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Synthesis

Tension between opportunities and risks of deep learning in social-ecological systems research

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ABSTRACT. Deep learning is rapidly reshaping many scientific disciplines, yet often the speed of change in the algorithmic landscape outpaces critical reflection on the epistemological implications of this paradigm shift. Social-ecological systems (SES) present a uniquely tense setting for deep learning's promise and risk: although deep learning may facilitate methodological leaps in SES research by mitigating challenges that have been traditionally intractable, these advances may widen epistemological rifts in this multi-disciplinary field. Deep learning accelerates data translation and enables fluid movement of information between qualitative and quantitative domains, helping to resolve mismatches in the nature and scale of social and ecological data and ultimately supporting integrated, whole-system analysis. However, the nature of deep learning algorithms and architectures aligns closely with a positivist epistemology focused on objectivity, trends, and abstractions, at the expense of approaches focused on reflexivity, context, and nuance. Deep learning may therefore exacerbate existing SES challenges in merging ecological and social research paradigms. We conclude with a perspective on the future of deep learning in SES research that may leverage technological advances, while enabling critical interrogation of deep learning algorithms.

Key Words: *artificial intelligence; big data; deep learning; process-relational thinking; social-ecological systems; sustainability*

INTRODUCTION

Deep learning (DL) is reshaping the way researchers interact with data, sparking breakthroughs across many domains through improved processing of images, text, and audio (Table 1, Box 1; Bickel 2017, Grossmann et al. 2023). These shifts are especially valuable in the era of the data revolution, marked by ever-increasing data volume, velocity, and variety, that has given rise to massive amounts of unstructured data (Bell et al. 2009). Although these paradigm shifts hold significant consequences for most scientific fields, the implications will vary depending on disciplinary methods and theory, creating a need for field-specific evaluation of risks and opportunities.

The implications of the DL revolution for the study of social-ecological systems (SES) are wide-reaching, with key opportunities to mitigate the persistent challenges of understanding SES as complex adaptive systems shaped by dynamic human-nature interactions (Kittinger et al. 2013). Social-ecological systems contain inseparable, coupled human and natural subsystems that interact to produce outcomes and feedbacks at the SES level (Ostrom 2009). Failure to comprehensively consider both human and ecological components can lead to a failure of management and loss of resilience and sustainability (Carpenter et al. 2006). A lack of frameworks and models linking different kinds of data presents a key barrier to understanding the complexity of SES (Haapasaari et al. 2012). This limitation is largely driven by a mismatch in the nature of quantitative ecological metrics and qualitative social information (Redman et al. 2004, Marshall et al. 2018, Meredith et al. 2022). Additionally, embracing an integrative, complex systems view of a SES requires transcending traditional disciplinary boundaries and incorporating theories and frameworks from both the natural and social sciences (Brunson 2012, Barnes et al. 2019). However, integrating knowledge and ways of knowing from diverse actors presents epistemological and ontological challenges, with interdisciplinary science and management often hindered by disciplinary differences in research paradigms and approaches (Levin et al. 2016, Blythe et al. 2017).

Changes in the nature and availability of data, as well as the DL approaches used to take advantage of these changes, extend across all fields that SES is built upon. For example, ecological sciences have moved toward automated data collection and analysis pipelines to estimate biodiversity (Christin et al. 2019, Serra-Marin et al. 2025; Choton et al. 2025, *unpublished manuscript*) and detect, track, and classify species (Farley et al. 2018, Besson et al. 2022). In the field of GeoAI (Li and Hsu 2022), the integration of deep learning with geospatial data, such as satellite remote sensing imagery, has allowed researchers to predict wildlife risk (Ghali and Akhloufi 2023), classify land use (Kussul et al. 2017), and develop general purpose location embeddings that can be used to estimate social and environmental conditions in data-limited regions (Rolf et al. 2021, Brown et al. 2025, *unpublished manuscript*). Similarly, a deluge of text representing the social world has emerged from the digitization of policy and cultural documents (Ducre and Moore 2011, Shimizu et al. 2020), as well as networked digital communications that create long-term records of social interactions (Liu et al. 2015). Natural language processing has been used to categorize and label this data at scale (Grimmer et al. 2022).

In contrast, the application of DL for understanding interactions between social and ecological systems is limited relative to its use within each subsystem, largely because SES problems are often

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Table 1. Glossary of key concepts in social-ecological systems research and deep learning used in this paper.

