Interpretable biome-aligned temperature zones for climate classification via average monthly temperatures

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Abstract

We introduce temperature zones based on average monthly temperatures that closely align with biome boundaries, intended for use in climate classification. This new system retains the simplicity and interpretability of existing classifications, such as those of Köppen-Geiger and Trewartha, while providing an improved fit to biome boundaries. Unlike previous classifications, we developed our system by analyzing contemporary climate and land cover datasets. Our classification focuses on temperature, but it is designed so that future analyses could combine our results with precipitation criteria from new or existing systems to offer a more comprehensive climate classification framework.

Introduction

An effective climate classification can serve many scientific and educational purposes. Rather than relying on arbitrary criteria, many existing systems were designed to align with biome and ecosystem boundaries, as biomes naturally reflect varying climatic conditions [1–5]. A common priority of climate classifications is simplicity; classifications that are easily understood may be preferable to more complex ones with only a marginally better fit to biome boundaries.

Many existing climate classifications are based on two criteria, temperature and precipitation, which are used either alone or combined to classify a location. Arguably, the simplest such classification is a chart that plots biome types along axes of mean annual temperature and mean annual precipitation [2]. Although easy to understand, this classification lacks detail because it fails to consider seasonal variation in temperature and precipitation, which significantly affect vegetation. Similarly, the Thornthwaite and Holdridge life zone systems also aimed to use climate to describe dominant life forms but involve more complex calculations of potential evapotranspiration [4, 5], limiting their accessibility compared to simpler classifications.

Two of the most popular climate classifications are the Köppen-Geiger and Trewartha classifications. The Köppen-Geiger classification accounts for seasonality of temperature and precipitation [1]. However, it has its flaws; for instance, its definition of subtropical climates is overly broad, covering regions with both deciduous forests adapted to cold winters and evergreen forests adapted to year-round warmth. Another widely used climate classification, the Trewartha model, was designed to address some shortcomings of the Köppen-Geiger system, especially in providing more granularity in mid-latitudes [3]. Nevertheless, it too has notable inaccuracies, such as its placement of an oceanic climate between the subtropical and continental climates in the eastern U.S. and China, despite significant continentality.

Our objective was to create temperature zones that are highly correlated with biome locations while being simple enough to be derived from visual inspection of a climate graph without requiring involved calculations. Our approach was informed by modern, data-driven methods, leveraging geospatial datasets of climate and vegetation.

Materials and methods

Given a region delineated by a temperature classifier (for example, all land regions where at most 2 months exceed a mean temperature of 8 °C), this section outlines our approach to quantifying how well such a region corresponds to the actual location of a biome.

Temperature classifiers

We used the following simple temperature classifiers, all of which can be determined through visual inspection of a climate graph:

- wm: mean temperature of the warmest month in degrees Celsius.
- cm: mean temperature of the coldest month in degrees Celsius.
- tr: annual temperature range in degrees Celsius, defined as wm − cm.
- ma$T$: number of months with a mean temperature of at least T degrees Celsius.
- mb$T$: number of months with a mean temperature below T degrees Celsius.

Note that wNm $\geq T$ is equivalent to writing ma$T \geq N$. Furthermore, the annual average temperature of a location can be approximated as the maximum value of T that satisfies ma$T \geq 6$. This quantity is easier to determine from visual inspection of a climate graph.

Quantifying biome-classifier fit

We quantified how well a temperature classifier fits a biome using the following methodology:

Let the domain D be a portion of Earth's surface that includes both the biome of interest, B, and the region that it is to be distinguished from, $\neg B$. Note that D should be defined to exclude surface regions that are irrelevant to the classification task. So for example, if we wanted to separate land ice cap from all other land biomes, we would define the domain D to consist only of land and not water surfaces.

By applying an inequality threshold to a temperature classifier, for instance, ma8 ≤ 2, we divide D into a region C that satisfies the inequality, in this case the region that satisfies ma8 ≤ 2, and a region $\neg C$ that does not satisfy the inequality, in this case the region that satisfies ma8 > 2. Our goal was to choose a threshold and classifier such that C corresponds roughly to B and $\neg C$ corresponds roughly to $\neg B$. We formalize this approach as follows:

We define the false positive area (FPA) as the surface area of the region in the domain where $\neg B$ and C overlap. We define the false negative area (FNA) as the surface area of the region in the domain where B and $\neg C$ overlap. If the inequality used for the threshold is $<$ or $\leq$, as the threshold increases, FPA would increase and FNA would decrease. Meanwhile, if the inequality used for the threshold is $>$ or $\geq$, as the threshold increases, FPA would decrease and FNA would decrease. To ensure that both FPA and FNA are low, we aimed to minimize the maximum of false positive and negative area (MFPNA). We also restricted our classifier to integer parameters and thresholds to ensure simplicity and ease of recall.

Datasets and data preprocessing

We constructed a global gridded dataset of average monthly temperatures over land and ocean surfaces by combining the WorldClim 2.1 monthly averages [6] with the ERA5 2-meter above surface monthly averages [13] for the years 1970-2000. The dataset incorporates high-resolution WorldClim data over continental areas where available and uses bicubic-interpolated, smoothed ERA5 data for oceanic regions.

We sourced ground truth data for biome locations from the MODIS MCD12Q1 v061 land cover map of 2001 [7] and the Copernicus CGLS-LC100 land cover map of 2015 [8]. In regions dominated by buildings and cultivated land, we used a potential natural vegetation (PNV) map based on the BIOMES 6000 dataset [9]. We also employed the GTOPO30 digital elevation model [10] to exclude highland areas in certain analyses.

We performed all calculations in Google Earth Engine [11].

Results

In this section, we present several biome definitions and the temperature classifiers that best correspond to them.

Ice cap / tundra classifier

We defined ice cap as all land regions with permanent ice and snow. A temperature classifier that separates ice cap from tundra is equivalent to one that separates ice cap from all other biomes, as ice cap is adjacent to tundra. Thus, we defined the domain D as all land on Earth, and the biome B as all land with permanent ice and snow (MODIS class 15).

Since ice caps regions are marked by year-round cold conditions without sufficient warmth to melt the ice, we tested hypotheses of the forms $\mathrm{wm} \leq T$ and $\mathrm{ma}T \leq N$ for integer values of T. The classifier with the least MFPNA was $\mathrm{wm} \leq 3$ with 246,000 and 269,000 square kilometers of FPA and FNA (Fig 1). All other classifiers of these forms yielded over 300,000 square kilometers of MFPNA. Altogether, these results suggest that $\mathrm{wm} \leq 3\,°\mathrm{C}$ is the optimal simple classifier for distinguishing ice cap from non-ice-cap land regions. This threshold is slightly higher than that of the ice cap climate of Köppen-Geiger and Trewartha, defined as $\mathrm{wm} \leq 0$, which yields a FPA and FNA of 35,000 and 611,000 square kilometers of FPA and FNA. Our findings suggested that land ice can occur in regions where the mean temperature of the warmest month is slightly above freezing, rather than strictly below freezing.

