6 Socio-economic data and exploratory analysis

6.1 Introduction

The previous Chapter reviewed literature on relationships between Mediterranean socio-economic sectors and climate. To further expand the field of knowledge concerning climate impacts upon the Mediterranean to include extremes, appropriate socio-economic data has been gathered (Section 6.2.1), a number of key indices have been identified (Section 6.2.2), and quantative relationships have been explored (Section 6.3) for agriculture (Section 6.3.1), electricity consumption (Section 6.3.2), and mortality (Section 6.3.3). Thus, this chapter describes an investigative process for relationships between variables in the same manner as Chapter 3. In this chapter, however, it is necessary to consider a number of additional specifically socio-economic issues:

- Data issues such as comparability (Section 6.2.1),
- That socio-economic variables may show statistical relationships with climate for different reasons in different seasons (Section 6.4),
- And socio-economic factors beyond those of direct interest. Either as variables that can explain long term trends (Section 6.2.2), or potentially as non-linear explanatory factors (Section 6.3)

The rest of this Chapter explores these (and other) issues concerned with the investigation of the null hypotheses presented at the end of Chapter 5.

6.2 Socio-economic data and indices

6.2.1 Socio-economic data sources

In order to explore the sectors of human activity identified in Chapter 5 for the impacts of climate extreme behaviour, data are required that measure the number of deaths (mortality), the amount of power used (consumption), and the volume of harvested crops (yield) for individual Mediterranean countries at appropriate temporal resolutions, over the same time period as used in previous chapters (i.e., 1958-2000). However, certain issues arise when attempting to acquire socio-economic data that may not occur with climate data (Section 3.2.1). Socio-economic data are often of poor quality (i.e., contain inhomogeneities) and are mainly non-experimental (Gujurati, 2003). Data may include observational errors, approximations, and round-offs. Further, socio-economic data are generally only available at a highly (spatially and temporally) aggregated level (e.g. national, annual) (Gujurati, 2003). Issues concerning comparability (including observational bias) and resolution are discussed below.

Comparability

Comparability can become a serious issue with respect to national socio-economic statistics, particularly if studying countries that may not possess standardized reporting procedures (Knowles, 2005), including common classifications, survey methods, and definitions (WHO, 2003; Eurostat, 2006b). Units of measurement may not be universal, and it can be difficult to convert from one to another. Systematic bias may arise in socio-economic studies due to forms of measurement that vary regionally or over time (Knowles, 2005). Such bias is very common in the social sciences and researchers often have no way of knowing the types of measurement errors that might have been made by the primary data collecting agency (Gujurati, 2003). It is therefore important to ensure that data is 'harmonized' when comparing national statistical information (Knowles, 2005). European (and global) administrative bodies exist that provide harmonized data freely, and check collated information for comparability and systematic bias across countries, variables, and previous years, including:

- Eurostat,
- The World Bank,
- The World Health Organisation (WHO),
- The Food and Agricultural Organisation (FAO),

All socio-economic data used in this study have been acquired from the above bodies to ensure that they have been harmonized. Mortality data and agricultural yield data are routinely collected by national offices and measured in relatively simple terms (i.e. number of deaths and tonnage), but harmonization is useful in ensuring that common codes/categories for cause of death are used, age categories are defined with common cut-off points (e.g. end of year, last birthday), and that yield measurements treat volumes of loss or waste in a consistent fashion (i.e. either included, or excluded, from total yield) (Eurostat, 2006b; WHO, 2006).

Harmonization is an issue of continuing importance, but generally western European data is well co-ordinated and more reliable than that for other countries, including some of the Balkan nations (including Albania and Bosnia-Herzegovina), which may not effectively and accurately utilise standard methods of observation due to regional infrastructural problems (WHO, 2003).

Temporal Resolution

The international statistical bodies identified above are generally much younger than their meteorological equivalents. Reliable weather stations were first established across Europe and the U.S. during the 19th century (Bradley *et al.*, 1985), whereas Eurostat, the European Commission's body for the collation of statistics from member states, was initially developed as part of the European Coal and Steel Community in 1953 (Eurostat, 2006b). It has taken time for Eurostat and other bodies to build the required networks and protocols to ensure that data can be acquired from national statistical offices using standardized forms of observation (Eurostat, 2006b). As a result, time series of European statistical data on a range of subjects that can be compared between nations are generally (but not always) shorter than time series for meteorological data.

However, with the exception of periods of severe civil unrest, socio-economic European data sets are often complete for the period from their beginning to present (Eurostat, 2006a; FAO, 2006; WHO, 2006), as the greatest difficulty in collecting such data tends to lie in the construction of important observational protocols. Records of indicators that are highly relevant to national governance, and that have appropriately well-defined observation methods, generally begin in the early 1960s (e.g. mortality, agricultural data), while data on various commodities (e.g. power) begin later (generally in the mid 1980s). Mortality and yield data therefore possess complete records for a period on the scale of decades (1960-2000), comparable (in terms of record length) with the climate data used in this study (Chapter 3.2.1). Power consumption data series possess complete records, but over shorter periods (1985-2000).

To make meaningful comparisons with the climatological data used in Chapters 2, 3, and 4, socio-economic data should display seasonal or greater resolution (Chapter 3.4.1), but this is not always possible, or relevant. Socio-economic data is collated at a range of temporal scales and may depend on the quality measured (Gujurati, 2003). Agricultural yield data (for example) are largely meaningless and incomparable at monthly resolutions, as the growing period of crops are often a year or more long, different crops take different lengths of time to harvest, and may require harvest during different parts of the year. Studies using variations in agricultural yield commonly compare annual values (Harrison and Butterfield, 2000; Gitay *et al.*, 2001; Cantelaube and Terres, 2005; Marrachi *et al.*, 2005). Thus annual agricultural yield data are used in this study, while both mortality and electricty consumption data were acquired at monthly resolutions.

Spatial resolution

The socio-economic data required for this study were all acquired at the national level from international bodies (see above) whose main concerns are the monitoring and comparison of international development (Eurostat, 2006b). Numerous studies relate spatially-aggregated climate variables to national or (for larger countries) state-level statistics (Watson and Woods, 1997; Sailor, 2001; Valor *et al.*, 2001; Chen *et al.*, 2004; Bindi and Moriondo, 2005), less common are studies that utilise single sites as climatological proxies for large regions (Amato *et al.*, 2005). For both types of study, socio-economic variables are most often compared at national or state scales (Watson and Woods, 1997; Sailor, 2001; Valor *et al.*, 2001; Chen *et al.*, 2004; Amato *et al.*, 2005; Bindi and Moriondo, 2005). However, the (large-scale) spatial resolution of socio-economic data has implications for the choice of model methodology (Gujurati, 2003), as discussed in Chapter 7.

To explore the null hypotheses presented at the end of the previous chapter, the following national data were acquired:

- monthly electricity consumption data from 1985-2000, from Eurostat (Bower, 2003; Galeotti *et al.*, 2004),
- annual agricultural data from 1961-2000, from the FAO (Cantelaube and Terres, 2005)
- monthly total mortality data from 1960-2000, from Eurostat (Galeotti *et al.*, 2004)
- annual mortality data from 1960-2000 broken down by age, from the WHO (Langford and Bentham, 1995)

6.2.2 Socio-economic Indices

As for much of the literature discussed in Chapter 5, the following analysis utilises diagnostic indicators of risk, rather than of vulnerability (Adger *et al.*, 2004). The following indices are not representative of underlying factors that make a given society susceptible to extreme climatological conditions, such as poverty, or literacy, or equity: the root causes of deleterious or positive impact from extreme climate change are beyond the scope of this study (Jessamy, 2003). Instead, as the study of climate extremes is still under development (Chapter 2) and impacts of extreme conditions are themselves poorly constrained (Chapter 5), the indices used below are structured to function as measures of risk (with the indices of extremes identified in Chapter 3 representing exposure).

Agricultural yield per hectare anomaly (AYA)

Issues related to pricing and policy (Section 6.2.2, Chapter 5.3.3) are often accounted for by utilising yield per hectare (hectogrammes per hectare) measures in European impacts studies (Cantelaube *et al.*, 2004; FAO, 2006). Although it implicitly assumes that farmers will attempt to maximise the amount of crop production on every hectare of available land (and that fluctuations in response to pricing occur with respect to the total area of land farmed rather than the amount harvested from each unit of land), European farming over the 1985-2000 period has tended toward the highly intensive (for the target area, and crops detailed below), with annual variations in yield per hectare largely characterised by a technologically driven upward trend over the study period (Cantelaube *et al.*, 2004).

