

In association with the Met Office and the Institute for Animal Health

# The impacts of weather and climate change on the spread of bluetongue into the United Kingdom

Submitted by Laura Elizabeth Burgin to the University of Exeter as a thesis for the degree of Doctor of Philosophy in Geography in May 2011

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### Abstract

A large epizootic of the vector-borne disease bluetongue occurred in northern Europe from 2006-2009, costing the economies of the infected countries several hundreds of millions of euros. During this time, the United Kingdom (UK) was exposed to the risk of bluetongue by windborne incursions of infected *Culicoides* biting midges from the northern coast of mainland Europe. The first outbreaks which occurred in the UK in 2007 were attributed to this cause. Although bluetongue virus (BTV) no longer appears to be circulating in northern Europe, it is widely suggested that it and other midge-borne diseases may emerge again in the future, particularly under a changing climate.

Spread of BTV is strongly influenced by the weather and climate however limited use has been made of meteorologically based models to generate predictions of its spread to the UK. The extent to which windborne BTV spread can be modelled at timescales from days to decades ahead, to inform tactical and strategic decisions taken to limit its transmission, is therefore examined here.

An early warning system has been developed to predict possible incursion events on a daily timescale, based on an atmospheric dispersion model adapted to incorporate flight characteristics of the *Culicoides* vectors. The system's warning of the first UK outbreak in September 2007 was found to be greatly beneficial to the UK livestock industry. The dispersion model is also shown to be a useful post-outbreak epidemiological analysis tool.

A novel approach has been developed to predict BTV spread into the UK on climatechange timescales as dispersion modelling is not practical over extended periods of time. Using a combination of principal component and cluster analyses the synoptic scale atmospheric circulations which control when local weather conditions are suitable for midge incursions were determined. Changes in the frequency and timing of these large scale circulations over the period 2000 to 2050 were then examined using an ensemble of regional climate model simulations. The results suggest areas of UK under the influence of easterly winds may face a slight increase in risk and the length of the season where temperatures are suitable for BTV replication is likely to increase by around 20 days by 2050. However a high level of uncertainty is associated with these predictions so a flexible decision making approach should be adopted to accommodate better information as it becomes available in the future.

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### **Author's Declaration**

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The provision of data from field and laboratory experiments and expert advice regarding midge flight behaviour were provided by collaborators at the Institute for Animal Health, as detailed in separate sections in Chapter 3 entitled "midge data used in model development". Other work in this chapter regarding adaptation to the existing NAME model and its subsequent use was carried out solely by the author as detailed in the "model modifications" and results sections. This included writing new FORTRAN code, running the model, analysing the results and producing the images and data required for the early warning website.

All other research, presented in Chapters 4 and 5, was all carried out solely by the author.

# **Abbreviations**

ADNS	Animal Disease Notification System
AHSV	African horse sickness virus
AWS	Automatic weather station
BL	Boundary layer
вти	Bluetongue virus
CMIP	Coupled Model Intercomparison Project
Defra	Department for Environment, Food and Rural Affairs
ECMWF	European Centre for Medium-Range Weather Forecasts
EIP	Extrinsic incubation period
EHDV	Epizootic hemorrhagic disease virus
FBL	Flight boundary layer
GCM	General (or Global) Circulation Model
GHG	Greenhouse gas
IAH	Institute for Animal Health
IPCC	Intergovernmental Panel on Climate Change
IPCC AR4	The Fourth Assessment Report of the Intergovernmental Panel on Climate Change
IPCC FAR	The First Assessment Report of the Intergovernmental Panel on Climate Change
MME	Multi-model ensemble
MSLP	Mean sea level pressure
NAME	Numerical Atmospheric-dispersion Modelling Environment
NAO	North Atlantic Oscillation
NDVI	Normalized Difference Vegetation Index
NWP	Numerical weather prediction
OIE	World Organisation for Animal Health (formerly the Office International des Epizooties)
PCA	Principal component analysis
PCs	Principal components

PDF	Probability density function
PP	Pressure pattern
PPE	Perturbed physics ensemble
PRUDENCE	Prediction of Regional scenarios and Uncertainties for Defining European Climate change risks and Effects
RCM	Regional climate model
RPC	Rotated principal component
SRC	Standardized regression coefficient
UKCP09	UK Climate Projections 2009
UM	Unified model
z	Zulu Time or Universal Coordinated Time

# Symbols

С	Concentration
$d\xi$	Increment of a random process
$\Delta t$	Timestep
K	Eddy diffusivity
К	Molecular diffusivity
$M_{1}$	Temperature
$M_{2}$	Wind speed
$M_{3}$	Presence of rain
t	Time or Julian Day
$ au_{u}$	Lagrangian timestep in the horizontal
$ au_{_W}$	Lagrangian timestep in the vertical
и	Instantaneous wind velocity
u'	Fluctuating component of the instantaneous wind velocity
$\overline{u}$	Mean wind
$u(x, y, \eta)$	Wind velocity vector
$u'(x, y, \eta)$	Turbulence velocity vector
$u_l(x, y, \eta)$	Low-frequency meander vector
x	Position in the x-direction
$x(x, y, \eta)$	Particle position vector
$\sigma_{u}$	Horizontal velocity variance
$\sigma_{_w}$	Vertical velocity variance
$\sigma_{\scriptscriptstyle e\!f\!f}$	Effective velocity variance
μ	Expected number of midges

## **Chapter 1**

## Introduction

Although the links between weather, climate and vector-borne disease are increasingly appreciated, the degree to which current meteorologically based models are able to apply this knowledge to generate tactical and strategic predictions of risk is not fully understood. Such predictions would be valuable for increased vigilance and control. This thesis therefore examines the extent to which the spread of an insect-borne virus, bluetongue virus (BTV), can be modelled at timescales from days to decades ahead, based on an understanding of the impact weather and climate have on the pathogen and the insects which transmit it. In this chapter an introduction is given to the subject area, followed by specific details about BTV, the effect meteorology has on its spread, and the subsequent threat it presents to livestock industries in northern Europe. Based on this information the motivation for the thesis is discussed and its aims are established.

#### 1.1 Weather, climate change and vector-borne diseases

Weather is the term given to describe the current state of the atmosphere and its variations on short timescales, generally from minutes to weeks, and is defined by meteorological variables such as temperature, precipitation, wind and humidity. Climate encompasses the statistics of weather and describes average atmospheric conditions over longer periods, such as months to centuries.

Since the publication of the first assessment report of the Intergovernmental Panel on Climate Change (IPCC FAR) in 1990, the body of evidence which shows that the climate of the world is changing in response to the emissions resulting from human activities has continued to accumulate. The latest assessment of the IPCC from 2007 (IPCC AR4) states that global mean surface air temperature over the past century (1906-2005) has increased by  $0.74 \,^{\circ}$ C (with a 90% confidence interval of  $0.56 \,^{\circ}$ C to  $0.92 \,^{\circ}$ C) (IPCC, 2007). By the end of this century, this value is expected to increase by a further 1.8 to  $4.0 \,^{\circ}$ C under different emissions scenarios, relative to a 1980-1999 baseline (IPCC, 2007). More specifically for the UK, the UK Climate Projections 2009 (UKCP09) project an increase of between 2.0 and  $6.5 \,^{\circ}$ C (at the 10% and 90% probability levels) in the mean summer temperature under a medium emission scenario

for south east England by the 2080s, relative to a 1961–1990 baseline. Mean summer precipitation has a large range of uncertainty in its projections over this period, between -48 to 7%, and summer wind speed projections are generally skewed towards a slight reduction of around -0.2ms<sup>-1</sup> (UKCP09, 2009).

Observational evidence shows that many natural systems are being affected by these changes, and the IPCC AR4 suggests that some changes to the health of the world's population can be attributed to climate change (IPCC, 2007). In addition to the direct effects of changes in the climate, human and animal health are affected indirectly through its effect on air and water quality, agriculture, ecosystems and other socio-economic aspects, such as changes to industry and the economy. The IPCC AR4 states that, in general, the effects of these direct and indirect impacts on health are currently small but are expected to become progressively worse in the coming century (Confalonieri et al., 2007).

One concern to human and animal health in the future is the potential for an increase in the incidence and intensity of the transmission of some vector-borne diseases (Committee on Climate, Ecosystems, Infectious Diseases and Human Health et al., 2001; Confalonieri et al., 2007). The spread of diseases by insect vectors is influenced both directly and indirectly by a range of environmental variables in a variety of different ways and these effects can be either immediate or act in a cumulative way. Development rates, activity levels and survival of individual insects and timing of emergence, distributions, abundance levels and migrations of populations are determined to differing, but often very significant, extents by weather and climate (Chan et al., 1999, Martens et al., 1995, Sutherst, 2004). The pathogen spread by the vector is itself also regulated by climate, generally reproducing at a faster rate under warmer conditions (Mellor, 2000). However, an optimal stage is reached when the detrimental effects of temperature on epidemiological factors such as vector survival begins to reduce the overall net transmission rate (Mellor and Leake, 2000). As vector-borne diseases are highly susceptible to environmental conditions, it would therefore appear they are likely to respond rapidly to a change in climate (Confalonieri et al., 2007).

The importance of the role of non-climatic factors in the spread of vector-borne disease is also widely recognized, where socio-economic aspects and nutritional status determine the level of exposure and resistance to disease (Randolph and Rogers, 2010, Reiter et al., 2003). For example, the global decline in malaria since 1900, despite globally rising temperatures, demonstrates the influence disease control efforts

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and economic development can have on the of the incidence of a vector-borne disease (Gething et al., 2010).

The influence of climate change on the range of factors regulating vector-borne disease transmission are summarised in Figure 1.1. Here it can be seen that climate change affects a range of inter-related biological, ecological and sociological factors which in turn impact the epidemiologic outcomes. A holistic view of the epidemiology of vector-borne diseases therefore appears to be essential for assessing future changes in their spread (Reiter, 2008).



**Figure 1.1:** Summary of biological, ecological, and sociological components of vector-borne disease dynamics influenced by climate change (solid arrows) and their interactions and effects on the epidemiology of a disease (dashed arrows) (adapted from Chan *et al.*, (1999)).

The impact of climate change on the spread of human vector-borne diseases has received much attention. For example, many studies have reported associations between climate and spatial or temporal patterns of transmission of malaria and dengue (reviewed in Confalonieri et al., 2007). However their results are not always entirely consistent and demonstrate the complexity of the dynamics of the diseases and their relationships with climate (Pascual et al., 2006, Sumilo et al., 2007). In contrast, relatively few studies have focussed on the consequences of climate change

on animal health, as noted by Baylis and Githeko (2006), despite being environmentally and economically important and given the potential for zoonotic diseases (diseases of animals that are transmissible to humans) to spread into human populations. This may be partly because the majority of epizootics (a rapid and persistent increase in a virulent disease in an animal population above normal levels), such as foot-and-mouth disease, Newcastle disease, avian influenza, African swine fever and classical swine fever, are caused by the movements of animals and animal products and are not generally attributed to climate change (Baylis and Githeko, 2006).

Recently the unexpected emergence of vector-borne pathogens such as West Nile virus in North America and BTV in Europe has highlighted our limited knowledge of the interactions between climate, wildlife, livestock and humans. As a result, greater importance is now being placed on fully understanding the factors involved in arrival, establishment and spread of other emerging diseases (Randolph and Rogers, 2010). In particular, introduction of disease is normally assumed, sometimes incorrectly, to be climate-independent and as such the effect of climate change on this aspect of disease emergence is under-studied.

A review was carried out by Gale et al. (2007) to assess the extent to which climate change may affect the emergence of different livestock diseases in the UK. They used a qualitative risk assessment framework which assessed the impact of climate change on the pathogen, the hosts, the vectors, and on routes of spread including direct animal contact and environmental routes (e.g. air, water or soil). They concluded that diseases transmitted by *Culicoides* biting midges, including bluetongue, are amongst those which pose a particular risk to UK livestock due to climate change. This conclusion was also reached by another risk assessment carried out for France (Dufour et al., 2008). This used a two-step method to identify diseases whose incidence or distribution would be affected by a warming climate and to subsequently rank them in order of importance, based on the likelihood of their occurrence in Europe and the potential health and economic consequences of an outbreak. They identified six priority diseases, and ascertained bluetongue posed the highest overall risk to France, and as such also places the UK at risk.

#### 1.2 Bluetongue and its Culicoides vectors

#### 1.2.1 BTV

A virus consists of genetic material (DNA or RNA molecules) surrounded by a protective protein coat and an envelope of fat in some cases. They exist inside living cells of organisms which replicate the virus many thousands of times. BTV is a double-stranded RNA virus belonging to the Reoviridae family, which affect the gastrointestinal system and respiratory tract, and within the genus *Orbivirus* which are named after their doughnut or ring shaped structure. There are currently 25 subdivisions of the virus strain, known as serotypes, which are distinguished by their outer protein that determines its antigenic specificity.

BTV is non-contagious and can infect all wild and domestic ruminants, although typically only some breeds of sheep, particularly common wool breeds in Europe, and some species of deer develop severe clinical signs (Stott et al., 1982, Howell and Verwoerd, 1971, Darpel et al., 2007). Clinical signs of the disease, bluetongue, resulting from infection by BTV include fever, lameness, swelling of the head and tongue, abortion and can potentially result in death (Darpel et al., 2007).

Bluetongue is of great importance economically. During 2006 and 2007 large outbreaks occurred in northern Europe and it has been estimated that the direct costs, including loss of animals and other deteriorations in productivity resulting from weight loss, abortions and reduction in milk yields, of these outbreaks were  $\in$ 1.1m and  $\in$ 150m in 2006 and 2007 respectively (Hoogendam, 2007, Wilson and Mellor, 2008). However more economically significant costs arose through indirect effects of export restrictions and surveillance measures introduced to limit spread of the virus and are suspected to be in the order of several hundreds of millions of euros (Carpenter et al., 2009a). Due to the serious consequences of an outbreak, bluetongue is regarded as amongst the most important diseases by the World Organisation for Animal Health (formerly the Office International des Epizooties (OIE)). It is therefore classified by the OIE as one of their 'List A' notifiable diseases, defined as "*transmissible diseases that have the potential for very serious and rapid spread, irrespective of national borders, that are of serious socio-economic or public health consequence and that are of major importance in the international trade of animals and animal products" (OIE, 2005).* 

BTV is transmitted between ruminants by adult females of certain biting midge species of the genus *Culicoides* (Diptera: Ceratopogonidae) (Du Toit, 1944). These flies are among the smallest haematophagous insects with a typical wingspan of 2mm. They are present worldwide except for the Pacific Islands, New Zealand and Antarctica.

There are more than 1500 species (47 present in the UK), of which a few are biological vectors of important livestock diseases, including BTV (Mellor et al., 2000).

Female *Culicoides* require a blood meal for the maturation of their eggs and may take more meals in subsequent egg production cycles depending on their survival time. When taking a blood meal the female midge may ingest virus which is circulating in the small blood vessels in the skin of an infected host animal. Once inside the gut of the midge, the virus then infects the cells of the posterior mid-gut wall. Virus particles then enter the haemocoel, the insects body cavity, where they then spread to the salivary glands. Here a second cycle of replication takes place and the insect then becomes infectious, passing on the virus through its saliva during subsequent blood-feeding on a host animal.

This transmission cycle of BTV by the *Culicoides* midge (Figure 1.2) has several stages which are modulated by environmental conditions, particularly temperature which accelerates the rate at which most processes take place (Mellor, 2000, Wittmann et al., 2002, Adkison et al., 1987, Carpenter et al., 2006b). The main effects of the temperature and precipitation on the vector and pathogen determined from the literature are summarised as follows:

- The competence of the vector is generally increased at warmer temperatures (Paweska et al., 2002, Wittmann et al., 2002).
- The extrinsic incubation period (EIP), the interval between the acquisition of an infectious agent by a vector and the vector's ability to transmit the agent, is decreased at higher temperatures: this can vary from between a few days at warm temperatures to a few weeks when conditions are cooler (Wittmann et al., 2002, Mullens et al., 2004).
- At high temperatures the midge's mid-gut barrier can be by-passed allowing dissemination of virus in non-vector species. The "leaky-gut phenomenon" was found to occur in *C. nubeculosus* that were raised at temperatures of 33-35 °C (Mellor et al., 2000, Wittmann et al., 2002).
- Virus can persist at low levels inside adult midges for 35 days at low temperatures and is able to replicate again when temperatures rise (Mellor et al., 1998). The survival rate of *Culicoides* is optimal at approximately 10-20 °C but greatly reduced above 30 °C (Birley and Boorman, 1982, Wittmann et al., 2002). These factors combined can lead to overwintering of the disease where

some of the infected adult *Culicoides* population might survive long enough to bridge the gap between transmission seasons (Wilson *et al.*, 2008).

- Increased rain can increase vector population size by creating moist soil suitable for breeding sites and prevents desiccation of adults (Purse et al., 2004b, Mellor and Leake, 2000).
- The seasonality of populations and therefore the transmission season of the virus are modified by weather conditions (Purse et al., 2008)
- The weather greatly influences many aspect of midge flight. These are discussed in detail in Section 1.2.2 below.



**Figure 1.2:** Transmission cycle of BTV (adapted from Purse et al., 2005). (Photos used with permission from Chris Sanders, Institute for Animal Health and John Gloster, Met Office).

#### 1.2.2 Midge flight behaviour and the influence of the weather

Many aspects of insect flight are affected by the weather. In the case of vector species, this therefore has an effect on the spread of the diseases they carry. The initiation of flight is particularly influenced by the weather. Flight can be triggered either passively, where energy from outside of the organism such as a gust of wind induces flight, or

actively by an increase in temperature which allows the thoracic flight muscles of an insect to be warm enough to provide the necessary power for take-off (Pedgley, 1982). Activity levels of *Culicoides* are greatest at warm temperatures around 20-22 °C (Carpenter et al., 2008). The weather also has a limiting effect on midge activity, with cold temperatures, high wind speeds and precipitation rates known to reduce the number of midges becoming airborne (Kettle, 1957, Blackwell, 1997).

Once midges are airborne, two distinct types of flight are recognized; short distance 'appetitive' movements or longer distance 'migratory' movements (Pedgley, 1982). 'Appetitive' or 'vegetative' movements are directed towards a goal such as food, shelter, a mate or breeding site and are readily interrupted when the resource is encountered. This type of behaviour takes place in a region where wind speed is less than the flight speed of the insect, termed the 'flight boundary layer' (FBL) (Taylor, 1974). The flight speed of *Culicoides* has not been measured precisely, but a mean air speed of 0.4 ms<sup>-1</sup> has been estimated based on their wing span and body length (Sellers et al., 1977). Wind speeds are generally greater than this, so as a result the FBL of *Culicoides* will often be limited to a very shallow depth near the surface or active flight will be constrained to areas with sheltered microclimates. As a result, most flights do not extend more than a kilometre from breeding habitats (Kettle, 1957, Blackwell, 1997, Carpenter et al., 2008)

Above their FBL, midges may become engaged in long distance movements, as the wind there can transport individuals much further and faster than would be possible by self-propelled flight. It is not certain if midges actively initiate these movements by sustained climbing out of their FBL, like many other insects (Reynolds et al., 2006), or if they are accidentally carried aloft by updraughts. Weakly flying insects have long been known to have some control over the height of their flight by choosing to beat their wings, keep them extended or close them (Thomas et al., 1977). Studies, using entomological radar, have found evidence that some insects control their vertical movements. For example, aphids were found to actively maintain enough lift to remain neutrally buoyant (Reynolds and Reynolds, 2009) and noctuid moths were discovered to form layers in the atmosphere where temperature and wind speeds are advantageous for long range migrations (Wood et al., 2010). Although feasible, it is not technically possible to investigate midge flight behaviour with this technique, as millimetre-wavelength entomological radar, necessary to study tiny insects, has not yet been developed (Riley *et al.*, 2007).

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Long distance movements of *Culicoides* can end when they actively choose to land in response to 'vegetative' stimuli or they run out of energy reserves (Reynolds et al., 2006). Midge flight can also be terminated when they are forced out of the atmosphere by unsuitable weather, such as heavy rain associated with frontal systems (Sellers and Maarouf, 1991) or by the presence of topography (Bishop et al., 2004).

Due to their tiny size *Culicoides* midges can be carried by the wind for several hundred kilometres in a night and due to this phenomena, windborne infected midges have been implicated for rapid introduction of bluetongue into wide geographical areas, particularly over water (see Section 2.1.3). In some of these cases, disease spread has been linked to particular synoptic patterns (Braverman and Chechik, 1996, Sellers et al., 1977, Sellers and Pedgley, 1985a, Murray, 1987).

#### 1.2.3 BTV in Europe

Prior to 1998, BTV was broadly confined to latitudes between 35 °S and 40 °N and only made infrequent, short-lived incursions into the fringes of Europe, including an outbreak of BTV-10 on the Iberian peninsula between 1956 and 1960 and an outbreak of BTV-4 in the Greek Islands in 1979-80. In the subsequent decades several serotypes of the disease became firmly established in southern Europe spreading from the near Middle East and North Africa (Figure 1.3) (Wilson and Mellor, 2008). Purse et al. (2005) found bluetongue incidence in southern Europe had occurred in areas where temperature changes between the 1980s and 1990s (which corresponds to before and during the southern European bluetongue epidemic) were greatest. They therefore concluded the emergence of bluetongue in southern Europe was driven by regional climate change creating suitable environmental conditions for northward expansion of the traditional Afro-Asiatic vector, Culicoides imicola Kieffer. However, BTV was found in areas such as Bulgaria where C. imicola was absent which implicated the involvement of northern Palearctic species of Culicoides (Purse et al., 2006b). The vector competence of these northern European species was examined by Carpenter et al. (2006a), who recorded similar levels of competence to that of C. imicola in species of the Culicoides obsoletus and Culicoides pulicaris groups, suggesting further spread through Europe was possible outside of the range of *C. imicola*.



**Figure 1.3:** Routes of introduction of several serotypes of BTV into Europe during 1998-2006 (Courtesy of Peter Mertens, Institute for Animal Health).

The virus was thus predicted to spread slowly through Europe in the following decades as climate became more suitable for *C. imicola* (Wittmann and Baylis, 2000) and subsequent onwards spread occurred by the Palearctic species (Purse *et al.*, 2005). The sudden emergence of BTV-8 in northern Europe, in the Netherlands in August 2006, was therefore completely unforeseen (Enserink, 2006). The cause of the outbreak remains unknown with introduction by both importation of infected animals and windborne midges having been discounted (Mintiens et al., 2008). The ubiquitous farm-associated species of the *C. obsoletus* and *C. pulicaris* groups were implicated as the potential vectors for spread in the region (Mehlhorn et al., 2007, Meiswinkel et al., 2007, Dijkstra et al., 2008). By the end of the season, 2122 cases were entered into the European Commission's Animal Disease Notification System (ADNS) (EUROPA, 2010) mainly in the Netherlands, Belgium and Germany, with the last outbreak confirmed in January 2007 (Saegerman et al., 2008). It was hoped that the vector-free period in northern Europe would be too long for the virus to overwinter in the *Culicoides* population and that BTV would not return in 2007.

Unfortunately however BTV-8 did appear to have successfully overwintered in the region: in June 2007 the German authorities confirmed the virus had been circulating in north Rhine-Westphalia since April (as reported in Wilson et al., 2007). The virus

spread rapidly across a wide region, reaching as far as Denmark, Switzerland and the Czech Republic, infecting tens of thousands of holdings and causing devastating losses of livestock (Carpenter et al., 2009b). On 28 September 2007 BTV was confirmed for the first time in the UK at Baylham Farm, Surrey and within the next few weeks the virus was believed to be circulating locally in East Anglia. By the end of the season 125 holdings had been infected in 13 counties in the south and east of England (Defra, 2008).

In 2008 BTV-8 again re-emerged throughout much of the previously infected region, particularly in France where 15,000 new cases were declared. The virus also spread to southern Norway and Sweden in the north, and Hungary, Italy, Poland and Romania to the south and west. Further complications also arose in 2008 with the arrival of four other serotypes into northern Europe. BTV-1 continued to spread northwards from Morocco, through Spain and eventually overlapped with some of the BTV-8 region in France, coming close to the UK when it reached the Cherbourg peninsula (Figure 1.4). Additionally, BTV-6 appeared in the Netherlands and Germany and genetic testing indicated a high similarity with a modified live vaccine strain (Eschbaumer et al., 2010). Finally, a case of BTV-11 was identified in a sample from a cow in Belgium in November during routine testing and subsequent testing in the region identified several more farms as infected. Genetic sequencing indicated a high similarity with the reference strain that was used to produce the South African modified live vaccine for BTV-11, the use of which was illegal in Europe (SCoFCAH, 2009). Finally a bluetongue-like virus was detected in goats in Switzerland and was eventually determined as a new serotype of bluetongue; BTV-25 (Hofmann et al., 2008).

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**Figure 1.4:** BTV-1 and BTV-8 outbreaks in France at 26 November 2008. Green regions = BTV-1 and BTV-8 restriction zones, blue regions = BTV-8 restriction zones, yellow regions = extension to green region from the previous week. Blue dots = BTV-1 and BTV-8 outbreaks, yellow dots = BTV-1 outbreaks, red dots = BTV-8 outbreaks (Ministère de l'alimentation de l'agriculture et de la pêche, 2008).

In 2009 the situation vastly improved due to an extensive vaccination campaign carried out by the affected countries. Only a small numbers of outbreaks occurred in northern Europe. France reported only 8 cases of BTV-1 and 45 cases of BTV-8 and in Germany only 9 outbreaks of BTV-8 occurred in the period between 1 May 2009 and 5 March 2010 (EU-BTNET, 2010). In 2010 no outbreaks occurred in northern Europe, however, the restriction zones shown in Figure 1.5 remain in place until the absence of bluetongue virus circulation has been demonstrated.



**Figure 1.5**: Bluetongue restriction zones as of 1 January 2011. (http://ec.europa.eu/food/animal/ diseases/controlmeasures/bt\_restrictedzones-map\_2011.jpg accessed 1 February 2011).

The *Culicoides* midge is also the vector for 50 other viruses, including those causing the animal diseases African horse sickness (AHS), epizootic hemorrhagic disease, equine encephalosis, Akabane and bovine ephemeral fever (Mellor et al., 2000). Considering the rapid spread of BTV-8 and BTV-1 through northern Europe, it would appear there is the potential that the other serotypes of BTV and *Culicoides*-borne viruses could follow (MacLachlan and Guthrie, 2010). AHS which affects all equids is particularly acute in horses, in naïve animals over 90% of those affected die, and there is currently no treatment (Kahn, 2008). An incursion of AHS into countries that are extensively involved in the international trade of horses would be economically devastating. The cost of a large outbreak in the UK to its equine industry has been estimated as £3.5 billion thus there is substantial concern regarding potential spread of

AHS into Europe (AHS Working Group, 2009). Unfortunately the virus has already begun to shown signs of spreading northwards from sub-Saharan Africa and is now periodically found in Morocco and Spain.

Overall, it would appear that several aspects, both climatic and non-climatic, were important in attributing to the spread of BTV through Europe. The spread of several serotypes into the Mediterranean has been related to regional climate change creating suitable environmental conditions for northward expansion of the traditional *C. imicola* vector (Purse et al., 2006b). However the role of non-climatic factors was also evident in the sudden emergence of BTV-8 in northern Europe in 2006. The original importation of the BTV-8 to the Netherlands (Mintiens et al., 2008) and the use of illegal live vaccines causing outbreaks of further serotypes in the region (Eschbaumer et al., 2010, SCoFCAH, 2009) were important non-climatic aspects causing the widespread epizootic.

#### **1.3 Research Motivation and Aims**

In 2006, prior to the emergence of BTV in northern Europe, The UK Government's Department for Environment, Food and Rural Affairs (Defra) funded a collaborative research project between the UK Met Office and the Institute for Animal Health (IAH) to research the effects of meteorology on the spread of BTV into the UK. The foresight to establish this project was a result of earlier research carried out at IAH which suggested midge-borne diseases, such as bluetongue, may pose a future threat to northern Europe under climate change (e.g. Purse et al. 2005). Much of the Met Office contribution to the project is formed by the research carried out in this thesis.

One of the main objectives of the project was to devise a model, based on the data from field and laboratory experiments, capable of providing advance warning of the time periods and locations exposed to a high risk of BTV infection due to windborne incursion of infected midges. Defra envisaged that early warning of virus introduction would allow for rapid detection and containment. The first aim of this thesis was to address the modelling aspect of this objective, specifically to:

 Investigate if data on the impacts of the weather on the flight of *Culicoides* can be combined with current meteorological models to develop an early-warning system of BTV incursions and to evaluate the extent to which it provides useful information to policy-makers.

The rapid spread of BTV-8 over much of Europe in 2007 demonstrated that the climate and midge populations present in northern Europe were suitable for circulation of

midge-borne virus and highlighted the potential for other serotypes of BTV and other midge-borne viruses to become established in future decades and pose a threat to the UK. Additionally, with climate change hypothesized in the literature to increase the presence of vector-borne diseases in northern Europe in the future, it appeared important to not only assess the current risk posed to the UK of windborne midge incursions but to assess the extent to which climate change may effect the likelihood of these events in future. However at these longer, climate change timescales the high resolution meteorological datasets used in the model for the early warning system are not readily available and may be of limited accuracy. Additionally, it would be prohibitively computationally expensive to operate this type of model over an extensive time period. The second aim addressed in the course of this research was therefore to:

 Devise a technique to determine the large scale climatic conditions which influence the occurrence of midge incursion events, thereby providing a method to utilize lower resolution meteorological data from climate models to make predictions for future decades.

