

# **The generation of monthly gridded datasets for a range of climatic variables over the United Kingdom**

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## **Abstract**

Monthly or annual 5 km x 5 km gridded datasets covering the UK are generated for the 1961–2000 period, for 36 climatic parameters. As well as the usual elements of temperature, rainfall, sunshine, cloud, wind speed, and pressure, derived temperature variables such as growing season length, heating degree days, and heat and cold wave durations, and further precipitation variables such as rainfall intensity, maximum consecutive dry days, and days of snow, hail and thunder, are analysed.

The analysis process uses geographical information system (GIS) capabilities to combine multiple regression with inverse-distance weighted interpolation. Geographic and topographic factors such as easting and northing, terrain height and shape, and urban and coastal effects are incorporated either through normalisation with regard to the 1961–1990 average climate, or as independent variables in the regression. Local variations are then incorporated through the spatial interpolation of regression residuals.

For each of the climatic parameters, the choice of model is based on verification statistics produced by excluding a random set of stations from the analysis for a selection of months, and comparing the observed values with the estimated values at each point. This gives some insight into the significance, direction, and seasonality of factors affecting different climate elements. It also gives a measure of the accuracy of the method at predicting values between station locations.

The datasets are being used for the verification of climate modelling scenarios and are available via the internet.

**Keywords:** climate; United Kingdom; spatial interpolation; regression; gridded datasets; GIS

## **1. Introduction**

The Met Office has a historical database containing observations of weather elements. These observations come from an irregularly spaced and gradually evolving network of meteorological stations across the United Kingdom.

The aim of the work described in this paper is to add value to these data by producing a consistent series of climatic statistics which enables comparisons to be made across space and time. In order to do this, methods have been developed, following on from those used by Lee et al. (2000), using GIS technology, to create gridded datasets from the point data.

There is an increasing demand for gridded datasets of climate variables from fields such as hydrology, forestry, ecology, agriculture, climate change research, and climate model

verification. Consequently there have been numerous attempts made at spatial interpolation, using a variety of methods.

Climate data are often strongly related to topographic and geographic variables, and it is important to incorporate these factors. This can be done using multiple regression techniques (Agnew and Palutikof, 2000; Ninyerola et al., 2000), or by normalising the monthly values with respect to the long-term average (e.g. 1961–1990) climate (Brown and Comrie, 2002; New et al., 1999). The increase in accuracy gained by using high resolution climatology for temperature is demonstrated by Willmott and Robeson (1995). Spatial interpolation can then be used, either on the regression residuals to account for unexplained variance or on the monthly anomalies. The methods described in this paper include normalisation, regression and interpolation for many of the climate variables, with the regression modelling general circulation patterns and trends particular to each month, and the interpolation accounting for local variations.

Available interpolation methods include geostatistics e.g. kriging, inverse-distance weighting (IDW), and smoothing splines. Kriging has been used for the interpolation of temperature and precipitation regression residuals across a wide region (the Mediterranean) by Agnew and Palutikof (2000), while Holdaway (1996) used residual kriging for the interpolation of temperature in a forest area, and Goovaerts (2000) used co-kriging to incorporate elevation into the mapping of rainfall. Brown and Comrie (2002) used ordinary kriging for the interpolation of monthly temperature anomalies, but preferred IDW for precipitation. A distance-weighted method was also used by New et al. (1999) for interpolating monthly global climate anomalies, and by Willmott and Robeson (1995). Splines have been used by Vicente-Serrano et al. (2003) for annual precipitation and temperature in a small area, and Jarvis and Stuart (2001) for daily temperature over England and Wales, in comparison with other methods.

Spline functions are likely to generate unrealistically smooth surfaces given the range of variables and environments covered by this work. Kriging will give unbiased, optimal estimates based on the spatial correlation between values, but may produce too smooth a surface (Brown and Comrie, 2002), and is a computer intensive method. Inverse-distance weighting was chosen for this work due to the fact that it captures local variations well, and draws exactly to values at co-located grid points. It is also easy to implement, which is important given the size of this task, and able to give good results for a large range of different variables.

Most authors have only been concerned with temperature and/or precipitation, although New et al. (1999) created global gridded monthly datasets for a range of seven variables. The work described here is notable for the wide range of climate elements analysed: gridded data sets at 5 km by 5 km resolution over the whole of the United Kingdom have been produced for 36 monthly or annual climate variables, for the period 1961–2000. This is a total of over 14,000 grids, each comprising 9,700 values. The start date of 1961 was chosen because there is a significant increase in the availability of digitised data from this point. An extension of the series back beyond 1961 is planned for some key variables.

Twenty-four of the climate variables have been produced with funding from the UK Climate Impacts Programme (UKCIP), and are freely available for research purposes from the following web address: <http://www.metoffice.gov.uk/research/hadleycentre/obsdata/ukcip/index.html>.

The data sets are already being used for a wide variety of research purposes, including the verification of climate change scenarios, ecological and hydrological modelling, agricultural studies, and energy resource assessments. They have also been used for the creation of areal climatic series against which the recent climate is routinely compared.

Section 2 of this paper describes the station data used, and section 3 describes the methods used in the generation of gridded datasets, and the procedure used to optimise these methods.

Section 4 covers verification testing and errors associated with the methods, section 5 gives the regression model and interpolation settings used for each climate variable, and section 6 goes on to give some examples of the final datasets and their applications. Finally, section 7 gives some concluding remarks and areas for further work.

