Probabilistic decision tools for determining impacts of agricultural development policy on household nutrition

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Key Points:

- Probabilistic decision modeling can be used to integrate expert knowledge, considering system complexity and uncertainty
- Decision modeling with Bayesian Networks can be applied to quantify the pathways from agricultural policy to impact on household nutrition
- Decision analysis of Uganda's agricultural development strategy illustrates the use of the approach to identify nutrition outcomes

Abstract

Governments around the world have agreed to end hunger and food insecurity and to improve global nutrition, largely through changes to agriculture and food systems. However, they are faced with a lot of uncertainty when making policy decisions, since any agricultural changes will influence social and biophysical systems, which could yield either positive or negative nutrition outcomes. We outline a holistic probability modeling approach with Bayesian Network (BN) models for nutritional impacts resulting from agricultural development policy. The approach includes the elicitation of expert knowledge for impact model development, including sensitivity analysis and value of information calculations. It aims at a generalizable methodology that can

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be applied in a wide range of contexts. To showcase this approach, we develop an impact model of Vision 2040, Uganda's development strategy, which, among other objectives, seeks to transform the country's agricultural landscape from traditional systems to large-scale commercial agriculture. Model results suggest that Vision 2040 is likely to have negative outcomes for the rural livelihoods it intends to support; it may have no appreciable influence on household hunger but, by influencing preferences for and access to quality nutritional foods, may increase the prevalence of micronutrient deficiency. The results highlight the tradeoffs that must be negotiated when making decisions regarding agriculture for nutrition, and the capacity of BNs to make these tradeoffs explicit. The work illustrates the value of BNs for supporting evidence-based agricultural development decisions.

Plain language summary

Governments around the world have agreed to end hunger and food insecurity and improve global nutrition, largely through changes to agriculture and food systems. However, they are faced with a lot of uncertainty when making policy decisions, which could yield either positive or negative nutrition outcomes. We outline a holistic probability modeling approach for determining the nutritional impacts resulting from agricultural development policy. The approach includes the elicitation of expert knowledge for model development and analysis. It aims at a generalizable methodology that can be applied in a wide range of contexts. To showcase this approach, we develop an impact model of Uganda's development strategy, which, among other objectives, seeks to transform the country's agricultural landscape from traditional systems to large-scale commercial agriculture. Model results suggest that the strategy is likely to have negative outcomes for the rural livelihoods it intends to support; it may have no appreciable influence on household hunger but, by influencing preferences for and access to quality nutritional foods, may increase the prevalence of micronutrient deficiency. The results highlight the tradeoffs that must be negotiated when making decisions regarding agriculture for nutrition, Decision analysis tools can make these tradeoffs explicit and support evidence-based agricultural development decisions.

1 Introduction

Governments around the world have agreed to the ambitious goals of ending hunger and food insecurity and to improving nutrition globally by 2030 (SDG 2; United Nations, 2015). Improved nutrition can be achieved through many pathways, e.g. through higher nutrient contents in crops (DellaPenna, 1999; Nestel, Bouis, Meenakshi, & Pfeiffer, 2006), greater nutritional diversity (Hoddinott & Yohannes, 2002) or improved awareness about childhood nutrition (Ruel, Alderman, & Maternal, Child Nutrition Study Group, 2013). For any given context, however, it is difficult to decide *a priori*, which pathway will be most effective. Some pathways may not produce positive outcomes at all, for instance certain foods may never reach vulnerable groups (e.g. rural poor). The root causes of hunger and malnutrition are complex and multidimensional, making it very difficult to develop meaningful indicators (FAO & WHO, 2014; Webb et al., 2006). Consequently, agricultural research and development aimed at improving nutrition is often unable to articulate clearly how, and to what degree, nutrition objectives will be achieved (Leroy, Ruel, & Verhofstadt, 2009; Olney, Talukder, Iannotti, Ruel, & Quinn, 2009).

Given the complexity of agriculture and food systems, it is rarely feasible to close all knowledge gaps or to fully capture complex system dynamics, particularly regarding impact pathways for interventions aiming to improve nutrition (Tijhuis et al., 2012) or other agricultural outcomes (Luedeling & Shepherd, 2016). The research that should be supporting these decisions often fails to consider the range of ecological, socioeconomic, cultural and political factors that influence agricultural systems (Black et al., 2013). Consequently, research results often fail to supply decision-makers with relevant information and support (Hardaker & Lien, 2010; Luedeling & Shepherd, 2016).

Rational prioritization among actions promoting agriculture for nutrition requires an evaluation approach that can accommodate complex relationships and translate agricultural activities into probable nutritional outcomes. There is thus a need for new approaches for analyzing the impacts of agricultural interventions on food and nutrition systems. Successful research approaches to support the improvement of nutrition interventions must embrace the complexity of agriculture and nutrition, e.g. by recognizing political and social aspects (Black et al., 2013) and co-benefits between agriculture and health interventions (Picchioni et al., 2017).

Decision analysis offers such an approach. It can be used to meet the common challenges of system complexity and data scarcity, inherent in development decisions (Hardaker, Fleming, & Lien, 2009), particularly regarding agriculture (Hardaker & Lien, 2010; Rosenstock et al., 2017). The modeling methods applied in this field offer a promising way forward, because they have been designed to support decision-making with imperfect information and limited research budgets (Hardaker & Lien, 2010; Luedeling & Shepherd, 2016). Among these approaches, Bayesian Network (BN) models are emerging as a leading solution (Neil, Littlewood, & Fenton, 1996). They offer an intuitive and robust strategy for characterizing causal relationships in complex systems and for evaluating the impacts of system interventions, even in the face of uncertainty about model structure or parameters (Fenton & Neil, 2012). They can supply decision makers with actionable information on probable impact pathways. By capturing the interactions of a complex range of factors, they can produce probabilistic projections of system outcomes for particular interventions. BN modeling approaches are used in many applications, e.g. engineering and computer science (cf. Korb & Nicholson, 2004), ecology (cf. Iqbal & MacLean, 2010; Kuhnert, Martin, & Griffiths, 2010) and agriculture (cf. Yet et al., 2016). BN models are ideally suited to model complex systems (Cowell, Dawid, Lauritzen, & Spiegelhalter, 2006), where exact data are limited but extensive expert knowledge is available, as is often the case in agriculture (Yet et al., 2016).