Mata-Porras (1993) argued that the long-term trends in European agricultural yield were dominated by changes affected by the CAP, and when studying the exceptionally warm UK summer of 1995, Subak (1997) assumed that all national yield per hectare impacts were due to climate except for a linear yield increase, due to changes in policy governed inputs and cultivars. Chen *et al.* (2004) utilised a deterministic time trend for a similar purpose (to serve as a proxy for the non-stochastic advance of agricultural technology). Cantelaube *et al.* (2004), when comparing EU national agricultural wheat production, used smoothing to remove an approximated near-linear trend before normalising yield per hectare data, thus producing an easily comparable agricultural yield anomaly (AYA) time series. The same method is used here, prior to analysis, to account for the evolution of policy and technology and to form an appropriate index of annual agricultural yield per unit area. For each crop (c), the agricultural yield anomaly is therefore calculated as:

$$AYA_c = Y_c / A_c - T_c \qquad \textbf{(6.1)}$$

Where AYA is the annual agricultural yield anomaly, Y the total agricultural yield, A the total area harvested, and T a linear trend. In some cases (i.e. Greek and Portuguese maize) yield data displays a break point (e.g. 1979-80 and 1984-1985) between two differing long-term trends. In both cases the break point coincides with periods before and after EU accession and the resultant adoption of the CAP (Table 5.1), and linear trends are evident for both before and after periods (Fig. 6.1). As this study is concerned with anomalies, trends are fitted to each period separately. Values for the interim period are treated as missing.

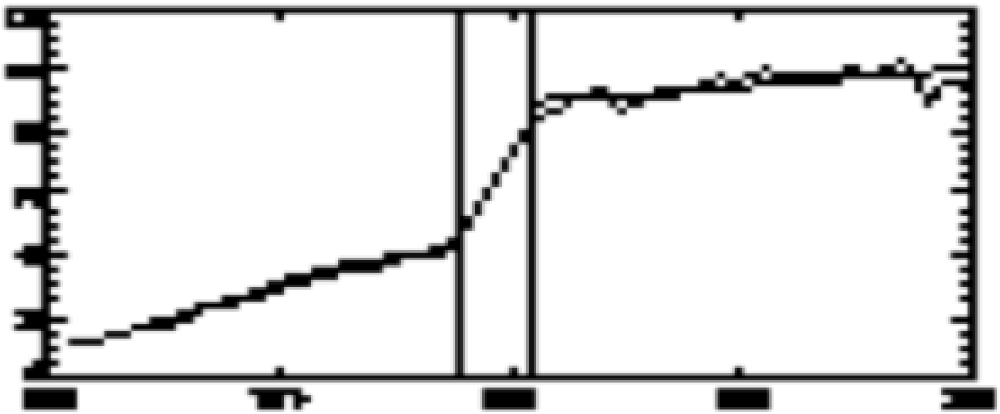

Figure 6.1: Yield per hectare for Greek maize (1,000 hectogrammes per hectare), with pre- and post- EU accession linear trends.

With regard to the crop types discussed in Chapter 5, the following determinate, permanent, and tuber crops were chosen for analysis, covering variations in CO_2 response, growing periods, and sensitivity to weather, with anomalies calculated separately for each crop:

- Wheat (C4 cereal),
- Maize (C3 cereal),
- Grapes (permanent crop)
- Citrus fruit (permanent crop),
- Potatoes (tuber)

Sectoral electricity consumption per capita anomaly (ECA)

As explained above (Section 6.2.1) this study utilises electricity consumption data rather than production data. Monthly data is aggregated to form summer and winter electricity consumption totals as previous studies have shown that climate induced seasonal fluctuations are much smaller during the transition seasons than for summer or winter (Valor *et al.*, 2001; Giannakopoulos and Psiloglou, 2005). Summer usage peaks during June, July, and August, and winter usage during December, January, and February (Fig 6.2). The seasons used for electricity consumption therefore follow the same definitions as those for climatological seasons (Chapter 2.2.1). Each season is also separately analysed for commercial and residential usage as sensitivities may vary between the two sectors (Sailor, 2001; Amato *et al.*, 2005).

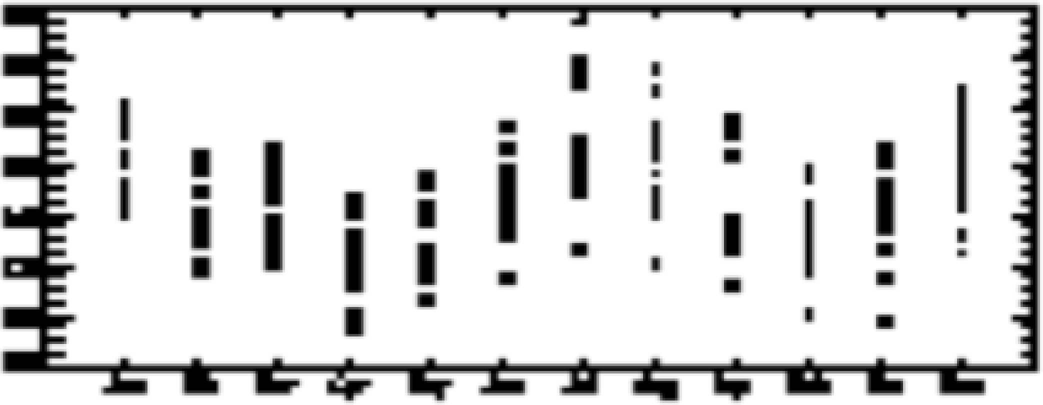

Figure 6.2: Greek energy consumption (gigawatt hours per person) by month (1985-2000), each point represents values for a different year.

The consumption of electricity is dependent upon economic growth (Amato *et al.*, 2005; Giannakopoulos and Psiloglou, 2005) and non-weather sensitive energy demand is associated with factors including income per capita, the size of households and businesses, and the proliferation of electrical goods (including heating and cooling technologies) (Chapter 5.3.4). Annual GDP data is freely available from 1960 onwards (World Bank, 2006), has been utilised as a proxy for economic growth (Munich Re, 2003), is largely inflexible to climatology (Palutikof *et al.*, 1997), and can be shown to partially account for technological and economic progress in energy-use models (Watson and Woods, 1997). For these reasons, annual GDP data has been acquired for each country under consideration. GDP can be utilised to remove a trend from consumption data to compensate for the proliferation of both technologies that require power and those that act as heating or cooling devices (Watson and Woods, 1997). GDP can also be used to compensate for economic anomalies that may affect energy consumption (such as the 1973 oil crisis). Further, to ensure that models are comparable from one country to another, totals must be expressed in terms of total population (Sailor, 2001; Amato, 2005), so for this study all consumption values are presented in per capita terms. Calculated separately for winter and summer, where the energy consumption anomaly (*ECA*) is then:

$$ECA=(ECC_n-GDP_n)*SD(ECC)+MEAN(ECC) \quad \textbf{(6.2)}$$

Where ECC_n is the normalised total seasonal electricity consumption (by sector), GDP_n is normalised annual gross domestic product per capita, and *SD(ECC)*, and *MEAN(ECC)* are the standard deviation and mean of *ECC*.

Excess Mortality Index (EMI)

In impact studies, indices of mortality, much like the indices identified above, are often expressed as anomalies (Koppe *et al.*, 2004; Conti *et al.*, 2005). Such mortality anomalies are referred to as representing attributable or ‘excess’ mortality (Koppe *et al.*, 2004; Kovats and Jendritzky, 2006). The impact of events such as heatwaves upon mortality can be far greater than the number of deaths reported as due to classical heat stress. The true excess can be approximated if assuming a baseline mortality, which might have occurred in the absence of the heatwave (Kovats and Jendritzky, 2006). Although there is little consensus on the exact calculation of excess mortality, it is generally formulated by subtracting the ‘expected’ mortality from values observed during episodes of extreme heat or cold (Koppe *et al.*, 2004).

Expected mortality may be calculated by the use of values from preceding years (Conti *et al.*, 2005), values from within the same year (Healy, 2006), moving averages (Rooney *et al.*, 1998), trends calculated over a particular study period (Katsouyanni *et al.*, 1998; Kysely and Huth, 2003), or a combination of one or more of the above techniques (Huynen *et al.*, 2001). Estimates of attributable mortality are sensitive to the method used (Koppe *et al.*, 2004; Conti *et al.*, 2005) but there is no ‘correct’ method (Kovats and Jendritzky, 2006). If directly utilising values from prior years to calculate expected mortality, when considering multi-decadal records, complications may arise should extreme conditions occur in consecutive years (as with Spanish temperatures in 1994 and 1995) (Chapter 2.4.2). Further, as mortality displacement effects can create links between two consecutive years in terms of both delayed fatalities (Bouchama, 2004) and the available pool of susceptibles (Kalkstein, 1995), the reference method may prove problematic when studying more than one specific event. As expected mortality should represent long term changes in values (i.e. a baseline mortality) and linear and near linear trends can be seen to offer a poor fit for (particularly Portuguese) Mediterranean mortality data, seasonally calculated 5-year moving averages have been utilised instead (Fig 6.3). Although there is a large degree of uncertainty surrounding mortality displacement and adaptation affects, it is reasonable to assume that the 5-year window is longer than any temporal lag effect in patterns of mortality due to climate extremes.

