Università degli Studi di Napoli "Federico II"

Dipartimento di Economia e Politica Agraria

Dottorato in Valorizzazione e Gestione delle Risorse Agro-Forestali

XX Ciclo

Tesi di Dottorato

Potential for risk management in agriculture through index-based weather derivatives

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NOVEMBRE 2007

Acknowledgements

I would like to manifest my greatest gratitude to Dr. Carlo Cafiero who has always taken care of my graduate education, step by step, since the beginning of such wonderful adventure. His insights, advices and suggestions guided me through a tireless exploration of my personal attitude toward the enchanting field of the scientific research. I hope the faith he has always placed in me will remain the principal strength that supports my professional experiences. Thanks again.

I am also extremely thankful to Prof. Gary Thompson for his important advices and suggestions that have conferred completeness and solidity to this research. His experience as researcher and professor has been an important example I will carefully preserve.

My last acknowledgement goes to those people who sincerely helped me during difficult periods. I thank them for their patience and loving empathy.

I dedicate this research to two special persons who always have encouraged me to outdo my personal limits and taught me how to spread love and respect between people.

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Abstract

The research is aimed to study the feasibility and efficacy of using index-based weather derivatives to manage yield risk in agriculture. Weather indexes that are highly correlated with yields can be used to write insurance contracts which mitigate problems related to asymmetric information. A new methodology for constructing weather indexes is tested on grape, soft and durum yield data referring to the Italian province of Grosseto. Historic variability of weather in the province has been captured by a limited number of variables obtained by applying a principal component analysis on weather data collected on 18 weather stations over the period 1990 to 2004. The indexes have been constructed by fitting the historic yields with a linear combination of the variables obtained from principal component analysis. The feasibility of using such indexes has been explored by setting a damage trigger value and by simulating the actuarially fair premium for each contract. The analysis reveals that such contracts would have been attractive for farmers characterized by reasonable degrees of risk aversion. The feasibility of such index-based weather contracts would depend on the possibility of transferring the systemic component of the agricultural risk into wider financial markets. As an alternative, index-based compensation could be used to reconsider the kind of public interventions in agricultural risk management typical of Italy in the past thirty years.

Chapter 1. Introduction

The importance of risk management in agriculture resides in the direct association between agricultural income variations and instability of consumptions patterns of farmers' households.

The impact of income variations on households' welfare is certainly greater in developing countries, where agricultural incomes represent the major if not the only component of total household's income available for consumption. In developed countries, several strategies are applicable for hedging agricultural income shocks, such as diversification of household's income and recourse to financial institutions for short-term loans. In fact, steady off-farm income generating activities contribute to greatly reduce the variability of the household income, while access to credit allows farming families to smooth occasional consumption shocks in case of shortfalls in agricultural incomes.

Nevertheless, even in developed countries agricultural risk management has historically attracted the attention of both researchers and policy makers. One of the crucial considerations to be made is that agricultural income risk is linked to two factors: yields and prices variability. Variations of prices do not always imply a proportional variation in farming income. Indeed, in case of negative correlation between price and yields, as commonly occurs in segmented or local markets, the mechanism of *natural hedge* might mitigate the effect of unpredicted price variability on producers' income. Obviously, such a mechanism is less likely to apply for commodities which are traded on more integrated or global markets, where price variations are not strictly correlated with the dynamics of local supply or demand shocks. In such cases, price risk deserves more consideration in that price volatility, not correlated with yields variations, may proportionally affect the stability of producers' income.

Another usual aspect making price volatility difficult to address with private mechanisms by the individual farmers, is that price variability gives rise to uncertainties common to every producer in the market. Price risk tends to be highly spatially correlated (or systemic), something that has traditionally justified public intervention in the sector. Nevertheless, commodity price risk has been and still can be efficiently managed through preharvest agreements, which set a price for future delivery. These kinds of contracts are nowadays represented by *forward* and *futures* contracts, regularly traded in exchanges or in over-the-counter markets.

When price variation is limited by public sector price supports, or when price risk is not spatially correlated, production or yield risk becomes the major concern of risk-averse farmers.

Production risk management has been a widely discussed topic in the economics literature. It is best understood with reference to the principle of risk layering, for which production risk can be split up in three risk layers, each of which has a preferred strategy (Hess, Skees, Barnett and Nash, 2005).

The first layer includes the range of high-probability, low-impact events. The first layer could be denominated the 'risk retention' layer. Farmers can individually manage such risks by adopting agricultural precautionary measures or using financial services in case of revenue losses. The second layer refers to predictable events that cause considerable and frequent yield losses, to the extent that farmers prefer to bear a cost to *transfer* the risk to insurance providers. The second layer is named the 'market insurance' layer. The third layer includes the range of low-probability high-impact events, called the 'market failure' layer. Events in this layer are difficult to forecast and their effects on agricultural activities are often catastrophic. Companies that would provide insurance for this risk layer could not be able to guarantee indemnities, in that outlays for indemnities could be much higher than premium income. A high discrepancy between indemnities and premium income causes insurance companies to raise the premium rates to the extent that farmers are no more willing to purchase insurance policies to hedge such risks.

As opposed to industrial production, agricultural production risk is mostly characterized by peculiar events that affect farmers differently or all farmers in different times. Unlike price risk, production risk is not generally considered as highly spatially correlated and as such the idiosyncratic (or independent) character of production risk makes yield insurance a reasonable tool to manage such risk. However, production risk is not perfectly idiosyncratic. In fact, unfavorable weather events affecting limited areas cause the same damages to all farmers within such areas. Weather variability could render production risk relatively spatially correlated. Indeed, production risk has been defined by Skees and Barnett (1999) as *in-between* risk. Also the presence of a systemic component caused by weather variability reduces the efficiency of crop insurance in hedging yield shortfalls.

In addition to the problems related to the systemic nature of a relevant component of agricultural production risk, the efficacy of yield crop insurance is affected also by asymmetric information among the involved parties, a problem that is exacerbated by the spatial distribution of the agricultural activities and the length of the production processes, which make monitoring problematic.

In response to the limited efficacy of traditional yield crop insurance, researchers have devised innovative insurance tools capable of reducing the impact of asymmetric information and to hedge the systemic component of production risk coming from weather variability.

A promising line of research is based on use of appropriately designed weather indexes. On one hand, use of objectively determined indexes, proven to be highly correlated with yields, might reduce the informational problems that affect insurance contracts. On the other hand, given the proven ability of financial tools to hedge systemic risk by transferring it to other agents, appropriately designed weather indexes could be used as underlying assets of financial derivatives that could be traded on regular exchange or over-the-counter markets.

The potential of weather indexes to mitigate agricultural production risk resides in their capability of manifesting an objective and stable correlation with yields, preferably individual farmers yields. The objective of the thesis is to explore the possibility that the most relevant production risks, that is those directly or indirectly related to variations in weather conditions, could be dealt with the use of properly designed derivative contracts whose underlying asset is based on a combination of objectively measured local weather indexes. The thesis focuses on the construction of a local weather index using meteorological and agricultural data from the Italian province of Grosseto in Tuscany. Then, a feasibility analysis of insurance contracts based on those weather indexes is conducted.

The thesis is organized as follows. Next chapter provides an overview on risk management in agriculture. The third chapter presents the data, including a description of the agricultural area chosen for the analysis, and introduces the innovative methodology, describing the processes applied to construct the weather indexes.

The fourth chapter presents the results of the construction of the weather indexes on the study area, and contrasts them with those obtained through an alternative method based on the use of growing degree days. The fifth chapter discusses the feasibility of possible weather index-based insurance contracts based on the proposed indexes. The last chapter provides conclusions and suggestions for further research.

Chapter 2. Review of risk management in agriculture

2.1. **Problems in agricultural risk management**

Informational asymmetry between farmers and insurers has been addressed in the agricultural economics literature as the principal cause of insurance markets inefficiency (Chambers, 1989; Just, Calvin and Quiggin, 1999). Two well-known effects of asymmetric information commonly plague traditional yield crop insurance programs worldwide: moral hazard and adverse selection.

Moral hazard occurs because individual farmers, once insured, have the incentive to reduce inputs below their optimal level and to avoid precautionary measures to prevent damages. This change of behavior increases the probability of yield losses, which in turn fosters the likelihood of larger claims. Insurers are compelled to monitor insured farmers and to apply adjustments in claim expectations. The latter measures are often costly and crop insurance might disappear in a long-run market context (Chambers, 1989; Turvey and Zhao, 1999).

Adverse selection arises in crop insurance markets when insurers do not have sufficient information to rate individual farmer's risk exposure and create homogeneous risk pools. In fact, insurers usually do not have access to individual yields and the publicly available estimates of yields are not always reliable. Instead, farmers who are well informed about the distribution of their own yields are able to estimate the actuarial fairness of the premiums they pay better than insurers. Accordingly, high-risk farmers, whose expected indemnities exceed the paid premiums, have the highest incentives to participate in crop insurance programs. So, in the long run, insurers could become insolvent, and the loss-ratio[1] of the insurance pool exceeds one (Skees and Reed, 1986), that is, the cost of compensation frequently exceeds the total premium income, thus generating a vicious circle if insurers raise the premiums in order to circumvent frequent high indemnity outlays, selecting a smaller pool of more risky farmers (Miranda, 1991).

In the long run, moral hazard and adverse selection would inevitably drive crop insurance markets to failure if no market inefficiency adjustment is implemented (Nelson and Loehman, 1987).

Miranda and Glauber (1997), instead, argue that systemic, non-diversifiable risks in crop yields might be the most burdensome cause of crop insurance market failure, especially when widespread natural disaster occurs. Harmful events, like natural calamities, are difficult to accurately predict and cause damages and losses to all farmers at the same time. The property of low predictability and high spatial correlation gives rise to systemic risks. Although yield crop insurance is diffusely used in sharing production risks, it works efficiently only in hedging uncorrelated risks. Production risks have a remarkable systemic component which could be reduced through use of exchange markets, which are efficient in hedging highly spatially correlated risks (Skees and Barnett, 1999).

In presence of both asymmetric information and systemic risk, many authors have suggested that public intervention is needed to avoid crop insurance market failure.

[1] The loss-ratio is the index used by insurers to relate loss outlays to premium income.

2.2. **Public policy**

An important aspect of agricultural risk management has traditionally concerned the involvement of the public sector. Governments are involved in hedging agricultural risk in different ways. When farmers experience considerable losses owing to natural calamities, government intervenes to compensate for damages. This intervention is commonly called *ex-post disaster relief*.

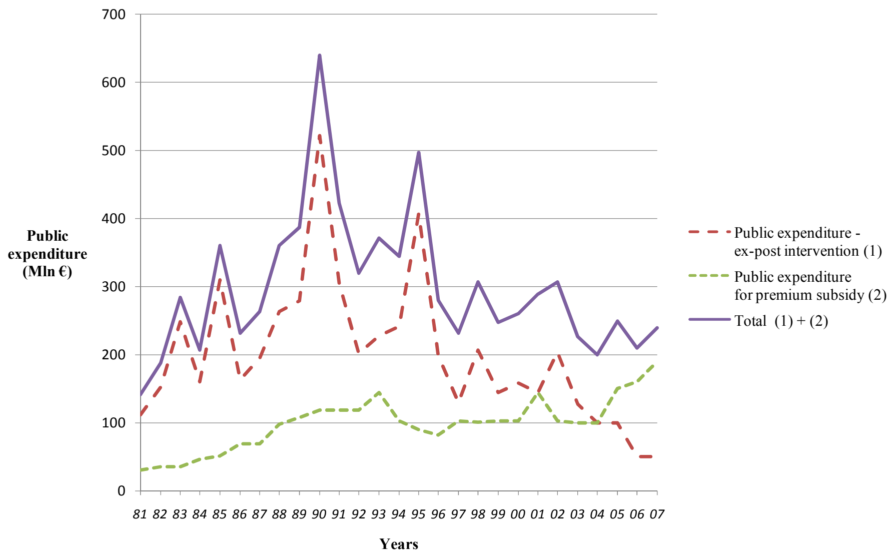
The public action is also involved in insurance markets with subsidies in premium payments for farmers and with reimbursements of administrative and operating costs for insurers.

Two examples of such public policy are the *Federal Crop Insurance Improvement Act* in the United States, from 1980, and the Italian *Fondo di Solidarietà Nazionale*, from 1974.

The Italian experience of the Fondo di Solidarietà Nazionale (FSN) shows how, over time, allocation of public funds has emphasized ex-post relief more than premium subsidies (figure 1). The trend of nominal expenditures on premium subsidies indirectly traces the evolution of the farmers' participation to the subsidized insurance market. Such trend indicates a slow increment over time and an increasing rate in the last three years. Low participation in subsidized insurance is likely due to the possibility of farmers receiving compensations for natural disaster even without insurance policies (Cafiero, 2003). The increment in the last three years is likely caused by the diminishing availability of public funds for ex-post relief. Further, much of ex-post compensation was implemented under political pressures without objective assessments of actual losses.

A similar scenario unfolded in the United States and Nicaragua. In 1994, the United States Congress, in order to reduce the public expenditures, stipulated indemnities would be paid to farmers for disaster relief only if they hold an insurance policy. Congress policy did not experience a significant increment of farmers' participation in insurance market. The policy was rendered ineffective when indemnities for disaster relief were granted to all farmers regardless of any insurance subscription (Glauber, 2004).

Figure 1: Italy FSN nominal expenditure for compensation payments and insurance premium subsidies 1981 – 2007 (Mln €)



Source: Italian Ministry of Agriculture

In 1998, the Nicaraguan government rejected a pilot project, proposed by the World Bank, to implement an index-based risk management. The Nicaraguan government considered the project superfluous because it could rely on international aid in case of natural disasters (Hess, Skees, Barnett and Nash, 2005).

Although some theoretical studies have shown that *ex ante* regulations prove to be economically more efficient than *ex post* disaster relief as the former provide farmers with production incentives such that moral hazard is no longer a stimulus[2], ex post relief is still common in many developed countries.

2.3. **Innovative insurance tools**

Several insurance programs have been studied and designed with *ad hoc* contractual mechanisms intended to mitigate moral hazard and adverse selection. The most common is area-yield crop insurance which bases the assessment of actuarial premiums and expected indemnity outlays upon distributions of average area yields rather than individual ones. With this program, the classification of farmers by risk exposure is more accurate and the pools are more homogeneous (Skees, Black and Barnett, 1997; Chambers and Bourgeon, 2003). Area-yield crop insurance is designed to hedge only the systemic component of the production risk. It follows that area-yield mechanism is not able to hedge against the idiosyncratic component of farmers' total risk exposure (Miranda, 1991). Such programs, however, do not guarantee complete coverage of the individual risk. Indeed, since the trigger values of the indemnities mechanism refer to an assessment of the central tendency of yields, area-yield crop insurance has an inevitable associated basis risk (Skees, Black and Barnett, 1997).

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[2] Further details on the topic can be found in Turvey, Islam and Hoy (1999) and Innes (2003)

2.4. **Weather derivatives**

Recently, research on crop insurance has analyzed new insurance tools based upon weather indexes. Indexes of relevant weather variables could be used to write financial derivatives, called weather derivatives. They can be brokered as an over-the-counter traded option or used to define the indemnity payment trigger of insurance contracts (Turvey, 1999a).

Weather data are collected worldwide, especially in developed countries, and provide objective information about specific weather conditions. Intuitively, agricultural production risk can be both directly and indirectly linked to specific weather conditions: hail, frosts, droughts and floods are examples of direct linkages, while pest, viral and fungal infestations are examples of indirect linkages. Weather indexes might therefore provide farmers and other agents exposed to or merely interested in weather risk, with the possibility of designing specific contracts, thereby spreading their individual risk worldwide.

However, one of the critical aspects of the use of weather derivatives is how they should be priced. The feasibility and difficulty of pricing a weather derivative depends upon the fact that the underlying asset, the index, is not a marketable good, but potential demand and supply for such indexes in fact do exist. Cao and Wei (2004) and Taylor and Buizza (2006) proposed two different frameworks for a temperature derivative and evaluated the factors affecting its pricing. Turvey provides a description of a drought insurance whose pricing is based upon an economic evaluation of rainfall (Turvey 1999a). He also proposes a pricing model for growing degree insurance based on intra-year risk (Turvey 2005).

Even though the problems in pricing weather derivatives have not been fully explored, there are no impediments in researching and designing optimal weather indexes. Skees, Barnett, Ibarra and Syroka (2006) provide a detailed description of the framework for constructing an optimal *local* weather index. The area represented by the *local* index has to be homogenous in terms of pedo-climatic conditions[3]. Farmers in such an area are naturally exposed to the same systemic risk. Differences in individual yields would vary to the extent farmers adopt different agricultural practices. Weather data have to come from weather station(s) located within the area. The index constructed by using local weather data must somehow be highly correlated with yields. Once the correlation between the weather index and yields is ascertained, especially if the index provides reliable out-of-sample predictions, the weather index will be able to predict low values of yields and to directly assess the extent of damages. A likely basis risk might occur only in case of non-perfect correlation between the weather index and the distribution of yield: the lower the correlation, the higher the probability of basis risk. The distinction between systemic risk and basis risk, however, depends on the extension of the area covered by the index. In theory, if a weather index were constructed to cover a single farm area, there would be no "systemic" risk, and then index-based weather insurance might be directly compared to traditional insurance, with the advantages of reduced monitoring and loss-adjustment costs. As the area gets larger (including more than one farm), the increasing presence of the idiosyncratic component of the risk could weaken the correlation between the index and (relatively local) yields and would make index-

[3] Homogeneous pedo-climatic condition refers to similar soil and climatic condition in a delimited agricultural area.

based insurance system more similar to area-yields crop insurance, with the possibility of basis risk.

The availability of long time series of both weather and yield data is an essential requirement to make the assessment of the premium actuarially sound. The characteristics of a credible weather index are (Skees, Barnett, Ibarra and Syroka, 2006):

- Objectivity: the measurements are taken by non-human weather surveyors;
- Transparency: the information collected cannot be strategically altered;
- Independence: weather conditions are not contingently affected by human behaviors.

A crop insurance market, based on a reliable and credible local weather index, theoretically would not be plagued by asymmetric information. Moreover, the financial exposure of a local weather derivative might be shared with a non-agricultural sector whose returns are negatively correlated with the underlying index. Opposite stances for summer precipitations, for example, make tourism to be one such non-agricultural sector suitable for sharing risk as long as tourist and agricultural activities lie on the same area.

Unlike previous studies, where the construction of suitable weather indexes is guided by knowledge of agronomical relationships between yields and some weather variables (Vedenov and Barnett, 2004), the approach presented in this thesis is based on the idea of deducing a purely statistical relationship between yields and weather variability. This approach makes sure the resulting index accounts only for the yield variation caused by weather variability. The index definition, hence, proves not affected by both farmers' risk exposure and idiosyncratic component of single farmers' production risk.

Chapter 3. Data and Methodology

As clarified in the previous parts, the possibility of effectively managing yield risk through index-based contracts stands on the property that the weather-index is highly correlated with the agricultural production. This thesis proposes the construction of such a weather-index through the fit of historical data on agricultural yields with a multiple linear regression of *pseudo* weather variables obtained through principal component analysis of actual weather data. In this particular context, linear regression is therefore used to reveal the relationship that, on average, existed between yields and historic weather data, and to use the fitted models to predict yields as the definition of the suitable weather indexes.

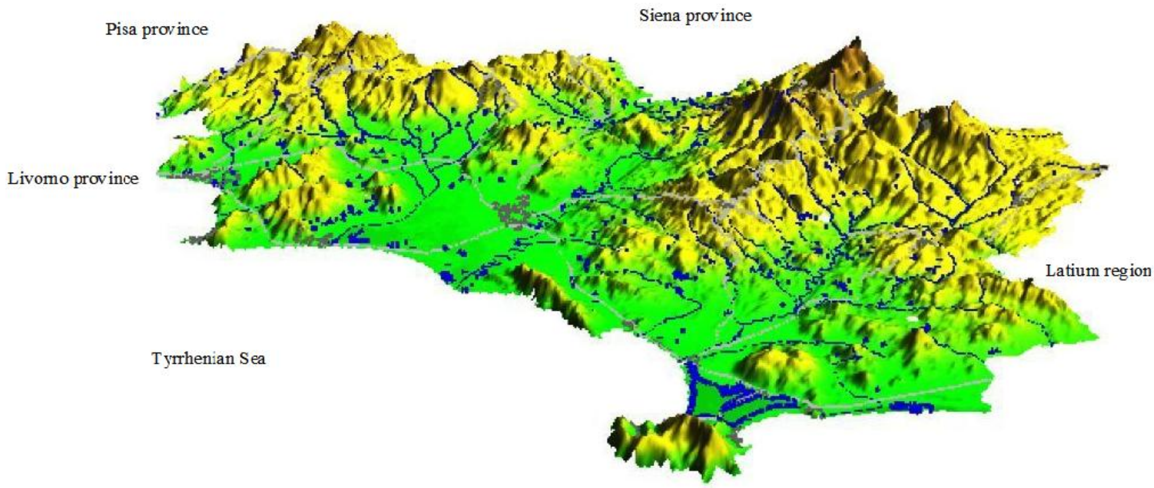
A preliminary review of the Italian province of Grosseto is provided by two introductory sections. The first describes the province by its physical and climatic profiles. The second focuses on the structural aspects of the agricultural sector and offers a description of agriculture production of the province of Grosseto.

The model is presented in several sections, describing the processes of: variable selection (both weather and yield data), variable reduction through application of the principal component analysis and linear regression fit of agricultural yield data. A final section presents the results.

3.1. **Physical geography and climate of Grosseto province**

The distribution of the land relief of the region (orography), covering a surface of 1,739 square miles or 450,400 ha, includes flat lands near the coast, rolling hills and valleys along its interior and the Appennine range on the border with Siena province (see figure 2).

Figure 2: Orography of Grosseto province

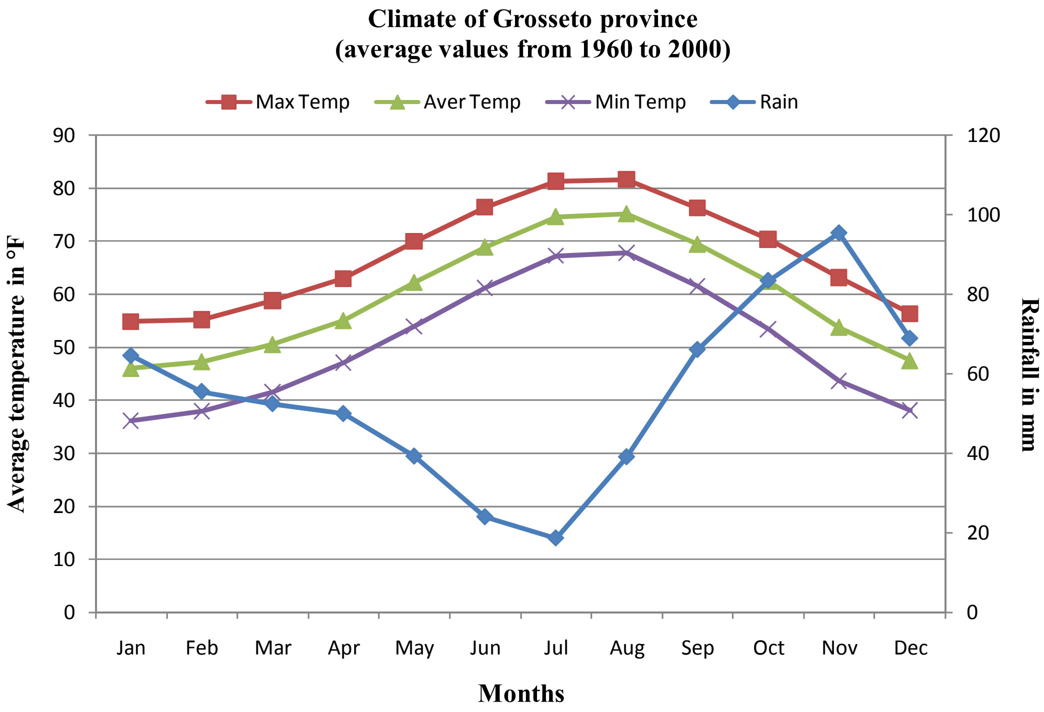


Source: Agrifauna Italia

The Ombrone, Albegna and Fiora rivers cross the valleys, where sun exposure reaches eleven hours during the summer season, creating an ideal micro-climate for wine grapes. The climate of the province varies throughout its extension. On the coast a Mediterranean climate prevails and the average temperature ranges between 50 (10) in the winter and 75.2°F (24°C) in summer. The interior area of the province is characterized by a continental climate, with average temperatures in the range of 37.4°F (3°C) – 70°F (21°C) between the winter and summer seasons. The coexistence of Mediterranean and continental climates provides the hilly areas with optimum weather conditions for cattle-breeding, wine grapes and wheat crops. However, wine grapes and wheat crops are often damaged by frost and hail during the spring and by fires occurring in the summer. In fact, the most common crop-yield insurance contracts are designed to hedge farmers against the frost and fire.

The average temperatures and rainfalls of the province, from 1960 to 2000, are summarized in the following figure, where the overlapping graphs give an intuitive indication of the strong correlation between temperature and rainfall trends.

Figure 3: Annual average temperatures and rainfalls trends in Grosseto province



Source: Regional Agency for the Development and Innovation in Agriculture (ARSIA), Tuscany

Indeed, the average rainfall is negatively correlated with temperatures, except for December, indicating that droughts are likely to occur during the summer season. In fact, in 2003, no rain was recorded during 125 days, from April 22th and August 25th in the hilly areas and less than 1 mm of rain for 40 summer days in the coastal areas. Droughts do not jeopardize crop production, rather they are responsible for considerable damages to the quality of the harvesting and, in particular periods[4], might reduce yields.

[4] For cereals, a drought in between spring and summer might cause yields reduction.

3.2. **Agriculture in Grosseto province**

The total utilized agricultural area and the shares destined to the main crops in the province of Grosseto are listed as follows:

Table 1: Utilized agricultural area in the province of Grosseto

	Mountain	Hill	Plain	Total UAA
Annual crops	9,045 *(47.24%)*	121,089 *(76.39%)*	25,294 *(87.45%)*	155,429 *(75.24%)*
Tree crops	3,364 *(17.57%)*	19,567 *(12.34%)*	2,492 *(8.62%)*	25,423 *(12.31%)*
Grasses and pastures	6,738 *(35.19%)*	17,852 *(11.26%)*	1,140 *(3.94%)*	25,729 *(12.45%)*
Total UAA	19,147	158,508	28,926	206,5809

Source: Italian Institute of Statistics (ISTAT), Fifth Agricultural Census, 2000
Note: Percentages refer to column values

Plain and hilly areas are mostly devoted to annual crops, which in total occupy more than 75% of the total utilized agricultural area. Tree crops are particularly concentrated in hilly areas whose extension covers the almost the 10% of the total utilized agricultural area. The remaining 15% of the total utilized agricultural area is distributed in mountains and plains.

Among annual crops and fruits cultivated in hill and plain areas, cereals, olive and wine grapes are the most common. In particular, durum and soft wheat jointly exceed 75% of the total cereals' utilized agricultural area and 35% of the annual crops' utilized agricultural area. Mountains are covered by woods in which the production of dried fruits is prominent. Table 2 illustrates the aforementioned distribution of the total utilized agricultural area per crop. Durum and soft wheat predominate because of high subsidies per hectare provided by the European Union since 1994. These EU subsidies provided incentives for expanded cultivations (also those non-agronomically elected for wheat crops growing) and cultivation of wheat without proper rotation.

Table 2: Distribution of the main crops' utilized agricultural area in the province of Grosseto

	Mountains	Hills	Plains	Total
Durum wheat	2,821	39,993	9,131	51,945
% on cereals' area	*61.5*	*71.8*	*79.2*	*72.3*
% on total UAA	*14.7*	*25.2*	*31.6*	*25.1*
Soft wheat	235.3	2,477	787	3,500
% on cereals' area	*5.1*	*4.4*	*6.8*	*4.9*
% on total UAA	*1.2*	*1.6*	*2.7*	*1.7*
	Mountains	Hills	Plains	Total
Olive	1,890	12,371	1,689	15,950
% on tree crops' area	*56.2*	*63.2*	*67.8*	*62.7*
% on total UAA	*9.9*	*7.8*	*5.8*	*7.7*
Grape	216.5	5,022	583	5,822
% on tree crops' area	*6.4*	*25.7*	*23.4*	*22.9*
% on total UAA	*1.1*	*3.2*	*2.0*	*2.8*

Source: Italian Institute of Statistics (ISTAT), Fifth Agricultural Census, 2000

The mono-culture of wheat crops without rotation have implied over time a reduction in yields, in particular for durum wheat. Olive and wine grape, grown mainly in hilly areas, jointly amount to more than 85% of bearing-fruit plants and represent the second most important crops of the province. Net profitability of the main crops is presented in table 3. Such presentation provides a comparison between the average crops' profitability with and without the direct support.

Table 3 clearly shows the differences between presence and absence of support in average net incomes for the main crops. For durum and soft wheat, the presence of supports increased the average net income by four and two times respectively, while for grape the discrepancies are less remarkable.

Table 3: Net profitability outline (€/ha) of the main crops in the Italian province of Grosseto

	Mountain		Hill		Plain	
	w/ supp	w/out supp	w/ supp	w/out supp	w/ supp	w/out supp
Grape						
average	€ 4,958	€ 4,270	€ 4,676	€ 4,135	€ 4,441	€ 3,957
stdev	*2503.41*	*2496.39*	*1735.31*	*1680.23*	*1518.46*	*1371.12*
CV	0.505	0.585	0.371	0.406	0.342	0.347
Durum wheat						
average	€ 836.06	€ 195.14	€ 842.61	€ 237.10	€ 822.00	€ 219.08
stdev	*121.27*	*111.36*	*99.74*	*90.00*	*80.61*	*72.71*
CV	0.145	0.571	0.118	0.380	0.098	0.332
Soft wheat						
average	€ 393.94	€ 128.95	€ 470.74	€ 217.31	€ 676.72	€ 366.25
stdev	*109.54*	*146.71*	*141.09*	*146.46*	*112.20*	*139.34*
CV	0.278	1.138	0.300	0.674	0.166	0.380

Source: own elaboration on 1996-2000 data - Italian Farm Accounting Data Network (FADN)

Comparing the coefficients of variation (CV) between presence and absence of support, table 3 clearly shows that the support system is able to hedge income variations of durum and soft wheat. The EU supports do not reduce variability for grape's average net income, although the variations in net income are wider. In the light of a declining support system, mainly for wheat, and a higher and variable profitability of grape, these crops have been selected for testing a new methodology for the construction of weather indexes to be used as assets of insurance derivative contracts.

3.3. **Variable selection**

Ideally, to design an efficient index based insurance contract, one would need series of historic farm-level yield and weather data. Unfortunately, individual time series on yields are not publicly available, and it is not common for a farm in Italy to have a weather station within the farm.

The level of aggregation of the agricultural yield data used in this thesis is the provincial level. Provincial averages of crop yields have been obtained from the RICA database of the Italian institute of agricultural economics (INEA), which is part of the European Union Farm Accounting Data Network (FADN), whose task is to select and monitor samples of farms representative of a particular agricultural zone at the level of the region.[5]

These data present some problems. First, provincial data may not be representative given that representativeness of the FADN is ensured only at regional level; second, by using data aggregated at the provincial level, differences in performance of individual farmers located in areas like coastal plains, hills and interior mountains can be hidden, and this is a fact to be considered when evaluating the results. Moreover, given that for regulatory reasons, farmers can participate to the FADN selection only for a limited lapse of time, there is a lack of continuity in the sample that is used to form the provincial series.

