

POLITECNICO DI TORINO

Collegio di Ingegneria Gestionale – Classe LM-31

Corso di Laurea Magistrale in Ingegneria Gestionale (Engineering and Management)



**Politecnico
di Torino**

Prediction of hydrogeological risks in Italy: data taxonomy,
database creation and preliminary regressor analysis

Relatore:

Guido Perboli

Candidato:

Chiara Vandoni

Relatore aziendale:

dott.ssa Valeria Lazzaroli

Anno Accademico 2021-2022

ABSTRACT

In an increasingly globalized environment, vulnerabilities emerge from an increasingly interdependent and interconnected world, and risks are no exception: climate change is an example of how disasters can express themselves on a global scale and transfer rapidly from one sphere to another.

Arisk offers itself as a solution by developing software with underlying algorithms that can measure any type of risk objectively and comparably over time and space.

The final objective of the work is to analyze the correlation between hydrogeological risk and the financial performances of small and medium-sized enterprises, with a focus on wineries.

This thesis covers only the first part of the overall work and aims to create accurate models for forecasting total annual rainfall. Specifically, it seeks to understand what correlation (and if any) exists between inputs such as temperature and humidity and annual rainfall. An input is a variable defined as a characteristic surveyed or measured on statistical units and can be: quantitative variable (modes are real numbers) or qualitative variable (modes are non-numeric attributes).

To perform predictive modeling (the problem of developing a model using historical data to make a prediction on new data for which the answer is unknown) an initial database containing data from 31 municipalities in the Langhe (Piedmont) for six different years was initially created, and 3 different approaches were used on this: Linear Regression, Neural Network, and Random Forest.

Later with the aim of finding the best model, a second database (municipalities in the Prosecco area in Veneto) was created, because by expanding the database the predictive modeling is more effective.

The results showed that random forest is the best estimator for this type of analysis and that the total precipitation range can be predicted with 78% accuracy.

These results suggest that by further expanding the database and covering diversified areas of Italy, the accuracy of prediction can be improved. On this basis, we can say that it is absolutely worth continuing with the next phases of the study.

INDEX

INTRODUCTION	4
CHAPTER 1.....	4
1.1 CLIMATE RISK.....	4
1.2 HYDROGEOLOGICAL RISK	7
1.2.1. LANDSLIPS	8
1.2.2. FLOODS	15
CHAPTER 2.....	21
2.1 RISK OF MSEs	21
2.2 CLIMATE CHANGE	22
2.3 PREVENTION AND PROTECTION	24
2.4 PREVENTION AND PROTECTION FOR SMEs.....	25
CHAPTER 3.....	28
3.1 ARISK'S HYDROGEOLOGICAL RISK FORECASTING TOOL.....	28
3.2 STATISTICAL INVESTIGATION	28
3.2.1 DEFINITION OF THE OBJECTIVES OF THE RESEARCH	28
3.2.2 DEFINITION OF THE TYPE OF STUDY.....	29
3.2.3 DEFINITION OF THE POPULATION OF INTEREST	29
3.2.4 DEFINITION OF VARIABLES OF INTEREST AND MEASUREMENT SCALES.....	30
3.2.5 DEFINITION OF DATA SOURCE	31
3.2.7 SAMPLE SELECTION	32
3.2.8 DATA COLLECTION AND ORGANIZATION OF COLLECTED DATA	33
3.3 FINAL DATABASE OF PIEDMONT.....	37
CHAPTER 4.....	39
4.1 STATISTICAL ANALYSIS.....	39
4.2 REGRESSION PROBLEM	39
4.2.1 APPROACHES.....	41
4.3 MODEL COMPARISON	46
4.4 SHAP ANALYSIS	51
4.5 DATABASE VENETO	55
CHAPTER 5.....	58
5.1 PUNCTUAL VALUE COMPARISON	58
5.2 COMPARISON OF ACCURACY INTERVAL.....	68
CONCLUSION	71
SITOGRAPHY.....	73

INTRODUCTION

In today's increasingly globalized environment, vulnerabilities emerge from an increasingly interdependent and interconnected world.

And risks, too, are no exception: climate change and Covid-19 represent examples of how disasters can express themselves on a global scale and transfer quickly from one sphere to another.

Health and climate emergencies have many points in common: both, first and foremost, impact the entire socioeconomic system, and both, if not managed properly, can have devastating impacts.

It is necessary to ask the question of what can threaten the survival of individuals and of businesses in order to identify the threats that can cause irreversible damage.

With this approach, and by agreeing to face possible risks, it is possible to access one of the fundamental capacities of human beings: being able to imagine adverse scenarios and take appropriate countermeasures

to neutralize the risks.

With respect to the risk of climate change, this process must be applied.

The slow degradation of the conditions in which we live, measured in relation to human life, has led to our not realizing in time the consequences that are unfolding. But, fortunately, awareness of the problem has increased in recent years in tandem with the acceleration of extreme weather events.

Italy is one of the countries, at the European level, most vulnerable to climate change. The damage caused by these disasters has serious repercussions on the economic stability and growth of the affected areas paradoxically, however, Italy is one of the countries where SMEs most underestimate the impact of extreme weather events on their business.

In Italy, SMEs do not have adequate tools to assess and manage these phenomena.

CHAPTER 1

1.1 CLIMATE RISK

Climate is the set of weather conditions that characterize a given place over time.

Climate provides the necessary resources for human activities, but it can also pose a threat to them.

Climate-related natural phenomena are characterized by a natural and inevitable variability and therefore great uncertainty in their determination both in terms of their occurrence and intensity.

Climate risk refers to the set of possible negative consequences that climate-determined natural events may have on human activities.

The reason it is being talked about more frequently recently is because the impact of climate on human activities is increasing dramatically due to several factors.

One of these factors is that the climate is changing and that its change, for many situations, results in an increase in the intensity and frequency of extreme weather-related natural phenomena.

The most important climate-related natural phenomena in terms of the damage and consequences they cause are:

- Floods
- Lightning
- Heavy rainfall
- Hail
- Landslides
- Wind and tornadoes
- Extreme temperatures

All these phenomena are triggered by weather processes that depend on climatic conditions. As climatic conditions change, the frequency and intensity of these phenomena can change. Consequently, the risk associated with each of these phenomena depends closely on the climate and its change.

The inevitable variability and uncertainty of climatic conditions do not prevent the fact that decisions on economic and social activities must still be made.

The analytical tool that allows decisions to be made is risk assessment; in other words, risk assessment is the translation of uncertain but probable events into economic terms, such as costs and benefits, that can be used as inputs for decision making.

Risk is determined by the combination of hazard, vulnerability, and exposure.

It is a measure of the expected damage in a given time interval, based on the characteristics of the area, strength of the exposed assets and their economic value.

- Hazardousness

Hazardousness is the probability of an event happening.

Its characteristics are the frequency and intensity of the event. More precisely, dangerousness expresses the probability that a phenomenon will occur at a certain place with a certain intensity, in a certain time interval.

More generally, we can understand hazard as the presence of factors that can potentially cause damage.

- Vulnerability

The extent of the impact that a potential hazard factor can generate on a certain territorial context is closely related to the intrinsic susceptibility of that area to damage, which may involve anthropogenic or natural elements.

Thus, the concept of vulnerability (V) of properties and people is introduced, which is the possibility of damage that an event has in relation to its intensity on the affected structures. It can also be seen as the predisposition of a property to be damaged.

The more vulnerable it is (by type, inadequate design, poor quality of materials and construction methods, poor maintenance), the greater the consequences.

- Exposure

Exposure, or the greater or lesser presence of assets exposed to risk, is the possibility of suffering economic damage, related to the presence of material and machinery, people, as well as cultural property.

Exposure differs from vulnerability in that a subject can be very exposed and not vulnerable (a concrete wall on the bank of a river) to flooding, or very vulnerable but not exposed (a thatched house away from the river).

It represents the economic value of the property and the material in it. Factors such as area and volume, building materials, and flood protection all contribute in determining the exposed value.

Exposed value can be calculated through property inventories and appraisals, or through commercial, financial, and insurance valuation companies.

The formula for quantifying risk:

$$R = H * V * E$$

Risk quantification is calculated based on hazard and vulnerability curves that depend on the intensity of the natural event.

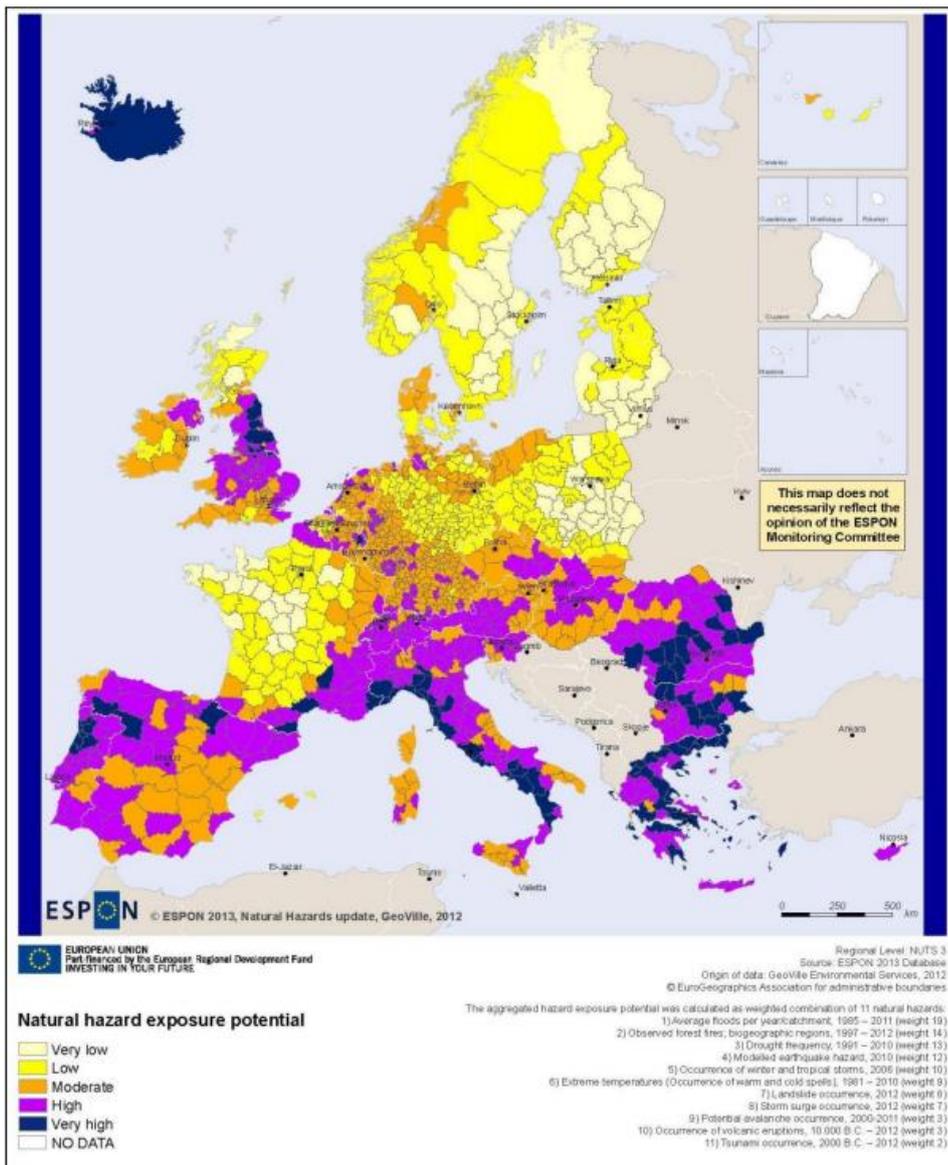
From the combination of the curves and the exposed value, the risk is determined in the form of a curve.

The risk curve represents the damage on a given property consequent a natural event at different levels of probability. Small damage will have a higher probability than large damage, and so on.

Therefore, to compare the risk of different assets, it will be necessary to quantify the risk for each, i.e., determine the risk curve, and then compare the curves.



(fig. 1 - Risk curves)



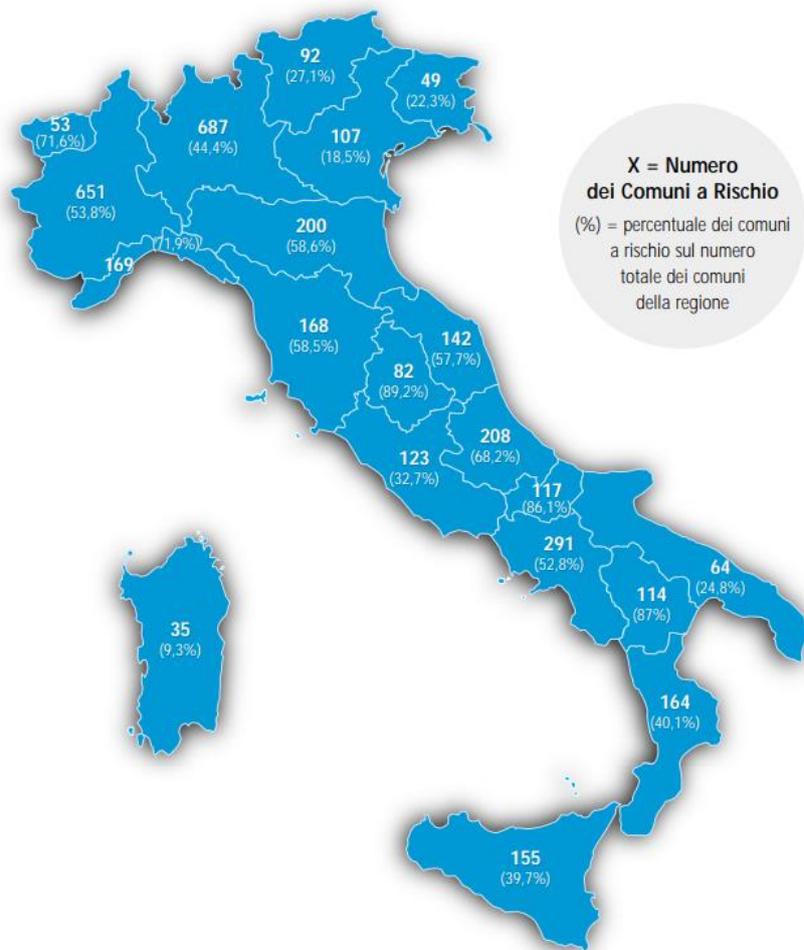
(fig. 2 - Natural hazard exposure potential in Europe, source: ESPON 2013)

1.2 HYDROGEOLOGICAL RISK

According to ISPRA's 2018 report, there are more than 80,000 Italian companies subject to high landslide hazard and nearly 600,000 to high flood hazard.

Italy alone accounts for about a third of the total landslide phenomena in Europe.

This is why dealing with climate risk and in particular hydrogeological risk in Italy is not only necessary, but also urgent.



(fig. 3 - Municipalities with the level of attention for hydrogeological risk Very High and High, source: Classificazione dei comuni italiani in base al livello di attenzione al rischio idrogeologico, Ministero dell'ambiente)

1.2.1. LANDSLIPS

Landslides are extremely widespread phenomena in Italy, even taking into account that 75% of the national territory is mountainous-hilly. Of the approximately 900,000 landslides surveyed in the databases of European countries (Herrera et al., 2018), almost 2/3 are contained in the Inventory of Landslide Phenomena in Italy carried out by ISPRA and the Autonomous Regions and Provinces. The most important factors for triggering landslide phenomena are short and intense precipitation, persistent precipitation, and earthquakes.

Landslides surveyed in the Inventory of Landslide Phenomena in Italy number 620,808 and affect an area of 23,700 km², or 7.9 percent of the national territory.

Italy suffered until 1989 a major delay in the promulgation of regulations requiring the consideration of phenomena of natural origin, such as landslides and floods, in territorial and urban planning.

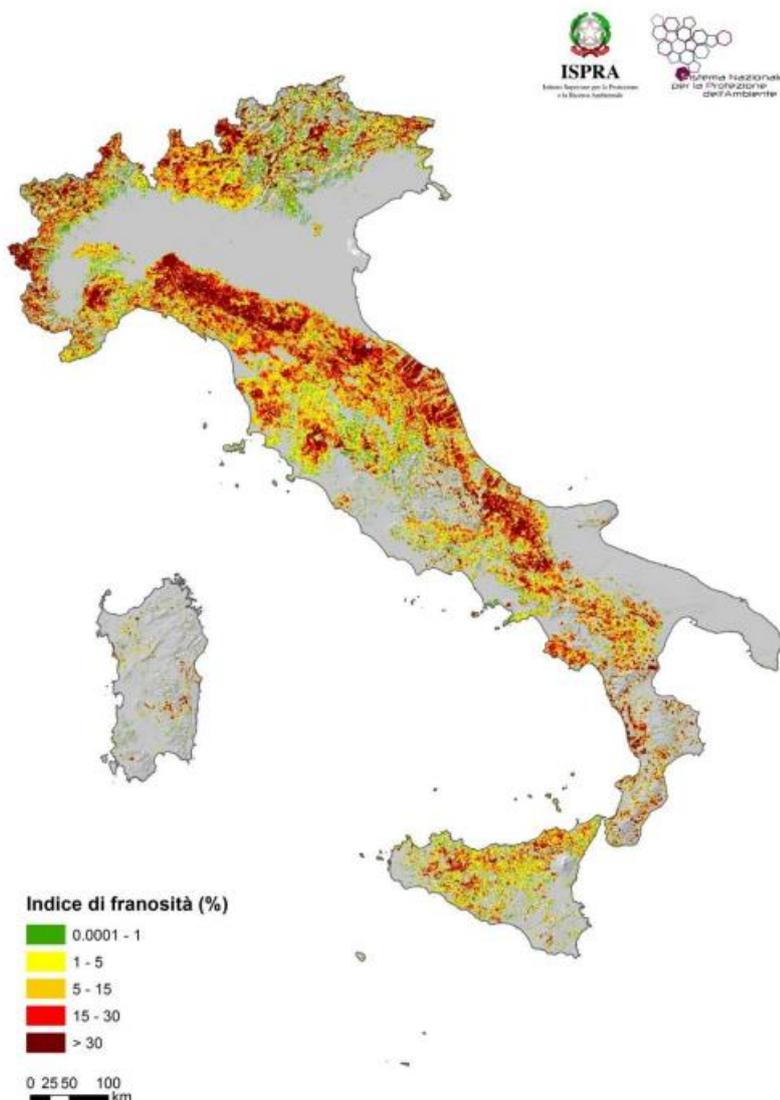
Law No. 183 of May 18, 1989, inspired by the results of the De Marchi Commission, is in fact the first organic norm for the organizational and functional reorganization of soil defense that identifies

the hydrographic basin as the territorial base of reference for hydrogeological protection and the Basin Authorities as the institutions responsible for the preparation of the Basin Plan.

Landslide hazard represents the probability of occurrence of a potentially destructive phenomenon of a given intensity at a given time and in a given area.

The greatest criticality in landslide hazard analysis generally stems from the lack of information regarding the dates of landslide triggering and thus the difficulty in determining the time of recurrence.

Because of these limitations, the most commonly performed analysis is that of susceptibility or spatial hazard, which makes it possible to identify the portions of land with a higher probability of landslide occurrence. Landslide hazard areas of the Hydrogeological Structure Plans include not only landslides that have already occurred, but also areas of possible evolution of the phenomena and areas potentially susceptible to new landslide phenomena.



(Fig. 4 - Landslide density (landslide area/cell area) on mesh of side 1 km, ISPRA 2017)

Mosaication of landslide hazard.

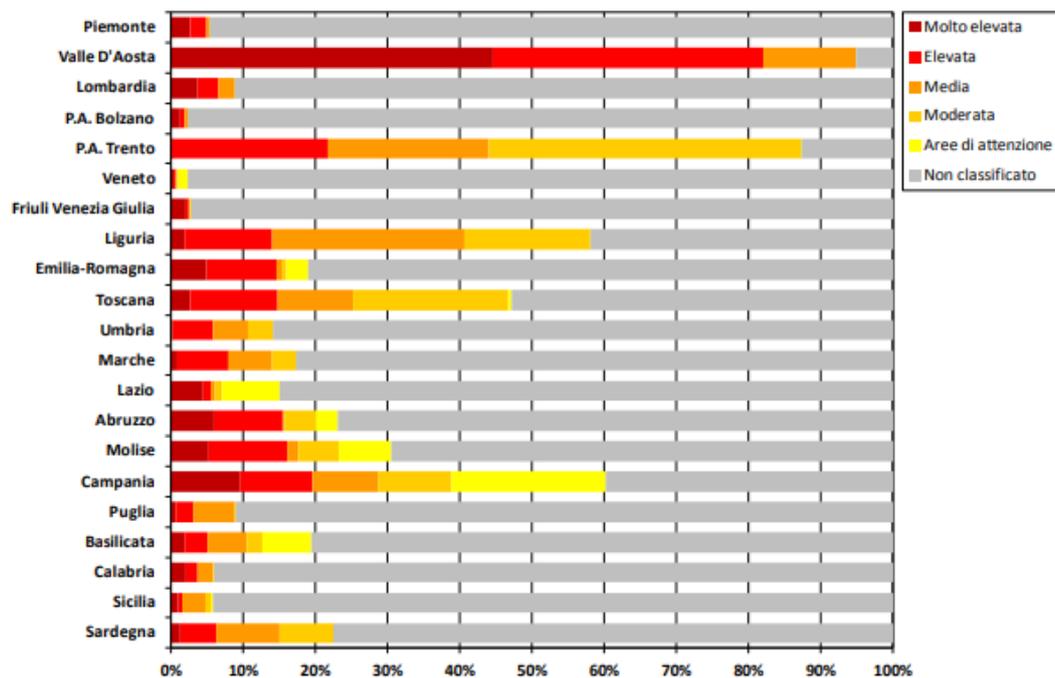
ISPRA, in order to update the landslide hazard map over the entire national territory, carried out in 2017 the new National Mosaication (v. 3.0 - December 2017) of the hazard areas of the Hydrogeological Structure Plans - PAI. This mosaicking was used to produce the new landslide hazard indicators.

The ISPRA mosaicking activity included the following steps:

- 1) Requesting updated data on hazard areas from the District Basin Authorities (July 2017);
 - 2) Data analysis:
 - (a) analysis of the methodology (Sec. 1.3) and landslide hazard classification adopted by each Basin Authority, using the information contained in the General Reports of the PAIs and map annexes.
 - (b) analysis of the Implementation Rules of the PAIs that define land use constraints and prescriptions.
 - (c) Interlocutions, technical clarifications and in-depth discussions with officials of the District Basin Authorities on the data transmitted by uploading to the ISPRA platform.
 - 3) Data homogenization:
 - (a) use of the hazard classification for the entire national territory in 5 classes: very high hazard P4, high P3, medium P2, moderate P1, and areas of attention AA, taking into account the Act of Guidance and Coordination for the identification of criteria relating to the fulfillments referred to in Article 1, paragraphs 1 and 2, of Decree-Law No. 180 of June 11, 1998 (DPCM September 29, 1998);
 - (b) Use of a landslide hazard reclassification table for each Hydrogeological Structure Plan in order to assign the aforementioned national classes to the PAI polygons.
 - 4) Mosaicking of data:
 - (a) reprojection of files into a single reference system (WGS84 UTM spindle 32);
 - (b) topology checking (e.g., elimination of self-intersections in polygons);
 - (c) elimination of any overlapping geometries, giving prevalence to the highest hazard classification.
 - 5) Homogeneity assessment of PAIs.
- Any determination regarding possible interventions is subject to the preparation of an adequate geomorphological study aimed at ascertaining the level of hazard existing in the area.

Landslide hazard area			
		km ²	% over national territory
P4	Very High	9136	3%
P3	High	16257	5,4%
P2	Medium	13836	4,6%
P1	Low	13953	4,6%
AA	Attention Area	6782	2,2%
TOT		59964	19,9%

(tab. 1 - Landslide hazard area PAI in Italy, Mosaicking 2017)



(fig. 5 - Percentage distribution of PAI landslide hazard areas in the regional territory -Mosaicking 2017)

COD PRO	Provincia	Regione	Area Provincia	Aree a pericolosità da frana				Aree di attenzione	Aree a pericolosità da frana elevata e molto elevata	
				Molto elevata	Elevata	Media	Moderata		AA	P4 + P3
				P4	P3	P2	P1			
				km ²	km ²	km ²	km ²			
1	Torino	Piemonte	6.827	330,5	192,8	28,5	0	0	523,3	7,7%
2	Vercelli	Piemonte	2.082	8,7	5,3	6,8	0	0	14,0	0,7%
3	Novara	Piemonte	1.340	1,5	0,9	2,4	0	0	2,4	0,2%
4	Cuneo	Piemonte	6.895	167,3	202,9	25,9	0	0	370,1	5,4%
5	Asti	Piemonte	1.510	24,9	36,2	1,5	0	0	61,1	4,0%
6	Alessandria	Piemonte	3.559	71,4	88,9	0,1	0	0	160,3	4,5%
96	Biella	Piemonte	913	4,7	5,2	11,4	0	0	9,9	1,1%
103	Verbano- Cusio-Ossola	Piemonte	2.261	43,3	46,4	21,7	0	0	89,7	4,0%
7	Aosta	Valle D'Aosta	3.261	1.451,2	1.220,5	424,2	0	0	2.671,7	81,9%
12	Varese	Lombardia	1.198	16,6	6,1	22,0	0	0	22,7	1,9%
13	Como	Lombardia	1.279	41,2	62,5	47,4	0	0	103,7	8,1%
14	Sondrio	Lombardia	3.196	206,5	265,9	222,1	0	0	472,4	14,8%
15	Milano	Lombardia	1.575	0,0	0,0	0,0	0	0	0,0	0,0%
16	Bergamo	Lombardia	2.746	244,9	91,4	48,9	0	0	336,3	12,2%
17	Brescia	Lombardia	4.785	222,9	139,6	128,8	0	0	362,5	7,6%
18	Pavia	Lombardia	2.969	61,7	93,3	39,7	0	0	154,9	5,2%
19	Cremona	Lombardia	1.770	0,0	0,0	0,0	0	0	0,0	0,0%
20	Mantova	Lombardia	2.341	0,0	0,0	0,0	0	0	0,0	0,0%
97	Lecco	Lombardia	815	69,5	16,2	36,9	0	0	85,7	10,5%
98	Lodi	Lombardia	783	0,0	0,0	0,0	0	0	0,0	0,0%
108	Monza e della Brianza	Lombardia	405	0,0	0,0	0,0	0	0	0,0	0,0%
21	Bolzano	Trentino- Alto Adige	7.398	93,2	38,5	37,2	1	0	131,7	1,8%
22	Trento	Trentino- Alto Adige	6.207	0,1	1.344,8	1.380,4	2.692	0	1.345,0	21,7%
23	Verona	Veneto	3.096	9,9	1,7	0,8	1	0	11,6	0,4%
24	Vicenza	Veneto	2.722	9,0	8,9	4,3	5	31	17,9	0,7%
25	Belluno	Veneto	3.672	27,8	43,8	22,2	17	226	71,6	2,0%
26	Treviso	Veneto	2.480	0,8	1,3	0,2	3	2	2,2	0,1%
27	Venezia	Veneto	2.473	0,0	0,0	0,0	0	0	0,0	0,0%
28	Padova	Veneto	2.144	0,1	2,2	2,9	1	6	2,3	0,1%
29	Rovigo	Veneto	1.819	0,0	0,0	0,0	0	0	0,0	0,0%
30	Udine	Friuli Venezia Giulia	4.907	117,1	29,3	9,0	4	0	146,4	3,0%
31	Gorizia	Friuli Venezia Giulia	467	0,2	1,2	0,5	0	0	1,4	0,3%
32	Trieste	Friuli Venezia Giulia	213	0,9	0,5	0,1	0	0	1,3	0,6%
93	Pordenone	Friuli Venezia Giulia	2.275	35,9	5,4	1,6	4	0	41,3	1,8%
8	Imperia	Liguria	1.155	8,6	100,4	583,2	369	0	109,0	9,4%

COD PRO	Provincia	Regione	Aree a pericolosità da frana					Aree di attenzione	Aree a pericolosità da frana elevata e molto elevata	
			Area Provincia	Molto elevata	Elevata	Media	Moderata		AA	P4 + P3
				P4	P3	P2	P1			
			km ²	km ²	km ²	km ²	km ²	km ²	km ²	%
9	Savona	Liguria	1.546	12,1	98,3	317,9	310	0	110,4	7,1%
10	Genova	Liguria	1.834	55,4	401,2	427,3	219	1	456,6	24,9%
11	La Spezia	Liguria	881	25,4	50,5	116,4	52	0	75,9	8,6%
33	Piacenza	Emilia-Romagna	2.586	100,9	353,6	4,8	0	0	454,4	17,6%
34	Parma	Emilia-Romagna	3.447	208,3	406,8	5,0	0	0	615,2	17,8%
35	Reggio nell'Emilia	Emilia-Romagna	2.291	128,2	180,2	2,4	0	0	308,4	13,5%
36	Modena	Emilia-Romagna	2.688	91,4	270,4	0,9	4	13	361,8	13,5%
37	Bologna	Emilia-Romagna	3.702	36,3	454,1	18,5	76	604	490,4	13,2%
38	Ferrara	Emilia-Romagna	2.635	0,0	0,0	0,0	0	0	0,0	0,0%
39	Ravenna	Emilia-Romagna	1.859	28,5	92,6	7,4	4	51	121,2	6,5%
40	Forlì-Cesena	Emilia-Romagna	2.378	388,0	346,7	114,4	65	0	734,7	30,9%
99	Rimini	Emilia-Romagna	865	96,5	95,2	0,6	0	0	191,7	22,2%
45	Massa Carrara	Toscana	1.155	33,7	64,9	181,3	1	0	98,6	8,5%
46	Lucca	Toscana	1.773	50,6	404,6	157,6	828	0	455,2	25,7%
47	Pistoia	Toscana	964	9,4	115,7	90,1	378	25	125,1	13,0%
48	Firenze	Toscana	3.514	132,6	502,5	764,6	1.247	98	635,1	18,1%
49	Livorno	Toscana	1.213	8,8	55,9	28,1	18	0	64,7	5,3%
50	Pisa	Toscana	2.445	63,6	192,9	485,7	298	0	256,5	10,5%
51	Arezzo	Toscana	3.233	57,9	279,2	264,3	1.563	0	337,1	10,4%
52	Siena	Toscana	3.821	108,6	433,3	400,1	424	0	541,9	14,2%
53	Grosseto	Toscana	4.503	117,6	712,9	3,2	1	0	830,4	18,4%
100	Prato	Toscana	366	2,7	20,3	44,3	171	7	23,1	6,3%
54	Perugia	Umbria	6.337	4,1	353,7	312,2	275	0	357,8	5,6%
55	Terni	Umbria	2.127	4,1	131,1	97,1	19	0	135,2	6,4%
41	Pesaro e Urbino	Marche	2.568	52,8	168,5	132,9	94	0	221,3	8,6%
42	Ancona	Marche	1.963	4,5	171,5	88,4	42	0	176,1	9,0%
43	Macerata	Marche	2.779	12,9	189,6	215,4	120	0	202,5	7,3%
44	Ascoli Piceno	Marche	1.228	5,8	63,5	51,4	15	0	69,3	5,6%
109	Fermo	Marche	863	2,4	64,0	80,7	51	0	66,3	7,7%
56	Viterbo	Lazio	3.615	30,7	96,0	5,7	18	69	126,7	3,5%
57	Rieti	Lazio	2.750	6,9	61,0	16,0	9	0	67,9	2,5%
58	Roma	Lazio	5.363	114,7	32,5	8,5	37	340	147,2	2,7%
59	Latina	Lazio	2.256	113,5	4,4	2,7	9	105	118,0	5,2%
60	Frosinone	Lazio	3.247	479,6	13,9	53,4	91	856	493,5	15,2%
66	L'Aquila	Abruzzo	5.047	356,1	229,1	7,7	232	328	585,2	11,6%
67	Teramo	Abruzzo	1.954	74,2	234,9	3,3	66	0	309,0	15,8%

COD PRO	Provincia	Regione	Aree a pericolosità da frana					Aree di attenzione	Aree a pericolosità da frana elevata e molto elevata	
			Area Provincia	Molto elevata	Elevata	Media	Moderata		AA	P4 + P3
				P4	P3	P2	P1			
			km ²	km ²	km ²	km ²	km ²	km ²	km ²	km ²
68	Pescara	Abruzzo	1.230	56,0	146,6	0,0	46	0	202,6	16,5%
69	Chieti	Abruzzo	2.600	150,9	430,4	0,0	139	0	581,3	22,4%
70	Campobasso	Molise	2.925	102,0	439,7	13,9	183	82	541,7	18,5%
94	Isernia	Molise	1.535	126,6	48,7	55,1	68	242	175,2	11,4%
61	Caserta	Campania	2.651	340,2	12,4	25,0	55	477	352,6	13,3%
62	Benevento	Campania	2.080	210,0	145,6	152,5	54	574	355,6	17,1%
63	Napoli	Campania	1.179	105,6	92,9	48,2	83	0	198,5	16,8%
64	Avellino	Campania	2.806	361,1	293,9	197,9	79	726	655,0	23,3%
65	Salerno	Campania	4.954	286,1	830,5	807,0	1.121	1.153	1.116,5	22,5%
71	Foggia	Puglia	7.007	103,2	456,6	1.097,2	11	9	559,9	8,0%
72	Bari	Puglia	3.863	1,2	3,5	3,0	10	0	4,7	0,1%
73	Taranto	Puglia	2.467	4,9	4,4	14,4	1	0	9,3	0,4%
74	Brindisi	Puglia	1.861	0,9	1,0	0,4	0	0	1,9	0,1%
75	Lecce	Puglia	2.799	8,8	8,3	6,9	0	0	17,1	0,6%
110	Barletta- Andria- Trani	Puglia	1.543	0,7	1,2	3,1	1	1	1,9	0,1%
76	Potenza	Basilicata	6.594	143,0	246,4	280,5	137	667	389,4	5,9%
77	Matera	Basilicata	3.479	35,0	87,2	267,8	76	12	122,2	3,5%
78	Cosenza	Calabria	6.710	154,4	104,2	140,1	12	0	258,5	3,9%
79	Catanzaro	Calabria	2.415	51,5	37,4	76,5	6	0	88,9	3,7%
80	Reggio di Calabria	Calabria	3.210	51,3	74,5	58,8	8	0	125,8	3,9%
101	Crotone	Calabria	1.736	12,7	16,2	24,7	1	0	29,0	1,7%
102	Vibo Valentia	Calabria	1.151	24,5	18,8	27,1	3	0	43,3	3,8%
81	Trapani	Sicilia	2.470	27,8	7,6	28,2	10	3	35,4	1,4%
82	Palermo	Sicilia	5.009	103,3	62,8	258,8	73	20	166,1	3,3%
83	Messina	Sicilia	3.266	58,9	33,7	160,9	57	21	92,6	2,8%
84	Agrigento	Sicilia	3.053	17,6	25,0	127,1	34	3	42,7	1,4%
85	Caltanissetta	Sicilia	2.138	9,7	6,0	92,4	12	4	15,6	0,7%
86	Enna	Sicilia	2.575	6,4	9,7	90,2	22	11	16,2	0,6%
87	Catania	Sicilia	3.574	4,1	6,5	41,9	8	3	10,6	0,3%
88	Ragusa	Sicilia	1.624	5,5	1,2	2,5	10	8	6,7	0,4%
89	Siracusa	Sicilia	2.124	6,3	2,4	0,7	0	0	8,7	0,4%
90	Sassari	Sardegna	7.692	41,5	359,7	737,0	461	0	401,2	5,2%
91	Nuoro	Sardegna	5.638	157,1	621,7	887,4	965	0	778,8	13,8%
92	Cagliari	Sardegna	1.249	11,7	30,2	82,4	111	0	41,9	3,4%
95	Oristano	Sardegna	2.990	13,6	92,1	112,4	58	0	105,7	3,5%
111	Sud Sardegna	Sardegna	6.531	69,4	100,6	292,8	206	0	170,0	2,6%
Totale Italia			302.066	9.153	16.257	13.836	13.953	6.782	25.410	8,4%

(fig. 6 - Provincialmente basate PAI aree di rischio frana - Mosaicking 2017)

1.2.2. FLOODS

In the history of floods in Italy there are events that more than others have remained in common memory, in different aspects: the 1951 flood in the Polesine with its images of a land becoming an immense expanse of water and its heavy long-term social and economic repercussions; the flood that hit Florence in 1966 whose emotional impact, aroused by the damage caused by the flood to the artistic and cultural heritage, triggered a general mobilization; the Soverato event in 2000, when as a result of a particularly intense meteoric event and the very rapid concentration of runoff, the Beltrame torrent, a fiumara that originates from Aspromonte, fell with its mass of water and debris on a campsite, located in the floodplain area of the torrent, which housed almost all disabled people and their carers; the floods of the Tanaro in 1994 and the Po in 2000 with the thousands of displaced people and the images of interrupted roads, collapsed bridges, submerged homes and businesses. In more recent memory other events thicken over areas whose names are repeated more often than others, Capoterra, Messina, Genoa, Le Cinque Terre, Lunigiana, Val di Vara, Massa Carrara.

Directive 2007/60/EC or Floods Directive (FD), emphasizes that although floods are natural phenomena that are impossible to prevent, some anthropogenic activities, such as the growth of human settlements, the increase in economic activities, the reduction of the natural rolling capacity of the soil due to the progressive sealing of surfaces and the subtraction of areas of natural flood expansion, contribute to increasing the probability of the occurrence of floods and aggravating their consequences.

On the other hand, the morphological characteristics of the national territory, in which spaces and distances granted to the hydrographic network from mountain ranges and the sea are mostly very modest, make it particularly exposed to flood events, known as flash floods or flash floods, often triggered by short and intense weather phenomena.