Concepts in social-ecological systems research	
Social-ecological system	"[Social-ecological systems (SES)] are composed of multiple subsystems... such as a resource system, resource units, users, and governance systems [that] are relatively separable but interact to produce outcomes at the SES level, which in turn feed back to affect these subsystems and their components, as well as other larger or smaller SESs" (Ostrom 2009:419).
Epistemology	The nature or theory of knowledge. A philosophical concept for "how we know what we know," i.e. "a way of looking at the world and making sense of it" (Al-Ababneh 2020:77).
Ontology	"The nature of reality" (Al-Ababneh 2020:76). The philosophical study of being.
Positivism	"Positivism provides assurance of unambiguous and accurate knowledge of the world... In the positivism philosophy, researchers deal with issues objectively without impacting the real problem being studied. Thus, positivism philosophy needs very well structured methodology, quantifiable observations and statistical analysis... Consequently, positivism supposes that researchers make an objective analysis and interpretation for collected data" (Al-Ababneh 2020:79-80).
Social constructivism	"Constructivism proposes that each individual mentally constructs the world of experience through cognitive processes. It differs from the scientific orthodoxy of logical positivism in its contention that the world cannot be known directly, but rather by the construction imposed on it by the mind" (Young and Collin 2004:375).
Mental model	A concept that can "broaden the rarefied, abstract notion of philosophical paradigm to reflect the more grounded, intuitive, dialogic notion of a mental model as the underlying framework or logic of justification for social research" (Greene 2007:53).
Process-relational thinking	"[Conceptual framework that takes] processes and relations as the main constituents of reality instead of fundamental substances or essences" (Garcia et al. 2020:221). "Rather than specifying as the basic unit of analysis 'the social' and 'the ecological' as separate and stable entities that may interact, relational approaches start from social-material processes or ways of becoming from which entities emerge and manifest as stable. Relational perspectives are particularly aware of the role research and researchers play in constructing entities" (Klein et al. 2024:1-2).
Inductive vs. deductive reasoning	"Induction, or inductive reasoning, involves the identification of cues and the collection of data to develop general theories or hypotheses. For this reason, inductive reasoning is often described as being 'bottom-up' reasoning... deductive reasoning can be viewed as the opposite to induction, with specific conclusions drawn from general theories. So... deductive reasoning can be viewed as 'top-down'... Induction allows us to build theory from data, and deduction allows us to test theory and hypotheses (Barrett and Younas 2024:6).
Saturation	"A methodological principle in qualitative research. It is commonly taken to indicate that, on the basis of the data that have been collected or analysed hitherto, further data collection and/or analysis are unnecessary... From a grounded theory standpoint... 'the point in coding when you find that no new codes occur in the data'" (Saunders et al. 2018:1893).
Concepts in deep learning	
Neural networks and hidden layers	"Neural networks are models that process information in a way inspired by biological processes, with highly interconnected processing units called neurons working together to solve problems. Neural networks have three main parts: (a) an input layer that receives the data, (b) an output layer that gives the result of the model, and (c) the processing core that contains one or more hidden layers. What differentiates a conventional neural network from a deep one is the number of hidden layers, which represents the depth of the network. Unfortunately, there is no consensus on how many hidden layers are required to differentiate a shallow from a deep neural network" (Christin et al. 2019:1633).
Black box	When the "internal logic and inner workings [of a machine learning system] are hidden to the user and even experts cannot fully understand the rationale behind their predictions" (Carvalho et al. 2019:1). "In AI, the difficulty for the system to provide a suitable explanation for how it arrived at an answer is referred to as 'the black-box problem'" (Adadi and Berrada 2018:52138).
Feature	"An attribute, characteristic or measurable property of an object that is being observed" (Dhal and Azad 2022:4544).
Embedding	"[An embedding] stores the main characteristics of data by mapping it onto a [low-dimensional] numerical vector" (Dai et al. 2022:307).
Foundation model	A model "trained on broad data (generally using self-supervision at scale) that can be adapted to a wide range of downstream tasks... their scale results in new emergent capabilities, and their effectiveness across so many tasks incentivizes homogenization. Homogenization provides powerful leverage but demands caution, as the defects of the foundation model are inherited by all the adapted models downstream" (Bommasani et al. 2021, *unpublished manuscript*).
Natural language processing	"Natural language processing employs computational techniques for the purpose of learning, understanding, and producing human language content" (Hirschberg and Manning 2015:261).
Text mining	"Text mining refers generally to the process of extracting interesting information and knowledge from unstructured text" (Hotho et al. 2005:19).
Language models and large language models (LLMs)	Language models "modeling the generative likelihood of word sequences, predicting the probabilities of upcoming or missing [sections of text]... Large language models (LLMs) achieve substantially enhanced capabilities by scaling up model size, training data, and computational resources in accordance with established scaling laws ... The transformative potential of LLMs became widely recognized with the launch of ChatGPT, an advanced dialogue-oriented model that sparked global interest in generative AI" (Zhao et al. 2026:2-3).
Multimodal machine learning	"Our experience of the world is multimodal - we see objects, hear sounds, feel texture, smell odors, and taste flavors. Modality refers to the way in which something happens or is experienced and a research problem is characterized as multimodal when it includes multiple such modalities... Multimodal machine learning aims to build models that can process and relate information from multiple modalities" (Baltrušaitis et al. 2019:423).
Explainable/ interpretable AI/ML	"Interpretable machine learning tackles the important problem that humans cannot understand the behaviors of complex machine learning models and how these models arrive at a particular decision.... [Interpretable machine learning] gives machine learning models the ability to explain or to present their behaviors in understandable terms to humans, which is named interpretability or explainability" (Du et al. 2019:69).
Human-in-the-loop	"Researchers are defining new types of interactions between humans and machine learning algorithms, which we can group under the umbrella term of Human-in-the-loop machine learning (HITL-ML)... Depending on who is in control of the learning process, we can identify different approaches to HITL-ML. [For example, with machine teaching (MT)], human domain experts have control over the learning process by delimiting the knowledge that they intend to transfer to the machine learning model" (Mosqueira-Rey et al. 2023:3005-3006).
Chain of thought (CoT) prompting	An approach in which large language models "perform few-shot prompting for reasoning tasks, given a prompt that consists of triples: {input, chain of thought, output}. A chain of thought is a series of intermediate natural language reasoning steps that lead to the final output" (Wei et al. 2022:24825).
Retrieval- augmented generation (RAG)	An approach to augmenting language model agents "with external databases and information retrieval tools... This method can alleviate hallucinations and outperforms traditional fine-tuning methods by integrating external knowledge more effectively, particularly for applications demanding high accuracy and up-to-date information" (Sanmartin 2024, *unpublished manuscript*).

