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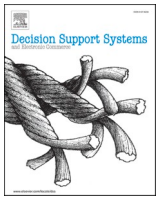
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# Designing AI-based decision support systems for carbon stock estimation and planning: A design science research☆

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ABSTRACT

Mitigating climate change presents significant challenges, particularly in effective carbon stock estimation and planning. Decision-making based on quantified carbon stock is essential for enabling carbon sequestration efforts in natural ecosystems, yet traditional field measurements are labor-intensive, geographically constrained, and difficult to be adopted at scale. Motivated by this practical challenge, we undertook a design science research (DSR) project to develop AI-based decision support systems that enhance the efficiency, accessibility, and scalability for carbon stock estimation and planning. Guided by technology affordance theory, our iterative design, development, demonstration, and evaluation process has led to the conceptualization of four affordance-based design principles that build on and contribute to the growing design knowledge for environmental sustainability. This research advances our understanding of the critical problem and solution domains of carbon stock estimation and planning. It also facilitates the emerging discourse on balancing AI and human intelligence in designing systems for complex decision-making challenges for sustainability. This study provides an exemplar of DSR for supporting Sustainable Development Goal 13 by demonstrating how to design systems that facilitate carbon sequestration and societal transition toward environmental sustainability.

## 1. Introduction

Climate change is a pressing societal challenge that demands immediate global action, as highlighted in United Nations Sustainable Development Goal 13 (SDG 13: Climate Action) [1]. The Paris Agreement also highlights the net-zero goal of not exceeding the 1.5 °C threshold of global warming, urging socioeconomic and technological transformations in all nations [2].

Mitigating climate change requires two complementary pathways: reducing carbon emissions and increasing carbon sequestration [3]. The former involves decreasing emissions across societal activities, while the latter focusing on capturing and storing atmospheric carbon dioxide as carbon stock. Carbon stock is defined as the quantity of carbon that can be held and stored in systems at a given time, including natural ecosystems such as terrestrial and marine habitats, as well as artificial systems such as carbon capture and storage [4–6]. Nature-based solutions support both pathways through protecting, managing, and restoring ecosystems [7]. They also create co-benefits, including biodiversity conservation, improved water quality, and support for local communities [8,9], further contributing to sustainable development. Mechanisms such as the Australian Carbon Credit Unit (ACCU) scheme [10] and Reducing Emissions from Deforestation and Forest Degradation plus (REDD+) [11] have been established to incentivize and support their implementation.

Nevertheless, carbon stock estimation and planning remains one of the major challenges for realizing the full potential of nature-based solutions. For lands to be certified to participate in these mechanisms, landholders need to provide information on their carbon stock and propose plans for expanding carbon stock [12,13]. Meanwhile, investors and governments need to acquire and verify such information for decision-making and governance [14]. However, the traditional field measurements for quantifying carbon stock employ a manual process of collecting and weighing biomass, which has been time-consuming, destructive to vegetations, costly, and potentially difficult for humans to access in remote and dangerous areas [15,16]. These needs and constraints motivate this study to design more effective solutions leveraging information systems (IS).

In addition, this study responds to the calls for conducting solution-

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oriented research for addressing pressing environmental sustainability challenges [17–19]. In particular, we employ a design science research (DSR) approach that enables the innovation of system solutions and the conceptualization of design knowledge [20,21]. Extant DSR studies on environmental sustainability have, for example, developed environmental sensemaking support systems [22], wildlife management analytics systems [23], and watershed sustainability decision support systems (DSS) [24]. Building on and contributing to this growing design knowledge base, this study focuses on designing system solutions for carbon stock estimation and planning, a distinct problem domain in which obtaining key environmental information remains the primary obstacle. To this end, we leverage the learning and computing capabilities of artificial intelligence (AI) into system design [25], to effectively perceive and process key environmental information. Acknowledging both the promises and challenges at the intersection of environment, AI, and design science [26,27], this study explores the design of AI-based DSS for complex environmental sustainability challenges [28]. By balancing autonomous AI and human expertise [28], our design aims to improve the efficiency, accessibility, and scalability of carbon stock estimation and planning [25,28,29]. Taken together, this paper explores the following research question: "***How to design AI-based DSS for carbon stock estimation and planning*?**"

We initiate a DSR project following the Peffers et al. (2007) DSR process model [30]. Specifically, we design DSS that integrate convolutional neural networks (CNNs) with geographic information systems (GIS) to detect vegetation features from remote sensing images, perform allometric estimation of carbon stock in forest trees, and visualize carbon stock planning activities. After two rounds of system design, development, demonstration, and evaluation, we refine our design knowledge into affordance-based design principles [31,32]. The four key affordances are: *mapping* areas of interests on GIS-based interactive maps; *detecting* key vegetation features from remote sensing images using CNNs; *estimating* carbon stock from the detected vegetation features through allometric equations; *strategizing* future carbon stock generation activities. These affordances guide the formulation and evolution of our design principles, which can further inform a class of system design for carbon stock estimation and planning.

The theoretical contributions are threefold. First, this study builds on and extends the design knowledge base for environmental sustainability. By unpacking the problem domain, solution essence, and design knowledge embedded in extant studies, including Corbett (2013) [33], Seidel et al. (2018) [22], Pan et al. (2021) [23], and Zampou et al. (2022) [34], we identify carbon stock estimation and planning as a distinct and critical problem domain and propose design principles for AI-based DSS that advance the solution domain. Moreover, this study contributes to the emerging discourse on the effective and responsible design of AI for complex decision-making and societal challenges [25,28], by exploring how to balance AI and human expertise in both descriptive and prescriptive aspects of decision-making. Lastly, we reflect on the role of affordance-based DSR in guiding our design evolution.

Beyond its theoretical contributions, this DSR project has societal implications by enhancing the efficiency, accessibility, and scalability of carbon stock estimation and planning, thereby supporting carbon sequestration and climate change mitigation. By demonstrating the DSR process in designing such system solutions, this study contributes to SDG 13 and serves as an exemplar of how DSR can be used to advance sustainable development and improve societal outcomes.

## 2. Literature review

### 2.1. Designing IS for environmental sustainability

As the foundation for human development [35], environmental sustainability refers to a balanced condition of ecosystems that meets present human needs without compromising those of future generations [36,37]. A broad societal consensus has emerged among governments, organizations, and individuals that the environment should not be sacrificed for economic growth alone, as doing so risks the destructive consequences of climate change, pollution, and biodiversity loss [38]. In this context, emerging technologies play a key role in driving the societal transition toward environmental sustainability by optimizing processes and minimizing environmental damage [17].