## **2. Data**

The density of the station network varies between elements, from an average over the 40 year period of one station per  $59 \times 59 \text{ km}^2$  over the UK for pressure, cloud and wind (70 stations), to  $29 \times 29 \text{ km}^2$  for sunshine (290 stations),  $24 \times 24 \text{ km}^2$  for hail, thunder, and grass minimum temperature (430 stations),  $21 \times 21 \text{ km}^2$  for maximum and minimum temperature (540 stations), and  $7 \times 7 \text{ km}^2$  for rainfall (4400 stations).

The density of the network varies gradually throughout the period 1961 to 2000, as can be seen in Figure 1. The density of the rainfall network increases to a peak in 1974 before decreasing gradually. For temperature, the density is quite stable, peaking in 1994, and for sunshine the peak is in 1970, followed by a steady decline in station numbers.

There are considerable spatial variations, with comparatively sparse networks in certain areas, especially those which are sparsely populated, e.g. the Scottish Highlands. Figure 2 shows an example of the network of stations used, in this case the temperature network (climate stations reporting daily) for January 2000, and the subset of stations which also recorded pressure (synoptic stations reporting hourly).

The daily observations made at these stations have passed through a rigorous quality control procedure, with substitutions made for poor quality and some missing data. Basic range and consistency checks have been applied to hourly data. These data have then been used to

calculate monthly and annual climate averages, totals, and extremes for a range of variables. These statistics have been loaded to an Oracle database of climate statistics and used as the source of input data for the gridding process.

The annual statistics were derived from temperature (T) or rainfall data using the following definitions:

- Growing Season Length = period (days) bounded by daily  $T_{\text{mean}} > 5\text{ }^{\circ}\text{C}$  and  $< 5\text{ }^{\circ}\text{C}$  (after 1<sup>st</sup> July) for  $\geq 6$  days.
- Heating Degree Days =  $\sum 15.5 - \text{daily } T_{\text{mean}}$  for  $T_{\text{mean}} < 15.5\text{ }^{\circ}\text{C}$ .
- Growing Degree Days =  $\sum \text{daily } T_{\text{mean}} - 5$  for  $T_{\text{mean}} > 5\text{ }^{\circ}\text{C}$ .
- Heat Wave Duration =  $\sum$  days with daily  $T_{\text{max}} - 1961\text{-}1990$  daily normal  $> 3\text{ }^{\circ}\text{C}$  for  $\geq 6$  consecutive days.
- Cold Wave Duration =  $\sum$  days with  $1961\text{-}1990$  daily normal - daily  $T_{\text{min}} > 3\text{ }^{\circ}\text{C}$  for  $\geq 6$  consecutive days.
  - Heat Wave and Cold Wave durations are calculated separately for summer and winter half-years.
- Consecutive Dry Days = Maximum number of consecutive days with rainfall  $< 0.2\text{ mm}$ .
- Rainfall Intensity = Total rainfall on Raindays  $\geq 1\text{ mm}$  / Number of Raindays  $\geq 1\text{ mm}$ .

For rainfall variables, stations were not used for gridding if they have any missing data in the month, because of the high daily variability of rainfall. This does not greatly affect the high density of the rainfall network, and ensures that the rainfall data are unbiased. For other elements, station months with up to two missing days were used in the analysis.

All available monthly data is used in the analysis in order to make maximum use of the information available and ensure that the most accurate possible representation of the climate

can be made for each month. Thus, unlike some studies where a constant set of long-period stations is used (e.g. Ninyerola et al. 2000), this study also makes use of data from stations with short and intermittent records. Consequently, the network of stations used changes slightly each month, and the methods used are designed in order to minimise the impact of these changes on the consistency of the datasets through time.

### **3. Methods**

#### *3.1 Gridding*

The production of the monthly and annual grids is carried out using functionality programmed into the ESRI ArcView 3.2 GIS. Code has been written in Avenue (the ArcView scripting language) and Visual Basic that allows the user to take a set of irregularly spaced point data (i.e. station observations) and create a regular grid of values from them. It is planned to migrate to ArcGIS 9 for the next version.

The method is a two-stage process of multiple regression of the climate variable (which may be normalised first) with geographic factors as the independent variables, followed by interpolation of the model residuals. The regression surface and the interpolated residual surface are then added together to get the final gridded datasets, which are de-normalised if necessary.

Many meteorological elements exhibit dependencies on geographic features, especially topography. Two options are available for reducing or removing geographic effects prior to interpolation, either or both of which can be used.

- normalisation i.e. either subtracting the long-term average (LTA) from the raw values, or dividing the raw values by the LTA (for rainfall and sunshine);

- conversion to regression residuals i.e. creating a model of geographic effects using regression analysis and then subtracting the regression estimate from the raw values.

### *3. 2 Regression*

There are a range of geographic and topographic quantities available to include as independent variables in the regression analysis, as follows:

- Easting and northing (to capture spatial variations);
- Terrain elevation (to capture altitude effects);
- The mean altitude over a 5 km radius centred 10 km to the north, east, south and west of the station, or alternatively the mean altitude within a 5 km radius of the station (to capture terrain shape effects);
- The percentage of open water (including lakes as well as sea) within a 5 km radius of the station (to capture coastal effects);
- The percentage of urban land use within a 5 km radius of the station (to capture urban effects). This is derived from land use dataset from the mid 1970's at 100 m x 100 m resolution.

