on road infrastructure. This multi-parameter approach provides a comprehensive evaluation of rockfall hazard intensity by combining susceptibility, kinematic, and dynamic characteristics of potential rockfall events. The weighting coefficients adopted in the here formulated composite indices are heuristic and expert-informed values introduced for screening purposes. They are fully adjustable and may be recalibrated according to local priorities, data quality, or stakeholder needs. The hazard parameters include rockfall susceptibility, representing the spatial likelihood of rockfall propagation along potential rockfall paths expressed as continuous values ranging from 0 to 1 it does not incorporate temporal frequency or return-period information; impact velocity, quantifying the kinetic energy potential in meters per second; and impact energy, measuring the destructive potential in kilojoules. Although impact velocity and kinetic energy are physically related variables, they were both retained as complementary proxies of rockfall intensity within the regional-scale framework. Velocity reflects the dynamic interaction of moving blocks with road infrastructure (e.g., momentum, bouncing potential, sudden obstruction), whereas kinetic energy is more directly associated with potential damage severity. It is worth noting that the proposed framework is also not specific to Flow-R outputs and can also incorporate parameters derived from more advanced rockfall trajectory models explicitly considering block mass, rebound mechanics, fragmentation, or block-size distributions. These parameters are extracted from high-resolution raster datasets generated through physically based runout modelling of the study area. Spatial extraction of hazard parameters employs a buffer-based methodology to account for the spatial uncertainty inherent in road segment positioning and rockfall impact zones. Buffer zones of 5-m radius are generated around each road segment centreline, and statistical aggregation is performed within these zones. The maximum values within each buffer zone are selected for hazard assessment, following the precautionary principle that prioritizes worst-case scenario evaluation for infrastructure risk assessment. The hazard classification process follows a two-step methodology. First, individual parameters undergo classification into discrete categories based on established thresholds. Susceptibility classes range from very low (0.0-0.2) to very high (0.8-1.0) in equal intervals of 0.2. Velocity classification employs thresholds of 4, 8, 12, and 16 m per second to define very low through very high categories, respectively. Energy classification utilizes thresholds of 100, 200, 300, and 400 kJ for the corresponding classification levels. Each class receives a numerical value from 1 (very low) to 5 (very high). The composite hazard score calculation employs a weighted aggregation of the classified parameter values. The weighting factors were defined through expert judgment as a pragmatic assumption tailored to the objectives of this study. Greater importance was assigned to susceptibility (0.4) in order to emphasize the identification of potential rockfall paths and the spatial likelihood of road exposure. Velocity and impact energy were each weighted 0.3, as they represent complementary measures of event intensity once rockfall propagation occurs. These coefficients should therefore be interpreted as study-specific expert-based weights rather than universally established values. Within the proposed analysis framework, the weights are treated as user-defined parameters and can therefore be adjusted according to site-specific conditions, expert

interpretation, or sensitivity-analysis requirements. The weighted hazard score is calculated as:

$$H = 0.4 \times S_class + 0.3 \times V_class + 0.3 \times E_class$$

where H represents the composite Hazard score, S_class is the Susceptibility class value (1-5), V_class is the Velocity class value (1-5), and E_class is the Energy class value (1-5). The resulting composite score is then classified into hazard categories using thresholds of 4.5 (very high), 3.5 (high), 2.5 (moderate), 1.5 (low), and below 1.5 (very low). Spatial hazard zonation distinguishes three primary categories based on the relationship between road section and rockfall runout patterns. Runout zone directly intersects areas where the binary runout extent raster equals 1, indicating confirmed rockfall trajectory modelling. Area of attention are located within slope units containing documented rockfall sources but remain outside modelled runout zones, representing areas of high concern despite the absence of direct trajectory intersection. Sections classified as not at risk fall outside both runout zones and attention areas, indicating minimal rockfall exposure based on current modelling results.

3.3. Index of consequences

3.3.1. Intrinsic value of element at risk

The intrinsic value (IV) assessment quantifies the inherent importance of road segments based on their functional characteristics within the road network hierarchy. This evaluation draws upon standardised attributes from the Italian National Database (DBSN - Database di Sintesi Nazionale; Istituto Geografico Militare; <https://www.igmi.org/it/dbsn-database-di-sintesi-nazionale>; last access 30/04/2026), ensuring consistent classification across the study region. The methodology employs a multi-criteria decision analysis framework incorporating four primary road characteristics. Road type classification (tr_str_ty) receives a weight of 0.3 and distinguishes between infrastructure categories, including indifferentiated roads, pedestrian sections, intermodal connections, and interchange ramps. The scoring system assigns maximum values to indifferentiated roads and intermodal connections, reflecting their critical role in regional connectivity. Road function classification (tr_str_cf) carries the highest weight of 0.4, acknowledging the primary importance of functional hierarchy in road network. This parameter differentiates between highways, main extra-urban roads, secondary extra-urban roads, urban arterials, and local urban roads. The score system follows the established road hierarchy, with highways receiving maximum scores and local roads receiving minimum values. Road condition assessment (tr_str_sta) contributes a weight of 0.2 and evaluates the operational status of infrastructure segments. Active roads in operation receive maximum scoring, while roads under construction receive intermediate values, and out-of-service segments receive minimum scoring. Toll status (tr_str_ped) receives the lowest weight of 0.1, with toll roads receiving higher scores than non-toll roads based on their typically enhanced construction standards and maintenance protocols. The composite intrinsic value calculation follows the weighted aggregation formula:

$$IV = W_1S_1 + W_2S_2 + W_3S_3 + W_4S_4$$

where IV represents the intrinsic value score, W represents the assigned weights, and S represents the individual scores for each attribute. Final normalisation ensures values remain within the 1-5 scale through the constraint: $IV_norm = \min(5, \max(1, IV))$.

3.3.2. Network relevance analysis

Network relevance analysis employs graph theory principles to quantify the topological importance of individual road segments within the broader road network structure. This approach transforms the road network into a mathematical graph where road intersections become nodes and road segments become edges, enabling systematic analysis of connectivity patterns and critical infrastructure identification. The analysis provides a topological measure of connectivity relevance at regional scale and does not account for transport-demand attributes such as origin-destination flows, road capacity, hierarchy constraints, observed traffic flows, congestion, or travel-time assignment. Accordingly, the resulting indicators should be interpreted as measures of structural network criticality rather than operational traffic performance. The primary metric for network importance assessment is edge betweenness centrality [58], which measures the fraction of shortest paths between all node pairs that traverse each specific segment [59]. This metric identifies segments that serve as crucial connectors in the network topology, with higher values indicating greater importance for overall network connectivity. The betweenness centrality calculation follows the established formula:

$$BC(e) = \Sigma(\sigma_{st}(e)/\sigma_{st})$$

where BC(e) represents the betweenness centrality of edge e, σ_{st} represents the total number of shortest paths between nodes s and t, and $\sigma_{st}(e)$ represents the number of those shortest paths that pass-through edge. To complement this indicator, each segment was also evaluated through edge-removal simulation using four additional measures: components increase (CI), largest component reduction (LCR), isolated nodes ratio (IR), and reachability impact (RI). Here, LCR represents the reduction in the size of the largest connected component after segment removal.

