Socio-Economic Planning Sciences xxx (xxxx) xxx-xxx

Contents lists available at ScienceDirect

Socio-Economic Planning Sciences

journal homepage: http://ees.elsevier.com

Assessing disaster risk by integrating natural and socio-economic dimensions: A decision-support tool☆

Giovanni Marin [a], Marco Modica [b,*], Susanna Paleari [c], Roberto Zoboli [d]

[a] *Department of Economics, Society and Politics, University of Urbino 'Carlo Bo', Urbino, and SEEDS, Italy*
[b] *GSSI Gran Sasso Science Institute, L'Aquila*
[c] *IRCrES-CNR, Milano, Italy*
[d] *Catholic University of Milan, IRCrES-CNR, Milano, and SEEDS, Italy*

ARTICLE INFO

JEL classification
Q51
Q54
Q58
R11

Keywords
Decision support tool
Natural disasters
Vulnerability
Resilience

ABSTRACT

The paper provides a conceptual framework for a multi-dimensional assessment of risk associated to natural disasters. The different components of risk (hazard, exposure, vulnerability and resilience) are seen in a combined natural and socio-economic perspective and are integrated into a Disaster Risk Assessment Tool (DRAT). The tool can be used to support disaster management strategies, as well as risk mitigation and adaptation strategies at very disaggregated geographical or administrative scales. In this paper, we illustrate the features of the DRAT and we apply the tool to 7556 Italian municipalities to map their multidimensional risk. DRAT can be particularly useful to identify hotspots that are characterized by high hazard, exposure and vulnerability and by low resilience. In order to identify hotspots, we perform a cluster analysis of the Italian municipalities in terms of their risk ranking based on DRAT. We also suggest how the tool may be exploited within the processes of disaster risk policy.

1. Introduction

Over the last years, human beings have experienced a raising frequency of natural disasters and of the associated costs. According to UNDRR [1]; more than 7000 natural hazard events (accounting for an estimated cost of about 3 trillion dollars) have occurred in the last two decades. In general, the most common immediate consequences of natural disasters are: i) deaths and injuries; ii) physical damages to infrastructures; iii) cost of the emergency operations; iv) socio-economic disruptions (e.g. number of working days lost); and v) environmental impacts [2]. This typically results, in the short term, in further socio-economic effects, such as temporary migration and displacement; loss of housing; loss of business and industrial production; disruption of the transport system and loss of housing values [3,4]. Instead, long-term consequences of natural disasters include the reduction in population size, a lower average income and human capital level [5–7], as well as psychosocial impacts [2].

However, as argued by Hallegatte [8]; the short and long-term impacts of a disaster on wealth depend on the physical characteristics of the affected places, the level of damage to assets, and the capacity of the territories to cope with disasters, recover and reconstruct. In this regard, it is important to note that "*while improvements have been made in terms of early warnings, disaster preparedness and response, which have led to a reduction in loss of life in single-hazard scenarios, it is also clear that the increasingly systemic nature of disaster risk, i.e. the overlap of events and the interplay between risk drivers such as poverty, climate change, air pollution, population growth in hazard-exposed areas, uncontrolled urbanization and the loss of biodiversity, requires greater strengthening of disaster risk governance*" (p. 7; [1].

The aim of this paper is to develop a framework to assess disaster risk that integrates the natural hazard and socio-economic dimensions. In line with the previous literature on multi-hazard risk assessment, we follow the general setting of similar articles that adopt a semi-quantitative approach (see for more details Johnson at al., 2016). For instance, Greiving [9] provides a multi-risk assessment of European regions, where the risk (namely the likelihood that a place is affected by a given hazard) is obtained by multiplying the indexes of vulnerability and hazards. Similarly, Johnson et al. [10]; in assessing the multi-hazard risks

☆ We acknowledge financial support from the research project '*La valutazione economica dei disastri economici in Italia*' funded by Fondazione Assicurazioni Generali. Giovanni Marin also acknowledges funding from the PRIN 2017 project 20177J2LS9 004 'Innovation for global challenges in a connected world: the role of local resources and socio-economic conditions'. Usual disclaimers apply.

* Corresponding author.
E-mail addresses: giovanni.marin@uniurb.it (G. Marin); marco.modica@gssi.it (M. Modica); susanna.paleari@ircres.cnr.it (S. Paleari); roberto.zoboli@unicatt.it (R. Zoboli)

https://doi.org/10.1016/j.seps.2021.101032
Received 29 May 2020; Received in revised form 26 December 2020; Accepted 1 February 2021
Available online xxx
0038-0121/© 2021.

in two districts of Honk Kong, create an indicator of risk by linearly aggregating composite indexes of vulnerability and hazards. However, the literature on risk assessment shows that this approach is typical in business studies (see e.g. Ref. [11] and that it usually consists of several different steps. First, risks are identified and a common set of assessment criteria is defined. Second, values are assigned to any risk. Third, risk interactions are considered and jointly evaluated. Fourth, the risk is prioritized by comparing the level of risk against specified target risk levels. Finally, the results of risk assessment are used to improve risk mitigation and prevention.

Even though the approach we propose is aimed at supporting risk management by institutions and public authorities, rather than business and firms responses, we believe that the steps suggested by Curtis and Carey [11] can be also used to assess natural disaster risk. Thus, building on their research and on the methodological procedure of Johnson et al. [10]; we outline our approach, which is made by four steps: (1) we develop relative intensity maps for each natural hazard; (2) we derive a multi-hazard integrated map, encompassing all the hazards addressed by the present work; (3) we develop socio-economic exposure, vulnerability and resilience maps, based on composite normalized indicators; and (4) we obtain an integrated risk map, as a product of all the previous indicators.

In doing this kind of analysis we know that hazard, exposure, vulnerability, resilience and risk are recurrent concepts in the analysis of natural and man-made disasters. However, all of these are multi-faceted concepts that take different "shades" according to the case-study, aim and scholars' background in the different analyses. Thus, we preliminary provide the definition of these key concepts.

Hazard is related to the natural event possibly affecting different areas and people [12]. It is usually assessed through models that measure the probability of its occurrence. *Exposur*e is defined as all the assets and people that can be harmed by a natural disaster; it encompasses physical and socio-economic components. It can be divided into direct exposure and indirect exposure (e.g. potential losses due to disruption of local and global supply chains of the production activities, [13]. The latter can even potentially affect the macroeconomic growth of countries and the long-run local development of disaster-hit regions [14].

Vulnerability is defined as all '*inherent characteristics of the exposed objects/areas that create the potential for harm'* regardless from the actual occurrence of hazards [15] p. 805). It is generally measured through composite indicators, including many variables that are selected by researchers according to highly subjective criteria and depending on the issue under investigation (e.g. see Refs. [16,17].

Resilience is the ability of a system to recover from or to adapt to a shock [18,19], so that the impact of the disturbances affecting the system is reduced. As in the case of vulnerability, resilience is often measured through composite indicators covering several issues which are selected based on the type of shock under consideration (e.g. financial crises, natural disasters, etc.) and on the object of the analysis [20–26].

Disaster risk, according to an ex-ante and restrictive interpretation, is the result of the interaction between the hazard of a natural event (in particular, its frequency and the severity), the elements exposed to the hazard and their vulnerability [27]. More formally, the risk consists of the potential likely level of loss, given the severity of the hazard and the vulnerability [28]. In this case, vulnerability is the ability of the system to withstand a shock. However, if we enlarge the concept of disaster risk to a wider post-event time horizon (since we also want to address the long-term economic effects of disasters), resilience fits into the analysis as a factor that allows the system to adapt and recover (see Refs. [29,30] for more insights on the relationship between resilience and vulnerability). Therefore, resilience is an important aspect to be included in a disaster risk assessment tool, even though it cannot be considered as a component of the short-term risk.

Given this background, we derive a Disaster Risk Assessment Tool (DRAT) to provide information on hazard, exposure, vulnerability and resilience, and consequently the risk of small geographical areas. The DRAT may be used as a decision-support tool for policy makers in risk-reduction and resilience-increasing strategies. Furthermore, this tool is characterised by a high degree of adaptability to different scenarios and hazards. For instance, even if this is not the primary goal of the paper, our work can be adapted in order to assess the current COVID-19 situation. It could be applied, e.g., to evaluate the degree of vulnerability of a region to business interruptions following local lockdowns or to identify criticalities of local health facilities.

DRAT is applied to the Italy as a case study by mapping multidimensional integrated risk (and its components: hazard, exposure, vulnerability and resilience) for different types of hazards (earthquake, floods, landslides, volcanic eruptions) at the municipal level. Italy is one of the countries in the world suffering more from different natural hazards [31,32] and disasters costs. Moreover, the country has a huge heterogeneity in terms of local geographical and socio-economic characteristics. Therefore, Italy provides a good example of how assessing both the natural and socio-economic dimensions of risk for multiple hazards in fine-grained administrative units (municipalities) can usefully support policy makers in improving the management of disaster risk.

The paper is organized as follows: in the next section, we illustrate the research background of the analysis of natural disasters. Section 3 describes data and method. Results are presented in Section 4, where the tool is complemented by a cluster analysis to support policy makers, public authorities and first responders in identifying hotspots. In Section 5 we discuss how to strengthening the disaster risk governance shaping and implementing appropriate risk management policies and measures, especially within the complex processes of disaster risk management in a country like Italy. Finally, Section 6 concludes.