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[5] Within the European Union, the classification of regions is done through the "Nomenclature of Territorial Units for Statistics (NUTS).
See: http://ec.europa.eu/eurostat/ramon/nuts/home_regions_en.html

Unfortunately, for privacy reasons, data at the individual farm level are not made available and therefore there is no feasible way to control for any lack of representativeness.

The dependent variable considered for the weather index is *yield* and the selected crops are wine grapes, soft and durum wheat. Yield data have been analyzed to test for the presence of a significant trend. The following linear model is estimated to test for the significance of a linear trend:

$$Y_t = \alpha + \beta\left(t - 1989\right) + e_t,\ t = 1990, \ldots 2004$$

A simple t-test on the hypothesis H_0: $\beta = 0$ is then performed to test for significance of the linear trend. In case the hypothesis $\beta = 0$ cannot be rejected (only for durum wheat, where a *negative* trend is found), the trend component is calculated as:

$$Y_t^{tr} = \hat{\alpha} + \hat{\beta}\left(t - 1989\right)$$

where $\hat{\alpha}$ and $\hat{\beta}$ are the estimated coefficients, detrended yield time series are then calculated as:

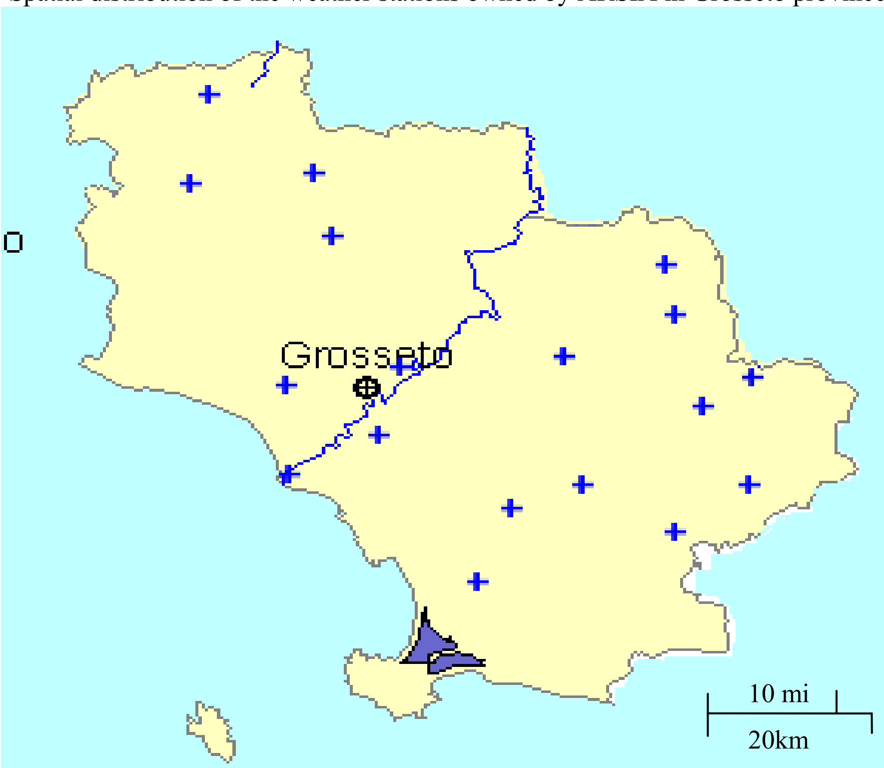
$$Y_t^{\det} = Y_t - Y_t^{tr} + \overline{Y}$$

where Y_t are actual yields , $\overline{Y}$ is the average yield and $Y_t^{\det}$ are the detrended values. Results of the statistical test, actual and detrended time series of yields from 1990 to 2004, and the relative descriptive statistics are listed in table A.1. in the Appendix.

The meteorological data have been obtained from several weather stations uniformly located throughout the province. The stations are owned and managed by the Regional (Tuscany) Agency for the Development and Innovation in Agriculture (ARSIA) which publishes daily time series of the most common weather variables, such as maximum and minimum temperature, rainfall and maximum and average humidity. In 1990 ARSIA owned only a few stations and, during the following four years, it expanded the network to 18 units. Thus, not all stations have daily time series in the early years of the sample. The number of missing observations per weather station is shown in table A13 in the Appendix. The column entries of table A13 represent the number of missing daily observations per weather variable. The illustration of the spatial distribution of the weather stations in the Grosseto province is given in figure 4.

For purpose of inference, annual crop yields must be matched with meteorological data. Starting from daily weather observations, annual weather variables have been constructed.

Figure 4: Spatial distribution of the weather stations owned by ARSIA in Grosseto province



Source: Regional Agency for the Development and Innovation in Agriculture (ARSIA), Tuscany

First, month-variables of annual observations were created: for each weather station, the following variables have been created for each month:

- monthly maximum temperature – $\max_i \mathrm{Tmax}_i$
- monthly average of the maximum temperatures - $n^{-1}\sum_{i=1}^{n} \mathrm{Tmax}_i$;
- monthly minimum temperature – $\min_i \mathrm{Tmin}_i$;
- monthly average of the minimum temperatures – $n^{-1}\sum_{i=1}^{n} \mathrm{T\,min}_i$;
- monthly average temperature – $n^{-1}\sum_{i=1}^{n} \left[\left(\mathrm{Tmax}_i + \mathrm{T\,min}_i\right)/2\right]$;
- monthly average maximum level of humidity – $n^{-1}\sum_{i=1}^{n} \mathrm{Hummax}_i$;
- monthly maximum humidity – $\max_i \mathrm{Hummax}_i$;
- monthly cumulative rainfall – $n^{-1}\sum_{i=1}^{n} \mathrm{Prec}_i$;
- number of rainy days in the month.

with *i* representing daily observations.

Temperature is measured in degrees Celsius; humidity has a percentage range between 0 and 100, rainfall is measured in millimeters, and rainy days measured in integer numbers. All the variables are continuous measurements, except rainy days which is discrete. As expected, the created weather month-variables of annual observations present missing values, especially in the early years of the series. The resulting missing observations have been replaced with the average of the remaining annual observations of the respective month-variable. For example, in the weather station of Stacciole, the missing maximum temperatures for February from 1990 to

1992 are filled by taking the average of all the maximum temperatures for February from 1993 to 2004 in the same weather station of Stiacciole.

The nine variables were chosen with the aim of delineating a climatic pattern of the province, as to subsequently match crop yields and weather variations. It must be recalled that the purpose of this thesis is neither to understand the relationships between the aforementioned weather events nor to discover which of the adverse events affects agricultural yields more and why.

With 18 weather stations, 12 months and 9 weather variables, there are a total of 18x12x9 = 1944 monthly variables. A sketch of the layout of the weather variables is given in table A14 in the Appendix.

Second, given that the yields cannot be affected by future weather events, and since the annual production cycle of crops does not necessarily correspond to the calendar year, the dates of crop production and weather variables must be matched to obtain reasonable subsets of variables. For soft and durum wheat which are sown between August and September and harvested in June in Italy, relevant weather information is considered from August of the previous year to May of the harvesting year[6]. The subset of relevant variables for wheat (wheat dataset) therefore contains 18x9x10 = 1620 variables. For grapes, observations on weather conditions from January to September of the harvest year have been considered. Such period corresponds to the growing stages from the appearance of flower buds to the grape harvesting[7]. The grape subset contains thus 18x9x8 = 1458 variables (grape dataset).

[6] One month before the harvesting the caryopsis is already ripe. During the last month there is stage of drying process and only a fire could jeopardize the crop.
[7] During the period between grape harvesting and appearance of flower buds (winter), vines remain in a dormant status.

With only 15 observations on yields, from 1990 to 2004, it would be impossible to make any inference by using such large numbers of different variables. Therefore, the need arises to synthesize the information contained in the 1944 variables into a smaller number of variables.

The process of data reduction is presented in the following section.

3.4. **Variables "reduction"**

In order to reduce the number of variables while retaining most of the information they carry, a natural choice is to perform a principal component analysis.

Principal component analysis is a descriptive statistical method mainly applied to reduce the number of explanatory variables in a dataset and to explore the possible underlying structure of a large set of variables. According to Jolliffe (2002), principal component analysis is one of the most applied techniques in a wide variety of disciplines, such as agriculture, psychometrics, facial recognition, gas chromatography, genetics, climatology and meteorology (spatio-temporal atmospheric science data) and social sciences.

The dimensionality reduction process is conducted through a linear transformation applied to variables, aimed at retaining as much variation as possible. A lower dimensional set of independent (or uncorrelated) principal components will be *extracted* and it is considered to be an *underlying structure* of the old one. Hence, it is able to represent or to "transfer" the inner relationships between the original sample variables onto a new system of coordinates[8].

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[8]The software used to perform principal component analyses is SPSS®.

The application of principal component analysis to the meteorological variables considered in this thesis is motivated by the fact that the weather variables are likely to be highly correlated to each other, and therefore the original dataset would certainly contain redundant information. In particular, having only 15 observations, there would exist a 15-dimensional space capable of fully representing the variability contained in the original datasets.

Principal components are constructed in a way that they are uncorrelated with each other but correlated to the original variables. Each original variable gives a contribution to the variation of every single component. Such contribution is usually called *factor loading*. The "underlying meaning" of each component can be inferred by ranking the contributions in a decreasing order and excluding contributions lower than a certain magnitude (usually a factor loading lower than 0.4 is considered a scarce contribution).

In this study, the principal components are correlated to p = 1620 and 1458 spatial-temporal variables respectively. With such a large number of variables, it would be a painstaking task, and maybe not possible, to give a meaningful "meteorological" interpretation of each principal component. This is not new to users of principal component analysis: Jolliffe (2002) in fact, remarks the possibility that the interpretability of the principal components could be non-obvious and sometimes not even possible.

To the purpose of this work, this is not a major drawback, given that the objective is to use the principal components in subsequent analysis to form an index which is correlated with yields.

Coded in the standard routines implemented in the SPSS® software, there are three different methods to extract principal components, each of them producing scores with mean zero:

1. Anderson-Rubin: it gives uncorrelated scores with standard deviations equal to one;
2. Bartlett: it gives unbiased scores, correlated only with their own factors, with standard deviation equals to one;
3. Regression: it gives scores that could be correlated, with variance equals to the square of the multiple correlation between the estimated factor loadings and the true factor values.

These three methods produce equivalent *factor scores* when principal component analysis is applied. In factor analysis (FA), instead, those methods would produce different estimates of factor scores. Factor scores are the *pseudo-observations* (cases) of the variables obtained from the principal components. Therefore, each new principal component, used as an explanatory variable in the subsequent analysis, has 15 observations like the sample ones.

As expected, for both crops, principal component analyses show that the first 14 principal components will account for 100% of the variation of the datasets. But it is not necessary to use all fourteen of them to predict yields. In any of the extracting procedures, principal components are extracted in decreasing order of explained variance. The hope in conducting principal component analysis is that the first *few* components could account for a large share of the total variability.

The question arises of how many components to retain. One criterion of choice suggests to retain only principal components having eigenvalues greater than one, based on the consideration that such components would account for more variation than the average original variables. Another typical choice criterion adopted by researchers is to set an *a priori* range of variation which, in turn, will determine how many principal components to retain for further analysis. Common cut-off ranges are between *70*% and *90*% of the total variation. In other words, if the researcher sets a cut-off of 80%, he would retain the minimum number of principal components capable of accounting for at least 80% of the total sample variability. The choice of the cut-off, however, is to some extent arbitrary, and it could change according to the particular relationships between sample variables and principal components (Jolliffe, 2003)[9].

Given the purpose of relating yields variations to weather variability, the criterion adopted here that might lead to a convenient selection of principal components is to retain the particular subset of principal components for which the adjusted R^2 of the yield-fitting model is the largest, conditional on explaining at least 80% of the of variation of the original sample.

[9] For more details, see I.T. Jolliffe, *Principal Component Analysis*, (2nd Ed.) Sect. 6 – par. 6.1.

3.5. **Yield fitting**

Although many different functional forms might be chosen to model the complex relationship between yield and weather variations, the limited number of observations does not allow for specification searches. As a simple yet flexible enough form, a linear relation between yield and weather variability is assumed here.

In order to discover the linear combination of weather variables that best follows the variations in yields, a linear regression is calculated between yields as the dependent variable, and the first n principal components as regressors.

By indicating the sets of explanatory variables, extracted from principal component analysis, as $G = \{\mathbf{g}_1, \ldots, \mathbf{g}_n\}$ and $W = \{\mathbf{w}_1, \ldots, \mathbf{w}_n\}$ for grape and wheat respectively, the following multiple linear regressions have been estimated:

1. $\mathbf{Y}_{GR} = \mathbf{G}\boldsymbol{\beta} + \mathbf{e}$
2. $\mathbf{Y}_{SW} = \mathbf{W}\boldsymbol{\delta} + \mathbf{e}$
3. $\mathbf{Y}_{DW} = \mathbf{W}\boldsymbol{\omega} + \mathbf{e}$

where $\mathbf{Y_{GR}}$, $\mathbf{Y_{SW}}$ and $\mathbf{Y_{DW}}$ are vectors of 15 observations on yields and $\boldsymbol{\beta}$, $\boldsymbol{\delta}$ and $\boldsymbol{\omega}$ are the vectors of coefficients.

Goodness of fit and F-test are the only critical statistics through which the reliability of such weather-indexes can be checked. In general, it might be important to consider the parameter estimates and their standard errors, but, once again, the concern here is on the ability of the overall function to closely follow yields, rather than on interpretation of particular coefficients. On the other hand, because the explanatory variables are not easily interpreted, also the meaning of each single estimated coefficient would be difficult if not impossible to interpret. Instead, the value of the adjusted R^2, which gives a measurement of the goodness of fit, provides a reliable and objective measure of the correlation between the hypothesized weather indexes and yields.

A high goodness of fit will imply that the index is able to follow the variations of yields. The more explanatory variables are added to the model, the higher is the flexibility of the model. Unfortunately, the limited number of observations (only 15 years) does not allow inclusion of many variables, lest the model would overfit for lack of degrees of freedom.

In the next chapter the results of this innovative methodology are discussed and compared to the results of an alternative method commonly proposed in literature, that is the use of growing degree days and cumulative rain to predict yields.

Chapter 4. Results and comparison

4.1. **Efficient weather index obtained through linear regression on principal components**

Principal component analysis was applied to weather variables in both grape and wheat subsets. As expected, the correlation matrices are singular, producing only 14 eigenvalues different from zero, which account for 100% of the total variation of the subsets. Tables A2.a and A2.b report the description of the variance explained by each eigenvalue. For both principal component analyses, the first ten principal components explain more than 90% of the variability in the sample.

The sensitivity analysis on the number of principal components to include in the regressions, showed that the highest value of adjusted R^2 is produced by nine principal components for grape and durum wheat and by eight principal components for soft wheat, as depicted in figures A1.a, .b and .c, in the Appendix.

The principal components included in the regression on grape yields account for 87.7% of the total variation of the grape weather variable subset, while those included in the regressions on soft and durum wheat yields account for 84.4% and 88.8% respectively.

From the component matrices in Tables A3.a and A3.b it might be possible to provide an interpretation to every single principal component, by looking at their ordered entries (factor loadings), whose values express the relative weight of the sample weather variables on the principal components. As mentioned before, the interpretation of the principal components, although feasible and worthy, would require the expertise of a weather expert and would be beyond the objectives of this research. Nevertheless, a possible interpretation is given in tables A4.a and A4.b.The results of the regressions, reported in tables A5.a, .b and .c provide all the necessary information to construct the indexes and to check their correlations with the respective yield variables. Even though the parameter estimates and their individual significance are not of peculiar importance, their values[10] are discussed.

The weather index for *grape yields*, shown in figure A2.a, can be constructed as:

$$\hat{Y}_{GR} = 94.59^{*} + 14.70^{*}\mathbf{g}_1 - 1.16\mathbf{g}_2 + 5.98\mathbf{g}_3 + 10.89^{**}\mathbf{g}_4 - 7.66\mathbf{g}_5 + 0.27\mathbf{g}_6 + 7.80\mathbf{g}_7 - 16.76^{*}\mathbf{g}_8 + 20.07^{*}\mathbf{g}_9$$

The F value in regression 1 (*grape*) is statistically significant at 5% level (p-value equal to 0.025) suggesting the hypothesis that all coefficients are not different from zero must be rejected; the parameter estimates cannot be interpreted, but the t-tests show that $\mathbf{g}_{1,}$ $\mathbf{g}_8$ and $\mathbf{g}_9$ are statistically significant at 5% level and $\mathbf{g}_4$ at 10% level; the R^2 of the regression, 0.924, indicates a high goodness of fit.

The weather index for *soft wheat yields*, shown in figure A2.b, can be constructed as:

$$\hat{Y}_{SW} = 28.26^{*} + 3.62^{*}\mathbf{w}_1 - 2.26^{*}\mathbf{w}_2 - 1.06\mathbf{w}_3 + 0.11\mathbf{w}_4 + 0.78\mathbf{w}_5 - 0.46\mathbf{w}_6 - 1.78\mathbf{w}_7 + 2.93^{*}\mathbf{w}_8$$

In regression 2 (*soft wheat*) the F value is statistically significant at 10% level (p-value equal to 0.064); t-tests for parameter estimates show that $\mathbf{w}_{1,}$ $\mathbf{w}_2$ and $\mathbf{w}_8$ are statistically significant at 5% level, while the other ones have significance at a level

[10] * Statistically significant at 5% level
** Statistically significant at 10% level

much more higher than 10%, resulting not significant; the R^2 of the regression, equal to 0.832, show a reasonable goodness of fit.

The weather index for *durum wheat yields*, shown in figure A2.c, can be constructed as:

$$\hat{Y}_{DW} = 29.77^{*} + 4.23^{*}\mathbf{w}_1 - 2.16^{*}\mathbf{w}_2 + 0.50\mathbf{w}_3 - 0.27\mathbf{w}_4 - 1.35\mathbf{w}_5 + 0.43\mathbf{w}_6 + 2.33^{*}\mathbf{w}_7 + 1.24\mathbf{w}_8 + 1.45\,\mathbf{w}_9$$

In regression 3 (*durum wheat*) the F-test is statistically significant at 10% level (p-value equal to 0.053); t-test for parameter estimates show that $\mathbf{w}_1$ and $\mathbf{w}_7$ are statistically significant at 5% level, while $\mathbf{w}_2$ at 10% level; the R^2 is equal to 0.893, showing a reasonable goodness of fit.

It can be noticed that, with only few significant parameter estimates, the R^2 of the regressions are high. This evidence confirms the hypothesis that a low number of degrees of freedom actually affects the goodness of fit causing an overfitting. The magnitude of the coefficients of determination ascertains the capability of the indexes to predict observed yield in sample.

A test of the predictive ability of the model is performed. A principal component analysis is conducted on weather variables excluding the last observation, year 2004. The weather variables, with observations from 1990 to 2003, obtained from principal components have been used as explanatory variables in three regressions. The factor loadings of the resulting principal components have been then used to predict *out-of-sample* the factor loading "2004" for each principal component. The parameter estimates of the regressions and the predicted factor loadings for "2004" produced the out-of-sample prediction of yields in 2004.

The out-of-sample prediction accuracy is illustrated in table 4. Assuming a normal distribution for yield, the extent of the confidence intervals suggests that the accuracy of the predictions for each crop is reasonable, though the difference between actual and predicted values for durum wheat is remarkable.

Table 4: Out-of-sample prediction accuracy for grape, soft and durum wheat yields*

yields	Grape	Soft wheat	Durum wheat
actual value	108.33	35.00	42.37
predicted value	113.97	29.78	32.15
% difference	5%	15%	24%
standard deviation[11]	18.79	4.38	4.63
confidence interval at 95% level	[65.66 - 162.29]	[17.63 - 41.94]	[19.30 - 45.01]

Source: own elaboration
*Note: Durum wheat yields are detrended observations

Even if the normal distribution does not prove as sufficiently appropriate as the beta for modeling actual yield distributions, at least one study has shown the assumption of normality of yields distribution cannot be severely rejected (Ker and Coble, 2003). Given that in the literature there is still uncertainty about modeling actual yields distribution, the hypothesis of normality has been tested by implementing the D'Agostino-Pearson K^2 *omnibus* statistic on the regressions' residuals. The test results, reported in tables A5.a, .b and .c, indicate the null hypothesis of normality of yields is strongly rejected. As such, the estimated standard errors may not be consistent.

[11] The standard deviation has been computed as $stdev = \sqrt{\hat{\sigma}^2 \left(I + X_{2004} \left(X'X \right)^{-1} X'_{2004} \right)}$, with X_{2004} as the *out-of-sample* predicted case "2004" for each principal component; $\hat{\sigma}^2$ and X are in-sample variance and data values.

In order to find a more parsimonious model, three linear regressions were run by regressing yields on only statistically significant principal components of the previous regressions. The results, in tables A6.a, .b and .c in Appendix, do confirm that those principal components prove to be statistically significant, though the in-sample goodness of fit does not fully satisfy the weather-index requirements. Hence, the in-sample predictions of the indexes, in figures A3.a, .b and .c in the Appendix, do not closely follows yields variations, especially yields shortfalls.

Again, the availability of longer time series would allow more degrees of freedom in the application of both principal component analyses and linear regressions with less impact on the goodness of fit.

Indeed, even if a longer time series included important climate change, such considerable variations could be accounted for by principal components. In this sense, principal component analysis proves to be a powerful analytical tool, especially in disciplines like climatology in which the inner relationship between weather variables is not easy to model. Instead, more can be done to explore the effects of technological progress both on agricultural production, increasing yields and resistance to adverse weather events, and climate, lowering the emission of polluting elements considered to be the most important cause of climatic changes.

The availability of longer time series on yield and weather variables is the only remedy to avoid overfitting and produce effective out-of-sample predictions. Again, those regressions are not intended to explain or understand the reasons for residual yield variation, but to design a weather index that is positively correlated to the yield. The indexes obtained will be used to perform an analysis of sensitivity on farmers' willingness to pay for a weather index-based insurance contract.

However, the availability of short time series and provincial level data makes this experimental methodology not quite reliable. The comparison of the latter with a different approach would clear legitimate doubts about the results of the principal component analyses and the subsequent regressions. Therein, a different linear model is applied to fit yields with growing degree days and cumulative rain. The "growing degree days" approach for constructing a weather index is presented in the next section.

4.2. **Growing Degree Days method**

The indexes constructed by regressing grape, soft and durum wheat yields on the weather variables obtained from principal components provide good in-sample predictions, but the limited possibility of testing the ability to predict out-of-sample values, due to the limited number of available observations to conduct the test, cannot exclude the possibility of overfitting due to few degrees of freedom. An alternative way of assessing the desirability of the proposed index is to compare it with the performance of an index constructed through a different approach. Yields have been regressed on two weather measurements that have been proposed, in the literature (Vedenov and Barnett, 2004; Skees, Barnett, Ibarra and Syroka, 2006), as likely to be highly correlated with agricultural production. The first one is the so called number of *growing degree days* (GDD) and the second one is the *cumulative rain* (CR).

GDD is a measure of cumulative temperature which expresses the amount of heat a plant needs to complete its phenological stages. GDD are used in agronomy generally to forecast the time of crops' growth and to program the growth time of crops in a controlled environment, such as in greenhouses. In this work, the GDD have been computed according to the following formula:

$$GDD = \sum_{i=1}^{n} \frac{T_{i\max} + T_{i\min}}{2} - T_{base} \,,$$

where n represents the number of days of the plant's cycle, $T_{\max}$ and $T_{\min}$ are daily temperature values, maximum and minimum of the day respectively, and T_{base} is the temperature threshold value under which the plant have no vegetative activity. T_{base} for grape is 10°C, T_{base} for cereals, including soft wheat, is 0°C (Skees, Barnett, Ibarra and Syroka, 2006). The agronomical period considered for grape crop goes from the vegetative resumption to the harvesting, corresponding to the period January-September. The agronomical period considered for soft wheat goes from the seeding to one month before the reaping, corresponding to the period August-May.

GDD, however, is an index related directly to the growth of the plant, it does not necessarily express a direct relationship between temperature and yields. There could be cases when the plant has a low productivity in spite of its successful growth. Such cases are common especially during rainy seasons when rain and humidity create an ideal micro-climate for fungi growth. Therefore, the cumulative rainfall (in millimeters) (CR) for the concerned periods has been computed as follows:

$$CR = \sum_{i=1}^{n} r_i \,,$$

where r is the amount of rain and n is the number of days in the concerned period, and used as explanatory variable in the regressions.

GDD and rainfall variables have been computed using daily data from each of the eighteen weather stations. The explanatory variables in the regressions are *meanGDD*, *varGDD*, *skewGDD* and *meanRain*, representing respectively average, variance and skewness of GDD and average of the cumulative rainfall computed over the 18 weather stations for each year. The two databases obtained are presented in tables A7.a and A7.b.

Three regressions on each yield variable have been run:

1. $yield = \alpha + \alpha_1 meanGDD + \alpha_2 meanRain + e$
2. $yield = \alpha + \alpha_1 meanGDD + \alpha_2 varGDD + \alpha_3 meanRain + e$
3. $yield = \alpha + \alpha_1 meanGDD + \alpha_2 varGDD + \alpha_3 skewGDD + \alpha_4 meanRain + e$

The degrees of freedom in the regressions on grape yields, having 15 observations, are in turn 12, 11 and 10. Those in the regressions on soft and durum wheat are 11, 10 and 9, given 14 observations. Therefore, the risk of overfitting in these regressions is lower than when using principal components as explanatory variables.

4.3. **Results**

None of the regressions run on grape yields appears to give a reliable index. In fact, the p-values of the F-tests are higher than 30% significance level, none of the parameter estimates are significant, and the R^2 are low (Table A8.a). The predicted values generated by the three regressions, in figures A4.a, .b and .c, do not follow appropriately the variation of the actual values.

The regressions on soft wheat yields, from the first to the third respectively, present increasing p-values of the F-test, from less than 5% to 11% of significance, and increasing R^2. The unique parameter estimate resulting significant at 5% level in each regression is the one referred to the *meanRain* variable (Table A8.b). The predicted values, as reported in figures A5.a, .b and .c, although following the variation of the actual observations, present large discrepancies at peak levels, thereby the resulting index could not be considered a good predictor of extreme yields.

The first two regressions on the de-trended durum wheat yields do not present any significant parameter estimate (Table A8.c). In the third regression, the parameter estimates relative to *skewGDD* and *meanRain* result significance at 10% level and the coefficient of determination, equal to 0.44, expresses a reasonable goodness of fit. Here too the in-sample predicted values, depicted in figures A6.a, .b and .c, although following the variation of the actual yields, over-predict yields shortfalls. Out-of-sample predictions of yields in 2004 have been computed for all the regressions of each crop. The out-of-sample prediction accuracy, illustrated in tables A9.a, .b and .c in the Appendix, show that for soft and durum wheat all the predicted values are lower than the lower bound of the respective confidence intervals. Each out-of-sample prediction of year 2004 for grape remarkably differs from the actual yield value and the extents of the confidence intervals suggest that the accuracy of the predictions in each regression is low. Even if the number of degrees of freedom does not affect the goodness of fit in each regression, the GDD model does not seem to be superior to the experimental model presented before.

Next chapter introduces and discusses the performance of possible insurance contracts, where indemnity payments are linked to the values of weather indexes constructed through the previously introduced model.

Chapter 5. Feasibility analysis of index-based weather derivatives

The weather indexes constructed by fitting yield variables with weather variables obtained by principal component analysis provide good in-sample predictions of the respective observed yields. In particular, they are able to forecast low observed values rather accurately, as shown in figures A2.a, .b and .c in the Appendix. Such indexes, however, cannot be proven accurate in predicting out-of-sample yields for lack of information. Nevertheless, a feasibility study of a local yield crop insurance contract based on those weather indexes can be performed.

5.1. **Index-based insurance contract**

The hypothesized contract would pay indemnities every time the weather index falls below a pre-fixed trigger value I*, such that the amount of the compensation will be I* – I. For example, supposing a trigger value I* equal to 75 for grape, 20 for soft wheat and 25 for durum wheat expressed as q/ha, from figures A7.a, .b and .c in the Appendix it can be noticed that, over the period considered, the contracts for grape and durum wheat yields would have paid indemnities four times and the one for soft wheat yield twice.

Then, representative farmers with yields equal to the average of those included in the sample data, owning such a contract, would have been able to eliminate the risk that their yields fell below 75 q/ha for grape crop, 20 q/ha for soft wheat crop and 25q/ha for durum wheat crop respectively. Compared to a pure yield crop insurance contract, both weather index contracts would have slightly overcompensated in the years 1994, 1997 and 2001, for grape farmers, and in the years 1998 and 2003, for soft wheat farmers. Indeed, such contracts, constructed at the provincial level, would be as effective as an area-yield insurance contract. There would be residual basis risk to the extent that there would be a difference between individual yields and those predicted by the index.

A perfectly competitive market would made such an insurance system potentially feasible depending solely on the difference between the farmers' willingness to pay for such a contract and the predictable premium. Since the contract is based on the index, not on actual yields, insurance companies will not have to bear administrative and management costs, such as loss adjustments and monitoring, and the premium could be very close to the actuarially fair premium.

Knowing the long-run distribution of yields and weather variables, the actuarially fair premium can be estimated as the contract's expected indemnity. Farmers' willingness to pay, instead, depends on their degree of risk aversion and on their perception of risk exposure. Indeed, if the historical distributions of yields and index were the same, that is if there were a perfect correlation between yields and index in the long run, the willingness to pay for a premium of a risk neutral farmer would exactly be equal to the actuarially fair premium and no market would exist. It follows that any degree of risk aversion or any pessimistic misperception of the actual yield risk by farmers would make the willingness to pay of farmers higher than the actuarially fair premium.

One of the most important advantages of an index-based insurance of the kind presented is that it would reward virtuous farmers, in that the incentive is maintained to use farmers' ability to avoid a shortfall of yields any time the index predicts values lower than the threshold. Indeed, risk-averse farmers possessing better information on how to control yields might actually express a willingness to pay more than the actuarially fair premiums. Hence, since indemnities are computed according only on the value the index predicts, they can receive a higher benefit if they know they can adopt agronomic corrective or protective measure in case the index falls below the threshold. Such a mechanism for yield-risk protection gives incentives to farmers for reducing their yield risk exposure, completely eliminates incentive problems due to moral hazard and provides incentives for a "virtuous" selection. Farmers with a low risk exposure will have a higher incentive to participate, as opposed to the adverse selection which usually afflicts traditional crop insurance programs.

5.2. **Simulation and sensitivity analysis**

Because of the limited length of the available time series, the precise distribution of the identified weather indexes, as well as the exact actuarially fair premium cannot be determined with high accuracy. The availability of longer time series for the concerned weather stations would make a more accurate characterization of the indexes' distributions possible, for example through a kernel analysis, providing the required conditions for the actuarially fair premium to be computed as the expected revenue from the contracts over a long lapse of time.

