Causal interpretations can be based on mechanistic knowledge

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Article Type: Review

Running Headline: causal interpretations based on mechanistic knowledge

Keywords (4): causal knowledge, causal inference, mechanistic causal knowledge, coastal marshes

In Press, August 15, 2025

Citation: Grace, J.B., Guntenspergen, G.R., Buffington, K.J., Neville, J.A., Thorne, K.M., Osland, M.J., Martinez, M., Carr, J.A., & Willard, D.A. 2025. Causal interpretations can be based on mechanistic knowledge. *Journal of Ecology* (in press).

Abstract

1. There exists a long-standing disconnect between statistical and mechanistic approaches to the development of causal understanding. Statistical approaches, which have dominated the literature, have focused on the need to obtain perfectly unbiased estimates of causal effects often using either experimental, quasi-experimental, or other methods. Mechanistic approaches have instead focused on investigating how systems work by elucidating the structures and processes whereby variations in one system property can propagate to other system properties. Explicit references to "causal effects" have tended to require adherence to statistical methods and standards, inadvertently downplaying the suitability of mechanistic knowledge for that purpose.
2. It has been recently demonstrated that both mechanistic and statistical approaches can contribute to the long-term goal of developing causal knowledge and understanding. Proponents of statistical causal inference have seldom recommended that mechanistic evidence be relied upon to support causal interpretations. This paper provides a clear and thorough example where a causal interpretation can be supported based on mechanistic knowledge.
3. Arguing for a causal interpretation based on knowledge of mechanisms has typically been an informal process and one that has thus far infrequently led to explicit declarations of causal knowledge by scientists. To overcome this problem, we illustrate a recently-described procedure referred to as "causal knowledge analysis" to summarize explicit support for causal interpretations.
4. In this paper, we first clarify the basis of the longstanding disagreement by describing the crux of the problem as viewed from a statistical perspective and by describing how it can be overcome when there is sufficient mechanistic knowledge. We then offer a proof-of-concept example based on robust documentation and description of the mechanisms whereby plants causally regulate the responses of coastal marsh elevation to changes in sea level.
5. *Synthesis* – The evidential requirements for declaring a relationship to be causal have been obscured until very recently, leading to a long neglect of this issue by scientists. Meanwhile, subject matter experts have accumulated a vast body of undeclared causal knowledge that we now need to recognize in order to position scientists as essential players in defending causal interpretations.

1 | INTRODUCTION

Ecologists commonly present causal interpretations based on the results obtained from nonexperimental investigations, though statisticians have long cautioned against this practice. Typically, investigators use words such as 'effects', 'responses', 'drivers', or 'influences', while avoiding the use of the terms 'cause' or 'causal'. This practice is often reflected in the titles of articles through statements such as, 'Grazing regulates temperate grassland stability by influencing below-ground bud density' and 'Light competition affects how tree growth and survival respond to climate'. It is generally understood that interpretations in such cases are supported by accumulated knowledge of conveying mechanisms, though they may also be supported by other evidence. Typically, subject matter experts do not expressly address the concerns of statisticians when making such statements, and objections to stated inferences only arise when other experts disagree based on their own assessments.

Currently ecologists are being exposed to literature advertising data analysis methods for "causal inference" (Ferraro et al. 2019; Arif & MacNeil 2022; Dee et al. 2023; Siegel & Dee 2025). While this phrase can be imagined to be one with broad meaning encompassing a wide variety of situations and scientific ambitions, there actually exists a specialized literature associated with this phrase that imbues it with a very specific and circumscribed meaning, as well as a limited range of application. Ferraro et al. (2019) provide the following definition: "Causal inference … exploits experimental or quasi-experimental variation in one or more variables to isolate causal relationships and judges success by the credibility of untestable assumptions." They go on to differentiate causal inference methods from traditional methods of data analysis, which they refer to as "predictive inference" methods. Explaining further, these authors explain how mechanistic models that judge success by model-data consistency represent predictive inference and that such models are not considered to be causal and need not include any variables with causal effects.

In order to better understand the assumptions behind the representations of causal inference methods provided to ecologists, it is important to consider the source material, which many trace back to Rubin (1974) and Holland & Rubin (1987). Here we confine our presentation to the information most relevant to the focus of this paper. General treatments of the subject can be found in Imbens & Rubin (2015) and Morgan & Winship (2015).

Holland (1986) begins his discussion of *Statistics and Causal Inference* by saying, "The reaction of many statisticians when confronted with the possibility that their profession might contribute to a discussion of causation is to immediately deny that there is any such possibility." Holland goes on to make it clear that the above sentiment most generally applies to non-experimental settings. Scientists and the general public have long been made aware of the dim view statisticians hold for the attribution of causal interpretations based on non-experimental information. A consequence of this reservation has been a tendency throughout the modern era of science for ecologists and many others to avoid using the word "causal" when summarizing their interpretations, regardless of their knowledge of underlying mechanisms. We feel that the reasoning behind such caution has not been well explained, thereby impeding progress in this area.

The practical application of statistical causal inference is most commonly based on the Potential Outcomes statistical model (Rubin 1974; Holland 1986). For each study unit, there are a pair of potential responses that represent the expected values for some variable Y at a later time if it turns out to be exposed or not exposed (i.e., in the control) to the active treatment. At the population level, the average causal effect measures the difference between groups of units that are on average comparable but exposed to either one value or another of some treatment. There exists an extensive literature on all this. What is incompletely discussed are certain underlying assumptions as well as the important matter of evidential standards – the criteria by which methods are judged. We discuss evidential standards in the next section, but since our focus in this paper is on the use of mechanistic evidence, we direct attention first to what Holland & Rubin (1987) admit about statistical causal inference. Their specific and revealing statement is,

> Philosophical discussions of causality often emphasize the *meaning* of causation. Scientists are usually concerned with *understanding* causal mechanisms. Purely statistical discussions of causality are substantially more limited in scope, because the unique contribution of statistics is to *measuring* causal effects and not to the understanding of causal mechanisms.

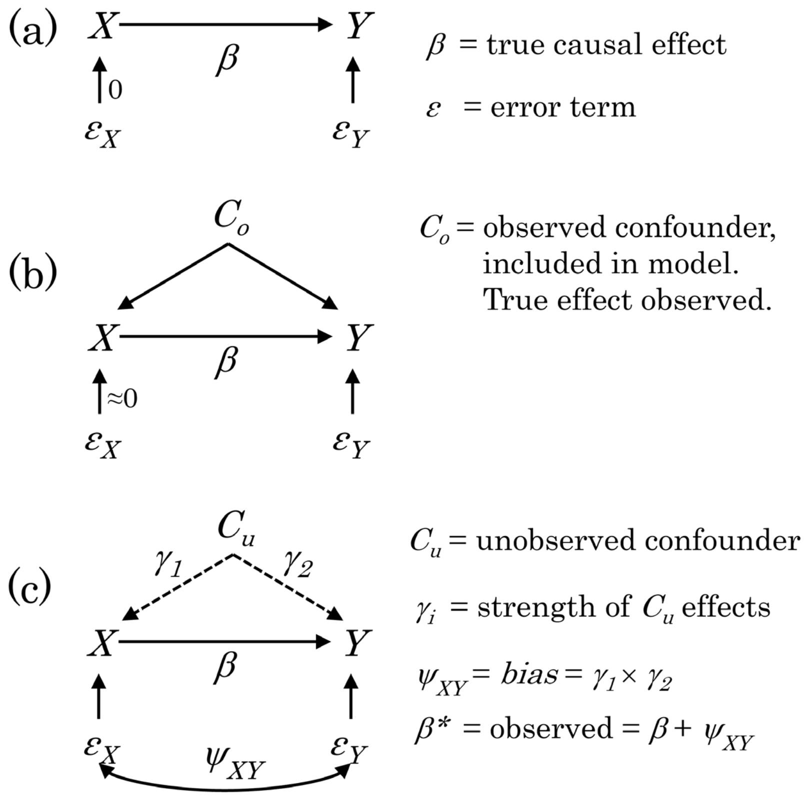
We do not find this disclosure commonly presented in the literature, which may potentially contribute to the long-standing controversy over the role of statistical causal inference in causal investigations (e.g., Schwartz & Prins 2025). That said, modern treatments of statistical causal inference describe the use of "domain knowledge" as a basis for statistical conditioning in calculating causal effects. Knowledge of the structures and processes (aka the machinery) that generate causal relationships is not incorporated into the calculation of statistical causal effects however.

In what follows, we first seek to clarify the challenge facing causal interpretations of statistical associations. That presentation is intended to clarify both the rationale for the statistical causal inference paradigm and for alternative approaches. We then present an alternative paradigm with an expanded ambition – that of building causal knowledge and allowing for multiple forms of evidence to contribute to that ambition, including mechanistic knowledge. Our particular focus in this paper is on demonstrating convincingly that causal interpretations might at times be justified based on mechanistic knowledge. This possibility serves to recognize the essential role that scientists and their expert knowledge play in causal investigations.

2 | THE CHALLENGE FACING A CAUSAL INTERPRETATION OF STATISTICAL ASSOCIATIONS

Wu et al. (2016) and Schwartz & Prins (2025) refer to statistical causal inference as a paradigm because of its distinctive world view. Grace (2024) has recently developed a representation of the challenge facing the causal interpretation of statistical associations in order to demystify that world view and to provide a basis for scientists to understand why it is so restrictive and why Ferraro et al. (2019) describe it as a methodology that, "judges success by the credibility of untestable assumptions". Fig. 1 seeks to explain the most common concern related to statistical causal inference in the upper frame. A corresponding listing of *evidential standards* that might be used to assess evidence when drawing conclusions is provided in the lower portion of the figure.

Fig. 1 represents the challenge facing causal statistics. Fig. 1A reflects the situation where there are no common-cause confounders (defined as additional variables that influence both X and Y). In such cases, commonly used statistical estimation methods can recover the true causal effect estimate (β). Fig. 1B reflects the case where there are confounding variables (C_o) that are observed and measured, allowing for their influences to be *controlled for* in analyses (for a discussion of control strategies, see Grace & Irvine 2020 page 8, section 3, paragraph on "conditioning"). In this case, it is still possible to obtain an unbiased estimate of the true causal effect using standard methods. Fig. 2C shows how unmeasured confounders (denoted as C_u)



<u>The Perfection Standard</u>: $\psi_{XY} \equiv 0$
Must guarantee by procedures that estimated effect is free of all forms of bias, otherwise result is not causal.
– "*Causal in the Statistical Sense*" ($\psi_{XY} \equiv 0$).

<u>The Perfection-Seeking Standard</u>: $\psi_{XY} \approx 0$
Must strive to ensure estimated function is bias-free.
– "*Statistical Causal Inference*"

<u>The Useful Approximation Standard</u>: $\beta > \psi_{XY}$
Relies on support from mechanistic knowledge that variations in X can lead to changes in Y.
– "*Causal in the Scientific Sense*" ($X \rightarrow Y$)

Figure 1. Representation of the challenge of estimating from some dataset the causal effect of some variable X on another variable Y (modified from Grace 2024). (a) Causal diagram for the case where there are no confounders and no errors in measuring X. (b) Causal diagram for the case where observed confounders C_o have been measured and are included in the model and thereby controlled for. Minimal measurement error in X is an additional assumption. (c) Causal diagram illustrating the case where there are unobserved confounders C_u omitted from the model. In the lower portion of the figure, three contrasting evidential standards are defined. The so-called Causal Inference Paradigm is based on the perfection-seeking standard as a limited approach to approximating results from randomized experiments.

introduce a component of bias into the observed association (β^*) by creating a "backdoor" $X \leftarrow C_u \rightarrow Y$ between the variables. Causal statistics is preoccupied with the task of avoiding or eliminating sources of parameter bias, with the benchmark method of experiments with random treatment assignment as the inspiration for statistical causal inference (Holland 1986). It is important to note that bias can emerge from other sources aside from omitted confounders, even in randomized experiments, as described in detail in Kimmel et al. (2021).

As Grace (2024) has pointed out, there has been a tremendous amount of confusion resulting from the lack of sufficient terminology for discussing the enterprise of building causal knowledge. Philosophers have long warned about conceptual confusion associated with discussions of causation resulting from the "one word with many meanings" problem (Cartwright 2004). A practical approach to this problem is to create terminology that can represent the important distinctions. The glossary in Grace (2024 Box 1) represents a first attempt at that challenge. Here we provide a brief set of terms and definitions related to the focused intent of this paper (Box 1).

In the lower frame of Fig. 1, we describe a variety of evidential standards, which reflect underlying and often undisclosed criteria used for deciding how conclusions will be reached. In legal proceedings, the standards of evidence are formally declared and meant to match the situation. Statisticians have historically relied on what we call *the perfection standard*, which requires a *causal method* guaranteed to yield a bias-free (perfect) causal effect estimate when successfully implemented. More recently "causal inference" (perhaps more accurately referred to as statistical causal inference) still acknowledges the perfection standard but attempts to relax the standard by adopting or approximating a *quasi-experimental* approach. Such an approach attempts to approximate random assignment to treatments and *counterfactual* (all-else-equal) comparisons using data purification and adjustment techniques. Accessible treatments of this approach can be found in Reichardt (2019) and Siegel and Dee (2025). Strictly speaking, both experimental and nonexperimental approaches by themselves cannot guarantee perfect estimates due to remaining untestable assumptions. As a consequence, Grace (2024) suggests referring to such methods as adopting a *perfection-seeking standard*. It should be noted that not all methodologists endorse the same techniques or adopt the same standards for approximating estimates of parameters (even with deviations from one study to the next).

From a scientific viewpoint, there exists the possibility of adopting an alternative to the perfection and perfection-seeking standards, which is to present evidence that one has achieved a useful approximation (Fig. 1, *the useful approximation standard*). Essentially, a useful approximation is an estimate that is predominantly causal. In fact, this standard is very widely used by scientists, though without formal declaration. Convincing others that a useful approximation has been achieved is of course very dependent on the knowledge base of the individuals to be convinced and its explication. The rise in popularity of statistical causal inference is now presenting a new challenge for scientists – how to explain the evidence supporting a determination of useful approximation to a statistical methodologist not in possession of the non-statistical direct knowledge possessed by the relevant subject matter experts.

The challenge for this approach is that the exact magnitude of bias created by unmeasured confounders in a statistical analysis is unknowable, thus any support for a useful approximation standard will come from other, non-statistical information. In the natural sciences, this alternative knowledge will often be an understanding of the underlying mechanisms connecting

X to Y, i.e., those structures and processes that constitute the actual machinery conveying effects. However, consideration of mechanistic evidence in causal analysis implies the need for an alternative to the Causal Inference Paradigm that recognizes existing causal knowledge and considers both its properties and how it is accumulated across studies.

3 | A PARADIGM FOR BUILDING CAUSAL KNOWLEDGE

An alternative paradigm has been recently described, referred to here as the Multi-Evidence Causal Investigation Paradigm (aka *the Multi-Evidence Paradigm*), which starts from a different set of premises reflective of a mechanistic view of the world (Grace 2024). These premises include: (1) that causal influences result from underlying mechanistic processes, (2) causal knowledge can be described in terms of both direct and indirect knowledge of those mechanisms and the manifestations they produce, and (3) a driving goal in science is the aspiration to understand those mechanisms. One additional premise articulated as a core presumption of the Multi-Evidence Paradigm is that there is no single approach to developing causal knowledge that will apply to all situations and circumstances. Most scientific investigations will benefit from considering all forms of evidence relevant to their situation.

Grace (2024) describes the philosophical underpinnings of the Multi-Evidence Paradigm. It is proposed as a world view consistent with scientific investigation that recognizes the existence of a great variety of individual situations, which in turn must avoid adopting a narrow view of evidence. Fig. 2 is meant to be inclusive of statistical evidence (via association investigations), mechanistic evidence (the focus of this paper), but also other sources of evidence, such as from the study of temporal dynamics via empirical dynamic modeling and convergent cross mapping (Sugihara et al. 2012; Deyle et al. 2016; Runge et al. 2019). Cross-linking arrows in Fig. 2 represent the potential within this paradigm for combining evidence types, as demonstrated by Benedetti-Cecchi et al. (2018).

