Appendix B – Modelling the impact of climate change on soils using UK climate projections

Work Package 3,4 & 5
Defra Project SP0571

Use of 'UKCIP08 Scenarios' to determine the potential impact of climate change on the pressures/threats to soils in England and Wales

Work Package 3-5

David Cooper¹, Richard Gooday², Paul Hallett³, Brian Irvine⁴, Katrina Morrow², Ragab Ragab⁵, Barry Rawlins⁶

Mark Richards⁷, Pete Smith⁷, Andy Tye⁶

¹Centre for Ecology and Hydrology, Bangor
²ADAS Wolverhampton
³Scottish Crop Research Institute (SCRI)
⁴Leeds University
⁵Centre for Ecology and Hydrology, Wallingford
⁶British Geological Survey
⁷Aberdeen University
## Contents

**B1. Introduction** .................................................................................................................... 4  

**B2. Data required for soil threat modelling** ........................................................................ 4  
   A. Climate data .................................................................................................................... 4  
   B. Soil and land cover variables (JULES) ........................................................................ 14  
   C. Soil and land cover parameters ................................................................................... 14  

**B3. Carbon modelling with ECOSSE** ................................................................................. 15  
   The threat and the model ................................................................................................... 15  
   Model application ............................................................................................................ 17  
   Uncertainty in the simulations ........................................................................................ 22  

**B4. Water erosion modelling using PESERA** ................................................................... 23  
   The threat and the model ................................................................................................... 23  
   Model application ............................................................................................................ 25  
   Discussion ......................................................................................................................... 29  

**B5. Wind erosion modelling using RWEQ** ........................................................................ 29  
   The threat and the model ................................................................................................... 29  
   Model application ............................................................................................................ 35  
   Uncertainties and limitations............................................................................................ 39  
   Discussion ......................................................................................................................... 40  

**B6. Contamination – (i) phosphorus modelling using PSYCHIC** ................................... 41  
   See Appendix C ................................................................................................................. 41  

**B7. Contamination – (ii) acidification modelling using VSD** .......................................... 41  
   The threat and the model ................................................................................................... 41  
   Model application ............................................................................................................ 42  
   Discussion ......................................................................................................................... 47  

**B8. Compaction modelling using the Workable Days model** ........................................ 48  
   The threat and the model ................................................................................................... 48  
   Model application ............................................................................................................ 49  
   Discussion ......................................................................................................................... 54  

**B9. Salinity modelling using SALTMED** .......................................................................... 55  
   The threat and the model ................................................................................................... 55  
   Model application ............................................................................................................ 55  
   Discussion ......................................................................................................................... 4  

**B10. Soil biodiversity and landslides** ................................................................................. 5  

**B11. Discussion** ................................................................................................................. 6  
   Acknowledgements .......................................................................................................... 7  
   References - general ........................................................................................................ 8  
   References - carbon ......................................................................................................... 8  
   References - Wind erosion ............................................................................................... 10  
   References - Phosphorus ................................................................................................. 11  
   References - VSD ............................................................................................................ 11  
   References - Compaction ............................................................................................... 12  
   References - Salinity ....................................................................................................... 12  
   References - Biodiversity ............................................................................................... 13
B1. Introduction

Following selection of seven models for soil threats in Work Packages 1 and 2 (Appendix A), Work Packages 3 to 5 cover the application of these seven models to provide projections of climate change effects on the specified soil threats in England and Wales up to 2100. We first discuss the data required to run the soil threat models, followed by a description of the models and their application and a discussion of the results and their implications. We focus on 5 decades, a baseline of the 2000s, followed by the 2020s, 2030s, 2050s and 2090s. Models were run by members of the original consortium with the exception of the phosphorus model PSYCHIC which was subcontracted to ADAS Wolverhampton. The contribution of ADAS is a self-contained report as Appendix C.

B2. Data required for soil threat modelling

A. Climate data

The soil threat models require climate projections as drivers, and these must be provided before the models can be run. UK climate projections (UKCIP09; http://ukclimateprojections.defra.gov.uk/) were released in summer 2009 for a range of variables from the present to 2100 on a 25km model grid. Access to the data is through a web-based user interface. The original intention was to use the UKCIP09 data as climate drivers for models of soil threats. In the event this presented a number of difficulties. Access to daily projections was point-wise through the point-and-click user interface, generating large amounts of data from a set of randomisations of model runs. This was impractical for use at national scale. Monthly data on a 25km grid were more readily available from the UKCIP09 website, but data at this temporal scale were not suitable for use with some models. In addition, a number of variables needed for models were absent from UKCIP09, notably short and long wave radiation.

The UKCIP09 projections were derived from the HadRM3 downscaled GCM projections (http://badc.nerc.ac.uk/data/hadrm3-ppe-uk/) on the same 25km grid. The daily HadRM3 data comprise outputs from an 11-member ensemble of runs of the Hadley Centre model. These data are readily available and downloadable in model-accessible form from the British Atmospheric Data Centre (BADC; http://badc.nerc.ac.uk/home/). The wide range of variables generated by the HadRM3 model includes all those required for soil threat modelling which are absent from the UKCIP09 data set. To overcome the difficulties of using the UKCIP09 data we therefore used data directly from the HadRM3 database, which assume a medium emission scenario (A1B; http://www.ipcc.ch/pdf/special-reports/spm/sres-en.pdf). Because of computational limitations, we chose a single example ensemble run HadRM3Q0 to provide climate drivers, rather than attempt to use all 11 members. This inevitably limits the assessment of uncertainty in the results of model runs, since the variability which HadRM3 can generate from run to run is not accounted for. The HadRM3 data are also not bias-corrected for the UK. These two limitations are absent from the UKCIP09 data, which account for the variability in the 11-member ensemble and are bias-corrected against historic data.

Our modelling focuses on the decades 2000s, 2020s, 2030s, 2050s and 2090s. For some models a continuous run of data is required through the 21st century to provide continuity and appropriate initial conditions between decades. Daily HadRM3 data have therefore been downloaded to 2100. A full analysis of the spatial and temporal variability of the data is not appropriate here, but illustrative
examples are provided. Figure B2.1 shows the distribution of daily precipitation and mean temperature by decade at two example locations in the UK. The data presented are for the 25km squares centred at Didcot, Oxfordshire (NGR 451900 192590) an example from lowland southern England, and Ullswater (NGR 336780 516950) in the English Lake District an example from northern and upland England and Wales.

Figure B2.1. Distribution of HadRM3 projected daily values at Didcot by decade. Vertical arrows along x-axis show mean values. Rainfall graphs exclude zero values which are included in the means.
Figures B2.1 and B2.2 show the greater variance in the July temperature distribution compared with January, with a longer tail at higher temperatures. For example, the number of days in July in the 2090s at Didcot with mean temperature greater than 30° is not negligible. Such temperatures are outside the range currently experienced. A lack of uniformity in rainfall trends between decades and by location is apparent. On the basis of the HadRM data at these two sites, we do not see a steady trend in rainfall distributional properties over the coming decade, unlike temperature.

The trajectory of the projections given by the single HadRM3Q0 ensemble member deviates from the central values of the UKCIP projections. To assess the extent of deviation, HadRM3 daily projections of temperature and rainfall have been aggregated to coincide spatially and temporally with the UKCIP09 data. This comparison has been made for monthly data for each 25 km square. UKCIP09 data are provided by decade, and the decadal values are computed over a 30 year period centred on the decade of interest. We have therefore aggregated HadRM data over the 30 year periods corresponding to the 2020s and the 2080s. We then regressed the UKCIP09 values on the HadRM aggregate values using location (by 25km grid square) and month as explanatory variables to provide a predictive equation for removing bias with respect to UKCIP09 data from the HadRM3Q0 projections. For both the 2020s and the 2080s the regression coefficients associated with location and month were similar (Figure B2.3), and on the basis of this, the same regression equation was used for the remaining decades of interest. This procedure provided a monthly and a site bias removal factor which was applied to all daily HadRM rainfall (multiplicative factors) and temperature (additive factors).
Figure B2.3. Bias in HadRM3 data with respect to UKCIP09 based on decadal averages for the decades 2020s and 2080s. Rainfall bias values relate to ln(rainfall). Diagonal lines are 1:1, not fitted.

It would also be possible to bias correct using historic data, but since the original intention had been to use (bias-corrected) UKCIP09 data, bias correction to these data was thought more appropriate. Bias correction with respect to UKCIP09 for radiation and potential evaporation was not possible because radiation values were not provided by UKCIP09.

The selected spatial scale for modelling was 5km, this being a compromise between the 1km scale at which relatively stable land characteristic data were available, and the 25km scale of the climate projections. Nevertheless there is some doubt as to the suitability of climate projections at a scale finer than 25km (or even as fine as 25km) as drivers for environmental models. The use of projections at this spatial scale are best regarded as a feasibility exercise aiding in the provision of general understanding of the regional consequences of climate changes in a particular direction (Nature, 2010).

After bias-correcting precipitation and temperature data, the HadRM data were downscaled from the 25km to the 5km grid using methods appropriate to each variable used in modelling. The HadRM3 climate variables needed for the various soil threat models were:

- Precipitation
- Temperature (daily min, mean and max)
- Potential evaporation
- Wind speed
- Specific humidity
- Short wave radiation
- Long wave radiation
Methods of downscaling were as follows:

Precipitation

The long-term annual average rainfall is available as the SAAR (Standard-period Average Annual Rainfall) at a 1km grid, the standard period being 1961 to 1990 (http://www.metoffice.gov.uk/climate/uk/averages/). The SAAR value is based on an interpolation formula used with point measurements of rainfall at Meteorological Office sites. This formula accounts for elevation, a major influence on rainfall. We first aggregated the SAAR data to give an estimate of the 1961-1990 rainfall for each 5km and 25km square. The ratio of each 5km square value to the 25km square value is then assumed to be stable into the future. We used this ratio used to downscale the bias-corrected HadRM3 25 km data to 5km.

Temperature

We also used a model-based downscaling for temperature. The mean elevation at 5km scale and 25km scale was obtained from the IHDTM, a digital elevation model http://www.nwl.ac.uk/ih/nrfa/spatialinfo/Index/overviewCatchmentSpatialInfo.html. The difference in height between grid squares at the two scales was used to provide a temperature adjustment based on the standard lapse rate of 6.5° C per 1000m.

Potential evaporation

Potential evaporation is not a directly measured variable, and inspection of HadRM3 values suggested they were strongly biased. To investigate this, a more detailed comparison was carried out for the years 2000 to 2005 for which data were available from the Met Office (MORECS; http://www.metoffice.gov.uk/environment/morecs.html), and a simple estimate based on solar radiation and mean temperature, both of which are available as HadRM3 outputs. The MORECS data, although interpolated, are based on field measurements of evaporation. The comparison, shown in Figure B2.4 tended to confirm over-prediction by the HadRM3 data. In view of this, the simple estimate was used, following Samani and Pessarakli (1986):

\[ ET = 0.0162 \times \frac{SR}{58.5} \times (DT + 17.8) \]

where SR is total solar radiation (calories cm\(^{-2}\)), and DT is mean temperature (°C). Alternative estimates of evaporation have been investigated by Kay and Davies (2008), and these should be considered in a fuller analysis. Some soil threat models have an internal computation of evaporation, for which they use wind speed and specific humidity, so that evaporation is not estimated consistently across models.
Figure B2.4. Evaporation estimates for 6006 5km squares 2000-2006 from 3 sources: HadRM3 downscaled; simple estimate based on Samani and Pessarakli (1986); MORECS based on field measurement

Wind speed

Wind speed estimates over the period 1971-1999 are available on 1km grid (http://www.metoffice.gov.uk/climate/uk/averages/) and have been aggregated to 5km. Under the assumption that the relative wind speeds within a 25km grid would be unchanged during the prediction period the 25 km grid HadRM3 values were scaled accordingly to generate projections on the 5km grid.

Specific humidity, short and long wave radiation

Interpolation by distance weighting was used to downscale, excluding any 25km HadRM3 data points over the sea. Radiation is influenced by slope and aspect, but on a 5km grid the overall effect of this was considered unlikely to be a major source of inaccuracy for most squares.

The interpolation schemes for all the variables are a potential source of uncertainty, and could be refined. However, there is a risk of over-interpretation of the interpolated data, particularly when used with climate projections.

Summaries for projected climate data
It is instructive to summarise the behaviour of the climate change projections used in modelling, to provide a general indication of possible changes.

**Temperature**

Figure B2.5 shows the spatial distribution of annual mean temperature for the 2000s at a 5km scale, and projections for the 2050s. The 5km scale data are bias-corrected and downscaled. The HadRM3 and UKCIP09 data are as downloaded, but displayed on the same 5km grid. The pattern generated by the underlying 25km grid is apparent for the HadRM3 and UKCIP grids, but the downscaling has largely removed immediate evidence of the coarser grid, largely due to the altitude correction. It has also eliminated the unwanted influence on landward projections of marine-centred 25km grid squares, notably on some NW facing coasts. There may be some residual influence of the 25km grid square pattern to the east of the Pennines, and the interpolation procedure is expected to be open to improvement.

