“Development of an MSE Multi-Peril Risk Management Concept”

Technical Report - Armenia

submitted by the

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Authors:

Max Hofmann
Florian Schierhorn
Daniel Müller
Bekhzod Egamberdiev
Ihtiyor Bobojonov

Leibniz Institute of Agricultural Development in Transition Economies (IAMO)
Theodor-Lieser-Str. 2
06120 Halle (Saale)
Germany

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Executive summary

In the present study, German Sparkassenstiftung for International Cooperation e.V. (DSIK), the Hydrometeorology and Monitoring Center of the Ministry of Environment of the Republic of Armenia (HMC), and Leibniz Institute of Agricultural Development in Transition Economies (IAMO) have jointly worked on a nation-wide assessment about the effect of climate change on micro- and smallholder farmers in Armenia.
We here provide empirical evidence for the impact of past and future climatic conditions and weather extremes on agricultural production in the country. For this, we first characterized the agricultural sector of Armenia and selected the economically most important crops (work package 1). We sourced and processed environmental datasets to characterize historical climatic trends and the occurrence of wildfires in the country (work package 2). We analyzed the historical effects of different climate and weather parameters on the production and suitability of the selected crops (work package 3) and projected how yields and suitability will change in the future under different climate change scenarios (work package 4).

Work package 1

In work package 1, we provide an overall description of the agricultural sector in Armenia, define the target groups, select the most important crops and take stock of existing climate risk management strategies. Based on the key literature and official agricultural data, we characterized the agricultural sector and how it has changed over time on a sub-national level.

The first part of WP1 provides an overview of farm structures, agricultural production and crop area. Despite regional differences across the economic zones of Armenia, we highlight several predominant characteristics:

- Agriculture is one of the most important sectors in Armenia, contributing 12% of its GDP.
- In 2019, the real gross value of agricultural production was 852,800,000 million AMD. The regions Armavir, Ararat and Gegharkunik contributed the most to this value.
- Vegetables contribute the highest share to the gross harvest of the main agricultural products in Armenia.
- Most farms in Armenia are either commercial or family farms. Many farms are without legal status and have less than five workers. Agricultural holdings without legal status typically have a size between 0.1 and 3 hectares, whereas those with legal status have farm sizes between 1 and 20 hectares. The annual economic turnover is between 1000 and 15,000 Euro for family farms, and between 1000 to 50,000 Euro for commercial farms.
- Family farms outnumber commercial farms in sown area for all types of crops. Commercial farms tend to substitute forage crops for grain crops and legumes. Family farms show decreases in sown area for both grain crops, legumes and forage crops over time.

In the second part of WP1, we selected the economically most important crops of Armenia, based on production levels, harvested area, and yield: *Apricot, peach, apple, plum, winter wheat, spring barley, tomato, berries, potato and cucumber*. However, because of data constraints, we had to change this selection for the subsequent work packages and exchanged *plum* and *berries* for *silage maize, pear, quince* and *cornel*.

Ultimately, we synthesized existing risk management concepts. Based on the Resilience Index Measurement and Analysis approach, we constructed four important capacity building pillars *(Access to Basic Services, Assets, Adaptive Capacity and Social Safety Nets)* by applying Structural Equation Modelling. The underlying data was obtained from selected specialists and from a previous survey called "On Commodity Supply Chains in Central Asia and Caucasus". Given the significance of adaptive capacity, the magnitude of relationship with the household resilience capacity index was very high. Efforts to improve the adaptive capacity of households will translate into an increased ability to mitigate climate change consequences. In this case, the households would become more adapted for example by improving access to extension services, strengthening the capacity of farms to fulfilling quality requirements as well as providing subsidies to enable the adaptation of technologies.

Work package 2

In work package 2, we established the basis for the subsequent work packages by analyzing free and open-access geospatial environmental data. We processed daily rainfall records from the *Climate Hazards group Infrared Precipitation with Stations* dataset *(CHIRPS,* https://data.chc.ucsb.edu/products/CHIRPS-2.0/global_daily/netcdf/p05) and hourly temperature records from the *ERA5-Land* dataset (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land) of the *Copernicus* program. Both *CHIRPS* and *ERA5-Land* are gridded reanalysis products with a spatial resolution of 0.5 degrees (~5.5 km) and 0.1 degrees (~11 km), respectively, and are continuously updated in near-real time, which permits for updates of our results once new data becomes available. We used the *Caucasus Land Cover Map* from the *SILVIS lab of the University of Wisconsin* (http://silvis.forest.wisc.edu/data/caucasus) to create a cropland mask for the entire country of Armenia. We applied this mask to the data from *CHIRPS* and *ERA5-Land* to calculate historical trends of changes in precipitation and temperature in agriculturally used areas of each administrative district of Armenia. In addition, we also applied the cropland mask in assessing the trend in number and intensity of cropland fires by combining it with NASA's *Fire Information for Resource Management System* (*FIRMS*, https://firms.modaps.eosdis.nasa.gov/active_fire).

Work package 3

In work package 3, we developed predictive models to estimate the historical effects of climate and weather on the production of the most important crops in Armenia. To do so, we combined the data from work package 2 with official province-level yield statistics from the years 2005 to 2020 published by the Statistical Committee of the Republic of Armenia, and with phenological observations and temperature measurements, which were recorded at a total of 48 agrometeorological stations and kindly provided by HMC.

For **grain crops and vegetables** (winter wheat, spring barley, silage maize, potato, cucumber, and tomato), we used the phenological observation record to define crop-specific development stages for which we summarized the climatic conditions of each growing cycle with a total of five climatic mean (minimum, average and maximum temperature, cumulative precipitation, and growing degree days) and six extreme weather variables (day heat, night heat, day heat waves, night heat waves, heavy precipitation, and frost). To understand which climate mean and extreme weather variables have been most important in determining yield in the past, we used these variables as yield predictors in a random forest model, a machine learning technique that has been widely used in crop modeling and is particularly capable of handling colinear predictor variables (Feng et al., 2018; Jeong et al., 2016; L Hoffman et al., 2020; Roell et al., 2020; Schierhorn et al., 2021; van Klompenburg et al., 2020; Vogel et al., 2019). In each crop-specific model, we obtained an importance value and a depiction of the functional relation with yield for each climatic variable, which we discussed in the light of the prevailing production patterns in the country and with respect to the existing literature on climate and weather effects on yield. Overall, we found that climatic means have been more important for yield levels than extreme weather events. Nevertheless, particularly the results of the grain crop models indicated negative effects of heavy precipitation during different development stages. For winter wheat, our model results disclosed the negative effect of high maximum temperature during anthesis, which is a typical characteristic of wheat (Farooq et al., 2011; Innes et al., 2015). Our vegetable models also revealed negative effects of heavy precipitation, but largely positive effects of high temperatures.

For **pomaceous and stone fruits** (apple, pear, quince, apricot, cornel, and peach), we determined the amount of chill temperatures that accumulate from autumn until the beginning of bud bursting in spring. Fruit trees require such intermediate chill temperatures during winter for proper development (Fraga and Santos, 2021; Luedeling et al., 2011; Luedeling and Brown, 2011). We calibrated this model with phenological and temperature data from the agrometeorological stations and then applied it to the whole country. Through this process, we obtained maps of the long-year average amount of accumulated chill temperatures, which we classified to obtain maps of the past suitability for the production of each fruit type. Our results suggest that entire Armenia has been suitable for the production of the six fruit types considered. The mountainous regions of the northeastern part of the country provide more chilling than these fruits actually require, yet production levels are very low in these areas, probably due to other factors, such as adverse accessibility, which complicates the marketing of the produce, and low population density.

Work package 4

In work package 4, we integrated future climate data into the models developed in the previous work package to predict future crop yields for grain crops and vegetables, and future suitability for pomaceous and stone fruits. We analyzed daily climate projections of four climatic variables (minimum, average and maximum temperature, and precipitation), for two future scenarios (RCP 4.5 and RCP 8.5) and for two future periods (2041-2060 - "near future"; 2081-2099 - "far future"). We obtained these data from the *ISIMIP* repository (https://data.isimip.org) and restricted our analysis to the four climate forcing models for which data is available for all mentioned parameters and scenarios: GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR and MIROC-5. To calculate relative and absolute future climatic changes, we compared the future predictions with the historical baseline model of 1971-2005. We did not restrict our analysis to a cropland mask, since the future allocation of cropland is highly uncertain. For grain crops and vegetables, we assumed that the crop phenology and hence the onset dates of the development stages would not change in the future.

For winter wheat and spring barley, we predicted the highest decreases in the southern part of the country, and increases in some provinces in the north, whereas for tomato and cucumber, we mostly predicted yield losses. Our results also suggest that the suitability for pomaceous and stone fruits will decrease with increasing future warming, i.e. suitability will be lower under RCP 8.5 than under RCP 4.5 and lower in the far future than in the near future. We showed that pomaceous fruits (apple, pear, and quince) may be more susceptible to future warming than stone fruits (apricot, cornel, and peach). However, our models predict that the entire country will remain suitable for the production of all studied fruit crops, since the future amount of chilling is not projected to fall below the historically observed minima in any region. In the future, fruit production might have to gradually shift to higher altitudes to ensure sufficient winter chilling under ongoing climate change. In all these calculations, we did not account for any possible future adaptation measure in crop management, land use, or technology. The results should therefore be interpreted as what could be the climatic impacts on crop yields and suitability with current crop production, but under future climate conditions.

Work Package 1:

"Sector characteristics, crop selection, and climate risk management"

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1. Subnational assessment of the agricultural sector

1.1 Agricultural Sector

Agriculture is one of the most important sectors in Armenia, contributing 12% of GDP. In 2019, there was 2.04 million ha (Mha) of agricultural land out of total 2.974 Mha of available land in Armenia (Table 1). Almost half of the total land area of the country belongs to the mountain plateau, which is not suitable for intensive cropping. Therefore, there is a scarcity of arable land representing 0.444 Mha out of total agricultural land with 2.044 Mha. Remaining 0.036 Mha and 0.121 Mha are perennial grass and plough-land respectively. Moreover, around 1.051 Mha land is used as pastures.

Table 1: Total land area and agricultural lands (000, ha)

Land	2015	2016	2017	2018	2019
Total Land Area	2974.3	2974.3	2974.3	2974.3	2974.3
including:					
agricultural land	2045.7	2045.5	2043.8	2044.5	2044.2
arable land	446.7	446.4	446.0	445.6	444.8
perennial grass	34.4	34.7	34.8	35.3	36.4
plough-land	121.1	121.1	121.0	121.0	121.1
pastures	1051.3	1051.3	1050.8	1051.6	1051.1
others	392.2	392.0	391.2	391.0	390.8

Source: (NSS 2020c)

In 2019, a real gross value of agricultural production was 852,800,000 million AMD (NSS 2019). In the gross agricultural output, Armavir, Ararat and Gegharkunik mostly contributed with its more than 100 million AMD in 2019. Next regions such as Shirak, Aragatsotn, Kotayk, Lori and Syunik produced agricultural production more than 50 million AMD. The least contributing regions are Tavush, Vayots dzor and Yerevan city.

Although there was a decline in gross agricultural output for the last years, more than a fifth of population were still employed in agriculture in 2019 (Table A 1). At the same time, agriculture plays a significant role for income generation for rural population. For example, there was a noticeable rise in the share of household per capita agricultural income (Table A 2). Looking at the gross harvest of main agricultural products, the largest share of crops in Armenia is explained by vegetables, which has decreased from 1.007 million tonnes (Mt) to around 0.622 Mt over the last 5 years (Figure 1).

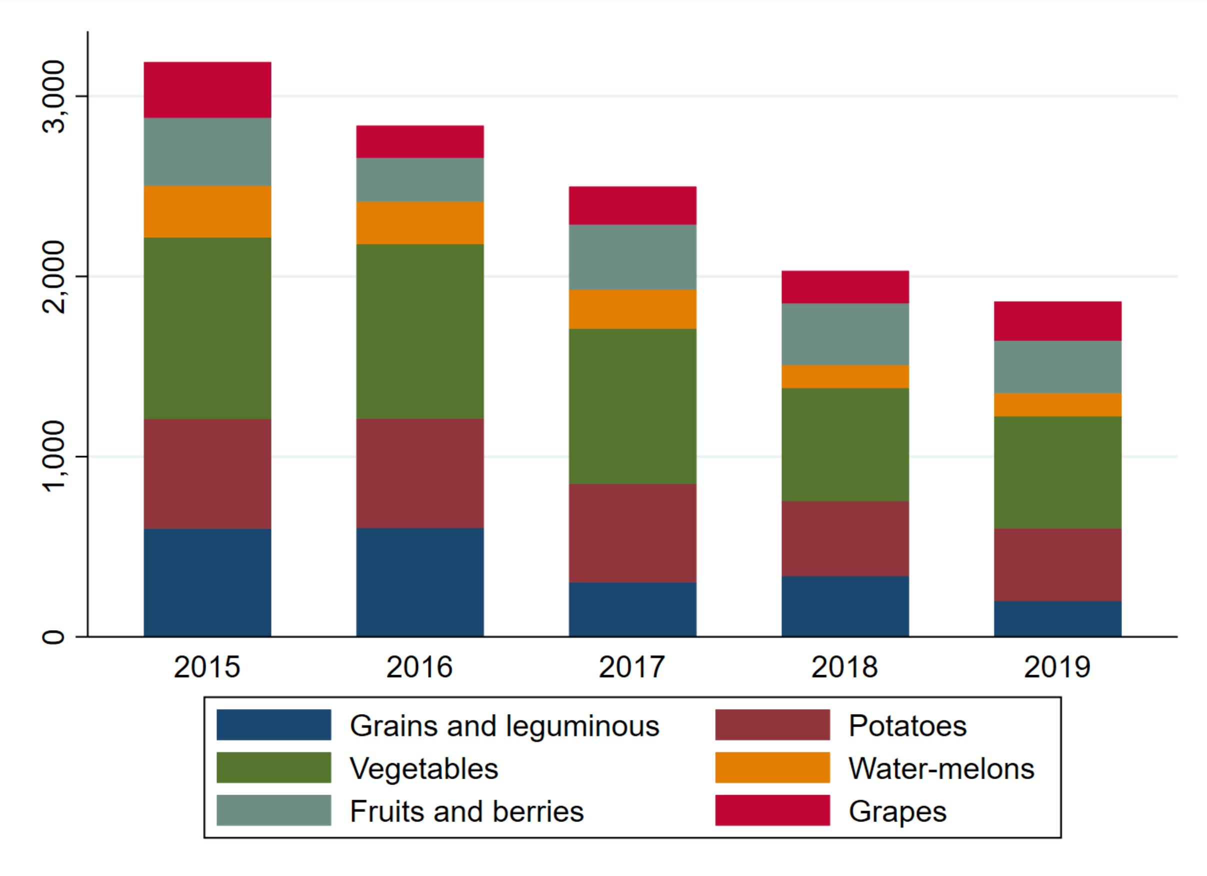

Figure 1: Agricultural production (1,000 tonnes)

Source: (NSS 2020c)

The share of vegetables was 0.612 Mt or about 33% of agricultural production in 2019. The production is higher in Armavir and Ararat (Table A 3). Correspondingly, these both regions produce more than 80% of vegetables. In this case, yields of vegetables are around 30 tonnes/ha in the regions. However, the production decreased by about 40% in the last years. Looking at dynamics, a similar decreasing pattern is observed in potato productions. For the regional perspectives, Gegharkunik has the largest share by producing 0.170 out of 0.404 Mt (Table A 4). Similarly, Shirak, Lori and Armavir predominate in the production of potatoes. In the majority of these regions, the average crop capacity of hectare is more than 20 tonnes/ha. The third largest crop production is related to fruits and berries, particularly from fruits. In the production of them, a regional disparity is relatively high. For instance, Armavir and Ararat lead in the gross harvest by producing around than 0.09 and 0.07 Mt in turn out of total 0.290 Mt (Table A 5). Respectively, the average crop capacity by producing more than 10 tonnes/ha is a typical characteristic of these regions. As for Aragatsotn, Kotayk and Syunik, each contributes to the production by harvesting well above 0.01 Mt. Other remaining regions have just under 0.01 Mt of production. The production of grapes is the next dominant crop representing 12% of total production or around 0.217 Mt. Looking at the dynamics of production, there has been a small decline over the last 5 years. Most of the production is related to Armavir and Ararat, where more than 80% of vineyard harvest is realized (Table A 6). Correspondingly, the average crop capacity in these regions is comparatively high, which makes up more than 20 tonnes/ha in Ararat and 15 tonnes/ha in Armavir. There is a noticeably decreasing pattern in the grain and legume crops showing well above 0.198 Mt of production in 2019. A regional similarity in the production of these crops is relatively high because only Vayots dzor, Tavush and Ararat harvest around 0.01 Mt (Table A 7). For the grain and legume crops, wheat harvest also declined by almost three times for the last years from 3.627 Mt to about 0.113 Mt (NSS 2020b).

1.2 Farm Structure and Target Group

Although there is no clear definition of family farm or smallholder farms (FAO 2019b), the structure of agricultural farms in Armenia is characterized by either commercial or family farms. Looking at both substantive and statistical definitions, family farms mean agricultural holdings managed and operated by a household or family members being reliant on family capital and labor (FAO 2021).

Table 2: Agricultural output by farm structure (at current price, percent)

	2015	2016	2017	2018	2019
Total	100	100	100	100	100
including					
Commercial farms	2.9	3.2	3.5	5.1	6.2
Household plots/ Family farms	97.1	96.8	96.5	94.9	93.8

Source: (NSS 2020c)

According to the National Statistical Service of Armenia, household plots are defined as family or individual (peasant) farms engaged in agriculture (NSS 2020c). Farms in Armenia operate their agricultural activities with or without legal status. With their legal status, farms are registered as legal entities and private entrepreneurs; otherwise, individual or family farms function by obtaining the membership of horticultural associations being farms without any legal status (NSS 2014). According to the secondary data, the majority of farms involved in agricultural activities were operating without any legal status (Table A 8). Although there are some limitations in the documentation of labours, an existing documented census indicates that a very large majority of farms without legal status had up to 5 members (Table A 9). This implies that many representatives of farmers in Armenia are household farms without legal status by having up to 5 workers. Lands of agricultural holdings for those without legal status shows that it represents ranges from 0.1 to 3 ha compared to those with legal status under the range of 1 to 20 ha (Table A 10). The largest average agricultural land per family farm is in Shirak and Syunik accounting for more than 2 ha. Armavir region has the average agricultural land by 182.23 ha per farms with a legal status. Looking at turnover, family farms have the range between 1000 up to 15,000 Euro while commercial farms are characterized by annual turnover ranging from 1000 to 50,000 Euro. Looking at productions, 93.8% of gross agricultural outputs are produced by family farms (Table 2). In other words, more than 800 bln AMD gross agricultural products were produced by household plots and family farms compared to 52.7 bln AMD products produced by commercial farms. Looking at sown areas, 0.224 Mha belongs to household plots, while 0.003 ha is used by commercial organizations (NSS 2020c). Despite the fact that main types of agricultural outputs are produced by family farms; nevertheless, the share of commercial farms in the production rises noticeably. For example, the share of commercial organizations in vegetable crops have increased from 0.005 to 0.026 Mt over the last 5 years (Table A 11). Over the same period, the contribution of family farms in vegetable output drops by about almost twice from 1.001 to 0.595 Mt. Other dominating crops such as grains, legumes and potatoes decline in the production of family farms. The production of grapes by commercial farms jumps from 0.003 to 0.012 Mt while the share of family farms declines by about 0.100 Mt.

1.3 Sown Area

The area sown to annual and permanent crops changes depending on the types of crops. For example, there is a rise on the sown area to high value crops due to changing the market structure in other sectors, and rising the demand for certain crops. A major difference for the sown areas is that family farms predominantly outnumber commercial farms in all types of crops. Looking at the dynamic perspectives, increasing pattern of grain and legume sown area or decreasing pattern of forage crop area is very typical of the commercial farms. As for family farms, sown areas for the grain and legumes together with forage crops decrease noticeably.

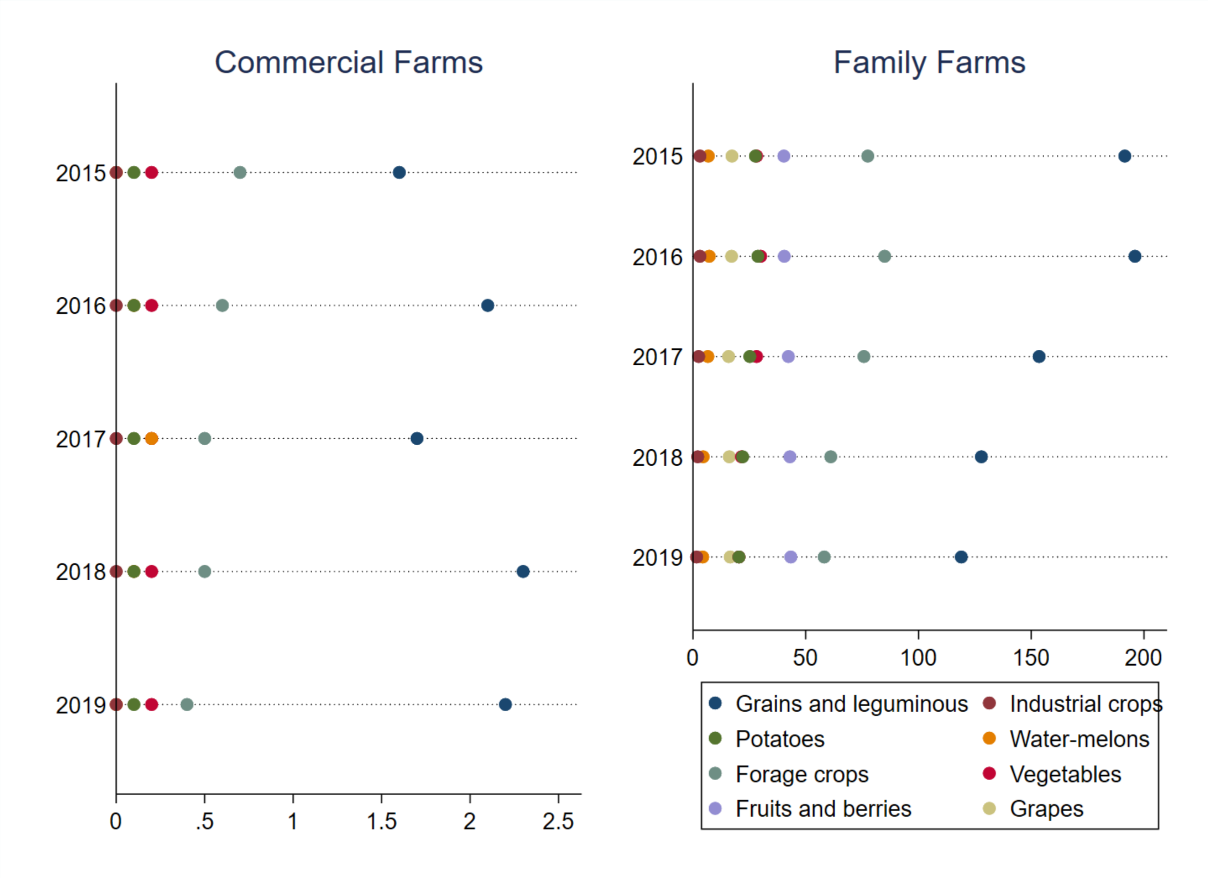

Figure 2: Sown areas by farm structure in 2019 (1,000 ha)

Source: (NSS 2020c)

In terms of sown areas under family farms, more than 0.121 Mha was used to cultivate grains and legumes in 2019 (Figure 2). Although there is a decline in the area for grains and legumes, it still dominates in the structure of family farm plot allocation and represents more than 50% of sown areas. Next predominant type is characterized by the forage crop area, which decreases noticeably reaching close to 0.060 Mha. There is a small rise in the plots used for fruit and berry plantations. A total planation area of these crops makes up well above 0.043 Mha. Both potato and vegetable crop areas have experienced a noticeable decrease over the last five years. Moreover, the area of grape plantations also decreases from 0.017 to 0.016 Mha. Remaining water-melons and industrial crops are less used areas, which have a decreasing pattern.

2. Selection of ten most important crops

Crop analysis is carried out based on production levels, harvest area and yield capacity (Sud et al. 2017). Three criteria are fundamental to farmers and policymakers for the decision making. Selected crops in Table 3**Fehler! Verweisquelle konnte nicht gefunden werden.** shows that it generally covers cereal and leguminous, industrial, vegetable and fruit crops.

Table 3: Selected crops

Crops	Production (Mt)	Crop area (Mha)	Crop capacity (tonnes/ha)	Income (USD/tonne)
Apricot	0.060	0.013	6.57	820
Peach	0.060	0.004	12.85	510
Apple	0.081	0.010	8.11	420
Plum	0.023	0.002	9.70	355
Wheat	1.113	0.059	1.60	246
Barley	0.068	0.049	1.50	241
Tomato	0.159	0.004	36.5	260
Berry	0.012	0.001	32.2	-
Potato	0.404	0.002	26.3	250
Cucumber	0.044	0.001	24.2	402

Source: (NSS 2020c; FAO 2019a)

The level of marketability in individual crop selection is important as it is one of particular ways to increase the gross margin per acre (Dixie 2005). In this circumstance, farmers should focus on the commercial viability by reducing the probability of market failure for the crop. Correspondingly, we focus on the level of marketability for the main 10 agricultural crops as being one of selection criteria. Looking at the primary data, the significance of marketing for agricultural production is mentioned. Precisely, more than a third respondents mentioned the problem of market power in the supply chain. One of possible explanations of this problem is due to the concentration to gain substantial monopolistic power of large companies in the supply chain. Moreover, close to 20% of farmers had the difficulty explained by the available market information for the crop marketability. The third common problem was the availability of price information causing challenges to strengthen a farm market orientation.

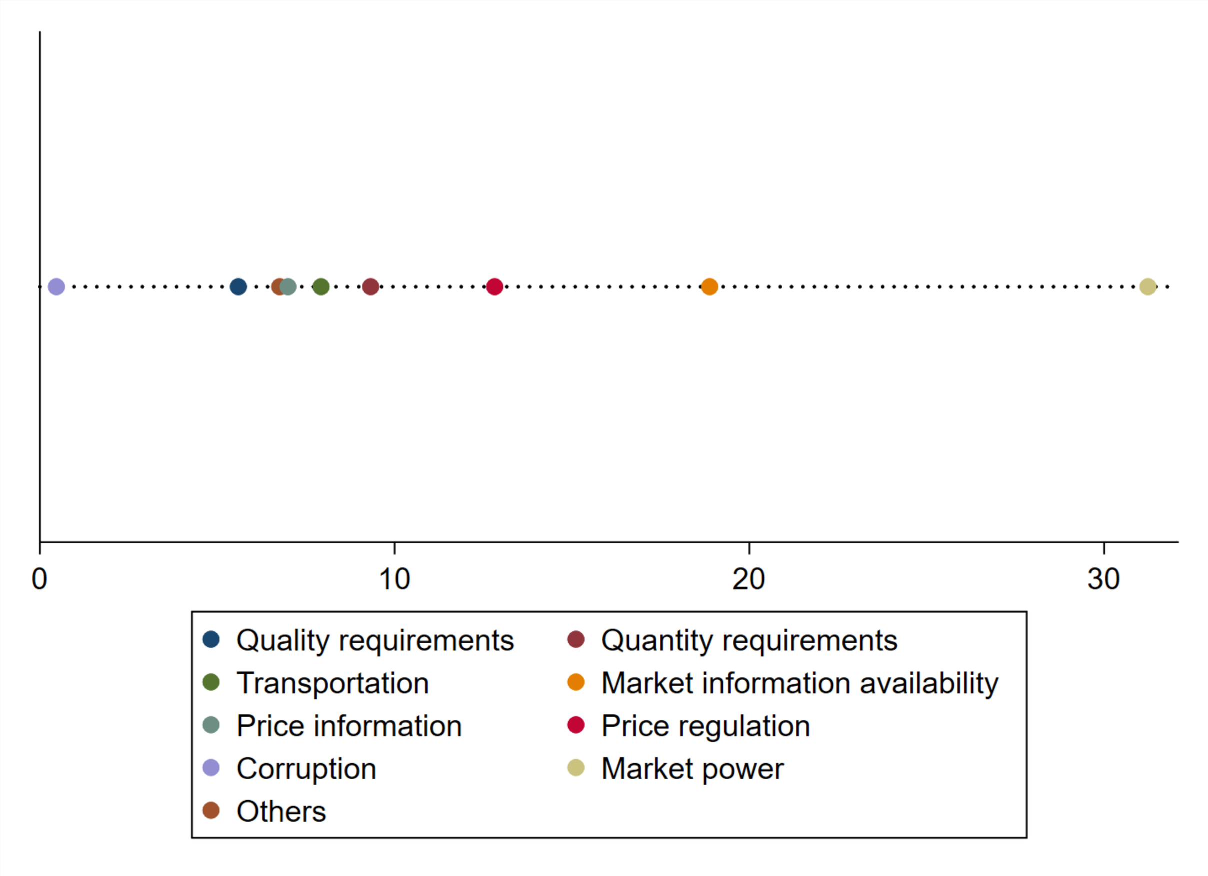

Figure 3: Crop marketing problems (percent)

Source: Commodity supply chains in Central Asia and Caucasus, 2015

Above mentioned three factors defining the condition of agro-market in Armenia signal low functioning of market efficiency. However, certain crop groups are still relatively efficient in terms of marketability. Looking at the country level, the highest marketability level is apparent in the water-melons and grapes, which makes up more than 90% (Figure 4). Following this, vegetables and fruits with berries are the next most marketable crops accounting for more than 80% and 60% respectively. The marketability for potato represents more than 40% compared to the level in grain and legumes which is above 30%. Generally, water-melons, grapes and vegetables are crop groups which have the highest marketability.

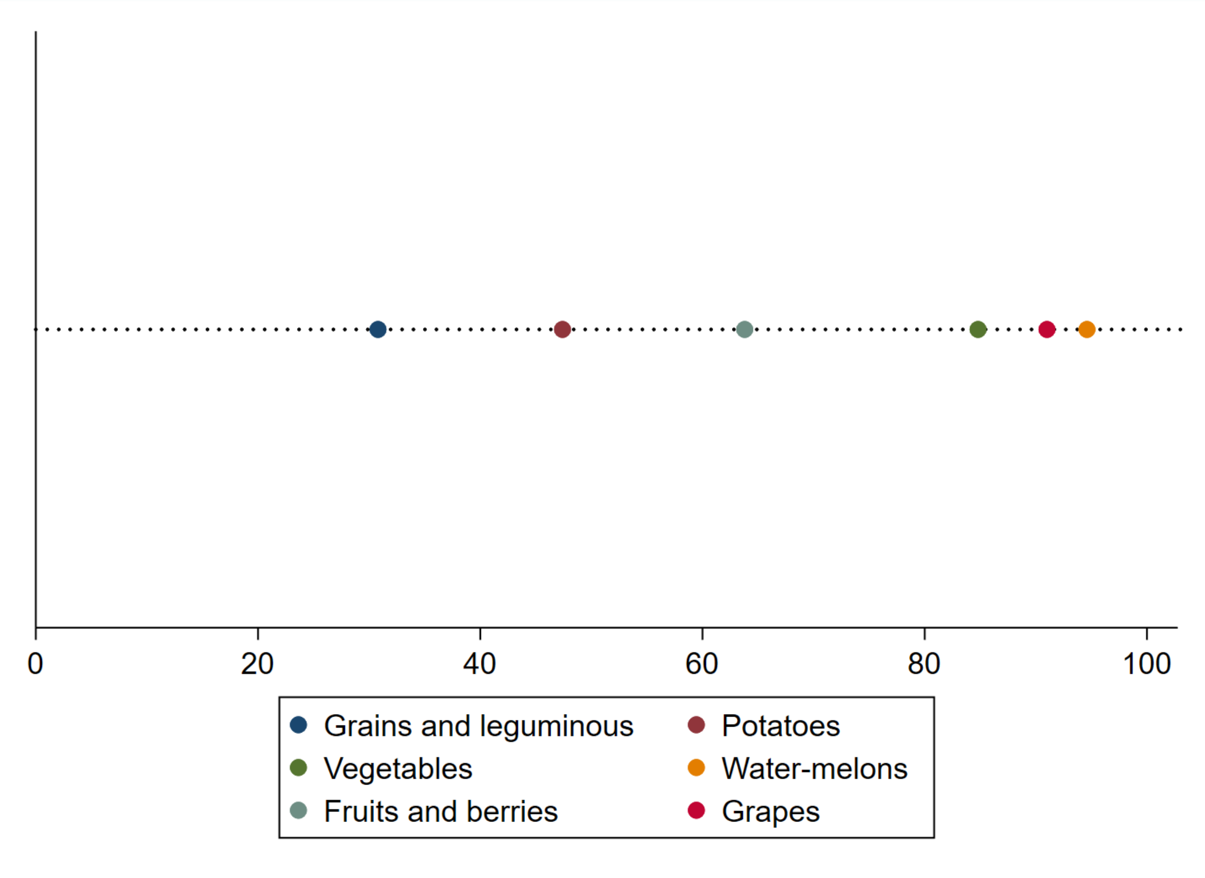

Figure 4: Marketability of main agricultural crops in 2020 (percent)

Source: (NSS 2020a)

Although, the trend is clear in terms of marketability for the types of crops, there is the existence of regional differences. Aforementioned high level of marketability dominance in certain crops is apparent in some regions (Figure 5). For example, Armavir and Ararat are the regions, where the level was higher than 50% for all crops in 2020. Except grain and legume crops together with grapes, Aragatsotn also relatively dominates with the marketability level. The level is also comparable for potato crops in Gegharkunik and Shirak.

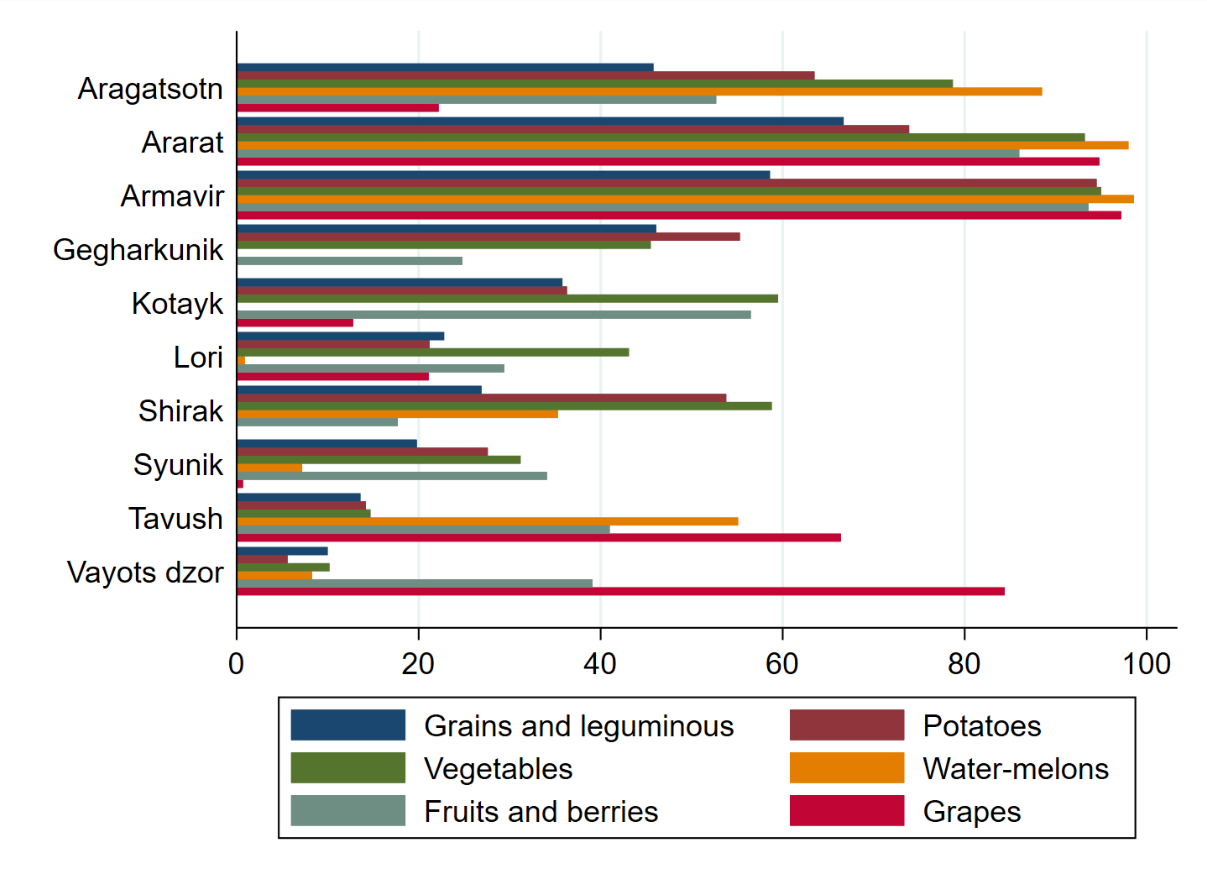

Figure 5: Marketability of main agricultural crops in Armenia for 2020 (percent)

Source: (NSS 2020a)

Such regional diversity of marketability levels may probably depend on the number of available farms for processing and selling agricultural products in the country. For example, only available Agricultural Census data of Armenia indicates that Armavir, Gegharkunik, Ararat, Aragatsotn, Lori, Shirak and Tavush are leading regions with the number of farms engaged in processing and selling of agricultural products (Table A 8).

Linked with the level of marketability, water-melons, grapes and vegetables were the foremost crops sold in the market in 2019 (Table 3). For instance, Ararat and Armavir regions have the highest market realization of melon products ensuring more than 90% and 80% of sales in turn (Figure A 1). Lori, Syunik, Tavush and Vayots dzor regions use water-melons for own household consumption. On the other hand, Ararat, Armavir and Vayots dzor regions are dominant in the sale of grapes compared to other regions (Figure A 2). At the same time, Syunik, Lori, Kotayk and Aragatsotn regions use grapes for the household consumption. Armavir, Ararat, Aragatsotn and Kotayk dominate in the trade while Tavush and Vayots dzor consume vegetables in the households (Figure A 3). For the case of potato, the situation is very similar to the realization of vegetables, where Armavir, Ararat, Gegharkunik and Aragatsotn have the highest market realization (Figure A 4). Correspondingly, Vayots dzor and Tavush process potatoes for the household consumption. Fruits and berries are also commonly marketed in certain regions. For instance, Ararat and Armavir have the percentage of marketing at more than 80% (Figure A 5). Syunik, Shirak and Lori regions use more than

50% of fruits and berries for the consumption. For the household consumption, grain and legume crops are dominant by representing 44% out of which 41.3% is recycled.

This situation is also true for many regions of Armenia. For example, Vayots dzor, Tavush and Syunik regions had more than 50% of own consumption out of which more than one a third was recycled in 2019 (Figure A 6).

Table 4: Realization of main agricultural crops (percent)

	Total	sold	exchanged for goods	exchanged for services	used in the household	*from which* recycled	others
Grain and Legumes	100	24.9	5.1	0.8	44.1	41.3	25.1
Vegetables	100	82.6	1.9	0.3	11.8	34.7	3.4
Potatoes	100	41.5	5.0	0.9	21.3	-	31.3
Fruit and Berries	100	59.6	2.9	1.3	23.0	42.8	13.2
Water-melons	100	94.2	0.2	0.2	5.3	1.3	0.1
Grapes	100	90.4	0.4	0.2	7.0	70.1	2.0

Source: (NSS 2020a)

A comparative analysis of vegetable crops indicates that tomato is the dominant crop harvested. The production was around 0.159 Mt in 2019 (Figure 6). Respectively, the harvest area is also the highest at 0.004 Mha (Table A 12). In this case, the average crop capacity of tomato is more than 36.5 tonnes/ha, which is the highest between vegetable crops. Looking at the farm profitability, farms were able to earn 260 USD/tonne in 2019 (FAO 2019a). By the highest production of vegetable crops, cucumber is also one of the most harvested crops in Armenia. Accordingly, it was 0.044Mt by having the capacity of 24.2 tonnes/ha and income 402 USD/tonne in 2019 (FAO 2019a). Therefore, the highest income was earned by producing cucumber in vegetable crops.

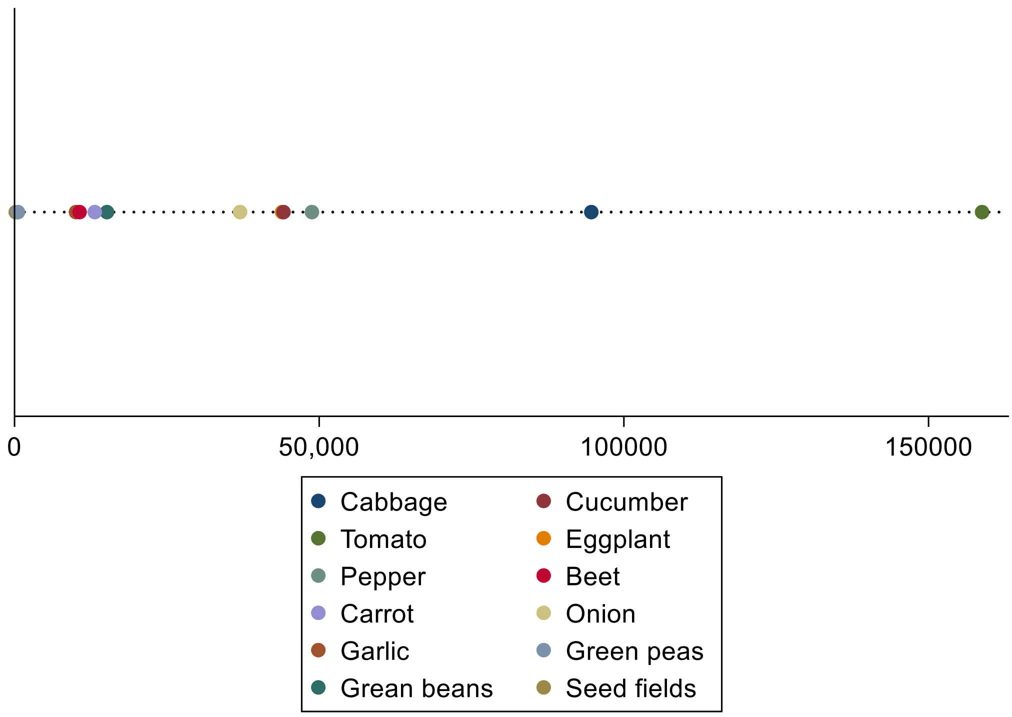

Figure 6: Vegetable harvest (tonnes)

Source: (NSS 2020c)

A total production of stone fruits in Armenia is the second largest with more than 0.170 Mt. Accordingly, the average capacity of stone fruits makes up 8.32 tonnes/ha (Table A 13). Apricots and peaches with nectarines were most harvested stone fruits accounting for more than 0.060 Mt each in 2019 (FAO 2019a). Correspondingly, the average capacity of apricots represents 6.57 tonnes/ha while peaches and nectarines show 12.85 tonnes/ha. In this case, the farm income in apricots shows 820 USD/tonne representing the highest contribution of agricultural products. The third largest harvest is related to pome fruits, which represents 0.095 Mt. A total planation area is 0.013 Mha by having 7.3 tonnes/ha crop yield (Table A 13). In this group of fruits, the largest share belongs to apples representing 0.081 Mt (FAO 2019a). As for the income by pome fruits, the highest contribution to farm income realized by apples at 420 USD/tonne by having 8.11 tonnes/ha crop yield.

