Rethinking the Landes Forest face to the Future Challenges

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Work in Progress

Abstract

The Aquitaine massif, in the South-West of France, is home to the largest Pinus pinaster monoculture forest in Europe. In light of the possibility of occurrence of severe natural hazards, such as the pine wood nematode (PWN), what could or should be done with the bare ground historically dedicated to the culture and the exploitation of maritime pine? In order to address this critical question, we make use of the well-known portfolio management and apply it to the spectrum of opportunities that can be seized in the Aquitaine region. The computation of optimal allocations of assets is built upon two models from the literature on portfolio theory, i.e. the Markowitz Mean-Variance model and the Expected-Shortfall model. Historical data and Monte Carlo simulated data are both considered in the study. According to our results, the Mean-Variance optimization is more prone to the combination of a few assets, whereas the Expected-Shortfall one is further reflected in greater portfolio diversification. While the minimization conducted from data following a non-normal distribution mostly relies on low-risk investments, that from a normal distribution operates through high-risk investments.

Keywords: Bioeconomics, Portfolio Management, Expected-Shortfall, Natural Hazards, Pine Wood Nematode

1 Introduction

The Aquitaine massif, in the South-West of France, is home to the largest Pinus pinaster monoculture forest in Europe, which had been planted for industrial purposes in the 18th century. The forest occupies a total area of 10,000 square kilometers. A series of extreme weather events – hurricane Martin in 1999; hurricane Klaus in 2009; storm Xynthia in 2010 – provoked enormous amounts of windthrow in the region. Many living trees have then been turned into dead broken or uprooted woody debris. Negative effects from natural disasters have also been exacerbated by insect pest damages. As a result, the largest European reforestation project to date had to be implemented (GIS GPMF, 2014).

Another serious threat to the French South-Western territory is the probability of arrival of Bursaphelenchus xylophilus, also known as the pine wood nematode (PWN), which is an invasive pest of pine forests (Mallez et al., 2013). The risk of PWN spread is both a conjunction of natural spread and of timber trade (Robertson et al., 2011). The microscopic worm is now widely distributed in North America and in Asia. As for the European continent, PWN was first detected in the Portuguese subregion of the Setúbal Peninsula (Mota et al., 1999). Additional outbreaks have since been recorded in the center of Portugal and in Spain (Abelleira et al., 2011; Robertson et al. 2011; Fonseca et al., 2012). The parasite provokes the pine wilt disease through a complex biological process that combines the nematode, an insect vector and a susceptible tree. The disease is considered to be dramatic, for it typically kills affected trees within a few weeks to a few months (Donald et al., 2003).

If we now consider the worst-case scenario, in which the parasite enters the Landes area and provokes the death of the forest, what could or should be done with the bare ground historically dedicated to the culture and the exploitation of maritime pine? In order to address this critical question, we shall make use of the well-known portfolio management and apply it to the spectrum of opportunities that can be theoretically seized in the Aquitaine region. The possibility of restarting the plantation and the exploitation of Pinus pinaster, as well as the possibility of enlarging the production of agricultural crops such as cereals, not to mention that market gardening or the production of photovoltaic solar energy could be introduced instead, are part of all the scenarios that can be envisaged in a managed portfolio of activities.

A widely used measure of risk is variance or standard deviation. Since Markowitz

(1952, 1959), the trade-off between the expected return of a portfolio of assets and its combined variance has been at the core of portfolio management. A specific weighted combination of assets is selected to calculate the risk-return optima, that is, so as to minimize the portfolio variance subjected to a given target return (Mostowfi and Stier, 2013). The model has been applied to the study of fish populations, biodiversity, genes, land use, mixed-species forests and forest stand types (Messerer et al., 2017). In biotechnical models, the portfolio selection is employed with the purpose of determining the combinations of biotechnical assets, such as the tree species (Brunette et al., 2017), that allow for an effective productivity-risk tradeoffs. Nevertheless, variance is inappropriate for the highly skewed fat-tailed distributions (Mausser and Rosen, 2000), which can be observed in commodity markets (González Pedraz, 2017). In that case, the probability of extreme losses is much larger than what would be predicted by the normal distribution. As a result, the minimum-variance portfolio is inefficient with respect to unexpected losses (Arvanitis et al., 1998).

Value-at-Risk (VaR) is defined as the maximum potential loss that should be achieved with a given probability over a given period (Manganelli and Engle, 2001). It is a quantile of the distribution of losses associated with the asset holding and solely reflects the information contained in the distribution tail. Unfortunately, VaR as a threshold disregards extreme losses beyond the quantile. Likewise, it fails to be subadditive, be it a property that enables to achieve reduction in the portfolio risk through asset diversification (Yamai and Yoshiba, 2002). Therefore, Artzner et al. (1997) introduced the Expected-Shortfall (ES), also known as the Conditional-Value-at-Risk (CVaR), to overcome the limits encountered with VaR. In short, ES measures the average losses in states beyond the VaR level.

In the following work, the computation of optimal allocations of assets in the Aquitaine region is built upon the above-quoted models from the literature on portfolio theory, i.e. the Markowitz Mean-Variance model and the Expected-Shortfall model. Historical data and Monte Carlo simulated data are both considered in the study. According to our results, the Mean-Variance optimization is more prone to the combination of a few assets, whereas the Expected-Shortfall optimization is further reflected in greater portfolio diversification. While the minimization conducted from data following a non-normal distribution mostly relies on low-risk investments, that from a normal distribution operates through assets with high-risk investments.

The paper proceeds as follows. Section 2 presents the portfolio model. Section 3 illustrates our simulation examples. Section 4 discusses the results. In Section 5, we offer up our concluding remarks.

2 Model

2.1 Mean-Variance framework

Following Dragicevic et al. (2016) and Brunette et al. (2017), consider an investor that has at his or her disposal a set of N assets, which correspond, for a given geographical area, to different types of agricultural, forestry or energy productions. The investor would like to invest in those risky assets and expects a positive return, in form of a positive rate of change in the economic value of assets, from the overall investment.

An asset is considered to be risky, because its return – dependent on the changes in prices – can be volatile over time. The upward trend of the market provides with increasing returns. On the contrary, when the market is bearish, the volatility with a declining trend exposes him or her to economic losses in comparison with the initial investment. By combining the assets, in a way that takes account of their characteristics, the investor seeks to minimize these potential losses. His or her choice on what to invest in is then represented by an $N \times 1$ vector array of asset allocations or weights $\mathbf{w} = (w_1, ..., w_N)'$.

