Crop Health Analysis via Water and Carbon Cycles

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Introduction

Modern agriculture increasingly relies on data-driven methods to monitor crops and forecast yields. Reliable yield prediction before harvest provides early warning for food security and supports decisions on food import/export; it also helps agribusiness in setting crop pricing, insurance, and stock planning (mdpi.com). Remote sensing and machine learning now enable crop monitoring at scale, but understanding the **physiological indicators** behind the data is crucial.

Two key indicators of crop function are **evapotranspiration (ET)** and **gross primary productivity (GPP)**. ET and GPP link directly to plant water use and carbon uptake, respectively, making them powerful proxies for crop health and vigor. By tracking ET and GPP, engineers and data scientists can infer soil moisture conditions, plant stress levels, and growth rates – information essential for managing inputs and predicting yields.

This paper provides a technical overview of ET and GPP in the context of crop modeling and precision agriculture, focusing on California’s high-value **berry crops (strawberries, raspberries)** and **almonds**. We review definitions and measurement techniques for ET and GPP, illustrate how these metrics feed into models for crop health and yield, and discuss practical applications (from irrigation scheduling to disease detection). Case studies in California almonds and berries demonstrate real-world uses, and we explore how ET/GPP monitoring connects to emerging trends in regenerative agriculture and carbon farming. The aim is a comprehensive yet accessible guide for engineers and data scientists to leverage ET and GPP in agricultural analytics.

Evapotranspiration (ET) and Its Role in Agriculture

Definition and Components: Evapotranspiration (ET) is the combination of two processes by which water leaves the land surface: **evaporation** from soil or wet surfaces and **transpiration** from plant leaves. In essence, ET represents the total water use of a crop field. Evaporation is the direct loss of moisture from soil and plant residue, while transpiration is the water vapor flux through plant stomata during photosynthesis. Together, these processes consume significant water – for example, agriculture accounts for about 80% of water used in California (news.ucsb.edu), and ET is the mechanism behind that consumption. ET is often expressed in depth units (mm or inches), representing the equivalent depth of water lost. It varies with weather (hot, dry, windy conditions drive higher ET) and crop characteristics (leaf area, growth stage). Importantly, ET has two forms in practice: **potential ET** (the water loss if water is not limiting) and **actual ET** (water loss given the actual soil moisture and plant conditions). If a crop is well-watered and unstressed, actual ET approaches the atmospheric demand (potential ET); under water stress, actual ET falls below potential due to stomatal closure.

Indicator of Water Use and Crop Stress: ET is a direct indicator of crop water use and can reveal soil moisture status and stress. A healthy, well-watered crop will transpire at a high rate (assuming sufficient evaporative demand), whereas a water-stressed or diseased crop will reduce transpiration. In fact, under non-optimal conditions such as pests, disease, or nutrient deficits, crops develop less leaf area and partially close stomata, **reducing ET below the expected norm** fao.org. Thus, measuring ET can flag stress: if a field's ET is significantly below the theoretical ET for a well-watered crop under current weather, it may indicate drought stress, pest infestation, or other growth-limiting factors. Conversely, an adequately watered crop in peak growth will exhibit high ET, reflecting strong evaporative cooling and water throughput. Because ET integrates soil and plant water status, farmers use it to guide irrigation – replacing the water that was "lost" to ET to keep the soil moisture in an optimal range. ET also correlates with biomass production up to a point (more transpiration can mean more carbon intake), a concept used in some yield models (discussed in Section 4).

ET Calculation and Equations: In agronomy, a common approach is to calculate **crop evapotranspiration (ET_c)** by scaling a reference evaporation rate to the specific crop. The basic equation is:

$$ETc = ETo \times Kc$$

where **ETo** is the *reference evapotranspiration* (the ET from a reference crop, usually a well-watered grass, under the given weather) and **Kc** is the *crop coefficient* that adjusts for crop type and growth stage almonds.com. Reference ET (ETo) encapsulates climate factors (sunlight, temperature, humidity, wind), and is often computed via the **Penman-Monteith equation**, a physics-based formula. The FAO-56 Penman–Monteith equation for daily reference ET (for a grass reference) is:

$$ET_o = \frac{0.408\,\Delta\,(R_n - G) + \gamma\,\frac{900}{T+273}\,u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34\,u_2)}$$

ETo=Δ+γ(1+0.34u2)0.408Δ(Rn−G)+γT+273900u2(es−ea)

where RnR_nRn is net radiation (MJ m⁻² day⁻¹), GGG is soil heat flux, TTT is mean air temperature (°C), u2u_2u2 is wind speed at 2 m, es−eae_s-e_aes−ea is the vapor pressure deficit, Δ\DeltaΔ is the slope of the saturation vapor pressure curve, and γ\gammaγ is the psychrometric constant rpubs.com. Equation (1) essentially balances energy and aerodynamic factors to estimate how much water could evaporate/transpire. Once ETo is known (from weather data or networks like California's CIMIS), it is multiplied by Kc to get ET_c for a specific crop and growth stage (Kc values are tabulated from experiments). For instance, in almonds, Kc is low (~0.4) during dormant winter and up to ~1.1 in mid-summer when the canopy is full almonds.com. If ETo on a hot July day is 8 mm, an almond orchard with Kc 1.1 would use ~8.8 mm of water that day as ET_c.

