A roadmap toward scalably quantifying field-level agricultural carbon outcome

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1. Introduction

Agriculture contributes about a quarter of global greenhouse gas (GHG) emissions, with approximately 14% directly from agricultural activities and 10% through clearing land to create new croplands and pastures [1]. In many countries with intensified crop production, such as the U.S., GHG emissions associated with soil and fertilizer management contribute to more than half of the total agricultural emissions [2]. Reducing these emissions is critical for limiting global warming to the Paris

Agreement of 1.5 ℃ or 2.0 ℃, but requires rapid adoption of multiple and coordinated solutions [3–6] . On the other hand, certain farming practices have the potential to reduce GHG emissions and/or sequester carbon. These carbon-outcome-related practices, which strongly overlap with "conservation practices" and have recently been re-formulated as "regenerative agricultural practices" or "carbon farming practices", include but are not limited to no-till, cover cropping, precision nitrogen (N) fertilizer management, biochar application, intercropping, etc [5,7]. The surge of the public's perceived urgency in combating climate change and achieving sustainable development has spurred climate-pledges by individual companies to cut their carbon footprints and stimulate the growth of agricultural carbon markets to incentivize farmers to adopt these carbon-outcome-related practices. For either individual companies' carbon emission reduction or carbon markets in the context of agriculture, the foundation is built upon accurate quantification of carbon emission and carbon sequestration based on adopting various practices. However, existing scientific literature is not yet conclusive as to where, when, if and by how much these carbon-outcome-related practices might lead to genuine GHG reduction or carbon removal [8–10].

Regardless of the debates on the exact effectiveness in carbon-outcome-related practices for GHG reduction and carbon removal, agricultural carbon markets are around the corner given the strong political pushes in the European Union, the U.S., China, and other nations, as well as their real co-benefits for soil health, water quality and air quality [8]. It is thus more urgent than ever that the scientific community should develop a credible way to quantify the amount of carbon that is removed or avoided, because these estimates will be the basis for rigorously assessing the climate mitigation potential of carbon-outcome-related practices, and perhaps more importantly, to ensure the market rewards mitigation actions fairly and accurately. In this perspective, we argue that field-level quantification of carbon outcomes is not only fundamental to a trustworthy, transparent, and cost-effective agricultural carbon market, but also critical to any other sustainability-oriented program for ecosystem services. Existing literature started the discussion [9,11] but has not charted actionable roadmaps and pathways to quantify field-level carbon outcome, and we believe that it is dangerous for the public to believe this problem has been solved and could move forward with large-scale government and/or private investment. To close the loop, we discuss a foundational framework to quantify field-level carbon-related outcome, and propose an R&D agenda that can substantiate not only agricultural carbon markets but also sustainable indicators for agroecosystem management.

2. Foundational framework to scalably quantify field-level carbon-related outcome for agroecosystems

2.1 Criteria for a successful quantification technology for field-level carbon outcome

Effective quantification technology of carbon outcome should be at the field level, accurate, scalable, and cost-effective. "Field-level accuracy" is needed if carbon outcome is associated with rewarding individual farmers' practice; it is also required for traceability of any aggregated carbon outcome in carbon footprint quantification. "Scalable" here means that the quantification solution must have an independently verified accuracy across all possible fields; in other words, showing that a solution works well at a few demonstration sites, as many existing measurement, reporting and verification (MRV) efforts do, is not enough. Instead, true "scalability" means one method must demonstrate an acceptable accuracy of the solution at randomly selected 'real-world' validation sites. Due to the challenges of achieving scalability at the individual field scale, some practitioners argue that aggregated-level accuracy is sufficient because carbon markets have buyers mostly purchase carbon credits in bulk. We argue that aggregated-level and field-level accuracy are complementary and both important to achieve. Aggregated-level accuracy, which is almost impossible to validate, must come from field-level accuracy. Finally, for any technology, there is a tradeoff between cost and accuracy, and the desired solution should be sufficiently cost-effective to achieve the needed accuracy [12].

2.2 Our framework of field-level carbon outcome quantification

Here we propose a foundational framework of how to quantify field-level carbon-related outcomes for farmland, and identify the scientific challenges in existing solutions and discuss how we can overcome them to achieve scalable deployment. The foundational framework is proposed as below (Figure 1):

Agroecosystem Outcome = Crops (*C*) × Management (*M*) × Environment (*E*).

Here, agroecosystem outcome includes crop productivity and various sustainability-related metrics (e.g. GHG emission, soil carbon sequestration, nutrient leaching etc). To calculate field-specific outcome, three dimensions of information (C, M, E) as well as their interactions (i.e. two "×" in the equation) must be well represented at the field level. Specifically, ***E*** primarily refers to weather and soil information, which is often available as public, gridded products. However, these datasets may contain significant uncertainty at the field level, and strategic soil sampling and local sensing may be needed to improve their accuracy. ***M*** primarily refers to farmers' management practices. Since certain "actions" determine the carbon-related outcomes, both monitoring and auditing for M are needed. The default method to collect M information through farmer reporting is inefficient, error-prone, and leads to privacy concerns. Recent advancements in remote sensing and geospatial intelligence have unlocked an opportunity to generate accurate, unbiased and verifiable estimates for M. ***C*** refers to location-specific crop information such as crop variety and their interactions with M and E, which is manifested in pheno-stages, maturity group, photosynthetic capacity, crop water use strategy, crop responses to stresses, etc. Obtaining ***C*** information at the field-level is extremely challenging, but missing this information and especially how ***C*** interacts with ***E*** and ***M***, can lead to the biggest uncertainties in quantifying agroecosystem carbon credits (Figure 1b). Without using ***C*** information in quantifying carbon outcome is a fundamental gap in the current modeling-based solutions. Finally, even when we have all the three types of information, the two "×" indicate the outcome quantification requires us to quantify the interactions among C, E, and M; and rich literature and long history are behind this, lumped as “crop models”, “ecosystem models”, or “soil biogeochemistry models”, and later under the “modeling” section we will discuss this in particular.

