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Review Article

Use of meteorological data in biosecurity

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Pests, pathogens and diseases cause some of the most widespread and damaging impacts worldwide — threatening lives and leading to severe disruption to economic, environmental and social systems. The overarching goal of biosecurity is to protect the health and security of plants and animals (including humans) and the wider environment from these threats. As nearly all living organisms and biological systems are sensitive to weather and climate, meteorological, 'met', data are used extensively in biosecurity. Typical applications include, (i) bioclimatic modelling to understand and predict organism distributions and responses, (ii) risk assessment to estimate the probability of events and horizon scan for future potential risks, and (iii) early warning systems to support outbreak management. Given the vast array of available met data types and sources, selecting which data is most effective for each of these applications can be challenging. Here we provide an overview of the different types of met data available and highlight their use in a wide range of biosecurity studies and applications. We argue that there are many synergies between meteorology and biosecurity, and these provide opportunities for more widespread integration and collaboration across the disciplines. To help communicate typical uses of meteorological data in biosecurity to a wide audience we have designed the 'Meteorology for biosecurity' infographic.

Introduction

Biological systems embrace all of life on Earth. Maintaining the health and security of ecosystems is an immense global challenge, yet it is vital for ensuring economic, social and environmental resilience, and progress towards the UN Sustainable Development Goals [1,2]. Biological security, 'biosecurity', refers to the precautions taken to minimise risks to biological systems from harmful organisms (pests and pathogens) and their associated diseases [3]. Although biosecurity activities may focus on specific sectors, e.g. agricultural management [4], risks, e.g. avian influenza outbreaks [5], or locations, e.g. infectious diseases in Central Africa [6], the overarching principles of biosecurity call for risk-based, interdisciplinary approaches with close collaboration and communication across sectors, organisations and regions [3,7,8].

In recent decades, biosecurity risks have increased rapidly as the global growth in trade and travel have multiplied international connectivity, and as environmental changes have modified the distribution and behaviour of living organisms [9]. Meteorology (including weather and climate) is one of the key environmental drivers of these changes, and it is therefore an important consideration for biosecurity.

Meteorological, 'met', data have a wide range of uses in biosecurity, e.g. as input to bioclimatic models for understanding and predicting organism behaviour or distribution [10], for Early Warning Systems (EWSs) to manage outbreaks [11], and for assessing future climate change effects on pests, pathogens or diseases [12]. Given the vast and diverse availability of met data sources, understanding their suitability and availability for use in biosecurity applications is a challenge.

In this paper, to address this challenge we first summarise the different types of met data available. We then discuss how met data are used for a wide range of biosecurity applications and consider synergies and opportunities for improvements (highlighted in text boxes).

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Overview of meteorological data

Met data are available from an array of instruments, sensors and models, covering different spatial and temporal resolutions and with varying levels of uncertainty. This section provides an overview of the main types of met data with examples of how these are used for biosecurity. For clarity, met data are categorised into seven broad types: (a) Land and ocean *in situ* and gridded observations; (b) Microclimate observations and model estimates; (c) Atmospheric dispersion and trajectory model estimates; (d) Satellite products; (e) Reanalyses; (f) Model forecasts and projections. Table 1 provides examples of common data sets for each of these types and web links for data access. The importance of uncertainty estimates, which are routinely estimated across met data types, is also highlighted. Many of the sources of data discussed here are regularly used in biosecurity, although some are less well known to the biosecurity community and may provide additional opportunities in this field.

Land and ocean *in situ* and gridded observations

The World Meteorological Organisation (WMO) Global Observing System (GOS) coordinates the surface-based observing systems of over 20 000 sites around the world — including about 11,500 land stations, 1000 weather radars, 4000 reporting ships, 1250 drifting buoys, 500 moored buoys [13]. Despite being composed of a multitude of small observing networks operated by nations and international bodies, observing standards and reporting practices are followed and billions of observations are exchanged in real time between WMO members each day. These include a wide range of variables mostly observed at hourly or three hourly intervals. Weather radars have been used to identify the type and intensity of precipitation since the 1950s. The WMO provide details on current radar locations across the globe and a database of recent observations (https://wrd.mgm.gov.tr/).