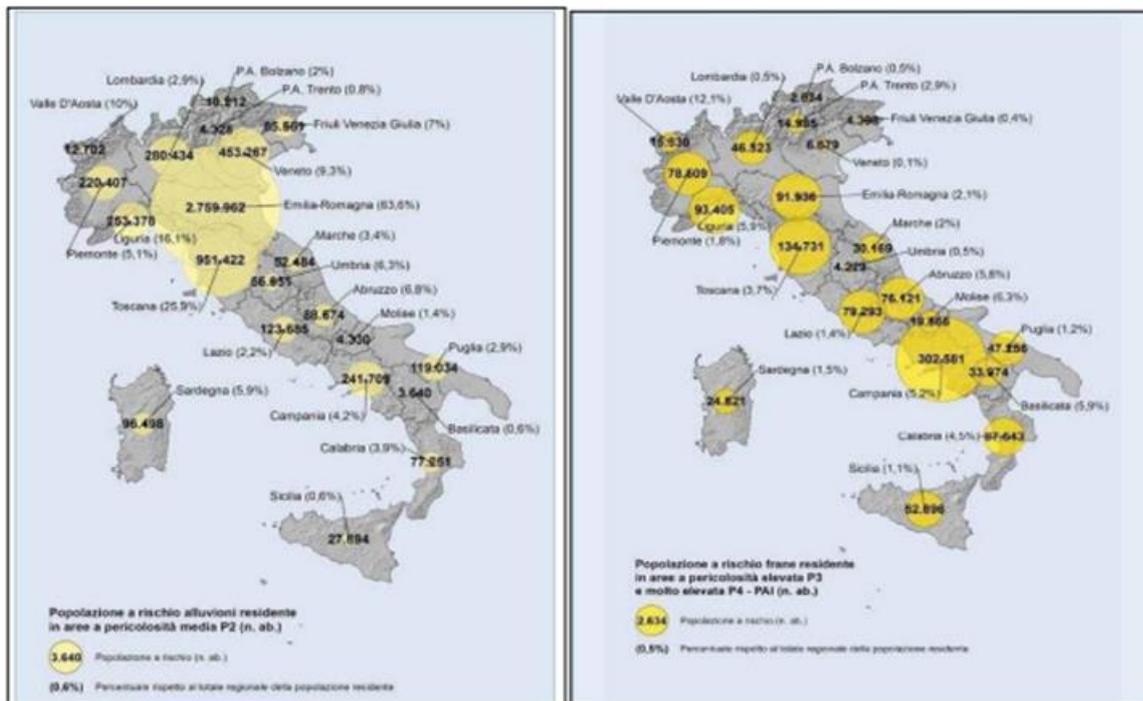
Studies carried out in the last decade (Drobinski et alii, 2018; Marchi et alii, 2010) show an increase in the frequency of such events due to the combined effect of significant climatic variations, which alter the thermo-pluviometric regime, and of the ever-increasing land consumption (ISPRA, 2018), which accentuates the impulsive character of the resulting response to the soil in terms of runoff.

With respect to the unpredictability of flood events, there is, however, a kind of repetitiveness in the occurrence of the events themselves, in the sense that same portions of the territory over time have been affected by floods and some of them due to morphological and land use characteristics, which condition the dynamics of the event and the type, and for the numerosity and value of the elements exposed to potential damage are configured as Potential Significant Flood Risk Area (APSEFR, art. 5 of the FD).

Therefore, for the purpose of identifying such areas, it is essential to acquire a Preliminary Flood Risk Assessment (PFRA, Art. 4 of the FD) that involves the systematized collection of information such as location, spatial extent and consequences associated with so-called historical events (past floods), but also the identification of those areas that due to their topographical and morphological characteristics, current or future level of anthropization (long-term developments), possible ineffectiveness of existing defense works and effects of climate change can be configured as exposed to flood risk (potential future floods).

The hazard maps contain the delineation of areas that could be affected by floods according to three probability (i.e., hazard) scenarios: low (extreme events), medium (return time ≥ 100 years), and high.

Each scenario should be characterized through the extent (flood extent), levels, and if appropriate, velocities or flow rates; the hazard maps indicate the potential adverse consequences for people, economic activities, the environment, and cultural property under the above three probability scenarios.



(fig. 7 - population at risk of landslides on the left and population at risk of flooding on the right, ISPRA 2016)

Mosaicking of hydraulic hazard

ISPRA, in order to update the map of hydraulic hazard over the entire national territory, carried out in 2017 the new National Mosaicking (v. 4.0 - December 2017) of the areas of hydraulic hazard, delimited by the District Basin Authorities.

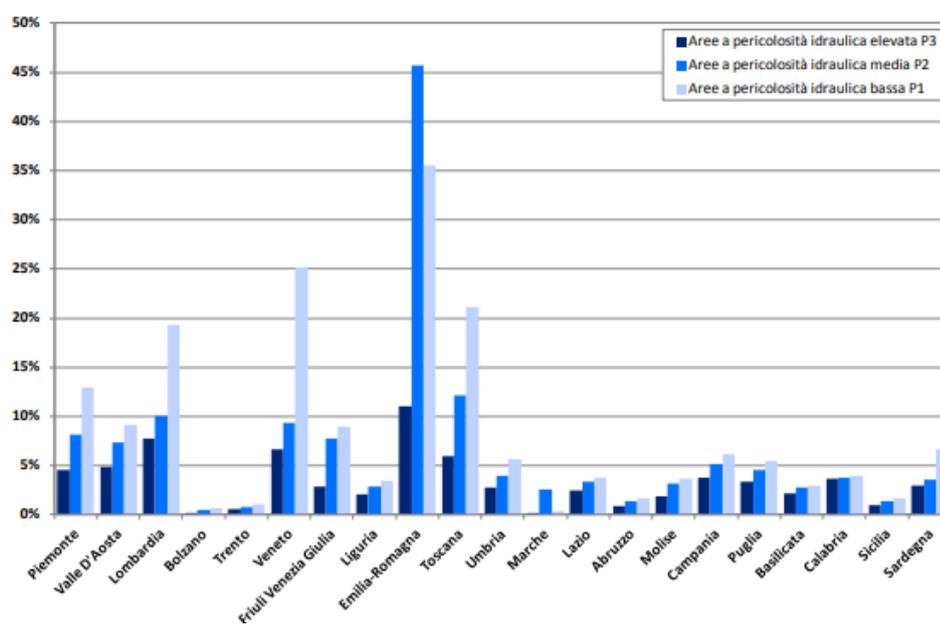
The hazard mosaicking was carried out according to the three scenarios of Legislative Decree 49/2010:

- high probability with return time between 20 and 50 years (frequent floods);
- medium probability with return time between 100 and 200 years (infrequent floods);
- low probability (low probability of floods or extreme event scenarios).

Hydraulic hazard area

		km ²	% over national territory
P3	High	12405,3	4,1%
P2	Medium	25397,3	8,4%
P1	Low	32960,9	10,9%

(tab. 2 - Hydraulic hazard area PAI in Italy, Mosaicking 2017)



(Fig. 8 - Percentage of territory with hydraulic hazard areas on a regional basis - Mosaic 2017)

COD PRO	Provincia	Regione	Aree a pericolosità idraulica - Scenari D.Lgs. 49/2010								
			Area Provincia		Elevata - P3			Media - P2		Bassa - P1	
			km ²		km ²	%	km ²	%	km ²	%	
1	Torino	Piemonte	6.827	308,6	4,5%	579,7	8,5%	931,8	13,6%		
2	Vercelli	Piemonte	2.082	113,0	5,4%	169,1	8,1%	359,5	17,3%		
3	Novara	Piemonte	1.340	53,1	4,0%	141,5	10,6%	278,4	20,8%		
4	Cuneo	Piemonte	6.895	216,3	3,1%	447,5	6,5%	596,0	8,6%		
5	Asti	Piemonte	1.510	47,5	3,1%	115,4	7,6%	164,7	10,9%		
6	Alessandria	Piemonte	3.559	266,9	7,5%	424,5	11,9%	696,3	19,6%		
96	Biella	Piemonte	913	23,3	2,6%	34,3	3,8%	55,6	6,1%		
103	Verbano-Cusio-Ossola	Piemonte	2.261	119,6	5,3%	154,0	6,8%	190,1	8,4%		
7	Aosta	Valle D'Aosta	3.261	157,4	4,8%	239,2	7,3%	298,9	9,2%		
12	Varese	Lombardia	1.198	130,2	10,9%	156,9	13,1%	187,8	15,7%		
13	Como	Lombardia	1.279	117,4	9,2%	128,6	10,1%	143,9	11,2%		
14	Sondrio	Lombardia	3.196	116,3	3,6%	151,9	4,8%	286,4	9,0%		
15	Milano	Lombardia	1.575	62,2	3,9%	107,7	6,8%	161,7	10,3%		
16	Bergamo	Lombardia	2.746	111,3	4,1%	145,3	5,3%	182,6	6,6%		
17	Brescia	Lombardia	4.785	370,5	7,7%	426,8	8,9%	568,4	11,9%		
18	Pavia	Lombardia	2.969	298,2	10,0%	376,8	12,7%	673,6	22,7%		
19	Cremona	Lombardia	1.770	172,2	9,7%	265,0	15,0%	592,5	33,5%		
20	Mantova	Lombardia	2.341	317,7	13,6%	415,9	17,8%	1.394,8	59,6%		
97	Lecco	Lombardia	815	82,9	10,2%	86,7	10,6%	113,9	14,0%		
98	Lodi	Lombardia	783	77,4	9,9%	132,0	16,9%	276,1	35,3%		
108	Monza e della Brianza	Lombardia	405	3,9	1,0%	12,1	3,0%	17,2	4,2%		
21	Bolzano	Trentino-Alto Adige	7.398	15,5	0,2%	33,2	0,4%	48,4	0,7%		
22	Trento	Trentino-Alto Adige	6.207	37,1	0,6%	45,7	0,7%	65,7	1,1%		
23	Verona	Veneto	3.096	242,6	7,8%	253,7	8,2%	487,6	15,7%		
24	Vicenza	Veneto	2.722	43,1	1,6%	75,9	2,8%	109,4	4,0%		
25	Belluno	Veneto	3.672	0,3	0,0%	0,6	0,0%	0,9	0,0%		
26	Treviso	Veneto	2.480	99,1	4,0%	145,8	5,9%	188,7	7,6%		
27	Venezia	Veneto	2.473	413,6	16,7%	573,3	23,2%	1.340,2	54,2%		
28	Padova	Veneto	2.144	245,8	11,5%	384,3	17,9%	715,8	33,4%		
29	Rovigo	Veneto	1.819	186,6	10,3%	279,9	15,4%	1.792,7	98,5%		
30	Udine	Friuli Venezia Giulia	4.907	121,2	2,5%	476,3	9,7%	521,3	10,6%		
31	Gorizia	Friuli Venezia Giulia	467	68,3	14,6%	91,9	19,7%	122,3	26,2%		
32	Trieste	Friuli Venezia Giulia	213	0,5	0,3%	1,0	0,5%	1,9	0,9%		
93	Pordenone	Friuli Venezia Giulia	2.275	39,2	1,7%	41,1	1,8%	54,4	2,4%		
8	Imperia	Liguria	1.155	12,5	1,1%	16,8	1,5%	20,3	1,8%		
9	Savona	Liguria	1.546	26,6	1,7%	37,7	2,4%	53,8	3,5%		
10	Genova	Liguria	1.834	28,3	1,5%	35,8	2,0%	45,4	2,5%		
11	La Spezia	Liguria	881	44,1	5,0%	63,3	7,2%	69,4	7,9%		
33	Piacenza	Emilia-Romagna	2.586	188,9	7,3%	597,2	23,1%	490,0	19,0%		
34	Parma	Emilia-Romagna	3.447	327,6	9,5%	857,0	24,9%	757,7	22,0%		
35	Reggio nell'Emilia	Emilia-Romagna	2.291	133,0	5,8%	1.058,7	46,2%	580,7	25,3%		

COD PRO	Provincia	Regione	Area Provincia		Aree a pericolosità idraulica - Scenari D.Lgs. 49/2010					
					Elevata - P3		Media - P2		Bassa - P1	
			km ²		km ²	%	km ²	%	km ²	%
36	Modena	Emilia-Romagna	2.688	164,3	6,1%	1.108,5	41,2%	1.035,3	38,5%	
37	Bologna	Emilia-Romagna	3.702	496,8	13,4%	1.853,1	50,1%	1.848,5	49,9%	
38	Ferrara	Emilia-Romagna	2.635	525,2	19,9%	2.627,6	99,7%	2.621,0	99,5%	
39	Ravenna	Emilia-Romagna	1.859	415,1	22,3%	1.488,1	80,0%	635,5	34,2%	
40	Forlì-Cesena	Emilia-Romagna	2.378	148,3	6,2%	490,2	20,6%	3,9	0,2%	
99	Rimini	Emilia-Romagna	865	85,6	9,9%	172,1	19,9%	7,0	0,8%	
45	Massa Carrara	Toscana	1.155	30,5	2,6%	50,2	4,3%	82,8	7,2%	
46	Lucca	Toscana	1.773	130,2	7,3%	204,8	11,6%	336,0	18,9%	
47	Pistoia	Toscana	964	62,8	6,5%	154,4	16,0%	219,8	22,8%	
48	Firenze	Toscana	3.514	114,9	3,3%	263,4	7,5%	444,1	12,6%	
49	Livorno	Toscana	1.213	121,6	10,0%	243,6	20,1%	538,8	44,4%	
50	Pisa	Toscana	2.445	266,9	10,9%	582,7	23,8%	883,2	36,1%	
51	Arezzo	Toscana	3.233	64,4	2,0%	218,7	6,8%	381,4	11,8%	
52	Siena	Toscana	3.821	144,8	3,8%	343,6	9,0%	599,9	15,7%	
53	Grosseto	Toscana	4.503	423,2	9,4%	675,0	15,0%	1.268,8	28,2%	
100	Prato	Toscana	366	21,2	5,8%	54,4	14,9%	90,2	24,7%	
54	Perugia	Umbria	6.337	173,3	2,7%	261,1	4,1%	394,8	6,2%	
55	Terni	Umbria	2.127	58,4	2,7%	75,6	3,6%	84,5	4,0%	
41	Pesaro e Urbino	Marche	2.568	1,6	0,1%	69,8	2,7%	n.d.	n.d.	
42	Ancona	Marche	1.963	n.d.	n.d.	61,9	3,2%	n.d.	n.d.	
43	Macerata	Marche	2.779	0,6	0,0%	36,4	1,3%	0,8	0,0%	
44	Ascoli Piceno	Marche	1.228	10,0	0,8%	41,7	3,4%	34,1	2,8%	
109	Fermo	Marche	863	n.d.	n.d.	31,3	3,6%	n.d.	n.d.	
56	Viterbo	Lazio	3.615	84,3	2,3%	107,3	3,0%	120,3	3,3%	
57	Rieti	Lazio	2.750	90,8	3,3%	97,1	3,5%	98,7	3,6%	
58	Roma	Lazio	5.363	191,6	3,6%	252,1	4,7%	282,6	5,3%	
59	Latina	Lazio	2.256	28,5	1,3%	63,4	2,8%	70,8	3,1%	
60	Frosinone	Lazio	3.247	34,4	1,1%	52,5	1,6%	74,3	2,3%	
66	L'Aquila	Abruzzo	5.047	18,4	0,4%	37,2	0,7%	48,2	1,0%	
67	Teramo	Abruzzo	1.954	29,2	1,5%	36,1	1,8%	42,2	2,2%	
68	Pescara	Abruzzo	1.230	17,4	1,4%	30,8	2,5%	31,0	2,5%	
69	Chieti	Abruzzo	2.600	32,0	1,2%	45,8	1,8%	57,6	2,2%	
70	Campobasso	Molise	2.925	69,2	2,4%	103,0	3,5%	121,5	4,2%	
94	Isernia	Molise	1.535	16,3	1,1%	36,3	2,4%	40,0	2,6%	
61	Caserta	Campania	2.651	311,1	11,7%	378,3	14,3%	435,6	16,4%	
62	Benevento	Campania	2.080	46,0	2,2%	58,5	2,8%	61,0	2,9%	
63	Napoli	Campania	1.179	34,5	2,9%	47,2	4,0%	93,8	8,0%	
64	Avellino	Campania	2.806	22,1	0,8%	35,4	1,3%	43,0	1,5%	
65	Salerno	Campania	4.954	98,2	2,0%	180,1	3,6%	209,7	4,2%	
71	Foggia	Puglia	7.007	324,3	4,6%	454,3	6,5%	523,5	7,5%	
72	Bari	Puglia	3.863	74,8	1,9%	94,3	2,4%	107,0	2,8%	

COD PRO	Provincia	Regione	Area Provincia	Aree a pericolosità idraulica - Scenari D.Lgs. 49/2010					
				Elevata - P3		Media - P2		Bassa - P1	
				km ²	%	km ²	%	km ²	%
73	Taranto	Puglia	2.467	108,9	4,4%	140,6	5,7%	200,3	8,1%
74	Brindisi	Puglia	1.861	32,6	1,8%	41,9	2,3%	49,6	2,7%
75	Lecce	Puglia	2.799	35,1	1,3%	64,9	2,3%	82,1	2,9%
110	Barletta-Andria-Trani	Puglia	1.543	74,8	4,9%	88,5	5,7%	97,4	6,3%
76	Potenza	Basilicata	6.594	47,2	0,7%	57,5	0,9%	62,2	0,9%
77	Matera	Basilicata	3.479	169,2	4,9%	219,2	6,3%	232,6	6,7%
78	Cosenza	Calabria	6.710	221,8	3,3%	226,3	3,4%	233,4	3,5%
79	Catanzaro	Calabria	2.415	96,0	4,0%	98,7	4,1%	109,5	4,5%
80	Reggio di Calabria	Calabria	3.210	126,4	3,9%	126,8	3,9%	130,6	4,1%
101	Crotone	Calabria	1.736	61,6	3,5%	67,6	3,9%	70,3	4,0%
102	Vibo Valentia	Calabria	1.151	57,3	5,0%	57,3	5,0%	57,7	5,0%
81	Trapani	Sicilia	2.470	15,5	0,6%	16,1	0,7%	17,6	0,7%
82	Palermo	Sicilia	5.009	11,8	0,2%	12,7	0,3%	14,2	0,3%
83	Messina	Sicilia	3.266	3,0	0,1%	3,2	0,1%	3,5	0,1%
84	Agrigento	Sicilia	3.053	14,6	0,5%	15,4	0,5%	16,7	0,5%
85	Caltanissetta	Sicilia	2.138	13,2	0,6%	13,4	0,6%	15,2	0,7%
86	Enna	Sicilia	2.575	14,1	0,5%	17,4	0,7%	23,3	0,9%
87	Catania	Sicilia	3.574	107,4	3,0%	197,6	5,5%	253,9	7,1%
88	Ragusa	Sicilia	1.624	0,0	0,0%	0,0	0,0%	0,0	0,0%
89	Siracusa	Sicilia	2.124	65,9	3,1%	77,3	3,6%	80,7	3,8%
90	Sassari	Sardegna	7.692	149,0	1,9%	169,7	2,2%	246,7	3,2%
91	Nuoro	Sardegna	5.638	114,2	2,0%	136,4	2,4%	206,1	3,7%
92	Cagliari	Sardegna	1.249	91,8	7,4%	108,2	8,7%	248,3	19,9%
95	Oristano	Sardegna	2.990	167,8	5,6%	198,3	6,6%	313,3	10,5%
111	Sud Sardegna	Sardegna	6.531	183,2	2,8%	244,8	3,7%	587,6	9,0%
Totale Italia			302.066	12.405	4,1%	25.398	8,4%	32.961	10,9%

(Fig. 9 - Areas of hydraulic hazard on a provincial basis - Mosaicking 2017)

CHAPTER 2

2.1 RISK OF MSEs

Table below shows the number, on a national basis, of IED and Seveso facilities falling in floodable areas (plants exposed to flood risk) for the three flood hazard scenarios, in absolute terms (number of plants) and as a percentage of total plants.

In the specific case of plants, the risk associated with their presence in flood-prone areas consists not only in the possible loss of value of the asset as a result of damage, but in the possibility that these plants could be a source of accidental pollution.

PLANTS	HPH High Probability Hazard		MPH Medium Probability Hazard		LPH Low Probability Hazard	
	# of plants	(%)	# of plants	(%)	# of plants	(%)
<i>IED</i>	466	11,6	1.039	25,8	1.530	38,0
<i>RIR</i>	127	12,8	245	24,7	342	34,5

(tab. 3 - Plants present in flood-prone areas for different flood probability scenarios at the national level, ISPRA Mosaic 2020)

The Seveso III Directive and its Italian transposition Legislative Decree 105/2015 reiterated the need to investigate the consequences of scenarios on the environment:

The operator is therefore required to provide in the safety report appropriate technical documentation, accompanied by plans in distinct information layers, including in georeferenced vector format, containing at least: - a detailed description of the environment surrounding the establishment/plant; - a hydrogeological-hydrological model of the site aimed at both the identification of migration pathways (direct and indirect) of hazardous substances in soil, surface water and groundwater, and the estimation of the extent of contamination in relation to propagation rates, any protection measures taken and the timing of intervention; - reference to literature data/thematic cartography and/or any findings of geognostic investigations carried out at the updated site and information on the models/procedures used by the operator.

The transposition of the IED Directive has introduced significant and substantial new features and, among them, the need, for installations producing, releasing or discharging relevant hazardous substances, as defined by the European classification system (EC Regulation 1272/2008), the obligation to submit the "baseline report" giving information on the quality status of soil and groundwater before the commissioning of a new installation, or, for existing installations, at the first modification of the permit.

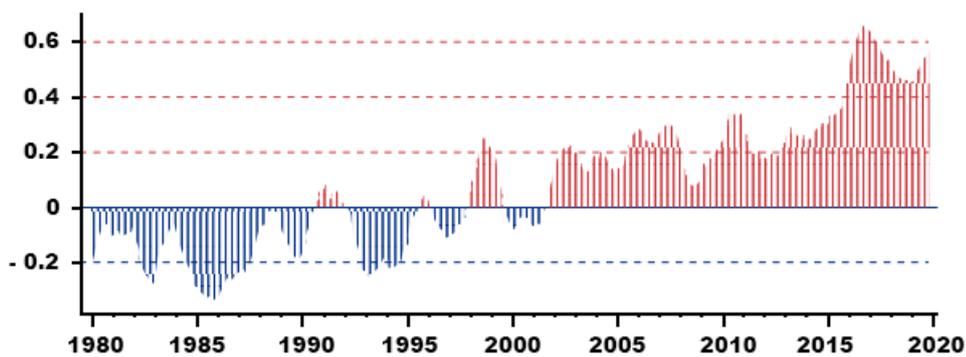
2.2 CLIMATE CHANGE

For climate risk assessment, we not only need to be concerned with climate-related natural phenomena and thus the risks associated with them, but also with the fact that the climate is changing and thus the risks are also changing.

Climate change is any systematic change in long-term statistics of climate variables. Climate change can be caused by natural forcings (change in solar radiation or Earth's orbit, natural processes internal to the Climate System) or it can be human-induced. The climate is changing, and the effects are evident both globally and regionally in the Mediterranean area and Italy.

In terms of surface temperature, for example, analysis of the evolution of mean monthly temperature anomalies in Europe, compared to the average between 1981 and 2010, shows a clear warming trend, with several months having mean temperature anomalies greater than 1 degree globally and 2 degrees in Europe.

Locally, these increases in average temperatures result in extreme temperature increases of 2-5 degrees, and an increase in the frequency of heat waves.



(fig. 10 - 12 month global surface temperature anomalies (°C) relative to 1981-2010)

A changing climate leads to an increase in the frequency of extreme weather events, making it absolutely necessary and strategic that we prepare for weather conditions that are structurally different from the current ones.

The climate mechanisms that link climatic conditions to the occurrence of natural events are very complex and depend not only on the characteristics of the affected territory, but also on the spatial and temporal scale of reference.

In Italy, climate change is likely to lead to an increase in the frequency and intensity of some hydro-meteo-geological phenomena and thus to an increase in climate impact and risk.

In various countries, including Italy, observations show that precipitation tends to be increasingly concentrated in shorter periods, during which it reaches more intense maximums. This variation causes more and more damage, especially to countries with high hydrogeological risk.

Looking ahead, for the Mediterranean region, projections discussed in IPCC ('Inter-governmental Panel on Climate Change') reports give, for the summer months, an increase in the frequency of heat waves and a possible reduction in precipitation. For the intermediate seasons, where the contrast between a warm Mediterranean Sea source of warm air masses with increasing concentrations of moisture, projections give an increased likelihood of events with precipitation or extreme winds.

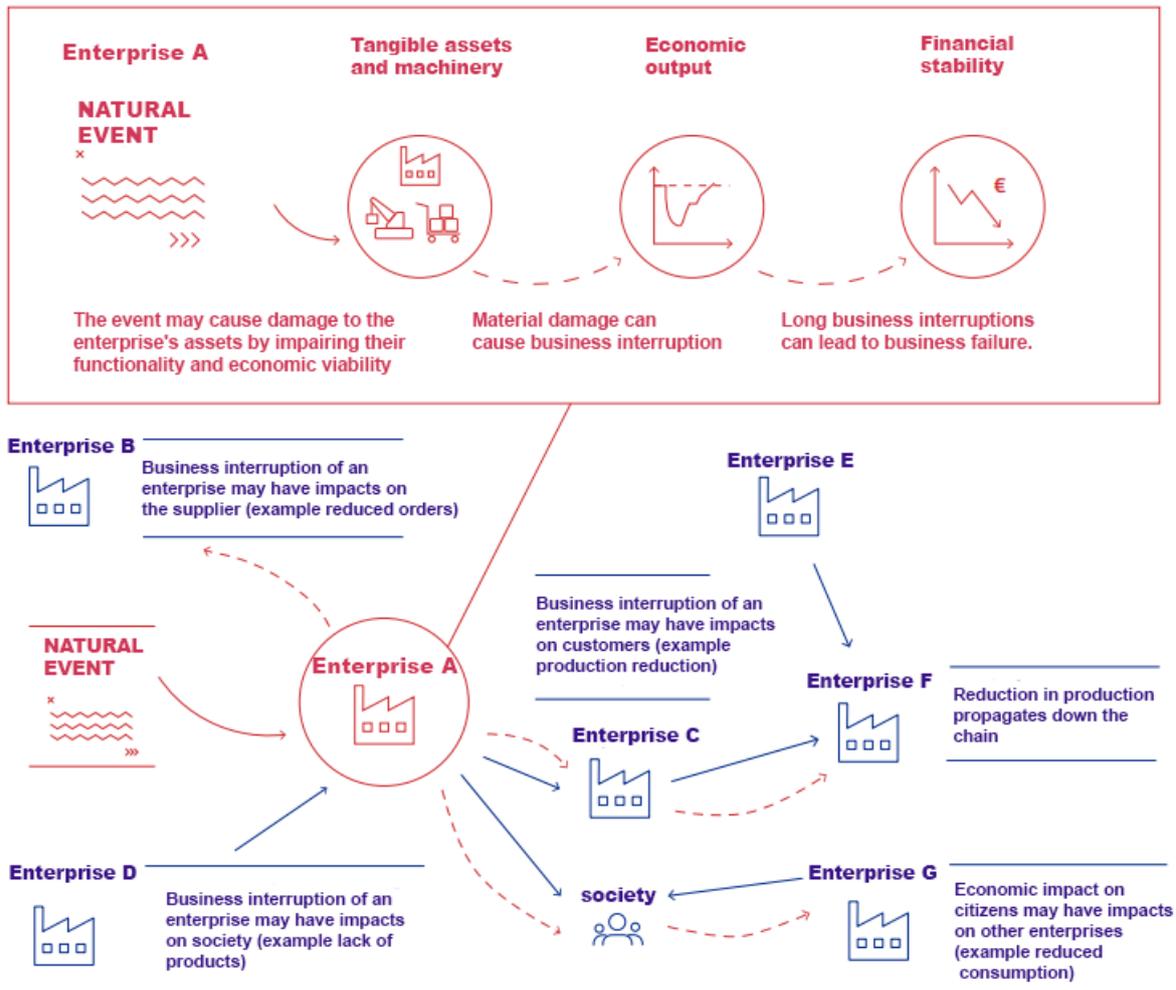
Climate change has impacts on most human activities, and can cause financial, economic, and socio-political crises. It is necessary to understand how adverse effects on some sectors of the economy that are particularly exposed -for example, agriculture- can spill over to others to the point of creating macroeconomic, financial, and geo-political instability. Prevention and adaptation actions must not only resolve the immediate crisis but produce lasting impacts that are foundations for long-term developments.

In a complex system such as our society, impacts are interconnected and depend on the dependency relationships that each individual or business inevitably has with others. The extent of impacts goes far beyond the element directly affected by the natural event.

At the system level, each enterprise is linked to another both as a supplier of goods and services and as a customer, just as society is both a beneficiary of the products and services of enterprises and a labor resource for them. A natural event that strikes a business inevitably also produces impacts on its related businesses and on society more generally. The impacts of climate risk are much broader than an initial analysis might suggest. They affect not only businesses and citizens directly affected by hydro-meteo-geological phenomena, but also affect individuals who might be in different territories and in a different climatic situation and generally characterized by apparently lower levels of risk.

At the level of the individual enterprise, the natural event can have a direct impact on tangible and instrumental assets such as buildings, machinery and goods, which, in addition to causing direct damage due to the costs required to restore them, lose their functionality and thus their economic viability for a time. From this, indirect damage is generated due to the total or partial interruption of business activity resulting in economic loss.

Interruption of business activity beyond a certain duration or beyond a certain significance may be irreversible and cause business failure.



(fig. 11 - How a natural event impacts other businesses, society, and customers)

Proper risk management is not only geared toward reducing risk, which is equivalent to reducing one of the factors characterizing risk such as hazard, vulnerability, and exposure, but more importantly it is geared toward changing behavior and activities to adapt to risk.

Proper risk management enables the prediction of possible risks so as to create the tools to transfer it.

2.3 PREVENTION AND PROTECTION

Between 1998 and 2004, Europe suffered more than 100 major flooding events, including the catastrophic floods along the Danube and Elbe rivers in the summer of 2002. In the wake of these events, the European Commission has embarked on the development of a European policy on flood risk management, resulting in a proposal for a floods Directive that was tabled in January 2006.

This Directive now requires Member States to assess if all water courses and coast lines are at risk from flooding, to map the flood extent and assets and humans at risk in these areas and to take adequate and coordinated measures to reduce this flood risk.

But today, as a result of climate change, this is no longer sufficient. At the state level, each country should undertake stronger prevention policies in order to limit flood damage.

2.3.1 BEST PRACTICE: UNITED KINGDOM

The winter of 2013-2014 was the wettest on record, with 11,000 homes and commercial properties flooded, while in 2019-2020 some parts of the country experienced a month of rain in just 24 hours.

Between April 2015 and March 2021, the government invested £2.6 billion in the flood and coastal defense investment program. Capital investment in flood and coastal erosion risk management is critical to achieving the government's long-term ambition of creating a nation more resilient to future flood and coastal erosion risks.

The 2014 Investment Plan: Reducing the risks of flooding and coastal erosion, included an investment of £2.3 billion, and the goals it set out to achieve were:

- better protect homes, businesses and infrastructure at risk of flooding
- support economic growth by avoiding flood damage
- keep pace with increased flood risk caused by climate change
- maintain and restore existing flood defense structures

Over the course of the program, the government provided additional grants for flood defense projects that met specific criteria, such as when they would support the regeneration of the most disadvantaged communities. These additional investments brought the total investment to 2.6 billion pounds.

At its conclusion in 2021, the Environment Agency and partners exceeded the target of better protecting 300,000 homes. The program saw the implementation of more than 850 flood defense projects and better protected more than 314,000 homes across England on time and on budget.

2.4 PREVENTION AND PROTECTION FOR SMEs

In the face of increasingly frequent and severe damaging events produced by climate change, prevention and protection measures can enable businesses to minimize the negative consequences for people, property and business continuity.

It is therefore important to highlight two factors within the logical process of risk management that contribute to a higher rate of success in business recovery: being prepared before the event occurs so as to reduce the risk or transfer it and knowing how to act when the event occurs.

Before emergency situations occur, it is always important to assess the risk exposure of one's assets: this analysis is done by taking into consideration the location and characteristics of the sites being assessed, such as the presence of underground rooms and structures or proximity to a watercourse that can cause flooding in the event of heavy rainfall.

- Example On November 2, 2010, a violent wave of bad weather invaded vast areas of the Veneto region, causing countless damages to the territory and population. Cloudbursts,

thunderstorms, landslides and flooding involved more than 300 municipalities, devastating several agricultural areas, homes and businesses. A company producing mechanical components for the oil and gas industry is also invaded by floodwaters. Water and mud damage the production department and the archives, located in the basement of the company in which more than 15,000 blueprints and the entire document archive, which represented the bulk of the company's know-how, since the documentation had not been transferred to digital media. At the same time as the buildings are being salvaged and electromechanically reclaimed from 4 presses and 5 CNC machining centers, the documents are immediately sorted, weighed and frozen in order to prevent their degradation to be subsequently dried using the vacuum freeze-drying method. The documents, previously frozen, are dried in a vacuum chamber at a maximum pressure of 6 mbar. Below this value (triple water point), there is a total absence of water in the liquid state and the ice immediately turns into water vapor, which is removed from the vacuum chamber. Post-treatment processes include reconstruction of document flatness, deodorization, sanitization, anti-mold treatment, and other specific restoration measures. After a few weeks, the documents are returned to the company, becoming available again for necessary consultation. In this case, the lack of an assessment of site-specific characteristics thus put the document archive, which represented the bulk of the company's own know-how, in serious jeopardy.

Proximity to a watercourse can cause major flooding that can affect businesses in adjacent areas.

- Example This is what happened, for example, on October 3, 2020, when an exceptional wave of bad weather hit Piedmont. Most severely affected were companies invaded by more than a meter of water that brought with it mud and debris, disrupting the proper functioning of machinery and abruptly interrupting normal work activities. A historic company in the faucet industry also suffered the harsh consequences of the flood: production interrupted, damaged machinery, offices destroyed by the power of the water, unfulfilled orders and consequent fear of losing its customers. The rapid rescue and mechanical and electrical/electronic remediation of production equipment, such as transfer lathes, CNC lathes, leak test benches, laser markers, pad printing machines, 3D printers and assembly lines, as well as the remediation of the buildings, was instrumental in coping with the recovery and allowing the shipping department to restart only ten days after the flood event, resulting in the fulfillment of orders on order.

When an accident occurs, it is therefore crucial to put in place the first emergency measures right away to minimize direct damage and consequent indirect damage.

- Example This is what happened, for example, in the Modena area when in 2014, following a flood event, a company specializing in precision machining, (Automotive sector), was invaded by water and mud. In addition to the economic damage suffered by machinery and equipment, the main fear for the entrepreneur was certainly that of losing key customers who, as a result of the potential delays caused by the emergency suffered, could have directed existing orders to competing companies. The mechanical and electrical/electronic

remediation of 18 CNC machining centers, 1 shot blasting machine and 3 drilling machines made it possible to restore the production department in just 5 days, allowing orders to be fulfilled on time and consequently reassuring customers without running the risk of losing market share.

However, speed of action following an emergency is also crucial to best deal with the aftermath of a disaster, turning a crisis situation into an opportunity.

- Example In October 2014, heavy rainfall hit the city of Genoa, causing streams to overflow and flooding of roads, homes, supermarkets, and businesses. During the flooding event, one of the main outlets of a company active in large-scale retailing was invaded by water and mud with devastating consequences: overturned shelves, downed merchandise, and stopped cold rooms and chillers. Immediately, sanitization and environmental restoration activities begin, particularly electromechanical remediation of refrigeration equipment and cash counters. At the same time, waste is sorted and packaged according to the different types in order to correctly identify the waste and contain the cost of disposing of the goods destroyed by the flood. After only one week after the flood event, the store reopened to the public, even before many other competitors could reopen, recording a five-fold increase in sales.

Even in the case of natural catastrophic events, where unpredictability is a determining factor, planning allows one to hypothesize possible emergency situations and be prepared for the risk scenarios one may encounter.

Estimating the impacts of possible adverse events on a company's processes and resources, analyzing the risk posed by such events, and preparing to deal with the consequences they bring with hands-on simulation and training exercises, is key to being prepared to handle a crisis situation. Every claim is different from another, but the basic information needed to plan a Crisis Management activity is often the same and even more often trivial.

First of all, it is necessary to assess the risk exposure of one's assets: this analysis is done by taking into consideration the location and technical characteristics of the sites being assessed, such as the presence of underground rooms and structures or the proximity to a watercourse that can cause flooding in the event of heavy rainfall.

It is then essential to identify departments and functions that, in the event of a disaster, must restart in the shortest possible time, and to have a list of key suppliers to call on in crisis situations to whom priorities can be given to intervene in order to reduce business interruption.

Last but not least, it is critical to identify departments and functions that must be made independent in their activities in the event of an IT system outage.

Not gathering the necessary information in advance, or not having qualified information, increases the chaos and consequently the delay with which the most appropriate decisions are made to deal with the emergency situation in the best possible way.

CHAPTER 3

3.1 ARISK'S HYDROGEOLOGICAL RISK FORECASTING TOOL

Arisk's goal is to measure catastrophic events in order to generate a forecast database that enables companies to avoid business interruption and gives them the tools to create resilience plans.