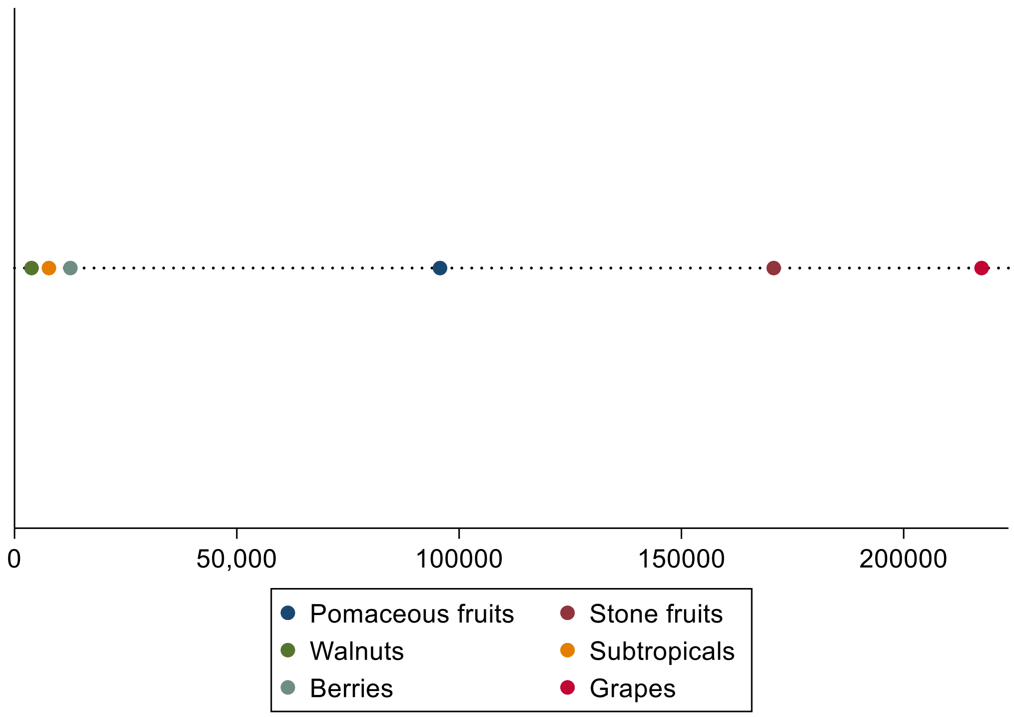

Figure 7: Fruit orchard, berry and grape harvest (tonnes)

Source: (NSS 2020c)

The production of winter and spring wheat in Armenia was close to 1.113 Mt in 2019, which was the largest among grain and legume crops (see Figure-9). A harvested area for total wheat takes 0.059 Mha by having more average crop capacity at more than 1.60 tonnes/ha (Table A 14). Annual farm income was 246 USD/tonne in 2019 (FAO 2019a). Moreover, the production of potato is also dominant in Armenia which represents 0.404 Mta in 0.002 Mha area by having 2.3 tonnes/ha capacity (NSS 2020c). The income from potato production represents 250 USD/tonnes.

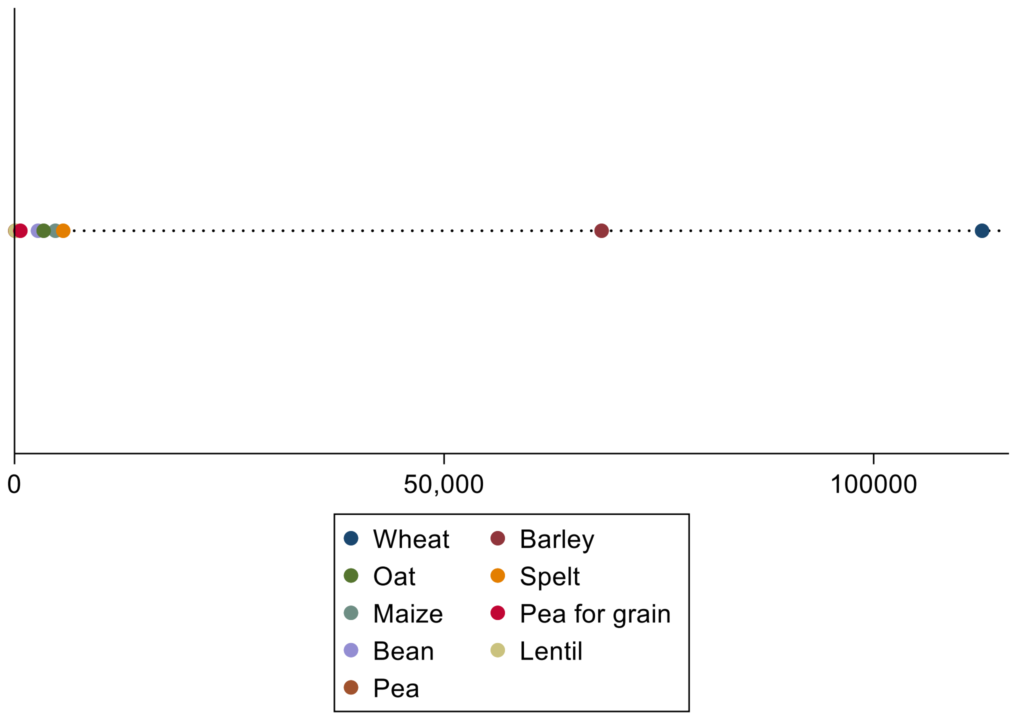

Figure 8: Grain and leguminous crop harvest (tonnes)

Source: (NSS 2020c)

3. Synthesis of existing risk management concepts

A resilience as a proxy is measured through observable factors (pillars). It shows how the households are able to cope with climate change shocks by activating available risk management techniques. By definition and statistical properties, resilience is defined as the capacity ensuring climate shocks do not have long-lasting consequences in farm livelihoods. According to RIMA methodology, there are four main factors or pillars to represent the resilience (FAO 2016). One of the key objectives of RIMA methodology is that it represents the linkage between resilience with climate change impact by analysing the response mechanisms of households.

- Assets (AST) represent household capital (mainly agricultural) to withstand the shock;
- Access to Basic Services (ABS) represent facilities and infrastructure of the household that is important to respond to the shock;
- Adaptive Capacity (AC) is related to the adaptability or ability to cope with the shock;
- Social Safety Nets (SSN) is related to any social capital or ties that can be used to react and bounce back from the shock.

In this respect, each pillar is measure through factor analysis (FA) under observable variables. Through factor analysis, the resilience itself can be formalized as:

$$Resilience\ Capacity\ Index\ (RCI)_h = f\ (AST_h, ABS_h, AC_h, SSN_h) \qquad (1)$$

Available primary data from the survey "On Commodity Supply Chains in Central Asia and Caucasus" with 359 sample size include observable factors describing resilience characteristics (Table A 15). Generally, the result of household resilience as a climate change mitigation strategy stresses a notable need to improve all pillars as provided in Figure 9. The need to improve the resilience capacity through Access to Basic Services (ABS) is important. Since the pillar represents the irrigation system in Armenia, related risk mitigation strategies by enhancing translates into improved resilience capacity towards climate change. Outreaching and building climate resilience of the most vulnerable farms are encouraged to apply water-saving irrigation technologies such as drip irrigation. For example, in Arnasay 7000 ha of 220 household farms are equipped with drip irrigation system under CBA project (UNDP 2011). For strengthening the resilience in the face of severe natural events, the implementation of water-saving irrigation and rehabilitation of water reservoirs in Sugd Province of Tajikistan is another example strengthening climate change adaptation measures (GIZ 2018). The project implemented by FAO supports sustainable land and water management in dry lands of Kyrgyzstan (FAO 2020). In this case, water-saving irrigation and water-efficient crops reinvigorate farmers to implement adaptation measures in agriculture. For example, introduction water-saving irrigation accompanying the use of quality seed and the rehabilitation of water reservoirs under the project by the German Federal Ministry for Economic Cooperation and Development (BMZ) encourage poor households in the mountain valleys and foothills of Batken Province in Kyrgyzstan (GIZ 2018).

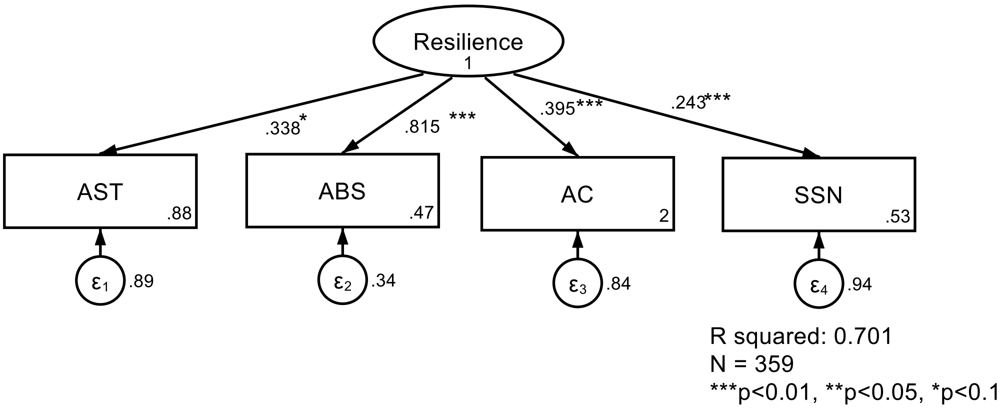

Figure 9: Resilience measurement through Structural Equation Modelling (SEM), (AST-Assets; ABS-Access to Basic Services; AC-Adaptive Capacity; and SSN-Social Safety Nets)

Given the significance of Adaptive Capacity (AC), the magnitude of relationship with household resilience capacity index is one of the highest. Efforts to improve the adaptive capacity of households will translate into increased ability to mitigate climate change consequences. In this case, the capacity of households becomes more adapted by strengthening using different types of subsidies, receiving extension services, fulfilling quality requirements and others (Table A 15).

- Precisely, using machinery, credit, fuel, fertilizer, and seed subsidized inputs tend to increase household ability to adapt to the changing environment. In a practice, the agricultural sector is inherently resilient from one side due to the National Agriculture and Rural Development Strategy (NARDS) by establishing the Regulation on Subsidies for the period of 5 years (2017-2021) in Moldova (Gerciu et al. 2017) or the law *"On state support of agriculture in Ukraine"* (OECD 2020). Similarly, the resolutions of Kazakhstan by the Ministry of Agriculture have been adopted to support farm activities through subsidy on inputs (FAO 2012).
- Both availability market information and extension services for farmers imply that households become more adapted by improving their conditions in their own environment. Considering extension possibilities taken under this pillar, farms participation in extensions services is likely to strengthen a risk coping probability, coupled with the availability of market information or marketing opportunities. For example, the project implemented to improve national extension services shows that extension services are likely to increase the likelihood to adapt in the climate change mitigation (FAO 2020a). For example, the context of Turkmenistan shows that developing access to climate smart advisory service under resilient extension approaches increases the capacity of farmers to apply climate adaptation strategies (Adaptation Fund 2017).
- Related number of plots involved in agriculture and fulfilling quality requirements retain the same functions to reorganize capacity of a household in reacting to climate changes. A similar approach to increase farm resilience is realized through the development of quality standards for drought-tolerant varieties and the establishment

of portfolios adapted to drought conditions in Uzbekistan. The project is initiated in expanding the development of fruit and vegetable variety portfolios under drought conditions and extreme temperature fluctuations in Uzbekistan (CGIAR 2017). Seed and seeding production for drought in different agro-ecological zones are also supported that makes available super-elite and elite seeds demanded by beneficiaries or farmers. To ensure a strengthening local seed and seedling production systems (Table A 16), there has been a support to increase the supply and update the guidelines for seed production, testing, registration and certification (World Bank 2020).

With regard to the resilience sensitivity, AST and SSN both have relatively lower contribution. Bearing in mind that TLU, agricultural assets and other types of assets are used to construct the variable, it is still recommended to give a priority attention to improve them.

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Work Package 2:

“Data preparation and characterization of historical climatic trends”

Content

Figures

1. Data preparation

We describe here the process of collating and processing the basic geospatial datasets needed to accomplish the following work packages. We collect, analyze and evaluate land-use maps, climatological information, and historical fire records.

1.1 Land-Cover and Cropland Maps

To represent the status of land cover, we used the *Caucasus Land Cover Map* from the *SILVIS lab of the University of Wisconsin* (http://silvis.forest.wisc.edu/data/caucasus/) from the year 2015. The land-cover map is based on the classification of Landsat imagery and has a spatial resolution of 30 meters. The methodology used to derive the land-cover map is described in Buchner et al. 2020[1].

Cropland was classified from the Landsat imagery based on the shapes of the cultivated fields, the detection of evidence for plowing, and the vegetation greening cycle over the year. Sparsely vegetated areas, shrubs, and grassland were labelled as rangeland. The 2015 land cover map shows that the lowland areas of Armenia are characterized by a mix of rangelands and croplands, whereas the mountainous areas are dominated by deciduous forests (Figure 1). Cropland is relatively evenly distributed across Armenia; however, the share of cropland is rather low in the northern provinces of Lori and Tavush.

In terms of land cover changes, Buchner et al. (2020) find that of the total land area of Armenia, only 9% was continuously cultivated since 1987. Armenia experienced a reduction of its cropland extent by 10% from 1987 to 2015. Most of the lost cropland transitioned to rangeland, i.e., to sparsely vegetated areas, shrubs, and grassland.

We extracted all pixels that belong to the cropland class from the 2015 land cover map and resampled these to a resolution of 300 meters to omit isolated pixels and to increase the computational speed of later processing steps. This resulted in a cropland mask that we use as the boundary layer to restrict subsequent analyses to areas that are used for crop production. Figure 2 shows the final cropland mask that we used for all subsequent analyses.

[1] Buchner et al. (2020), Remote Sens. Environ.: https://doi.org/10.1016/j.rse.2020.111967

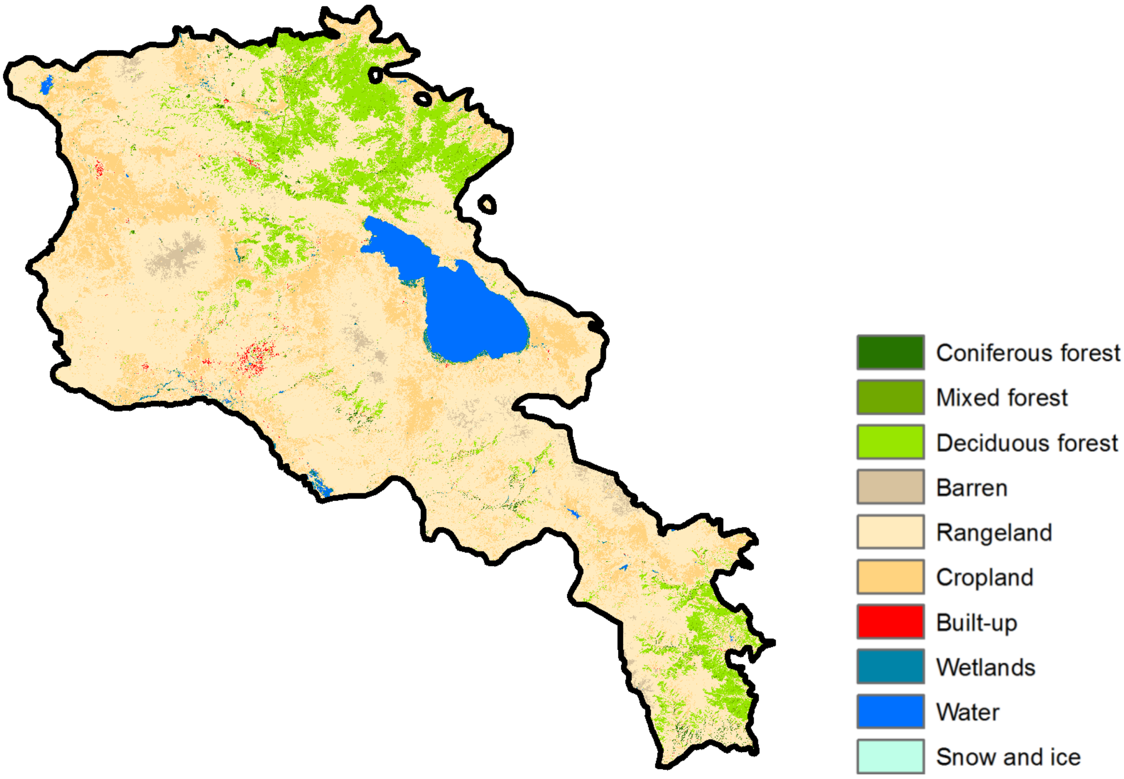

Figure 1: Land cover of Armenia in 2015. Source: Caucasus Land Cover Map, SILVIS lab of the University of Wisconsin (http://silvis.forest.wisc.edu/data/caucasus/)

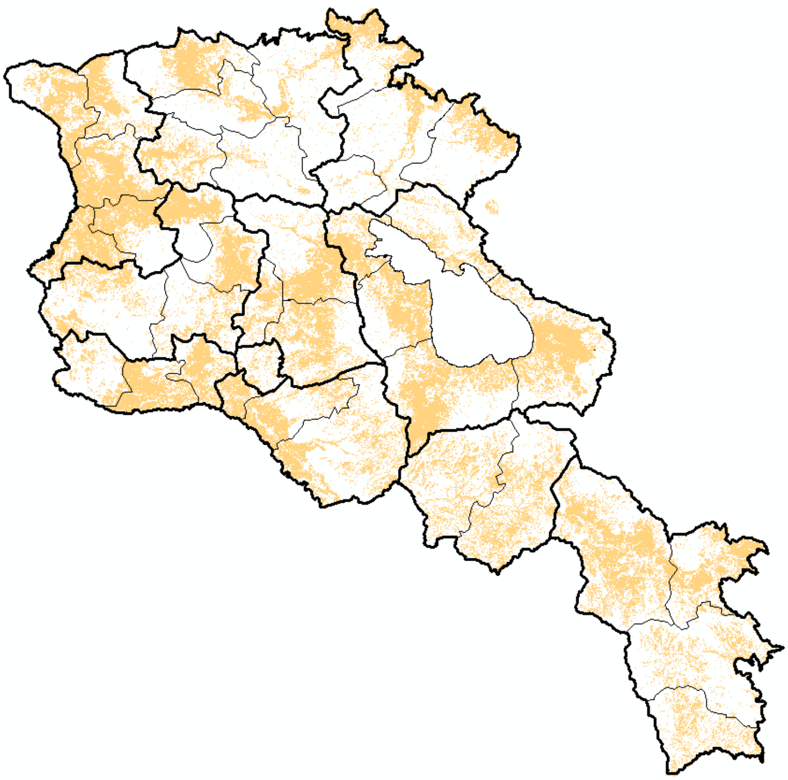

Figure 2: Cropland mask for Armenia from the Caucasus Land Cover Map, resampled to a spatial resolution of 300 meters.

1.2 Modelled Climatological Data

We sourced rainfall data from the *Climate Hazards group Infrared Precipitation with Stations* dataset (CHIRPS, https://data.chc.ucsb.edu/products/CHIRPS-2.0/global_daily/netcdf/p05/), which comprises daily gridded estimates based on satellite and weather station data with a spatial resolution of 0.05° (~5 km). Temperature data stem from the reanalysis dataset *ERA5-Land* (**Fehler! Linkreferenz ungültig.**), provided by the climate data store of the *Copernicus* program and available at a spatial resolution of 0.1° (~11 km) and a temporal resolution of one hour. Both CHIRPS and ERA-Land are available for free and since January 1st, 1981. We used all data until December 31st, 2020 (14,610 days in total). Among the gridded climate datasets that are freely available, CHIRPS and ERA5-Land have the highest available spatial and temporal resolution. Moreover, both datasets are continuously updated in near-real time, which permits for updates of our results once new data becomes available.

We converted the downloaded CHIRPS NetCDF files into daily TIFF images. For the ERA5 product, we first summarized hourly values into daily minimum, average, and maximum values, transformed them from degrees Kelvin to degrees Celsius, and then converted them into daily TIFF images. The database with the preprocessed precipitation and temperature images contains a total of 4 x 14,610 = 58,440 files. Figure 3 exemplifies one layer for average temperature and one for precipitation.

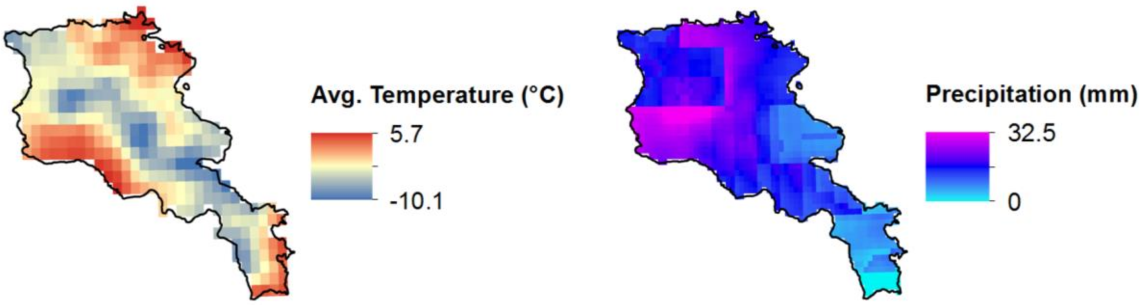

Figure 3: Average temperature on January 1st, 1981, from ERA5-Land (left) and precipitation on October 15th, 1981, from CHIRPS (right).

1.3 Historical Fire Records

Fires are a considerable threat to crop production in the region. We analyzed fire occurrence and intensity from the active fire data provided via *NASA's Fire Information for Resource Management System* (FIRMS, https://firms.modaps.eosdis.nasa.gov/active_fire/). We use these data to assess the spatiotemporal occurrence of cropland fires in Armenia. The FIRMS data are derived using a global algorithm that analyzes data from the *Moderate Resolution Imaging Spectroradiometer* (MODIS) imagery aboard the Terra and Aqua satellites (**Fehler! Linkreferenz ungültig.**) and from the *Visible Infrared Imaging Radiometer Suite* (VIIRS) aboard the Suomi NPP satellite, launched in 2011 (https://viirsland.gsfc.nasa.gov/ index.html). For the sake of consistency, we only relied on the fire data derived from the MODIS sensors to extract daily information about fire occurrences from 2001 to 2020 at a spatial resolution of 1 km. The VIIRS data has a higher spatial resolution at 375 meters, but is only available since 2012.

We downloaded all active fire records for Armenia from 2001 to 2020 from the MODIS dataset. We then removed all records with a fire detection confidence below 20% to reduce the number of false alarms (see Giglio et al. 2016[2]). To focus on fires related to crop production, we only included those fires that occurred on cropland or less than 300 m away from the nearest cropland using the cropland mask (see chapter 1.1). The final data selection includes 4,071 active fire records.

All results area available online in an interactive format at:

https://rpubs.com/max_hof_mann/fires_armenia

In the map "*Locations*", each dot represents a single fire occurrence as recorded by the MODIS fire detection algorithm between 2001 and 2020. The brighter the dot, the hotter is a fire, measured in megawatts of fire radiative power (FRP). When zooming out, individual fire pixels are combined into clusters.

In a next step, we calculated the mean number and intensity of fires for each year from 2001 to 2020 within each district. The map "*Mean Yearly Number*" visualizes the average yearly counts. The map "*Change in Number*" shows the trend in number of fires from 2001 to 2020 based on the slope of a linear regression. For each district, we performed a Mann-Kendall test that assesses whether the calculated trend in number of fires over time is significant, considering both the normal variability in yearly fires and the occurrence of outlier years with exceptionally high or low numbers of fires. Districts with a significant trend line are highlighted with a black outline in the change map. We used the FRP measures to map the "*Mean Intensity*" of all fires per district and for all years. For the map "*Change in Intensity*", we calculated for each district the average FRP of all fires in each year, and then fitted a linear regression model to calculate the change in yearly mean fire intensity from 2001 to 2020. Again, we performed Mann-Kendall tests to assess the significance of these changes. Districts with significantly positive or negative changes are highlighted with a black outline.

[2] Giglio et al. (2016), Remote Sens. Environ.: http://dx.doi.org/10.1016/j.rse.2016.02.054

The district with the highest average number of fires per year is Sisian (27 fires), followed by Tashir (12 fires) and Vardenis (11 fires, Figure 4). We found the highest significant positive changes in number of fires in Hrazdan (increase by 1.2 fires per year), Martuni (1.1 fires per year) and Kotayk (0.7 fires per year, Figure 5). A substantial share of these districts is also covered by cropland (Figure 2). The districts with the highest average fire intensity are Noyemberyan (41 MW), Vayk (40 MW) and Yeghegnadzor (34 MW, Figure 6). Significant increases in fire intensity occurred in seven districts, all located in the center of the country, with yearly increases between 0.6 and 1.5 MW (Figure 7). Amasia is the only province where there was a significant decrease in fire intensity (1.2 MW). Tumanian experienced an average yearly increase of 4.6 MW, but this trend was not significant and is due to a series of fires with high FRP in 2020 (Figure 8).

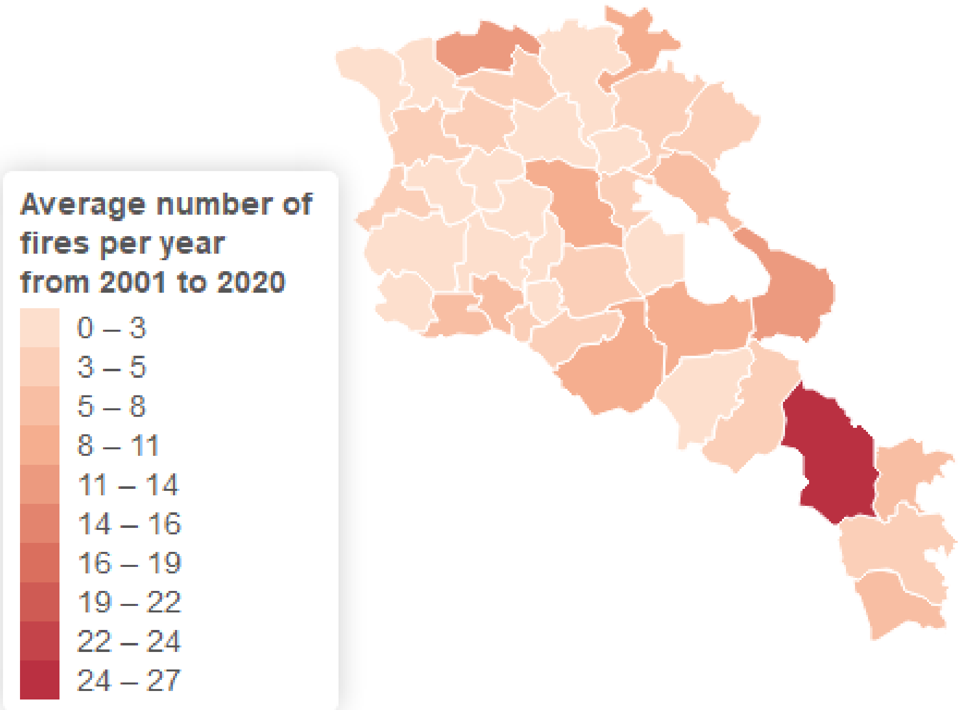

Figure 4: Average number of fires per year in Armenia.

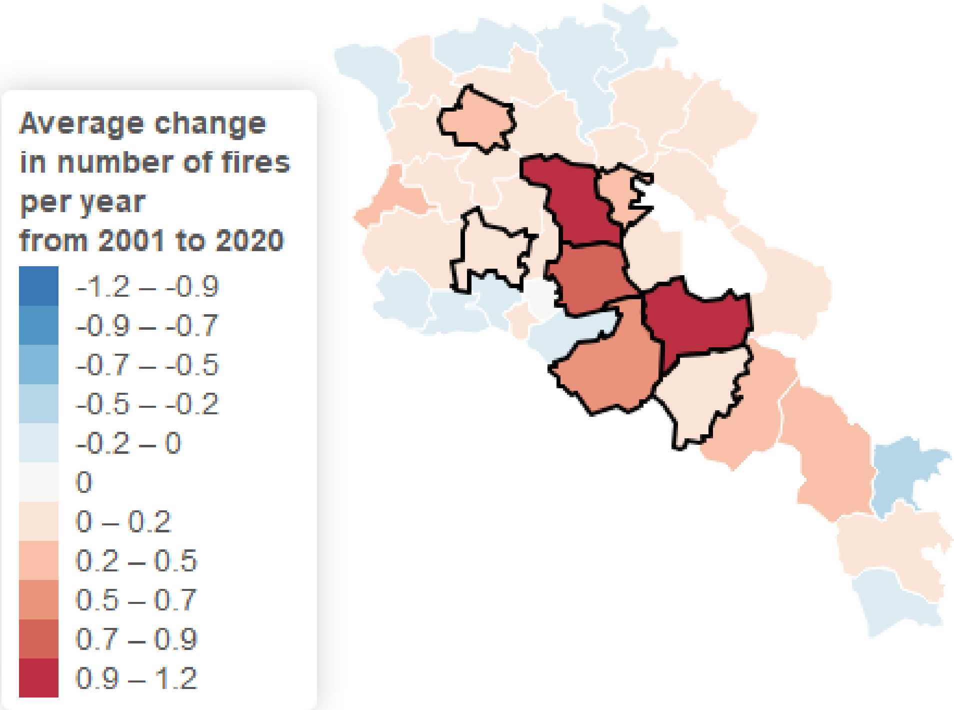

Figure 5: Average change in number of fires per year in Armenia. Districts with a black outline had a significant positive or negative change between 2001 and 2020.

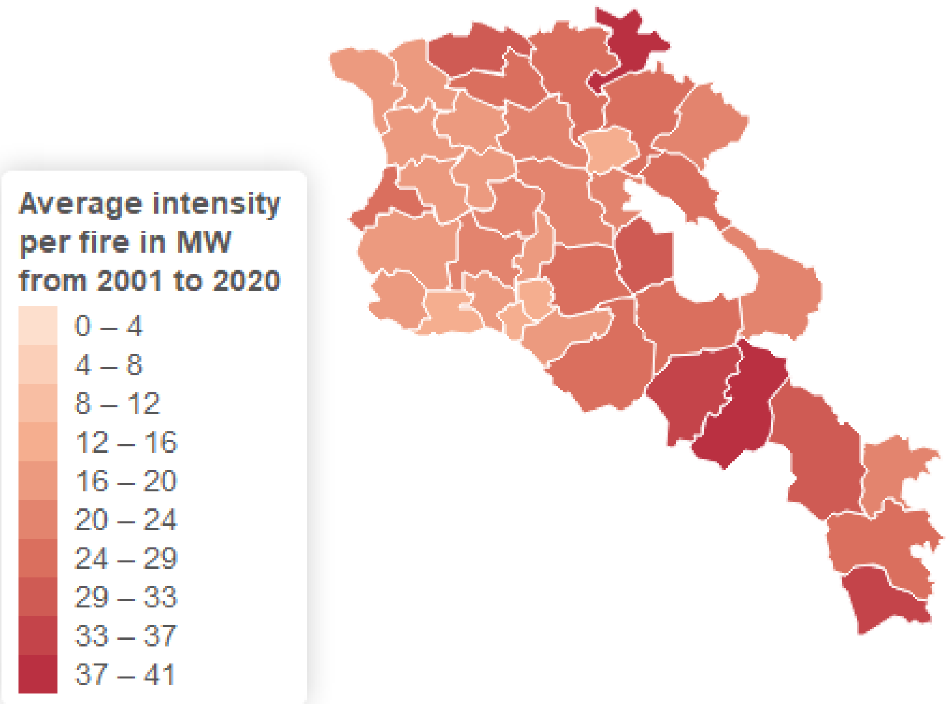

Figure 6: Average fire intensity in Armenia.

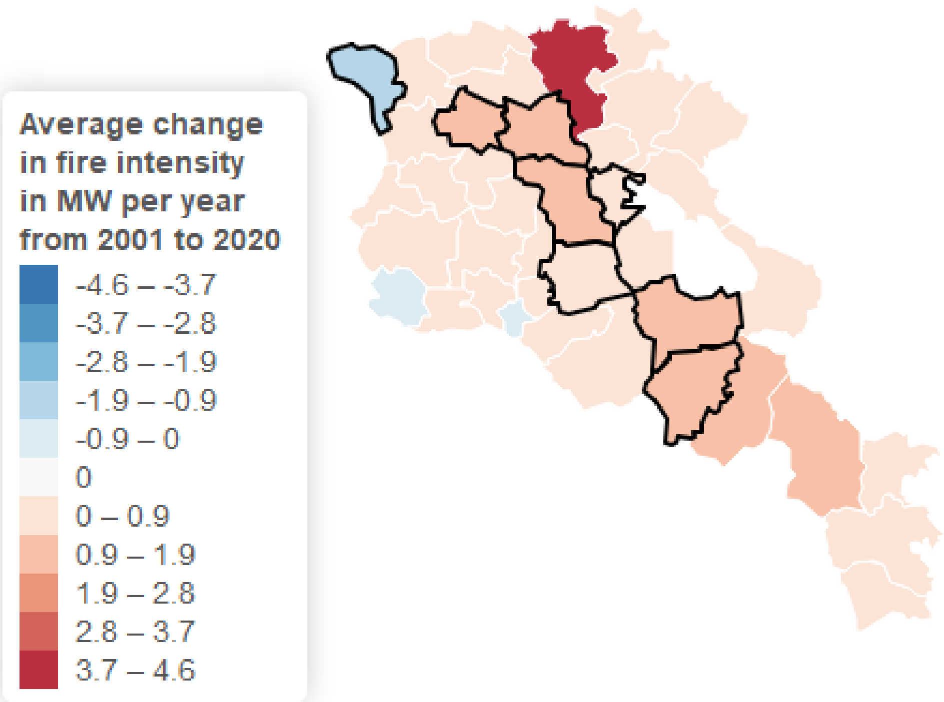

Figure 7: Average change in fire intensity per year in Armenia. Only districts with a black outline show a significant change between 2001 and 2020.

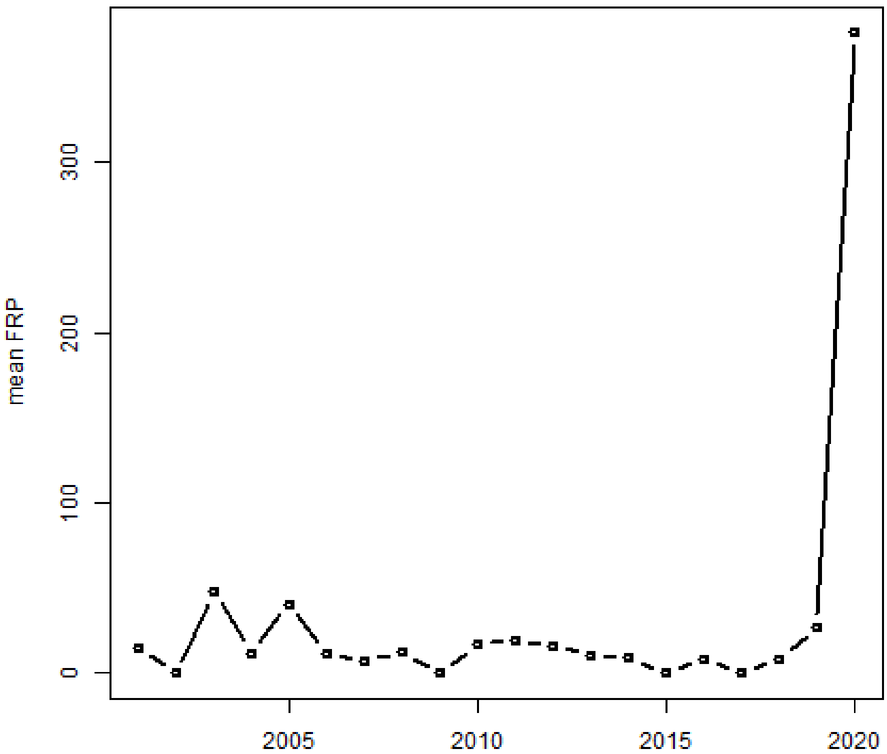

Figure 8: Yearly mean fire radiative power in megawatts, in Tumanian district.

Satellite-sensed fire records have a series of limitations and one should be careful when drawing conclusions from this data:

- There is no information on the duration of a fire. Fires that lasted a few hours, and fires that lasted for days, are not distinguishable from one another.
- There is no information on the area that was burnt by a fire. MODIS images are composed of pixels with a size of 1x1 km. A pixel is classified as an active fire as soon as the algorithm detects a fire therein, irrespective of the size that the fire actually covers.
- If two separate fires happen within one 1x1km pixel, they count as one fire.
- If a fire spans over several 1x1 km pixels, it will count as several separate fires.
- There is no information on the movement of fires. If a fire passes from one pixel to another, it will count as a new fire.
- There is no certainty about the type of fire. Natural wildfires, campfires, larger barbecues, or gas flares cannot be separated from each other.

We abstain from making any inferences about the future development of fire activity and intensity.

Vegetation fires are mediated by the biophysical conditions that prevail in a specific location, such as the availability of soil moisture, topographic features, such as slope and aspect, wind speed and direction, as well as precipitation and temperature patterns. Arguably, with rising average temperatures and more frequent drought periods, many landscapes in the Caucasus will become more susceptible for fires, including more frequent and more severe fires. However, it remains extremely challenging to anticipate future fire behavior because the occurrence of fire depends not only on biophysical conditions but on additional, often unpredictable management factors. These include, for example, land use management, such as the type and intensity of grazing. Higher extraction of biomass through grazing will reduce fuel loadings and thus tend to reduce the susceptibility of landscapes to fire. Moreover, some crop cultivation systems are more prone to fire than others. Stubbles left on the field, for example, can be easily ignited and can provide sufficient fuel loads to enable large cropland fires. Also changes in land use, such as the abandonment of cropland, will alter fuel loadings and can lead to higher fire risk, depending on the type of successional vegetation and the fuel load it provides. Hence, it has been shown that changes in land cover, land use, and land management are key factors for fire behavior, which is why it is not possible to predict fire occurrence into the future with any degree of confidence.

2. Characterization of historical climatic trends

2.1 Introduction

To get an overview on how climate has changed across crop production regions of Armenia during the last four decades, we analyzed modelled climatic datasets with a daily resolution from 1981 until 2020. We use the CHIRPS dataset for precipitation and the ERA5-Land dataset for temperature. To focus only on cropped areas, we only consider those areas that fall into the cropland mask (defined in chapter 1.1). For one part of the analysis, we only considered the time period during a year that is relevant for crop growth. To do so, we define a main growing season from October to June, because crop yields in the study area are typically not affected by climate conditions during midsummer (July-September). However, we are aware that this is only a coarse approximation and specific crops might have a very different critical window during which climate can have a high impact on plant growth. Therefore, we also calculated climatic trends on a monthly basis. We analyze climatic trends with more detail in work package 3.

2.2 Approach

The workflow to estimate climate trends, including the processing steps of the cropland mask and ERA5-Land temperature data (see chapters 1.1 and 1.2), is illustrated in Figure 9. We first multiplied the binary cropland mask with all 14,610 daily layers of the four climate parameters from CHIRPS (precipitation) and ERA5-Land (minimum, average and maximum temperature), respectively (see chapter 1.2). We then overlaid all resulting 58,440 raster layers with the districts shapefile and calculated zonal mean statistics for each district. This procedure results in one value for mean precipitation, mean minimum temperature, mean average temperature, and mean maximum temperature for each district and day from January 1st, 1981, to December 31st, 2020 (see Figure 10). From these values, we calculated the sum of precipitation and mean temperature values for each month and for each growing season. That resulted in time series of 40 values for each month, and 39 growing season values. For each time series, we fitted a linear regression model to calculate the yearly trend in precipitation or temperature and the change from 1981 to 2019 (growing season values) or from 1981 to 2020 (monthly values) (Figure 11). The changes in precipitation and temperature shown in the subsequent maps always refer to the total change between 1981 and 2019/2020. We used the nonparametric Mann-Kendall test to assess if the observed changes in precipitation and temperature are statistically significant.

