

Earth Observation for Monitoring Cereal Crop Responses to Multiple Stressors (EO4Cerealstress)



IMPACT ASSESSMENT REPORT SCIENCE CASE (IAR-SC)

Task Lead	University of Guelph, Canada
Task Partners	UoS, UK BOKU, Austria UoSev, Spain ITC, Netherlands AAFC, Canada



University of Natural Resources
and Life Sciences, Vienna



DOCUMENT RELEASE SHEET

	Name	Signature	Date
Task lead	Aaron Berg (UofG)		
Contributing Authors	Victor Rodriguez-Galiano (UoSev), Andy Nelson (UT-ITC), Roshanak Darvishzadeh (UT-ITC), Omid Ghorbanzadeh (BOKU), Zaibunnisa (UoS), Catherine Champagne (AAFC)		
Approval (internal)	Jadu DASH (UoS)		
Approval (ESA)	Espen Volden		
Distribution	Public		

DOCUMENT CHANGE LOG

Issue	Issue date	Pages affected	Relevant information
V1.0	17-09-2025	All	First draft version
V2.0	25-11-2025	4-7, 9-11, 14-15	First draft revision

Table of Contents

Summary	4
CASE I: Assess the Impact of Drought in Canada Using Existing Earth Observation (EO) Datasets	4
1. Introduction.....	4
2. Materials and Methods	5
3. Results	6
4 Outlook	8
Case II: EO4CerealStress Workflow Implementation at the Elora Research Site	9
5. Introduction.....	9
6. Methods	10
7. Results.....	13
8. Overall Summary: Assessing the value of stress indicators for mitigating productivity losses	15
9. References	16

Summary

This document is the first version of the Impact Assessment Report (Science), highlighting the results of activities in Task 5 developed under the EO4Cereal Stress Project funded by ESA. This report presents innovative experimental methodologies designed to address key scientific questions and bridge critical knowledge gaps in the understanding of crop responses to multiple stresses. A regional-scale analysis was carried out to assess the effects of multiple stress factors on crop physiological processes, with a particular focus on productivity and water balance. Two primary components were developed under this task:

Case I: Using existing Earth observation data, a study was conducted to evaluate vegetation stress indicators for drought impact monitoring across Canada's Prairies region. This work provides a foundation for operational monitoring using EO-based stress metrics.

Case II: Field experiments were carried out using large weighing lysimeters combined with hyperspectral cameras. These experiments leveraged software tools, spectral indices, and applications developed within the EO4-Cereal Stress science use case, providing inferences into plant stress responses under controlled yet scalable conditions.

Together, these methodologies contribute to the development of a robust, transferable use case example for crop stress detection and monitoring at both field and regional scales.

CASE I: Assess the Impact of Drought in Canada Using Existing Earth Observation (EO) Datasets

1. Introduction

A preliminary assessment of the impact of drought on crop yields was conducted over the Canadian Prairies (as reported in Mardian et al., 2024). The Prairie region of Canada is a key wheat-producing area, facing chronic water scarcity and limited irrigation infrastructure. Agriculture and Agri-Food Canada (AAFC) produces a monthly assessment of drought released as the Canadian Drought Monitor. The monthly data set tracks the location, intensity, and evolution of drought using a large combination of meteorological and satellite data sources and expert analysis. While the product is important for classifying the intensity and locations where drought is occurring, the linkage to the impact on crop stress has not been established. To address this research gap, a study was conducted to combine the existing Canadian Drought Monitor (CDM; AAFC, 2025a) with an assessment of crop stress as identifiable through EO data. In this work, we adopted a risk assessment approach using the IPCC's definition of risk as a function of hazard, exposure, and vulnerability to link how drought severity and timing may influence spring wheat yield losses.

2. Materials and Methods

Spring wheat yield data at the township-scale ($\sim 95 \text{ km}^2$) were obtained from AAFC through provincial crop insurance agencies and converted to kilograms per hectare (kg/ha). Over the Prairie Region, yield data were available over a total of 7,320 townships, and a subset of 4,905 was selected based on consistent wheat cultivation (present in at least 75% of years from 2010–2021). The overall model framework is presented in **Figure 1**.

