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The Arctic Species Trend Index

Tracking trends in Arctic vertebrate populations through space and time

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Executive summary

The Arctic, being over three times the size of Europe, comprises a vast, cold, and mostly remote area, demanding complex and costly logistics for initiating monitoring programs. These challenges, in particular, have limited our ability to collect continuous, long-term data in order to detect and understand change in Arctic ecosystems. As the Arctic plays a vital role in regulating the physical, chemical, and biological processes of the Earth and with this region undergoing accelerated change, it becomes even more imperative that we make strategic and wise decisions regarding not only how we monitor these ecosystems but also how we manage them.

This report builds on *The Arctic Species Trend Index 2010: Tracking trends in Arctic wildlife* (McRae *et al*. 2010), which provided our first broad measure of trends in vertebrate populations at a pan-Arctic scale.

Follow-up work conducted in 2011 consisted of two types of investigations:

1. revision and updating of the Arctic Species Trend Index (ASTI) data set, an update of the ASTI, and a closer look at the marine data sets (McRae *et al*. 2012.); and,
2. an exploration of spatial biodiversity data analysis techniques using the ASTI data set (this report). Both reports are summarised in an overview report (REF).

Arctic marine environment. Photo: Chris Howey/Shutterstock.com

The spatial analysis

Utilizing the ASTI data (890 vertebrate populations from 323 species spanning a time period from 1951 to 2010), we expanded the original investigation to examine broad-scale spatial patterns of biodiversity change across the Arctic. These patterns were looked at in relation to climatic and other environmental data to investigate potential causal mechanisms of biodiversity change. As well, we evaluated the spatial distribution and quality of biodiversity monitoring across the Arctic for use in identifying critical gaps in monitoring coverage.

The spatial analysis of time span (time series length) and annual records (time series fullness) showed that while some areas are well monitored (e.g., northern Scandinavia, Bering Sea), data are sparse for other regions (e.g., northern Russia). Examining population trend data by decade highlighted the reduction in data sets since 2000, either by dropping existing monitoring sites or by not initiating new monitoring programs. However, it is possible that some of these data are simply not available in the literature yet. Gaps can be filled both by initiating new monitoring and, in some cases, by obtaining already existing data.

Understanding of underlying factors for population declines and increases is vital to guide population management decisions. Several spatial analyses allow for this kind of analysis. In this report we employed Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) analyses to reflect the spatial nature of the underlying data. A prime consideration was the need to avoid violating statistical assumptions about the data by addressing issues caused, for example, by spatial autocorrelation and the variability of data across space. To assess the usefulness of these methods for our data set we collected predictor variable information available on a number of environmental and climatic factors.

When there were differences among regions in the variance of the predictor variable, we used additional statistical modelling to produce a prediction of population trends across space. Predictions from the resulting model showed a relatively good fit to the observed data, with a less good fit in regions with either rapid declines or rapid increases. Based on our limited treatment of the data, our models did not explain much of the population trend variability across the North. However, testing this statistical approach highlights the usefulness of the ASTI data set for spatial analyses of vertebrate population trends, both across the whole of the Arctic as well as across specific sub-regions for which data of particularly good quality are available. Steps that are likely to improve the power of these predictive models include: incorporating additional possible explanatory variables into future analysis using regional sub-sets as the basis for analysis; splitting analysis by species groups (numerically increasing versus decreasing; spatially expanding versus contracting populations); improved handling of multiple populations in a single area; and, deriving variables representing change in environmental or climatic conditions over time.

We recommend the following next steps to improve the already extensive data set:

- close geographical gaps in data coverage by focussing efforts on obtaining and aggregating readily available monitoring data to cover these gaps (work that is underway through the CBMP expert networks);
- start monitoring programs in under-represented regions; and,
- encourage existing programs to carry out monitoring for additional species—this may help to assess whether observed population trends are congruent among species in the same area or whether some species are declining or increasing more significantly than others.

Sarek National Park, Sweden. Photo: Sander van der Werf/Shutterstock.com

Introduction

Ivory gull. Photo: Todd Boland/Shutterstock.com

Arctic wildlife contributes significantly to global biodiversity by supporting globally important populations of vertebrates, for example, 80% of the global goose population (Zöckler 2008) and over 50% of the world's breeding shorebirds (Zöckler *et al*. 2003). Monitoring of Arctic biodiversity has become an integral part of its conservation (McRae *et al*. 2010) and can serve as an early indicator of ecosystem response to rapid environmental change. Limited functional redundancy in Arctic ecosystems poses a particular risk to their long term persistence as the loss of a single species could lead to cascading effects on ecosystem state and function (Post *et al.* 2009). Biodiversity indicators such as the Arctic Species Trend Index (ASTI) can reveal patterns of vertebrate trends, as well as serve as tools for predicting future trends, based on improved understanding of drivers of biodiversity change and the impacts these drivers have on ecological relationships. The ASTI, as with most biodiversity indicators, has predominantly focussed on temporal trends in vertebrate population abundance. However, population trends vary both temporally and spatially; the spatial trends have not previously been subject to analysis.

Spatial patterns underlie many aspects of conservation biology. For example, species-rich locations may become focal areas for targeted conservation action. In addition, the threat processes affecting wildlife are not homogeneously distributed across space. Hunting pressure, for example, is likely to be higher in areas with relatively easy access for humans. The spatial distribution of human impacts can have a pronounced effect on the spatial distributions of species, masking natural patterns that may exist in the absence of anthropogenic threat (Nogués-Bravo *et al*. 2008).

Within the Arctic system, climate change is predicted to lead to dramatic changes in ecosystems (e.g., Post *et al*. 2009). Species composition in the high Arctic may be altered due to northward movement of, and subsequent increase in, low and sub Arctic species (McRae *et al*. 2010). Developing a better understanding of the spatial pattern of Arctic vertebrate trends can serve as an important tool for prioritising limited resources towards conservation and other management efforts.

Arctic grayling. Photo: Pi-Lens/Shutterstock.com

In this report we focus on describing the spatial distribution of wildlife population trends from 1951 to 2010 in order to provide a baseline against which future changes across the Arctic region can be assessed. This should also lead to an improvement in understanding of causal drivers of population trends. We implement geostatistical techniques, in particular Geographically Weighted Regression (GWR), to model spatial relationships and predict population trends in unsampled locations.

Geostatistics are becoming more popular in epidemiological (Dogan *et al.* 2010) and ecological analyses, such as habitat modelling and population studies (e.g., Bellier *et al.* 2010; Kleisner *et al*. 2010), yet these techniques have not been widely applied in biodiversity monitoring, despite their great potential for informing conservation action. A recent review has shown that more than 80% of published ecological research analysing spatial data sets ignored spatial modelling techniques (Dormann 2007). However, geostatistical methods such as kriging and regression techniques have previously been used in the context of conservation prioritisation (e.g., Tchouto *et al.* 2006), and exploration of spatial distributions of organisms in relation to resource distribution (e.g., Ettema *et al*. 1998).

Other current projects with an Arctic focus are also employing spatial techniques, such as the Bering Sea Sub-Network (BSSN) and WWF's Rapid Assessment of Circumarctic Ecosystem Resilience (RACER) project. These projects take slightly different perspectives, with the work of the BSSN focussing on resource use and changes in species important to indigenous communities and RACER focussing on identifying areas of socio-ecological resilience under future climate change predictions (Gofman & Smith 2009; WWF 2009).

In this report, we briefly describe each of the techniques used (see the Appendix) and assess them in terms of their applicability to future monitoring of spatial trends across the Arctic region. As such, we provide a first step in assessing the suitability of the ASTI data set for spatial analysis and we trial the techniques that may be used on such data, which will aid in directing future efforts of spatial data exploration and analysis.

Effective large-scale monitoring of biodiversity demands close attention to the quality of the data set which feeds into the analysis. Part of this report evaluates the available time series data in order to assess whether there are significant gaps in coverage and quality. Future projects can then target these gaps, resulting in more efficient use of limited resources.

Arctic landscape. Photo: Wild Arctic Pictures/Shutterstock.com

Methods

Arctic population trend data

Arctic population trend data were compiled from both the Living Planet database, which contains vertebrate population trend data from across the globe (Loh *et al*. 2005; Collen *et al*. 2009, www.livingplanetindex.org), and the ASTI (Circumpolar Biodiversity Monitoring Program 2011), the Arctic component of the LPI. In total, the data set contains 890 population records from 323 Arctic vertebrate species (Table 1). Note that the term 'population' is not used here in an ecological sense—it refers to a sub-group of a species for which repeated abundance measurements are available at a specified location. Each population data set included geographical information which was plotted in ArcGIS. For some locations, population time series from more than one species were obtained, resulting in a total of 366 unique locations with wildlife trend data from across the Arctic.

	Mammals	Birds	Fishes	Total
Species	53	201	69	323
Populations	245	472	173	890

Table 1. Number of species and populations in the ASTI

To examine spatial patterns of population trends, we computed two measures of abundance change over time for each population. This gave us the option of selecting the optimum measure for spatial analysis. First, an annual rate of change was calculated for each population using a Generalised Additive Modelling framework following the method described in Collen *et al*. (2009). Secondly, two trend measures were obtained for each population: the average annual rate of change and a measure of the total rate of change over the entire time period (Collen *et al*. 2011). For locations with records from multiple populations and species, average and total rates of change were calculated as average values from all recorded populations in that location. No weighting was given with regard to the number of populations per point location.

Attributes that might determine the quality of each population data set for the purposes intended here include: time series length (the time span of the data set), number of annual data points in the data set, and time series fullness (the number of data points divided by the number of years). To examine data quality across space, we generated three maps displaying time series length, number of data points, and time series fullness per location, using average values for those locations with more than one population record (Figure 7, Figure 8, and Figure 9).

Predictor variables for spatial relationships

In addition to threat and species information from the ASTI data set, a broad range of spatial predictor variables was included in the spatial analysis (Appendix Table 1) pertaining to climatic conditions, land cover, unevenness of data coverage, and the physical and human environment. From these variables we generated a set of hypotheses that might be tested to account for regional differences in population trends (Table 2). Details of the sources and nature of the predictor variables are given in Appendix Table 1. Each variable was designated as 'marine', 'terrestrial' or 'all' relating to whether it was a land-based or sea-based measure. As a result, the time series data were divided into terrestrial and marine bins according to both the type of species being measured and also whether the location of the monitored population was on land or at sea.

Predictor variables were calculated for each population location according to the terrestrial or marine designation described. An ideal data set would consist of polygons that fully describe the extent of each vertebrate population, across which each predictor variable could be summarised. However, as it is only possible to deduce point locations for each population estimate area, we used a combination of point locations and buffers to summarise predictor variables (see Appendix Table 1).

Overall, more variables were available for terrestrial population data than for marine populations (see Appendix Table 1). Variables were derived either by assigning the given value for the variable in question at each point location (e.g., for climatic variables, human population density) or by calculating an average of values across a buffer around the point location (e.g., land cover type). By providing a representation of each population's surroundings, buffers account for the fact that many vertebrates are not confined to a single locality and that spatial error may exist in the recorded location. The use of buffers also allows us to account for differences in spatial resolution of the underlying data layers. Four different buffer sizes were used to evaluate predictor variables (radius of 10 km, 25 km, 50 km, and 100 km), allowing for a range of spatial scales over which a population of a certain species may operate. Given the large variation of species in the data set and the resulting wide range of spatial scales occupied by these species, these buffer sizes were not chosen to accommodate particular species, but to allow general analysis at a number of different spatial scales. Minimum distance to nearest neighbour location and number of additional locations within a buffer radius of 250 km (determined as the average minimum distance between locations + standard deviation) were used as proxies of uneven data coverage.

Spearman's rank correlation (Spearman 1904) was used to preliminarily assess the range of predictor variables against total and average rates of change. Any variables significant at $p<0.1$ were included in the model selection process.

Table 2. Hypotheses tested or considered for spatial analysis of the ASTI vertebrate population trend data set.

Hypothesis	**Explanation**	**Status**
Factors associated with sub-Arctic populations correlate with positive population trends, e.g., latitude, temperature range, forest land cover.	Sub-arctic species are overall showing positive population trends (McRae *et al*. 2010). The sub Arctic is characterised by lower latitudes, wider annual temperature ranges, different land cover types. These factors are not necessarily drivers of vertebrate population trends, but descriptors of the sub Arctic conditions.	Not a useful hypothesis to test but rather a set of factors to consider when interpreting results.
A decrease in sea ice density or extent drives a decrease in population trends of sea ice associated species.	Populations occurring in areas of permanent or temporary sea ice are often dependent on this habitat and will therefore be negatively affected by a reduction in sea ice density (Kovacs *et al*. 2010).	Not tested: requires acquisition of additional data sets and more in-depth analysis. Recommended.
An increase in the extent of protected area within a population's vicinity leads to an increasing population trend.	We assume that protected areas are effective at sustaining healthy populations and minimising threats.	Tested.
Hypothesis with human density as an underlying driver		
An increase in the area of anthropogenic land cover types (cultivated land, urban areas) drives a decrease in population trends.	Human-induced land cover change such as for agricultural expansion and urbanisation presents one of the most dominant threats to vertebrate populations worldwide (Hoffmann *et al*. 2010). It also presents a proxy of human pressure.	Tested.
An increase in the area of natural land cover types drives an increase in population trends.	Larger extents of natural land cover are likely to sustain healthier vertebrate populations and may also harbour less human pressure.	Tested.
An increase in mountainous area and elevation drives an increase in population trends.	Mountainous and high elevation areas are less influenced by anthropogenic pressure.	Tested.
An increase in human population density drives a decrease in vertebrate population trends	Anthropogenic threats drive vertebrate declines worldwide (Hoffmann et al. 2010).	Tested.

Ordinary Least Squares models

Preliminary data analysis was carried out to assess normality of the data and check for extreme outliers. Ordinary Least Square (OLS) models were used to examine the influence of our variables on the spatial relationships within the data set. Models were selected for both response variables (total and average rates of change) and for terrestrial and marine systems separately. All candidate variables were initially included in the model-fitting process and deleted from the model using a backward stepwise elimination approach (Beale *et al*. 2010). Redundancy between variables was assessed in the early stages of model selection using the variance inflation factor (VIF) and any variables with an uncharacteristically high VIF were removed. The Akaike Information Criterion (AIC) and Joint Wald statistic were used to assess relative goodness-of-fit and significance of the model, respectively. Model residuals were also examined for spatial autocorrelation using Moran's I, to ensure spatial independence to fulfil statistical assumptions (Beale *et al*. 2010). Spatial autocorrelation within a model implies that some underlying spatial processes are having an effect on the model and hence may invalidate any significance within the fitted model itself.

