Project no. 022704 (SSP)

FOOTPRINT

Functional Tools for Pesticide Risk Assessment and Management

Specific Targeted Research Project

Thematic Priority: Policy-orientated research

Deliverable DL9

Representative climatic records

Due date of deliverable: 31 December 2006
Actual submission date: 31 December 2006

Start date of project: 1 January 2006 **Duration: 36 months**

Organisation name of lead contractor for this deliverable: University of Newcastle Upon Tyne

Revision: N/A

Project co-funded by the European Commission within the Sixth Framework Programme (2002-2006)		
Dissemination Level		
PU	Public	X
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (including the Commission Services)	

Table of Contents

Foreword

The present report was prepared within the context of the work package WP2 ('High resolution scenario-based spatial zonation') of the FOOTPRINT project (http://www.eu-footprint.org).

Data have been provided through the PRUDENCE data archive, funded by the EU through contract EVk2-CT2001-00132. Data are available for download from http://prudence.dmi.dk/. The CRU dataset TS 2.0 was made available by Dr David Viner of the Climatic Research Unit, University of East Anglia. The European Climate Assessment Dataset is available from http://eca.knmi.nl/.

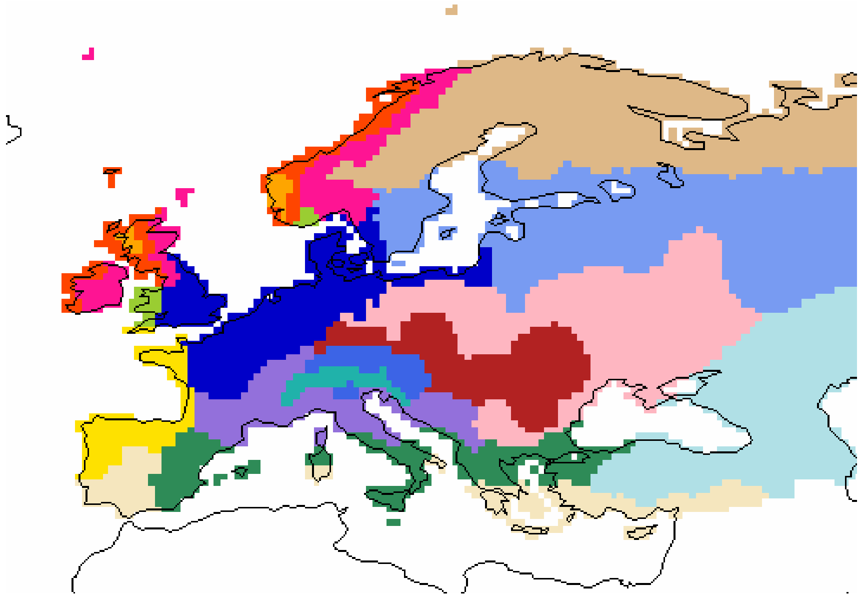
The preferred reference to the present document is as follows:
Blenkinsop S., Fowler H.J., Burton, A., Nolan B.T., Surdyk N. & Dubus I.G. (2006). Representative climatic records. Report DL9 of the FP6 EU-funded FOOTPRINT project [www.eu-footprint.org], 59p.

Executive summary

The aims of the work reported in this deliverable were to i) undertake a climatic zonation of Europe; and, ii) define climatic scenarios which will be subsequently used for modelling the environmental fate of pesticides within the context of FOOTPRINT.

Extensive modelling was first undertaken to simulate the fate of various pesticides in different soils under different climatic conditions. Univariate and multivariate statistics were then used to relate predicted pesticide losses to climatic characteristics in order to identify the key climatic factors influencing pesticide fate. A total of eight climatic variables were selected on the basis of these investigations and a climatic classification for Europe was constructed using these objective criteria. This involved using a data reduction method to identify the main patterns of variability from the selected variables. The main patterns were then used in a clustering routine to group areas with similar characteristics. One of the difficulties in the work was to decide on an appropriate number of climatic zones given the need to identify distinct climates and yet produce a manageable number of zones for subsequent within-zone modelling. This balance was achieved through the production of a classification of 16 regions (the 'FOOTPRINT climatic zones') which are physically plausible in terms of the input variables and of knowledge of the European climate. Representative climate series were selected for each of the 16 FOOTPRINT climatic zones using an objective method which was able to identify stations which were most typical of each climatic zone.

The approach represents a major scientific improvement over earlier methods which rely on the subjective selection and combination of climate statistics. The FOOTPRINT climatic zones which cover the EU25 and the candidate countries will form the basis of subsequent modelling activities within the project.



The 16 FOOTPRINT climatic zones

1 INTRODUCTION: REVIEW OF CLIMATE CLASSIFICATIONS

The classification of climate has been defined as the grouping of conditions for locations which show similar conditions defined by boundaries applied to one or more meteorological element (Essenwanger, 2001). The earliest noted attempt at climate classification was made by the Greek scholar Aristotle who hypothesized that the earth was divided into three types of climatic zones, each based on distance from the equator. These zones were termed “Torrid”, “Temperate” and “Frigid”. The tradition of geography as a descriptive discipline concerned with such classification of natural environments persisted into the 20^{th} century. The most well-known and most widely reproduced global climatic classification was that of Köppen who published his first global classification in 1918, with a revised forms published subsequently (Köppen & Geiger, 1928, 1936; Figure 1). This system of classification was updated and modified until Köppen’s death and it has since been modified by several geographers e.g. Strahler (1963), Walter & Leith (1960). The classification is based on average annual and monthly precipitation and average monthly temperature, and comprises six major climate regions, with the European climate divided between Mild-Mid-latitude, Severe Mid-latitude and Highland Types. Each of the 6 regions may however be divided into further sub-regions; typically 24 sub-categories based on temperature and precipitation. An attempt was made by Thran & Broekhuizen (1965) to adapt the Köppen classification to a specific application by emphasising the time of year when assessing climate data. They viewed winter data as not relevant for the pest problems of spring crops and so created an agro-climatic classification based on only important phenological periods, thus describing 76 sub-areas within Europe. A simplified version of this scheme is shown in Figure 2.

Climate classifications are still used and developed for the application of current problems. Guttman (1993) applied classification methods to US precipitation, using cluster analysis to define 104 regions as part of a national study of water management. Wang & Overland (2004) used the Köppen classification as a means of assessing Arctic climate change by examining trends in the coverage of the tundra group of climates. Within the discipline of climatology however, the classification of climate is largely concerned not with the regionalisation of surface climate, but with that of atmospheric circulation, in the identification of an objective means of summarising daily circulation patterns (e.g. Jones et al., 1993) or in the application of statistical downscaling (e.g. Goodess & Palutikof, 1998) or in the assessment of climate model output (e.g. Huth, 2000).

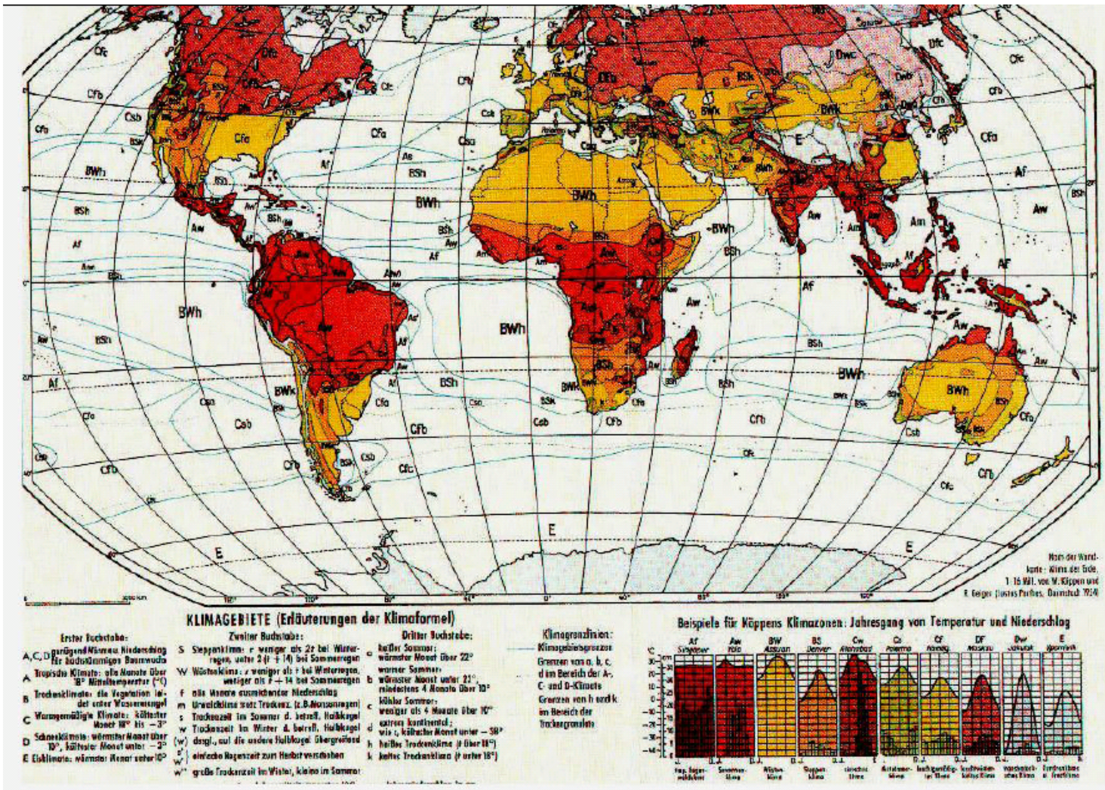


Figure 1. The global climatic classification of Köppen & Geiger (1936).

Figure 2. The agro-climatic classification of Thran & Broekhuizen (1965).

The classification of European climates has recently been most widely employed in ecological applications. Bunce et al. (1996a) indicate that traditionally, in this field, such classifications are primarily intended for mapping purposes and are based on field sampling of habitats which are described from samples located subjectively. Quantitative procedures have largely been ignored because intuitive methods are more easily applied. They describe an objective statistical method for classifying the ecology of Great Britain using climatic, topographical, human and geological parameters using a procedure described in Bunce et al. (1996b). Hossell et al. (2003) also produced a bioclimatic classification of Britain and Ireland for use in examining the effects of climate change on natural habitats. The three-stage procedure involved the selection of 89 relevant variables, principal components analysis to reduce the dimensionality of the data, and finally a hierarchical clustering method to determine the final classification of 21 bioclimate types.

Bouma (2005) noted that climatic conditions are important for the speed of growth of plants and for crop safety before, during and after the application of agrochemicals. A European classification of agro-climatic zones for crop efficacy and safety was therefore devised. Identifying the main conditions which are important for this application, the classifications of Köppen & Geiger (1928), and others discussed above, were used to subjectively identify 4 large agro-climatic zones which they termed Mediterranean, Maritime, North-east and Central (Figure 3). Metzger et al. (2005) undertook a more substantial objective classification of Europe with the aim of providing a resource to aid the sampling and modelling of ecological resources. They used 20 key climatic variables which were selected on the basis of past experience and used principal components analysis to identify the dominant modes of variability. An ISODATA clustering algorithm was then used to identify 84 strata which were subsequently aggregated into 13 Environmental Zones across Europe. Jongman et al. (2006) indicated that such a stratified approach would aid the monitoring of biodiversity and habitats by enabling the determination of convenient units. They demonstrated further subdivisions of strata by dividing Alpine areas further by altitude to create substrata.

A number of climate zonations have been defined within the specific field of pesticide registration, mainly under the hospices of the FOCUS groups. FOCUS

Figure 3. The proposed agro-climatic classification of Bouma (2005).

(1995) first presented a total of 10 climatic scenarios which were aimed to cover the variability in climates in Europe (Figure 4). Although the report is not explicit about this aspect, it appears that the zonation reflects differences in annual temperatures and rainfall. The FOCUS working group on soil persistence models (FOCUS, 1997a) combined information on average annual temperature and the net precipitation amount (defined as the difference between average annual sums of precipitation and evapotranspiration) to result in eight climatic zones (Figure 5). The first FOCUS surface water group (FOCUS, 1997b) did not produce any specific zonation and climatic scenarios, but called for the ad hoc development of scenarios based on i) Average annual hydraulically effective rainfall; ii) Average annual temperature; iii) Average winter temperature (during the months of December, January & February); iv) Average summer temperature (during the months of June, July& August); v) Frequency of rainfall events; and, vi) Intensity of rainfall events. The second FOCUS surface water group (FOCUS, 2001) defined a number of agro-environmental scenarios which partly reflected variations in climate across Europe. The climatic data considered in their analysis were the average annual precipitation, the daily maximum spring rainfall, the average spring (March, April and May) and autumn (September, October and November) temperatures and the average annual recharge. These various variables were plotted for the whole of Europe on the basis of the CRU dataset. The FOCUS groundwater group (FOCUS, 2000) developed a total of nine scenarios to be used in the registration of pesticides and weather data were attached to each of these scenarios. The various scenarios were developed on the basis of average annual temperatures and rainfall and the data were taken from the MARS European database (Vossen and Meyer-Roux, 1995) and CRU dataset where MARS data were deemed inappropriate.

Figure 4. The ten climatic zones proposed by FOCUS in 1995 (after FOCUS, 1995).

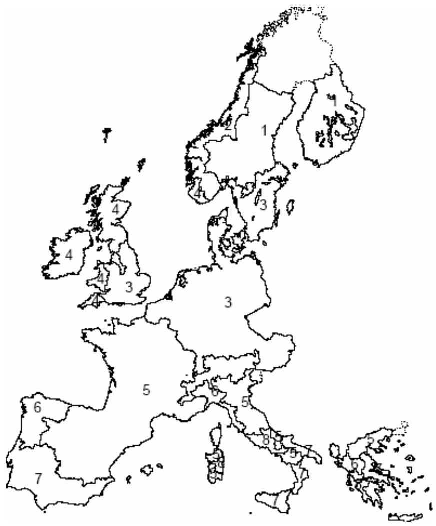


Figure 5. The eight climatic zones proposed by FOCUS in 1997 (after FOCUS, 1997a).

In the present study, modelling investigations were undertaken to identify the climatic factors which most influence pesticide fate. The variables identified were then use to support the development of a climatic zonation of Europe. Principal components analysis was used to identify the dominant modes of variability of the key eight variables. K-means clustering was then used to identify 16 coherent climatic zones (the 'FOOTPRINT climatic zones') relevant for pesticide fate by leaching and drainage across Europe.

2 IDENTIFICATION OF CLIMATIC FACTORS AFFECTING PESTICIDE LOSS BY DRAINAGE AND LEACHING

2.1 Methodology

The transport of three pesticides by leaching and to drains was simulated for six different climatic series and five application dates in the spring and autumn using the pesticide leaching model MACRO. Output statistics were generated for 78 modelling scenarios, based on two site locations (Oxford, UK, and Zaragosa, Spain) and variations in soil type, season, applied pesticide, and leaching either to 1-m depth or to tile drains (in the case of Oxford) at depths of 0.6 – 0.8 m. The transport scenarios are referred to as "leaching" or "drainage," respectively. Fifty-four modelling scenarios comprising over 1,600 MACRO simulations were conducted using climatic data series generated from conditions at Oxford, and 24 leaching scenarios comprising an additional 720 simulations were conducted based on conditions in Zaragosa.

2.1.1 Soils

Soil series were selected to represent the whole spectrum of potential transfer of pesticides through soil profiles in northwestern Europe. The four soils retained for leaching simulations were (listed here in order of increasing clay of from 9 – 40% in the top two layers): Cuckney (CU), Hall (HA), Ludford (LU), and Enborne (EN) (Dubus et al., 2002). These soil series were used in both the Oxford and Zaragosa simulations. The five soils retained for drainage simulations (Oxford only) had 13 – 56% clay in the top two layers: Quorndon (QU), Clifton (CL), Brockhurst (BR), Hanslope (HS), and Denchworth (DE) and were used by Brown and colleagues (Brown et al., (2004) as part of a spatially-distributed modelling exercise aimed at assessing the variability in the assessment of the risk of pesticide being transferred to drainage in England and Wales. The soils were initially identified from the SEISMIC database (Hallett et al., 1995) as representative of the spectrum of vulnerabilities for the transport of pesticides to drainage systems as part of maize cultivation in the UK. Soils were selected based upon soil factors including organic carbon content, texture, likelihood of macropore flow and average depth to groundwater. MACRO was parameterised for the soils using procedures described in detail in Dubus & Brown (2002) and Brown et al. (2004).

2.1.2 Pesticides

Three pesticides were considered in the modelling in an effort to cover some of the variability which may arise from the use of compounds with different environmental fate properties. Pesticides 1 and 2 have the same environmental fate properties as those used previously by Dubus and colleagues to investigate the sensitivity of pesticide leaching models -including MACRO - to changes in input parameters (Dubus & Brown, 2002; Dubus et al., 2003). Pesticide 1 has a Koc value of 20 ml/g and a laboratory DT50 of 7.8 days at 20°C whilst Pesticide 2 has a Koc of 100 ml/g and a laboratory DT50 value of 23.3 days at 20°C. As noted by Dubus et al. (2003), although hypothetical, the properties of the two compounds fall with the range of those registered for use in Europe. Pesticide 3 was selected to reflect compounds which sorb more strongly to soils, but which exhibit slower degradation in the field. Pesticide 3 has a Koc of 220 ml/g and a laboratory DT50 of 88 days. Degradation of the three compounds was assumed to follow first order kinetics. The compounds were assumed to be applied at various dates in the autumn or in the spring (see application scenarios below) to a winter wheat crop.