The final aim of this thesis builds upon the method and results of the second aim, applying them to data from climate models to:

 Assess changes in the synoptic scale climatic conditions suitable for incursions of midges into the UK to estimate how the risk of introduction of bluetongue or other midge-borne diseases may be altered in future decades, and to discuss the implications of these predictions on decisions taken by government and other stakeholders.

#### 1.4 Thesis Outline

As the overall aim of the thesis is to examine changes in the spread of bluetongue to the UK at a range of timescales, different modelling techniques are required to achieve this. A review of the literature is carried out in chapter 2 to describe the various techniques which are available to study the influence of weather and climate change on vector-borne disease spread and discusses the reasons for why the methods chosen are the most appropriate to meet the aims of the study. The different approaches are outlined in Figure 1.6 and those utilised in this thesis are highlighted.



**Figure 1.6**: Outline of modelling techniques available for different timescales, with those used in the thesis highlighted in dark green.

The adaptations carried out to an atmospheric dispersion model to incorporate data on midge flight are then described in detail in chapter 3. This is followed by an account of how the early warning system based on the adapted model was devised, and an evaluation of its use in providing useful information to Defra. Chapter 4 discusses the synoptic climatology method used to investigate the large scale climatic conditions which are suitable for midge incursions into the UK, thereby providing a technique to estimate the occurrence of these events based on lower resolution data from climate models. This method is then applied in chapter 5 using data from a regional climate model (RCM) (a higher resolution model on a smaller domain nested inside a global climate model (GCM)) to estimate potential changes in the level of risk posed to the UK in future decades and the implications of these predictions for decision makers are discussed. Finally a concluding chapter (chapter 6) is provided which discusses the successes and limitations of the modelling techniques and how their predictions could be integrated into wider epidemiological models of vector-borne disease spread to provide a more holistic assessment of risk in the future.

# **Chapter 2**

### **Literature Review**

The review of the literature conducted in this chapter is divided into two main sections. Firstly the traditional approaches used to study the spread of viruses by wind-borne disease vectors are described, with particular emphasis placed on their application to the spread of bluetongue. A discussion then follows to explain why the techniques used by most of these previous studies are not suitable to meet the aims of the thesis. The second part of the chapter therefore provides further information about the alternative modelling methods which are used instead.

#### 2.1 Modelling techniques for the spread of bluetongue

There are two main approaches generally used to study the effects of weather and climate on vector-borne disease spread: those which statistically analyse patterns in the data and those which model the biological processes which generate these patterns. Following the terminology of Rogers and Randolph (2006) these are termed here as "statistical methods" and "process-based models". A sub-category of process-based models are those which explicitly model the trajectories taken by insect vectors between two localities. In this review, these "trajectory-type" models are considered separately from other process-based models because they adopt this different technique.

Each of these approaches has different suitability depending on the particular application, the temporal and spatial scales in question and the availability of data. They can therefore often be complementary in nature. In this chapter the use of each of these techniques in the study of bluetongue spread is described, highlighting their particular benefits and drawbacks. The reasons for the choice of a trajectory-type model to form the basis for much of the research in this thesis, and why the statistical and process-based methods are not appropriate, are then discussed.

#### 2.1.1 Statistical models of changes in bluetongue distribution

One method of determining changes in the geographical distribution of a vector-borne disease is to establish a statistical relationship between the distribution of the vector species and environmental data. This relationship can then be applied to areas with

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known environmental variables to make predictions of disease outcomes based on the suitability of the climate and the habitat for its vectors (Clements and Pfeiffer, 2009, Rogers, 2006). This technique, often referred to as determining the 'climate envelope' of a species' distribution, has been widely used since the 1980s (e.g. Box, 1981) in the study of the environmental factors which drive the distributions of a range of flora and fauna. The obvious advantage of this method is that once a relationship is derived it can make predictions for other areas where species abundance data is limited. Also with the use of projections of climate change the potential re-distribution of a species' climate envelope in the future can be estimated (Berry et al., 2002, Pearson et al., 2002, Rogers and Randolph, 2000, Thomas et al., 2004).

Sellers and Mellor (1993) made the first simplistic attempt to predict the climate envelope of BTV on a Europe-wide scale. An isotherm of 12.5 °C for the average daily maximum temperature of the coldest month, representing where *C. imicola* (presumed to be the main vector for BTV) could persist all year round, was used to delineate areas of the Mediterranean at risk to BTV and included parts of Greece, Italy, Sardinia, Corsica and southern France.

Following this preliminary investigation, many studies then made use of statistical regression techniques to determine relationships between observed or satellite derived climate data and distributions of *C.imicola*. One of the earliest models was based on a correlation of midge trap data with a normalized difference vegetation index (NDVI) and minimum wind speed in Morocco (Baylis et al., 1998). However, the model's predictions for the presence of vectors in northern Iberia were inaccurate (Baylis and Rawlings, 1998), highlighting that due to complex interacting biological and climatological factors, the envelope of suitability for a species in a certain locality is not necessarily applicable in another.

Three other statistical-regression models were developed from *C.imicola* abundance data in Iberia and Morocco (Baylis et al., 2001), Iberia (Wittmann et al., 2001) and Portugal (Tatem et al., 2003). Predictions were made by the models for other areas of Europe, but crucially were limited to those areas with similar environmental conditions to the original training dataset. The models were tested using field data of *C.imicola* abundances for many countries in the region including Portugal (Capela et al., 2003), Italy (Calistri et al., 2003, Conte et al., 2003), Israel (Purse et al., 2004a), Sicily (Purse et al., 2004b) and Sardinia (Pili et al., 2006). From these verification studies it appears that the regression models gave a broadly accurate prediction of vector distribution, but many discrepancies were found on a local scale.

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Wittmann et al. (2001) used a regression model in a simplistic way to investigate the effect of climate change. An increase of 2 °C was included in their model and the range of *C.imicola* was seen to expand as expected. However, the model's specific predictions are unlikely to be accurate as it did not include differential regional warming or other climatic variables such as precipitation.

A more comprehensive study of future distributions of vector species of *Culicoides* in Europe under climate change was carried out by Purse et al. (2006a). A relationship involving seasonal temperature and precipitation variables for current climate and areas of bluetongue distribution was derived and then extrapolated to 2015 and 2030 using time series of monthly climate data from the Met Office Hadley Centre general circulation model (GCM), HadCM3. The results for the current climate, however, did not correspond well with the observed distribution and are therefore also unlikely to correspond well in future. The authors state that a relationship for fine-scale disease distribution cannot easily be extrapolated to a coarse climate change scenario. These prediction maps are therefore only useful as a guide to future distributions of BTV.

The results from the application of statistical models to bluetongue have demonstrated some of the drawbacks of this approach. In the wider literature other limitations are noted. One widely used, but sometimes inaccurate, assumption is that a species' current distribution is constrained by climate and their relationship is in equilibrium (Araujo and Pearson, 2005, Hijmans and Graham, 2006). Other factors such as biotic interactions, barriers to dispersion or migration and human interaction for example can limit a species range (Davis et al., 1998, Pearson and Dawson, 2003). The involvement of non-climatic biotic and abiotic factors is likely to be extremely important but their inclusion in predictive models is difficult, particularly if their role is unknown at the time of the formation of the model (Mustin et al., 2007). Climate envelope methodologies may therefore not represent absolute limits to species ranges and future distributions based on these assumptions may be an underestimate of the true range of climate variation that a species is able to tolerate (Araujo and Pearson, 2005).

The statistical approach provides a good first approximation of the broad pattern of future bluetongue distribution but should not necessarily be taken as accurate simulations of distributions at local scales (Pearson and Dawson, 2003). This approach can provide a useful means of investigating the key environmental variables leading to epidemiological outcomes (Guisan and Thuiller, 2005) but predictions should be based on biological understanding and interpreted with a thorough understanding of the limitations involved (Pearson and Dawson, 2003).

#### 2.1.2 Process-based models of bluetongue transmission

The process-based approach involves the formation of mathematical descriptions of biological systems such as insect life-cycles or transmission dynamics of a disease. To achieve this, a thorough quantitative understanding of the relationships between the environmental and biological parameters must be established. This relies on detailed field or laboratory experimental data being available, and therefore the approach can only be applied to certain, well studied species.

A common approach in environmental science to predict the occurrence of a particular developmental stage in a biological process is to use a degree day model. For example, the EIP of the bluetongue pathogen inside the midge can be predicted based on the number of hours where temperature exceeds a certain developmental threshold. Wilson *et al.* (2007) found an accumulation of 835 degree-hours above a threshold of 14.3 °C allowed for completion of the EIP in *C. sonorensis*. This model suggested that re-emergence of BTV-8 in Maastricht in 2007 would not be possible until at least late April. This was later found to be the likely date of re-emergence of the disease.

Large-scale climate envelope models generally do not contain sufficient local scale environmental data needed to provide decision makers with knowledge of potential spread within and between farms following an initial outbreak. However, biological models based on an index such as basic reproduction number ( $R_0$ ) can in theory be applied at any scale.  $R_0$  is defined as the average number of secondary infections caused by one infected individual when it is introduced into a susceptible population. If  $R_0>1$  disease incidence will increase and invade a host population. Models of  $R_0$  have been used to study the spread of a range of diseases such as AHS (Lord et al., 1996) and trypanosomiasis (Rogers, 1988), for example.

Gubbins et al. (2008) derived  $R_0$  for bluetongue spread in the UK based on estimates from the literature for each stage of the disease cycle such as the average time taken between feeding by the vector, vector and host mortality rate, the duration of viraemia in the hosts animals and mean EIP in the vector. However many uncertainties are associated with the model due to limitations of the available datasets from the literature. For example, the estimations of the parameters relating to the vectors were mainly based on outbreaks in the USA and the Mediterranean. The transmission model also only includes a single vector, whereas multiple species are thought to have been involved in the recent outbreaks in northern Europe. It also ignores a number of other heterogeneities which would be needed for a full risk assessment, including the

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distribution of ruminant and vector populations and regional variations in environmental factors, particularly temperature.

Szmaragd et al. (2009) adapted this formulation of  $R_0$  into a stochastic model for disease transmission within and between farms on a national scale, a commonly used technique in the study of other livestock diseases such as foot-and-mouth disease (Ferguson et al., 2001) and scrapie (Gubbins, 2005). A mathematical model was developed to determine the probability of an unaffected farm acquiring infection on a particular day, including terms to account for distance between farms, presence of sheep or cattle and temperature. Parameters were derived from the 2006 outbreak in northern Europe and the resulting model was found to provide an adequate replication of the 2007 outbreak in the UK. It was found to be particularly sensitive to the choice of transmission kernel, used to implicitly represent all the modes of transmission between farms, suggesting that predictions made by the model are unlikely to be robust.

The  $R_0$  model developed by Gubbins *et al.* (2007) was also used in the ENSEMBLES project to predict the transmission potential of BTV in Europe from 1960 to 2050 using RCM data (Morse et al., 2009). The mean of the ensemble of RCM results suggests an increase in bluetongue disease risk, particularly in the UK and Scandinavia due to more favourable temperature conditions, and in the Mediterranean, where the change is related to an increase in the abundance of the *C. imicola* vector. Although the mean relative value of  $R_0$  of the ensemble members shows a moderate increase, a large range is found for future predictions from the individual members, reaching from between -70% to greater than 100% in the 2040s, and demonstrates that large uncertainty is associated with these predictions.

In summary, process-based models are derived from experimentally determined biological relationships and therefore have the potential to reflect epidemiological outcomes more accurately under novel conditions, than models based purely on statistical correlations. Process-based models can also incorporate non-climatic factors such as number of host animals and their mortality rates. However, their use is limited by the availability and quality of the data used to formulate the individual components, and therefore favours species which are well-studied. This also becomes an important issue for future predictions under climate change where many of the input factors, particularly the non-climatic ones, and their relationships are unknown.

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#### 2.1.3 Trajectory models of wind-borne vector spread

Wind-borne dispersal of insects can often be an important component of spread for some vector-borne diseases. In these cases, an approach to directly calculate the movements of vector insects can often be useful to analyse the spread of these diseases. The method is generally used for short timescale, deterministic analysis of spread between localities. Through time the sophistication of the techniques used to do this has improved from using trajectories manually constructed with the use of synoptic charts of wind patterns to utilization of complex atmospheric dispersion models. The approach is mainly used retrospectively to analyse the role of the wind in the spread of disease.

Early studies led by Sellers (Sellers et al., 1977, Sellers et al., 1978, Sellers et al., 1979, Sellers and Pedgley, 1985b) used synoptic charts to determine if wind patterns were able to explain outbreaks of bluetongue, AHS and Akabane in Spain, Cyprus, Cape Verde Islands, Portugal and Western Turkey by windborne infected midges. However due to uncertainty in the timings of outbreaks, and as high resolution computational models were not available at the time, these studies could only give a general guide to the presence of suitable winds.

Weather pattern analysis was also used by Murray (1987) and Murray and Kirkland (1995) in the study of Akabane, bluetongue and Douglas virus epizootics in the Hunter Valley, New South Wales, Australia. The timings of seroconversions of sentinel herds located there were found to be associated with the dispersal of *Culicoides* on warm north-easterly winds generated by high pressure over the Tasman Sea. Similarly, Braverman and Chechik (1996) found outbreaks of bluetongue in Israel in 1964, 1966 and 1988 were consistent with north-westerly prevailing winds linked to the Persian trough air-stream system.

In addition to large scale weather pattern analysis, flight trajectories, based on air currents, have long been calculated for a variety of insects (see reviews in Pedgley, 1982 and Reynolds et al. 2006). Due to a lack of modern computing, early models relied on meteorological data from surface observation stations or data from a restricted number of altitudes and had low temporal resolution. For example backwards trajectories for outbreaks of bluetongue in Florida, USA (Sellers and Maarouf, 1989) and British Columbia, Canada were calculated at only 3 pressure levels with a 6-hourly timestep.

In later years simple trajectory models were enhanced with the use of data from numerical weather prediction (NWP) models which provide a more detailed
representation of the atmosphere. Trajectories based on NWP model data have been calculated for a number of bluetongue outbreaks. Alba et al. (2004) investigated the possibility that bluetongue was introduced to the Balearic Islands in 2004 by the windborne infected *Culicoides* using backward trajectories. Their use of 3-dimensional NWP data meant their trajectories were not restricted in the vertical. However, their modelling was limited to trajectories from only 3 initial pressure levels at 6-hourly timesteps.

Ducheyne et al., (2007) studied the dispersal of *Culicoides* in Greece and Bulgaria during outbreaks of bluetongue from 1999 to 2001. They computed 2-dimensional wind trajectories to and from outbreak sites, based on horizontal and vertical wind components of the European ReAnalysis-40 (ERA-40) dataset from ECMWF. This wind component data was at a resolution of 0.5°x0.5° in the horizontal with four pressure levels (700, 850, 925 and 1000 hPa) at 6-hourly intervals. Forward trajectories were calculated at noon and those with a wind speed below 3ms<sup>-1</sup> and above 11ms<sup>-1</sup> were excluded. They constructed an overall density map of the wind trajectories and compared this with the general outbreak pattern. The authors conclude that overall their calculated trajectories had a good fit with the pattern of long-range spread of bluetongue both over land and sea. However there were some situations which did not fit with their predicted trajectories due to inadequacies in the model; it used low resolution meteorological data and the trajectories were restricted to 2dimensional pressure levels. This data was not adequate for capturing the atmospheric flows near the surface, where most midge flight occurs, or the influence of topography. Additionally, the wind speed thresholds used to define suitable conditions for midge activity and the timing for the commencement of flight in the middle of the day are contrary to midge flight behaviour described in the literature (see Section 1.2.2).

The same technique was applied to the north-west European BTV-8 outbreak in 2006 (Hendrickx et al., 2008). A correlation was established between the density of wind trajectories and the pattern of spread of BTV. This study also found that medium and long distance disease spread (between 5 and 31km and greater than 31km) were more strongly linked to wind trajectories than short distance spread (less than 5km), where it is suggested that active midge flight dominates. The results from this model suffer from the same flaws as described above for the analysis of bluetongue spread in Greece and Bulgaria (Ducheyne et al., 2007). Furthermore for both analyses there are two additional limitations. Both studies used only one single 2-dimensional trajectory with a timestep of six hours for a very limited number of pressure levels. These deterministic calculations cannot capture the complex stochastic nature of the atmosphere,

particularly over the mountainous terrain present in the study regions. These models relied on historical re-analysis meteorological data and can therefore only be used for retrospective analysis following an epizootic. Although they may provide guidance over the possible role of the wind in disease spread, they cannot be used to provide useful information in an emergency response situation.

One model which has the capability to be used during an outbreak to directly model the windborne spread of midges is the UK Met Office's Numerical Atmospheric-dispersion Modelling Environment (NAME) (Jones et al., 2007). This fully three-dimensional Lagrangian model releases particles into a mathematical representation of the atmosphere, driven by a numerical weather prediction model, the Met Office Unified Model (UM) (Davies et al., 2005). This NWP model can provide both high resolution historical and forecast meteorological data, making it highly suitable for both post outbreak analysis and for forecasting disease spread. NAME was used to determine if air from the area of the first bluetongue outbreak in northern Europe in the Netherlands in August 2006, could be traced back to an infected area (Gloster et al., 2007b). It was found that for the majority of time the air reaching the infected areas in northern Europe had travelled from the Atlantic and was never found to come from the nearest known source of BTV-8 in Algeria. NAME was also used to determine if spread from the outbreak centre at Maastricht to disease clusters present in the west of the Netherlands, western Germany and north-eastern France could be linked to the windborne dispersal of midges (Gloster et al., 2007a). Plumes, made up of several hundred thousand particle trajectories, were calculated to describe where air from a source in Maastricht had travelled for each evening during the outbreak. Several of these were found to pass over each disease cluster, with none passing to disease free regions in the north, in the Netherlands and south-east, around Bonn in Germany, suggesting a windborne component was probably present in this outbreak. Although this model used high resolution meteorological data, a full 3-dimensional representation of the atmosphere and many thousands of particles, the resulting plumes only described where a parcel of air may have been dispersed to as a proxy for where midges may have been carried. The particular impacts of meteorology on the activity and flight behaviour of midges were not accounted for.

Overall it can be seen it is possible to directly model the wind-borne spread of some vector-borne diseases between two areas using trajectory models. Over time more sophisticated models have evolved which provide a better description of the winds which can carry some vectors. Most of these models however use low resolution meteorological data and only a single trajectory at few pressure levels to represent the

complex, stochastic nature of the atmosphere. This type of model is also often limited by the availability of epidemiological and meteorological data so can only be applied retrospectively and not in real-time to forecast disease spread. The unavailability of high resolution data from climate models also limits their use to current or historical situations. Finally their use is clearly restricted to the spread of diseases whose pathogen or vector is dispersed by the wind and the role of animal movements or human interaction cannot be included.

# 2.1.4 Discussion of the modelling approaches in relation to the thesis aims

Three different approaches to modelling the spread of bluetongue at different spatial and temporal scales have been described. Climate envelope models were found to be useful for broad-scale first approximations of potential changes in distributions of species in the future under climate change. They can also gauge the suitability of environmental conditions for vectors under current climate where species abundance data is absent, and hence predict areas susceptible to disease spread. However, this approach only tells you where a species can occur, not where it does occur. This technique could be used to say if the UK will be environmentally suitable for different vector species in the future, but it cannot be used to determine the frequency or timing of species invasions as is required to meet the aims of the thesis.

Most process-based models applied to bluetongue spread are mathematical formulations of the epidemiological cycle and indicate the level of transmission which would be expected in a population. Through combination with a transmission kernel, disease spread between localities can be modelled. This technique is therefore useful to describe spread on a regional scale, following the introduction of virus into a susceptible area, but is again not suitable to meet the aims of the thesis, where individual entry events of virus into the UK are required be modelled.

Trajectory modelling provides an alternative method where virus or insect-vectors are known to be spread by the wind. This method is particularly applicable to explicit modelling of disease spread between two localities. Many models have used single trajectories, with limited observational or NWP data, to describe vector spread but these cannot represent the true turbulent flows in the atmosphere. Where real-time or forecast meteorological data is available the models have the potential to quickly provide vital information about disease spread to stakeholders to limit its spread. These models therefore have much scope to be adapted to meet the first aim of the thesis, to provide early warning of wind-borne incursions of potentially infected midges to the UK. However, as dispersion models require high resolution meteorological data which is

currently unavailable from climate models, they have limited use for predicting dispersion on long climate change timescales. As discussed in the next section (Section 2.2) alternative methods, not previously used in the modelling of bluetongue spread, will be utilised instead.

# 2.2 Background to the modelling approaches used in the thesis

The first aim of the thesis is to devise a model capable of predicting long-range spread of *Culicoides* from the near-continent into the UK which could be used to provide early warnings of the timings and locations of potential disease incursions to Defra. As discussed above (Section 2.1.4) the most obviously applicable approach to meet this aim is a trajectory or dispersion model, due to their potential to be adapted to explicitly model vector flight between locations at high temporal and spatial resolution.

The dispersion model NAME has previously been used in a basic way to model the winds which could have dispersed infected vectors (see Section 2.1.3). However many aspects of meteorology are known to influence midge activity and flight, and due to the flexibility of a multi-purpose atmospheric dispersion model such as NAME there is the potential for inclusion of these interactions directly within its source code. This would allow explicit modelling of midge flight from an infected source area to other areas downwind and could therefore form the basis of an early warning system to predict likely timings and locations at risk of bluetongue. Further description of atmospheric dispersion modelling is provided below in Section 2.2.1 and the specific adaptations made to NAME to model midge flight to meet the first aim of the thesis are discussed in chapter 3.

The second aim of the thesis is to estimate the potential changes to the frequency and timings of *Culicoides*-borne disease incursions under climate change. Statistical and process-based models aim to predict changes in the suitability of environmental or transmission conditions for vectors or diseases once introduced to an area, and do not explicitly model insect dispersal, so they are not suitable for this aim. Atmospheric dispersion models are also not of use as they require meteorological data at a resolution which is not yet available from climate models. A different approach is therefore required.

Large scale synoptic systems, which influence local weather conditions, have previously been linked to the spread of *Culicoides*-borne diseases (see Section 2.1.3) and can be predicted in climate models with greater skill than local wind speeds and directions. Therefore, a method is developed in chapter 4 to investigate the pressure

systems which are present during midge incursions into the UK and which can then be used as a proxy for local wind conditions in climate models. This method is based on a combination of synoptic climatology techniques. This modelling approach is described in further detail below in Section 2.2.2. Finally, to meet the second aim of the thesis, changes to the occurrence of pressure patterns associated with midge incursions in future decades are investigated with the use of an ensemble of RCMs in chapter 5. In Section 2.2.3 below an introduction to climate models and the uncertainty associated with their projections is therefore provided and previous analyses of changes in pressure patterns under climate change are also described.

# 2.2.1 Atmospheric dispersion modelling

It has been discussed above that the atmospheric dispersion model, NAME, will be used to address aim 1 of the thesis. Background information describing atmospheric dispersion modelling in general is therefore provided below and specific details about NAME are given in chapter 3.

Atmospheric dispersion modelling is the mathematical simulation of the release, transport, mixing and transformation of airborne gases or particulates and their depletion or removal from the atmosphere. In practice, dispersion models aim to determine the distribution of the concentration of a substance, given a specified source term and information on the meteorological conditions and nature of the underlying terrain (see Pasquill and Smith, 1983 and Arya, 1999 for a full discussion of dispersion modelling).

Dispersal of material in the atmosphere is governed by atmospheric flow which can be resolved into two components; a fluctuating component, u', superimposed on a mean,  $\overline{u}$ . Thus instantaneous wind velocity is defined as:

$$u = \overline{u} + u' \tag{2.1}$$

Broadly, the mean wind is driven by synoptic scale meteorology with additional mesoscale features, such as sea breezes, superimposed. At local scales the flow can also be altered by surface features such as topography and buildings. Turbulence is the term given to the stochastic fluctuation of the velocity of the flow around its mean. The lower part of the atmosphere, the boundary layer (BL), is almost always turbulent due to friction and wind shear (mechanical turbulence) and buoyancy forces generated by heating of the surface (convective turbulence). The production of turbulence is largely controlled by the stability of the atmosphere, and therefore by the temperature stratification of the air. Generally, warm, sunny conditions lead to an unstable, deep

convective boundary layer allowing greater diffusion of material, whereas stable conditions, often occurring overnight as the earth cools warming the atmosphere from below, suppress vertical motion and reduces dispersal. These diurnal changes in the structure of the boundary layer are described in Figure 2.1 (for further details see Oke, 1978).



**Figure 2.1:** Schematic of the variation in height and structure of the boundary during the course of the day (Adapted from Arya, 1999).

The aim of an atmospheric dispersion model is therefore to represent these processes in a manner which will allow useful predictions of concentrations of substances. Traditionally, models have been designed to predict the downwind concentration of pollutants emitted from sources such as industrial plants, vehicular traffic or accidental chemical or nuclear releases, such as the Chernobyl accident. Other specialised applications of dispersion models include forecasting plumes of volcanic ash (e.g. Witham et al., 2007) and viruses such as foot-and-mouth disease virus (e.g. Gloster et al., 2010). Here this type of modelling is applied to the dispersion of *Culicoides* midges, in order to predict the spread of bluetongue.

Atmospheric dispersion models can use either an Eulerian or Lagrangian description of fluid flow. Eulerian measurements of flows are made at a fixed point in space where as Lagrangian measurements are made following a fluid parcel as it moves through space and time. In a dispersion model specified by an Eulerian system, statistics of the flow are calculated from the particle trajectories passing through a point. Conversely, a Lagrangian dispersion model calculates statistics based on all the particle trajectories which emanate from a source point (for full details of Eulerian and Lagrangian fluid mechanics see Wilson and Sawford, 1995 or Rodean, 1996).

In an Eulerian reference frame the fluid velocity, u(x,t), and the concentration of material, C(x,t), are defined at a fixed point, x, at time t. The evolution of C is described by a Navier-Stokes and conservation equation:

$$\frac{\delta C}{\delta t} + u \cdot \nabla C = \kappa \nabla^2 C \tag{2.2}$$

Where  $\kappa$  is the molecular diffusivity.

The problem with this Eulerian formulation for the evolution of the flow is the presence of a nonlinear advection term. Approximations can be introduced to overcome this closure problem but they are not always applicable. For example, if turbulence is assumed to generate a movement of material from an area of high concentration to a lower concentrated region, and the rate of this movement is proportional to the mean gradient, the resulting gradient transfer model can be defined as:

$$\overline{uC} = -K \frac{\delta C}{\delta x}$$
(2.3)

where K is the eddy diffusivity. However, this requires the length scale of the turbulence to be small in comparison to the distribution of material. This is a suitable assumption at long distances where the plume is diffuse, but not close to the source where the plume is narrow.

In Lagrangian methods the mass conservation equation has a simpler form:

$$\frac{dC}{dt} = \kappa \nabla^2 C \tag{2.4}$$

By defining the frame of reference as following the motion, the non-linear advection terms are included implicitly, without approximation. At high Reynolds numbers (where the ratio of inertial to viscous forces is large, such as in the turbulent boundary layer), molecular diffusion can be neglected. The conservation equation (2.4) becomes trivial and the concentration of the fluid particles remains constant throughout the flow. Concentration statistics of the fluid are calculated only from the redistribution of the particles. Calculating the change in their displacement can be carried out by modelling the Lagrangian velocity only and does not rely on approximations of the concentration field.

The atmospheric dispersion model forming the basis of this research, NAME, is of Lagrangian type. This type of model implicitly allows flexibility in the scale over which

the dispersion calculations are carried out on and does not suffer from approximations to address nonlinear advection terms as in Eulerian models (Maryon et al., 1999)

# 2.2.2 Synoptic climatology

From the review of the literature of previous models of bluetongue occurrence under climate change (Section 2.1) it was found that the commonly used approaches were not suited to predict the frequency of incursion events into the UK. The use of a dispersion model is also not an option, as the meteorological data available for future decades from climate models is not at high enough spatial and temporal resolution to be used to accurately initialise NAME. To develop an alternative method to the traditional approaches is therefore the second main aim of this thesis and is described in chapter 4. This approach will utilize synoptic climatology techniques, therefore background information to this methodology is provided below.

Synoptic climatology is the study of the relationship between atmospheric circulation and the local surface environment. The aim of most analyses using synoptic climatological techniques is to assess how variations in large scale processes in the atmosphere induce changes in the environment at local or regional scales. These analyses cover a wide variety of applications such as heavy precipitation (Serra et al., 1998), dust storm frequency (Ekstrom et al., 2004), snowstorms (Esteban et al., 2005), tropospheric ozone episodes (Hart et al., 2006), heat-related mortality (Kysely and Huth, 2004), dispersion of white pine blister rust fungus (Frank et al., 2008) and wine quality (Jones and Davis, 2000).