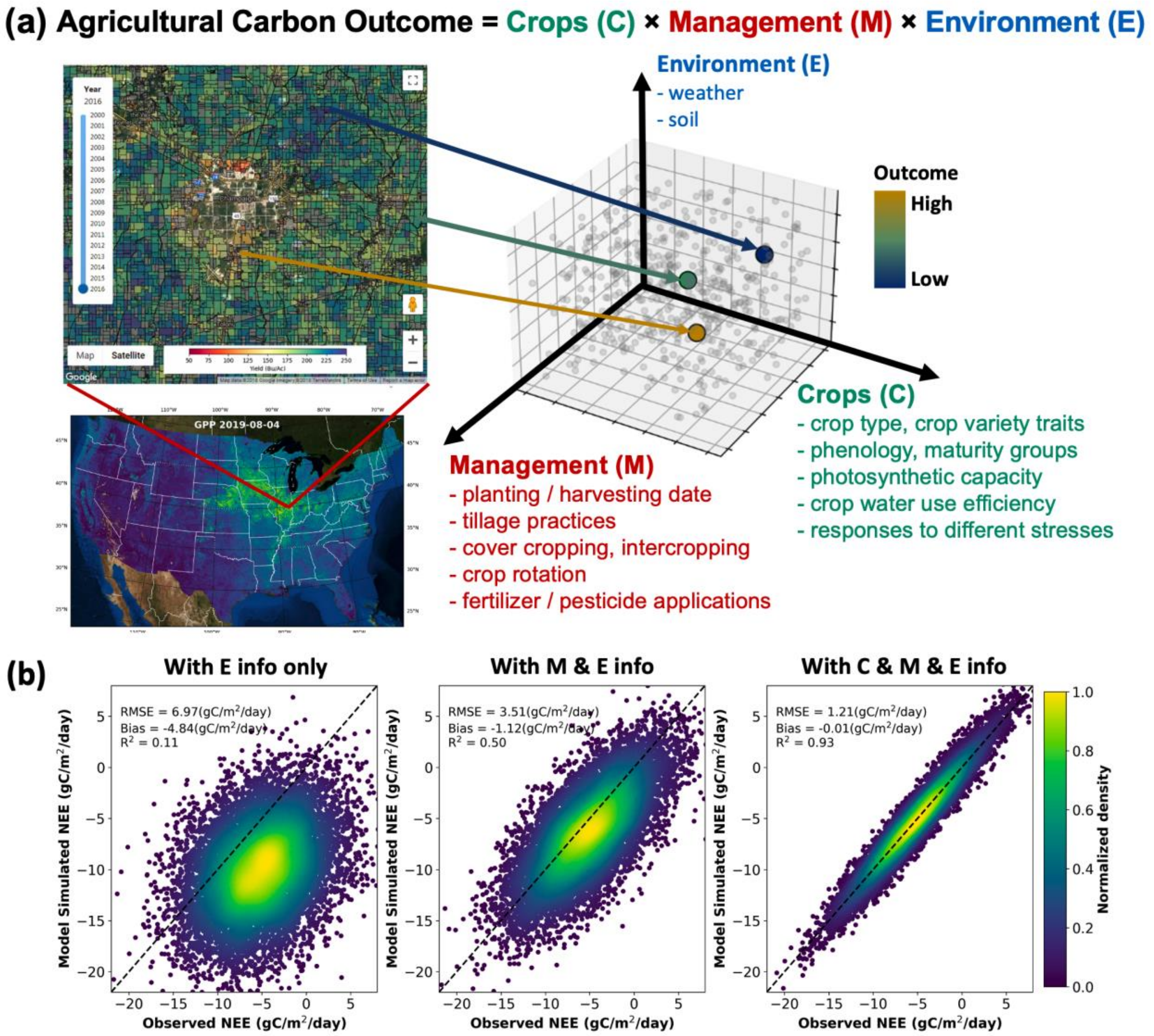

Figure 1. Conceptual diagram of quantifying agroecosystem carbon outcomes at the field level for agroecosystems. (a) Carbon credit outcome is determined by three factors as well as their interactions. (b) Accuracy of the quantification methods improves significantly as more information is constrained at the field level; the given example is to quantify net ecosystem exchange (NEE), which is the net CO_2 exchange between land and atmosphere, and the direct measurements are usually based on eddy-covariance flux tower sites in the U.S. Midwest [13].

2.3 Issues in the existing quantification methods

Based on the above framework, we can identify shortcomings of existing methods for carbon outcome quantification, including: (1) direct field measurements (such as soil sampling for SOC change [14–16], and eddy-covariance sensors to measure GHG emissions [17,18]); (2) emission factor estimation, in which a fixed linear factor is used to approximate the “outcome” based on different management practices [19]; and (3) process-based modeling [17,18,20,21].

