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Chapter 5
Environmental Data and Modeling for CSI Research in the Arctic

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Abstract Forecasting the likely future prevalence of CSIs in the Arctic requires prediction of how environmental conditions, both aquatic and on the land, will change under a changing climate, together with knowledge of how these changes relate to the environmental conditionals for viability of CSI host organisms. This requires the use of land surface and hydro-climatic models that have been tested against past data and can be driven by climate projections provided by Global Circulation Models for a range of climate scenarios (Representative Concentration Pathways). Uncertainties in the climate projections combine with uncertainties in the environmental models, and this combined uncertainty propagates through into subsequent CSI occurrence modelling. This chapter will describe the available environmental models, together with the data needed to drive and test them, and how we can address the uncertainty within these models, in the context of Arctic CSI prediction.

5.1 Introduction

Understanding and predicting the evolution of CSIs in the Arctic under climate change relies on using current data with biophysical or statistical models to identify the factors that control CSIs and then predicting how these factors will change in the future. The collection of data on CSI incidence and its relation to environmental variables are described in Chapter 4 of this volume. Table 5.1, below, shows which variables are considered the most important for a range of potential CSIs. This provides the context within which we can evaluate the relevance of datasets and models for predicting CSI behaviour.

Table 5.1 Environmental variables affecting several potential Climate Sensitive Infections (CSIs). Quantities derived from these primary variables, such as temperature extremes and values during previous years, may also influence the behaviour of CSIs. fAPAR is fraction of absorbed photosynthetically active radiation whose possible influence is indicated by parentheses. The second row shows the relevant disease vectors

	Borreliosis	Brucellosis	Tickborne encephalitis	Tularemia
	ticks	domestic animals, air	ticks	Ticks, deer flies
land cover	x	x	x	x
fAPAR	(x)	x	(x)	x
leaf area index (LAI)	x	x	x	x
length of growing season	x	x	x	x
soil temperature		x		x
soil moisture	x	x	x	x
evapotranspiration		x		x
runoff				x
snow covered area	x	x	x	x
snow water equivalent		x		x
timing of snowmelt	x	x	x	x
soil freeze/thaw				x
air temperature	x	x	x	x
precipitation	x	x	x	x
humidity	x	x	x	x
solar radiation				x

soil properties		x		

The environmental variables are almost all time-varying and fall into four broad classes:

1. Climate: air temperature, precipitation, solar radiation, humidity;
2. Land surface: land cover, fraction of absorbed photosynthetically active radiation (fAPAR), leaf area index, length of growing season, soil properties, soil temperature;
3. Hydrological: soil moisture, evapotranspiration, runoff;
4. Cryospheric: snow covered area, snow water equivalent, timing of snowmelt, soil freeze/thaw.

These variables interact in complex ways that need to be represented in any attempt to model current and future behaviour.

One of the key approaches to unravelling these interactions and feedbacks is through biophysical models that attempt to represent the physical processes involved. This requires land surface and hydrological models that typically are driven by climate variables. There are many points of contact between these two types of model, since credible models of vegetation processes must represent hydrological variables, such as soil moisture, while hydrological models need, for example, information on vegetation cover and its dynamics. However, many land surface models do not contain elements such as water routing that are fundamental in models devoted to quantifying the water cycle.

For developing and testing models that describe current or past behaviour we can use a wide range of datasets provided by meteorological or Global Circulation Models (GCMs), but these are increasingly being supplemented by satellite data that provide pan-Arctic datasets on vegetation and cryospheric variables. However, for prediction the models must be able to be run independently of measurements, which means that all relevant time-dependent processes, such as snow cover, land cover change, LAI etc., must be controlled by internal parameters. Hence a crucial use of current data is in parameterising the models.

Naturally, as we look into the future, we become less and less sure of what we predict. Hence a essential aspect of modelling is to try to quantify what controls its uncertainty, how this grows with time and how this affects our predictions about CSIs. This has many facets. Perhaps most fundamental is how humanity will respond to climate change as regards its use of fossil fuels and land management. The Intergovernmental Panel on Climate Change (IPCC) encapsulates these different possible responses in “Representative Concentration Pathways” (RCPs) that drive the climate models. Differences in the RCPs are then exacerbated by differences in the models themselves. There are also significant differences in how the land surface and hydrological models represent the ensuing processes. In the following Sections we describe how these model-data-uncertainty elements are entangled in understanding the future of CSIs in the Arctic.

5.2 Environmental datasets

During the past decades, Arctic and subarctic areas have seen increases of mean air temperatures well above the globally documented average (IPCC, 2019). Warming of the Arctic has been manifested by changes in the Earth’s cryosphere. Earth observation datasets, spanning nearly four decades, show reductions in monthly average sea ice extent, in particular for the ice minimum in the summer and autumn months (Stroeve et al., 2012). This reduction in sea ice has been shown to contribute strongly to increased volatility in winter precipitation patterns; following estimates of continuing sea ice decline, this been projected to increase precipitation by more than 50% in the Arctic (Bitanja & Andry, 2017). These seasonally varying changes are further likely to contribute to increased variability in soil moisture and snow cover conditions. This is corroborated by reductions in the extent, duration and mass of seasonal snow cover across the northern hemisphere land areas (Brown et al., 2017). These changes in snow cover dynamics have potentially significant impacts on the global climate system, snow-dependent ecosystems, and the water cycle (Sturm et al., 2017). In spring and summer months, the increase of snow-free terrain presents a positive feedback mechanism to warming, as does the increase in open sea, which both exhibit increased absorption of solar radiation compared to sea ice or snow cover (Derksen and Brown, 2012). On the other hand, in particular mountain watersheds storing freshwater provide a vital resource, which may be under threat in a warming climate. Currently, seasonal snow provides the main source (> 50%) of freshwater runoff for 1/6th of the world's population (Barnett et al., 2005). Under present RCP scenarios, the increase in greenhouse gas emissions will continue to affect Arctic temperatures, potentially further aggravating changes in the Earth's cryosphere.