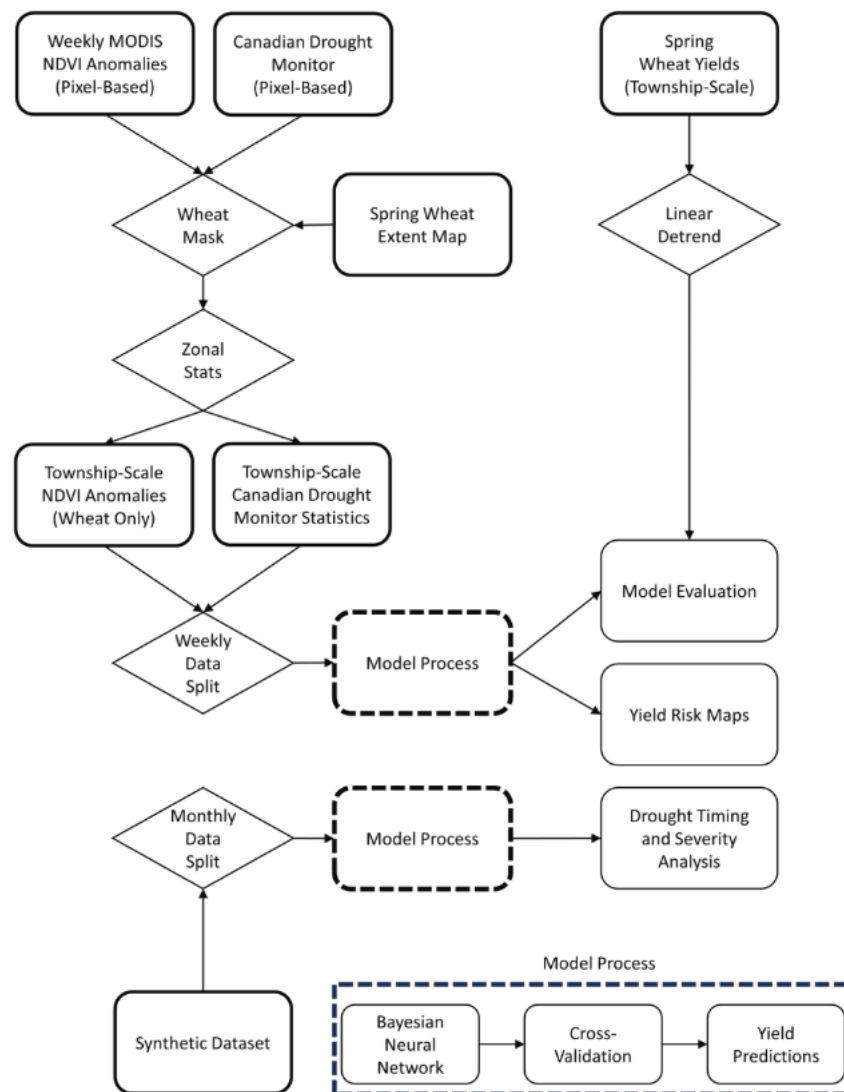


Figure 1 Model workflow (Mardian et al. 2024). Data integrated into this analysis includes the Canadian drought monitor (AAFC 2025a), MODIS NDVI data was also processed from AAFC (AAFC 2025b); The yield data is was a proprietary dataset.

A trend analysis demonstrated that yield data increased over the study period due to factors like improved technology and farming practices. Therefore, the yield data were detrended to isolate climate-driven variability. A linear detrending method was applied

using ordinary least squares (OLS) regression for each township. The rainbow test confirmed that a linear model was appropriate in 94.5% of cases.

Normalized Difference Vegetation Index (NDVI) data from the MODIS satellite (250 m resolution; AAFC 2025b) were used to monitor in-season crop growth. Weekly NDVI anomalies (2002–2021 baseline) from the Canadian Ag-Land Information System (CALMS) were averaged to the township level. Historical NDVI means and standard deviations were included as predictors to help the model interpret current vegetation status relative to normal conditions.

Monthly drought severity maps from the Canadian Drought Monitor (CDM) were acquired from Agriculture and AgriFood Canada. The data was categorized from “No Drought” to “Exceptional Drought” (D4). The drought code value was resampled to weekly intervals to align with NDVI data and aggregated to the township scale, enabling spatial and temporal consistency with yield datasets.

AAFC’s Annual Crop Inventory (ACI; AAFC 2025c) was used to identify spring wheat fields within each of the townships for each growing season, ensuring that only wheat-specific vegetation signals were used in yield prediction models. All non-wheat land covers were masked out to avoid signal contamination from other crops. With classification accuracies typically above 85–90%, the ACI also excludes fields too wet to seed, preventing fallow land from being misclassified as drought-affected. Originally at a 30 m resolution, ACI data were resampled to 250 m using a majority filtering approach where each 250m grid cell was assigned the most common crop type it contained.

Bayesian Neural Networks (BNNs) were selected for modelling yield predictions as BNNs allow for the quantification of uncertainty. To account for uncertainty in the yield forecasts, we attempted to incorporate aleatoric uncertainty (data noise) through probabilistic output distributions that mimic measurement error and environmental variability; and epistemic uncertainty (model uncertainty) via Monte Carlo sampling to estimate a distribution of the model weights. We trained separate models for each week of the growing season (from late April to late September), using NDVI and CDM data from the current and previous three weeks. Model training was performed using a leave-one-out cross-validation over the 12-year dataset (2010–2021). We optimized both yield accuracy and uncertainty using a Gaussian Negative Log-Likelihood loss function. The model hyperparameters were tuned using the Hyperband optimization algorithm.

The model performance was evaluated using the Normalized Root Mean Square Error (nRMSE) for absolute accuracy; Mean Absolute Error (MAE) and MAE% for yield-specific error, R^2 and Pearson correlation coefficient (r) for model fit, and Interval Coverage Scores to assess uncertainty calibration. The overall impact of drought timing and severity on yields was quantified monthly.

3. Results

Between week of year (WOY) 29-34 were found to be the period with the highest prediction accuracy, with R^2 of 0.7, Pearson correlations of 0.84, and mean absolute

errors of 400 kg/ha (13%). These results suggest similar to improved performance relative to previous research (Mkhabela et al., 2011; Qian et al., 2009). However, we identified the potential benefits of our approach to include: a) enhance spatial resolution (95km² vs. 35,000km²), b) continuous spatial coverage as it uses data from satellite rather than weather stations, and c) the model is relatively simple as it only involves NDVI and CDM data as inputs.

With respect to model accuracy, yield forecasting accuracy improves significantly starting from WOY 27 (~July 2–8), aligning with key wheat growth stages and findings from previous NDVI-based studies. Early-season predictions (WOY18–WOY21) are unreliable due to vegetation visible from satellite imagery; accuracy gradually improves through WOY26 during the jointing stage and rises sharply in WOY27–29, corresponding to the sensitive heading stage. Model performance peaks around WOY32 (August 6–12), coinciding with the soft dough stage when wheat reaches physiological maturity. Accuracy remains high until WOY35, after which it declines as harvesting reduces green vegetation detectable by NDVI. Figure 2 illustrates the model accuracy (mean absolute errors in kg/ha) and the week of highest prediction accuracy.