These are the key aspects of resilience that enable the company to keep climate change risks under control and to gradually increase its level of resilience:

1. IDENTIFY HYDROGEOLOGICAL RISKS AND POSSIBLE IMPACTS
2. IDENTIFY ACTIONS TO SECURE ASSETS, STRUCTURES AND FACILITIES
3. DEFINE PROCEDURES FOR RISK PREVENTION AND MANAGEMENT
4. ASSESS FINANCIAL IMPLICATIONS
5. ENSURE BUSINESS CONTINUITY IN THE EVENT OF AN EMERGENCY
6. INCREASE AWARENESS OF THE RISKS TO WHICH IT IS EXPOSED

3.2 STATISTICAL INVESTIGATION

In order to carry out a statistical analysis, it is important to carry out careful planning. The stages of a statistical analysis can be summarized as follows:

- Defining the objectives of the research
- Definition of the type of study
- Definition of the population of interest
- Definition of the variables of interest and measurement scales
- Definition of the data source
- Definition of the survey technique (construction of the instrument and mode of data collection)
- Sample selection (for sample surveys)
- Data collection and organization of collected data
- Statistical analysis

3.2.1 DEFINITION OF THE OBJECTIVES OF THE RESEARCH

In studying a problem of interest, it is necessary to specify and state the objectives in order to properly define the nature of the information to be collected and the statistical tools with which to examine the data.

The objective of the study is to build a national hydrogeological risk prediction model by collecting data from the wine-growing area of two Piedmont.

The ultimate goal is to identify a number of essential aspects that a winery must keep track of to increase its resilience to climate change, particularly with respect to hydrogeological risks.

3.2.2 DEFINITION OF THE TYPE OF STUDY

The typology of the study may differ in particular with reference to:

- to the collective to be examined;
- To the temporal mode of survey;
- to the periodicity of the study;
- to the mode of intervention of the researcher;
- to the purposes of the research

With reference to the collective to be examined, it was chosen to conduct a partial survey by initially focusing on the territory of the Langhe in Piedmont Italy and then eventually expanding the database by adding new territories.

With reference to the temporal mode of detection, it was chosen to conduct longitudinal studies (prospective, retrospective, repeated measures): for each survey unit, data are collected at multiple time instants; in the case of this analysis, 6 years from 2016 to 2021 were chosen.

With reference to the periodicity of the study, it was conducted only once in time.

With reference to the mode of intervention of the researcher, an observational study was conducted: there is passive observation of the reality of interest without intervention by the researcher.

With reference to the purpose of the research, the researcher's interest is to predict certain hydrogeological phenomena and to grasp relationships between these phenomena and the financial performance of wineries in the Langhe area.

3.2.3 DEFINITION OF THE POPULATION OF INTEREST

A statistical unit is defined as the element (individual, structure, entity, company, product, ...) on which the survey or measurement of one or more characteristics relevant to the problem under study is carried out.

Population is defined as the set of statistical units affected by the problem under study.

The population of interest is the set of municipalities in the Langhe area.

The Langhe is a territory or geographical sub-area of lower Piedmont, located between the provinces of Cuneo and Asti, consisting of an extensive hill system, bounded by the course of the Tànarò, Belbo, Bòrmida di Millesimo and Bòrmida di Spigno rivers and bordered by Astesana, Monferrato and Roero.

It can be subdivided into:

- Bassa Langa: the area between the Tanaro to the north and the Belbo to the south, with altitudes generally below 600 m; it is the area of Albese, wines and truffles (the white Alba truffle is renowned).

- Alta Langa: this is the area on the border with Liguria, with maximum altitudes of 750 m and a peak of 896 m in the municipality of Mombarcaro; forests and the cultivation of the prized "tonda gentile delle Langhe" variety of hazelnuts dominate here.
- Langa Astigiana: area in the south of the province of Asti, with Canelli to the north and the Bormida di Spigno river to the east, with a peak of 851 m in the municipality of Serole.

The Bassa Langa has a typical Po Valley climate, although temperate in maximum temperatures in the highlands. In the Alba plain, on the other hand, maximum temperatures above 30°C in the summer quarter are not uncommon.

In the Alta Langa, the climate can be described as Apennine with Po Valley influences. Summers are generally cooler and breezier than in the Lower Langa (average July temperatures around 20 °C degrees in the highlands); winters are cold in the valleys (lows of -5/-10 °C are frequent even in the Savona hinterland) and milder in the hills (average lows around 0 °C). Thermal inversions are very frequent because of the difference in insolation.

Annual precipitation varies from about 800 mm in Alba to 1100 in the Apennine watershed. The rainfall pattern is sublittoral, with a main summer minimum (July) and a secondary winter minimum; the absolute maximum is autumn, while spring rainfall tends to be highly variable from year to year. Between June and July, especially after a stingy spring, the risk of aridity (also accentuated by the dry and windy climate) is frequent. In the summer quarter, however, an average precipitation of about 100-150 mm is guaranteed (often concentrated in a few violent thunderstorms, even accompanied by hail).

Sometimes, however, in summer, especially in May, June, and July, a wind, called a "marin," can blow, bringing some coolness to the high altitudes, as the air coming in from the south is affected by the still cold Ligurian Sea.

The Langhe, despite being one of the points where the Apennines come closest to the sea, are very snowy, with an annual average of 50-100 cm even at low altitudes and a ground stay of more than 30 days. However, in recent years, there has been a serious reduction in precipitation, including snowfall, especially from late spring, and an increase in daily autumn intensity (on September 15, 2006, more than 100 mm of rain fell in 24 hours).

3.2.4 DEFINITION OF VARIABLES OF INTEREST AND MEASUREMENT SCALES

A variable (or character) is defined as a characteristic detected or measured on statistical units. Variables take different values (modes) on the various statistical units and can be:

- Quantitative variables: modes are real numbers.
- Qualitative or categorical variables: modes are non-numeric attributes.

Quantitative variables can be:

- Discrete variables can take on only values belonging to the set of natural numbers {1,2,...}.
- Continuous variables can take on any value contained in a given real interval.

In the case of our analysis, the variables are all continuous quantitative variables:

- Altitude m
- Area km²
- Landslide hazard areas - Very high P4 (km²)
- Landslide hazard areas - high P3 (km²)
- Landslide hazard areas - medium P2 (km²)
- Landslide hazard areas - low P1(km²)
- Landslide hazard areas - AA (km²)
- Landslide hazard areas - P3+P4 (km²)
- Hydraulic hazard areas - high P3 (km²)
- Hydraulic hazard areas - medium P2 (km²)
- Hydraulic hazard areas - low P1 (km²)
- Total precipitation (mm)
- Maximum daily precipitation (mm)
- Number of rainy days (prec.>=1mm)
- Average precipitation
- Number of rainy days between 0 and 1mm
- Average temperature
- Minimum Temperature °C
- Maximum temperature °C
- Average minimum temperature °C
- Average maximum temperature °C
- Ice days (E+M) n. dd
- Average humidity (E) -%
- Average minimum humidity (E) -%
- Average maximum humidity (E) -%

A measurement scale is defined as the type of measurement or set of modes adopted for observing a variable.

Contributing to the choice of measurement scale are:

- the objectives of the survey;
- the typology of the variable.

The identification of the measurement scale and the type of variable are essential for proper selection of the statistical analysis procedures to be applied.

The scale is called numerical if a set of numerical values (mode) is identified to measure the variable of interest.

3.2.5 DEFINITION OF DATA SOURCE

Information on the variables of interest to the problem under study can be derived from:

- Primary sources: information is collected from scratch by a particular survey technique (interview or direct observation,...).
- Secondary sources: information is derived from previously conducted studies, such as data from official statistical sources (ISTAT, National Statistical System, Eurostat, ...), studies published in scientific articles, data available via the Web,

Only secondary sources were used for this type of analysis.

Data for structural variables (Landslide hazard areas - Very high P4 (km²), Landslide hazard areas - high P3 (km²), Landslide hazard areas - medium P2 (km²), Landslide hazard areas - low P1(km²), Landslide hazard areas - AA (km²), Landslide hazard areas - P3+P4 (km²), Hydraulic hazard areas - high P3 (km²), Hydraulic hazard areas - medium P2 (km²), Hydraulic hazard areas - low P1 (km²)) were extracted from ISTAT databases.

Data for point variables (Total precipitation (mm), Maximum daily precipitation (mm), Number of rainy days (prec.>=1mm), Average precipitation, Number of rainy days between 0 and 1mm, Average temperature, Minimum Temperature °C, Maximum temperature °C, Average minimum temperature °C

Average maximum temperature °C, Ice days (E+M) n. dd, Average humidity (E) -%, Average minimum humidity (E) -%, Average maximum humidity (E) -%) were extracted from the Sistema Piemonte databases.

3.2.6 DEFINITION OF THE SURVEY TECHNIQUE (CONSTRUCTION OF THE INSTRUMENT AND DATA COLLECTION METHODS)

When the data source is primary, it is necessary to define the survey technique.

When the data source is secondary, it is necessary to know the survey technique. The term survey technique refers to the procedure for contacting the statistical units involved in the survey and retrieving the information of interest.

The choice of the most appropriate survey technique to collect the information being researched is one of the most important aspects in planning and executing a survey and is closely related to such considerations as: the problem being investigated, the objectives of the survey, the possible sampling strategy, the resources of the survey (in terms of finance and personnel), the time constraints of the survey, and the implications of the chosen survey technique on data quality, in terms of non-response and measurement error.

In the case of our analysis, the data are secondary and come from sensors in the Piedmont region.

3.2.7 SAMPLE SELECTION

When the survey is sample-based, it is necessary to define the sampling strategy and then proceed to sample selection. The sample represents a set of statistical units drawn from the population of interest.

Initially we focused on municipalities in the Langhe and Roero area so as to analyze the impacts of climate on wineries and grape varieties.

31 Piedmont municipalities between Alba and Cuneo:

Alba
Baldissero D'Alba
Barbaresco
Barolo
Bossolasco
Bra
Caraglio
Castino
Dogliani
La Morra
Canale
Castiglione Falletto
Clavesana
Costigliole Saluzzo
Cravanzana
Guarene
Mango
Mombarcaro
Monforte D'Alba
Montelupo albese
Neive
Piobesi D'Alba
Santo Stefano Belbo
Serralunga D'Alba
Serravalle Langhe
Canelli
Castel Boglione
Coazzolo
Costigliole D'Asti
Nizza Monferrato
San Damiano D'Asti

3.2.8 DATA COLLECTION AND ORGANIZATION OF COLLECTED DATA

Data collection and organization of collected data are operational steps in which data are collected based on choices made regarding the type of study, source of data, and survey technique, and data are organized into a format (database, database, dataset) useful for proceeding with statistical analysis.

Data were collected for the Langhe and Roero municipalities, for proper and effective statistical analysis the data were entered into a matrix:

- The rows represent the statistical units, the municipalities in the years 2016, 2017, 2018, 2019, 2020, 2021.
- The columns contain the variables.

MUNICIPALITY	Altitude m	Area km ²	Landslide hazard areas (km ²)		Hydraulic hazard areas (km ²)		Total precipitation (mm)	Maximum daily precipitation (mm)	Number of rainy days (prec>1mm)	Average precipitation (mm)	Number of rainy days between 0 and 1mm	Average temperature °C	Minimum temperature °C	Maximum temperature °C	Average minimum temperature °C	Average maximum temperature °C	Ice days (E-M) n. dd	Average humidity (%)	Average minimum humidity (%)	Average maximum humidity (%)							
			Very high high P3	medium P moderate area of at P3+P4	high P3	medium P low P1																					
Alba	2021	172	54.00	0.01025	0.02735	0	0	0	0.0376	0.6742	10.1078	13.3058	568.8	32	65	9.029	48	13.95	-7.4	37.2	7.63	20.26	71	74.54	45.58	95.85	
Baldissero D'Alba	2021	380	15.00	0.22321	0	0	0	0.22321	0.04583	0.21504	0.21504	630.8	51.3	64	9.856	71	11.72	-10.9	36	4.97	18.48	116	83.35	53.42	99.15		
Barbaresco	2021	274	7.00	0.31257	0.13597	0	0	0.44854	0.31897	1.85307	1.91581	629	36	65	9.677	54											
Barolo	2021	213	5.69	0.73192	0.10897	0	0	0.177089	0.57503	0.57503	0.57503	591.6	51.6	69	8.574	33	14.16	-7.6	37.2	8.04	20.29	58	72.85	53.4	88.37		
Bossolasco	2021	757	14.00	0.77568	3.84155	0.00257	0	0.461177	0.65863	0.65863	0.65863	484.4	67.4	60	8.073	35	12.32	-8.3	34.9	7.43	17.2	62	71.4	45.92	91.19		
Bra	2021	285	59.00	0	0	0	0	0.36669	3.27882	18.2511	18.2511	591	41	68	8.691	54	12.84	-6.4	33.7	6.64	19.03	86	78.79	51.99	96.32		
Caraglio	2021	638	41.00	0.04923	0.10253	0	0	0.15175	0.52808	1.03565	1.54669	701.4	91.6	73	8.608	54											
Castino	2021	525	15.50	0.45434	1.37709	0	0	0.183149	0.30103	0.47236	0.49049	526	35.2	68	7.735	53	12.67	-7.1	39.5	7.86	17.49	50	80	73.42	47.85	95.43	
Dogliani	2021	300	35.68	3.00545	1.24379	0	0	0.424923	0.0915	0.09722	0.10488	546.4	59.8	65	8.406	46	13.89	-6.5	36.5	8.07	19.71	59	72.71	49.52	91.08		
La Morra	2021	513	24.3	0.00742	0.01227	0.00005	0	0.019699	0.12281	1.4191	1.42098	493.6	44	68	7.259	37	14.08	-5.9	35.9	8.89	19.27	47	67.83	47.09	86.39		
Canale	2021	194	18	0.18331	0.12472	0.00005	0	0.030803	0.44788	1.03015	1.44465	608	51.6	63	9.651	55	13.68	-5.4	34.8	8.11	19.24	59	82.1	61.21	98.39		
Castiglione Falletto	2021	350	4.72	0.33207	0.69987	0	0	0.103194	0.3268	0.34004	0.36454	577.6	43	66	8.752	42	14.38	-4.9	37	8.81	19.95	57	69.01	48.17	87.37		
Clavenna	2021	300	17.15	0.01067	0.00647	0	0	0.001713	3.33319	5.65571	5.77912	594	61.2	72	8.250	31	13.51	-8.3	36.1	8.45	18.57	51	70.99	49.47	88.58		
Castiglione Saluzzo	2021	476	15	0	0	0	0	0.121799	2.20709	4.10721	4.10721	696	84	72	9.617	37	11.93	-8.4	34.5	5.82	18.04	96	73.91	47.1	92.97		
Crawanzana	2021	585	8.2	0.38055	3.73832	0	0	0.411886	0.57207	0.57207	0.57207	555.6	44.6	63	8.689	78	12.4	-12.6	37.4	5.84	18.95	86	78.21	50.85	95.59		
Guarene	2021	360	13.4	0.85165	2.7963	0	0	0.364795	0.12224	0.63136	1.78669																
Mango	2021	521	19	2.72416	0.63836	0	0	0.76251	2.24973	2.24973	2.24973	601.2	36.6	65	9.249	32	12.93	-5.1	34.2	9.08	16.79	39	72.74	54.23	87.67		
Mombacaro	2021	896	20	0.05807	0.53247	0	0	0.59054	0.65283	0.83028	0.90413																
Montforte D'Alba	2021	480	25	0.05807	0.53247	0	0	0.422073	1.94097	1.94097	1.94097																
Monteuolo albesse	2021	564	6.4	1.21567	3.00506	0	0	0.277956	0.92257	0.92357	0.92357	520	45.8	63	8.254	36	14.02	-5.3	35.5	8.73	19.31	37	72.66	50.97	91.07		
Neive	2021	308	21.2	1.72397	2.47602	0	0	0.149999	0.92506	2.58547	3.09002	496.8	32.6	62	8.013	54	14.08	-3.6	35.7	9.35	18.82	29	72.12	53.15	89.21		
Piobesi D'Alba	2021	194	3	0.2364	0.50606	0	0	0.74246	0.20345	0.28777	0.28777	807.8	63.4	70	8.683	62	13.19	-6.3	36.7	7.23	19.16	74	77.68	51.2	96.83		
Santo Stefano Belbo	2021	170	23	0.0042	0.00083	0	0	0.00504	0.65283	0.83028	0.90413	592.2	37.6	70	8.489	39	14.58	-4.4	36.5	9.66	19.5	28	73.76	59.16	90.49		
Serralunga D'Alba	2021	414	8.44	1.50746	0.3073	0	0	0.181476	0.37127	0.48539	0.48659	432.9	39.6	59	7.332	50	14.36	-6.7	37.4	8.82	19.89	50	73.73	52.29	90.14		
Serravalle Langhe	2021	762	9	2.57206	0.30971	0	0	0.288177	0.14648	0.14648	0.14648	503	52.8	68	7.987	31	12.78	-6.8	35.2	7.71	17.85	52	74.37	51.25	92.18		
Canelli	2021	316	23.43	0.02351	0.01407	0	0	0.037559	0.66073	1.6473	3.52255	654.6	60.4	69	9.487	38	14.67	-4.8	38	9.11	20.22	37	77.98	52.81	88.79		
Castel Boglione	2021	260	12	0.0041	0	0	0	0.0041	0.13301	0.13301	0.14177	606.4	74	66	9.188	33	14.42	-5.8	37.4	9.23	19.61	39	70	47.52	95.82		
Coazzolo	2021	291	4.12	0.04035	0	0.13502	0	0.004035	0.03938	0.11161	0.11161	629.4	38.2	71	8.865	62	12.65	-4.6	36.6	6.03	19.27	102	80.64	49.3	99.04		
Castiglione D'asti	2021	242	36	1.5026	0.93122	0.13502	0	0.243881	0.01066	2.60879	5.81648																
Nizza Monferrato	2021	137	30.4	0.00132	9.5E-05	0	0	0.00142	0.11057	2.09046	4.54711	522	49.2	66	7.909	51											
San Damiano D'asti	2021	179	48	0.08651	0.80644	0.52887	0	0.89295	1.40954	3.67896	4.56632	505.2	29.4	61	8.282	45	13.43	-6.3	37	7.54	19.32	72	79.11	49.92	98.34		
Alba	2020	172	54.00	0.01025	0.02735	0	0	0.0376	0.6742	10.1078	13.3058	670.8	77.4	71	9.448	50	11.79	-5.9	38.8	5.38	18.2	117	84.58	60.1	99.21		
Baldissero D'Alba	2020	380	15.00	0.22321	0	0	0	0.22321	0.04583	0.21504	0.21504	661	87.8	68	9.771	63											
Barbaresco	2020	274	7.00	0.31257	0.13597	0	0	0.44854	0.31897	1.85307	1.91581	611	62	62	10.187	35	14.91	-3.2	37.2	9.8	20.02	30	74.5	54.36	89.61		
Bossolasco	2020	757	14.00	0.77568	3.84155	0.00257	0	0.461177	0.65863	0.65863	0.65863	487.2	79.2	45	10.827	49	12.79	-5	33.5	7.92	17.65	44	77.69	54.13	93.67		
Bra	2020	285	59.00	0	0	0	0	0.36669	3.27882	18.2511	18.2511																
Caraglio	2020	638	41.00	0.04923	0.10253	0	0	0.15175	0.52808	1.03565	1.54669	945.4	61.8	82	11.529	45											
Castino	2020	525	15.50	0.45434	1.37709	0	0	0.183149	0.30103	0.47236	0.49049	630.6	63.6	75	8.408	29	13.17	-3.5	34.8	8.48	17.86	31	80.45	56.31	97.14		
Dogliani	2020	300	35.68	3.00545	1.24379	0	0	0.424923	0.0915	0.09722	0.10488	771.8	105.5	76	10.155	41											
La Morra	2020	513	24.3	0.00742	0.01227	0.00005	0	0.019699	0.12281	1.4191	1.42098	711.4	64.4	71	10.020	32	13.87	-4.5	36.6	9.04	18.7	26	80.08	59.85	95.85		
Canale	2020	194	18	0.18331	0.12472	0.00005	0	0.030803	0.44788	1.03015	1.44465	668.2	77.6	72	9.281	54	14.21	-4.1	37.4	8.62	19.79	42	79.12	55.67	96.66		
Castiglione Falletto	2020	350	4.72	0.33207	0.69987	0	0	0.103194	0.3268	0.34004	0.36454	672	73	69	9.736	47	14.82	-3.8	38.4	9.2	20.44	29	73.17	50.6	90.5		
Clavenna	2020	300	17.15	0.01067	0.00647	0	0	0.001713	3.33319	5.65571	5.77912	678	70.6	70	9.828	52	14.02	-5.8	36.6	9.29	20.44	29	73.17	50.6	90.5		
Castiglione Saluzzo	2020	476	15	0	0	0	0	0.121799	2.20709	4.10721	4.10721	678	70.6	70	9.828	52	14.02	-5.8	36.6	9.29	20.44	29	73.17	50.6	90.5		
Crawanzana	2020	585	8.2	0.38055	3.73832	0	0	0.411886	0.57207	0.57207	0.57207	697	91	78	8.936	64	13.31	-6.3	35.8	6.76	17.86	78	79.37	54.07	96.3		

MUNICIPALITY	Altitude m	Area km²	Landslide hazard areas (km²)				Hydraulic hazard areas (km²)		Total precipitation (mm)	Maximum daily precipitation (mm)	Number of rainy days (prec.>1m)	Average precipitation n	Number of rainy days between 0 and 1mm	Average temperature e	Minimum temperature °C	Maximum temperature °C	Average minimum temperature °C	Average maximum temperature °C	Ice days (E-M) n.dd	Average humidity (E) %	Average minimum humidity %	Average maximum humidity (E) %				
			Very high	high	P moderate	area of at P3+P4	high P3	medium P low P1																		
																							0	0	0	0
Alba	2021	172	54.00	0.01025	0.02735	0	0	0.00376	0.6742	10.1078	13.3058	568.8	32	63	9.029	48	13.95	-7.4	37.2	7.63	20.26	71	74.54	45.58	95.85	
Baldissero D'Alba	2021	380	15.00	0.22321	0	0	0	0.22321	0.04583	0.21504	0.21504	630.8	51.2	64	9.856	71	11.72	-10.9	36	4.97	18.48	116	83.35	53.42	99.15	
Barbresco	2021	274	7.00	0.31257	0.13597	0	0	0.44854	0.31897	1.85307	1.91581	629	36	65	9.677	54	13.4856	-6.736	36.04	7.9588	19.024	59.56	76.48	51.21154	92.69346	
Barolo	2021	213	5.69	0.73192	0.03897	0	0	0.177089	0.57503	0.57503	0.57503	591.6	51.6	69	8.574	33	14.16	-7.6	37.2	8.04	20.29	58	72.85	53.4	88.37	
Bossolasco	2021	757	14.00	0.77569	3.84155	0.00257	0	0	4.61717	0.65863	0.65863	484.4	67.4	60	8.073	35	12.32	-8.3	34.9	7.45	17.2	62	71.4	45.92	91.19	
Bra	2021	285	59.00	0	0	0	0	0	0.36669	3.27882	18.2511	591	41	68	8.691	34	12.84	-6.4	33.7	6.64	19.03	86	78.79	51.99	96.32	
Caraglio	2021	638	41.00	0.04923	0.10253	0	0	0.015175	0.52808	1.03655	1.45669	701.4	91.6	73	9.608	54	13.4856	-6.736	36.04	7.9588	19.024	59.56	73.42	47.85	93.43	
Castino	2021	525	15.50	0.45434	1.37709	0	0	0.183143	0.30103	0.47236	0.49049	526	36.2	68	7.735	53	12.67	-7.1	35.5	7.86	17.49	50	75.003333	51.21154	92.69346	
Dogliani	2021	300	35.68	0.30055	1.24379	0	0	0.424923	0.0915	0.09722	0.10488	546.4	59.8	65	8.406	46	13.89	-6.5	36.5	8.07	19.71	59	72.72	49.52	91.08	
La Morra	2021	513	24.3	0.00742	0.0127	0	0	0.01969	0.12281	1.4191	1.42096	495.6	44	68	7.259	37	14.08	-5.9	35.9	8.89	19.27	47	67.83	47.09	86.39	
Canale	2021	194	18	0.18331	0.12472	0.0005	0	0	0.38083	0.44788	1.03015	1.44465	608	51.6	63	9.651	55	13.68	-5.4	34.8	8.11	19.24	59	82.1	61.21	98.35
Castiglione Falletto	2021	350	4.72	0.33207	0.69987	0	0	0.103194	0.3268	0.34004	0.36454	577.6	43	66	8.752	42	14.38	-4.9	37	8.82	19.57	57	69.01	48.17	87.37	
Clavesana	2021	300	17.15	0.01067	0.00647	0	0	0.001713	0.33319	5.65571	5.77912	594	61.2	72	8.250	31	13.51	-6.3	36.3	8.45	18.57	51	70.93	49.47	88.58	
Costigliole Saluzzo	2021	476	15	0	0	0	0	0	1.21799	2.20709	4.10721	696	84	72	9.667	37	11.93	-8.4	34.5	5.82	18.04	96	73.91	47.1	92.97	
Cravanzana	2021	585	8.3	0.38055	3.7862	0	0	0	4.11886	0.57207	0.57207	555.6	44.6	63	8.619	78	12.4	-12.6	37.4	5.84	18.95	86	78.21	50.85	95.59	
Guarene	2021	360	13.4	0.85165	2.7983	0	0	0	3.64795	0.12224	0.63136	1.78669	572.8667	50.1926	66.259	8.946	46.7057	13.4269	-6.736	36.04	7.9588	19.024	59.56	75.003333	51.21154	92.69346
Mango	2021	521	19	2.72416	0.60386	0	0	0	8.76251	2.24973	2.24973	601.2	36.6	65	9.249	32	12.93	-5.1	34.2	9.08	19.79	39	72.74	54.23	87.67	
Mombacaro	2021	896	20	0.05807	0.53247	0	0	0	0.59054	0.65283	0.80208	0.90413	554.1556	50.192	66.259	8.363	46.7	13.4856	-6.736	36.04	7.9588	19.024	59.56	75.003333	51.21154	92.69346
Monforte D'Alba	2021	480	25	1.21567	0.30506	0	0	0	4.22073	1.94097	1.94097	554.1556	50.192	66.259	8.363	46.7	13.4856	-6.736	36.04	7.9588	19.024	59.56	75.003333	51.21154	92.69346	
Monteuolo Albesse	2021	564	6.4	0.21145	2.58812	0	0	0	2.77956	0.92257	0.92257	520	45.8	63	8.254	36	14.02	-5.3	35.5	8.73	19.31	37	72.66	50.97	91.03	
Neive	2021	908	21.2	1.72397	2.47602	0	0	0	4.19999	0.32899	2.85847	3.09002	499.8	32.6	62	8.013	54	14.08	-3.6	35.7	9.35	18.82	29	72.12	53.15	89.21
Piobesi D'Alba	2021	194	3	0.2364	0.50606	0	0	0	0.74246	0.20345	0.28777	0.28777	607.8	63.4	70	8.683	62	13.19	-6.3	36.7	7.23	19.16	74	77.68	51.2	96.83
Santo Stefano Belbo	2021	170	23	0.0042	0.00083	0	0	0	0.00504	2.18719	2.97597	4.59664	594.2	37.6	70	8.489	39	14.58	-4.4	36.5	9.66	19.5	28	79.76	59.16	95.31
Serralunga D'Alba	2021	414	8.44	1.50746	0.3073	0	0	0	1.81476	0.37127	0.48539	0.48539	432.6	39.6	59	7.332	50	14.36	-6.7	37.4	8.82	19.89	50	73.73	52.29	90.14
Serravalle Langhe	2021	762	54.00	0.01025	0.02735	0	0	0	1.81476	0.37127	0.48539	432.6	39.6	59	7.332	50	14.36	-6.7	37.4	8.82	19.89	50	73.73	52.29	90.14	
Canelli	2021	516	25.43	0.02351	0.02407	0	0	0	0.03759	0.65073	1.6473	9.5258	654.6	60.4	69	9.487	38	14.67	-4.8	38	9.11	20.22	37	77.98	52.81	95.89
Casti Boglione	2021	260	12	0.0041	0	0	0	0	0.0041	0.13301	0.13301	0.14177	606.4	74	66	9.188	33	14.42	-5.9	37.4	9.23	19.61	39	70	47.52	88.74
Cozzuolo	2021	291	4.12	0.04035	0	0	0	0	0.04035	0.03938	0.11161	0.11161	629.4	38.2	71	8.865	82	12.65	-10	36.6	6.03	19.27	102	80.64	49.3	99.02
Costigliole D'asti	2021	242	36	1.5026	0.93122	0.13502	0	0	2.43381	0.01066	2.60879	5.81468	554.1556	50.192	66.259	8.363	46.7	13.4856	-6.736	36.04	7.9588	19.024	59.56	75.003333	51.21154	92.69346
Nizza Monferrato	2021	137	30.4	0.00132	9.3625	0	0	0	0.00142	0.11057	0.29046	4.54711	522	49.2	66	7.909	91	13.426	-6.736	36.04	7.9588	19.024	59.56	74.59	53.83	90.59
San Damiano D'asti	2021	179	48	0.08651	0.80544	0.52887	0	0	0.89395	1.40954	3.67896	4.56902	505.2	29.4	61	8.282	45	13.45	-6.3	37	7.64	19.32	72	78.11	49.92	98.34
Alba	2020	172	54.00	0.01025	0.02735	0	0	0	0.00376	0.6742	10.1078	13.3058	686.837	78.037	68.333	10.051	51.778	13.991	-4.86	37.33	8.608	19.271	43	78.19	54.836	93.455

(fig. 13 - Piedmont database with missing data estimated by method 1)

- Method 2: Each missing variable was calculated by averaging the values for that variable for that municipality in different years.
Example: to estimate the data for Average temperature in Bossolasco in 2016, the Average temperature in Bossolasco of the years 2017, 2018, 2019, 2020, 2021 was averaged.

MUNICIPALITY	Altitude m	Area km²	Landslide hazard areas (km²)				Hydraulic hazard areas (km²)		Total precipitation (mm)	Maximum daily precipitation (mm)	Number of rainy days (prec.>1m)	Average precipitation n	Number of rainy days between 0 and 1mm	Average temperature e	Minimum temperature °C	Maximum temperature °C	Average minimum temperature °C	Average maximum temperature °C	Ice days (E-M) n.dd	Average humidity (E) %	Average minimum humidity %	Average maximum humidity (E) %			
			Very high	high	P moderate	area of at P3+P4	high P3	medium P low P1																	
																							0	0	0
Alba	2021	172	54.00	0.01025	0.02735	0	0	0.00376	0.6742	10.1078	13.3058	568.8	32	63	9.029	48	13.95	-7.4	37.2	7.63	20.26	71	74.54	45.58	95.85
Alba	2020	172	54.00	0.01025	0.02735	0	0	0.00376	0.6742	10.1078	13.3058	825.53333	81.6	67	12.321	63	13.853333	-8.1333333	37.9	7.7	20.003333	76	74.46	45.755	95.465
Alba	2019	172	54.00	0.01025	0.02735	0	0	0.00376	0.6742	10.1078	13.3058	984.8	101.4	78	12.626	74	14.57	-8.9	41.7	8.18	20.96	73	74.38	45.93	95.08
Alba	2018	172	54.00	0.01025	0.02735	0	0	0.00376	0.6742	10.1078	13.3058	825.53333	81.6	67	12.321	63	13.853333	-8.1333333	37.9	7.7	20.003333	76	74.46	45.755	95.465
Alba	2017	172	54.00	0.01025	0.02735	0	0	0.00376	0.6742	10.1078	13.3058	825.53333	81.6	67	12.321	63	13.853333	-8.1333333	37.9	7.7	20.003333	76	74.46	45.755	95.465
Alba	2016	172	54.00	0.01025	0.02735	0	0	0.00376	0.6742	10.1078	13.3058	923	111.4	60	15.383	67	13.04	-10.1	34.8	7.29	18.79	85	74.46	45.755	95.465
Baldissero D'Alba	2021	380	15.00	0.22321	0	0	0	0.22321	0.04583	0.21504	0.21504	630.8	51.2	64	9.856	71	11.72	-10.9	36	4.97	18.48	116	83.35	53.42	99.15
Baldissero D'Alba	2020	380	15.00	0.22321	0	0	0	0.22321	0.04583	0.21504	0.21504	670.8	77.4	71	9.448	50	11.79	-9.3	38.8	5.38	18.				

3.3 FINAL DATABASE OF PIEDMONT

MUNICIPALITY	Year	Altitude m	Area km ²	Landslide hazard areas (km ²) Very High P3	Landslide hazard areas (km ²) High P2	Landslide hazard areas (km ²) medium P1	Landslide hazard areas (km ²) low P1	Landslide hazard areas (km ²) AA	Landslide hazard areas (km ²) A1	Landslide hazard areas (km ²) A2	Hydraulic hazard areas (km ²) High P3	Hydraulic hazard areas (km ²) medium P2	Hydraulic hazard areas (km ²) low P1	Total precipitation (mm)	Maximum daily precipitatio (mm)	Number of rainy days (prec>1mm)	Average precipitatio (mm)	Number of rainy days between 0 and 1mm	Average temperature	Minimum temperature °C	Maximum temperature °C	Average minimum temperature °C	Average maximum temperature °C	Ice day n. dd	Average humidity (E-%)	Average humidity (E-%)	Average maximum humidity (E-%)
Alba	2021	172.00	54.00	0.0102	0.0274	0.0000	0.0000	0.0000	0.0000	0.0376	0.6742	10.1078	13.3058	968.8	32	63	9.029	48	13.95	-7.4	37.2	7.63	20.26	71	74.54	45.58	95.85
Baldissero D'Alba	2021	380.00	15.00	0.2132	0.0000	0.0000	0.0000	0.0000	0.0000	0.2132	0.0458	0.2150	0.2150	630.8	51.2	64	9.856	71	11.71	-10.4	36	4.97	18.48	116	83.35	53.42	99.15
Barbarico	2021	274.00	7.00	0.3126	0.1360	0.0000	0.0000	0.0000	0.0000	0.4485	0.3190	1.8531	1.9158	629	36	65	9.677	54	13.4858	-6.786	36.04	7.9588	19.0124	59.56	76.48	51.111538	92.6938462
Barolo	2021	213.00	5.69	0.7319	0.1090	0.0000	0.0000	0.0000	0.0000	1.7709	0.5750	0.5750	0.5750	591.6	51.6	69	8.074	33	14.16	-7.6	37.2	8.04	20.29	58	72.85	53.4	88.37
Bossolasco	2021	757.00	14.00	0.7756	0.3845	0.0026	0.0000	0.0000	0.0000	4.6172	0.6586	0.6586	0.6586	484.4	67.4	60	8.733	35	12.32	-8.3	34.9	7.43	17.2	62	71.4	45.92	91.19
Bra	2021	285.00	59.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.3667	3.2788	18.2511	591	41	68	8.691	34	12.84	-6.4	35.7	6.54	19.03	86	78.79	51.99	96.31
Caraglio	2021	638.00	41.00	0.0492	0.1025	0.0000	0.0000	0.0000	0.0000	0.1518	0.5281	1.0357	1.5467	701.4	91.6	73	9.608	54	13.4858	-6.736	36.04	7.9588	19.0124	59.56	74.42	47.85	98.44
Castino	2021	525.00	15.50	0.4543	1.3771	0.0000	0.0000	0.0000	0.0000	1.8314	0.3010	0.4724	0.4905	526	36.2	68	7.735	53	12.67	-7.1	33.5	7.86	17.49	50	75.0033	51.111538	92.6938462
Dogliani	2021	300.00	35.68	3.0054	1.2438	0.0000	0.0000	0.0000	0.0000	4.2492	0.9015	0.0972	0.1049	546.4	59.8	65	8.406	46	13.89	-6.5	36.5	8.07	19.71	59	72.72	49.52	91.08
La Morra	2021	513.00	24.30	0.0074	0.0123	0.0000	0.0000	0.0000	0.0000	0.0197	0.1228	1.4191	1.4210	493.6	44	68	7.259	37	14.08	-5.9	35.9	8.89	19.27	47	67.83	47.09	86.39
Canale	2021	194.00	18.00	0.1833	0.1247	0.0005	0.0000	0.0000	0.0000	0.3080	0.4479	1.0301	1.4446	648	51.6	65	9.651	55	15.58	-5.4	34.8	8.11	19.24	59	82.1	61.21	98.39
Castiglione Falletto	2021	350.00	4.72	0.3321	0.6999	0.0000	0.0000	0.0000	0.0000	1.0319	0.3268	0.3400	0.3645	577.4	43	66	8.752	42	14.38	-4.9	37	8.82	19.95	57	69.01	48.17	87.37
Civesana	2021	300.00	17.15	0.0107	0.0065	0.0000	0.0000	0.0000	0.0000	0.0171	3.3332	5.6557	5.7791	594	61.2	72	8.250	31	13.51	-4.3	36.3	8.45	18.57	51	70.93	49.47	88.58
Castiglione Saluzzo	2021	476.00	15.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.2180	2.2071	4.0772	696	84	72	9.667	37	11.93	-8.4	34.5	5.82	18.04	96	73.91	47.1	92.97
Cranzavanna	2021	585.00	8.20	0.3805	3.7383	0.0000	0.0000	0.0000	0.0000	4.1189	0.5721	0.5721	0.5721	555.6	44.6	63	8.819	78	12.4	-12.6	37.4	5.84	18.95	86	78.21	50.85	95.59
Guarene	2021	360.00	15.40	0.8516	2.7963	0.0000	0.0000	0.0000	0.0000	3.6479	0.1222	0.6314	1.7867	572.8667	50.1926	66.2593	8.646	46.7007	13.4526	-6.736	36.04	7.9588	19.0124	59.56	75.0033	51.111538	92.6938462
Mango	2021	521.00	19.00	2.7242	0.0384	0.0000	0.0000	0.0000	0.0000	8.7625	2.2497	2.2497	2.2497	601.2	36.6	65	9.249	32	12.93	-5.1	34.2	9.08	16.79	39	72.74	54.23	87.67
Monbarco	2021	896.00	20.00	0.0581	0.5325	0.0000	0.0000	0.0000	0.0000	0.5905	0.6528	0.8303	0.9041	554.1556	50.192	66.2593	8.363	46.7	13.4858	-6.736	36.04	7.9588	19.0124	59.56	75.0033	51.111538	92.6938462
Monforte D'Alba	2021	480.00	25.00	1.2157	3.0051	0.0000	0.0000	0.0000	0.0000	4.2207	1.9410	1.9410	1.9410	554.1556	50.192	66.2593	8.363	46.7	14.5	-5.4	35.9	9.91	19.09	32	74.17	54.29	90.07
Monteuolo albesse	2021	564.00	6.40	0.2114	0.2681	0.0000	0.0000	0.0000	0.0000	2.7798	0.9226	0.9226	0.9226	520	46.8	63	8.254	36	14.02	-5.3	35.5	8.73	19.31	37	72.66	50.97	91.07
Neive	2021	308.00	21.20	1.2740	2.4760	0.0000	0.0000	0.0000	0.0000	4.2003	0.9251	2.5855	3.0900	496.8	61.2	66	8.013	54	14.08	-3.6	35.7	8.35	18.82	29	72.12	53.15	99.21
Piobesi D'Alba	2021	194.00	3.00	0.2364	0.5061	0.0000	0.0000	0.0000	0.0000	0.7425	0.2034	0.2878	0.2878	607.8	63.4	70	8.683	62	13.19	-6.3	36.7	7.23	19.16	74	77.68	51.2	96.83
Santo Stefano Belbo	2021	170.00	23.00	0.0042	0.0008	0.0000	0.0000	0.0000	0.0000	0.0050	2.1872	2.9760	4.5496	594.2	37.6	70	8.489	39	14.58	-4.4	36.5	9.66	19.5	28	79.76	51.6	95.31
Serralunga D'Alba	2021	414.00	8.44	1.5075	0.3073	0.0000	0.0000	0.0000	0.0000	1.8148	0.3713	0.4854	0.4866	432.6	39.6	59	7.332	50	14.36	-6.7	37.4	8.82	19.89	50	73.73	52.29	90.14
Serravalle Langhe	2021	762.00	15.00	0.2571	0.3097	0.0000	0.0000	0.0000	0.0000	2.8818	0.1465	0.1465	0.1465	608	52.7	68	7.937	31	14.78	-6.9	35.2	7.71	17.85	52	74.37	52.18	92.18
Canelli	2021	316.00	23.43	0.0235	0.0141	0.0000	0.0000	0.0000	0.0000	0.0376	0.6607	1.6473	3.5225	654.6	60.4	69	9.487	38	16.67	-8.4	36.8	9.11	20.12	37	77.98	52.81	95.89
Castel Boglione	2021	260.00	12.00	0.0041	0.0000	0.0000	0.0000	0.0000	0.0000	0.0041	0.1330	0.1330	0.1418	606.4	74	66	9.188	33	14.42	-5.9	37.4	9.23	19.61	39	70	47.52	88.74
Coazzolo	2021	291.00	4.12	0.0403	0.0000	0.0000	0.0000	0.0000	0.0000	0.0403	0.0394	0.1116	0.1116	629.4	38.2	71	8.865	82	12.65	-10	36.6	6.03	19.27	102	80.64	49.3	99.00
Castiglione D'Asti	2021	242.00	36.00	1.5026	0.9312	0.1350	0.0000	0.0000	0.0000	2.4338	0.0107	2.6088	5.8165	554.1556	50.192	66.2593	8.363	46.7	13.4858	59.56	59.56	59.56	59.56	75.0033	51.111538	92.6938462	
Nizza Monferrato	2021	137.00	30.40	0.0013	0.0000	0.0000	0.0000	0.0000	0.0000	0.0014	0.1106	2.0905	4.0771	521	49.2	66	8.013	51	13.4858	-6.736	36.04	7.9588	19.0124	59.56	74.59	53.85	99.25
San Damiano D'asti	2021	179.00	48.00	0.0865	0.8064	0.5289	0.0000	0.0000	0.0000	0.8930	1.4095	3.6790	4.5663	685.837	78.037	68.333	10.051	51.778	13.991	-4.86	37.23	8.608	19.271	43	78.19	49.92	98.34
Alba	2020	172.00	54.00	0.0102	0.0274	0.0000	0.0000	0.0000	0.0000	0.0376	0.6742	10.1078	13.3058	968.837	78.037	68.333	10.051	51.778	13.991	-4.86	37.23	8.608	19.271	43	78.19	49.92	98.34
Baldissero D'Alba	2020	380.00	15.00	0.2132	0.0000	0.0000	0.0000	0.0000	0.0000	0.2132	0.0458	0.2150	0.2150	670.8	77.4	71	9.448	50	11.79	-9.3	38.8	5.38	18.2	117	84.58	60.1	99.21
Barbarico	2020	274.00	7.00	0.3126	0.1360	0.0000	0.0000	0.0000	0.0000	0.4485	0.3190	1.8531	1.9158	661	87.8	68	9.127	62	13.991	-4.86	37.23	8.608	19.271	43	86.54	54.836	93.455
Barolo	2020	213.00	5.69	0.7319	0.1090	0.0000	0.0000	0.0000	0.0000	1.7709	0.5750	0.5750	0.5750	631.6	62	62	10.187	35	14.91	-3.2	37.2	9	20.02	30	74.5	54.36	89.6
Bossolasco	2020	757.00	14.00	0.7756	0.3845	0.0026	0.0000	0.0000	0.0000	4.6172	0.6586	0.6586	0.6586	487.2	79.2	45	10.227	49	12.79	-5	35.5	7.92	17.65	44	77.69	54.13	95.67
Bra	2020	285.00	59.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.3667	3.2788	18.2511	685.837	78.037	68.333	10.051	51.778	13.991	-4.86	37.23	8.608	19.271	43	78.19	54.836	93.455
Caraglio	2020	638.00	41.00	0.0492	0.1025	0.0000	0.0000	0.0000	0.0000	0.1518	0.5281	1.0357	1.5467	945.4	61.8	82	10.829	45	13.991	-4.86	37						