Measurement Techniques for ET: Directly measuring ET can be challenging, but several techniques exist. **Lysimeters** physically measure water loss by weighing a soil block with plants – essentially detecting the weight change as water evapotranspires. This yields very accurate ET data on a small scale. **Eddy covariance flux towers** offer a high-tech approach: they measure vertical wind and humidity fluctuations to directly compute the vapor flux from a field en.wikipedia.org, en.wikipedia.org. Eddy covariance systems provide continuous ET measurements (along with CO₂ flux for GPP) at ecosystem scale (footprint of ~1–10 ha), and are used in research and to validate remote sensing. **Satellite Remote Sensing** is another key method: using observations of land surface temperature, reflectance, and meteorological data, one can model ET over large areas. Many remote-sensing ET models implement an **energy balance** approach, where the satellite-derived surface temperature and albedo are used to estimate how much of the Sun's energy is going into evaporation (latent heat) versus heating the air (sensible heat). Well-known models like METRIC (Mapping Evapotranspiration at high Resolution with Internalized Calibration) and SEBAL use this approach. These models, combined with thermal imagery (e.g. from Landsat or MODIS satellites), can map ET for every field. For example, the METRIC model uses surface temperature differences to solve for ET and has been used to estimate crop water consumption and even infer yield, as discussed later acsess.onlinelibrary.wiley.com. Simpler remote approaches use vegetation indices (like NDVI) as a proxy for Kc, essentially scaling reference ET by greenness fraction – useful when high-resolution thermal data are not available. Regardless of method, measuring or estimating ET in agriculture is crucial for **irrigation management** and **drought monitoring**. It directly ties the physical climate to the biological response of crops, making ET a foundational variable in agro-hydrological models and on-farm decision support.

Gross Primary Productivity (GPP) and CO_2 Flux Measurements

Definition and Link to Photosynthesis: Gross Primary Productivity (GPP) is the total amount of carbon (as CO_2) that plants assimilate through photosynthesis per unit area and time. In simpler terms, GPP is the **rate of photosynthetic carbon fixation** by all green plants in an ecosystem (here, a crop field). It is typically expressed in units like grams of carbon per square meter per day (g C m^{-2} d^{-1}). GPP is “gross” because it represents all CO_2 taken in by photosynthesis, without subtracting the CO_2 lost by respiration. Some fraction of the carbon fixed is later respired by plants (for growth and maintenance); the remainder after respiration is net primary production (NPP), which contributes to plant biomass (yields, roots, etc.). In context of crop health, GPP is an excellent indicator of growth vigor – a high GPP means the crop canopy is actively photosynthesizing and growing, while a low GPP suggests slow growth or stress. Over a season, GPP is directly related to biomass accumulation and yield potential, since carbon from CO_2 ends up as plant matter (fruits, grains, etc.). This makes GPP a valuable metric for yield forecasting models and for assessing the effects of management (e.g., if a fertilizer boosts photosynthesis, GPP will reflect that increase).

Measuring GPP with CO_2 Flux Towers

Gross carbon flux cannot be measured directly by simple instruments; instead, researchers measure the *net* exchange of CO_2 between the crop and atmosphere and then infer GPP. The standard tool is an **eddy covariance flux tower** equipped with fast CO_2 sensors and anemometers. The tower measures **Net Ecosystem Exchange (NEE)** of CO_2, which is the net balance of CO_2 going in and out of the ecosystem. By convention, if we take the atmosphere’s perspective, NEE > 0 means CO_2 release to the atmosphere (net respiration) and NEE < 0 means net CO_2 uptake (net photosynthesis). GPP and respiration are partitioned from NEE by measuring CO_2 flux under various conditions (e.g., nighttime NEE represents respiration since photosynthesis is zero in the dark, allowing estimation of total respiration). The relationship can be stated as:

∗∗NEE=Reco−GPP∗∗,**NEE = R_{eco} - GPP**,∗∗NEE=Reco−GPP∗∗,

where RecoR_{eco}Reco is ecosystem respiration (CO_2 released by plants + microbes) pmc.ncbi.nlm.nih.gov. Rearranged,

∗∗GPP=Reco−NEE∗∗.**GPP = R_{eco} - NEE**.∗∗GPP=Reco−NEE∗∗.

If we use the sign convention that NEE is positive when the ecosystem loses CO_2 (source), then in daylight when plants uptake CO_2, NEE is negative and subtracting it indeed adds a positive GPP. In practice, flux tower software applies models to partition NEE into GPP and

RecoR_{eco}Reco. For instance, using nighttime data to model respiration at a given temperature and then applying that respiration rate during daytime to estimate how much of the daytime NEE was offset by GPP. Through such methods, flux towers provide continuous GPP estimates for research. This has yielded insights like daily GPP curves, seasonal totals, and responses of GPP to stress. For example, flux tower studies in California specialty crops have measured how coastal fog can enhance strawberry farm GPP and water-use efficiency by reducing plant stress on hot days agupubs.onlinelibrary.wiley.com. Flux measurements are also key to validating satellite-driven GPP models globally pmc.ncbi.nlm.nih.gov.

Estimating GPP via Remote Sensing

Because flux towers are sparse, remote sensing approaches are used to estimate GPP at field to regional scales. The most common approach is the **Light-Use Efficiency (LUE) model**. In this framework, GPP is modeled as a function of the amount of light absorbed by vegetation and the efficiency with which plants convert light to biomass. A simple formulation is:

$$GPP = PAR \times f_{PAR} \times \epsilon$$

where **PAR** is the incident photosynthetically active radiation (the light available for photosynthesis), fPARf_{\text{PAR}}fPAR is the fraction of PAR actually absorbed by the plant canopy (this relates to leaf area and greenness), and ε\varepsilonε (epsilon) is the light-use efficiency – the amount of carbon fixed per unit of light absorbed deepblue.lib.umich.edu. This equation deepblue.lib.umich.edu encapsulates that a dense green canopy (high fPARf_{\text{PAR}}fPAR) under bright light will have high potential GPP, but the actual GPP also depends on ε\varepsilonε which is reduced by stresses (extreme heat, nutrient limitations, etc.). Satellite data can provide PAR (from solar models) and estimate fPARf_{\text{PAR}}fPAR via vegetation indices like NDVI or via products like FPAR from MODIS. The maximum ε\varepsilonε for a crop type is often known from literature (e.g., well-watered crops might have a max ε≈2−4\varepsilon \approx 2-4ε≈2−4 gC per MJ of light), and then a reduction factor is applied based on conditions (temperature, drought, etc.). For instance, NASA's MOD17 GPP product uses a variant of this model, with ε\varepsilonε adjusted for temperature and vapor-pressure deficit deepblue.lib.umich.edu (Running et al., 2004). Another emerging remote metric related to GPP is **solar-induced chlorophyll fluorescence (SIF)** – a faint glow emitted by chlorophyll during photosynthesis. SIF measured from satellites can correlate with GPP, offering a direct physical proxy for photosynthetic activity. However, SIF data is still coarse-resolution and mostly research-oriented.