The time span and spatial distribution of surface records varies considerably. In some places, met observations, particularly temperature, have been recorded for hundreds of years. However, it wasn't until around 1880 that formal weather stations became abundant enough to provide a clear representation of global temperature. Data rescue projects recover written data from various surface records, e.g. the Atmospheric Circulation Reconstructions over the Earth project (ACRE, [14]) digitises historical surface met records spanning the last 200–250 years and uses these in reanalyses to provide freely available global 3D met reconstructions. Gridded daily and monthly data sets are created by interpolating between station observations onto a regular grid. Such data are available for a wide range of grid resolutions and regions, including global [15,16]. Although the spatial resolution of gridded data for each data set is typically the same across the region of interest or globe (typically between 0.25°–5° for global data), some regions, e.g. parts of Siberia, Africa and central Amazon, are represented by very few met stations which can introduce significant uncertainties in the gridded data. Many gridded data sets now include estimates of these uncertainties with the product.

In situ and gridded surface observations have been used extensively in biosecurity applications, especially as input for biological models to predict species or disease distributions and understand sensitivities to weather and climate changes. As well as providing data on precipitation, weather radar is also emerging as a useful tool for studying insect dispersal e.g. https://biodarproject.org.

Microclimate observations and model estimates

There are many definitions of microclimate. Broadly, it is regarded as high resolution spatial and/or temporal climate variations that occur at the interface between the surface and the atmosphere and are decoupled somewhat from the background atmosphere [17]. Spatial scales less than 100 m and temporal scales of seconds to hours are typical [18,19]. Microclimates develop as a result of high-resolution variability in biotic and abiotic features including topography, soil type, and land surface (particularly vegetation) characteristics. This detail is not captured by met stations which aim to represent background near-surface atmospheric conditions. While some satellite sensors can capture high resolution surface information (up to 10 m with EU Copernicus' Sentinel 2 [20]) and LIDAR for finer resolutions [21], microclimate data are usually either collected using tiny loggers located within habitats or simulated with a microclimate model [22]. Microclimate data are not routinely available online, although some databases are being developed (see Table 1).

Microclimates are particularly relevant for biosecurity because most pests and pathogens are small, and their life cycles are conducted in microclimates e.g. buried in soil, underneath leaves or within small water bodies [23].

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Table 1. Use of meteorological data in biosecurity Part 1 of 2

Type	Common met data sets and access links
Station and gridded observations	◆ ***CEDA Archive*** UK Natural Environment Research Council's Data Repository for Atmospheric Science and Earth Observation: https://catalogue.ceda.ac.uk ◆ ***Copernicus/C3S*** Copernicus Climate Change (C3S) service — gridded Essential Climate Variables and indices for Europe: https://surfobs.climate.copernicus.eu/ ◆ ***ECA&D*** European Climate Assessment and Dataset project — including E-OBS Europe daily gridded climate observations and indices: https://www.ecad.eu/ ◆ ***GCOS*** Global Climate Observing System — including wide range of global surface data and Argo network of ocean temperature/salinity data: https://www.ncdc.noaa.gov/gosic/global-climate-observing-system-gcos ◆ ***HadOBS*** UK Met Office Hadley Centre observations datasets — including ***HadCRUT4*** and ***HadCRUH*** (global monthly gridded temperatures and humidity), ***HadISST*** (global sea-ice and sea-surface temperature), ***HadEX*** (Indices of climate extremes), ***HadCET*** (Central England temperature record): https://www.metoffice.gov.uk/hadobs/ ◆ ***NOAA - NCEI*** US National Oceanic and Atmospheric Administration — National Centres for Environmental Information, wide range of surface and other data sets: https://www.ncdc.noaa.gov/data-access
Microclimate observations and model estimates	◆ ***MICROCLIM*** observation database and model code: https://sites.google.com/view/microclim ◆ ***Microclim*** microclimate database: http://microclim.org/ ◆ ***SOILTEMP*** soil temperature observations: https://soiltemp.weebly.com/
Atmospheric Dispersion Model outputs	◆ ***CEDA Archive*** Dispersion model footprint data for various sites, see link above ◆ ***WMO*** list of various dispersion models and database links: https://community.wmo.int/dispersion-models
Satellite products	◆ ***Airbus' GeoStore***: https://www.intelligence-airbusds.com/geostore/ ◆ ***CEDA Archive*** Satellite data, see link above ◆ ***ESA*** European Space Agency's earth online: https://earth.esa.int/eogateway/ ◆ ***EU Copernicus*** satellite data access hub: https://www.copernicus.eu/en/copernicus-satellite-data-access ◆ ***GIS Geography*** range of satellite data for GIS applications: https://gisgeography.com/free-satellite-imagery-data-list/ ◆ ***Google*** Earth Engine public data archive: https://earthengine.google.com ◆ ***NOAA-NCEI*** Including satellite data, see link above ◆ ***NASA***'s Earth Observing System Data and Information System (EOSDIS): https://earthdata.nasa.gov/earth-observation-data
Reanalyses	◆ ***ACRE ERA-20C*** *NOAA* Atmospheric Circulation Reconstructions over the Earth 20th century reanalysis: http://www.met-acre.org/ ◆ NCEP Reanalysis (R2) US National Centres for Environmental Prediction global: https://climatedataguide.ucar.edu/climate-data/ncep-reanalysis-r2 ◆ ***NOAA-NCEI*** Including reanalysis data, see link above ◆ ERA-15 European Centre for Medium Range Weather Forecasting global reanalysis: https://climatedataguide.ucar.edu/climate-data/era-15 ◆ See summary table of wide range of reanalysis and data links: https://climatedataguide.ucar.edu/climate-data/atmospheric-reanalysis-overview-comparison-tables.
Model forecasts and projections	**Weather** ◆ ***Global open data index***: https://index.okfn.org/dataset/weather/ ◆ ***NOAA-NCEI*** Including National Weather Prediction and RADAR data, see link above ◆ ***WMO*** official weather forecasts global: https://worldweather.wmo.int/en/ **Medium range** ◆ ***ECMWF*** medium range (15 day ahead) forecasts ECMWF: https://www.ecmwf.int/en/forecasts/documentation-and-support/medium-range-forecasts **Subseasonal, seasonal to decadal** ◆ ***C3S*** Copernicus seasonal forecast products: https://climate.copernicus.eu/seasonal-forecasts ◆ ***NOAA-NCEI*** Including seasonal forecast data out to 9 months, see link above