Furthermore, BN models can be generated and parameterized through the use of expert knowledge, integrated into model calculations (Yet et al., 2016; Henderson & Burn, 2004). Many examples have illustrated the use of structured elicitation techniques to gather expert knowledge for generating BN model structures and eliciting model parameters (cf. Martin et al., 2012; Bolger & Rowe, 2015; Kuhnert et al., 2010; Clemen & Winkler, 1999). Expert-based model construction can be facilitated through holistic expert knowledge elicitation (EKE) techniques that include the holders of scientific and political as well as traditional knowledge (cf. Bolger & Wright, 2017). *Papakosta et al.* (2017) created a BN, through the integration of both EKE and literature sources, to predict expected economic losses (housing losses) from wildfires in Cyprus. *Iqbal and MacLean* (2010) presented BN models for predicting defoliation risks in forests, which were produced during repeated expert meetings and subsequently subjected to peer review by other experts. The EKE can be based on a relatively small number of elicited values from a single (Kemp-Benedict, 2008) or multiple experts (Kuhnert et al., 2010). *Oedekoven et al.*

(2017), for example, used expert elicitation (from 10 experts) to create a BN to predict the abundance and movement of endangered right whales through the mid-Atlantic in order to avoid threats of collisions with ships and entanglement in fishing gear.

Agricultural systems are an excellent candidate for applying BN methodologies (cf. Rosenstock et al., 2017). Agriculture is often highly variable and depends on complex interactions between environmental factors (e.g. climate), public policies (e.g. subsidies), international contexts (e.g. crop prices), cultural factors (e.g. religion and taboo) and social factors (e.g. gender, access to education) (cf. Waage, Hawkes, & Turner, 2012). The relationship between agricultural production and nutrition is particularly complex (Khoury et al., 2014; Graham et al., 2007), and the many mediating factors, such as income, policy, sanitation and markets, make it difficult to quantify or predict outcomes of interventions. Understanding these relationships requires approaches that can incorporate uncertainty and complexity (cf. Tijhuis et al., 2012).

Despite their widespread applications, BN models have not been exploited in the agriculture and nutrition domain. Yet, BN models are highly suited for this context, since they are able to combine information from various sources, e.g. hard data and expert knowledge, into comprehensive causal models (Nielsen & Jensen, 2009). The use of BN models in this domain could result in more accurate impact forecasts than using data or expert knowledge alone.

Overall, the work presented here seeks to outline the use of impact modeling to identify plausible nutrition outcomes of agricultural decisions. To that end, this paper outlines modeling techniques that can be used to generate a BN for the impact of agricultural development decisions on nutrition by (i) showcasing a set of expert knowledge elicitation (EKE) techniques for developing BNs and (ii) applying decision modeling using a BN to identify plausible household nutrition outcomes of agricultural policies. While we aim at a generalizable methodology that can be applied in a wide range of contexts, we have used a case study to demonstrate the approach. The specific case studied is the agricultural and nutrition strategy proposed in the long-term development strategy of the Government of Uganda 'Vision 2040' (NPA, 2007).

The laws and regulations that follow Vision 2040 will have the broad aim to address poverty, food insecurity and malnutrition in the country (NPA, 2007; NPA, 2011). However, information is lacking to provide clarity about how this transformation will influence household nutrition. To meet this need, we developed a probabilistic causal impact pathway model for assessing nutrition outcomes at the household level that may result from agricultural interventions proposed by Vision 2040. We used the approach to generate a BN model, aiming to describe the changes in probabilities of hunger (a.k.a. protein energy deficiency) and micronutrient deficiency (MND) under Vision 2040. We present a step-by-step, reproducible methodology to apply the BN approach to model impact pathways for changes based on agricultural policy and generate probabilistic simulations of system effects on household nutrition. The model identifies consequences for household nutrition of the decision to implement Vision 2040 vs. maintaining smallholder homegarden systems in Uganda.

2 Materials and Methods

2.1 Bayesian Networks

We use Bayesian Network (BN) models as a decision analysis tool for probabilistic impact modeling of agricultural impacts on nutrition. BN models are directed acyclic graphs consisting of nodes, arcs and probability tables underlying the nodal relationships (Nielsen & Jensen, 2009). A BN is a network of probabilistic relationships between nodes, referred to as child and parent nodes according to their arrangement in the model (cf. Fig. 3). Conditional Probability Tables (CPTs) are the core elements of BN models (Fenton & Neil, 2012). They are used to define the probabilities for each state of each child node conditional on its parents (Papakosta et al., 2017). Ranked-scale nodes can be used to represent most relationships, with states (e.g. very low, low, medium, high, very high; cf. Fig. 3) representing qualitative variables as abstractions of the underlying continuous quantities.

