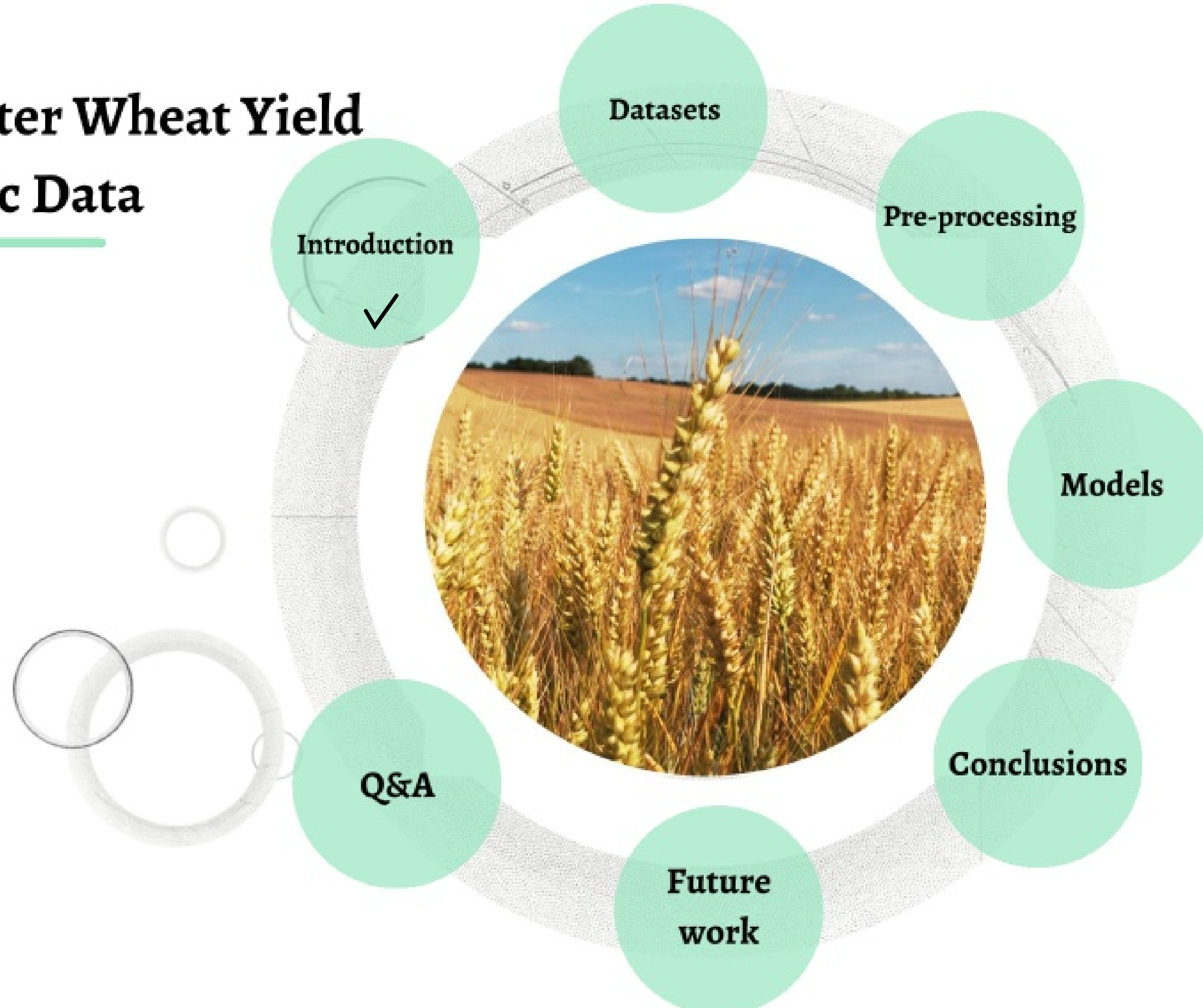
Prediction of Winter Wheat Yield Loss using Climatic Data

Maria Gil Rodriguez



Introduction

- Annual Winter Wheat Yield : Amount of grain harvested by unit of area in a given year (in tonnes per hectare)

- Depends on the characteristics of the region and the climatic conditions. Values vary greatly between regions and years

- Important to accurately predict yield loss.
    - Harvest planning
    - Management of stocks
    - Strategic information in international markets.

Objective

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The objective of this capstone is to develop tools to classify as accurately as possible the wheat yield loss in France.

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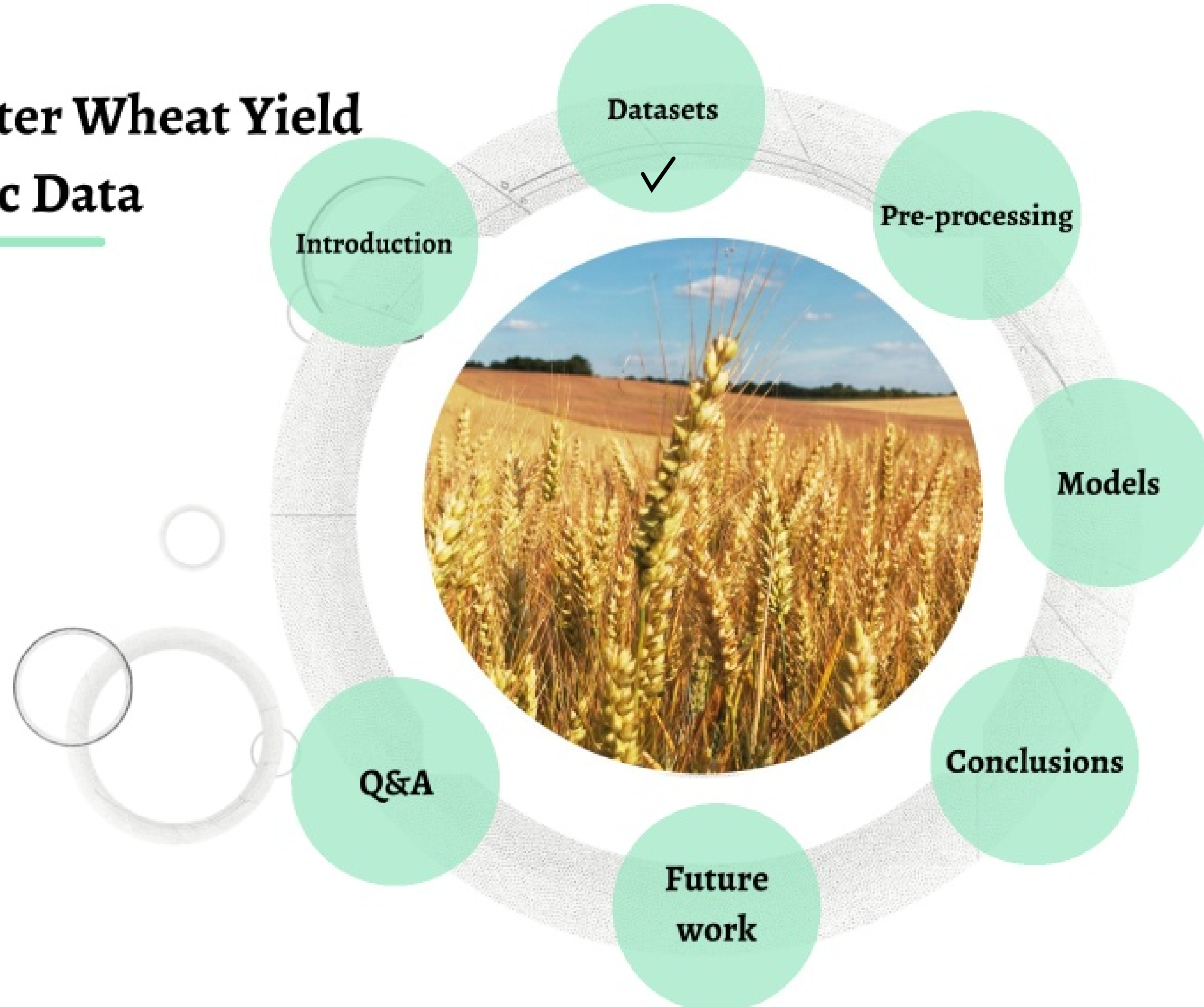