Geographically Weighted Regression (GWR) and predicting rates of change across space

In cases of non-stationarity of the OLS model, i.e., where the relationship between the predictor and response variable is not equal across space, GWR allows a better model fit, as it fits local regressions to every point in the data set. Using the best-fit variables from our OLS analysis, we used GWR to model rates of change in all cases where the Koenker's studentized Bruesch-Pagan statistic (Koenker (BP) statistic) indicated non-stationarity in the data set. All GWR analyses used fixed kernels to solve each local regression and AICc bandwidth determination to specify kernel extent. We tested the fit of the resulting model by predicting rates of change for all locations in our data set and comparing these to our observed values by plotting prediction error (predicted error minus observed error) across space. We also tested our model on 1,000 randomly generated locations. While the random location generation mechanism included many data points at lower latitudes than our original data set, this provided a large-scale test for our model and highlights the possibilities of the proposed methodology.

Arctic fox. Photo: Wild Arctic Pictures/Shutterstock.com

Results

Arctic population trends

The spatial representation of Arctic vertebrate population trend data (Figure 2) suggests that some regions such as northern Scandinavia and areas around the Bering Sea are well represented. Conversely, northern Russia is sparsely covered, particularly considering its large land area. However, multi-species records (i.e., records for more than one population per location) were particularly common in Russia, as well as in northern Scandinavia (Figure 2). For these locations, the following analysis is based on average population trends (i.e., all species are combined at each location).

Northern Canada. Photo: Marcel Clemens/Shutterstock.com

Figure 3 to Figure 6 show the spatial distribution of total rates of change (total lambda) as an example of population trends for: all vertebrate (Figure 3), bird (Figure 4), mammal (Figure 5), and fish (Figure 6) populations. Visual inspection of the combined data (Figure 3) shows high concentrations of population records in northern Scandinavia and the Bering Sea. No clear broad-scale pattern of population trends is apparent—however, looking more closely at the population data sets reveals that there are clusters of population growth and decline across vertebrates. The Labrador Sea (mainly cod, American plaice, herring, ocean perch, and Arctic char) and the Queen Elizabeth Islands (mainly caribou, lemmings, and shorebirds) both show multiple populations undergoing a marked decline. Disaggregating the data by taxonomic class highlights some interesting patterns. While fish stocks appear to be declining rapidly in the Labrador Sea, many show a slight increase in the Bering Sea. Many bird and mammal populations along the Labrador Sea coast are showing declines. However, in the Bering Sea, both birds and mammals (mainly sea otters) are faring worse than fish. For birds, this is particularly true in the far north-eastern reaches of Siberia where downward trends reflect declines in some terrestrial and shorebird populations on the mainland and some island-dwelling marine bird populations.

While data coverage is variable across space (Figure 2), high quality data in terms of time series length are much more equally spread among locations (Figure 7). Time series of 20 years length or more are particularly concentrated around the Bering Sea, but coverage is also very good in Iceland and northern Scandinavia. Relatively few of the wildlife population census locations in Russia are long time series and the number of data points per time series is particularly low in this area (Figure 8). Again, time series with the largest number of data points are found in the eastern Bering Sea region, northern Scandinavia and Iceland (Figure 8), suggesting that it is these regions which have the highest quality data available for population trend analysis.

Figure 9 shows very full time series data in these regions, as well as around the Kamchatka peninsula. However, time series data in other areas are much less complete. For example, in Canada, many time series comprise only about half the number of possible annual data points, while in the westernmost Aleutian Islands, time series data are even less complete (Figure 9).

Figure 10 shows, by decade, the spatial coverage of Arctic population trend data, as well as the direction of the trends. While there are few population time series available for the 1950s and 1960s, availability of data increases substantially in the 1970s, particularly across northern Canada and Russia. Figure 10F shows a recent gap in data coverage from northern Canada, particularly from populations that had previously reported declines.

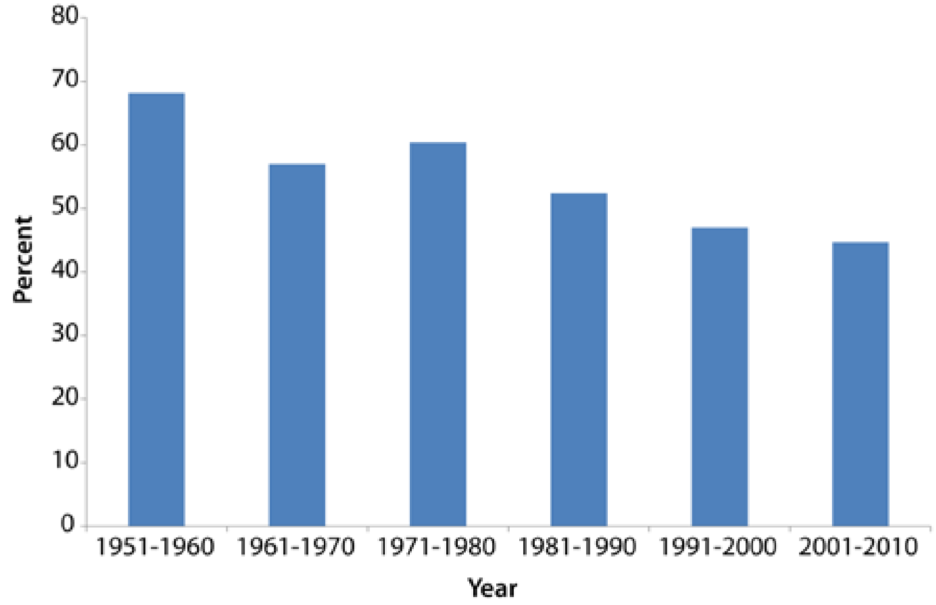

Figure 1. Percent of locations with increasing or stable populations by decade, 1951 to 2010

Numbers of locations with increasing and decreasing populations are presented in Table 3. The proportion of locations with increasing or stable populations has declined over time, when the data are combined for all locations and looked at by decade (Figure 1). This could reflect a change in the nature of the monitoring programs themselves—if there has been a shift in monitoring focus in recent decades from primarily monitoring more abundant, utilised species for management purposes to also monitoring more declining species for conservation purposes.

The breakdown of trends by decade and location (Figure 10) can be used to examine how trends have changed over time in specific regions. For example, in far-eastern Russia, population trends seemed to have continued to decline over time, while recent years have seen some recovery in at least two populations in the Labrador Sea.

	Time period (decade)					
Number of populations	**1951-60**	**1961-70**	**1971-80**	**1981-90**	**1991-2000**	**2001-2010**
Increasing	29	48	116	131	144	96
Decreasing	14	37	76	121	168	117
Stable	1	1	0	2	5	2
Total	44	86	192	254	317	215

Table 3. Number of locations with increasing/decreasing population trends, over time

Figure 11 shows the availability of data per location over time, highlighting locations where data have subsequently become unavailable (locations where data were available in previous decades but were not available for specified decade). Monitoring appears to have declined in more recent times, particularly in the last decade (2001-2010). It should be noted that this does not necessarily mean that monitoring has ceased in all of these locations—the shortage of data for 2001-2010 may largely be due to these more recent data have not yet having been published or otherwise made publicly available.

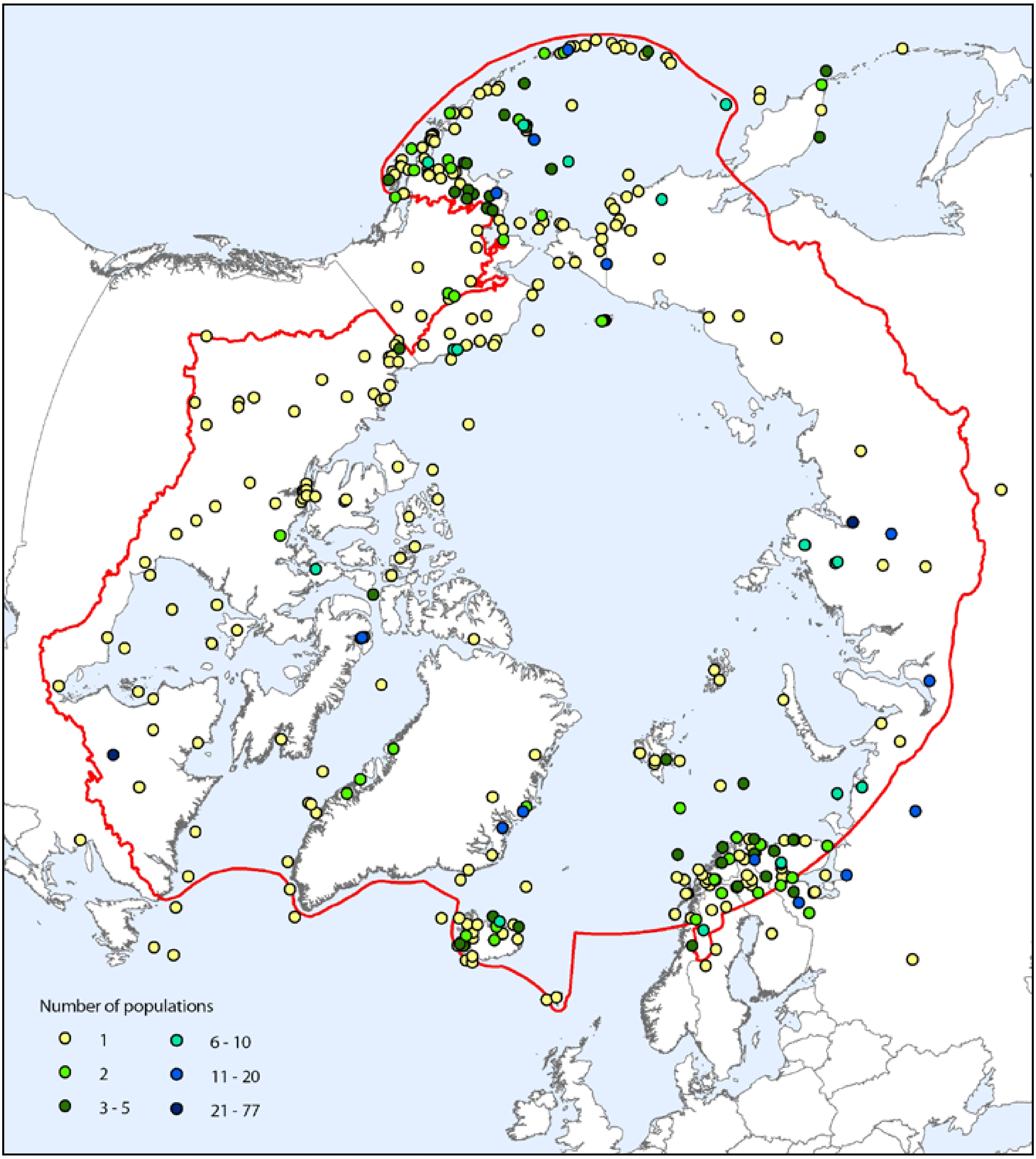

Figure 2. Distribution of population time series data across the Arctic, 1951 to 2010
Number of populations per location are indicated by colour.

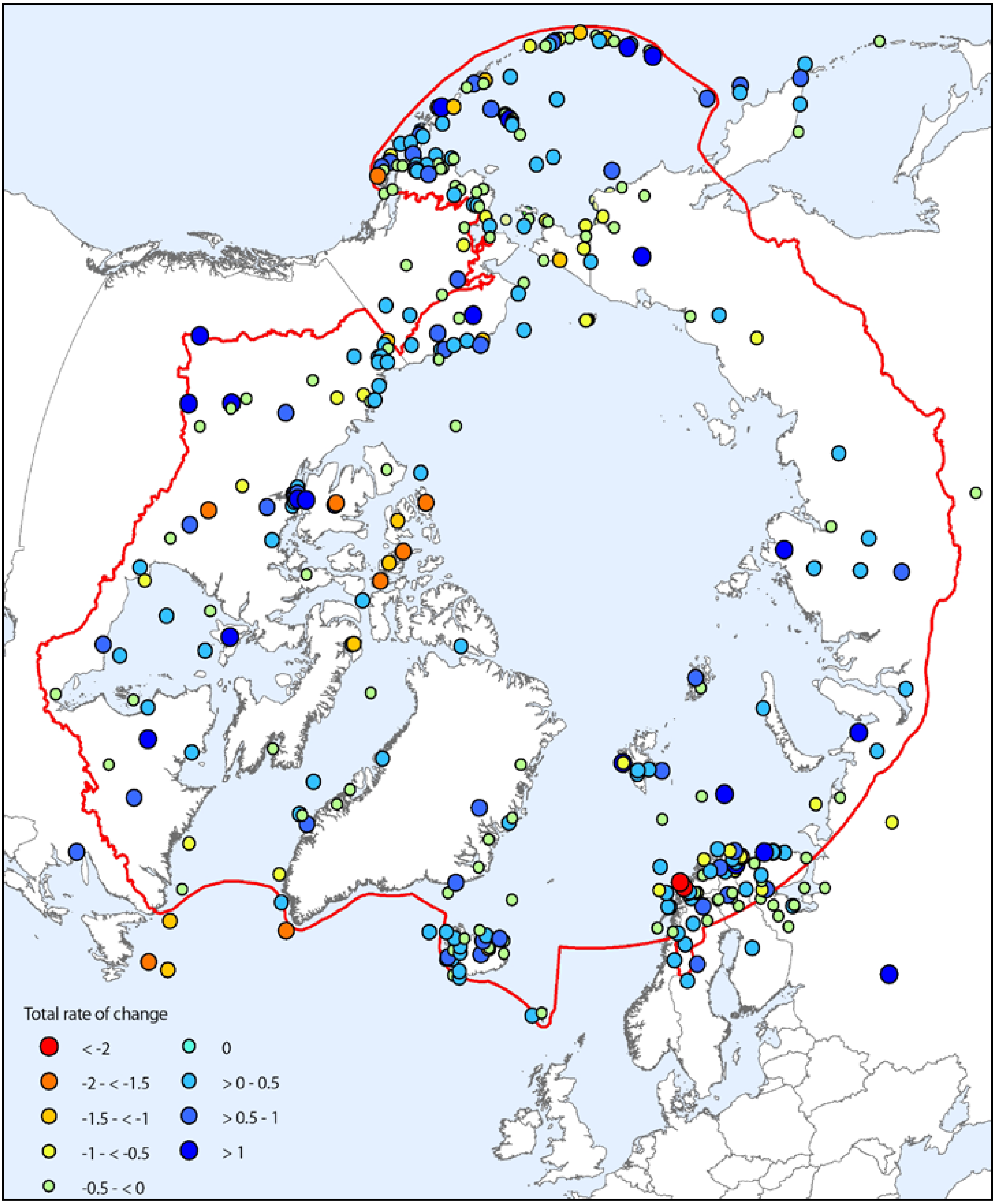

Figure 3. Spatial distribution of population trends in the ASTI data set, for all populations (birds, mammals, amphibians, fish) , 1951 to 2010
Red circles indicate negative rates of change (i.e., declines); blue circles show positive rates of change (i.e., increases). Total lambda is a measure of the rate of change over the entire time period (see methods).