All synoptic climatological studies classify atmospheric circulations in some way in order to reduce the size of large datasets to simplify the complex climate system. Classification allows the main variations in the atmosphere to be identified and described by a relatively small number of distinct categories, which can then be related to the local environmental variable in question. There are a wide variety of approaches and methodologies to classify circulation patterns. These are summarised below (see Yarnal (1993), Huth et al., (2008) and Philipp et al., (2010) for full details).

The first distinction in approaches arises through how the atmospheric classification and surface environment are determined to relate to one another and have been termed as either a "circulation-to-environment" or an "environment-to-circulation" method by Yarnal (1993). In the former the classification is compiled first and later related to the environmental data, and in the latter the circulation data are classified based on environmental criteria. The "environmental-to-circulation" approach generally

involves averaging maps of the climate variables of interest which occur at specific situations, in a process known as compositing. This approach can be particularly useful to look at extreme or rare events, as there is no a priori choice of circulation types so less frequently occurring atmospheric states are not obscured by more dominant patterns. However this averaging process can result in a false impression of the atmospheric patterns which occur during a particular phenomenon, particularly if the patterns are very disparate. More details on the "circulation-to-environment" approach are provided in the rest of this discussion.

There are three distinct groups of techniques for the classification of circulation data which "circulation-to-environment" methodology; use а subjective/manual classifications, hybrid/mixed, and automated/objective. In the first group, commonly referred to as subjective or manual, the classification types are subjectively defined a priori, and the assignment of individual cases to the types is carried out manually. This procedure relies on expert knowledge to define the weather types and to subsequently assign individual days into the categories. The two most widely used classifications include the Lamb weather catalogue (Lamb, 1972), a classification of winds over the British Isles into seven basic types and the European Grosswetterlagen (GWL) (Hess and Brezovsky, 1977). The 29 GWL regimes are readily identifiable large-scale circulation patterns focussed on central Europe but extending over the whole continent and the North-East Atlantic. The GWL catalogue is subjectively assessed using surface and upper air charts to classify periods of several days into one of the 29 weather regimes. Each GWL is assumed to last for at least 3 days so transitory patterns are not included. The catalogue was originally created retrospectively back to 1881 (Hess and Brezovsky, 1977) and is now maintained by Germany's National Meteorological Service, the Deutscher Wetterdienst (http://www.dwd.de/GWL).

Classifications where the types are defined subjectively, but the cases are assigned by objective criteria, are referred to as hybrid or mixed. Different techniques, such as distance measures or threshold criteria, can be used to assign cases to the predefined types. Both the Lamb and the Hess-Brezovsky GWL catalogues have been objectified. In the objective-Lamb classification, numerical criteria are set for the direction, intensity and vorticity of airflow (James, 2006) and in the objective-GWL system pattern correlations are used as a distance measure (James, 2007). Further details of the James (2007) objective-GWL are provided in Section 4.3.2.

The final category of classification systems are referred to as automated or objective as both the categorisation types and assignment of cases are determined by numerical

procedures. However it should be noted that there are still some stages of the process which involve subjective decisions to be taken and these can considerably affect the outcome of a study. Objective classification techniques are further sub-divided into correlation based and eigenvector based classifications as described below.

Correlation based methods, originally developed by Lund (1963), use the similarity between daily patterns as a criterion to objectively assign cases into discrete categories. The degree of similarity can be assessed in terms of correlations or a sum-of-squares difference. Prior to the procedure, a correlation-coefficient or sum-of-squares threshold is defined. The pattern with the largest number of correlations with all other patterns exceeding the threshold is determined. The patterns that are highly correlated with this pattern, determined as those which have a coefficient which exceeds the defined threshold, are then classified along with the first key pattern and all are removed from the dataset. This iterative procedure continues until all days are classified.

In eigenvector based techniques three entities are considered: an atmospheric variable, time and a spatial component (station or grid-point). The analysis is carried out by holding two of these fixed and allowing the third to vary, which results in 6 different possible modes of decomposition termed O, P, Q, R, S, T (Richman, 1986). In synoptic climatology the main modes used are P, which analyses variables varying over time, and S which concerns one variable varying over space. Synoptic typing attempts to capture the nature of atmospheric variations over time at one location and is not concerned with spatial variations; P-mode is therefore the appropriate configuration. Map-pattern classifications aim to show spatial variations within a collection of surface variables; usually these show variations in pressure patterns such as pressure centres and gradients. For this type of classification S-mode is used to target the main modes of spatial variation. For both map-pattern classification and synoptic typing the classification procedure firstly uses a principal components analysis (PCA) as a data reduction technique to find the main modes of variation in the dataset, the principal components (PCs). Using empirical or mathematical methods the number of PCs which represent the majority of variation in the dataset are determined. The variance field for each original pressure grid is an amalgamation of these PCs, with different weight from each. A clustering technique is used to partition these different weights into the most common combinations. Each spatial pattern or combination of weather variables in each cluster is then averaged to form the map-pattern classification or synoptic type respectively.

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# 2.2.3 Ensembles of climate models

The final aim of the thesis is to assess changes during future decades in the largescale circulations, deduced from synoptic climatology techniques to be associated with midge incursions into the UK, to allow changes in the risk of bluetongue spread to be assessed. This aim will be tackled using data from climate models, and in particular an ensemble of regional climate models will be used in order to provide a estimate of the uncertainty involved in the predictions. In this section information is therefore provided about climate models in general, their sources of uncertainty and the different approaches taken to explore this uncertainty. Finally the results from previous studies which have assessed changes in circulation patterns in the past and from climate model data are described, to determine if there is any evidence that changes may occur in the next few decades.

# 2.2.3.1 Climate models

General circulation models, also known as global climate models, are the main tool used to investigate the processes of the climate system. They are used to both understand the role of various natural and anthropogenic forcings which have led to observed changes in the climate and to make projections of the climate system's response to future forcing scenarios. GCMs numerically solve the equations of fluid dynamics that describe the motions of the atmosphere and the ocean. This high level of complexity requires large computational requirements and subsequently the models have low horizontal resolutions, generally several hundreds of kilometres (Christensen et al., 2007b). For many impact studies this resolution is too coarse to resolve processes sensitive to fine-scale climate variations, such as in ecological systems. Additionally areas of complex topography, coastlines or heterogeneous land surface are not explicitly resolved, and therefore some features such as orographic precipitation, sea breezes and urban heat islands effects are not described by GCMs (Mearns et al., 2003). The two main approaches taken to capture these effects and provide information at scales more relevant for regional and local applications are dynamical and statistical downscaling (Leung et al., 2003).

Dynamical downscaling involves the use of higher resolution models, with observations or lower resolution GCM data as their boundary conditions. One approach to dynamical downscaling is to run an atmosphere-only version of a GCM at higher resolution, over a shorter "time-slice" within a transient GCM simulation (Giorgi et al., 2001, Christensen et al., 2007b). This method assumes that the atmosphere is in equilibrium with its lower boundary conditions which provide information on the slower-evolving oceans

components (Mearns et al., 2003). However the lack of feedback between the atmosphere and ocean has been found to lead to inconsistencies between atmosphere only models and those with a coupled atmosphere and ocean (Bretherton and Battisti, 2000). Alternatively, regional climate models (RCMs) can be produced by nesting a higher resolution model inside a GCM (Giorgi et al., 2001, Christensen et al., 2007b). The GCM supplies information about the large-scale fields such as winds, temperature and moisture as lateral boundary conditions (LBCs), and sea surface temperature (SST) and sea ice information at the lower boundary. The use of LBCs allows the RCM to remain consistent with the driving atmospheric circulations represented by the GCM, however this also means the reliability of the RCM is dependent on the driving GCM (Christensen et al., 2007b). Furthermore as an RCM is based on physical principles, the relationships between climate variables are coherent (Mearns et al., 2003). Overall RCMs have been found to generate observed fine-scale processes not captured by the GCMs and improve the description of regional and local atmospheric circulations, such as synoptic and frontal extratropical systems and mesoscale convective systems (Antic et al., 2006).

In statistical or empirical downscaling, relationships are derived from observational datasets between large scale climate variables and those at local or regional scales. These relationships are then applied to GCM data to obtain their regional equivalents (Wilby et al., 2004). Statistical downscaling methods are computationally inexpensive and can achieve results on finer scales than dynamical methods. However they require long observational datasets on which to train the relationships. Their main drawback is that they assume the derived relationships will be consistent under future climate regimes. Additionally, the technique can produce relationships which are not coherent between multiple climate variables.

Many impact studies using dynamically or statistically downscaled data have focussed on a scenario approach which takes a single route through the modelling process; the choice of emission scenario, calculation of concentrations of greenhouse gases (GHGs) and the climate forcing, the model of the climate response to the forcing, the downscaling technique and then finally the impacts model. This single scenario approach does not provide any information about its likelihood (Jones, 2000). Provision of probabilistic information, based on a thorough analysis of the uncertainties which arise at each stage of the modelling process, is therefore necessary in order for assessments based on relative risk to be made (Stainforth et al., 2007a, New et al., 2007, Moss, 2007).

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# 2.2.3.2 Sources of uncertainty in climate models

Uncertainty in predictions made by climate models arises from all stages of the modelling process leading to 'a cascade' of uncertainty (Mearns et al., 2001). Some of this uncertainty results from a lack of information, but in other cases is due to inherent unpredictability (Moss, 2007).

Firstly there is uncertainty associated with future external forcings of climate, such as anthropogenic emissions of GHGs or natural forcings, principally large volcanic eruptions and solar cycles. In order to provide guidance on future emissions the IPCC published a Special Report on Emission Scenarios (SRES) (Nakicenovic et al., 2000) in 2000 which describes several emissions scenarios based on different 'storylines' of demographic, technological and economic effects on greenhouse gas sources and sinks. However precise quantification of these future forcings is impossible, therefore the uncertainty associated with choice of emissions scenario cannot be removed (Stainforth et al., 2007a). There are also uncertainties associated with how a given emissions scenario translates into concentrations of GHGs and the resulting radiative forcing changes (Mearns et al., 2001). To reduce the uncertainty in these processes, GCMs which accurately simulate the carbon cycle and atmospheric gas and aerosol chemistry are needed.

Modelling the response of the climate to a given forcing also introduces uncertainties in several ways mainly due to incomplete understanding of climate system processes and their imperfect representation in climate models. The climate system has natural internal variability which arises due to its chaotic nature, and varies from small-scale storms to large-scale circulations such as El Niño. The uncertainty associated with these unpredictable events can be sampled using a model with different initial conditions, and is therefore often termed 'initial condition uncertainty' (ICU). Different climate models produce different projections even when driven by the same forcings. This occurs because climatic processes are represented in models in different ways, both in the construction and design of the model ('structural uncertainty') and in the values chosen for parameterizations of physical processes ('parameter uncertainty') (Collins, 2007). 'Model inadequacy' also causes uncertainty, which arises because even the most complex, high-resolution climate model cannot provide a perfect representation of the real world's climate (Stainforth et al., 2007a).

Finally uncertainty exists in the methods applied to downscale the GCM data into a useable scale for impacts models. Different RCMs, or statistical downscaling methods, yield different results even when forced by the same GCM (Murphy, 1999). The relative

importance of all the different sources of uncertainty on the final impact will vary depending on the particular situation (Mearns et al., 2003).

#### 2.2.3.3 Ensembles of climate models to explore model uncertainty

There are two main approaches to quantify modelling uncertainties of projections of future climate. In both of these the general methodology is to use an ensemble of projections to sample uncertain aspects of the models, and then present these results in the form of the probability of different outcomes. The first of these approaches consists of forming a multi-model ensemble (MME) of several GCMs developed by different international research centres (Cubasch et al., 2001, Meehl et al., 2005). Each model in the ensemble produces a different projection which can be considered as a different realisation of climate change. The variance of the model results about the ensemble mean provides an indication of uncertainty in the results. Unrelated model errors tend to average out and the MME mean provides a better estimate of climate change than the result from any individual model (Lambert and Boer, 2001). Alternatively, modelling uncertainties can be explored using a perturbed physics ensemble (PPE) which consists of varying uncertain model parameters within a single GCM (Murphy et al., 2007, Stainforth et al., 2005). This approach allows for systematic exploration of parameter uncertainties which cannot be achieved with MMEs. Large ensembles, using hundreds to thousands of versions of a GCMs, can also be produced and allows for probabilistic assessments of impacts to be made (New et al., 2007). The results of these large ensembles are often presented in the form of probability density functions (PDFs) which describe the relative likelihood of different model projections (Harris et al., 2010). A PPE method, based on variants of a single GCM, does not allow uncertainty arising due to structural differences in GCMs to be sampled.

Uncertainty in the use of downscaling techniques has been studied to a lesser extent. The earlier PRUDENCE (Prediction of Regional scenarios and Uncertainties for Defining European Climate change risks and Effects) program (Christensen et al., 2007a) and the more recent EU ENSEMBLES project (van der Linden and Mitchell, 2009) aimed to address the relative importance of spatial scale in the overall cascade of uncertainty. PRUDENCE succeeded in producing high-resolution climate change simulations for Europe based on four GCMs and eight RCMs and characterised the uncertainties in these projections due to model formulation and internal climate variability. The ENSEMBLES project had an overall aim to construct an end-to-end climate prediction system, with links from GCM, to RCM and statistical downscaling methods though to climate change impact models. This project built on the earlier PRUDENCE methodology to produce 25 different projections based on 15 RCMs

driven by boundary conditions from 5 different GCMs. The RCMs were analysed against gridded climate observation data sets allowing their uncertainties to be investigated. An examination of the relationship between the RCMs and their driving GCMs was also carried out. Overall the projections made by the RCMs were found to be consistent with larger-scale changes and the wider uncertainty defined by the GCMs.

2.2.3.4 Evidence for changes in circulations in observations and climate models Previous studies have found some evidence which suggests that the occurrence of particular atmospheric circulations in the North Atlantic and Europe region has changed in the recent past and may continue to change in future decades due to changes in radiative forcings. Changes in large scale circulations could have implications for the frequency or seasonal occurrence of winds which lead to midge incursions, and

therefore potentially midge-borne disease spread, into the UK.

Studies of trends in recent historical data have generally shown an increase in westerly or south-westerly flow across Europe. An increase in winter westerlies over the Atlantic during the period 1949-1994 was noted by (Corti et al. (1999) through an empirical orthogonal function (EOF) analysis of northern hemisphere 500hPa geopotential height anomalies. These results were also determined in another analysis, based on the same method but a different dataset (Hsu and Zwiers, 2001). An objective synoptic classification of Euro-Atlantic circulations was carried out by (Casado et al., 2009) using a PCA of ERA-40 data over the period 1962-2002. They identified an increase in the occurrence of a pattern associated with a positive phase of the NAO, hence suggesting an increase in the frequency of westerly winds. Werner et al. (2000) also identified a shift to increasing westerly weather types during 1981-1990 in the Hess-Brezowsky classification of Grosswetterlagen (Hess and Brezovsky, 1977). Additionally, van Oldenborgh and van Ulden (2003) observed an increase in south-westerlies in the period from February to April during 1950 to 2000 from recordings of wind speed at De Bilt, the Netherlands.

Studies which have investigated how circulation types may continue to change in future decades under the influence of changes in GHG concentrations show a range of results. Some suggest minimal changes to weather type frequency, such as Hay et al. (1991) whose results indicate circulation patterns over Delaware, USA are unlikely to change. In contrast, noticeable trends have been noted in some model simulations of future climatic circulations. Donat et al. (2007) used the objective scheme of Jones et al. (1993) to analyse the frequency of circulation types in a MME of GCMs for 2081-

2100 under an A1B emissions scenario with respect to 20<sup>th</sup> century simulations. For winter months, most models suggested an increase in days with westerly flow and anticyclonic flow with a corresponding decrease of days with easterly and cyclonic flow. In summer months, the models exhibited a decreasing number of days with cyclonic flow and increasing days with anti-cyclonic flow. An increase in westerly flow was also suggested by (Terray et al., 2004). They found an ensemble of GCM scenarios for 2070-2099 showed anthropogenic climate change strongly projects onto the positive phase of the NAO in wintertime.

Changes in circulation statistics of central Europe were also determined during the PRUDENCE project. Van Ulden and van Oldenborgh (2006) examined the simulations of three circulation indices, the west and south component of the geostrophic wind at the surface and the geostrophic vorticity, from five GCMs for a domain over central Europe for the period 2060-2100 under an A1B emissions scenario. The models were generally found to simulate stronger westerlies in winter and stronger easterlies in late summer. Weaker changes were observed in the southerly component. With respect to vorticity, the models generally simulated an increase in anticyclonic conditions in the summer. Overall, however, there was an appreciable range in responses from the five models. A similar study was carried out by van Ulden et al. (2007), using three GCMs and 9 RCMs (with boundary conditions from the same single GCM) for a control period of 1961-1990 and under an A2 emissions scenario for 2071-2100. For winter, the RCMs, their forcing GCM and one other GCM showed almost no change in vorticity, but a weak enhancement of southerly flows and a strengthening of westerly flows were found. The response of the final GCM contrasted these results which instead showed an enhancement of north-westerlies. In the summer the responses of all the models were more similar, showing a weakening of westerlies and a slight decrease in southerlies. The strong influence of the driving GCM on the circulation biases inherited by RCMs was also noted by Räisänen et al. (2004). They ran an RCM with two different driving GCMs and examined changes to mean sea level pressure (MSLP) patterns between the periods 1961-1990 and 2071-2100 using both an A2 and B2 emissions scenarios. Overall they found the RCMs showed varying results with the different GCMs producing a more dominant effect than the different scenarios.

# 2.3 Summary

This review of the literature has described the traditional method used to study the spread of bluetongue. The statistical or "climate-envelope" approach is useful to determine environmental suitability of a region for future disease spread but cannot be

used to predict the timing of future invasions. R<sub>0</sub> process-based models can be used to predict disease dynamics once introduced to an area but again do not describe the incursion stage. Hence is was concluded that a trajectory or dispersion model would provide a suitable approach to meet the first aim of the thesis, to model windborne spread of potentially infected midges into the UK. Chapter 3 therefore describes how the NAME dispersion model has been adapted in order to achieve this aim.

The second part of this thesis aims to estimate changes in the frequency of windborne incursions into the UK under a changing climate in future decades. The review of synoptic climatology techniques here suggests that they would provide a useful method to study changes in synoptic weather patterns associated with midge incursions. An objective map-pattern classification is therefore produced in Chapter 4 and related to results from the dispersion modelling from Chapter 3 to identify which synoptic types are associated with windborne midge spread into the UK.

This review has also discussed the cascade of uncertainty in projections of future climate change. One approach to explore this uncertainty is to use an ensemble of different climate models. Therefore in Chapter 5 MSLP data from an ensemble of RCMs from the ENSEMBLES project are used to analyse changes in the pressure patterns associated with midge incursions into the UK under climate change from 2001 to 2050.

# **Chapter 3**

# Modelling the wind-borne transport of midges as an atmospheric dispersion problem

This chapter describes the adaptations which have been made to a complex atmospheric dispersion model to explicitly represent midge flight behaviour and its subsequent use to provide early warnings of disease incursion events to the UK. Firstly, an introduction is given of the underlying atmospheric dispersion model, NAME. Next, the development of NAME to incorporate midge flight is described, including how several versions were progressively produced as experimental data from collaborators became available. An analysis of the sensitivity of the final model to its meteorological inputs is carried out and an estimate of its uncertainties is given. Several case studies are then also used to evaluate the model results. Finally, a description of the early warning system is provided and its application in government planning and emergency response situations is discussed.

# **3.1 Introduction to NAME**

The UK Met Office's atmospheric dispersion model NAME is a Lagrangian model in which concentrations of a gas or particulate 'species' are determined by releasing large numbers of model particles into its representation of the atmosphere (Jones et al., 2007). The particles are carried along passively by the ambient three-dimensional wind flow with a random component superimposed to simulate turbulence. Each particle represents a proportion of the mass of the released substance, which can be reduced over time by different loss processes. In the following sections a summary of the main parameterizations used in NAME are given (for further details see Maryon et al. (1999)) and the results from campaigns carried out to evaluate the model against observations and other dispersion models are provided.

# 3.1.1 Meteorological data

The basic meteorological data which initialises the calculations in NAME comes from the UK Met Office's NWP model, the Unified Model (UM) (Davies et al., 2005). There are three different grids on which UM data is produced; a global domain (~40km

horizontal resolution with 70 vertical levels), a grid which covers the North Atlantic and Europe (NAE) (~12km horizontal resolution with 38 vertical levels), and a smaller region which covers the UK (~4km horizontal resolution with 70 vertical levels), as displayed in Figure 3.1. NAME can be run in a manner which allows the highest resolution data available for the location and time to be used.





# 3.1.2 Source information

The source of gas or particulate 'species' in NAME is specified by its start and end times, release rate, location, lower and upper limits and shape (cuboid or ellipsoid). Several sources can be defined and complex release profiles produced by using multiple sources at different heights and times. When a particle is released, its position is randomly chosen between the upper and lower limits and within the defined source area. The time of release is also chosen randomly within the timestep.

# 3.1.3 Advection and dispersion

Particles are advected in three dimensions by the mean wind, with an additional component calculated to simulate turbulence. At short ranges (typically <10km), a random walk technique is used which includes correlations in time between particle

velocities. At longer ranges a simpler, less computationally expensive, Wiener process is usually applied.

#### 3.1.3.1 Near-source scheme (random walk technique)

In the random walk technique particles are advected each timestep using:

$$x_{t+\Delta t} = x_t + [u(x_t) + u'(x_t) + u'_t(x_t)]\Delta t$$
(3.1)

where  $x(x, y, \eta)$  are the particle position vectors and  $u(x, y, \eta)$ ,  $u'(x, y, \eta)$  and  $u'_{l}(x, y, \eta)$  are the wind velocity, turbulent velocity and low-frequency meander vectors respectively, and  $\Delta t$  is the timestep. Turbulent velocities are calculated by different forms of the Langevin equation according to the type of turbulence, as described below.

The turbulent velocity component assumed to be homogeneous in the horizontal direction is obtained from:

$$du' = adt + bd\xi \tag{3.2}$$

which describes a drift (memory) term and a diffusion (innovation) term. The coefficients a and b are defined as:

$$a = -\frac{u'}{\tau_u} \tag{3.3}$$

$$b = \left(\frac{2\sigma_u^2}{\tau_u}\right)^{0.5}$$
(3.4)

Where  $\tau_u$  is the Lagrangian timescale (the time over which particle velocities are no longer correlated) for the *x* component of the turbulence and  $\sigma_u$  the horizontal velocity variance. The  $d\xi$  are increments of a random process; they are taken here to be a Gaussian distribution with a mean of zero and a variance equal to dt. The turbulent velocity component is therefore expressed as:

$$u'_{t+\Delta t} = u'_t \left(1 - \frac{\Delta t}{\tau_u}\right) + \left(\frac{2\sigma_u^2 \Delta t}{\tau_u}\right)^{1/2} r_t$$
(3.5)

where  $r_{t}$  is a random Gaussian number of zero mean and unit variance.

Vertical velocity variance,  $\sigma_w$ , varies with height. To prevent particles accumulating in regions of low,  $\sigma_w$ , and to conform to the well-mixed criteria, which states that particles which are well-mixed in position and velocity space must remain that way, different specifications of the parameters in the Langevin equation have been defined (Thomson, 1987).

For Gaussian turbulence, where the probability that a sampled vertical velocity will be equally positive or negative, the vertical turbulent velocity, w', can be calculated, using a Lagrangian timescale equal to  $\tau_w$ , as:

$$w'_{t+\Delta t} = w'_t \left(1 - \frac{\Delta t}{\tau_w}\right) + \left(\frac{2\sigma_w^2 \Delta t}{\tau_w}\right)^{1/2} r_t + \frac{\Delta t}{\sigma_w} \frac{\partial \sigma_w}{\partial z} (\sigma_w^2 + w'_t^2)$$
(3.6)

The final term on the right represents a 'drift' velocity, which prevents particles collecting in regions of low  $\sigma_w$ .

When the turbulence is non-Gaussian (skewed), for example in convective conditions characterized by strong narrow updraughts and larger areas of weak downdraughts, the drift and diffusion coefficients, a and b, of the Langevin equation are specified differently. They are calculated in relation to the rate of dissipation of turbulent kinetic energy, the Monin-Obukhov length (a function of air density, temperature, sensible heat flux and friction velocity) and the probability of being in a updraught or downdraught (see Maryon *et al.*, 1999 and Thomson, 1987 for details).

#### 3.1.3.2 Long range scheme (Wiener process)

The random walk technique is computationally expensive so a simpler scheme, based on a Wiener process, is often used for dispersion calculations at longer ranges. The Lagrangian timestep is taken as the model timestep,  $\Delta t$ , and the change in particle position is calculated as:

$$\Delta x = \sqrt{2K\Delta t}r_t \tag{3.7}$$

Where *K* is a turbulent diffusion coefficient and  $r_t$  is a a random Gaussian number of zero mean and unit variance.

The turbulent velocity, u', is then:

$$u' = \sqrt{\frac{2K}{\Delta t}} r_t \tag{3.8}$$

An effective velocity variance,  $\sigma_{\scriptscriptstyle eff}$  , is chosen so that:

$$K \approx \sigma_u^2 \tau_u = \sigma_{eff}^2 \Delta t \tag{3.9}$$

Using a Lagrangian timescale equal to  $\tau_{\mu}$ 

resulting in:

$$u' = \sqrt{2}\sigma_{eff}r_t \tag{3.10}$$

which describes parabolic spread of the plume.

#### 3.1.3.3 Turbulence profiles

The equations for the turbulent velocity components are based on estimates of  $\sigma$  and  $\tau$ , which can be derived from published empirical fits to observational data. Homogeneous profiles, with constant values of  $\sigma$  and  $\tau$  used throughout the boundary layer, are less expensive and are used at long range. Above the boundary layer  $\sigma$  and  $\tau$  are set to constant free tropospheric values. Different profiles are specified for stable and unstable conditions in both the homogeneous and more expensive inhomogeneous schemes (for details see Webster et al., 2003).

#### 3.1.4 Loss processes

The processes by which material is lost from the atmosphere depend on the species and options specified, but can include wet and dry deposition to the ground, radioactive decay and chemical reactions. Wet deposition involves two main processes; washout, where impaction by rain droplets causes material to be 'swept out', and rainout, where particles act as cloud condensation nuclei and are removed as cloud forms around them. Dry deposition describes the loss of material by impaction with the surface. The flux of pollutant to the ground is calculated from the concentration of particles near the ground and a constant called the deposition velocity. For details of particle loss due to radioactive decay and chemical transformation processes see Maryon *et al.* (1999).

# 3.1.5 Model output

Results from NAME are generally presented as 'plumes' displaying the concentration of particles in each output grid box after a specified time interval. This output grid is user defined and its resolution can therefore be modified to suit individual applications. In addition the accumulated 'dosage' or maximum concentration received by each grid box can also be represented. The individual particle positions can also be plotted and

are generally shown as trajectories connecting their locations at each timestep. It is also possible to print out the raw data as time-series at specified locations.

# 3.1.6 Model evaluation

NAME has been compared against other dispersion models and/or observations in several different cases. For example, the Kincaid field experiment has been used extensively in the evaluation of several dispersion models including ADMS, AEROMOD and HPDM. In this field campaign, carried out in 1980 and 1981, a buoyant plume of the tracer  $SF_6$  was released from the Kincaid power plant, Illinois, USA. Hourly-averaged maximum ground level concentrations of the tracer were measured from 500m to 5km away from the stack. NAME concentrations compared satisfactorily with these observations; the predictions of plume spread compared well with the spread in the observations but there was a slight over-prediction in the mean concentrations (Jones et al., 2007).

Results from NAME's use in emergency response situations have also been evaluated. A major explosion occurred at the Buncefield oil depot in Hemel Hempstead, UK on 11 Dec 2005 creating a large plume of black smoke. Simulation of the smoke plume by NAME was used to provide guidance to the emergency services and was found to be in very good agreement with satellite images of the smoke plume (Webster et al., 2007). NAME output is also used by the London Volcanic Ash Advisory Centre (VAAC) to provide advice to the Civil Aviation Authority (CAA) and National Air Traffic Services (NATS) following volcanic eruptions. The predictions made by NAME during the eruption of the Icelandic volcano Grimsvötn in Nov 2004 showed good agreement with the results from four different models used by other VAAC's in Darwin, Washington, Montreal and Toulouse (Witham et al., 2007). NAME was also used to forecast ash from the eruption of Eyjafjallajökull, Iceland in 2010 and compared well with measurements taken by ground-based lidar (Devenish et al., submitted).

A further model inter-comparison was carried out between 6 dispersion models used by international research institutes to forecast the airborne spread of foot-and-mouth disease; NAME, VetMet, PDEMS, AIWM, MLCD and NARAC (Gloster et al., 2010). In general the models all predicted similar areas where livestock would be at risk, with the differences thought to be related to the underlying meteorological data used.

# 3.2 Development of NAME to model midge flight

# 3.2.1 Overview of the method

Development of the model was carried out in collaboration with entomological experts at the Institute for Animal Health, Pirbright (IAH). This collaboration project involved four main stages; to identify what information would be required to include midge flight behaviour in a dispersion model, to devise and carry out experiments to acquire this data, to incorporate it into the model's code and finally to investigate the limitations of the modelling. The first stage was carried out jointly between the two partners. IAH then devised and carried out the experimental work (Sanders et al., submitted). In this section the model development is described.

