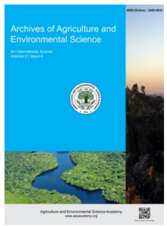
Archives of Agriculture and Environmental Science 6(3): 397-407 (2021)
https://doi.org/10.26832/24566632.2021.0603021

e-ISSN: 2456-6632

This content is available online at AESA

Archives of Agriculture and Environmental Science

Journal homepage: journals.aesacademy.org/index.php/aaes



CASE STUDY

CrossMark

Scalability constraints in Disruptive Agricultural Technologies (DATs) along Value Chain on agricultural production in South Sudan

David Lomeling

Department of Agricultural Sciences, College of Natural Resources and Environmental Studies (CNRES), University of Juba, P.O. Box 82 Juba, South SUDAN
E-mail: dr.david_lomeling@gmx.net

ARTICLE HISTORY

Received: 06 July 2021
Revised received: 14 September 2021
Accepted: 22 September 2021

Keywords

Backcasting
Bayesian Belief Network
Conditional Probabilities
Disruptive Agricultural Technologies
Input variables

ABSTRACT

Scalability known as the capacity of input variables along the Value Chain (VC) to effect transformative changes on agricultural production was evaluated for a farming system in Juba County of Central Equatoria State (CES), South Sudan. These transformative input variables commonly referred to as, Disruptive Agricultural Technologies (DATs) in the form of advisory, material as well as technological variables were shown to positively influence agricultural production from a default state. The objective of this study was to find out how a probability-based Bayesian Belief Network (BBN) software NETICA could be applied to assess as well as upscale the level of agricultural production $P(Prod_{level} \mid \mathbb{D})$ from a data input domain D. Simulation using a 700 kg ha^{-1} of cowpea yield at 50% Cumulative Probability Distribution (CPD) as a calibrant, the backcasting method showed that, scaling up of marginal probabilities in agrotechnology and financial resources from 0.025 to 0.1 (25% *increment*) and from 0.015 to 0.03 (50% increment) respectively, while keeping other input variables unchanged, increased cowpea yield from 692.9 to 783.1 kg ha^{-1} (about 12% increment). Conversely, where no DATs were introduced as in the worst-case scenario, production level was comparatively lower. The BBN model is thus, an indispensable tool that can provide useful information on scaling up agricultural production and hence improve livelihood opportunities in Juba County. However, for sustainable agricultural production, scalability may be constrained by spatial-temporal, environmental and socio-economic imperatives as well as on availability, accessibility, affordability of all input variables.

Citation of this article: Lomeling, D. (2021). Scalability constraints in Disruptive Agricultural Technologies (DATs) along Value Chain on agricultural production in South Sudan. *Archives of Agriculture and Environmental Science*, *6*(3), 397-407, https://dx.doi.org/10.26832/24566632.2021.0603021

INTRODUCTION

According to the Integrated Food Security Classification Phase, IPC 2020 Report (IPC 2020 Report 2 to 4), food insecurity with regional variabilities and extremities in S. Sudan has continued to worsen affecting more than 51% of the entire population, especially ever since the start of the self-inflicted war in 2013 between the government and the opposition forces. Compounded with climatic shocks (erratic rainfall and subsequent floods of 2019 and 2020), economic woes due to drop in GDP, skyrocketing food prices, hyperinflation, locust invasion in early February 2020, over 6 million people are facing acute food insecurity and are unable to feed themselves. Consequently, the number of meals per family per day has reduced from about three to one with significant food quality reduction (Lomeling, 2015). Although natural and man-induced factors have significantly impacted on food insecurity, the lack of coherent infrastructure along the food Value Chain (VC) coupled with the absence of any functional Disruptive Agricultural Technologies (DATs), has further exacerbated the already dire situation. Under DATs, are all digital and non-digital innovations that enable smallholder farmers overcome their current production constraints and increase their yields, generate more income, improve nutritional status and increase resilience to the effects of climate change.