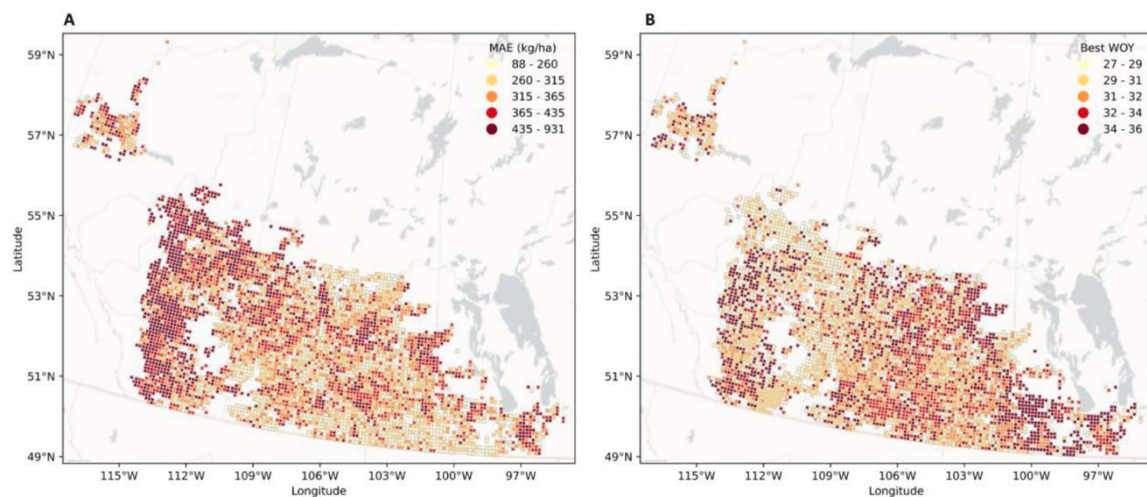


Figure 2 (A) Lowest mean absolute error (kg/ha) spring wheat yield predictions and the week of year that this occurred (B)

The BNN model was retrained using historical data (2010–2021) to simulate how drought timing and severity may impact wheat yield outcomes. We found that spring wheat yields respond to varying drought severities (ND to D4) across different months. Results show that drought during June, July, and August has the most significant impact on yield anomalies, with D2 to D4 events reducing yields by 12–25% on average and up to 40% in some areas. Uncertainty is lowest in August, indicating more reliable predictions late in the season.

In May, drought impacts are variable and generally weaker due to early crop development and limited training data. However, early-season water stress still adversely affects seedling growth. In June, drought increasingly impacts yields, especially during the jointing stage, although the effects vary by region. July shows stronger and more

consistent yield losses, particularly if they occur during the heading stage, a critical period for water sensitivity. Uncertainty of the model decreases in July, suggesting better model confidence. In August, slight drought conditions (D0 and D1) may enhance yields through physiological stress responses that boost grain filling. This counterintuitive result highlights the crop's adaptive mechanisms during late growth stages. Drought impacts on yield anomalies as a function of month are shown in Figure 3.

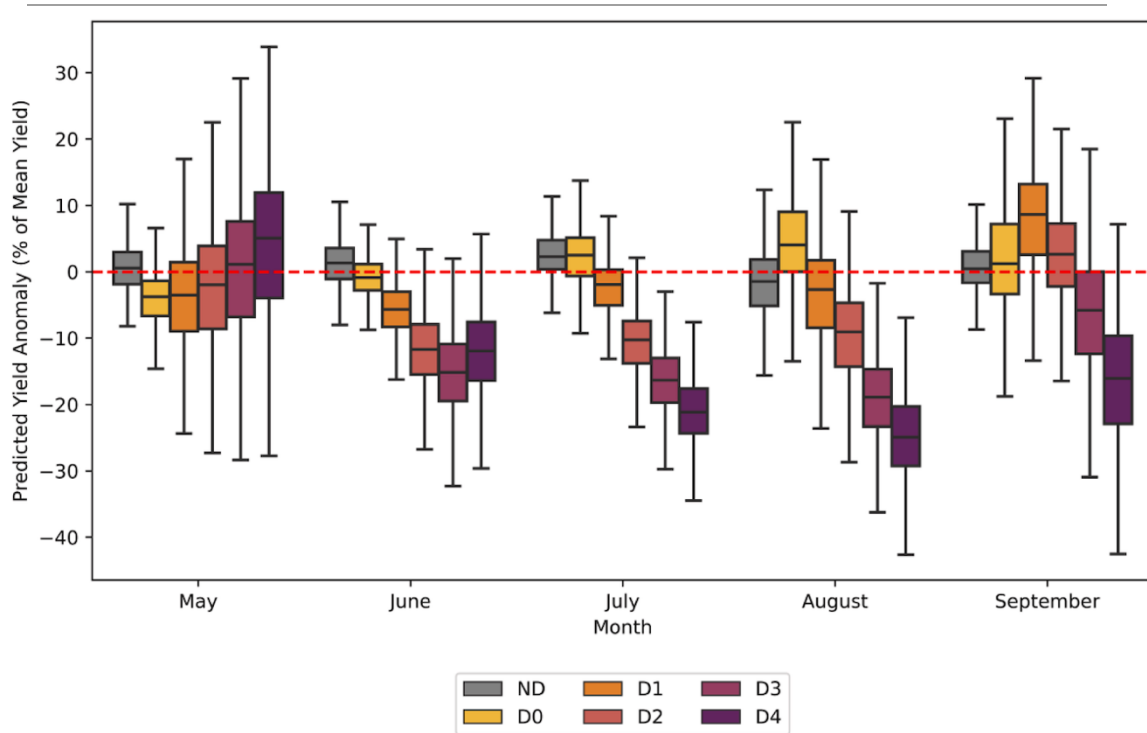


Figure 3. Average yield anomaly predictions (as a% of mean yield) for townships across the Canadian Prairies under different drought severities.