From the early discussion stages it was determined that there was much scope to improve on the earlier trajectory models for bluetongue such as those developed by Hendrickx et al. (2008) and Ducheyne et al. 2007 (see Section 2.1.3). The effects of meteorology on the take-off rates of midges was not well known, so this was outlined as one main focus of the experimentation part of the project. This section discusses how these results were used in the coding of the NAME to vary the 'mass' of model particles, representing midges, released as a source in the model according to the meteorology at the release time and location. In addition it was found that maximum flight times of midges and processes resulting in their removal from the atmosphere by precipitation were not well understood or captured in previous trajectory models of bluetongue spread and these would therefore be modelled in NAME according to results of the experiments carried out. As the main objective of the research project was to predict the introduction of the virus into the UK via midge dispersal from mainland Europe, it was decided that the focus would be on modelling long-range dispersion (typically >100km). Shorter-range 'vegetative' flight was not included in the model as it was assumed that this type of flight would be resource driven and not strongly influenced by meteorology.

It was originally envisaged in the project that the model would be developed over a three year period, from 2006 to 2009, and be fully operational before outbreaks of bluetongue occurred in northern Europe at some unknown time in future years. However as BTV-8 suddenly emerged in the Netherlands in 2006 and posed a strong threat to the UK in 2007, a model to warn of windborne incursions was required from the start of the research contract before any experiments or adaptations to NAME could be made. This section therefore describes the four versions of the model that were developed each year throughout the research contract period in response to the

disease situation on the near-continent, from the initial un-modified version in 2007 to the final version in 2009. The latest experimental data available from IAH were incorporated into the model each year allowing each subsequent version of the model to become more sophisticated and more representative of midge flight. Each year the most recent version of the model was used to form the basis of an early warning website to provide estimates of the risk to the UK government of an incursion of bluetongue to the UK by infected midges from the near-continent. This early warning system is described in more detail in Section 3.5.

# 3.2.2 NAME midge model version 0 (2007)

# 3.2.2.1 Midge data used in model development

The threshold values for wind speed, precipitation and temperature used to indicate when conditions suitable for midge flight were only based on the expert opinion of entomologists at IAH (Mellor, P., and Carpenter, S., pers. comm. 2007) in the initial version of the model as only limited research had been carried out before a version of the model was required for an early warning system due to disease circulating in northern France and Belgium since 2006 (see Section 3.5).

# 3.2.2.2 Model modifications

NAME was initially used in an unmodified configuration to model the spread of bluetongue into the UK from 1 April 2007 (Gloster et al., 2008). It was operated using a timestep of 10 minutes, using data from the 12km domain of the UM without nesting of higher resolution data (see Figure 3.1), and each run typically took around 2 hours. 'Inert-tracer' particles were released in the model as a proxy for the movement of air from potentially infected areas. Release sites where chosen in consultation with Defra to represent different sections of the northern coastline of the European mainland and defined as 85kmx5km area sources. A continuous area source along the whole coastline was not used in order to allow the source of different parts of the plume to be identified more easily. The release sites did not relate to known sources of BTV as this data was unavailable at the start of the midge season when the model set-up was determined.

Meteorological data from observation stations at the release sites were examined manually to determine if conditions were likely to be suitable for midge flight, based on the thresholds provided by IAH (see above, Section 3.2.2.1). A standard number of particles were released between 18Z and 21Z (Zulu Time/Coordinated Universal Time (UTC)) and allowed to disperse for 12 hours overnight. The level of risk of a bluetongue

incursion was assigned using a traffic light colour scheme (red=high, yellow=medium, green=low and black=none), based on the flow chart in Figure 3.2.



Figure 3.2: Flowchart used in conjunction with NAME midge model version 0

# 3.2.3 NAME midge model version 1 (2008)

# 3.2.3.1 Midge data used in model development

The results from field and laboratory experiments carried out by IAH in 2007 were not available before the start of the 2008 midge season, therefore the thresholds for when meteorological conditions were assumed to be suitable for midge flight remained the same as in model version 0, based on the expert opinion of entomologists at IAH (Mellor, P., and Carpenter, S., pers. comm. 2007).

# 3.2.3.2 Model modifications

The first adaptations made to NAME to include midge flight incorporated the thresholds used in the flow chart (Figure 3.2) into the FORTRAN code of the model. Firstly a new particle type, 'midge', was defined. Each time a 'midge' particle was due to be released, NAME would determine if weather conditions were suitable for midge activity (wind speed less than 3ms<sup>-1</sup>, precipitation less than 1mmhr<sup>-1</sup> and temperature greater

than 10 °C). If these conditions were not met, the particle's mass was decreased to zero and did not contribute to further calculations. However when weather conditions were determined as suitable the particles were released from a height of 10m. This was assumed to be above their FBL and would therefore exclude midges undertaking 'vegetative' flight. At later timesteps after the release period, the particles were dispersed using the standard long range dispersion scheme (Section 3.1.3.2). The standard wet and dry deposition processes used in NAME (Section 3.1.4) were not included as the 'rainout' mechanism was not thought to be appropriate for midges. Instead when precipitation levels were greater than 1mmhr<sup>-1</sup> at any time step in the model run the 'midge' particles were excluded from further calculations as they were assumed to not survive this washout process. The model was operated as in the previous version, using the same release sites with un-nested data from the 12km domain of the UM and a timestep of 10 minutes. The approximate run time of this version of the model was also 2 hours.

The results from the model were plotted in relative units of risk as real midge population numbers were not available. In order to define the high, medium and low risk categories, contours of the concentration of midge particles were scaled against a case study, where it appeared very likely that a windborne incursion of midges had caused the outbreak. The case study used in the scaling of the contours was the first outbreak in the UK in September 2007, believed to have been initiated by a windborne incursion on 4 August 2007 (see Section 3.4.1). The high risk category was scaled to reach UK on this date, and medium and low risk contours were defined as factors of ten smaller. Due to a lack of a way to verify this contouring (see Section 3.4), these levels can only be taken to show relative concentrations and therefore which areas are likely to be at higher risk.

An example of version 1 of the NAME midge model is shown for the overnight period on 1-2 July 2008 (Figure 3.3) and demonstrates the improvement upon model version 0. On the left the original 'inert-tracer' particles are shown (in pink) and the new 'midge' particles are shown on the right (in purple). The results from the new version show how heavy precipitation later in the night removes 'midge' particles and consequently results in reduced risk to the south-east of England. This effect of this rainfall was not identified in the 2007 version of the model, which only examined weather parameters at the source locations. Version 0 of the model would have overestimated the level of risk posed to the east and south-east of England.

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**Figure 3.3:** Comparison of 'inert-tracer' particles (pink) and 'midge' particles (purple) overnight on 1-2 July 2008, using version 1 of the NAME midge model.

# 3.2.4 NAME midge model version 2 (2009)

# 3.2.4.1 Midge data used in model development

Several field experiments were carried out by IAH during 2007 and 2008 to correlate the activity levels of midges with meteorological variables, using light traps and automatic weather station (AWS) equipment (Carpenter et al., 2008, Sanders et al., submitted).

It was established that the impacts of wind speed and temperature on midge flight were not distinct thresholds as assumed in previous versions of the model. Graduated thresholds, as described in Tables 3.1 and 3.2, were estimated to more accurately reflect this (Sanders, C., pers. comm. 2009). The effect of precipitation could not be examined further at this stage as high temporal resolution rainfall data was not available from the AWS.

Temperature (℃)	% of 'midge' particle mass to release in NAME
>15	100
10-15	95
5-10	50
0-5	10
<0	0

Table 3.1: Temperature thresholds used in the source term of model version 2

Wind Speed (m/s)	% of 'midge' particle mass to release in NAME
<1	100
1-2	95
2-3	75
3-4	50
4-5	25
5-6	17.5
6-7	10
7-8	5
>8	0

Table 3.2: Wind speed thresholds used in the source term of model version 2

The flight duration of *Culicoides* was also examined by IAH in a laboratory using a flight mill (Sanders, C., unpublished data). This involved suspending an individual midge with a fine tether in a wind tunnel which provided an air current to stimulate it to fly. They found some midges to be capable of maintaining flight at least 10 hours.

In order to examine the diurnal cycle of midge activity, data at a higher temporal resolution than the daily catches from the light traps were required. To achieve this, entomologists at IAH collected midges in situ using a large net fixed to the roof of a car, a 'truck-trap', which was driven around a field once every hour for up to 24 hours at a time. The results from one 24-hour long experiment on 30 June 2008 are shown at Figure 3.4 (Sanders et al., submitted), from which a clear peak around sunset is noted, with a secondary peak around two-thirds of the size at sunrise.

Seasonal cycles of activity rates were examined using trap data from Jersey (Sanders et al., 2010) and southern England (Holmes & Boorman, 1987; Sanders, C., unpublished data) which show populations peak in late spring and again in late summer (Figure 3.5).

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**Figure 3.4:** Total *Culicoides* caught by a 'truck-trap' at a farm at Compton during hourly intervals on 30 June 2008 (adapted from Sanders et al., submitted)



Figure 3.5: Seasonal cycle of Culicoides during 2008 (adapted from Sanders et al., submitted).

#### 3.2.4.2 Model modifications

The model was operated as in previous years (using the same release sites, model timestep and 12km UM data) but several enhancements were made using the results

of the experiments carried out by IAH, described above in Section 3.2.4.1. The source term was altered, to include the graduated thresholds estimated in Tables 3.1 and 3.2, with progressively less mass of 'midge' particles being released as wind speed increased and temperature decreased (Sanders, C., pers. comm. 2008). The mass of particles to release was taken as the more restrictive threshold from either the effect of temperature or wind speed. For example if temperatures were between 10 and  $15 \,^{\circ}$ C (suggesting 95% of the mass should be released) but wind speeds were 6-7 ms<sup>-1</sup> then only 10% of the total mass was be released.

Based on the results of the flight mill experimentation, the estimated flight duration of midges used in version 1 of the model, of 12 hours, was found to be a good estimate for conditions which may be experienced outside the laboratory. The maximum duration of dispersion of the 'midge' particles in NAME was therefore kept at 12 hours. The findings from the 'truck-trap' indicated that midges become particularly active at sunrise in addition to at sunset. Therefore the mass of particles released on a particular day was divided into 60% at sunset and 40% at sunrise. The times of release around sunset and sunrise were changed manually in the model on a weekly basis. The seasonal cycle was also reflected in the model by scaling the mass of 'midge' particles released against the curve in Figure 3.5.

#### 3.2.5 NAME midge model version 3 (2010)

#### 3.2.5.1 Midge data used in model development

Statistical analysis was carried out by collaborators at IAH on data taken from the Rothamsted Insect Survey (Harrington & Woiwood, 2007), a network of suction traps across the UK which has operated since the mid-60s. They analysed the correlations between the number of midges caught daily at 12 sites in England during 2008 and the effects of seasonality and temperature, wind speed and rainfall at sunset in a Bayesian framework using generalised linear models assuming Poisson errors and a log link function (Sanders et al., submitted).

The resulting equation for expected number of midges ( $\mu$ ) on day *t* (Julian day number) was determined by researchers at IAH as:

$$\log_{e}(\mu(t)) = b_{0} + b_{11}\sin\left(\frac{2\pi t}{366}\right) + b_{21}\cos\left(\frac{2\pi t}{366}\right) + b_{12}\sin\left(\frac{4\pi t}{366}\right) + b_{22}\cos\left(\frac{4\pi t}{366}\right) + c_{1}M_{1}(t) + c_{2}M_{2}(t) + c_{3}M_{3}(t)$$
(3.11)

where  $M_1$  = temperature (°C),  $M_2$  = mean wind speed (ms<sup>-1</sup>),  $M_3$  = presence of rain (no=0, yes=1) at sunset and the mean value of the seasonal parameters are  $b_0 = -1.71$ ,  $b_{11} = -1.56$ ,  $b_{21} = -3.74$ ,  $b_{12} = -1.49$ ,  $b_{22} = -1.00$ ,  $c_1 = 0.07$ ,  $c_2 = -0.20$  and  $c_3 = -0.18$ .

Full summary statistics of the marginal posterior densities of the parameters are available at (Sanders et al., submitted). The model was found to adequately capture the data in terms of overall fit, total daily catch and time of first appearance in the season (Sanders et al., submitted).

# 3.2.5.2 Model modifications

Overall the model was operated as in previous years but the midge activity equation (Equation 3.11) was included into the NAME code so that the mass of 'midge' particles to be released from a particular source is calculated from the temperature, wind speed and precipitation levels (taken from the 12km domain of the UM for the release location and time) and day of the year on  $\mu$ . This mass was again divided into two periods at sunset (60% of the total) and sunrise (40% of the total) to represent the diurnal cycle of midge activity as in version 2. Additionally in this version of the model a FORTRAN routine was included to automatically calculate sunrise and sunset and modify the release times accordingly. This routine was adapted from code used in the Met Office Night Illumination Model (MONIM) (Revell and Hignett, 2004). The seasonal cycle was now also included implicitly from the use of Equation 3.11 and did not require manual scaling.

# 3.3 Uncertainty and sensitivity analyses of the midge activity equation

Uncertainty and sensitivity analyses were carried out to assess the robustness of the output from the midge activity equation (Equation 3.11) to potential errors in the meteorological input data and the values chosen for the seasonal parameters. The main aim of the analysis was to highlight which variables have the greatest contribution to the output in order to determine the extent to which inaccuracies in their values will propagate through to the predictions made by the model. The analysis was also used to show if there are particular times when the model output has greater uncertainty.

# 3.3.1 Uncertainty analysis in the seasonal parameters

A sampling-based uncertainty analysis following Helton and Davis (2008) was carried out using 1000 replicates of the seasonal parameters in the midge dynamics equation, randomly selected from their posterior distribution. The seasonal parameter replicates

used in the analysis were provided by IAH (Gubbins, S., pers. comm.). The expected number of midges,  $\mu$ , was evaluated for each of the 1000 sets of values using meteorological data for 18Z on every evening during the midge season from 1 April to 30 November during 2005, 2006 and 2007 for six release sites along the coast of the near-continent.

The median, 2.5<sup>th</sup> and 97.5<sup>th</sup> percentiles of  $\mu$  are shown at Figure 3.6 for the release site at Dieppe as an example (each of the other sites shows very similar results). A consistent pattern is noted for each year where the largest range of uncertainty occurs in May and June (when the value of  $\mu$  is at its peak). Another smaller peak in the range of uncertainty occurs around September and October, corresponding with a second peak in midge numbers. Overall this analysis suggests a small amount of uncertainty propagates into the model results from the choice of seasonal parameters in the equation.



**Figure 3.6:** Results from Dieppe of the sampling-based uncertainty analysis showing the median (solid black line),  $2.5^{\text{th}}$  (blue dashed line) and  $97.5^{\text{th}}$  percentiles (red dashed line) of  $\mu$  calculated using 1000 replicates of the posterior distribution of the statistical parameters in the midge dynamics equation.

# 3.3.2 Sensitivity analysis of the meteorological variables

The value of  $\mu$  in the midge activity equation (Equation 3.11) was again calculated each evening during the midge season from 1 April to 30 November during 2005, 2006 and 2007 for six release sites along the coast of the near-continent using constant median values of the seasonal parameters. The sensitivity to each meteorological parameter recorded at 18Z during this period was firstly explored visually using scatter and box plots. The results from all six sites again showed similar relationships. Figure 3.7 shows the results for Dieppe as an example.

As expected, a positive correlation between temperature and midge numbers was found, however consistently large spread in the data was noted throughout its range. Negative correlation was shown with wind speed, but very low midge numbers are calculated for some occasions all ranges of wind speed, suggesting the results can be limited by other factors. As the presence or absence of rain is a binary variable, a box plot was used to analyse its relationship with midge activity. Wide variation is particularly noted during dry conditions possibly suggesting the effects of temperature and wind speed become dominant at these times. The relationship between rain and midge numbers is positively skewed and less overall compared to dry times, but the box plot shows midges are still present in high numbers on some occasions during periods of rain.







**Figure 3.7:** Scatter plots of  $\mu$  against (a) temperature and (b) wind speed (with a least-squares linear regression line fitted) and a box plot (c) of the values of  $\mu$  during the presence and absence of rain at Dieppe.

These relationships were then quantified using a stepwise regression analysis, which indicates the order of importance of the input variables on the output, whilst allowing for correlations between them (e.g. Helton & Davis, 2008). With this approach a sequence of regression models is constructed. The first model contains the single input variable which has the largest correlation with the output variable. The second model contains the input variable from the first step and the second input variable which has the largest correlation input variable not accounted for by the first variable. Additional models are constructed until a point where no meaningful increase in the amount of uncertainty explained by the variables is found.

The results from the stepwise regression analysis for the source at Dieppe are shown in Table 3.3, which contains values of their standardized regression coefficients (SRC) and individual and overall  $R^2$  values. The SRCs represent the change in the dependent variable (the expected trap catch) that results from a change of one standard deviation in an independent variable (meteorology variable), allowing a better comparison between predictors with different units of scale. This is achieved by standardizing their variance to 1. The SRC value is calculated as the value of the regression coefficient (coeff) for the independent variable (*x*) multiplied by the ratio of the standard deviation of *x* to the standard deviation of the dependent variable (*y*):

$$SRC = coeff * stdev(x) / stdev(y)$$
(3.12)

The individual  $R^2$  values are calculated as the product of the SRC and the correlation between output (expected trap catch) and the individual input (meteorology) variables (e.g. *x1*) used in the construction of the model:

$$R^{2}(x1) = SRC * cor(y, x1)$$
 (3.13)

If the individual  $R^2$  values equal the total  $R^2$  for the model this indicates that the variables are independent from one another.

The analysis shows that the equation is most sensitive to temperature, which explains 39%, of the variance in the expected midge numbers. Wind speed is found to be the second most important input variable, and together with temperature explains 41% of the variance. Finally the equation is shown to be least sensitive to precipitation, with the overall variance increasing to 44% with its inclusion. It should also be noted that the total of the individual  $R^2$  values of the variables differ slightly from the total  $R^2$  values for the overall models, indicating a degree of correlation between the variables.
Step	Variables	SRC	Individual R <sup>2</sup>	Total R <sup>2</sup>
1	temperature	0.625	0.3926	0.3926
2	temperature	0.5242	0.3284	0.4125
	wind speed	-0.3014	0.1122	
3	temperature	0.5117	0.3206	0.4411
	wind speed	-0.3454	0.1286	
	precipitation	-0.0530	0.0049	

**Table 3.3:** Results from the stepwise regression analysis for the sensitivity of the midge seasonal dynamics equation to the meteorological input data at Dieppe.

### 3.3.3 Uncertainty associated with the meteorological input

From an analysis of the sensitivity of the midge equation (Equation 3.11) to the different meteorological inputs it was found that temperature attributed the most variance to the output (Table 3.3). The equation was also found to be sensitive to wind speed and to a lesser extent precipitation. There is also added uncertainty in these variables due to potential error in the NWP data, from the UM, used by NAME. Extensive verification of the UM is carried out at the UK Met Office (e.g. Mittermaier and Roberts, 2010) so this will not be discussed in detail here. However one simple standard diagnostic produced, the mean error of the NWP data against observation data is shown in Figure 3.8. The error in the temperature data from the NAE model, the domain used by the midge model in predicting bluetongue incursions to the UK, is found to be around -0.1 to -0.2 °C during the period of the forecasts, from 2007 to 2010. The error in the wind speed is also found to be low at between 0 and 0.3 ms<sup>-1</sup> during this period. This implies that although the midge activity equation is sensitive to temperature and wind speed, minimal error will propagate through into its results from the NWP input data.

The presence of precipitation is not a continuous variable, so quantification of the skill in its forecast is measured using categorical statistics. One such measure used in its verification is the equitable threat score (ETS), defined by Schaefer (1990) as:

$$ETS = \frac{AD - BC}{(B + C)(A + B + C + D) + (AD - BC)}$$
(3.12)

where A = number of hits (correct forecasts), B = number of false alarms (incorrect forecasts of non-events), C = number of misses (incorrect forecasts), D = number of correct rejections (correctly forecast non-events).

For a perfect correspondence between prediction and occurrence of rain, the value of ETS will equal 1. For a threshold value of 1mm the ETS for the NAE domain during 2007-2010 is not particularly high, at between 0.2 and 0.26. Moreover the equation is not very sensitive to the value of precipitation so this error will affect the output to a lesser extent.



**Figure 3.8:** Mean error in surface temperature and surface wind speed for NWP data from the UM where red = NAE domain and blue = global domain (the mesoscale domain shown in green was discontinued in 2006). (Adapted from Bush, M., unpublished data).

## 3.4 Evaluation of the midge dispersion model using case studies and model inter-comparisons

Determining the accuracy of the results from the NAME midge model is problematic as it is near impossible to get direct observations of the wind-borne carriage of insects over hundreds of kilometres with which to compare the model results to. Some larger species may be followed visually for a few hundred metres, or tracked on entomological radar (Riley et al., 2007). "Mark-release-recapture" experiments have also been used with some success with other species, where markers such as dyes and radioactive chemicals, or even small radio-transmitters, have been used to trace individuals such as southern pine beetles (Turchin and Thoeny, 1993) and mormon crickets (Sword et al., 2005). However this type of experiment would be extremely difficult to carry out in practice for midge dispersion across large distances. Other circumstantial evidence which could be used to determine the occurrence of a migration event of insects includes sudden mass arrivals in association with particular kinds of weather systems, especially first arrivals in areas that do not have a local population. Again, this is not a technique which could be used here, as local midge species are similar on the near-continent and in southern England.

With a lack of data on direct insect movements, evidence can be inferred in some cases from sudden outbreaks of diseases presumed to be introduced by vector-insects (see Section 2.1.3). This is the approach adopted here. Five outbreaks of BTV in Europe (in the UK, Denmark, Norway, Sweden and the Balearic Islands) have been used as case studies. In all of these situations the outbreaks occurred in coastal areas on the opposite side of a stretch of sea from another infected region and no other mechanism of disease transport, such as animal movements, could be determined, despite intensive epidemiological investigations. This circumstantial evidence suggests incursions of wind-borne infected midges can be assumed to be the most probable cause of disease introduction and the outbreaks therefore provide good case studies to test the validity of the model.

Outbreak details were provided by the veterinary institutes in each of the affected countries or were available from the literature. The model was then run from the nearest locations known to have virus circulating during the likely introduction period, determined through discussion with local epidemiological experts or those at IAH. In most of the cases results from the final version of the model are displayed, although the most recent version available was used during the original investigations carried out at the time of the outbreaks. Plumes displaying 12 hour integrated concentrations

of particles were produced and relative concentration contours were used as described in Section 3.2.5. Finally, the results were evaluated to determine if they were consistent with the circumstances of the outbreak, and therefore provide a valid representation of disease spread.

In two of the case studies, the NAME model output was additionally compared to results from two different dispersion models available from the literature. This intercomparison provides a further test of the validity of the model. For the outbreaks in Sweden the results from NAME were compared to the Multiscale Atmospheric Transport and Chemistry (MATCH) model developed at the Swedish Meteorological and Hydrological Institute (SMHI). This model uses an Eulerian framework and is driven by different NWP data from the HIRLAM model (Robertson et al 1999). For further details of the inter-comparison see Ågren et al. (2010). The outbreaks on the Balearic Islands were originally investigated using single-particle trajectories with data from ECMWF by Alba et al. (2004) (see Section 2.1.3). For comparison NAME was also operated in the same manner, using backward trajectories, to re-analyse the outbreak. However trajectories for 100 particles were plotted using NAME to highlight the issues associated with producing only one representation of a possible trajectory in a turbulent atmosphere.

### 3.4.1 Results

The details of the outbreaks and results from the NAME modelling are displayed in Table 3.4 and described in detail in the following section.

In each of the case studies only one or two dates were identified in the infection window on which an incursion of bluetongue could have occurred by wind-borne midges. In each case, the region predicted to be infected by these particular plumes aligns well with the observed areas of outbreaks.

 Table 3.4: Details of the case study outbreaks

Outbreak	Suspected source	Infection window	Possible incursion dates	Figure	Midge model version	Reference
Baylham Farm, Suffolk, UK on 21 Sep 2007	Ostend, Belgium	1 Aug - 18 Sep 2007	4-5, 20-21 & 26-27 Aug 2007	3.9	Version 0	Gloster et al., 2008
Sakskøbing, Lolland, Denmark on 11 Oct 2007	Northern coast of Germany from Lübeck to Kiel	14 Sep - 7 Oct 2007	17-18, 22-23, 25-26 & 29-30 Sep 2007	3.10	Version 3 (version 0 used in original analysis)	-
Vest-Adger, Norway in late February 2009*	Ringskøbing Skjern, Denmark & Halland, Sweden	1 Sep - 31 Oct 2008**	7-8 Oct 2008	3.11	Version 3 (version 2 used in original analysis)	Burgin et al., 2009
Halland, Sweden on 26 Aug 2008	Jutland, Denmark & northern coast of Germany	31 Jul - 19 Aug 2008	6-7 Aug (Germany) 14- 15 Aug (Denmark)	3.14	Version 3 (version 2 used in original analysis)	Ågren et al., 2010
Minorca & Mallorca, Balearics, Spain in Oct 2000	Sardinia or northern coast of Africa	1 Aug - 30 Sep 2000	1-2, 2-3 Aug (Tunisia), 17-18 Aug (Tunisia, Algeria) 19-20, 20-21, 24-25, 25-26 (Algeria)	3.15, 3.16	Version 0	Alba et al., 2004

\*Detected post-outbreak by bulk milk sampling (clinical signs not present).

\*\* Incursion assumed to have occurred before the end of the previous year's midge season.

The first UK outbreak occurred at Baylham Farm in Suffolk on 21 September 2007 (blue dot in Figure 3.9). Results from the NAME midge model (Figure 3.9), operated prior to the outbreak on 4-5 August 2007, showed this area of the eastern coast area of East Anglia was at high risk of an incursion.



**Figure 3.9:** Model output of a likely incursion of midges overnight on 4-5 Aug 2007 leading to the first UK outbreak in Suffolk at Baylham Farm, indicated by a blue dot (adapted from Gloster et al., 2008).

In the Danish outbreak, the island of Lolland was predicted to be the area at greatest risk from infected areas of northern Germany. Figure 3.10 shows the most likely incursion date on 22-23 September 2007 from an area of infection around Wismar. The results form NAME, shown in Figure 3.10, are found to align well with where the first outbreak occurred near Sakskobing, on Lolland.



**Figure 3.10:** Most likely incursion of midges on 22-23 Sep 2007 from Wismar, northern Germany leading to outbreak near Sakskobing on Lolland, Denmark (blue dot).

In Norway only the very southern coast was suggested to be at risk by NAME, as shown by the plume in Figure 3.11. It was in this localised area where the first outbreaks occurred (Figure 3.12).



**Figure 3.11:** NAME midge model results from a source in Denmark for the overnight period on 7-8 Oct 2008 which potentially led to the outbreak in southern Norway.



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**Figure 3.12:** Locations of farms in Norway, as of 5 April 2009, found to test positive during bulk milk sampling for BTV-8 antibodies (indicated as red dots).

(http://www.vetinst.no/nor/Forskning/Aktuelle-tema/Blaatunge/Blaatunge-Situasjonskart/Kartover-blaatungeundersoekelser-pr-5.-april-2009 - accessed 14/04/09)

The pattern of outbreaks in Sweden (Figure 3.13), in the south and west of the country, also matches the areas predicted by to be at risk by NAME particularly well (Figure 3.14). The inter-comparison between MATCH and NAME for the Swedish otubreaks (Figure 3.14) shows the models give very similar results despite MATCH being a Eulerian model and NAME being Lagrangian and each model using different NWP data. Both models identified the same dates on which an incursion of infected midges was most likely and the areas predicted to be at risk by the two models was also very similar. However MATCH was not adapted in the same way as NAME to limit midge flight in the source term. MATCH therefore gave several additional time episodes for possible introduction, whereas due to the meteorological limitation criteria in NAME only two days were found to be suitable for midge incursions.



**Figure 3.13**: Locations of the outbreaks in Sweden until February 2009. The first outbreak location is indicated with a black dot. (Agren, E. pers. comm.)



**Figure 3.14**: Results from MATCH (left) and the NAME midge model (right) analysis of outbreaks in Sweden showing potential incursions on 14-15 Aug 2008.

The results from the NAME back-trajectory modelling carried out to replicate the investigations carried out by Alba et al. (2004) into the source of the bluetongue outbreaks in Minorca and Mallorca are shown at Figure 3.15. It can be seen that only very few of the 100 trajectories reaches Sardinia and instead the majority are found to spread northwards after an initial easterly movement. This suggests that most of the air

mass reaching the outbreak came from further north and not from Sardinia as found by the limited trajecotory modelling carried out by Alba et al. (2004). NAME was then additionally used to investigate other alternative potential sources of virus for the outbreak. It was found that trajectories released from sources on the north coast of Africa appear more likely to have caused a wind-borne incursion of disease (Figure 3.16).



**Figure 3.15:** 36-hour back trajectories on 17-18 Aug 2000 calculated by Alba et al. (2004) (left) at heights of 990 hPa (red) 1000 hPa (light blue) and 1010 hPa (dark blue) and NAME (right) with 100 particles allowed to disperse in 3-dimensions.