![Figure B2.5. Projected annual mean temperature: comparison of methods](image)

The difference between the 2000s and the 2050s 5km projections are shown in Figure B2.6. The projected regional difference between these changes is less than 0.5°C to 2030, rising to around 1°C in the 2090s, with greater projected temperature rises in the south east of England.
Figure B2.6. Projected annual mean temperature change for selected decades

Figure B2.7 shows the variation in monthly temperatures, averaged spatially, for the decades of interest. The range bars indicate the maximum and minimum mean monthly temperatures for the decade and month in question. The range therefore relates to the 10 monthly values in a decade. Although there is an evident increase in decadal average temperature through the century, the variability in the mean monthly temperature is considerable. Daily variation within each decade would be even greater.
Figure B2.7. Variability in spatially averaged monthly temperature and rainfall for selected decades

Rainfall

Figure B2.8 is analogous to Figure B2.5, for rainfall. Major differences between the 2000s and 2050s are not immediately evident in these absolute values. Figure B2.9 shows proportional changes in rainfall in selected decades in relation to projections for the 2000s. The data show a decline in rainfall to the 2050s and a subsequent recovery by 2090, and varying patterns spatially across England and Wales. This lack of consistent trends is believed to be a result of using a single ensemble run of the HadRM3 model for a variable whose future behaviour is highly uncertain. The lower portion of Figure B2.7 shows the monthly rainfall variability. While there is a possible trend towards drier summers and wetter winters, the variability in monthly mean rainfall within decades is considerable.
Other variables

Figure B2.10 shows monthly within-decade variability for short and long-wave radiation, averaged spatially over England and Wales. It is the long-wave radiation which shows the major change over
the coming century, the direct solar radiation associated with short wave radiation being little changed.

![Figure B2.10. Monthly short and long wave radiation projections for selected decades.](image)

**B. Soil and land cover variables (JULES)**

Downscaled HadRM3 variables are sufficient as drivers for most of the soil threat models. However, ECOSSE requires projected net primary productivity (NPP) values, and the Working Days model (compaction) requires projected water content through the soil profile. These variables are provided by the the JULES land surface water and energy budget model (Blyth et al., 2010), which itself uses HadRM3 outputs as drivers. JULES has been run at a 5km grid scale with England and Wales soil and vegetation properties, along with the appropriate GCM outputs.

**C. Soil and land cover parameters**

Soil and land cover parameters are required as parameters of the JULES and the soil threat models. The key soil parameters are those which are associated with the amount of water the soil can hold, and the rate at which water can be transmitted though it. These hydraulic parameters have been empirically derived for each England and Wales soil class, and for this project have been provided under licence by Cranfield University from its Land Information System (Landis [http://www.landis.org.uk/]). The key datasets which were used to generate soil property information at the 1 kilometre grid scale were: i) the National Soil Map (1:250 000 scale) which includes information on the spatial distribution of all Soil Associations, ii) the proportions of the different Soil Series within the Associations, and iii) the property information within individual soil
horizons of the Soil Series. These datasets are linked in a Geographic Information System (GIS) using identifiers which can be used to generate estimates of a variety of topsoil properties across England and Wales including soil organic carbon content (%), texture (proportions of sand, silt and clay particles), bulk density (g cm\(^{-3}\)), parameters of the van Genuchten soil water release curve, saturated hydraulic conductivity, water content at certain fixed water potentials. These hydraulic data are provided for different horizons within the soil profile.

The chemical and biological properties of the soil (and possibly bedrock) are important for some threats, notably acidification. The sources of these more model-specific parameters are provided under the descriptions of the individual models.

In the 5km square grid-based modelling we used the parameters of the dominant soil class in each grid square. In reality, local soil properties may vary greatly within a 5km square, and in this case the use of the dominant class may be a significant approximation. Some of these properties, such as soil texture, vary over short scales (100-200 metres) and so the 1km grid data provide typical values for each grid square.

The JULES model distributes water and energy through 4 (idealised) soil layers of depths of .1, .25, .65 and 2m. Soil hydraulic parameters are estimated for each soil depth.

Vegetation influences evapotranspiration and therefore water accumulation in the soil following rainfall. Vegetation classes (“plant functional types” or PFTs) used in JULES are broad-leaved trees, needle-leaved trees, crops, grass and shrubs. Non-vegetated land classes are urban, lake and soil (i.e. bare soil). The finer classification of the LCM2000 (http://www.ceh.ac.uk/sci_programmes/BioGeoChem/LandCoverMap2000.html) is the basis for defining the five PFTs. Vegetation classes are identified at a 1km grid square scale, and the dominant class is used for 5km scale modelling using JULES. Each vegetation class is assigned a set of global-scale parameters associated with its physiological response to climate and season. It is likely that the use of global parameters introduced bias in the vegetation response in England and Wales.

The salinity model SALTMED uses crop data taken from the annual Defra survey 2km square estimates available to researchers from UKBORDERS (http://edina.ac.uk/ukborders/).

B3. Carbon modelling with ECOSSE

The threat and the model

Climate change has been implicated as the cause of an observed mean loss of soil organic C of 0.6% yr\(^{-1}\) between 1978 and 2003 in England and Wales based on data from the National Soil Inventory (Bellamy et al. 2005). As discussed by Smith et al. (2007), those findings contradict evidence that UK and European soils as a whole are a net CO\(_2\) sink (Janssens et al. 2003). The Countryside Survey reported that carbon concentration in the top layer of the soil (0-15 cm) increased in Great Britain between 1978 and 1998, and decreased between 1998 and 2007 (Emmett et al. 2007). The Countryside Survey found no overall change in carbon concentration in Great Britain between 1978 and 2007 and could not confirm the loss reported by the National Soil Inventory. Data from another long term study of soil organic C in British woodlands (Kirkby et al. 2005) suggested a small increase in soil organic matter over 30 years (0.094% increase yr\(^{-1}\)). Our results provide modelling evidence
that will allow the threat of climate change on the soil organic C stocks of England and Wales to be quantified by incorporating direct climate impacts on the soil and indirect effects via temperature and precipitation driven changes in net primary production (NPP).

The ECOSSE (Estimation of Carbon in Organic Soils – Sequestration and Emissions) model was used to assess the threat to soil carbon stocks from climate change. ECOSSE was chosen for this task because a) it simulates changes in soil C and N in response to climate in highly organic as well as mineral soils and b) it allows simulations of soil C and N turnover using only the limited meteorological, land use and soil data that is available at the national scale.

The model is able to function at field as well as national scale which has allowed the uncertainty expected in national scale simulations to be evaluated for Scotland (Smith et al. 2010). The simulated total C and change in C content of the soil showed a high degree of association with measurements obtained from the National Soils Inventory of Scotland. The average deviation between measured and simulated values of percentage change in soil C was 11%, significantly lower than the experimental error (53%). Only a small bias in the simulations was observed compared to the measured values, suggesting that a small underestimate of the change in soil C should be expected at the national scale (-4%). In summary, ECOSSE was selected due to its ability to run national scale simulations using limited driving data with the relatively low error and bias in the results at this scale.

A complete and detailed description of the structure and formulation of the ECOSSE model is given in Smith et al. (2010a). In summary, ECOSSE was developed from concepts originally derived for mineral soils in the RothC (Jenkinson & Rayner 1977, Jenkinson et al. 1987, Coleman & Jenkinson 1996) and SUNDIAL (Bradbury et al. 1993, Smith et al. 1996) models. Following these established models, ECOSSE uses a pool type approach, describing soil organic matter (SOM) as pools of inert organic matter (IOM), humus (HUM), biomass (BIO), resistant plant material (RPM) and decomposable plant material (DPM). The soil is divided into 5cm layers, to facilitate the accurate simulation of these processes down the soil profile. All of the major processes of C and N turnover are included in the model, but each process is simulated using only simple equations driven by readily available inputs. This allows the model to be applied at the field scale and national scale, without a high loss of accuracy.

**Decomposition**

Plant inputs are added monthly to the DPM and RPM pools (in proportions $P_{DPM}$ and $P_{RPM}$). During the decomposition process, material is exchanged between the SOM pools according to first order rate equations, characterised by a specific rate constant for each pool, and modified according to rate modifiers dependent on the temperature, water content, plant cover and pH of the soil. Under aerobic conditions, the decomposition process results in gaseous losses of carbon dioxide (CO$_2$) whereas under anaerobic conditions methane (CH$_4$) losses dominate.

Anaerobic decomposition is described in a similar way to aerobic decomposition, using rate modifiers that are set according to relationships formulated for the anaerobic decomposition process. A proportion of the CH$_4$ produced during anaerobic decomposition is converted back to CO$_2$ depending on the transportation of CH$_4$ in plants, the rate of diffusion through the soil and the thickness of the aerobic region crossed by the CH$_4$. 
Soil nitrogen

The model of the N content of the soil follows the decomposition of the SOM, with a stable C:N ratio (that changes with soil pH) defined for the BIO and HUM pools and N being either mineralised or immobilised to maintain that ratio. Carbon and N may be returned to the soil by plant inputs, inorganic fertilisers, atmospheric deposition or organic amendments. Carbon and N may then be lost from the soil by leaching, denitrification, volatilisation or crop offtake.

Leaching is simulated by simple piston (Saffigna and Philips 2006) and bypass flow (Addiscott and Whitmore 1991). Losses of nitrate (NO$_3^-$-N) are modelled following the approach used in SUNDIAL. The amount of dissolved organic C (DOC) produced by a SOM pool follows the approach of Aguilar and Thibodeaux (2005) using a first order rate equation modified by soil water content, temperature, crop cover and pH. The amount of DON produced is calculated from the amount of DOC produced and the C:N ratio of the pool.

Activity of the soil organic matter

Because the SOM pools have different rate constants, the relative proportions of these pools determines the activity of the SOM to decomposition and other processes; a greater proportion of a rapidly decomposing pool will result in a greater overall activity of the SOM, whereas a greater proportion of a slowly decomposing pool will result in a lesser overall activity. Therefore it is important to accurately determine the amount of C in each SOM pool at the start of the simulation.

In order to estimate the SOM pool sizes at the start of the simulation from measured soil C and the organic inputs, ECOSSE employs an iterative procedure following the approach used in RothC, for example by Smith et al. (2005). For the first iteration an initial estimate of the organic inputs is used and the model is run until the total soil C reaches steady state. The C in the SOM pools at steady state provides an estimate of the total C simulated using these organic inputs. The simulated total C is then compared to the measured soil C and a new value for the organic inputs is estimated that will provide a simulated total soil C value that is closer to the measured soil C. The model is then rerun to obtain a revised estimate of the total soil C at steady state and the process is repeated until the simulated and measured values are within 0.0001 kg C ha$^{-1}$ layer$^{-1}$. The resulting SOM pool sizes and calculated organic inputs are used to represent the pools and inputs needed to achieve the observed soil C at steady state. This provides size of the SOM pools at the start of the simulation period. The model can then be run forward applying changes in climate and NPP to calculate the impact of changes on the rate of SOM turnover. This iterative procedure is a useful approach for national simulations as it provides an estimate of the rate of decomposition using very little input data but has the drawback that it assumes the soil to be in a steady state. This may not always be the case; for example, if the area underwent a recent change in land use the soil may not have had sufficient time to reach a new equilibrium.

Model application

In order to estimate the effects of climate change on soil C stocks ECOSSE was run twice: once with climate change and once without climate change. The differences in predicted C stocks between the two simulations were used to infer the climate change induced impacts on soil C content.
The climate change simulation utilised predicted temperature and precipitation values derived from the HadRM3 model for the simulation period 2010-2100. The no-climate change simulation used repeated long term average temperature and precipitation calculated from the HadRM3 output for 1980-2009. In both simulations NPP was estimated from the temperature and precipitation data used for the simulation.

**Soil data**

The 5 most extensive soil types within each cell were used. The soil distribution data set and the soil characteristics data set are used as described in Falloon et al. (2006). The data set of Falloon et al. (2006) also describes the four land use types arable, grassland, forestry and semi-natural. For each soil series and for each of arable, grassland, forestry and semi-natural land uses the following soil characteristics of the 0-30 cm and 30-100 cm soil layers were used: % C, C (kg x 10^6 km^-2), % clay, % silt, % sand and bulk density (g cm^-3).

Total soil C was used to determine the organic inputs to the soil and the amount of C in each of the SOM pools at the start of the simulation as described above (under Activity of the soil organic matter). The percentage clay was used to calculate the proportion of SOM retained in the soil on decomposition following the approach of Coleman and Jenkinson (1996), and together with the bulk density and silt content, to estimate the water content at field capacity using the equation derived for soils from England and Wales provided by Hall et al. (1977).

The limitations associated with the soil data have been discussed in detail by Falloon et al. (2006). The current approach of using the five most dominant soil types within each 5-km square could lead to significant errors, particularly where soils are very heterogenous. The aggregation of soil horizons into 0-30 and 30-100 cm layers could lead to errors in predicted C stocks and C fluxes, particularly in soils which show a high degree of variation in C concentration between horizons. Soil series with incomplete data were excluded from the simulations with this mostly affecting organic soils. Therefore, a significant portion of the English and Welsh SOC stock was not included in the simulations.

**Land-use data**

Land use in ECOSSE is represented using 4 main types: arable, grassland, forestry and semi-natural/natural and is used to determine plant inputs prior to the start of the simulation, the depth distribution of plant inputs and the soil characteristics under a particular soil series.

The land use at the start of the simulation was taken as the proportion in each 5 km cell of 5 plant functional types (PFTs) used in the JULES model: broadleaf tree, needle leaf tree, grass, shrub and crop. Areas of human settlement/infrastructure and water bodies were excluded from the simulation. The JULES PFTs were mapped to the ECOSSE land use types as follows: broadleaf and needle leaf tree were amalgamated to forestry, grass to grassland, shrub to semi-natural/natural and crop to arable. Since the aim of this study was to assess the threat from climate change on soil organic C stocks land use was kept fixed for the period of the simulation.

**Net primary productivity (NPP) data**
Monthly NPP is required in order to estimate the monthly plant inputs during the simulation. The original intention had been to use NPP data output from JULES (driven with the HadRM climate data) for the various plant functional types. However, the NPP output from JULES showed values which appeared not to be consistent with our understanding of the carbon budget, so an alternative approach was adopted.