Interpretation in Agricultural Context

In crops, GPP closely tracks crop growth stages. During early growth, GPP rises as leaf area expands. A peak GPP indicates a full canopy with intense photosynthesis (often just before flowering or during early fruiting for many crops). Later in the season, GPP may plateau or decline (e.g., leaves age or are removed, or the plant shifts energy to fruits). Monitoring GPP over time thus gives a picture of the crop's performance: if GPP is lower than expected for a given stage, the crop might be underperforming due to stress (water, nutrients, disease). Because GPP is tied to carbon uptake, and yield in many crops is proportional to total biomass or total assimilated carbon, GPP data can improve yield estimates. For example, an unexpectedly sharp drop in GPP during what should be peak growth could signal a problem that might reduce final yields (such as a pest attack in a raspberry field reducing leaf area). On the other hand, consistently high GPP through the season often correlates with good yields, assuming that carbon is being partitioned to the harvested organs (berries or nuts). In Section 4 and 5, we will see how GPP data is used alongside ET in modeling and management for better yield prediction and real-time decision support.

Modeling Crop Health and Yield Using ET and GPP

In agricultural analytics, combining biophysical data (like ET and GPP) with remote sensing and machine learning models has opened new possibilities for predicting crop outcomes. **Crop health** (the current status of growth and stress) and **yield forecasting** (predicting the final produce) can be significantly improved by incorporating ET and GPP, as these variables encapsulate water and carbon dynamics fundamental to crop performance.

Integrating ET and GPP in Models

Traditional yield prediction models often rely on weather data and vegetation indices (e.g., NDVI) as proxies for crop condition. By adding ET and GPP data, either from ground sensors or derived from satellites, models gain more direct information about the plant's physiological state. For example, actual evapotranspiration (ET_a) is directly related to crop water consumption and can indicate if the crop experienced water stress during the season. Gross primary productivity provides insight into the cumulative photosynthetic activity which drives biomass production. Researchers have demonstrated the value of these inputs. In one study, Khan et al. (2019) proposed using **satellite-based ET** and simple crop growth algorithms to estimate crop biomass and yield, as an alternative to complex crop simulation models acsess.onlinelibrary.wiley.com. By feeding remote-sensed ET_a from the METRIC model into a growth model (derived from CropSyst), they achieved good yield estimations across 30 m pixels for multiple years acsess.onlinelibrary.wiley.com. This approach leverages the strong linkage between water use and growth – essentially, if a certain amount of water was transpired, a proportional amount of biomass should have been produced (up to water-limited yield potential). Such models provided yield estimates matching observed yields at several test sites, confirming that ET data can anchor yield predictions in physical reality.

GPP integration is similarly powerful. A satellite-driven crop model in Australia, for instance, used GPP to estimate the carbon uptake of wheat fields and then translated that to grain yield researchgate.net. This model ("satellite-driven crop model… uses GPP to estimate carbon and then wheat yield" researchgate.net) essentially treats remote-sensing GPP as input into a yield formation model. The rationale is straightforward: if you know how much carbon the crop accumulated (via GPP), you can predict yield by allocating a fraction of that carbon to the harvestable product (taking into account harvest index, etc.). These approaches have shown success in regional yield forecasting, especially when ground-based GPP data (from flux towers) are used to calibrate the satellite models. In fact, calibrating models with local flux measurements can markedly improve accuracy – one global study found that optimizing the light-use efficiency in a GPP model using flux tower data improved the R^2 by ~15% and reduced errors by one-third agupubs.onlinelibrary.wiley.com.

Yield Prediction and Machine Learning

In the era of AI, machine learning models (like random forests, neural networks, and nowadays transformer-based models) are being applied to crop yield prediction. These models can ingest a variety of features: weather time series, remote sensing indices, soil data, etc. ET and GPP are increasingly used as features in these models. For example, a yield prediction system might include cumulative ET up to mid-season, average daily GPP during key growth stages, and stress indices derived from ET/GPP anomalies. Because ET and GPP capture different dimensions (water and carbon) of crop status, they often add predictive power beyond using vegetation indices alone. Ground truth data from flux towers or in-field sensors can also be fused with satellite data to create hybrid models. A notable advantage is seen when matching satellite observations to the exact footprint of flux towers: one study showed that using high-resolution Landsat data aligned to flux tower footprints improved the performance of a GPP estimation model by 14% for croplands mdpi.com. This underscores that **using ground-based ET/GPP sensors in tandem with satellite data can sharpen model accuracy**, by providing calibration points and capturing fine-scale variability that pure satellite models might miss.

To illustrate, consider yield modeling for an almond orchard: A regression model that tried to predict annual yield from total annual ET alone found only a weak correlation (R^2 ~0.08), meaning ET by itself didn't explain much of the yield variability digitalcommons.calpoly.edu. Almond yield depends on many factors beyond water use (such as pollination success, heat waves, etc.), so a single-variable model is insufficient. However, when the model included additional factors like regional rainfall, winter chill hours, and location, the yield-ET relationship strengthened markedly (R^2 ~0.63) digitalcommons.calpoly.edu. This indicates ET is indeed a significant piece of the puzzle but works best in a multi-variable context. If GPP or NDVI were added as predictors, we might capture effects of canopy health and nutrition, further improving predictions. In practice, modern yield forecasting frameworks combine metrics – for example, cumulative GPP (or NDVI integral) to represent total growth, ET-based indices to represent water sufficiency, and perhaps weather extremes as separate features. Data-driven models trained on historical yield outcomes can then learn the optimal weighting of these features. Studies have shown that such integrated models can forecast yields with higher fidelity, giving farmers and supply chain managers earlier and more reliable estimates of final production mdpi.com.

