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There aren't plenty more fish in the sea: A causal network approach

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The current research investigated how lay representations of the causes of an environmental problem may underlie individuals' reasoning about the issue. Naïve participants completed an experiment that involved two main tasks. The causal diagram task required participants to depict the causal relations between a set of factors related to overfishing and to estimate the strength of these relations. The counterfactual task required participants to judge the effect of counterfactual suppositions based on the diagrammed factors. We explored two major questions: (1) what is the relation between individual causal models and counterfactual judgments? Consistent with previous findings (e.g., Green *et al.*, 1998, *Br. J. Soc. Psychology*, 37, 415), these judgments were best explained by a combination of the strength of both direct and indirect causal paths. (2) To what extent do people use two-way causal thinking when reasoning about an environmental problem? In contrast to previous research (e.g., White, 2008, *Appl. Cogn. Psychology*, 22, 559), analyses based on individual causal networks revealed the presence of numerous feedback loops. The studies support the value of analysing individual causal models in contrast to consensual representations. Theoretical and practical implications are discussed in relation to causal reasoning as well as environmental psychology.

Despite its crucial importance for the survival of humanity, now more than ever before, marine biodiversity is at the brink of collapse. After climate change, the main culprit is overfishing. This occurs when fish and other marine species are caught faster than they can reproduce. According to the Food and Agriculture Organization (2014), over 70% of the world's fisheries are 'fully exploited', 'over exploited' or 'significantly depleted'. In fact, some species have already been fished to commercial extinction, and more are on the verge of disappearance. Simply put, overfishing is the outcome consumers' growing demand for seafood around the world, combined with poor management of fisheries and development of new, more effective fishing techniques. Unfortunately, the devastating effects of overfishing are not limited to loss of biodiversity and ecosystems. One billion people rely on fish as a key source of daily protein, and as the main source of food in many developing countries. Millions of people, and entire coastal communities, depend on fisheries for their employment. In addition, and often forgotten, collapsing fish stocks aggravate climate change by creating large ecological dead zones with no oxygen in the oceans.

Despite these tragic consequences, overfishing, like most environmental problems of this day and age, is another complex tragedy of the commons. The extensive number of

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causes that surround the problem generates the element of complexity. Furthermore, the interactions between these causes tend to unfold across different time frames and inevitably become too convoluted for their effects to be predictable. Nonetheless, consumers, or lay people, still manage to form beliefs about the roles of these various causes and their probable effects. In the light of the complexity involved, these beliefs are likely to be oversimplified and inaccurate (White, 2008). As oversimplified or partial as they may be, these beliefs may still form the basis of ordinary people's understanding and therefore reasoning about the phenomenon.

White (2008) pointed out that as ordinary people can make a difference by the force of their opinions and values, there is an obvious practical importance in ascertaining the content and structure of lay beliefs about causal processes related to environmental problems. When it comes to overfishing, even if most of the damage cannot be reversed, a large portion can be saved and eventually restored if people started making sustainable decisions. Therefore, understanding how people's causal representation of overfishing may mediate the way they reason about the problem has significant practical implications.

The value of discovering naïve causal structures of a given environmental problem resides in the fact that they convey how people understand the problem as a system of interconnected parts (White, 2008). In other words, individual causal relations are not isolated from each other but tend to be linked in dynamic systems. Given that environmental problems are the product of an entrenched system made up of numerous interdependent actors, they tend to be immensely intricate. For this reason, it does not make sense, nor it is fruitful, to focus on isolated causal beliefs. Instead, as White (2000) points out, the scope should be to integrate 'collections of individual events into an organized representation of chains and networks of causal relations'.

Past research in causal cognition has already explored complex causal structures (Lagnado, Waldmann, Hagmayer, & Sloman, 2007; Sloman & Lagnado, 2005; Waldmann, Hagmayer, & Blaisdell, 2006). A central finding from this research is that people do indeed create and use causal models to structure their learning and inference. However, only a few studies have looked at the role of feedback loops (e.g., Kim, Luhmann, Pierce, & Ryan, 2009) or dynamical systems (e.g., Rottman & Keil, 2012). Consequently, especially when it comes to environmental problems, not much is known about how individual causal beliefs are related in an overall dynamic causal structure and the form of that structure.

For example, knowing that people believe that destructive fishing gear causes overfishing carries little meaning unless this individual belief can be placed in a network of beliefs about entities related to fishing gear and overfishing. People might also believe that their consumption of unsustainable fish is not related to the use of destructive fishing gear. If this is their causal model of overfishing, then people may believe that consumption of unsustainable fish does not affect overfishing at all. In other words, naïve causal models need to be ascertained as a network of causal beliefs.

Methods to examine the relationship between someone's causal model and their actions remain underdeveloped. However, the most promising and established method to achieve this is causal network analysis (Green, Muncer, Heffernan, & McManus, 2003). Network analysis of causal beliefs is a method that has been pioneered by Lunt (1988) in a study of perceived causes of failure. Essentially, causal network analysis is a method of representing a set of causes and links between them. For example, in Lunt (1988), the entities were possible causes of failure, such as having little intelligence or poor concentration, and the links were judged causal relations. Lunt's study revealed a network of interrelations between these different causes. For instance, low intelligence was causally related to poor concentration, and both were deemed to lead to poor time allotment.