IS research has shown growing interest in leveraging digital technologies to address environmental sustainability challenges [17–19,36], particularly through solution-oriented research that moves beyond theory to create real-world impact [18,19,39]. In response, DSR has emerged as a powerful approach for generating design knowledge and creating innovative artifacts across a variety of problem domains in environmental sustainability [19,20]. Examples of DSR studies include the design of sensemaking support systems for environmental sustainability transformation [22], analytical systems for wildlife conservation [23], data-driven systems for coastal resilience [40], and intelligent systems for assessing climate risk response readiness [41]. To mitigate climate change, designing IS solutions for reducing carbon emissions have been demonstrated by Corbett [33] and Zampou et al. [34]. The former focuses on articulating design knowledge of persuasive carbon management systems that enable behavioral change toward environmental sustainability in organizations [33]; the latter presents design theory for energy and carbon management systems that enable environmental data collection, exchange, analysis, and report for enhancing decision making and practices in the supply chain context [34].

Overall, these studies have established a design knowledge base for IS addressing environmental sustainability challenges. Design knowledge is multifaceted and emerges from the interaction between problem and solution domains [42]. Accordingly, we unpack this design knowledge base by examining these domains to inform the objectives of this study, as presented in Table 1.

In the problem domain, we identify that while efforts to reducing

**Table 1**
Selected studies on designing is for environmental sustainability.

| Study | Problem domain | Solution domain | |
|---|---|---|---|
| | | Solution essence | Design knowledge |
| Corbett (2013) [33] | *Reducing carbon emissions* in *organizations* through behavior change | The systems enable desirable change through the integration of *reducing complex tasks, tailoring to specific context, and complementing with other resources* | Design principles for persuasive carbon management systems that enable environmentally sustainable behavior |
| Seidel et al. (2018) [22] | *Facilitating environmental sustainability transformation* in *organizations* through sensemaking | The systems *facilitate the sensemaking process of environmental information* that can be translated into environmentally sustainable practices | Design principes for sensemaking support systems toward environmental sustainability |
| Pan et al. (2021) [23] | *Improving wildlife conservation* by *governments* through wildlife management | The systems leverage existing datasets to provide analytical insights to *assess and anticipate the status of wildlife and optimize practices* | Design principles for wildlife management analytics systems |
| Zampou et al. (2022) [34] | *Reducing carbon emissions* in *organizations* across supply chains | The systems enable *environmental information flow from collecting data to decision making and practicing in supply chains* | Design principles for energy and carbon management systems that support decision-making and practice in supply chain |

carbon emissions within organizations has been emphasized, there is a lack of attention to system designs that facilitate carbon sequestration, another essential pathway for mitigating climate change [3]. In the solution domain, the existing design principles focus on enabling behavioral change toward environmental sustainability and enhancing decision-making through promoting information flow and analysis, after acquiring the environmental data. These insights serve as a solid foundation for our DSR study, highlighting two critical needs: (1) the need to understand the underexplored problem domain of carbon sequestration, and (2) the need to advance design knowledge for systems that tackle the challenges of obtaining and quantifying critical information, which remain a primary obstacle to subsequent decision-making in certain environmental sustainability contexts.

Building on these needs, this study aims to contribute to the accumulation and evolution of design knowledge for environmental sustainability by designing AI-based DSS for carbon stock estimation and planning. Recognizing the pressing challenges in this problem domain, we propose integrating AI into DSS as the solution to improve the efficiency, accessibility, and scalability of carbon stock estimation and planning. AI technologies such as machine learning models can significantly reduce manual effort in data collection, accelerate data processing, and augment human decision-making, thereby enabling more efficient and informed actions that support environmental sustainability [25,26,28,43]. While solutions in extant DSR studies rely on environmental data that is either available [23] or relatively easy to collect [34], the essence of our solution lies in obtaining and quantifying critical environmental information that has been difficult to acquire (e.g., carbon stock). Our solution extracts this information by integrating CNNs, enabling subsequent information flows necessary for effective decision-making in carbon stock estimation and planning.

Taken together, the significance of the problem domain and the distinctive solution highlight the need to extend the existing design knowledge by developing design knowledge tailored to AI-based DSS for carbon stock estimation and planning as a new class of systems.

### 2.2. *Technology affordance as the theoretical Lens to inform system design*

Affordance theory was proposed by Gibson in ecological psychology to capture the co-existence and interdependence between the environment and animals [44]. As the theory has evolved in its original discipline [45,46], it has been adapted in IS as technology affordance theory to examine the interaction between humans and technology artifacts [47]. Technology affordance refers to the action potential arising from the relationship between technology artifacts and goal-oriented actors [48], which can be realized through actions [49,50]. As a relational concept, it acknowledges the importance of both technology and human agency, avoiding the extremes of either technological determinism or social constructivism [47,51]. Moreover, by recognizing the probabilistic nature of human actions and certain algorithms, technology affordance allows for greater flexibility in understanding technology design and use [32].

In design-oriented research, technology affordance theory is adopted to inform the design process and guide the conceptualization of design knowledge [31]. Norman highlighted the importance of perceived affordances that designers need to specify to ensure users can perceive them [52]. As design theory develops, the relational nature of affordances offers greater explanatory power to inform system design for a class of problems, compared to function-based design [53]. It captures the "entanglement" among actors, i.e., the interdependent relationships among artifacts, designers, and users within certain contexts, allowing for a more dynamic perspective on understanding and guiding the design process [53]. In such affordance-based design, designers interact with both artifacts and users iteratively to align instantiated affordances through appropriate material properties with the affordances needed by users [53]. Overall, affordance theory provides the theoretical basis for system design by explicating the role of designers in identifying the affordances needed and instantiating material properties.

Technology affordance theory has been increasingly used as a theoretical lens for conducting DSR studies [54]. It has been applied to formulate design principles that shape subsequent design processes in various contexts [22,23,31,32]. As illustrated in Fig. 1, the fundamental DSR process – from initial design to evaluation – closely aligns with the affordance-based design model. Building on this alignment, we use the technology affordance theory to inform our system design and theorize design knowledge emerged from our DSR journey.

## 3. DSR approach

We adopt the DSR approach to formulate design knowledge [21]. Specifically, as a constructive DSR project, this study generates prescriptive design knowledge in the form of design principles, through the creation and evaluation of novel IS artifacts [55,56]. For the initial theorization, we use the template of design principles outlined in Chandra et al. (2015) [31], which highlights three elements: materiality, action, and boundary conditions. After two rounds of iterations, we theorize the revised design principles based on the design principle schema proposed in Gregor et al. (2020) [32], to comprehensively specify the actors, the mechanisms, and the rationale.

We follow the Peffers et al. (2007) process model to conduct our DSR, shown in Fig. 2 [30]. This model depicts a sequential and iterative process, allowing researchers to choose their entry points and adapt the process as needed [30]. With flexibility, adaptability, and methodological rigor, it has been widely adopted in the DSR literature [57]. As this study is problem-driven, we enter the DSR process from problem identification and motivation. After we specify the problem, we define the scope of the solutions by identifying the key affordances and formulating an initial set of design principles to guide the design process.