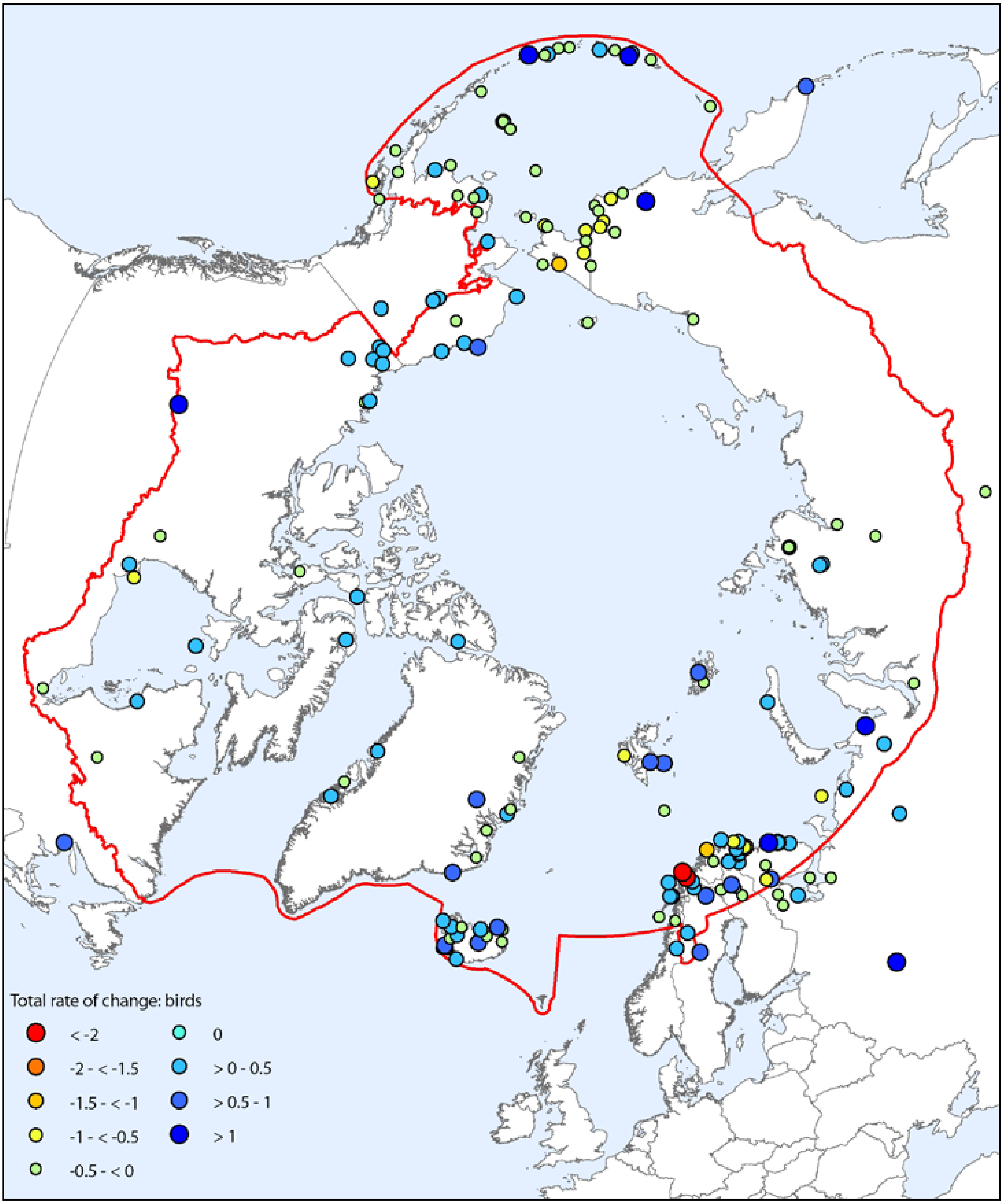

Figure 4. Spatial distribution of bird population trends in the ASTI data set, 1951 to 2010
Red circles indicate negative rates of change (i.e., declines), blue circles positive rates of change (i.e., increases). Total lambda is a measure of the rate of change over the entire time period (see methods).

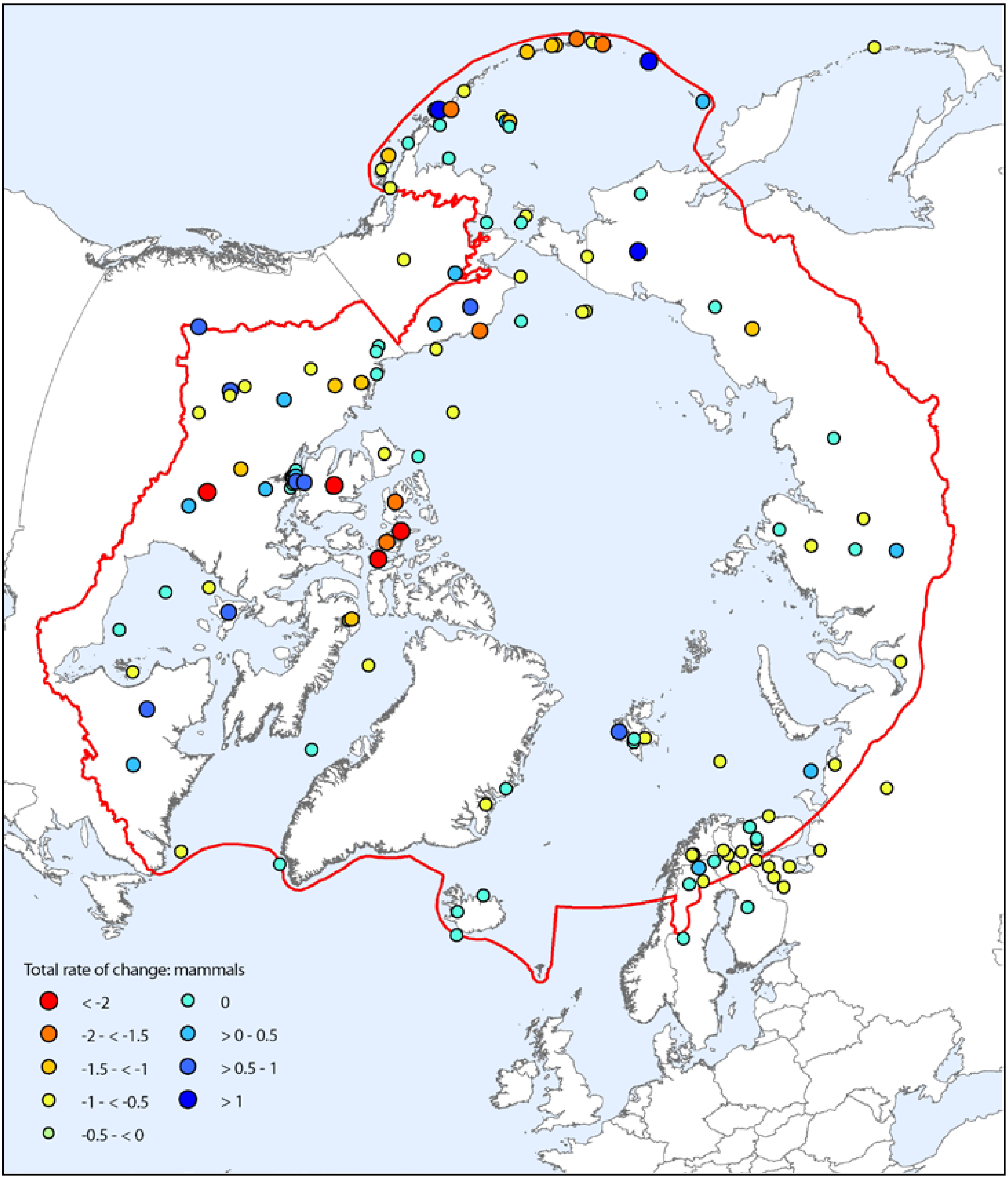

Figure 5. Spatial distribution of mammal population trends in the ASTI data set, 1951 to 2010
Red circles indicate negative rates of change (i.e., declines); blue circles show positive rates of change (i.e., increases). Total lambda is a measure of the rate of change over the entire time period (see methods).

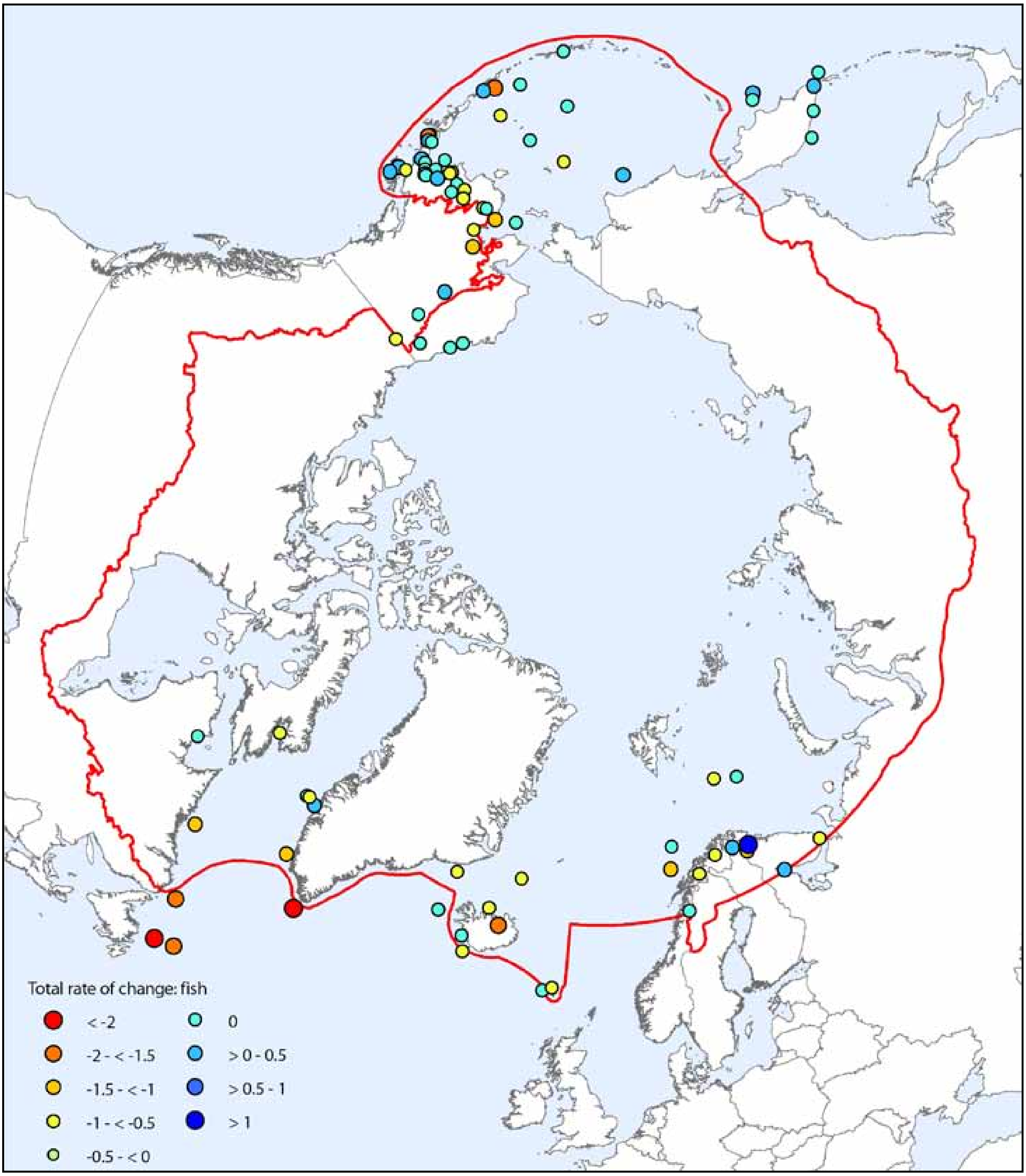

Figure 6. Spatial distribution of fish population trends in the ASTI data set, 1951 to 2010
Red circles indicate negative rates of change (i.e., declines); blue circles show positive rates of change (i.e., increases). Total lambda is a measure of the rate of change over the entire time period (see methods).