**Figure 3.16:** 24-hour long trajectories of 100 particles plotted in NAME from other potential sources of virus in Tunisia (left) and Algeria (right) at 18Z on 17 Aug 2000.

#### 3.4.2 Summary of the case study results

Overall, the model results were found to be consistent with the epidemiological evidence from the outbreaks, so it is concluded that the model can provide reliable results for the timing and location of outbreaks. In each case only a few occasions were

identified as possible incursion dates during the infection window, so it is suggested that the model has an acceptable rate of false positive predictions.

However it should be noted that the model only shows the relative levels of concentrations of midge particles as it would be impossible to provide accurate numbers of midges becoming airborne in a local source area because field data of the level required cannot easily be collected and made available. It should also be noted that the concentration levels do not give any indication of actual virus spread and merely indicate where midges are likely to be dispersed to. Accurate epidemiological evidence to determine likely source areas is essential to provide predictions of virus spread.

## 3.5 Application of the model in an early warning system

### 3.5.1 Aim of the early warning system

The aim of all early warning systems is to communicate information about impending risks to vulnerable groups or individuals before a hazardous event occurs, thereby allowing mitigating action to be taken to reduce potential harm. The bluetongue early warning system was designed to inform Defra of the likely locations and timings of disease outbreaks following a windborne incursion of infected midges. In 2007, when the early warning system was first operated, bluetongue was almost unheard of in the farming community. The main purpose of the system was therefore to inform Defra which areas of the UK were particularly at risk to allow them to target these areas with education campaigns designed to raise stakeholders' awareness of the symptoms and inform them of statutory disease control procedures. It was envisaged that through early notification of an outbreak, there would be opportunity to minimise the transmission of virus, preventing rapid spread over a wide geographical area with the designation of restriction zones surrounding the outbreak.

The warning system also aimed to provide assistance to Defra following an outbreak in the UK. By analysing the results from NAME for the weeks prior to the outbreak, it was expected that a date (or several dates) when an incursion could have potentially taken place could be determined. This would allow an estimate to be made for the number of disease cycles which had taken place, hence how far the disease had spread through midge dispersal or animal movements out of the region during the infected period, and could therefore inform on the necessary size of restriction zones around the outbreak. Additionally, information on the other areas shown to be affected by the plume would allow Defra to target surveillance at these high risk areas.

The final aim of the system was to identify high risk area which should be prioritised by Defra when designing targeted vaccination programmes.

### 3.5.2 Design and operation of the early warning system

The early warning system was designed in the form of a website which could be updated daily, providing Defra quick and easy access to the results from the NAME midge model showing the risk of an incursion of midges from the near-continent (Figure 3.15). The website contains a two month archive of the risk maps produced by the model along with the option to print the results in a user-friendly layout (Figure 3.17). The plots were produced in a GIS format so the data could be sent to Defra for inclusion in other GIS databases if required.

To produce the risk maps, the most recent version of the NAME midge model available each year was run every morning during the midge season, from April to October throughout 2007 to 2010. These runs analysed the potential spread of midges from the near-continent at sunset by producing concentration plots of 'midge' particles after a period of 12 hours. In 2009 a sunrise release was also included. Maps were also produced using 'inert-tracers', which would represent a worst-case scenario, where meteorology had no limiting impact on midge flight. Source areas for the model were defined along the coast of the near-continent from the north-west coast of France to Jutland, Denmark and were chosen to be representative of areas posing a risk to the UK. Separation between the source areas was used so they would remain distinguishable from one another (an example shown at Figure 3.18).

The website was found to provide a large amount of information, so a more concise summary was also sent to Defra every fortnight to highlight the areas at greatest risk. This summary listed the number of occasions each county in the UK had encountered a plume of either 'inert-tracer' or 'midge' particles and from which area of the nearcontinent these plumes had originated in. The level of risk posed by each plume was then discussed based on knowledge of the presence of disease at that source.

The website was also adapted to monitor the risk of spread to Northern Ireland and Jersey, at the request of the Department for Agriculture and Rural Development (DARD) in Northern Ireland and the States Veterinary Officer on Jersey. Potential spread was calculated using the same approach, with different sources chosen to represent areas which could potentially cause risk to these regions.

Met Office: NAME output for Bluetongue virus - Mozilla Fire - 8 <u>File Edit View History Bookmarks Tools H</u>elp • G• < 🕨 🔻 😵 🏫 🖾 http://www.metoffice.gov.uk/bluetongue/ 🗟 Most Visited 🔻 🏾 🏶 Getting Started 🛛 Latest Headlines 🎙 Met Office de scala Search Met Office ME output for Bluetongue vir NAME output for Bluetongue virus Add this page to my bookmarks The Met Office and the Institute for Animal Health are supporting Defra in assessing the risk of bluetongue entering the UK by indected airborne Culicades midges from the near Continent. Since 2006 bluetongue has been present on the near Continent and an incursion of the virus to the UK occurred in August 2007, as alreted by this service. Indected midges could potentially be carried again to the UK in 2010 if the disease becomes prevalent on the near Continent of the near Cont First steps • This advisory service provides a daily risk asse Days ahead ment based on a combination of factors i Months ahead 
Months ahead The charts contained on this web page have been generated using the Met Office dispersion model NAME III. The the transport of standard particles from selected areas on the coast of the near-continent to the UK and the best of airborne midget trajectories. Each day the model is run for midges which become active around sunset and sun Further details of how the model estimates the risk to the UK livestock can be obtained from the Met Office. WINDE NWPSAF . Unified model These plots are for authorised internal use only and must not be released to the public without the authority of Laura Burgin (01392 884858), John Gloster (01483 231023) or Matthew Hort (01392 886242). Numerical methods workshop . Marine me Spread to UK from the Continent Spread to Northern Ireland Accuracy of forecasts 📀 sunrise Wed 28 Apr 2010 🔻 • Select a day 🔻 • Select a day Select a day Go Go Go Go rative projects ord-protected a Regi ter for your Spread to Jersey rd Existing users login sunrise sunset • • Select a day Select a day Go Go Joint climate change

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Figure 3.17: Screenshot of the early warning website (www.metoffice.gov.uk/bluetongue)



Figure 3.18: Example of the data available from the early warning website, shown in the printout format.

### 3.5.3 Use of the system in an emergency response situation

### 3.5.3.1 Meteorological modelling of the UK outbreak

The UK experienced its first outbreak of bluetongue, caused by BTV-8, in Suffolk in September 2007. At the request of Defra, the model was used to determine if and when an incursion of infected midges could have occurred. As described in Section 3.4.1, the original version of the model was used to determine that 4 August 2007 was the most likely date for an incursion of disease by windborne midges (Gloster *et al.*, 2008).

As an early warning system had been put in place, meteorological monitoring had been ongoing since the beginning of the midge season so the risk maps were readily available. The fortnightly summaries also allowed the probable dates for incursions to be narrowed down quickly and were therefore passed to Defra almost immediately and used to make decisions on procedures aiming to curtail spread. The rapid interpretation of the epidemiology of the outbreak allowed assessment of the likely scale and pattern of BTV outbreaks and additionally provided focus areas for follow up veterinary investigations.

### 3.5.3.2 Vaccination programme

Prior to 2007 all of the UK ruminant livestock populations were susceptible to all strains of BTV. However in 2008 a vaccine for BTV-8 became available early in 2008. Defra placed an order for 22.5 million doses and the first consignment of 9.4 million doses arrived in April. In order to determine where to make the vaccine available first, a rollout programme was developed by Defra. A summary of the highest risk counties, based on modelling carried out for the early warning website in 2007 was used to help determine where to target with the vaccination program. Livestock in the outbreak areas in East Anglia were considered the highest priority. Vaccine was then made available to farmers progressively westwards and northwards. By the end of June 2008, vaccine was available for livestock from Cornwall to Kent and up the east coast as far as the Humber estuary. The take-up of vaccine, particularly in areas that had been infected in 2007, was high, with much of the south of England exceeding a rate of 80 per cent (Defra, pers. comm., 2008). Consequently, the numbers of bluetonguesusceptible animals in the south and east of England was drastically reduced. BTV-8 positive antibodies were only found during post-import testing of animals from the nearcontinent and no outbreaks due to windborne incursions of infected midges appeared to have occurred. The vaccination was therefore determined to be a success.

It was suggested by some members of the farming community that inclement weather may have also played a large role in preventing the outbreaks. A study was therefore carried out to examine this possibility (Burgin et al., 2009a). Temperatures were compared during the midge season from April to October in 2006, 2007 and 2008 using data from CRUTEM3, a gridded dataset of global historical land surface temperature anomalies (Brohan et al., 2006). This data showed 2006 was a particularly warm year. 2007 and 2008 were cooler but still warmer than the baseline and showed a similar pattern of warming to each other (Figure 3.19). NAME was also run over the three year period from infected areas of the near-continent and the results describing which counties in England were intersected by inert-tracers and midge particles are shown in Figure 3.20. This graph shows higher number of incursions took place into East Anglia in 2006 and 2007 but in 2008 the counties at highest risk were generally the more western and southern counties. Overall the NAME modelling results suggest there were more incursions in 2008 than in either of the other years. It was therefore concluded that the meteorology in 2008 was conducive to midge dispersal into the UK, and perhaps even more potential incursion events occurred in this year compared to 2006 and 2007. The main differing factor was the use of vaccination early in the 2008 midge season.







**Figure 3.20:** Number of days identified by NAME as having winds directed from infected areas on the near Continent to coastal south east counties of England (Lincolnshire, Norfolk, Suffolk, Essex, Kent, Sussex, Hampshire, Isle of Wight, Dorset and Devon & Cornwall) in 2006 (light red), 2007 (light green) and 2008 (light blue). Number of days where NAME identified successful transport of midges for 2006 (dark red), 2007 (dark green) and 2008 (dark blue) are overlaid.

### 3.5.4 Summary of the midge model's use in an early warning system

It has been shown that the model performed its main aims in an early warning system and in post-outbreak analysis well. The system provided advance warning of the first incursion to the UK and provided guidance on the likely area at risk, allowing Defra to implement movement restrictions, preventing a UK-wide epizootic. The decisions made by Defra during its implementation of a vaccination programme, using information provided by the NAME midge model and expert opinion from the Met Office and IAH, were also praised by the then Prime Minister, Gordon Brown, who highlighted the economic benefits provided by the early warning system:

"British science is not just helping people across the world – it is protecting jobs and livelihoods in Britain too. For example, when British scientists used meteorological data to predict that midges bearing bluetongue virus would be carried to specific parts of the UK from the continent – they enabled selective vaccination of livestock and saved nearly £500 million, together with 10,000 jobs." *Prime Minister Gordon Brown, Romanes Lecture, Oxford, 27 February 2009.* 

### 3.6 Discussion

The development of an explicit midge dispersal scheme within an atmospheric dispersion model has improved the ability to simulate wind-borne spread of bluetongue by these vectors. A dispersion model has the ability to directly calculate the movement of vectors between localities and therefore has advantages over the use of a statistical or  $R_0$ -based model for some applications. The technique is therefore particularly applicable to analyse the potential wind-borne component of an outbreak and for use in early warning systems of disease incursions.

The model developed here advances upon the earlier synoptic chart methods of analysing winds (Sellers et al., 1979, Sellers et al., 1977, Sellers et al., 1978, Sellers and Pedgley, 1985a) and simple single-particle trajectory analyses (Alba et al., 2004, Ducheyne et al., 2007, Hendrickx et al., 2008) of the spread of infected *Culicoides*. The midge model is based on a sophisticated dispersion model, NAME, which is a fully 3dimensional Lagrangian model, containing parameterizations of processes such as turbulence and convection to represent flows in the atmosphere. The accuracy of NAME has been assessed in experimental campaigns where its results were found to compare well against observations and other models and it has also been shown to perform well in emergency response situations, such as the Eyjafjallajökull volcanic eruption (Devenish et al., submitted). Additionally the meteorological data which NAME utilizes is high resolution NWP data from an operational weather forecasting model, the UM. This is in contrast to the models and underlying data which has been used previously (Alba et al., 2004, Ducheyne et al., 2007, Hendrickx et al., 2008, Sellers and Maarouf, 1989). In these models atmospheric flow has been simulated in a limited way through the use of only one, or very few, trajectories constrained to a single height in the atmosphere which are constructed using low temporal and spatial resolution meteorological data. These single particle trajectory models cannot capture the stochastic motions of the atmosphere unlike full atmospheric dispersion models, such as NAME, which simulate the trajectories of hundreds of thousands of particles as they

move freely throughout the atmosphere, governed by mean winds and turbulence calculated at high frequency time steps.

The midge model developed here is the first which contains explicit midge flight behaviour within an atmospheric dispersion model. The algorithms for midge flight were derived using results from field and laboratory experiments (Sanders et al., 2010, Sanders et al., submitted) and are therefore based on the current best estimates for the correlations between midge activity and meteorology. The results of these experiments showed midges are more active in calm conditions, which contradict the filtering thresholds used by Ducheyne et al. (2007) and Hendrickx et al. (2008) who removed winds at low wind speeds. The model also includes diurnal and seasonal cycles of midge activity obtained from field experiments which have not previously been considered in other trajectory models. Again the approach taken by previous trajectory models (Ducheyne et al., 2007, Hendrickx et al., 2008), where midges are presumed to become airborne at noon, is contrary to these findings. In contrast the model developed here releases midges around sunset and sunrise, as determined by experimental results. The NAME midge model has a further advantage over the simpler trajectory models. Due to its Lagrangian structure it allows representation of meteorology at the exact particle location throughout its trajectory. This advantage is utilized here by a scheme which removes 'midge' particles mid-trajectory when rainfall exceeds a threshold estimated to be too high for midge survival. In Section 3.2.3 it was shown that not allowing for deposition of the particles due to precipitation can affect the outcome of disease risk predictions.

The seasonal and meteorological parameters in the midge activity equation used in the final version of the model to determine the mass of particles to release were subjected to uncertainty and sensitivity analysis. It was found that a small degree of uncertainty arises in the model's results due to the choice of seasonal parameters. The model was also found to be most sensitive to variations in the temperature parameter, with wind speed and precipitation to lesser extents. However in the NWP data used to run the model, temperature is found to have a low error, therefore the model's results are only affected in a minimal way. Future work could make use of the parameter distributions derived in the midge activity equation to produce more probabilistic results. These could be sampled to produce plumes describing a range of low, medium and high predictions thereby indicating the range of uncertainty in the results.

The final version of the NAME midge model was tested using 5 case studies, where windborne incursion of disease was believed to be the most likely cause of

introduction, and produced results which were consistent with the epidemiological situation. Additionally in one case study an inter-model comparison was also carried out where NAME's results were found to compare well to those of another dispersion model MATCH. However MATCH has not been adapted in the same way as NAME to limit midge flight behaviour based on the effects of meteorology. MATCH therefore gave several additional dates for possible introduction. It is concluded that the NAME midge model is an enhancement on standard atmospheric dispersion models. However despite NAME providing results which appear to be consistent with the evidence of the outbreaks in each of the case studies, it is impossible to say with certainty that the model's predictions are accurate due to the difficulties associated with direct observations of midge dispersal over long distances.

There are also still a number of factors in the model which remain unknown or uncertain. The flight duration time of midges was examined in the laboratory (Sanders, C., unpublished data), but this cannot easily be studied in the field. Instead proxy information based on the time taken for winds to carry midges across known distances in cases where midge incursions are presumed to have introduced disease are relied upon. In all the case studies described in Section 3.4, midge incursions took place in 12 hours or less. Some other studies have suggested flight times of 20 hours (Sellers et al., 1977) or even 24 to 36 hours (Alba et al., 2004). However these findings by Alba et al. (2004) were disputed in Section 3.4.1, where the NAME midge model showed disease seemed to have spread to the Balearic Islands from nearer areas of North Africa rather than Sardinia, suggesting shorter flight times are more likely. The motions of the midges once airborne are also not fully understood. Entomological radar has previously been used to study larger insects whilst airborne (Riley et al., 2007, Wood et al., 2010), but midges are too tiny to make this a viable observing method. Limited data available from aerial trapping has been relied upon here to show midges are present throughout the boundary layer. Finally, there is also currently little experimental evidence which can be used to describe midge dispersal on local scales, particularly over land areas with steep topography which have atmospheric flows that are more difficult to resolve in an atmospheric dispersion model. Future experiments and higher resolution modelling will be carried out in the future to understand this further.

Despite these uncertainties and limited methods for verification the model performed its role in an early warning system well. It correctly warned several weeks in advance of the first incursion to the UK. Information from the system was also used by Defra in education campaigns and to make decisions regarding movement restriction zones and

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targeted vaccination programmes. However there are some limitations to the system. The results provided by the NAME midge model only show plumes of relative concentration of midges. These are based on the assumption that a standardised number of midges become airborne from each source area of the near-continent which is only modified by seasonal and local meteorological conditions. No data are available on local midge population numbers on the near-continent to improve this estimate. The plumes also describe all midge movement and make no attempt to estimate the proportion which could be infected. Instead the system relies on written summaries of the disease situation on the near-continent to communicate the risk of disease actually posed.

It could also be useful for the system to provide further lead-time on the predictions of suitable winds for incursions, at seasonal or even longer time scales, which would provide greater time to allow disease prevention measures to be put in place or long term planning to take place. A method to address this is described in chapter 4 and its application to provide predictions on decadal timescales is discussed in chapter 5.

## 3.7 Summary

A Lagrangian atmospheric dispersion model, NAME, has been adapted to explicitly include the flight behaviour of *Culicoides* biting midges, allowing the spread of midgeborne diseases such as bluetongue to be modelled more accurately. The meteorological parameters which control when they become active and constrain where they will fly, were determined by collaborators at IAH, Pirbright. As the experimental results became available each year these were incorporated into an updated version of the NAME midge model which calculated the concentrations of newly defined dispersal species termed 'midge' based on the suitability of the meteorology for midge flight. A standard midge activity equation relating temperature, wind speed and the presence of rain was ultimately determined and formed the basis of the source term in the latest version of the midge model.

Evaluation of the model by direct observation is not possible. Instead the occurrence of disease in a previously uninfected region, which could not be explained by other means, was used as a proxy for insect dispersal. The model was tested in five such cases and showed results for wind-borne incursions of infected midges which were consistent with the epidemiological situation present in each outbreak. The NAME midge model is concluded to be an enhancement on other dispersion models and a useful post-outbreak epidemiological analysis tool.

The model also formed the basis of an early warning scheme to provide the UK government with information regarding the highest risk areas of an incursion of BTV from the near-continent. A website was designed which was operated throughout 2007 to 2010 to give Defra quick and easy access to maps showing when and where incursions of midges from the near-continent to the UK were likely to occur.

After the first UK outbreak in September 2007 the model was used by Defra to help in decision making processes such as how large to make restriction zones and where to target vaccine when it became available. The actions taken as a result of these decisions prevented widespread outbreak, greatly benefitting the UK livestock industry.

# Chapter 4

# Synoptic scale circulation patterns associated with windborne incursions of *Culicoides* into the UK

In the previous chapter a dispersion model was developed to simulate midge incursions into the UK on a daily timescale. The purpose of this chapter is to identify a method, which will be used in the next chapter, to allow predictions to be made of incursions at longer lead times of months to decades, and thereby provide information relevant for strategic decisions. Variability in the weather at high temporal and spatial resolution cannot be predicted by NWP models at these longer timescales. However large scale circulation systems, which influence the local weather, can be predicted over long timescales using GCMs and RCMs. The aim of this chapter is therefore to identify if a relationship exists between these synoptic scale circulations and local meteorological conditions found to influence midge flight identified in the previous chapter. This relationship could then allow climate models to be implemented to estimate the likelihood of incursion events at monthly to decadal timescales (as carried out in chapter 5). This chapter firstly provides a detailed outline of the methodology taken to provide a classification of the pressure patterns. The results of this process applied to north-west Europe are then presented and each pattern's relationship with local meteorological variables and midge incursions are then discussed. Additionally a comparison is made against an alternative weather type classification system in order to assess the robustness of the results produced here.

### 4.1 Introduction

In chapter 3 relationships between local weather variables and midge flight were used as the basis for a model of midge dispersal. However forecast lead times for the NAME midge dispersion model are limited to the availability of forecast NWP data which drives the model. Currently for the NAE domain of the UM, as used by the early warning system, the forecast period is 48 hours. However predictions of the likely frequency of midge incursions made several weeks, months or even years ahead could potentially be very useful in the mitigation of their potential impacts, by providing

information relevant to strategic decisions taken for future preventative measures such as vaccine development.

Weather on a local scale is driven by atmospheric processes at a continuous range of scales from the micro scale (mm) through to the mesoscale (<100km). These smaller scale processes are influenced by synoptic scale pressure systems (>100km). Therefore there is often a strong correlation between local or regional weather and particular atmospheric circulation regimes.

Some previous studies have found evidence to suggest that large scale atmospheric circulation systems are linked to spatial or temporal patterns of midge-borne disease spread. For example, outbreaks in Israel have been attributed to carriage of infected midges from Turkey on winds caused by the Persian trough system (Braverman and Chechik, 1996), and the timing of AHS outbreaks in South Africa have been linked to the effects of precipitation associated with the warm phase of the El Niño/Southern Oscillation (Baylis et al., 1999).

This chapter therefore aims to understand if a relationship also exists between synoptic conditions and local surface winds in north-west Europe which influence midge dispersal into the UK. This relationship could then subsequently be used to predict the risk of the spread of *Culicoides*-borne viruses to the UK at monthly to decadal timescales where high resolution wind data necessary to drive a dispersion model, such as the NAME midge model, may be of limited availability and accuracy. Running a dispersion model over long timescales would also be very computationally expensive, this alternative approach provides a much more efficient method to estimate changes in risk.

## 4.2 Data and Methods

### 4.2.1 Overview

To assess which, if any, particular synoptic situations are prevalent during midge incursions into the UK it is first necessary to elucidate the circulation types that are typical for the region. As discussed previously, in Section 2.2.2, there are a number of methods for extracting different modes of variation in the atmosphere. An automated methodology outlined by Yarnal (1993) was chosen to ensure a time-efficient, largely objective, and reproducible map pattern classification. This methodology is an example of the circulation-to-environment approach, in which the synoptic classification is produced first and then related to the environmental variable in question.

Here the relationship between synoptic circulations conditions and midge transport across the English Channel is investigated using a combination of map pattern classification and dispersion modelling for the period 2005-2007 (the most recent three years with data available at the time of the study). A catalogue of typical MSLP patterns is created to characterise daily synoptic-scale circulation patterns for the region. The map pattern catalogue is then related to midge incursion data derived from the NAME midge model to identify circulation types that are more associated with high risk of trans-channel transport of midges from the European continent to the UK. The local meteorological conditions during such events are then detailed using wind and temperature measurements from observation stations on the south coast of England. Finally a comparison against the results from an alternative classification system is carried out in order to assess the results obtained in this analysis.

### 4.2.2 Data

### 4.2.2.1 Meteorological Data

MSLP data from the UM (Davies et al., 2005) was used to produce the circulation patterns. The UM is the suite of numerical modelling software developed and used operationally at the Met Office to provide numerical forecasts of the atmospheric state for periods of a few hours to several days ahead. A typical run consists of a period of data assimilation followed by a period of prediction. The data assimilation scheme constructs the model state to be the best statistical fit to the observed data. Data from this analysis phase of the model run was used at a resolution of 0.11° in a domain from 46°N to 56°N (approximately from Lyon, France to Aberdeen, UK) and 13°W to 15°E (west of Ireland to Germany/Poland border). This region of northern Europe was chosen to ensure the inclusion of anticyclonic systems located over eastern Europe and frontal systems moving in from the Atlantic. MSLP grids were extracted for all days in 2005-2007 at 00Z to represent the conditions during each overnight midge incursion event.

Hourly measurements of wind speed and direction at 10m and air temperature at 2m for 0Z were extracted from the Met Office, UK observation database for the three year period of the study (2005-2007) for Langdon Bay, UK (51.13N, 1.35E) (Figure 4.1) to represent the local surface climate associated with midge incursions into the south-east of the UK. This station was chosen as it was nearest available to the release sites on the near-continent and therefore thought to be most representative of the winds arriving

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on the south-east coast. Due to time limitations it was not possible to extract the data from the Met Office database and examine it for several stations around the coastline.

## 4.2.2.2 Midge incursion events

Midge incursion events were identified during three midge seasons (from 1 April to 30 November) from 2005 to 2007 using version 1 of the NAME midge model (Section 3.2.3). This version was the most recent available at the time of this analysis. NAME was run using a 10 minute timestep and used the 12km domain version of the UM with no nesting of higher resolution data. The study period was limited to only three seasons due to the high computational cost of running NAME. The winter period was not included to save on computing time when it was assumed that temperatures would rarely rise above 10 °C and conditions would therefore not be suitable for midge flight (see Figure 3.2).

Release sites were selected at two locations on the coast of the near-continent to represent bluetongue outbreak sites which were likely to pose the highest potential risk to the UK (Figure 4.1). The other release sites from the standard run developed for the early warning system (Section 3.5.2) were not included because they were likely to require different synoptic conditions to lead to incursions due to their geographical location. Dates on which 'midge' particles successfully reached the UK, (i.e. when the weather was suitable for midge activity and winds were suitably directed) were classed as an incursion event.



**Figure 4.1:** Example of output from the NAME model used to determine midge incursion events. Location of the observation station at Langdon Bay is also displayed.

### 4.2.3 Map pattern classification method

The automated method used here is an eigenvector-based map pattern classification based on a PCA of standardised daily 00Z MSLP patterns in combination with a clustering technique, to identify the significant modes of atmospheric circulation across the study area, as described in Yarnal (1993). The classification procedure involves several steps of analysis, each of which is detailed in the sections below.

### 4.2.3.1 High-pass data filtering

Prior to the PCA, the MSLP data was subjected to a high-pass filter to remove variability on time scales longer than the typical duration of regional weather systems, as otherwise the PCA would be dominated by the strong seasonal variability in the pressure data. Unwanted temporal variability in the data was removed following a method outlined in Hewitson and Crane (1992). Using the tool REDFIT (Schultz and Mudelsee, 2002), all pressure grid timeseries were subjected to a spectral analysis to identify the most common first significant harmonic in the study area, which can be considered to represent the typical duration of weather systems in the study region.

The duration of the harmonic is used to define the length of a moving average filter, which when applied to a timeseries of pressure data represents variability on a timescale longer than typical weather events.

By removing the smoothed values from the original pressure series, variability occurring on timescales less than the significant harmonic is preserved whilst variation associated with lower frequencies is removed. Here, to retain the spatial pattern within each daily pressure grid, a timeseries of average grid values was created and the moving average filter was applied to these (where the length of the moving average is the length of the significant harmonic -1 day). Here the moving average filter was set to 8 days. The difference between the original grid values and the filtered average timeseries values was then calculated. These standardised pressure grids were then used in all the subsequent analyses.

### 4.2.3.2 Principal component analysis

PCA is a technique to reduce the dimensionality of a dataset by retaining those components that contribute most to its variance, whilst minimising any loss of information (e.g. Jolliffe, 2002). PCA is often used in atmospheric science as a tool to help identify spatial or temporal variability in physical fields by condensing a data set into its underlying fundamental modes of variation (e.g. Preisendorfer, 1988).

PCA finds linear functions, the principal components (PCs), which maximise the variance of the dataset whilst remaining orthogonal to each other in multidimensional space. A data matrix, where rows represent time and columns represent grid points, was used to produce a dispersion matrix. A correlation dispersion matrix was chosen rather than a covariance dispersion matrix to prioritise map pattern shape over the identification of areas of maximum variance (Yarnal, 1993). A component-loadings matrix, which describes how each variable weighs on each component, and a component-scores matrix, which is found by multiplying the dispersion matrix with the loadings matrix, are both also computed. The scores matrix describes the relationship between the observations and the PCs. Here, the PCA was carried out using the correlation matrix in S-mode decomposition giving spatially distributed loadings and temporally distributed scores for the selected number of PCs (Yarnal, 1993). When clustering the PC scores, days with similar weight (scores) on the different PCs are grouped together using a clustering technique (described in Section 4.2.3.3).

PCA, although strictly a mathematical algorithm, involves elements of subjectivity in the selection of the number of PCs to retain and whether to rotate the selected PCs or not.

The choice of the optimal number of PCs to retain can be aided by a number of different methods. North et al. (1982) provided a rule-of-thumb which proposes that the cut-off should occur where the sampling error of a particular eigenvalue ( $\lambda$ ) is comparable to or larger than the spacing between  $\lambda$  and a neighbouring value. The sampling error is given as  $\delta\lambda \sim \lambda (2/N)^{1/2}$ , where N is the number of variables over which the PCA is carried out on. Two graphical aids, the scree test (Cattell, 1966) and the log scree test (Davis and Kalkstein, 1990) have also been used. In the former, the point where the slope of the plot levels off is assumed to represent the point at which little is added to the explained variance by adding further PCs, while in the latter a dip in the log-transformed eigenvalue is used as the indicator.

