Remotely sensed evapotranspiration for corporate water stewardship: Opportunities and limitations in agricultural landscapes

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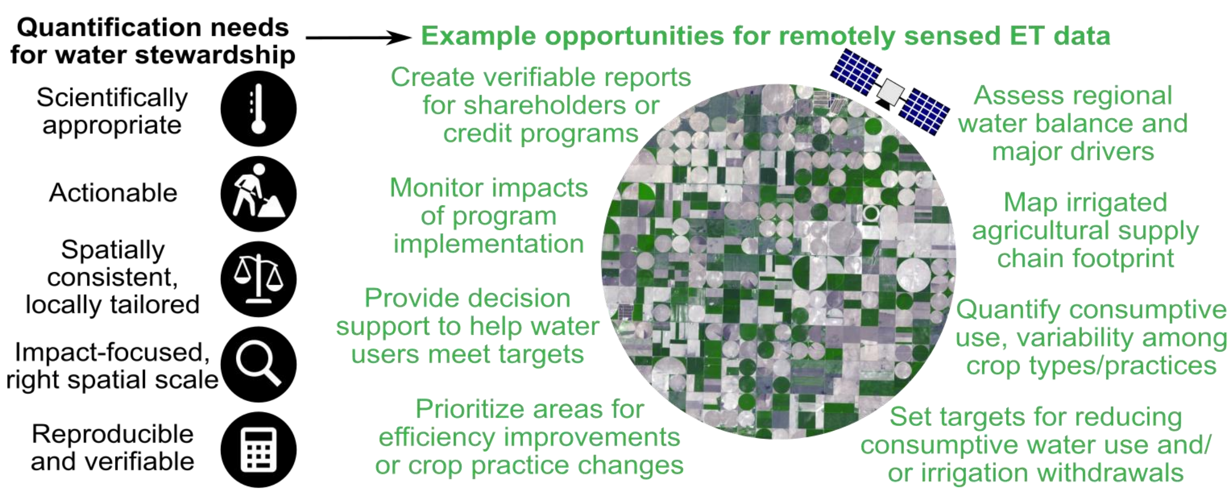
Abstract

Corporate water stewardship (CWS), in which companies engage in or incentivize actions to advance sustainable water management, can positively affect water resources, reduce water-related business risks, and support Environmental, Social, and Governance (ESG) and sustainability reporting. Agricultural landscapes affect diverse industries including finance, technology, fuel production, insurance, and food/beverage companies but distributed agricultural supply chains make quantifying water use and impacts of CWS activities difficult. Here, we review and integrate literature related to CWS and remotely sensed evapotranspiration (RSET) in agricultural landscapes to identify opportunities and limitations for improved agricultural water management through CWS. First, we identify five key principles for hydrologic analysis to support effective CWS: variables should be scientifically-appropriate, actionable, spatially consistent but locally tailored, impact-focused at a relevant operational scale, and reproducible and verifiable. RSET has potential relevance for many CWS activities including understanding risks, setting corporate commitments, quantifying historic conditions, and outcome monitoring/reporting. Most directly, RSET methods provide a reproducible and verifiable input for calculating consumptive water use, which is the total evapotranspiration (ET) of a crop within a period of time such as a growing season and is often related to total agricultural water use. Calculating irrigation applications and/or withdrawals requires accounting for additional processes beyond ET and therefore involves additional modeling or monitoring approaches. There are many opportunities for RSET to integrate with CWS to advance agricultural water management, as long as care is taken to focus on suitable applications and communicate uncertainty.

Graphical Abstract:



1. Introduction

Water resources are stressed worldwide, with an estimated 1.5 billion people and 17% of global food production located in areas with freshwater stress and water storage loss (Huggins et al., 2022), indicating a critical need to improve global stewardship of water resources. National and multi-national corporations are uniquely positioned to drive meaningful change in water management through environmental stewardship efforts due to their substantial economic and political influence (Folke et al., 2019; Österblom et al., 2022, 2015; Sojama and Rudebeck, 2024). Corporate water stewardship (CWS) is a broad term describing corporations' assessment and management of water-related risks to their business and hydrologic impacts of their activities, including within their supply chain and sourcing regions (Hepworth and Orr, 2013; Jones et al., 2015; Rozza et al., 2013), and integrates closely with Environmental, Social, and Governance (ESG) and Sustainability reporting efforts (Minea et al., 2025; Wahyuningrum et al., 2025). Within the context of reporting, CWS may occur in response to corporate disclosure expectations, customer or investor pressure, policy, and/or supply-chain risk management needs (Jia et al., 2019).

Despite the global extent of water stress, the impacts of water use are largely felt within the watershed or aquifer where the water use occurs, and CWS often takes the form of place-based implementation of programs intended to improve local water resource conditions while meeting a corporation's water commitments. The local nature of impacts places water stewardship in contrast to other global common pool resource management challenges such as greenhouse gas emissions, which affect the entire globe regardless of where emissions occur due to the well-mixed nature of the atmosphere (Cho et al., 2026). However, while impacts of water use are primarily felt locally, many drivers of water use are global in nature such as international trade (Lenzen et al., 2013; Wiedmann and Lenzen, 2018). For example, 45% of the agricultural products grown using water from the U.S. High Plains Aquifer are consumed outside of the states overlying the aquifer (Marston et al., 2015). This indirect export of water, in the form of water that is used to grow crops that are then exported, is referred to as 'virtual water' and creates complex global relationships between water, food, and trade through agricultural supply chains (D'Odorico et al., 2019; Pastor et al., 2019). Globally, 11% of nonrenewable groundwater use for irrigation goes to international food trade, and most of the world's population lives in countries that import food crops from regions with ongoing groundwater depletion (Dalin et al., 2017). Due to the global drivers and local impacts of water use, effective water stewardship requires integrating global goals with local water management solutions (Zipper et al., 2020).

Well-designed CWS efforts by multinational corporations can generate local hydrologic benefits, and therefore CWS represents one approach to bridge global drivers of water use with local solutions. Agriculture is of particular interest to CWS efforts because agriculture makes up ~70% of global water use (United Nations, 2026), and therefore irrigation is a widespread cause of water stress. Diverse industries including food/beverage companies, finance, technology, and insurance affect and/or are affected by agriculture and are involved in CWS efforts (Kapnick, 2026). For example, Silva (2024) highlights examples of corporate actions to improve water supply and safety by global companies including Coca-Cola, Unilever, and Toshiba. CWS efforts can have significant impacts on water management, even exceeding impacts of government interventions (Barbosa et al., 2024). However, for CWS efforts within these industries to effectively translate global corporate risks and impacts to local solutions, CWS needs a firm, data-driven scientific foundation that is both hydrologically meaningful and can be effectively used by corporate procurement, sustainability, and reporting teams involved in CWS efforts (Freiberg et al., 2021; Vlachos and Aivazidou, 2018). Additionally, since a given corporation may have a supply chain spanning multiple regions around the world and a single farm or region may be part of the agricultural supply chain for multiple corporations, navigating integration across scales/regions and coordination among producers and corporations requires clear understanding of when, where, and why water is being used (Sojamo and Rudeback, 2024).

Agricultural water use is one of the primary variables used for CWS efforts, but high-quality agricultural water use data is notoriously challenging due to the widely distributed nature of irrigation practices and the lack of consistent guidelines for measuring and reporting (Marston et al., 2022). As a result, CWS often relies on proxies, heuristics, models or self-reported data rather than measured agricultural water use (Jia et al., 2019), and trusted data that characterizes water use has potential to strengthen transparency, effectiveness, and durability of water conservation programs (Gustafsson et al., 2024; Wuepper et al., 2026). Consumptive water use is the flux of water from the land surface to the atmosphere as evapotranspiration (ET) over a period of interest such as a growing season or year (some definitions of consumptive water use also include water harvested in plant tissues, but harvested water is small relative to ET). While consumptive water use is not equivalent to total agricultural water use due to factors such as irrigation efficiency, soil salinity management, and frost protection (more details in Section 3.2), it can be a useful indicator of the amount of water leaving a region of interest such as a field, watershed, or aquifer and therefore has potential value for CWS efforts.

One emerging data product that can accelerate the accurate and reproducible calculation of consumptive water use is remotely sensed evapotranspiration (RSET). Remote sensing methods offer a unique opportunity for landscape-scale ET monitoring since they often have continuous worldwide coverage, collect data at fine enough spatial resolution to resolve many individual fields, and increasingly have long periods-of-record from satellite missions such as Landsat, which first launched in 1972 and underpins many RSET products (Muturi et al., 2025; Fisher et al., 2026). Additionally, recent application-ready datasets such as OpenET (Melton et al., 2022) have lowered the barrier to obtain and use RSET data (specific RSET data sources are discussed in more detail in Section 3). However, ET data is rarely used in CWS programs (reviewed in Section 2) and, as a result, RSET has not yet seen widespread integration into CWS activities.