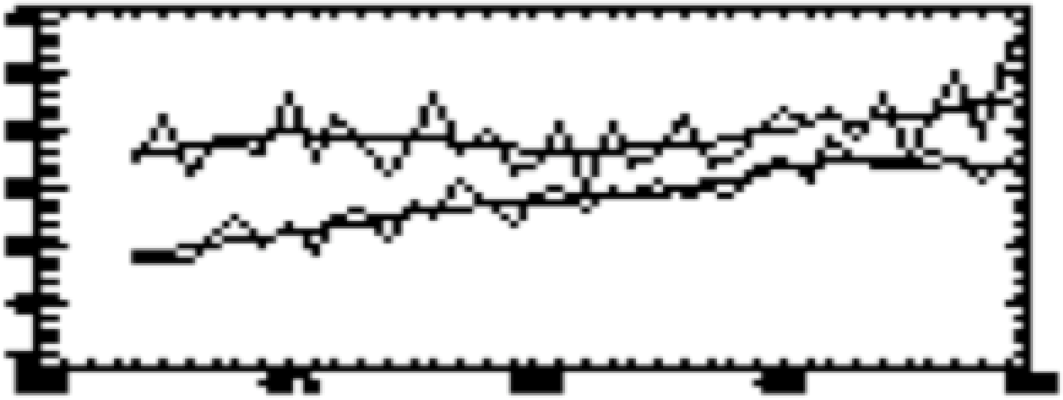

Figure 6.3: Portuguese (upper) and Greek (lower) winter mortality (x1,000 deaths, solid lines) with a 5 year moving average (dotted lines).

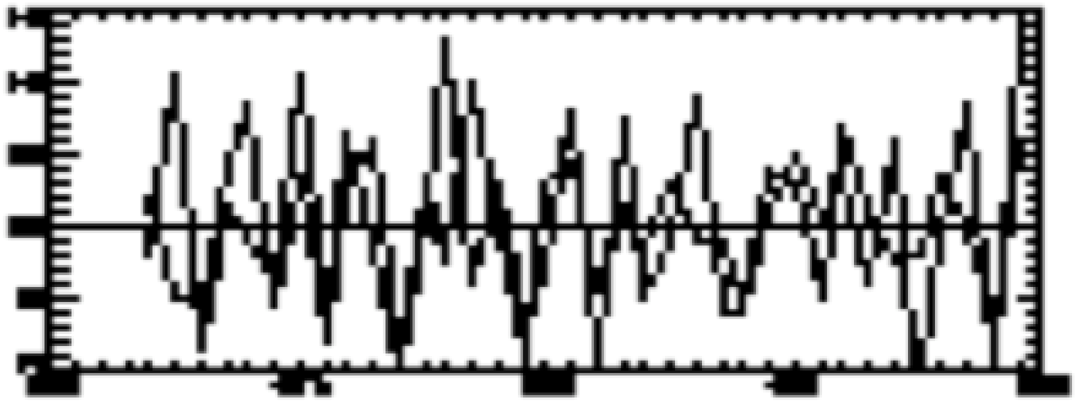

Figure 6.4: Portuguese (dashed) and Greek (solid) excess winter mortality as a percentage of expected mortality.

Excess mortality is a useful method for expressing mortality anomalies, but anomalies may be difficult to compare from one country to another as they are dependent on the total population of each country under consideration. In order to compensate for differences in population both between countries and over time, excess mortality is expressed here as a proportion of expected mortality, as shown in Fig. 6.4, and as used in a number of other studies (McMichael and Kovats, 1998; Rooney *et al.*, 1998; Huynen *et al.*, 2001; Conti *et al.*, 2005; Kovats and Jendritzky, 2006).

As explained in Chapter 5.3.5, mortality in different seasons may be due to differing climate events (e.g. winter cold snaps, autumn floods) so in this study mortality is analysed for each season separately, with seasons defined in the same way for mortality as for climate indices (Langford and Bentham, 1995). With the exception of values for winter, a seasonal excess mortality index (EMI) can be calculated as:

$$EMI=(TM/EM)*100 \qquad \textbf{(6.3)}$$

Where *TM* is total seasonal mortality, and *EM* is the expected seasonal mortality value, calculated from the 5-year running mean. As outbreaks of influenza affect winter mortality independent of climate (Chapter 5.3.5) studies should, where possible, take influenza-related mortality into account (Langford and Bentham, 1995). Causes of death are available (1960-2000) from the WHO, allowing for the inclusion of influenza-related mortality in appropriate models. A wide range of other causes of mortality may be affected by weather, but further disaggregation of data does not necessarily lead to an improvement in relationships (Kalkstein and Greene, 1997). Although Mediterranean influenza mortality is generally less than 1% of all-cause mortality, winter mortality may therefore be defined as in equation 6.3, but with the number of deaths attributable to influenza removed from mortality totals prior to the calculation of expected mortality. Therefore:

$$EMI_{DJF}=[(TM_{DJF}-IM)/(EM_{DJF}-IM)]*100 \qquad \textbf{(6.4)}$$

Where *IM* is the total number of deaths due to influenza.

Furthermore, as proportions of excess mortality have been shown to be significantly higher for the elderly than other age categories (Conti *et al.,* 2005) the following index is also used:

$$EMI_{65}=[(TM_{65}-IM_{65})/(EM_{65}-IM_{65})]*100 \quad \textbf{(6.5)}$$

The calculation for EMI_{65} is similar to that for EMI_{DJF}, although mortality data broken down by age is only available at the annual level.

Table 6.1 summarises the socio-economic predictands developed in this section.

6.3 Assumptions and non-climatic influences

The previous section describes a number of normalisation and trend removal methods that can be utilised to control for non-climatic influences in socio-economic indices. However, there are some socio-economic factors that have been previously used as predictor variables in agricultural, electricity consumption, or mortality models (Chen *et al.,* 2004; Amato *et al.,* 2005; Ebi, 2006) that have not yet been discussed. If these factors are not accounted for through the methods used to construct the socio-economic indices in Section 6.2- as has been implicitly assumed- error, additional nonlinearities, or unaccounted for (spatial or temporal) variability, may appear in model results. Thus, this section identifies the major non-climatic influences relevant to each sector, and ensures that (where feasible) the implicit assumptions identified in Section 6.2 are explicitly explored.

6.3.1 Agriculture

Implicit within the agricultural yield per hectare anomaly approach (Section 6.2.2) are the following assumptions:

- Within the constraints provided by optimum growing conditions (such as ideal spacing), farmers will always attempt to maximise yield per hectare of any farmed crop.
- Although farmers may have substituted one crop variety (e.g. different varieties of potato) for another over the target period, such substitutions result in minor differences to a given crops response to climate variability, beyond a linear increase in yield.
- On an annual basis, the use (and technological improvement) of pesticides controls for pest activity and disease.
- The effects of CO_2 upon yield are linear over the target period, and can be accounted for in the overall linear trend of yield.
- Improvements in irrigation are linear, and can be accounted for in the overall linear trend of yield.

Although it is quantitatively difficult to constrain the first assumption without pervasive monitoring, in a 'perfect' economic market, it will always be true (Turner *et al.*, 1993). As has been suggested (Chapter 5.3.3) the European agricultural market is not perfect, and is heavily influenced by Common Agricultural Policy (CAP). However, until recent reforms in 2003, the CAP has linked subsidy to production and promoted the general intensification of farming (DEFRA, 2005), which implies that the first assumption given above holds true over the target period. With regard to the second assumption, it has been suggested by Chen *et al.* (2004) that controlling for technological change takes substitution of crop varieties into account, and that after controlling for such change, variations in yield variability are largely due to climate change, rather than substitutions of crop variety. In order to constrain the third assumption given above, across the Mediterranean, very large volumes of data would be required concerning the use of pesticides and the efficiency and use of a variety of pesticides. Such data are not available from FAOSTAT (Section 6.2.1) and the compilation of a comparable and homogenous relevant data set is beyond the scope of this thesis. To that extent, assumptions regarding pesticides and disease may introduce error or (spatial or temporal) variability into model results given in the next chapter.