Monthly NPP for the period 2010-2100 and the 1980-2009 long-term average was estimated using the MIAMI model introduced by Leith (1972). MIAMI links NPP to annual mean temperature and annual precipitation. NPP is assumed to increase with both increasing temperature and increasing precipitation and can be limited by either factor. MIAMI does not allow for a negative effect from too much precipitation or temperatures that are too high.

**Meteorological data**

ECOSSE requires monthly precipitation and air temperature data which are used to calculate the soil water content and temperature modifiers used in the decomposition processes and to simulate leaching, denitrification and volatilisation as described by Bradbury et al. (1993). For the initialisation of the SOM pools (see above under Activity of the soil organic matter) the model is run using long term average climate data. The long-term average climate data were taken from the downscaled 5 km grid HadRM3 data for the period 1980-2009. This period was used because it represents the period immediately prior to the start of the simulation and the conditions under which the soil is assumed to be at steady state. HadRM3 data was used instead of observed meteorological data in order to eliminate the possibility of anomalous transient behaviour resulting from any remaining bias in the downscaled HadRM3 data relative to the observed climate.

For the simulation period (2010-2100) monthly precipitation and air temperature data calculated from the downscaled HadRM data were used.

The soil C stocks at the start of the simulation, as derived from the Falloon et al. (2006) soil data (see under Soil Data), are shown in Fig. B3.1. The distribution of soil C follows the expected pattern with high C contents in peat areas such as the Pennines, the Somerset Levels and The Fens. It is important to be aware that these C stock values are not intended to represent the actual C stock at the start of the simulation, i.e. in 2010, since these data are not available. Instead, they provide a recent, empirically derived start point from which to estimate proportional changes in C content resulting from climate change.
Fig B3.1. Soil C stocks to a depth of 1 m at the beginning of the simulations.

The projected percentage changes in soil C content relative to the initial C content across England and Wales as estimated by ECOSSE for 2020, 2050 and 2080 are shown in Fig. B3.2. Changes in soil C stocks due to climate change occurring between 2010 and the reported year contribute to the projected changes in soil C stocks estimated for the reported year, for example climate changes occurring between 2010 and 2050 contribute to the projected changes in soil C stocks estimated for 2050.
Fig. B3.2. ECOSSE simulations of changes in soil C stocks due to climate change relative to 2010 soil C stocks across England and Wales in 2020, 2050 and 2080. Grey area = cells excluded from simulations.

The overall projected changes in total soil C content for England and Wales are -1.06% by 2020, -3.09% by 2050 and -5.17% by 2080. These equate to changes of -0.11 %, -0.08% and -0.07% yr\(^{-1}\) respectively, which are comparable to those reported for England and Wales between 1978 and 2003 by Smith et al. (2007) using the Roth C soil carbon model with changes in climate and NPP included.

The simulated annual rates of change are small compared to the observed +0.4 % yr\(^{-1}\) between 1978 and 1998 and -0.72 % yr\(^{-1}\) between 1998 and 2007 in Great Britain reported by the Countryside Survey (Emmett et al. 2007) and the -0.6 % yr\(^{-1}\) between 1978 and 2003 for England and Wales reported by Bellamy et al (2005). The observed rates of change include the effects of drivers other than climate, such as changes in land use and management. As discussed by Smith et al. (2007), changes in climate can only be responsible for 10%-20% of the observed changes in soil C content between 1978 and 2003.
The results from the ECOSSE simulations suggest that climate change, based on the HadRM3Q0 ensemble run which assumes a medium emission scenario, will only be responsible for relatively small (ca. -5%) changes in soil C content in England and Wales over the period 2010 to 2080. Based on the recent observed rates of soil C change it is likely that other drivers (e.g. land use/management) have a greater potential to affect soil C stocks than climate change. Smith et al. (2005, 2006) using the RothC model, similarly found small impacts of climate change in European grassland, cropland and forest soils, with increased inputs to the soil from increasing plant productivity largely offsetting temperature-induced increases is soil organic matter decomposition rates.

Uncertainty in the simulations

Uncertainty in national scale simulations has two components, uncertainty due to errors in the model and uncertainty due to the reduced detail and precision in data available at national scale.

Firstly, at national scale the uncertainty in simulations is likely to be greater than at field scale due to the reduced detail of the inputs. For example in croplands, detailed management factors such as sowing date and timing of fertiliser applications cannot usually be specified when the resolution of the simulations is larger than the size of the management unit. The resolution of the simulation here was a 25 km² grid cell, whereas the size of a management unit might be a 5 ha (.05 km²) field, so there will be many different values for the management factors within each 25 km² cell.

Uncertainty in national scale simulations is also greater than at field scale due to the reduced precision of the input data. For example, the C content of the soil in a 5 ha field can be precisely measured and the error in the measurement defined using replicates, whereas for at the national scale the soil C content for grid cells is estimated from typical or averaged soil C values for the major soil types identified in the cell (e.g. Batjes 2009). Additional uncertainty may arise from unrecorded land use.

The uncertainty due to the reduced detail and precision of data available at the national scale can be quantified by evaluating the model at field scale, but using only input drivers that are available that are available at national scale. In order to obtain a good representation of the uncertainty, a range of sites across the whole area to be simulated should be included in this field scale evaluation. As part of a previous study the ECOSSE model was evaluated using data for 62 sites from the National Soils Inventory of Scotland (NSIS, Lily et al. 2009) to determine the uncertainty in national scale simulations of changes in the soil stocks of Scotland (Smith et al. 2010b). There is typically a large uncertainty associated with measurement of soil C content compared to the size of observed changes in soil C. This is especially true for semi-natural upland sites where the inherent measurement error is greater because variations in vegetation and topography introduce greater spatial variation in soil characteristics than in arable or grassland sires (Lindsay et al. 1985). Because of the large measurement error, only NSIS sites where land use had changed was the change in soil C significant, and so only these sites were used to evaluate the model (Smith et al. 2010b).

The soil C content at the 62 sites were sampled between 1978 and 1988 and then re-sampled in 2007. The sites encompass a range of organic, organo-mineral and mineral soils found across Scotland. The average deviation between the simulated and measured values of percentage change in soil C at these sites was 11%, well within the experimental error (53%). A bias of -4% was observed
in the simulations compared to the measured values, suggesting that a small underestimate of the change in soil C should be expected at the national scale. Although these uncertainty estimates were established for the simulation of Scottish soils they provide a useful guide to the approximate levels of uncertainty that might be expected in the current simulations for English and Welsh soils.

However, further uncertainty in the simulations carried out here is introduced by the larger grid cell size (5 km grid cells compared to 1 km grid cells used for the Scottish simulations), uncertainty in the predicted meteorological data from the HadRM model and NPP from the JULES model. The extra uncertainty introduced by these factors has not been quantified.

**B4. Water erosion modelling using PESERA**

**The threat and the model**

Soil erosion by overland flow is a natural process. Soil erosion in the context of a threat to soil, is 'accelerated soil erosion', which results from anthropogenic activity, in excess of accepted rates of natural soil processes. Non-stationary climate pressure may also be considered a factor in 'accelerated soil erosion'. The PESERA model has been selected as an appropriate methodology to assess the risk of accelerated soil erosion under climatic pressure. Estimated erosion risk for current and projected future climate (HadRM3) is determined for England and Wales under fixed land use conditions.

Centred on hydrology, the PESERA model uses climatic data to simulate vegetation growth and estimate runoff and erosion (Kirkby et al., 2008). The core of the model (Figure B4.1) is a partition of precipitation into components for overland flow (infiltration excess, saturation excess and snowmelt), evapo-transpiration and changes in soil moisture storage. Transpiration is used to drive a generic plant growth model for biomass, constrained as necessary by land use decisions, primarily on a monthly time step. The runoff threshold for infiltration excess overland flow depends dynamically on vegetation cover, organic matter, soil moisture level and soil properties, varying over the year, and runoff is estimated by summing over rainfall events which exceed this threshold. Soil erosion is driven by erodibility, derived from soil properties, the sum of squared overland flow discharges and gradient; it is assessed at the slope base to estimate total loss from the land, and delivered to stream channels.
Figure B4.1: Schematic diagram showing the inter-relationships within the PESERA model.

Before applying the model, we have compared the statistical properties of the HadRM3 data over recent years with measured field data. A variable of particular relevance is the coefficient of variation of rain per rain day, which is used as an estimate of rainfall intensity. Values have been computed from the HadRM3 5km data as drivers for PESERA. These values are higher than those extracted from area rain gauge data and may overestimate runoff and erosion. In view of this, spatial output results focus on change in erosion rates (or risk) rather than absolute values. These results are shown in Figure B4.2
**Figure B4.2: Change in climate variables**

**Model application**

Average water erosion rates driven by projected HadRM3 climate variables are estimated for the five decades of interest. Although estimated erosion is seen to increase through the next century by 0.1 tonnes ha$^{-1}$ yr$^{-1}$ to an average of 0.55 tonnes ha$^{-1}$ yr$^{-1}$, localised areas of arable and pasture areas can be identified as high risk and require further consideration with finer detail of local management practice. Erosion rates vary seasonally and spatially, and the overall mean may not be a good indicator of active response/mitigation. However, projected erosion rates are summarised for each decade and major land use in Table B4.1 and Table B4.2 respectively.

<table>
<thead>
<tr>
<th>Decade</th>
<th>mean</th>
<th>std dev</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>0.44</td>
<td>0.82</td>
<td>17.1</td>
</tr>
</tbody>
</table>
Table B4.2: Estimated average erosion rates by major land use class (tonnes ha⁻¹ yr⁻¹)

<table>
<thead>
<tr>
<th>Decade</th>
<th>Land use</th>
<th>area (km²)</th>
<th>mean</th>
<th>std dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>arable</td>
<td>45584</td>
<td>0.3</td>
<td>1.11</td>
</tr>
<tr>
<td></td>
<td>pasture</td>
<td>73523</td>
<td>0.38</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>forest/moorland</td>
<td>12885</td>
<td>0.53</td>
<td>1.19</td>
</tr>
<tr>
<td>2090</td>
<td>arable</td>
<td>45584</td>
<td>0.4</td>
<td>1.62</td>
</tr>
<tr>
<td></td>
<td>pasture</td>
<td>73523</td>
<td>0.47</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td>forest/moorland</td>
<td>12885</td>
<td>0.57</td>
<td>1.36</td>
</tr>
</tbody>
</table>

Change in seasonal and monthly erosion rates

Projected monthly erosion rates are presented in Figure B4.3 where it can be seen that erosion rates for March increase most significantly at low erosion rates. Considering seasonal changes, Figure B4.4, erosion in autumn and winter is significantly influenced by changes in rainfall while erosion in summer may be more influenced by the cropping calendar and/or reduced cover due to limited water availability (AET / PET >> 1). Some parts of Wales and the Lake District show a reduction in projected erosion in autumn and winter, despite an increase in rainfall. The factor influencing this is the vegetation cover, which PESERA predicts will increase, providing greater protection from erosion.

Although there is a projected increase in rainfall in winter, interception (due to the increased biomass) is greater and runoff less. Predicted rainfall in autumn is more significant than winter and the additional rainfall would appear to be greater than the increased biomass interception. Therefore net runoff and erosion is increased.
Figure B4.3: Variation in monthly erosion rates.
Figure B4.4: Seasonal change in erosion rates, 2000-2090
Discussion
The erosion projections use the HadRM3 data provided, and the coefficient of variation of rain per rain day for the present day HadRM3 data appear to be higher than that direct measurements. This may drive a higher rate of erosion than that observed. It could therefore be concluded that the rate of change of erosion (both annual and seasonal) considered as a change in erosion risk are more reliable/realistic output than considering absolute value. Baseline conditions derived from observed rainfall network would improve confidence in results.

Although average estimates tend towards a tolerable erosion rate, areas of both arable and pasture can be identified as high erosion risk and require further consideration with finer detail of local management practice and cropping calendar. As erosion rates vary seasonally and spatially the mean value is a poor indicator of active response/mitigation.

The projected increases in rainfall are small in relation to the changes in erosion, as a result of the non-linear relationship between flow rate and erosive power. This suggests erosion is particularly sensitive to changes in rainfall patterns, and should be the subject of further investigation. **The observation that extremes of projected rainfall over the current period appear not to follow the statistical properties of measured values needs investigating further, in view of the influence of these extremes on erosion.**

**B5. Wind erosion modelling using RWEQ**

**The threat and the model**
The threat of wind erosion to soils across England and Wales is greatest in areas of arable agriculture where the soil is exposed, most notably: i) sandy soils of the Midlands and also parts of East Anglia, ii) soils developed over aeolian deposits in part of Lincolnshire and the Vale of York, and iii) the organic-rich fenland soils of East Anglia are also susceptible to wind erosion (Boardman and Evans, 2006; Evans, 1990). There are no published data for long-term measurements of wind erosion rates on arable soils in England and Wales. A study using the radioactive isotope $^{137}$Cs estimated net losses of 0.6 t ha$^{-1}$ yr$^{-1}$ for a 19 km$^2$ region of East Anglia (Chapell and Warren, 2003) and a detailed site-specific modelling study estimated annual erosion rates of 1.56 t ha$^{-1}$ yr$^{-1}$ for a site in Suffolk (Bohner et al., 2003). Erosion fluxes due to wind on upland soils have been estimated as 0.46 to 0.48 t ha$^{-1}$ yr$^{-1}$ at a site in the Northern Pennines (Warburton, 2003). No single model has been developed and validated for upland, organic-rich soils. Our approach was therefore to apply the most appropriate soil erosion model for lowland mineral soils where the wind erosion threat is generally considered to be most significant.