Datasets

CLAND Challenge

- Training set
- Blind test set

Metadata

Distributions

Correlations

Metadata

- 94 Departments
- 58 years
- Climatic data: months Sep-Jun
  - Potential Evapotranspiration (mm/day)
  - Solar Radiation (W/m²)
  - Precipitation: monthly values (mm/day), # rainy days
  - Temperatures: Max (C), min (C), # days with extreme values
- Yield loss: 1 = loss 0 = no loss

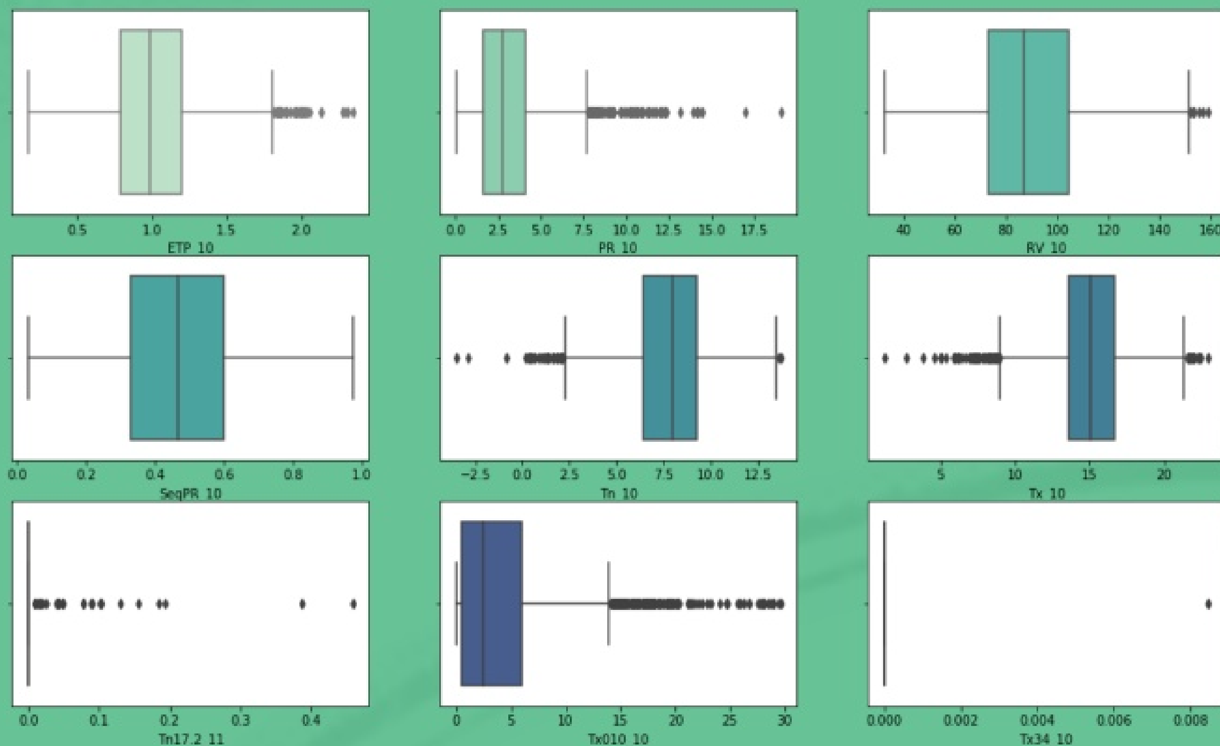
Metadata

For each year and Department:

- Potential Evapotranspiration (mm/day):
  ETP_9, ETP_10, ETP_11, ETP_12, ETP_1, …, ETP_6
- Precipitation: monthly values (mm/day) and # rainy days:
  PR_9, PR_10, PR_11, PR_12, PR_1, …, PR_6
  SeqPR_9, SeqPR_10, SeqPR_11, …, SeqPR_6
- Solar Radiation (W/m2):
  RV_9, RV_10, RV_11, RV_12, RV_1, …, RV_6
- Temperatures: Max (C), min (C), # days with extreme values
  Tx_9, Tx_10, Tx_11, Tx_12, Tx_1, …, Tx_6
  Tn_9, Tn_10, Tn_11, Tn_12, Tn_1, …, Tn_6
  Tx34_9, Tx34_10, Tx34_11, …, Tx34_6 — # days with daily maximum T > 34 C
  Tx010_9, Tx010_10, Tx010_11, …, Tx010_6 — # days with daily maximum T between 0 and 10 C
  Tn17.2_9, Tn17.2_10, Tn17.2_11, …, Tn17.2_6 — # days with daily minimum T < -17 C