In this thesis, the fair premium is computed by a simulation. As a first approximation, the underlying distribution of the indexes has been estimated by re-sampling from a normal distributions with the same mean and variance of the available series (μ = 94.6 and sd = 35.66 for grape index; μ = 28.26 and sd = 6.38 for soft wheat index; μ = 29.77 and sd = 5.83 for durum wheat index). The simulation has been conducted extracting n = 500,000 random values I such to compute the actuarially fair premium as $FairP = \sum_{i=1}^{n} \max\left[\left(\mathrm{I}^* - \mathrm{I}_i\right), 0\right] \Big/ n$. The resulting fair premiums[12] are 6.062 for grape contract (I* = 75), 0.205 for soft wheat contract (I* = 20) and 0.679 for durum wheat contract (I* = 25) respectively.

The second simulation of the actuarially fair premium has been performed by re-sampling from the realized values of the indexes applying a non-parametric bootstrap. The sample is obtained by extracting at random n values from a Uniform distribution [0,1] and by associating each extracted value to the index observations. Such sample is composed by n = 500,000 observations such to compute the actuarially fair premium as $FairP = \sum_{i=1}^{n} \max\left[\left(\mathrm{I}^* - \mathrm{I}_i\right), 0\right] \Big/ n$. The resulting fair premiums are 4.056 for grape contract (I* = 75), 0.458 for soft wheat contract (I* = 20) and 0.659 for durum wheat contract (I* = 25) respectively.

Given the estimated actuarially fair premiums, it is possible to determine the series of yield that farmers in the area would have had over the 15 years considered, both with and without the hedge provided by the weather index contracts. The descriptive statistics of the series, in Tables A10.a, .b and .c, show that the standard deviations of the "hedged" series are lower than the non-"hedged" ones, implying that a reduction in risk would occur.

Sensitivity analysis is then performed to check whether or not the farmers in the sample would be willing to accept the contracts and pay for such premiums. The change in the certainty equivalent, implied by the purchase of the contract, is hence

[12] Fair premiums and indemnities are meant to be the product between price and quantities of crop per hectare (q/ha), assuming the price constant and equal to one.

measured for five different degrees of risk aversion, assuming a Constant Relative Risk Aversion (CRRA) utility function. The assumption of CRRA utility function is quite common, especially in asset pricing literature, though researchers have controversial opinions about its empirical applications in agriculture (Coyle, 1999). Nevertheless, several CRRA utility functions are usually described in the literature, such as the logarithm and the exponential; both posses the desirable property that the degree of risk aversion does not change for changes in wealth. Another reason for assuming CRRA utility functions is that there is evidence that the initial level of wealth does not alter the riskiness of investment choices. Hence, the sensitivity analysis does not depend on farmers' wealth.

The CRRA utility function applied is the exponential and its functional form is $u(x) = \frac{x^{1-\rho}}{1-\rho}$, with $\rho > 0$ representing the degree of risk aversion; $u'(x) = x^{-\rho} > 0$; $u''(x) = -\rho x^{-(\rho+1)} < 0$. The measure of the relative risk aversion is then $R^R = -\frac{u''(x)}{u'(x)}x = -\frac{-\rho x^{-(\rho+1)}}{x^{-\rho}}x = -\frac{-\rho x^{-(\rho+1)}}{x^{-(\rho+1)}} = \rho$ which is *constant*.

Assuming x to be the crop yield and letting ρ varying discretely from 1 to 3, in increments of 0.5, levels of utility for the series with and without hedge are computed. Taking the average of the utility levels $\bar{u}$ for each of the three series and inverting the utility function, the certainty equivalents are computed for six different degrees of risk aversion: $CE = (1-\rho)\bar{u}^{\frac{1}{1-\rho}}$.

The sign of the change in certainty equivalent, ΔCE, that is the difference between the "hedged" CE and non-"hedged" CE, will tell whether or not a farmer in the area would be willing to subscribe to the contract. A positive sign implies the farmer is willing to accept the contract.

The results of the sensitivity analysis are reported in tables A11.a, .b and .c where it is shown that for reasonably low values of risk aversion ρ, ΔCE are positive. Such results suggest that such contracts would be suitable also for farmers in the area characterized by low risk aversion.

Chapter 6. Conclusion and discussion for further research

This thesis tests a new methodology for constructing a local weather index and analyzes the feasibility of a yield crop insurance contract based on the index, to hedge yield variation of three crops in the Italian province of Grosseto in Tuscany. Such a contract is aimed to hedge, within the province, the systemic exposure of farmers to yield risk.

Three objective weather indexes have been constructed using detailed weather data through an innovative statistical procedure, based on a combination of data reduction, through principal component analysis, and function fitting, through regression analysis. For comparison, the approach has been contrasted to the more traditional use of indexes based on growing degree days.

The limited length of the time series of weather variables makes the results of the applied principal component analyses and of the regressions tentative, especially because of overfitting due to few degrees of freedom. Faced with limited time series of data, a simulation of the indexes' distribution has nevertheless been conducted to compute the actuarially fair premium and to explore possible performances of the proposed insurance schemes.

The three objective weather indexes, constructed using data from 1990 to 2004 of 18 weather stations in the Italian province of Grosseto, manifest a high correlation with grape, soft and durum wheat yields in the province. The growing degree days method, intended to provide a methodological comparison, did not predict yields well. Nor would the linear model if only the first 3 or 4 principal components were used.

Given data limitations, the indexes are shown to be able to follow the lower tails of yields distributions, which is the most desirable property for a local index intended to be used as the underlying asset of a crop yield insurance derivative contract.

Ideally, yields should be analyzed at the level of more homogeneous areas. Yields at provincial level in Italy might reduce the efficacy of the weather index since the area of interest presents non-homogeneous pedo-climatic conditions. Nevertheless, the feasibility analysis provides evidence that, for reasonable degrees of risk aversion, experienced farmers of the province would be willing to purchase a weather index-based insurance contract, paying even more than the actuarially fair premium. Indeed, given indemnities' estimation is based uniquely upon the predictions of the weather index and assured a perfect correlation between index and yields, the feasibility analysis highlights that farmers might receive larger benefits from such index-based insurance mechanism if they adopt corrective measures to reduce the actual yield loss. Hence, the application of index-based coverage provides incentives for a "virtuous" selection and what one might call a "moral advantage", unlike what commonly happens with traditional yield crop insurance plagued by adverse selection and especially by moral hazard. In fact, in a traditional yield crop insurance system, farmers that are more exposed have the highest incentive to participate and further they have the incentive *not to engage in risk mitigation activities once the insurance contract has been signed*.

Moreover, the insurance mechanism suggests that farmers' associations, at provincial level, might exploit the possibility of using the weather index to hedge the systemic component of yield risk, while adopting other solutions, such as mutual funds, to hedge the more idiosyncratic components of individual farmers' yield risk.

The access to existing longer time series, for both yields from RICA[13] and weather data from CNR[14], would make the risk analysis more effective, especially if analyses could be extended to more restricted and homogeneous areas, in which the systemic component of the agricultural yield risk increases. Available local yield data will also exploit in a more efficient way the wealth of information on weather data. Local weather measurement, in fact, are meanly used to perform weather forecasting, but such weather information, if employed by the proposed weather index, would be able to link directly or indirectly the fundamental yields variation to local weather conditions with high accuracy.

The proposed weather index could be adopted by public sector as an alternative tool to the complex and expensive procedures of catastrophic damage assessment

Finally, one other potential advantage of insurance contracts based on objective weather indexes is that they can be traded on exchange or over-the-counter markets as derivative contracts, to the extent that they are uncorrelated to risky assets of investors which might include them in their portfolio. Further, if the trigger values are set at a lower level, such index-based weather derivatives might prove to be suitable at reinsuring the risk exposure of insurance providers who had offered the original contract.

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[13] RICA is the Rete di Informazione Contabile Agricola. It is a branch of the Italian institute of agricultural economics (INEA), which is part of the European Union Farm Accounting Data Network (FADN), whose task is to select and monitor samples of farms representative of a particular agricultural zone at the level of the region.

[14] CNR is the Consiglio Nazionale delle Ricerche, the Italian National Research Council.
For more information visit the website http://www.cnr.it/sitocnr/Englishversion/Englishversion.html.

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Appendix

Table A1: Actual and detrended yield time series from 1990 to 2004

	Grape	Soft wheat	Durum wheat	
	Y_t	Y_t	Y_t	$Y_{t,det}$
1990	90.28	23.31	42.22	34.854
1991	101.16	28.28	34.96	28.646
1992	76.56	22.44	38.66	33.399
1993	85.08	26.88	30.33	26.121
1994	64.11	31.82	29.77	26.611
1995	132.82	35.00	39.00	36.895
1996	109.58	26.61	24.38	23.328
1997	70.01	28.11	29.04	29.040
1998	199.49	16.98	21.36	22.412
1999	89.10	34.50	31.80	33.905
2000	97.30	37.00	30.00	33.157
2001	61.30	25.00	18.00	22.209
2002	77.50	35.00	27.00	32.261
2003	56.20	18.00	15.00	21.314
2004	108.50	35.00	35.00	42.366
average	*94.60*	*28.26*	*29.77*	*29.77*
stdev	*35.663*	*6.383*	*7.758*	*6.168*
skew	*1.940*	*0.318*	*0.337*	*0.310*

	Grape	Soft wheat	*Durum wheat*
trend coefficient	-0.466	0.287	-1.052
st. error	2.208	0.388	0.383
t-stat	-0.211	0.740	-2.751
p-value	0.836	0.473	0.017
R2	0.003	0.040	0.368

Source: own elaboration on FADN data

Table A2.a: Total variance explained for grape subset of weather variables.

Component	Variance	% of Variance	Cumulative %
1	304.2	20.9	20.9
2	159.2	10.9	31.8
3	156.3	10.7	42.5
4	139. 9	9.6	52.1
5	139.4	9.6	61.6
6	122.5	8.4	70.1
7	92.4	6.3	76.4
8	84.7	5.8	82.2
9	80.2	5.5	87.7
10	60.8	4.2	91.9
11	45.3	3.1	95.0
12	33.2	2.3	97. 3
13	28.2	1.9	99.2
14	11.8	0.8	100.0
15 – 1458	0		

Extraction Method: Principal component analysis.

Table A2.b: Total variance explained for wheat subset of weather variables.

Component	Variance	% of Variance	Cumulative %
1	304.2	18.8	18.8
2	220.9	13.6	32.4
3	191.9	11.8	44.3
4	172. 6	10.7	54.9
5	142.7	8.8	63.7
6	124.1	7.7	71.4
7	112.9	7.0	78.4
8	98.6	6.1	84.4
9	70.1	4.3	88.8
10	66.2	4.1	92.9
11	45.4	2.8	95.7
12	35.5	2. 2	97.8
13	26.4	1.6	99.5
14	8.5	0.5	100.0
15 – 1620	0		

Extraction Method: Principal component analysis.

Table A.4.a: Likely interpretation of the 14 principal components for grape subset of weather variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Sum
weather stations	all	all	all	all	all	all	all but #1	all	all but #3,#8	#3,4, 5,8, 11,13, 14,16, 17,18	#3,4,5,8, 10,12,14	#3,4,5, 12,14	#3,4, 5,10, 12,14	#4	
prevailing months	Feb-Aug	Jan-Apr	Jun and Sept	Jun-Sept	Jan-Apr	July	May-July	Jan-Mar	Mar-Aug	Jan-Apr	Jan-Mar	May	Jun-Jul	Feb-Apr	
prevailing weather measurements	all	all	low Temp rain	low Temp, rain, humidity	low Temp, rain	low Temp, rain, humidity	high Temp, rain, humidity	low Temp, rain	rain, humidity	all	rain, humidity	low Temp, rain	rain, humidity	low Temp, rain	
# of variables	437	194	160	136	123	106	65	57	52	23	34	41	22	8	1458
likely interpretation	Spring-Summer	Spring	mild weather	rainy and cold summer	rainy and cold spring	rainy and cold July	summer sultry weather	rainy and cold winter	rainy spring - summer	hilly spring	rainy spring on hill	cold May on hill	rainy summer on hill	rainy and cold spring in Capalbio	

Source: own analysis

Table A4.b: Likely interpretation of the 14 principal components for wheat subset of weather variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Sum
weather stations	all	all	all	all	all	all	all but #15	all	#3,4,5,6, 8,10,11, 12,14, 16,17,18	all but #4,13	#3,4,5, 8, 10,12, 14	#3,4,5 ,12,14	#3,4,5,1 0,12,14	#4	
prevailing months	Nov-Apr	Nov-Mar	Oct-Nov Mar-Apr	Jan-Mar	Nov-Jan	Oct, Apr-May	Mar-May	Aug-Dec	Oct-Feb	Aug-Sep	Mar	Mar-May	Aug-Dic	Jan-Apr	
prevailing weather measurements	all	rain	rain, humidity	low temp, rain	low temp	rain, humidity	rain, humidity	rain, humidity	low temp, humidity	rain	rain	high temp	high temp	low temp	
# of variables	375	229	217	171	153	112	71	69	56	34	47	51	28	7	1620
likely interpretation	winter - spring	rainy winter - spring	rainy and humid fall-spring	cold and rainy winter	cold fall	humidity in mid fall and spring	rainy spring	rainy fall	cold and humid winter	rainy end summer	rainy March on hill	warm spring on hill	warm fall on hill	cold spring in Capalbio	

Source: own analysis

Tables:

A5.a:
Linear regression on grape yields

Variable	Parameter estimates
cons	94.59*
	(4.25)
g1	14.70*
	(4.40)
g2	-1.16
	(4.40)
g3	5.98
	(4.40)
g4	10.89**
	(4.40)
g5	-7.66
	(4.40)
g6	0.27
	(4.40)
g7	7.80
	(4.40)
g8	-16.76*
	(4.40)
g9	20.07*
	(4.40)
R^2	0.924
adjusted R^2	0.787
F-stat.	6.742
p-value	0.025
K^2-stat	13.81
p-value	0.001
Obs	15

A5.b:
Linear regression on soft wheat yields

Variable	Parameter estimates
cons	28.26*
	(1.03)
w1	3.62*
	(1.07)
w2	-2.66*
	(1.07)
w3	-1.06
	(1.07)
w4	0.11
	(1.07)
w5	0.78
	(1.07)
w6	0.46
	(1.07)
w7	-1.78
	(1.07)
w8	2.93*
	(1.07)
R^2	0.832
adjusted R^2	0.608
F-stat	3.715
p-value	0.064
K^2-stat	13.48
p-value	0.001
Obs	15

A5.c:
Linear regression on durum wheat yields

Variable	Parameter estimates
cons	29.77*
	(0.87)
w1	4.23*
	(0.90)
w2	-2.16**
	(0.90)
w3	0.50
	(0.90)
w4	-0.27
	(0.90)
w5	-1.35
	(0.90)
w6	0.43
	(0.90)
w7	2.33*
	(0.90)
w8	1.24
	(0.90)
w9	1.45
	(0.90)
R^2	0.893
adjusted R^2	0.700
F-stat	4.624
p-value	0.053
K^2-stat	7.49
p-value	0.023
Obs	15

Note: Standard Errors in parenthesis,
* Statistically significant at 5% level,
** Statistically significant at 10% level.

Tables:

A6.a:
Linear regression on grape yields

Variable	Parameter estimates
cons	94.59*
	(4.86)
g1	14.70**
	(5.04)
g4	10.89***
	(5.04)
g8	-16.76*
	(5.04)
g9	20.07*
	(5.04)
R^2	0.800
adjusted R^2	0.721
F-stat.	10.031
p-value	0.002
Obs	15

A6.b:
Linear regression on soft wheat yields

Variable	Parameter estimates
cons	28.26*
	(1.00)
w1	3.62*
	(1.04)
w2	-2.66**
	(1.04)
w8	2.93**
	(1.04)
R^2	0.706
adjusted R^2	0.625
F-stat.	8.793
p-value	0.003
Obs	15

A6.c:
Linear regression on durum wheat yields

Variable	Parameter estimates
cons	29.77*
	(0.92)
w1	4.23*
	(0.96)
w2	-2.16**
	(0.96)
w7	2.33*
	(0.96)
R^2	0.736
adjusted R^2	0.664
F-stat	10.214
p-value	0.002
Obs	15

Note: Standard Errors in parenthesis,
* Statistically significant at 1% level,
** Statistically significant at 5% level,
*** Statistically significant at 10% level.

Table A7.a: Database for regressions on GDD moments and Rain for grape yields

year	grape yields	averGDD	varGDD	skewGDD	averRain
1990	90.28	1,784.32	59,985.01	-1.71	334.33
1991	101.16	1,625.13	35,310.67	-1.74	460.58
1992	76.56	1,608.17	123,775.35	-1.48	415.83
1993	85.08	1,555.88	83,393.17	-1.52	268.15
1994	64.11	1,645.54	96,310.50	-1.17	370.71
1995	132.82	1,285.59	122,561.15	-1.64	413.15
1996	109.58	1,265.13	113,800.30	-1.67	600.94
1997	70.01	1,564.61	97,958.23	-1.30	383.78
1998	199.49	1,536.81	101,950.94	-0.72	460.66
1999	89.10	1,505.89	130,347.57	-0.46	438.61
2000	97.30	1,582.67	132,646.52	-0.62	321.77
2001	61.30	1,639.11	152,485.86	-0.77	398.23
2002	77.50	1,465.47	116,369.96	-0.91	485.03
2003	56.20	1,677.50	123,086.71	-0.89	328.81
2004	108.50	1,278.68	119,721.53	-0.73	453.81

Source: own elaboration on daily weather data from ARSIA

Table A7.b: Database for regressions on GDD moments and Rain for soft and durum wheat yields

year	soft wheat yields	durum wheat yields	averGDD	varGDD	skewGDD	averRain
1991	28.28	34.85	3,787.15	563,980.54	-1.95	745.85
1992	22.44	28.65	4,173.38	21,541.49	0.21	723.98
1993	26.88	33.40	4,060.75	111,994.41	-1.89	498.60
1994	31.82	26.12	4,081.83	91,128.01	-1.21	611.15
1995	35.00	26.61	4,035.42	83,674.34	-0.82	418.75
1996	26.61	36.90	3,736.66	135,610.92	-1.49	678.59
1997	28.11	23.33	3,888.39	142,455.02	-1.30	607.98
1998	16.98	29.04	4,000.66	142,972.18	-0.78	790.29
1999	34.50	22.41	3,773.10	149,850.84	-0.57	516.78
2000	37.00	33.90	4,024.45	189,300.96	-0.45	584.96
2001	25.00	33.16	4,259.34	216,948.23	-0.63	793.64
2002	35.00	22.21	3,929.00	130,628.49	-1.01	405.68
2003	18.00	32.26	3,818.25	185,533.29	-0.65	699.28
2004	35.00	21.31	3,813.29	165,730.02	-0.57	711.91

Source: own elaboration on daily weather data from ARSIA

Table A8.a: Linear regressions on grape yields

Variables	Regr. 1	Regr. 2	Regr. 3
cons	165.73	250.86	351.43
	(163.64)	*(187.68)*	*(210.58)*
averGDD	-0.07	-0.10	-0.12
	(0.08)	*(0.08)*	*(0.09)*
varGDD		0.00	0.00
		(0.00)	*(0.00)*
skewGDD			29.06
			(27.9)8
averRain	0.08	0.06	0.05
	(0.15)	*(0.15)*	*(0.15)*
R^2	0.18	0.24	0.31
adjusted R^2	0.04	0.03	0.04
F-stat	1.30	1.15	1.14
p-value	0.31	0.37	0.39

Table A8.b: Linear regressions on soft wheat yields

Variables	Regr. 1	Regr. 2	Regr. 3
cons	63.55	48.97	59.48
	(36.75)	*(40.31)*	*(41.21)*
averGDD	0.00	0.00	0.00
	(0.01)	*(0.01)*	*(0.01)*
varGDD		0.00	0.00
		(0.00)	*(0.00)*
skewGDD			3.36
			(3.14)
averRain	-0.032*	-0.037*	-0.042*
	(0.01)	*(0.01)*	*(0.01)*
R^2	0.428	0.472	0.532
adjusted R^2	0.324	0.314	0.324
F-stat	4.121	2.986	2.557
p-value	0.046	0.083	0.111

Table A8.c: Linear regressions on durum wheat yields

Variables	Regr. 1	Regr. 2	Regr. 3
cons	56.54	59.24	80.70**
	(42.60)	*(48.59)*	*(43.37)*
averGDD	0.00	-0.01	-0.01
	(0.01)	*(0.01)*	*(0.01)*
varGDD		0.00	0.00
		(0.00)	*(0.00)*
skewGDD			6.86**
			(3.31)
averRain	-0.02	-0.02	-0.029**
	(0.01)	*(0.02)*	*(0.01)*
R^2	0.172	0.174	0.441
adjusted R^2	0.022	-0.074	0.193
F-stat	1.144	0.701	1.776
p-value	0.354	0.573	0.218

Note: Standard Errors in parenthesis,
* Statistically significant at 5% level,
** Statistically significant at 10% level.

Tables A9: Out-of-sample prediction accuracy for grape, soft and durum wheat yields in GDD model

a) Explanatory variables: *meanGDD* and *meanRain*

yields	Grape	Soft wheat	Durum wheat
actual value	108.33	35	42.37
predicted value (1)	117.67	24.64	26.45
% difference	9%	30%	38%
standard deviation[15]	53.39	5.02	4.52
confidence interval at 95% level	[-8.01 - 224.67]	[25.06 - 45.93]	[32.52 - 52.22]

b) Explanatory variables: *meanGDD*, *varGDD* and *meanRain*

yields	Grape	Soft wheat	Durum wheat
actual value	108.33	35	42.37
predicted value (2)	159.69	21.50	24.72
% difference	47%	39%	42%
standard deviation	57.32	4.68	4.79
confidence interval at 95% level	[-17.83 - 236.19]	[24.69 - 45.31]	[31.82 - 52.91]

c) Explanatory variables: *meanGDD*, *varGDD*, *skewGDD* and *meanRain*

yields	Grape	Soft wheat	Durum wheat
actual value	108.33	35	42.37
predicted value (3)	121.09	23.85	28.14
% difference	12%	32%	34%
standard deviation	57.39	4.80	3.77
confidence interval at 95% level	[-19.53 - 236.19]	[24.31 - 45.69]	[33.97 - 50.77]

Source: own elaborations

[15] The standard deviation has been computed as $stdev = \sqrt{\hat{\sigma}^2 \left(I + X_{2004} \left(X'X\right)^{-1} X'_{2004}\right)}$, with X_{2004} as the actual cases "2004" of the explanatory variables; $\hat{\sigma}^2$ and X are in-sample variance and data values.

Table A10.a: Hedging grape crops through a weather index (threshold I* = 75)

year	Return w/o hedge (R_1)	Value of the Index (I)	Indemnity (I*- I) if I < I*	Return w/ hedge (R_2)$^{(1)}$	Return w/ hedge (R_3)$^{(2)}$	I*=75
premium				4.056	6.056	
1990	90.28	93.93	0.00	86.22	84.22	
1991	101.16	92.76	0.00	97.10	95.10	
1992	76.56	94.12	0.00	72.50	70.50	
1993	85.08	110.86	0.00	81.02	79.02	
1994	64.11	57.07	17.93	77.98	75.98	
1995	132.82	131.50	0.00	128.76	126.76	
1996	109.58	103.07	0.00	105.52	103.52	
1997	70.01	66.90	8.10	74.05	72.05	
1998	199.49	191.13	0.00	195.43	193.43	
1999	89.10	91.21	0.00	85.04	83.04	
2000	97.30	87.21	0.00	93.24	91.24	
2001	61.30	62.41	12.59	69.84	67.84	
2002	77.50	78.04	0.00	73.44	71.44	
2003	56.20	52.79	22.21	74.35	72.35	
2004	108.50	105.98	0.00	104.44	102.44	
mean	94.60	94.60	4.06	94.60	92.60	
stdev	35.66	34.28	7.52	32.25	32.25	

Source: own elaborations

(1) Premium obtained by sampling from actual index values

(2) Premium obtained by assuming normal distribution of index value

Table A10.b: Hedging soft wheat crops through a weather index (threshold I* = 20)

year	Return w/o hedge (R_1)	Value of the Index (I)	Indemnity (I*- I) if I < I*	Return w/ hedge (R_2)(1)	Return w/ hedge (R_3)(2)	I*=20
premium				0.458	0.205	
1990	23.31	28.40	0.00	22.85	23.10	
1991	28.28	28.99	0.00	27.82	28.07	
1992	22.44	28.85	0.00	21.98	22.23	
1993	26.88	28.66	0.00	26.42	26.67	
1994	31.82	32.24	0.00	31.36	31.61	
1995	35.00	33.68	0.00	34.54	34.79	
1996	26.61	25.16	0.00	26.15	26.40	
1997	28.11	26.11	0.00	27.65	27.90	
1998	16.98	16.30	3.70	20.22	20.47	
1999	34.50	33.27	0.00	34.04	34.29	
2000	37.00	34.06	0.00	36.54	36.79	
2001	25.00	23.83	0.00	24.54	24.79	
2002	35.00	34.39	0.00	34.54	34.79	
2003	18.00	16.81	3.19	20.73	20.99	
2004	35.00	33.18	0.00	34.54	34.79	
mean	28.26	28.26	0.46	28.26	28.52	
stdev	6.38	5.82	1.22	5.62	5.62	

Source: own elaborations

(1) Premium obtained by sampling from actual index values

(2) Premium obtained by assuming normal distribution of index value

Table A10.c: Hedging durum wheat crops through a weather index (threshold I* = 25)

year	Return w/o hedge (R_1)	Value of the Index (I)	Indemnity (I*- I) if I < I*	Return w/ hedge (R_2)[(1)]	Return w/ hedge (R_3)[(2)]	I*=25
premium				0.659	0.679	
1990	34.86	29.95	0.00	34.20	34.18	
1991	28.65	29.90	0.00	27.99	27.97	
1992	33.40	30.42	0.00	32.74	32.72	
1993	26.13	30.44	0.00	25.47	25.45	
1994	26.62	26.81	0.00	25.96	25.94	
1995	36.90	35.77	0.00	36.24	36.22	
1996	23.33	23.85	1.15	23.82	23.80	
1997	29.04	29.79	0.00	28.38	28.36	
1998	22.42	22.56	2.44	24.20	24.18	
1999	33.91	33.60	0.00	33.25	33.23	
2000	33.16	34.22	0.00	32.50	32.48	
2001	22.21	22.60	2.40	23.96	23.94	
2002	32.26	32.60	0.00	31.60	31.58	
2003	21.32	21.11	3.89	24.55	24.53	
2004	42.37	42.96	0.00	41.71	41.69	
mean	29.77	29.77	0.66	29.77	29.75	
stdev	6.17	5.83	1.24	5.35	5.35	

Source: own elaborations

(1) Premium obtained by sampling from actual index values

(2) Premium obtained by assuming normal distribution of index value

Table A11.a: Benefits to grape farmers from hedging through a weather index (threshold I* = 75)

year	Return w/o hedge (R_1)	Return w/ hedge (R_2)[1]	Return w/ hedge (R_3)[2]	I*=75
premium		4.056	6.056	
1990	90.28	86.22	84.22	
1991	101.16	97.10	95.10	
1992	76.56	72.50	70.50	
1993	85.08	81.02	79.02	
1994	64.11	77.98	75.98	
1995	132.82	128.76	126.76	
1996	109.58	105.52	103.52	
1997	70.01	74.05	72.05	
1998	199.49	195.43	193.43	
1999	89.10	85.04	83.04	
2000	97.30	93.24	91.24	
2001	61.30	69.84	67.84	
2002	77.50	73.44	71.44	
2003	56.20	74.35	72.35	
2004	108.50	104.44	102.44	
mean	94.60	94.60	92.60	
stdev	35.66	32.25	32.25	
Δ Certainty Equivalent $\rho = 1$		1.21	-0.85	
Δ Certainty Equivalent $\rho = 1.5$		1.84	-0.24	
Δ Certainty Equivalent $\rho = 2$		2.46	0.37	
Δ Certainty Equivalent $\rho = 2.5$		3.08	0.97	
Δ Certainty Equivalent $\rho = 3$		3.69	1.57	

Source: own elaborations

(1) Premium obtained by sampling from actual index values

(2) Premium obtained by assuming normal distribution of index value

Table A11.b: Benefits to soft wheat farmers from hedging through a weather index (threshold I* = 20)

year	Return w/o hedge (R_1)	Return w/ hedge (R_2)[(1)]	Return w/ hedge (R_3)[(2)]	I*=20
premium		0.458	0.205	
1990	23.31	22.85	23.10	
1991	28.28	27.82	28.07	
1992	22.44	21.98	22.23	
1993	26.88	26.42	26.67	
1994	31.82	31.36	31.61	
1995	35.00	34.54	34.79	
1996	26.61	26.15	26.40	
1997	28.11	27.65	27.90	
1998	16.98	20.22	20.47	
1999	34.50	34.04	34.29	
2000	37.00	36.54	36.79	
2001	25.00	24.54	24.79	
2002	35.00	34.54	34.79	
2003	18.00	20.73	20.99	
2004	35.00	34.54	34.79	
mean	28.26	28.26	28.52	
stdev	6.38	5.62	5.62	
Δ Certainty Equivalent ρ = 1		0.20	0.46	
Δ Certainty Equivalent ρ = 1.5		0.32	0.58	
Δ Certainty Equivalent ρ = 2		0.46	0.72	
Δ Certainty Equivalent ρ = 2.5		0.60	0.87	
Δ Certainty Equivalent ρ = 3		0.76	1.02	

Source: own elaborations

[(1)] Premium obtained by sampling from actual index values

[(2)] Premium obtained by assuming normal distribution of index value

Table A11.c: Benefits to durum wheat farmers from hedging through a weather index (threshold I* = 25)

year	Return w/o hedge (R_1)	Return w/ hedge (R_2)(1)	Return w/ hedge (R_3)(2)	I*=25
premium		0.659	0.679	
1990	34.86	34.20	34.18	
1991	28.65	27.99	27.97	
1992	33.40	32.74	32.72	
1993	26.13	25.47	25.45	
1994	26.62	25.96	25.94	
1995	36.90	36.24	36.22	
1996	23.33	23.82	23.80	
1997	29.04	28.38	28.36	
1998	22.42	24.20	24.18	
1999	33.91	33.25	33.23	
2000	33.16	32.50	32.48	
2001	22.21	23.96	23.94	
2002	32.26	31.60	31.58	
2003	21.32	24.55	24.53	
2004	42.37	41.71	41.69	
mean	29.77	29.77	29.75	
stdev	6.17	5.35	5.35	
Δ Certainty Equivalent ρ = 1		0.16	0.14	
Δ Certainty Equivalent ρ = 1.5		0.25	0.23	
Δ Certainty Equivalent ρ = 2		0.34	0.32	
Δ Certainty Equivalent ρ = 2.5		0.43	0.41	
Δ Certainty Equivalent ρ = 3		0.52	0.50	

Source: own elaborations

(1) Premium obtained by sampling from actual index values

(2) Premium obtained by assuming normal distribution of index value

Table A12: Weather stations in the Italian province of Grosseto

Weather station	altitude	number
Alberese	3.28	1
Argentario	1,197.20	2
Braccagni	59.04	3
Capalbio	52.48	4
Casotto Pescatori	16.40	5
Magliano	623.30	6
Manciano	1,148.00	7
Massa Marittima	1,069.28	8
Montenero	656.00	9
Pitigliano	1,1049.60	10
Pomonte	557.60	11
Rispescia	131.2	12
Roccalbegna	1,148.00	13
Roccatederighi	1,607.02	14
Santa Flora	2,656.80	15
Seggiano	1,771.20	16
Semproniano	1,620.32	17
Stiacciole	196.80	18

Source: ARSIA Toscana

Note: altitude is measured in feet above sea level; number refers to the database labeling.

