Model prediction of the effect of RCP4.5 climate change scenario on worldwide wheat production in 2070

Introduction

Wheat (*Triticum* L.) was one of the earliest domesticated crops, originating in the Near-East during the Pre-Pottery Neolithic era, from where it was spread around the world by humans (Lev-Yadun et al. 2000). It is also the world's most widely cultivated food crop, with highest global grain production (Gulbitti-Onarici et al. 2009). *Triticum aestivum*, known as "common wheat" or "**bread wheat**" is an annual plant from the grass family Poaceae (Haider 2012). The present distribution of wheat is pictured in (Figure 1) (GBIF.org 06 December 2018). Wheat is an excellent source of dietary fiber and carbohydrates; its production worldwide continues to grow as its gluten protein is an important component in many processed foods which are becoming ever more commonly consumed throughout the world in a "westernization" of diets (Shewry & Hey 2015).

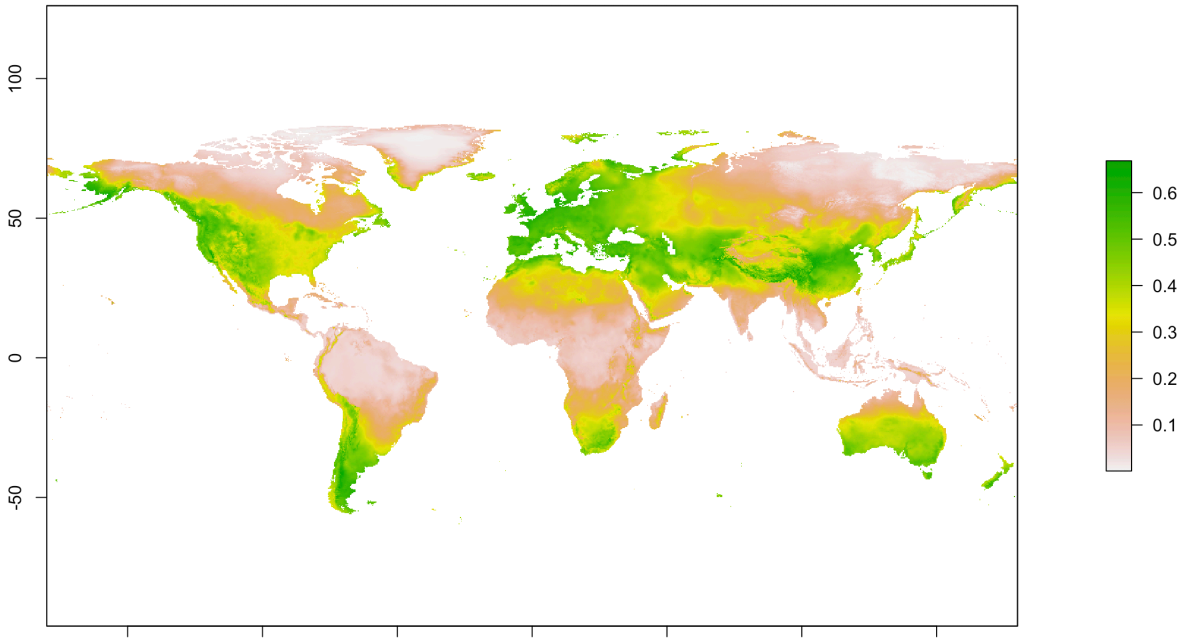

Figure 1: present distribution of Triticum aestivum (GBIF.org 06 December 2018)

Methodology

Maxent open-source software was used to model species niches and distributions using the "maximum entropy modelling" (for the most uniform distribution estimate) machine learning technique (Phillips et al.). *T. aestivum* occurrence data was downloaded from GBIF.org (06 December 2018), and gridded climate data with a 1 km^2, 5 minute spatial resolution was downloaded from worldclim.org for both the current climate and projected future climate using the GCM HadGEM2-AO model of the International Panel on Climate change (IPCC) fifth assessment representative concentration pathway 4.5 (RCP4.5) scenario (Hijmans et al. 2005).