To help advance CWS efforts that support effective local agricultural water management, this review asks the question, where and how can RSET data effectively support CWS activities that improve water management in agricultural landscapes? To do so, we review and integrate two distinct bodies of literature: (i) current approaches to CWS and (ii) current applications and accuracy of RSET methods, focused specifically on agricultural landscapes. For both bodies of literature, we used a mixed-method approach to identify relevant literature to review. First, we identified reports and manuscripts known to our team of co-authors which includes experts in both corporate partnerships and physical science related to agricultural water management and RSET. From this initial set of documents, we developed a larger corpus through backwards- and forwards-citation tracing to identify additional relevant content to review. We then supplemented this sample of literature with targeted searches on Google Scholar as well as Google (since many CWS commitments and programs are not in the form of peer-reviewed literature) using key terms that we identified during the citation-tracing method (e.g., "corporate water stewardship agriculture", "environmental stewardship irrigation", "remote sensing irrigation", etc.).

The core novelty of this review, therefore, is in the integration of distinct bodies of literature to identify opportunities for RSET to integrate with CWS activities and improve agricultural water management. Although specific CWS activities often depend on local needs and context, we present a general CWS framework and approaches to incorporate RSET in such a way that these concepts may be applied to a wide range of water-scarce agricultural regions globally. We first provide an overview of CWS approaches and describe a common eight-stage lifecycle for CWS activities. Based on this, we identify key principles for hydrologic data to support stewardship decision-making and sustainability reporting. We then review relevant aspects of ET in agricultural landscapes, including key variables with relevance to CWS and approaches for quantification, and assess where in the CWS lifecycle RSET can provide useful data. Based on this, we highlight types of applications where RSET is well-suited for use in CWS and areas where caution is merited, and provide a hypothetical but illustrative case study for how RSET data may be used to enhance CWS efforts in a heavily-stressed aquifer. Through this review and synthesis, we identify opportunities for RSET data to enhance agricultural water management efforts that address local water resource challenges and reduce supply chain risk.

2. Corporate water stewardship activities and needs

This section reviews current approaches to corporate water stewardship (Section 2.1), uses this review to identify a generalizable set of eight steps in the CWS lifecycle (Section 2.2), and then identifies key data principles to support these CWS efforts based on environmental decision-making literature (Section 2.3).

2.1 Current corporate water stewardship approaches

Water is included in many prevalent frameworks for ESG and Sustainability reporting. For example, the Global Reporting Initiative is used by a variety of Fortune 500 countries and requires reporting on water use throughout a company's supply chain (Global Reporting Initiative, 2018), while the European Union's Corporate Sustainability Reporting Directive (CSRD) includes a variety of water-related metrics. To help meet these reporting needs and create opportunities for positive corporate influence on water resources, a wide variety of CWS frameworks have been developed. Here, we review CWS 'frameworks', by which we refer to a structured approach used for the development of CWS efforts, which can then be operationalized by a corporation when setting specific commitments, designing programs, and developing approaches for quantification.

Efforts like the CEO Water Mandate and Alliance for Water Stewardship provide frameworks for companies to develop water stewardship plans, including suggestions about workflows and aspects of plans, but do not require or suggest any specific commitments, quantification approaches, or outcomes. There are also frameworks that are more prescriptive in their approach. For example, the Field to Market: Alliance for Sustainable Agriculture developed a set of sustainability metrics, which include a standardized approach for calculating irrigation water use sustainability based on the ratio of irrigation water applications to the yield benefits from irrigation. This approach provides a relatively simple calculator with minimal input data requirements, and the calculation prioritizes improvements in irrigation efficiency. However, efficiency-focused metrics are vulnerable to 'rebound effects' in which efficiency improves but the amount of water used for irrigation remains stable or increases since the metric may incentivize switching to more water-intensive, higher-yielding crops (Freire-González, 2019; Ghoreishi et al., 2021; Junquera et al., 2025; Kalthof et al., 2026). Additionally, efficiency improvements can lead to reduced water availability locally or in downstream areas due to lost irrigation return flows (Glose et al., 2022; Kendy and Bredehoeft, 2006; Redaelli et al., 2026), or expansion of irrigated area as efficiency improvements increase farm profitability and conserved water can be repurposed elsewhere (Paul et al., 2019).

Other frameworks that prescribe calculation methods include Volumetric Water Benefit Accounting (VWBA) and the Science-Based Targets for Nature (SBTN) initiative. VWBA is an approach in which the effectiveness of a water stewardship intervention is calculated as the difference between conditions "with" and "without" the project. This is a flexible framework that can be tailored to locally-important hydrologic variables and goals. However, many hydrologic variables potentially affected by agriculture, including irrigation applications (Whittemore et al., 2023) and the impacts of pumping on streamflow (Zipper et al., 2022), are highly sensitive to year-to-year weather variability. As a result, isolating the impact of an intervention can be challenging and require either averaging over a wide range of weather conditions (meaning that quantification is possible only years after the intervention is introduced) or developing a modeled counterfactual condition to simulate conditions without the intervention (which can introduce significant complexity to the calculations). SBTN similarly provides a standardized approach to assess pressures of corporate activities on water resources, with impacts assessed based on locally-designed hydrological benchmarks. While the current SBTN approach is largely focused on surface water resources, there are likely approaches to adapt it to groundwater resources as well.

2.2 Commonalities among corporate water stewardship approaches

The CWS frameworks discussed above encompass both more general and more prescriptive approaches, and differ in specifics such as the variables calculated and the approach for setting commitments (Silva, 2024; Jones et al., 2015). Based on our review, we generalize the various implementations of CWS efforts into a cycle of eight steps (Figure 1):

1. <u>Understanding risks and impacts</u>, in which a corporation assesses water-related risks to its business operations and the ways that its business operations impact water resources.
2. <u>Framework development</u>, in which a corporation determines what framework(s) it wants to use or develop for CWS and how it wants its stewardship activities to address risks and impacts.
3. <u>Setting corporate commitments</u>, in which a corporation determines and commits to specific and quantifiable water-related goals, standards, or targets.
4. <u>Program design</u>, in which a corporation works with local partners and stakeholders to develop programs of interventions that can help meet its commitments.
5. <u>Program implementation</u>, in which a corporation supports or incentivizes partners to carry out the programs.
6. <u>Outcome monitoring</u>, in which a corporation assesses the outcomes of the programs relative to its water stewardship commitments.
7. <u>Reporting and disclosure</u>, in which a corporation shares information about its water stewardship commitments, programs, and outcomes with relevant groups including stakeholders, shareholders, boards, and the public.
8. <u>Iterative refinement</u>, in which a corporation revises its framework, plan, commitments, and programs based on results of past efforts and new information.

These steps are bounded by a corporation's sphere of influence, which includes its direct operations, supply chain, and shareholder interests. Additionally, throughout each of these steps, close integration with local stakeholders is critical to successful CWS efforts (Fraser and Kunz, 2018; Sojamo and Rudebeck, 2024), since ultimately the programs will be implemented and the outcomes will be experienced by these stakeholders. Relevant stakeholders will vary substantially based on a corporation's activities and supply chain, but may include state and federal agencies, water managers, researchers, other supply chain companies, non-governmental organizations (NGOs), and producers. Regardless of the stakeholder group involved, identifying overlapping or similar motivations or concerns among stakeholders is critical to developing effective water-related solutions (Ellermann et al., 2026).