2. A framework for natural disaster analysis

This paper builds on Modica and Zoboli [33] regarding the socio-ecological framework for natural disaster analysis. However, we have worked on that model to better explain its main elements and clarify their relationships. We have also identified the concepts that might be mostly influenced by public policies.

According to Modica and Zoboli [33]; the socio-economic system (e.g. all the social and economic factors that influence local communities) may be thought as integrated with nature, because human activity is contingent on the natural system (i.e. on all the factors spontaneously regulated by the course of nature, which influence humans and their lives). On the same line, human activities have a significant impact on the environment through several channels and, in this context, land use plays a very important role. Fig. 1 illustrates the relationship between the different factors under analysis: i) factors that are only related to natural/physical aspects; ii) factors that are only related to the socio-economic system; iii) factors that derive from the interaction between the natural and the socio-economic systems.[1]

In general, we connect hazard to the natural system, since the former can be only indirectly affected by the socio-economic system (e.g. through the anthropogenic contribution to global warming, which increases the frequency and the severity of extreme natural events; [34,35]. Instead, exposure, vulnerability and resilience are related to the socio-economic characteristics of the area under analysis. Finally,

[1] Differently Modica and Zoboli [33] in this paper we consider the concepts of exposure, vulnerability and resilience mainly in the socio-economic realm, even though the natural system plays an important role. We mainly focus on the socio-economic aspects of these concepts, as this classification is more useful for developing our empirical analysis.

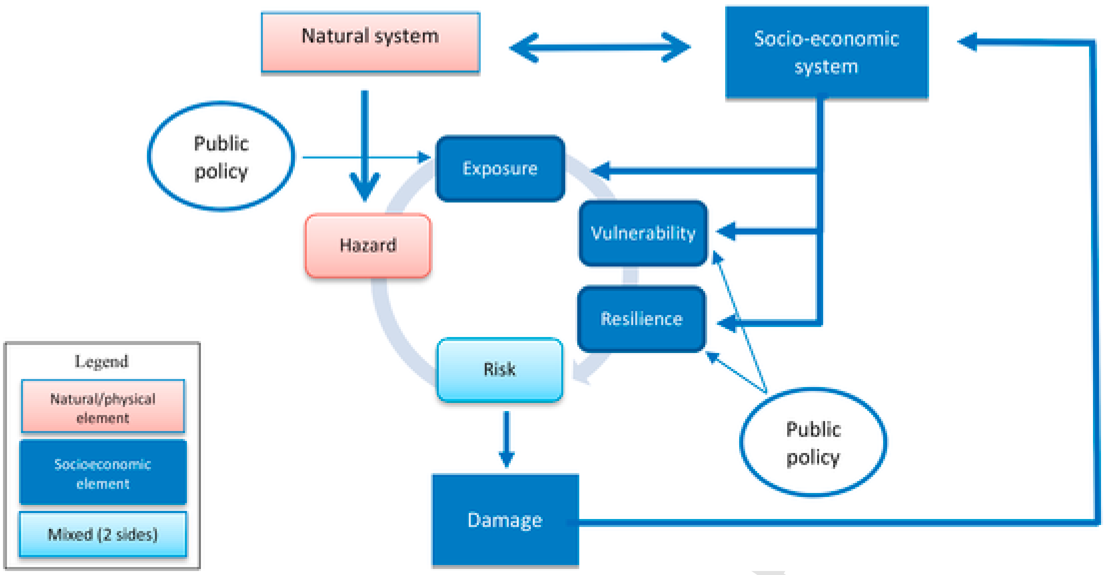


Fig. 1. Socio-ecological framework for natural disaster analysis (based on [33].

risk directly derives from the relationship between the natural and the socio-economic systems.

We provide a further conceptualization of the framework shaped by Modica and Zoboli [33] as follows: exposure is mainly affected by the socio-economic system, for instance, as illustrated in Fig. 1, by public policies. In particular land use planning, which is typically a responsibility of local policy makers, may prohibit building in high-hazard areas (e.g. in flood-prone areas), resulting in the absence (or reduction) of exposed goods in those areas.

In addition, socio-economic systems influence vulnerability and resilience. For instance, wealthier areas have a lower degree of vulnerability (e.g. because of a better quality of buildings) and a higher capacity to recover and adapt to a shock (e.g. since wealthy people can quickly invest in reconstruction by using available savings). Moreover, public and private behaviours may also reduce vulnerability or enhance resilience. Similarly, different strategic choices made by entrepreneurs after a natural disaster can affect their firms (e.g. the penetration of new markets or product innovation may increase the resilience of the firms and, in general, of the related socio-economic system). Nonetheless, the relationship between vulnerability and resilience needs to be further clarified, since, in the literature, there is no agreement on how the two concepts differ and interact [30]. Three different links may be identified: i) resilience as an outcome of vulnerability [36]; ii) vulnerability and resilience as two different concepts [29,30]; iii) vulnerability and resilience as separate (though likely correlated) concepts that share common characteristics [32].

In our paper, we adopt the latter approach, assuming that the characteristics that are relevant for defining the level of vulnerability of a given system may also be considered for the analysis of resilience. For example, poverty is important for measuring vulnerability, since poor people are more likely to live in risky-prone areas than wealthy people. At the same time, poverty is generally associated to the lack of resilience, since wealthy people are more capable to recover from a shock, because of higher savings [32].

Hazard, exposure, vulnerability and resilience are all risk components. It has long been recognized that hazards are just risk triggers and that they may cause more or less damage depending on the exposure and vulnerability of the affected areas. These negative effects will stand longer the lower is the degree of resilience of those areas [37–39]. The level of damage is therefore function of severity of hazard and of the interaction between the nature and the man-made environment, however any damage will influence the overall socio-economic system, for instance lowering the wealth of the affected areas. This will lead to a change in the exposure, vulnerability and resilience local characteristics modifying again the risk of the area. Public policies that are able to continuously adapt to different scenario and context both in the ex-ante and ex-post perspectives become therefore fundamental in the disaster governance.

3. Materials and method

In this section, we develop a composite indicator that integrates all the dimensions playing a role in the ex-ante and ex-post assessment of disaster risks. While several works have proposed composite disaster risk indexes (see e.g. Ref. [40], the DRAT composite indicator is proposed as a *Decision* Support *Tool* for both ex-ante and ex-post disaster risk management in a multi-hazard perspective and in an integrated natural and socio-economic perspective. Ex-ante, because, since the DRAT can be applied at a very narrowly defined geographical level (the municipality level, in our case study), it provides relevant information to shape mitigation strategies or to identify high-risk areas (hotspots) that should be prioritized for the implementation of risk reduction measures. Ex-post, because the tool highlights the weaknesses of the socio-economic systems actually affected by natural disasters and it can, therefore, contribute to fostering their reconstruction/recovery or, even better, to improving their capacity to adapt to the new situation and use natural disasters as an opportunity for future development.

However, it is important to note that, although the DRAT includes several composite indicators for hazard, exposure, vulnerability and resilience and provides a synthetic general score, it is still able to capture only quantifiable aspects of risk assessment/management, while more qualitative, though important, factors fall outside its scope.

Below we illustrate the features of the DRAT and we apply the tool to 7556 Italian municipalities to map their multidimensional risks, even though the DRAT might be adapted to different contexts and types of hazard and used for both single and multiple hazards scenarios. We focus on Italy because of the peculiarities of this country, which is affected by several heterogeneous hazards and is one of the most disaster-prone countries in the world [41]. The DRAT can be particularly useful to identify hot spots that are characterized by high hazard, exposure and vulnerability and by low resilience.

3.1. Hazard

Hazard is typically measured based on estimates provided by institutional sources. Using ISTAT (Italian National Statistical Office) data, we calculate, for each municipality[2]: i) a specific measure of the four main hazards affecting Italy (i.e. landslides, floods, earthquakes and volcanic eruptions); ii) a synthetic measure of the different above-mentioned hazards (multi-hazard risk index).

With regard to landslides, ISTAT provides information on the area (km^2) of the municipalities that are at risk of landslides, according to 5 different degrees of probability, from high to low. The data are scaled between 0 and 1 according to the area that is in each hazard category and for all the degrees of probability and, then, a weighted average is calculated to obtain a proxy of the landslide hazard of the whole municipality (Fig. 2a), which is again scaled between 0 and 1 for all Italian municipalities.[3] A similar process is used to map flood hazard (Fig. 2b). Also in this case, ISTAT provides information on the area (km^2) of the municipalities that are at risk of floods, according to 3 different degrees of probability of hazard occurrence. The data are again scaled between 0 and 1.

Based on the analysis performed by the National Institute of Geophysics and Volcanology, ISTAT publishes seismic risk data. We calculate the seismic risk as a scaled value between 0 and 1 of the maximum municipal value of the peak ground acceleration (Fig. 2c).

Finally, in Italy, there are also areas exposed to volcanic hazard (less than 150 municipalities). Since the related risk depends on the maximum distance that the pyroclastic emissions could reach, we distinguish between areas that are potentially highly affected (e.g. the *Red Zone* for the areas around Vesuvius) and areas that may be only incidentally affected (e.g. the *Yellow Zone* for the areas around Vesuvius) by volcanic eruptions. We assign the value of 1 to the municipalities of the former group and the value of 0.5 to the municipalities in the latter group.[4]

All these measures of hazard are then aggregated to obtain a multi-hazard map for all the Italian municipalities, as a simple average of the rescaled values of the different hazards (Fig. 2d).

