Agricommend: An Intelligent Crop Recommendation Tool

Mehmed Nazif Taşbaş

20 Jul 2022

METU SAMSUNG TBV TÜRKİYE BİLİŞİM VAKFI UNDP 2 ZERO HUNGER

Outline

- Background
- Dataset
  - Feature Engineering
  - Descriptive Statistics
  - Exploratory Data Analytics
- Models
  - Base model, Decision Tree
  - Other models
  - Model Comparison
- Hyperparameter Tuning
- Conclusion
  - Limitations
  - Future Work
  - References & Further Reading

Background

- Global Events converge into a looming food crisis
  - Supply chain issues
  - Agricultural land & crop loss due to climate crisis
  - Inflation
    - Fertilizer prices are up 50%, oil prices are up 66% and food prices are up 33% since last year*
  - Russian invasion of Ukraine
    - Russia and Ukraine provides
  - Food protectionism across the globe

* UN Estimates, taken from UN Secretary-General António Guterres' Remarks on 18 May, 2022

More information at github repo: https://tinyurl.com/SIC-agricommend

CNBC

Search quotes, news & videos

MARKETS BUSINESS INVESTING TECH POLITICS CNBC TV INVESTING CLUB PRO MAKE IT

FOOD ECONOMICS

FOOD ECONOMICS

The food security crisis could kill more people than Covid has, says Senegal minister at G-20

PUBLISHED MON, JUL 18 2022•9:17 PM EDT | UPDATED TUE, JUL 19 2022•9:31 AM EDT

Su-Lin Tan
@SULIN_TAN

SHARE

Supermarkets

Average UK food bill rises by £454 a year as grocery inflation nears 14-year high

Prices of butter, milk and pet food rise at the fastest rates as shoppers face cost of living squeeze

Sarah Butler *and* Phillip Inman

Tue 19 Jul 2022 17.04 BST

UK shoppers sought ways to cut their food bills amid rising prices. Photograph: Neil Hall/EPA

Supermarket inflation is expected to reach the highest level since at least 2008 in August after rising to almost 10% this month, amid the worst squeeze on household budgets on record.

Opinion
Famine

The Guardian view on the global food crisis: no time to lose

Editorial

Thu 7 Jul 2022 18.42 BST

114

Russia's invasion of Ukraine has exacerbated a desperate situation. Famine is not inevitable – but action must be swift

A convoy of trucks, part of the World Food Programme, on their way to Tigray, Ethiopia. 'In parts of Ethiopia, Somalia, South Sudan, Yemen and Afghanistan, sections of the population are enduring catastrophic levels of hunger.' Photograph: Eduardo Soteras/AFP/Getty Images

npr

SIGN IN NPR SHOP DONATE

NEWS CULTURE MUSIC PODCASTS & SHOWS SEARCH

WORLD

Record number of people worldwide are moving toward starvation, U.N. warns

July 7, 2022 · 2:15 AM ET

THE ASSOCIATED PRESS

Rising global food protectionism amid Ukraine war risks worsening inflation

Countries are restricting exports to cope with high prices that have been exacerbated by the war in Ukraine

Topics

food export | Russia Ukraine Conflict | food security

Low De Wei | Bloomberg

Last Updated at May 25, 2022 08:28 IST

WFP World Food Programme

SAVING LIVES CHANGING LIVES

ENGLISH

WHO WE ARE | OUR WORK | WHERE WE WORK | GET INVOLVED | MEDIA & RESOURCES | DONATE

Home › Publications › War in Ukraine drives global food crisis

24 June 2022

War in Ukraine drives global food crisis

Reports | Conflicts

A global food crisis fuelled by conflict, climate shocks and the COVID-19 pandemic is growing because of the ripple effects of the war in Ukraine driving rising prices of food, fuel and fertilizer. Millions of people across the world are at risk of being driven into starvation unless action is taken now to respond together and at scale. Due to the unprecedented overlap of crises, WFP's annual operational requirements are at an all-time high of US$22.2 billion, with confirmed contributions so far at US$4.8 billion (22 percent). WFP is calling for coordinated action to address this crisis.

United Nations | UN News
Global perspective Human stories

Search
Advanced Search

Home | Topics | In depth | Secretary-General | Media

AUDIO HUB SUBSCRIBE

Global hunger crisis pushing one child per minute, into severe malnutrition

United Nations | UN News
Global perspective Human stories

Search
Advanced Search

Home | Topics | In depth | Secretary-General | Media

AUDIO HUB SUBSCRIBE

World is moving backwards on eliminating hunger and malnutrition, UN report reveals

Problems & Solutions

- Problems
  - Agricultural **efficiency**
  - **Misutilization** of agricultural land
  - Access to agricultural **expertise** in developing countries
- Solutions
  - Dire need to boost global food production by any means
  - Boosting agricultural efficiency through knowledge
  - Recommending small scale food producers which crops to plant, using AI
- SDG's
  - SDG 2, End World Hunger

Dataset

- Dataset taken from Kaggle user @atharvaingle
- 2.2k lines of data
  - **22 crops**, 100 records each
- Features
  - N, P and K amounts (kg/hectare)
  - Temperature (Celsius)
  - Relative Humidity
  - pH
  - Rainfall (mm)
- Crops ranging from legumes to fruits

Feature Engineering

- Dataset already tabularized
  - No data cleanup needed
- New feature is derived
  - **Absolute humidity** from temperature and relative humidity
- Limitations of derivation
  - Pressure assumed constant (no data on pressure or elevation), ignored in calculations

$$AH = \frac{RH \times P_s}{R_w \times T \times 100}$$

AH = Absolute Humidity

RH = Relative Humidity

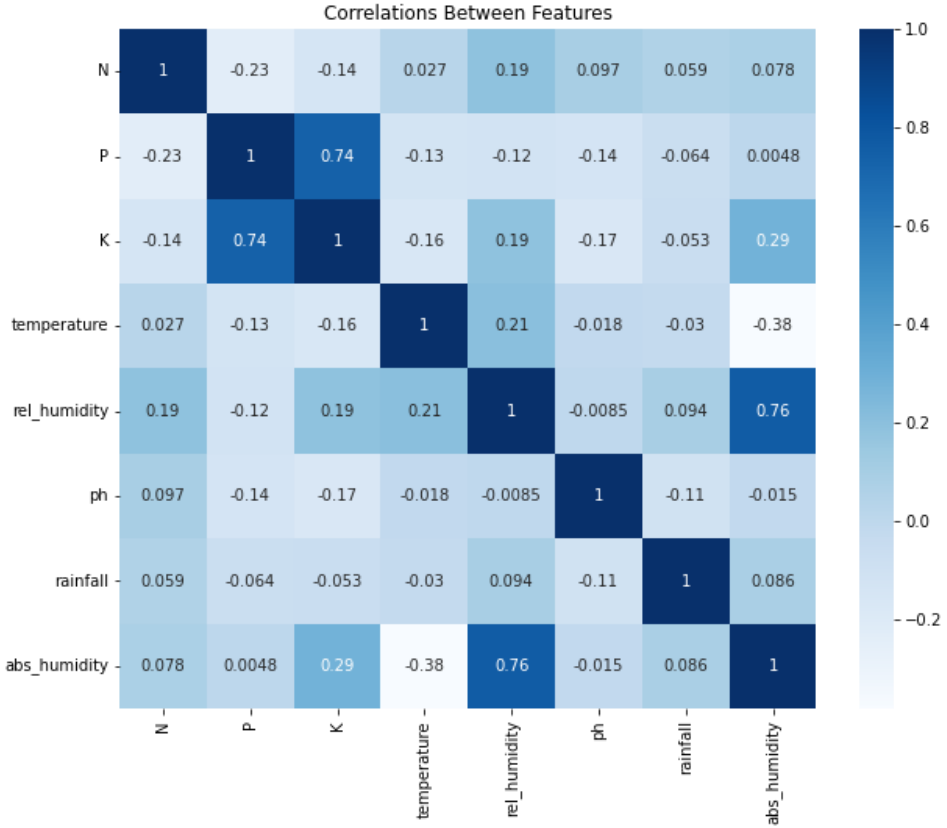
Ps = Saturation Vapor Pressure

Rw = Constant for water vapor

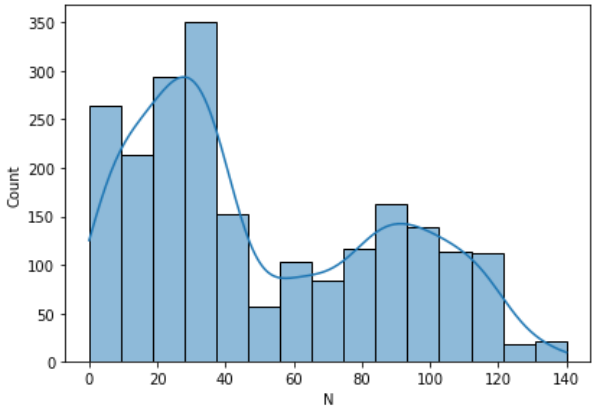
T = Temperature

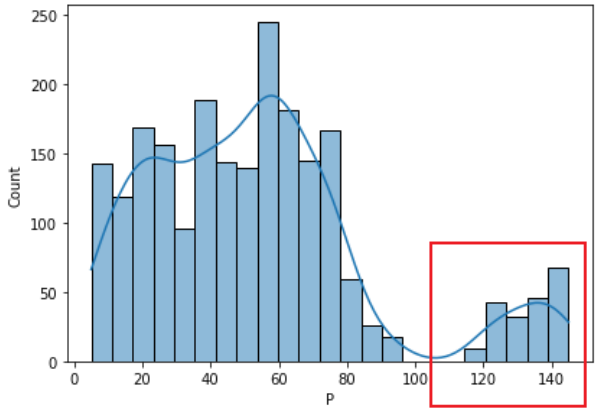
Descriptive Statistics

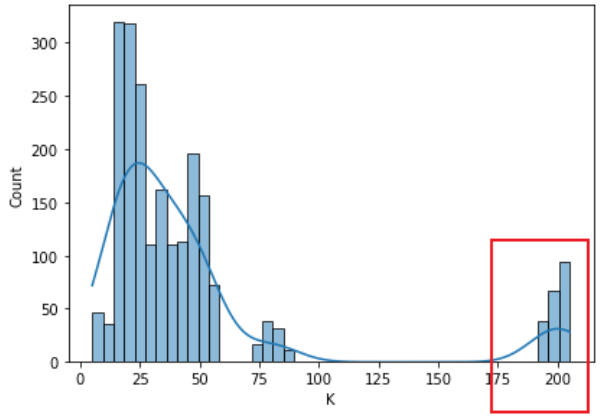
- Correlations
  - Potassium & Phosphorus
  - Relative & Absolute Humidity

