Learning From The Past. Forecasting Community Disaster Resilience after the 2016 Central Italy Earthquake via Supervised Machine Learning.

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1 Introduction

Socio-Natural Disasters and climate change are today a central social and political issue, interesting governments and scientists around the world. Indeed, due to the increase in both occurrence and number of people affected over the last years, the topic of how to improve the resilience of nations and communities has been a central focus of the UN agenda with the "2005-2015 Hyogo Framework for Action" (Basabe, 2013) - first - and the "Sendai Framework for Disaster Risk Reduction 2015-2030" (Aitsi-Selmi et al., 2015) - now.
Guided by this UN agenda, the concept of resilience is today the principal framework linking scientific studies on Socio-Natural Disasters and climate change with the reality of politics and policies (Norris et al., 2008).

Disasters triggered by natural phenomenons affect, without discrimination, coastal and mountainous areas, urban or rural. By impacting on the built environment and both the social and economic structure, Socio-Natural Disasters can be particularly detrimental for those areas that were already locked-in in a difficult situation or in an underdevelopment path (Wilson, 2014). Nonetheless, studies focused on the communities' ability for resilience (Hassink, 2010; Corbo et al., 2016; Zautra et al., 2008) showed that facing such disastrous events could also provide a positive opportunity for those communities to fight negative trends and exit the dependency path. Indeed, by disrupting the economic and social structure of communities, disastrous events generate a temporary window of opportunity by "suspending the everyday life" (Berger and Luckmann, 1966).
Granted that fitting actions and policies are put into action during the recovery phase, this temporary window of opportunity might represent a turning point in the development path of these communities. A focus on resilience and communities is instrumental to exploit this window of opportunity by addressing the issue of guiding and selecting the fitting actions and policies for different scenarios and situations.
This paper aims at creating a forecasting model, via Supervised Machine Learning, that can be used to evaluate the resilience ability of Italian rural communities. Our research strategy is strongly tied to its context of application, therefore both the training process and application of the model will concentrate on rural communities of Central Italy with their peculiarities and characteristics.
Today, such context-specific quantitative analysis, are possible thanks to the increase in computational capacity and data creation and collection which enabled us to apply advanced statistical techniques to problems in social sciences. If channelled, the continuous revolution in computational capacity and data collection of the last decade, could give a renewed strength to social sciences in their ability to create significant impact on reality. At the least, it cannot be ignored considering that it is already impacting social sciences and how we think the world, study it and make decisions (Labrinidis and Jagadish, 2012; Mayer-Schönberger et al., 2013).
Exploiting the potential of these advanced computational tools could be especially relevant for fields like Disaster Studies and Climate Change studies, where the ability to forecast the outcome of a recovery process can, for example, help administrations to allocate resources and policies where they are most needed.
To test and discuss the potentiality and limits of this approach, it will be applied to the communities affected by the Summer 2016 Central Italy earthquake.
Italy presents itself as an interesting case study for Community Disaster Resilience, especially when focusing on rural communities and the link of Disaster Resilience with their general development trend.

The entire country sits on the meeting point between the Eurasian Plate and the Adriatic Plate. As a result, the Apennine Mountains - crossing the country from North to South - concentrate many seismic faults, causing Italy to have an incredibly high amount of tectonic activity and seismic hazardous events (Valensise et al., 2017). Due to its particular geographical characteristics, three out of four major seismic event of the last decades, affected the rural areas of the country, particularly the Central Apennines at the intersection between the four regions of Abruzzo, Marche, Umbria and Lazio, which is of particular interest for our study.
Indeed, this area - commonly referred to as Central Italy - is mostly inhabited by rural communities which share a common socio-economic structure and a long history of depopulation, ageing and economic decline.
To forecast the resilience ability of such rural communities affected by the last major earthquake (in 2016),

we applied a Machine Learning solution to the specific case study. Specifically, we applied a Supervised Machine Learning solution, allowing to maintain a great deal of control on both the selection of training cases and relevant variables. This (highly) supervised strategy fits quite well with the complexity of social sciences. Indeed, Machine Learning solutions commonly follow a data-driven strategy but - in order to deal with the specificities of our case study and the complexity of the concept of resilience - we proposed a *Context-Bound* strategy where the learning process is performed only on similar communities affected by seismic events over a set of variables accurately selected from specific literature on the disaster resilience ability of rural communities.
As a result of this strategy, the forecasting model will be very accurate for the specific case - and similar comparable ones - despite not being completely generalizable. A generalizable model, able to forecast community resilience for different kind of communities, situation and disasters, is theoretically possible but still out of reach due to lacking enough training cases and a consistent collection of data. As well as being a study on a specific case, this paper also works as proof of concept for the use of Machine Learning solution applied to problems and questions in social sciences.
While tools and techniques from the field of Machine Learning have been steadily implemented in many disciplines since the nineties (e.g.(Konenko, 2001; Way, 2012)), Social Sciences have been - historically - quite resistant to this kind of implementation. This is not because of a bad disposition of social scientists to quantitative analysis and data-driven strategies, rather because of the extremely complex nature of the social world. Today, the computational and data revolution presents an opportunity for the future of social sciences.
In calling for more studies mixing a context-bound approach with the data-driven strategy typical of these computational tools, the author strongly believe that it will give social science a new strength to create real impact for the benefit of society.
The paper is organised as follows. The next section will present the concept of Community Resilience

alongside the challenges to develop a heuristic measure. Section 4.3 instead, presents the data employed with a specific focus on i) the case study and the selection of training cases ii) how the target variable is defined and its implications.
Section 4.4 discusses the empirical strategy of the research and how the model is constructed from scratch. Due to Machine Learning being a relative new trend in Social Sciences, different steps are here discussed even if not implemented in the final model. Finally, the last section presents and then discusses the model and the developed forecasted scenario. Here the results are connected with specific policy indication to build more resilient communities.

2 Measuring Community Resilience

The concept of resilience, especially in the context of disaster studies, became - over the last decades - one of the main focuses of academic studies and public policies to improve the response of society to adverse events (Cutter, 2012; Tiernan et al., 2019). The concept itself, imported from physics (Holling, 1973; Alexander, 1997), gained a lot of attention across many disciplines in social sciences - from sociology to economics, disaster studies, regional studies, geography etc. - partially thanks to its metaphorical nature and its communicative power (Norris et al., 2008; Carpenter et al., 2001). This widespread, almost chaotic, enthusiasm about the concept of resilience brought different disciplines to frame and define it according to different interests and subject of study (Mayunga, 2007; Southwick et al., 2014).
In the field of disaster studies, one of the most prolific frameworks for the concept of resilience, proposed

from sociological contributions, is the one of *Community Resilience* (Gaillard, 2007) which focuses on capturing resilience along a series of sub-dimensions of the social structure (Faggian et al., 2018), highlighting the complexity of society and making it a key strength of the approach. Following the definition given by Norris (Norris et al., 2008), community resilience is a *"Dynamic process composed by many adaptive capacities to response and change after adverse events"*.
The strength of such a theoretical definition can be found in how it highlights the complexity of the concept, but also in the fact that it does not directly translate into a heuristic measure. This is central for us. Indeed, it allows - pushes almost - researchers to develop heuristic measurements of resilience based on the characteristics and the needs of the affected communities rather than relying on general measures.
In a context, and in a field, where most studies focus on the disaster resilience ability of urban communities (Baker, 2012; Chamlee-Wright and Storr, 2009; McCreight, 2010; Peacock et al., 1997) and mostly deals with rural communities only in comparison with them (Cutter et al., 2016; Paton and Johnston, 2017), such place-based approach is the most suited for our case study.
Prominent studies about communities' resilience to natural disasters employ composite indexes (Mayunga, 2007; Cutter et al., 2008) to keep together the different feature composing this ability. This popular approach focuses the measurement of resilience on the communities' overall ability, subdivided over a set of defined indicators. While this approach is very powerful in comparing communities and showing their strength and weak points, it is also very susceptible to how features[1] are presumed to impact positively or negatively on resilience. Rural communities are inherently very different from urban communities (Barca et al., 2012; Roberts et al., 2017) and, when such indexes are applied to communities with very different socioeconomic situation, these presumed positive or negative features can instead have different behaviours. Despite the fact that such indexes hold great communicative power, they loose any possible theoretical justification if directly applied to the rural, mountainous and mostly agricultural communities interesting this study.
Following a *context-based* approach, we designed a research strategy where the relevant features composing the ability for resilience (and how they behave) are not presumed but directly selected from the context using Machine Learning solutions.
Instead of defining resilience as composed by certain features and add them up to have an overall measure, we - first - defined a dynamic measure for resilience which is used to find a group of features (from a wider set) to compose a model of the ability.
In order to perform such task in Machine learning, the algorithm will need to train over defined examples of resilient and not resilience communities. To provide such examples we - first - need a dynamic measurement discriminating between them.
Ecological studies on disaster resilience show how resilience can be inferred from the effect on dynamic processes over time across the perturbation (Lam et al., 2015). Considering the socioeconomic characteristics of Central Italy rural communities and the decades-long processes of depopulation and ageing, we believe that the most suited way of inferring the resilience of communities is by looking at the dynamics of population variation over time and after a natural disaster[2].
In some way, it can be viewed as a thermometer for the health of a community. In the same way, a thermometer measures the internal temperature of a body and you can tell if someone is ill or not, using population variation, we measure the health of communities by focusing on the dynamic aspect of it and looking if the population is growing or decreasing. Like measuring the internal temperature of a body, this is not a direct measure of health and does not say anything about what is wrong or not, but - since we already know what is wrong with our communities (they have been affected by a Socio-Natural disaster) - this way we can evaluate their response or, in other words, the effect of their resilience ability.
Using such measurement to define resilient and not resilient communities, we will train our algorithm over a wide range of features to find the most *context-suitable* set composing their ability for resilience to natural disasters.

[1] While social scientists commonly refer to quantitative indicators as *variables*, in the field of Machine Learning they are indicated by the term *features*. In the interdisciplinary context of this chapter I will use both as synonym.

[2] The relationship between such dynamic process and disaster resilience in Central Italy rural context has been further discussed in Chapter **??**

3 Data

3.1 Case Study description

The area of Central Apennines, between the four regions of Lazio, Abruzzo, Umbria and Marche is one of the most seismically active in Italy. In 2016, from the end of the summer to mid-autumn, a long earthquake swarm has put many communities of the area down to their knees, causing a great deal of destruction and taking away many lives. The seismic event (as reported by the INGV, Istituto Nazionale di Geofisica e Vulcanologia) started on August 24th at 3:36:32 (UTC+2) with a shock of 6.2 moment magnitude and the epicentre located near the municipality of Accumuli at a depth of 8 Kilometres (working group on the Amatrice earthquake, 2016). The earthquake swarm continued all night and for the following weeks culminating with two other big seismic events on October 26th and 30th, respectively of 5.4 and 6.5 moment magnitude(Figure 1).

