CLIMATE PROTECTION GAP: METHODOLOGICAL TOOLBOX FOR THE AGRIBUSINESS

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1. Introduction

Climate change represents a relatively new risk compared with other traditional insurance and financial risks. Nevertheless, it gained priority in the agendas of governments, public institutions, and private stakeholders. Climate change mainly involves two kinds of risks: the physical and the transitional risks. The former determines effects directly from climate change due to the physical impact of increasing severity and frequency of extreme climate change-related weather events, and the latter effects arising from the change to a carbon-neutral economy, to meet the objectives of the Paris Climate Agreement.

The main features of climate-related risks rely on the long-term nature of the related events, being the impact likely structural, irreversible, and non-linear (European Insurance and Occupational Pensions Authority [EIOPA], 2022). They affect the insurability of risks, impacting on affordability and availability of financial and insurance products, also determining the protection gap. Typically protection gaps are areas in which societal risks are not covered by the insurance industry, either because of lack of penetration, or because the risks are uninsurable in profit-oriented markets.

In this chapter, we support the early identification of protection gaps and the development of shared resilience solutions between the insurance industry and public protection facilities, by setting out methodological toolboxes in the agribusiness context. Agriculture both contributes to climate change and is affected by climate change. Crops need suitable soil, water, sunlight, and heat to grow. Warmer air temperatures have already affected the length of the growing season over large parts of Europe. Flowering and harvest dates for cereal crops are now happening several days earlier in the season. These changes are expected to continue in many regions. In general, agriculture and forestry are highly exposed to the impact of rising global temperatures: increased fluctuations in seasonality disrupt farming cycles, while substantial challenges arise from changing rainfall patterns and extreme weather events, such as heat waves, droughts, storms, and floods. In other terms, agriculture has a key passive and active role in climate change and resilience against adverse climate events can start from this important sector. The insurance industry can pilot climate resilience solutions, by providing parametric insurance bundled with loan contracts can reduce also credit rationing in this sector (Biffis et al., 2022). The chapter aims to set out a methodological tool-box for supporting the insurance industry in developing contractual solutions for adverse climate events, in the agribusiness field. The toolbox is based on the copula approach for describing the dependence between yields in agribusiness and bioclimatic indicator trends. Section 2 explains data and results starting from a practical case based on Italian data. Section 3 presents the conclusion.

2. Methodological toolbox in agribusiness

We set out methodological principles to develop solutions for smallholder farmers against weather shocks. In particular, we evaluate the effectiveness of the bioclimatic indicators in terms of their

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relationship with wheat yields. The data refer to two groups of time series, one for Northern Italy and the other for Central Italy. Bioclimatic indicators have been built from satellite data from the NASA-MERRA-2 (Bosilovich et al., 2016) database and measure the drought as a combination of exceeded heat and precipitation deficit. Yields are obtained from the wheat price listed on the Bologna Commodity Exchange[1]. Bioclimatic indicators have been developed based on two different methodologies: the first starts from the analysis of the historical series through the Seasonal ARIMA (SARIMA) model class, and the other one with the use of temporal dynamic random forest (Carannante et al., in press). The relationship between yields and bioclimatic indicators is analyzed through an Archimedean copula.

Table 1 and Table 2 show the dependency structure of data, using Pearson linear correlation coefficient and Kendall rank correlation coefficient.

Table 1. Pearson linear correlation coefficient among bioclimatic indexes and wheat yields

Pearson linear correlation		*XGBoost*		*Yields*		*SARIMA*	
		Precipitation	*Heat*	*Wheat North*	*Wheat Centre*	*Precipitation*	*Heat*
XGBoost	*Precipitation*	1	0.397	0.111	0.117	0.031	-0.002
	Heat	0.397	1	-0.175	-0.177	0.127	0.474
Yields	*Wheat North*	0.111	-0.175	1	0.995	0.191	-0.153
	Wheat Centre	0.117	-0.177	0.995	1	0.189	-0.153
SARIMA	*Precipitation*	0.031	0.127	0.191	0.189	1	0.199
	Heat	-0.002	0.474	-0.153	-0.153	0.199	1