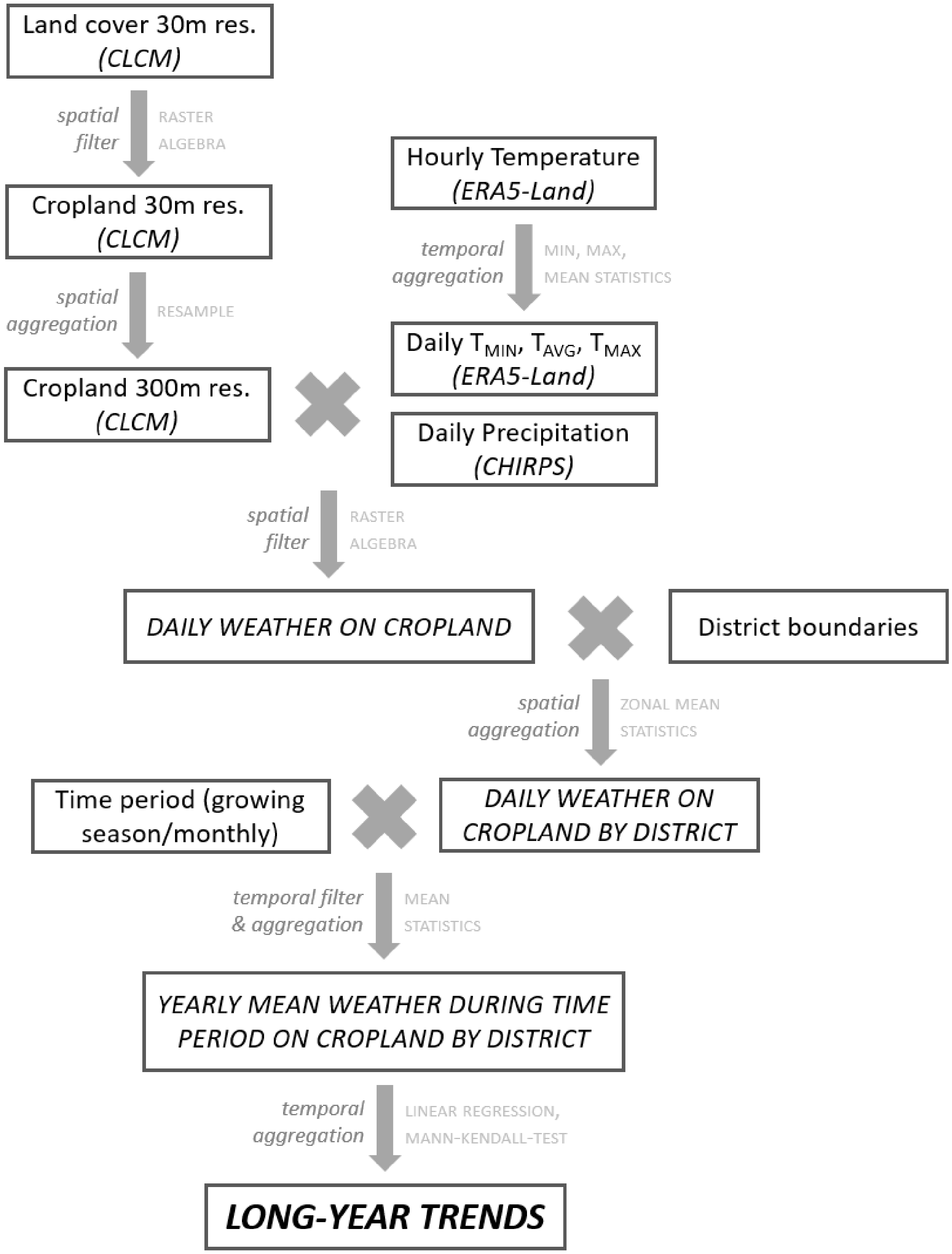

Figure 9: Workflow for estimating long-term climatic trends from cropland mask, daily temperature and precipitation data and district boundaries.

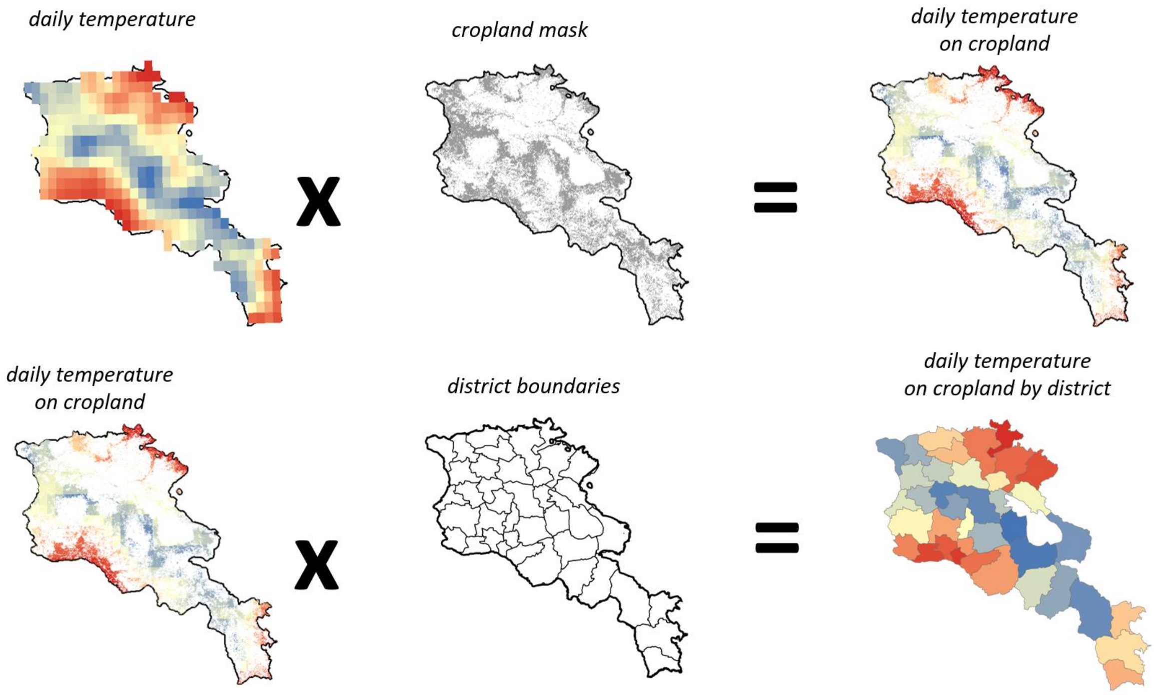

Figure 10: Illustration of a part of the workflow described in Figure 9. Daily temperature values are only kept for cropland locations. For each district, we summarized the underlying temperature values into one district average.

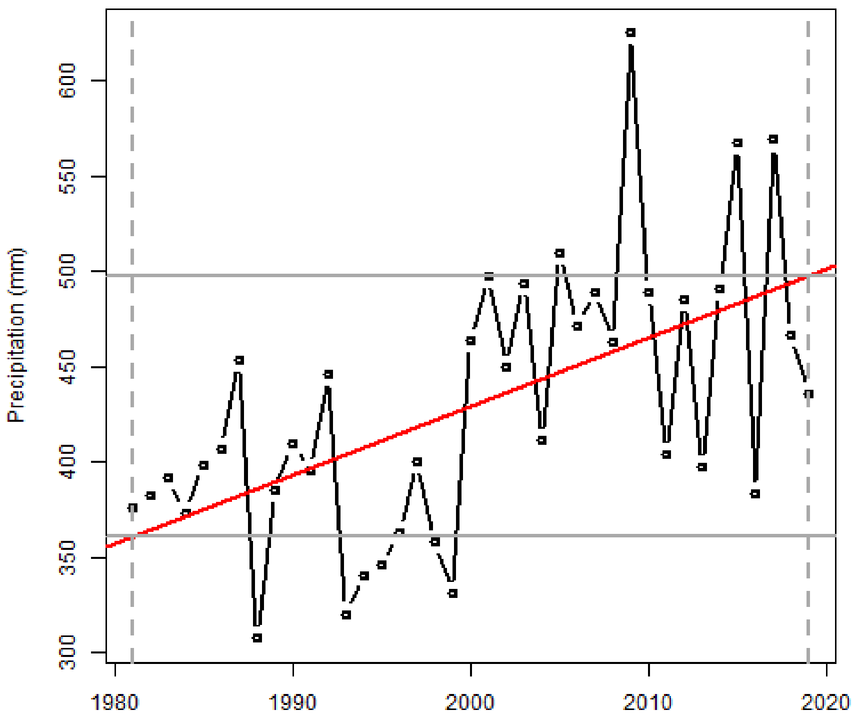

Figure 11: Yearly precipitation in Amasia rayon during the growing season October-June. Total growing season precipitation has risen from 361 mm in the season 1981/1982 to 497 mm in the season 2019/2020, equivalent to a yearly increase of about 3.6 mm, or a total increase of 136 mm since 1981.

2.3 Results & Discussion

All results area available online in an interactive format at:

https://rpubs.com/max_hof_mann/climate_armenia

The link contains the growing season and month-specific trends for precipitation, minimum, average, and maximum temperature on the croplands and summarized for each district. We here only present the maps for precipitation and average temperature.

Growing season average temperature has significantly increased in all districts of the country (Figure 12). The southwestern part of Armenia is most severely affected by rising temperatures. The district with the highest increase in average temperature is Artashat (2.6 °C). The districts in that region with a particularly high share of agricultural land are Ani, Armavir, Vagharshapat and Masis (Figure 2). Here, temperature has increased between 2.2 and 2.5 °C in the last four decades.

Overall, since 1981 large parts of Armenia have become wetter during the growing season from October to June. This trend is not significant in the southern part of the country and for some districts in the provinces of Aragatsotn and Kotayk (Figure 13). The districts with the highest increase in precipitation are all located in the northern part of the country, e.g. Tumanian (166 mm), and Noyemberyan, Idjevan, Stepanavan and Tavush (all about 150 mm, respectively). However, the share of agricultural land in these districts is rather low (Figure 2). Average temperatures have substantially increased across Armenia during the last four decades, including during most months and in most districts (Figure 14). In February and March, croplands have warmed up the most, particularly in the southwestern and southern parts of the country. High increases in February and March temperature also occurred in the northern districts Tumanian and Noyemberyan. However, there is only little cropland in this region (Figure 2). Temperature changes in April are insignificant and partly negative (at the moment, we cannot explain why the temperature patterns in April deviate from the overall patterns). All districts experienced significant increases in average temperature during May and June, which is a critical phase for most crops. The significant increase in August temperature may not have had considerable effects on many crops, as most of them are harvested before August. For the months July, September and November to January, temperature increases are modest and only significant for a few districts.

Many months and districts have become wetter in Armenia since 1981 (Figure 15). This change is most pronounced for January and September, for which the increase is significant for many districts. Precipitation increases during May and June, which are critical months for many crops, are insignificant for most districts, however significant and comparatively high in May in the districts of Vayk (43 mm) and Yeghegnadzor (34 mm), which do have a considerable amount of area under agriculture (Figure 2). February, August and November tend to become drier in many districts, however this decrease in precipitation is not significant for any district.

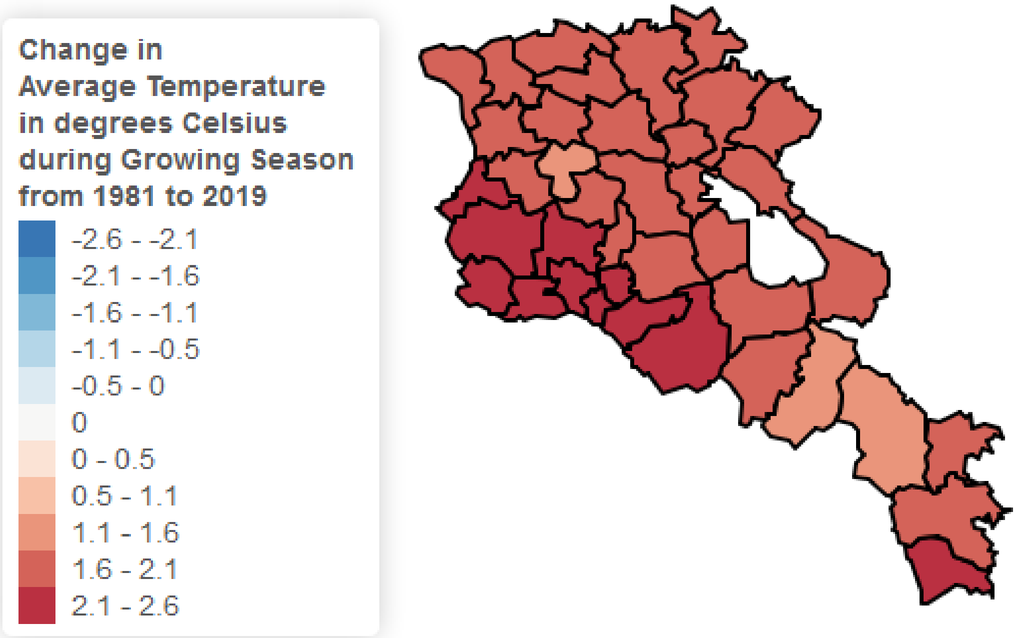

Figure 12: Total change in average temperature on croplands during the growing season. Only districts with a black outline show a significant change between 1981 and 2019.

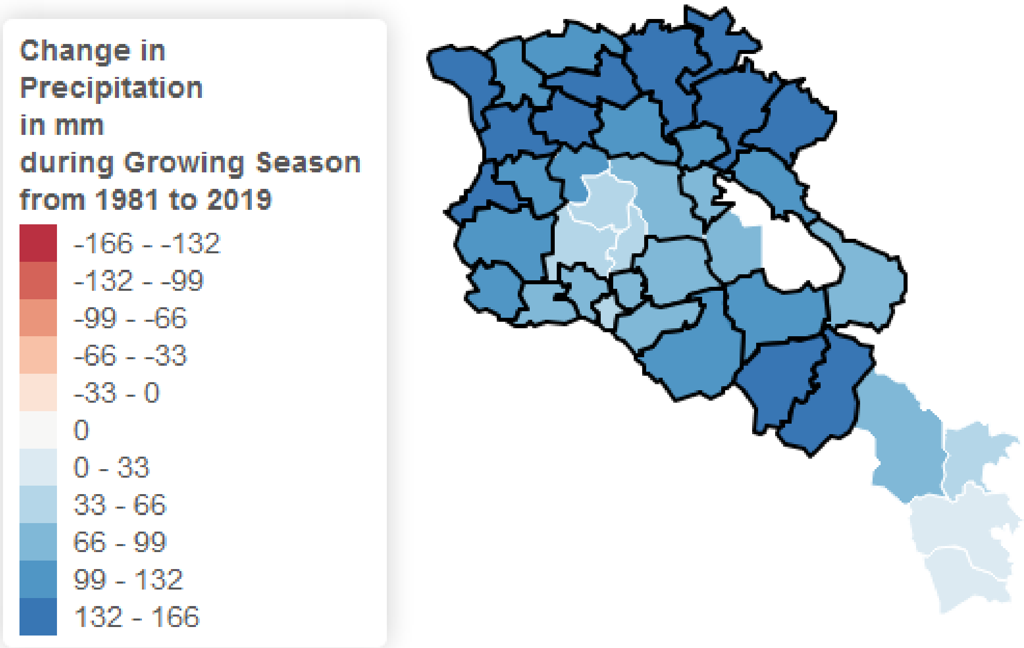

Figure 13: Total change in precipitation on croplands during the growing season. Only districts with a black outline show a significant change between 1981 and 2019.

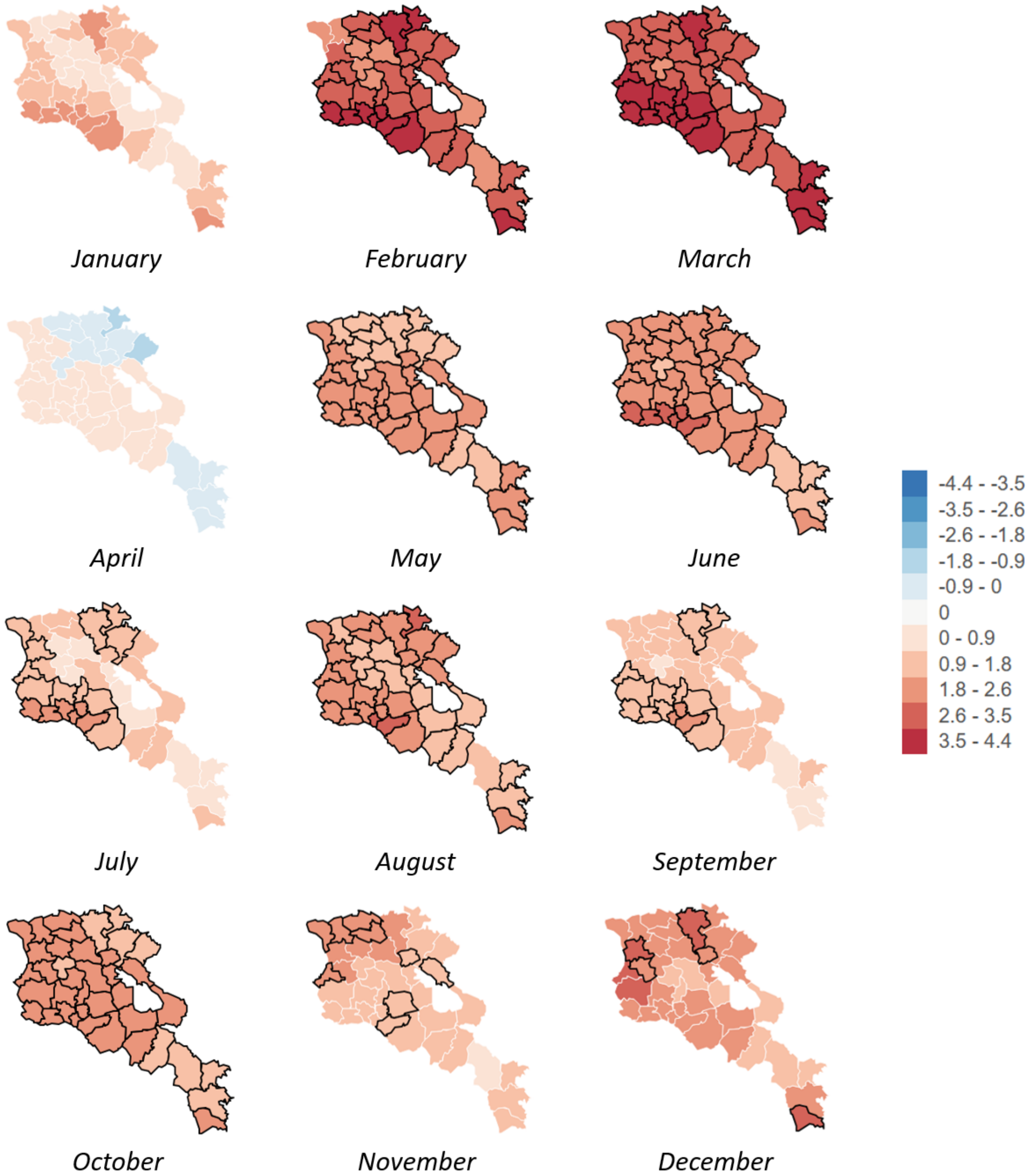

Figure 14: Total monthly change in average temperature on croplands from 1981 to 2020 in degrees Celsius. Only districts with a black outline show a significant change between 1981 and 2020.

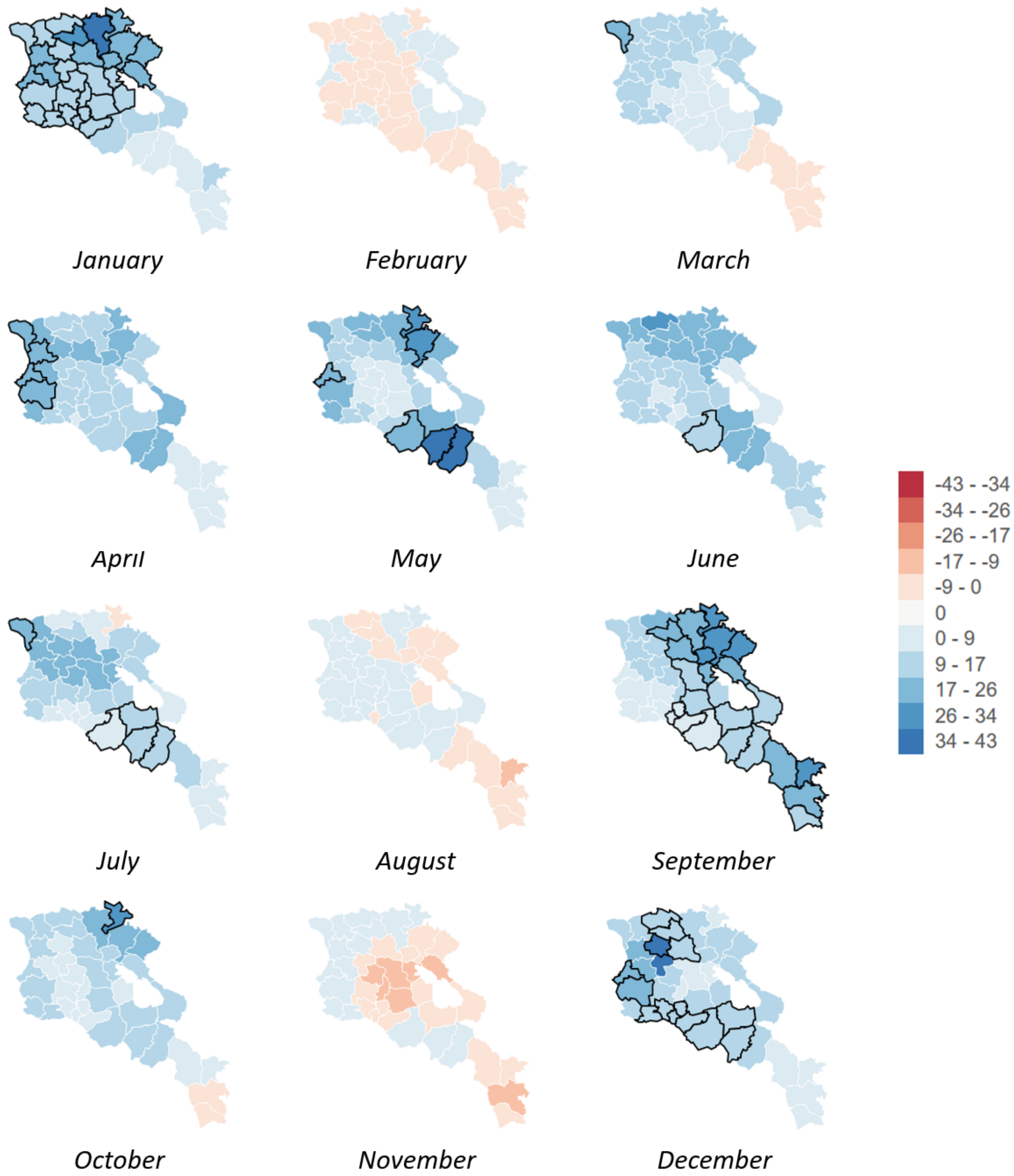

Figure 15: Total monthly change in precipitation on croplands from 1981 to 2020 in millimeters. Only districts with a black outline experienced a significant change between 1981 and 2020.

Work Package 3:

"Effects of Historical Climate and Extreme Weather Events on Yields and Crop Suitability"

Content

Annex

Figures

Tables

1. Introduction

The aim of WP3 is to develop predictive models to estimate the historical effects of climate and weather on the production of the most important crops of Armenia.

The occurrence of more frequent and intensive extreme weather events is one of the key challenges of ongoing climate change. Weather extremes constitute rare but impactful interruptions to crop production and already exert large damages globally (Asseng et al., 2011; Lesk et al., 2016; Zampieri et al., 2017). Smallholder farmers can be more resilient to weather extremes when they rely on a diversified production portfolio (Christensen, 2018). However, the impacts of weather extremes can nevertheless jeopardize the livelihoods of small and medium-sized farmers who rely on marketing surplus production for cash income from a few crops or are capital-strapped, and therefore more vulnerable to weather extremes (Jensen and Barrett, 2017) . Quantifying the changes in weather extremes together with the effect of long-term climate trends provides crucial impetus for informing and building adaptation strategies that improve the resilience of small and medium-sized farms.

Previous studies have shown the importance of climate and weather conditions in explaining crop yields (Lobell et al., 2012; Ray et al., 2015; Schierhorn et al., 2021). Long-term climatic means, such as average temperature and precipitation totals, are important determinants of yields because crops have specific temperature and precipitation requirements. For example, cereal crops need sufficient water during specific plant developmental stages (Ortiz-Bobea et al., 2019), and fruit trees require specific chilling conditions (Atkinson et al., 2013). In addition to climatic means, short-term extreme weather events can crucially impact crop yields. Severe weather conditions outside the norm of long-term weather observations include heavy droughts, excessive precipitation, extreme frost, or extreme heat. It is important to note that the impacts of weather extremes on crop yields depend on when they occur during plant growth (Farooq et al., 2011; Schierhorn et al., 2021).

High variability of crop yields may indicate that climate and weather conditions have decisively affected crop yields. In Armenia, subnational statistical data suggests that crops yields are highly variable. However, the compound effects of climatic means and weather extremes on crop yields in Armenia, particularly for specific plant development stages, are not well understood to date. We here assess the impacts of long-term climatic means and extreme weather events on yields for the developmental stages of six grain and vegetable crops with the help of Random Forests. We use detailed phenological observations to determine crop-specific developmental stages and characterize historical climate conditions and the occurrence of different types of extreme weather events during these stages. We couple this information with official province-level agricultural yield statistics to quantify which stage-specific weather and climate variables had the largest impact on the yields of these crops in Armenia between 2005 and 2020. For a total of six pomaceous and stone fruit types, we apply a Chill Unit model to characterize the suitability for the production of these crops considering the amount of chill temperatures that accumulate between autumn and spring, particularly during winter dormancy, which is a critical phase for proper plant development in fruit trees.

2. Data Preparation

2.1 Agricultural Statistics

2.1.1 Yield, Sown Area, Harvested Area and Production Amount

In WP1, we identified the 10 target crops that are most important for Armenia in terms of production amounts, sown area, yield, income revenues and value chains. From this selection, we excluded plum and raspberry production here because we lacked phenological and yield data for these crops; instead, we included silage maize and other fruits for which suitable phenological data were available, resulting in a total of 12 crops (Table 1).

Table 1: Target crops in Armenia

Crop	***Group***	***Crop-specific statistics available***	***Model approach***
Winter Wheat	Grain Crops	Yes	Random Forest models
Spring Barley			
Maize for silage			
Potato	Vegetables		
Cucumber			
Tomato			
Apple	Pomaceous Fruits	No	Chill Unit models
Pear			
Quince			
Apricot	Stone Fruits		
Cornel			
Peach			

We obtained annual province-level agricultural statistics on yield, sown area, harvested area and production from 2005 to 2020 from official reports published by the Statistical Committee of the Republic of Armenia (*ArmStat*). We excluded the statistics reported for the city of Yerevan from all further analyses. We used yearly crop yield estimates of grain crops and vegetables as the response variable in the Random Forest models. For pomaceous fruits and stone fruits, agricultural statistics were only available for the aggregated fruit group. In contrast to grain crops and vegetables, we could therefore not run crop-specific models with yield as the response variable. However, the Chill Unit models to predict the suitability for different types of pomaceous and stone fruits do not require yield statistics (see chapter 4.2).

To assess the validity of the agricultural statistics reported by ArmStat, we compared the province-level total sown area of *ArmStat* for 2015 with the province-level cropland area extent from the *Caucasus Land Cover Map* for 2015 (CLCM, *SILVIS lab of the University of Wisconsin*, http://silvis.forest.wisc.edu/data/caucasus/). This map was derived by classifying satellite imagery and has been validated with on-site observations. We found good overall agreement between the two estimates (Figure 1). For Armavir, the cropland extent from CLCM is lower than the cropland extent reported by ArmStat. For all other provinces, cropland extent from CLCM is higher than the cropland extent reported by ArmStat, up to a factor of four for the province Vayots Dzor. This analysis serves as a standard check of data quality, but did not affect our analysis and the use of the yield estimates reported by ArmStat.

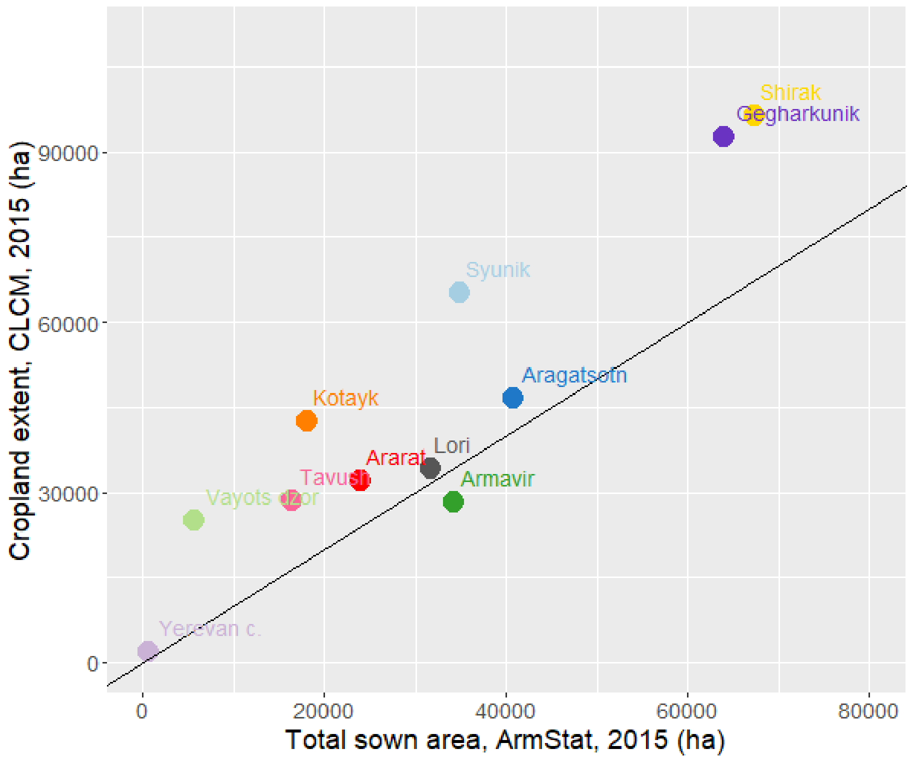

Figure 1: Cropland estimate from the Caucasus Land Cover Map (CLCM) in 2015 against total sown area reported by ArmStat for 2015. Dots near the black line have more similar values on both axes.

For each province and each crop or fruit group, we calculated the mean yield, mean sown area, mean harvested area, and mean production across all years from 2005 to 2020. This allows to summarize the overall production patterns (Figure 2; harvested area not shown). Most grain crops were produced in the northern part of the country from 2005 to 2020, with Ararat and Armavir being the highest-yielding provinces during this period. Potato was mostly cultivated in the province of Gegharkunik, but yields were highest in Ararat and Armavir as well. Production of cucumber and tomato concentrates in Ararat and Armavir. For pomaceous fruits, the agreement between sown area, yield, and production is low, arguably because different types of fruits dominate in different parts of the country. However, both production and yield of pomaceous fruits are generally highest in Ararat and Aragatsotn. Stone fruit production was highest in Ararat and Armavir, but yields are also high in Shirak, Aragatsotn and Tavush (Figure 2).

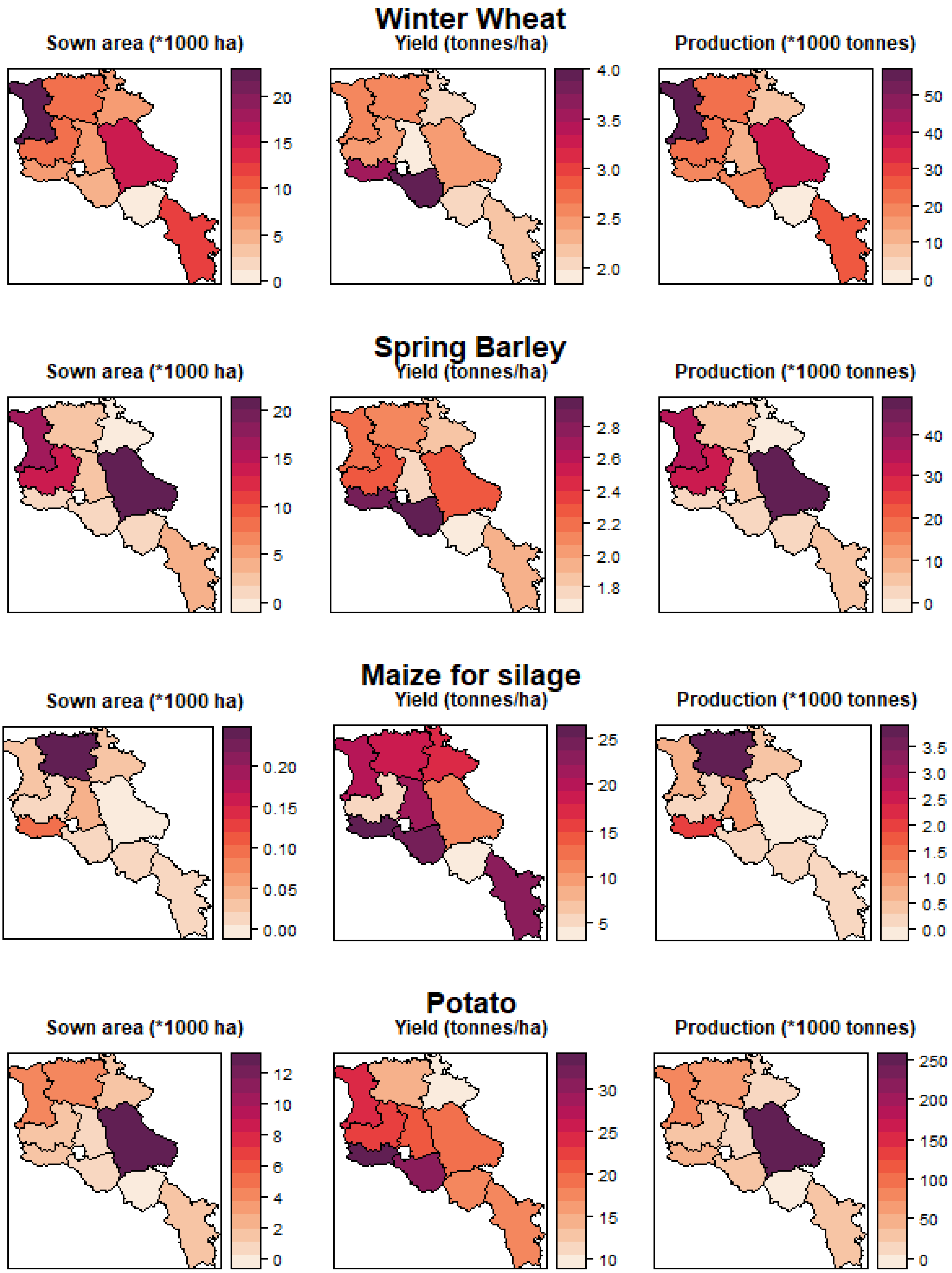

Figure 2: Mean sown area, yield and production from 2005 to 2020 for the target crops. Harvested area is almost identical to sown area and is not shown here.

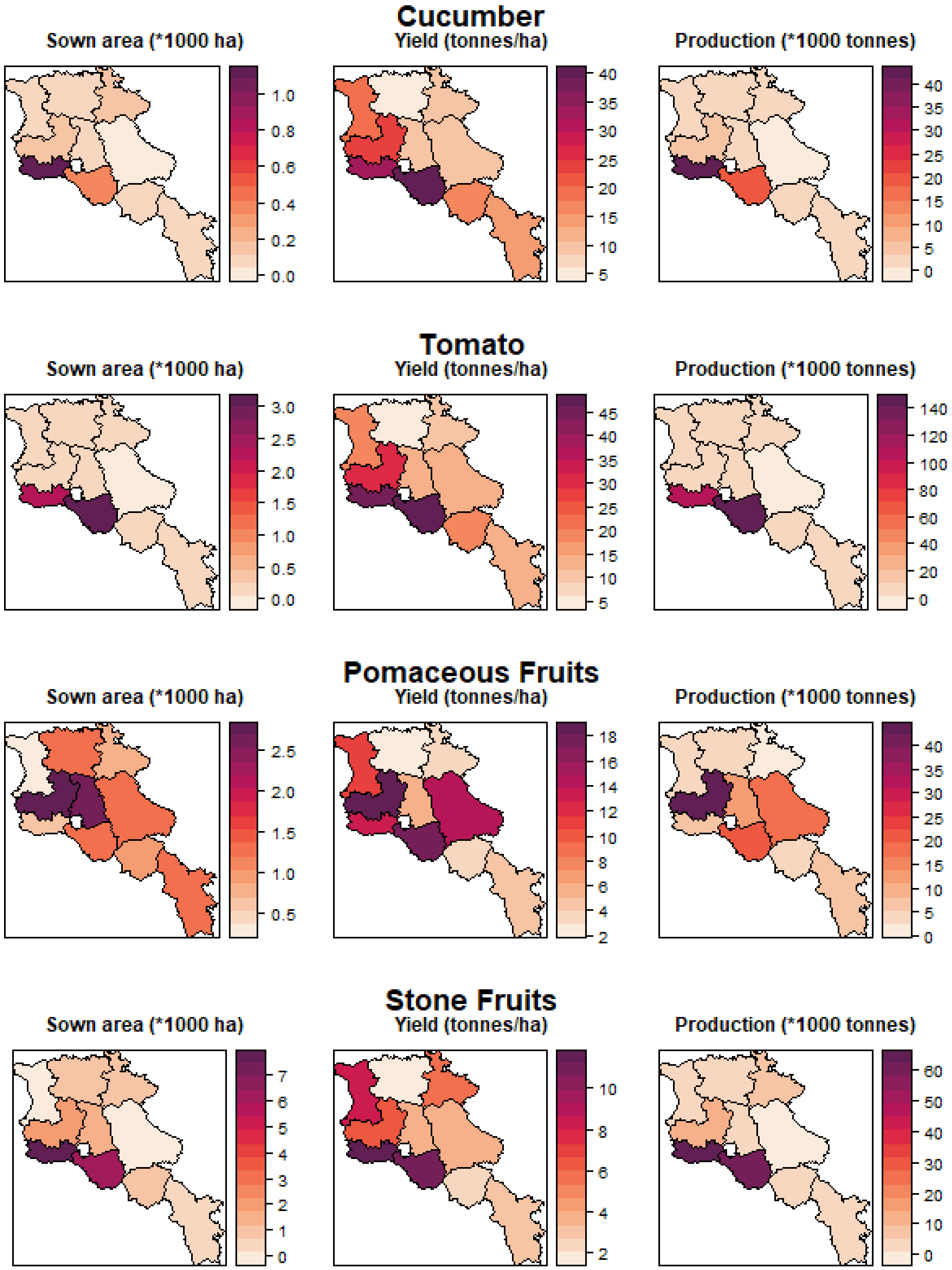

Figure 2 (continued): Mean sown area, yield and production from 2005 to 2020 for the target crops. Harvested area is almost identical to sown area and is not shown here. Individual pomaceous fruits and stone fruits are not shown because agricultural statistics are only available for the respective group of fruits.

2.1.2 Irrigation

Crop production heavily relies on adequate amounts of precipitation during specific crop developmental stages. For example, most grain crops require a certain amount of moisture during the vegetative stage. Irrigation systems can compensate moisture deficits and ensure that yield levels are maintained even under drought conditions. It is therefore important to consider the extent to which irrigation systems are in place when attributing climatic conditions to yields.

Province-level and crop-specific data on the extent of irrigated sown area are available from the *Agricultural Census of the Republic of Armenia,* but only for the crop cycle 2013/14 (https://armstat.am/en/?nid=124). While irrigation data are available for all 12 crops, we were not able to calculate the share of irrigated and non-irrigated area for pomaceous and stone fruits because of the lack of crop-specific sown area and production statistics for these fruits (see chapter 2.1.1). For maize, irrigation data does not distinguish between silage and grain maize. Therefore, we were only able to calculate the share of irrigated sown area for winter wheat, spring barley, potato, cucumber and tomato. Generally, the Agricultural Census shows that the provinces of Ararat and Armavir have the largest share of irrigated area; in Armavir, almost all winter wheat is grown under irrigation conditions (Figure 3). However, we do not know about the actual withdrawal rates and whether in areas classified as irrigated, irrigation levels are as high as they should be with regards to the amount of water required by the crops grown in the respective regions.

Since irrigation data is only available for one year and only for five crops, we were not able to use irrigation as a variable in our models. However, we do consider the available information about irrigation when we discuss the results of our models (see chapter 4.1).

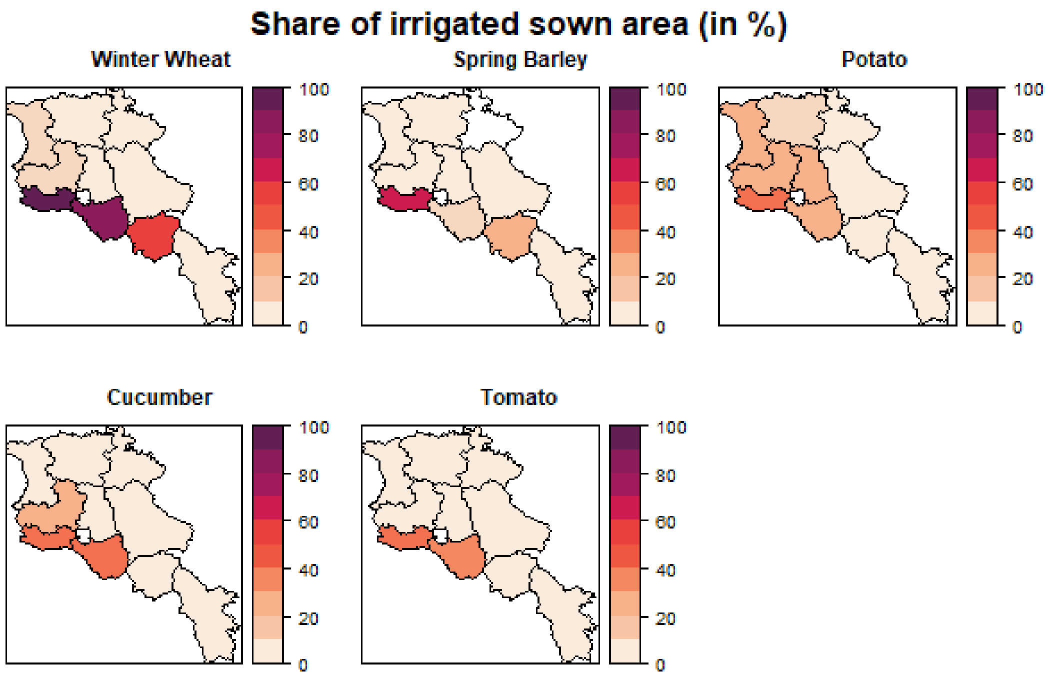

Figure 3: Share or irrigated sown area by crop in 2014, in %.