Next, we begin two rounds of iterations. Our DSR team is formed by three IS researchers and five computer scientists. In the first round design and development, we instantiate the initial set of design principles into the first prototype. Given the availability of resources, we adopt the "Quick and Simple" evaluation strategy [58], with one major evaluation episode for each iteration. When the first prototype becomes usable, we conduct an interim demonstration and evaluation to assess the technical performance of the AI models and to gather formative feedback for improving system design in the second round. Based on the revised design principles, we decide to develop a second prototype that can better incorporate an additional design principle. Following system development, we conduct the summative evaluation to refine design knowledge [58], including a demonstration to practitioners, qualitative interviews with 16 new informants, and quantitative assessment through the System Usability Scale (SUS) [59]. Finally, we summarize our findings using the structured design principle schema [32]. The main activities are summarized in Table 2.

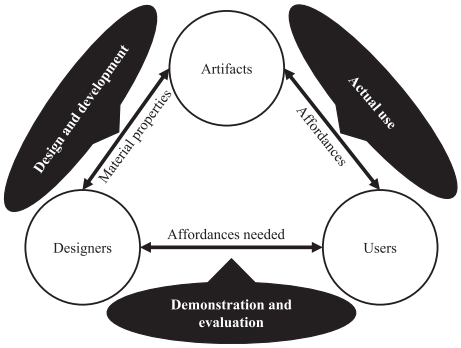



**Fig. 1.** Affordance-based design and DSR (Adapted from [53]).

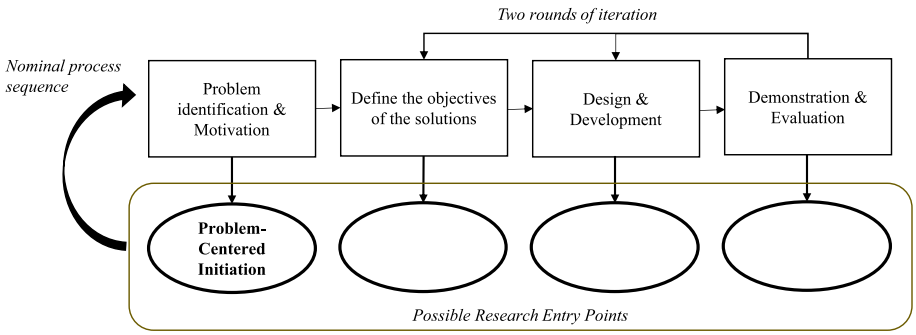



**Fig. 2.** Peffers et al. (2007) process model [30].

**Table 2**
Summary of two rounds of design activities.

| Activities | First Round | Second Round |
|---|---|---|
| Design and Development | - Collaboration of 3 IS researchers and 5 computer scientists<br>- Instantiated the initial design principles and developed the first prototype | - Collaboration of 3 IS researchers and 4 computer scientists<br>- Instantiated the revised design principles and developed the second prototype |
| Demonstration and Evaluation | - Presented at a decarbonization exposition with over 850 attendees and collected feedback from 15 informants during the exposition<br>- Conducted formative evaluation through internal meetings and 5 interviews within the DSR team<br>- Revised the design principles and added the fourth one | - Demonstrated the systems to a carbon trading company with 10 specialists<br>- Conducted summative evaluation with 16 new informants including researchers and practitioners in the relevant fields<br>- Consolidated the design principles based on the design principle schema |

## 4. Define the objective of the solutions

Our research objective is to design, develop, demonstrate, and evaluate AI-based DSS for carbon stock estimation and planning, and to conceptualize design knowledge for this distinct and significant class of systems. Specifically, our design goals include: (1) instantiating prototypical systems with state-of-the-art performance, and (2) deriving design knowledge that can inform the future design of this class of systems by enhancing their efficiency, accessibility, and scalability.

### 4.1. Problem specification

To explore our research objective, we choose to focus on trees in terrestrial forests for instantiation, while acknowledging the significance of other vegetation types for carbon sequestration, such as shrubs [60] and mangroves [61].

In the field measurement approach, diameter at breast height, tree height and wood density are key variables that have a strong relationship with aboveground biomass in allometric equations for estimating forest carbon stock [62]. In remote sensing, a heuristic approach has been employed to approximate the regression-based calculation of forest carbon stock [63].

In this study, we use tree canopy coverage as the heuristic proxy for tree size. It is defined as the percentage of area covered by tree canopies divided by total area, obtained through tree semantic segmentation. Other proxies for tree coverage, including individual crowns and canopies, have been used to capture information on tree size [64,65]. Tree canopy coverage has been empirically shown to be more pragmatic than individual tree crown delineation for large-scale applications [66].

By combining this proxy with data on forest structure and species, we develop an algorithm for estimating forest carbon stock based on allometric equations. The current accuracy benchmarks of remote sensing-based forest carbon stock estimation indicate that LiDAR data achieves the highest accuracy, with R-squared values ranging from 0.74 to 0.98, and multi-source remote sensing achieves R-squared values ranging from 0.67 to 0.82 [67–71]. Nevertheless, the reliability of remote sensing-based approaches is constrained by the availability and quality of high-resolution data [67], and by whether the models are trained under similar vegetation types. For instance, we expect our models to work reliably in areas with high forest coverage [72].

### 4.2. Formulation of the initial set of design principles

After specifying the problem, we identify the key affordances the system should embed and their corresponding material properties, informed by relevant literature in environmental science, ecology, geoinformatics, and computer science. We then formulate the initial set of design principles based on these affordances and material properties [31], which define the scope of the solutions in the context of carbon stock estimation and planning, as presented in Table 3.

The first affordance is mapping, referring to visualizing and specifying areas of interest for carbon stock estimation and planning. It is

**Table 3**
The initial set of design principles.

| Design Principles (DP) | Affordances | Material Properties |
|---|---|---|
| DP1: Provide the systems with *features to navigate to and bound areas of interest on interactive maps [material property]* in order for users to *map areas of interest [affordance]* for *carbon stock estimation and planning [boundary condition]*. | Mapping | Features to navigate to and bound areas of interest on interactive maps |
| DP2: Provide the systems with *features to integrate CNNs for vegetation detection on remote sensing data [material property]* in order for users to *automatically detect vegetation features [affordance]* for *carbon stock estimation and planning [boundary condition]*. | Detecting | Features to integrate CNNs for *vegetation detection on remote sensing data* |
| DP3: Provide the systems with *features to quantify carbon stock based on the detected vegetation [material property]* in order for users to *estimate carbon stock in areas of interest [affordance]* for *carbon stock estimation and planning [boundary condition]*. | Estimating | Features to quantify carbon stock based on the detected vegetations |

identified based on prior studies and applications that have demonstrated the importance of maps for visualizing and extracting relevant environmental information, for example, tree distributions [73], carbon stock and biodiversity [9], and investible forest carbon [74]. Mapping can be achieved through the material properties of interactive maps built on satellite images [75], with features that allow navigation to specific locations and delineation of areas of interest [76]. These material properties enable users to visually access and specify areas of interest with a bird's-eye view, which expands the scale of carbon stock estimation and planning by providing wider access to remote or conflict-affected areas [16].