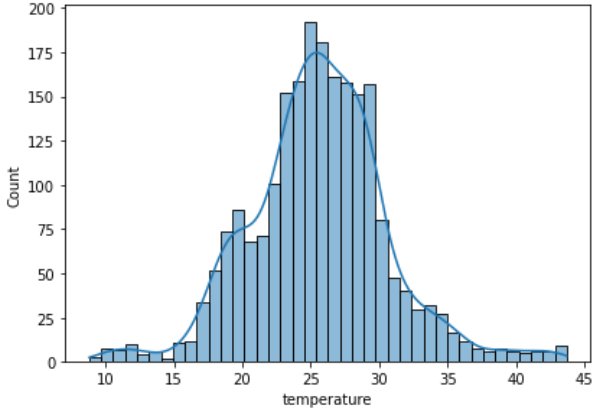


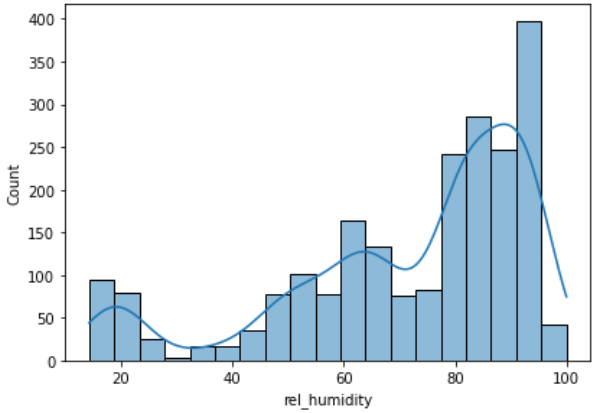
Distributions of Features

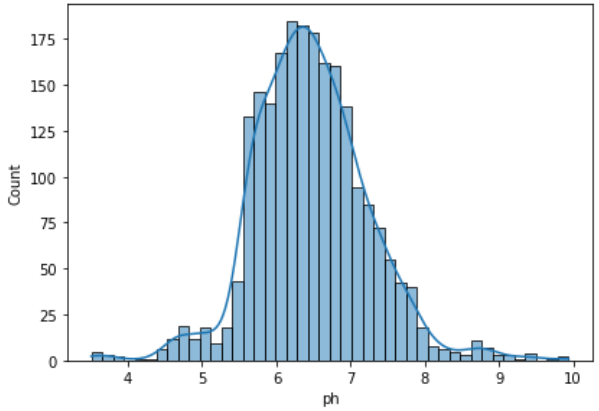


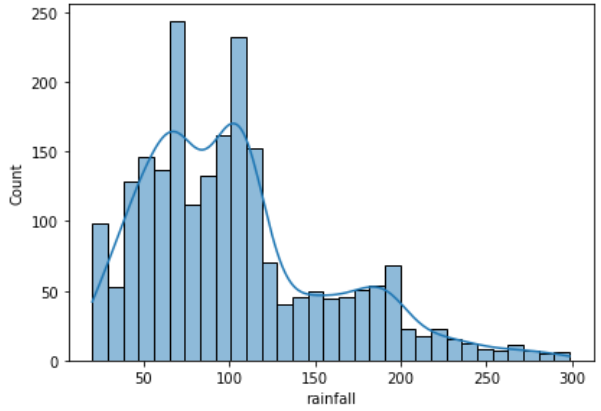


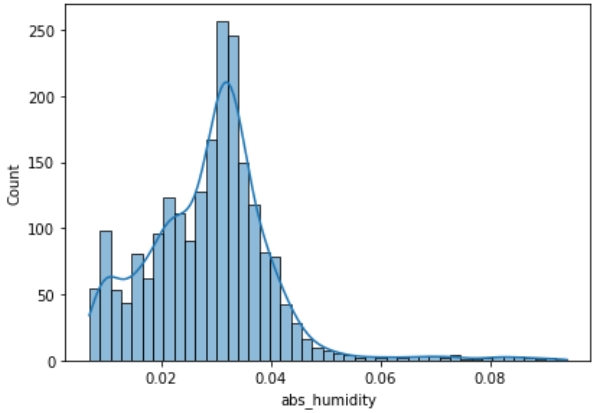




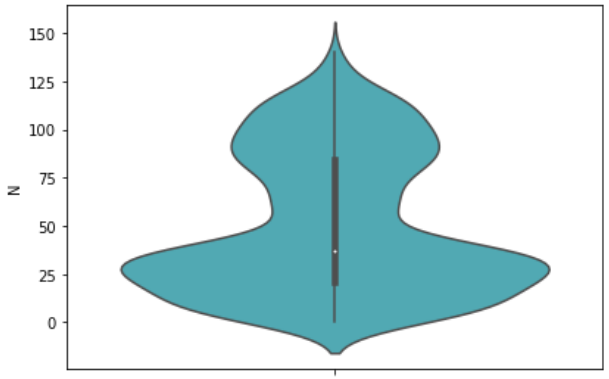


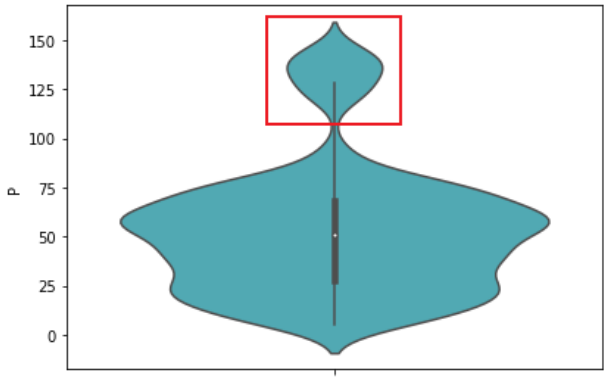


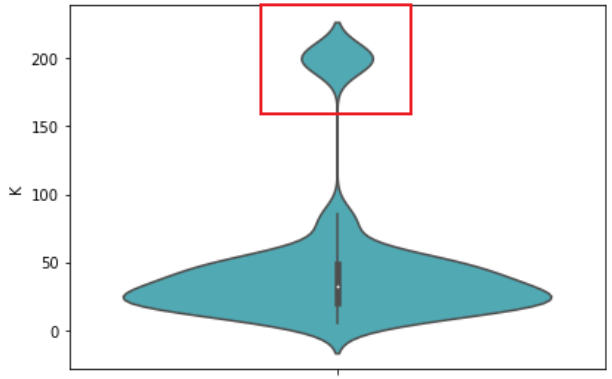


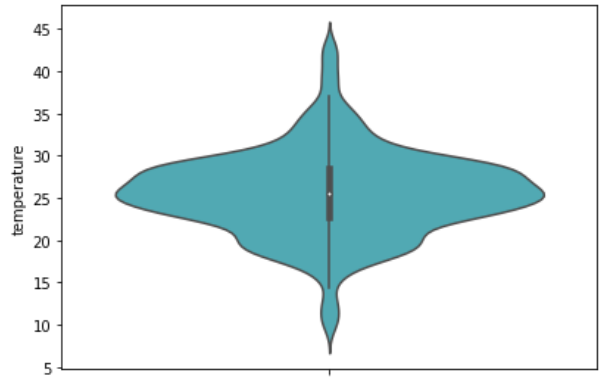


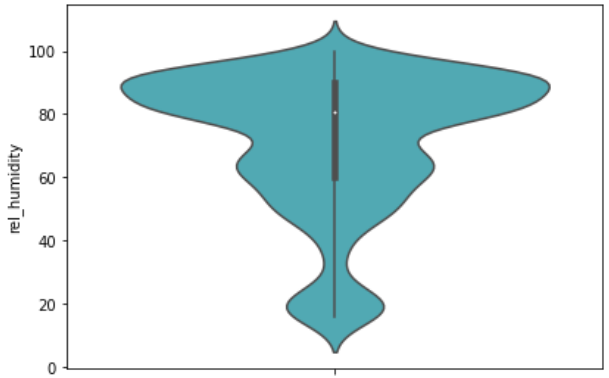
Distributions of Features

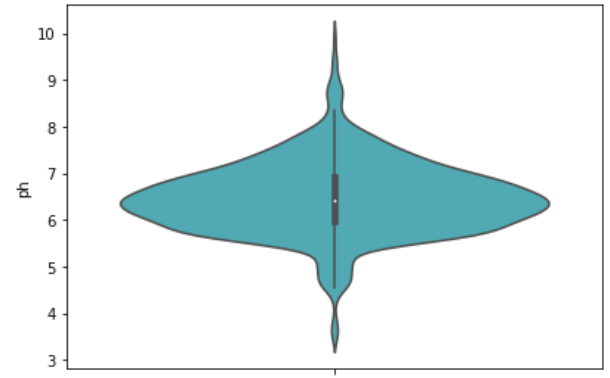


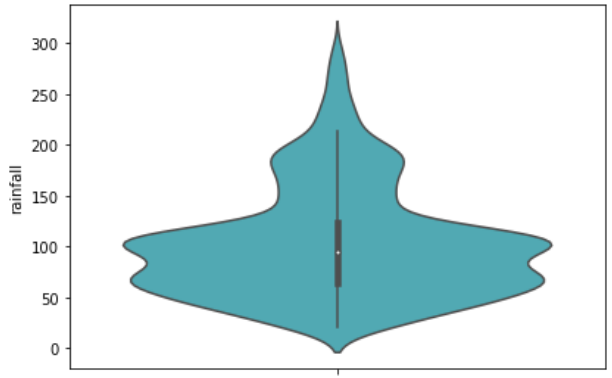


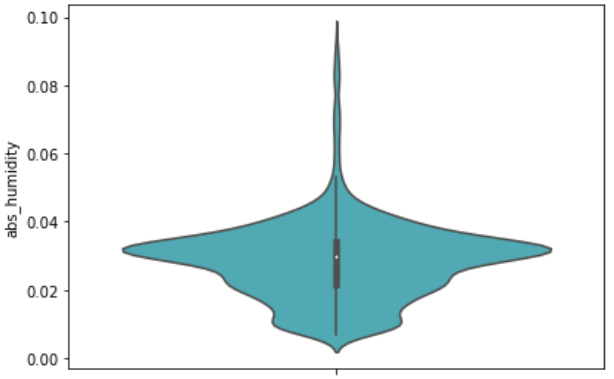




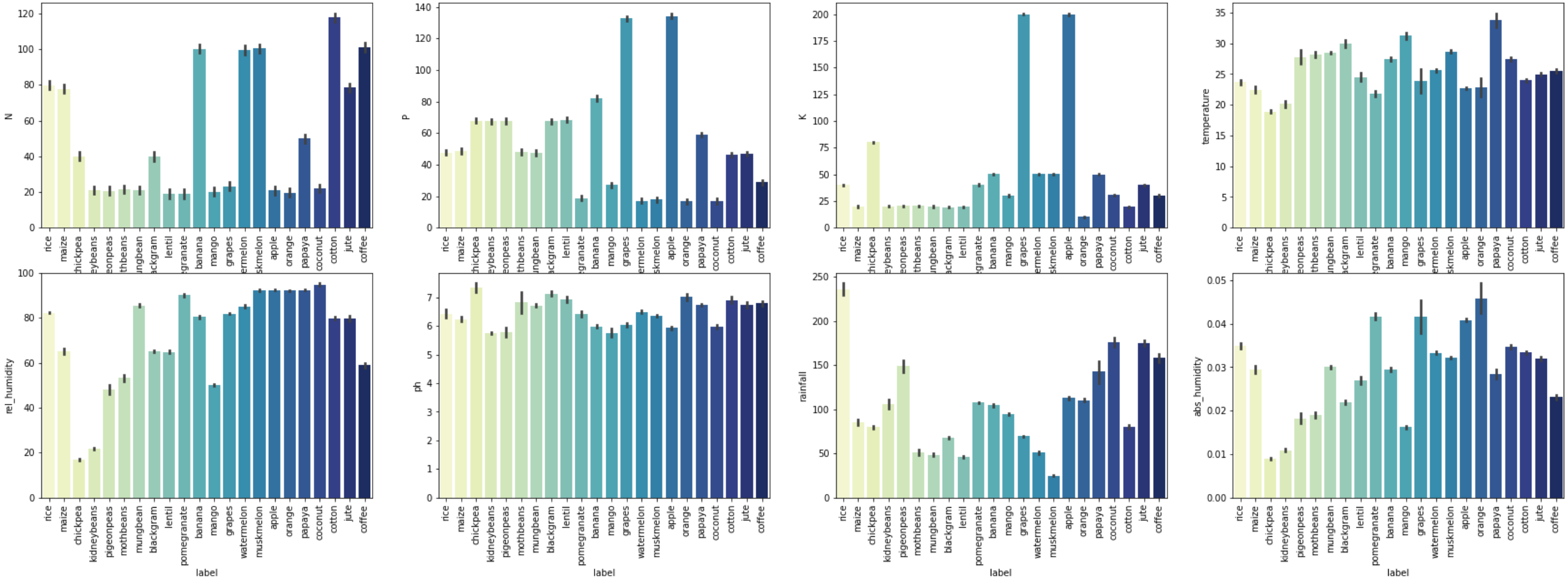








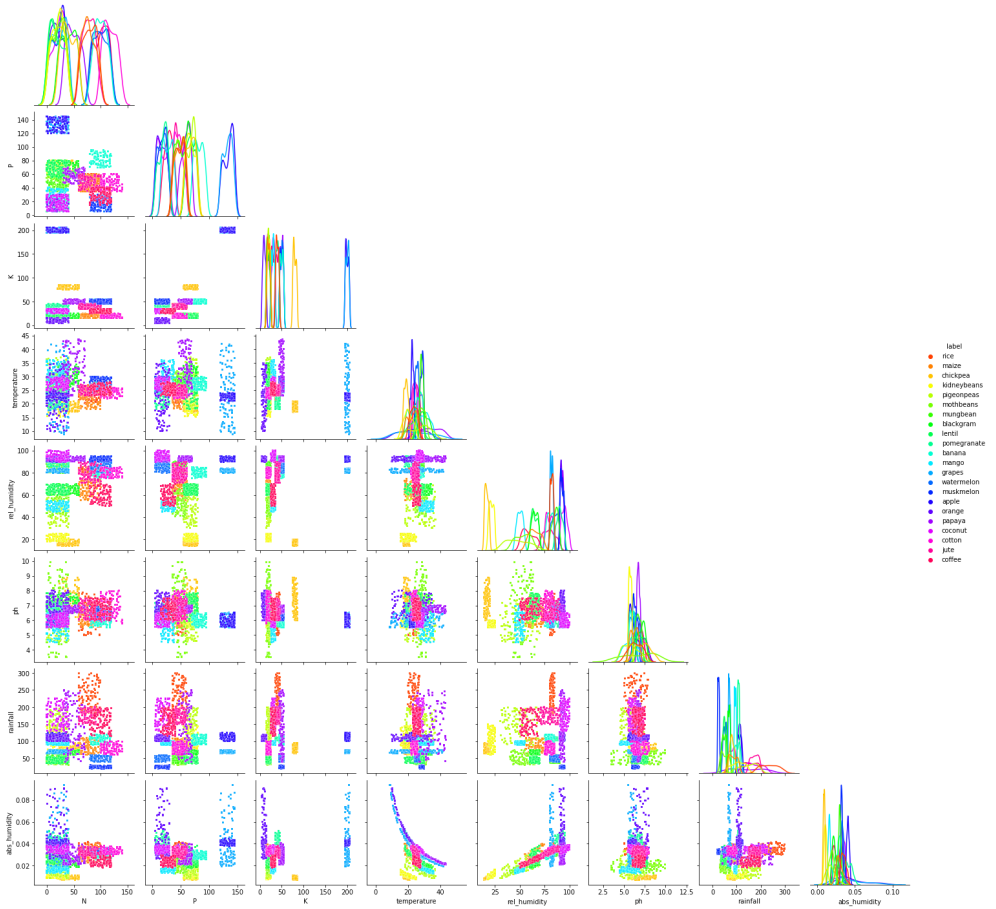
Crops vs Features View

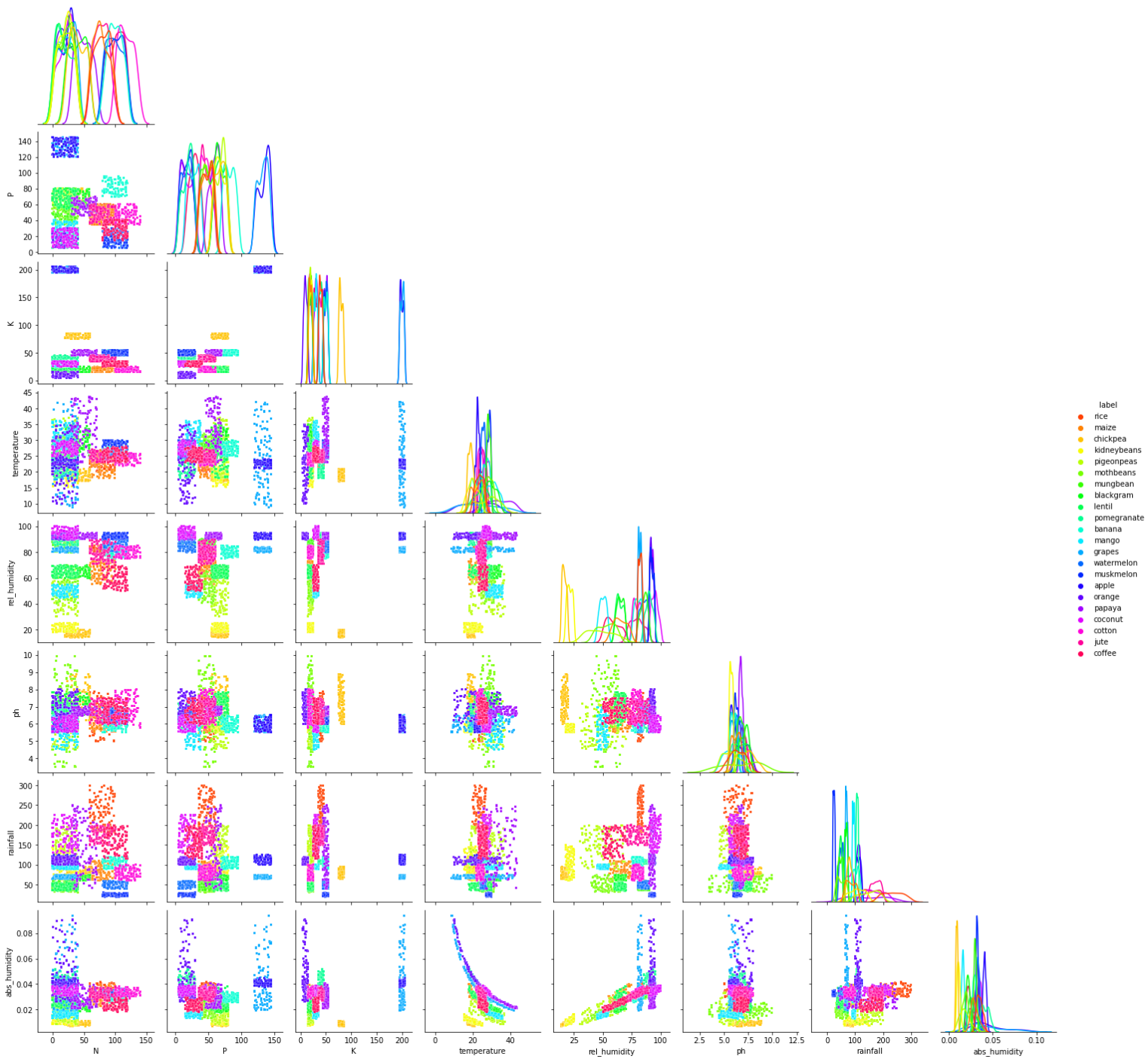


Pair Plots

- Pair plots show how grouped / disperse the dataset is

- Observations:
  - Features are highly diverged on most crops

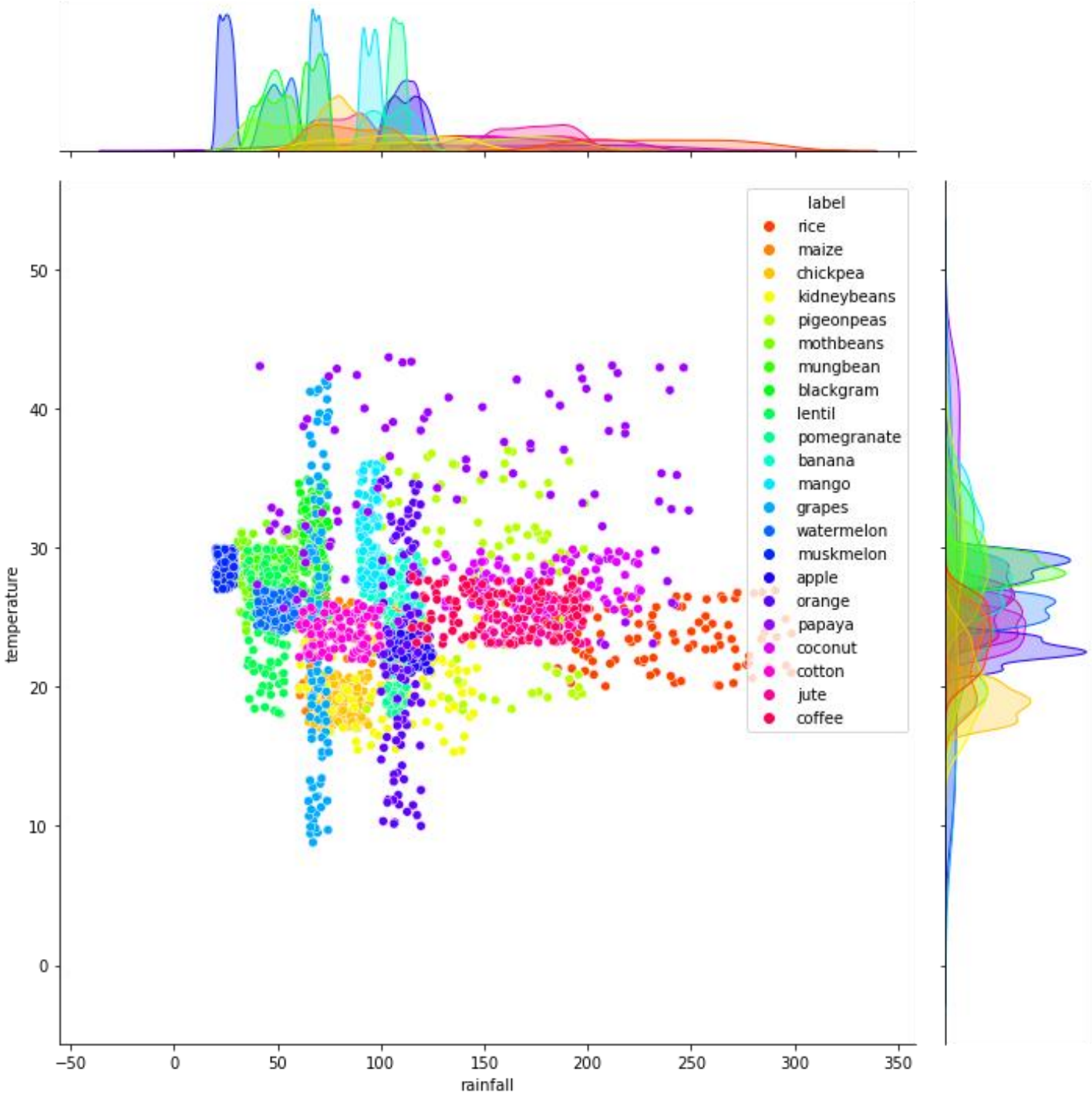


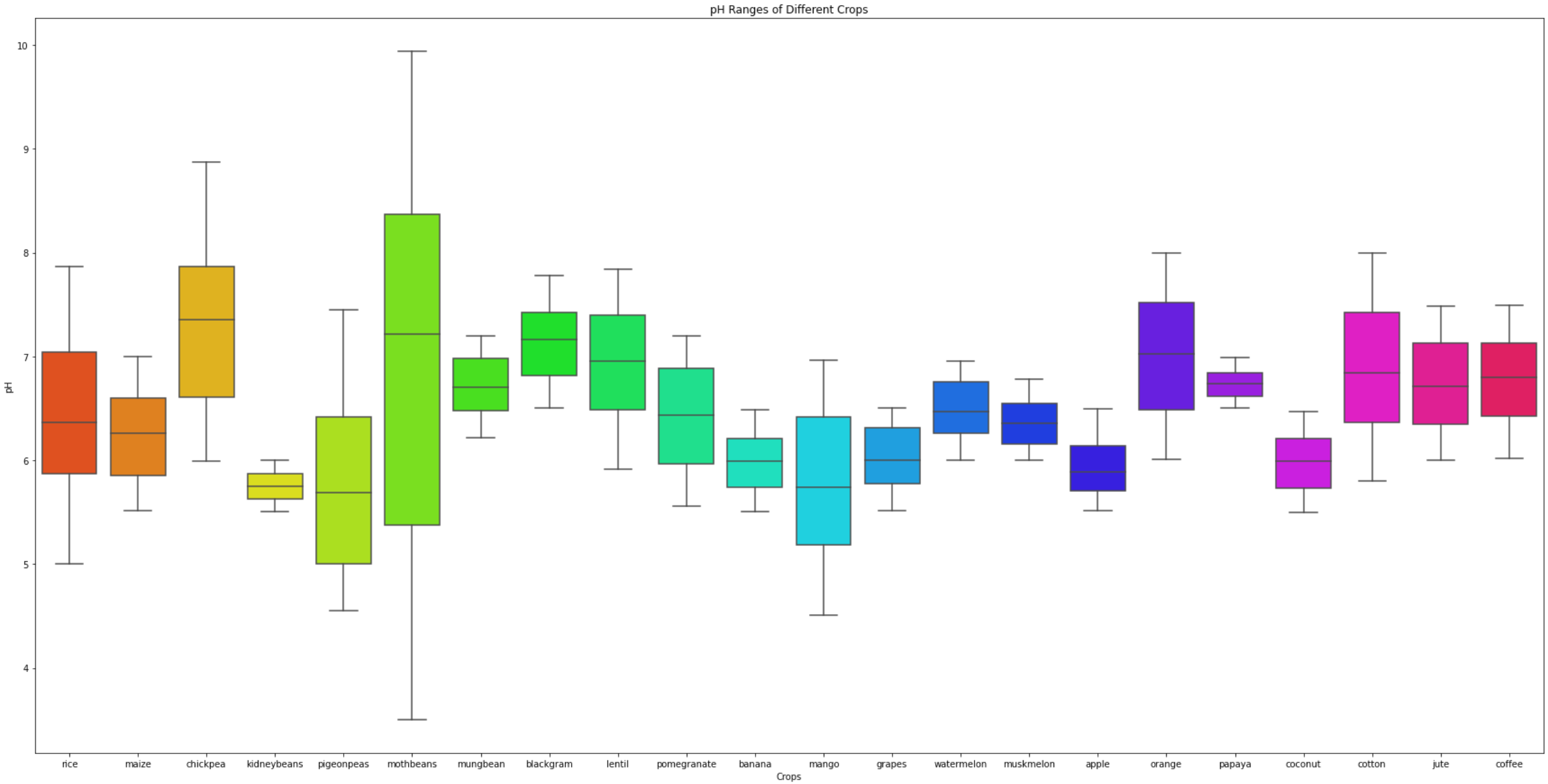

label
rice
maize
chickpea
kidneybeans
pigeonpeas
mothbeans
mungbean
blackgram
lentil
pomegranate
banana
mango
grapes
watermelon
muskmelon
apple
orange
papaya
coconut
cotton
jute
coffee
N
P
K
temperature
rel_humidity
ph
rainfall
abs_humidity

Exploratory Data Analysis

- Exploring the data to see trends and anomalies
- “Data describing itself”

```
Which crops require high ratio (>120) of Nitrogen content in soil ?     ['cotton']
Which crops require high ratio (>100) of Phosphorus content in soil ?   ['grapes' 'apple']
Which crops require high ratio (>200) of Potassium content in soil ?    ['grapes' 'apple']
Which crops require high (>200) rainfall ?      ['rice' 'papaya' 'coconut']
Which crops require low (<30) rainfall ?        ['muskmelon']
Which crops can grow under low (<10) temperature ?      ['grapes']
Which crops can grow under high (>35) temperature ?     ['pigeonpeas' 'mango' 'grapes' 'papaya']
Which crops can survive acidic (<5) soil?       ['pigeonpeas' 'mothbeans' 'mango']
Which crops can survive basic (>9) soil?        ['mothbeans']
```


label
rice
maize
chickpea
kidneybeans
pigeonpeas
mothbeans
mungbean
blackgram
lentil
pomegranate
banana
mango
grapes
watermelon
muskmelon
apple
orange
papaya
coconut
cotton
jute
coffee
temperature
rainfall
0
10
20
30
40
50
−50
0
50
100
150
200
250
300
350


pH Ranges of Different Crops
pH
10
9
8
7
6
5
4
rice
maize
chickpea
kidneybeans
pigeonpeas
mothbeans
mungbean
blackgram
lentil
pomegranate
banana
mango
grapes
watermelon
muskmelon
apple
orange
papaya
coconut
cotton
jute
coffee
Crops