Node isolation potential quantifies the number of network nodes that become completely disconnected following segment removal. This metric identifies segments that serve as sole access routes to specific network regions. Reachability disruption measures the overall degradation in network accessibility, calculated through changes in average shortest path lengths across the remaining connected network.

The composite network relevance score was then calculated as:

$$NR = 0.3 \times BC + 0.2 \times CI + 0.2 \times LCR + 0.15 \times IR + 0.15 \times RI$$

where NR represents network relevance, BC represents betweenness centrality, CI is the components increase, LCR is largest component reduction, IR is the isolated nodes ratio, and RI express the reachability impact. The weighting scheme prioritizes betweenness centrality while incorporating disruption indicators to provide a comprehensive network importance assessment.

3.3.3. Exposure proxy

The exposure factor integrates intrinsic value and network relevance components to provide a comprehensive measure of consequence potential for road infrastructure elements. In this context, the exposure factor is intended to represent the potential consequences associated with the damage or disruption of a road segment. This integrated approach acknowledges that infrastructure importance derives both from inherent functional characteristics and from topological position within the broader network structure. Accordingly, the two components were selected to capture both the local importance of the road asset itself (intrinsic value) and its structural role within the wider network (network relevance). The methodological framework employs weighted aggregation, with intrinsic value receiving priority weighting of 0.75 compared to network relevance weighting of 0.25. The weighting scheme was defined through expert judgment as a pragmatic, study-specific assumption. At this scale, greater importance was assigned to intrinsic value because the characteristics of the road segment itself were considered the main determinant of exposure, while network relevance was included as a complementary connectivity-based component. These coefficients should therefore be interpreted as user-defined parameters rather than universally established values. Normalisation procedures ensure compatibility between the two component measures. Intrinsic value scores, originally calculated on a 1-5 scale, undergo linear transformation to a 0-1 scale through formula $(IV - 1)/4$. Network relevance scores are directly utilised in their native 0-1 normalised format, maintaining consistency with the established graph theory metrics. The composite exposure factor calculation follows:

$$EF = 0.75 \times IV_norm + 0.25 \times NR_norm$$

where EF represents the exposure factor, IV_norm represents normalised intrinsic value, and NR_norm represents normalised network relevance. The resulting exposure factor values undergo classification into four primary categories using thresholds at 0.25, 0.50, and 0.75: low (0.0-0.25), medium (0.25-0.50), high (0.50-0.75), and very high (0.75-1.0). A very low category is available for exceptional cases where exposure factors fall below typical ranges.

3.3.4. Road vulnerability

Vulnerability assessment employs a binary classification system based on physical protection characteristics inherent in road infrastructure design and positioning. This simplified approach acknowledges the regional scale of analysis while focusing on readily identifiable protection features that significantly reduce rockfall impact potential. The classification methodology utilizes two primary attributes from the DBSN database: roadbed type (tr_str_sed) and road level (tr_str_liv). These attributes provide standardised information about physical infrastructure characteristics that influence vulnerability to rockfall impacts.

Protected infrastructure (vulnerability = 0) includes segments where roadbed type equals tunnel (code '03') or road level equals underpass (code '01'). These configurations provide inherent protection through either artificial cover structures or below-grade positioning that shields the roadway from direct rockfall impact. Vulnerable infrastructure (vulnerability = 1) encompasses all remaining road segments that lack such protective characteristics. The binary vulnerability assignment follows:

$$V = \begin{cases} 0 & \text{if (roadbed='03' OR level='01')} \\ 1 & \text{otherwise} \end{cases}$$

3.4. Risk ranking of the road network

The proposed classification integrates hazard-related, vulnerability, and consequence indicators through a simplified multiplicative index intended for comparative ranking of road segments. It should be interpreted as a semi-quantitative prioritisation tool rather than as a probabilistic estimate of expected losses. This approach ensures that risk values reflect the simultaneous contribution of hazard intensity, infrastructure vulnerability, and consequence magnitude as established in quantitative risk analysis frameworks. The basic risk calculation follows:

$$RI_raw = H \times V \times EF$$

where RI_raw represents the raw risk index score, H represents the hazard score (1-5 scale), V represents the vulnerability indicator (0-1 binary), and EF represents the exposure factor (0-1 continuous). Special case handling addresses segments with specific risk characteristics. Protected infrastructure with vulnerability equal to 0 automatically receives a risk classification of "Not at Risk" ($R = -1$), regardless of hazard or exposure values, reflecting the effective protection provided by tunnels and underpasses. Segments within areas of attention, located in slope units containing rockfall sources but outside modelled runout zones, receive a risk value of 0, indicating elevated concern warranting monitoring despite the absence of direct trajectory intersection. Normalisation procedures convert raw risk scores to a standardised 1-5 scale through linear transformation:

$$RI_norm = 1 + 4 \times (RI_raw - R_min) / (R_max - R_min)$$

where RI_norm represents the normalised risk index score, R_min equals 0, and R_max equals 5, representing the theoretical maximum risk value achievable through the multiplicative combination of maximum hazard, vulnerability, and exposure values. Final risk

classification employs threshold-based categorisation with four primary classes. Very high risk encompasses normalised scores of 4.0 and above, high risk includes scores from 3.0 to 4.0, moderate risk covers scores from 2.0 to 3.0, and low risk includes scores below 2.0. The special classifications of "Not at Risk" ($R = -1$) and "Area of Attention" ($R = 0$) maintain their distinct status for risk management prioritisation purposes. This classification framework enables systematic identification of priority segments for risk reduction interventions while providing a transparent methodology for risk-informed decision making in road infrastructure management.

More advanced fragility approaches may be applied in subsequent detailed studies, particularly within high-priority sectors highlighted by the present territorial-scale screening.