Guarene	2018	360,00	13,40	0,8516	2,7963	0,0000	0,0000	0,0000	0,0000	3,6479	0,1222	0,6314	1,7867	1,165,00	62,6	101	11,535	84	13,93	-8,6	36,9	8,29	19,56	84	82,4	57,55	97,46
Mango	2018	521,00	19,00	1,2742	6,0384	0,0000	0,0000	0,0000	0,0000	8,7625	2,2497	2,2497	2,2497	1,198,00	64,2	92	13,022	27	13,11	-6,6	32,2	9,55	16,68	37	78,76	61,88	92,23
Mombacaro	2018	896,00	20,00	0,0581	0,5325	0,0000	0,0000	0,0000	0,0000	0,5905	0,6528	0,8303	0,9041	1,197,00	99,4	101	11,851	73	11,17	-11,7	30,5	8,05	15,35	56	83,26	65,05	96,12
Monforte d'Alba	2018	480,00	25,00	0,0581	0,5325	0,0000	0,0000	0,0000	0,0000	0,5905	0,6528	0,8303	0,9041	1,306,40	71,4	103	12,683	31	14,89	-9,2	35,6	10,61	19,17	18	78,88	60,14	92,65
Monteulupo albese	2018	564,00	6,40	1,2157	3,0051	0,0000	0,0000	0,0000	0,0000	4,2207	1,9410	1,9410	1,9410	1,201,20	64	105	11,440	43	13,948	-9,389	35,6	8,978	18,915	53,947	76,84	54,27	95,28
Neive	2018	308,00	21,20	1,7240	2,4760	0,0000	0,0000	0,0000	0,0000	4,2000	0,9251	2,5855	3,0900	1,060,00	66,2	99	11,398	46	13,948	-9,389	35,6	8,978	18,915	53,947	83,1	64,29	96,89
Piobesi D'Alba	2018	194,00	3,00	0,2364	0,5061	0,0000	0,0000	0,0000	0,0000	0,7425	0,2034	0,2878	0,2878	1,095,20	69,6	92	11,904	57	13,6	-8,9	34,6	8,39	18,82	73	82,98	58,09	98,81
Santo Stefano Belbo	2018	170,00	23,00	0,0042	0,0008	0,0000	0,0000	0,0000	0,0000	0,0050	2,1872	2,9760	4,5496	1,240,40	92,6	94	13,156	56	13,948	-9,389	35,6	8,978	18,915	53,947	83,18	64,45	96,98
Serralunga D'Alba	2018	414,00	8,44	1,5075	3,0737	0,0000	0,0000	0,0000	0,0000	1,8148	0,3713	0,4854	0,4866	1,051,20	63,4	101	10,808	54	14,8	-9	37,4	9,55	20,04	46	77,97	55,04	93,84
Serravalle Langhe	2018	762,00	9,00	2,5721	0,3097	0,0000	0,0000	0,0000	0,0000	2,8818	0,1465	0,1465	0,1465	1,323,80	80,2	103	12,452	56	12,87	-10,6	34,3	8,45	17,28	51	78,9	58,91	93,84
Caneelli	2018	316,00	25,43	0,0235	0,0141	0,0000	0,0000	0,0000	0,0000	0,0376	0,6607	1,5473	3,5225	1,202,80	59,6	98	12,273	58	13,948	-9,389	35,6	8,978	18,915	53,947	82,28	58,02	95,28
Castel Boglione	2018	290,00	12,00	0,0041	0,0000	0,0000	0,0000	0,0000	0,0000	0,0043	0,1330	0,1330	0,1418	1,225,00	59,8	98	12,500	49	15,13	-7,7	38,2	9,87	20,39	42	74,83	51,95	92,42
Coazzolo	2018	291,00	4,12	0,0403	0,0000	0,0000	0,0000	0,0000	0,0000	0,0043	0,1330	0,1116	0,1116	1,128,00	61,4	98	11,818	89	13,84	-13	37,2	7,26	20,42	91	83,59	52,44	99,51
Costigliole D'asti	2018	242,00	36,00	1,5026	0,9312	0,1350	0,0000	0,0000	0,0000	2,4338	0,0107	2,6088	5,8165	1,058,80	60	98	10,804	68	14,15	-7,9	36	9,12	19,18	49	81,15	59,18	97,21
Nizza Monferrato	2018	137,00	30,40	0,0013	0,0001	0,0000	0,0000	0,0000	0,0000	0,0014	0,1106	2,0905	4,5471	1,130,00	45,6	94	10,221	60	14,94	-8,3	38	9,38	20,49	52	84,39	61,69	98,98
San Damiano D'asti	2018	179,00	48,00	0,0865	0,8064	0,5289	0,0000	0,0000	0,0000	0,8930	1,4095	3,6790	4,5663	919,6	60,8	90	10,218	59	14,12	-9	37,6	8,61	19,62	63	80,59	55,67	97,21
Alba	2017	172,00	54,00	0,0102	0,0274	0,0000	0,0000	0,0000	0,0000	0,0376	0,6742	10,1078	13,3058	488,428	39,579	53,517	9,127	35,621	13,912	-7,117	38,041	8,245	19,579	60,000	72,0136	48,2114	91,0529
Baldissero D'Alba	2017	380,00	15,00	2,2232	0,0000	0,0000	0,0000	0,0000	0,0000	0,2232	0,0398	0,2150	0,2150	488,428	39,579	53,517	9,127	35,621	13,912	-7,117	38,041	8,245	19,579	60,000	72,0136	48,2114	91,0529
Barbaresco	2017	274,00	7,00	0,3126	0,1360	0,0000	0,0000	0,0000	0,0000	0,4485	0,3190	1,8531	1,9158	44,8	28,6	55	8,142	39	16,22	-4,5	41	10,32	22,11	23	75,96	53,56	92,63
Barolo	2017	213,00	5,69	0,7319	1,0390	0,0000	0,0000	0,0000	0,0000	1,7709	0,5750	0,5750	0,5750	44,8	28,6	50	8,852	25	14,68	-7,4	38,3	9,17	20,13	55	69,33	48,04	87,68
Bossolasco	2017	757,00	14,00	0,7756	3,8415	0,0026	0,0000	0,0000	0,0000	4,6172	0,6586	0,6586	0,6586	448,2	32,6	50	8,964	44	12,89	-5,9	36	7,7	18,07	63	70,33	51	87,79
Bra	2017	285,00	59,00	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,3667	3,2788	18,2511	46,2	41,8	53	8,853	46	13,16	-14	35,8	6,81	19,52	80	78,16	52,01	95,15
Caraglio	2017	638,00	41,00	0,0492	0,1025	0,0000	0,0000	0,0000	0,0000	0,1518	0,5281	1,0357	1,5467	630,6	50,2	69	9,139	32	12,34	-11	35,4	5,42	19,26	104	74,34	45,08	95,14
Castino	2017	525,00	15,50	0,4543	1,3771	0,0000	0,0000	0,0000	0,0000	1,8314	0,3010	0,4724	0,4905	443	33,2	53	8,358	24	13,27	-6,1	36,2	8,33	18,2	50	73,78	50,08	93,73
Dogliani	2017	300,00	35,88	3,0054	1,2438	0,0000	0,0000	0,0000	0,0000	4,2492	0,0915	0,0972	0,1049	540,4	48,8	55	9,825	27	13,8	-5,9	37,5	8,77	18,83	59	72,0136	48,2114	91,0529
La Morra	2017	513,00	24,30	0,0074	0,0123	0,0000	0,0000	0,0000	0,0000	0,0197	0,1228	1,4191	1,4210	508	47,4	51	9,961	27	13,71	-6,7	36,1	8,61	18,82	62	48,13	95,33	
Canale	2017	194,00	18,00	0,1833	0,1247	0,0005	0,0000	0,0000	0,0000	0,3080	0,4479	1,0301	1,4446	45,2	46,2	51	8,875	43	14,12	-7,1	38,3	8,13	20,1	59	71,8	48,47	92,82
Castiglione Falletto	2017	350,00	4,72	0,3321	0,6999	0,0000	0,0000	0,0000	0,0000	1,0319	0,3268	0,3400	0,3645	451	36,6	52	8,673	31	14,833	-6,6	39,3	8,91	20,74	56	68,86	44,76	86,68
Claivesana	2017	300,00	17,15	0,0107	0,0065	0,0000	0,0000	0,0000	0,0000	0,0171	3,3352	5,6557	5,7791	528,6	49,6	57	9,274	22	14,17	-5,6	38,3	9,04	19,31	48	63,63	43,42	82,2
Costigliole Saluzzo	2017	476,00	15,00	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	1,1880	2,2071	4,1072	983,8	29	59	9,386	31	12,48	-8,8	36,7	5,98	18,59	102	70,11	42,49	89,39
Crevanzana	2017	585,00	8,20	0,3805	3,7383	0,0000	0,0000	0,0000	0,0000	4,1189	0,5721	0,5721	0,5721	456,6	34	51	8,953	44	12,72	-9,3	38,7	6,87	18,58	75	74,22	49,19	92,7
Guarene	2017	360,00	13,40	0,8516	2,7963	0,0000	0,0000	0,0000	0,0000	3,6479	0,1222	0,6314	1,7867	40,4	64,4	42	9,748	52	13,41	-9,7	38,7	6,68	20,14	87	76,14	48,27	95,66
Mango	2017	521,00	19,00	1,2742	6,0384	0,0000	0,0000	0,0000	0,0000	8,7625	2,2497	2,2497	2,2497	557,6	35	56	9,957	25	13,29	-4,8	35,2	9,42	17,16	42	68,37	49,52	84,83
Mombacaro	2017	896,00	20,00	0,0581	0,5325	0,0000	0,0000	0,0000	0,0000	0,5905	0,6528	0,8303	0,9041	40,2	32,8	51	8,024	57	11,87	-6,5	32,9	7,81	15,93	58	73,96	53,66	90,41
Monforte D'Alba	2017	480,00	25,00	0,0581	0,5325	0,0000	0,0000	0,0000	0,0000	0,5905	0,6528	0,8303	0,9041	558,4	45	50	11,168	27	14,89	-4,2	38,1	10,02	19,77	41	69,56	49,07	87,45
Monteulupo albese	2017	564,00	6,40	1,2157	3,0051	0,0000	0,0000	0,0000	0,0000	4,2207	1,9410	1,9410	1,9410	518,4	34,2	54	9,600	28	14,28	-5,7	37,4	7,77	19,78	49	67,79	44,55	88,49
Neive	2017	308,00	21,20	1,7240	2,4760	0,0000	0,0000	0,0000	0,0000	4,2000	0,9251	2,5855	3,0900	44,2	31,6	55	8,076	27	14,65	-5	38,8	9,85	19,44	37	72,65	53,02	89,94
Piobesi D'Alba	2017	194,00	3,00	0,2364	0,5061	0,0000	0,0000	0,0000	0,0000	0,7425	0,2034	0,2878	0,2878	503,6	32,6	52	8,685	24	13,27	-8,5	37	7,22	19,32	80	76,28	49,12	96,48
Santo Stefano Belbo	2017	170,00	23,00	0,0042	0,0008	0,0000	0,0000	0,0000	0,0000	0,0050	2,1872	2,9760	4,5496	464	45	52	8,923	39	15,07	-5,6	39,1	9,94	20,19	34	74,14	52,95	91,66
Serralunga D'Alba	2017	414,00	8,44	1,5075	3,0737	0,0000	0,0000	0,0000	0,0000	1,8148	0,3713	0,4854	0,4866	504,4	36,2	52	9,700	36	14,77	-6,9	39,4	8,67	20,74	55	69,97	45,78	89,87
Serravalle Langhe	2017	762,00	9,00	2,5721	0,3097	0,0000	0,0000	0,0000	0,0000	2,8818	0,1465	0,1465	0,1465	500,6	39,6	52	9,627	33	12,98	-5,2	38,1	7,98	17,99	48	69,81	49,99	87,61
Caneelli	2017	316,00	25,43	0,0235	0,0141	0,0000	0,0000	0,0000	0,0000	0,0376	0,6607	1,5473	3,5225	499,4	43,6	55	9,080	35	15,2	-5,6	40,2	9,39	21,02	43	72,71	47,83	81,06
Castel Boglione	2017	290,00	12,00	0,0041	0,0000	0,0000	0,0000	0,0000	0,0000	0,0043	0,1330	0,1330	0,1418	446,4	43,4	57	8,800	33	15,48	-5,3	40,4	9,58	21,38	44	64,02	40,57	84,67
Coazzolo	2017	291,00	4,12	0,0403	0,0000	0,0000	0,0000	0,0000	0,0000	0,0043	0,0394	0,1116	0,1116	490,2	37,8	57	8,600	58	13,59	-10,3							

CHAPTER 4

4.1 STATISTICAL ANALYSIS

After obtaining a complete database with no missing data, statistical analysis can be carried out, which involves processing data samples to discover patterns and trends.

The method for working out the relationship between a dependent variable (the data you want to measure) and an independent variable (the data used to predict the dependent variable) is regression.

4.2 REGRESSION PROBLEM

Machine learning is closely related to pattern recognition and computational learning theory and explores the study and construction of algorithms that can learn from a set of data and make predictions about it, inductively building a model based on samples.

Machine learning is employed in those fields of computer science where designing and programming explicit algorithms is impractical; possible applications include email filtering to avoid spam, detecting intruders in a network or intruders trying to breach data, optical character recognition, search engines, and computer vision.

Machine learning is the core principal behind predictive modeling.

Predictive modeling is the problem of developing a model using historical data to make a prediction about new data whose answer is unknown.

Predictive modeling can be described as the mathematical problem of approximating a mapping function (f) from input variables (X) to output variables (y).

This is the so-called function approximation problem.

The main goal of machine learning is for a machine to be able to generalize from its experience, that is, to be able to perform inductive reasoning.

In this context, generalization refers to a machine's ability to accurately complete novel examples or tasks, which it has never faced, after gaining experience on a training data set.

A training set (or training set) is a set of examples to each of which is associated a response, the value of an attribute-objective, i.e., a categorical value, i.e., a class, or a numerical value.

Such examples are used to train a supervised predictive model (typically a classifier or regressor) capable of determining the target-value for new examples.

A trained model can be evaluated on a new set of examples, the test set, not used in training.

Classifier

Predictive classification modeling is the task of approximating a mapping function (f) from input variables (X) to discrete output variables (y).

The output variables are often called labels or categories. The mapping function predicts the class or category for a given observation.

For example, a text e-mail may be classified as belonging to one of two classes: "spam" and "non-spam."

A classification problem requires examples to be classified into one of two or more classes.

A classification can have real or discrete input variables.

A problem with two classes is often called a two-class or binary classification problem.

A problem with more than two classes is often called a multiclass classification problem.

A problem in which more than one class is assigned to an example is called a multi-label classification problem.

It is common for classification models to predict a continuous value as the probability that a given example belongs to each output class. Probabilities can be interpreted as the likelihood or confidence that a given example belongs to each class. A predicted probability can be converted to a class value by selecting the class label that has the highest probability.

Regressor

Predictive regression modeling consists of approximating a mapping function (f) from input variables (X) to a continuous output variable (y).

A continuous output variable is a real value, such as an integer or floating-point value. It often involves quantities, such as amounts and sizes.

For example, a house may be predicted to sell for a given dollar value, perhaps in the range of 100,000 to 200,000.

A regression problem requires the prediction of a quantity.

A regression can have input variables of real or discrete value.

A problem with multiple input variables is often called a multivariate regression problem.

A regression problem in which the input variables are ordered in time is called a time series prediction problem.

Since a predictive regression model predicts a quantity, model skill must be reported as error in such predictions.

There are many ways to estimate the skill of a predictive regression model, but perhaps the most common are to calculate the root mean square error, abbreviated as RMSE, and the mean absolute percentage error, abbreviated as MAPE.

Having 6 years available, it was decided to create 3 different combinations of years to make up the training dataset and the test dataset so as to evaluate at a later time which is the best combination.

- database training: 2016-2017-2018-2019
database test: 2020-2021
- database training: 2017-2018-2020-2021
database test: 2016-2019

- database training: 2016-2017-2019-2021
database test: 2018-2020

Training databases are used to train a regressor since all the input values and the output one are numerical values.

As for the output, two were chosen, for each pair of databases (training + testing) one model was built that has Average precipitation as output and another that has Total precipitation as output.

The software used for predictive modeling is Orange 3.

Orange is an open-source toolkit for data visualization, machine learning and data mining.

It presents a visual programming front-end for rapid, exploratory analysis of qualitative data and interactive data visualization.

Orange's components are called widgets and range from simple data visualization, subset selection and preprocessing, to empirical evaluation of learning algorithms and predictive modeling.

4.2.1 APPROACHES

The first approach evaluated is to use the linear regressor for each database set.

Linear regression is perhaps one of the best known and most understood algorithms in statistics and machine learning.

Linear regression is a linear model, for example, a model that assumes a linear relationship between the input variables (x) and the single output variable (y). More precisely, y can be calculated from a linear combination of the input variables (x).

Inputs

Data: input dataset

Preprocessor: preprocessing method(s)

Outputs

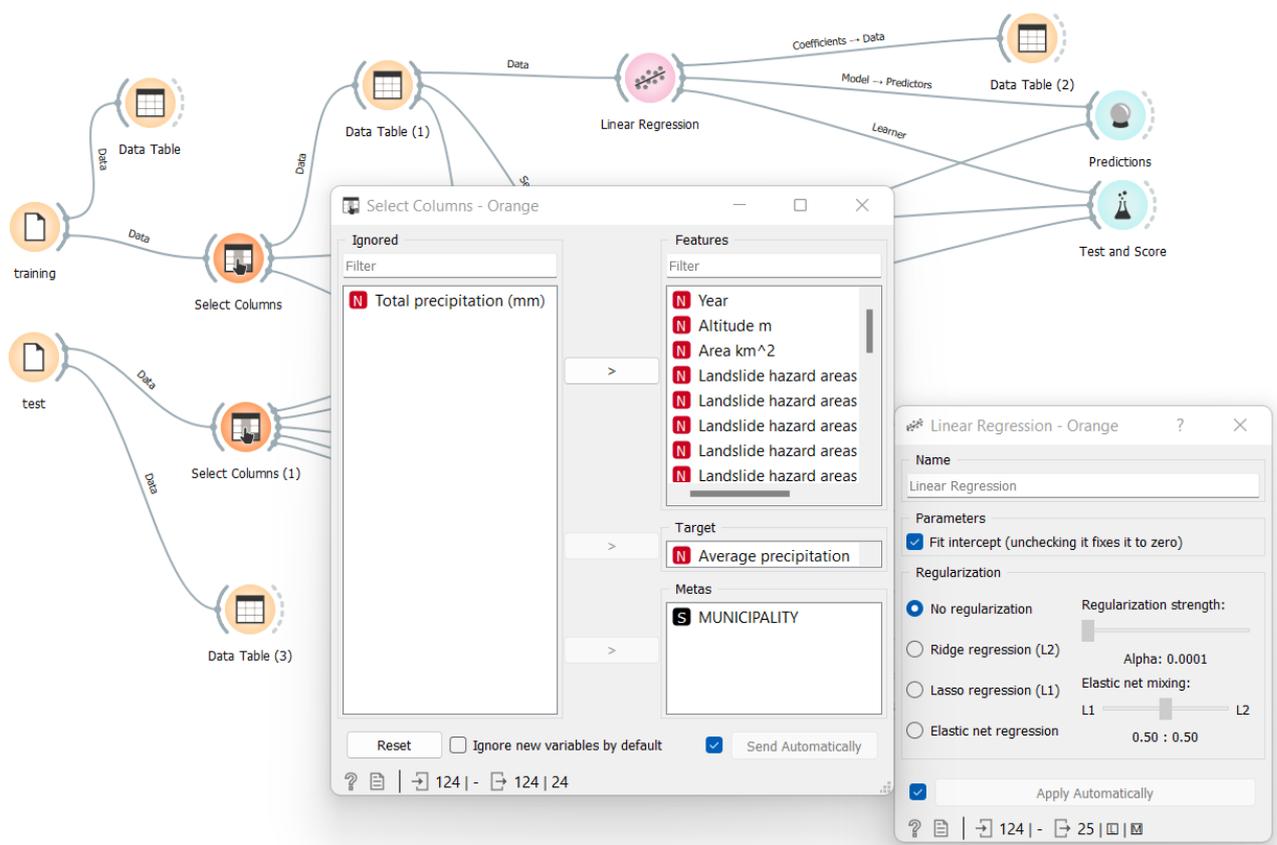
Learner: linear regression learning algorithm

Model: trained model

Coefficients: linear regression coefficients

The Linear Regression widget (on Orange) constructs a learner/predictor that learns a linear function from its input data.

Linear regression works only on regression tasks.



(fig. 16 – Linear regression widget on Orange)

In the case of a database with a small number of data, the linear regressor may prove not to be the best estimator for the model, so we evaluated other approaches such as Random Forest.

Random forest is a supervised machine learning algorithm widely used in classification and regression problems. It constructs decision trees on different samples and takes their majority vote for classification and the mean in the case of regression.

One of the most important features of the Random Forest algorithm is that it can handle data sets containing continuous variables as in the case of regression and categorical variables as in the case of classification.

Inputs

Data: input data set

Preprocessor: preprocessing method(s)

Outputs

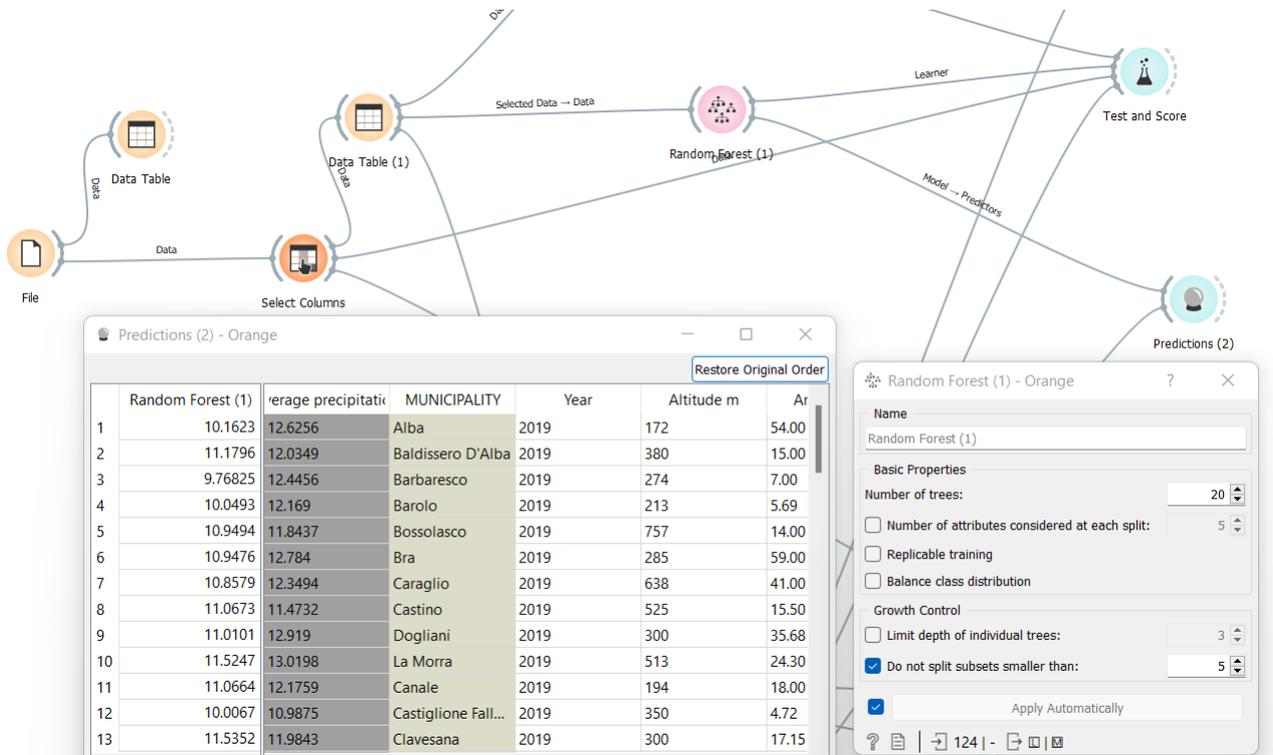
Learner: random forest learning algorithm

Model: trained model

Random forest is a collective learning method used for classification, regression and other tasks.

Random Forest constructs a set of decision trees. Each tree is developed from a bootstrap sample of the training data. When individual trees are developed, an arbitrary subset of attributes is extracted (hence the term "Random"), from which the best attribute is selected for partitioning. The final model is based on the majority vote of individually developed trees in the forest.

Random Forest works for both classification and regression tasks.



(fig. 17 – Random Forest widget on Orange)

Because this type of algorithm works best for the classifier, we also added the neural network to the model.

A neural network is an artificial intelligence method that teaches computers to process data in a way that is inspired by the human brain. It is a type of machine learning process, called deep learning, that uses interconnected nodes or neurons in a layered structure that resembles the human brain. It creates an adaptive system that computers use to learn from their mistakes and continuously improve. Artificial neural networks thus try to solve complex problems, such as summarizing documents or recognizing faces, with greater accuracy.

The architecture of the neural network is inspired by the human brain. The cells of the human brain, neurons, form a complex and highly interconnected network and send electrical signals to each other to help humans process information. Similarly, an artificial neural network is made up of artificial neurons that work together to solve a problem. Artificial neurons are software modules, called nodes, and artificial neural networks are software programs or algorithms that basically use computational systems to solve mathematical calculations.

A basic neural network has artificial neurons interconnected on three levels:

- Input Level: Information from the outside world enters the neural network from the input level. Input nodes process the data, analyze or categorize it, and transfer it to the next layer.
- Hidden layer: hidden layers take their input from the input layer or other hidden layers. Artificial neural networks can have a large number of hidden layers. Each hidden layer analyzes the output from the previous layer, processes it further, and transfers it to the next layer.
- Output layer: the output layer returns the final result of all data processing through the artificial neural network. It can have one or more nodes. For example, if we have a problem with binary classification (yes/no), the output layer will have only one output node, which will result in 1 or 0. If, at any rate, we have a multi-class classification problem, the output layer might consist of multiple output nodes.

A node follows the pattern of a neuron in the human brain. With neuron-like behavior, nodes activate in the presence of sufficient stimuli or input. This activation spreads throughout the network, creating a response to the stimuli (output). The connections between these artificial neurons act as simple synapses, allowing signals to be transmitted from one to another. The signals cross layers as they travel from the first input layer to the last output layer and are processed along the way.

When a request or problem is posed to be solved, the neurons perform mathematical calculations to figure out if there is enough information to pass to the next neuron, and they read all the data to figure out where the strongest relationships exist.

A multilayer perceptron (MLP) algorithm with backpropagation.

Inputs

Data: input data set

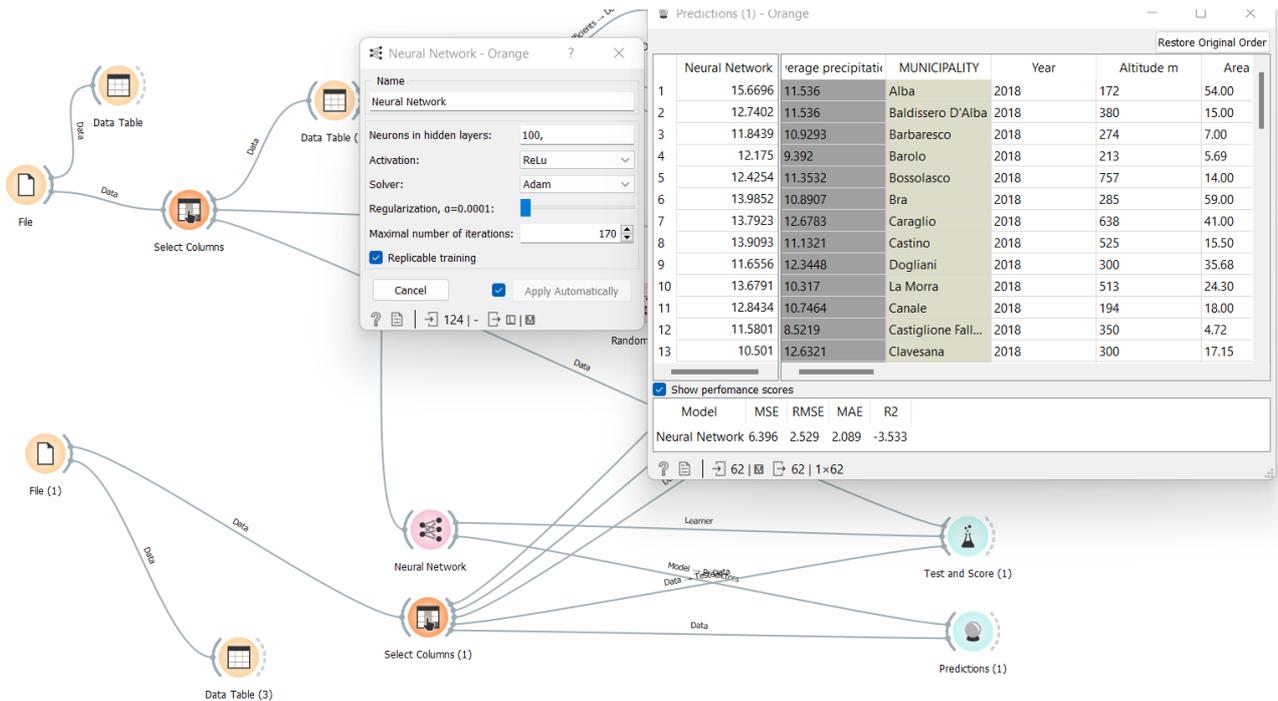
Preprocessor: preprocessing method(s)

Outputs

Learner: multilayer perceptron learning algorithm

Model: trained model

The Neural Network widget uses sklearn's multilayer Perceptron algorithm, which can learn nonlinear and linear models.



(fig. 18 – Neural Network widget on Orange)

At this point we have 3 pairs of databases (training+test) and we used 3 different methods to estimate either Average precipitation or Total precipitation.

To evaluate which model is actually the best, we need to compare them.

Measuring forecast accuracy (or error) is not an easy task as there is no one-size-fits-all indicator. The first distinction to be made is the difference between the accuracy of a forecast and its bias:

- Bias represents the historical average error. In practice, will your forecast be, on average, too high (i.e., did you exceed the total/average precipitation) or too low (i.e., did you underestimate the total/average precipitation)? This gives the overall direction of the error.
- Accuracy measures the deviation between the forecast and the actual value. The precision of a forecast gives an idea of the magnitude of the errors, but not their overall direction.

Right now, we choose to focus only on accuracy.

Root Mean Squared Error (RMSE) is defined as the square root of the mean square error.

$$RMSE = \sqrt{\frac{\sum_{t=1}^T (\hat{y}_t - y_t)^2}{T}}$$

In fact, many algorithms (especially for machine learning) rely on the mean square error (MSE), which is directly related to the RMSE.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2.$$

Many algorithms use the MSE because it is faster to compute and easier to manipulate than the RMSE. But it is not scaled to the original error (since the error is squared), which results in a KPI that cannot relate models with different outputs.

For this reason, we will also use the mean absolute percentage error (MAPE), which is one of the most widely used KPIs for measuring forecast accuracy.

$$\text{MAPE} = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right|$$

4.3 MODEL COMPARISON

- Model 1: output average precipitation (ignored total precipitation)
 database training: 2016-2017-2018-2019
 database test: 2020-2021

The screenshot shows the 'Test and Score' window in Orange Data Mining. The settings on the left are: Cross validation (Number of folds: 10, Stratified checked), Cross validation by feature (empty), Random sampling (Repeat train/test: 10, Training set size: 70%, Stratified checked), Leave one out (unchecked), Test on train data (unchecked), and Test on test data (checked).

The main results area contains a table with the following data:

Model	MSE	RMSE	MAE	R2
Linear Regression	79.707	8.928	3.140	-74.540
Neural Network	217.029	14.732	3.696	-204.682
Random Forest	4.630	2.152	1.882	-3.388

Below this table, the 'Compare models by' dropdown is set to 'Mean square error' and 'Negligible diff.' is 0.1. A comparison matrix is shown below:

	Random Forest	Neural Network	Linear Regressi...
Random Forest			
Neural Network			
Linear Regression			

A note at the bottom states: 'Table shows probabilities that the score for the model in the row is higher than that of the model in the column. Small numbers show the probability that the difference is negligible.'