The second affordance is detecting, which denotes the action potential for automatically detecting vegetation features within the mapped areas. Automating the extraction of key information on vegetation features is critical for enhancing the efficiency and scalability of carbon stock estimation and planning [67]. It can be achieved by material properties that employ CNNs on remote sensing data. Recent research has demonstrated the effectiveness of training CNNs for identifying dryland trees and shrubs [77], delineating individual tree crowns [64], and classifying tree species [78]. By integrating CNNs for vegetation detection on remote sensing data, the systems enable users to detect key vegetation features for carbon stock estimation and planning without manual annotation.

The third affordance is estimating, which refers to the action potential for estimating biomass and, consequently, carbon stock. It can be achieved through material properties that afford the quantification of carbon stock based on the detected vegetation within the mapped areas. For terrestrial ecosystems, allometric equations are commonly used to capture the relationship between biomass and vegetation features, thereby calculating carbon stock proportionally [62,79]. By embedding features to quantify carbon stock based on the detected vegetation, the systems allow users to estimate key information for decision-making in carbon stock estimation and planning [74], and more broadly, climate change mitigation policies [80].

## 5. First round of design, development, demonstration, and evaluation

We conducted the first round of design and development between February and September 2023. The instantiation of material properties for each design principle is summarized in Table 4, and the prototype is presented in Fig. 3.

To afford *mapping (DP1)*, we build an interactive map using a web-based GIS that loads a global satellite map with zoom-in and zoom-out functions, providing a bird's-eye view for visual understanding of the landscape. Then we introduce the features that allow users to navigate to and bound the areas of interest on the interactive map. In the top left corner, the search box can navigate users to the areas of interest through keywords, addresses, or coordinates. In the top-right corner, the toolbox enables users to create, edit, and delete areas of interest defined by bounding boxes and other geometric shapes on the map.

**Table 4**
The initial instantiation.

| Design Principles | Instantiation of Material Properties |
|---|---|
| DP1 | • Web-based GIS that allows zoom-in and zoom-out<br>• A search box for navigating to areas of interest via addresses or coordinates<br>• A toolbox for bounding the areas of interest in geometric shapes on the map |
| DP2 | • Preprocessed and standardized remote sensing data<br>• Trained CNNs for tree semantic segmentation |
| DP3 | • API that connects with the CNNs and GIS interface in the backend<br>• A display for the estimated carbon stock based on detected tree coverage and other data on forest structure and species |

To afford *detecting (DP2)*, we instantiate features to integrate CNNs for vegetation detection in remote sensing images, by focusing on tree semantic segmentation on aerial and satellite images. First, preprocessing remote sensing data from different sources and modalities is a prerequisite for training the CNNs. We standardized the three-dimensional Light Detection and Ranging (LiDAR) point cloud [81] and high-resolution orthorectified camera imagery [82] datasets from the National Ecological Observation Network (NEON) through dimension projection, size rematching, and resolution transformation [66]. These standardized NEON images are complemented by publicly available satellite images to enhance the scalability and adaptability. In total, we have 86,088 training images and 21,768 validation images, with a spatial resolution of 1.194 $m^2$ per pixel. Second, we adopted the DeepLabv3+ as the baseline model for tree semantic segmentation [83], using the NEON images for training and validation, and the satellite images for testing. Integrating the tree semantic segmentation models in the backend allows automatic vegetation detection that provides the key inputs for carbon stock estimation and planning.

Lastly, to afford *estimating (DP3)*, we instantiate features to quantify carbon stock. We use Application Programming Interface (API) in the backend to connect the CNNs and GIS interface. It allows real-time processing of users' requests for detecting vegetation, thereby quantifying carbon stock for the mapped areas, combined with other data on forest structure and species. On the interactive map, there is a display for the estimated carbon stock for the areas of interest.

After building the prototype, we conduct a formative evaluation to guide decisions on how to further improve the system and design knowledge [58]. As an interim phase, our evaluation focuses on gathering feedback from relevant stakeholders through demonstration, assessing the technical performance of the AI models, and specifying the needed improvements for the next round.

For the demonstration, our research team presented the project at an exhibition themed on frontier innovation for clean energy and decarbonization, which attracted over 850 attendees from government, industry, and research institutions. We engaged with 15 academic researchers and industry practitioners, including environmental scientists, computer scientists specializing in climate and sustainability, and professionals from carbon and remote sensing companies during the exhibition to evaluate our prototype. While they acknowledge the technical novelty and the practical need for our system to provide carbon stock information, they point out the lack of guidance from the prototype on “what would be the next steps”. Stakeholders in the carbon trading markets, including investors and landholders, need to navigate through complex contexts for individual carbon projects and make decisions on how to expand carbon stock over time to meet a list of requirements. These discussions led us to investigate the latest government schemes and initiatives, for example, Living Carbon Grant [12], to identify other key information required to support more comprehensive decision-making.

Evaluating technical performance is critical for rigorous of AI-based system design. We evaluate model performance using Intersection over Union (IoU), a common metric that compares the predicted segmentation and the real object in computer vision [84]. The mean IoU between vegetation and background classes of our models on annotated satellite images is 65.14%. Given the shift from aerial to satellite images, this performance is reasonable for building applications.

In addition, we conduct an interim qualitative evaluation through group meetings within our DSR team and individual interview sessions to reflect on the alignment between our intended design and the system's realized affordances, and to identify gaps for further improvements. The first-round prototype successfully serves as a proof-of-concept that reflects the three DPs of mapping, detecting, and estimating. Nevertheless, we recognize that it focuses on providing descriptive information, based on feedback received and further investigation into recent carbon initiatives and relevant practical applications. To enable more comprehensive decision support for carbon stock estimation and planning, the