Several different methods were tested to represent the shape of the terrain surrounding each point. Slope and aspect and the mean difference in altitude compared with the surrounding area in all directions, generally gave less significant results. The inclusion of altitudes offset in four directions allows the aspect and exposure of the location to be taken into account, and the parameters can vary according to prevailing conditions. Different radii were considered, but the 5 km radius at 10 km distance gave the best results in most cases. Different radii were also considered for the sea and urban factors.

### 3. 3 Interpolation

Two versions of inverse-distance weighted (IDW) interpolation were used to interpolate the regression residuals onto a regular grid;

- standard IDW averaging;
- custom IDW averaging (uses a modified weighting function with an option not to go to infinity when station and grid point coincide, and includes an adjustment for variations in station density);

The custom method was developed to overcome perceived deficiencies in the standard approach. However, both methods were available and the final choice was based objectively on the verification statistics. In both cases, the value for each grid cell is calculated as a weighted average of values from surrounding stations. The standard and custom versions of the IDW method use different methods to determine the radius within which stations are used. The standard version has a minimum sample of twelve points, and the radius parameter  $r$  is extended to meet this requirement if necessary. The custom version takes all stations within the radius  $r$ . The interpolated value at location  $(x,y)$  is given by:

$$(1) \quad F(x, y) = \frac{\sum_{i=1}^n w_i f_i}{\sum_{i=1}^n w_i}$$

where  $n$  is the number of stations in the set,  $f_i$  are the data values at the stations, and  $w_i$  are the weight functions assigned to each station, where;

$$(2) \quad w_i = \frac{u_i}{d_i^p}$$

or, if infinite weights are not selected;

$$(3) \quad w_i = \frac{u_i}{1 + (d_i/m)^p}$$

where  $p$  is the power parameter,  $d_i$  is the distance from the station to the interpolation grid centre,  $m$  is a scaling parameter, and  $u_i$  is a density weighting parameter.

In each case the user can control the parameters of the interpolation e.g. the power of the IDW relationship, the radius, and the scaling parameter, as well as whether to include the density weighting function, and whether to allow infinite weights. If the density function is not used then  $u_i = 1$ , and otherwise it is obtained from a density surface created using an Avenue function which adds together kernel density functions (extending to radius  $r$  km) fitted over each station.

$$(4) \quad u_i = \frac{1}{1 + \sum_{i=1}^n k_i}$$

where the  $k_i$  are the values of the kernel function from each station.

### 3.4 Optimisation

In order to select the regression model and interpolation method to be used for each climate variable, several different methods were tested. The initial hypothesis was a model based on prior knowledge of the topographical and geographical factors affecting each climate variable, and the statistical distribution of the variable. Subsequent test runs were altered by adding or removing regression variables, changing the interpolation settings, or changing the input data (actual or anomaly).

The optimisation analyses were carried out with a 10% random sample of stations excluded from the analysis as if they were missing. Estimated values for these stations were then interpolated from the final grid, and compared with the corresponding observed values. Each test was made using a sample of twelve randomly-selected months (one January, one February etc.) between 1961 and 2000. Annual statistics used six randomly-selected years.

Various statistics were automatically calculated, both for the set of withheld stations, and for the analysis stations. These were used to compare the analysis profiles, with particular importance attached to the root mean square error (RMSE) of the verification stations (the error of the predicted value at the station location from the observed value at the station). The mean error (ME) was used to detect any bias in the estimates.

#### **4. Verification Testing**

##### *4.1 Choice of Methods*

Long term average grids for the 1961–1990 period were available for some variables (the methods used to create these are described by Perry and Hollis (submitted for publication), and for these it was generally found to be preferable to normalise the data with respect to the 1961–1990 average prior to its analysis. This removes all of the long-term patterns captured by the climate grids, including altitude dependency. It was especially important where the variable showed complex geographical patterns such as rainfall. For some variables, LTA grids were not yet available, and for others normalisation was not necessary: in these cases, actuals were analysed.

Regression was always used, even when the data had first been normalised. This is because there are usually broad spatial trends even in the normalised monthly data which can be

removed by regression on latitude and longitude. These trends are caused by monthly variations in the dominant circulation types and patterns of prevailing weather conditions affecting the UK. There may also be monthly variations in the strength and pattern of other geographic effects. Thus the quantity which was interpolated was residuals obtained from a regression analysis of either actual or normalised data.

#### *4.2 Regression Model*

Cross-polynomial terms in easting and northing were used for all variables to model the pattern of spatial variation over the UK. For elements with a sparse network of stations, a low power of 1 (3 parameters) or 2 (5 parameters) was used, to avoid unrealistic extrapolation of the surface. Terms up to a power of 3 (10 parameters) were used when greater flexibility in the spatial trend surface was required, e.g. for rainfall and temperature.

When normalised data was used, any additional terms were often of little significance, because most of the topographical variations were being described through the climate average. It was difficult to determine whether correlations between topographical factors and temperature anomalies had any physical basis, or were spurious effects. It was decided for the most part (rainfall, days of rain, pressure, thunder and maximum and minimum temperature) to use only the spatial terms. For 'days of frost' however, except for the summer months, altitude, coastal and urban effects were found to reduce the grid error at test stations by a small amount (about 0.1 days). For sunshine, the coastal effect was used for the summer months.

The elements for which actual data was used have more intuitive regression models. Growing season length, and growing degree days have a strong altitude dependency, and quadratic altitude terms were used. Heat wave and cold wave durations have especially strong coastal effects.