Fig 1. Classifier $\mathrm{wm} \leq 3$ applied to ice cap domain. Colors represent true positive (red), true negative (blue), false positive (red), false negative (orange), and out-of-domain (white) regions.

Tundra / boreal forest classifier

We defined polar land regions as ice cap and tundra, and all other land cover types as non-polar (including boreal forest). Thus, a temperature classifier that separates polar and non-polar biomes also effectively separates tundra from boreal forest. We defined the domain D as all land with an elevation below 1000 m that is not cultivated land (Copernicus class 40), urban build-up (Copernicus class 50), or herbaceous wetland (Copernicus class 90), hence eliminating ambiguous land regions that are irrelevant to classification. The elevation filter ensured our classifier focused on separating polar tundra and boreal forest, rather than separating alpine tundra from subalpine regions. We defined the biome B as the subset of D that is tundra or ice cap—specifically, the subset of D where ma10 ≤ 2 and land cover is either permanent snow and ice (Copernicus class 70), herbaceous vegetation (Copernicus class 30), bare / sparse vegetation (Copernicus class 60), or moss and lichen (Copernicus class 100). The temperature threshold ma10 ≤ 2 was crucial because the Copernicus dataset does not distinguish tundra from equatorward grasslands. This specific threshold was chosen based on the observation that the stricter threshold of ma10 $= 0$, used in the Köppen-Geiger and Trewartha classifications, often misclassifies large tundra areas as subpolar (as shown later). Meanwhile, the less restrictive threshold of ma10 ≤ 3, used in the Köppen-Geiger and Trewartha classifications, would include some temperate grassland on the equatorward fringes of the boreal forest. Our chosen threshold of ma10 ≤ 2 includes nearly all true tundra in B while still curtailing the inclusion of temperate grassland.

Since a distinguishing feature of the tundra is a short growing season, we tested hypotheses of the form ma$T \leq N$ for integer values of T and N. Classifiers that yielded a particularly low MFPNA included ma9 ≤ 2 with 1,015,0000 and 652,000 square kilometers of FPA and FNA (Fig 2), ma8 ≤ 2 with 482,000 and 1,501,000 square kilometers of FPA and FNA, ma10 ≤ 1 with 665,000 and 1,623,000 square kilometers of FPA and FNA, and ma12 $= 0$ with 551,000 and 1,649,000 square kilometers of FPA and FNA. In comparison, Köppen-Geiger and Trewartha both defined a polar climate (tundra or ice cap) as one satisfying wm < 10, which yields 37,000 and 3,984,000 square kilometers of FPA and FNA, indicating a bias towards false negatives. We instead recommend the classifier ma9 ≤ 2 or ma8 ≤ 2 to distinguish tundra from boreal forest.

Fig 2. Classifier ma9 ≤ 2 **applied to polar domain.** Colors represent true positive (red), true negative (blue), false positive (red), false negative (orange), and out-of-domain (white) regions. The domain did not include Antarctica and places north of 78° latitude due to missing data, but these regions are expected to lie in the true positive regions and thus not significantly affect misclassified land areas.

Boreal / hemiboreal forest classifier

We defined boreal forest as the biome consisting of predominantly conifers found directly equatorward of the tundra. To find a temperature classifier that distinguished between boreal forest and the more equatorward biomes, we defined the domain D as all land with an elevation below 1000 m that is not cultivated land (Copernicus class 40), urban build-up (Copernicus class 50), or herbaceous wetland (Copernicus class 90), thus eliminating ambiguous land regions that are irrelevant to classification. The elevation filter excluded alpine regions in our analysis. We defined the biome B as the subset of D composed of boreal forest or a more polar biome—specifically, the subset of D where ma10 ≤ 4 and land cover consists of shrubs (Copernicus class 20), needleleaf forest (Copernicus clases 111, 112, 121, and 122), or a more poleward vegetation scheme—permanent snow and ice (Copernicus class 70), herbaceous vegetation (Copernicus class 30), bare / sparse vegetation (Copernicus class 60), or moss and lichen (Copernicus class 100). We applied the temperature filter ma10 ≤ 4 since the Copernicus data does not differentiate boreal forest from temperate or more equatorward coniferous forests. This filter relaxes the Köppen-Geiger and Trewartha criterion of a subpolar climate (ma10 ≤ 3) to include more of the equatorward fringes of the boreal forest. We did not include hemiboreal forest—a region of mixed coniferous and deciduous trees located equatorward of the boreal forest and poleward of the temperate deciduous forest—in our definition of B.

Since boreal forest is marked by a limited growing season, we tested hypotheses of the form ma$T \leq N$ for integer values of T and N. Classifiers yielding a particularly low MFPNA included ma8 ≤ 4 with 1,340,000 an 1,334,000 square kilometers of FPA and FNA (Fig 3), ma9 ≤ 3 with 1,412,000 and 1,675,000 square kilometers of FPA and FNA, and ma10 ≤ 3 with 2,276,000 and 714,000 square kilometers of FPA and FNA. The classifier ma10 ≤ 3 also coincides with that used by Köppen-Geiger and Trewartha to distinguish subpolar from temperate climates, but we found two other classifiers with similar performance.

Fig 3. Classifier ma8 ≤ 4 **applied to boreal forest domain.** Colors represent true positive (red), true negative (blue), false positive (red), false negative (orange), and out-of-domain (white) regions.

Hemiboreal / temperate forest classifier

We defined the hemiboreal forest as the region with a mixture of conifers and deciduous trees located between between the largely coniferous boreal forest and the largely deciduous temperate deciduous forest. Since the distribution of vegetation is often obfuscated by human activity in these regions, we instead used potential natural vegetation data to define our domain and biome. We defined the domain D as all land regions with an elevation below 1000 m where PNV is either cool mixed forest (PNV class 9) or temperate deciduous broadleaf forest (PNV class 13), encompassing all areas with either hemiboreal or temperate deciduous forest. Furthermore, we defined the biome B as the subset of D that is cool mixed forest (PNV class 9).

We tested hypotheses of the form ma$T \leq N$ for integer values of T and N. Classifiers yielding a particularly low MFPNA included ma12 ≤ 4 with 4,060,000 and 4,401,000 square kilometers of FPA and FNA (Fig 4), ma11 ≤ 4 with 3,001,000 and 4,735,000 square kilometers of FPA and FNA, and ma8 ≤ 5 with 4,313,000 and 4,895,000 square kilometers of FPA and FNA.

Fig 4. Classifier ma12 ≤ 4 **applied to hemiboreal domain.** Colors represent true positive (red), true negative (blue), false positive (red), false negative (orange), and out-of-domain (white) regions.