3.2. Exposure

Exposure is the potential magnitude of the damages from a disaster. We assess the direct components of exposure based on the following variables: sales and capital stock of firms, and market values of residential buildings. Sales indicate the potential direct costs arising from business interruption because of natural disasters. Capital stock of firms is a measure of the potential destruction of capital assets. Furthermore, we also consider exposure in terms of the market value of all residential buildings. Average housing values in 2015 are provided by OMI (Osservatorio Mercato Immobiliare). For estimating firms' sales at the municipal level, we use data from the Italian Business Registry (Archivio Statistico delle Imprese Attive, ASIA, by ISTAT). Finally, capital stock is estimated, first, at the sectoral level, using national accounts and, then, it is attributed to municipalities, according to the share of municipal-level employees for each sector.[5]

According to Yaseen et al. [42]; Input-Output Model can be used to estimate disruptions in disasters like floods. This model has been generalised by Marin and Modica [13] in order to estimate the indirect exposure in Italian municipalities, based on data from Input-Output tables and by considering economic activities at potential risk within a radius of either 20 km or 50 km from the centroid of the municipality under scrutiny. In this paper, we improve the above-mentioned approach, by adopting a more 'economic' concept of indirect exposure and we identify the relevant economic-geographical area for local shocks diffusion, i.e. the Local Labour System area.[6] Building on Marin and Modica [13]; we provide two different measures:

- ✓ *Destination of final goods as intermediates*: it is computed as the share of sales, produced in the municipality of reference, that can be absorbed by firms operating in other (downstream) sectors, but belonging to the same Local Labour System area and identified according to national input output tables.
- ✓ *Source of intermediate inputs*: it considers the extent to which firms within the same Local Labour System area contribute to supplying intermediate inputs to (upstream) firms in the municipality of reference.

Both these measures are able to capture the propagation of the shock to municipalities that are not directly affected by the disaster, but that may suffer from an interruption of the production activity, due to the link between their supply chain and those of the affected municipalities.

Finally, for the multi-hazard composite indicator, all the components of exposure are re-scaled between 0 and 1, by subtracting the minimum and dividing by the difference between maximum and minimum. In this way, we obtain relative homogenous values that are then aggregated in a single composite indicator defined as the simple average of all the components, which is again rescaled to range between 0 and 1 (Fig. 3).[7]

It must be noted that we do not include population-related variable in the exposure indicator, which encompasses economic activities and assets only. Instead, population and some of its relevant attributes (density, age, family structure, female condition, education) are included in the set of indicators of vulnerability and, partly, resilience. This choice is driven by our system of normalisation of the indicators, including population number among the exposures (as it is usually done) would imply to assign to this so important variable the same consideration as the one given to economic assets. Instead, by 'qualifying' population beyond its pure number through multiple indicators within vulnerability/resilience can give a more holistic role to population in disaster risk assessment.

3.3. Vulnerability and resilience

The construction of the indicators of vulnerability and resilience is based on Modica et al. [32]. The authors list all the indicators that have been used to measure vulnerability and resilience in the existing

2 Due to changing borders of provinces and municipalities, we decided to exclude from the analysis the Sardinia region.

3 Here and in the following indexes, data are rescaled by subtracting the minimum value and dividing by the difference between the minimum and maximum values.

4 In Italy there are two main volcanos, Vesuvius and Etna, and other very small ones: for the latter cases (8 municipalities: Barano d'Ischia, Casamicciola Terme, Forio, Ischia, Lipari, Lacco Ameno, Pantelleria and Serrara Fontana) we assign the value of 0.5. As only few municipalities are affected by volcanic hazard, we do not report the map, which is available upon request.

5 Refer to Marin and Modica [13] for further details regarding the estimation of municipality-level sales and capital stock.

6 Labour Market Areas define groups of municipalities characterized by substantial within-area commuting patterns and limited commuting patterns with municipalities in other Labour Market Areas. Labour Market Areas are defined by the Italian Institute of Statistics every 10 years, using data on commuting patterns from the decennial general census of population.

7 Weighting options different from a simple average can be adopted by giving different weights to different types of disaster.

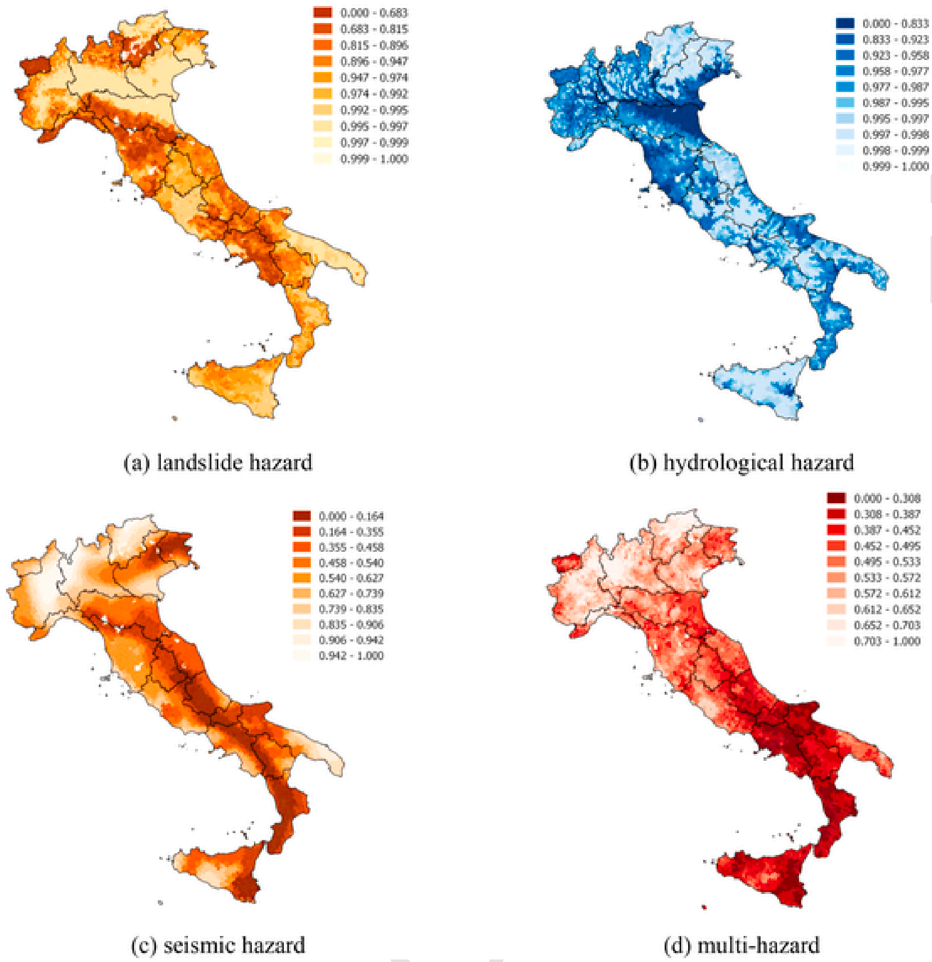


Fig. 2. Hazard of natural disasters for Italian municipalities.

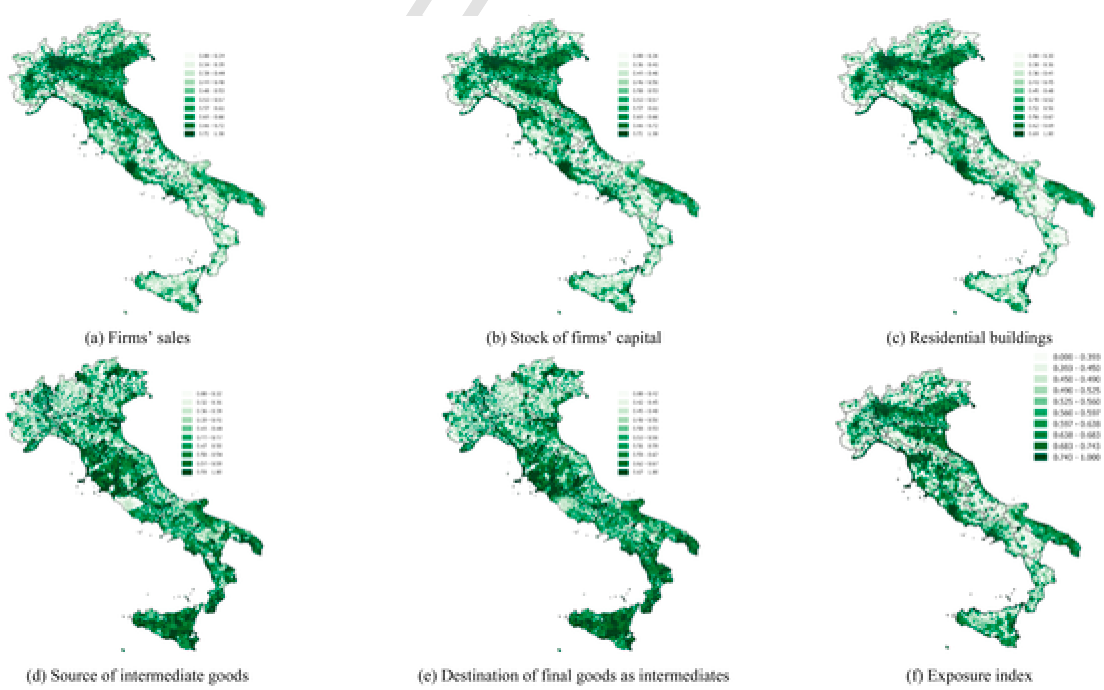


Fig. 3. Measures of exposure.

literature. In this paper, we exploit the knowledge gathered by Modica et al. [32] to build our composite indicators of vulnerability and resilience. Indeed, we rely on the existing literature to identify the relevant indicators, but we limit the arbitrariness of the process by selecting the variables that appear in at least 15% of the reviewed papers. According to this rule, 17 variables have been selected for the vulnerability index and 13 for the resilience index (Tables 1 and 2).

