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Developing climatic scenarios for pesticide fate modelling in Europe

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The FOOTPRINT climatic zones provide an objective climatic classification and daily climate series that may be used for the modelling of pesticide fate across Europe.

Abstract

A climatic classification for Europe suitable for pesticide fate modelling was constructed using a 3-stage process involving the identification of key climatic variables, the extraction of the dominant modes of spatial variability in those variables and the use of *k*-means clustering to identify regions with similar climates. The procedure identified 16 coherent zones that reflect the variability of climate across Europe whilst maintaining a manageable number of zones for subsequent modelling studies. An analysis of basic climatic parameters for each zone demonstrates the success of the scheme in identifying distinct climatic regions. Objective criteria were used to identify one representative 26-year daily meteorological series from a European dataset for each zone. The representativeness of each series was then verified against the zonal classifications. These new FOOTPRINT climate zones provide a state-of-the-art objective classification of European climate complete with representative daily data that are suitable for use in pesticide fate modelling.

Keywords: Pesticide; Modelling; Europe; Climate; Zones

1. Introduction

FOOTPRINT is an EU FP6 project which aims to develop pesticide risk prediction and management tools for use by end-user communities at the farm, catchment, and national/EU scale. The tools will be based on state-of-the-art knowledge of processes, factors and landscape attributes influencing pesticide fate in the environment. They will integrate innovative components, allowing users to identify contamination pathways and sources of pesticide contamination in the landscape, estimate pesticide concentrations and make scientifically based assessments of how the implementation of mitigation strategies will reduce pesticide contamination of adjacent water resources. Climate is a key determinant of the fate of such contaminants and the use of a simplified climatic classification offers considerable advantages for the modelling of the transfer and fate of such pollutants across Europe. The most well-known and most widely reproduced climatic classification system is that of Köppen (1918) which has been updated and modified many times (e.g. Walter and Leith, 1960; Strahler, 1963), and is based on mean temperature and precipitation characteristics. The Köppen classification has been further developed for specific applications such as agroecology and bioclimatology (e.g. Thran and Broekhuizen, 1965; Bouma, 2005; Metzger et al., 2005; Jongman et al., 2006).

A number of climate zonations have been defined specifically for pesticide registration, mainly under the auspices of the FOCUS (FOrum for the Coordination of pesticide fate models and their USe) working groups (FOCUS, 2001a).

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FOCUS (1995) first presented 10 climatic scenarios to cover the variability of climate in Europe based on differences in annual temperature 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 precipitation and evapotranspiration) to produce eight climatic zones. The first FOCUS surface water group (FOCUS, 1997b) then called for the *ad hoc* development of scenarios based on (i) average annual hydraulically effective rainfall; (ii) average annual temperature; (iii) average winter temperature; (iv) average summer temperature; (v) frequency of rainfall events; and (vi) intensity of rainfall events. The FOCUS groundwater group (FOCUS, 2000) developed nine scenarios to be used in the registration of pesticides and attached weather data to each. The scenarios were developed using average annual temperature and rainfall and weather data taken from the MARS European database (Vossen and Meyer-Roux, 1995). The recommendations from FOCUS (1997b) were followed up by the second FOCUS surface water group (FOCUS, 2001b) who defined agro-environmental scenarios which partly reflect variations in climate across Europe. In their classification they considered the climatic variables of average annual precipitation, daily maximum spring rainfall, average spring and autumn temperature and average annual recharge. In all FOCUS initiatives the selection of variables to derive climate scenarios was made using expert judgement on the likely influence of climatic characteristics on pesticide transfer in the environment.

As part of the FOOTPRINT (2006) project, we used a three-stage process to objectively define a state-of-the-art climatic classification which may be applied to pesticide fate modelling:

1. Eight climatic variables were selected on the basis of the results of a sensitivity analysis of pesticide fate models for climatic factors (Nolan et al., submitted for publication).
2. Principal components analysis was used to identify the dominant modes of variability within these variables.
3. Finally, *k*-means clustering was deployed to identify 16 coherent climatic zones relevant for pesticide fate by leaching and drainage across Europe.

These FOOTPRINT climatic zones (‘FCZs’) are described in quantitative terms using summary climate statistics and are compared to previous initiatives in the field. As the purpose of this exercise is to produce a classification which is of practical use in the field of pesticide registration, we also employ an objective method to identify representative daily meteorological series for each zone which may be used as input into a pesticide fate model.

2. Methodology

2.1. Identification of climatic characteristics affecting the fate of pesticides

Extensive pesticide fate modelling was undertaken and modelling results were analysed statistically to identify the climate characteristics which most influence the transfer of pesticides to depth via leaching and to surface water via drainage. Only a brief description of the methodology and results obtained are presented below as Nolan et al. (submitted for publication) and Blenkinsop et al. (2006) provide an extensive description for the Oxford (UK) and Zaragosa (Spain) meteorological stations, respectively.

The transport of three contrasting 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 (Jarvis et al., 1991; Larsbo et al., 2005) Version 4.3, resulting in 20-year daily series of predicted pesticide concentrations for 78 modelling scenarios. Overall, 54 modelling scenarios comprising 1593 MACRO leaching and drainage simulations were conducted using climatic data series generated from conditions at Oxford (Nolan et al., submitted for publication) while 24 leaching scenarios comprising an additional 720 simulations were conducted based on conditions in Zaragosa (Blenkinsop et al., 2006). Pearson correlations between climatic variables and predicted pesticide loss in leaching and drainage were computed for all 78 season–soil–pesticide combinations, to better understand relations between pesticide loss and specific climate factors. Although the sensitivity analysis used only data from Oxford and Zaragosa, these locations represent considerable variability in European climatic conditions (in terms of both temperature and precipitation). The sensitivity analysis also included multiple soil types intended to encompass the full range of variability in Europe. Thus, the model sensitivity analysis focused not just on climate but on interactions between climate, soils, and other factors that influence pesticide transport.

The results suggested 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 (Nolan et al., submitted for publication), there was 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, were more likely to be 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 larger clay content, which are typically subject to preferential flow phenomena. Oxford results obtained for drainage suggested that the same climatic factors were important, although the influence of climatic conditions shortly after application and the positioning of extreme events in relation to application were clearly greater.

At Zaragosa (Blenkinsop et al., 2006) and in contrast to Oxford, temperature effects were more widespread and the influence of winter rain was substantially reduced. This may be due to the warmer average annual temperature at Zaragosa (14.5 °C), and the greater frequency of daily rain events of 10 mm or less at Oxford. The influence of lag time was more prevalent at Zaragosa than at Oxford, especially for two of the three pesticides on less structured soils. Unlike Oxford, however, lag time was positively correlated with pesticide loss, which may be an artefact of the univariate correlation analysis. Relations between lag time and pesticide loss were non-monotonic at Zaragosa. Similar to Oxford, short-term climatic variables (primarily rain within 7 days) were noted for two of the pesticides on more structured soils at Zaragosa. On the basis of these results the eight key variables presented in Table 1 were selected as sensitive climatic indicators for the environmental fate of pesticides from the 91 variables which were investigated.

