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Neural Network Modelling of Crop Phenology in Support of Agricultural Monitoring – A Base Map Approach

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Abstract:

Remote sensing technologies are at the heart of contemporary approaches to the monitoring of agricultural conditions, processes, and outcomes. Such monitoring can serve many purposes. Aid organizations rely on early warning systems to ensure food security in regions impacted by climate change and societal conflict. Fiscal authorities are frequently charged with keeping track of the type and volumes of agricultural production. Environmental conditions, such as water scarcity, may further require regulatory entities to monitor what farmers produce. In all of these examples, crop identification is seen as a useful or even essential activity.

We present a research study investigating cropping practices in the Imperial Valley, situated in the extreme south-east corner of California, U.S.A. Despite being located almost entirely below sea level and characterized by hot desert climate, the region's proximity to the Colorado river has nevertheless allowed the emergence of a thriving agricultural sector. Following changes in water distribution policy meant to improve water delivery and on-farm efficiency and incentivize fallowing (2003-2017), many open questions remained about how farmers were responding, specifically in their cropping practices. Our work us meant to improve understanding of these practices, with a focus on characterizing crop sequencing occurring over the course of a growing year.

Given its many potential applications, crop identification is a very active research focus across the globe. Much research attention is rightfully being paid to hyperspectral approaches, with their potential for identifying species and conditions of individual crops at a fine-grained spectral level. However, certain long-established, widely used, and affordable remote sensing products and techniques leveraging a relatively small number of spectral channels may still yield significant value, especially in longitudinal monitoring extending back to periods before today's most advanced platforms had been launched. A prime example are vegetation indices derived from Landsat imagery, with NDVI (Normalized Difference Vegetation Index) being the most prominent example. NDVI combines reflectance in the red (R) and near-infrared (NIR) channels as follows: NDVI = (NIR-R)/(NIR+R). Longitudinal or time-series capture of NDVI, with repeat observations spaced a few days or weeks apart during an agricultural growing cycle, generates crop-specific phenology and could thus be used for crop identification, especially when ground truth crop data are available. Broadly, that is the approach used in the current study.

In combination with a layer of the boundaries of individual fields (Figure 1), Landsat 5/7/8 imagery spanning the years 2000-2018 were used to derive NDVI observations in eight-day intervals, averaged for each field. For a given year, each field becomes associated with a time series of 46 NDVI values, which is interpreted as a phenology signature for that year. Crucially, quarterly crop cultivation for many fields was obtained from the U.S. Bureau of Reclamation (USBR), which allowed relating the annual phenology signature of a field (i.e. time-series of NDVI) to the known quarterly growing sequence. For example, a growing sequence of alfalfa-alfalfa-fallow-lettuce corresponds to alfalfa being present during the winter and spring quarters (January – June), followed by fallowing in the summer and lettuce being grown in the fall. One could now proceed to generate a suitable machine learning model to predict quarterly crop sequences for individual fields, based on each field's phenology. However, a particular goal of our study was to contribute to the growing calls for "explainable AI" that goes beyond typical black-box machine learning. To that end, we use annual, field-level, NDVI vectors (159,144 vectors, each with 46 values) to train a self-organizing map consisting of a two-dimensional lattice of 160,000 neurons (400 x 400). Combined with ground-truth quarterly growing sequences for the training fields, a type of base map of cropping practices in the Imperial Valley emerges (Figure 2). It exposes cropping practices in two layers. Fine-grained quarterly growing sequences are indicated by white boundaries, with boundaries between identical sequences having been dissolved. For clarity in the static display of Figure 2, only the largest of the resulting sequence areas are labelled in dark-green. Growing sequences are further aggregated

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according to dominance within the sequence, forming areas delineated and labelled in red. For example, polygons representing growing sequences consisting of at least three quarters of alfalfa are aggregated into a single polygon simply labelled "Alfalfa". Other regions are characterized by dominant combinations of crops within the sequence, such as "Vegetables/Sudan" or "Grains/Sudan". Some categories are naturally stable across quarterly sequences, such as "Fruits/Nuts" and "Nursery/Greenhouse".