The second element of subjectivity involves whether or not to rotate the retained PCs. Buell (1975) demonstrated that in S-mode analysis, unrotated PCs give resulting loading maps with regular characteristic patterns which are statistical artefacts and nearly independent of the spatial variation in the data. A visual inspection of the unrotated PC loading patterns showed evidence of Buell patterns, suggesting the need for rotation of the selected PCs. For this application the orthogonal Varimax rotation (Kaiser, 1958) was used. The Varimax transformation changes the relationship between the components but retains the orthogonality constraint. For a full discussion of the advantages of rotation see Richman (1986).

The pca was conducted using the programming language R (http://www.r-project.org/) using the subroutine "eof" written by the RCLIM initiative (R software for CLIMate analysis) at the University of Exeter (http://www1.secam.ex.ac.uk/rclim-initiative.dhtml).

### 4.2.3.3 Cluster analysis

To group the days with similar characteristics, based on their similarity to the different loading patterns, the PC scores were submitted to a cluster analysis. This was carried out using the standard "kmeans" subroutine in R (http://www.r-project.org/). Two fundamentally different approaches can be taken when clustering data depending on the underlying structure of the data; hierarchical and non-hierarchical cluster analysis (e.g. Wilks, 1995). In the former, the analysis repeatedly merges subsequent pairs of observations which are most similar to build a hierarchy of sets of groups. This method works well when there is a natural hierarchical structure to the data, for example in taxonomy or genetic sequencing. The non-hierarchical approach does not assume a structure exists in the data and allows for reallocation of observations which have been mis-grouped earlier. For the map-classification study there was no reason to assume

that the MSLP data had an underlying hierarchical structure hence a non-hierarchical method was used.

Clustering relies on a distance measure, either within or between clusters, to assess the degree of similarity in the observations. For this study the method of k-means was used where k observations are initially chosen randomly as starting centroids and each observation is assigned to a cluster based on its Euclidean distance from its nearest centroid. Observations are iteratively re-assigned to globally optimise the within-cluster sum of squared distances. The process was repeated using several different numbers of clusters (k was increased from 2 to 20) and the optimum cluster number was determined as the smallest total within-cluster sum-of-squared errors for all clusters. To reduce the risk of finding a local minimum the procedure was repeated 100 times with different initial seeds for each value of k. The spatial characteristics of each cluster were then represented by a composite of all de-seasonalised grids included in each separate cluster (e.g. Yarnal, 1993).

## 4.3 Results

## 4.3.1 PCA and cluster analysis

Guided by the selection procedures outlined in Section 4.2.3.2, 5 PCs were retained. The sampling error and spacing of the eigenvalues are seen to reach the same magnitude at about PC6 (North's rule of thumb, North *et al.*, 1982) (Figure 4.2a), the scree plot shows that the variance explained by the PCs tails off after PC5 (Figure 4.2b) and peaks in the distance between the PCs are seen in the log scree plot at PC2 and PC5 (Figure 4.2c). Together, the 5 retained PCs also explain over 95% of the variance in the dataset (Table 4.1).



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**Figure 4.2:** Graphical aids use to determine the number of PCs to be retained. (a) componentto-component change in eigenvalues (•) with sampling error (○) (North's rule of thumb) (b) scree plot of the eigenvalues (c) component-to-component change in the natural logarithm of the eigenvalues.

Table 4.1: Results of the PCA								
Cumulative explained								
variance (%)								
48.6								
78.2								
88.4								
93.0								
95.4								
96.6								
97.3								
97.8								
98.2								
98.5								

The loading patterns of the rotated PCs (RPCs) describe the main modes of variation in the de-seasonalised pressure grids (Figure 4.3). RPC1 displays features of the North Atlantic Oscillation, with high pressure centred over the Azores and a low pressure system centred over Iceland (Figure 4.3a); RPC2 shows a trough extending from the south-west to the north-east from France through to Denmark (Figure 4.3b); a centre of high pressure situated over the UK dominates the pattern of variability shown by RPC3 (Figure 4.3c); RPC4 (Figure 4.3d) shows a distinct high pressure region to the northeast of the domain, with a low pressure system situated over continental Europe and RPC6 shows pronounced low pressure in the south-east with a ridge of high pressure extending across the UK (Figure 4.3e).



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To identify days with similar spatial characteristics in terms of circulation, a cluster analysis was used to separate days with similar weight (using the PC scores) on the different loading patterns. The circulation pattern associated with each cluster was then generated by averaging the de-seasonalised pressure patterns for all days within each cluster.

The optimization criteria (see Section 4.2.3.3) suggested 5 clusters would best represent the data. These are subsequently referred to as pressure pattern (PP) 1-5 (Figure 4.4). The seasonal and annual relative frequency of each PP is displayed in Table 4.2 and the persistence of each PP is shown in Table 4.3.

PP1 displays a large area of high pressure over most of the near-continent (Figure 4.4a) which would be expected to generate light south-westerly winds over the English

Channel. This PP was found to be most frequent in winter and to persist for up to six days.

PP2 was the most common pattern annually, with a relative frequency of 34.2%, and shows a pressure gradient extending from low pressure in the north west of the domain to and area of high pressure over eastern Europe, leading to south-westerly flow over the UK (Figure 4.4b). PP2 was found to occur frequently throughout the year and persist for up to seven days.

PP3 shows north-westerly flow across the UK, generated by a centre of low pressure system situated to the north-east of the domain and high pressure in the south-west (Figure 4.4c). This PP was the second most common annually during the study period, with an annual relative frequency of 30.1% and it was found to persist for up to six days.

In PP4 a very strong pressure gradient is found across the region, caused by a centre of very low pressure to the north-west and high pressure in the south-east (Figure 4.4d). These tight isobars indicate strong south-westerly winds would be present across the UK. This PP occurred fairly infrequently throughout the study period, with an annual relative frequency of 9.2%, although it was slightly more common in winter where it occurred 16.3% of the time. PP4 persisted for up for five days.

PP5 was the third most common annually and shows a centre of high pressure situated towards the centre of the region, with a slack gradient towards lower pressure in the south-east of the domain (Figure 4.4e).



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Figure 4.4: Average de-seasonalised pressure patterns (hPa) for each cluster (a-e)

		Relati	ve frequen	су (%)	
PP	DJF	MAM	JJA	SON	YEAR
1	14.8	6.5	2.2	5.9	7.3
2	28.5	33.3	32.6	42.5	34.2
3	25.6	33.3	39.9	21.6	30.1
4	16.3	7.2	4.3	9.2	9.2
5	14.8	19.6	21.0	20.9	19.1
N	270	276	276	273	1095

**Table 4.2:** Seasonal and annual relative frequency distribution of each PP. *N* is the number of observations in each season and for the whole year

Table 4.3: Relative frequency of PP persistency. N is the total number of days in each cluster

		<b>Relative F</b>	requency ('	%)	
Days	PP1	PP2	PP3	PP4	PP5
1	12.5	16.3	18.2	14.9	19.1
2	6.3	8.3	11.2	4.0	11.5
3	5.0	4.8	4.2	6.9	9.6
4	3.8	2.1	2.4	4.0	3.3
5	1.3	1.3	0.0	2.0	1.4
6	1.3	0.5	1.2		
7		0.3			
Ν	80	375	330	101	209

## 4.3.2 Comparison of the results from the map-pattern classification with an alternative objective-GWL catalogue

At the time the analysis was carried out to produce the map-pattern classification, only three years of NAME data were available (from 2005-2007). In addition only a limited number of years of UM MSLP data (from 2003-2007) were available on the 12km model domain. Therefore to ensure that the map-patterns produced over the relatively short time period, from 2005-2007, are representative of the synoptic patterns over north-west Europe on climate timescales a comparison has been carried out with an alternative classification system, the James (2007) objective-GWL catalogue, which contains data for a period of nearly 60 years.

This catalogue was constructed by James in 2007 is now maintained by the UK Met Office. It assigns the weather regimes over the Europe into one of 29 different types based on the classification originally defined by Hess and Brezovsky (1977) (see Section 2.2.2 for further details). The objective catalogue was defined by firstly producing composite base patterns for each of the given daily GWL defined in the original Hess and Brezovsky system. These were determined using daily mean MSLP from ERA-40 re-analysis dataset (Simmons et al., 2005) for the period September 1957 to August 2002 on a 1° by 1° grid. Base patterns were defined for two six-month

periods; winter (16 October to 15 April) and summer (16 April and 15 October). The base patterns for each of the 29 GWL for both summer and winter are available to view in James (2007).

The objective catalogue was then produced using a pattern correlation technique to relate weather regimes of at least 3 days to the base patterns. Correlation coefficients are calculated for each pair of grid points, and the GWL composite with the highest correlation to the daily ERA-40 MSLP grid are assumed to be the first-guess GWL for that day. Each event must last for at least 3 days to be classed as a weather regime, therefore GWL lasting for only 1 or 2 days are re-assigned. Single-day events are replaced with the previous or subsequent day's GWL based on their correlation values. Two-day events are either expanded or replaced with surrounding the GWL classification type, again depending of the associated correlations.

The resulting objective catalogue, updated daily, is available from the UK Met Office, along with seasonal and annual frequency statistics of the different GWL for 1948-2007. These statistics are shown at Table 4.4.

To deduce if the years analysed here for the map-classification were anomalous to the general climatology of Europe, the statistics of the frequency of occurrence of each PP during 2005-2007 were compared to the occurrence of the GWL over the period from 1948 to 2007. Firstly the similarity of the 29 GWL to the 5 map-patterns was determined subjectively. The results of this comparison are also shown in Table 4.4. It was found that the GWL patterns indicating south-westerly flow across the region showed similarity to PP2 in summer and PP4 in winter (see Figure 4.5 for an example). It was therefore not possibly to class the south-westerly GWL as similar to either one of the two individual south-westerly map-patterns. In the comparison these two PPs are therefore grouped together and compared with all the GWL with south-westerly flow.

Table 4.5 shows the total frequency of occurrence of each group of GWL which are similar to each PP. Comparing these results with Table 4.2, which shows the frequency of occurrence of the map-patterns, shows that overall they are not anomalous to climatology over a longer period. PP1 was found to occur 7.3% of the time during 2005-2007. The group of similar GWL are found 8.1% of the time. PP2 and PP4 were found in total to occur on 43.4% of days during the map-pattern classification period. The GWL which also show these south-westerly flows comprise 44.9% of the days during the 1948-2007 period. PP3 occurred 30.1% of days in 2005-2007, which is slightly greater, but not too dissimilar, with the group of GWL which show north-westerly flow occurred on 21.9% of days. In map-pattern classification, PP5 was found

to occur 19.1% of the time and 19.8% of days were found to have similar GWL patterns over the longer time period. In the GWL classification there were two patterns which did not show similarity to any of the map-patterns. However, these two patterns only comprise a small percentage (5.4%) of the total period from 1948-2007.

This analysis suggests that overall the map-pattern classification adequately represents the main synoptic types present over the Europe, and the frequency of their occurrence is similar to the climatology over an almost 60 year period.



**Figure 4.5:** Examples of the James (2007) objective-GWL base patterns (for SWZ), showing south-westerly flow across Europe in (a) summer, which compares well with PP2, and (b) winter, which compares well with PP4.

				Relativ	e Frequer	ncy (%)	
GWL	Description	Similar to PP	DJF	MAM	JJÅ	SON	YEAR
WA	Anticyclonic Westerly	2 / 4	9.2	3.5	7.4	8.2	7.1
WZ	Cyclonic Westerly	2 / 4	11.0	6.8	12.5	9.3	10.0
WS	South-Shifted Cyclonic Westerly	2 / 4	4.3	3.1	5.2	2.1	3.7
WW	Maritime Westerly (Block E.Europe)	2 / 4	5.9	5.4	5.0	6.5	5.7
SWA	Anticyclonic South-Westerly	2 / 4	4.6	3.1	4.8	6.5	4.8
SWZ	Cyclonic South-Westerly	2 / 4	4.7	4.4	2.9	4.1	4.0
NWA	Anticyclonic North-Westerly	3	4.2	3.4	4.7	6.4	4.7
NWZ	Cyclonic North-Westerly	3	7.5	4.9	5.6	4.3	5.6
HM	High over Central Europe	5	5.2	4.0	3.4	5.7	4.6
BM	Zonal Ridge across Central Europe	1	5.6	5.2	6.8	7.2	6.2
ТМ	Low over Central Europe	3	1.8	3.9	1.8	1.7	2.3
NA	Anticyclonic Northerly	5	0.8	1.8	2.3	1.3	1.5
NZ	Cyclonic Northerly	3	2.3	3.4	2.3	1.7	2.4
HNA	Icelandic High, Ridge C.Europe	5	2.8	3.4	2.4	2.6	2.8
HNZ	Icelandic High, Trough C.Europe	2 / 4	2.1	5.0	3.0	1.3	2.9
HB	High over the British Isles	5	4.0	3.1	3.4	3.2	3.4
TRM	Trough over Central Europe	3	2.3	3.8	4.9	2.5	3.4
NEA	Anticyclonic North-Easterly	5	1.9	2.1	3.9	0.7	2.2
NEZ	Cyclonic North-Easterly	2/4	1.8	2.5	2.5	1.4	2.1
HFA	Scandinavian High, Ridge C.Europe	3	2.3	2.2	2.2	1.6	2.1
HFZ	Scandinavian High, Trough C.Europe	1	1.5	2.4	2.6	1.2	1.9
HNFA	High Norway-Iceland, Ridge C.Eur.	3	1.3	2.2	1.2	1.0	1.4
HNFZ	High Norway-Iceland, Trough C.Eur.	5	1.9	2.6	1.3	0.8	1.6
SEA	Anticyclonic South-Easterly	5	1.4	2.6	0.8	2.8	1.9
SEZ	Cyclonic South-Easterly	n/a	1.7	2.5	0.7	2.0	1.7
SA	Anticyclonic Southerly	5	1.9	1.5	0.9	2.9	1.8
SZ	Cyclonic Southerly	2/4	1.8	2.7	0.4	2.9	1.9
TB	Low over the British Isles	2 / 4	1.7	4.4	1.7	2.9	2.7
TRW	Trough over Western Europe	n/a	2.5	3.9	3.4	4.9	3.7

Table 4.4: Seasonal and annual relative frequencies of each GWL from the James objective classification for 1948-2007 (UK Met Office).

		Relati	ve Frequenc	;y (%)	
GWL group	DJF	MAM	JJA	SON	YEAR
GWL similar to PP1	7.1	7.5	9.4	8.4	8.1
GWL similar to PP2 and 4	47.0	41.0	45.5	45.3	44.9
GWL similar to PP3	21.7	23.8	22.6	19.2	21.9
GWL similar to PP5	19.9	21.0	18.4	20.0	19.8

**Table 4.5**: Seasonal and annual relative frequencies of each group of GWL similar to the mapclassification PPs.

#### 4.3.3 Surface climate characteristics of the pressure patterns

In order to verify if the winds indicated by the PPs were representative of the local surface conditions, measurements from an observation station on the south-east coast of England at Langdon Bay have been examined for the same period, April to November during 2005 to 2007 (location shown in Figure 4.1). These observations also provide some indication of the meteorological characteristics of the air mass present over the study region. However, differences are expected between the geostrophic winds indicated by the pressure maps and observational data due to the influence of the local environment.

Wind roses for each of the PPs have been plotted which describe the wind speed and direction at 0Z at Langdon Bay (Figure 4.6) on all dates in the particular cluster. In general there is a good agreement between the observed wind speeds and directions and the atmospheric circulation expected by examination of the isobars on the PPs. The wind rose for cluster 1 shows light winds from all directions, as would be expected in a slack pressure situation described by PP1. The winds for cluster 2 are mainly light to moderate with southerlies, south-westerlies and westerlies dominating. This corresponds reasonably well with PP2 which shows south-westerly geostrophic winds over the UK. PP3 indicates north-westerly winds would be predominant over the UK during dates in this cluster. The wind rose shows some agreement, with moderate and occasionally strong winds mainly from the west through to the north. The winds on dates in cluster 4 are generally moderate to strong and the wind rose shows a large dominance in direction from the west, south-west and south. These surface observations correspond well with the pressure distribution described by PP4, with dense isobars indicating strong south-westerly winds. Winds at 00Z during dates in cluster 5 show larger components from the south, south-east and east and are generally light. There is fairly good correspondence between these winds and the pressure distribution described by PP5, but a greater north-westerly component might be expected.

The distribution of temperatures at 00Z for each date in the clusters have also been examined at Langdon Bay and are displayed as boxplots (Figure 4.7). The temperatures in each cluster span a similar range from around -2 to  $17 \,^{\circ}$ C. However, cluster 3 has a slightly larger range, from -3 to  $19 \,^{\circ}$ C, and the temperatures are slightly positively skewed, suggesting slightly cooler temperatures in general. Clusters 2 and 5 are slightly negatively skewed and show medians that are slightly warmer than the other clusters at 10 and 11  $^{\circ}$ C indicating slightly warmer temperatures overall on dates in these clusters. The synoptic conditions represented by clusters 2 and 5 occur more frequently in spring, summer and autumn, where as the circulation patterns represented by clusters 1 and 4 occur more often in winter (Table 4.2). This difference in seasonality combined with differences in the origin of the air mass may explain why variations are seen in the temperature statistics for each cluster.



**Figure 4.6:** Wind roses showing wind speed and direction at 00Z for clusters 1-5 (a-e) at Langdon Bay during Apr-Nov 2005-2007. Light-grey=1-5ms<sup>-1</sup>, mid-grey=5-10ms<sup>-1</sup>, black=greater than 10ms<sup>-1</sup>, number of calms (less than 1ms<sup>-1</sup>) shown as a percentage in the centre.

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**Figure 4.7:** Boxplots showing the range, median and upper and lower quartiles for temperature at 00Z during Apr-Nov 2005-2007 for each cluster at Langdon Bay, UK.

## 4.3.4 Representation of the synoptic situation during midge incursion events by the map pattern classification

Results describing the association between midge incursions identified from the NAME midge model and circulation types are displayed in Table 4.5 which shows the seasonal and annual frequency of incursion events associated with each PP.

It is noted from Table 4.4 that two PPs represent ~83% of all midge incursions to the UK: PP2 and PP5. To analyse if these PPs accurately demonstrate the synoptic situation present during these events the pressure distribution on the incursion dates, as identified by NAME, in each cluster have been plotted as composites and analysis synoptic charts on midge days have been examined (Figure 4.8).

The composite maps for dates of midge incursions in cluster 2 and cluster 5 show similarities to the synoptic situation described by the map classification for PP2 and PP5. The pressure distribution in PP2 and in the composite of midge incursions in cluster 2 are both dominated by a gradient associated with the NAO. However, in the midge event composite a large area of high pressure is also found in the north east of the domain over northern Germany. The synoptic situation in both PP5 and in the composite for midge incursions in cluster 5 is described by a blocking high. However,

the location of the anticyclone differs slightly; it is located toward Denmark in the midge incursion composite and is found more centrally in PP5.

The representativeness of the composite maps of pressure distribution on dates of midge incursions in each of the main clusters has also been evaluated against analysis synoptic charts from the UK Met Office archive. An example chart for an incursion in cluster 2, on 4 Sep 2005, again demonstrates the NAO gradient with high pressure towards the north east. The chart for an incursion event in cluster 5, on 27 Apr 2007, shows that a large blocking high dominates the weather over the UK in a similar way to the high pressure found in PP5 and the composite for midge days in cluster 5. Overall some local differences are noted between the re-analysis charts and the composites but the general geostrophic flow was found to be similar in each case.

**Table 4.5:** Seasonal and annual relative frequency distribution of midge days associated with each PP. *N* is the number of observations in each season and for the whole year

		Relati	ve frequen	су (%)	
PP	DJF	MAM	JJA	SON	YEAR
1	0.0	2.9	0.0	3.7	2.2
2	0.0	62.9	65.1	65.4	64.8
3	0.0	8.6	11.1	3.7	7.3
4	0.0	5.7	3.2	12.3	7.8
5	0.0	20.0	20.6	14.8	17.9
N	0	35	63	81	179



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**Figure 4.8:** Composite MSLP patterns for all dates of midge incursions in (a) cluster 2 and (c) cluster 5 and example synoptic charts for a midge incursion in (b) cluster 2 on 04/09/05 and (d) cluster 5 on 27/04/07.

## 4.3.5 Comparison of the results from the map-pattern classification with the James objective-GWL catalogue for midge incursion days

The results from the PCA-based map-pattern classification described in this chapter are again compared to the James objective-GWL classification system (James, 2007) to assess if the patterns which they suggest are related to midge incursion events are consistent and hence that the map-pattern classification can be assumed to provide suitable results for use in predictive systems.

The frequency of weather types classed by the objective-GWL system as present on a date calculated by the NAME midge model to have experienced a midge incursion event during 2005-2007 is displayed at Figure 4.9. Four weather types (Anticyclonic South-Westerly, Cyclonic South-Westerly, High over Central Europe and Anticyclonic Southerly) are found to account for 60% of all midge incursions (Figure 4.10) and small percentages occur during several other types.

In general these weather types are consistent with the results from the mapclassification derived in this chapter. Anticyclonic South-Westerly (Figure 4.10a) and Cyclonic South-Westerly (Figure 4.10b) are similar to PP2, with a cyclonic system present over the UK, leading to warm, moist south-westerly winds, suitable for midge carriage across the English Channel. High over Central Europe (Figure 4.10c) and Anticyclonic Southerly (Figure 4.10d) show similarity to PP5 with high pressure situated over the north-east of the domain leading to warm southerly winds from the continent, again suitable for midge incursions. The classifications are not entirely comparable as the objective-GWL classification shows midge incursion events are found in low numbers in several other weather types. However most of these additional types do not appear to show patterns which would be expected to drive local winds causing midge dispersal into the UK.



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**Figure 4.9:** Midge incursions events classed by weather types from the James (2006) objective-GWL classification.







**Figure 4.10:** The main weather types from the James (2006) objective-GWL classification found to be present during midge incursion events (a) Anticyclonic South-Westerly, (b) Cyclonic South-Westerly, (c) High over Central Europe, (d) Anticyclonic Southerly (James, 2006).

#### 4.4 Discussion

A map pattern classification of MSLP fields for northwest Europe for the period 2005-2007 has been produced and used to establish a relationship between large-scale atmospheric circulation and local surface winds which influence incursions of midges, acting as vectors for infectious agents, into the UK from mainland Europe. Two particular PPs were found to be more commonly associated with midge incursions than the other three PPs. These two patterns showed different attributes in terms of pressure distribution, air mass characteristics, occurrence in each season and persistency.

PP2 is the most common PP associated with midge days and also the most frequent pattern which occurs annually over the region. Surface measurements of wind speed, wind direction and temperature observed in association with this pattern suggest that the tropical maritime air mass associated with this pattern would, in general, be suitable for the carriage of midges to the UK. Light and moderate south, south-west and westerly winds were generally present and temperatures were found to be slightly warmer at these times. From the results of field experiments, as described in chapter 3, it is known that midges tend to be high in numbers and become more active during humid, warm weather (Pedgley, 1982, Carpenter et al., 2008, Sanders et al.,

submitted, Sanders et al., 2010). They will also not become airborne during strong winds, however very light winds will not be sufficient to carry them across the English Channel. Moderate winds therefore create the highest risk situation to coastal areas in south east England.

PP5 also describes synoptic conditions suitable for midge carriage to the UK. Geostrophic winds determined from the isobars and verified by surface observations show easterly and south easterly winds would be associated with this pressure distribution. Originating from the continent, this air mass has the potential to create very warm conditions which are ideal for high midge take-off rates. Airborne midges would be carried to the UK on the gentle to moderate winds indicated by this PP.

The other PPs describe situations which are not particularly suitable for midge take-off and/or transport to the UK. The winds in PP1 were found to be too light and variable, associated with the weak pressure gradient over the near-continent. In PP3 northerly winds are suggested by the pressure distribution, which would carry midges away from the UK. PP4 shows a strong pressure gradient creating wind strengths which would be unsuitable for midges to become airborne in.

To further assess the representativeness of the PPs for circulation types present on midge incursion dates they were compared to composites of the MSLP fields on midge incursion dates in each particular cluster and example analysis synoptic charts. In general the map-classification was found to be a suitable representation of the synoptic situation during midge incursions, but some local differences occurred. These PPs could therefore not be used for detailed predictions of locations likely to be at risk in the future, but could be used as a guide to the frequency and timing of suitable air masses for incursion events. Other local effects of, for example, topography and land/sea breezes are not captured in the map patterns due to the low spatial and temporal resolution of the MSLP data used.

The association between the PPs and precipitation rates have also not been examined here; moderate to high rainfall could prevent midges from successfully crossing the English Channel, even if winds are of a suitable strength and direction. Additionally the map-pattern classification was only produced for a three year period as the dispersion modelling data was computationally expensive to produce. To determine if this short time period may be too limited to adequately capture the synoptic climatology of the region, the results were compared to the frequency of occurrence statistics from the Jams (2007) objective-GWL catalogue. The frequency of occurrence of the map-pattern PPs were found to compare well with this alternative catalogue and it is

concluded that the classification developed here suitably represents the climatology of northern Europe.

To test if too few clusters had been used to capture all the variations in pressure distributions which influence midge incursions a further comparison was made against the catalogue produced by James (2007). 60% of midge incursions were found to mainly occur on just 4 of the 29 different GWL types, and these 4 patterns were consistent with the results of the map-classification. However, the objective-GWL also suggested low percentages of midge incursions were related to several other weather types. This may be because the objective-GWL does not class individual daily weather types but instead categorises the data into weather regimes lasting at least 3 days. This approach filters out some patterns which form a transition between regimes and those which are fairly temporary within a regime and the resulting pattern for an individual day may therefore be incorrectly classified as relating to midge incursions. In most cases, these other objective-GWL weather types show patterns which would not be expected to lead to midge incursions as the local winds suggested by the pressure patterns would be in an unsuitable direction. Conversely, the map-pattern classification defined in this chapter may have been too broad. The two patterns found to be most associated with midge incursions accounted for 82.7% of these events, leaving 17.3% of days unaccounted for. This suggests that some modes of variation related to midge incursions may be obscured by more dominant patterns in the map-pattern classifications developed here.

Despite this, the relationship determined here appears to capture the main modes of pressure distribution variation which are related to midge incursion events into the UK. The resulting patterns are physically sensible and compare satisfactorily against surface weather conditions and patterns derived from an alternative weather regime catalogue. The system can therefore be used to provide a useful way to investigate changes in the level of risk posed to the UK of midge-borne disease incursions in the future. This process is carried out in the next chapter, where the method is applied to simulated MSLP data from RCMs to assess changes in the frequency of the PPs found to be related to local winds causing dispersal of midges into the UK.

#### 4.5 Summary

This study provides insight into the relationship between large scale synoptic circulation patterns and the likelihood for incursions of vector midges, potentially infected with viruses such as bluetongue, into the UK from the northern coast of France and

Belgium. This relationship assumes the activity levels and flight paths of the midges are controlled by the characteristics and movements of local winds, which are in turn governed by large scale atmospheric flows described by the PPs deduced in this study.

Two PPs were found to characterise the synoptic situation present during most midge incursion events. The main pattern which gives rise to ~65% of all midge days was also the most common pattern found over northern Europe by the analysis. This PP indicated south-westerly winds over the UK, generally associated with warm, moist tropical maritime air. The other pattern which is associated with ~18% of midge incursions was found to be fairly infrequent over northern Europe during the period of the analysis. The winds associated with this pattern were directed from the continent, so the associated air mass would generally be warm and dry. These two patterns describe synoptic situations which would lead to persistent warm winds towards the UK from the coast of the near-continent and hence appear physically sensible for midge incursions. The PPs related to midge incursions also compare satisfactorily against surface observations and the weather types associated with incursion events from an alternative classification system.

The technique described here has established a relationship between large scale circulation patterns and local winds driving midge dispersal into the UK which can be used to assess changes to midge-borne disease incursions in the future, and which cannot be achieved using other standard approaches such as climate-envelope or dispersion models. These changes on a decadal timescale are investigated in the next chapter with the use of data from RCMs.

### Chapter 5

# The effect of climate change on incursions of midges into the UK in future decades

It was established in the previous chapter that midge incursions into the UK are associated with certain synoptic scale atmospheric circulation patterns. This was achieved by relating results from the NAME midge model developed in chapter 3 to a map pattern classification of MSLP for northern Europe. This relationship is used in this chapter to estimate changes to the frequency of midge incursions under projections of future climate. Data from each decade during 2001 to 2050 from an ensemble of RCMs are subjected to the same statistical techniques developed in chapter 4. Changes in the frequency of circulation patterns found previously to be associated with midge incursions are then examined over each decade in the study period. Based on these results, an assessment is made of the risk of windborne introduction of midge-borne pathogens to the UK from the north coast of mainland Europe in future decades.

#### 5.1 Introduction

In chapters 3 and 4 it was established that certain meteorological conditions are strongly related to many aspects of midge activity and the likelihood of their dispersal into the UK. Large scale circulation patterns influence when local weather conditions will be conducive to midge take-off and when winds will be suitably directed to result in midge dispersal from the near-continent into the UK. Changes in the occurrence of these circulation patterns in future decades can be estimated from climate model data, thereby allowing a projection to be made of the frequency of midge incursions in the future under climate change.