The standard Mean-Variance optimization problem is defined as

$$\begin{aligned} \min_{\mathbf{w}} \quad & \mathbf{w}'\boldsymbol{\Sigma}\mathbf{w} \\ \text{s.t.} \quad & \mathbf{w}'\mathbf{r} = \bar{\mathbf{r}} \\ & \mathbf{w}'\mathbf{1} = 1 \end{aligned} \tag{1}$$

where $\mathbf{w}'\boldsymbol{\Sigma}\mathbf{w}$ represents the portfolio risk to be minimized, with weights $\mathbf{w} = (w_1, ..., w_N)'$ and the covariance matrix of returns $\boldsymbol{\Sigma}$. The first constraint is the portfolio expected return, obtained from N assets $\mathbf{r} = (r_1, ..., r_N)$, set equal to a target return $\bar{\mathbf{r}}$ decided by the investor. The second constraint $\mathbf{w}'\mathbf{1} = 1$ denotes the vector array of ones and corresponds to the standard budget constraint.

Solving the minimization problem provides us with information on the optimal weights of different assets that minimize the portfolio risk for a given level of portfolio return. The efficient frontier of the mixed-asset portfolios is then the superior segment of a parabola originating from the linear combination of assets.

2.2 Expected-Shortfall framework

The Expected-Shortfall from a portfolio is a function of uncertain returns of different assets and their weights in the portfolio. It considers the levels of losses that exceed the expectations of the investors by more than a given percentage (Pettenuzzo et al., 2016). Following Pachamanova and Fabozzi (2010), consider a set of weights $\mathbf{w}$, in form of a vector of exposures to risk factors, such that the portfolio return amounts to $\mathbf{r_p} = \mathbf{r}'\mathbf{w}$, with $\mathbf{r}'$ the transposed vector of expected returns obtained from the risk factors. CVaR is then a function of portfolio weights that determine the probability distribution of $\mathbf{r_p}$ with density function f. It can be written in the following form

$$\mathrm{CVaR}_{1-\epsilon}(r) = \frac{1}{\epsilon} \cdot \int_{-r \geq \mathrm{VaR}_{1-\epsilon}(r)} (-r) \cdot f(r) dr \tag{2}$$

The expression being integrated is the expected value of the portfolio loss at the $(1-\epsilon)$ quantile of the loss distribution, with $\epsilon \in [0, 1]$, which represents the confidence level.

Rockafellar and Uryasev (2000) showed that ES was a tractable risk measure. It thus enables to define a portfolio of VaR measures through the vector of risk levels (Francq and Zakoïan, 2013). Instead of using the CVaR function defined above, the first authors propose to use an alternative auxiliary objective function as a conditional expectation with respect to the portfolio loss, that is,

$$F_{1-\epsilon}(\mathbf{w}, \xi) = \xi + \frac{1}{\epsilon} \cdot \int_{-r \geq \xi} (-r - \xi) \cdot f(r) dr \tag{3}$$

The value of ξ corresponds to the portfolio VaR value. However, due to $-r - \xi \geq \mathrm{VaR}_{1-\epsilon}(r)$, with $-r \geq \xi$, the minimum value of the auxiliary function now equals CVaR, for the $(1 - \epsilon)$ quantile of the distribution takes all possible losses into account.

Provided the difficulty in estimating the joint probability density function of the returns of all assets in the portfolio, a set of scenarios $s = 1, ..., S$ – all equally likely to occur – is used in its place, where historical data observed at a given time step represents a scenario. They provide with auxiliary decision variables $y_s = y_1, ..., y_S$, the role of which is to linearize the piecewise function in the definition of the CVaR risk metric and to measure the portfolio losses in excess of VaR (Topaloglou et al., 2010).

The portfolio CVaR minimization problem becomes

$$\begin{aligned} \min_{\mathbf{w},\xi,\mathbf{y}} \quad & \xi + \frac{1}{\epsilon \cdot S} \cdot \sum_{s=1}^{S} y_s \\ \text{s.t.} \quad & y_s \geq -\mathbf{r}'\mathbf{w} - \xi, \quad s = 1, ..., S \\ & y_s \geq 0, s = 1, ..., S \\ & \mathbf{r}'\mathbf{w} \geq \bar{\mathbf{r}} \\ & \mathbf{w}'\mathbf{1} = 1 \end{aligned} \tag{4}$$

The set of two first constraints restricts the auxiliary variables such that $y_s \geq -\mathbf{r}'\mathbf{w} - \xi \geq 0$. The third constraint is the portfolio return obtainable at a given level of CVaR. The last constraint corresponds to the budget constraint.

Provided the underlying risks, the variables in the optimization problem are the weights, or sizes, of the portfolio activities, which have to be in reasonable proportions (Mausser and Rosen, 2000). Therefore, solving the minimization problem structures the portfolio of activities in such a way that a target return is achieved under the CVaR constraints of potential losses.

3 Simulations

Our study deals with the potential changes in land use, due to natural hazards, in the event of disinvestment in maritime pine. The former revolves around a bundle of six assets that can be theoretically envisaged in the investment project in the Landes department. Those include the productions of fruits, vegetables, cereals, maritime pine and the production of electricity through solar panels.

As regards the cereals, we mainly focus on the production of wheat. As a matter of fact, the Nouvelle-Aquitaine administrative region is already the leading maize producing region in France, with a harvest of 4,226 million tonnes in 2016 (FranceAgriMer, 2017d). It is only the 5th largest wheat producing region in France – with a harvest of 3,275 million tonnes in 2016 –, which opens up some additional investment opportunities.

In view of the differentiated market prices of standard lumber and industrial-oriented wood uses of Pinus pinaster, which depend on the tree diameter put up for sale, we have decided to distinguish between these two possible types of production. The main uses of maritime pine sawn timber are joinery (moldings, flooring, skirting boards and paneling) and the manufacture of furniture and of frameworks. The species is also used for the fabrication of products for outdoor fittings (cladding and street furniture). Likewise, it serves in the field of packaging and for the manufacture of pallets (FrenchTimber, 2018).

The gross profit of agricultural productions – such as cereals, fruits and vegetables – is in the following form

$$r_{x,t} = p_{x,t} - c_{x,t} \tag{5}$$

where $p_{x,t}$ corresponds to the market price of agricultural asset x in a given year t and $c_{x,t}$ its production cost. The rotations of cereal crop and market gardening are implicitly set at one-year length.

The calculation of the expected profit from timber sales is as follows

$$r_{y,t} = \left(p_{y,t} \frac{1}{(1+i)^{40}} - c_{y,t} \right) \frac{i\,(1+i)^{40}}{(1+i)^{40} - 1} \tag{6}$$

where $p_{y,t}$ corresponds to the market price of silvicultural asset y in a given year t and $c_{y,t}$ its yearly production cost. The discount factor i is of 3%. The rotation length of a silvicultural plan is defined to be of 40 years.