Inspired by this methodology, Green and McManus (1995) explored the idea that individuals construct causal models of reality and use them to think about possible actions in the world. Green and McManus (1995) employed the causal network analysis method to examine individuals' causal model of risk factors for coronary heart disease (CHD) and related these to their judgments of preventive actions. They required individuals to draw a network diagram of the risk factors, or causes, for CHD (e.g., high blood pressure, fatty foods and exercise). Specifically, individuals were asked to represent a causal relationship between two factors by drawing a line connecting them. They were also asked to indicate the direction of the causal influence using an arrowhead. In the diagrams created, a causal factor could be connected to another factor in a variety of ways. It could have a direct path to the connected factor, or it could have an indirect path to it via some other factor, or it could have both a direct path and an indirect path to the target factor. For example, they found that eating fatty foods was deemed to increase the risk of CHD directly, but also indirectly through increasing cholesterol. Therefore, the diagram represented what individuals spontaneously considered to be the critical pathways. In addition to representing a path, individuals were required to rate the strength of each causal path on a scale from zero to one hundred. The same individuals also rated the effectiveness of different preventive actions related to the factors (e.g., reducing blood pressure).

Green and McManus (1995) showed that the total path strength of a factor (the strength of both direct paths and all indirect paths) predicted participants' ratings of the effectiveness of the different preventive actions. Total path strength accounted for two thirds of the variance in these ratings. In a subsequent study, Green, McManus, and Derrick (1998) examined perceptions of a person's prospects of employment. They confirmed the importance of path strengths in predicting the ratings of effectiveness of different actions designed to increase a person's employment prospects. Furthermore, it extended the previous findings by showing that the total path strengths added considerably more than just the direct paths; almost doubling the variance explained in the effectiveness ratings.

Green and McManus' analysis involved investigating the presence or absence of causal paths as well as the strengths of those paths. However, another advantage of causal network analysis is that apart from allowing investigation of its content features, it allows inspection of its structural features. White (2008) argued that causal models could have various kinds of embedded structures that convey broad ideas about how people understand the phenomenon (e.g., overfishing). Based on this idea, he conducted a series of studies concerned with the structure of people's beliefs about causal processes in complex natural environments. His main aim was to discover whether people construct causal processes in nature in a systems-like manner, involving one-way causal hierarchies. White (2008) derived a set of factors in relation to forest ecosystems and climate change (e.g., human population, atmospheric carbon dioxide levels, fires and several biological features such as extinction rates). In two experiments, participants were presented with each pair of factors and asked whether change in one would produce change in the other. From the participants' judgments, he constructed a causal network that reflected consensual causal beliefs. This method of network elicitation has been termed the 'grid method' (Green *et al.*, 2003) and differs from the one employed by Green and McManus (1995) and Green *et al.* (1998).

White found the resultant causal network to be unidirectional. In other words, the network did not encompass any feedback loops, but was composed of linear causal chains mostly arranged in a unidirectional hierarchy. Some factors, such as humans, functioned as causal origins and others, such as extinction rates, functioned as effects. These results are consistent with White's previous research White (1992, 1995, 1997, 1999, 2008) showing unidirectional patterns of thinking about causality in natural systems. White argues that such findings reveal a general failure to appreciate the interactive processes that govern the operations of natural systems.

Conversely, the results do not mean that people are unable to create interactive models of ecological systems. Green (2001) presented participants with a food web and asked participants to explain a complex pattern of fluctuation over time in the population of an herbivore. He found that most people were able to construct interactive accounts involving two, and in some cases three, entities (plant, herbivore and carnivore). However, as argued by White (2008), the system, or food web, comprised only three entities and individuals were constrained to explain a complex pattern presented to them, rather than envisaging themselves what sort of pattern might occur. It is therefore not clear whether the interactive thinking exhibited in that study is characteristic of reasoning about ecological systems outside the psychological laboratory. Nonetheless, studies by Green (1997, 2001) do suggest that people have a capacity to think about interactions in natural systems, but that this capacity might be overwhelmed by task complexity.

The complexities of interactive systems with multiple entities are admittedly hard to grasp, but failure to fully appreciate interactions and feedback loops in these systems could have detrimental consequences for the global ecosystem. In other words, how humans treat the world must to some extent reflect what they believe about the effects of that treatment – if people believe that anything can be done to nature, without repercussions for the human world, they are less likely to exhibit sustainable behaviour. Kempton (1986) pointed out that lay models about physical systems influence real life decision-making. He found that people's mental models of thermostats accounted for how they treat the control of heat in their homes. Those who possessed one theory tended to behave more economically than those who possessed the other theory. Kempton (1986) proposed, on the basis of interviews, that people used two distinct models of home heating systems. In the (incorrect) valve model, the thermostat is thought to regulate the rate at which the furnace produces heat. Therefore, setting higher makes the furnace work harder. In the (correct) threshold model, the thermostat is viewed as setting the goal temperature, but not as controlling the rate of heating. Hence, the furnace runs at a constant rate. Kempton then examined thermostat records from real households and found that the patterns of thermostat settings fitted nicely with the two models he had found.

Current study

The first aim of the current study was to elicit individual causal models of overfishing to examine the relationship between these models and the ratings of effectiveness of various related actions. The second aim was to investigate whether people think about overfishing in an oversimplified linear and unidirectional way.

The study employed the method advocated by Green and McManus (1995) and Green *et al.* (1998) to elicit participants' causal network of overfishing. One potential weakness of the causal network analysis is that the network obtained, and its structural features, depend on the factors selected for the study. Clearly, there are many possible factors one could include as causes of overfishing (and each of these could be unpacked almost *ad infinitum*). As White (2008) points out, one solution is to rely on expert assessments of the relative importance of different factors. To this end, a number of expert sources (e.g., Hilborn, 2012) were reviewed and four factors were selected as the main causes of overfishing (*consumption*, *market*, *monitoring* and *gear*).