Continued

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Table 1. Use of meteorological data in biosecurity Part 2 of 2

Type	Common met data sets and access links
	◆ ***UK MO*** global long-range model probabilities 2–4 months ahead: https://www.metoffice.gov.uk/research/climate/seasonal-to-decadal/gpc-outlooks/glob-seas-prob ◆ ***S2S*** Subseasonal to seasonal prediction project: http://s2sprediction.net/ ◆ ***SPECS*** Seasonal-to-decadal climate prediction model outputs on CEDA archive: https://catalogue.ceda.ac.uk/uuid/2d9c5f2cc621fb9bc0062356851b31b9 **Climate/Earth System Model ensembles including projections** ◆ ***PCMDI – CMIP*** Program for Climate Model Diagnosis and Intercomparison – Climate Model Intercomparison Project: https://pcmdi.llnl.gov/about.html ◆ ***ENSEMBLES*** climate change projections: http://www.ensembles-eu.org/

Atmospheric dispersion and trajectory model estimates

Atmospheric dispersion models (ADMs) are mechanistic models that describe the spatial and temporal transport of gases and particles (including chemical pollutants, particulates, bioaerosols, dust and radioactive matter) in the atmosphere [24]. Various input data are required to parameterise and drive ADM simulations, e.g. meteorological variables, surface characteristics and particle traits, and their main outputs are spatial and temporal estimates of particle concentrations in the atmosphere and deposition rates on surfaces [25]. There are a wide range of modelling approaches employed by ADMs depending on the requirements and limitations of the applications [26].

ADMs are used in biosecurity for estimation of pest, pathogen or virus airborne incursions, tracing of source locations, and identification of dispersal behaviour mechanisms [27,28].

Satellite products

Satellite remote sensing provides a primary source of data for large-scale environmental mapping and surveillance [29]. Over the last 50 years, advances in satellite and sensor technology have introduced substantial refinements in spatial, temporal, spectral and radiometric resolutions, enabling increasingly diverse applications [17,30]. At the same time, the number and variety of satellite products have increased spectacularly (see https://gisgeography.com/earth-satellite-list/), ranging from direct observations of surface radiance to derived products that apply algorithms to radiance measurements to estimate the variable of interest.

Data are available from two main types of satellites — polar-orbiting and geostationary. Polar-orbiting satellites circle the earth in a sun-synchronous orbit at lower altitudes than geostationary and are, therefore, generally able to sense higher spatial resolution, with temporal resolution that is dependent on the orbit return time. In contrast, geostationary satellites sample a large area of the earth at relatively high temporal resolution.

Many satellite products are relevant for biosecurity applications, e.g. land surface temperature, sea surface temperature, near-surface humidity, soil moisture, ocean colour, land cover and type, and indices of vegetation health such as Normalised Difference Vegetation Index (NDVI). Although there are massive volumes of satellite data available, there are also many tools, techniques and guidance to access and analyse the data (see Table 1).

