Dynamic Bayesian Networks for decision support and sugar food security

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Abstract

Food security, access to sufficient safe, nutritious food for active and healthy lives, is enormously important for individuals and a key responsibility of national and international governments. Food security is determined by a huge range of factors over many scales ranging from global climate and water to individuals' food choices and waste behaviours. Food security policy decision-makers need to take account of these factors and their interdependencies using available data and experts judgements. Dynamic Bayesian networks are powerful models that are able to capture the dependencies between variables and combine data with expert opinion in a rigorous fashion as they develop over time. They have been shown to be appropriate for various types of decision support; however their application to food security policy is novel. Here we design a Dynamic Bayesian network approach to provide decision support for food security as associated with potential instabilities within the sugar industry.

1 Introduction

The prediction of a global population of 9 Billion by 2050 (Nature [2010]) plus the 2008 and 2011 peaks in food prices with the consequent riots have brought the issue of food security firmly on to the agenda of governments in the wealthy nations of the world (Lagi et al. [2011]; Kneafsey et al. [2013]). Food security is dependent on a complex system of environmental, economic and social factors and intelligible and accurate risk-based decision-making requires appropriate statistical analysis and intelligent inference for information from different sources (Mengersen and Whittle [2011]). Bayesian Networks (BNs) are a robust method for combining disparate types of information and have been used to provide decision support in the nuclear industry (Leonelli and Smith [2013a,c]), algae control (Johnson et al. [2014]), ecology (Pollino et al. [2007]) and a number of other settings (e.g. Mengersen and Whittle [2011], Baesens et al. [2002], Jansen et al. [2003]). BNs are particularly suited to the role of decision support as they build in the knowledge of domain experts, provide a narrative for the system and can be transparently and coherently revised as the domain changes. Dynamic Bayesian Networks (DBNs) are able to accommodate systems which change over time. Here, the use of DBNs for food security decision support is illustrated using the sugar market. This is the first use of a DBN to model the supply of a foodstuff through to the end-user and is the first in a suite of such models which will networked together appropriately to model the whole food system. The sugar model is used in conjunction with the influential Chatham House Report (Amber-Edwards et al. [2009]) to illustrate the consequences of the various scenarios they identify on the supply of food and its effect on food poverty in the UK.

1.1 UK food security

Food security is defined by the UK's Department for environment, food and rural affairs (DEFRA) as 'consumers having access at all times to sufficient, safe and nutritious food for an active and healthy life at affordable prices.' (Defra [2008]). For food security to exist, food supply must be reliable and resilient to shocks and crises and should be produced in an environmentally sustainable way to avoid longer-term problems. In addition to availability, there must also be access, affordability and awareness for individual consumers (Kneafsey et al. [2013]). Since the 1960s, the world has focused mainly on the food security needs of less developed countries, but the peaks in the Food and Agriculture Organisation of the United Nations (FAO) food price index of 2008 and 2011 brought the issue of food security firmly on to the agenda of individuals and governments also in the developed world (e.g. in April 2014 an UK All Party Parliamentary Group (APPG) launched an inquiry into hunger and food poverty in Britain, Field [2014]). The causes of the 2008 and 2011 price rises have been attributed to income growth, changing patterns of consumption, inelasticity of short-term supply, reductions in export from producers, increase demand from countries wishing to stockpile, low inventory stocks (Evans [2008]), U.S. biofuel policy (Lagi et al. [2011]) and the dramatic increase in the volume of non-commercial transactions on the futures market (HLPE [2011]). Meeting the increased food demand caused by the expected increase in world population to around 9 Billion is also giving cause for concern.

There is a large body of research on the qualitative aspects of food security (Donkin et al. [1999]; Dowler et al. [2001]; Gurkan [2006]; Evans [2008]; Defra [2008]; Collier [2009]; Amber-Edwards et al. [2009]; Nature [2010]; Hallam and Abbassian [2013]; CEBR [2013]; Lillywhite et al. [2013]; Bar-Yam et al. [2013]; Ingram et al. [2013]; Kneafsey et al. [2013]; FoodEthicsCouncil [2014]). Quantitative approaches are very varied both in the techniques used and the aspects of food security which they address; there have been no attempts to model the whole system. Quantitative research in food security has shown that biofuel production from grain is accelerating grain price increases and the deregulation of the US futures market is adding price volatility to the market (Lagi et al. [2011], Lagi et al. [2012]) and this, in turn, may even bring civil unrest (Lagi et al. [2011]; Gros et al. [2012]). Fuzzy inference has been used to assess risk levels for national food insecurity (Abdul Kadir et al. [2013]). A machine learning approach has been used to classify households in Uganda as food insecure or food secure (defined as energy intake per person of 1800Kcal per day or more, Okori and Obua [2011]). Agent-based models also have been developed to quantify access to healthy food and optimal placement for mobile markets in U.S. 'food deserts' (areas under-served by full-service supermarkets where residents lack adequate access to healthy foods: Widener et al. [2012, 2013]). Okori and Obua [2013] compared ordinary linear regression, Bayesian linear regression and Gaussian process approaches to assess the contribution of prior knowledge to predicting changes in food crop prices. Finally, fuzzy cognitive mapping is now employed to encapsulate qualitative knowledge of expert stakeholders about the interdependencies between the important parts of a bio-based economy, including the food element (Penn et al. [2013]).

The dependence of food security on a complex system of environmental, economic and social factors makes it challenging to foresee the consequences of decision-making on all the disparate elements of this system. A system that is able to reconcile the often conflicting goals of resilience, sustainability and competitiveness and that is able to meet and manage consumer expectations will become the new imperative (Amber-Edwards et al. [2009]). Bayesian Networks are able to bring together the qualitative and quantitative elements of this complex system. In this paper, the use of Dynamic Bayesian Networks for decision support are explored as a way to connect, in a principled manner, the key local and international factors influencing the UK supply and price of sugar, to evaluate the effects of various shocks to the system and to uncover the consequent levels of UK food poverty.

1.2 Bayesian Networks

Bayesian Networks are an established type of probabilistic graphical model which have previously formed the basis of successful decision support tools (Fenton and Neil [2007]; French et al. [1995]; Leonelli and Smith [2013b,c]). Any decision support system needs to be transparent, principled, feasible and lead to fast identification of good countermeasures and policies. In this context, being principled is interpreted as expected utility maximisation for which the underlying theory is well-known and fully justified (Smith [2010]). Bayesian networks have the advantage that they are transparent with respect to the information used to formulate a response and, when used for decision support or policy evaluation, are also transparent with respect to the decision-making process itself. This allows a decision-maker relying on it to explain and justify the decisions made to an auditor (e.g.regulator). Being based purely on a probability model, Bayesian networks have agreed semantic meanings. Furthermore, under suitable conditions (which are plausible for food security applications) BNs can be used for coherent evaluation of policies that take proper regard of legitimate uncertainties. These uncertainties might come from sampling error or more often from domain experts who provide their subjective probabilities or degrees of belief in uncertain propositions. Other methods (including agent based models, fuzzy systems, etc.) do not enjoy these advantages. Bayesian networks are also now supported by a wide variety of software: Netica (Norsys [2010]) is used in this analysis but many more are available including Genie, Hugin, R (R Core Team [2014]) and MATLAB [2011].

A Bayesian network is a multivariate statistical model for a set of random variables $\mathbf{X} = \{X_1, X_2, \ldots, X_n\}$ comprising a directed acyclic graph (DAG) and a set of $n-1$ conditional independence statements. The DAG captures the qualitative structure of the system being modelled, by using vertices to represent the variables and edges to indicate statistical dependence between the variables. A BN can be thought of as a convenient way of representing a factorisation of a joint probability mass function or density function of the random variables $\mathbf{X}$. The usual rules of probability allow the joint mass function or density function $p(\mathbf{x})$ of $\mathbf{X}$ to be written as the product of conditional mass functions:

$$p(\mathbf{x}) = p_1(x_1)p_2(x_2|x_1)p_3(x_3|x_1,x_2)\ldots p_n(x_n|x_1,x_2,\ldots,x_{n-1}). \tag{1}$$

Each node of the graph is associated with a probability function that takes as input a particular set of values for the node's parent variables and gives the probability of the variable represented by the node.

The advent of Dynamic Bayes Networks (Dean and Kanazawa [1990]), which can be seen as a type of object-oriented Bayesian Network (OOBN, Koller and Pfeffer [1997]), allow the use BNs in changing environments like the food system (Smith [2010]). DBNs are a series of BNs created for different units of time relevant to the application, with each BN called a time slice. The time slices are connected through temporal links to form the full model. In this way the dependence, for example, of this years' supply of a crop on last years' demand and price can be captured whilst retaining a DAG structure. If the probability of a variable at time $t+1$ conditioned on the probability at time t is the same as the probability at time $t+2$ conditioned on the probability at time $t+1$, then this is a DBN or 2-time-slice model.

There are a number of steps to be followed when building a Bayesian network: see Smith [2010] for a full exposition. The DAG is formed by eliciting qualitative relationships between the variables from the domain experts and encodes agreed common knowledge about the system. Data (where it exists), official documents and elicited expert judgement can be used to uncover the conditional probability distributions of the system of variables (O'Hagan et al. [2006]). The elicited Bayesian Network encodes a set of independence statements, which can then be checked with the decision-maker, before the system is populated with numerical judgements, to confirm that they are plausible, and establish that the network structure is requisite.

