Dynamic Change Arcs to Reveal Causal Effects

**Abstract**

In many planning applications, a computational model is used to make predictions about the effects of management or engineering decisions. To understand the implications of alternative scenarios, a user typically adjusts one or more of the input parameters, runs the model, and examines the outcomes using simple charts. For example, a time series showing changes in productivity or revenue might be generated. While this approach can be effective in showing the projected *effects* of changes to the model’s input parameters, it fails to show the mechanisms that cause those changes. In order to promote understanding of model mechanics using a simple graphical device, we propose dynamic change arcs. Dynamic arcs graphically reveal the internal model structure as cause and effect linkages. They are signed to show both positive and negative effects. We implemented this concept using a species interaction model developed for fisheries management based on a system of Lotka-Volterra equations. The model has 10 economically important fish species and incorporates both predation and competition between species. The model predicts that changing the catch of one species can sometimes result in changes in biomass of another species through multi-step causal chains. The dynamic change arcs make it possible to interpret the resulting complex causal chains and interaction effects. We carried out an experiment to evaluate three alternative forms of arcs for portraying causal connections in the model. The results show that all linkage representations enabled participants to reason better about complex chains of causality than not showing linkages. However, none of them were significantly better than the others.

**Keywords**

Causality, network visualization, time series, ecological model, fisheries management, models, interaction

# Introduction

In an increasing number of design applications, a model is used to make predictions and the results are displayed graphically, usually by means of one or more time series plots. The classic example of this is the business model spreadsheet. Such models contain various parameters representing costs of production, product marketing, distribution, and so on, and typically generate a profit forecast projected out a number of years. These models enable business executives to explore *what if* scenarios. For example, what if the cost of raw materials rises by a certain amount? What if a lower rate of interest can be obtained for a business loan? Changing a single number in the spreadsheet can produce a new forecast. The first “killer app” for personal computers, namely VisiCalc, supported exactly this kind of activity and is often credited with the rise of the personal computer in business. 1

Despite the power of VisiCalc and its eventual successor Microsoft Excel, using a spreadsheet to explore a model suffers from the shortcoming that although it shows the *effect* of changes in parameter values instantaneously, it fails to show the *reasons* for those changes. The only way of discovering the chain of causal linkages that resulted in a particular outcome is to delve into the spreadsheet code itself. Our work aims to provide a partial solution to this problem in the form of *dynamic change arcs*. These are graphical devices designed to show internal model linkages and enable the user to understand both the consequences of a change in a model parameter and the causal linkages leading to those consequences. For the purpose of evaluation, we implemented our design ideas in an interactive visualization of an ecosystem-based model built for fisheries management. We carried out study where participants were required to use the visualization to produce explanations of the effects of changes in fishing practice.

# Prior research

There have been a number of more recent developments in the field of data visualization that provided inspiration for our design. Vensim is a commercial tool for visualizing and analyzing simulation results.2 Vensim supports an interactive activity the authors called “causal tracing”. It allows users to simultaneously view multiple time series corresponding to causal influences on a particular effect and thereby infer the causal chain. However, the time series plots are not directly integrated with the causal influence graph and this was one of the goals or our current work.

The Influence Explorer and the Attribute Explorer were experimental visualization tools intended to help with complex interactive design decisions. 3, 4 They linked a visualization with a computational model. The interactive visualization in the Influence Explorer was based on a Monte-Carlo simulation of the design model. The user was able to select various design parameter settings and see instantly how the different design simulations performed according to a number of performance parameters.

Another important design was aimed at revealing the computational structure of spreadsheets. 5 The authors developed a number of techniques, including showing transient incoming and outgoing relationships. When a spreadsheet cell was moused over (a hover query), a set of lines appeared linking that cell visually to the cells that depended on it in the computational chain, thus providing a kind of interactive data flow graph.