Distributions

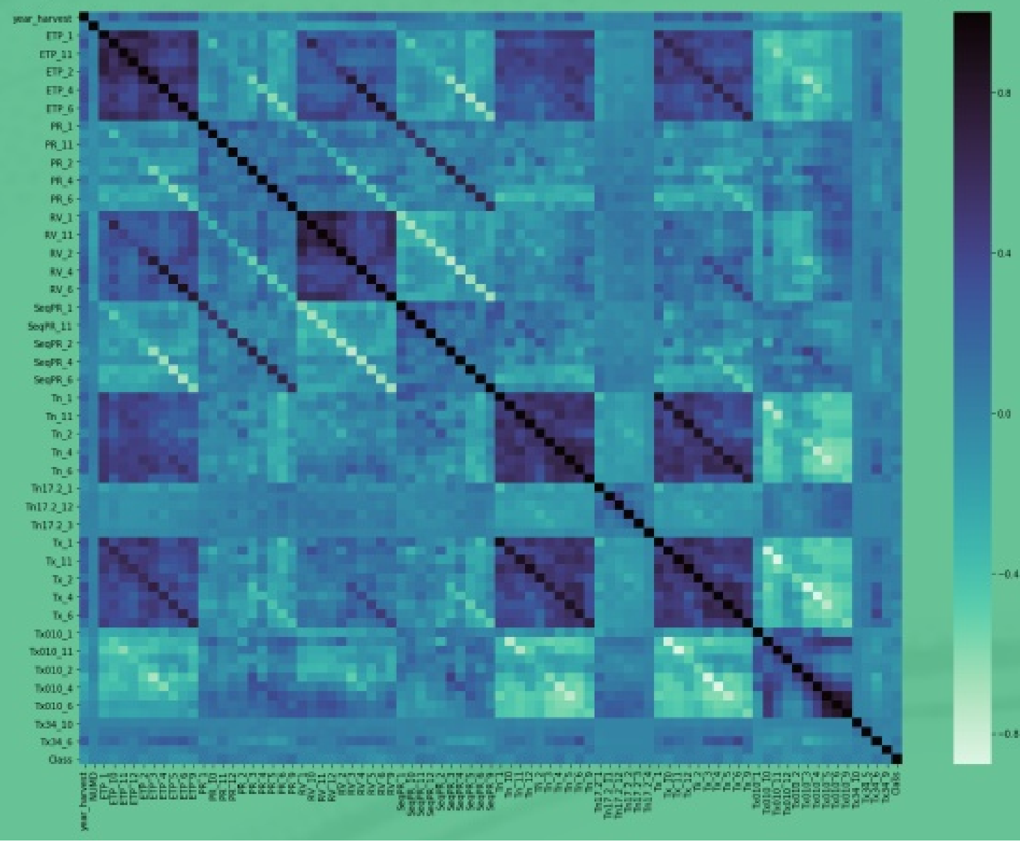
Boxplots of climatic variables in October (except for Tn17.2, which corresponds to November)



Noise,
noise,
noise...

Can't remove
outliers!

Correlations



Variables for one month: strong positive and negative correlations

↓

Difficult to drop without losing information

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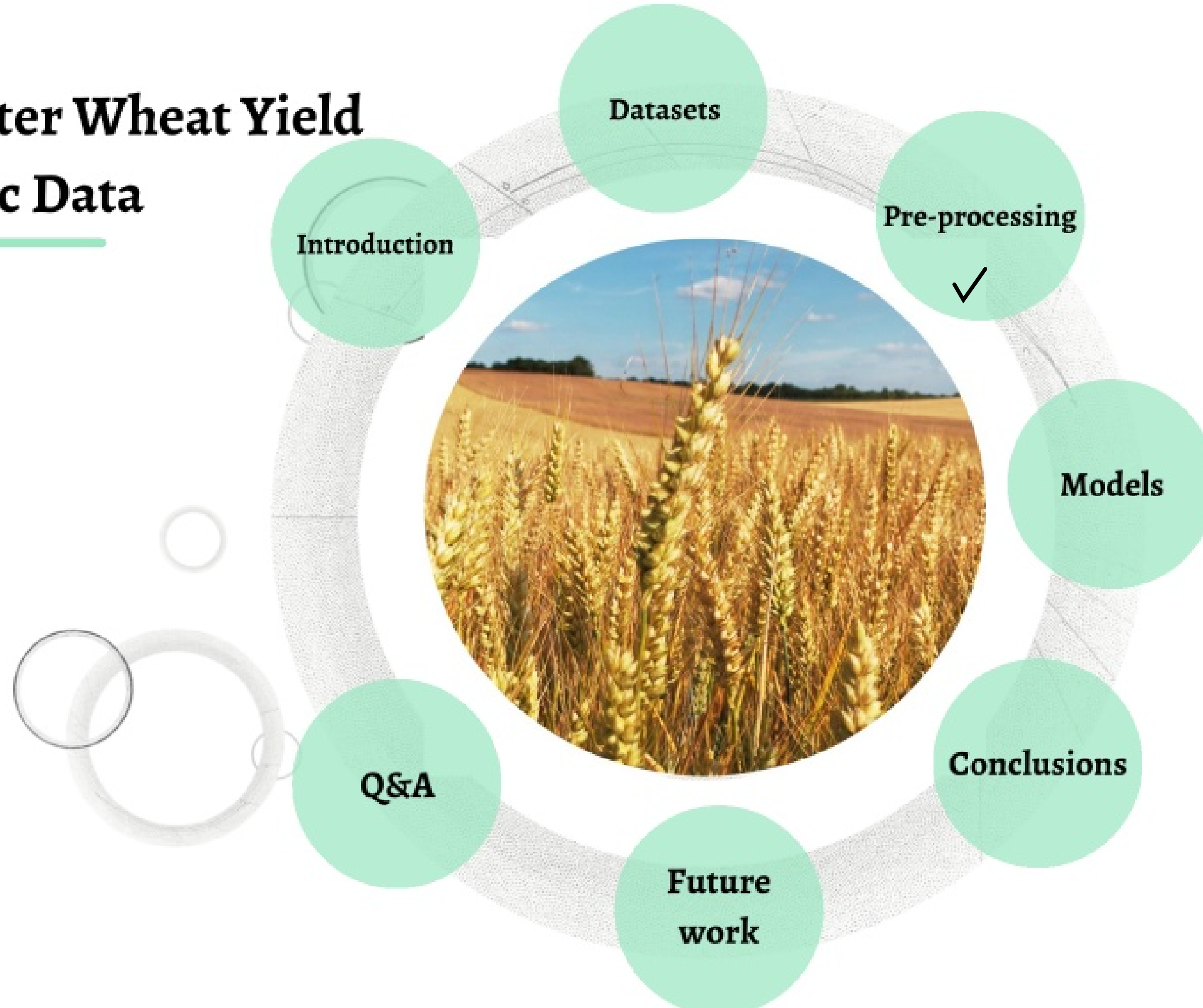
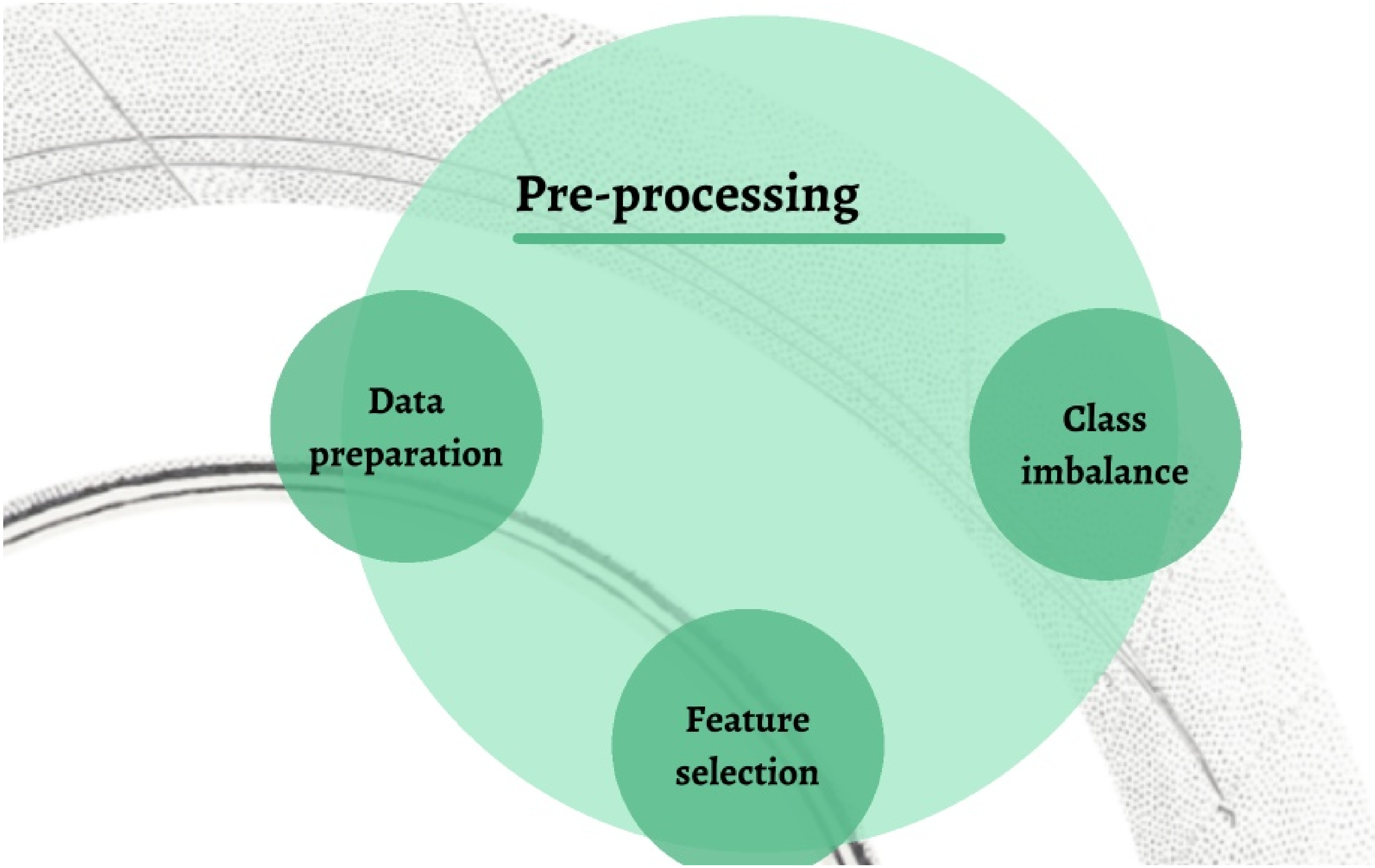