Topographic effects on cloud cover were difficult to model due to the lack of high-altitude stations. However, altitude was shown to make a significant improvement to the model in summer and autumn months, and the coastal effect was important except for in the summer months.

Altitude and terrain shape variables were unsurprisingly very important for days of snow lying and falling, as well as for rainfall intensity and the greatest annual 5-day rainfall total.

The independent variables used in the regression model for each element, and an indication of whether the data was normalised first, can be seen in Table 1.

#### *4.3 Interpolation Methods*

The power of the weighting function with distance has a significant effect on the result: decreasing the power has the effect of smoothing the interpolation surface around stations with high residuals, while increasing the power brings the surface closer to the actual station values. Inverse distance cubed was used as the weighting function for most variables, as this gave a good degree of closeness to the observed data, while taking surrounding values into account. Cloud cover, and maximum, minimum, mean, and grass minimum temperature were analysed using a power of two, as for these variables the use of the squared weighting gave a slightly lower grid RMSE for the verification stations, while increasing the grid RMSE for the analysis stations, compared with a power of three.

The radius was set at between 100 and 150 km for most variables. Precipitation variables, with their higher spatial variability, were analysed using a lower radius of between 50 and 75 km. The test grid RMSE was fairly insensitive to small changes in radius. All stations within the radius have been used regardless of their geographical location because the normalisation /

regression should remove the main climatological variations to leave a smoothly varying surface.

The custom IDW method gave lower test grid RMSE values than the standard method for most temperature variables, as well as wind speed, pressure and thunder, while the standard method performed better for other elements, including precipitation and sunshine. The density weighting function was used with the custom method, but did not have a significant impact on the results. Infinite weighting at station locations was only removed for maximum, minimum and mean temperature; for other variables, the surface was forced to pass through the station values (depending on how close the station location is to the grid centre).

#### *4.4 Grid Accuracy*

The verification statistics also give a good indication of the accuracy of the gridding process at estimating values of each climate variable at locations where we do not have observed data.

Table 2 shows the average value of the RMS error of the grid estimates for test stations, using the best method for each variable. It also shows variation across the test period, showing especially the strong seasonality present in some variables. The errors also vary spatially over the UK, with higher errors in areas of sparser station coverage and areas of complex terrain. For maximum temperature, the RMSE for test stations in North Scotland is 1.3 deg C compared with the average of 0.7 deg C. South-east England and the Midlands have the lowest errors of 0.3 and 0.4 deg C respectively. For precipitation, north and west Scotland have the highest RMSE of 30 mm, while East Anglia and south-east England have an RMSE of about 9 mm.

The RMSE has also been expressed as a percentage of the range of grid values over the UK, averaged across the test months/years. Using this measure, the lowest errors are for mean sea level pressure, heating degree days, and mean temperature. These are all fairly smoothly varying quantities, and the analysis is able to closely predict values at points between stations.

Precipitation also has a low percentage error of 3.6, although this may be partly due to the highly skewed distribution of values inflating the range.

Heat wave and cold wave duration, and days of hail, thunder, and ground frost were especially difficult to model, with a high degree of spatial variability which was not covered by the geographical or topographical variables used in the regression.

## **5. Gridding results**

### *5.1 Quality Checking*

The regression residuals from the analysis were inspected, and outliers for each variable were investigated further by inspection of the relevant maps. Climatological knowledge was used to assess whether monthly input station values were dubious, based on surrounding station values and the appearance of the maps (looking for bulls-eyes for example). Dubious data were investigated further by looking at the daily data from which the monthly values were derived. Erroneous data were thus identified and removed, with the affected months / variables being re-run. A sample of the final maps was inspected to check that the patterns and levels of the variables fitted with our knowledge of the UK climate.

### *5.2 Regression Results*

Table 1 shows the data and regression variables used in the analysis of each climatic parameter (in addition to the spatial terms, easting and northing, which are used for all elements). It also shows the average  $R^2$  values for each climatic parameter over the 40-year period, indicating how much of the variation in the actual or anomaly data is explained by the variables used in the regression analysis. This will generally be lower when anomaly data is used, because normalisation by the long term average removes much of the explainable variation.

The highest  $R^2$  values were achieved for mean sea level pressure, daytime maximum and minimum temperatures, and heating and growing degree days, with over 90% of the variation explained by the model. These elements also had low verification RMSE as a percentage of the range, and are smoothly varying or have strong geographic dependencies. The lowest  $R^2$  values were for ground frost and thunder (from anomaly data), and hail and cold wave duration (from actual data). Ground frost data is subject to inconsistencies caused by different measuring periods (0900 to 0900 or dusk to 0900) and soil type. Along with cold wave duration, it is also a 'days exceeding a threshold' variable, which is subject to increased random variations. Days of hail and thunder are also difficult to model as they occur in small quantities, and without a strong geographical pattern.

## **6. Examples of Output and Applications**

The final datasets were converted to ASCII grid format and those for 24 variables were made available on the internet. Figure 3 shows some examples of the maps produced. Figure 3a shows the number of days of hail for March 1995 (a month when hail was especially common) and is an example of a variable which was difficult to model; there are apparently random variations over England and Wales, with very high levels of hail in the western and northern fringes of Scotland, but low levels over the rest of Scotland. Figure 3b, a map of rainfall intensity for 1978, shows a similar pattern to that of rainfall, with a strong orographic effect. Variations in annual heating degree days (Figure 3c is the map for the year 2000) were very well modelled, and the strong altitude effect as well as the urban effect for London and Manchester can be seen. The strong coastal effect can be seen in the temperature range map for August 1995 (Figure 3d). This month had large temperature ranges, especially in central and southern England.