2.1.3 Production in Greenhouses

Greenhouses can both (i) shield crops from excessive water supply by heavy precipitation and (ii) cushion negative effects from low temperatures that would otherwise compromise yields. On the other hand, greenhouses can also exacerbate heat waves and hence negatively affect crop growth in the absence of adequate ventilation or cooling. It is therefore important to consider the extent to which a crop is produced in greenhouses when attributing climatic conditions to yields.

Statistics on sown areas in greenhouses and the respective production amounts are available from the *Agricultural Census of the Republic of Armenia* for the crop cycle 2013/14 (https://armstat.am/en/?nid=124). Virtually all greenhouses are maintained by producers without legal status, which is the reason why we here only present the data for this group. The census does not capture crop-specific data and only differentiates between the groups "all crops" and "vegetables". Most greenhouses are in the provinces of Armavir and Ararat; vegetables account for almost all the production in greenhouses (Figure 4). According to a report by the *International Center for Agribusiness Research and Education foundation* (ICARE), the total area of greenhouses in Armenia has increased from about 30 hectares in 2011 to 1,300 hectares in 2019, with tomato, cucumber, pepper, and flowers being the most important crops in greenhouses (ICARE 2020).

Since province-level greenhouse data is only available for one year and not crop-specific, we were not able to use it as a variable in our models. However, we do consider the available information about greenhouses when we discuss the results of our models (see chapter 4.1).

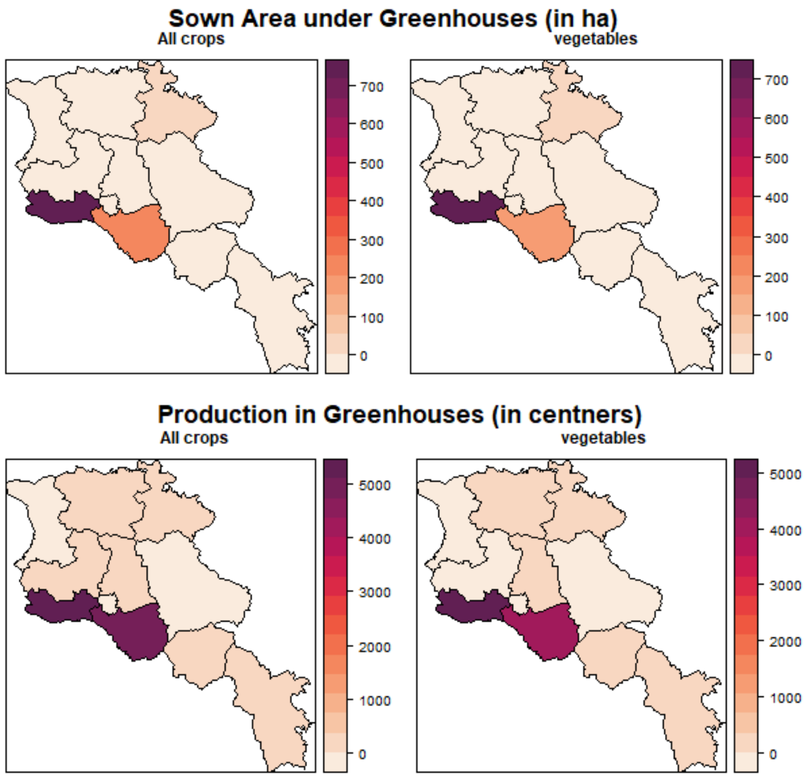

Figure 4: Production and sown area under greenhouse conditions in 2014.

2.2 Phenological Observations and Crop Development Stages

Crops go through different development stages in their biological life cycle, such as the emergence of flowers or the ripening of fruits. The dates of such events are documented in phenological observation records and can change in response to weather anomalies or to long-term changes in climate. The timing and duration of these stages differ between crops, locations, and over time. Climatic conditions and weather extremes have distinct effects on yields during each development stage, and phenological observations are therefore important to associate the relationships between climatic means and weather extremes with crop yields (Schierhorn et al., 2021).

We obtained crop-specific annual phenological observations from the *National Hydro-meteorological Service of Armenia* for the years 1995 to 2020 from a total of 29 phenological stations (Figure 5). The number of stations, station years and varieties differed for each crop (Table 2). Station years are the number of crop cycles with data, taken from all stations and all years. The more station years there are for a crop, the more statistically robust becomes the analysis for this crop. For maize, we lacked phenological data specific to silage or grain maize; we assumed that the available phenological observations represent silage maize.

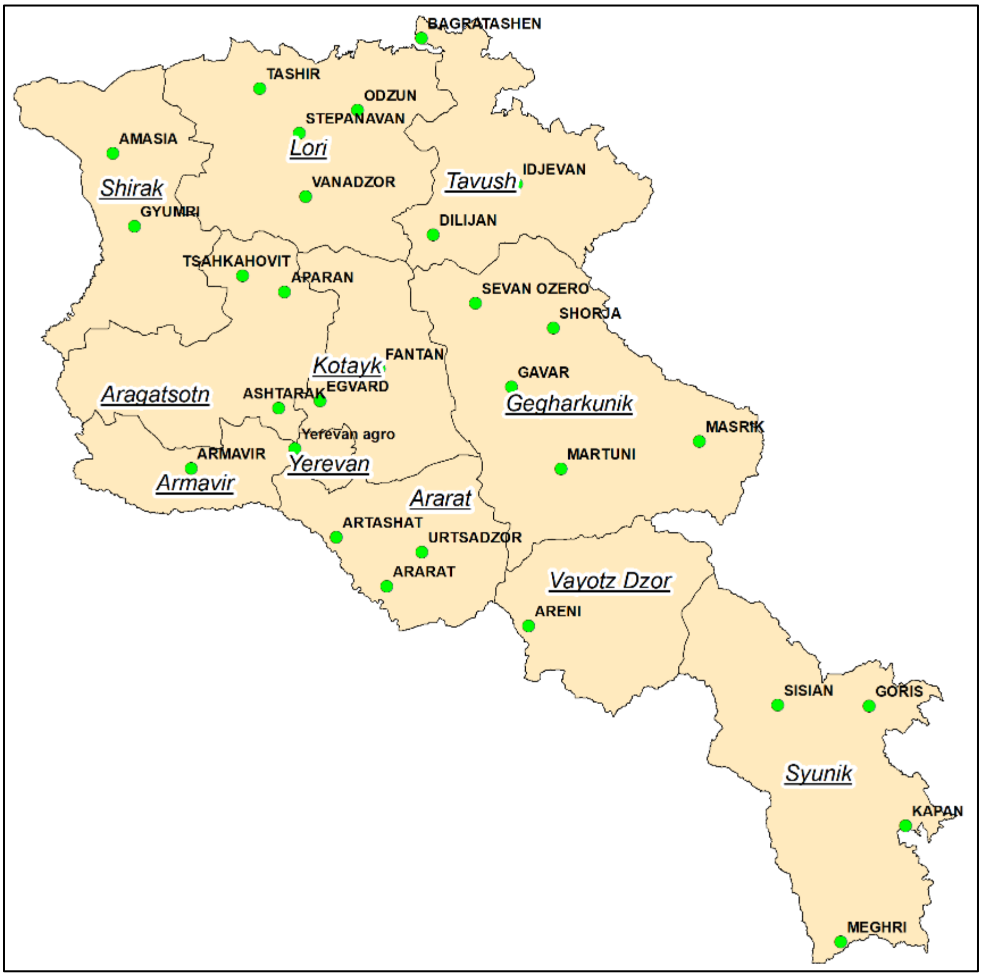

Figure 5: Location of the 29 phenological stations in Armenia.

Table 2: Summary of the amount of phenological information about each crop.

Crop	***No. of stations***	***Station years***	***Varieties***
Winter wheat	8	205	6
Spring barley	6	155	1
(Silage) Maize	3	77	2
Potato	12	307	12
Cucumber	1	26	2
Tomato	6	156	13
Apple	9	232	5
Pear	6	152	4
Quince	2	44	2
Apricot	6	151	2
Cornel	2	42	1
Peach	4	103	2

2.2.1 Grain Crops and Vegetables

To account for the different impacts of climatic means and weather extremes during the distinct plant development stages, we calculate the onset and duration of each stage for each grain crop and vegetable with the phenological observations. Since yield data are only available at the province level, we average the dates for each stage and a given year from all phenological stations within a province. In the following, we briefly review the literature on the sensitivity of the studied grain crops and vegetables to climatic means and weather extremes during specific development stages, and summarize the phenological observations for each crop at the country level. Detailed phenological differences between stations, varieties, and years are reported in Annex A.

Winter Wheat

Wheat is the most widely grown crop in the world, mainly because of its high climate tolerance. However, wheat is sensitive to very high and very low temperatures, particularly to extreme heat and drought conditions during the reproductive and grain filling stages as well as to late frost during ear emergence and anthesis (Harkness et al., 2020; Innes et al., 2015; Lobell et al., 2012). Exposure of wheat to short episodes of temperatures higher than 22°C during the reproductive stage causes male and female sterility and triggers damage to pollen tube growth and fertilization, resulting in lower grain number and grain yield; whilst later in the growing season, temperatures above 32°C during anthesis and above 34.3°C during grain filling are detrimental to grain weight, particularly if they occur as a heat wave (Farooq et al., 2011; Innes et al., 2015). Wheat growth and hence yield are also affected by frost: Wheat transitions through a process of cold acclimation toward hardened wheat plants, which protects the plants to low temperatures in winter (Barlow et al., 2015). However, severe frost in the absence of an isolating snow cover can lead to leaf chlorosis and hence to yield loss (Harkness et al., 2020; Kolár et al., 2014). Scientific evidence from peer-reviewed international journals on the impact of climate change on wheat yields in Armenia are not available to the best of our knowledge.

In Armenia, winter wheat is typically sown in autumn, enters a winter dormancy stage by the end of November, and resumes growth around mid of March (https://ipad.fas.usda.gov/rssiws/al/crop_calendar/aag.aspx, Figure 6). Depending on the climatic conditions during autumn, the phenological observations show that plants already develop sprouts and nodal roots and form bushes before winter dormancy in some years. However, in most years these phenological stages occur after winter dormancy in spring. Usually, it should not have an effect on the plant's fitness whether these phases are observed before or after winter dormancy. The emergence of the lower stem node occurs on average in the mid of May. One month later, the plants enter the reproductive stage, that starts with the onset of anthesis (Farooq et al., 2011). Harvest occurs between late June and early September, but mostly in early August (Figure 6). We defined five plant development stages of winter wheat (see Farooq et al. 2011, Schierhorn et al. 2021) for which we calculated climatic means and weather extremes (Table 3). The dates of the development stages differ for each year and for each phenological station. Since the phenological stations are not evenly distributed and do not cover all provinces, we joined province-level yields with observations from representative phenological stations (see Table 4) by averaging the dates of phenological observations if more than one station was assigned to a province.

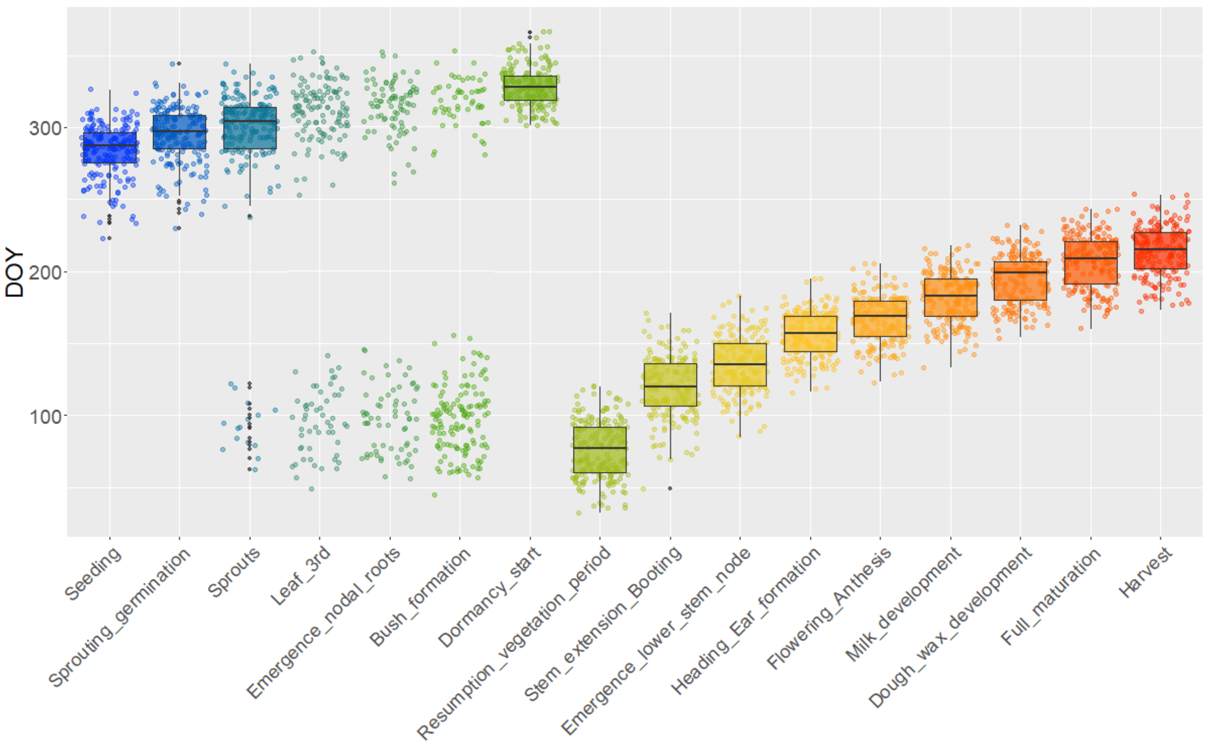

Figure 6: Phenological stages of winter wheat. DOY = day of the year. The dots represent the actual dates of an observation. Each boxplot extends from the first to the third quartile of the data (interquartile range, IQR), i.e. encompasses the inner 50% of the points. The black horizontal line represents the median (50% of the observations are below and 50% above). Black dots represent outliers that are further than 1.5 IQR away from the box.

Table 3: Development stages of winter wheat used in the analysis.

	Start	***End***
Phase A (*Vegetative stage I*)	Seeding	One day before the onset of Dormancy
Phase B (*Winter dormancy*)	Dormancy	One day before the resumption of the vegetation period
Phase C (*Vegetative stage II*)	Resumption of the vegetation period	One day before the emergence of the lower stem node
Phase D (*Reproductive stage*)	Emergence of the lower stem node	One day before Anthesis
Phase E (*Grain filling*)	Anthesis	Harvest

Table 4: Phenological stations of winter wheat by province.

Province	***Phenological stations***		***Province***	***Phenological stations***
Shirak	Gyumri		Ararat	Urtsadzor
Lori	Odzun, Stepanavan		Kotayk	Fantan, Egvard
Tavush	Odzun, Stepanavan		Gegharkunik	*all stations*
Aragatsotn	Aparan		Vayots Dzor	*all stations*
Armavir	Yerevan agro		Syunik	*all stations*

Spring Barley

Globally, barley ranks fourth in both produced quantity and sown area of cereal crops. It grows from the equator to the arctic circle at various altitudes. Like other cereals, barley is susceptible to extreme weather conditions, particularly heat and drought: Extremely high temperatures (generally above 35°C) around anthesis can severely reduce yield through reduced fertility, reduction in grain weight, and fewer grains per spike (Hossain et al., 2012; Murray and Brennan, 2010). High temperatures during the day followed by high night temperatures have further adverse effects on yield (Ugarte et al., 2007). Drought stress, particularly together with heat stress during the critical period for yield determination, results in severe yield reductions (Hossain et al., 2012; Murray and Brennan, 2010). This effect is particularly strong during anthesis (Arisnabarreta and Miralles, 2008; Frederiks et al., 2012). During the grain filling stage, severe drought stress lowers the net photosynthetic rate, shortens the grain-filling period, and decreases the number and weight of the grains per plant (Sánchez-Díaz et al., 2002). Climate change leads to more frequent exposure to heat stress, especially during the reproductive and grain filling stages (Hasanuzzaman et al., 2013). A few degrees increase in average daily temperature already results in significant yield losses in cereals (Lobell et al., 2011). For example, a temperature increase of 3 to 4°C would reduce barley yields by 15 to 35% in Africa and Asia, and by 25 to 35% in the Middle East (Ortiz et al., 2008). Research published in international peer-reviewed journals on the impact of climate change on barley yields in Armenia is not available to our knowledge.

In Armenia, the phenological stages of spring barley are similar to those of winter wheat, but spring barley has no winter dormancy (Table 5). On average, spring barley is sown during the second half of April (Figure 7). The lower stem node emerges in late June and anthesis occurs around mid-July. Unfortunately, the phenological records lacked data on anthesis; we thus calculated these dates from averaging the dates of ear formation and milk development. The harvest period can stretch from June to September, but most often occurs around mid-August (Figure 7). Again, the phenological stations are not evenly distributed and do not cover all provinces; we therefore joined province-level yield measurements with observations from representative phenological stations and averaged the respective dates in case of more than one station being assigned to a province (Table 6)

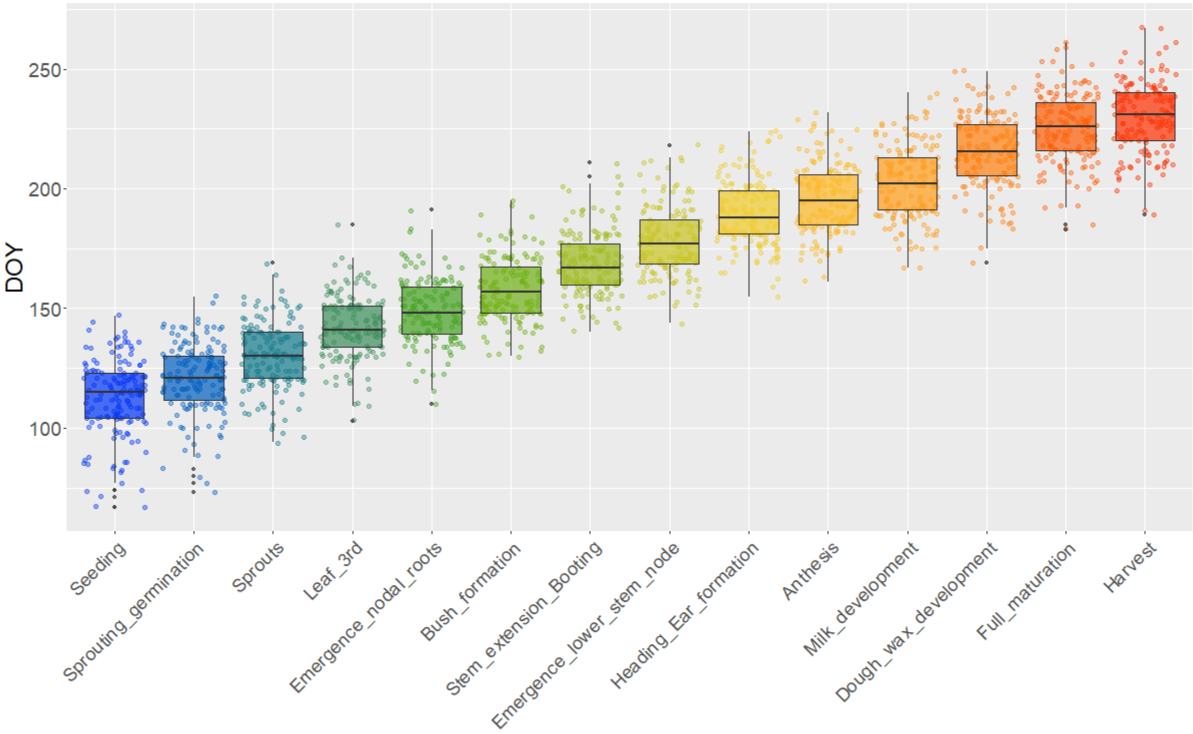

Figure 7: Phenological stages of spring barley. DOY = day of the year. The dots represent the actual dates of an observation. Each boxplot extends from the first to the third quartile of the data (interquartile range, IQR), i.e. encompasses the inner 50% of the points. The black horizontal line represents the median (50% of the observations are below and 50% above). Black dots represent outliers that are further than 1.5 IQR away from the box.

Table 5: Development stages of winter wheat used in the analysis.

	Start	***End***
Phase A (*Vegetative stage*)	Seeding	One day before the emergence of the lower stem node
Phase B (*Reproductive stage*)	Emergence of the lower stem node	One day before anthesis
Phase C (*Grain filling*)	Anthesis	Harvest

Table 6: Phenological stations of spring barley by province.

Province	***Phenological stations***		***Province***	***Phenological stations***
Shirak	Tsahkahovit, Aparan		Ararat	*all stations*
Lori	Tsahkahovit, Aparan		Kotayk	Tsahkahovit, Aparan
Tavush	Sevan Ozero		Gegharkunik	Sevan Ozero, Martuni, Masrik
Aragatsotn	Tsahkahovit, Aparan		Vayots Dzor	*all stations*
Armavir	*all stations*		Syunik	Sisian

Maize

Maize is sensitive to extreme heat and drought, particularly if both conditions occur simultaneously (Waqas et al., 2021). Yield variability is more strongly associated with changes in grain number per plant than with variability in weight per grain, especially when the plant is exposed to heat stress around silking (Cicchino et al., 2010). Grain numbers are determined during a period ranging from approximately 10 days before until 15 days after anthesis (Tollenaar et al., 1979). Therefore, climate conditions affecting maize growth during the flowering period are critical for yield. Heat stress during the flowering stage increases the interval between pollen shedding and silk emergence, which is commonly referred to as silk delay, loss of synchrony, protandrous flowering, or more recently as the anthesis-silking interval (Edmeades et al., 2015). Moisture deficit is another important abiotic constraint to maize production: When drought occurs at flowering, silking is delayed, although anthesis and anther dehiscence may be accelerated slightly by higher air temperatures and lower relative humidity of the dry plots (Edmeades et al., 2015). Maize is particularly sensitive to drought a few days before to about 20 days after silking; water deficit during this period sharply reduces grain numbers (Badr et al., 2020).

In Armenia, maize is sown between mid-April and late May and enters the reproductive stage around mid-July (Figure 8). The critical stage of silking occurs in early August and is about two weeks long. Harvest is between mid-August and mid-October, but mainly mid-September (Figure 8). We defined three plant development stages of maize for which we calculated climatic means and weather extremes (Table 7). Only three phenological stations exist for maize in the northernmost province of Lori and the southernmost province of Syunik. For all other provinces, we averaged the dates from these stations (Table 8).

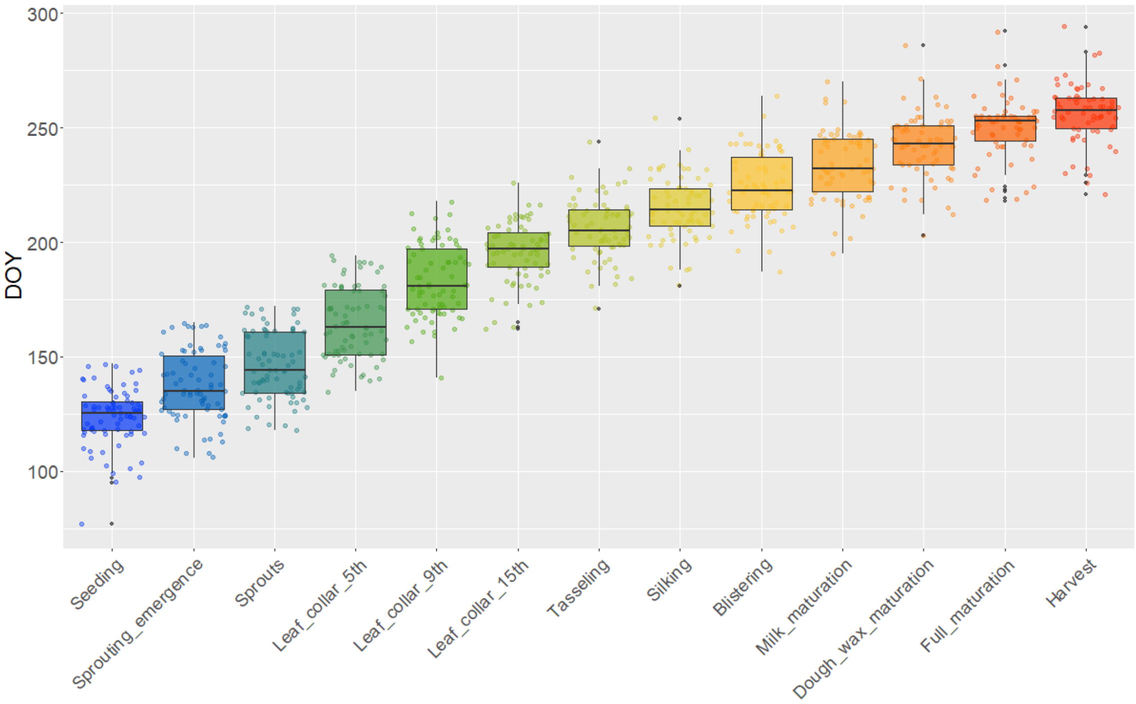

Figure 8: Phenological stages of maize. DOY = day of the year. The dots represent the actual dates of an observation. Each boxplot extends from the first to the third quartile of the data (interquartile range, IQR), i.e. encompasses the inner 50% of the points. The black horizontal line represents the median (50% of the observations are below and 50% above). Black dots represent outliers that are further than 1.5 IQR away from the box.

Table 7: Development stages of maize used in the analysis.

	Start	***End***
Phase A (*Vegetative Stage*)	Seeding	One day before the emergence of the 15th leaf collar
Phase B (*Reproductive Stage*)	Emergence of the 15th leaf collar	One day before silking
Phase C (*Grain Filling*)	Silking	Harvest

Table 8: Phenological stations of maize by province.

Province	***Phenological stations***		***Province***	***Phenological stations***
Shirak	Odzun		Ararat	*all stations*
Lori	Odzun		Kotayk	*all stations*
Tavush	Odzun		Gegharkunik	*all stations*
Aragatsotn	*all stations*		Vayots Dzor	*all stations*
Armavir	*all stations*		Syunik	Goris, Kapan

Potato

Potato is grown mainly in temperate climates and grows best in cool but frost-free seasons (Haverkort and Verhagen, 2008). It is not well adapted to extreme heat and develops best around 20°C. Optimum temperatures for the aboveground part of the plant and for tubers vary. Experiments in growth chambers have shown that haulm growth is most rapid in a temperature range of 20°C to 25°C (Rykaczewska, 2015). The optimal range for tuber formation and growth is at 15°C to 20°C soil temperature. Soil temperature differs from air temperature, which complicates to quantify the impacts of climate and weather on yield. Extreme heat substantially inhibits tuber formation and the distribution of photo-assimilation to tubers, which leads to a drastic reduction in yield (Birch et al., 2012).

In Armenia, potato is sown from late March to early June. Blossoming occurs mainly in July, and harvest can be as early as late July, although mostly happens in September (Figure 9). We defined two plant development stages of potato for which we calculated climatic means and weather extremes (Table 9). Again, the phenological stations for potato are not evenly distributed and do not cover all provinces; we therefore joined province-level yield measurements with observations from representative phenological stations and averaged the respective dates in case of more than one station being assigned to a province (Table 10)

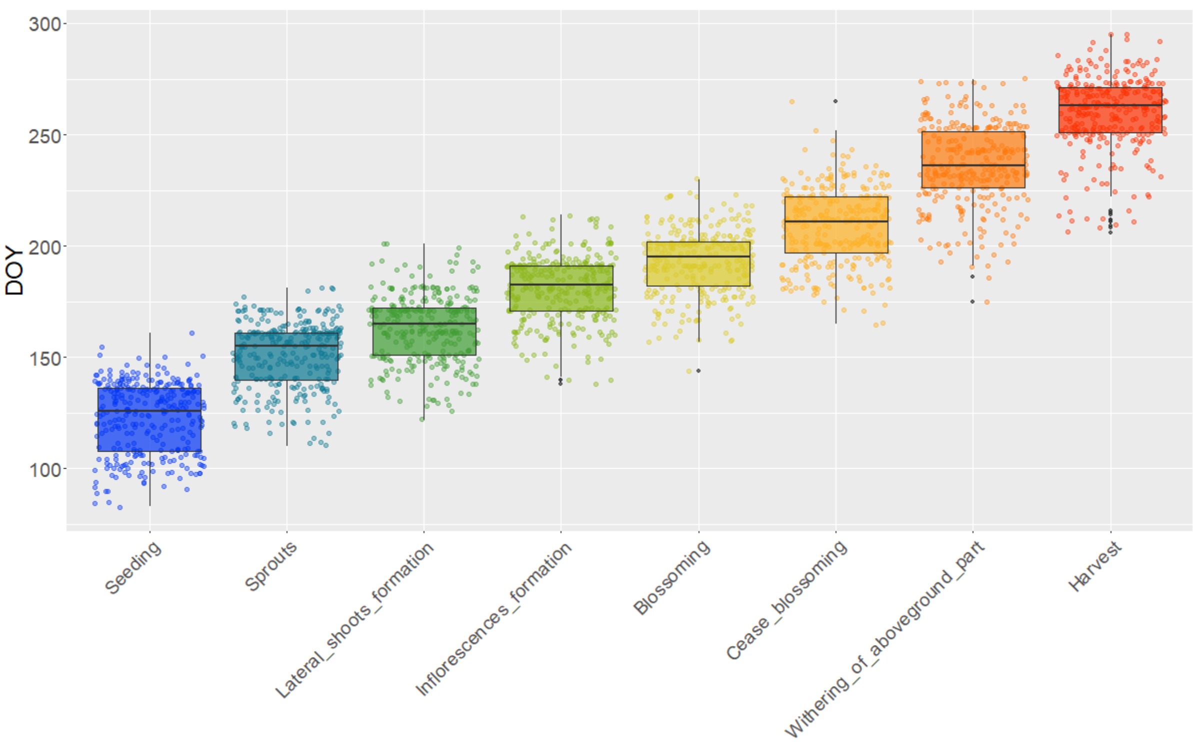

Figure 9: Phenological stages of potato. DOY = day of the year. The dots represent the actual dates of an observation. Each boxplot extends from the first to the third quartile of the data (interquartile range, IQR), i.e. encompasses the inner 50% of the points. The black horizontal line represents the median (50% of the observations are below and 50% above). Black dots represent outliers that are further than 1.5 IQR away from the box.

Table 9: Development stages of potato used in the analysis.

	Start	***End***
Phase A (*Vegetative Stage*)	Seeding	One day before blossoming
Phase B (*Reproductive Stage*)	Blossoming	Harvest

Table 10: Phenological stations of potato by province.

Province	***Phenological stations***		***Province***	***Phenological stations***
Shirak	Amasia		Ararat	*all stations*
Lori	Tashir, Odzun, Stepanavan, Vanadzor		Kotayk	*all stations*
Tavush	Ijevan		Gegharkunik	Sevan Ozero, Gavar, Shorja, Masrik, Martuni
Aragatsotn	*all stations*		Vayots Dzor	Masrik, Martuni, Goris
Armavir	*all stations*		Syunik	Goris

Cucumber

Cucumber is one of the most important horticultural crops globally. It is a warm season crop and mostly planted in subtropical and temperate regions. Most suitable temperatures for growth and development are between 15°C and 32°C. High temperatures above 32°C, especially at the vegetative stage, may limit cucumber yield and quality, and can cause physiological injury to membrane lipids, carbon, and nitrogen metabolism (Zhao et al., 2011). Heat can also constrain photosynthesis and root growth (Xu et al., 2018). All these factors may translate into reduced yield and quality. Because of shallow root distribution and high water requirements, cucumber is also susceptible to drought (Li et al., 2014). Drought stress leads to various biochemical and physiological responses, which compromises cucumber growth and reduces yield (Li et al., 2018).

We defined two plant development stages of cucumber for which we calculated climatic means and weather extremes (Table 11). In Armenia, phenological observations for cucumber were only available for one station, Kapan, from the province of Syunik, and we assumed that this station would be representative for all provinces (Table 12). Seeding at this station occurred between late April and late May, blossoming between late June and late July, and harvest between early August and late September (Figure 10).

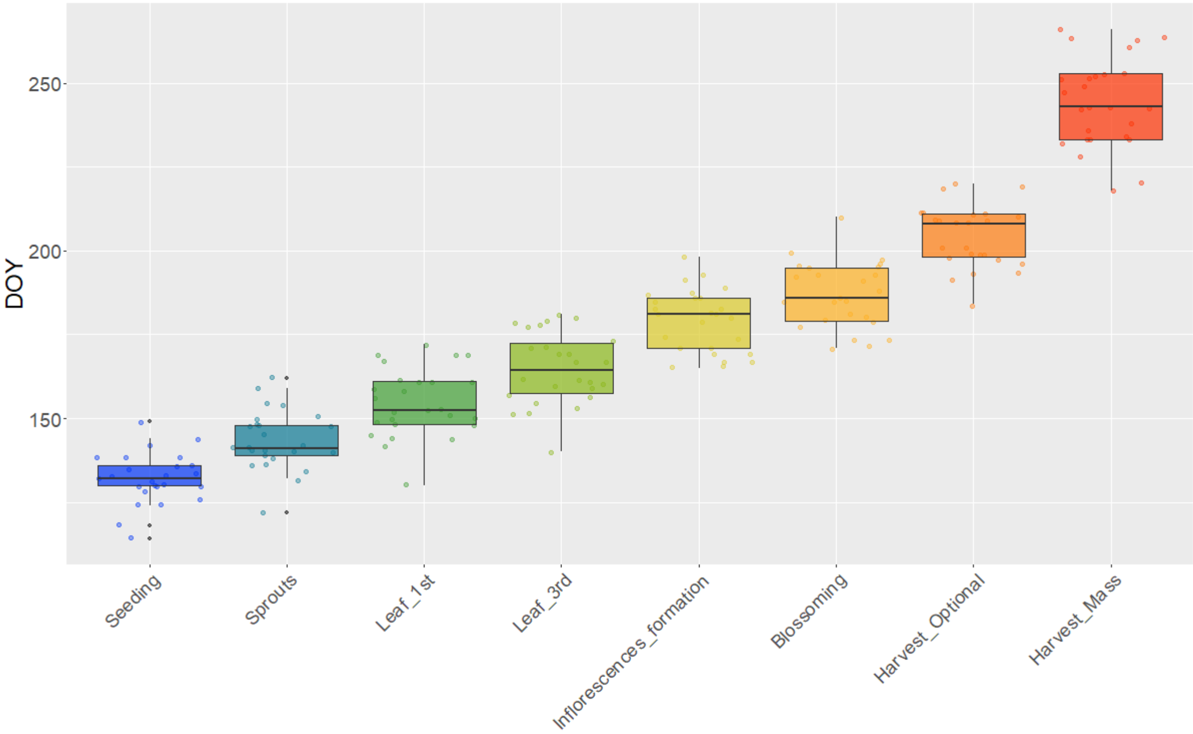

Figure 10: Phenological stages of cucumber. DOY = day of the year. The dots represent the actual dates of an observation. Each boxplot extends from the first to the third quartile of the data (interquartile range, IQR), i.e. encompasses the inner 50% of the points. The black horizontal line represents the median (50% of the observations are below and 50% above). Black dots represent outliers that are further than 1.5 IQR away from the box.

Table 11: Development stages of cucumber used in the analysis.

	Start	***End***
Phase A (*Vegetative Stage*)	Seeding	One day before blossoming
Phase B (*Reproductive Stage*)	Blossoming	Harvest

Table 12: Phenological stations of cucumber by province.

Province	***Phenological stations***		***Province***	***Phenological stations***
Shirak	Kapan		Ararat	Kapan
Lori	Kapan		Kotayk	Kapan
Tavush	Kapan		Gegharkunik	Kapan
Aragatsotn	Kapan		Vayots Dzor	Kapan
Armavir	Kapan		Syunik	Kapan

Tomato

Tomato is an important vegetable that is consumed all over the world. Tomato grows under a wide range of climate conditions, with an optimal mean daily temperature range between 20°C and 25°C (Firon et al., 2006). Heat stress reduces tomato yield and quality, mainly by affecting male gametophyte development (Alsamir et al., 2021). Day temperatures above 26°C and night temperatures above 20° interrupt the fruit-set of most tomato cultivars (Lohar and Peat, 1998). However, modern, heat-tolerant genotypes can cope with higher temperatures (Pham et al., 2020). Cool temperatures also harm tomato yield because the plants are sensitive to chilling, which limits not only its productivity but also its geographical distribution (Allen and Ort, 2001; Ronga et al., 2018). Yield reductions occur if tomato plants experience temperatures below 10°C for more than 14 days or below 5°C for more than 6 to 8 days (Alsamir et al., 2021; www.omafra.gov.on.ca/english/crops/facts/info_tomtemp.htm). Temperatures below 10°C during flowering may affect pollination and cause fruit death (Alsamir et al., 2021).

In Armenia, sprouting of tomato occurs between late March and early June. Blossoming typically happens around June but can be as late as second half of July, and harvest happens between early August and late October (Figure 11). We defined two plant development stages of tomato for which we calculated climatic means and weather extremes (Table 13). Again, the phenological stations for tomato are not evenly distributed and do not cover all provinces; we therefore joined province-level yield measurements with observations from representative phenological stations and averaged the respective dates in case of more than one station being assigned to a province (Table 14)

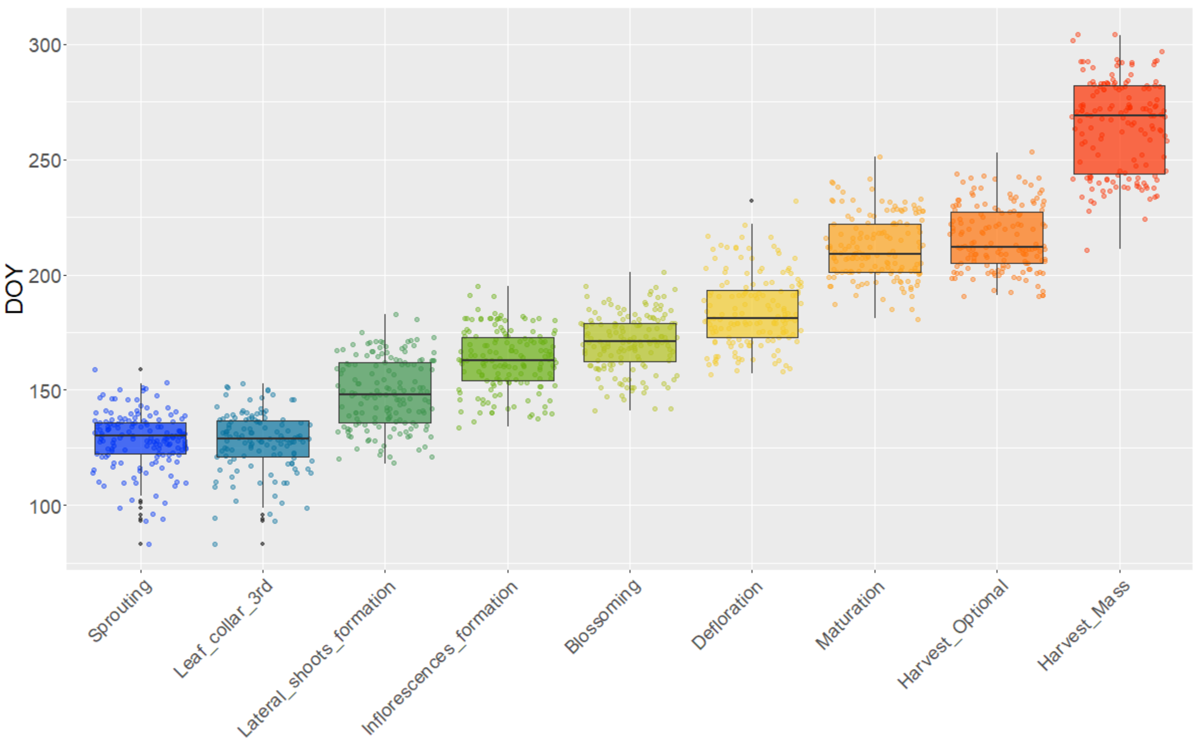

Figure 11: Phenological stages of tomato. DOY = day of the year. The dots represent the actual dates of an observation. Each boxplot extends from the first to the third quartile of the data (interquartile range, IQR), i.e. encompasses the inner 50% of the points. The black horizontal line represents the median (50% of the observations are below and 50% above). Black dots represent outliers that are further than 1.5 IQR away from the box.

Table 13: Development stages of tomato used in the analysis.

	Start	***End***
Phase A (*Vegetative Stage*)	Sprouting	One day before blossoming
Phase B (*Reproductive Stage*)	Blossoming	Harvest

Table 14: Phenological stations of tomato by province.

Province	***Phenological stations***		***Province***	***Phenological stations***
Shirak	*all stations*		Ararat	Artashat, Ararat
Lori	*all stations*		Kotayk	Yerevan agro
Tavush	*all stations*		Gegharkunik	*all stations*
Aragatsotn	Yerevan agro, Armavir		Vayots Dzor	Kapan, Meghri, Artashat, Ararat
Armavir	Yerevan agro, Armavir		Syunik	Kapan, Meghri

2.2.2 Pomaceous and Stone fruits

In Armenia, yields of pomaceous and stone fruits show overall low inter-annual variability (https://maxhofmann.shinyapps.io/ARM_statistics/) and are not available for specific fruit types, so Random Forest models are not suited to model yields here. Pomaceous and stone fruits predominantly depend on the amount of chill units that accumulate over the crop cycle, whereas extreme weather events mostly impact the quality and aesthetical aspects of the fruits (Fraga and Santos, 2021; Luedeling et al., 2011).