Pre-processing
Data preparation
Class imbalance
Feature selection

Data preparation

- **Data Cleaning**

  Delete columns of straight zeros

  ↓

  80 features and 3571 instances

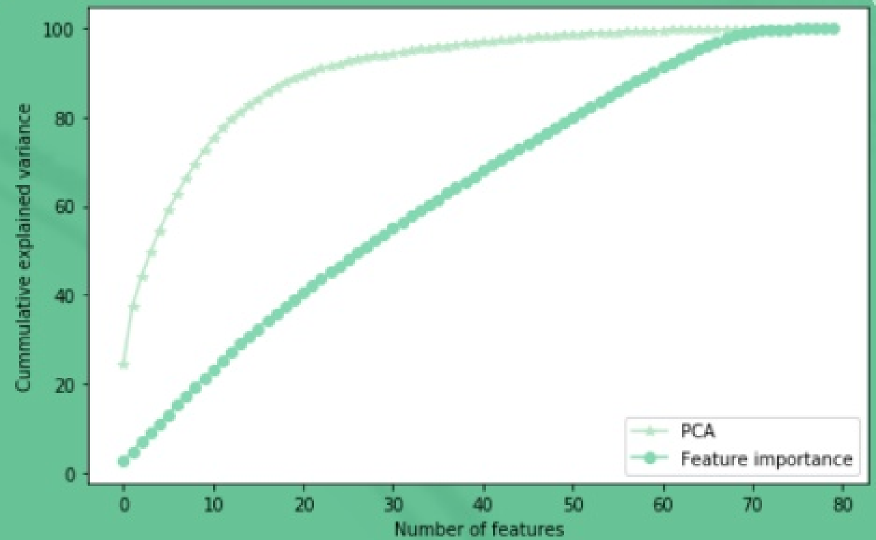
- **Splitting**

  Random: 75% train - 25% test

  (Stratified splitting didn't work well)

- **Normalization**

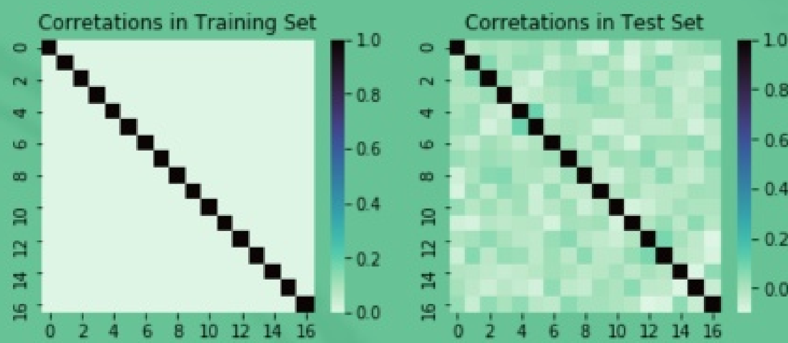
Feature selection



PCA

Feature selection

After PCA:



PCA

Why does PCA overperform?