However, any sustainable food security program in S. Sudan and in Juba County specifically is premised by the development of clear value chain infrastructure upon which actionable DATs can be implemented. According to the Food Security and Agricultural Development (FSAD) program of the (*Gesellschaft für Internationale Zusammenarbeit* GmbH (GIZ), assessing scalability of DATs would have been likely within the Green Belt of Greater Equatoria, which since 2010 had already some established food value chains among smallholder farmer groups of Morobo, Magwi and Nzara counties. Countrywide however, there are practically no farmer organizations. Scalability, within the S. Sudanese context, would be perceived as the quantitative change in size of an input variable as part of an overall agricultural production system. It requires a differentiated approach both horizontally, in terms of widespread extension and vertically, in terms of intensification of individual components or inputs along the food value chain (Pachico and Fujisaka, 2004). Thus, scalability of input variables even within the production stage would require a differentiated focus on those easily accessible and available inputs, e.g. ox-plough, traditional shared cultivation practice (*mòlë* in Bari language), application of organic fertilizers (*cow dung from abundant livestock*) than for example, industrially manufactured inorganic fertilizers, pesticides or delivery of foreign made farm machinery. On the other hand, scalability within the processing stage would focus more on increased sorting, drying and handling of local agricultural farm produce to generate some value addition (Matthew, 2018).

Matching empirical data obtained from the smallholder farmer groups of the three counties of Morobo, Magwi and Nzara which all had with more, or less developed agricultural production value chain, one could easily highlight the challenges and shortcomings of any DATs applications and scalability countrywide.

Challenges in the application of DATs in the S. Sudanese context can broadly be divided into three major categories along the agricultural value chain (Table 1).

a) Production
b) Processing
c) Sales and Marketing

Production constraints

As aforementioned, some major constraints limiting scalability of DATs at the production or farm-level are the lack of, or inconsistency in sustaining production inputs and processes. S. Sudan´s has abundant virgin and fertile lands with subsistence agriculture only covering about 5% of its entire area. However, the lack of systematic soil analysis and research, has constrained the qualification and establishment of fertility parameters and hence efficient and effective fertilizer application for especially nitrogen-poor soils. With subsidized prices for nitrogen fertilizers, e.g. urea for most countries of Sub Saharan Africa ranging between $0.7-1.6/kg (Bonilla *et al*., 2020), this is unaffordable even for oil-producing S. Sudan whose GDP has continued to decline from about $1,111 in 2014 to less than $200 in 2017 and with about 82% of the population considered poor based on the $1.90 2011 purchasing power parity (PPP) poverty line (World Bank, 2021). With hardly any seed sector infrastructure and research, provision of certified and biofortified seeds to smallholder farmers in S. Sudan remains a big challenge. Most farmers have had to purchase uncertified seeds through informal channels or unauthorized commercial agents from Uganda or Kenya, thereby compromising the output or yield per acreage. S. Sudan has only about 390 km of paved roads with the almost 17,000 km road network comprising of dirt unpaved roads that are mostly impassable during the rainy season, thus making any farm-market linkages and access impossible. Poor outreach program and infrastructure has only further exacerbated the already deficient extension work and advisory services especially to the rural smallholder farmers, who are entirely dependent on sur place technical knowledge than on digital platforms.

Processing constraints

Agriculture is inherently a risky and uncertain undertaking. Thus, assessing the anticipated economic returns in monetary terms is directly a function of interactions of all production factors and processes along the food value chain. Scalability, therefore, is built on the premise that some input variables or production factors have specific threshold values, upon which this can be expounded or increased. Within the S. Sudanese context, having all production variables at the needed times and amounts is often difficult or challenging thus, any quantitative predictions on the net economic returns and attainment of some degree of food security becomes a speculative and probabilistic exercise. In this case, the use of Probabilistic Relational Models (PRM) of the Bayesian Belief Networks (BBN) becomes an indispensable option. The BBN model attempts to assess the "*uncertain*" impacts of any one of these variables jointly, or otherwise, and to express these in the form of probabilities. Further, the impacts of these variables on the dependent variables can then be described as having a causal relationship and so expressed in terms of conditional probability through a Directed Acyclic Graph (DAG). In the model, all input and resources at production stage may be assumed as independent variables and therefore, (*parents*), while those at the processing stage as dependent (*children*). The Bayesian model has been used in supply chain risk assessment (Sharma and Sharma, 2015); analysis and prediction of ecological water quality (Forioa *et al*., 2015); on nutrient regulating ecosystem services (Bicking *et al*., 2019); reliability control of fresh food e-commerce logistics systems (Zhang *et al*., 2020); grower´s adaptive pre-harvest burning decisions (Price *et al*., 2018) on green supply chain performance prediction (Rabbi *et al*., 2020).

Table 1. Schematic Representation of Disruptions the Value Chain Approach for smallholder farmers in Juba County of Central Equatoria State (CES) of South Sudan.