Direct field measurements have been widely viewed as the gold-standard solution for quantifying carbon outcomes, although they are in general cost prohibitive and thus not scalable. However, direct measurements alone may not necessarily quantify the real climate benefits or genuine “carbon credit”, a fact that has not been treated with caution among practitioners and even scientists. As one example, we use a hypothetical corn-soybean rotation field in the U.S. Midwest to illustrate that soil sampling alone cannot measure the real carbon outcome of adopting cover crops with a ten-year commitment (Figure 2). In the “business-as- usual” scenario, this field is losing SOC over time as many other fields in the U.S. Midwest [22]. Adding cover cropping may not reverse the overall declining trend of SOC in most cases, but can slow down the declining rate [23]. The cumulative difference of the ΔSOC between the two scenarios is the real carbon benefit that the system generates in a period. Two important implications must be noted in this case. First, “additionality” requires us to know the SOC stock in the two scenarios, one with newly adopted cover cropping in which SOC stock can be directly measured, and another counterfactual scenario for “business-as-usual” in which SOC stock can no longer be measured but must be estimated through modeling. Second, because soil sampling cannot measure ΔSOC that involves a hypothetical “business-as-usual” scenario, this “gold standard” method actually is not able to quantify the exact carbon benefits (e.g. carbon credit). Furthermore, soil sampling has its own inherent measurement uncertainties, which are found to be much larger than the detectable year-to-year changes in SOC stock [24] (Figure 2d), making soil sampling unfeasible as a short-term (i.e. annual) quantification tool but rather a tool to set the baseline (i.e. measure initial SOC stock) or periodic verification after 5+ years of practice changes.

Emission factor methods, as the most widely used approaches in past IPCC reports[19] and also the easiest method to use, suffer from their weakness in capturing spatial and temporal heterogeneity of ***E*** and ***C*** and cannot comprehensively track the dynamics embedded in the interactions between E, C and M. Assuming the same (or a linear scaling of) emission or sequestration outcome based on a particular “action” (***M***) across different fields is not only inaccurate, but also unfair for individual farmers in a carbon market.

Process-based modeling has been regarded as the most mechanistic method to quantify carbon outcome. Process-based models can simulate “business-as-usual” scenarios and other counterfactual scenarios, and thus are able to overcome soil sampling issues laid out before (Figure 2) and can calculate the actual carbon benefit. However, the use of process-based modeling often suffers from “misconceptions” held by stakeholders. **First, “model denial”** stems from modeling uncertainty leading some to not believe any quantification through modeling-based approaches. We argue that models can be useful even with uncertainty, as long as they pass rigorous evaluation in a well-designed validation process (see more discussion in Section 4). **Second, “model overconfidence”** exists among a large number of practitioners who use models as black boxes without calibration or validation. Some recent estimates for carbon sequestration using models without rigorous validation or any constraints on model parameters should be discouraged [25]. This misuse of models could confuse the public, who in general cannot perceive modeling complexity and rely on practitioners to interpret the model output; if the stakeholders realize the modeling results were not trustworthy, their confidence in this approach could erode and lead to "model denial" perceptions. **Third, "infinite model improvement"** is common among academicians. We agree that theoretical advances in science should be ultimately incorporated into existing models to improve simulation of relevant processes, but models with more detailed mechanistic representations are not necessarily better than simpler models in practice. Therefore, instead of debating of "good" vs. "bad" models, we should focus on two fundamental questions: (1) Is a specific process indispensable for simulating the specific outcome and also achieving the desired accuracy? (2) Are there sufficient data to parameterize that specific process at both field and regional scales? If the answer to either question is no, then including the new process may not necessarily benefit the quantification of carbon outcome. Bringing this discussion back to our framework, the biggest challenges we see in the existing **process-based models** for carbon outcome quantification is the lack of spatially resolved information about C, M, and E that should be used to input and constrain model quantification, which leads to large uncertainty in the carbon outcome quantification (Figure 1b).