2.2. Supporting climatic data

Two sources were used to provide European-wide climatic data from 1961 to 1990 for the eight identified climatic variables. The European climatologies for mean temperature and precipitation (Table 1, 1–4) were derived from the CRU TS 2.0 dataset (Mitchell et al., 2004), whilst those based on daily precipitation thresholds (Table 1, 5–8) were constructed from data provided by the European Climate Assessment & Dataset (ECA&D) (Klein Tank et al., 2002). A climatology for each variable was constructed for the European spatial domain shown in Fig. 1.

The CRU TS 2.0 dataset (CRU) is a gridded global series of monthly climate means for the period 1901–2000. The dataset was 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). The ECA&D contains 5162 series of daily observations at 1529 meteorological stations throughout Europe and the Mediterranean for nine variables including temperature and precipitation. A total of 113 stations were selected from the dataset to satisfy two criteria:

(1) to obtain a reasonable spatial coverage for Europe, and particularly for the member states of the European Union;
(2) to identify series that were of the highest quality.

The ECA&D uses four statistical tests to assess homogeneity: the 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). For this study, daily precipitation series were selected from those classified as "useful", i.e. stations where no more than one test rejects the null hypothesis that there is no discontinuity at the 1% level. The stations selected to calculate each of the precipitation threshold variables are also shown in Fig. 1. Due to the requirement for high quality data, a number of gaps in the coverage are unavoidable, most notably for southern Italy and Poland. Nonetheless, an adequate coverage was obtained for the scale of analysis to be performed in the study. To obtain coverage at the same resolution as CRU, the threshold exceedence data were interpolated onto the same 0.5° by 0.5° grid using an inverse distance weighted interpolation algorithm (NCAR, 2006). The resultant climatologies derived for each of the eight input variables from CRU and ECA&D are shown in Fig. 2.

Table 1
The eight input variables used to define the climatic zones

		Definition
1	T_SPR	Mean April to June temperature (°C)
2	T_AUT	Mean September to November temperature (°C)
3	R_WIN	Mean October to March rainfall (mm)
4	R_ANN	Mean annual rainfall (mm)
5	R2_SPR	Number of days (April to June) where daily rainfall >2 mm
6	R20_SPR	Number of days (April to June) where daily rainfall >20 mm
7	R50_SPR	Number of days (April to June) where daily rainfall >50 mm
8	R20_AUT	Number of days (September to November) where daily rainfall >20 mm

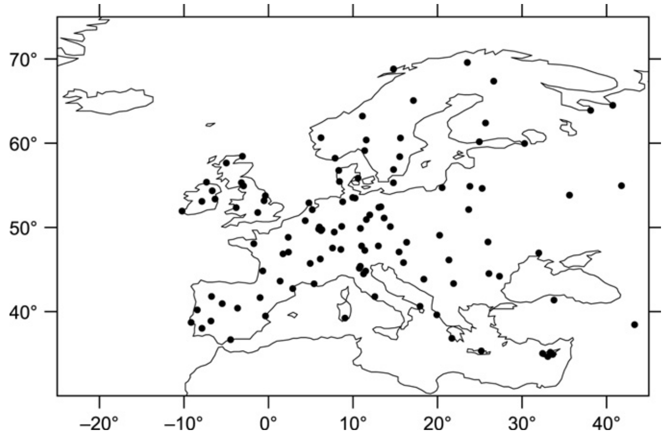

Fig. 1. The selection of 113 stations from the European Climate Assessment & Dataset used to calculate the daily threshold variables.

In the construction of representative time series for each of the final climatic zones, an additional data source was used. Data for potential evapotranspiration, wind speed and solar radiation were obtained from the MARS-STAT dataset (MARS, 2007), hereafter referred to as MARS. MARS provides a set of meteorological data interpolated on to a 50×50 km grid covering most of Europe and is available from the year 1975 onwards (http://agrifish.jrc.it/marsstat/datadistribution/).

2.3. Methodology for climate zonation

Each of the variables listed in Table 1 were used in the next two stages to determine the climate zonation. As a degree of correlation was likely between some variables, principal components analysis (PCA) was first used to reduce the dimensionality of the data. Subsequently, *k*-means cluster analysis was performed on the retained components to derive the final climatic regions.

The PCA was performed on all eight gridded variables which were subsequently standardised. Due to the likelihood of correlation among the data, an oblique rotation solution