characterized by interdependent dynamics that are difficult to address using a single model. However, some existing applications of DL have demonstrated that DL can offer complementary perspectives to support SES management and decision making (Appendix 1). For example, agent-based models (ABM) have integrated DL to improve optimization procedures, thereby increasing the ability to assess management strategies and understand emergent properties of SES (Bone and Dragićević 2010). Additionally, deep reinforcement learning approaches decision problems through a lens similar to adaptive environmental management, offering the potential to inform effective decisions in complex social and ecological environments (Chapman et al. 2023). As DL increasingly reshapes methods and workflows of SES research, important epistemological and ethical questions must be considered, including what kinds of knowledge are produced, whose perspectives are prioritized, and how uncertainty is handled in such AI-driven approaches (Maitra 2020, Cheng et al. 2021, Ahmed et al. 2023).

Because the analysis of coupled human-natural systems is fundamentally distinct from analyses within each subsystem, the opportunities and risks presented by DL approaches in SES are also distinct from those discussed within discipline-specific social or ecological research. Here we present a conceptual outline of a tension presented by the application of DL in SES: while DL increases the fluidity and malleability of information to resolve mismatches in SES data, the inherent properties of DL algorithms align with only a subset of the diverse epistemological approaches within SES research. Consequently, this limitation may reinforce biases toward ways of knowing that prioritize objectivity and abstraction, while marginalizing approaches grounded in contextual, relational, or situated knowledge. How these opportunities and risks interact have important implications for realizing the benefits of technological advances, while ensuring productive progress as an integrated, pluralistic field.

As a heterogeneous group of scholars, we combine interdisciplinary backgrounds in environmental data science, artificial intelligence, geography, socioeconomics, and natural resource management. Our team was brought together by the 2025 Environmental Data Science Summit hosted by the National Center for Ecological Analysis and Synthesis (NCEAS), where we identified a shared interest in understanding how deep learning may reshape research at the intersection of social and ecological systems. We have explored the opportunities and risks of DL for SES research through review of literature and iterative discussions. Below, we highlight ways in which DL facilitates or inhibits integration of disparate data and ways of knowing (Fig. 1), and we conclude with a perspective on the future of DL as an integrated tool in SES research workflows (Fig. 2).

Box 1: What exactly is deep learning? Deep learning (DL) is a subset of a broader family of machine learning approaches. Machine learning (ML) broadly refers to algorithms with the capacity to detect patterns in data and generate models automatically, allowing users to identify relationships of undefined functional forms in large datasets (Mohammed et al. 2016). In the field of SES, ML approaches have long been used for dataset dimensionality reduction (e.g., principal component analysis, Shumway et al. 2014), data clustering (e.g., K-means, Cattau et al. 2022), and regression and prediction tasks (e.g., random forests, Sanchez-Cuervo and Aide 2013). A key distinction between ML and DL algorithms is the capacity of DL to automatically learn and detect non-specified patterns ("features") in raw data (LeCun et al. 2015). To do so, DL algorithms use complex architectures with many "hidden layers" to learn more complex relationships between inputs and outputs, a mechanism that requires large amounts of training data and computational resources (Robles Herrera et al. 2022). Examples of common DL algorithms include generative adversarial networks (GANs) and convolutional and recurrent neural networks (CNNs/RNNs; Shrestha and Mahmood 2019), and the transformer networks often used in large language models (LLMs) (Vaswani et al. 2017).

Take, for instance, the exercise of identifying areas impacted by wildfires using remotely sensed imagery in order to plan post-fire management. For a traditional ML approach, a user would need to manually extract features of interest from imagery prior to analysis based on pre-existing knowledge about the system (e.g., spectral indices, topographic features, or textural metrics; e.g., Roodsarabi et al. 2025). However, using DL approaches, a user could provide raw imagery with minimal pre-processing, from which an algorithm would learn the relevant spatial, spectral, and textural patterns associated with the provided training data (e.g., Alkan and Karasaka 2024).

OPPORTUNITIES: RESOLVING MISMATCHES IN THE NATURE, VOLUME, AND RESOLUTION OF SES DATA

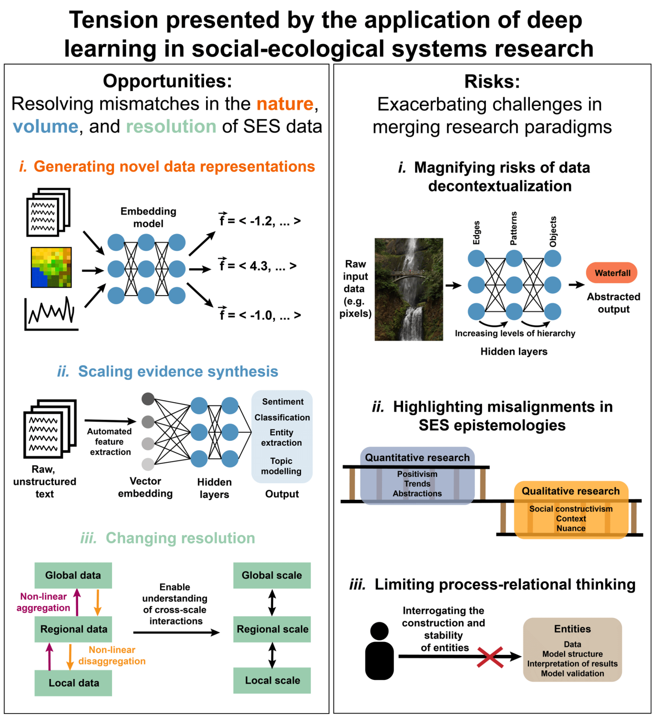
Analyzing social-ecological systems involves mixing information representing social and ecological processes, yielding data heterogeneity that has historically prohibited meaningful integration at scale. This heterogeneity includes mismatches in data nature (i.e., qualitative vs. quantitative), volume (i.e., natural science data outpacing social science data), and resolution (i.e., differing spatial and temporal resolutions of ecological and social processes) that challenge translation across datasets. By accelerating the transformation of data, DL can mitigate some of these challenges.

