

The Role of Structural Equation Modeling in Causal Investigations

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Abstract

Causal investigations represent a long-standing tradition in science that strives to build causal knowledge and understanding of the real-world. A major focus in causal methods in recent years has been on purely statistical techniques (causal statistics) that stand in stark contrast to the form and purpose of structural equation modeling (SEM). Recent efforts have expanded our understanding of the full domain of causal methodology and provided a basis for an interdisciplinary alignment of concepts and terminology, which was badly needed. This broad perspective allows us to see more clearly the role that SEM plays in causal investigations as a method for representing and evaluating system-level causal network understanding. This presentation describes a scientific perspective on how SEM contributes to causal investigations as an abductive method for learning through repeated evaluations of knowledge/theory-based expectations.

Keywords: causal investigations; structural equation modeling; abductive methods.

1. Introduction

A series of published papers and unpublished Research Briefs (see www.jbgrace.com) have described an expanded paradigm for causal studies meant to consolidate yet distinguish a variety of popular approaches to the study of causation (Fig. 1). The current literature is dangerously fragmented, underexplained, and inconsistent. Rarely in history do we have a basis for aligning concepts and terminology across disciplines, subdisciplines, and even groups. The National Academies of Science, Engineering, and Medicine recently published a Consensus Report on Causal Frameworks (NASEM 2022) that affords us a basis for aligning statistical and scientific perspectives on causal methods. This information has now been integrated into a multi-evidence paradigm for causal investigations that seeks an even broader integration (Fig. 1).

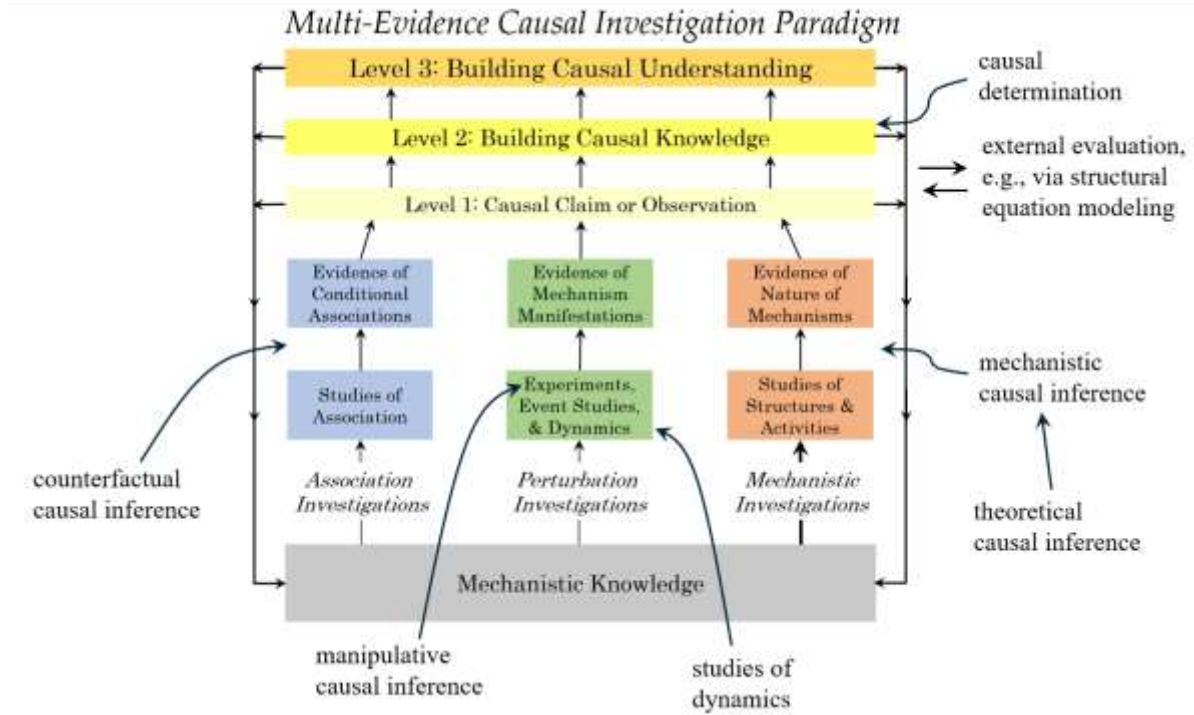


Figure 1. Expanded multi-evidence paradigm for causal investigations (modified from Grace 2024).

2. Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) represents a tradition reaching back over 100 years that remains in wide usage today. Its persistent popularity with scientists comes from the fact that it attacks the challenge scientists know to be important, developing a system-level understanding of phenomena. Causal statistics, in contrast, focuses on the reliability of estimates of individual statistical parameters referred to as counterfactual causal effects (Grace et al. 2025a). The *statistical causal inference paradigm* (Rubin 2005; Wu et al.) defined by the blue boxes in Figure 1 is a quasi-experimental method that seeks the estimation of counterfactual causal effects without manipulation and randomization. The estimands themselves are point estimates and their defensibility as causal parameters is based entirely on the data without reliance on mechanistic knowledge. This means, the evidential requirement for a counterfactual causal effect estimate is a complete absence of confounding of any sort (a perfection requirement) that cannot be guaranteed nor confirmed. Statistical causal inference adopts instead a perfection-seeking standard based on documenting efforts to avoid all confounding (Grace et al. 2025b, Fig. 1). In practice, statistical causal inference can be seen to be a Devil's Advocacy perspective preoccupied with a fear of a Type I error. This makes it a useful method for certain situations (drug efficacy testing), but not for the aspiration of building mechanistic causal knowledge (as is typically required for disease detection or designing the drugs to be tested). Generally, SEM is not considered to be a "causal inference" methodology. Instead, its focus is on evaluating external consistency between theoretical/mechanistic expectations and new observations (note its position in Figure 1). This focus makes it an *abductive method* – one that evaluates all evidence so as to arrive at the best multi-evidence explanation given all the existing relevant information (Holt 2015; Heckman and Singer 2017; Nichols and Cooch 2025).

Unsurprisingly, causal statisticians do not endorse SEM because of its fallibility as a estimation method, though a great many generalist statisticians have contributed to implementations of the methodology, leaving the abductive justifications to the scientists. The importance of abduction in causal investigations is reflected in a quote from Nobel laureate James Heckman (2022),

“The current literature on causality is filled with monologues of various participants hawking their wares, ignoring what others have to say. I have read the literature in statistics [potential outcomes model] and computer science [structural causal model] closely. It has had a big influence on many fields ... often to their detriment. Much of the current “causal inference” literature ... conflates estimation methods with conceptual definitions of causality. I have long practiced abductive inference [reasoning to the best explanation], building and testing models using all sources of data (quantitative and qualitative).”

SEM is prized for its flexibility. This is not just because of its ability to represent network models and to model latent factors, but also because its recognition that the study of causation is an extended investigative process. There is a formal recognition in SEM that it can be applied for (a) exploration/model-building, (b) model comparison, and (c) confirmation/model-testing, which is often declared in publications to avoid confusion of intent. In today’s environment, its use suffers from the absence of formal presentation of existing mechanistic causal knowledge relevant to system under investigation. Support for mechanistic causal inference is easily underestimated (Grace 2025b). If we are to build causal knowledge of how the world works efficiently scientists need to do a better job at this sort of documentation.

3. Brief Illustration of the Use of SEM in a Causal Investigation

A major controversy involving the “Hump-backed Model of Plant Diversity” (Grime 1973) was ultimately resolved using SEM (Grace et al.. 2016).

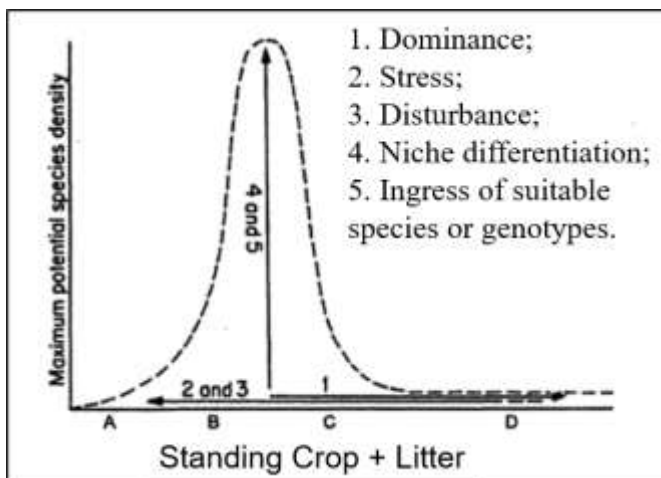


Figure. 2. Hump-backed model of plant diversity that was the subject of a historic 40-year debate in ecology (1973-2016).

Most scientists deal with systems. This is conspicuous with those who study ecosystems. Unsurprisingly the questions of interest and of societal importance are at the system level and call for system-level explanations, which places them out of the realm of counterfactual causal statistics and in the realm of causal investigations. Such investigations involve the pursuit of understanding through a series of interconnected studies that progressively build sufficient evidence and knowledge to represent a causal explanation of the problem.

The problem tackled in this case was the development of a substantial number of competing and conflicting models/theories attempting to explain the common observation that plant diversity exhibits a distribution along gradients of ecosystem productivity/standing biomass having a modal or hump-shaped upper boundary. Decades of exchanges in the literature led to better and better data compilations to remove that issue as a source of disagreement. A constant limitation to progress was the use of regression models to evaluate complex theoretical models (as illustrated in Figure 2 by the numerous processes proposed to be involved in this one model). An impasse was reached in 2015 when a pair of papers in *Science* magazine reached opposite conclusions with no path forward towards resolution.