Maxent was set to use continuous response curves of selected climate data to "train" the model, with logistical data output. Bioclim variables to use for modelling were selected with a spearman correlation matrix (Figure 2), retaining only non-correlating variables which were deemed the most useful for describing the potential range of *T. aestivum*. Bio2 (annual mean diurnal temperature range), Bio4 (temperature seasonality-standard deviation), Bio10 (mean temperature of warmest quarter), Bio12 (annual precipitation) and Bio15 (precipitation seasonality- coefficient of variation) were chosen as the non-correlated variables in this model.

	bio1	bio10	bio11	bio12	bio13	bio14	bio15	bio16	bio17	bio18	bio19	bio2	bio3	bio4	bio5	bio6	bio7	bio8	bio9
bio1	1	0.924331	0.975835	0.258385	0.355261	−0.23577	0.322128	0.328169	−0.18069	0.046696	0.008898	0.346076	0.880657	−0.84913	0.876866	0.964107	−0.77651	0.809628	0.92047
bio10	0.924331	1	0.834066	0.041766	0.150996	−0.35949	0.36064	0.122007	−0.31768	−0.11375	−0.12493	0.458411	0.694838	−0.61037	0.979381	0.815787	−0.51981	0.812795	0.845823
bio11	0.975835	0.834066	1	0.377466	0.45323	−0.1397	0.256922	0.43071	−0.07829	0.13958	0.110719	0.257205	0.936849	−0.93876	0.777356	0.995197	−0.88274	0.749216	0.918615
bio12	0.258385	0.041766	0.377467	1	0.934698	0.613963	−0.22859	0.954575	0.668071	0.835963	0.656702	−0.40361	0.363804	−0.50199	−0.04771	0.401764	−0.56427	0.209546	0.221691
bio13	0.355261	0.150996	0.45323	0.934698	1	0.38056	0.076059	0.994285	0.436715	0.813974	0.445907	−0.23664	0.453627	−0.54359	0.066816	0.461267	−0.57183	0.340682	0.273265
bio14	−0.23577	−0.35949	−0.1397	0.613963	0.38056	1	−0.79219	0.417339	0.988029	0.578665	0.809681	−0.62191	−0.14215	−0.00387	−0.43267	−0.09118	−0.12267	−0.21151	−0.20385
bio15	0.322128	0.36064	0.256922	−0.22859	0.076059	−0.79219	1	0.028895	−0.77332	−0.16582	−0.6374	0.494634	0.275166	−0.15078	0.383404	0.21326	−0.05111	0.383743	0.217918
bio16	0.328169	0.122007	0.43071	0.954575	0.994285	0.417339	0.028895	1	0.472861	0.827847	0.48008	−0.26703	0.430874	−0.52958	0.03793	0.441115	−0.56327	0.308538	0.254315
bio17	−0.18069	−0.31768	−0.07829	0.668071	0.436715	0.988029	−0.77332	0.472861	1	0.609957	0.841323	−0.61697	−0.08272	−0.06783	−0.39362	−0.02925	−0.18416	−0.17306	−0.14619
bio18	0.046696	−0.11375	0.13958	0.835963	0.813974	0.578665	−0.16582	0.827847	0.609957	1	0.415141	−0.35323	0.177244	−0.25912	−0.20498	0.15797	−0.31765	0.195898	−0.06731
bio19	0.008898	−0.12493	0.110719	0.656702	0.445907	0.809681	−0.6374	0.48008	0.841323	0.415141	1	−0.51838	0.08648	−0.22386	−0.18746	0.159719	−0.3251	−0.16668	0.142847
bio2	0.346076	0.458411	0.257205	−0.40361	−0.23664	−0.62191	0.494634	−0.26703	−0.61697	−0.35323	−0.51838	1	0.379921	−0.12393	0.581321	0.188971	0.067766	0.326059	0.289758
bio3	0.880657	0.694838	0.936849	0.363804	0.453627	−0.14215	0.275166	0.430874	−0.08272	0.177244	0.08648	0.379921	1	−0.93975	0.658675	0.926337	−0.8613	0.652206	0.833071
bio4	−0.84913	−0.61037	−0.93876	−0.50199	−0.54359	−0.00387	−0.15078	−0.52958	−0.06783	−0.25912	−0.22386	−0.12393	−0.93975	1	−0.54407	−0.94511	0.975094	−0.57979	−0.82313
bio5	0.876866	0.979381	0.777356	−0.04771	0.066816	−0.43267	0.383404	0.03793	−0.39362	−0.20498	−0.18746	0.581321	0.658675	−0.54407	1	0.749517	−0.42708	0.764122	0.810366
bio6	0.964107	0.815787	0.995197	0.401764	0.461267	−0.09118	0.21326	0.441115	−0.02925	0.15797	0.159719	0.188971	0.926337	−0.94511	0.749517	1	−0.90561	0.729917	0.916544
bio7	−0.77651	−0.51981	−0.88274	−0.56427	−0.57183	−0.12267	−0.05111	−0.56327	−0.18416	−0.31765	−0.3251	0.067766	−0.8613	0.975094	−0.42708	−0.90561	1	−0.49971	−0.76858
bio8	0.809628	0.812795	0.749216	0.209546	0.340682	−0.21151	0.383743	0.308538	−0.17306	0.195898	−0.16668	0.326059	0.652206	−0.57979	0.764122	0.729917	−0.49971	1	0.583158
bio9	0.92047	0.845823	0.918615	0.221691	0.273265	−0.20385	0.217918	0.254315	−0.14619	−0.06731	0.142847	0.289758	0.833071	−0.82313	0.810366	0.916544	−0.76858	0.583158	1