For each month and variable, the grid values within each county, climate district and country of the UK, as well as the UK as a whole, were averaged. The climate districts divide the UK into ten regions, e.g. south-west England and south Wales, based on their climatological characteristics. These areal averages provide a series against which the most recent month's weather can be put into context. Looked at over the period from 1961 onwards, they can also provide an interesting summary of temporal patterns in the climate, including seasonality, trends, and random variability. Figures 4 and 5 show a time series of growing season length and rainfall intensity by country. Linear regression models for each of the climate districts show increasing trends in growing season length and rainfall intensity, with increases in growing season length over the 40-year period varying from 0.4 days per year (N Scotland) to 1.0 days per year (SE England), and increases in rainfall intensity between 0.002 mm per rainday per year (NW England and N Wales) and 0.026 per rainday per year (W Scotland). The graphs show a high degree of year-to-year variability, especially for growing season length, although there has been a fairly steady increase since the particularly short growing season of 1979.

The range of variables gives a fairly complete picture of the climate. Patterns of variables which are not often analysed, such as cloud cover, humidity, hail, and temperature range can be seen. Temperature indices such as growing season length and growing and heating degree days give objective assessments of the impacts of climate change on areas such as agriculture, ecology and energy use. Changes in the distribution of rainfall amounts, extremes, and intensity can be investigated with impacts for flood risk. This paper does not attempt to provide a thorough analysis of trends and patterns in the datasets, but further analysis is being undertaken and it is hoped that this will be presented in a future paper.

## **7. Conclusions**

Gridded datasets can be created from station data and grids of explanatory variables, for a wide range of climate variables, using the described methodology which uses GIS capabilities to combine multiple regression and inverse-distance weighted interpolation.

The values of climate variables at locations between observing stations have been estimated to a good degree of accuracy, producing detailed and representative maps of the UK climate. This is possible due to the use of all available station data, providing a dense network of measurements, together with the use of detailed long-term climatology and digital elevation model. Spatial and temporal variability and trends in the UK climate over the last 40 years can be investigated using the results of the gridding, which provide a consistent set of data.

The accuracy varies, however, and is dependent on the nature of the variable, and the density and representativity of the station network. Errors will be highest in areas of sparse station coverage, particularly the Scottish Highlands which are also areas of complex mountainous terrain. The average proportion of variance in the data explained by the regression models varies between 21% (normalised days of ground frost) and 95% (mean sea level pressure). The verification RMSE as a percentage of the range of values is also a useful guide to the level of error, and it ranges from 2.7% (mean sea level pressure) to 19.3% (cold wave duration). It is below 10% for 29 of the 36 variables.

There may be potential for improving the results further, for example by including further factors into the regression model. Johansson and Chen (2003) and Kyriakidis et al. (2001) include predictors to model interaction with the lower atmosphere, such as wind and humidity, for precipitation mapping. Daly et al. (2003) incorporate expert knowledge into their regression model. The use of a locally varying (Price et al., 2000) or geographically-weighted regression model (used for precipitation by Brunson et al., 2001) also merits further investigation. Localised effects on the climate such as frost hollows, and effects caused by soil type and

forests, have not been taken into account. Future work may include investigating the impact of incorporating these and other effects into the model, through the development and use of further gridded independent variables. Agnew and Palutikof (2000) and Brown and Comrie (2003) used stepwise regression to select from a large range of variables, which would allow the regression model to vary between months.

The gridded series are being extended backwards in time to 1914 for rainfall and temperature, and to 1929 for sunshine through a programme of digitization of monthly station data.

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Figure 1: The changing density of the station network from 1961 to 2001, for precipitation, temperature and sunshine.

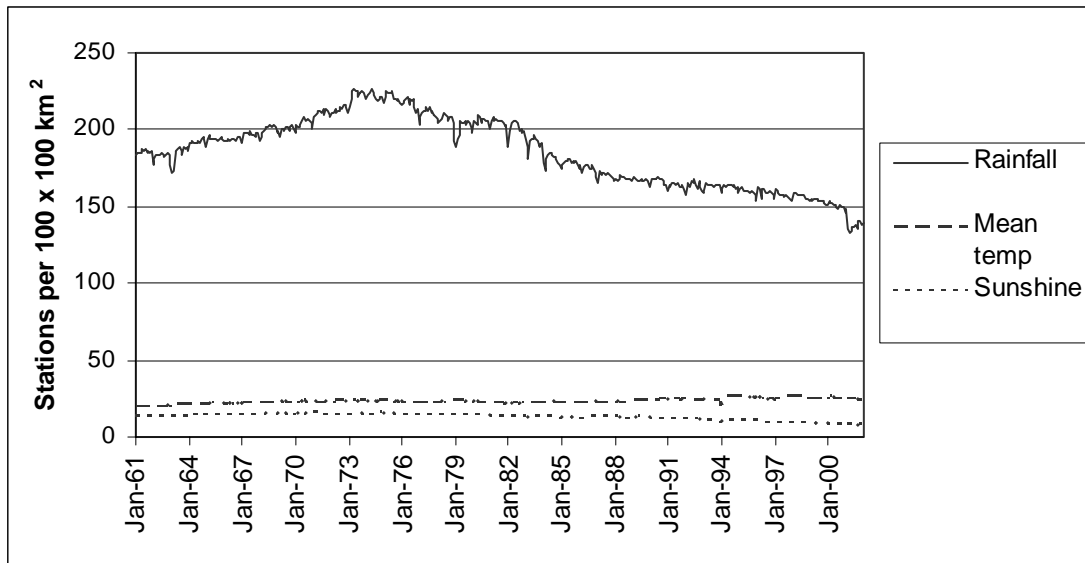


Figure 2: Spatial distribution of Temperature and Pressure stations, January 2000