The main-shock, on August the 24th, caused the death of 299 people, 236 in the municipality of Amatrice, 11 in Accumuli and 49 in Arquata del Tronto. The Italian department for risk prevention and management (Protezione Civile) reports that more than 350 people were severely injured during the seismic event. Between August and October, the earthquake swarm caused a great deal of damage in 131 municipalities in the area, as acknowledged by the Italian government in the emergency decree (D.L. 17 October 2016, n. 189 and D.L. 30 October n. 205). Among these 131 municipalities the ones of Amatrice, Accumuli, Arquata del Tronto, and Norcia suffered the most, particularly the two municipalities of Amatrice and Accumuli were almost completely torn down by the main-shock on August the 24th.

While the consequences of this Socio-Natural Disaster regarding the loss in human life and the destruction of buildings and infrastructure are clear, the long-term consequences for this region and for the communities that live there are more complex to predict. Figure 1 shows the whole affected area as defined by the Italian government. Among the 131 municipalities, more than 60% of them are classified as “Inner Areas” by the Italian Agency for Economic Development and Cohesion (Dipartimento per lo Sviluppo e la Coesione Economica). The classification, born in 2012 (Lucatelli, 2014), aims at individuating socially and economically vulnerable municipalities to develop local policies and eventually reduce their gap in development.

All Italian Inner Areas have common characteristics, they are economically vulnerable rural communities situated far away from cities and big urban agglomerates. In addition to the vulnerable economic situation, the communities of Central Italy also are affected by decades-long processes of ageing and depopulation.

Almost the 70% of the territory is considered mountainous (more than 900 meters over the sea level) and the built environment is accounted only for the 1,3% of it (data from ISTAT). The resulting population density is, as aspected, very low (14.5 inhabitants per square kilometre) and the average age of the population very high. Indeed, as registered for all Italian Inner Areas, the age of the population is above the Italian average and 28,3% of the inhabitants are 65 or more years old. This is not very surprising, considering that since the seventies all these territories are suffering from structural processes of population ageing and depopulation, but is an important indicator of the vulnerability of these territories.

Both the *structural dependence index* (proportion between the 0-14 years old population plus the 65 or more years old population and the population in working age) and the *oldness index* (proportion between the 65 or more years old population and the 0-14 years old population) indicate not only that these territories are quickly and constantly ageing but also that there is a big discrepancy between people in working age and who is too young or too old to work.

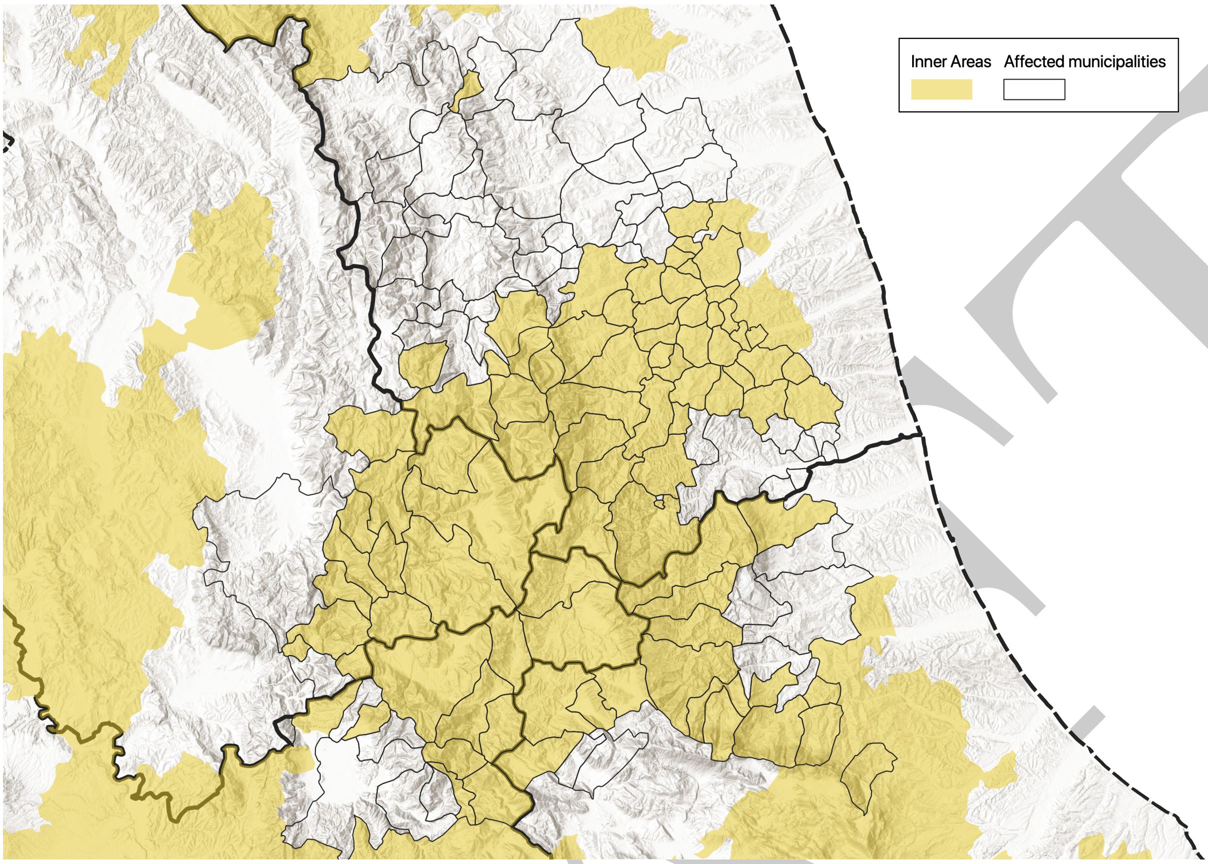


Figure 1: Summer 2016 earthquake affected area.

Population, despite the presence of some small urban centres, is widely dispersed among many little inhabited nuclei, farms, and single dispersed houses. This wide dispersion is related to the territorial conformation of the area, predominantly mountainous, and has important consequences for the labour market and mobility. Indeed, the percentage of the employed population working in the same municipality of residence is 65.2%, higher than the Italian average (ISTAT, census 2011). The economic structure of the area is predominated by the agricultural sector, mainly composed by family owned business. Agriculture has a high impact on the population, in terms of the number of farms per inhabitants employment and number of jobs, but the situation is very different for what regards the industrial and services sectors. Indeed, both the industrial and services sectors have a low added value per person of around 8400 Euro, against the Italian mean value of 16000 Euro (ISTAT elaboration on MEF data, 2014).
In this situation, the damages caused to the socio-economical structures by the earthquake can be much

more significant than expected, due to this processes, but - at the same time - the recovery period could also a turning point towards a new development path (Zautra et al., 2008).

3.2 Training cases

The training cases are a set of instances (municipalities, in this specific case) on which the algorithm will learn to classify resilient communities from not resilient ones, therefore an adequate selection of these cases is essential. Training cases are to be selected outside of our case study and, since we are employing a Supervised Machine Learning strategy, they need to be attached with their relative outcome (whether they are resilient or not).
For the initial selection of our training cases, we followed a general condition: being affected by a major earthquake in the last 20 years. There are interesting cases of municipalities affected by major earthquakes before the 1990s (e.g. the Friuli earthquake in 1976 and the Irpinia earthquake in 1980) but, due to changes in the structure and content of the Italian Census over the years, we are missing much of the data required for the training.
In addition to the Central Italy summer 2016 earthquake, there have been three major earthquakes in

Italy over the last 20 years. All three of them affected mostly rural communities and two of them hit the mountainous regions of Central Italy. Respectively, these events are known as: the *Umbria & Marche earthquake of 1997*, which affected rural communities across the border between the two regions of Umbria and Marche. The *L'Aquila earthquake of 2009*, famously known for its devastating impact on the city of L'Aquila, the capital city of the Abruzzo region and the surrounding rural communities. Last, the *Emilia earthquake of 2012*. The Emilia 2012 earthquake is the most different among the four since it affected municipalities of the Centre-North of the country in the Emilia-Romagna region. Unlike most Italian rural communities, rural communities in Emilia are mostly situated in non-mountainous areas and maintains high levels of production (for both intensive agriculture and industrial) and exportation.
Figure 2 shows the spatial distribution of these seismic events on the Italian territory.