Ground-Based vs. Satellite-Only Models

The question often arises: how much do in-situ sensors (like flux towers or soil-moisture/ET stations) help compared to using satellite data alone? While satellites provide uniform coverage, ground sensors deliver higher precision and can capture sudden changes (e.g., an irrigation failure or disease outbreak) sooner. Integrating ground data tends to improve model accuracy. We saw an example with flux towers improving GPP estimates mdpi.com. Another benefit is temporal resolution – satellites might pass weekly, whereas an on-site sensor logs continuously. If a heat wave caused acute stress for 3 days affecting yield, a tower measuring a sharp drop in GPP and ET could flag that, whereas a satellite might miss the event if not imaging on those days. On the flip side, ground sensors cover limited area and are costly to deploy widely. A practical compromise is emerging: use satellite models to get wall-to-wall coverage, but use a **sparse network of ground sensors for calibration and validation**. For instance, an almond grower cooperative might have flux towers or sap-flow sensors in a few representative orchards to fine-tune the regional satellite-based ET and GPP estimates. This synergy can reduce bias in satellite products (which might have cloud-related gaps or modeling uncertainties). Indeed, many regional water and carbon modeling efforts (like the OpenET project for evapotranspiration, or FLUXCOM for carbon fluxes) use machine learning trained on flux tower data to upscale ET and GPP to larger areas agupubs.onlinelibrary.wiley.com. The result is improved accuracy that approaches what ground instruments would read, but across every field.

In summary, ET and GPP serve as **cornerstone inputs** for advanced crop models. ET informs the water balance and stress status, GPP reflects the growth and productivity. By merging these with remote sensing and AI, we achieve a more complete representation of crop health, leading to better yield forecasts and the ability to diagnose limiting factors. The next section will translate these modeling capabilities into practical applications that growers and agronomists can use in precision agriculture.

Applications for Growers: Precision Agriculture

Integrating ET and GPP data into farm management can improve decision-making in several areas of precision agriculture. Below we highlight key applications for growers of water-intensive and high-value crops like almonds and berries in California:

- **Irrigation Management:** Perhaps the most direct application of ET is in scheduling irrigation. In drought-prone regions like California, giving crops exactly the water they need (and not much more) is critical for both yield and water conservation. ET-based irrigation scheduling uses the principle of “replace what the crop used.” For example, if the orchard's ET_c was 5 mm today, an equivalent amount of water is supplied via irrigation (adjusted for any rainfall) to refill the soil. Farmers often obtain daily reference ET (ETo) values from local weather networks (such as CIMIS in California) and multiply by the crop coefficient for their crop/stage to get daily water use almonds.com. This approach accounts for weather variability – hotter days get more water, cooler days less – and avoids rigid calendar schedules. By using ET data (from weather stations or newer satellite tools like OpenET), growers can **optimize irrigation** timing and amounts. This has real benefits: studies have shown ET-based scheduling can improve water use efficiency significantly (8–40% improvement) without harming yields acsess.onlinelibrary.wiley.com. In practice, many almond growers use smartphone apps or irrigation calculators that input ET and soil properties to recommend irrigation durations. On a seasonal scale, ET monitoring helps ensure the crop is not under-watered during critical growth periods (avoiding yield loss from stress) and not over-watered in other periods (avoiding wasted water and leaching. Precision irrigation guided by ET thus maintains crop health while saving water – a key sustainability win in arid farming. When water allocations are limited (as under California's Sustainable Groundwater Management Act), ET data provides a transparent way to quantify water use per field news.ucsb.edu, enabling equitable water trading or deficit irrigation strategies. For drip-irrigated strawberries, ET monitoring can prevent both drought stress (which would reduce berry size) and waterlogging (which can cause root disease), thereby improving fruit quality and resource efficiency.

- **Fertilization Optimization:** Gross primary productivity is closely tied to nutrient status, especially nitrogen (N). Nitrogen is a critical element in chlorophyll and enzymes like Rubisco, so a nitrogen-deficient crop will typically have reduced photosynthesis and thus lower GPP. By monitoring GPP (or related indices like NDVI which indicate leaf chlorophyll), farmers can gauge whether crops are reaching their photosynthetic potential or if nutrients might be limiting. For instance, if one section of a raspberry field consistently shows lower GPP or NDVI despite adequate water, it could signal a need for additional fertilizer in that zone. Precision agriculture systems use such data to do **variable-rate fertilization** – applying more N where the crop vigor is low and likely limited by N, and less where the crop is already lush. Research in precision nutrient management has shown that plant spectral properties reflect crop N status ars.usda.gov, enabling in-season adjustments. GPP can serve as an integrative indicator – if GPP picks up after a fertilization, it indicates improved nutrient uptake and photosynthesis; if not, perhaps another issue persists. In strawberries, for example, balancing N is tricky: too little reduces yield, too much can cause excessive leaf growth at the expense of fruit and can lead to pest issues. Continuous GPP or NDVI monitoring provides feedback on how the crop is responding to feeding. Over time, growers can use these data to fine-tune fertilizer schedules and amounts, improving **nutrient use efficiency** (more crop per unit of fertilizer) and reducing runoff of excess nutrients. This not only cuts costs but also benefits the environment by minimizing nitrate leaching into groundwater. In summary, pairing GPP data with precision fertigation systems allows "feeding" the crop only as much as it can productively use, matching nutrient supply to the crop’s physiological demand.

