Imbalanced Datasets and Crop Yield Prediction

Application of Preprocessing Techniques for Regression Tasks in Agriculture

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Agriculture and Agri-Food Canada

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Introduction

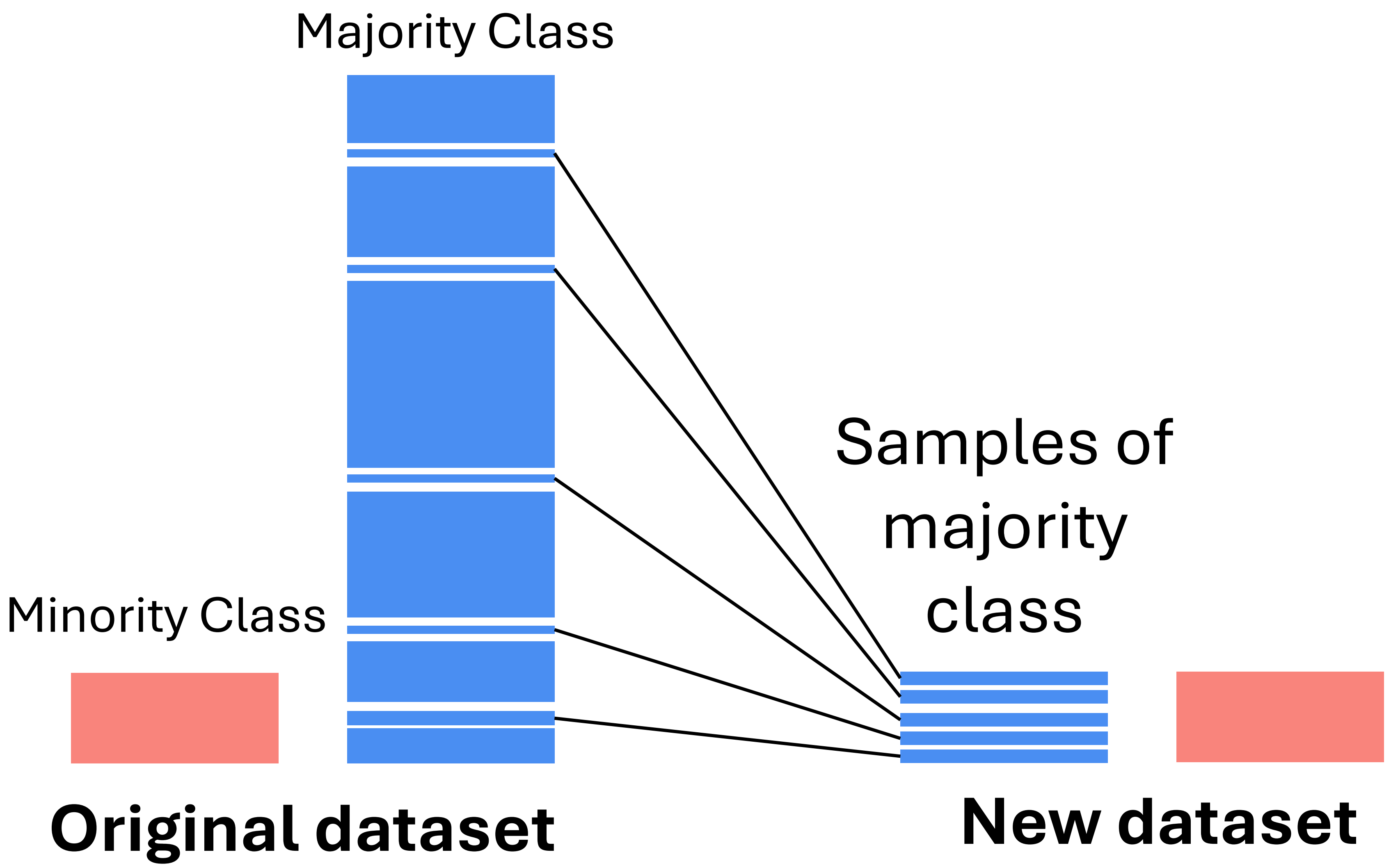
- Increase in drought and extreme weather years