2.1.3 Climate and investigations into the influence of application dates

At both Oxford and Zaragosa, two application scenarios (spring and autumn) were considered for the three compounds. Five application dates representing the likely window of variability in the application date of an herbicide compound in northern Europe were used. The dates were: 1 September, 15 September, 30 September, 15 October and 31 October for the autumn application; 1 April, 16 April, 30 April, 15 May and 31 May for the spring application. Climatic series were generated as follows.

The modelling was undertaken using a synthetically-generated rainfall series of 100 years for the city of Oxford (Lat. 51°45' N, Long. 1°15' W) in the UK and for the city of Zaragosa in Spain (Lat. 41°39' N, Long. 0°52' W). In each case, a synthetic rainfall series was simulated by fitting the stochastic rainfall model, RainSim (Burton et al., 2004), to five daily rainfall statistics: mean rainfall, proportion of dry days (pdry), variance of daily rainfall, lag-1 autocorrelation and the skewness coefficient. Figure 6 shows the observed, fitted and simulated reference statistics for Oxford and Figure 7 shows the same for Zaragosa.

Simulated rainfall statistics do not exactly match the fitted statistics. The difference between observed and fitted statistics corresponds to the closest approximation that the rainfall model can make, according to its stochastic structure, to a given set of statistics. Certain combinations of statistics may be unphysical or it may not be possible to obtain an exact match using the model. However, the results shown here indicate a very good match between the observed statistics and fitted model. An exception to this can be seen in Figure 6(c). The fitting procedure for pdry contains an approximation which introduces a bias. The blue curve in Figure 6(c) indicates a bias-corrected pdry to which the model is fitted. The simulated data is then seen to match the observed data (black line) well.

Synthetic data was simulated to represent the sensitivity to changes in one of four characteristics of the rainfall: the annual total, seasonality, proportion of dry days and skewness. A set of target statistics were developed for each characteristic and for each variation step. These are referred to as target statistics as they take the place of observed statistics in the fitting procedure. Appendix 1 gives more detail on the rainfall datasets produced for use in this sensitivity study.

For Oxford, the 100-year dataset was first sectioned in five 20-year subsets and a sixth 10-year climatic series was obtained by selecting data for the period covering the years 1965 to 1975.

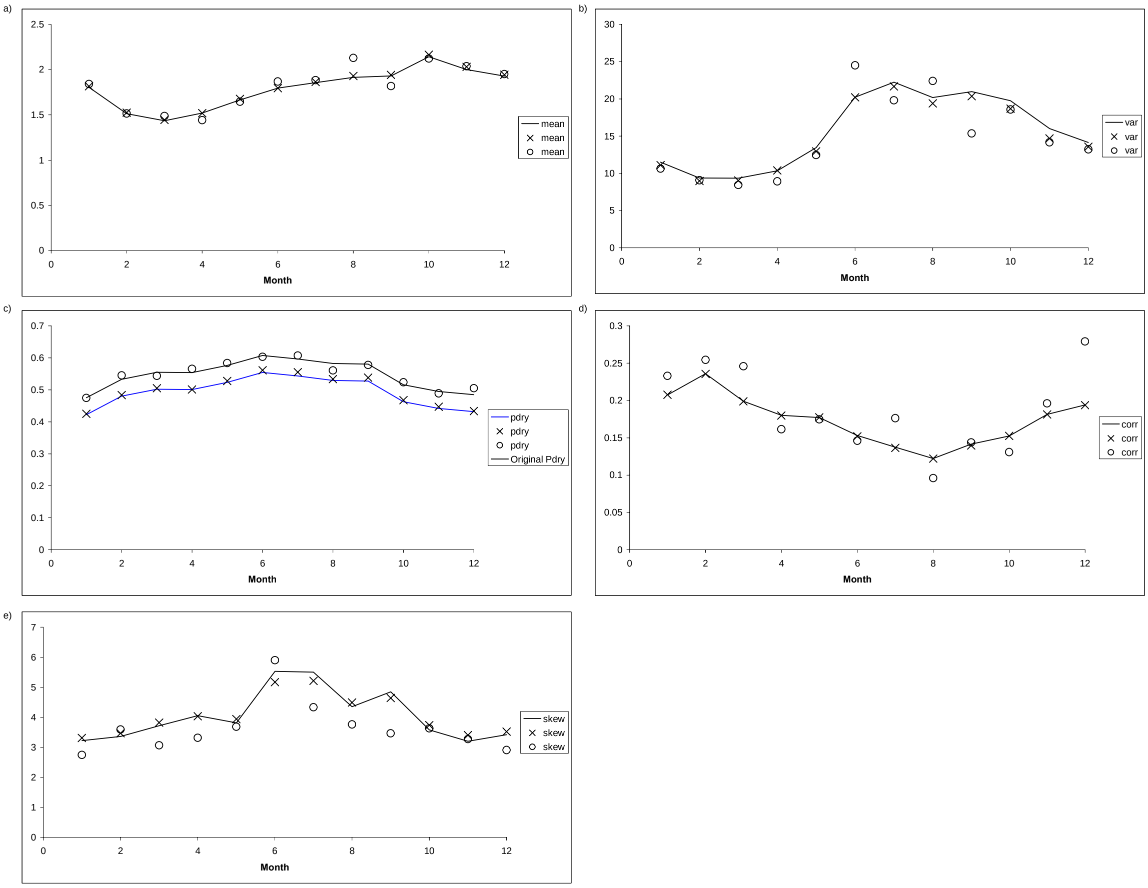


Figure 6. The Oxford rainfall series.
Daily statistics of the observed climate (solid black line) and the synthetic series (crosses= fitted; circles=simulated): a) mean (mm/d); b) variance (mm^2/day^2); c) proportion of dry days, *pdry*; d) lag-1 autocorrelation; e) skewness coefficient

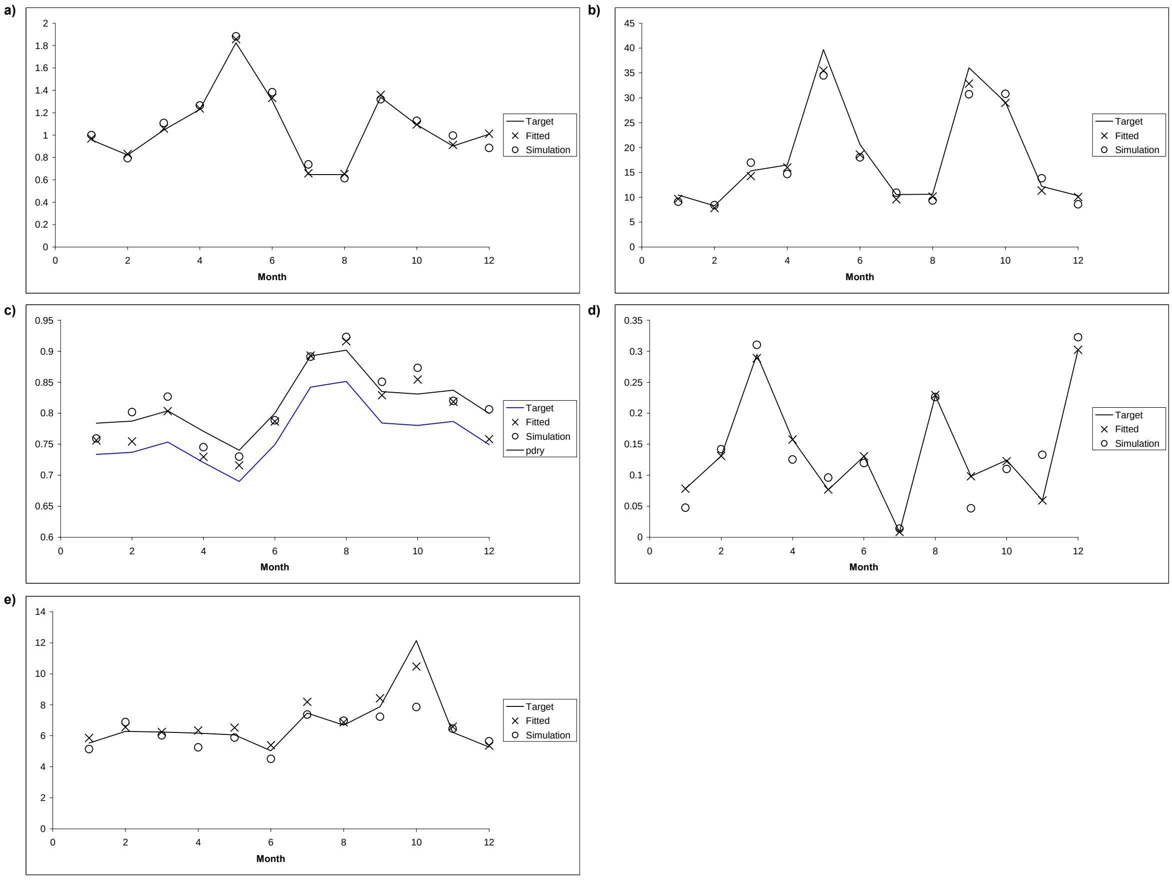


Figure 7. Zaragosa rainfall series
Daily statistics of the observed climate (solid black line) and the synthetic series (crosses= fitted; circles=simulated): a) mean (mm/d); b) variance (mm^2/day^2); c) proportion of dry days, *pdry*; d) lag-1 autocorrelation; e) skewness coefficient

The rainfall data were combined to synthetic temperature and PET data included in the SEISMIC database (Hallett et al., 1995) for the Cambridge weather station (Lat. 52°12'N, Long. 0°07'E). The Cambridge data were originally synthesised using the WGEN weather generator (Richardson, 1985). Checks on the relevance of the synthetic data to represent real conditions have been conducted as part of earlier modelling activities (Brown et al., 2004). The Oxford and Cambridge data were taken as representative of north-western European climate as part of a modelling exercise aimed at investigating the influence of change in application dates on losses in drainage and leaching across the major climate types throughout Europe (data not shown). For Zaragosa, PET and temperature data were obtained through the European MARS dataset for the grid cell covering Zaragosa.

2.1.4 Modelling strategy

A warm-up period of 1 year was included in the modelling to allow the model to equilibrate prior to a single pesticide application in year 2. Each modelling run involved one application of a pesticide and the simulation of its fate for a relevant number of years (6 years for Pesticide 1, 10 years for Pesticide 2 and 19 years for Pesticide 3). The number of years sufficient to allow a complete transfer of the three pesticides was determined through preliminary modelling experiments.

The MACRO modelling was undertaken for the i) three pesticides; ii) the four leaching soils *or* five drainage soils; iii) the two application scenarios; iv) the five application dates for each application scenario; v) and the six climatic series, potentially resulting in 720 leaching observations and 900 drainage observations. At the Oxford site, however, significant rain (59 mm) occurred on the 1 September application date associated with the fifth climate series. Because farmers would not apply pesticides under such conditions, we excluded this application date from the analysis. The final Oxford data set consisted of 708 leaching and 885 drainage observations. The 1 September application date was dry or had nominal rain at Zaragosa, resulting in 720 observations for this site. At both sites, the MACRO output variable which was considered to be of interest within the scope of the present study was the cumulative pesticide loss over the simulation period (expressed in mg/m^2).

2.1.5 Derivation of climatic variables

Climate statistics were derived for each of the six climatic series and are as follows:

Rx [x = -91, -61, -30, -20, -14, -10, -7, -6, -5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, 6, 7, 10, 14, 20, 30, 61, 91, 122, 152, 183, 213, 244, 274, 305, 335, 365, 729, 1095, 1825, 3650, 5475, 7300] is the cumulative rainfall (in mm) for the period from day x to the pesticides application date (x<0) in the case of antecedent rain, or from the application date to day x (x>0);

Cy [y=2, 5, 10, 20, 50, 100] is the number of days after application until y mm of *cumulative* rainfall occurs;

Tx [x = 0, 1, 2, 3, 4, 5, 6, 7, 10, 14, 20, 30, 61, 91, 122, 152, 183, 213, 244, 274, 305, 335, 365, 719] is the average temperature in ºC over the x days following application;

Ly [y = -30, -20, -10, 10, 20, 30] is the number of days before or after application until a y-mm amount of *daily* rain occurs (Ly is referred to as the "lag time"); y<0 indicates that a rain event of y mm occurred before the date of pesticides application, and y>0 indicates that the rain event occurred after application;

WRA_m_n [m = September, October, November; n = March, April] is the cumulative daily rainfall between the beginning of month m and the end of month n;

WRE_m_n [m = September, October, November; n = March, April] is the cumulative daily recharge between the beginning of month m and the end of month n, where recharge is defined as the difference between daily rainfall and potential evapotranspiration. Potential evapotranspiration was estimated using the Penman-Monteith method, based on measured weather data in the study area.

2.1.6 Statistical methods

Predicted, cumulative pesticide losses at 1-m depth (Oxford and Zaragosa) and in drains (Oxford only), climate factors (cumulative rain, cumulative winter rainfall and recharge, average temperature, lag time), and other descriptive variables in the data set (average percent clay in the first two horizons, season of pesticide application) were organized by season-soil-pesticide scenarios and analyzed with nonparametric statistics. We computed Spearman correlations for all of the climate variables to determine the strength of monotonic relations between predicted pesticide loss and all climate variables listed above, for each of the 78 season-soil-pesticide scenarios. Because Spearman correlations are based on ranked data, they are resistant to the effects of extreme values which commonly occur with environmental data (Helsel and Hirsch, 1992). We anticipated that Spearman correlations would yield insight into relations between pesticide loss and specific climate factors for the individual season-soil-pesticide combinations. We used SAS version 8.01 (SAS, Institute Inc., 2006) to compute Spearman correlations.

2.2 Results for Oxford

Modelling results

Results of individual modelling trials for climatic conditions at Oxford are shown in Annexes 1 – 105 in the separate appendix document (each annex shows instantaneous or cumulative pesticide losses for six climatic data series). In general, water and contaminant transport in the vadose zone are driven by precipitation inputs and other factors. The modelling results indicate that pesticide loss depends on the timing of rainfall relative to the application date of the pesticide. For example, Annex 2 shows total pesticide loss predicted by MACRO at 1 m depth after 10 years for the six climate series. In the first climate series ("year #1" in the figure), significant pesticides loss occurs after the first and second application dates (September 1 and 15, year 1). Losses following the October 1 application date are substantially less, indicating that the onset of significant precipitation occurred sometime before October 1. In the fourth climate series (Annex 2, Application in year #4), major rainfall probably occurred shortly after the October 1 application. In the fifth climate series (Annex 2, Application in year #5), one can assume that a major rain event occurred between September 1 and September 15. In the sixth climate series (Annex 2, Application in year #6), all solute losses start at the same time regardless of application date, and losses are somewhat greater after the November 1 application date. In this case, significant precipitation occurred sometime after November 1. Presumably, pesticides applied earlier in the season had more time to degrade or to diffuse into the soil matrix.

The effects of application date are easily seen for pesticide 1, but the effects are less noticeable for pesticide 2 (Annex 4) and even less so for pesticide 3 (Annex 6), the least mobile of the three pesticides. Overall, it is difficult to draw conclusions on the effect of the timing of rain because the weather patterns have considerable uncertainty, which is reflected in the various climatic data series.

MACRO-predicted pesticide losses were aggregated for each site location (Oxford leaching scenarios, Oxford drainage scenarios, and Zaragosa leaching scenarios) to generate percentiles of total pesticides loss based on all modelling observations in each group. Results for Oxford indicate that percentiles of total pesticide loss were about the same for leaching and drainage scenarios (median = 0.012 mg/m^2 and 0.011 mg/m^2, respectively) (Table 1). Pesticide losses expressed as percent of the applied mass (2 mg/m^2) were 0.60% and 0.55%, respectively, for the median observations, and reached a maximum of 29 and 14%, respectively. A Wilcoxon Rank Sum test indicates that differences in cumulative pesticide loss for leaching and drainage are statistically insignificant ($p = 0.154$). Maximum cumulative pesticide loss is somewhat higher for leaching (0.58 mg/m^2) than for drainage (0.28 mg/m^2), which may reflect differences in soil properties and/or the hypothetical configuration of the drains. Three soils used in drainage scenarios have an organic carbon content of 1.9% or more, compared with two such soils in leaching scenarios. Increased organic carbon content in soils generally results in increased sorption of pesticides, reducing or delaying pesticide loss. Leaching scenarios predict pesticide loss at 1-m depth directly beneath the point of pesticide application. In contrast, drainage scenarios assume interception of a fraction of water and dissolved pesticides, with the remainder leaching vertically to ground water. Based on common practice in the soils studied, drain depth was varied from 0.6 to 0.8 m in MACRO simulations, with intervals of 2 – 30 m between drains. Wider intervals may have resulted in less recovery of pesticide mass by the drains (i.e., smaller predicted losses).