- **Disease and Stress Early Warning:** One of the promises of using ET and GPP in precision ag is **early detection of stress**, including disease, pest attacks, or other problems. Often, by the time a human scout notices visual symptoms (wilting, discoloration), the crop has already been stressed for days or weeks. ET and GPP can reveal subtler, earlier changes. For example, a plant pathogen that attacks roots will impair water uptake – the crop’s transpiration (ET) may drop measurably as stomata close due to the root stress, even before leaves visibly wilt. If a section of an almond orchard has a sudden unexplained dip in ET (given similar weather) compared to the rest, it could indicate localized root disease or irrigation blockage. Similarly, foliar diseases or insect defoliation reduce green leaf area and photosynthesis, causing GPP to fall. Detecting these anomalies in ET/GPP data can trigger an alert for growers to inspect that field zone. In practice, remote sensing platforms or IoT sensor networks can be set to look for deviations: e.g., a thermal infrared drone flight might map canopy temperature, from which ET can be inferred (hotter canopy = lower transpiration). If one block of strawberries shows hotter canopies, it might be under attack by spider mites (which cause stomatal closure) or have a soilborne disease – prompting targeted intervention. As a concrete example, the FAO reports that pests and diseases can significantly reduce a crop’s evapotranspiration below its potential fao.org. Thus, tracking ET against expected values (ET_c) provides a quantitative measure of crop health. GPP data from flux towers or high-resolution satellites could similarly be used to flag areas where “photosynthesis per unit leaf” is lower than it should be. Modern analytical tools can integrate weather, ET, and GPP to differentiate causes of stress. For instance, if GPP drops but ET stays high, perhaps leaves are still transpiring but not fixing carbon well (maybe due to nutrient deficiency affecting photosynthesis); if both GPP and ET drop, it might be a stomatal closure issue (water stress or vascular disease). Early warnings allow growers to respond faster – applying fungicides or insecticides only where needed, fixing irrigation issues, or other remedies – minimizing crop damage and economic loss. In high-value crops like berries, catching a disease outbreak even a few days early can make a big difference in saving the crop.

- **Harvest Planning:** Beyond in-season management, real-time physiological indicators can assist in **predicting optimal harvest timing and yields**. By monitoring GPP trends, a grower can assess when the crop has reached peak production and is starting to plateau or decline (signaling maturation). For annual crops, the point at which GPP no longer increases (or begins to drop) often corresponds to the onset of maturation or seed fill – an indicator that harvest time is approaching. For example, in processing tomatoes (an annual crop), the NDVI (proxy for GPP) starts declining as fruits ripen, which is used to schedule harvest arable.com. In a similar vein, for strawberries which are continuously harvested over a season, tracking GPP could help predict flushes of production (e.g., after a period of high GPP, more fruit might ripen a couple of weeks later). If real-time GPP or NDVI data shows the crop’s growth has peaked, managers might start organizing harvest crews for the expected peak yield window. This is crucial for labor planning in crops like berries that require hand-picking. Additionally, having an estimate of cumulative GPP by mid-season can improve yield forecasting – if GPP is far above average due to a great season, the grower can anticipate a bumper yield and prepare storage/market channels; if below average, they might contract for less sales. **Optimal harvest time** can also be inferred by the plant's physiological maturity. Remote sensing indices can indicate when a majority of the crop has reached physiological maturity doktar.com. For instance, a plateau and slight decline of NDVI/GPP in an almond orchard late summer might indicate the nuts have fully developed and the trees are beginning to withdraw resources from leaves, suggesting that shaking the almonds at that point would maximize yield and quality. In precision viticulture (grapes) and potentially berries, indices like PRI or fluorescence, combined with GPP, have been studied to pick the best harvest date for peak flavor which correlates with certain stress/assimilation dynamics. Overall, using ET and GPP data for harvest planning leads to **data-informed decisions** on when to harvest for maximum yield and quality, and provides yield predictions that inform downstream logistics.

In summary, ET and GPP are not just theoretical metrics; they have practical on-farm applications that can save water, increase input efficiency, reduce losses, and improve timing of operations. Farmers and agronomists are beginning to access these through user-friendly dashboards: e.g., some irrigation companies offer ET-based scheduling tools, and some satellite services provide field-level GPP or biomass estimates. As these become more integrated into farm management systems (potentially augmented by AI that analyzes the data), we can expect more precise and adaptive farming – a necessity in the face of resource constraints and climate variability.

Case Studies: California Almonds & Berry Crops

To ground the discussion, we consider how ET and GPP are being applied specifically in California's **almond** orchards and **strawberry/raspberry** fields. These crops present different challenges – perennial trees vs. short-cycle berries – but in both cases ET and GPP-based approaches have driven improvements in management.

- **Almonds (Water Stress Reduction using ET-based Irrigation):** California almonds have gained a reputation for high water use, as a mature almond orchard in the Central Valley can use on the order of 50–60 inches (~1300–1500 mm) of water per year through ET almonds.com, almonds.com. With recurring droughts and regulation of groundwater, almond growers have turned to precision irrigation with ET data to reduce water stress and usage without sacrificing yield. The Almond Board of California actively promotes ET-based scheduling: understanding the changing water demand of almond trees via ET is the first step toward optimal irrigation almonds.com. Practically, many almond growers use weekly ETo reports from CIMIS and adjust irrigation run times according to crop coefficient curves for almonds. By ensuring the trees get just enough to match ET_c, growers avoid both under-irrigation (which would cause tree stress, dropping yield and potentially harming next year's flowering) and over-irrigation (which wastes water and can leach nutrients). For example, during the peak summer months, an almond orchard might use ~8–9 mm/day almonds.com, and growers will replenish that via drip or micro-sprinklers daily or every few days. If a heatwave hits (spiking ETo), the ET data prompts increased irrigation to preempt stress. Conversely, after a cool spell or rain, ET drops and irrigation can be scaled back, saving water. The impact on yield comes through maintaining tree health: a well-watered almond tree can keep its stomata open, photosynthesize (high GPP), and fill kernels properly. Under deficit irrigation, trees may survive but kernel size and yield can diminish. Some growers employ **Regulated Deficit Irrigation (RDI)** at specific times (e.g., slightly stressing post-harvest or during certain stages) to save water – but even RDI strategies are guided by tracking ET deficits to ensure stress is controlled, not arbitrary. A case in Kern County showed that when drought cut water availability, farms that closely managed irrigation by ET data maintained better yields than those on fixed schedules, essentially doing "more crop per drop." Another important use of ET in almonds is in **irrigation system design and evaluation**: by comparing seasonal ET_c to total applied water, growers can calculate their irrigation efficiency and identify losses to runoff or deep percolation. With tools like OpenET (which provides satellite-based ET for fields news.ucsb.edu), even growers without local weather stations can access ET estimates to guide their water management. The result across the industry has been improvements in water productivity. California's almond yield (lbs of nuts per acre) has steadily risen in part due to better water and nutrient management – and ET data has been central to that. Using ET as a feedback metric, some growers have reported reducing their water use by 10–20% while keeping yields constant, through measures like eliminating one irrigation set if ET data shows the soil is still moist enough. In drought emergency years, ET monitoring helps to triage which orchards to water and which to let go dry (fallow) by quantifying water needs and yield trade-offs. In summary, almonds demonstrate how ET data can directly inform **precision irrigation** to reduce water stress. This not only secures yields but also has broader implications: conserved water can be used to sustain more orchards or left in aquifers, aiding regional water sustainability.