Observed and predicted changes in precipitation, soil moisture, snow cover and other components of the water cycle are likely to impact also animal and bacterial populations in Arctic and sub-Arctic areas. Perceived changes include the introduction of invasive mammal species to Northern areas (Hellmann et al. 2008), as especially snow cover is a main factor in the survival of many mammal species. Since these species act as carriers of different zoonotic and other diseases, these changes will potentially impact the spread of new CSIs across the Arctic. For example, populations of white-tailed (Odocoileus virginianus) are strongly dependent on snow cover and have in recent years expanded in Scandinavia and Finland; there are indications this species may play an important role in spreading Salmonella, Yersinia and STEC (Sauvala et al., 2019). Simultaneously, receding snow cover and changes in winter precipitation will likely affect the survival of different native species, such as reindeer. The increase of events such rain-on-snow precipitation and Arctic greening have been shown to introduce potential hazards to reindeer survival (Fauchald et al., 2017; Langlois et al. 2017), also rendering weakened populations vulnerable to infections. Consequently, the monitoring of environmental parameters, in particular related to the cryosphere, provide valuable indicators when estimating stress factors imposed on Arctic ecosystems by ongoing climate change.

The CLINF GIS database gathers together a suite of key environmental datasets which serve several purposes. Firstly, the data can be used to track past trends in Earth processes over the Arctic, which, together with information on disease prevalence, can be used to derive climate-related proxy indicators for disease spread and identify potential CSIs. Secondly, the data are needed to drive and test climate and hydrological models which predict future scenarios on relevant environmental conditions. The data entail a combination of observed and modeled (reanalysis) data, which rely both on satellite sensors and ground-based observation networks. Basic climatological information on, e.g., air temperature, precipitation, radiation, wind, pressure, and humidity are derived from the ERA-Interim database; these are atmospheric reanalysis datasets released by the European Centre for Medium-range Weather Forecasts (ECMWF). The assembled data cover a period from 1979-2016. The data are required as driving data for land surface models, but can also be independently applied to derive indicators based on, e.g., variations in air temperature or precipitation over areas of interest.

Further, accurate land surface information is critical for hydrological modeling and for tracking climate-induced and anthropogenic changes in land use. The European Space Agency (ESA) Land Cover Climate Change Initiative (CCI) Climate Research Data Package (CRDP), included in the database for years 1992-2015, contains an annual time series of consistent global land cover maps at a spatial resolution of 300 m. Further land surface related parameters include fAPAR and the leaf area index (LAI), derived from satellite observations for the years 2002-2017. These high-resolution (500 m) data serve to inform on changing vegetation conditions for tracking, for example, Arctic greening.

Earth observation is a powerful tool for monitoring Arctic areas, where sparse population and low level of infrastructure limit conventional surface (weather station) observations and also the accuracy of reanalysis products. While collected ERA-Interim data cover such parameters as snow depth, sea ice extent, soil moisture and soil freezing, these are complemented by satellite-observed datasets.

Data on sea ice extent and Snow Water Equivalent (SWE), i.e., the total amount of freshwater stored in snow given by the product of snow depth and density, are derived from an ensemble of satellite datasets extending back to 1979. The ESA CCI Soil Moisture products provide harmonized estimates of soil moisture variability for 1979 to 2016; similarly to sea ice extent and SWE, the data are compiled from observations by several satellite systems. These data are available typically at moderate to coarse resolution (tens of km). Several indicators of climatic changes can be derived from the dataset. As an example, Figure 5.1 depicts the date of snow clearance (the date when the seasonal snowpack has completely melted) in spring over the Northern Hemisphere. Depicted is also the trend of the average date of snow clearance for land areas above 40°N. Although there is large variability from year to year, on average snow clearance occurred two days earlier per decade over the study period.

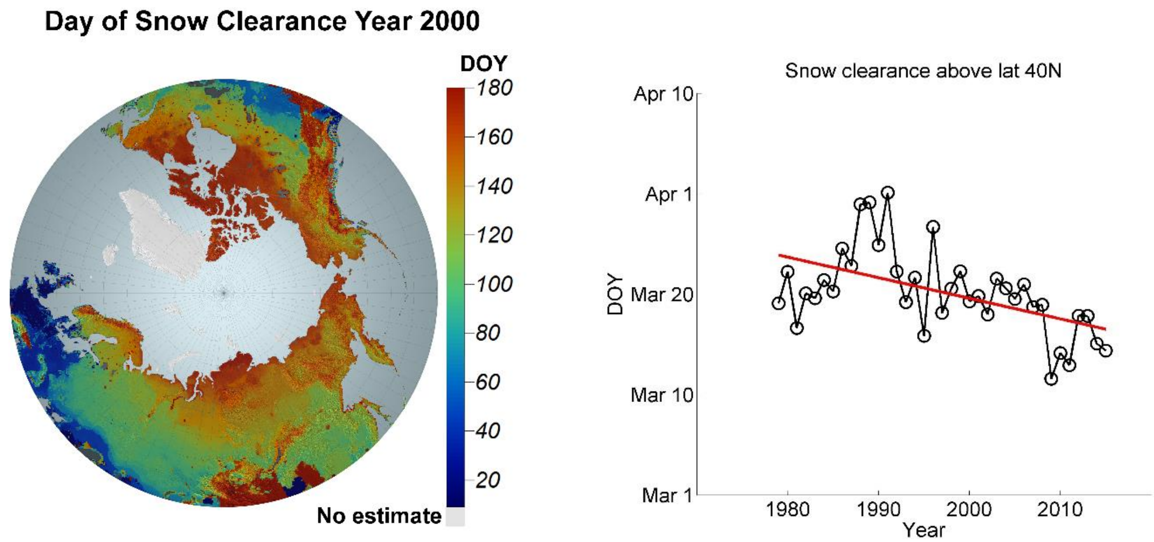


Fig. 5.1 Left: Day of snow clearance as day-of-year from January 1st in the year 2000, using method by Takala et al. (2009) (from Pulliainen et al. 2017). Right: the trend of mean snow clearance date above latitude 40°N.