The expected profit obtained from the production of photovoltaic electricity is defined as

$$r_{z,t} = \left(p_{z,t} \frac{1}{(1+i)^{20}} - c_{z,t} \right) \frac{i\,(1+i)^{20}}{(1+i)^{20} - 1} \tag{7}$$

where $p_{z,t}$ corresponds to the electricity price per kilowatthour of solar panel z in a given year t and $c_{z,t}$ the yearly cost of installation and functioning per kilowatthour. The discount factor i is of 3%. The life span of a solar panel at full capacity is considered to be of 20 years. Although solar panels can operate shortly after their fitting, we consider that the investment takes place on a yearly basis so as to take account of the variation of electricity prices on the gross margin.[1]

The optimization was performed from the yearly rates of change of the returns.[2] The latter have been computed from the results of the equations formulated above. For example, an expected profit which is subject to a negative rate of change between two consecutive years is considered as a negative return in that time interval. Those of fruits and vegetables have been obtained by weighting, by a gross margin of 34.42%[3] (Crédit Agricole, 2017), the retail prices of their representative baskets sold to the French hypermarkets and supermarkets from 2008 to 2016 (FranceAgriMer, 2017a; FranceAgriMer, 2017b). The gross profit of cereals has been calculated as the difference between the gross grain prices stored between 2004 and 2015 (Joubert, 2015) and the costs of wheat production recorded between 2001 and 2016 (FranceAgriMer, 2017c). The gross profit of solar panels has been assessed by subtracting the estimated cost of solar panels per watt (EnergySage, 2018) from the modified electricity prices per kilowatthour in France (Eurostat, 2017). The silvicultural expected profits were obtained from the database on timber prices held by the French newspaper entitled *La forêt privée*, dedicated to private forest owners and industry players, and from an expert opinion on the costs per hectare engaged during a management plan. The costs per cubic meter of Pinus pinaster were estimated from the study of Chevalier and Henry (2012). All the missing data, due to different endpoints of the respective time series, have been filled through five-year moving averages.

In the case of Mean-Variance optimization, the standard deviation around the portfolio return – reflecting the market volatility – was considered to be a measure of risk. In the case of Expected-Shortfall minimization, the risk was identified as the expected value of

[1]Indeed, the optimization being performed from the yearly rates of change of returns, it would have not been possible to conduct it by considering discounted cash-flows with respect to the first date of the time series.

[2]We do not parameterize the historical data, such that they would follow a fixed probability distribution, for the methodology artificially creates a strong dependence to the model.

[3]Indicative average value developed from the INSEE data "Income statement and balance sheet data for natural persons."

the portfolio loss in states beyond the VaR level, within a 95% confidence level, where each year represented one possible scenario.

3.1 Mean-Variance framework

Setting a series of target returns yielded a range of optimal portfolios minimizing the overall market risk. Table 1 summarizes the characteristics of the optimal portfolios obtained by means of the Markowitz Mean-Variance model. For each pair of risk-return values, there exists an optimal allocation of assets that sum up to 1. One target return was fixed below the average silvicultural return observable from the time series of timber prices. Ten return targets were pegged above.

Table 1: Optimal portfolios obtained from the Markowitz Mean-Variance model

Optimal outputs	1	2	3	4	5	6	7	8	9	10	11
Portfolio return	0.00	0.50	1.00	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80
Portfolio risk	0.28	3.37	6.76	7.45	8.13	8.81	9.50	10.18	10.86	11.54	12.23
Optimal weights											
Fruits	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Vegetables	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Cereals	47%	72%	44%	39%	33%	28%	22%	17%	11%	6%	0%
Pinaster (lumber)	43%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Pinaster (industry)	1%	28%	56%	61%	67%	72%	78%	83%	89%	94%	100%
Solar panels	9%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

The combinations of optimal levels of risk and return give rise to an efficient frontier illustrated in Fig. 1. Such as commonly outlined in the literature on portfolio management, the superior segment of a parabola represents the efficient frontier of mixed-asset portfolios. As can be noticed, the higher the risk, the higher the expected return from the investment. That way, each additional risk-taking is theoretically rewarded with greater expected return. Nevertheless, because the segment is slightly concave, the increase in return falls progressively.

Unlike the efficient frontier achieved by taking into account different types of investments, the blue star $(6.48, 1.01)$ only considers the market valuation of Pinus pinaster and corresponds to the average levels of risk and return computable from the records of timber prices and costs. We see that it is almost situated on the frontier, implying an

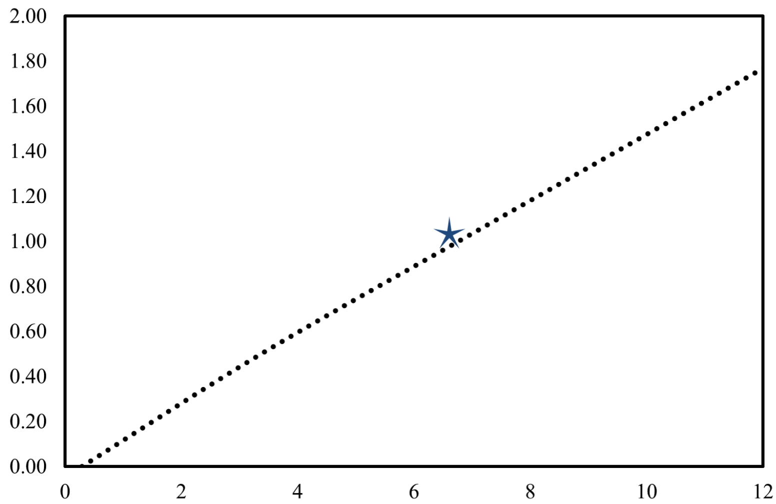

Figure 1: Efficient frontier of the optimal portfolios, minimizing the portfolio risk, obtained from the Markowitz Mean-Variance model. By means of the standard deviation, the x-axis represents different levels of risk. The y-axis measures the average portfolio returns. The blue star ($\star$) depicts the average silvicultural risk-return coordinates.

optimal investment at moderate levels of risk and relatively high levels of return. Therefore, investing in maritime pine appears to be a worthwhile investment when the latter is assessed by means of market returns. Nevertheless, the latter do not (necessarily) take account of the natural risks that weigh on the Landes forest.

Fig. 2 illustrates the optimal allocations of assets in the portfolios. Three different patterns can be identified. The first one corresponds to low levels of risk (≤ 3.37) and shows that the optimal portfolio is relatively diversified. Despite the prominence of cereals, four assets appear in the optimal compositions. It can also be noted that both lumber and industry-oriented timber emerge in these optimal portfolios. As the level of risk increases (≥ 6.76), the early productions of lumber and solar panels are rapidly replaced by greater investment in industrial timber. We thus observe a predominance of industrial Pinus pinaster and, to a lesser extent, diminishing weights of cereals. The third and last pattern matches with high levels of risk (≥ 7.45), where the quasi-exclusivity of the industry-oriented timber is to be found. It can be emphasized that, when the risk is represented by the variance of expected profits, cereals and timber behave like substitutes. Thereby, with regards to the Markowitz portfolio management, the Landes forestry turns out to be not only an activity yielding strong investment returns, but also that minimizing the overall portfolio risk in the presence of high volatility. The unexpected trait of this graphic