## Representing causal networks

In an extensive series of studies, Michotte showed that viewers strongly perceive *causality* when viewing an object that begins to move after being contacted by another object.6 He conducted an extensive series of experiments on the temporal contingencies of the percept and found, for example, that if there was more than a 200 msec delay between the contact and the second object moving, the perception of causality was lost. This served as a basis for Ware et al.’s visual causality vector (VCV) concept.7 With VCV, a causal influence was visually represented by a device that conveyed an effect from one node to another. They argued that if the perception of causality could be incorporated into a node link diagram then the diagram might be understood in a more immediate fashion and with little or no explanation. One of the VCV metaphors was a ball, which was emitted from one node and struck another, ‘causing’ it to vibrate. Their evaluation showed that temporal synchrony between the animation of the metaphor and the changes in the recipient node is more critical than the type of metaphor for showing causal relationships. Ware later revisited this work in the context of multi-touch screens to convey causal eﬀect enhancements, causal effect reductions, and causal blocking effects using colored pulses.8 Among other things the results showed that negative effects could be conveyed, but were less reliably judged than positive effects. A problem with these methods is that they rely on precise timings and therefore cannot be extended to complex networks; repeated animations are needed to allow users to study causal changes and timings will propagate though a network along multiple paths, so arrival times will rapidly become scrambled, which makes it impossible to control visual causal effects in combination. Also, the obvious way of showing positive and negative effects is by growing and shrinking nodes, but nodes can neither grow nor shrink indefinitely.

Kadaba et al. expanded upon Ware et al.’s VCV work to compare between static and animated causal visualizations.9 In their static design, positive influences were indicated with a plus sign (+) glyph and negative influences were indicated with a minus sign (−) glyph attached to the link between two entities in the network. The size of the moving glyph represented the magnitude of the influence on the recipient node and glyphs of the same color described a multiplication effect on the recipient node. Their animated design featured “bullets” traveling along the links toward the recipient node to indicate causal influences. As a bullet hit the recipient node, the size of the recipient node either enlarged or shrank. They found that subjects could interpret animated and static representations equally accurately, but formed responses slightly quicker with animated representations.

# Key design ideas

Our goal in the design was to both make it possible to instantaneously see the effects of a management decision, and to understand the causal chains that resulted in the effects. We decided to abandon the ideal of using Michottian causality perception but retain some of the ideas from prior work:

1) The effects of changing model input parameters are calculated in real time. Adjustments of the allowed fishing catch are made using sliders. Each slider is designed to show the status quo position and the amount of change from the status quo.

2) The biomass of the fish species is represented on time series plots designed to show changes from the status quo projection. These time series plots are instantly updated and are the nodes in the network.

3) The time series plots are connected by means of arc diagram links designed to graphically indicate the amount of *change* relative to the status quo. We call these links dynamic change arcs.

## The fisheries model

To evaluate our ideas we implemented a visualization of a simple food web model developed for fisheries management.

The fisheries model is a system of Lotka-Volterra equations.10, 11 The original Lotka-Volterra model is a pair of differential equations where a change in one species is a function of the biomass of another. For example, the rate of change in a fox population might depend on the number of rabbits and the rate of change of the rabbit population might depend (inversely) on the number of rabbits. The equations might be of the form *A/t = A(p - q∙B)*, meaning that the change in species *A* over time is given by the mass of species *B* multiplied by a scaling value *q*. Different scaling parameters are used to represent the extent to which one species eats or competes with another.

The fisheries model underlying our visualization is MS-PROD, which is a multispecies production model developed by NOAA scientists Gamble and Link.12 This model is described by a system of equations where the change in biomass of one species is a function of two kinds of interaction with other species in the model. One kind of interaction is predator prey relationships (given by *α* in the model); another kind of interaction is competition between species (given by *β* in the model). This term competition accounts for cases when two species may compete with one another for a resource such as habitat space or low level food sources. An additional term in the model is harvesting by humans by means of various kinds of fishing. The goal of fisheries management is to obtain a situation where harvesting is sustainable over a long period. The MS-PROD model is based on the following formula:

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|  | (1) |

where *N* is species biomass, *ij* represents competition between species *i* and species *j*, *ij,* represents predation of species *i* on species *j*. *H* represents the harvest effort. Other terms represent carrying capacity, normal species growth rate in the absence of completion, predation or harvest.