Reanalyses

Reanalyses, 'retrospective analyses', are a blend of historic met observations and models, where observation data from a range of sources, including surface stations, ships, aircraft and satellites, are incorporated into a met model using a process known as data assimilation [31,32]. For a global reanalysis, typically millions of individual observations are assimilated at every model time step, usually 6 to 12 h [33]. Reanalyses differ from weather forecasts (see below), which also employ data assimilation, in that the model used in a reanalysis is unchanging throughout the length of the historic period over which it is run. This avoids artificial changes in outputs that may occur as a result of periodic model improvements [34].

Reanalysis data are available from a wide range of models, historic periods and regions [33]. They are popular in weather and climate research because of the many met variables available over long time periods, typically decades. They also offer a wide range of modelled variables and complete, realistic representations of

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atmospheric processes, enabling multiple processes and inter-relationships to be studied. While observations are integral to reanalyses, it is important to remember that reanalysis data are model derived, with strengths and weaknesses associated with the specific variables, time periods, techniques and models. Spurious trends and variability have been observed in reanalysis data, and particular caution is recommended for hydrological variables such as precipitation and evaporation [34].

For biosecurity applications, reanalysis data have many uses, including as inputs for risk assessments [35], species distribution modelling [36], and climate suitability mapping [37].

Model forecasts and projections

Like reanalyses, met forecasts and projections are based on numerical models and observations. These models estimate the physical processes and dynamics of the atmosphere, and other processes in the Earth system that interact with meteorology, such as atmospheric chemistry and land and ocean exchanges. To provide a representation of the uncertainties involved, most met forecasts and projections are based on ensembles — multiple different, but plausible, realisations of the conditions.

Weather forecasts are the most publicly well-known applications of met models. These predict the short-term (∼ 1 h to 1 week ahead) changes in weather for the spatial domain of the model. They have been used extensively for biosecurity applications that require rapid data dissemination and response, such as EWSs, outbreak management, and pesticide application [38].

Medium-range weather forecasts generally extend to 10 days ahead. At these timescales the influence of initial atmospheric conditions, used to initialise the model, reduces and chaotic processes in the Earth system become more dominant. These timescales are considered the limit for day-to-day predictability [39]. Forecasts are also available for extended- and long-range (46 days and 3–7 months ahead, respectively) associated with longer-term predictability in the climate system. Services based on medium-range forecasts are particularly useful for farmers to guide decisions on pest and disease predictions and control measures [40].

Subseasonal, seasonal to decadal forecasts make use of important long-term sources of predictability within the Earth system, e.g. the Madden-Julian Oscillation or El-Niño Southern Oscillation, which provide potential for forecasts from 1 month up to 1 decade ahead [39,41–43]. Although these forecasts are generally more uncertain than weather forecasts, for biosecurity applications there are many opportunities to utilise these as input to pest, pathogen and disease EWSs [44], or for strategic agricultural decisions, e.g. the type of crop to sow [40].

Climate and Earth System Models (ESMs) are essentially similar to forecast models, except they are configured with data and information relevant for climate timescales and forced with past or future projections of external factors that influence climate, including long-lived greenhouse gases, aerosols, land use change, and volcanic eruptions [45]. Future projections usually use Representative Concentration Pathways (RCPs), which are plausible future descriptions of the external factors based on socio-economic scenarios of global societal development. Coordinated ESM simulations using a range of models and experiments, e.g. the Coupled Model Intercomparison Project (CMIP), are commonly used for multi-model comparisons and uncertainty estimation [46]. Model projection data have been applied to many biosecurity applications to assess the potential influence of future climate change on pest, pathogen or disease distributions [47,48].

Representing uncertainties

Uncertainties are inherent in all meteorological observations and model data. They occur for a variety of reasons depending on the instruments, platforms and modelling approach. Efforts to represent these have increased over recent decades, and it is now standard for met data to either be accompanied by uncertainty estimates, or for models to run ensembles (multiple plausible realisations) to enable uncertainties across the ensemble to be represented [49–52].

For weather or climate/earth system models three broad types of uncertainty are generally considered - Natural variability, Scenario uncertainty and Model uncertainty [53]. Natural variability explains the temporal variations in weather or climate variables around a mean state due to non-anthropogenic processes. These processes may be 'internal', within the weather or climate system, e.g. El Niño, or 'external' as a result of natural forcings outside this system, e.g. solar activity. Scenario uncertainty occurs when models are used for future projections. In this case, models are driven by socio-economic scenarios, e.g. RCPs, that span a range of assumed possible futures. Lastly, Model uncertainty arises because models by their nature are incomplete

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representations of reality. Some processes and parameterisations vary between models, and multi-model ensembles are used to try to quantify the spread in modelled outputs due to these differences.