Table A13: Number of missing observations per weather station

	max temp	average max temp	min temp	average min temp	average temp	average max humidity	average humidity	rainfall	rainy days	missing years		
Alberese	84	84	84	84	84	84	84	84	84	1990-1996		
Argentario	65	65	65	65	65	65	65	64	64	1990-1995		
Braccagni	8	8	8	8	8	8	8	8	8	1990		
Capalbio	0	2	5	2	2	2	2	0	0		08-09/1996	
Casotto Pescatori	12	12	12	12	12	12	12	12	12	10/2002	12/2002	06/2003
Magliano	39	39	39	39	39	39	39	39	39	1990-1993		
Manciano	62	62	62	62	62	62	62	62	62	1990-1994	06/1998	
Massa Marittima	38	38	38	38	38	39	39	38	38	1990-1992		
Montenero	48	48	48	48	48	48	48	48	48	1990-1993		
Pitigliano	31	31	31	31	31	31	31	31	31	1990-1991	10-12/1994	01-04/1995
Pomonte	36	36	36	36	36	36	36	36	36	1990-1994		
Rispescia	0	0	0	0	0	0	0	0	0			
Roccalbegna	47	47	47	47	47	52	52	47	47	1990-1993		
Roccatederighi	32	32	32	32	31	37	36	33	33	1990-1992		
Santa Flora	61	61	61	61	61	67	67	68	68	1990-1994		
Seggiano	50	50	50	50	50	49	49	49	49	1990-1993	11-12/1994	12/1997
Semproniano	50	50	50	50	50	50	50	50	50	1990-1993	08-09/1996	06/1995
Stiacciole	40	40	40	40	40	40	40	40	40	1990-1992	01-02/1995	

Source: elaboration from ARSIA meteorological archive

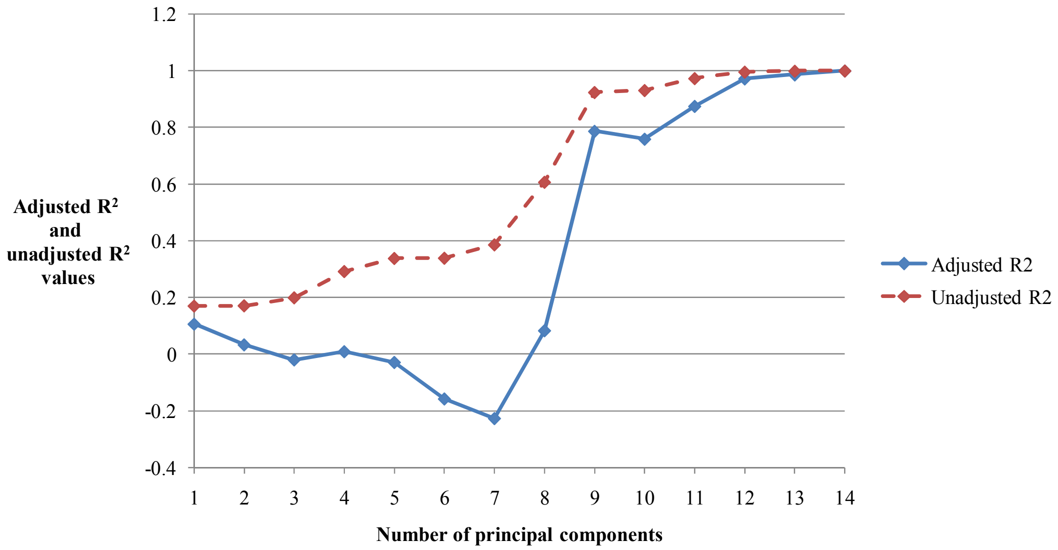
The monthly variables are labeled as *Vi_j_k*, where *V* denotes variable, *i* indicates the weather station, i = 1,…,18, j indicates the month, j = Jan(1), Feb(2),…, Dec(12), k indicates the weather variable, k = max temp(1), min temp(3),…, rainy days(9).

Table A14: Arrangement of the monthly variables by station, month and weather measurement

Year	V1_1_1	V1_1_2	.	.	V1_1_9	V1_2_1	V1_2_2	.	V1_2_9	.	V8_3_1	.	V10_2_3	.
1990	90	84	.	.	15	91	81	.	7	.	.	.	89	.
1991	87	82	.	.	13	89	83	.	10	.	.	.	85	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
2004	85	78	.	.	20	87	82	.	11	.	.	.	81	.

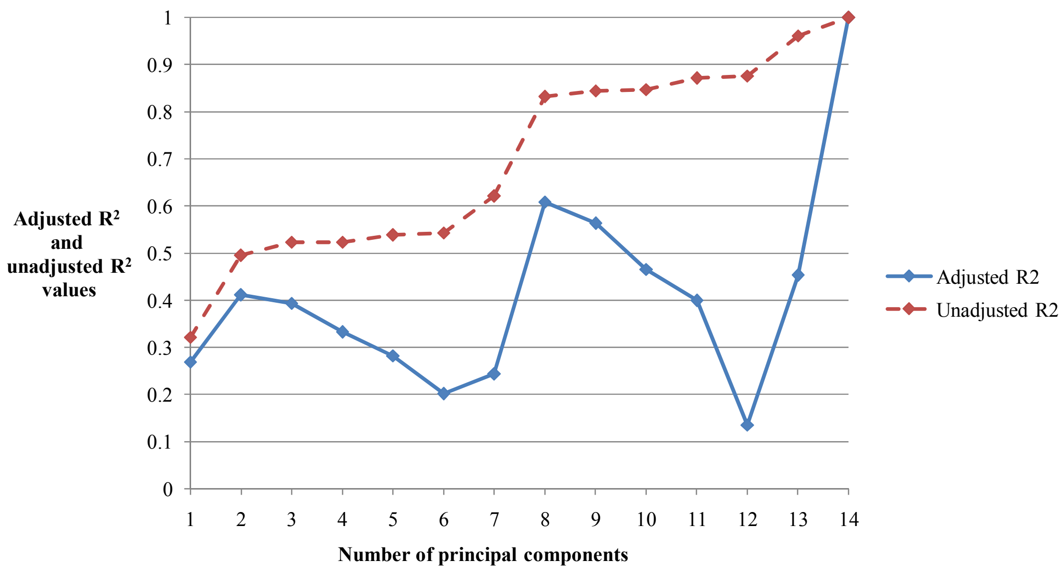
Source: own representation

Figure A1.a: Adjusted R^2 vs number of principal components for grape



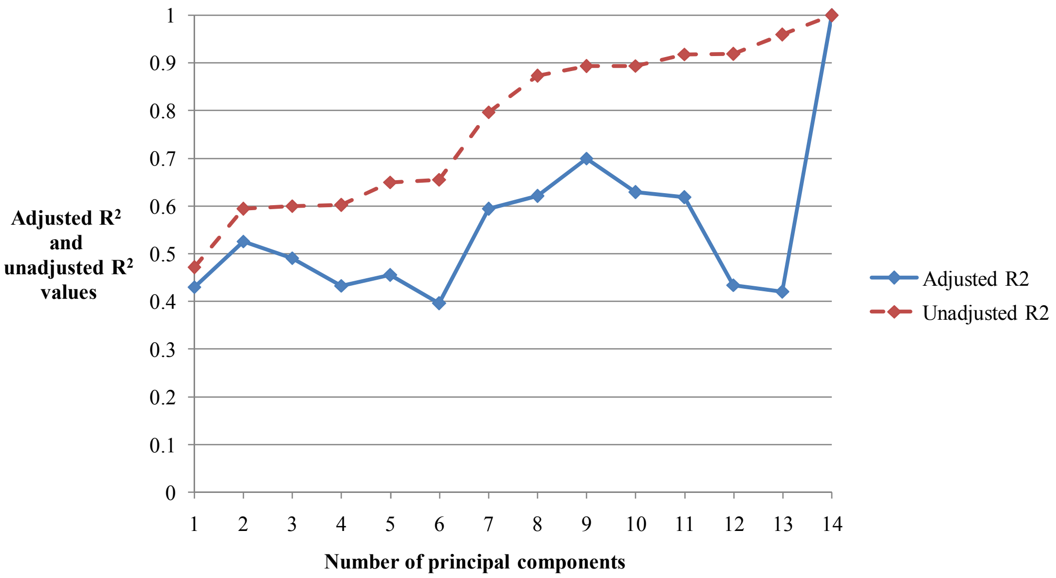
Source: Own elaboration

Figure A1.b: Adjusted R^2 vs number of principal components for soft wheat



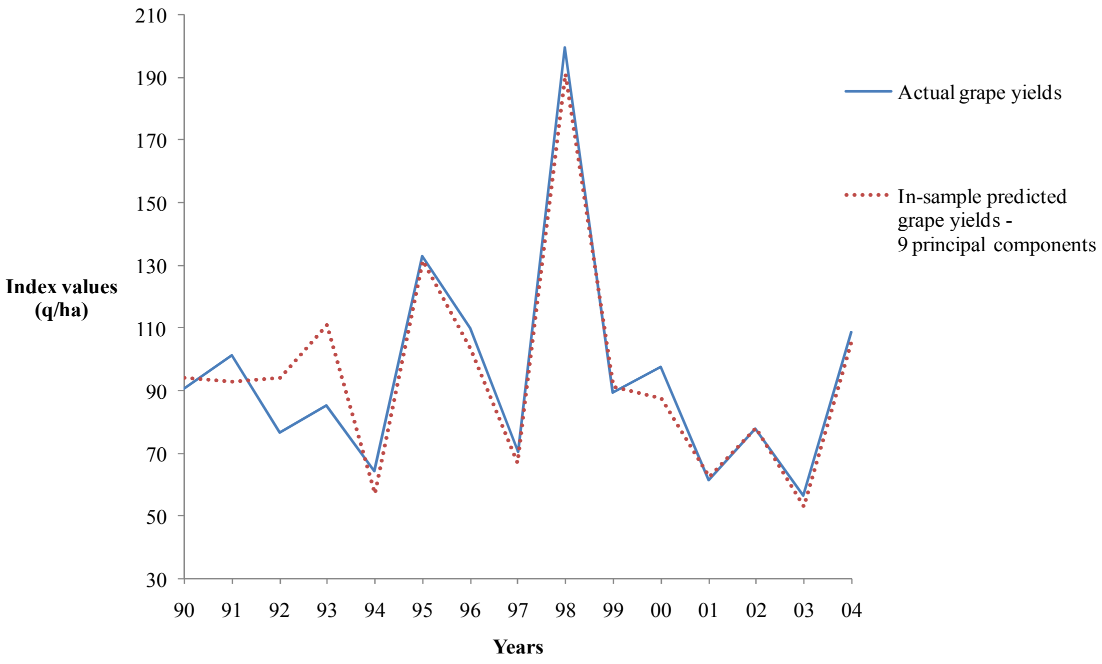
Source: Own elaboration

Figure A1.c: Adjusted R^2 vs number of principal components for durum wheat



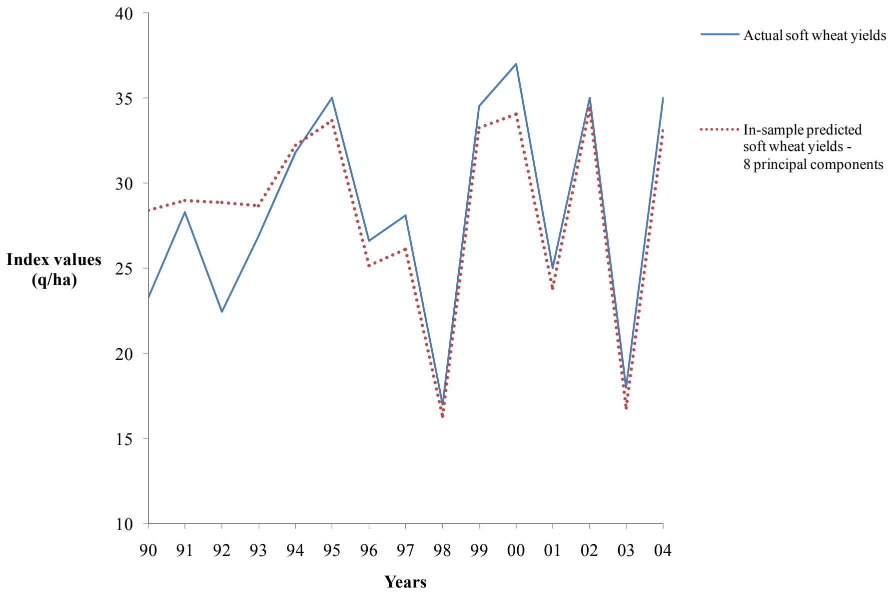
Source: Own elaboration

Figure A2.a: Comparison between actual grape yields and index values (in-sample prediction)



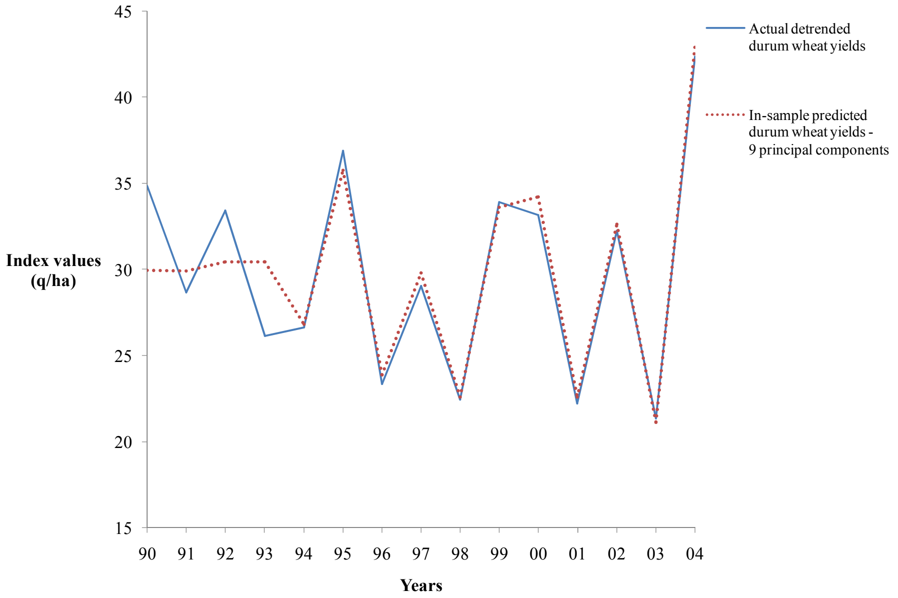
Source: own elaboration

Figure A2.b: Comparison between actual soft wheat yields and index values (in-sample prediction)



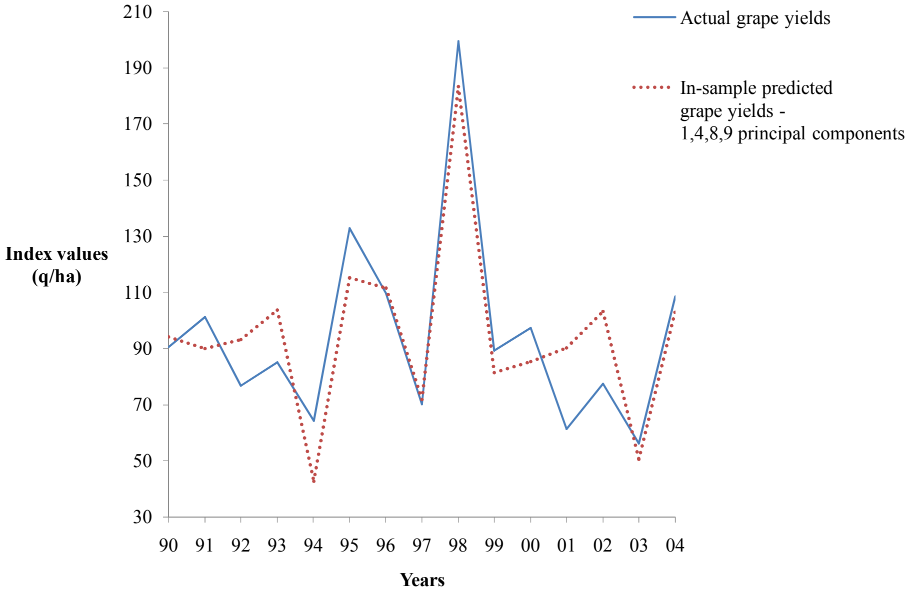
Source: own elaboration

Figure A2.c: Comparison between actual detrended durum wheat yields and index values (in-sample prediction)



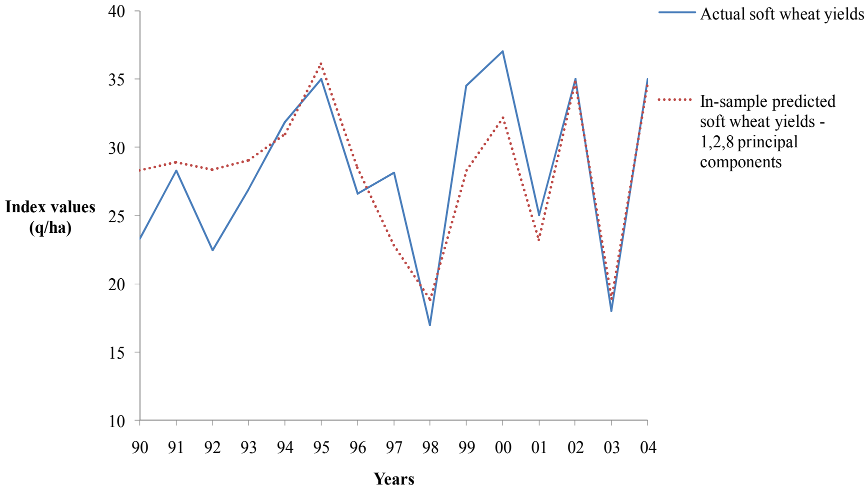
Source: own elaboration

Figure A3.a: Comparison between actual grape yields and index values (in-sample prediction)



Source: own elaboration

Figure A3.b: Comparison between actual soft wheat yields and index values (in-sample prediction)



Source: own elaboration

Figure A3.c: Comparison between actual detrended durum wheat yields and index values (in-sample prediction)

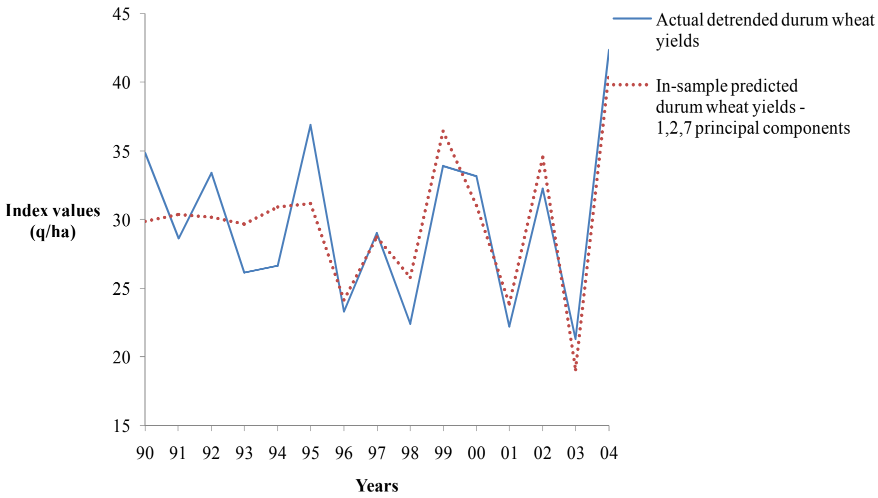
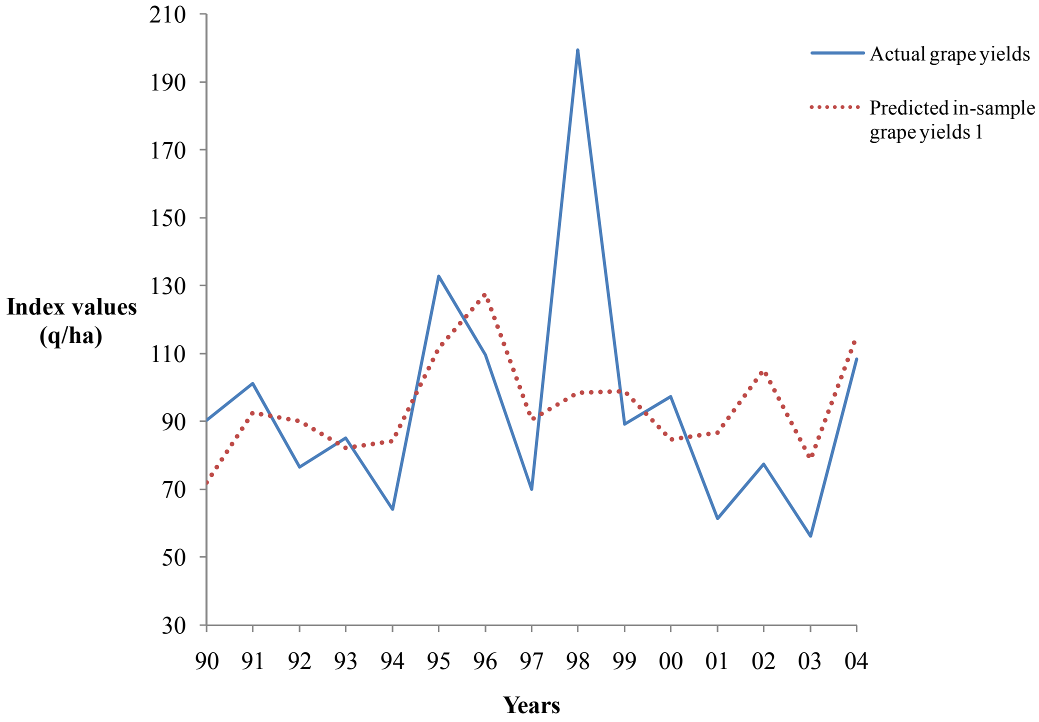
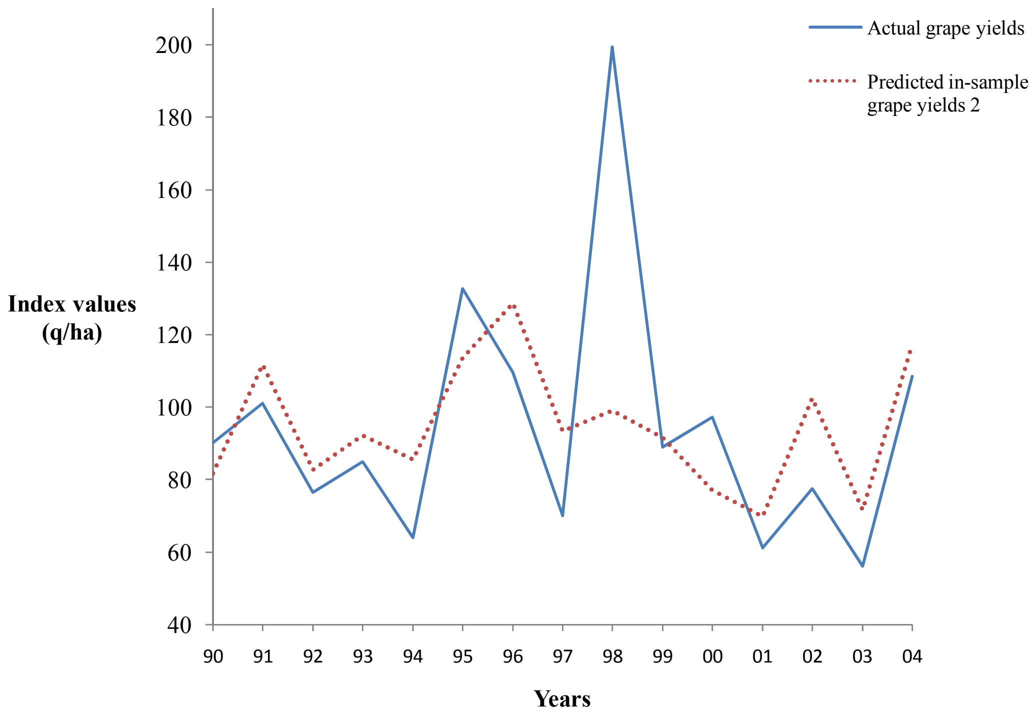


Figure A4.a: GDD method – linear regressions on grape yields



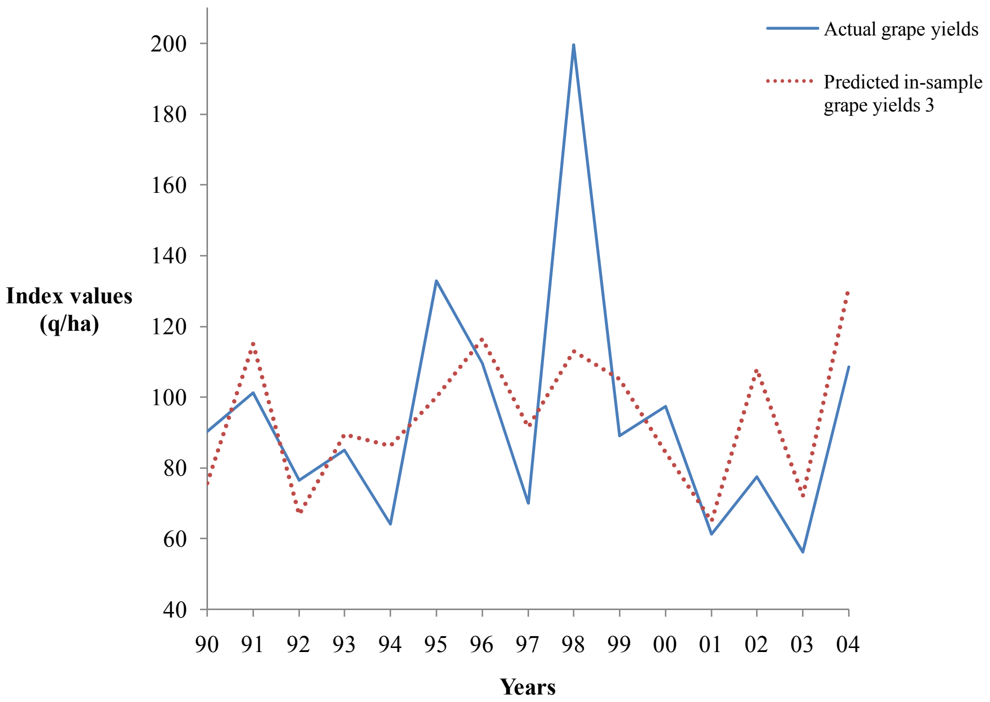
Explanatory variables: meanGDD, meanRain

A4.b: GDD method – linear regressions on grape yields



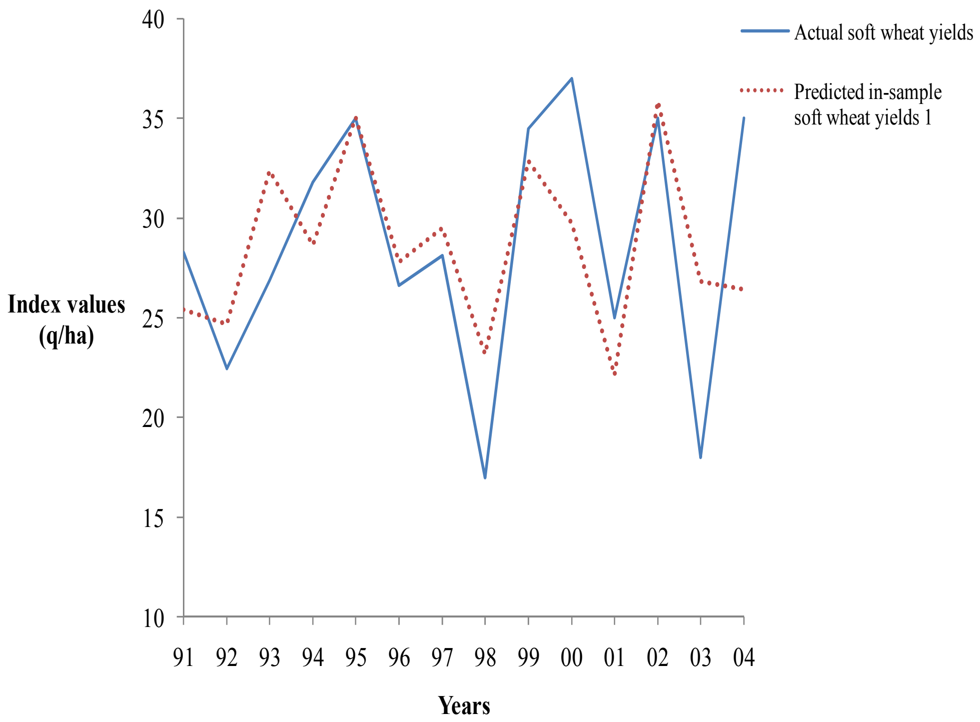
Explanatory variables: averGDD, varGDD, averRain

A4.c: GDD method – linear regressions on grape yields



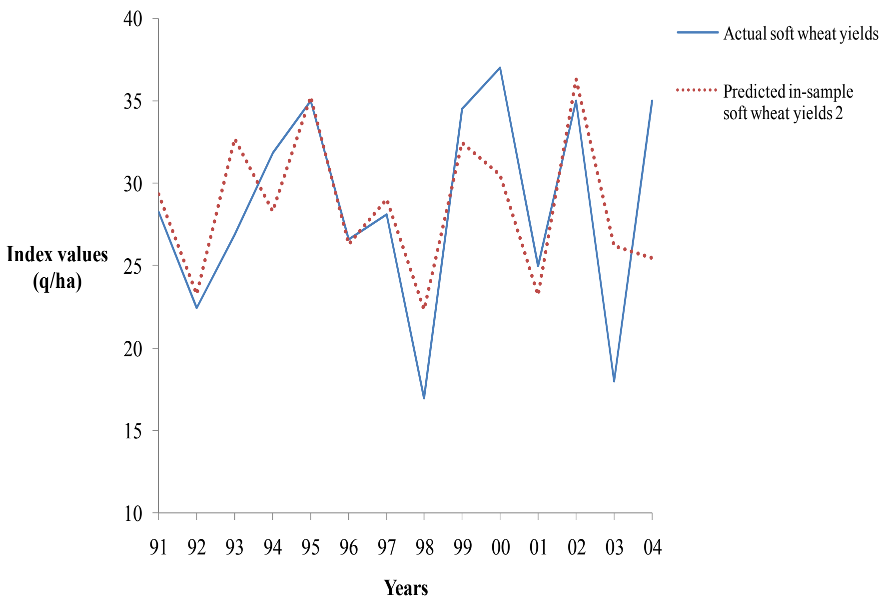
Explanatory variables: averGDD, varGDD, skewGDD, averRain
Source: Own elaborations