Although RWEQ can provide a good estimate of sensitivity to wind erosion over much of the arable and grassland of England and Wales, it cannot do so for upland and peat rich soils; these areas were excluded from the analysis (see Figure B5.1).
The strengths of the RWEQ model are that an estimate of soil erosion can be calculated at the national scale – one of the main requirements for this study – and that it has been widely applied and validated (see Appendix B). One area of weakness in estimating wind erosion potential is the limitation in altering land use and vegetation cover which will have a substantial impact on wind erosion potential. In this study, wind erosion potential has been estimated across England and Wales assuming a bare soil surface. Although this scenario is unrealistic, providing a ‘worst-case’ estimate, one advantage is that it accounts for future transformations to arable land in areas currently under different land cover types. The estimation of wind erosion potential is justifiable at the national, 5km scale because the model has been validated over a broad range of soil and climatic conditions; with the exception of calcium carbonate content, the soil data are available at an appropriate spatial resolution. There are insufficient data on field lengths and wind barriers for these factors to be incorporated in a national-scale assessment. There is a non-linear increase in wind erosion potential above threshold windspeeds – assumed here to be 5 ms\(^{-1}\) – which accounts for the occurrence of more extreme erosive events.

The RWEQ model (Fryrear et al., 1998) determines the erosive potential of the wind by estimating its maximum sediment transport capacity \(Q_{\text{max}}\) (kg m\(^{-1}\)). This is the total airborne mass of soil between the ground and 2 metres elevation and is calculated as:

\[
Q_{\text{max}} = a(WF \times EF \times SCF \times K' \times COG)
\]  \hspace{1cm}  B5.1

where \(a\) is a constant, \(WF\) is the weather factor (kg m\(^{-1}\)), \(EF\) is the erodible fraction of the soil, \(SCF\) is the soil crust factor, \(K'\) is the surface roughness factor, \(COG\) are crop factors. Neither the crop nor the surface roughness factor can be calculated using available data and were therefore excluded from this analysis. So equation B5.1 reduces to:
\[ Q_{\text{max}} = a(WF \times SF) \] \hspace{1cm} B5.2

\[ SF = EF \times SCF \] \hspace{1cm} B5.3

In our analysis we have computed the spatial distributions of the weather factor (WF) and the soil factor (SF). This is the sensitivity to wind erosion which is determined by static soil properties.

Spatial variation in the mineral soil erodible fraction (EF) is calculated using a multivariate linear regression equation for soil texture, organic matter and calcium carbonate content which has been shown to account for 67% of the variation in EF:

\[ EF = 0.01 \times \left( 29.09 + 0.31 \times Sa + 0.17 \times Si + 0.33 \times \left( \frac{Sa}{Cl} \right) - 2.59 \times OM - 0.95Ca \right) \] \hspace{1cm} B5.4

In equation B5.4 *Sa* is the sand fraction (%), *Si* the silt fraction (%), *Cl* the clay fraction (%), *OM* the organic matter (%) and *Ca* the calcium carbonate content (%). The RWEQ equation for EF is only for use with mineral soils where their OM content is less than 5%. The soil crust factor (SCF) provides an estimate of the protective capacity of crusting at the land surface with clay contents in excess of 5%:

\[ SCF = 1 / \left( 1 + 0.0066 \times Cl^2 + 0.021 \times OM^2 \right) \] \hspace{1cm} B5.5

The occurrence of wind erosion is greatest when the soil surface is dry and exposed to a strong wind. By contrast, wind erosion is minimal when the soil is covered by snow. These three components of the weather are considered in the weather factor (WF):

\[ WF = SW \times Wf \times Sd \times \left( \frac{\rho}{g} \right) \] \hspace{1cm} B5.6

where SW is soil wetness, Wf is the wind factor, Sd is snow cover, \( \rho \) is the density of the air (kg m\(^{-3}\)) and \( g \) is acceleration due to gravity (ms\(^{-2}\)). The weather factor was computed for monthly periods using the HadRM climate data. Data on snow cover and duration were not available from the climate projections and so Sd was set to 1. Changes in soil wetness (SW) were also calculated for monthly periods using the empirical equation:

\[ SW = \left( \frac{1}{ET} \right) \times \left( ET - (R + I) \times \left( \frac{Rd}{Nd} \right) \right) \] \hspace{1cm} B5.7

In equation B5.7 ET is potential evapotranspiration (mm), R is rainfall over the period (mm), I is irrigation (mm), Rd is number of rainfall days over the period, and Nd is the length of period (number of days). Small values of SW indicate wet soils where rainfall exceeds evaporation; larger values of SW equate with dry soils to a maximum value of 1 for rain-free periods. Reliable data on the amounts and distribution of irrigation are not available and were therefore set to zero; so the SW values are maximum estimates. Potential evapotranspiration (mm) was estimated using equation B5.8 from Samani and Pessarakli (1986):
\[ ET = 0.0162 \times \left( \frac{SR}{58.5} \right) \times (DT + 17.8) \]  

where SR is total solar radiation (calories cm\(^{-2}\)), and DT is average temperature (°C).

In modelling wind erosion and the application of RWEQ, it has been shown that the range of wind speeds which occur at a site can be estimated using a Weibull distribution whose parameters are derived from local mean wind speed and regional parameterisation. The following formula can be used to estimate the probability \( P_v \) that a threshold windspeed \( V \) will be exceeded:

\[ P_v = 1 - \exp \left( -\frac{V}{C} \right) \]

and

\[ V = c \times \left( \ln \left( \frac{1}{1 - P_v} \right) \right)^{\frac{1}{k}} \]

where \( c \) and \( k \) are Weibull coefficients whose values have been estimated as 1.12 and 1.85 respectively for temperate maritime climates such as the UK (ESDU, 1987). The cumulative probability distributions of wind speeds for each month and 25 km grid square in the HadRM3 climate projections were calculated. Output from HadRM3 provides windspeeds at 10 metres above the ground surface. To convert these to windspeeds at 2 metres elevation – the height needed for wind erosion assessment – the relationship of Skidmore and Tatarko (1990) was applied:

\[ V_2 = V_{10} \times (0.2)^{1/7} \]

The wind speed estimates for 2 metres elevation were then separated into 250 wind speed increments of equal probability and the distribution was used to derive a wind value based on the non-linear increase in the probability of wind erosion in exceedance of a threshold value:

\[ W = \sum_{i=1}^{J} V_i \times (V_i - V_t) \]

where \( W \) is the wind value (m\(^2\) s\(^{-2}\)), \( V_i \) is the \( i \)th wind increment (ms\(^{-1}\)), \( V_t \) is the threshold wind speed (assumed to be 5 ms\(^{-1}\)) and \( J \) is the number of wind speed increments (here 250). The Wind factor \( Wf \) is estimated as:

\[ Wf = \left( \frac{W}{J} \right) \]

In local applications of the RWEQ model, SCF is estimated once total accumulated rainfall is greater than 12 mm since previous tillage. Such temporal resolution could not be accounted for in this study and so SCF values were calculated for soil which meet the clay (>5% content) and OM (<4.8%) criteria. These values for each 1km pixel across England and Wales were calculated from the LandIS database as described above.
To compute the RWEQ soil factor $SF$, the product of $EF$ and $SCF$ are computed for each 1km pixel of England and Wales. The values calculated are shown in Figure B5.2. Large values of $SF$ suggest greater sensitivity to wind erosion. The soils with greatest sensitivity to wind erosion are found in parts of East Anglia, west of London, parts of the Cheshire plain, the soils developed over the sand-rich Sherwood Sandstone parent material (central England). The $SF$ shown for parts of central and eastern England over calcareous soil parent materials may provide an overestimate of erodibility due to the lack of quantitative data on soil calcium carbonate content.

The $EF$ and $SCF$ values were computed for surface soil horizons of all series and applied to their spatial distribution without regard to land use. Therefore, the values in the map represent sensitivity to erosion assuming land is used for arable agriculture, even in locations where these soils are not currently utilised for arable production. It therefore provides an overestimate of wind erosion sensitivity because soils under grassland or other vegetative cover will be substantially less prone to wind erosion than arable soils.

![Soil factor map](image)

**Figure B5.2 – Soil factor from RWEQ across England and Wales – excluding soils with organic matter contents > 5%.** Larger values indicate more erodible soils. The erodible fraction ($EF$) and soil crust factor ($SCF$) values were calculated using LandIS soil horizon data for each soil series. Each value represents an area-weighted mean for the pixel (resolution 1km) based on the 3 most dominant soil series. Digital Soils Information from NSRI: NATMAP, SOILSERIES and HORIZON © Cranfield University (NSRI) 2006.

**Climate contributions to wind erosion – the weather factor**

The daily climate data described above (rainfall, temperature, wind and solar radiation) were available from the HadRM3 projections on a 25km grid. These daily data were aggregated to a monthly time step to compute $SW$. An example of the spatial variation in soil wetness by month for the year 2000 is shown in Figure B5.3. The monthly pattern of soil wetness depicts the combined effect of rainfall, topography and evapotranspiration. In general, the north and west of England and Wales have wetter soils than the south and east, but there is a certain amount of local variation.
The spring (March, April) and autumn (September, October) months have the greatest potential for wind erosion when soils in areas of arable agriculture (in the east of England) are dry.

**Figure B5.3 – Soil wetness by month for the year 2000: larger values indicate drier soil.**

**Wind factor**

Equation B5.6 was used to compute estimates of monthly wind factor values for each 25km² grid square across England and Wales. Mean monthly variation of the RWEQ wind factor is shown in Figure B5.4 for five years (2000 to 2004 inclusive). However, that monthly data on a 25km grid are averages and do not give an indication of the extremes of wind likely to be encountered at a finer scale. In general, the strongest winds over monthly periods occur along the coastline, noticeably the stronger winds extend inland on the east coast during the winter months. The summer months generally have the lowest wind speeds. Monthly variation in the weather factor (EquationB5.13) was calculated from the soil wetness and wind factors. The spatial variation in the mean monthly weather factor for five years (2004 to 2004 inclusive) is also shown in Figure B5.4.
Figure B5.4 – Mean RWEQ wind and weather factors (2000 to 2004) by month; larger values indicate stronger winds and greater erosive potential respectively.

In general, the areas with monthly weather conditions leading to the greatest potential wind erosion are the autumn and winter months (September to April). The eastern parts of England and Wales generally have monthly weather conditions which are likely to lead to greater erosive losses, with the exception being part of the southern and western coasts.

**Model application**

Monthly values of wind erosion potential were calculated using the soil factor data and monthly weather factor data based on the RWEQ equation. Monthly values were calculated in each of five years spanning five-year periods: 2000-2004, 2020-2024, 2030-2034, 2050-2054 and 2090-2094. The calculations were originally made on the 1 km soil grid and subsequently upscaled to the 5km grid by taking the mean of the finer resolution data. In local areas where soils have organic matter contents both above and below 5%, estimates of wind erosion potential are only available for the latter, so the mean values are biased towards the soils with smaller organic matter contents. Fryrear et al. (1998) calculated a value of 109.8 for their constant $a$ in equation B5.2 based on a regression from measured and estimated values of $Q_{max}$ from wind erosion events in the USA. No such data are available to determine an equivalent value for our study. A value of 90 was adopted in a previous study where RWEQ was applied to soil and climate data from England and Wales (Defra, 2006) to translate values onto a quantitative scale. To ensure comparisons could be made with the previous study, the constant used in the study reported here was set to the same value (90). The wind erosion potential values presented in this study are not in the same units as presented by Fryrear et
al. (1989), but provide a quantitative estimate of relative wind erosion potential, in both space and with time.

The quantitative estimates of wind erosion potential do not account for land cover. Wind erosion will be greatest in areas of tilled arable land and will be limited in areas of permanent vegetation cover (e.g. permanent grassland and forest). In general, arable land is confined to the eastern and southern regions of England and Wales, so these areas are the most sensitive to wind erosion.

![Figure B5.5 – Qmax (year 2090) providing a quantitative, relative scale of wind erosion potential](image)

Examples of seasonal wind erosion potential (Qmax) across England and Wales are shown for the years 2000 and 2090 (Figure B5.5). In these images, the greatest wind erosion potential covering the largest area occurs during April 2000; regions with the largest projected Qmax values include Norfolk, the Midlands, the Cheshire basin and some coastal regions. Wind erosion potential is often greatest in the spring quarter of the year because topsoil moisture contents are smaller than in winter but with strong wind. Of these areas, both Norfolk and the Midlands are dominated by arable land and so are sensitive to wind erosion, whilst the other regions including coastal areas are largely under permanent vegetation and so are considerably less sensitive.

To make an assessment of the potential impacts of climate change we need to compare Qmax over longer periods of time to assess whether there is any evidence of a temporal trend. The soil factor across England and Wales is constant in our calculations of wind erosion potential, so temporal changes (months, years or decades) in Qmax are a function of the spatial variation in the climate projection data. A summary of the statistical distribution of mean monthly Qmax for the five year periods between 2000 and 2090 is shown in Figure B5.6. Greater overall wind erosion potential is shown by distributions shifted further to the right of each plot (larger monthly Qmax values). There is no overall trend in projected wind erosion potential between 2000 and 2090 by month; the time-steps of monthly erosion potential values show considerable variation by month. It is useful to consider in more detail the months of September and February where wind erosion is likely to be most severe because soil is exposed on arable land before winter and spring crops, respectively, are
sown. The overall distribution of mean projected wind erosion potential for September shows a small decline between 2000-2004 and 2090-2094. In the case of mean monthly wind erosion potential in February, there is no clear pattern of change; the period with the smallest projected mean values is 2050-2054.