Temperate / subtropical forest classifier

We defined the subtropical forest as the region of predominantly evergreen forest found equatorward of the temperate deciduous forest. Examples of such forests include the southeastern conifer forests of the U.S. and the evergreen broadleaf forests of southern China. Since natural vegetation in these regions is obfuscated by human activity, we used potential natural vegetation data. To find a temperature classifier distinguishing temperate deciduous forest from subtropical forest, we defined the domain D as all land regions with an elevation below 1000 m where PNV is either temperate deciduous broadleaf forest (PNV class 13) or warm-temperate evergreen broadleaf and mixed forest (PNV class 4). Furthermore, we defined the biome B as the subset of D that is warm-temperate evergreen broadleaf and mixed forest (PNV class 4).

Hypothesizing that subtropical forest can be distinguished by a limited cold season, we tested classifiers of the form cm $\geq T$ and mb$T \leq N$ for integer values of T and N. For classifiers of the form cm $\geq T$, those yielding the lowest MFPNA included cm ≥ 4 with 794,000 and 1,018,000 square kilometers of FPA and FNA, as well as cm ≥ 3 with 1,285,000 and 517,000 square kilometers of FPA and FNA. Classifiers of the form mb$T \geq N$ yielded an even lower MFPNA; those yielding the lowest MFPNA were mb15 ≤ 6 with 536,000 and 620,000 square kilometers of FPA and FNA (Fig 5), mb10 ≤ 4 with 303,000 and 631,000 square kilometers of FPA and FNA, mb9 ≤ 4 with 726,000 and 274,000 square kilometers of FPA and FNA, and mb8 ≤ 3 with 742,000 and 561,000 square kilometers of FPA and FNA.

Fig 5. Classifier mb15 ≤ 6 **applied to subtropical domain.** Colors represent true positive (red), true negative (blue), false positive (red), false negative (orange), and out-of-domain (white) regions.

Subtropical / tropical classifier

Due to the blurry distinction between tropical and subtropical vegetation types, we used a latitude-based definition of the tropics as regions between the Tropic of Cancer and Tropic of Capricorn. This definition encompasses both land and water, enabling us to test classifiers on land-only, water-only, or land-and-water regions in the tropics.

0.0.1 Land and water

To find a classifier that differentiated between tropical and non-tropical regions on both land and water, we defined the domain D as all locations on Earth's surface with an elevation of at most 1000 m. Furthermore, we defined the biome B as the subset of D located between the Tropic of Cancer and Tropic of Capricorn. Since a tropical climate is marked by year-round warmth, we tested hypotheses of the form cm $\geq T$ for integer values of T. Classifiers that yielded the lowest MFPNA were cm ≥ 19 with 15,316,000 and 14,770,000 square kilometers of FPA and FNA (Fig 6), cm ≥ 20 with 8,382,000 and 21,858,000 square kilometers of FPA and FNA, and cm ≥ 18 with 23,714,000 and 9,673,000 square kilometers of FPA and FNA.

Fig 6. Classifier cm ≥ 19 **applied to tropical domain.** Colors represent true positive (red), true negative (blue), false positive (red), false negative (orange), and out-of-domain (white) regions.

0.0.2 Land

To find a classifier that differentiates between tropical and non-tropical land regions, we defined the domain D as all land regions with an elevation of at most 1000 m, and the biome B as the subset of D located between the Tropic of Cancer and Tropic of Capricorn. Testing hypotheses of the form cm $\geq T$ for integer values of T, those yielding the lowest MFPNA were cm ≥ 17 with 5,373,000 and 3,931,000 square kilometers of FPA and FNA, cm ≥ 18 with 3,731,000 and 5,836,000 square kilometers of FPA and FNA, and cm ≥ 16 with 7,693,000 and 2,268,000 square kilometers of FPA and FNA.

0.0.3 Water

To find a classifier that differentiates between tropical and non-tropical land regions, we defined the domain D as all land regions with an elevation of at most 1000 m, and the biome B as the subset of D located between the Tropic of Cancer and Tropic of Capricorn. Testing hypotheses of the form cm $\geq T$ for integer values of T, those that yielded the lowest MFPNA were cm ≥ 20 with 8,372,000 and 11,207,000 square kilometers of FPA and FNA, cm ≥ 19 with 15,089,000 and 6,918,000 square kilometers of FPA and FNA, and cm ≥ 21 with 3,435,000 and 18,490,000 square kilometers of FPA and FNA.

Midlatitude land / water classifier

The Köppen-Geiger and Trewartha classifications identify oceanic and continental subtypes for midlatitude climates, specifically temperate and subpolar. This choice is reasonable, as given the minimal biome diversity in polar regions and reduced continentality in subtropical and tropical regions, a land-water classifier is arguably more relevant in the midlatitudes. To find an improved land/water classifier for the midlatitudes, we defined the domain D as all parts of Earth's surface between 30° and 60° latitude or between $-30°$ and $-60°$ degrees latitude. We did not add an elevation filter, as elevation does not significantly affect continentality. We further defined the biome B as all land surfaces in D (MODIS class not equal to 17).

We hypothesized that continental regions can be simply distinguished by greater variation between summer and winter temperatures, testing classifiers of the form tr $\geq t$ for integer values of t. Classifiers of this form with the lowest MFPNA included tr ≥ 17 with 7,822,000 and 7,913,000 square kilometers of FPA and FNA (Fig 7), tr ≥ 16 with 9,216,000 and 6,482,000 square kilometers of FPA and FNA, as well as tr ≥ 18 with 6,638,000 and 9,260,000 square kilometers of FPA and FNA. Meanwhile, under the same domain and biome definitions, the Köppen-Geiger criterion for a continental climate, cm ≤ 0, yields much greater FPA and FNA areas of 18,757,000 and 16,621,000 square kilometers. This indicates that annual temperature range is a more reliable indicator of continentality than the mean temperature of the coldest month.

Fig 7. Classifier tr ≥ 17 **applied to midlatitude land domain.** Colors represent true positive (red), true negative (blue), false positive (red), false negative (orange), and out-of-domain (white) regions.

Discussion and conclusion

Our temperature zones were highly correlated with biome locations and represented a clear improvement on past analyses (Fig 8). One of the challenges in our and any analysis of the relationship between climate and biome locations must address is that changes in land cover lag behind changes in climate, but the exact duration of this time lag is uncertain and very likely varies across different biomes [12]. Hence, it is challenging to determine which historical period's average temperatures, if held in a long-term steady state, would result in the land cover reflected by the datasets in this paper. Our approach used data from 1971-2000.

Fig 8. Proposed temperature zones and corresponding map.

Both Köppen-Geiger and Trewartha defined an ice cap climate as one satisfying wm ≤ 0. We propose adhering to this criterion, despite wm ≤ 3 yielding a slightly lower MFPNA, due to its simplicity and potential to account for time-lag.

Both Köppen-Geiger and Trewartha defined a polar climate, corresponding to tundra and ice cap, as one satisfying wm ≤ 10. We found that this definition is prone to false negatives, and instead recommend the classifier ma8 ≤ 2. Even though ma9 ≤ 2 yielded a slightly lower MFPNA, we preferred a slightly more conservative classifier to account for potential time-lag.