Table 2. Kendall rank correlation coefficient among bioclimatic indexes and wheat yields

Kendall rank correlation		*XGBoost*		*Yields*		*SARIMA*	
		Precipitation	*Heat*	*Wheat North*	*Wheat Centre*	*Precipitation*	*Heat*
XGBoost	*Precipitation*	1	0.114	0.022	0.005	0.013	0.144
	Heat	0.114	1	-0.340	-0.234	-0.322	-0.156
Yields	*Wheat North*	0.022	-0.34	1	0.733	0.778	0.201
	Wheat Centre	0.005	-0.234	0.733	1	0.862	0.120
SARIMA	*Precipitation*	0.013	-0.322	0.778	0.862	1	0.125
	Heat	0.144	-0.156	0.201	0.120	0.125	1

Table 1 shows that the precipitation index obtained with the XGBoost method has a positive linear correlation of 0.11 with the yield of North wheat. In fact, as precipitation decreases, a higher yield is obtained. The SARIMA precipitation indicator detects the same linear correlation with the yield of the same wheat, slightly higher (0.19). Since the SARIMA model is linear, shows a greater linear correlation than the XGBoost. However, as will be seen from Table 2, data may present non-linear aspects that the seasonal time series model fails to capture. The heat indicator, on the other hand, has a negative linear correlation with North wheat, both what is calculated with XGBoost (-0.17) and with SARIMA (-0.15). As the heat increases, the yield of the crop is lower. As for the yield of Centre wheat, the results are very similar. In particular, the deficit precipitation indicator shows a positive linear correlation of (0.11) when calculated with XGBoost and (0.18) with the SARIMA method. Similar to the previous performance, it registers a negative correlation when it is evaluated with the heat indicator with both methodologies.

Table 2 shows that the SARIMA method, unlike the XGBoost method, fails to grasp the non-linear dependence that exists between the bioclimatic indicators and North/Centre wheat. In fact, according to the XGBoost bioclimatic precipitation indicator, there is a positive non-linear dependence for North wheat with a tau of 0.14 and a tau of 0.17 for Centre wheat. The SARIMA method, on the other hand, estimates 0.089 and 0.086 Kendall correlations for the yields of the North and the Centre, respectively. A tau close to 0 would assume no dependency between indicators, but

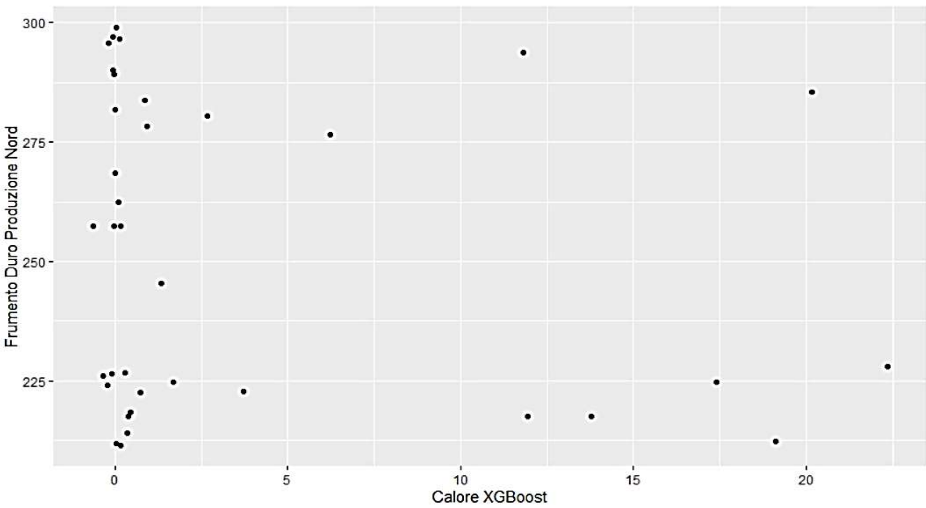
[1] https://www.bo.camcom.gov.it/it/borsa-merci/listino-settimanale-dei-prezzi-rilevati-il-gioved%C3%AC

this is not true. Keep in mind that the seasonal time series method is linear, so it cannot grasp non-linear aspects of the Kendall tau as the XGBoost method does. Moreover, the SARIMA method fails to grasp the negative dependence that exists between the heat indicator and the performance of North wheat (0.10) and Centre wheat (0.11), detected instead by the XGBoost methodology with a tau of -0.16 and -0.13, respectively.