Moreover, the number of occurrences of each variable in the different papers, as reported by Modica et al. [32]; allows us to calculate a weighted synthetic indicator, based on how many times an attribute appears in the literature. In both the indicators, the role of economic variables is remarkable (i.e. wealth measures appear in half of the papers on vulnerability and in 71% of the papers on resilience), while some specific characteristics are peculiar to the two concepts. For instance, in the vulnerability indicators, variables related to agricultural (34%), demographic (44%), and building characteristics (25%) appear more frequently than in the resilience indicators. On the contrary, variables related to education (26%), institutions (26%) and business density (19%) appear more frequently in the resilience indicators.

All the indicators composing the vulnerability and resilience indexes are rescaled to range between 0 and 1 and the final indicators consist of the weighted averages of the different components, using the occurrence of each attribute in the literature as weight. The final indicators are, again, rescaled to range between 0 and 1 (Tables 1 and 2). Fig. 4 provides the maps of vulnerability (a) and resilience (b). The darker is the colour, the higher is the vulnerability of the area and the lower is its resilience.

3.4. Building the tool

In this section, we discuss the DRAT by aggregating all the components defined in the previous sections into a synthetic indicator that summarizes the overall multiple risk of the Italian municipalities. Hazard, exposure, vulnerability and resilience are all risk components. Therefore, disaster risk can be described, for each municipality i and each hazard type j, by the following general function (see for example [44]:

$$R_{ij} = f(H_{ij}, E_i, V_i, Res_i) \tag{1}$$

where H_{ij} is the natural hazard score in municipality i and hazard j, E_i is the socio-economic exposure, V_i is the socio-economic vulnerability, and Res_i is the socio-economic resilience. While it is possible to argue about the appropriate functional form of this relationship, it has, however, to be recognized as multiplicative, with all variables ranging between 0 (minimum) and 1 (maximum):

$$R_{ij} = H_{ij} \times E_i \times V_i \times (1 - Res_i) \tag{2}$$

The multiplicative form implies that if at least one of the different dimensions is very low (or high for resilience), this results in a very low risk.[8] For example, independently from exposure, resilience and vulnerability, the absence of natural hazards entails no risk. Similarly, the absence of exposure (e.g. areas with very small population and few economic activities) is associated to a low risk, no matter the hazard, vulnerability and resilience. Finally, as long as V and Res are proper measures of, respectively, vulnerability and resilience, the risk is likely to be low for high resilience and/or low vulnerability, even in presence of high hazard and exposure, as the area would not be affected much by the disaster (low vulnerability) and/or could recover promptly from possible damages (high resilience).

[8] This is the same approach followed by the DRMKC-INFORM tool developed by the European Commission Disaster Risk Management Knowledge Centre (see https://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Risk/Methodology).

4. Results

In this section, we present the main results of the application to Italy. First, we illustrate the single components of the DRAT (Figs. 2–4). Then, we adopt a step-by-step approach, to build a complete DRAT synthetic indicator for disaster risk assessment in Italian municipalities. Finally, we summarise our findings by means of a cluster analysis that allow us to identify disaster risk hot spots.

Fig. 2 illustrates the geographical distribution of all the hazards covered by this analysis. The areas with the highest probability to be affected by multi-hazards are those located along the Apennines in Central Italy and in the Campania, Calabria and Sicily regions. Instead, with reference to direct components (i.e. sales, capital stock and value of residential buildings), Fig. 3 (a, b and c) highlights that the Northern regions are characterised by the highest exposed value. When considering, instead, indirect exposure, it emerges that the municipalities of some Central and insular regions (e.g. Tuscany, Lazio and Sicily) heavily depend on firms within a small radius area (within, the same Labour Market Area, see Fig. 3d and e). Overall, however, the synthetic index of exposure, as defined above (Fig. 3f), shows higher values in the Northern regions (i.e. in the most economically developed regions). Finally, based on Fig. 4, the regions of Southern Italy are characterised by a more critical situation, due to a high socio-economic vulnerability associated with low resilience.

In Fig. 5, we build a synthetic DRAT index that includes only hazard, vulnerability and resilience. This index measures not only the potential risk, due to the probability to be affected by a natural disaster, but also the extent to which municipalities are prepared to mitigate the damage and quickly react to the event. The darker areas identify the municipalities with a high potential damage (high hazard and vulnerability) that are also expected to experience difficulties in recovering from the shock. In Italy, most of these critical areas, as highlighted by Fig. 5a, are in the South, particularly in the following regions: Campania, Abruzzi, Apulia, Calabria and Sicily. The scenario changes according to the type of hazard considered. For instance, when focusing on the landslide and hydrogeological hazards, also other regions show some criticalities (Valle d'Aosta with regard to landslides and the Northern part of Emilia Romagna with regard to the hydrogeological hazard, the so-called Bassa Padana).

Finally, we also include (direct) exposure to get a complete DRAT synthetic indicator for disaster risk assessment (equation (2)). It is important to take into account the exposed assets and economic activities, since there may be situations where the high probability of hazard occurrence is combined with low economic values in the area. Fig. 6 shows the results for the aggregated hazard (a), as well as for the single types of hazard (b, c and d). When adding exposure to the analysis, we note that the potential to suffer an economic damage is relatively low for some municipalities that are characterised by very high hazard, vulnerability and lack of resilience (see Fig. 5). This is especially true for some municipalities in Central and Southern Italian regions, such as Abruzzi, Campania and Molise, where exposure is low. On the contrary, some municipalities in northern Tuscany, which show a moderate/high level of hazard and vulnerability, might potentially suffer severe economic damages, because of a low level of resilience and a high exposure.

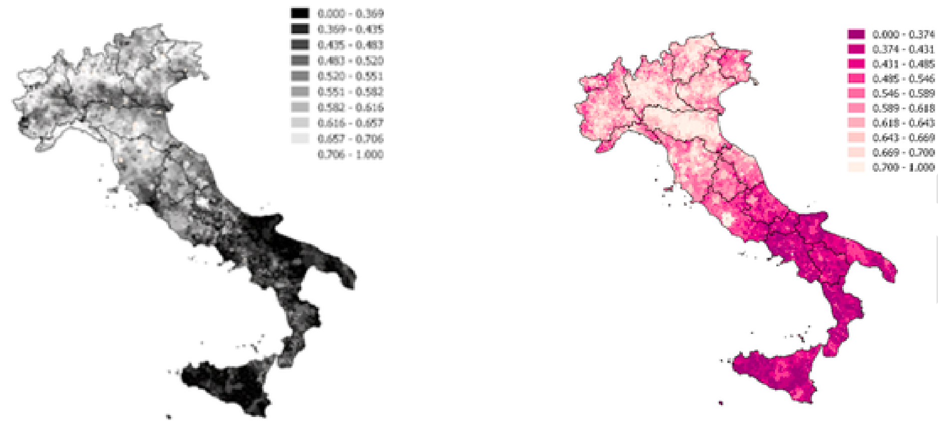
Results reported in Figs. 5 and 6 may hide relevant interactions between the different dimensions of risk. For example, we cannot control whether, given the hazard, a low risk depends on high resilience, low vulnerability or low exposure. In order to take into account such interactions, we combine resilience, vulnerability and exposure (direct and indirect exposure, separately) by means of cluster analysis to identify common patterns across different municipalities. We first look only

Table 1
The components of the vulnerability index.

	Vulnerability	Appearance	Data source	Note	Weights	
1	Extension of agriculture	34.4	Agricultural Census 2010	Percentage of agricultural land	7.1473	+
2	Dependency on agriculture	15.6	Agricultural Census 2010	Number of cattle per person	3.2412	+
3	Age	43.8	Population Census 2011	Dependency ratio	9.1004	+
4	Wealth	56.3	Ministry of Economy and Finance.	Average income per household	11.697	–
5	Poverty	40.6	Population Census 2011	Households with potential economic discomfort	8.4355	+
6	Inequality	21.9	Atlante Prin-Postmetropoli	Gini Index	4.5502	+
7	Unemployment	25	Population Census 2011	Unemployment rate	5.1943	+
8	Institutional capacity	18.8	Atlante Prin-Postmetropoli	Synthetic index defined as the simple average of Z-scores of the two following indicators: - Employees in the Public administration over total population - Employees in state education over total population - Employees in public health	3.9061	–
9	Political rights	15.6	Ministry of Interior	Turnover of 2014 EU Parliament election	3.2412	–
10	Population pressure	40.6	Population Census 2011	Population density	8.4355	+
11	Urbanisation	15.6	ISPRA	Land use per capita	3.2412	+
12	Building characteristics	25	Atlante Prin-Postmetropoli	Herfindahl-Hirschman index for residential, non-residential buildings (functional mix)	5.1943	+
13	Ecosystem conversion	15.6	Agricultural Census 2010	% of agricultural area actually used (SAU) on total agricultural area	3.2412	+
14	Education	43.8	Population Census 2011	Ratio between people in the age 15–24 who does not attend a regular course of study and population of 15–24 years	9.1004	+
15	Family structure	15.6	Population Census 2011	Ratio between the number of single-parent households over total number of households	3.2412	+
16	Female condition	15.6	Population Census 2011	Male employment rate over female employment rate	3.2412	+
17	Health	37.5	Ministry of Health	Hospital beds for 10,000 inhabitants	7.7914	–