3.5. Indirect exposure of population

To quantify the population's indirect exposure to rockfalls along the MAR, we developed a composite indicator that integrates resident population, road network length, and municipal area. The Exposed Population Index (EPI) is calculated as

$$EPI_j = (N_i/L_i)/A_i$$

Where N_i the resident population as number of inhabitants, L_i is the total road length in km, and A_i is the municipal area of i -municipality expressed in m^2 . The index was subsequently normalised using a min-max transformation to range between 0 and 1, enabling direct spatial comparison. In this study, the analysis was restricted to municipalities containing road segments classified as moderate, high, or very high risk, to focus on the sectors most relevant for potential landslide-induced damaging. Higher normalised values indicate municipalities where a relatively large population relies on a limited and spatially concentrated road network along these higher-risk segments, reflecting increased indirect exposure to landslide hazards.

4. Results

4.1. Rockfall susceptibility analysis and rockfall propagation modelling

The first outcomes of the analysis lead to the definition of a ML-based rockfall initiation susceptibility map of the MAR, with specific relevance to the road network. Susceptibility is expressed as the rockfall initiation probability ranging from 0 to 100%. High susceptibility values are mainly concentrated in the eastern and southeastern sectors of the MAR (e.g., Simbruini, Prenestini and Tiburtini Mountains), where steep slopes, incised valleys, and carbonate lithologies dominate and where several secondary roads are located.

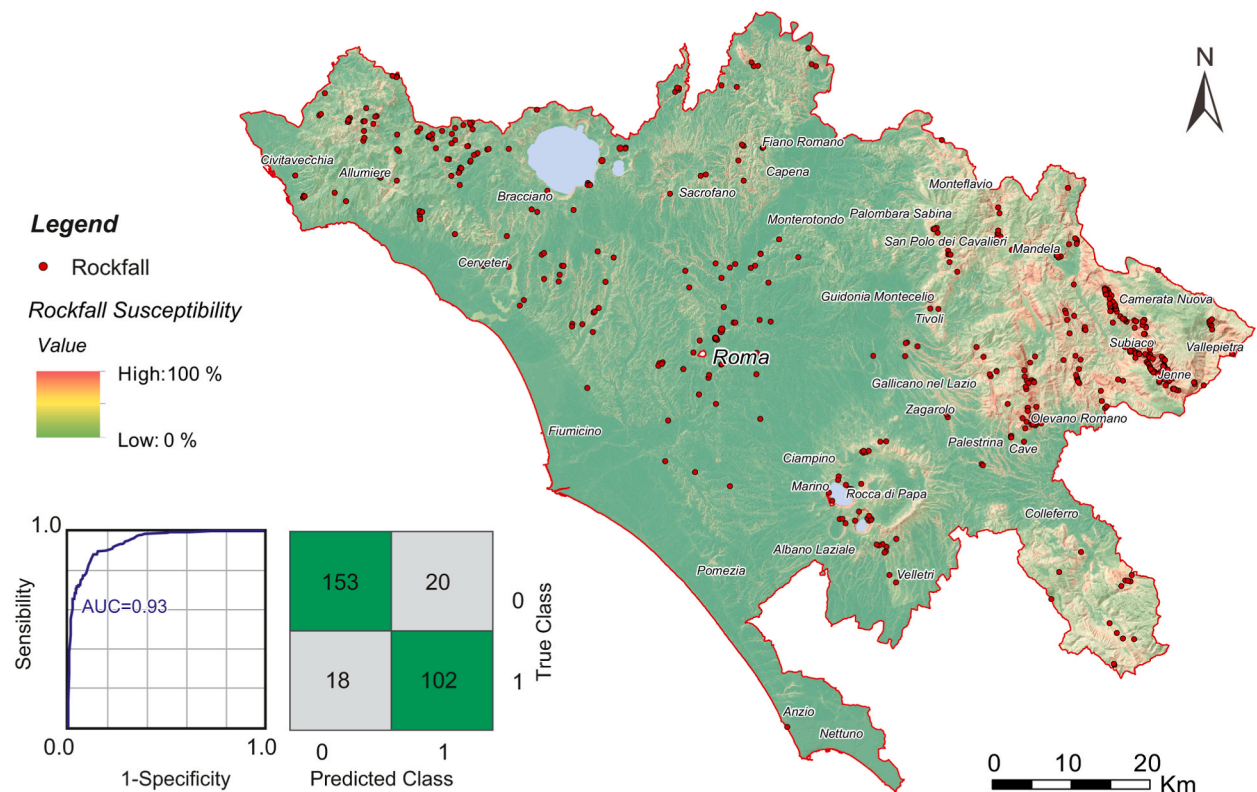


Fig. 7. Rockfall susceptibility map, ROC curve and Confusion Matrix derived by the Random Forest model.

High susceptible areas locate in the steep flank of the Colli Albani volcanic edifice. In contrast, lowland and coastal areas show generally low susceptibility, reflecting more stable geomorphological conditions at the scale of the analysis.

The spatial distribution of observed rockfalls (red dots in Fig. 7) shows a strong agreement with medium-to-high susceptibility classes, indicating that the model effectively captures the main controlling factors of rockfall occurrence along roads. Model performance is supported by the ROC curve ($AUC = 0.93$) and the confusion matrix, which indicate high predictive accuracy with balanced sensitivity and specificity.

The variable importance is ranked by the Permutation Feature Importance (PFI, Fig. 8) shown in the figure, which highlights the relative contribution of each predictor to the rockfall susceptibility model. "Slope_1" is by far the most influential variable, confirming its primary role in controlling rockfall initiation along road corridors. Lithology and rainfall follow, emphasizing the importance of rock mass properties and climatic preparation to instability.

Variables related to infrastructure proximity, such as distance to major roads (DIS_Mroad) and distance to roads (DIS_road), also show a non-negligible contribution, reflecting the strong interaction between rockfall processes and road cuts presence. Seismic forcing (PGA_RM) further contributes to susceptibility, representing a proxy of rock mass fracturing, particularly in tectonically active sectors of the study area.

Hydro-morphometric indices (e.g., TWI, SPI, TPI at multiple spatial scales, and curvature measures) display moderate to lower importance, indicating a secondary but still relevant role in modulating local slope conditions and drainage patterns. Overall, the variable importance analysis supports the physical consistency of the model and reinforces the reliability of the susceptibility map for identifying sectors exposed to rockfall hazard.

This product refers exclusively to the probability of rockfall initiation, while it does not consider the potential spatial extent and runoff of the phenomenon. In the second stage, runoff modelling has been conducted from the ensemble of rockfall source areas, identified and by selecting clumps in the frequency distribution in the maximum class of susceptibility (Fig. 5)

4.2. Workflow of risk classification of the road network

The risk assessment on the road network provides an integrated, province-scale overview of potential rockfall impact affecting the road network. The spatial probability of rockfall impact highlights how potentially affected road segments are not uniformly distributed (Fig. 9a), largely reflecting the initiation susceptibility of Fig. 7.