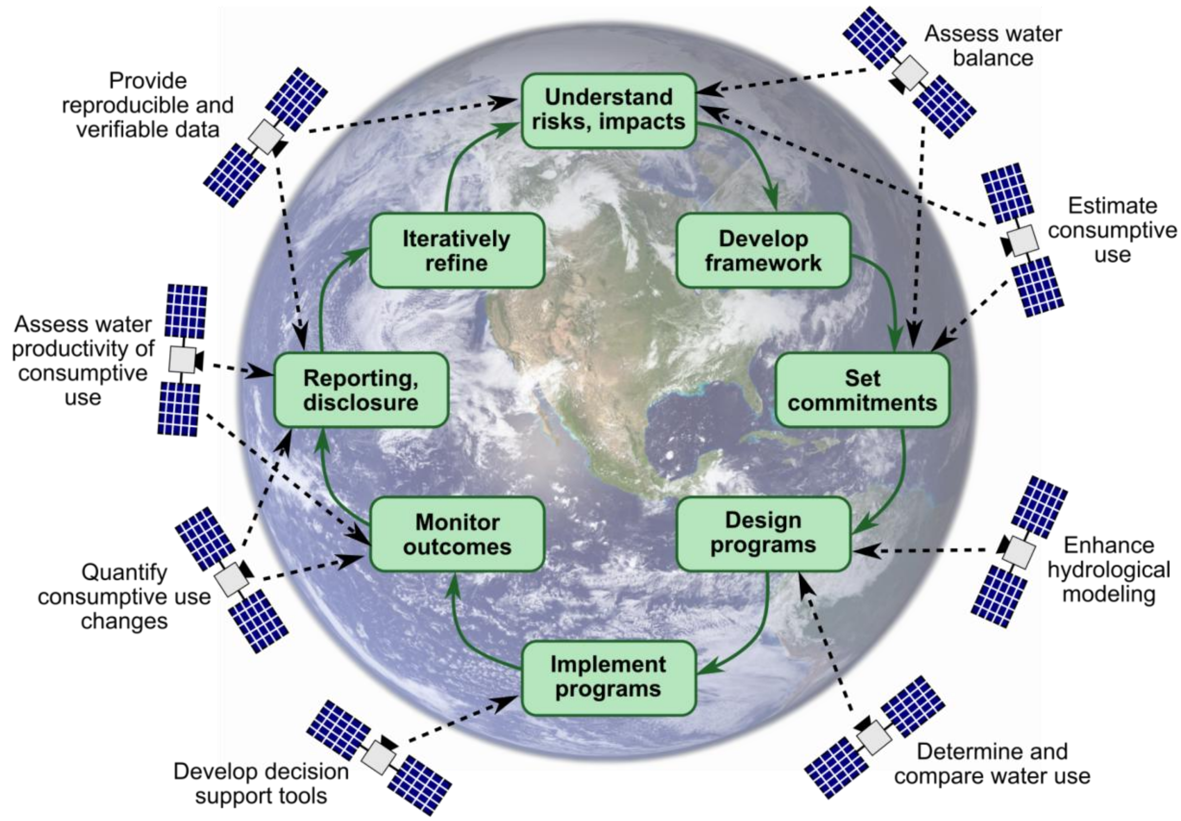


Figure 1. Overview of a common lifecycle for corporate water stewardship (CWS) approaches, shown as colored boxes corresponding to the eight steps described in the text. These CWS activities are bounded by the scope of a corporation's direct operations, supply chain, and shareholder interests, and stakeholder involvement should be integrated into each step. Opportunities for RSET data at each step are shown in orbit around the Earth and discussed in the text.

2.3 Need for hydrologic quantification to support corporate water stewardship

Many of these steps require quantification of hydrologic variables such as streamflow, groundwater availability, or water use. For example, understanding risks and impacts (step 1) will typically require assessment of the current status of water resource availability and its response to corporate activities, while setting commitments (step 3) requires identifying hydrologic conditions that provide desired outcomes and are achievable from corporate activities (see Section 3 for a full overview of each step). For steps where hydrologic quantification is necessary, we develop five principles for determining appropriate variable selection and calculation (Figure 2):

1. Scientifically appropriate, meaning that the variables are reasonable indicators of the underlying hydrological and industrial processes they are intended to represent, and the variables can be accurately estimated with quantified uncertainties.

2. Actionable, meaning that the corporation has the potential to make a meaningful difference in the processes or outcomes being evaluated, and those impacts can be effectively monitored.
3. Spatially consistent and locally tailored, meaning that calculations should be done in a consistent way across space and time, but commitments and impacts should be reflective of local conditions (e.g., impacts of using 10 mm of water differ in a wet region vs. a dry region).
4. Impact-focused at operational scale, meaning that variable(s) selected should be focused on environmental impacts that are trackable and integratable across the supply chain at the relevant spatial scale (such as a field), and should avoid incentivizing practice adoption without quantification of impacts. Additionally, impacts should be considered across scales to avoid unintended externalities (e.g., alterations to streamflow as a result of irrigation efficiency changes).
5. Reproducible and verifiable, meaning that the input datasets and necessary calculations should be clearly described and reproducible by others to build trust.

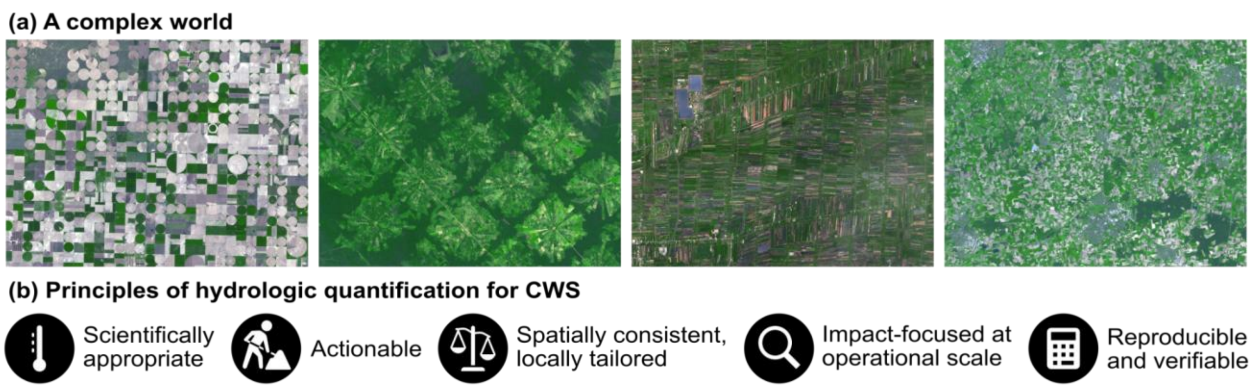


Figure 2. (a) Corporate water stewardship efforts often require quantifying hydrological processes in complex agricultural landscapes, with examples of distinct agricultural systems shown from the USA, Bolivia, Thailand, and Germany (left to right). Images public domain from NASA Earth Observatory (2006). (b) To do this, we suggest five principles of hydrologic quantification for integration into CWS efforts.

These principles emerge from the broader literature focused on environmental decision support modeling. For example, seminal literature on groundwater decision support has described that management decisions inevitably requires locally-targeted, problem-specific model development that provides estimates of desired variables with uncertainty bounds that can be used for cost-benefit and trade-off analyses (Doherty and Moore, 2020; Doherty and Simmons, 2013). Similarly, the past decade has included a broad push towards 'FAIR' (Findable, Accessible, Interoperable, and Reusable) data products to increase transparency and reproducibility of derived scientific products (Hall et al., 2022; Wilkinson et al., 2016), which has recently expanded to include increased focus on FAIR models (Hut, 2022; Reinecke et al., 2022). In the agricultural realm, there is strong promise from recent digital innovations that enable transparent and open tracking of data and products across supply chains (Meemken et al., 2024).

3. ET in agricultural landscapes

This section provides an overview of approaches for estimating ET in agricultural landscapes (Section 3.1) and ET-related variables most relevant to CWS efforts (Section 3.2). With this as context, we then review the state of the science on remote sensing methods for estimating ET with particular attention paid to the relatively new OpenET product (Section 3.3).

3.1 Measuring and estimating ET using ground-based instrumentation

ET is a particularly challenging variable to monitor (Wanniarachchi & Sarukkalige, 2022). The most common methods to quantify ET using ground-based instrumentation deployed within agricultural fields are weighing lysimeters and the eddy covariance (EC) approach applied to micrometeorological instrumentation deployed on flux towers (Alfieri et al., 2020; Hatfield et al., 2016). Weighing lysimeters are devices that are installed in the soil profile that (depending on design) measure the mass of water stored in the root zone and/or the movement of water in and out of the soil column, which can then be used to calculate ET using a water balance. EC towers measure the air's water vapor content and vertical wind speeds many times per second, and use these data to compute the net upwards movement of water vapor. Therefore, both lysimeters and EC towers provide point-based calculations of ET, though with different spatial footprints. Lysimeters require extraction and re-installation of soil, and therefore typically have a coverage area less than 10 square meters. In contrast, EC towers measure a wider spatial footprint (hundreds to thousands of square meters) which varies based on the height of the EC tower, vegetation growing nearby, and wind direction/speed. Both EC towers and lysimeters are expensive to install, operate, and maintain, and therefore they are sparsely distributed relative to other types of hydrologic monitoring (e.g., streamflow gaging stations, rain gauges, groundwater monitoring wells).