The Multi-Evidence Paradigm leads to a recognition of several neglected concepts, such as *causal inquiry* (seeking to establish a causal understanding), *causal investigation* (the pursuit of causal observations and causal knowledge towards the goal of causal understanding), *causal mechanisms* (collections of spatiotemporally contiguous structures and processes in the real world along which a signal that is propagated, aka *mechanistic machinery*), and *causal knowledge* (accumulated evidence of manifestations, properties of the underlying mechanistic machinery, and external consistency/transportability). The Multi-Evidence Paradigm additionally supports reliance on combinations of methods, including (1) the use of experiments of different types – field, greenhouse, lab, (2) statistical causal inference techniques, (3) mechanistic evidence grounded in direct observations and existing knowledge from physics, biology, and chemistry, and (4) other approaches as complementary sources of information for supporting causal interpretation, consistent with the National Academies Consensus Report on Causal Methods (NASEM 2022).

Since the Multi-Evidence Paradigm adopts the perspective that causal knowledge is built across multiple studies, there is an inherent necessity for accumulating evidence representing causal knowledge. It has been necessary to develop a formal approach to documenting this characterization of evidence to counter the skeptical view from adherents to causal statistics. *Causal Knowledge Analysis* involves the evaluation of existing evidence related to potential underlying mechanisms for some relationship or question of interest. While a conceptually appealing idea, the important question is whether it can support causal interpretations in real-world situations.

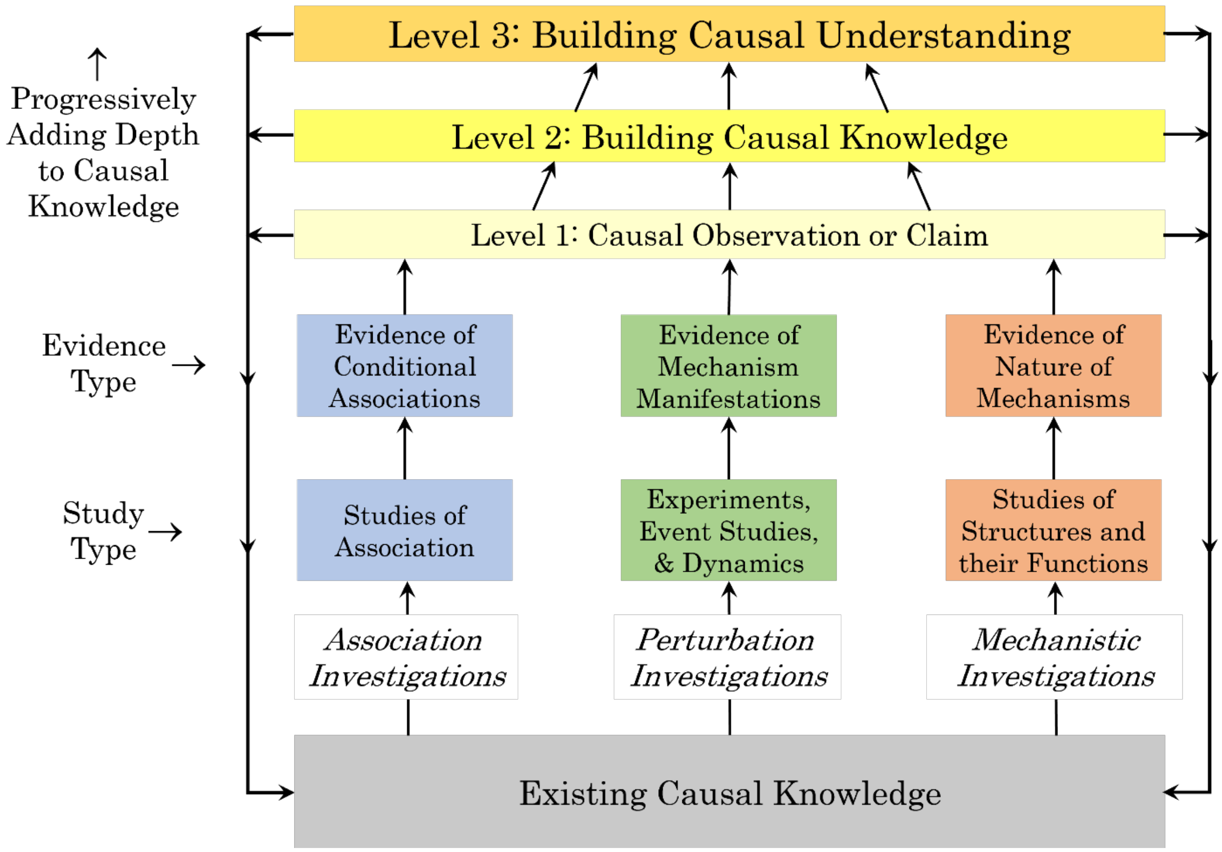


Figure 2. Representation of the Multi-Evidence Causal Investigation Paradigm (modified from Grace 2024). Two of the most important features of this paradigm that contrast it with statistical approaches to causal inference are: (1) its expanded focus that includes the long-term goal of building causal knowledge, and (2) its recognition that there are multiple forms of evidence that contribute to building causal knowledge, including a key role for mechanistic investigations.

4 | CAUSAL KNOWLEDGE ANALYSIS

A causal knowledge analysis can be defined as an evaluation of existing evidence relevant to the question of whether some relationship or model qualifies for causal interpretations. Following Grace (2024), "*Causal knowledge* can be established by (1) evidence of manifestations indicative of an underlying mechanism, (2) characterization of the underlying mechanistic elements, and (3) demonstrated external consistency or transportability with other samples and/or studies." The suggestion that mechanistic knowledge be a required component of causal knowledge comes from numerous science philosophers (Campaner 2011; Clarke et al. 2014; Williamson 2021, but also from a recent National Academies Consensus Report on Causal Methods – NASEM 2022). Because of the specific nature of mechanisms, this form of evidence will usually be judged by subject matter experts rather than against some universal set of criteria. It is not expected in the great majority of cases that the evidence provides for complete characterizations. Rather, the standard to be applied for a causal investigation is that progress is being made in evaluating and adding to current knowledge, a commonly applied standard in scientific investigations. The example developed in this paper is one where there has been a sustained effort to make incremental progress towards causal understanding over many years (as discussed below under "Brief history of causal investigation").

4.1 | The characteristics of causal mechanisms

Characterizations of causal mechanisms focus on the evidence that convinces us that two or more variables are connected through some mechanism or means such that variations in one variable can propagate to subsequent variations in the other. Mechanisms can be seen to be made up of *mechanistic elements* representing *specific structures and processes* that work in combination. A variety of types of evidence can be used to characterize causal mechanisms. For the example that follows, these include direct observations, responses to perturbations, certain types of theoretical analyses, and established knowledge from physics, chemistry, and biology. In this paper, we will distinguish the *core machinery* that establishes causal connections from the *inputs* that determine what is produced by that machinery. While the core machinery determines the properties of the underlying mechanism, the inputs play a critical role in specific manifestations. For our featured example, the core machinery tells us how coastal marshes may respond to future changes in sea level, but any projections will depend on the specific inputs of materials for a given situation, along with any site-specific conditional influences.

4.2 | The causal knowledge diagram

To both help define a problem and to facilitate the evaluation of existing evidence, we describe the use of a *causal knowledge diagram*. Such a diagram represents a way of referencing existing or hypothesized knowledge of structures and processes capable of conveying cause-to-effect influences and is conceptually distinct from causal diagrams that describe statistical relationships (described in Grace & Irvine 2020). The causal knowledge diagram is a device to aid in the evaluation of existing evidence for a proposed compound mechanism. One purpose of the diagram is to support the documentation of evidence in a way that corresponds with the proposed underlying mechanism. A second purpose is to strive to develop the empirical expectations one would observe based on a proposed underlying mechanism. It is expected that subsequent studies will critique, evaluate, and bring to bear additional evidence so as to refine and deepen our mechanistic understanding. Thus, causal knowledge diagrams and the associated documentation of evidence are expected to evolve over time. They do not have to be complete or perfect to be causal representations. The general evidential standard for causal investigations is preponderance of evidence. As shown in the next section, a number of questions are considered in order to characterize the sufficiency and reliability of mechanisms.

4.3 | Interrogation of the evidence

Grace (2024) suggests a set of questions to assess the existing knowledge relevant to a relationship of interest (Table 1). This is not a definite list for all situations but is meant to be adapted for particular problems and situations across scientific topics. The first question in Table 1 directs our attention to think clearly about the hypothesized mechanistic driver(s) and response(s) of main interest. Since a causal relationship is typically thought of in terms of how variations in some Y could come about due to variations in some X, it is important that we pay attention to how variations in a proposed cause of interest can come about. The use of thought experiments aids in considerations of what can actually qualify as a cause. Constructing a causal knowledge diagram (as shown below) should make clear whether there is a describable mechanism connecting a proposed cause to some response. Similar thinking is needed to make clear what concepts can be studied as responses under a mechanistic conceptualization. For both causes and responses, concepts that are multi-faceted and do not behave like a single consistent property (i.e., complex causes and responses) will require special consideration (see discussion of complex causes in Grace 2024).

Table 1. Suggested questions for assessing evidence relevant to a relationship of interest

1. What is the nature of the cause(s) of interest and the response(s) of interest?
2. Are there observed manifestations that suggest the existence of a mechanism connecting causes to responses?
3. Are there known or plausible mechanisms connecting the variables of interest?
4. Are there plausible competing explanations?
5. How sufficient is our knowledge of mechanisms and conditional influences that may affect expressions of the mechanisms?
6. How reliable are the mechanisms and conditional influences based on available knowledge?
7. How exact/repeatable are the processes and associated parameters?
8. How transportable are the mechanisms to other cases or situations?

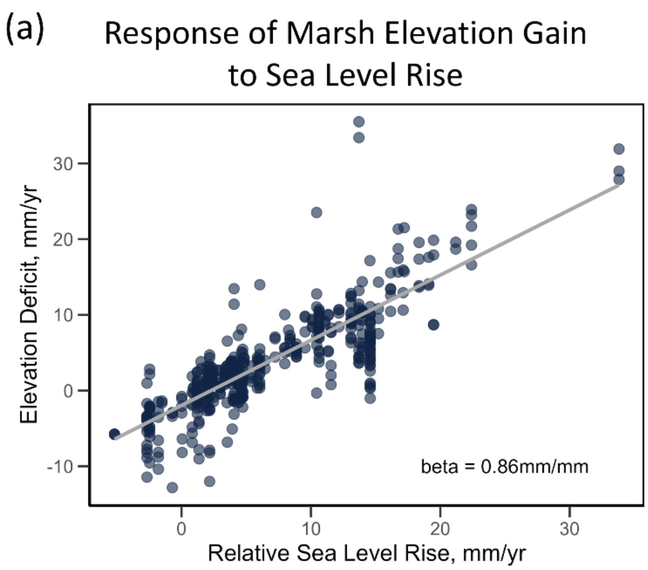
The second question in Table 1 asks us to consider broadly the manifestations that might suggest a causal interpretation. These can be: (1) data relationships, such as conditional associations, (2) temporal dynamics, such as seen with predator-prey cycles, or (3) direct observations of structures and processes. The third question, which relates to whether there are known or plausible mechanisms will often benefit from creation of a causal knowledge diagram (demonstrated below), followed by documentation supporting and characterizing the described mechanism. The objective here is to present to others the specialized subject matter knowledge that leads one to suggest a causal mechanistic connection. A critically important fourth question asks investigators to consider whether there are alternative explanations for the manifestations observed. Concerns about spurious relationships are the most obvious thing to consider. Beyond a relationship being explained entirely by other processes than the ones proposed, it is normal for proposed mechanisms to be incomplete or open to improvement.

Finally, for the last four questions in Table 1, attention is given to the expected properties of the various mechanistic elements and connecting process based on their actual attributes. These questions focus on key aspects of causal knowledge such as the sufficiency of the chain, the expected reliability of expression, the exactness of processes (is there a universally-held process or parameter), and the transportability of those underlying structures and processes. Characterizations of these properties represent a harvest of important. often neglected knowledge that can aid in understanding observed dynamics and in forecasting (Lewis et al. 2023).

5 | THE EXAMPLE: CAUSAL MECHANISMS WHEREBY PLANTS REGULATE MARSH ELEVATION

Saintilan et al. (2022) compiled data from coastal marsh elevation monitoring stations located in North America, Northern Europe, Australia, and South Africa to determine whether the monitored coastal marshes around the world have been able to build sufficient elevation so as to keep up with increasing sea-level rise rates (Fig. 3). The underlying premise is that as water levels increase, the plants growing in coastal marshes trap mineral sediments that settle out on the surface from the water column and produce abundant roots and rhizomes beneath the surface, thereby causing the soil elevation to build at a rate that keeps pace with rising seas. There is concern that in many situations the ability of marshes to build elevation may lag behind the increasing rates of sea-level rise, resulting in marsh conversion to open water. Interest in coastal marsh persistence has stimulated the development of monitoring stations, as depicted in Fig. 4. Surface elevation change monitoring involves a number of measurements that provide mm-level precision estimates of total elevation, surface accretion of new materials, and subsurface elevation changes resulting from plant contributions and sediment compression or expansion.

Monitoring sites were established by installation of surface elevation tables (Cahoon 2024), which are composed of a multi-segment vertical rod pounded into the substrate to the point of refusal (Fig. 4, left side of drawing). The base of the benchmark rod serves as a fixed reference point in vertical space against which marsh elevation change is measured. A portable arm is attached perpendicular to the benchmark rod at each visitation, and replicate pins are lowered to the marsh surface to record change in surface elevation.



(b) Data Characteristics

- Opportunistic compilation of samples.
- Common measurement methods.
- Data pooled without any adjustment.
- Does not conform to quasi-experimental variation standard.

Figure 3. (a) Correlation obtained by Saintilan et al. (2022, *Science*, 377: 523-527, reconstructed) based on monitoring stations located at 97 sites around the world. The authors interpret this finding as support for the claim that marsh sediment accretion increases in response to rising sea levels, though where sea level is increasing faster than marsh elevation, an elevation deficit develops that will, if continued, lead to marsh drowning and eventual conversion to open water. Beta represents the slope of the relationship in mm of elevation deficit created per mm of relative sea-level rise per year for the sample of sites. (b) Some characteristics of the data.

In addition to the elevation table and at the time of installation, replicate layers of visually distinctive material are deposited on the marsh surface adjacent to the vertical benchmark. These become the “marker horizons” for the initial surface of the marsh, and at each measurement time, replicate cores are extracted to determine the depth of material that has been deposited above the original surface over time (i.e., accretion). In addition to measuring the changing elevation of the marsh surface and the depth of accumulated surface accretion, a measure of shallow subsidence or expansion of the sediment column can be obtained as the difference between total elevation change and depth of surface accretion. Benchmarks are georeferenced against nearby tide gauges, which are in turn georeferenced to each other via satellite so as to provide a common reference elevation for the measurements taken at a site.

5.1 | Anatomy of a causal investigation

That coastal salt marsh accretion tracks rising sea level has been recognized since the mid-19th century, when Dawson (1855) and Mudge (1858) studied vertical sections of salt marsh that preserved thick peat sequences (3-6 m) composed of salt marsh vegetation. The proposition that salt marsh peats increased in thickness at pace with rising sea level was further advanced by Knights (1934) through stratigraphic analysis of peats in Long Island Sound (New York, USA). Since the mid-20th century, advances in capabilities for sediment sampling, geochronology, elevational surveying, and analysis of paleoenvironmental and geochemical proxies have facilitated high-resolution studies that document varying rates of marsh accretion and aggradation during the last few thousand years. Using plant macrofossils and foraminifers from well-dated sediment cores (see Shaw & Ceman, 1999; Kemp et al., 2014; Gerlach et al., 2017; Selby et al., 2022), long-term changes in relative sea level have been constructed for coastal sites around the world, extending the period of sea-level record to times well before instrumental or historical records are available. Thus, we have long known there is a causal relationship between increases in sea level and marsh vertical accretion based on direct observation and interpretation of physical evidence. At the most basic level of examination, the simple fact that sediment cores extracted from coastal marshes are composed of marsh peat permeated with mineral sediment (as shown in Fig. 4) provides indirect evidence that plants make a causal contribution to changes in marsh elevation over time. A detailed presentation of the accumulated evidence related to causal mechanisms whereby plants influence marsh elevation is presented in Cahoon et al. (2021).