The relative kinetic energy associated with rockfall impacts shows a more localized pattern, with high to very high energy values confined to specific sectors of the MAR, where steep and long slopes overlooks road segments with a non-null impact spatial probability (Fig. 9b). These areas generally coincide with steep and morphologically constrained environments, where rockfalls can maintain significant energy upon reaching the road network, thus increasing their potential for damage.

Road network exposure, computed according to DBSN attributes, emphasizes the role of infrastructure characteristics in the risk framework (Fig. 9c). Higher exposure values are associated with primary roads with high traffic volume, underscoring the functional importance of the affected road segments. At this scale, network centrality becomes less important, gaining a relative relevance in the exposure factor in remote areas, where corridors are less connected.

By combining impact probability, kinetic energy, and road exposure, the final rockfall risk classification delineates a limited number of high- and very-high-risk sectors at the metropolitan scale (Fig. 9d). These zones correspond to locations where energetic rockfalls intersect highly exposed road infrastructure, while the majority of the territory falls within *Low-Risk* or "*Area of Attention*" classes.

The first focus area provides a detailed view of the road risk assessment workflow in the Subiaco area, representing one of the main areas of attention identified at the regional scale. The layout reported in Fig. 10 highlights the progressive integration of hazard and exposure components into a comprehensive risk framework, expressing the high initiation susceptibility (Fig. 10a) and the potential invasion of the road elements under a worst-case condition of rockfall activation (Fig. 10b). In the absence of runoff modelling, areas historically affected by rockfalls were designated as '*Areas of Attention*.' Consequently, road segments located within Slope Units with documented rockfall events were classified accordingly (Fig. 10d and e).

Rockfall initiation susceptibility map outlines a homogeneous high susceptibility, however only a small number were modelled as

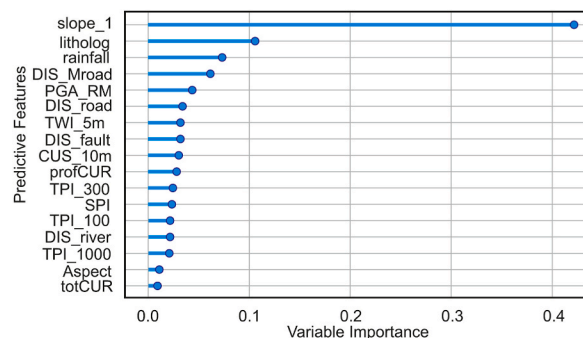


Fig. 8. Permutation Feature Importance of the Predictive variables adopted in the study.

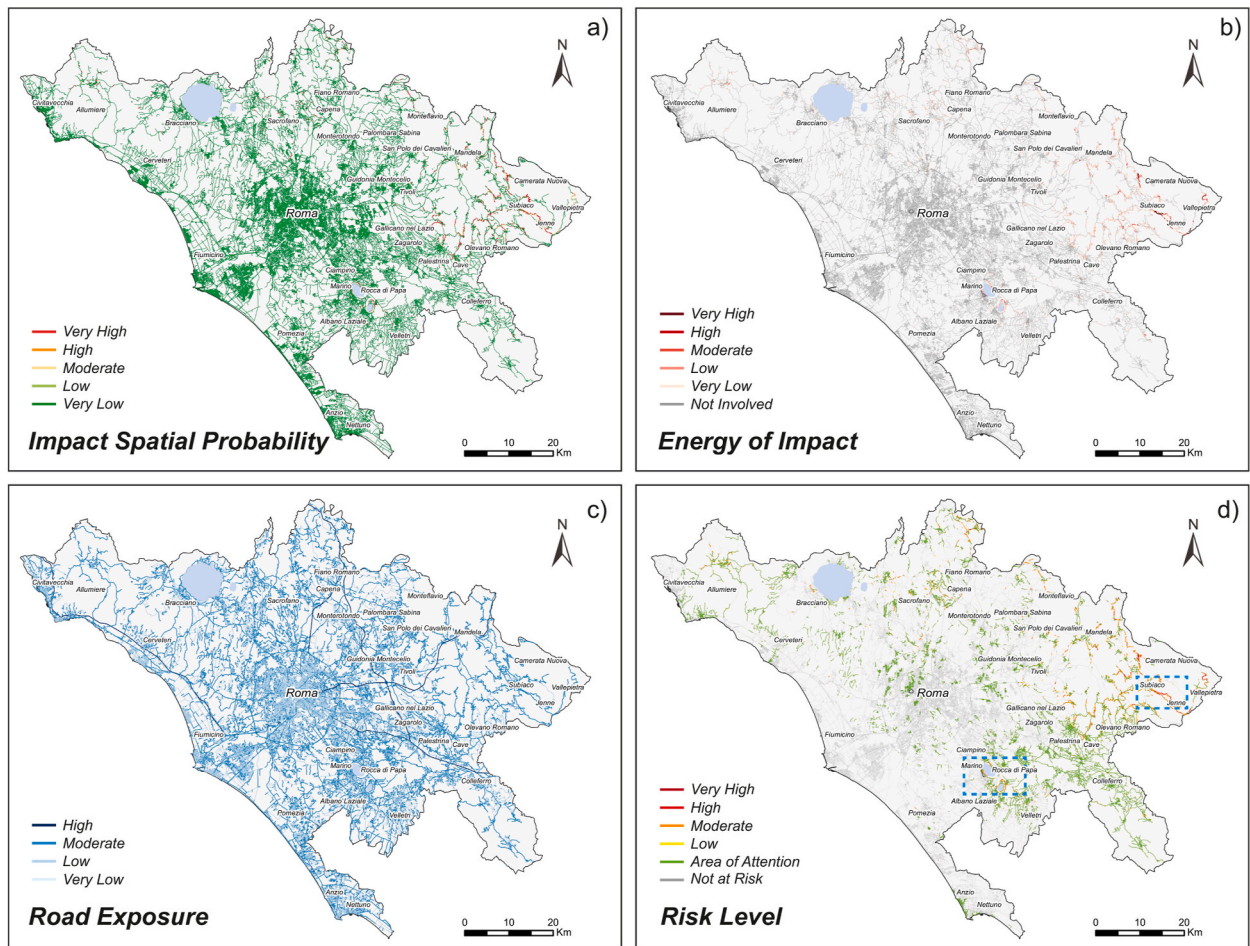


Fig. 9. Assessment of Rockfall Impact probability (a), relative Kinetic Energy (b) and Road network Exposure (c) according to DBSN attributes. Final rockfall Risk Classification for the whole province is reported in d). Focus areas of the Subiaco and Albano Lake, hereafter analysed in Figs. 10 and 11, are enclosed in light blue dashed lines.

potential source areas (Fig. 10b).