Chill units reflect the total amount of temperatures between 1.5 and 12.5 degrees Celsius that fruit and nut trees require to end winter dormancy and enter the flowering stage normally (Luedeling and Brown, 2011; Mehlenbacher, 1991; Salama et al., 2021). Chill units are essentially a conversion of daily temperatures, and are usually calculated for the period that starts when temperatures fall below 12.5 °C for the first time (typically in September or October) until the date when the buds of the fruit or nut trees burst in spring. For each phenological station, crop, and year, we determined the amount of chill units accumulated by the time of bud bursting by analyzing temperature measurements recorded at the same stations. We then analyzed modelled grid-level temperature data (*ERA5-Land* dataset, see WP2) for the whole country to examine where the amount of chill units accumulated at bud bursting has historically been reached at the end of the crop cycle. We assume that a location is suitable for production when, at the end of the crop cycle, the amount of accumulated chill units is at least as high as the amount accumulated at the time of bud bursting at the phenological stations (for more details, see chapter 4.2). We therefore did not average the dates of phenological observations to the province level as we did for grain crops and vegetables. The date of bud bursting differs considerably between the studied crops: Bud bursting occurs the earliest in cornel, with an average date around early March, whereas in apple, it happens mostly in late April (Figure 12). Information about all other phenological observations of pomaceous and stone fruits and insights about differences between stations, varieties, and years are available in Annex A.

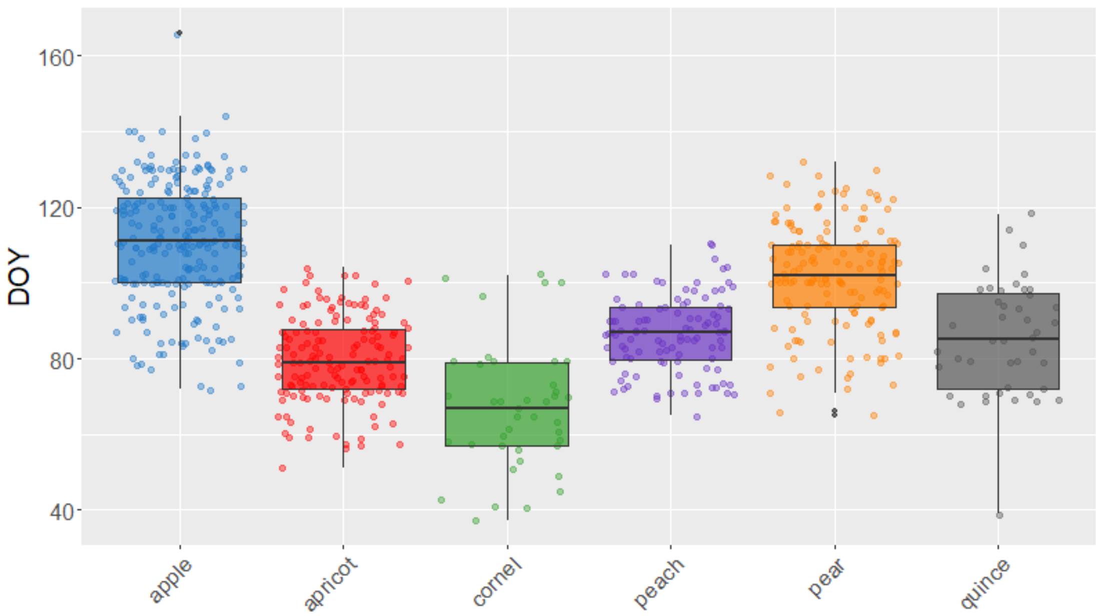

Figure 12: The date of bud bursting in different pomaceous and stone fruits. DOY = day of the year. The dots represent the actual dates of an observation. Each boxplot extends from the first to the third quartile of the data (interquartile range, IQR), i.e. encompasses the inner 50% of the points. The black horizontal line represents the median (50% of the observations are below and 50% above). Black dots represent outliers that are further than 1.5 IQR away from the box.

2.3 Weather Station Measurements

We obtained daily meteorological measurements from the *National Hydrometeorological Service of Armenia* for the years 1995 to 2020 for 48 weather stations (Figure 13). These include the 29 stations from which we obtained phenological observations (chapter 2.2). The meteorological dataset comprises 18 different parameters (Table 15), however not all parameters were available for each station and year (see Annex B for a detailed overview of the coverage of meteorological data). We used the minimum and maximum air temperature measurements of the 19 stations for which phenological observations of pomaceous and stone fruits are available. The temperature record for these stations was almost complete, except for some years and particularly for the stations *Areni* and *Egvard* (see Annex B). We discarded station years with large gaps or entirely missing data from the analysis and filled smaller gaps of up to three days using linear interpolation.

Figure 13: Location of the 48 meteorological stations in Armenia.

Table 15: Meteorological parameters measured at the 48 meteorological stations.

Parameter	***Unit***	***Parameter***	***Unit***
Maximum air temperature		Precipitation	mm
Minimum air temperature		Relative humidity	%
Average air temperature		Vapour pressure	hPa
Soil temperature at a depth of 5 cm		Snow cover	cm
Soil temperature at a depth of 10 cm		Average wind speed	m/sec
Soil temperature at a depth of 15 cm	°C	Maximum wind speed	m/sec
Soil temperature at a depth of 20 cm		Wind direction	degrees
Maximum soil temperature		Sunshine duration	hours
Minimum soil temperature			
Average soil temperature			

3. Characterization of Climate and Weather Conditions

3.1 Grain crops and Vegetables

For grain crops and vegetables, we used modelled daily temperature and precipitation data that we corrected for cropland allocation (*ERA5-Land* and *CHIRPS*, see WP2 for further details) to characterize climatic mean and extreme weather conditions for each crop, development stage, year, and province. We calculated standard climatic mean conditions (average minimum, maximum, and mean temperature, precipitation and growing degree days (GDD), Table 16) and a total of six different extreme weather variables (Table 17). We defined heat wave events as periods of elevated temperatures for three or more consecutive days. For the characterization of day heat, day heat waves and GDD, we applied different heat thresholds for each crop and development stage, depending on the specific heat tolerance (Table 18). GDD reflect the accumulated sum of daily temperatures above 0°C and below the crop- and stage-specific heat threshold, GDD are therefore not recorded on days with frost, day heat or day heat wave events. The yearly values for each climatic mean and extreme weather variable, development stage and province are available in Annex D. The long-year average values and trends in these yearly values over the period from 2005 to 2020 are available in Annex E. Trends are in many cases not significant and should therefore be interpreted with caution.

Table 16: Climatic mean variables studied.

	name
PRCP	Precipitation
TAVG	Average Temperature
TMIN	Minimum Temperature
TMAX	Maximum Temperature
GDD	Growing Degree Days

Table 17: Definitions of studied extreme weather events.

	name	***condition***	***minimum spell***	***calculation of stage values:***
DH	Day heat	Max. temp. above a crop- and stage-specific heat threshold	-	Sum of daily temperature differences between max. temp. and respective heat threshold
DHW	Day heat wave		3 days	
NH	Night heat	Min. temp. >= 20°C	-	Sum of daily temperature differences between min. temp. and 20°C
NHW	Night heat wave		3 days	
HP	Heavy precipitation	Precip. >= 20 mm	-	Sum of daily differences between precip. and 20mm
FR	Frost	Min. temp. < 0°C	-	Sum of daily temperature differences between min. temp. and 0°C

Table 18: Crop- and phase-specific heat thresholds for the calculation of DH, DHW and GDD.

	Winter wheat	**Spring barley, silage maize**	**Potato**	**Cucumber**	**Tomato**
Phase A	30.0°C	21.4°C	35°C	30°C	30°C
Phase B	*NA (winter)*	32.0°C	35°C	30°C	35°C
Phase C	21.4°C	34.3°C	*NA*	*NA*	*NA*
Phase D	32.0°C	*NA*	*NA*	*NA*	*NA*
Phase E	34.3°C	*NA*	*NA*	*NA*	*NA*

3.2 Pomaceous and Stone fruits

Pomaceous and stone fruit require adequate chilling for breaking their winter dormancy (Atkinson et al., 2013; Campoy et al., 2011). We therefore analyzed the amount of chill units accumulated until bud bursting for each pomaceous and stone fruit. We only included weather stations and years that had a full record of minimum and maximum temperatures for the respective crop cycle, and for which we had an observation of bud bursting for at least one pomaceous or stone fruit.

Chill Unit models simulate the amount of intermediate temperatures that a crop is exposed to, and require a record of hourly temperatures. We calculated hourly temperatures from daily temperatures for each weather station by assuming a sine curve for daytime warming and a logarithmic decay function for nighttime cooling, accounting for the daylength by considering the latitude of the weather station and the respective date (Figure 14). We then converted hourly temperatures to hourly chill units, assuming that temperatures between 2.5°C and 9.2°C provide optimal chilling, whilst temperatures below 1.5°C and above 16°C have no chilling effect (Tharaga et al., 2021); higher temperatures even have an opposite effect (Table 19). We then summed up hourly chill units to daily chill units. If the daily sum of hourly chill units was negative, this sum was set to zero (Tharaga et al., 2021). We defined each crop cycle to start on August 1st and to end on July 31st of the next year, and accumulated daily chill units for this period. The relationship between daily average temperature, daily chill units, and accumulated chill units is illustrated in Figure 15 for the station *Yerevan Agro*: Chilling occurs in autumn and spring when temperatures are between 1.5 and 12.5°C, which is why accumulation starts mid-October, stagnates during winter when temperatures are low, resumes in early March, and reaches its maximum in late April when temperatures become too high. Chill unit accumulation curves for all years and stations can be reviewed in Annex C.

We used the accumulation curves to determine for each fruit type how many chill units accumulated at each station and in each year until bud bursting. These values then serve as a reference to approximate the suitability for a fruit (see chapter 4.2). We found a considerable spread in these chill unit values: For example, apple buds bursted already at 1000 chill units in some instances, whilst in other cases only at 2500 chill units (Figure 16). We assume that these amounts reflect the amounts that are actually required by each of the crops. There are some minor differences between stations and varieties, but these are mostly insignificant. Subsequently, we ignored the effects of stations or varieties in the further analysis. The differences in accumulated chill units at bud bursting for different stations and varieties can be reviewed in Annex C.

To map crop suitability, we repeated the above procedure of deriving station-level accumulated chill units with modelled temperature data on a grid cell level (*ERA5-Land* dataset, see WP2). For each crop cycle, we calculated and mapped the amount of chill units accumulated by July 31st (Figure 17). We then derived a long-year average that we used for crop suitability classification (Figure 18). We assume that a grid cell is suitable for production if, at the end of a crop cycle, it has accumulated at least as many chill units as are accumulated at the time of bud bursting. We also assume that the amount of chill units accumulated by the time of bud bursting are equivalent to the amount that is actually required for bud bursting.

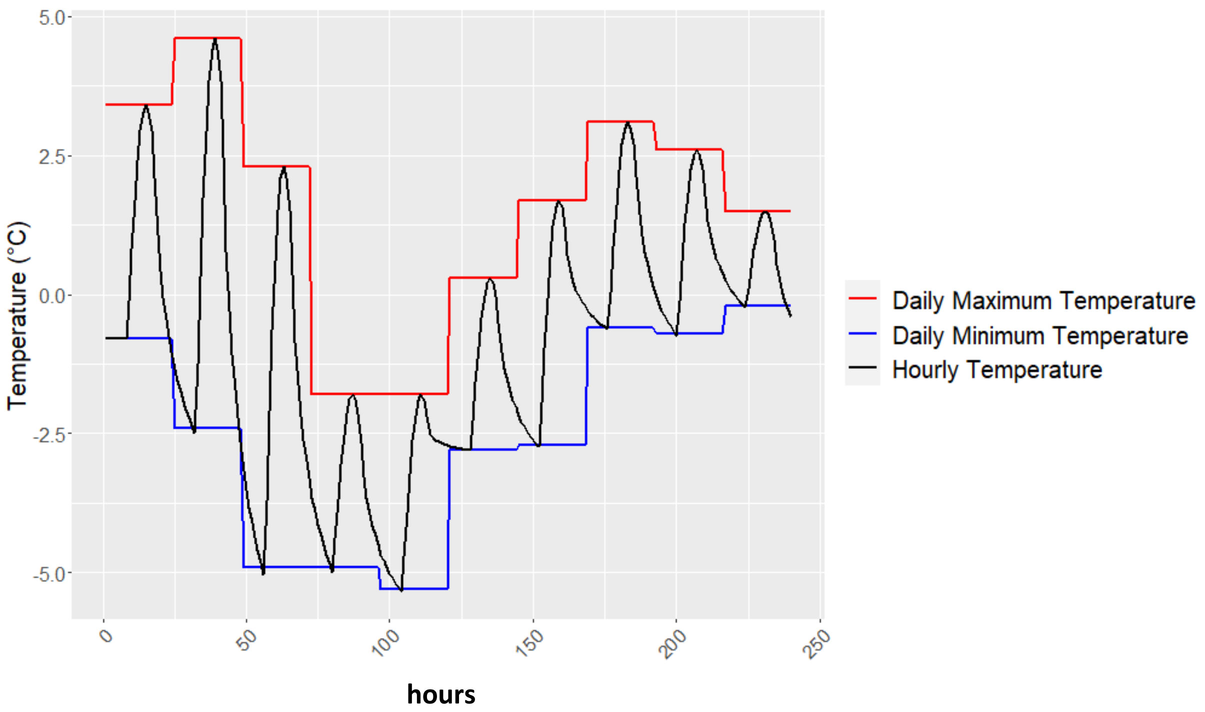

Figure 14: Daily maximum and minimum temperatures and retrieved hourly temperatures at Ararat station, January 1 to 10, 1995.

Table 19: Conversion of hourly temperatures to hourly chill units, adapted from Tharaga et al. 2021.

Hourly temperature (T)	***Hourly chill unit***
< 1.5	0
1.5 <= T <= 2.5	0.5
2.5 <= T <= 9.2	1
9.2 <= T <= 12.5	0.5
12.5 <= T <=16.0	0
16.0 <= T <= 18.0	-0.5
> 18.0	-1

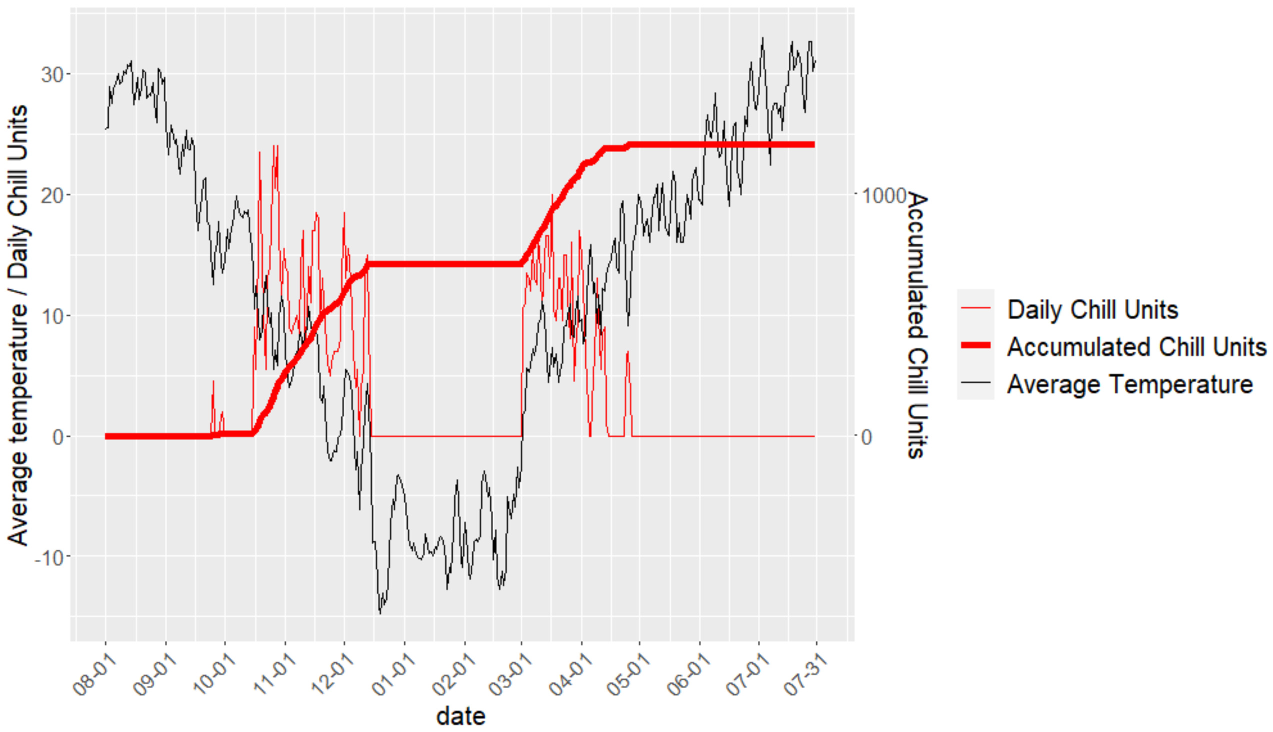

Figure 15: Daily average temperature, daily chill units, and accumulated chill units from August 1 2016, to July 31 2017 at Yerevan Agro station.

Figure 16: Chill units accumulated at the time of bud bursting.

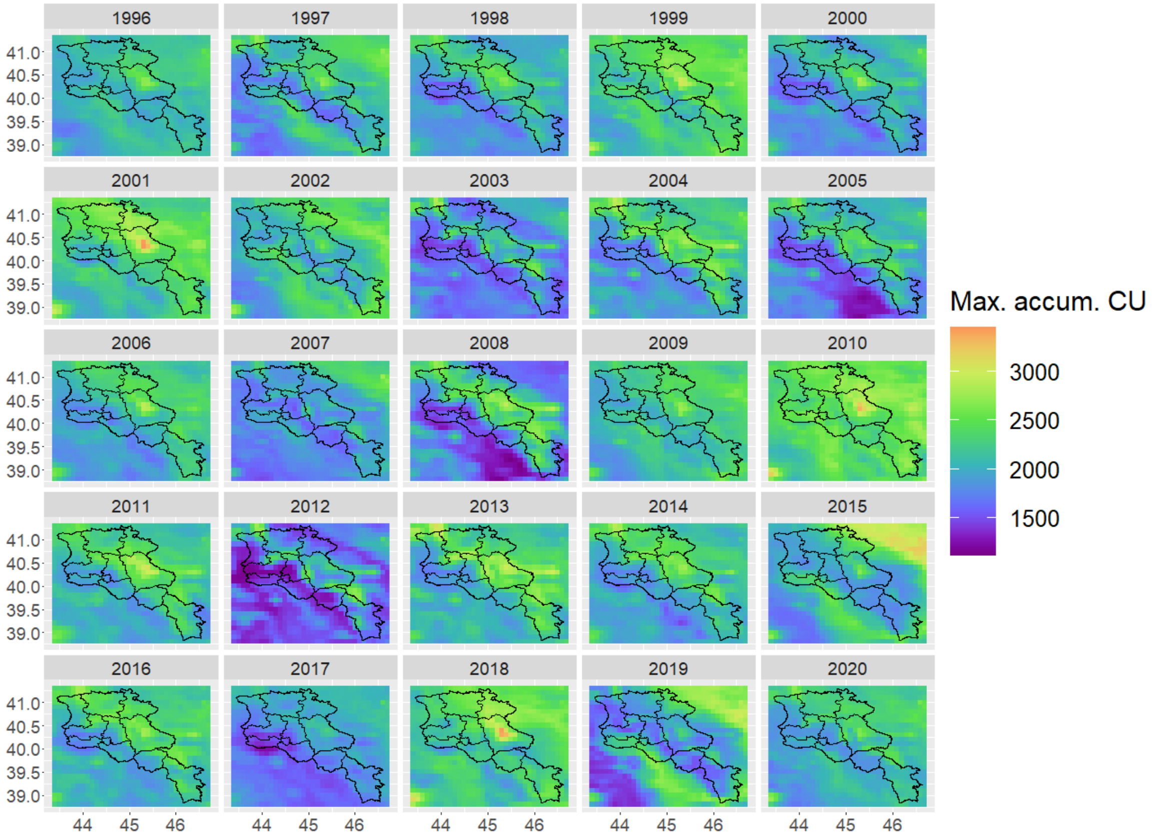

Figure 17: Yearly maximum amount of chill units accumulated throughout the respective crop cycle. Each year refers to the end of the crop cycle (based on modelled temperature data from ERA5-Land).

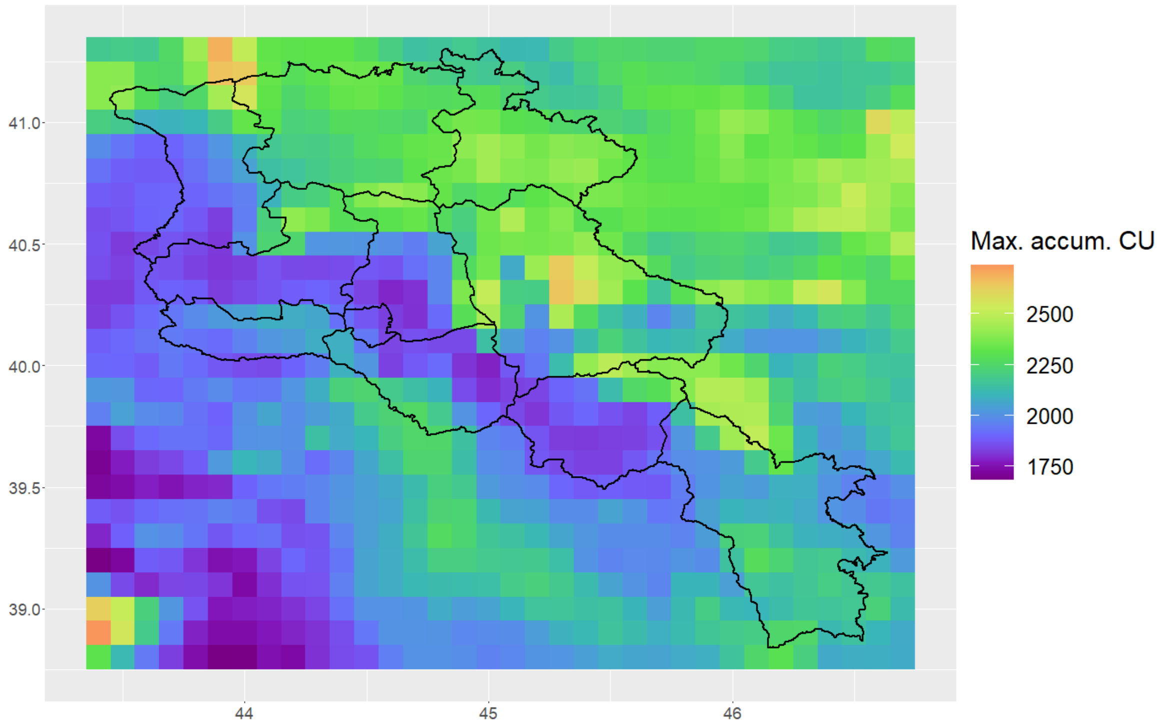

Figure 18: Long-year (1996-2020) average maximum amount of chill units accumulated at the end of a crop cycle (based on modelled temperature data from ERA5-Land).

4. Yield Models and Historical Crop Suitability

4.1 Grain Crops and Vegetables

To predict historical yields with climatic mean and weather extreme variables, we used Random Forest models, a nonparametric machine learning algorithm (Breiman, 2001). Random Forest models have been widely applied in crop yield prediction (Feng et al., 2018; Jeong et al., 2016; L Hoffman et al., 2020; Roell et al., 2020; Schierhorn et al., 2021; van Klompenburg et al., 2020; Vogel et al., 2019) and are particularly suitable for our purposes because they can handle collinearity among the input data, a common issue for datasets that include many climate and weather variables (Breiman, 2001). However, whilst collinearity is not a problem for prediction, it can inflict on assessments of variable importance (Schierhorn et al., 2021). Therefore, prior to running the models, we assessed the collinearity of the predictor variables and reduced these in an iterative procedure until a sufficiently low level of collinearity was reached. Moreover, we excluded technological improvements that raise yields in the longer run (such as optimized fertilization and pesticide application, till practices, cultivar selection and mechanization) by detrending the yield data using a linear regression against time (Lu et al., 2017). Different provinces may have different agricultural policies, technological standards, and cropping practices, which we accounted for by including a province identifier in our models, similar to a random effect in a regression model. For each crop, we averaged the results of 50 model runs. In each run, we randomly assigned 70% of the observations as training dataset to predict the values of the remaining 30%, and assessed the model quality by calculating the R^2-value between observed and predicted yield levels. For each predictor variable, we assessed the mean variable importance across all model runs, expressed as the increase in mean squared error (%IncMSE) that the model would experience if the respective variable was excluded from the analysis. This permits to identify the variables that are most important in determining historical yield levels. The higher the %IncMSE value is for a given variable, the more would the predictive power of the model suffer if this variable would not be available. Note that the %IncMSE values are only comparable within one model, i.e. they cannot be compared to each other for different crops. We also calculated partial dependencies and plotted them to assess the functional relationships between climatic means or weather extremes and predicted yields. To obtain a measure of variable importance at the province level, we calculated the Pearson correlation coefficient between the yield data and all climate and weather variables for each province and crop development stage.

Winter wheat

The Random Forest models for winter wheat had an average R^2 of 0.62. There is considerable interannual variability in winter wheat yields in Armenia (https://maxhofmann.shinyapps.io/ARM_statistics/) and our models seem to explain that variation fairly well. The most important variable was heavy precipitation (HP) during phase C, followed by precipitation (PRCP) in phases B and C (Figure 19). HP during phase C and PRCP in phases B and C had a strong negative relationship with yield (Figures 20 and 21), arguably due to excessive amounts of rain that cause flooding and water-logging (Malik et al., 2002). Maximum temperature (TMAX) was an important yield-limiting variable in phase D, which is the period around anthesis and flowering and hence when wheat is particularly sensitive to heat (Farooq et al., 2011). Frost (FR) in phase A had a considerable effect: High amounts of accumulated temperatures below zero may have damaged plants because these conditions delay dormancy, which causes the seedlings to be susceptible to winter frost, particularly in the absence of an isolating snow cover (Schierhorn et al., 2021). Even though our Random Forest results for winter wheat seem plausible, irrigation might mask some of the effects of weather and climate on yields. Wheat irrigation is very common in the provinces of Armavir and Ararat, where yields are also highest (Figures 2 and 3).

The province-level variable importances (Figure 22) mostly reflect the variable importances at the country level (based on Random Forest models, Figures 19 to 21). For example, TMAX in phase D was highly negatively correlated with yield in almost all provinces, except for Armavir and Ararat.

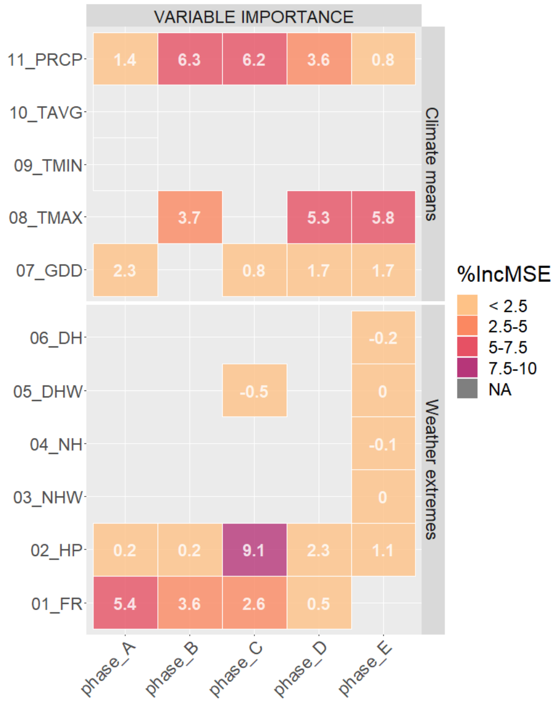

Figure 19: Variable importance for winter wheat. Darker colors indicate higher variable importance for yield prediction.

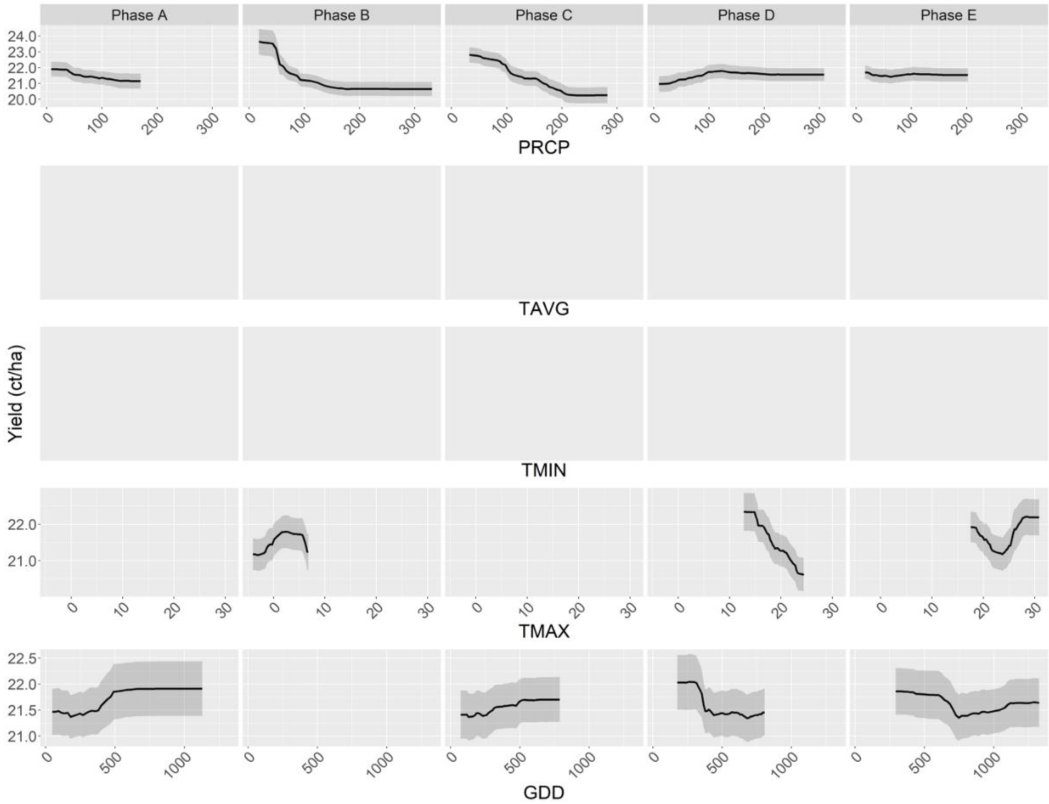

Figure 20: Partial dependencies of climatic mean variables and winter wheat yield. The shaded area around the lines represents one standard deviation.

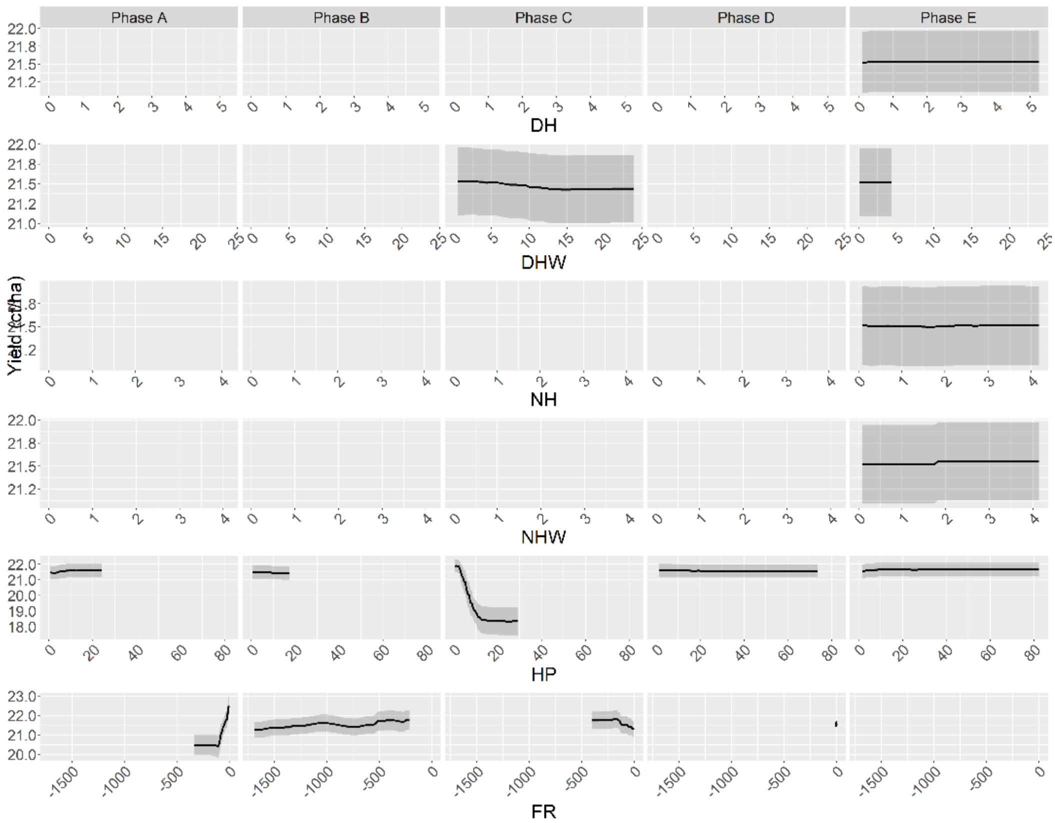

Figure 21: Partial dependencies of extreme weather variables and winter wheat yield. The shaded area around the lines represents one standard deviation.

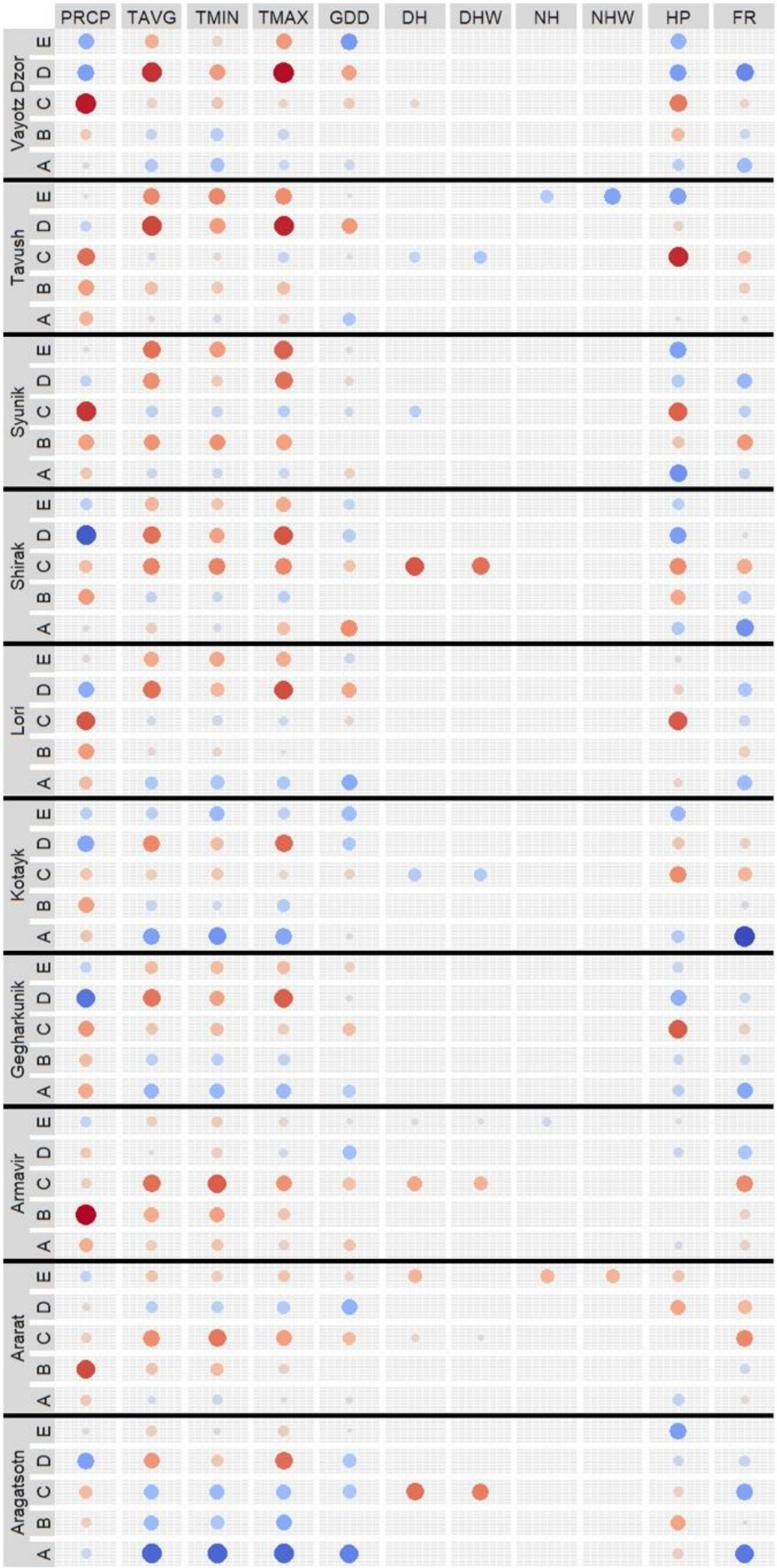

Figure 22: Variable importance for winter wheat at the province level, expressed as correlation coefficient with yield. The darker and larger the dot, the more correlated a variable is to yield levels. Red circles indicate negative correlations, blue circles indicate positive correlations. Frost is measured in accumulated negative temperatures, so blue circles imply that high amounts of frost are associated with low yield.

Spring Barley

The Random Forest models for spring barley had an average R^2 of 0.41. The most important variable was maximum temperature (TMAX) during phase B (Figure 23). In contrast to winter wheat, we do not detect a decrease in yields with increasing TMAX (Figure 24); this is surprising, because the literature suggests that spring barley is susceptible to high temperatures during anthesis (Hossain et al., 2012; Ugarte et al., 2007). One possible explanation is that Armenia has not yet experienced temperature levels that are too high for spring barley during anthesis. Another possible reason is that farmers predominantly plant heat-resistant varieties. Growing degree days (GDD) during phase A was the second most important variable and has a positive relationship with yield until levelling off at about 600 °C. Precipitation in phase B is associated with lower yields, which signals the importance of excessive rain and water logging during this phase (Malik et al., 2002). Extreme weather events generally had no or only small effects on spring barley yield (Figures 23 and 25). The variable importance at the province level shows high agreement with the country-level variable importance and partial dependencies from the Random Forest model, e.g. with GDD in phase A (Figure 26). However, it provides insights into regionally distinct effects, e.g. of heavy precipitation (HP) and frost (FR) in phase A. The models should be interpreted with caution, because irrigation, which is particularly high for spring barley in Armavir (Figure 3), might have distorted our results.

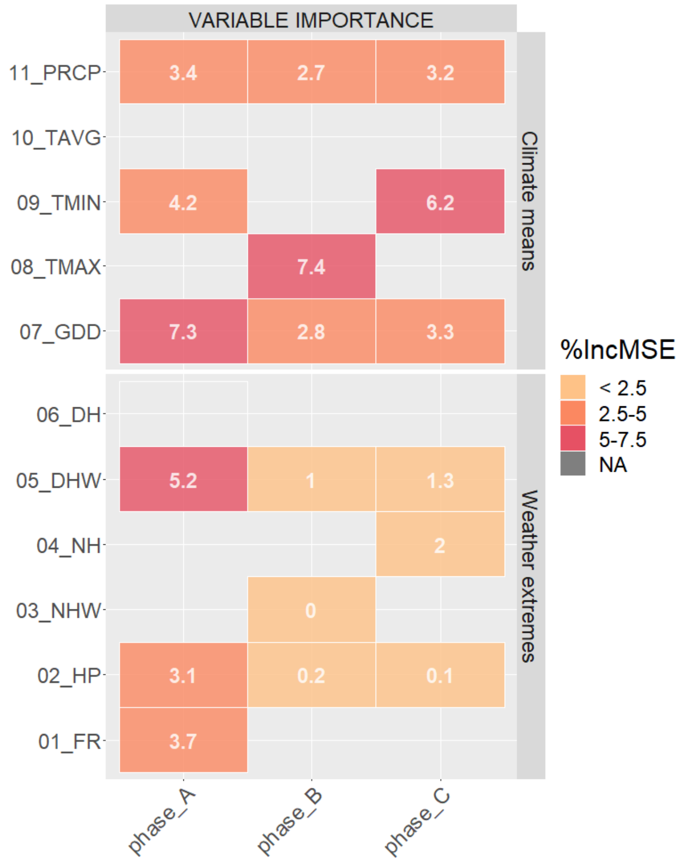

Figure 23: Variable importance for spring barley. Darker colors indicate higher variable importance for yield prediction.

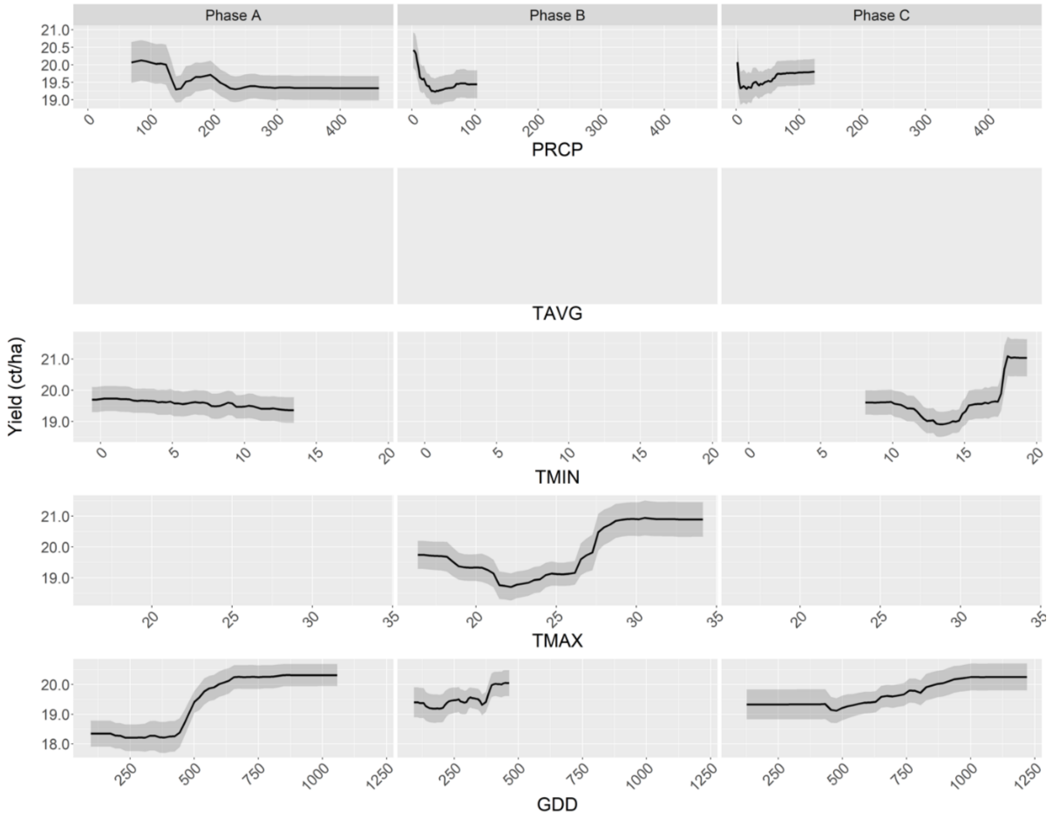

Figure 24: Partial dependencies of climatic mean variables and spring barley yield. The shaded area around the lines represents one standard deviation.