Food Value Chain	**Inputs, Resources and Production**	**Processing**	**Sales and Marketing**
	i. Human: professional and skilled labor ii. Financial: grants, loans, credits from public and private financial institutions iii. Fertility level: available fertile lands iv. Water resources: adequate and available rain or surface water v. Agro-Technology: farm equipment, fertilizer, insecticides, herbicides, hybrid and biofortified seeds etc.	i. Timely harvest and reduction in harvest losses ii. Efficient handling (drying, cooling, storage) and packaging	i. Timely produce delivery from production sites to markets ii. Direct produce retailing and wholesaling iii. Agents and distributors
Challenges where DAT interventions are applicable	i. Poor ICT, (Data Analytics, IoT) and network coverage ii. Poor incentivization, financial inclusion of smallholder farmers and general lack of investment in agriculture iii. Lack of certified and biofortified seeds iv. Lack of research, soil, water, seed testing laboratories v. Lack of qualified and skilled labor (tractor operators and mechanical servicing workshops) vi. Poor extension and advisory services as well as access to farm equipment and inputs vii. Increased violence, displacement and rural-urban migration viii. Unpredictable rainfall patterns and inability to access and exploit available water resources ix. Lack of business mindset for commercially driven farming	x. Lack or poor storage facilities xi. Poor or lack of adequate post handling technologies xii. Lack of constant energy supply for cooling and preservation of fresh produce xiii. Lack of small-scale processing industries	xiv. Poor network coverage xv. Lack of customized e-Commerce mobile Apps xvi. Poor roads to markets xvii. Lack of agricultural stock exchange markets xviii. Lack of value addition to produce xix. Poor knowledge of price-demand dynamics

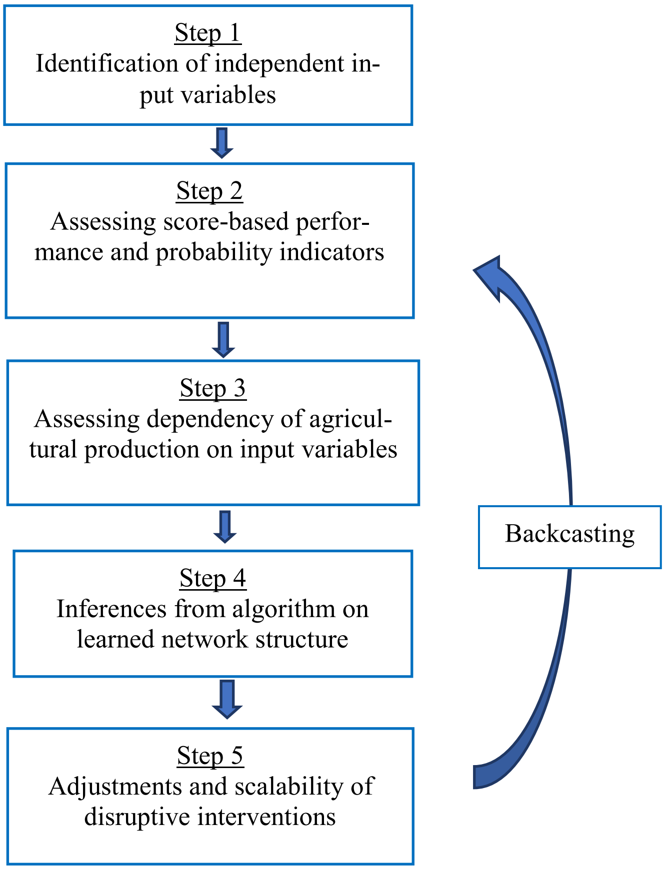


Figure 1. *Steps towards modelling probabilities from independent input variables.*

Sales and marketing constraints

Agricultural production in S. Sudan is still very subsistence with yields as low as 0.97 tons/ha for cereals and about 1.2 tons/ha for cowpeas (Lomeling and Huria, 2020) obtained from relatively small farms 0.4-1.5 ha in size. Lack of entrepreneurial mentality, poor market access and marketing information system, lack of microfinancing institutions and infrastructure are only a few of the sales and marketing constraints limiting intensive agricultural production in S. Sudan. This paper shall focus more on production constraints while leaving out the processing and sales and marketing constraints for yet another review paper.

The objective of this review paper was to identify major constraints and possibilities in scalability along the value chain on agricultural production in S. Sudan using Bayesian Belief Network model as well as find out the most appropriate and significant DATs and interventions for a sustainable agricultural production.