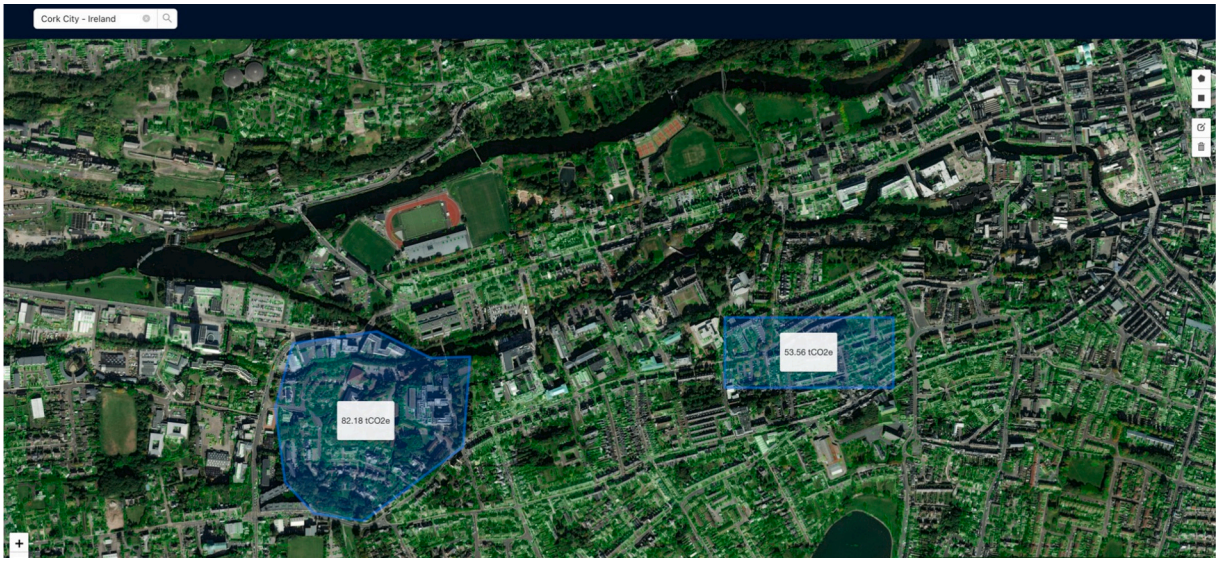



**Fig. 3.** The prototype developed in the first round.

system needs to be complemented by predictive and prescriptive analysis. As the technical lead suggested:

*This (current) prototype is focused on descriptive analytics, like estimating carbon stock. Predictive analytics, such as forecasting impact and ROI, needs to be developed… (we should) work on prescriptive analytics and decision optimization, like where to plant trees, where to put renewable activities, and where to build factories… Eventually, we want the system to support complex decisions.*

This direction for further development is aligned with feedback we received from the demonstration and the needs of stakeholders in the carbon trading markets. For landholders, in particular, they not only need information on the current status of carbon stock but also require further decision support to strategize activities for expanding carbon stock, as decarbonization is inherently a future-oriented goal. As emphasized by another team member:

*We want to add features for users to strategize their land use… like managing a portfolio of projects, but it's not there yet.*

Another potential direction for improvement that our team discussed is to introduce uncertainties into AI models, because policy change and environmental risks such as bushfires and floods can significantly impact carbon stock generation over time. However, despite the importance of uncertainty modeling, we agree on predictive and prescriptive capabilities as the priority for the next round of design and development, as actionable planning comes before impact assessment.

Taken together, the interim demonstration and evaluation lead to the conceptualization of the fourth affordance of strategizing, which captures the action potential for proactively exploring strategies to expand carbon stock for the future. By introducing this new affordance, the system design evolves from providing static information to enabling dynamic decision-making, which facilitates future-oriented planning, especially for the landholders and developers. Correspondingly, the fourth design principle is formulated as the following:

**DP4:** Provide the systems with *features to organize vegetation plantation and sustainable land development activities [material property]* in order for users to ***strategize*** *their future carbon stock generation [affordance]* for *carbon stock estimation and planning [boundary condition]*.

## 6. Second round of design, development, demonstration, and evaluation

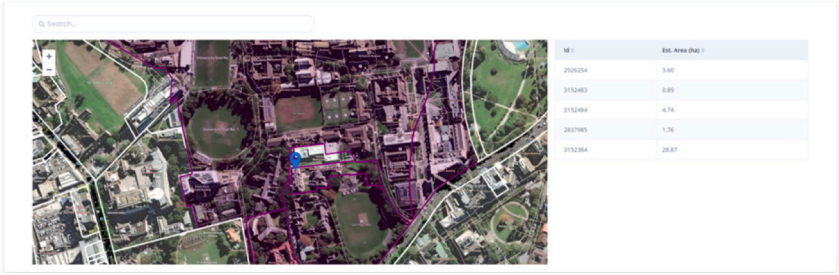
The second-round design and development were conducted from February to November 2024. Incorporating the fourth design principle and other improvements requires significant changes to the system architecture. Therefore, our DSR team has decided to build the second prototype as the revised instantiation. The second prototype features a more complex architecture with additional layers and a more unified interface. The revised instantiation is summarized in Table 5.

In the second round, to better instantiate DP1, we redesign the prototype to make two key improvements, shown in Fig. 4 (a). First, to afford mapping for multiple users, we build a new GIS platform with user authentication that allows users to manage, inspect, and save different projects. These projects are shown as listings on the platform that can serve as a marketplace for carbon projects to connect landholders and investors. Second, we introduce bounded land parcels by extracting available information from the official land repositories. Users can select and combine various pre-defined land parcels to bound the areas of interest, which simplifies the process of bounding the areas of interest. Overall, these revised features pave the way for introducing the strategizing affordance by setting up the concepts of portfolios and marketplace.

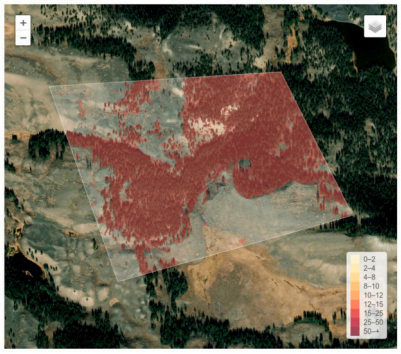
To better instantiate DP2 and DP3, we visualize the segmented trees on the map with a colored differentiation of heights when the

**Table 5**
The revised instantiation.

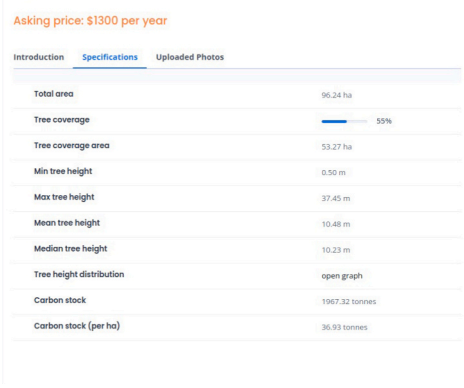
| Design Principles | Instantiation of Material Properties |
|---|---|
| DP1 | • Web-based GIS platform with user authentication that allows users to create and manage various carbon projects<br>• A search box for navigating to areas of interest via keywords or coordinates<br>• A toolbox for bounding the areas of interest in geometric shapes on the map<br>• The map displayed with parcel boundaries and land information extracted from official repositories that allows users to select and combine land parcels to bound their areas of interest |
| DP2 | • Preprocessed and standardized remote sensing data<br>• Trained CNNs for tree semantic segmentation<br>• API that connects with the CNNs and GIS interface in the backend |
| DP3 | • A display for the estimated carbon stock based on detected tree coverage and other data on forest structure and species, and other information about the trees in the areas of interest |
| DP4 | • Visualized tools for organizing vegetation plantation and other sustainable land development activities for future carbon stock generation<br>• Visualized tools for calculating costs and predicting future carbon offsets from the planned carbon stock generation activities |