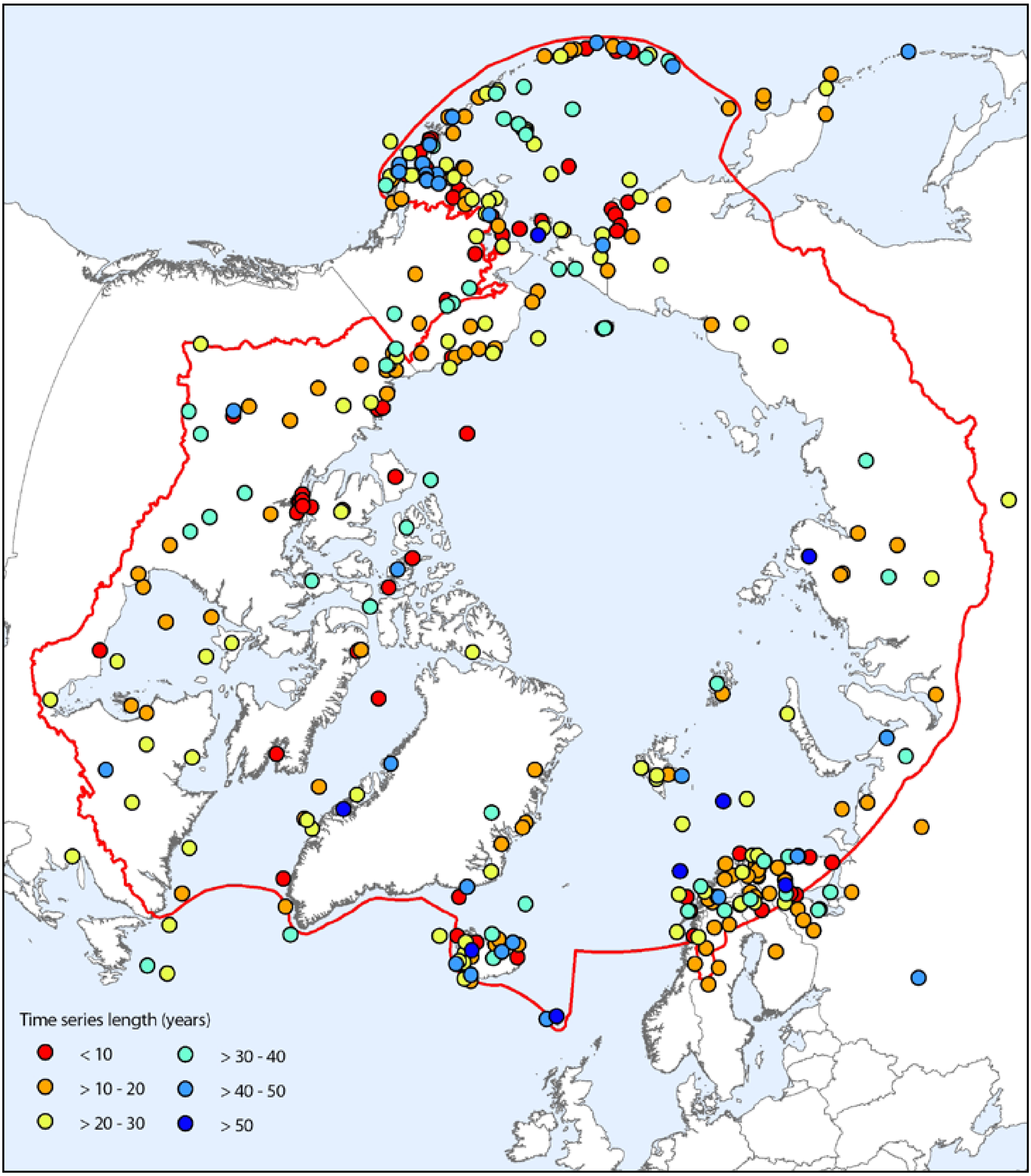

Figure 7. Quality of time series data across the Arctic by time series length, 1951 to 2010

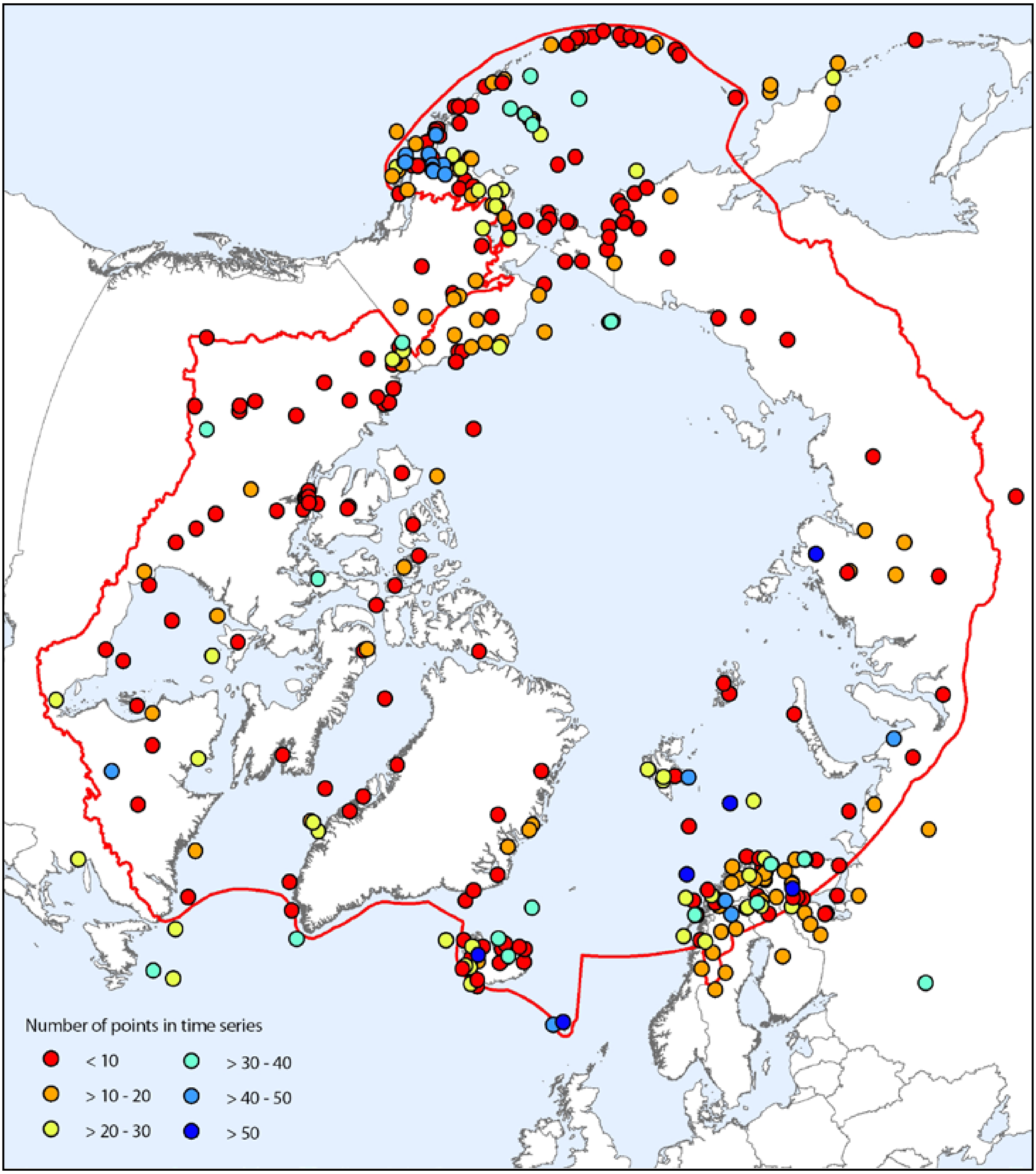

Figure 8. Quality of time series data across the Arctic by number of points in time series, 1951 to 2010

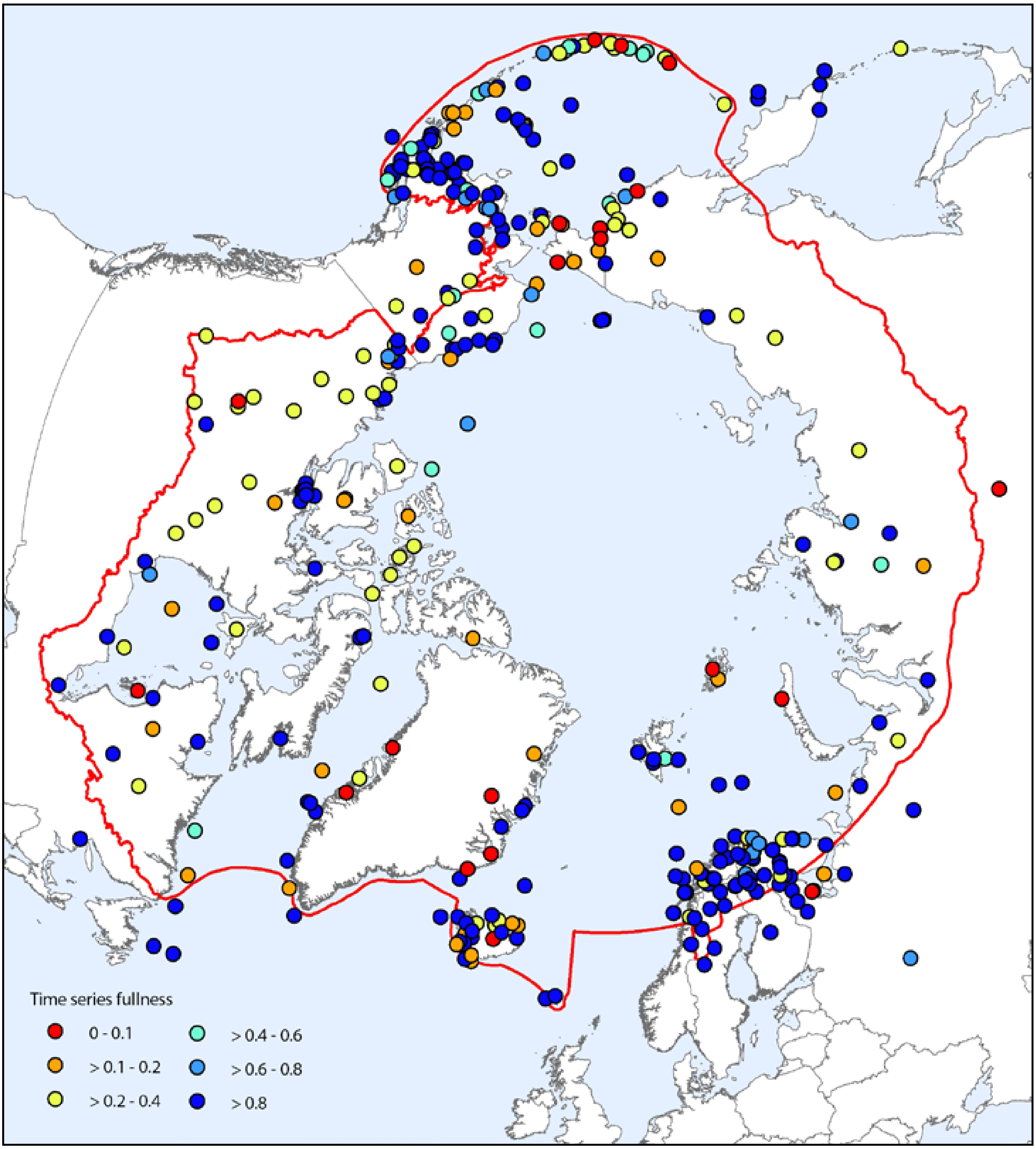

Figure 9. Quality of time series data across the Arctic in terms of time series fullness, 1951 to 2010
Calculated as number of data points divided by time series length. 1.0 = complete time series.

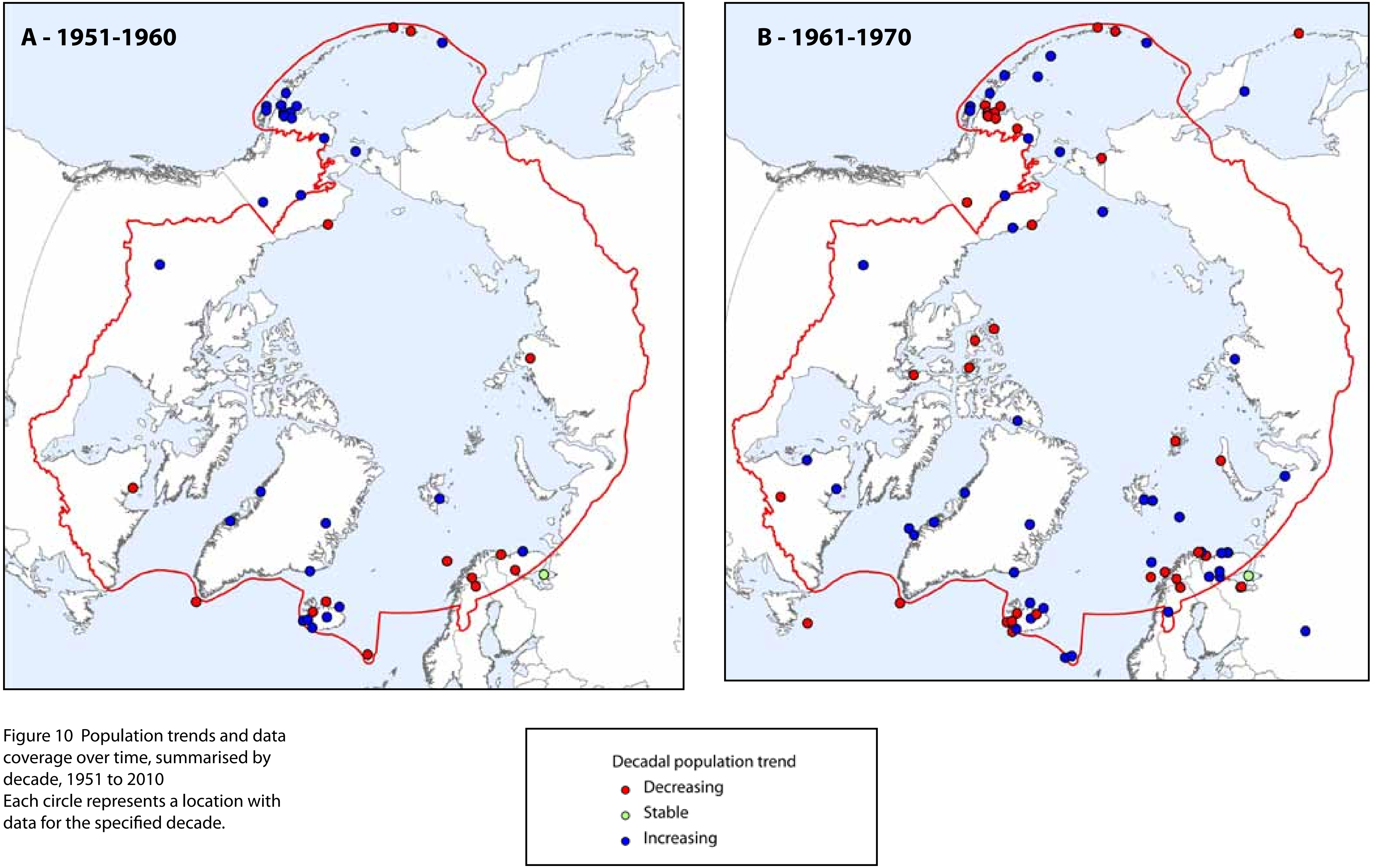

Figure 10 Population trends and data coverage over time, summarised by decade, 1951 to 2010
Each circle represents a location with data for the specified decade.