Table 5.2 Environmental datasets collected for the CLINF GIS database. The table is not exhaustive as further datasets continue to be added based on availability and relevance to the spread of CSIs.

Table 5.2 Summary of main environmental datasets in CLINF GIS database.

Data class	Dataset name	Temporal range	Data source
Climate	air temperature	1979-2016	ERA Interim (ECMWF)
	precipitation	1979-2016	ERA Interim (ECMWF)
	radiation	1979-2016	ERA Interim (ECMWF)
	wind	1979-2016	ERA Interim (ECMWF)
	air pressure	1979-2016	ERA Interim (ECMWF)
	humidity	1979-2016	ERA Interim (ECMWF)
Land surface	land cover	1992-2015	Land Cover CCI Climate Research Data Package
	fAPAR	2002-2017	MODIS (Aqua+Terra)
	leaf area index (LAI)	2002-2017	MODIS (Aqua+Terra)
	length of growing season	2002-2017	derived from fAPAR and LAI
	soil properties	NA	ISRIC World Soil Information (SoilGrids)

	soil temperature	1979-2016	ERA Interim (ECMWF)
	topography	NA	Global 30 Arc-Second Elevation (GTOPO30)
Hydrological	soil moisture	1979-2010 1980-2017	ERA-Interim/Land reanalysis[a] GLEAM-3.2a model[b]
	evapotranspiration	1979-2010 1980-2017	ERA-Interim/Land reanalysis[a] GLEAM-3.2a model[b]
	runoff	1901-2012	GSIM[c]
Cryospheric	snow covered area	1995-2010	ESA GlobSnow SE v1.5
	snow water equivalent	1979-2016	ESA GlobSnow SWE v3.0
	sea ice extent	1979-2016	NOAA Sea Ice Index, Version 3
	soil freeze/thaw	2009 - 2016	SMOS Level 3 Soil F/T

[a] European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA)-Interim/Land reanalysis datasets

[b] Global Land Evaporation Amsterdam Model (GLEAM-3.2a)

[c] Global Streamflow Indices and Metadata (GSIM) archive

5.3 Modelling land surface processes for CSI prediction

The disproportionately increased warming in the Arctic due to climate change will cause (and is causing) drastic changes in the terrestrial energy, carbon and water balances of the Arctic, with large effects on such biophysical variables as growing season, land cover (including species changes), snow cover, soil moisture, soil freeze-thaw and permafrost thaw. Many of these variables and associated processes are related to the behaviour of CSIs (see Table 5.1). There are also major consequences for insect, animal and human populations in the Arctic.

These processes are highly inter-dependent, with complex interactions and feedbacks that cannot be considered in isolation when trying to assess the effects of climate change on the land surface. For example, land cover plays a major role in the energy balance and in the transfers of water, heat and trace gases between the surface and the atmosphere. However, vegetation activity has exhibited major changes over recent decades, as evidenced by the greening of the tundra but browning of high latitude forest systems (Miles and Esau 2016). Because it has much lower albedo than snow, vegetation contributes to Arctic warming, with increased effects as low vegetation is replaced by shrubs that emerge from the snow cover. Such vegetation changes modify the niches available for CSI vectors such as ticks. Vegetation is also important in the heat input to the soil from the atmosphere both by shading and, as in the case of Arctic mosses, providing an insulating layer between the atmosphere and the soil, hence affecting diseases like brucellosis and tularemia (Table 5.1). Furthermore, the vegetation-soil system plays a major role in the hydrological cycle through evapotranspiration to the atmosphere (Section 5.4). For CSI prediction it is therefore essential to quantify the spatial and temporal variation in vegetation, and how this is linked to other biophysical variables. Similar considerations apply to all the variables affecting CSIs.

Simultaneous consideration of the multiple interacting high latitude processes and feedbacks relevant to CSIs requires the use of land surface models (LSMs) that can treat all these processes within a consistent framework. The development of LSMs has been driven largely by the need to understand interchanges of trace gases, water and energy between the land and the atmosphere under a changing climate and, as such, they form a core component of the Earth System Models (ESMs) used to inform IPCC projections of future climate. However, the enormous international effort in climate modelling has led to numerous LSMs, which differ in the processes they try to represent (e.g. fire, the nitrogen cycle, permafrost, etc.) and in how these processes are parameterised. A key consideration in CLINF is whether any of these models are suitable for use in CSI prediction.