ET can also be indirectly estimated for a region using water balance approaches, in which ET is calculated as the residual of inflows of water (predominantly precipitation but can also include lateral inflows of water through the surface or subsurface), outflows of water (including streamflow and groundwater flow), and changes in storage (such as increases or decreases in groundwater and soil moisture storage). These approaches can be highly uncertain since many of these input variables, such as changes in groundwater storage, are also rarely known, and as a result water balance-based estimates of ET are often done over large areas and/or multiple years to average out variability in storage (Gyawali et al., 2015; Chu et al., 2025). Due to the challenges of directly measuring or calculating ET, agricultural applications often use reference ET (ET_{ref}) , which is the expected ET from a standardized well-watered land cover such as grass or alfalfa based on meteorological conditions (abbreviated ET_o for a grass reference crop or ET_r for an alfalfa reference crop). ET_{ref} can then be scaled to specific crops using coefficients that vary based on growth stage. This approach is useful for estimating ET but often struggles when crops experience stress due to water/nutrient limitations, pests, or other causes. A full overview of ET-related terms and definitions is available in Fernández (2023) and ASCE Environmental and Water Resources Institute (2025).

3.2 ET-derived variables relevant to CWS

CWS activities may affect various components of hydrological or agricultural systems. For example, CWS efforts related to agriculture are often intended to address impacts of irrigation for crop production, which can include groundwater declines (Deines et al., 2020; Scanlon et al., 2012; Wada et al., 2010), streamflow depletion (Barlow and Leake, 2012; Zipper et al., 2024a, 2026), and harm to groundwater-dependent ecosystems (Brown et al., 2011; Huggins et al., 2023; Rohde et al., 2017). To mitigate these impacts, CWS efforts often focus on maintaining or maximizing crop production while minimizing water extractions. The specific variables of importance depend on local considerations, including the source of water used for irrigation (surface water or groundwater), the degree of connectivity between the stream and the aquifer system, climatic conditions, and typical agricultural practices and markets.

ET is rarely the variable used for a direct commitment in CWS programs, which most often make commitments for specific improvements to water use, water efficiency, water consumption, and water quality (Jones et al., 2015; Rozza et al., 2013). However, ET is strongly influenced by human activities such as irrigation and therefore highly relevant for many CWS efforts, and can represent a critical input to these efforts. For agriculture, which is the largest global user of water, there are several distinct concepts that fall under the umbrella of water use quantification but important to distinguish (Figure 3):

- *Irrigation water withdrawals* are the amount of water removed from a groundwater or surface water system at the spatial resolution of a point of diversion, such as a groundwater well or irrigation canal. Irrigation water withdrawals are most often expressed in units of volume, such as cubic meters or acre-feet.
- *Irrigation water applications* are the amount of water put on a field by an irrigation system. Irrigation water applications are quantified at the spatial resolution of a place of use, such as an irrigated field, and are most often expressed in units of depth, such as mm or inches. Applications differ from withdrawals due to potential irrigation system losses, such as conveyance issues, and based on the area in which the irrigation water is used.
- *Consumptive water use* is typically defined as the amount of water evapotranspired over a period of interest (such as a growing season). Consumptive water use can therefore be quantified directly from ET data at any spatial scale where ET data are available, and is a relevant parameter for both rainfed or irrigated agriculture. In irrigated fields, consumptive water use differs from irrigation water applications in that consumptive water use also includes ET derived from rainfall, and subtracts out any losses of irrigation water that do not contribute to ET. These losses may include

water applied for non-consumptive purposes such as frost protection or soil salinity management as well as water lost to runoff, deep percolation beyond the root zone, or changes in soil moisture storage.

Irrigation water withdrawals and applications can be directly measured using flowmeters attached to irrigation systems, either at the point of diversion (for withdrawals) or the place of use (for applications). However, flowmeter data are rarely available (Foster et al., 2020), can be subject to reporting errors, and generating accurate data requires calibration and verification of flowmeter accuracy. Additionally, flowmeters are typically installed at the location where water is extracted from a river or groundwater, and therefore can be difficult to link to specific places of use unless field-specific flowmeters are installed (Earnhart and Hendricks, 2023; Ott et al., 2024; Zipper et al., 2024b). This combination of factors makes flowmeter data challenging to scale within CWS efforts, even where data are available.

Depending on the specific goals of CWS efforts and hydrological context where programs are taking place, any or all of these three variables may be relevant. For example, where the water table is shallow, irrigation applications in excess of consumptive use can quickly return to the aquifer as irrigation return flows if other water losses such as runoff are minimal (Redaelli et al., 2026), which means that the net water balance of the aquifer may be more strongly determined by consumptive water use than irrigation water withdrawals (in addition, these return flows may degrade water quality). In contrast, in settings where the water table is deep it can take decades for changes in irrigation efficiency to alter aquifer inflows (Glose et al., 2022), meaning that irrigation water withdrawals are the strongest control over the water balance of the aquifer (Butler et al., 2023). Ultimately, these local considerations related to hydrological conditions should determine which variable(s) must be quantified as part of CWS development, including understanding impacts, program design/implementation, and outcome monitoring/reporting (Figure 3; more details about each step in Section 4).

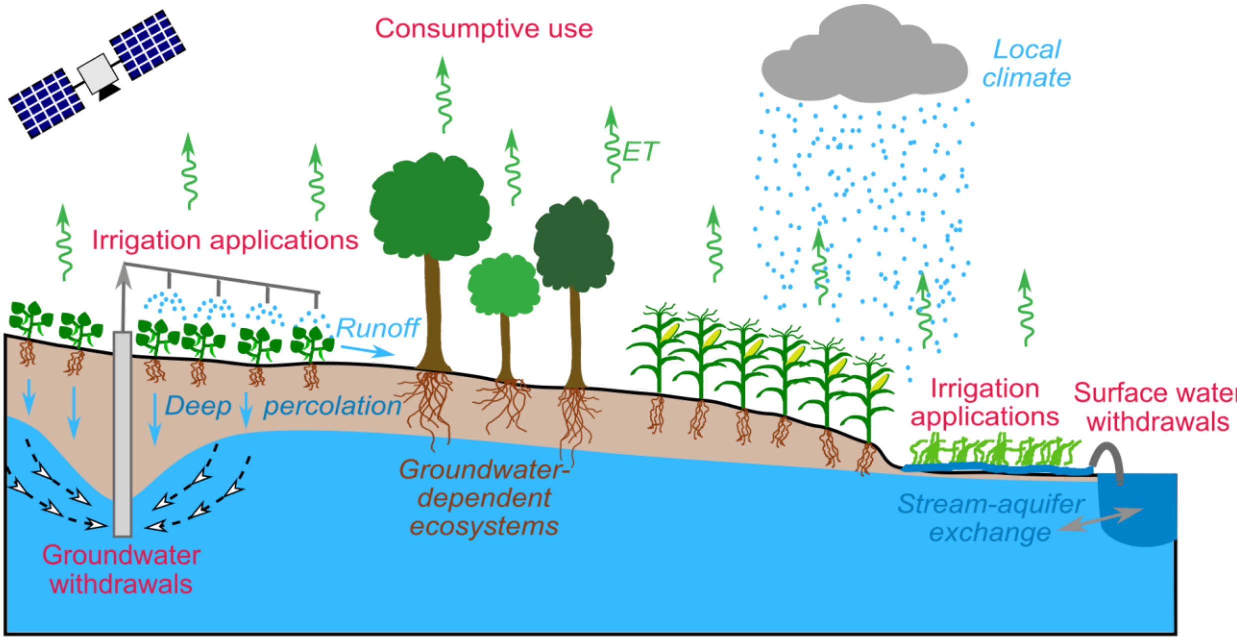


Figure 3. Conceptual diagram showing key hydrologic fluxes relevant to agricultural CWS activities. Irrigation water withdrawals, irrigation applications, and consumptive use, which are discussed as closely linked to RSET data, are labeled in red. Other fluxes relevant to CWS efforts are also included.

3.3 Remotely sensed ET (RSET) overview and accuracy

Remote sensing methods are an additional indirect approach to quantifying ET that rely on data collected from satellites or aircraft (Hatfield et al., 2016) and can be calculated at a variety of different spatial scales and resolutions (McCabe and Wood, 2006). While remotely sensed data can be used to quantify many aspects of the water cycle, including streamflow, reservoir storage, and groundwater levels, here we focus specifically on ET. Two key concepts related to RSET data are spatial resolution, which describes the size of each measurement pixel, and spatial coverage, which describes the total extent of data available from that RSET source. CWS activities often require fine spatial resolution (such as individual fields or management zones within large fields) to identify the impacts of management activities, and extensive spatial coverage (such as supply sourcing regions, aquifers, or watersheds) to span a corporation's area of interest. RSET approaches that rely on satellite data from sensors such as Landsat and Sentinel provide both a spatial resolution and coverage extent that is well-aligned with these goals. Each satellite-based dataset has its own unique spatial and temporal coverage and resolution, and RSET approaches often integrate data from multiple satellites along with gridded meteorology, topography, and land cover datasets. Since RSET data are based on satellites which collect data over vast regions, RSET data is highly scalable and can track impacts at the resolution of individual fields (30 - 100 m), with potential for reproducibility where open source models and processing algorithms are shared. However, RSET has historically had a high barrier to entry in terms of technical knowledge and data requirements given the complex processing approaches needed to derive ET from satellite data.