Participants were also asked to evaluate the effectiveness of different actions based on these diagrammed factors. These questions were phrased as counterfactual questions and the response was in the form of a quantitative judgment. Subjects were told to imagine that a 30% change (increase or decrease) has occurred in the factor in question and are asked to judge the amount of change this would cause to overfishing. So, for example, subjects were told to imagine that there has been a 30% increase in consumption of unsustainable fish. They were then asked to say whether there would be an increase, decrease or no change in overfishing. For the former two, they were asked to give an estimate of the amount of change that would occur in percentage.

The counterfactual questions encouraged participants to reason about the counterfactual suppositions as if they were external interventions on overfishing. Sloman and Lagnado (2005) showed that when reasoning about the consequences of a counterfactual supposition of an event, most people do not change their beliefs about the state of the normal causes of the event. Therefore, when participants answer these questions they should not change their causal beliefs about overfishing, but just reflect upon the effect of the mentally changed event (e.g., consumption). In addition, the counterfactual supposition involved a quantified change (30%) to ensure all participants simulated the same amount of change. This also means that judgments across the different questions were more comparable to each other. Hence, any relationship between the diagrams and the counterfactual judgments should be revealed by a positive correlation between total path strength for each factor (direct and indirect paths) and the judgments.

In addition to computing total path strength, Green and McManus (1995) also computed the direct path strengths alone, and the total number of paths emanating from each factor (ignoring their strength). The same analysis was carried out in the present study. If the perceived strength of a causal path was important, then total path strength should correlate significantly more with the counterfactual judgments than direct path strengths alone or number of paths.

The second aim of the current study was to investigate whether people think about overfishing in an oversimplified linear and unidirectional way. Previous studies by White (1992, 1995, 1997, 1999, 2008) investigated the structural features of causal networks, namely the presence of feedback loops, on the consensual network. In other words, he constructed the causal model based on the aggregated data from all participants. This method has two main drawbacks. First, there are obvious theoretical problems in deciding on an appropriate threshold for the inclusion of paths. There are different thresholds that can be used and these yield very different causal networks that vary in the degree of complexity and therefore structure. Second, even though the consensual representation of a phenomenon may be interesting in its own right, there is plenty of variety and individual differences in the individual causal representations. These could involve significant structural features, such as feedback loops, that get obscured in the creation of the consensual model because they might differ in the type or number of factors they comprise.

For this reason, the current study adopted a novel approach and investigated the presence of feedback loops at the individual level. The causal network diagram method of elicitation encourages participants to focus on the overall structure of the network, which is visible to the participant as they proceed with the line-drawing task. Thus, participants never lost sight of the overall structure of their beliefs. Consequently, any feedback loops drawn are likely to reflect genuine causal beliefs. In the study by Green *et al.* (2003), the diagram method yielded a network with no feedback loops, so there is no evidence that a graphical method improves the likelihood of obtaining feedback loops. Therefore, employing this methodology might also provide a more rigid test of representation of feedback loops.

Method

Participants

Forty participants were recruited through the University College London Psychology Subject Pool. The subject pool in question is open to everybody and therefore not limited to university students. The study was advertised as investigating reasoning about causes and effects. All participants were paid £4. Eleven of them were males (27.2%) and 29 were females (72.5%). The mean age was 23 years (SD = 4.18; range 17–37 years). Thirty-three participants completed the task satisfactorily; the remaining seven either failed to label all paths with an indication of direction or failed to give a numerical estimate of strength for each of the paths. The participants' environmental values were comparable to those reported in other studies (e.g., Dunlap, Van Liere, Mertig, & Jones, 2000) – their mean score was 22.12 (SD = 3.75). Thirty of the 33 participants were UK nationals.

Design

The order in which participants completed the diagram task and the counterfactual judgment task was counterbalanced. The order in which the casual factors were presented in the diagram task and the order in which the counterfactual judgments questions were presented, were both randomized. The framing of the counterfactual judgments (increase or decrease frame) was counterbalanced. The questionnaire ended with a series of demographic questions.

Materials

The materials consisted of a written questionnaire. The first page of the questionnaire provided a simple definition of overfishing followed by a few sentences detailing some of its effects (e.g., environmental problems). In addition, participants were informed that the survey was part of a project to discover the best approaches to decrease overfishing. The second page was an instruction sheet. Then, according to the counterbalancing condition, participants were either given the diagram task followed by the counterfactual judgments task, or vice-versa. Following both tasks, participants were given two questions concerning their fish consumption as well as a series of demographic questions that included the New Environmental Paradigm. Pro-environmental values were measured using a reduced (6-item) version of the New Environmental Paradigm (NEP) scale (alpha = 0.7) (Dunlap *et al.*, 2000).

The causal diagram task

Participants were asked to draw a diagram indicating how, in their view, a set of causes or factors are linked to overfishing and to each other. They were instructed as follows:

> There are a number of causes or factors as explanations of overfishing. We would like you to draw a diagram (on the next page) of how you think various factors (listed below) are linked to overfishing and each other, using arrows to indicate the direction of the effect. Label each arrow with either 'increases' or 'decreases' to clarify the type of effect. The names of the factors to be diagrammed are listed below. Beside each factor you will find a short description. The expression 'unsustainable fish' will be used throughout the survey. This simply means fish that are overfished or caught or farmed in ways that harm other marine life or the environment.