This result confirms that the choice of machine learning methods allows for obtaining more performing bioclimatic indicators than traditional methodologies.

The next step concerns the choice of the most suitable copula to analyze the dependence among bioclimatic indicators and yields. Figures 1–6 compare the bioclimatic indicators estimated with XGBoost or SARIMA and the yields.

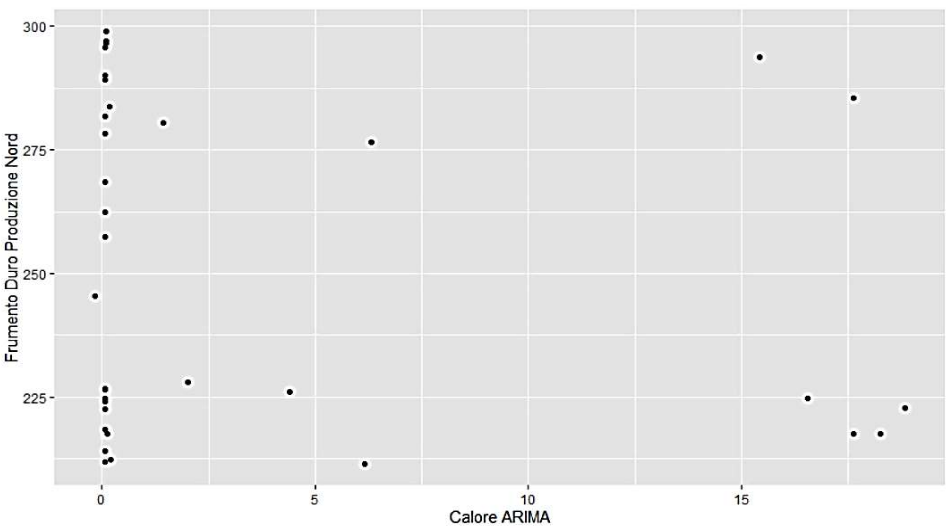
Figure 1. Heat and North wheat correlation



As can be seen from Figure 1, the relationship between wheat yields and heat presents heat values concentrated around zero in most cases with a variation in production yields. There are also cases of high heat and lower efficiency.

Figure 2 shows that yields are concentrated mainly when the heat indicator is zero.

Figure 2. Heat and North wheat correlation



Given the evident non-linear relationship between adverse weather events and loss of performance, we use a Frank copula.