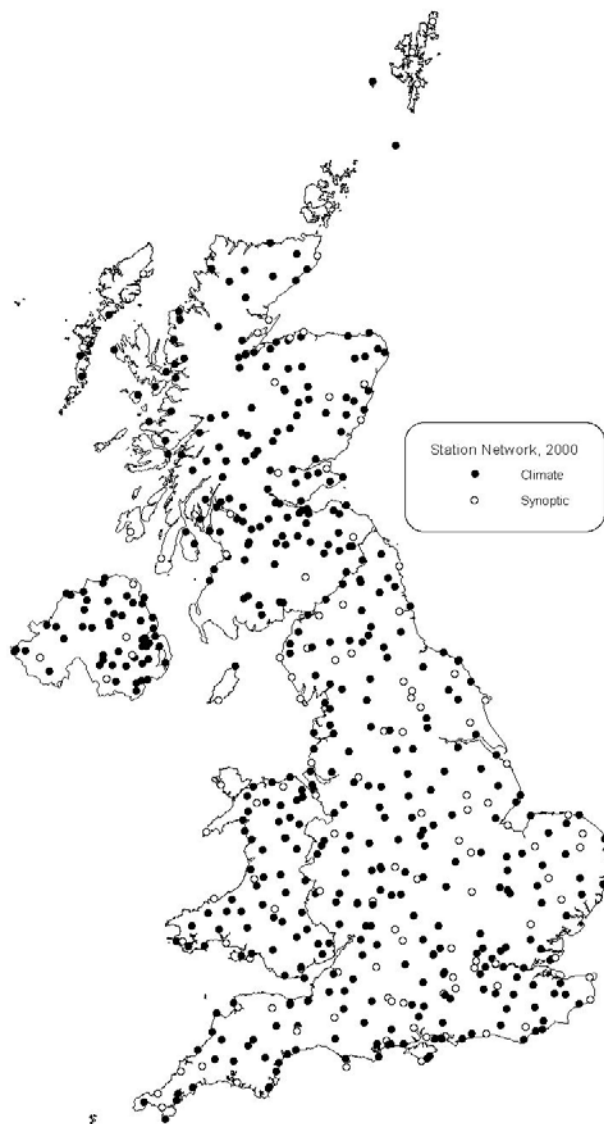


Figure 3: Examples of maps produced; a) Days of Hail for March 1995, b) Rainfall Intensity (mm per rainday) for 1978, c) Mean Diurnal Temperature Range (deg C) for August 1995, d) Heating Degree Days for 2000.