The four factors that were presented to participants are reported in Table 1. The order in which they were presented was randomized. *Overfishing* was also included in the list.

Participants were told to indicate the connection of these factors (which could be either direct or indirect) to overfishing by including *overfishing* in their diagram. Finally, participants were presented with an example of a schematic diagram, which bore no factor names, as an example.

After drawing the diagram, participants were instructed to rate the strength of each of the links they drew on the previous page. They were told go back to the previous page and write a number between 0 and 100 where 0 meant no relation and 100 meant an invariable relation. An example was provided to clarify (inspired by Green *et al.*, 1998): 'So, for instance, when water boils at 100°C, steam comes off. There is an invariable relation between the two'.

The counterfactual judgment task

The instructions for the counterfactual judgment task were as follows:

> There are a number of factors that may affect overfishing. We would like you to evaluate how certain changes in certain factors may affect the amount of overfishing (the extent to which fishermen catch unsustainable fish). The amount of change is always given as 30%: this is just a convenient figure with no special significance. Your task is to decide whether the change will cause an 'increase', 'decrease' or 'no change' in the amount of

Table 1. Causal factors presented in the diagram task

Factor names	Interpretation
Consumption	People buy and consume unsustainable fish
Market	Unsustainable fish is sold on the market
Overfishing	Fishermen catch unsustainable fish (resulting in overfishing)
Monitoring	The government monitors and enforces fishing laws
Gear	Fishermen use fishing gear that does not permit capturing only the targeted species

> overfishing. When you have decided, put a circle round the answer you've chosen. If you've chosen increase or decrease, please also write your estimate of how much change will occur in the space provided. You should do this by giving a percentage estimate, from 1 to 100% (0% would be no change). If you choose 'no change' you do not need to give a percentage estimate. It isn't easy giving an exact percentage judgment, but please do the best you can, basing your judgments on your understanding of how things work. This not a test and there are no right or wrong answers, we are simply interested in the way people think about these things.

Participants were then presented with four questions. Subjects are told to imagine that a 30% change (increase or decrease) has occurred on the factor in question and are asked to judge the amount of change this would cause on overfishing. So, for example, subjects are told to imagine that there has been a 30% increase in consumption of unsustainable fish. They are then asked to say whether there would be an increase, decrease or no change in overfishing. For the former two, they are asked to give an estimate of the amount of change that would occur in percentage. An example of a question, related to *consumption* is shown below:

> Imagine that people decrease their consumption (eating and buying) of unsustainable fish by 30%.
>
> What effect would this have on overfishing (the extent to which fishermen catch unsustainable fish)?
>
> - Would increase overfishing.
> - Would decrease overfishing.
> - Would cause no change in overfishing.
>
> How much change would occur? Please write a number from 0 to 100%. ___%.

Consumption questions

Participants were asked to indicate how many times a month they consumed fish. In addition, they were asked whether they took sustainability or overfishing into account when purchasing fish.

Procedure

Participants took part individually or in groups of two or three in a large seminar room. If in groups, participants were positioned so that nobody could see what the others were doing. Participants were supervised by an experimenter who introduced the study, handed out informed consent forms and invited participants to ask questions if anything in the instructions was not clear. There were no questions concerning the present study. At the end, participants were thanked and given their pay as well as a debriefing sheet that explained the aims of the research. The whole study lasted on average 25 min.

Results

Causal network analysis

The 33 participants included an average of eight paths in their diagrams (SD = 3.3; range 3–20). For the causal network analysis, the quantitative estimates were disregarded, and

Table 2. Endorsement frequencies of causal links

	Effect				
Cause	1	2	3	4	5
1 Consumption	–	21	1	7	20
2 Market	20	–	4	8	9
3 Monitoring	−7	−22	–	−15	−24
4 Gear	1	3	1	–	21
5 Overfishing	20	2	6	0	–

only the direction of change (increase, decrease or no change) was considered (White, 2008). The data from each subject therefore consisted of a 5 × 5 matrix. Any given cell in the matrix could contain either + (*judged increase*), − (*judged decrease*) or 0 (*judged no change*). Scoring judged increase as +1 and judged decrease as −1 enables a net score to be calculated across subjects for each cell of the matrix. This matrix is presented in Table 2. These net scores formed the basis for the construction of the causal network.

Lunt (1988) proposed two criteria for selecting links to be included in the causal network. One is the 'minimum systems criterion' (MSC). This is the value at which all causes are included in the system, to determine the network nodes. Accordingly, causal links are added hierarchically to the network, in the order of net scores, until the MSC is reached. In this study, the MSC was a net score of 21 (as used by White, 2008), with four links meeting this criterion. Each link in this network was endorsed by at least 63.7% of participants, suggesting a moderately high consensus. The resultant network is shown in Figure 1.

The second criterion for selecting links to be included in the causal network is Inductive Eliminative Analysis (IEA), wherein every network produced when working towards the MSC is checked for endorsement. Originally developed to deal with binary adjacency matrices, networks were deemed consensual if endorsed by at least 50% of participants (Hevey, Collins, & Brogan, 2013). The resultant network is shown in Figure 2.

In this instance, adopting IEA resulted in a more stringent network with two less links. The number of participants representing each path in the resulting consensual networks, as well as the judged mean strength, is reported in Table 3.