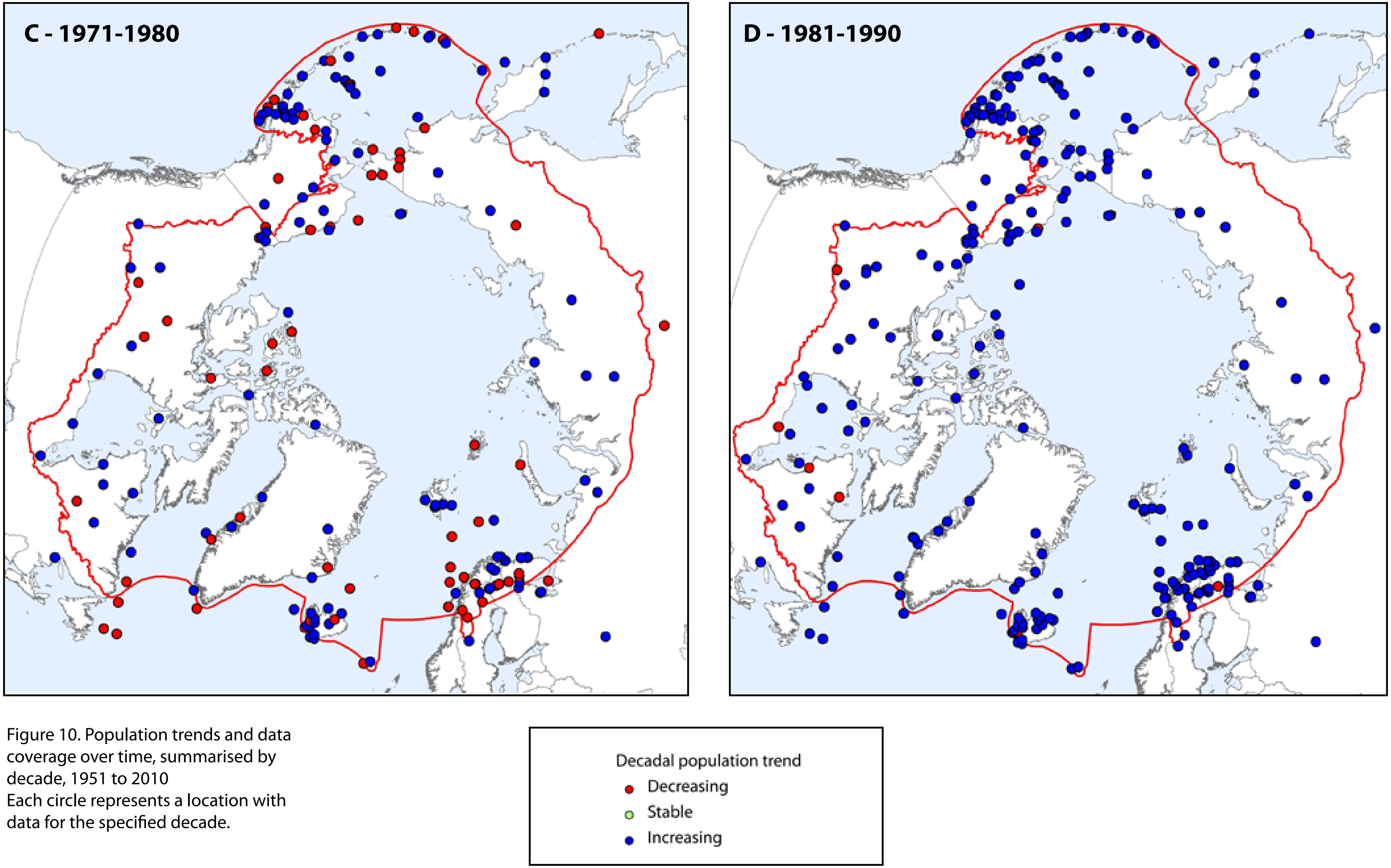

Figure 10. Population trends and data coverage over time, summarised by decade, 1951 to 2010
Each circle represents a location with data for the specified decade.

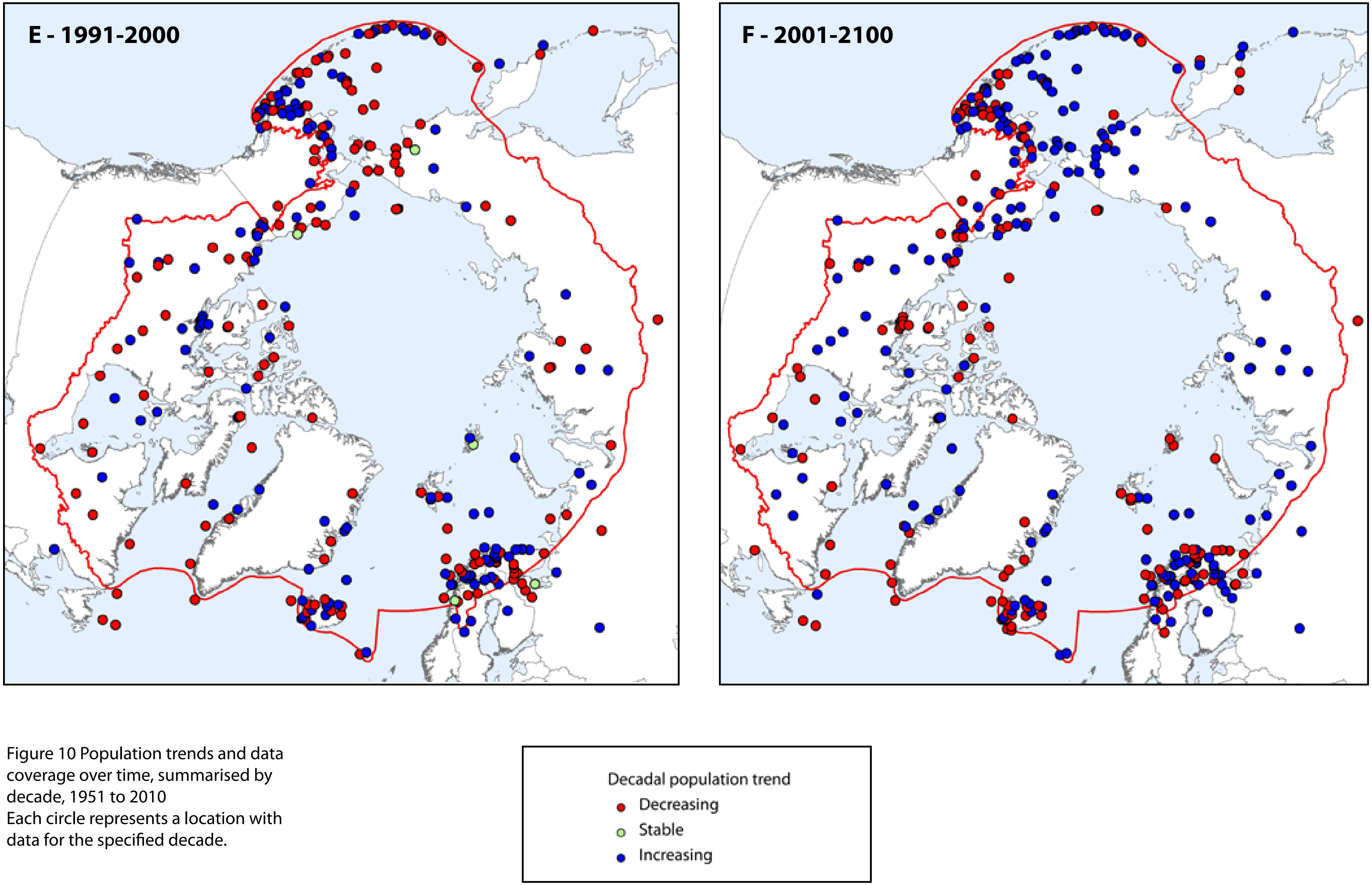

Figure 10 Population trends and data coverage over time, summarised by decade, 1951 to 2010
Each circle represents a location with data for the specified decade.

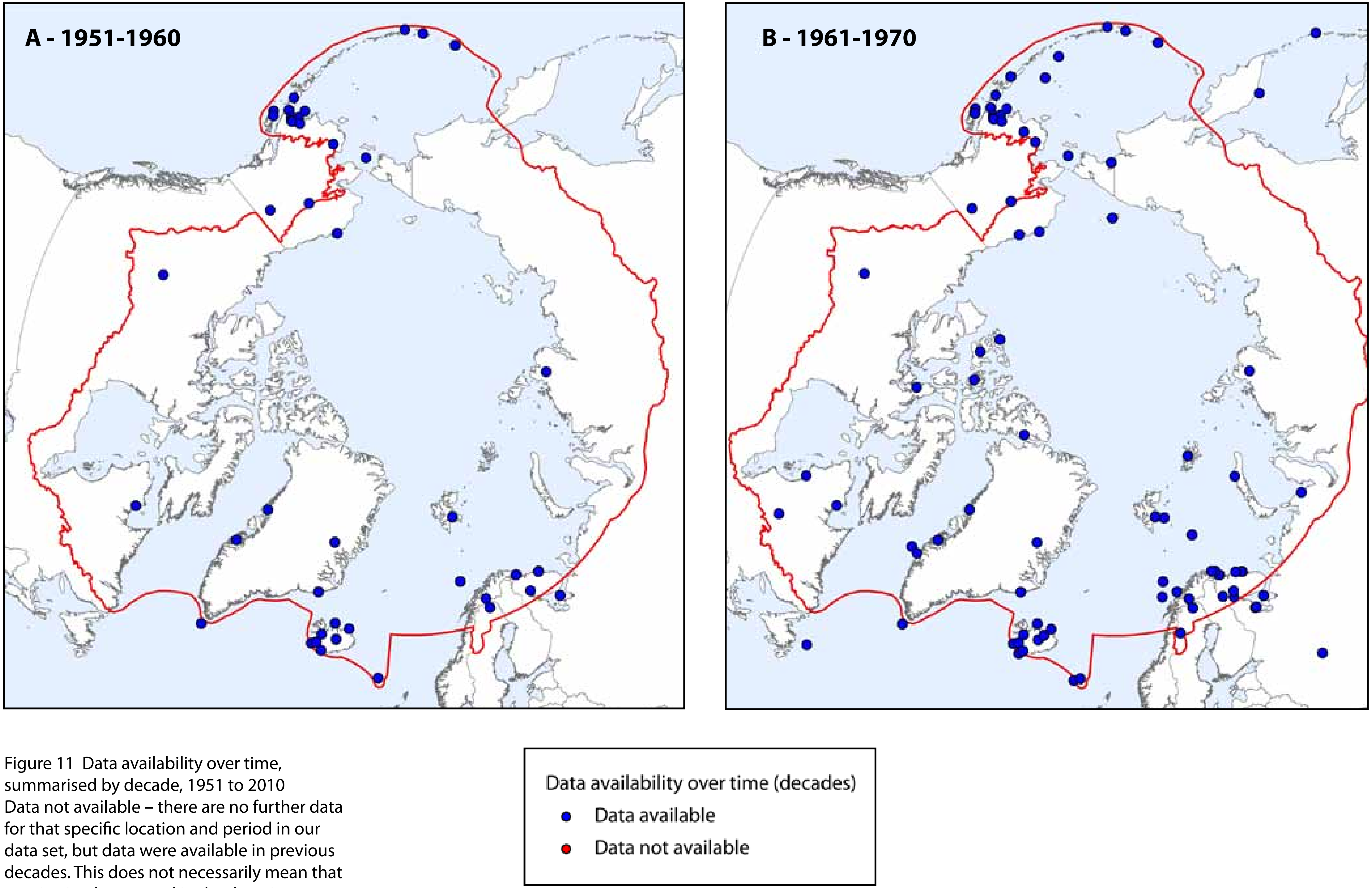

Figure 11 Data availability over time, summarised by decade, 1951 to 2010
Data not available – there are no further data for that specific location and period in our data set, but data were available in previous decades. This does not necessarily mean that monitoring has ceased in that location.