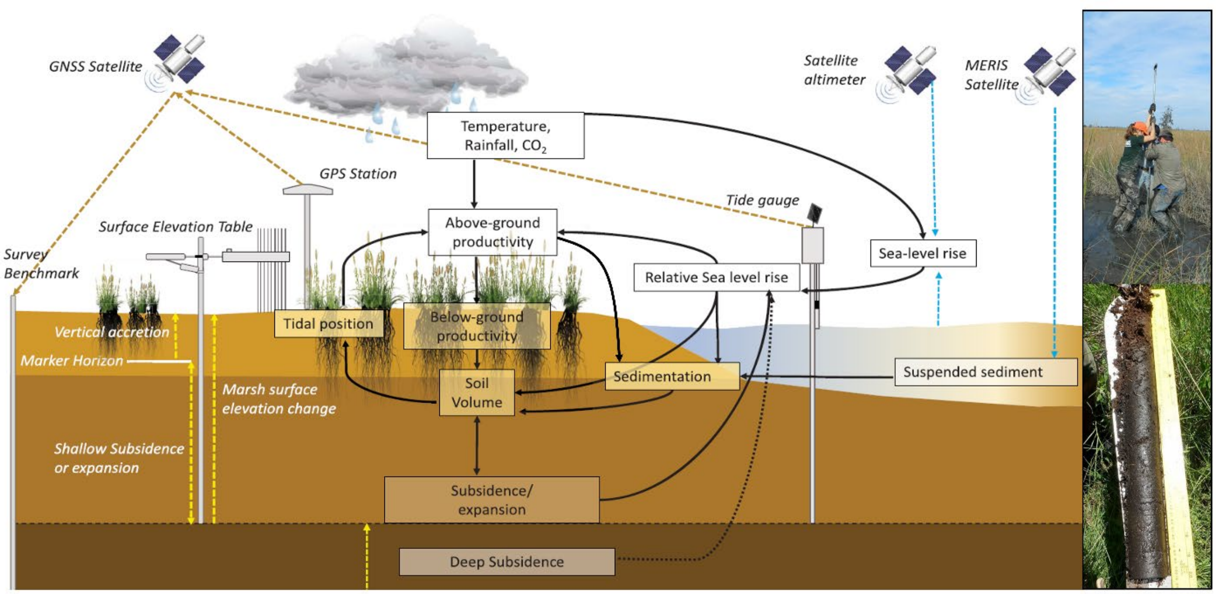


Figure 4. Pictorial representation of a coastal marsh highlighting key variables of importance and the measurements taken at monitoring sites (from Saintilan et al. 2022, with permission from the American Association for the Advancement of Science, with slight modification). Inset photos – Illustration of an examination of coastal marsh history by coring (right upper photo, from https://www.usgs.gov/media/images/savannah-river-december-2012) and conspicuous demonstration of buried roots and rhizomes contributing to organic matter accumulation in sediment cores (right lower photo, from https://www.usgs.gov/media/images/peat-auger-core-collected-back-barrier-marsh-Assateague).

Subsequent efforts have focused on developing a deeper understanding of mechanistic processes (e.g., Nienhuis et al. 2023) but also on quantifying the contributing processes and rates of change. While there has been an awareness by geologists that ocean levels were rising since the beginning of the 20^{th} century (Marmer 1951), interest increased later in the 20^{th} century as greater documentation of coastal wetland loss to open water took place, particularly in certain geographical areas where vast areas of wetland were disappearing (Craig et al. 1979). The societal and ecological consequences of this loss motivated efforts to develop more precise monitoring methods such as the Surface Elevation Table – Marker Horizon (SET-MH) method depicted in Fig. 4 (Cahoon et al. 1995). Refinements and widespread adoption of this approach have helped to create a global monitoring network now used to address questions on a larger scale.

Nearly 30 years ago, scientists began to create mechanistic numerical models as a way of consolidating information and discerning knowledge gaps, thereby contributing to what has come to be a focused causal investigation by a community of scientists. We begin our description of existing causal knowledge by describing what has been learned from this persistent effort in mechanistic numerical modeling and associated empirical studies.

5.2 | Evidential Standards for Causal Determination

The term *causal determination* refers to the evaluation of evidence as to whether there is a causal relationship between some variables of interest. The National Academies Consensus Report on Causal Methods (NASEM 2022) recognizes five qualitative interpretations of evidence. It should be noted that this approach was specifically created to address epidemiological analyses of exposure-response relationships. However, the NASEM report considered not only health effects but also effects on ecosystems and thus reflects a broad realm of application for their approach. The five determination categories, which were found to be without objection in the NASEM report are, (1) "causal relationship", (2) "likely to be a causal relationship", suggestive of, but not sufficient to infer, a causal relationship", "inadequate to infer the presents or absence of a causal relationship", and "not likely a causal relationship". Determinations usually involve reviews of all available and relevant information and research results by panels of subject matter and technical experts.

Causal knowledge analysis focuses more on describing the evidence to support mechanistic causal understanding than it does to simply declare whether a relationship is causal or not with different qualitative levels of confidence. Within a broader view of science as envisioned by the Multi-Evidence Paradigm, we imagine that criteria for causal determination will be linked to a decision framework rather than a universal set of rules. In the current paper, it is our general assessment that the relationship in Fig. 3 meets the minimum requirements for being causal and our focus is on causal investigation rather than simply determination.

5.3 | Mechanistic numerical modeling efforts as a crucible for building causal knowledge

Numerical modeling efforts are used across many disciplines and can be particularly useful for evaluating existing causal knowledge for several reasons. One is because such studies often lead over time to some degree of consensus among experts on the dominant processes generating observable relationships of interest. The more mechanistic the thinking about how to model natural processes, the greater the potential for convincing causal inferences. As with causal knowledge diagrams, such models do not usually attempt to include every feature operating in the real world, but instead, aspire to capture the most widespread and dominant controlling processes. They are typically accompanied by empirical evaluations that judge their abilities to replicate field observations (e.g., Coleman et al. 2022). Especially useful is that the development of numerical models promotes efforts to obtain measurements that can quantitatively characterize the functional forms of mechanistic elements, taking us closer to the underlying causal processes.

Statistical and probabilistic modeling efforts, in contrast, frequently fail to represent the characteristics of the underlying machinery and provide only superficial approximations, though they may still represent summary properties of underlying mechanisms. These approaches were prominent in the literature during the early days of marsh sea-level rise vulnerability modeling (e.g., Browder et al. 1985; French 1993). Thus, not all models are equally mechanistic, and not all provide the same degree of support for causal interpretations. The development of numerical models that attempt to emulate how coastal marshes might respond to rising seas have been stimulated by concerns about the need to forecast the long-term consequences of sea-level rise. During the investigation of the relationship between sea-level rise and marsh elevation that has occurred during the past several decades, mechanistic numerical models have been created at several points in time, each building on the previous ones by incorporating new knowledge (e.g., Callaway et al. 1996; Morris et al. 2002; Swanson et al. 2014; Buffington et al. 2021). These models have not been exclusively interested in sea-level rise but have also sought to more fully understand how marsh landscapes evolve, how they respond to a variety of environmental changes, and how the various processes interact.

Several studies have been able to provide calibration and validation results based on field data through the use of radioactive isotopes in the soil (e.g., ^{137}Cs peaks from the 1986 Chernobyl accident, and 1963 nuclear weapons testing, as well as ^{210}Pb decay) and SET-MH networks (Brand et al. 2022). There are ongoing efforts to refine models based on comparisons between the paleo and contemporary records as well (Saintilan et al. 2022). There have also been efforts to provide site-specific models based on the incorporation of local sediment supplies and custom parameters for local plant species assemblages (Buffington et al. 2021). Altogether, these models and numerous empirical investigations provide us with a rich body of knowledge to consider in a causal knowledge analysis of the relationship between sea-level rise and coastal marsh resilience.

Appendix S1 provides a summary of the model developed by Buffington et al. (2021) for the reader with detailed interest. The structure of that model is described by a set of mechanistic equations representing the following groups of processes: (A) Annual changes in marsh elevation relative to sea level are caused by contributions from mineral and organic materials, and losses from offsetting effects of decomposition and sea-level rise. (B) Mineral inputs result from sediment deposition flux, which in turn is the result of the physical processes of settling and erosion caused by tidal current shear stress. Mechanistic characterizations for these processes are presented in equations 1-5 in Appendix S1. (C) The non-linear dependence of below-ground biomass contributions on water depth is known to be modal for marsh plant species. The exact form of the response function reflects a complex but constrained set of biological processes, and as a result, can be modeled either as a general-form mechanism or as a more refined species-specific relationship. (D) Decomposition of organic contributions from below-ground production is an important, though fairly regular process. Decomposition rates decline over time as labile materials are consumed leaving behind increasingly refractory materials. These fractions can vary over time in their bulk densities, contributing to a general soil-depth-dependency of compaction. Buffington et al. (2021) additionally model how successional changes in species composition can vary the influences of organic matter and mineral sediment trapping on the dynamics of marsh elevation.

5.4 | A mechanistic causal explanation of the correlation between rates of relative sea-level rise and elevation deficits

The details of the causal knowledge analysis for the relationship in Fig. 3a are presented in Appendix S1. Here we present a brief summary of that analysis and select findings.

5.4.1 | The nature of the cause and response of interest:

The context for the study by Saintilan et al. (2022) relates to the ability of coastal marshes to persist over time (i.e., their resilience). As discussed in a prior section, evidence from the paleorecords shows that coastal marshes in many areas, but not all, have persisted during past periods of moderate sea-level rise (Froomer 1980). A question of current interest and importance is whether coastal marshes will continue to survive in place through vertical increases in elevation and adjustment within the tidal frame as rates of sea-level rise continue to accelerate. The persistence of marshes is determined by their ability to build elevation through vertical accretion of mineral sediment and below-surface accumulation of organic materials (e.g., roots, peat). One distinctive feature of this system is that marshes often have the capacity to increase their rate of elevation gain in response to an increase in the rate of sea-level rise, up to some point beyond which their capacity to respond decreases and marsh transformation occurs (Kirwan & Timmerman 2009; Morris et al. 2002). Resilience in the face of rising seas depends on their ability to build elevation rapidly enough to avoid chronic submergence leading to conversion to unvegetated mudflats and eventually open water (Couvillion et al. 2017; Osland et al. 2024).

5.4.2 | Manifestations suggesting an underlying mechanism:

The example in this paper affords us an opportunity to illustrate non-statistical evidence that supports a causal interpretation of nature. As described earlier, one form of evidence that a causal process exists connecting water levels to marsh surface elevation comes directly from sediment cores taken by paleontologists (Fig. 4). Cores taken in coastal marshes provide direct documentation of the inputs of mineral sediment and plant organic material that have built the column of material upon which today's surface resides. The external validity of this manifestation is demonstrated by the wide range of locations around the world where columns of sediment are comprised of accumulated partially-decomposed peat mixed with various amounts of mineral materials. While much more information suggestive of various processes is routinely obtained from cores, the recognition that most of the organic component in the material lying beneath coastal marshes is made up of residual fractions of marsh plant roots and rhizomes confirms the conclusion that marsh ecosystems raise their elevations as water levels change. This increase in marsh elevation is observed to be accomplished by accumulations of mineral sediment (trapped by marsh plants) in addition to residual organic material (produced by plants). All these observations constitute direct evidence of causal processes and a characterization of the structures involved (depicted in Fig. 5a).

Saintilan et al. (2022) provide a succinct description of the presumed mechanism allowing marsh elevation to adjust its position to water, "We conceptualize surface elevation trends as a function of elevation gains (through mineral and organic matter accumulation, and sediment volume expansion, including root mass gain) and losses (through sediment erosion, and sediment volume losses associated with subsidence, auto-compaction, and decomposition of organic matter)." To help document the evidence suggesting that there is a sufficient causal chain or network behind the correlation presented in Fig. 3a, we created a causal knowledge diagram based on existing mechanistic knowledge, which is shown in Fig. 5b. To aid the presentation, we juxtapose a drawing of the vertical profile of structures and processes developed by Cahoon et al. (2021) in Fig. 5a.

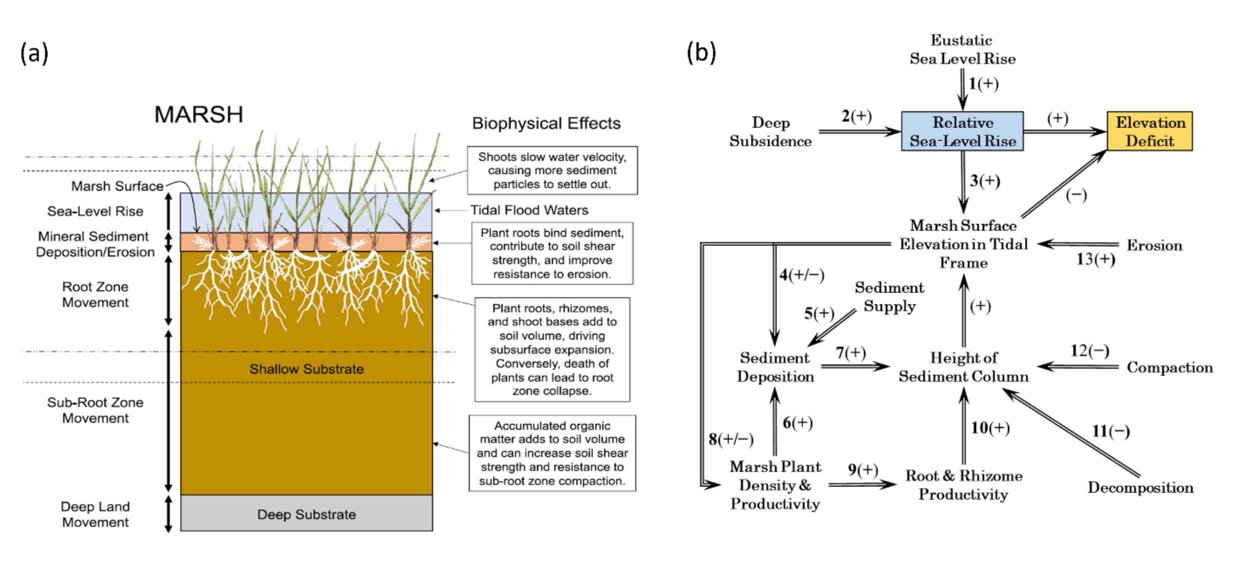


Figure 5. (a) Profile view of a coastal marsh showing structures and processes contributing to changes in marsh surface elevation (from Cahoon et al. 2021, with permission from Springer Nature). (b) Causal knowledge diagram for the relationship between Relative Sea-Level rise and Elevation Deficit. The *X* and *Y* variables in Fig. 3a are enclosed in boxes in the causal knowledge diagram, while the unenclosed items make up the mechanistic elements leading to their covariation through a nonlinear feedback set of processes. The numbers next to the arrows in (b) are included to cross-reference the diagram with the descriptions of evidence in Appendix S1 where more detail is provided.

5.5 | A Causal Knowledge Diagram for the correlation of interest

The task assigned to the causal knowledge diagram is to describe a causal chain or network of structures and processes that can help to explain how changes in relative sea-level rise rates can lead to changes in marsh surface elevation. Saintilan et al. (2022) chose to reference the rate of marsh surface elevation increase to the rate of relative sea-level rise so as to track whether marsh elevation increase is keeping pace with sea level, a requirement for long-term survival of the marsh. This led them to plot marsh elevation deficit (Elevation Deficit) against the rate of local relative sea-level rise (Fig.3a), two variables highlighted in the causal knowledge diagram in Fig. 5b by being enclosed in boxes. The other variables and linkages in the figure represent our knowledge of the core machinery leading to their correlated behavior. The diagram in Fig. 5b is labeled with 13 nodes and 13 process connections, all of which we consider in the full presentation in Appendix S1.

5.5.1 | Overview of the evaluation:

We can envision that the manifestations of the system of interest will depend on: (1) the core machinery, which is shown in the causal knowledge diagram, (2) conditional influences, and (3) inputs. Our primary focus in this presentation is on the core machinery, which represents the structures and processes thought to be general to the system of interest. It is recognized that conditional influences will lead to situational variations in the general behavior, and while much is known about many such influences, they are not a focus of this presentation. Further, for any given location, inputs of materials, such as sediments and biological structures, will influence the elevation changes measured at individual sample sites.