APPROACH AND METHODOLOGY

The basic idea of the BBN model in simulating agricultural production, is to maximize the probability

$$\mathbf{P}(Prod_{level}|\mathbb{D}) = \mathbf{P}(Prod_{level}|\mathbb{D})/\mathbf{P}(\mathbb{D})$$

of a network structure $(Prod_{level})$ given the database $\mathbb{D}$ made up of independent input variables {*human, financial, water resources, agrotechnology and fertile lands*}. This involves learning

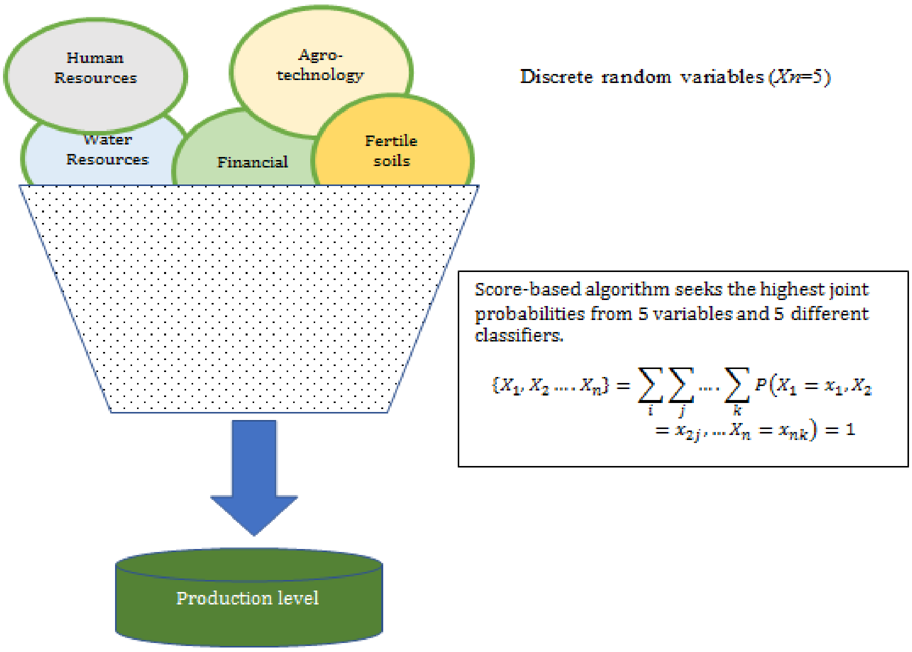


Figure 2. *A simplified graphical abstract illustrating the joint probabilities of discrete random variables on agricultural production level using the Belief Bayesian Network (BBN).*

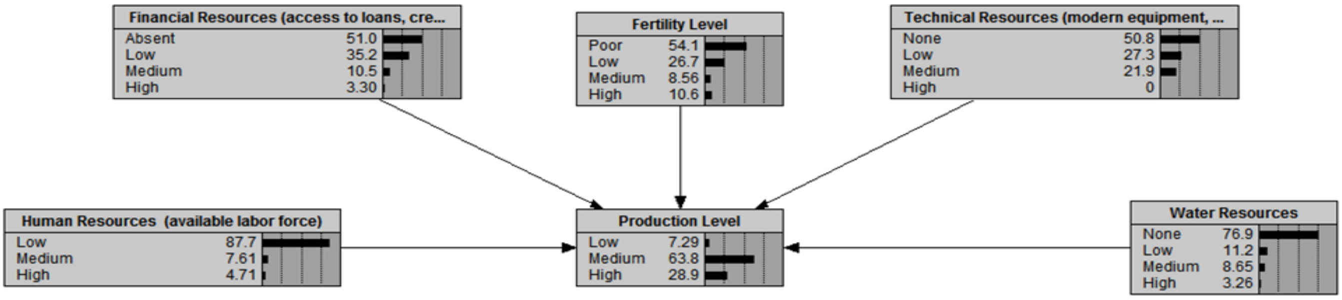


Figure 3. *Default case typical of much of S. Sudan´s contributions of input variables for food production.*