Figure A5.a: GDD method – linear regressions on soft wheat yields



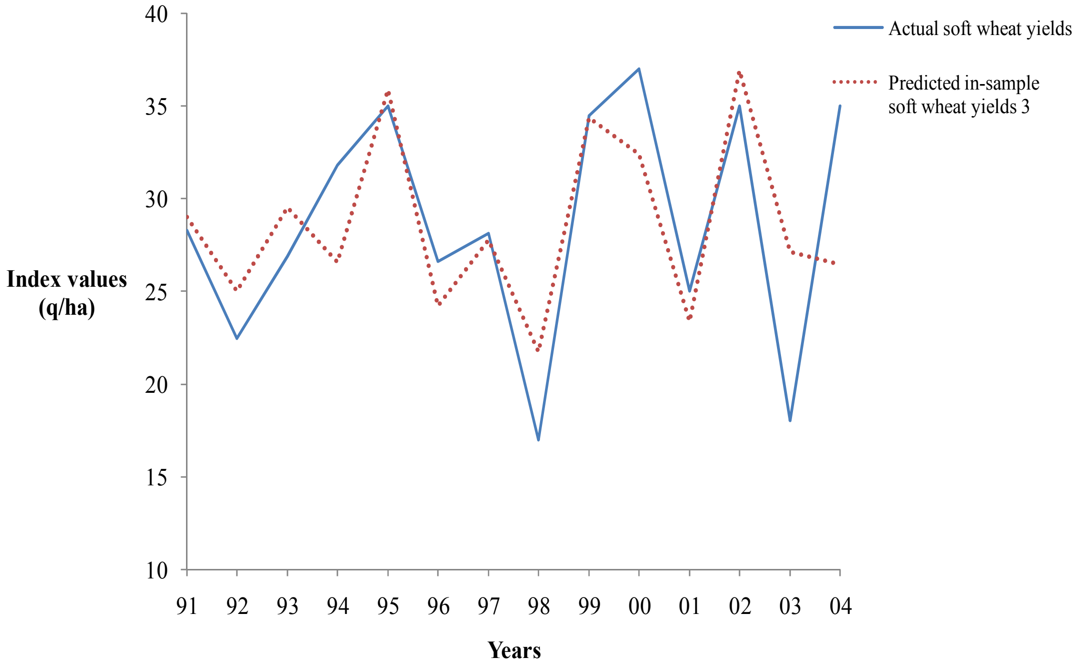
Explanatory variables: meanGDD, meanRain

A5.b: GDD method – linear regressions on soft wheat yields



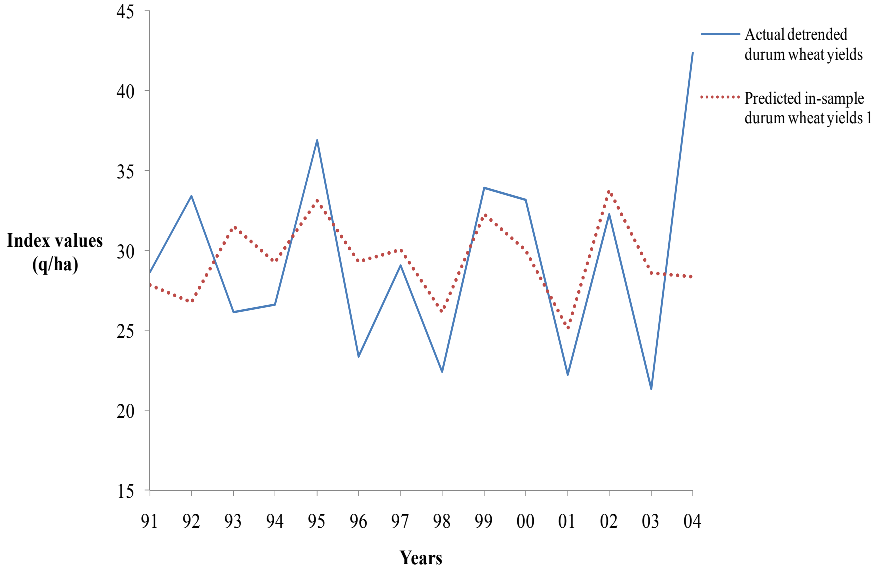
Explanatory variables: meanGDD, varGDD, meanRain

A5.c: GDD method – linear regressions on soft wheat yields



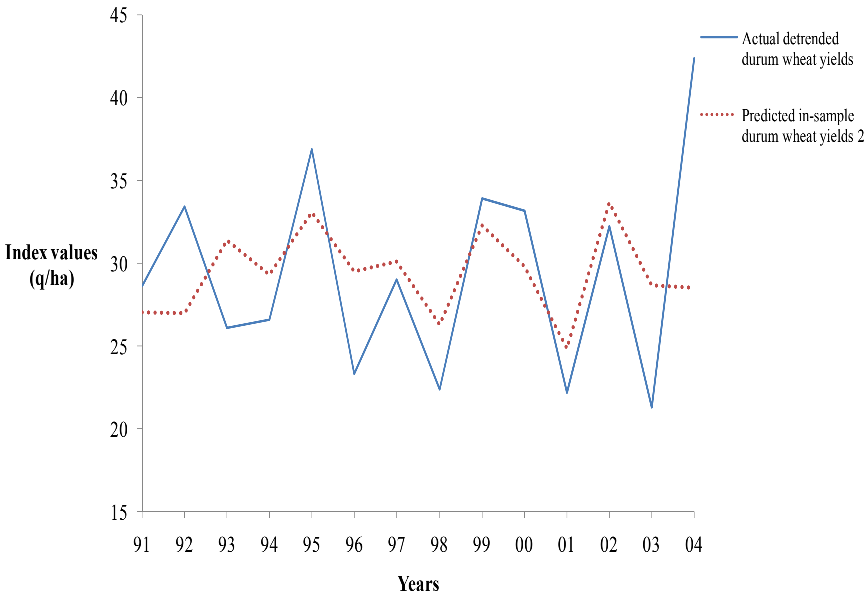
Explanatory variables: meanGDD, varGDD, skewGDD, meanRain
Source: own elaborations

Figure A6.a: GDD method – linear regressions on durum wheat yields



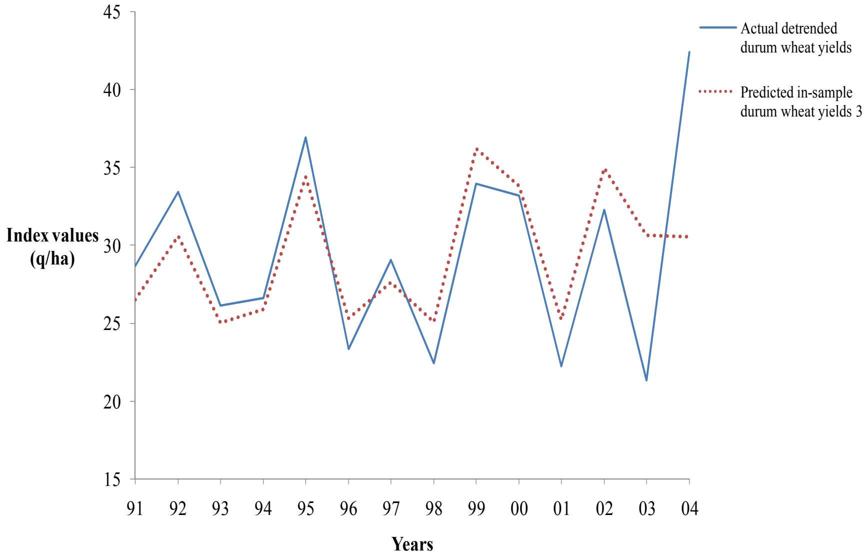
Explanatory variables: meanGDD, meanRain

A6.b: GDD method – linear regressions on durum wheat yields



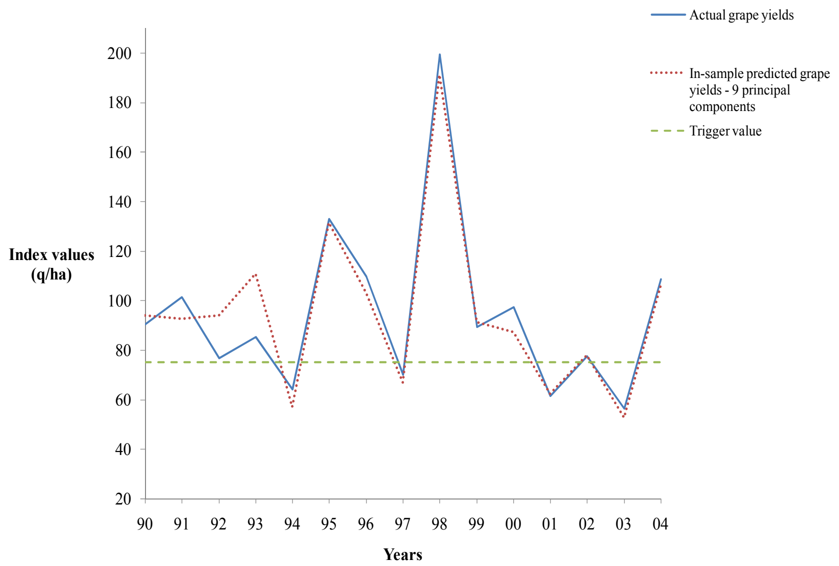
Explanatory variables: meanGDD, varGDD, meanRain

A6.c: GDD method – linear regressions on durum wheat yields



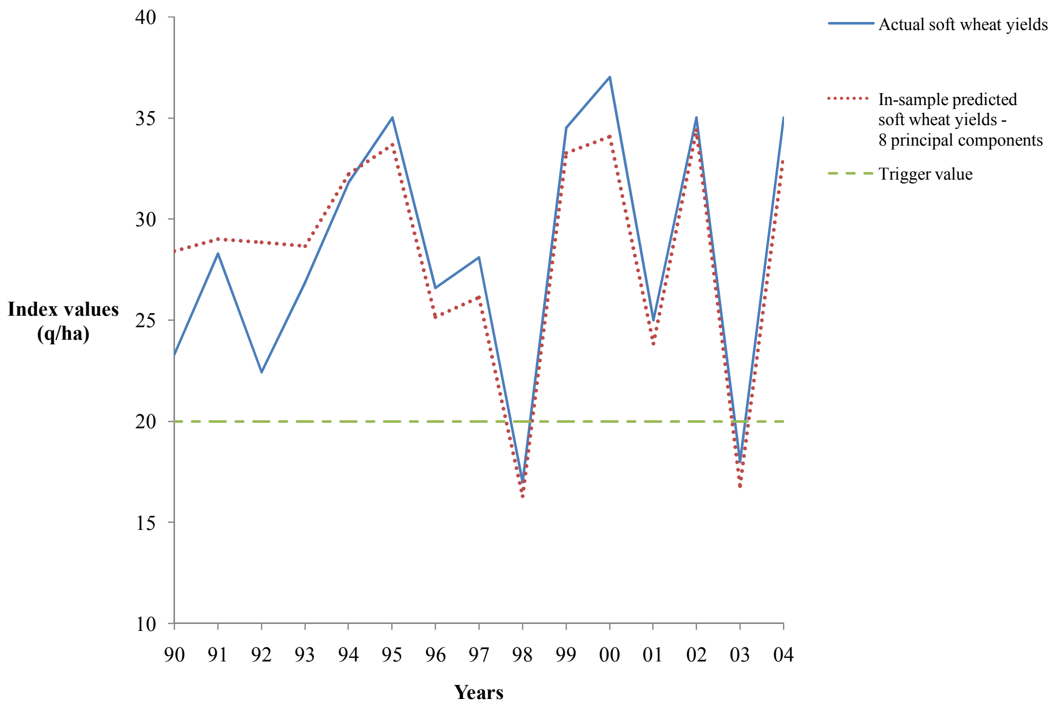
Explanatory variables: meanGDD, varGDD, skewGDD, meanRain
Source: own elaborations

Figure A7.a: Threshold value in an index-based weather insurance contract for grape yields



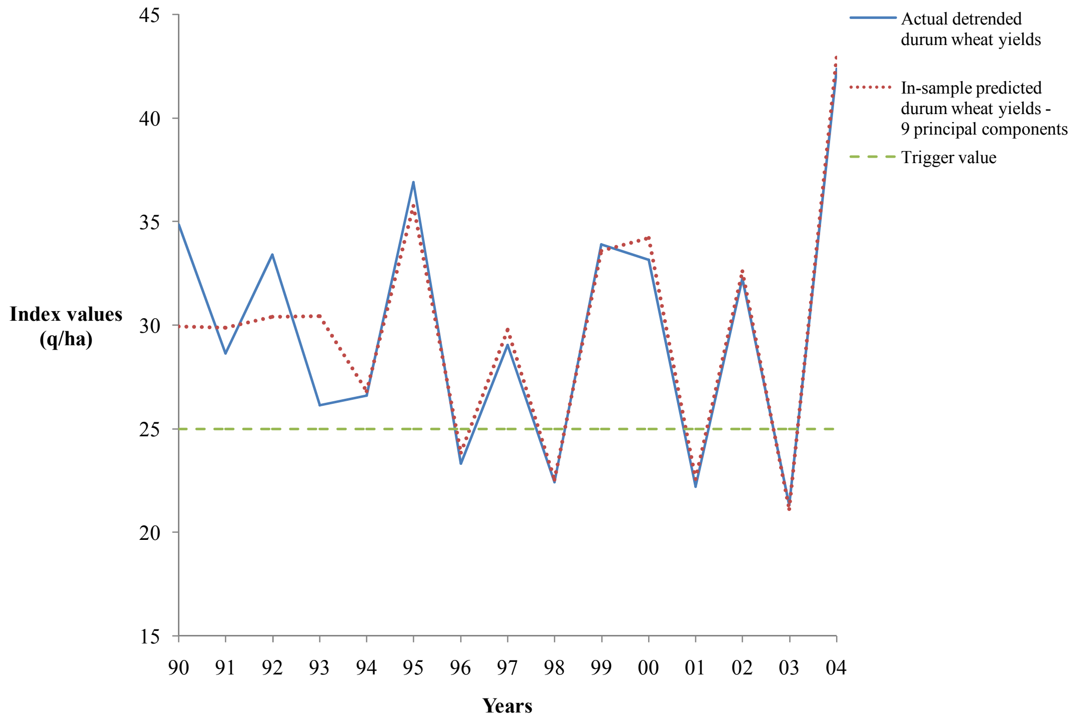
Source: own representation – trigger value = 75

A7.b. Threshold value in an index-based weather insurance contract for soft wheat yields



Source: own representation – trigger value = 20

A7.c Threshold value in an index-based weather insurance contract for durum wheat yields



Source: own representation – trigger value = 25

Table A3.a.: Component matrix for grape subset of weather variables (a)

	Component													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
V2_8_4	-.946													
V15_8_4	-.940													
V7_2_7	.939													
V2_8_2	-.938													
V18_8_5	-.926													
V15_8_5	-.920													
V8_8_5	-.917													
V16_8_6	.915													
V7_2_6	.912													
V18_8_2	-.909													
V7_8_4	-.903													
V7_8_5	-.902													
V14_8_5	-.901													
V2_8_5	-.898													
V11_8_5	-.896													
V12_8_5	-.895													
V8_2_9	.895													
V11_8_4	-.895													
V15_5_9	.889													
V3_8_5	-.887													
V11_5_5	-.886													
V9_8_5	-.882													
V13_8_5	-.882													
V10_8_6	.881													
V11_2_7	.881													
V16_8_4	-.880													
V10_8_2	-.878													
V13_8_4	-.875													
V16_8_5	-.873													
V10_8_7	.871													
V15_5_5	-.870													
V7_8_2	-.869													
V6_8_5	-.868													
V5_8_2	-.868													
V11_2_9	.866													
V18_8_7	.865													
V10_5_5	-.865													
V9_8_2	-.864													
V6_8_2	-.863													
V8_8_4	-.862													
V16_8_7	.862													
V9_8_7	.858													
V15_5_4	-.857													
V13_8_7	.856													
V15_8_2	-.854													
V15_5_2	-.850													
V17_5_2	-.848													
V6_2_7	.845					-.441								

V13_6_3	-.843													
V8_6_5	-.842													
V6_5_5	-.842													
V6_2_6	.840					-.427								
V8_8_6	.839							.429						
V17_5_1	-.838													
V18_5_2	-.838													
V5_8_5	-.836													
V4_2_6	.835													
V11_2_6	.835													
V8_6_2	-.833													
V2_8_1	-.832													
V14_8_2	-.831													
V9_8_4	-.831													
V6_8_7	.830													
V11_5_2	-.829													
V18_5_5	-.829													
V6_8_4	-.828													
V9_2_7	.827					-.418								
V18_8_6	.827													
V11_8_6	.827							.453						
V13_2_7	.825								-.411					
V8_2_7	.824													
V8_2_6	.822													
V18_8_4	-.822													
V9_8_6	.822													
V13_8_6	.822													
V8_8_1	-.820													
V18_8_1	-.820													
V17_8_4	-.820													
V11_5_4	-.819													
V16_5_4	-.819													
V13_8_2	-.818													
V11_8_2	-.818													
V6_8_6	.817							.405						
V16_5_5	-.816													
V3_8_7	.815													
V9_5_2	-.815				.433									
V8_8_2	-.815													
V16_8_2	-.813													
V3_8_2	-.813													
V3_8_6	.812													
V3_2_6	.809													
V3_2_7	.808													
V9_8_1	-.808													
V15_6_3	-.807													
V4_8_5	-.807													
V15_8_1	-.806													
V7_2_9	.804						-.456							
V6_5_2	-.803				.453									

V8_8_7	.803							.406						
V17_5_5	-.802					.431								
V11_8_7	.801													
V12_6_4	-.800													
V17_5_4	-.799					.500								
V12_8_6	.797													
V6_5_7	.796													
V10_8_5	-.794												.446	
V6_8_1	-.792													
V9_2_6	.789					-.455								
V8_6_4	-.788													
V13_6_5	-.788													
V15_4_7	.786													
V13_6_2	-.785													
V7_4_3	.783													
V9_5_5	-.782				.441									
V13_5_2	-.781													
V13_6_4	-.780													
V5_2_7	.780													
V8_2_8	.780													
V12_6_5	-.779													
V7_8_1	-.779													
V1_2_7	.777													
V12_8_2	-.777													
V10_8_1	-.775													
V13_8_1	-.773													
V17_8_2	-.773													
V4_2_7	.772													
V10_5_4	-.772													
V12_8_1	-.769													
V2_6_3	-.768			-.411										
V14_8_1	-.768			.418										
V14_8_6	.767													
V15_2_9	.765													
V10_5_7	.764													
V4_8_4	-.763				-.440									
V15_8_7	.762													
V17_8_7	.761							.412						
V17_8_5	-.760													
V7_8_3	-.760						-.442							
V4_8_6	.755													
V10_5_2	-.752				.426									
V15_6_2	-.751	-.445												
V12_8_7	.748													
V15_6_8	-.747			-.498										
V11_6_5	-.745	-.425												
V5_2_9	.744													
V4_8_1	-.742				-.415									
V6_4_6	.742													
V7_5_2	-.742													

V18_4_6	.741													
V18_6_5	-.741	-.539												
V15_5_7	.740													
V8_5_2	-.740				.465									
V16_5_2	-.738													
V15_8_6	.738													
V5_8_1	-.736													
V16_2_7	.735													
V8_5_5	-.732				.473									
V17_2_6	.731							.515						
V12_8_4	-.731													
V17_8_6	.728							.587						
V15_6_5	-.727													
V13_5_5	-.726				.490									
V9_5_6	.726				-.484									
V11_6_4	-.724													
V13_5_7	.722					.483								
V17_8_1	-.722									.424				
V3_2_9	.722				-.409									
V13_2_6	.722			-.434					-.454					
V12_5_3	-.722													
V9_8_3	-.721						-.426							
V1_2_6	.721				.492									
V15_9_7	.720		-.433											
V15_4_6	.720													
V9_5_7	.719			.437										
V18_2_9	.717						-.400							
V13_5_6	.716	.468												
V2_8_6	.715													
V2_8_7	.715													
V18_5_1	-.715						.473							
V8_8_3	-.713						-.462							
V17_2_7	.711							.557						
V18_5_4	-.710					.423								
V6_5_6	.708													
V3_8_4	-.708													
V13_2_8	.706													
V4_8_7	.705							.407						
V7_8_7	.705							.423						
V15_2_8	.705					-.406								
V14_8_7	.705													
V15_6_4	-.705													
V7_5_5	-.704													
V18_6_2	-.703	-.581												
V2_5_7	.702	-.497												
V18_4_7	.702	-.461												
V16_5_9	.701			.522										
V5_8_4	-.700													
V18_6_3	-.700	-.524												
V9_2_4	.699				.520	-.407								

V1_8_5	-.698				-.632									
V2_6_2	-.696													
V16_8_1	-.695			.469										
V3_8_1	-.695													
V16_9_7	.695					.515								
V17_6_5	-.694													
V10_8_9	.694									-.444				
V2_4_3	.693				.414									
V16_4_3	.688	-.478												
V13_2_9	.688													
V1_4_3	.687	-.412												
V18_6_4	-.687													
V7_8_6	.684							.512						
V12_8_9	.683			-.416										
V11_6_2	-.681	-.500												
V6_6_5	-.679	-.510												
V1_8_2	-.678				-.475									
V5_8_7	.678													
V7_5_9	.677		-.406											
V15_5_3	-.676					.569								
V6_9_7	.676													
V2_9_8	-.675				-.482									
V16_9_6	.675					.542	.409							
V7_5_7	.675					.477								
V9_5_9	.673			.547										
V3_5_9	.671			.429					.465					
V4_9_7	.671													
V1_8_6	.670							.431						
V9_6_3	-.670	-.556												
V4_6_4	-.670			-.456										
V7_5_4	-.670	.453				.405								
V10_2_6	.669													
V2_2_9	.669						-.494		-.403					
V17_6_2	-.668		-.452											
V16_6_5	-.667	-.417												
V1_2_4	.667				.488									
V17_6_4	-.667				-.461									
V13_4_6	.667								-.495					
V7_6_2	-.666		-.464											
V6_8_3	-.664													
V11_6_9	.663						.418		-.534					
V11_8_1	-.661													
V9_7_6	.660					.635								
V13_4_7	.660								-.421					
V1_6_9	.659													
V10_4_6	.659		.488											
V6_5_4	-.657					.615								
V4_6_5	-.655													
V10_9_7	.655													
V9_9_7	.654		-.523											

V6_6_4	-.653	-.415												
V4_8_2	-.652													
V16_2_4	.652				.578									
V15_9_6	.651		-.414											
V7_5_3	-.648			.457		.546								
V15_5_8	.648													
V7_6_5	-.648		-.415											
V14_8_4	-.646							.411						
V14_5_8	.646													
V16_6_4	-.646													
V6_4_3	.646	-.553												
V11_4_6	.645		.415	.434										
V6_6_2	-.645	-.605												
V15_5_1	-.645													
V12_2_9	.644													
V13_5_4	-.644				.535									
V10_2_7	.643							.475						
V1_5_2	-.643													
V6_9_6	.641										-.450			
V17_5_7	.639					.577								
V1_5_1	-.639		-.535											
V11_5_8	.638						-.561							
V7_2_4	.638				.413									
V9_6_2	-.637	-.532												
V6_5_1	-.636				.400		.495							
V16_2_8	.635								.479					
V18_9_7	.635		-.562											
V16_8_9	.634													
V18_2_8	.634									.436				
V13_5_1	-.634	.502												
V11_2_8	.632					-.512								
V1_5_5	-.631		-.513											
V1_2_5	.630				.555									
V18_8_9	.629		-.432											
V10_7_8	.629													
V3_2_8	.628				-.482									
V12_9_6	.628					.426								
V12_7_8	.627		-.425											
V9_5_4	-.627				.464									
V9_9_6	.627		-.440			.433								
V3_8_3	-.627						-.426							
V7_6_7	.627							-.436						
V7_2_5	.626				.435									
V12_2_6	.626				.455									
V8_5_4	-.625				.538									
V7_6_6	.625													
V15_2_7	.623							.401						
V18_8_3	-.622										.423			
V7_9_7	.620						.494							
V4_9_6	.619	.405												

V15_8_3	-.618						-.547							
V11_6_3	-.616	-.488												
V14_2_6	.616													
V10_9_6	.616	.484												
V7_8_8	.615			-.475		.459								
V1_8_3	-.615													
V14_4_3	.615			.464										
V2_6_4	-.615			-.483										
V12_6_2	-.614												-.517	
V8_9_7	.613		-.417											
V6_2_8	.613						-.509							
V9_6_5	-.612	-.452												
V2_6_9	.612				.479									
V3_6_5	-.609		-.403										-.402	
V18_5_7	.609		-.577											
V4_2_9	.609						-.473							
V11_5_9	.608													
V8_7_8	.608								-.463					
V12_8_3	-.607													
V5_2_6	.607									-.457				
V7_6_4	-.605													
V16_6_2	-.604	-.457												
V2_8_3	-.603						-.463							
V1_8_1	-.602													
V10_6_3	-.601	-.438		-.407										
V11_9_7	.600					.499								
V3_8_8	.600			-.430										
V8_5_1	-.599				.543									
V8_5_7	.599					.531								
V10_8_8	.598		-.461											
V11_5_1	-.598						.415							
V4_8_3	-.597							.410						
V17_9_7	.596						.504							
V7_9_6	.595						.445							
V14_2_7	.592										.419			
V17_8_3	-.592							.449						
V11_9_6	.591					.462								
V11_5_7	.591					.459								
V16_2_3	.591	-.432			.401									
V10_8_3	-.590												.441	
V1_8_7	.590	-.401						.426						
V3_6_4	-.589													
V5_8_3	-.589						-.507							
V13_5_9	.589			.471					.565					
V16_5_8	.587					-.478	-.466							
V10_2_9	.585						-.519							
V18_2_7	.583													
V10_4_3	.582	-.573												
V6_4_7	.582			.537										
V7_2_2	.580				.422									

V8_5_9	.579			.456				-.426						
V7_2_3	.574			-.471			.436							
V2_6_5	-.574			-.433										
V13_8_3	-.574								-.506					
V9_2_3	.572													
V8_4_6	.572													
V9_6_4	-.571			-.411			-.407							
V6_2_4	.571				.525									
V5_9_7	.571													
V11_2_4	.570				.527	-.451								
V14_8_9	.570		-.456											
V17_2_9	.569		.415	-.468										
V17_2_2	.569				.472		.430							
V1_7_5	-.569		-.513		-.491									
V16_2_9	.568				-.415			.558						
V10_6_4	-.567	-.404												
V4_4_7	.566			.421	-.446									
V11_8_3	-.564							.510	-.515					
V11_3_3	-.562				.445			.419						
V1_2_3	.561								.539	.445				
V12_6_6	.560					.453								
V10_6_5	-.560	-.419												
V4_5_3	-.559													
V12_2_7	.558				.425						.433			
V9_4_7	.557			.555										
V15_5_6	.555					.406								
V2_8_9	.554								.436					
V15_4_3	.554	-.512			.401									
V15_3_3	-.551			-.503	.544									
V12_8_8	.550		-.456											-.497
V5_2_4	.547				.460						.544			
V7_7_8	.545	-.509				-.466								
V9_2_8	.544				-.491									
V17_3_1	-.542							.525						
V14_9_6	.542					.417	.419							
V17_6_3	-.541													
V16_5_3	-.538			.406		.535								
V17_5_8	.538								.526					
V6_6_6	.538			-.428					-.438					
V5_2_8	.530					-.410						-.421		
V18_2_3	.529										.422			
V14_2_4	.529				.435			.407						
V3_6_3	-.528													
V3_9_7	.526						.462				-.433			
V11_5_6	.526				-.440	.428								
V12_9_7	.525					.464						-.421		
V13_7_4	-.525						.509							
V16_5_6	.525								-.415					
V11_8_8	.523		-.440				.424			-.440				
V3_9_6	.522						.454				-.415			

V18_3_3	-.519				.506									
V16_1_8	-.517	.446					-.422			.449				
V8_9_6	.515													
V13_6_7	.515	.461		-.400					-.447					
V10_7_7	.514													
V13_7_9	.514		-.469		.446									
V6_6_3	-.513	-.449							-.441					
V16_8_3	-.510							.468	-.455					
V15_8_9	.510		-.431				.508							
V14_9_7	.509												-.479	
V8_1_9	-.508	.416												
V15_4_9	.508		.477											
V10_6_2	-.507	-.426											-.416	
V15_2_3	.507			-.410			.418							
V3_6_2	-.507	-.410	-.454										-.499	
V9_5_1	-.506	.474												
V3_4_6	.504			.424							-.412			
V18_2_6	.503										.483			
V8_7_6	.500					.450								
V1_6_3	-.500			-.489										
V14_2_9	.498					-.407		.445						
V3_8_9	.496		-.409	-.491						-.423				
V12_2_4	.488				.402	-.458								-.467
V2_9_7	.488		-.439					.422	.459					
V10_5_1	-.487								.408					
V18_7_5	-.487							.405			.402			
V12_9_3	-.487		.435											
V3_1_1	.479		.446			.414								
V18_7_4	-.478							.467						
V18_7_2	-.474						.464	.420			.458			
V8_4_7	.472						.436							
V15_2_6	.471		-.445											
V9_5_3	-.469			.408	.434									
V12_6_3	-.461	-.401												
V16_9_8	.452	.400	-.421			.440								
V10_2_3	.451			-.401										
V5_5_3	-.443													
V6_8_9	.425													
V12_6_7	.407													
V11_1_4		.943												
V11_1_3		.940												
V16_1_4		.931												
V1_1_4		.921												
V9_1_5		.910												
V11_1_5		.908												
V10_1_4		.906												
V1_1_5		.905												
V1_1_8		.896												
V9_1_3		.894												
V7_1_7		.890												

V10_1_5	.886												
V17_1_7	.884												
V9_1_4	.883												
V5_1_4	.878												
V4_1_5	.872												
V10_1_3	.871												
V5_1_5	.867												
V1_1_3	.855							.463					
V15_4_4	-.853												
V16_1_3	.852												
V16_1_5	.849												
V7_1_8	.847												
V13_1_5	.845												
V7_1_4	.840												
V7_1_3	.836												
V13_1_4	.829												
V17_1_3	.828												
V13_1_2	.827												
V12_1_5	.823					-.406							
V8_1_3	.819												
V15_4_5	-.817												
V11_4_5	-.812												
V1_1_2	.809			.409									
V17_1_6	.806												
V4_1_4	.803												
V12_1_4	.798					-.481							
V6_1_7	.794												
V2_1_4	.789												
V2_1_5	.784												
V7_1_5	.782				.406								
V11_4_4	-.781												
V2_7_8	-.780						.429						
V10_1_7	.775												
V6_4_4	-.767												
V10_4_4	-.766												
V4_7_9	-.761												
V7_1_6	.758												
V8_1_7	.756				.483								
V5_1_3	.754								-.423				
V16_1_7	.745												
V1_9_1	-.743			-.407									
V2_1_3	.737		-.489										
V18_1_5	.731				.421								
V15_4_2	-.722	-.401											
V18_4_5	-.720												
V11_4_2	-.718	-.576											
V9_1_2	.712												
V16_1_2	.707				.536								
V18_1_4	.699		.450		.401								
V18_4_2	-.698				.469								