4 Outlook

This study has enhanced the understanding of crop stressors using a multi-factor drought model based on the Canadian Drought Monitor (CDM) integrated into a crop-specific risk assessment framework for spring wheat yield prediction within the Canadian Prairies. A Bayesian Neural Network (BNN), trained on CDM data and NDVI, was developed to predict wheat yields with high spatial resolution, continuous coverage, uncertainty estimates, and minimal predictors. Our vulnerability assessments under different drought timings and severities demonstrated that wheat yield is most sensitive in July–August, while mild dryness in August is potentially beneficial. Yield uncertainty decreased mid-season, suggesting opportunities for the application of earlier mitigation approaches. High-resolution risk maps translate findings into actionable tools for farmers; ultimately, this could support the use of cost-benefit decisions across different risk scenarios. The relatively simple framework is adaptable to other crops and regions.

Overall, this section of this report has provided an overview of the paper published on this research (Mardian et al. 2024). We envision that there are several opportunities for improvement to the approach described. The quantification of risk (low to exceptional risk) should likely be further quantified into predicted yield anomalies. We also acknowledge that there are several limitations to the use of NDVI as an indicator of crop health. Satellite products more sensitive to crop growth anomalies in spring wheat, such as those emerging from research in EO4-CerealStress, and potentially those derived from upcoming Sentinel Expansion Missions, could be substituted and applied at a finer spatial scales and provide more physically relevant indicators of crop stress.

Case II: EO4CerealStress Workflow Implementation at the Elora Research Site

5. Introduction

The impact of fine-scale, physically relevant drought indicators from Earth observation on risk assessment was evaluated at a well-instrumented site in Ontario, Canada. Evapotranspiration (ET) is a key component of the global water budget, returning more than 60% of land precipitation to the atmosphere. It influences climate, energy exchange, and agricultural productivity, making accurate estimation critical for water resource management, drought forecasting, and precision irrigation. Direct measurements using instruments like lysimeters are accurate but limited in scale and cost, while remote sensing (RS) and modelling approaches provide broader coverage. For applications related to crop stress monitoring, RS-based approaches, which include temperature-driven models (e.g., METRIC, ALEXI) that exploit surface thermal properties, and conductance-based models (e.g., Penman-Monteith, big-leaf) that rely on vegetation attributes such as leaf area index (LAI), it is clear that both approaches face challenges: temperature-based models suffer under cloud cover and energy-limited conditions, while conductance-based models require detailed canopy information and often underestimate ET.

Vegetation indices (VIs), particularly NDVI and LAI, have been widely used to link canopy characteristics to transpiration, but their effectiveness is limited by saturation at high values. Alternatives such as SAVI, EVI, and indices leveraging hyperspectral or physiological signals (e.g., PRI, WI, RVSI, MCARI) may improve performance, but these results are not always consistent (Kross et al, 2015). This study examines nine VIs derived from hyperspectral data at the University of Guelph's Elora lysimeter site, aiming to quantify their relationship with ET and identify spectral regions or new indices that better capture crop-specific ET dynamics for wheat, corn, and soybean.

Further analysis was completed to evaluate the applicability of the framework developed as part of the EO4 Cerealsstress and included in the Algorithm Theoretical Basis for the prediction of field-measured LAI (D3.1).

6. Methods

This study was carried out at the University of Guelph's Elora Research Station, situated in Elora, Ontario, Canada (**Figure 4**). This facility is equipped with 18 large weighing lysimeters designed to continuously measure evapotranspiration (ET) in situ. The lysimeters have a depth of 1.5 m and a surface area of 1 m², each housing an undisturbed soil monolith that rests on a tension load cell capable of detecting mass changes equivalent to 10 g/m² or 0.01 mm/m² of water. ET is determined by monitoring weight changes in both the soil monolith and the drainage tank within each lysimeter. The lysimeters contain two different soil types: a sandy loam monolith collected from near Cambridge, Ontario, and a silt loam collected from Elora, Ontario. Crop management practices among the lysimeters vary; 12 of the lysimeters were subject to a diversified crop rotation of corn-soybean-wheat, while the remaining 6 lysimeters were treated with a corn-soy rotation.