1.3 The sugar industry

The UK sugar industry was selected as a running example since the UK is partly self-sufficient in sugar through the sugar beet crop and partly dependent on imports, particularly of cane sugar, from the tropical regions with Brazil as the

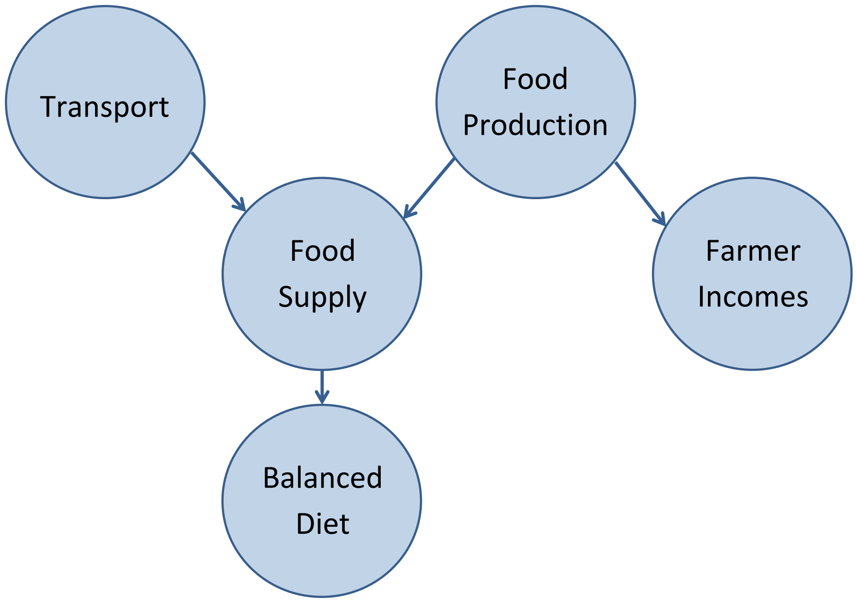

Figure 1: In this illustrative example, Balanced Diet depends on Food Supply. Food Supply depends on Food Production, which also dictates Farmer Incomes. Food Supply is also dependent on the ability to transport the food from the production site to where it is needed. Food Production and Transport are called the parents of Food supply. The conditional probability distribution is of the form $p(x_i|pa(x_i))$ for each variable (node) given its parents $pa(x_i)$.

world's major producer. In addition to being used for food (largely in processed foods) and for animal feed, sugar is also a major feedstock for bio-ethanol to the extent that sugar prices have followed oil prices in recent years (Gurkan [2006], Hallam and Abbassian [2013]) and Brazil's domination of the market makes it the price setter (ISO Statistics Commitee [2012]). Production vulnerabilities include the reliance on Brazil as the major producer of sugar cane and the geographic concentration of UK production of sugar beet so that regional weather conditions or other crop blights could affect world and UK production severely. In addition, 'Sugar, Jam, Syrups, Chocolate and Confectionery' is one of the elements in the food section of the 'basket of goods' used to calculate the UK Consumer Prices Index (CPI, Gooding [2013]), to monitor the cost of living. This sugar element contributes 11/106 of the price of food in the CPI, and food is 106/1000 of the whole collection of representative goods and service currently used to calculate CPI. The sugar market therefore contributes significantly to the UK cost of living.

2 Methods

A Dynamic Bayesian Network was built for the supply of sugar into the UK. The model's objective was defined as its ability to represent the UK sugar market sufficiently well to analyse the short and medium term effects of policy changes or uncontrolled factors, such as weather events, on the system's various elements.

2.1 Building the model

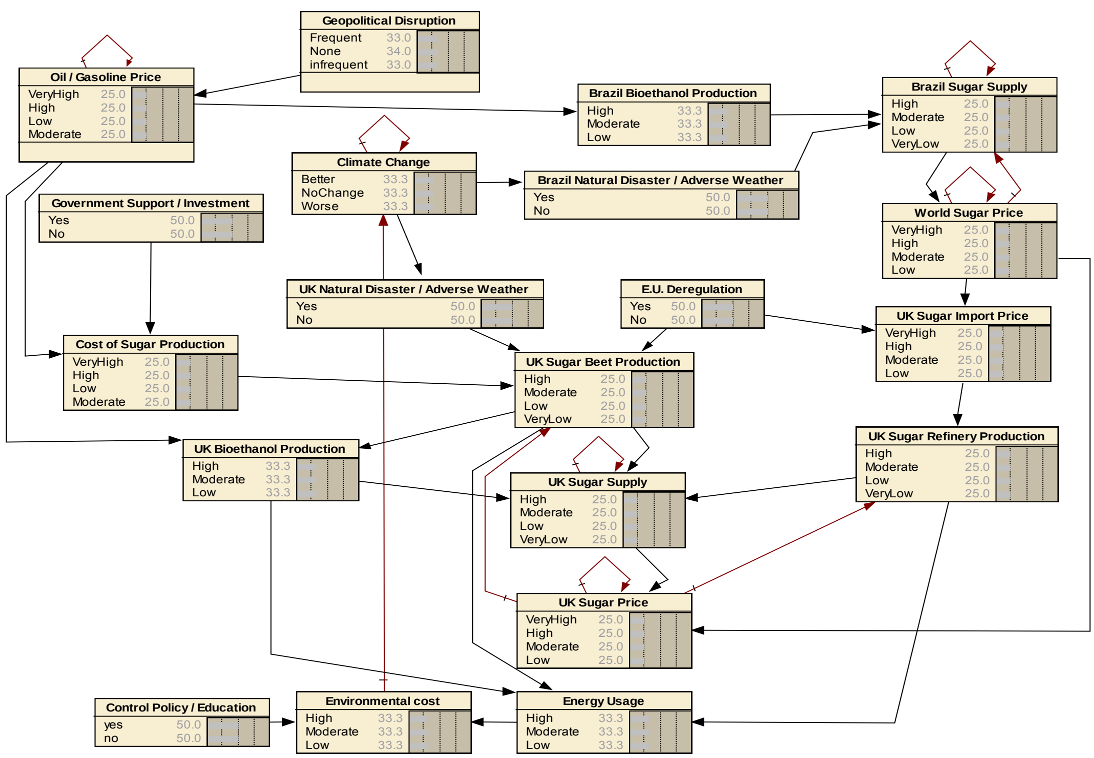

Figure 2: Dynamic Bayesian Network for the UK sugar market. This shows the qualitative dependence structure before the elicited conditional probabilities were added. Each arrow show the influence of a variable on another, and those coloured red indicate that the influence occurs in the next time period.

A literature review was undertaken and over 50 factors which may influence the UK sugar market were identified. A parsimonious subset of these was then identified with the help of academic experts in the sugar industry and a DAG was constructed which captured their expertise on the relationships between the variables. The continuous variables were discretised since full data is not available for all of them and the purpose of the model is to ascertain the level of sugar price and supply based on the conditions and policies. Coarse models are appropriate since policy-makers typically wish to act on large-scale changes to supply and price which are evidence of significant change, rather than on small fluctuations which are usual. In some cases, the domain in question may use only categorical measurements (French et al. [2009]; Nicholson et al. [2010]; Korb and Nicholson [2011]). Additionally, elicitation of probabilities is often easier for the domain experts if the questions are phrased in terms of categories rather than distribution (O'Hagan et al. [2006]). In this analysis, prices and costs were categorised into 'very high', 'high', 'moderate' and 'low' and supply was categorised into 'high', 'moderate', 'low' and 'very low'. The International Sugar Organisation (ISO) forecasts a 3% average annual growth in sugar prices over the next 10 years (OECD-FAO [2011]) and this was used as a benchmark, with the low and high categories defined in relation to this. A similar protocol was followed for the other variables. These categorisations enable the model to identify the particularly disadvantageous scenarios of very high prices or very low supply which lead to severe insecurity with respect to sugar supply with consequent impact on its derivative foodstuffs and on UK food poverty. The Bayesian network was produced by encoding the conditional probabilities elicited from the experts producing 15 conditional probability tables (CPTs) associated with the nodes of the Bayesian network. There may be a great many possible combinations of variables and levels within variables, for example in Figure 2, the UK sugar price has 64 combinations of variable levels with probabilities to be elicited for each and this is just one of the conditional probability tables in the full network. The influence of a variable on its own value at a future time point is shown as a self loop in the DBN in Figure 2 and all links relating to future time points are coloured red.

2.2 Testing the model

After entering the conditional probability tables elicited from the experts, calibration was carried out to verify that the posterior distributions produced were broadly in line with expert knowledge of the system and that the variables which are shown to contribute most to the outcomes of interest are plausible to the experts. Where these were found to be inconsistent with expert judgement, the CPTs were revisited and refined with the help of the relevant domain experts until satisfactory relationships were produced. These exercises have been detailed below.

3 Results

The Dynamic Bayesian Network approach was successful in representing the UK sugar market in line with expert opinion and able to display short and medium term effects of changes on the various elements of the system. From this, the likely availability and price of sugar in the UK under various scenarios was calculated. The proportion of the UK population likely to be in food poverty in a high sugar price regime was also estimated.

3.1 Sensitivity and calibration

Sensitivity analyses revealed that the model outputs are in line with the experts' expectations under various changes. Sensitivity to finding analysis determines how the Bayesian Network's posterior distributions change under different conditions. The standard metrics used are mutual information (entropy) reduction and variance of beliefs (posterior probability). The mutual information, I, between two nodes, say Q and F, measured in bits is defined as

$$I = H(Q) - H(Q|F) = \sum_q \sum_f p(q,f) log_2 \frac{p(q,f)}{p(q)p(f)}. \tag{2}$$

This is also expressed as a percentage of the mutual information of the query node, $H(Q)$ (Norsys [2010]). Variance of belief or posterior probability is the square of the expected change of the beliefs of Q, taken over all its states, due to a finding at F calculated

$$S^2 = \sum_f \sum_q p(q,f) \left[p(q|f) - p(q) \right]^2. \tag{3}$$

These measures are available for each node and were used in the validation of the model with the experts. The two nodes of greatest interest for the application as a decision support tool are UK sugar price and UK sugar supply.

Tables 1 and 2 show the most influential inputs for UK sugar price and UK sugar supply respectively.

The DBN (Figure 3) hypothesises that UK sugar price is directly influenced by UK sugar supply and world sugar price, plus indirectly by UK sugar refinery and UK sugar beet production through their impact on UK sugar supply. Similarly, UK sugar import price is itself affected by world sugar price and changes UK sugar price through its leverage on UK sugar refinery production. Similarly, UK sugar supply is informed directly by UK sugar beet production UK sugar cane refinery production. Energy usage is important for sugar beet production and UK sugar refinery production. UK sugar price is forced by UK sugar supply and world sugar price which impacts UK sugar supply via UK sugar import price and UK sugar refinery production. EU Deregulation affects both UK sugar import price and UK sugar beet production, which inform UK sugar supply respectively via UK Sugar import price and directly.