Although some biosecurity studies have included meteorological uncertainties, e.g. [54], opportunities exist for more routine representation of met uncertainties in biosecurity risk assessments and forecasts.

Application of met data in biosecurity

In this section, we draw on examples from around the world to highlight how met data have been used for biosecurity applications. For clarity, the discussion is structured around the following four pillars of biosecurity identified by the UK Biological Security Strategy (2018). These characterise the general actions taken to manage biosecurity risks regardless of the sector, timescale or location:

Understand *the biological risks we face today and could face in the future.*

Prevent *biological risks from emerging (where possible) or from threatening the UK and UK interests.*

Detect*, characterise and report biological risks when they do emerge as early and reliably as possible.*

Respond *to biological risks that have reached the UK or UK interests to lessen their impact and to enable a rapid return to business as usual.*

Overarching these pillars is the requirement for all stages in the response to be supported by sound scientific knowledge and data, and strong international and cross-sector collaboration. Synergies and opportunities for improved uses and collaborations between the biosecurity and meteorology communities are discussed throughout and summarised at the end of this section.

Understand

To implement appropriate biosecurity policies and actions, it is first necessary to understand the nature and sources of biological risks. This is typically done through risk assessments that integrate quantitative data and qualitative information on specific hazards, vulnerabilities and exposures to provide estimates of risk that are useful for end users [55].

Met data are often a vital part of biosecurity risk assessments because many pests, pathogens and diseases are sensitive to changes in weather or climate. For example, met data are regularly combined with biological models to, (i) assess pest, pathogen or disease sensitivities to weather variations [56] or climate trends [57], (ii) understand the risk of establishment of non-native species [58] or spread of native species [59], (iii) understand the epidemiology and dynamics of diseases [60], and (iv) assess the timing of organism activity in order to estimate risks to host species [61]. When process-based biological models are unavailable, correlative models that use met and other environmental data as model covariates (or predictors), e.g. soil moisture, land cover or vegetation condition indices, have proved successful especially for modelling the distribution of arthropod vectors, such as ticks, which have sensitivities to both meteorology and habitat [62]. When deriving statistical relationships between climate data and species responses it is important to consider recent trends in climate e.g. warming, and how the time span of the climate data used may influence the estimated relationships.

Data derived from future climate projections using ESMs improves understanding of how different RCPs may affect biosecurity risks and the subsequent biosecurity implications of and changes [63], e.g. area with a suitable climate for establishment of new or emerging pests, pathogens or diseases [64–66], waterborne pathogen concentrations [67], or human infectious disease risk and potential for adaptation [68].

Met observation, satellite and model data are also available over lakes and oceans to assess biosecurity risks to aquatic species and environments. These can be linked with other environmental data, e.g. sea surface temperature, salinity or ocean colour, to understand specific sensitivities and responses, as well as forecast and monitor changes [69].

Well-established species distribution or climate suitability models such as CLIMEX or MaxEnt use met variables, including monthly minimum and maximum temperature, rainfall, and relative humidity, as inputs [70,71]. These models have been used globally to predict potential geographical distributions of pests, pathogens and diseases, e.g. regions of overwintering of the beet armyworm, *Spodoptera exigua*, in China [72], potential geographical distribution of *Aedes albopictus* and *Aedes aegypti*, the mosquito vectors for a range of human diseases, in South Korea [73], or mapping worldwide ecoclimatic niches of *Culicoides imicola*, the midge vector for Bluetongue and African Horse Sickness viruses [66].

Meteorology influences biosecurity risks in many ways. Temperature is particularly important for understanding risks from vector-borne diseases transmitted by ectothermic (cold-blooded) arthropod species such as mosquito, tick, sandfly or blackfly [74–76]. Met extremes and thresholds are also important for assessing the potential for overwintering survival [77] or for tolerance to heatwaves and droughts [78]. Many vectors and viruses are sensitive to a combination of met conditions during different life cycle stages, e.g. dengue fever risk is associated with moisture availability for the development of the *Aedes* mosquito vector at breeding sites [79], then temperature, humidity and wind influence adult vector longevity, feeding, mating and dispersal as well as virus replication [80,81].

Wind speed and direction are vital for understanding dispersion plumes and potential incursions across borders, e.g. incursions of *Culicoides*, the Bluetongue midge into UK [82] or Sicily [83], or Wheat rust diseases in Ethiopia [84]. Although wind data are available from most sources of met observations or models and can be used for simple dispersion estimates, ADMs or trajectory models (see above) are typically needed to capture the complex dynamics and interdependencies involved in atmospheric dispersion and deposition [25].