There are numerous existing RSET products available from sources including governments, research agencies, and universities. For example, the MODIS satellite provides a global map of ET every 8-days at 500 m resolution through the MOD16A2 product, and the U.S. Geological Survey has provided estimates of ET across the continental U.S. for the years 2000-2020 using the SSEBop model based on Landsat data (Senay, 2018; Senay et al., 2013, 2025). There are also publicly-released algorithms that can be used to calculate ET directly from remotely sensed data (after integration with other necessary input datasets such as ground-based meteorology), including FLUXCOM (Jung et al., 2019), GLASS (Xie et al., 2022), GLEAM (Miralles et al., 2011, 2025), HRMET (Zipper and Loheide, 2014), METRIC (Allen et al., 2007), S-SEBI (Basit et al., 2018), SEBAL (Bastiaanssen et al., 1998), and TSEB (Anderson et al., 2024).

One recent RSET product experiencing increased uptake is OpenET. OpenET is a platform providing archived monthly and on-demand daily calculations of ET from (as of the time of writing) October 1999 to present day at 30 m spatial resolution over the continental U.S. (Melton et al., 2022). OpenET provides data from six different algorithms as well as an ensemble mean, which is calculated after automated removal of any outliers. Algorithms included in OpenET are ALEXI/DisALEXI (Anderson et al., 2018, 2007), eeMETRIC (Allen et al., 2011, 2007, 2005), geeSEBAL (Bastiaanssen et al., 1998; Laipelt et al., 2021), PT-JPL (Fisher et al., 2008), SIMS (Melton et al., 2012; Pereira et al., 2020), and SSEBop (Senay, 2018; Senay et al., 2013). To compute ET, OpenET integrates a variety of datasets including satellite remote sensing data from multiple platforms, gridded meteorological data, topography, soil information, and land use. In addition to ET, OpenET also provides supporting datasets such as precipitation, reference ET (ET_o), and the Normalized Difference Vegetation Index (NDVI), which is an indicator of vegetation greenness. Since OpenET integrates multiple models and provides application-ready data, it lowers the barrier to entry for use of RSET data for hydrologic studies and CWS programs. Given its increasing use, we focus our discussion of accuracy around OpenET, though the opportunities and limitations we discuss are broadly true regardless of RSET data source.

Published accuracy assessments for OpenET data have relied on comparisons to EC towers and regional water balance assessments, which is typical for evaluation of other RSET methods globally (Tran et al., 2023). Specifically for croplands, Melton et al. (2022) and Volk et al. (2024) conducted the most comprehensive accuracy assessments of OpenET via comparison with EC towers. Across 66 cropland sites (combined between the two studies), they reported a mean absolute error (MAE) in the ~15-20 mm/month range, which corresponds to ~16-17% of mean observed monthly ET at these sites, while growing season and water year totals of ensemble ET had MAE 11% to 13% of mean ET at the cropland sites. At the annual timescales, the mean bias error for ensemble ET in croplands was between -5.1% (calendar year) and -7.5%

(water year), indicating a slight underestimate by the OpenET ensemble relative to EC towers, with mean bias errors for all models ranging from -14.8% to 7.6% (Volk et al., 2024). OpenET performance was generally worse for non-cropland land covers such as forests, grasslands, and wetlands, with total growing season MAE of the ensemble ET ranging from ~51-135 mm in comparison to flux towers, which corresponds to ~22-37% of the observed mean for EC towers used (Volk et al., 2024). Across all land covers, developing performance-weighted ensembles, which give relatively greater importance to models that perform better in certain settings, have been shown to improve agreement with flux tower data across all land covers (Reitz et al., 2025).

These large-scale assessments of OpenET are broadly consistent with regional assessments. For example, Huntington et al. (2022) found that OpenET's estimates were within 15% of EC towers for the Upper Colorado River Basin, Purdy et al. (2024) found a monthly MAE that was 17% of the cropland mean in the Utah portion of the Colorado River Basin, and Knipper et al. (2024) found that annual ET was generally within 20% of the sum of irrigation and precipitation for almond orchards in California. In irrigated maize production systems in Texas, Stöckle et al. (2025) compared OpenET data to ET calculated from weighing lysimeters and reported an average error of 7.91% of lysimeter-estimated ET across fields and years, with all fields and years having errors below 15.15%, while noting that ET from OpenET was lower than ET from the lysimeters during the middle of the growing season.

Based on these different accuracy assessments, we summarize key findings and their implications for use of OpenET data in CWS activities. First, the calculated ET from the OpenET ensemble mean is well-correlated with EC data for croplands, with seasonal to annual mean absolute error of the ensemble within ~12% of observations, a bias within ~7.5%, and a slope of 0.91-0.93. Second, the OpenET ensemble mean generally outperforms individual models and is recommended for use unless a local accuracy assessment suggests otherwise. Third, agreement between OpenET-calculated ET and EC ET is better for agricultural lands than natural vegetation. Finally, agreement between OpenET and validation datasets generally improves when the data are averaged over longer time periods (i.e., monthly or total growing season agreement is better than daily agreement). Overall, RSET approaches generally have a suitable spatial resolution and coverage for integration with other datasets to carry out the hydrologic quantification necessary for some CWS activities. By providing application-ready data following open science principles, OpenET provides a straightforward entry point to the application of RSET data.

4. Opportunities and limitations for RSET within CWS lifecycle

This section brings together the CWS literature reviewed in Section 2 with the ET literature reviewed in Section 3 to critically assess the potential role for RSET data within the CWS lifecycle (Figure 1). We identify opportunities where RSET data can support CWS in agricultural landscapes at each phase of the CWS lifecycle (Section 4.1), assess the alignment of RSET data with principles for hydrologic quantification (Section 4.2), and discuss potential limitations and applications where caution is merited related to agricultural water management (Section 4.3).

4.1 Opportunities for RSET within CWS lifecycle

4.1.1 Understand risks and impacts

Water-related risks arise when a corporation has exposure to some sort of water-related hazard. For agricultural applications, CWS risks may include hazards related to insufficient water (e.g., groundwater or surface water depletion, droughts) or excessive water (e.g., flooding, waterlogging), while exposure may take the form of a corporation's activities (either their direct operations or supply chain) being in a region affected by these sorts of hazards. Water-related impacts in agricultural landscapes include changes in groundwater, streams, wetlands, and other ecosystems caused by agriculture-driven changes to the water cycle. These water cycle changes can be driven by direct water use for irrigation as well as changes to hydrologic fluxes such as runoff or groundwater recharge relative to non-agricultural land cover (Figure 3). Risks and impacts are often interlinked, since water impacts (e.g., water use) can contribute to increased hazards (e.g., by depleting groundwater or surface water resources).

Understanding risks and impacts typically requires quantifying the status of water resources and the dominant factors influencing water resources in an area of interest such as a supply region. While hydrologic variables such as precipitation and streamflow are generally well-monitored (though monitoring gaps remain, in particular for non-perennial rivers; Krabbenhoft et al., 2022), ET is challenging to measure at regional scales (Hatfield et al., 2016) and there is often little data on groundwater conditions or water use (Marston et al., 2022). By providing ET data, RSET can be integrated with other hydrological datasets such as precipitation and streamflow to develop a holistic quantification of the water balance for an area of interest such as a water management district, watershed, or aquifer, including management-relevant variables such as consumptive water use. This can then be used to assess impacts, such as groundwater or streamflow depletion, and risks, such as areas where water supply is insufficient to meet current or future demands.

For impact assessment, RSET data can provide direct estimates of consumptive use (Duan et al., 2026). RSET data from OpenET has accuracy of ~12% in agricultural land covers at the annual scale (Volk et al., 2024), which is the typical temporal resolution for CWS activities. However, RSET-based consumptive water use data should not be considered equivalent to total irrigation water withdrawals or applications, as discussed in Section 3. Estimating irrigation water applications or withdrawals requires additional modeling, in which RSET can be a valuable input dataset (Brookfield et al., 2024; Filippelli et al., 2022; Foster et al., 2020; Ji et al., 2025; Laluet et al., 2026; Ott et al., 2024; Zipper et al., 2024b). Nevertheless, estimates of either consumptive use (directly from RSET data) or irrigation water applications/withdrawals (through RSET-supported modeling efforts) can provide information for corporations to understand risks to and impacts of their activities and supply chains.