5.5.2 | Structures:
The main structural components of the system of interest by volume include land, water, plant material, and air trapped in the sediment. Land in this case refers to the layered solid materials beneath the marsh surface. These intergrade from a continuously developed surface layer made of mineral and organic components, to a root-zone layer that is typically rich with root and rhizomes, to a progressively consolidating sub-root-zone layer, to firmer layers beneath (Fig. 5a). The resilience of coastal marshes depends on the ability of marsh plants to promote the trapping of sedimentary material and/or the accumulation of biological material, thereby adding to the height of the sediment column and raising the surface elevation of the marsh. Descriptions of each numbered link in Fig. 5b are presented in Appendix S1. Here we provide brief summaries of the detailed results.

5.6 | Assessment of evidence related to the Causal Knowledge Diagram

5.6.1 | Sufficiency of the core mechanism:
An essential question to address is whether there is evidence to indicate a sufficiently continuous chain or network of structures and processes to connect the cause of interest to the response of interest. The substantial and sustained efforts contributing to our knowledge of this system gives us confidence that there is sufficient evidence to view Fig. 3a as a causal relationship. This is an easy conclusion to defend as the contributions of processes to marsh elevation reflect the summation of components that can be observed through physical measurements. The slope of the relationship observed is 0.86mm/mm. This should be viewed as a summary of the sample rather than a mechanistic parameter because it represents the combined influences of the causal network, the particular conditional influences at the locations of the samples including subsidence rates, and a result of the material supplies for the individual sites. That said, the slope of the relationship, which represents the mm of elevation deficit created per mm of RSLR for the sample, is an informative number implying that on average many of the marshes are not keeping up with accelerated rates of sea-level rise, a conclusion reached by Saintilan et al. (2022). Beyond the simple question of sufficiency, there are certainly places where our understanding of the functional forms of relationships can be improved (see Appendix S1).

5.6.2 | Reliability of the core mechanism:
In the context of causal analysis, reliability refers to the frequency with which a process operates in independent samples or locations. It does not, however, refer to the quantitative magnitude of its influence. From that perspective, when we consider the various processes in the core mechanism, we expect a high degree of reliability except in extreme environments. The processes of sedimentation, compaction, deep subsidence, and edge erosion can be expected to

operate reliably nearly everywhere coastal marshes occur, though certainly conditional influences will override their effectiveness where physical conditions are unsuitable. The biological processes should also be reliable to a substantial degree as evidenced by the wide-spread distribution of coastal marshes and their persistence in the paleo record over thousands of years.

5.6.3 | Exactness of processes:
Exactness in this context refers to the constancy of a mechanism. For our example in this paper, numerical models provide us with insights into this issue. For example, some of the processes involved in sediment deposition (e.g., see equations 2-4 in Appendix S1) involve numerical constants. While these may only approximate the true process, they suggest a degree of exactness for the operation of certain mechanistic elements. In contrast, some biological mechanistic elements will show substantial quantitative variation. An obvious example is the depth distribution of root growth (Fig. S5). In numerical models, the distribution of plant production as a function of water depth is typically represented using polynomial or other equations that approximate the shape of the distribution but without meaningful coefficients. The exactness of such mechanisms is therefore low.

5.6.4 | Transportability:
One of the hallmark features of causal mechanisms is external consistency, the repeated operation of underlying processes in different situations. Mechanisms are transportable when there are structures and processes that are repeated in space in time. The global distribution of SET-MH stations established by different researchers around the globe provide us the opportunity to see if manifestations consistent with the machinery in Fig. 5b are widely observed. There are a number of types of conditional variations reported in different studies, including future evolutionary changes; nonetheless, there is strong and consistent body of evidence indicating widespread transportability of the core machinery. Observed major departures are thought to represent boundary conditions where physical factors exceed biological tolerances (see Chapters 4, 10-12 in Perillo et al. 2019). The case has been made repeatedly that coastal mangrove forests possess sufficiently similar biological features to those in coastal marshes that the mechanisms whereby they are able to track rising sea levels are roughly the same. Further, it can be anticipated that plant growth may increase due to atmospheric and oceanic warming and from increasing atmospheric CO_2. This constitutes another level of transportability where mechanistic elements are common to distinctly different situations, resulting in recognizably similar behavior.

5.6 | Overall assessment of evidence to support a causal interpretation:
It is our assessment that existing causal knowledge supports an interpretation of the relationship in Fig. 3a as reflective of an underlying causal mechanistic process. We do not arrive at this conclusion through quantitative analysis of data, but through scientific knowledge of structures and processes accumulated over many studies. What repeated investigation has found is that plants have the capability of increasing rates of marsh vertical growth in response to increasing rates of water level rise, up to some point where their capacity is overwhelmed. This involves a nonlinear feedback such that when rates of sea-level rise are low, increases in marsh elevation keep pace. As annual rates of sea-level rise increase, the system has a capacity to increase its vertical growth rate to keep pace. Eventually the capacity of the marsh system is exceeded and

elevation increase falls behind, eventually leading to conversion to open water (Morris et al. 2002). Recent results have also shown a surprising and previously underappreciated sensitivity of sediment compression in response to surface accretion (e.g., Keogh et al. 2021; Saintilan et al. 2022). This finding has reconciled paleo and contemporary estimates of vertical growth rates in response to sea-level rise rates, deepening our understanding of the system.

6 | DISCUSSION

Schwartz & Prins (2025) argue based on decades of study of causal methodology that, "Researchers should take debates about causation seriously because with or without our awareness, and with or without our consent, these debates shape the questions we ask, the methods we use, [and] the narratives we construct about our study results." Such a statement suggests that the subject of causal methods demands careful scrutiny, which we attempt in this paper.

Numerous ecologists have argued for causal explanation as a general scientific aspiration (e.g., Holt 2015; Nichols and Cooch 2025; Pickett et al. 2007). Scheiner & Willig (2008) have proposed a general scientific framework for ecology that describes a theory as "A framework or system of
concepts and propositions that provides causal explanations of phenomena within a particular domain." Hone et al. (2023) provide a specific context for arguing for reliance on a combination of evidence types as causal criteria for wildlife management. However, the means for documenting the causal content of ecological studies has been obscured until recently.

In discussing the primary example in this paper, we point out that the determination that there is a causal relationship between rates of increase in marsh surface elevations and rates of increase in sea levels can be made from observations and existing knowledge of physics, biology, and chemistry. The most fundamental limitation of causal statistics is that it typically ignores the actual machinery, which is our primary source of evidence for causal interpretations. The fact that some (e.g., Siegel & Dee 2025) dismiss the possibility of arriving at causal interpretations based on mechanistic knowledge is indicative of the need for subject matter experts to document and defend their causal conclusions when appropriate. As pointed out by an insightful peer reviewer of this work, the potential consequences of ecologists adopting the statistical causal inference paradigm as it has been described in the literature could be to suggest a wide-spread absence of evidence for causal relationship in ecology, eroding the relevance for ecology to solving the great environmental issues of our time.

In addition to the example presented here, Grace (2024) and Grace et al. (2025) have presented other examples of correlations having clear causal interpretations. Generally, organismal traits are often subjects for causal interpretations due to structure-function relationships (e.g., Laughlin, 2023; McGill et al., 2006). Beyond the work mentioned here, the National Academies of Science, Engineering, and Medicine have recently completed a Synthesis Report on Causal Methods that fully supports the central role that mechanistic knowledge plays in causal determination (NASEM 2022).

We hope that the in-depth example presented in this paper provides material proof beyond a reasonable doubt that it is possible to support causal interpretations when there is a sufficient body of knowledge about underlying mechanisms. If such a conclusion is accepted for even a single example, it supports the contention that a multi-evidence paradigm should be considered for the goal of building causal knowledge and understanding. Further, it counters resistance from advocates of statistical causal inference that may lead to substantial confusion in the literature and that promote a pervasively skeptical view of existing causal knowledge. Accommodating multiple forms of evidence in causal investigations opens up much uncharted territory, which is a natural consequence of viewing our task as one of building causal knowledge across studies. The perspective promoted in this paper is one that places scientists at the center of the panel of jurors who evaluate evidence and determine the state of causal knowledge.

ACKNOWLEDGEMENTS

We thank Frederik De Laender and three anonymous reviewers for exceptionally insightful suggestions for improving the manuscript. Thanks also to Neil Saintilan, Don Cahoon, Matthew Kirwan, Beth Middleton, and Glenn Suir for reviews and comments. Study supported by the U.S. Geological Survey, Ecosystems Mission Area, Land Change Science Program. Any use of trade, firm or product names is for descriptive purposes only and does not imply endorsement by the US Government.

AUTHOR CONTRIBUTIONS

The lead author wrote the first draft of the introductory sections and all authors contributed critically to the review of wetland information, contributed to manuscript preparation, and gave final approval for publication.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AND CODE AVAILABILITY STATEMENT

Data for replotting Figure 3a obtained from https://doi.org/10.1126/science.abo7872 - Supplementary Materials - Data S1. No unique code was used in preparing this paper.

SUPPORTING INFORMATION

Supporting information is provided in Appendix s1.

REFERENCES

Arif, S., & MacNeil, M. A. (2022). Predictive models aren't for causal inference. *Ecology Letters, 25*, 1741-1745.

Benedetti-Cecchi, L., Bulleri, F., Dal Bello, M., Maggi, E., Ravaglioli, C., & Rindi, L. (2018). Hybrid datasets: integrating observations with experiments in the era of macroecology and big data. *Ecology*, *99*(12), 2654-2666.

Brand, M. W., Buffington, K., Rogers, J. B., Thorne, K., Stein, E. D., & Sanders, B. F. (2022). Multi-decadal simulation of marsh topography under sea level rise and episodic sediment loads. *Journal of Geophysical Research: Earth Surface, 127*, p.e2021JF006526.

Browder, J. A., Bartley, H. A., & Davis, K. S. (1985). A probabilistic model of the relationship between marshland-water interface and marsh disintegration. *Ecological Modelling, 29*, 245-260.

Buffington, K. J., Janousek, C. N., Dugger, B. D., Callaway, J. C., Schile-Beers, L. M., Borgnis Sloane, E., & Thorne, K. M. (2021). Incorporation of uncertainty to improve projections of tidal wetland elevation and carbon accumulation with sea-level rise. *PLoS One, 16*. p.e0256707.

Cahoon, D. R., Reed, D. J. & Day, J.W. Jr. (1995). estimating shallow subsidence in microtidal salt marshes of the Southeastern United States: Kaye and Barghoorn revisited. *Marine Geology* 128:1‑9.
Cahoon, D. R., McKee, K. L., & Morris, J. T. (2021). How plants influence resilience of salt marsh and mangrove wetlands to sea-level rise. *Estuaries and Coasts, 44*, 883-898.
Callaway, J. C., Nyman, J. A., & DeLaune, R. D. (1996). Sediment accretion in coastal wetlands: a review and a simulation model of processes. *Current topics in Wetland Biogeochemistry, 2*, 2-23.
Campaner, R. (2011). Mechanistic causality and counterfactual-manipulative causality: recent insights from philosophy of science. *J Epidemiol Community Health, 65*, 1070-1074.
Cartwright, N. (2004). Causation: one word, many things. *Philosophy of Science* 71: 805–819.
Clarke, B., Gillies, D., Illari, P., Russo, F., & Williamson, J. (2014). Mechanisms and the evidence hierarchy. *Topoi*, *33*, 339–360.
Coleman, D. J., Schuerch, M., Temmerman, S., Guntenspergen, G. R., Smith, C.G., & Kirwan, M. L. (2022). Reconciling models and measurements of marsh vulnerability to sea level rise. *Limnology and Oceanography Letters* 7:140-149.
Couvillion B. R., Beck H., Schoolmaster D., & Fischer M. (2017). *Land area change in coastal Louisiana 1932 to 2016: U.S. Geological Survey Scientific Investigations Map 3381, 16 p. pamphlet, https://doi.org/10.3133/sim3381*.
Craig, N. J., Turner, R. E., & Day, J. W. (1979). Land loss in coastal Louisiana (U.S.A.). *Environmental Management, 3*, 133–144.
Dawson, J. W. (1855). *Acadian Geology*. Edinburgh, UK 388 pp.
Dee, L. E., Ferraro, P. J., Severen, C. N., Kimmel, K. A., Borer, E. T., Byrnes, J. E., Clark, A. T., Hautier, Y., Hector, A., Raynaud, X., Reich, P. B., et al. (2023). Clarifying the effect of biodiversity on productivity in natural ecosystems with longitudinal data and methods for causal inference. *Nature Communications, 14*, p.2607.
Deyle, E. R., May, R. M., Munch, S. B., & Sugihara, G. (2016). Tracking and forecasting ecosystem interactions in real time. *Proceedings of the Royal Society B: Biological Sciences*, *283*(1822), 20152258.
Ferraro, P. J., Sanchirico, J. N., & Smith, M. D. (2019). Causal inference in coupled human and natural systems. *Proceedings of the National Academy of Sciences of the United States of America, 116*, 5311–18.
French, J. R. (1993). Numerical simulation of vertical marsh growth and adjustment to accelerated sea-level rise, North Norfolk, UK. *Earth Surface Processes and Landforms, 18*, 63-81.
Froomer, N. L. (1980). Sea level changes in the Chesapeake Bay during historic times. *Marine Geology, 36*, 289-305.
Gerlach, M. J., Engelhart, S. E., Kemp, A. C., Moyer, R. P., Smoak, J. M., Bernhardt, C. E., & Cahill, N. (2017). Reconstructing common era relative sea-level change on the Gulf Coast of Florida. *Marine Geology, 390*, 254-269.
Grace, J. B. (2021). Instrumental variable methods in structural equation models. *Methods in Ecology and Evolution, 12*, 1148-1157.
Grace, J. B. (2024). An integrative paradigm for building causal knowledge. *Ecological Monographs, 94*, p.e1628. https://doi.org/10.1002/ecm.1628
Grace, J. B., Huntington-Klein, N., Schweiger, E. W., Martinez, M., Osland, M. J., Feher, L. C., Guntenspergen, G. R., & Thorne, K. M. (2025). Causal effects vs causal mechanisms: two

traditions with different requirements and outcomes. *Ecology Letters, 28, e70029*. https://doi.org/10.1111/ele.70029
Holland, P. W. (1986). Statistics and causal inference. *Journal of the American statistical Association*, *81*(396), 945-960.
Holland, P. W., & Rubin, D. B. (1987). Causal inference in retrospective studies. *ETS Research Report Series*, *1987*(1), 203-231.
Holt, R. D. (2015). Inference towards the best explanation: reflections on the issue of climate change. *Israel Journal of Ecology and Evolution 61*, 1–12.
Hone, J., Drake, V. A., & Krebs, C. J. (2023). Evaluation options for wildlife management and strengthening of causal inference. *BioScience*, *73*, 48–58.
Imbens, G. W., & Rubin, D. B. (2015). *Causal Inference for Statistics, Social, and Biomedical Sciences*. Cambridge: Cambridge University Press.
Kemp, A. C., Bernhardt, C. E., Horton, B. P., Kopp, R. E., Vane, C. H., Peltier, R., Hawkes, A. D., Donnelly, J. P., Parnell, A. C., & Cahill, N. (2014). Late Holocene sea- and land-level change on the U.S. Southeastern Atlantic Coast. *Marine Geology, 357*, 90-100. http://dx.doi.org/10.1016/j.margeo.2014.07.010
Keogh, M. E., Törnqvist, T. E., Kolker, A. S., Erkens, G., & Bridgeman, J. G. (2021). Organic matter accretion, shallow subsidence, and river delta sustainability. *Journal of Geophysical Research: Earth Surface, 126*, e2021JF006231.
Kimmel, K., Dee, L. E., Avolio, M. L. & Ferraro, P. J. (2021). Causal assumptions and causal inference in ecological experiments. *Trends in Ecology & Evolution* 36: 1141–1152.
Kirwan, M. & Temmerman, S. (2009). Coastal marsh response to historical and future sea-level acceleration. *Quaternary Science Reviews, 28*, 1801-1808.
Knights, J. B. (1934). A Salt-Marsh Study. *American Journal of Science, Fifth Series, 28*, 161-181.
Laughlin, D. C. (2023). *Plant strategies: The demographic consequences of functional traits in changing environments.* Oxford: Oxford University Press.
Lewis, A.S., Rollinson, C.R., Allyn, A.J., Ashander, J., Brodie, S., Brookson, C.B., Collins, E., Dietze, M.C., Gallinat, A.S., Juvigny-Khenafou, N. and Koren, G., 2023. The power of forecasts to advance ecological theory. *Methods in Ecology and Evolution*, *14*(3), pp.746-756.
Marmer, H. A. (1951). Changes in sea level determined from tide observations. *Coastal Engineering Proceedings*. Chapter 6, pp62-67.
McGill, B. J., Enquist, B. J., Weiher, E., & Westoby, M. (2006). Rebuilding community ecology from functional traits. Trends in Ecology & Evolution 21: 178–185.
Morgan, S. L. & Winship, C. (2015). *Counterfactuals and Causal Inference*. Cambridge: Cambridge University Press.
Morris, J. T., Sundareshwar, P. V., Nietch, C. T., Kjerfve, B., & Cahoon, D. R. (2002). Responses of coastal wetlands to rising sea level. *Ecology, 83*, 2869-2877.
Mudge, B. F. (1858). The salt marsh formations of Lynn. *Proceedings of the Essex Institute* 2: 117-119.
NASEM (National Academies of Sciences, Engineering, and Medicine). (2022). *Advancing the framework for assessing causality of health and welfare effects to inform national ambient air quality standard reviews*. Washington, DC: The National Academies Press. https://doi.org/10.17226/26612.