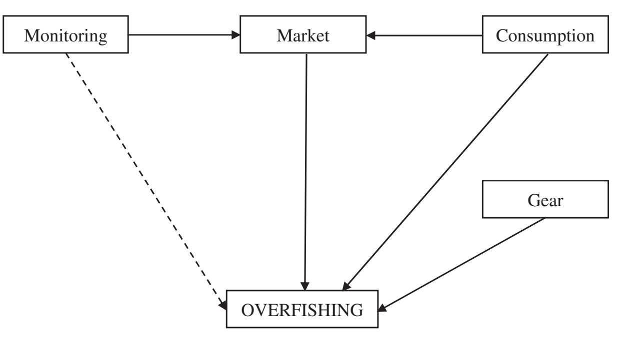

Figure 1. Consensual Causal Network created using MSC. Dashed line indicates a causal relation labelled as 'decrease'.

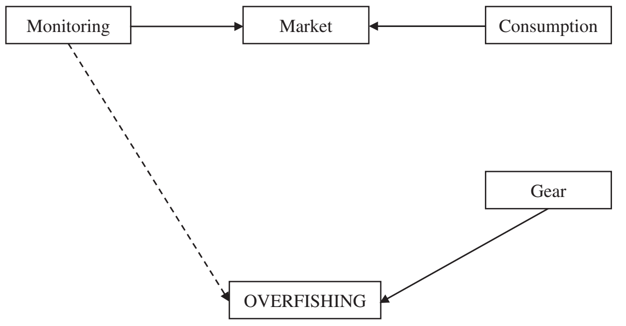

Figure 2. Consensual Causal Network created using IEA. Dashed line indicates a causal relation labelled as 'decrease'.

Table 3. Paths and mean path strengths of consensual network created using MSC

Cause factor	Effect factor	*N* (%) representing the path	Mean path strength (*SD*)
Monitoring	Overfishing	24 (80)	−0.66 (0.24)
Monitoring	Market	22 (73.3)	0.6 (0.21)
Consumption	Market	21 (70)	0.86 (0.22)
Gear	Overfishing	21 (70)	0.69 (0.27)
Consumption	Overfishing	20 (66.7)	0.74 (0.28)
Market	Overfishing	19 (63.3)	0.82 (26.4)

Causal models and counterfactual judgments

The first research question concerned the relationship between a person's causal diagram of overfishing and their counterfactual judgments. To examine the relationship between diagrams and judgments, Green and McManus (1995) and Green *et al.* (1998) used a method that is formally identical to path analysis. Participants' ratings of path strength are treated as being equivalent to standardized path coefficients. The same method is used to address the current question.

First, the total path strength of each factor to overfishing was calculated. For example, there might be a direct path from factor A to overfishing and an indirect path via factor B. In that case, the total path strength from factor A to overfishing would be an additive combination of the strength of the direct path, and the strength of the indirect path. The strength of the indirect path is the strength of the path from A to B (e.g., 20% or 0.2) times the strength of the path from B to the target (e.g., 30% or 0.3). In this instance, it would be 0.06 (0.2 times 0.3). If the strength of the direct path from A to the overfishing were 0.4 (40% or 0.4) then the total path strength would be 0.46 (0.4 + 0.06) and so on for any more complex set of paths between any two factors. The mean path strengths are reported in Table 4. Table 5 shows the mean (*SD*) counterfactual judgment for each factor.

The second step involved calculating, separately for each individual, the correlation between each of the factors' total path strength and those same factors' corresponding counterfactual judgment, using a conventional Pearson correlation r. In the present experiment, the mean correlation across individuals (i.e., the mean of a set of r correlations), was 0.66 (SD = .55, N = 33), accounting for 44% of the variance

Table 4. Mean (*SD*) total path strengths from each factor to overfishing

Factor	Mean (*SD*)
Consumption	0.9 (0.73)
Market	0.87 (0.5)
Monitoring	−1.36 (1.29)
Gear	0.58 (0.73)

Table 5. Mean (*SD*) counterfactual judgments. Judgments based on the decrease frame have been reversed to compute the means

Factor	Mean (*SD*)
Consumption	31.21% (23.8)
Market	27.42% (18.81)
Monitoring	−35.06% (26.74)
Gear	12.93% (31.87)

in the counterfactual judgments. This correlation was significantly different from zero, $p < .001$. A paired samples *t*-test was then used to calculate the difference between the mean total path correlation ($r_m = .66$, $SD = .51$) and the mean direct path correlation ($r_m = .55$, $SD = .57$). This difference was significant: $t(32) = 2.89$, $p < .001$, suggesting that the variance in individuals' counterfactual judgments is better explained by looking at the factors' total path strength (sum of direct and indirect paths), as opposed to looking at the direct path strengths alone. On the other hand, the difference between the mean total path correlation and the mean indirect path correlation ($r_m = .60$, $SD = .48$) was not significant: $t(32) = .68$, $p > .05$. The correlation between judgments and number of paths emanating from each factor was -0.44 ($SD = .56$).

An independent samples *t*-test revealed that total path correlations were affected by whether participants completed the diagram task before or after the counterfactual judgment task. The group completing the diagram task first had significantly higher correlations ($r_m = .89$, $SD = .19$, $N = 16$) than the group completing the counterfactual judgment task first ($r_m = .44$, $SD = .62$, $N = 17$): $t(31) = -2.82$, $p < .05$. To investigate this further, a mixed model analysis of variance was carried out with the type of correlation as the within subjects dependent variable and task order as the between subjects dependent variable. Both the type of correlation and the task order were significant, but there was no interaction between the two.