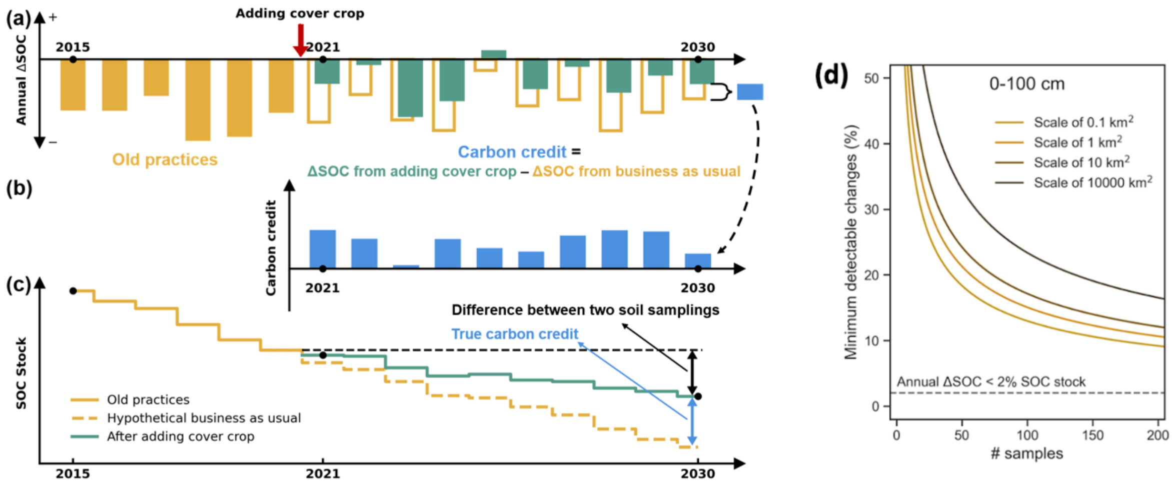

Figure 2. Illustration of the "additionality" concept for agricultural carbon credit, using a hypothetical corn-soybean rotation field in the U.S. Midwest as an example, assuming cover cropping is newly adopted in 2021 with a ten-year commitment. (a) Annual change in the SOC stock (i.e. ΔSOC) since 2015, with hypothetical scenarios from 2021 to 2030. (b) Generated annual carbon credit from 2021 to 2030. (c) Change in SOC stock over time. (d) Soil sampling accuracy (i.e. minimum detectable change, in terms of relative change in the SOC stock) as a function of the number of soil samples and field sizes, which is much larger than the annual change of SOC stock in reality [24].

3. "System-of-Systems" Solutions represent the most viable pathway

For any technology of carbon quantification, there is a tradeoff between cost and accuracy (Figure 3). Although no clear criterion has been established so far to accept or reject a technology, we argue that for any quantification technology to be scalable, its per-acre operational cost must be meaningfully lower than expected monetized carbon values from adopting regenerative practices. In the U.S. agriculture carbon market, for example, this criterion roughly means costs should be significantly lower than <\$10/acre/year for soil carbon and <\$50/acre/year for N_2O quantification for large-scale deployment, including installation, calibration, operation, and hardware lifetime. At the same time, the technology should be able to achieve less than 20% error at the field level [12]. No single existing technology can meet both of these expectations. Instead, we argue the most viable path for quantification is through an integration of sampling, sensing, and modeling - here defined as the "**system-of-systems" solution**.

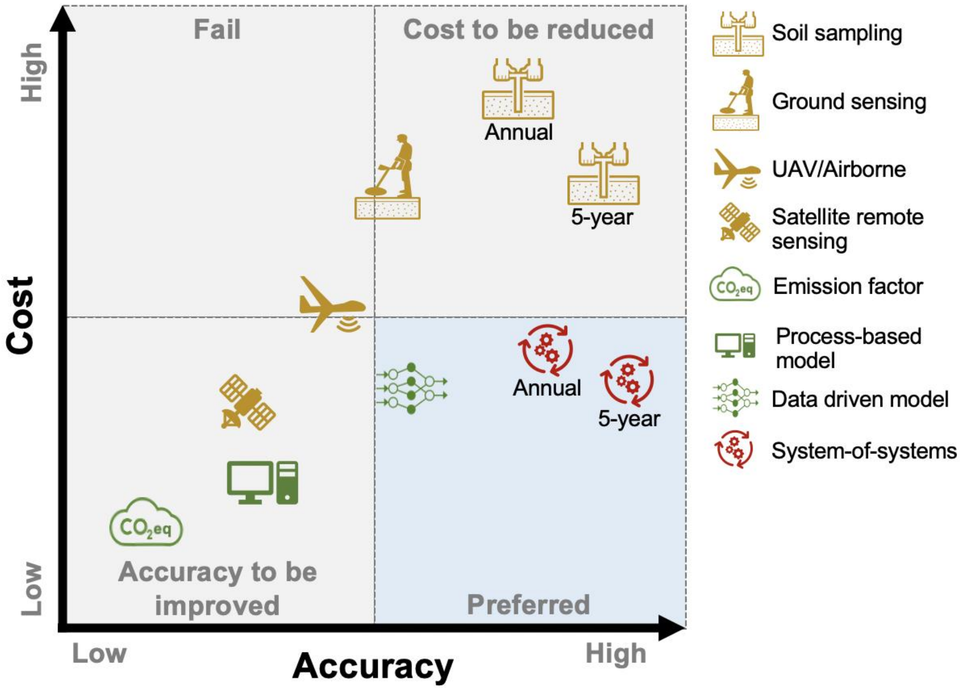

Figure 3. How different technological solutions for quantifying field-level carbon credit fit in the accuracy and cost diagram.

Such a "system-of-systems" solution should simultaneously provide the following three features (Figure 4): **(1)** scalable ground truth collection and cross-scale sensing of ***C***, ***M***, and ***E*** at the local field level; **(2)** AI-assisted Model-Data Fusion, i.e. robust and efficient methods to integrate sensing data and models at each local farmland level; and **(3)** high computation efficiency to enable scaling to millions of individual fields with low cost. Thus the "system-of-systems" solution is a holistic system including multiple sub-systems for sensing, monitoring, modeling, and model-data fusion, targeting to assure field-level accuracy, scalability, and cost-effectiveness.