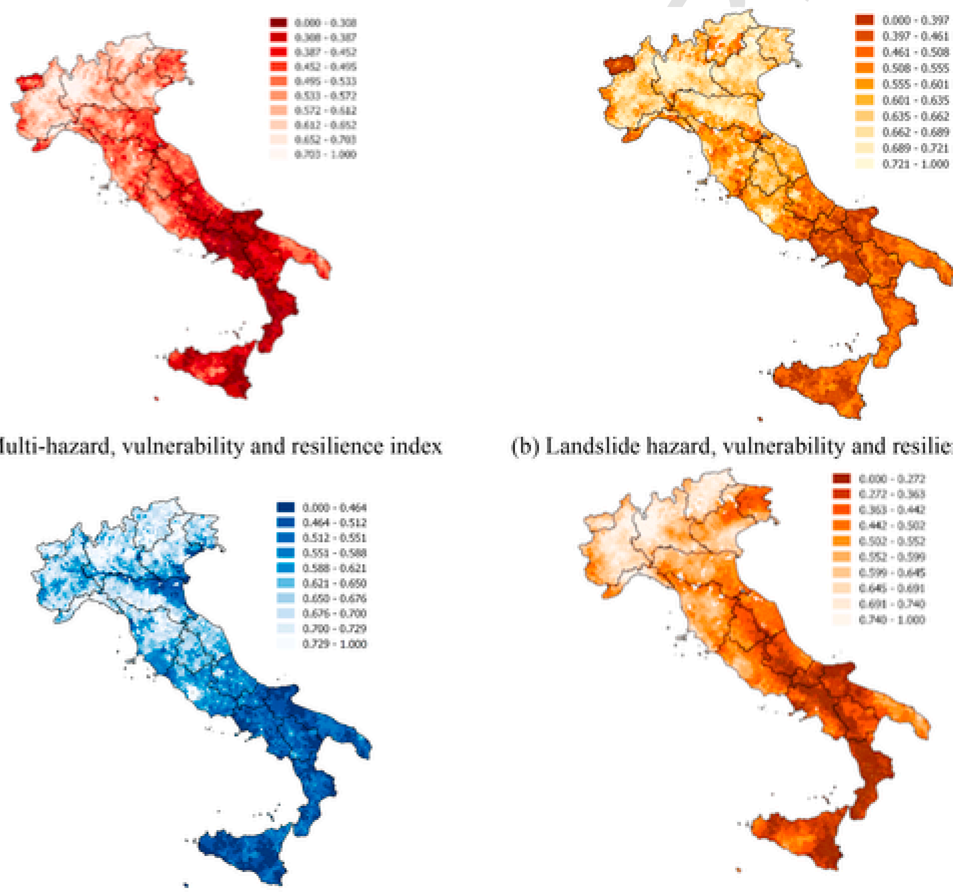
Table 2
The components of the resilience index.

	Resilience	Appearance	Data source	Note	Weights	
1	Density of business	19.4	DB	Number of local units per km2	5.2277	+
2	Wealth	71	Ministry of Economy and Finance.	Average income per household	19.132	+
3	Debt	22.6	AIDA - PA	Debt of the public administration per capita	6.0900	–
4	Poverty	29	Population Census 2011	Households with potential economic discomfort	7.8146	–
5	Homeownership	19.4	OMI - Fiscal Agency	Affordability index	5.2277	+
6	Unemployment	51.6	Population Census 2011	Unemployment rate	13.905	–
7	Productivity	22.6	Asia - Istat	Sales per employee	6.0900	+
8	Sectorial dependence	16.1	DB	Herfindahl-Hirschman concentration index of employees in the economic sectors	4.3385	–
9	Government effectiveness	19.4	AIDA- PA	Paid expenditure/Committed expenditure of municipal governments	5.2277	+
10	Institutional capacity	25.8	Atlante Prin-Postmetropoli	Synthetic index defined as the simple average of Z-scores of the 3 following indicators: - Employees in the Public administration over total population - Employees in state education over total population - Employees in public health	6.9523	+
11	Education	25.8	Population Census 2011	Ratio between resident in the age 15–24 who does not attend a regular course of study and resident population of 15–24 years	6.9523	+
12	Health	22.6	Ministry of Health	Hospital beds for 10,000 inhabitants	6.0900	+
13	Social capital	25.8	Nannicini et al. [43]	Synthetic index defined as the simple average of normalized scores of the following indicators: - No. of non-profit association - Employees in non-profit association - Blood donations - No. of non-sport newspapers sold/1000 person - Answer to ‘tolerance’ question in the WVS - Answer to ‘trust’ question in the WVS	6.9523	+



(a) Vulnerability index (b) Resilience index

Fig. 4. Vulnerability and resilience index in Italy.



(a) Multi-hazard, vulnerability and resilience index (b) Landslide hazard, vulnerability and resilience index

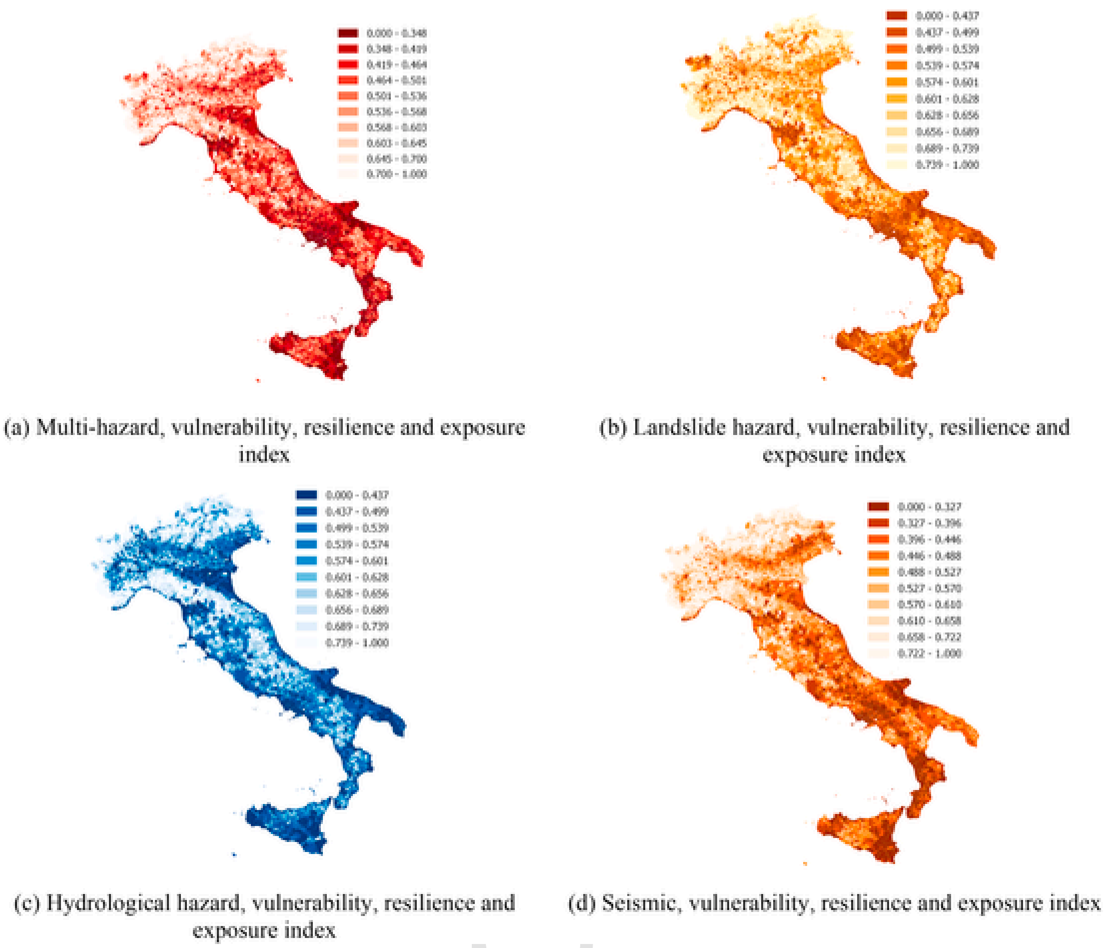
(c) Hydrological hazard, vulnerability and resilience index (d) Seismic, vulnerability and resilience index

Fig. 5. Composite index of hazard, vulnerability and resilience in Italy.

at the socio-economic components, and then we add the natural hazards.

The cluster analysis is based on the synthetic indicators of resilience, vulnerability and direct and indirect exposure.[9] We adopt a two-step procedure to define the optimal composition of clusters, as suggested by Hair et al. [45]. First, we perform hierarchical clustering to establish the "optimal" number of clusters [46]. As a second step, we use the resulting clusters (and corresponding centroids) as a starting point for the optimal re-attribution of municipalities into clusters, by

[9] As cluster analysis is particularly susceptible to outliers, we transform our synthetic indicators in percentile ranks.



(a) Multi-hazard, vulnerability, resilience and exposure index

(b) Landslide hazard, vulnerability, resilience and exposure index

(c) Hydrological hazard, vulnerability, resilience and exposure index

(d) Seismic, vulnerability, resilience and exposure index

Fig. 6. Disaster risk assessment index.

means of non-hierarchical clustering.[10] Based on this process, six clusters have been identified. Table 3 reports the average percentile rank for the clustering variables, across the six different clusters of municipalities, together with the total surface and population of the municipalities within each cluster.[11]

The different clusters are, then, synthetically described by labels that reflect their characteristics in terms of exposure, resilience and vulnerability:

✓ Cluster 1 "*Low values exposed and resilient*". It groups together municipalities with relatively low direct and indirect exposure (well below the median) and with the lowest vulnerability across all the clusters. These municipalities are also quite resilient, with a score that is, on average, right above the median. Therefore, the municipalities belonging to this cluster are not particularly sensitive to natural disasters, as the economic exposure and vulnerability are very low and resilience is medium-high.