- Limited data

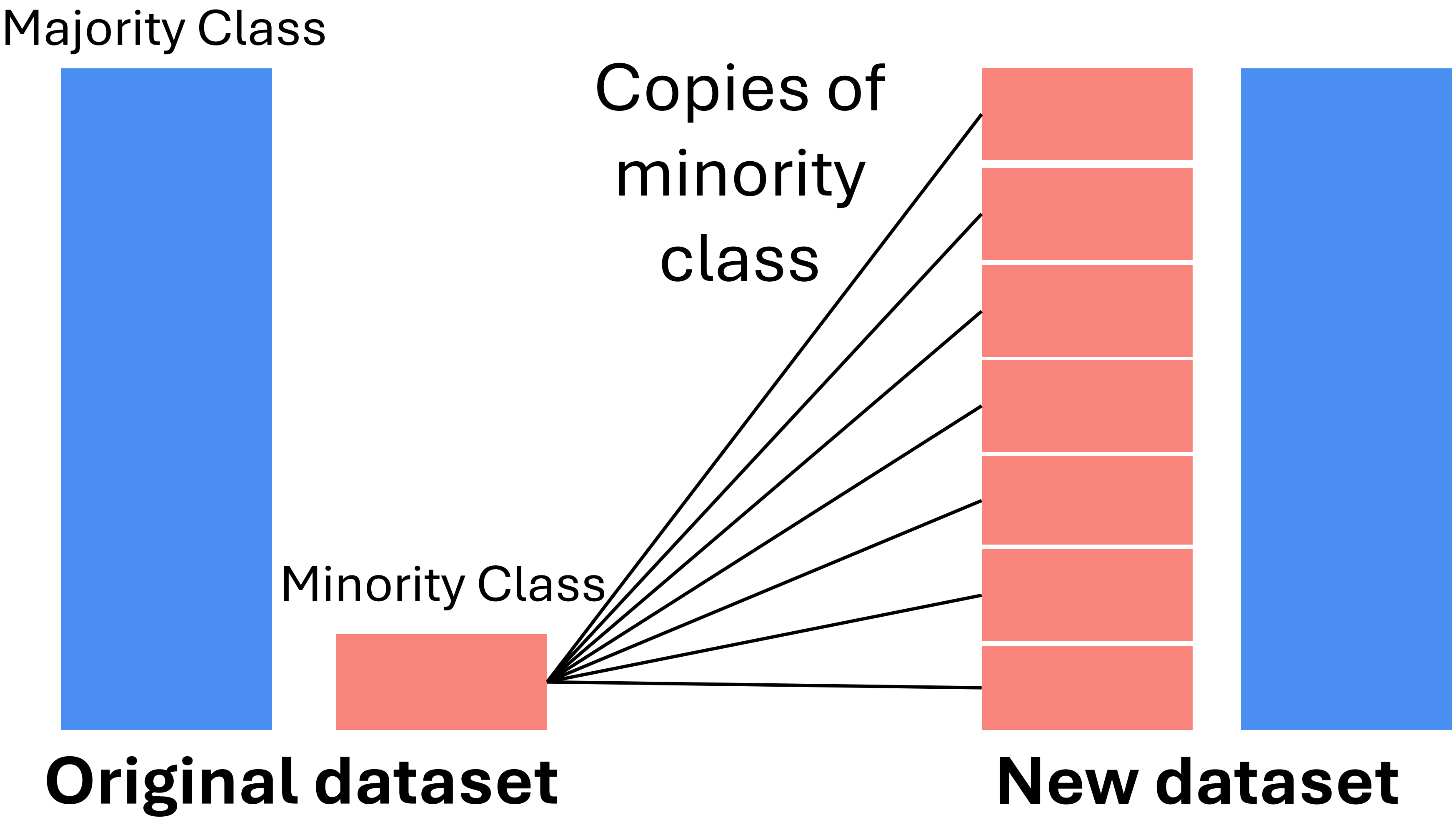
- Unbalanced datasets

- Poorer Predictions

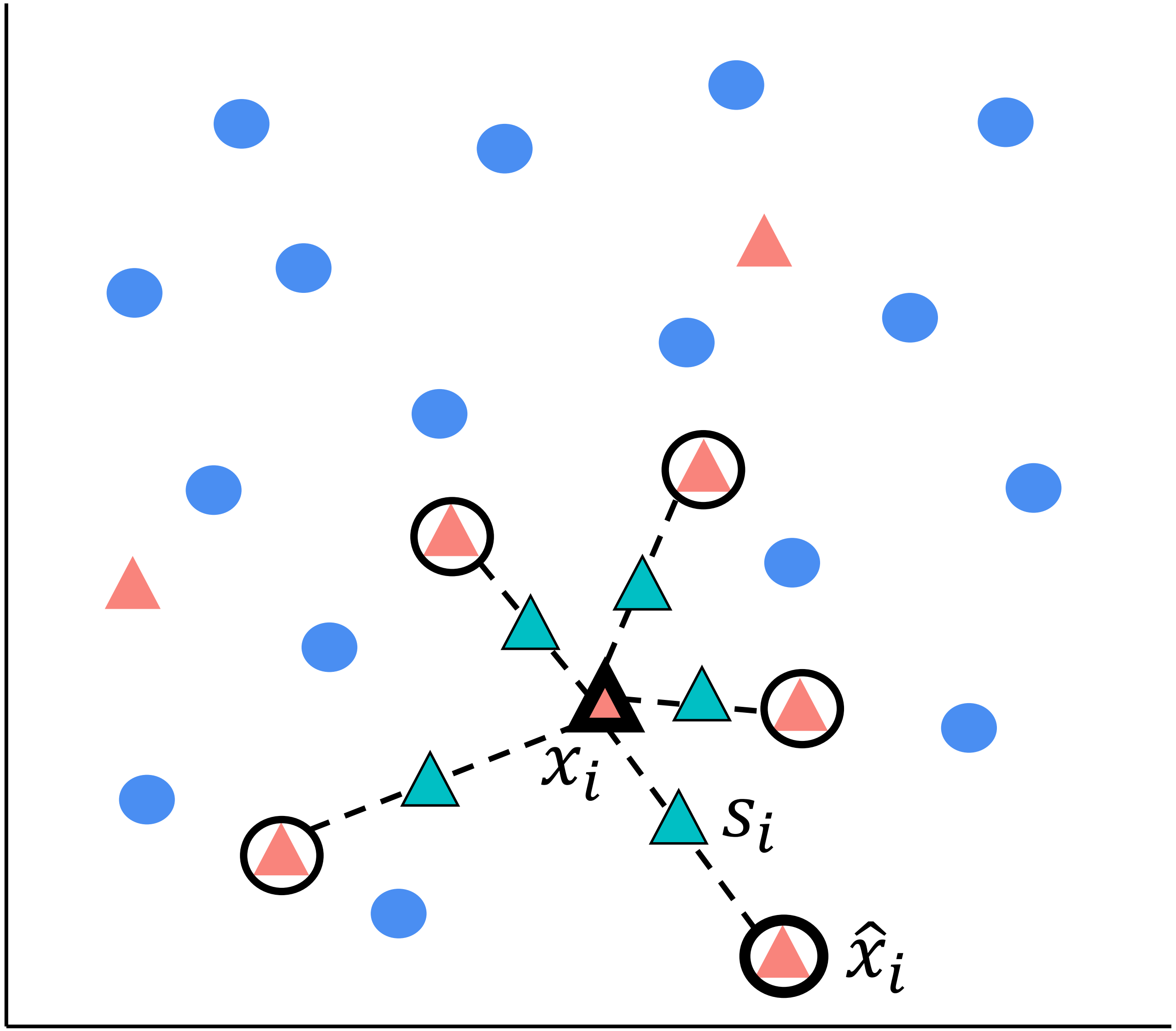
Undersampling (US)



Oversampling (OS)



SMOTER (synthetic minority oversampling technique regression)