Achieving data fluidity

The nature of data is not a fixed quality: while the structure and character of data is often understood as either quantitative or qualitative, mixed-methods scholars are increasingly referring to this nature not as an inherent property of data, but instead as an attribute of a transformed representation (Valsiner 2000, Schoonenboom 2023). Sandelowski (2014) states that data are neither quantitative nor qualitative, but rather "aspects of experiences or phenomena transformed into words, numbers, visual forms...each of which may in turn be transformed again into other forms" (Sandelowski 2014:5).

Deep learning algorithms and architectures are particularly effective at realizing this fluidity of form (Fig. 1, Opportunities item *i*). These algorithms are well suited for analyzing large volumes of raw data in diverse formats, uncovering complex data patterns, and extracting novel data representations (Najafabadi et al. 2015). By both accelerating the speed and robustness of data transformation and creating new pathways between qualitative and quantitative attributes, information can move more freely between qualitative and quantitative domains and exist in liminal spaces necessary for fostering communication among disciplines (Van Pelt et al. 2015). For example, harmonization across data modalities to create a common semantic space, referred to as "multimodal ML," has been applied to environmental challenges, including predicting air pollution by combining numerical and image data (Ko and Jung 2022) and developing disaster response planning support using image, text, and statistical data (Ochoa and Comes 2021, *unpublished manuscript*). Although existing applications of DL in environmental science typically involve conversion of text, image, and audio information into numerical formats, there are opportunities for other modes of DL-based data translation, like natural language generation or audio

Fig. 1. Conceptual figure highlighting the trade-off between opportunities and risks with the application of deep learning in social-ecological systems research. Opportunities: (i) Embeddings are common inputs to deep learning algorithms that represent complex, high-dimensional, diverse data in a unified, low-dimensional space. (ii) Deep learning automates the process of discovering features in the data, which allows processing of highly unstructured data. (iii) Deep learning algorithms can be used to find non-linear mappings across spatial and temporal resolutions. Risks: (i) Deep learning neural network layers are hierarchical, corresponding to successive levels of abstraction that may yield decontextualized outputs. (ii) Deep learning can widen rifts between epistemologies across social-ecological systems (SES) sub-disciplines. (iii) The opacity of deep neural networks limits critical interrogation associated with process-relational thinking.



generation from images, that may expand the use of DL in SES research beyond the quantification of non-numerical data formats (He and Deng 2017, Guei et al. 2024).

Broadening evidence synthesis

The efficiency of DL-based evidence synthesis provides opportunities to broaden the types of data that SES research can gather (Chang et al. 2025), allowing data representing social dimensions to better match the volume of the field, sensor, and satellite data typically used to represent ecological dimensions (Fig. 1, Opportunities item *ii*). As DL has become a dominant approach in natural language processing (NLP) and text mining, these DL-based language models can support systematic identification and retrieval of unstructured text data from various sources such as social media, news articles, and policy documents that represent social dimensions of SES research (Bickel 2017, Farrell et al. 2024). The speed of text coding increases by orders of magnitude when DL-based NLP replaces or augments manual methods (Grimmer et al. 2022, Ash and Hansen 2023), and by detecting recurring keywords and themes across data, text mining can help researchers assess whether data collection has achieved saturation (Christou 2025).

Similarly, applications of computer vision (CV) in SES increasingly enable automated processing and analysis of heterogeneous image data (Richards and Tunçer 2018, Spiesman et al. 2024). Deep learning architectures like convolutional neural networks (CNNs) can allow image analysis at large scales, providing opportunities to leverage vast public datasets, like Flickr and Instagram, to evaluate public attitudes toward environmental issues (Cardoso et al. 2022, Xu et al. 2025). Beyond expanding sample size, these DL models also promote evidence synthesis by using large volumes of standardized public data to replace private data that often have inconsistent formats and qualities (Kroodsma et al. 2018).