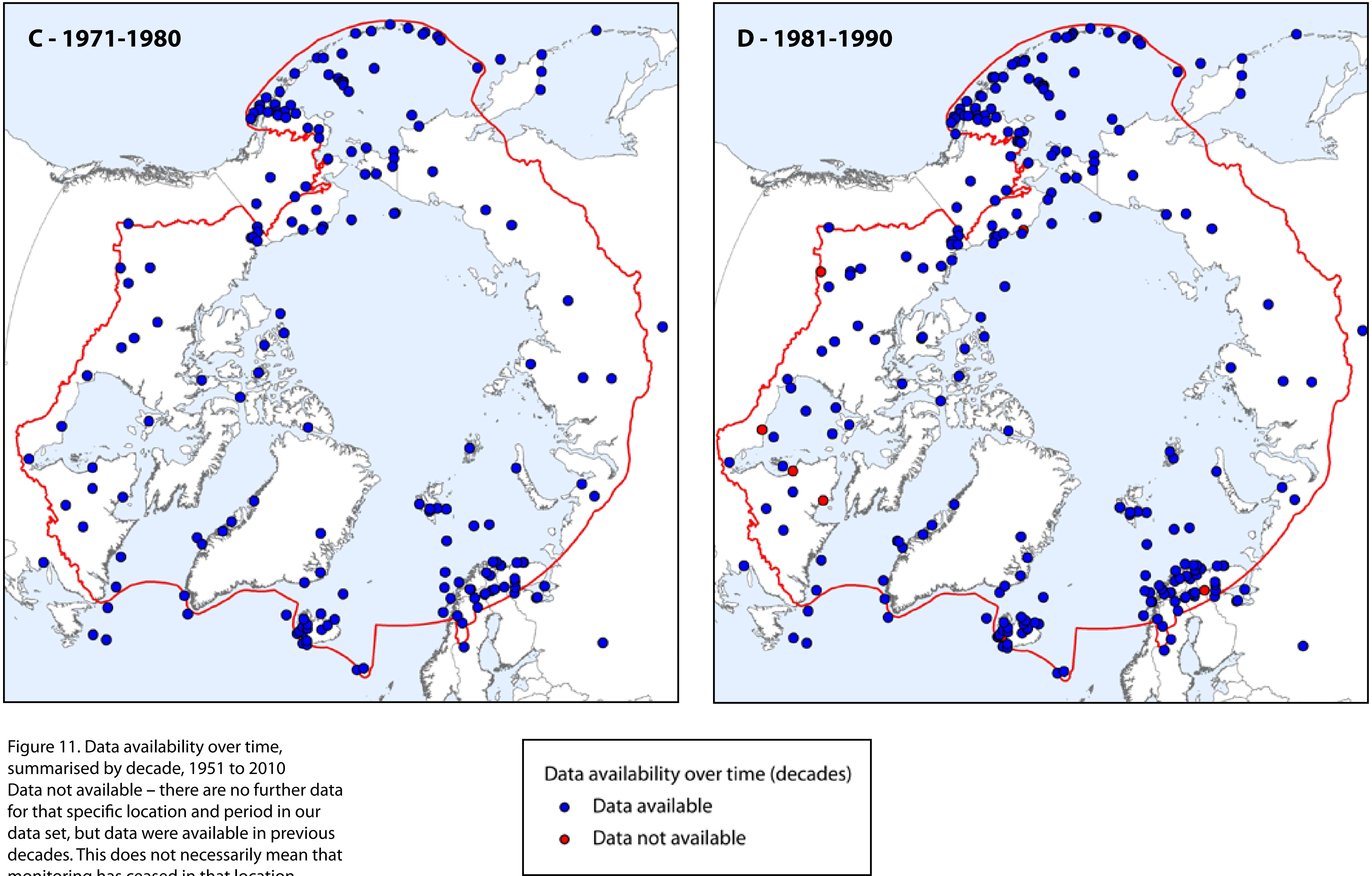

Figure 11. Data availability over time, summarised by decade, 1951 to 2010
Data not available – there are no further data for that specific location and period in our data set, but data were available in previous decades. This does not necessarily mean that monitoring has ceased in that location.

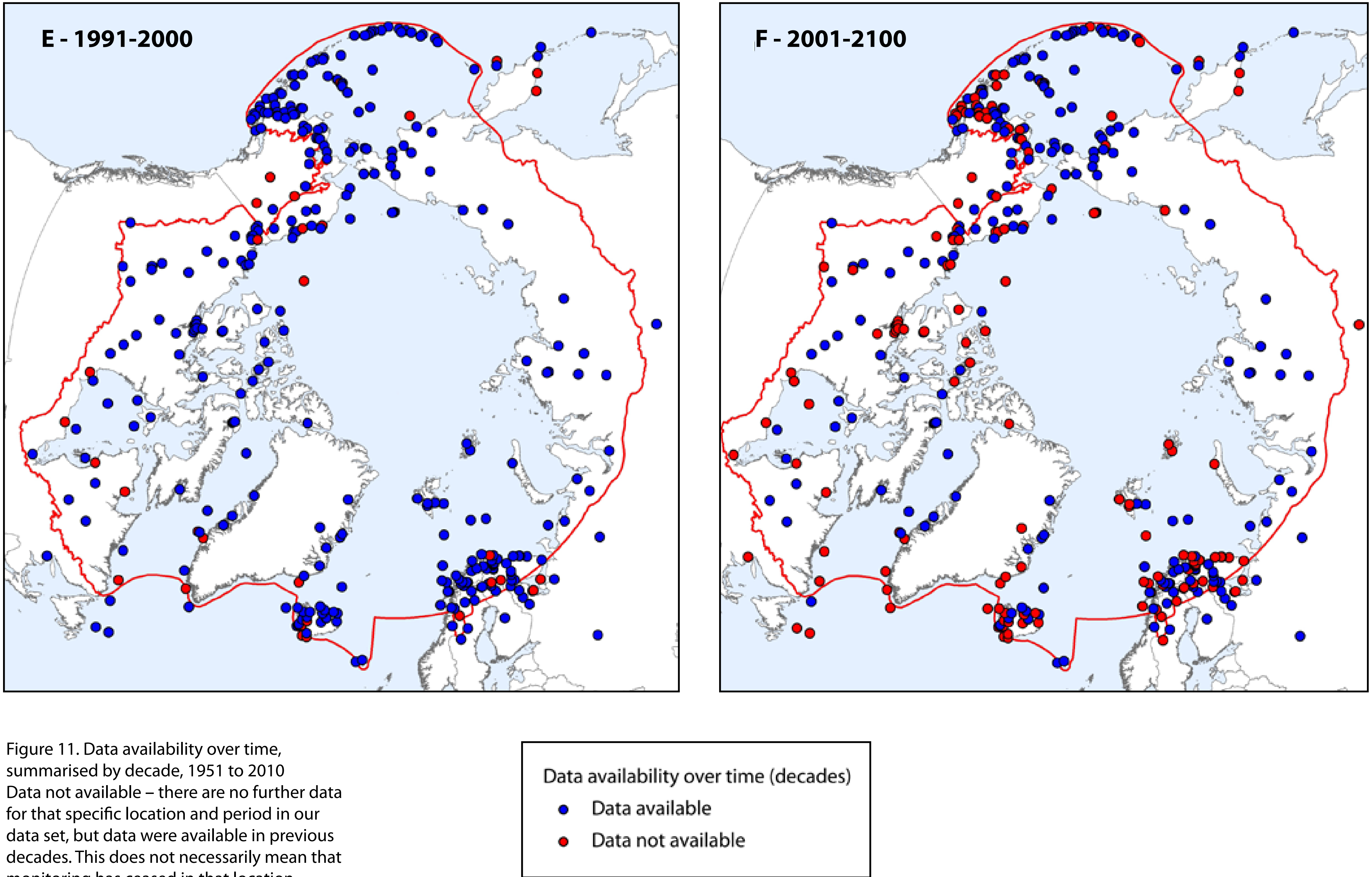

Figure 11. Data availability over time, summarised by decade, 1951 to 2010
Data not available – there are no further data for that specific location and period in our data set, but data were available in previous decades. This does not necessarily mean that monitoring has ceased in that location.

Statistical associations between predictors and population growth rate

A number of land-use and climatic variables were significantly correlated with population trend (both annual average rate of change and total rate of change) in the terrestrial data set, although none of the variables explained more than 25% of the variation in vertebrate population trends (Spearman's rho < 0.5; Table 4).

Population trends of terrestrial populations appeared to be negatively correlated with:

- increases in human population density (Dens_change variable) (Figure 12);
- increases in the area of bare areas, and artificial surfaces and associated areas (Otherlc_*x*k variable); and,
- increases in the area of natural and artificial water bodies (Water_*x*k variable) (Table 4).

These results suggest support for hypotheses associated with human population density as an underlying driver (Table 2).

On the other hand, terrestrial population trends were positively correlated with:

- regions of higher ice and snow (Ice_*x*k variable);
- area of mosaic habitat (Mosaic_*x*k variable);
- mean elevation (Mean_elev_*x*k variable); and,
- temperature range (Temp_range variable) (Table 4).

None of the predictor variables in the marine data set were significantly correlated with population trend. This may be a reflection of the shortage of data on predictor variables for the analysis of marine data (see Appendix Table 1).

Table 4. Significant correlations between rates of change and predictor variables for terrestrial data using Spearman's rank correlations
* denotes variables included in Ordinary Least Squares models.

Variable	**Description**	**Average rates of change *rho***	**Total rates of change *rho***
Dens_change	Change in human population density between 1990 and 2010	-0.191*	-0.218*
Dens 1990	Human population density in 1990	NS	-0.136*
Ice_100k	Area of permanent terrestrial ice within 100k buffer	0.184*	0.172*
Ice_50k	Area of permanent terrestrial ice within 50k buffer	0.165	0.150
Mean_elev_100k	Mean elevation within 100k buffer	0.124*	0.123*
Mosaic_100k	Area of mosaic habitat within 100k buffer	0.175*	0.143
Mosaic_50k	Area of mosaic habitat within 50k buffer	0.173	0.142*
Mosaic_25k	Area of mosaic habitat within 25k buffer	0.136	NS
Otherlc_100k	Other land cover (e.g., bare areas) in 100k buffer	-0.149	-0.127
Otherlc_50k	Other land cover (e.g., bare areas) in 50k buffer	-0.165*	-0.155*
Otherlc_25k	Other land cover (e.g., bare areas) in 25k buffer	-0.148	-0.141
Otherlc_10k	Other land cover (e.g., bare areas) in 10k buffer	-0.125	NS
Otherf_lc_50k	Other forest area within 50k buffer	0.127*	NS
Temp_range	Mean diurnal temperature range at location	0.148*	0.152*
Water_100k	Area of water within 100k buffer	-0.174	-0.185
Water_50k	Area of water within 50k buffer	-0.179*	-0.200*
Water_25k	Area of water within 25k buffer	-0.130	-0.172
Water_10k	Area of water within 10k buffer	NS	-0.123

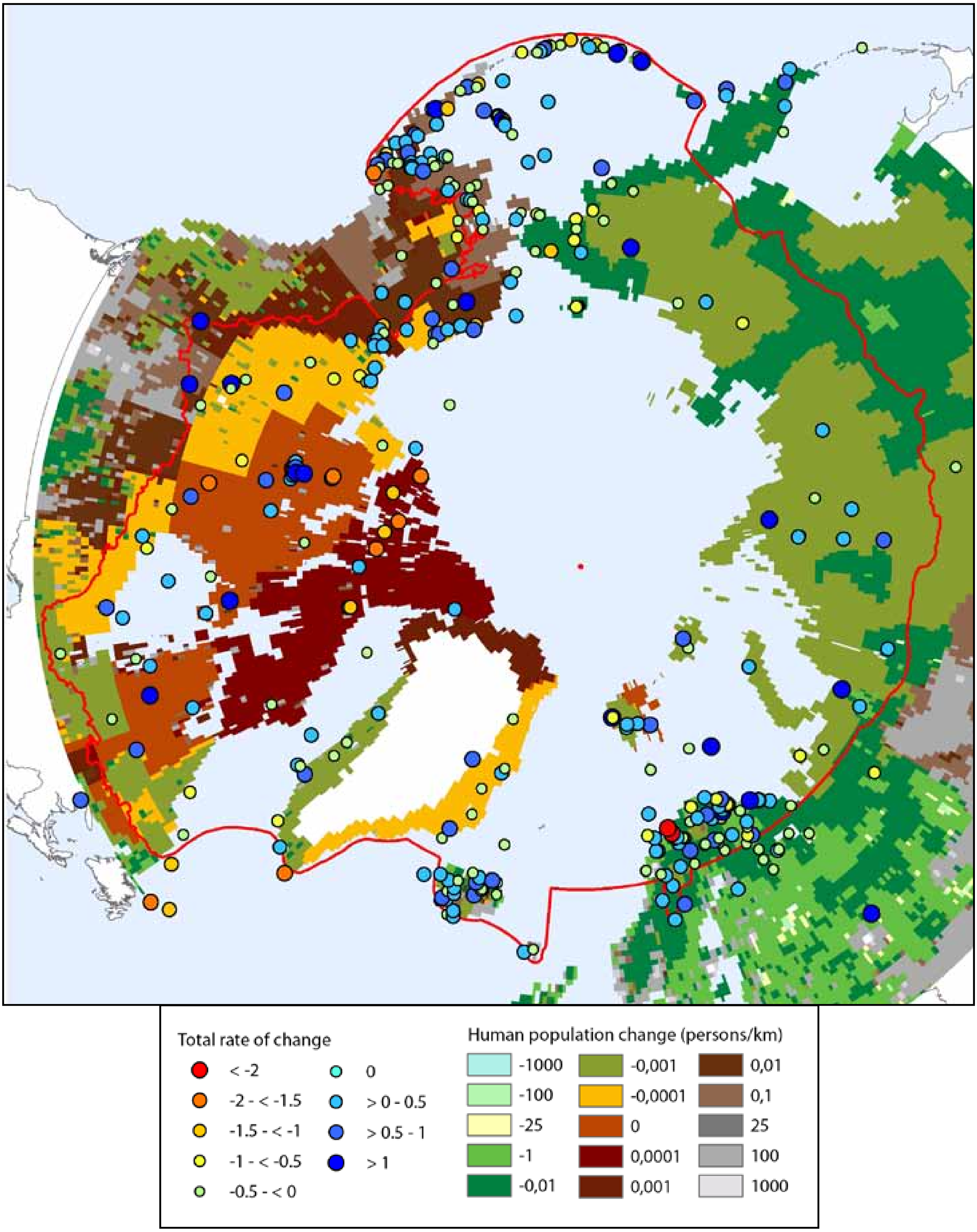

Figure 12. Changes in human population density and vertebrate population trends, 1951 to 2010
Total lambda is a measure of the rate of change over the entire time period

Because of duplication of explanatory variables in the analysis, caused by assessing variables at different buffer sizes, we used the variance inflation factor (VIF) to check for redundancy within the terrestrial model. Explanatory variables that would merely duplicate an effect on the response variable (e.g., Ice_100k and Ice_50k were both significant, see Table 4) were excluded from further analyses in OLS models. Daily temperature range (Temp_range) and area of water (Water_50k) were predominant predictors of both average and total rates of change. Inclusion of area of ice (Ice_100k) only marginally changed the goodness-of-fit for total rates of change (Table 5, Model 1).

The foregoing is a suggested approach to modelling the spatial attributes of the ASTI data. In the future, a more thorough analysis would involve *a priori* defining of the key drivers that affect northern populations, selection of species to which those drivers most apply, and design of a more focussed regional and species oriented analysis using available predictor variables or derived variables that reflect the identified key drivers.