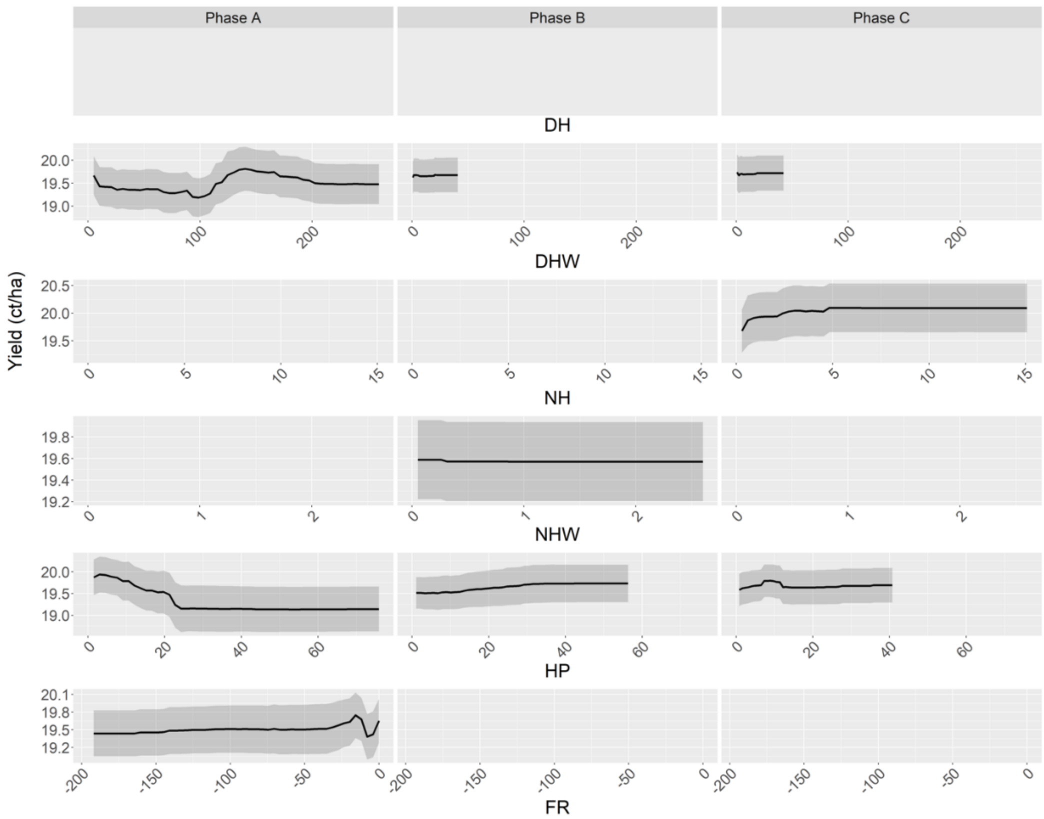

Figure 25: Partial dependencies of extreme weather variables and spring barley yield. The shaded area around the lines represents one standard deviation.

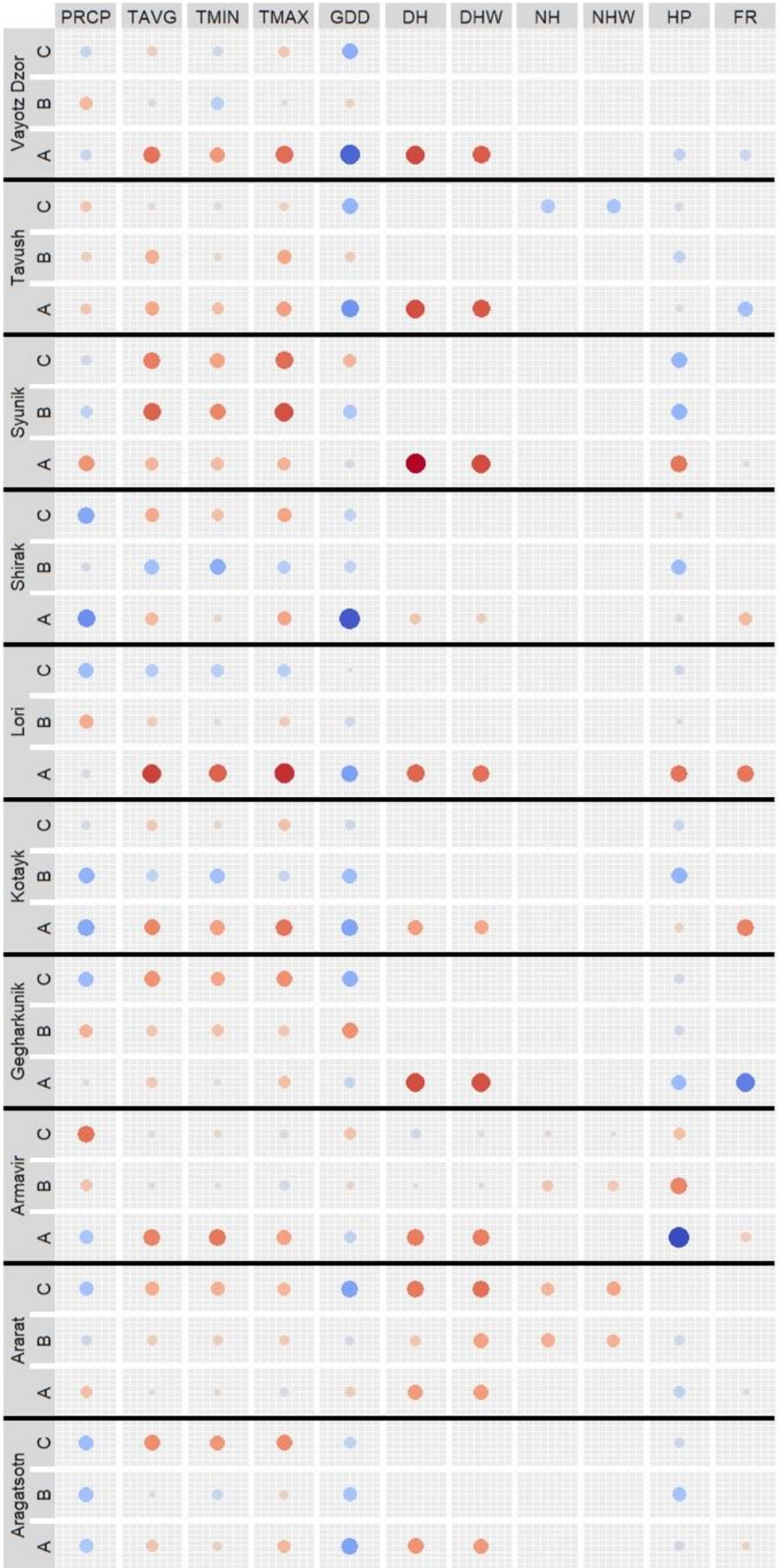

Figure 26: Variable importance for spring barley at the province level, expressed as correlation coefficient with yield. The darker and larger the dot, the more correlated a variable is to yield levels. Red circles indicate negative correlations, blue circles indicate positive correlations. Frost is measured in accumulated negative temperatures, so blue circles imply that high amounts of frost are associated with low yield.

Maize

The Random Forest models for silage maize had an average R^2 of 0.41. One reason for this comparatively low model performance is arguably that fewer observations (than for wheat and barley) entered the model because yield data for silage maize were not available for each province and year (https://maxhofmann.shinyapps.io/ARM_statistics/). The most important variables were minimum temperature (TMIN) in phase C and maximum temperature (TMAX) in phase B (Figure 27). Maize can tolerate higher temperatures slightly better than wheat and barley (Eyshi Rezaei et al., 2015), which could explain the positive association between temperatures and yield levels in our model results (Figure 28). However, global warming is likely to turn this soon into a negative correlation between temperature and yield in Armenia. Extreme weather events had negligible effects on silage maize yield (Figures 27 and 29). The variable importance at the province level only partly matches the variable importance estimated at the country-level and the partial dependencies from the Random Forest models (Figure 30). For example, minimum temperature (TMIN) in phase C had a strong negative association with yield in Vayotz Dzor, even though the overall model results suggest that increasing TMIN during this phase had a positive effect on yields.

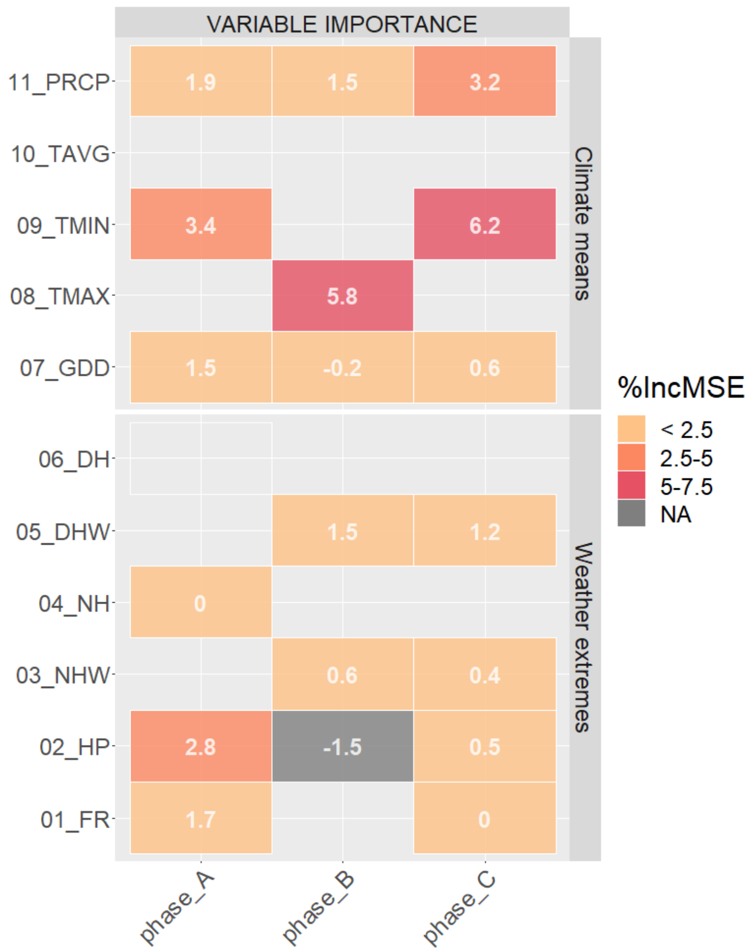

Figure 27: Variable importance for silage maize. Darker colors indicate higher variable importance for yield prediction.

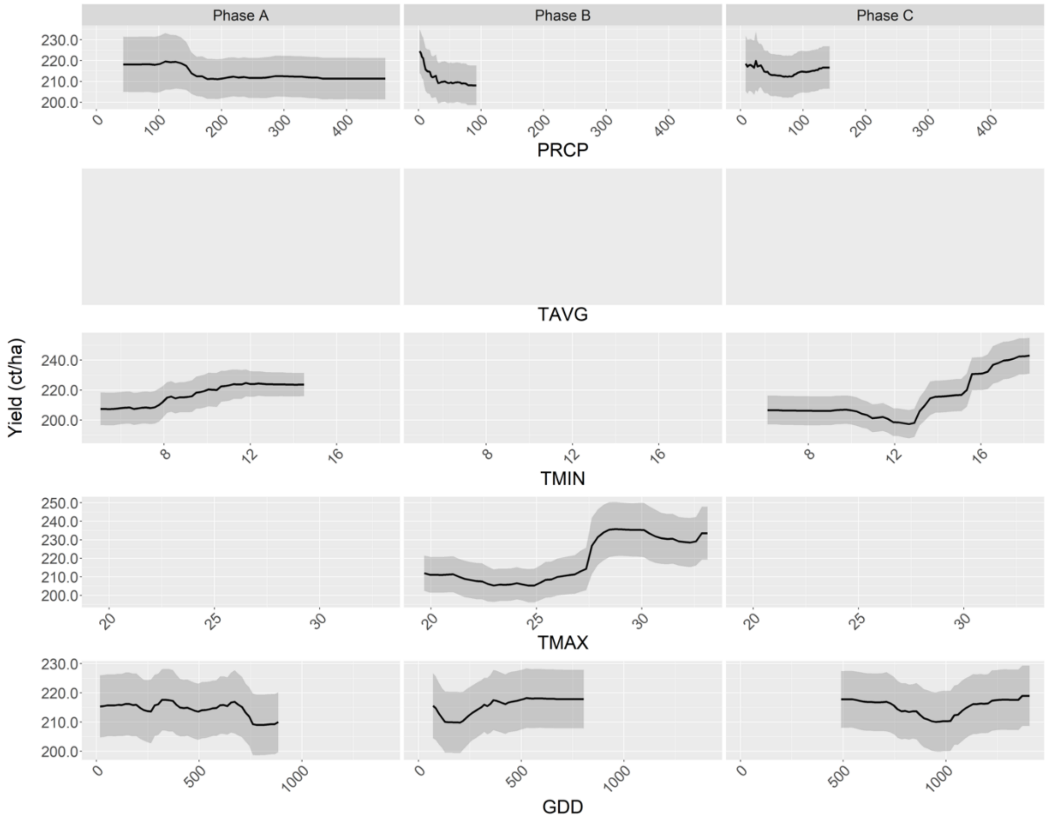

Figure 28: Partial dependencies of climatic mean variables and silage maize yield. The shaded area around the lines represents one standard deviation.

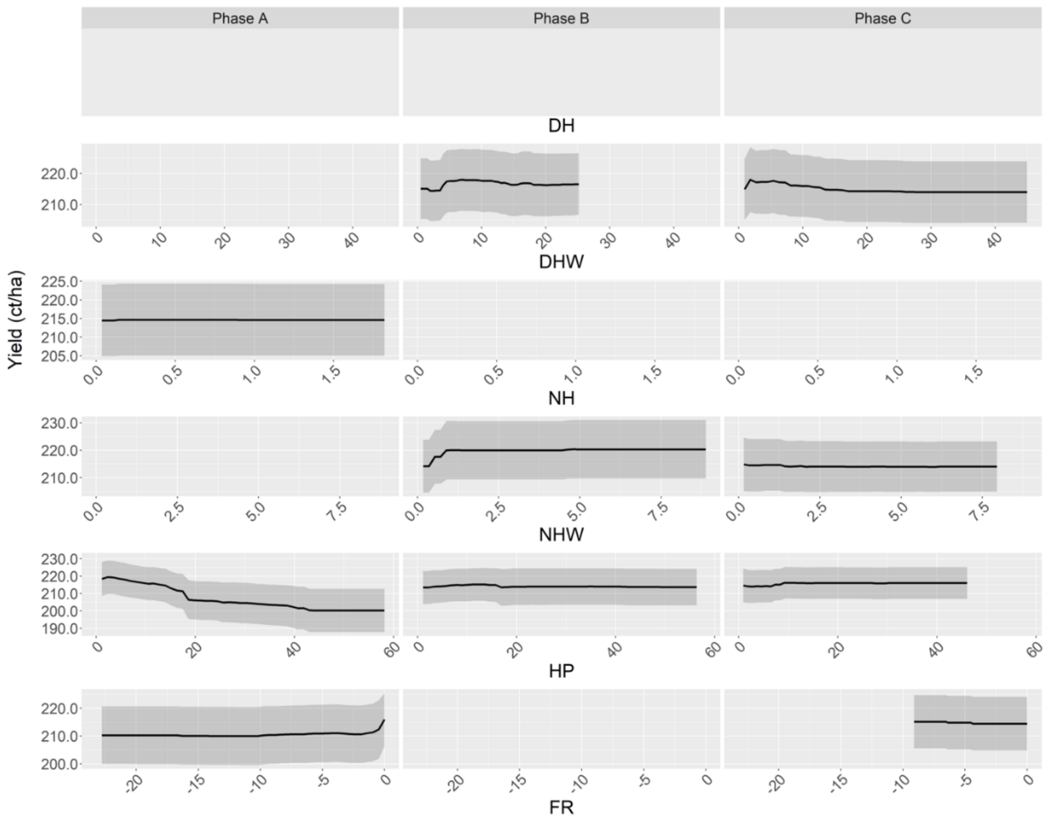

Figure 29: Partial dependencies of extreme weather variables and silage maize yield. The shaded area around the lines represents one standard deviation.

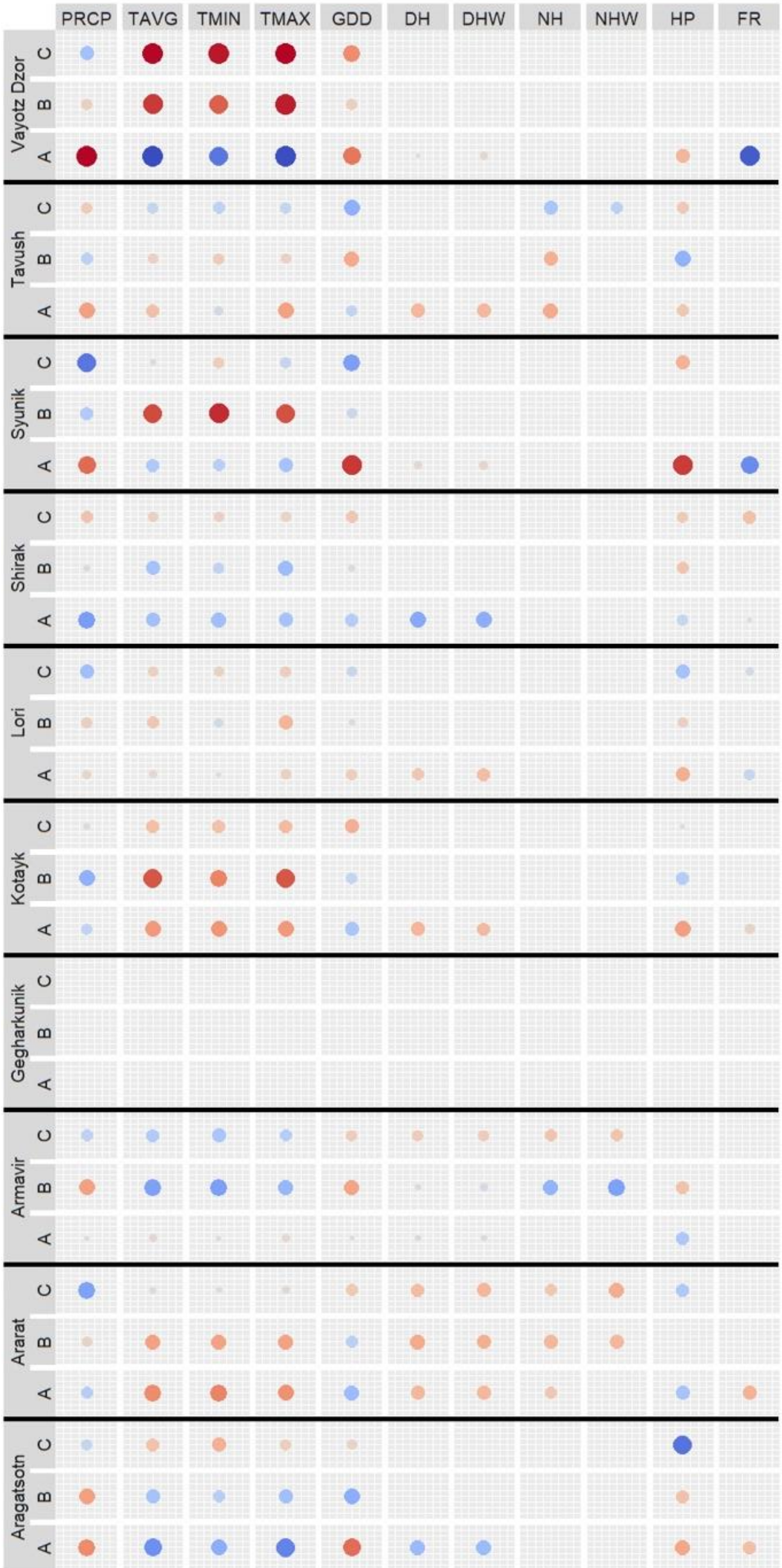

Figure 30: Variable importance for silage maize at the province level, expressed as correlation coefficient with yield. The darker and larger the dot, the more correlated a variable is to yield levels. Red circles indicate negative correlations, blue circles indicate positive correlations. Frost is measured in accumulated negative temperatures, so blue circles imply that high amounts of frost are associated with low yield.

Potato

With an average R^2 of 0.87, the potato models performed particularly well, however inter-annual yield variability is rather low in Armenia (see https://maxhofmann.shinyapps.io/ARM_statistics/) and the good model performance might be due to good predictions of a few extreme values in the observed data. The fact that many weather and climate variables are positively correlated with yield in some provinces and negatively correlated in others (Figure 34), further signals that the model results should be interpreted with caution.

Minimum temperature (TMIN) had the highest variable importance (Figure 31) and there is a clear positive relationship with yield in phase A (Figure 32). Precipitation (PRCP) in phase A was the third most important variable and shows a negative relationship with yield, which may indicate a high susceptibility of potato to excess water supply. Extreme weather variables showed generally low variable importance and weak associations with yield (Figures 31 and 33).

Potato is partly irrigated in Armenia, particularly in the province of Armavir (Figure 3), which is also the province with the highest yields (Figure 2). It is therefore difficult to make conclusions about the actual effect of temperature and precipitation on yields, because irrigation might distort these effects. For example, irrigation increases soil moisture and might also decrease soil temperature. Nevertheless, all heat variables (DH, DHW, NH, NHW) are negatively correlated with yield in Armavir (Figure 34), which might be an indication that irrigation can at least not fully compensate the negative effects of heat on yield in this province.

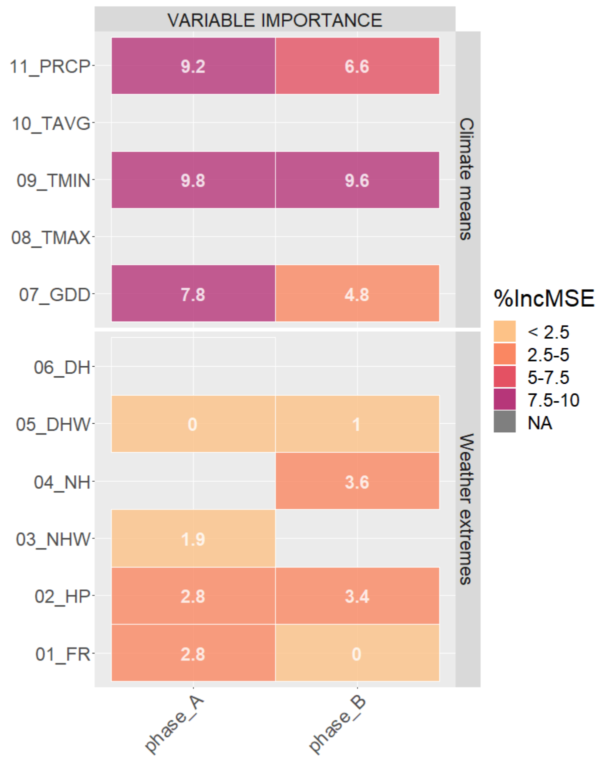

Figure 31: Variable importance for potato. Darker colors indicate higher variable importance for yield prediction.

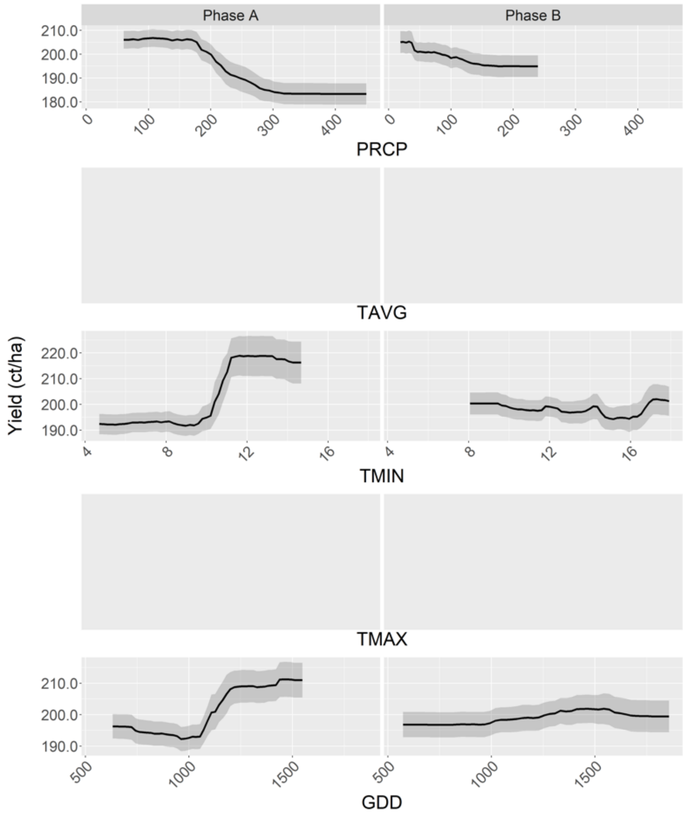

Figure 32: Partial dependencies of climatic mean variables and potato yield. The shaded area around the lines represents one standard deviation.

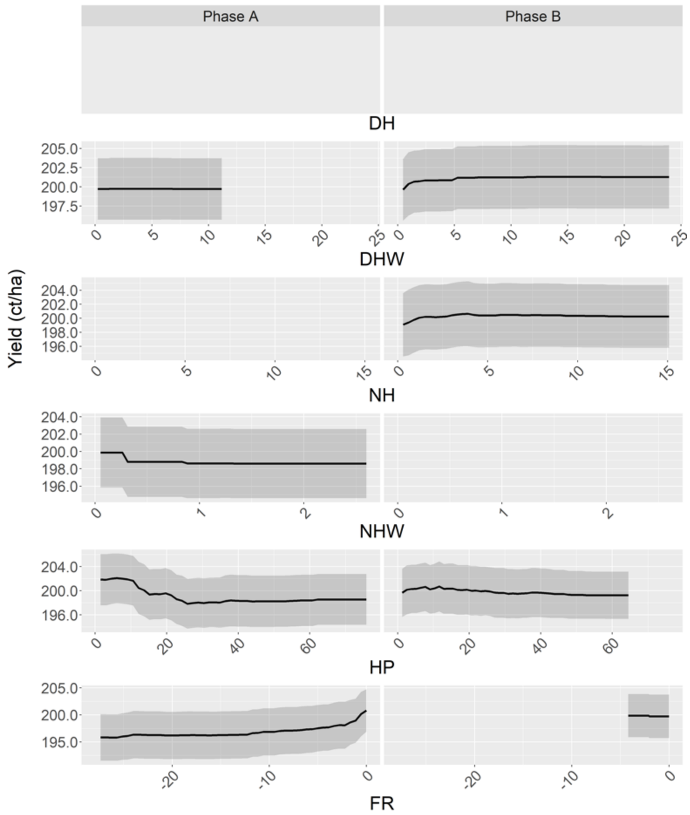

Figure 33: Partial dependencies of extreme weather variables and potato yield. The shaded area around the lines represents one standard deviation.

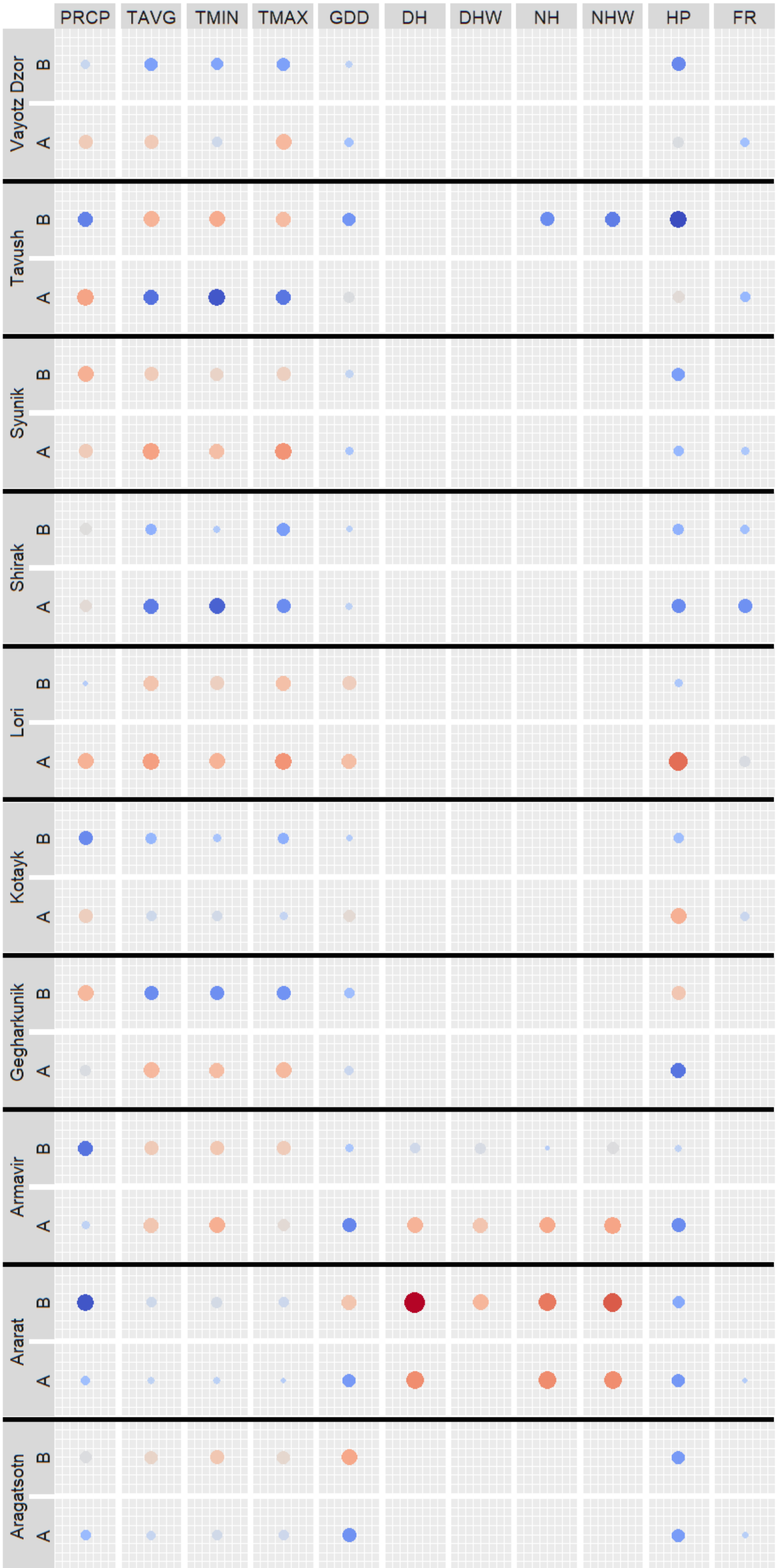

Figure 34: Variable importance for potato at the province level, expressed as correlation coefficient with yield. The darker and larger the dot, the more correlated a variable is to yield levels. Red circles indicate negative correlations, blue circles indicate positive correlations. Frost is measured in accumulated negative temperatures, so blue circles imply that high amounts of frost are associated with low yield.

Cucumber

The Random Forest models for cucumber have a very high mean R^2 of 0.84 and seem to have performed very well. However, there is little interannual yield variability (**Fehler! Linkreferenz ungültig.**), and the good model performance might stem from good predictions of a few extreme values. Cucumber is both irrigated in Armenia, and grown in greenhouses (Figures 3 and 4, chapter 2.1.3). Armavir, the province with both the highest share of irrigated land and the highest amount of greenhouse area, shows positive associations with yield for all variables except precipitation (PRCP) and frost (FR) in phase A, whilst these association are opposite or do not exist in almost all other provinces (Figure 38). This is a strong indication that irrigation and/or greenhouses could be the most important determinants of yield in this province and that they compensate possible negative climate and weather effects on yield.

The most important variables in our models are maximum temperature (TMAX) and day heat waves (DHW) in phase B (Figure 35 and 36). Cucumber needs a certain level of high temperatures, but yields decrease if temperatures become too high (Zhao et al., 2011). While we do observe an increase in yield with TMAX and DHW in phase B, there is no turning point in the partial dependence plot of predicted yield on temperature, but rather a plateau (Figure 36). This could mean that Armenia might not have reached temperatures and heat levels, that are critical for cucumber, yet. The inverse relationship between precipitation (PRCP) in phase B and yield from the country-wide Random Forest model (Figure 36) is contrary to the largely positive province-level correlation of precipitation in phase B with yield (Figure 38) and might be driven by the high yield levels in Armavir, which is why the results should be interpreted with caution.

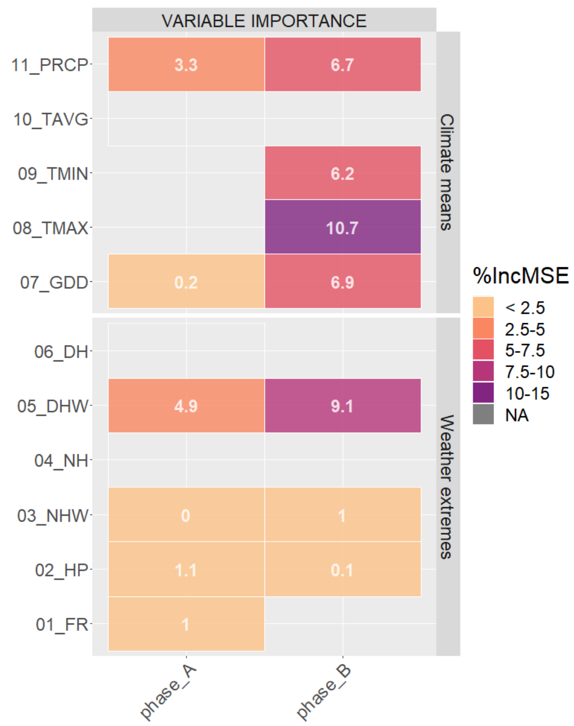

Figure 35: Variable importance for cucumber. Darker colors indicate higher variable importance for yield prediction.

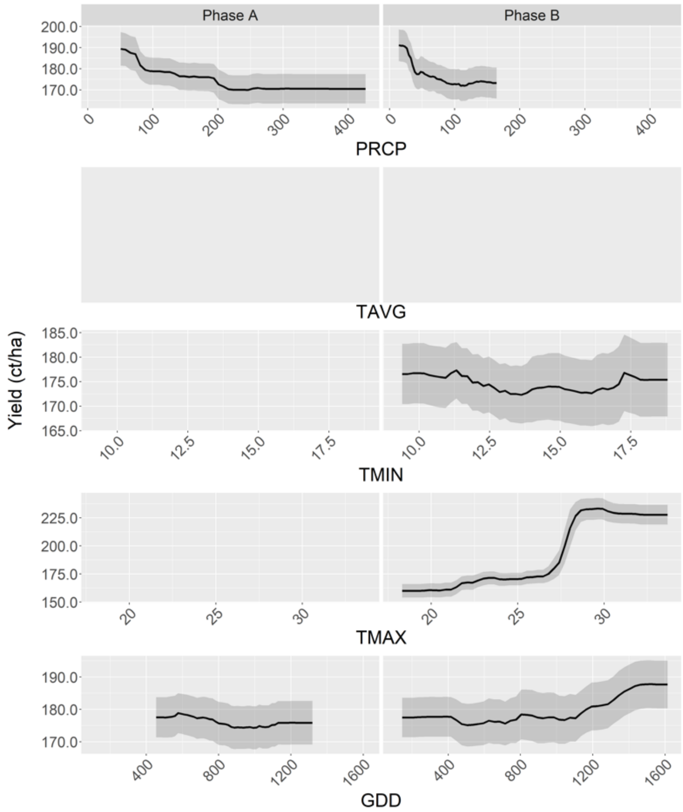

Figure 36: Partial dependencies of climatic mean variables and cucumber yield. The shaded area around the lines represents one standard deviation.

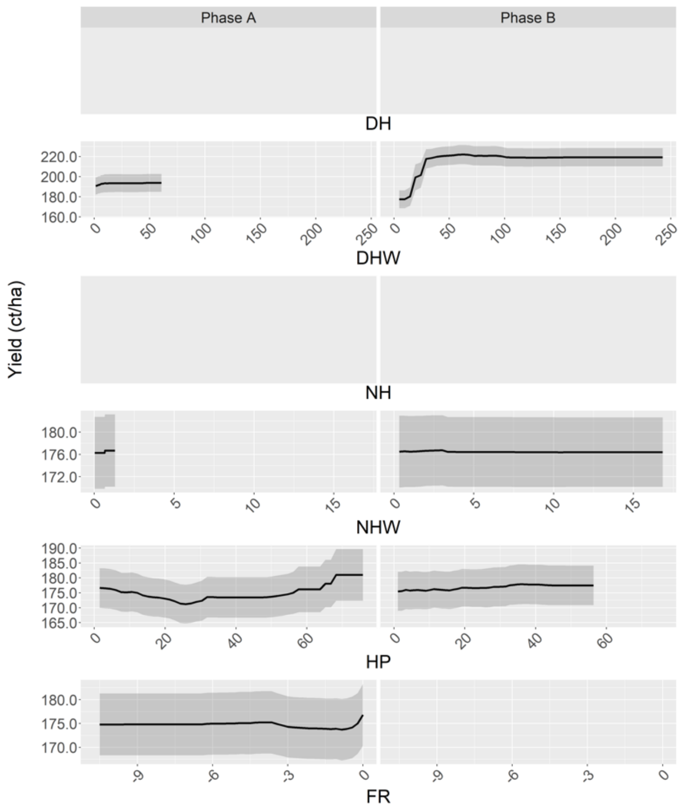

Figure 37: Partial dependencies of extreme weather variables and cucumber yield. The shaded area around the lines represents one standard deviation.

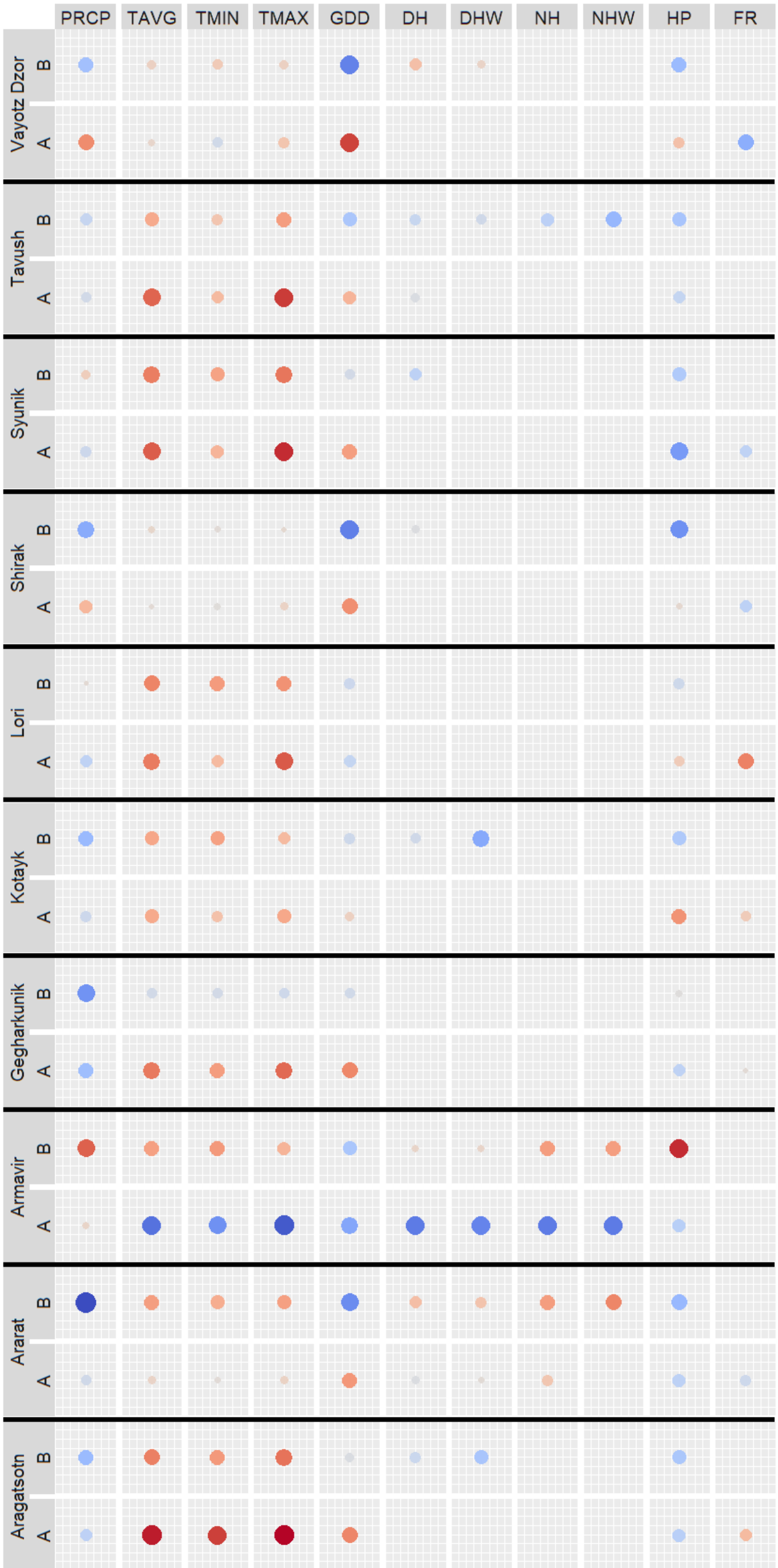

Figure 38: Variable importance for cucumber at the province level, expressed as correlation coefficient with yield. The darker and larger the dot, the more correlated a variable is to yield levels. Red circles indicate negative correlations, blue circles indicate positive correlations. Frost is measured in accumulated negative temperatures, so blue circles imply that high amounts of frost are associated with low yield.