A key challenge using met data in biosecurity risk assessments is ensuring the spatial and temporal scale of the data are comparable with the scale relevant for the organism [17,85]. Estimates of organism responses to met variations have been shown to vary significantly depending on the scale of the climate data used [86]. This is particularly important in data sparse regions, e.g. a review of studies on met variability and infectious disease in Central Africa identified 23% of studies with a mismatch in spatial scales between the met and disease data used [6]. Microclimate observations and models help to bridge the gap in scales between met data and organism size [87].

Opportunities exist for biosecurity applications to make more use of the range of earth system variables available from satellites, reanalyses, forecast models and ESM projections, e.g. land and ocean surface temperature, vegetation indices, and soil moisture.

Prevent

To prevent biological risks from emerging or threatening the health and security of humans, animals or plants it is necessary to pre-empt or forecast the occurrence of the risk and put measures in place to impede or eradicate it. Building the resilience of species or systems at risk helps to reduce or prevent impacts. With diseases, it is also possible to develop prophylactic medication to prevent illness.

EWSs and other decision support tools that utilise met data are central to many biosecurity prevention efforts. These have proved particularly successful for crop and livestock protection via web tools, EWSs and bulletins that inform about emerging risks, e.g. [38]. Likewise for human health risks met-based EWSs and outlook forums have been developed to predict and disseminate disease forecasts, such as the Malaria Early Warning Systems (MEWS) for Africa which incorporate health and climate information to provide an operational EWS for malaria bringing together met and health experts from the responsible national agencies [88].

Horizon scanning, the systematic examination of future potential threats and opportunities from invasive alien species (IAS), is an essential part of managing new and emerging pest and pathogen risks [89,90]. It is regularly combined with surveillance and expert guidance to prioritise preventative actions and build resilience in threatened systems, e.g. [91]. Met data, particularly climate projections, have been used extensively as inputs for horizon scanning activities and tools [92].

Another, relatively recent form of EWS for plant pests and pathogens is the International Plant Sentinel Network [93]. This uses individual plants, 'sentinels', that are outside their native range to monitor and understand the damage caused by pests or pathogens they would not usually encounter. These exotic plants are located within botanic gardens and arboreta where surveillance is relatively straightforward, and often met

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observations are available on site. This network is ideal for validating pest/pathogen model estimates and identifying which botanic gardens should be matched.

Opportunities exist to support more rapid and widespread communication of biosecurity warnings by greater integration of meteorological and biosecurity EWSs and existing national and international dissemination networks around the globe.

Detect

Rapid and reliable detection of biosecurity risks is essential for implementing appropriate responses and minimising damage. As well as proactive and targeted inspection programmes (e.g. the USDA Animal and Plant Health Inspection Service [94], UK Government Fish Health Inspectorate [95], Keeping Watch Biosecurity New Zealand [96], passive surveillance methods include large-scale monitoring of risk indicators, e.g. radar detection of insect pest migration and swarms [97,98], or citizen science efforts to identify pest species or disease symptoms [99,100].

Combining met data with pest, pathogen or disease surveillance can be a powerful approach for predicting and verifying occurrence and spread, e.g. met and surveillance data were used to develop a predictive model of dengue fever incidence in Indonesia that was skilful up to two months ahead [81]. Such informed surveillance is particularly effective for threats that can be observed remotely or modelled in near real time with sufficient accuracy to enable targeted responses, e.g. in north-eastern Italy, daily land surface temperature data from the MODIS Terra and Aqua satellites were used to predict locations of short-term invasion by the tiger mosquito, *Aedes albopictus*, with 200 meter resolution [101].

Time lags in the development or spread of pests, pathogens or diseases enables early detection of threats. For example, in Eastern Province, Saudi Arabia, climate data and land cover characteristics were combined with surveillance data to identify mosquito larva breeding sites, from which average flying distance estimates identified three major high-risk clusters where management control measures were recommended [80].

For airborne outbreaks, ADMs and trajectory analysis have proved invaluable for detecting their source and pathway [25], e.g. an ADM was used to identify the likely route of Schmallenberg virus from Southern England into Ireland via infected *Culicoides*, biting midges in the summer of 2012 [102].

Opportunities exist to help identify the most suitable locations and timings for surveillance using the latest met data and forecasts.

Respond

Despite best efforts, pest, pathogen or disease outbreaks will still happen. To respond rapidly and effectively, it is essential that the necessary capabilities and resources are in place and these are flexible enough to adapt to new and multiple risks as they arise. Preparations and resilience-building measures discussed in the other three pillars are vital for supporting these responses.