Table 5. Best fit OLS spatial model for total rates of change for terrestrial population trends

Variable	Coefficient	Standard error	Robust t-Stat	Robust p	AIC	Wald chi sq	p
MODEL 1							
Intercept	0.154	0.055	2.797	0.006*	325.98	295.121	<0.0001*
Temp_range	-0.0001	0.00006	-9.393	<0.0001*			
Ice_100k	0.046	0.042	2.120	0.035*			
Water_50k	-0.347	0.120	-2.282	0.024*			
MODEL 2							
Intercept	0.159	0.055	2.883	0.004*	325.24	301.327	<0.0001*
Temp_range	-0.0001	0.00006	-9.655	<0.0001*			
Water_50k	-0.326	0.118	-2.207	0.029*			

Although none of the model residuals showed significant spatial autocorrelation, the Koenker (BP) statistic was significant at $p<0.014$ for the model of average rates of change (Table 6). This suggests that there is non-stationarity in the spatial processes explained by the predictor variables, which in turn implies that either the predictors may have different variances across space or there are other important predictor variables missing from this analysis. Since OLS fits a single regression equation across space, any such regional variation in variance is lost. As such, it is worthwhile to use Geographically Weighted Regression (GWR), which fits a regression equation to every point in the data set rather than producing one global regression equation. Models 1 and 2 of total rates of change (Table 5) did not show any significant non-stationarity, but the resulting models only explained around 5% of variation (Model 1: adjusted $R^2 = 0.041$; Model 2: adjusted $R^2 = 0.040$). These results highlight the need to consider other predictor variables, conduct smaller regional analyses, or focus on particular species or species groups to help understand the complexity of the real world.

Table 6. Best fit OLS spatial model for average rates of change for terrestrial population trends

Variable	Coefficient	Standard error	Robust t-Stat	Robust p	AIC	Wald chi sq	p
Intercept	0.0077	0.006	1.286	0.200	-480.31	52.791	<0.0001*
Temp_range	-0.000005	0.000006	-3.011	0.003*			
Water_50k	-0.0328	0.0130	-1.380	0.169			

Geographically Weighted Regression to predict rates of change across space

Given that the OLS model of average rates of change showed significant non-stationarity, we used the best-fit OLS model (Table 6) as a case study to predict rates of change across the Arctic region using Geographically Weighted Regression (GWR). GWR increased the predictive power of the OLS ($R^2 = 0.112$; adjusted $R^2 = 0.063$), with the improved model explaining approximately 6 to 11% of variation in the data, compared to 5% using OLS.

The GWR model was used to predict the range of values for our data set in order to allow comparison with observed values (Figure 13). Overall, the model predictions fit the observed data relatively well. For example, the model provided an adequate representation of the declines in the far east of Russia. The model's main shortcoming is the prediction of extreme values, such as the more severe population declines observed in some parts of the Arctic. Figure 13 shows prediction error over space, again highlighting that errors were largest where observed average rates of change were either largest or smallest. For example, on Victoria Island and the adjacent mainland (northern Canada), the observed average rate of change was particularly high (up to 0.265 in one location), while in northwestern Alaska and the Queen Elizabeth Islands the observed average rate of change was particularly low (< 0.1).

When the model is refined and run in combination with information on distribution of vertebrate species, it can be used to predict population trends in regions where data are sparse. Further, if in the future predictor indicators characterised by change are built into the analysis (e.g., climate change, change in sea ice), these models could be used to reconstruct historic trends or project future trends under scenarios of future environmental conditions. As well, in any future analysis it will be important to construct the model with a sub-set of the population trend data and then compare actual versus predicted trends in the sub-set that was not originally modelled. This would improve our confidence in the predictive power of the model.

Northern lights. Wild Arctic Pictures/Shutterstock.com

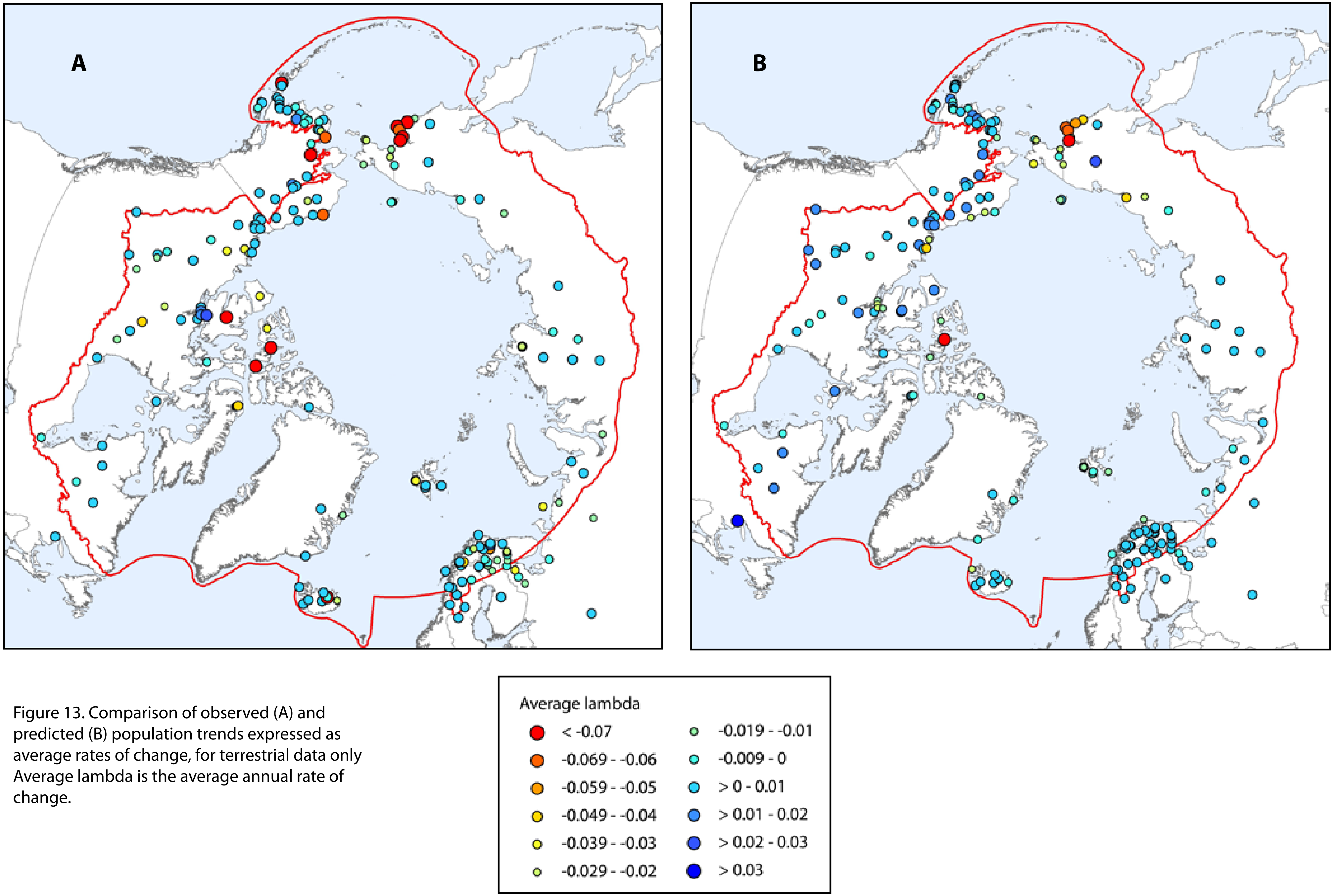

Figure 13. Comparison of observed (A) and predicted (B) population trends expressed as average rates of change, for terrestrial data only Average lambda is the average annual rate of change.

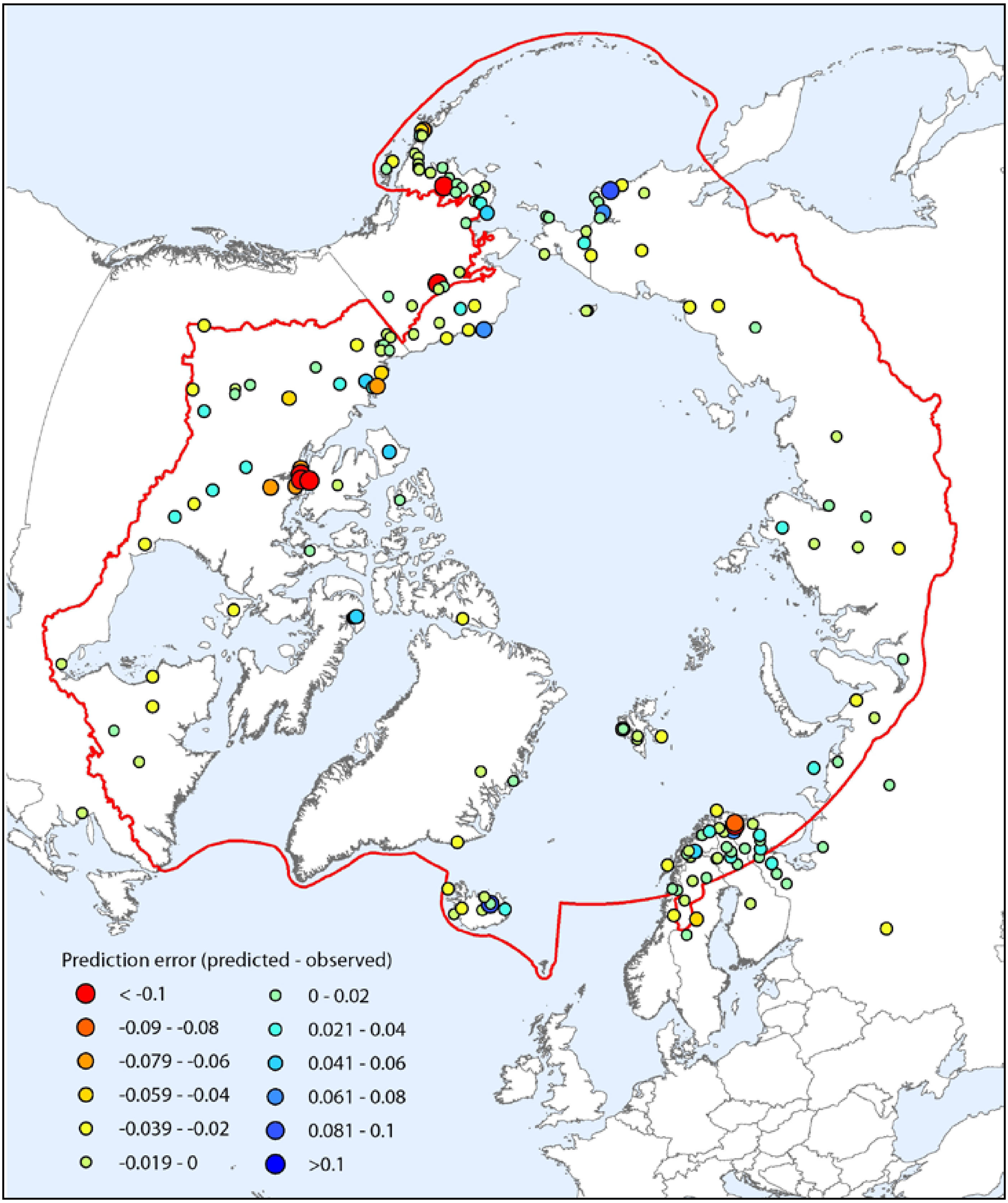

Figure 14. Prediction error of GWR predictive model (predicted minus observed value) for terrestrial data only
Larger values (blue) represent an over-estimation of the population trend, smaller values (red) an under-estimation.

Discussion

While temporal population trends have previously been the subject of detailed analyses (e.g., Arctic species trends, McRae *et al*. 2010), it is vital that these trends are also considered in a spatial context. Environmental conditions and human impacts vary across space, while populations in themselves are very much a spatial as well as a temporal entity. As a result, spatial representations of population trend data can help to highlight:

- gaps in the spatial data coverage and data quality;
- areas or regions that show most pronounced decreases in populations or the most consistent decreases over time;
- spatial relationships of population trends with land use, physical, and climatic predictor variables; and,
- spatial patterns across the Arctic from model predictions.

Data quality and coverage

At present, the Arctic data set comprises population trend data from 366 unique locations across the Arctic. However, these are not evenly distributed throughout the region, with large clusters in northern Scandinavia and the Bering Sea region. Russia, on the other hand, is sparsely covered, making analysis of spatial patterns in the region difficult, if not impossible. However, the few Russian locations contain information on a large number of vertebrate populations and for long time periods (albeit with a small number of data points within each time series). This allows for the analysis of congruence in population trend patterns across species. Other obvious gaps in spatial coverage of the ASTI data set are found in Greenland, particularly northern parts, and islands off the northern coast of Canada.

ASTI marine data are primarily concentrated in the Bering Sea but are currently sparse elsewhere. These gaps may indicate real gaps in monitoring effort or may simply indicate failure to obtain already existing data for certain areas, or a combination of the two. While all efforts have been made to collect all available data, this still has implications for interpreting data coverage, as lack of data does not necessarily imply lack of monitoring.

Analysis of spatial data gaps can, and should, spark initiatives to address these deficiencies. However, it is also important to address other aspects of data quality, such as length and completeness of time series, when designing future monitoring programs or when considering changes to current monitoring. Many of the series in the present data set start in the 1970s and 1980s and cover at least 10 years, although some of the data from northern Canada are characterised by shorter time series with a smaller number of data points. In northern Scandinavia and the Bering Sea, the majority of time series are both long and complete, providing a sound basis for analysis of long-term trends.

Population trends across the Arctic region

Observed population trends differ widely across the Arctic region and also across taxa. Three geographical areas of particular concern are the Labrador Sea (fish), Queen Elizabeth Islands and surrounding areas (mammals) and the Bering Sea region (particularly seals, some cetaceans, and birds). Populations in far-eastern Russia (included in the Bering Sea region) have been declining for the past four decades.

Population monitoring coverage has improved over time, although some data gaps have become apparent for the most recent decade of population trend collection (i.e., 2001-2010). This may be due to the fact that these data have not appeared in the published literature yet. In any case, it highlights the importance of timely reporting of monitoring data. For example, the data suggest recent increases in fish populations in the Labrador Sea, but this is based on only two spatial data points. In the past, data were available from at least six locations, where populations were rapidly decreasing. Similarly, there appears to be a recent data gap emerging across the Queen Elizabeth Islands and adjacent regions in Canada. Since this coincides with an area of population decline for mammals (specifically, caribou), it is vital that monitoring in this area be resumed, or even intensified.