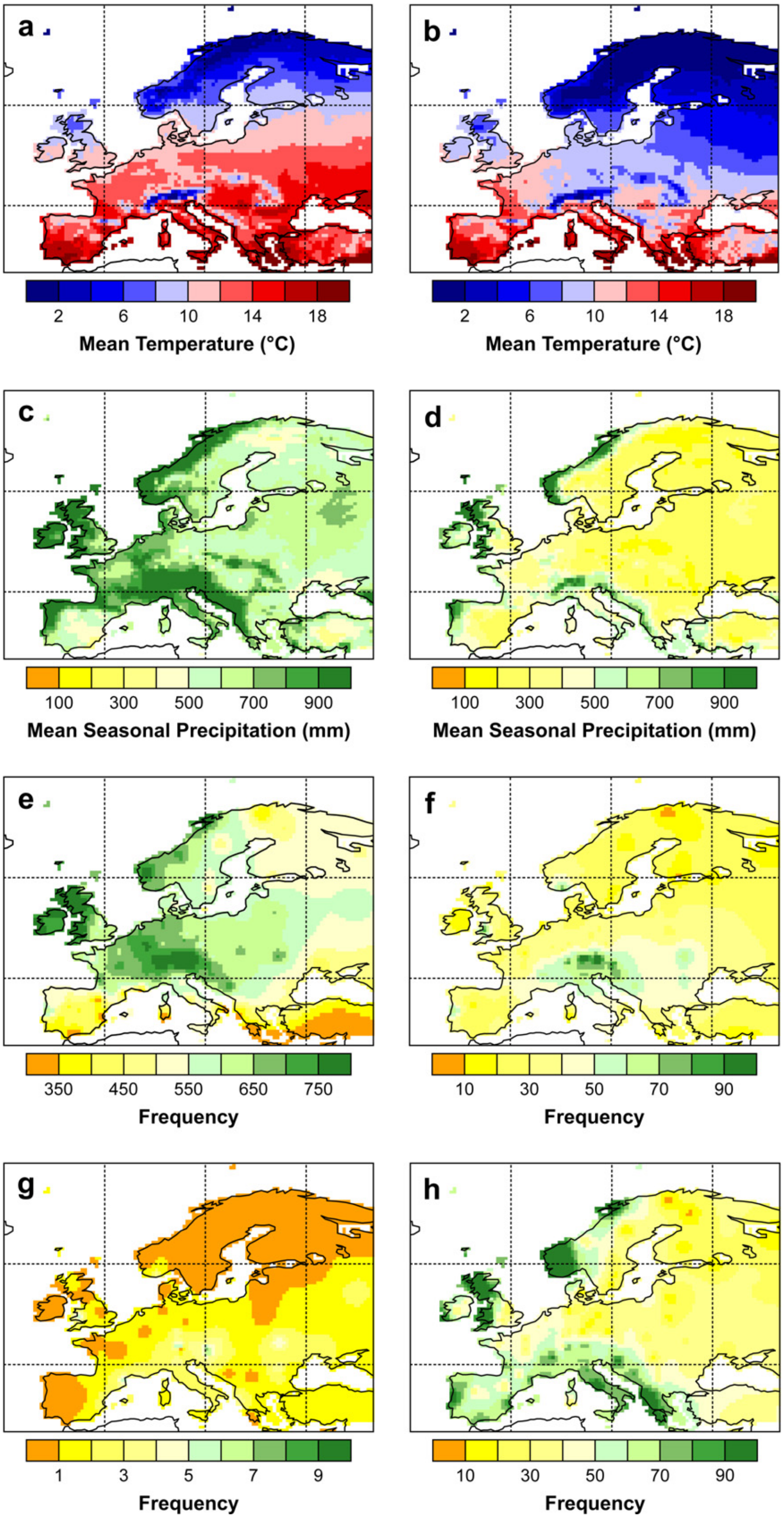

Fig. 2. Climatic maps used as input variables to derive the climatic zones. The input variables are (a) T_SPR, (b) T_AUT, (c) R_WIN, (d) R_ANN, (e) R2_SPR, (f) R20_SPR, (g) R50_SPR and (h) R20_AUT. Variable definitions are provided in Table 1.

was used to better identify components (Field, 2005). A number of objective methods have been described to determine the number of principal components or factors that should be retained for subsequent analysis. One of the standard methods is to use a scree plot of eigenvalues for each of the factors and to identify a point of inflexion to discard redundant factors. Alternatively, Kaiser (1960) recommends retaining only those factors with eigenvalues greater than 1, whilst Jolliffe (1972, 1986) suggests the retention of factors whose eigenvalues are more than 0.7. All three criteria were tested and this suggested the retention of three components, with the third and fourth factors having eigenvalues of 1.2 and 0.4 respectively. The three retained factors explain a total of 87.1% of the variability.

Fig. 3 shows scores of the first three principal components over the European domain. The first principal component (PC1) exhibits properties of the observed distribution of rainfall, with the largest positive scores along western coasts and high altitude areas such as the Alps (Fig. 3a). The scores of each variable on each of the factors shown in Table 2 indicate that PC1 is a general precipitation signal, reflecting the distribution of the precipitation variables listed in Table 1. The second principal component (PC2) is clearly related to the temperature variables, with negative scores observed over northern Europe and mountainous areas and increasingly positive scores over southern Europe (Fig. 3b). The final principal component (PC3) also provides a rainfall signal but both the scores shown in Table 2 and the spatial distribution (Fig. 3c) indicate that this component relates to the distribution of spring rainfall, particularly extremes.

Cluster analysis was performed using the scores on each retained component and, additionally, the latitude and longitude of each grid cell centroid to encourage the grouping of contiguous regions. The method used here was *k*-means clustering which 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 these seeds. 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. This offers the advantage over hierarchical methods that cluster members can be reallocated to more appropriate groups throughout the procedure (Wilks, 2005). The most significant disadvantage of *k*-means clustering is that the number of clusters, *k*, must be predefined. 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 subsequent modelling demands. A range of *k* from 12 to 18 was therefore examined following discussions within the FOOTPRINT consortium. Using values of *k* at the lower end of this range resulted in classifications with extensive regions containing large internal variability in climatic parameters. However, when using values of *k* at the upper end of this range, the clustering procedure split the smaller zones which occur in the wettest areas into even smaller sub-zones whilst producing less spatially contiguous regions.

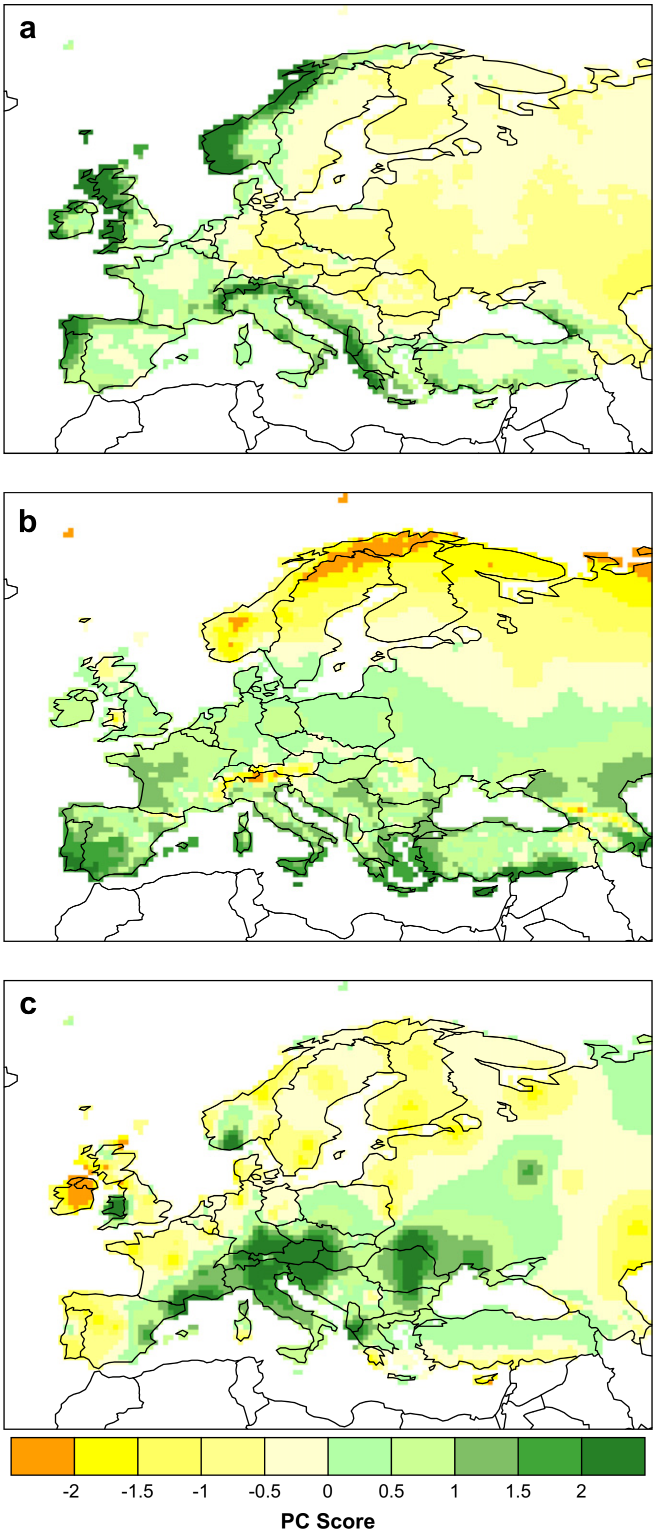

Fig. 3. Scores of principal components, (a) PC1, (b) PC2, (c) PC3, derived from the variables listed in Table 1. Note that for (a), a contour interval of 1 is used for positive loadings but 0.5 for negative loadings.