Usually:

It is recommended to remove highly correlated variables before PCA

↓

Correlated variables point in the same direction making that component stronger

In our case:

We have roughly the same number of variables for each month

Class Imbalance

Oversample with SMOTE while using GridSearchCV

SMOTE + cross validation: Pipeline

Wrong

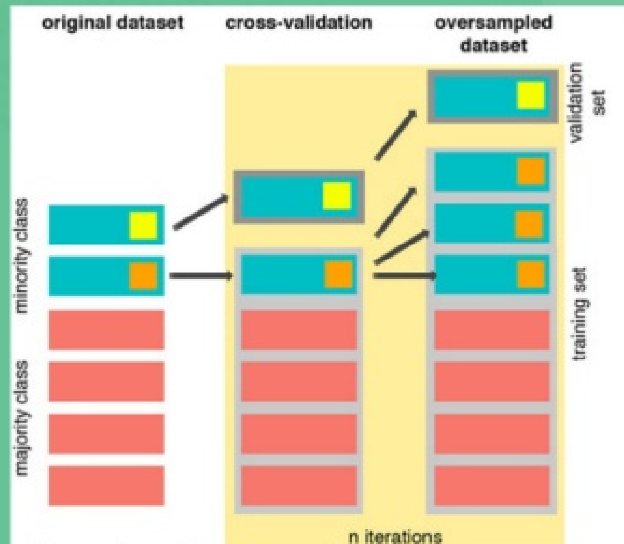
Source: https://www.marcoaltini.com/

Class Imbalance

Oversample with SMOTE while using GridSearchCV

SMOTE + cross validation: Pipeline

Right



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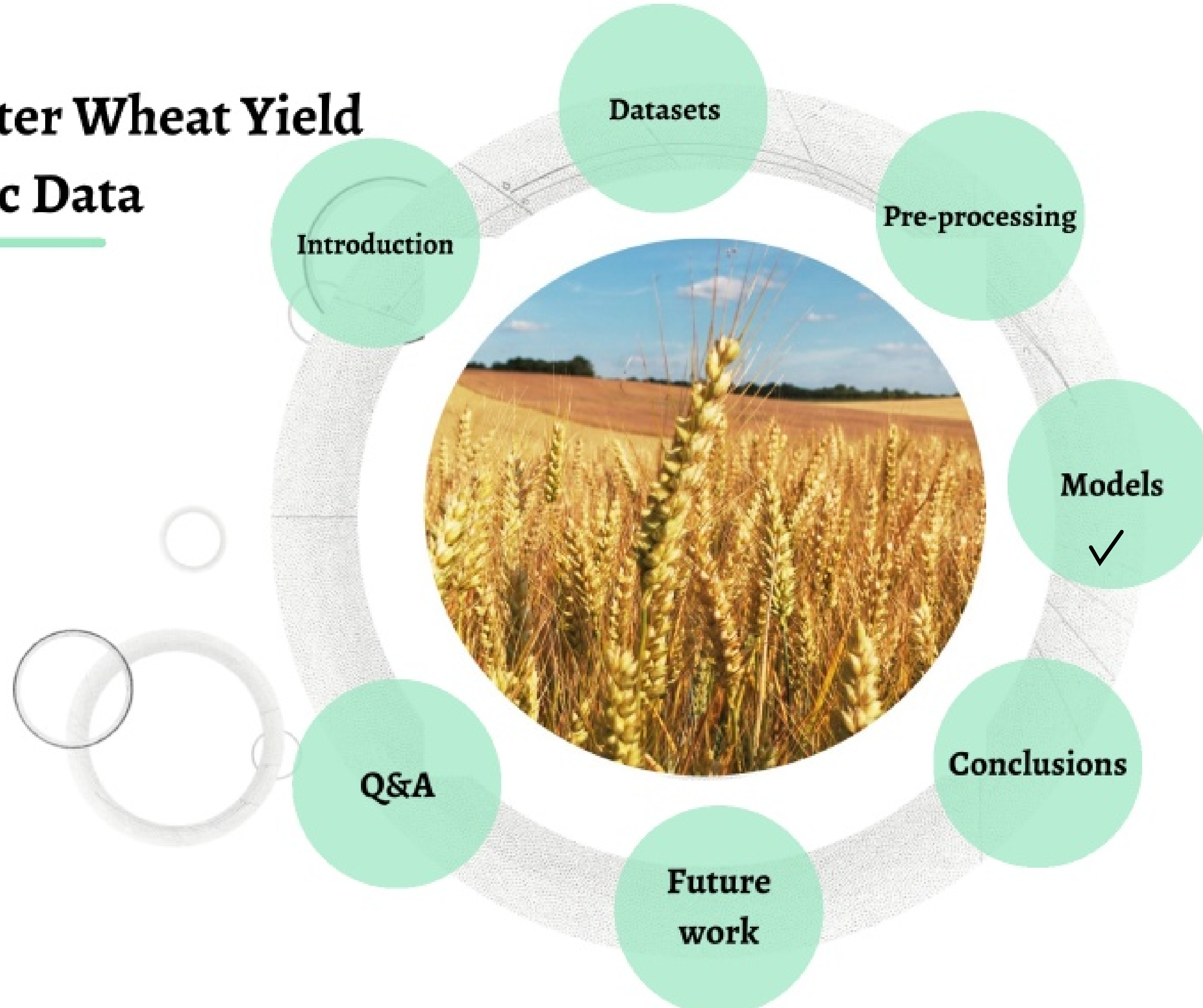
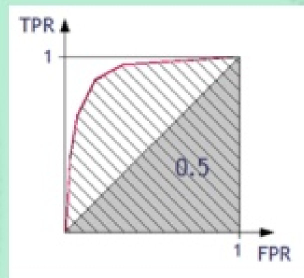


Models

Metric: Area under the ROC curve



Logistic Regression

SVC

KNN

Gradient Boosting

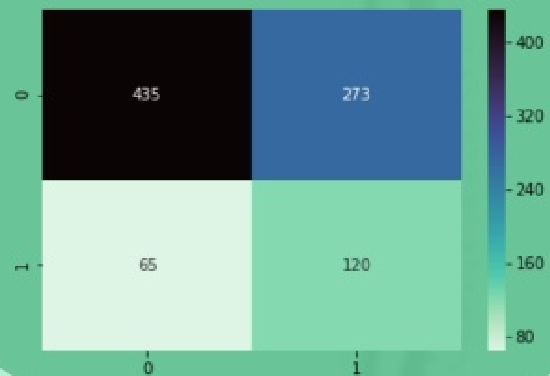
Random Forest

Logistic Regression

```
Train set score:                  0.68
Best cross validation score:      0.66
Test set score:                   0.66
Report:
              precision    recall  f1-score   support

           0       0.87      0.61      0.72       708
           1       0.31      0.65      0.42       185

   micro avg       0.62      0.62      0.62       893
   macro avg       0.59      0.63      0.57       893
weighted avg       0.75      0.62      0.66       893
```