Models

- Dataset split as **80%** (n=1760) train and **20%** (n=440) test
  - **Stratification** according to the labels

- Normalization done using **sklearn.StandardScaler()**
  - Normalized data used in some select models

- Scaling done using **sklearn.MinMaxScaler()**
  - Scaled data used in visualizations

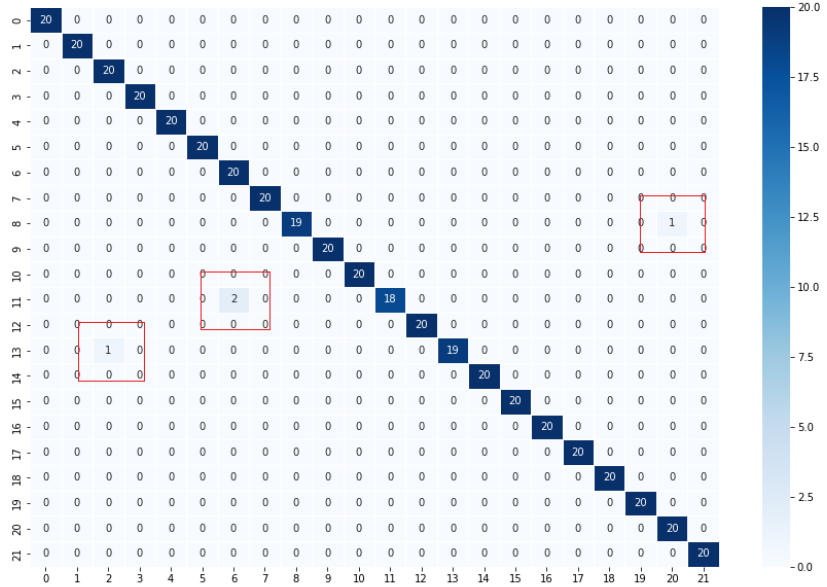
Decision Tree

- Base model

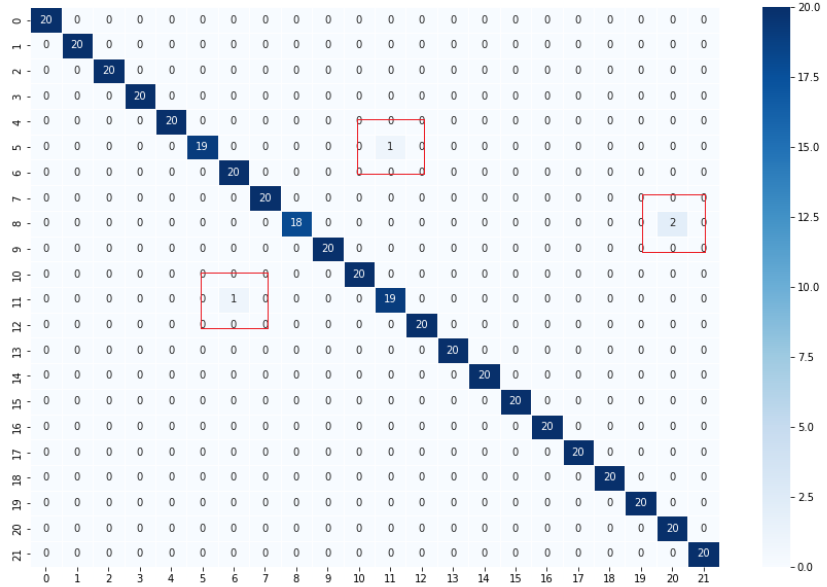
- 4 derivatives created
  - Criterions = **gini** and **entropy**
  - Dataset = regular and normalized