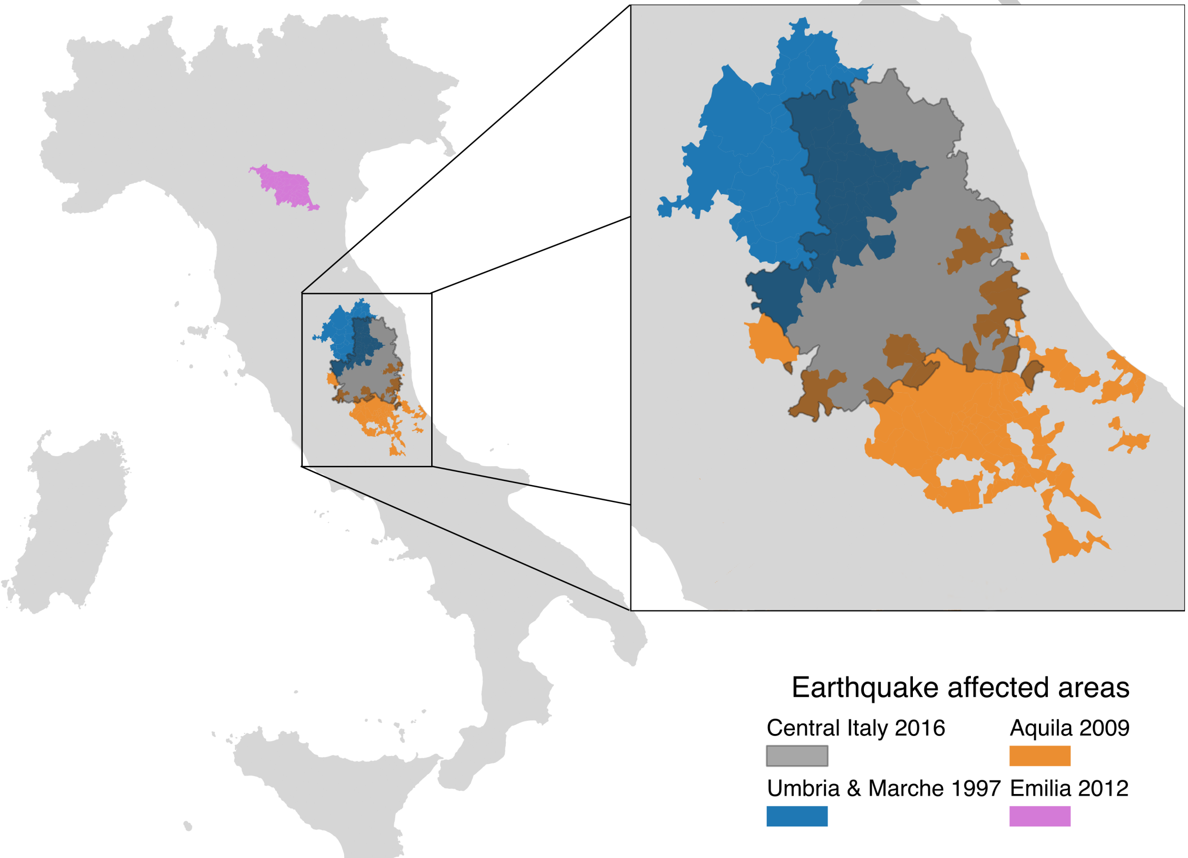
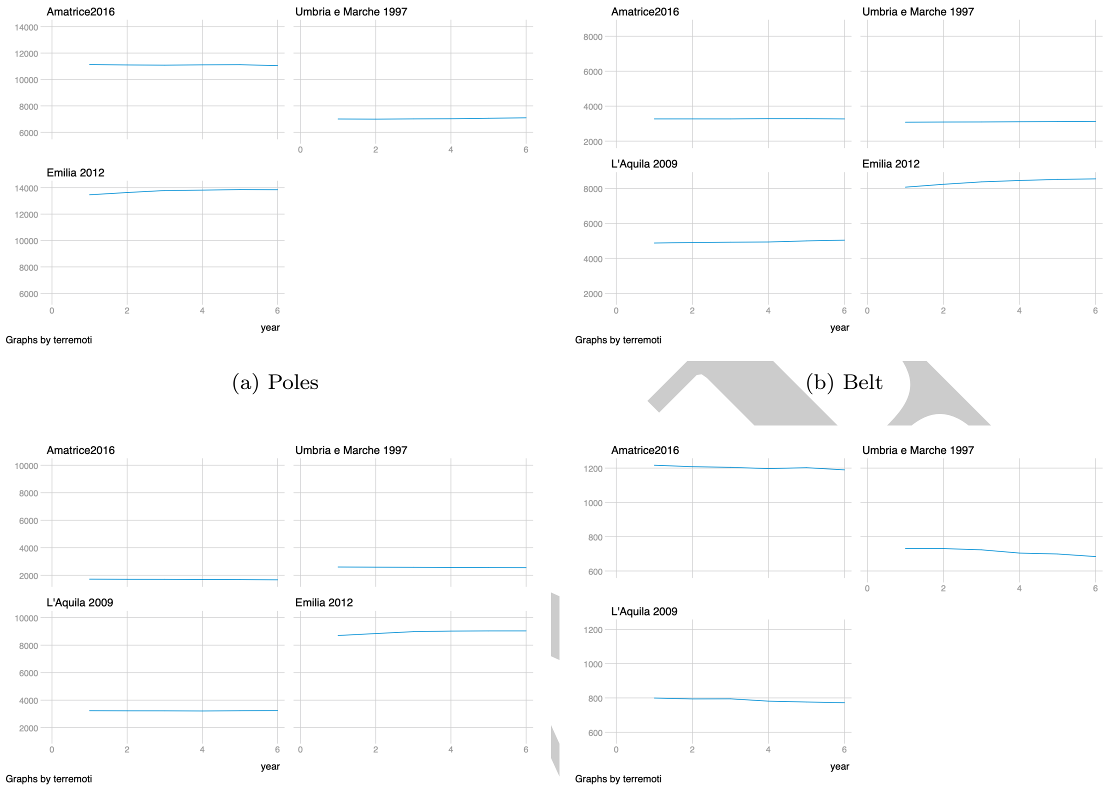


Figure 2: Italy, major earthquakes events in the last 20 years.

The image above shows clearly that the Emilia 2012 earthquake affected a very different area of the country from the other seismic events. This is even truer moving from a purely geographical level to a socio-economical one.
Emilia is, indeed, one of the richest regions not only in Italy but in Europe (Russo et al., 2000). Its flat lands produce cereals, dairy and manufacturing products (e.g. the Italian Parmesan cluster and Ferrari are both situated near the affected area) focused on exports. Emilia, as a region, holds a very long city-state and artisanship history, which Central Italy has not, and today is not only very rich but also has impressive employment rates.
Despite these clear geographical, cultural, social and economic differences, some argument about considering them as training cases could still be made. Indeed, a considerable part of the affected area is considered rural and, despite some differences, it too makes a livelihood thanks to agriculture.
Following a data-driven approach, adding the Emilia 2012 cases to the training should only help with the learning process. We are indeed adding a few more cases for the training and, considering that both target and features will be normalized, the fact that these cases are structurally quite different should not be an insuperable problem. The real problem emerges when the different dynamics of population variation are taken into consideration.
Figure 3 shows the mean resident population for five years before each earthquake. To highlights struc-

tural differences between the four earthquake-affected areas, the graphs are divided by Italian *Inner Areas* categories[3]. *Poles* (poles of services and Inter-municipal poles of services) and *Belt* are urban areas, while *Intermediate* and *Peripheral* are rural areas.



(a) Poles (b) Belt

(c) Intermediate (d) Peripheral

Figure 3: Population Trend for Affected areas before the earthquakes.

Differently from the other three groups, the municipalities of Emilia 2012 are more populated in each category (there are no Peripheral areas among the municipalities of Emilia 2012). Moreover, considering population variation, they have a positive trend of population variation over time, while the majority of the other municipalities (both the ones considered for training and the ones in the case study) are suffering from a constant depopulation process.
Interpreted in a context-bound framework, these different dynamics in population variation are incredibly relevant, especially when considered that population variation is the key feature we use to define resilient and not-resilient communities. Indeed, while depopulation is the central issue to overcome for the communities of Central Italy, for the municipalities of Emilia this is only a marginal problem in relation to which we cannot confidently evaluate the communities ability for resilience. Continuing in our research we decided to exclude cases of municipalities affected by the Emilia earthquake of 2012 from our training.

3.3 Defining the Target

The key step in a Supervised Machine Learning problem, where the role of the scientist is most relevant, is the definition and selection of the target. The target is, indeed, what the machine will be trained to recognize during training and later forecasts for our case study. The target variable itself can take different structures and it defines the "type" of machine learning problem and which set of algorithms can be applied. In our research design, the target variable is represented by a measurement of resilience based on the dynamic of population variation over a period of time before and after an earthquake.
Due to the relatively low number of cases at our hand to perform the training, we decided to select a

[3] Such classification is a the result of a composite index developed by the Italian Department for Programming and Coordination of Economic Policy. The index focuses on highlighting socio-economic vulnerable territories.

dichotomous target variable (categorical variable with only two states defined as (0) and (1)) reducing our problem to a classification problem. The machine will be trained to classify case studies on two classes: "successfully resilient" and "unsuccessfully resilient".
Classification problems, especially with a dichotomous target, can be resolved with good accuracy and reliability even without thousands of cases from which to train with (Beleites et al., 2013).
We use population variation over a period of time before and after an earthquake. Specifically, we use the mean yearly population variation over a five year period before and after the earthquake. Considering that rural communities in Central Italy have a slowly - but steadily - increasing rate of depopulation, we defined - for the communities composing our training set - as "successfully resilience" those communities which, in the five years after the earthquake[4] had a higher mean rate of population variation compared to the five years before. All other communities were classified as "unsuccessfully resilient".
Population - declined as population variation, depopulation, re-population rate and more - has been frequently used in literature about community disaster resilience as a proxy for the resilience of a community (Aldrich and Meyer, 2014; Wickes et al., 2015; Chamlee-Wright and Storr, 2009). Here is employed as a direct measure to highlight which of our training cases had a successful recovery, projecting them in a better trend than before the earthquake. Our classification algorithm trains to classify communities in this respect using a wide range of features.

3.4 Data Source

All data used for the descriptive statistics, analysis and the algorithm's training are freely available data provided by the Italian Institute for Statistics (ISTAT) and other Italian institutional sources. Specifically, all data used for the training of the machine[5] are Italian Census data aggregated at the municipal level. For each set of learning cases, we used data from the Census before the earthquake, creating in this way a time-lag between the features and the target variable. Data about cases from Umbria & Marche 1997 earthquake are collected from the 1991 Census, while data for Aquila 2009 earthquake are collected from the 2001 Census and, data for the Central Italy 2016 earthquake affected municipalities comes from the 2011 Census.
Regarding the target variable, yearly inter-census data on resident population are employed.

4 Empirical Strategy

Supervised Machine Learning is a heuristic technique where the researcher and the machine work together to develop a model. By working together each applies to the problem his/her/its best talents. One is rational the other intuitive. Indeed, where the machine brings enormous - and rigorous - computational ability, it can only reason inside the boundaries of its rational programming (at least for now). On the other hand, the social scientist - assisted by its flawed and limited biological brain - has unknowingly trained for years to find and recognise patterns and connections with very limited and chaotic information (Lindsay and Norman, 2013). To produce a good model using this technique, they have to work in synchronous. The data scientist knows the field, he/she knows - or can infer - patterns or correlations even before the study is performed. He/she knows all about the context, its history and past studies, but he/she never works directly on the computation of the model. The machine computes the model. The machine does all the computational works and looks for patterns and correlations. Performing different, separated, tasks the two must work together.
There are different extents of this *collaboration* in Machine Learning. Supervised Machine Learning is the branch of ML where the collaboration is not only necessary but is the most relevant aspect of the technique itself.
We applied this Supervised strategy to the problem of classifying which community has the characteristics to be resilient, respond, and react after being affected by the Summer 2016 central Italy earthquake. The classification will be performed by an algorithm trained on data from Italian municipalities affected by earthquakes in the last 20 years.
Our empirical strategy is distinguishable in three phases. First, we select the relevant cases and features

[4]the two years right after the events were not considered for the means
[5]All but one, this will be discussed in the next section.

(variables) to train our model with, this is done starting from the literature on disaster community resilience. The selection of the training cases has been already discussed, section 4.4.1 will present all the variables considered for the training job and the process with which the variables employed in the model are chosen. Before the second step, data for all variables are standardised and normalised. The second step is to select the most fitting algorithm to represent our problem, which is done via a Cross Validation process described in section 4.4.2. This is a critical step in building the machine where different algorithms are trained and compared using their accuracy (the share of instances they can correctly classify). This step is very important since it allows to compare how different algorithms are able to represent the data, aiming to select the algorithm most suitable to our data and context. For the Cross Validation process, only data with known outcome (the target - or dependent - variable is known) are employed, this is called a training set. The training set employed for this task is composed of municipalities affected by the 1997 Umbria and Marche earthquake and by the 2009 L'Aquila earthquake. For the Cross Validation process to work first the training set (composed of 135 cases) is randomly split in two (80/20). The 80% split is used to compare algorithms while the 20% split (also called validation set) is only used at the end of the process to evaluate the performance of the selected algorithm on previously unseen data. As the third and final step, we perform what is called a selection of features. In this step both, the individual correlation between the variables and the target, and their cumulative explanatory capacity, are evaluated. This is done to i) show which variables are more relevant for the context; ii) control the robustness of the model; iii) check if a model employing a reduced set of variables can be more accurate than the model employing all variables, therefore individuate variables which could be adding noise in the analysis.

At this point, the model is ready to be trained and applied to our classification problem for the municipalities affected by the 2016 Central Italy earthquake.