Both Köppen-Geiger and Trewartha used the criterion of ma10 ≤ 3 to separate polar and subpolar biomes from temperate biomes. We found that this threshold yields an acceptable MFPNA, and maintain its usage.

However, in temperate zones, the warm-summer continental, hot-summer continental, oceanic, and subtropical temperature classifications of Köppen-Geiger align poorly with temperate biomes. Instead, we propose a hemiboreal or cool temperate zone defined by $4 \leq$ ma10 ≤ 5, corresponding to regions with a mixture of deciduous trees resembling more equatorward forests and conifers resembling the more poleward boreal forest. We also propose a regular temperate zone for regions satisfying ma10 ≥ 6 but not satisfying subtropical or tropical criteria, corresponding to more equatorward temperate regions with mostly deciduous forests. In both temperate and subpolar regions, we find that the simple classifier tr ≥ 18 is suitable for distinguishing continental from oceanic regions, vastly outperforming the Köppen-Geiger definition.

We differ from both Köppen-Geiger and Trewartha in our definition of a subtropical climate. We believe that an intuitive definition of a subtropical climate is one that is, in colloquial terms, "never too cold" and "warm on average." As such, we define a subtropical climate as one satisfying both cm ≥ 4 and ma13 ≥ 6, but not satisfying the criterion for a tropical climate. We define two subtropical subtypes: subtropical warm, where wm < 22, and subtropical hot, where wm ≥ 22. These categories are designed so that a temperate continental climate transitions into a subtropical hot climate if the mean temperatures of all months increased by the same amount, while a temperate oceanic climate merges transitions into a subtropical warm climate under the same transformation.

Finally, we find that the tropical threshold of $cm \geq 18$ used by both the Köppen-Geiger and Trewartha classifications performs fairly well for distinguishing between non-highland terrestrial regions in the tropics from those in the subtropics, and maintain its usage.

Plotting our temperature zones on a map reveals several major global climatic phenomena. In the Atlantic Ocean, the Gulf Stream shifts the subtropical warm climate type into far northerly latitudes. Meanwhile, cold ocean currents off the west coasts of North and South America sometimes shift subtropical climates in coastal regions into strictly tropical latitudes. In the Northern Hemisphere, the continental climates extend farther south on the eastern sides of their respective continents, likely due to decreasing oceanic moderation of temperature. Continental climates are virtually nonexistent in the Southern hemisphere, likely due to a lack of wide land regions enabling a large annual temperature range. For the same reason, bands of oceanic climates in the Northern hemisphere feature more latitudinal variation than in the Southern hemisphere.

Future research will likely focus on combining these temperature zones with precipitation zones, allowing further classification into well-known humidity-based subtypes such as arid, semi-arid, humid, Mediterranean, and monsoonal. Another direction of future research is mapping historic and forecasted changes of these temperature zones to visualize the effects of climate change.

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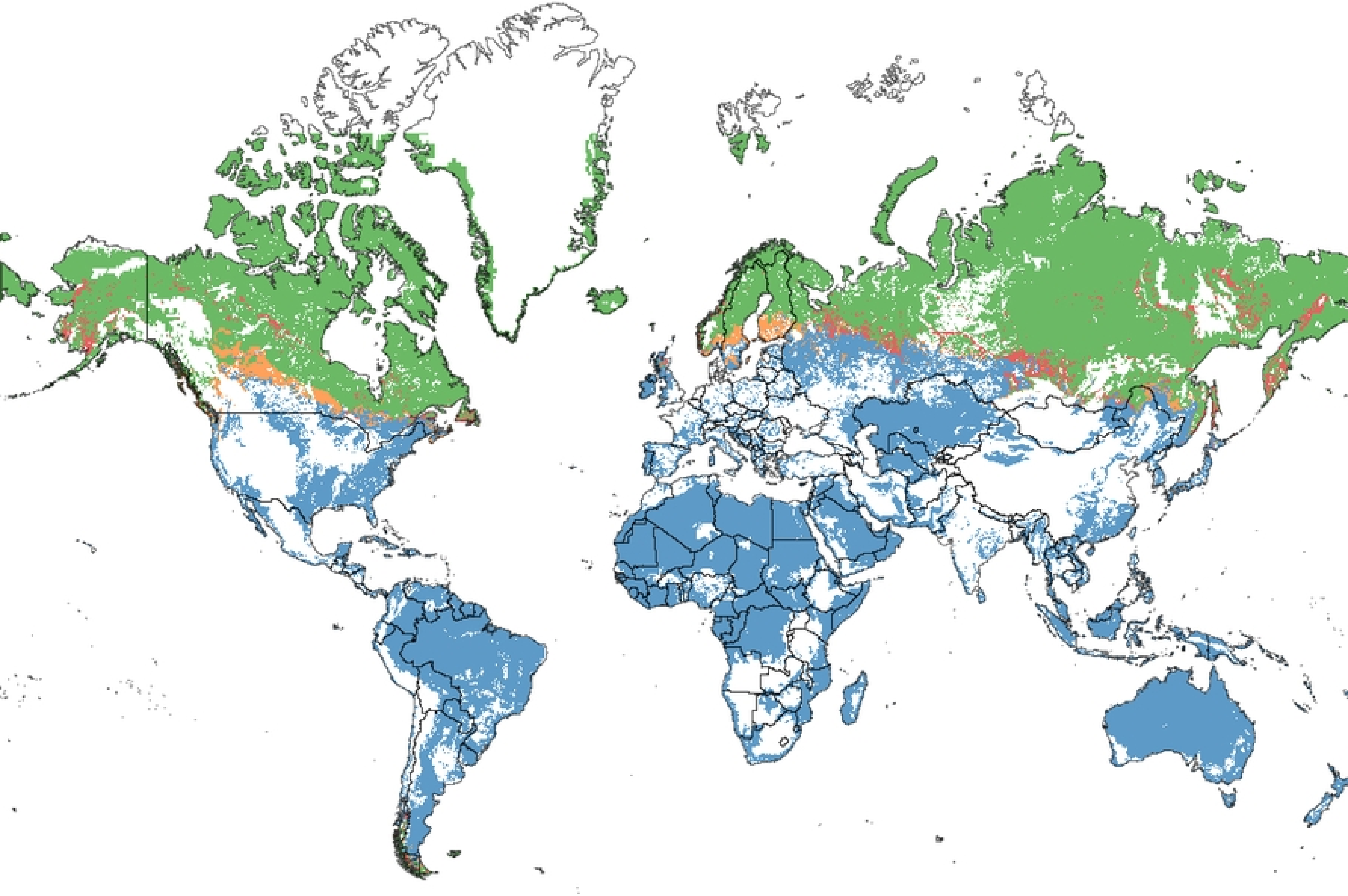