A key remit of National Meteorological and Hydrological Services (NMHSs) around the world is provision of met data and rapid communications to support emergency and disaster response efforts. This includes forecasts and early warnings of hazardous weather, rapid expert interpretation and guidance, widespread dissemination channels, and established collaborations with responders. Consequently, there are examples of how met data and services are used to help respond to outbreaks, e.g. 3-month real-time dengue forecasts, which integrate weather forecasts and dengue models, are used in Singapore to guide timely, practical responses to potential outbreaks, including hospital bed management, public health interventions, recruitment of ground staff, and education camps [103]. Also, to respond to agricultural pest outbreaks in the Emilia-Romagna region of northern Italy, a warning service was developed that integrates data from forecast models and field monitoring to provide precise warnings on pest outbreaks and guidance on the most appropriate control strategy [104].

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However, despite concerted international efforts to improve multi-hazard EWSs and cross-sector responses, there is still a general lack of multi-disciplinary and transboundary cooperation which limits the effectiveness of outbreak responses [105,106].

Opportunities exist to respond more effectively to current and future biological outbreaks by improving the integration of the most up-to-date biological models within operational weather forecasts (weather, medium range, seasonal, decadal) and dissemination networks.

Synergies and opportunities

There are many synergies between Meteorology and Biosecurity. As well as strong relationships between met conditions and the distribution and behaviour of specific pests, pathogens or diseases, both disciplines are supported by risk-based science, international agreements and organisations, practical protocols, networks for rapid and efficient collection and sharing of data, national and international communication channels, and established service delivery and emergency response mechanisms.

Given these synergies, widespread opportunities exist to better integrate met and biosecurity data and services through routine collaboration between scientists, decision-makers and practitioners across these fields. For example, throughout this paper we have highlighted the following specific opportunities:

- More routine representation of met uncertainties in biosecurity risk assessments and forecasts.
- More use of the range of earth system variables available from satellites, reanalyses, forecast models and ESM projections, e.g. land and ocean surface temperature, vegetation indices, and soil moisture.
- Greater integration of meteorological and biosecurity EWSs and existing national and international dissemination networks around the globe.
- Utilise the latest met data and forecasts to help prioritise the locations and timings for biosecurity surveillance.
- Improve the integration of biological models within operational weather forecasts (weather, medium range, seasonal, decadal) and dissemination networks to respond more effectively to current and future biological outbreaks.

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Infographic

The infographic was devised to highlight the role of meteorology in biosecurity and extend the reach of the information contained within the paper through an alternative, accessible format (Figure 1).

At its centre is an adapted version of the biosecurity logo; this depicts the three elements of the One Health concept (human, animal, and plant) with cupped hands replacing the 'pincers' to symbolise the aspect of human care required, and a gridded Earth illustrating the modelling component of biosecurity. Surrounding this is a cycle representing the four pillars of the UK Government's Biological Security Strategy (Understand, Prevent, Detect, Respond) with text outlining how these relate to meteorology in biosecurity in the corresponding quadrants. In the background there are some subtle visual examples of meteorological observing equipment in situ together with potential ways pests, pathogens or diseases may be conveyed or transported.

Summary

- Pests, pathogens and diseases are sensitive to meteorology. Making use of the most appropriate met data and models is an important consideration for ensuring accurate and timely biosecurity applications.
- There are many examples of good practice in the use of met data for a wide range of biosecurity applications.
- Opportunities exist to better integrate met and biosecurity services by enhancing collaboration between scientists, decision-makers and practitioners across these fields.