Node	(I) Mutual information	Percentage of node I	Variance of beliefs
UK Sugar Price [0]	1.83403	100	0.4927529
World Sugar Price [0]	0.44327	24.2	0.0285613
UK Sugar Import Price [0]	0.30595	16.7	0.0179849
UK Sugar Price [1]	0.17164	9.36	0.0118983
World Sugar Price [1]	0.13353	7.28	0.0075809
UK Sugar Import Price [1]	0.10472	5.71	0.0056309
UK Sugar Refinery Production [0]	0.06742	3.68	0.0038778
UK Sugar Refinery Production [1]	0.04090	2.23	0.0020152
UK Sugar Supply [0]	0.03087	1.68	0.0020891
Brazil Sugar Supply [0]	0.03026	1.65	0.0016302
UK Sugar Beet Production	0.02743	1.5	0.0013359
Energy Usage [1]	0.02356	1.28	0.0012677

Table 1: **Sensitivity to finding measures for UK Sugar Price**. [1] indicates a time-delay link

Node	(I) Mutual information	Percentage of node I	Variance of beliefs
UK Sugar Supply [1]	1.64872	100	0.4342531
UK Sugar Supply [0]	0.04692	2.85	0.0043068
UK Sugar Refinery Production [1]	0.04612	2.8	0.0068532
UK Sugar Price [1]	0.02389	1.45	0.0026960
UK Sugar Beet Production	0.01984	1.2	0.0012420
Energy Usage [1]	0.01437	0.872	0.0014371

Table 2: **Sensitivity to finding measures for UK Sugar supply**. [1] indicates a time-delay link

3.2 Scenarios

Various scenarios where there would be food security crises have been reported in key publications by DEFRA and Chatham House reports (Defra [2008], Amber-Edwards et al. [2009]) and we now examine the impact of four of these scenarios on the sugar market. The baseline model with computed conditional probabilities is given in Figure 3.

3.2.1 Geopolitical Disruption

The first scenario we consider here is that of high oil prices caused by geopolitical disruption (see Figure 4). Recall that sugar can be a feedstock for bio-ethanol production and that, if oil price is high, it is profitable for producers to divert their crops away from the food and fodder markets towards the biofuel market. By setting the geopolitical disruption to 'Frequent' with 100% probability and the oil price to 'very high' with 100% probability, the short-term effects of this

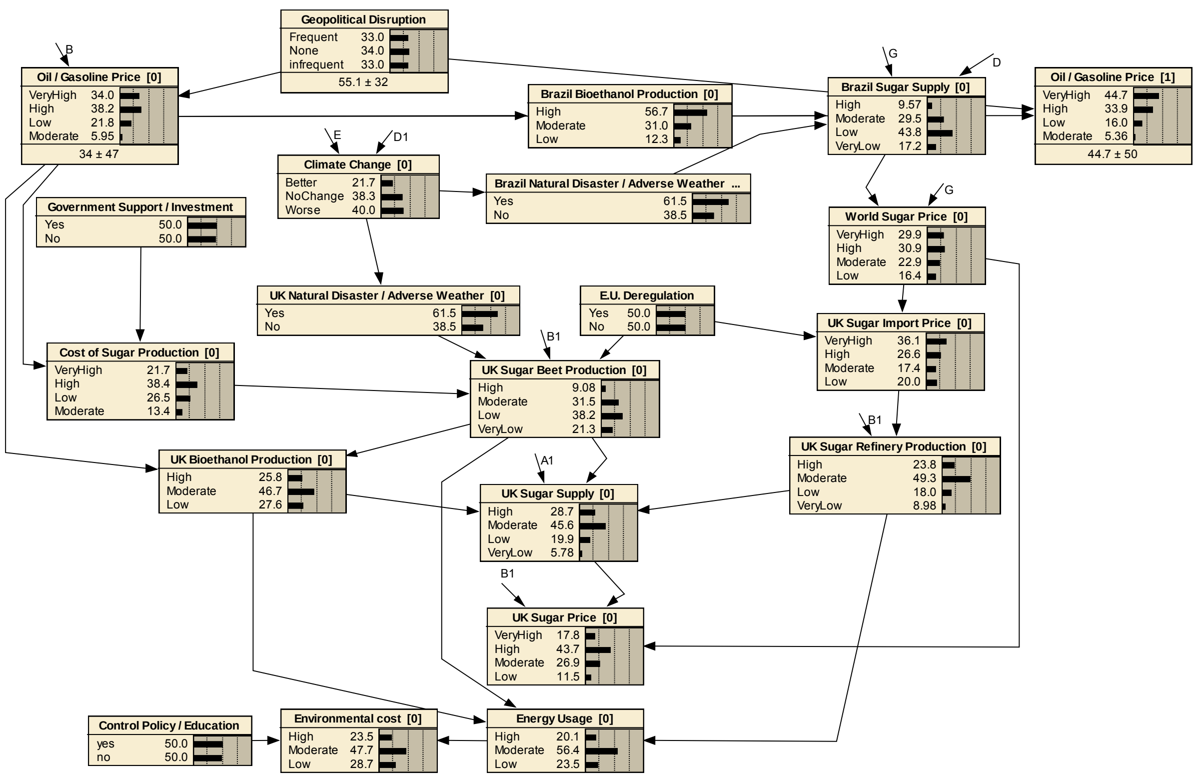

Figure 3: Dynamic Bayesian Network for the UK sugar market when compiled using the experts' probability distributions. The scenarios that follow document the deviations from this initial position.

scenario on the remainder of the system were evaluated. The direct influence on UK sugar beet production is through raising the cost of production to high (35% probability) or very high (55% probability); very little UK sugar beet goes to ethanol production, so the net result is a reduction in UK sugar beet production. On the other hand, Brazil, as a large supplier of cane sugar, is likely to switch to bio-ethanol production with the probability of high Brazil bio-ethanol production rising from 57% (Figure 3)to 80% (Figure 4)in the immediate aftermath of the disruption, according to the DBN model.

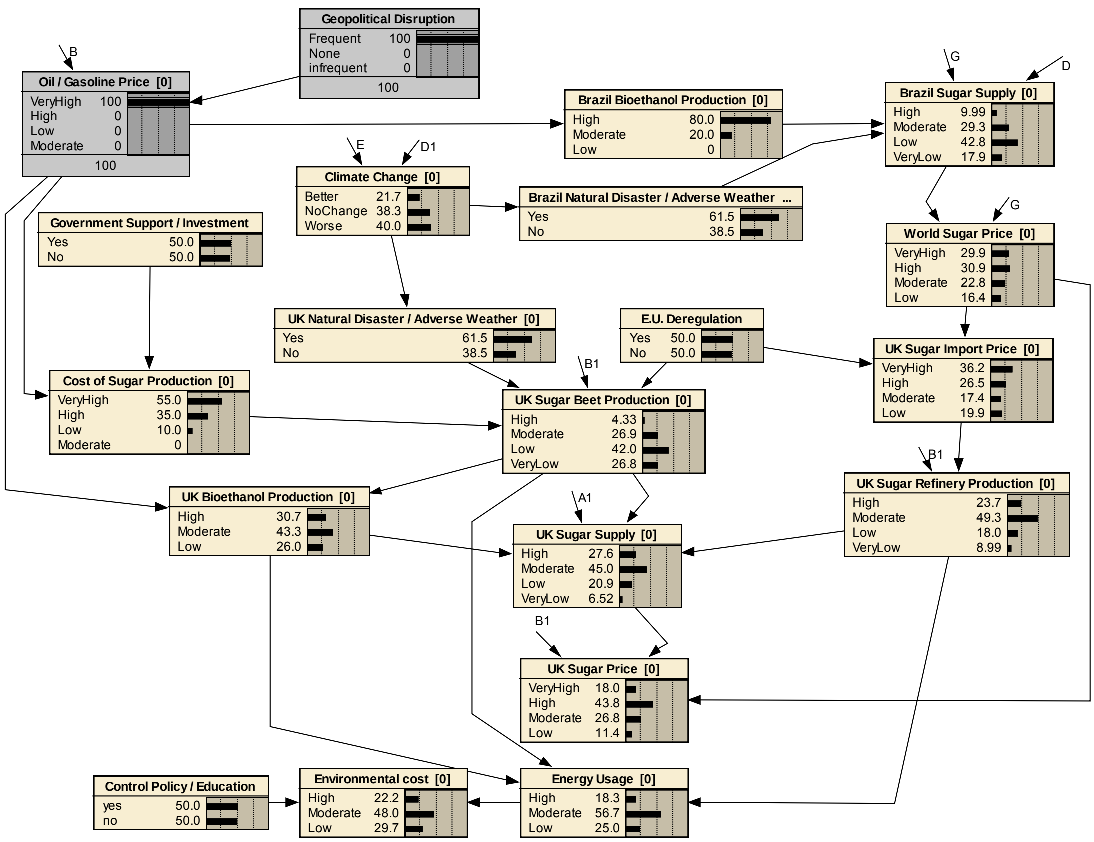

Figure 4: Dynamic Bayesian Network for the UK sugar market under the influence of geopolitical disruption and very high oil price: The immediate response. The bars and numbers are the probability distributions.