(fig. 19 – output model 1)

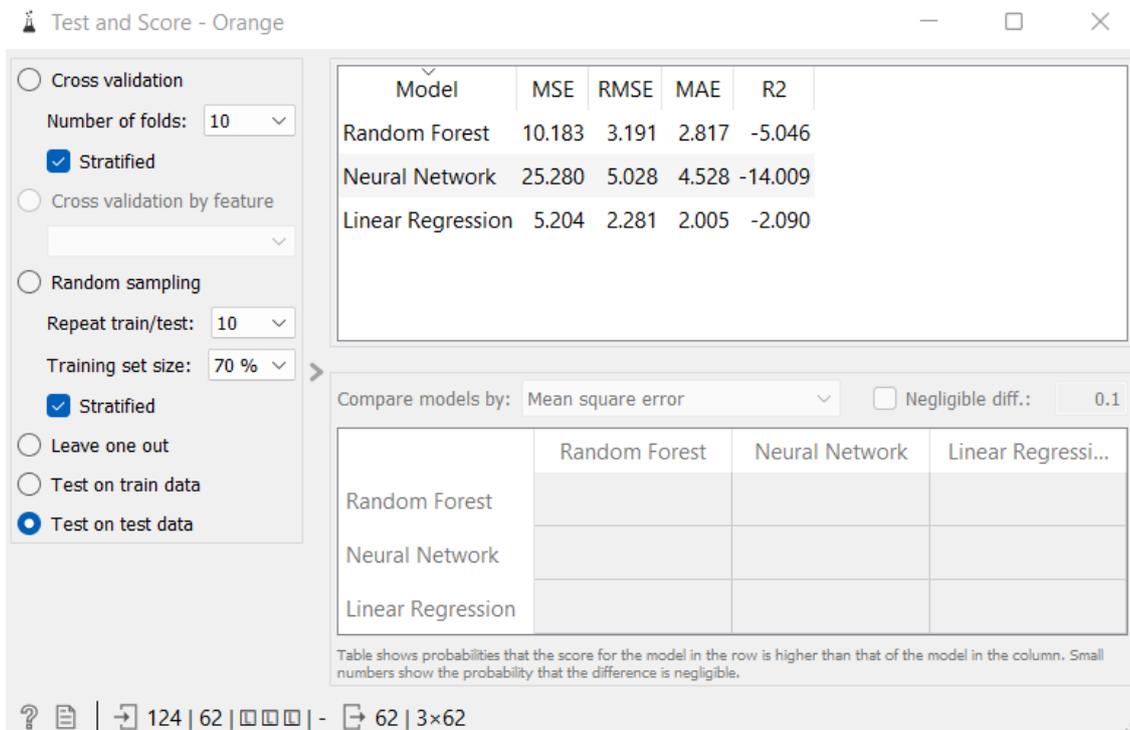
MAPE

Linear Regression: 35,6%

Neural Network: 41,6%

Random Forest: 21,2%

- Model 2: output average precipitation (ignored total precipitation)
 database training: 2017-2018-2020-2021
 database test anni: 2016-2019



(fig. 20 – output model 2)

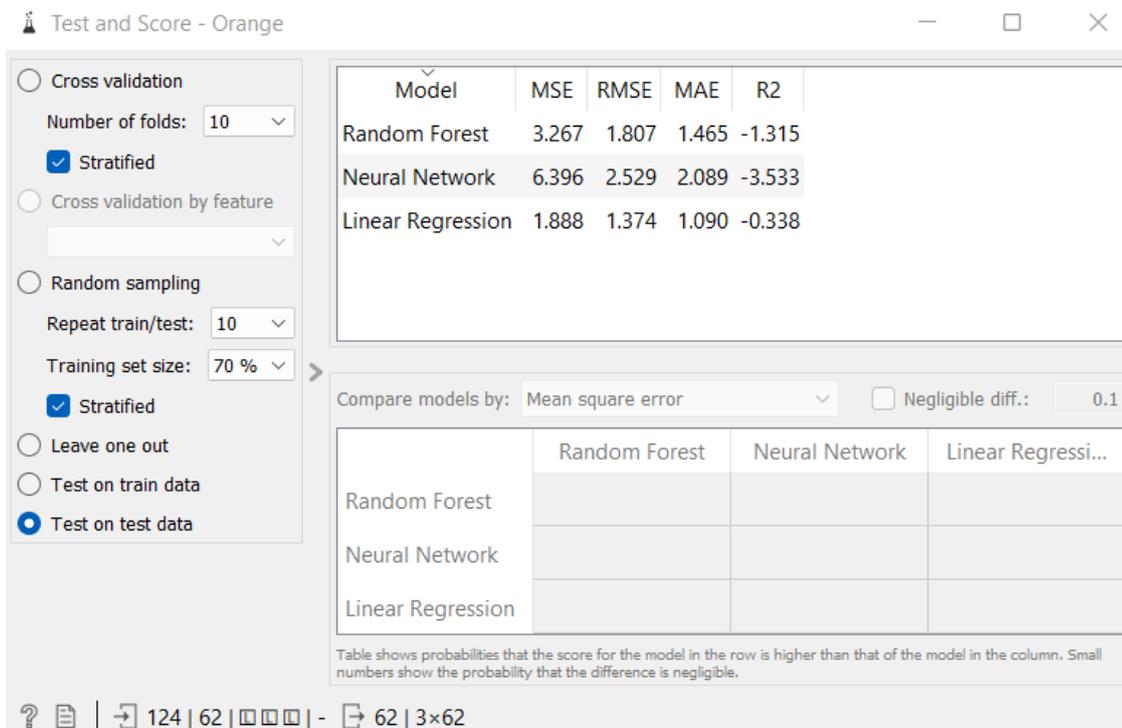
MAPE

Linear Regression: 14,7%

Neural Network: 21,4%

Random Forest: 34,0%

- Model 3: output average precipitation (ignored total precipitation)
 database training: 2016-2017-2029-2021
 database test: 2018-2020



(fig. 21 – output model 3)

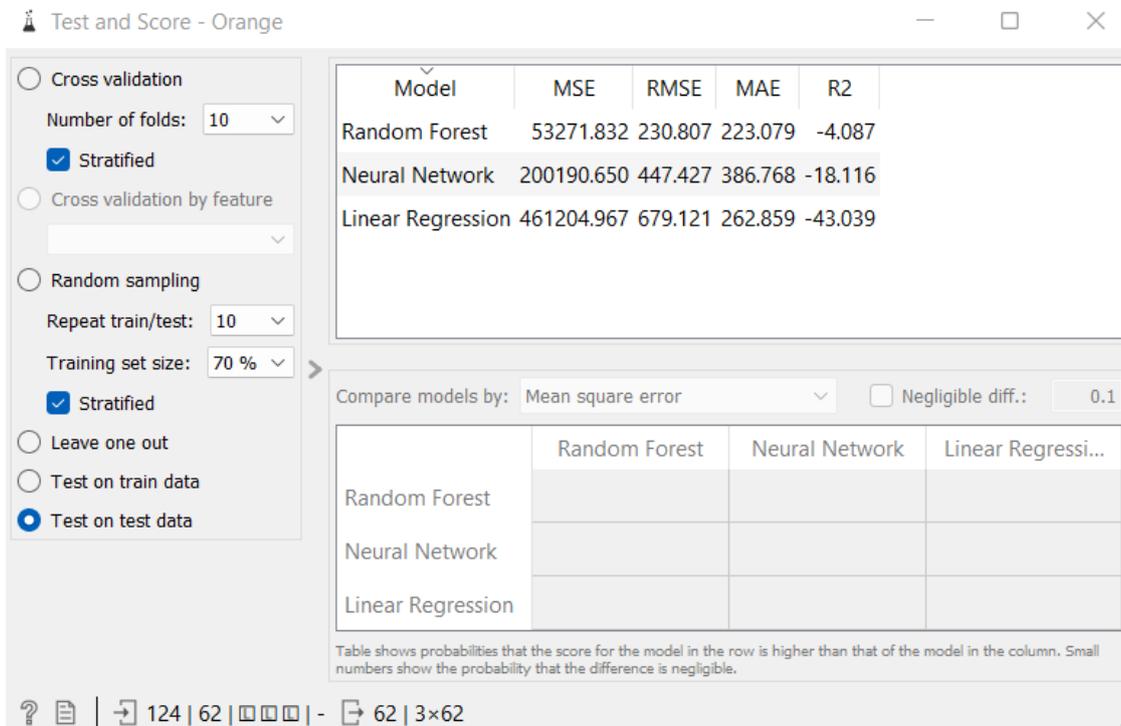
MAPE

Linear Regression: 10,7%

Neural Network: 19,8%

Random Forest: 15,0%

- Model 4: output total precipitation (average precipitation ignored)
 database training: 2016-2017-2018-2019
 database test: 2020-2021



(fig. 22 – output model 4)

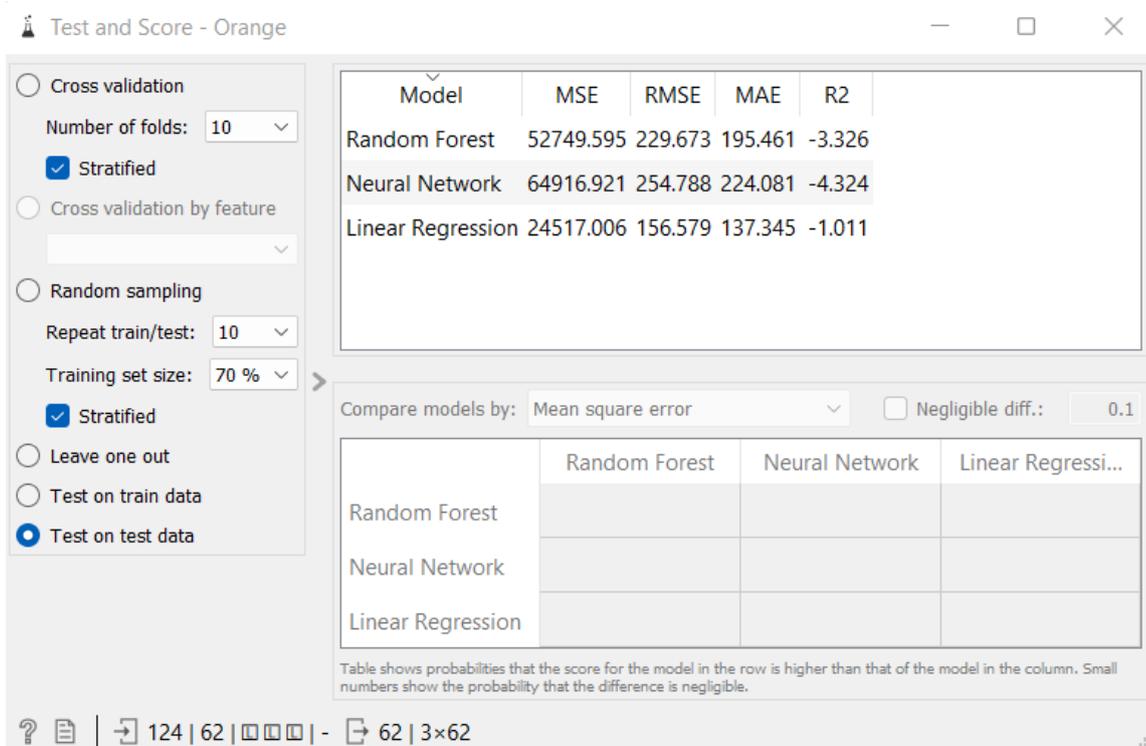
MAPE

Linear Regression: 44,5%

Neural Network: 61,5%

Random Forest: 40,4%

- Model 5: output total precipitation (average precipitation ignored)
 database training: 2017-2018-2020-2021
 database test: 2016-2019



(fig. 23 – output model 5)

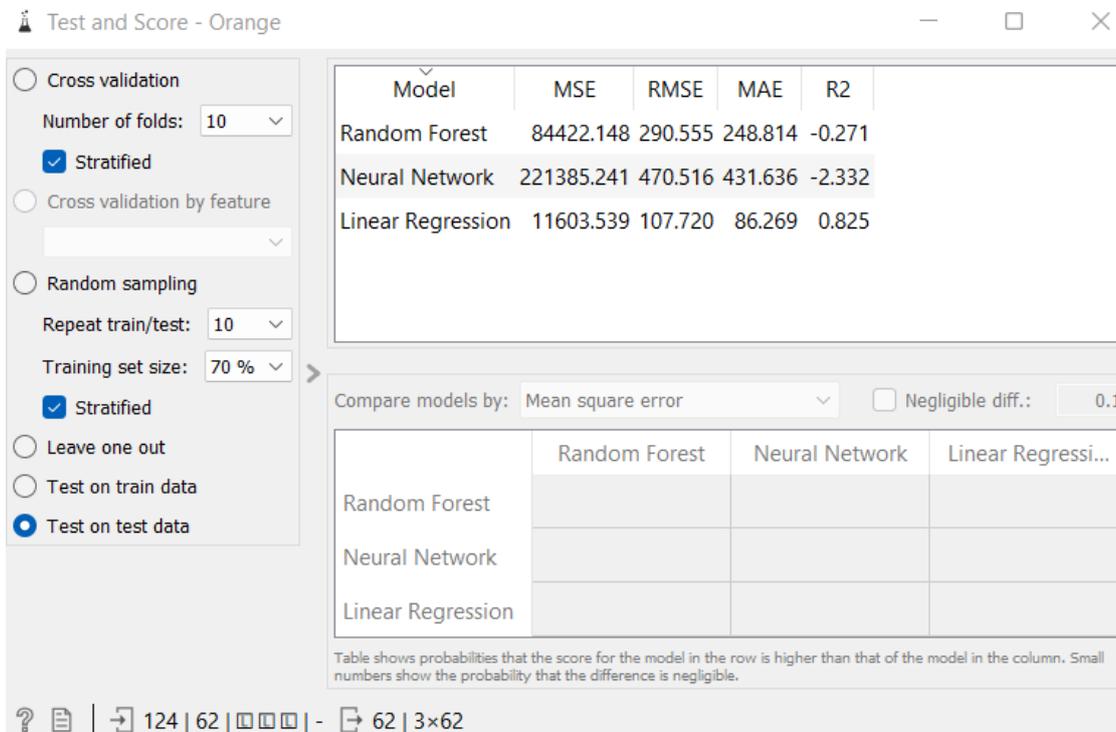
MAPE

Linear Regression: 13,7%

Neural Network: 22,5%

Random Forest: 18,6%

- Model 6: output total precipitation (average precipitation ignored)
database training: 2016-2017-2029-2021
database test anni: 2018-2020



(fig. 24 – output model 6)

MAPE

Linear Regression: 10,5%

Neural Network: 46,3%

Random Forest: 26,6%

After this analysis it is evident that the model that best estimates the output is model 3.

Looking at MAPE and MSE one realizes how the linear regressor seems to be the best method for estimating output despite being the simplest regressor, the reason being that the database is too sparse and needs to be expanded to get more correct information.

4.4 SHAP ANALYSIS

Before searching for the actual data to add to the database, it is necessary to understand which inputs have the greatest impact on the model and which can be eliminated, so that the data search can focus on only the most important ones.

One of the most popular techniques for explaining predictions is SHAP analysis, which stands for SHapley Additive ExPlanations.

The goal of SHAP is to explain the prediction of an instance x by calculating the contribution of each feature to the prediction. The SHAP explanation method calculates Shapley values from coalitional game theory. The feature values of a data instance act as players in a coalition. Shapley values tell us how to distribute the "payout" (= prediction) equally among features. An innovation brought by SHAP is that the Shapley value explanation is represented as an additive feature allocation method, a linear model.

SHAP summary graph.

The summary graph combines the importance of features with the effects of features. Each point on the summary graph is a Shapley value for a feature and an instance. The position on the y-axis is determined by the feature and on the x-axis by the Shapley value.

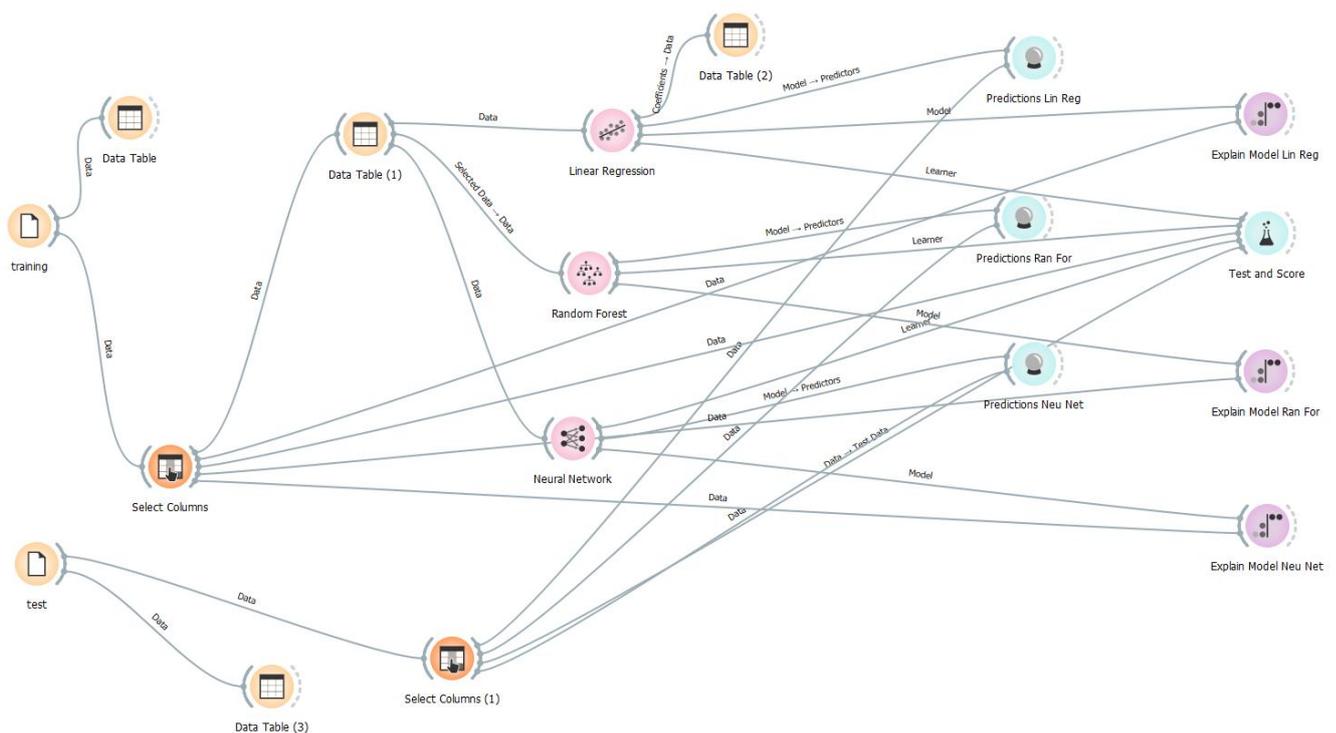
The color represents the value of the feature, from low to high.

The overlapping points are staggered in the direction of the y-axis to get an idea of the distribution of Shapley values for each feature.

Features are sorted according to their importance.

On Orange we add Explain Model to Linear Regression, Random Forest and Neural Network and add another connection passing data.

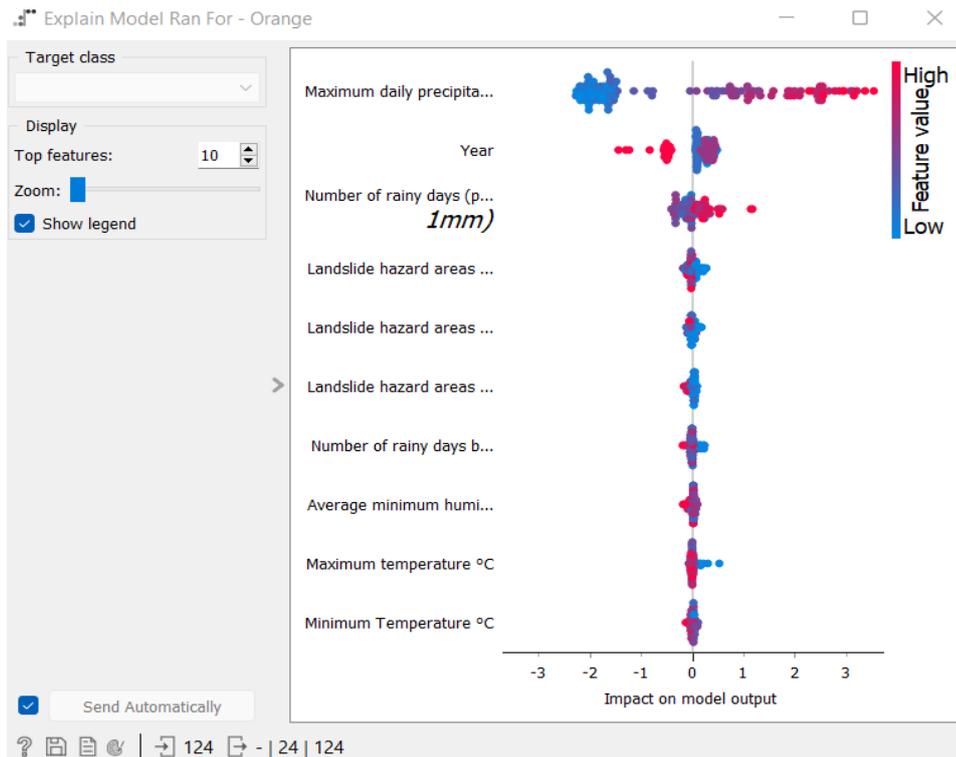
The workflow should look like this:



(fig. 25 – workflow on Orange to carry out the SHAP analysis)

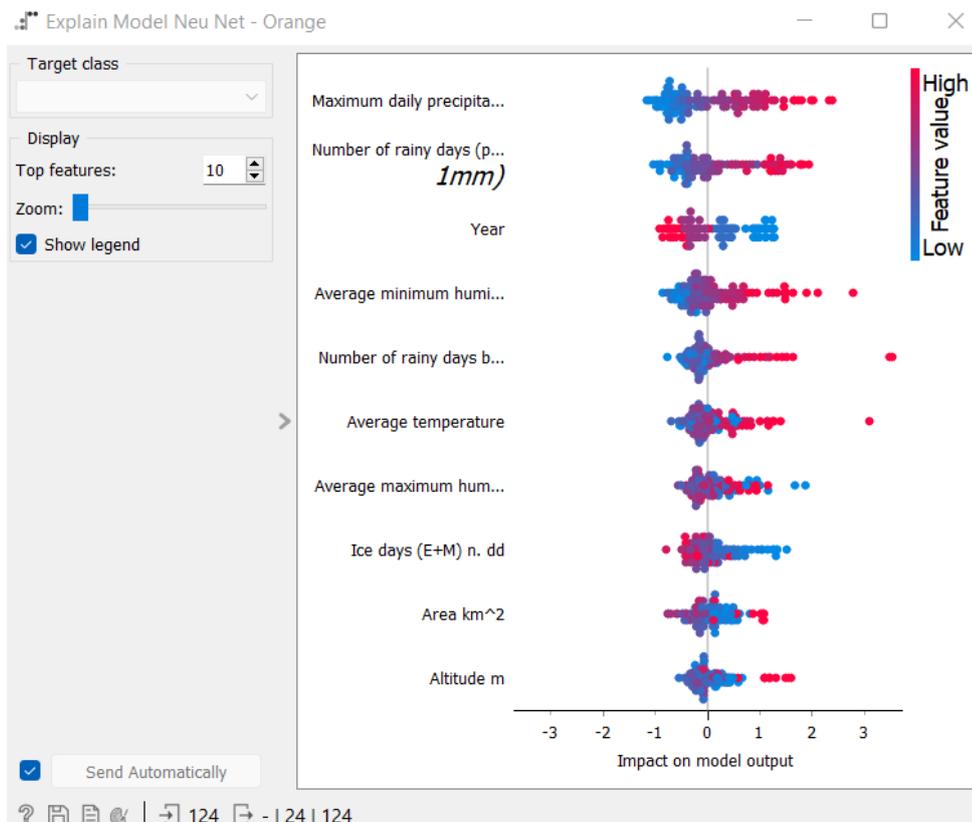
Explain Model shows the SHAP summary graph, the widget lists top ranked variables, which means they contribute the most to the selected target/output variable.

For Random Forest:



(fig. 27 – output of SHAP analysis for Random forest)

For Neural Network:



(fig. 28 – output of SHAP analysis for Neural network)

The highest ranked variable for Random Forest and Neural Network are Maximum daily precipitation and Number of rainy days >1mm.

The analysis for Random Forest model and Neural Network model turn out to be more consistent than the Linear Regression model in fact visually we see blue dots on the left and red dots on the right, which means high values have a positive correlation with the output while low values have a negative correlation.

4.5 DATABASE VENETO

At this point I know the variables that are most important for the model and I know the ones that are redundant; therefore, for the creation of the new database I focus only on the most important ones:

- Altitude m
- Area km²
- Landslide hazard areas - Very high P4 (km²)
- Landslide hazard areas - high P3 (km²)
- Landslide hazard areas - medium P2 (km²)
- Landslide hazard areas - low P1(km²)
- Landslide hazard areas - AA (km²)
- Landslide hazard areas - P3+P4 (km²)
- Hydraulic hazard areas - high P3 (km²)
- Hydraulic hazard areas - medium P2 (km²)
- Hydraulic hazard areas - low P1 (km²)
- Total precipitation (mm)
- Maximum daily precipitation (mm)
- Number of rainy days (prec.>=1mm)
- Average precipitation
- Average temperature
- Minimum Temperature °C
- Maximum temperature °C
- Average minimum temperature °C
- Average maximum temperature °C
- Average minimum humidity (E) -%
- Average maximum humidity (E) -%

Variables deleted:

- Ice days (E+M) n. dd
- Average humidity (E) -%
- Number of rainy days between 0 and 1mm

For the new database, it is important to choose an area that has some characteristics similar to the Langhe but is a different geographical area. For this reason, the Veneto wine area was chosen.

The morphology of the production area of the DOCG Conegliano Valdobbiadene Prosecco consists of a series of hilly reliefs elongated "cordonata," referred to as a "hogback" system, arranged with a north-south direction in the southernmost part and with an east-west in the northern part.

These hills are separated by a series of valleys traversed by small streams.

The area to the north rests on the prealpine chain, which acts as a natural barrier to the entry of cold currents, while to the south the area enjoys the mild temperatures of the Venice Lagoon, from which it is only 40 km away.

The east-west arrangement of the hilly terrain, the steep slope, the consequent south-facing lay of the vineyards, allows maximum interception of the sun's rays, creating an ideal area for the cultivation of white grapes destined for the Conegliano Valdobbiadene Prosecco.

The soils of the area originated from the uplift of seabed sea and were subsequently modified by the action of the glaciers and rivers.

The soils consist mainly of sandstones and marls, which are alternating with moraine and alluvial layers.

Such a profile favors the constant drainage of water.

The climate of the Conegliano Valdobbiadene area is of a temperate, with well-defined seasons, characterized by a nighttime thermal inversion that allows for, in the period of maturation of the grapes, marked temperature ranges between night and the day, thanks to the descent down the hillsides, of cool air from the foothills of the Alps.

Frequent rains in the summer period ensure the supply sufficient water for the Glera vine, which is sensitive at the same time to both to water stagnation and drought. This particular condition is achieved thanks to the steep slope and the low thickness of soil explorable by the roots of the vines.

In the heart of the appellation is a small subzone called Cartizze, of only 106 ha, whose soils have a particular slope and southern exposure that creates a sort of natural amphitheater, much appreciated in terms of quality and landscape.

The hilly area of Conegliano Valdobbiadene Prosecco boasts a very ancient tradition linked to the cultivation of vines; the first written evidence dates back to the tombstones of Roman settlers.

Through sensors from the Veneto Region, we obtain information from 31 municipalities between Belluno and Treviso:

Agordo
Auronzo di Cadore
Bassano del Grappa
Belluno
Castelfranco Veneto
Conegliano
Cortina D'Ampezzo
Crespano del Grappa
Domegge di Cadore
Falcade

Farra di Soligo
Feltre
Gaiarine
Lamon
Maser
Mogliano Veneto
Oderzo
Perarolo di Cadore
Ponte di Piave
Roncade
San Martino d'Alpago
Santo Stefano di Cadore
Sospirolo
Treviso
Valdobbiadene
Valle di Cadore
Vazzola
Villorba
Vittorio Veneto
Volpago del Montello
Zero Branco

For proper and effective statistical analysis, the data collected for the municipalities in the Veneto region were entered into a matrix along with the data previously collected for the Piedmont region.

- The rows represent the statistical units, the municipalities (Piedmont + Veneto) in the years 2016, 2017, 2018, 2019, 2020, 2021.
- The columns contain the variables.

CHAPTER 5

5.1 PUNCTUAL VALUE COMPARISON

Once I get a single database that has twice as much data as the previous one I build the two models that had proven to be the best with the previous database.

- Old Model 3:** output average precipitation (total precipitation ignored)
 database training: 2016-2017-2029-2021
 database test: 2018-2020
- Old MAPE**
 Linear Regression: 10,7%
 Neural Network: 19,8%
 Random Forest: 15,0%
- Old Model 5:** output total precipitation (average precipitation ignored)
 database training: 2017-2018-2020-2021
 database test: 2016-2019
- Old MAPE**
 Linear Regression: 13,7%
 Neural Network: 22,5%
 Random Forest: 18,6%

New model 3:

Training database:

MUNICIPALITY	Year	Altitude m	Area km ²	Landslide hazard areas (km ²) Very high P4	Landslide hazard areas (km ²) high P3	Landslide hazard areas (km ²) medium P2	Landslide hazard areas (km ²) low P1	Landslide hazard areas (km ²) AA	Landslide hazard areas (km ²) P3+P4	Hydraulic hazard areas (km ²) high P3	Hydraulic hazard areas (km ²) medium P2	Hydraulic hazard areas (km ²) low P1	Total precipitation (mm)	Maximum daily precipitation (mm)	Number of rainy days (prec.>=1 mm)	Average precipitation	Average temperature	Minimum temperature °C	Maximum temperature °C	Average minimum temperature °C	Average maximum temperature °C	Average minimum humidity (E)-%	Average maximum humidity (E)-%
Agordo	2016	611,000	23,740	0,908	0,607	0,561	0,794	0,923	1,515	0,000	0,000	0,000	1193,800	11,850	119,000	10,032	9,500	-5,700	26,400	4,600	15,600	19,000	97,000
Auronzo di Ca	2016	826,000	220,500	1,075	1,486	0,495	3,670	10,717	2,561	0,000	0,000	0,000	1277,600	16,333	120,000	10,647	7,500	-6,600	25,000	2,800	13,800	22,000	100,000
Bassano del G	2016	129,000	46,000	0,190	0,053	0,002	0,010	0,258	0,243	0,076	0,115	0,416	1399,400	16,271	107,000	13,079	14,200	1,200	30,400	10,500	18,800	26,000	100,000
Belluno	2016	390,000	147,200	0,067	0,379	0,027	0,311	2,230	0,446	0,063	0,069	0,077	1423,000	15,769	117,000	12,162	11,000	-4,700	27,800	6,000	17,100	20,000	100,000
Castelfranco V	2016	42,000	50,930	0,000	0,000	0,000	0,000	0,000	0,000	0,067	0,240	0,658	1114,600	21,080	97,000	11,491	13,700	-1,500	31,700	8,600	19,500	24,000	100,000
Conegliano	2016	74,000	36,000	0,000	0,035	0,017	0,000	0,000	0,035	0,001	0,000	0,000	1333,000	19,629	101,000	13,198	14,600	1,100	30,600	10,500	18,800	21,000	100,000
Cortina D'Ampezzo	2016	1224,000	254,500	6,369	5,813	6,784	3,933	11,250	12,182	0,000	0,000	0,000	1065,600	15,086	116,000	9,186	7,100	-5,000	22,400	2,900	12,500	16,000	98,000
Crespano del Grappa	2016	300,000	17,000	0,000	0,000	0,000	0,000	0,003	0,000	0,000	0,000	0,000	1584,800	18,843	115,000	13,781	12,000	-0,400	27,800	8,200	16,700	23,000	100,000
Domegge di Cadore	2016	775,000	50,400	0,000	0,233	0,031	0,000	3,241	0,233	0,000	0,000	0,000	1249,200	18,440	113,000	11,055	9,000	-4,400	24,900	4,800	14,900	24,000	100,000
Falcade	2016	1148,000	52,800	1,644	0,856	0,463	0,552	1,553	2,500	0,000	0,000	0,000	1105,600	11,327	130,000	8,505	6,800	-5,900	22,600	2,400	12,600	21,000	100,000
Farra di Soligo	2016	163,000	28,200	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1492,400	20,133	108,000	13,819	13,300	-0,500	29,800	8,700	18,500	21,000	100,000
Feltre	2016	325,000	100,000	0,054	0,520	0,071	0,488	1,546	0,574	0,034	0,060	0,083	1290,800	18,214	110,000	11,735	11,200	-4,900	29,200	6,100	18,000	19,000	98,000
Gaiarine	2016	20,000	28,700	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1288,400	18,325	103,000	12,509	13,600	-2,600	31,600	8,100	19,800	27,000	100,000
Lamon	2016	594,000	54,360	0,000	0,046	0,002	0,009	3,007	0,046	0,000	0,000	0,000	1156,200	13,969	119,000	9,716	10,300	-1,900	25,800	6,500	15,100	25,000	100,000
Maser	2016	147,000	26,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1291,400	15,560	104,000	12,417	13,600	-0,700	30,200	8,900	18,700	26,000	100,000
Mogliano Veneto	2016	8,000	46,150	0,000	0,000	0,000	0,000	0,000	0,000	0,734	1,526	7,129	1144,600	20,433	99,000	11,562	13,800	-0,900	30,500	9,200	18,900	25,000	100,000
Oderzo	2016	14,000	42,000	0,000	0,000	0,000	0,000	0,000	0,000	0,646	6,223	8,203	1232,600	17,725	100,000	12,326	13,600	-1,700	31,600	8,900	19,200	27,000	100,000
Perarolo di Cadore	2016	532,000	43,600	0,097	0,325	0,203	0,000	1,746	0,422	0,000	0,000	0,000	1105,600	15,971	110,000	10,051	9,500	-3,900	26,800	5,500	15,600	20,000	99,000
Ponte di Piave	2016	12,000	32,800	0,000	0,000	0,000	0,000	0,000	0,000	12,541	19,693	21,938	1307,200	21,886	103,000	12,691	13,100	-2,700	30,200	7,800	18,800	29,000	100,000
Roncade	2016	8,000	61,780	0,000	0,000	0,000	0,000	0,000	0,000	4,723	11,019	20,696	1211,600	18,311	101,000	11,996	13,200	-2,500	30,900	7,900	19,000	28,000	100,000
San Martino di Montebelluna	2016	647,000	44,900	1,299	1,714	0,335	0,016	5,180	3,013	0,000	0,000	0,000	1839,400	20,900	134,000	13,727	10,100	-1,300	24,600	6,800	14,600	24,000	100,000
Santo Stefano	2016	908,000	100,200	0,007	0,043	0,275	0,000	13,117	0,050	0,000	0,000	0,000	1237,600	14,750	124,000	9,981	6,900	-8,300	25,100	2,300	13,500	22,000	100,000
Sospirolo	2016	447,000	66,000	0,001	0,000	0,000	0,000	2,497	0,001	0,000	0,000	0,000	1710,800	18,343	125,000	13,686	11,000	-2,200	26,700	7,200	16,100	20,000	100,000