4.1 Choosing the relevant variables

An important advantage of using Machine Learning techniques is that it makes fairly easy and convenient to work with a big number of different variables (Kotsiantis et al., 2007). Thanks to many computational operations the algorithm can fit itself on relevant variables and ignore the ones which are useless or even problematic (by generating noise and outliers). Accordingly, one strategy we could have chosen was to train the machine on all the variables available at our hand. On the other hand, given the relative low number of cases for our training - which, paired with an unbalanced high number of variables would have increased the noise and the possibility of overfitting our model - and the specificity (and, at least partial, internal homogeneity) of our case studies we preferred to perform an a-priori *feature selection* based on relevant literature on the subject and the specificities of our case study.
Contributes to Community Disaster Resilience were considered to perform this initial feature selection

(Cutter et al., 2008; Mayunga, 2007; Aldrich and Meyer, 2014; Birkmann, 2007; Morrow, 2008; Hallegatte and Przyluski, 2010; Capello and Perucca, 2017; Islam and Akmam, 2017). According to literature, community disaster resilience is - by definition - composed of many adaptive capacities (Norris et al., 2008). This heterogeneous set of capacities is usually measured by a wide range of features (variables) describing different spheres of the community's life. The table in Appendix A shows a comprehensive list of all the variables which were considered for the training of the machine. The list envisions 6 categories of features depicting 6 different dimensions of the community: Demographic, Economic, Infrastructural, Geographical, Institutional and Social.
Literature agrees that all the dimensions are relevant in composing the community ability for resilience (Mayunga, 2007; Cutter et al., 2010), but specific studies focusing on rural communities show that the difference between urban and rural communities creates some general distinction. According to a study performed in North America (Cutter et al., 2016) - comparing how the resilience ability of communities is composed between urban-rural communities - not only urban communities are more resilient than rural ones, but they also have different drivers. In urban contexts, resilience is driven by the infrastructural and economic dimension, while (according to the paper) for rural communities the dimensions contributing the most to the overall resilience index are the social (Social Capital) and environmental.
From the existing literature, we composed a list of 41 indicators, subdivided into 6 dimensions, able to

measure the community disaster resilience ability for Italian case studies. The list in Appendix A reflects the indicators used for studies in North America and has been fitted to the Italian context.
For our learning process, we selected only a part of these indicators, due to two main reasons. Some

variables, however relevant and interesting, were kept out only due to data collection problems. This is especially the case of many indicators of the institutional dimension on which we, unfortunately, have data only for the last five to ten years (e.g. Environmental public expenditure, Administrative transparency, Num. of No-profits controlled by administration), but notably also of the share of population living where they were born.
The second reason is due to the empirical setting of the research, considered the context of our case study, we decided to keep out of this supervised learning process some variables which would have not helped the training[6]. This selection has been made with two principles in mind i) eliminate variables which are not relevant in the specific context (Cutter et al., 2016; Capello and Perucca, 2017; Murphy, 2007; Wilson, 2014), this is the case of variables such as credit access, the share of creative workers and the mean house price; ii) eliminate variables which are quite homogeneous in the affected areas and would have only added noise to the model. For example, this is the case of the digital divide, number of hospital beds, number of schools, and national parks.
Balancing the number of training cases at our hand with the available features, we selected the following

22 to start running the learning process on:
Population dimension (Aldrich and Meyer, 2014): Total resident population at the Census.
Population variation trend (Aldrich and Meyer, 2014): Yearly population variation for a five years period before each earthquake.
Elderly (Morrow, 2008): Share of inhabitants over 65 years old, out of the total number of inhabitants.
No diploma (Morrow, 2008; Norris et al., 2008): Share of inhabitants with no high school diploma, over the total number of 18+ years old inhabitants.
Italian speaker (Morrow, 2008): Share of inhabitants speaking Italian as first language, out of the total number of inhabitants.
Share of daily commuters (Tierney, 2009): Share of inhabitants commuting daily out of the municipality for work or study, out of the total number of inhabitants.
Income (Norris et al., 2008; Mayunga, 2007): Mean income. The value is expressed in Euro and adjusted for inflation.
Employment (Mayunga, 2007; Norris et al., 2008): Share of employed inhabitants, out of the total number of inhabitant in working age (15-64 years old).
Female employment share (Cutter et al., 2010): Share of women employed, out of the total number of employed inhabitants.
Singol sector employment (Adger, 2000; Berke and Campanella, 2006): Share of workers employed only in agriculture, out of the total number of workers.
Small business (Mayunga, 2007; Norris et al., 2008): Share of business with 3 or less employ, out of the total share of business.
Urban population share (Tierney, 2009): Share of inhabitant living in urban centres, out of the total number of inhabitants.
Old houses (Mileti and Noji, 1999): Shares of houses built before 1971, out of the total number of residential buildings.
Renting families (Cutter et al., 2008): Shares of families living in renting situations, out of the total number of families.
Cooperative workers (Norris et al., 2008; Murphy, 2007): Shares of workers in social cooperatives, out of total employed workers.
Voters turnout (Morrow, 2008): Voters turnout for the European elections prior to each earthquake. These are: 1989 elections for cases of the 1997 Umbria & Marche earthquale, 1999 elections for cases of the 2009 Aquila and 2012 Emilia earthquake, and 2009 elections for the summer 2016 Central Italy earthquake.
Number of no-profit (Murphy, 2007): The number of no-profit associations for thousand inhabitants.
Religious marriages (Murphy, 2007; Morrow, 2008; Vale and Campanella, 2005): The share of religious marriages, out of the total number of marriages.
Numerous families (Vale and Campanella, 2005): The share of families with five or more members, out of the total number of families.
Distance from pole (Valensise et al., 2017; Mayunga, 2007): Linear distance from the nearest pole of services. Poles are defined as cities with more than 25000 inhabitants.
Altitude (Valensise et al., 2017; Mayunga, 2007): The median altitude of the municipality.

[6]Due to the relatively limited number of cases available for the training, a decision was made to not use all the available variables to reduce the total dimensions on which the algorithm has to fit in, thus improving its reliability for the specific context

Public founds for reconstruction[7] (Mayunga, 2007; Godschalk, 2003): The amount of public founds allocated for the reconstruction and recovery of the affected area. This value is equal for each municipality inside the same crater area, and it represent the public resourced planned to be allocated over a 20 years period. The value is expressed in Euro (adjusted for inflation) per inhabitant of the crater area.
Variables are recorded at municipal level from freely available census data (provided by ISTAT) or other freely available national database[8]. Data are recorded with a comparable time-lag for each separate affected area, specifically: for the municipalities affected by the 1997 Umbria and Marche earthquake, data from the 1991 Census are used; for the municipalities affected by the 2009 L'Aquila earthquake, data from the 2001 Census were used; finally, for the municipalities affected by the 2016 Central Italy earthquake, data from the 2011 Census were used.
All 22 are allocated for the training of the algorithm considering that i) a further feature selection will be performed afterwards to create a *reduced model* and test it ii) during the training process the algorithm will shrink the coefficient of non-influential variables close to 0 (L2 - Ridge regression - regularization).

4.2 Cross Validation

Since we don't know which algorithm is best suited (is able to fit our training data but also to be generalised) to model our classification problem, we started by comparing simple different classification algorithms using a cross validation process. We selected seven classification algorithms among the most common and simple (again to reduce the problem of over-fitting the data in training).
The seven algorithms[9] are: Logistic Regression Classifier (LR), K-Neighbors Classifier (KNN), Decision Tree Classifier (CART), Naive-Bayes Gaussian Classifier (NB), Linear Support vector Machine Classifier (LinearSVM) and a simple Neural Network(MLPClassifier).
Before feeding the algorithms, data have been normalized using the Min-Max method and centred on 0. This data transformation has been done to simplify the learning process for the algorithms, but also because it *bounds* our measurements to the case study by transforming them into relative scores on a scale composed only by our observations.
The Training set is composed of a total of 135 observations (91 classified as "Unsuccessfully Resilient" and 44 as "Successfully Resilient"). For the cross validation process, algorithms are trained and tested only on 80% (108 observations) of this observations. 20% (27 observations) of them are held out for the final validation of the selected algorithm on previously unseen data. This 20% is selected randomly but accounting for the different proportion between "Unsuccessfully Resilient" and "Successfully Resilient".
To compare the performance of different algorithms, we employed a repeated CV (Cross Validation) strategy with 5 splits and 100 repeats. In more practical terms, the training set is split into five subgroups (subgroups are randomized via a randomly generated number) each composed of 21 observation, than each algorithm trains on four of these groups, and finally is validated on its classification accuracy over the last one. In other words, the strategy consists of training the algorithm on 4/5 of the training set and test it on the remaining cases.
This operation is repeated 100 times with different groups for train and validation.

[7]Data on these public founds are not produced by ISTAT. They have been collected by the authors consulting multiple dossier produced by the Italian Chamber of Deputies.
[8]Such as the declared income from the Italian Ministry of Economy and Finance, and the National Historical Archive of Elections.
[9]The algorithms selected are the most common and simple employed for classification tasks. The different logical and mathematical functioning of the algorithms is not discussed here, only the two most accurate algorithms (LR and SVC) are described more in depth. For a specific introduction on how a specific algorithm works, please refer to Aggarwal (2014).

Table 1: Cross Validation results

Algorithm	Accuracy
Baseline	0.558272 (0.104473)
LR	0.841841 (0.075418)
KNN	0.773377 (0.081325)
CART	0.713217 (0.087962)
NB	0.801668 (0.075208)
SVC	0.833020 (0.076095)
NeuralN	0.803190 (0.078815)
Training size	108
Validation size	27

Algorithms are compared using the Mean Accuracy and its Standard Deviation. The Accuracy Score is conceptually very simple but also very powerful when used to compare algorithms performances. Each CV repetition gives us the share of the correct classifications. The Cross Validation scores presented in Table 1 are the means of such share of correct forecasts. The first entry of the table (Baseline) shows the accuracy for a random selection algorithm. This algorithm is not considered as candidate for the model construction, it is only shown to provide a baseline for comparison between the other algorithms and a random selection of the target.
The comparison of the CV results shows that the two most accurate algorithms are the Logistic Regression Classifier (84,2% acc.) and the Support Vector Classifier (83,3% Acc.). The two algorithms perform almost identical, which is not surprising since they are fairly similar.
It can be useful - at this point - to go a little in depth on how these two algorithms works, in order to justify the selection of one over the other.
Support vector machine algorithm tries to find the hyperplane that has the maximum margin in an N-dimensional space (N = the number of features) that distinctly classifies the data points. Data points falling on either side of the hyperplane can be attributed to different classes. On the other hand, in logistic regression, we take the output of the linear function and squash the value within the range of [0,1]. Typically, if the squashed value is greater than a threshold value we assign it a label 1, else we assign it a label 0.
So, while SVC maximizes the margin between the closest support vectors while LR produces the posterior class probability. However, among the two, we selected the LR algorithm since empirical comparisons show that it is preferable when dealing with univariate classifications (Salazar et al., 2012). Moreover, by producing class probability instead of a predicted class, the LR algorithm does not assume that the given data are enough to produce a final decision.
This property fits perfectly into our empirical strategy and provides important information on the confidence the machine has in classifying single cases.