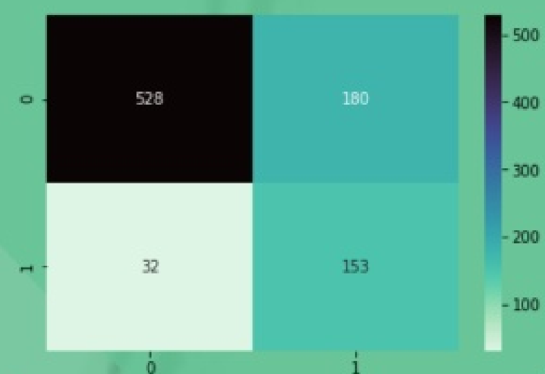


KNN

```
Train set score:                0.92
Best cross validation score:    0.86
Test set score:                 0.88
Report:
              precision    recall  f1-score   support

           0       0.94      0.75      0.83       708
           1       0.46      0.83      0.59       185

   micro avg       0.76      0.76      0.76       893
   macro avg       0.70      0.79      0.71       893
weighted avg       0.84      0.76      0.78       893
```

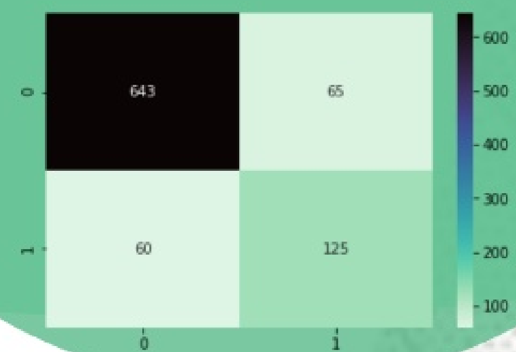


Random Forest

```
Train set score:               1.0
Best cross validation score:   0.88
Test set score:                0.89
Report:
              precision    recall  f1-score   support

           0       0.91      0.91      0.91       708
           1       0.66      0.68      0.67       185

   micro avg       0.86      0.86      0.86       893
   macro avg       0.79      0.79      0.79       893
weighted avg       0.86      0.86      0.86       893
```

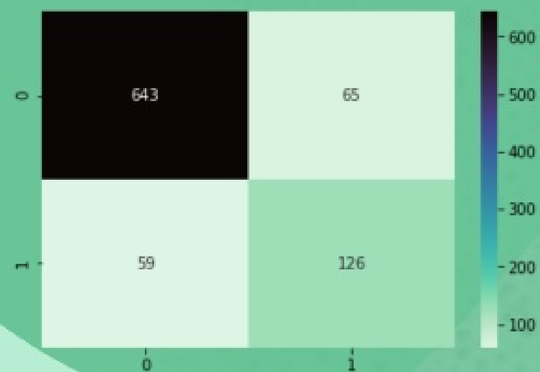


Gradient Boosting

```
Train set score:                  1.0
Best cross validation score:      0.87
Test set score:                   0.88
Report:
              precision    recall  f1-score   support

           0       0.92      0.91      0.91       708
           1       0.66      0.68      0.67       185

   micro avg       0.86      0.86      0.86       893
   macro avg       0.79      0.79      0.79       893
weighted avg       0.86      0.86      0.86       893
```

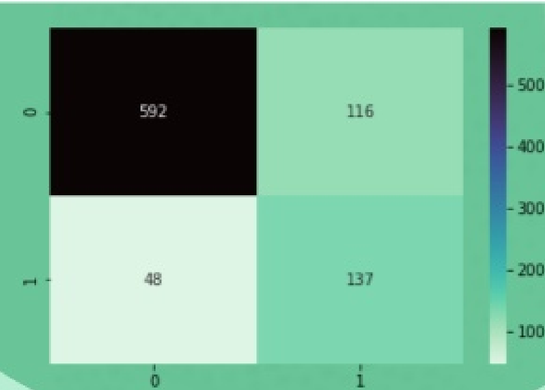


SVC

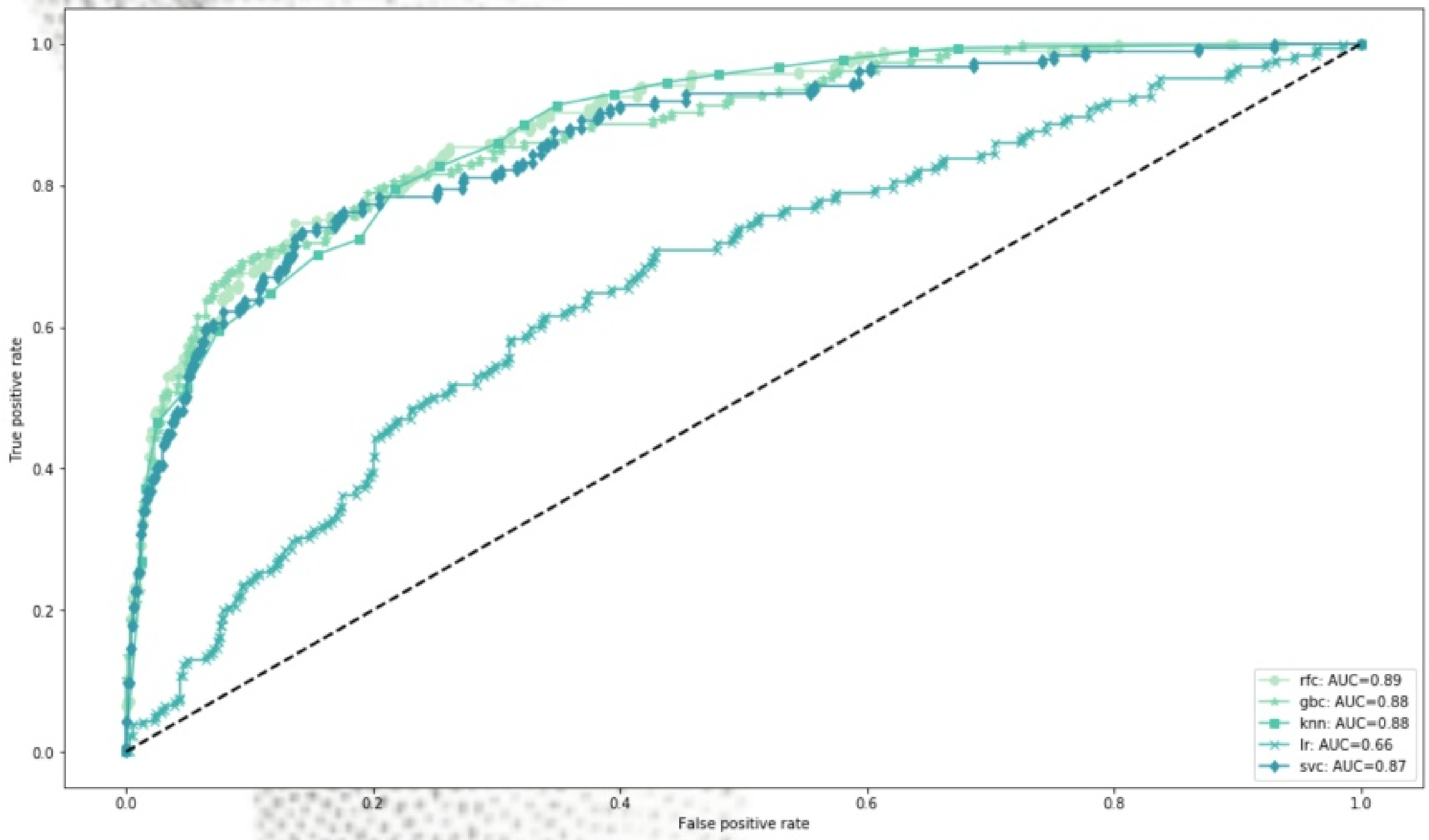
```
Train set score:                 0.96
Best cross validation score:     0.85
Test set score:                  0.87
Report:
              precision    recall  f1-score   support

           0       0.93      0.84      0.88       708
           1       0.54      0.74      0.63       185

   micro avg       0.82      0.82      0.82       893
   macro avg       0.73      0.79      0.75       893
weighted avg       0.85      0.82      0.83       893
```