In the Gable and Link model, there are 10 commercial species of fish interacting. The MS-PROD authors provided us with a parameter file which listed these 10 species chosen from the Northeast United States Continental Shelf Large Marine Ecosystem (NEUSLME), listed here by functional group:

* Elasmobranchs: Skates, Spiny Dogfish
* Flatfish: Windowpane, Winter Flounder, Yellowfin Tuna
* Groundfish: Cod, Haddock, Redfish
* Small Pelagics: Herring, Mackerel

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| **Figure 1.** The overall design is illustrated. |

The MS-PROD model runs simulations for 30 years with an annual time step to predict individual biomasses.

# The design

There are three critical elements in our design: *time series plots* to show forecast trends, *arcs* to show model linkages, and *interactive sliders* to allow the user to interactively change particular values. These are illustrated together in Figure 1. A critical part of our design is a graphical device known as an “arc diagram”. This name was coined by Wattenberg, though the method was invented earlier; Knuth used arc diagrams to illustrate interaction of characters in Victor Hugo’s novel *Les Misérables*.13,14 While the arc diagram may fail to properly depict the structure of a network, Heer et al. point out it is advantageous because the one-dimensionality allows for other features to be easily displayed near the nodes.15 This is the property that is useful in our design, fitting well with a simple stack of time series plots. The time series plots stand for nodes in the food web network, with each plot representing a single species. The time series plots are organized into four “functional groups”, each distinguished using a different color code. Functional groups are sets of species that have habitat, ecosystem function, and other characteristics in common. The four interactive sliders control the fishing effort for each functional group. By adjusting a slider, the amount of fishing effort for a particular functional group can be changed and the results visualized.

In the following sections we first discuss the design of the parameter adjustment sliders and the time series plots before describing in detail the design decisions leading to the dynamic arcs.

## Parameter adjustment sliders

The sliders shown on the left-hand side of the interface panel in Figure 1 enable users to interactively adjust the amount of fish caught in different functional groups. Underneath each slider, a colored rectangle indicates differences from the baseline effort settings. Blue indicates the effort value has been increased since the baseline was set, while red indicates the effort value has been decreased. In the example shown, the effort for “elasmobranchs” was originally set to 1.0 and now it is approximately 1.5. The time series plots show the resulting forecast changes in the biomass of the entire set of species according to the model. When a slider is adjusted, the model is recomputed and the time series are recalculated in real time, with no discernible lag.

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| (a) |  |
| (b) |  |
| **Figure 2.** (a) The status quo time series is given by the gray line. The colored line with dots indicates the new forecast. (b) The status quo time series is given by the bottom of the shaded portion. | |

## Time series plots

The time series plots each show 30 year projection based on the model. Because of the considerable differences in biomass between the species, each plot has a different y-axis scale. This can be difficult to read and it is easy to assume that the different plots are showing comparable ranges. To help show the actual amounts of each species the absolute biomass indicators (shown in the background of the time series plots in Figure 1) were introduced to represent how biomass changes over time. These show the absolute biomass of the population as the area of a circle, making comparison across species possible. To avoid occlusion, these indicators are drawn at five-year intervals across the thirty-year time span.

## Visualization of change

In order for modelers and other stakeholders to understand and compare decisions, the ability to perceive *changes* in biomass resulting from *changes* in the fishing effort is required. We designed two alternatives to represent time series change from a baseline. The first, shown in Figure 2(a), is a conventional dotted gray line which shows the baseline forecast in addition to the current forecast, which is shown as a heavier colored line with dots at yearly intervals. The second, shown in Figure 2(b), is a shaded area originating from the curve of the current forecast. The shading diminishes in opacity as it approaches the curve of the baseline forecast. Early evaluation with various stakeholders found the shaded version to be better and so it became part of the standard presentation.

## Inter-species relationships

The MS PROD model is a system of Lotka-Volterra equations, so *explaining* (as opposed to simply showing) the results of a particular parameter change is a matter of making these parameter values explicit. This is the role of the arcs in Figure 1. These relationships can be stated in terms of cause and effect. For example, increasing the catch of elasmobranchs causes a decline in the population of spiny dogfish and skates (the two elasmobranch species in the model). A secondary effect is that the elasmobranchs eat less cod and so the population of cod fish increases.