4.3 Variable Selection

Aiming at improving the accuracy of the model and test its robustness, we performed a feature selection to reduce the number of features used. This is done to eliminate eventual non-relevant and noise-adding features (Byeon and Rasheed, 2008). After the selection of only relevant features, we will test the algorithms' accuracy one last time, to decide if adopting a reduced set of features will sensibly improve our model.
We started by performing an F Test on all the features, to test the difference in group means for our dependent (target) variable. The F Test checks for individual correlation between the features and the classes of the target, highly correlated features are given higher scores and less correlated features are given lower scores.

The F Test only captures correlation and is not able to capture non-linear effects. In order to consider the combined effect of features, we also performed a recursive feature elimination (RFE) with cross validation (Guyon et al., 2002).

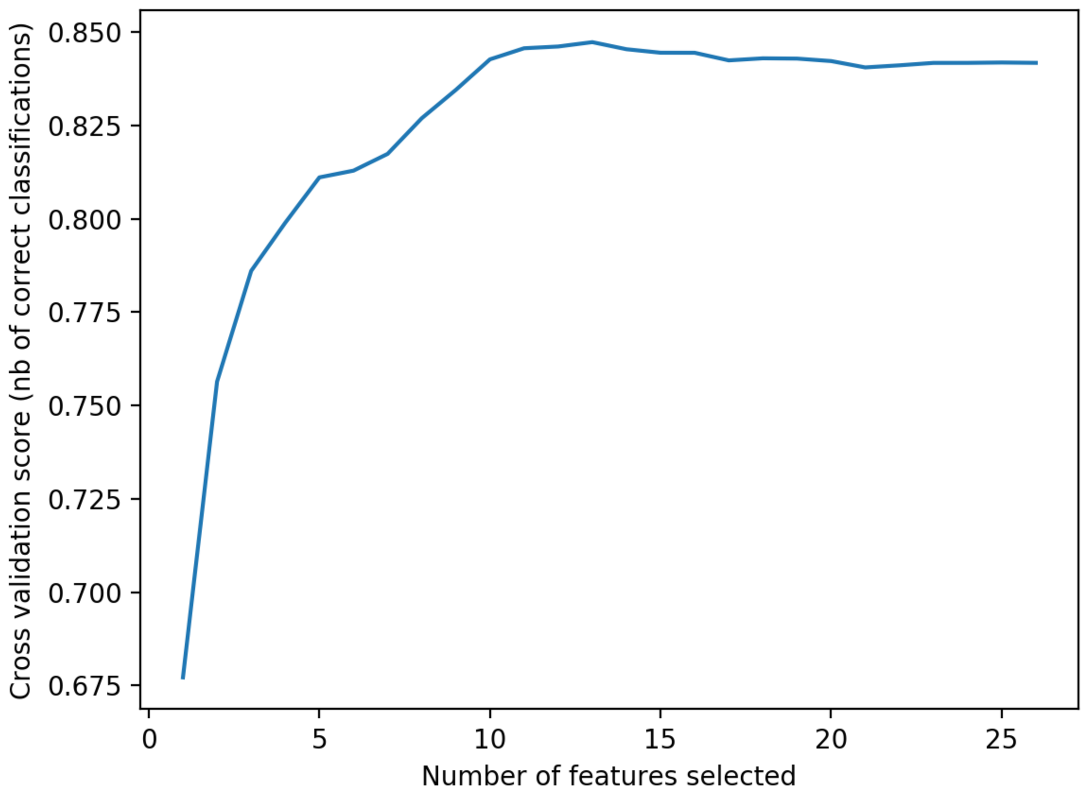


Figure 4: Recursive Feature Selection

RFE works recursively by training the model on all the given features, then the algorithm uses the weight of each feature to rank them (the weights' absolute value is used here to reflect the importance of the features) and removes the least important one. The task is repeated until all features are ranked.
Recursive feature selection returns a reduced model (using only 13 of the 22 features) scoring 0.858755 in accuracy, which is a small increase in mean accuracy from the Logistic Classifier Model with complete features scoring 0.841841.
As shown in Figure 4 the difference in accuracy is very small when using 13 or more features. Table 2 shows the correlated feature ranks and F values for each feature. While the F-Values show the variables' individual correlation with the classes of the dependent variable, the column labelled "feature ranks" shows the marginal explanatory capacity of variables.

Table 2: Feature Importance and Feature ranks.

Feature	F-value	Feature rank
Population dimension	1.00048260e-02	8
Depopulation Trend*	.	**1**
Elderly	6.92341868e-05	**1**
No diploma	1.02330821e+01	10
Italian speakers	9.08249742e-01	**1**
Income	4.10787190e-01	**1**
Employment	8.86017479e-01	11
Female employment	1.19576229e+01	**1**
Singol sector employ.	2.95181341e+01	**1**
Small Businnes	7.59481130e-02	14
Urban population share	3.77185494e+00	12
Old houses	8.38137527e+00	4
Renting families	9.34000764e-03	**1**
Cooperative workers	2.46660801e-01	7
Voters turnout	7.67911491e+00	**1**
No-profit	2.47073832e+00	3
Religious Marriages	2.95662181e-01	**1**
Numerous Families	2.94107017e-01	**1**
Distance_pole	9.78069419e+00	**1**
Altitude	3.93885562e+00	9
Daily commuters	5.20758576e+00	**1**
Public founds	3.30615470e+01	2

* The depopulation trend is composed by five separate features indicating the yearly depopulation rate up to five years before the earthquake. Two have been selected for the reduced model.

Variables with a rank of 1 are the ones selected for the reduced model using recursive feature selection. Higher ranks indicate that the variable is dropped in an earlier iteration during RFE.
Interesting enough, variables with rank 1 are quite dissimilar between them and address different characteristics of the communities (demographic, economic, social and spatial). Moreover, there is no correspondence between the individual correlation of variables (measured via the F-values) and their recursive ranking. Indeed, both the two most individually correlated[10] (Singol sector employment, F-value = 2.95181341e+01 and Female employment share, F-value = 1.19576229e+01) and the two least correlated (Share of elderly population, F-values = 6.92341868e-05 and the share of renting families, F-values = 9.34000764e-03) are ranked 1.
The reduced model (composed by only variables ranking 1) scores 0.858755 in accuracy, while the model with all variables scores 0.841841. The small increase in accuracy (1,7%) is not enough to justify the adoption of a reduced model. Despite that, both the F-values and the RFE ranks already produce interesting information (even if preliminary) that will be discussed in the last paragraph.

4.4 The Model

The Logistic Regression Classifier algorithm, trained over the full set of 22 features is chosen as the classification model. The model accuracy is tested on previously unseen data. This *validation set* is part of the training set (is a 20% of the whole training set), but it has not yet been used in the training of the algorithm.

[10]The variable "Public founds" actually has second highest F-Value, but it cannot be compared to other variables in this regards since it has the same value for each municipality inside different affected areas.

Table 3: Classification Report

	Precision	**Recall**	**f1-score**	**Support**
Unsuccessfully Resilient	0.85	0.94	0.89	18
Successfully Resilient	0.86	0.67	0.75	9
micro avg	0.85	0.85	0.85	27
macro avg	0.85	0.81	0.82	27
weighted avg	0.85	0.85	0.85	27

Our trained algorithm can classify previously unseen data with an accuracy of 0.851852 (85.18%). The Classification Report shown in table 3, reports the main classification metrics on a per-class basis. These metrics indicate the ability of the classifier i) not to label an instance positive that is actually negative (Precision); ii) to find all positive instances (Recall). Finally, the f1-score is a weighted harmonic mean of precision and recall and the Support column indicates the number of actual occurrences of the class in the training dataset.
The bottom half of the table reports micro average (which in our binary classification corresponds to the accuracy of the model), macro average (averaging the unweighted mean per class), weighted average (averaging the support-weighted mean per class).
Specifically, it classifies correctly 23 out of the 27 cases submitted. Among these 4 miss-classified cases 3 of them are classified as "unsuccessfully resilient" even though they are not and only 1 case is miss-classified as "successfully resilient".
As shown in the "recall" column of the table the model if fairly confident in classifying "unsuccessfully resilient" cases, while having less confidence when classifying cases as "successfully resilient". Despite that, the overall accuracy of the model is quite robust (85%) and miss-classification issues can be partially dealt with by taking advantage of the confidence intervals (Elazmeh et al., 2006) provided by the Logistic Regression Classifier.
The algorithm is finally trained over all the available cases. The final model uses a logistic Regression Classifier with a "liblinear" solver[11], no intercept scaling and no weights for the parameters. To reduce the possibility of overfitting issues, a soft L2 regularization (Ridge regression) is employed penalizing high-valued regression coefficients (Friedman et al., 2001).
The equation for the final model is specified below, coefficients for each feature are instead reported in table 4:

$$Pr(Y_i = 1|X_i) = \frac{exp(-0.38924986 + \beta_1 X_i + ... + \beta_{26} X_{26})}{1 + exp(-0.38924986 + \beta_1 X_i + ... + \beta_{26} X_{26})} \qquad (1)$$

In the next section, we apply this forecasting model to the rural communities affected by the Summer 2016 Earthquake. Once put onto a map, the result will draw a possible scenario, 5-7 years after the earthquake, indicating which affected municipalities have the right set of features composing the ability for resilience to not only bounce back but also maybe thrive after the terrible event. More importantly, this scenario will highlights which areas and municipalities do not have a sufficient set of feature to be resilient, allowing for aimed interventions, policies and public investments.
Table 4, reporting the coefficients applied to each variable after the training process, already provides interesting information on how the resilience ability is composed in such rural context. All variables are standardised and normalised before the training process, so the resulting coefficients are quite comparable among them.

[11] Liblinear is an open-source library for large-scale linear classification. The solver is a linear classificator that supports logistic regression and linear support vector machines. It's recommended when you have high dimension dataset.

Table 4: Coefficients of the features.

Feature	**Coefficient**
Population dimension	-0.2527850
Depopulation Trend*	0.51475177
Elderly	-0.85899727
No diploma	-0.32133558
Italian speakers	-0.93317191
Income	0.80492563
Employment	0.0422328
Female employment	0.58916836
Singol sector employment	1.28532207
Small Businnes	0.34305905
Urban population share	0.28080971
Old houses	0.23114208
Renting families	-0.82183
Cooperative workers	-0.03734153
Voters turnout	0.4573984
No-profit	0.33665399
Religious Marriages	-0.54789452
Numerous Families	-0.23111276
Distance_pole	-1.61226599
Altitude	0.05839417
Daily commuters	1.38585454
Public founds	0.35977537

* The depopulation trend is composed by five separate features indicating the yearly depopulation rate up to five years before the earthquake.
The mean value of the coefficients is shown here.