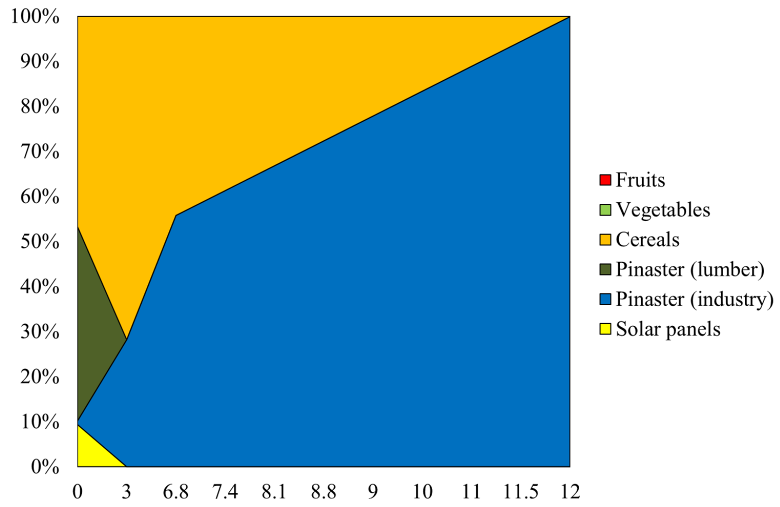

Figure 2: Compositions of optimal portfolios, minimizing the portfolio risk, obtained from the Markowitz Mean-Variance model. By means of the standard deviation, the x-axis represents different levels of risk. The y-axis measures the optimal weights of different assets.

representation comes with the near absence of lumber or that of solar panels, except in the areas of low risk.

Table 2 shows the Pearson r-coefficients of correlation between the portfolio return and the optimal weights. Likewise, the table displays the correlation coefficients between the portfolio variance and the optimal weights. From the statistical point of view, we see that only two assets stand out. On the one hand, cereals have a strong negative relationship with respect to both return and variance at an asymptotic significance of $p < 0.01$. That is, a disinvestment in cereals follows the increase in the portfolio return and risk. On the other hand, the weights of industry-oriented timber increase proportionally with both portfolio characteristics, for a perfect positive correlation has been estimated at $p < 0.01$.

Table 2: Pearson correlation coefficient

	Return		Variance	
Optimal weights	r-coefficient	p-value	r-coefficient	p-value
Fruits				
Vegetables				
Cereals	$-0.8592^{\star\star}$	0.000706	$-0.8688^{\star\star}$	0.000532
Pinaster (lumber)	-0.7348	0.010121	-0.7218	0.012289
Pinaster (industry)	$1.0000^{\star\star}$	0.000010	$0.9998^{\star\star}$	0.000010
Solar panels	-0.7348	0.010121	-0.7218	0.012289

We then conducted a linear regression in order to refine the analysis on which assets contribute to minimizing the portfolio variance the most. The exercise enabled us to obtain the standardized coefficients, presented in Table 3, which compare the effects of each individual asset on the portfolio level of risk. Once again, the estimation shows that two assets affect significantly ($p < 0.0001$) the level of risk that is tolerated for a target level of return. Whereas cereals contribute to minimizing the overall risk ($\beta = -0.0340; t = -64.6240$), the industry-oriented timber increases it ($\beta = 0.9700; t = 1824.914$). The other assets are not explanatory. In any case, the results show coherence with Fig. 2, where cereals dominate the portfolio composition at low levels of risk and where industrial timber outweighs in the portfolio at high levels of risk.

Table 3: Regression of minimized Variance

	Standardized coefficients		Student's t-test	
Asset	β-value	Standard error	t-statistic	p-value
Fruits	0.0000	0.0000		
Vegetables	0.0000	0.0000		
Cereals	−0.0340	0.0010	−64.6240	< 0.0001
Pinaster (lumber)	0.0000	0.0000		
Pinaster (industry)	0.9700	0.0010	1824.914	< 0.0001
Solar panels	0.0000	0.0000		

3.2 Expected-Shortfall framework

Table 4 outlines the characteristics of the optimal portfolios obtained by means of the Expected-Shortfall model. An optimal allocation of assets was computed for each pair of levels of Expected-Shortfall – as an alternative measure of risk – and return.

Fig. 3 unveils a similar configuration, characterized by a linear segment, where the frontier is both convex and concave. This time, an increase of the portfolio expected loss is obtained with a linear return increase. Despite being unusual, the result is encountered in the literature on reward-to-shortfall ratios relating the excess return in comparison with the risk-free return (Pederson and Satchell, 2002; Kühn, 2006).

Table 4: Optimal portfolios obtained from the Expected-Shortfall model

Optimal outputs	1	2	3	4	5	6	7	8	9	10	11
Portfolio return	0.00	0.50	1.00	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80
Portfolio risk	0.00	60	120	132	144	156	168	180	192	204	216
Optimal weights											
Fruits	0%	0%	13%	0%	0%	0%	0%	0%	3%	0%	0%
Vegetables	90%	66%	79%	66%	68%	61%	93%	96%	3%	0%	0%
Cereals	7%	8%	7%	12%	7%	28%	4%	0%	0%	0%	2%
Pinaster (lumber)	0%	0%	0%	2%	1%	0%	3%	4%	90%	92%	89%
Pinaster (industry)	0%	0%	1%	0%	0%	0%	0%	0%	2%	8%	9%
Solar panels	3%	26%	0%	21%	24%	11%	0%	0%	3%	0%	0%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

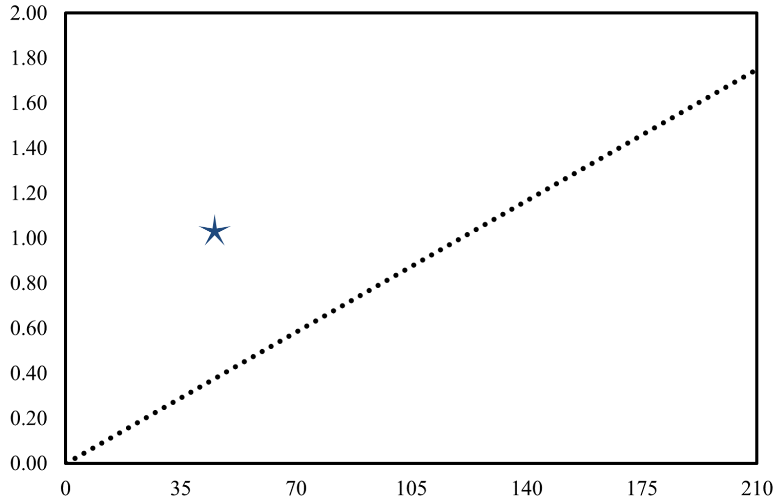

Figure 3: Efficient frontier of the optimal portfolios, minimizing the portfolio risk, obtained from the Expected-Shortfall model. By means of CVaR (95%), the x-axis represents different levels of risk. The y-axis measures the average portfolio returns. The blue star ($\star$) depicts the average silvicultural shortfall-return coordinates.