A generic diagram of the structure of the type of LSM used in CLINF is shown in Fig. 5.2 below. Its emphasis is on vegetation, soil and water processes, rather than energy balance, although vegetation and soil temperature and temperature gradients are accounted for. The versions of the LSMs used (JULES [Comyn-Platt et al. 2019], CLM5 [Lawrence et al. 2019], LPJ-GUESS [Hickler et al. 2012] and two forms of the ORCHIDEE model [Druel et al. 2017; Guimberteau et al. 2018]) were chosen because they include specific components relevant to high latitudes, including Arctic vegetation types and permafrost, unlike many LSMs designed for global application. In a full Earth System Model, each of them would be coupled with an atmosphere-ocean model, but in CLINF we run the models separately and drive them with climate variables provided by one of the Global Circulation Models. They are all designed to be predictive, which means that all processes within them are parameterised, including land cover change, vegetation activity, fire, snowmelt, etc., which can be observed at large scales from satellites (see Section 2); such observations can then be used to constrain model parameters.

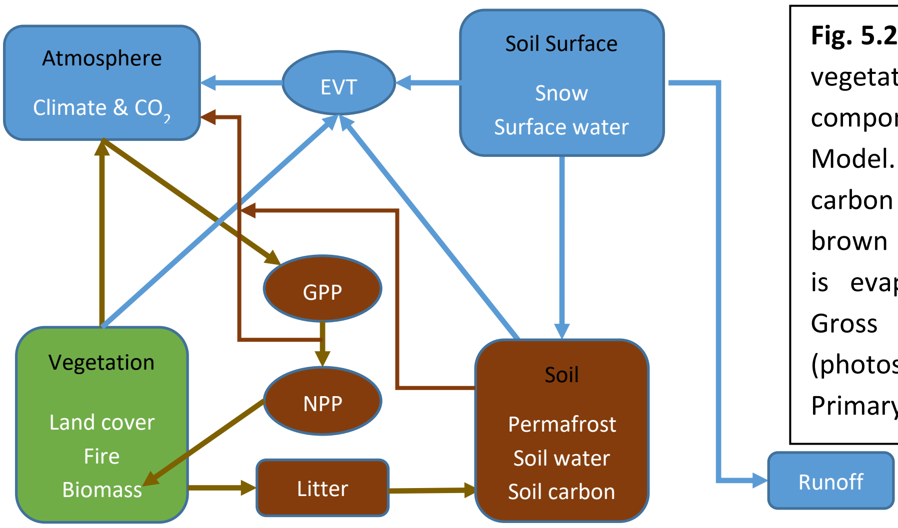
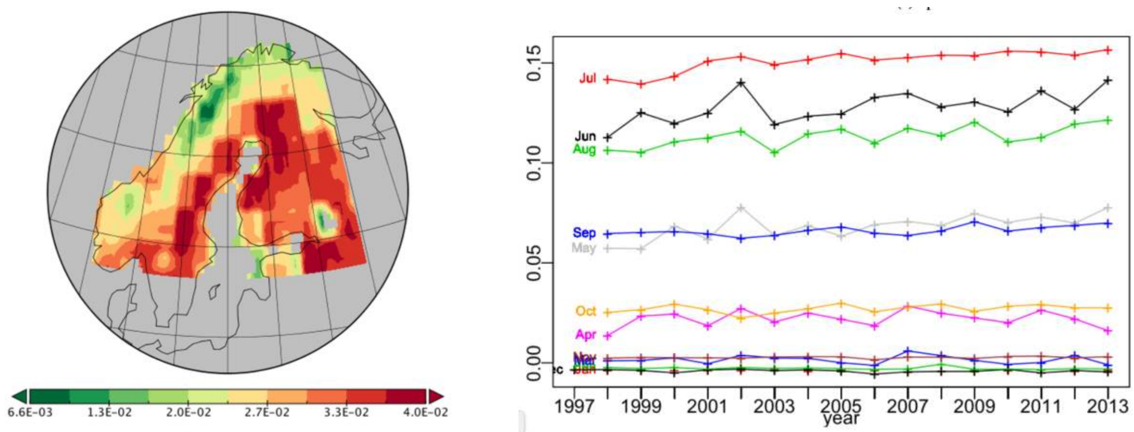


Fig. 5.2 Generic structure of the vegetation-soil-atmosphere component of a Land Surface Model. Flows of water and carbon are shown by blue and brown arrows respectively. EVT is evapotranspiration, GPP is Gross Primary Production (photosynthesis) and NPP is Net Primary Production.

Of the environmental variables identified as affecting potential CSIs (Table 5.1), the atmospheric variables and soil properties (the last five entries in the table), together with atmospheric carbon dioxide concentration, are drivers of the LSMs; all other variables are calculated (the models may be initialised with current land cover but land cover change is then under the control of the model). However, different models use different process representations and parameters, so make different predictions, not just the future but also about past behaviour. To assess their value for CSI prediction we therefore need to evaluate the variability in the models across the range of variables in Table 5.1.