Fig 3

- if cm ≥ 18:
  - **tropical**
- if ma10 ≥ 6 *and* cm < 18:
  - if cm ≥ 4 *and* ma13 ≥ 6:
    - if wm ≥ 22: **subtropical hot**
    - if wm < 22: **subtropical warm**
  - otherwise:
    - if tr < 18: **temperate oceanic**
    - if tr ≥ 18: **temperate continental**
- if 4 ≤ ma10 ≤ 5:
  - if tr < 18: **cool temperate oceanic**
  - if tr ≥ 18: **cool temperate continental**
- if ma8 ≥ 3 *and* ma10 ≤ 3:
  - if tr < 18: **subpolar oceanic**
  - if tr ≥ 18: **subpolar continental**
- if ma8 ≤ 2:
  - if wm > 0: **polar tundra**
  - if wm ≤ 0: **polar ice**

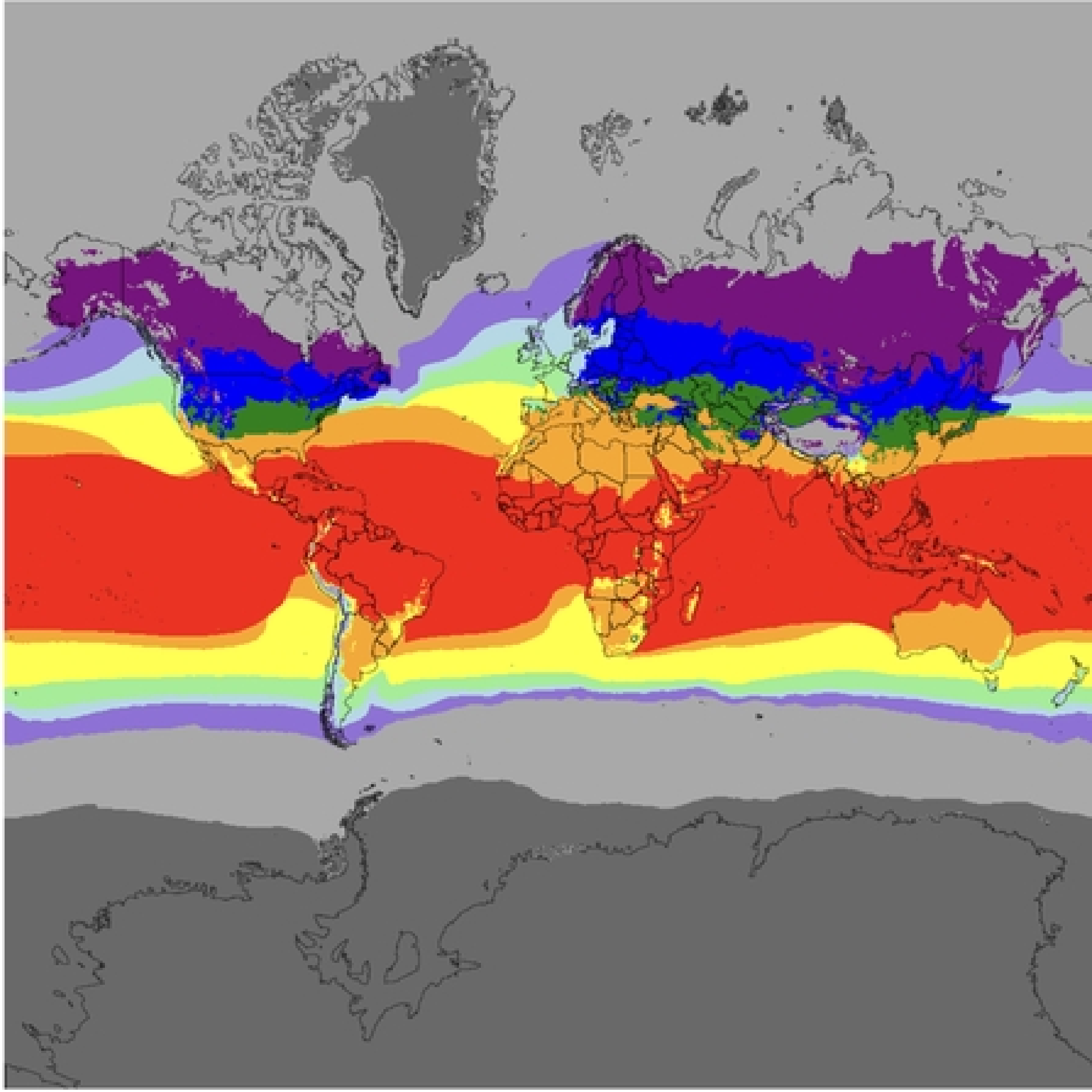

Fig 8

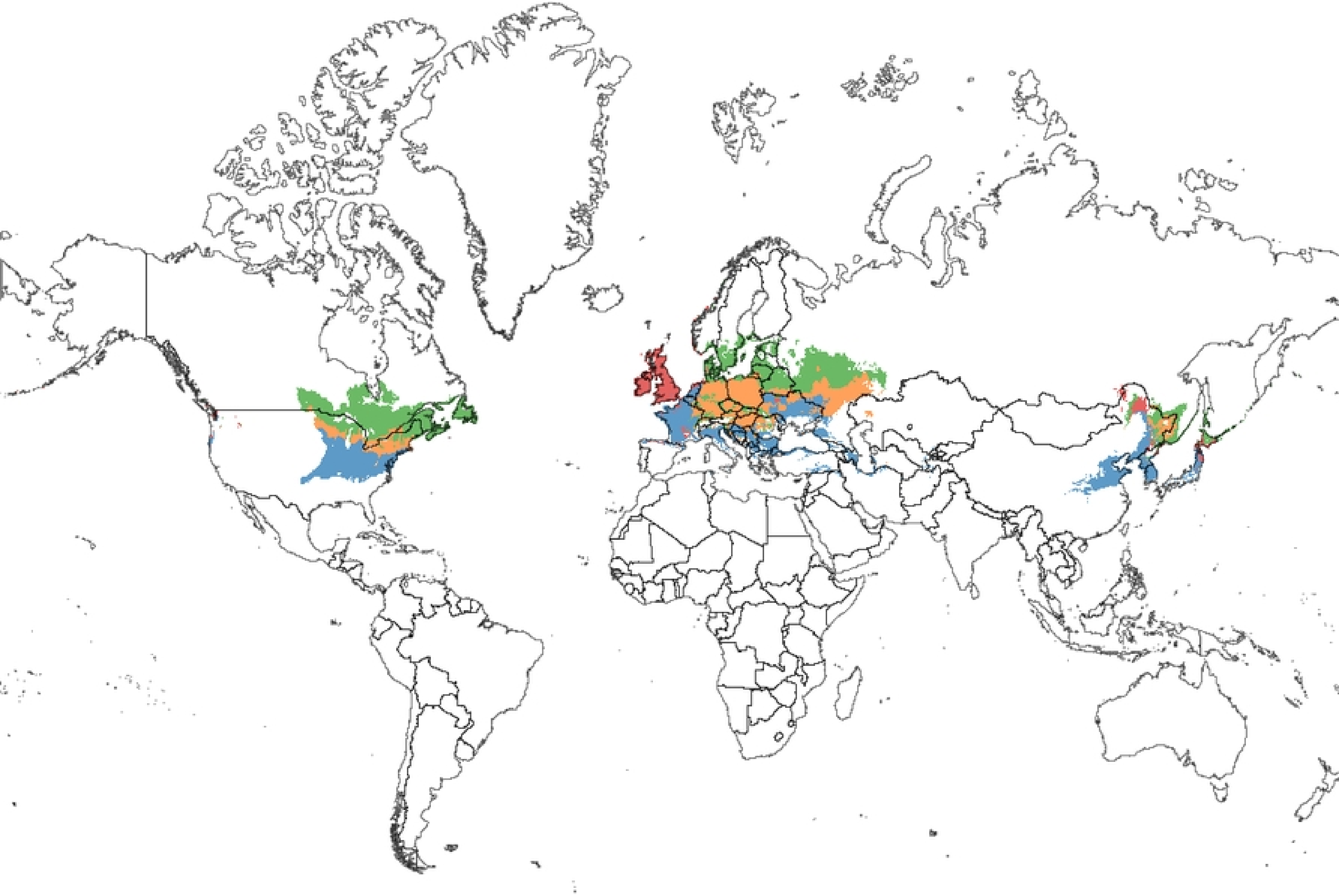

Fig 4