Table 2
Loadings of each variable on each of the retained principal components

	Principal component		
	1 (precipitation)	2 (temperature)	3 (spring extremes)
T_SPR	0.14	**0.93**	−0.17
T_AUT	0.38	**0.84**	−0.29
R_WIN	**0.82**	−0.22	−0.48
R_ANN	**0.84**	−0.40	−0.22
R2_ SPR	0.58	−0.51	0.41
R20_ SPR	0.78	0.23	**0.51**
R50_ SPR	0.54	0.47	**0.58**
R20_AUT	0.81	−0.76	−0.29

The figures in bold denote the two variables with the highest loadings.

Hossell et al. (2003) identified a similar pattern within a classification of British climates which produced small fragmented classes in upland regions. The most robust and optimal solution was obtained for $k = 16$, i.e. when the clustering routine produced spatially contiguous regions whilst not splitting very small zones into further sub-zones. The resultant classification is not a definitive classification of European climate, but rather one which best represents the compromise between reflecting the climatic diversity of Europe and providing a workable number of zones for subsequent modelling. Notwithstanding the limited ability of these FOOTPRINT Climatic Zones (FCZs) to reflect the detailed variability of European climate they represent a significant advance on previous work by including important indices of extreme precipitation and employing objective classification methods to define them.

3. Results

3.1. Description of the FOOTPRINT climatic zones (FCZs)

The final climatic zonation identified by the cluster analysis is shown in Fig. 4, with a brief description of each FCZ listed in Table 3. The distribution of zones was found to be physically plausible, with the influence of temperature producing a north-south zonation, particularly in the drier continental interior. The influence of the precipitation variables in the production of the FCZs was noticeable on western coasts and also in topographically complex areas where extreme events are a significant factor, e.g. the UK, western Scandinavia and the Alps. The climate zonation may be divided into six broad categories which reflect the influences of the input variables; Northern (FCZ 1 and 2), Temperate (FCZ 3 and 4), Maritime (FCZ 5–8), Continental (FCZ 9–11), Mediterranean (FCZ 12–14) and Alpine (FCZ 15 and 16). Summary mean (Table 4) and standard deviation (Table 5) statistics for the eight input variables for each zone enable a quantitative assessment of the typical climate and an indication of intra-zone variability. They also provide an indication of the climate variables used by the clustering procedure to determine each climate zone. Fig. 5 shows monthly mean temperature and rainfall for each zone, further enabling physical distinctions between the zones to be identified.

The 'Northern' climates (FCZ 1, 2) have similar precipitation regimes (Fig. 5a), being characterised by low precipitation totals (R_ANN, 568 mm and 616 mm, respectively) but are

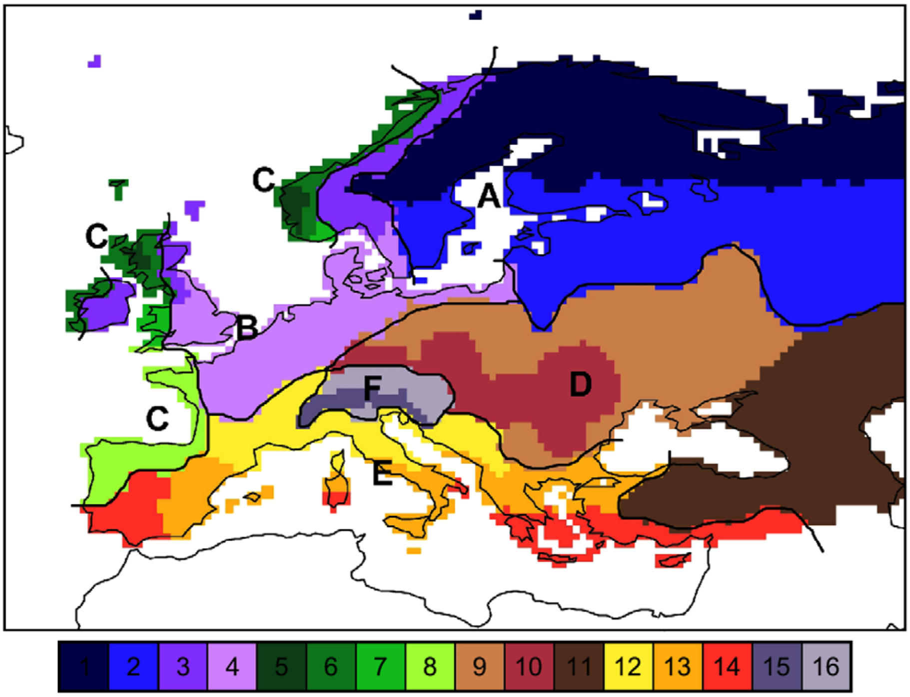

Fig. 4. Final classification of the European region into 16 FOOTPRINT climatic zones. Each zone belongs to one of six general climate types; Northern (A), Temperate (B), Maritime (C), Continental (D), Mediterranean (E) or Alpine (F).

Table 3
Summary description and member states for each of the 16 FOOTPRINT climatic zones (FCZs) identified by the cluster analysis

Climate type	FCZ	Description
Northern	1	North European climate, cold and dry
	2	North European climate, cool and dry
Temperate	3	Modified temperate maritime-influenced climate, cool with moderate precipitation
	4	Temperate maritime-influenced climate, warm with moderate precipitation
Maritime	5	Very wet, mountainous maritime climates, with more frequent extremes
	6	Wet, maritime climates, on exposed western coasts, more frequent extremes
	7	Modified upland maritime climate, more frequent extremes
	8	Warmer maritime climate, wetter but fewer wet spring days
Continental	9	Continental climate, warm and dry
	10	Continental climate, warm and dry with moderate frequency of extremes
	11	Continental climate, warm and dry
Mediterranean	12	North Mediterranean climate, warm and moderate precipitation
	13	Mediterranean climate with more frequent extreme rainfall
	14	Mediterranean climate, warmer, lower rainfall with more dry days but higher winter rainfall
Alpine	15	Alpine climate, cool and wet, relatively more extremes
	16	Sub-Alpine continental climate, warm, moderate rainfall but low winter rainfall, moderate frequency of extremes

differentiated on the basis of lower temperatures in FCZ 1 (T_SPR, 4.8 °C) compared with FCZ 2 (10.2 °C).

