I. Introduction & Motivation

GRASSLAND FORAGE PROVISION
- Important ecosystem service
- Potential often unknown
- Expensive/laborious analysis

REMOTE SENSING OF FORAGE PROVISION
→ Mapping of grasslands
→ Hyperspectral modelling of forage provision

Research gap → Objectives
So far, only regional modelling of forage quality (metabolizable energy - ME)
→ "Trans-climatic" modelling of forage quality by hyperspectral readings
→ Different predictor variables and model training/learning methods

II. Study Site & Methods

Methods for hyperspectral readings from grassland canopies
- Field Spectrometer
- Derivations of spectra
- Hyperspectral canopy reflection
- Features & Indices

Chemical analysis of metabolizable energy (ME)
- Machine learning (PLSR & RFR models)

Model validation of regional and trans-climatic prediction models of forage quality based on absorption features, vegetation indices and 1st derivation of the reflectance spectra. Model accuracy was quantified with the normalized root mean square error ($nRMSE$) and the coefficient of determination ($R^2$).

Validation of the partial least squares regression (PLSR) models

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Predicted ME (Mj/kg DM)</th>
<th>Observed ME (Mj/kg DM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperate</td>
<td>$n_{RMSE} = 12.98$</td>
<td>$R^2 = 62.05$</td>
</tr>
<tr>
<td>Tropical</td>
<td>$n_{RMSE} = 10.83$</td>
<td>$R^2 = 58.72$</td>
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<td>Trans-Climatic</td>
<td>$n_{RMSE} = 11.56$</td>
<td>$R^2 = 61.13$</td>
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Highlights
- High model accuracy of trans-climatic forage quality prediction
- More data will improve trans-climatic models
- Possible forage predictions for other grassland regions

Results predictors & models
1. Best model accuracy with 1st derivative of spectra, followed by models based on absorption features & vegetation indices
2. Slight underestimation of high forage quality values → more data input needed

III. First Results

Validation of the partial least squares regression (PLSR) models

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<td>$n_{RMSE} = 12.39$</td>
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<tr>
<td>$n_{RMSE} = 10.07$</td>
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<td>$n_{RMSE} = 10.10$</td>
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IV. Conclusion & Outlook

Conclusion
Trans-climatic prediction models can have similar qualities as regional models, but need more input data points

Outlook
- More data from other regions, continents, climate zones
- Spatial/climatic cross validation
- Comparing results to deep learning methods
- Biomass prediction with hyperspectral readings

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