On the other hand, counterfactual judgments were generally unaffected by task order with the exception of *gear*: the mean change rating of participants who completed the diagram first ($M = 28.43$, $SD = 25.86$) was significantly higher than that of participants who completed the change judgment task prior to the diagram task ($M = -1.64$, $SD = 30.62$): $t(31) = -3.03$, $p < .01$. There was no effect of task frame on total path correlations: $t(31) = -1.636$, $p > .05$, nor on any of the counterfactual judgments (all *p*s $> .05$). NEP scores did not vary as a function of individual causal models or counterfactual judgments.

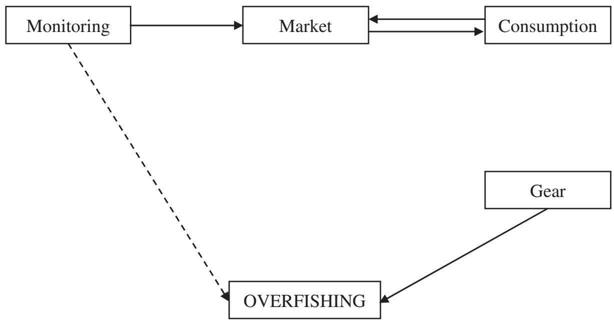

Figure 3. Example of an individual network with a feedback loop.

Analysis of feedback loops
Each individual causal network was inspected for the presence of feedback loops. Of networks, 52% had at least one feedback loop. An example of an individual network is shown in Figure 3.

The mean number of loops across all networks was 1.58 (SD = 2.3). The mean number of loops across only the networks containing loops was 3 (SD = 2.48), ranging from 1 to 10 loops per network. Loops involved 2 to 5 factors. The most common loop was *market-consumption* (N = 9).

The sample was then divided into two groups based on the presence of the *market-consumption* loop. An independent samples t-test was used to compare reported fish consumption in the group that constructed the loop (N = 9, M = 2.44, SD = 2.23) and the group that did not represent the loop (N = 24, M = 6.13, SD = 5.78). A significant difference in fish consumption was found: $t(31) = -2.635$, $p = .01$ (equal variances not assumed), suggesting that participants who included the *market-consumption* loop consumed fish less often than the participants who had not represented it in their diagrams. Across the general sample, consumption varied from 0 to 20 times per month (M = 5.12, SD = 5.29).

GENERAL DISCUSSION

The leading goal of the present research was to investigate how lay causal models of an environmental problem are related to reasoning about the issue. The first aim was to extend work by Green and McManus (1995) by showing, in an environmental domain, that a person's causal network diagram correlates with their ratings of the effectiveness of actions based on these factors. In the current experiment, participants completed two main tasks. The causal diagram task involved drawing a network diagram of how a set of factors related to overfishing may affect overfishing and each other. The counterfactual task consisted in judging the effectiveness of a series of counterfactual suppositions, based on the diagrammed factors, in reducing overfishing. The experiment explored the relation between these two tasks. Consistent with our experimental hypotheses, total path strength of the diagrammed factors correlated more significantly with the counterfactual judgments than direct path strengths alone, or simply the number of paths emanating from a factor. The total path strength was found to explain 44% of the variance in the counterfactual judgments. In addition, participants who had a high score on a scale measuring concern with future consequences, had significantly higher correlations between the diagram and the counterfactual judgments, than the group who had a low score.

The second aim was to investigate the extent to which people think about overfishing in a unidirectional way. Previous studies by White (2008) analysed participants' consensual network of forest ecosystems and found no feedback loops. In contrast, the current experiment analysed individual networks and found that over half of the participants built loops into their network diagrams. These loops varied in factors and sizes. In addition, the current experiment showed that participants who drew a feedback loop involving unsustainable fish consumption and presence of unsustainable fish on the market, reported consuming significantly less fish than the group who did not represent that specific loop.

The present findings have major theoretical implications for two domains. The first of these disciplines is that of cognitive science, aiming to elucidate the processes underlying general causal reasoning. The second field is that of environmental psychology, as well as the specific phenomenon of overfishing. Theoretical implications will be discussed in respect to each of these fields.

The current experiment showed that total path strength of the diagrammed factors correlated more significantly with the counterfactual judgments than direct path strengths alone, or simply the number of paths emanating from a factor. The first thing this implies is that when people engage in causal reasoning about a phenomenon, they can and do recruit a whole causal model as opposed to just individual direct causal relations (Lagnado *et al.*, 2007). Naturally, the current experiments utilized only four factors, so it is difficult to generalize this implication to situations involving more variables. When reasoning about more factors, participants would increase the load on working memory – this might result in people resorting to a more simplified strategy based on explicit representation of direct path strengths only. Participants in the Green and McManus (1995) and Green *et al.* (1998) studies represented up to 12 factors, therefore suggesting that at least with that many factors, people can recruit a holistic causal representation of the phenomenon in question.

The current findings clearly establish that it is the strength of the causal paths as opposed to the sheer presence of them that is important. However, the present research cannot elucidate on the cognitive mechanisms that operate when people reason and combine the strengths of direct and indirect causal relations. Total path strengths were calculated by summing the strengths of direct and indirect paths, whilst indirect path strength was calculated by multiplying the strengths of indirect paths. This formula is intuitive because it weighs direct paths more than indirect paths. Similarly, it accounts for the fact that the weight of an indirect path decreases as the number of indirect paths increases. In other words, as the number of steps that it takes to get from a cause to an effect increases, the importance of each of these steps decreases. This method of computing total paths strengths explains only 44% of variance in the counterfactual judgments. A different algorithm for computing total path strengths might provide a better account. However, even though the present research adopted a quantitative approach in extracting and analysing causal representations, people's spontaneous representation of causal relations might be qualitative (Lagnado, 2011; Pearl, 2000). In other words, even though it is clear that people take causal strengths into consideration, they do not need to have access to their precise values.