Figure 3. Precipitation deficit and North wheat correlation

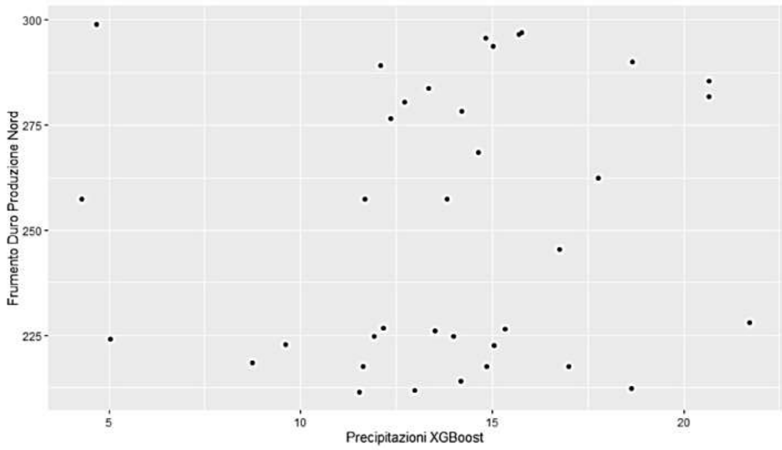


Figure 4. Precipitation deficit and North wheat correlation

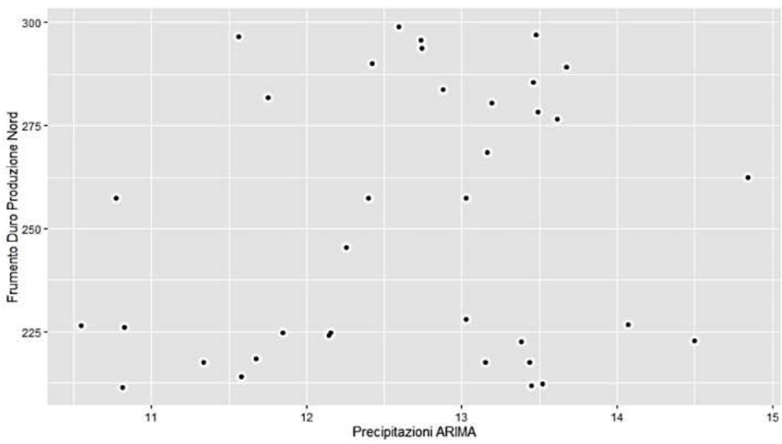


Figure 3 and Figure 4 show the precipitation indicator with North durum wheat, instead, show that in both methods there are random and independent values. This could be explained by considering that the yield of wheat is not affected by climatic precipitation. In this case, it is not necessary to estimate the copula, as no dependency between the data is verified.

Figure 5 and Figure 6 show a strong asymmetry between the data, no longer concentrated in zero. It should also be noted that the hybrid policy takes rainfall deficit as a benchmark.

Figure 5. Precipitation deficit and Centre wheat correlation

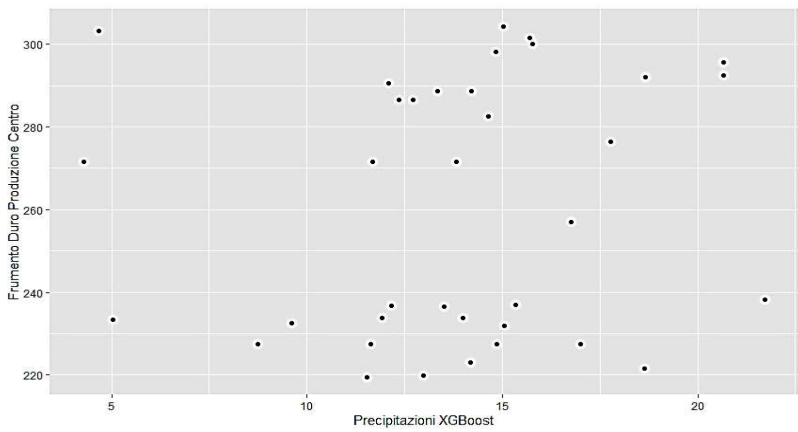
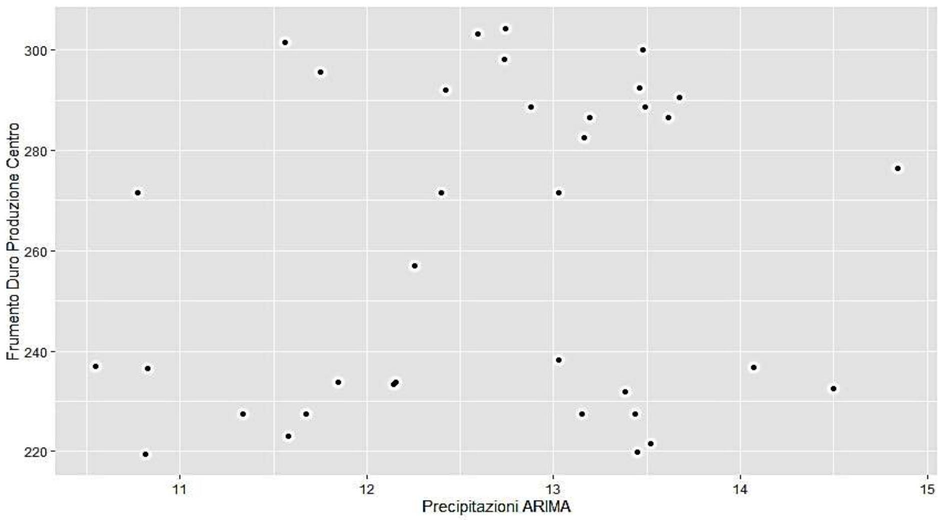


Figure 6. Precipitation deficit and Centre wheat correlation



Once the most suitable copula has been chosen to model the dependency structure between the data, the results are compared in Table 3.