The blue star $(40.23, 1.01)$ situates the Expected-Shortfall of the silvicultural portfolio with respect to the current level of return. We notice that it is relatively away from the efficient frontier obtained from the multi-asset investment. In detail, for a rather low level of expected tail losses, the level of portfolio return is much greater than what could have been achieved with other types of productions. Nevertheless, the losses in the silvicultural production do not (necessarily) consider exposure to natural risks detailed in the introductory section.

As we now take a look on the optimal weights of assets in the portfolios minimized with respect to the Expected-Shortfall, Fig. 4 depicts allocations significantly different from those obtained with the Markowitz model. Indeed, we observe greater portfolio

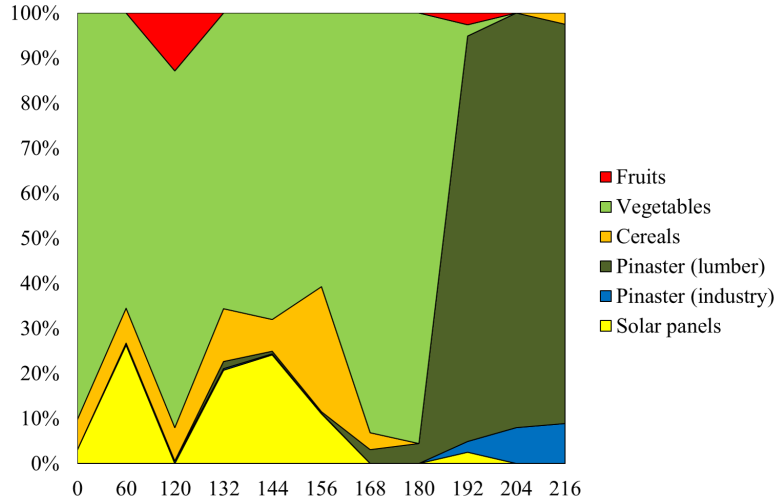

Figure 4: Compositions of optimal portfolios, minimizing the portfolio risk, obtained from the Expected-Shortfall model. By means of CVaR (95%), the x-axis represents different levels of risk. The y-axis measures the optimal weights of different assets.

diversification, but also greater swings in the optimal allocations throughout the level of risk. Four patterns can be detected. When the expected tail losses are set to be low (≤ 60), great portions of vegetables and moderate portions of solar panels, along with a marginal share of cereals, are privileged in the optimal allocations. At levels of expected tail losses defined to be moderate (≤ 120), fruits supplant both solar panels and cereals. When the expected tail losses are slightly elevated, the optimality depends mostly on the same assets as earlier, be it vegetables, solar panels and cereals. It should be highlighted that a negligible appearance of lumber also takes place. As the levels of expected tail losses become important (≥ 132), the portion of vegetables increases significantly. Indeed, the production of solar panels makes way to more vegetables, with the maintenance of a bit of lumber. The fourth pattern is the prevailing of timber, at high levels of expected tail losses (≥ 192), with an overwhelming weight of lumber.

The most striking feature of this outcome is related to the late arrival of wood outputs, which substitute with vegetables that held a majority share in the previous optimal compositions. In sum, without considering the natural risks that might jeopardize the wood production in the Aquitaine massif, the appreciation of reasonable levels of expected tail losses issued from the market risks excludes the production of timber for the benefit of market gardening and power generation. In addition, it could be observed that the latter never achieves a breakthrough.

Table 5 indicates the Pearson r-coefficients of correlation between the portfolio return or Expected-Shortfall and the optimal weights. Unlike the previous case, the table shows no significant relationship between the portfolio characteristics and the optimal weights of assets at $p < 0.01$.

Table 5: Pearson correlation coefficient

	Return		Expected-Shortfall	
Optimal weights	r-coefficient	p-value	r-coefficient	p-value
Fruits	−0.0593	0.893192	−0.0594	0.863192
Vegetables	−0.5759	0.064236	−0.5760	0.063666
Cereals	−0.2570	0.445527	−0.2571	0.445527
Pinaster (lumber)	0.6236	0.040351	0.6237	0.040309
Pinaster (industry)	0.5619	0.072018	0.5621	0.071894
Solar panels	−0.3644	0.271122	−0.3646	0.271122

The linear regression enabled us to confirm the results obtained with the Pearson correlation coefficient. Table 6 shows the standardized coefficients. The only asset that affects positively the minimized increase of Expected-Shortfall is lumber ($\beta = 1.2050; t = 1.6930$). Albeit the effect does not seem to be significant with 99% of confidence, the probability level is less than the t-statistic.

Table 6: Regression of minimized Expected-Shortfall

	Standardized coefficients		Student's t-test	
Asset	β-value	Standard error	t-statistic	p-value
Fruits	0.0120	0.3460	0.0330	0.9750
Vegetables	0.5800	1.4790	0.3920	0.7110
Cereals	0.2420	0.5680	0.4260	0.6880
Pinaster (lumber)	1.2050	1.6930	0.7120	0.5090
Pinaster (industry)	0.1010	0.7220	0.1390	0.8950
Solar panels	0.0000	0.0000		

3.3 Monte Carlo method

After conducting various studies from historical data presented earlier, from which a projection on non-market risks cannot be handled, let us now consider these types of risks by generating random sampling through the Monte Carlo method. Even if a single method does not exist, many simulations (1) model a system as a probability density function; (2) repeatedly sample from that function; and then (3) compute the statistics of interest (Harrison, 2010). The non-market risks concern mainly non-agricultural crops, for their rotation lengths exceed a one-year time frame.

We decide to consider a normal distribution, nonetheless defined over the statistics – such as mean and standard deviation – issued from the time series at disposal, from which we randomly sample a series of fictitious data. Despite the fact that normal distribution underestimates both the frequency and magnitude of extreme negative events (Sheikh, 2009), Gaussian distribution allows for negative market returns (Ho and Lee, 2004), what happens to have been observed in the real time series. In order to take account of the risks at stake, these data are then weighted by predetermined risk factors. For example, due to natural risks, such as storms, fires or biotic attacks, a major destruction of a forest is considered to occur every 70 years. The risk on forest production was then evenly distributed, by a factor of $\frac{1}{70}$, on data generated by the Monte Carlo method. Likewise, by reason of extreme weather events, the risk of power generation shutdown was evenly distributed, by a factor of $\frac{1}{100}$, on data generated by the simulation method. This implies that a storm capable of destroying the solar panel park takes place every 100 years.

Table 7 presents the characteristics of the optimal compositions, obtained from the Monte Carlo simulations, by applying the Markowitz Mean-Variance model. Its outputs are respectively depicted in Figs. 5 and 6. Contrary to the previous case, the efficient frontier is steeper at low levels of risk (≤ 4.09), which in terms of optimal allocations corresponds to a progressive replacement of vegetables by cereals. A small weight of fruits can also be mentioned. Beyond this level of risk (≥ 5.85), a clear pattern of diminishing portions of cereals and of increasing portions of fruits can be distinguished. At high levels of risk (≥ 28.93), the optimal portfolio is almost exclusively composed of fruits. By applying natural risks to timber production as well as to photovoltaic electricity production, the total absence of wood assets and solar panels is clearly discernible.