4.1.2 Develop framework

Framework development requires a corporation determining how they would like to prioritize their CWS activities based on their risks and impacts. As a result, this step in the process likely would not directly involve RSET data, but it would rely on the findings from Step 1, which may include RSET data. For example, an assessment of impacts may determine that a corporation's supply chain has an outsized footprint in a sourcing area where consumptive use exceeds water available, which could guide CWS frameworks to prioritize reducing impacts in these high-risk areas.

4.1.3 Set corporate commitments

RSET data can support corporations in determining and committing to specific and quantifiable water-related stewardship goals through multiple mechanisms. First, through the assessment of the regional water balance (see Section 4.1.1), commitments to corporate water stewardship can be set that reduce or eliminate undesirable imbalances in the water budget. For example, if there has been a concerning decrease in streamflow over time, RSET data can assess if and whether that has been associated with an increase in consumptive water use. If evidence suggests a strong interconnection between streamflow and consumptive water use, a corporation could make a commitment to reduce supply chain consumptive water use or enhance available water supplies (sometimes termed 'hydrological offsets' or 'replenishment', e.g., through enhanced groundwater recharge) of a magnitude that would alleviate the streamflow deficit. Second, in irrigated settings, consumptive water use is an indicator for the minimal water needed to support the current land use at its current levels of productivity. Therefore, regional consumptive use estimates can, after accounting for precipitation variability, be used to identify feasible levels of irrigation that can support current cropping systems. These levels can be adopted as part of a more comprehensive corporate stewardship goal on consumptive water use for agricultural production which could then be used to target reductions in system losses (leaky irrigation systems, overirrigation leading to deep percolation or runoff, etc.). Third, at the field-scale, RSET data can be used to calculate baseline consumptive use for a location. These baselines can provide a reference point that can then be used to reduce consumptive water use by a certain percentage.

However, an important caveat is that matching irrigation applications to total consumptive water use merely means that a field or region is using water efficiently, which does not necessarily equate to a sustainable or desirable level of water use. Even efficient water use can have impacts on water resources, for example via streamflow or groundwater depletion (Butler et al., 2018; Lapides et al., 2022; Zipper et al., 2022). While some regions have found that irrigation efficiency improvements can lead to meaningful reductions in agricultural water use (Berbel et al., 2015; Cameron-Harp and Hendricks, 2025; Deines et al., 2021, 2019; Orduña Alegría et al., 2024), elsewhere efficiency improvements have led to a 'rebound effect' where water savings are reallocated elsewhere and overall water use does not decrease or even increases through expansion of the total irrigated area (Freire-González, 2019; Ghoreishi et al., 2021; Junquera et al., 2025; Paul et al., 2019; Pfeiffer & Lin, 2014), potentially exacerbating water supply risk.

Additionally, water efficiency improvements can reduce groundwater recharge from water that percolates below the bottom of the root zone, which is often referred to as irrigation return flows or irrigation-enhanced recharge (Glose et al., 2022; Kendy and Bredehoeft, 2006; Walker et al., 2020). Large water withdrawal reductions have been observed from shifts from flood to more efficient center-pivot irrigation systems (Cameron-Harp and Hendricks, 2025), suggesting that efficiency-driven gains are often associated with reduced irrigation return flows. If recharge is reduced due to a shift to higher-efficiency practices, it can lead to water shortages for other users or surrounding groundwater-dependent ecosystems that may have relied on recharge from irrigation (Kendy and Bredehoeft, 2006). Therefore, commitments should extend beyond maximizing efficiency to develop a holistic understanding of ways to reduce pressure on water resources.

4.1.4 Design programs

Program design involves identifying actions that can achieve the commitments set in step 3, and therefore requires developing relationships between management actions and hydrological outcomes. RSET data could help identify pathways to meet commitments through comparison of the impacts of different land use, cover, or management practices (alterations to irrigation practices, shifting to less water-intensive crops, implementing soil health or regenerative agricultural practices, etc.) on consumptive water use. For example, Asarian et al. (2025) used RSET data to compare consumptive use changes during irrigation curtailment. Comparing consumptive use across land uses or management practices can provide a simple approach for determining what types of actions can achieve a corporation's commitments.

For more complex analyses, hydrological models capable of simulating the response of processes such as streamflow and groundwater dynamics to different climate or management scenarios are a critical tool to design appropriate programs that can achieve commitments. Historically, hydrological models have been calculated by matching simulation output to observed streamflow or groundwater levels, with ET estimated as either a direct model input or as part of the process of estimating groundwater recharge (Foster et al., 2021; Hoekema et al., 2025; Kniffin et al., 2020). RSET data can enhance hydrological modeling through two approaches. In models where ET is an input, RSET can provide improved spatial and temporal resolution and coverage of model input data. In models where ET is an output, RSET data can be used as an additional calibration variable, which is valuable since calibration to multiple hydrologic variables generally improves model performance (Stisen et al., 2018). ET can be uniquely valuable because it provides a representation of a land surface process that typical model calibration targets like streamflow and groundwater levels do not directly measure (Enemark et al., 2019), and therefore helps to constrain aspects of model behavior related to water partitioning at the land surface (Beven, 2006). For both input data and calibration purposes, the uncertainty of RSET data can be incorporated into the simulation output to provide estimates of overall model uncertainty for variables of interest.

4.1.5 Implement programs

Once programs are designed, RSET tools can assist in implementation by supporting effective water management practices. For example, if the corporation makes commitments to either reduce supply chain consumptive water use or replenish water resources (e.g., through enhanced groundwater recharge) by a certain amount, then RSET data can support these programs through multiple pathways. To reduce consumptive use, RSET data can help support crop selection via quantification of consumptive use among different crop types (discussed in Section 4.1.4), or support more efficient irrigation management through the integration with other datasets to provide irrigation scheduling support. For replenishing water resources, RSET data can help quantify basin-scale water budgets (discussed in Section 4.1.1) to determine meaningful volumes of water for replenishment to achieve goals.

4.1.6 Monitor outcomes

RSET data is useful for outcome monitoring in many of the same ways it can be used for understanding risks and impacts (Section 4.1.1). For example, RSET data can be an input to regional water balance assessments or field-scale quantification of impacts from CWS activities. To extend beyond water balance accounting, RSET data can be used to calculate the water productivity of consumptive use, which is a measure of how much crop yield benefit is obtained per unit of water evapotranspired (e.g., kcal per mm of water, bushels per acre-inch, etc.). Where data on crop productivity are available, water productivity of consumptive use can be calculated as an indicator of the beneficial agricultural water use and help prioritize which practices may be generating the most crop production per unit of water (Wong et al., 2026).

Where commitments relate to land use or land cover, RSET data can provide a particularly effective approach for detecting the extent and timing of irrigation by identifying where ET exceeds the supply of water from precipitation. Since irrigated extent is one of the primary determinants of overall regional irrigation water use (Wei et al., 2022), developing refined maps of irrigated extent can be a valuable tool to improve estimates of total irrigation water use and how it changes in response to CWS activities at a scale such as a watershed, aquifer, or management district. This is likely most feasible in semi-arid to arid climates where irrigated lands are more evidently different than rainfed fields in satellite imagery (Xu et al., 2019). Since land stewardship can often require calculating agricultural footprints, using RSET data to help improve monitoring of irrigated acreage for supporting corporate land and water stewardship goals.

4.1.7 Reporting and disclosure

When combined with open science principles and open data policies, RSET data can support reporting and disclosure through the reproducible and verifiable development of automated and well-documented workflows for the outcome monitoring steps described above. For example, water consumption and water resource availability are common variables that need to be reported on for the water stewardship efforts described in Section 2.1. This is often challenging in agricultural landscapes since water use is rarely measured and reported in a standardized way, as discussed in Section 3.2. Since many RSET products are available with field-scale spatial resolution and regional coverage, they can be incorporated into these reporting efforts by providing estimates of consumptive water use and assessing the regional-scale water balance, as described in Section 4.1.1, which can then be aggregated within a company's supply chain to quantify the total consumptive water use of their agricultural footprint. Since many RSET products, such as OpenET, follow open science principles, they can be used to track these variables in a reproducible way across a corporation's supply chain as needed. Ultimately, this can provide a basis for credible and region-specific estimates of consumptive water use for products across a corporation's distributed agricultural supply chain, facilitating transparent CWS, ESG, and sustainability reporting.

4.1.8 Iterative refinement

Iterative refinement encompasses the re-evaluation and modification of the other seven steps, and therefore the opportunities discussed above apply to this step. Since the necessary satellite and meteorological input datasets for RSET data are being continuously collected, datasets such as OpenET are continuously updating their products, and new RSET algorithms and modeling approaches are being developed, RSET is well-suited for continuous refinement of CWS plans.