V6_1_6		.693												
V18_4_4		-.691		.469										
V5_7_8		-.689			.415									
V13_1_7		.688												
V7_1_9		.684					-.484							
V6_4_5		-.681												
V8_1_8		.681												
V16_4_4		-.677		.461										
V16_4_5		-.675		.460										
V12_4_5		-.675												
V18_1_8		.674							.485					
V16_1_6		.670						-.410						
V2_5_1		.667		-.479	.448									
V14_7_8		-.667											.430	
V11_1_9		.662					-.594							
V7_1_2		.662		-.429		.540								
V15_7_9		-.661			.439	.475								
V2_1_2		.660												
V17_4_3	.482	-.658												
V17_1_4		.657				.542								
V1_4_4		-.644		.525										
V2_5_6	.572	-.643												
V12_4_4		-.640										.428		
V17_4_4		-.640				.535			-.454					
V8_1_6		.636				.508								
V13_1_6		.634			-.412				-.458					
V10_4_5		-.634	-.413											
V1_1_9		.633	.476											
V10_1_6		.633												
V17_1_5		.633				.483								
V15_1_3		.626		-.502										
V17_1_9		.625		-.401										
V14_6_3		-.624												
V4_1_2		.622												
V8_6_3	-.548	-.622												
V11_1_8	-.535	.621												
V14_1_8	-.463	.615									.429			
V18_1_9		.613		.544										
V7_4_8		.609	.501							-.408				
V8_2_3		-.607			.522									
V6_7_8		-.605				-.409								
V8_4_4		-.604		.438							.403			
V16_7_8		-.602			.403				-.436					
V5_4_8		.601									.453			
V14_1_5		.599				.472								
V17_1_8		.597		-.458										
V4_4_4		-.597										.467		
V2_7_7		-.597					-.439							
V13_6_6	.424	.592							-.529					
V2_4_7		-.590				-.473								

V16_6_6		.590												
V16_4_2		-.589	-.495											
V4_1_3		.584												-.580
V3_4_5		-.581										.461		
V1_7_8		-.581	-.514											
V11_1_2		.581				.559								
V4_4_5		-.580										.540		
V1_9_4		-.579	.417		-.404									
V7_5_6	.430	-.577				.405								
V18_9_3		-.571	.436											
V13_1_8		.570												
V1_4_6		-.565	.446	.421										
V18_4_3		-.565	.439											
V1_4_5		-.565	-.534											
V2_7_6		-.563					-.524							
V2_1_7		.559					-.473							
V10_6_6	.529	.557	.449											
V3_4_4		-.556										.408		
V12_4_3		-.555	.429											
V14_2_3		-.552									.542			
V15_7_8		-.550	-.524		.468									
V2_7_3		.547			-.444				.467					
V13_2_1		.544		.508	.512									
V8_6_6		.543	.455						-.523					
V11_4_8		.541						.402						
V11_9_3	-.462	-.539												
V5_1_8	-.428	.539					-.484							
V12_7_9		-.538			.419								.484	
V18_7_8		-.533					-.485							
V1_9_8		-.533	-.456						.496					
V5_1_2		.532					.417							
V6_2_3		-.529		-.416										
V9_8_8		-.526	-.497	-.506										
V5_6_5		-.525										.467		
V11_4_3	.512	-.518					-.413							
V3_4_3		-.517	.460	.486										
V5_6_3		-.517	.426									.402		
V16_8_8		-.510				.425			-.432					
V10_1_8	.447	.507					-.503							
V5_6_2		-.507										.456	-.425	
V18_7_6		.507			.469									
V4_1_7		.499					-.447							
V8_4_3	.446	-.493		.424		.424								
V4_1_8		.482					-.422							
V8_4_5		-.479		.464							.426			
V7_5_1		.472				.409								
V9_1_7		.468	.417				-.442		.417					
V14_7_9		-.465			.441	.438							.452	
V3_9_4		-.462	.452											
V13_8_8		-.460	-.428											

V5_4_3	.424	-.453	.424								-.439			
V7_7_2		.449			-.447				.447					
V13_9_6		.428	-.403		-.416									
V14_5_7														
V4_4_3														
V13_6_1			-.894											
V7_6_1			-.890											
V8_9_1			.883											
V12_9_2			.863											
V8_9_2			.853											
V16_9_1			.851			-.424								
V16_9_5			.841											
V18_9_1			.837											
V5_9_2			.834											
V2_6_6			.826											
V7_9_1			.826											
V6_9_2			.824											
V15_3_9			.821	.416										
V13_9_1			.820											
V1_4_2			-.813											
V6_9_1			.807											
V16_9_2			.807											
V9_9_2			.803											
V7_9_2			.803	-.429										
V5_9_1			.803											
V9_9_5			.802											
V6_9_5			.802	-.415										
V8_9_5			.799											
V15_9_1			.799											
V10_9_1			.796											
V9_9_1			.794											
V6_6_1			-.793											
V14_1_6			.792											
V16_9_4			.784											
V12_9_1			.784						.405					
V15_9_5			.780											
V9_6_1			-.773							.431				
V11_6_1			-.769											
V15_3_8			.764											
V15_4_8			.762											
V18_9_2			.760											
V5_9_5			.759											
V15_9_2	-.431		.756											
V18_9_5	-.402		.755											
V7_9_5			.750	-.565										
V1_6_6			.746											
V5_9_9			-.745											
V18_5_8			-.739				-.497							
V11_9_1			.739											
V14_9_5	-.512		.739											

V12_9_9			-.734											
V7_4_2			-.725					-.403						
V13_9_9			-.718	.507										
V15_9_4			.717											
V17_9_1			.717											
V6_9_4			.716											
V11_9_2			.716											
V4_9_1			.715											
V14_6_6			.715											
V7_9_4			.713	-.583										
V18_6_1			-.712							.490				
V16_9_9			-.706											
V10_6_1			-.706											
V13_9_5	-.445		.706		.461									
V17_9_4			.704											
V13_9_2	-.433		.704		.504									
V12_9_5			.702											
V1_4_1		-.532	-.700											
V7_6_8		-.497	.700											
V8_9_9			-.697	.474										
V11_9_5			.694											
V8_9_4		-.464	.692											
V3_9_2			.681		.404									
V14_1_7			.679			.489								
V17_9_5			.677	-.475										
V9_9_9			-.676	.432										
V9_9_8	.505		-.671											
V10_4_8			.670											
V3_9_9			-.669	.454										
V17_6_1	-.434		-.664		-.409									
V4_9_9			-.663											
V14_9_1			.663											
V18_9_9			-.663	.545										
V8_6_1	-.473		-.661											
V10_9_2	-.415		.660											
V3_6_1			-.659										-.491	
V14_9_2	-.548		.656											
V1_6_7			.655											
V3_9_1			.654											
V2_9_1		-.428	.652											
V17_9_2	-.485		.649											
V4_9_5			.649											
V1_9_9			-.646	.529										
V1_2_9		-.511	-.646											
V16_9_3			.645			.525								
V3_9_5			.642											
V1_3_2			-.639		.551									
V5_9_4			.638											
V18_9_8			-.636		-.444									
V15_6_1			-.633						.444					

V13_9_4	-.452		.632		.438									
V1_6_1	-.461		-.630					-.427						
V4_9_2			.625	-.482										
V9_7_3			-.625		-.541									
V11_9_4			.624					.439						
V1_7_6			.623			.534			.438					
V17_1_2			.618			.449								
V1_4_8			.615			.468								
V9_9_4			.614	-.414				.455						
V4_8_9			-.612											
V9_6_6			.610											
V2_4_8			.610	-.429										
V1_6_5	-.538		-.606											
V12_3_6			.605							.434				
V18_5_9	.537		-.604	.445										
V5_6_1			-.595							.447				
V13_8_9			-.594	-.401										
V16_6_1			-.592				-.508							
V18_9_4		-.463	.592											
V7_4_1			-.591				.541	-.437						
V10_9_5			.589										.411	
V2_6_7	.555		.588											
V1_7_4	-.583		-.588											
V5_9_3	-.467		.586											
V15_9_3		-.538	.582			.507								
V9_8_9	.546		-.582	-.441										
V3_4_2			-.581		.562									
V11_6_6	.439		.581		-.425									
V16_4_8		.460	.579											
V4_6_1			-.578		-.424					.415				
V14_5_9	.506		-.577											
V13_7_8	.469	-.413	-.577											
V11_1_7		.527	.577											
V12_4_6	.431		.576			.504								
V11_4_7	.452		.570	.447										
V10_3_8			.567											
V14_6_7			.564				.424							
V8_5_8	.476		-.562							.499				
V18_9_6	.525	.442	-.562											
V7_7_3		.512	-.560						.526					
V14_9_3		-.531	.559											
V1_9_5		-.468	.558		-.426									
V18_5_6			-.557					.416			-.431			
V8_9_3	-.451	-.493	.556											
V17_6_6	.470	.470	.556											
V3_3_9			.555	.490						-.499				
V17_4_7			.554	.449										
V7_9_9			-.552	.422		.504								
V1_8_8			-.552					.402						
V11_8_9	.418		-.552				.447			-.422				

V12_3_7			.550	.520										
V15_7_7	.475		-.550			.421								
V10_9_8			-.540			.404							.431	
V17_7_8	.430		-.539							.408				
V10_4_7	.493		.537											
V2_8_8	.488		-.535	-.446										
V9_4_2			-.533	.442										
V1_5_4	-.523		-.532											
V4_4_2			-.531									.469		.423
V2_9_4			.531	-.483										
V6_8_8		-.424	-.527						.455					
V11_9_9			-.527	.440	-.401									
V15_7_3			-.527					.434	.495					
V3_5_3			-.524	.499		.495								
V1_6_2	-.522		-.524											
V5_8_8	.414		-.523			.425								
V10_6_7	.497		.522			-.478								
V2_9_2	-.409		.514											
V7_9_3	-.442		.508	-.444										
V10_4_2			-.505											
V12_7_4	-.445		-.504					.413						
V1_5_3	-.435		-.502						-.410					
V14_4_6	.485		.501											
V4_9_4			.498					.425						
V9_9_3	-.442		.485											
V5_7_9	.468		-.480		.472									
V11_7_9			-.476					.437						
V14_7_4			-.470								.437			
V13_9_3	-.421		.470	.425	.441	.400								
V10_9_4		-.451	.466	-.419										
V1_9_2		-.422	.465		-.445									
V14_9_9			-.455										-.445	
V12_4_8			.454											
V3_7_4			-.450		-.447									
V9_6_7	.414	.423	.444					-.443						
V4_7_4			-.444											
V3_4_8			.430		-.426									
V14_4_7		-.420	.423											
V12_5_9			-.414											.405
V4_9_3														
V7_3_6				.888										
V2_3_6				.872										
V7_3_3				-.867										
V7_3_7				.855										
V17_3_7				.851										
V17_3_6				.849										
V16_3_7				.833										
V13_4_4				.833	.406									
V5_3_7				.830										
V16_3_6				.828										
V1_3_8				.826										

V7_3_9				.806										
V10_3_6				.772										
V1_3_7				.770					-.422					
V9_4_4		-.525		.767										
V2_3_7				.765										
V18_1_3				.758										
V1_3_6				.755										
V17_6_8				-.754										
V6_3_8				.754						-.446				
V2_9_9				.752	-.467									
V9_4_5				.739										
V13_3_8				.735										
V11_3_6			.400	.731										
V8_3_9				.730						-.490				
V8_3_7				.728										
V9_3_8				.723						-.495				
V7_4_6	.437			.722										
V6_3_7				.720					-.542					
V6_1_3				-.720										
V11_3_8				.719						-.524				
V1_8_9				-.718										
V13_3_9				.712						-.611				
V16_4_7				.703					-.401					
V13_4_5				.700	.509									
V2_1_9			-.469	.699										
V10_3_7				.698										
V5_3_8				.692										
V9_3_7			.401	.692										
V1_5_7				.689		.496								
V6_3_9		.403		.688		.402								
V7_1_1				-.687				.440						
V8_3_6				.686					-.470					
V8_3_8				.681						-.545				
V18_3_8				.681			-.549							
V16_3_9				.677						-.564				
V14_3_7			.431	.677										
V9_3_6				.664		-.450								
V5_3_6				.661						-.501				
V5_3_9				.659						-.440				
V4_1_1	-.420			-.655										
V6_3_6				.653					-.522					
V7_3_8			.621	.650										
V13_4_3	.444		.488	.648										
V11_3_7			.509	.646					-.445					
V14_3_8				.644					.433				.425	
V8_8_8			-.403	-.643										
V17_3_9				.638					.525					
V9_3_9				.636						-.431				
V17_8_9	.519			-.636										
V2_2_3				-.632	.480									

V7_4_7	.483			.628										
V2_9_5			.455	-.626										
V16_3_8			.412	.626										
V11_3_9				.626						-.615				
V5_4_7				.623										
V1_5_6				.623		.456								
V8_2_1				.620	.565									
V18_1_6				-.618				.550						
V14_3_6			.506	.617										
V14_3_9				.617			-.439							
V2_6_8				-.616	.531									
V13_3_7	.404			.612					-.577					
V10_3_9				.605										
V1_7_1		.452		.605										
V13_4_9		-.429		.599						.538				
V10_5_3	-.552			.599										
V13_4_1	-.453			.598										
V16_4_1	-.460			.597										
V17_4_6	.427		.509	.589										
V17_8_8	.504			-.588										
V4_8_8				-.588		.473								
V15_9_9			-.572	.588										
V16_4_9				.588				.542						
V15_4_1				.588			.446							
V1_4_7		-.520	.442	.588										
V17_6_9			.568	-.588										
V14_1_3				.583		.578								
V3_3_7				.581		-.460								
V11_4_9		-.436		.581						.442				
V12_3_9				.581		-.424								
V4_7_6				-.580										
V8_8_9	.419		-.440	-.577						-.437				
V6_7_7			-.410	-.576		.552								
V8_7_1		.540		.575		-.403								
V17_2_8	.544			-.574										
V13_6_8	-.459			-.572										
V4_3_7				.568				.521						
V8_4_1				.567							.517			
V9_4_1	-.407		-.403	.565										
V13_5_3	-.422			.565	.488									
V4_6_3	-.529			-.558										
V16_4_6	.444			.555	.463				-.405					
V12_3_8				.553									.490	
V13_4_2			-.430	.553	.477									
V17_3_2				-.548	.442			.402						
V4_6_7		.428		-.548							.508			
V14_4_9				.546				.508			.432			
V6_4_1	-.440			.544										
V7_7_7			-.418	-.543					-.461					
V3_4_1				.541			.433							

V8_5_3	-.526			.539	.431									
V7_8_9	.452		-.428	-.539										
V16_6_3	-.495	-.522		-.535										
V2_6_1				-.533		-.428	-.475							
V3_3_6				.531			.520							
V1_6_8			.492	-.530		.522								
V9_4_9		-.409		.529						.509				
V18_6_7	.524	.418		-.528										
V9_4_3	.459	-.426		.526										
V14_5_3				.525		.408								
V1_6_4	-.519		-.507	-.521										
V8_7_7				-.517		.444	.424							
V17_2_3				-.515	.427			-.413						
V15_8_8			-.414	-.511										
V6_3_4		-.413		-.510						.460				
V3_4_7	.479			.510										
V17_6_7	.504			-.509										
V7_6_3	-.471	-.422		-.509										
V14_8_8	.491			-.504										
V6_6_7	.483	.415		-.500					-.442					
V3_6_8			.410	-.491										
V9_4_6				.488						.481				
V16_5_7	.442			.487										
V18_1_7				-.485					-.441					
V10_4_1	-.444			.480			.413							
V12_4_7		-.405	.463	.478		.452								
V2_9_6				.476										
V18_7_7	.427			-.474										
V4_4_9		-.442		.455										
V11_2_1				.452					.443					
V2_2_2					.837									
V6_2_2					.813									
V2_3_3					.812									
V18_3_5					.801									
V2_2_5					.795									
V18_2_2					.792									
V9_7_5					-.790									
V2_2_4					.790									
V10_2_2					.781			-.411						
V3_2_2					.780									
V13_2_5					.778									
V9_7_2					-.775									
V8_3_5					.774			.425						
V2_4_1					.769									
V2_2_1		.412			.767									
V8_2_5					.764									
V6_2_1				.424	.762									
V8_2_4	.511				.753									
V15_3_4	-.429				.745									
V15_3_5	-.407				.744									

V18_2_5					.742						.455			
V6_3_2					.742									
V13_2_2		.432			.742									
V10_2_5	.414				.736									
V9_2_2					.735									
V6_2_5	.451				.733									
V8_2_2					.727		.411							
V9_7_4			-.540		-.724									
V13_2_4	.433				.722									
V8_3_4					.721									
V6_3_5					.716									
V2_3_4					.710									
V13_3_5		.433			.705									
V8_3_2					.702			.481						
V2_5_3					.695	.463								
V13_3_2		.481			.693									
V6_1_8					-.691									
V5_3_5					.690			.464						
V2_3_5		.401			.689									
V9_3_5		.412			.688									
V12_3_5					.687									
V15_3_2				-.559	.685									
V7_3_4		.543			.683									
V18_3_4					.683									
V1_8_4	-.554				-.680									
V2_4_5			-.449		.674									
V17_7_9				-.455	.674	.404								
V12_2_2					.672									-.400
V13_3_3		.404			.672									
V12_3_2					.671			.408						
V2_3_2			-.402		.670									
V18_3_2	-.448				.670									
V9_2_5	.533				.669									
V9_3_4					.668									
V3_7_9					.663									
V6_3_1					.661			.512						
V3_2_5					.660						.407			
V3_3_5					.659									
V10_9_9				.449	-.657									
V11_3_4					.654									
V2_3_1					.654	-.490		.407						
V15_1_7		.579			-.645									
V2_4_2			-.578		.642									
V13_3_4				.401	.641									
V1_2_2	.474				.640									
V5_3_4					.635									
V11_2_2	.463				.635		.467							
V11_3_5	-.438				.633									
V7_3_5		.486		-.470	.631									
V8_3_1					.628			.505	.468					

V3_3_2					.627									
V15_1_6		.577			-.625									
V5_3_2				-.453	.625									
V11_2_5	.506				.624									
V16_2_2	.525				.622									
V9_3_1					.621									
V2_5_2	-.611				.620									
V2_1_8			-.433		-.620									
V9_3_2	-.408				.618									
V4_3_5					.618									
V10_3_5					.617									
V1_7_9					.617									
V10_2_4	.508				.614									
V1_3_5			-.518		.613									
V2_5_5	-.593				.609									
V16_2_5	.578				.608									
V5_2_2					.608						.452			
V15_2_5	.508				.607									
V2_4_4			-.491	.439	.606									
V18_2_1					.606						.462			
V1_3_4				.506	.604									
V9_2_1		.496			.600									
V4_2_2					.599		.429							-.401
V15_2_4	.590				.599									
V17_3_4					.595			.472						
V1_5_8	.425		-.427		.595									
V6_4_2		-.407	-.442		.593									
V9_3_3					.592			.421						
V14_2_2					.589	.444								
V9_7_9				-.474	.588									
V12_6_1					-.588					.439				
V9_7_8				-.440	.586									
V14_2_5	.521				.585									
V17_2_5	.565				.578		.506							
V15_1_8		.432			-.578		-.511							
V2_5_4	-.510	.534			.576									
V1_2_1	.572				.576									
V17_2_4	.570				.576		.420							
V11_3_2				-.407	.573									
V15_2_2	.448				.569		.483							
V10_3_4		.414			.565			.452						
V5_2_5	.499				.565						.437			
V17_3_5				-.451	.565			.466						
V14_9_8					-.565									
V18_2_4	.483				.564						.502			
V12_2_5	.473				.556									-.454
V9_2_9	.484				-.551		-.401							
V16_7_4					-.546		.529							
V4_3_2					.544			.488						
V17_7_5					-.540	-.419	.519							

V3_3_4					.540	-.467								
V13_9_7			-.449		-.540									
V10_3_2	-.401		-.401		.533									
V12_3_4					.531							-.461		
V7_6_9	.476			.521	-.529									
V3_5_1					.525							.507		
V16_3_1					.524	-.422		.462						
V1_1_1			-.415		-.524	-.478								
V7_3_2		.421	-.442	-.508	.521									
V14_7_2		.514			-.519						.406			
V4_7_2		.449			-.515		.495	.417						
V5_3_1					.513			.480	.453					
V4_3_4					.505									
V10_5_9	.498				-.504		-.497							
V15_1_9	.415				-.504		-.483		-.416					
V4_7_5					-.503		.430	.404						
V4_6_6	.421			-.403	-.497									
V18_7_9	.460		-.467		.495	.420								
V4_2_5	.473				.494									-.473
V8_4_2					.479						.456			
V11_6_7	.430		.418	-.435	-.464									
V3_3_1					.461									
V12_7_5					-.456	-.409	.423							
V10_3_1					.422									
V6_7_9						.869								
V17_7_7						.831								
V14_5_2						.823								
V14_1_2						.810								
V17_7_6						.809			.448					
V14_5_5						.801								
V6_9_9	.401					.772								
V1_1_6			.439			.756	.405							
V13_7_1						-.721								
V17_7_1					-.554	-.719								
V2_4_6		-.527				-.718								
V14_5_4						.708								
V2_7_2						-.707				-.431				
V11_7_1						-.704								
V18_7_1				.571		-.703								
V5_5_7						.699				-.410				
V17_4_5		-.525				.698								
V11_7_7				-.409		.698								
V16_7_1					-.638	-.690								
V3_1_2				-.424		.689								
V13_9_8					-.465	.680								
V7_7_1					-.413	-.679								
V14_7_1		.502				-.679								
V6_1_5						.675				.450				
V10_1_2		.448				.671								
V2_7_1	-.631					-.669								

V12_5_6	.435					.669								
V2_3_9						.665	.403							
V9_7_7	.579					.663								
V18_4_8		.552				.661								
V6_7_1					-.419	-.659								
V15_1_5						.656								
V9_7_1						-.652	.479							
V1_1_7		.410	.430			.650								
V18_1_2		.437			.456	.648								
V17_4_2			-.498			.645								
V2_9_3	-.479					.641								
V6_6_9						.638	.410							
V6_5_3		-.608				.638								
V14_1_4		.577		.406		.637								
V11_7_6	.441					.636								
V12_1_2		.485				.633		.406						
V14_5_1		.408	-.486			.631								
V2_7_5			-.514			-.629								
V8_1_2						.628			.432					
V12_5_7						.627								
V17_2_1			.467			-.622								
V6_1_9						.622								
V6_4_9						.621								
V15_1_2						.617		.481						
V15_7_5	-.445					-.614								
V18_6_9						.614		.438						
V15_3_1					.559	-.612								
V8_5_6	.440					.609	.436							
V14_4_2			-.458			.608								
V7_2_1		.427				-.608								
V17_9_3	-.453		.434			.608								
V15_2_1				.405		-.604			.496					
V17_5_6	.595					.603								
V6_9_8					.497	.597				-.494				
V1_7_7			.516			.596			.461					
V15_7_1					-.515	-.593								
V14_4_5						.589								
V8_6_9	.496					.589								
V12_1_6			.577			.581								
V13_7_2	-.507					-.571								
V4_9_8						.571							.410	
V6_2_9		.489				.569								
V1_9_3			.401			.569								
V13_7_7	.544			-.443		.567								
V16_7_2	-.434				-.423	-.565								
V6_4_8		.482				.562								
V14_2_8	.511					-.561								
V7_9_8						.560								
V15_7_2	-.449					-.558								
V11_9_8						.557								

V12_1_7			.494			.554	-.401							
V10_2_8	.472					-.549	-.431							
V16_7_7	.446					.549				.444				
V15_1_4		.486				.549	-.431							
V7_2_8	.527					-.547	-.450							
V18_6_6		.514	-.479			-.545								
V12_3_3						-.543								
V16_2_1						-.542			.470					
V14_4_4				.440		.541								
V11_2_3		-.412				-.540	.400							
V8_1_5		.449				.540								
V10_7_6				-.460		.539		-.433						
V6_7_6				-.502		.538								
V6_1_4				-.501	-.413	.537				.425				
V6_5_9		.425				.537								
V13_7_6	.418			-.518		.536								
V10_4_9						-.535								
V7_3_1		.470				-.534								
V6_1_2	-.455	.401				.532								
V14_3_2						.529		.522						
V4_7_1		.486				-.526								
V6_9_3			.497			.526	.426							
V13_7_5	-.516					-.523	.408							
V3_3_3	-.506					-.515								
V15_7_4	-.422					-.513			.463					
V8_1_4		.485				.511								
V12_7_6						.508			.451					
V2_7_4					-.455	-.508				-.461				
V8_7_9					.410	.506								
V16_7_5	-.409				-.472	-.506	.407							
V14_4_1				.461		.498				.403	.456			
V15_7_6			-.424		-.404	.497								
V3_2_4					.481	-.495					.484			
V18_5_3	-.459			.410		.490								
V4_7_7				-.449		.481								
V4_5_7	.433					.477							-.431	.414
V16_7_9					.452	.476								
V16_6_8						.474			-.404	.428				
V12_6_8			.409			.474	.422							
V10_7_5						-.472					.436			
V3_6_9						.469							.408	
V13_4_8			.435	.410		.463								
V10_1_9		.417				-.463	-.449				.443			
V14_7_7						.460	.442						.455	
V12_4_2		-.449				.455								
V4_3_9				.402		-.452	-.440			-.419				
V5_3_3	-.411					-.421								
V16_1_9							-.807							
V17_4_1	-.420						.772							
V18_3_9				.578			-.724							

V7_5_8	.452						-.704							
V9_1_9		.476					-.696							
V2_5_9							-.653		.403					
V10_5_8	.459						-.644							
V17_7_3							.639	.407						
V6_3_3				-.562			.628							
V9_6_8						.404	.627		.539					
V3_6_6						-.439	.623							
V18_6_8							.622							
V14_8_3	-.585						-.618	.406						
V15_9_8		.436					.609							
V6_7_4					-.457		.603							
V9_1_8		.506					-.603							
V3_7_6	.409						.597				-.470			
V6_5_8	.510						-.591							
V11_4_1	-.478						.585							
V3_5_6							.581				-.448			
V14_6_4							-.574							
V17_7_4					-.542		.573							
V13_5_8		.436					-.569							
V18_4_1	-.461			.414			.569							
V5_1_9		.438					-.565				.421			
V3_7_7							.560				-.537			
V11_6_8							.557		-.502					
V17_7_2					-.529	-.479	.556							
V6_7_5					-.497		.545							
V12_7_2					-.520		.545							
V6_7_2					-.478		.539							
V16_7_6	.470					.472	.538							
V17_9_6	.468						.537							
V12_4_1							.527							
V11_1_6			.490				-.523			.441				
V14_6_5	-.448						-.522							
V11_7_2					-.455	-.419	.522							
V3_6_7							.518					-.410		
V4_4_1							.511							
V14_6_1			-.465				-.498						-.446	
V11_7_5						-.472	.495							
V3_1_3					.418		-.488		.452					
V12_1_3		.486					-.488						.415	
V9_6_9							.487		-.427					
V8_7_2		.413					.481							
V3_1_9						.408	-.474							
V11_7_4						-.417	.466	.424						
V14_6_2	-.416						-.441						-.439	
V5_7_4					-.423		.441							
V7_4_9							-.441							
V17_3_3				-.411			.439	.432						
V4_1_6							-.409							
V5_6_4				-.404			-.409							

V13_7_3								.737					
V9_4_8						.434		-.725					
V15_1_1								.720					
V10_7_3			-.422					.709					
V12_7_3								.703					
V6_6_8								.689					
V17_1_1			.454					.684					
V18_7_3								.671					
V16_1_1								.664	.615				
V6_7_3								.662					
V11_1_1								.655					
V14_3_3								.653					
V11_7_3			-.400				.418	.642					
V8_7_3								.641					
V16_7_3		.506						.640					
V11_7_8		-.549						.637					
V2_2_8								.636					
V3_1_6								.627		.412			
V14_1_1						.410		.616					
V14_3_1							-.495	.612					
V4_7_3								.611	.442				
V11_3_1					.530			.609					
V10_7_4							.426	.604					
V12_3_1					.426			.585				-.404	
V18_3_1					.566			.583					
V10_7_9								.575					
V14_7_3								.569			.546		
V2_2_7	.427							.546					
V2_1_1		-.408		-.444				.529					
V4_3_1					.457			.525	.421			-.448	
V6_1_1		-.412		-.460				.521	.400				
V13_2_3					.500	-.436		-.521					
V14_3_5						.501		.520					
V8_3_3	-.495				.504			.519					
V10_3_3								.519					
V7_7_9		-.404				.479		.517					
V14_7_6			.508					-.512					
V7_4_5			-.483					-.507		.504			
V3_7_3								.497					
V4_3_8				.465				-.492					
V10_9_3		-.447					.422	.490					
V3_7_2							.464	.488			.442		
V12_4_9								.483					
V5_6_7			.426				.458	-.466					
V12_1_1								.462					-.418
V18_8_8	.446							-.453					
V12_9_4		-.436	.420					.450					
V8_7_4	-.412							.448					
V14_3_4							-.419	.447					
V1_3_1	.401			-.424				.445	.445				
V3_7_5							.401	.435					

V17_9_9					-.404				.779		
V16_6_9									-.761		
V17_5_9	.429								.740		
V2_1_6					.431				-.717		
V17_4_9									.687	.414	
V15_6_9									-.682		
V11_5_3	-.529								-.679		
V1_5_9									.662		
V10_7_1						-.539			.656		
V17_9_8							.471		.650		
V17_3_8				.493				-.413	.648		
V16_3_3									.648	.421	
V13_3_6	.430								-.646		
V1_2_8			-.521						.644		
V15_6_6	.405				-.439				-.635		
V1_4_9								.572	.630		
V13_1_3		.575							-.625		
V1_3_9								.481	.621		
V16_3_5					.442				.620	.445	
V14_6_9	.477					.438			-.614		
V2_3_8				.513					.612		
V14_2_1				.513					.591		
V1_7_3			-.470					.490	.591		
V1_7_2					-.566				.588		
V2_4_9					-.505				.586		
V16_3_2									.585	.493	
V9_5_8									.582		
V1_3_3		.403			.497				-.576		
V12_7_7						.489			.576		
V16_3_4					.437				.576	.429	
V15_3_7	.409								-.573		
V13_6_9			-.490		-.546				-.565		
V2_7_9			-.447						-.561		
V15_3_6	.473			.409					-.549		
V2_2_6		-.462			.476				-.549		
V8_6_7		.509	.446						-.542		
V2_5_8					.405				.537		
V13_1_9		.425					-.495		-.537		
V7_7_6				-.404					-.525		
V15_6_7	.455				-.408				-.525		
V17_5_3	-.497					.515			-.521		
V13_3_1					.480				.520		
V9_1_1		.505					-.405		.516		
V10_2_1						-.429			.514		
V17_4_8			.485					-.404	.505		
V5_7_3									.485		.441
V7_7_4					-.476		.477		.478		
V1_9_6	.446			.417				.417	.474		
V9_1_6							-.463		.473		
V3_7_1									.469		
V7_7_5		.424			-.466				.468		

V1_9_7	.451			.442					.457					
V8_6_8	.411		.445						-.453					
V18_4_9				.551						.687				
V16_5_1										-.682				
V5_1_6										-.654				
V3_4_9		-.422								.644				
V8_4_9										.624				
V18_1_1										-.623				
V3_1_4		.478								.595				
V8_1_1									.460	-.594				
V8_4_8					-.527					.578				
V5_5_6										-.542				
V18_3_7									-.503	.533				
V3_1_5		.523								.528				
V5_4_6										-.522				
V7_4_4								-.484		.521				
V18_3_6									-.403	.503				
V4_6_8										.499				
V16_2_6	.468				.455				-.451	-.496				
V16_6_7							.434		-.429	.491				
V5_1_7						.483				-.490				
V13_1_1		.460						.427		-.480				
V5_6_6										-.425				
V5_4_1			-.402								.702			
V8_9_8					-.571						-.696			
V5_9_8						.415					-.678			
V5_1_1											.676		-.449	
V12_7_1											.669			
V5_4_5											.657			
V5_2_3											.653	.433		
V4_1_9							-.428				.640			
V10_7_2											.632			
V12_1_9							-.509				.623			
V3_9_8											-.597	-.493		
V10_1_1											.595			
V5_4_2			-.506								.594			
V12_2_3											.591			
V14_1_9			.437								.578			
V12_1_8		.524									.536			
V5_4_9										.512	.527			
V14_4_8					-.400	.412					.514			
V5_6_9											.491	.450	.473	
V5_8_9				-.424							.482			
V3_1_8		.438									.458			
V14_7_5					-.424						.456			
V5_6_8						.427			-.407		.437			
V8_7_5							.406				.431			
V3_5_8												-.864		
V5_5_5	-.440											.831		
V5_5_2	-.465											.821		

V5_5_4	-.413											.743		
V5_5_8												-.735		
V5_5_1	-.451											.728		
V4_5_5	-.596											.718		
V4_5_2	-.550											.697		
V4_5_4	-.549											.693		
V12_5_4	-.597											.671		
V5_5_9												-.669		
V12_5_5	-.618											.664		
V5_2_1												-.636		
V3_5_5	-.561											.630		
V12_5_2	-.518					.401						.627		
V12_5_1	-.533											.626		
V3_5_2	-.506				.420							.608		
V4_5_1	-.530											.592		
V3_2_1					.545							-.582		
V12_2_1					.447							-.568		-.450
V12_9_8											-.495	-.563		
V3_1_7										.408	.480	.559		
V12_2_8	.504											-.554		
V3_5_4	-.503											.546		
V4_2_8	.505									.434		-.538		
V3_5_7	.447						.404					-.520	-.489	
V3_9_3	-.506											-.519		
V3_2_3					.438						.477	.489		
V5_4_4												.457		
V4_5_9							-.447					-.455		.409
V14_5_6													-.791	
V10_5_6	.454												-.731	
V5_7_1						-.450							-.730	
V4_6_9													.730	
V5_7_6									.448				.729	
V14_6_8													.705	
V10_8_4	-.531												.635	
V5_9_6	.424												.625	
V10_6_9						-.573							.612	
V5_7_7												.496	.592	
V10_6_8			.435	-.469									.590	
V5_8_6	.508												.589	
V14_9_4			.449										-.564	
V5_7_5													-.554	
V3_7_8		-.478											.532	
V5_7_2													-.531	
V4_5_8													.515	.461
V3_3_8				.421			.401			-.487			.497	
V4_6_2	-.459					.419							-.465	
V12_6_9			.452									.418	.454	
V12_5_8					.412							-.444	.446	
V4_7_8														-.828
V4_5_6					-.485									.685

V4_2_3											.494			-.655
V4_2_1												-.455		-.649
V4_3_6				.451				.429						.595
V4_4_6	.572													.584
V4_3_3						-.414								-.514
V4_2_4	.484													-.495
V4_4_8														-.463

Extraction Method: Principal Component Analysis.
(a) 14 components extracted.