Treviso	2016	15,000	55,500	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1161,000	22,080	100,000	11,610	13,800	-1,100	31,800	8,900	19,500	25,000	100,000	
Valdobbiaden	2016	247,000	60,700	0,000	0,004	0,000	0,000	0,024	0,004	0,000	0,000	0,000	0,000	1543,400	22,357	108,000	14,291	13,400	0,400	29,300	9,600	17,900	25,000	100,000
Valle di Cadore	2016	851,000	40,640	0,631	0,985	0,001	0,684	1,098	1,615	0,000	0,000	0,000	0,000	1220,200	15,857	119,000	10,254	9,100	-3,900	25,500	4,800	15,000	22,000	100,000
Vazzola	2016	30,000	26,160	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,001	1282,800	18,200	99,000	12,958	13,500	-1,800	30,500	8,400	18,900	23,000	100,000
Villorba	2016	26,000	30,600	0,000	0,000	0,000	0,000	0,000	0,000	0,051	0,060	0,065	1155,200	19,200	101,000	11,438	13,500	-2,400	32,000	8,300	19,700	25,000	100,000	
Vittorio Venet	2016	138,000	82,000	0,716	0,853	0,025	2,923	1,475	1,569	0,000	0,000	0,000	0,000	1498,000	19,243	115,000	13,026	13,800	0,300	30,000	9,600	18,600	23,000	98,000
Volpago del Iv	2016	91,000	44,700	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1341,800	17,700	100,000	13,418	13,800	0,000	31,000	9,400	19,000	27,000	100,000	
Zero Branco	2016	7,000	26,100	0,000	0,000	0,000	0,000	0,000	0,000	0,195	0,252	0,562	1176,200	22,733	95,000	12,381	13,700	-1,000	31,900	9,000	19,500	28,000	100,000	
Alba	2016	172,000	54,000	0,010	0,027	0,000	0,000	0,000	0,038	0,674	10,108	13,306	923,000	111,400	60,000	15,383	13,040	-8,100	34,800	7,290	18,790	55,250	93,220	
Baldissero D'A	2016	380,000	15,000	0,223	0,000	0,000	0,000	0,000	0,223	0,046	0,215	66,960	10,720	107,210	66,960	13,492	13,820	-5,480	35,660	8,480	19,610	55,250	93,220	
Barbaresco	2016	274,000	7,000	0,313	0,136	0,000	0,000	0,000	0,449	0,319	1,853	1,916	859,200	100,400	62,000	13,858	14,680	-6,300	39,000	9,070	20,290	58,340	94,490	
Barolo	2016	213,000	5,690	0,732	1,039	0,000	0,000	0,000	1,771	0,575	0,575	5,775	882,200	104,200	68,000	12,974	14,020	-4,400	36,100	8,680	19,360	52,790	91,060	
Bossolasco	2016	757,000	14,000	0,776	3,842	0,003	0,000	0,000	4,617	0,659	0,659	6,599	968,200	142,600	69,000	14,032	13,820	-5,480	35,660	8,480	19,160	55,250	93,220	
Bra	2016	285,000	59,000	0,000	0,000	0,000	0,000	0,000	0,000	0,367	3,279	18,251	821,400	102,600	61,000	13,466	13,700	-4,000	35,700	7,360	19,250	55,320	97,930	
Caraglio	2016	638,000	41,000	0,049	0,103	0,000	0,000	0,000	0,152	0,528	1,036	1,547	1053,000	125,000	85,000	12,388	13,820	-5,480	35,660	8,480	19,160	55,290	96,900	
Castino	2016	525,000	15,500	0,454	1,377	0,000	0,000	0,000	1,831	0,301	0,472	4,090	690,400	112,800	64,000	10,788	12,970	-5,400	33,600	8,360	17,580	55,890	95,960	
Dogliani	2016	300,000	35,680	3,005	1,244	0,000	0,000	0,000	4,249	0,092	0,097	0,105	983,800	130,000	68,000	14,468	13,530	-4,500	33,900	8,760	18,290	52,210	84,680	
La Morra	2016	513,000	24,300	0,007	0,012	0,000	0,000	0,000	0,209	0,123	1,419	1,421	1094,600	101,600	64,000	17,103	13,360	-5,800	34,300	8,610	18,100	53,370	97,420	
Canale	2016	194,000	18,000	0,183	0,125	0,000	0,000	0,000	0,308	0,448	1,030	1,445	852,600	78,600	68,000	12,538	14,070	-5,100	36,400	8,500	19,650	54,600	93,230	
Castiglione Fa	2016	350,000	4,720	0,332	0,700	0,000	0,000	0,000	1,032	0,327	0,340	3,365	889,000	104,200	67,000	13,269	14,520	-5,000	36,900	9,040	19,990	51,200	88,500	
Clavesana	2016	300,000	17,150	0,011	0,006	0,000	0,000	0,000	0,017	3,333	5,656	5,779	117,800	140,000	68,000	16,438	13,890	-3,900	35,800	9,110	18,670	52,500	83,950	
Costigliole Sal	2016	476,000	15,000	0,000	0,000	0,000	0,000	0,000	0,000	1,218	2,207	4,107	954,200	132,800	62,000	15,390	13,820	-5,480	35,660	8,480	19,160	47,940	92,140	
Cranzavana	2016	585,000	8,200	0,381	3,738	0,000	0,000	0,000	4,119	0,572	0,572	5,772	906,600	110,400	77,000	11,774	13,820	-5,480	35,660	8,480	19,160	55,250	93,220	
Guarene	2016	360,000	13,400	0,852	2,796	0,000	0,000	0,000	3,648	0,122	0,631	1,787	841,600	88,400	62,000	13,574	13,210	-7,700	35,200	7,150	19,280	55,250	93,220	
Mango	2016	521,000	19,000	2,724	6,038	0,000	0,000	0,000	8,763	2,250	2,250	2,250	830,800	109,000	65,000	12,782	13,820	-5,480	35,660	8,480	19,160	55,040	88,920	
Mombarcaro	2016	896,000	20,000	0,058	0,532	0,000	0,000	0,000	0,591	0,653	0,830	0,904	903,410	107,210	66,960	13,492	13,820	-5,480	35,660	8,480	19,160	55,250	93,220	
Monforte D'Al	2016	480,000	25,000	0,058	0,532	0,000	0,000	0,000	0,591	0,653	0,830	0,904	1011,400	129,600	67,000	15,096	14,530	-3,100	35,200	10,010	19,050	54,890	91,180	
Montelupo all	2016	564,000	6,400	1,216	3,005	0,000	0,000	0,000	4,221	1,941	1,941	1,941	922,000	104,000	64,000	14,406	14,240	-3,100	35,500	9,020	19,450	50,890	90,610	
Neive	2016	308,000	21,200	1,724	2,476	0,000	0,000	0,000	4,200	0,925	2,585	3,090	715,800	89,400	61,000	11,734	14,300	-4,100	35,200	9,710	18,500	58,080	92,840	
Piobesi D'Alba	2016	194,000	3,000	0,236	0,506	0,000	0,000	0,000	0,742	0,203	0,288	0,288	933,600	118,800	64,000	14,588	13,060	-7,800	34,600	7,390	18,740	55,250	93,220	
Santo Stefano	2016	170,000	23,000	0,004	0,001	0,000	0,000	0,000	0,005	2,187	2,976	4,550	864,800	86,400	73,000	11,847	14,670	-2,700	36,100	9,850	19,480	59,200	94,660	
Serralunga D'	2016	414,000	8,440	1,507	0,307	0,000	0,000	0,000	1,815	0,371	0,485	0,487	909,800	111,000	63,000	14,441	14,590	-4,500	36,700	9,040	20,140	50,860	92,540	
Serravalle Lan	2016	762,000	9,000	2,572	0,310	0,000	0,000	0,000	2,882	0,146	0,146	0,146	999,600	149,600	75,000	13,328	11,660	-4,100	30,600	7,270	16,050	65,150	95,350	
Canelli	2016	316,000	23,430	0,024	0,014	0,000	0,000	0,000	0,038	0,661	1,647	3,523	848,400	90,200	68,000	12,476	14,670	-5,900	36,900	9,490	19,860	59,070	94,000	
Castel Boglione	2016	260,000	12,000	0,004	0,000	0,000	0,000	0,000	0,004	0,133	0,133	0,142	835,800	66,000	74,000	11,295	13,820	-5,480	35,660	8,480	19,160	55,250	93,220	
Coazzolo	2016	291,000	4,120	0,040	0,000	0,000	0,000	0,000	0,040	0,039	0,112	0,112	835,800	85,600	63,000	13,267	13,480	-9,800	38,400	6,090	20,860	59,520	99,750	
Costigliole D'A	2016	242,000	36,000	1,503	0,931	0,135	0,000	0,000	2,434	0,011	2,609	5,816	878,800	104,000	59,000	14,895	13,770	-5,500	37,700	8,330	19,220	58,440	96,070	
Nizza Monferr	2016	137,000	30,400	0,001	0,000	0,000	0,000	0,000	0,001	0,111	2,090	4,547	871,200	73,400	74,000	11,773	14,520	-6,400	37,900	8,470	20,580	60,400	98,750	
San Damiano I	2016	179,000	48,000	0,087	0,806	0,529	0,000	0,000	0,893	1,411	3,679	4,566	903,410	107,210	66,960	13,492	13,820	-5,480	35,660	8,480	19,160	55,250	93,220	
Agordo	2017	611,000	23,740	0,908	0,607	0,561	0,794	0,923	1,515	0,000	0,000	0,000	1147,400	31,867	101,000	11,360	9,500	-8,600	27,100	4,100	15,900	20,000	98,000	
Auronzo di Ca	2017	826,000	220,500	1,075	1,486	0,495	3,670	10,717	2,561	0,000	0,000	0,000	1212,600	20,200	106,000	11,440	7,400	-10,300	26,800	1,900	14,500	20,000	100,000	
Bassano del G	2017	129,000	46,000	0,190	0,053	0,002	0,010	0,258	0,243	0,076	0,115	0,416	961,200	18,343	84,000	11,443	14,300	-1,600	31,700	10,500	19,100	22,000	100,000	
Belluno	2017	390,000	147,200	0,067	0,379	0,027	0,311	1,230	0,446	0,063	0,069	0,077	1306,800	25,233	103,000	12,687	10,800	-8,300	29,000	5,300	17,200	19,000	100,000	
Castelfranco V	2017	42,000	50,930	0,000	0,000	0,000	0,000	0,000	0,000	0,067	0,240	0,658	980,400	17,150	81,000	12,104	13,400	-4,900	32,800	7,900	19,700	26,000	100,000	
Conegliano	2017	74,000	36,000	0,000	0,035	0,017	0,000	0,000	0,035	0,001	0,000	0,000	1048,600	18,620	82,000	12,788	14,300	-1,900	31,000	10,100	18,500	19,000	100,000	
Cortina D'Ampe	2017	1224,000	254,500	6,369	5,813	6,784	3,933	11,250	12,182	0,000	0,000	0,000	1028,800	13,143	98,000	10,498	7,100	-8,000	23,500	2,500	12,800	17,000	99,000	
Crespano del P	2017	300,000	17,000	0,000	0,000	0,000	0,000	0,003	0,000	0,000	0,000	0,000	1146,800	22,244	92,000	12,465	11,900	-3,400	28,700	7,900	16,700	22,000	100,000	
Domegge di C	2017	775,000	50,400	0,000	0,233	0,031	0,000	3,241	0,233	0,000	0,000	0,000	1163,200	19,486	107,000	10,871	8,800	-7,300	25,800	4,100	15,000	20,000	100,0	

Neive	2017	308,000	21,200	1,724	2,476	0,000	0,000	0,000	4,200	0,925	2,585	3,090	444,200	31,600	55,000	8,076	14,650	-5,000	38,800	9,850	19,440	53,020	89,940
Piobesi D'Alba	2017	194,000	3,000	0,236	0,506	0,000	0,000	0,000	0,742	0,203	0,288	0,288	503,600	32,600	52,000	9,685	13,270	-8,500	37,000	7,220	19,320	49,120	96,480
Santo Stefano	2017	170,000	23,000	0,004	0,001	0,000	0,000	0,000	0,005	2,187	2,976	4,550	464,000	45,000	52,000	8,923	15,070	-5,600	39,100	9,940	20,190	52,950	91,670
Serralunga D'	2017	414,000	8,440	1,507	0,307	0,000	0,000	0,000	1,815	0,371	0,485	0,487	504,400	36,200	52,000	9,700	14,700	-6,900	39,400	8,670	20,740	45,780	89,860
Serravalle Lan	2017	762,000	9,000	2,572	0,310	0,000	0,000	0,000	2,882	0,146	0,146	0,146	500,600	39,600	52,000	9,627	12,980	-5,200	38,100	7,980	17,990	49,990	87,610
Canelli	2017	316,000	23,430	0,024	0,014	0,000	0,000	0,000	0,038	0,661	1,647	3,523	499,400	43,600	55,000	9,080	15,200	-5,600	40,200	9,390	21,020	47,830	91,670
Castel Boglion	2017	260,000	12,000	0,004	0,000	0,000	0,000	0,000	0,004	0,133	0,133	0,142	444,600	43,400	57,000	7,800	15,480	-5,300	40,400	9,580	21,380	40,570	84,090
Coazzolo	2017	291,000	4,120	0,040	0,000	0,000	0,000	0,000	0,040	0,039	0,112	0,112	490,200	37,800	57,000	8,600	13,590	-10,300	41,300	5,810	21,360	43,500	98,100
Costigliole D'A	2017	242,000	36,000	1,503	0,931	0,135	0,000	0,000	2,434	0,011	2,609	5,816	561,800	40,000	58,000	9,686	13,790	-6,900	37,700	7,980	19,600	50,140	94,660
Nizza Monferr	2017	137,000	30,400	0,001	0,000	0,000	0,000	0,000	0,001	0,111	2,090	4,547	499,600	46,600	51,000	9,796	14,690	-8,800	40,400	8,280	21,090	51,720	95,970
San Damiano I	2017	179,000	48,000	0,087	0,806	0,529	0,000	0,000	0,893	1,410	3,679	4,566	426,600	29,400	52,000	8,204	13,920	-8,500	40,900	7,600	20,230	46,000	91,350
Agordo	2019	611,000	23,740	0,908	0,607	0,561	0,794	0,923	1,515	0,000	0,000	0,000	1912,200	35,358	125,000	15,298	10,400	-4,700	27,700	5,400	16,800	24,000	100,000
Auronzo di Ca	2019	826,000	220,500	1,075	1,486	0,495	3,670	10,717	2,561	0,000	0,000	0,000	1638,000	25,200	131,000	12,504	8,000	-7,400	27,200	3,000	14,700	26,000	100,000
Bassano del G	2019	129,000	46,000	0,190	0,053	0,002	0,010	0,258	0,243	0,076	0,115	0,416	1455,000	24,900	96,000	15,156	14,700	0,000	30,600	11,200	19,200	27,000	100,000
Belluno	2019	390,000	147,200	0,067	0,379	0,027	0,311	2,230	0,446	0,063	0,069	0,077	2053,000	32,350	114,000	18,009	11,600	-5,500	29,500	6,400	17,800	21,000	100,000
Castelfranco V	2019	42,000	50,930	0,000	0,000	0,000	0,000	0,000	0,000	0,067	0,240	0,658	1468,600	21,500	106,000	13,855	14,000	-2,900	31,000	8,900	19,600	30,000	100,000
Conegliano	2019	74,000	36,000	0,000	0,035	0,017	0,000	0,000	0,035	0,001	0,000	0,000	1466,000	28,450	99,000	14,808	15,100	0,000	30,400	11,100	19,200	24,000	100,000
Cortina D'Ami	2019	1224,000	254,500	6,369	5,813	6,784	3,933	11,250	12,182	0,000	0,000	0,000	1469,400	27,100	121,000	12,144	7,400	-5,900	23,700	3,200	12,900	16,000	100,000
Crespano del C	2019	300,000	17,000	0,000	0,000	0,000	0,000	0,003	0,000	0,000	0,000	0,000	2045,000	32,400	113,000	18,097	12,500	-4,700	28,000	8,700	17,200	27,000	100,000
Domegge di C	2019	775,000	50,400	0,000	0,233	0,031	0,000	3,241	0,233	0,000	0,000	0,000	1484,400	25,800	126,000	11,781	9,300	-4,700	26,500	5,100	15,200	26,000	100,000
Falcede	2019	1148,000	52,800	1,644	0,856	0,463	0,552	1,553	2,500	0,000	0,000	0,000	1671,800	26,250	138,000	12,114	7,300	-7,200	25,400	2,700	13,600	23,000	99,000
Farra di Soligo	2019	163,000	28,200	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1873,400	36,150	108,000	17,346	13,900	-1,600	30,000	9,300	18,900	26,000	100,000
Feltre	2019	325,000	100,000	0,054	0,520	0,071	0,488	1,546	0,574	0,034	0,060	0,083	2235,600	33,048	112,000	19,961	11,800	-5,500	30,300	6,800	18,400	29,000	100,000
Gaiarine	2019	20,000	28,700	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1593,200	26,850	97,000	16,425	14,200	-3,100	31,800	8,800	20,600	25,000	100,000
Lamon	2019	594,000	54,360	0,000	0,046	0,002	0,009	3,007	0,046	0,000	0,000	0,000	1869,400	29,300	123,000	15,198	10,700	-2,800	26,900	6,700	15,700	21,000	100,000
Maser	2019	147,000	26,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1315,000	23,550	101,000	13,020	14,100	-2,200	30,500	9,300	19,300	28,000	100,000
Mogliano Ven	2019	8,000	46,150	0,000	0,000	0,000	0,000	0,000	0,000	0,734	1,526	7,129	1297,600	33,333	84,000	15,448	14,300	-1,700	30,600	9,700	19,600	26,000	100,000
Oderzo	2019	14,000	42,000	0,000	0,000	0,000	0,000	0,000	0,000	0,646	6,223	8,203	1398,000	19,188	95,000	14,716	13,900	-2,000	31,000	9,200	19,400	34,000	100,000
Perarolo di Ca	2019	532,000	43,600	0,097	0,325	0,203	0,000	1,746	0,422	0,000	0,000	0,000	1579,000	25,120	120,000	13,158	10,000	-4,500	27,700	6,000	15,700	24,000	98,000
Ponte di Piave	2019	12,000	32,800	0,000	0,000	0,000	0,000	0,000	0,000	12,541	19,693	21,938	1354,000	21,440	90,000	15,044	13,800	-3,000	30,500	8,500	19,500	31,000	100,000
Roncade	2019	8,000	61,780	0,000	0,000	0,000	0,000	0,000	0,000	4,723	11,019	20,696	1435,400	21,375	92,000	15,602	13,800	-2,600	30,400	8,600	19,600	30,000	100,000
San Martino d	2019	647,000	44,900	1,299	1,714	0,335	0,016	5,180	3,013	0,000	0,000	0,000	2180,000	30,650	120,000	18,167	10,700	-2,100	25,600	7,300	15,100	26,000	100,000
Santo Stefano	2019	908,000	100,200	0,007	0,043	0,275	0,000	13,117	0,050	0,000	0,000	0,000	1553,000	23,290	129,000	12,039	7,700	-8,300	27,300	3,000	14,200	22,000	100,000
Sospirolo	2019	447,000	66,000	0,001	0,000	0,000	0,000	2,497	0,001	0,000	0,000	0,000	2171,800	38,650	124,000	17,515	11,700	-2,800	28,300	7,700	16,800	21,000	100,000
Trivio	2019	15,000	55,500	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1354,400	24,840	93,000	14,563	14,300	-2,000	31,700	9,300	20,200	26,000	99,000
Valdobbiadene	2019	247,000	60,700	0,000	0,004	0,000	0,000	0,024	0,004	0,000	0,000	0,000	1795,000	23,173	114,000	15,746	14,000	-0,600	29,600	10,100	18,300	28,000	100,000
Valle di Cadore	2019	851,000	40,640	0,631	0,985	0,001	0,684	1,098	1,615	0,000	0,000	0,000	1726,600	31,760	130,000	13,282	9,400	-4,700	26,900	5,100	15,400	22,000	100,000
Vazzola	2019	30,000	26,160	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,001	1414,800	24,420	91,000	15,547	14,000	-2,500	30,800	8,900	19,500	25,000	100,000
Villorba	2019	26,000	30,600	0,000	0,000	0,000	0,000	0,000	0,000	0,051	0,060	0,065	1094,400	26,060	90,000	12,160	13,900	-2,900	31,700	8,900	19,800	28,000	100,000
Vittorio Venet	2019	138,000	82,000	0,716	0,853	0,025	2,923	1,475	1,569	0,000	0,000	0,000	1639,800	37,750	104,000	15,767	14,300	-0,600	30,600	9,900	19,300	27,000	100,000
Volpago del N	2019	91,000	44,700	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1460,800	26,460	102,000	14,322	14,300	-1,000	30,300	9,900	19,300	28,000	100,000
Zero Branco	2019	7,000	26,100	0,000	0,000	0,000	0,000	0,000	0,000	0,195	0,252	0,562	1165,600	20,657	89,000	13,097	14,100	-1,900	31,600	9,400	19,900	27,000	99,000
Alba	2019	172,000	54,000	0,010	0,027	0,000	0,000	0,000	0,038	0,674	10,108	13,306	984,800	101,400	400,000	12,626	14,570	-8,900	41,700	8,180	20,960	45,930	99,000
Baldisservo D'A	2019	380,000	15,000	0,223	0,000	0,000	0,000	0,000	0,223	0,046	0,215	0,215	1035,000	95,200	86,000	12,035	11,870	-11,300	42,100	5,330	18,400	58,160	99,450
Barbaresco	2019	274,000	7,000	0,313	0,136	0,000	0,000	0,000	0,449	0,319	1,853	1,916	983,200	103,200	79,000	12,446	13,820	-6,172	39,680	8,279	19,410	53,353	92,580
Barolo	2019	213,000	5,690	0,732	1,039	0,000	0,000	0,000	1,771	0,575	0,575	0,575	1022,200	64,600	84,000	12,169	14,595	-5,300	40,500	8,530	20,650	53,430	89,210
Bossolasco	2019	757,000	14,000	0,776	3,842	0,003	0,000	0,000	4,617	0,659	0,659	0,659	1030,400	90,600	87,000	11,844	12,740	-3,600	35,900	7,960	17,530	52,050	90,840
Bra	2019	285,000	59,000	0,000	0,000	0,000	0,000	0,000	0,000	0,367	3,279	18,251	1040,340	93,430	81,380	12,784	13,820	-6,172	39,680	8,279	19,410	60,180	89,660
Caraglio	2019	63																					

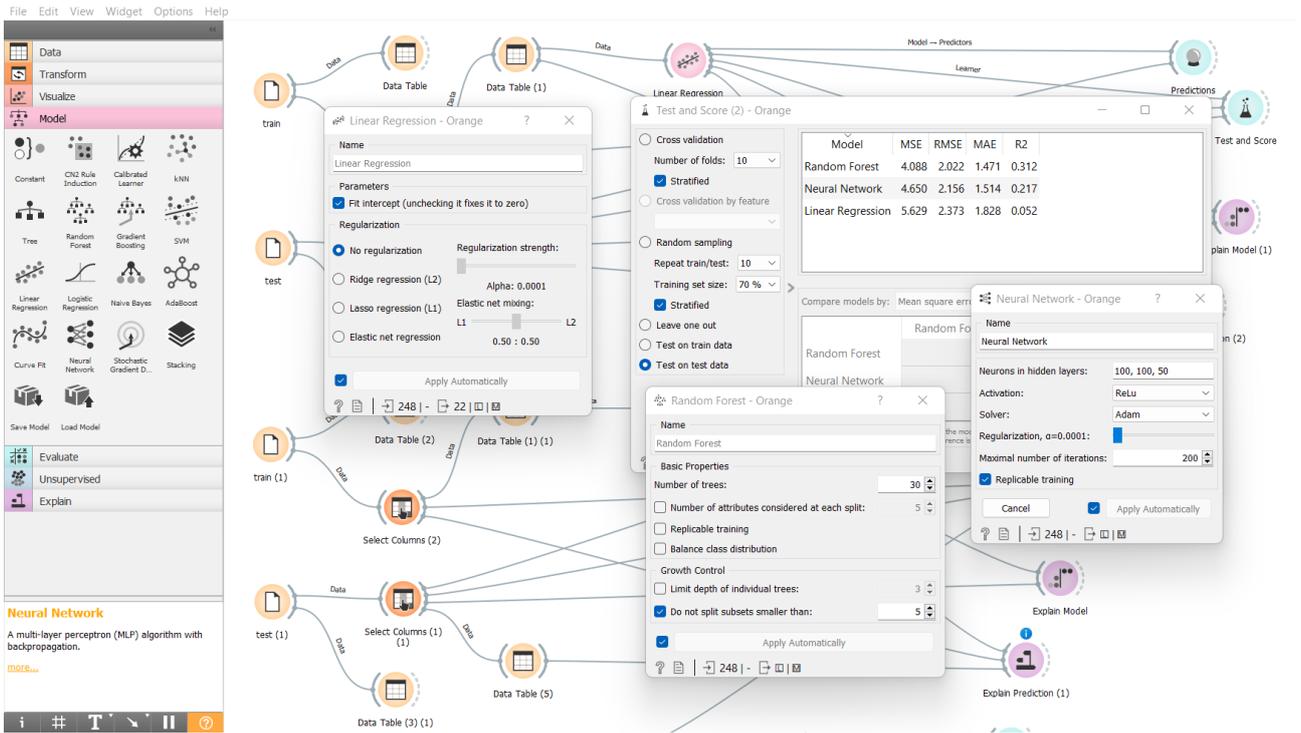
Perarolo di Ca	2021	532,000	43,600	0,097	0,325	0,203	0,000	1,746	0,422	0,000	0,000	0,000	1097,200	18,800	104,000	10,550	9,000	-5,700	26,200	4,800	14,700	29,000	98,000	
Ponte di Piave	2021	12,000	32,800	0,000	0,000	0,000	0,000	0,000	0,000	12,541	19,693	21,938	808,600	20,280	77,000	10,501	13,100	-2,000	30,300	7,200	19,100	26,000	100,000	
Roncade	2021	8,000	61,780	0,000	0,000	0,000	0,000	0,000	0,000	4,723	11,019	20,696	796,800	21,880	73,000	10,915	13,200	-1,700	30,200	7,500	19,300	29,000	100,000	
San Martino d	2021	647,000	44,900	1,299	1,714	0,335	0,016	5,180	3,013	0,000	0,000	0,000	1443,800	20,575	112,000	12,891	9,800	-3,200	24,900	6,300	14,500	28,000	100,000	
Santo Stefano	2021	908,000	100,200	0,007	0,043	0,275	0,000	13,117	0,050	0,000	0,000	0,000	1250,800	19,244	110,000	11,371	6,200	-10,600	25,300	1,300	13,300	31,000	100,000	
Sospirolo	2021	447,000	66,000	0,001	0,000	0,000	0,000	2,497	0,001	0,000	0,000	0,000	1418,400	29,800	98,000	14,473	10,600	-3,700	26,600	6,600	15,800	28,000	100,000	
Treviso	2021	15,000	55,500	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	890,800	22,040	82,000	10,863	13,600	-1,000	31,200	9,500	19,600	24,000	99,000	
Valdobbiaden	2021	247,000	60,700	0,000	0,004	0,000	0,000	0,024	0,004	0,000	0,000	0,000	1423,400	20,083	91,000	15,642	13,200	0,000	29,000	9,300	17,800	26,000	100,000	
Valle di Cadore	2021	851,000	40,640	0,631	0,985	0,001	0,684	1,098	1,615	0,000	0,000	0,000	1199,600	21,200	105,000	11,425	8,300	-6,700	25,100	3,700	14,500	31,000	100,000	
Vazzola	2021	30,000	26,160	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,001	937,200	16,900	84,000	11,157	13,100	-1,400	30,300	7,600	18,800	29,000	100,000	
Villorba	2021	26,000	30,600	0,000	0,000	0,000	0,000	0,000	0,000	0,051	0,060	0,065	953,000	21,267	84,000	11,345	13,200	-1,800	31,000	7,600	19,500	26,000	100,000	
Vittorio Venet	2021	138,000	82,000	0,716	0,853	0,025	2,923	1,475	1,569	0,000	0,000	0,000	1303,800	27,100	92,000	14,172	13,500	0,100	29,700	9,100	18,500	25,000	100,000	
Volpago del N	2021	91,000	44,700	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1108,600	26,467	87,000	12,743	13,600	0,000	30,500	9,000	18,900	27,000	100,000	
Zero Branco	2021	7,000	26,100	0,000	0,000	0,000	0,000	0,000	0,000	0,195	0,252	0,562	873,200	25,840	80,000	10,915	13,400	-0,900	30,500	8,500	19,400	27,000	99,000	
Alba	2021	172,000	54,000	0,010	0,027	0,000	0,000	0,000	0,038	0,674	10,108	13,306	568,800	32,000	63,000	9,029	13,950	-7,400	37,200	7,630	20,260	45,580	95,850	
Baldissero D'A	2021	380,000	15,000	0,223	0,000	0,000	0,000	0,000	0,223	0,046	0,215	0,215	630,800	51,200	64,000	9,856	11,720	-10,900	36,000	4,970	18,480	53,420	99,150	
Barbaresco	2021	274,000	7,000	0,313	0,136	0,000	0,000	0,000	0,449	0,319	1,853	1,916	629,000	36,000	65,000	9,677	13,486	-6,736	36,040	7,959	19,012	51,210	92,690	
Barolo	2021	213,000	5,690	0,732	1,039	0,000	0,000	0,000	1,771	0,575	0,575	0,575	594,200	51,600	69,000	8,574	14,160	-7,600	37,200	8,040	20,290	53,400	88,370	
Bossolasco	2021	757,000	14,000	0,776	3,842	0,003	0,000	0,000	4,617	0,659	6,659	6,659	484,400	67,400	60,000	8,073	12,320	-8,300	34,900	7,430	17,200	45,920	91,190	
Bra	2021	285,000	59,000	0,000	0,000	0,000	0,000	0,000	0,000	0,367	3,279	18,251	591,000	41,000	68,000	8,691	12,840	-6,400	33,700	6,640	19,000	51,990	96,320	
Caraglio	2021	638,000	41,000	0,049	0,103	0,000	0,000	0,000	0,152	0,528	1,036	1,547	701,400	91,600	73,000	9,608	13,486	-6,736	36,040	7,959	19,012	47,850	93,430	
Castino	2021	525,000	15,500	0,454	1,377	0,000	0,000	0,000	1,831	0,301	0,472	0,472	490,200	36,200	68,000	7,735	12,670	-7,100	33,500	7,860	17,490	51,210	92,690	
Dogliani	2021	300,000	35,680	3,005	1,244	0,000	0,000	0,000	4,249	0,092	0,092	0,092	1,015	546,400	59,800	65,000	8,406	13,890	-6,500	36,500	8,070	19,710	49,520	91,080
La Morra	2021	513,000	24,300	0,007	0,012	0,000	0,000	0,000	0,020	0,123	1,419	1,421	493,600	44,000	68,000	7,259	14,080	-5,900	35,900	8,890	19,270	47,090	86,390	
Canale	2021	194,000	18,000	0,183	0,125	0,000	0,000	0,000	0,308	0,448	1,030	1,445	608,000	51,600	63,000	9,651	13,680	-5,400	34,800	8,110	19,240	61,210	98,390	
Castiglione Fa	2021	350,000	4,720	0,332	0,700	0,000	0,000	0,000	1,032	0,327	0,340	0,365	577,600	43,000	66,000	8,752	14,380	-4,900	37,000	8,820	19,560	48,170	87,370	
Clavesana	2021	300,000	17,150	0,011	0,006	0,000	0,000	0,000	0,017	3,333	5,656	5,779	594,000	61,200	72,000	8,250	13,910	-6,300	36,300	8,450	18,570	49,470	88,580	
Castiglione Sal	2021	476,000	15,000	0,000	0,000	0,000	0,000	0,000	0,000	1,218	2,207	4,107	696,000	84,000	72,000	9,667	11,530	-8,400	34,500	5,820	18,040	47,100	92,970	
Cranvanzana	2021	585,000	8,200	0,381	3,738	0,000	0,000	0,000	4,119	0,572	0,572	0,572	555,600	44,600	63,000	8,819	12,400	-12,600	37,400	5,840	18,950	50,850	95,590	
Guaresne	2021	360,000	13,400	0,852	2,796	0,000	0,000	0,000	3,648	0,122	0,631	1,787	554,156	50,192	66,259	8,363	13,486	-6,736	36,040	7,959	19,012	51,210	92,690	
Mango	2021	521,000	19,000	2,724	6,038	0,000	0,000	0,000	8,763	2,250	2,250	2,250	601,200	36,600	65,000	9,249	12,930	-5,100	34,200	9,080	16,790	54,230	87,670	
Mombarcaro	2021	896,000	20,000	0,058	0,532	0,000	0,000	0,000	0,591	0,653	0,830	0,904	554,156	50,192	66,259	8,363	13,486	-6,736	36,040	7,959	19,012	51,210	92,690	
Mionforte D'Al	2021	480,000	25,000	1,216	3,005	0,000	0,000	0,000	4,221	1,941	1,941	1,941	554,156	50,192	66,259	8,363	13,486	-5,400	35,900	9,910	19,090	54,290	90,030	
Montelupo all	2021	564,000	6,400	0,211	2,568	0,000	0,000	0,000	2,780	0,923	0,924	0,924	520,000	46,800	63,000	8,254	14,020	-3,300	35,500	8,730	19,310	50,970	91,070	
Neive	2021	308,000	21,200	1,724	2,476	0,000	0,000	0,000	4,200	0,925	2,585	3,029	496,800	32,600	62,000	8,013	14,080	-3,600	35,700	9,350	18,820	53,150	89,210	
Probesi D'Alba	2021	194,000	3,000	0,236	0,506	0,000	0,000	0,000	0,742	0,203	0,288	0,288	607,800	63,400	70,000	8,683	13,190	-6,300	36,700	7,230	19,160	51,200	96,830	
Santo Stefano	2021	170,000	23,000	0,004	0,001	0,000	0,000	0,000	0,005	2,187	2,976	4,550	594,200	37,600	70,000	8,489	14,580	-4,400	36,500	9,660	19,500	59,160	95,310	
Serralunga D'	2021	414,000	8,440	1,507	0,307	0,000	0,000	0,000	1,815	0,371	0,485	0,487	432,600	39,600	59,000	7,332	14,360	-6,700	37,400	8,820	19,890	52,290	90,140	
Serravalle Lan	2021	762,000	9,000	2,572	0,310	0,000	0,000	0,000	2,882	0,146	0,146	0,146	503,000	52,200	68,000	7,397	12,780	-6,900	35,200	7,710	17,850	51,250	92,180	
Canelli	2021	316,000	23,430	0,024	0,014	0,000	0,000	0,000	0,038	0,661	1,647	3,523	654,600	60,400	69,000	9,487	14,670	-4,800	38,000	9,110	20,220	52,810	95,890	
Castel Boglior	2021	260,000	12,000	0,004	0,000	0,000	0,000	0,000	0,004	0,133	0,133	0,142	606,400	74,000	66,000	9,188	14,420	-5,900	37,400	9,230	19,610	47,520	88,720	
Coazzolo	2021	291,000	4,120	0,040	0,000	0,000	0,000	0,000	0,040	0,039	0,112	0,112	629,400	38,200	71,000	8,865	12,650	-10,000	36,600	6,030	19,270	49,300	99,040	
Castiglione D'A	2021	242,000	36,000	1,503	0,931	0,135	0,000	0,000	2,434	0,011	2,609	5,816	105,800	50,192	66,259	8,363	13,486	-5,950	35,560	5,960	19,560	51,211	92,694	
Nizza Monferr	2021	137,000	30,400	0,001	0,000	0,000	0,000	0,000	0,001	1,111	2,090	4,547	522,000	49,200	66,000	7,909	13,486	-6,736	36,040	7,959	19,012	53,830	90,930	
San Damiano I	2021	179,000	48,000	0,087	0,806	0,529	0,000	0,000	0,893	1,410	3,679	4,566	505,200	29,400	61,000	8,282	13,430	-6,300	37,000	7,540	19,320	49,920	98,340	

(fig. 29 – training database (Piedmont + Veneto) of model 3)

Test database:

MUNICIPALITY	Year	Altitude m	Area km ²	Landslide hazard areas (km ²) Very high P4	Landslide hazard areas (km ²) high P3	Landslide hazard areas (km ²) medium P2	Landslide hazard areas (km ²) low P1	Landslide hazard areas (km ²) AA	Landslide hazard areas (km ²) P3+P4	Hydraulic hazard areas (km ²) high P3	Hydraulic hazard areas (km ²) medium P2	Hydraulic hazard areas (km ²) low P1	Total precipitation (mm)	Maximum daily precipitation (mm)	Number of rainy days (prec.>=1mm)	Average precipitation	Average temperature	Minimum temperature °C	Maximum temperature °C	Average minimum temperature °C	Average maximum temperature °C	Average minimum humidity (%)	Average maximum humidity (%)
Agordo	2018	611,000	23,740	0,908	0,607	0,561	0,794	0,923	1,515	0,000	0,000	0,000	1706,200	98,433	125,000	13,650	10,200	-3,500	27,200	5,400	16,500	22,000	100,000
Alba	2018	172,000	54,000	0,010	0,027	0,000	0,000	0,000	0,03														