We learn from Table 8 that fruits and cereals respectively have a strong positive and a negative relationship with both the portfolio return and variance at a probability level of $p < 0.01$.

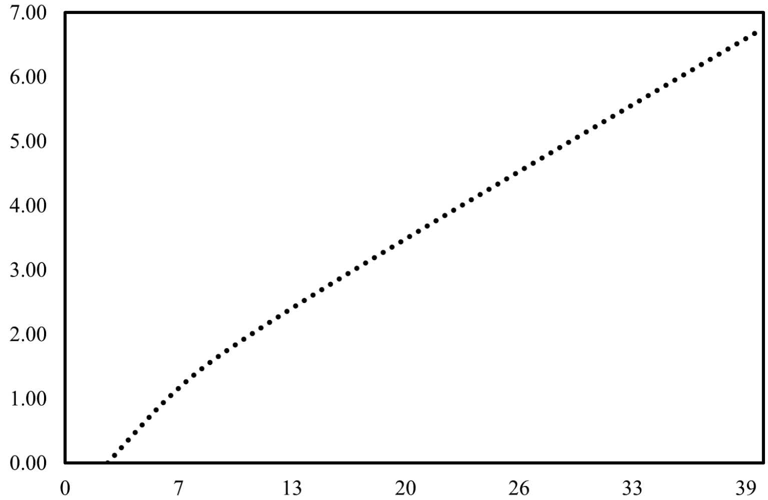

Figure 5: Efficient frontier of the optimal portfolios, minimizing the portfolio risk, obtained from the Monte Carlo simulations by applying the Markowitz Mean-Variance model. By means of the standard deviation, the x-axis represents different levels of risk. The y-axis measures the average portfolio returns.

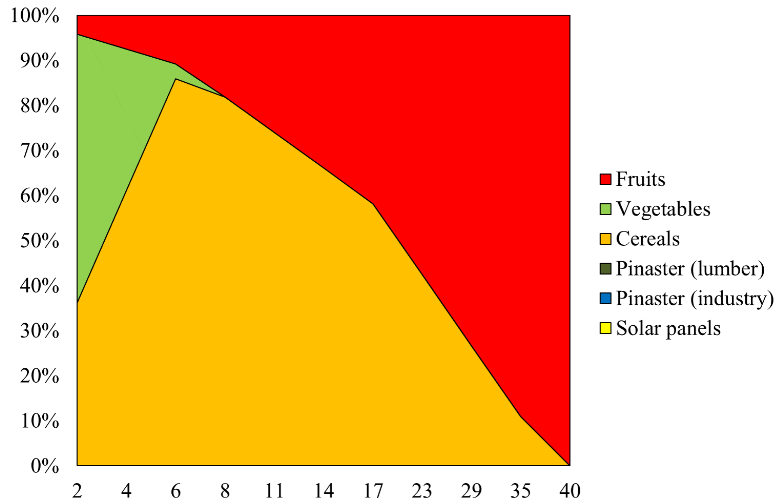

Figure 6: Compositions of optimal portfolios, minimizing the portfolio risk, obtained from the Monte Carlo simulations by applying the Markowitz Mean-Variance model. By means of the standard deviation, the x-axis represents different levels of risk. The y-axis measures the optimal weights of different assets.

Table 7: Optimal portfolios obtained from the Monte Carlo simulations by applying the Markowitz Mean-Variance model

Optimal outputs	1	2	3	4	5	6	7	8	9	10	11
Portfolio return	0.00	0.50	1.00	1.50	2.00	2.50	3.00	4.00	5.00	6.00	6.70
Portfolio risk	2.43	4.09	5.85	7.98	10.64	13.54	16.54	22.69	28.93	35.22	39.61
Optimal weights											
Fruits	4%	7%	11%	18%	26%	34%	42%	58%	73%	89%	100%
Vegetables	60%	31%	3%	0%	0%	0%	0%	0%	0%	0%	0%
Cereals	36%	61%	86%	82%	74%	66%	58%	42%	27%	11%	0%
Pinaster (lumber)	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Pinaster (industry)	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Solar panels	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Table 8: Pearson correlation coefficient

	Return		Variance	
Optimal weights	r-coefficient	p-value	r-coefficient	p-value
Fruits	0.9974**	0.000010	0.9995**	0.000010
Vegetables	−0.5892	0.056570	−0.5256	0.097267
Cereals	−0.7713**	0.005468	−0.8173**	0.002141
Pinaster (lumber)				
Pinaster (industry)				
Solar panels				

Table 9 shows the standardized coefficients issued from the linear regression. Given that the portfolio variance depends on fruits, for the β-value is significant at $p < 0.0001$ ($\beta = 1.0000; t = 84.696$), the coefficients partially confirm the results of the correlation analysis. However, the estimates do not take account of cereals as an explanatory variable.

Table 9: Regression of minimized Variance

	Standardized coefficients		Student's t-test	
Asset	β-value	Standard error	t-statistic	p-value
Fruits	1.0000	0.0120	84.696	< 0.0001
Vegetables	0.0010	0.0120	0.1220	0.9060
Cereals	0.0000	0.0000		
Pinaster (lumber)	0.0000	0.0000		
Pinaster (industry)	0.0000	0.0000		
Solar panels	0.0000	0.0000		

Table 10 presents the characteristics of the optimal compositions, obtained from the Monte Carlo simulations, by applying the Expected-Shortfall model. The illustration of the model outputs is to be found in Figs. 7 and 8. Like in the case obtained from historical data, the shape of the efficient frontier is linear. As for the optimal compositions, the big picture presents more diversified allocations than in the Markowitz case. Likewise, greater swings in the optimal allocations throughout the risk level are to be pointed out. Four patterns can be detected. Yet, a general observation can be made. Despite the occasional emergence of an asset, such as solar panels or those belonging to market gardening, there is a regular primacy of cereals and timber – with more industry-oriented timber than lumber – along the axis of risk. As a matter of fact, only at high levels of expected tail losses do fruits take advantage over cereals. What is also surprising in the optimal configurations is the constant presence of timber production in spite of the natural hazards mentioned before.