We have used this two-dimensional base map and its underlying 46-dimensional neuron vectors to predict actual growing sequences at the field level (not reported here), which was among the original intentions of this study. However, from a cartographic perspective the most novel contribution lies in this being the first-ever attempt at map-like visualization of crop sequences based on NDVI-derived phenology patterns. Ongoing experiments include a variety of overlays onto this map, such as the commercial value of particular crops, in the pursuit of such questions as whether farmers respond to limitations in water availability by switching from lower-value to higher-value crops.

Figure 1. Landsat imagery and field boundaries.

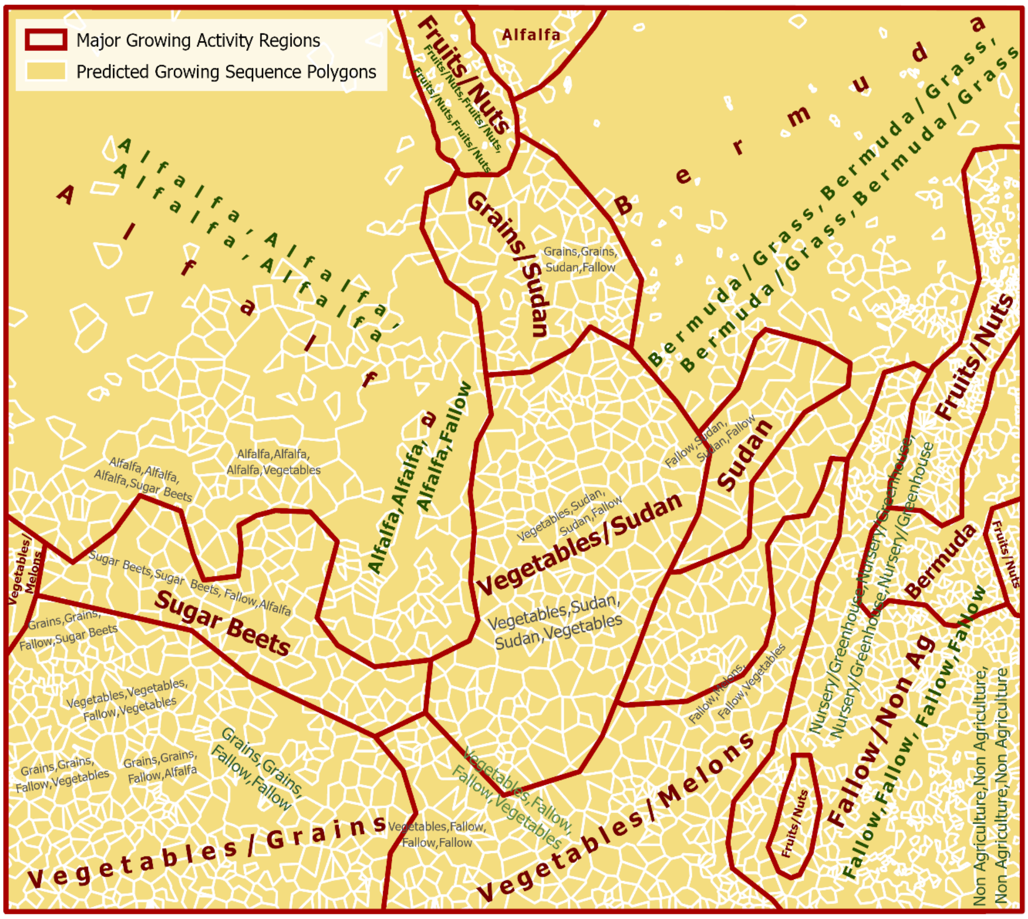

Figure 2. Major growing regions and quarterly crop sequences associated with a two-dimensional neural model of phenology.

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