Two colors were used for the arcs to differentiate the types of model interaction terms: orange for predation and blue for competition. Both predation and competition relationships are directed and in order to represent this we used three cues in the non-animated version. First, we used fading opacity based on Holten and van Wijk’s recommendation of dark-to-light shading along each arc.16 Second, triangular marks are drawn in the middle of the arcs to point from the source species to the recipient species. Third, our arcs follow a clockwise direction; arcs on the right-hand side are all directed downward, whereas arcs on the left-hand side are directed upward. This serves both the reinforce directionality and to provide a principled way of decluttering the diagram. Without this left right separation, it would be very difficult to show reciprocal relationships between species. The directionality can also be indicated with animation. With the animation option, the color of the arc alternates with gray and the stripes of colors travel from the source species (e.g., predator) to the recipient species (e.g., prey).

We created three alternative versions of the arcs to show the underlying model parameters: static arcs, dynamic arcs, and dynamic with animation arcs.

*Static.*With the static style of the arcs, all arcs are drawn at all times, as shown in Figure 1. The width of an arc corresponds to the magnitude of the relationship as defined in the predation or competition term in the model. The downside is that viewing all arcs at once can be overwhelming because the display becomes somewhat cluttered.

In addition, reasoning about cause and effect relationships using the static arcs can be difficult. The effect of a change in the amount of fishing of one species on another that it eats is weighted by the amount of change in the first species, as well as the biomass of the first species and the second species. Thus, although the static arc view does provide all the information needed to understand causal chains resulting from a fisheries decision, the reasoning process can involve a significant amount of mental calculation.

*Dynamic.*Dynamic arcs, illustrated in Figure 3, were motivated by need to simplify reasoning about causal chains occurring in the food web model. They have the additional benefit of eliminating or at least reducing the visual clutter created by the static arcs. Dynamic arcs are necessarily a simplification of the effects of an iterative process; in a forecast the model is recomputed at yearly intervals and the biomass values of a species and its influence on other species has 30 different values in a 30 year forecast. The arcs can represent only a single value.

In our final design, the width of each directed arc is proportional to a weight *wij*: for effects of the *j*th species on the *i*th species. In the case of predation,

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| *wij = ij ∙ 100000 ∙ (N’j,30 – Nj,30)/(Ni,0 + 100000)* | (2) |

where *ij* represents the model coefficient representing predation of species *j* on species *i*, *Ni,0* represents the initial biomass of the prey species, *Nj,30*  is the biomass at year 30 for the predator species according to the current forecast, and *N’j,30* is the biomass at year 30 for the predator species according to the baseline forecast. If the predator species biomass at year 30 did not change between the forecasts, then (*N’j,30 – Nj,30*) equals zero, resulting in a *w* of zero, so the arc will not be drawn.

In other words, the link width is given by the size of the predation coefficient, weighted by the overall change in biomass of the predator species over 30 years and inversely weighted by the biomass of the prey species at the start of the forecast.

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| **Figure 3.** The design illustrated with dynamic arcs to show causal relationships between the species. |

In the MS-PROD model, the rate of change in a species is proportional to its own biomass. In this regard, a somewhat subtle point must be made; in a *visual sense* the effects on a prey species are inversely weighed by the biomass of the prey, simply because of the different scales used for the different time series plots. So, for example, in Figure 3, the change in biomass of haddock appears visually small relative to the change in biomass of winter flounder, whereas in fact because there are far more haddock the actual absolute change in haddock is more than twice as large. Because of the different scales, what we perceive in the time series plots is a *relative change*, not an absolute change. Going back to Equation (1), *Ni*is a multiplier of for all terms on the right hand side and we can eliminate this multiplier by dividing both left and right by *Ni* to give the relative change *dNi/Nidt*. The bottom term *Ni,0* in Equation (2) is there solely to prevent arcs getting too fat in the case of the largest prey species. It has a small effect for the other species.