✓ Cluster 2 "*Only directly exposed, but ready to react*". It has the highest level of direct exposure, combined with the highest resilience and a low vulnerability and indirect exposure. Municipalities in this cluster may be sensitive to disasters directly affecting them, but they appear prepared to reduce the losses and recover after the shock.

✓ Cluster 3 "*High exposure, but ready to react*". It is very similar to Cluster 2, with the exception that municipalities in this cluster are also characterized by high indirect exposure (i.e. these municipalities need to consider also the hazards of neighbouring municipalities).

✓ Cluster 4 "*Low values exposed and vulnerable*". It groups together municipalities that, despite the relatively small value of direct and indirect exposure, are particularly vulnerable to disasters.

✓ Cluster 5 "*Fragile, but only indirectly exposed*". It is also particularly vulnerable and weak in terms of resilience, but it includes municipalities that are only indirectly exposed, while direct exposure is the lowest on average.

✓ Cluster 6 "*Hotspots*". It includes those municipalities with the highest average vulnerability, the lowest average resilience and very high values of both direct and indirect exposure.

Fig. 7 illustrates the geographical distribution of municipalities across different clusters. "Hotspots" and "Fragile, but only indirectly exposed" municipalities are almost exclusively located in the Centre-South of Italy. Municipalities belonging to "Low values exposed and resilient" and "Low value exposed and vulnerable" are more evenly distributed across different regions, while "High exposure, but ready to react" and "Only directly exposed, but ready to react" municipalities are mainly concentrated in the Northern regions. The cluster analysis confirms the North-South divide identified in the previous sections.

[10] Hierarchical clustering techniques sequentially split clusters and do not allow for the re-allocation of observations across different branches of the clustering tree. Non-hierarchical clustering techniques are more flexible and allow for re-allocation of observations to render clusters more homogeneous and distinct. As a clustering algorithm, we use the average linkage algorithm, which computes the squared Euclidean distance in clustering variables across all possible pairs of observations across different clusters.

[11] To ease the interpretation, we invert the scale of resilience compared to Fig. 4b, with larger values indicating here higher levels of resilience.

Table 3
Profiling of cluster (average percentile).

Cluster	Direct exposure	Indirect exposure	Resilience	Vulnerability	Surface (km2)	Population (in 1000)
1 Low values exposed and resilient	24	38	54	23	45394	1469
2 Only directly exposed but ready to react	78	26	81	30	30924	16211
3 High exposure but ready to react	73	76	73	33	53210	17162
4 Low values exposed and vulnerable	38	24	43	68	34656	2773
5 Fragile but only indirectly exposed	21	75	20	78	69411	3712
6 Hotspots	70	70	20	80	39990	16055
Total	50	50	50	50	273587	57382

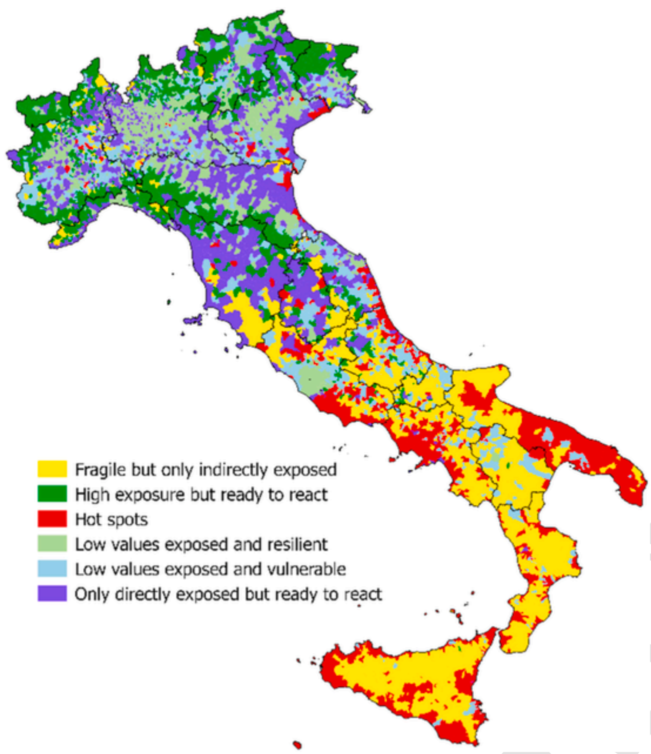


Fig. 7. Municipalities by cluster.

Table 4
Hazards (average percentile) by cluster.

Cluster	Multi-hazard	Landslides	Floods	Earthquakes
1 Low values exposed and resilient	38	64	42	45
2 Only directly exposed but ready to react	26	27	54	38
3 High exposure but ready to react	34	40	60	40
4 Low values exposed and vulnerable	58	45	45	51
5 Fragile but only indirectly exposed	80	62	38	71
6 Hotspots	77	48	44	61

Table 5
Average hazard in other municipalities within the same local labour market area (average percentile) by cluster.

Cluster	Multi-hazard	Landslides	Floods	Earthquakes
1 Low values exposed and resilient	39	62	46	44
2 Only directly exposed but ready to react	28	37	61	38
3 High exposure but ready to react	37	45	61	40
4 Low values exposed and vulnerable	52	48	54	51
5 Fragile but only indirectly exposed	78	58	37	72
6 Hotspots	79	53	39	62

Finally, we take into consideration the natural hazards of municipalities belonging to different clusters. The underlying idea is that, while exposure, vulnerability and resilience are the results of human activities and historical development paths, hazard (within the municipality or in neighbouring municipalities in the same Labour Market Areas) is largely exogenous and related to the geomorphological features of each specific area. In particular, natural disasters occurring in the hotspots and in the fragile municipalities (cluster 5 and 6) are likely to generate substantial losses and recovery is expected to be very problematic, due to the low degree of resilience. Therefore, exposure, vulnerability and resilience jointly allow identifying the short and long-term losses due to the occurrence of an exogenous natural event (hazard).

Table 4 shows the average percentile of different categories of hazards in different municipalities, while Table 5 reports the average percentile of hazard of neighbouring municipalities belonging to the same Labour Market Area.[12] Overall, the highest within-municipality (i.e. direct) multi-hazard score (Table 4) is recorded in the fifth and sixth clusters, which are the least resilient and the most vulnerable ones. When considering the different categories of hazards separately, instead, evidence is more mixed, with floods and landslides hazards being rather evenly distributed across the clusters and earthquake hazard being very high in the fifth cluster. Moving to hazards in neighbouring municipalities other than the focal municipality (Table 5), we observe a very similar distribution across different clusters, suggesting that the spatial correlation of hazard across municipalities within the same local labour market is high.

Overall, we have some preliminary evidence that the two most sensitive clusters (5 and 6) are also the ones with the highest levels of multi-hazard. For illustrative purposes, Table 6 reports the distribution of municipalities across clusters and quartiles of multi-hazard score.[13]

[12] It is important to take into account of hazards of other municipalities within the same local labour market when considering indirect exposure, which responds to shocks in areas connected with the focal municipalities by means of input-output relationships.

[13] Results for the different hazards are not reported and are available upon request.

Table 6
Distribution of municipalities by cluster and quartile of multi-hazard score.

Cluster	Q1 (low hazard)	Q2	Q3	Q4 (high hazard)	Total
1 Low values exposed and resilient	428	383	329	51	1191
2 Only directly exposed but ready to react	858	516	186	7	1567
3 High exposure but ready to react	502	426	307	24	1259
4 Low values exposed and vulnerable	83	406	423	290	1202
5 Fragile but only indirectly exposed	14	99	312	976	1401
6 Hotspots	4	59	332	541	936
Total	1889	1889	1889	1889	7556

Among the 936 municipalities that belong to the cluster "Hotspots", as many as 541 lie in the highest quartile of multi-hazard score, meaning that they are both extremely susceptible to disasters and, at the same time, located in high multi-hazard areas.

Fig. 8 and Table 7 show that these 541 municipalities, accounting for 18.19% of the Italian population, are mostly located in the regions of the South, with a few exceptions in Liguria, Emilia-Romagna, Tuscany and Marche. Campania is the NUTS2 region with the highest share of population (almost 80%) living in these very risky municipalities and very high shares (above 50%) are reported also in Sicily and Calabria. When focusing on a more disaggregated geographical level (provinces, NUTS3), it emerges that in 13 provinces more than half of the population lives in risky municipalities, with the extreme case of the province of Naples (with a share of 97.73%).

Fig. 8. Municipalities in hotspot cluster with high (fourth quartile) multi-hazard score.

Table 7
Share of population in municipalities in 'hotspot' cluster with high multi-hazard score (fourth quartile) – Average by region and top-20 provinces.