Majority class

Minority class

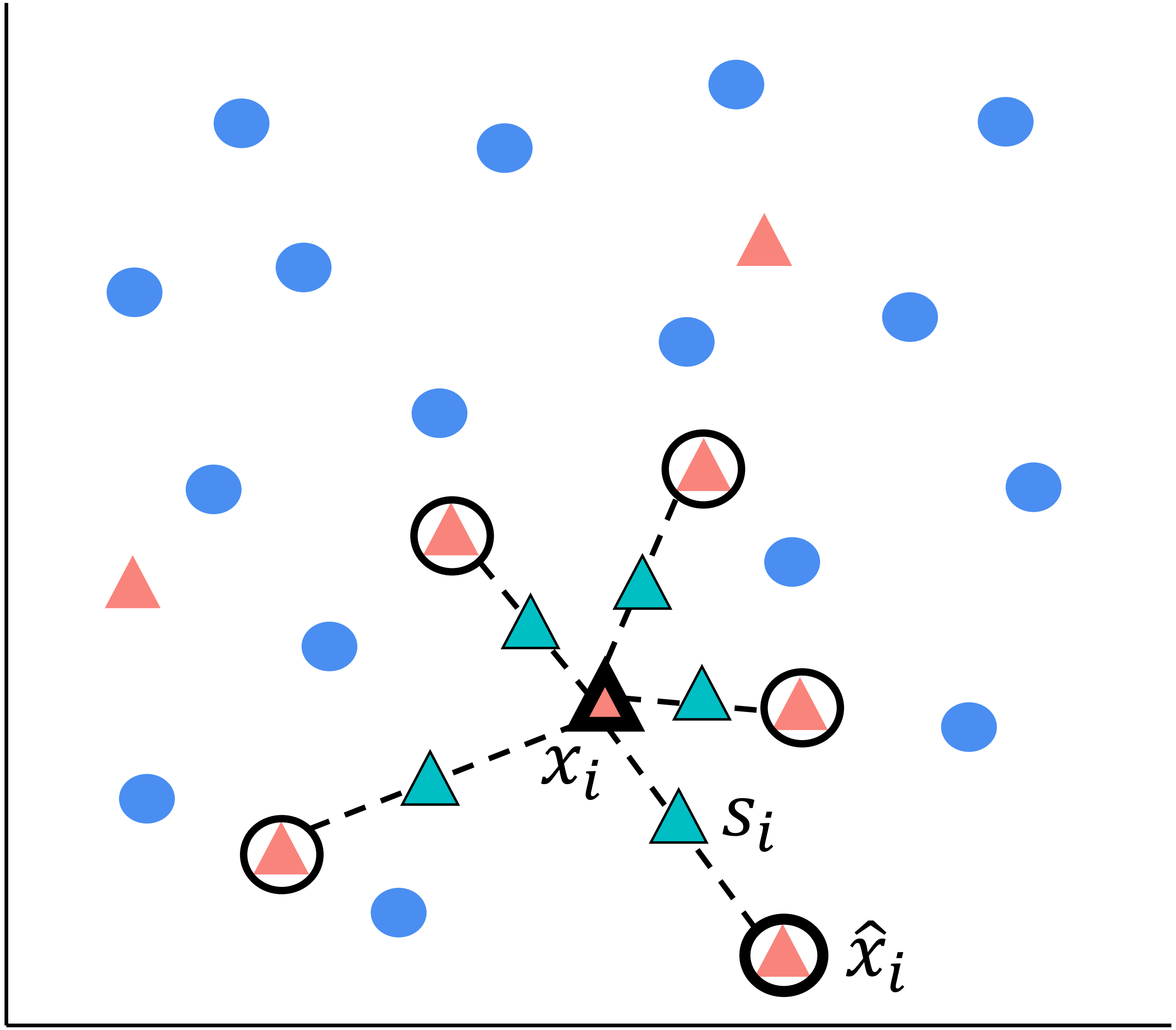
Randomly selected minority class datapoint

Randomly selected k-nearest neighbours

Synthetic minority instance

(Chawla et. al, 2002)

SMOTER (synthetic minority oversampling technique regression)



Continuous

$$s_i = x_i + RANDOM(0,1)(x_i - \hat{x}_i)$$

Categorical

Randomly select between x_i and $\hat{x}_i$

Target

$$s_{i_y} = \frac{d_2 * \hat{y}_i + d_1 * y_i}{d_1 + d_2}$$

$$d_1 = \mathrm{DISTANCE}\left(s_{i_y}, \hat{x}_i\right)$$

$$d_2 = \mathrm{DISTANCE}\left(s_{i_y}, x_i\right)$$

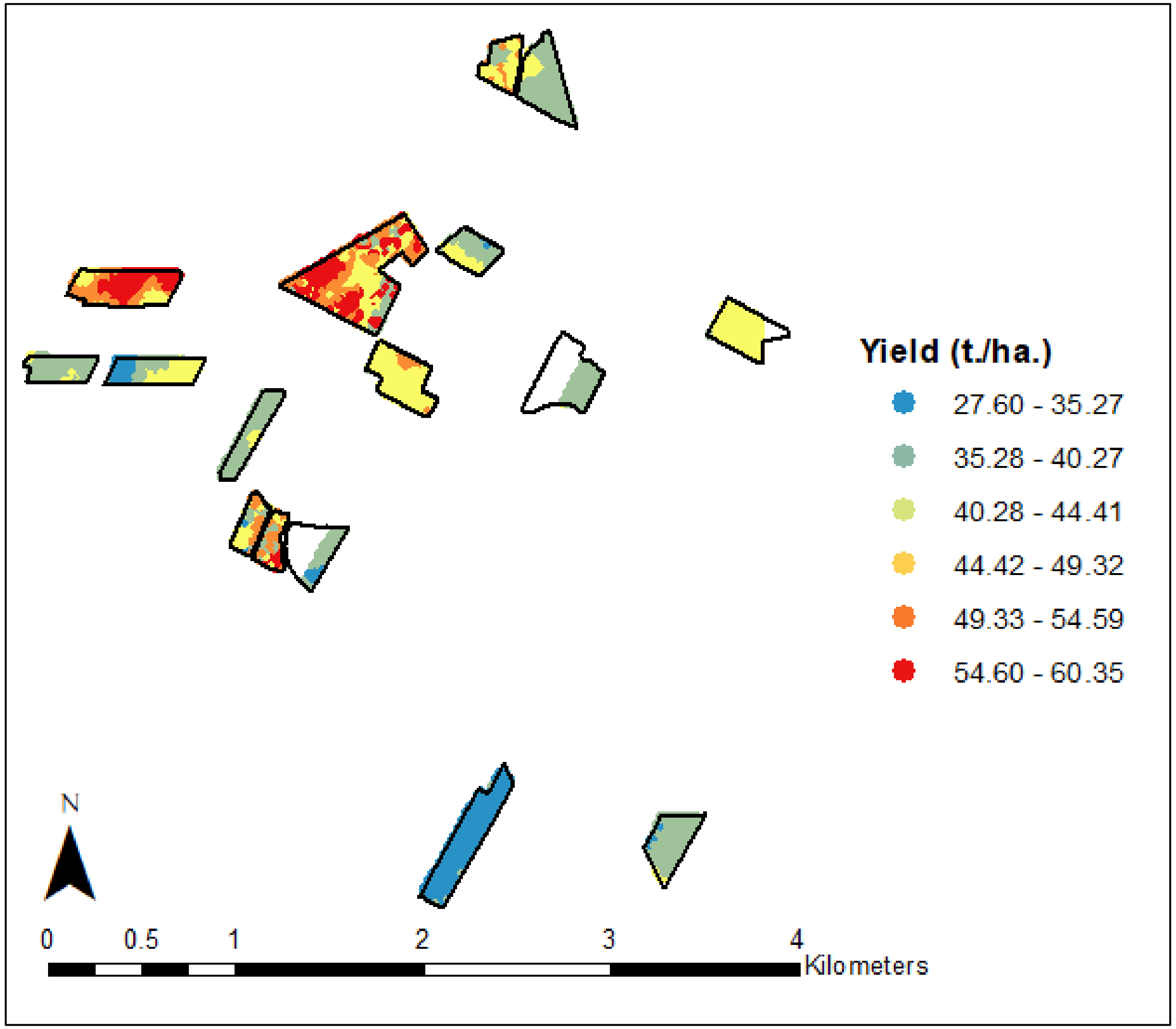
(Chawla et al., 2002, Torgo et al., 2013, 2015)