The ‘Temperate’ climates (FCZ 3, 4) have more moderate precipitation totals (R_ANN, 959 mm and 733 mm, respectively). These zones are subdivided on the basis that FCZ 3 is cooler and wetter (by >5 °C and >200 mm year^{-1}) than FCZ 4.

The ‘Maritime’ climates (FCZ 5−8) have a moderate annual temperature cycle (Fig. 5a) and are associated with high annual and winter precipitation due to their westerly location. High frequencies of precipitation extremes are observed in the autumn relative to the spring. FCZs 5 and 6 are almost identical in terms of seasonal mean temperature (T_SPR 7.4 °C and 7.3 °C, respectively), but as the former is located at higher altitudes in Scotland and Norway annual precipitation is much larger (R_ANN 2365 mm and 1500 mm, respectively). Given the lack of significant agricultural activities in these landscapes, these two zones were merged for modelling purposes in the FOOTPRINT project. FCZs 7 and 8 are differentiated on the basis of both temperature and precipitation with the more southerly zone (FCZ 8) characterised by the warmest temperatures (T_SPR 13 °C) and lowest precipitation totals (R_ANN 942 mm).

The ‘Continental’ climates (FCZ 9−11) are characterised by relatively dry rainfall regimes and warm mean spring temperatures (13.3−14.4 °C), FCZ 11 being the warmest zone and driest when considering annual rainfall. Fig. 5b indicates that, in terms of the seasonal means used to determine the zonation, there is relatively little difference between these three zones, particularly in terms of winter rainfall. Table 4 indicates that the main differentiating variables are annual rainfall and the precipitation threshold variables. FCZ 10 in particular is characterised by more rain days during the spring and also by higher frequencies of extreme events (R20_SPR 47 days compared with 34 days and 24 days for FCZ 9 and 11, respectively).

The ‘Mediterranean’ climates (FCZ 12−14) are all warm with low to moderate rainfall totals, but relatively high frequencies of extreme rainfall. The most northerly zone (FCZ 12) is cooler than the other two zones and has ca. 300 mm more annual precipitation. FCZ 14 has similar mean temperatures as FCZ 13, but is characterised by a smaller occurrence of extreme rainfall events compared to the other two zones.

Table 4
Mean climate statistics for grid cells within each of the FOOTPRINT climatic zones (FCZ)

FCZ	T_SPR (°C)	T_AUT (°C)	R_WIN (mm)	R_ANN (mm)	R2_SPR	R20_SPR	R50_SPR	R20_AUT	PC1	PC2	PC3	n	Area (×000 km^2)
1	4.8	0.5	246.8	567.8	525.9	21.4	0.7	28.4	−0.380	−1.421	−0.440	992	1406
2	10.2	4.6	259.4	615.5	538.3	24.1	1.0	28.9	−0.443	−0.307	−0.421	1020	1454
3	6.2	4.1	512.5	959.1	674.7	28.3	0.7	69.0	1.015	−0.757	−0.746	216	294
4	11.5	9.8	368.3	733.3	649.1	30.8	1.1	41.8	−0.093	0.518	−0.434	465	663
5	7.4	6.2	1408.8	2364.6	789.5	38.9	0.8	210.0	6.621	−0.813	−0.807	28	39
6	7.3	6.1	877.3	1499.7	744.3	33.5	0.9	105.6	2.870	−0.493	−0.755	169	228
7	9.6	8.8	835.2	1411.2	779.0	57.5	3.0	145.4	2.978	−0.647	2.399	32	44
8	13.0	13.0	605.7	942.0	549.0	34.3	0.8	62.3	1.146	0.995	−0.779	147	201
9	13.3	8.0	243.2	589.1	550.6	34.0	1.7	33.8	−0.597	0.278	0.488	743	1064
10	13.4	9.3	244.8	644.1	611.4	47.4	2.4	37.4	−0.685	0.305	1.578	319	453
11	14.4	9.8	247.9	515.7	382.5	23.9	1.1	31.8	−0.357	0.598	−0.326	688	975
12	13.4	11.7	485.3	935.9	609.6	51.0	2.2	65.5	0.641	0.546	1.298	261	359
13	16.1	15.2	420.9	642.2	453.2	36.7	1.9	67.3	0.507	1.153	0.668	316	425
14	17.8	17.0	478.6	614.1	317.7	24.4	1.1	55.4	0.713	1.706	−0.578	280	396
15	5.9	4.8	765.1	1694.9	730.1	65.1	2.5	63.7	1.940	−1.135	1.967	50	73
16	11.9	8.8	392.0	994.6	744.7	73.0	3.6	60.6	0.022	−0.204	3.479	83	118

PC1, PC2 and PC3 refer to the grid cell scores on the three principal components. The total number of grid cells belonging to each zone is denoted by n and total $n = 5809$. The area calculated is an approximation of the land area due to some grid cells containing both land and sea.

Table 5
Standard deviations of each variable for grid cells constituting within each of the FOOTPRINT climatic zones (FCZ)

FCZ	T_SPR (°C)	T_AUT (°C)	R_WIN (mm)	R_ANN (mm)	R2_SPR	R20_SPR	R50_SPR	R20_AUT	PC1	PC2	PC3
1	2.0	1.7	51.8	80.1	37.6	4.2	0.28	9.0	0.25	0.47	0.43
2	1.5	1.6	26.0	51.6	36.9	3.6	0.33	4.2	0.14	0.37	0.43
3	3.5	4.2	135.7	183.7	60.8	6.6	0.32	26.0	0.56	1.05	0.87
4	1.0	1.3	73.0	101.9	50.2	4.3	0.35	12.3	0.39	0.31	0.45
5	1.1	1.4	270.7	441.7	79.3	3.1	0.49	67.6	1.16	0.49	0.62
6	2.3	2.9	156.4	255.0	74.4	6.8	0.32	43.5	0.87	0.74	0.80
7	1.5	2.4	204.9	288.9	80.5	13.5	1.04	51.4	1.01	0.77	1.64
8	1.7	1.7	190.3	251.5	67.7	7.4	0.38	13.6	0.78	0.42	0.48
9	1.3	1.9	34.2	78.8	55.5	5.4	0.43	5.1	0.19	0.35	0.45
10	2.0	1.7	46.7	112.8	48.4	5.0	0.61	6.5	0.29	0.47	0.78
11	2.9	2.9	119.0	220.0	57.8	4.2	0.42	9.2	0.58	0.67	0.53
12	2.2	2.4	96.3	176.0	79.9	6.9	0.75	10.3	0.44	0.52	0.86
13	1.8	2.3	134.8	170.1	57.3	5.5	0.43	23.4	0.72	0.52	0.57
14	2.1	2.4	109.6	114.1	79.7	5.2	0.49	18.8	0.53	0.50	0.51
15	3.4	2.6	112.4	242.9	53.9	8.7	0.54	4.6	0.57	0.71	0.72
16	2.5	1.9	107.1	242.1	101.5	13.9	1.00	12.4	0.60	0.60	1.28

PC1, PC2 and PC3 refer to the grid cell scores on the three principal components.