Decision Tree Models

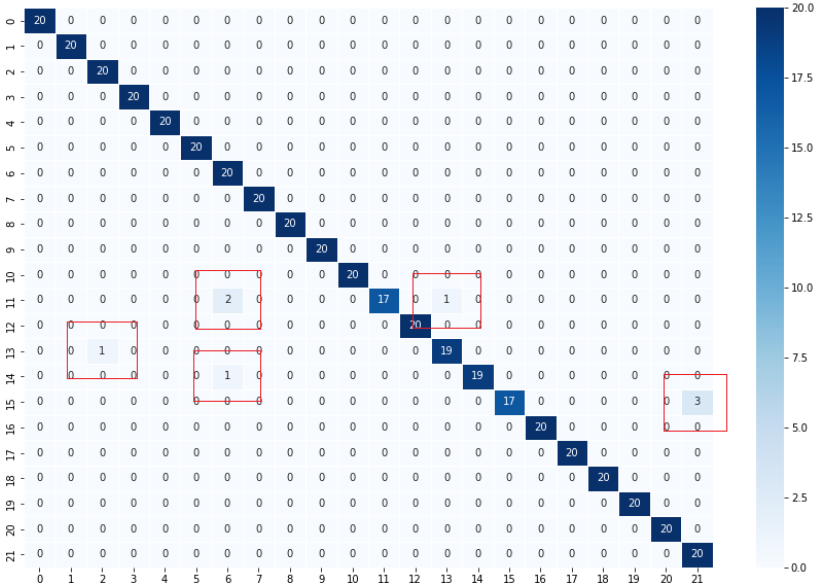
Gini



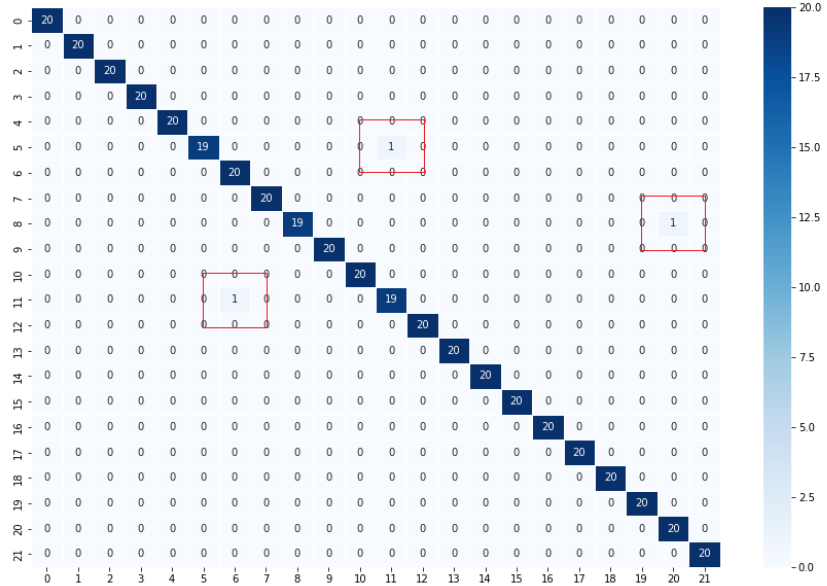
Entropy



Gini, Normalized Data



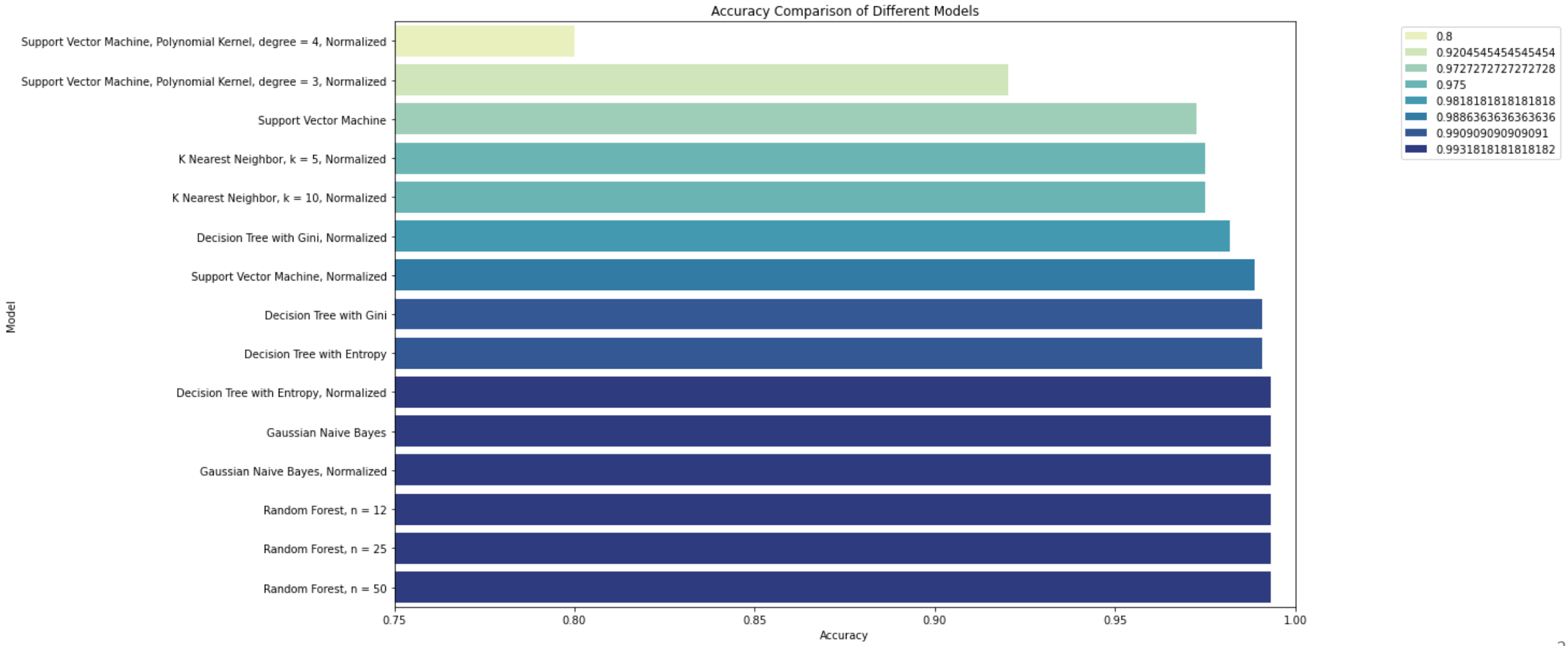
Entropy, Normalized Data



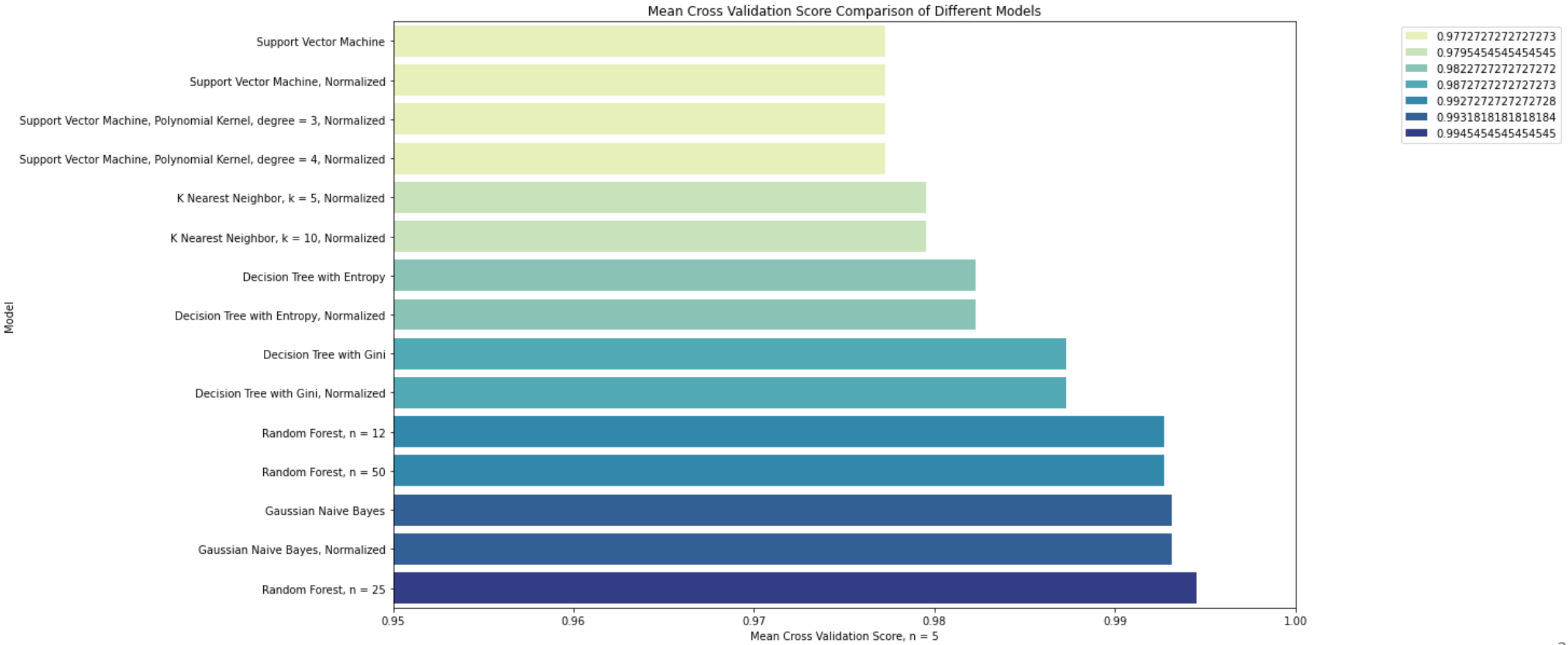
Other Models

- **Naïve Bayes**, 2 models
  - Regular and normalized data
- **SVM**, 2 models
  - Regular and normalized data
- **SVM** polynomial kernel, 2 models
  - n = 3 and n = 4, normalized data
- **Random Forest**, 3 models
  - n = 12, n = 25 and n = 50, regular data
- **KNN**, 2 models
  - k = 5 and k= 10, normalized data

Model Comparison



Model Comparison



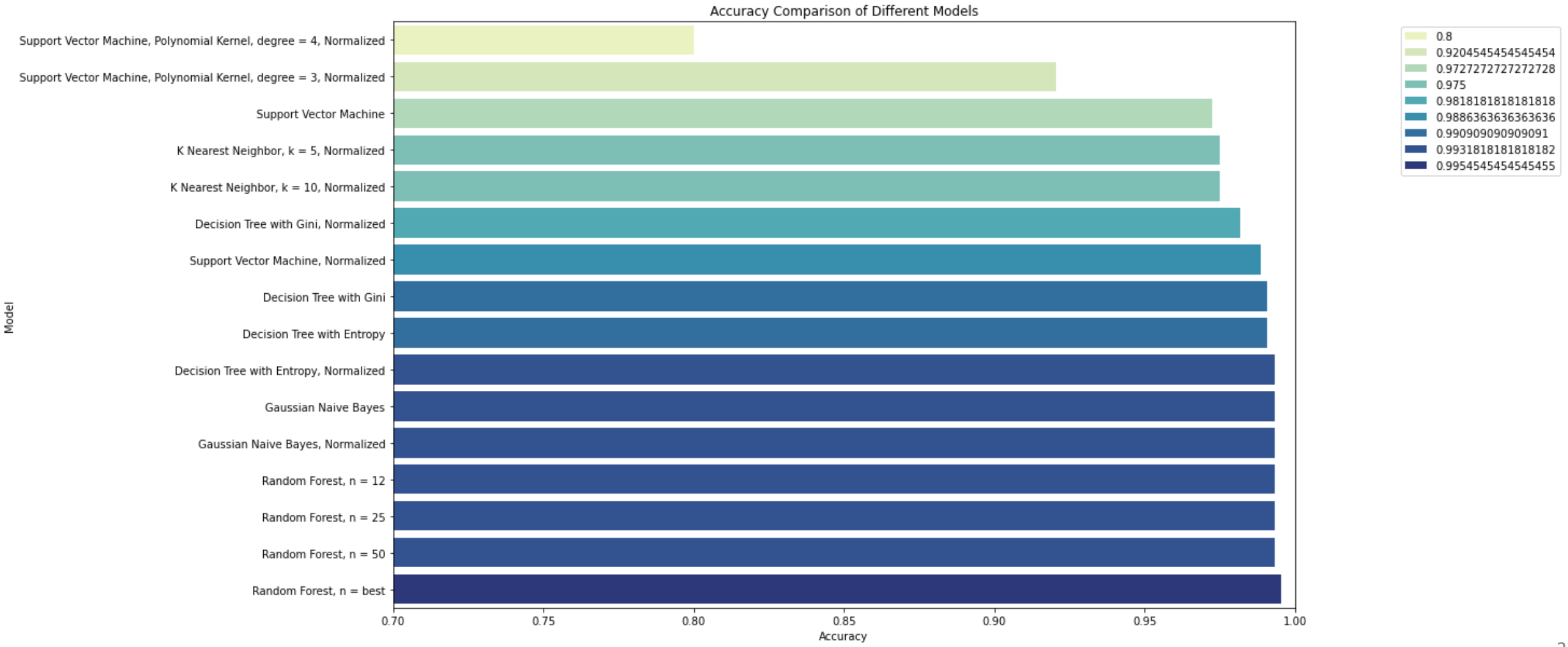
Hyperparameter Tuning

- Best performing model selected
  - Random forest, n = 25
  - Accuracy = **0.9931**
  - Due to its performance in CV

- 900 cycles of tuning
  - Done using sklearn.RandomizedSearchCV()

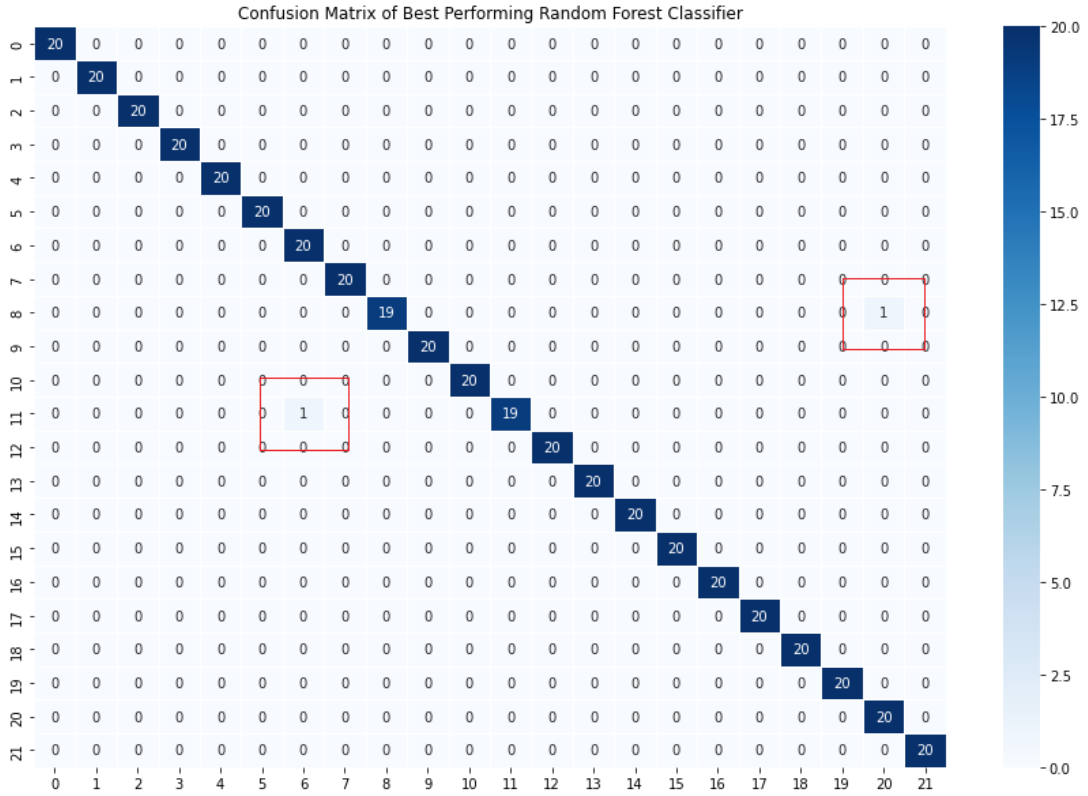
- Best model
  - n = 410, min_split = 8 and min_leaf = 1
  - Accuracy = **0.9954**