Figure 2: Spearman correlation table of climatic variables affecting T. aestivum. Red highlighted variables (bio10, bio12, bio15, bio 2, and bio4) were the non-correlated variables chosen for Maxent modeling.

In addition to their non-correlation with each other, these specific climatic data where chosen due to their likely high influence on the modeled crop, bread wheat (*T. aestivum)*. Bread wheat is an annual crop with many cultivars which have been adapted to a range of climate conditions from xerophytic to littoral, but the optimum growing temperature is about 25°C, with higher temperatures leading to lower yields due to heat stress (Briggle 1980; Curtis 2002). Minimum growth temperature range is between 3° to 4°C and maximum is between 30° to 32°C (Briggle 1980). Moisture is important for wheat, but too much moisture can lead to disease and root issues; between 375 and 875 mm of annual precipitation is the optimal amount, but growth with a range of 250 and 1750 mm of rainfall per year is possible (Leonard & Martin 1963). "Winter wheat" varieties mature in 7 to 8 months, requiring a period of cold temperatures (0° to 5°C) in order to stimulate head formation, while spring varieties mature in around four months (United States Department of Agriculture 2010). These growth variables mean that an increase in annual mean diurnal temperature range (Bio2), seasonality of temperature (Bio4) and mean temperature of warmest quarter (Bio10) can affect crop yields; while annual precipitation (Bio12) above or below certain parameters during the growing season (Bio15) can also reduce the viability of the crop.