Table A3.b: Component matrix for wheat subset of weather variables (a)

	Component													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
V18_8_5	.944													
V8_8_5	.944													
V14_8_5	.925													
V8_8_1	.925													
V8_8_2	.924													
V18_8_2	.915													
V7_8_1	.914													
V16_8_5	.914													
V11_8_5	.914													
V9_8_5	.913													
V15_8_5	.906													
V15_8_2	.904													
V18_8_1	.900													
V15_8_4	.900													
V11_8_4	.896													
V16_8_4	.896													
V9_8_2	.896													
V2_8_2	.895													
V7_8_2	.895													
V13_8_5	.891													
V7_8_5	.890													
V16_8_2	.890													
V16_8_7	-.889													
V13_8_2	.887													
V6_8_1	.885													
V9_8_7	-.884													
V13_8_1	.881													
V7_8_4	.879													
V9_8_4	.875													
V2_8_4	.873													
V12_8_1	.872													
V8_8_4	.871													
V12_8_5	.865													
V12_8_2	.863													
V11_8_2	.862													
V2_8_5	.861													
V9_8_1	.859													
V18_8_7	-.859													
V5_8_5	.853													
V6_8_5	.852													
V2_4_7	.849													
V9_9_7	-.848													
V11_8_1	.848													
V9_8_6	-.847													
V6_8_2	.843													
V6_8_4	.840													
V13_8_4	.838													
V18_8_4	.838				-.420									

V10_8_2	.838											
V5_8_2	.837											
V9_8_9	-.831											
V15_8_1	.830											
V16_9_7	-.828											
V14_8_2	.825											
V4_8_5	.819											
V17_8_2	.818											
V17_8_4	.817											
V3_8_5	.816											
V8_10_6	-.813											
V17_8_5	.812											
V6_4_6	.810											
V6_4_7	.802											
V2_8_1	.802											
V16_8_1	.796											
V9_9_6	-.795											
V13_8_7	-.792											
V6_8_7	-.792					.453						
V15_8_7	-.790		.434									
V3_8_2	.790											
V15_12_6	-.790											
V2_8_8	-.789				-.461							
V18_9_7	-.784	-.427										
V10_8_7	-.784											
V15_12_7	-.782											
V7_5_5	-.781											
V3_8_8	-.780							-.464				
V10_8_1	.780											
V16_8_6	-.779					.473						
V9_10_6	-.776											
V2_4_6	.775											
V18_8_9	-.774											
V8_8_7	-.773											
V14_2_9	.771											
V1_4_3	.769											
V12_8_8	-.769											.436
V5_8_1	.767							.479				
V8_8_6	-.767											
V3_8_4	.766				-.442							
V16_8_9	-.765											
V15_9_7	-.765											
V7_4_7	.764			.504								
V17_9_1	.761					.411						
V12_8_9	-.759											
V7_8_3	.758			-.505								
V14_8_4	.756				-.505							
V5_8_4	.755				-.454							
V18_10_7	-.755											
V3_8_7	-.754											
V4_8_2	.754											

V18_8_6	-.750							
V2_5_7	.750	-.472						
V15_8_6	-.746							
V4_8_4	.744				-.446			
V18_12_7	-.744							.435
V6_12_7	-.741		.492					
V9_4_7	.741			.488				
V7_12_7	-.736	.403						
V17_8_3	.735							
V17_8_1	.734						-.533	
V6_8_3	.734							
V16_9_6	-.734							
V4_4_9	.733					-.426		
V7_5_4	-.732	.452						
V10_8_5	.732							
V7_8_8	-.729							
V18_10_1	.727						.524	
V15_8_9	-.726		.561					
V11_8_7	-.725					.480		
V3_8_1	.724							
V11_2_6	.724							
V7_5_2	-.722		-.508					
V15_8_8	-.719	.438						
V2_8_7	-.719					.459		
V14_8_9	-.718							
V11_1_2	-.717				.544			
V4_8_1	.717							
V2_4_3	.717				.526			
V15_1_7	-.714		.437					
V9_3_6	.712							
V18_10_6	-.711							
V11_8_6	-.711					.569		
V7_2_6	.710							
V6_1_2	-.709				.445			
V15_2_1	.706							-.409
V6_8_8	-.705				-.513			
V7_4_6	.705			.419			.459	
V3_2_6	.705							
V6_12_6	-.705		.498					
V14_9_5	.704	.607						
V2_5_6	.703	-.455						
V1_8_8	-.702				-.627			
V6_8_6	-.701					.549		
V13_8_8	-.700					-.466		
V16_4_3	.698	-.481						
V1_2_7	.697							
V8_9_7	-.695							.466
V14_8_1	.694					-.432		
V14_8_8	-.694							
V17_5_1	-.694		-.572					
V15_9_6	-.693	-.478						

V6_9_7	-.691					.439		.412		
V17_10_1	.690						.444			
V1_4_7	.689			.608						
V17_8_7	-.689			.480						
V11_4_3	.688									.425
V13_1_8	-.686									
V7_8_9	-.686		.460							
V3_4_3	.685			.511						
V9_9_8	-.683	-.447								
V10_8_8	-.683									
V13_9_5	.682									
V3_4_7	.678			.468						
V9_4_3	.678			.439						
V11_1_5	-.677				.503					
V8_10_7	-.677				.484					
V7_12_6	-.676	.531								
V3_3_6	.676	.433							-.454	
V10_8_6	-.675					.526				
V14_9_2	.674	.570								
V9_10_7	-.674	.465					-.410			
V1_12_9	-.674				-.401					
V7_5_1	-.672					.491				
V3_2_7	.672									
V13_8_6	-.671		.407			.491				
V15_9_1	.670			.491						
V9_8_3	.670			-.587						
V2_12_8	-.669	.517								
V8_1_6	-.669				.608					
V13_9_2	.669						.421			
V8_8_3	.669				-.439					
V11_2_8	.668		.439							
V11_4_6	.668			.568						
V3_8_6	-.668									
V7_8_7	-.667									
V18_8_8	-.664							-.462		
V8_8_8	-.662							-.444		
V11_2_1	.662									-.445
V2_12_7	-.661	.519								
V12_8_4	.660				-.628					
V6_12_1	.659							.494		
V4_8_7	-.657					.611				
V17_5_5	-.657		-.650							
V9_12_7	-.655		.544							
V13_8_9	-.655		.450							.488
V14_5_1	-.654				.572		.413			
V10_9_1	.654	.523								
V17_4_6	.653			.516						
V13_9_4	.652		-.458							
V16_9_2	.652	.572								
V1_8_5	.651						-.443			
V1_2_6	.650				.410	.467				

V2_8_9	-.649			.570	-.416								
V12_10_1	.647						.574						
V7_3_9	.647			.410		-.403							
V17_9_2	.646	.535											
V4_1_2	-.646				.508								
V11_8_9	-.645												
V5_2_7	.645												
V4_1_1	-.643												
V14_5_2	-.643			.424	.403								
V11_8_8	-.643						.413						
V13_4_3	.642				.506								
V1_8_2	.642						-.496						
V4_12_7	-.641		.517										.440
V10_3_9	.641								.501				
V18_4_7	.641	-.580											
V7_2_8	.641		.525			-.409							
V15_10_1	.639						.516						
V5_8_8	-.638								.409				
V16_4_7	.637												
V17_8_8	-.637			.437				-.442					
V8_8_9	-.637												
V1_4_6	.635			.587									
V15_9_2	.634	.606											
V10_4_9	.632				-.471								
V6_4_8	-.631						-.503						
V16_9_1	.631			.580									
V9_8_8	-.631	.466											
V14_2_8	.630												
V16_2_1	.630												
V5_8_7	-.630												
V17_12_7	-.630	.549											
V4_9_7	-.628	-.421				.546							
V11_9_2	.628	.544											
V7_9_7	-.626			.523									
V14_2_6	.626									.421			
V11_4_9	.626			.538									
V2_8_3	.625	.460		-.457									
V18_12_1	.624	.431						.456					
V3_8_9	-.624												
V12_8_7	-.623			.405		.467							
V2_8_6	-.622					.599							
V3_5_9	.622						.491						
V9_3_7	.619												
V13_4_9	.618								-.484				
V8_2_4	.618				.433	.482							
V10_10_9	.617	.412					-.424						
V4_8_9	-.617												
V10_4_7	.616		.468										
V10_3_8	.615								.405				
V10_4_3	.614												
V15_8_3	.614			-.403									

V13_12_9	-.614							-.442		.473
V7_1_2	-.614				.561					
V14_8_7	-.613			.552						
V16_9_5	.613	.553								
V18_4_6	.612	-.440								
V5_9_7	-.611	-.450								
V10_8_9	-.611									
V7_2_7	.610		.486							
V8_9_2	.609	.596								
V7_8_6	-.608					.469	.437			
V3_3_7	.608	.593								
V16_4_9	.608			.463					-.470	
V3_1_2	-.608				.484					
V15_4_3	.608	-.489								
V11_12_1	.606		.456					.508		
V11_10_1	.606						.529			
V14_4_3	.603			.555	.449					
V6_2_6	.603			-.485						
V9_3_9	.603			.471					.413	
V15_2_4	.601			-.484		.528				
V10_9_7	-.601					.429				
V5_9_3	.600									
V14_9_1	.599	.413							-.574	
V15_5_1	-.598		-.555							
V11_9_5	.598	.550								
V16_2_4	.597			-.452		.518				
V8_12_7	-.597		.471							
V14_4_6	.596			.486						
V9_2_4	.595			-.554						
V17_2_1	.595									
V9_4_9	.595						.445		-.472	
V17_4_7	.594			.504						
V5_9_9	-.593			-.519						
V7_1_5	-.593		.504		.553					
V8_12_8	-.593									
V6_2_7	.592		.429	-.495						
V2_3_6	.591	.419								
V15_1_4	-.591				.500			-.473		
V16_3_8	.590	.403		.423					.487	
V5_8_9	-.590								.459	.404
V16_12_6	-.590	.492								
V5_9_2	.589	.588								
V12_9_2	.587	.554		.435						
V8_4_3	.587			.561						
V17_1_8	-.585		.479					-.519		
V1_3_6	.585			.548						
V16_12_7	-.583	.571								
V10_12_7	-.582		.478							
V15_1_3	-.582		.479							
V8_9_6	-.581	-.467						.534		
V4_1_5	-.580		.479		.467					

V10_2_8	.580		.498										
V18_2_1	.580										.439		
V9_1_8	-.579					-.532							
V9_4_6	.579		.405	.451									
V11_1_4	-.579		.466		.506								
V16_3_9	.577			.403					.462				
V1_12_8	-.576	.525				-.475							
V17_3_7	.576	.436		.410									
V18_1_7	-.575	-.443						.407					
V11_1_3	-.574		.516										
V11_12_7	-.573	.420	.547										
V17_8_9	-.573			.451				-.498					
V10_12_6	-.573	.472											
V12_1_4	-.572		.457		.434								
V11_9_6	-.571					.550							
V16_12_1	.567												
V7_9_6	-.567	-.419											
V13_9_1	.567												
V2_9_7	-.565	-.442											
V3_4_6	.565								-.401		-.419		
V6_3_6	.564	.411						.466					
V4_9_6	-.563	-.562				.461							
V12_1_5	-.562		.444		.527								
V4_10_7	-.562							-.497					
V11_2_7	.561		.555										
V1_8_9	-.561				-.450								
V7_3_6	.560	.419											
V14_2_7	.560												
V6_1_3	-.559		.534										
V17_8_6	-.559			.415		.436							
V18_12_6	-.558							.526					
V14_8_6	-.555			.507		.535							
V11_12_9	-.554									.435			
V1_8_1	.554		.441				-.537						
V16_9_4	.554	.502		.447									
V10_11_9	.553	.518											
V8_12_6	-.552							.522					
V7_4_3	.551	-.527											
V10_1_5	-.551		.533		.528								
V4_12_8	-.550												.463
V3_8_3	.549			-.409	-.439				.407				
V18_12_8	-.548	.442				-.407		-.425					
V4_1_4	-.546		.467		.422								
V8_2_7	.546		.413	-.454									
V14_10_8	-.545					-.482							
V17_2_6	.543	-.426			.487								
V15_12_9	-.542	.522	.464										
V12_12_7	-.542			.539									
V15_2_8	.542		.533					-.401					
V14_5_5	-.540			.443	.486								
V9_2_6	.540		.512	-.511									

V7_9_9	-.538						-.402	.407					
V2_12_9	-.537	.530				-.402							
V12_4_9	.537					-.499			-.406				
V11_1_8	-.537	.533				-.512							
V9_9_1	.536	.500		.477									
V5_3_7	.534	.430		.439									
V7_5_9	.534	-.478					.409						
V4_10_6	-.534												
V6_9_6	-.533	-.400						.482					
V11_8_3	.532			-.445	-.405								
V11_3_7	.532			.465						.409			
V11_3_6	.531	.402		.509									
V8_12_9	-.530			.495				-.449					
V2_5_5	-.529		-.485										
V4_1_8	-.527										.416		
V2_1_8	-.525					-.464	.484						
V11_5_8	.525	-.423				-.409							
V10_4_6	.525		.467										
V12_4_3	.524							-.425					
V18_2_4	.524												
V10_10_6	-.524			.408	.469								
V13_3_8	.523	.489							.462				
V1_3_7	.523	.510		.445									
V13_12_8	-.522	.502											
V16_2_8	.520	-.409						-.489					
V5_3_9	.519					-.424						.429	
V12_2_6	.519					.456							
V16_1_8	-.517	.483								.457			
V8_2_6	.515			-.485									
V6_1_4	-.513	-.472											
V10_12_4	-.512	.463	.489										
V3_9_7	-.507	-.410						.466					
V6_3_7	.506	.402						.492					
V9_5_9	.505						.420						
V1_5_1	-.503	.486					.503						
V1_2_4	.503			-.429	.412								
V12_9_7	-.500					.439							-.433
V10_3_7	.500												
V1_5_2	-.500	.407	-.427				.406						
V5_4_3	.499			.413							-.459		
V17_3_6	.498	.442		.439	.461								
V12_9_9	-.497			-.423									
V18_2_5	.495				.418	.404							
V12_2_9	.494						.407						
V4_8_3	.487				-.469				.406				
V9_5_1	-.487	.431								-.420			
V5_2_8	.484		.428									.404	
V1_2_5	.480				.443		.414						
V2_5_2	-.476	.442	-.424	-.456									
V4_2_9	.476	-.422											
V4_3_7	.474				.441								

V4_2_6	.472		.448		.436						
V4_4_3	.471			.406							
V12_2_7	.464										
V3_10_6	-.456					-.419					-.408
V13_2_8	.456		.438				.453				
V14_9_6	-.449					.448					
V2_2_6	.449							.446			
V5_9_6	-.445									-.432	-.407
V5_2_9	.445		.419								
V8_9_1	.439	.432		.423		.425					
V4_3_8	.430							-.412			
V18_2_9	.417										
V4_2_7	.417										
V15_11_9		.924									
V8_12_4		.913									
V8_12_5		.904									
V18_10_8		.891									
V6_10_8		.865									
V11_11_9		.851									
V18_12_5		.840									
V1_10_8		.837									
V13_12_4		.833									
V7_10_8		.829									
V13_12_5		.824									
V15_9_3		.824									
V8_12_2		.814									
V16_11_8	.407	.800									
V15_10_8		.794									
V9_11_8		.791									
V16_11_9		.791									
V1_12_5		.780									
V8_11_8		.778									
V8_11_3		.774							.403		
V16_11_3		.768	.451								
V16_10_7		.763			.454						
V3_11_8		.760									
V7_11_9		.760									
V8_11_9		.758									
V13_12_2		.757						.449			
V7_11_7		.756	.432								
V13_11_4		.756		-.536							
V16_11_7		.756				.545					
V1_12_3	-.498	.754									
V8_1_9		.753						-.461			
V7_11_6		.753	.414								
V1_12_4		.752									
V15_12_5		.748	.432								
V18_9_1		.748									
V15_11_3		.745		-.427							
V1_12_2		.742									
V8_9_9	-.451	-.741									

V5_9_1		.738								
V16_12_8		.735								
V18_12_2		.729						.472		
V6_12_2		.726	.455							
V18_9_2	.586	.722								
V16_10_8		.720					-.439			
V15_12_2		.719								
V15_2_6		-.718						.474		
V3_11_9		.714	-.458							
V15_12_4	-.407	.714	.485							
V14_11_8		.713						-.452		
V5_10_8		.710								
V8_11_4		.709			-.430					
V13_11_3		.709		-.420						
V16_12_2		.708								
V10_12_2		.707								
V3_11_3		.707			-.453					
V1_10_9		.706								
V17_9_3		.704								
V13_11_5		.699		-.568						
V8_12_3		.696							-.453	
V14_9_3		.696		.436						
V15_9_4	.404	.696		.435						
V18_12_4		.695								
V6_9_5	.456	.694								
V16_12_5		.690	.427							
V6_9_2	.592	.689								
V18_9_5	.564	.688								
V18_10_9		.687					-.495			
V9_11_9		.686	-.505							
V13_2_1		.681			.459					
V3_9_2	.436	.678								
V1_1_5		.677								
V8_9_5	.494	.676								
V16_12_4	-.418	.675	.450							
V15_11_8		.674		-.460						
V15_9_5	.546	.671								
V17_11_7		.670				.416				
V15_9_8		-.669		.495						
V14_1_8	-.421	.666								
V18_9_4	.411	.665		.427						
V5_11_9		.665								.483
V17_12_6	-.552	.662								
V2_9_6		-.661						.441		
V18_1_6		-.660								
V9_12_8	-.495	.659								
V9_9_5	.539	.658								
V8_3_8		.657							.419	-.457
V6_9_4		.657		.476						
V2_9_1		.656								
V2_9_2	.499	.656								

V8_9_4		.656		.471							
V13_5_4		.654	-.610								
V9_9_9		-.654									
V11_11_8		.654									
V18_11_9		.651	-.501								
V11_12_5		.651	.436								
V8_9_3	.459	.650									
V1_11_9	-.401	.650					.531				
V13_11_2		.649		-.547				.404			
V8_11_5		.648							.502		
V1_1_4		.648	.419								
V18_9_3		.648								.452	
V18_9_6	-.611	-.647									
V14_1_9		.646									.521
V7_9_3	.470	.646		.480							
V3_9_9		-.644									
V13_4_1		.643	-.401					.460			
V13_5_5		.642	-.624								
V11_9_3		.640								.461	
V1_12_7	-.548	.640		.419							
V18_11_3		.639			-.561						
V7_11_3		.639	.445	-.483							
V16_12_9	-.464	.639									
V5_10_9		.639									
V7_9_2	.596	.639									
V8_2_9	.492	-.637									
V11_10_9		.637					-.531				
V9_9_2	.628	.636									
V15_5_6		-.632		.507							
V11_12_2		.631	.515					.423			
V6_9_3		.630		.544							
V10_11_8		.629		-.420		.422					
V6_12_5		.628	.591								
V2_9_4		.626					.467				
V6_11_8		.625				.415					
V7_9_4		.625		.510							
V2_2_1		.624		-.604							
V3_9_5	.419	.624									
V2_9_5		.623					.412				
V2_10_9	.530	.622									
V18_11_8		.622				.543					
V16_9_3	.422	.621									
V16_10_9		.620					-.531				
V10_12_5	-.415	.619	.494								
V10_11_3		.618			-.575						
V17_3_9		.617						-.479			
V13_5_1	-.416	.617	-.481								
V12_10_9		.614									-.542
V11_9_4	.401	.613									
V6_11_9		.613			.583	.404					
V1_1_8		.607	.472								

V8_3_7		.606						.407			
V10_9_2	.564	.606									
V13_12_3		.605	.446								
V7_11_1		-.605				.515					
V8_10_9		.605							-.433		
V9_5_3		.603	-.471								
V13_12_1	.451	.601						.592			
V2_12_6	-.559	.601									
V1_9_5		.601				.432				.411	
V7_10_9		.598					-.491				
V3_9_1		.597	-.509								
V16_8_8	-.528	.596		-.528							
V1_9_2		.596								.473	
V17_11_6	-.425	.595				.403					
V7_9_5	.519	.595									
V2_9_3		.591			-.548						
V9_9_3	.425	.590		.464							
V16_9_8	-.535	-.589				.409					
V13_3_1		.588						-.536			
V12_10_8	-.421	.587									
V1_12_6	-.439	.586		.555							
V13_3_4		.586	-.446		.519						
V2_12_4	-.521	.584	.408								
V8_2_1	.505	.583			.420						
V8_1_8	-.435	.582									
V13_4_5		.582	-.496								
V18_11_5		.582			-.501				.502		
V16_9_9	-.573	-.576					-.440				
V6_10_9		.576			.522				-.425		
V9_9_4		.575		.460							
V2_10_8		.574				.452		-.486			
V6_5_6		-.572									
V2_12_5	-.407	.572									
V9_3_4		.569			.529						
V11_12_4	-.434	.569	.453								
V15_9_9		-.569	-.458					.514			
V7_9_1	.554	.568		.417							
V10_9_9		-.568						.559			
V10_10_8		.568			.417						-.452
V1_11_1		-.565									
V15_5_7		-.564						.436			
V1_9_1		.564						.462		.504	
V16_3_4		.563						-.553			
V1_1_9		.563					-.455				
V11_11_3		.562		-.489	-.459						
V13_2_3	.438	.562							.505		
V4_9_5	.409	.562									
V17_2_7	.412	-.560			.522						
V6_1_1		-.559	-.540					-.433			
V17_10_9		.558						-.512			
V16_3_7	.416	.558									

V3_3_4		.557		-.431								.455	
V7_3_8	.495	.557						-.446					
V13_10_9	.440	.556					-.546						
V9_11_3		.556			-.456								
V7_1_8		.554				-.415							
V6_4_3	.536	-.554											
V15_2_7		-.553						.504					
V8_2_8	.483	-.552	.445										
V13_4_4		.552	-.440										
V13_5_3		.551	-.541										
V10_9_4		.547			-.451								
V13_3_5		.547	-.458	-.413	.509								
V1_9_4		.546		.451									
V5_11_8		.545			-.409					.410			
V17_4_3	.538	-.541											
V17_10_8		.541		.424		.458							
V18_9_9		-.541				-.499		.413					
V1_3_1		-.540		-.504									
V1_3_8		.540			.457								
V12_12_3		.540					.477						
V18_1_8	-.510	.539						-.423					
V5_3_3		.538		-.461									
V9_2_1	.434	.538		-.413	.486								
V13_4_2		.538	-.507										
V12_9_5	.476	.536											
V14_3_8		.536		.432				-.484					-.435
V3_12_2		.535			.483								
V11_9_9	-.490	-.535								.410			
V18_3_8		.534			.461	-.447							
V8_12_1	.476	.532						-.481					
V8_3_6		.530						.528					
V10_9_5	.488	.529											
V4_12_2		.527	.487										
V9_11_6		.526			-.526								
V4_9_2		.525				.469							
V12_9_3	.477	.525											
V6_3_9		.524		.412	.508								
V2_5_4	-.501	.523			.403								
V18_1_4		.522	.433	.443	.454								
V14_12_9	-.452	.522											
V5_9_5	.486	.521											
V1_4_1		-.521			-.456		.422						
V14_12_8		.520											
V13_2_6		-.520	.469					.515					
V5_1_8	-.426	.519				-.414							
V2_4_5		.519			.410								
V4_11_1		-.518											.458
V13_9_9	-.502	-.514											
V12_12_2		.513									.410		.410
V5_3_8	.410	.512											-.442
V15_4_6		-.511	.436										

V13_3_9		.510							.503				
V7_3_7	.508	.508						.420					
V9_11_7		.507			-.469	.477							
V13_2_7		-.504	.437					.502					
V7_1_1	-.442	-.503											
V2_10_6		.501					-.471						
V7_12_3		.499					.442						
V3_3_3		.496		-.474								.462	
V15_4_7	.461	-.495	.485										
V4_9_4		.494		.471									
V16_2_9		-.492				-.478							
V1_1_3		.484			.434								
V16_3_6		.481		.467				.403					
V3_9_6	-.443	-.481						.417					
V11_1_9		.480				-.461							
V13_2_2		.480		-.436	.446								
V12_9_4		.480											-.453
V9_3_1		.480		-.476		-.436							
V10_3_6	.460	.476		.451									
V6_2_1	.459	.473			.473								
V8_3_9	.434	.467		.422					.453				
V1_9_3		.463								.417			
V14_3_9		.456											
V2_2_8		-.456		.444		-.435							
V3_9_4		.450						.405					
V3_12_1	.429	.449											
V7_10_7		.442					-.411	.430					
V3_11_7		.428											
V10_9_8		-.402											
V6_5_2			-.826										
V10_5_2	-.412		-.822										
V9_12_1			.797										
V13_10_6			.790			.436							
V8_10_4			-.788		.421								
V8_10_3			-.783										
V11_5_5	-.454		-.776										
V8_5_4		.497	-.776										
V11_5_2	-.450		-.770										
V18_5_2			-.769										
V15_1_9			.769										
V13_9_6			.766										
V3_2_8			.765										
V8_5_5		.486	-.764										
V16_5_4	-.438		-.760										
V8_5_2		.451	-.758										
V6_5_5	-.444		-.757										
V6_5_1			-.755										
V11_5_4			-.754										
V18_5_5	-.454		-.752										
V6_4_2			-.751						.435				
V8_10_5			-.749				.465						

V10_5_5	-.515		-.745						
V13_9_7	-.429		.742						
V15_5_4	-.487	.416	-.735						
V16_10_4			-.734		.427		.469		
V3_4_2			-.734						
V18_5_4			-.732						
V17_12_2			.731						
V16_5_5	-.488		-.729						
V10_1_8			.726						
V9_5_5	-.428	.519	-.717						
V18_3_1			-.717						
V18_4_2			-.716	.460					
V6_3_5			-.714	-.503					
V1_5_4			-.712						
V9_5_2	-.462	.517	-.712						
V9_10_3			-.710						
V3_2_9		-.409	.709						
V8_5_1		.412	-.701						
V16_10_3			-.698			-.420			
V15_5_5	-.530		-.697						
V16_5_2	-.459		-.697						
V13_9_3	.436		-.697						
V18_5_3			-.697						.459
V15_5_2	-.526		-.696						
V18_10_5			-.694				.463		
V7_12_2	-.402	.489	.694						
V1_5_3			-.694					.485	
V9_5_4		.516	-.693						
V15_10_3			-.690					.406	
V17_5_2	-.646		-.689						
V17_5_8			.689					-.579	
V6_10_3	-.427		-.688						
V13_1_7	-.415		.688					.415	
V13_10_3			-.687						
V1_9_7			-.684						
V17_1_9	-.515		.681						
V17_12_5		.468	.680						
V10_4_8			.678				-.470		
V18_5_1			-.677						
V1_5_5	-.449		-.675						
V8_4_2			-.674						
V6_12_4		.501	.673						
V18_3_2			-.672						
V3_3_1			-.668						
V10_5_4	-.405		-.668						
V17_12_4		.484	.668						
V1_11_3		.651	.667						
V10_5_7	.528		.665						
V10_4_1			-.663				.456		
V15_10_4			-.662				.646		
V15_11_6	-.513		.660						