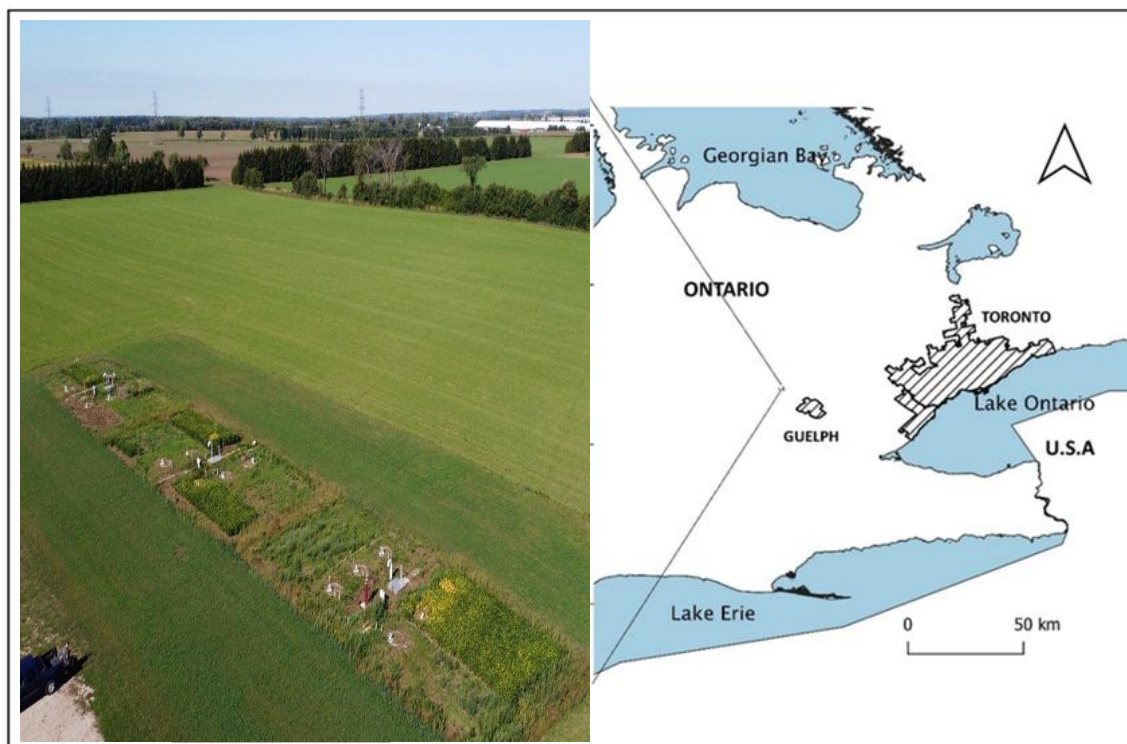


Figure 4. The lysimeter site within the Elora Research Station near Elora Ontario.

Our study encompasses three consecutive summer seasons, from 2020 to 2022, with data gathered during semi-regular weekly visits from May to September each year. Initially, in 2020, our study focused on 12 lysimeters planted with winter wheat. Subsequently, in both the 2021 and 2022 seasons, all 18 lysimeters were planted with corn and soy covers, respectively. ET measurements were aggregated to hourly estimates corresponding with field visits. Additionally, leaf area index (LAI) was collected using LI-COR Biosciences' handheld LAI-2200c plant Canopy Analyzer.

Headwall's Nano-Hyperspec instrument, mounted on a DJI Matrice M600 Uninhabited Aerial Vehicle (UAV), was flown weekly during the growing season. The instrument has a spectral resolution of 2.24 nm and captures spectral reflectance values from 400 – 1000 nm across 270 bands. Routine flights were conducted on a semi-regular weekly schedule, dependent on local weather conditions. The UAV followed a consistent NE-W flight path, completing four overpasses with a 60% overlap between swaths. Before each UAV flight, the sensor was calibrated using a white reflectance panel placed on the ground to determine the optimal speed dependent on sun exposure conditions. Generally, flight altitude is maintained 30 m above the surface, at flight speeds between 1-5 m/s, resulting in a pixel size of 3.42 cm². Post-flight, the data was processed using SpectralView software and the reflectance panel. Several vegetation indices were processed from processed imagery as reported in Table 1. The vegetation index values

Table 1: List of VIs used, their abbreviations, as well as formulas and wavelengths used in their calculations, Where ρ_x refers to reflectance at that band, and $L = 0.5$, which is applied as a correction factor applied to the formula to account for bare soil evaporation, and all wavelengths are shown in nm (Glenn et al., 2007, Carpintero et al., 2020).

Vegetation Index	Abbrv.	Formula	Version Used	Reference
Normalized Difference Vegetation Index	NDVI	$\frac{\rho_{865} - \rho_{655}}{\rho_{655} + \rho_{865}}$	$\frac{\rho_{866.028} - \rho_{655.785}}{\rho_{866.028} + \rho_{655.785}}$	Glenn et al., 2007, Marshall et al., 2016
Soil Adjusted Vegetation Index	SAVI	$\frac{(\rho_{865} - \rho_{655})(1 + L)}{(\rho_{865} + \rho_{655} + L)}$	$\frac{(\rho_{866.028} - \rho_{655.785})(1 + L)}{(\rho_{866.028} + \rho_{655.785} + L)}$	Glenn et al., 2007, Marshall et al., 2016
Greenness Index	GI	$\frac{\rho_{539}}{\rho_{682}}$	$\frac{\rho_{539.48}}{\rho_{682.624}}$	Zarco- Tejada et al., 2005
Red-Edge Vegetation Stress Index	RVSI	$0.5(\rho_{722} + \rho_{763}) - \rho_{733}$	$0.5(\rho_{722.884} + \rho_{763.143}) - \rho_{734.067}$	Merton & Huntington, 1999
Hyperspectral Normalized Difference Vegetation Index	HNDVI	$\frac{\rho_{827} - \rho_{668}}{\rho_{827} + \rho_{668}}$	$\frac{\rho_{828.005} - \rho_{669.205}}{\rho_{828.005} + \rho_{669.205}}$	Oppelt and Mauser, 2004
Water Index	WI	$\frac{\rho_{895}}{\rho_{983}}$	$\frac{\rho_{895.104}}{\rho_{982.333}}$	Penuelas et al., 1997
Photochemical Reflectance Index	PRI	$\frac{\rho_{550} - \rho_{531}}{\rho_{550} + \rho_{531}}$	$\frac{\rho_{550.663} - \rho_{530.534}}{\rho_{550.663} + \rho_{530.534}}$	Gamon et al., 1992
Modified Chlorophyll Absorption Ratio Index	MCARI	$\frac{\rho_{712}(\rho_{712} - \rho_{682}) - 0.2(\rho_{712} - \rho_{539})}{\rho_{682}}$	$\frac{\rho_{711.701}(\rho_{711.701} - \rho_{682.624}) - 0.2(\rho_{711.701} - \rho_{539.480})}{\rho_{682.624}}$	Daughtry et al., 2000