Region (NUTS2)	Share of municipalities in 'danger' (weighted by population)	Province (NUTS3)	Region (NUTS2)	Share of municipalities in 'danger' (weighted by population)
Campania	0.7929	Naples	Campania	0.9773
Sicily	0.6486	Ragusa	Sicily	0.8289
Calabria	0.5648	Catania	Sicily	0.8213
Apulia	0.2355	Palermo	Sicily	0.8116
Abruzzo	0.1737	Reggio di Calabria	Calabria	0.7069
Molise	0.0795	Siracusa	Sicily	0.6987
Basilicata	0.0518	Benevento	Campania	0.6756
Lazio	0.0339	Catanzaro	Calabria	0.6661
Emilia-Romagna	0.0171	Caserta	Campania	0.6484
Umbria	0.0094	Messina	Sicily	0.6343
Marche	0.0055	Barletta-Andria-Trani	Apulia	0.5892
Tuscany	0.0044	Salerno	Campania	0.5430
Liguria	0.0032	Foggia	Apulia	0.5255
Friuli-Venezia Giulia	–	Avellino	Campania	0.4859
Lombardy	–	Cosenza	Calabria	0.4794
Piedmont	–	Crotone	Calabria	0.4330
Trentino-Alto Adige	–	Caltanissetta	Sicily	0.3799
Valle d'Aosta	–	Vibo Valentia	Calabria	0.3730
Veneto	–	Teramo	Abruzzo	0.3553
Total	0.1819	Trapani	Sicily	0.3410

5. Discussion: strengthening disaster risk governance

The present section aims at providing some insights into how the DRAT can support the governance of natural disasters. In particular, it illustrates how the tool may be exploited within the multilevel processes of disaster risk policy in Italy.

First of all, the DRAT could play a role in risk prevention and mitigation (RPM). In Italy, Government spending in RPM, although showing an increasing trend, still represents a small share of the estimated national RPM financial need [41,47]. It is, therefore, crucial that the available financial resources are efficiently used to cope with the most critical situations. However, the distribution of these resources among recipients is generally based on hazard indicators, sometimes complemented with selected indicators of direct exposure and vulnerability. For instance, in 2010–2016, the National Plan for seismic risk prevention allocated 965 million Euros to reduce the seismic vulnerability of public and private buildings and prepare seismic micro-zonation studies. The budget was distributed among the Regions in proportion to a seismic risk index, which mainly took into account their seismic hazard, exposed population/buildings and engineering measures of seismic vulnerability of buildings (see for example [48]. Similarly, the financial plan of the National Program for reducing the hydrogeological risk provides for the allocation of 9.9 billion Euros in the 2015–2023 period [49]. To distribute these resources among Regions, an indicator was defined by DPCM of 5th December 2016 [50] which includes hazard and exposure dimensions (surface area of the Region, overall population and population exposed to very high/high landslide hazard or average flood hazard), with no consideration for either physical or social vulnerability. More recently, the 2019 Budget Law [51]; Art. 1.107) has allocated 400 million Euros to small municipalities in 2020, in order to fund public investments aimed at securing schools, roads, public buildings and municipal property (also when exposed to the hydrogeological risk); the available resources are to be distributed depending on the population of municipalities (exposure).

The above examples show that the DRAT, by integrating all the different components of risk (hazard, exposure, vulnerability and resilience) and developing a broad picture of socio-economic exposure (direct and indirect components), vulnerability and resilience could support a more informed and meaningful allocation of the limited public resources destined for RPM. Moreover, the tool may also support the preparation of the provincial and municipal civil protection plans, which, pursuant to the Civil Protection Code [52] is classified as a non-structural prevention activity. The plans shall describe the operational strategies and the intervention model to manage expected and ongoing natural disasters. They shall be shaped according to regional guidelines which usually rely on selected indicators related to hazard, physical exposure and vulnerability to develop local risk scenarios. Also in this case, these indicators may be usefully complemented by the DRAT.

Secondly, the DRAT may be a valuable decision-support tool for policy makers also in the recovery phase, after disaster occurrence. In Italy, for instance, there is not to date a stable and predictable legislative framework for ex-post disaster management [53]. Since the country has no compulsory or semi-mandatory insurance against natural disasters, compensation for damages is provided on a case-by-case basis by the Government, through grants or in the form of tax benefits. When the Council of Ministers declares the state of emergency, grants are allocated for reconstruction and recovery based on the estimate of the financial needs by the involved Regions and the Civil Protection Department. However, there is neither a standardised methodology to measure the regional and local financial needs nor an indicator commonly used to allocate the available financial resources to critical recipients/sectors. The DRAT could, therefore, be exploited to make the whole process less dependent on purely political decisions. In particular, its resilience component could play a role with this regard, thanks to its ability to capture the medium/long term capacity of a territory to recover or to adapt to a shock.

6. Conclusions

The tool developed by this paper can support the integrated assessment of disaster risk from a socio-economic perspective. The set of indicators we have created and the related cluster analysis provide information, at the municipal level, on natural hazards and socio-economic exposure, vulnerability and resilience, which are merged into integrated risk indicators. In addition, it can cover multiple risks, thus providing an integrated socio-economic multi-risk assessment tool. At the same time, each component can be separately investigated. Therefore, DRAT is innovative and versatile and it may be useful to the actors involved in the (ex-ante and ex-post) governance of natural disasters at different levels. In particular, it may support the priority-setting process with regard to the measures to be implemented to prevent/mitigate natural risks and to foster recovery after disasters occurrence, the best allocation of the available financial resources and the identification of potential recipients in term of sectors and social groups.

The set of indicators presented in the paper may be further refined and improved. For instance, exposure indicators could be extended to measure the value of the cultural heritage, the industrial composition of disadvantaged areas (such as the so-called inner areas) or to account for the flow of tourists in specific periods of the year. Since our work is mainly built on the existing literature, these limitations turn out to be suggestions for further research. Moreover, we recognise that not all the aspects that are relevant for risks/disasters assessment can be translated into indicators.

The application of the tool to the Italian case study reveals that, based on the composite-indicator measure of different hazards, critical regions/areas are located both in the North and in the South of the country. However, the Northern regions, although characterised by the highest values of exposure (especially of direct exposure), are affected by a lower socio-economic vulnerability, compared to the regions of the South, and perform better in terms of resilience. The cluster analysis confirms this North-South divide, by showing that Southern regions host the largest part of the hotspots (i.e. municipalities with the highest average vulnerability, the lowest average resilience and with very high values of both direct and indirect exposure).

Overall, the picture that emerges from the application of the tool suggests that the governance of natural disasters should be a national priority, while there is not, to date, in Italy, a long-term, coherent and sound ex-ante risk reduction strategy, in spite of the very articulated process of disaster risk planning at different government levels. Ex-ante disaster prevention and mitigation policy is generally weak (see Ref. [54]. Even when considering ex-post measures, while the Civil Protection is quite effective in coping with the short-term effects of natural disasters, financial assistance from the Government for post-disaster recovery is not predictable and it is provided on an ad-hoc basis, so that, in the end, the resilience of local and regional communities and administrations is a crucial asset. DRAT may, therefore, contribute to improving disaster risk management for both prevention and mitigation strategies in an ex-ante perspective and allocation of financial resources in the ex-post.

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. We acknowledge financial support from the research project '*La valutazione economica dei disastri economici in Italia*' funded by Fondazione Assicurazioni Generali. Giovanni Marin also acknowledges funding from the PRIN 2017 project 20177J2LS9 004 `Innovation for global challenges in a connected world: the role of local resources and socio-economic conditions'. Usual disclaimers apply.

References

[1] UNDRR The human cost of disasters: an overview of the last 20 years (2000-2019). Geneva, Switzerland: Published for the UN Office for Disaster Risk Reduction; 2020.
[2] S. Bradshaw Socio-economic impacts of natural disasters: a gender analysis. ECLAC; 2004.
[3] M. Modica, R. Zoboli, F. Meroni, V. Pessina, T. Squarcina, M. Locati 'Near miss' housing market response to the 2012 northern Italy earthquake: the role of housing quality and risk perception. Urban Studies; 2020. 0042098020943490.
[4] M. Pelling, A. Özerdem, S. Barakat The macro-economic impact of disasters. Prog Dev Stud 2002;2(4):283–305.
[5] A. Cas, E. Frankenberg, W. Suriastini, D. Thomas The impact of parental death on child wellbeing: evidence from the Indian ocean tsunami. Demography 2014;51(2):437–457.
[6] T. McDermott, F. Barry, R. Tol Disaster and development: natural disasters, credit constraints and economic growth. Oxf Econ Pap 2014;66(3):750–773. 2014.
[7] I. Noy, Y. Okuyama, Y. Sawada The long-run socio-economic consequences of a large disaster: the 1995 earthquake in Kobe. PloS One 2015;10(10):e0138714.
[8] S. Hallegatte The indirect cost of natural disasters and an economic definition of macroeconomic resilience. The World Bank; 2015.
[9] S. Greiving Multi-risk assessment of Europe's regions. In: J. Birkmann, editor. Meas. Vulnerability nat. Hazards disaster resilient socpp; 2006. p. 210–226.
[10] K. Johnson, Y. Depietri, M. Breil Multi-hazard risk assessment of two Hong Kong districts. Int J Disaster Risk Reduct 2016;19:311–323.
[11] P. Curtis, M. Carey Risk assessment in practice by deloitte and touche LLP. The committee of sponsoring organizations of the treadway commission (COSO). 2012. Retrieved on December 4th, 2020 at https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Governance-Risk-Compliance/dttl-grc-riskassessmentinpractice.pdf.
[12] B. Wisner, P. Blaikie, T. Cannon, I. Davis At risk. London: Routledge; 2004.