	Leaching		Drainage	
Statistic	**Total pesticide loss, mg/m²**	**Percent loss**	**Total pesticide loss, mg/m²**	**Percent loss**
0th percentile (minimum)	0.000001	0.000050	0.0000031	0.00016
25th percentile	0.00096	0.048	0.0010	0.050
50th percentile (median)	0.012	0.60	0.011	0.55
Mean	0.048	2.4	0.031	1.6
75th percentile	0.046	2.3	0.042	2.1
100th percentile (maximum)	0.58	29	0.28	14

Table 1: Statistics of predicted, total solute loss for aggregated MACRO output under leaching (N = 708) and drainage (N = 885) scenarios at Oxford.

Percent loss is based on a pesticide application rate of 2 mg/m².

Identification of climatic factors

Spearman correlations between climatic variables and pesticide loss in leaching (Table 2) and drainage (Table 3) were computed for all 78 season-soil-pesticide combinations, to better understand relations between pesticide loss and specific climate factors. Soils in Table 2 and Table 3 are presented in order of increasing susceptibility, based primarily on percent clay and percent organic carbon in the first two layers. Susceptibility generally increases as percent clay increases. However, the Hall soil (clay = 11%) is more susceptible than the Ludford soil (clay = 22%) because the Hall has less organic carbon at depth (0.3% at 50 – 70 cm) compared with the Ludford (0.5% at 50 – 75 cm for) (Dubus et al., 2002). Table 2 and Table 3 show the five climatic variables with the highest Spearman correlation coefficients for leaching and drainage for specific soil×pesticide scenarios. A colour coded scheme is used to increase the readability of the results. Initial analysis indicated that WRA_m_n is highly correlated with WRE_m_n (Spearman's rho ≅ 1 for the same months m_n, for leaching data) and that the results are redundant if both are used. Also, correlation results are essentially the same regardless of which variable is used. Therefore, WRE_m_n was excluded from subsequent analysis and the following discussion is based on WRA_m_n and the remaining variables described above.

Spring						Fall					
Cuckney						Cuckney					
Pesticide 1		Pesticide 2		Pesticide 3		Pesticide 1		Pesticide 2		Pesticide 3	
T244	-0.758	R729	0.853	R1825	0.917	R244	0.775	WRA_oct_apr	0.917	R729	0.738
T213	-0.745	WRA_oct_apr	0.782	R1095	0.906	R152	0.759	WRA_oct_mar	0.909	R1825	0.728
T274	-0.727	WRA_nov_apr	0.762	L30	-0.889	R213	0.755	WRA_sep_apr	0.890	R1095	0.700
R729	0.711	R1095	0.753	R729	0.830	R183	0.753	WRA_nov_apr	0.889	R3650	0.675
T305	-0.683	R365	0.687	R3650	0.827	R274	0.750	R152	0.879	R7300	0.520
Ludford						Ludford					
Pesticide 1		Pesticide 2		Pesticide 3		Pesticide 1		Pesticide 2		Pesticide 3	
R10	0.494	WRA_nov_apr	0.862	WRA_oct_apr	0.973	R152	0.632	WRA_oct_mar	0.857	WRA_oct_mar	0.973
R61	0.487	WRA_nov_mar	0.822	WRA_nov_apr	0.971	WRA_nov_apr	0.623	WRA_sep_apr	0.856	WRA_sep_apr	0.969
C100	-0.474	WRA_oct_apr	0.813	WRA_sep_apr	0.925	WRA_oct_mar	0.620	WRA_nov_mar	0.846	WRA_oct_apr	0.966
R20	0.463	WRA_sep_apr	0.789	WRA_oct_mar	0.918	T61	-0.616	WRA_sep_mar	0.832	WRA_nov_apr	0.930
L20	-0.439	WRA_oct_mar	0.787	WRA_nov_mar	0.869	WRA_nov_mar	0.615	R152	0.830	R152	0.923
Hall						Hall					
Pesticide 1		Pesticide 2		Pesticide 3		Pesticide 1		Pesticide 2		Pesticide 3	
R10	0.627	L20	-0.583	R729	0.860	T61	-0.631	R213	0.754	WRA_oct_mar	0.950
R20	0.597	R61	0.560	R365	0.724	T30	-0.616	WRA_nov_apr	0.753	WRA_nov_apr	0.942
R14	0.557	R91	0.536	R1095	0.716	T20	-0.579	R244	0.752	WRA_sep_apr	0.942
C50	-0.503	R10	0.532	WRA_nov_apr	0.710	T1	-0.578	R183	0.746	R213	0.941
R30	0.449	R183	0.513	WRA_oct_apr	0.679	T91	-0.571	WRA_oct_apr	0.744	R183	0.940
Enborne						Enborne					
Pesticide 1		Pesticide 2		Pesticide 3		Pesticide 1		Pesticide 2		Pesticide 3	
R10	0.466	R335	0.852	WRA_oct_apr	0.978	T1	-0.708	WRA_nov_mar	0.860	WRA_oct_mar	0.972
R20	0.386	R365	0.847	WRA_nov_apr	0.959	T30	-0.674	WRA_sep_apr	0.855	WRA_oct_apr	0.963
R14	0.368	R305	0.840	WRA_oct_mar	0.938	T2	-0.672	WRA_oct_mar	0.853	WRA_sep_apr	0.956
T122	-0.341	WRA_oct_apr	0.836	WRA_sep_apr	0.937	T61	-0.666	WRA_nov_apr	0.850	WRA_nov_apr	0.949
T1	-0.329	WRA_nov_apr	0.803	WRA_nov_mar	0.872	T14	-0.660	WRA_oct_apr	0.831	R183	0.933

Color key

Winter rainfall	Short-term rainfall (≤ 91days)	Long-term rainfall (>91 days)	Cumulative rainfall	Lag times to rainfall	Short-term temperature (≤ 91days)	Long-term temperature (> 91days)

Table 2: The top five Spearman correlations for climatic variables under each season-soil-pesticide scenario for Oxford leaching simulations

See text for a detailed description of the variables.

Spring						Fall					
Quorndon						Quorndon					
Pesticide 1		Pesticide 2		Pesticide 3		Pesticide 1		Pesticide 2		Pesticide 3	
R305	0.825	WRA_sep_apr	0.854	R365	0.936	R152	0.826	WRA_sep_mar	0.781	WRA_oct_apr	0.959
R335	0.796	WRA_oct_mar	0.826	WRA_oct_apr	0.929	WRA_oct_mar	0.815	WRA_sep_apr	0.773	WRA_sep_apr	0.933
R365	0.770	WRA_nov_mar	0.824	WRA_nov_apr	0.906	WRA_oct_apr	0.799	WRA_oct_mar	0.747	WRA_nov_apr	0.920
R274	0.723	WRA_nov_apr	0.819	R335	0.904	WRA_sep_apr	0.795	WRA_nov_mar	0.736	WRA_oct_mar	0.914
R729	0.702	WRA_oct_apr	0.808	R305	0.857	WRA_nov_apr	0.782	R152	0.709	R152	0.859
Clifton						Clifton					
Pesticide 1		Pesticide 2		Pesticide 3		Pesticide 1		Pesticide 2		Pesticide 3	
R10	0.468	T365	-0.534	R1095	0.969	T61	-0.644	WRA_oct_apr	0.891	R1095	0.860
R20	0.394	T335	-0.511	R729	0.949	T91	-0.631	WRA_nov_apr	0.873	WRA_oct_apr	0.752
R14	0.362	T244	-0.499	R3650	0.806	WRA_nov_apr	0.622	WRA_oct_mar	0.866	R213	0.723
R6	0.320	T719	-0.488	R365	0.675	R152	0.620	WRA_sep_apr	0.852	R183	0.677
T152	-0.319	L-20	0.476	L30	-0.660	R305	0.613	R183	0.852	WRA_nov_apr	0.672
Brockhurst						Brockhurst					
Pesticide 1		Pesticide 2		Pesticide 3		Pesticide 1		Pesticide 2		Pesticide 3	
R10	0.503	R10	0.492	R3650	0.929	T61	-0.698	R213	0.879	R213	0.854
R20	0.442	C100	-0.483	R1095	0.850	T30	-0.672	R183	0.874	R244	0.854
R14	0.420	R20	0.474	L30	-0.824	T91	-0.651	WRA_oct_apr	0.845	R1095	0.837
C50	-0.364	L20	-0.469	R729	0.770	T20	-0.629	R244	0.831	R274	0.831
T122	-0.350	C50	-0.451	R5475	0.767	T1	-0.629	WRA_oct_mar	0.828	R365	0.817
Hanslope						HS					
Pesticide 1		Pesticide 2		Pesticide 3		Pesticide 1		Pesticide 2		Pesticide 3	
R10	0.491	R10	0.534	R729	0.850	T61	-0.696	WRA_nov_apr	0.809	WRA_oct_mar	0.955
R20	0.421	R20	0.478	WRA_nov_apr	0.848	T30	-0.665	WRA_sep_apr	0.805	WRA_sep_apr	0.946
R14	0.405	R61	0.470	R365	0.842	T1	-0.654	WRA_oct_mar	0.804	WRA_nov_apr	0.945
T122	-0.356	C100	-0.454	WRA_oct_apr	0.834	T20	-0.634	WRA_oct_apr	0.798	R213	0.944
T1	-0.352	R14	0.432	R335	0.790	T91	-0.624	WRA_nov_mar	0.795	WRA_oct_apr	0.943
Denchworth						Denchworth					
Pesticide 1		Pesticide 2		Pesticide 3		Pesticide 1		Pesticide 2		Pesticide 3	
R10	0.485	R10	0.518	WRA_nov_apr	0.872	T61	-0.687	WRA_oct_mar	0.831	WRA_oct_mar	0.963
R20	0.413	R20	0.466	WRA_oct_apr	0.844	T30	-0.643	WRA_sep_apr	0.831	WRA_sep_apr	0.953
R14	0.396	R61	0.455	R365	0.819	T1	-0.640	WRA_nov_apr	0.826	R183	0.949
T122	-0.354	C100	-0.453	R729	0.819	T91	-0.620	WRA_nov_mar	0.823	WRA_nov_apr	0.947
T1	-0.346	L20	-0.423	R335	0.769	T20	-0.612	WRA_oct_apr	0.816	WRA_oct_apr	0.947

Color key

Winter rainfall	Short-term rainfall (≤ 91days)	Long-term rainfall (>91 days)	Cumulative rainfall	Lag times to rainfall	Short-term temperatures (≤ 91days)	Long-term temperatures (>91 days)

Table 3: . The top five Spearman correlations for climatic variables under each season-soil-pesticide scenario for Oxford drainage simulations.

See text for a detailed description of the variables.

At Oxford, none of the rainfall statistics describing the rainfall patterns and magnitude shortly before application was found to play a predominant role in the determination of pesticide loss. This result seemingly is corroborated by laboratory studies that found no significant relation between initial soil moisture content and the leaching of isoproturon or its concentration in soil pore water (Beulke et al., 2004). Additionally, variations in soil moisture content were found to have no significant effect on losses of isoproturon, chlorotoluron, and linuron to drains in field experiments conducted on Denchworth heavy clay soils (Brown et al., 2001). However, this contrasts with other studies reported in the literature which tend to show that the water content of the soil at the time of application may have a significant effect on the transport of pesticides. Processes invoked to explain these differences include diffusion and sequestration in micropores and/or organic matrices (Rocha et al., 2006), and the increased accessibility of sorption sites as organic matter becomes more hydrophilic with increasing moisture (Ochsner et al., 2006). Neither of these processes is explicitly considered in MACRO.

For leaching at Oxford, the main climate statistic determining the extent of losses for Pesticide 3 - the pesticide displaying the smallest mobility - was winter rainfall between October/November and March/April immediately following the pesticide application, irrespective of the application scenario considered (spring and fall) (yellow variables in Table 2). Correlations between pesticide loss and winter rainfall typically were > 0.80, and the maximum correlation was 0.98 (spring application, Enborne soil, Pesticide 3). An exception to this overall dominance of winter rainfall statistics was noted for the more sandy soil (Cuckney series) where an influence of more long-term rainfall statistics (cumulative rainfall typically from 5 months to 5 years) was identified (light blue in Table 2). The specific behavior noted for the Cuckney can be related to the leaching patterns of Pesticide 3 which spans over ca. 15 years (data not shown). For Pesticide 1 which can be considered as the more mobile of the three compounds, an effect of winter rainfall following application was still apparent for the less susceptible soils for fall applications (Cuckney and Ludford; yellow variables) while leaching losses for the more susceptible soils (Hall and Enborne) were negatively correlated with short-term air temperatures (1-day to 3-month average temperatures; dark orange variables), especially after fall application. This specific behaviour of Pesticide 1 is consistent with the transfer of a rapidly degrading compound moving quickly down the profile through preferential pathways.

For spring applications, losses of Pesticide 1 could be linked to a number of statistics describing the rainfall conditions after application, including i) the cumulative rainfall over the 10 to 61 days following application (R10 to R61; dark blue); the number of days until the profile receives an 'extreme' rainfall event (e.g. L20, the number of days from application to a 20-mm daily rainfall event; green); or, the number of days after application until a cumulative rainfall volume of 50 or 100 mm is reached (C50 or C100; purple). In contrast to winter rain statistics, these correlations all were < 0.80 (absolute value basis). Again, the Cuckney soil (where flow occurs primarily in the soil matrix) displayed more long-term behaviour, with an influence of average temperatures computed over a period from 7-10 months (light orange). Results for Pesticide 2 were found to be intermediate between those described above for Pesticide 1 and Pesticide 3. For fall applications, the influence of winter rainfall following application on losses of Pesticide 2 was widespread amongst the various soils considered (yellow). In contrast, losses of Pesticide 2 following spring applications were determined by winter rainfall, but also by long-term rainfall (light blue), rainfall volumes shortly after application (dark blue) and the time to extreme rainfall events (green).

For drainage at Oxford and in contrast to results obtained for leaching, a stronger influence of the more dynamic aspects of the meteorological conditions shortly after application was apparent, especially for Pesticide 1 and 2 (Table 3). Winter rainfall after application was again found to be related to pesticide loss (yellow), but its influence mainly was limited to the transfer to drains of Pesticides 2 and 3 following fall applications and to transfers for the less structured Quorndon soil for spring applications. As before, correlations with winter rainfall typically were > 0.80; the maximum correlation was 0.96 (fall application, Quorndon soil, Pesticide 3). Again, the influence of rainfall and temperature conditions shortly after application (dark blue and dark orange) was clear for Pesticide 1 in the soils excepting the Quorndon. A similar behaviour was noted for Pesticide 2 in more clayey soils, in contrast to the results obtained for leaching. The influence of lag time to 20- and 30-mm rain events (green) was more prevalent for drainage than for leaching and was limited to pesticides 2 and 3 following spring application of pesticides on more structured soils.

2.3 Results for Zaragosa

Modelling results

The results of individual modelling trials for climatic conditions at Zaragosa are shown in Annexes 109 – 155 of the separate appendix document. The influence of the timing of rain in relation to pesticide application date is similar to that described above for Oxford.

Compared with Oxford, total pesticide loss typically was less for Zaragosa observations. Expressed as percent of applied mass (2 mg/m^2), pesticide loss was 0.0178% for the median of the observations, and the maximum percent loss (considering all 720 modelling observations) was 4.9%, which corresponds to a total loss of 0.098 mg/m^2 as shown in Table 4. Percent pesticide losses at Zaragosa presumably are less because smaller rainfall events are less frequent (discussed below).

	Total pesticide loss, mg/m^2	**Percent loss**
0th percentile (minimum)	1.7E-18	<0.00001
25th percentile	0.0000025	0.00013
50th percentile (median)	0.00036	0.018
Mean	0.0067	0.34
75th percentile	0.0066	0.33
100th percentile (maximum)	0.098	4.9

Table 4: Statistics of predicted, total solute loss for aggregated MACRO output for Zaragosa leaching scenarios (N = 720).

Percent loss is based on a pesticide application rate of 2 mg/m^2.

Identification of climatic factors

Spearman correlations for Zaragosa leaching scenarios differ from those at Oxford in that temperature effects are more widespread and the influence of winter rain is substantially reduced (Table 5). Temperature (light orange) was moderately to strongly correlated with pesticide loss for all soils except the Hall, for both spring and fall applications. The influence of temperature was seen primarily for pesticides 1 and 2, the more mobile of the three compounds, but also for pesticide 3 on the more structured soils (Ludford and Enborne). The influence of winter rain at Zaragosa, (yellow) is limited to pesticides 2 and 3 applied to the Hall, which has intermediate susceptibility (clay in first two layers = 11%, organic carbon in first two layers = 1.9%, and organic carbon at 50-70 cm = 0.3%).

Similar to Oxford, short-term climatic variables (primarily rain within 7 days) were noted for pesticides 1 and 2 on more structured soils. Short-term temperature was less prevalent than at Oxford and limited to pesticide 1 on the more structured soils (Ludford and Enborne). Unlike Oxford, antecedent rain (R-x) within three months (dark blue) was positively correlated with losses of pesticides 1 and 2 following fall application, and negatively correlated with pesticide 3 on the less structured Cuckney.