Objectives

- Evaluate the effects of applying the three preprocessing techniques
- Assess the quality of the synthetic data generated by SMOTER

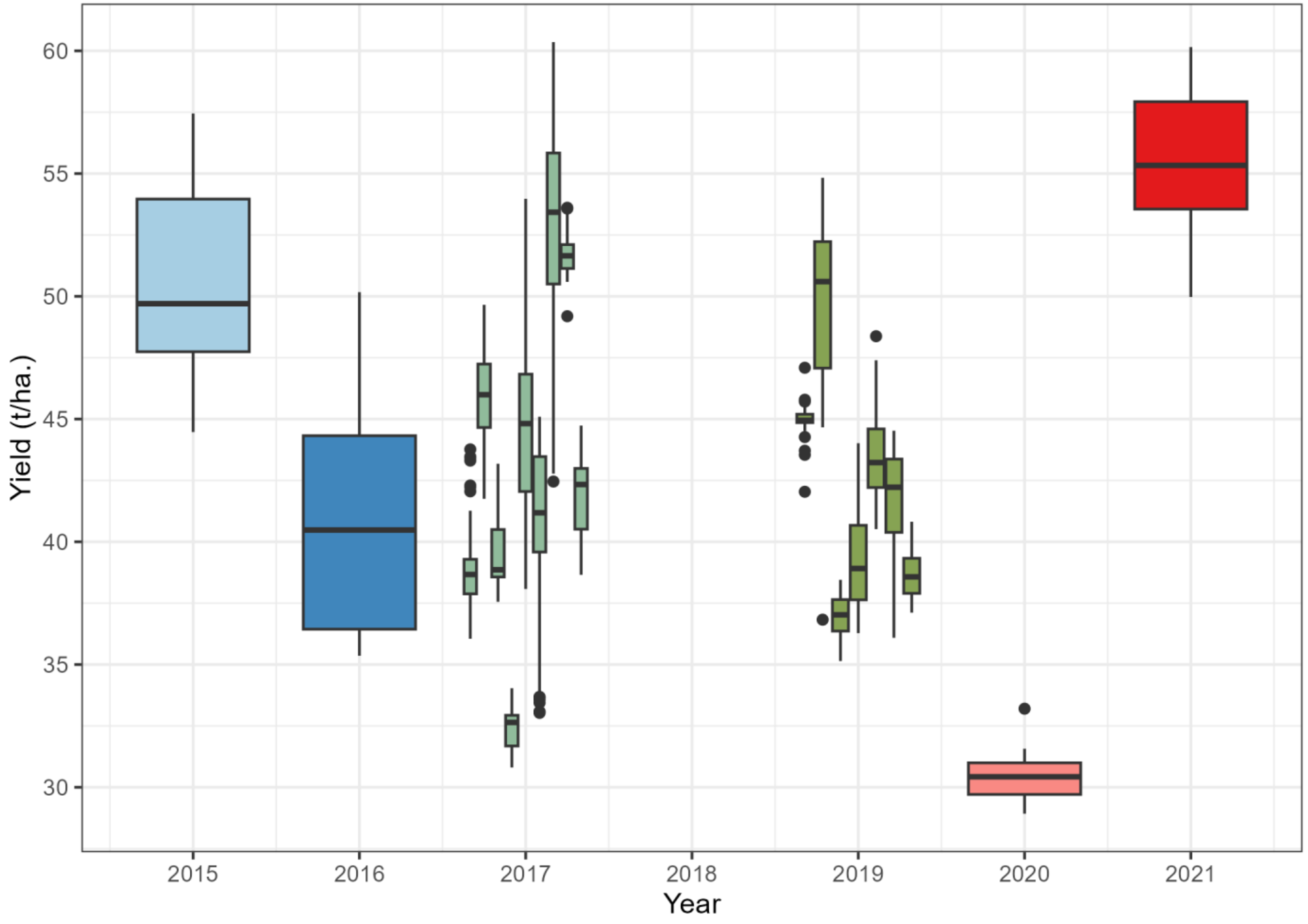
Data

Imagery ©2024 NASA, TerraMetrics, Map data ©2024 Google 100 km

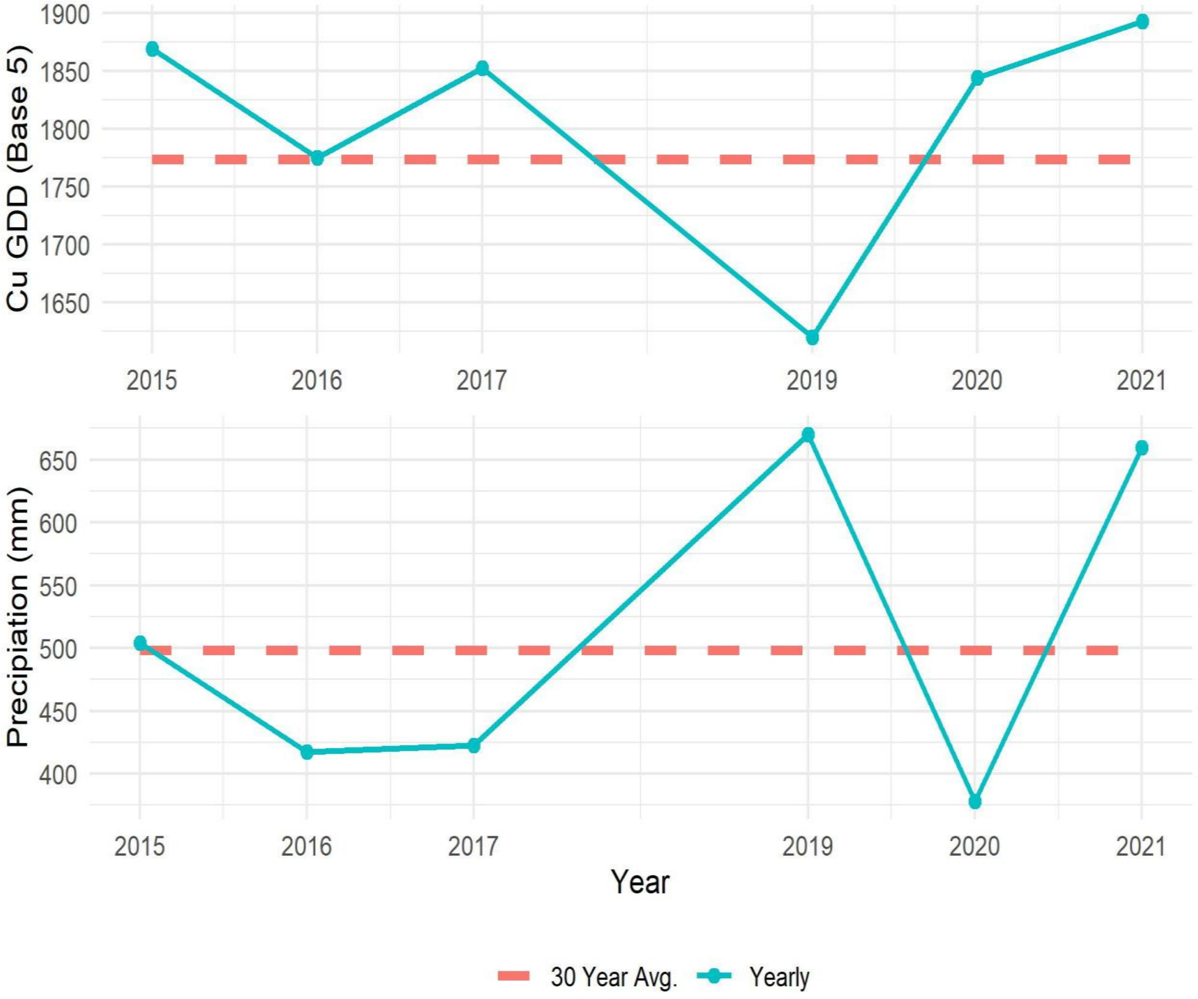


- Russet Burbank Potato