In working on this problem for over 20 years, it was first determined that SEM was the best approach for the scale of the issue. Then a systematic investigation was pursued with substantial effort towards developing both a mechanistic understanding of the key proximate processes and a capability for modeling approximations to those mechanisms. Ultimately, the paper in which a resolution was presented (Grace et al. 2016) included 47 pages of Supporting Information summarizing the information justifying modeling choices and results interpretations. Key parts of the causal investigation that built the knowledge supporting the study are summarized in Table 1. It can be seen that numerous targeted field experiments were used, including validation studies for SEM observational models. Studies of particular mechanisms led to the discovery of “cryptic competition” (suppression of germination by established vegetation) and its regulation and gradients in species pools are key to understanding how diversity regulation operates.

Table 1. Various studies contributing to the causal investigation preceding Grace et al. (2016).

Ref/year	Nature of Study	Type of Study	Conclusion
Grace & Pugese (1997)	SEM model evaluation corresponding to the interplay of factors theorized to control species richness.	Observational study of wet grasslands sampling along dominant environmental gradients.	Key assumptions in need of experimental evaluation in subsequent study.

Gough & Grace (1997)	Experimental field study of plant competition & light on species diversity.	Field experiment monitoring seasonal dynamics of competitive exclusion	Showed how light dynamics in the understory regulates seasonal shifts in dominance and diversity.
Grace & Pugsek (1998); Pugsek & Grace (1998)	Explanations of basic principles of SEM in response to unfounded criticisms by statistical ecologists untrained in SEM.	Theoretical analyses and data reanalyses.	Addressed criticisms of SEM based on misuse of the methodology via path analysis and misinterpretations of the foundations.
Gough & Grace 1999	Experimental evaluation of key causal assumptions made in Grace & Pugsek (1997).	Multi-year field transplant experiments matching conditions sampled in prior study.	Qualitative verification for all key assumptions. Quantitative verification for situations where experiment manipulations fell with the sampled ranges of initial study.
Grace & Guntenspergen (1999)	Reconstruction of previous events on species diversity distributions using SEM	Landscape-scale evaluation of community control from past storm events.	Illustrated use of predict-test abilities of SEM.
Grace (1999)	Development of general dynamic model of diversity.	Literature review and theoretical modeling.	Established basis for mechanistic model for plant diversity dynamics.
Grace & Jutila (1999)	Demonstrated quasi-experimental analysis methods using SEM.	Evaluation of grazing effects on diversity in coastal wetlands in Finland.	Demonstrated flexibility of SEM for handling confounders in SEM studies.
Grace et al. (2000)	Evaluating general model using SEM and data from coastal prairie.	Field gradient study.	Development and use of composite variables in SEMs to represent complex causal effects.

Grace (2001)	Theoretical study of the effects of species pools on diversity distributions.	Theoretical study.	Established SEM expectations based on mechanistic theoretical models.
Jutila & Grace (2002)	Effects of different disturbance types on germination and diversity dynamics.	Experimental sod studies under greenhouse conditions.	Validated that ground-level light dynamics explain safe-site germination.
Grace (2003a & b)	Linking community ordination to SEM and multi-group SEM.	Theoretical study.	Demonstrate another type of complex causation modeling.
Grace et al. (2007)	Evaluation of diversity effects on productivity in native grasslands.	Meta-analysis of SEMs for biodiversity effects in undisturbed areas.	Concluded that biodiversity effects difficult to detect in undisturbed small plots.
Grace et al. (2014)	Explained why causal networks clarify productivity–richness relations while bivariate plots do not.	Theoretical discussion with empirical demonstration.	Began to establish that the diversity-productivity controversy cannot be resolved using simple variables – theoretical underidentification problem.

5. Summary

Causal investigations are mechanistic studies supplemented with knowledge obtained as to the potential behavior of the system. This combined information provides documentation for anticipating the real-world repeatability of controlling mechanisms. Assessments of mechanistic understanding adheres to a minimum requirement of external consistency with mechanistic expectations and a maximum aspiration of a full understanding (rarely achieved). Structural equation modeling, while not classified as a “causal inference method”, can play an essential role in evaluating mechanistic causal knowledge. The value of SEM in any specific situation depends on many factors and here the focus is on clearly explaining how SEM is to be described so as to avoid confusion and support its best usage.