Width values calculated using Equation (2) can be both positive and negative. Both competition and predation relationships inhibit the growth of the recipient species because the source species either consumes the recipient species itself or its resources. If there is an increase in a predator species biomass the effect on a prey species will be negative and their population will decline. The reverse is also true, if a predator species decreases, then the prey species will benefit and its population will increase. We chose to use plus signs (+) for the cases where *w* is negative—i.e., when the predator species declines between forecasts which is “good” for the prey species—and minus signs (−) for the cases where *w* is positive— i.e., when the predator species increases between forecasts which is “bad” for the prey species—as Kadaba et al. used in their static causal visualizations. 9 Plus signs were drawn in black and minus signs were drawn in white with a black outline to allow for some redundant coding. Several sign glyphs are drawn along each arc to allow the user to easily determine the signage of a dynamic arc.

The dynamic links between the harvest sliders and the harvested species behave similarly. Their width is a function of the change in harvest from the baseline.

Figure 3 shows the dynamic arc representation for the same scenario given in Figure 1. There has been an increase in fishing effort on the functional group of elasmobranchs from 1.0 to about 1.5. The spiny dogfish and skate biomasses both decreased as a result of the increase in fishing, as is indicated by the shaded area between the baseline forecast and the current forecast. Spiny dogfish predate on cod, so the arc between them has plus signs and this explains the large increase in cod population. A more subtle effect is the decrease in haddock biomass. This is occurring because cod compete with haddock and so the haddock population declines (see the blue arc on the left hand side from cod to haddock).

*Dynamic with animation.* The final style for the arcs is dynamic with animation. All of the rules concerning non-animated dynamic arcs apply. Additionally, the plus signs (+) or minus signs (−) travel from the source species (e.g., the predator) to the recipient species (e.g. the prey). Also, the color of the arc – orange or blue – alternates with the color grey. These alternating stripes of colors also travel along the arc to give a stronger indication of the directionality.

# Evaluation

We were interested in how different arc visualization alternatives enhance a user’s understanding of the complex relationships between the fish species and the effects of those relationships as a result of changes in fish catch. In other words, are there benefits to using static arcs, dynamic arcs, or animated dynamic arcs over no arcs? To investigate this question, we designed and conducted a user study to measure the performance of different arc depiction alternatives.

Our method involved having participants manipulate a dynamic slider to change the fish harvest for a species, then report on the resulting changes in population. They were asked first to report the effects of a change in terms of a change in population of a species. Next, they were asked to explain the *causes* of the change, with questions that ranged from straightforward to complex. An example of a simple question would be to explain a change in a species that had declined because the fishing effort had increased for that species. A complex question would require the participant to explain a complex causal chain of predation and/or competition. For example, spiny dogfish (a member of the elasmobranch group) eats cod, so increasing the catch of elasmobranchs results in a decrease of spiny dogfish, which in turn leads to an increase of cod. We hypothesized that only the complex questions would benefit from the presence of arcs.

The experimental conditions were as follows:

1. **No arcs** – Only the time series are displayed on the screen.
2. **Static arcs** – Arcs are drawn between the time series to show predation or competition. The width of each arc is based on the model coefficient defining the relationships between a pair of species. All arcs are drawn at all times.
3. **Dynamic arcs without animation** – The arcs change in width according to causal linkage.
4. **Dynamic arcs with animation** – The arcs change in width dynamically and also are animated to help indicate the direction of the relationship.

## Method

The study was conducted at a screened-off table in a student union building at the University of New Hampshire. A paid undergraduate research assistant conducted the study and responses from the study were graded by two paid undergraduate research assistants.

Each participant conducted the experiment task for only one of the four conditions. The experiment began with a brief training session which was tailored according to the experimental condition – i.e., arcs were explained only for conditions B, C, and D; the meaning of dynamic arcs was explained only for conditions C and D. Feedback about the quality of the participant’s answers was given only during the training phase.

In the remainder of the experiment, the participant followed on screen instructions to manipulate one of the sliders controlling the fish catch. The participant then answered questions about the resulting effects and the reasons for the effects. A single experiment lasted approximately fifteen minutes.

## Apparatus

We conducted the experiment using a standard Dell laptop with an extra Dell monitor. The window with the model visualization was maximized on the extra screen, while the window with the experiment questions was maximized on the laptop screen. Participants used the mouse to interact with the model visualization and entered their answers using the laptop keyboard and mouse.