V17_5_4	-.633		-.660							
V1_9_6	-.411		-.659							
V6_1_6			.657							
V10_5_3			-.654	.502						
V5_1_5			.652							
V18_3_5			-.652		.421					
V15_3_4			-.650	-.458						
V15_4_2			-.650				.491			
V9_12_6	-.544		.648							
V6_4_1		.450	-.647							
V2_1_1		-.550	-.646							
V16_10_5			-.646				.610			
V9_12_2			.645					.462		-.417
V13_12_7	-.477		.645					.524		
V11_3_3			-.644	-.488					-.418	
V8_4_5			-.643							
V11_5_1			-.643							
V13_5_2	-.408	.611	-.642							
V18_10_4	.407		-.642							.437
V7_12_9			.641			-.557				
V18_11_1			-.641						.581	
V9_4_2			-.640						.495	
V12_4_8			.640	.422						
V6_3_2			-.638	-.615						
V1_10_7			-.637		.459					
V6_4_5			-.637	.422			.412			
V11_4_2			-.636				.405			
V1_8_7	-.461		-.636					.426		
V7_10_3			-.636							
V12_4_2			-.633							
V7_1_6	-.427	.424	.633							
V8_4_4			-.633	.429						
V6_3_1			-.632		.451					
V7_1_7	-.488		.630		.458					
V6_5_4	-.480		-.628	.413						
V17_11_2			.625	-.566						
V17_10_3	-.410		-.625							
V13_10_4			-.622		.413		.492			
V16_1_3			.620		.498					
V8_5_3		.597	-.619							
V10_5_1			-.618							
V7_12_4	-.539	.472	.614							
V6_11_3			.614		-.518					
V7_1_9		.467	.613			-.435				
V7_12_5	-.476	.530	.613							
V8_3_5			-.611		.523					
V9_5_6			.609	.516						
V9_2_7	.457		.609	-.470						
V2_1_7		.432	.607							
V15_4_5			-.604	.457						
V4_12_6	-.585		.604							

V3_3_2			-.602	-.495										
V8_3_1			-.601											
V1_4_2			-.601				.534							
V8_10_2			-.601				.549							
V15_5_3	-.418		-.599	.454										
V17_1_6		.437	.599		.484									
V18_10_3			-.598						-.406					
V15_3_3	-.500		-.598	-.487										
V16_5_8	.466		.596											
V8_3_2			-.594		.477									
V16_1_4	-.414		.593		.567									
V5_1_4	-.477		.592		.481									
V11_10_4			-.592				.448		-.404					
V7_11_2			.592	-.590										
V16_5_3		.439	-.591	.425										
V6_1_7			.590											
V7_12_1	.414		.589											
V9_12_5		.404	.589					.438						
V13_2_9			.588			-.515								
V7_2_9	.438		.585											
V14_10_3			-.584											
V8_3_3			-.583											
V12_3_2			-.583	-.463	.424									
V10_4_2			-.583				.479		.454					
V10_5_9			.583			-.544								
V10_1_4	-.513		.579		.505									
V7_5_3	-.403	.401	-.578	.532										
V13_1_6	-.548		.576					.541						
V7_1_3	-.465		.575	-.455	.409									
V1_10_6			-.574	.438										
V12_4_1			-.573											
V13_10_7			.571		.410									
V15_4_4			-.570	.490						.460				
V8_11_7			.567	-.429		.429								
V10_1_7	-.409		.567		.453									
V10_1_9			.567			-.429								
V7_11_5	-.413		.565	-.531										
V17_2_9			.563		.426									
V11_4_5			-.560		-.422									
V11_10_3			-.560		.448									
V7_1_4	-.555		.559		.546									
V9_12_4		.476	.558											
V15_12_8	-.536	.458	.556											
V17_11_3			.551		-.538	.516								
V9_2_8		-.530	.548				.444							
V4_12_1			.548	-.453								-.508		
V18_3_4		.415	-.548		.457									
V17_1_3	-.414		.547	-.443	.461									
V7_11_4			.547	-.468										
V4_11_6			.545		-.414	.484								
V4_4_8			.545			.419								-.468

V10_10_3			-.544					.473				
V12_3_1			-.544		.453							.409
V9_4_5			-.541	.410			.416					
V10_3_1			-.541	-.412						-.470		
V5_1_3			.541							-.472		
V18_3_3		.505	-.539									
V2_2_9	.407		.539									
V6_9_8			-.539				.514			.454		
V10_12_8		.510	.537									
V15_1_8	-.508		.536									
V16_4_1		.491	-.535				.410					
V3_10_5			-.534				.433					
V13_11_1			-.534					.524				
V9_5_7	.429		.534	.512								
V6_11_7			.531	-.430								
V6_3_4		-.499	-.531			.419			-.414			
V3_4_5			-.529				.440					-.442
V4_11_7			.529			.494						
V12_5_3		.412	-.529									
V17_2_8			.526	-.430				-.448				
V11_3_4		.463	-.524	-.456								
V1_8_6	-.497		-.524			.518						
V15_11_7	-.498	.437	.523									
V11_2_9	.503	-.446	.523									
V17_4_2			-.522	.510								
V16_4_2			-.516				.483		.509			
V9_4_1		.504	-.515				.415	.461				
V11_11_1		-.454	-.514			.509						
V13_3_3		.498	-.513		.448							
V10_1_6	-.404		.512									
V3_4_1			-.511				.419					
V4_10_3			-.511									
V12_3_5			-.509	-.466	.401							.421
V9_10_5			-.508	-.419	.417		.433					
V4_5_3			-.505									
V12_11_1			-.505									.498
V10_2_9	.454		.503			-.417						
V11_4_1			-.497		-.404			.429				
V2_10_3	-.404	-.486	-.493									
V9_3_5		.474	-.492	-.482	.456							
V1_9_9		-.432	-.492					.409				
V17_4_1			-.484			.475						
V11_12_6	-.480	.412	.482	.417								
V12_10_3			-.481			-.412						
V11_3_1			-.473	-.472			-.429					
V5_12_2			.473								.469	
V12_4_5			-.470	.406								-.415
V8_4_6			.469			.404		.427				
V8_4_7			.455	.405		.431						
V1_10_3			-.453		.420			.420				
V11_4_4			-.453	.440								

V10_1_3	-.439		.453									
V4_3_1			-.437									.424
V11_1_7	-.428		.429									
V4_4_1												
V2_11_2				-.845								
V2_3_2				-.839								
V7_3_1				-.813								
V2_3_9				.806								
V7_3_2	-.403			-.802								
V14_4_4				.785								
V7_3_5				-.784								
V15_3_1				-.779								
V2_11_5				-.774				.433				
V14_12_6				.772								
V14_12_7				.745								
V7_3_3				-.745		.455						
V1_11_2				-.744								
V16_4_4				.736								
V2_2_2				-.731								
V7_3_4				-.730	.449							
V2_3_5				-.725								
V14_12_3				.724								
V14_12_2				.723								
V18_4_4				.714								
V2_3_3			-.424	-.714								
V2_2_5				-.710		.457						
V2_12_2				-.704								
V2_3_1				-.703								
V15_3_2			-.524	-.703								
V17_9_8		-.491		.699			-.404					
V2_11_4				-.697				.496				
V2_2_4				-.691								
V2_11_3				-.687				.458				
V1_5_6				.686								
V11_2_4	.489			-.684								
V16_11_2				-.678								
V2_2_3				-.674		.497						
V14_10_6				.673								
V3_2_4				-.666							.455	
V2_11_1				-.665				.410		.417		
V18_1_3		.483		.664								
V2_3_4				-.660								
V6_4_9				.660	.462							
V7_5_6		-.560		.658								
V12_4_7	.471			.658								
V14_12_4		.409		.655		-.486						
V9_11_2			.479	-.654								
V6_8_9				.650	.526							
V18_4_5			-.533	.650								
V11_4_7	.626			.646								
V15_11_5				-.645	-.521							

V17_5_6				.644	.551				
V6_5_3		-.459	-.429	.638					
V16_11_5		.421		-.637					
V6_1_9				.636	.582				
V1_10_1				-.635			.590		
V7_5_7		-.414		.634					
V1_5_7				.634	.480				
V2_4_2				-.631					
V13_8_3	.454	.434		-.630					
V15_11_2				-.630	-.535				
V17_9_9				.629			-.588		
V17_11_5			.489	-.629		.439			
V6_3_8	.412			.628					.487
V2_5_1	-.486			-.625					
V11_3_2			-.470	-.623					
V10_3_5			-.428	-.622					
V16_3_1				-.621					
V16_4_5			-.408	.620			.426		
V1_1_6				.619		.609			
V9_11_5				-.619	-.430				
V11_5_6			.414	.617					
V14_12_5				.616		-.587			
V5_3_2			-.472	-.610					
V15_3_5			-.602	-.608					
V11_5_7			.435	.608	.511				
V11_2_5	.496			-.607		.551			
V4_4_7	.494		.433	.607					
V12_12_6				.607					
V7_2_1				-.606					
V15_11_4		.473		-.605	-.449				
V14_4_7	.520			.604					
V9_2_5	.498			-.604					
V10_2_4	.461			-.604					
V9_3_2			-.506	-.600					
V18_11_6				-.599	-.516				
V9_11_4		.482		-.598	-.480				
V12_9_1		.412		.597					
V9_10_1				-.594	.508				
V1_3_2			-.428	-.594					
V5_4_7	.512			.593					.410
V11_3_5			-.552	-.591					
V14_1_3				.587	.579				
V11_11_2				-.584					.457
V6_12_3				.583	-.420				-.418
V11_11_5				-.583	-.496				
V11_11_4		.438		-.583	-.530				
V9_3_3		.472	-.405	-.582					
V17_4_5		-.432	-.451	.582					
V9_4_4	.530			.580					
V2_1_3	-.490		.429	-.580					
V16_11_4		.536		-.578					

V17_3_2				-.578					-.458					
V4_3_2				-.575										
V14_4_5				.575										
V14_3_6	.416			.575										
V14_5_7	.480			.575										
V3_3_5			-.504	-.575										
V8_4_8				.572					-.466					
V6_9_1	.501	.454		.569					-.408					
V6_11_6			.474	-.568										
V10_8_3				-.566	-.490									
V10_3_4				-.566	.439									
V10_3_3			-.417	-.565					-.505					
V10_3_2			-.535	-.564										
V1_11_5				-.564		-.418								
V17_12_3			.414	.562					-.417					
V9_10_4			-.530	-.562	.441									
V13_4_8				.561				-.411	.418					
V7_2_4				-.561		.543								
V16_8_3	.487			-.560										
V2_4_1		.519		-.559		.467								
V6_5_9			.429	.558	.451									
V17_3_5				-.558			-.421							
V13_3_2		.467	-.401	-.557	.434									
V12_2_4	.449			-.556										-.480
V6_4_4		-.552		.554										
V12_3_3				-.553										
V12_5_6				.553		.432								
V17_9_7	-.550			.552				.418						
V5_5_7				.551					.477	-.445				
V14_4_1				.551	.409		.442							
V4_11_5				-.551	-.509									
V5_3_5			-.498	-.549	.479									
V1_10_5			-.494	-.548			.510							
V1_10_2			-.500	-.547			.523							
V5_8_3	.544			-.547										
V13_2_4	.496			-.547	.451									
V17_11_4			.506	-.546		.442								
V18_4_3	.536			.545				-.443						
V14_3_7	.412			.545										
V17_9_6		-.445		.545				.495						
V3_2_5		.433		-.545										
V5_2_4				-.538							.527			
V17_4_4		-.440	-.505	.536				.424						
V9_3_8		.477		.533						-.414				
V10_2_5	.436			-.532		.476								
V4_3_3				-.532										-.528
V1_4_4	.505			.527			.463							
V4_3_5				-.527								.424		
V18_4_1			-.499	.525										
V4_2_4				-.525										-.503
V4_11_2				-.525										

V12_5_7				.523	.439				.409					
V14_1_7				.522	.401	.418	-.461							
V5_1_7				.517					.424	-.449				
V5_3_1			-.448	-.516								.423		
V4_2_5	.418			-.514										-.476
V6_11_2				-.514	-.414				.488					
V5_11_2				-.511					.460					
V1_10_4			-.451	-.511			.444							
V10_4_4				.506	-.420									
V18_2_7	.420	-.484		-.500										
V12_2_5	.466			-.500										-.462
V12_4_6				.499		.420								
V18_4_9	.439			.497					-.468					
V16_4_8		.407	.436	.496										
V9_2_2				-.495		.494								
V13_2_5	.442	.413		-.494	.465									
V2_5_8		-.414		-.488				-.487						
V5_11_5				-.484								.474		
V12_3_6				.484						.477				
V3_4_8				.484										
V18_2_6	.407			-.480							.432			
V3_4_4				.473	-.450									
V4_9_3		.440		.472										
V1_11_4		.412	.401	-.471										
V12_4_4				.462	-.456							-.412		
V8_11_6	-.418			-.456		.452								
V4_12_3				.453			.431							
V14_4_8				.444										
V2_11_9					-.821									
V9_1_2	-.445				.780									
V12_1_2	-.421				.769									
V14_3_5					.769									
V17_1_5	-.461				.730		-.417							
V17_1_4	-.532				.727									
V14_3_4					.722	-.435								
V16_5_6					.721			.484						
V13_1_2		.531			.717									
V18_1_2					.710									
V14_2_4	.401				.707									
V10_11_4					-.689									
V14_3_2					.687									
V16_5_7					.682			.421						
V14_2_5	.481				.676									
V16_1_2					.675					-.440				
V14_1_2				.588	.671									
V8_1_7	-.559				.668									
V6_5_7					.667									
V6_12_9				.469	.667									
V11_10_6					.665	.403								
V18_11_4		.550			-.662									
V14_1_5					.658									

V12_11_4		.433		-.471	-.658								
V17_5_7				.544	.651								
V14_1_4				.519	.647								
V2_1_2					.640	.482							
V2_11_7					-.637								
V2_1_5	-.465				.632								
V3_1_9					.630								
V11_10_7					.629	.437							
V13_5_7			.450		.626								
V8_1_2					.626			-.461					
V2_5_3					.624								
V9_1_5	-.470	.433			.622								
V8_1_3		.522			.622								
V17_1_2					.617		-.572						
V1_1_2	-.416				.614								
V2_4_4					.612		.559						
V8_5_7					.610			.519					
V13_1_5		.594			.610								
V12_11_3		.584			-.609								
V14_10_5					.607				-.521				
V8_1_5		.446			.607			-.422					
V3_1_5					.604								
V14_5_4					.603								
V15_5_9		-.494			.601								
V15_5_8				-.459	.600								
V14_10_2		-.450			.599								
V16_2_7	.541				.598								
V13_5_6			.516		.598			.461					
V3_11_4					-.592								.479
V2_1_4	-.501				.590								
V17_1_7		.483	.432		.587								
V14_2_2					.586	.490							
V16_1_5			.535		.584								
V14_3_3					.583	-.542							
V6_11_4			.486		-.582								
V3_1_4					.580								
V16_1_7		.561			.577								
V18_11_7				-.515	-.576								
V6_2_9			.433	.468	.575								
V15_4_9	.539				.575								
V13_1_4		.528			.569								
V12_11_5				-.504	-.569								
V16_4_6	.508				.567								
V5_4_8					.566						.450		
V4_11_4		.433		-.497	-.566								
V1_3_4		.415			.559			.410					
V18_4_8	-.458			.478	.558								
V18_1_5		.532			.558								
V1_2_1	.487			-.523	.555								
V8_1_4		.501			.554								
V9_1_4	-.493	.480			.554								

V14_5_3		.401			.553						
V10_11_5					-.553						-.462
V5_1_9					.550					.488	
V8_5_6					.545			.484			
V1_9_8	-.454				-.541			.463			
V5_3_4					.541						
V14_8_3	.513				-.541						
V10_1_2	-.509				.538						
V8_3_4		.443	-.532		.536						
V4_11_3		.458			-.535						
V1_3_5			-.418		.533			.411			
V7_11_8		.421			-.533					.466	
V11_2_3	.416			-.453	-.532						
V10_2_6	.458				.520						
V2_11_6			-.455		-.516						
V6_11_5			.433		-.515						
V10_2_7					.514						
V14_3_1					.513						
V15_1_5	-.446				.513		-.457	-.449			
V18_5_7		-.450			.512		.423				
V3_1_8					.502			-.458			.436
V9_1_3	-.464	.454	.431		.502						
V12_8_3	.487				-.500						
V6_1_5	-.488				.499						
V3_11_5				-.487	-.494						
V12_10_6				.450	.490						
V10_2_1					-.485			-.441			
V17_3_4			-.449	-.425	.483						
V14_2_1	.421				.471			-.458			
V14_4_2					.460		.455				
V15_2_9	.426				.446						
V18_1_9		.402		.420	.446						
V3_1_1					.418		-.416				
V12_10_7					.417						
V12_11_6						.797					
V14_11_1						-.763					
V8_11_1						.722					
V17_2_2	.476					.720					
V12_11_7						.717					
V1_1_1					-.400	-.716					
V17_2_5	.434					.715					
V18_5_6						-.713					
V6_12_8		.594				-.700					
V17_2_4	.426			-.453		.682					
V6_2_4	.509			-.444		.669					
V4_2_2						.658					
V1_11_6		.470				.655					
V17_11_1						.653	-.456				
V4_8_6	-.594					.651					
V15_2_2	.520					.648					
V16_11_6		.507			.470	.647					

V4_11_8						.645							
V7_2_3		-.430				.645							
V16_2_2	.428			-.436		.643							
V6_2_5	.504			-.444		.642							
V12_8_6	-.547			.435		.640							
V2_3_7	.548	.419				-.634							
V8_2_2	.465					.633							
V11_11_6		.494				.631							
V11_2_2	.486			-.464		.631							
V17_9_4		.622				.631							
V9_1_9			.495			-.631							
V12_12_8						-.629							.502
V17_2_3				-.476		.627							
V7_5_8					.428	-.624							
V15_2_3	.447			-.521		.621							
V14_11_6				.457		.621							
V16_10_6					.526	.615							
V7_2_2				-.533		.612							
V13_1_1						-.611				-.477			
V16_2_5	.544			-.412		.606							
V6_9_9					.562	.605							
V9_2_9		-.446	.566			-.604							
V7_2_5				-.528		.603							
V17_9_5	.465	.582				.597							
V11_11_7		.508				.593							
V11_9_7	-.580					.590							
V2_5_9						-.590		-.525					
V15_2_5	.575			-.422		.590							
V14_11_2						-.584				-.578			
V4_3_9	.455					-.582			.416				
V10_5_8					.562	-.580							
V6_2_3		-.491				.576							
V13_5_8					.477	-.575							
V16_2_3	.560	-.424				.574							
V8_2_5	.540				.426	.571							
V6_1_8					-.448	-.562							
V9_2_3	.480					.559							
V15_1_1						-.558				-.410			
V1_1_7					.456	.551							
V12_3_9	.488	.440				-.551							
V10_9_6	-.452					.550							
V4_9_1		.532		.410		.549							
V9_4_8						.548			.494				
V10_2_2				-.406		.547							
V9_11_1		-.446			-.437	.546	-.404						
V8_2_3	.471					.539							
V5_2_2						.539					.501		
V3_12_8						-.538							.476
V6_3_3						.536			-.470				
V14_11_7					-.511	.535							
V10_11_6		.420	.407			.533							

V10_11_7		.478				.532						
V5_12_8		.513				-.531						
V1_11_7		.473		.423		.523				.403		
V10_2_3						.523		-.448				
V3_12_3		.444				-.521	.504					
V6_2_2	.449			-.465		.519						
V2_2_7		-.441		-.483		-.512						
V18_3_9						-.511			.449			
V12_2_2						.508						
V4_10_9		.445		-.490		-.505						
V11_12_8	-.438					-.504						
V18_1_1				.408		-.501						
V13_11_8		.476				.500		-.475				
V3_2_2		.469				.497						
V18_2_3						.495		-.460				
V11_3_8		.470				-.495			.490			
V5_11_1		-.434	-.492			.494						
V12_9_6	-.458					.477						
V16_12_3				.431		-.458			-.416			
V5_9_4		.429		.442		.457						
V3_10_7						-.455						
V11_12_3						-.449						
V14_2_3	.417					.446						
V18_2_2	.413					.414						
V7_4_2							.918					
V14_5_9	.428						.812					
V11_10_2							.809					
V7_4_5							.808					
V17_10_5							.792					
V6_10_2							.790					
V1_4_8							-.780					
V10_10_1	.443						.779					
V15_10_2							.777					
V7_4_1							.763					
V18_5_9							.763					
V5_10_1							.755					.454
V17_10_4							.754					
V7_10_2		-.506					.751					
V7_10_5		-.481					.750					
V15_12_1							-.738					
V16_10_1	.530						.734					
V6_10_5			-.452		.462		.732					
V11_4_8	-.419						-.722					
V17_10_2					.453		.722					
V7_10_4		-.427			.416		.720					
V16_10_2		-.417					.720					
V10_10_2			-.432				.717					
V15_10_5			-.535				.711					
V6_10_1	.533						.709					
V17_10_7		.426	-.519				-.693					
V17_1_1							-.691					

V11_10_5			-.509				.685					
V13_10_2			-.501				.685					
V1_2_8							.682	-.455				
V1_4_5			-.525				.679					
V3_10_1	.565						.678					
V15_10_9	.414	.443					-.675					
V8_5_8		-.425					.671					
V18_10_2			-.559				.662					
V7_4_8			.522				-.662					
V4_10_1					.498		.657					
V2_10_1				-.522			.655					
V11_5_9	.408						.654					
V17_3_1						-.410	-.653					
V7_4_4		-.497					.647					
V2_10_2		-.416					.647					
V7_10_1	.402						.646					
V17_12_1	.402				.438		-.643					
V2_10_4		-.446					.643					
V8_10_1	.614						.636					
V1_2_9	.424		-.422				.630					
V14_1_6			.467	.454			-.630					
V4_10_2							.629					
V5_10_2							.624					.420
V10_10_5							.620				-.539	
V17_10_6		.477	-.525				-.620					
V15_3_8	.472			.410			-.620					
V2_1_9						-.522	.619					
V14_5_8			.558				.619					
V2_4_8			.601				-.617					
V4_9_9	-.404						-.610					
V13_10_1	.477			-.421			.609					
V2_10_5		-.505					.608					
V8_5_9	.550						.608					
V13_10_5			-.546				.606					
V13_10_8		.435					-.603					
V15_4_8				.520			-.600					
V2_10_7		.472					-.595					
V4_9_8							-.583					-.402
V18_5_8				-.421		-.562	.580					
V9_12_3		.465					.577					
V6_10_4			-.555		.520		.573					
V9_10_9		.480					-.569					
V3_10_2			-.537		.411		.569					
V2_12_3		.417				-.541	.561					
V5_12_3							.559					
V1_5_8	.500				.468		.550					
V9_10_2		-.540			.456		.549					
V14_1_1				.514			-.544					
V12_10_5			-.446				.538					.415
V12_10_2			-.500				.538					
V15_1_2					.462		-.538	-.438				

V13_5_9	.481						.535	-.423			
V16_5_9	.464		.449				.532				
V2_9_8	.476			-.471			-.531				
V1_11_8		.436				.402	.528				
V10_12_3		.403					.510				
V11_1_1							-.509			-.407	
V1_2_2				-.422	.425	.415	.503				
V16_11_1						.401	-.502				
V15_4_1			-.422	.451			.500				
V3_3_9	.492			.416			-.500				
V15_3_9		.411		.466			-.499				
V6_2_8			.412			-.427	.495				
V15_12_3				.438			.494				
V15_10_6	-.432						-.485	.409			
V10_4_5			-.477	.410			.481		.472		
V14_12_1				.408			-.474				.406
V3_5_3			-.436				.457				
V18_2_8							.452				
V3_11_6							.417				
V17_11_9		.468						-.762			
V9_1_6	-.463							-.703			
V17_5_9			.491					-.700			
V17_12_9				.549				-.695			
V17_12_8		.402		.478				-.695			
V13_1_3			.466					.672			
V4_8_8	-.425					.439		-.661			
V17_11_8		.420						-.658			
V9_5_8			.456					-.658			
V13_12_6	-.445		.580					.652			
V13_3_6			.565					.647			
V11_5_3			-.420					.644			
V9_1_7	-.485		.450					-.639			
V15_3_7					.494			.628			
V16_3_3		.454				.468		-.613			
V13_11_9					-.452			-.611			
V17_3_8		.467						-.611			
V17_4_9						.480		-.596			
V2_1_6		.418						.594			
V13_3_7				.436				.591			
V3_1_3		.483			.452			-.589			
V16_3_5		.449						-.587	-.402		
V17_5_3	-.485		-.490					.582			
V18_12_3				.473			.432	.581			
V10_9_3		.529						.581			
V16_2_6				-.424	.411			.576	.482		
V13_11_6			.551					.565			
V1_3_3		.477			.414			.565			
V17_4_8						.484		-.562			
V13_11_7			.486					.560			
V18_12_9	-.551							-.552		.469	
V14_11_9		.487				-.434		-.551			

V16_3_2								-.543	-.483			
V7_12_8						-.515		.541				
V4_1_7	-.455							-.540				
V4_1_6	-.458		.402					-.539				
V12_1_7					.427			-.536				
V13_4_6			.500					.531				
V15_3_6			.434		.510			.525				
V2_3_8		.521						-.525				
V2_12_1					.418			.523				
V1_2_3	.430						.436	-.522				
V5_12_7	-.407							.520				
V2_11_8						.485		-.513				
V12_1_6								-.510		.412		
V7_4_9	.496					-.467		-.503				
V6_5_8	.464					-.412		-.501				
V2_4_9				.452				-.500		-.402		
V9_1_1					.416			-.497		-.413		
V2_9_9	.406	-.425						.492				
V13_9_8								.470				
V13_4_7			.424					.464				
V1_5_9								-.460		-.417		
V7_10_6			-.404	.420			-.406	.438				
V15_10_7								.415				
V14_10_4									-.725			
V5_5_6									.698		-.427	
V5_10_6									.697		-.456	
V5_4_6									.687			
V18_11_2		.426							.663			
V14_10_9									.651			
V6_10_6									-.651			
V6_10_7							-.408		-.638	.456		
V3_1_6									-.589		.448	
V8_10_8		.538							-.588			
V12_11_2				-.440					.587			
V5_2_6	.479								.584			
V8_11_2		.542							.572			
V11_3_9	.459					-.435			.570			
V5_11_6									.564	-.444		
V8_9_8							-.474	.414	-.555			
V12_11_8		.460				.415			-.555			
V14_10_7				.477					-.546			
V3_4_9	.433			.406					-.543	.400		
V17_3_3						.437			-.541			
V11_10_8		.401						.516	.539			
V14_9_8							-.444		.529			
V3_11_2				-.512					.528			
V6_11_1			-.523				-.440		.523			
V18_8_3	.516								.521			
V3_10_4									-.520		-.430	.424
V10_11_1						.464			.510			
V5_3_6									.510			

V5_11_7					-.406				.501	-.414			
V5_12_6								.413	.496				
V10_12_9			.406			-.420			.496				
V11_9_1	.480	.456							-.492				
V5_5_3			-.480						.492				
V16_1_6		.417			.412				.472				
V3_5_6									-.462		-.428		.424
V10_10_7					.443				-.458				
V3_10_3													
V14_11_3										-.730			
V18_3_7	.423									.675			
V11_9_8								.522	.438	.629			
V14_11_4						-.588				-.627			
V14_11_5						-.617				-.623			
V16_5_1			-.420						.535	-.618			
V18_9_8										.617			
V5_1_6				.409					.553	-.615			
V15_1_6	-.565									-.612			
V1_4_9						-.449		-.444		-.610			
V7_9_8								.563		.604			
V9_10_8							-.434			.601			
V16_1_9						-.480				.595			
V1_3_9						-.523		-.431		-.593			
V1_8_3			.496							.582			
V18_3_6	.569									.576			
V11_1_6								-.539		.573			
V13_1_9			.404		.422					.546			
V5_1_2					.448	.448				-.519			
V1_8_4	.512									.517			
V16_1_1						-.483		-.494		-.516			
V1_12_1			.435	-.457						.513			
V8_1_1							-.440			-.501			
V9_12_9						-.442		-.415		.495			
V4_11_9		.441								.494			
V15_11_1								.418		.461			
V5_9_8	-.406						-.447	.421	-.416	.461			
V8_4_9									-.415	.459			
V12_11_9		.453								.454			
V12_3_7				.434						.450			
V5_4_1											.736		
V3_12_7											.735	-.475	
V5_2_3											.734		
V5_1_1											.695		.424
V4_1_9											.679		
V5_4_2			-.514								.664		
V12_2_3											.661		
V3_1_7											.652	-.421	
V12_1_9	-.412										.633		
V3_10_8		.537									-.626		
V5_4_5			-.471								.616		
V3_10_9		.573									-.613		

V10_12_1							-.449				.611			
V3_2_3				-.470							.598	-.421		
V4_10_4									-.500		-.581			
V12_1_8	-.467										.575			
V10_11_2					-.434						-.574			
V12_10_4									-.467		-.563			
V10_1_1											.560			
V14_9_4		.417									.551			
V14_10_1					.462						.544			
V8_4_1			-.451								.532			
V5_10_7									.466		-.530			
V12_1_1						-.494					.523			
V14_9_7	-.440										.515			
V5_10_3			-.410								-.509	.431		
V5_2_5				-.463		.465					.505			
V5_4_9					.467						.504			
V10_10_4							.425				-.500			
V5_8_6	-.418										-.498			
V10_8_4	.447										-.487			
V3_12_6									-.467	-.452	.482			
V4_10_5							.441				-.480	.434		
V12_12_1	.445							.403			.466		.433	
V5_4_4				.405							.465			
V5_12_1				-.455							.459	-.448	.400	
V14_4_9	.407			.403							.453			
V14_9_9											.453			
V3_5_8												.836		
V5_5_2												-.802		
V5_5_5												-.773		
V5_5_8												.744		
V5_2_1												.732		
V4_5_5			-.479									-.673		
V4_5_2			-.466									-.673		
V5_5_4			-.437								.525	-.651		
V5_10_5											-.482	.646		
V5_5_1												-.627		
V12_5_5			-.497									-.625		
V3_5_2			-.605									-.624		
V12_5_2			-.485									-.612		
V5_11_3		.520										.608		
V4_5_4			-.500									-.608		
V5_5_9							.450					.606		
V5_10_4											-.578	.598		
V3_5_5			-.532									-.596		
V12_5_4			-.506									-.587		
V5_11_4				-.464								.570		
V3_2_1	.491											.540		
V4_5_1		.401							-.428			-.540		
V12_2_8			.435									.538		
V12_5_1												-.521		
V12_2_1	.424											.521		-.483

V3_5_1		.442	-.411									-.500		
V4_2_8			.469									.495		
V4_4_5			-.424									-.494		
V12_5_8												.490		
V12_3_4												.485		
V4_5_9												.468		
V3_5_4		.417	-.431									-.447		
V4_4_4												-.431		
V4_3_4												.408		
V12_5_9														
V4_10_8													-.827	
V14_5_6													.801	
V10_5_6					.456								.740	
V3_12_4						-.447							.701	
V12_9_8	-.414												-.654	
V3_12_5													.632	
V5_12_4		.430											.628	
V3_9_8							-.519						-.594	
V3_11_1			-.480						.409				.591	
V12_12_4		.461											.576	
V12_3_8													-.568	
V5_12_5		.401	.447										.567	
V3_5_7												.456	.563	
V4_12_9	-.472					-.405							.558	
V12_12_5		.524											.549	
V3_12_9						-.456							.549	
V3_3_8										-.442			-.533	
V4_12_5		.487	.424										.530	
V4_12_4		.458	.470										.525	
V5_12_9								-.427					.513	
V12_12_9	-.429	.422				-.423							.497	
V3_9_3	.467	.409								.418			-.482	
V4_5_7				.422									.469	.413
V12_1_3	-.404												-.459	
V4_5_8												.432	-.454	.433
V4_5_6													.413	.699
V4_2_1												.402		-.667
V4_2_3											.513			-.647
V4_3_6	.408													.591
V4_1_3	-.454													-.573
V4_4_6			.412											.572
V4_4_2			-.475											.549

Extraction Method: Principal Component Analysis.
a 14 components extracted.