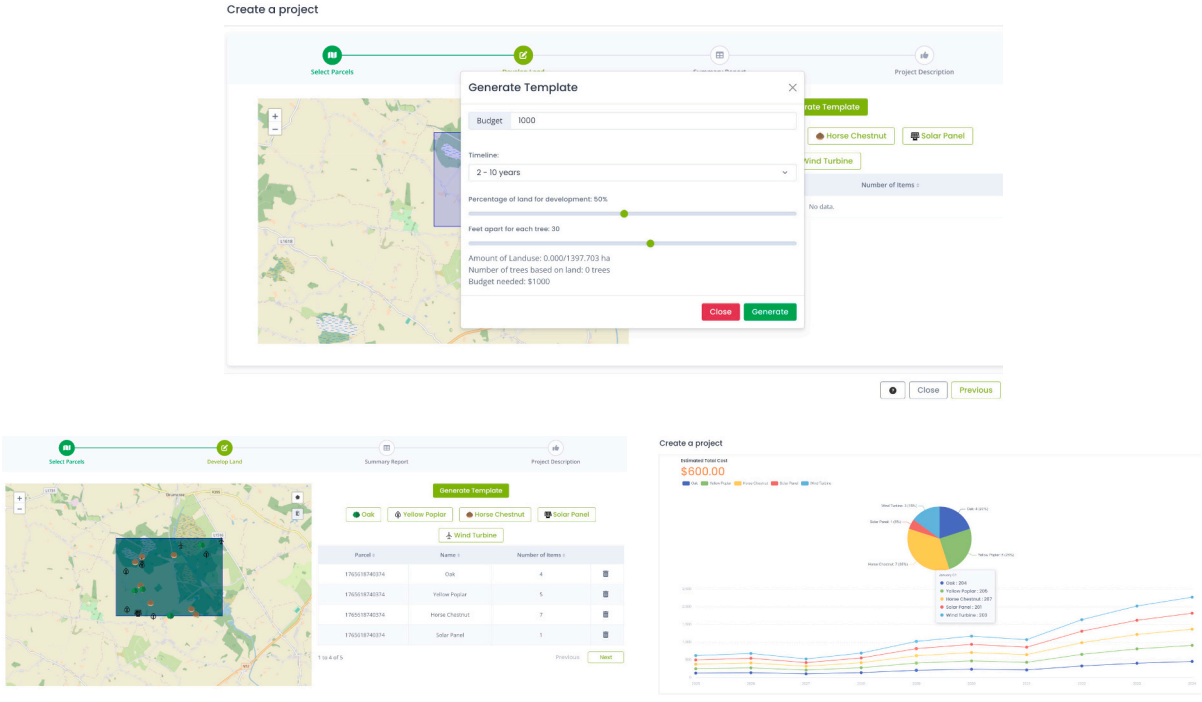
(a) Revised Features for Mapping



(b) Revised Features for Detecting




(c) Revised Features for Estimating




(d) Features for Strategizing

**Fig. 4.** The prototype developed in the second round.

information is available, as shown in Fig. 4 (b). After detecting, additional information for decision-making, including total area, percentage of tree coverage, and statistics on tree heights, is provided, as illustrated in Fig. 4 (c).

To afford *strategizing (DP4)*, we instantiate the material properties of organizing vegetation plantation and sustainable land development activities, which embed both prescriptive and predictive decision support. We begin with developing visualized tools for organizing vegetation plantation and other sustainable land development activities for future carbon stock generation, including planting various types of vegetation and installing solar panels and wind turbines. These land development activities can be organized manually or generated from templates, which incorporate prescriptive capabilities into the system. We acknowledge the complexities of land development, particularly as species variations are region-specific. To surface this challenge, we experiment to provide a list of local vegetation species to facilitate

plantation planning in a specific region, although this feature needs to be tailored based on different contexts.

Building on these features, we build the visualized tools for setting timelines, analyzing costs, and predicting future carbon offsets from carbon stock generation activities, illustrated in Fig. 4 (d). These features represent descriptive and predictive analyses to enable strategizing. Nevertheless, as prices are time-variant and depend on various factors, the tools we developed represent a basic analytical framework rather than a comprehensive system with thorough financial modeling.

Following the second-round development, we conducted the summative evaluation to gather empirical evidence on whether our design goals, enhancing the efficiency, accessibility, and scalability of carbon stock estimation and planning, are achieved [58]. This procedure also allows us to examine the validity of our design knowledge claims [85].

To achieve this, we organize demonstration and evaluation activities that engage our identified stakeholders with different focuses, summarized in Table 6. These activities aim to evaluate whether our affordances can be perceived, what shared understandings are formed, and whether these understandings align with our design goals, which serve as the evaluation criteria.

In December 2024, we conducted the first second-round demonstration and evaluation activity with 10 practitioners at a carbon trading company. Our team presented our design journey and prototypical systems before collecting feedback. As these company leaders and carbon specialists actively engage in on-land development and investment for carbon sequestration, they offer practical perspectives as landholders and investors, with two key insights.

First, they highlight the benefits of reducing time and labor costs by employing such systems for the initial assessment of carbon stock in rural lands and crafting development plans, especially compared to the traditional manual approaches. They acknowledge that this class of systems can enhance the efficiency, accessibility, and scalability of carbon stock estimation and planning in practical settings, providing evidence supporting the criterion validity of our designed artifacts [85]. Second, the practitioners can perceive the affordances and point out the generalizability and adaptability of our design knowledge for applications in other scenarios. For example, as our systems currently focus on trees in forests, they suggest the potential for adaptation to other vegetation types and ecosystems, such as grasses and shrubs in desert areas.

Nevertheless, this demonstration and evaluation activity allows limited time for detailed evaluation and captures only the perspectives of landholders and investors. To collect complementary evidence and validate our findings, we commenced another demonstration and evaluation activity in parallel through longer and more detailed interviews with informants from other stakeholder groups.

These interview sessions were conducted with 16 additional informants representing research and government perspectives, with details listed in Table 7. Each session lasted for one hour on average and was recorded digitally. For each session, we first explored their backgrounds and expertise before proceeding to open-ended questions on environmental sustainability, climate change mitigation, and the role of digital technologies, including AI, in facilitating these processes. We then introduced the informants to our project, guiding them to experiment with and use the two prototypes, and collected their feedback during and after use, leading to in-depth discussions.

After their use, the informants also participated in the survey for quantitatively assessing the system usability. SUS is a widely used Likert scale that includes 10 questions related to usability, with responses ranging from ‘strongly disagree’ to ‘strongly agree’ [59], whose result is a single number representing the overall usability. In our case, the result is 68.21, which indicates our system design passes the benchmark of 68 calculated based on 500 studies [86]. The feedback we received further suggests that this usability can be further enhanced by incorporating more instructions and prompts on the interface to facilitate users. It is also worth noting that the SUS score only reflects system usability and perceived usefulness, rather than indicating scientific accuracy of the estimation results and commercial value of the evaluated systems.

The interview and focus group sessions provide detailed evidence from the perspectives of researchers and practitioners, suggesting that the affordances of mapping, detecting, estimating, and strategizing can be perceived. Furthermore, their actualization in use can enhance transparency, efficiency, accessibility, and scalability of carbon stock estimation and planning, as the expected and unintended outcomes that align with our design goals.