## Participants

There were 92 participants who took part in the study, all of whom were recruited by a poster affixed to the backside of the privacy screen. The responses of three participants were eliminated because of errors in even the most basic questions indicating a lack of understanding of the task. Participants were randomly assigned to the four conditions, such that there were at least 20 in each condition.

Participants were asked to report their college membership at the university (e.g., engineering, nursing, business, liberal arts). From this information, we devised a pseudo-category based on quantitative skills. Students who reported being from the College of Liberal Arts were placed in the “low quantitative” category and “high quantitative” if they were from any other college. Our reasoning was that students in fields such business, science, or engineering were more likely to have experience reading charts. We attempted to obtain equal numbers in each of the categories but were not entirely successful. The numbers we recruited are shown in Table 1.

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| |  |  |  |  |  | | --- | --- | --- | --- | --- | |  | No arcs | Static arcs | Dynamic | Dynamic & animated | | Low quant. | 11 | 10 | 9 | 10 | | High quant. | 12 | 14 | 11 | 12 | |
| **Table 1.** The numbers of students recruited for each of the four conditions, separated by quantitative level. |

## Task

Initially, all fishing effort sliders were set to the value of one. Participants were instructed to increase or decrease the fishing effort of a specific functional group – e.g., “Using the sliders, double the harvest effort on elasmobranchs.”

Next, the participants were asked to answer one or more questions of the form, “What was the effect on (fish species)?” For example, “What was the effect on haddock?” Participants answered this “What…?” question with one of five options from a drop-down menu:

* Increased a lot
* Increased a little
* Stayed about the same
* Decreased a little
* Decreased a lot

Finally, the user was asked, “Why? [Try to explain in no more than three sentences.]” A large text box was provided for the participant to type a response. If this question was the last question in its set, then the sliders were all reset to one and a new instruction was given for the next set of questions until all questions were answered.

As mentioned earlier, the questions varied in terms of difficulty. The instructions and questions were designed so that the “Why?” questions would fit in one of two difficulty categories:

* **First-order** – These questions were simpler because they concerned a fish species whose biomass changed directly as a result of increased or decreased fishing effort.
* **Higher-order** – These questions were more difficult because they concerned a fish species whose biomass changed indirectly as a result of changed fishing effort. The explanation involved following a second-order or higher causal effect.

In total, there were three instructions for adjusting the harvest effort and seven pairs of “What?” and “Why?” questions. All participants were given the same instructions and asked the same questions in the same order, regardless of condition.

For example, the participant may be instructed, “Double the harvest effort on elasmobranchs.” The participant would then be asked, “(a) What was the effect on cod? (b) Why?” Answering correctly requires looking at a second order effect: “(a) Cod increased a lot. (b) Spiny dogfish is a type of elasmobranch, so its biomass went down because it was being fished more. Spiny dogfish prey on cod, so the cod biomass increased since there were less predators.” There were even more difficult questions such as, “(a) What is the effect on haddock? (b) Why?” The correct explanation would look something like, “(a) Haddock decreased a lot. (b) Spiny dogfish, which are elasmobranchs, prey on cod, so the cod biomass increases as more spiny dogfish are fished. Cod competes with haddock, so as the cod biomass increases, the effect of the competition is stronger and the haddock biomass declines.” Both of these examples fall into the higher-order difficulty category.

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| **Figure 4.** Mean grades for the higher-order explanations given by study participants under the four conditions. Means of both high quantitative and low quantitative participants are shown. |

## Results

The answers to the questions of the evaluation were graded on a scale of zero (i.e., completely wrong) to three (i.e., completely correct), with partial points allowed. “What…?” questions, which were answered using a drop-down, were graded automatically by a script, while “Why?” questions were graded by two graders. The average of the two scores was taken and these averages were used in our analyses. The correlation coefficient (Pearson’s *r*) between the scores assigned by the two graders was 0.7.

Separate ANOVAs were run with Tukey HSD tests for each of these three types of questions (what, first-order, and higher-order). There were no significant differences between the four conditions for the seven “What…?” questions and the three first-order “Why?” questions. However, there was a significant effect for the four conditions with the higher-order “Why?” questions, shown by (*F*[3, 81] = 13.2; *p* < 0.001) . A Tukey HSD test on the four conditions showed that all of the arc conditions were better than the no arcs conditions. However, there were no significant differences between the three conditions with arcs.