The most severe wind erosion events are caused by strong winds blowing across dry, bare soil surfaces and so it is also important to consider the maximum monthly wind erosion potential for the same periods (Figure B5.7). In common with the distributions for projected mean wind erosion potential, there is no clear pattern of change through time from 2000-2004 and 2090-2094. The impact of variations in monthly climate has a greater impact in wind erosion potential than the variation over the periods of climate projections. The months of September and February when arable soils are most susceptible to erosion show the pattern as that observed for the mean figures; a small decline over the projected time periods during September and large variations in February but no clear temporal pattern with time.
Figure B5.6 – Projected Mean Qmax (a quantitative, relative scale of wind erosion potential) by month for 5-year periods between 2000-2004 and 2090-2094
Figure B5.7 – Projected maximum Qmax (a quantitative, relative scale of wind erosion potential) across England and Wales by month for 5-year periods between 2000-2004 and 2090-2094

Uncertainties and limitations

There are two main types of uncertainty and limitation associated with the predictions of wind erosion potential: i) the uncertainties inherent in the climate variable predictions and, ii) the limitation of the RWEQ model. We deal with these separately below.

Much of the uncertainty associated with the climate variable data has been discussed in earlier sections of this report. Given that wind speed is the dominant driver of wind erosion, we focus on this component of the climate projections. No wind speed projections were provided as part of the
UKCIP09 probabilistic climate projections because they were considered to be subject to too much uncertainty (UKCIP09, 2010). There is very poor agreement between different global and regional climate models on wind speed prediction. In a study of prediction of extreme near-surface wind speeds, Rockel and Woth (2007) concluded that, “an ensemble of models is essential in assessing the future change in extreme wind speeds: only in a few regions and for a few months did all models even agree on the sign of the change”. This is clearly of great significance for estimating wind erosion potential and raises important questions over the confidence that should be placed on the modelled outputs presented above. We can state that there was no discernible change in the predicted decadal wind factor values from 2000-2004 and 2090-2094 (calculated using Equation 13 above). An analysis of UKCIP wind speed projections for 2080 have suggested a small (0.5%) overall increase in annual mean wind speeds averaged across the UK, but with more significant seasonal trends of 15% increases in winter wind speed in southern England (Harrison et al., 2008). If climate change does lead to significant changes in wind speeds, then the RWEQ model outputs cannot be relied upon. However, if we assume there is no substantial change in wind speeds over the period considered here, the RWEQ model can still inform us whether projected changes in soil moisture (rainfall and evapotranspiration) will affect wind erosion potential.

Validation studies where predictions of wind erosion potential have been made with RWEQ have demonstrated a certain amount of bias and other limitations. The RWEQ model tends to underestimate the observed wind erosion measurements by approximately 45 per cent at measured erosion values of 300 kg m⁻². It was also shown that the model is highly sensitive to variations in soil surface crusting in reference plots, represented by the soil crusting factor (Equation 5) which measures the susceptibility of the soil to form crust depending mainly on its clay content (Buschiazzo and Zobeck, 2008). Soil surface crusting – which largely depends on rainfall quantities – is critical in determining wind erosion (Zobeck, 1991). No universally accepted method to measure crusting has been developed and very few models include this variable in erosion estimates (Zobeck et al., 2003). Although the full model version of RWEQ includes a link between climatic conditions and SCF, permitting prediction of crust formation and degradation with time, this dynamic calculation is not incorporated into the Qmax component of RWEQ used for wind erosion estimation in this study.

**Discussion**

In a previous report assessing wind erosion potential across England and Wales (Defra, 2006), a preliminary assessment of the wind erosion potential across England and Wales had been undertaken using climate data for the period between 1961 and 1990. As we might expect the overall patterns of wind erosion potential reported in that study and the current study are similar. The previous study compared the RWEQ wind factor (Equation B5.13) for the period 1961-1990 and climate projection data for 2050 using HadRM3 with the SRES A2 emissions scenario. The authors concluded that their preliminary analysis did not indicate an increase in wind erosion potential over this period, there was some evidence for a small decline in the wind factor. Wind speeds across England and Wales are known to be seasonal; the highest wind speeds occur during the winter. An analysis of UKCIP wind speed projections for 2080 have suggested a small (0.5%) overall increase in annual mean wind speeds averaged across the UK, but with more significant seasonal trends of 15% increases in winter wind speed in southern England (Harrison et al., 2008). On the basis of HadRM3 climate projections and assuming no substantial changes in land use, we conclude that there is unlikely to be a substantial change in the magnitude of wind erosion of mineral soils (<5% organic
matter content) across England and Wales. If land use patterns change towards increasing the proportion of arable land, the area where wind erosion may increase substantially is the Cheshire plain and some parts of the West Midlands where land use is currently grassland.

B6. Contamination – (i) phosphorus modelling using PSYCHIC

See Appendix C

B7. Contamination – (ii) acidification modelling using VSD

The threat and the model

One source of soil contamination which has been of concern in recent decades is acidification due to atmospheric deposition of oxides of sulphur (S) and nitrogen (N). The mechanisms involved are described by Reuss et al. (1987). Following reductions in emissions of these oxides to the atmosphere there is widespread evidence of the soil and fresh water recovery predicted by modelling, although this recovery is generally still in progress (Evans et al., 2001). Widely applied models of the soil acidification process include the Model of Acidification of Groundwater in Catchments (MAGIC) (Cosby et al., 1985), the Soil Acidification model of Forest Ecosystems (SAFE) (Alveteg and Walse, 1998), and Very Simple Dynamic (VSD) model (Posch and Reinds, 2009). We have chosen to apply the VSD model to investigate the influence of climate change in England and Wales on the acidification status of soils. The model has been applied at a European scale for critical load estimation (Posch and Reinds, 2009) and is used in the UK for the same purpose (Evans et al., 2007).

The processes modelled by VSD focus on the chemical budget of the soil and account for mass and charge balance for major ions, with well-established equilibrium equations for aluminium/pH (gibbsite) and bicarbonate equilibrium. Organic ion equilibrium with H⁺ and DOC uses a relation derived by Oliver et al. (1983). Exchangeable cation equilibrium is described by either of the well-known Gaines-Thomas or Gapon equations. The N and C dynamics are an important part of the model, including immobilisation, denitrification and mineralisation terms for N, with restrictions on the C/N ratio in the organic pool. The model is driven by atmospheric deposition and net rainfall, after accounting for evaporative loss, at a 1 year time step and at a spatial resolution which adequately accounts for variability in the key variables influencing acidification status. The model is run at UK scale on a 1km grid.

VSD is dependent on estimates of annual rainfall evaporation and atmospheric deposition of major ions as input driving variables. In routine application, the deposition terms are assumed to be based on standard emission scenarios. These values are available for the UK on a 1km grid, based on measurement and modelling (Smith et al., 2000). The model also requires a range of soil properties which influence the chemical budget of key chemical constituents in solution. These have been estimated for UK soils by Evans et al. (2004) based on soil maps and field measurement of the properties of each soil class at a limited number of locations. Weathering rates for present day conditions have also been estimated and are also considered fixed over time (Hall et al., 2003).
Further details of the sources of soil parameters are provided by Hettelingh et al. (2008). Standard values of runoff are based on 1941-70 average annual rainfall estimates on a 1km grid. Evaporation at this scale is estimated using the Penman equation at limited measurement sites, interpolated across the UK. Actual evaporation has been calibrated against observed runoff data, not over a fixed period. Some detail of this procedure is provided by Boorman (1996).

**Model application**

VSD is in routine use in critical load assessment, with model runs into the future assuming changes in deposition following standard emission scenarios, but without accounting for other aspects of climate change. They assume, for example, constant runoff and temperature into the future. For the present project the model has been modified to allow for the effects of projected climate change on some processes. Changing the water budget potentially alters the dilution effect of precipitation, with further effects on the ionic and other chemical balance of soil water. Temperature affects chemical and biological process rates, notably weathering. Temperature effects are not explicitly included in the standard version of VSD, and the model has been extended to allow temperature-dependence of weathering. The method used follows Posch et al. (2002). These authors have suggested that higher temperatures, changed precipitation patterns and modified net primary production generally increase critical loads. That is to say, the deposition load which can be accommodated without damage to ecosystems increases. Posch et al. (2002) note the dependence of weathering on temperature, and suggests the use of the equation:

\[ W(T) = W(T_0) \exp\left(\frac{A}{T_0} - \frac{A}{T}\right) \]

In equation B7.14 T is temperature in °K, \(T_0\) is a reference temperature and A is 3600 °K. Equation B7.14 provides a multiplicative factor for estimating weathering rates. In addition to changing weathering rates, Posch et al. (2002) change the estimated runoff used in the model and net primary productivity.

The results presented here are for changes in soil pH. A more refined analysis would consider UK changes in critical load in response to climate change. The cation exchange processes, aluminium and bicarbonate equilibrium and nitrogen cycle processes may also be temperature dependent, but this has not been accounted for in the modelling. These should be considered in a fuller modelling exercise. However, there are major approximations to soil processes whose uncertainty in field application has not been fully understood. This needs to be taken into consideration in assessing the value of including a climate change response in the model.

The VSD model has been run using HadRM annual projections of rainfall and temperature. Figures B7.1a-f show projected changes in pH for the land cover classes considered by VSD. Individual classes may be absent from parts of England and Wales.
Figures B7.1a–f. Projected pH for 6 land cover classes in the 2020s, 2030s, 2050s and 2090s.

The acidification status of soils in England and Wales is not at equilibrium but is recovering from past high atmospheric inputs. Further recovery from acidification is anticipated regardless of climate change. The VSD model has therefore also been run with drivers which assume no change in climate and standard emission scenarios. The pH differences computed between these two scenarios are presented in Figures B7.2a–f. The plots show small differences in pH, both negative (slower recovery from acidification) and positive. In general there is faster projected recovery under climate change in southern and eastern England, and slower projected recovery in Wales. Projected recovery in the Pennines is variable. The suggested changes in the rate of recovery of soil pH given the projected climate change data and the assumed process response are not major. In terms of mechanisms, the temperature effect is to increase base cation weathering, which should has a net effect of raising the projections of pH generated by VSD. The effect of changes in the water budget is to reduce pH through increased evaporation.
Figures B7.2a-f. Differences in projected pH under climate change and non-climate change scenarios

The pH time series trajectories for the six land cover classes are shown in Figure B7.3. The plotted values are the mean pH for all 5km grid squares where the land cover class is present. The scatter in the climate change simulations reflects the variability in output from the HadRM model, while for the non-climate change data, runoff and temperature are held constant. An overall slight reduction in the rate of recovery from acidification is apparent.
Figure B7.3. Comparison of spatially averaged acidification recovery rates under climate change and no climate change.

Discussion

The VSD model has been widely used in the UK and elsewhere. In making modifications to allow for changes in temperature and water budget, we have assumed only that weathering rates change with temperature, and according to the formula provided by Posch et al. (2002). Other processes in the soil are likely to be temperature dependent, but the temperature response is not quantified, so cannot be included in the model. The calculation of runoff into the future depends on rainfall and evaporation estimates. Both rainfall and evaporation estimates are available from the HadRM3 simulations, although as discussed, the modelled evaporation values are not compatible with standard models or filed measurements. The JULES model also provides estimates of evaporation and runoff which tend to favour higher evaporation and runoff over recent decades than has been observed or independently modelled. In practice, we have calibrated present day estimates of runoff given by JULES against the runoff values used in VSD, assuming an additive adjustment fixed over time. This adjustment is significant for low rainfall areas.

Simulations suggest that climate change will have a minor effect on recovery from acidification, despite the significant increase in base cation weathering. The base cations released largely go towards replenishing the exchangeable cations in the soil, rather than raising the pH of the runoff. The conclusion is that recovery from acidification is not likely to be significantly affected by
climate change. The minor effect of increased weathering in increasing pH is offset by increased evaporation in increasing ionic concentrations generally, including protons.

B8. Compaction modelling using the Workable Days model

The threat and the model

Soils in England and Wales are very vulnerable to compaction because of the frequency of wet soil conditions (Jones et al., 2003). Although the soils are less susceptible to compaction than many areas of Europe, climatic factors increase the threat considerably. In the Workable Days model a day is defined as ‘workable’ if the soil is drier than field capacity (FC; -5 kPa water potential). In the work of Cooper et al. (1997) this was changed to 110% FC as some soils they examined in Scotland had 0 workable days if a drier threshold was defined. Our approach used -10 kPa water potential to define FC as a wetter threshold produced large areas with greater than 360 workable days. Workable Days provides a simple method to assess relative changes in the vulnerability of soil to compaction, but it does not predict the extent of potential damage. Moreover, some soils will be damaged by compaction at water contents drier than FC, but data on the mechanical behaviour of soils and England and Wales is insufficient to apply a more mechanistic model.

Field capacity is a vague term related to the “drainage of excess water”. The threshold can vary from -5 kPa (UK assumption) to -100 kPa for heavy clays. Soils with large amounts of organic carbon present a particular challenge. FC is often estimated from water retention curves using the van Genuchten model, but this can lead to inaccuracies (Twarakavi et al. 2009). However, for the implementation of the JULES model at 5 km resolution for England and Wales, this is the only viable approach without considerable extra work in modifying models and analysing soil texture versus FC thresholds in greater detail.

The model is essentially parameter-free as it works only with soil water content. This is computed externally to the Working Days model itself. For this application the soil water content has been estimated using the JULES model. JULES was used to model soil water content at depth increments of 0-10 cm (topsoil) and 10-35 cm (subsoil). The limitations of JULES are described elsewhere. FC at -10 kPa was obtained from Van Genuchten parameters available for each depth increment for a particular soil. This is a potential source of error given the small-scale spatial variability of soil hydrological properties. Moreover, water retention characteristics depend on stress history (e.g. previous compaction, flooding damage), changes in soil management and vary temporally depending on tillage, weather and soil structure dynamics. Existing knowledge does not allow for these processes to be considered. It should be possible to extend JULES to define more accurate FC thresholds by incorporating recent research by Twarakavi et al. (2009). This would not be a trivial task.