BN models are distinct from other forms of statistical modeling, in that they focus on determining an optimal graphical model to describe probabilistic inter-relationships among processes rather than on specific measurement data. BN models are a multivariate technique, which can accommodate one or many dependent variables. The approach can be used to investigate risk factors and causal pathways, which is important in health-related systems (cf. Lewis & McCormick, 2012). BN models attempt not only to identify associated variables but also to separate them into those that have a direct and those that have an indirect influence on the outcome variables (Lewis, 2012). This gives BN models the potential to reveal key features of complex systems (Constantinou, Yet, Fenton, Neil, & Marsh, 2016; Lewis & McCormick, 2012) and may make them preferable to standard approaches for inferring statistical dependencies from complex observational data (Lewis & McCormick, 2012; Korb & Nicholson, 2004). Another major advantage of BN models is that they facilitate integration of information from various sources into a single model (Papakosta et al., 2017). For example, they can be used to build predictive models of impact pathways that incorporate both hard data and expert judgment (Yet et al., 2016).

2.2 BN model structure development

Defining the context and finding the appropriate parameters to explore with the model is the first step in developing a BN. To achieve this, we use decision modeling approaches (Luedeling et al., 2015), inspired by the principles of Applied Information Economics (cf. Hubbard, 2014). This is then complemented with innovative group work techniques for eliciting expert knowledge to construct a logical framework to describe system interactions and outcomes (i.e. an impact pathway). Expert knowledge is thereby used to generate BN model structures (Bolger & Rowe, 2015; Papakosta et al., 2017; Kuhnert et al., 2010) and integrated into model calculations (cf. Yet et al., 2016).

Experts can be consulted in workshops to build BN models of expected agricultural policy impacts on nutrition. During the workshops, graphical models can be developed by individual experts and then peer reviewed by other experts (cf. Iqbal & MacLean, 2010). Workshop participants should represent a mix of stakeholders such as academic institutions (e.g. nutritionists and agronomists), government institutions, local villages and development organizations. The overall context for the BN model can be defined specifically in plenary discussions. The model should have the broad aim to describe the effects of agricultural decisions on specific nutrition outputs such as hunger (a.k.a. global energy and macronutrient deficiency) and micronutrient deficiency (MND).

Once the experts have been gathered and have clarified the development decision to be modeled, there are several steps that can be taken in order to ensure accuracy in model structures and variable estimates. The first step of the modeling procedure is calibration training, inspired by

Applied Information Economics (AIE) from Hubbard Decision Research (Hubbard 2014), whereby participants learn to minimize potential biases in probability estimation. The calibration training consists of several exercises aiming to reveal to the participants their personal biases (overconfidence or underconfidence) by assessing their performance on a series of iterative tests in the form of trivia questions. Experts are trained to assess their subjective uncertainty and express it as a confidence interval with a predefined chance (e.g. 90%) of containing the right value. Perfectly calibrated experts should get around 90% of answers correct and any deviation (outside a narrow band of stochastic variation) from this optimal figure indicates estimation bias. The training includes several tools to help participants to improve their ability to estimate their own state of uncertainty and thereby reduce errors of judgment (Hubbard 2014).

Another important set of tools for model development aims to help overcome the problems of variation among experts (cf. Bolger & Rowe, 2015; Bolger & Wright, 2017). It begins with breaking the decision down into several important questions in plenary discussions. Random interchanging working groups of experts are led through three stages of collaborative thinking (think on own, share with immediate neighbor, share with working group) designed to help interact, brainstorm and aim for consensus in EKE (Fig. 1) (cf. Clemen & Winkler, 1999). Each group can then explore details of the expected impacts and disaggregate the impact pathway into intermediate steps and influencing factors that they consider important to the decision (i.e. draw a model of nodes and edges; cf. Fig. 3).

These EKE techniques can be repeated until all experts have worked on each question (Fig. 1) and are satisfied that all specific relationships have been identified. Resulting models can then be brought before the whole group of experts for plenary discussion and re-drawn, aiming for consensus about the relationships in each model. The end result should be one model per question with the contributions of all experts. Corrections and further feedback can be gathered for model verification as a final stage of model development.

2.3 BN model quantification

Despite the simplified node structures, CPTs specifying the relationships between parent and child nodes sometimes contain large numbers of conditional probabilities, especially where several parents with multiple possible states are involved. Estimating large numbers of probabilities can overwhelm experts, which may in turn lead to inconsistencies (Fenton, Neil, & Caballero, 2007). This can easily lead to unreliable models (Cain, 2001; Marcot, Steventon, Sutherland, & McCann, 2006). To mitigate this concern, we derive expert knowledge from prior distributions for nodes, the relative influence of the parents, and the effects of each state of the parent nodes, as well as the strength of the response (cf. Fig. 2).

Past studies have shown that attempting to understand and express relationships through the use of weighted averages and ranked nodes simplifies the complex task of constructing and editing BNs (Fenton et al., 2007). Therefore, experts can be asked to provide a typical distribution of each variable (prior probability) together with the strength of the response and a weighting factor for each state of the child node and each state of the parent nodes (cf. Fig. 2). These can then be used to calculate the CPTs (see Luedeling & Whitney, 2017), by using the likelihood method to elicit influence weights rather than whole tables of probabilities from experts (Kemp-Benedict, Bharwani, de la Rosa, Krittasudthacheewa, & Matin, 2009).

For each node and edge, expert groups were asked to fill input sheets (cf. Fig. 2) or a CPT directly for smaller tables. These were then peer reviewed, as in the model structure procedures. Procedures for producing CPTs from these inputs (see Supplementary Information) were implemented in the decisionSupport package (Luedeling & Goehring, 2017) in the R programming language (R Core Team 2017). This approach helped us to gather expert knowledge for all model parameters. Once completed and verified with the literature and other sources, the BN was shared with experts again for verifying its logical consistency and receiving final feedback.