The effect for high versus low quantitative (*F*[1,81] = 1.82; *p* = 0.18) failed to reach significance. These results are graphically summarized in Figure 4.

# Expert feedback

Our visualization was assessed by two model developers and one fisherman who has been a member of the New England Fishery Management Council. The overall response of these three expert users was positive. The modelers liked the ability to change fishing effort parameters, see an instantaneous result, and easily perceive differences between two forecasts. They appreciated that using the visualization was much quicker and much more informative than the alternative of rerunning the model and graphing its output in Microsoft Excel. All three users preferred dynamic arcs over static arcs for depicting the causal relationships between the fish species. Two of the experts admitted that the underlying relationships and their counterintuitive effects can confuse even them without the aid of a visualization, despite being quite familiar with the 10 species involved. Dynamic arcs, however, made the relevant relationships more obvious, and helped them to understand the complex interactions. One of them noted that the dynamic arcs “help to follow the flow [of the relationships] more easily,” especially when they are animated. The three experts agreed that the visualization could play an important role in convincing people to make use of more complex models like MS-PROD.

# Conclusion

The broad goal of this research has been investigate ways of visually representing causal chains in a complex model to allow users to reason about why various effects occur when changes are made to critical model parameters.

The key components of our solution are as follows:

* Sliders to dynamically change model input parameters.
* Real time recalculation of model forecasts.
* Nodes containing time series showing the forecasts and making clear *differences* from some alternative or baseline scenario.
* Links showing *changes in causal effects* of one model component on another as a result of the change in model parameters.

Our evaluation of the depictions of the inter-species relationships in a fisheries showed that having weighted causal links is superior to no links for answering higher-order questions about changes in biomass. This was not surprising, since answering higher-order questions involved complex, indirect effects from changes in fishing effort and without links the user would have to guess the answer.

An important question regarding our solution is how general purpose is it? Can it be used in other fields such as business, economics, medicine or engineering? There are two major issues relating to this. Firstly, will it *scale* to more complex models? Our design combining stacked time series plots with a dynamic arc diagram works well for 10 interacting components of a system, and this number could perhaps be doubled and still be clear, but larger models would require a different approach. An alternative for larger causal networks might be to use a spring layout node-link diagram where each node contains a much smaller time series plot. So long as interactions between components only involved small subgraphs of the network, the dynamic change arc approach would be effective in decluttering the diagram. Interactive methods where topologically nearby nodes and links are enhanced (e.g., one and two links away from a selected node) have been demonstrated to make node link diagrams with several hundred nodes usable for reasoning.17 Another technique that might be used for larger networks would be an interactive hierarchical network view using a method such as the intelligent zoom technique. 18, 19 Also, fisheye methods might be used to expand the nodes, and their embedded time series plots for sub-components of a model relating to a selected node. 20, 21 Secondly, how are the arcs *visually weighted to express the model*? In the case of the MS-PROD model, our dynamic change arcs represented a simplification of a series of interactions occurring over 30 discrete time steps. This is a relatively complex case and many models are simpler. To use dynamic change arcs, it is only necessary to determine a function that describes a node to node causal effect (either positive or negative). We believe that many models may fit into this class. For example, it should work well with the kind of disease factor models discussed by Kadaba et al.9

A second, more concrete goal of this research has been to help the fishery management community make informed decisions with the use the MS-PROD model through our interface. Declaring whether we achieved this long-term goal requires public unveiling of the MS-PROD model by its original authors and time to determine if it actually benefits managers, fishermen, and other significant stakeholders. Therefore, no conclusion can be drawn yet. On the other hand, it is already being used by the model developers. Our informal interviews with expert users has led us to believe we have succeeded in creating an effective visualization. All of the informal interviews we conducted supported the dynamic arc version as the most informative, and most of the interviewees liked the animated version best of all. Our visualization has been already been used in a number of meetings and seminars by the model developers. More widespread release will depend on validation of the model itself. We hope that our visualization of MS-PROD will go on to assist fishery managers with their decisions and possibly contribute to future generations also enjoying usage of our oceans.

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