As discussed in Section 5.3.3, carbon dioxide concentrations (Assumption 4) also have an important, potentially non-linear, effect upon certain kinds of crops (e.g. wheat). The concentration of CO_2 may limit rates of photosynthesis and can affect efficient use of water (Harrison *et al.*, 2004). Models that include changes in yield for C4 crops may benefit from the inclusion of CO_2 data which are available from the World Data Centre for Greenhouse Gases (WDCGG) of the WMO Global Atmosphere Watch (GAW) project, for a number of observatories (WMO, 2004). The longest CO_2 records are available from Mauna Loa observatory in Hawaii (1960-2005) but CO_2 measurements taken from within the Mediterranean (Mt. Cimone, Italy, 44° 11' N, 10° 42' E, 2165m) have only been conducted since 1985 (Ciatagllia *et al.*, 1987; Cundari *et al.*, 1995). As the lifetime of atmospheric CO_2 is long (around 100 years) and concentrations are therefore well mixed within the atmosphere, Mauna Loa observations are often used as a proxy for global CO_2 concentration, and the Mediterranean and Hawaiian series are highly correlated (r=0.93) (WDCGG, 2006). Differences between the two series exist due to latitudinal effects (WMO, 2004) and regionally persistent circulation effects (Ciatagllia *et al.*, 1987), largely affecting interannual variability. For this study, the Mauna Loa series is utilised to investigate the effect of inter-annual global changes in CO_2 concentration, but it should be noted that seasonal and regional (i.e. Mediterranean), effects may be under- or over-estimated by as much as four parts per million (ppm) (WDCGG, 2006). There are, however, no significant or stable correlations between the Mauna Loa time series of CO_2 and the detrended yield per hectare indices constructed in Section 6.2.2. As CO2 is known to have a positive growth effect on many crops, including wheat (Maracchi *et al.*, 2005) and grape (Bindi and Howden, 2004), it seems likely that the positive (near-linear) trend evident in CO_2 time series has already been accounted for during the detrending process.

Data concerning irrigation (Assumption 5) has been acquired from the World Bank (2006) for the 1960-2000 period. When plotted against time (Figure 6.5) it can be seen that improvements in irrigation over the period have largely been linear for France, Greece, and Spain (with Greek trends reflecting the break illustrated in Figure 6.1). However, Italian irrigation shows steps in progress (3.6% between 1968 and 1971, 3.5% between 1989 and 1993) that are not linear, and Portuguese irrigation improves by roughly 5.6% in the last 10 years of the record. It is clear that for these latter two countries, a linear detrending process may not adequately take changes in irrigation into account. Analysis of statistical relationships between irrigation data and detrended agricultural yields show no significant or stable correlation for the majority of countries and crops considered here, so the detrending process would appear to have been largely effective in controlling for irrigation. However, this is not true for Italian and Portuguese potato yields (+0.33 and +0.37, respectively), and Italian citrus yields (+0.53). Irrigation data for these two countries also fail to show stable and significant correlations with temperature or rainfall indices. It has therefore been considered as a predictor variable for the above in the next chapter.

Figure 6.5: Annual trends in irrigation data (% of total crop land irrigated) sourced from the World Bank (2006) for the 1960-2000 period.

6.3.2 Electricity

Assumptions implicit in the normalisation and detrending process for an electricity consumption per capita index are much less complex than those for agriculture, due to the short time lags between electricity demand, supply, and consumption (Chapter 5.3.4). Generally consumption is related only to non-climate factors through commodity pricing, the gradual emplacement of wealth (Chapter 5.3.4), and changes in building quality (Amato *et al.*, 2005). The latter two can be controlled for (to some extent) through the use of GDP (Section 6.2.2). However, although any commodity is likely to respond to price (Anderson, 1973; Gujurati, 2003), data regarding changes in energy price are not available at the required temporal resolution (i.e. monthly) across the Mediterranean. In addition, complex lag effects and feedbacks between energy price, oil availability, and consumption (Amato *et al.*, 2005) make the effects of pricing very difficult to account for at the temporal resolutions considered in this study. Pricing shifts may therefore account for some of the temporal or spatial variability in the results shown in Chapter 7, not otherwise explained by climate variability.

It has been implicitly assumed in the Section 6.2 that the rate of urbanisation does not affect electricity consumption beyond the implied link to an increase in the emplacement of goods and services. However, insulation and 'thermal mass' properties often differ between urban housing and rural housing (Healy, 2003), and changes in the proportion of urban:rural population may alter per capita electricity consumption. In addition, heat island effects occur in urban centres, and not in rural settlements (Piervitalli *et al.*, 1997), so a change in rate of urbanisation may potentially alter the exposure of populations to heat. Urbanisation data (urban population as a percentage of the total), acquired from the World Bank (2006) has been analysed for correlations with detrended electricity consumption, and although stable and significant correlations have been found, they are the same magnitude as correlations between urbanisation and temperature indices for each country. Thus, although the detrending process has not entirely controlled (implicitly) for the effects of urbanisation, urbanisation data is not needed as an additional predictor in the next chapter, as its inclusion would effectively account for temperature variability twice over.

6.3.3 Mortality

The formulation of an excess mortality index, as described in the Section 6.2, assumes that non-climatic factors that influence mortality do not change over periods less than five years. For a full model of environmental stress, the effects of personal adaptation (e.g. the influence of clothing and heat avoidance strategies) and other short-term acclimatization processes (e.g. biological, architectural) might prove useful (Malchaire *et al.*, 2002). However, although full heat stress models are highly appropriate for occupational health studies and the formulation of health and safety requirements for workplaces (Malchaire *et al.*, 2002), applying such models at the regional scale for entire populations is likely to prove highly challenging and is beyond the scope of this thesis.

Relationships have been tested between levels of urbanisation (which may change significantly within five years) and mortality, as urbanisation is a potential measure of the proportion of population subject to elevated risk (Chapter 5.3.5). However, no significant or stable relationships have been found.

Expenditure on health may prove to be a useful variable in the future as the effects of heatwaves are more thoroughly understood. However, as French expenditure on public health (which has been steadily increasing over time) is among the highest in the EU, the relatively high level of mortality during 2003 for France (World Bank, 2006) showed that expenditure may not have been a mitigating factor over the study period. Most heat-related, regional-scale epidemiological studies use air temperature alone, or as the main indicator (Kovats and Jendritzky, 2006), and for this study, only influenza data is used in addition to indices of climate. The same issues regarding potential acclimatization that apply to power consumption (Chapter 5.3.4, Section 6.3.2) also apply to health (Chapter 3.5.5) (Kovats and Jendritzky, 2006).

6.4 Predictor variables

6.4.1 Climate indices as predictors

Previous studies have utilised energy prices (Section 6.3.2), income, and indices of energy demand in multivariate models concerned with changes in energy consumption or demand (Badr and Nasr, 2001). A number of studies also use mean temperatures, or cooling or heating degree days (Chapter 5). This exploratory study seeks to add information regarding extremes of climate to previous impacts studies concerning the energy sector, and also agriculture, and health. Thus the indices listed in Table 6.1 have been correlated with potential climatological predictor values for both the same year, and where appropriate, the preceeding year. In the case of both electricity use and mortality, the indices described in Chapter 3 may prove particularly useful as the use of percentiles rather than static thresholds may partially address issues concerned with acclimatization. Climate indices that reflect percentile extremes (TN10, TX90) and exceedances over or under specific thresholds (TNFD, HWDI) may be more appropriate than cooling or heating degree days as they represent both magnitude and duration components of heating and cooling, and are not dependent on arbitrary values. TX90 and TN10 values may be respectively above or below crop yield critical temperatures (Chapter 5.3.3) (Rosenzweig and Liverman, 1992), depending on location.

Each of the socio-economic sectors studied here are discussed below in terms of the climate indices that provide significant and stable correlations (Chapter 3.3.5) over the period of study. All correlations discussed below are expressed as r values (Chapter 3.3.4), are significant at the 0.10 level or above (see Table 3.2 for definitions of high/moderate/poor correlation), and unless noted otherwise are averages of significant values over a given region. Table 6.2 summarises those indices that, based on these criteria, may serve as useful predictors. Additionally, the relevant Figures (6.5-6.56) can be found at the end of this chapter.

6.4.2 Agriculture

Citrus

This part of the analysis concerns Figs. 6.6-6.11.

Citrus crops (including lemons, limes, and oranges) are one of the two ‘permanent’ crops considered here. Citrus yield values may show sensitivity to a wide range of climate factors over the year of harvest, and previous years, particularly in terms of extremes (Chapter 5.3.3). Figures 6.6-6.11 indicate that citrus yields are highly sensitive to temperature extremes, with spring, summer, and autumn temperatures all affecting annual yield. During spring, persistent frosts (TNFD) may negatively affect crop yields. Spring frost correlations (Figure 6.6) are highly significant for Montseny Turo (North eastern Spain, -0.58), Skyros (Greece, -0.57) and Ponferrada (Spain, -0.50), and moderately significant (around -0.36) through much of Spain and Greece. High spring maximum temperatures (TMAX), however, tend to positively affect yields (Figure 6.6). High temperatures (TMAX) are important (highly significant) for every station in Iberia (e.g. up to +0.58 for Portalegre, Portugal, and +0.67 for Reus, Spain), and moderately significant for some in Northern Italy (e.g. Pisa, Forli, and Pescara, around +0.30). While eastern, and (particularly) central Iberian, citrus crops benefit from early hot conditions, and are harmed by an extended frost season, crops further north and west (in France) may suffer under spring bursts of heat. In contrast, high spring temperatures (TMAX) in the south of France (Biarritz, Tarbes, Agen, and Embrun) are (moderately) negatively correlated with citrus yield (average of -0.35).