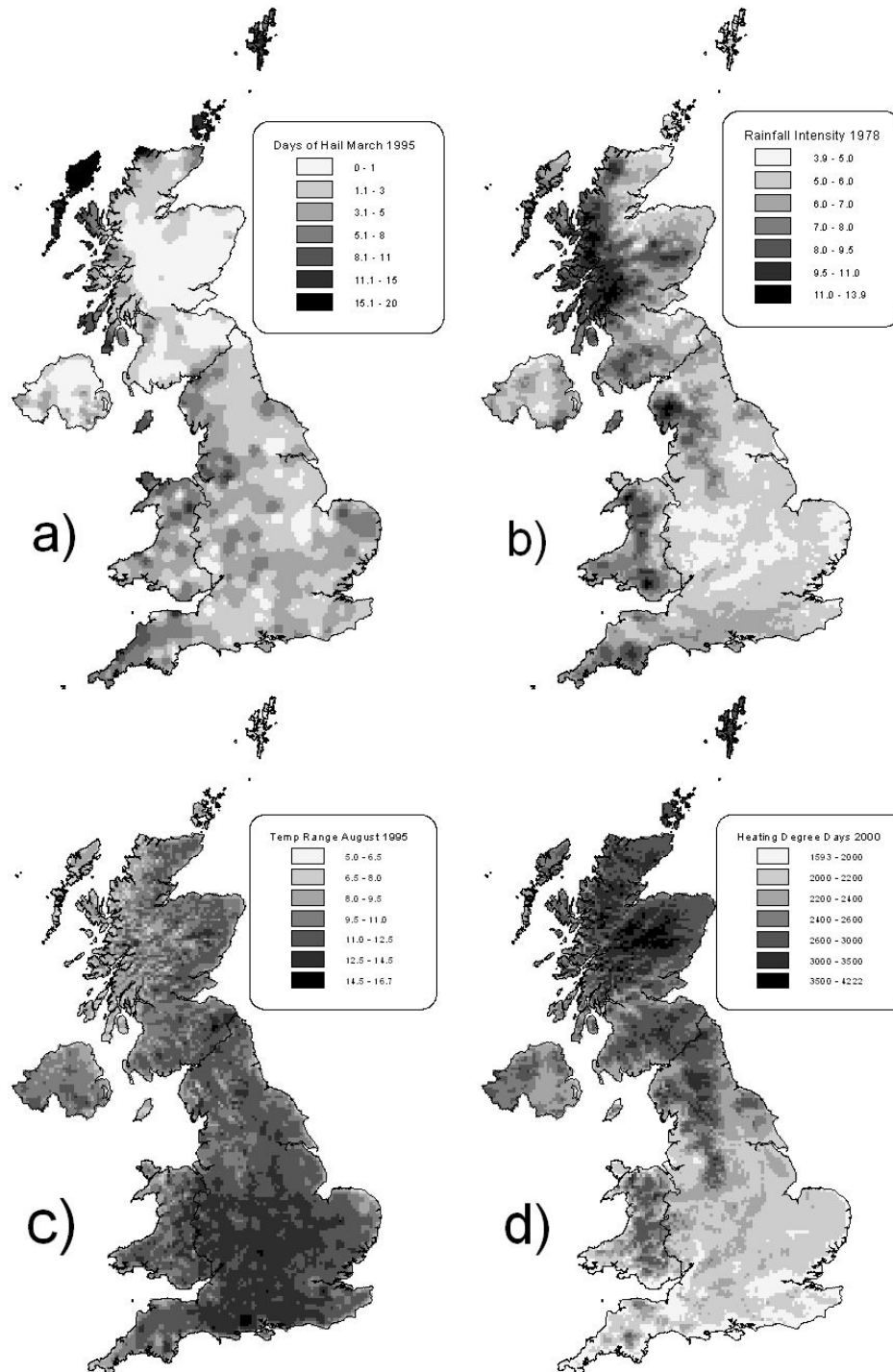


Figure 4: Country averages of Growing Season Length; time series for 1961–2000 period.

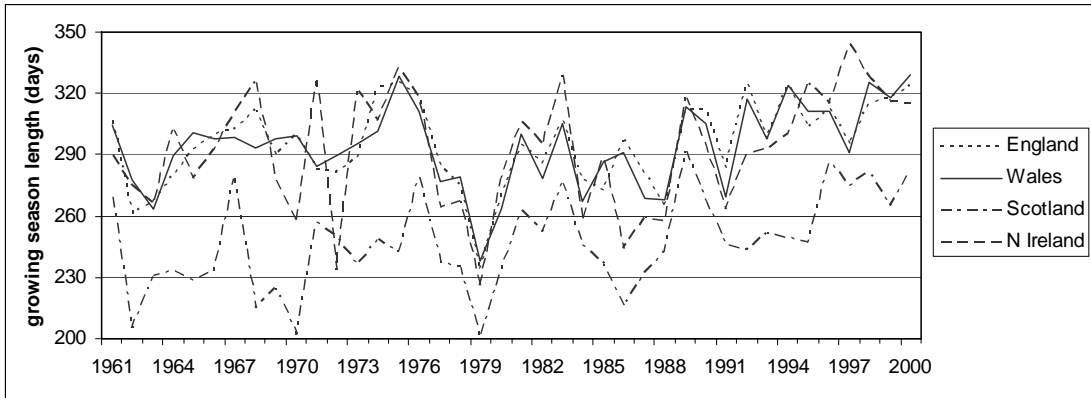


Figure 5: Country averages of Rainfall Intensity; time series for 1961–2000 period.

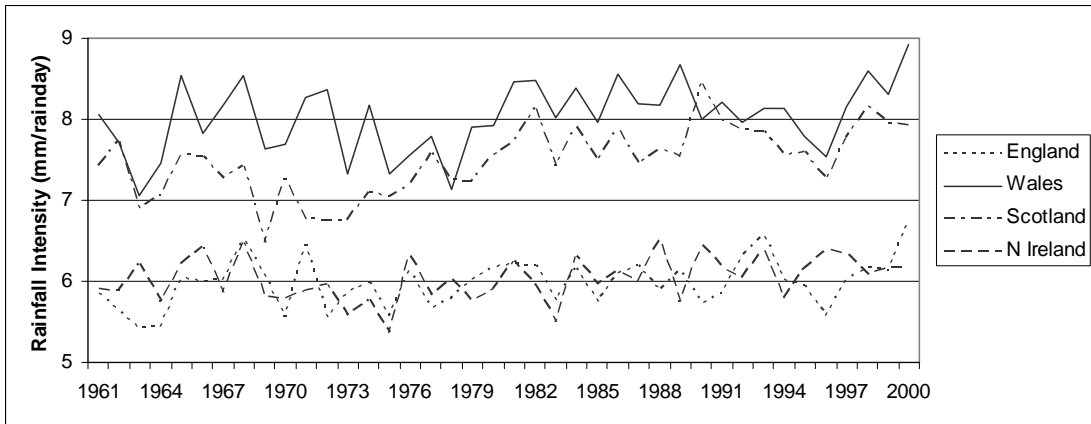


Table 1: Regression Variables used, and average R<sup>2</sup> values.