Previous studies have suggested circulations have changed in recent decades over Europe and simulations of future climate conducted using GCMs and RCMs have also predicted these changes to continue (Section 2.2.3.4). However these studies do not provide all information necessary to produce estimates of future midge incursions to the UK. This chapter therefore examines changes to the circulation patterns in climate models which are relevant to midge incursions, namely south-westerly cyclonic and easterly anticyclonic synoptic situations.

Projections of future climate made by GCMs are on spatial scales of several hundred kilometres. RCMs produce data at smaller scales and therefore provide better resolution of features such as frontal systems and synoptic scale atmospheric circulations (Antic et al., 2006) which are now known from chapter 4 to influence midge dispersal. The aim of this study was to produce a less computationally expensive alternative method to dispersion modelling to estimate future frequencies of midge incursions. It was therefore unnecessary to use statistical downscaling methods to derive very high resolution data capable of driving a dispersion model. Additionally, statistically downscaled data assume the derived relationships between the large and small scale remain stable when the climate is perturbed. This method also cannot accommodate regional feedbacks and there can be a lack of coherency among multiple climate variables derived this way (see Section 2.2.3.1).

It has been noted previously that there are many sources of uncertainty which cascade through the modelling of the impacts of climate change. These include uncertainties in future GHG emissions, natural climate variability, modelling uncertainties associated with structural and parameter choices, and uncertainty introduced by downscaling techniques (Section 2.2.3.2). For climate models to provide information which allows informed, robust decisions to be made, quantification of the uncertainty associated with the estimate of the climate impact is necessary (Stainforth et al., 2007b). In order to explore the uncertainty associated with the use of RCMs in estimating future incursions of midge-vectors to the UK, an ensemble of RCMs from the ENSEMBLES project (van der Linden and Mitchell, 2009) is used in this study. The individual models are also compared with observations to assess the quality and reliability of their simulations of future climate.

This chapter firstly reviews the methodology used to examine changes in circulation patterns associated with midge incursions and a summary of the ENSEMBLES RCM data used is provided. The results are then displayed for each decade from 2001 to 2050 and the uncertainties associated with the RCM projections are highlighted. A discussion of the results in terms of decisions related to future disease incursions is then provided and finally the overall conclusions of the study are stated.

#### 5.2 Data and Methods

#### 5.2.1 Overview

The overall approach taken is adapted from the analysis pathway described by Stainforth et al. (2007a) which outlines a methodology for the use of ensembles of

climate model data in decision-making. The key steps in the process which are used here are described below.

- Step 1 review whether climate change is likely to affect the decision, and to allow for consideration of other, possibly more overriding, influences on the decision making process.
- Step 2 determine which aspects of the decision are relevant to climate change. Again it is noted here that climate may not be the only, or most important, influence on these aspects.
- Step 3 identify the variables from model simulations which can be used to provide information about the climate change aspects of the decision.
- Step 4 extract the relevant variables and construct an ensemble of their values. The model results should also be evaluated against observations to assess their performance.
- Step 5 assess how the results affect the climate relevant factors of the decision.
- Step 6 determine the message for the decision and to decide if further modelling is required using other variables.

In the study carried out here it is assumed that a range of decisions will be made by government and stakeholders relating to changes in the frequency of incursions of potentially infected midges in the future under climate change. Examples of these types of decision could include the level of investment to place into research and development of vaccines or whether to carry out large educational campaigns in the farming community. For these decisions it is acknowledged that economic constraints or practical limitations may outweigh information derived from climate models but that their results are still an influencing factor.

The meteorological variables which are important in determining the level of midge activity were identified in chapter 3 as temperature, precipitation and wind speed. In chapter 4, as a proxy for these individual variables, large scale pressure patterns which influence when local weather variables are suitable for midge incursions were determined. Changes in the frequency of the occurrence of these MSLP patterns in climate models can therefore be examined as a more computationally efficient alternative to dispersion modelling. The data and method taken to do this are discussed in detail below and the discussion in Section 5.5 assesses how the results may impact on decisions faced in the future to reduce the spread of midge-borne diseases.

#### 5.2.2 Data

The climate model data used here are from the EU ENSEMBLES project (van der Linden and Mitchell, 2009). This project, as discussed previously in Section 2.2.3.3, provides high resolution data for use in impact studies in the form of 25 GCM/RCM combinations, of which 22 are available to download at the project website (http://ensembles-eu.metoffice.com) (Figure 5.1). Descriptions of the models are available at the project's data portal (http://ensemblesrt3.dmi.dk/) and from the references listed in Table 5.1.

This MME of RCMs allows the range of uncertainty in projections to be estimated from different sources including structural uncertainties (associated with model construction) and parameter uncertainties (associated with the parameterizations of physical processes). Additionally, uncertainty associated with the use of boundary conditions from different GCMs can be explored.

Daily mean MSLP and 2m temperature data at a resolution of 25km from 16 RCM/GCM combinations, covering a common domain over Europe (see Figure 5.2), were used. The remaining 9 model combinations were not used as they were either not available for download or were produced on a mapping projection not supported by the algorithms developed previously for the statistical calculations. In addition to the 5 standard GCMs used, another model, HadCM3, was also operated with low, medium and high climate sensitivities. These 3 members of HadCM3 are considered as separate GCMs in ENSEMBLES (Christensen et al., 2009). All the RCMs provide projections for the period 1951-2050, with some also extending to 2100. The period used here was therefore 2001-2050 to allow for comparison of all model results and covers the period under which many decisions relating to midge-borne disease incursions are likely to be made. One emissions scenario, SRES A1B (a moderately high emissions scenario, characterised by rapid economic growth, wise use of new technologies and a balance of energy sources), was used for all RCM projections as the choice of emission scenario is considered to be a relatively unimportant source of climate uncertainty for the early decades of the 21<sup>st</sup> century (Christensen et al., 2009).

Observation data from the ERA-Interim reanalysis conducted by the European Centre for Medium-Range Weather Forecasts (ECMWF) was used for comparison purposes with the RCM data for the period 2000-2010 (Dee et al., 2011). This dataset is produced with a sequential data assimilation scheme, where in each 12 hour cycle available observations are combined with prior information from a forecast model to estimate the state of the atmosphere. This produces a coherent record which is

consistent with available observations. The ERA-Interim archive contains 6-hourly gridded estimates of 3-dimensional meteorological variables, and 3-hourly estimates of a large number of surface parameters and other 2-dimensional variables, for all dates from 1 January 1989 at a resolution of 1.5°.

Name	Research Institute	Reference
GCMs		
HadCM3	Met Office Hadley Centre (METO-HC)	Gordon et al. (2000)
ECHAM5	Max Planck Institute for Meteorology (MPIMET)	Roeckner et al. (2006)
IPSL	Institut Pierre Simon Laplace (IPSL)	Marti et al. (2006)
ARPEGE	Centre National de Recherches Météorologiques (CNRM)	Deque et al. (1994)
BCM	Nansen Centre and University of Bergen	Furevik et al. (2003)
CGM3	Canadian Centre for Climate Modelling and Analysis (CCCma)	Scinocca et al. (2008)
RCMs		
HadRM	Met Office Hadley Centre (METO-HC)	Murphy et al. (2007)
REMO	Max Planck Institute for Meteorology (MPIMET)	Jacob et al. (2001)
ALADIN	Centre National de Recherches Météorologiques (CNRM)	http://www.cnrm.meteo.fr/aladin
HIRHAM	Danish Meteorological Institute (DMI)	Christensen et al. (1996)
	Norwegian Meteorological Institute (Met. NO)	http://regclim.met.no/results/gtr9.pdf
CLM	Helmholtz-Zentrum Geesthacht Centre for Materials and Coastal Research (GKSS)	http://www.cosmo-model.org/content/ model/documentation/core/default.htm
	Swiss Federal Institute of Technology, Zurich (ETH)	
RACMO	Royal Netherlands Meteorological Institute (KNMI)	Lenderink et al. (2003)
RegCM	International Centre for Theoretical Physics (ICTP)	http://users.ictp.it/~pubregcm/RegCM3/
RCA3	Swedish Meteorological and Hydrological Institute (SMHI)	Kjellström et al. (2005)
	The Community Climate Change Consortium for Ireland (C4I)	
PROMES	University of Castilla-La Mancha (UCLM)	http://momac.uclm.es/indexEng.html
CRCM	Ouranos - consortium of Quebec government, Hydro-Québec and Environment Canada (OURANOS)	Plummer et al. (2006)
VMGO	Voeikov Main Geophysical Observatory (VMGO)	Shkolnik (2008)

Table 5.1: GCMs and RCMs used by different research institutes in the ENSEMBLES project.

RCM RCM	HadCM3 (Low)	HadCM3 (Std)	HadCM3 (High)	ECHAM5	' TSdI	ARPEGE	BCM	CGM3
METO-HC HadRM	HadRM3Q0	HadRM3Q3	HadRM3Q16					
MPIMET <i>Reno</i>				MPI M REMO				
CNRM ALADIN						CNRM RM4.5		
dmi <i>Hirham</i>				DMI_HIRHAM5_ ECHAM5		DMI_HIRHAM5_ ARPEGE	DMI_HIRHAM5_ BCM	
ETH CLM		ETHZ_CLM						
KNMI <i>RACMO</i>				KNMI_RACMO2				
ICTP RegCM				ICTP_REGCM3				
SMHI <i>RCA3</i>		SMHIRCA_ HadCM3Q3		SMHIRCA_ ECHAM5			SMHIRCA_BCM	
UCLM PROMES	UCLM_PROMES							
C4I RCA3			C4IRCA3_ HadCM3Q16	C4IRCA3_ ECHAM5				
GKSS CLM					GKSS CCLM4.8			
Met.No <i>HIRHAM</i>	METNOHIRHAM_ HadCM3Q0						METNOHIRHAM_ BCM	
OURANOS CRCM								OURANOS MRCC4.2.1
VMGO VMGO	VMGO-RRCM							

**Figure 5.1** The combination of RCMs (name of the institute and model name) and driving GCMs (model name) available from the ENSEMBLES website. Those used here are shown in grey.

#### 5.2.3 Analysis of pressure patterns in the RCMs

The method developed in chapter 4 is again applied here to data from the ENSEMBLE RCMs to produce map pattern classifications of MSLP for each decade during the period 2001-2050 (see Section 4.2.3 for full details). The method is also repeated using data for the first decade (2001-2010) of the study period from the ERA-Interim dataset for evaluation purposes (see section 5.2.4 below).

Firstly the seasonal trends in the MSLP data from each individual RCM and from ERA-Interim were de-seasonalised using a high-pass filter (see Section 4.2.3.1). The data were then subjected to a PCA, in S-mode orientation using a correlation matrix (see Yarnal, 1993), to reduce the dataset to the optimal number of PCs as determined using the methods detailed in Section 4.2.3.2. As before, the retained PCs were then rotated using a Varimax rotation to remove statistical artefacts (Kaiser, 1958). A nonhierarchical k-means clustering technique was then applied (see Section 4.2.3.3) to group the pressure patterns with similar spatial characteristics. The number of clusters chosen in each case was kept constant at 5 to allow for direct comparison between the results. This was found in chapter 4 to be the optimal number of regimes to classify MSLP over Europe and also by Terray et al. (2004). A composite of all the MSLP grids in each separate cluster were then plotted to produce map-pattern classifications of each decade in each model. Finally the spatial patterns were manually categorised into different types according to the locations of the pressure centres and the direction of flow across the main area of interest, the English Channel between the south-east of England and Belgium.

The results of this classification are firstly analysed to investigate variations between the RCMs for the number of occurrences of each weather type during each decade to deduce how robust their results are and which pressure types contain the largest amount of uncertainty. For the first decade (2001-2010) the results from the RCMs are also compared to the observations from ERA-Interim (see Section 5.2.4). Changes in the frequency of occurrence of each type across each decade for each RCM in the ensemble are then also analysed to investigate possible trends, thereby allowing estimates of future increases or decreases in numbers of midge incursions to be made.

#### 5.2.4 Evaluation of the RCMs with observation data from ERA-Interim

The RCMs performance in their simulation of MSLP is assessed using observations from the ERA-Interim dataset over the period 2001-2010. Quantification of how well the RCMs represent pressure patterns in the recent past can be used as an indication of

the quality and reliability of their simulations of MSLP for future decades. Evaluation of the models against observations highlights those individual models with inadequately modelled processes and may perhaps also indicate the presence of systematic biases in the whole ensemble of models. Evaluation of climate models has been a standard process in the IPCC assessments (Randall et al., 2007, McAvaney et al., 2001) and various other model inter-comparison projects such as the Coupled Model Intercomparison Project (CMIP) (Meehl et al., 2005).

Additionally, performance metrics of how well model results compare to observations can be used to weight or rank individual models. The reliability of projections might be improved using these weighted models or a subset of the top ranking models (Knutti et al., 2010). Here the RCMs are therefore ranked by how well they simulate MSLP patterns in comparison to the ERA-Interim observations and a subset of the top ranking models are used as the best estimate of future projections of MSLP patterns.

## 5.2.5 Analysis of the seasonal occurrence of pressure patterns in the RCM and ERA-Interim datasets

The map pattern classification technique and the analyses of its results described above in Section 5.2.3 include data for all days in each year of the study period. However incursions of midges to the UK are restricted to when temperatures are warm enough for active populations of midges to exist on the near-continent. The risk of bluetongue spread is also only present when temperatures are warm enough for virus replication. Therefore possible changes in the seasonal occurrence of pressure patterns are an important consideration. Increases in the total number of these patterns are of no consequence if they occur during the winter, when midge populations are not present in northern Europe and virus replication is not possible.

In order to analyse changes in the occurrence of the pressure patterns associated with midge incursions during the period where temperatures are suitably warm for bluetongue spread, it was first necessary to determine when this period occurs in each of the RCMs. The start of the bluetongue season was estimated as the first day in the year where the running mean temperature of the previous 30 days was above 14.3 for the grid box around Ostend, Belgium (taken to be a representative source area for incursions). This estimate was based on the day degree model of Wilson et al. (2007) for the completion of EIP in *Culicoides sonorensis*. The end was estimated as the last day when this accumulated temperature threshold was no longer exceeded, and would therefore be too cold to allow completion of viral replication. This process was carried

out for each year and averaged for each decade in the study period for each RCM. Finally the numbers of occurrences of the patterns associated with midge incursions during the average bluetongue season in each decade of each RCM were then calculated.

Finally this process was also repeated using daily mean temperature at 2m from ERA-Interim for the period 2001-2010. The results from the RCMs were again compared with this reanalysis dataset and ranked according to their performance.

#### 5.3 Results

#### 5.3.1 Pressure pattern classification

Overall the map-pattern classifications produced for each decade of data from each RCM showed consistently similar results. Figures 5.2-5.6 provide examples of these patterns from each decade in KNMI-RACMO2, the RCM operated at KNMI and driven by ECHAM5. It can be seen in this example that the same dominant patterns are present in each of the decades. This is also true for the other RCM MSLP maps with the exception of HadRM3Q0 and HadRM3Q16, the low and high climate sensitivity versions of HadRM3. Their results are therefore excluded from the rest of the analysis as they are not directly comparable.

The first pattern (a) in each decade is dominated by south-westerly flow across the study region around the English Channel generated by a centre of low pressure to the north of the UK and high pressure over central Europe. This pattern is therefore termed "south-westerly". Pattern (b) in each decade of each model generally shows north-westerly flow across the UK, Germany and Scandinavia, caused by a pressure gradient between high pressure to the west of France and low pressure over northern Norway. This pattern is termed "north-westerly". The third pattern, (c), is characterised by a gentle pressure gradient between high pressure over Scandinavia and low pressure of the Mediterranean. This indicates gentle easterly winds across the study region and this pattern is therefore classed as "easterly". Pattern (d) in the RCM results displays a strong cyclonic system over or near the UK and is therefore named here as "cyclonic". The fifth pattern, (e), is dominated by tightly spaced isobars indicating strong westerly flow across the centre of the region caused by a deep low to the north of the region with high pressure in the south. This final pattern is classed as "westerly".

The results from the RCMs are broadly consistent with the results from ERA-Interim (Figure 5.7). The locations of the pressure centres are somewhat different from the pressure centres displayed by the RCMs, however the overall resulting flows are of

similar directions with south-westerlies (Figure 5.7a), north-westerlies (Figure 5.7b), easterlies (Figure 5.7c), a cyclonic system (Figure 5.7d) and westerlies (Figure 5.7e) present over the UK. These winds originate from similar areas to the winds displayed by the RCMs and therefore the characteristics of the air masses present in the study area will be similar and have a comparable influence on midge flight.

Three of the patterns from the RCMs show strong similarities to the map classification produced in chapter 4. Pattern (a) is consistent with PP2 (Figure 4.4b), pattern (b) matches PP3 (Figure 4.4c) and pattern (c) is similar to PP5 (Figure 4.4e). Patterns (d) and (e) both show some similarity to PP4 (Figure 4.4d), which has a strong gradient much like pattern (e) but its low pressure is centred over the UK in a similar manner to pattern (d). The first pattern in the previous classification (Figure 4.4a) is not found here. Due to their strong similarities with the pressure patterns determined earlier to be associated with midge incursions (PP2 and PP5), the "south-westerly" and "easterly" classifications of RCM MSLP data are therefore assumed to also indicate conditions suitable for midge spread into the UK. A comparison of PP2 and PP5 and the "south-westerly" and "easterly" patterns for 2001-2010 from KNMI-RACMO2 are shown in Figure 5.7 which demonstrates the similarity of the winds over the UK from observations and those produced by the RCM.



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**Figure 5.2:** Map-pattern classification of de-seasonalised MSLP (hPa) from KMNI-RACMO2 for 2001-2010.



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**Figure 5.3:** Map-pattern classification of de-seasonalised MSLP (hPa) from KNMI-RACMO2 for 2011-2020.



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**Figure 5.4:** Map-pattern classification of de-seasonalised MSLP (hPa) from KNMI-RACMO2 for 2021-2030.



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**Figure 5.5:** Map-pattern classification of de-seasonalised MSLP (hPa) from KNMI-RACMO2 for 2031-2040.



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**Figure 5.6:** Map-pattern classification of de-seasonalised MSLP (hPa) from KNMI-RACMO2 for 2041-2050.



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**Figure 5.7:** Map-pattern classification of de-seasonalised MSLP (hPa) from the ERA-Interim dataset for 2001-2010.



**Figure 5.8:** A comparison of (a) PP2 and (c) PP5 from the map-classification of deseasonalised MSLP (hPa) produced in chapter 4and the (b) "south-westerly" and (d) "easterly" patterns of de-seasonalised MSLP (hPa) for 2001-2010 from KNMI-RACMO2.

#### 5.3.2 Variations in the frequency of the pressure pattern types between RCMs

The results from each ENSEMBLE RCM for the frequency of occurrence of each of the classifications of MSLP for each decade are displayed in Figure 5.9 (a)-(e). These graphs show the total number of times each pattern occurs within the decade for each model. The mean and standard deviation for each classification type are also displayed to indicate the extent of variation in the simulations and highlight where the largest ranges of uncertainty exist. Additionally for 2001 to 2010 the results from ERA-Interim are also displayed to indicate which models compare most closely with observations over this period.

Overall consistent results are noted between the decades, with the cyclonic and westerly classifications showing smaller numbers of occurrences but far less variation between the models. The other three types occur more frequently and display a much greater range of results, with the north-westerly type generally having the largest variation.

For all the classification types in all decades the majority of models show results within 1 standard deviation of the mean. The outliers in several cases are produced by the same RCMs, for example METNOHIRHAM\_HadCM3Q0 repeatedly shows a much higher number of occurrences of the easterly type than all the other models.

The observations from ERA-Interim for 2001-2010 are also displayed at Figure 5.9 (a). Table 5.2 displays the differences between the results from the RCMs and the reanalysis dataset and also ranks the models based on these differences. It is noted that the results from ERA-Interim are all within 1 standard deviation of the mean, suggesting that the majority of the RCMs produce results which are comparable with the observations. From Table 5.2 it is found that no individual model compares most closely to the observations for each classification type. Overall MPI\_M\_REMO, the model operated at MPIMET with boundary conditions from ECHAM5, ranks highest when taking into account the performance of the models across all the classification types by summing their individual rankings. The mean of the models is ranked sixth and C4IRCA3\_HadCM3Q16 operated by C41 and driven by HadCM3 compares least well to ERA-Interim during this decade.

The uncertainty associated with the south-westerly, north-westerly and easterly types is much greater than the cyclonic and westerly type and the reason for this does not seem to be clear. Impact models relying on simulations of either of cyclonic or westerly types are therefore likely to be more robust to the choice of RCM, where as models utilizing the other types will show a greater range of results associated with their larger range of uncertainty. Estimation of the risk of future midge incursions are made here based on the south-westerly and easterly weather types. These estimates will therefore have a large range of uncertainty associated with the variation in the simulations of these pressure pattern types by the ensemble of RCMs. The models which rank highest in a comparison to ERA-Interim for the south-westerly and easterly types are SMHIRCA\_BCM and ETHZ\_CLM\_SCN respectively. The projections made by these models for future decades could be considered more reliable than models which cannot accurately reflect current atmospheric conditions.




2011-2020



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**Figure 5.9:** The frequency of each pressure pattern classification types in the ENSEMBLES RCMs for (a) 2001-2010, (b) 2011-2020, (c) 2021-2030, (d) 2031-2040 and (e) 2041-2050. The mean and standard deviation are also displayed (black horizontal lines). In addition for (a) the results from ERA-Interim are shown (black crosses).

Table 5.2: Comparison of the frequency of each pressure pattern type calculated from the RCMs against the results from ERA-Interim for 2001-2010

Model	Over- all Rank	No. of SW (Difference from ERA- Interim)	Rank	No. of NW (Difference from ERA- Interim)	Rank	No. of E (Difference from ERA- Interim)	Rank	No. of C (Difference from ERA- Interim)	Rank	No. of W (Difference from ERA- Interim)	Rank
ERA-Interim		779		1023		778		600		470	
MPI_M_REMO	1	866 (+87)	7	1028 (+5)	1	677 (-101)	5	585 (-15)	2	496 (+26)	6
SMHIRCA_ECHAM5	2	731 (-48)	3	1100 (+77)	2	707 (-71)	3	537 (-63)	10	577 (+107)	15
SMHIRCA_HadCM3Q3	3	725 (-54)	4	875 (-148)	6	891 (+113)	6	589 (-11)	1	520 (+50)	11
KNMI_RACMO2	4	661(-118)	8	1184 (+161)	7	738 (-40)	2	563 (-37)	4	506 (+36)	8
C4IRCA3_ECHAM5	5	864 (+85)	6	1120 (+97)	4	652 (-126)	7	478 (-122)	15	486 (+16)	3
HadRM3Q3	6	724 (-55)	5	894 (-129)	5	941 (+163)	11	559 (-41)	6	482 (+12)	2
Mean	7	812 (+33)	2	837 (-186)	9	916 (+138)	8	556 (-44)	7	505 (+35)	7
ETHZ_CLM_SCN	8	624 (-155)	10	1194 (+171)	8	787 (+9)	1	528 (-72)	12	467 (-3)	1
METNOHIRHAM_BCM	9	643 (-136)	9	930 (-93)	3	1002 (+224)	12	567 (-33)	3	510 (+40)	10
DMI_HIRHAM5_ECHAM5	10	941 (+162)	12	820 (-203)	10	687 (-91)	4	650 (+50)	8	554 (+84)	14
METNOHIRHAM_HadCM3Q0	11	1000 (+221)	13	526 (-497)	12	927 (+149)	10	639 (+39)	5	508 (+38)	9
C4IRCA3_HadCM3Q16	12	1099 (+320)	15	522 (-501)	13	916 (+138)	8	526 (-74)	13	537 (+67)	13
DMI_HIRHAM5_ARPEGE	13	1076 (+297)	14	508 (-515)	14	1129 (+351)	13	487 (-113)	14	452 (-18)	4
GKSS_CCLM	14	618 (-161)	11	564 (-459)	11	1357 (+579)	14	536 (-64)	11	525 (+55)	12
SMHIRCA_BCM	15	790 (+11)	1	459 (-564)	15	1414 (+636)	15	544 (-56)	9	445 (-25)	5

### 5.3.3 Changes in the frequency of pressure pattern types

Changes in the number of occurrences of each of the classifications of MSLP for the ENSEMBLES RCMS over each decade in 2001-2050 are described by Figure 5.10. These graphs again demonstrate that the individual RCMs show different magnitudes for the occurrence of each pressure classification but overall the majority, and the ensemble means, do not show any strong trends in their frequency between decades. Some individual models, however, display exceptions to this general result, showing large variations between decades for each different pressure classification. For example, ETH\_CLM\_SCN indicates large alternations between decades in the occurrences of the south-westerly and north-westerly type. DMI\_HIRHAM5\_ARPEGE and MPI\_M\_REMO also show notable deviations in their results for the majority of the MSLP types.

No classification type indicates a consistent upward or downward trend across all model results. However for four of the classifications a large majority of the models indicate a trend in the same direction. For the south-westerly and westerly classifications, 9 and 10 of the 14 models respectively show an upwards trend between 2001 and 2050. For both the easterly and cyclonic types, 9 of the total 14 models show a decrease in frequency over the period. The north-westerly type has an even division of models indicating an increasing and a decreasing trend.

The results from the three models which rank highest against observations from ERA-Interim are displayed at Figure 5.10 a) ii), b) ii), c) ii), d) ii) and e) ii). These results generally agree with the results from the majority of the other RCMs. For the southwesterly and westerly classifications the top three ranking models, which agree very closely with the observations for the first decade, all show a slight overall increase over the study period. For the cyclonic pattern, the three models which compare most closely to observations all show a slight decrease in occurrence by 2050. The three highest ranking models for the easterly and north-westerly patterns show very little trend overall by the end of the study period. In both cases two RCMs indicate a very slight decrease and the third shows a slight increase.

Overall the results for the majority of the models and those which rank highest against observations are consistent with other studies of changes in circulation in climate models carried out by Terray et al. (2004), van Ulden and van Oldenborgh (2006) and van Ulden et al (2007) (see Section 2.2.3.4), which also suggest an increase in westerly flow in the coming decades.

In relation to incursions of midges, these results suggest that there may be a slight increase in their occurrence due to an increase in the frequency of south-westerly winds but also a slight decrease in incursions associated with a decrease in easterly winds. However, with large variations in the magnitude of the results, additional between-decadal variations for some models, and no consistent or strong trends across the ensemble of RCMs, a large amount of uncertainty is attached to these projections.



ii)

Top Ranking South-Westerly RCMs



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Top Ranking Easterly RCMs

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**Figure 5.10:** The change in frequency of the (a) i) south-westerly, (b) i) north-westerly, (c) i) easterly, (d) i) cyclonic and (e) i) westerly pressure pattern classifications from the ENSEMBLES RCMs during each decade from 2001 to 2050. The mean of the ensemble is shown in black and observations from ERA-Interim are indicated with a black cross. Also displayed are the top three ranking RCMs from a comparison to the ERA-Interim observations for each pressure pattern type: (a) ii) south-westerly, (b) ii) north-westerly, (c) ii) easterly, (d) ii) cyclonic and (e) ii) westerly.

### 5.3.4 Changes in occurrence of pressure patterns associated with midge

### incursions during the bluetongue season

The average length of the bluetongue season in each decade, calculated for each ENSEMBLE RCM is displayed in Figure 5.11. An increasing trend is found for all model members, consistent with projections of increasing temperatures. The overall mean of the ensemble is found to increase by 20 days over the study period, suggesting the season for risk of bluetongue spread may increase by almost three weeks by 2050.

The results from ERA-Interim for the average length of the bluetongue season during 2001-2010 are also shown at Figure 5.11. From this dataset the length of the season was calculated as 110 days. ETHZ\_CLM\_SCN, KNMI\_RACMO2 and MPI\_M\_REMO in particular are found to agree well with these observations. However C4IRCA3 HadCM3Q16 is found to overestimate the length and METNOHIRHAM BCM to underestimate the length. Nevertheless these models still indicate the same overall trend as the majority of the ensemble.



Length of bluetongue season

**Figure 5.11:** The average length of the bluetongue season for the Ostend area, in each decade as calculated from the ENSEMBLES RCMS for the grid point in the models closest to Ostend. The observations from ERA-Interim for Ostend are indicated with a black cross.

To account for the bias in the temperatures which affects the length of the bluetongue season, as evident in Figure 5.11, a correction was applied to the results from the RCM using the observational data from ERA-Interim. The average difference in length between the start of the season in each of the individual RCMs and the ERA-Interim data for Ostend was calculated for 2001-2010, and this difference was removed from the results for each of the subsequent decades. This was also carried out for the end of the bluetongue season. The resulting bias corrected length of the bluetongue season for the RCMs is shown in Figure 5.12. This figure clearly demonstrates the overall trend in the models for a slight increase of around 20 days in the length of the season over the study period.



Length of bluetongue season (bias corrected)

**Figure 5.12:** The average length of the bluetongue season for the Ostend area after bias correction against the observations from ERA-Interim (indicated with a black cross).

The numbers of occurrences of each of the pressure pattern types associated with midge occurrences, south-westerly and easterly, during the bias corrected bluetongue season calculated for each RCM are shown in Figure 5.13. The results from ERA-Interim for 2001-2010 are also displayed and a comparison between the datasets is contained in Table 5.3.