Model Comparison: ROC Curves



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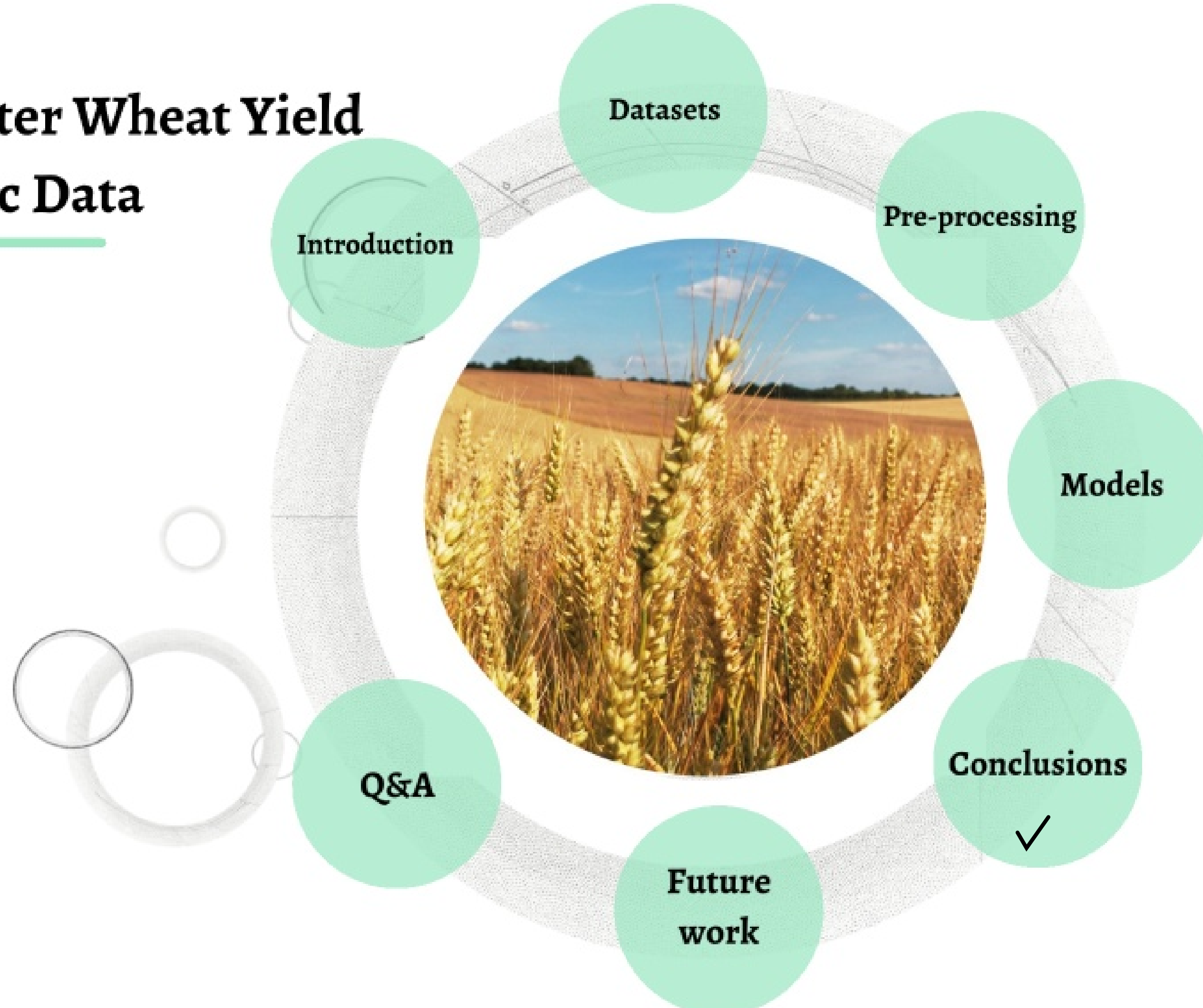

Conclusions

- Climate variables are relatively good predictors of wheat yield loss in France. The predictions are valuable in order to plan harvests, manage stocks, optimize contracts and operate in international markets.
- Random Forest was the best model, with an area under the ROC curve of 0.89.
- The results would be much better with a less noisy data. That could be achieved by working with local data (vs generalized for an entire Department) or using the data of several stations for one Department.