The catchment parameters needed are described for JULES. They are available at the scale of the study, but soil hydrology data were defined by soil type alone. Differences due to previous compaction stress and variability of soil hydrological properties for a particular soil series could not be considered. Climate drivers influenced only the output of JULES, which is described in Chapter B2.
Workable Days applies to any traffic occurring on soil, whether it is from arable farming, livestock or forestry. However, the timing of operations will depend on land use, so seasonal workable days were also evaluated. Arable farming and forestry can limit traffic to outside of winter periods, whereas livestock can impact soil throughout the year. Changes in cropping resulting from climate change or location were not considered.

**Model application**

Field capacity values at -10 kPa calculated using the Van Genuchten equation are shown for England and Wales in Figure B8.1. Most FC values fall between 0.2 and 0.5, which are realistic. There are isolated areas with FC less than 0.1, suggesting difficulties with estimating FC.

The decade averages of annual workable days are shown in Figure B8.2 for 2000-2009. In general the west of England and Wales has fewer workable days than the east. There are some regions such as central Wales and East Anglia where drier FC values correspond to more annual workable days. Likewise, a patch of soil in northeast England with a wetter FC value corresponded to fewer workable days. These trends, however, are isolated. The unrealistically dry FC values found for isolated patches result in 150-300 workable days.

![Field Capacity and Workable Days Maps](image)

*Figure B8.1 Field capacity and average annual workable days for 2000-2009 calculated for soil at 0-10 cm and 10-35 cm depth.*

*Figure B8.2 shows the predicted differences in annual workable days between future decades and 2000-2009. These correspond to the annual precipitation data presented in Figure B2.9, where the*
north of England is shown to have increased precipitation in 2020-2039 and the south of England and east Wales have the greatest reduction in precipitation in 2050-2059.

**Figure B8.2** Difference in average annual workable days between future decades and 2000-2009.

The effect of greater precipitation in northern England in 2020-2039 has a greater impact on Workable Days of subsoil (10-35 cm), whereas, less precipitation in 2050-2059 in southern England has a greater impact on workable days of topsoil (0-10 cm). Figure B8.3 shows the cumulative percentage of annual average workable days for the various decades modelled. There is a shift towards more workable days in the future, although only by a few days in total.

**Figure B8.3** Difference in average annual workable days between future decades and 2000-2009.

Average seasonal workable days for 2000-2009 are shown in Figure B8.4. As would be expected, winter (December-February) months have the least Workable Days, with very few in much of Wales and western England. Eastern England has more workable days, although limitations to the modelling described previously probably lead to the patches with 90 Workable Days. Water flux and storage calculations in JULES need to be adjusted to model processes in wet soils more accurately.
Average seasonal workable days are summarised for topsoil in Table B8.1 and subsoil in Table B8.2. Summers have a small increase predicted by 2090. The minimum number of workable days also increases. Winter has a greater increase in workable days but there remain areas with very limited workable days, showing that the threat of soil compaction will persist. Spring and autumn workable days, which are important to many field operations such as planting and harvesting, increase by a few days on average.

![Seasonal Workable Days 2000 (0-10cm)](image1)

![Seasonal Workable Days 2000 (10-35cm)](image2)

**Figure B8.4 Average workable days for Winter (December-February), Spring (March-May), Summer (June-August) and Autumn (September-November) for 2000-2009.**

**Table B8.1. Estimated average seasonal topsoil (0-10 cm) Workable Days per decade**

<table>
<thead>
<tr>
<th>Decade</th>
<th>Winter (Dec-Feb)</th>
<th>Spring (Mar-May)</th>
<th>Summer (Jun-Aug)</th>
<th>Autumn (Sep-Nov)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>std dev</td>
<td>min</td>
<td>mean</td>
</tr>
<tr>
<td>2000</td>
<td>36</td>
<td>23</td>
<td>0</td>
<td>69</td>
</tr>
<tr>
<td>2020</td>
<td>44</td>
<td>24</td>
<td>0</td>
<td>73</td>
</tr>
<tr>
<td>2030</td>
<td>43</td>
<td>25</td>
<td>0</td>
<td>69</td>
</tr>
<tr>
<td>2050</td>
<td>52</td>
<td>26</td>
<td>0</td>
<td>73</td>
</tr>
<tr>
<td>2090</td>
<td>47</td>
<td>24</td>
<td>0</td>
<td>73</td>
</tr>
</tbody>
</table>
Table B8.2. Estimated average seasonal subsoil (10-35 cm) Workable Days per decade

<table>
<thead>
<tr>
<th>Decade</th>
<th>Winter (Dec-Feb)</th>
<th>Spring (Mar-May)</th>
<th>Summer (Jun-Aug)</th>
<th>Autumn (Sep-Nov)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>std dev</td>
<td>min</td>
<td>mean</td>
</tr>
<tr>
<td>2000</td>
<td>42</td>
<td>25</td>
<td>0</td>
<td>68</td>
</tr>
<tr>
<td>2020</td>
<td>47</td>
<td>27</td>
<td>0</td>
<td>73</td>
</tr>
<tr>
<td>2030</td>
<td>46</td>
<td>28</td>
<td>0</td>
<td>69</td>
</tr>
<tr>
<td>2050</td>
<td>54</td>
<td>28</td>
<td>0</td>
<td>73</td>
</tr>
<tr>
<td>2090</td>
<td>46</td>
<td>28</td>
<td>0</td>
<td>72</td>
</tr>
</tbody>
</table>

The differences in projected seasonal Workable Days between future years and 2000-2009 are illustrated in Figure B8.5 for spring and summer, and Figure B8.6 for winter and autumn. Parts of northern England are predicted to have fewer autumn Workable Days in 2030 and spring Workable Days in 2020. By 2050 these differences diminish and autumn Workable Days increase in parts of southwest England and Wales.
Figure B8.5 Difference in Spring (March-May) and Summer (June-August) average workable days between future decades and 2000-2009.
Discussion

Workable days provides a crude estimate of days when traffic will not damage soil by compaction (Cooper et al., 1997). For national scale modelling of climate change impacts it provided the only viable option, as it is based entirely on soil water properties. It does not account for susceptibility of soils to compaction, and soils may be damaged if drier than the -10 kPa threshold that was set, depending on the load and hydromechanical properties. The resolution provided by an Expert Model (Jones et al., 2003) would not have detected the observed small shifts in workable days. Mechanistic models account for the magnitude of the applied load and the hydromechanical properties of soil, but they are too complex to apply to large-scale modelling without considerable further work. Models like SOCOMO (van den Akker, 2004) require information on the compression characteristics of soil (Fritton 2008; Horn & Fleige, 2003) that are not available for England and Wales.

All uncertainties with predicting soil water and climate change discussed previously will also apply to the estimation of workable days. The derivation of field capacity from Van Genuchten parameters is a source of error. Water retention curves are influenced by soil stress history and can vary considerably over small distances and temporally. Modelling soil water with JULES appears to be another source of error that is evident from the large areas of land predicted to have few nonworkable days in spring, summer and autumn.

The conclusion is that under the projected climate change scenarios used, there would be a small increase in the number of workable days generally, due to lower soil water content due to increased evaporation at higher temperatures. However, areas will persist with few workable days, so the localised threat of soil compaction will remain. Data on the compression characteristics of
soils in England and Wales are required to implement mechanistic models. These estimate the extent of soil compaction from the mechanical properties of soil and imposed stresses.

**B9. Salinity modelling using SALTMED**

**The threat and the model**

Salinity has been identified as a threat at European scale, although this threat is not evenly distributed across the continent. At the wider scale salinity issues are generally important in heavily irrigated areas where there is also high evaporation and use of brackish water. This may allow little flushing of salts from the soil either artificially or by rainwater percolation. At the present time salinisation is not of agricultural concern in the UK. There is widespread use of irrigation in some parts of the UK which receive relatively low rainfall (c. 500mm/yr). However, high rainfall and low evaporation in winter months prevent any accumulation of salts, even where evaporation exceeds rainfall in summer. In addition, irrigation water used in the UK is not notably saline. The nearest location in Europe where salinisation is a major concern is the Iberian peninsula.

One source of salinisation of local concern in the UK is seawater inundation. Some coastal and low-lying areas are vulnerable to storm surges which are liable to cause short-term flooding with seawater until breaches in defences are sealed. We have taken this as an example of salinisation for modelling, despite its restricted importance in the UK.

This short study aims to investigate the possible impact of future climate on soil salinity and plant survival in some high risk coastal sites (Figure B9.1). For this investigation, the SALTMED model (Ragab 2002; 2005) has been selected to study soil salinity evolution over time as a result of seawater inundation and also to investigate the impact of salinity stress on the vegetation cover.

**Model application**

The seven regions shown in Figure B9.1 were initially selected as low land with a possible risk of seawater inundation, and a single 5km square identified within each region for modelling (Table B9.1). Estimated storm surge water levels provided by the Met Office indicated that three sites out of the seven were at higher risk (Figure B9.2). Subsequently, these three sites were considered in this study. They are the Parrett estuary, The Fens and the Norfolk Broads.

**Table B9.1. Sites at high risk of inundation**

<table>
<thead>
<tr>
<th>Location</th>
<th>easting</th>
<th>northing</th>
<th>Elevation (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sussex coast</td>
<td>482500</td>
<td>102500</td>
<td>4.5</td>
</tr>
<tr>
<td>Parrett estuary</td>
<td>327500</td>
<td>142500</td>
<td>4.6</td>
</tr>
<tr>
<td>Foulness</td>
<td>597500</td>
<td>192500</td>
<td>3.4</td>
</tr>
<tr>
<td>Fens</td>
<td>557500</td>
<td>307500</td>
<td>1.7</td>
</tr>
<tr>
<td>Norfolk Broads</td>
<td>642500</td>
<td>322500</td>
<td>2.6</td>
</tr>
<tr>
<td>Humber estuary</td>
<td>522500</td>
<td>422500</td>
<td>4.5</td>
</tr>
<tr>
<td>Morecambe Bay</td>
<td>337500</td>
<td>447500</td>
<td>6.9</td>
</tr>
</tbody>
</table>

The elevations of these sites (Table B9.2) were obtained from the Institute of Hydrology Digital Terrain Model (IHDTM). Heights are interpolated between high water mark (for which an elevation of 3m has been assumed) and the contour lines on OS 1:50,000 maps, which are at a vertical interval
of 10m and are therefore only approximate. The elevations in the Wash and Norfolk Broads are less than 3m because in these areas there is a 0 m contour.

SALTMED (www.safir4eu.org) was developed for agricultural water management using fresh and saline water (Ragab, 2002 and 2005). The model represents the vertical movement of saline water through the soil profile. Water movement is based on Richards’ equation and solute movement is on the convection dispersion equation. Details of the numerical scheme used are provided at the website above. The model also calculates the stress to vegetation due to drought and salinity. The stress that the plant is subjected to is estimated as a ratio between the actual water uptake and the maximum / potential water uptake. More details can be found in Ragab (2002).

The model uses Richards’ equation to represent the vertical flow of water through the soil, with material in solution transported vertically by advection-dispersion. Only physical transport is considered. The model accounts for the height of the above-ground head of water present in salt-water flooding, and for crop growth and the effect of salt stress on water uptake for a range of crops.

The SALTMED model requires the hydraulic properties of the soil for use in Richards’ equation and the convection-dispersion equation. These parameters are provided by the LandIS database. Crop parameters are also required describing crop growth in response to water availability and salinity constraints. The timing and extent of inundation is also required, and these depend on the elevation of the land. In reality, they also depend on the effectiveness of sea defences. In principle the probability of an overtopping, coupled with the extent of an ensuing breach, can be estimated. That is not attempted here. Following a breach, the severity of salinisation would also depend on the speed at which a breach could be repaired, and water evacuated from flooded land by natural drainage or pumping. These aspects of seawater flooding are not considered.
Table B9.3 shows the dominant soil series and land cover at the seven sites. These have been obtained from the NSRI soil map of England and Wales.

**Table B9.3. Dominant soil series and land cover**

<table>
<thead>
<tr>
<th>Site</th>
<th>Dominant soil series</th>
<th>Dominant Vegetation cover</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parrett estuary</td>
<td>NEWCHURCH</td>
<td>Permanent grass</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Wheat</td>
</tr>
<tr>
<td>Fens</td>
<td>DOWNHOLLAND</td>
<td>Wheat</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sugar beet</td>
</tr>
<tr>
<td>Norfolk Broads</td>
<td>WALLASEA</td>
<td>Permanent grass</td>
</tr>
<tr>
<td>Site</td>
<td>Dominant soil series</td>
<td>Dominant Vegetation cover</td>
</tr>
<tr>
<td>-------------</td>
<td>----------------------</td>
<td>---------------------------</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Spring Barley</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Wheat</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sugar beet</td>
</tr>
</tbody>
</table>

The soil hydraulic parameters were based on the NSRI soils series data, also used in JULES (Table B9.4). Crop parameters are based on personal communication (Prof. Tim Flowers, Sussex University, Dr. Owen Mountford, CEH Wallingford), Met Office MORECS system and the FAO data (http://www.fao.org/nr/water/aquacrop.html).