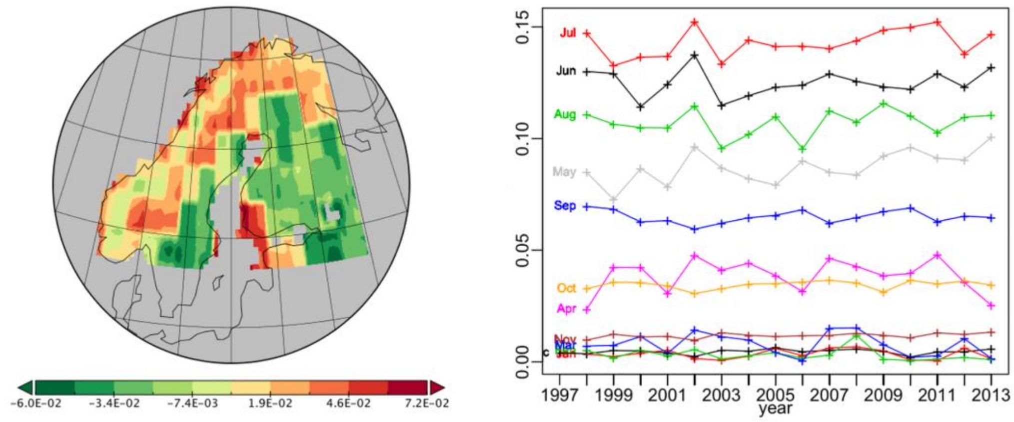
Methods to quantify such spatio-temporal variability (Leibovici 2010, Leibovici et al. 2019) allow the inter-model variability to be decomposed into its common spatial, temporal and model-specific components. An example is shown in Fig. 5.3 for Net Primary Production, which is the amount of biomass produced by photosynthesis, so is strongly related to the length of the growing season, fAPAR and LAI. The analysis shows that 90% of the variation between the models is captured by the product of a single spatial pattern (Fig. 5.3a) and a single temporal pattern (Fig. 5.3b), together with a model-specific multiplier varying by less than 14% between the LSMs (Leibovici et al. 2019). Hence using different LSMs introduces little uncertainty into subsequent CSI predictions based on the variables associated with NPP, i.e. fAPAR, LAI and growing season.



(a) Spatial dimension (b) Temporal dimension

Fig. 5.3 The spatial and temporal patterns capturing 90% of the variability in Net Primary Production from the Land Surface Models over the CLINF region for the period from 1998 to 2013

The same type of analysis applied to the *differences* between the LSMs provides specific information on how the LSMs disagree. Fig. 5.4 shows the spatio-temporal pattern that most closely captures these differences (Leibovici et al. 2019). Within this pattern, all the LSMs give similar values except that due to Druel et al. (2017), which over the whole time-period gives smaller values of NPP than the other LSMs in the red regions (Fig. 5.4a) and greater in the green regions.



(a) Spatial dimension (b) Temporal dimension

Fig. 5.4 Spatial and temporal patterns capturing the main differences in Net Primary Production for the Land Surface Models used in CLINF over the CLINF region for the period from 1998 to 2013.

However, for other variables the models do not show the same level of consistency. One of the most important is land cover. This is driven by model-specific parameters that control the suitability of a given plant functional type to exist in a grid-cell under the given climate and soil conditions, and hence its ability to colonize new ground as this becomes available due to plant mortality or improved growth conditions. The extent of model differences is illustrated in Fig. 5.5, which shows the predicted changes in the dominant proportion of vegetation type in the CLINF region over the 21st century for the LPJ-GUESS and ORCHIDEE models (both with climate forcing provided by IPSL-CM5A-LR under RCP 8.5). The most obvious difference is that LPJ-GUESS predicts far more cover by C3 grass than ORCHIDEE and a significantly increasing area of boreal needleleaf evergreen forest. The only clear point of agreement is that both LSMs predict a decline in shrub cover over the century, but this contradicts current observations of the spread of shrub cover in the Arctic (Myers-Smith et al. 2011). The differences between the LSMs and their inconsistency with data indicate that the parameters controlling land cover dynamics in both models need significant reappraisal. Similar remarks apply to the other LSMs considered. This type of analysis therefore provides significant motivation for the community to improve their models, with the study of CSIs giving an important underpinning requirement for such improvement.

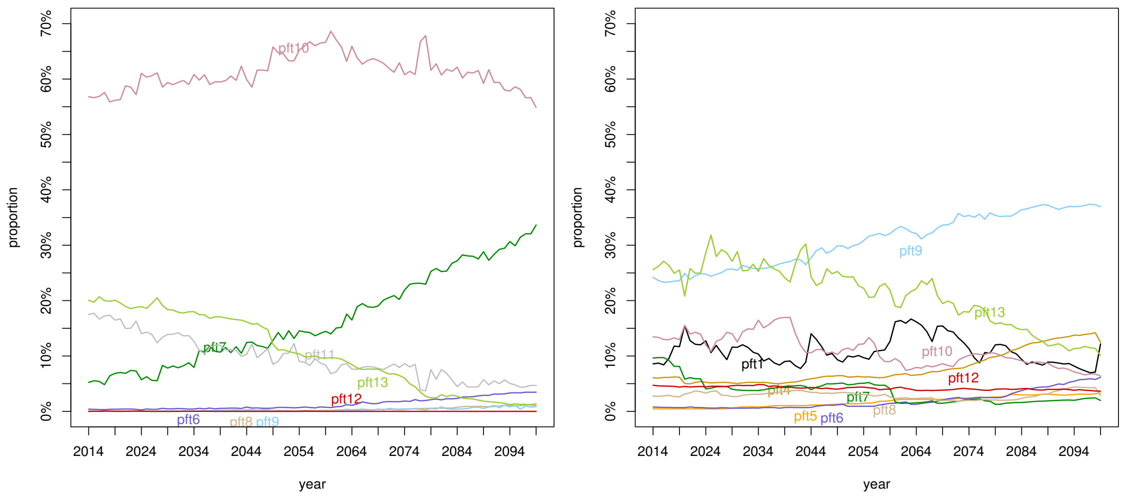


Fig. 5.5 Changes in the proportions of dominant plant functional types (pfts) across the CLINF region as predicted over the 21st century by LPJ-GUESS (left) and ORCHIDEE (right). The pft numbering is as follows: 1: bare ground; 4: temperate needleleaf evergreen; 5: temperate broadleaf evergreen; 6: temperate broadleaf summergreen; 7: boreal needleleaf evergreen; 8: boreal broadleaf summergreen; 9: boreal needleleaf summergreen; 10: C3 grass; 11: C4 grass; 12: nonvascular moss & lichen; 13: boreal broadleaf shrubs; 14: C3 arctic grass. The right-hand fig. is from Leibovici and Claramunt (2019).