- 20 Field-Years

Data

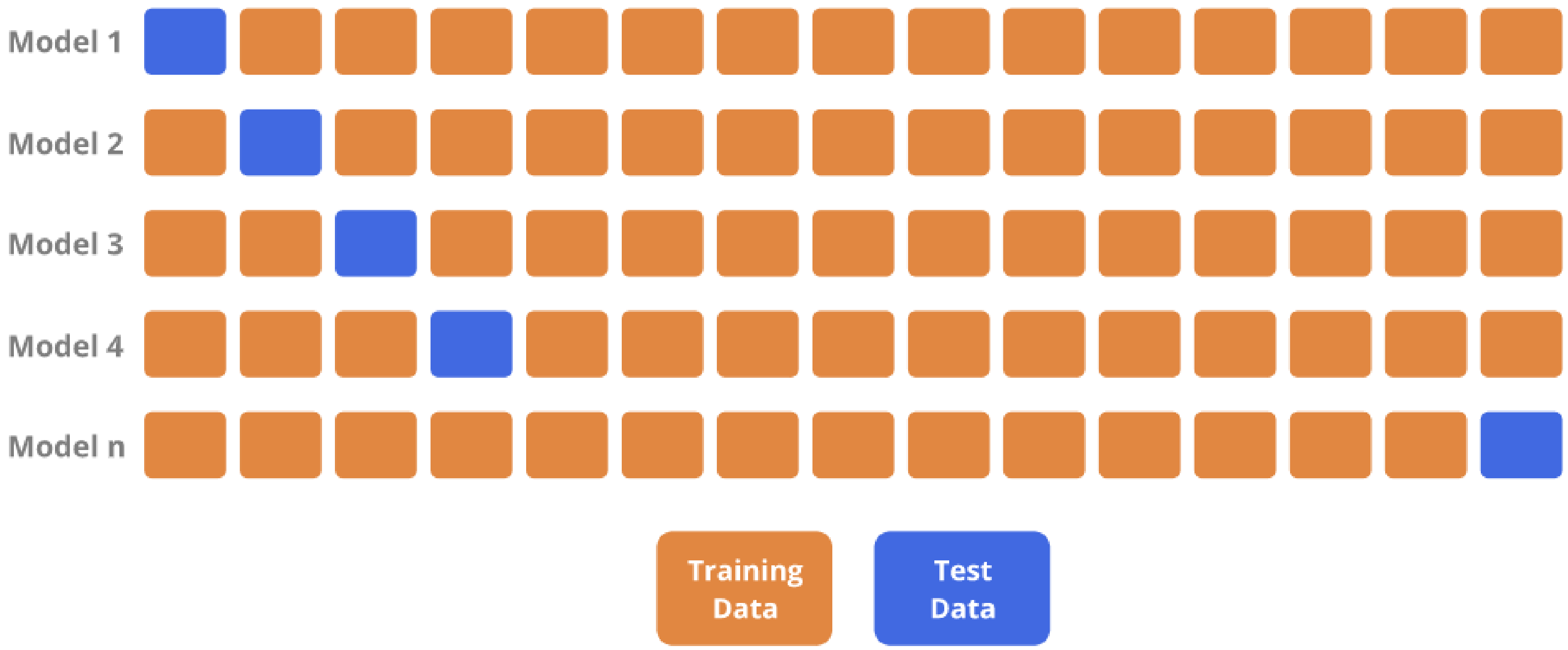


Yield (t/ha.)
60
55
50
45
40
35
30
2015
2016
2017
2018
2019
2020
2021
Year



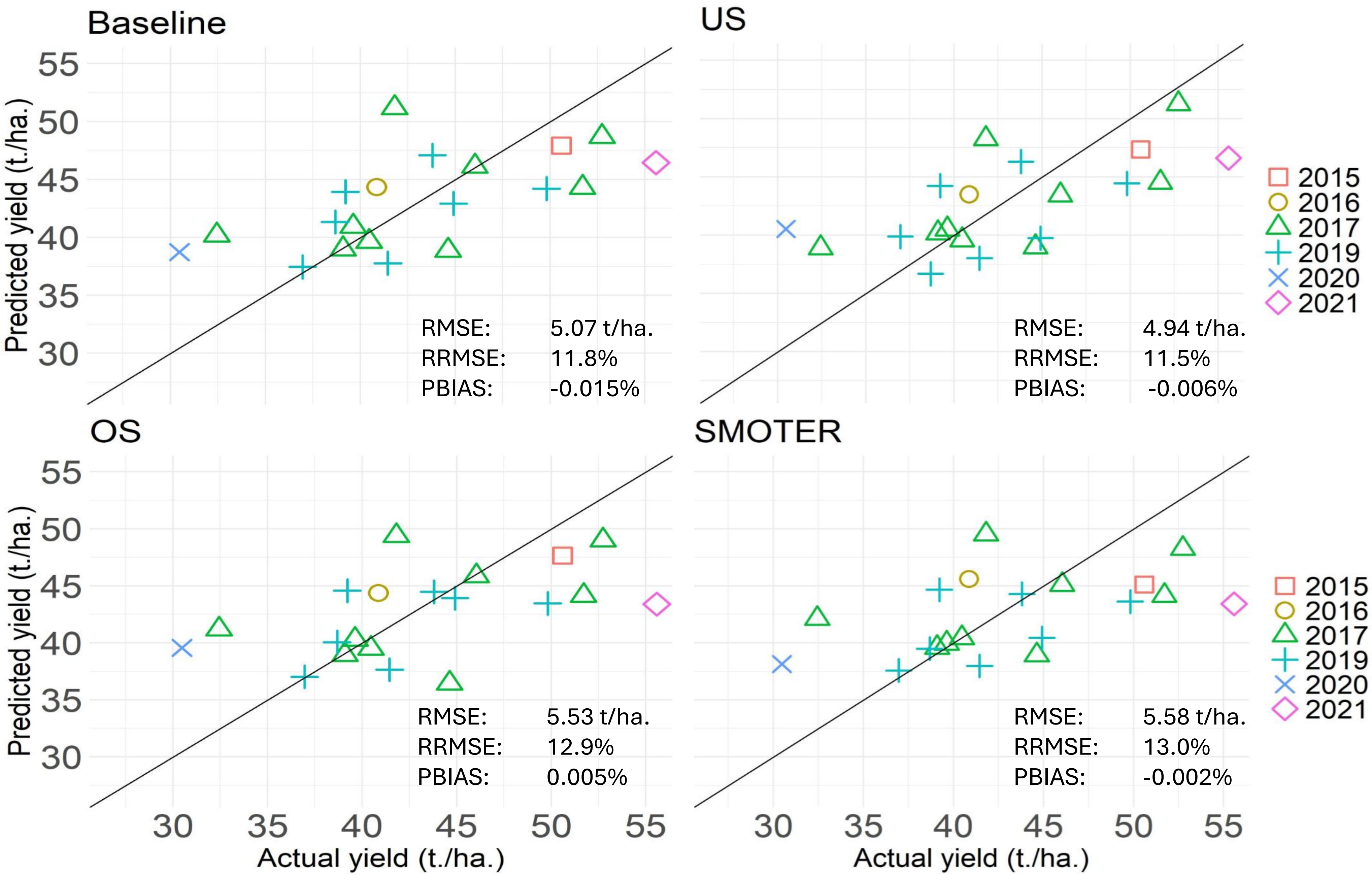
Cu GDD (Base 5)
1900
1850
1800
1750
1700
1650
2015
2016
2017
2019
2020
2021
Precipitation (mm)
650
600
550
500
450
400
2015
2016
2017
