Estimation of plant biophysical parameters using machine learning downscaling

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Abstract
To estimate plant growth status at a particular location and time, the most important variables are those related with the availability of water and the potential losses via transpiration through plants stomata. These indicators can be obtained in various datasets, among them the MODIS leaf area index (LAI) product is one of the most widely used. Even though its temporal resolution is considered sufficient for most purposes, its spatial resolution is not useful for monitoring a crop's physiological status. Finer resolution alternatives are based on radiative transfer models (RTM) or in combination with machine-learning. A purely machine-learning automated approach was developed to obtain LAI at 10m resolution using MODIS products and Sentinel-1 and 2. Results show good agreement with existing products with the benefits of being a multiplatform web-based approach and the possibility to analyse results on-the-fly.

Keywords
MODIS, Sentinel, Downscaling, Deep learning, Bayesian networks

Introduction
As a result of the rapid increase of information obtained from automated proximal and remote sensors, data driven volume-intensive modelling methodologies have become popular in transforming the information obtained from worldwide multi-temporal hyperspectral imagery, purpose-designed on-the-go tractor proximal sensors and multiple networks of weather stations, among others. The techniques show promising results when trying to model the environment and produce successful forecasting under multiple scenarios. To estimate plant growth status at a particular location and time, the most important variables are in principle those related with the availability of water and the potential losses via transpiration through plants stomata(Shimshi and Ephrat, 1975). So far, the most used and universal biophysical indicators in agricultural and environmental sciences are those directly related with the soil-plant continuum. These indicators can be obtained worldwide in various datasets, among them the MODIS leaf area index (LAI) product is used in an important number of global products (Jia et al., 2019).

As a part of the activities of the "Future Farm" project, this study explores the downscaling of the 4-day period MODIS MCD15A3H Leaf Area Index product, using a Bayesian neural network modelling approach and Sentinel 1 and Sentinel 2 satellite imagery. The method was implemented in the Google Earth Platform and is entirely web-based.

Methods
Strip trial and satellite imagery

The Future Farm project is a national scale project with trial sites in five of the Australian states. The methodology was tested in a commercial wheat paddock located in South Australia at latitude -34.2025S and Longitude 138.70235E. A strip trial was established in the 2019 season with two Nitrogen enriched strips and seven Nitrogen reduced blocks to investigate the effect of different fertilization levels on wheat grain quality and final yield (Figure **1**).

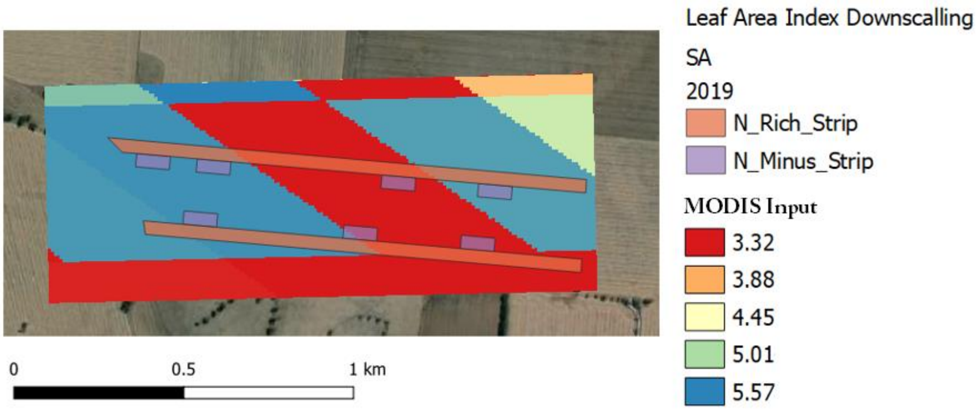

Figure 1. Strip trial and MODIS- MCD15A3H product visualization

All the imagery, including Sentinel-2 surface reflectance visible and Near infrared bands, Sentinel 1 Vertical and Horizontal polarization bands, and MODIS-MCD15A3H LAI bands were obtained and processed using the Python API of Google Earth Engine.

Sentinel-2 surface reflectance imagery was cloud-masked using the QA60 band removing clouds and cirrus data. Only descending orbit Sentinel-1 imagery with an interferometric wide swath mode were used in this approach, and this filtered Sentinel-1 dataset was enhanced using a refined Lee despeckling filter (Yommy et al., 2015).

Modelling

Both Sentinel datasets and the MODIS product were filtered using a 50 km buffer surrounding the area of interest. As the three satellite orbits are not temporally aligned, at each MODIS image timestamp, Sentinel images were averaged using an eight-day window (4 days in the past and four days in the future). With this procedure each MODIS image will have corresponding Sentinel 1 and 2 images for the same timestamp (Figure **1**).