First, they highlight an unintended yet critical outcome of mapping – its role in promoting transparency in carbon initiatives, particularly from the governance perspective. Beyond visualization, mapping based on satellite images captured from space and maintained by independent organizations is seen as a mechanism for ensuring the objectivity of carbon stock data. This objectivity is essential for building trust in carbon offset markets, as it minimizes the risk of data manipulation and supports credible carbon stock assessments. Informant O, a director-level government representative specialized in carbon trading markets and environmental policy, underscored its significance:

> The quality of the data is independently maintained by people who don't profit from it looking better than it is. I think it's a good thing for transparency, right? If a company says they're using this data to estimate the carbon stock that they're saving and that's what they're using, then other people can rely on (it), they know that this data is at least as accurate. Like there's no one creating the data that has an incentive to make it look different than it was.

**Table 6**
Invited stakeholders during the second round demonstration and evaluation.

| Stakeholder Groups | Our focuses | Invited Informants |
|---|---|---|
| Landholders and investors | Evaluating whether the systems can enhance the efficiency, accessibility, and scalability of carbon stock estimation and planning in the practical contexts | Practitioners from a carbon trading company that holds, develops and invests in carbon sequestration on land |
| Governments | Evaluating the systems from the governance and policy-making perspective | A director level government representative specialized in carbon trading markets and environmental policy |
| Researchers in environmental sustainability | Evaluating the design rigor and collecting technical feedback; Assessing the validity of our design knowledge | Researchers in climate risks, SDG, and digital sustainability |

**Table 7**
List of informants for the second round evaluation.

| Informants | Roles | Specialization |
|---|---|---|
| Informant A | Researcher | Climate adaptation, climate risk, electricity price modeling |
| Informant B | Researcher | Digital sustainability in the architecture, engineering, and construction sector |
| Informant C | Researcher | Climate risks, green bond pricing |
| Informant D | Researcher | Climate change and insurance, climate risk, SDG |
| Informant E | Researcher | Digital sustainability, climate change and data science |
| Informant F - L | Researcher | Environmental, Social, and Governance (ESG) |
| Informant M | Researcher | Climate risks |
| Informant N | Practitioner | ESG in the technology industry |
| Informant O | Practitioner | Carbon trading markets and environmental policy in the government |
| Informant P | Researcher | Digital sustainability in the architecture, engineering, and construction sector, AI-based urban planning |

Second, the importance of *detecting* is emphasized, particularly in how it can improve the efficiency and accessibility of carbon stock estimation and planning. Employing AI-enabled detection can reduce both time and costs associated with manual measurements on-site, thereby enhancing efficiency and accessibility. As articulated by Informant N,

> I think the main point is that it can help make the efficiency and processes for users more optimized. Otherwise, in situations where users' financial resources are not very abundant, they would end up investing a lot of labor to physically go to the site, measure vegetation across a city or even larger areas, manually collect data, and then perform calculations. This could incur very high costs. If this task can be solved through a system or AI, it could significantly improve efficiency and greatly reduce overall costs.

Third, they suggest the need for *estimating* carbon stock in the initial assessments and rapid surveys for nature-based carbon projects, aligning with the evidence gathered from the carbon trading company. Such estimation facilitates decision-making, not only for landholders to secure investment, but also for governments to allocate funds, which in turn, promotes the scalability of carbon stock estimation and planning. Informant E, a digital sustainability researcher commented:

> On decarbonization, there is a lot of focus from the government. Allocating funding for these projects on planting trees and all that… apart from organizations, if you're willing to like to go for those. I think this tool will help them because then you can easily say I have this much (carbon stock) of the land.

Last, they endorse the newly introduced affordance of *strategizing*, as the informant P remarked:

> In a way, it could help me to take the right decision…I need some evidence-based recommendations that I could implement the decarbonization initiative.

They also provide extensive feedback for future research based on their expertise. For example, Informant C, a researcher on climate risks and modeling, suggests incorporating region-specific modeling for extreme weather events such as bushfires and flooding. Informant P, a researcher on AI-based urban planning, suggests embedding generative AI to facilitate planning for carbon-generation activities. These domain-specific suggestions also reflect the complexities of contextualized strategizing. To capture and address these complexities comprehensively, human expertise should be combined with AI-based DSS. Fundamentally, human and AI are complementary in shaping decision-making outcomes through distinct information access and processing approaches [87]. In carbon stock estimation and planning, human expertise such as vegetation planting, financial budgeting, and stakeholder engagement complements AI-based DSS for more effective decision-making. Furthermore, recursive interaction between human and AI is essential for supervising tasks, implementing actions, and improving decisions in practice [88].

The evidence from the demonstration and evaluation activities suggests that our identified stakeholders can perceive the affordances and form a shared understanding that our design goals are achieved when the systems can enhance the efficiency, accessibility, and scalability of carbon stock estimation and planning, further supporting the criterion validation of our design knowledge. Improved transparency also emerged as an unintended outcome from the government perspective.

Building on our design journey, we present our final set of design principles in Table 8, based on the design principle schema [32], with examples included to guide future design projects.

**Table 8**
The final set of design principles.

| | |
|---|---|
| **DP1: Principle of Mapping** | |
| Aim, Implementer, and User | For designers (implementers) to build mapping tools in AI-based DSS for carbon stock estimation and planning (aim) for use by landholders, investors, and governments (users) |
| Context | In carbon stock estimation and planning |
| Mechanism | Navigate to and specify areas of interests on the interactive map |
| Rationale | Because mapping allows users to perceive and specify their areas of interests with visual experience, and promotes transparency for governance |
| Example Features for Future Design | An interactive map loading the latest satellite images in real time; A display of 3D image construction of selected areas of interests |
| **DP2: Principle of Detecting** | |
| Aim, Implementer, and User | For designers (implementers) to integrate CNNs for detecting vegetation features in AI-based DSS for carbon stock estimation and planning (aim) for use by landholders, investors, and governments (users) |
| Context | In carbon stock estimation and planning |
| Mechanism | Automatically detect the vegetation features on remote sensing images |
| Rationale | Because detecting using CNNs enhances efficiency, reduces costs, and broadens access to areas that are otherwise difficult to reach for collecting data on vegetation features, compared to traditional field measurements |
| Example Features for Future Design | Trained CNNs for vegetation detection based on species in ecosystems including deserts, wetlands, and ocean |
| **DP3: Principle of Estimating** | |
| Aim, Implementer, and User | For designers (implementers) to provide carbon stock information in AI-based DSS for carbon stock estimation and planning (aim) for use by landholders, investors, and governments (users) |
| Context | In carbon stock estimation and planning |
| Mechanism | Quantify and display the estimated carbon stock based on detected vegetation features and other relevant data |
| Rationale | Because estimating carbon stock based on detected vegetation features improves efficiency and reduces costs for gaining the key information on the current status and supporting decision-making for carbon trading |
| Example Features for Future Design | An enhanced estimation algorithm based on more metrics obtained from the detected vegetation |
| **DP4: Principle of Strategizing** | |
| Aim, Implementer, and User | For designers (implementers) to design tools for organizing carbon stock generation activities in AI-based DSS for carbon stock estimation and planning (aim) for use by landholders, investors, and governments (users) |
| Context | In carbon stock estimation and planning |
| Mechanism | Strategize carbon stock generation activities with descriptive, predictive, and prescriptive capabilities covering environmental and financial aspects |
| Rationale | Because strategizing facilitates organizing future oriented vegetation planation and sustainable land use activities, which are contextually constrained by ecological conditions and financial resources |
| Example Features for Future Design | An optimization-based recommendation system that include financial management and value prediction; An AI-based chatbot that allows effective incorporation of human expertise for planning |