Citrus yield displays less significant sensitivity to summer temperatures (Figure 6.8) than those for spring, although, particularly in the case of very high temperatures for the western basin (+0.20 TX90), the spatial distribution of results is similar to that for spring. During the warm season, Spanish temperatures, even when high, appear beneficial to citrus crops for both the current and (more so) following years, but the central/eastern summer regime may create heatwave conditions that are too hot for high yield volumes. For the majority of Spanish stations, and to a lesser extent, Mora (Portugal, +0.19), citrus yield is more sensitive (highly significant correlation) to extreme high temperatures of the previous summer (+0.41 TX90) than current values (Figure 6.9). For Italy (Monte Scuro, Prizzi, Pescara, and Bobbio Centrale), and to a lesser extent Greece (Agrinion, Naxos), high summer temperatures (Figure 6.8) may adversely affect citrus yield (-0.37 TMAX for Italy, -0.35 HWDI for Greece). During autumn, citrus yield may be affected (very highly significant correlation) by low temperatures (Figure 6.10) throughout most of northern Spain (e.g. up to +0.65 TMIN at Burgos) and to a lesser extent (moderately significant correlation), parts of Greece (e.g. around +0.15 TN10 for Thessaloniki, Kozani, Naxos, and Skyros). Citrus yields in both Spain and Greece benefit from a mild autumn without cold snaps.

Citrus yields are sensitive to both spring rainfall (Figure 6.7) and autumn rainfall (Figure 6.11), with the most significant correlations between dry spells (PCDD) for both seasons. Very dry and warm spring conditions seem to aid citrus crops for central and southern latitudes of the Mediterranean, but yields decline if dry conditions exist in summer and autumn. For spring, dry spell correlations are positive for Italy (+0.35 PCDD) and Iberia (+0.43 PCDD), but negative for southern France (around -0.36 PCDD for Biarritz, Tarbes, Bordeaux, Agen, and Lyon) and northern Italy (-0.30, Turin, Paganella). During autumn, significant dry-day correlations are negative (-0.30 PCDD) for most of Spain.

Grape

This part of the analysis concerns Figs. 6.12-6.16.

Grape, the second permanent crop considered in this study, may be expected to have similar seasonal sensitivities to citrus fruit due to the prolonged nature of its growth. As for citrus fruit, relationships with winter temperature indices are neither stable nor significant. However, spring temperatures show significant negative correlations across all temperature indices for the western basin as part of the vernalisation process (Figure 6.13). For some crops, such as grape, it can be important that winter cold temperatures are prolonged, and should spring temperatures exceed a particular temperature (dependent on crop) then the spring flowering process may be negatively affected (Wolfe, 2004). For this reason it is important that mean temperatures and high (rather than low) extremes (TX90) are low, and the high number of stable and significant correlations (-0.29 to -0.45 TX90) across Spain, southern France, and northern Italy reflects the need for vernalisation. For Portugal and Greece the relationship with temperature is, in places (e.g. Santarem, Agrinion, and Milos), positive (+0.30 TX90), implying that for these regions high temperatures may benefit growth. By comparison, summer temperatures are less important (Figure 6.15), although they do show positive correlations for most of France (+0.14 TMIN), Portugal (+0.38 TMAX), and northern Italy (+0.35 TX90) and negative correlations for eastern and north western Spain (-0.19 TMAX / -0.20 TX90). The highest levels of significance (still less than 0.01) occur between grape yield and: minimum temperatures (-0.39 TMIN), for the Barcelona region; extreme high temperatures, for Valencia (-0.45 TX90); and extreme high temperatures, in northern Italy (+0.40 TX90). Results presented in Chapter 3.4.2 suggest that, for most indices, summer temperatures in the east and south east of Iberia are particularly high, and very high temperatures may significantly reduce grape yield (Chapter 5.3.3).

Rainfall also affects grape yield, through winter (Figure 6.12) and spring (Figure 6.14), and for the autumn of the previous year (Figure 6.16) For the previous autumn, dry days are moderately significant through most of the Mediterranean basin, but highly significant (e.g. up to +0.50 PCDD for Skyros) for central and eastern Greece, Nice (France), Alcantarilla, and Vigo Peinador (both in Spain). Winter rainfall (Figure 6.12) is positively (but only moderately) significant (+0.33 PN90) across the west of each country (e.g. for Vigo Peinador, Ponferrada, Mora, and Agrinion), excluding Italy. Grape yield displays negative correlations with heavy spring events (Figure 6.14) (-0.25/-0.33 PINT/PX5D) on the west coast of Iberia (e.g. Vigo Peinador, Santarem) and positive correlations (+0.35/+0.40 PF90/PX5D) with heavy spring events on the east coasts of both Spain and Italy (e.g. Valencia, Pescara). As explained in Chapter 3.5.3, the west coasts of Mediterranean countries are more prone to heavy rainfall than other regions. Although high numbers of western winter rainfall events may prove beneficial, particularly intense and prolonged rainfall events may waterlog or otherwise damage crops during spring. By contrast, east-coast locations may benefit from heavy rainfall due to a generally dry regime that, although beneficial during the previous autumn, has no effect upon yield during spring.

Maize

This part of the analysis concerns Figs. 6.17-6.22.

Maize is one of two cereal crops considered in this study. With the exception of areas in south-western Spain (e.g. Prat de Llobregat and Valencia), very high temperatures across most of the Mediterranean, for spring (Figure 6.18), summer (Figure 6.20), and the autumn of the previous year (Figure 6.22), seem of benefit to maize yield. Spanish yields of maize are particularly sensitive to spring temperatures (+0.35 TMIN) across the whole country (Figure 6.18), with highly significant correlations shown for Alicante (+0.55 TX90, +0.53 TMAX). High summer temperatures (Figure 6.20) are also significantly correlated for Spain (+0.35 TX90), southern France (+0.30 TX90), and central Italy (+0.45 TX90). Very high summer temperatures (TX90) show particularly significant correlations for:

- Ponferrada (+0.37), and Alicante (+0.42) in Spain,
- Forli (+0.41) and Monteombraro (+0.54) in Italy,
- and Ierapetra (+0.43), in Greece.

High temperatures also show significant correlations with yield in the autumn of the previous year (Figure 6.22), with positive correlations in Italy (e.g. +0.43 TMAX for Monteombraro, +0.43 TMAX for Trevico) and negative correlations with high temperatures in southern Spain (e.g. -0.34 TMAX for Prat de Llobregat, -0.26 TMAX for Valencia). As suggested by Wolf and van Diepen (1995) an increase in temperatures is likely to reduce maize yields for the southern edge of Europe.

Results show negative winter rainfall (PREC) correlations (Figure 6.17) and positive dry day (+0.25 PCDD) correlations for Spanish maize yield, but the reverse for the eastern basin (-0.46 PCDD). For winter, Iberian rainfall may be enough to damage maize crops (-0.35 PN90) (Chapter 5.3.5), while Greek crops appear to benefit from any moisture available. A dry Portuguese spring season (Figure 6.19) appears important for good yields (+0.37 PCDD), but the same conditions in Greece are harmful (-0.28 PCDD). Evidently there are important differences in the response of maize to rainfall in different parts of the Mediterranean basin. During the summer season (Figure 6.21) rainfall is negatively correlated with maize yields for western Greece (-0.22 PREC), northern Italy (-0.41 PREC), and southern France (-0.46 PREC) all of which also show positive correlations with dry days (+0.10, +0.42, and +0.38 PCDD). Concerning the positive sensitivity of maize to high summer temperatures, it would seem that long, hot, dry, summers are the most beneficial for yields. Extreme rainfall may negatively affect maize yield if it occurs during summer in the north of the basin (e.g. -0.37 PN90 and -0.39 PX5D for southern France), but conditions are so dry in the extreme south (Seville, Prizzi, Ierapetra) that such events are beneficial (+0.36 PN90).

Potato

This part of the analysis concerns Figs. 6.23-6.27.

During autumn, potato (a tuber crop) shows a west/east contrast between lagged temperature relationships in a similar fashion to that between maize and precipitation. Temperatures in the previous autumn (Figure 6.26) are beneficial (positively correlated) in the west and harmful (negatively correlated) in the east. In the former case very high temperatures show the most significant correlations (e.g. +0.43 TX90 for Santiago, Spain), in the latter, minimum temperatures are more important (e.g. -0.51 TMIN for Kalamata, Greece). During winter (Figure 6.23) the negative eastern correlation with temperature becomes more widespread (e.g. -0.54 TMIN for Milos, -0.51 TMIN for Samos, -0.49 TMIN for Kalamata), but low temperature correlations are much less significant than those for high temperatures in both Greece (e.g. -0.66 TX90 for Kalamata, -0.61 HWDI for Kythira), and the south of France (-0.30 TMAX). Although winter temperature correlations in Spain, Portugal, and Italy, are generally insignificant or unstable, winter warm spells may significantly reduce annual Greek and French yields of potato. As suggested by Gitay *et al.* (2001) high temperatures may reduce the growing period of tuber crops (including potato) and thus produce negative impacts upon yield, higher temperatures may also lead to an increase in pest activity and fungal infection (Section 6.3.1). During summer (Figure 6.24) both western and eastern temperature correlations are negative and statistically highly significant, again more so for high temperature extremes (e.g. -0.66 TMAX for Agen, Bordeaux, and Agrinio) than low extremes (e.g. -0.56 TMIN for Thessaloniki, -0.53 TN10 for Bordeaux). Spanish potato yield, in particular, is much more susceptible to very high summer temperatures (TX90) than other indices, and more so in the northern and eastern regions (e.g. -0.52 TX90 for Alicante) than elsewhere.