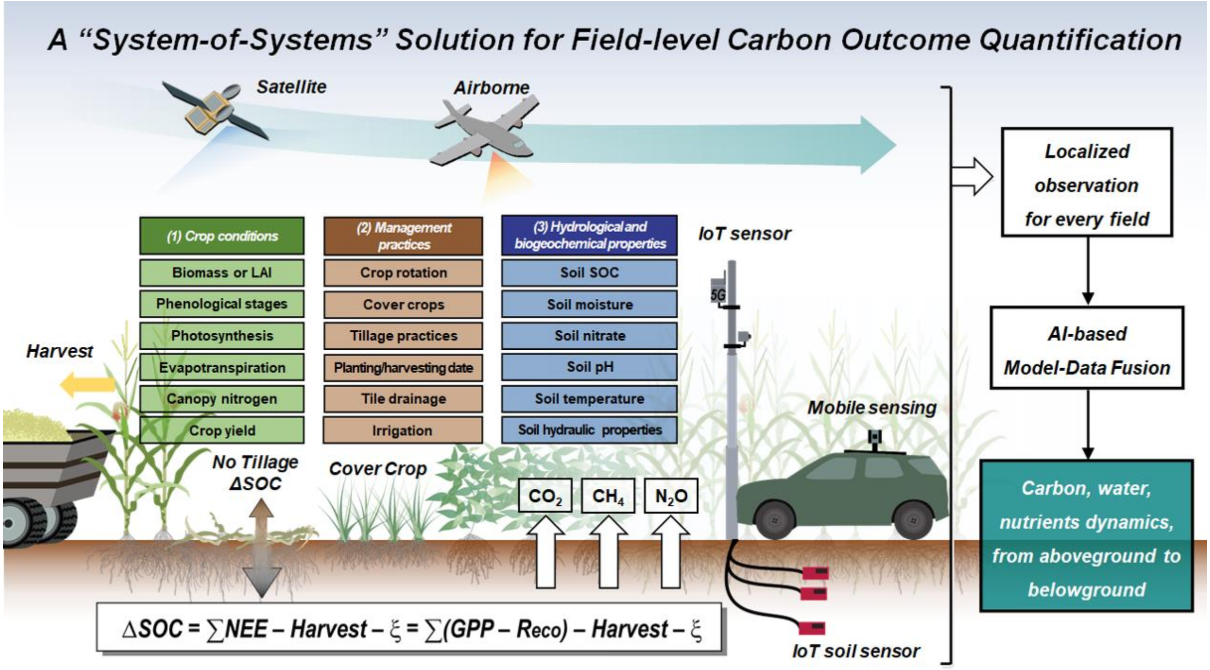

Figure 4. Illustration of a "system of systems" solution for quantifying field-level carbon outcome, including above and belowground processes. The "system of systems" solution includes sensing, monitoring, modeling, and model-data fusion, targeting to assure field-level accuracy, scalability, and cost-effectiveness. ξ represents carbon loss from leaching, which is usually very small (<0.5%) and thus can be neglected in most cases.

3.1 Scalable ground truth collection and cross-scale sensing of field-level information

Scalable sensing/estimating local information of ***C***, ***E***, and ***M*** at the field level is the first step, which involves two seemingly different and inherently connected tasks: (1) ground truth collection, and (2) cross-scale sensing. Ground truth here is broadly defined as information that is collected on the ground to train, constrain and/or validate models. Agricultural ground truth is scarce and expensive to collect. For example, the gold-standard carbon flux data requires eddy-covariance flux towers (e.g. SMARTFARM Phase 1 sites), which are generally costly to set up (~$100K needed to set up) and operate. We argue that the need for ground truth data is non-negotiable and should be a major investment with the public funding (see Section 4). However, even with low-cost sensing technology or crowdsourcing efforts, one cannot collect ground truth for every field. Instead, we will need cross-scale sensing approaches, especially those enabled by remote sensing, to scale-up "ground truth" collection to large scales.

Cross-scale sensing can be demonstrated by the most recent development of deriving field-level photosynthesis information. Photosynthesis is the only term for land carbon input and also the largest carbon budget term [26]. Correctly quantifying photosynthesis at the field level puts significant constraint and reduces uncertainty on simulating crop carbon dynamics, crop residues and soil carbon dynamics [13,27,28]. The recent decade's breakthrough in the remote sensing of photosynthesis is made possible only because the full integration of leaf-level chamber/sensor measurements, canopy-level hyperspectral sensing (especially solar-induced fluorescence, SIF) [29], and regional-scale mapping through satellite fusion data (Figure 5) [30]. The cross-scale sensing here is guided by the domain knowledge of plant physiology, radiative transfer modeling, and hyperspectral theories; the ground truth data - in particular, leaf-level samples and eddy-covariance flux tower data - are extensively used in the model development stage, but once the translation from ground-truth data to satellite-scale signals can be robusted developed, satellite fusion data can expand the photosynthesis information for every single field every day since 2000 to present [31].