2019
2020
2021
Year
30 Year Avg.
Yearly

Random Forest Models



- 2-fold cross validation
- Grid search
  - *Mtry* – number of features sampled at each node split
  - *Ntree* – number of trees built
  - *Nodesize* – number of terminal nodes (tree size)

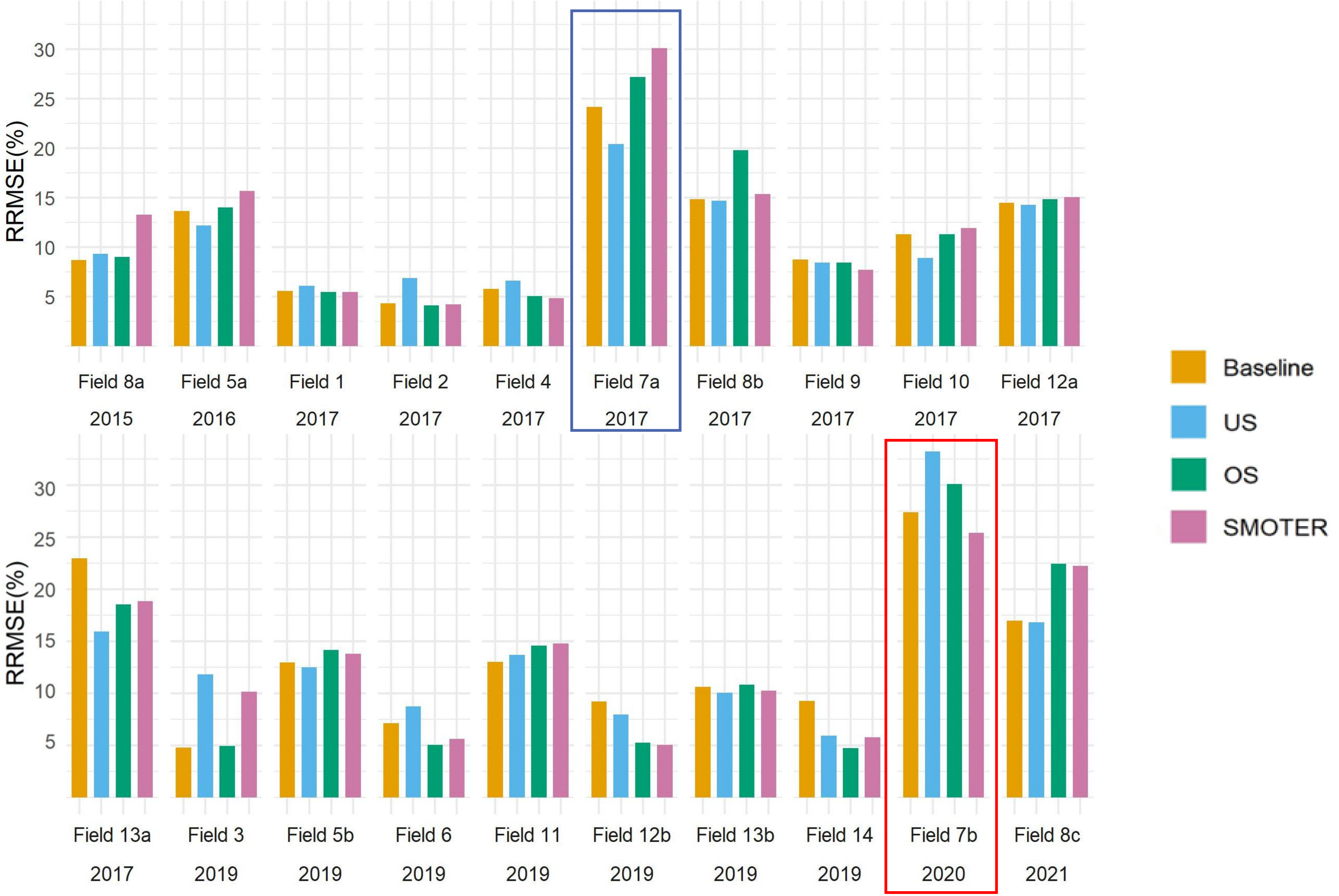
(Gareth et al., 2013)