**Table B9.4. Soil hydraulic properties for running the SALTMED model**

<table>
<thead>
<tr>
<th>Soil Series</th>
<th>Hb cm</th>
<th>λ</th>
<th>Ksat mm/d</th>
<th>θ fc m³/m³</th>
<th>θ sat m³/m³</th>
<th>θ wp m³/m³</th>
</tr>
</thead>
<tbody>
<tr>
<td>NEWCHURCH</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1307</td>
<td>30.4</td>
<td>0.1939</td>
<td>753.408</td>
<td>0.29021</td>
<td>0.4836</td>
<td>0.14473</td>
</tr>
<tr>
<td></td>
<td>30.2</td>
<td>0.198898</td>
<td>243.648</td>
<td>0.18666</td>
<td>0.3155</td>
<td>0.09142</td>
</tr>
<tr>
<td></td>
<td>29.8</td>
<td>0.1955</td>
<td>72.576</td>
<td>0.17262</td>
<td>0.29</td>
<td>0.08558</td>
</tr>
<tr>
<td></td>
<td>30.7</td>
<td>0.203198</td>
<td>127.008</td>
<td>0.17609</td>
<td>0.3001</td>
<td>0.08492</td>
</tr>
<tr>
<td>WALLASEA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2270</td>
<td>29.8</td>
<td>0.202</td>
<td>788.832</td>
<td>0.26719</td>
<td>0.4566</td>
<td>0.12939</td>
</tr>
<tr>
<td></td>
<td>29.8</td>
<td>0.202</td>
<td>788.832</td>
<td>0.26719</td>
<td>0.4566</td>
<td>0.12939</td>
</tr>
<tr>
<td></td>
<td>29.9</td>
<td>0.190902</td>
<td>31.968</td>
<td>0.17051</td>
<td>0.2827</td>
<td>0.08595</td>
</tr>
<tr>
<td></td>
<td>30.4</td>
<td>0.1997</td>
<td>72.576</td>
<td>0.17177</td>
<td>0.2906</td>
<td>0.08389</td>
</tr>
<tr>
<td>DOWNHOLLAND</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>314</td>
<td>31.2</td>
<td>0.200501</td>
<td>1638.144</td>
<td>0.39079</td>
<td>0.659</td>
<td>0.19035</td>
</tr>
<tr>
<td></td>
<td>31.2</td>
<td>0.200501</td>
<td>1638.144</td>
<td>0.39079</td>
<td>0.659</td>
<td>0.19035</td>
</tr>
<tr>
<td></td>
<td>31.2</td>
<td>0.200501</td>
<td>1638.144</td>
<td>0.39079</td>
<td>0.659</td>
<td>0.19035</td>
</tr>
<tr>
<td></td>
<td>31.2</td>
<td>0.200501</td>
<td>1638.144</td>
<td>0.39079</td>
<td>0.659</td>
<td>0.19035</td>
</tr>
</tbody>
</table>

In Table B9.4 the soil series name and standard code are given, and the parameters are as follows:

- **Hb**: Air entry potential
- **λ**: Pore size distribution index
- **Ksat**: Saturated hydraulic conductivity
- **θ fc**: Field capacity water content
- **θ sat**: Saturated water content
- **θ wp**: Wilting point water content

The risk of inundation at the sites has been based on Met Office estimates of the distribution of storm surges at the identified risk locations. The surges were estimated from an ensemble of the Hadley Centre model HadCM3 (Gordon et al. 2000), by perturbing the physical parameters within the model (the ensemble also contained the unperturbed member). These global models are too coarse to provide the necessary boundary conditions for the surge model, so it was down-scaled with the regional climate model HadRM3, in such as way as to maintain a consistent regional ensemble. This provided the wind and surface pressure fields required to drive the surge model POLCS3 (http://www.pol.ac.uk/ntslf/model.html, used operationally at the Met Office). The surge
model was run for the complete 150 years (from 1950 to 2100). From this time series of surface elevation was extracted for the seven locations specified. The scenario is that of the unperturbed member of the ensemble, under the A1B scenario (http://www.grida.no/publications/other/ipcc_tar/?src=/climate/ipcc_tar/wg3/081.htm). The exact offset that used for the elevation of each site is expected to introduce uncertainty into the system.

Figure B9.2. Estimated storm surge heights for the 7 sites for 2000-2099 (note, sites are numbered from 0 to 6).

The susceptibility of the three sites to inundation varies, as shown in Table 8.5. The Broads site is least affected, with the Parrett and the Fens approximately equally affected.

<table>
<thead>
<tr>
<th>Decade</th>
<th>Parrett</th>
<th>Fens</th>
<th>Broads</th>
</tr>
</thead>
<tbody>
<tr>
<td>2020</td>
<td>2.3</td>
<td>2.5</td>
<td>0.9</td>
</tr>
<tr>
<td>2030</td>
<td>2.9</td>
<td>2.8</td>
<td>1</td>
</tr>
<tr>
<td>2050</td>
<td>3.1</td>
<td>3.1</td>
<td>0.9</td>
</tr>
<tr>
<td>2090</td>
<td>4.2</td>
<td>3.6</td>
<td>0.9</td>
</tr>
</tbody>
</table>

The SALTMED model was run for 2020-2029, 2030-2039, 2050-2059 and 2090-2099. A summary of the results is shown in Table B9.6. Note that in all these model runs a breakthrough of any defences is assumed to occur at the start of the decade, with all subsequent surges allowed free access through the breach. This is not a realistic scenario, but allows demonstration of the capabilities of the SALTMED model.

Considering the three sites in order, at the Parrett estuary, (grass and wheat), during the first month of 2020, the salinity in the top 2m reached over 40 dS/m, by March 2020 the salinity front reached 4m and by November the salinity of the 10 meters soil profile was very close to the seawater value of 45dS/m. Salinity stayed close to that level for the rest of the decade as the rainfall was not
<table>
<thead>
<tr>
<th>Site &amp; decade</th>
<th>Dominant Soil Series</th>
<th>Total infiltration m³/m²</th>
<th>Total salt input Kg/m³</th>
<th>Total actual water uptake in 10 years m³/m²</th>
<th>Potential water uptake in 10 years m³/m²</th>
<th>Salinity Stress factor</th>
<th>Actual water Uptake/potential water uptake</th>
<th>Plant Survival of 45 dS/m seawater storms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parrett estuary - Grass</td>
<td>NEWCHURCH</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2020-2029</td>
<td>332</td>
<td>9377</td>
<td>58</td>
<td>3283</td>
<td>0.0175</td>
<td></td>
<td></td>
<td>poor</td>
</tr>
<tr>
<td>2030-2039</td>
<td>411</td>
<td>11686</td>
<td>52</td>
<td>3246</td>
<td>0.0160</td>
<td></td>
<td></td>
<td>poor</td>
</tr>
<tr>
<td>2050-2059</td>
<td>457</td>
<td>13008</td>
<td>49</td>
<td>3182</td>
<td>0.0153</td>
<td></td>
<td></td>
<td>poor</td>
</tr>
<tr>
<td>2090-2099</td>
<td>562</td>
<td>16040</td>
<td>2</td>
<td>3096</td>
<td>0.0008</td>
<td></td>
<td></td>
<td>poor</td>
</tr>
<tr>
<td>Parrett estuary - Wheat</td>
<td>NEWCHURCH</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2020-2029</td>
<td>332</td>
<td>9377</td>
<td>9</td>
<td>2481</td>
<td>0.0037</td>
<td></td>
<td></td>
<td>poor</td>
</tr>
<tr>
<td>2030-2039</td>
<td>411</td>
<td>11687</td>
<td>6</td>
<td>2472</td>
<td>0.0024</td>
<td></td>
<td></td>
<td>poor</td>
</tr>
<tr>
<td>2050-2059</td>
<td>457</td>
<td>13011</td>
<td>7</td>
<td>2426</td>
<td>0.0031</td>
<td></td>
<td></td>
<td>poor</td>
</tr>
<tr>
<td>2090-2099</td>
<td>562</td>
<td>16040</td>
<td>4</td>
<td>2386</td>
<td>0.0018</td>
<td></td>
<td></td>
<td>poor</td>
</tr>
<tr>
<td>The Wash - Wheat</td>
<td>DOWNHOLLAND</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2020-2029</td>
<td>5495</td>
<td>158221</td>
<td>3</td>
<td>2415</td>
<td>0.0014</td>
<td></td>
<td></td>
<td>poor</td>
</tr>
<tr>
<td>2030-2039</td>
<td>5629</td>
<td>162092</td>
<td>3</td>
<td>2442</td>
<td>0.0014</td>
<td></td>
<td></td>
<td>poor</td>
</tr>
<tr>
<td>2050-2059</td>
<td>5684</td>
<td>163675</td>
<td>3</td>
<td>2377</td>
<td>0.0014</td>
<td></td>
<td></td>
<td>poor</td>
</tr>
<tr>
<td>2090-2099</td>
<td>5747</td>
<td>165498</td>
<td>3</td>
<td>2377</td>
<td>0.0014</td>
<td></td>
<td></td>
<td>poor</td>
</tr>
<tr>
<td>The Fens - Sugar beet</td>
<td>DOWN-HOLLAND</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Site &amp; decade</td>
<td>Dominant Soil Series</td>
<td>Total infiltration m³/m²</td>
<td>Total salt input Kg/m³</td>
<td>Total actual water uptake in 10 years m³/m²</td>
<td>Potential water uptake in 10 years m³/m²</td>
<td>Salinity Stress factor</td>
<td>Actual water Uptake/potential water uptake</td>
<td>Plant Survival of 45 dS/m seawater storms</td>
</tr>
<tr>
<td>---------------</td>
<td>----------------------</td>
<td>--------------------------</td>
<td>------------------------</td>
<td>---------------------------------------------</td>
<td>------------------------------------------</td>
<td>-----------------------</td>
<td>---------------------------------------------</td>
<td>---------------------------------------------</td>
</tr>
<tr>
<td>2020-2029</td>
<td></td>
<td>587</td>
<td>158221</td>
<td>5</td>
<td>1359</td>
<td>0.0038</td>
<td>poor</td>
<td></td>
</tr>
<tr>
<td>2030-2039</td>
<td></td>
<td>589</td>
<td>161959</td>
<td>5</td>
<td>1356</td>
<td>0.0038</td>
<td>poor</td>
<td></td>
</tr>
<tr>
<td>2050-2059</td>
<td></td>
<td>5685</td>
<td>163719</td>
<td>5</td>
<td>1332</td>
<td>0.0038</td>
<td>poor</td>
<td></td>
</tr>
<tr>
<td>2090-2099</td>
<td></td>
<td>5746</td>
<td>165477</td>
<td>5</td>
<td>1336</td>
<td>0.0037</td>
<td>poor</td>
<td></td>
</tr>
<tr>
<td><strong>Norfolk Broads - Grass</strong></td>
<td>WALLASEA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2020-2029</td>
<td></td>
<td>6</td>
<td>14</td>
<td>2394</td>
<td>3205</td>
<td>0.7470</td>
<td>Very good</td>
<td></td>
</tr>
<tr>
<td>2030-2039</td>
<td></td>
<td>11</td>
<td>147</td>
<td>2044</td>
<td>3207</td>
<td>0.6372</td>
<td>Good</td>
<td></td>
</tr>
<tr>
<td>2050-2059</td>
<td></td>
<td>10</td>
<td>132</td>
<td>1667</td>
<td>3052</td>
<td>0.5463</td>
<td>Medium</td>
<td></td>
</tr>
<tr>
<td>2090-2099</td>
<td></td>
<td>23</td>
<td>485</td>
<td>731</td>
<td>3008</td>
<td>0.2429</td>
<td>Low</td>
<td></td>
</tr>
<tr>
<td><strong>Norfolk Broads - S.Barley</strong></td>
<td>WALLASEA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2020-2029</td>
<td></td>
<td>6</td>
<td>14</td>
<td>972</td>
<td>1358</td>
<td>0.7153</td>
<td>Very good</td>
<td></td>
</tr>
<tr>
<td>2030-2039</td>
<td></td>
<td>11</td>
<td>149</td>
<td>771</td>
<td>1360</td>
<td>0.5670</td>
<td>Medium</td>
<td></td>
</tr>
<tr>
<td>2050-2059</td>
<td></td>
<td>10</td>
<td>139</td>
<td>389</td>
<td>1311</td>
<td>0.2969</td>
<td>Low</td>
<td></td>
</tr>
<tr>
<td>2090-2099</td>
<td></td>
<td>23</td>
<td>485</td>
<td>106</td>
<td>1313</td>
<td>0.0806</td>
<td>poor</td>
<td></td>
</tr>
<tr>
<td><strong>Norfolk Broads - Sugar beet</strong></td>
<td>WALLASEA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2020-2029</td>
<td></td>
<td>6</td>
<td>14</td>
<td>986</td>
<td>1311</td>
<td>0.7524</td>
<td>Very good</td>
<td></td>
</tr>
<tr>
<td>2030-2039</td>
<td></td>
<td>11</td>
<td>149</td>
<td>891</td>
<td>1301</td>
<td>0.6846</td>
<td>Good</td>
<td></td>
</tr>
<tr>
<td>2050-2059</td>
<td></td>
<td>10</td>
<td>138</td>
<td>513</td>
<td>1263</td>
<td>0.4065</td>
<td>Medium</td>
<td></td>
</tr>
<tr>
<td>2090-2099</td>
<td></td>
<td>23</td>
<td>486</td>
<td>199</td>
<td>1243</td>
<td>0.1601</td>
<td>Low</td>
<td></td>
</tr>
</tbody>
</table>
sufficient to leach out the salt from the deeper layers. A similar trend was noticed for 2030-2039, 2050-2059, 2090-2099 but with earlier dates, i.e. soil salinity progressed relatively faster with time from 2020 to 2099. This reflects the higher storm surges during the later decades. Where any breach in the sea defences is left open, and there are frequent inundations, the soil becomes saline within a year. Figure B9.3 shows the transition from essentially fresh water soil moisture content to salt water through the profile between the beginning and the end of 2020 for grassland at the Parrett estuary. This pattern is repeated for this site and the Fens for all decades and crops, with increasing rapidity through the decades as the frequency and magnitude of storm surges increases. While there may be occasional temporary recovery by the top layers of soil following rainfall, inundation is too frequent to allow recovery through the soil profile.
25 November 2020

Figure B9.3. Evolution of salinity profile at the Parrett Estuary, 2020

In contrast to the Parrett and the Fens, the Norfolk Broads site is less susceptible to salinity since inundation is less frequent. Here we can see periods of recovery as salt is washed from the soil profile by rainfall. Figure B9.4 shows examples of this. By the end of each decade the salinity profile does not show complete replacement of fresh by salt water. The precise pattern of salinity down the profile depends largely on the previous history of rainfall and inundation, partly influenced by crop cover. Figure B9.5 shows some variability in the profile for different crops. Note that these have been subject to the same atmospheric inputs and are computed for the same soil conditions. The difference between the salinity profiles for the difference in crops would repay further study, but is believed to be a reflection of different water uptake patterns.