1.1. Sensitivity and Value of Information analysis

Probabilistic sensitivity analysis and Value of Information (VoI) procedures can be used to determine whether additional information on certain input variables in the BN model could increase confidence about the emerging decision recommendation (cf. Constantinou et al., 2016). Results can be used for prioritizing knowledge gaps that should most urgently be narrowed in order to improve certainty about the decision (Constantinou et al., 2016; Whitney et al., 2017). More follow-up measurements and disaggregation of any identified variables can help inform the design and prioritization of future research and provide guidance about the best pathways for implementing the current decision.

Probabilistic sensitivity analysis can be performed on BN models to measure the influence of small changes in individual model input variables on the overall model outputs (Laskey, 1995). It is used to determine how estimates might change, if different values are assigned for inputs to the BN model (Oakley & O'Hagan, 2004). The expected value of perfect information (EVPI) is a VoI tool that can help decision makers to consider both the probability of decision change and the resulting difference in payoff (Felli & Hazen, 2003). EVPI is the difference between the expected value of a decision made with perfect information and the expected value of the decision with current imperfect information (Hubbard, 2014). EVPI is calculated for BN models to identify a selected subset of important model variables. To achieve this, utility nodes are used to assign monetary value to model outputs (cf. Constantinou et al., 2016; Yet et al., 2016).

The Expected Monetary Value (EMV) is a key part of the EVPI calculation. It is the weighted average of the payoffs for a decision alternative, where weights are the probabilities of the different states of nature (Table 1). EVPI is the maximum amount that one should be willing to pay for additional information about the decision. EVPI is the expected value for the decision (payoff), if perfect information is available about the states of nature, minus the expected value for the decision, if perfect information is not available.

Table 1 shows the hypothetical calculation of EVPI in a BN for the variable *Diversity of household diets*. The main part of the table is populated with a 'utility value' for diverse diets under each of the 'states of nature', e.g. the upper right value of -4 represents the utility value of low household dietary diversity in the scenario where decision-makers decide not to implement Vision 2040. The likelihood of each of the states of *Diversity of household diets* is shown in the row labelled with *Probability*. EMV is calculated for each state of the Vision 2040 decision by adding the utility values after multiplying them by the probability for each state of *Diversity of household diets*. The maximum EMV is the highest of these two (27.7). Expected value with perfect information (EV with PI) is calculated for each column by selecting the highest value for each state of *Diversity of household diets* (29.7). EVPI is calculated using the resulting values $EVPI = EVwithPI - max(EMV)$.

3 Probabilistic decision modeling in practice

Here we outline the BN decision modeling approach using a case study of the long-term development agenda of the Uganda's Vision 2040 (NPA, 2007). The development outcome of interest was identified as the expected impact of the agricultural aspects of the Vision 2040 decision on the nutritional status of households in Uganda. A BN model was designed to determine the nutritional status of Ugandan households, comparing household-level nutrient supply per year through smallholder and homegarden production (current systems) with the industrial agricultural systems proposed in Vision 2040. The model had the specific aims to describe the effects of the Vision 2040 decision on both household hunger and MND.

3.1 Agriculture and nutrition in Uganda

Uganda has a population of just over 39 million people (World Bank, 2017), who experience relatively stable political conditions and economic growth, but the gross national income (GNI) is still very low by international standards (700 USD/capita/year), ranking 177th out of 195 countries (World Bank, 2017). Rates of unemployment, underemployment and inadequate employment are high (9.4, 8.9 and 18.5%, respectively, according to UBOS, 2016). Twenty percent of the population live below the national poverty line (World Bank, 2017), and few are able to meet minimum international standards for well-being (Levine, Muwonge, & Batana, 2012). Ugandans live with little infrastructure (World Bank, 2012) and high levels of disease (UBOS & ICF, 2017). Uganda's high population growth rate, coupled with a young population, is likely to exacerbate land scarcity, poverty (UBOS & ICF, 2017) and food insecurity (IFPRI, 2016) in the future. Currently, 89% of Ugandans live in rural areas (FAO, 2017), yet many are migrating from rural to urban areas for work (UBOS, 2016).

Agriculture is the main economic activity in Uganda (NPA, 2007), consisting mainly of small-scale producers engaged in producing a wide range of crops and other commodities (UBOS, 2014a). Seventy-two percent of Ugandans are engaged in agriculture and over 40% are small-scale subsistence farmers (UBOS, 2014b; UBOS, 2016). These small-scale farmers occupy 99% (99,018.6 km^2) of Uganda's agricultural land (UBOS, 2016) and are responsible for 75 to 80% of the total agricultural output (NPA, 2015).

Despite the intimate food production setting, food and nutrition insecurity are still pressing issues for development in Uganda, where rates of hunger and MND are high (occurring in around 30% and 50% of households respectively; FAO & IFAD, 2015) and dietary diversity is low (e.g. just 14% of children have a minimum acceptable diet; UBOS & ICF, 2017). The country has a food deficit (284 kcal/capita/day; FAO, 2017) and 15.2 million people experience malnutrition (FAO, 2017). Around 30% of the children who are less than five years of age are stunted (low height for age), 4% are wasted (low weight for height) (UBOS & ICF, 2017) and more than 10% are underweight (low weight for age) (FAO, 2017; UBOS & ICF, 2017).

Agricultural development is being aggressively targeted by Vision 2040, which seeks to shift agriculture from subsistence farming to commercial production (NPA, 2011; NPA, 2007; MAAIF, 2010), with specific goals to reduce agriculture's share of the GDP from 22.4% down to 10.4%, decrease the share of agricultural jobs within the labor force from 65.6% to 31%, and increase annual per capita income from agriculture from 390 to 6,790 USD (NPA, 2007). Vision 2040 seeks to move rural people away from agriculture (UBOS, 2014a; NPA, 2007) by distributing labor among other sectors, raise income from agriculture by five percent annually, and increase employment in the industry and service sectors by more than nine percent. The government intends to implement land reforms to urbanize rural populations (UN, 2002; NPA, 2011) and facilitate the acquisition of land for planned urbanization, infrastructure development, and agricultural commercialization (NPA, 2007). However, high population growth, low agricultural productivity and poor access to land create many challenges for nutrition-related policy implementation (FAPDA, 2015). Due to the lack of systems to track and share progress, development funds earmarked for nutrition are spent on activities that are not relevant to nutrition (cf. Adero et al., 2015).