Table 3. Copula estimation

	North wheat and heat		***Centre wheat and precipitation***	
	XGBoost	***ARIMA***	***XGBoost***	***ARIMA***
Copula	Frank	Frank	Frank	Frank
Parameter	-1.579	0.556	1.581	0.805
P-Value	0.618	0.010	0.461	0.382
Statistics	0.033	0.106	0.031	0.033

To model the dependence between the yields of North wheat with the bioclimatic indicator of heat, it was considered for the XGBoost method a Frank copula with parameter -1.58 while for the indicator estimated with the SARIMA method it was considered a Frank copula of parameter 0.56.

Table 3 shows that in the case of the heat indicator, the machine learning method is better than the SARIMA method in terms of p-value. The test, in fact, does not reject the null hypothesis in which the estimated dependence structure is equal to the observed dependence structure. In this way, accepting this hypothesis, it is asserted that there is no difference between the estimated and the observed structure of dependence. The test, however, is rejected for the heat indicator by the traditional method.

It can therefore be said that there is a structure of dependence between the two variables, and not only that, this dependence is estimated by Frank copula. It is therefore possible to assume that the heat indicator used in the hybrid policy for the cultivation of North wheat allows mitigating the basic risk.

As for the copula between the Center wheat and the precipitation, it is estimated a Frank (1.58) for the XGBoost method and a Frank (0.80) for the SARIMA method. Also in this case we can confirm what was said before, the machine learning method allows us to have indicators whose dependence structure is detectable through the copula function with a significant p-value.

To carry out a sensitivity analysis of the policy under consideration, several scenarios were examined to observe how the nature of the events the soil type, and the premium rate affect the refund of an insurance contract. The objective of this analysis was to identify the optimal composition of the soil in the number of hectares in order to ensure the solvency of the insurance company.

To proceed with this goal we divided the analysis into several working steps:

1) The first analysis to be carried out concerns the extreme case, considering the prevalence of hectares in the different types of soil;

2) An intermediate scenario was then studied in order to identify the limit composition;

3) Once the two limit cases have been obtained, the optimal composition of the consortium in terms of Solvency Capital Requirement and Fair Premium has been assessed.

In order to assess how the Solvency Capital Requirement and the fair premium affect the policy definition, several scenarios have been developed in which the composition of the soil type and the premium rate have been changed.

In particular, it is observed how the type of soil affects the probability of the event, extreme or not extreme, due to the strong correlation that exists between bioclimatic factors and the nature of the soil. Based on the pixel corresponding to the ground, the probabilities of the adverse event, extreme or not extreme, on which it is possible to build insurance policies are determined.

As a result, the combinations of the different types of soil and the probability of occurrence of the event were taken into account and based on this the different types of contracts were constructed.

Subsequently, three new scenarios were considered, assuming the distribution of the number of hectares in the following way:

- Scenario 1: 50 hectares per A, 40 hectares per B, 10 hectares per C.
- Scenario 2: 40 hectares per A, 10 hectares per B, 50 hectares per C.
- Scenario 3: 10 hectares per A, 50 hectares per B, 40 hectares per C.