Final Accuracy Comparison



Metrics

- Overfit control
  - Train accuracy = 1.0
  - Test accuracy = 0.995454



Prediction

```
# the order of values are as following:
# ["N", "P", "K", "temperature", "rel_humidity", "ph", "rainfall", "abs_humidity"]

data_to_be_predicted = np.array([[60, 20, 40, 35, 50, 5, 1000, 200]])
prediction = rf_best.predict(data_to_be_predicted)
print(prediction)
```

[62] ✓ 0.9s

```
['coffee']
```

```
# the order of values are as following:
# ["N", "P", "K", "temperature", "rel_humidity", "ph", "rainfall", "abs_humidity"]

data_to_be_predicted = np.array([[60, 60, 20, 25, 50, 9, 50, 200]])
prediction = rf_best.predict(data_to_be_predicted)
print(prediction)
```

[72] ✓ 0.1s

```
['maize']
```

Limitations

- Transferability of results to Turkey
  - Dataset is made for India
  - If crops' needs are met, there shouldn't be any issues

- Derived feature, absolute humidity
  - India's avg elevation is **621mt***
    - **0.93 atm** avg pressure
  - Turkey's avg elevation is **1141 mt***
    - **0.87 atm** avg pressure
  - Under same conditions of temperature & relative humidity
    - India's avg absolute humidity levels should be **%6.89** higher than Turkey's

- Dataset is very small
  - There was no budget **(30 $)** to buy a better dataset
    - plantsforafuture.com Temperate Plant Database

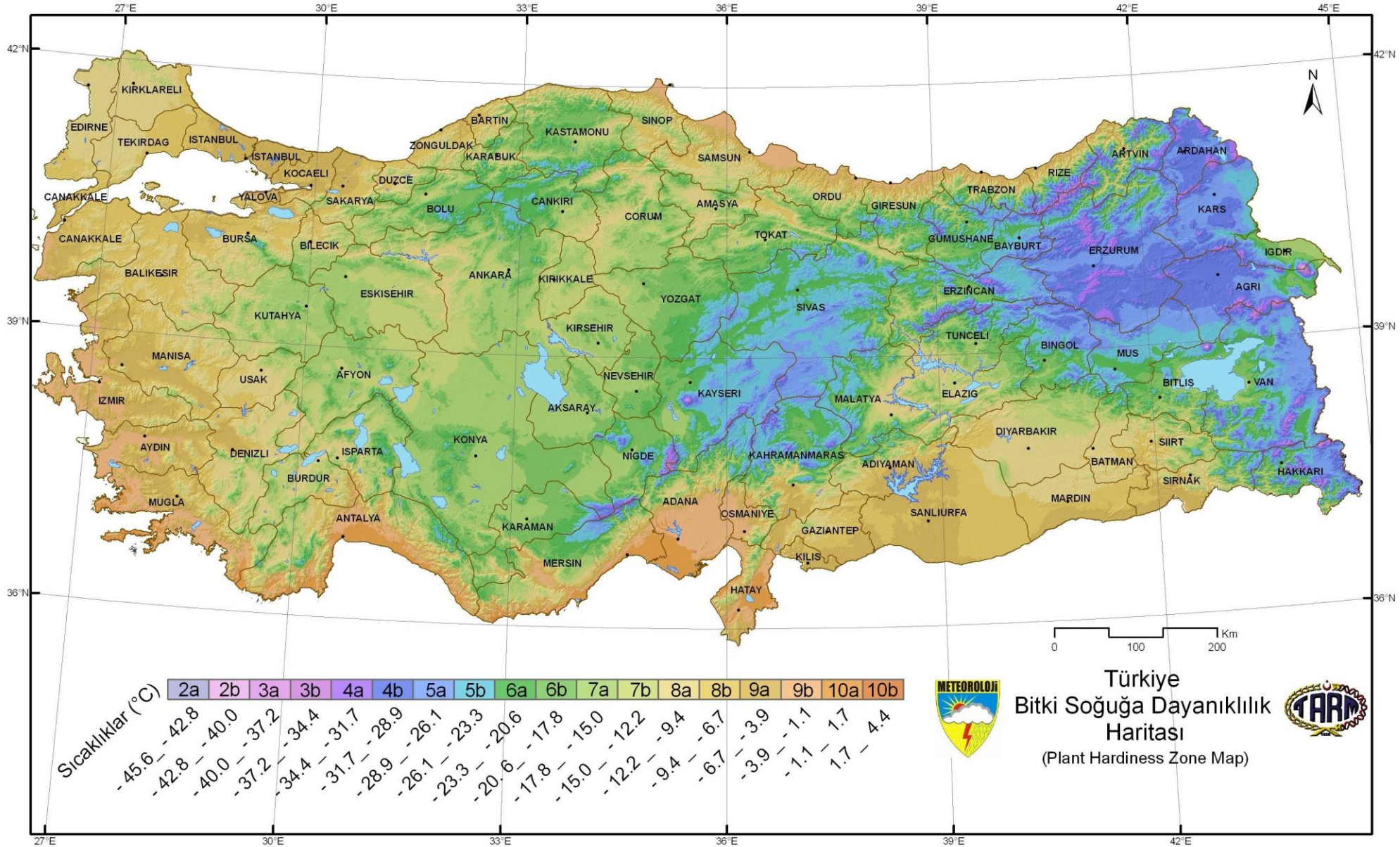
*Wikipedia/List of countries by average elevation

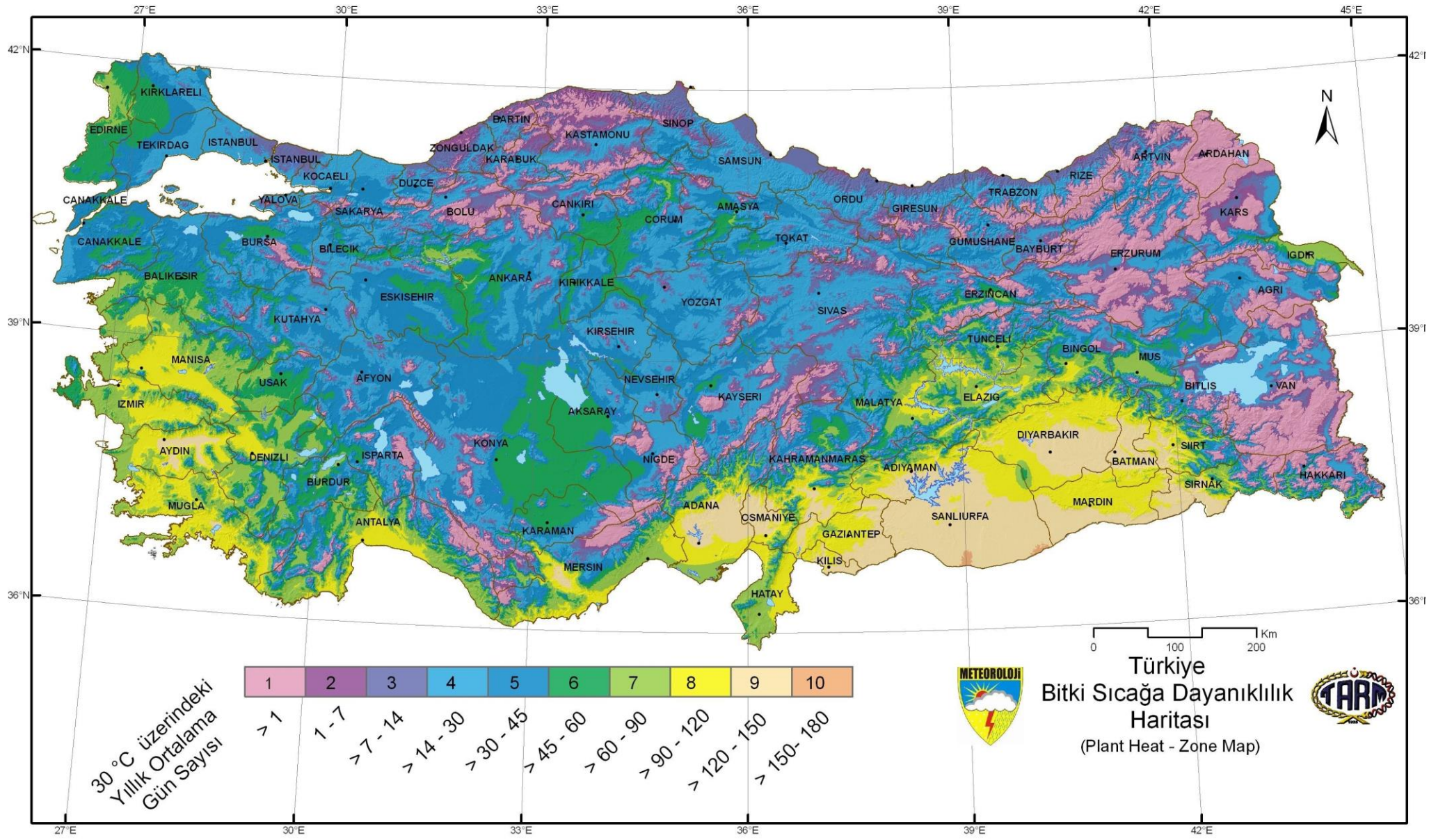
Future Work

- Improving the dataset
  - Adding **Plant Hardiness Zones**
    - Most widely used system to assess plant survivability
    - Developed by **US Dept. of Agriculture**
  - Adding **Plant Heat Zones**
    - Days with temperatures above 30 C
  - Adding **Köppen Climate Classification** tags
    - Most widely used climate classification system
- Adding market value data of crops
  - Real-time queries, using a market maker API
  - May suggest crops in response to **price trends**