Baseline
US
OS
SMOTER
Predicted yield (t./ha.)
Actual yield (t./ha.)
55
50
45
40
35
30
RMSE: 5.07 t/ha.
RRMSE: 11.8%
PBIAS: -0.015%
RMSE: 4.94 t/ha.
RRMSE: 11.5%
PBIAS: -0.006%
RMSE: 5.53 t/ha.
RRMSE: 12.9%
PBIAS: 0.005%
RMSE: 5.58 t/ha.
RRMSE: 13.0%
PBIAS: -0.002%
2015
2016
2017
2019
2020
2021

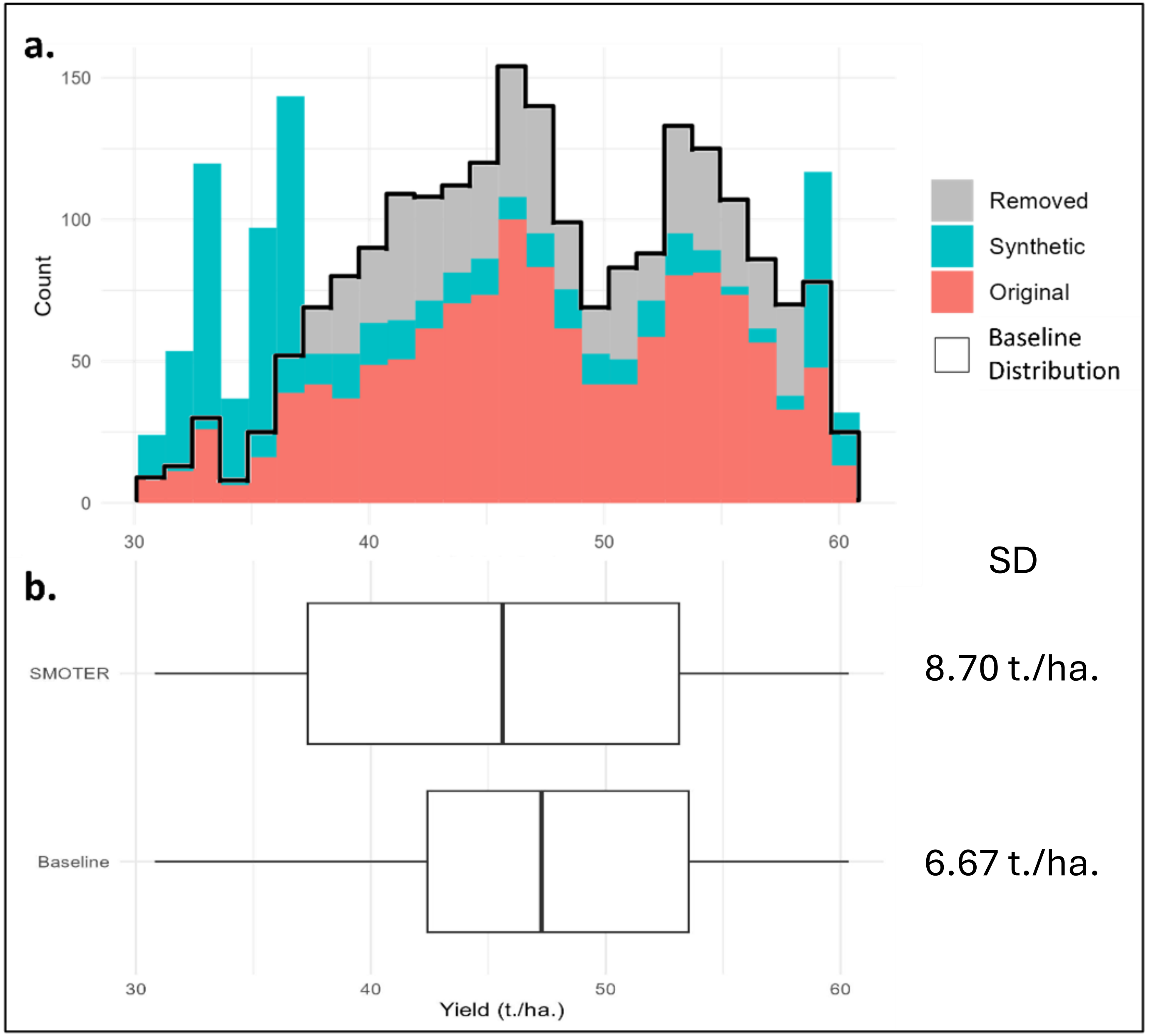
Wins/Losses

		Best	Win	Loss
Average Whole-Field Predicted Yield	baseline	4	-	-
	OS	2	7	13
	SMOTER	5	9	11
	US	9	12	8
RRMSE	baseline	3	-	-
	OS	3	9	11
	SMOTER	5	10	10
	US	9	12	8
PBIAS	baseline	2	-	-
	OS	4	9	11
	SMOTER	5	8	12
	US	9	12	8