Model Output

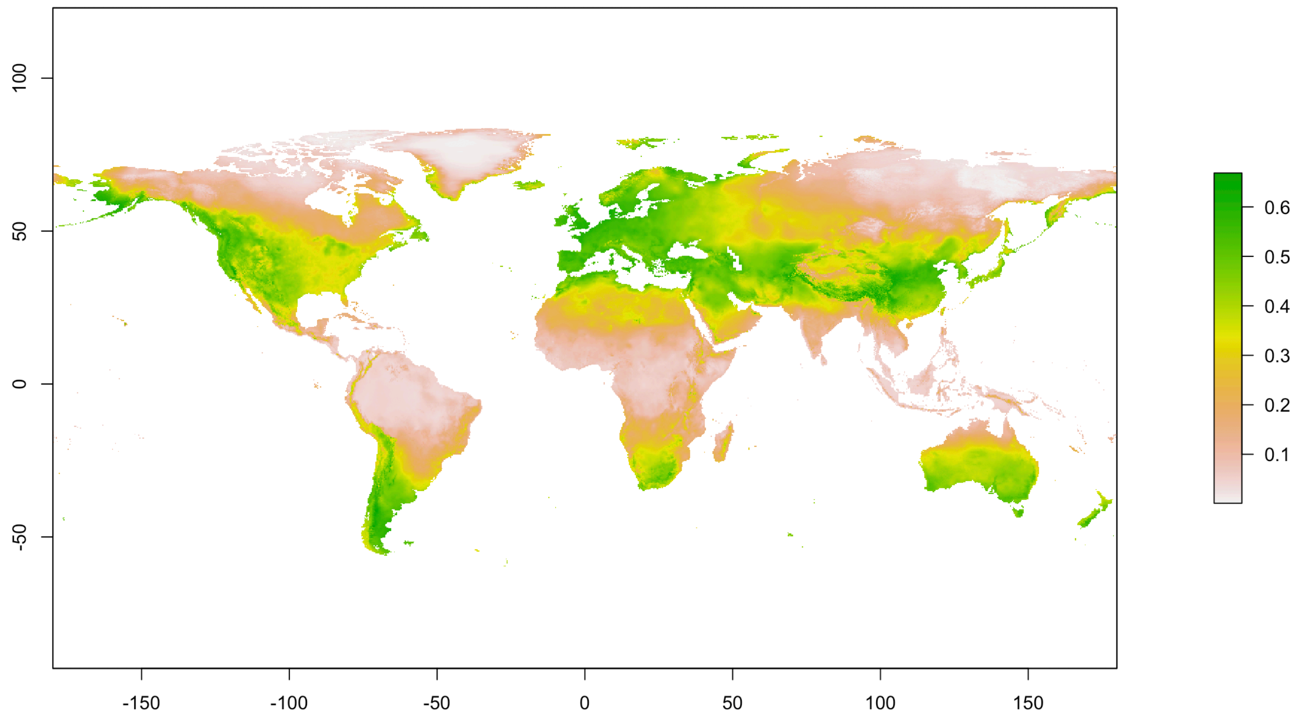

Figure 3: Present (1960-1990) distribution of T. aestivum

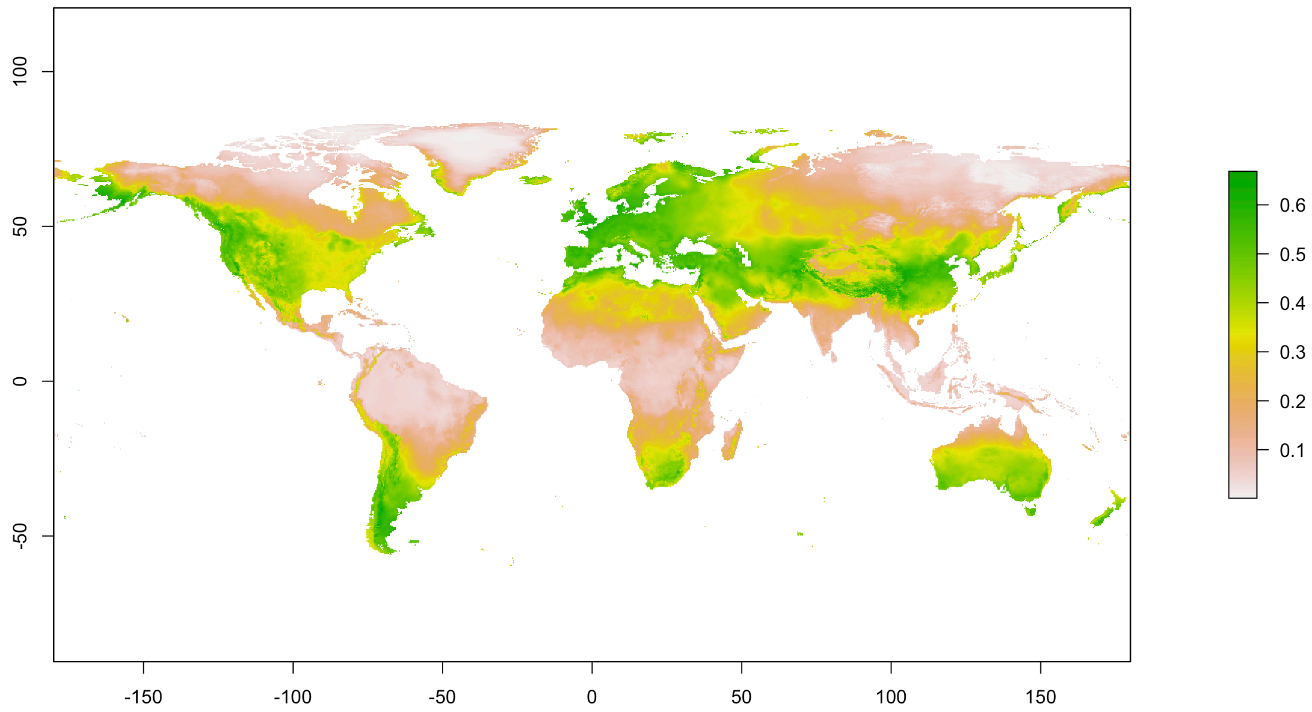

Figure 4: Future (2070) distribution of T. aestivum (IPCC RCP 4.5 climate scenario)

Analysis of model performance

According the receiver operating characteristic (ROC) curve analysis of sensitivity versus 1-specificity (Figure 5), the area under the curve (AUC) is only 0.674, not very much better than a random prediction of 0.5. In order for this model to be considered a good prediction, we would expect an AUC of at least 0.7. This is an expected result, as the large range and number of observations of the modeled species makes it hard for the model to distinguish a meaningful prediction from the background.