## 7. Discussion

This study presents a DSR journey for designing AI-based DSS to enhance carbon sequestration, directly contributing to SDG 13. It serves as a DSR exemplar, motivated by the pressing societal challenge of climate change, and demonstrates how DSR can provide both design knowledge and system solutions that facilitate societal transitions toward environmental sustainability. By integrating AI into DSS for carbon stock estimation and planning, this study illustrates how DSR can extend existing design knowledge base while addressing real-world environmental challenges.

### 7.1. Theoretical implications

First, this study responds to the calls for creating IS solutions to tackle climate change [18,19,26] by contributing to the growing design knowledge base for environmental sustainability [22,23,33,34]. Focusing on a critical problem domain, carbon stock estimation and planning for effective carbon sequestration [7,89], we identify acquiring the key environmental information as the primary and distinct obstacle to initiating decision-making. To address this through system solutions, we theorize the key affordances that enable decision-making in this problem domain. Correspondingly, in the solution domain, we consolidate four sequential design principles for AI-based DSS that can be applied and extended to other scenarios in carbon stock estimation and planning, such as mangroves in marine ecosystems [90], and seagrasses in coastal ecosystems [91]. More broadly, the design knowledge of this study extends our understanding of the problem and solution domains of designing IS for environmental sustainability by leveraging AI to process critical environmental information and initiate planning.

Second, this study contributes to the emerging discourse on the role of AI in decision-making, specifically on balancing AI and human intelligence in designing DSS for complex challenges [25,28]. We employ CNNs to extend human perception, which captures vegetation features as the heuristics for quantifying carbon stock [67]. Although this approach is still bounded by the availability of large-scale and high-quality remote sensing data, it can effectively enhance the efficiency, accessibility, and scalability of obtaining descriptive information for decision-making. This aligns with the primary role of AI in transforming information and augmenting decision-making by reducing repetitive tasks [25]. Nevertheless, despite the exponential growth of AI-driven autonomous decision-making across various applications [25,92], integrating AI for prescriptive decision-making remains challenging in our context. The complexities of environmental sustainability planning emerge from the intersection of dynamic ecosystems, constrained resources, and ever-evolving policies, posing significant challenges to relying solely on AI for prescriptive analysis and intervention implementation. Overall, this study explores design paths that balance human expertise and AI in decision-making for environmental sustainability [28].

Third, technology affordance has played a significant role in guiding the evolution of system design throughout the iterative DSR process. As affordance-based design and the DSR process are closely aligned, affordances underpin the system design and development while being iteratively refined through demonstration and evaluation. This suggests that affordance-based DSR allows system design to remain focused on key affordances while providing a variety of instantiation possibilities depending on specific contexts [93]. In this study, theorizing the affordances enables us to identify the core improvement needed and progress to the next phase. Specifically, we found that our initial affordances focused only on enabling descriptive decision-making for assessing current states, without incorporating predictive and prescriptive aspects crucial for planning future states and supporting long-term sustainability goals. Nevertheless, this approach can introduce ambiguity when prioritizing design decisions. For instance, identifying strategizing as an additional affordance creates multiple potential development paths and leads to challenges for instantiation. In addition, as AI is evolving rapidly, the mismatch between AI development timelines and the longer-cycled DSR process can create potential lags for designing AI-based systems.

### 7.2. Practical implications

For landholders and investors, AI-based DSS can support efficient land assessment and exploration of development strategies at lower costs, improving access to participation in carbon trading markets and climate change mitigation activities. For governments, AI-based DSS can support monitoring nature-based projects at scale and detecting potential fraudulence, enabling more transparent and effective governance of carbon initiatives. Collectively, by improving the efficiency, accessibility, and scalability of carbon stock estimation and planning, this study can enable climate change mitigation activities and facilitate transitions toward environmental sustainability.

### 7.3. Limitations and future research

We acknowledge that our approach to estimating carbon stock is a heuristic proxy that embeds methodological constraints and validation challenges. While the performance of CNNs can be validated against ground truth, it depends on the quality and scale of annotated remote sensing data. Furthermore, although field measurements for carbon stock are available for specific regions, they are collected at certain timepoints and cannot fully capture the dynamics of natural ecosystems [63,72]. As a result, the ground truth of carbon stock at the global scale remains fundamentally unknown. In addition, this study only explores one instantiation pathway of our proposed design principles, i.e., CNNs-based semantic segmentation for trees in terrestrial forests.

These limitations indicate the following directions for future research. First, the accuracy of carbon stock estimation can be further enhanced by curating drone imagery data and employing techniques including 2D—3D image reconstruction to extract more comprehensive information. Second, future studies can transcend the geographical boundary conditions of this study to focus on diverse vegetation types and ecosystems by acquiring novel datasets, fine-tuning models, and implementing alternative image detection approaches. Lastly, future design projects can integrate generative AI for providing recommendations and modeling scenarios, allowing benchmarking of AI-driven prescriptive decision-making against human-centric strategizing.

## 8. Conclusion

Carbon stock estimation and planning is essential for climate change mitigation, a pressing sustainability challenge. This study responds to the need for innovative IS solutions by developing AI-based DSS to address this challenge through the DSR approach. Using technology affordance theory, we conceptualize key affordances to understand the problem domain, which also guided two cycles of design, development, demonstration, and evaluation. Through this process, we developed two prototypes and refined four affordance-based design principles of mapping, detecting, estimating, and strategizing. This study serves as an example of how DSR can be adopted to tackle pressing societal challenges. Specifically, we advance the design knowledge base for environmental sustainability by focusing on obtaining critical environmental information, i.e., carbon stock, and explore how AI and human intelligence can be balanced in designing DSS for complex decision-making. Alongside its practical impact, we hope this research inspires further studies using the DSR approach to create solutions for addressing societal challenges and fosters discussion on effectively integrating AI into system design for complex decision-making problems.

## CRediT authorship contribution statement

**Amelia S. Li:** Writing – original draft, Formal analysis, Data curation, Conceptualization. **Shan L. Pan:** Supervision, Resources, Methodology, Investigation, Conceptualization. **Yenni Tim:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Hoang D. Nguyen:** Writing – review & editing, Software, Resources, Methodology, Data curation.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

the work reported in this paper.

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