Feltre	2018	325,000	100,000	0,054	0,520	0,071	0,488	1,546	0,574	0,034	0,060	0,083	1754,200	76,967	112,000	15,663	11,900	-3,800	31,000	6,900	18,700	25,000	100,000
Gaiarine	2018	20,000	28,700	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	108,800	18,000	100,000	1,088	14,600	-1,400	32,800	9,100	20,600	25,000	100,000
Guarenne	2018	360,000	13,400	0,852	2,796	0,000	0,000	0,000	3,648	0,122	0,631	1,787	1165,000	62,600	101,000	11,535	13,930	-8,600	36,900	8,290	19,560	57,550	97,460
La Morra	2018	513,000	24,300	0,007	0,012	0,000	0,000	0,000	0,020	0,123	1,419	1,421	1093,600	89,200	106,000	10,317	13,770	-9,900	35,000	9,210	18,330	56,210	97,700
Lamon	2018	594,000	54,360	0,000	0,046	0,002	0,009	3,007	0,046	0,000	0,000	0,000	1586,400	53,500	125,000	12,691	10,700	-2,400	27,300	6,800	15,900	24,000	100,000
Mangò	2018	531,000	19,000	2,724	6,038	0,000	0,000	0,000	8,763	2,250	2,250	2,250	1198,000	64,200	92,000	13,022	13,110	-8,600	32,200	9,550	16,800	61,800	92,230
Maser	2018	147,000	26,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1318,400	24,875	106,000	12,438	14,300	-0,700	31,100	9,600	19,500	25,000	100,000
Mogliano Ver	2018	8,000	46,150	0,000	0,000	0,000	0,000	0,000	0,734	1,526	7,129	915,200	17,133	86,000	10,642	14,700	-0,300	31,700	10,100	19,800	28,000	100,000	
Mombarcaro	2018	896,000	20,000	0,058	0,532	0,000	0,000	0,000	0,591	0,653	0,830	9,904	1197,000	99,400	101,000	11,851	11,700	-11,700	30,500	8,050	15,350	65,050	96,120
Monforte D'A	2018	480,000	25,000	0,058	0,532	0,000	0,000	0,000	0,591	0,653	0,830	9,904	1306,400	71,400	103,000	12,683	14,890	-9,200	35,600	10,610	19,170	60,140	92,650
Montelupo al	2018	564,000	6,400	1,216	3,005	0,000	0,000	0,000	4,221	1,941	1,941	1,941	1201,200	64,000	105,000	11,440	13,948	-9,389	35,600	8,978	18,150	54,200	95,280
Neive	2018	308,000	21,200	1,724	2,476	0,000	0,000	0,000	4,200	0,925	2,585	3,090	1060,000	66,200	93,000	11,398	13,948	-9,389	35,600	8,978	18,915	64,290	96,850
Nizza Monfer	2018	137,000	30,400	0,001	0,000	0,000	0,000	0,000	0,001	0,111	2,090	4,547	1130,000	45,600	94,000	12,021	14,940	-8,300	36,000	9,380	20,490	61,690	98,980
Oderzo	2018	14,000	42,000	0,000	0,000	0,000	0,000	0,000	0,646	6,223	8,203	1040,600	18,057	100,000	10,406	14,400	-0,800	31,500	9,600	19,900	32,000	100,000	
Perarolo di Ca	2018	532,000	43,600	0,097	0,325	0,203	0,000	1,746	0,422	0,000	0,000	0,000	1500,200	69,800	115,000	13,045	9,900	-2,800	27,400	5,600	16,000	22,000	99,000
Piobesi D'Alb	2018	194,000	3,000	0,236	0,506	0,000	0,000	0,000	0,742	0,203	0,288	0,288	1095,200	69,600	92,000	11,904	13,600	-8,900	34,600	8,390	18,820	58,990	98,810
Ponte di Piav	2018	12,000	32,800	0,000	0,000	0,000	0,000	0,000	0,000	12,541	19,693	21,938	987,600	17,486	90,000	10,973	14,100	-1,400	31,800	8,900	19,800	30,000	100,000
Roncade	2018	8,000	61,780	0,000	0,000	0,000	0,000	0,000	0,000	4,723	11,019	20,696	962,200	20,767	94,000	10,236	14,300	-1,100	32,100	9,200	20,000	27,000	100,000
San Damiano	2018	179,000	48,000	0,087	0,806	0,529	0,000	0,000	0,893	1,410	3,679	4,566	919,600	60,800	90,000	10,218	14,120	-9,900	37,600	8,610	19,620	55,670	97,210
San Martino c	2018	647,000	44,900	1,299	1,714	0,335	0,016	5,180	3,013	0,000	0,000	0,000	1928,600	51,171	126,000	15,306	10,600	-0,200	25,700	7,300	15,000	22,000	100,000
Santo Stefanc	2018	170,000	23,000	0,004	0,001	0,000	0,000	0,000	0,005	2,187	2,976	4,550	1240,400	92,600	94,000	13,196	13,948	-9,389	35,600	8,978	18,915	64,450	96,980
Santo Stefanc	2018	908,000	100,200	0,007	0,043	0,275	0,000	13,117	0,050	0,000	0,000	0,000	1380,400	50,743	123,000	11,223	7,600	-9,400	26,600	2,900	14,400	22,000	100,000
Serrallunga D'	2018	414,000	8,440	1,507	0,307	0,000	0,000	0,000	1,815	0,371	0,485	0,487	1051,200	63,400	101,000	10,408	14,800	-9,900	37,400	9,550	20,040	55,040	93,840
Serravalle Lar	2018	762,000	9,000	2,572	0,310	0,000	0,000	0,000	2,882	0,146	0,146	0,146	1323,800	80,200	103,000	12,852	12,670	-10,600	34,300	8,450	17,280	58,910	93,840
Sospirolo	2018	447,000	66,000	0,001	0,000	0,000	0,000	2,497	0,001	0,000	0,000	0,000	1688,400	58,667	120,000	14,070	11,700	-1,300	28,300	7,900	16,900	21,000	100,000
Treviso	2018	15,000	55,500	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1047,800	17,289	97,000	10,802	14,500	-0,400	32,100	9,700	20,400	24,000	99,000
Valdobbiad	2018	247,000	60,700	0,000	0,004	0,000	0,000	0,024	0,004	0,000	0,000	0,000	1370,800	31,367	103,000	13,309	14,100	-0,500	30,000	10,400	18,500	26,000	100,000
Valle di Cadov	2018	851,000	40,640	0,631	0,985	0,001	0,684	1,098	1,615	0,000	0,000	0,000	1591,000	55,657	119,000	13,370	9,200	-8,200	26,000	5,200	15,300	22,000	100,000
Vazzola	2018	30,000	26,160	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,001	1056,800	23,286	95,000	11,124	14,300	-1,100	31,500	9,300	19,700	23,000	100,000
Villorba	2018	26,000	30,600	0,000	0,000	0,000	0,000	0,000	0,000	0,051	0,060	0,065	1074,800	18,900	98,000	10,967	14,300	-1,500	31,600	9,400	20,300	26,000	100,000
Vittorio Vene	2018	138,000	82,000	0,716	0,853	0,025	2,923	1,475	1,569	0,000	0,000	0,000	1398,200	30,200	111,000	12,596	14,500	0,500	31,200	10,300	19,500	25,000	100,000
Volpago del A	2018	91,000	44,700	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1223,200	28,943	94,000	13,013	14,500	0,400	31,400	10,100	19,600	28,000	100,000
Zero Branco	2018	7,000	26,100	0,000	0,000	0,000	0,000	0,000	0,195	0,252	0,252	0,562	864,600	20,520	89,000	9,715	14,400	-0,700	32,400	9,800	20,200	25,000	99,000
Agordo	2020	611,000	23,740	0,908	0,607	0,561	0,794	0,923	1,515	0,000	0,000	0,000	1789,000	45,683	104,000	17,202	10,000	-4,600	26,100	4,400	16,300	22,000	100,000
Alba	2020	172,000	54,000	0,010	0,027	0,000	0,000	0,000	0,038	0,674	10,108	13,306	686,837	78,037	68,333	10,051	13,991	-4,860	37,230	8,608	19,271	54,836	93,455
Auronzo di Ca	2020	826,000	220,500	1,075	1,486	0,495	3,670	10,717	2,561	0,000	0,000	0,000	1767,000	35,109	104,000	16,990	7,600	-6,200	25,000	2,600	14,400	26,000	100,000
Baldissere D'	2020	380,000	15,000	0,223	0,000	0,000	0,000	0,000	0,223	0,046	0,215	0,215	670,800	77,400	71,000	9,448	11,790	-9,300	38,800	5,380	18,200	60,100	99,210
Barbresco	2020	274,000	7,000	0,313	0,136	0,000	0,000	0,000	0,449	0,319	1,853	1,916	661,000	87,800	68,000	9,721	13,991	-4,860	37,230	8,608	19,271	54,836	93,455
Barolo	2020	213,000	5,690	0,732	1,039	0,000	0,000	0,000	1,771	0,575	0,575	0,575	631,600	62,000	62,000	10,187	14,910	-3,200	37,200	9,800	20,020	54,360	89,600
Bassano del C	2020	129,000	46,000	0,190	0,053	0,002	0,010	0,258	0,243	0,076	0,115	0,416	1460,800	18,169	93,000	15,708	14,600	-3,300	29,800	11,000	19,200	27,000	100,000
Belluno	2020	390,000	147,200	0,067	0,379	0,027	0,311	2,230	0,446	0,063	0,069	0,077	1662,400	26,347	108,000	15,393	11,400	-4,200	28,100	6,100	17,800	29,000	100,000
Bossolasco	2020	757,000	14,000	0,776	3,842	0,003	0,000	0,000	0,000	0,659	0,659	0,659	487,200	79,200	45,000	10,827	12,790	-5,000	33,500	7,920	17,600	54,130	93,670
Bra	2020	285,000	59,000	0,000	0,000	0,000	0,000	0,000	0,000	0,367	3,279	18,251	686,837	78,037	68,333	10,051	13,991	-4,860	37,230	8,608	19,271	54,836	92,730
Canale	2020	194,000	18,000	0,183	0,125	0,000	0,000	0,000	0,308	0,448	1,030	1,445	668,200	77,600	72,000	9,281	14,210	-1,400	37,400	8,620	19,700	55,670	96,660
Canelli	2020	316,000	23,430	0,024	0,014	0,000	0,000	0,000	0,038	0,661	1,647	3,523	776,000	113,600	70,000	11,086	15,210	-5,500	40,200	9,510	20,910	56,340	96,980
Caraglio	2020	638,000	41,000	0,049	0,103	0,000	0,000	0,000	0,152	0,528	1,036	1,547	945,400	61,800	82,000	11,529	13,991	-4,860	37,230	8,608	19,271	54,836	94,760
Castel Boglior	2020	260,000	12,000	0,004	0,000	0,000	0,000	0,000	0,004	0,133	0,133	0,142	669,800	45,200	68,000	9,850	14,900	-9,300	39,000	9,730	20,240	50,090	90,880
Castelfranco V	2020	42,000	50,930	0,000	0,000	0,000	0,000	0,000	0,000	0,067	0,240	0,658	1108,800	14,343	89,000	12,470	13,800	-1,600	31,000	8,400	19,800	24,000	100,000
Castiglione Fr	2020	350,000	4,720	0,332	0																		



(fig. 31 – widget on Orange of model 3)

New MAPE

Linear Regression: 25,8%

Neural Network: 23,1%

Random Forest: 22,01%

After the increase of data in the database the model is more realistic in fact the linear regressor is now the worst estimator compared to neural network and random forest which is consistent with the theory that sees the linear regressor as the simplest and least accurate regressor.

New Model 5: training database:

MUNICIPALITY	Year	Altitude m	Area km ²	Landslide hazard areas (km ²) Very high P4	Landslide hazard areas (km ²) high P3	Landslide hazard areas (km ²) medium P2	Landslide hazard areas (km ²) low P1	Landslide hazard areas (km ²) AA	Landslide hazard areas (km ²) P3+P4	Hydraulic hazard areas (km ²) high P3	Hydraulic hazard areas (km ²) medium P2	Hydraulic hazard areas (km ²) low P1	Total precipitation (mm)	Maximum daily precipitation (mm)	Number of rainy days (prec.>=1 mm)	Average precipitation	Average temperature	Minimum temperature °C	Maximum temperature °C	Average minimum temperature °C	Average maximum temperature °C	Average minimum humidity (E) -%	Average maximum humidity (E) -%
Alba	2021	172,000	54,000	0,010	0,027	0,000	0,000	0,000	0,038	0,674	10,108	13,306	568,800	32,000	63,000	9,029	13,950	-7,400	37,200	7,630	20,260	45,580	95,500
Baldissero D'Alba	2021	380,000	15,000	0,223	0,000	0,000	0,000	0,000	0,223	0,046	0,215	0,215	600,000	51,200	64,000	9,856	11,720	-10,900	36,000	4,970	18,480	53,420	99,150
Barbaresco	2021	274,000	7,000	0,313	0,136	0,000	0,000	0,000	0,449	0,319	1,853	1,916	629,000	36,600	65,000	9,677	13,486	-6,736	36,040	7,959	19,012	51,210	92,690
Barolo	2021	213,000	5,690	0,732	1,039	0,000	0,000	0,000	1,771	0,575	0,575	0,575	591,600	51,600	69,000	8,574	14,160	-7,600	37,200	8,040	20,290	53,400	88,370
Bossolasco	2021	757,000	14,000	0,776	3,842	0,003	0,000	0,000	4,617	0,659	0,659	0,659	484,400	67,400	60,000	8,073	12,320	-8,300	34,900	7,430	17,200	45,920	91,190
Bra	2021	285,000	59,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	3,279	18,251	591,000	41,000	68,000	8,691	12,840	-6,400	33,700	6,640	19,030	51,990	96,320
Caraglio	2021	638,000	41,000	0,049	0,103	0,000	0,000	0,000	0,152	0,528	1,036	1,547	701,400	91,600	73,000	9,608	13,486	-6,736	36,040	7,959	19,012	47,850	93,430
Castino	2021	525,000	15,500	0,454	1,377	0,000	0,000	0,000	1,831	0,301	0,472	0,490	526,000	36,200	68,000	7,725	12,670	-7,100	33,500	7,860	17,490	51,210	92,690
Dogliani	2021	300,000	35,680	3,005	1,244	0,000	0,000	0,000	4,249	0,092	0,097	0,105	546,400	59,800	65,000	8,406	13,890	-6,500	36,500	8,070	19,710	49,520	91,080
La Morra	2021	513,000	24,300	0,007	0,012	0,000	0,000	0,000	0,020	0,123	1,419	1,421	493,600	44,000	68,000	7,259	14,080	-5,900	35,900	8,890	19,270	47,090	86,390
Canale	2021	194,000	18,000	0,183	0,125	0,000	0,000	0,000	0,308	0,448	1,030	1,445	608,000	51,600	63,000	9,651	13,680	-5,400	34,800	8,110	19,240	61,210	96,390
Castiglione Falletto	2021	350,000	4,720	0,332	0,700	0,000	0,000	0,000	1,032	0,327	0,340	0,365	577,600	43,000	66,000	8,752	14,380	-4,900	37,000	8,820	19,950	48,170	87,370
Clavesana	2021	300,000	17,150	0,011	0,006	0,000	0,000	0,000	0,017	3,333	5,656	5,779	594,000	61,200	72,000	8,250	13,510	-6,300	36,300	8,450	19,580	49,470	88,580
Castiglione Sa	2021	476,000	15,000	0,000	0,000	0,000	0,000	0,000	0,000	1,218	2,207	4,107	696,000	84,000	72,000	9,667	11,930	-8,400	34,500	5,820	18,040	47,100	92,970
Cravanzana	2021	585,000	8,200	0,381	3,738	0,000	0,000	0,000	4,119	0,572	0,572	0,572	555,600	44,600	63,000	8,819	12,400	-12,600	37,400	5,840	20,290	50,850	95,590
Guarene	2021	360,000	13,400	0,852	2,796	0,000	0,000	0,000	3,648	0,122	0,631	1,787	554,156	50,192	66,259	8,363	13,486	-6,736	36,040	7,959	19,012	51,210	92,690
Mango	2021	521,000	19,000	2,724	6,038	0,000	0,000	0,000	8,763	2,250	2,250	2,250	601,200	36,600	65,000	9,249	12,930	-5,100	34,200	9,080	16,790	54,230	87,670
Mombarcaro	2021	896,000	20,000	0,058	0,532	0,000	0,000	0,000	0,591	0,653	0,830	0,904	554,156	50,192	66,259	8,363	13,486	-6,736	36,040	7,959	19,012	51,210	92,690
Montforte D'Alba	2021	480,000	25,000	1,216	3,005	0,000	0,000	0,000	4,221	1,941	1,941	1,941	554,156	50,192	66,259	8,363	14,500	-5,400	35,900	9,910	19,090	54,290	90,630
Montelupo al	2021	564,000	6,400	0,211	2,568	0,000	0,000	0,000	2,780	0,923	0,924	0,924	520,000	46,800	63,000	8,254	14,020	-5,300	35,500	8,730	19,310	50,970	91,070
Neive	2021	308,000	21,200	1,724	2,476	0,000	0,000	0,000	4,200	0,925	2,585	3,090	496,800	32,600	62,000	8,013	14,080	-3,600	35,700	9,350	18,820	53,150	89,210
Piobesi D'Alba	2021	194,000	3,000	0,236	0,506	0,000	0,000	0,000	0,742	0,203	0,288	0,288	607,800	63,400	70,000	8,683	13,190	-6,300	36,700	7,230	19,160	51,200	96,830
Santo Stefano	2021	170,000	23,000	0,004	0,001	0,000	0,000	0,000	0,005	2,187	2,976	4,550	594,200	37,600	70,000	8,489	14,580	-4,400	36,500	9,660	19,500	59,260	95,310
Serralunga D'Alba	2021	414,000	8,440	1,507	0,307	0,000	0,000	0,000	1,815	0,371	0,485	0,485	473,000	39,600	59,000	7,332	14,360	-6,700	37,400	8,820	19,890	52,290	90,140
Serravalle Lariccia	2021	762,000	9,000	2,572	0,310	0,000	0,000	0,000	2,882	0,146	0,146	0,146	503,000	52,200	68,000	7,397	12,780	-6,900	35,200	7,710	17,850	51,250	92,180
Canelli	2021	316,000	23,430	0,024	0,014	0,000	0,000	0,000	0,038	0,661	1,647	3,523	654,600	60,400	69,000	9,487	14,670	-4,800	38,000	9,110	20,220	52,810	95,890
Castel Bolognese	2021	260,000	12,000	0,004	0,000	0,000	0,000	0,000	0,004	0,133	0,133	0,133	604,000	74,000	66,000	9,188	14,420	-5,900	37,400	9,230	19,610	47,520	88,720
Coazzolo	2021	291,000	4,120	0,040	0,000	0,000	0,000	0,000	0,040	0,039	0,112	0,112	629,400	38,200	71,000	8,865	12,650	-10,000	36,600	6,030	19,270	49,300	99,040
Castiglione D'Alba	2021	242,000	36,000	1,503	0,931	0,135	0,000	0,000	2,434	0,011	2,609	5,816	554,156	50,192	66,259	8,363	13,486	-5,950	35,950	9,560	19,560	51,210	92,690
Nizza Monferrato	2021	137,000	30,400	0,001	0,000	0,000	0,000	0,000	0,001	0,111	2,090	4,547	522,000	49,200	66,000	7,909	13,486	-6,736	36,040	7,959	19,012	53,830	90,930
San Damiano	2021	179,000	48,000	0,087	0,806	0,529	0,000	0,000	0,893	1,410	3,679	4,566	505,200	29,400	61,000	8,282	13,430	-6,300	37,000	7,540	19,320	49,920	98,340
Alba	2020	172,000	54,000	0,010	0,027	0,000	0,000	0,000	0,038	0,674	10,108	13,306	686,837	78,037	68,333	10,051	13,991	-4,860	37,230	8,608	19,271	54,836	93,455
Baldissero D'Alba	2020	380,000	15,000	0,223	0,000	0,000	0,000	0,000	0,223	0,046	0,215	0,215	670,800	77,400	71,000	9,448	11,790	-9,300	38,800	5,380	18,200	60,100	99,210
Barbaresco	2020	274,000	7,000	0,313	0,136	0,000	0,000	0,000	0,449	0,319	1,853	1,916	661,000	87,800	68,000	9,721	13,991	-4,860	37,230	8,608	19,271	54,836	93,455
Barolo	2020	213,000	5,690	0,732	1,039	0,000	0,000	0,000	1,771	0,575	0,575	0,575	631,600	62,000	62,000	10,187	14,910	-3,200	37,200	9,800	20,020	54,360	89,600
Bossolasco	2020	757,000	14,000	0,776	3,842	0,003	0,000	0,000	4,617	0,659	0,659	0,659	487,200	79,200	45,000	10,827	12,790	-5,000	33,500	7,920	17,650	54,130	93,670
Bra	2020	285,000	59,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	3,279	18,251	686,837	78,037	68,333	10,051	13,991	-4,860	37,230	8,608	19,271	54,836	92,730
Caraglio	2020	638,000	41,000	0,049	0,103	0,000	0,000	0,000	0,152	0,528	1,036	1,547	945,400	61,800	82,000	11,529	13,991	-4,860	37,230	8,608	19,271	54,836	94,760
Castino	2020	525,000	15,500	0,454	1,377	0,000	0,000	0,000	1,831	0,301	0,472	0,490	630,600	63,600	75,000	8,408	13,170	-3,500	34,800	8,480	17,860	56,310	97,140
Dogliani	2020	300,000	35,680	3,005	1,244	0,000	0,000	0,000	4,249	0,092	0,097	0,105	771,800	78,800	76,000	10,155	13,991	-4,860	36,600	8,608	19,410	53,110	91,550
La Morra	2020	513,000	24,300	0,007	0,012	0,000	0,000	0,000	0,020	0,123	1,419	1,421	711,400	64,400	71,000	10,020	13,870	-4,500	36,600	9,040	18,700	54,836	95,850
Canale	2020	194,000	18,000	0,183	0,125	0,000	0,000	0,000	0,308	0,448	1,030	1,445	668,200	77,600	72,000	9,281	14,210	-4,100	37,400	8,620	19,790	55,670	96,660
Castiglione Falletto	2020	350,000	4,720	0,332	0,700	0,000	0,000	0,000	1,032	0,327	0,340	0,365	672,000	73,000	69,000	9,739	14,820	-3,800	38,400	9,200	20,440	50,600	90,500
Clavesana	2020	300,000	17,150	0,011	0,006	0,000	0,000	0,000	0,017	3,333	5,656	5,779	687,800	70,600	70,000	9,826	14,020	-5,800	36,600	9,090	18,950	50,680	88,540
Castiglione Sa	2020	476,000	15,000	0,000	0,000	0,000	0,000	0,000	0,000	1,218	2,207	4,107	985,000	74,000	84,000	11,726	13,991	-4,860	37,230	8,608	19,271	47,920	90,490
Cravanzana	2020	585,000	8,200	0,381	3,738	0,000	0,000	0,000	4,119	0,572	0,572	0,572	697,000	91,000	78,000	8,936	12,310	-6,300	35,800	6,760	17,860	54,070	96,340
Guarene	2020	360,000	13,400	0,852	2,796	0,000	0,000	0,000	3,648	0,122	0,631	1,787	416,800	77,400	51,000	8,173	13,991	-5,700	37,230	7,510			

Bra	2017	285,000	59,000	0,000	0,000	0,000	0,000	0,000	0,367	3,279	18,251	469,200	41,800	53,000	8,853	13,160	-14,000	35,800	6,810	19,520	52,010	95,150		
Caraglio	2017	638,000	41,000	0,049	0,103	0,000	0,000	0,000	0,528	1,036	1,547	630,600	50,200	69,000	9,139	12,340	-11,000	35,400	5,420	19,260	45,080	95,140		
Castino	2017	525,000	15,500	0,454	1,377	0,000	0,000	0,000	0,000	1,831	0,301	0,472	0,490	443,000	33,200	53,000	8,358	13,270	-6,100	36,200	8,330	18,200	50,080	93,730
Dogliani	2017	300,000	35,680	3,005	1,244	0,000	0,000	0,000	0,000	4,249	0,092	0,097	0,105	540,400	48,800	55,000	9,825	13,800	-5,900	37,500	8,770	18,830	48,211	91,053
La Morra	2017	513,000	24,300	0,007	0,012	0,000	0,000	0,000	0,000	0,020	0,123	1,419	1,421	508,000	47,400	51,000	9,961	13,710	-6,700	36,100	8,610	18,820	46,130	95,330
Canale	2017	194,000	18,000	0,183	0,125	0,000	0,000	0,000	0,448	1,030	1,445	452,600	40,200	51,000	8,875	14,170	-7,100	38,300	8,130	20,100	48,470	92,820		
Castiglione Fc	2017	350,000	4,720	0,332	0,700	0,000	0,000	0,000	0,000	1,032	0,327	0,340	0,365	451,000	36,600	52,000	8,673	14,830	-6,600	39,300	8,910	20,740	44,760	86,680
Clavesana	2017	300,000	17,150	0,011	0,006	0,000	0,000	0,000	0,000	0,017	3,333	5,656	5,779	528,600	49,600	57,000	9,274	14,170	-5,600	38,300	9,040	19,310	43,420	82,200
Castiglione Sa	2017	476,000	15,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,218	2,207	4,107	553,800	29,000	59,000	9,386	12,480	-8,800	36,700	5,980	18,990	42,490	89,390
Cravanzana	2017	585,000	8,200	0,381	3,738	0,000	0,000	0,000	0,000	4,119	0,572	0,572	0,572	456,600	34,000	51,000	8,953	12,720	-9,300	38,700	6,870	18,580	49,190	92,700
Guarene	2017	360,000	13,400	0,852	2,796	0,000	0,000	0,000	0,000	3,648	0,122	0,631	1,787	409,400	64,400	42,000	9,748	13,410	-9,700	38,700	6,680	20,140	48,270	95,660
Mango	2017	521,000	19,000	2,724	6,038	0,000	0,000	0,000	0,000	8,763	2,250	2,250	2,250	557,600	35,000	56,000	9,957	13,290	-4,800	35,200	9,420	17,160	49,520	84,830
Mombarcaro	2017	896,000	20,000	0,058	0,532	0,000	0,000	0,000	0,000	0,591	0,653	0,830	0,904	409,200	32,800	51,000	8,024	11,870	-6,500	32,900	7,810	15,930	53,660	90,410
Monforte D'A	2017	480,000	25,000	0,058	0,532	0,000	0,000	0,000	0,000	0,591	0,653	0,830	0,904	409,200	32,800	50,000	11,168	14,890	-4,200	38,100	10,020	19,770	49,070	87,450
Montelupo al	2017	564,000	6,400	1,216	3,005	0,000	0,000	0,000	0,000	4,221	1,941	1,941	1,941	518,400	34,200	54,000	9,600	14,280	-5,700	37,400	8,770	19,780	44,550	88,490
Neive	2017	308,000	21,200	1,724	2,476	0,000	0,000	0,000	0,000	4,200	0,925	2,585	3,090	444,200	31,600	55,000	8,076	14,650	-5,000	38,800	9,850	19,440	53,020	89,940
Probesi D'Alb	2017	194,000	3,000	0,236	0,506	0,000	0,000	0,000	0,000	0,742	0,203	0,288	0,288	503,600	32,600	52,000	9,685	13,270	-8,500	37,000	7,220	19,320	49,120	96,480
Santo Stefan	2017	170,000	23,000	0,004	0,001	0,000	0,000	0,000	0,000	0,005	2,187	2,976	4,550	464,600	45,000	52,000	8,923	15,070	-5,600	39,100	9,940	20,190	52,950	91,670
Serralunga D'	2017	414,000	8,440	1,507	0,307	0,000	0,000	0,000	0,000	1,815	0,371	0,485	0,487	504,400	36,200	52,000	9,700	14,700	-6,900	39,400	8,670	20,740	45,780	89,860
Serravalle Lar	2017	762,000	9,000	2,572	0,310	0,000	0,000	0,000	0,000	2,882	0,146	0,146	0,146	507,600	39,600	52,000	9,627	12,980	-5,200	38,100	7,980	17,990	49,990	87,610
Caneelli	2017	316,000	23,430	0,024	0,014	0,000	0,000	0,000	0,000	0,038	0,661	1,647	3,523	499,400	43,600	55,000	9,080	15,200	-5,600	40,200	9,390	21,020	47,830	91,670
Castel Boglio	2017	260,000	12,000	0,004	0,000	0,000	0,000	0,000	0,000	0,133	0,142	0,133	0,142	444,600	43,400	57,000	7,800	15,480	-5,300	40,400	9,580	21,280	40,750	84,090
Coazzolo	2017	291,000	4,120	0,040	0,000	0,000	0,000	0,000	0,000	0,112	0,112	0,112	0,112	490,200	37,800	57,000	8,600	13,590	-10,300	41,300	5,810	21,360	43,500	98,100
Castiglione D'	2017	242,000	36,000	1,503	0,931	0,135	0,000	0,000	0,000	2,434	0,011	2,609	5,816	561,800	40,000	58,000	9,686	13,790	-6,900	37,700	7,980	19,600	50,140	94,660
Nizza Monfer	2017	137,000	30,400	0,001	0,000	0,000	0,000	0,000	0,000	0,001	0,111	2,090	4,547	499,600	46,600	51,000	9,796	14,690	-8,800	40,400	8,280	21,090	51,720	95,970
San Damiano	2017	179,000	48,000	0,087	0,806	0,529	0,000	0,000	0,000	0,893	1,410	3,679	4,566	426,600	29,400	52,000	8,204	13,920	-8,500	40,900	7,600	20,230	46,000	91,350
Agorzo	2017	611,000	23,740	0,908	0,607	0,561	0,794	0,923	1,515	0,000	0,000	0,000	0,000	1147,400	31,867	101,000	11,360	9,500	-8,600	27,100	4,100	15,900	20,000	98,000
Auronzo di Cè	2017	826,000	220,500	1,075	1,486	0,495	3,670	10,717	2,561	0,000	0,000	0,000	0,000	1212,600	20,200	106,000	11,440	7,400	-10,300	26,800	1,900	14,500	20,000	100,000
Bassano del G	2017	129,000	46,000	0,190	0,053	0,002	0,010	0,258	0,243	0,076	0,115	0,416	961,200	18,343	84,000	11,443	14,300	-1,600	31,700	10,500	19,100	22,000	100,000	
Belluno	2017	390,000	147,200	0,067	0,379	0,027	0,311	2,230	0,446	0,063	0,069	0,077	1306,800	25,233	103,000	12,687	10,800	-8,300	29,700	5,300	17,200	19,000	100,000	
Castelfranco V	2017	42,000	50,930	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,067	0,240	0,658	980,400	17,150	81,000	12,104	13,400	-4,900	32,800	7,900	19,700	26,000	100,000
Conegliano	2017	74,000	36,000	0,000	0,035	0,017	0,000	0,000	0,000	0,035	0,001	0,000	0,000	1048,600	18,620	82,000	12,788	14,300	-1,900	31,000	10,100	18,500	19,000	100,000
Cortina D'Am	2017	1224,000	254,500	6,369	5,813	6,784	3,933	11,250	12,182	0,000	0,000	0,000	0,000	1028,800	13,143	98,000	10,498	7,100	-8,000	23,500	2,500	12,800	17,000	99,000
Crespano del	2017	300,000	17,000	0,000	0,000	0,000	0,000	0,003	0,000	0,000	0,000	0,000	0,000	1146,800	22,244	92,000	12,465	11,900	-3,400	28,700	7,900	16,700	22,000	100,000
Domègge di C	2017	775,000	50,400	0,000	0,233	0,031	0,000	3,241	0,233	0,000	0,000	0,000	0,000	1163,200	19,486	107,000	10,871	8,800	-7,300	25,800	4,100	15,900	20,000	100,000
Falcedè	2017	1148,000	52,800	1,644	0,856	0,463	0,552	1,553	2,500	0,000	0,000	0,000	0,000	1089,600	18,633	102,000	10,682	8,600	-9,500	24,100	1,900	12,900	22,000	100,000
Farra di Solig	2017	163,000	28,200	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1244,400	41,200	94,000	13,238	13,100	-3,800	30,600	8,200	18,500	20,000	100,000
Feltre	2017	325,000	100,000	0,054	0,520	0,071	0,488	1,546	0,574	0,034	0,060	0,083	1340,400	26,971	91,000	14,730	11,100	-9,500	30,800	5,300	18,400	21,000	99,000	
Gaiarine	2017	20,000	28,700	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1116,400	27,571	85,000	13,134	13,600	-5,800	32,500	7,700	19,800	25,000	100,000
Lamon	2017	594,000	54,360	0,000	0,046	0,002	0,009	3,007	0,046	0,000	0,000	0,000	0,000	1167,600	24,433	93,000	12,555	10,400	-4,600	27,200	6,100	15,900	23,000	100,000
Maser	2017	147,000	26,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1067,600	17,075	91,000	11,732	13,400	-4,000	31,100	8,400	18,800	24,000	100,000
Mogliano Ver	2017	8,000	46,150	0,000	0,000	0,000	0,000	0,000	0,734	1,526	7,129	841,400	17,400	74,000	11,370	13,700	-3,600	31,700	8,700	19,100	25,000	100,000		
Oderzo	2017	14,000	42,000	0,000	0,000	0,000	0,000	0,000	0,646	6,223	8,203	1003,600	17,000	82,000	12,239	13,400	-4,000	31,700	8,400	19,300	27,000	100,000		
Perarolo di Cè	2017	532,000	43,600	0,097	0,325	0,203	0,000	1,746	0,422	0,000	0,000	0,000	0,000	1260,400	25,743	103,000	10,237	9,200	-7,400	27,400	4,600	15,700	18,000	97,000
Ponte di Piav	2017	12,000	32,800	0,000	0,000	0,000	0,000	0,000	0,000	0,000	12,541	19,693	21,938	947,200	15,543	87,000	10,887	13,000	-5,500	31,700	7,300	19,100	25,000	100,000
Roncade	2017	8,000	61,780	0,000	0,000	0,000	0,000	0,000	0,000	0,000	4,723	11,019	20,696	956,200	21,200	82,000	11,661	13,200	-5,400	32,100	7,500	19,200	25,000	100,000
San Martino d	2017	647,000	44,900	1,299	1,714	0,335	0,016	5,180	3,013	0,000	0,000	0,000	0,000	1504,800	22,000	101,000	14,899	10,200	-3,400	25,800	6,700	14,700	20,000	100,000