Figure 7. Scenario 1

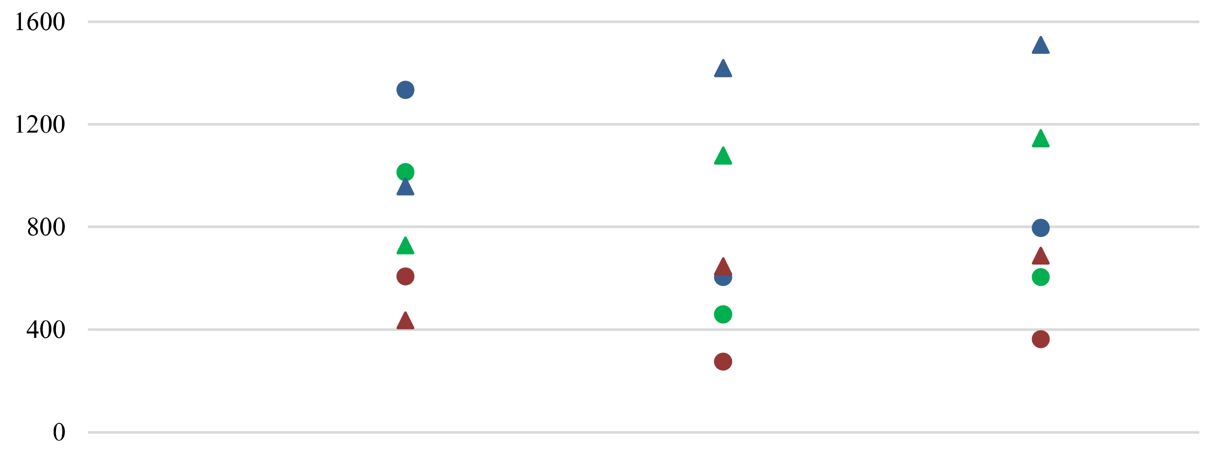


Figure 8. Scenario 2

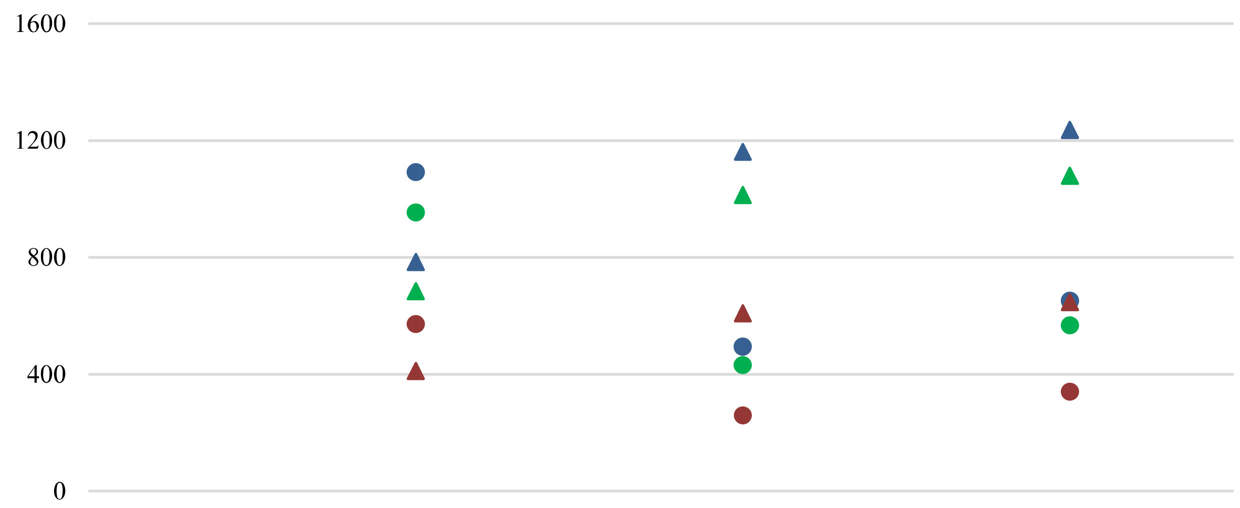
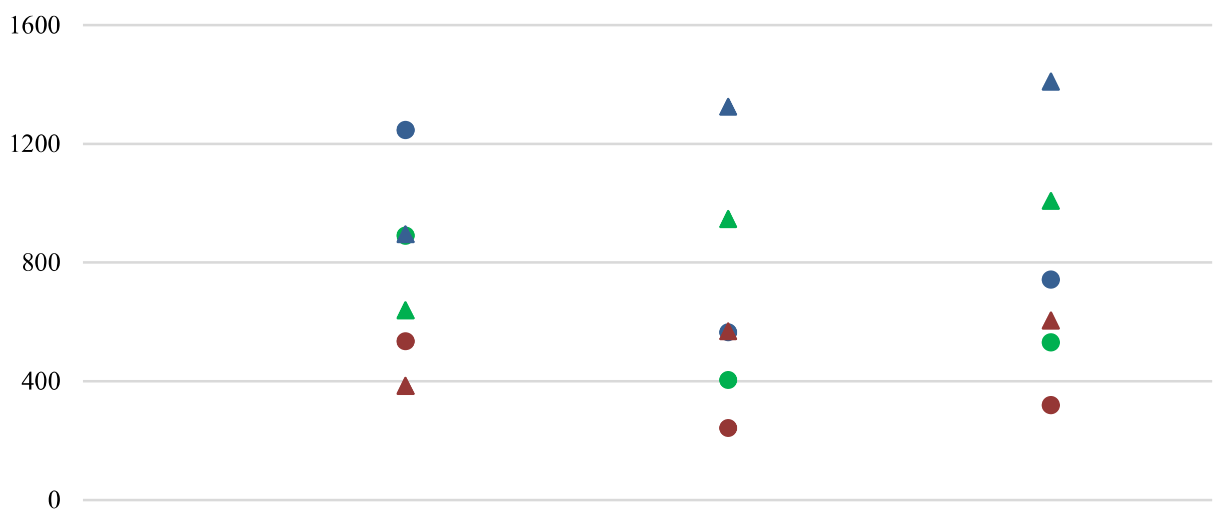