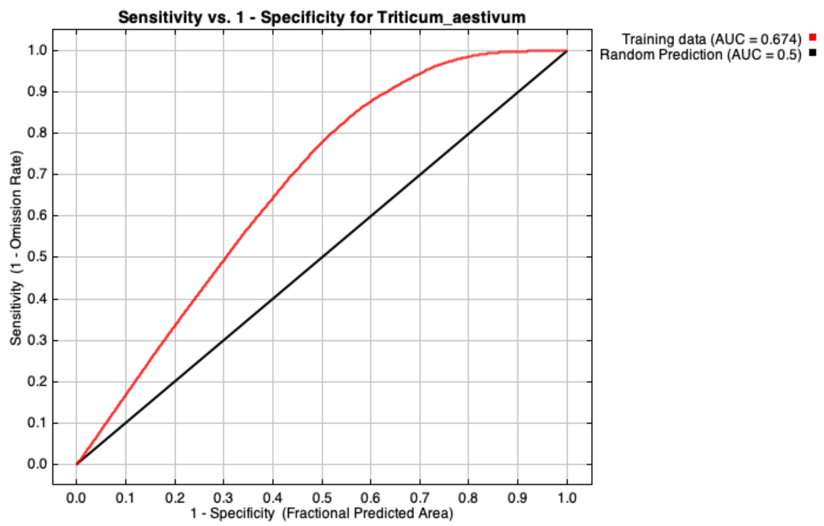

Figure 5: Receiver operating characteristic (ROC) curve analysis

Analysis of variable contributions

According the *Maxent* analysis of variable contributions (Figure 6), temperature seasonality-standard deviation (Bio4) contributes by far the most to the model at 65%, while mean temperature of warmest quarter (Bio10) contributes 27%. Annual precipitation (Bio12), precipitation seasonality- coefficient of variation (Bio15) and annual mean diurnal temperature range (Bio2) all have very low percent contributions to the model. The high importance of Bio4 makes sense as with climate change, temperature seasonality (temperature change over the course of the year by the standard deviation of the mean monthly temperature) will change and there will be greater temperature variability in most regions. This means that farmers will be less able to accurately predict the variability of seasonal temperatures as they fluctuate more, probably leading to more crop failures.

Variable	Percent contribution	Permutation importance
bio4	65.4	54.9
bio10	27.3	33.5
bio12	3.9	3.7
bio15	2.3	3.1
bio2	1.1	4.8