were then correlated to daily actual evapotranspiration (AET) values estimated from the lysimeters using a Pearson’s Correlation Test to determine the relationship strength.

Beyond comparisons to the individual vegetation indices, we also applied a workflow using 4SAIL (Verhoef et al. 2007) and PROSPECT-PRO (Feret et al. 2021) to generate reflectance curves for calculating Leaf Area Index (LAI) estimation for comparison with field measurements. Following the procedure from the EO4CerealStress Algorithm Theoretical Basis document (D3.1) for the Andalusia site, a predictive model was generated using “Gaussian Process Regression” based on hyperspectral data taken at our lysimeter site in Elora, ON. The data used were the hyperspectral and LAI data collected during the 2021 growing season (corn). Crop-specific characteristics for corn, such as carotenoid content and leaf angle, were taken from the literature (e.g. Lu et al. 2021). An outline of these values can be seen in Table 2.

Table 2. Input values for PROSPECT-PRO modeling for the Elora Research Site

Variable	Short Name	Mean	Min	Max	Distribution
Chlorophyll	CHL	35	20	50	Normal
Carotenoid	CAR	10	0	15	Normal
Anthocyanin	ANT	0	0	0	
Thickness of water	EWT	0.02	0.015	0.025	Normal
	LMA	0.0048	0.0035	0.006	
Brown pigment	BROWN	0	0	0	Uniform
Protein content	PROT	0.0015	0.0015	0.0015	Uniform
Carbon-based constituents	CBC	0.01	0.01	0.01	Uniform
Leaf structure	N	2.2	1.4	4	Uniform
Soil brightness coefficient	PSOIL	-	0.01	0.05	Uniform
Average leaf angle	LIDFa	30	20	50	Poisson
Leaf area index	LAI	4	0	7	Uniform
Hot spot effect	q	-	0.01	0.5	Uniform
Diffuse/direct radiation	skyl	-	0.2	0.3	Uniform
Solar zenith angle	SZA	-	15	55	Uniform
Observer zenith angle	OZA	0	0	0	Uniform
Relative azimuth	rAA	0	0	0	Uniform
Solar brightness coefficient	asoil	-	0.2	0.28	Uniform

7. Results

Correlations of several vegetation indices to actual evapotranspiration measured from the lysimeters showed that HNDVI and NDVI had the strongest relationships for winter wheat ($r = 0.84$ and 0.83 ; $SD = 0.12$ for both). Corn results were notably weaker, with MCARI ($r = 0.23$, $SD = 0.31$) and RVSI ($r = 0.20$, $SD = 0.29$) as the top vegetation indices for ET, but with substantial variability. For soybean, HNDVI ($r = 0.41$, $SD = 0.27$), NDVI ($r = 0.39$, $SD = 0.27$), and GI ($r = 0.38$, $SD = 0.16$) were most effective. Indices such as PRI, RVSI, and MCARI consistently underperformed, often exhibiting weak or even negative correlations with AET, particularly during the soy season. The seasonal relationships (correlations) among the various vegetation indices are also summarised in Figure 5.

Table 3.

Crop	Top Indices	Mean Correlation	SD
Wheat	HNDVI, NDVI	0.84, 0.83	0.12, 0.12
Corn	MCARI, RVSI	0.23, 0.20	0.31, 0.29
Soy	HNDVI, NDVI, GI	0.41, 0.39, 0.38	0.27, 0.27, 0.16