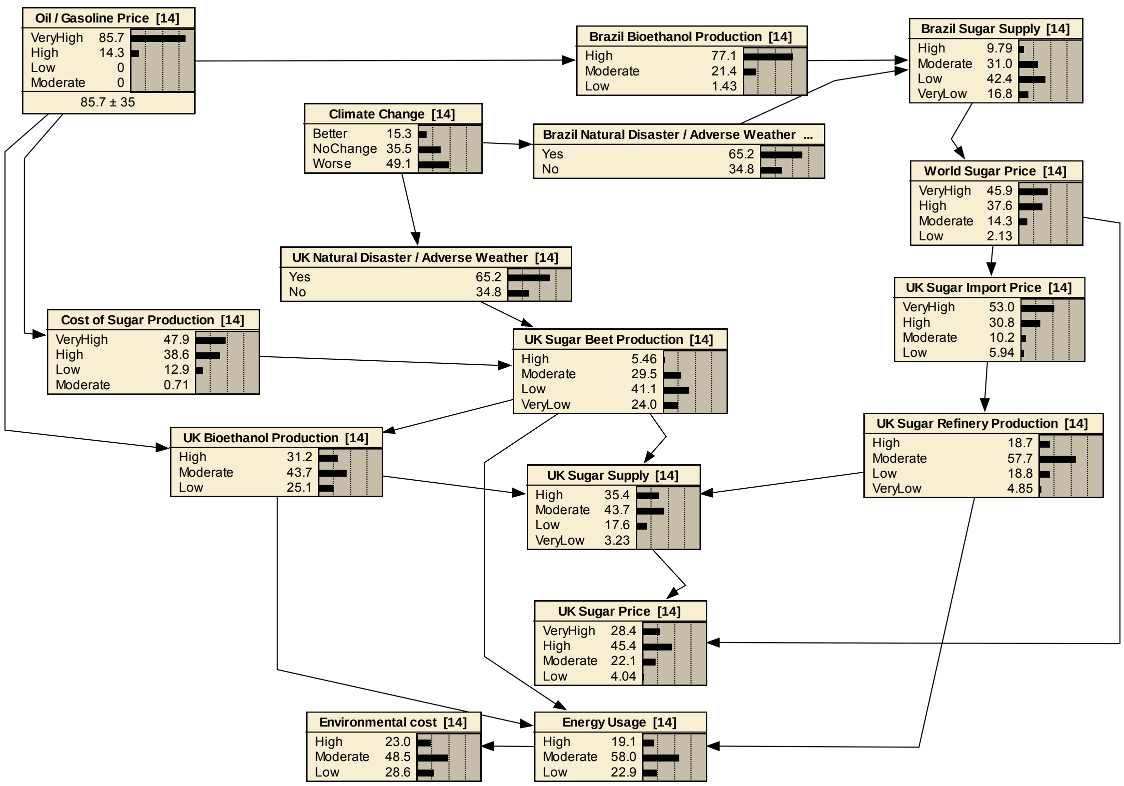

Figure 5: Dynamic Bayesian Network for the UK sugar market under the influence of geopolitical disruption and very high oil price. The state of the system after 14 years.

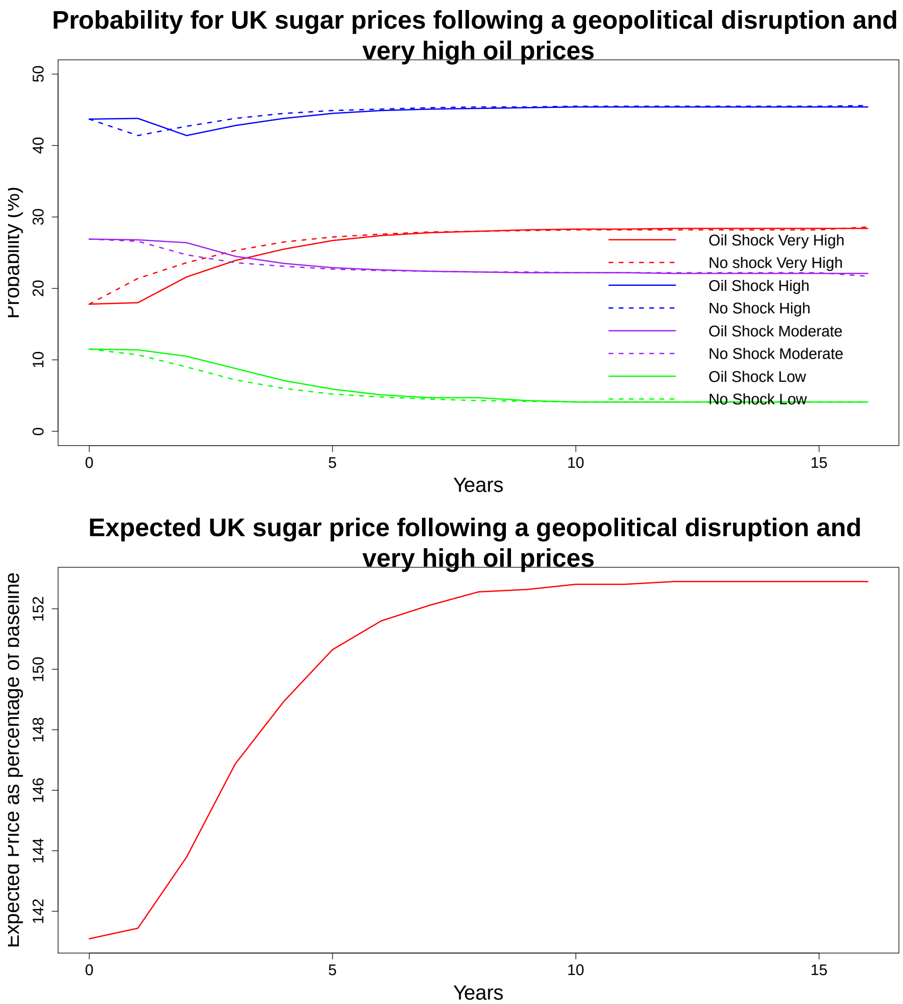

Figure 6: Upper: Probability for UK sugar price levels following a geopolitical disruption and very high oil prices. Dotted lines show the no-shock scenario. Lower: Expected UK sugar price as percentage of baseline following a geopolitical disruption and very high oil prices. High and Very High sugar prices correspond to a 50% and 100% rise in the cost of sugar, moderate as a 10% increase and Low as a reduction to 0.9 of the baseline price. Expected price is calculated $E = 200 \times p(veryhigh) + 150 \times p(high) + 110 \times p(moderate) + 90 \times p(low)$ at each time point. Intervals can be calculated if required.

In order the assess the likely medium term effects of this spike in oil prices, the 2-time-slice DBN was run for 14 time steps, to approximate 14 years (see Figure 5). The model shows that oil price remains high, with an 86% probability of still being high 14 years after the initial geopolitical oil price shock. The probability that world sugar price is very high increases markedly from

30% in the immediate aftermath to 46% by the 9th year and remaining there, becoming the most likely outcome, followed by a high price. The probability distributions for the UK sugar supply and the UK sugar price shift towards the high end by 14 years compared with the immediate aftermath of the oil price spike. The general trend for this scenario is to increase sugar prices rapidly in the first 2-3 years and continue the upward trend more slowly until a stable, higher price is reached at around the 7th year after the event. The evolution for the probabilities of the various levels of UK sugar price for the oil price shock scenario are compared to the no-shock scenario in Figure 6. We see that the oil price shock causes a perturbation in the probability distribution but then, in the absence of further shocks or policy interventions, the system equilibrates to the levels that were predicted in the no-shock scenario after about 7 years.

3.2.2 Natural Disaster

A second scenario that we consider is that of natural disaster or extreme adverse weather at a key location (see Appendix, Figures 8, 9, 10). The Brazil natural disaster when set to 'Yes' with probability 100% causes the model to predict that Brazil sugar supply will be low (probability 45%) or very low (probability 25%), which in turn raises the probability of a very high UK Sugar import price slightly from 38.% to 39.%. The price of oil under this scenario is high (probability 39%) or very high (probability 34%), which impacts the cost of sugar production. UK sugar supply is most likely moderate (probability 46%) and UK sugar price is high (probability 44%) or moderate (probability 26%). The 14-year effects are very significant, with a greater probability (36% up from 28%) of high UK sugar supply. Expected UK sugar price, too stays higher than before the natural disaster, with the probability of a very high price rising from 20% to 28% whilst the probability of a high price remains similar. Again, perturbation of the probability distribution in the early years after the disaster is followed by equilibration to the no-disaster scenario predictions, provided there are no further shocks or policy or regulatory changes. If flood prevention or other policy changes were made, the model could be update by adjustment to the probabilities, or by changing the structure of the DBN, as appropriate.

3.2.3 Education

Introducing a regulatory or educational intervention to tackle environmental cost (which in turn links to climate change), is successful in reducing environmental impact, but in the one-year scenario, as might be expected, climate change remains unaffected (see Appendix, Figures 11, 12, 13). The initial effect is to increase the probability of low environmental cost from 28% before the intervention to 38% with a matching reduction in the probability of high environmental cost which is largely maintained in the 14-year scenario, equilibrating at the no-intervention levels. This suggests that such an intervention needs to be sustained for a long-term impact.

3.2.4 EU deregulation

Deregulation of EU sugar production is a policy over which governments have more influence than natural disaster or geopolitical disturbance overseas. Currently, EU regulation imposes a quota on sugar beet production in EU countries and imposes tariffs on out-of-quota imports of cane sugar. A successful bid to deregulate the sugar market has been made and some claim this will lead to a healthy market with a lower price for sugar, boosting profits for industries using sugar in significant quantities. According to our model (see Appendix, Figures 14, 15, 16), setting the EU deregulation to 'Yes' with 100% probability would produce an immediate effect of increase to UK sugar beet production, shrinking the probability that it would be very low and increasing the probability that it would be low or moderate. The 14-year scenario is for this trend to continue with a small, further uplift in the probabilities of low or moderate production at the expense of very low production and high production. UK sugar supply will be most likely moderate (46%) or high (30.%) changing to 44% and 39% respectively after 14 years. The probability that UK sugar price would be high is shown as 44%, a slight rise from before the deregulation, rising to 46% after 14 years, whilst the probability that it would be very high climbs substantially from 18% to 28%, with the probability of a low price falling. However, our model suggests that this long-term behaviour would have occurred without deregulation.

3.3 Predicting changes in levels UK food poverty

Food poverty has been described as the inability to consume an adequate quality or sufficient quantity of food in socially acceptable ways, or uncertainty that one will be able to do so (Dowler et al. [2001]).