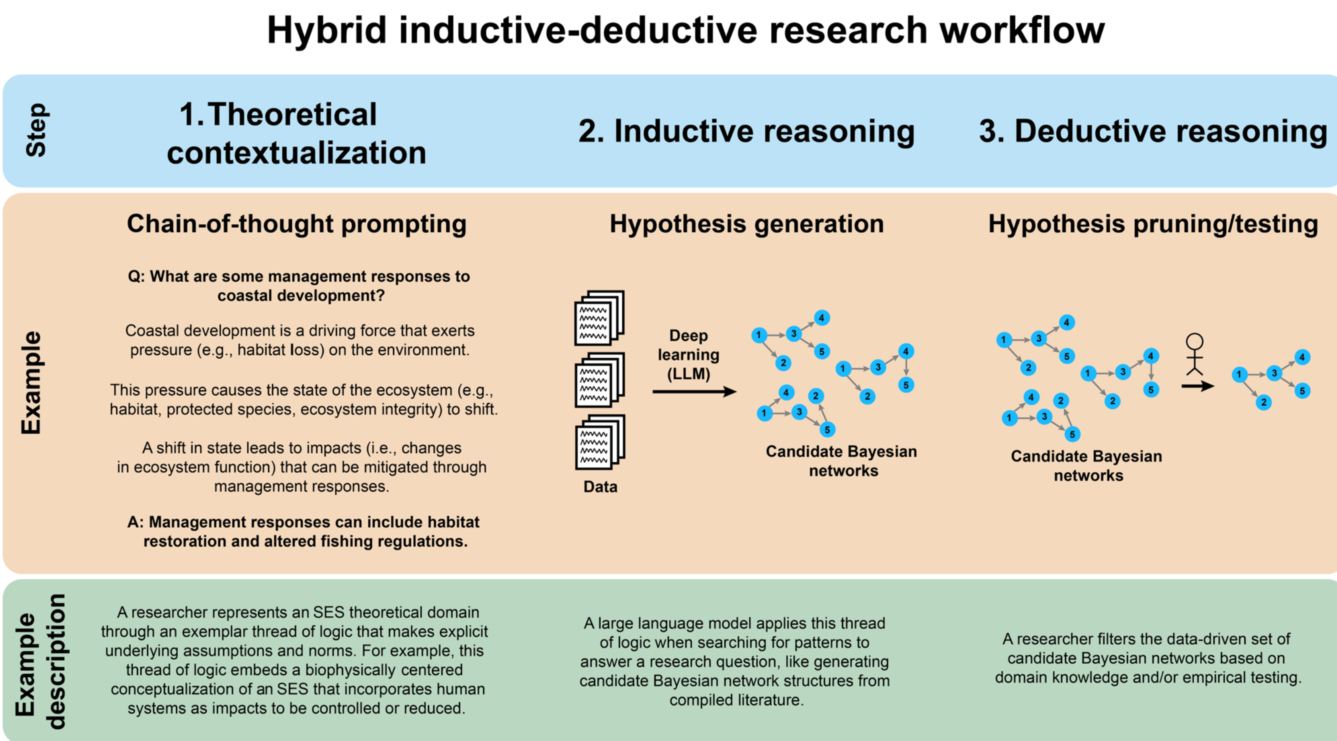
Advances in deep learning toward foundation models are the present state of the art in AI, but are not yet widely applied in SES disciplines (Han et al. 2023, Morera 2024). Foundation models are trained on massive datasets and then fine-tuned on smaller, task-specific datasets to retain their generalizability while improving performance on particular tasks (Bommasani et al. 2021, *unpublished manuscript*). In this way, the volume and multimodality underlying the foundational model can be later used to extract more detailed or nuanced information from sparse datasets (Doherty et al. 2024). We expect adoption of foundation models in SES to expand rapid, multi-format evidence synthesis.

Changing resolution

Cross-scale interactions are a characteristic feature of social-ecological systems, as the way in which social and ecological systems change over time often arises from their interactions with phenomena at other spatial and temporal scales (Scholes et al. 2013). Socioeconomic components commonly act at different scales from natural systems (Bergsten et al. 2014), and the spatial and temporal resolutions of data across these subsystems are not always aligned (Cumming et al. 2006). For example, observation systems for ecosystem services often gather and express data at multiple scales: data such as landcover maps can range from resolutions of a few meters to several kilometers, while human development datasets are often aggregated to or reported at socially relevant units, such as that of provinces, states, or municipalities (Scholes et al. 2013).

Aggregation and disaggregation are common statistical methods used to probabilistically achieve finer or coarser resolution of information. The SES field can take advantage of DL methods used to disaggregate or aggregate data between different spatial or temporal scales using the structure and known associations of subresolution phenomena (Fig. 1, Opportunities item *iii*). Such methods are increasingly adopted in climate science; for example, artificial neural networks have been applied to temporally disaggregate rainfall time series data from hourly to sub-hourly time increments (Burian et al. 2001, Nourani and Farboudfam 2019). As the scaling rules across SES scales are often complex and nonlinear (Gonzalez et al. 2020), the flexible and nonlinear data processing layers associated with deep neural networks hold promise for translating information across SES resolutions and enabling understanding across scales (Allen and Starr 2017).

Fig. 2. Deep-learning embedded research workflow, progressing from theoretical contextualization, to data-driven inductive reasoning, and finally deductive reasoning. An example includes (1) A researcher incorporates chain-of-thought prompting to structure a large language model's (LLM) reasoning and logic and make explicit underlying norms and assumptions, as well as a researcher's positionality and infusion of values. Here, a researcher specifies an example logical structure between a question and answer, making explicit the theories brought to the research question. The example is adapted from the Driver-Pressure-State-Impact-Response (DPSIR) framework described by Levin et al. 2016. (2) A large language model applies this theoretical domain while learning Bayesian network structure from text data. (3) A researcher reduces the set of Bayesian network structure hypotheses through incorporation of domain knowledge or empirical testing.



RISKS: FAVORING GENERALIZATION AND POSITIVIST APPROACHES AT THE EXPENSE OF CONTEXT AND NUANCE

Aligned data is only one piece of SES research, as the multi-dimensional nature of SES involves not only mixing heterogeneous data but also mixing heterogeneous epistemological and methodological styles (Brunson 2012, Barnes et al. 2019). Much of this heterogeneity is rooted in differences in how generalization and individual understanding is valued. The very nature of deep learning algorithms and their ability to accelerate and expand the scope of analyses may exacerbate misalignments in epistemologies and reinforce biases toward certain ways of knowing.