5.4 Hydrological surface and subsurface changes influencing communities

The climate in the Arctic is changing at almost three times the rate and magnitude experienced in the rest of the world and this is affecting Arctic peoples, animals and the environment (Hoberg et al., 2015). The Arctic region also comprises a range of different ecological and physical environments that interact with, and feed back on, the global climate system. These changes can threaten northern societies but also open new opportunities: for example, warming may open new local sources of moisture, such as open water previously under ice (Bintanja & Selten, 2014), while the melting of glaciers (Dyurgerov et al., 2010) and permafrost thaw can strongly influence both water (Karlsson et al., 2012) and carbon (Schuur et al., 2015) cycling conditions throughout the Arctic. Furthermore, ecosystem regimes may shift (Karlsson et al., 2011; Wrona et al., 2016), and infrastructure damages may occur, with critical consequences for regional water security and health (Daley et al., 2014).

Wetlands constitute a large proportion of the Arctic landmass and play an important role in sustainable regional development, as they are linked to ecosystem services and the livelihoods of local people, and their opportunities to adapt to climate change (Seifollahi-Aghmiuni et al., 2019). There is so far weak evidence for the correlation of observed changes in Arctic vegetation density with hydroclimatic changes over the Arctic region (Groß et al., 2018), but hydroclimatic changes are known to considerably affect the resilience of Arctic wetland ecosystems and are causing shifts in current regimes (Karlsson et al., 2011). Nevertheless, the combined effects of natural and human pressures and management efforts on Arctic wetland ecosystems, their biodiversity and functioning, and the benefits they provide to human wellbeing and health, are still poorly understood (Seifollahi-Aghmiuni et al., 2019).

Permafrost in the northern circumpolar region has been disappearing in recent decades (Romanovsky et al., 2010), with important surface implications. Thawing of permafrost can release large amounts of carbon to the atmosphere (Schuur et al., 2015) and lead to re-emergence of long-frozen pathogens, posing increased risks to the health and wellbeing of animals and humans (Revich et al., 2012). There is thus an urgent need to quantify and predict permafrost changes under ongoing and future warming conditions. Systematic model simulations of different surface warming trends combined with various local soil-permafrost conditions have indicated that thaw-driven regime shifts in wetland/lake ecosystems, and associated releases of previously frozen carbon and pathogens, may be expected to occur in and be more severe for peatlands than for other soils (Selroos et al., 2019).

Use of GCM and ESM projections for water-related change assessment and planning typically relies on regional downscaling, either through physically-based regional climate models (Sun et al., 2016) or by various statistical means (Mizukami et al., 2016), sometimes further processed through hydrological models. However, all downscaled results ultimately depend on the ability of the driving GCM/ESM to adequately represent the hydroclimate of land areas at relevant scales (Bring et al., 2015). Direct GCM/ESM use to simulate and project hydroclimatic changes has been found to represent observed temperature better than observed water conditions, in terms of precipitation, evapotranspiration and runoff (Asokan et al., 2016). The spatial scale of process resolution may be a reason for such differences between modelled and observed values, although some studies have found small or no effects of scale on GCM performance for hydroclimate on land (Asokan et al., 2016; Bring et al., 2015).

In view of the key role of hydroclimatic conditions for different types of changes in the Nordic-Arctic region, Bring et al. (2019) tested the performance of GCMs/ESMs specifically for the hydroclimate of this region, extending from Western Greenland to Eastern Siberia, and including Sweden, Finland, Norway, Iceland, Greenland and Russia. There were four main reasons for this geographic delineation. First, it includes a gradient of Arctic environments, including ice caps and glaciers, tundra and boreal forests. Second, it covers a range of Arctic communities, including Inuit, Sami and several indigenous peoples in Russia, but also several of the largest Arctic urban areas, such as Reykjavik, Tromsø and Murmansk. Third, it enables use of the longest time series of data from direct hydroclimatological observations (Bring and Destouni, 2014) and the most detailed global and downscaled climate model simulations (Figure X1). Fourth, the selected region includes most of the areas identified as hotspots of projected future hydroclimatic change (Bring et al., 2017). These hotspots coincide with a relatively high concentration of population compared to other parts of the pan-Arctic region, indicating that the highest density of change impacts on humans in the Arctic may be concentrated here.

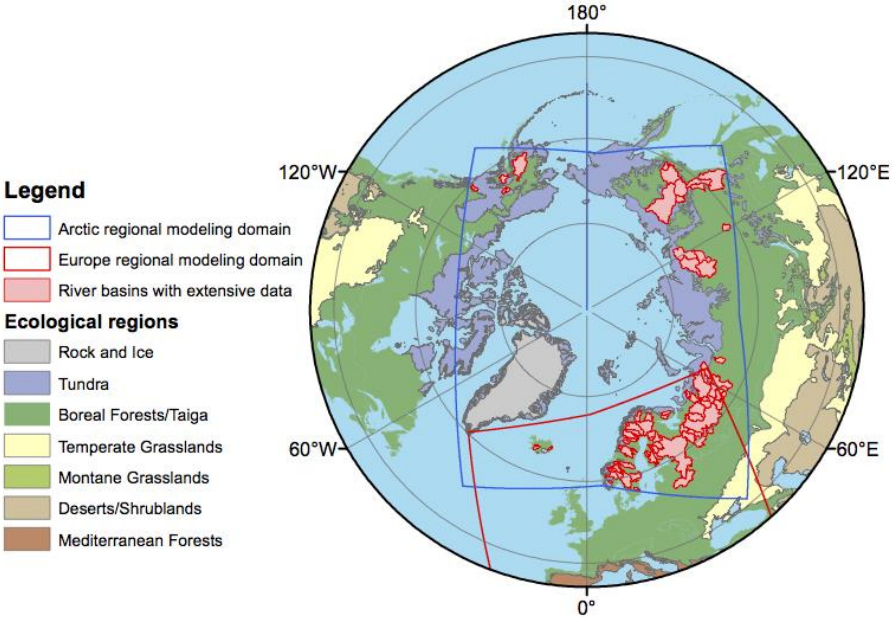


Fig. 5.6 Hydrological basins (red) within the pan-Northern region for which extensive and complete hydroclimatic data series are openly available.