Nienhuis, J. H., Kim, W., Milne, G. A., Quock, M., Slangen, A. B., & Törnqvist, T. E. (2023). River deltas and sea-level rise. *Annual Review of Earth and Planetary Sciences* 51:79-104.

Nichols, J. D. & Cooch, E. G. (2025). Predictive models are indeed useful for causal inference. *Ecology, 106*, e4517.

Osland, M. J., Chivoiu, B., Grace, J. B., Enwright, N. M., Guntenspergen, G. R., Buffington, K. J., Thorne, K. M., Carr, J. A., Sweet, W. V., & Couvillion, B. R. (2024). Rising seas could cross thresholds for initiating coastal wetland drowning within decades across much of the United States. *Communications Earth & Environment, 5*, 372.

Perillo, G., Wolanski, E., Cahoon, D. R., & Hopkinson , C. S. (editors) 2019. *Coastal wetlands: an integrated ecosystem approach*. Second Edition, Elsevier.

Pickett, S. T. A., Kolasa, J., & Jones, C. G. (2007). Ecological Understanding: The Nature of Theory and the Theory of Nature, 2nd ed. Burlington, MA: Academic Press.

Reichardt, C. S. (2019). *Quasi-experimentation: A guide to design and analysis*. Guilford Publications.

Rubin, D. B. (1974), Estimating causal effects of treatments in randomized and nonrandomized studies," *Journal of Educational Psychology*, 66, 688-701.

Runge, J., Bathiany, S., Bollt, E., Camps-Valls, G., Coumou, D., Deyle, E., et al. (2019). Inferring causation from time series in Earth system sciences. *Nature Communications*, *10*(1), 2553.

Saintilan, N., Kovalenko, K. E., Guntenspergen, G. R., Rogers, K., Lynch, J. C., Cahoon, D. R., Lovelock, C. E., Friess, D. A., Ashe, E., Krauss, K. W., & Cormier, N. (2022). Constraints on the adjustment of tidal marshes to accelerating sea level rise. *Science, 377*, 523-527.

Scheiner, S. M., & Willig, M. R. (2008). A general theory of ecology. *Theoretical Ecology, 1*, 21–28.

Schwartz, S. & Prins, S. J. (2024). *Causal inference and the people's health*. Oxford University Press.

Selby, K. A., Roe, H. M., Wright, A. J., van de Plassche, O., & Derrett, S. R. (2022). Saltmarsh archives of vegetation and land use change from Big River Marsh, SW Newfoundland, Canada. *Vegetation History and Archaeobotany, 31*, 137-154.

Shaw, J., & Ceman, J. (1999). Salt-marsh aggradation in response to Late-Holocene sea-level rise at Amherst Point, Nova Scotia, Canada. *The Holocene, 9*, 439-451.

Siegel, K. J., & Dee, L. E. (2025). Foundations and future directions for causal inference in ecological research. *Ecology Letters* 28:e70053.

Sugihara, G., May, R., Ye, H., Hsieh, C. H., Deyle, E., Fogarty, M., & Munch, S. (2012). Detecting causality in complex ecosystems. *science*, *338*(6106), 496-500.

Swanson, K. M., Drexler, J. Z., Schoellhamer, D. H., Thorne, K. M., Casazza, M. L., Overton, C. T., Callaway, J. C. & Takekawa, J. Y. (2014). Wetland accretion rate model of ecosystem resilience (WARMER) and its application to habitat sustainability for endangered species in the San Francisco Estuary. *Estuaries and Coasts, 37*, 476-492.

Williamson, J. (2021). Introducing evidential pluralism. *The Reasoner* 15:45–47.

Wu, P., Tang, W., Chen, T., He, H., Gunzler, D. & Tu, X. M. (2016). Causal inference: a statistical paradigm for inferring causality. In: He, H., Wu, P., & Chen, D. G. (editors) *Statistical Causal Inferences and Their Applications in Public Health Research.* ICSA Book Series in Statistics. Springer, Cham, Switzerland.

SUPPORTING INFORMATION

Supporting information is provided in Appendix S1 in the online material.

GLOSSARY

Box 1. Glossary of select terms.

Average Causal Effect/Causal Effects – the quantitative difference between treated and untreated groups of study subjects that are assumed to be, on average, equivalent in their potential responses to exposure. In theory, there can exist individual-level causal effects but since only performance in either treated or untreated conditions can be measured for a single individual, the average causal effect is the implied meaning of estimated "causal effect."

The Counterfactual Approach – Statistical causal inference procedures frequently adopt the focus on obtaining estimates of "What would the value for a study unit have been at time t+1 if that individual unit was not exposed to the active treatment at time t" for estimating causal effects.

Causal Relationship – Situation where two variables are connected through some mechanism or means such that variations in one can propagate to subsequent variations in the other.

Causal in the Statistical Sense – Causal statistical effect estimates are ones presumed to be pure and isolated counterfactual differences (usually between treated and untreated individuals, groups, or numeric categories). The purpose of such a strict requirement is to enable causal inferences to be drawn in the absence of adequate supporting knowledge.

Causal in the General Scientific Sense – A causal effect estimate between two entities (say X and Y) might be considered to be causal in the general scientific sense if there is reason to think that the estimated value is at least a useful approximation of the unbiased effect estimate. Most commonly useful approximations are likely to be supported based on knowledge of causal mechanisms, though they can also be supported by mechanistic theoretical analyses and potentially other types of evidence.

Causal Mechanism – Typically some collection of spatiotemporally contiguous structures and processes along which a signal can be propagated from one entity to another resulting in a response.

Causal Statistics aka *Statistical Causal Inference* – Terminology, including informal meanings, evolve over time. As of the time of this writing, statistical approaches to estimating some causal quantity have evolved to include not just those methods that are true causal methods adhering to the perfection requirement (as defined in Fig. 1) but now include procedures attempting to conform to the perfection-seeking standard.

Causal Inference – A vague term with disparate general and specialized meanings. We advise that it should be taken to refer to statistical causal inference unless otherwise qualified.

Causal Knowledge Analysis – Procedures for documenting *Causal Knowledge*, which includes evidence of: (1) manifestations that are indicative of an underlying mechanism, (2) some characterization of the underlying mechanism(s), and (3) demonstrated external consistency or transportability with other samples and/or studies.

Sufficiency of a Mechanism – a judgement as to whether all the necessary mechanistic elements exist to convey a causal effect. Animals, for example, typically require food and water (at a minimum) to survive. A mechanism that provides water is not, by itself, sufficient to sustain life.

Reliability of a Mechanism – a characterization of how often the median response is observed. For example, the sun rises above the horizon every day, but rain does not fall every day and has a less reliable influence.

Exactness – a parameter that represents a faithful translation of information will be considered to be exact. For example, the increase in elevation of coastal marshes as sea level rises will be the summation of mineral and organic contributions and subtraction of decomposition, compaction, and erosion processes. The conversion of a kilogram of root biomass to increases in vertical elevation (in mm) will be less exact as the conversion coefficient will be potentially influenced by a number of specific factors.

Transportability - The ability to extrapolate a causal interpretation to a related but different situation. It will be expected that this is achieved most commonly where the same or similar mechanistic elements or machinery occurs in different situations.

Supporting Information starts on next page.

Supporting Information for: "Causal interpretations can be based on mechanistic knowledge"

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Article Type: Review

Running Headline: causal interpretations based on mechanistic knowledge

Keywords (4): causal knowledge, causal inference, mechanistic causal knowledge, coastal marshes

ACKNOWLEDGEMENTS
We thank Frederik De Laender and three anonymous reviewers for exceptionally insightful suggestions for improving the manuscript. Thanks also to Beth Middleton for review of an earlier version of the manuscript. Appreciation is expressed to Neil Saintilan, Donald Cahoon, and Matthew Kirwan for final approvals for the use of their figures. Study was supported by the U.S. Geological Survey, Ecosystems Mission Area, Land Change Science Program. Any use of trade, firm or product names is for descriptive purposes only and does not imply endorsement by the US Government.

AUTHOR CONTRIBUTIONS
The lead author wrote the first draft of the introductory sections and all authors contributed critically to the review of wetland information, contributed to manuscript preparation, and gave final approval for publication.

DATA AND CODE AVAILABILITY STATEMENT
Data for replotting Figure 3a obtained from https://doi.org/10.1126/science.abo7872 - Supplementary Materials - Data S1. No unique code was used in preparing this paper.

CONFLICT OF INTEREST STATEMENT
The author declares no conflicts of interest.

Supporting Information for:

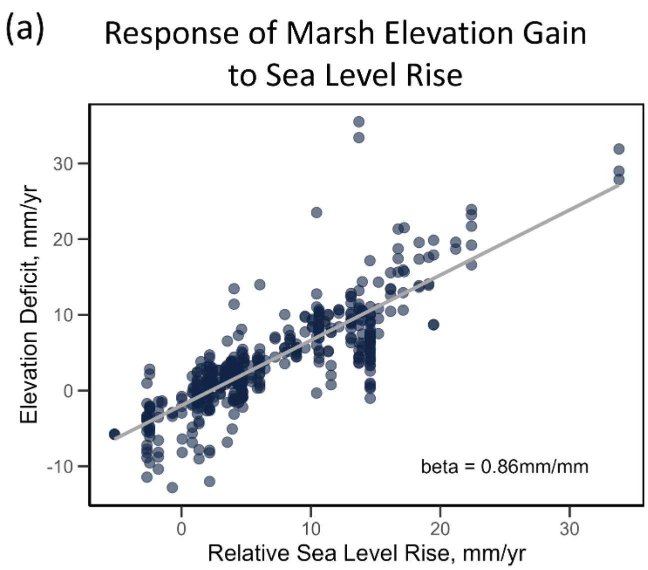
“Causal interpretations can be based on mechanistic knowledge”

Appendix S1

Note: Some material is repeated here from the main text to make this document stand-alone readable.

AN EXAMPLE CORRELATION FOR CAUSAL ANALYSIS

For this demonstration, we chose a recent result from a paper by Saintilan et al. (2022). Figure S1 presents a relationship obtained from the analyses of a global dataset described below. As discussed in the main text, this relationship does not qualify for causal effect estimation under the Statistical Causal Inference Paradigm. In this document, we repeat some basic information about the sample and then present the details of the Causal Knowledge Analysis summarized in the main text.



(b) Data Characteristics

- Opportunistic compilation of samples.
- Common measurement methods.
- Data pooled without any adjustment.
- Does not conform to quasi-experimental variation standard.

Figure S1. Correlation obtained by Saintilan et al. (2022, Science, 377: 523-527; reconstructed) based on monitoring stations located at 97 sites around the world. The authors interpret this finding as support for the claim that marsh sediment accretion increases in response to rising sea levels, though where sea level is increasing faster than marsh elevation, an elevation deficit develops that will, if continued, lead to marsh drowning and eventual conversion to open water. Beta represents the slope of the relationship in mm of elevation deficit created per mm of relative sea-level rise per year for the sample of sites. (b) Some characteristics of the data.

Primary Measurements
A causal knowledge analysis can be conducted either with or without a specific data relationship in mind. In this paper, we choose to work with a particular result as we believe it better serves our heuristic purposes. The correlation shown in Figure S1 serves as our starting point for the description of causal knowledge analysis. This figure comes from a paper by Saintilan et al. (2022) who compiled data from coastal marsh elevation change monitoring stations around the world. For this work, the authors chose data from locations that have used a common standard method for monitoring changes in marsh surface elevation relative to local rates of sea-level rise, the Surface Elevation Table–Marker Horizon (SET–MH) monitoring method (Cahoon 2024). Other selection criteria included a length of measurement record greater than 3 years (average length of 10.1 years) and avoidance of sites that have experienced hydrological or experimental manipulation. This resulted in data from 477 tidal marsh SET–MH stations from 97 sites from North America, Northern Europe, Australia, and South Africa.

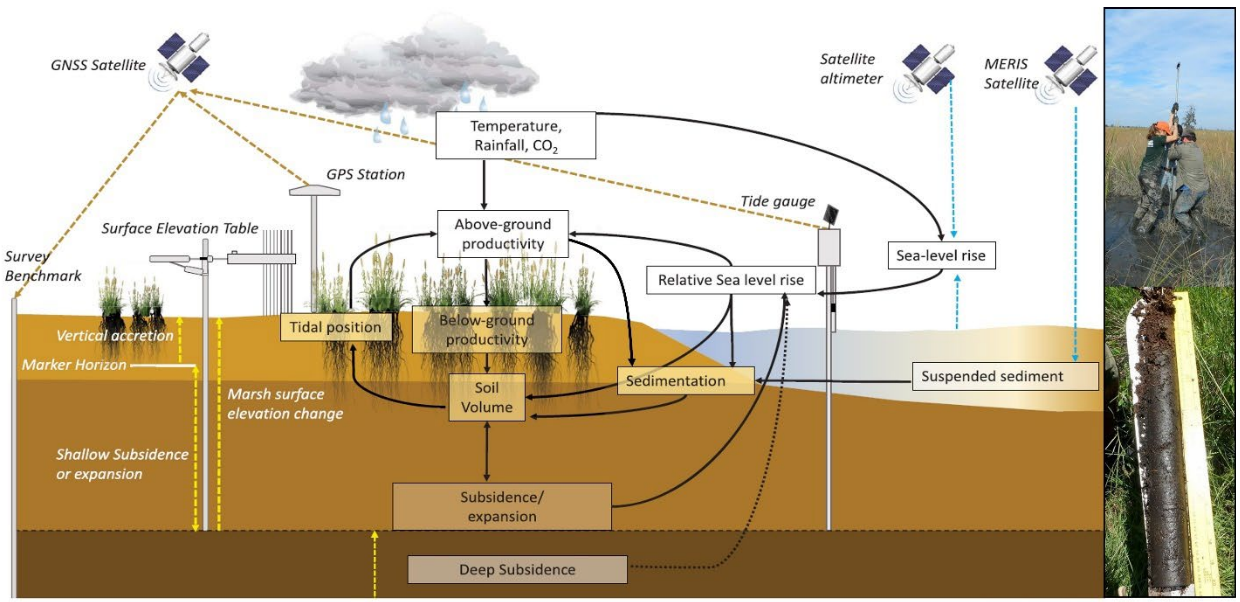


Figure S2. Pictorial representation of a coastal marsh highlighting key variables of importance and the measurements taken at monitoring sites (from Saintilan et al. 2022, with slight modification). Inset photos – Illustration of an examination of coastal marsh history by coring (right upper photo, from https://www.usgs.gov/media/images/savannah-river-december-2012) and conspicuous demonstration of buried roots and rhizomes contributing to organic matter accumulation in sediment cores (right lower photo, from https://www.usgs.gov/media/images/peat-auger-core-collected-back-barrier-marsh-Assateague).

Monitoring sites were established by installation of a SET benchmark, which is composed of a multi-segment vertical rod pounded into the substrate to the point of refusal in firm substrate (Figure S2, left side). The base of the benchmark rod serves as a fixed reference point in vertical space against which marsh elevation change is measured. A portable SET arm is attached perpendicularly to the benchmark rod at each visitation and nine replicate pins are lowered to the marsh surface at four positions around the vertical benchmark rod. At each position, the heights of each pin above the portable arm are measured at each visit. As marsh surface increases over time relative to the base of the vertical rod (for example), pin heights above the horizontal arm get higher. All 36 pin readings taken at each station at each time are averaged to get a single reading for that time. Rate of change in elevation is assessed by estimating the slope for the multiple readings over time.