The runout modelling results show the propagation paths of falling blocks and their interaction with the road infrastructure, highlighting the maximum runout and spreading areas, and the influence of slope angle and slope curvature on reach probability (Fig. 10b).

The kinetic energy classes estimated at the point of impact on elementary road segments reveal strong spatial variability, with higher energy values associated with sectors directly exposed to steep and elevated source areas (Fig. 10c). These results are synthesized into the hazard classification, which reflects the combined effect of impact probability and expected intensity (Fig. 10d).

Finally, the risk classification of the road network highlights critical segments where high hazard intersects with elevated vulnerability (e). Notably, road sections characterized by null vulnerability, due to the presence of tunnels (Fig. 10b), are consistently classified as *Not at Risk*, despite their location within potentially hazardous areas (Fig. 10d). This emphasizes the effectiveness of structural protection measures and demonstrates the ability of the methodology to discriminate between exposed and effectively protected road segments at a detailed spatial scale, given the large informative value of the Italian DBSN.

Similar trends are observed along the slopes bordering Lake Albano (Fig. 11), which have experienced numerous rockfalls in recent years. In this case, kinetic energy classes primarily reflect the total fall height, while the highest hazard levels characterize areas with elevated activity rates (e.g. Via dei Pescatori, Via Acqua Acetosa).

Overall, the workflow demonstrates the reliability of the regional susceptibility-runout model combination as a decision-support tool for road network management, allowing the identification and prioritisation of critical road sections exposed to rockfall hazard and supporting risk mitigation and maintenance planning.

5. Discussion

The territory of the MAR is characterized by widespread susceptibility to rockfall processes, largely controlled by the geological and

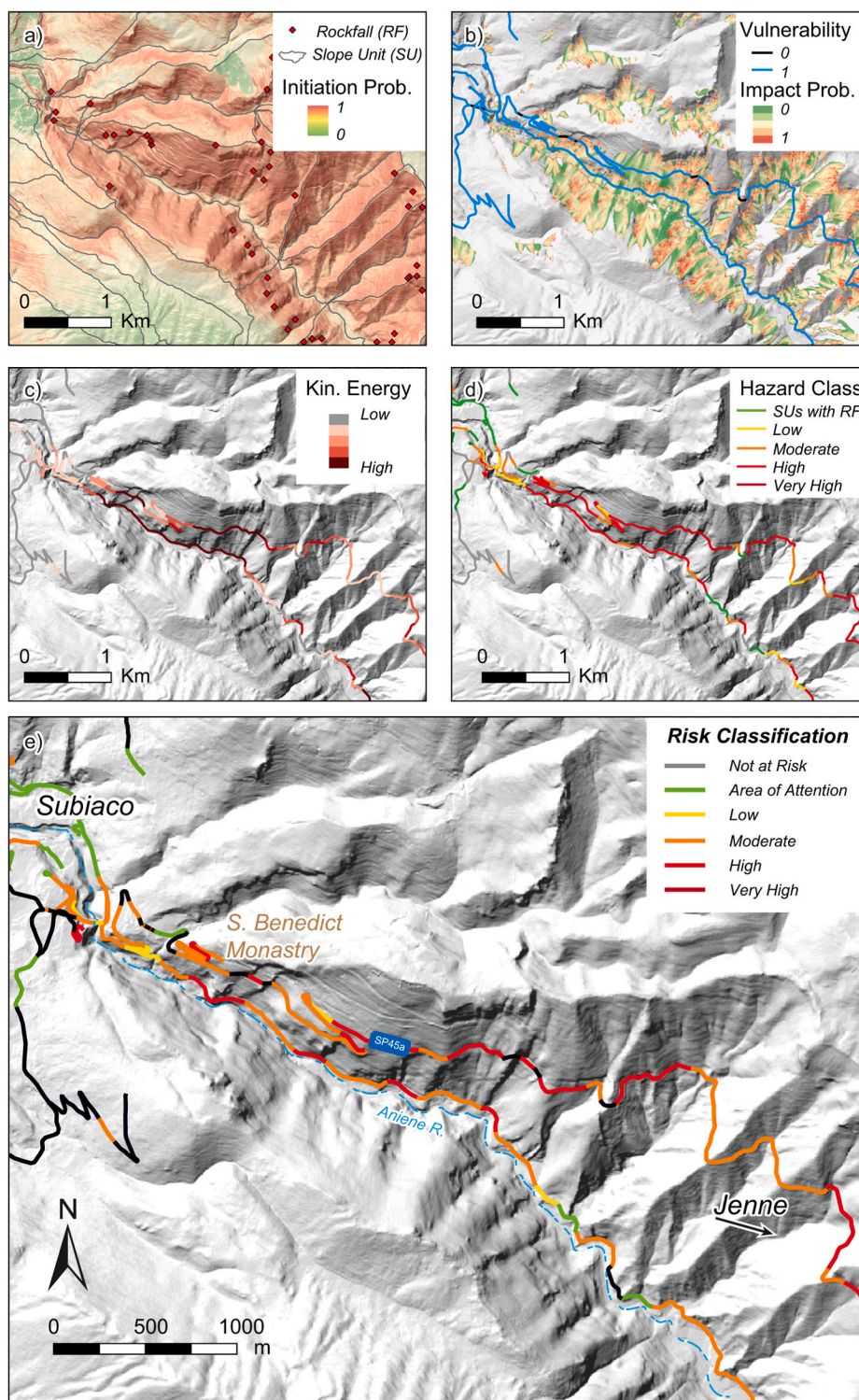


Fig. 10. Close-up view of Road Risk classification to rockfall process in the Area of Subiaco. a) rockfall initiation Susceptibility, b) runout modelling results and Vulnerability level of the road network, c) classes of Kinetic Energy of impact on the elementary road segments, d) Hazard classification and e) Risk classification of the network. Note how the segments featured by null vulnerability to rockfall given by the presence of a tunnel, result as Not at Risk.