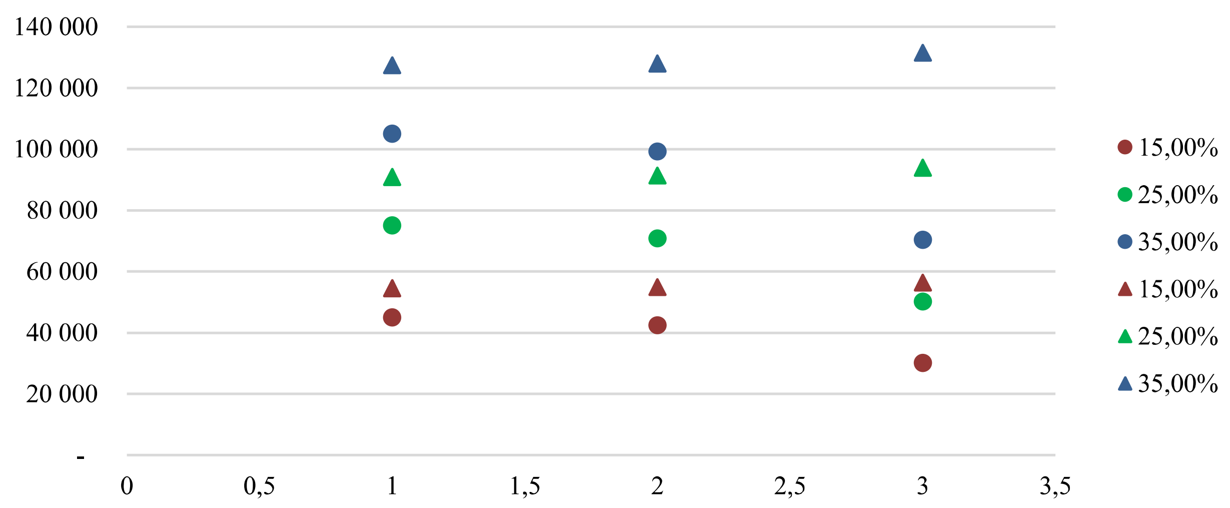
Figure 9. Scenario 3



Even when the composition of the consortium changes, for all three scenarios and premium rates taken into consideration, for soil A, a more expensive solvency capital, is obtained than the premium.