- **Strawberries & Raspberries (Disease Detection and Nutrient Management with GPP insights):** Berry crops like strawberries and raspberries are high-value, short-cycle crops predominantly grown along California's coast (Salinas, Watsonville, Santa Maria regions). They are typically fertigated (combined fertilization and irrigation through drip) and are susceptible to issues like soilborne diseases (e.g., verticillium wilt in strawberries), foliar diseases (mildews), and nutrient imbalances. Remote sensing of crop vigor has started to play a role in managing these issues. One example is using **NDVI and GPP to compare different soil treatments** after the phase-out of methyl bromide fumigant. USDA researchers evaluated if remote sensing could measure plant growth differences under alternative fumigation, and whether NDVI correlated with strawberry yield ars.usda.gov. They found that NDVI (taken via aerial imagery and handheld sensors) did correlate well with plant size and yield, validating that remote measurements of productivity reflect on-ground performance. For a grower, this means they can use drone or satellite NDVI maps to identify weak areas in the field. If a certain zone has persistently lower NDVI/GPP, it could indicate soil disease or nematode issues reducing root efficiency. Those areas might benefit from targeted soil treatments or crop rotation. On a more immediate timescale, anomalies in GPP can signal emerging problems: for instance, if a normally uniform raspberry field shows a patch with dropping GPP over a week, it might be an early infestation of spider mites or a nutrient deficiency. The grower can scout that patch sooner, perhaps preventing a larger outbreak. Berries are often grown on raised beds with plastic mulch, which can complicate remote sensing (soil background effects), but high-resolution imagery and careful calibration can overcome this ars.usda.gov, ars.usda.gov. Once calibrated, the **vegetation index or GPP data becomes a map of crop health**. Some strawberry growers have begun using subscription services that provide such health maps every week. They overlay these with management zones to do variable-rate fertilization – e.g., if one part of the field shows lower vigor, maybe increase nitrogen there. Because strawberries have a long harvest season with multiple pickings, maintaining an even, healthy canopy is important for sustained yield. GPP data also ties into **disease management**: research is ongoing into using thermal cameras (for ET surrogates) to detect plants infected with diseases like Macrophomina or Phytophthora before they collapse. A diseased strawberry plant often has reduced transpiration, so it appears warmer in thermal imagery. Spotting a cluster of warmer plants amid a cooler well-watered field is a red flag to remove those plants or apply fungicide. Similarly for raspberries, water stress or cane diseases could be mapped. Another aspect is **nutrient use**: strawberries are heavy feeders, and residual soil nitrogen is a concern for water quality. By monitoring how effectively the crop is converting inputs into growth (via GPP), growers and advisors can tweak fertigation regimes. For example, if adding an extra fertigation leads to no uptick in GPP, it may indicate diminishing returns (perhaps luxury consumption of N without yield gain), so they might reduce rates to avoid waste. In contrast, if GPP is lagging and leaves show subtle yellowing, that cues a boost in nitrogen. These decisions can now be data-supported rather than purely visual or based on fixed schedules. Precision ag trials in berries have shown the potential to reduce fertilizer use by using sensor data to guide applications, with no loss in yield – aligning with both economic and environmental goals. Lastly, yield forecasting for berries can benefit from GPP monitoring: since berries are picked continuously, knowing the likely "peak flush" of production helps in labor planning. Some farms use models that input weather and NDVI to predict when the main harvest flush will occur. High GPP periods generally precede high harvest periods (fruits mature following high carbon gain periods). Thus, berry growers can marry GPP trends with phenology models to schedule labor more efficiently, ensuring enough pickers during peak and not overscheduling during dips. In all, strawberries and raspberries illustrate how high-frequency, high-resolution tracking of crop physiological metrics can inform everything from pest management to fertilization to harvest logistics, directly improving profit margins and sustainability.

These case studies highlight that while ET and GPP might seem abstract, they have tangible benefits in crop management across different systems. Almonds show the water side – how ET data leads to water savings and stress avoidance; berries show the carbon/growth side – how vigor data leads to targeted interventions for health and inputs. Together they underscore a broader point: **data-driven agriculture** using physiological indicators can adapt to each crop's needs. California's innovative growers, faced with scarce water and labor and strict environmental regulations, are increasingly tapping into such tools (often in collaboration with universities and agtech companies). As sensor costs decrease and analytics improve, these approaches are likely to become standard practice.

Regenerative & Carbon Farming Connections

Beyond immediate farm management, monitoring ET and GPP has implications for long-term sustainability efforts such as **regenerative agriculture** and participation in **carbon markets**. These practices aim to improve soil health, increase carbon sequestration in farmlands, and reduce agriculture's environmental footprint. ET and GPP are key variables in understanding and verifying these improvements.