Expenditure on food is the most flexible part of individual household budgets as the amount spent on food is often whatever is left over when all the essential bills have been paid, especially in low-income households. When sudden or unexpected costs arise, expenditure on food is cut to balance the budget. Russian statistician Ernst Engel observed in 1857 that as income rises the proportion of income spent on food falls, even if actual expenditure on food rises (Engel's law). The reason is that food is a necessity, which poor people have to buy. As people get richer they can afford better-quality food, so their food spending may increase, but they can also afford luxuries beyond the budgets of poor people.

The UK suffered severe food shortages in the second World War and some food rationing continued until 1954 (Knight [2007]). In the post-war years, incomes were low and the proportion of income spent on essentials correspondingly high. The proportion of household income spent on housing, utility bills and food decreased until 2003 but from 2005 to 2011, for the first time in post-war Britain, the overall combined proportion of household incomes spent on these has increased each year (Field [2014]).

Here, for illustrative purposes, we define food poverty as expenditure on food needing to exceed 20% of a household's disposable income. This is analogous to fuel poverty which is defined as a household needing to spend more than 10% of disposable income on fuel. Using data from the UK Office for National Statistics (ONS) the effect of a 50% and 100% rise in the cost of sugar, corresponding to high and very high sugar prices, is illustrated (see Table 3), assuming that prices of all other foods remain constant.

First note that the group in the lowest disposable income decile is always classed as being in both fuel poverty and food poverty, even when supported by state financial aid in the form of housing benefit. Similarly, without housing benefit the second decile group is in both food and fuel poverty. So this group is vulnerable to changes in state support for those on low incomes. Second note the effect of price rises in a single foodstuff (sugar) on the most poor. Those with incomes close to the lower boundary the second decile are close to food poverty even with housing benefit when the UK sugar price is very high and those with incomes near the lower boundary in the third decile (or upper boundary in the second decile) are similarly close to food poverty without housing benefit. It is possible that, even without crises like these, those in the second decile will feel the pressure in the longer-term, should incomes fail to keep pace with predicted price rises. Some have defined food poverty as 10% or more of disposable income (CEBR [2013]), under which definition these price increases would register as a very dramatic effect, affecting all but the highest two deciles. Foods which contribute a higher proportion to the cost of living than sugar and its derivatives would have a bigger effect (i.e. dairy (13/106), Vegetables (14), Bread (16) and meat (21)). Furthermore, it is likely that scenarios such as increases in oil price or natural disaster would also increase other food prices, exacerbating the effects shown here.

	Lowest ten per cent	Second decile group	Third decile group	Fourth decile group	Fifth decile group	Sixth decile group	Seventh decile group	Eighth decile group	Ninth decile group	Highest ten per cent	All house-holds
Lower boundary of group (£ per week)		168.00	244.00	315.00	396.00	477.00	578.00	689.00	833.00	1104.00	
Disposable income + Housing Benefit	122.70	211.70	289.60	359.10	437.80	525.90	632.10	755.70	950.70	1710.60	599.70
Average weekly household expenditure (£)											
Food & non-alcoholic drinks	29.00	36.70	42.20	47.80	54.20	60.50	62.30	72.70	71.90	90.60	56.80
Housing(net)1, fuel & power	47.40	49.90	56.20	67.60	67.80	72.90	70.10	78.00	73.90	95.70	68.00
Fuel and power	15.10	18.00	18.10	22.00	22.40	23.20	24.40	26.70	28.10	33.70	23.20
Fuel & Power % of Disposable income + Housing Benefit	12.30	8.50	6.30	6.10	5.10	4.40	3.90	3.50	3.00	2.00	3.90
Fuel & Power % of lower boundary	-	10.70	7.40	7.00	5.70	4.90	4.20	3.90	3.40	3.10	-
Food % of Disposable income + Housing Benefit	23.60	17.30	14.60	13.30	12.40	11.50	9.90	9.60	7.60	5.30	9.50
Food % of lower boundary	-	21.80	17.30	15.20	13.70	12.70	10.80	10.60	8.60	8.20	-
Sugar increase by 1.5											
Food % of Disposable income + Housing Benefit	24.90	18.20	15.30	14.00	13.00	12.10	10.40	10.10	8.00	5.60	10.00
Food % of lower boundary	-	23.00	18.20	16.00	14.40	13.30	11.30	11.10	9.10	8.60	-
Sugar increase by 2											
Food % of Disposable income + Housing Benefit	26.10	19.10	16.10	14.70	13.70	12.70	10.90	10.60	8.30	5.80	10.50
Food % of lower boundary	-	24.10	19.10	16.80	15.10	14.00	11.90	11.60	9.50	9.10	-

Table 3: **Food poverty changes as a result of changes in the UK sugar price** From ONS Tables: Household expenditure by disposable income decile group, 2012 and Household income and expenditure by income decile group 2012

4 Discussion

We have presented the first in a suite of models for UK food supply which will be suitably networked together to form a probabilistic model capable of evaluating the effect on the UK food system of policy interventions and other pressures and influences to the system. We have demonstrated the efficacy of Dynamic Bayesian Networks for decision support for food security. The sugar market is important area of research since 'Sugar, Jam, Syrups, Chocolate and Confectionery' makes up 10% of the cost of food in the UK CPI.

A decision support system for the UK food security covering the entire UK food system would be supported by DBNs for each broad food category, suitably networked together (Massa and Lauritzen [2010]; see Figure 3) and work is in hand to produce these. For each food category, there is a distinct panel of domain experts to provide judgements to inform the relevant DBN. It is necessary to ensure that such a composite system is itself coherent (Leonelli and Smith [2014]), or if this is not possible, to be able to measure the extent of the violation of coherence and the effect of this on the certainty of the outputs. Further theoretical work is under way to provide a robust basis for statements about coherence of networked Bayesian systems.

In the proof-of-concept work presented here, the prior conditional probabilities have been treated as point estimates, but further sophistication can be introduced by entering these as suitable probability distributions, and therefore propagating the uncertainty in the expert judgements and other data into the model outputs. In some cases, uncertainty requires summaries to be identified which can be used for efficient message-passing algorithms for optimisation. Food security analogues are required for work done in other application domains (Leonelli and Smith [2013b]). Uncertainty-handling is critical in decision support systems used for emergency response management in dynamic and uncertain environments, and this has been studied with respect to the nuclear emergency management (Leonelli and Smith [2013a]). That research forms the basis of further work for the food security emergency management. Food emergencies could arise through natural disaster which can both restrict people's access to food outlets and destroy crops or agricultural land (e.g. the UK floods of 2014 left some communities cut off and reliant on food deliveries for weeks and also severely impacted the UK farming industry, prompting the UK government to announce a £10 million Farming Recovery Fund). Another food emergency could be food adulteration (including food crime such as the UK horse-meat scandal of 2013), which could reduce the supply of a particular food type: whilst the relatively wealthy could afford the demand-driven increased costs of the substitutes, the impact on the poor, vulnerable or disadvantaged would be particularly acute.

In this example DBN, the decision support had been the output of the posterior probabilities for each element of the sugar system. Multi-attribute utility theory is well-developed and can be used to define and optimise a strategy or to test competing policies using DBNs (Smith [2010]). In the case of the UK food system, attributes might include the survival and good health of the population,

viability of business, minimisation of waste and energy consumption, sustainable environmental impact and issues of societal justice (e.g access, affordability and availability of nutritious food for all).
Food security is closely connected to energy security and to water security; these are frequently referred to as the water, energy and food security nexus to acknowledge that the three sectors are inextricably linked and that actions in one area more often than not have impacts in one or both of the others. A global nexus approach would integrate management and governance across sectors and scales.

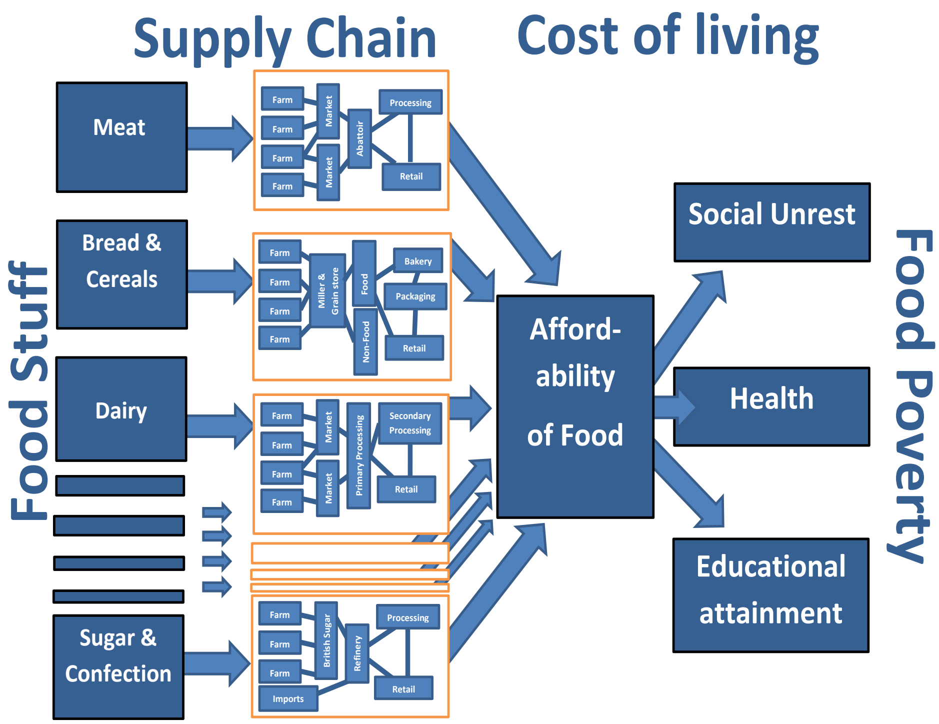

Figure 7: Schematic of the UK food supply system: Foods are categorised into types using the CPI and each food type has a distinct supply chain model, equivalent to the sugar model above. When networked together, a decision support system of this type will be used to predict the effects of retail price of food on attributes of interest, here social unrest, health and educational attainment. A full decision support model would include consumer access and awareness, international relations, economic factors and other relevant elements

In future work, we will investigate other consequences of food poverty including those identified by local government experts, namely social unrest, educational attainment and excess mortality.