![Salinity Profile Graphs]

Figure B9.5 Between-crop variability in final soil salinity for the Norfolk Broads projected from 2020s (note scale differences)
Figure B9.6 show the differences between the salinity at the Norfolk Broads site between different decades for spring barley. All show a banded pattern reflecting the balance between inundation severity and frequency and rainfall. While concentrations are lower in 2029 than in 2039 or 2059, we cannot confidently attribute this to climate change because of the high variability in inundation and rainfall.

Norfolk Broads Spring Barley 31/12/2029
Norfolk Broads Spring Barley 31/12/2039
Norfolk Broads Spring Barley 31/12/2059

Figure B9.6 Between-decade variability in final soil salinity for the Norfolk Broads under spring barley

At the Wash (wheat and sugar beet) projected soil salinity in the top 3m reached above 40 dS/m by the third week of January 2020. By the second week of February, salinity above 40dS/m reached 6 meters depth and by end of March 2020 water at 40dS/m salinity had reached the 10 meters depth. This salinity level stayed for the rest of the decade with insufficient rainfall to wash out the salt throughout the profile. The same trend was seen in the other decades, 2030-2039, 2050-2059, 2090-2099. The projected salinity of 40ds/m reached 10 metres depth around March of the first year. A similar pattern was seen at the Parrett, although the projected salinity front moved a little less quickly through the soil profile.
At the Norfolk Broads site (grass), after 3 years (April, 2023), projected soil salinity of the top metre only reached around 15 dS/m, then 32 dS/m by June 2024. Salinity then fell to 24 dS/m by September, 2024 and fluctuated thereafter due to the rainfall effect on leaching the salt out of the soil profile. The rainfall did affect the salinity levels and salt distribution with depth; however, it was not sufficient to significantly reduce the salinity. The same was noticed with the Norfolk Broads spring barley and sugar beet as the salinity fluctuated over the decades and the salinity level increased over the years and decades. The difference between the Norfolk Broads site and the Wash and Parrett Estuaries is the lower projected frequency of storm surges. The results from this site are likely to be more representative of the true situation in which any breach in the sea defences is repaired within a few days, and accumulated seawater either drained out at low tide or pumped out. The salt content of the soil is then dependent on infiltration over a few days, followed by recovery through flushing with rainwater over a period of months or years until a further breach.

The impact of salinity stress on the most dominant vegetation of the three sites was evaluated under the chosen scenario. The stress impact is calculated as a ratio of actual plant water uptake in presence of salt to the maximum/potential plant water uptake under fresh water condition. If the stress factor is equal to 1, the plant water uptake is considered to be at its potential level. Plants differ in their uptake rates due to their inherited tolerance levels. In SALTMED model, the stress level is calculated for a given period as the total actual water uptake divided by the total potential water uptake under no stress condition. This factor if multiplied by the maximum yield obtainable in the region under optimum no stressed conditions, is taken as an estimate of the actual yield. In the model, we need to give as input two parameters, the maximum yield obtainable in the region under stress free conditions and the plant tolerance level to salinity, $\pi_{50}$ which is defined as the salinity level after which, the water uptake would drop by 50% of the potential level. Based on various literature and personal communication (Prof Tim Flowers, Head of plant stress unit of Sussex University), $\pi_{50}$ values for grass, wheat, spring barley, sugar beet are assumed to be 20, 12.5, 15 and 16 dS/m respectively. Table B9.6 summarizes the results obtained for the three sites. The table shows that the plants in the Wash and Parrett estuary sites are likely to suffer and will have poor survival chances. At the Norfolk Broads site the crop would be less affected in the first decade as the water uptake is between 70% and 75% of the potential uptake. Because of a greater frequency of inundation in later decades under the chosen scenario, the crop would suffer greater damage in later decades.

A range of graphical outputs from the SALTMED model is presented in Appendix D.

**Discussion**

Modelling salinity has focussed on inundation by the sea. The major sources of salinisation worldwide are associated with irrigation with brackish water, and high evaporation rates in relation to irrigation applied. This second source of salinisation is not considered a likely problem in the UK, even under climate change.

The analysis presented here has assumed a breach occurs in sea defences at the start of each decade and that this breach is not subsequently filled. In reality breaches would be repaired allowing some recovery of inundated land. The analysis is nevertheless considered valuable in modelling the response of the soil to extended periods of inundation. The greatest component of the coastal
effects of climate change is the additional cost of defences to prevent inundation, or of remedial measures once inundation has occurred. These must be set against the loss of soil function if inundation is allowed. A modelling exercise of this sort should establish likely recovery times following irrigation. The loss in agricultural production, or changes in land use to accommodate soil changes, then needs to be assessed in relation to the cost of continuing to provide coastal defences.

The conclusion is that the risk of inundation is greater later in the century due to higher storm surges. Saline water entering the soil during short-term inundation could be diluted to a lower and possibly un-harmful salinity level to soil and plants if followed by a significant rainfall shortly after. However, this is very much dependant on initial soil salinity, duration and intensity of the rainfall that follows the short-term inundation

B10. Soil biodiversity and landslides

Theory proposes that high soil diversity generally contributes to a greater resilience of ecosystem services to environmental change and disturbance (De Ruiter et al., 2005). The sensitivity of soil organisms to stressors that could be associated with a warming climate, notably drought and water-logging under changing rainfall patterns, means that it is easily conceivable that climate change will have both direct and indirect effects on the diversity, abundance and activity of soil organisms. As outlined above there are currently no consistent frameworks or models that can be used to predict exactly what the nature of these changes may be or to identify the most suitable indicators to monitor them. While no single framework exists, there is evidence of relevant effects coming from plot and mesocosm scale experiments that have investigated the effects of climate change associated driver (changing atmospheric CO₂, higher temperatures, increased rainfall intensity, more frequent drought) on key soil functional groups. These data-sets represent a useful resource that can be used to support systematic reviews and modelling approaches that can link climate change drivers to changes in soil biodiversity and ultimately soil ecosystems. Review and meta-analysis of data and expert opinion held in UK and EU surveys and peer reviewed publications, with classification according to habitat, land use, soil characteristics, and soil biotic community is an achievable first step toward such model development.

One of the challenges that will arise from any meta-analysis of available data on climate change focused experiments is the diversity of metrics used to assess community level and functional impacts. In the UK the Soil Indicators Consortium has actively been developing broadly applicable biological indicators for soil. However even if consistent measures of diversity are used, previous work suggests that different soil functional groups and the ecosystem functions that they are linked to (i.e. carbon cycling, decomposition), will vary in sensitivity to climate phenomena (drying, warming, water-logging and drought) over different timescales (Briones, et al. 2007). Such vulnerability differences need to be captured in any model designed to predict the consequences of climate associated stressors on soil communities.

Once a suitable data-base of outcomes from relevant studies of climate effects is compiled, it then becomes feasible to use statistical modelling approaches to predict the impacts of individual and multiple climate stressors on soil communities. One approach that could be used for this type of predictive assessment is weighted analogies prediction implemented through case based reasoning. As highlighted above, this approach uses characteristics of a question case (e.g. ecosystem habitat type, land use, soil type, soil biotic community and climate stressor) to identify analogous cases in
the available database. These analogous cases can then be weighted and summarized in a prediction. This means that even if no results of microcosm or mesocosm experiments have been published for a particular change in local climatic conditions, it is still possible to predict an effect by using the results of experiments performed on other soils or in different habitats. Predictions made using this method can be expressed in terms of no effect, slight effect and clear effect change for each functional group and can be presented graphically using a similar approach as that which is currently included within the PERPEST model. By providing some indication of the type and magnitude of uncertainties, this will also indicate the types of data that must be gathered for more refined predictions. The refined model can then be used to translate spatially and temporally distributed measured or modelled data into climate change effects on soil biota.

Derivation of a methodology that makes use of the available data on climate effects on soil communities represents a reasonable first step towards the development of a prediction of the likely consequences of climatic change. Such prediction, however, will require independent validation. Here UK wide and international soil monitoring programs, including Countryside Survey and bespoke specifically designed plot and mesocosm experiments will be key approaches. Since the soil biodiversity consequences of climate change remain a major uncertainty, further experiments across different biomes, land uses and ecosystems can be expected that can be used for model refinement and validation.

The feasibility study into modelling the effect of climate change on the incidence and severity of landslides in response to climate change in England and Wales suggested there was little prospect of producing quantifiable projections. A number of models of landslide processes exist, and the one with the greatest potential was judged to be Enhanced GeoSure. However, the response of landslides in the United Kingdom to present day climatic triggers is not fully understood, so the changes brought about by future climate change are not known.

**The conclusion is that additional work is needed to produce models which will reliably predict change in landslides and biodiversity due to climate change.**

### B11. Discussion

It is unfortunate that UKCIP09 data proved to be unsuitable for general use in modelling at the time of their release. The work-around of using a single HadRM ensemble member as driver meant some lack of consistency with results which would have been used had UKCIP been suitable. Aggregation of HadRM data to a monthly scale by decade allowed comparison with UKCIP data at the same scale for precipitation and temperature. This provided bias reduction for these variables at the 25km scale, on the assumption the the bias reduction applied to the UKCIP data prior to their release was appropriate. Lack of bias correction for the remaining variables may be a source of error, and bias correction at a monthly scale does not necessarily account for bias in daily values. Many distributions of daily values may give the same mean monthly value, and evidence from modelling erosion risk suggests that the distribution of extremes of daily rainfall given by the downscaled HadRM3 data does not match the extremes found in the measured data record. Since extremes are particularly important for erosion, discrepancies of this sort need further investigation. However, it was never the purpose of HadRM3 data to reproduce the extreme behaviour of variables at scales of a few kilometres and of duration of the order of hours. Downscaling and bias correction from
coarser scale models for regional or local use are likely to be continuing research areas for some time to come.

Interpolation or downscaling has used a number of approaches for different variables, sometimes using a model which accounts for the influence of important covariates, notably elevation. In downscaling from 25 to 5 sq km no attempt has been made to add uncertainty to the interpolated values. The downscaling process is deterministic and is unlikely to generate the actual spatio-temporal correlations observed at this scale in the field.

Some plots suggest that improvements could be made to the interpolation methods used here. There is some evidence of a residual artefact of interpolation in the pattern of the 5 km square values. This occurs where there are large changes in altitude between adjacent 25 km squares. Both temperature and rainfall estimates at 5 km square resolution use an adjustment for altitude, based on the mean altitude of the associated HadRM square. This may lead to a slight mismatch for 5 km squares along the boundaries of adjacent 25 km squares.

The performance of the JULES model at UK scale continues to be investigated. Evidence from this project suggests that evaporation estimates are higher than measured values, and that simulated net primary productivity for some plant functional types can be negative over long periods, against empirical evidence. This has meant that neither JULES evaporation nor NPP simulations have been suitable as soil threat model drivers. JULES simulations of soil water contents have been used for compaction modelling, with apparent success. It is likely that the evaporation and NPP discrepancies are related, and associated either with the JULES drivers and parameters, or with the representation of the hydrological budget in the JULES model. This needs further investigation. However, since evaporation estimates provided directly from the HadRM3 also appear biased, estimation of this variable also needs to be addressed (Kay and Davies, 2008).

Aspects of the modelling exercise for individual threats, including uncertainties and limitations, have been discussed under individual chapters. The main achievement of the project has been to demonstrate the feasibility of linking from a climate change model, through a land surface model, through a soil threat model to provide estimates of the effect of climate change on soil threats. The results generated show the success of this model linkage exercise. It has also helped to identify aspects of the modelling where there are apparent discrepancies with the known behaviour of some variables. These areas requiring consolidation, in part through taking full account of existing scientific understanding. The results presented here should be considered a first pass at predicting soil threats. The causal linkages through the various models need further research and testing against measured data if the projections generated are to be able to withstand close scrutiny.

**Acknowledgements**

Thanks are due to Dr. Jonathan Tinker Climate Research Scientist Met Office Hadley Centre who provided the surge (inundation data), Professor Tim Flowers, Sussex University for providing the information on salinity tolerance, Mr. David Morris, CEH Wallingford for providing the elevation data and Dr. Owen Mountford, CEH Wallingford for providing information on the UK grass varieties and distribution.
References - general


References - carbon


http://www.abdn.ac.uk/ibes/staff/jo.smith/ECOSSE


**References – Wind erosion**


**References – Phosphorus**

See Appendix B

**References - VSD**


UNECE, 1999. Protocol to the 1979 convention on long-range transboundary air pollution to abate acidification, eutrophication and ground-level ozone

**References - Compaction**


**References - Salinity**


References - Biodiversity