Spring						Fall					
Cuckney						Cuckney					
Pesticide 1		Pesticide 2		Pesticide 3		Pesticide 1		Pesticide 2		Pesticide 3	
T274	-0.760	T335	-0.665	L20	-0.710	L30	0.581	L30	0.765	R-91	-0.472
T244	-0.748	T305	-0.636	R5475	-0.553	T213	-0.577	L20	0.714	R7300	0.427
T305	-0.715	T365	-0.633	C50	0.541	T122	-0.520	R365	-0.604	R3650	0.421
T213	-0.672	T274	-0.589	C100	0.504	L20	0.509	L10	0.543	C20	0.396
T335	-0.625	T244	-0.532	L30	-0.433	T152	-0.509	R335	-0.536	R-61	-0.381
Ludford						Ludford					
Pesticide 1		Pesticide 2		Pesticide 3		Pesticide 1		Pesticide 2		Pesticide 3	
R5475	-0.305	T274	-0.676	T305	-0.496	T213	-0.591	L30	0.727	L30	0.736
T183	-0.240	T305	-0.669	T335	-0.488	T122	-0.568	L20	0.663	L20	0.553
R2	-0.223	T335	-0.620	T274	-0.464	T152	-0.565	L10	0.567	R365	-0.550
R10	-0.208	T244	-0.599	T365	-0.439	T183	-0.565	T213	-0.541	T244	-0.537
WRA_nov_mar	-0.207	T365	-0.497	L30	0.387	T91	-0.561	R365	-0.509	T213	-0.493
Hall						Hall					
Pesticide 1		Pesticide 2		Pesticide 3		Pesticide 1		Pesticide 2		Pesticide 3	
R3	0.857	R5	0.695	WRA_nov_apr	0.778	R20	0.729	R3650	0.810	R3650	0.946
R4	0.855	R3	0.689	WRA_nov_mar	0.760	R3	0.722	WRA_nov_mar	0.782	WRA_nov_apr	0.903
R5	0.854	R4	0.678	R3650	0.737	R6	0.717	WRA_nov_apr	0.768	WRA_nov_mar	0.892
R6	0.821	R6	0.657	WRA_oct_apr	0.708	R4	0.705	R729	0.726	R729	0.850
R7	0.783	WRA_nov_mar	0.645	WRA_oct_mar	0.654	R7	0.697	R5475	0.690	WRA_oct_apr	0.819
Enborne						Enborne					
Pesticide 1		Pesticide 2		Pesticide 3		Pesticide 1		Pesticide 2		Pesticide 3	
R3	0.856	T335	-0.837	R7300	0.644	T122	-0.532	T719	-0.939	R7300	0.815
R4	0.854	T305	-0.809	R5475	0.605	T61	-0.519	T365	-0.788	R5475	0.670
R5	0.852	R183	0.746	T719	0.499	R-61	0.514	C100	-0.742	C100	0.527
R6	0.817	R152	0.741	L30	0.458	T91	-0.511	T213	-0.689	R3650	0.455
R7	0.779	T274	-0.741	R91	-0.455	T719	-0.494	R-91	0.662	L10	0.428

Color key

Winter rainfall	Short-term rainfall (≤ 91days)	Long-term rainfall (>91 days)	Cumulative rainfall	Lag times to rainfall	Short-term temperature (≤ 91days)	Long-term temperature (> 91days)

Table 5: The top five Spearman correlations for climatic variables under each season-soil-pesticide scenario for Zaragosa leaching simulations.

See text for a detailed description of the variables.

The influence of lag time (green) is more prevalent at Zaragosa than at Oxford, especially for pesticides 2 and 3 on less structured soils (Cuckney and Ludford). Unlike Oxford, however, lag time is positively correlated with pesticide loss, which seems counter-intuitive. We expected decreasing pesticide loss with increasing time to extreme rain events. At Zaragosa, the relation between lag time and pesticide loss is non-monotonic, so correlation analysis may be inappropriate for this variable. Scatterplots indicate a negative relation between lag time and predicted pesticide loss within discrete data clusters representing specific climatic series, but “average” pesticide loss for each cluster generally increases with time, so the net effect is positive (data not shown). This behaviour might be related to climatic differences between the two sites. Cumulative distribution functions indicate that Oxford has up to 30% more daily rain events of 10 mm or less in size, compared with Zaragosa. Figure 8 shows results for the third climatic data series and is typical. The cumulative effect of the increased frequency of rain is manifested as strong, positive correlation between winter rain and pesticide loss at Oxford (yellow cells in Table 2). In contrast, the climate at Zaragosa is somewhat warmer and drier and the predominant variable is temperature, which is inversely correlated with pesticide loss for several scenarios (light orange cells in Table 5). Average annual temperature is 9.4 ºC at Oxford and is 14.5 °C at Zaragosa.

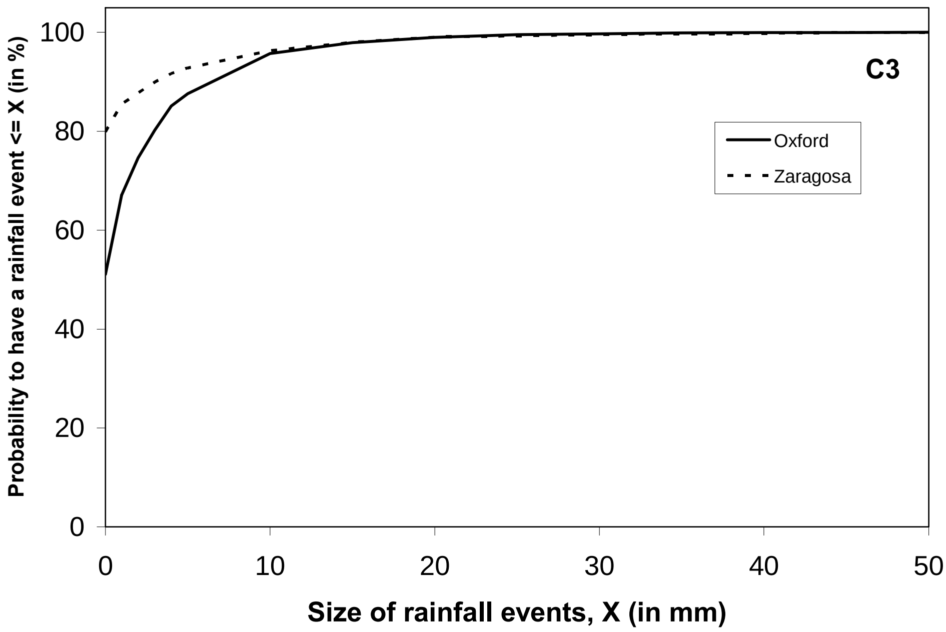


Figure 8: Frequency of rainfall events ≤10 mm in size at Oxford and Zaragosa, for the third climatic data series.

2.4 Conclusions on climatic variables to be used in the climatic zonation

Modelling

No consistent rules can be drawn regarding the amount of predicted pesticide loss and date of application because of the uncertainty of weather patterns reflected in the synthetic climatic data series. Depending on the series, either an early or a late application can yield maximum pesticide loss by leaching, as can intermediate dates of application. Additionally, total pesticide loss can be very different for the same soil depending on climatic series.

In general, curves representing pesticide loss are smooth in sandy soil whereas in clay soils they have more peaks. The amount of pesticide loss was equal in sandy and clay soils. Considering pesticide loss, no particular soil was less at risk, as shown in Annexes 2 and 22 for leaching, and in Annexes 20 and 50 for drainage.

In drainage simulations, initial losses often occurred in the same year as application (Annex 25). In leaching simulations, initial losses appeared in the year following application (Annex 1). However, in sandy soils, initial pesticide loss by leaching can occur two to three years after application.

At Oxford, the first losses of pesticide 1 by leaching appear generally during the first winter following the application, even if the application occurred in spring. This was observed for Zaragosa as well (Annex 110). Following application of pesticide 3, several years are needed to realize the first losses (Annex 77). At Zaragoza,, the first (and only) losses of pesticide 3 can appear 15 years after application if the decade is dry or a few years after application if the decade is wet (Annex 155).

Losses of pesticide 3 occurred during each winter for almost 20 years regardless of the time of application (Annex 5). In contrast, there are almost no losses of pesticide 1 four years after application (Annex 1). This is true for drainage scenarios as well (Annex 21 and Annex 29).

Influence of climatic factors

The results suggest that the climatic factors influencing pesticide loss tend to be specific to soil-pesticide combinations to some extent, but general rules can nevertheless be drawn. For Oxford leaching scenarios, there is an overall strong influence of winter rainfall following application in spring or fall, especially for the more retained and less degraded compounds. In contrast, the correlations revealed that losses of pesticides exhibiting smaller sorption capacities and hence being more mobile in the profile are likely to be more controlled by the meteorological conditions shortly after application and the length of time between application and extreme events. This is especially true following spring application and in those soils with a larger clay content, which are typically subject to preferential flow phenomena. Oxford results obtained for drainage suggest that the same climatic factors are important, although the influence of climatic conditions shortly after application and the positioning of extreme events in relation to application are clearly greater.

At Zaragosa and in contrast to Oxford, temperature effects are more widespread and the influence of winter rain is substantially reduced. This may be due to the warmer average annual temperature at Zaragosa (14.5 °C), and the increased frequency of daily rain events of 10 mm or less in size at Oxford. The influence of lag time is more prevalent at Zaragosa than at Oxford, especially for pesticides 2 and 3 on less structured soils (Cuckney and Ludford). Unlike Oxford, however, lag time is positively correlated with pesticide loss, which may be an artefact of the univariate correlation analysis. Relations between lag time and pesticide loss are non-monotonic at Zaragosa. Similar to Oxford, short-term climatic variables (primarily rain within 7 days) were noted for pesticides 1 and 2 on more structured soils at Zaragosa.

3 CLIMATIC DATA

Two data sources were used to define the climatological regions in this study on the basis of the key eight variables that were selected based on expert judgement and results from the modelling sensitivity analysis. The European climatologies for mean temperature and precipitation variable (Table 6, 1-4) were derived from the CRU TS 2.0 data set whilst those based on daily precipitation thresholds (Table 6, 5-8) were constructed from the data provided by the European Climate Assessment & Dataset (ECA&D). Each of these climatologies was constructed based on data over the 1961-1990 period for a spatial domain covering the EU member states. As this also included the 4 candidate countries of Bulgaria, Croatia, the Former Yugoslav Republic of Macedonia (FYROM) and Romania, the analysis was extended slightly to include the whole of the fifth nation, Turkey.

		Definition
1	**SPR_TMP**	Mean April to June temperature (°C).
2	**AUT_TMP**	Mean September to November temperature (°C).
3	**WIN_PRE**	Mean October to March precipitation (mm)
4	**ANN_PRE**	Mean annual precipitation (mm).
5	**SPR_2**	Number of days (April to June) where total precipitation > 2mm
6	**SPR_20**	Number of days (April to June) where total precipitation > 20mm
7	**SPR_50**	Number of days (April to June) where total precipitation > 50mm
8	**AUT_20**	Number of days (September to November) where total precipitation > 20mm

Table 6: Definitions of the 8 input variables used to define the climatic zones.

3.1 CRU TS 2.0

The CRU TS 2.0 data set (Mitchell et al., 2004) is a gridded global series of monthly climate means for the period 1901-2000. The data were constructed by the interpolation of station data onto a 0.5° by 0.5° grid and is an updated version of earlier datasets described in New et al. (1999, 2000).

3.2 European Climate Assessment & Dataset (ECA&D or ECA)

The ECA dataset contains 5162 series of observations at 1529 meteorological stations throughout Europe and the Mediterranean at a daily resolution for a total of 9 variables including temperature and precipitation. A total of 113 stations were selected from the dataset to satisfy two criteria:

- to obtain a reasonable spatial coverage for Europe, particularly the EU25
- to select series that were of the highest quality. The ECA&D used 4 statistical tests to assess homogeneity, standard normal homogeneity test (Alexandersson, 1986), the Buishand range test (Buishand, 1982), the Pettitt test (Pettitt, 1979) and the von Neumann ratio (von Neumann, 1941). Series were selected from those classified as “useful” which are stations where no more than 1 test rejects the null hypothesis that there is no discontinuity at the 1% level.

The stations used to calculate each of the threshold variables are shown in Figure 9. The list of relevant stations was obtained after the removal of a number of stations were identified which on inspection of metadata were not typical of the climate of the region. In order to obtain coverage at the same resolution as that for the CRU TS 2.0 series the threshold exceedence data were interpolated onto the same 0.5° by 0.5° grid using an inverse distance weighted interpolation algorithm (NCAR, 2006).

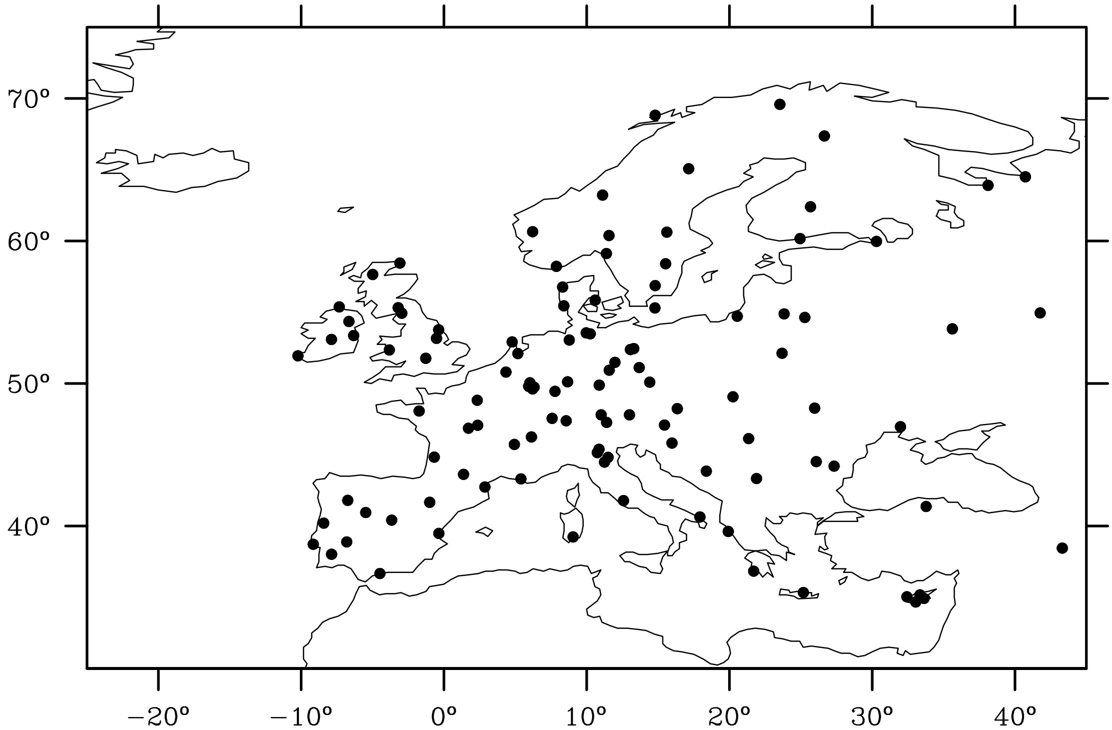


Figure 9: The selection of 113 stations from the European Climate Assessment & Dataset used to calculate daily threshold variables.

4 METHOD FOR DETERMINING THE FOOTPRINT CLIMATIC ZONES (FCZs)

Each of the variables listed in Table 6 was derived from the relevant data source at the same 0.5° by 0.5° resolution. Maps of each of these input variables are shown in Appendix 2. The derivation of climatic zones was then undertaken using a two-stage procedure. Given that a number of the variables were likely to be correlated, principal components analysis was initially undertaken to reduce the dimensionality of the data. A cluster analysis was then performed on the retained components to derive the final regions.

The principal components analysis was undertaken using all 8 variables which were first standardised due there being a range of different units. Due to the likelihood of correlation between the variables, an oblique rotation solution was undertaken to obtain better identification of components (Field, 2005). The choice of how many principal components or factors should be retained is an important part of the procedure and may be determined using a number of objective criteria. One of the most common methods is to use a scree plot of eigenvalues (Figure 10) for each of the factors and to identify a point of inflexion which may be used to discard redundant factors. Alternatively, Kaiser (1960) recommends retaining only factors with eigenvalues greater than 1 whilst Jolliffe (1972, 1986) suggests a more relaxed criterion of retaining factors whose eigenvalues are more than 0.7. In the present analysis, the scree plot suggests the retention of three components whilst a similar judgement is obtained from using the component eigenvalues, with the third and fourth factors having eigenvalues of 1.2 and 0.4, respectively. The selection of three factors is consistent on all the three rules and the three first factors explain 81.7% of the variability.