Another frontier effort of cross-scale sensing is to use intermediate sensing to (1) augment traditional ground truth collection, and (2) enable the scaling from leaf-level or plot-level ground measurements with coarse satellite pixel size - a classic problem in the area of remote sensing. A typical example is airborne hyperspectral imaging (AHI). Hyperspectral imaging can provide estimates of soil and plant traits with very high accuracy [32], although its application for scalable mapping has been limited by the high cost. The novel use of AHI is to treat AHI as an intermediate bridge between ground truth collection and satellite scale-up. A general procedure is to first develop robust methods to translate AHI signals with targeted estimates (i.e. surface SOC, cover crop biomass) based on data from intensive lab and field experiments; and then to use AHI as a strategic sampler to selectively "sample" over space and time; and finally, to use satellite data overlaid with the AHI sampled area to translate satellite multispectral signals along with environmental variables to the plant and soil related estimation, thus deriving targeted C, M, E variables ubiquitously using satellite data. Though similar approaches have been used and achieved impressive success in mapping forests canopy biogeochemistry [33,34], they have rarely been used in agroecosystems. We have developed an advanced and automated pipeline to conduct AHI collection and data processing [35,36] and applied it to estimate crop canopy nitrogen content, cover crop biomass, and crop residue fraction and tillage practices. Figure 6 shows a demonstration of how we used AHI as a way to scale up the estimation of cover crop adoption and biomass at the regional scale. Other sensing solutions, such as mobile vehicle sensing [37], IoT sensing network and robotics [38,39], could also achieve a similar function to augment ground truth collection and enable satellite scaling-up to regional scales.

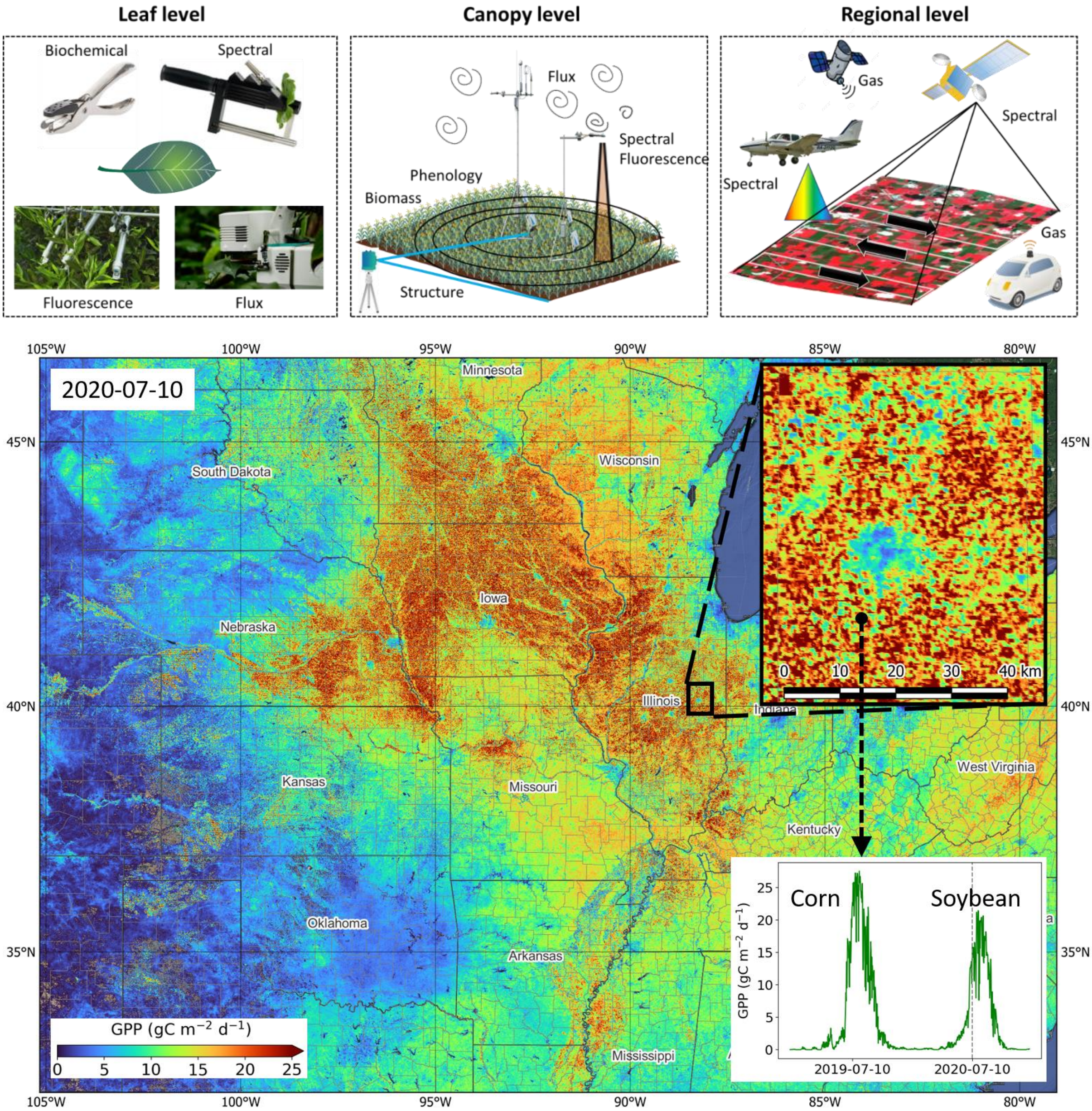

Figure 5. Cross-scale sensing to generate photosynthesis information at the field level. (Top) The cross-scale sensing from leaf to canopy, and to regional levels for estimating photosynthesis. (Bottom) A snapshot of field-level estimation of photosynthesis on 07-10-2020, derived from the large-scale SLOPE photosynthesis data at daily frequency [31], showing field-level Champaign County pattern and a field-level daily time series of photosynthesis.