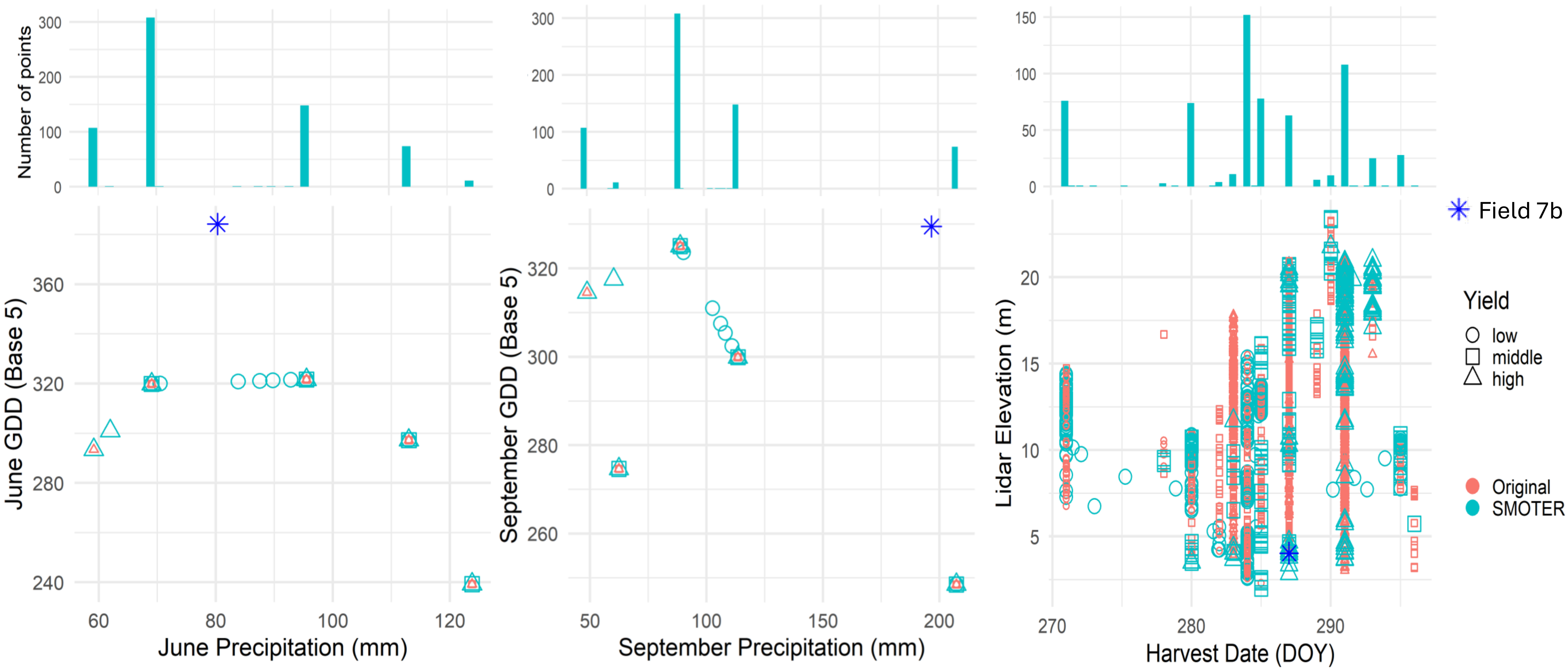
RRMSE
per field-year



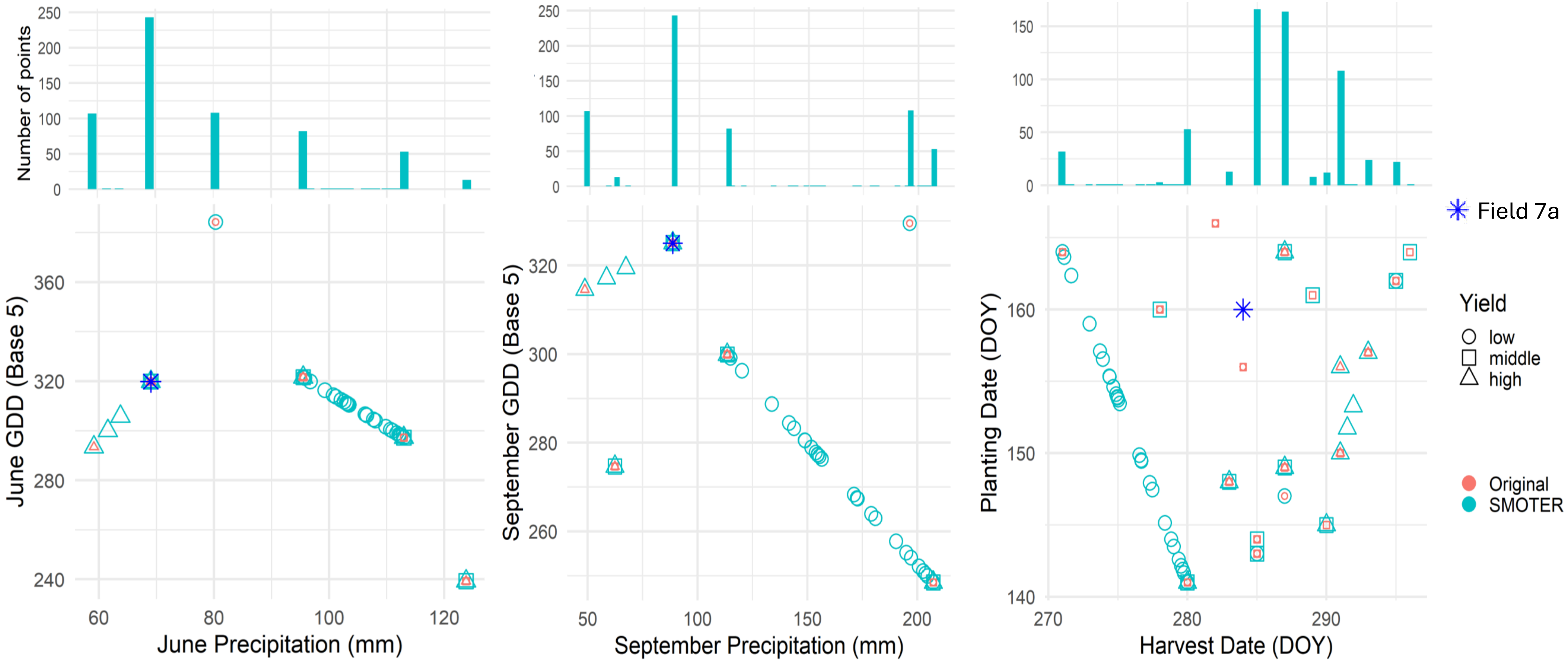
Field 7b – New Training Set Distribution with SMOTER



Field 7b (Drought Year) – SMOTER Feature Space



Field 7a (2017) – SMOTER Feature Space



Conclusion

- US performed best overall
- SMOTER had best performance for drought year
- SMOTER increases the variability within feature space
- Potential to improve predictions for cases of limited data due to drought or extreme years

- Fine-tuning of SMOTER parameters
- Future experiments with more drought or extreme years
- Expand to more models

References

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Thank you

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