While many variables interact as expected in the model (e.g. the share of elderly, share of people with no diploma, income or the share of renting families. But also, related to the context in consideration, the Single sector employment and the share of small business), the sign and value of the coefficients for some other variables show some interesting behaviour. Regarding the Economic sub-dimension, it is interesting to note that while both Employment (the share of employed working-age inhabitants) and Female employment (which records the female participation to the job market) are positive but the coefficient for the latter is sensibly higher than for the first one. This suggests that improving female participation in the job market could actually create more chances to be resilient than improving the overall employment level (which is the smallest positive coefficient in the model) of the municipality.
Another interesting behaviour is shown by the Social sub-dimension. Specifically, both the share of Religious marriages and Numerous families have negative coefficients, while the number of No-profit and the share of Voters turnout are positive.
This suggests that more traditional and conservative communities are less able to be resilient than more community-involved and inclusive[12] communities.
Finally, Spatial and Geographical sub-dimension also shows interesting information. Indeed, while most of its variables behave as expected (e.g. Distance from the nearest pole or the Urban share of inhabitants), the variable altitude (registering the median altitude of the municipality) as a positive coefficient. This could suggest that - in an all-rural context such the one under analysis - while the remoteness (distance from pole) of the community still plays an expected negative role, the actual altitude of the community does not.
The model, as presented, is applied to the municipalities affected by the Summer 2016 earthquake. The

results will be presented and discussed in the next section, comparing the forecasting scenario and the composition of the model.

[12] Indeed, the variable Italian speakers, registering the share of inhabitants speaking Italian as first language, is negative.

5 Results and Discussion

Our forecasting model provides a scenario 5-7 years after the earthquake for the 133 municipalities affected by the Summer 2016 earthquake. This scenario, based on a wide range of features, indicates which municipality has the right set of features and characteristics to make the most from the reconstruction and recovery process.
Inside our model, such municipalities are those classified as "Successfully resilient".
We provide two approaches to our results, first a spatial assessment of how the different classes are distributed, then an empirical analysis of which features can be considered "drivers" of a successfully resilient recovery process.
Figure 5 shows the spatial and geographical distribution for our simulation.

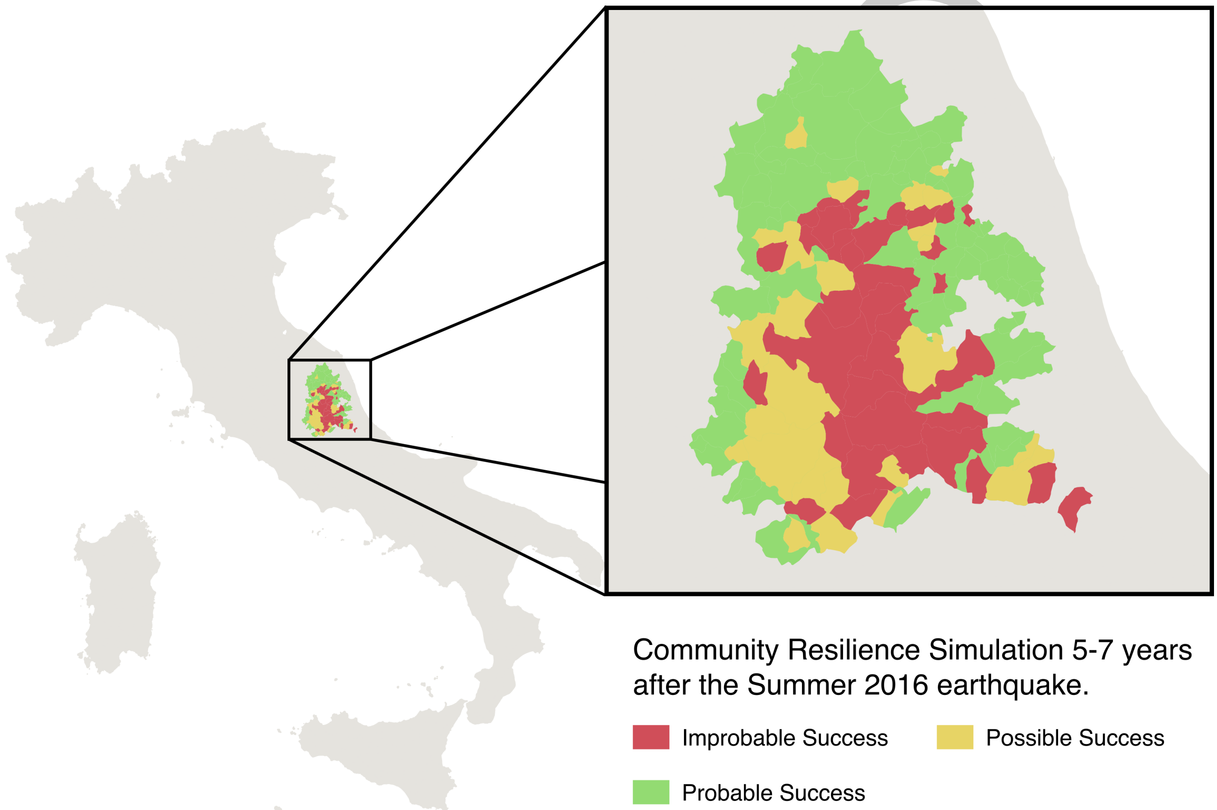


Figure 5: Scenario of the ability for Community Resilience after the Summer 2016 earthquake.

Our algorithm classifies municipalities into two categories, "Successfully resilient" and "Unsuccessfully resilient". As mentioned before we are aware that our algorithm isn't 100% accurate. More in detail our algorithm has a slight tendency to miss-classify some bordering (bordering between the two classes) municipalities.
To deal with this attitude of the model we exploited the confidence intervals provided by the algorithm to create a third intermediate class. The three final classes are: "Improbable Success", "Possible Success" and, "Probable Success".
Visualized in the form of a map of the affected area, our results show some geographical patterns. The probability of success changes from high to low moving towards the center of the area. Municipalities with a higher chance of being resilient are clustered at the border and in the northern part of the affected area. Conversely, lower probabilities of success are found in the southern part of the affected area (the heart of the Central Apennine Ridge), which is also the most affected and closer to the epicenter. Four administrative Italian regions were involved in the earthquake (Marche 83, Abruzzo 22, Umbria 14, Lazio 14). Among those, Marche and Umbria have the largest relative share of "Possible Success" (68% and 50%) while Abruzzo holds the largest share of "Improbable Success" (41%), followed by Lazio (28%). Table 5 shows the 10 most probably successful and in-successful municipalities, the complete list can be

found in Appendix B.

Table 5: Most probably successful and in-successful municipalities.

Municipality	Forecast	Proba Insuccess	Proba Success
Cerreto d'Esi	Probable Success	.01827178	.9817282
Rotella	Probable Success	.024168359	.97583163
Esanatoglia	Probable Success	.04726027	.95273972
Folignano	Probable Success	.05176425	.94823575
Ortezzano	Probable Success	.05180617	.94819385
Castel di Lama	Probable Success	.055337202	.94466281
Urbisaglia	Probable Success	.060038012	.93996197
Cittaducale	Probable Success	.061732151	.93826783
Petriolo	Probable Success	.064399831	.93560016
App. del Tronto	Probable Success	.064423069	.93557692
...			
...			
...			
Amatrice	Improbable Success	.82695925	.17304073
Monte Cavallo	Improbable Success	.84773397	.15226603
Pievebovigliana	Improbable Success	.84937859	.15062141
Bolognola	Improbable Success	.86425179	.13574819
Fiastra	Improbable Success	.87670648	.12329351
Montegallo	Improbable Success	.87849617	.12150381
Poggiodomo	Improbable Success	.88256621	.11743378
Micigliano	Improbable Success	.88529682	.11470317
Cittareale	Improbable Success	.9295277	.070472308
Cessapalombo	Improbable Success	.93571448	.064285502

Social and economic features are very significant in our model and, generally, are the main focus of policies attempting to generate sensible outcomes. To determine some of the driving factors in our model, we show (Figures 6 and 7) the geographical distribution for some of the most impactful economic and social feature. Figure 4.6D and 4.6E show patters quite similar to our scenario, especially comparing their forth quartiles with the distribution of "Probable success".
Female participation to the job market (Figure 4.6C) is also shown to be highly correlated with our scenario, while the share of cooperative workers (Figure 4.6B) and the share of workers employed in agriculture (Figure 4.6A) are not distributed accordingly.
On the social side (Figure 7), the share of people commuting daily for work or study (Figure 4.7A) shows

the most similar distribution to our scenario, where the "Probable success" class has the highest shares of commuters. Considered together, figure 4.7B (share of people with no High School diploma), 4.7E (share of people speaking Italian as first language) and 4.7C (share of numerous families) seem to suggest that more open and untraditional communities hold the higher capacity for resilience.
Finally, despite not showing a similar distribution to our scenario, the 4th quartile in figure 4.7D (Number of no-profit associations per thousand inhabitants) is mostly clustered in the same area classified as "Possible Success". This suggests that, while not having a primary role, the presence of no-profit associations can be a sort of balance needle towards a successful recovery process.
Similarities between the distribution of these features and our scenario indicate that they are impactful drivers on which to build more resilient communities. Moreover, such similarity of patterns also suggests that acting individually on such features could create direct and positive outcomes with targeted policies. Overall, from our scenario emerges a socio-economic profile of the "Successfully Resilient" municipality.

Indeed, the analysis suggests for communities characterised by an open and inclusive social structure and less "traditional" job market to have better chances being successfully resilient. While the - quite homogeneous - economic structure does not seem to have direct correlations with the output (differently from job market and income), the participation to the community social life might play a very impactful role. Registered using levels of electoral participation and the number of no-profit associations, high levels of participation in the social life of the community are mostly found in a big cluster of municipalities. This geographical cluster (green in Figure 4.7D) mostly overlaps with a big area classified as "Possible

Success" in our scenario.
From a policy-design point of view this is very interesting. Indeed, regarding many other socio-economic characteristics this cluster is no different from the rest of the southern part of the affected area. Following our results, is possible to suggest for the higher levels of social participation found in these communities to be the key driver in the push from "Improbable" to "Possible" success. Despite needing further deepening (and a specific analysis), this last results is a clear example of how they could be very easily translated into policies and actions with a direct and perceivable impact on the affected communities.
Such connections between our forecasting model, scenario and possible policy indications are the key aim of this research and will be further discussed in the next paragraph.