Although seasonality of rainfall was not explicitly introduced as a factor in the statistical approach used for the determination of the zonation, FCZ 14 displays a strong seasonality in its precipitation regime and is characterised by very low summer rainfall totals (Fig. 5b).

The 'Alpine' climates (FCZ 15–16) are characterised by moderate to high precipitation totals and frequent extreme events. FCZ 15 may be described as the 'high Alps' and, as such, is cooler than FCZ 16 by 4–6 °C and has an additional 700 mm of annual precipitation.

The contribution of variables introduced in the statistical selection procedure varies between the various climatic zones, some zones being distinguished by just one variable (e.g. FCZs 5 and 6 which are largely determined by precipitation indices) and others by several variables (e.g. FCZs 5 and 8 which are determined by both precipitation and temperature).

Examining the standard deviations shown in Table 5 enables some comments on the heterogeneity of the FCZs. For temperature the most internal variability is shown by FCZs 3, 11 and 15, whilst FCZs 4 and 5 show the least. For precipitation, given the large differences in zonal means, the coefficient of variation was calculated for each FCZ (not shown). These indicate that zones 1, 3, 7 and 11 exhibit the greatest variability suggesting that overall FCZs 3 and 11 are the most heterogeneous zones, followed by zone 15. It may be observed therefore, that zonal heterogeneity is independent of the size of the zone.

3.2. Selection of representative meteorological data

Modelling activities require representative long-term meteorological data series to be assigned to each of the zones defined through the classification procedure described above. Within the context of the FOOTPRINT project, the requirement was for series of 26 years of daily data for seven climatic variables (Table 6). ECA data were considered the preferred source wherever possible given that the database contains observed data. In instances where ECA meteorological variables were not available (for evapotranspiration, wind speed and solar radiation), data were extracted from the MARS database which contains spatially interpolated data (Table 6).

An objective method to determine the location of a representative series for each FCZ was developed using the score of each grid cell on each of the three retained principal components. This selected data for a station displaying 'average characteristics' in relation to other stations present in the FCZ. For each FCZ, the cluster centroid co-ordinates in three-dimensional space, corresponding to each of the retained components, were first obtained. Then, the deviation of the three PC scores from the cluster centroid was calculated for each grid cell. The mean of these deviations were plotted and the location of candidate stations from ECA&D with daily temperature and precipitation series were overlaid. A visual inspection of candidate stations enabled a sample station to be selected for each FCZ based on the lowest possible absolute mean score deviation. Fig. 6 shows an example of the mean of the deviations and possible candidate stations for FCZ 8. In this particular case, station 1 was retained as it showed the lowest absolute mean score deviation among the stations available.

Where stations that were used in the initial analysis did not correspond to areas with low mean score deviations, additional candidate series were identified from the ECA&D. However, because of the generalisation inherent in any regional climatic classification and given the limited distribution of high quality observed meteorological series, obtaining one time series which perfectly matches the ''parent'' zone is difficult to achieve. In order to measure the representativeness of the daily temperature and precipitation series assigned to each FCZ using the method described above, the statistics T_SPR, T_AUT, R_WIN_ and R_ANN were calculated for each representative series and compared with the zonal statistics shown in Table 4. To provide a standard for each FCZ a (subjective) target of obtaining a meteorological series for each FCZ for which at least three of these four statistics were within one standard deviation of the ''parent'' FCZ mean was used.

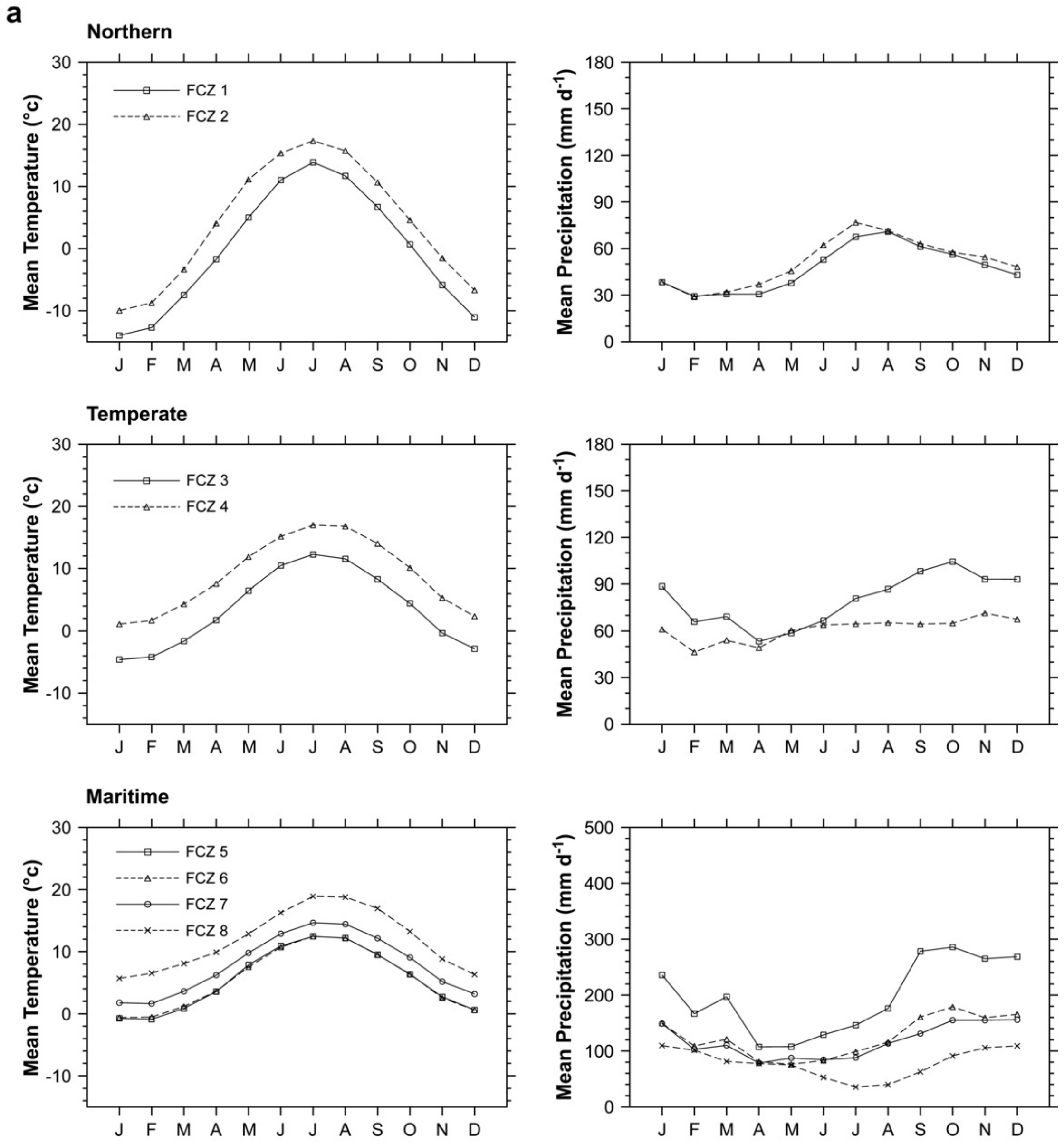

Fig. 5. (a) Monthly mean temperature (left column) and precipitation (right column) for each of the Northern, Temperate and Maritime climate types (FCZ 1 to FCZ8). Note the different vertical scale for precipitation for the Maritime climate types. (b) Monthly mean temperature (left column) and precipitation (right column) for each of the Continental, Mediterranean and Alpine climate types.