In addition to the table, at the time of installation replicate layers of visually distinctive material (e.g., feldspar clay) are deposited on the marsh surface adjacent to the vertical benchmark. These become the "marker horizons" for the initial surface of the marsh and at each measurement time, replicate cores are extracted to determine the depth of material that has been deposited above the original surface over time (i.e., accretion). In addition to measuring the changing elevation of the marsh surface and the depth of accumulated surface accretion, a measure of shallow subsidence or expansion of the sediment column can be obtained as the difference between total elevation change and depth of surface accretion. SET benchmarks are georeferenced against nearby tide gauges to provide a common reference elevation for the measurements taken at a site. Additional variables are measured or computed to aid in comparisons among sites.

Lynch et al. (2015) provide much more detail regarding the sampling protocol at: http://dx.doi.org/10.13140/RG.2.1.5171.9761

A CAUSAL KNOWLEDGE ANALYSIS FOR THE RELATIONSHIP BETWEEN COASTAL MARSH RESILIENCE AND RELATIVE SEA-LEVEL RISE

Interrogation of Evidence

Table S1. A progression of questions to consider when performing a causal knowledge analysis (from Grace 2024).

1. What is the nature of the cause(s) of interest? the response(s) of interest?
2. Are there observed manifestations that suggest the existence of a mechanism connecting causes to responses?
3. Are there known or plausible mechanisms connecting the variables of interest?
4. Are there plausible competing explanations?
5. How sufficient is our knowledge of mechanisms and conditional influences that may affect expressions of the mechanisms?
6. How reliable are the mechanisms and conditional influences based on available knowledge?
7. How exact are the processes and associated parameters?
8. How transportable are the mechanisms to other cases or situations?

Question 1: The Nature of the Cause and Response of Interest

The context for the study by Saintilan et al. (2022) relates to the ability of coastal marshes to persist over time, i.e., their resilience. Evidence from the paleo records shows that coastal marshes in many areas, but not all, have persisted during past periods of moderate changes in sea level that have occurred over geologic time. A question of current interest and importance is whether coastal marshes will continue to survive in place through vertical increases in marsh elevation and adjustment within the tidal frame as rates of sea-level rise accelerate. The persistence of marshes is determined by their ability to build elevation through vertical accretion of mineral sediment and organic matter. This process is known to involve their ability to trap sediments from the water column and add organic matter produced by marsh plants to the sediment column. One distinctive feature of this system is that marshes often have the capacity to increase their rate of vertical accretion in response to an increase in the rate of sea-level rise up to some point beyond which their capacity to respond decreases. Resilience in the face of rising seas depends on their ability to build elevation fast enough to avoid chronic submergence leading to conversion to unvegetated mudflats and eventually open water. To evaluate marshes' current and future status, scientists track the rate of change in marsh elevation relative to the rate of change in sea level. If sea level is increasing faster than marsh elevation is increasing, then there is an elevation deficit that will, if continued, lead to marsh drowning and eventual conversion.

Question 2: Manifestations Suggesting an Underlying Mechanism
The example in this paper affords us an opportunity to illustrate non-statistical evidence that supports a causal interpretation. One form of evidence that there exists a causal process connecting water levels to marsh surface elevation comes directly from sediment cores taken by paleontologists (inset photo in Figure S2 on right side). Actually, the study of the earth's history has long relied on the analysis of vertical cores of sediments that chronical the changes that have taken place as new surface materials have been deposited over layers of older materials over long periods of time. Cores taken in coastal marshes provide direct documentation of the inputs of mineral sediment and plant organic material that have built the column of material upon which today's surface resides. The external validity of this manifestation is clearly demonstrated by the wide range of locations around the world where columns of sediment are comprised of accumulated partially-decomposed peat mixed with various amounts of mineral materials. While much more information suggestive of various processes is routinely obtained from cores, the recognition that most of the organic component in the material lying beneath coastal marshes is made up of residual fractions of marsh plant roots and rhizomes confirms the conclusion that marsh ecosystems can adjust their elevations as water levels rise. This increase in marsh elevation is observed to be accomplished by accumulations of mineral sediment (trapped by marsh plants) and residual organic material (produced by plants). All these observations constitute direct evidence of causal processes and a characterization of the structures involved. Additional studies of mechanistic processes by physical scientists, chemists, and biologists serve to help us understand the dynamic processes connecting structural elements.

Question 3: Known Mechanisms Enabling Marsh Elevation to Adjust to Sea Levels
Saintilan et al. (2022) provide a succinct description of the presumed mechanism allowing marsh elevation to adjust its position, "We conceptualize surface elevation trends as a function of elevation gains (through mineral and organic matter accumulation, and sediment volume expansion, including root mass gain) and losses (through sediment erosion, and sediment volume losses associated with subsidence, auto-compaction and decomposition of organic matter)." To consider the evidence suggesting that there is a sufficient causal chain or network behind this conceptualization, we employ a causal knowledge diagram (Figure S3).

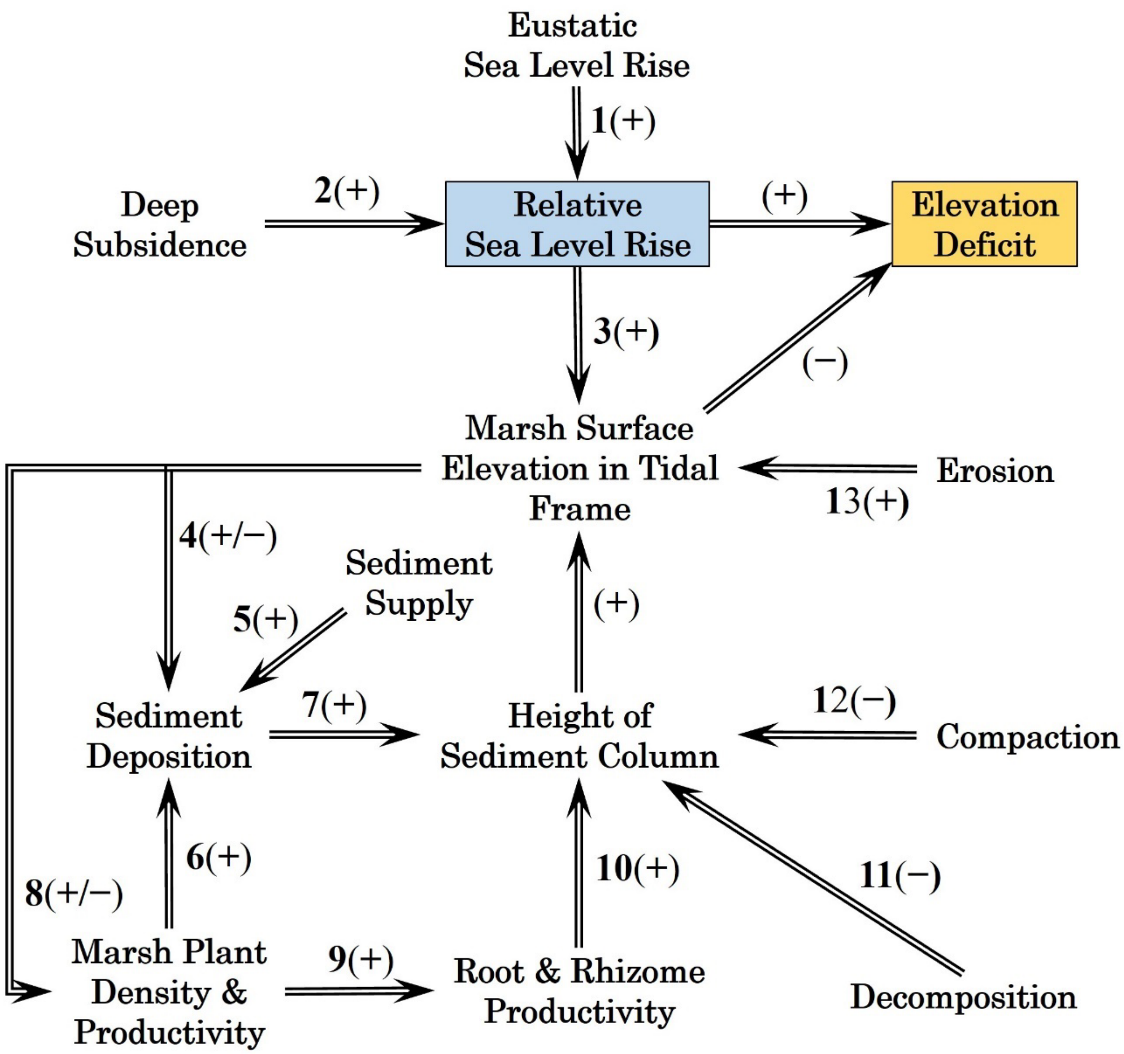


Figure S3. Causal knowledge diagram for the relationship between Relative Sea-level Rise and Elevation Deficit.

The task assigned to the causal knowledge diagram is to describe a causal chain or network of structures and processes that can help to explain how changes in RSLR can lead to changes in marsh surface elevation. Saintilan et al. (2022) chose to reference the rate of marsh surface elevation increase relative to the rate of RSLR to track whether marsh elevation increase is keeping pace with sea level, a requirement for long-term survival of the marsh (i.e., resilience). This led them to plot marsh elevation deficit (Elevation Deficit) against RSLR, two variables highlighted in the causal knowledge diagram in Figure S3 by being enclosed in boxes. The other variables and linkages in the figure represent our view of the core machinery leading to their correlated behavior.

As stated above, a causal knowledge diagram is a type of diagram for which there exists evidence of a mechanistic basis for the links. For this type of diagram, double-line arrows are used instead of standard single-line arrows to distinguish them from the types of diagrams used in causal statistics and structural equation modeling. Note also that causal knowledge diagrams are not meant to be complete representations of the data generating process but instead aspire to be sufficient to represent the mechanism of interest and the expected manifestations. The diagram in Figure S3 is labeled with 13 nodes and 13 process connections, which we consider in numerical order.

Overview of the Evaluation:
We can envision that the manifestations of the system of interest will depend on: (1) the core machinery, which is shown in the causal knowledge diagram, as well as (2) conditional influences, and (3) inputs. Our primary focus in this presentation is on the core machinery, which represents the structures and processes thought to be general to the system of interest. It is recognized that conditional influences will lead to situational variations in the general behavior. For any given location inputs of materials, such as sediments and biological structures, will influence the elevation changes measured at individual sample sites.

Structures:
The main structural components of the system of interest by volume include land, water, air trapped in the sediment, and plant material. Land in this case refers to the layered solid materials beneath the marsh surface, including the biological components. These intergrade from a continuously developed surface layer made of mineral and organic components, to a root-zone layer that is typically rich with root and rhizomes, to a progressively consolidating sub rootzone layer, to firmer layers beneath. The resilience of coastal marshes depends on the ability of marsh plants to promote the trapping of sedimentary material and deposition of biological material, thereby adding to the height of the sediment column and raising the surface elevation. The descriptions that follow characterize the processes that causally influence the short-term dynamics of the system as it relates to the association in Figure 2.

The Core Machinery
Connections 1 & 2: The Effects of Eustatic Sea-level Rise and Deep Subsidence on Relative Sea-level Rise
As Rovere et al. (2016) succinctly state, "Sea-level changes can be driven by either variations in the masses or volume of the oceans, or by changes of the land with respect to the sea surface. In the first case, a sea-level change is defined 'eustatic'; otherwise, it is defined 'relative'." Changes to both the ocean volume and height of underlying land are influenced by both slow processes (e.g., ocean mixing and tectonic movements) but also processes leading to changes contributing to short-term elevation dynamics. We use the term "deep subsidence or uplift" in this context to refer to vertical land movements that occur beneath the base of SET benchmark rods or other benchmarks used to calibrate SETs. "Shallow subsidence or expansion" refers to vertical changes that take place above the base of the SET benchmark, which are routinely measured along with surface elevation changes.

While eustatic sea-level changes are of primary interest because of their connection to climate change, their measurement is complex. Since 1992, satellite altimetry methods (e.g., https://sealevel.jpl.nasa.gov/missions/topex-poseidon/summary/; https://sealevel.nasa.gov/missions/jason-3) have supplemented the historical reliance on tide gauges. Satellite altimetry measures a distance to the ocean that is relative to the altitude of the satellite (the "range"). The altitude of the satellite is established with respect to an ellipsoid that represents an arbitrary and fixed surface approximating the shape of the Earth. The difference between the altitude of the satellite and the range is defined as the sea surface height (SSH).

Once corrected for seasonal variations due to ocean currents and other factors such as glacial isostatic adjustment, the global average SSH can be used to define the global mean sea-level change, which can be considered the eustatic, globally averaged sea-level change (Rovere et al. 2016).

Increases in eustatic sea level result from processes that cause changes in the volume of the ocean. Changes in the mass of the oceans occur either as a result of melting or accumulation of continental ice sheets over time (glacio-eustasy) and as a consequence of water redistribution between different hydrological reservoirs such as snow, surface water, sediment moisture, and groundwater, excluding glaciers (hydroeustasy). Changes in the volume of the ocean, however, are caused by variations in ocean water density due to cooling or warming of water masses (thermal expansion) or changes in salinity (halo-steric changes).

Vertical land movements (VLM) combine with eustatic sea-level rise to determine relative RSLR around the world's coasts (Rovere et al. 2016; Nicholls et al. 2021; Odenhen et al. 2023). Such movements result from both natural geological processes, but also from human activities such as groundwater withdrawal. Aside from its general importance, there is growing concern about the influence of VLM on estimates of coastal marsh elevation change. Site-specific measurements of marsh elevation changes using the SET-MH method typically make comparisons with the RSLR at long-term tide gage stations (Figure 3). Tide gages provide estimates of water levels relative to a local network of tidal benchmarks. However, the land to which the tide gages are referenced is typically undergoing VLM and as a result, estimates of RLSR may deviate significantly from the water levels marshes are actually exposed to (Cahoon and Guntenspergen 2024).

Hensel et al. (2024) used repeated real-time kinematic global positioning system survey campaigns at multiple time periods to estimate rates of VLM at geodetic control points used for benchmarking SET-MH sites. The authors found an average downward VLM value of 6.0 ± 0.7 mm year, which corresponded to >80% of the elevation gain measured using the SET-MH method. This deviation reflects a source of error in RSLR estimates that is now starting to be addressed more systematically.

Synopsis for Connections 1 & 2: The degree of flooding of marshes is determined by both local tide level variations driven by the volume of water in the ocean and movements of the land below the bottom of the SET benchmarks (Rovere et al. 2016). The terms "deep subsidence or uplift" refer to vertical land movements that occur beneath the base of SET benchmarks. "Shallow subsidence or expansion" refers to vertical changes that take place above the base of the SET benchmarks, which are routinely measured along with surface elevation changes. A final point of importance is the recognition that the conversion of coastal marshes to open water, the ultimate consequence of a loss of resilience, is not instantaneous but takes place over some period of years (Törnqvist et al. 2021). The processes involved temporal variations in water and land are physical and clearly qualify as causal mechanistic processes.

Connection 3: The Effect of RSLR on Marsh Elevation within the Tidal Frame

The tidal frame is defined as the area between the mean high tide and the mean low tide and encompasses the vertical range that is alternately flooded and exposed by tidal fluctuations. Tides determine the area available for capture and accumulation of tidally-borne mineral and organic matter and thus the lateral limits of coastal marshes. Changes in sea level alter the tidal frame. The fate of tidal marshes is determined by their ability to adjust their position vertically and laterally. Whether they retain their vertical position in the tidal frame depends on their capacity to build elevation in step with sea-level rise rates. The term "elevation capital" refers to the elevation of a marsh relative to the lowest elevation at which plants can survive (Reed 2002). When the elevation capital is reduced, marshes are seen as increasing in risk of drowning. As described in the next section, a marshes position within the tidal frame can influence the critical processes of sedimentation and erosion, as well as rates of biological production, which is why Saintilan et al. (2022) and many others emphasize position in the tidal frame (aka tidal position) as an important functional feature for the processes influencing elevation dynamics.