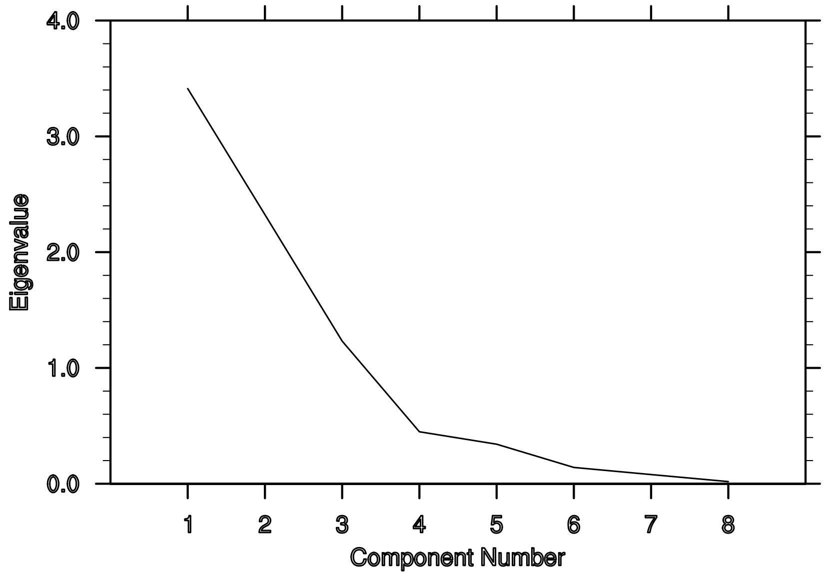
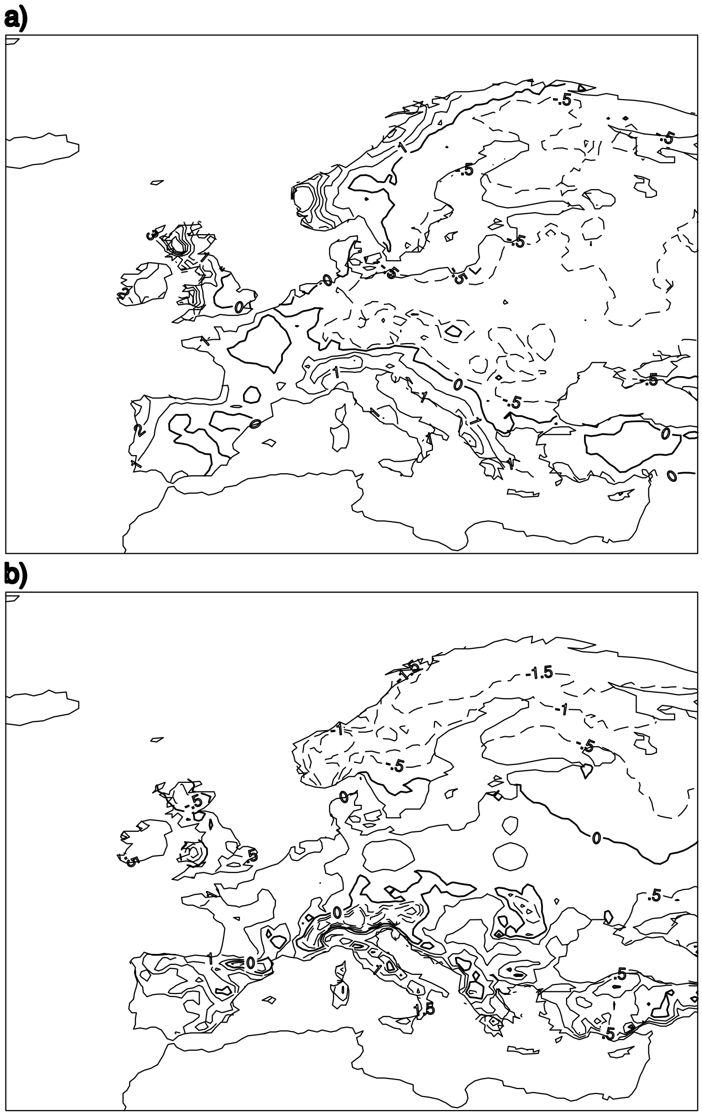


Figure 10: Scree plot indicating the eigenvalues for each of the components derived from the principal components analysis.

The first principal component (PC1) appears to represent a general distribution, exhibiting properties of the observed distribution of rainfall with the largest positive scores along western coasts and high altitude areas such as the Alps (Figure 11a). The loadings of each variable on each of the factors shown in Table 2 indicate that this reflects the distribution of the mean rainfall variables and rain daily occurrence most strongly but also the distribution of extremes, particularly SPR_20 (Table 6). The second principal component (PC2) is clearly related to the temperature variables, with negative loadings observed over northern Europe and also over mountainous areas, with increasing positive loadings over southern Europe (Figure 11b). The final principal component (PC3) is also a rainfall signal, but both the loadings shown in Table 7 and the spatial distribution (Figure 11c) indicate that this component relates to the distribution of spring rainfall, particularly extremes.



c)

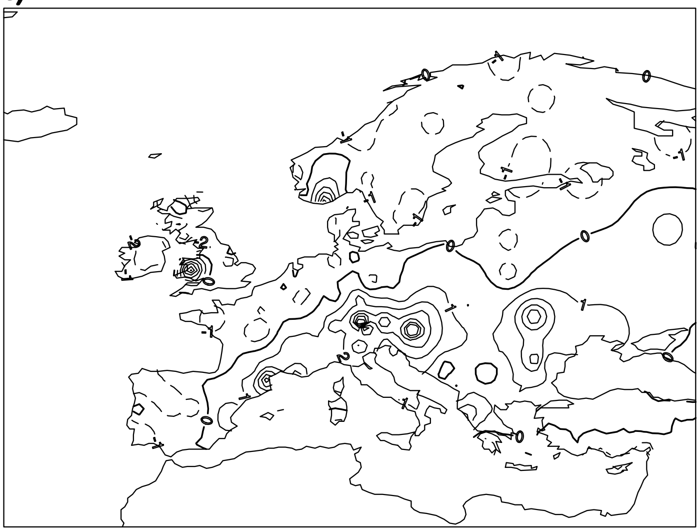


Figure 11: Loadings of a) Principal Component #1, b) Principal Component #2 and c) Principal Component #3 derived from the variables listed in Table 6.

Note that for Figure 11a, a contour interval of 1 is used for positive loadings, but 0.5 for negative loadings.

	Principal Component		
	1	**2**	**3**
SPR_TMP	0.14	0.93	-0.17
AUT_TMP	0.38	0.84	-0.29
WIN_PRE	0.82	-0.22	-0.48
ANN_PRE	0.84	-0.40	-0.22
SPR_2	0.58	-0.51	0.41
SPR_20	0.78	0.23	0.51
SPR_50	0.54	0.47	0.58
AUT_20	0.81	-0.76	-0.29

Table 7: Loadings of each variable on each of the retained factors. (See Table 6 for the explanation of the factors)

Cluster analysis was performed using the scores on each of the three retained components. A non-hierarchical method was considered most appropriate as this avoids a significant problem associated with hierarchical methods. This latter group of methods works by iteratively constructing a hierarchy of sets of groups which are merged, in pairs, from previous collections of groups based on some distance measure in *k*-dimensional space. However, they offer no mechanism by which vectors given membership to an inappropriate group at an early stage may be reallocated to a more appropriate group and so errors made during early iterations are propagated throughout the clustering procedure (Wilks, 2006).

The most commonly used non-hierarchical method is *k*-means clustering which, as with hierarchical methods, is based on distance measures but begins either by a random partition into the specified number of *k* groups or from an initial selection of *k* seed points with cluster membership decided by closeness to seeds (Wilks, 2006). The centroids of the initial clusters are computed and group memberships are reallocated on the basis of proximity to the cluster centroids. The algorithm is iterated until each data vector is closest to its group centroid i.e. no further reallocations of membership are made.

The most significant disadvantage of *k*-means clustering is that the number of clusters *k* must be predetermined before commencing the procedure. It is therefore important to try *k*-means with a range of initial values of *k*. The range of possible values was constrained in this case by the need to obtain a classification that adequately identified regions that were clearly different in terms of their climate and not over-simplify the European region, whilst maintaining a number of zones that would be practical in terms of future modelling demands. The range of solutions was therefore examined for between 12 and 18 climate zonations. At the lower end of this range regions were produced which were extensive and might have encompassed too large a range of climatic conditions. However, at the upper end of this range, the clustering procedure created new classifications from some of the smaller zones which occur in the wettest areas whilst also producing less spatially continuous regions. Hossell et al. (2003) identified a similar feature with a classification of Britain which produced small fragmented classes in upland regions The solution provided when *k*=16 was considered optimal as it produced regions which had a physically plausible mechanism and was also realistic in terms of subsequent modelling workloads within the scope of the project.

5 CLIMATE ZONATION

The final zonation identified by the cluster analysis is shown in Figure 12, whilst a brief description of the climate, and member states where each may be found, is provided in Table 8. Only zone 5 does not include any of the present member states of the European Union. The distribution of zones is physically plausible, with the influence of temperature producing a north-south zonation, particularly in the drier continental interior. The precipitation variables are also important in producing types which are found on western coasts but also in terms of topographically complex areas where extreme events are a significant factor such as the UK, western Scandinavia and the Alps. Hence, although the main basis of derivation of the zones was climatic factors influencing the environmental fate pesticides, the zonation also reflects existing knowledge in the distribution of climates throughout Europe.

It is possible to summarise the zonation into 6 broad categories which reflect the influences of the input variables.

- “Atlantic” climates (zones 7, 11, 12 and 13) with high annual and winter precipitation totals and generally more frequent extremes in autumn than in spring.
- “Temperate” climates with more moderate precipitation and fewer extremes. The two zones, 2 and 16 may be distinguished from each other on the basis of the latter being cooler and slightly wetter.
- “Northern” climates (zones 4 and 10) are characterised by drier conditions and lower temperatures with temperature being the important factor in separating the member zones.
- “Continental” climates (zones 5, 14 and 15) which are all warm interior climates and which tend to be subdivided on the basis of the precipitation threshold variables.
- “Mediterranean” climates (zones 1, 8 and 9) are all warm with low to moderate mean precipitation but relatively more frequent extremes. The northern Mediterranean zone (zone 1) may be distinguished from the other zones by distinct temperature and rainfall climatologies.
- “Alpine” climates (zones 3 and 6) are characterised by relatively frequent extreme precipitation events and are subdivided on the basis of temperature and mean precipitation.

Summary variable and principal component statistics were calculated for each of the zones. Table 9 shows the mean statistics for each of the input variables for each zone and offers an insight into the differentiation between the regions. The merging of zones 7 and 12 for example was considered, but these are clearly differentiated in terms of the magnitude and seasonality of extreme precipitation events. In order to give an indication of intra-class variability, Table 10 shows the standard deviations of each variable for each zone. Analysis of these figures with the spatial distribution of principal component scores indicates that there is greater variability within some zones than others and that this tends to be greatest within the smaller wet zones which are more loosely clustered. The calculation of the co-efficient of variation (not shown) indicates that there is most variability for mean precipitation within zones 5, 8 and 11 whilst for temperature the standard deviations indicate large intra-zone variability in zones 6 and 16. One of the zones which might have been expected to have been subdivided on the basis of prior climate knowledge was the temperate zone 2, however this has relatively low intra-zone variability when compared with the other zones. Any undertaking to create further zones would require careful consideration to establish the objective criteria on which this might be based.

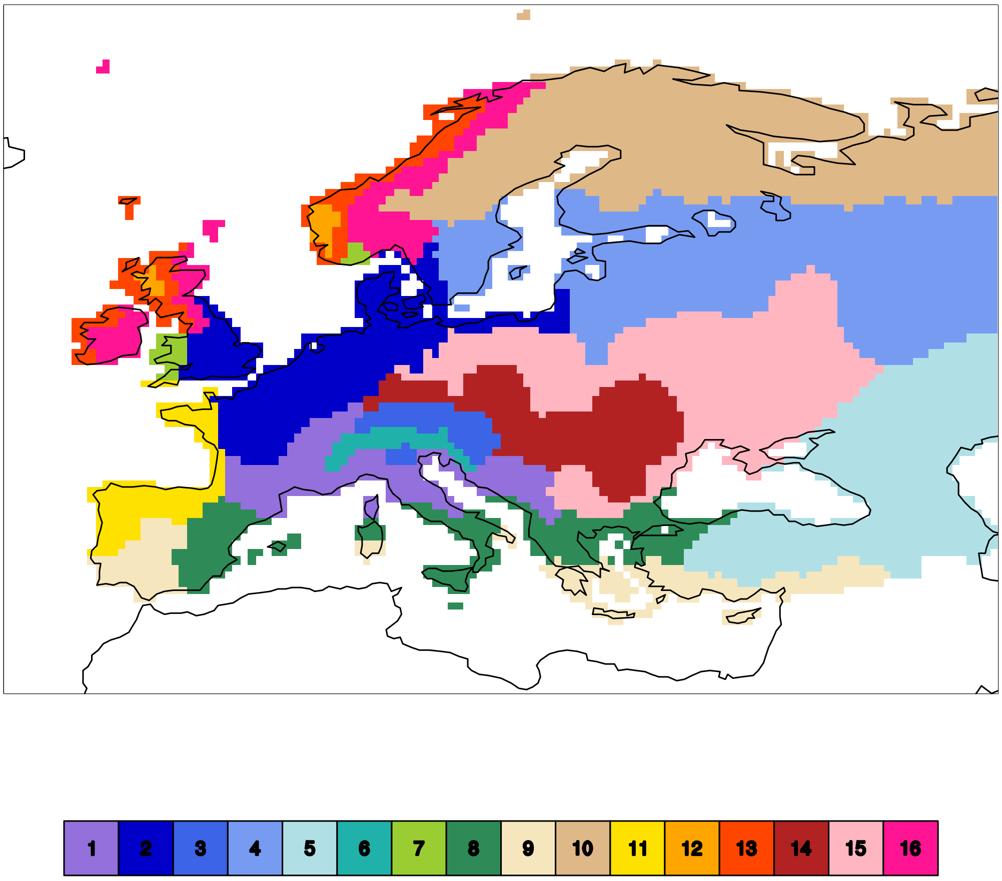


Figure 12: Final classification of the European region into 16 climatic zones.

Footprint Climatic Zone	Description	Member countries
1	North Mediterranean climate, warm and moderate precipitation.	**France, Germany, Italy, Slovenia, Spain** (Albania, Bosnia & Herzegovina, Croatia, FYROM , Serbia, Switzerland)
2	Temperate maritime climate.	**Belgium, Denmark, France, Germany, Lithuania, Luxembourg, Poland, UK** (Russia)
3	Sub-Alpine continental climate, warm, moderate rainfall but low winter rainfall, moderate frequency of extremes.	**Austria, Germany, Hungary, Italy, Slovenia** (Croatia, Bosnia & Herzegovina)
4	North European and continental climate, cool and dry.	**Finland, Estonia, Latvia, Lithuania, Poland, Sweden** (Belarus, Russia)
5	Continental climate, warm and dry.	(Armenia, Azerbaijan, Georgia, Russia, Turkey)
6	Alpine climate, cool and wet, relatively more extremes.	**Austria, France, Italy, Slovenia** (Bosnia & Herzegovina, Croatia, Switzerland)
7	Modified upland temperate maritime climate, more frequent extremes.	**UK** (Norway)
8	Mediterranean climate, with more extreme rainfall.	**Italy, Greece, Malta, Spain** (Albania, Bulgaria, FYROM, Turkey)
9	Mediterranean climate, warmer, lower rainfall with more dry days but higher winter rainfall.	**Cyprus, Greece, Portugal, Spain** (Turkey)
10	North European climate, cold and dry.	**Finland, Sweden,** (Norway, Russia)
11	Modified temperate maritime climate, warmer and wetter but fewer wet spring days.	**France, Portugal, Spain, UK**
12	Very, wet, mountainous maritime climates, more frequent extremes.	**UK** (Norway)
13	Wet, maritime climates, on exposed western coasts, more frequent extremes.	**Ireland, UK** (Norway)
14	Continental climate, warm and dry with moderate frequency of extremes.	**Austria, Czech Republic, Germany, Hungary, Poland, Slovak Republic** (Bulgaria, Croatia, Moldova, Romania, Serbia, Ukraine)
15	Continental climate, warm and dry, but more frequent wet days.	**Czech Republic, Germany, Hungary, Poland, Slovak Republic,** (Belarus, Bulgaria, FYROM, Romania, Serbia,) Ukraine)
16	Modified temperate maritime climate, cool with moderate precipitation.	**Ireland, Sweden, UK** (Norway)

Table 8: Summary description and member states for each of the 16 regions identified by the cluster analysis.

Member countries that are in the European Union are shown in bold type.