3.2 Vision 2040 model development and calibration

Twenty-three experts were consulted in a week-long workshop in November 2016 to build a BN of the impact of Vision 2014 on nutrition. Selected experts represented three academic institutions, four government institutions, four local villages, two development organizations and one activist organization in Uganda. A BN model was designed to determine the effects on the nutritional status of Ugandan households resulting from the implementation of the Vision 2040 strategy by comparing household-level nutrient supply per year through smallholder and homegarden production (current systems) with the industrial agricultural systems proposed in Vision 2040.

Experts identified five guiding questions that were further explored to examine Vision 2040's impact on household nutrition: (i) *What hinders diverse diets?* (ii) *Where will displaced people live?* (iii) *How will diets change (Rural & Urban)?* (iv) *How will displaced farmers earn an income?* and (v) *How will crop diversity change?*. Graphical models were developed through discussions on these questions, during which nodes and edges of causal relationships were defined.

EKE on all specific relationships was then undertaken (Fig. 1) and repeated until all experts had worked on each of the five questions. Whenever possible we also confirmed expert opinion (updated priors) with available statistics, e.g. from demographic and health surveys (c.f. UBOS, 2016), economic studies (World Bank, 2017) and agricultural databases (FAO, 2017) (see Luedeling & Whitney, 2017). Resulting models were then brought before the whole group of experts for plenary discussion and re-drawn, aiming for consensus about the relationships in each model. The end result was one model per question with the contributions of all experts and analysts. Once it was completed, the BN model was shared with experts again for verifying its logical consistency. Corrections and further feedback were gathered for model verification as a final stage of model development.

The resulting BN model had 29 main variables, which were found to adequately describe the impact pathway from the decision to implement Vision 2040 to household nutrition (Fig. 3). The model was developed and analyzed using the AgenaRisk software (Fenton & Neil, 2012; Fenton & Neil, 2017). The decision to implement Vision 2040 (probability of implementation = 65%) was expected to have an important influence on implementation of policies related to nutritional awareness and promotion of exports. Through various model interactions, the decision was also expected to influence five economic variables (land tenure, location *[proxy for access to goods and services]*, exported production, occupation, and food access), seven social variables (displacement of farmers, nutritional education and sensitization, traditional knowledge, nutrition awareness, diversity of agricultural systems, food preferences, and nutritional quality), and seven variables related to both micronutrients (production, availability, demand, consumption and deficiency [MND]) and macronutrients (production, availability, demand, consumption and hunger) (Luedeling & Whitney, 2017). The relationships were converted into a BN model, which was parameterized with the estimates of experts for each node and edge (Fig. 3).

3.2.1 Graphical Bayesian Network model of Vision 2040 development decision

The BN indicates that implementation of Vision 2040 risks a slight increase in the probability of a household experiencing hunger, from 26%, under the baseline scenario, to 27.7%. For micronutrient deficiency, even greater negative effects were projected, with the probability of a household lacking in important micronutrients increasing from 47.7% to 56.2% (Fig. 3).

However, these increases in probability of hunger and malnutrition are not the main findings from this modeling exercise. The impact pathway indicates that the Vision 2040 decision will have a potentially major impact on the current farming systems and may replace many, if not most, small-scale farms and homegardens of the country. Furthermore, industrialization of agricultural systems will require the urbanization of rural communities, which may also negatively impact nutrition outcomes for households by removing their easy access to diverse foods (Luedeling & Whitney, 2017). These insights come mainly from the overall model structure (the impact pathway) and are robust to changes in the experts' elicited probabilities.

3.2.2 Model sensitivity and value of information analysis

VoI calculations were performed using utility nodes of expected annual costs of hunger, MND and the implementation of Vision 2040. We estimated that the annual costs of hunger for Uganda range between 100 and 400 million USD, based on the results of the Cost of Hunger in Africa (COHA) model (World Food Programme, United Nations Economic Commission for Africa, & African Union Commission, 2013). For MND, we estimated annual costs ranging between 100 and 200 million USD, based on a World Bank estimate stating that Uganda loses around 145 million USD due to vitamin and mineral deficiencies annually (World Bank, 2017).

The factors with the greatest leverage in this decision model (identified by sensitivity analysis) were food preferences and nutritional quality, as well as access to and consumption of foods (Fig. 4, Fig. 5). The probability of a household experiencing hunger was most sensitive to variation in nutritional quality, food preferences (diversity and sufficiency), and macronutrient consumption (Fig. 4). For micronutrient deficiency, variation in micronutrient consumption, nutritional quality, and micronutrient demand were the most influential variables (Fig. 5).

Results of the EVPI calculations indicated five diet-related variables that would be the most valuable sources of more information on the model outcome (Table 2). Policy on nutritional awareness and nutritional education and sensitization had the highest EVPI regarding both the cost of hunger (utility value range 100 to 400 million USD) and the costs of MND (utility value range 100 to 200 million USD) (Table 2). Additionally, information on the macronutrient availability, policy promoting exports, exported production and macronutrients on markets had a positive EVPI value regarding the costs of hunger (Table 2).

The EVPI values given in Table 2 represent the amount that the Ugandan Government should be willing to pay to learn more about these variables to have greater certainly about the overall model outcomes (all relatively low). The selected variables with EVPI values could also be treated as priority variables, to be disaggregated in order to better understand the interactions within the Vision 2040 decision model.