References

- Grime, J.P. 1979. *Plant Strategies and Vegetation Processes*. John Wiley.
- Grace, J.B. and B. Pugsek. 1997. A structural equation model of plant species richness and its application to a coastal wetland. *American Naturalist* 149:436-460.
- Gough, L. and J.B. Grace. 1997. The influence of vines on an oligohaline marsh community: results of a removal and fertilization study. *Oecologia* 112:403-411.
- Grace, J.B. and B.H. Pugsek. 1998. On the use of path analysis and related procedures for the investigation of ecological problems. *American Naturalist* 152:151-159.
- Grace, J.B. 1999. The factors controlling species density in herbaceous plant communities: an assessment. *Perspectives in Plant Ecology, Evolution and Systematics* 2:1-28.
- Grace, J.B. and H. Jutila. 1999. The relationship between species density and community biomass in grazed and ungrazed coastal meadows. *Oikos* 85:398-408.
- Grace, J.B. and G.R. Guntenspergen. 1999. The effects of landscape position on plant species density: evidence of past environmental effects in a coastal wetland. *Ecoscience* 6:381-391.
- Gough, L. and J.B. Grace. 1999. Predicting effects of environmental change on plant species density: experimental evaluations in a coastal wetland. *Ecology* 80:882-890.
- Grace, J.B., L. Allain, and C. Allen. 2000. Factors associated with plant species richness in a coastal tall-grass prairie. *Journal of Vegetation Science* 11:443-452.
- Grace, J.B. 2001. The roles of community biomass and species pools in the regulation of plant diversity. *Oikos* 92:191-207.
- Grace, J.B. 2003. Examining the relationships between environmental variables and ordination axes using latent variables and structural equation modeling. In: B. Pugsek, A. Tomer, and A. von Eye (eds.) Chapter 7, *Structural Equation Modeling: Applications in Ecological and Evolutionary Biology Research*. Cambridge University Press.
- Grace, J.B. 2003. Comparing groups using structural equations. In: B. Pugsek, A. Tomer, and A. von Eye (eds.) Chapter 11, *Structural Equation Modeling: Applications in Ecological and Evolutionary Biology Research*. Cambridge University Press.
- Grace, J.B., Anderson, T.M., Smith, M., Seabloom, E., Andelman, S., Meche, G., Weiher, E., Allain, L.K., Jutila, H., Sankaran, M., Knops, J., Ritchie, M.E. and Willig, M.R. 2007. Does species diversity limit productivity in natural grassland communities. *Ecology Letters* 10:680-689.
- Grace, J.B., Adler, P.B., Harpole, W.S., Borer, E.T., and Seabloom, E.W. 2014. Causal networks clarify productivity–richness interrelations, bivariate plots do not. *Functional Ecology*, 28:787-798. DOI: 10.1111/1365-2435.
- Grace, J.B., Anderson, T.M., Seabloom, E.W., Borer, E.T. Adler, P.B., Harpole, W.S., et al. 2016. Integrative modelling reveals mechanisms linking productivity and plant species richness. *Nature* 529:390–393.
- Grace, J.B., 2024. An integrative paradigm for building causal knowledge. *Ecological Monographs*, 94:e1628.
- Grace, J.B. et al., 2025a. Causal effects vs causal mechanisms: Two traditions with different requirements and outcomes. *Ecology Letters* 28:e70029.
- Grace, J.B. et al., 2025b. Causal interpretations in ecology can be based on mechanistic knowledge. *Journal of Ecology*, 113:3084–3098.
- Heckman, J. J. 2022. Interview with James Heckman. *Observational Studies* 8: 7–22.
- Heckman, J.J. and B. Singer. 2017. Abducting economics. *Am Econ Rev*. 107:298–302. doi:10.1257/aer.p20171118.

- Holt, R.D. 2015 Inference towards the best explanation: Reflections on the issue of climate change. *Israel Journal of Ecology & Evolution* 61:1–12 (2015).
- Jutila, H and J.B. Grace. 2002. Effects of disturbance and competitive release on germination and seedling establishment in a coastal prairie grassland. *Journal of Ecology* 90:291-302.
- National Academies of Sciences, Engineering, and Medicine (NASEM) 2022. *Advancing the Framework for Assessing Causality of Health and Welfare Effects to Inform National Ambient Air Quality Standard Reviews* The National Academies Press. <https://doi.org/10.17226/26612>.
- Nichols, J.D. and Cooch, E.G. 2025. Predictive models are indeed useful for causal inference. *Ecology* 106:e4517.
- Pugesek, B.H. and J.B. Grace. 1998. On the utility of path modeling for ecological and evolutionary studies. *Functional Ecology* 12:853-856.
- Rubin, D.B. 2005. Causal inference using potential outcomes: design, modeling, decisions. *Journal of the American Statistical Association* 100:322–331.
- Wu, P., W. Tang, T. Chen, H. He, D. Gunzler, X. M. Tu, Causal inference: a statistical paradigm for inferring causality, in *Statistical Causal Inferences and Their Applications in Public Health Research* (Springer International Publishing, 2016), pp. 3-25.