Rainfall values during the preceeding autumn (Figure 6.27) display moderately significant potato yield correlations that are largely positive for PF90, PQ90, PN90 and PINT across western Spain (e.g. Coruna, Zamora, Leon, Alcuescar, and Jerez de la Frontera), Italy (e.g. Trevico, Monteombraro, Lazzaro Alberoni), and Naxos in Greece. Particularly significant correlations exist for Naxos (+0.50 PINT, +0.46 PF90), Monteombraro (+0.53 PQ90, +0.51 PF90, +0.56 PN90), and Leon (+0.62 PQ90, +0.45 PN90). Winter correlations are largely insignificant and unstable and spring rainfall displays little coherent correlation. Summer correlation values (Figure 6.25) are positive and highly significant throughout most of central and northern Italy (+0.37 PF90, +0.43 PREC, +0.50 PINT), parts of southern France (e.g. +0.32 PREC, and +0.34 PINT for Embrun, Lyon, and Tarbes) and northern Spain (e.g. +0.32 PINT and +0.41 PQ90 for Barcelona, Santander, Zamora, and Leon). During summer, days without rain are also important for Bordeaux (-0.39 PCDD), and Lyon-Bron (-0.45 PCDD) in France, and Turin (-0.58 PCDD), and Ligonchio (-0.44 PCDD) in Italy. The highly significant link between rainfall and Mediterranean potato yield identified above supports earlier work conducted by Galeotti *et al.* (2004).

Wheat

This part of the analysis concerns Figs. 6.28-6.33.

Wheat is the second cereal crop considered in this study. Wheat yields are found to be sensitive to winter temperatures (Figure 6.28), with negative correlations in Portugal (-0.47 TMIN), southern Italy (e.g. -0.36 TX90, Trevico, Monte Scuro, and Prizzi), and northern Greece (e.g. -0.30 HWDI, Thessaloniki, Agrinion, Alexandroupoli, Skyros, and Naxos). High spring temperatures (Figure 6.30) also produce a negative impact (negative significant correlations) for Greece (-0.49 TX90), Italy (-0.34 TMAX), and eastern Spain (e.g. -0.34 TX90, Alcantarilla, Valencia, and Montseny Turo), reflecting the fact that wheat crops also require vernalisation (Harrison and Butterfield, 1996; Moriondo and Bindi, 2006). For summer, the negative impact of high temperatures (Figure 6.32) is evident for Greece (-0.20 TN10) and northern Spain (e.g. -0.35 HWDI, Zamora, Salamanca, Burgos, and Soria, Daroca) but for northern Italy (e.g. Forli, Turin, Pisa, Bosco, Ligonchio, and Monteombraro) high temperatures may be beneficial (+0.36 TX90). Otherwise, high temperatures can be shown to negatively affect wheat yields for most of the Mediterranean basin, as illustrated by significant losses of yield during the 2003 heatwave (EEA, 2004), through a reduction of growing period (Gitay *et al.*, 2001), early harvests (Beniston, 2004), and scorched grain (Xoplaki *et al.*, 2001).

Relationships between winter rainfall and wheat yield (Figure 6.29) are similar to those for rainfall and maize yield. The frequency and volume of heavy winter rainfall produces a negative impact on yields in northern Spain (e.g. -0.30 PF90, -0.35 PQ90 for

Villafranca, Leon, Burgos, and Barcelona), southern France (e.g. -0.30 PQ90 for Embrun) and northern Italy (e.g. -0.37 PQ90 for Monte Scuro), but a positive impact for central and southern Greece (e.g. +0.20 PQ90 for Agrinion, Tripoli, and Skiros). In a similar fashion western Iberian intense rainfall is negatively correlated with Spanish and Portuguese yield values during spring (e.g. -0.30 PINT for Santiago, Vigo Peinador, Leon, and Penhas Douradas), but spring rainfall amounts (Figure 6.31) are positively correlated with Greek wheat yield (+0.43 PREC, -0.40 PCDD). South eastern Spanish spring rainfall also shows significant positive correlation with wheat yields (e.g. +0.37 PINT, +0.44 PN90, +0.46 PREC for Alcantarilla, San Javier, and Alicante). In already damp regions, excess rainfall may damage crops, but in the more arid parts of the Mediterranean any rainfall is of benefit as water stress may hinder the grain filling period of growth (Chapter 5.3.3), implying threshold effects and potential non-linearities. During summer (Figure 6.33), average levels of rainfall and measures of frequency of extreme event are positively correlated for south eastern Spain (e.g. +0.24 PREC, +0.45 PN90 for Alicante and San Javier). However, negative correlations between rainfall and wheat yield occur across northern Italy (e.g. -0.37 PREC, -0.39 PINT, -0.46 PN90, for Rome, Paganella, Ligonchio, and Bosco Centrale) and in the case of high volumes of rainfall, southern Spain (e.g. -0.35 PQ90, Jerez de La Frontera, San Javier, and Alicante), with positive impacts from dry days (PCDD) occurring for the same locations. During summer wheat yields benefit from dry conditions throughout the majority of the basin.

6.4.3 Electricity consumption

Winter

This part of the analysis concerns Figs. 6.34-6.35.

As can be seen from the asymmetric u-shaped distribution shown in Figure 5.2, residential electricity use shows strong links with seasonal temperatures, stronger in winter (Figure 6.34), when low temperatures result in high consumption. Both commercial (Figure 6.34) and residential (Figure 6.35) energy use show stable and highly significant negative correlations (-0.51 to -0.77 TAVG) between national electricity consumption and winter mean temperatures in the north of Spain (for Huesca, Soria, Logrono, Ponferrada, Zamora and Salamanca) and on the eastern Iberian coast (Alicante, Valencia, Tarragona). A natural bias might be expected toward urban regions. However, temperatures for the Barcelona region do not display a stable correlation with commercial energy use, but do with residential values (-0.51 TAVG for Prat de Llobregat). There are a larger number of stable and significant negative residential consumption correlations with temperature across central, south eastern and western Spain (e.g. -0.77 TAVG Santiago, -0.70 TAVG Soria), than commercial electricity consumption values. For Italy, only Pisa (-0.43 TAVG) and Pescara (-0.58 TAVG) temperatures relate significantly to national residential electricity consumption, and only Monte Scuro temperatures relate to commercial usage (-0.36 TAVG). For French residential electricity, the most important southern region is Marignane (-0.58 TAVG).

In terms of winter extremes and residential usage, the sensitivity of national consumption is stronger for mean temperature than any extreme value. Indices of high temperature (TMAX, TX90) are more important than low temperatures (TMIN and TN10), and the outer parts of the temperature distribution (TN10 and TX90) produce less stable and significant relationships than those closer to the mean (TMIN and TMAX). However, the number of local winter cold spells (TNFD) is second only to mean temperature in the number and magnitude of significant (positive) correlations with residential consumption (Figure 6.35), and the sensitive areas are similar (+0.52 TNFD for northern Spain and +0.49 TNFD for southern France). Thus, electricity consumption seems particularly sensitive to the occurrence of frost. Winter warm spells (HWDI) can be seen to have very little effect upon residential consumption outside of Blagnac (-0.44 HWDI) and Agen (-0.52 HWDI), in southern France, where correlations are negative.

The variations between correlations for indices of extremes and mean temperature values described above do not hold for commercial electricity consumption (Figure 6.35). Indices of low temperature (TMIN, TN10) are far more important in most areas (excluding Nice and Embrun in southern France) than indices of high temperature (TMAX, TX90), and average minimum (TMIN) and maximum (TMAX) values produce more significant and stable relationships than the mean (TMEAN). The most important extreme climate index for commercial consumption is the number of frost days (TNFD), which shows stable and significant positive correlations for most of northern Spain (+0.62 TNFD). However, as for residential consumption, only Blagnac (-0.48 HWDI) and Agen (-0.52 HWDI) show stable and significant correlations between winter warm spells (HWDI) and national consumption.

Summer

This part of the analysis concerns Figs. 6.36-6.37.

Summer mean temperatures only show stable and significant correlations with commercial electricity consumption (Figure 6.36) for the south of France (particularly Biarritz, Bordeaux, Agen, Blagnac, and Marseille), where relationships are negative (-0.35 TAVG), implying that sensitive regions are more affected by cold weather than warm weather even in summer, and that the commercial use of air conditioning may be minimal (Bouchama, 2004).