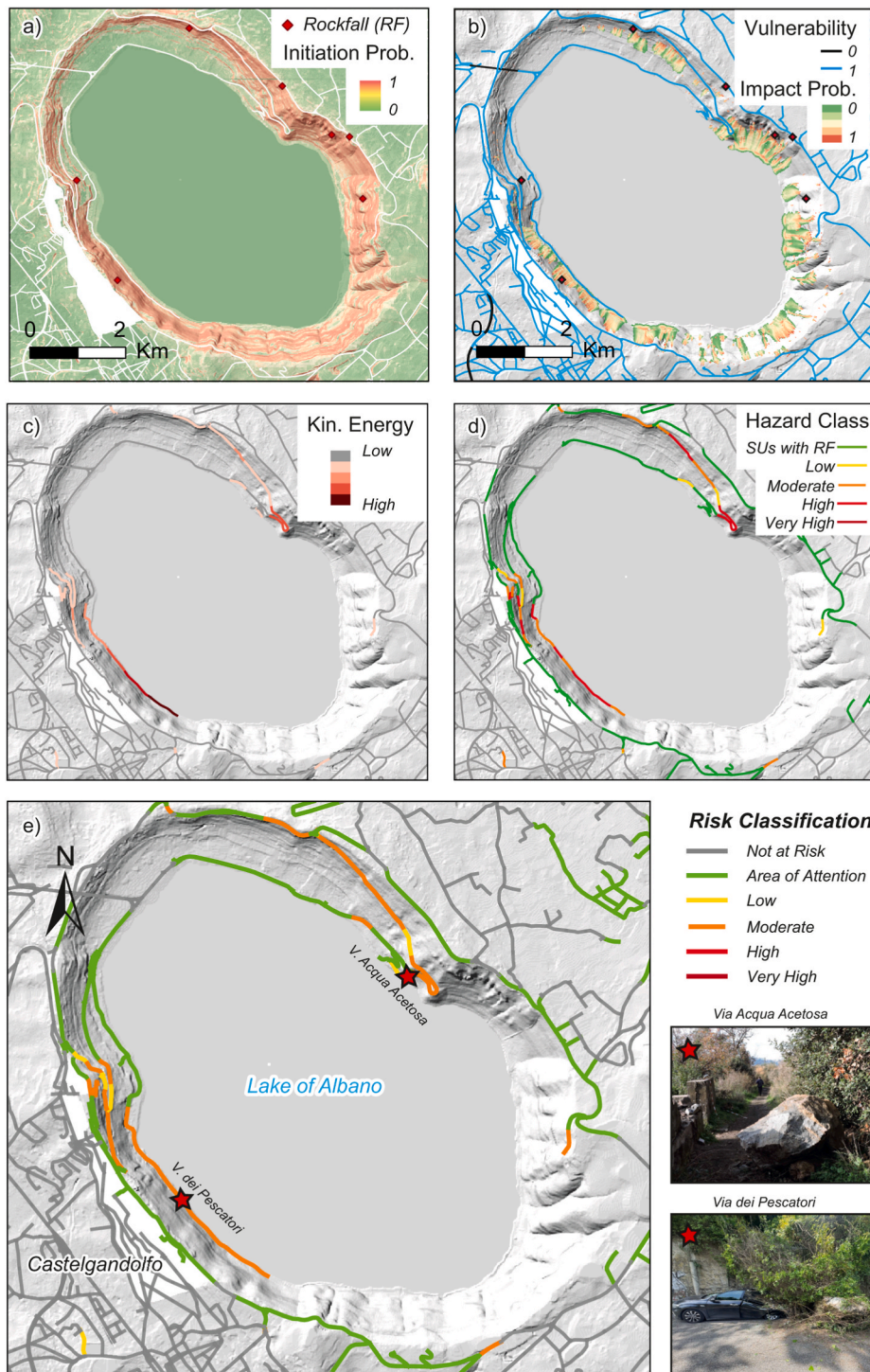


Fig. 11. Close-up view of Road Risk classification to rockfall process in the area of Albano Lake. a) rockfall initiation Susceptibility and location of the rockfall effects available in the DB, b) runout modelling results and Vulnerability level of the road network, c) classes of Kinetic Energy of impact on the elementary road segments, d) Hazard classification and e) Risk classification of the network and examples of recent rockfalls occurred along the road bounding the Lake of Albano.

geomorphological setting of the area, with the maximum level located in the eastern sector of the study area, within the physiographic domain of the carbonate Apennine chain, as much as in the steep slopes developed on volcanic and pyroclastic units of the Colli Albani and Mt. Sabatini districts.

Over these areas, the deeply incised valleys induce conditions favourable to block detachment and cliff failures, whose spreading represents a significant hazard for numerous municipalities (Fig. 12) in the MAR, affecting transport corridors, residential areas, and important cultural-heritage sites located along steep valley slopes (e.g. Fig. 10).

The results of analysis on the population's indirect exposure to rockfall hazard show that Vicovaro, which contains very high-risk road segments, is the municipality with the highest normalised EPI value (0.8–1.0). Among municipalities with high-risk segments, Nemi (0.8–1.0) and Marano Equo (0.4–0.6) exhibit the highest index values, although other municipalities in this class display lower exposure levels. Within moderate-risk segments, Albano Laziale (0.8–1.0) and Pomezia (0.4–0.6) stand out as the most exposed municipalities, while others show comparatively lower index values. These findings highlight the spatial variability of indirect population exposure, reflecting the combined influence of demographic pressure, municipal area, and road network length along road segments with different landslide risk levels.

Within the MAR, the majority of road segments exposed to rockfall risk fall in classes of *Not at Risk* and *Area of Attention*, while progressively smaller portions fall into the *Low*, *Moderate*, *High*, and *Very-High Risk* classes (Fig. 13a), showing a clear decrease in length with increasing risk level. Higher risk conditions mainly affect secondary extra-urban roads and motorways (Fig. 13b), consistent with the geomorphological setting where major transport infrastructures cross steep slopes. From a management perspective, *High* and *Very-High Risk* segments are concentrated along roads managed by national and metropolitan authorities (e.g., ANAS and the MCRC) (Fig. 13c).

A key contribution of this study lies in the definition of wide-area spatial impact scenarios, explicitly designed to support both strategic planning and operational decision-making. Unlike event-based or site-specific analyses, the proposed framework provides a homogeneous and spatially exhaustive representation of potential rockfall impacts on the entire road network of the MAR. These scenarios represent pre-defined spatial configurations that become operationally relevant when triggering conditions are reached.