[13] G. Marin, M. Modica Socio-economic exposure to natural disasters. Environ Impact Assess Rev 2017;(64):57–66.
[14] P.S. Mohan, B. Ouattara, E. Strobl Decomposing the macroeconomic effects of natural disasters: a national income accounting perspective. Ecol Econ 2018;146:1–9.
[15] D. Sarewitz, R. Pielke, M. Keykhah Vulnerability and risk: some thoughts from a political and policy perspective. Risk Anal 2003;23(4):805–810.
[16] Q. Ding, X. Chen, R. Hilborn, Y. Chen Vulnerability to impacts of climate change on marine fisheries and food security. Mar Pol 2017;83:55–61.
[17] UNDP Human development report 2015–work for human development. New York: Published for the United Nations Development Programme (UNDP); 2015.
[18] S.L. Pimm The complexity and stability of ecosystems. Nature 1984;307:321–326.
[19] R.L. Martin Regional economic resilience, hysteresis and recessionary shocks. J Econ Geogr 2012;12:1–32.
[20] O.D. Cardona, M.G. Ordaz, M.L. Carreño, M.C. Marulanda, A.H. Barbat Fiscal impact of future earthquakes and country's economic resilience evaluation using the disaster deficit index. Paper presented at the 14th World Conference on earthquake engineering; 2008. Beijing, China.
[21] S.L. Chan, W.M. Wey, P.H. Chang Establishing disaster resilience indicators for Tan-sui river basin in Taiwan. Soc Indicat Res 2014;115(1):387–418.
[22] S.L. Cutter, B.J. Boruff, W.L. Shirley Social vulnerability to environmental hazards. Soc Sci Q 2003;84(2):242–261.
[23] K.A. Foster Case study approach to understanding regional resilience. Working paper 2008–07. Berkeley: Institute of Urban and Regional Development, University of California; 2007.
[24] S. Hallegatte Economic Resilience: definition and measurement. 2014. World Bank Policy Research Working Paper No. 6852. Available at: SSRN https://ssrn.com/abstract=2432352.
[25] J.S. Mayunga Understanding and applying the concept of community disaster resilience: a capital-based approach. Summer academy for social vulnerability and resilience building; 2007. p. 1–16.
[26] C.W. Zobel, M. Baghersad Analytically comparing disaster resilience across multiple dimensions. Soc Econ Plann Sci 2020;69:100678.
[27] J. Birkmann Risk and vulnerability indicators at different scales: applicability, usefulness and policy implications. Environ Hazards 2007;7:20–31. 200.
[28] D.E. Alexander Confronting catastrophe: new perspectives on natural disasters. Harpenden, UK and New York: Terra and Oxford University Press; 2000.
[29] B. Balaei, S. Wilkinson, R. Potangaroa, P. McFarlane Investigating the technical dimension of water supply resilience to disasters. Sustain CitiesSoc 2020;56:102077.
[30] S.L. Cutter, L. Barnes, M. Berry, C. Burton, E. Evans, E. Tate, et al. A place-based model for understanding community resilience to natural disasters. Global Environ Change 2008;18:598–606.
[31] E. Guidoboni, G. Valensise, D. Mariotti, C. Ciuccarelli, F. Bernardini, M.G. Bianchi, et al. Il peso economico e sociale dei disastri sismici in Italia negli ultimi 150 anni. Bononia University Press; 2011.
[32] M. Modica, A. Reggiani, P. Nijkamp Vulnerability, resilience and exposure: methodological aspects. Advances in spatial and economic modelling of disaster impacts. Cham: Springer; 2019. p. 295–324.
[33] M. Modica, R. Zoboli Vulnerability, resilience, hazard, risk, damage, and loss: a socio-ecological framework for natural disaster analysis. Web Ecol 2016;16(1):59–62.
[34] NASEM - National Academies of Sciences, Engineering, and Medicine Attribution of extreme weather events in the context of climate change, 352. National Academies Press Science; 2016. p. 1517–1518. 6293.
[35] P. Stott How climate change affects extreme weather events. Science 2016;352(6293):1517–1518.
[36] S.B. Manyena The concept of resilience revisited. Disasters 2006;30:433–450.
[37] UNDRO Natural disasters and vulnerability analysis. Report of experts group meeting of 9-12 july 1979. Geneva, Switzerland: UNDRO; 1980.
[38] O.D. Cardona, M.K. van Aalst, J. Birkmann, M. Fordham, G. McGregor, R. Perez, et al. Determinants of risk: exposure and vulnerability. In: C.B. Field, V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, editors, et al.. Managing the risks of extreme events and disasters to advance climate change adaptation. A special report of working groups I and II of the intergovernmental panel on climate change (IPCC). Cambridge, UK, and New York, NY, USA: Cambridge University Press; 2012. p. 65–108.
[39] UNISDR Global assessment report on disaster risk reduction: revealing risk. Geneva: Redefining Development. United Nations International Strategy for Disaster Reduction; 2011.
[40] F. Pagliacci, M. Russo Be (and have) good neighbours! Factors of vulnerability in the case of multiple hazards. Ecol Indicat 2020;111:105969.
[41] S. Paleari Natural disasters in Italy: do we invest enough in risk prevention and mitigation? Int J Environ Stud 2018;75(4):673–687.
[42] Q.M. Yaseen, R. Akhtar, M.K.U. Khalil, Q.M.U. Jan Dynamic inoperability input-output modeling for economic losses estimation in industries during flooding. Socio-Economic Planning Sciences; 2020. p. 100876.
[43] T. Nannicini, A. Stella, G. Tabellini, U. Troiano Social capital and political accountability. Am Econ J Econ Pol 2013;5:222–250.
[44] IFRC World disasters report 2020: come heat or high water. Switzerland: IFRC/RC; 2020.
[45] J.F. Hair, W.C. Black, B.J. Babin, R.E. Anderson Multivariate data analysis. seventh ed. Prentice Hall Higher Education; 2009.
[46] G.W. Milligan, M.C. Cooper An examination of procedures for determining the number of clusters in a data set. Psychometrika 1985;50(2):159–179.
[47] OECD OECD reviews of risk management policies. Paris: Italy. OECD; 2010.
[48] OCDPC 171/2014 Contributi per gli interventi di prevenzione del rischio sismico per l'anno 2013. GU n. 145 of 25.06.2014 n. 171 of 19 June 2014. 2014.
[49] Presidenza del Consiglio dei Ministri Italiasicura – il Piano nazionale di opere ed interventi ed il Piano finanziario per la riduzione del rischio idrogeologico. Appendice I; 2017.
[50] DPCM Approvazione dell'indicatore di riparto su base regionale delle risorse finalizzate agli interventi di mitigazione del rischio idrogeologico 5 December 2016. GU n 2016;21. del 26.01.2017.
[51] Law 145/2018. 30 December 2018, n. 145. Bilancio di previsione dello Stato per l'anno finanziario 2019 e bilancio pluriennale per il triennio 2019-2021. GU n. 302 of 31.12.2018 S.O. n. 62..
[52] Legislative Decree 1/2018 Codice della protezione civile, GU n.17 of 22.01.2018 2 January 2018, n. 1. 2018.
[53] A. Contrino Le misure per le attività produttive. In: L. Basilavecchia, L. Del Federico, A. Pace, C. e Verrigni, editors. Interventi finanziari e tributari per le aree colpite da calamità tra norme interne e principi Europei. Torino: Giappichelli Editore; 2016. p. 235–259.
[54] IRCrEs-CNR, IDPa-CNR, IRPI-CNR, INGV, SEEDS con il supporto di Fonazione Generali La valutazione economica dei disastri naturali in Italia -. Rapporto sui principali risultati (mimeo); 2018.

Biography

Giovanni Marin is Associate Professor of Applied Economics at the Department of Economics, Society and Politics, University of Urbino Carlo Bo (Italy) and research affiliate at Sustainability Environmental Economics and Dynamics Studies (SEEDS). Formerly, he was post-doctoral researcher at IRCrES-CNR (Italy) and visiting researcher at OFCE SciencesPo (France). He holds a Ph.D. in Economics, Markets, Institutions, IMT Institute for Advanced Studies Lucca (Italy, 2012). He is author of several articles on international journals on environmental policy, environmental innovation and environmentally extended input-output analysis.

Marco Modica is Assistant Professor of Applied Economics at the Gran Sasso Science Institute. Formerly, he was post-doctoral researcher at IRCrES-CNR (Italy). He holds a Ph.D. in Economics, Markets, Institutions, IMT Institute for Advanced Studies Lucca (Italy, 2013). He is Member of the scientific committee of the Consortium REDI (REducing risks of natural Disaster). He has carried out various consultancy activities and published articles in international scientific journals on regional and urban resilience; environmental policy; economics of natural disasters.

Susanna Paleari is Researcher at the Research Institute on Sustainable Economic Growth (IRCrES) of the Italian National Research Council (CNR). She holds a PhD in Policies and institutions, Catholic University of Milan with fellowship at the Global International Waters Assessment (GIWA), University of Kalmar, Sweden. Since 2002, through IRCrES, she has been collaborating with the international consortium European Topic Center which supports the work of the European Environment Agency. She has carried out various consultancy activities and published articles in international scientific journals on legislation and environmental policies, environmental institutions and their interactions.

Roberto Zoboli is Full Professor of Political Economy in the Faculty of Political and Social Sciences of the Catholic University of the Sacred Heart, where he teaches Economic Policies for Resources and the Environment. He has been collaborating on topics such as green economy, circular economy and economics of natural disasters with the EEA (European Environment Agency) through Seeds, the inter-university research center on the economy of sustainability, of which the Catholic University is part.