Figure 6: Analysis of variable contributions to model output

Response to Future Scenario

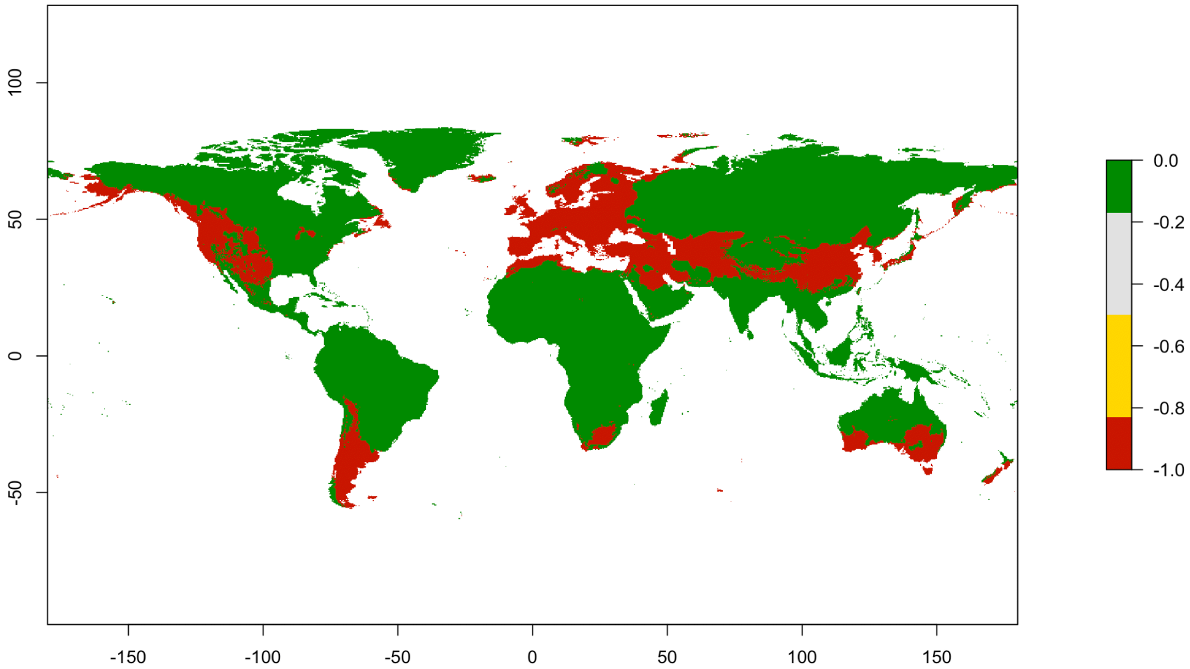

Figure 7: Future (2070) distribution change of T. aestivum (IPCC RCP4.5 climate scenario)

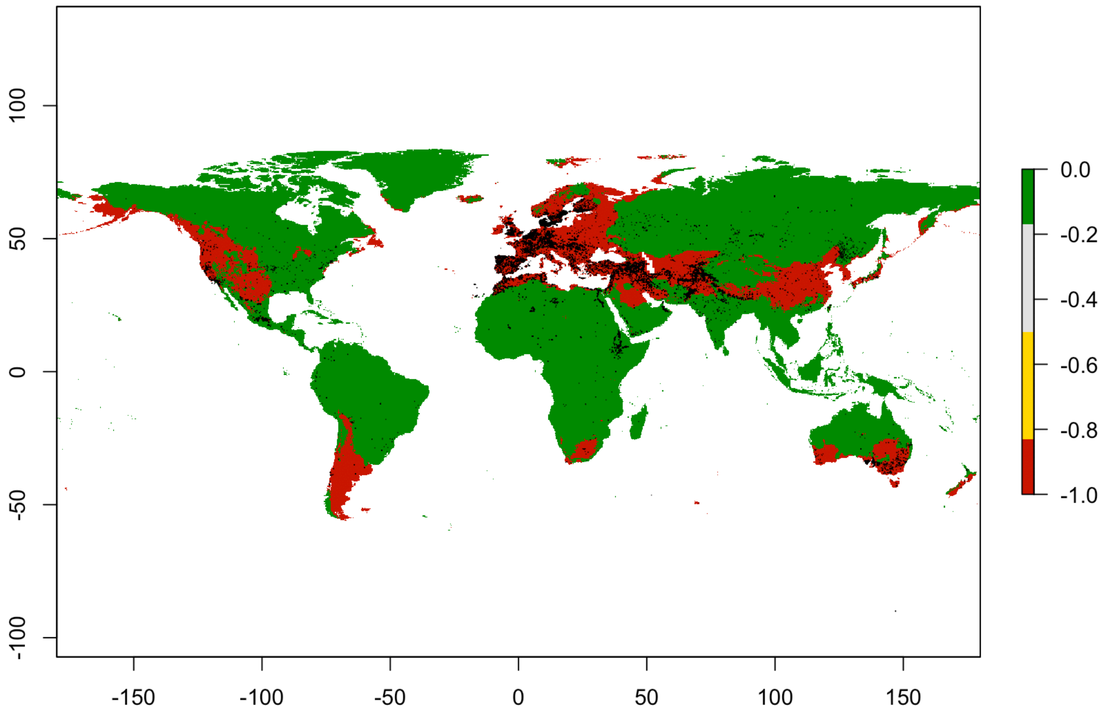

Figure 8: Future (2070) distribution of T. aestivum (IPCC RCP4.5 climate scenario) including GBIF observation points (black dots)

Green shaded areas in Figure 7 and Figure 8 represent regions where the suitability to grow *T. aestivum* is not expected to change dramatically, while red shaded areas are regions where suitability for *T. aestivum* is expected to much less. This model did not show any regions where *T. aestivum* suitability is expected to decrease moderately (grey or yellow shaded). This model also did not compute any regions where suitability to grow *T. aestivum* is likely to increase.