For the south-westerly type (Figure 5.13a) the majority of models do not show any strong trends. The magnitudes of the results show a fairly large range of variability, with

the majority of the ensemble ranging between 10 and 100 occurrences in each decade during the average bluetongue season calculated for each individual RCM. The variations in these results are partly a result of the individual RCM's simulations of MSLP and also of their different predictions in the length of the bluetongue season.

Overall, 7 models show a slight decline, 3 show no trend and 4 show an increase in the south-westerly type over the average bluetongue season in each decade from 2001-2050. The results from the three models which agree most closely with ERA-Interim during the first decade (SMHIRCA\_HadCM3Q3, KNMI\_RACMO2 and HadRM3Q3) are displayed at Figure 5.13 a) ii). These models all show some slight variability between decades, but an overall decreasing trend over the period.

The results from 4 RCMs, however, do not agree well with the rest of the ensemble. METNOHIRHAM\_HadcM3Q0 and ETHZ-CLM\_SCN show very variable results between the decades, MPI-M-REMO shows an anomalously high value for 2001-2010 and DMI\_HIRHAM5\_ECHAM5 shows values for the period which are higher than the rest of the ensemble.

Overall the results from the models, particularly those which compare closest to the observations and are therefore thought to be more reliable, indicate a decreasing risk of bluetongue spread into the UK by winds associated with south-westerly pressure patterns. However, the uncertainty associated with this prediction is large as displayed by the variation in the RCM results.

For the easterly type no strong trends are again indicated by the RCMs (Figure 5.13b). In this type there is also wide variation in the magnitude of the results, with a range from 100 to 900 occurrences during bluetongue seasons in each decade. Large variation between decades is also present in some of the individual RCM results. The majority of models suggest a slight increase and the remaining five suggest a slight decrease in the occurrence of easterly types during the bluetongue seasons over the period 2001-2050. The results from ERA-Interim for 2001-2010 are most closely represented by ETHZ\_CLM\_SCN, KNMI\_RACMO2 and (Figure 5.13b) ii)). KNMI\_RACMO2 and SMHIRCA\_ECHAM5 show very little variation between decades and but a very slight increase overall. ETHZ\_CLM\_SCN shows some variation between the decades and a small decrease over the period.

Overall the results from the RCMs and their comparison to ERA-Interim suggest a slight increase in risk of bluetongue incursions due to easterly winds. Large

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uncertainties are again present in this estimate, associated with the variations in the simulations of MSLP and length of the bluetongue season by the RCMs.

Model	No. of SW (Difference from ERA- Interim)	Rank	No. of E (Difference from ERA- Interim)	Rank
C4IRCA3_ECHAM5	41 (-41)	8	127 (-115)	5
C4IRCA3_HadCM3Q16	29 (-53)	11	411 (+159)	10
DMI_HIRHAM5_ARPEGE	31 (-51)	10	556 (+304)	13
DMI_HIRHAM5_ECHAM5	127 (+45)	9	134 (-118)	6
ETHZ_CLM_SCN	61 (-21)	6	275 (+23)	1
GKSS_CCLM	10 (-72)	14	917 (+665)	15
HadRM3Q3	65 (-19)	4	372 (+120)	7
KNMI_RACMO2	68 (-14)	3	200 (-52)	2
METNOHIRHAM_BCM	13 (-69)	13	518 (+266)	12
METNOHIRHAM_HadCM3Q0	77 (-5)	5	435 (+183)	11
MPI_M_REMO	337 (+255)	15	127 (-125)	8
SMHIRCA_BCM	22 (-60)	12	869 (+617)	14
SMHIRCA_ECHAM5	56 (-26)	7	187 (-65)	3
SMHIRCA_HadCM3Q3	103 (+21)	2	357 (+105)	4
Mean	74 (-8)	1	393 (+141)	9

**Table 5.3:** Comparison of the frequency of each pressure pattern type during the bluetongueseason calculated from the RCMs against the results from ERA-Interim for 2001-2010





South-westerly type during bluetongue season (bias corrected)

ii)

Top ranking south-westerly RCMs during bluetongue season (bias corrected)



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Easterly type during bluetongue season (bias corrected)



ii)

Top ranking easterly RCMs during bluetongue season (bias corrected)



**Figure 5.13:** The change in frequency of the (a) i) south-westerly and (b) i) easterly pressure pattern classifications from the ENSEMBLES RCMs during the average bias corrected bluetongue season in each decade from 2001 to 2050. The mean of the ensemble is shown in black and the observations from ERA-Interim are indicated with a black cross. Also displayed are the top three ranking models in a comparison to ERA-Interim for (a) ii) south-westerly and (b) ii) easterly pressure patterns.

### 5.3.5 The influence of the driving GCM on the results from the RCMs

Time series of the total number of occurrences of the patterns associated with midge incursions on individual days in the year during each decade were plotted for each RCM to further investigate disparities in their simulations of the seasonality of the pressure patterns. The plots show the number of times each RCM shows either a south-westerly pattern (indicated in green) or an easterly pattern (shown in blue) on each day of the year, with greater numbers of occurrences indicated by longer and darker coloured bars.

These plots clearly indicate the influence of the GCM on the results of the RCMs. Figures 5.13-5.16 highlight two examples where the GCM appears to dominate the timing of the occurrences of the two pressure patterns. Figure 5.14 and Figure 5.15 show two different RCMs, RACMO2 and RCA respectively, driven by the same GCM, ECHAM5. Figure 5.15 again shows results from the regional model, RCA but with the global model, BCM providing its boundary conditions in this case. BCM also acts as the driving GCM for the HIRHAM RCM in Figure 5.16.

Both regional models driven by ECHAM5 (Figure 5.14 and 5.15) display a fairly even spread of occurrences of south-westerly patterns for most of the year, but with a decrease in their frequency in summer. The easterly patterns are shown to be more frequent in spring and early summer, with fewer generally occurring in the winter.

The results for RCA are remarkably different when its boundary conditions are provided by a different GCM, BCM (Figure 5.16). In this example, the south-westerly pressure patterns occur very infrequently in summer, and are restricted to autumn, winter and spring. The easterly patterns show the opposite, occurring very frequently in summer and in very restricted numbers in winter. This pattern is also repeated by another RCM, HIRHAM5, when driven by BCM (Figure 5.17).

Visual inspection of time series plots (not shown here) of other overlapping RCM/GCM combinations (see Figure 5.1) also demonstrate that the GCM plays the dominant role in determining the seasonal distributions of MSLP patterns.

In terms of impact models or decisions based on the estimates for changes in the seasonal distribution of these pressure patterns, it would appear essential to include results from RCMs which are driven by different GCMs as they have such a dominant effect, resulting in widely different projections.



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**Figure 5.14:** Changes to the seasonal occurrence of south-westerly (green) and easterly (blue) pressure patterns types in RACMO2 driven by ECHAM5. The length of bars and colours are graduated to indicate the total number of occurrences of the pressure type on that particular day of the year during the specified decade.



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**Figure 5.15:** Changes to the seasonal occurrence of south-westerly (green) and easterly (blue) pressure patterns types in RCA driven by ECHAM5. The length of bars and colours are graduated to indicate the total number of occurrences of the pressure type on that particular day of the year during the specified decade.



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**Figure 5.16:** Changes to the seasonal occurrence of south-westerly (green) and easterly (blue) pressure patterns types in RCA driven by BCM. The length of bars and colours are graduated to indicate the total number of occurrences of the pressure type on that particular day of the year during the specified decade.



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**Figure 5.17:** Changes to the seasonal occurrence of south-westerly (green) and easterly (blue) pressure patterns types in HIRHAM driven by BCM. The length of bars and colours are graduated to indicate the total number of occurrences of the pressure type on that particular day of the year during the specified decade..

## 5.4 Discussion

The final stages of the methodology, based on the analysis pathway described by Stainforth et al. (2007a) (Section 5.2.1), involve assessing the results in terms of the decisions being made. The decisions considered here are not specific but include any where information about the changes in the future likelihood of midge-borne disease incursions could be valuable. These could range from whether to make use of insecticides on farms or to place a high level of investment in vaccine development and manufacture.

All of the models in the ensemble produced here demonstrated an increase in the length of the season where temperatures would be warm enough for bluetongue virus replication. Although there was wide variation in the magnitude of the individual RCM results, on average they suggested a lengthening of the season by 20 days. As this is long enough for an extra disease cycle it increases the risk of onwards spread following an incursion and could therefore have implications for many decisions.

Despite an increase in the average bluetongue season length, the majority of the ensemble members displayed a slight decrease in the occurrence of the south-westerly pressure pattern. Conversely, during this period easterly patterns were shown to slightly increase by the majority of models. The models which compared most closely to the results from the ERA-Interim dataset were also consistent with these trends. Overall the results suggest the risk of windborne incursions of midges, potentially acting as vectors, is not likely to significantly increase, nor will the risk strongly decrease. However if disease becomes established again on the coastline around Belgium, areas of the UK exposed to easterly winds from this region may face a slight increase in risk. An incursion of a midge-borne disease, such as on 4 Aug 2007 (Section 3.4.1), therefore remains a strong possibility if outbreaks occur again on the northern coast of the near-continent.

However it should be noted that these trends, for a slight decrease in south-westerly patterns and a slight increase in easterly patterns during the bluetongue season, are only found for the majority of models in the ensemble. In both cases a small minority of models differ from the other ensemble members in terms of the overall trend. A range of variation is also noted in the numbers of occurrences of each type. However some of the models which did not follow the overall trend also did not compare well to the ERA-Interim results. Their projections for future decades are therefore thought to be less reliable than those which more accurately represent current conditions.

Using data for the whole year period, the majority of RCMs suggested an increase in the number of occurrences of south-westerly pressure patterns. As it was also found that the frequency of south-westerly patterns would slightly decrease during the summer months (the bluetongue season), this suggests a large proportion of the overall increase would take place during the winter months. The converse was found here for easterly patterns. These results compare well with previous studies discussed in section 2.2.3.4. Studies of trends in recent historical data have found either an increase in westerly or south-westerly winds in northern Europe, particularly in winter (Casado et al., 2009, Corti et al., 1999, Hsu and Zwiers, 2001, Oldenborgh and van Ulden, 2003, Werner et al., 2000). Studies of changes to circulation types in future decades also suggest a similar trend for increasing westerly or anticyclonic flow in winter and decreasing westerly flow in summer (Donat et al., 2007, Terray et al., 2004, van Ulden and van Oldenborgh, 2006, van Ulden et al., 2007).

Only an initial evaluation of the models was carried out here, using observations from only one decade, as a full validation of the models was not the focus of this study. This should be addressed in future work to provide a more thorough assessment of the likelihood of different model projections and allow further quantification of the uncertainty in predictions of the risk of bluetongue spread under different synoptic conditions. Assigning probabilities to different models could be produced through a Bayesian framework such as the approach used in UKCP09 (Murphy et al., 2009). There are also issues surrounding the use of a subset of different RCMs to make predictions of future levels of risk, as different RCMs may not provide consistent projections of future climate. Future work could examine other performance metrics to further assess the quality of the RCMs allowing a fully weighted ensemble to be produced (Knutti et al., 2010).

The use of an ensemble of models, such as that used here, provides a useful approach to identify areas of uncertainty in their projections. One particularly large source of variability in the results appears to be the choice of GCM. The seasonal occurrence of the pressure patterns associated with midge incursions appears to be strongly dominated by the GCM. The PRUDENCE project also concluded that uncertainty in model predictions was generally larger from the choice of boundary conditions than the choice of RCM (Donat et al., 2007). Raisanen et al. (2004) suggests that regional differences between GCMs depend on differences in the model's large-scale circulation response to warming, and these differences are transferred to the RCM.

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Other sources of variability were likely to be a result of the subjective elements of the map-pattern classification technique. For example, the MSLP data were partitioned into 5 clusters for each decade for each RCM. This number of clusters was chosen based on the results from chapter 4 and was consistent with the results from Terray et al. (2004). However this may have resulted in too few clusters in some cases. This potentially could have caused some less commonly occurring patterns to be obscured by more dominant patterns. The final map-patterns were also manually classed into synoptic types through visual inspection. This process contained an element of subjectivity so may have led to some variation in the results, however in general the same common synoptic patterns were clearly visible in the map-patterns from the RCMs.

It should also be noted that the range of uncertainty presented for the results here does not represent the full 'cascade of uncertainty' (see Section 2.2.3.2). Some of the uncertainty has been explored using the ensemble of RCMs but a response may be possible outside the range presented here (Stainforth et al. 2007a). In particular, the influence of the climate sensitivity of the RCMs was not addressed here. The low and high climate sensitivity versions of HadRM3 did not produce comparable results with the other RCMs so were excluded from the analysis. The effect of climate sensitivity should be addressed in future work.

The results shown here, for changes in the frequency of windborne midge incursions, are only one aspect in a chain of the effects of climate change on the spread of midgeborne diseases into the UK. Decisions made in future relating to their control should also integrate estimates of the effects of climate change on changing distributions of vector midge species due to land use and agricultural practice changes, changes to the length of the midge season, midge activity levels and time for the virus to complete its EIP. Other non-climatic factors must also be given important consideration, including changes to animal susceptibility through both the use of vaccine or by increased natural immunity, and other sources of importation of foreign virus through increased tourism, movements of animals or transport of goods.

Given the wide uncertainty present in the results determined here any decisions made should be as robust to this uncertainty as possible (New et al., 2007). The decision-making processes should allow decisions can be reviewed and adjusted as new and improved information becomes available (Moss, 2007).

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# 5.5 Summary

Following the statistical techniques described in chapter 4, map-pattern classifications of MSLP have been produced for an ensemble of RCMs from the ENSEMBLE project for each decade in 2001-2050. Five different pressure patterns were found to consistently occur during each decade of the study period for the 16 RCMs used here. Two of these patterns, termed "south-westerly" and "easterly" due to the dominant flow direction indicated by the pressure distributions in each, showed strong similarity to the two pressure patterns found, in the previous chapter, to be associated with midge dispersal into the UK. The south-westerly and easterly patterns present in the RCMs are therefore also assumed to represent conditions conducive to midge incursions.

Changes in the frequency of occurrence of both of these patterns over the study period were analysed as changes in their frequency are assumed to indicate a proportional change in the incidence of favourable conditions for midge incursions. The analysis showed a slight increase in south-westerly patterns and a slight decrease in easterly patterns. However, these trends were not consistent across all of the ensemble members and large variability in the number of occurrences of each pressure type by the different models was noted.

As midge dispersal and bluetongue virus replication have strong seasonal dependence, changes in the occurrences of the pressure patterns associated with incursions were also investigated on a seasonal basis. This firstly required changes in the length of the bluetongue season, defined as when temperatures are warm enough for completion of the EIP in the vector, in each RCM to be examined. All of the models showed an increasing trend over the study period, with an average increase of 20 days. Examination of the changes in the frequency of pressure patterns during the average bluetongue season of each decade in each RCM showed a contrasting result to the occurrence of the patterns across the whole year. During the summer months, south-westerly patterns were indicated by the majority of models to slightly decrease and easterly patterns to slightly increase. The RCMs which compared most closely to the ERA-Interim observations for 2001-2010 were found to agree with these trends. However these trends were not consistent across all of the ensemble members and high levels of variability in the magnitude of their results were present. The use of different GCMs to force the RCMs was highlighted as a key source of uncertainty in the results. The dominant effect of the GCM boundary conditions was found to be clearly evident in the seasonal distributions of the pressure patterns.

In terms of the decisions which could be faced in future to prevent the spread of midgeborne diseases, it should be considered that the risk of an incursion remains a strong possibility if disease once again becomes established on the northern coast of the near-continent. Areas of the UK exposed to easterly winds from the area around the Belgian coast may face also face a slight increase in risk. The results found here also suggest the bluetongue season length could increase by an enough to allow an extra disease cycle to occur, therefore increasing the risk of spread following an incursion.

However due to the high level of uncertainty in the results, decisions should be made as robust to the different outcomes as possible and flexible approaches should be adopted to allow decisions to be adapted as better information becomes available. The results presented here should also only be considered as one part of the complex effects of climate change on midge-borne disease spread. Decisions should take an integrated approach to incorporate other important climatic and non-climatic factors.

# **Chapter 6**

# Conclusions

# 6.1 Thesis summary

Weather and climate strongly influence the spread of vector-borne diseases in both direct and indirect ways, through a range of environmental variables which can have either immediate or cumulative effects. As vector-borne diseases are highly susceptible to environmental conditions they are likely to respond rapidly to a change in climate. Due to the effects of the weather on the life-cycle and flight of its vector and the effects of temperature on development of its pathogen, bluetongue is one such disease whose future incidence could be greatly altered by climate change. It has been suggested, due to its spread northwards into Europe since 1998 that climate change has indeed already begun to effect its distribution. Large epizootics of several serotypes of the virus occurred in northern Europe from 2006 to 2009 which infected tens of thousands of holdings causing devastating losses of livestock and were estimated to have cost the economies of the affected countries several hundreds of millions of euros. The UK, with its situation as an island, is protected from short-distance 'vegetative' flight of the vector midges, but is susceptible to incursions of the disease when meteorological conditions are suitable for windborne carriage of infected insects from the near-continent. The overall aim of this thesis was therefore to devise methods to predict incursions of potentially infected midges into the UK at both daily and decadal climate change timescales to provide information to help inform decisions in the immediate and longterm in order to mitigate the impacts of the disease.

The two specific aims of the research project were to:

- Create a model capable of predicting occurrences of windborne incursions of midges into the UK from the near-continent, which could then form the basis of an early warning system to advise the UK government of time periods and locations exposed to a high risk of midge-borne disease outbreaks.
- Investigate if climate change may alter the frequency or timing of incursions of midges, potentially acting as vectors, by firstly determining under what current large-scale climatic conditions midge incursion events into the UK occur and

then assessing changes to these conditions in future decades with the use of data from climate models.

Previous models of bluetongue spread have used one of three main approaches, "statistical", "process-based" or trajectory models, which have different suitability depending on the particular application, and the temporal and spatial scales in question. Neither statistical nor process based approaches can be used to directly model movements of vectors between two localities, as was necessary to achieve the first aim of this research project. A mechanistic technique, based on a dispersion model, was utilised instead because of its potential capability to explicitly model windborne spread of the vector insects at high temporal and spatial resolution. The three traditional methods of modelling disease spread were deemed as not suitable to address the second aim of the thesis. This prompted the development of a new approach based on synoptic climatology techniques.

The first aim was achieved in chapter 3 where adaptations were made to a complex Lagrangian atmospheric dispersion model, NAME, to explicitly incorporate midge flight behaviour. The new midge dispersion model uses a quantitative estimate of the effects of temperature, precipitation, wind speed and the time of day and season on midge activity as its source term, and a new deposition scheme was developed to include the effect of precipitation on midge flight during their subsequent windborne dispersal. Case studies, where outbreaks of bluetongue were found in regions separated from the nearest source of virus by stretches of sea, were used to evaluate the model. In each of the five cases examined the timing and locations of the windborne midge plumes calculated by the model were consistent with the epidemiological situation. The NAME midge model was thus concluded to perform well as a tool for post-outbreak epidemiological analysis. In addition, the model was used to form the basis of an early warning system operated for Defra from 2007 to the present. The system predicted the location of the first UK outbreak of bluetongue in September 2007 and was used to inform decisions which greatly benefited the UK economy.

The second aim of this project was completed in two stages, the first of which, as described in chapter 4, was to determine the large scale climatic conditions under which midge incursion events into the UK occur. Firstly a map-pattern classification of MSLP was produced, using a combination of PCA and cluster analysis, to elucidate the main circulation patterns present over the study area of northern Europe. Results from the NAME midge dispersion model were related to the map-patterns and it was determined that the majority of incursions are associated with two circulation patterns.

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These patterns were dominated by pressure distributions which lead to either southwesterly or easterly winds from the near-continent towards the UK and appeared to be physically consistent with current knowledge of the effects of local weather on midge flight.

The second part of the final aim was accomplished in chapter 5, where changes to the occurrence of the pressure patterns associated with midge incursions in the UK were investigated in future decades using data from RCMs. Following the statistical techniques developed in chapter 4, map-pattern classifications of MSLP were produced for an ensemble of RCMs from the ENSEMBLE project for each decade in 2001-2050. Patterns indicating south-westerly winds and easterly winds over the UK were present in the results from each decade in each RCM and showed strong similarity to the pressure patterns found in the previous chapter to be associated with midge incursions.

Analysis of changes in the frequency of occurrence of both of these patterns over the study period, when taking into account all days in the year, showed a slight increase in south-westerly patterns and a slight decrease in easterly patterns. However examination of changes in their occurrence during just the bluetongue season showed the opposite trend was present. One further important finding determined during this analysis was that all the ensemble members showed a lengthening of the bluetongue season by enough to allow an extra disease cycle to occur on average. In all the results high level of uncertainty was present and should be an important consideration in any decisions taken.

## 6.2 Conclusions

This thesis has developed two different modelling approaches which have allowed predictions to be made of incursions of midges, potentially acting as vectors of bluetongue, into the UK at both daily and decadal timescales. These predictions have been used to provide advice to the UK government during the 2006-2009 bluetongue epizootic and could be used in decision making processes in the future to limit the impact of future vector-borne disease incursions under climate change.

The midge dispersion model developed in chapter 3:

 Is the first to explicitly include midge flight parameters and is based on the latest and most comprehensive set of experimental data available for the effects of meteorology on their daily and seasonal levels of activity.

- Has been demonstrated to be a useful tool in post-outbreak analysis; it was consistent with epidemiological evidence in five case studies and during an inter-comparison with an unmodified Eulerian dispersion model was found to compare well and provide fewer false positive results.
- Was also found to perform well in forecast mode, where the location of the first UK incursion of bluetongue in September 2007 was highlighted by the early warning system to be at risk in the preceding August.
- Provided input into decisions taken by the UK government regarding restriction zones and targeted vaccination schemes which were stated to have saved the UK economy £500 million and 10,000 jobs.
- Also has some limitations. The NAME midge model only shows plumes of relative concentrations of 'midge' particles as no data are available for local midge populations becoming airborne on the near-continent to improve the estimate of the source term. The results also describe movements of all midges and not just those which are infected.

The synoptic climatology techniques applied in chapter 4:

- Were a novel approach to understand the effects of meteorology on midgeborne disease spread by providing insight into the relationship between largescale synoptic circulation patterns and the local weather suitable for incursions of vector midges into the UK from the near-continent.
- Produced a map-pattern classification of MSLP over northern Europe which compared satisfactorily with observations.
- Determined that the two large-scale pressure patterns are particularly associated with midge incursions into the UK. The first displays south-westerly winds associated with cyclonic conditions over the UK and suggests the presence of a tropical maritime air mass. The second pattern shows easterly winds directed towards the UK associated with anti-cyclonic conditions and tropical continental air.
- Could also be applied to data from climate models to investigate changes in the synoptic scale conditions related to midge incursions.
- Were, however, only produced for a three year period due to computational limitations. This short period may have been too limited to be a complete representation of the synoptic scale pressure patterns which occur over the

region. Additionally the partitioning of the data into 5 clusters may have been too broad, resulting in less frequently occurring patterns becoming obscured by the dominant modes of variation.

In chapter 5, synoptic climatology techniques applied to an ensemble of RCMs to analyse the effects of climate change on midge incursions found:

- The south-westerly and easterly patterns, representing conditions conducive to midge incursions, were found to slightly increase and slightly decrease respectively in the majority of models when considering all days in the year in the study period from 2001-2050.
- During days in the bluetongue season only the opposite trends were present, with a slight decrease in south-westerly patterns and a slight increase in easterly patterns shown by the majority of RCMs and those which compared well against observations.
- An increase in the length of the bluetongue season by an average of 20 days over the study period as a whole.
- High level of uncertainty was present in all of the results. The influence of the GCM boundary conditions on the individual RCM's seasonal distribution of pressure patterns was clearly evident.
- In terms of the decision faced in future to mitigate the effects of midge-borne disease, it should be considered that the risk of an incursion remains high if a source of virus becomes established on the near-continent. Areas under the influence of easterly winds from infected areas may face a slight increased level of risk. The risk of increased spread following an introduction event is also suggested to be heightened, due to the average lengthening of the bluetongue season by long enough for an extra disease cycle.
- Decisions based on these results should, however, be flexible to allow for different adaptation options to be considered as better information becomes available.

# 6.3 Scope for future work

The research carried out here has improved our understanding of the meteorological effects on the invasion of bluetongue and subsequently has increased our capability of predicting these events. However successful transmission of vector-borne disease involves the integration of several components; firstly the environment must be suitable for the vectors and pathogen, these must then invade the area, become established and subsequently spread can occur. As shown in Figure 6.1 and described in Chapter 2, different modelling approaches have been designed to predict other aspects of disease transmission dynamics. In order to provide an enhanced picture of the effects of climate change on vector-borne disease, future work should aim to take a holistic approach involving models for each component contributing to their spread. The influence of non-climatic factors and mitigation and adaptation measures taken to limit disease spread are also often neglected. Their potentially important effects should also be included in future studies.



**Figure 6.1**: A schematic representation of a holistic approach to the modelling of vector-borne disease transmission dynamics, displaying how different methods can be used to model the different components. The techniques used in this thesis to model the invasion component by vector dispersal are highlighted.

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Within the invasion component of disease transmission which was the focus in this thesis there are two main aspects which could benefit from further research. The work here has only considered long-distance dispersal of bluetongue into regions separated by stretches of sea, in order to rule out spread by 'vegetative' midge movements which are poorly understood and therefore difficult to model. Research has recently begun to be carried to understand the role of meteorology in local scale midge flight and future version of the NAME midge model will include these effects where possible to allow predictions to be made of bluetongue spread within-country following an introduction event. The other area with much potential for future research involves the prediction of bluetongue incursions on a seasonal timescale. It may be possible, as skill improves in seasonal forecasting, to combine knowledge of synoptic conditions for the coming months with the results found here for the large-scale climatic conditions suited to midge incursions to estimate their likelihood in advance of the bluetongue season.

Both the dispersion and synoptic climatology approaches developed in the course of this research are immediately applicable to other midge-borne diseases currently not present in northern Europe and could easily be transferred to other areas of the world exposed to disease risk. Other serotypes of bluetongue are still entering Europe on an annual basis and related orbiviruses which share the same or similar vectors, such as AHSV and EHDV, present a real possible threat to the UK in the coming years. The early warning website, originally developed for the spread of BTV-8 into the UK is not limited to this function. The case studies carried out for post-outbreak analysis of bluetongue spread into Denmark, Sweden and Norway demonstrate the adaptability of the modelling to other areas of the world. The model could therefore also have been operated as an early warning system in these, and other, cases.

Finally there is vast scope for NAME to be adapted to other vectors, pests, viruses and spores which damage the health of humans, animals or plants. For example, initial work has begun to include the specific flight parameters of moths within NAME (Chapman et al., 2010) and to study the dispersal of fungal plant spores.

## 6.4 Concluding remarks

This thesis has investigated the impacts of weather and climate change on windborne spread of bluetongue into the UK from the near-continent of Europe and describes two novel methods to predict these incursions at a range of temporal scales. The NAME midge model developed here has already played an important role in decisions taken by the UK government to curtail the impact of bluetongue during the 2006-2009

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northern European epizootic. Future predictions of vector-borne disease spread under climate change should take a holistic approach to incorporate a range of modelling approaches suited to each different aspect of disease transmission. The synoptic climatology techniques described here provide a new, alternative approach to evaluate the invasion component of disease spread. Both modelling techniques developed in this thesis could be adapted to encompass a range of vectors, pests, viruses and spores potentially posed to threaten the UK, or other areas of the world, in future decades due to climate change and hence provide useful input to decisions taken to mitigate their impact.

# Glossary

**eddy** a transient (both spatially and temporally) fluid motion of a rotational character, superimposed on the mean flow.

**epizootic** a rapid and persistent increase in morbidity and/or mortality, above normal levels, in a given population by a virulent disease agent during a specific time period.

**extrinsic incubation period** the interval between the acquisition of an infectious agent by a vector and the vector's ability to transmit the agent.

**geostrophic wind** the speed and direction of atmospheric flow which results from a balance between the Coriolis force and the pressure gradient force.

**haematophagous** insects which require blood either as a major nutrient or for production of fertilized eggs.

**Normalized Difference Vegetation Index** a measure calculated from visible and nearinfrared light reflected by vegetation which indicates the level of live green vegetation present.

**overwintering** the survival of an infectious agent or its vector through the winter, during which time it does not infect a host.

**Palearctic** one of eight ecozones dividing the Earth's surface and includes Europe, Asia north of the Himalaya foothills, northern Africa, and the northern and central parts of the Arabian Peninsula.

**sentinel** an animal known to be susceptible to an infectious agent that is placed in the area suspected of being contaminated in order to monitor virus spread.

**seroconversion** the development of detectable specific antibodies as a result of infection or immunization.

**serotype** a subdivision of a virus strain distinguished by a protein that determines its antigenic specificity.

**synoptic** the scale at which regional weather phenomena occur (generally several hundred kms).

**thoracic** refers to the thorax; the abdomen of an insect where the wings and legs attach.

**vector competence** the ability of an arthropod (insect) to acquire, maintain, and transmit microbial agents.

**zoonotic** a disease of animals that is transmissible to humans.
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