Supporting Carbon Sequestration Efforts: One principle of regenerative agriculture is to increase soil organic carbon (through practices like cover cropping, reduced tillage, and compost application). The idea is that more carbon in soil not only helps climate mitigation but also improves soil structure and water holding capacity. How do we know if we are sequestering carbon? GPP is directly related – it measures how much CO_2 the plants are drawing from the atmosphere. Not all of that carbon ends up stored in soil (a lot leaves as harvested product or respired back), but a portion (root exudates, crop residues) can become soil organic matter. By tracking GPP over years, one can gauge if an agricultural system's productivity is improving (perhaps due to better soil health). An increase in GPP could mean more carbon inputs to soil. Coupling GPP with measurements of **ecosystem respiration** (from flux data) can even allow estimation of Net Ecosystem Carbon Balance. For example, a cover-cropped, no-till system might show high GPP and relatively lower off-season respiration, indicating net carbon storage in the system. ET monitoring also plays a role: healthier soils often infiltrate and store water better, which might lead to slightly higher transpiration (plants can use water that would otherwise run off). So a regenerative field might show a shift from evaporation to transpiration – meaning more water goes through plants (productive) rather than evaporating unproductively. This can be captured by metrics like **ecosystem water use efficiency (eWUE = GPP/ET)** mdpi.com. A higher GPP/ET ratio suggests more carbon gain per unit water – often an indicator of a well-functioning, resilient system. In an almond study, researchers quantified GPP and eWUE over multiple years and found values comparable to natural ecosystems mdpi.com, mdpi.com, highlighting that well-managed orchards can be efficient in carbon and water use. By parameterizing such indices, we can track progress in sustainability. For instance, a farmer adopting regenerative practices might monitor eWUE as a KPI (Key Performance Indicator): if it improves over time, it's a sign that the soil-plant system is becoming more efficient (perhaps due to better soil structure or rooting depth from cover crops). In the context of climate change adaptation, maintaining productivity (GPP) while reducing water use (ET) is vital – something regenerative methods claim to do via enhanced soil moisture retention. Remote sensing offers a scalable way to monitor these outcomes across fields and seasons.

Carbon Credit Markets and MRV: With the rise of voluntary carbon markets, some farmers are exploring selling carbon credits for practices that increase soil carbon or reduce emissions. A big challenge in these projects is **MRV (Measurement, Reporting, and Verification)** – essentially proving that carbon is being sequestered. Traditionally, MRV relies on soil sampling (to measure soil carbon changes) and modeling. However, remote sensing is increasingly part of the MRV toolkit to ensure continuous, cost-effective monitoring catona.com. ET and GPP data feed into these models. Companies like Boomitra, for example, combine on-ground soil samples with satellite imagery to estimate soil carbon at scale boomitra.com. While the satellites don't measure carbon directly, they pick up on vegetation signals and moisture (via optical and radar data) that correlate with soil organic matter. GPP trends can indicate increased biomass input to the soil, and ET (especially when partitioned into transpiration vs evaporation) can indicate changes in plant cover. A field that consistently maintains cover (through cover crops or perennial grasses) will have a different ET signature (more year-round transpiration, less bare-soil evaporation) than a conventionally fallow field. Such differences can be detected with remote sensing and used as evidence of regenerative practice implementation. Additionally, climate-smart practices often aim to reduce inputs like irrigation or synthetic fertilizer. ET data can verify reductions in water withdrawals (useful if selling water savings or reporting for sustainability metrics), and GPP data can show maintained yield despite reduced inputs (indicating success of practices). Some carbon programs also consider avoided emissions – e.g., if better water management (guided by ET) leads to less pumping, that's energy saved and carbon emissions reduced.

Water and Carbon Nexus

There is a strong nexus between water management and carbon sequestration. For example, if a grower improves soil carbon, the soil can hold more water, potentially reducing the need for irrigation (a co-benefit). Conversely, deficit irrigation might stress plants and reduce GPP, limiting carbon inputs to soil. Finding the right balance is part of regenerative ag. By monitoring ET and GPP, farmers can ensure that water-saving measures don't overly compromise carbon gain (and yield). If a certain deficit strategy causes GPP to plummet, they might dial it back to keep the system sequestering carbon and producing yield. These data streams thus enable an *adaptive management* approach to carbon farming: adjust practices and immediately see the effect on plant water use and growth. Over multiple seasons, a rich dataset of ET, GPP, yield, and soil carbon can be built, helping to refine practices and also provide documentation to stakeholders (be it certifiers, consumers, or policymakers) that the farm is improving in sustainability. For instance, an almond grower in a carbon program could show that after 5 years of cover cropping, their orchard's peak GPP is higher, ET is used more effectively, and soil carbon samples confirm a gain – a holistic proof of regenerative success.

Participation in Carbon Credit Markets

When it comes to selling carbon credits, credibility is paramount. Projects need to demonstrate actual carbon removal. Remote sensing, including vegetation indices, is being used by verification bodies to ensure that fields under a carbon contract actually have the promised cover crops or management changes throughout the project period catona.com, catona.com. If a farmer claims no-till with continuous cover, but satellite data shows the field was bare and tilled, that's a red flag. On the flip side, strong signals of year-round greenness (NDVI), stable or increasing GPP, and appropriate ET are positive indicators aligning with increased carbon input. Some advanced approaches even aim to estimate NPP (Net Primary Production) from remote data and infer how much might be going into the soil. While there is still uncertainty, combining multiple data sources (satellite, ground sensors, models) is creating robust systems. For example, a "triangulation" approach uses satellite GPP/NDVI, flux tower proxies, and soil model simulations together to estimate soil carbon change – reducing reliance on any single method catona.com, catona.com. Such methods may soon complement or partially replace intensive soil sampling, making carbon projects cheaper to monitor and thus more accessible to farmers.

In essence, **ET and GPP monitoring form a bridge between farm management and ecosystem services accounting**. They allow quantifying benefits like water efficiency gains and carbon sequestration in real time. This is important not just for external credits but for the farm's own resilience. A regenerative farm would like to know: are my practices actually improving the system? By watching ET and GPP, they get immediate feedback. If soil health is improving, they might see higher spring GPP (due to better soil moisture retention) or less drop in GPP during a minor drought (due to resilience). Likewise, they might see ET patterns smoothing out (less extreme runoff events, more steady use). These are data-driven confirmations of qualitative benefits often claimed by regenerative agriculture.

