

Supplemental Material

Revisiting energetic limits on crop coefficients in heterogeneous canopies

1 Remote Sensing Details

1.1 Methodology

We used Google Earth Engine (GEE) to process satellite imagery and compute vegetation and temperature indices for almond orchard blocks across the state of California. The LandIQ land-use datasets for 2018-2023 were filtered to retain only polygons that were categorized as almond orchard per the California Crop Mapping legend (CROPTYP2 = D12). Each polygon geometry was cleaned by buffering by 0-10m in order to fix any geometry errors, and important attributes (UniqueID, county, total feature acreage) were preserved from the LandIQ dataset.

We analyzed Landsat imagery for January–December of each year using Collection 2 Level-2 data from Landsat 8 and 9 (OLI/TIRS). All images within each year were selected and preprocessed as follows:

1) Cloud and quality masking: We used the Landsat QA_PIXEL band to mask out low-quality pixels. Specifically, pixels flagged as high-confidence clouds or cloud shadows (QA bits 3–4) and snow (QA bit 5) were excluded. Water bodies were also flagged and masked for consistency. This ensures only clear-sky surface data was used.

2) Reflectance calibration and NDVI: Surface reflectance bands (blue, green, red, NIR) from the SR product were scaled from their digital number (DN) value to reflectance (0–1) using the product’s gain (0.0000275) and offset (−0.2). We then computed the Normalized Difference Vegetation Index (NDVI) as $(\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$.

3) Land Surface Temperature (LST) conversion: The Landsat thermal band (TIRS band 10) was converted from DN to at-sensor brightness temperature in °C using the official Collection 2 scaling following USGS guidelines for Landsat L2 data:

$$LST_C = ((DN \times 0.00341802) + 149.0) - 273.15, \quad (1)$$

Each Landsat image was thus transformed into masked surface reflectance

bands plus an LST layer. We merged Landsat 8 and 9 images to maximize data density, and added the NDVI band to each image collection.

1.1.1 Monthly Compositing

To reduce residual noise and fill gaps, we aggregated the pre-processed images into monthly composites. For each month of each year (January–December, 2018–2023), we took the median value of all valid NDVI and LST pixels within that month. This produced a set of 12 monthly median images per year, each containing NDVI and LST_C bands. Each composite image was tagged with its year and month.

1.1.2 Extraction of Orchard and Buffer Statistics

For each monthly composite, we extracted summary statistics over each orchard polygon and its surroundings. In particular, for every orchard feature we defined the following zones:

Orchard interior (polygon): the orchard polygon itself.

External buffer (0.5 km): a 500m radial buffer around the orchard, excluding the orchard area (i.e. the surrounding landscape).

Nested inner buffers: six concentric rings inside the orchard, defined by successive 30m offsets from the edge. Specifically, we buffered the polygon inward by 30, 60, 120, 180, 240, and 300m to create inner rings 0–30m, 30–60m, 60–120m, 120–180m, 180–240m, and 240–300m from the original boundary. Small orchards may have empty inner zones. In such cases, results were explicitly marked “NA” to ensure that GEE populated the entire dataframe and did not exclude columns that were initially empty.

For each zone and for each monthly image, we computed the mean and standard deviation of NDVI and LST_C . This was done using zonal reduction at 30m resolution (the native Landsat scale) to match the imagery. For example, the mean orchard NDVI ($NDVI_{mean_poly}$) and its standard deviation ($NDVI_{std_poly}$) were computed over the orchard polygon geometry. Similarly, mean and standard deviation of NDVI and LST were computed over the 0.5km buffer zone ($NDVI_{mean_buffer}$, etc.) and over each inner ring ($NDVI_{mean_inner30}$, ..., $LST_{std_inner300}$). We also recorded the polygon area (m^2 and ha) and the areas of the buffer and inner zones.

Horizontal temperature gradients between the orchard interior and its surroundings can help to infer the potential for advection, as thermal gradients in heterogeneous landscapes can drive significant horizontal heat flux that affects local temperature patterns. A systematically higher LST in outer rings than the orchard core would suggest advective warming from the surroundings, whereas the reverse would suggest cooling advection.

1.1.3 Data Output and Multi-Year Analysis

The above steps were applied independently for each year from 2018 through 2023. For each year, the output is a table of orchard–month records, where each

record includes the orchard ID, month, year, and the computed NDVI and LST statistics for each zone. Key fields such as UniqueID, COUNTY, and ACRES were preserved from the orchard dataset.

References