In particular, the integration of spatially distributed rockfall susceptibility and runout modelling enables the activation of scenarios under the exceedance of rainfall triggering thresholds, paving the way for a *nowcasting-oriented* application. This perspective is especially relevant in light of recent advances in rainfall threshold definition at national scale, such as those developed within the e-ITALICA framework [33,60]. While such thresholds provide a robust reference, the present results highlight the importance of adapting them to the local geomorphological and infrastructural context, where slope geometry, lithotechnical properties and road-cut

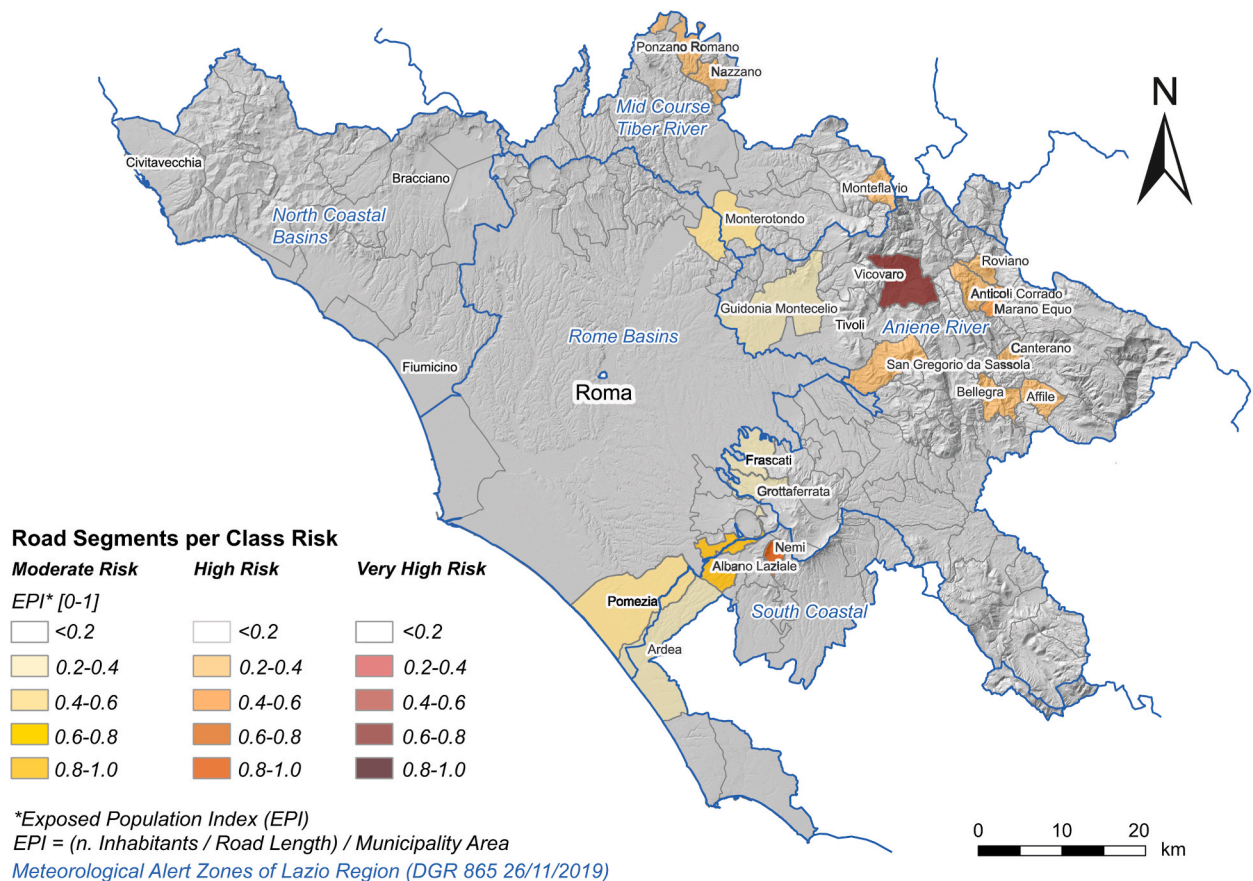


Fig. 12. Exposed Population Index to rockfalls process for the Municipalities featured by road segments with risk classes from Moderate to Very High. Extension of Meteorological Alert Zones in Lazio Region are also reported.

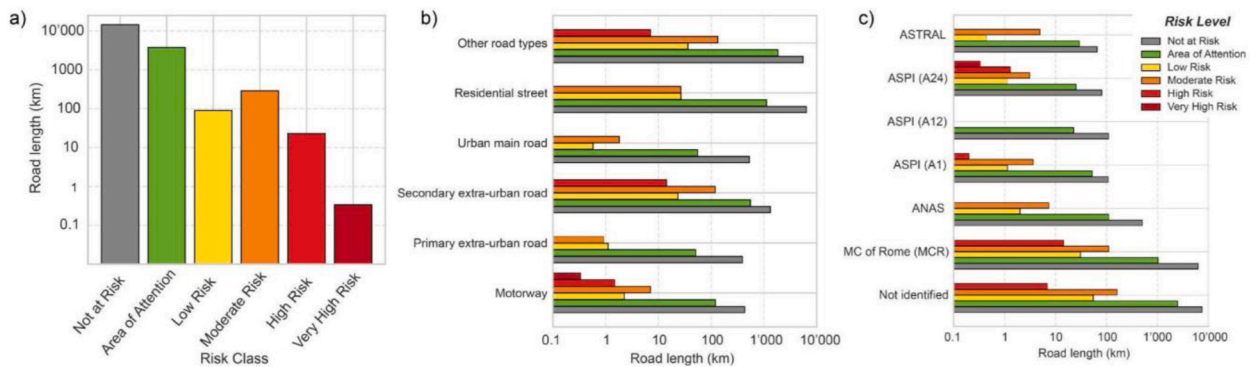


Fig. 13. (a) Distribution of total rockfall risk per length (km) along the road network; (b) rockfall risk categorised by road type and by road management authority (public or private) (c) within the Metropolitan area of Rome.

configurations strongly modulate the effective hazard.

From a civil protection standpoint, the ability to spatially identify road segments potentially impacted under specific rainfall scenarios represents a substantial advancement, allowing the transition from generic meteorological alerts issued for broad homogeneous warning zones (bulletins on wide alert areas; Fig. 12), which are highly effective for regional preparedness purposes but may be less suited to identifying asset-specific criticalities along extensive road networks, to impact-based warning and response strategies. In this context, the proposed framework may in future complement official alerts by translating area-wide warnings into higher-resolution indications of road segments requiring surveillance, precautionary inspections, or targeted response measures.

Beyond hazard identification, the proposed methodology provides a screening-level assessment of the potential strategic consequences of rockfall-related disruptions on the road network, particularly in terms of accessibility continuity, emergency routing, and territorial resilience. By distinguishing between potentially obstructed and unobstructed road segments and by analysing alternative access and evacuation routes, the framework supports the adopted Italian policies for Microzonation Studies (MS; [61]) and in particular a definition of Limit Conditions for Emergency (CLE) at a broader provincial scale [62].