FYROM : Former Yugoslav Republic of Macedonia

	SPR_TMP (°C)	AUT_TMP (°C)	WIN_PRE (mm)	ANN_PRE (mm)	SPR_2	SPR_20	SPR_50	AUT_20	PC1	PC2	PC3	*n*
1	13.4	11.7	485.3	935.9	609.6	51.0	2.2	65.5	0.641	0.546	1.298	261
2	11.5	9.8	368.3	733.3	649.1	30.8	1.1	41.8	-0.093	0.518	-0.434	465
3	11.9	8.8	392.0	994.6	744.7	73.0	3.6	60.6	0.022	-0.204	3.479	83
4	10.2	4.6	259.4	615.5	538.3	24.1	1.0	28.9	-0.443	-0.307	-0.421	1020
5	14.4	9.8	247.9	515.7	382.5	23.9	1.1	31.8	-0.357	0.598	-0.326	688
6	5.9	4.8	765.1	1694.9	730.1	65.1	2.5	63.7	1.940	-1.135	1.967	50
7	9.6	8.8	835.2	1411.2	779.0	57.5	3.0	145.4	2.978	-0.647	2.399	32
8	16.1	15.2	420.9	642.2	453.2	36.7	1.9	67.3	0.507	1.153	0.668	316
9	17.8	17.0	478.6	614.1	317.7	24.4	1.1	55.4	0.713	1.706	-0.578	280
10	4.8	0.5	246.8	567.8	525.9	21.4	0.7	28.4	-0.380	-1.421	-0.440	992
11	13.0	13.0	605.7	942.0	549.0	34.3	0.8	62.3	1.146	0.995	-0.779	147
12	7.4	6.2	1408.8	2364.6	789.5	38.9	0.8	210.0	6.621	-0.813	-0.807	28
13	7.3	6.1	877.3	1499.7	744.3	33.5	0.9	105.6	2.870	-0.493	-0.755	169
14	13.4	9.3	244.8	644.1	611.4	47.4	2.4	37.4	-0.685	0.305	1.578	319
15	13.3	8.0	243.2	589.1	550.6	34.0	1.7	33.8	-0.597	0.278	0.488	743
16	6.2	4.1	512.5	959.1	674.7	28.3	0.7	69.0	1.015	-0.757	-0.746	216

Table 9: Mean climate statistics for grid cells within each of the climatic zones. PC1, PC2 and PC3 are the mean scores on the 3 principal components.

The total number of grid cells belonging to each zone is denoted by *n* and total *n*=5809.

A description of the various variables can be found in Table 6

	SPR_TMP (°C)	AUT_TMP (°C)	WIN_PRE (mm)	ANN_PRE (mm)	SPR_2	SPR_20	SPR_50	AUT_20	PC1	PC2	PC3
1	2.2	2.4	96.3	176.0	79.9	6.9	0.75	10.3	0.44	0.52	0.86
2	1.0	1.3	73.0	101.9	50.2	4.3	0.35	12.3	0.39	0.31	0.45
3	2.5	1.9	107.1	242.1	101.5	13.9	1.00	12.4	0.60	0.60	1.28
4	1.5	1.6	26.0	51.6	36.9	3.6	0.33	4.2	0.14	0.37	0.43
5	2.9	2.9	119.0	220.0	57.8	4.2	0.42	9.2	0.58	0.67	0.53
6	3.4	2.6	112.4	242.9	53.9	8.7	0.54	4.6	0.57	0.71	0.72
7	1.5	2.4	204.9	288.9	80.5	13.5	1.04	51.4	1.01	0.77	1.64
8	1.8	2.3	134.8	170.1	57.3	5.5	0.43	23.4	0.72	0.52	0.57
9	2.1	2.4	109.6	114.1	79.7	5.2	0.49	18.8	0.53	0.50	0.51
10	2.0	1.7	51.8	80.1	37.6	4.2	0.28	9.0	0.25	0.47	0.43
11	1.7	1.7	190.3	251.5	67.7	7.4	0.38	13.6	0.78	0.42	0.48
12	1.1	1.4	270.7	441.7	79.3	3.1	0.49	67.6	1.16	0.49	0.62
13	2.3	2.9	156.4	255.0	74.4	6.8	0.32	43.5	0.87	0.74	0.80
14	2.0	1.7	46.7	112.8	48.4	5.0	0.61	6.5	0.29	0.47	0.78
15	1.3	1.9	34.2	78.8	55.5	5.4	0.43	5.1	0.19	0.35	0.45
16	3.5	4.2	135.7	183.7	60.8	6.6	0.32	26.0	0.56	1.05	0.87

Table 10: As for Table 4 but standard deviations of each variable for grid cells within each of the FOOTPRINT climatic zones.

6 SELECTION OF REPRESENTATIVE CLIMATE DATA

The final stage of the classification procedure was to derive typical climate series for a selection of variables that typify each region. An objective method for determining the location was developed using each grid cell's score on each of the 3 retained principal components. For each climate region, 3D co-ordinates of the cluster centroids were obtained and for each grid cell within the region the deviation of the 3 PC scores was obtained for each of these dimensions. The mean of these deviations were then plotted with the location of possible stations overlaid. A visual inspection of candidate stations enables a sample station to be derived based upon the lowest possible mean score deviation. Figure 3 shows a "fictional" example of a possible region with candidate stations for example series. In this case, station 2 has the lowest mean score deviation and would be most appropriate for the extraction of the required climate variables. Where stations that were used in the initial analysis did not coincide with the area of the lowest mean score deviation, additional candidate series were identified from the ECA dataset. The full list of climatic variables extracted to represent each climatic region and their source is listed in Table 11. These were selected on the basis of the environmental fate models which will be used in the future within FOOTPRINT (see section 2).

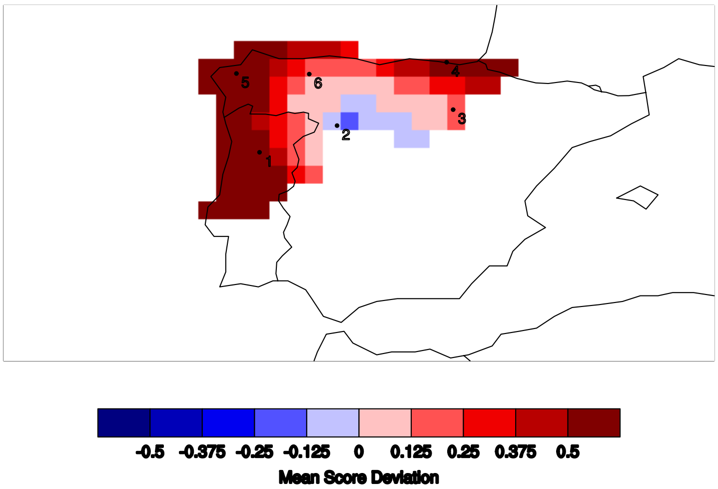


Figure 3: An objective method for the selection of regional climate series based on mean score deviation on the 3 retained principal components.

Possible station locations are identified by stations 1 to 6.

Variable	Source
Precipitation	ECA
Maximum Temperature	ECA
Minimum Temperature	ECA
Mean Temperature	ECA
Potential Evapotranspiration	MARS
Wind Speed	MARS
Solar Radiation	MARS

Table 11: Extracted daily series of climate variables representative of each of the 16 climatic regions.

Each of the variables is to be provided at a daily resolution covering a period of approximately 20 years. Complete datasets for each of these variables for the 16 climate zones will be provided in the final report of WP2 along with summary statistics of each series.

7 CONCLUSIONS AND PERSPECTIVES

A three-stage process was used to derive a climatic classification of Europe which reflects the environmental fate of pesticides. Climatic variables influencing the fate of pesticides in the environment were first identified through the undertaking of modelling for various soils, pesticides, application dates and climatic series. Climatologies of the 8 selected variables were extracted from available data sources for the 1961-1990 period and used to define the climatic regions. In order to reduce the dimensionality of the data given the likely correlation between several of the input variables a dimension reduction procedure was performed using principal components analysis which resulted in the retention of 3 factors. These factors were then used as variables in a cluster analysis (*k*-means) which objectively created 16 groups of grid cells with similar characteristics. The final solution produced 16 regions (the 'FOOTPRINT climatic zones') which is a compromise between producing a detailed classification and the need for a manageable number of regions for subsequent modelling work. The resulting regions are physically plausible in terms of the input variables used in the analysis and in terms of the physical mechanisms which underpin the climate of Europe. A simple method was subsequently outlined for the objective identification of representative climate series for each of the 16 zones.

The final zones produced by this objective procedure range from 28 grid cells in size to 1020 and it would be possible given the knowledge of local climates to further subdivide zones into sub-classes. This again might be achieved objectively by repeating the cluster analysis on a class by class basis as required. However, the purpose of this study was not to produce a detailed climatic classification of Europe, but to produce a manageable classification of practical use to pesticide fate modellers. In this regard, a reasonable compromise has been achieved between these two outcomes. This work provides the means for distinct climatological zones to be modelled in terms of pesticide fate and forms a considerable advance on previous work. In future, the availability of a gridded daily climatology for Europe provided by the EU-funded ENSEMBLES project (ENSEMBLES, 2006) offers the potential to produce a more detailed examination across Europe, providing the potential to apply models on a more local scale.

8 REFERENCES

Alexandersson H. (1986). A homogeneity test applied to precipitation data. International Journal of Climatology, 6: 661-675.

Beulke S., Brown C.D., Dubus I.G., Fryer C.J. & Walker A. (2004). Evaluation of probabilistic modelling approaches against data on leaching of isoproturon through undisturbed lysimeters. Ecological modelling, 179:131-144

Bouma E. (2005). Development of comparable agro-climatic zones for the international exchange of data on the efficacy and crop safety of plant products. OEPP/EPPO Bulletin, 35: 233-238.

Brown C.D., Dubus I.G., Fogg P., Spirlet M. & Gustin C. (2004). Exposure to sulfosulfuron in agricultural drainage ditches: field monitoring and scenario-based modelling. Pest Management Science, 60:765-776.

Brown, C.D., Fryer, C.J. & Walker, A. (2001). Influence of topsoil tilth and soil moisture status on losses of pesticide to drains from a heavy clay soil. Pest Management Science 57:1127-1134.

Buishand T.A. (1982). Some methods for testing the homogeneity of rainfall records. KNMI Scientific Report WR 81-7, De Bilt, The Netherlands.

Bunce R.G.H., Barr C.J., Clarke R.T., Howard D.C. & Lane A.M.J (1996a). Land classification for strategic ecological survey. Journal of Environmental Management, 47: 37-60.

Bunce R.G.H., Barr C.J., Clarke R.T., Howard D.C. & Lane A.M.J. (1996b). ITE Merlewood Land Classification of Great Britain. Journal of Biogeography, 23: 625-634.

Burton, A., Kilsby, C.G., Moaven-Hashemi, A. & O'Connell, P.E. (2004). Neyman-Scott Rectangular Pulses Rainfall Simulation System, BETWIXT project Technical Briefing Note 2.

Dubus I.G. & Brown C.D. (2002). Sensitivity and first-step uncertainty analyses for the preferential flow model MACRO. Journal of Environmental Quality, 31:227-240.

Dubus I.G., Beulke S. & Brown C.D. (2002). Calibration of pesticide leaching models: critical review and guidance for reporting. Pest Management Science, 58:745-758

Dubus I.G., Brown C.D. & Beulke S. (2003). Sensitivity analyses for four leaching models. Pest Management Science, 59:962-982

ENSEMBLES (2006). http://www.ensembles-eu.org/.

Essenwanger O.M. (2001). Classification of climates. In, World Survey of Climatology, Volume 1c, General Climatology. Elsevier, Amsterdam,

Field A. (2005). Discovering statistics using SPSS. Sage, London.

FOCUS (1995). FOCUS Leaching Modelling Workgroup: "Leaching models and EU registration", 123p.

FOCUS (1997a). Soil persistence models and EU registration, 77p.

FOCUS (1997b). Surface water models and EU registration of plant protection products. European Commission document 6476/VI/96, 231p.

FOCUS (2000). FOCUS groundwater scenarios in the EU plant protection product review process. Report of the FOCUS Groundwater Scenarios Workgroup, EC document reference SANCO/321/2000.

FOCUS (2001). FOCUS surface water scenarios in the EU evaluation process under 91/414/EEC. Report of the FOCUS working group on surface water scenarios, EC document reference SANCO/4802/2001-rev2, 245p.

Goodess C.M. & Palutikof J. (1998). Development of daily rainfall scenarios for southeast Spain using a circulation-type approach to downscaling. International Journal of Climatology, 18: 1051-1083.

Guttman N.B. (1993). The use of L-Moments in the determination of regional precipitation climates. Journal of Climate, 6: 2309-2325.

Hallett SH, Thanigasalam P & Hollis JM. (1995). SEISMIC: a desktop information system for assessing the fate and behaviour of pesticides in the environment. Comput Electron Agr, 13:227–242.

Hossell J.E., Riding A.E. & Brown I. (2003). The creation and characterisation of a bioclimatic classification fro Britain and Ireland. J. Nat. Conserv., 11 : 5-13.

Huth R. (2000). A circulation classification scheme applicable in GCM studies. Theoretical and Applied Climatology, 67: 1-18.

Jolliffe I.T. (1972). Discarding variables in a principal component analysis, I: artificial data. Applied Statistics, 21: 160-173.

Jolliffe I.T. (1986). Principal component analysis. Springer-Verlag, New York.

Jones P.D., Hulme M., & Briffa K.R. (1993). A comparison of Lamb circulation types with an objective classification scheme. International Journal of Climatology, 13: 655-663.

Jongman R.H.G., Bunce R.G.H., Metzger M.J., Mücher C.A., Howard D.C. & Mateus V.L. (2006). Objectives and applications of a statistical environmental stratification of Europe. Landscape Ecology, 21: 409-419.

Kaiser H.F. (1960). The application of electronic computers to factor analysis. Educational and Psychological Measurement, 20: 141-151.

Klein Tank A.M.G. & co-authors (2002). Daily dataset of 20th-century surface air temperature and precipitation series for the European Climate Assessment. International Journal of Climatology, 22: 1441-1453.

Köppen W. & Geiger R. (1928). Klimakarte der Erde. Verlag Justus, Gotha. (In German)

Metzger M.J., Bunce R.G.H., Jongman R.G.H., Mücher C.A. & Watkins J.W. (2005). A climatic stratification of the environment of Europe. Global Ecology and Biogeography, 14: 549-563.

Mitchell, T.D., Carter, T.R., Jones, P.D., Hulme, M. & New, M. (2004). A comprehensive set of high-resolution grids of monthly climate for Europe and the globe: the observed record (1901-2000) and 16 scenarios. Tyndall Working Paper 55, Tyndall Centre, UEA, Norwich.

NCAR (2006). http://ngwww.ucar.edu/ngdoc/ng/ngmath/dsgrid/dshome.html.

New, M., Hulme, M. & Jones, P.D. (1999). Representing twentieth-century space-time climate variability. Part I: Development of a 1961-90 mean monthly terrestrial climatology. Journal of Climate, 12: 829-856.

New, M., Hulme, M. & Jones, P.D. (2000). Representing twentieth-century space-time climate variability. Part II: Development of 1901-96 monthly grids of terrestrial surface climate. Journal of Climate, 13: 2217-2238.

Ochsner T.E., Stephens B.M. et al. (2006) Sorption of a hydrophilic pesticide: Effects of soil water content. Soil Sci Soc Am J, 70:1991-1997.

Pettitt A.N. (1979). A non-parametric approach to the change-point detection. Applied Statistics, 28: 126-135.

Richardson CW. (1985). Weather simulation for crop management models. Trans ASAE, 28:1602–1606.

Strahler A.N. (1963). The Earth Sciences. Harper and Roe, New York.

Thran P. & Broekhuizen S. (1965). Agro-Ecological Atlas of Cereal Growing in Europe, Volume 1, Agroclimatic Atlas of Europe. Elsevier, Amsterdam.

Von Neumann, J. (1941). Distribution of the ratio of the mean square successive difference to the variance. Annals of Mathematical Statistics, 13: 367-395.

Vossen P. & Meyer-Roux J. (1995). Crop monitoring and yield forecasting activities of the MARS project. In: EUR EN 16232, King D., Jones R.J.A. and Thomassen A.J. (eds.). European Land Information Systems for agro-environmental Monitoring., Office for the official publications of the European Communities, Luxembourg, pp. 11-30.

Walter H. & Leith H. (1960). Klimadiagram-Weltatlas. VEB Gustav Fischer Verlag, Jena (In German).

Wang M. & Overland J.E. (2004). Detecting Arctic climate change using Köppen climate classsifcation. Climatic Change, 67: 43-62.

Wilks D.S. (2006). Statistical methods in the atmospheric sciences. Academic Press.

9 APPENDIX 1: SENSITIVITY ANALYSIS RAINFALL TIME SERIES GENERATION

The sensitivity datasets were split into four cases each designed to represent changes in one of four characteristics of the rainfall: the annual total, seasonality, proportion of dry days and skewness. A set of target statistics were developed for each characteristic and for each variation step. These are referred to as target statistics as they take the place of observed statistics in the fitting procedure. In each case, the target properties were derived by small changes to the reference statistics of the relevant raingauge. This shown, for example, for Oxford in Figure A1.