Tomato

The tomato models have an average R^2 of 0.85, however most provinces show low interannual yield variability (https://maxhofmann.shinyapps.io/ARM_statistics/) and the good model performance might stem from good predictions of a few extreme values. Tomato is both irrigated in Armenia and grown in greenhouses (Figures 3 and 4, chapter 2.1.3). For Armavir and Ararat, the correlation coefficients of temperature variables with yield are largely opposite to those of the other provinces (Figure 42). In these two provinces, irrigation and greenhouses are common in tomato production, which is a strong indication that irrigation and/or greenhouses could be the most important determinants of yield in these provinces and that they compensate possible negative climate and weather effects. The model results should hence be interpreted with caution.

Maximum temperature (TMAX) in phases A and B was the most important variable in the Random Forest models (Figure 39) and is positively associated with yield (Figure 40). There are tomato cultivars that can tolerate heat (Pham et al., 2020) and it is possible that Armenia has not yet experienced temperatures that were sufficiently high to have had negative effects on tomato yields. However, there is a clear negative correlation of maximum temperature in phase A with yield in the province of Lori (Figure 42). Extreme weather variables showed generally low variable importance and weak associations with yield (Figures 39 and 41).

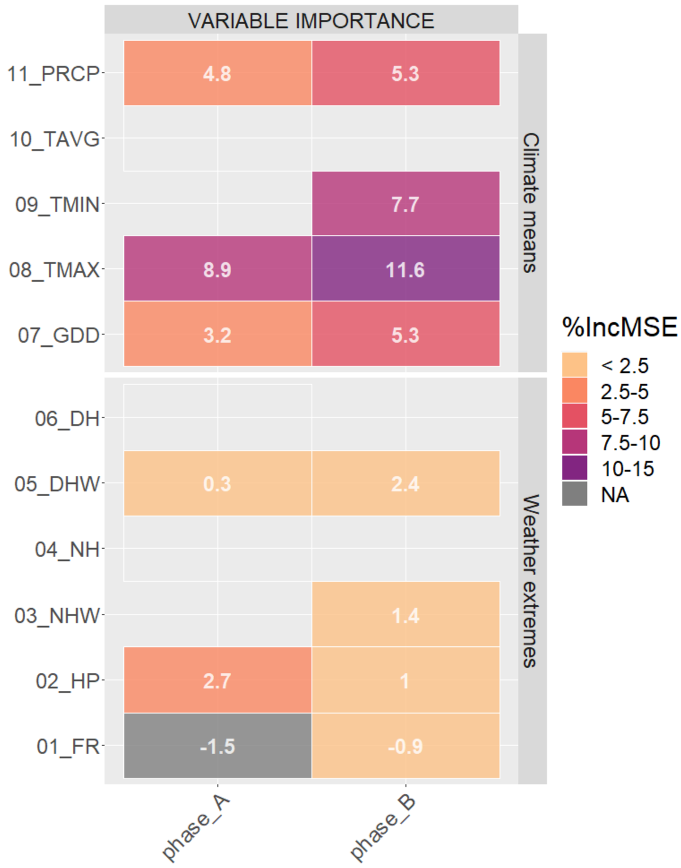

Figure 39: Variable importance for tomato. Darker colors indicate higher variable importance for yield prediction.

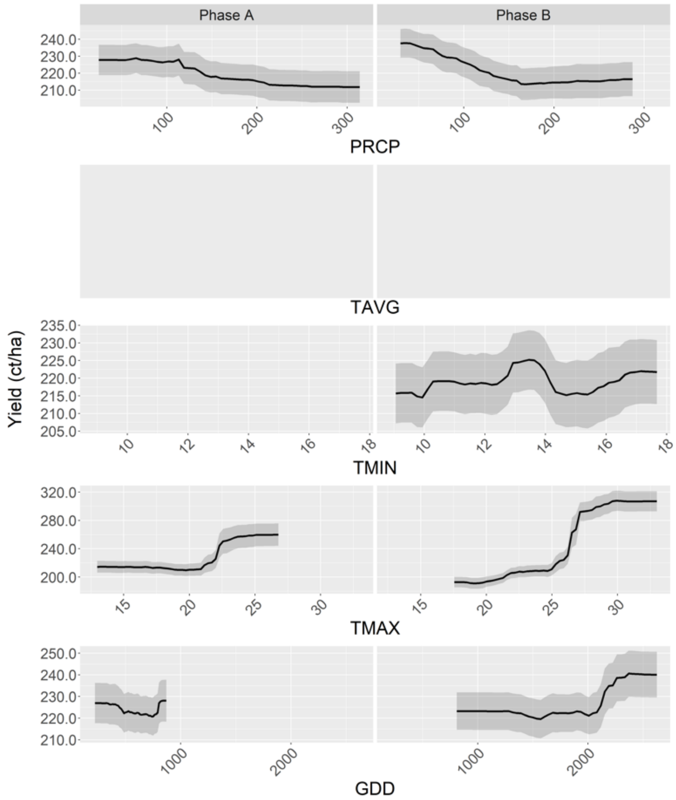

Figure 40: Partial dependencies of climatic mean variables and tomato yield. The shaded area around the lines represents one standard deviation.

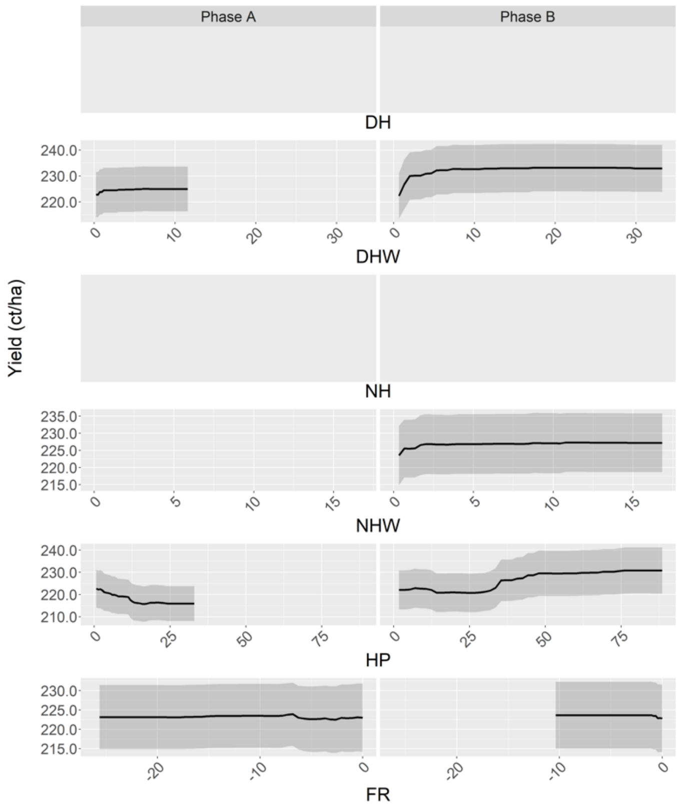

Figure 41: Partial dependencies of extreme weather variables and tomato yield. The shaded area around the lines represents one standard deviation.

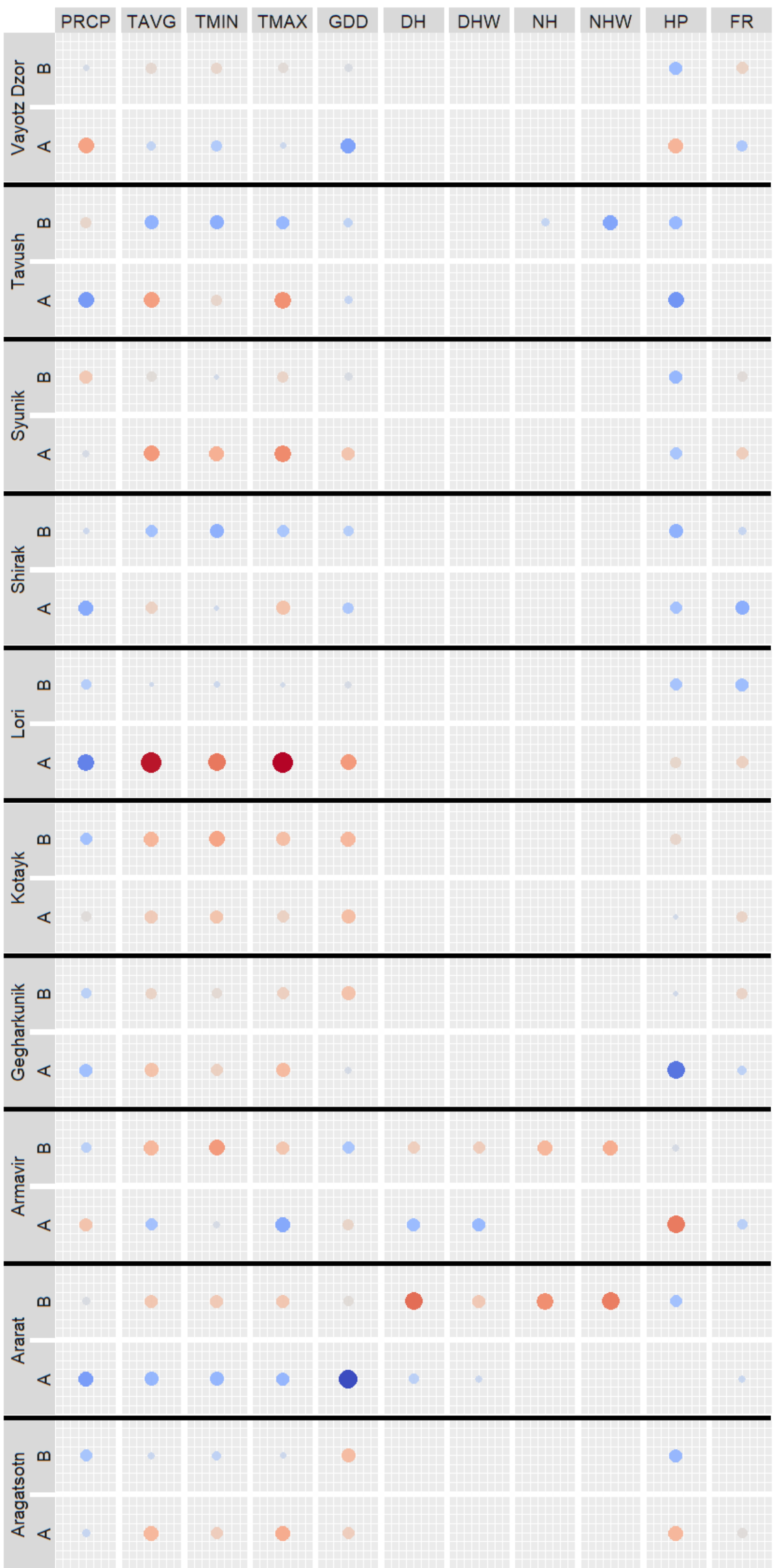

Figure 42: Variable importance for tomato at the province level, expressed as correlation coefficient with yield. The darker and larger the dot, the more correlated a variable is to yield levels. Red circles indicate negative correlations, blue circles indicate positive correlations. Frost is measured in accumulated negative temperatures, so blue circles imply that high amounts of frost are associated with low yield

4.2 Pomaceous and Stone fruits

We determined crop-specific thresholds that characterize the distribution of chill units reached at the time of bud bursting (Table 20) and used these thresholds to recategorize the map of the long-year average of maximum accumulated chill units derived from modelled, grid-cell level temperature data (Figure 18) into five suitability classes:

A. **insufficient amount of chill units (CU) beyond current observations**: Long-year average amount of chill units at the end of the crop cycle is below the minimum observed amount of chill units accumulated at bud bursting.

B. **amount of CU is below average, but sufficient**: Long-year average amount of chill units at the end of the crop cycle is above the minimum and below the 1st quartile of the observed amount of chill units accumulated at bud bursting (= lower 25% of the observed data).

C. **optimal amount of CU**: Long-year average amount of chill units at the end of the crop cycle is above the 1st quartile and below the 3rd quartile of the observed amount of chill units accumulated at bud bursting (= inner 50% of the observed data).

D. **amount of CU is above average**: Long-year average amount of chill units at the end of the crop cycle is above the 3rd quartile and below the maximum of the observed amount of chill units accumulated at bud bursting (= upper 25% of the observed data).

E. **amount of CU is above average and beyond current observations**: Long-year average amount of chill units at the end of the crop cycle is above the maximum observed amount of chill units accumulated at bud bursting.

Historically, sufficient chill units have been available for the production of the six fruit types throughout the entire country and regional shortcomings in chill unit supply seem therefore absent to date (Figure 43). The distribution of class C largely resembles the production patterns of pomaceous and stone fruits (Figure 2), however a direct comparison is not possible because statistics are not available at the level of individual fruit types. Although areas in the northeastern part of the country provide a great surplus amount of chill units, particularly for stone fruits, these values were much higher than all observed chill units at bud bursting (class E in Figure 43). These areas are located in provinces with low production amounts for these crops (Figure 2) and in mountainous regions where production might be low due to other restrictions, such as high terrain inclination, adverse accessibility, or low population density. However, as climate change progresses and low-lying regions may become warmer, the mountainous areas in the northeast might become the only regions in the country that provide sufficient winter chilling in the future. As stone fruits have an overall lower level of chill units accumulated at bud bursting (Figure 16, Figure 43), they might be more resistant to warming winters than pomaceous fruits.

Table 20: Crop-specific thresholds that define the five suitability classes.

crop	min. observed	1st quartile	3rd quartile	max. observed
Apple	1020	1620	2040	2750
Apricot	830	1160	1570	2120
Cornel	1010	1500	1870	2250
Peach	880	1280	1660	2180
Pear	1010	1560	1950	2390
Quince	1200	1700	2060	2610

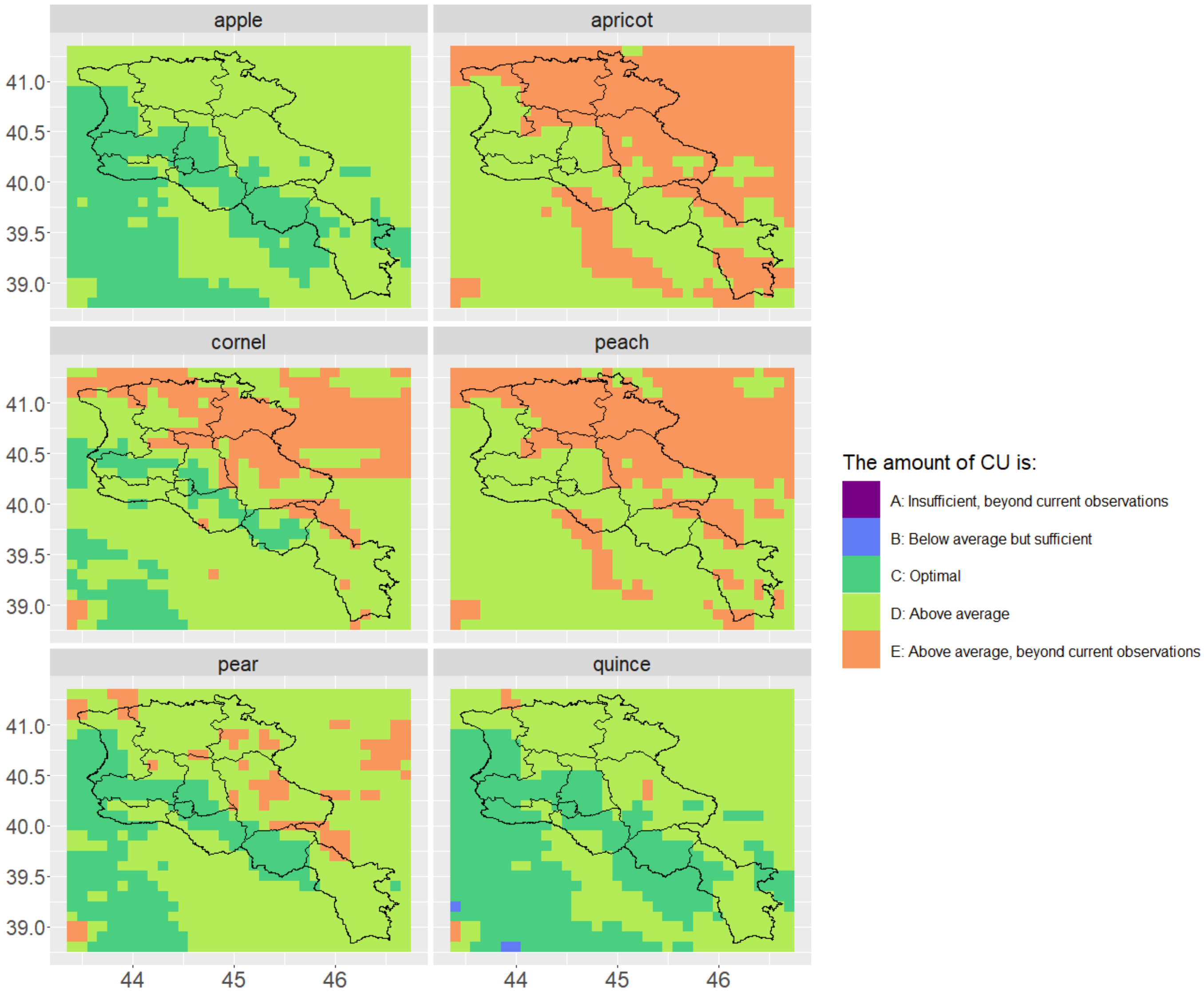

Figure 43: Historical suitability for fruit production based on the average amount of CU that accumulate until the end of a crop cycle.

5. Summary and Recommendations

Our results provide detailed insights into the climatic and weather factors that determine the production patterns of the 12 selected crops in the country. We used Random Forests to model historical, sub-national yields of three grain crops and three vegetables with detailed phenological, climate and weather data. We applied a Chill Unit Model to map the historical suitability of three types of pomaceous fruits and three types of stone fruits. The statistical analyses indicate possible explanations of historical yield variability. All results should be discussed and put into perspective with local experts, who can share their expertise on the specific regional conditions.

Grain crops and vegetables

Overall, we found that climatic means, such as temperature and precipitation, have been more important for yield levels than extreme weather events, such as heat waves or frost. Nevertheless, the results of the grain crop models indicated negative effects of excess precipitation during different development stages. For winter wheat, our model results disclosed the negative effect of high maximum temperature during anthesis which is known from other countries (Farooq et al., 2011; Innes et al., 2015). Our vegetable models also revealed negative effects of excess precipitation, but largely positive effects of high temperatures.

The vegetable models reached higher predictive power than the grain crop models. However, yield variability has been lower for vegetables, and as a result these models might have been overfitted. All modelled grain crops and vegetables are, at least partly, irrigated in Armenia. This complicates the assessment of the contribution of climate and weather on yields because irrigation affects soil moisture, soil temperature, and hence yield. Unfortunately, detailed data on irrigation is missing, which prohibits to differentiate between rainfed production and irrigated production. While the grain crop models nevertheless produced largely plausible results, the vegetable models are difficult to interpret: Both yields and production amounts of vegetables are disproportionately high in two provinces, Armavir and Ararat. In these two provinces, irrigation and greenhouses are most widespread, which can distort the results, particularly for tomato and cucumber. The partly contrasting province-level variable importances for Ararat and Armavir compared to the other provinces underline this possible source of bias, and further stress the need to acquire appropriate data on irrigation and greenhouses to be considered in such models.

We modelled yield with climatic mean and extreme weather variables while accounting for long-term technological improvements and for regional differences in management, policies, and mechanization levels by using detrended yield levels and province identifiers. This is a simplification that we cannot avoid with the available data. More accurate yield models would require data on additional parameters, for example, for pesticide and fertilizer application rates and cropping practices. There is also a series of other environmental variables that can affect yields and that we cannot model, such as hail events, landslides, soil parameters, or pest infestations. We also did not consider quality aspects of the crops.

The data that we processed with the Random Forest models have a series of limitations, which complicates the assessment of climate impacts on yields. To improve on this, we have the following technical recommendations:

- The yield data possibly suffers from different or inaccurate data collection methodologies, and should be validated by local experts. Yield information is only available at the province level and for the past 16 years. We know that province-level yields for the years 1995 to 2004 are available at the national statistical archives. These data can extend the time series considered in the yield predictions from 16 to 26 years. A longer time series would yield statistically more robust results and better allows for assessments of the effect of climate change on crop production, for which long time-series of crop yield data are necessary.

- There is no detailed information in the literature about the crop varieties cultivated in Armenia and the climate and weather requirements of these varieties. Our definitions of weather extreme variables hence stem from the literature of other countries, which may not properly reflect the physiology of Armenian cultivars. For example, our results suggest that weather extremes are less important yield determinants than climatic means, but it remains unclear if this is because the Armenian crop cultivars are well adapted to extreme weather conditions. This should be further discussed with local experts.

- The phenological data used in this report is very detailed and of high quality. However, the observations stem from locations that might not be representative for the whole country. The representativeness of these stations should be validated by local experts. If phenological observations from additional stations and for additional years are available, these should be integrated in future assessments.

- We used modelled, coarse-resolution temperature and precipitation data from *ERA5-Land* and *CHIRPS* for our analysis because of delays in the delivery of weather station measurements. A thorough analysis using the weather station data could greatly improve the accuracy of the climatic mean and weather extreme variables that were used for the yield predictions.

Pomaceous and stone fruits

The results of our Chill Unit models showed that entire Armenia has been suitable for the production of the six fruit types considered in this report. The mountainous regions of the northeastern part of the country provide more chilling than these fruits actually require, yet production levels are very low in these areas, probably due to other factors, such as adverse accessibility, which complicates the marketing of the produce, and low population density, but we lack detailed insights on such constraints. We suspect that under climate change, winter chilling will consistently decrease across the whole country, and higher elevations might become the only areas where the production of pomaceous and stone fruits may be still possible in the future. We will assess that in work package 4.

Although there was high variation in the amount of chill units accumulated at the time of bud bursting, we did not detect substantial differences between cultivars and locations. We acknowledge that production of pomaceous and stone fruits might also be constrained by other factors than chilling, such as water supply and irrigation, yet such input data are lacking.

The data that we processed with the Chill Unit models have a series of limitations. Several technical improvements may relieve some of these limitations:

- We did not establish a link between suitability and yield because province-level yield data is not available for individual pomaceous and stone fruits in Armenia. However, we suspect that local yield observations may be available from the agrometeorological stations for which we obtained phenological and temperature data. Such data would benefit the validation of the suitability maps.

- We used daily temperature measurements from the meteorological stations to model hourly temperatures. We suggest to consider mobilizing actual hourly temperatures measurements, if available.

- We used modelled, coarse-resolution temperature data from *ERA5-Land* to map country-wide crop suitability because of delays in the delivery of weather station measurements. A more thorough analysis with weather station data could greatly improve the accuracy of the crop suitability maps.

6. Literature

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Work Package 4:

"Future Effects of Climate and Extreme Weather Events on Yields and Crop Suitability"

Content

Annex

Figures

1. Introduction

Future climate change will crucially affect crop yields worldwide (Jägermeyr et al., 2021; Zhao et al., 2017). Armenia already experienced an average temperature increase of 1.2°C between 1929 and 2016. Total precipitation declined by 9% since 1935. The combination of warming and less precipitation contributes to Armenia's rising vulnerability to droughts (Melkonyan, 2014). Weather station data reveal that the number of tropical nights and heat waves has increased, while the number of frost days has decreased (UNDP & GEF, 2020). With ongoing climate change, this trend is expected to continue in the future (World Bank Group and Asian Development Bank, 2021).

Future climate projections have been developed for so-called Representative Concentration Pathways (RCPs). These describe the components of the radiative forcing that shape the global climate system, i.e. greenhouse gas emissions, aerosol concentration, and land use (van Vuuren et al., 2011). The RCPs span various stabilization and mitigation scenarios until 2100 and are expressed as the radiative forcing in Watt per square meter on the ground (W/m^2). RCP 8.5, for example, is a pathway characterized by high GHG concentration in the atmosphere that contributes to an estimated radiative forcing of about 8.5 W/m^2 and closely represents the trajectory of GHG emissions at the time of writing. RCP 4.5 is an intermediate pathway that anticipates substantial emissions reduction where GHG concentrations stabilize at around 650 ppm, equivalent to about 4.5 W/m^2.

Until 2050, the mean annual temperature in Armenia is projected to rise by 1.7 °C under RCP 4.5, and by 2.5 under RCP 8.5 (World Bank Group and Asian Development Bank, 2021). Precipitation is likely to decrease, but model results are not consistent (UNDP & GEF, 2020). Heat waves are expected to intensify and become more frequent, particularly in Southern Armenia (Galstyan et al., 2021). Besides, Armenia will likely experience a significant increase in the number of days with maximum temperatures above 35°C. The annual probability of drought is projected to increase by 80% under RCP 8.5 (World Bank Group and Asian Development Bank, 2021).

Future climate change is expected to result in a decline of productivity of most of the crops that we selected to study in this assignment. Additionally, increasing frequency and intensity of droughts and heat will likely render production more volatile. The increase in the number of days with extremely high temperatures will likely lead to more frequent yield damages for most crops that are currently cultivated in lowland areas (World Bank Group and Asian Development Bank, 2021). It has been estimated that the average water requirement of Armenia's crops will double as temperatures will continue to rise (Melkonyan, 2015), and it is highly uncertain if the increase in future water demand will be met by precipitation and irrigation.

In work package 3 (WP3), we show that historical changes in climate and weather conditions have already substantially affected crop yields in Armenia. We used Random Forest models, a machine learning algorithm, to assess the impacts of climatic mean and weather extreme variables on yields of the most important grain crops and vegetables, and Chill Unit models to approximate the historical suitability for the production of six types of pomaceous and stone fruits. In WP4, we integrate future climate and weather data in our models to predict future crop yields for grain crops and vegetables, and future suitability for pomaceous and stone fruits. To our knowledge, comparable models for Armenia are not available to date.

However, we caution the reader to interpret the modeling results with care because we had to take several assumptions for these calculations, and because of the uncertainty of future developments. First, we used the relationships from the historical models to predict future yield effects. This implies that we keep the functional relationships between climate, weather, and yields constant. This in turn abstracts from any adaptation of farmers in terms of land management or land use. In reality, farmers will adapt input use, crop types planted, and where land use takes place to the changing climatic conditions. Besides, technological improvements in plant breeding and digitalization will allow to adapt crop management to changing climate and weather conditions. These adaptation measures cannot be accounted for with our approach. The results should therefore be interpreted as what could be the impacts on crop yields with current crop production, but under future climate conditions.

2. Future Yield Predictions and Crop Suitability

We analyzed future climate projections of four daily climatic variables (minimum, average and maximum temperature, and precipitation), for two future scenarios (RCP 4.5 and RCP 8.5) and for two future periods (2041-2060 - “near future”; 2081-2099 - “far future”). We obtained these data from the ISIMIP repository (https://data.isimip.org/search/) and restricted our analysis to the four climate forcing models for which data was available for all mentioned parameters and scenarios: GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR and MIROC-5. The datasets are in a gridded format and have a resolution of 0.5 degrees, which in Armenia is equivalent to a cell size of approximately 55 km height x 39 km width. Bias-corrected climate projections with a higher spatial resolution are, unfortunately, not available from ISIMIP. To calculate relative and absolute future climatic changes, we compared the future predictions to the historical baseline model of 1971-2005. We did not restrict our analysis to a cropland mask, since the future allocation of cropland is highly uncertain.

2.1 Grain Crops and Vegetables

We used the future climate projections to calculate five daily climatic mean and six daily weather extreme variables for each target crop and each development stage (see WP3, Tables 16 to 18). To approximate the start and end date of each development stage in the future, we averaged the respective start and end dates of all historical observations, i.e., across all years and all phenological stations, which resulted in a future crop calendar (Figure 1). We hence assume that phenology will not change in the future, and so the crop calendar does not distinguish between near and far future. We calculated stage-specific climatic mean and weather extreme variables on the grid-cell level for each year, RCP, and climate forcing model. We then averaged the estimates for the plant development stages for all years and all periods (historical baseline, near future, far future), and averaged the resulting estimates across the four climate forcing models to obtain long-year model ensemble rasters for each RCP and period. For each crop, development stage, climatic mean and weather extreme variable, RCP, and future period, we visualized these long-year model ensemble rasters and the absolute changes between them and the historical baseline in Annex A.

We applied a zonal mean function to the long-year model ensemble rasters to estimate climatic variables at the provincial level. We used the resulting data to run a separate Random Forest model for each province (see WP3, chapter 4.1) that we first trained on the historical climatic and yield data. We report the variable importances of these models for each crop and province in Annex B. We then re-estimated the trained model with the future climatic data to predict future yield levels under each RCP and for each future time period. Finally, we compared the future yield estimates against the historical long-year average yields (2005 to 2020) and calculated percent yield changes (Figures 2 to 7).

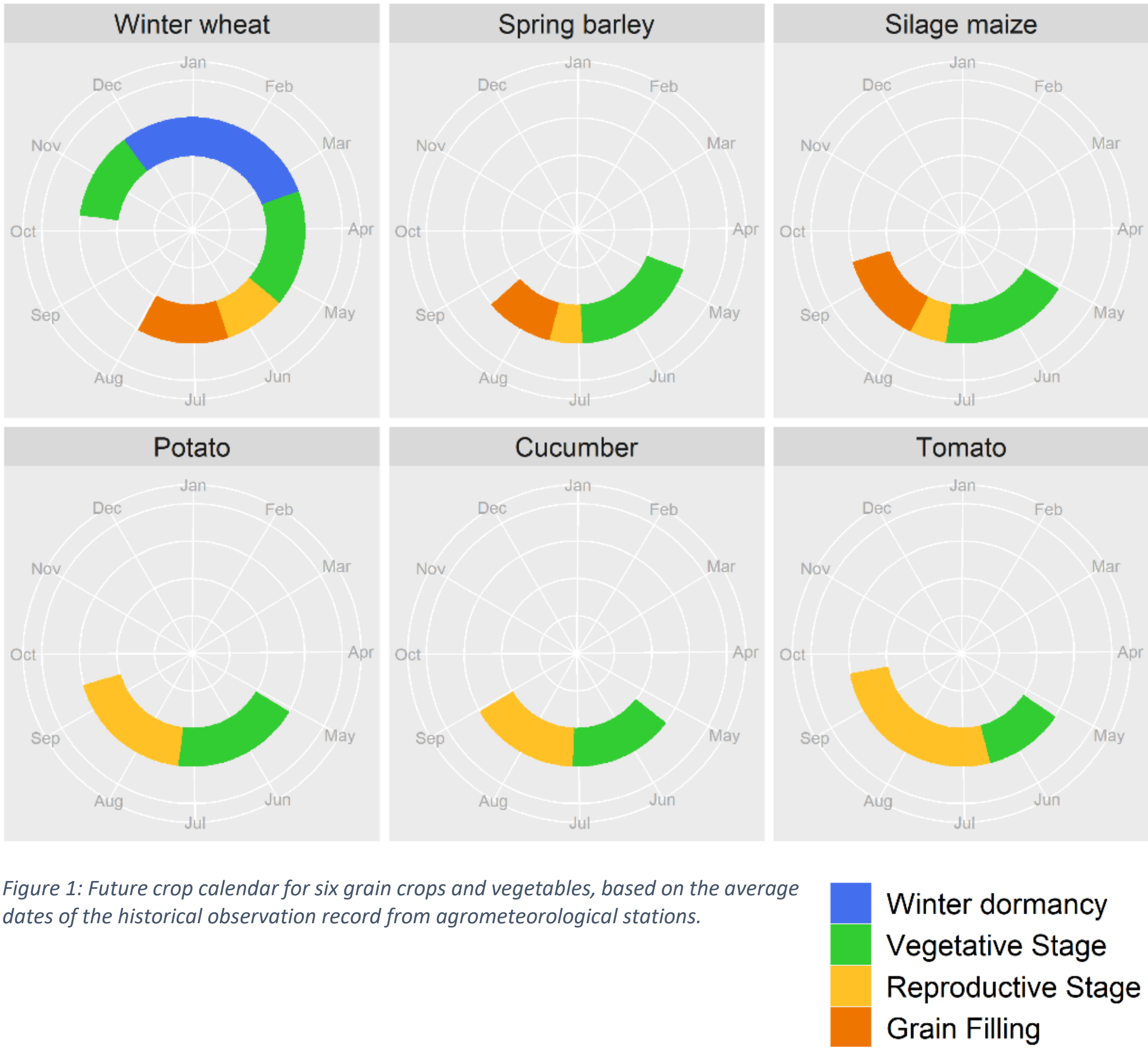

Figure 1: Future crop calendar for six grain crops and vegetables, based on the average dates of the historical observation record from agrometeorological stations.

Winter Wheat

We project slight yield increases for Armavir and Ararat (Figure 2), where winter wheat yields are highest in the entire country (WP3, Figure 2), and slight decreases for Shirak and Gegharkunik (Figure 2), where wheat production is highest (WP3, Figure 2). For Armavir and Ararat, variable importances are generally low (Annex B), and it is hence difficult to conclude which climatic variable drives the predicted increases in yield. Since most winter wheat is irrigated in Armavir and Ararat (WP3, Figure 3), attention should be paid to secure sufficient water supply in the future to also compensate for higher evapotranspiration rates due to warming. For both Shirak and Gegharkunik, the most important variable is precipitation during the reproductive phase (Annex B), which is positively correlated with yields in these two provinces (WP3, Figure 22). The future decrease in precipitation during the reproductive phase (Annex A) may explain the yield decreases projected for Shirak and Gegharkunik. We project the highest increase in wheat yield for Tavush, and the highest decrease for Vayotz Dzor (Figure 2). The most important variable in the model for Tavush is heavy precipitation during the grain filling phase (Annex B), which is positively correlated with yield (WP3, Figure 22). Heavy precipitation will decrease in the near future during grain filling (Annex A), which contradicts the predicted yield increase in Tavush. Maximum temperature during the reproductive phase is the most important variable in the model for Vayotz Dzor (Annex B) and is highly negatively correlated with yield (WP3, Figure 22). During this phase, when anthesis happens, wheat is particularly susceptible to heat (Farooq et al., 2011). The predicted future increase in maximum temperature during the reproductive phase (Annex A) could explain the predicted yield decrease for Vayotz Dzor. With further increasing temperatures, special attention should be paid to this critical stage, particularly because extreme heat can eventually even lead to sterilization in wheat (Innes et al., 2015; Sehgal et al., 2018).

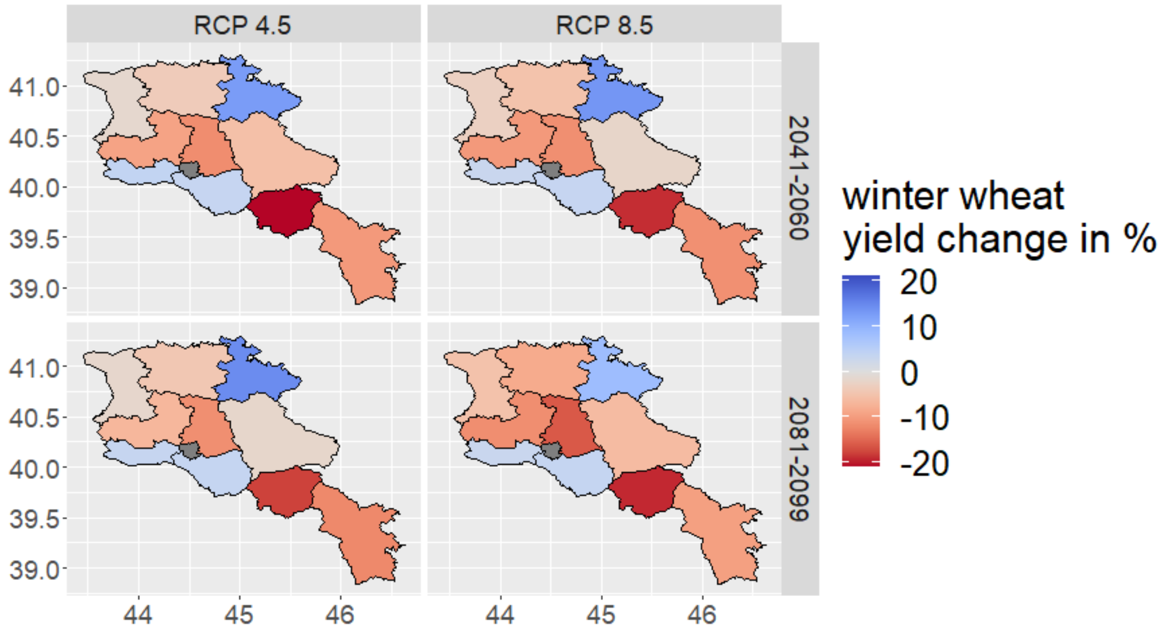

Figure 2: Predicted change in winter wheat yield in %, compared to historical long-year average yield levels (2005-2020), for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099). Blue provinces are expected to experience an increase in yield in the future; red provinces are expected to experience a decrease.

Spring Barley

The patterns of spring barley production largely resemble those of winter wheat: The highest yields are found in Armavir and Ararat, whereas production is highest in Gegharkunik and Shirak (WP3, Figure 2). Irrigation of spring barley is highest in Armavir (WP3, Figure 3). We predict slight yield decreases for Ararat, Gegharkunik and Shirak (Figure 3). The variable importances of these models are rather low (Annex B), and it is hence difficult to conclude which climatic variables drive the predicted decreases in yield in these three provinces. Controversially, for Armavir and Tavush, our models predict a yield decrease under RCP 4.5, but an increase for both the near and far future under RCP 8.5 for Armavir, and an increase for the far future under RCP 8.5 for Tavush. For Armavir, the most important variable is precipitation during the grain filling phase (Annex B), which is negatively correlated with yield (WP3, Figure 26). The fact that precipitation during this phase is projected to decrease with increasing future warming (Annex A) could explain why we see a shift from decreasing to increasing yield between RCP 4.5 and 8.5 (Figure 3). The two most important variables for Tavush are maximum temperature during the reproductive phase, and precipitation during the grain filling phase (Annex B), which are both negatively correlated with yield (WP3, Figure 26). In Tavush, the negative effect of increasing future temperature might be compensated by the positive effect of decreasing future precipitation only in the far future under RCP 8.5 (see Annex A). We predict a high yield increase for Lori, whereas Syunik shows the highest decrease in most models (Figure 3). Growing degree days during the vegetative phase is the second most important variable in the Lori model (Annex B) and is positively correlated with yield (WP3, Figure 26). With overall increasing temperatures, there will be an increase in growing degree days in the future (Annex A), which may be the reason for the predicted yield increase in this province. However, the most important variable in Lori is heavy precipitation during the vegetative phase (Annex B), which, paradoxically, is negatively correlated with yield (WP3, Figure 26), but predicted to increase in the future, except for the far future under RCP 4.5 (Annex A). In Syunik, one of the most important variables is maximum temperature during the reproductive phase (Annex B). The predicted yield decreases in Syunik can be explained with rising temperatures during this phase in the future (Annex A) and their negative correlation with yield (WP3, Figure 26). From other countries, it is known that high temperature during the reproductive phase of barley can have negative yield effects (Hossain et al., 2012; Ugarte et al., 2007). This effect became evident in the models for Tavush and Syunik, and special attention should be paid to extreme temperatures in the future. For the areas with high amounts of irrigation, particularly Armavir, water supply must be ensured in the future, taking the predicted decreases in precipitation (Annex A) into account.

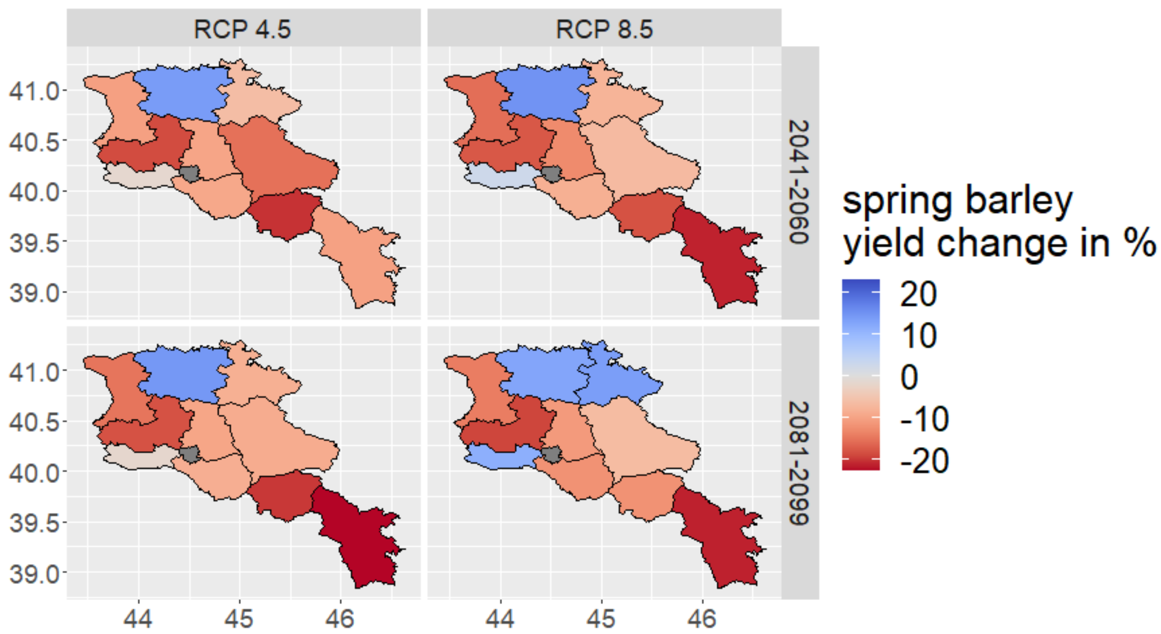

Figure 3: Predicted change in spring barley yield in %, compared to historical long-year average yield levels (2005-2020), for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099). Blue provinces are expected to experience an increase in yield in the future; red provinces are expected to experience a decrease.