Element	1961-00 average R <sup>2</sup>	Data analysed	Altitude	Terrain Shape	Coast	Urban
<b>Monthly</b>						
Minimum Temperature	0.39	Anomaly				
Mean Temperature	0.57	Anomaly	*	*		
Maximum Temperature	0.53	Anomaly				
Days of Ground Frost	0.21	Anomaly	*	*	*	*
Days of Air Frost	0.31	Anomaly	*	*	*	*
Sunshine	0.44	Anomaly			*	
Wind Speed	0.82	Actual	*	*	*	
Precipitation	0.44	Anomaly				
Days of rain >= 0.2 mm	0.57	Actual	*	*		
Days of rain >= 1mm	0.42	Anomaly				
Days of heavy rain >= 10mm	0.40	Actual	*	*		
Hours of relative humidity > 95%	0.46	Actual	*		*	
Vapour Pressure	0.81	Actual	*		*	
Mean Sea Level Pressure	0.95	Actual				
Cloud Cover	0.58	Actual			*	*
Days of Snow Falling	0.36	Anomaly	*	*		
Days of Snow Lying	0.48	Actual	*	*		
Daytime maximum temperature	0.93	Actual	*	*	*	*
Daytime minimum temperature	0.92	Actual	*	*	*	*
Night-time maximum temperature	0.83	Actual	*	*	*	*
Night-time minimum temperature	0.87	Actual	*	*	*	*
Concrete minimum temperature	0.74	Actual	*		*	
Grass minimum temperature	0.28	Anomaly	*		*	
Days of Concrete Frost	0.47	Actual	*		*	
Mean Diurnal Temp Range	0.64	Actual	*	*	*	*
Days of Thunder	0.22	Anomaly				
Days of Hail	0.24	Actual				
<b>Annual</b>						
Extreme Temperature Range	0.66	Actual	*	*	*	
Growing Season Length	0.68	Actual	*		*	
Heat wave Duration	0.41	Actual			*	*
Cold wave Duration	0.25	Actual	*	*	*	
Heating Degree Days	0.92	Actual	*	*	*	*
Growing Degree Days	0.93	Actual	*	*	*	*
Greatest 5-day Rainfall	0.46	Actual	*	*	*	
Rainfall Intensity	0.54	Actual	*	*		
Consecutive Dry Days	0.44	Actual	*		*	

Table 2: Error Statistics from the Verification Stations

Element	RMS Error at Verification Stations	Variation across test period			Average range of grid values over UK	RMSE as a percentage of the range of values
		Standard Deviation	Min	Max		
Monthly (12 test months)						
Mean Daily Minimum Temperature (deg C)	0.45	0.09	0.3	0.6	9.4	4.8
Mean Temperature (deg C)	0.36	0.04	0.3	0.45	10.4	3.5
Mean Daily Maximum Temperature (deg C)	0.66	0.12	0.38	0.79	12.2	5.4
Days of Ground Frost	2.24	0.78	0.7	3.4	17.4	12.9
Days of Air Frost	1.4	1.12	0	3.2	15.2	9.2
Sunshine (hours per day)	0.33	0.1	0.2	0.54	4.7	7.0
Mean Wind Speed (knots)	1.41	0.44	1.0	2.2	25.7	5.5
Total Precipitation (mm)	16	4.9	11	27	443	3.6
Days of Rain >= 0.2 mm	1.7	0.3	1.2	2.1	20	8.5
Days of Rain >1 mm	1.3	0.15	1.1	1.5	21.2	6.1
Days with Heavy Rain (>10 mm)	0.78	0.22	0.3	1.2	12.5	6.2
Hours of Relative Humidity > 95%	48	22	17	98	536	9.0
Vapour Pressure (HPa)	0.26	0.13	0.08	0.53	5.2	5.0
Mean Sea Level Pressure (HPa)	0.27	0.14	0.16	0.67	9.9	2.7
Cloud Cover (%)	2.69	0.86	1.6	4.6	40.7	6.6
Days of Snow Falling (not inc. Jul - Aug)	1.35	1.3	0	3.9	13.8	9.8
Days of Snow Lying (not inc. Jun - Sep)	1.1	1.1	0	2.7	15.3	7.2
Daytime maximum temperature (deg C)	0.47	0.15	0.26	0.7	12.0	3.9
Daytime minimum temperature (deg C)	0.47	0.14	0.31	0.79	11.2	4.2
Night-time maximum temperature (deg C)	0.75	0.35	0.33	1.57	10.9	6.9
Night-time minimum temperature (deg C)	0.61	0.19	0.37	0.92	10.3	5.9
Concrete minimum temperature (deg C)	0.65	0.19	0.43	1.02	10.7	6.1
Grass minimum temperature (deg C)	0.85	0.17	0.46	1.05	9.8	8.7
Days of Concrete Frost (not inc. July)	1.8	1.3	0.3	3.6	16.1	11.2
Mean Diurnal Temp Range (deg C)	0.66	0.17	0.42	0.99	6.9	9.6
Days of Thunder	0.48	0.41	0.08	1.43	4.0	12.0
Days of Hail	1.3	0.9	0.2	3.5	7.6	17.1
Annual (6 test years)						
Extreme Temperature Range (deg C)	2.15	0.51	1.6	2.7	23.6	9.1
Growing Season Length (days)	19.5	6.2	11	28	270	7.2
Heatwave Duration (days) [4 per half-year]	3.6	1.4	1.8	5.9	29.1	12.4
Coldwave Duration (days) [4 per half-year]	2.9	1.7	0	5.8	15.0	19.3
Heating Degree Days	106	16	80	125	3157	3.4
Growing Degree Days	100	10	87	116	2108	4.7
Greatest 5-day Rainfall (mm)	12.8	2.7	9.2	16.1	250	5.1
Rainfall Intensity (mm per rain day)	0.53	0.11	0.44	0.75	12.7	4.2
Consecutive Dry Days	3	1.2	1.4	5	29	10.3