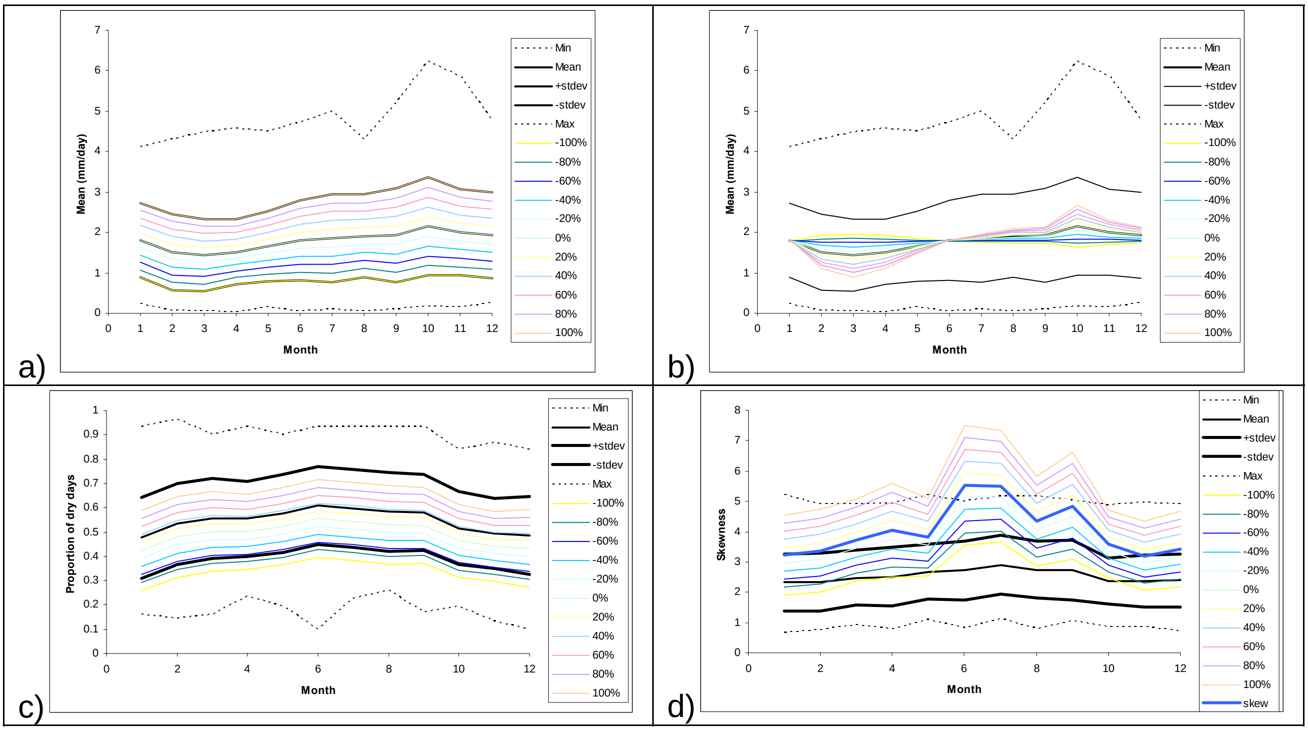


Figure A1. Observed rainfall properties and specification of sensitivity time series.
a) Mean daily rainfall; b) Seasonality of daily rainfall; c) Proportion of dry days; d) Skewness of daily rainfall

9.1 Change in annual rainfall

To evaluate changes in annual totals, each observed dataset was analysed to obtain a monthly timeseries of mean daily rainfall amount. This was then analysed to determine the minimum, maximum, mean and standard deviation of calendar month estimates of mean daily rainfall amounts. These are shown as black (and dashed) curves in Figure A1(a) for the Oxford raingauge. The target climatic sensitivities were then calculated as $\mu \pm \sigma$ (the mean plus/minus one standard deviation) – this range was then split into 11 equal increments (Figure A1(a) coloured curves). In this way the mean climatology should vary by an amount equivalent to the observed variation in monthly rainfall amounts. The variance statistic was also changed so as to retain a constant coefficient of variation. All other observed statistics were kept unchanged. Such an approach means that the greatest variation in rainfall amounts occurs in months with the highest rainfall totals.

This procedure was followed for the Zaragosa raingauge with only slight modification. At Zaragosa the standard deviation of mean daily rainfall amounts is higher than the mean for 4 months of the year. The procedure described consequently resulted in negative target values of mean daily rainfall for those months. To solve this, a minimum value of 0.1 mm day^{-1} was imposed for the target values at this raingauge. Figure A2 shows the target distributions resulting from this.

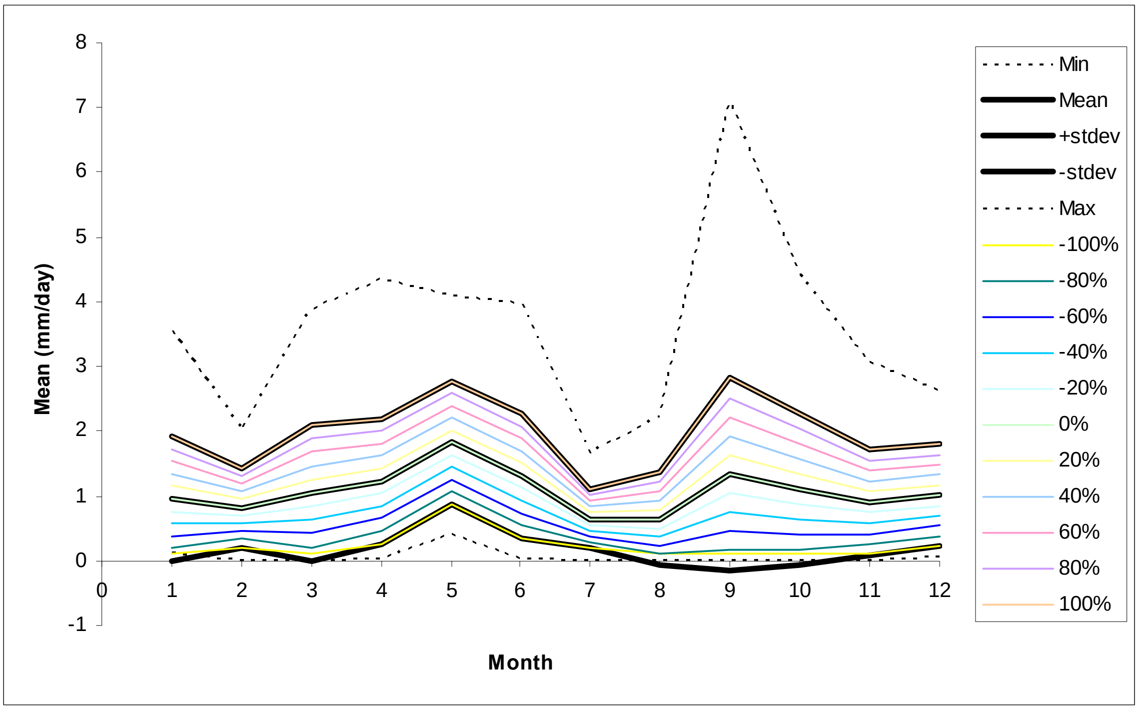


Figure A2. Target mean daily rainfall statistics for Zaragosa for the annual rainfall total sensitivity test showing the effect of a 0.1 mm minimum threshold

9.2 Change in rainfall seasonality

Seasonality was characterised for each year in the observed datasets, S_y, by considering the similarity of each year to the overall average seasonality:

$$S_y = \frac{1}{11\, s_{\bar{x}_i}^2} \sum_i \left(x_{iy} - \bar{x}_y\right)\left(\bar{x}_i - \bar{x}\right) \tag{1}$$

where x_{iy} is the average daily rainfall in month i of year y, $\bar{x}_y$ is the average daily rainfall for year y, $\bar{x}_i$ is the average daily rainfall for month i in the entire dataset, $\bar{x}$ is the average daily rainfall in the entire dataset and $s^2_{x_i}$ is the inter-monthly sample variance of 'the average daily rainfall for each calendar month'. The mean and standard deviation of the yearly seasonality series were then evaluated and used to define 11 equal increments for the range $\mu \pm \sigma$ (the mean plus/minus one standard deviation). These are shown in Figure A1(b) for the Oxford raingauge. The variance statistic was also changed to retain a constant coefficient of variation. All other observed statistics were kept unchanged.

The mean value of the annual time series of observed seasonality values estimated in this way is expected to be approximately one. However, for the Zaragoza raingauge the 12 complete annual records provided an estimate of mean seasonality of only 0.7. Therefore it was assumed that the 12 complete years were not a representative sample from the 42 year dataset. Instead a mean seasonality of 1.0 and a standard deviation of seasonality of 1.0 were assumed. The seasonality standard deviations for Oxford is 1.5, so this value lies within the valid range but may overestimate the variability in this region.

9.3 Change in proportion of dry days (pdry)

The pdry target case was generated in a way similar to that of the annual totals. The monthly time series of estimates of pdry were evaluated for each raingauge. These were then analysed to determine the minimum, maximum, mean and standard deviation of calendar month estimates of pdry. These are shown as black (and dashed) curves in Figure A1(c) for Oxford. The target climatic sensitivities of pdry were then calculated as 11 equal increments over the range $\mu \pm \sigma$ but allowing for the likely simulation bias in this statistic (e.g. Figure A1(c) coloured curves). All other observed statistics were kept unchanged.

9.4 Change in skewness coefficient

Monthly time series of estimates of the skewness coefficient were evaluated. These were analysed to determine the minimum, maximum, mean and standard deviation of calendar month estimates of skew. These are shown as black (and dashed) curves in Figure A1(d) for Oxford. This statistic is biased considerably by the short length of the observed series and therefore the mean is considerably different from that calculated for the whole series (skew in Figure A1(d)). Further, this statistic is highly noisy and it is unlikely that the high values correspond to the true skew of the population. For all raingauges, the target climatic sensitivities of skew were calculated as being 11 equal increments about the whole mean with a variation range with the same coefficient of variation of the monthly estimates (Figure A1(d) coloured curves). All other observed statistics were kept unchanged.

9.5 Model fitting and simulation

RainSim was fitted to the five statistics of each of the 11 equal increments for each of the four sensitivity cases for each raingauge. In each case, the model was used to generate a synthetic 100-year time series. The statistics of the resulting time series were analysed in a manner equivalent to the original observed time series. Since this represents 880 annual cycles of statistics, only a subset of this data is presented.

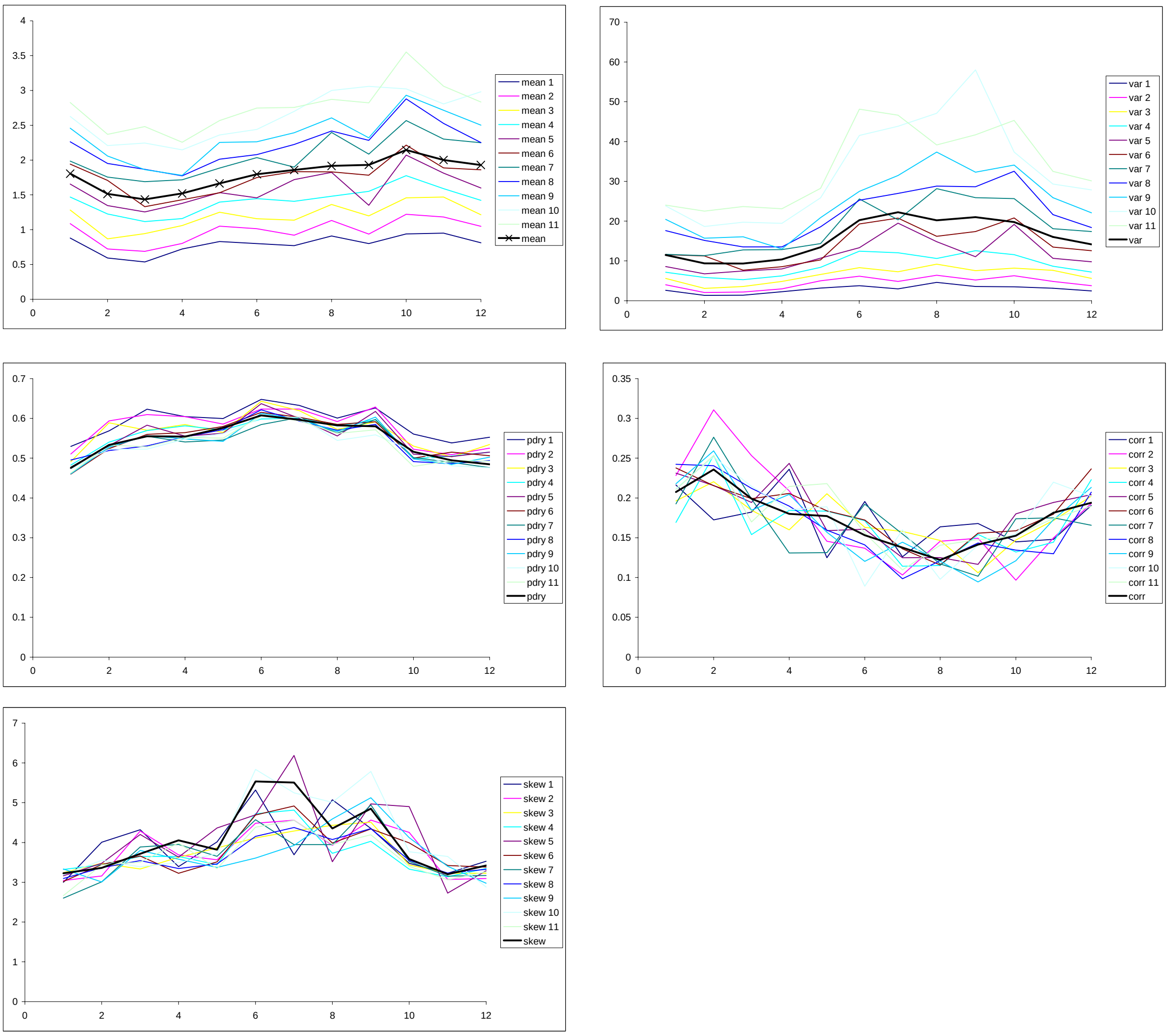


Figure A3. For Oxford, the five statistics for the 11 simulations in the annual totals sensitivity study

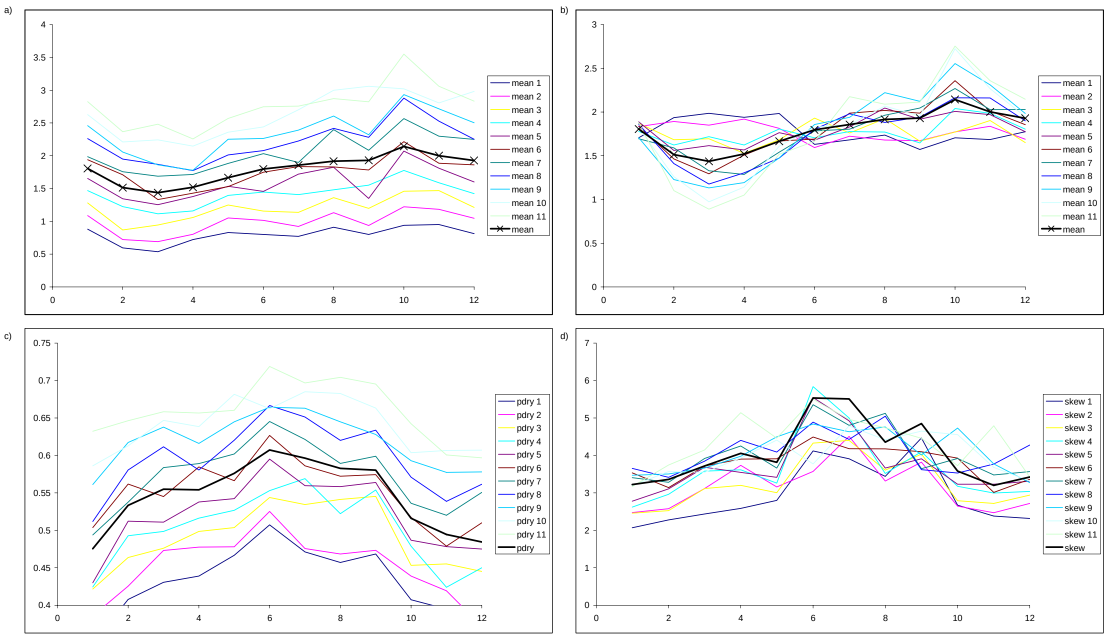


Figure A4. For the Oxford raingauge, the means, proportion of dry days and skewness as most relevant for all four sensitivity studies (omitting fixed statistics and the variance).
a) Annual totals; b) Seasonality; c) Proportion of dry days; d) Skewness