Biological Interpretation

As shown in the "response to future scenario" maps (Figure 7 and Figure 8 above), *T. aestivum*'s range is not expected to increase based on climate predictions in the IPCC 5th Assessment RCP4.5 scenario. In this model, the suitable range for growing bread wheat is expected to decline in major "bread basket" regions such as the western United States, Europe and Asia, where the high volumes of this grain are now grown. This decline in suitable range is likely based on the model's high reliance on the Bio4 climate statistic, which shows the standard deviation of temperature seasonality by mean monthly temperature (Figure 9). As seen in the Bio4 maps, more regions are expected to experience greater temperature seasonality in 2070 (right map) than currently (left map). This means that there will be greater overall temperature variability in these regions, making it more difficult for farmers to plant, grow and harvest wheat within suitable seasons.

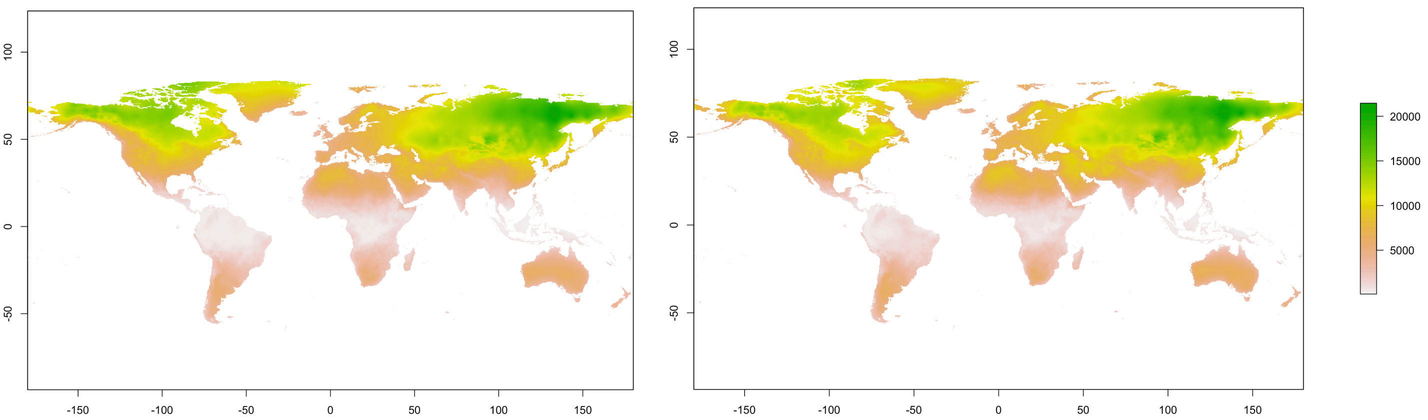

*Figure 9: **Bio4-Temperature seasonality-** temp. change over the course of the year by the standard deviation of the mean monthly temp. Left: Bio4 (present, 1960-1900 avg.); Right: Bio4 (future-2070)*

The mean temperature of warmest quarter (Bio10) will also increase in many regions, pushing more regions outside of the suitable growing range for wheat, a crop which does not tolerate heat stress well. Annual precipitation (Bio12) and precipitation seasonality- coefficient of variation (Bio15) have very low percent contributions to the model, meaning that although precipitation is of course important in growing wheat, these factors did not contribute as much to the modeled outcome. Annual mean diurnal temperature range (Bio2) was also not important, likely because wheat can tolerate a wide temperature fluctuation, so long as this does not fall outside of a moderate seasonality range and overall temperatures are not too high.

As wheat is a highly important food crop around the world, a range of cultivars exists to accommodate climatic conditions in various regions. New climatic conditions will likely motivate crop breeders to create new cultivars which are more tolerant of higher temperatures and drought. Also likely is the spread of other *Triticum* species such as of *T. turgidum var. durum*, which was bred to tolerate hot, dry conditions in Mediterranean Sea regions (Shewry & Hey 2015).

The model created in this exercise is only moderately useful, as it has a low AUC predictive value, only explaining slightly more than a random model would. Additionally, the model is likely biased as most of the observations used were located in Europe and the western United States, due to data availability. In order to model the future range of *T. aestivum* more accurately, it is recommended to include a smaller number of observations which are not so inaccurately biased towards specific regions, so that the machine learning can better distinguish them from the background. Also, there are many variables besides climate which will predict the cultivation of wheat in the future. Population growth, land-use change, food processing technology, growth of substitute crops and international trade policies are some other factors which may come into play in shaping the future of bread wheat.

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