This represents a significant extension of the CLE concept, traditionally applied at the scale of individual urban settlements, to a broader territorial and infrastructural dimension. The results show that even localised rockfall events, when affecting strategically positioned road segments, may lead to partial or total isolation of municipalities, increased travel times for emergency services, and reduced redundancy of access routes [63]. Such effects are particularly critical in the internal and mountainous sectors of the MAR, where network density is lower and alternative paths are scarce. In this sense, the 2016 Central Italy seismic sequence highlighted the relevance of numerous small rockfalls in disrupting road mobility[37].

The integration of runout modelling, road exposure assessment and network analysis therefore provides a coherent tool for scenario-based emergency planning, supporting both pre-event preparedness and real-time crisis management by civil protection authorities.

One of the most policy-relevant outcomes of this study is the result of the semi-quantitative and hierarchical evaluation of rockfall impact on the road network. While major highways and primary roads often attract most of the attention in risk management strategies, the analysis demonstrates that intermediate road classes (provincial and secondary municipal roads) concentrate a substantial portion of the overall risk, and thus large part of the costs in charge of local authorities for the adoption of risk mitigation strategies and maintenance. This evidence is particularly relevant, considering the progressive reduction of funding to local authorities for the management of provincial road network experienced in recent years in Italy, furthermore in correspondence of increasing extreme meteorological phenomena.

This apparent paradox is explained by the extensive spatial distribution of intermediate road classes, their frequent location along morphologically constrained slopes, and their essential role in ensuring local connectivity between municipalities. Even under moderate hazard conditions, the sheer number and capillarity of these road segments result in a cumulative risk that may exceed that associated with higher-category infrastructures, where invasive slope stabilisation solutions are invoked. Moreover, these roads are often characterised by older construction standards, limited protective works, and insufficient drainage systems, which further increase their vulnerability.

From an infrastructure management perspective, this finding suggests that effective risk reduction strategies should not be limited to high-profile assets, but should also prioritise diffuse, intermediate elements of the network, where maintenance costs, service disruptions and emergency repair demands are likely to be highest during and after triggering events. From a spending review perspective, segment-oriented approaches allow the prioritisation of mitigation measures. Recent studies have addressed road-network risk and resilience under other natural hazards, including earthquake-induced landslides and wildfires, often through advanced traffic-performance, optimisation, or recovery-based frameworks [64,65]. Such approaches provide important insights into system functionality but commonly require detailed demand data that are not always available. In this context, the present study pursues a complementary objective by proposing a territorially scalable and data-efficient framework focused on spatial prioritisation, integrating rockfall susceptibility, runout modelling, and network relevance within a single operational workflow.

Overall, the study confirms that the integration of machine-learning-based susceptibility assessment, physically based runout modelling and network-oriented impact analysis constitutes a robust decision-support framework for both road managers and civil protection authorities. While fully probabilistic risk models, including assessment of road fragility, remain desirable where detailed datasets are available, at metropolitan planning scale, relative prioritisation may be more operationally valuable than formally rigorous but data-intensive probabilistic risk estimates. Its strength lies not only in the scientific soundness of the individual components, but also in their integration into an operationally feasible workflow, compatible with existing institutional datasets and governance structures.

Future developments should focus on the formal integration of rainfall thresholds and real-time monitoring data to fully operationalise the nowcasting potential of the scenarios, as well as on the explicit treatment of uncertainties associated with model assumptions and input data. Additionally, extending the framework to include traffic data, indirect socio-economic impacts and other landslide typologies would further enhance its applicability for comprehensive risk governance at metropolitan and regional scales.

6. Conclusions

This study proposes an integrated and operational framework for assessing rockfall susceptibility, runout and related ranking of risk affecting road networks in metropolitan areas, with application to the Metropolitan Area of Rome. By combining machine-learning-based susceptibility modelling, physically informed runout simulation and network-oriented impact analysis, the approach provides spatially explicit and decision-oriented risk scenarios.

Results show that rockfall risk is widespread and strongly controlled by geological, geomorphological and infrastructural factors. While high-risk conditions locally affect primary corridors, a substantial portion of cumulative risk is concentrated on intermediate road classes, due to their extensive distribution, structural vulnerability and key role in local connectivity.

It is important to clarify that the primary aim of this study was not to provide a fully calibrated predictive tool, but rather to establish a coherent methodological framework conceived as a entry-level decision support system at the supra-local planning scale typical of large-scale territorial authorities, where strategic orientation prevails over detailed regulatory implementation.

Within this scope, some simplifying assumptions were intentionally adopted, particularly regarding the representation of asset vulnerability and the weighting of contributing factors. These choices are consistent with the intended level of application and with the current availability of ancillary data, which remains heterogeneous in both quality and spatial coverage.

The proposed framework should therefore be interpreted as a first operational step, modular and scalable in weighting schemes and designed to be progressively refined.

The proposed framework lay the foundations to support impact-based emergency management, including the evaluation of Limit Conditions for Emergency (CLE) at the provincial scale, and provides a rational basis for prioritising mitigation and maintenance measures. It is particularly suited to public authorities managing large road networks, where screening-level prioritisation is often more feasible, under constrained resources, than the widespread implementation of structural measures.

Overall, despite preliminary, the workflow represents a robust decision-support tool for road managers and civil protection authorities, with potential adaptation to nowcasting applications. In particular, for rockfall processes, it showed an ability to provide greater spatial resolution in alerting with respect to the current warning system, which is primarily based on meteorological forecasts over broad homogeneous warning zones and does not explicitly account for the local geomorphological and slope-specific conditions controlling rockfall occurrence.

Future developments will include the systematic back-analysis of documented case studies, aimed at validating and, where necessary, recalibrating both the modelling approach and the associated weighting scheme used in the (currently qualitative) risk assessment.

CRedit authorship contribution statement

G.M. Marmoni: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **G. Mastrantoni:** Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **R. Napolitano:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **G. Scarascia Mugnozza:** Writing – review & editing, Validation, Resources, Project administration, Investigation. **A. Argentieri:** Writing – review & editing, Resources, Project administration, Investigation, Conceptualization. **M. Fabiani:** Resources, Investigation, Data curation. **G. Rotella:** Resources, Project administration, Data curation. **C. Esposito:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Statements

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

During the preparation of this work the author(s) avails of LLMs (ChatGPT v.5.2) to revise and edit the English grammar and syntax. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request. The processing scripts developed for the susceptibility, runout, and road-network prioritisation analyses, together with a subset of test input data referring to the Subiaco area, are openly available in the following GitHub repository. https://github.com/gmastrantoni/rockfall_risk_road_network.git.

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