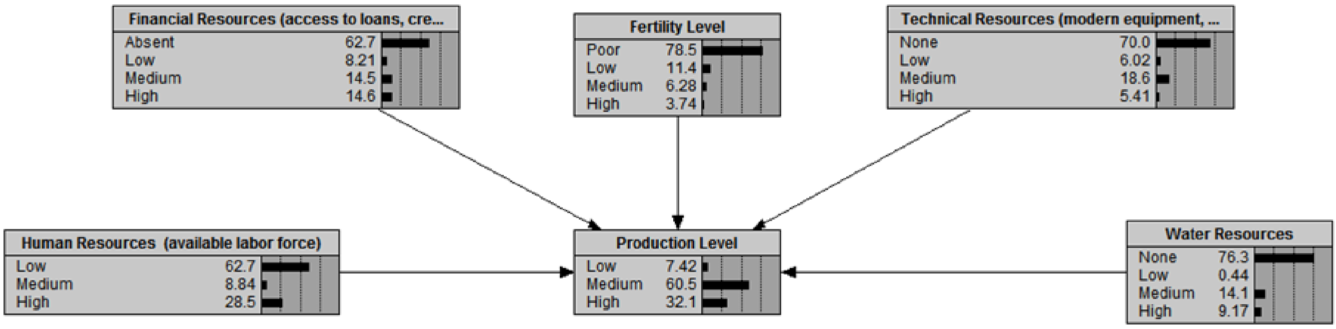


Figure 4. Worst case scenario with low values of all independent DAT input variables.

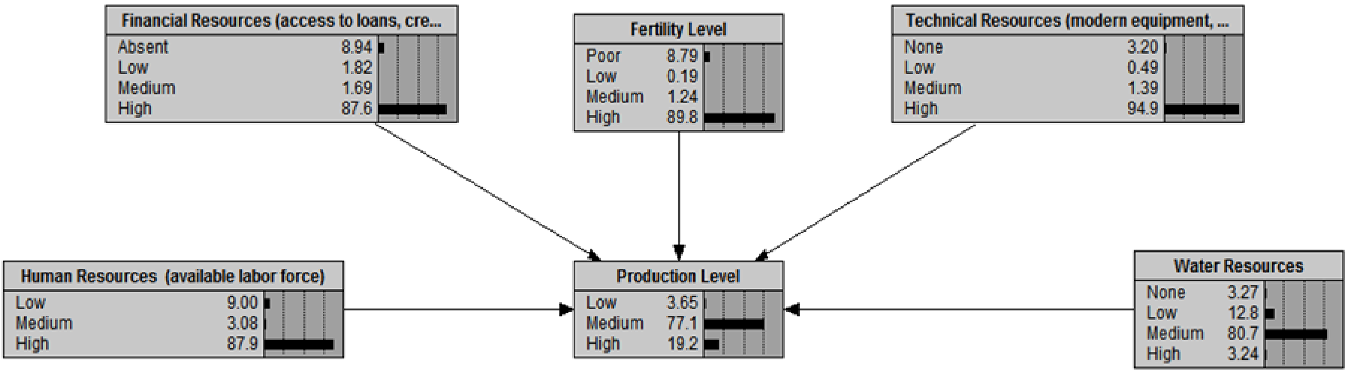


Figure 5. *Idealized best case scenario with optimal adjusted DAT input variables.*

the network structure of all possible conditional probability distributions from the several combinations of the different input variables and assigning the highest metric scores to the network structure that fits the data well (Cooper and Herskovitz, 1992; Heckerman *et al*., 1995). Therefore, the conditional probability of some threshold value of agricultural production $\mathrm{P}(Prod_{level}|\mathbb{D})$ in some given domain can be perceived as the product of joint probabilities of all parent input variables. The number of joint probabilities will depend on the number of input variables (*n*) and their respective classifiers for each given variable. Using the Conditional Probability Tables (CPT), several probabilities can be obtained. The algorithm in the NETICA software package then learns the data structure and makes the best choice of conditional probabilities from the different probability combinations of the input variables. As in this study, there were *n*=5 variables with *c*=19 (classifiers). Two steps consisting of i) *forecasting:* in which probabilities of agricultural production are assessed from *a priori* known input variables ii) *backcasting*: in which, desired or output probabilities of agricultural production are set *a priori* and the probabilities for the input variables backwardly assessed.

Such a BBN simply offers a set of fore- and backcast approximation probabilities of anticipated output, or input values. The herein applied software NETICA (Norsys Software Corp.) is a robust software that enables the application of backcasting method (Kanter *et al*., 2016; Robinson *et al*., 2011; Kok *et al*., 2011; Mulder and Biesiot, 1998; Anderson, 2001). Backcasting, in contrast to forecasting, is a method that sets *a priori* specific targets at some future date based on the current input of one or more independent variables (David *et al*., 2016). The desired and set target triggers an automated and backward adjustment on the input variables that is built in the software´s algorithm. Thus, any changes on the target values, there is a corresponding backward change in the input variables. This is very much a scalability identifying approach, as it enables users to upscale or downscale and rank individual variables, in order to reach a desired outcome.

FRAMEWORK DEVELOPMENT

The proposed research consists of five steps as described below in the proposed framework (Figure 1).