The second finding with implications for causal reasoning is that participants constructed feedback loops in their causal diagrams. On the surface, these findings appear to be in direct contrast with previous research by White (2008). However, the two cannot be directly compared as the present study adopted a novel experimental approach that involved analysing individual causal networks as opposed to the consensual network (the current study also used different causal factors and a different causal network elicitation method). Inherently, this implies there are significant individual differences in causal reasoning that, more often than not, get neglected at an experimental level. Future studies should aim to integrate individual differences as part of their approach.

The presence of feedback loops suggests that people can appreciate two-way causal relations within a complex network. This notion is reinforced by the finding that the most popular loop was also the most intuitively sensible one: most participants who constructed loops had a bidirectional link from consumption of unsustainable fish to the extent to which unsustainable fish is sold on the market. Furthermore, the group representing this loop reported consuming less fish than the group who did not represent that loop. This finding can be taken as preliminary evidence that people not only represent loops, but may also integrate them into their reasoning. Either way, further analyses would have to determine if a causal model involving loops provides a more accurate account of causal judgments than a model without loops. Similarly, further work is needed to explore the connection between the structure of individual causal representations and actual consumer behaviour.

Inspection of the individual causal diagrams, as well as the consensual network, revealed some interesting patterns that have potentially important implications for overfishing. In both experiments, the majority of participants had a direct link from *consumption* to overfishing.

Consumption is also understood to affect overfishing through *market* (majority had link from *consumption* to *market* and from *market* to overfishing). However, what is perhaps more striking is that only a minority recognizes that *consumption* and *market* may influence *monitoring* and *gear*. In other words, people seem to think that the extent to which the government monitors and enforces fishing laws, and the extent to which fishermen use destructive fishing gear, is not contingent on the consumption rate which sets market targets. This implies people are likely to view monitoring and gear as factors beyond their control. If people attribute responsibility to multiple factors they do not view as causally linked to them, this could result in the classic bystander effect (Latane & Darley, 1968), whereby intention to act decreases as shared responsibility for a problem increases. This is consistent with Belk, Painter, and Semenik's (1981) finding that participants who attributed an energy shortage to non-personal causal factors (e.g., government, oil companies) also tended to favour a non-personal solution to the problem.

More generally, the current study has important implications for the domain of environmental psychology. First of all, it highlights the need to incorporate a causal approach in its endeavours, both as a theoretical contribution and as an experimental method. Numerous theoretical frameworks have been developed to explain the gap between the possession of environmental knowledge or awareness and displaying pro-environmental behaviour. Although many hundreds of studies have been done, a comprehensive model is yet to be found (Kollmuss & Agyeman, 2002). Most existing theories adopted a social-psychological approach – examples are cognitive dissonance theory (Thogersen, 2004), norm-activation theory (Stern, Dietz, Abel, Guagnano, & Kalof, 1999), and the theory of planned behaviour (Ajzen, 1991). None of these frameworks are based on or include causal reasoning. Ajzen's theory of planned behaviour (TPB) seems to be the most widely used model to predict or explain variance in pro-environmental behaviour. Broadly speaking, TPB postulates that an intention to act environmentally is formed in a rational choice process weighting three different aspects: the person's attitudes towards the behaviour, the person's perception of social pressure to act in a certain way and the person' perception of behavioural control in the situation. Even though a person's perception of behavioural control is bound to be related to their causal model of the problem, the theory does not make explicit reference to causal models. As shown by the current findings, there are significant individual differences in causal models of environmental problems. Therefore, TPB is likely to provide a better account of pro-environmental behaviour by factoring in an extension that considers causal understanding of the problem.

In terms of experimental methodologies, past research in environmental psychology has looked mainly at attitudes towards nature (e.g., Milfont & Duckitt, 2010), pro-environmental intentions (e.g., Bamberg & Möser, 2007) and a relatively limited range of pro-environmental behaviours such as recycling and energy saving. With few exceptions, previous work has relied on self-report tools to measure attitudes, intentions and behaviours. Environmental knowledge has also been assessed through using multiple-choice questionnaires, surveys and factual tests. The present study points out how much can be learnt by relying on a causal network method that retrieves environmental beliefs as a function of an interconnected network.

The main drawback of using the network elicitation task is that it merely approximates people's pre-existing causal models of the phenomenon under scrutiny. The act of drawing the diagram leads participants to consider explicitly certain causal paths that would have normally been latent or implicit – that is before engaging in the study. This implies that reasoning explicitly about causality might change the nature of the models – at least marginally. This notion is consistent with the idea that certain conversations or discussion might also have this effect as individuals explore or seek to explain certain beliefs (Green *et al.*, 1998). Indeed, we examined the extent to which the relationship between the diagram task and the counterfactual judgment was affected by the order in which these two tasks were completed. We found that the group who completed the diagram task first had significantly higher total path correlations than the group who completed the counterfactual judgment task first. To investigate this further, we examined whether the type of correlation (total, direct or indirect) was adversely affected by task order, but we did not find a significant interaction. Importantly, we also investigated whether counterfactual judgments were affected by task order. We found a significant difference only for *gear*: the mean change rating of participants who completed the diagram was higher than that of participants who completed the change judgment task prior to the diagram task. In a sense such a result supports the idea that thinking about an issue, or learning more about it (see Green, 1997) alters its causal representation and related judgments. On the other hand, we found a link between endorsement of the feedback loop between *market-consumption* and the participants' self-reported consumption of fish. This is encouraging as it suggests that at least some of the elicited causal models do reflect pre-existing beliefs that relate to people's behaviour.