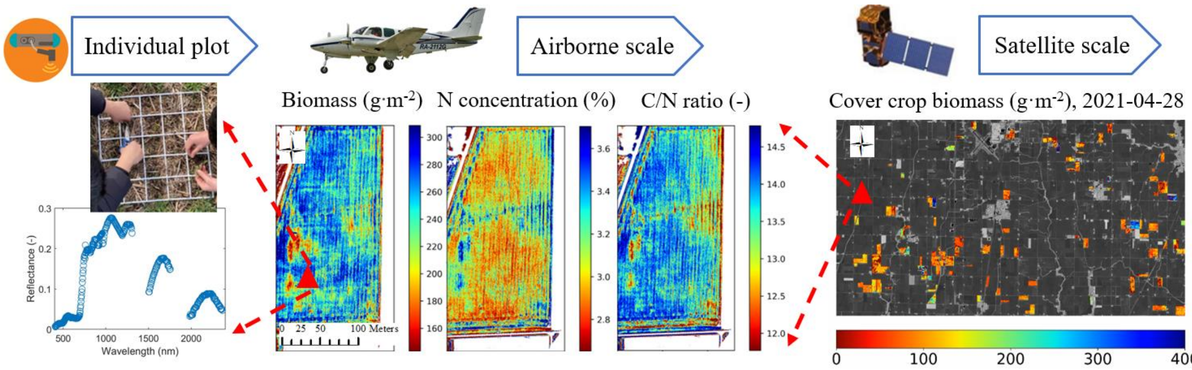

Figure 6. Cross-scale sensing to generate regional high-resolution cover crop information. Ground truth of cover crop growth variables (aboveground biomass, nitrogen concentration and carbon/nitrogen ratio) was collected from individual ground sampling plots. Then, airborne hyperspectral imaging along with machine learning and soil-vegetation radiative transfer modeling was applied to upscale plot level measurements to airborne scale. Finally, massive airborne hyperspectral survey derived cover crop variables were integrated with STAIR multi-source satellite fusion data [40] to derive regional cover crop growth information.

3.2 AI-assisted Model-Data Fusion with efficiency and robustness at individual fields

Model-Data Fusion (MDF) here refers to a set of techniques that constrains the uncertainty of states and parameters of process-based models or fine tunes data-driven models (e.g. statistical model or neural networks) with local information (i.e. field-level C-M-E data) to generate improved estimation of “carbon outcomes”. When implemented properly, MDF can effectively reduce uncertainties in observations, model inputs, model parameters and model processes [41]. MDF also has the ability to evolve by incorporating new sensors/sensing data or new model developments to this framework. But the downside of traditional MDF methods, like Bayesian Inference and Data Assimilation, is that they are computationally too expensive to run even at a few sites, making it impossible to scale to millions of individual fields.

We believe the recent AI boom could significantly advance the MDF approach through multiple avenues. For example, AI can speed up Bayesian Inference methods by providing computationally cheap surrogate models (also known as emulators) for calibrating parameters [41,42] or parameter learning that can effectively exploit the value of all available observations [43,44]. When coupling physical models with neural networks, Tsai et al. (2021)[45] showed that parameter learning can be several orders of magnitude faster than traditional parameter calibration algorithms while obtaining physically more sensible parameter sets. Moreover, modern probabilistic distribution learning methods such as normalizing flows offer opportunities to represent more general and empirical distributions that are better-suited for describing complex systems [46], and hence more accurate and efficient uncertainty estimation. As the integration of AI and MDF become an active research area [44], we expect more innovative methods will rise on the horizon.

3.3 High computation efficiency to enable scaling to millions of individual fields

Finally, the above efforts are required to be scaled to all the individual fields with similar accuracy and at a low cost. This will be a twofold problem including both scalable sensing to generate rich C-M-E information for constraining various aspects of agricultural carbon cycles [47] (as was discussed in Section 3.1) and scalable application of MDF over millions of individual fields. The latter, in particular, requires a transition from CPU-heavy to GPU-heavy models on supercomputing platforms for massive deployments. Fully upgrading existing agroecosystem models to GPU-accelerated systems would require intensive code redesign and rewrite, thus requiring longer coordinated efforts with dedicated funding support [48]. A more near-term (~5-10 years) solution is hybrid modeling. This could be achieved either by replacing the most time-consuming part of the process-based model (e.g. the ODE and PDE solvers) with deep learning modules for acceleration, or by developing deep learning models to learn complex patterns from data while incorporating domain-specific knowledge, such as physical rules (e.g. mass conservation), causality (e.g. dependency structure between variables) and nature of variables (e.g. states vs fluxes), informed by process-based models [44]. Knowledge Guided Machine Learning (KGML) is one such hybrid modeling approach that integrates scientific knowledge embodied in process-based models with machine learning, and thus can go much beyond the black-box use of data-centric deep learning and achieve better predictive generalization across space and time [49]. Although the early success of KGML mainly comes from hydrology and climate science in which physical rules are better described, some recent studies have demonstrated the huge potential of this method in boosting prediction accuracy for soil and crop dynamics, such as yield and soil carbon change [50] and nitrous oxide emissions [51]. Further research could make greater impacts by developing hybrid AI models that capture previously underrepresented physics, biogeochemistry, and missing dynamics that can be generalized (e.g. from local eddy-covariance observations to larger areas with sparse data through transfer learning), as well as investigating spatiotemporally optimal management practices for agroecosystem sustainability.