Magnifying risks of decontextualization

Spatiotemporal and cultural context is essential to ethical use of SES data because data can reflect legacies of social and political structures (Ellis-Soto et al. 2023) and environmental histories (Turner et al. 2020, Francois et al. 2025). Decontextualized data, particularly those that influence policy decisions, jeopardize the CARE (Collective Benefit, Authority to Control, Responsibility, Ethics) and FAIR (Findable, Accessible, Interoperable, Reusable) data principles (Carroll et al. 2020) and risk entrenching social and political inequities or misdirecting critical resources (Chapman et al. 2024). Abstraction is a fundamental characteristic of neural network-based approaches, with hierarchical layers transforming input data and extracting features at increasing distances from its original form (Ilin et al. 2017; Fig. 1, Risks item *i*). Even with traditional methods, meaning and context can be lost during data transformation (Schoonenboom 2023), and deep learning magnifies risks associated with decontextualization because of its reliance on abstraction. Transferability, or the ability to reuse knowledge from previous learning experiences when encountering unseen tasks, is also a key focus of deep learning algorithm development (Jiang et al. 2022, *unpublished manuscript*). However, SES behavior is often determined by context-specific, complex interactions, challenging this assumption that knowledge can feasibly be transferred from one SES context or geography to another (Magliocca et al. 2018, Nagel and Partelow 2022).

The large volume of data that deep learning algorithms require may mark a shift toward generalized, broad-scale inquiry that can be misaligned with common goals of SES research related to context-dependent processes. The large-scale datasets used in DL can be useful for understanding broad spatial and temporal patterns (Hansen et al. 2013) yet can be inadequate for causally linking social and ecological processes to observable, context-dependent conditions (Rindfuss et al. 2004, Magliocca et al. 2018). These large datasets also often inherently favor high-resource geographies and exclude many critical SES contexts in the Global South. For example, biodiversity data available in the Global Biodiversity Information Facility (GBIF) more closely trace macroeconomic patterns rather than latitudinal gradients of biodiversity (Chapman et al. 2024). Similarly, certain phenomena, like traditional livelihood activities and non-agricultural land-use, can remain undetected in global remote-sensing datasets (Fagan et al. 2026). Although emerging DL methods seek to better fill this gap (e.g., Rolf et. al. 2021), this selection bias can not only exacerbate global research inequalities but also introduce challenges of studying SESs as integrated wholes, where humans are embedded in both ecosystems and data-generating processes.

Additionally, English pretrained language models make up the backbone of many modern natural language processing systems (Blevins and Zettlemoyer 2022), which thus tend to exhibit cultural values more strongly associated with English-speaking and Protestant European countries (Tao et al. 2024) and overlook lower-resourced regions of high linguistic diversity, like Africa and South and Central Americas (Hadgu et al. 2023). This cultural and linguistic bias risks cultural misalignment when analyzing data from diverse cultural contexts and can exacerbate systemic bias already present in Eurocentric scientific communities and data.

Highlighting epistemological differences across SES sub-disciplines

Ecological and social sciences have largely developed independently (Ostrom 2009), resulting in epistemological differences across SES sub-disciplines, particularly along qualitative-quantitative lines. Quantitative and qualitative practitioners tend to approach research with different "mental models," or underlying frameworks and logics of justification for research (Greene 2007). Although quantitative and qualitative methods are not inherently incongruous, the properties and strengths of deep learning methods can enhance incompatibilities between these two paradigms. If these incompatibilities are ignored, unreflective uses of DL in SES research can further amplify the methodological rifts between quantitative and qualitative approaches rather than bridging them (Fig. 1, Risks item *ii*).

Although quantitative and qualitative data collection methods sometimes can generate the same format of data, a key distinction lies in the research questions that the data are often designed to answer. While quantitative approaches commonly focus on detecting patterns and trends of phenomena and searching for signal among noise (Isaac et al. 2014), qualitative approaches typically incorporate subjective and objective observations to provide contextual explanations and insights that value individual perceptions (Evans and Jones 2011, Bogezi et al. 2021). Deep learning's primary focus on abstraction and use of automated feature extraction and hierarchical hidden layers to distill complexity and find generalized patterns can be in direct conflict with the qualitative epistemological foci of context and nuance. By sacrificing context and critique for breadth and automation, deep learning inherently biases away from social constructivism, toward a more positivist way of knowing and can elicit distrust among interdisciplinary researchers.

In the data collection process, quantitative data processing often focuses on extracting specific and measurable information from raw datasets. Integrating deep learning algorithms in this process is a relatively common approach that can improve the accuracy of extracting and classifying quantitative data for downstream applications (Brown et al. 2022, Hermosilla et al. 2022). Conversely, reflexivity is a central component of qualitative research, emphasizing how a researcher's own background and identity can shape the interpretation of findings (Sultana 2007). A DL model's "identity," or its model structure and training, similarly shapes its interpretation yet does not provide a situated account of itself. Training AI to account for the contextual and interpretive elements of qualitative data also remains a significant obstacle in applying DL methods to qualitative data cleaning and processing (Christou 2023, Marshall and Naff 2024).

Limiting process-relational approaches

A critical component of SES analysis is less about the integration of knowledge and data from diverse actors and disciplines and more about the social-material processes through which environmental systems are understood (Klein et al. 2024). Process-relational approaches, increasingly used in the study and management of SES, recognize knowledge generation as a social and political process (Mancilla García et al. 2020, Schlüter et al. 2025). Here, attention is focused on the context, choices, and assumptions underpinning modeling practices and the processes by which worldviews are legitimized (Banitz et al. 2022, Klein et al. 2024).