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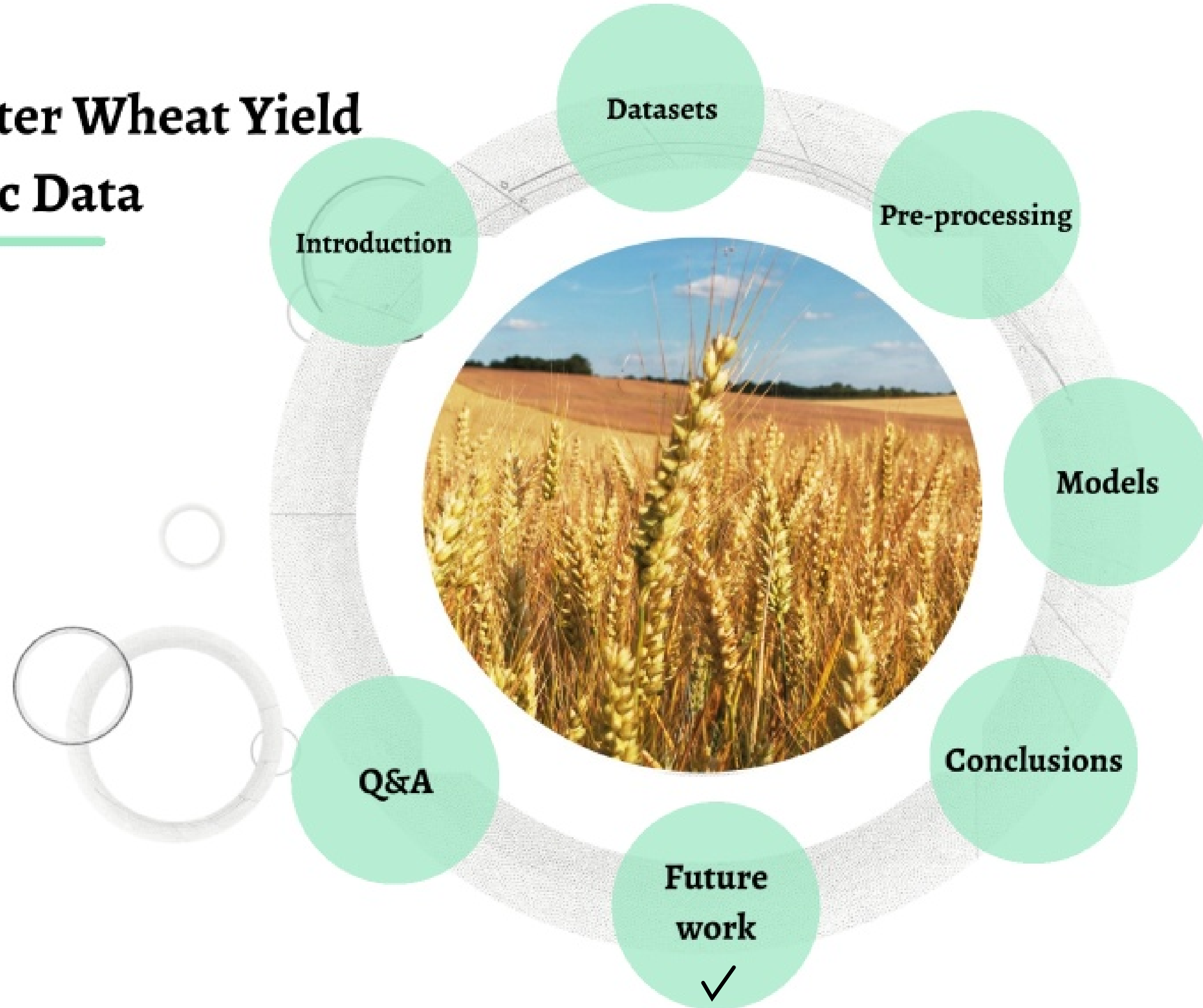

Future work

- France has 5 different climates. Thus, performing some clustering before using our ML models would be ideal and most likely improve the results.

- There is also some information in the NUMD (number of department) variable that might be worth to explore.

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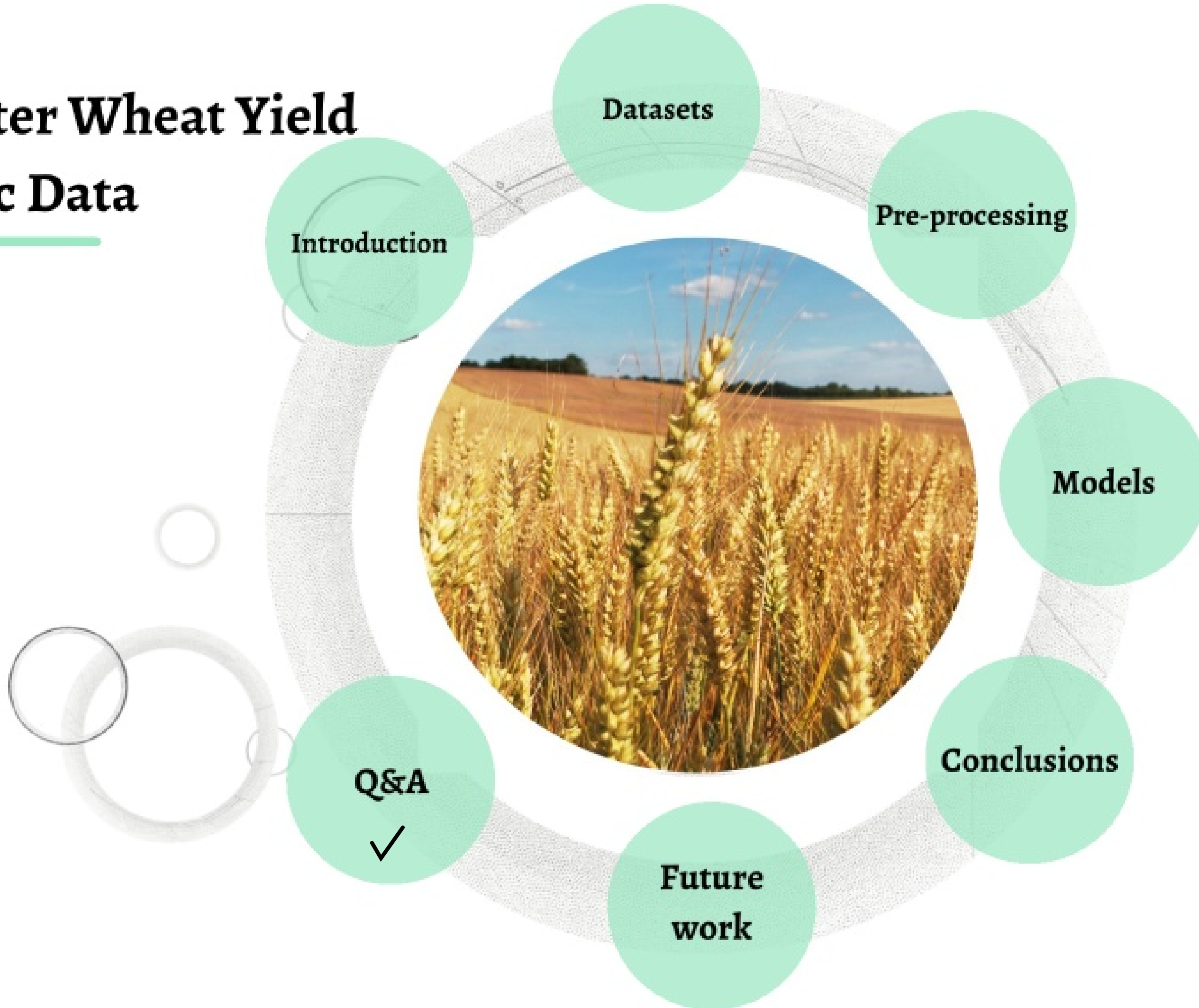


Q & A