4. Guidance of government investment for substantiating agricultural carbon market and sustainable agroecosystems

Looking forward, we argue that the "system-of-systems" solution will continue to be the only viable technology for field-level carbon outcome quantification. This integrated system consists of several components that are still at their nascent stages, thus requiring massive and persistent R&D investment by government and industry. Coincidentally, these investments will build the foundation for the next generation of precision agriculture whose scope has been expanded from site-specific management following spatial variability[60] to big data-driven integration of sensing, analytics and automation for guiding farming activities at various scales[61]. However, technical advances alone are insufficient for substantiating the agricultural carbon market or agricultural sustainability more broadly; the success also relies on synergies among citizens, researchers, corporations, and governments to remove scientific and practical hurdles.

First and foremost, there needs to be unified protocols that provide guidance on measurements and modeling schemes, especially standards for addressing uncertainties and biases. Such protocols must be established through community effort for the sake of scientific rigor and transparency. Existing efforts led by certification organizations such as Verra [52] and Climate Action Reserve [53] are important and valued, but tend to be simplistic and conservative given the limited empirical data and insufficient MRV tools [54]. To successfully establish carbon markets will require more advanced field work, data collection, and modeling assessment. It is anticipated that intense debates will increase as more disciplines and stakeholders become involved in the new phase of protocol development, especially when rigorous requirements for validation set a barrier to entry of technical sophistication that is beyond the comfortable zone of traditional quantification approaches. To foster open and constructive conversations that lead to credibility and market confidence, three principles must be emphasized. First, **the quantification uncertainty of field-level carbon outcome must be specifically emphasized, and especially for the carbon credit market the uncertainty of the calculated carbon credit should be reflected in its price** to ensure that the incentivized impact is not over- or under-compensated. For example, the standard deviation of a MRV system can be used to discount the value of credits generated [55]. This is an essential piece for the protocol to be usable and not just a subjective technical preference. Second, **validation is the only way to report system-wide uncertainty**. No exemption should be made for any quantification tool, even if the tool is widely used or peer-reviewed. There are some academic-based model intercomparison MIP efforts [56,57] that can shed light on how to set up such validation, but given the transaction purpose of carbon credits, a high bar must be set for acceptable model performance. **Third, demonstrating performance at the scale of an individual field is obligatory.** Due to the challenges to achieve scalability, some practitioners suggest compromise by focusing on the aggregated accuracy of quantified carbon credit. We argue that aggregated accuracy, which is almost impossible to validate, must come from field-level accuracy.

Next, **establishing a gold standard dataset for developing, calibrating and validating MRV systems** is essential to building stakeholder trust in these technologies. The gold standard dataset should ensure site representativeness to include different soil, weather, crop, and management types, and be open-source but compiled under a protocol of community-wide acceptance. An analogy is the ImageNet database [58] for computer vision research, with which new algorithms will be benchmarked to show their progress in visual object recognition. Modeling carbon emission and sequestration, however, is more complicated, and hence more challenging to establish an “ImageNet for Agriculture”. Due to the often large uncertainty associated with agricultural measurements, protocols for standardized data collection, and processing techniques must be carefully evaluated and imposed. Some long-term experiment and observation networks that have collected a complete suite of ***C, M, E*** variables have the great potential to be gold standard sites. Examples include the USDA Long-Term Agroecosystem Research (LTAR) network, some National Ecological Observatory Network (NEON) sites, and AmeriFlux sites in cropland and pasture land [18]. Further, the recently launched U.S. Department of Energy ARPA-E SMARTFARM sites have been collecting soil, crop, and GHG fluxes data with even greater spatial and temporal resolutions [59], thus can enable a new generation of R&D development such as high-resolution remote sensing monitoring, or novel modeling methods that can capture the hot-spot, hot-moment pattern of GHG emissions. Lastly, a large number of controlled experiment sites can be used to test the model scalability. These sites often have limited amounts of ground measurements but represent the real-world situation for operational use. However, **significant efforts are needed to harmonize the data that are measured by a wide range of methods and instruments**. Further investment on gold standard data collection should prioritize experiments that can help understand the carbon outcomes associated with different bundles of carbon-outcome-related practices, such as the combination of no-till and cover crop, as well as measurements that can disentangle the opaque "black box" of complex plant-soil-microbe interaction [60]. In addition, deep sampling of soils beyond the typical surface sampling depths (e.g. 0-30cm) is necessary to accurately quantify and monitor the extent of SOC changes [61] and to corroborate estimates by models.

While our discussion mainly focused on agricultural carbon outcomes, society may want to consider other environmental and economic co-benefits (e.g. improving soil health, reducing water and air pollution, and increasing climate resilience), even as part of carbon mitigation programs per se. Some recent case studies have demonstrated that, given the relatively low carbon credit price, participation of farmers may be primarily driven by these co-benefits [58,59]. The "system of systems" framework proposed in this perspective can be extended to assist the accounting of these co-benefits, and inform sustainable agroecosystem management by holistically studying the often coupled carbon, water, and nutrient cycles and human activities, a topic itself at the frontier of the earth system science.

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