Deep learning in SES analysis may limit the critical ontological reflection necessary in process-relational approaches (Fig. 1, Risks item *iii*). An advantage of DL lies in its ability to make highly accurate predictions by adapting its algorithmic structure to the properties of the dataset (Schiller et al. 2025). Understanding processes and principles that determine SES behavior is a key goal of many SES analyses (Schlüter et al. 2025), yet these DL models prioritize predictive performance at the cost of interpretability of modeling processes. Additionally, DL models with the greatest predictive power tend to have the most opaque architectures. This opacity comes from intentional concealment by intellectual property holders, technological illiteracy of users, and the inherently elusive nature of deep learning algorithms (Carabantes 2020). The subfield of explainable AI (xAI) has emerged to develop tools for deciphering the behavior of complex algorithms and producing more transparent predictions (Carvalho et al. 2019), which has been useful for enhancing both explainability and interpretability of black box models in ecology and other disciplines (Ryo et al. 2021, Tian et al. 2024). Evaluating how deep learning methods propagate assumptions can remain challenging. This limitation can compromise key concepts in process-relationship thinking, including understanding how entities are constructed and become stable, as well as interrogating the discursive practices that shape model structure and create the conditions for a model's emergent properties (Schlüter et al. 2025).

THE FUTURE OF DEEP LEARNING IN SOCIAL-ECOLOGICAL SYSTEMS

To successfully apply DL methods to understand social-ecological systems, researchers may use specific approaches that take advantage of these technological advances while allowing critical interrogation of DL algorithms and data-generating processes. Here we provide a perspective on how DL may change the nature of SES research questions and the processes used to answer them, and we highlight promising techniques and approaches evolving in the deep learning community.

Moving toward hybrid inductive-deductive SES research approaches

Many research questions in SES studies remain unanswered not because of a lack of data or analytical tools, but because the underlying hypotheses are often underspecified (Schlüter et al. 2019). Deep learning can be useful for generating hypotheses about SES model components and structure, guiding researchers toward more refined hypotheses. This shift reflects an epistemological framing of data-driven science that merges inductive and deductive reasoning. In contrast to traditional deductive designs that begin by generating hypotheses based on theory, an inductive-deductive hybrid approach would generate insights "born from the data," and these insights provide the basis for hypothesis formulation and deductive testing of their validity (Kitchin 2014). For example, deep learning algorithms can learn Bayesian network structures from data and synthesized literature, generating novel sets of model hypotheses (Flores et al. 2011). Incorporating domain expert knowledge can constrain or expand the model candidate space and form the basis for further evaluation (Amirkhani et al. 2016; Fig. 2).

Critically, however, the process of induction, of insights emerging from the data, is situated and contextualized within a theoretical domain, providing an opportunity to employ process-relational thinking (PRT) while applying deep learning methods (Fig. 2). The field of "human-in-the-loop" (HITL) machine learning has emerged in response to the need to have humans more involved in the AI model learning process (Mosqueira-Rey et al. 2023). Machine teaching is one HITL approach, where humans have control over the learning process by delimiting the knowledge transferred to the machine learning model (Ramos et al. 2020; Simard et al. 2017, *unpublished manuscript*). For example, chain of thought (CoT) prompting allows a human to structure a way of thinking by providing an exemplar chain of logic between a question and answer that a large language model (LLM) will apply when generating results (Wei et al. 2022). This CoT process can be used to formalize process-relational ideas, allowing researchers to become more reflexive regarding the contingency, value infusion, and underlying logic and norms that structure a DL model and provide the conditions for SES model inferences (Schlüter et al. 2025). Here, a researcher may be better positioned to interrogate one's situatedness in society, geography, and history in relation to one's assumptions, preconceptions, and training and understand how these nuances shape research (Wacquant and Bourdieu 1992). However, despite explicitly specifying guiding SES theory and assumptions, machine teaching approaches like CoT still do not attenuate the focus on abstraction and objectivity characteristic of DL models, nor do they inherently allow interrogation of the social-material consequences that arise from DL-based knowledge production (Unverzagt et al. 2025).

A challenge with the inductive, data-guided approach is that increasing data volume corresponds to increasing potential hypotheses, a larger haystack of spurious correlations that further obscures a needle. If a DL model reveals an unexpected pattern or effect that cannot be interpreted through existing theories, is this the pretense for novel discovery or a rabbit hole that will diminish DL's efficiency gains? Additionally, the inductive-deductive hybrid approach distributes greater agency to data in the research process, operating under the assumption that "big data" is exhaustive and captures an entire system (Kitchin 2014). Data will always be a sample of a system, a situated, non-neutral abstraction of the world (Haraway 1988), and if left unexamined, DL can propagate the values and biases of data producers and repositories (Rissing and Spangler 2025).

Facilitating SES synthetic analyses

Advancing social-ecological systems theory and concepts often involves comparative analyses of empirical case studies. Large comparative studies are rare, as they rely on highly systematized primary data collection on common variables or substantial secondary data mining and coding efforts (Gutiérrez et al. 2011, Cinner et al. 2012, Nagel and Partelow 2022). Artificial intelligence-integrated data storage and management systems change the way data is stored and retrieved, offering a promising opportunity for enabling SES synthetic analyses that can extend case-based knowledge.