For the training dataset, averaged Sentinel images were upscaled to MODIS resolution and sinusoidal projection, and for each timestamp a 100 random upscaled pixels were selected to construct a training dataset of ~7,300 samples that includes all the time slices (from January 2019 to June 2020).

A four layered perceptron neural network architecture was designed using the TensorFlow API, comprising an input layer with 10 neurons (Sentinel-2 bands 2,3,4,5,6,7,8 and 8A plus Sentinel-1 VH and VV bands), a hidden 100 neuron layer plus a 30% dropout layer to avoid overfitting and a final 10 neuron layer that fed a Bayesian linear model.

The Bayesian linear model extends the standard linear model by describing the output variable as a distribution rather than a single point-estimate. In doing so, the model can account for uncertainty. This is done by modelling the target outputs as a weighted linear combination of the inputs perturbed by some noise. In practice, the model weights and noise are unknown and must be inferred from the data.

Under the Bayesian approach, a distribution is placed over the model weights and noise. By reframing the linear model as a Bayesian system, uncertainty in the parameters can modelled. This allows estimates of uncertainty to be produced during inference. The uncertainty estimates capture uncertainty that can arise from a lack of observations and uncertainty that is caused by inherent noise in the system. For more information on the Bayesian linear model refer to Murphy (2012).

Ground truth
LAI measured with a Holland Scientific Crop Circle DAS43X instrument was surveyed on July 2019. Data was interpolated using block-kriging to the area of interest and it was used as a single time-slice ground truth observation.

Results
Model predictions were made on the projection and resolution of the MODIS MCD15A3H LAI product. The predictions had a significant ($p<0.05$) R^2 of 0.72 with an RMSE of 0.67. It was noted a better fit within LAI values in the range from 0 to 3, with an evident underestimation of values over LAI 4. These results were expected, as the training dataset was highly biased towards lower values as higher values are only achieved for a few weeks each season (data not presented).

The trained model was evaluated on native Sentinel-2 resolution for each of the time slices throughout the 2019 season, completing a total of 60 time-slices. Figure 2 shows the 10m resolution predictions for September 2019.

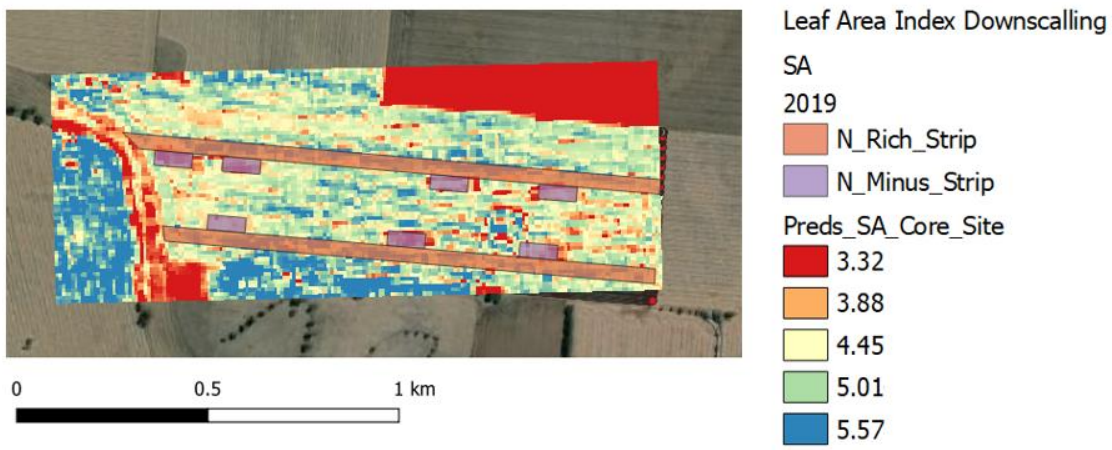

Figure 2. Predicted LAI for the 18th of September 2019.
The mean of LAI predicted values for both strip treatments for all the time-slices are presented in Figure 3, where the effect of Nitrogen fertilization on wheat LAI response is evident over the season.

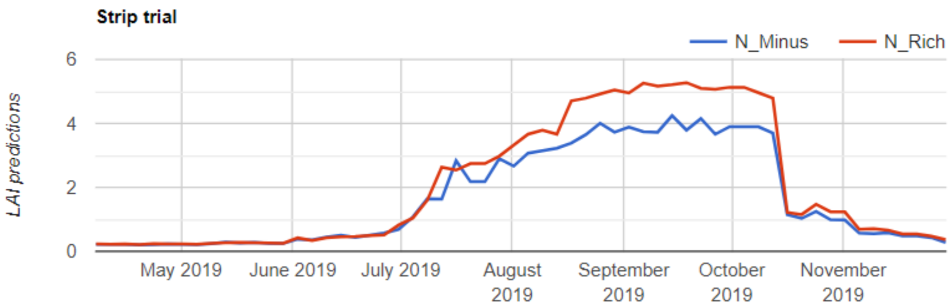

Figure 3. Predicted LAI mean values for N rich and N minus strip trials for season 2019.