Table 10: Optimal portfolios obtained from the Monte Carlo simulations by applying the Expected-Shortfall model

Optimal outputs	1	2	3	4	5	6	7	8	9	10	11
Portfolio return	0.00	0.50	1.00	1.50	2.00	2.50	3.00	4.00	5.00	6.00	6.70
Portfolio risk	0.00	60	120	180	240	300	360	480	600	720	804
Optimal weights											
Fruits	2%	2%	2%	2%	0%	0%	0%	0%	0%	40%	37%
Vegetables	4%	0%	0%	0%	0%	7%	0%	3%	20%	0%	6%
Cereals	42%	56%	49%	56%	30%	60%	57%	67%	0%	14%	11%
Pinaster (lumber)	42%	0%	13%	1%	44%	0%	0%	0%	0%	28%	28%
Pinaster (industry)	6%	26%	26%	32%	26%	33%	43%	30%	80%	17%	17%
Solar panels	4%	16%	10%	9%	0%	0%	0%	0%	0%	0%	0%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Despite some non-negligible levels of the r-coefficient, figures from Table 11 show that none of the assets' weights has a significant relationship with the portfolio return and risk at $p < 0.01$.

Table 11: Pearson correlation coefficient

	Return		Expected-Shortfall	
Optimal weights	r-coefficient	p-value	r-coefficient	p-value
Fruits	0.7156	0.013281	0.7157	0.013262
Vegetables	0.3882	0.238086	0.3883	0.237954
Cereals	−0.6353	0.035806	−0.6354	0.035806
Pinaster (lumber)	0.0036	0.991619	0.0038	0.991153
Pinaster (industry)	0.2401	0.477001	0.2400	0.477190
Solar panels	−0.6565	0.028389	−0.6566	0.028389

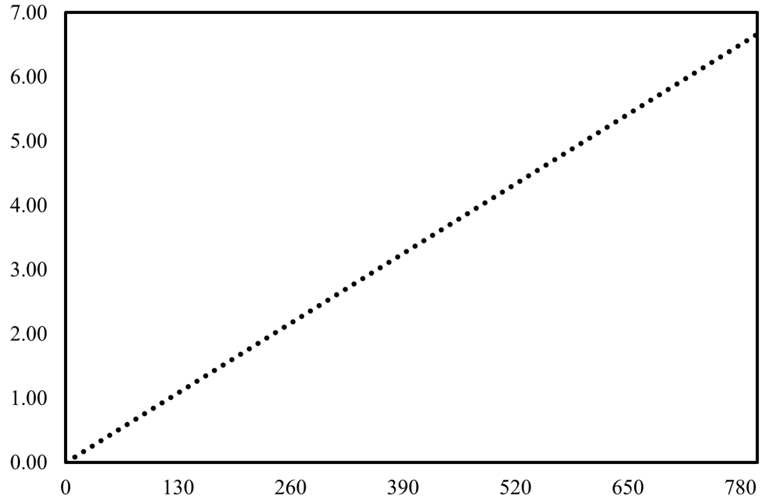

Figure 7: Efficient frontier of the optimal portfolios, minimizing the portfolio risk, obtained from the Monte Carlo simulations by applying the Expected-Shortfall model. By means of CVaR (95%), the x-axis represents different levels of risk. The y-axis measures the average portfolio returns.

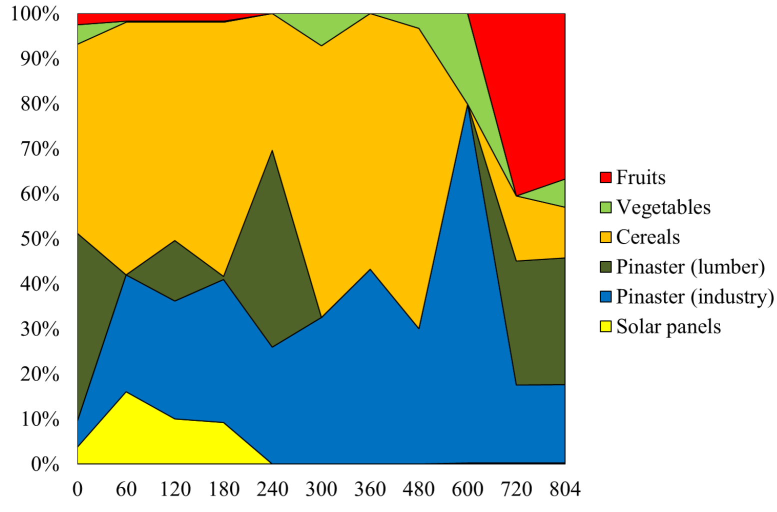

Figure 8: Compositions of optimal portfolios, minimizing the portfolio risk, obtained from the Monte Carlo simulations by applying the Expected-Shortfall model. By means of CVaR (95%), the x-axis represents different levels of risk. The y-axis measures the optimal weights of different assets.

The estimates from the linear regression shown in Table 12 bring to the fore that solar panels and lumber do not account for in the minimization of Expected-Shortfall. Furthermore, fruits turn out to be the most explanatory asset ($\beta = 1.9520; t = 5.8060$) at $p = 0.0020$. Cereals ($\beta = 1.6750; t = 3.2520$) and industry-oriented timber ($\beta = 1.0900; t = 2.8940$) also contribute to minimizing this type of portfolio risk, for their p-values are less than the t-statistics, but to a lesser extent.

Table 12: Regression of minimized Expected-Shortfall

	Standardized coefficients		Student's t-test	
Asset	β-value	Standard error	t-statistic	p-value
Fruits	1.9520	0.3360	5.8060	0.0020
Vegetables	0.4670	0.1990	2.3460	0.0660
Cereals	1.6750	0.5150	3.2520	0.0230
Pinaster (lumber)	0.0000	0.0000		
Pinaster (industry)	1.0900	0.3770	2.8940	0.0340
Solar panels	0.0000	0.0000		

4 Discussion

4.1 Historical data

Let us now make a comparative analysis between the average rates of change of both returns and risks observed from historical data and from the optimal compositions yielded by either the Markowitz Mean-Variance model or the Expected-Shortfall one. The synthetic results are presented in Table 13.

Table 13: Average rates of change observed from historical data

Assets	Return	Risk
Fruits	0.006	0.068
Vegetables	0.004	0.069
Cereals	0.093	0.518
Pinaster (lumber)	0.105	0.423
Pinaster (industry)	1.907	12.470
Solar panels	0.009	0.031

At low levels of portfolio variance, lumber and cereals appear to be investment complements. Both unveil low levels of return and risk. Were this the case, the minimization of a low portfolio risk would rely on their complementarity. Nevertheless, this hypothesis is unsupported by the Pearson r-coefficient at $p < 0.01$ ($r = 0.2845; p = 0.396485$). At moderate and high levels of portfolio variance, cereals and industry-oriented timber behave as investment substitutes. In detail, their correlation coefficient shows a significant strong negative relationship ($r = -0.8610; p = 0.000664$). This substitutability succeeds in minimizing moderate or high levels of Variance. While cereals unveil low return and low risk, industrial timber unveils high return and very high risk. Given that we are on the superior segment of the frontier parabola, higher risk implies higher expected return. Therefore, when the portfolio risk is high, a high return asset is needed to attain this portfolio objective.