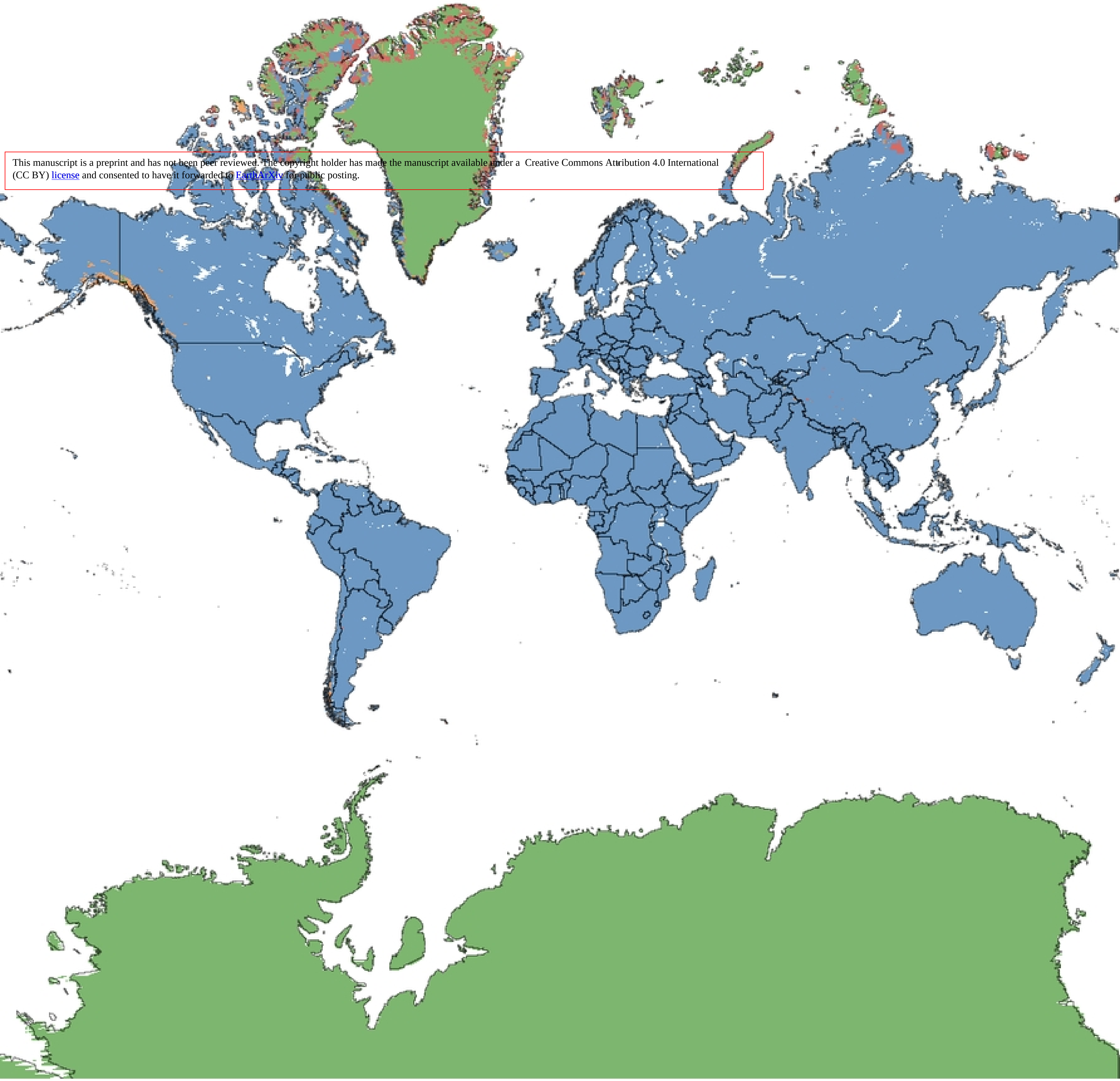

Fig 1

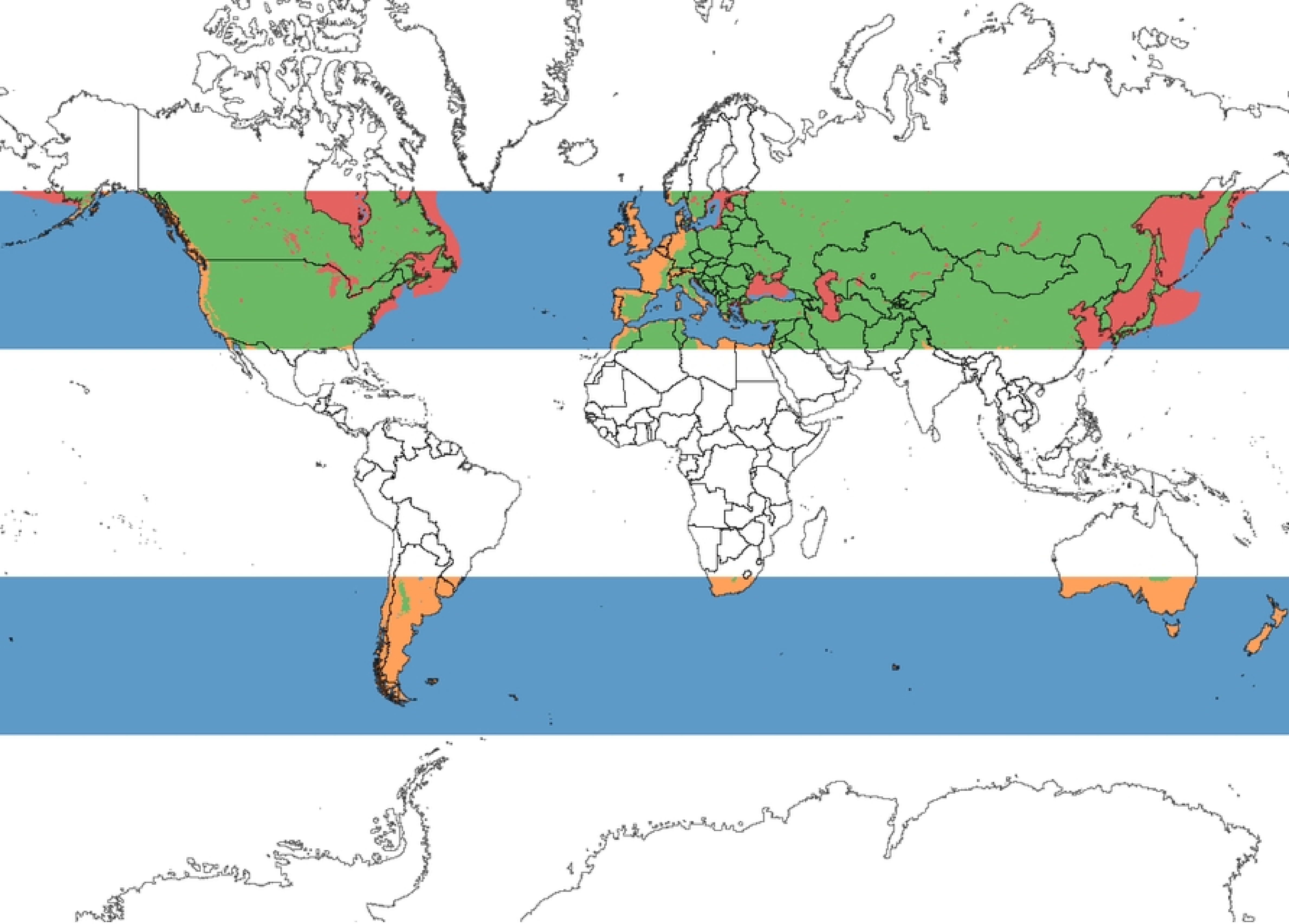

Fig 7

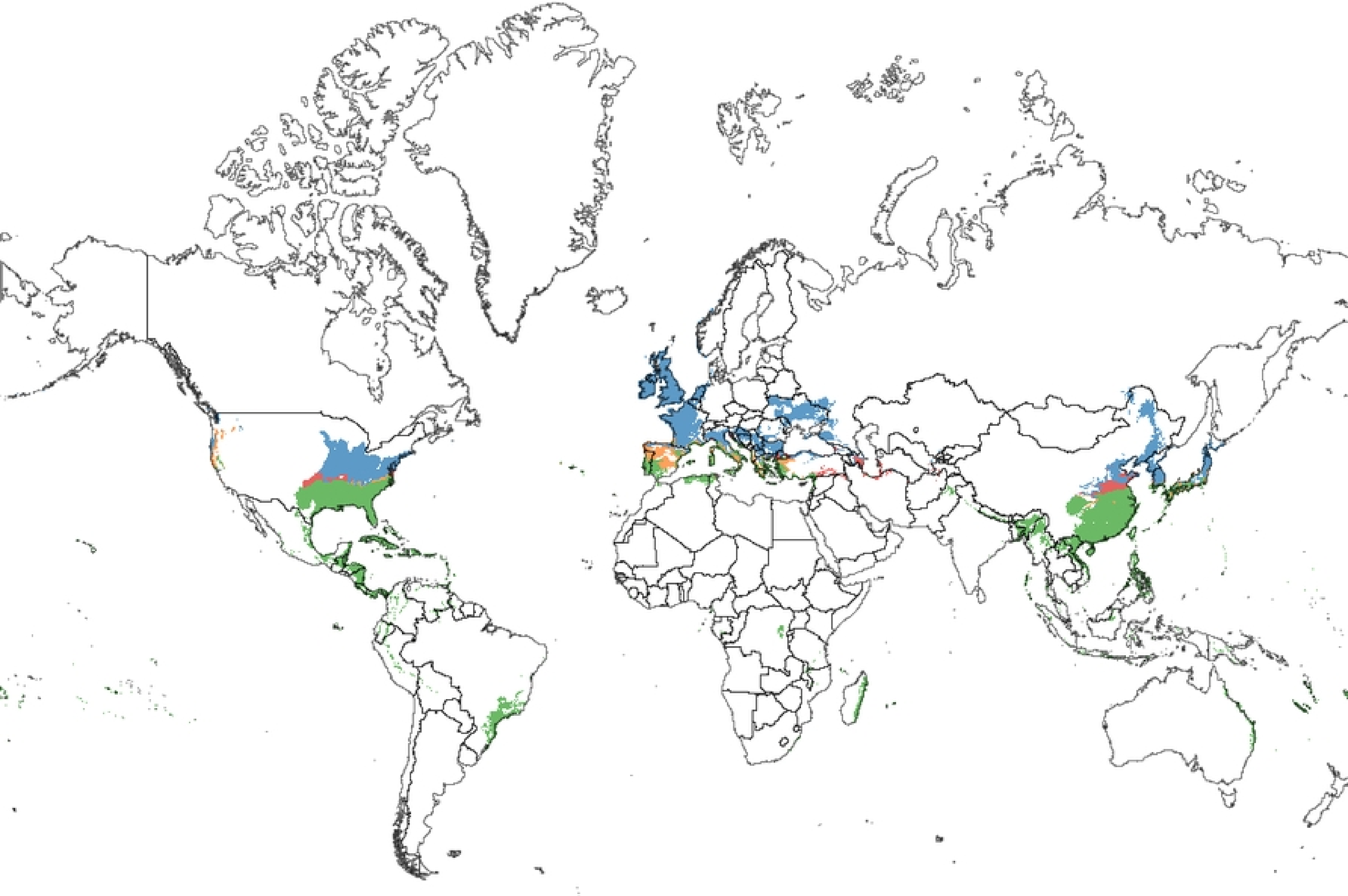

Fig 5

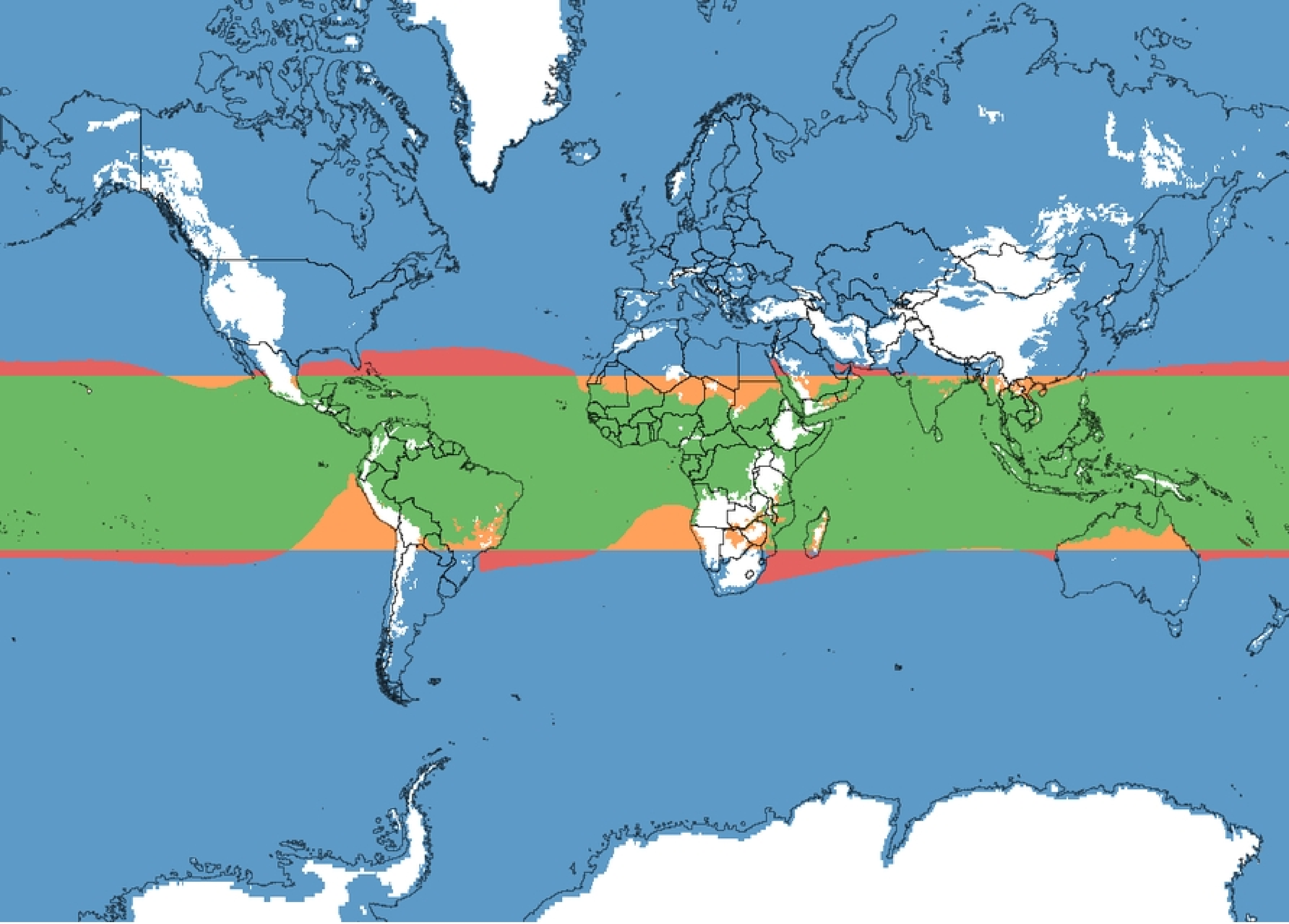

Fig 6

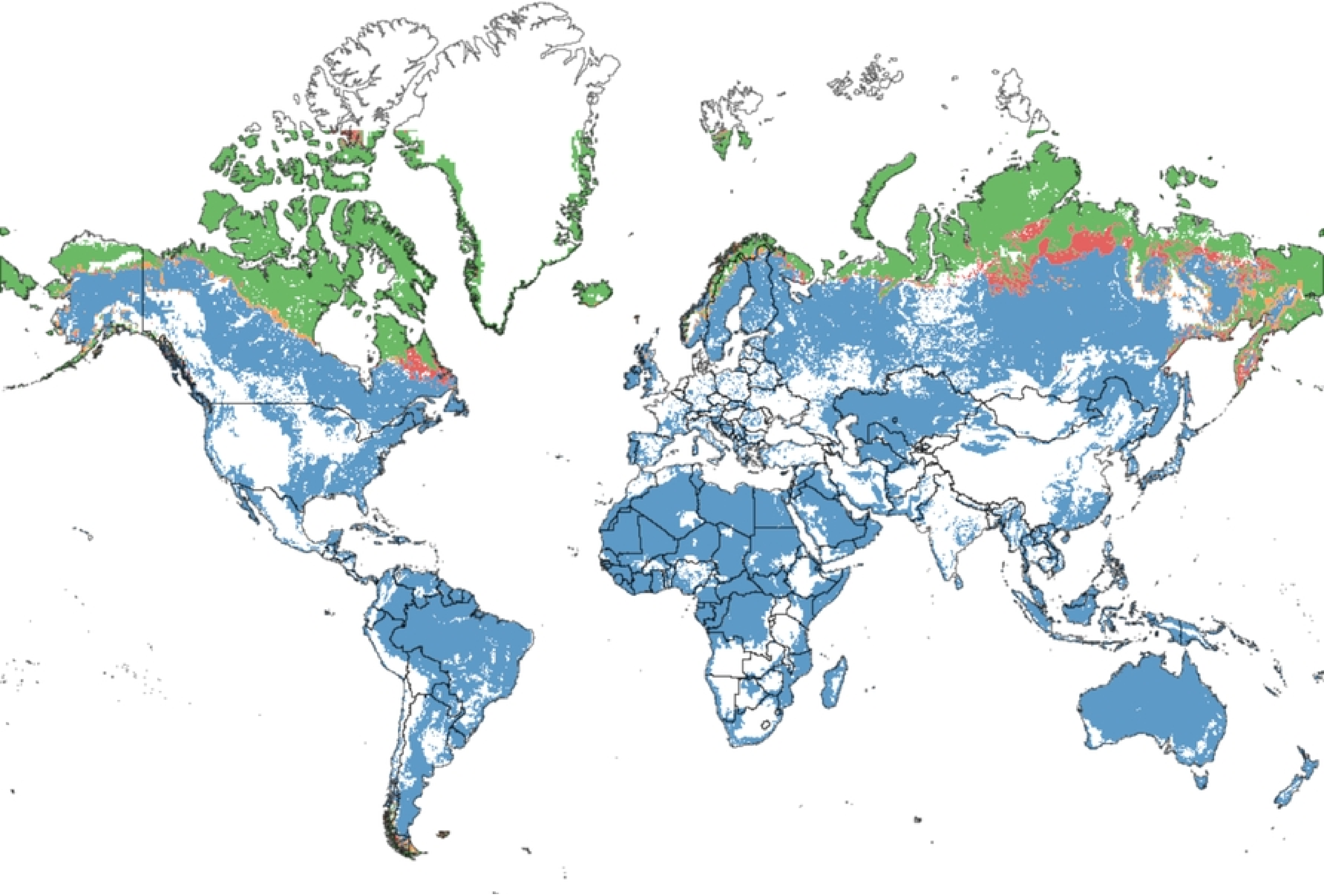

Fig 2