Step 1: Identification of independent input variables

Identification and enlisting of all major input (*discrete random*) variables and their respective probabilities that may impact agricultural production. These could be primary variables (*fertile soils, available water, skilled labor, etc.*) or secondary variables (*applied technology-equipment, fertilizers, insecticides, financial access, etc.*) in the domain $\mathbb{D}$.

Step 2: Assessing performance and probability indicators

The presence and significance of each input variable and probability is assessed. Performance indicators based on score-based approach are assigned probability values, $\{0 \leq x \leq 1,$ where x is any value between 0 and 1.0} or expressed as percentages (%) prior to adjustment. The algorithm is based on a scoring function that searches the goodness of fit and highest scores of each explored structure from the several probable combinations of joint probabilities of the input variables (Scanagatta *et al*., 2018, Scanagatta *et al*., 2019). Equally expert experience and good judgment on the nature and state of agricultural production systems in S. Sudan would give more realistic values. These then, can be used for computing the probability of each performance indicator in the BBN model.

Step 3: Assessing dependency of agricultural production on input variables

The influence and effects of the input variables and their performance on production level in the BBN model are assessed.

$$\mathrm{P}\{X_1, X_2 \ldots . X_n\} = \sum_i \sum_j \ldots . \sum_k \mathrm{P}\big(X_1 = x_1, X_2 = x_{2j}, \ldots X_n = x_{nk}\big) = 1$$

Here, several joint probability combinations of two or more discrete random variables (*parent nodes*) are generated in a Conditional Probability Table (CPT) and the best score of conditional probability to agricultural production (*child node*) assessed.

Step 4: Inferences from learned algorithm

From the learning algorithm of the NETICA software, inferences on the network structure can be made during each adjustments of input variables as in step 3. The inferences are made on which conditional probabilities of the input variables give the best performance indicator as shown by level of production.

Step 5: Backcasting and scalability of disruptive interventions

Desired performance measure of production level can be backcasted by adjustments or scaling up at the production node which simultaneously triggers change in the input variables. Different scenarios: worst, moderate and best-case scenarios can independently be modelled, and the different conditional probabilities assessed. In order to assess the effect of scalability on food production level, two scenarios were chosen: a) *worst case scenario*: in which all input variables were either none-existent or very low. This represented the default and typical state and nature of agricultural production system in S. Sudan whereas b) *best case scenario*: in which all input variables were disrupted or adjusted to medium or high levels, representing an idealized and desired state.

The BBN is made of two parts P = (", J). The first part, “"”, is a directed acyclic graph (DAG) which shows the *production node* represented by the independent variables or parent nodes $\{x_1 \ldots .. x_4\}$. The arcs are shown as the causal relationships with the *processing* and subsequently with the *sales and marketing* nodes. The second part of BBN is the conditional dependency distribution of J where, $\theta_{xi}|_{pxi}$ = PÂ($_{xi}|_{pxi}$), is the set of direct parent variables of x_i in ". Using the joint probability distribution, the network Â can be represented by:

$$\mathrm{P}(x_1, \ldots \ldots \ldots x_n) = \prod_{i=1}^{n} \mathrm{P}(x_i\,|px_i) = \prod_{i=1}^{n} x_i\,|px_i \quad (1)$$

$$\leq x \leq 1$$

The formula indicates that the conditional probability of an event in Λ is observed in terms of the interactions and magnitudes of the random variables $\{x_1 .... x_5\}$. The proposition statement posed *a priori* would be, that a threshold probability level of Λ is attainable based on given levels of all, each or some $\{x_1 .... x_5\}$ where x_1 human resources; $x_2 =$ financial resources; $x_3 =$ fertile lands/soils; $x_4 =$ agrotechnology $x_5 =$ *water resources.*

For five random input variables (*n=5*) at the production stage, the product of conditional probabilities generated from the chain rule produces:

$$\begin{aligned}
&\mathbf{P}(x_5, x_4, x_3, x_2, x_1) = \mathbf{P}(x_5|x_4, x_3, x_2, x_1)\\
&= \mathbf{P}(x_5|x_4, x_3, x_2, x_1)^*\mathbf{P}(x_4, x_3, x_2, x_1)\\
&= \mathbf{P}(x_5|x_4, x_3, x_2, x_1)^*\mathbf{P}(x_4|x_3, x_2, x_1)^*\mathbf{P}(x_3|x_2, x_1)^*\mathbf{P}(x_2, x_1)\\
&= \mathbf{P}(x_5|x_4, x_3, x_2, x_1)^*\mathbf{P}(x_4|x_3, x_2, x_1)^*\mathbf{P}(x_3|x_2, x_1)^*\mathbf{P}(x_2|x_1)^*\mathbf{P}(x_1)
\end{aligned}$$