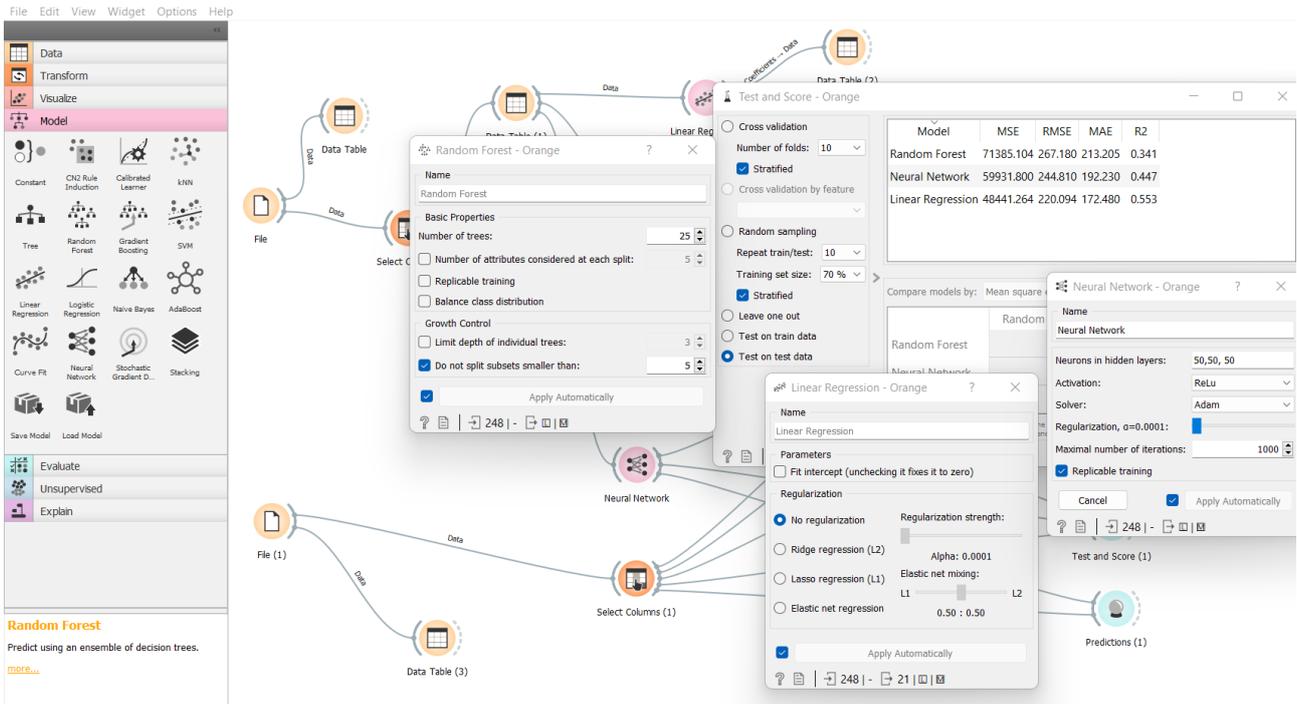
Perarolo di C	2020	532,000	43,600	0,097	0,325	0,203	0,000	1,746	0,422	0,000	0,000	0,000	1466,400	37,200	102,000	14,376	9,700	-3,200	25,800	5,600	15,300	28,000	98,000
Ponte di Piav	2020	12,000	32,800	0,000	0,000	0,000	0,000	0,000	0,000	12,541	19,693	21,938	984,600	18,917	93,000	10,587	13,500	-2,500	30,400	7,700	19,700	26,000	100,000
Roncade	2020	8,000	61,780	0,000	0,000	0,000	0,000	0,000	0,000	4,723	11,019	20,696	891,200	16,655	86,000	10,363	13,700	-2,100	30,300	8,000	19,800	29,000	100,000
San Martino d	2020	647,000	44,900	1,299	1,714	0,335	0,016	5,180	3,013	0,000	0,000	0,000	1871,800	29,943	114,000	16,419	10,500	0,100	24,800	7,000	15,100	26,000	100,000
Santo Stefan	2020	908,000	100,200	0,007	0,043	0,275	0,000	13,117	0,050	0,000	0,000	0,000	1565,200	36,077	107,000	14,628	7,400	-7,400	25,700	2,600	14,300	27,000	100,000
Sospirolo	2020	447,000	66,000	0,001	0,000	0,000	0,000	2,497	0,001	0,000	0,000	0,000	1824,400	31,217	110,000	16,585	11,500	-1,300	27,100	7,400	16,900	29,000	100,000
Triviso	2020	15,000	55,500	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	897,400	19,327	87,000	10,315	14,100	-0,900	31,500	8,900	20,400	25,000	99,000
Valdobbiader	2020	247,000	60,700	0,000	0,004	0,000	0,000	0,024	0,004	0,000	0,000	0,000	1653,400	22,717	95,000	17,404	13,800	2,000	28,900	9,800	18,400	27,000	100,000
Valle di Cado	2020	851,000	40,640	0,631	0,985	0,001	0,684	1,098	1,615	0,000	0,000	0,000	1514,000	33,964	105,000	14,419	9,200	-2,800	24,900	4,700	15,200	27,000	100,000
Vazzola	2020	30,000	26,160	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1167,000	19,200	88,000	13,261	13,700	-1,300	30,500	8,200	19,600	26,000	100,000
Villorba	2020	26,000	30,600	0,000	0,000	0,000	0,000	0,000	0,051	0,060	0,065	1052,000	19,733	90,000	11,689	13,800	-1,900	31,200	8,400	20,200	27,000	100,000	
Vittorio Vene	2020	138,000	82,000	0,716	0,853	0,025	2,923	1,475	1,569	0,000	0,000	0,000	1501,400	28,491	97,000	15,478	14,100	0,900	29,900	9,500	19,300	26,000	100,000
Volpago del A	2020	91,000	44,700	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1252,600	21,754	90,000	13,918	14,100	1,100	29,900	9,500	19,300	28,000	100,000
Zero Branco	2020	7,000	26,100	0,000	0,000	0,000	0,000	0,000	0,195	0,252	0,562	807,600	14,150	85,000	9,501	13,900	-1,000	30,800	9,000	20,100	28,000	99,000	
Agorde	2021	611,000	23,740	0,908	0,607	0,561	0,794	0,923	1,515	0,000	0,000	0,000	1201,200	23,867	103,000	11,662	9,000	-7,000	26,100	3,900	15,400	24,000	100,000
Auronzo di C	2021	826,000	220,500	1,075	1,486	0,495	3,670	10,717	2,561	0,000	0,000	0,000	1232,400	20,933	106,000	11,626	6,700	-9,200	25,300	1,600	13,600	29,000	100,000
Bassano del G	2021	129,000	46,000	0,190	0,053	0,002	0,010	0,258	0,243	0,076	0,115	0,416	1131,200	18,771	81,000	13,965	14,100	1,300	29,500	10,600	16,700	25,000	100,000
Belluno	2021	390,000	147,200	0,067	0,379	0,027	0,311	2,230	0,446	0,063	0,069	0,077	1278,000	18,771	99,000	12,909	10,500	-4,700	27,600	5,200	16,800	28,000	100,000
Castelfranco	2021	42,000	50,930	0,000	0,000	0,000	0,000	0,000	0,067	0,240	0,658	1073,000	18,757	79,000	13,582	13,300	-1,900	30,800	7,800	19,400	23,000	100,000	
Conegliano	2021	74,000	36,000	0,000	0,035	0,017	0,000	0,000	0,035	0,001	0,000	0,000	1179,000	17,533	89,000	13,247	14,400	0,900	30,200	10,200	18,800	25,000	100,000
Cortina D'Am	2021	1224,000	254,500	6,369	5,813	6,784	3,933	11,250	12,182	0,000	0,000	0,000	1085,000	20,978	94,000	11,543	6,400	-8,000	22,100	1,900	12,200	19,000	100,000
Crespano del	2021	300,000	17,000	0,000	0,000	0,000	0,003	0,000	0,000	0,000	0,000	0,000	1624,400	31,667	89,000	18,252	11,700	-0,900	27,200	7,800	16,500	26,000	100,000
Domègge di C	2021	775,000	50,400	0,000	0,233	0,031	0,000	3,241	0,233	0,000	0,000	0,000	1112,200	19,771	102,000	10,904	8,400	-6,300	25,000	3,800	14,500	28,000	100,000
Falceda	2021	1148,000	52,800	1,644	0,856	0,463	0,552	1,553	2,500	0,000	0,000	0,000	1133,000	19,089	109,000	10,420	6,800	-9,100	23,700	1,600	13,900	26,000	100,000
Farra di Solig	2021	163,000	28,200	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1384,000	20,311	93,000	14,882	13,000	-0,700	29,300	8,200	17,200	25,000	100,000
Feltre	2021	325,000	100,000	0,054	0,520	0,071	0,488	1,546	0,574	0,034	0,060	0,083	1496,400	26,433	94,000	15,919	10,900	-5,600	28,500	5,600	17,400	30,000	100,000
Gaiarine	2021	20,000	28,700	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1267,000	22,833	84,000	15,083	13,400	-2,000	31,100	7,500	19,500	26,000	100,000
Lamon	2021	594,000	54,360	0,000	0,046	0,002	0,009	3,007	0,046	0,000	0,000	0,000	1278,400	28,067	93,000	13,746	9,800	-4,100	25,700	5,600	15,100	26,000	99,000
Maser	2021	147,000	26,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1165,200	23,057	79,000	14,749	13,400	-0,900	30,000	8,300	19,200	25,000	100,000
Mogliano Ver	2021	8,000	46,150	0,000	0,000	0,000	0,000	0,000	0,734	1,526	7,129	774,600	16,314	83,000	9,333	13,700	-0,800	30,200	8,700	19,000	26,000	100,000	
Oderzo	2021	14,000	42,000	0,000	0,000	0,000	0,000	0,000	0,646	6,223	8,203	1004,000	19,200	82,000	12,244	13,200	-1,100	31,700	8,200	18,900	30,000	100,000	
Perarolo di C	2021	532,000	43,600	0,097	0,325	0,203	0,000	1,746	0,422	0,000	0,000	0,000	1097,200	18,800	104,000	10,550	9,000	-5,700	26,200	4,800	14,700	29,000	98,000
Ponte di Piav	2021	12,000	32,800	0,000	0,000	0,000	0,000	0,000	0,000	12,541	19,693	21,938	808,600	20,280	77,000	10,501	13,100	-2,000	30,300	7,200	19,100	26,000	100,000
Roncade	2021	8,000	61,780	0,000	0,000	0,000	0,000	0,000	0,000	4,723	11,019	20,696	796,800	21,880	73,000	10,915	13,200	-1,700	30,200	7,500	19,300	29,000	100,000
San Martino d	2021	647,000	44,900	1,299	1,714	0,335	0,016	5,180	3,013	0,000	0,000	0,000	1443,800	20,575	112,000	12,891	9,800	-3,200	24,900	6,300	14,500	28,000	100,000
Santo Stefan	2021	908,000	100,200	0,007	0,043	0,275	0,000	13,117	0,050	0,000	0,000	0,000	1250,800	19,244	110,000	11,371	6,200	-10,600	25,300	1,300	13,300	31,000	100,000
Sospirolo	2021	447,000	66,000	0,001	0,000	0,000	0,000	2,497	0,001	0,000	0,000	0,000	1418,400	29,800	98,000	14,473	10,600	-3,700	26,600	6,600	15,800	28,000	100,000
Triviso	2021	15,000	55,500	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	890,800	22,040	82,000	10,863	13,600	-1,000	31,200	8,500	19,600	24,000	99,000
Valdobbiader	2021	247,000	60,700	0,000	0,004	0,000	0,000	0,024	0,004	0,000	0,000	0,000	1423,400	20,083	91,000	15,642	13,200	0,000	29,000	9,300	17,800	26,000	100,000
Valle di Cado	2021	851,000	40,640	0,631	0,985	0,001	0,684	1,098	1,615	0,000	0,000	0,000	1199,600	21,200	105,000	11,425	8,300	-6,700	25,100	3,700	14,500	31,000	100,000
Vazzola	2021	30,000	26,160	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,001	937,200	16,900	84,000	11,157	13,100	-1,400	30,300	7,600	18,800	29,000	100,000	
Villorba	2021	26,000	30,600	0,000	0,000	0,000	0,000	0,000	0,051	0,060	0,065	953,000	21,267	84,000	11,345	13,200	-1,800	31,000	7,600	19,500	26,000	100,000	
Vittorio Vene	2021	138,000	82,000	0,716	0,853	0,025	2,923	1,475	1,569	0,000	0,000	0,000	1303,800	27,100	92,000	14,172	13,500	0,100	29,700	9,100	18,500	25,000	100,000
Volpago del A	2021	91,000	44,700	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1108,600	26,467	87,000	12,743	13,600	0,000	30,500	9,000	18,900	27,000	100,000
Zero Branco	2021	7,000	26,100	0,000	0,000	0,000	0,000	0,000	0,000	0,195	0,252	0,562	873,200	25,840	80,000	10,915	13,400	-0,900	30,500	8,500	19,400	27,000	99,000

(fig. 32 – training database (Piedmont + Veneto) of model 5)

Test database:

MUNICIPALIT	Year	Altitude m	Area km ²	Landslide hazard areas (km ²) Very high P4	Landslide hazard areas (km ²) high P3	Landslide hazard areas (km ²) medium P2	Landslide hazard areas (km ²) low P1	Landslide hazard areas (km ²) AA	Landslide hazard areas (km ²) P3+P4	Landslide hazard areas (km ²) high P3	Hydraulic hazard areas (km ²) medium P2	Hydraulic hazard areas (km ²) low P1	Total precipitation (mm)	Maximum daily precipitation (mm)	Number of rainy days (prec.>=1 mm)	Average precipitation	Average temperature	Minimum temperature °C	Maximum temperature °C	Average minimum temperature °C	Average maximum temperature °C	Average minimum humidity (E) - %	Average maximum humidity (E) - %
Agorde	2016	611,000	23,740	0,908	0,607	0,561	0,794	0,923	1,515	0,000	0,000	0,000	1193,800	11,850	119,000	10,032	9,500	-5,700	26,400	4,600	15,600	19,000	97,000
Auronzo di C	2016	826,000	220,500	1,075	1,486	0,495	3,670	1															

Vittorio Veni	2016	138,000	82,000	0,716	0,853	0,025	2,923	1,475	1,569	0,000	0,000	0,000	0,000	1498,000	19,243	115,000	13,026	13,800	0,300	30,000	9,600	18,600	23,000	98,000
Volpago del I	2016	91,000	44,700	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1341,800	17,700	100,000	13,418	13,800	0,000	31,000	9,400	19,000	27,000	100,000
Zero Branco	2016	7,000	26,100	0,000	0,000	0,000	0,000	0,000	0,000	0,195	0,252	0,562	1176,200	22,733	95,000	12,381	13,700	-1,000	31,900	9,000	19,500	28,000	100,000	
Alba	2016	172,000	54,000	0,010	0,027	0,000	0,000	0,000	0,038	0,674	10,108	13,306	923,000	111,400	60,000	15,383	13,040	-8,100	34,900	7,290	18,790	55,250	93,220	
Baldisserso D'	2016	380,000	15,000	0,223	0,000	0,000	0,000	0,000	0,223	0,046	0,215	0,215	903,410	107,210	66,960	13,492	13,820	-5,480	35,660	8,480	19,610	55,250	93,220	
Barbaresco	2016	274,000	7,000	0,313	0,136	0,000	0,000	0,000	0,449	0,319	1,853	1,916	882,200	104,400	62,000	13,858	14,680	-6,300	39,000	9,070	20,920	58,340	94,490	
Barolo	2016	213,000	5,690	0,732	1,039	0,000	0,000	0,000	1,771	0,575	0,575	0,575	982,200	104,200	68,000	12,974	14,020	-4,400	36,100	8,680	19,360	52,790	91,660	
Bossolasco	2016	757,000	14,000	0,776	3,842	0,003	0,000	0,000	4,617	0,659	0,659	0,659	868,200	142,600	69,000	14,032	13,820	-5,480	35,660	8,480	19,160	55,250	93,220	
Bra	2016	285,000	59,000	0,000	0,000	0,000	0,000	0,000	0,000	0,367	3,279	18,251	821,400	102,600	61,000	13,466	13,310	-7,400	35,700	7,360	19,250	55,320	97,930	
Caraglio	2016	638,000	41,000	0,049	0,103	0,000	0,000	0,000	0,152	0,528	1,036	1,547	1053,000	125,000	85,000	12,388	13,820	-5,480	35,660	8,480	19,160	49,690	96,900	
Castino	2016	525,000	15,500	0,454	1,377	0,000	0,000	0,000	1,831	0,301	0,472	0,490	690,400	112,800	64,000	10,788	12,970	-5,400	33,600	8,360	17,580	55,890	95,960	
Dogliani	2016	300,000	35,680	3,005	1,244	0,000	0,000	0,000	4,249	0,922	0,097	0,105	983,800	130,000	68,000	14,468	13,820	-5,400	33,900	8,760	18,290	52,210	84,680	
La Morra	2016	513,000	24,300	0,007	0,012	0,000	0,000	0,000	0,020	0,123	1,419	1,421	1094,600	101,600	64,000	17,103	13,360	-5,800	34,300	8,610	18,100	53,370	97,420	
Canale	2016	194,000	18,000	0,183	0,125	0,000	0,000	0,000	0,308	0,448	1,030	1,445	852,600	78,600	68,000	12,538	14,070	-5,100	36,400	8,500	19,650	54,600	93,230	
Castiglione F	2016	350,000	4,720	0,332	0,700	0,000	0,000	0,000	1,032	0,327	0,340	0,365	889,000	104,200	67,000	13,269	14,520	-5,000	36,900	9,040	19,990	51,200	88,500	
Clavesana	2016	300,000	17,150	0,011	0,006	0,000	0,000	0,000	0,017	3,333	5,656	5,779	1117,800	140,000	68,000	16,438	13,890	-3,900	35,800	9,110	18,670	52,500	83,950	
Castiglione S	2016	476,000	15,000	0,000	0,000	0,000	0,000	0,000	0,000	1,218	2,207	4,107	954,200	132,800	62,000	15,390	13,820	-5,480	35,660	8,480	19,160	47,940	92,140	
Cranzanna	2016	585,000	8,200	0,381	3,738	0,000	0,000	0,000	4,119	0,572	0,572	0,572	1072,000	110,400	77,000	11,774	13,820	-5,480	35,660	8,480	19,160	55,250	93,220	
Guarene	2016	360,000	13,400	0,852	2,796	0,000	0,000	0,000	3,648	0,122	0,631	1,787	841,600	88,400	62,000	13,574	13,210	-7,700	35,200	7,150	19,280	55,250	93,220	
Mango	2016	521,000	19,000	2,724	6,038	0,000	0,000	0,000	8,763	2,250	2,250	2,250	830,800	109,000	65,000	12,782	13,820	-5,480	35,660	8,480	19,160	55,250	93,220	
Mombarcaro	2016	896,000	20,000	0,058	0,532	0,000	0,000	0,000	0,591	0,653	0,830	0,904	903,410	107,210	66,960	13,492	13,820	-5,480	35,660	8,480	19,160	55,250	93,220	
Montforte D'	2016	480,000	25,000	0,058	0,532	0,000	0,000	0,000	0,591	0,653	0,830	0,904	1011,400	129,600	67,000	15,096	14,530	-3,100	35,200	10,010	19,050	54,890	91,180	
Montelupo a	2016	564,000	6,400	1,216	3,005	0,000	0,000	0,000	4,221	1,941	1,941	1,941	922,000	104,000	64,000	14,406	14,240	-3,100	35,500	9,020	19,450	50,890	90,610	
Neive	2016	308,000	21,200	1,724	2,476	0,000	0,000	0,000	4,200	0,925	2,585	3,090	715,800	89,400	61,000	11,734	14,300	-4,100	35,200	9,710	18,500	58,080	92,840	
Piobesi D'Alt	2016	194,000	3,000	0,236	0,506	0,000	0,000	0,000	0,742	0,203	0,288	0,288	933,600	118,800	64,000	14,588	13,060	-7,800	34,600	7,390	18,740	55,250	93,220	
Santo Stefan	2016	170,000	23,000	0,004	0,001	0,000	0,000	0,000	0,005	2,187	2,976	4,550	864,800	86,400	73,000	11,847	14,670	-2,700	36,100	9,850	19,480	59,200	94,660	
Serralunga D	2016	414,000	8,440	1,507	0,307	0,000	0,000	0,000	1,815	0,371	0,485	0,487	909,800	111,000	63,000	14,441	14,590	-4,500	36,700	9,040	20,140	56,860	92,540	
Serravalle La	2016	762,000	9,000	2,572	0,310	0,000	0,000	0,000	2,882	0,146	1,146	1,146	999,600	149,600	75,000	13,328	11,660	-4,100	30,600	7,270	16,050	65,150	95,350	
Canelli	2016	316,000	23,430	0,024	0,014	0,000	0,000	0,000	0,038	0,661	1,647	3,523	848,400	90,200	68,000	12,476	14,670	-5,900	36,900	9,490	19,860	59,070	94,000	
Castel Boglio	2016	260,000	12,000	0,004	0,000	0,000	0,000	0,000	0,004	0,133	0,133	0,142	835,800	66,000	74,000	11,295	13,820	-5,480	35,660	8,480	19,160	55,250	93,220	
Coazzolo	2016	291,000	4,120	0,040	0,000	0,000	0,000	0,000	0,040	0,039	0,112	0,112	1122,000	85,600	63,000	13,267	13,480	-9,800	38,400	6,090	20,860	59,520	99,750	
Castiglione D	2016	242,000	36,000	1,503	0,931	0,135	0,000	0,000	2,434	0,011	2,609	5,816	878,800	104,000	59,000	14,895	13,770	-5,500	35,700	8,330	19,220	58,440	96,070	
Nizza Monf	2016	137,000	30,400	0,001	0,000	0,000	0,000	0,000	0,001	0,111	2,090	4,547	871,200	74,400	74,000	11,773	14,520	-6,400	37,900	8,470	20,580	60,400	98,750	
San Damiano	2016	179,000	48,000	0,087	0,806	0,529	0,000	0,000	0,893	1,410	3,679	4,566	903,410	107,210	66,960	13,492	13,820	-5,480	35,660	8,480	19,160	55,250	93,220	
Argordo	2016	611,000	23,740	0,908	0,607	0,561	0,794	0,923	1,515	0,000	0,000	0,000	1912,200	35,358	125,000	15,298	10,400	-4,700	27,700	5,400	16,800	24,000	100,000	
Auronzo di C	2019	826,000	220,500	1,075	1,486	0,495	3,670	10,717	2,561	0,000	0,000	0,000	1638,000	25,200	131,000	12,504	8,000	-7,400	27,200	3,000	14,700	26,000	100,000	
Bassano del C	2019	129,000	46,000	0,190	0,053	0,022	0,010	0,258	0,243	0,076	0,115	0,416	1455,000	24,900	96,000	15,156	14,700	0,000	30,600	11,200	19,200	27,000	100,000	
Belluno	2019	390,000	147,200	0,067	0,379	0,027	0,311	2,230	0,446	0,063	0,069	0,077	2053,000	32,350	114,000	18,009	11,600	-5,500	29,500	6,400	17,800	21,000	100,000	
Castelfranco	2019	42,000	50,930	0,000	0,000	0,000	0,000	0,000	0,000	0,067	0,240	0,658	1468,600	21,500	106,000	13,855	14,000	-2,900	31,000	8,900	19,600	30,000	100,000	
Conegliano	2019	74,000	36,000	0,000	0,035	0,017	0,000	0,000	0,035	0,001	0,000	0,000	1466,000	28,450	99,000	14,808	15,100	-2,500	30,400	11,100	19,200	24,000	100,000	
Cortina D'Am	2019	1224,000	254,500	6,369	5,813	6,784	3,933	11,250	12,182	0,000	0,000	0,000	1469,400	27,100	121,000	12,144	7,400	-5,900	23,700	3,200	12,900	16,000	100,000	
Crespano del	2019	300,000	17,000	0,000	0,000	0,000	0,000	0,003	0,000	0,000	0,000	0,000	2045,000	32,400	113,000	18,097	12,500	-1,700	28,000	8,700	17,200	27,000	100,000	
Domegge di r	2019	775,000	50,400	0,000	0,233	0,031	0,000	3,241	2,233	0,000	0,000	0,000	1484,400	25,880	126,000	11,781	9,300	-4,700	26,500	5,100	15,200	26,000	100,000	
Falceda	2019	1148,000	52,800	1,644	0,856	0,463	0,552	1,553	2,500	0,000	0,000	0,000	1671,800	26,250	138,000	12,114	7,300	-7,200	25,400	2,700	13,300	23,000	99,000	
Farra di Solig	2019	163,000	28,200	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1873,400	36,150	108,000	17,346	13,900	-1,600	30,000	9,300	18,900	26,000	100,000	
Feltre	2019	325,000	100,000	0,054	0,520	0,071	0,488	1,546	0,574	0,034	0,060	0,083	2235,600	33,048	112,000	19,961	11,800	-5,500	30,300	6,800	18,400	29,000	100,000	
Gaiarine	2019	20,000	28,700	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1593,200	26,850	97,000	16,425	14,200	-3,100	31,800	8,800	20,600	25,000	100,000	
Lamon	2019	594,000	54,360	0,000	0,046	0,002	0,009	3,007	0,046	0,000	0,000	0,000	1869,400	29,300	123,000	15,198	10,700	-2,800	26,900	6,700	15,700	21,000	100,000	
Maser	2019</																							



(fig. 34 – widget on Orange of model 5)

New MAPE

Linear Regression: 14,5%

Neural Network: 16,2%

Random Forest: 14,6%

As with model 3, model 5 also improved after adding data to the database, again the MAPE of the linear regressor worsened from before while the other two estimators improved.

With a larger database, Model 5 turns out to be better than Model 3 in fact the output Total Precipitation turns out to be the most easily estimated output.

Although the linear regressor still seems to be the best method, the values obtained from the 3 methods (linear regressor, neural network and from the random forest) are very similar to each other, leading us to believe that the model works quite well for the small amount of data it handles.

5.2 COMPARISON OF ACCURACY INTERVAL

The main shortcoming of point estimators is that they generally provide the true value of the output with (virtually) zero probability.

If we want to get a true assessment of the prediction procedure, it would be better to replace the accuracy of the point prediction with an accuracy per interval in order to understand whether the model can predict a value at least close to the true value.

Accuracy is defined in terms of the ability of the interval to contain or not contain the true value of the output.

A range of +/- 2 mm was created for model 3, which has average precipitation as its output; while for model 5, which has total precipitation as output, a range of +/- 250 mm was used.

250mm	Total precipitation	250mm	Linear Regression	Random Forest	Neural Network	2mm	Average precipiti	2mm	Linear Regression	Random Forest	Neural Network
943.80	1193.80	1443.80	1428.3050	1285.5108	1224.5983	11.6496	13.6496	15.6496	17.1212	15.2519	16.269
1027.60	1277.60	1527.60	1680.4645	1154.8906	1592.6148	9.536	11.536	13.536	13.2209	12.5245	12.5593
1149.40	1399.40	1649.40	1440.8561	1293.6715	1331.9535	9.5831	11.5831	13.5831	14.4966	13.0741	12.5444
1173.00	1423.00	1673.00	1645.2351	1336.2073	1669.6115	9.536	11.536	13.536	12.3036	12.2606	12.2236
864.60	1114.60	1364.60	1264.2356	1121.2244	1251.6355	8.9293	10.9293	12.9293	12.0621	11.9909	11.9588
1083.00	1333.00	1583.00	1371.9723	1216.8665	1355.4761	7.392	9.392	11.392	12.1222	12.2014	13.127
815.60	1065.60	1315.60	1364.2649	1278.2433	1288.4036	9.9524	11.9524	13.9524	14.4918	13.762	14.2397
1334.80	1584.80	1834.80	1543.6710	1467.0191	1549.6611	12.5178	14.5178	16.5178	15.4953	16.5161	14.6255
999.20	1249.20	1499.20	1513.6179	1294.4704	1492.6895	9.3532	11.3532	13.3532	12.5704	12.2333	11.6555
855.60	1105.60	1355.60	1706.4734	1209.8878	1638.9433	8.8907	10.8907	12.8907	11.954	12.4037	11.693
1242.40	1492.40	1742.40	1425.2386	1469.2043	1400.0665	8.7464	10.7464	12.7464	12.2132	11.9398	11.7338
1040.80	1290.80	1540.80	1452.0804	1354.8255	1353.7125	10.2735	12.2735	14.2735	11.7488	12.3616	11.0399
1038.40	1288.40	1538.40	1282.6474	1177.7058	1248.2867	10.6783	12.6783	14.6783	13.2435	12.768	12.7769
906.20	1156.20	1406.20	1619.2173	1442.0449	1541.3927	10.5	12.5	14.5	12.0596	12.9243	12.5794
1041.40	1291.40	1541.40	1352.0958	1290.5432	1303.0759	9.8832	11.8832	13.8832	13.6515	13.28	12.8639
894.60	1144.60	1394.60	1265.0303	976.9197	1246.8151	6.5219	8.5219	10.5219	11.1275	12.1585	12.3187
982.60	1232.60	1482.60	1242.9219	1044.8892	1241.2994	9.1321	11.1321	13.1321	11.6775	12.1475	11.7892
855.60	1105.60	1355.60	1444.9956	1385.2911	1413.4663	10.6321	12.6321	14.6321	12.4493	12.7473	11.9188
1057.20	1307.20	1557.20	1190.4198	1048.3169	1284.8873	9.8184	11.8184	13.8184	12.169	13.1904	12.2865
961.60	1211.60	1461.60	1166.9921	1009.3108	1194.1924	8.6885	10.6885	12.6885	15.0523	14.1968	15.2661
1689.40	1839.40	2089.40	1806.7617	1483.4929	1800.6797	9.0496	11.0496	13.0496	14.1847	13.0719	12.2719
987.60	1237.60	1487.60	1528.8336	1158.9971	1470.5626	8.8041	10.8041	12.8041	12.8041	12.6741	10.9764
1460.80	1710.80	1960.80	1703.5597	1471.5290	1625.1669	10.1	12.1	14.1	12.7989	12.6008	11.477
911.00	1161.00	1411.00	1321.3271	1097.4487	1303.8051	9.5832	11.5832	13.5832	11.7151	12.027	12.2604
1293.40	1543.40	1793.40	1510.6701	1459.9297	1479.6066	11.4704	13.4704	15.4704	13.2148	12.6971	14.2266
970.20	1220.20	1470.20	1569.5644	1382.1889	1503.8898	10.3448	12.3448	14.3448	12.8178	12.8365	13.0816
1032.80	1282.80	1532.80	1282.1898	1146.6017	1299.8144	10.8	12.8	14.8	14.7733	13.8695	13.2067
905.20	1155.20	1405.20	1262.2652	1110.3082	1221.7557	9.1084	11.1084	13.1084	13.6477	12.8548	11.5962
1248.00	1498.00	1748.00	1553.8333	1443.5385	1425.1468	12.222	14.222	16.222	15.0415	15.4815	15.6397
1091.80	1341.80	1591.80	1331.1150	1196.2007	1287.8112	13.6625	15.6625	17.6625	16.7585	15.6887	17.3116
926.20	1176.20	1426.20	1215.1494	1011.6771	1186.7204	9.088	11.088	13.088	13.2769	12.4717	13.443
1662.20	1912.20	2162.20	1801.0122	1619.0415	1412.1623	9.5347	11.5347	13.5347	11.9736	11.9283	12.1845
1388.00	1638.00	1888.00	1727.9935	1300.5215	1416.5404	8.317	10.317	12.317	14.4719	13.1014	14.0954
1205.00	1455.00	1705.00	1277.9397	1226.7666	1203.6134	10.6912	12.6912	14.6912	16.4868	16.1768	14.704
1803.00	2053.00	2303.00	1861.1874	1526.0035	1524.6242	11.0217	13.0217	15.0217	11.7904	12.0109	11.4992
1218.60	1468.60	1718.60	1334.6778	1222.6630	1222.2147	10.4377	12.4377	14.4377	14.0916	14.0536	14.3733
1216.00	1466.00	1716.00	1327.4772	1201.5754	1352.9636	8.6419	10.6419	12.6419	12.8437	12.5434	12.1441
1219.40	1469.40	1719.40	1388.1582	1394.0618	1314.3210	9.8515	11.8515	13.8515	13.4605	13.2038	12.3843
1795.00	2045.00	2295.00	1497.3220	1577.7162	1543.8678	10.6835	12.6835	14.6835	12.7514	12.6657	12.8707
1234.40	1484.40	1734.40	1611.8882	1373.4193	1479.6179	9.44	11.44	13.44	12.4095	12.4936	11.8871
1421.80	1671.80	1921.80	1710.4368	1383.2890	1452.9227	9.3978	11.3978	13.3978	11.8654	12.0068	11.9126
1623.40	1873.40	2123.40	1407.9206	1486.2906	1419.0989	10.0213	12.0213	14.0213	11.0011	12.7272	11.7866
1985.60	2235.60	2485.60	1845.0415	1595.8657	1308.6214	8.406	10.406	12.406	13.0409	12.9735	13.8236
1343.20	1593.20	1843.20	1478.3309	614.4679	1041.9492	11.0452	13.0452	15.0452	15.6228	15.1263	14.7667
1619.40	1869.40	2119.40	1627.5000	1553.9835	1579.9520	9.9043	11.9043	13.9043	12.7608	11.781	12.1816
1065.00	1315.00	1565.00	1270.0484	1222.8501	1174.5716	8.9733	10.9733	12.9733	12.0642	12.3252	12.9962
1047.60	1297.60	1547.60	1061.4451	919.1513	963.9780	8.2362	10.2362	12.2362	12.9665	12.7757	13.4831
1148.00	1398.00	1648.00	1155.3640	1037.9955	1017.7949	8.2178	10.2178	12.2178	11.6787	12.1639	10.4052
1329.00	1579.00	1829.00	1521.8753	1390.6899	1300.7480	13.3063	15.3063	17.3063	15.9689	16.4184	16.6455
1104.00	1354.00	1604.00	993.0243	999.2338	1004.8888	11.1957	13.1957	15.1957	13.4042	12.4635	13.0911
1185.40	1435.40	1685.40	1034.0407	980.2139	941.6193	9.2228	11.2228	13.2228	13.9478	13.0367	11.4881
1930.00	2180.00	2430.00	1594.6417	1676.2154	1636.3041	8.4079	10.4079	12.4079	12.1632	12.3399	12.6081
1303.00	1553.00	1803.00	1523.3629	1225.7834	1357.4634	10.8524	12.8524	14.8524	12.2648	12.7252	12.0046
1921.80	2171.80	2421.80	1656.6560	1603.1223	1627.4297	12.07	14.07	16.07	16.5161	16.8153	16.7046
1104.40	1354.40	1604.40	1185.6226	1035.2632	1046.0593	8.8021	10.8021	12.8021	13.6262	12.5587	12.3136
1545.00	1795.00	2045.00	1528.6629	1467.2121	1525.0199	11.3087	13.3087	15.3087	14.8823	15.7574	14.5647
1476.60	1726.60	1976.60	1661.1802	1504.5481	1532.0404	11.3697	13.3697	15.3697	14.5994	14.2304	13.2077
1164.80	1414.80	1664.80	1145.3161	1137.3988	1077.0042	9.1242	11.1242	13.1242	13.8176	13.3252	13.5867
844.40	1094.40	1344.40	1115.4095	1079.0875	987.5637	8.9673	10.9673	12.9673	13.3188	12.7937	13.34
1389.80	1639.80	1889.80	1408.0282	1399.4222	1455.1973	10.5964	12.5964	14.5964	14.78	14.4203	15.2916
1210.80	1460.80	1710.80	1341.3845	1254.8036	1327.0977	11.0128	13.0128	15.0128	13.9953	13.8913	12.8879
915.60	1165.60	1415.60	1091.0209	938.6328	899.0979	7.71461	9.71461	11.71461	13.0776	12.4142	11.7691
734.80	984.80	1234.80	804.4648	778.7189	880.5833	15.2019	17.2019	19.2019	13.1832	14.254	13.6129
785.00	1035.00	1285.00	874.0575	1087.9544	875.5048	8.0513	10.0513	12.0513	12.4434	10.6336	11.3239
733.20	983.20	1233.20	863.8638	987.1815	802.8233	14.9904	16.9904	18.9904	12.5444	13.0066	11.2934
772.20	1022.20	1272.20	787.2521	688.5251	776.4685	7.44789	9.44789	11.44789	10.4359	10.3249	10.51
780.40	1030.40	1280.40	1015.9666	1045.6641	793.8916	7.72059	9.72059	11.72059	12.2057	10.9359	10.9662
790.34	1040.34	1290.34	780.6602	992.3083	899.3726	8.1871	10.1871	12.1871	10.4159	9.97692	8.70272
824.40	1074.40	1324.40	954.0679	1016.8634	840.6583	13.7075	15.7075	17.7075	13.7594	13.6132	13.6386
690.80	940.80	1190.80	806.9595	1011.2088	747.9151	13.3926	15.3926	17.3926	13.6521	14.9785	15.568
835.20	1085.20	1335.20	908.9190	1028.0061	802.5316	8.8267	10.8267	12.8267	10.7752	9.65699	9.24911

804.60	1054.60	1304.60	904.0053	1061.1652	729.8166	8.0513	10.0513	12.0513	11.2647	10.3761	10.5375	
760.60	1010.60	1260.60	912.6638	1005.8816	784.1521	7.28056	9.28056	11.28056	12.0838	11.1526	10.6752	
629.00	879.00	1129.00	750.8930	961.7380	722.3432	9.0857	11.0857	13.0857	14.2854	11.722	13.4126	
816.60	1066.60	1316.60	924.0437	1083.0687	858.8005	9.5293	11.5293	13.5293	11.0435	12.3183	9.55891	
818.00	1068.00	1318.00	869.9755	997.3882	766.8159	7.85	9.85	11.85	11.1454	10.3216	9.09351	
678.80	928.80	1178.80	730.3708	716.0069	599.3049	10.4697	12.4697	14.4697	12.8905	12.4217	12.7177	
594.60	844.60	1094.60	682.0828	690.9348	624.5228	7.73913	9.73913	11.73913	11.2896	10.2704	9.39257	
915.00	1165.00	1415.00	1039.8172	1024.0540	1036.1597	6.408	8.408	10.408	10.9067	12.1388	8.6989	
862.40	1112.40	1362.40	866.8045	1004.4308	1000.9080	7.82571	9.82571	11.82571	11.2019	9.797	10.0965	
790.34	1040.34	1290.34	882.3525	994.3559	900.0088	8.503	10.503	12.503	11.4261	10.5685	10.0708	
787.80	1037.80	1287.80	830.3276	967.4464	791.6933	12.2157	14.2157	16.2157	13.6851	13.299	13.8349	
709.00	959.00	1209.00	970.7856	1011.3023	962.9916	10.6661	12.6661	14.6661	11.5792	12.7219	11.7141	
816.80	1066.80	1316.80	1001.1015	1032.7559	913.5561	8.2257	10.2257	12.2257	10.5439	10.0111	11.2025	
854.80	1104.80	1354.80	952.8996	759.5415	1045.4178	9.7262	11.7262	13.7262	11.8684	12.3749	10.1863	
797.20	1047.20	1297.20	827.9148	969.8748	752.9995	6.9359	8.9359	10.9359	12.1265	12.3572	11.3392	
815.00	1065.00	1315.00	785.8563	1020.1414	888.7502	16.4968	18.4968	20.4968	13.2767	15.0528	14.9527	
1002.80	1252.80	1502.80	858.9174	862.1514	896.7470	8.1553	10.1553	12.1553	12.2717	12.8475	11.0037	
847.40	1097.40	1347.40	938.8345	1066.6061	827.2312	12.1584	14.1584	16.1584	12.4382	14.2073	11.8766	
939.80	1189.80	1439.80	880.9056	1074.8767	1031.0344	12.3175	14.3175	16.3175	11.1045	12.5836	9.97615	
820.00	1070.00	1320.00	873.4963	986.1553	736.1226	13.5861	15.5861	17.5861	13.3436	14.5112	14.4872	
734.80	984.80	1234.80	695.4353	753.1996	823.3564	18.7495	20.7495	22.7495	14.0548	16.2205	14.7838	
759.00	1009.00	1259.00	779.1010	751.7183	732.4569	10.9157	12.9157	14.9157	13.1001	12.7985	15.1805	
673.00	923.00	1173.00	807.3314	513.6637	947.7033	6.17255	8.17255	10.17255	10.9524	9.62349	9.19026	
653.41	903.41	1153.41	865.1027	666.6340	872.2685	8.0197	10.0197	12.0197	11.2193	10.5422	10.007	
609.20	859.20	1109.20	704.1968	562.5006	798.6734	13.1585	15.1585	17.1585	13.0226	15.2301	13.5565	
632.20	882.20	1132.20	854.3499	666.9139	730.8247	7.84848	9.84848	11.84848	12.7016	11.1378	11.3662	
718.20	968.20	1218.20	929.5283	695.0973	1074.0811	12.1146	14.1146	16.1146	13.2597	14.4912	14.064	
571.40	821.40	1071.40	681.5467	513.5571	942.3241	7.4825	9.4825	11.4825	12.5788	12.4368	13.5917	
803.00	1053.00	1303.00	1163.5578	1046.0824	1204.2964	8.3121	10.3121	12.3121	10.4318	10.3334	11.3142	
				75	68	64				61	78	74
				25	32	36				39	22	28

(fig. 35 - Accuracy comparison of precipitation intervals between model 5 and 3)

In green there are the predicted values that fall within the range and in red there are the predicted values that fall outside the range.

Model 3 is confirmed to be the best model for estimating precipitation.

From the analysis of accuracy per interval it is evident that the linear regressor is the worst estimator this is a symptom of the goodness of the model since with a larger database the simplest estimator becomes the worst.

The random forest turns out to be slightly better than the neural network getting to estimate the with an accuracy of 78% on 100 data.

The accuracy is expected that by increasing the database further the regressor will estimate with increasing accuracy.

CONCLUSION

This research aimed to identify a correlation between variables such as temperature and humidity and the amount of rain that fell in a given area in a year, with the goal of predicting future rainfall.

Based on a preliminary statistical analysis of data from the wine growing area of Langhe Piedmont and Conigliano Valdobbiadene Veneto, it can be concluded that it is possible to predict with an accuracy of about 80% a prediction range(mm) in which to find the total precipitation value.

The results indicate that by increasing the data the accuracy of the estimators improves. One of the main issues to be faced when trying to expand the database is the fact that in the databases of the different regions the data for the input variables, needed to create the model, are aggregated differently. For the construction of the final database, the input data were chosen after a careful SHAP analysis and once the hierarchical importance of the data was decided, they were scouted in the regional databases and uniformed.

Another important limitation of this study is the fact that the sensors collecting information regarding precipitation, temperature, humidity... are different from each other and could have different sensitivities and calibrations.

To solve this problem, the data were subjected to a regularity analysis and a correlation analysis between the indicators.

Despite limitations due to having to work with data provided by third parties the study yielded encouraging results, so it is planned to expand the thesis work by adding a second part.

Future steps include:

- The creation of a new database containing the main financial performance indicators (revenues, EBITDA...) of wineries in the municipalities analyzed in this thesis.
- Comparing financial performance with the hydrogeological conditions of the area in a given period and seeing if there is a correlation.

The ultimate goal is to raise awareness among small and medium-sized enterprises about the importance of forecasting and preventing natural disaster risks that could lead to business interruption, in fact in addition to direct damage, disasters also produce indirect damage due to interrupted activity and lost development.

Paradoxically, despite the fact that Italy is one of the countries most prone to hydrogeological disruption (landslides and floods) in Europe, it is also one of the countries with a worrying situation of under-insurance of its enterprises. In fact, Italy stands out for ex-post natural disaster damage management, relying almost exclusively on state intervention during reconstruction.

But due to climate change weather phenomena leading to natural disasters will be increasingly frequent and violent, and it is necessary to create more awareness and insurance education in the citizenry.

Arisk but more broadly, risk management aims to predict what risks a small to medium-sized business might face and creates resilience plans to avoid business failure by determining whether it is convenient to mitigate or transfer risk. Risk management creates value for one's business.

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