Synopsis for Connection 3: The tidal frame is defined as the area between mean high tide and mean low tide and encompasses the vertical range that is alternately flooded and exposed by tidal fluctuations. Tides determine the area available for capture and accumulation of tidally-borne mineral and organic matter and thus the lateral limits of coastal marshes. Changes in sea level alter the tidal frame (Ensign and Noe 2018). The fate of tidal marshes is determined by their ability to adjust their position vertically and laterally. Whether they retain their vertical position in the tidal frame depends on their capacity to build elevation in step with sea-level rise rates. Again, temporal changes in the tidal frame are physical and therefore causal.

Connections 4, 5, 6, & 7: The Contributions of Marsh Elevation, Sediment Supply, and Marsh Plants on Surface Sediment Deposition

Sediment capture is a vital process for the maintenance of marsh elevation. The elevation of the marsh surface in the tidal frame strongly influences sediment deposition due to its controls on the duration of tidal inundation and thus the amount of time during which suspended materials can settle out of the water column. Plants play a critical role in aiding deposition and retaining settled materials as well, which will be discussed below. Buffington et al. (2021) provide a mechanistic characterization of the process, which we summarize here.

The mineral sediment accumulation rate (*MAR*) is a function of the sediment deposition flux Q, which in turn is determined by settling, Q_{ds}, and erosion Q_e caused by tidal current shear stress, τ_0.

$$\frac{dQ}{dt} = Q_{ds} - Q_e \tag{1}$$

Shear stress, τ_0, is defined as

$$\tau_0 = \lambda\gamma U \tag{2}$$

where γ is the specific density of water (9.807 kN m-3), U is the horizontal water velocity in m·s^{-1} and is defined as

$$U = n\frac{D}{\lambda} \tag{3}$$

where n is the instantaneous change in the water level timeseries, D is water depth (m), and λ is a bottom friction coefficient, defined as

$$\lambda = \frac{8}{3\pi}\frac{U_0}{K^2} \tag{4}$$

where U_0 is the maximum tidal current (assumed to be 0.2 m·s^{-1}), and K is Chezy's friction coefficient, assumed to be 10 m$^{1/2}$·s^{-1}.

Deposition caused by settling, Q_{ds} is defined as,

$$Q_{ds} = \begin{cases} w_s C \left(1 - \frac{\tau_0}{\tau_d}\right) if\ \tau_0 < \tau_d \\ 0 \qquad\qquad\qquad if\ \tau_0 \geq \tau_d \end{cases} \tag{5}$$

where w_s is the settling velocity (m·$^{s-1}$, assumed to be a constant 1.0 x 10^{-4} and calibrated using sediment deposition data), C is the depth-averaged suspended sediment concentration, and τ_d is the shear stress limit above which sediment flocs do not settle and remain in the water column (0.1 N·m^{-2}). It is important to note that in addition to mineral materials, deposition can include organic material derived from the decomposition of marsh plants but also other sources.

Erosion flux, Q_e is defined as,

$$Q_e = \begin{cases} Q_{e0} \left(\frac{\tau_0}{\tau_d} - 1\right) if\ \tau_0 > \tau_d \\ 0 \qquad\qquad\qquad if\ \tau_0 \leq \tau_e \end{cases} \tag{6}$$

where τ_e is the critical shear stress needed to break up the bed (0.4 N m^{-2}), Q_{e0} is an empirical coefficient = 1/ρs x 3.0x10-4 m·s^{-1}, with ρs = 2600 kg·m^{-3}. Suspended sediment concentrations (SSC) were assumed constant during flood tides, but on ebb tide the instantaneous sediment concentration is reduced as particles settle on the surface,

$$\frac{dDC}{dt} = w_s C + C\frac{dh}{dt} \tag{7}$$

where h(t) is the water level (m, MSL) and D(t) is instantaneous water depth (m; D(t)-z).

These equations (1-7) illustrate the point that the settling of mineral sediment on the marsh surface is largely a physical process. Collectively it is a complex process and one that is of vital importance for marsh resilience.

Synopsis for Connections 4, 5, 6, & 7: Sediment capture is a vital process for the maintenance of marsh elevation. The elevation of the marsh surface in the tidal frame strongly influences sediment deposition due to the fact that it controls the duration of tidal inundation and thus the amount of time during which suspended materials can settle out of the water column. Plants play a critical role in aiding deposition and retaining settled materials as well. Buffington et al. (2021) provide a mechanistic characterization of the process, which is presented in the Supporting Information as a set of mechanistic equations. These equations illustrate the point that the settling of mineral sediment on the marsh surface is largely a physical process.

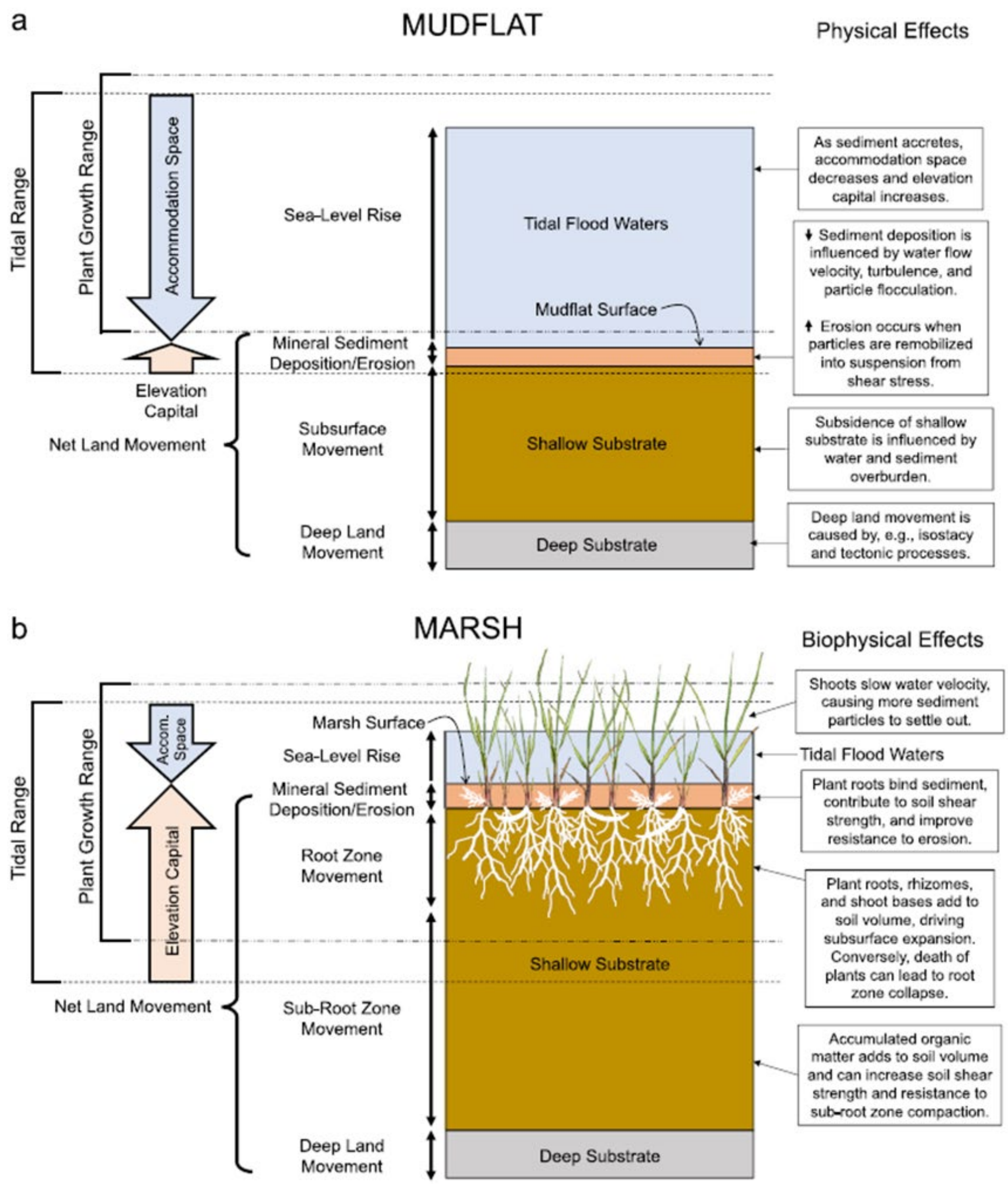


Figure S4. Diagrammatic representation of coastal marsh vertical profiles and processes describing (a) without plants and (b) with plants showing some of the biophysical effects of plants that support marsh resilience (From Cahoon et al. 2021).

Connections 8, 9, & 10: The Effects of Marsh Elevation on the Contributions by Marsh Plant Productivity to the Rate of Marsh Elevation Increase

Coastal marshes are formed and maintained by the emergent plants, which help to regulate marsh elevation and position within the intertidal zone (Cahoon et al. 2021). Plants play a major role that is especially important when the supply of mineral sediment inputs is low. The presence of plants contributes in three major ways by (1) enhancing the trapping and retention of mineral sediments, (2) adding organic matter to the sediment column, which contributes to vertical expansion, and (3) helping to bind and consolidate sediment materials and thereby stabilize the marsh platform. Figure S4 lists on the right side some of the ways plants contribute to marsh resilience. The paper by Cahoon et al. (2021) provides a description of the role plant play in marsh formation, maintenance, and tracking changes in sea levels.

The regulation of marsh elevation in the face of rising seas is influenced by the growth response of plants in relationship to variations in water depth (Morris et al. 2002; Kirwan and Guntenspergen 2012). Under favorable conditions, the vegetated area spans the tidal range. However, the amount of plant production and its influence can vary with water depth (Figure 7). While sediment trapping depends on above-ground plant material, organic contributions are largely determined by below-ground production. Kirwan and Guntenspergen (2012) have shown that the water depth responses by above- and below-ground production can be quite different, and, as a result, plant contributions to vertical adjustment can be expected to vary with water depth. Of importance, root zone processes typically dominate the response of marshes to sea-level rise, particularly when the supply of mineral sediment is limited. Thus, rates of marsh elevation increase are directly related to below-ground root and rhizome production, which result in vertical expansion of the rootzone.

For the majority of cases examined thus far, below-ground plant production follows a modal curve like those shown in Figure S5. This phenomenon has major implications for how marshes adjust their elevation in response to rising sea levels. When marshes occupy relatively high elevations within the tidal frame, water depths are shallower than those optimal for plant growth. In this situation, an increase in sea level will lead to an increase in organic accretion and marsh elevation up to some maximum value for the species present and growing conditions. In this zone, rates of marsh elevation growth will track increases in sea level if the latter do not exceed some level, reflecting a homeostatic response. However, when water depths are greater than those corresponding to the plant growth optimum, increasing rates of sea-level rise will lead to decreasing rates of plant production and organic accretion, eventually resulting in marsh drowning and loss. Rates of low sea-level rise tip the balance towards long-term stability, as evidenced by the observation that marshes having modest mineral sediment inputs have commonly survived for thousands of years (e.g. Redfield 1965).

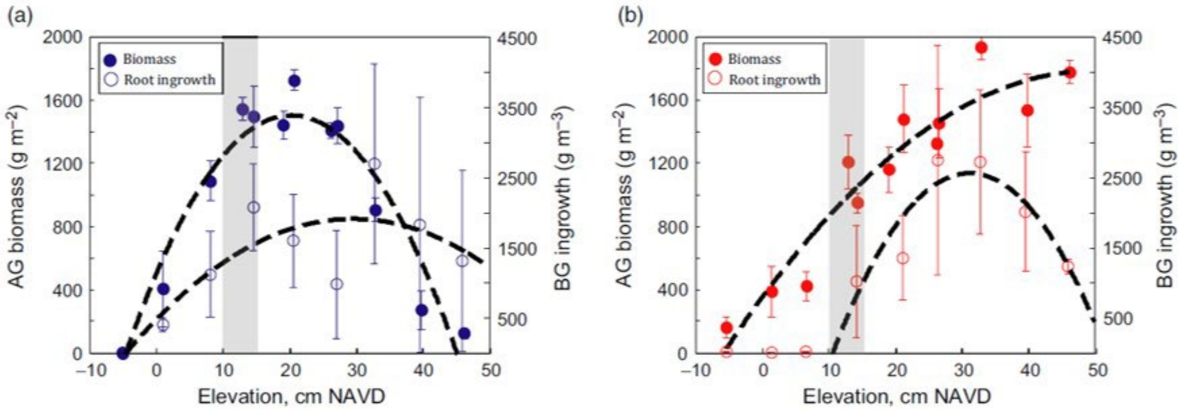


Figure S5. Results from a marsh plant growth experiment where plants of two species were grown in the field at 7 different elevations (Kirwan and Guntenspergen 2012). Elevation is expressed relative to the North American Vertical Datum, which relies on a leveling network across North America to ensure consistent elevation measurements. Grey shading denotes the approximate elevation of the adjacent marsh platform. Above-ground (AG) biomass (in solid circles) and root biomass (in open circles) were separately determined for two species From Kirwan and Guntenspergen (2012) with permission from John Wiley and Sons.

Synopsis for Connections 8, 9, & 10: Coastal marshes are formed and maintained by a non-linear response to flooding by the emergent plants. Plants contribute in three major ways to marsh elevation dynamics by (1) enhancing the trapping and retention of mineral sediments, (2) adding organic matter to the sediment column, which contributes to vertical expansion, and (3) helping to bind and consolidate sediment materials and thereby stabilize the marsh platform. When marshes occupy relatively high elevations within the tidal frame, water depths are shallower than those optimal for plant growth. In this situation, an increase in sea level will lead to an increase in organic accretion and marsh elevation up to some maximum value for the species present and growing conditions. In this zone, rates of marsh elevation growth will track increases in sea level if the latter do not exceed some level, reflecting a homeostatic response. However, when water depths are greater than those corresponding to the plant growth optimum, increasing rates of sea-level rise will lead to decreasing rates of plant production and organic accretion, eventually resulting in marsh drowning and loss. Historical rates of sea-level rise along many coasts during the past ~7000years have been sufficiently low that marshes have persisted via vertical gains in elevation (e.g. Redfield 1965; Saintilan et al. 2023). This part of the diagram reflects biological mechanisms that are variable and conditional, but sufficiently reliable to have a widespread causal influence on marsh elevation deficits.

Connections 11 & 12: The Effects of Decomposition and Sediment Compaction on the Height of the Sediment Column and Marsh Elevation

Rates of decomposition vary greatly with location within the vertical profile (Megonigal and Neubauer 2019). The supply of oxygen, which has a major influence on rates of decomposition, is largely supplied by diffusion from the overlying water column (though oxygen supplied by the roots of wetland plants can aerate the rhizosphere). Because an oxygen deficit develops very rapidly beneath the surface of marsh sediments, the depth of the water column is expected to have little influence on the decay of organic matter in wetland sediments. Kirwan et al. (2013)

investigated the expectation that organic decomposition rates will be insensitive to sea-level rise in a field experiment that exposed decomposition bags to a variety of water depths. This study found that inundation depth generally had no major influence on rates of organic decomposition beneath the sediment surface and concluded that increased rates of sea-level rise are not expected alter marsh elevation rates through influences on decomposition rates. At larger scales, rates of decomposition and peat formation are sensitive to major differences in climate (Perillo et al. 2019; Martini et al. 2019).

Rates of shallow compaction/expansion are now routinely estimated because of the widespread use of the SET-MH method. Procedurally, shallow compaction or expansion is measured as the component of total marsh elevation change attributed to changes occurring below the marker horizon (Figure S2). The component of change above the marker horizon is described as surface accretion. Interestingly, the naïve expectation that the elevation of the marker horizon above the base of the SET benchmark rod would be a constant is not aligned with empirical measurements. It has been recognized for a while that the depth of the marker horizon beneath the sediment surface can be very responsive to temporal dynamics in water levels, most noticeably seasonal variations (Cahoon et al. 2021), which must be controlled for when estimating year-to-year trends.

Recent syntheses of SET-MH data (e.g., Saintilan et al. 2021) have helped to establish that increased depths of surface accretion layers result in increasing levels of shallow compaction of the sediment column. This finding represents an important advance in our ability to forecast future responses of coastal marshes to increases in sea level and reconciles our estimates from numerical models with paleo-historical observations.

Synopsis for Connections 11 & 12: Organic peat accumulation in wetland soils results from oxygen depletion beneath the surface of the sediment surface. This biological process is nearly invariant and is of tremendous importance as wetlands cover only 5% of the land surface but contain 25% of global terrestrial carbon. At geographic scales, rates of decomposition and peat formation are sensitive to major differences in climate (Perillo et al. 2019). While organic production adds to the vertical growth of wetland soils, compaction constantly reduces that property. Recently it has been found that increased levels of surface mineral accretion result in increasing levels of shallow compaction of the sediment column. This finding represents an important advance in our ability to forecast future responses of coastal marshes to increases in sea level and reconciles our estimates from numerical models with paleo-historical observations.