At low levels of portfolio expected tail losses, vegetables and solar panels behave as complements. Both unveil very low levels of return and risk. However, this hypothesis is unsupported by the Pearson r-coefficient at $p < 0.01$ ($r = -0.1775; p = 0.601578$). Likewise, the investment complementarity between vegetables, cereals and solar panels is not supported by the estimation of the Pearson r-coefficient. At high levels of portfolio expected tail losses, vegetables and timber (quasi-exclusively lumber) behave as substitutes. This time, the hypothesis is verified by the estimation of the correlation coefficient at a probability level of 0.01 ($r = -0.9438; p = 0.000014$). Thereby, their substitutability succeeds in minimizing a high level of expected tail losses. While vegetables unveil very low return and very low risk, lumber is defined by low return and low risk. The extra presence of industrial timber, characterized by high return and very high risk, brings the additional return (and thus risk) that ought to be observed at high levels of expected tail losses. Therefore, in case of Expected-Shortfall, the portfolio risk achieves to be minimized through a combination of assets, the aggregation of which yields moderate returns.

We can see that, in our model, the Markowitz Mean-Variance optimization is more prone to the combination of a few assets, whereas the Expected-Shortfall optimization is further reflected in greater portfolio diversification. Likewise, the optimization conducted from data following a non-normal distribution relies more on assets characterized by low return and low risk. This implies that, in this case, the minimization of the portfolio risk outweighs the constraint of attaining a target level of return.

4.2 Simulated data

The comparative analysis is this time conducted with respect to the average rates of change of both returns and risks observed from the simulated data. The analysis takes also account of the optimal compositions yielded by either the Markowitz Mean-Variance model or the Expected-Shortfall one. Table 14 displays the synthetic results.

Table 14: Average rates of change observed from simulated data

Assets	Return	Risk
Fruits	7.801	40.361
Vegetables	0.423	1.422
Cereals	1.453	5.237
Pinaster (lumber)	1.270	5.118
Pinaster (industry)	1.105	4.209
Solar panels	0.080	0.840

At low levels of portfolio variance, the complementarity between vegetables and cereals is unsupported by the estimation of the Pearson r-coefficient at $p < 0.01$ ($r = -0.0598; p = 0.863192$). At moderate and high levels of portfolio variance, fruits and cereals do behave as investment substitutes. Their substitutability succeeds in minimizing this type of moderate or high risk. The hypothesis is verified by the estimation of the correlation coefficient at a probability level of 0.01 ($r = -0.8150; p = 0.002241$). While fruits unveil very high return and very high risk,[4] cereals unveil high return and high risk. Provided that the superior segment of the frontier parabola is at stake, high levels of risk imply high return, which corresponds here to the progressive replacement of a high-return high-risk asset by a very-high-return very-high-risk asset.

When comes to the portfolios minimizing the Expected-Shortfall, the statistical results are different. Despite the fact that cereals and timber, as well as fruits and lumber, behave as investment complements, none of the hypotheses is verified by means of the Pearson coefficients of correlation. All display insignificant relationships at an asymptotic significance of $p < 0.01$.

Like in the case of historical data, the Markowitz Mean-Variance optimization is prone to the combination of a few assets. In contrast, the Expected-Shortfall optimization

[4]Let us recall that the values come from a random sampling, such that two extreme values from the density function can consecutively yield a great rate of change, which, in return, impacts the average return and risk of that asset.

is further reflected in greater portfolio diversification. Furthermore, the optimization conducted from data following the normal distribution relies more on assets characterized by high return and high risk. It thus means that the constraint of attaining a target level of return counts as much as the minimization of the portfolio risk. This is mainly due to the fact that investments with significantly high expected returns also have high risks (Hull, 2006).

5 Conclusion

In the present paper, we have considered the optimal allocations of activities in the forest territory of the Aquitaine massif. Indeed, would the pine wood nematode (PWN) spread on a wide scale – not forgetting that other natural hazards might occur as well –, which combination of investments could be undertaken by considering the tools developed within the portfolio theory? Our results show that the Mean-Variance optimization yields a portfolio of a few assets only, while the Expected-Shortfall optimization leads to greater asset diversification. We also found that the minimization conducted from historical data, which did not follow a normal distribution, mostly relied on low-risk investments. A simulated normal distribution led instead to high-risk investments.

With respect to historical data, minimizing the portfolio Variance is most frequently achieved through cereals, which are characterized by low return and low risk. The result suggests that lowering the portfolio risk is predominantly related to investing in a low risk asset. If we now take a look at the current timber portfolio characteristics, such that the investor keeps the same risk profile, the optimization would lead to abandoning the production of lumber for the benefit of cereals. When the portfolio risk takes the form of Expected-Shortfall, the most frequent asset minimizing the portfolio risk is vegetables. This asset distinguishes itself by very low return and very low risk. If the investor kept the same risk profile as that of the current silvicultural portfolio, the optimization would lead to abandoning the production of timber for the benefit of producing vegetables, and, to a lesser extent, that of electricity and eventually cereals. Whatever the form of risk incurred by an investor, it can be stated that the exploitation of Pinus pinaster is mostly favored at high levels of risk.

As for the simulated data, yielded by the Monte Carlo method in which the inputs were forced to follow the normal distribution, the results differ from the historical case study. When the portfolio risk takes the form of Variance, the most frequent asset minimizing the portfolio risk is cereals. The latter unveils high levels of return and risk. If we consider the current portfolio characteristics, where the level of risk would remain as it is, the optimization would lead to abandoning the production of timber for the benefit of cereals and that of a small portion of fruits. In case the risk at stake is Expected-Shortfall, the most frequent asset minimizing the portfolio risk is lumber, that is, an asset with high return and high risk. Keeping the same risk profile would lead an investor to abandon the production of industry-oriented timber for the benefit of cereals and that of a marginal combination of fruits, vegetables and solar panels. In consequence, should the Variance reduction be the main objective, maintaining the silvicultural activities is not the best choice. When the Expected-Shortfall as a risk metric is taken into account, forestry is only recommended within a diversified portfolio of activities.

In light of various results, cereals appear as a plausible alternative to timber production would it be in serious jeopardy. This does not imply that forestry activities should be abandoned, for the results show that timber production has neither been initiated nor developed accidentally, but could instead be included within a wider portfolio of activities among which the grain production. This calls for reflecting upon the possibility to introduce agroforestry activities. Those correspond to the land use management system in which trees are grown around or among crops or pastureland. This is all the more interesting, for the combination of agriculture and forestry can sometimes lead to a better use of inputs than their separate practices (Terreaux and Chavet, 2005).

As a general remark, we can also mention that greater diversity in the portfolio goes with greater swings in the optimal allocations, such as illustrated by the results obtained from the Expected-Shortfall model. Yet, the issue of significant swings in the portfolio weights has been previously discussed by He and Litterman (1999). The last authors suggest to apply the Black-Litterman model according to which the market allocation and the investor's own views on the market should be jointly considered. An obvious extension of the present work could be aligned to their modeling framework.

Acknowledgment

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