Following outbreaks of violence attributed to severe food price rises (Lagi et al. [2011]; Kneafsey et al. [2013]), it has been suggested that it is for government to design regulation which allows both prosperity and stability. To date, there have been no food riots in rich countries like the UK, but it is a matter of concern to governments that such disturbances be avoided. Whilst at present there is no UK data available, it remains of interest to ascertain the levels of food poverty likely to precipitate such events, perhaps using experts' judgements.

It is widely believed that good nutrition is important to improved educational attainment, by promoting concentration and co-operative behaviour of school pupils. In a systematic review commissioned by the Food Standards Agency, there was found to be an association between breakfast provision and pupils' small cognitive and behavioural improvements (Ells et al. [2006]). However, the review concluded that there is insufficient evidence to identify an effect of nutrition on learning, education or performance since many studies failed to account for confounders or were very short-term. In estimating the efficacy of food security policy, it is important to be able to estimate its effects on educational outcomes, as supplied by expert opinion and research evidence.

It is likely that food poverty is a contributor to excess mortality (although there is currently no data on this) in the same way that fuel poverty is often blamed for excess mortality in winter. Rates of fuel poverty excess winter mortality vary between countries and socioeconomic indicators of wellbeing (poverty, income inequality, deprivation, and fuel poverty) have been associated with cross-country levels of excess winter mortality (Healey2003). Decision-makers need to ascertain the effect of candidate policies on food poverty excess mortality, seasonal or otherwise.

The ability to compare candidate policies with respect to their influence on financial and social factors as well as on the supply of food is important.

5 Conclusions

We have demonstrated that Dynamic Bayesian Networks can be used to produce decision support models which produce outputs in line with domain experts and the literature on food security. We used this model to estimate changes in the UK sugar supply and UK sugar price under a number of scenarios. We also have shown how UK food poverty would increase as a result of a high UK price for sugar. Having demonstrated the concept, we have embarked on the technical, mathematical and computational development necessary to extend the technique to the wider UK food security system.

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6 Appendix

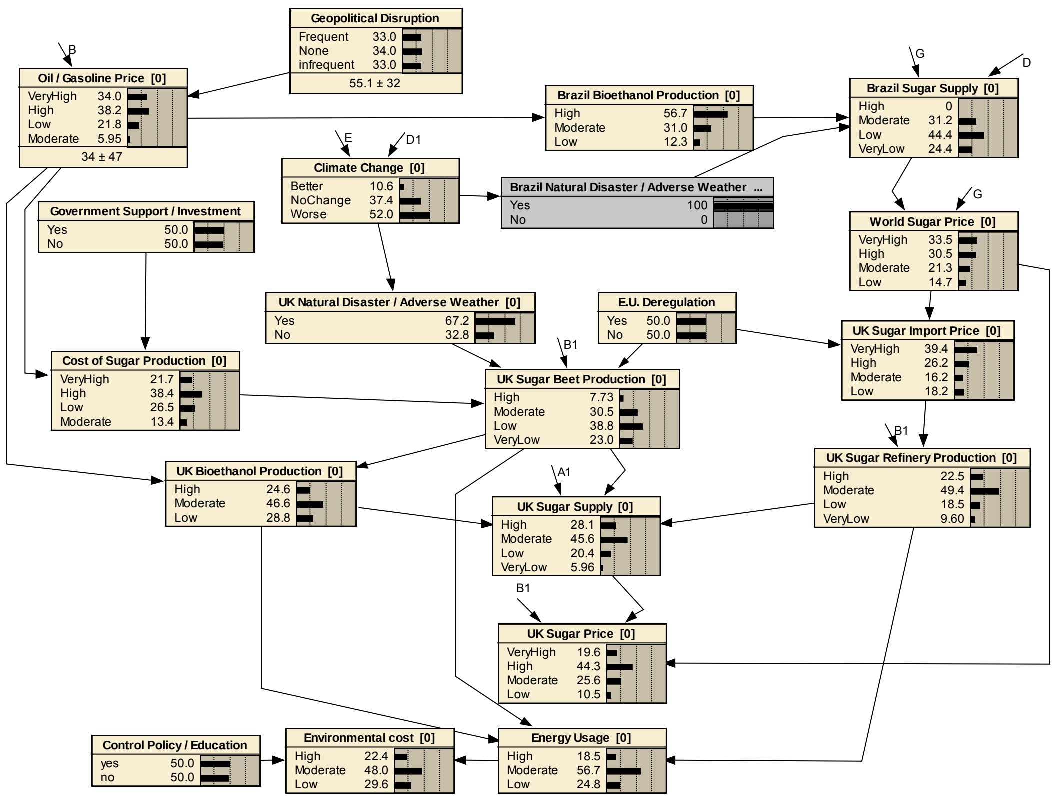

Figure 8: Dynamic Bayesian Network for the UK sugar market under the influence of a natural disaster or extreme weather event: The immediate response. The bars and numbers are the probability distributions.

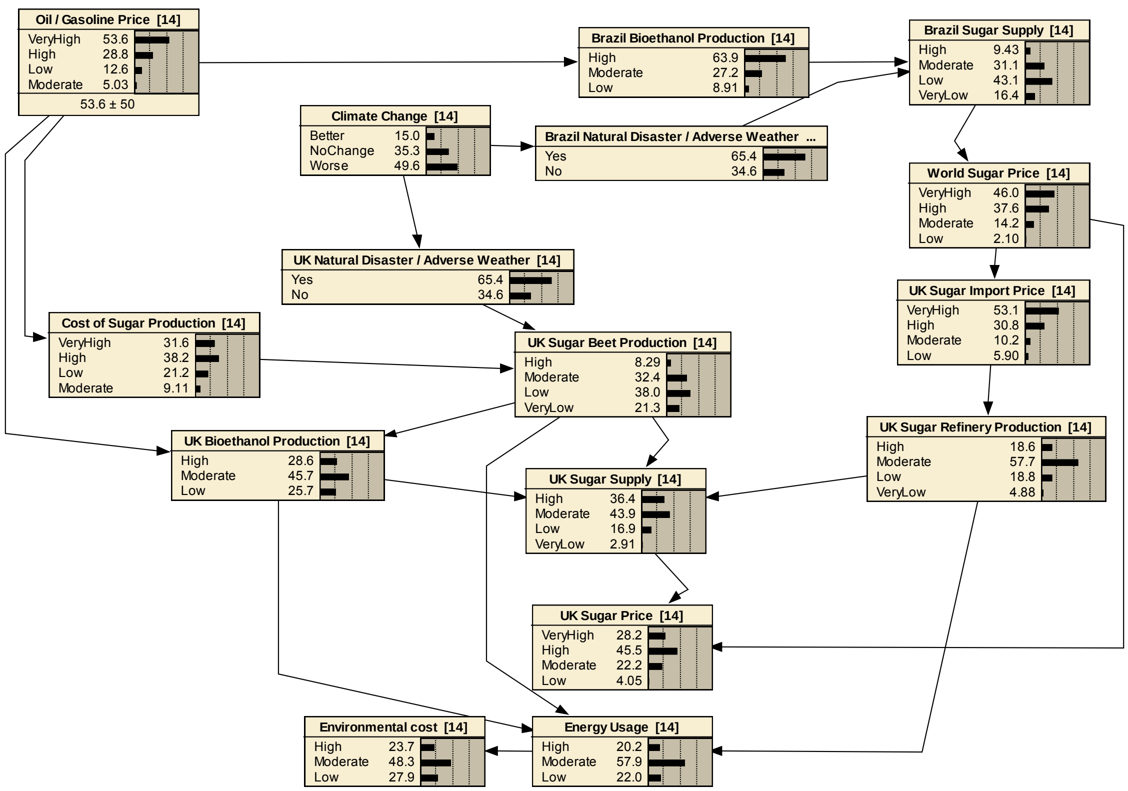

Figure 9: Dynamic Bayesian Network for the UK sugar market under the influence of a natural disaster or extreme weather event: The 14-year response. The bars and numbers are the probability distributions.

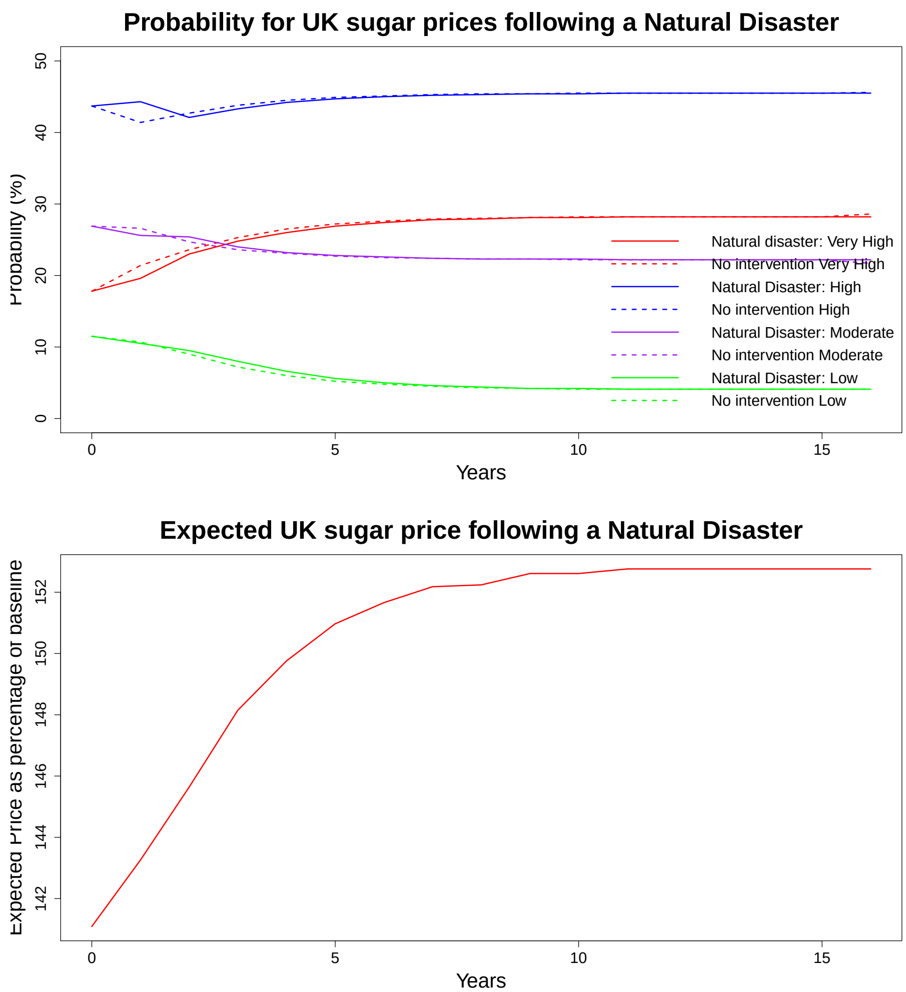

Figure 10: Upper: Probability for UK sugar price levels following a natural disaster or extreme weather event. Dotted lines show the no-shock scenario. Lower: Expected UK sugar price as percentage of baseline following an natural disaster or extreme weather event. High and Very High sugar prices correspond to a 50% and 100% rise in the cost of sugar, moderate as a 10% increase and Low as a reduction to 0.9 of the baseline price. Expected price is calculated $E = 200 \times p(veryhigh) + 150 \times p(high) + 110 \times p(moderate) + 90 \times p(low)$ at each time point. Intervals can be calculated if required.