Extreme values of summer temperature reflect the distinction between a commercial sensitivity to cold spells and a residential sensitivity to warm spells. Commercial electricity consumption is sensitive to only low temperature extremes (TMIN and TN10), and more so for very low temperatures, particularly in Marseille (-0.58 TN10) and Bordeaux (-0.57 TN10). Residential values (Figure 6.37), by comparison, are more sensitive to high temperatures indices (TMAX and TX90) than low temperature indices (TMIN and TN10), although the sensitivity of the south of France to low temperatures (TMIN) can also be found for residential values. Particularly significant correlations can only be found between high temperatures and residential consumption for the southern edge of the basin: Prizzi (+0.53 TX90), in Italy, and San Javier (+0.55 TX90), in Spain.

From the above it can be seen that electricity consumption is much less sensitive to summer temperatures than winter temperatures, thus supporting Figure 5.2. Residential correlations with summer frost days are stable and significant, but are probably suspect due to the very low number of such spells across the Mediterranean during summer. There are a large number of significant Greek summer correlations with temperature, but none of them are stable over the study period. Giannakopoulos and Psiloglou (2005) discovered significant relationships between temperature and energy use for Athens over the 1993-2000 period, but it seems likely that these relationships have become important recently, and were not significant during the 1980s. Chapter 3.4.4 shows that the eastern basin has been warming over the 1980-2000 period (i.e. detailed trends are stable). As might be expected (Chapter 5.3.4), correlations between electricity consumption and precipitation indices or lagged temperature indices are almost entirely nonsignificant or nonstable.

6.4.4 Mortality

Winter

This part of the analysis concerns Figs. 6.38-6.40.

Winter excess mortality is considered to be particularly sensitive to low temperatures (Section 5.3.5), with mortality increasing as temperature declines. Significant and stable correlations between excess mortality and winter temperature (Figure 6.38) confirm this, and are displayed across central and western Iberia (e.g. -0.52 TAVG, -0.44 TMIN, for all of the Portuguese stations, Coruna, Santiago, Vigo Peinador, Villafranca, Zamora, Salamanca, and Jerez de la Frontera), and Greece (e.g. -0.38 TMIN, for Thessaloniki, Larissa, Kozani, Skiros, Tripoli and Kalamata). Correlations are generally neither stable, nor significant for Italy or the south of France. Minimum temperatures (TMIN) display the greatest number of highly significant and stable correlations, followed by very low temperatures (TN10, -0.48 for western Iberia), frost days (TNFD, +0.45 for western Iberia), and then the mean (TAVG). High temperature indices (TMAX, TX90) give correlations that are largely neither significant nor stable, although excess mortality is positively related to winter warm spell conditions in Seville (+0.60 HWDI), and Nice (+0.47 HWDI), for reasons that are unclear, as these results can only be found for a few stations they may be statistical anomalies. High (lagged) autumn temperatures are also negatively correlated (-0.50 TMAX) with excess winter mortality (Figure 6.39) across most of western and northern Spain (including the Spanish stations listed above, and Barcelona).

Relationships between excess winter mortality and rainfall indices are generally unstable, and each index displays a differing area of sensitivity (PREC and northern Italy, PQ90 and Bordeaux/Agen, PN90 and northern Spain, PCDD and both Portugal and Barcelona). In addition relationships are almost entirely negative (as rainfall decreases, mortality goes up), it seems likely that winter rainfall values decrease as temperature decreases (Chapter 3.4.3), rather than that winter drought is a factor in excess seasonal mortality. Lagged autumn values (Figure 6.40) are only significant and stable for rainfall (+0.45 PREC, north western Spain) and dry periods (-0.44 PCDD, north and west Iberia) values. As the number of autumn dry days (amount of precipitation) decreases (increases) the number of winter deaths increase. As flash flooding produces instantaneous mortality (Chapter 5.3.5), then this effect is likely to be a cause of either population displacement, or more probably, as there are few significant correlations with indices of heavy rainfall, conditions conducive to illness (Chapter 5.3.5).

Spring

This part of the analysis concerns Figs. 6.41-6.44.

Temperatures for the previous winter (Figure 6.41) show significant correlations with excess spring mortality, for both Greek low extremes (-0.45 TN10) and Spanish high extremes (-0.35 TX90). Persistent cold temperatures evidently have a pronounced effect on excess spring mortality in a fashion that varies across the basin. As for winter mortality, low spring temperatures (Figure 6.43) may induce higher levels of excess seasonal mortality. Significant negative correlations between spring mortality and spring temperature indices are pronounced for all of Italy and Greece (for TMEAN, TMIN, TMAX, TN10 and TNFD). Low temperature indices are of particular importance for parts of southern France (e.g. -0.32 TMIN, Nice, Montelimar, and Lyon), northern Italy (e.g. -0.40 TMIN for Turin, Pisa, Forli, Rimini, Alfonsine, Bobbio, Bosco Centrale, Ligonchio, and Monteombraro), southern Italy (-0.43 TMIN, Monte Scuro and Prizzi) and Greece (e.g. -0.47 TMIN, the majority of Greek stations). Very low spring temperatures show no stable or significant correlation with spring mortality for Greece outside of Milos and Alexandroupoli, but the sensitive areas of

Italy (-0.35 TN10), France (-0.37 TN10), and southern Spain (e.g. -0.32 TN10 for Jerez de la Frontera and Alicante) are all larger for very low temperatures (TN10) than the respective sensitive areas for minimum temperature (TMIN). High spring temperature correlations (TMAX, TX90) are generally less significant than indices of cold or mean temperature. As for winter, spring frost days (TNFD) correlations show a distribution similar to, but magnitudes opposite to, values for very low temperatures (TN10).

Spring rainfall shows no stable or significant correlations with excess spring mortality. The frequency of extreme rainfall during the previous winter (Figure 6.42), however, is important in Agrinion (Greece), Turin (Italy) and Agen (France), which all display similar magnitude negative correlations (-0.38 PF90 and -0.37 PN90). Lagged autumn rainfall (Figure 6.44) is important for spring mortality in Portugal (-0.41 PN90, -0.39 PREC, -0.38 PX5D, and -0.35 PF90, for Santarem, Pegoes, Alvega, Mora, and Penhas Douradas) northern Spain (e.g. +0.58 PF90 and +0.56 PQ90 Bilbao), and northern Italy (+0.43 PREC, +0.38 PN90, and +0.43 PX5D, Alfonsine, Rimini, and Forli). Spring mortality seems to be increased by an increase in preceding autumn extreme rainfall events (high magnitude and high frequency), for both northern Spain and Italy. The amount of rainfall in autumn affects mortality in both winter and spring, so illness seems increasingly likely as a potential cause. However, Portuguese spring mortality is increased by a lack of extreme rainfall in the preceding autumn, which may be a facet of a relative increase in the pool of available susceptibles.

Summer

This part of the analysis concerns Figs. 6.45-6.48.

High winter temperatures seem conducive to high summer mortality (Figure 6.45), with warm extremes (+0.35 TMAX, +0.38 TX90) important in the western basin, and cold extremes (+0.20 TMIN) important (but less so) in the east. In years when winters are mild, a larger pool of susceptibles may be available for events in the following summer. There is some evidence to suggest, however, that short-term acclimatization takes place between spring temperatures and summer mortality (Figure 6.46), as significant negative correlations between them can be found for Greece (-0.55 TN10, -0.30 TX90, Larissa, Ioannina, Kalamata, Kithara, Milos and Skyros), and Spain

(-0.32 TX90 Alicante, Valencia, Logrono, Daroca and Barcelona). When spring temperatures are high in these locations, summer mortality decreases.

Summer mortality is, as expected from (Chapter 5.3.5), strongly related to summer high temperatures (Figure 6.47). Climate stations across Portugal, northern and central Italy, and the west coast of Greece, all display highly significant, stable, temperature correlations with excess mortality. The number and magnitude of such correlations increases from indices of very low temperature (TN10, very few significant correlations, mostly northern Italian) through mean temperatures (TMEAN, as above), toward indices of very high temperature that show highly significant correlations with the majority of stations through Sardinia (+0.51 TX90), Italy (+0.61 TX90), and Greece (+0.53 TX90), and significant correlations for Jerez de la Frontera, Daroca, Soria, and Santiago (+0.30 TX90, all Spanish stations) in addition to those for Portugal (+0.44 TX90). The highest correlation values can be found for very high temperatures and heatwave duration for: Rome (+0.62 TX90); Santarem (+0.54 HWDI), near Lisbon; Tripoli (+0.60 HWDI), near Athens; Thessaloniki (+0.60 TX90); and Alfonsine (+0.67 TX90), Italy.

Temperatures may have an affect upon summer mortality even when lagged from the previous summer (Figure 6.48) in the north west of Spain (+0.38 TMAX, +0.35 TX90) and northern Italy (-0.42 TMIN, -0.26 TMAX). In the former case, high temperatures may instigate or aggravate health problems that cause mortality in the following year, while in the latter case a mild summer may slightly increase the pool of susceptibles for the following year.