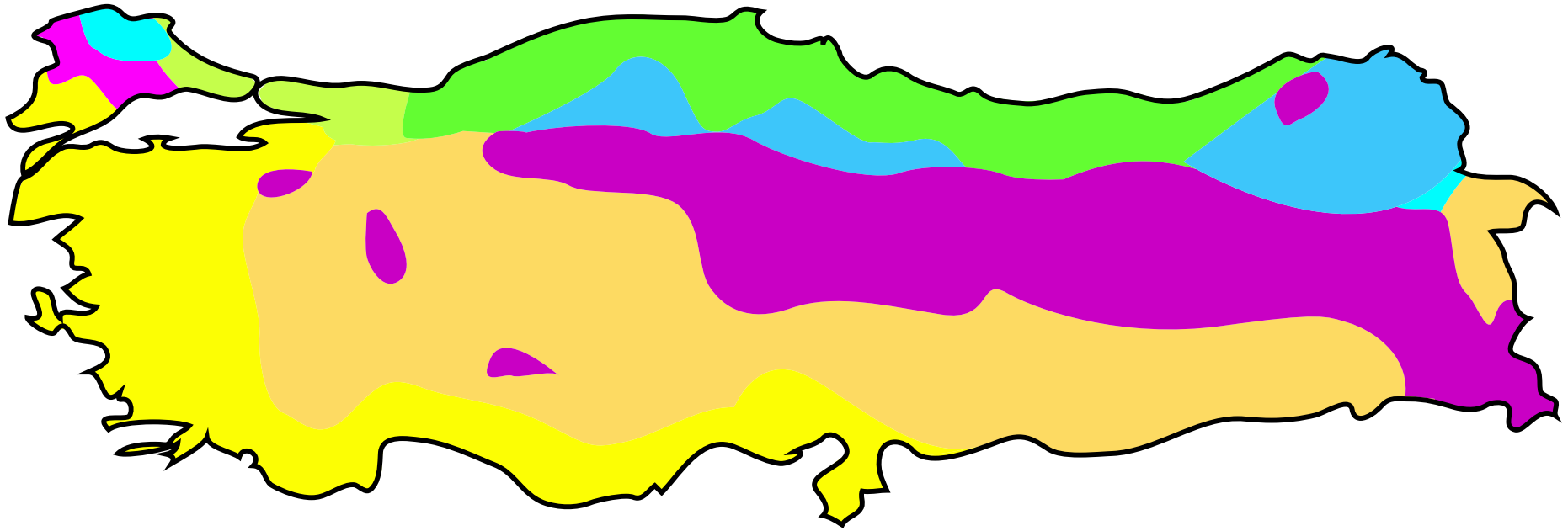
Future Work

- Introducing new crops
  - Pharmaceutical crops
  - Medicinal crops
- Deploying the app on a server
- Prediction UI improvements
  - Allow users to choose cities
  - Automatically fetch climate data for that city / region


27°E
30°E
33°E
36°E
39°E
42°E
45°E
42°N
39°N
36°N
N
KIRKLARELI
EDIRNE
TEKIRDAG
ISTANBUL
CANAKKALE
BARTIN
KASTAMONU
SINOP
ZONGULDAK
KARABUK
SAMSUN
ARTVIN
ARDAHAN
RIZE
TRABZON
KOCAELI
DUZCE
YALOVA
SAKARYA
BOLU
CANKIRI
AMASYA
ORDU
GIRESUN
KARS
CORUM
TOKAT
GUMUSHANE
BAYBURT
ERZURUM
IGDIR
BURSA
BILECIK
BALIKESIR
ANKARA
KIRIKKALE
ESKISEHIR
YOZGAT
SIVAS
ERZINCAN
AGRI
KUTAHYA
KIRSEHIR
TUNCELI
BINGOL
MUS
MANISA
USAK
AFYON
NEVSEHIR
KAYSERI
MALATYA
ELAZIG
BITLIS
VAN
IZMIR
AKSARAY
DIYARBAKIR
SIIRT
AYDIN
DENIZLI
ISPARTA
KONYA
NIGDE
KAHRAMANMARAS
ADIYAMAN
BATMAN
BURDUR
SIRNAK
HAKKARI
MUGLA
ADANA
MARDIN
ANTALYA
OSMANIYE
SANLIURFA
KARAMAN
GAZIANTEP
MERSIN
KILIS
HATAY
0
100
200
Km
Sıcaklıklar (°C)
2a
2b
3a
3b
4a
4b
5a
5b
6a
6b
7a
7b
8a
8b
9a
9b
10a
10b
- 45.6 _ - 42.8
- 42.8 _ - 40.0
- 40.0 _ - 37.2
- 37.2 _ - 34.4
- 34.4 _ - 31.7
- 31.7 _ - 28.9
- 28.9 _ - 26.1
- 26.1 _ - 23.3
- 23.3 _ - 20.6
- 20.6 _ - 17.8
- 17.8 _ - 15.0
- 15.0 _ - 12.2
- 12.2 _ - 9.4
- 9.4 _ - 6.7
- 6.7 _ - 3.9
- 3.9 _ - 1.1
- 1.1 _ 1.7
1.7 _ 4.4
METEOROLOJI
Türkiye
Bitki Soğuğa Dayanıklılık
Haritası
(Plant Hardiness Zone Map)
TARM


27°E
30°E
33°E
36°E
39°E
42°E
45°E
42°N
39°N
36°N
N
KIRKLARELI
EDIRNE
TEKIRDAG
ISTANBUL
CANAKKALE
BARTIN
KASTAMONU
SINOP
ZONGULDAK
KARABUK
SAMSUN
KOCAELI
DUZCE
YALOVA
SAKARYA
BOLU
CANKIRI
AMASYA
ORDU
GIRESUN
TRABZON
RIZE
ARTVIN
ARDAHAN
KARS
CORUM
TOKAT
GUMUSHANE
BAYBURT
ERZURUM
IGDIR
BURSA
BILECIK
BALIKESIR
ANKARA
KIRIKKALE
ESKISEHIR
YOZGAT
SIVAS
ERZINCAN
AGRI
KUTAHYA
KIRSEHIR
TUNCELI
BINGOL
MUS
MANISA
USAK
AFYON
NEVSEHIR
KAYSERI
MALATYA
ELAZIG
BITLIS
VAN
IZMIR
AKSARAY
AYDIN
DENIZLI
ISPARTA
KONYA
NIGDE
KAHRAMANMARAS
ADIYAMAN
DIYARBAKIR
BATMAN
SIIRT
SIRNAK
HAKKARI
BURDUR
MUGLA
ANTALYA
ADANA
OSMANIYE
KARAMAN
SANLIURFA
MARDIN
GAZIANTEP
KILIS
MERSIN
HATAY
0
100
200
Km
30 °C üzerindeki Yıllık Ortalama Gün Sayısı
1
2
3
4
5
6
7
8
9
10
> 1
1 - 7
> 7 - 14
> 14 - 30
> 30 - 45
> 45 - 60
> 60 - 90
> 90 - 120
> 120 - 150
> 150- 180
METEOROLOJi
Türkiye
Bitki Sıcağa Dayanıklılık Haritası
(Plant Heat - Zone Map)
TARIM

Turkey map of Köppen climate classification



- Cold semi-arid climate (BSk)
- Warm mediterranean climate (Csa)
- Warm oceanic climate/ Humid subtropical climate (Cfa)
- Temperate oceanic climate (Cfb)
- Warm continental climate/ Mediterranean continental climate (Dsa)
- Temperate continental climate/ Mediterranean continental climate (Dsb)
- Warm continental climate/ Humid continental climate (Dfa)
- Temperate continental climate/ Humid continental climate (Dfb)

References & Future Reading

- Our github repository
  - https://tinyurl.com/SIC-agricommend
- Secretary-General's remarks to the Global Food Security Call to Action Ministerial
  - https://www.un.org/sg/en/content/sg/speeches/2022-05-18/secretary-generals-remarks-the-global-food-security-call-action-ministerial%C2%A0
- Food Security Update, The World Bank
  - https://www.worldbank.org/en/topic/agriculture/brief/food-security-update
- Global Report on Food Crises 2022, Global Network Against Food Crises (GNAFC)
  - https://reliefweb.int/report/world/global-report-food-crises-2022
- The World's Food Supply is Made Insecure by Climate Change
  - https://www.un.org/en/academic-impact/worlds-food-supply-made-insecure-climate-change
- India Defends Wheat Export Ban
  - https://www.voanews.com/a/india-defends-wheat-export-ban-/6590477.html
- Food Prices Approach Record Highs, Threatening the World’s Poorest
  - https://www.nytimes.com/2022/02/03/business/economy/food-prices-inflation-world.html
- Yeni Tarım Düzeni, Ali Ekber Yıldırım, Sia Kitap, Şubat 2022

Special Thanks

- All the instructors
  - For their guidance & enthusiasm
- All the stakeholders
  - For the opportunity to learn & create
- Yulian Alexeyev
  - For their gorgeous photo, used in the backdrop of title slide
- icons8.com
  - For their free to use icons, found in the top right corner