More detailed analysis of the graphical output will undoubtedly highlight more areas that are in urgent need of conservation attention. Visual spatial representation of biodiversity indicators (e.g., population trend data) through mapping provides a powerful tool for visualizing areas of decline and gaps in knowledge in a non-technical way. This makes information accessible to a wide audience and provides tools for decision makers to identify areas in need of improvement and areas with conservation success stories.

Spatial relationships of population trends and inference of spatial patterns across the Arctic
In order to understand underlying factors for population increases and decreases, we used Ordinary Least Squares models and Geographically Weighted Regressions to test the suitability of the spatial data set for future more in-depth analyses. Using a limited number of explanatory (predictor) variables, we aimed to test a small set of hypotheses on Arctic vertebrate population trends. Temperature range and water body area (Temp_range, Water_50k) were the two most important factors in the regression analysis of predictor variables versus population trends. Terrestrial vertebrate population trend was positively correlated with temperature range (i.e., a greater temperature range across space was correlated with a positive population trend), and negatively correlated with area of water bodies within the surrounding area (i.e., population trends decreased with an increase in the area of nearby water bodies). ASTI analyses conducted previously showed that sub Arctic populations are faring better than those at higher latitudes (McRae *et al.* 2010), which is in line with the positive correlation of population trends with temperature range found in this analysis. With climate change expected to affect temperature regimes across the Arctic, future work should focus on climate and temperature scenarios in order to assess the possible effects on Arctic vertebrates across the region.

Basic preliminary and non-spatial analysis of correlations between predictor variables and vertebrate population trends also suggested that an increase in human population density is correlated with a decreasing population trend, and that an increase in mean elevation is correlated with an increasing population trend. However, neither of these variables were influential in the spatial analyses.
Overall, relatively little variation in the ASTI data was explained by the predictor variables. This suggests that important factors were missing from the analysis and any future work should thus aim to expand the variable set employed here.

The inclusion of variables related to threats in the analysis may be of particular importance. However, defining the extent and magnitude of threats across space is not always straightforward. It may be easiest for threats that are based on existing land cover data, such as habitat loss and fragmentation. Similarly, climate data time series need to be aggregated to describe the degree of climate change across space in any future research.

The underlying data are likely to harbour much more spatial complexity than has so far been investigated. It is likely that some factors interact with other variables in certain regions and less so in others. Some variables will have different effects for different species classes (e.g., different effects for birds than for mammals). So far, however, our analysis has only focussed on locations (by lumping multiple populations per location into one data point) as opposed to different species groups. Smaller scale analyses aimed at regions with good data coverage can also be used to overcome the problem of factors affecting populations differently across regions.

Recommendations

This study has provided a first look at spatial distribution of population trends from 1951 to 2010 in order to provide a baseline against which future changes across the Arctic region can be assessed. It has also allowed a first assessment of the quality of available time series data in terms of their spatial representation and the potential drivers underlying population trends. Particularly with regard to the quality of the data set, we are now in a position to address any significant gaps in data coverage, both through an increase in effort to obtain existing data for gap locations and through targeted monitoring projects, making more efficient use of limited resources.

Data coverage

In order to improve the quality of the data set, data collection efforts should be particularly focussed on areas of northern Russia and Greenland, as well as islands off the northern coast of Canada, where data are currently sparse. While multi-species monitoring is already taking place in many locations across the Eurasian Arctic, most of the population records across Canada are representative of a single species only. Establishing monitoring programs that focus on multiple species in a location would help with identifying whether observed population trends are congruent among species. Many population time series are represented by only a few data points, particularly in the western Aleutian Islands and at a number of locations in Canada. More frequent monitoring should be carried out in these areas to provide improved time series data, which could be used to pinpoint inflection points in the time series and distinguish between naturally occurring fluctuations and actual population reductions in a more timely manner.

The extensive and highly complete time series data available for certain regions, such as northern Scandinavia and the Bering Sea, provide a basis for further analysis of underlying spatial patterns and factors influencing population trends. Regional analyses such as these are likely to improve our understanding of particular local factors which could be exerting a large influence on vertebrate population trends.

Drivers of population trends

None of the predictor variables was able to describe a large amount of variation within the population trend data. This suggests that we were missing one or more important explanatory variables from the analysis. It is therefore recommended to derive additional explanatory factors from available data sources. In particular, variables of change in conditions need to be incorporated into the analysis, as it is these changes that are the likely drivers of population trends over time. However, obtaining these data is very time consuming and was not possible for the purpose of this initial study.

Additional explanatory variables which may be of particular importance are changes in sea ice extent for sea-ice dependent vertebrates and habitat fragmentation or connectivity variables for terrestrial vertebrates. Again, development of fragmentation variables is very time consuming and was therefore not achievable over the short timeframe of this study.

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Iceberg off coast of Greenland. Photo: jele/Shutterstock.com

Appendix: Spatial analysis—concepts and tools

Compared to non-spatial data analysis, spatial statistics are more complex due to the underlying effect of spatial autocorrelation and non-stationarity on the data. Spatial autocorrelation arises from the simple fact that measurements taken at geographically close points are more likely to be similar than those taken from locations further apart (Koenig 1999). Even ignoring external factors, a species' distribution is always autocorrelated, due to the underlying processes of aggregation and dispersal (Beale *et al*. 2010). However, extrinsic factors that shape a species' distribution or population characteristics, such as climate or soil type etc., are also spatially autocorrelated, so that environmental conditions at two adjacent localities are more likely to be alike than those at locations which are further apart (Beale *et al.* 2010).

Analyses which ignore spatial autocorrelation thus run the risk of finding significant results between explanatory and response variables when, in reality, these are only a reflection of underlying spatial effects (Type I error). Stationarity assumes that the relationship between the predictor and response variable constant across space, yet stationarity is unlikely to be the norm in spatial contexts (Brunsdon *et al*. 1996). As a result, simplification of models into a single global regression equation may not do justice to the complex interplay between spatially distributed factors. While dealing with the problems of spatial autocorrelation and stationarity appears to be complex, there are tools incorporating spatial considerations available in ArcGIS thus providing a user friendly and graphical way of analysing spatial data. We used two main tools, which we outline below.

Ordinary Least Squares regression to model spatial relationships

Ordinary Least Squares (OLS) regression is often the starting point for spatial data analysis. Although essentially a non-spatial approach, by creating a single regression line to fit the data and thus assuming a constant relationship across space, it provides a way of examining spatial relationships when coupled with tests for spatial autocorrelation, such as Moran's I. Due to the non-spatial nature of OLS, Type I errors become more common than when using spatially-explicit regression methods (Beale *et al*. 2010). Furthermore, coefficient estimates are less precise (Beale *et al*. 2007). However, in cases where residual spatial autocorrelation is negligible or non-existent, OLS and spatially-explicit regression models should provide satisfactory results (Beale *et al*. 2007).

Geographically Weighted Regression to predict spatial patterns

In cases where residuals from OLS still show significant spatial autocorrelation, spatially-explicit regression models will provide more sound results. Geographically Weighted Regression (GWR) considers local spatial relationships in the regression (Fotheringham *et al.* 2002) by creating a local regression equation for each data point, thus allowing the relationship between predictor and response variables to vary across space. GWR has been used in a number of ecological contexts, for example to examine the relationship between phytoplankton biomass and runoff (Wooldridge *et al*. 2006), avian diversity and climatic factors (Foody 2004) and in analyses of net primary productivity (Wang *et al*. 2005). Geographical weight is added to the regression by a user-defined spatial kernel which is used to incorporate spatial dependence into each location's regression equation (Miller *et al.* 2007). As a result, the method has outperformed simple OLS regression on multiple occasions (e.g., Wang *et al*. 2005; Shi *et al*. 2006).

Appendix Table 1: Variables included in the analysis

Variable name	Description	Source	Data type	Location/buffer	Time period	Spatial resolution	Data set
a) Climatic conditions							
Ann_temp	Annual mean temperature	WorldClim (bioclimatic variables)[1]	Grid	Location	1950-2000	1 km^2	Terrestrial
Temp_range	Mean diurnal temperature range	WorldClim (bioclimatic variables)[1]	Grid	Location	1950-2000	1 km^2	Terrestrial
Ann_prec	Annual precipitation	WorldClim (bioclimatic variables)[1]	Grid	Location	1950-2000	1 km^2	Terrestrial
Sea_ice	Sea ice density	National Ice Center	Polygon	Location	1974-2007	N/A	All
b.1) Land cover (general)							
Forest_lc	Forest land cover	GLC2000 [2]	Grid	Buffer	2000	1 km^2	Terrestrial
Broadleaf_lc	Broadleaf forest area	GLC2000 [2]	Grid	Buffer	2000	1 km^2	Terrestrial
Coniferous_lc	Coniferous forest area	GLC2000 [2]	Grid	Buffer	2000	1 km^2	Terrestrial
Mixed_lc	Mixed forest area	GLC2000 [2]	Grid	Buffer	2000	1 km^2	Terrestrial
Otherf_lc	Other forest area	GLC2000 [2]	Grid	Buffer	2000	1 km^2	Terrestrial
Shrub_lc	Area of shrub and herbaceous cover	GLC2000 [2]	Grid	Buffer	2000	1 km^2	Terrestrial
Cultivated_lc	Area of cultivated land	GLC2000 [2] Millennium Ecosystem Assessment[3]	Grid	Buffer	2000	1 km^2	Terrestrial
Mosaic_lc	Area of mosaic land cover	GLC2000 [2]	Grid	Buffer	2000	1 km^2	Terrestrial
Snow_lc	Area of snow and ice	GLC2000 [2]	Grid	Buffer	2000	1 km^2	Terrestrial
Water_lc	Area of water bodies	GLC2000 [2]	Grid	Buffer	2000	1 km^2	Terrestrial
Other_lc	Other land cover (e.g. bare areas; artificial)	GLC2000 [2]	Grid	Buffer	2000	1 km^2	Terrestrial
b.2) Land cover (polar-specific)							
Ice	Area of permanent ice (not sea ice, but ice sheets/shelves – terrestrial part only)	Millennium Ecosystem Assessment[3] Data origin: University of Alaska Fairbanks[4]	Grid	Buffer	2005	1 km^2	Terrestrial
Forest_tundra	Area of forest tundra	Millennium Ecosystem Assessment[3] Data origin: University of Alaska Fairbanks[4]	Grid	Buffer	2005	1 km^2	Terrestrial
Gram_tundra	Area of graminoid, dwarf-shrub and moss tundra	Millennium Ecosystem Assessment[3] Data origin: University of Alaska Fairbanks[4]	Grid	Buffer	2005	1 km^2	Terrestrial

Variable name	Description	Source	Data type	Location/buffer	Time period	Spatial resolution	Data set
Barren_tundra	Area of barren and prostrate dwarf-shrub tundra	Millennium Ecosystem Assessment[3] Data origin: University of Alaska Fairbanks[4]	Grid	Buffer	2005	1 km^2	Terrestrial
c) Geographical/physical environment							
Lat	Latitude of population	LPI5	Point	Location	2011	N/A	All
Long	Longitude of population	LPI5	Point	Location	2011	N/A	All
Mountain	Extent of mountain systems	Millennium Ecosystem Assessment[3] Based on: UNEP-WCMC[6]	Grid	Buffer	2005	1 km^2	Terrestrial
Mean_elev	Mean elevation of area	NOAA[7]	Grid	Buffer	2010	1 arc minute	Terrestrial
Elev_range	Elevation range of area	NOAA[7]	Grid	Buffer	2010	1 arc minute	Terrestrial
Mean_depth	Mean depth of area	NOAA[7]	Grid	Buffer	2010	1 arc minute	Marine
Depth_range	Depth range of area	NOAA[7]	Grid	Buffer	2010	1 arc minute	Marine
d) Human environment							
Pop_dens	Human population density	CIESIN8	Grid	Location	1990 & 2010	30 arc seconds	Terrestrial
Dens_change	Change in human population density	Calculated from Pop_dens, 2010-1990	Grid	Location	1990 & 2010	30 arc seconds	Terrestrial
Urban	Urban area	Millennium Ecosystem Assessment[3] Data origin: CIESIN, IPFRI, World Bank, CIAT[9]	Grid	Buffer	2005	30 arc seconds	Terrestrial
Cultivated	Cultivated area	Millennium Ecosystem Assessment[3] Based on: GLCCD[10]	Grid	Buffer	2005	1 km^2	Terrestrial
Threat	Threat type	LPI[5]	Point	Location	2011	N/A	All
e) Unevenness of data coverage							
Min_dist	Minimum distance to nearest data point	LPI5	Point	Location	2011	N/A	All
Pop_buffer	Number of additional population locations in 250km buffer around location	LPI5	Polygon	Buffer	2011	N/A	All
f) Other							
Protect	Area of protected land	WDPA[11]	Polygon	Buffer	2010	N/A	All
Taxa	Mammal, bird, fish	LPI[5]	Point	Location	2011	N/A	All

[1] http://www.worldclim.org/

[2] Global Land Cover 2000 database. European Commission, Joint Research Centre, 2003. http://bioval.jrc.ec.europa.eu/products/glc2000/glc2000.php

[3] Millennium Ecosystem Assessment. World Data Center for Biodiversity and Ecology, http://wdc.nbii.gov/ma/datapage.htm

[4] Dept. of Biology and Wildlife, University of Alaska Fairbanks, Fairbanks, AK 99775-6100

[5] Living Planet Index (LPI) Database, WWF & Zoological Society of London

[6] UNEP-WCMC, Mountain Watch

[7] National Oceanic and Atmospheric Administration (NOAA), http://www.ngdc.noaa.gov/mgg/global/relief/ETOPO1/data/bedrock/cell_registered/binary/

[8] Center for International Earth Science Information Network (CIESIN), Earth Institute at Columbia University, http://sedac.ciesin.columbia.edu/gpw/

[9] Center for International Earth Science Information Network (CIESIN), International Food Policy Research Institute (IPFRI), The World Bank, Centro Internacional de Agricultura Tropical (CIAT), Global Rural-Urban Mapping Project (GRUMP): Urban Extents

[10] Global Land Cover Characteristics Data set (GLCCD v2.0, USGS/EDC 2000)

[11] World Database on Protected Areas (WDPA), http://www.wdpa.org/

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