Obtaining a representative temperature series for FCZs 3, 5, 7 and 11 from the ECA&D proved difficult due to data scarcity and the relevant temperature series were therefore extracted by using the corresponding MARS grid cell. The validity of this was tested by obtaining correlation coefficients between temperature series in the cases they were available for both ECA&D and MARS. Correlations between the two series were high (>0.9) and statistically significant at the 1% probability level. Using the MARS data as a proxy for observed station series where data availability posed a problem was therefore considered appropriate.

The standard target set was achieved for 11 of the 16 FCZs (Table 7). Meeting this target for the remaining five FCZs (1, 5, 6, 13 and 15) was not possible due to the low number of stations with adequate temperature series in locations which also provide an adequate representation of precipitation. These five FCZs are generally zones with high spatial variability in precipitation (Table 5) and so obtaining a good fit for precipitation and temperature variables proved difficult. Four of the five zones have a representative series which was within one standard deviation of the zonal average for precipitation. The somewhat lower performance of the remaining zone (FCZ 15, high Alpine zone) was attributed to the fact that precipitation in this zone is highly variable and that the zone is poorly represented by candidate stations within the ECA&D. In practical terms, this zone is likely to sustain low levels of agricultural activity and the impact on subsequent modelling is expected to be relatively small. In all, given the limitations

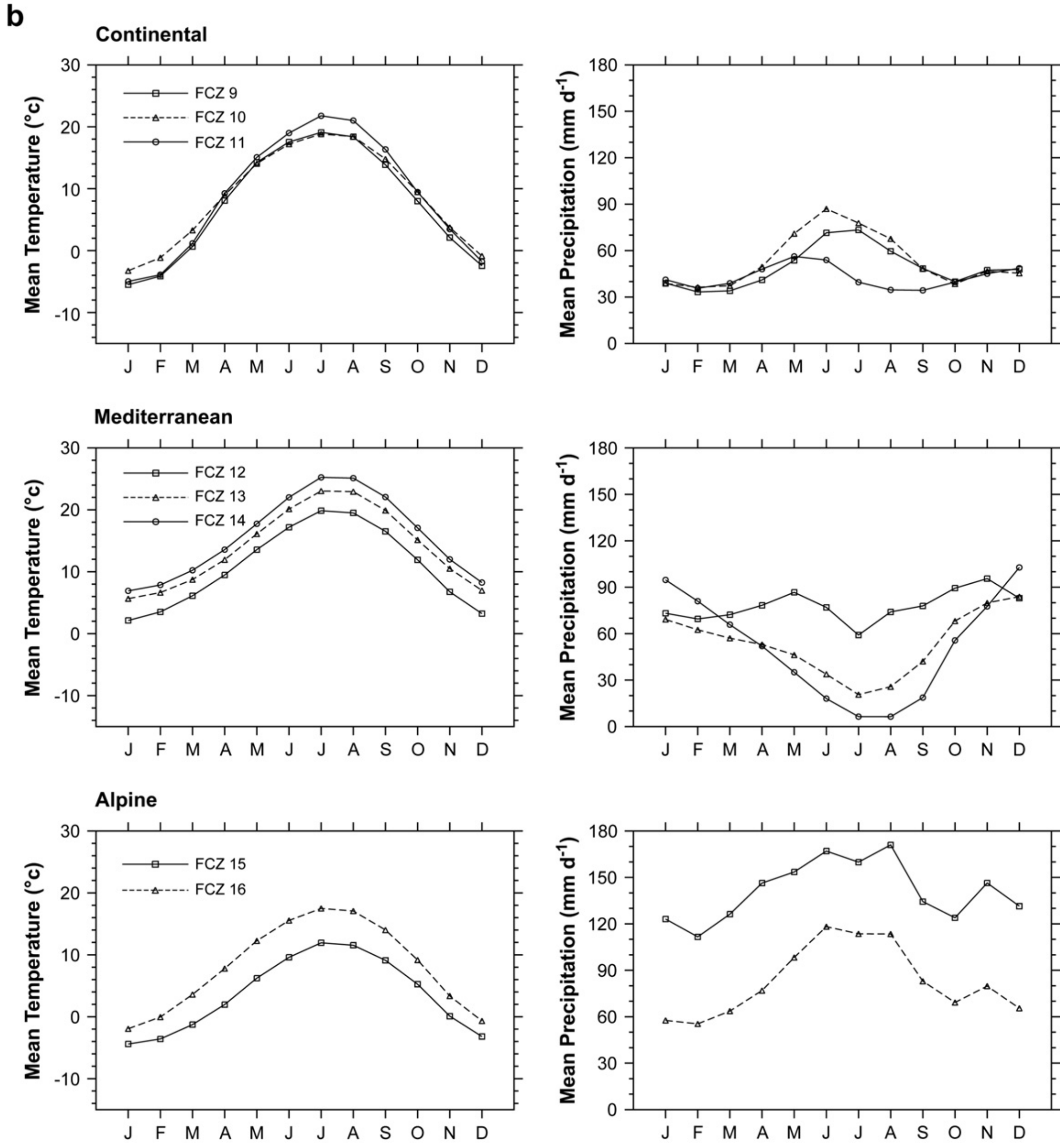

Fig. 5. (*continued*).

imposed by using a 16-zone classification the selected meteorological series represent a ‘‘best fit’’ for each of the FCZs and reasonably describe the characteristics of the zones in relative and absolute terms.