3.2.3 Discussion of Vision 2040 model

Experts identified the interactions and factors that affect Vision 2040's impact on nutrition, to be included in this decision model. A major focus of their discussions was the impact of urbanizing rural smallholder farmers, who currently make up a significant portion of the Ugandan population (UBOS & ICF, 2017; UBOS, 2014a). The majority of Ugandans still live in rural areas, as is the case throughout much of sub-Saharan Africa (FAO, 2017). The model shows that rural-to-urban migration is already common in Uganda (Luedeling & Whitney, 2017; from one to seven million between 1980 and 2014; UBOS, 2016) but it may not lead to poverty reduction (Christiaensen & Todo, 2014). Since these rural people are mainly smallholder farmers, who grow much of the food for their households (UBOS, 2016), the loss of this traditional food source is likely to negatively impact household nutrition (Luedeling & Whitney, 2017).

Modeling the various interacting factors involved in the Vision 2040 decision indicates that the implementation will pose substantial risks that need to be considered. Some important factors may be missing from the Vision 2040 strategy, if it is to address hunger and MND. The complex interactions between the different socio-political and biophysical aspects of the decision lead to a high level of uncertainty regarding nutrition outcomes. Overall, the BN model outputs suggest that implementation of Vision 2040 incurs the risk of negatively influencing nutrition (Fig. 3). The variables with the highest information value should be considered priorities to inform the design and prioritization of future research to support Vision 2040 (Table 2). BN model outputs indicate that malnutrition is strongly influenced by access to and demand for healthy food and is less strongly dependent on total food supply. This is especially true for the probability of MND (Table 2; Fig. 5) but also for the probability of hunger (Table 2; Fig. 4). Better estimates of these influential variables may help reduce the range of plausible outcomes of the BN model. Taking such measurements and re-running the analysis with updated input data would enhance clarity on the results. However, EVPI values were rather low in the present case, meaning that the initial outcomes sufficed for making recommendations for the Vision 2040 decision.

The focus of Vision 2040 on industrializing and commercializing agricultural systems indicates an implicit link between food insecurity and low agricultural production, which is also reflected in the national agricultural policy (NPA, 2011; NPA, 2007; MAAIF, 2010). The plan consequently seeks to replace subsistence farms with large-scale commercial agriculture. However, our model results support past studies showing that large-scale farms may not perform as well as traditional small-scale farms in supplying diverse and nutritious diets (Whitney et al., 2017; Kabunga, Ghosh, & Griffiths, 2014). Increasing food supply may not necessarily result in less hunger or MND in Uganda (Whitney et al., 2017). For example, Kabunga et al. (2014) showed that in rural smallholder households across Uganda, production of fruit and vegetables was related to more diverse dietary intakes, greater household food security and lower levels of anemia. The work of Kennedy et al. (2005) also shows that agricultural plant genetic diversity can be a good indicator of household dietary consumption.

Model results show that, in contrast to the main aims of Vision 2040, the incidence of malnutrition may have more to do with access to and demand for healthy food than with actual supply (Fig. 4, Fig. 5). This is to be expected, since the leading causes of food insecurity around the world are related to poverty and inequality, which limits access to food (cf. Sen 1981; IFPRI 2017), as is also the case throughout sub-Saharan Africa (Nyariki & Wiggins, 1997). Notably, this vision may risk reducing food access by eliminating the traditional small-scale farms that are the foundation of Uganda's current food systems.

Model outputs show that, in its current form, Vision 2040 may have negative implications on the nutritional status of households. BN model outputs offer a critique of the decision to industrialize the agricultural systems of Uganda and also provide useful insights into the important factors that are likely to affect the future status of malnutrition in the country's households. Our findings suggest that future occurrence of household malnutrition will have more to do with access to and demand for healthy food than with food supply. These results stand in stark contrast to the current development agenda. To reduce the nutrition burden, the Ugandan government should consider addressing food access and food quality, which is a notable juxtaposition to the current plan, since none of the main factors targeted in Vision 2040 (e.g. crop yields, employment) were of major importance to the model outcomes.

4 Discussion

Here we have demonstrated the use BN models as a decision analysis tool to address the inherent uncertainty in policy-related decision-making regarding linkages between agriculture and nutrition. We adapted and applied BN procedures for developing comprehensive impact pathways for agriculture interventions for nutrition. We have applied and adapted this technique for the analysis of agriculture for nutrition interventions in Uganda and demonstrated its ability to aid in decision-making under multiple uncertainties and imperfect information. By convening experts in the fields of agriculture and nutrition, as well as related disciplines we demonstrate the tool's ability to aid in constructing robust and reliable impact models. This was accomplished through the use of expert knowledge in BN model development. We have showcased this novel approach to using a BN for impact assessment in agricultural development decisions, by operationalizing a model that predicts the nutrition implications of a large-scale agricultural intervention. We show the use of a BN for a complete, vertical, integrated methodology from the identification of the decision, the design of the model, parameter estimation with calibrated participants, to model-building and validation of results. The results presented outline BNs as a useful tool to help predict nutritional status resulting from policies aimed at transforming farming systems. This study directly addresses both the system complexity and data scarcity in agriculture and nutrition by producing a tool that agricultural policy decision makers can use to determine the probability of malnutrition under different scenarios.

The experts designed an impact pathway model based on their intimate knowledge of the impact pathway, but with a structure that does not reflect the complexity that is possible in a BN. More edges may have been possible within the model, and it may have been possible to add more nodes to the model. However, more complexity was not seen as necessary. The experts' design was clear and based on a critical and thorough approach, the model structure was subject to peer review throughout the stages of development and for the final model.