Silage Maize

Similarly to winter wheat and spring barley, we only predict yield increases in silage maize for provinces in the northern and western parts of Armenia. Historical silage maize yield is highest in Armavir and production is highest in Lori (WP3, Figure 2). We predict increasing yields for Armavir, and moderate decreases for Lori (Figure 4). The variable importances are rather low for these two provinces (Annex B), and it is hence difficult to conclude which climatic variables drive these changes in yield. Although maize is generally better adapted to heat than many other crops (Eyshi Rezaei et al., 2015), we predict a high yield decrease for Kotayk (Figure 4), where maximum temperature during the reproductive phase is the most important variable (Annex B) and is highly negatively correlated with yield (WP3, Figure 30). As maximum temperature will continue to increase in Kotayk (Annex A), our models predict yield decreases under both RCP4.5 and RCP8.5 and for both future time periods. The models for silage maize have to be interpreted with special caution, because for three provinces (Gegharkunik, Syunik and Vayotz Dzor), yield data are only available for a few years, and production levels are overall comparably low throughout the entire country (WP3, Figure 2).

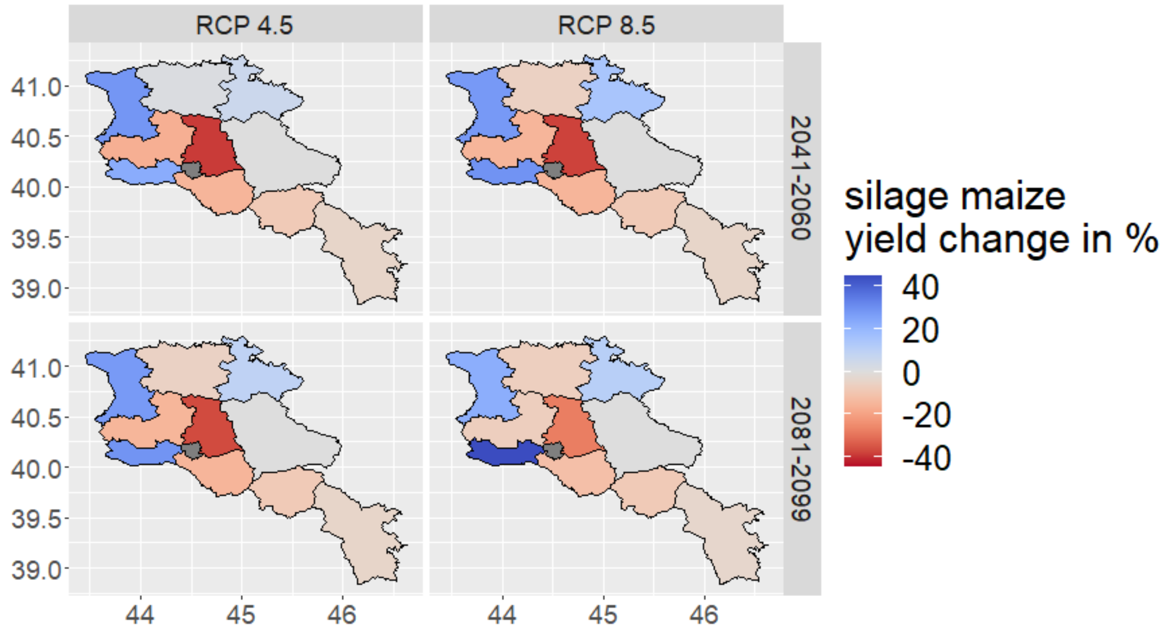

Figure 4: Predicted change in silage maize yield in %, compared to historical long-year average yield levels (2005-2020), for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099). Blue provinces are expected to experience an increase in yield in the future; red provinces are expected to experience a decrease.

Potato

Under all scenarios, the predicted changes in future potato yields are comparably low, ranging between -10 and 10 percent (Figure 5). We anticipate only moderate changes, mostly decreases, for Armavir and Ararat (Figure 5), the two provinces with highest potato yields in Armenia (WP3, Figure 2). While the low variable importances (Annex B) make it difficult to infer about which climatic variables drive the predicted changes in yield in Armavir, there is a very strong negative impact of day heat during the reproductive phase on yield in Ararat (Annex B; WP3, Figure 34). Day heat events will become more frequent and severe with future warming (Annex A) and can explain the predicted yield decreases in Armavir. The high yield decreases predicted for Lori (Figure 5) may be driven by increased future heavy precipitation (see Annex A) during the vegetative phase, which is the most important variable for this province (Annex B) and is negatively correlated with yield (WP3, Figure 34). We found considerable yield increases under climate change in Gegharkunik (Figure 5), where the highest quantity of potato is currently produced (WP3, Figure 2). Variable importances are all relatively low for Gegharkunik (Annex B), and it is hence difficult to conclude which climatic variables drive the predicted yield increase.

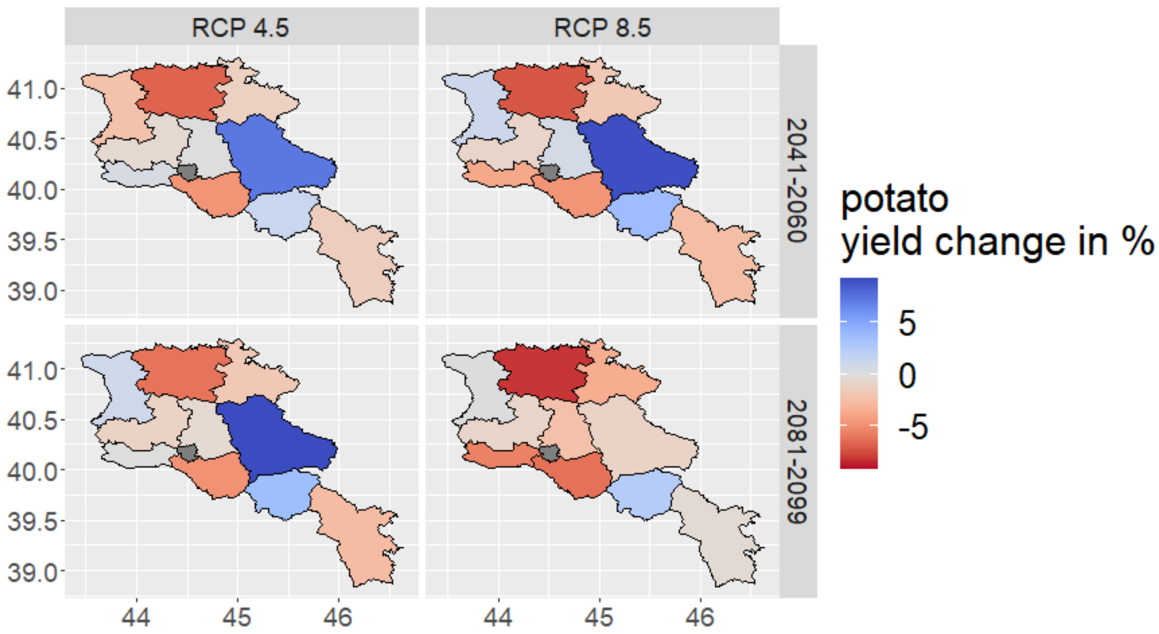

Figure 5: Predicted change in potato yield in %, compared to historical long-year average yield levels (2005-2020), for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099). Blue provinces are expected to experience an increase in yield in the future; red provinces are expected to experience a decrease.

Cucumber

For cucumber, we mostly predict yield decreases. Cucumber is mainly grown in Armavir and Ararat, where irrigation and greenhouses are most widespread (WP3, chapter 2.1). For these two provinces, we only predict slight yield changes. The highest yield decreases are predicted for Lori and Shirak in the northern part of the country (Figure 6). Maximum temperature during both the vegetative and reproductive phase was the most important variable for Lori (Annex B) and is negatively correlated with yield (WP3, Figure 38). The rising future maximum temperatures (Annex A) hence probably explain the decrease predicted for Lori. In the Shirak model, the most important variable was heavy precipitation during the reproductive phase (Annex B), which is positively correlated with yield (WP3, Figure 38). It is expected that there will be a slight decrease in heavy precipitation events in the future (Annex A), but we doubt that this can fully explain the predicted yield decreases for Shirak. As cucumber production heavily relies on irrigation in Armenia, adequate water supply will have to be ensured especially in the lowland regions of Armavir and Ararat in the future. Obtaining detailed time series data on greenhouses and irrigation and integrating them into the yield models is especially crucial for cucumber.

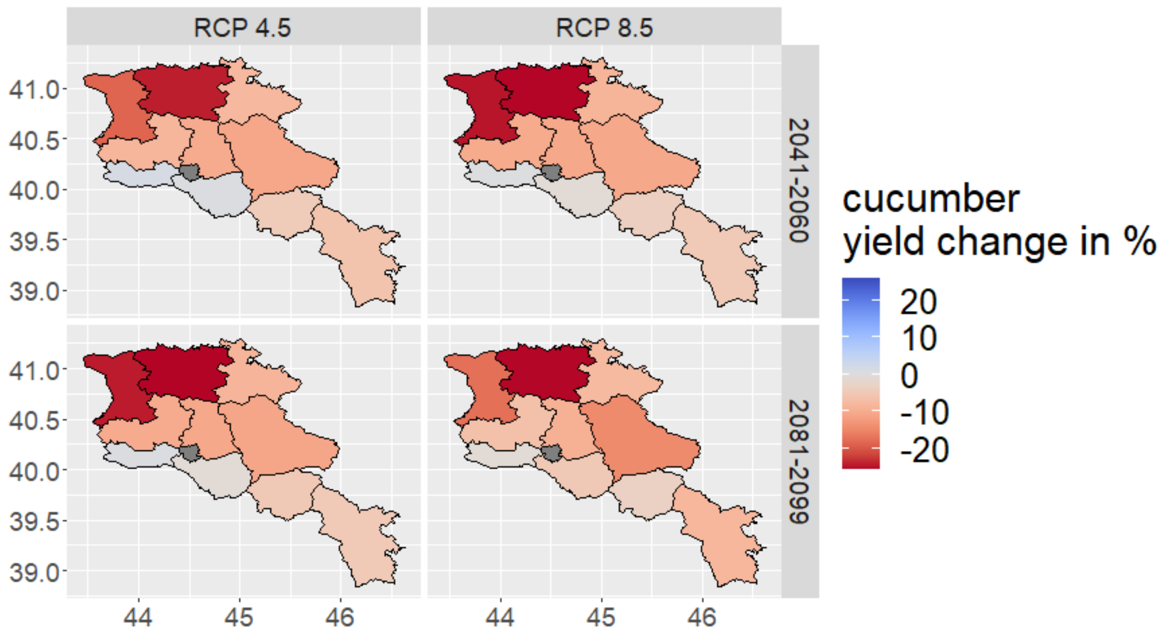

Figure 6: Predicted change in cucumber yield in %, compared to historical long-year average yield levels (2005-2020), for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099). Blue provinces are expected to experience an increase in yield in the future; red provinces are expected to experience a decrease.

Tomato

For tomato, we mostly predict yield decreases. Tomato is also mainly grown in Armavir and Ararat, where irrigation and greenhouses are most widespread (WP3, chapter 2.1). For these two provinces, we only predict slight yield changes (Figure 6). The highest yield decreases are predicted for Lori, Kotayk and Gegharkunik (Figure 6). The most important variables in the Lori model were precipitation, minimum temperature and growing degree days during the vegetative phase (Annex B). Precipitation is positively correlated with yield in Lori, while minimum temperature and growing degree days are negatively correlated (WP3, Figure 42). The projected future decrease in precipitation and increase in temperature (Annex A) hence well explain the yield loss predicted for this province. For Kotayk and Gegharkunik, the variable importances are rather low (Annex B), so it is difficult to conclude which climatic variables drive the yield decreases there. In Armenia, tomato production also heavily depends on irrigation, and water supply has to be secured in the future. As for cucumber, mobilizing detailed time series data on greenhouses and irrigation will be crucial to improve the models for tomato.

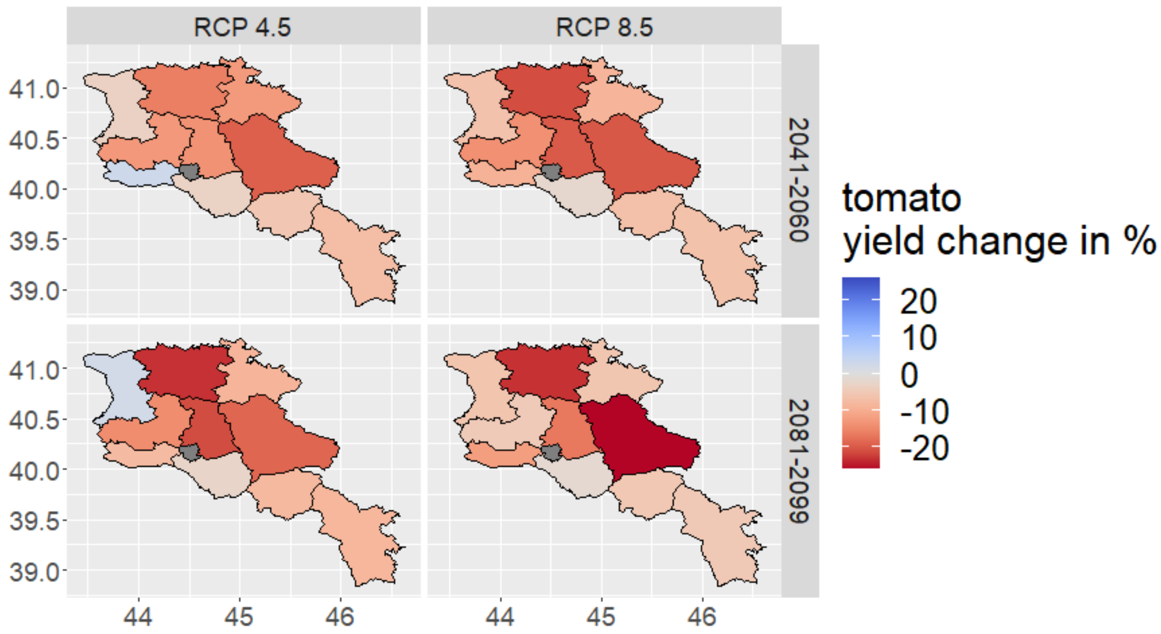

Figure 7: Predicted change in tomato yield in %, compared to historical long-year average yield levels (2005-2020), for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099). Blue provinces are expected to experience an increase in yield in the future; red provinces are expected to experience a decrease.

2.2 Pomaceous and Stone Fruits

We calculated accumulated chill units at the grid-cell level with the procedure described in chapter 3.2 in the report of WP3 for each year, RCP, and climate forcing model separately. We then averaged the yearly maximum amount of accumulated chill units across all years of the respective period (historical baseline, near future, and far future), and averaged the resulting estimates across all four climate forcing models to obtain long-year model ensemble rasters for each RCP (Figure 8). We calculated the change between the long-year model ensemble rasters and the historical baseline period for each future period and RCP (Figures 9). Finally, we reclassified the maps according to the procedure described in chapter 4.2 in the report of WP3 to obtain maps of future suitability for each crop (Figures 10 to 15).

Overall, the amount of accumulated chill units will be lowest in the western part of Armenia (Figure 8), and most regions will experience a decrease (Figure 9). However, we predict that the entire country will remain suitable for the production of the studied fruits (Figures 10 to 15). In Armenia, stone fruits (apricot, cornel, peach) open their buds earlier than pomaceous fruits (apple, pear, quince) (WP3, Figure 12), so they require less chilling. Accordingly, for stone fruits, the future amount of accumulated chill units coincides with higher percentile classes of the historical distribution of observed accumulated chill units at bud bursting, which suggests stone fruits might be less susceptible to reductions in future chill units. The total amount of chill units that accumulates at the end of a crop cycle in the future is still equivalent to average or above-average accumulated chill units historically observed at stone fruit bud bursting (see green and light green areas in Figures 11 to 13), whereas it is equivalent to below-average accumulated chill units observed at pomaceous fruit bud busting in large areas of the western part of the country (see blue areas in Figures 10, 14 and 15). However, we do not predict that the amount of accumulated chill units would fall below the historical minimum for any part of the country (these areas would be purple in Figures 10 to 15).

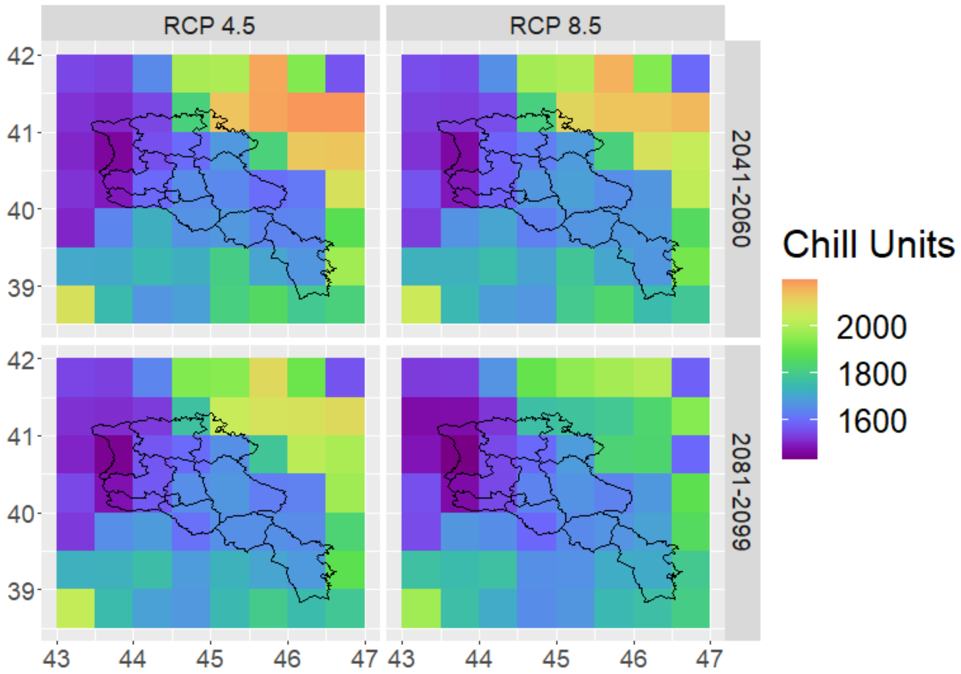

Figure 8: Maximum accumulated chill units for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099).

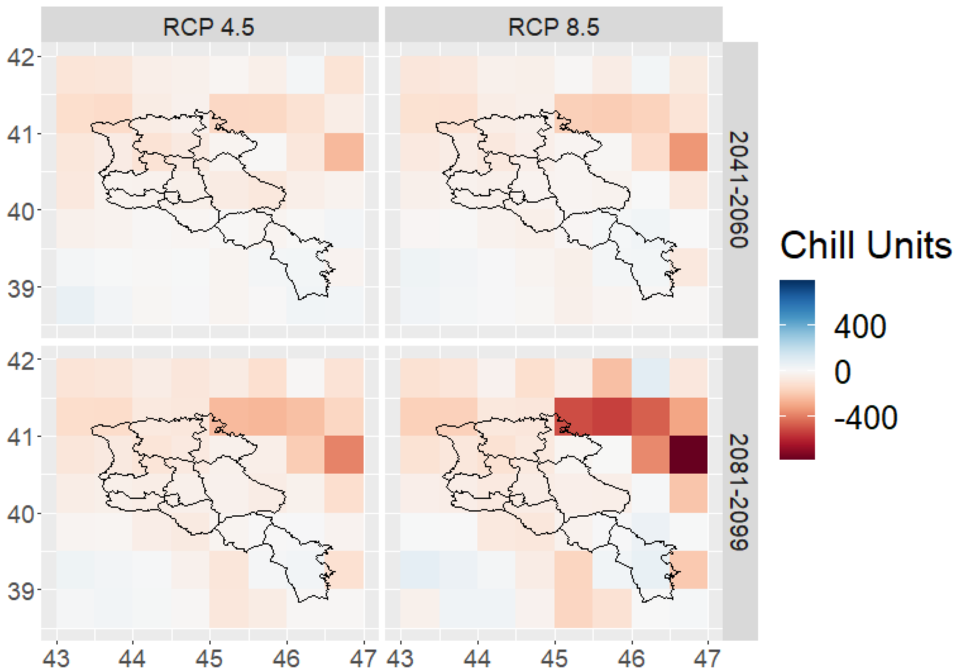

Figure 9: Change in maximum accumulated chill units for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099).

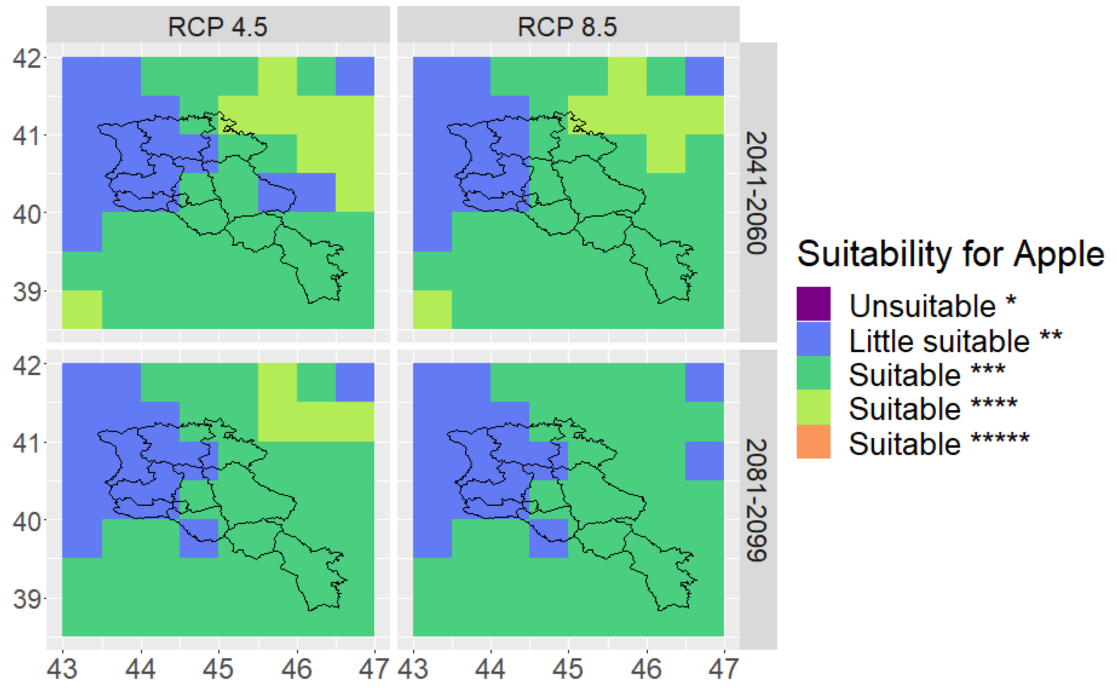

*Figure 10: Future suitability for the production of apple based on the average amount of chill units that accumulate until the end of each crop cycle, for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099). *Chill Units are below hist. minimum; **below hist. average but above hist. minimum; *** around hist. average; ****above hist. average but below hist. maximum; ***** above hist. maximum at the time of bud bursting.*

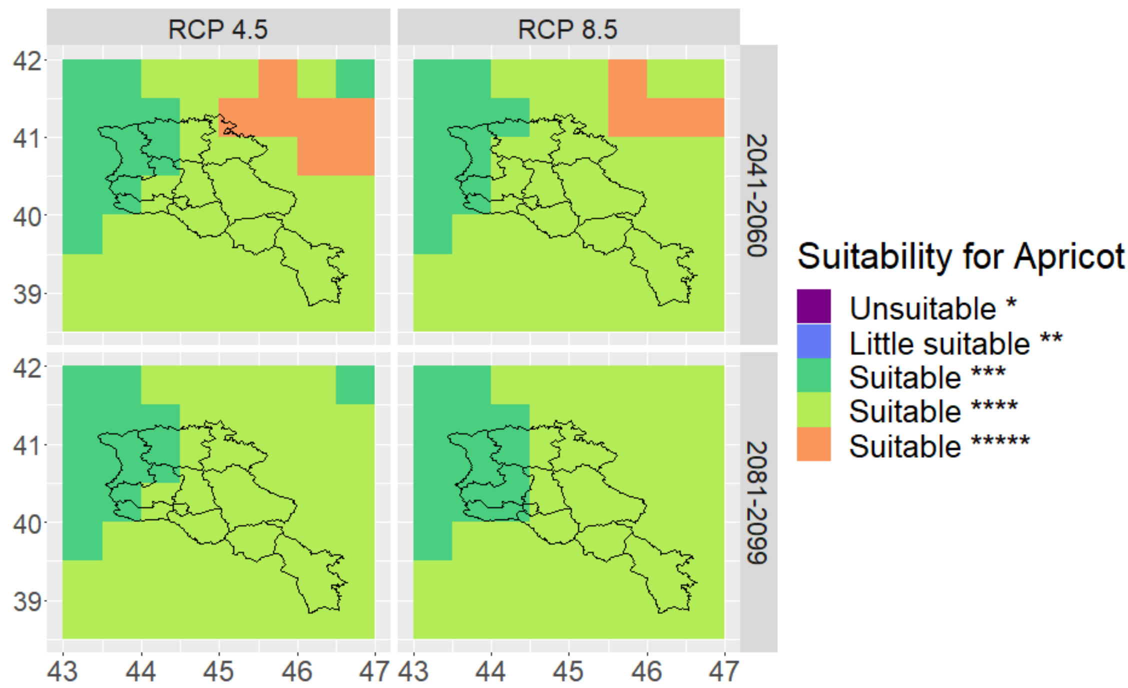

*Figure 11: Future suitability for the production of apricot based on the average amount of chill units that accumulate until the end of each crop cycle, for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099). *Chill Units are below hist. minimum; **below hist. average but above hist. minimum; *** around hist. average; ****above hist. average but below hist. maximum; ***** above hist. maximum at the time of bud bursting.*

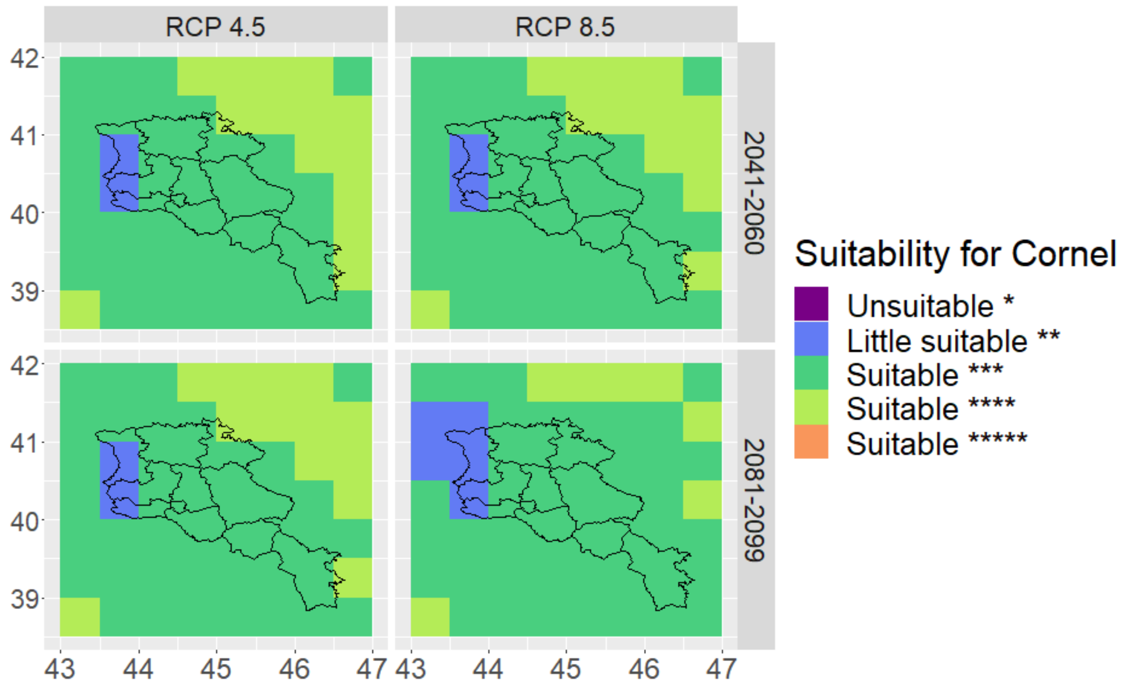

*Figure 12: Future suitability for the production of cornel based on the average amount of chill units that accumulate until the end of each crop cycle, for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099). *Chill Units are below hist. minimum; **below hist. average but above hist. minimum; *** around hist. average; ****above hist. average but below hist. maximum; ***** above hist. maximum at the time of bud bursting.*

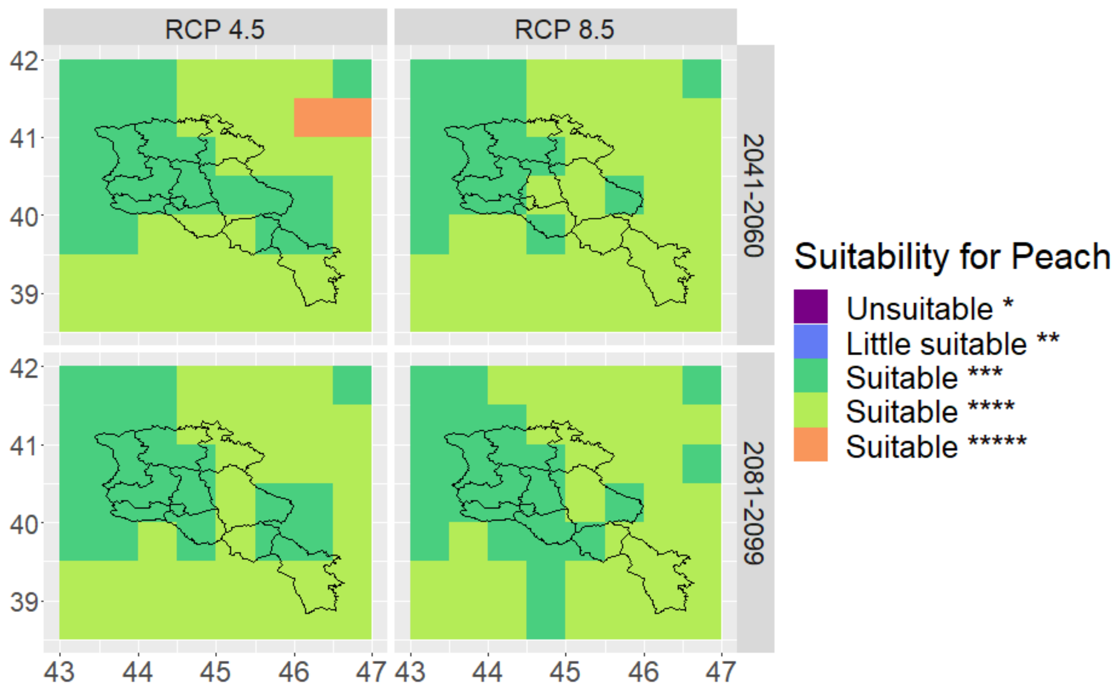

*Figure 13: Future suitability for the production of peach based on the average amount of chill units that accumulate until the end of each crop cycle, for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099). *Chill Units are below hist. minimum; **below hist. average but above hist. minimum; *** around hist. average; ****above hist. average but below hist. maximum; ***** above hist. maximum at the time of bud bursting.*

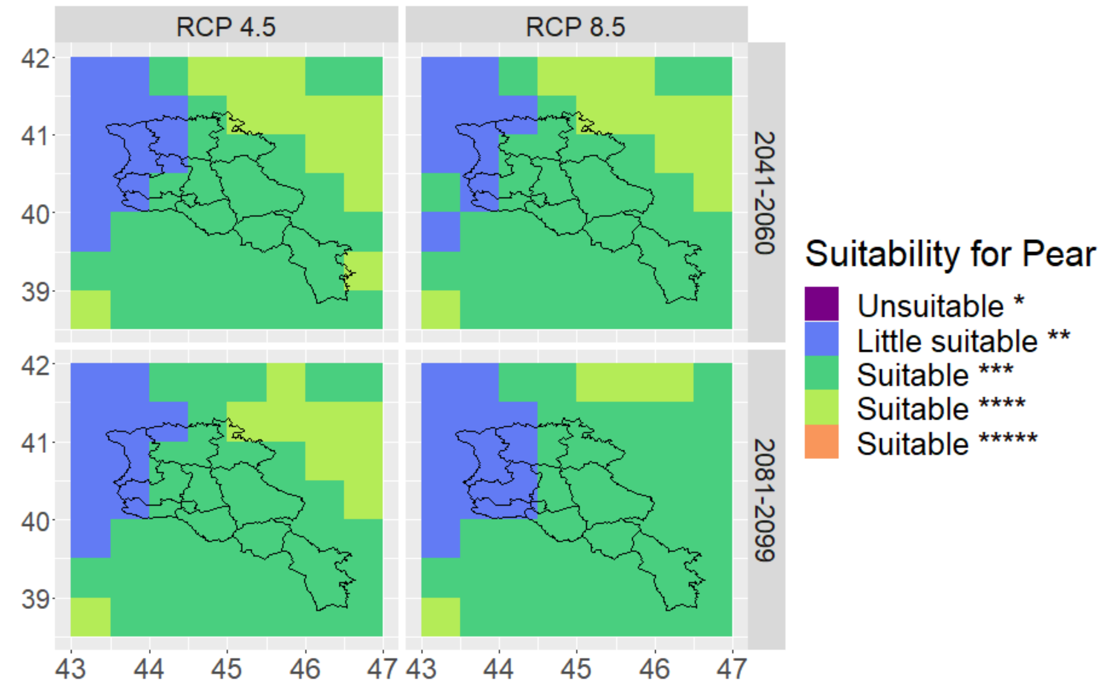

*Figure 14: Future suitability for the production of pear based on the average amount of chill units that accumulate until the end of each crop cycle, for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099). *Chill Units are below hist. minimum; **below hist. average but above hist. minimum; *** around hist. average; ****above hist. average but below hist. maximum; ***** above hist. maximum at the time of bud bursting.*

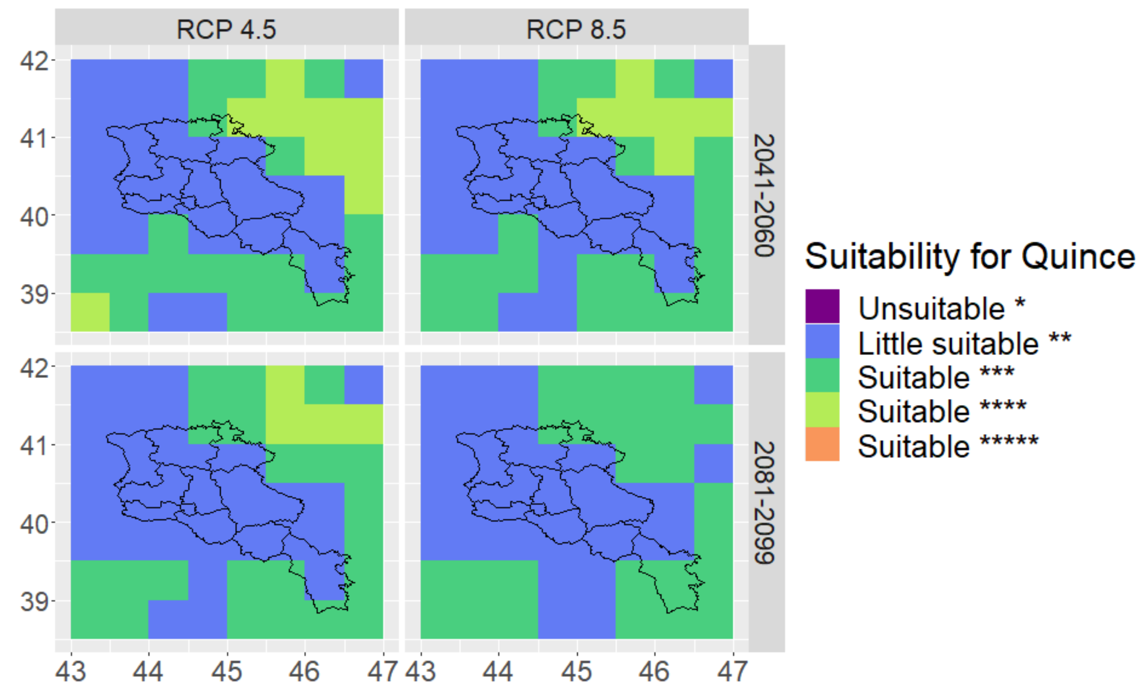

*Figure 15: Future suitability for the production of quince based on the average amount of chill units that accumulate until the end of each crop cycle, for two representative concentration pathways (RCP 4.5 and 8.5) and two future time periods (2041-2060 and 2081-2099). *Chill Units are below hist. minimum; **below hist. average but above hist. minimum; *** around hist. average; ****above hist. average but below hist. maximum; ***** above hist. maximum at the time of bud bursting.*

3. Discussion

We predicted future yield changes for grain crops and vegetables on the province level with climate projections and Random Forest models. We also predicted future production suitability for pomaceous and stone fruits on the grid cell level with a Chill Unit model. We assessed future conditions for two RCP scenarios and two time periods. Our results suggest that yields will considerably change in the future, and that there will be a tendency towards lower suitability for the production of fruits, particularly of pomaceous fruits. In these calculations, we did not account for any adaptation measure in crop management, land use, or technology.

Many grain crops and vegetables show considerable differences in predicted yield changes between provinces, and all crops show quite distinct overall spatial patterns, with decreases projected for most provinces. For winter wheat and spring barley, we predict the highest decreases in the southern part of the country, and increases in some provinces in the north. The positive correlation between heavy precipitation and winter wheat yield does not match our hypothesis that heavy precipitation towards the end of the crop cycle has negative effects on the harvesting process and arguably on yield. There is very little maize grown in Armenia and the yield record for this crop has large gaps for many provinces, so the results should not be overinterpreted. There is no clear spatial pattern for potato, however we mostly predict an increase in yield for Gegharkunik, where potato production is highest in the country. For tomato and cucumber, we mostly predict yield losses. The contribution of climatic factors such as temperature, heat and heavy precipitation to the predicted yield changes is very context-dependent and differs for crops and provinces. The high-yielding provinces of Armavir and Ararat, where irrigation and greenhouse production are widespread, seem to be only moderately affected by future yield changes in grain crops and vegetables. In general, there is a high agreement between the four yield prediction models that we carried out for each crop (RCP 4.5 and 8.5, near and far future). Predicted yield increases or decreases mostly intensify with higher future warming (RCP 8.5 represents more warming than RCP 4.5, and there is more warming in the far than in the near future).

Our results suggest that the suitability for pomaceous and stone fruits will decrease with increasing future warming, i.e. suitability is lower under RCP 8.5 than under RCP 4.5 and lower in the far future than in the near future. We showed that pomaceous fruits (apple, pear, and quince) are more prone to yield losses caused by insufficient chilling than stone fruits (apricot, cornel, and peach). However, our models predict that the entire country will remain suitable for the production of these crops, since the future amount of chilling is not projected to fall below the historically observed minima in any region. The western part of Armenia will likely experience the lowest total amount of chilling in the future. Most parts of the country will experience a moderate decrease in chilling; however, in the south, there will be a slight increase. While temperature increases in winter can lead to an increase in chilling when the minimum suitable temperature threshold of 1.5 °C is surpassed, temperature increases in spring can lead to less chilling when temperatures exceed 12.5 °C (see WP3, chapter 3.2 for methodological details). The predicted decreases in chilling accumulation suggest that the negative effects of spring warming may have outcompeted the positive effect of winter warming. Even though all areas of Armenia are predicted to experience amounts of chilling temperatures that are still within the range of historically observed amounts at bud bursting, we consider the overall tendency of decreasing chilling as a warning sign. In the future, fruit production might have to gradually shift to higher altitudes to ensure sufficient chilling under ongoing climate change.

The predicted yield changes and suitability maps should be interpreted with caution and only in relative terms. We emphasize to consider the following fundamental assumptions and limitations of our approach, in addition to the issues discussed in WP3:

- Our future yield predictions are based on empirical relationships between historical crop yields and historical climatic mean and weather extreme variables. We assume that these relationships will remain constant in the future. However, farmers will respond to climate change by adapting the crop management and the selection of crops and varieties planted. The deployment of irrigation systems or greenhouses and the use of drought-resistant cultivars could result in different empirical relationships between yield and climate in the future than what we found for the past. We cannot foresee how farmers will adapt to climate change and how the interlinkages between yield and climate will change in the future. It is also beyond the scope of this report to anticipate to which areas of Armenia cropland will likely expand in the future and where it may be abandoned.

- For some crops and regions, our models suggest considerable yield increases. Worldwide, agricultural yields have greatly improved over the last decades, but the annual percent yield gains have decreased in the last years and crops have physiological yield maxima that cannot be surpassed (Ray et al., 2012). We cannot account for such physiological limits in our models because we lack data about the cultivars grown in Armenia.

- We defined the future onset dates of crop development stages based on the average dates of the historical phenological record. However, crops will probably respond to climate change by changing their phenology. Our analyses indicate that such changes have already happened (see WP3, Annex A), but we cannot reliably forecast how such shifts will develop into the future under climate change. For example, between 1995 and 2020, the onset of early phenological phases in apricot has shifted and starts earlier across all agrometeorological stations, whereas later phases remain rather constant.

- In WP3, we discussed the limitations related to historical climate and weather data, phenological observations, and yield statistics. Future predictions contain much higher uncertainty: The uncertainty in the Random Forest models propagates and amplifies when we include future climate data. Moreover, the climate projections themselves contain uncertainty. While temperature can be predicted with high agreement among models, predictions of precipitation and extreme weather events are highly uncertain for the future.

4. Literature

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