Low summer precipitation is also linked to high mortality, as for winter, but again it is likely that this relationship is a facet of the connection between temperature and precipitation (Chapter 3.4.3), rather than, necessarily, a link between summer drought and mortality. Lagged spring and winter precipitation values show negative correlations only where temperatures show positive correlation values.

Autumn

This part of the analysis concerns Figs. 6.49-6.51.

Although summer and spring lagged temperatures are not important for autumn excess mortality, lagged temperatures from the preceeding winter (Figure 6.49) display moderately significant positive correlation values across most of southern France (+0.38 TMAX), implying that a mild winter in the previous year is conducive to high French autumn mortality.

Autumn excess mortality displays a striking number of negative correlations with autumn temperature (Figure 6.50) across the majority of the basin (including all Greek stations, and almost all Portuguese and Spanish stations). It is clear that the changeover from heat-induced mortality to cold-induced mortality is sudden. For Iberia, very low temperature is the most important index, showing highly significant correlations (-0.40 TN10) for all stations but three (Pegoes, Logrono and Soria), and the most significant correlations to the west (e.g. Portugal, Vigo Peinador and Coruna, up to -0.62 TMIN). For Greece, mean temperatures are more important, particularly in the north west (e.g. -0.55 TAVG for Ioannania, Kozani, and Agrinio). Frost days are also important for western and northern Iberia (+0.35 TNFD, up to +0.62 for Penhas Douradas) and Greece (+0.47 TNFD, up to +0.55 for Kalamata).

Rainfall indices, lagged or otherwise, display little in the way of consistently significant correlation with excess autumn mortality (Figure 6.51). Correlations do occur, particularly for France (-0.35 PREC, Bordeaux and Tarbes), and Rome (-0.52 PQ90), but only for small groups of stations, and generally only of moderate significance (at the 0.10 level).

Elderly Mortality

This part of the analysis concerns Figs. 6.52-6.56.

Excess elderly mortality shares many of the same sensitivities as total excess mortality, including very low winter temperatures (TN10) (Figure 6.52) across Greece (e.g. -0.48 for Thessaloniki, Kozani, Alexandroupoli, Skiros, Naxos, and Kythira), southern France (e.g. -0.42 for Marseille, Montelimar, Embrun, Biarritz, and Tarbes) and northern and eastern Spain (e.g. -0.40 for Santander, Bilbao, Huesca, Reus, Valencia and Alicante). For Greece, low temperatures and high numbers of frost days during spring (-0.40 TN10, +0.30 TNFD) (Figure 6.53) affect excess elderly mortality. However, summer temperatures (Figure 6.55) do not correlate significantly with excess elderly mortality, except for heatwaves at Alicante (+0.50 HWDI) in Spain, and Tripoli (+0.27 HWDI) in Greece, and for summer values of the previous year. For lagged summer values (Figure 6.56) both low extremes (e.g. +0.37 TN10 for south eastern France) and high extremes (e.g. -0.31 TX90 for Rome) may act to reduce the impact of one year, only to increase the pool of susceptibles for the next, thus increasing overall mortality.

Rainfall affects excess elderly mortality only in spring (Figure 6.54). Significant and highly significant rainfall and dry period correlation values are displayed across Atlantic facing western Portugal (+0.47 PREC, -0.35 PCDD) and Spain (e.g. +0.36 PREC and -0.32 PCDD) for Coruna, Ponferrada, Jerez de la Frontera, Seville, Santander, Bilbao, Biarritz, and Tarbes.

6.5 Summary

The study of socio-economic factors requires a data acquisition process as stringent as the process required for climate data, if not more so. However, problems can be reduced by using information from well-recognised data collection agencies concerning variables that are measured using internationally-consistent survey criteria. Once acquired, data can then be converted into diagnostic indices of risk, measured in real, comparable units. As this study is interested in the effects of extreme climate variability, indices of socio-economic risk have been calculated as anomalies, either with respect to a long-term trend (agricultural yield), expected values (mortality), or a proxy for economic growth (electricity consumption). This process implicitly takes a large number of external socio-economic and physical factors into account, as variables (such as irrigation) that are known to show relationships with relevant data do not show stable or significant covariance with the indices calculated above. Although relationships between some socio-economic indicators of risk and (generally mean) climate have been shown to increase or decrease in sensitivity over time (Valor *et al.*, 1999; Sailor, 2001) the analysis of relationships that are both stable and significant ensures some degree of persistence. Given the above and with reference to results discussed in Chapter 3, the following is concluded when analysing climate and socio-economic risk, for agriculture:

- Spanish and Greek crop yields are particularly at risk from extreme behaviour, although for differing reasons. There are differences in crop response between normally mild and wet western conditions (benefit from heat and dry periods) and normally hot and dry eastern conditions (benefits from mild and wet periods). The former is generally at risk from intense rainfall (increasing in occurence) (Chapter 3.4.4) and cold periods (declining), while the latter is at risk from both very hot (increasing) and cold conditions (declining), and dry periods (increasing). The west / east disparity is particularly evident for citrus, grape, maize, and wheat yields.
- There are also substantial differences between responses for northern and southern parts of the Mediterranean basin. Northern region yields are more at risk from intense cold (declining), and southern region yields more at risk from intense heat (increasing), particularly in the case of maize, wheat, and citrus crops, all of which benefit from high temperatures in the north, and are adversely affected by high temperatures in the south.
- The important spring process of vernalisation (for grape and wheat) is affected more by temperature extremes than the mean. The cold conditions which vernalisation requires are declining across the majority of the Mediterranean, more so for cold extremes than the mean.
- Crops are generally more susceptible to spring extremes than those of any other season.
- Increasing temperatures across much of the Mediterranean are likely to decrease the growing periods of tuber crops such as potato, therefore also reducing yields.

For electricity consumption:

- o Winter residential consumption is more sensitive to mean temperature than extreme conditions, although frost days are much more important than other extreme indices. Frost days are the most important climatic consideration for winter commercial consumption.
- o Summer consumption is much less sensitive to climate than winter consumption.
- o Commercial consumption for the south of France decreases as summer temperatures increase, but elsewhere commercial consumption shows no sensitivity to summer conditions.
- o Residential consumption shows significant and stable correlations only for the warmest parts of the Mediterranean. As Greek consumption has been linked to climate over the 1993-2000 period (Giannakopoulos and Psiloglou, 2005), and this study shows significant, but unstable relationships for Greek residential consumption, future research may find the behaviour of Greek sensitivity over time of interest.
- o Residential consumption relationships are naturally biased towards climatic conditions for large cities. However, no natural bias toward urbanised areas exists for commercial consumption (see below).

For excess mortality:

- o As might be expected, winter and summer mortality are more sensitive to extreme low and high temperatures than other climate conditions.
- o However, climate may affect mortality even when lagged by up to 3 seasons. In winter and spring, lagged mortality effects from the preceeding autumn are relatively common.
- o The impact of same-season rainfall extremes is confined to autumn excess mortality. For all other seasons rainfall is a factor only when lagged from the preceeding autumn, winter, or spring. This effect may be due to displacement, but is more likely due to preconditioning through illness or an effect on the pool of susceptibles.
- o Those sensitive to preceeding summer temperatures are not likely to contribute toward winter mortality totals, but low winter temperatures do have an effect upon summer mortality.

- Persistently low or high temperatures have an effect upon mortality as seasonal mortality is often correlated with both temperatures of the current and preceeding season with similar magnitudes.
- Excess elderly mortality is largely affected by the climate of the preceeding summer, winter and spring, and shows little to no dependence on current summer conditions.

The above detail goes some way to disproving the null hypotheses posed at the end of Chapter 5, but raises more questions in terms of the linearity of relationships. These issues are explored further in Chapter 7. Having identified the most promising relationships between extreme station-scale climate predictors and national-level socio-economic predictands, Chapter 7 is largely concerned with the most appropriate functional forms for the construction of socio-economic (econometric) upscaling models.

Table 6.1: Summary of socio-economic predictands.

Acronym		Full name	Temporal resolution	Normalised by	Data source
AYA	AYA_C	Agricultural yield per hectare anomaly (Citrus)	Annual	Linear trend	FAO, 2006
	AYA_G	Agricultural yield per hectare anomaly (Grape)			
	AYA_M	Agricultural yield per hectare anomaly (Maize)			
	AYA_P	Agricultural yield per hectare anomaly (Potato)			
	AYA_W	Agricultural yield per hectare anomaly (Wheat)			
ECA	ECC	Commerical electricity consumption per capita anomaly	Seasonal	GDP	Eurostat, 2006a World bank, 2006
	ERC	Residential electricity consumption per capita anomaly			
EMI	EMI	Excess mortality index	Seasonal	5-year moving average	WHO, 2003
	EMI_{65}	Excess elderly mortality	Annual	5-year moving average	WHO, 2003