Future research should aim to incorporate more behavioural measures that can be associated to the causal model of the phenomenon under scrutiny. In terms of overfishing, a starting point could be to include more self-report behavioural measures of general environmental behaviour as well as fish consumption. For instance, asking participants the extent to which they take into consideration the species of fish they consume. However, even more interesting would be to measure actual behaviour or to compare causal models of different groups. For example, do vegetarians have different causal models from non-vegetarians? Similarly, do consumers have different models from fishermen?

Another reason why the causal diagrams elicited in the current study remain approximations of pre-existing causal beliefs is that the factors that were employed were not idiosyncratic. The factors in the current study were selected based on expert assessment of the relative importance of different factors. This selection might omit causally relevant factors that may either alleviate overfishing or act against the factors that are judged to cause overfishing. The result might be a network representing a kind of vicious circle in which negative factors all interact to aggravate each other (White, 1995). The second problem for this method is that the factors selected do not constitute a closed system. In a way, this problem is unavoidable because there is no such thing as causally closed system. Therefore, the structural characteristics of the network may be affected by the omission of causally relevant items.

To overcome this potential issue, future research should aim to ask participants to generate their own factors and then create counterfactual judgments questions based on those factors. In addition, that would allow the participants to include the number of factors they deem appropriate without being restricted to the number selected by the experimenter. In fact, the degree of complexity, or granularity of the various causal diagrams might be an interesting variable to explore in its own right.

On this note, future studies would benefit from a computerized version of the task. Participants might have left the diagrams simplified or incomplete by shunning away from creating too many crisscrossing patterns or drawing too many arrows for representing links and loops. This means that they might have left out some paths in the pursuit of avoiding visual clutter rather than due to lack of awareness of causal paths. A computerized version would provide a neater and simpler workspace for future endeavours.

Finally, it would be important to explore how people understand the different ways in which causes combine to bring about an effect. There are several different functions that can mediate the impact of each individual cause on the final effect (Steiner, 1972; Waldmann, 2007). One of the difficulties in allocating causality arises from the fact that causes can combine in different ways to bring about an outcome. Three common functions are addition, conjunction or disjunction. In the additive case, each cause contributes something to the final outcome. For example, using destructive fishing gear and surpassing fishing quotas both contribute to overfishing. In the conjunctive case, all causes need to surpass a certain threshold. For example, fishing gear can only affect overfishing if the government does not monitor and enforce fishing laws properly. In the disjunctive case, it only takes one of several potential causes to bring about an outcome. For instance, the government might have two separate ways to monitor violations of fishing laws, either of which alone is sufficient for the desired outcome. Future research could explore how sensitive people are to these causal combination functions and especially how it mediates attributions of causal responsibility (Gerstenberg & Lagnado, 2010). For instance, Lagnado, Gerstenberg and Zultan (2013) showed that people assigned greater casual responsibility to conjunctive rather than disjunctive causes in simple game situations (including a public goods game). Thus, an agent is deemed more responsible if she is seen as a necessary element in causing the outcome (rather than just being one of two causal agents, either of whom is sufficient to cause the outcome). Does this sensitivity to causal combinations extend to more realistic situations such as overfishing?

Practical implications

Understanding the nature of public beliefs of the risk factors and prevention of overfishing and other environmental problems is critical to the design of communication programmes aimed at altering actions. In particular, such programmes need to ensure consumers understand how their purchasing choices are causally linked to overfishing. For example, some conservation societies (e.g., the Marine Conservation Society in the United Kingdom and the Monterey Aquarium in the United States) publish guides that allow consumers to see which fish are more sustainable. Fish tend to be categorized into three groups: 'eat, 'eat occasionally' and 'avoid'. The Marine Conservation Society defines the 'avoid' category is defined as follows: 'fish are from unsustainable, overfished, highly vulnerable or poorly-managed fisheries or farming systems'. The trouble with such explanation is precisely that it does not focus on causality. It almost implies that the fishing industry is responsible for overfishing through bad practices. Although this is true, the causal link between consumers and the fishing industry is not made evident. Similarly, consumers could be made aware of the causal link between their dinner choice and the tragic widespread effects of overfishing.

However, as indicated by the current findings, it is not sufficient to make people aware of the presence of a causal link between them and the undesired effect. Evidently, it is imperative to emphasize the causal strength of that link. Some campaigns do tell consumers that, along with seafood retailers and restaurants, they play a crucial role in the conservation of ocean resources. However, they do not quantify that role; they do not make it explicit that if consumers made the right choices, overfishing would not take place. As argued previously, the quantification does not necessarily need to come in a numerical format, but should convey an idea of magnitude of relation of some sort. For instance, sustainable fish guides could inform consumers that their role is deterministic.

The current findings also provide evidence that people can understand feedback loops, implying that environmental campaigns should also emphasize the cyclical nature of the natural ecosystem. Attention should be drawn on repercussions of unsustainable actions. For example, campaigns wishing to promote sustainable fish consumption could emphasize that consumers' choices today are determining what they will be able to choose from tomorrow – as well as more delayed feedback loops pertaining the options that will be available to future generations.

To conclude, this research shows how naïve causal models of a complex environmental problem might hold the key to unlocking the reasoning processes underlying people's decisions to support sustainable behaviour. Environmental psychology and ecological campaigns can achieve greater success in their pursuits by making causal reasoning one of their main driving forces.

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