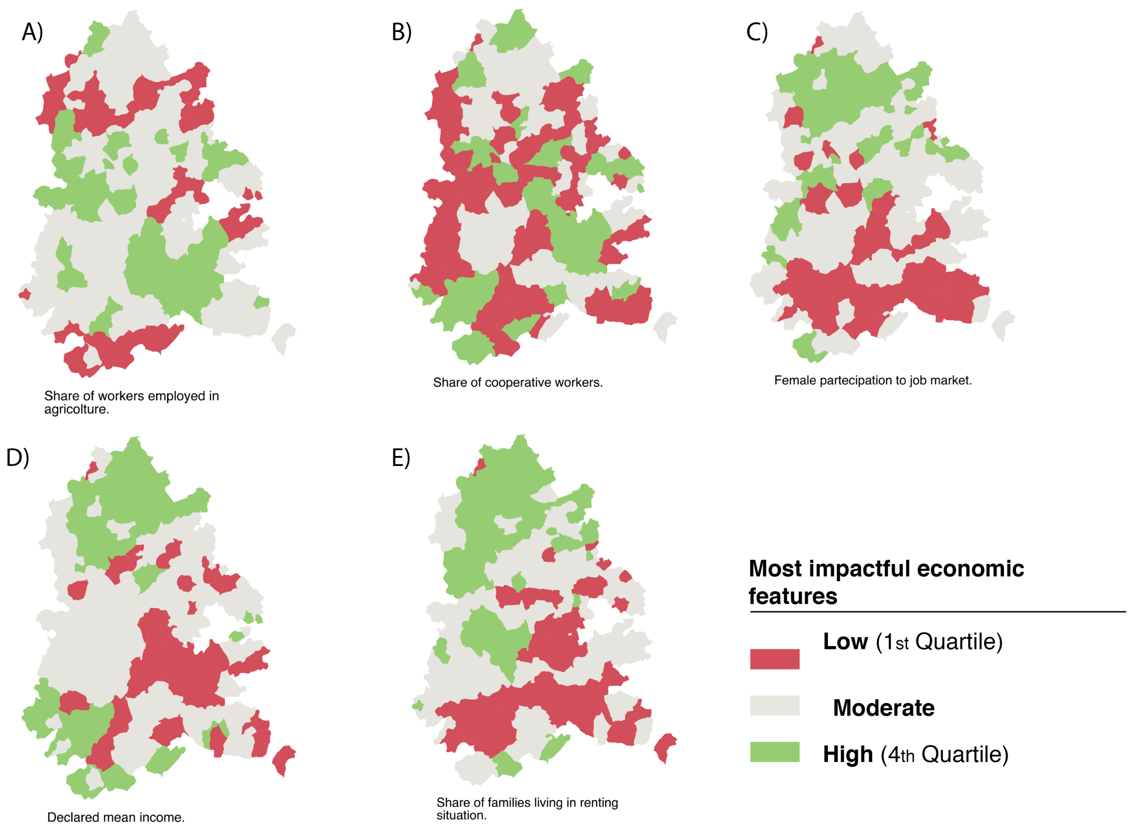


Figure 6: Most impactful economic features. A)Workers employed in agriculture B)Cooperative workers C)Female participation to job market D)Declared mean income E)Families living in renting situation.

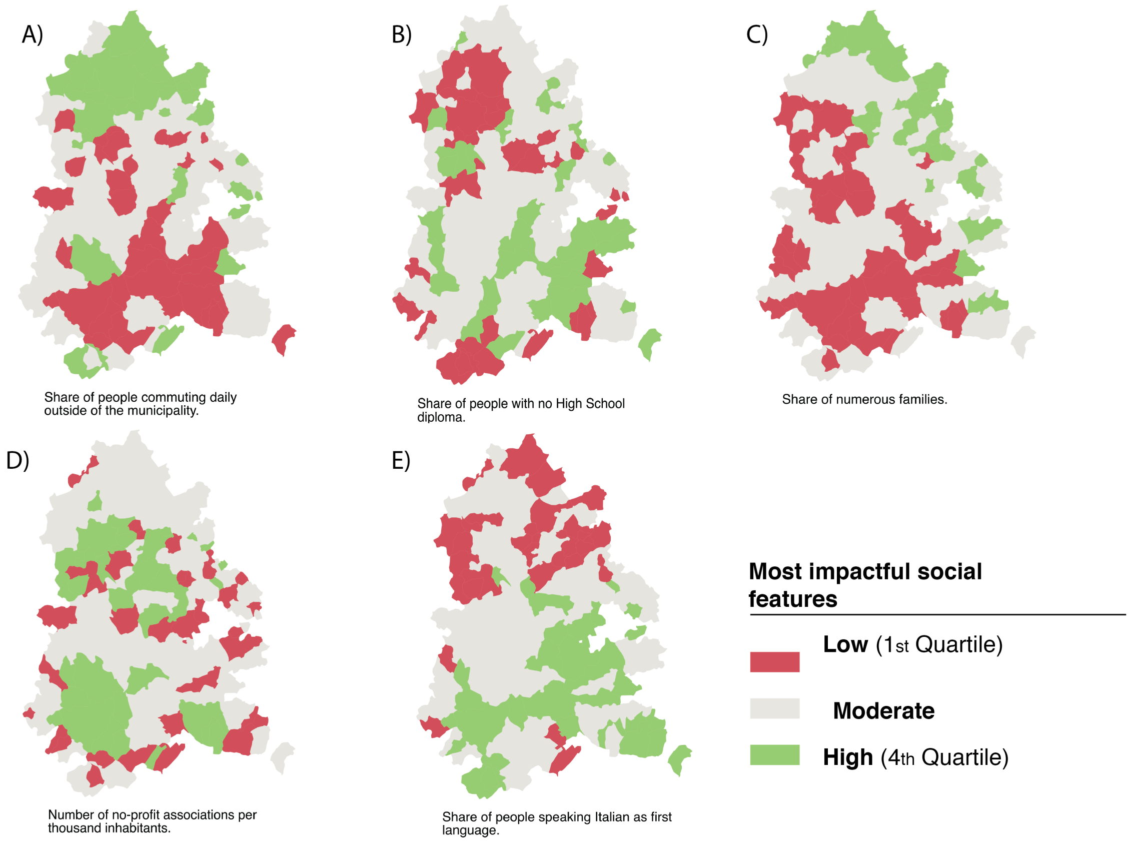


Figure 7: Most impactful social features.A)People commuting daily B)People with no High School diploma C)Numerous families D)Number of No-Profit E)People speaking Italian as first language.

6 Concluding Remarks

This paper is a first attempt at developing a *context-bound* approach for Community Disaster Resilience focused on rural communities. Our model is based on sound and robust literature from the field, minus the assumption about how the ability for resilience is composed and which set of components drives such ability.
Our model, alongside the connected scenario, is developed specifically for Italian rural communities, based on their characteristics and long-term socio-economic processes involving them. For this reason, the results emerging from the analysis of the scenario are specific to the context and cannot be generalized outside of it. However, both the methodology and the empirical *context-bound* strategy we employed are replicable for different scenarios.
The concept of resilience is still recent in its adoption into social sciences, thus studies like this one - aimed at a specific context - are important to advance our comprehension of the concept and its dynamics. Adopting a supervised Machine Learning strategy, our model provides a simple and communicative way of visualising and analysing the resilience capacity of communities which can be applied to many different scenarios. The true power of our approach is that it can be easily translated into practical policy indications for both increasing the communities' chances to recover successfully after a disaster and preventively help communities to be more resilient.
The singularity and novelty of our approach can be stated over three elements. First, our overall research strategy is based on the principle that geography and history are a key input in shaping the characteristics of regions and communities (Boschma and Martin, 2010; Wilson, 2014). Both geographical specificities and long-term socio-economic processes impact how the resilience capacity is composed and what means to be resilient for those communities. In the construction of our scenario, we use data from communities in the same area, over a 20 years long period, to learn which communities were resilient and how they were able to successfully recover after a natural disaster.
The second element regards the specific statistical methods we employed. We used Supervised Machine Learning to develop a statistical model for community disaster resilience of rural communities in Central Italy. The use of such methods enabled us to input a wide range of features in the modelling of our scenario. This choice enabled us not to assume which characteristic compose the ability for resilience in our specific case study and instead let the algorithm select them from all the feature and data available to us.
The third element of nuance in our approach is how we defined resilient communities. To free ourselves from the need to assume the composition of the ability for resilience, we decided to first define resilient communities and - from this - let the algorithm compose the model. Our empirical measure for resilience is thus derived from the impact on long-term socio-economic processes involving the area.
These choices led us to develop a model which is, at the same time, highly specific in its results and completely generalizable in its research design.
The major feat of this paper is that the specific results in our scenario, coupled with the analysis of the model behind them, can be easily translated into practical policy directions for the communities affected by the Summer 2016 earthquake.
The scenario emerging from our forecasting model is set 5-7 years after the disaster and provides indications about i) which municipalities already have the right set of characteristics to be able to successfully recover; ii) which municipalities need institutional interventions and investments to avoid falling behind even more. As shown in figure 5, municipalities with less chance to be resilient are clustered in the central-southern part of the affected area at the interception of the four administrative regions. This area is also closer to the epicenter, thus is expected to be the most affected. Conversely, the northern and eastern part of the affected area cluster the highest chances of a successful recovery process. From a geographical point of view, these areas benefit from being closer to bigger cities while still having a mountainous territory.
Our scenario only provides information about the probability of the affected municipalities to complete a successful recovery process given the current situation (a complete list of each affected municipality and their classification, including probability scores, can be found in Appendix B). The strength of such medium-term forecast is that the current situation can be changed and thus municipalities chances for a successful recovery improved.
Indeed, if on one side our scenario provides indications about which municipality and which area lacks the right set of characteristics to be resilient, on the other side, the analysis of our model can provide direct indications about which features are missing in a specific area and which can be improved to create

a positive impact.
An example of how our model can be easily translated into policy directions is provided in Figures 6 and 7. These maps represent the geographical distribution of the main economic and social features employed in the model and, altogether draw a picture of the resilient community.
In the context of Central Italy, municipalities with the highest chance for a successfully recovery are those holding higher levels of female participation in the job market, higher cultural capital, are more culturally open and inclusive and, generally, less traditional (as indicated by the negative coefficient of both the share of numerous families and the share of religious marriages). Municipalities with such characteristics and active community-life are those with the highest chances. The importance of the participation in the community life is here underlined by Figure 6 (D); the map shows that the cluster of municipalities with the highest number of no-profit associations (Figure 4.6D, south-est part of the affected area) is situated in a very traditional area (very low female participation to the job market, low shares of people not speaking Italian as first language ...). In our scenario, this specific area corresponds to the biggest cluster of municipalities classified as "Possible Success" (Figure 5, in yellow). The correlation of these patterns suggests that, even if communities in the area generally lack some of the main characteristics for a successful recovery process, intense social life and participation inside the communities generate positive outcomes increasing their resilience ability.
Both, individual features and the profile of a successful community we delineated, can be translated into policy direction. Moreover, a specific focus on a single municipality can provide further information and provide a baseline for specific actions and investments.
As stated before, this paper is a first attempt at providing a general model and research design which is to be applied to specific case studies and contexts. Such a strategy has the aim of generating a positive impact on disaster-affected communities.
The model shown in this paper is not perfect or complete in any regard. Indeed, the model is trained on a relatively small sample of data for both features and cases. Much can be improved in data collection, including more features, cases and longitudinal data. Despite these evident limitations, we believe our model to be based on sound literature and able to make accurate predictions.
Possibilities for further advancement of this work include the creation of a more general model to be applied for every rural community in Italy. With the inclusion of more data and information such model could be a valuable resource the Italian administration at several levels and a powerful and communicative tool for policymakers.