Our modeling approach has several advantages. First, it allows for the comparison of the prospects of different interventions for improving nutrition security, thus helping to identify the most promising approaches. Second, it allows for the consideration of risks to intervention success and identification of weak links in the impact pathway that require particular attention by intervention planners. Third, it permits the inclusion of intangible factors that are commonly omitted from models, thus creating opportunities for holistic research. Lastly the approach demonstrated here helps prioritize metrics that are critical to monitor during implementation, especially those variables with both high uncertainty and large potential impact on intervention outcomes.

We synthesize expert knowledge and other sources of information into BN models that provide credible probabilistic projections of the impact of agricultural interventions on nutrition outcomes. The models, as well as the participatory process from which they emerge, can also be used to define useful metrics for monitoring progress towards nutrition outcomes. Involving a diversity of stakeholders, including government institutions, in the model building process increases the possibility that the insights gained from the model will influence real-world development processes, such as policies resulting from implementation of the Vision 2040 strategy. Furthermore, by calibrating these participants and allowing them to express uncertainty, we decrease some of the expert bias that is considered a weak point of BNs (cf. Kuhnert et al., 2010; Clemen & Winkler, 1999).

5 Conclusions

Probabilistic impact models can be important tools for understanding implications of agricultural decisions for household nutrition. When creating BN models of agricultural systems, the structure of the models, as well as the priors and conditional probabilities included in them, are often difficult to attain. Here we have demonstrated an approach to elicit complex information from local communities and experts, using their knowledge to both build and parameterize BN models. By applying these methodologies, it is possible to create locally specific model structures, including relationships that may be difficult to capture in other modeling approaches. This approach demonstrates a way to involve local knowledge systems in decision analysis and an alternative to ignoring factors that are difficult to measure when considering the impact pathways of agricultural production interventions.

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The dataset and AgenaRisk model can be accesses on the Harvard DataVerse (Luedeling & Whitney, 2017).

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Table 1. Example table for calculation of the expected value of perfect information (EVPI) for a Bayesian Network model of utility values for value of diverse diets.

	Diversity of household diets			Expected Monetary Value (EMV)
States	Low	Medium	High	
Vision 2040 *implemented*	**-4**	**42**	60	EMV = 0.35(-4)+0.55(42)+0.1(60)=**27.7**
Vision 2040 *not implemented*	-11	31	**80**	EMV = 0.35(-11)+0.55(31)+0.1(80)=**21.2**
Probability	0.35	0.55	0.1	Max EMV = **27.7**
EV with PI	0.35(-4)+0.55(42)+0.1(80)=**29.7**			

EVPI	29.7-27.7=**2**

Table 2. Variables with a positive expected value of perfect information (EVPI) for the cost of hunger and cost of micronutrient deficiency (MND) given the implementation of Uganda's Vision 2040.

Utility node	Uncertainty node	EVPI (USD)
Cost of Hunger	Policy on nutritional awareness	56,728
	Nutritional education and sensitization	56,726
	Macronutrient availability	22,759
	Policy promoting exports	6,932
	Exported production	6,928
	Macronutrients on markets	6,792
Cost of MND	Nutritional education and sensitization	92,729
	Policy on nutritional awareness	92,722

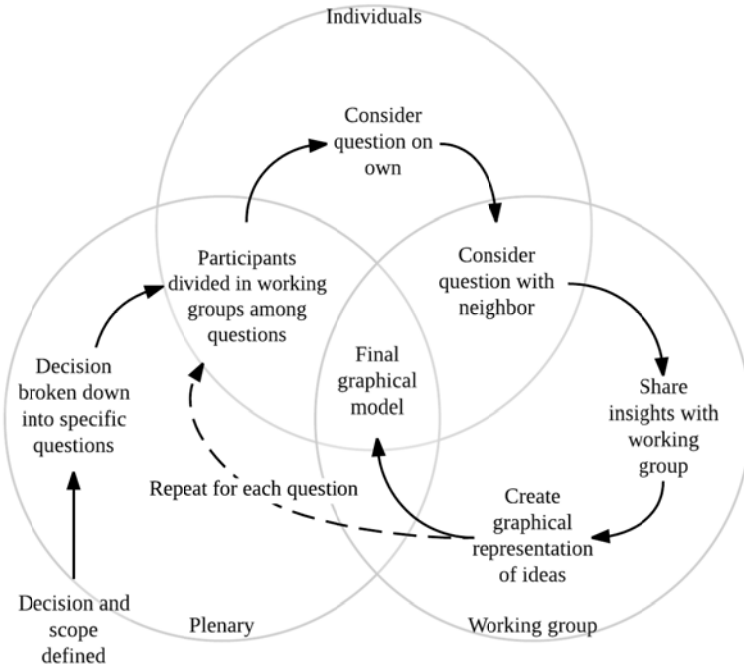

Fig. 1. Process used for eliciting graphical representations of decisions from expert groups to be used in developing a BN

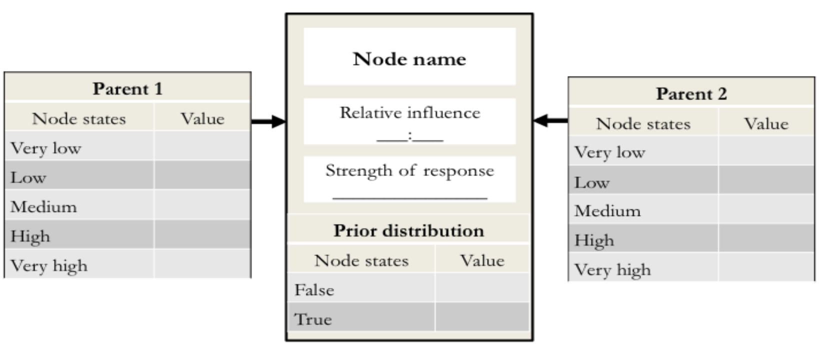

Fig. 2. Example of tool for translating expert knowledge into a Conditional Probability table (CPT) for use in a Bayesian Network.