4.2 Alignment with quantification principles and use-specific accuracy assessment

Overall, integration of RSET into CWS programs is well-aligned with the key principles for hydrologic quantification (Figure 2). Generally, RSET data is scientifically appropriate for applications related to quantifying the terrestrial water cycle, and therefore closely linked to CWS activities that affect land use, cover, and agricultural water management (Figure 3). As noted above, use-specific accuracy and uncertainty assessments should be integrated into these efforts. RSET data are also actionable because ET can be influenced by management activities such as changes in irrigation water use, land management, crop type, or efficiency gains, and therefore corporations can incentivize actions that alter ET in agricultural landscapes. These tools are impact-focused, since changes in ET quantify an impact of human alterations to the water cycle in response to a practice, rather than just documenting the practice itself without quantification of impacts. Furthermore, RSET data can be generated at an operational spatial scale since many RSET products, such as OpenET, can be calculated at the resolution of individual management zones within fields exceeding a few hectares to support monitoring where practices are implemented and tracking impacts across the supply chain. This minimum size is necessary to avoid edge effects/mixed pixels and exceed the native resolution of Landsat thermal imagery, which ranges from 60 to 120 m depending on the Landsat mission (Crawford et al., 2023), and is an input to many RSET algorithms. RSET data are spatially consistent but locally tailored, as they typically use a consistent calculation approach across space and time, and approaches can be modified or calibrated when sufficient local data are available to improve accuracy (Reitz et al., 2025). Finally, RSET data can be reproducible and verifiable where open-science workflows are used, and many RSET products, such as OpenET, have publicly available outputs and algorithms.

In addition to alignment with the key principles, the utility of RSET in any particular CWS program is likely to depend on the accuracy of the data relative to program needs and whether or not alternative options are available and appropriate. For instance, well flowmeters can be quite accurate for measuring groundwater withdrawals, but may not be available in many circumstances (Foster et al., 2020; Marston et al., 2022) or adequate for estimating consumptive use due to uncertainty regarding return flows (Deines et al., 2021; Glose et al., 2022; Walker et al., 2020). Other data sources may exhibit low relative errors, such as streamflow or groundwater levels, but may not be appropriate CWS evaluation tools when the effects of CWS activities are small relative to other processes or drivers of change.

Because RSET accuracy varies by region and land use, local evaluation of RSET is recommended to ensure that the data are sufficiently reliable for CWS goals and acceptable to key stakeholders. This could be done, for example, by comparing RSET-based hydrological variables (such as estimated irrigation applications) to observational data to quantify the program-specific accuracy and uncertainty for the specific variables and workflows used for CWS efforts, though reliable *in situ* data are often not collected or unavailable (Bouchat et al., 2026). Such tests can also provide an opportunity for corporate engagement with knowledgeable stakeholders such as management districts, researchers, and consultants working locally. Where a holistic accuracy assessment is infeasible, other types of local checks could involve comparing RSET rates among land covers and to typical water use practices in the region, evaluating simple water balance metrics such as the ratio of ET to precipitation, and getting feedback from stakeholders that calculated values are reasonable. In these cases, since program-specific uncertainty estimates would not be available, a presumptive uncertainty could be adopted from published accuracy assessments. For example, OpenET's published accuracy assessments report that total growing season or annual ET can be considered accurate within ~12% for croplands (Volk et al., 2024) and less accurate for non-agricultural land covers, while other studies have reported accuracy of OpenET and other RSET algorithms for specific regions or crop types. Once accuracy assessment is complete, uncertainty can then be propagated through whatever calculations are done to report CWS findings in terms of estimates and their confidence intervals.

4.3 Applications of RSET where caution is merited

There are certain types of analyses that may be useful for CWS efforts, but for which RSET data on their own are not well-suited and alternate approaches would be recommended.

4.3.1 Monitoring changes in irrigation efficiency and calculating water productivity of applied water

One practice with widespread investment is irrigation efficiency improvements, typically with the goal of reducing the total volume of water that is used for irrigation. RSET can be useful for calculating consumptive water use and estimating total irrigation water applications or use. However, changes in the volume of applied water resulting from efficiency gains are challenging to monitor with RSET. Generally, more efficient irrigation leads to a decrease in water applications while maintaining a consistent level of ET and associated consumptive use by minimizing water lost to deep percolation and runoff. While shifts to more efficient irrigation systems may reduce overall ET by reducing soil or wind-drift evaporation losses, generally the primary hydrologic changes resulting from efficiency improvements (reduced deep percolation and runoff) are not directly measured by RSET data. For settings where irrigation applications or irrigation withdrawals (see Figure 3, Section 3.2) are the primary hydrologic variable that needs to be quantified, RSET may fail to characterize their response to irrigation efficiency practices since these primarily impact non-ET components of the water balance (i.e., non-consumptive use). Similarly, it is impractical to calculate changes in water productivity of applied water (calculated as yield divided by irrigation applications) due to challenges in estimating irrigation water use.

For quantifying irrigation applications, the best possible data would be reported data from calibrated totalizing flowmeters at the place of use, but these types of data are rare and challenging to scale as discussed above (Foster et al., 2020). In this case, a recommended approach to develop regional-scale irrigation efficiency or water productivity estimates may be to integrate RSET into a locally-calibrated crop modeling framework that can simulate other aspects of the water balance (Deines et al., 2021). Alternatively, CWS efforts could support site-specific monitoring to develop locally-relevant water use datasets. This could include support for on-field monitoring equipment, such as flowmeters, EC towers, or alternative ET sensors, depending on whether irrigation withdrawals, applications, or consumptive water use are most relevant to their CWS efforts.

4.3.2 Applications in places/times with few cloud-free images

Satellite image frequency and quality should be carefully considered before application. The current workhorse data behind many field-scale RSET products is Landsat, which is a series of satellites launched beginning in 1972 (currently, both Landsat 8 and Landsat 9 are orbiting). Each Landsat satellite covers the globe every 16 days, so when two satellites are orbiting simultaneously, data can be obtained every 8 days at best. However, no useful Landsat data can be obtained when there is cloud cover over a location, and there are historical periods where only a single satellite was orbiting (prior to 1999 and in 2012), and therefore during these years there are less frequent satellite data available and even a single cloud-covered image would lead to a 32 day period between satellite images. Since seasonal to annual totals of RSET require interpolation or estimation between image collection dates, caution should be taken when cloud-free Landsat overpasses are less frequent, which may include certain years (prior to 1999 or during 2012) and in cloudy locations. RSET datasets that fuse data from multiple satellites, for example MODIS or Sentinel-2, that have different overpass timing and frequency may be better-suited for avoiding these issues. Regardless of data source, an assessment of the underlying image availability and reliability is critical. Purdy et al. (2024) recommend that consumptive use estimates from months with < 1 clear-sky image should not be used.

4.3.3 Places and times where RSET data are unavailable

RSET data are not evenly distributed in space and time. For example, OpenET is currently available for the contiguous U.S. starting in October 1999. Therefore, at present OpenET is not usable for CWS activities that occur in the distant past or in locations outside the U.S., though efforts are underway to expand coverage to other countries and further back in time. In contrast, MODIS ET data are available globally at a spatial scale of 1 km, but are also unavailable prior to 2000. Attempting to extrapolate information derived from RSET (for example, differences in consumptive water use among practices) outside the space or time domain being measured should be avoided. Future RSET developments are likely to increase the spatial and temporal coverage of available products, though there is a fundamental limitation to how far back in time RSET data can extend due to the timing of historic satellite data acquisition.

5. Example application to a corporate supply chain in a heavily-stressed aquifer

Since CWS frameworks are wide-ranging, there are numerous ways that RSET data can situate effectively within CWS programs. Here, we describe a hypothetical illustrative example of a corporation that relies on crops produced in a heavily-stressed aquifer as a major component of their supply chain and worries that water supply risks in the production area may translate to supply chain risks for its business operations. We identify where RSET data, in combination with other datasets, can be integrated into the CWS lifecycle to improve agricultural water management (Figure 4).

Understanding risks and impacts: The corporation can use datasets such as precipitation, groundwater levels, streamflow, and RSET to estimate the current status of water resources in its agricultural supply chain region and the relative importance of agricultural water use to any water budget imbalances that may lead to groundwater depletion (Martin et al., 2023; Butler et al., 2023). RSET data can then be used to map the agricultural footprint and consumptive water use at field-resolution (Martin et al., 2025; Duan et al., 2026), which could be aggregated to the corporation’s supply chain to assess their hydrological impacts. In settings where the relationship between water use and groundwater decline rates is well-known from observational data (e.g., western Kansas; Butler et al., 2023), this can directly link corporate impacts to groundwater depletion. These analyses will quantify the corporation's current risk exposure, the consumptive use of their supply chain, and how their agricultural supply chain is impacting groundwater levels.