Over this region, Bring et al. (2019) investigated available data from 64 Nordic-Arctic hydrological basins, and compared climate model results to observations across different scales and variables. They found an unexpectedly similar level of model-observation agreement for runoff and temperature, with model outputs for both having relatively small error and bias for different basins and on whole-region scale, compared to the other water cycle variables of precipitation and evapotranspiration. The results did not show clear or consistent differences in model performance for different basin sizes across the different hydroclimatic variables. However, the better performance of the temperature-runoff variable pair compared with the poorer performance of the precipitation-evapotranspiration variable pair only emerged fully at the whole-region scale. Moreover, a tendency was found for better model performance with increasing basin size for runoff and to some degree also for precipitation.

Performance ranking of the multiple GCMs/ESMs tested against hydroclimatic observations by Bring et al. (2019) showed no single climate model performed best across all studied variables. The overall poor climate model performance as regards precipitation and evapotranspiration has important implications for modelling of hydroclimatic responses. Specifically, it points at options for direct use of relatively good GCM/ESM results for regional runoff projections, instead of driving downscaled hydrological modelling of runoff by much poorer GCM/ESM results for precipitation and evapotranspiration.

5.4.1 Infectious disease sensitivity to hydroclimatic changes

Hydroclimatic changes, which may be particularly large at high latitudes, can also affect regional outbreaks of infectious diseases, jeopardising human and animal health. To assess the risk to health of such changes, it is necessary to identify the sensitivities of various diseases to variability and change in hydroclimatic conditions. Ma et al. (2019) developed a method for analysing this sensitivity for tularemia and its possible endemic disease level (N* in Fig. 5.7, top panels) under different prevailing hydroclimatic conditions.

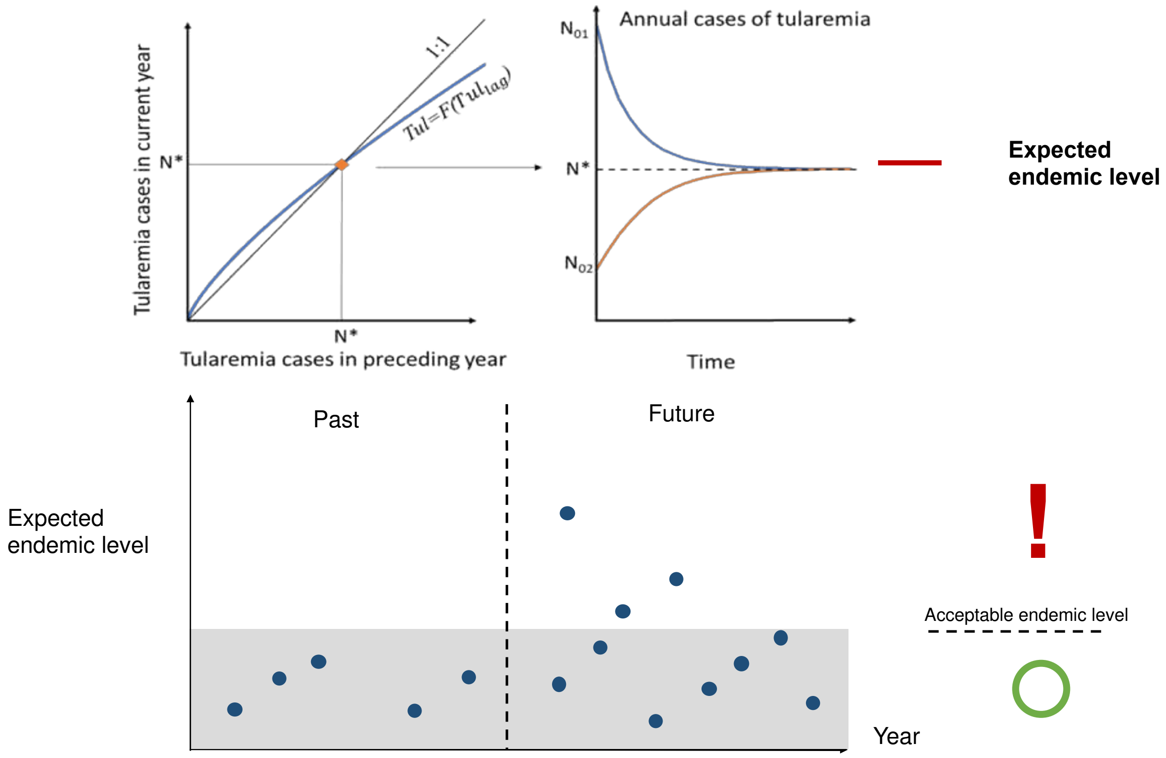


Fig. 5.7 (Top) Schematic diagrams of how the number of tularemia outbreaks, under any given combination of disease-relevant long-term average hydroclimatic conditions, converges to an expected endemic level N*: (top left) from each year to the next (blue line; the black line indicates the same number of cases in both years); (top right) over time, starting from any initial number of cases, N_{01} or N_{02}, the number still converges to the same N* level (dashed line) for the same hydroclimatic conditions. (Bottom) Schematic diagram of past and future values of expected endemic level, depending on prevailing/projected hydroclimatic conditions, which can/should be compared with some societally accepted endemic level (dashed line), beyond which projected disease changes are unacceptable and mitigation measures are required.