Therefore, any disruption on DATS and subsequent scalability is made easier. In other words, the BBN is composed of a set of interconnected nodes. Each node represents one variable within the model. For each variable/node, there are different possible states. The causal relationship between the variables is depicted in the form of arcs. The probability of the individual states of the nodes is determined from the probability of each possible state of all connected nodes and their causal relationship

BBN Structure on cause-effect relationships

The level of agricultural production is a function of interplay of several production factors and processes. In this study, five major input variables have been considered and the resultant impact expressed in terms of production level (Figure 2).

The basic BBN idea used here (Figure 3) consisted of five parent nodes (*input variables*) and arcs (*linkages*) built on the concept of adjusting either one, more or all jointly to prompt a desired level of production. At the second level, the production node (*child*) is then adjusted to effect changes at the processing node which in turn may be adjusted to effect changes on the sales and marketing node. The processing node as in much of S. Sudan consisted of post-harvest, handling and perhaps drying of predominantly cereal (*sorghum*, *millet*, *maize*); leguminous (*cowpeas*, *beans*); tubers (*cassava*, *yams*, *sweet potatoes*); oil crops (*sesame*, *peanuts*). The relationship between the independent input variables and levels of production under a default state of a typical agricultural setting in S. Sudan. Over 75% of financial (*loans, credits etc.*) and technical resources (*modern farm equipment, digitized/precision/ smart farming technology, hybrid seeds etc.*) inputs are low or outright non-existent, whereas human resources (traditional farmers with less or no education and skills on modern farming) and have a direct influence on the production level. Although S. Sudan is endowed with several seasonal rivers, wet plains especially the Sudd area, accessing water through irrigation for agriculture is practically non-existent.

Figure 4 shows the worst-case scenario and the effect of the input variables on production level. Comparing the production levels under default case (Figure 2) with that under worst-case, shows no significant differences, indicating the actual deplorable state of agricultural production in S. Sudan. Diao *et al.* (2012) showed that the average cereal yield level in S. Sudan was at 0.9 ton/ha, while this was at 3 and 2 tons/ha for Ethiopia and Kenya respectively, indicating a 30-50% lower production level. Obtaining an average value from the medium and high production levels showed a closer and corroborating value of about 45-47% below those of both countries. Disruption in the input variables had marked changes on agricultural production level. Although as an ideal and hypothetical scenario, the simulated medium production level increased from about 60% (*worst case*) to about 77% (*best case*) as in Figure 5 showing a 17% change. The degree of disruption of individual input variables may also vary in time and space. Changes in disruption of e.g. increased technical resources in form of applied hybrid seeds, good agricultural practices (smart and precision farming), extension and advisory services (about 91%); or of financial resources, e.g. access to soft loans and credit (about 74%) may be realized in the short term. Equally, disruption in facilitating human resources, e.g. in developing skilled labor force (about 60%), or of increasing soil fertility level (about 86%) may take a relatively longer time. Although S. Sudan has vast fertile agricultural lands, less than 4% of arable land is being used (Olympio *et al.*, 2014). Disruptions through innovative agrotechnology would significantly boost production in S. Sudan similar, to that experienced within the East African region (Krishnan *et al.*, 2020). Equally, agricultural underfunding by the government showed that the sectoral allocation (percent share) in the annual budget for the 2012/13 to 2014/15 FY (Attipoe *et al.*, 2013) did not exceed more than 3% of the GDP, significantly impacting on overall agricultural production.

Although no empirical studies on the impacts of digitization as a transforming force in agricultural production in S. Sudan have been conducted, it is known to significantly impact on agricultural productive processes elsewhere (Poppe *et al.*, 2013; Smith, 2018; Rotz *et al.*, 2019; Jouanjean, 2019; Trendov *et al.*, 2019). Agricultural transformation in S. Sudan through digitization may be in the form of increased internet connectivity and related digital services, where local farmers can easily access daily market prices, weather forecasts and seek online advisory services. According to (https://datareportal.com/reports/digital-2020-south-sudan), the number of mobile connections in South Sudan increased by three hundred thousand subscribers (ca. +16%) between January 2019 and January 2020, this about 20% of the total population (Olympio *et al.*, 2014). These mobile connections and services may be in the form of increased e-commerce, money transfers through the m-Gurush platform of the Zain Network as well as receiving actual market, soil and weather data for distant rural farmers. Similarly, much of S. Sudan´s rain-fed agriculture could be boosted by harnessing the vast water resources of the Nile through increased irrigation, construction of water pans and dykes especially in Upper Nile and Jonglei states (Clesensio and George, 2011).