The predicted LAI where consistently higher than those observed by the ground truth instrument, however a linear correlation was evident as observed in Figure 4.

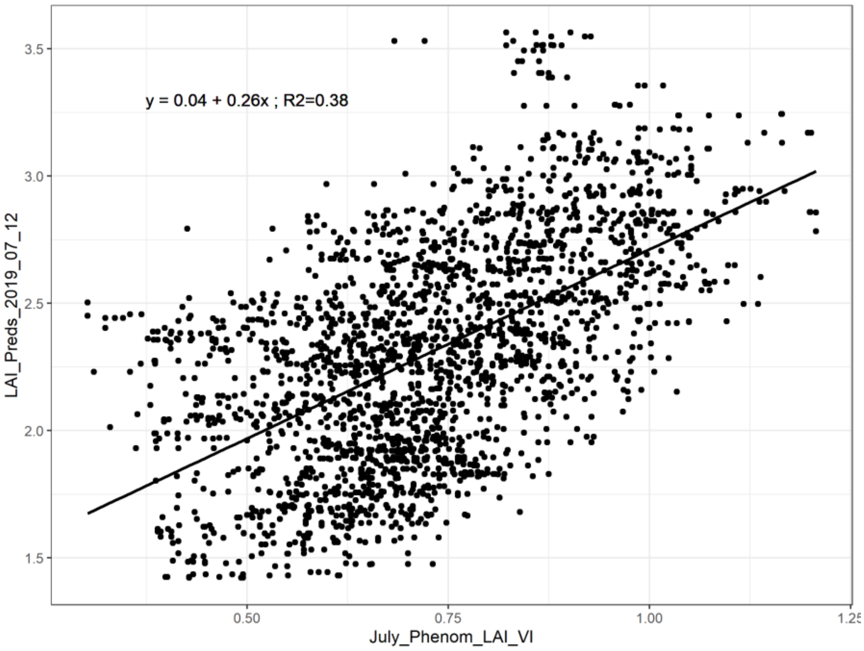

Figure 4. Performance of July LAI predictions vs ground truth LAI product.

Discussion and Conclusions

A multi-temporal 10m resolution LAI product was created using a purely machine learning approach. Compared with current products i.e. Sen2Agri (Matton et al., 2015) or ESA SNAP tool (Gascon and Ramoino, 2017) this method relies on a web-based server and offers more flexibility in terms of modelling and its results can be immediately plugged into a recommendation framework. It was observed that the methodology correctly captured the crop's response along the season, and it was comparable to field observations i.e. DAS43X.

There are implicit benefits in this modelling framework as it can be applied to a range of products. Analysis, not presented in this paper, showed good results when downscaling the MODIS evapotranspiration product using higher resolution Landsat-8 imagery. In that study, the same training sample was used, and the same Bayesian Neural network approach was successfully applied. Future work will explore a model improvement and the use of this methodology to downscale other important biophysical parameters.

References

Gascon, F., Ramoino, F., 2017. Sentinel-2 data exploitation with ESA's Sentinel-2 Toolbox, EGU General
Assembly Conference Abstracts, pp. 19548.

Jia, G., Shevliakova, E., Artaxo, P., Noblet-Ducoudré, D., Houghton, R., House, J., Kitajima, K., Lennard,
C., Popp, A., Sirin, A., 2019. Land-climate interactions, Climate Change and Land, pp. 131-247.

Matton, N., Canto, G.S., Waldner, F., Valero, S., Morin, D., Inglada, J., Arias, M., Bontemps, S., Koetz,
B., Defourny, P., 2015. An automated method for annual cropland mapping along the season for various globally-distributed agrosystems using high spatial and temporal resolution time series. Remote Sensing 7(10), 13208-13232.

International Conference on Intelligent Human-Machine Systems and Cybernetics. IEEE, pp. 260-265.

Murphy, K.P., 2012. Machine learning: a probabilistic perspective. MIT press, Cambridge,
Massachusetts.

Shimshi, D., Ephrat, J., 1975. Stomatal behavior of wheat cultivars in relation to their transpiration, photosynthesis, and yield 1. Agronomy Journal 67(3), 326-331.

Yommy, A.S., Liu, R., Wu, S., 2015. SAR image despeckling using refined Lee filter, 2015 7th