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A Appendix A

Feature	**Category**	**Data Source**
Pct Foregneirs	Demographic	Istat, Census
Pendolarism	Demographic	Istat, Census
Structural Dependency	Demographic	Istat, Census
Share non self-sufficient persons	Demographic	Istat, Census
Education Inequality	Demographic	Istat, Census
Population dimension	Demographic	Istat, Census
Employment rate	Economic	Istat, Census
Gini Index	Economic	Mef.
Credit access	Economic	Mef.
Public founds for reconstruction	Economic	Dossier Camera
Mean Income	Economic	Mef.
Mean house price	Economic	OMI
Female Employment participation	Economic	Istat, Census
Share of renting families	Economic	Istat, Census
Single sector Employment	Economic	Istat, Census
Small business	Economic	Istat, Census
Cooperative workers	Economic	Istat, Census
Digital Divide	Infrastructural	Istat, Census
Share old buildings	Infrastructural	Istat, Census
N. of schools	Infrastructural	Istat, Census
Emergency displacement beds	Infrastructural	Istat, Census
Hospital beds	Infrastructural	Istat, Census
Urban population share	Geographical	Istat, Census
Mountainuity	Geographical	Istat, Census
National Parks	Geographical	Istat, Census
Distance from Nearest Pole of services	Geographical	Istat, Census
Municipality fiscal capacity	Institutional	Mef.
No-profits controlled by administration	Institutional	Istat
Political stability	Institutional	Archivio Storico Elezioni
Environmental public expenditure	Institutional	Mef.
Administrative transparency	Institutional	Istat
Municipal environmental rating	Institutional	Istat
Already affected by disaster	Institutional	Own elaboration
Numerous families	Social	Istat Census.
Share of pop. living where it was born	Social	Istat, Census
Share of religious marriages	Social	Istat, Census
Share of creative workers	Social	Istat, Census
Voters turnout	Social	Archivio Storico Elezioni.
No-profits per thousand people	Social	Istat, Census
voluntary ass. per thousand people	Social	Istat, Census
Main shock PGA intensity	Effect	INGV

Table 6: List of Features considered for the modelling of disaster resilience ability.

B Appendix B

Code	Municipality	Forecast	prob. insuccess	prob. success
42013	Cerreto d'Esi	Prob. Success	.01827178	.9817282
43001	Acquacanina	Improb. Success	.71256989	.28743008
43002	Apiro	Prob. Success	.11937069	.8806293
43004	Belforte del Chienti	Prob. Success	.14699587	.85300416
43005	Bolognola	Improb. Success	.86425179	.13574819
43006	Caldarola	Poss. Success	.39668855	.60331148
43007	Camerino	Prob. Success	.20433357	.7956664
43008	Camporotondo di Fiastrone	Prob. Success	.24959727	.75040275
43009	Castelraimondo	Prob. Success	.11531502	.88468498
43010	Castelsantangelo sul Nera	Improb. Success	.56091017	.43908983
43011	Cessapalombo	Improb. Success	.93571448	.064285502
43012	Cingoli	Prob. Success	.11197006	.88802993
43014	Colmurano	Prob. Success	.32099393	.67900604
43015	Corridonia	Prob. Success	.072017841	.92798215
43016	Esanatoglia	Prob. Success	.04726027	.95273972
43017	Fiastra	Improb. Success	.87670648	.12329351
43018	Fiordimonte	Improb. Success	.61472899	.38527101
43019	Fiuminata	Prob. Success	.16966437	.83033562
43020	Gagliole	Poss. Success	.47668889	.52331108
43021	Gualdo	Improb. Success	.51204705	.48795298
43022	Loro Piceno	Prob. Success	.23974541	.76025456
43024	Matelica	Prob. Success	.11940028	.88059974
43025	Mogliano	Prob. Success	.20141339	.79858661
43027	Monte Cavallo	Improb. Success	.84773397	.15226603
43032	Monte San Martino	Poss. Success	.33850265	.66149735
43034	Muccia	Prob. Success	.30945182	.69054818
43035	Penna San Giovanni	Improb. Success	.63564962	.36435038
43036	Petriolo	Prob. Success	.064399831	.93560016
43037	Pievebovigliana	Improb. Success	.84937859	.15062141
43038	Pieve Torina	Poss. Success	.46608448	.53391552
43039	Pioraco	Prob. Success	.15502147	.84497851
43040	Poggio San Vicino	Prob. Success	.083783112	.91621691
43041	Pollenza	Prob. Success	.10487572	.89512426
43045	Ripe San Ginesio	Prob. Success	.3391431	.6608569
43046	San Ginesio	Prob. Success	.40092698	.59907299
43047	San Severino Marche	Prob. Success	.37782374	.62217629
43048	Sant'Angelo in Pontano	Poss. Success	.42295334	.57704663
43049	Sarnano	Improb. Success	.55560511	.44439489
43050	Sefro	Prob. Success	.17572086	.82427913
43051	Serrapetrona	Prob. Success	.3157478	.6842522
43052	Serravalle di Chienti	Prob. Success	.16099152	.83900845
43053	Tolentino	Prob. Success	.20529768	.79470229
43054	Treia	Prob. Success	.21890308	.78109694
43055	Urbisaglia	Prob. Success	.060038012	.93996197
43056	Ussita	Poss. Success	.46008542	.53991455
43057	Visso	Prob. Success	.17467698	.82532299
44001	Acquasanta Terme	Poss. Success	.3828612	.6171388
44005	Appignano del Tronto	Prob. Success	.064423069	.93557692
44006	Arquata del Tronto	Improb. Success	.64938939	.35061061
44011	Castel di Lama	Prob. Success	.055337202	.94466281
44012	Castignano	Prob. Success	.11190311	.88809687
44013	Castorano	Prob. Success	.18574895	.81425107
44014	Colli del Tronto	Prob. Success	.14987719	.85012281

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Code	Municipality	Forecast	prob. insuccess	prob. success
44015	Comunanza	Prob. Success	.12992953	.87007046
44016	Cossignano	Prob. Success	.076348431	.92365158
44020	Folignano	Prob. Success	.05176425	.94823575
44021	Force	Prob. Success	.093628198	.90637177
44027	Maltignano	Prob. Success	.11415944	.88584054
44032	Montalto delle Marche	Prob. Success	.1367113	.8632887
44034	Montedinove	Prob. Success	.089744002	.91025603
44038	Montegallo	Improb. Success	.87849617	.12150381
44044	Montemonaco	Improb. Success	.64666617	.35333386
44054	Offida	Prob. Success	.21962641	.78037357
44056	Palmiano	Improb. Success	.70733762	.29266241
44064	Roccafluvione	Prob. Success	.25046039	.74953961
44065	Rotella	Prob. Success	.024168359	.97583163
44073	Venarotta	Prob. Success	.18253767	.81746233
54007	Cascia	Poss. Success	.46254179	.53745824
54010	Cerreto di Spoleto	Poss. Success	.36035904	.63964099
54031	Monteleone di Spoleto	Poss. Success	.46188635	.53811365
54035	Norcia	Improb. Success	.59570813	.40429187
54042	Poggiodomo	Improb. Success	.88256621	.11743378
54043	Preci	Poss. Success	.47629455	.52370542
54045	Sant'Anatolia di Narco	Prob. Success	.14971949	.85028052
54047	Scheggino	Prob. Success	.066096798	.93390322
54048	Sellano	Prob. Success	.36037248	.63962752
54058	Vallo di Nera	Prob. Success	.12534188	.87465811
55005	Arrone	Prob. Success	.067604132	.93239588
55012	Ferentillo	Prob. Success	.27437878	.72562122
55019	Montefranco	Prob. Success	.21899822	.78100175
55027	Polino	Poss. Success	.45447692	.54552305
57001	Accumoli	Improb. Success	.51583099	.48416901
57002	Amatrice	Improb. Success	.82695925	.17304073
57003	Antrodoco	Poss. Success	.34253761	.65746242
57006	Borbona	Poss. Success	.44490558	.55509442
57008	Borgo Velino	Prob. Success	.097916096	.90208387
57009	Cantalice	Prob. Success	.21754263	.78245735
57015	Castel Sant'Angelo	Poss. Success	.37260598	.62739402
57016	Cittaducale	Prob. Success	.061732151	.93826783
57017	Cittareale	Improb. Success	.9295277	.070472308
57033	Leonessa	Poss. Success	.37919849	.62080151
57037	Micigliano	Improb. Success	.88529682	.11470317
57051	Poggio Bustone	Prob. Success	.12044789	.87955213
57057	Posta	Poss. Success	.42696381	.57303619
57060	Rivodutri	Prob. Success	.16196612	.83803385
66008	Barete	Poss. Success	.295003	.704997
66013	Cagnano Amiterno	Improb. Success	.5447787	.4552213
66016	Campotosto	Improb. Success	.65267849	.34732151
66021	Capitignano	Poss. Success	.42298996	.57701004
66056	Montereale	Improb. Success	.52795619	.47204381
66072	Pizzoli	Prob. Success	.069904812	.9300952
67008	Campli	Prob. Success	.23958984	.76041019
67010	Castel Castagna	Poss. Success	.47744924	.52255076
67012	Castelli	Improb. Success	.64022088	.35977912
67017	Civitella del Tronto	Prob. Success	.28138182	.71861815
67018	Colledara	Poss. Success	.34194613	.65805387
67022	Cortino	Improb. Success	.68720776	.31279224
67023	Crognaleto	Improb. Success	.72201139	.27798858
67024	Fano Adriano	Prob. Success	.19537079	.80462921

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Code	Municipality	Forecast	prob. insuccess	prob. success
67026	Isola del G. S. d'Italia	Poss. Success	.45070654	.54929346
67028	Montorio al Vomano	Prob. Success	.17944732	.82055265
67034	Pietracamela	Improb. Success	.69831002	.30169001
67036	Rocca Santa Maria	Prob. Success	.28134602	.71865398
67043	Torricella Sicura	Prob. Success	.089130647	.91086936
67045	Tossicia	Prob. Success	.19851521	.80148476
67046	Valle Castellana	Improb. Success	.59106922	.40893078
68019	Farindola	Improb. Success	.81861794	.18138207
109002	Amandola	Prob. Success	.26315787	.73684216
109003	Belmonte Piceno	Prob. Success	.30886486	.69113511
109005	Falerone	Poss. Success	.46318808	.53681195
109011	Massa Fermana	Poss. Success	.36012328	.63987672
109012	Monsampietro Morico	Improb. Success	.66299593	.3370041
109013	Montappone	Prob. Success	.23811948	.76188052
109014	Montefalcone App.	Improb. Success	.57122189	.42877814
109015	Montefortino	Improb. Success	.61512548	.38487449
109017	Montegiorgio	Prob. Success	.27281329	.72718674
109019	Monteleone di Fermo	Prob. Success	.25498655	.74501348
109020	Montelparo	Prob. Success	.0816295	.91837049
109021	Monte Rinaldo	Prob. Success	.069105819	.9308942
109026	Monte Vidon Corrado	Prob. Success	.32756299	.67243701
109029	Ortezzano	Prob. Success	.05180617	.94819385
109036	S. Vittoria in Matenano	Prob. Success	.17234257	.8276574
109038	Servigliano	Improb. Success	.50803888	.49196112
109039	Smerillo	Poss. Success	.3978962	.60210383

Table 7: Simulation results for community resilience ability after the Summer 2016 earthquake.