Setting corporate commitments: Based on the consumptive water use estimates, the corporation can make commitments for reducing supply chain consumptive water use, irrigation applications, and/or irrigation withdrawals to bring the local water budget into balance. If the goal is to halt groundwater decline, commitments may be set to bring water use into balance with other inflows to and outflows from the aquifer (Butler et al., 2020). As discussed in Section 3.2, the specific water use variable of interest (consumptive water use, irrigation applications, or irrigation withdrawals) will vary based on local hydrogeological conditions. However, each of these variables can be approximated using RSET-based approaches, whether directly in the case of consumptive water use (Doherty et al., 2026; Duan et al., 2026; Martin et al., 2025) or through integration with other models where irrigation applications or withdrawals are of interest (Zipper et al., 2024; Ott et al., 2024). Since many corporations have overlapping supply chains, targets underpinned by FAIR data may facilitate collaboration among corporations sourcing from the same agricultural region (de Souza et al., 2020; Rozza et al., 2013; Yamada, 2017).

Design and implement programs: The corporation can work with implementing partners and producers on local program design, which can take many forms. One opportunity is to use relationships between reported irrigation and RSET-estimated consumptive use to investigate irrigation efficiency (e.g., Ott et al., 2024; Ji et al., 2025) or quantify within-field uniformity (e.g., Boninsenha et al., 2024) and target areas for investment in irrigation system upgrades. Alternatively, RSET approaches to estimate differences in consumptive use of different types of irrigated crops (e.g., Duan et al., 2026) to identify and incentivize lower water use crops that are compatible with their supply chain needs. Once programs are designed, RSET data can also be integrated into tools that can help make or manage these programs, such as improved tools to monitor root zone soil water depletion to facilitate irrigation scheduling (Attalah et al., 2025; Katimbo et al., 2022; Stöckle et al., 2025).

Monitoring, reporting, and disclosure: RSET-based data, in conjunction with other data and/or models, can then be used to monitor the impacts of these programs and create verifiable reports on the status of water resources and impacts of CWS. Monitored and reported outcomes can include variables such as consumptive use, which can be directly quantified at field to regional scales using RSET (Haynes et al., 2023; Martin et al., 2025). Since many CWS frameworks require evaluating change relative to a baseline (sometimes an area without the CWS intervention, but more commonly conditions before the CWS intervention), these data can be integrated with models that account for climate variability to assess whether interventions have affected water use (Asarian et al., 2025; Deines et al., 2021). While many programs target irrigation efficiency improvements, as discussed in Section 4.3.1, RSET data on its own cannot quantify improvements in efficiency. However, where consumptive use data from RSET can be paired with a reliable alternative water use dataset (like measured water use from flowmeters), can be used to assess irrigation efficiency (Ott et al., 2024; Zipper et al., 2024). Since corporate stewardship goals often extend beyond water, RSET methods can also support the investigation of trade-offs among different desired outcomes, such as when water use reductions lead to reduced crop productivity (Wong et al., 2026). However, it is important that uncertainty of RSET data (and other datasets) is quantified in monitoring and reporting, as either over- or under-estimates of water use have implications for program assessment (Foster et al., 2020).

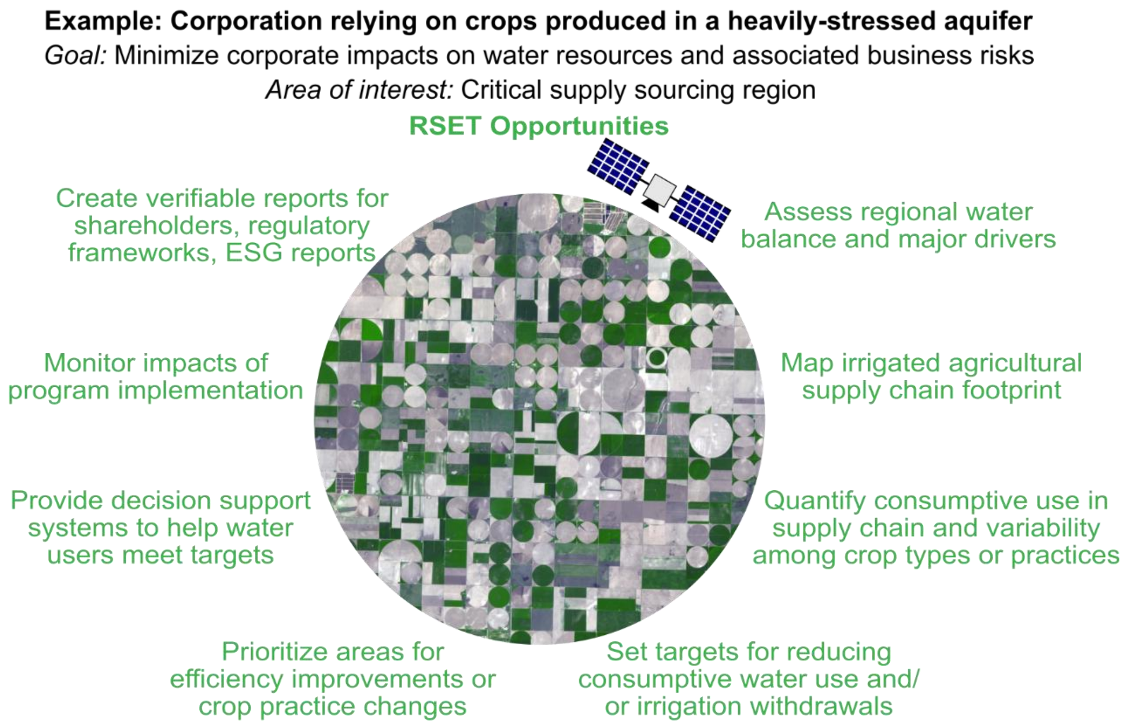


Figure 4. Opportunities for integrating RSET data into CWS activities for a corporation relying on crops produced in a heavily-stressed aquifer. Each of these opportunities would typically require integration of additional data beyond RSET. Image credit: NASA Earth Observatory (2006).

6. Conclusions

Corporate water stewardship (CWS), in which companies engage in or incentivize actions to advance sustainable water resource management, provides a mechanism by which corporations can support local water resource management and sustainability. We review and integrate literature related to CWS approaches and RSET methods in agricultural landscapes to critically assesses the potential role for RSET data within the CWS lifecycle. Our review reveals that RSET can enhance CWS activities related to agricultural water management thanks to its spatiotemporal consistency, which makes it well-suited for CWS activities such as local to regional assessment of the current status of water resources and corporate impacts when integrated with other datasets. The value of RSET data is particularly high in regions where hydrological monitoring infrastructure is limited. Since corporations often have agricultural supply chains distributed across multiple regions, this spatial and temporal consistency is uniquely valuable for developing estimates of consumptive water use, enhancing hydrological modeling efforts, and underpinning reproducible and verifiable outcome monitoring and reporting tools. However, RSET data are most directly related to consumptive water use, and as a result some agricultural water management activities such as improving irrigation efficiency cannot be directly measured with RSET and require additional modeling and data integration efforts. Ultimately, there are many opportunities for remotely sensed ET to be useful within CWS frameworks, as long as care is taken to focus on suitable applications and communicate uncertainty.

Realizing the potential for RSET to benefit CWS activities requires a closer integration of technical decision-support science and corporate quantification. On the technical side, continued work to develop local evaluations of RSET data can help ensure that uncertainties and biases are well-characterized and can be integrated into CWS quantification. This would be further supported by efforts to improve the spatial and temporal resolution of satellite products and improving the availability of high-resolution RSET products worldwide, both of which were identified as priorities by the National Aeronautics and Space Agency (NASA) Satellite Needs Working Group (Adams, 2026), as well as increased integration with *in situ* observational data (Bouchat et al., 2026). Beyond technical advances, however, continued effort to develop decision-relevant derived variables from RSET data products that are scientifically-appropriate, actionable, spatially consistent but locally tailored, impact-focused at a relevant operational scale, and reproducible will help facilitate the integrate of RSET data into CWS activities in agricultural landscapes.

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Data availability statement

This manuscript does not use any data.

Author contributions

Zipper: Conceptualization, Methodology, Investigation, Writing - Original Draft, Writing - Review & Editing, Visualization, Project administration, Funding acquisition; **O'Connor:** Conceptualization, Methodology, Investigation, Writing - Review & Editing, Visualization, Project administration, Funding acquisition; **Penny, Schlea, Amidi-Abraham, Schenkel, Hall:** Methodology, Investigation, Writing - Review & Editing.

Declaration of competing interests

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