Connection 13: The Effect of Erosion on RSLR

Fagherazzi et al. (2013) have pointed out that coastal marsh collapse does not necessarily require sea-level rise but that other factors, particularly erosion can play a role. They emphasize that while marshes have the ability to slowly adjust to increases in surface flooding, they are inherently unstable at their margins, particularly where waves and tidal energy are high. Generally, it is well known that erosion constitutes a situationally important process influencing coastal marsh resilience. SET-MH stations tend to be located at some distance from edges so as to avoid influences from edge erosion. Thus, we do not consider edge erosion in this treatment. However, there exists another form of erosive influence that does warrant consideration, which is marsh pond formation. Ganju et al. (2015) reported that suspended sediment concentrations and surface accretion rates are higher in deteriorating marshes where some areas are breaking up due to drowning (persistent elevation deficits). Such effects indicate that estimates of surface accretion and their contributions to marsh resilience must be interpreted in the context of the surrounding landscape and sediment transport processes to avoid misinterpretation of the processes involved.

Synopsis for Connection 13: Generally, it is well known that erosion constitutes a situationally important process influencing coastal marsh resilience. This represents a physical process that is reduced in importance by rooted plants.

Conditional Influences on the Operation of the Core Machinery:

For the conduct of our CKA, we give separate consideration above to what we call the core machinery (Figure S3) versus the conditional influences that may shift its behavior. We consider this separation to be important to allow a primary focus to be placed on what is known about the causal machinery connecting sea-level rise to marsh resilience (the question of whether the correlation in Figure S1 results from a causal process). Conditional influences we treat as of secondary importance because it is expected that the investigation of conditional influences will typically be an open-ended process focusing on refining out knowledge and on what we don't know rather than on what we do know. In this presentation we consider conditional influences in only the most general terms.

The behavior of biological components of mechanisms can be expected to be more conditional than physical components because of the influence of biological diversity. The settling of particles from the water column onto the sediment surface is ultimately determined by a limited set of physical forces. However, the degree of adherence of particles will depend on more than just physical processes, but also by any surface layer of fine roots, which can vary widely with the species of plants (Cahoon et al. 2021). Surface communities of algae and bacteria are also complex biological entities whose ability to consolidate surface deposits can vary widely (Möller & Christie 2019). As shown in Figure S5, plant species can vary significantly in both their abilities to contribute to sediment building and the depth distribution of their contributions (Cherry et al. 2009). Research into the species-specific contributions to marsh building has received increased attention as wetland-specific models have been developed and applied (Buffington et al. 2021). Beyond that, factors that influence the productivity of marsh plants can have substantial influences on their resilience, as shown by fertilization studies, manipulations of levels of atmospheric carbon dioxide, and temperature experiments.

Inputs:

We treat the biological contributions of organic material to marsh building as an endogenous part of our machinery in this treatment. Therefore, the dominant input to the system is mineral sediment. A large literature exists on the processes associated with mineral sediment delivery to coastal mudflats and marshes (e.g., Perillo et al. 2019) and won't be expounded upon here. Most relevant to this presentation is the substantial dichotomy between minerogenic and biogenic coastal marshes. As Cahoon et al. (2021) describe, coastal wetlands occur on a gradient from sediment-rich estuaries to sediment-poor coasts. Plant contributions to organic accretion are important for the resilience of nearly all wetlands but particularly where there is little mineral sediment input. Where productivity is high and/or deep subsidence is low, biogenic marshes can persist for long periods. That said, resilience can often be increased by sediment diversions or additions (e.g., Elsey-Quirk et al. 2019).

Question 4: Are there plausible competing explanations?
It is always important when presenting a case for a causal explanation for some phenomenon to consider whether there are plausible competing explanations. Alternative explanations can include completely different mechanisms but also spurious associations due to independent influences on the cause and response of interest. In this example, little weight is given to alternatives that deviate substantially from the mechanism described in Figure S3.

Questions 5-8: Sufficiency, Reliability, Exactness, and Transportability
Sufficiency of the Core Mechanism:
An essential question to address is whether there is evidence to indicate a sufficiently continuous chain or network of structures and processes to connect the cause of interest to the response of interest. The substantial and sustained efforts contributing to our knowledge of this system gives us confidence that there is sufficient evidence to view Figure S1 as a causal relationship. This is an easy conclusion to defend as the contributions of processes to marsh elevation reflect arithmetic process that can be observed through physical measurements. The slope of the relationship observed is 0.86mm/mm. This should be viewed as a summary of the sample rather than a mechanistic parameter because it represents the combined influences of the causal chain, the particular conditional influences at the locations of the samples including subsidence rates, and a result of the sediment supplies for the individual sites. That said, the slope of the relationship, which represents the mm of elevation deficit created per mm of relative sea-level rise for the sample, is a plausible number implying that on average the marshes are not keeping up with sea-level rise, a conclusion reached by Saintilan et al. (2021). Beyond the simple question of sufficiency, there are certainly places where our understanding of the functional forms of relationships can be improved, though that goes beyond the objectives in this paper.

Reliability of the Core Mechanism:
In the context of causal analysis, reliability refers to the frequency with which a process operates in multiple studies or locations. It does not, however, refer to the quantitative magnitude of its influence. From that perspective, when we consider the various processes in the core mechanism, we expect a high degree of reliability except perhaps in extreme environments. The processes of sedimentation, compaction, deep subsidence, and edge erosion can be expected to operate reliability nearly everywhere coastal marshes occur, though certainly conditional influences will override their effectiveness where physical conditions are unsuitable. The biological processes should also be reliable to a substantial degree as evidenced by the wide-spread distribution of coastal marshes and their persistence in the paleo record.

Exactness of Processes:
Exactness in this context refers to the constancy of mechanism. For our example in this paper, numerical models provide us with insights into this issue. For example, some of the processes involved in sediment deposition (e.g., equations 2-4 above) involve numerical constants. While these may only approximate the true process, they suggest a degree of exactness for the operation of mechanistic elements. In contrast, some biological mechanistic elements will show substantial quantitative variation. An obvious example is the depth distribution of root growth seen in Figure S5. In numerical models, the distribution of plant production as a function of water depth is typically represented using polynomial or other equations that approximate the shape of the

distribution but without meaningful coefficients. The exactness of such mechanisms is therefore low.

Transportability:
One of the most characteristic features of causal relationships is external consistency, the repeated observation of similar manifestations in different situations. Repeated manifestations result from there being transportable mechanisms. Mechanisms are transportable when there are structures and processes that are repeated in space in time. The global distribution of SET-MH stations established by different researchers in hundreds of locations around the globe provide us the opportunity to see if manifestations consistent with the machinery in Figure S3 are widely observed. There are a number of types of conditional variations reported in different studies; nonetheless, there is strong and consistent body of evidence indicating widespread transportability. Observed major departures are thought to represent boundary conditions where physical factors exceed biological tolerances (see chapters 4, 10-12 in Perillo et al. 2019). The case has been made repeatedly that coastal mangrove forests possess sufficiently similar biological features to those in coastal marshes that the mechanisms whereby the are able to track rising sea levels are roughly the same. This constitutes another level of transportability where mechanistic elements are common to distinctly different situations, resulting in recognizably similar behavior.

Overall Assessment of Mechanistic Evidence
It is our assessment that existing mechanistic knowledge supports an interpretation of the relationship in Figure S1 as reflective of an underlying causal mechanistic process. We do not arrive at this conclusion through quantitative analysis of data, but through scientific knowledge accumulated over many studies. Furthermore, it has long been understood that coastal wetlands occupied by marsh plants can in many cases build elevation through the accumulation of mineral sediment and organic material driven by increases in sea levels. What persistence investigation has found is how plants have the capability of increasing rates of marsh vertical growth in response to increasing rates of water level rise, up to some point where their capacity is overwhelmed. This involves a nonlinear feedback such that when rates of sea level are low, increases in marsh elevation keep pace. As annual rates of sea-level rise, the system has a capacity to increase its vertical growth rate to keep pace. Eventually the capacity of the marsh system is exceeded and elevation increase falls behind, eventually leading to conversion to open water (Morris et al 2002). Recent results have also shown a surprising sensitivity of sediment compression in response to surface accretion. This finding has reconciled paleo and contemporary estimates of vertical growth rates in response to sea-level rise rates, deepening our understanding of the system.

FURTHER COMMENTS REGARDING NUMERICAL RESULTS
Saintilan et al. (2022) report a number of results and we have focused on just one of them, the relationship between rates of relative sea-level rise and rates of change in marsh elevation deficit. Further, we emphasize the slope and intercepts, which provide useful approximations having causal interpretations, such as the rate of relative sea-level rise above which marsh elevation deficits begin to occur. If we were to present and discuss more of their findings, we would focus on their characterizations of mechanistic elements that are part of the core causal network, such as the relationship between accretion and elevation gain, which estimates the compressibility of

the sediment. We would again emphasize absolute values of parameters because they potentially represent mechanistic knowledge that could be incorporated into a numerical model.

Saintilan et al. (2022) do highlight in their paper certain causal implications of their findings. However, they also present standard statistical results, such as estimates of variance explanation, which do not have causal interpretations but are measures of association. Further, they conduct random forest and other analyses that may help to lead to hypotheses about conditional factors, but that do not contribute to mechanistic understanding. In the future, in causal investigations it will be important for researchers to explicitly note which analyses are characterizations of causal mechanistic elements (as done in Grace et al. 2025) and which are exploratory.

REFERENCES

Buffington, K. J., Janousek, C. N., Dugger, B. D., Callaway, J. C., Schile-Beers, L. M., Borgnis Sloane, E., & Thorne, K. M. (2021). Incorporation of uncertainty to improve projections of tidal wetland elevation and carbon accumulation with sea-level rise. *PLoS One, 16*. p.e0256707.

Cahoon, D. R., McKee, K. L., & Morris, J. T. (2021). How plants influence resilience of salt marsh and mangrove wetlands to sea-level rise. *Estuaries and Coasts, 44*, 883-898.

Cahoon, D. R. (2024). Measuring and interpreting the surface and shallow subsurface process influences on coastal wetland elevation: A Review. *Estuaries and Coasts, 47*, 1708–1734.

Cahoon, D. R., & Guntenspergen, G. R. (2024). Current advances in coastal wetland elevation dynamics: Introduction to the special issue. *Estuaries and Coasts*, *47*, 1703-1707.

Cherry, J. A., McKee, K. L., & Grace, J. B. (2009). Elevated CO_2 enhances biological contributions to elevation change in coastal wetlands by offsetting stressors associated with sea-level rise. *Journal of Ecology, 97*, 67–77.

Elsey-Quirk, T., Graham, S. A., Mendelssohn, I. A., Snedden, G., Day, J. W., Shaffer, G. P., Sharp, L. A., Twilley, R. R., Pahl, J. and Lane, R. R., (2019). Mississippi River sediment diversions and coastal wetland sustainability: Synthesis of responses to freshwater, sediment, and nutrient inputs. *Estuarine, Coastal and Shelf Science*, *221*, pp.170-183.

Ensign, S. H., & Noe, G. B. (2018). Tidal extension and sea-level rise: Recommendations for a research agenda. *Frontiers in Ecology and the Environment, 16*, 37–43.

Fagherazzi, S., Mariotti, G., Wiberg, P. L., & McGlathery, K. J. (2013). Marsh collapse does not require sea level rise. *Oceanography, 26*, 70–77.

Ganju, N. K., Kirwan, M. L., Dickhudt, P. J., Guntenspergen, G. R., Cahoon, D. R. & Kroeger, K. D. (2015). Sediment transport-based metrics of wetland stability. *Geophys. Res. Lett.*, 42:7992–8000.

Grace, J. B. (2024). An integrative paradigm for building causal knowledge. *Ecological Monographs, 94*, p.e1628.

Hensel, P., Cahoon, D. R., Guntenspergen, G. R., Mitchell, L., Whitbeck, M. & Scott, G. (2024). Incorporating Measurements of Vertical Land Motion in Wetland Surface Elevation Change Analyses. *Estuaries and Coasts* 47:2094-2105.

Kirwan, M. L. & Guntenspergen, G. R. (2012). Feedbacks between inundation, root production, and shoot growth in a rapidly submerging brackish marsh. *Journal of Ecology, 100*, 764-770.

Kirwan, M. L., Langley, J. A., Guntenspergen, G. R. & Megonigal, J. P. (2013). The impact of sea-level rise on organic matter decay rates in Chesapeake Bay brackish tidal marshes. *Biogeosciences, 10*, 1869-1876.

Martini, I. P., Morrison, R. I. G., Abraham, K. F., Sergienko, L. A., & Jefferies, R. L. (2019). Northern polar coastal wetlands: Development, structure, and land use. Chapter 4 (pp. 153-186) In: Perillo, G., Wolanski, E., Cahoon, D. R. & Hopkinson, C. S. (editors), *Coastal wetlands: An integrated ecosystem approach*. Second Edition, Elsevier.

Megonigal, J. P., & Neubauer, S. C. (2019). Biogeochemistry of tidal freshwater wetlands. (pp. 641-683). Chapter 19: In Perillo, G., Wolanski, E., Cahoon, D. R. & Hopkinson, C. S. (editors), *Coastal wetlands: An integrated ecosystem approach*. Second Edition, Elsevier.

Möller, I. & Christie, E. (2019). Hydrodynamics and modeling of water flow in coastal wetlands. Chapter 8 (pp. 289-323). In: In Perillo, G., Wolanski, E., Cahoon, D. R. & Hopkinson, C. S. (editors), *Coastal wetlands: An integrated ecosystem approach*. Second Edition, Elsevier.

Morris, J. T., Sundareshwar, P. V., Nietch, C. T., Kjerfve, B., & Cahoon, D. R. (2002). Responses of coastal wetlands to rising sea level. *Ecology, 83*, 2869-2877.

Nicholls, R. J., Lincke, D., Hinkel, J., Brown, S., Vafeidis, A. T., Meyssignac, B., Hanson, S. E., Merkens, J. L., & Fang, J. (2021). A global analysis of subsidence, relative sea-level change and coastal flood exposure. *Nature Climate Change, 11*, 338-342.

Ohenhen, L. O., Shirzaei, M., Ojha, C. & Kirwan, M. L. (2023). Hidden vulnerability of US Atlantic Coast to sea-level rise due to vertical land motion. *Nature Communications, 14*, 2038.

Perillo, G., Wolanski, E., Cahoon, D. R. & Hopkinson, C. S. editors, (2019). *Coastal wetlands: An integrated ecosystem approach*. Second Edition, Elsevier.

Redfield, A. C. (1965). Ontogeny of a salt marsh estuary. *Science, 147*, 50–55.

Reed, D. J. (2002). Sea-level rise and coastal marsh sustainability: Geological and ecological factors in the Mississippi Delta Plain. *Geomorphology, 48*, 233–243.

Rovere, A., Stocchi, P., & Vacchi, M. (2016). Eustatic and relative sea level changes. *Current Climate Change Reports, 2*, 221-231.

Saintilan, N., Kovalenko, K. E., Guntenspergen, G. R., Rogers, K., Lynch, J. C., Cahoon, D. R., Lovelock, C. E., Friess, D. A., Ashe, E., Krauss, K. W., & Cormier, N. (2022). Constraints on the adjustment of tidal marshes to accelerating sea level rise. *Science, 377*, 523-527.

Saintilan, N., Horton, B., Törnqvist, T. E., Ashe, E. L., Khan, N. S., Schuerch, M., Perry, C., Kopp, R. E., Garner, G. G., Murray, N., Rogers, K., Albert, S., Kelleway, J., Shaw, T. A., Woodroffe, C. D., Lovelock, C. E., Goddard, M. M., Hutley, L. B., Kovalenko, K., Feher, L., and Guntenspergen, G. R. (2023). Widespread retreat of coastal habitat is likely at warming levels above 1.5° C. *Nature, 621*, 112-119.

Törnqvist, T. E., Cahoon, D. R., Morris, J. T., & Day, J. W. (2021). Coastal wetland resilience, accelerated sea-level rise, and the importance of timescale. *AGU Advances*, *2*, p.e2020AV000334.