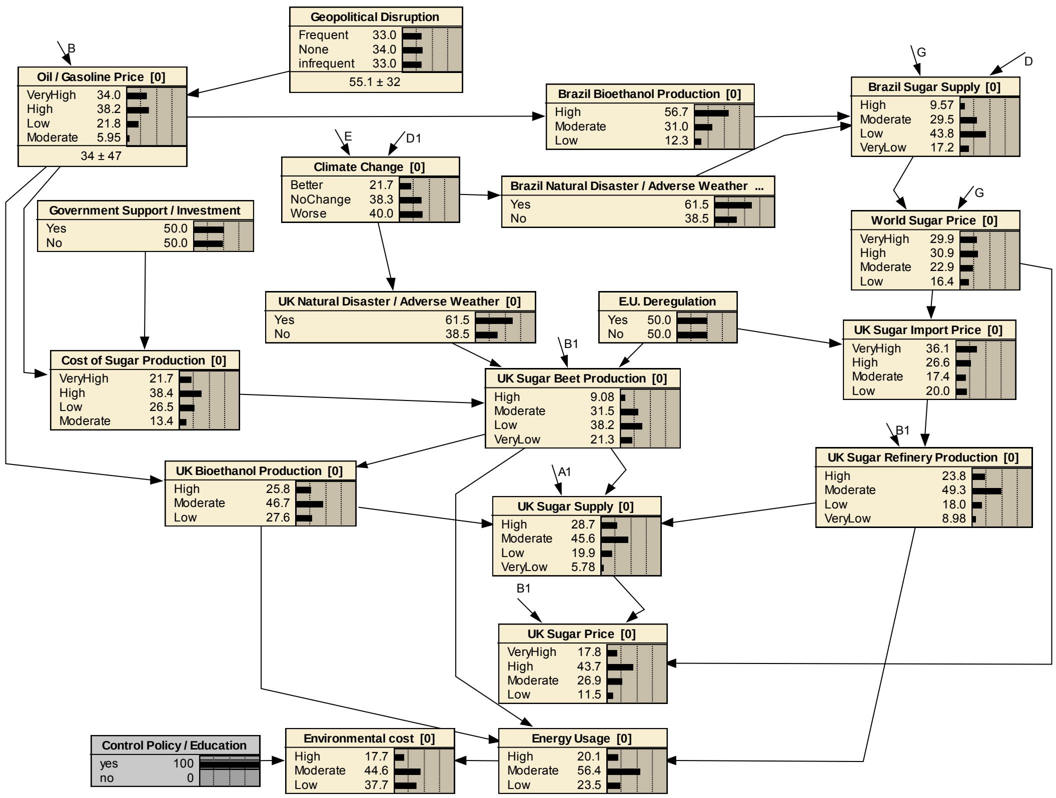

Figure 11: Dynamic Bayesian Network for the UK sugar market under the influence of an educational intervention to promote environmental sustainability: The immediate response. The bars and numbers are the probability distributions.

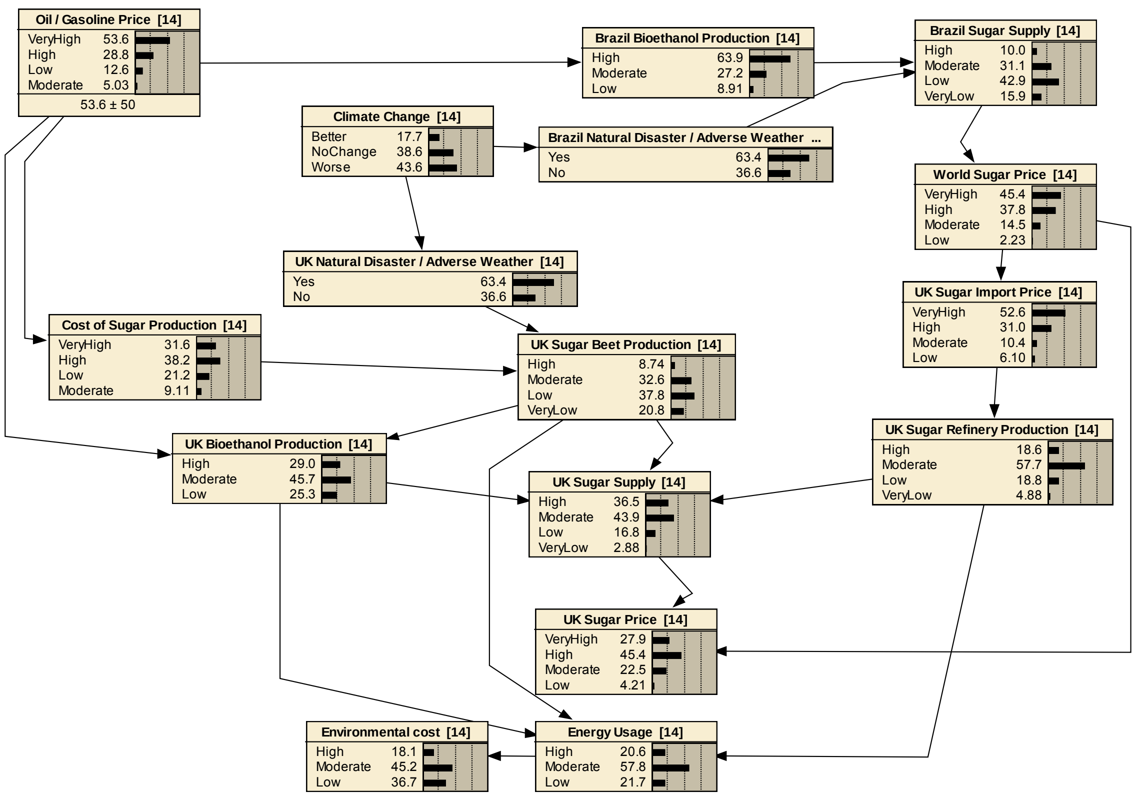

Figure 12: Dynamic Bayesian Network for the UK sugar market under the influence of an educational intervention to promote environmental sustainability: The 14-year response. The bars and numbers are the probability distributions.

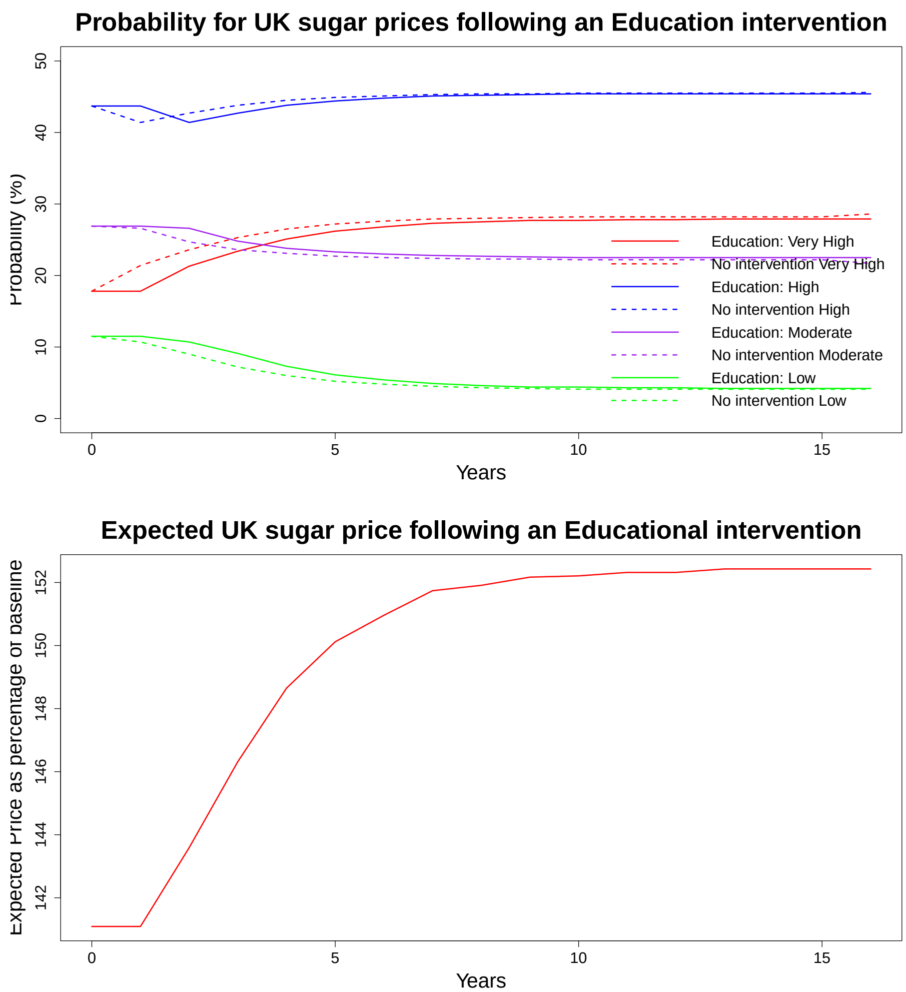

Figure 13: Upper: Probability for UK sugar price levels following an Education intervention to reduce environmental impacts. Dotted lines show the no-intervention scenario. Lower: Expected UK sugar price as percentage of baseline following an educational intervention. High and Very High sugar prices correspond to a 50% and 100% rise in the cost of sugar, moderate as a 10% increase and Low as a reduction to 0.9 of the baseline price. Expected price is calculated $E = 200 \times p(veryhigh) + 150 \times p(high) + 110 \times p(moderate) + 90 \times p(low)$ at each time point. Intervals can be calculated if required.