Finally, it's worth noting that government and industry initiatives on sustainability are beginning to incorporate such metrics. Water footprinting for crops uses ET data to compute how much water a crop "consumed" per yield. Carbon footprinting uses NPP/GPP data to see how much CO_2 was taken up vs. emitted. With increasing transparency demands, a large almond operation might report annually on its water-use efficiency (yield per ET) and perhaps on net carbon balance. Thus, the same ET and GPP measurements that help day-to-day farming also feed into **macro-level sustainability assessments and potential reward systems** (like carbon credits or ecosystem service payments).

Conclusion & Future Directions

ET and GPP have emerged as critical metrics for linking ground-level crop physiology with remote sensing and data analytics in agriculture. As reviewed, ET encapsulates the water dimension of crop health – indicating usage and stress – while GPP encapsulates the carbon and growth dimension – indicating productivity and vigor. Using these together provides a 360° view of crop status. In yield prediction models, incorporating ET and GPP has demonstrably improved accuracy, since these metrics carry direct information about plant function that generic indices alone may miss. On the farm, applications range from precise irrigation scheduling that saves water, to nutrient management that maximizes photosynthesis, to early stress detection and optimized harvest timing. Case studies in California almonds and berry crops illustrate real-world benefits: data-driven adjustments in practices leading to water savings, maintained yields, and more informed management under challenging conditions like drought and disease pressure. Furthermore, monitoring ET and GPP supports broader goals in sustainable agriculture – improving water use efficiency and carbon sequestration, which are key to climate resilience and participation in carbon markets.

Looking ahead, **emerging technologies** will further integrate ET, GPP, and artificial intelligence into user-friendly tools. For instance, NASA's ECOSTRESS mission is providing high-temporal-resolution thermal imagery that can measure field-level ET and stress every few days, even at times of day when water stress peaks. Combined with high-resolution optical satellites (Planet, Sentinel-2) that can monitor canopy development and even chlorophyll fluorescence, we are moving toward a future where real-time ET and GPP maps are available on-demand for every farm. This data firehose will be harnessed by AI models – for example, an AI could ingest continuous satellite ET/GPP data, weather forecasts, and sensor data to predict, *in real time*, an impending yield reduction or pest outbreak, and recommend mitigation steps. Some researchers are developing **digital twins** of farms where ET and GPP are key state variables updated from remote sensing, enabling scenario testing (e.g., "what if I irrigate 20% less next week, how will GPP and yield respond?"). On the ground, cheaper sensors like sap flow meters (for transpiration) and leaf gas exchange sensors (for photosynthesis proxy) could allow even more granular ground-truthing and control in high-value crops like greenhouses or vertical farms.

Integration is a big theme. Currently, many growers get bits of information from different sources: a weather station for ET, maybe a satellite NDVI image from a service, perhaps a separate handheld tool for chlorophyll or a pressure chamber for water stress. We can expect **consolidated platforms** that integrate these – indeed, the OpenET project's next-generation "FARMS" tool is aiming to put high-res ET data directly in farmers' hands with user-friendly interfaces nasa.gov, nasa.gov. Similar efforts are likely for GPP or crop growth metrics, possibly in the form of biomass or yield forecasting apps. These platforms, enhanced with machine learning, will likely provide recommendations (not just raw data) – for example, telling a strawberry grower: *"This field's transpiration is 15% below norm and GPP has dropped 10% in the last 3 days; possible stress detected – inspect for pests or irrigate if soil is dry."* In almonds, an app might combine ET and GPP to compute WUE and advise if it’s time to adjust irrigation or fertilization to stay on track for target yield.

Gaps and research needs remain. For instance, translating GPP improvements to actual yield depends on partitioning of carbon – in some cases, a high GPP might all go to vegetative growth and not increase fruit yield; understanding crop-specific growth dynamics is important to fine-tune models. ET-based irrigation works well on average, but extreme heatwaves or microclimate variations might require additional sensing (like soil moisture probes) to avoid underestimating plant stress – multi-sensor fusion is a continued research area. There is also a need for **better crop-specific calibration** of remote sensing models: berries and specialty crops are less studied than big commodities like wheat or corn. Ensuring that satellite algorithms estimate ET and GPP accurately for strawberries under plastic mulch, or almonds in different canopy architectures, needs targeted research and field experiments. Another challenge is scaling and computing – processing daily satellite data for thousands of fields and running AI models is computationally intensive, calling for cloud computing solutions and possibly edge computing on IoT devices. Privacy and data ownership concerns also arise as farms generate more data.

From a commercial implementation standpoint, demonstrating the return on investment (ROI) to growers is key to adoption. The technologies discussed promise a lot, but they must be cost-effective and show clear benefits. As more case studies and pilot projects document yield gains, water savings, or input reductions from using ET/GPP-driven systems, confidence will build. Industry stakeholders like irrigation companies, agtech startups, and farm management services are increasingly incorporating these scientific advances. For example, several irrigation controller products now have an “ET mode” that adjusts watering times based on weather/ET. We anticipate more “GPP mode” or “crop health mode” features in the future – perhaps fertilization controllers that use satellite GPP feedback to adjust dosing.

In conclusion, ET and GPP serve as vital signs of crop ecosystems – akin to pulse and respiration for the human body. By monitoring these vital signs with remote sensing and analytics, we gain a powerful diagnostic and prognostic tool for agriculture. The convergence of remote sensing, in situ sensing, and AI is enabling a shift from reactive farming to **predictive, adaptive farming**. California’s almond orchards and berry fields are at the forefront of this transformation out of necessity, but the lessons and technologies are applicable globally. Continued collaboration between agronomists, engineers, and data scientists will be needed to refine these tools and ensure they are robust under real-world farming conditions. The payoff is resilient, resource-efficient crop production – growing more food with less water, lower inputs, and a smaller environmental footprint, all while equipping farmers with better information to make decisions. ET and GPP, once the domain of eco-physiologists, have thus become practical metrics driving the next wave of precision agriculture and sustainable farming.

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