Ma et al. (2019) considered the case of tularemia based on a previously tested and established statistical model for this disease, developed by Rydén et al. (2012). Fig. 5.7 illustrates schematically how the number of disease outbreaks converges to the expected endemic level N* associated with the considered combination of hydroclimatic conditions, and how that level may go beyond some societally acceptable threshold value under changed hydroclimatic conditions in future years.

Tularemia is one of the most well-researched endemic diseases in high-latitude regions (Waits et al., 2018) with outbreak numbers quantitatively related to hydroclimatic conditions by the statistical disease model of Rydén et al. (2012). In their study of the implications of this model for possible future hydroclimatic changes, Ma et al. (2019) found high disease sensitivity to different combinations of hydroclimatic variable values, and the possibility of shifts in major disease increases even for relatively small changes from current average conditions, with variable values still remaining within the range of past regional observations.

Fig. 5.7 also illustrates the possibility of identifying threshold hydroclimatic conditions beyond which the endemic level of the disease goes above some societally accepted level, for instance defined by the World Health Organization. Further research is required on how projected hydroclimatic changes may affect outbreaks of various infectious diseases, with particular focus on potential threshold combinations of driving variable values, and on the spatio-temporal generality and transferability of quantitative disease models that can be used for such projections.

5.5 Conclusions and prospects

Fundamental to understanding and predicting the viability and spread of CSIs is identification of the environmental envelopes within which they can flourish, though this will almost certainly need to be supplemented by knowledge about the host and affected species and their risk of exposure to the disease (including for humans). Coherent, integrated environmental information is increasingly becoming available both from enhanced observational capabilities, especially from satellites, and advances in bio-geophysical models. Hence the framework needed to assess CSI risk and how this will develop is essentially in place. However, the value of this framework for CSI prediction is limited by two factors, spatial scale and uncertainty.

As regards CSI analysis, spatial scale is not a major limitation for many of the variables derived from satellite data (Table 5.2), since in many cases the observations have spatial resolution around a few hundred m. However, a basic factor in the spatial resolution of the LSMs and hydrological models is the grid-size of the climate models used to drive them, which for GCMs is typically around 0.5^{o} (around 50 km in latitude by 25 km in longitude at 60^{o}N). The models may attain an effective finer resolution by exploiting higher resolution land cover, for example, but this may still be insufficient to characterise the variety of environmental conditions within a landscape that affect CSI viability. Nonetheless, the analysis of tularemia described in Section 5.4 makes clear that while detailed mapping of disease hotspots are unlikely to be provided by models, the effect of changing conditions can be investigated by these models and this yields significant policy-relevant conclusions.

Uncertainty is intrinsic to any measurement or model estimate. For measurements, uncertainty describes the statistical distribution of estimated values of a given quantity, so is conceptually simple, though may be hard to quantify in practice. For example, estimating LAI from satellite measurements relies on a model for how solar radiation interacts with the vegetation canopy. Flaws in this model combine with effects such as sensor noise to give LAI estimates that may be biased as well as having significant dispersion. Nonetheless, this type of uncertainty is well understood and can be characterised if there are sufficient reference data to calibrate the estimates.

Uncertainty in LSM or hydrological model calculations is much harder to characterise because it contains many cumulative factors that cannot be adequately described simply by statistical methods, especially when it comes to prediction. First and foremost is how humanity will respond to climate change. Although the four Representative Concentration Pathways (RCPs) defined by the IPCC set out possible atmospheric greenhouse gas concentration trajectories, no probability is attached to them. Secondly, for a given RCP different GCMs make different predictions about how climate will behave, with particular disagreement as regards precipitation. The ensuing uncertainty feeds through into the climate drivers of LSMs and hydrological models. However, as we have shown above, the models themselves differ, even with the same drivers, either because of differences in process representation or in model parameterization. This adds another layer of uncertainty, all of which propagates into CSI models based on the values of land surface and hydrological variables. The implication is that, at our current level of understanding and capability, long-term prediction of CSI behavior is probably of little value for policy decisions. Much more useful will be the development of predictions looking no more than a decade or two into the future, since these will be strongly constrained by current observations of the state of the Arctic. Furthermore, the large set of observations we already have provide a major resource to winnow out the models that do not perform very well and to motivate model improvement.

As noted in Chapter 4 of this volume, addressing the complex effects of climate change on diseases in the Arctic and the ensuing societal impacts requires a highly multi-disciplinary team with expertise in health, geospatial statistics, data analysis, environmental observations from space, ecology, environmental modelling, and numerous aspects of social science. In addition, to have real impact CLINF needs to understand how to translate its findings into forms that can be assimilated by the many political, economic and social groups that intersect in the Arctic. One of the key contributions of CLINF is assembly of the necessary range of capabilities and, over time, learning how to make them interact with a common goal and within a common framework. This has inevitably been a slow process because of the lack of common methodologies, or even a common language, shared by different research communities. Equally inevitably, it has involved researchers moving out of their comfort zone and tackling questions that they have not been faced with before. However, doing so is both scientifically stimulating and leads to better understanding of the strengths and limitations of their own approaches to Arctic questions. Such insight is a prerequisite for improvement, with implications well beyond the CLINF project itself.

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