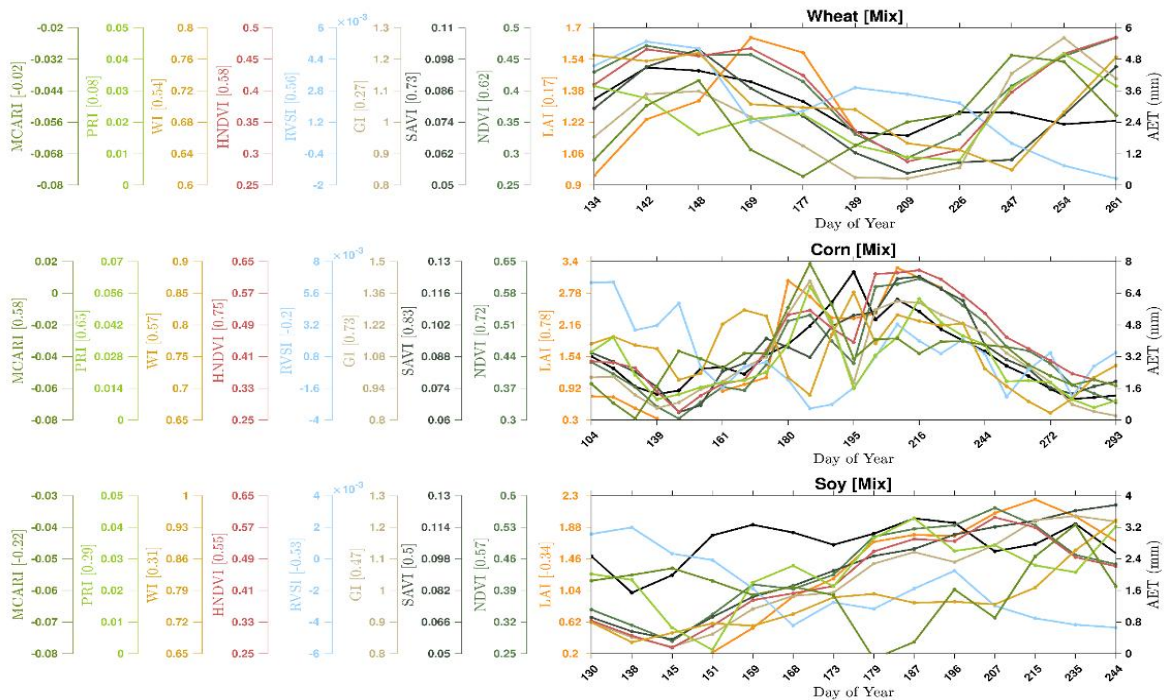


Figure 5. Relationships among several vegetation indices (y-axis) and actual evapotranspiration (AET) with correlation shown on the y-axis.

Results of the PROSPECT-PRO modelling, which used the hyperspectral images for predicting field-measured LAI, suggest fairly strong relationships, with an RMSE of 0.81, an R of 0.74, and an R^2 of 0.55. It showed a lower R^2 but higher RMSE relative to the performance of the model over the Andalusia site, which showed an R^2 of 0.71 and an RMSE of 1.353. Generally, the model struggled to estimate the true variability in LAI

compared to observations. The PROSPECT-PRO-based model developed as part of the EO4-CerealStress relative to observations is shown in **Figure 6**.

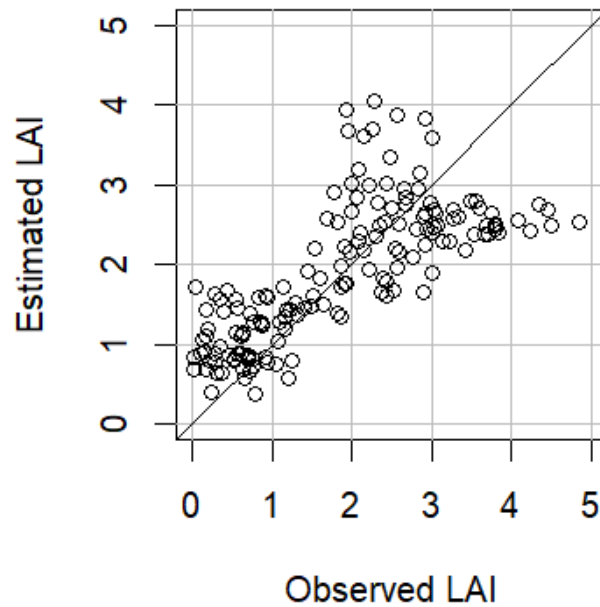


Figure 6. Observed vs. estimated LAI for corn during the 2021 growing season.

A comparable model for estimating LAI using Sentinel-2 data was used to derive LAI products from the Landscape Evolution And Forecasting (LEAF)-Toolbox over the study site (Fernandez et al. 2021). Compared to the hyperspectral drone data generated LAI values the GPR model tended to overestimate LAI in May and June. From July onwards, it showed better alignment with observed values than the Sentinel-2 derived data, capturing peaks and dips in LAI that Sentinel was unable to (**Figure 7**). The early season underestimation is possibly related to sensor issues, as the hyperspectral camera was recording unusually low reflectance values in the 800-1000 nm range. Better sensor calibration could lead to improved model output.

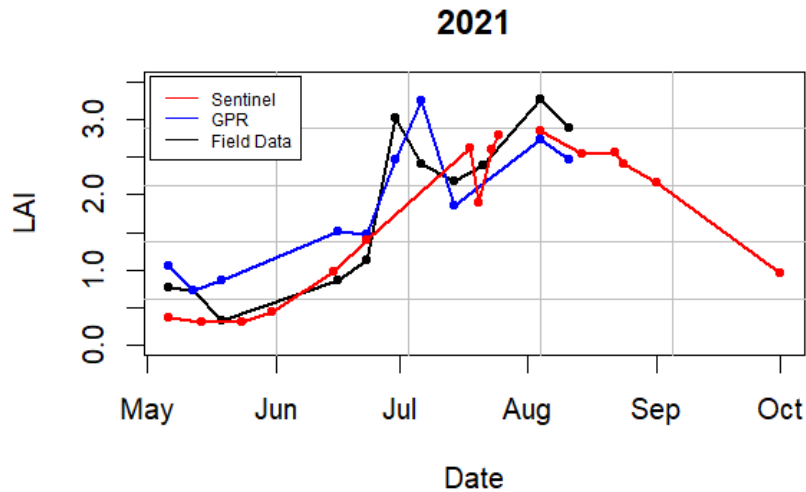


Figure 7. Time series of LAI over the 2021 growing season as derived from Sentinel-2, hyperspectral data, and as observed at the site.