Unlike traditional relational databases designed to handle structured and tabular data, the vector-based embeddings underlying AI databases allow flexible and efficient management of diverse, complex, and unstructured data types (Taipalus 2024). This flexibility is particularly useful for data management in SES analysis, as data are highly heterogeneous within and across SES studies, including text, image, raster, sensor, time-series, and numerical data (Magliocca et al. 2018). Additionally, techniques have been developed to enhance the knowledge of LLM-based agents that operate on vector-based embeddings, facilitating efficient identification of patterns and relationships across non-systemized data (Sanmartin 2024, *unpublished manuscript*). For example, Retrieval-Augmented Generation (RAG) approaches augment LLM agents via additional database and information retrieval mechanisms, helping to limit hallucinations and provide key relevant context and domain knowledge (Li et al. 2025). Although challenges can emerge when generating embeddings that integrate with LLMs, particularly spatial embeddings with remote sensing data (Chen et al. 2025), these advances have the potential to advance complex, multi-dimensional search queries of heterogeneous data common in cross-study SES analyses.

Because many individual SES case studies are not designed for comparison, specific actions can be taken to avoid risks of decontextualization. Database development should include machine-readable tagging systems to ensure methodological transparency and avoid highly abstracted and context-deficient conclusions from cross-study analyses (Partelow 2018). A possible organizational mechanism could include Ostrom's diagnostic method that organizes SES variables in a nested, multi-tier framework, which would help facilitate synthetic SES findings (Ostrom 2007, Hinkel et al. 2015).

Introducing novel social-ecological challenges

Although we focus on the direct research challenges and opportunities DL presents to SES fields, we would be remiss to not mention the considerable impacts that DL presents to social-ecological systems themselves and the SES research community. For example, the development and training of foundation DL models bring a steep cost to the environment through the intensive energy consumption, water usage, and carbon emissions of data centers (Luccioni et al. 2024). In addition, existing governance frameworks involved in siting of these resource-intensive data centers can fail to account for local realities of affected communities, with power imbalances, procedural exclusion, and regional variation shaping environmental outcomes (Bhandari 2025). Deep learning's increasing importance in SES research may also shift who is empowered in environmental and climate governance, with a likely greater distribution of power to actors in the private sector who are responsible for designing, owning, and controlling access to DL platforms (Scoville et al. 2021).

Applying relational approaches to SES requires understanding how systems of power and social structures shape the content and practice of science (Silver et al. 2022). Yet critical perspectives from the social sciences and humanities are often under-represented in interdisciplinary SES teams (Marshall et al. 2018). Artificial intelligence-driven shifts in labor markets may exacerbate this imbalance, as the speed and scale of changes in staffing and working practices associated with the AI technological revolution may lead to undesirable changes in the environmental sector (Sandbrook 2025). Shifting from manual to automated research methods, like image processing, may not only lead to missed unexpected ecological discoveries, but may also risk loss of human connection to ecological landscapes and training opportunities for the next generation of scientists (Barnas and Fisher 2025).

CONCLUSION

Addressing the challenges of social-ecological integration has plagued the field of sustainability science for decades, limiting progress in understanding the feedbacks and interactions that define these complex systems. The application of deep learning approaches in the study of SES may represent a methodological leap forward by enabling the data fluidity necessary to analytically unite ecological and social subsystems or synthesize across case studies. Deep learning-integrated research approaches may accelerate discovery through hybrid inductive-deductive reasoning, and the field of human-in-the-loop machine learning is evolving in ways that may be compatible with process-relational thinking. Taking advantage of these technological advances, however, will involve reconciling the ways in which deep learning privileges certain ways of knowing and magnifies the risks of data decontextualization.

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Data Availability:

Data/code sharing is not applicable to this article because no data and code were analyzed in this study.

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Appendix 1

Supplemental Table 1. Non-exhaustive list of emerging applications of deep learning (DL) in social-ecological systems research. Articles were selected if the analyzed system involved interacting natural and social subsystems and if DL was used to understand these interactions.

Example	Social-Ecological Systems Research Question	Deep learning method	Data Type	Analysis Type	Potential risks
Bone and Dragićević, 2010	Understanding outcomes of stakeholder interactions in forest management	*Reinforcement learning (RL)* RL algorithms evaluate landscape patterns and determine where and when forest harvesting strategies should take place to achieve management objectives	Simulated data	Agent-based modeling	An RL agent overfitted to a simulated environment may not generalize to "real" environments. Industry-maintained and developed RL algorithms introduce new actors in environmental problems, shifting the set of stakeholders
Gong et al., 2025	Balancing ecological integrity with the socio-economic demands of urbanization	*Self-organizing map* *S*elf-organizing mapping neural network model is used to integrate multi-sourced data and identify categories through a clustering process	Remote sensing, human activity, environmental variables	Ecological security patterning	Unsupervised clustering process abstracts data context and nuance

Kroodsma et al., 2018	Understanding the global footprint of fishing activities	*Convolutional neural network (CNN)* CNNs were trained to identify vessel characteristics and a second to detect automatic identification systems (AIS) positions indicative of fishing activity	GPS, ship characteristics, fishing logs, fuel prices	Behavioral mapping	Reliance on large datasets of fleets using automatic identification systems (AIS) excludes many critical SES contexts in the Global South, since fishing effort in regions of poor satellite coverage or in EEZs with a low percentage of vessels using AIS were underrepresented
Xu et al., 2025	Characterizing the spatial distribution of cultural ecosystem services	*Residual neural network (RNN)* RNN used to classify cultural ecosystem services-relevant content from social media images	Social media images, geotags	Ecosystem service valuation	Lack of opportunity for reflexivity and process-relational thinking, as the RNN (ResNet50) was trained on the ImageNet dataset, making it difficult to understand how bias and positionality propagate from training processes to model results

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