4. Discussion

A comparison between the FOOTPRINT zonation and the FOCUS (1995) classification enables further assessment of the influence of the objective method described above. As with the FOOTPRINT classification, the 10 FOCUS (1995) climatic zones are influenced by a combination of maritime, continental and topographic features (Fig. 7). Whilst the FOOTPRINT zonation has a clear maritime influence, it has a more subtle delineation than the FOCUS study which presents a non-maritime coastal climate that extends along the Mediterranean. Although the FOCUS classification identifies two types of Alpine/mountainous climates, similar to our study, the FOCUS zones are more strongly defined by

Table 6
Source of daily series of climate variables representative of each of the 16 climatic regions

Variable	Source
Precipitation	ECA
Maximum temperature	ECA
Minimum temperature	ECA
Mean temperature	ECA
Potential evapotranspiration	MARS
Wind speed	MARS
Solar radiation	MARS

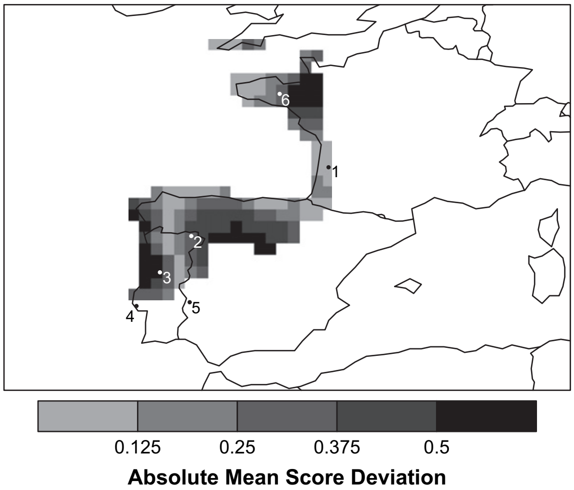

Fig. 6. Absolute mean score deviation of the three retained principal components for each grid cell in FCZ 8. The locations numbered 1–6 are possible candidate stations for the representative daily series.

topography. For example, much of the interior of southern Europe is classified as a southern, low mountain climate. Thus, there is much less variability in the classification of southern European climates in FOCUS, for example, the interior of Spain is classified as a single climate type compared to three in FOOTPRINT. Differences between the two classification systems are greatest in the north-west of Europe, with the FOCUS scheme dividing FCZ 4 into two zones on the basis of relative maritime and continental influences. Furthermore, the FOOTPRINT scheme identifies greater variability over the UK due to large variations in precipitation which are detected by the objective methodology.

This complexity was incorporated to some extent in the FOCUS (1997a) classification, which was based on a series of mean precipitation and temperature thresholds (Fig. 8). This classification bears a greater overall similarity to the FOOTPRINT scheme, particularly over the Mediterranean. However, since previous classifications of European climate have not included extreme statistics then we would expect the FOOTPRINT scheme to offer improved robustness for pesticide fate modelling. A significant difference between the latest FOCUS initiatives (FOCUS, 2000, 2001b) and our work relates to the selection of the representative climatic data for assignment to each of the scenarios. In contrast to the FOCUS work which attempts to subjectively integrate into the selection of the stations—and their associated meteorological data—some degree of ‘worst-caseness’ with regard to pesticide environmental fate (FOCUS, 2000, 2001b), the FOOTPRINT approach aims to represent average conditions for each of the FCZs on an objective basis. Still, the inter-annual variability in the FCZ data is expected to reflect a range of vulnerability with regard to the magnitude, duration and frequency of key climatic events.

Table 7
An assessment of the representativeness of each of the selected daily temperature and precipitation series

FCZ	T_SPR	T_AUT	R_WIN	R_ANN
1	2	2	1	1
2	1	1	1	1
3	2	1	1	1
4	x	1	1	1
5	2	2	1	1
6	2	2	1	1
7	1	1	1	1
8	1	1	1	1
9	1	2	1	1
10	1	1	1	1
11	1	1	1	1
12	1	1	2	1
13	2	2	1	1
14	1	1	1	1
15	2	2	x	x
16	1	1	1	1

The number represents the number of standard deviations of the zonal mean within which the selected daily series mean lies. Those marked with an x lie outside 2 standard deviations of the zonal mean.

5. Conclusions

A three-stage process was used to derive a climatic classification of Europe which reflects the potential for the environmental transfer of pesticides. The first stage identified eight key climatic variables affecting the fate of pesticides using a sensitivity analysis of pesticide fate modelling for two European climates: Oxford (UK) and Zaragosa (Spain) (Nolan et al., submitted for publication). Climatologies of the selected variables were extracted from available data sources for 1961–1990. Given the expected correlation between several of the climatic variables, a dimension reduction procedure was performed using principal components analysis which resulted in the retention of three factors which explained 87% of the climatic variability. These factors were then used in a k-means cluster analysis which objectively creates groups of grid cells with like characteristics. The most robust and optimal solution was found when $k = 16$, producing 16 spatially contiguous regions (climate zones). Finally, a method for the objective identification of representative daily meteorological series for each of the zones for use in pesticide fate modelling was outlined and the representativeness of the series associated with each zone was assessed.

The resulting FOOTPRINT climate zones are physically plausible in terms of the input variables used in the analysis and in terms of the physical mechanisms which underpin the European climate. The final climatic zonation bears some similarities to previous classifications, particularly over eastern Europe, but provides a greater degree of discrimination over the maritime climates of north-western Europe, largely on the basis of highly heterogeneous precipitation characteristics. This is most likely due to the innovation of introducing daily precipitation extremes as input variables as opposed to previous classifications based solely on annual means. The consideration of extreme statistics provides the FOOTPRINT climate zonation scheme with increased robustness for pesticide fate modelling, where extreme events and their relation to critical

Fig. 7. The FOCUS (1995) climatic classification for Europe. The climatic divisions are Northern Europe, maritime (1), North-West Europe, strong maritime (2), Northern Central Europe, maritime/continental (3), West Central Europe, maritime/continental (4), Central Europe, low mountains (5), Northern Alps (6), Southern Europe, high mountains (7), Western and South-West Europe, coastal (8), Southern Europe, low mountains (9), Southern Europe, without maritime (10).

pesticide application windows is known to drive losses of pesticides to depth and tile drains. The final 16 FOOTPRINT climatic zones do not represent a detailed climatic classification of Europe but provide a manageable classification, of practical use to pesticide fate modellers.

In future, the availability of a gridded daily climatology for Europe provided by the EU FP6 ENSEMBLES project (Mark New, personal communication) will offer the potential to produce a more detailed examination across Europe, providing the potential to apply models on a more localised scale. However, notwithstanding the availability of such data, such an approach would require a substantial increase in computational modelling resources. The discretization of Europe into a limited number of climate zones using robust, objective methods provides a significant advance on previous classifications which rely on the subjective selection and combination of climate statistics. The FOOTPRINT climatic zones, which cover the EU25 and the candidate countries, provide a state-of-the-art classification of European climate suitable for use in pesticide fate modelling, forming the basis of subsequent modelling activities within the FOOTPRINT project.

Fig. 8. The FOCUS (1997a) climatic classification for Europe. Scenarios are defined by annual precipitation excess and annual average temperature. The divisions are <400 mm, 0–5 °C (1), >400 mm, 0–5 °C (2), <400 mm, 5–10 °C (3), >400 mm, 5–10 °C (4), <400 mm, 10–15 °C (5), >400 mm, 10–15 °C (6), <400 mm, 15–20 °C (7), >400 mm, 15–20 °C.

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