8. Overall Summary: Assessing the value of stress indicators for mitigating productivity losses

To estimate crop risk to drought over a very large geographic area, the Canadian Prairie region (over 50 million ha), we used a Bayesian Neural Network (BNN) to combine Canadian drought monitor data and satellite-based NDVI anomalies (2010–2021) to predict high-resolution wheat yields with quantified uncertainty. The model achieved accuracy comparable to previous research, with 13–18% error and R^2 values of 0.43–0.70, peaking in early August. Results show that droughts from June to August reduce yields in proportion to severity, while abnormally dry conditions can benefit yields, particularly in August. Prediction uncertainty declines significantly from June to July, highlighting July as a critical point for mitigation efforts. The framework also produced operational risk maps combining yield vulnerability with CDM data, demonstrated through a case study. It is envisioned that these maps could provide near-real-time, actionable insights for farmers and decision-makers. This application was previously published (Mardian et al. 2024).

Indicators such as NDVI may not be appropriate for modelling all crops, as the indicator, while used broadly, has many notable weaknesses, such as saturation within dense canopies, limited sensitivity to chlorophyll, and strong influences of soil effects. Therefore, the use of other, more physically representative indicators and models more closely associated with crop stress is preferable. Using a framework developed by EO4-CerealStress on the Andalusia site, we evaluated the calculation of Leaf Area Index using hyperspectral drone data and a Gaussian Process Regression model trained for rice crops in Andalusia, Spain. The model was adapted for corn crops and evaluated over a research site in Ontario, Canada. The model shows promising results for generating LAI at a fine spatial resolution (~1m). Application of LAI using Sentinel-2 also showed a strong relationship to field measurements, suggesting that this data set could be used in

regional analysis of drought impacts and improve the spatial resolution and physical representativeness of existing drought monitoring approaches. Stakeholders that may use this data we anticipate would be decision makers (government agencies) who may be monitoring crop conditions for forecasting yield or crop losses. A publication based on this application is in preparation.

9. References

1. AAFC. (2025a). Canadian drought monitor. Retrieved from <https://agriculture.canada.ca/en/agricultural-production/weather/canadian-drought-monitor>
2. AAFC. (2025b). The Canadian Ag-land monitoring system (CALMS) [Dataset]. Retrieved from https://agriculture.canada.ca/atlas/data_donnees/calms/
3. AAFC.(2023c). Annual crop inventory. Retrieved from <https://open.canada.ca/data/en/dataset/ba2645d5-4458-414d-b196-6303ac06c1c9>
4. Brown, S., Wagner-Riddle, C., Debruyn, Z., Jordan, S., Berg, A., Ambadan, J. T., ... & Machado, P. V. F. (2021). Assessing variability of soil water balance components measured at a new lysimeter facility dedicated to the study of soil ecosystem services. *Journal of Hydrology*, 603, 127037.
5. Carpintero, E., Mateos, L., Andreu, A., & González-Dugo, M. P. (2020). Effect of the differences in spectral response of Mediterranean tree canopies on the estimation of evapotranspiration using vegetation index-based crop coefficients. *Agricultural Water Management*, 238, 106201.
6. Féret, J. B., Berger, K., De Boissieu, F., & Malenovsky, Z. (2021). PROSPECT-PRO for estimating content of nitrogen-containing leaf proteins and other carbon-based constituents. *Remote Sensing of Environment*, 252, 112173.
7. Fernandes, R., F. Baret, L. Brown, F. Canisius, J. Dash, N. Djamai, G.Hong, S. Kalimpalli, R. Latifovic, C. MacDougall, H. Shah, M. Weiss, K. Harvey and L. Sun., 2021, "LEAF Toolbox", Canada Centre for Remote Sensing, <https://github.com/rfernand387/LEAF-Toolbox/wiki>, DOI: 10.5281/zenodo.4321298.
8. Glenn, E. P., Huete, A. R., Nagler, P. L., Hirschboeck, K. K., & Brown, P. (2007). Integrating remote sensing and ground methods to estimate evapotranspiration. *Critical Reviews in Plant Sciences*, 26(3), 139-168.
9. Kross A, McNairn H, Lapen DR, Sunohara M, Champagne C (2015). Assessment of RapidEye vegetation indices for estimation of leaf area index and biomass in corn and soybean crops. *International Journal of Applied Earth Observation and Geoinformation*, 34, 235 - 248. (436). <http://dx.doi.org/10.1016/j.jag.2014.08.002>.

10. Lu, B., Proctor, C., & He, Y. (2021). Investigating different versions of PROSPECT and PROSAIL for estimating spectral and biophysical properties of photosynthetic and non-photosynthetic vegetation in mixed grasslands. *GIScience & Remote Sensing*, 58(3), 354–371
11. Mardian, J., Champagne, C., Bonsal, B., Daneshfar, B., & Berg, A. (2024). From drought hazard to risk: A spring wheat vulnerability assessment in the Canadian Prairies. *Agricultural and Forest Meteorology*, 353, 110056.
12. Mkhabela, M. S., Bullock, P., Raj, S., Wang, S., & Yang, Y. (2011). Crop yield forecasting on the Canadian Prairies using MODIS NDVI data. *Agricultural and Forest Meteorology*, 151(3), 385-393.
13. Qian, B., De Jong, R., & Gameda, S. (2009). Multivariate analysis of water-related agroclimatic factors limiting spring wheat yields on the Canadian prairies. *European Journal of Agronomy*, 30(2), 140-150.
14. Verhoef W., Xiao Q., Jia L., Su Z. (2007). Unified optical-thermal four-stream radiative transfer theory for homogeneous vegetation canopies IEEE Transactions on Geoscience and Remote Sensing, 45, 1808-1822