To get more information, we analyze the graph of the total pricing of the three scenarios considered.

Figure 10. Scenarios comparison



In this case, the main conclusions that can be drawn are as follows. For the premium rate at 15%, 25%, and 35% there are similar premiums for different scenarios, but the presence of fewer hectares in soil A (scenario 3) allows for having a lower SCR.

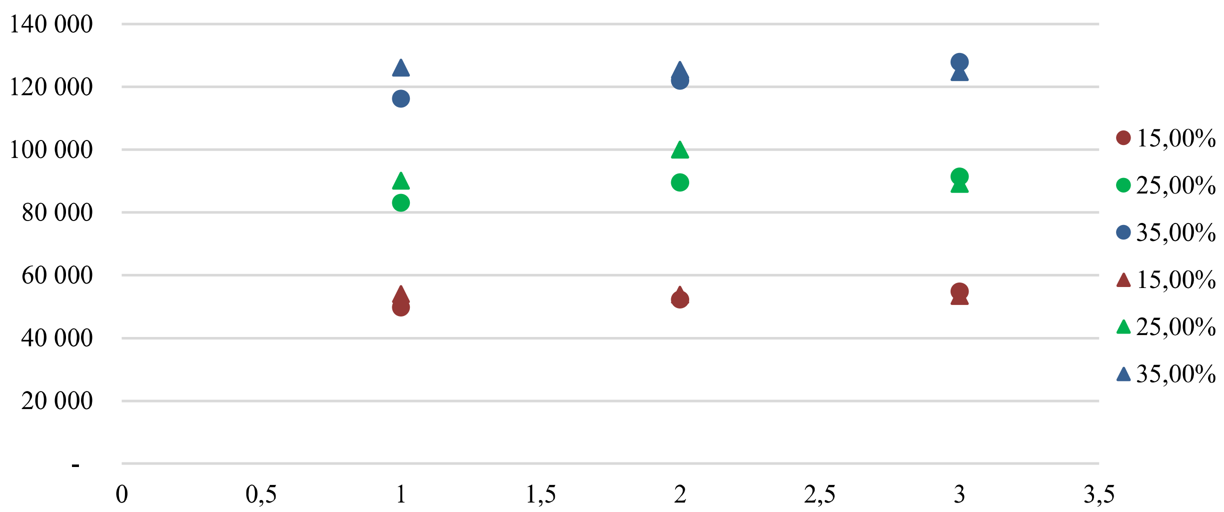
When the number of hectares is predominantly in acidic and saturated soil, values similar to scenario 1 are obtained, where acid and neutral soil prevail.

At this point, the results obtained for scenario 1 (50 hectares for soil A, 40 hectares for soil B, 10 hectares for soil C) and soil prevalence A were taken into account to assess the composition of the limit consortium (80 hectares for soil A, 10 hectares for soil B, 10 hectares for soil C) a saleable policy and an inadequate policy are obtained, respectively.

By fixing the premium rate at 15%, 25%, and 35% and the composition of soil C at 10 hectares, the composition of the soil was assessed as follows:

- 60 for A, 30 for B, 10 for C
- 65 for A, 25 for B, 10 for C
- 70 for A, 20 for B, 10 for C

Figure 11. Ideal scenario



From this, it is deduced that the company must fix the composition of soil A at 65%.

3. Conclusion

"It is all too well known that risks are high in agriculture and that exposure to uninsured risks is a major cause of low yields, slow growth, and persistent poverty" (Carter, 2014, p. 3). Uninsured weather shocks thus also affect farm workers, input suppliers, entrepreneurs and workers in agribusiness, and providers of non-tradable goods and services in the rural and non-rural economies. In other terms, the role of agribusiness is crucial and needs to be supported in particular against climate risks for developing the resilience of the whole economic system.

In this paper, we contribute to proposing methodological solutions for enhancing risk management and understanding how to assess climate-related risks, by offering a practical tool-box for promoting the insurability of these risks, in order to fill the climate protection gap. The results we show are promising and can be adapted to the case of the other European regions.

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