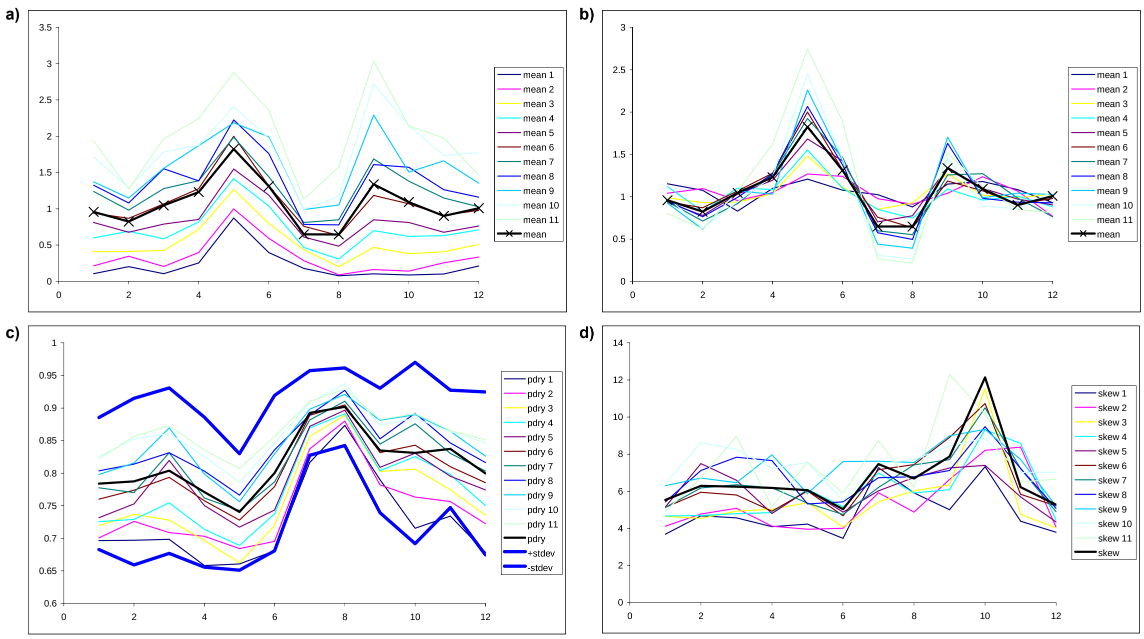


Figure A5. For the Zaragosa raingauge, the means, proportion of dry days and skewness as most relevant for all four sensitivity studies
a) Annual totals; b) Seasonality; c) Proportion of dry days; d) Skewness
b)

Figure A3 shows the five statistics for the 11 simulations in the annual totals sensitivity study for Oxford and Figure A4 shows the means, proportion of dry days and skewness as most relevant for all four sensitivity studies (omitting fixed statistics and the variance) for Oxford. Both of these figures show data that is affected by both model approximations and by stochastic variation. Variation in fixed statistics is considered reasonable given the stochastic variation in each of the statistics. Figure A5 shows the most relevant varying statistics arising from the Zaragosa raingauge,

9.6 Analysis of simulated datasets

Whilst the results presented in Figures A4 and A5 are a subset of that generated by the analysis of the simulated series, an analysis of all of the results reached a set of conclusions that are summarised here. The target statistics and their spreads were generally well reproduced by the simulations though the simulations do exhibit considerable stochastic variation as is expected. In particular, correlation and skewness statistics were found to be highly noisy but to be reasonably centred on the target values with the exceptions noted below.

For the case of varying

- annual total rainfall: it was noted that the Pdry statistic was sometimes simulated biased high and the skewness sometimes low.
- seasonality: all simulations matched the target statistics well.
- pdry: it was noted that a good spread of pdry statistics was obtained for Oxford but not for Zaragosa. The combination of statistics required by the sensitivity analysis could not be generated for this raingauge; instead a narrower range of pdry variation was generated.
- skew: high skewness coefficients cannot generally be matched in the simulations. All skewness statistics were found to be highly noisy and to generally reflect an increase in the skew. Variance was also found to increase with skew.

10 APPENDIX 2: SUPPORTING MAPS

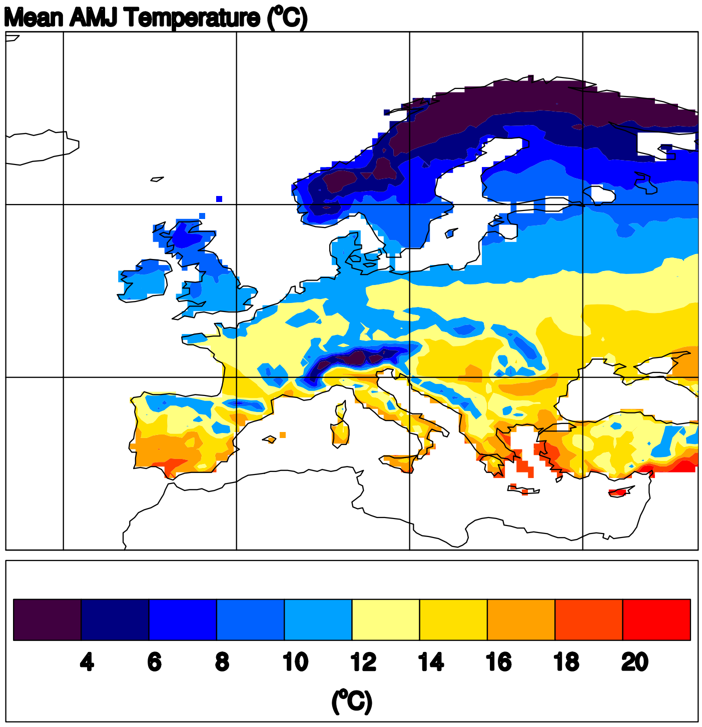


Figure A6: Mean April-June temperature (SPR_TMP) derived from the CRU TS 2.0 data set.

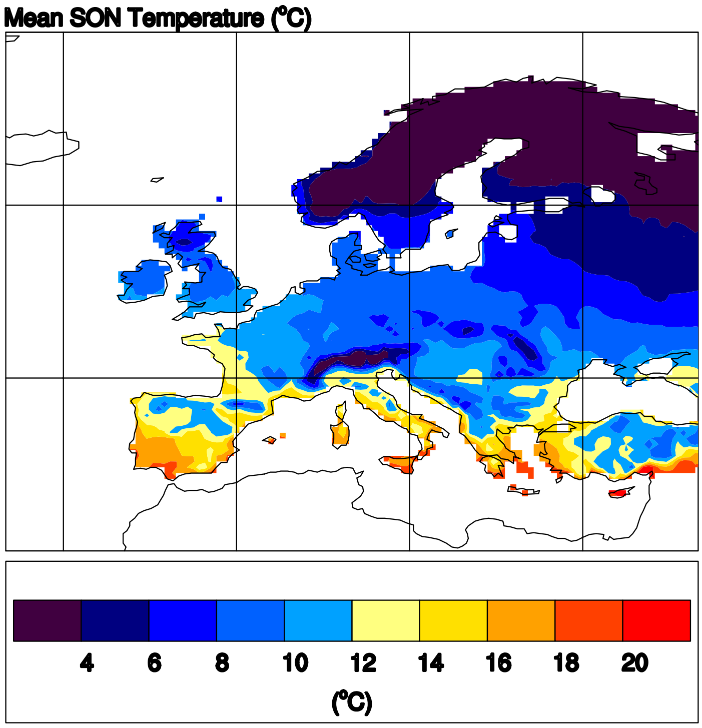


Figure A7: Mean September-November temperature (AUT_TMP) derived from the CRU TS 2.0 data set.

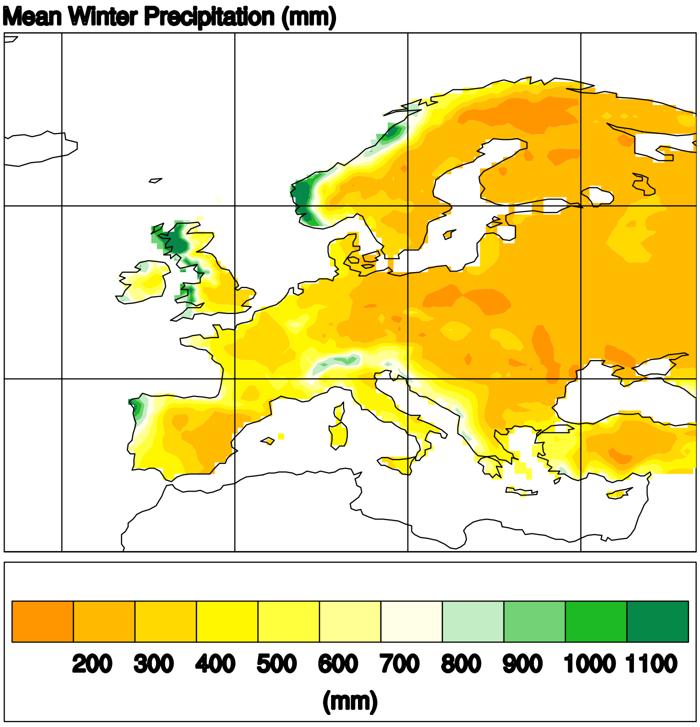


Figure A8: Mean October-March precipitation (WIN_PRE) derived from the CRU TS 2.0 data set.

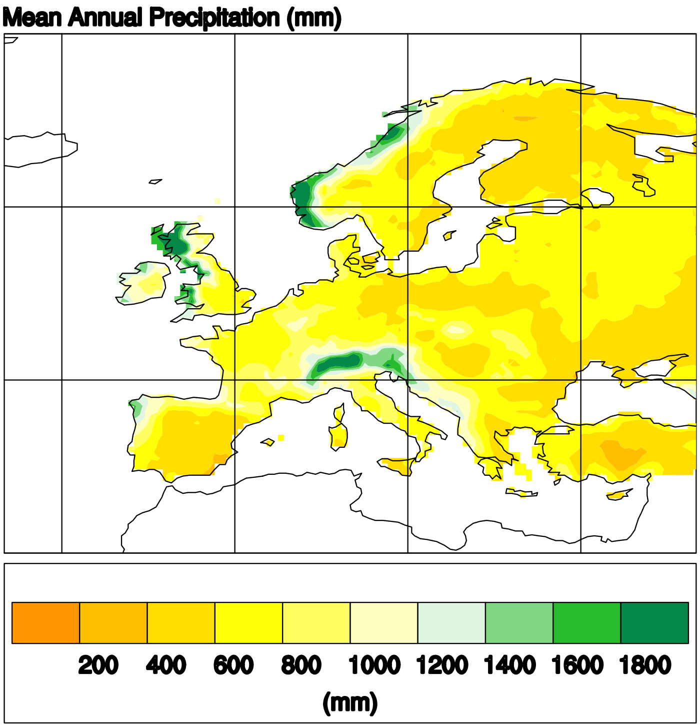


Figure A9: Mean annual precipitation (ANN_PRE) derived from the CRU TS 2.0 data set.

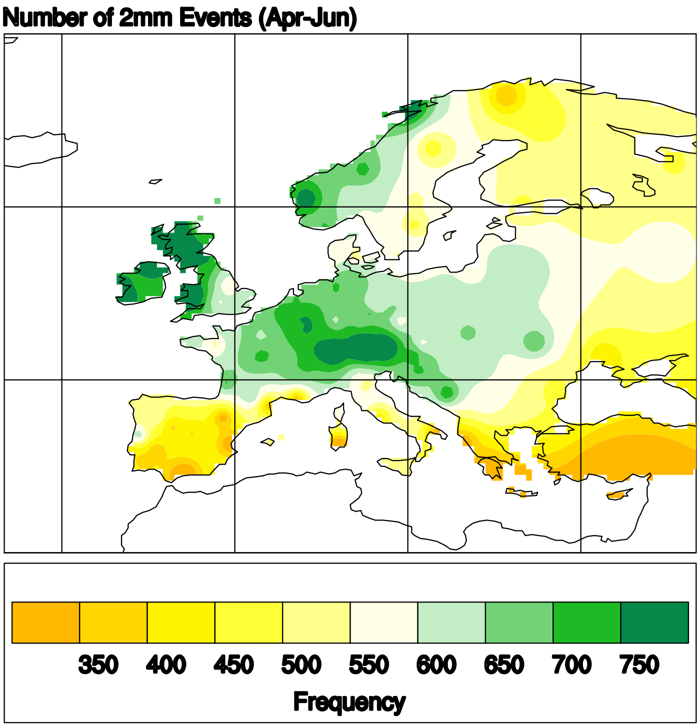


Figure A10: Frequency of daily precipitation events (April-June) greater than 2mm (SPR_2) derived from the interpolated ECA&D stations.

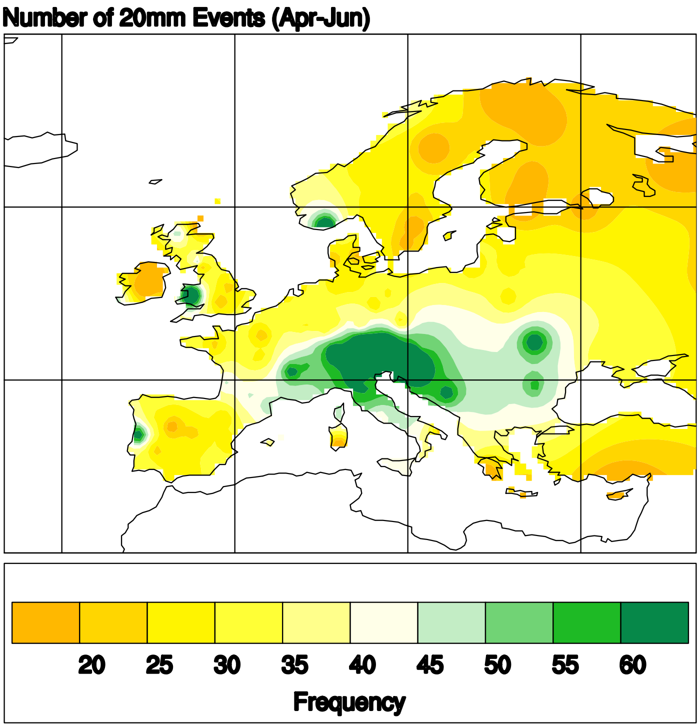


Figure A11: Frequency of daily precipitation events (April-June) greater than 20mm (SPR_20) derived from the interpolated ECA&D stations.

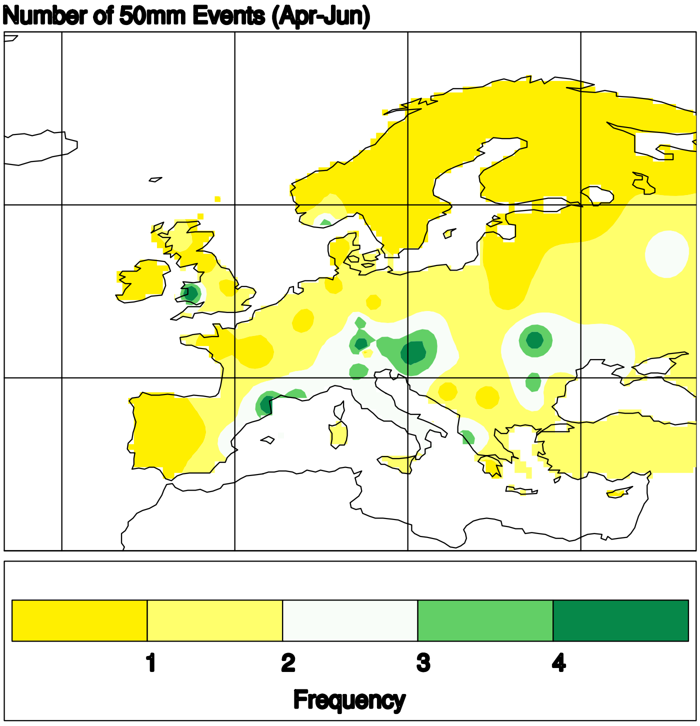


Figure A12: Frequency of daily precipitation events (April-June) greater than 50mm (SPR_50) derived from the interpolated ECA&D stations.

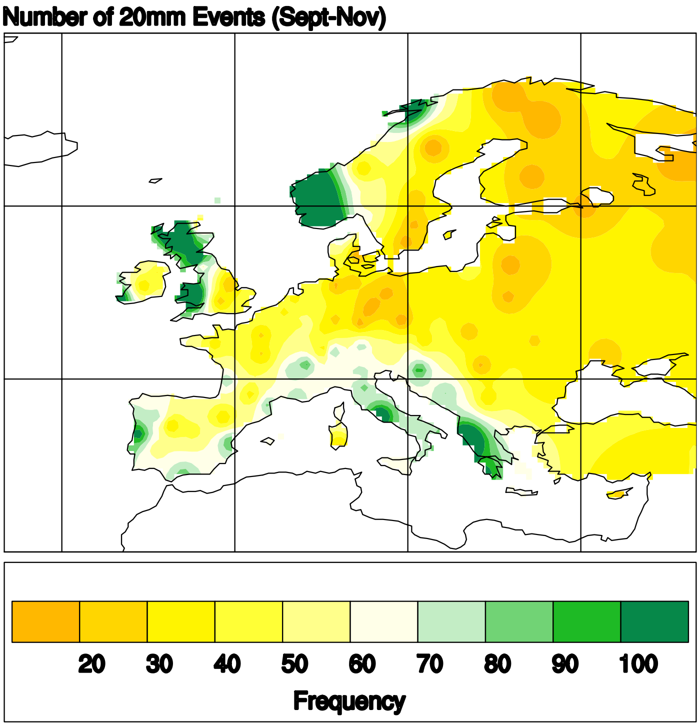


Figure A13: Frequency of daily precipitation events (September-November) greater than 20mm (AUT_20) derived from the interpolated ECA&D stations.