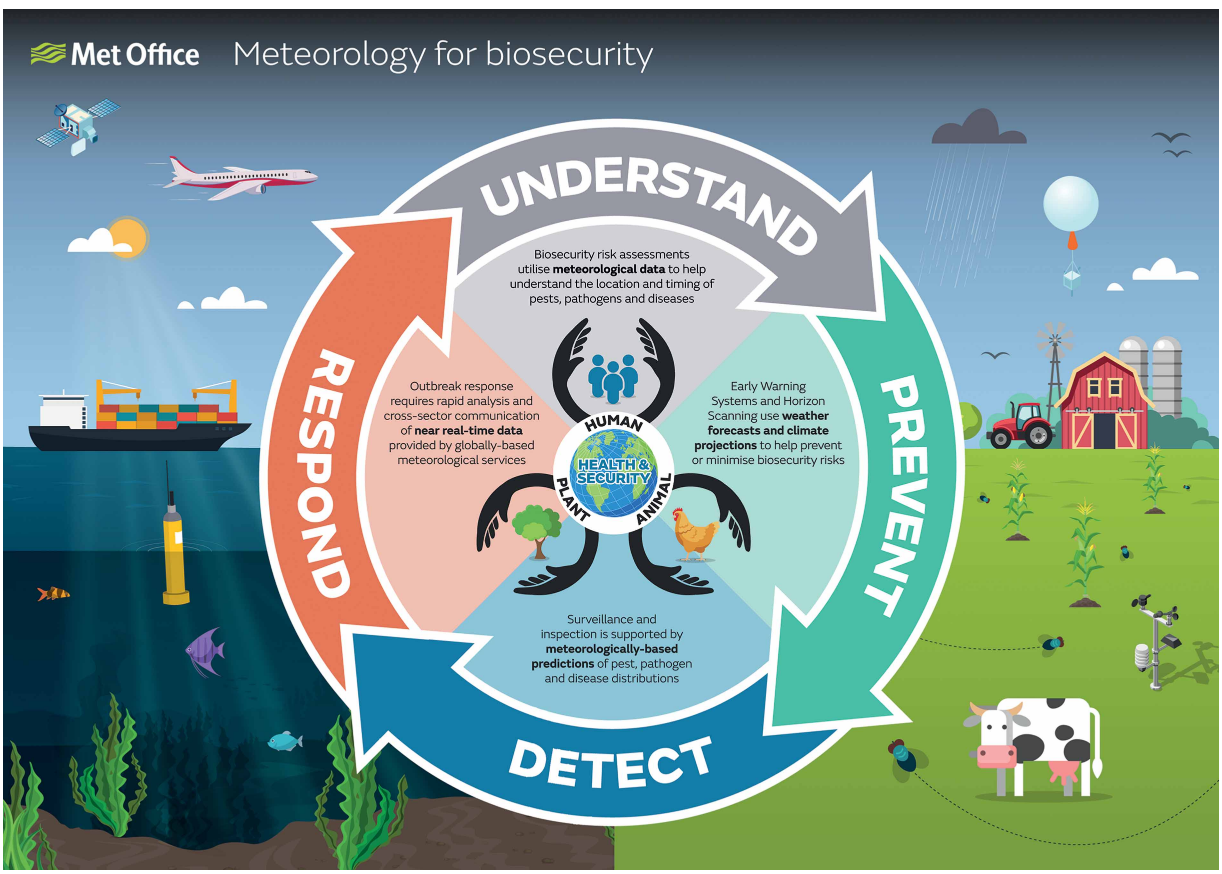

Figure 1. Infographic outlining the role of meteorology in biosecurity.

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Glossary of terms

Abiotic refers to non-living factors, such as radiation, wind, air temperature.

Alien species are 'species, subspecies, or lower taxon introduced outside their natural range (past or present) and dispersal potential (i.e. outside the range it occupies naturally or could not occupy without direct or indirect introduction or care by humans) and including any part…that might survive and subsequently reproduce' [106].

Biosecurity is regarded broadly as 'a strategic and integrated approach to analysing and managing relevant risks to human, animal and plant life and health and associated risks for the environment' [107], or 'the protection of the environment, economy and health of living beings from various diseases, bioterrorism and pests' [108, 109].

Biotic refers to living organisms.

Invasive Alien Species (IAS) or **Invasive Non-Native Species** (INNS) are 'naturalised alien species that are agents of change, and threaten human health, economy and/or native biological diversity' [106].

Meteorology is 'the science of the atmosphere; from the Greek *meteoros*, lofty or elevated and *logos*, discourse. Meteorology embraces both WEATHER and CLIMATE and is concerned with the physical, dynamical and chemical state of the earth's atmosphere (and those of the planets), and with the interactions between the earth's atmosphere and the underlying surface.' [110]

Pathogens are 'microbes or microorganisms (virus, bacterium, prion, or fungus) that causes disease in its animal or plant host' [106].

Pests are 'vertebrate or invertebrate organisms that are damaging to livestock, crops, humans, or the environment' [106].

Prophylactic refers to a medicine or preventative measure intended to prevent the development or occurrence of a disease.

Competing Interests

The authors declare that there are no competing interests associated with the manuscript.

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Author Contribution

D.H. prepared the main manuscript. K.M. designed the infographic and added contributions to the manuscript.

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Abbreviations

ADMs, Atmospheric dispersion models; CMIP, Coupled Model Intercomparison Project; ESMs, Earth System Models; EWSs, Early Warning Systems; IAS, invasive alien species; RCP, Representative Concentration Pathways; WMO, World Meteorological Organisation.

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