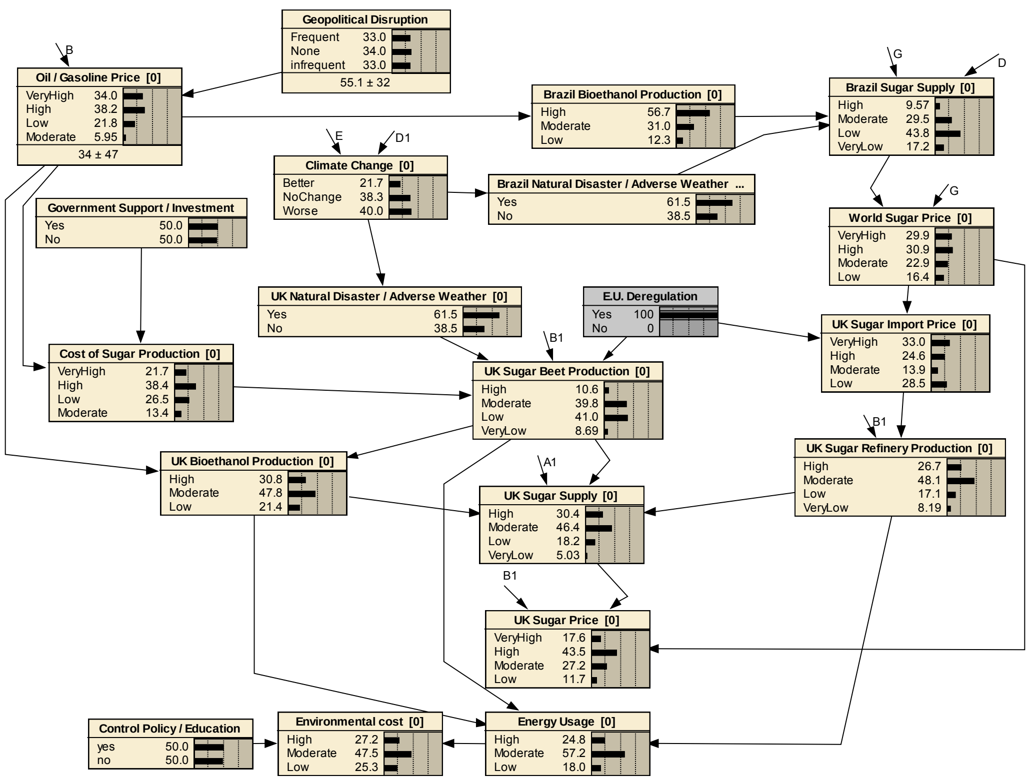

Figure 14: Dynamic Bayesian Network for the UK sugar market under the influence of EU deregulation: The immediate response. The bars and numbers are the probability distributions. Note deregulation is planned for 2017; at present the only information available about the changes to the market which will ensue is expert opinion.

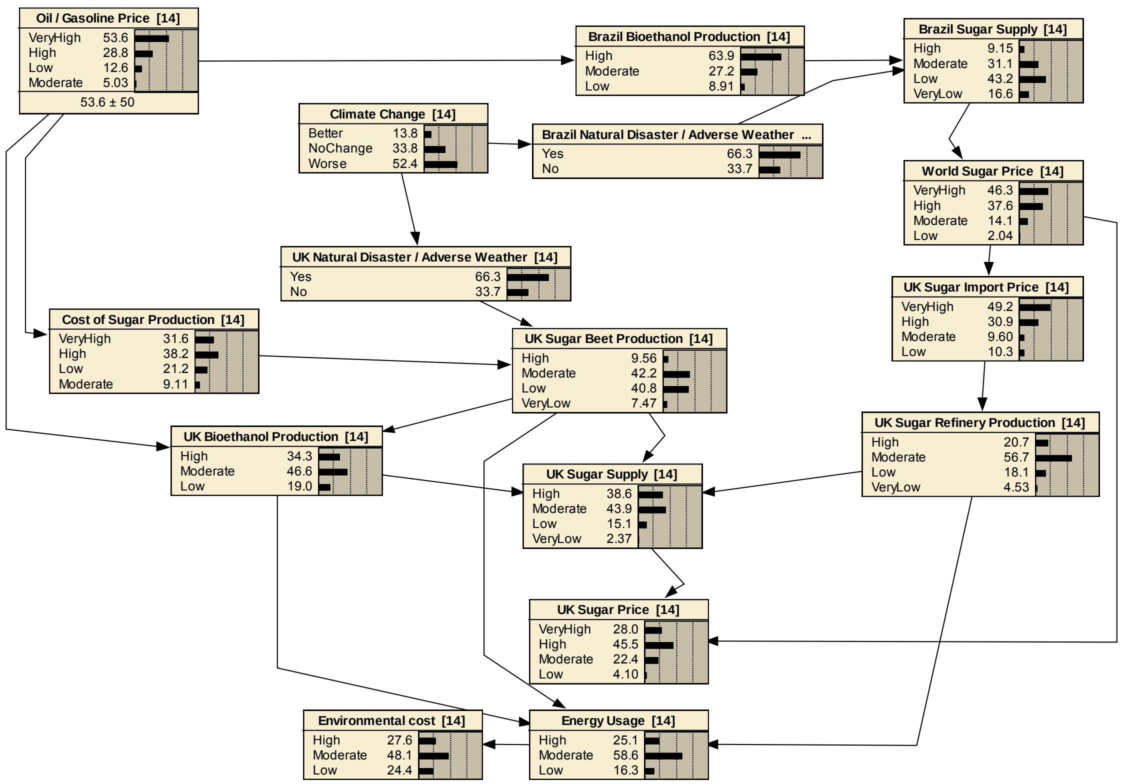

Figure 15: Dynamic Bayesian Network for the UK sugar market under the influence of EU deregulation: The 14-year response. The bars and numbers are the probability distributions. Note deregulation is planned for 2017; at present the only information available about the changes to the market which will ensue is expert opinion.

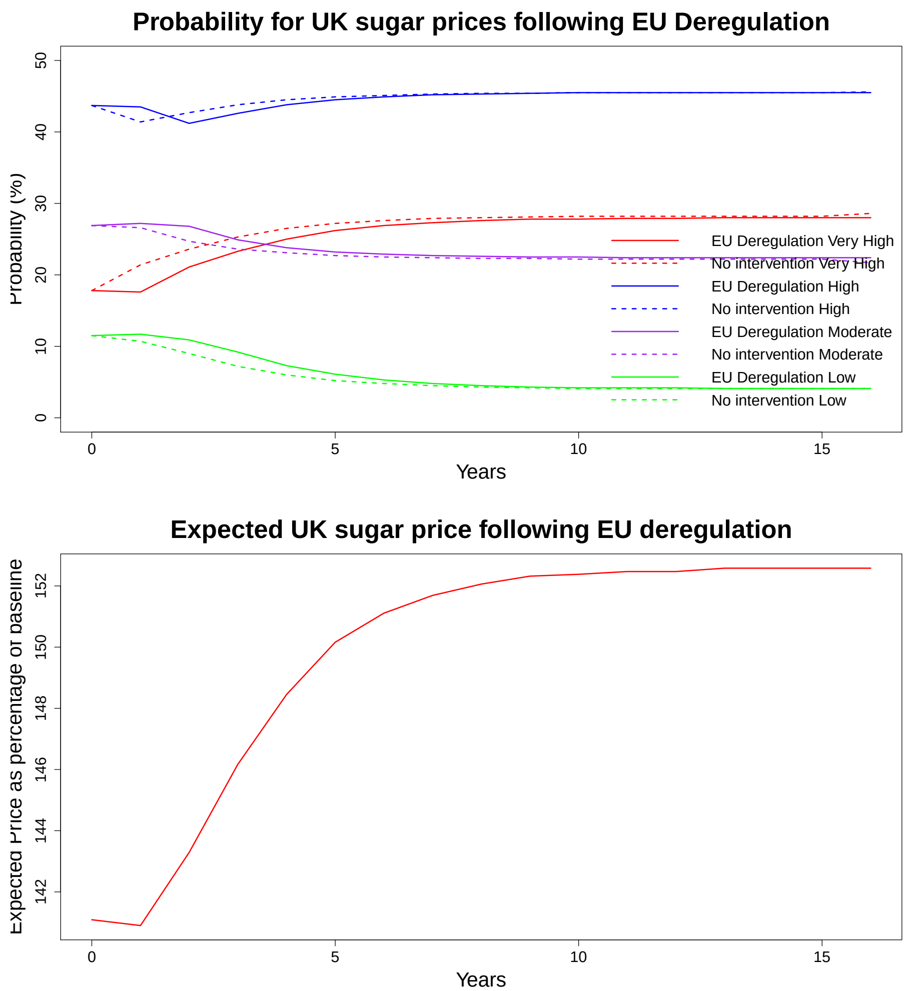

Figure 16: Upper: Probability for UK sugar price levels following EU deregulation. Dotted lines show the no-intervention scenario. Lower: Expected UK sugar price as percentage of baseline following EU deregulation. High and Very High sugar prices correspond to a 50% and 100% rise in the cost of sugar, moderate as a 10% increase and Low as a reduction to 0.9 of the baseline price. Expected price is calculated $E = 200 \times p(veryhigh) + 150 \times p(high) + 110 \times p(moderate) + 90 \times p(low)$ at each time point. Intervals can be calculated if required.