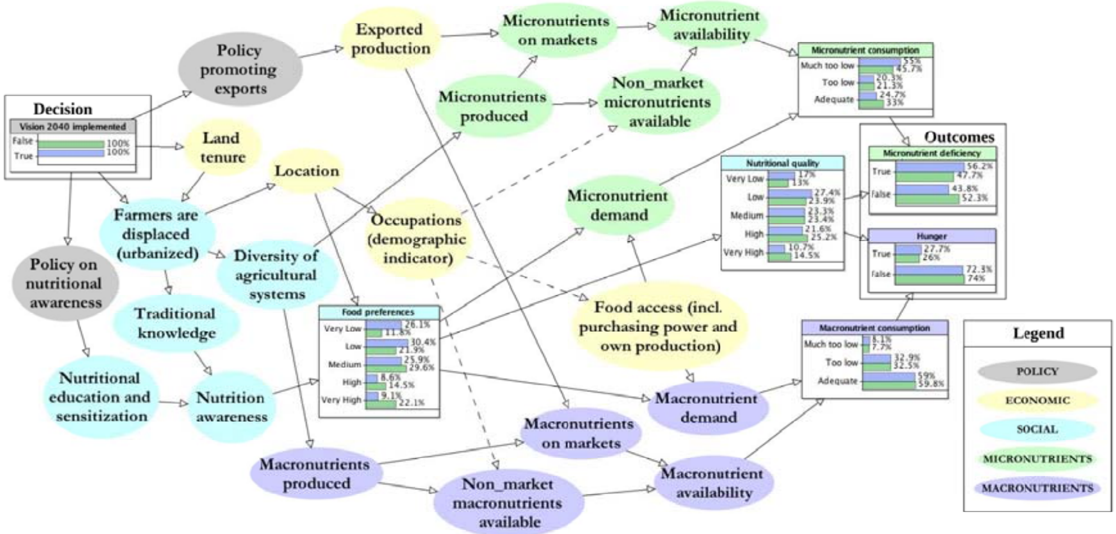

Fig. 3. Bayesian Network (BN) for impact of Vision 2040 on household nutrition in Uganda. Probabilities are shown (boxes) for outcome variables and variables with the highest value of information. Green bars show the probabilities for the node states for the scenario that the Vision 2040 decision is not implemented ('Vision 2040 false'), and blue bars show probabilities for the scenario that the Vision 2040 decision is implemented ('Vision 2040 true'). Dataset and AgenaRisk model available online (Luedeling & Whitney, 2017).

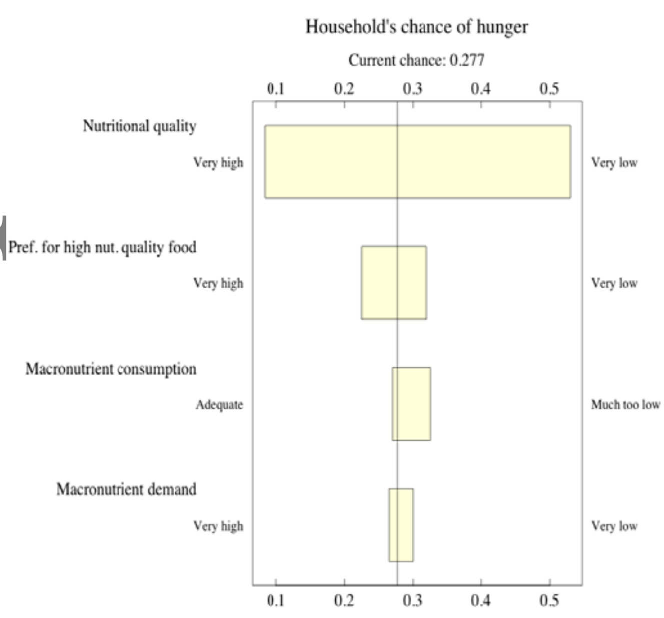

Fig. 4. Sensitivity analysis of a Bayesian Network for probability of household hunger within 10 years of the implementation of Vision 2040. *Pref. for high nut. quality food = preference for high nutritional quality foods*

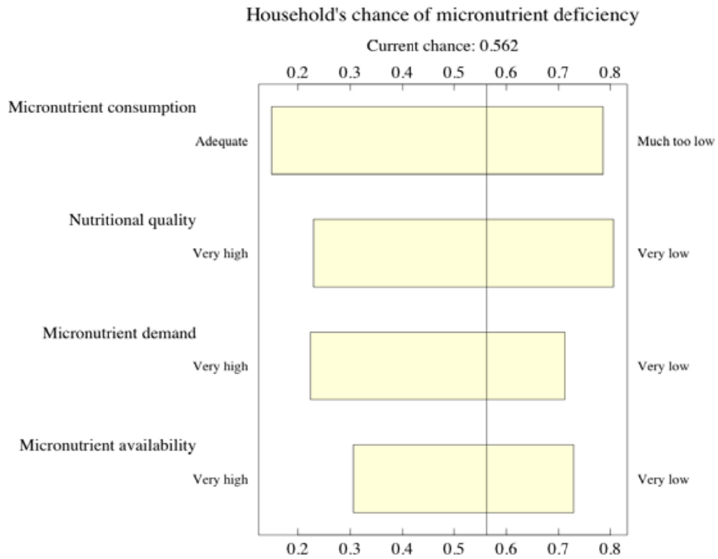

Fig. 5. Sensitivity analysis of a Bayesian Network for probability of household micronutrient deficiency within 10 years of the implementation of Vision 2040