A framework to predict start and end of future cropping seasons: potential and limitations

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Background

Farmers adapt start, end and duration of the cropping season to climate change. Crop modelers often use simple rule-based approaches to set the beginning of the cropping season under future climate. But does this represent what happens in practice in the field? How much does the farmers’ decision depend on weather and environmental variables? What is their predictive power using a data-driven approach?

Methods

Input – spatial covariates
- Topsoil class (BOFEK2020)
- Groundwater class (BRO-WDM)
- BRP (crop and preceding crop)
- ASAP crop mask (base map)

Input – time series
- Historical weather data (KNMI & JRC).
- Future weather from GCMs.

Target – markers
- From Groenmonitor (https://www.groenmonitor.nl/)
- Emergence dates
- Harvest dates

Data-driven model
- Convolutional Neural Networks
- Split data in:
  - Year-by-year (1 model per year)
  - Naive (random split)
  - Leave-year-out (unseen year as test)
- Train and test.
- Predict with future weather.
- Visualize in dashboard.

Results

<table>
<thead>
<tr>
<th>Split</th>
<th>Emergence</th>
<th>Harvest</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Year-by-year</td>
<td>Naive Leave-year-out</td>
</tr>
<tr>
<td>R²</td>
<td>0.29</td>
<td>0.30</td>
</tr>
<tr>
<td>MAPE</td>
<td>5.38</td>
<td>5.40</td>
</tr>
</tbody>
</table>

Table 1. Model performance on the test set.

Conclusions

- System can be improved with more years, as they become available. “Year effect” matters.
- Low explanatory power, but in line with other studies.
- Neural networks don’t perform well outside the range of the training data.
- Accurate predictions in the far future are likely not feasible.