Table 2. Estimated level of agricultural production of cowpeas (kg/ha) from marginal probabilities of different input variables under *worst case* scenario. (calibrated with 50% CPD production level of 700 kg/ha; *Lomeling and Huria*, 2020).

Discrete random variables	State/condition				Sum (∑)	Kg ha^{-1}
	Absent/None	Low/Poor	Medium	High		
Human Resources 1)		0.6270(0.2884)	0.0884(0.0407)	0.2850(0.1311)	(0.4602)	322.14
Financial Resources 2)	0.6270(0.0094)	0.0821(0.0012)	0.1450(0.0022)	0.1460(0.0022)	(0.0150)	10.49
Fertile Soils 3)		0.8990(0.2697)	0.0628(0.0188)	0.0374(0.0112)	(0.6437)	202.74
Agro-Technology 4)	0.7000(0.0175)	0.0602(0.0015)	0.1850(0.0046)	0.0541(0.0014)	(0.1087)	17.50
Water Resources 5)	0.7630(0.1526)	0.0044(0.0009)	0.1410(0.0282)	0.0917(0.0183)	(0.2000)	140.03
Sum (∑)	(0.1795)	(0.5021)	(0.0945)	(0.1642)		692.9
Kg ha^{-1}	125.65	351.47	66.15	114.94		

I. Marginal probabilities of each discrete random variable for minimal level of agricultural production: 1) 0.46; 2) 0.015; 3) 0.3; 4).0.025; 5)0.2.
II. Within brackets = calculated conditional probability dependent on marginal probability of input variable and classifier or state/condition (absent/none; low/poor; medium and high).
III. Outside brackets = probability level or state of input variable without any agricultural production.

Table 3. Estimated level of agricultural production of cowpeas (kg/ha) from marginal probabilities of different input variables under *best case* scenario. (calibrated with a 50% CPD production level of 700 kg/ha; *Lomeling and Huria*, 2020).

Discrete random variables	State/condition				Sum (∑)	Kg ha^{-1}
	Absent/None	Low/Poor	Medium	High		
Human Resources 1)		0.090(0.0414)	0.0310(0.0143)	0.8790(0.4043)	(0.4600)	322.03
*Financial Resources 2)	0.0894 (0.0027)	0.0182(0.0005)	0.0169(0.0005)	0.8760(0.0263)	(0.0299)	20.99
Fertile Soils 3)		0.0899(0.0269)	0.0124(0.0037)	0.8980(0.2694)	(0.3000)	210.00
*Agro-Technology 4)	0.0320(0.0032)	0.0049(0.0005)	0.01392(0.0039)	0.9492(0.0949)	(0.1025)	71.76
Water Resources 5)	0.0327(0.0065)	0.1280(0.0256)	0.8070(0.1614)	0.0324(0.0065)	(0.2262)	158.33
Sum (∑)	0.0124	0.0949	0.1838	0.8014		783.14
Kg ha^{-1}	8.68	66.43	128.66	560.98		

I. Marginal probabilities of discrete random variable for minimal level of agricultural production: 1) 0.46; 2) 0.03*; 3)0.3; 4) 0.1*; 5)0.2.
II. Within the brackets = calculated conditional probability dependent on marginal probability of discrete random variable and classifier or state/condition (absent/none; low/poor; medium and high).
III. Outside the brackets = probability level of discrete random variable without any agricultural production

Table 4. Scalability of some input variables on production levels of a typical agricultural system in Juba County of Central Equatoria State (CES), South Sudan.

Input variable or resource		Level of input (Worst case scenario) in %	Level of input (Best case scenario) in %	Level of scaling and change D (up/down) in %	Impact Classification
Financial	Low	15.8	11.1	4.7 ↓	Slight **
	Medium	16.3	38.5	22.2 ↑	Major ***
	High	26.8	19.5	7.3 ↓	Slight **
Soil fertility status	Low	52.2	15.7	36.5 ↓	Major ***
	Medium	33.0	59.0	26.0 ↑	Major ***
	High	8.66	14.7	6.04 ↑	Slight **
Technology	Low	5.52	3.56	1.96 ↓	Slight **
	Medium	28.9	64.1	35.2 ↑	Major ***
	High	26.1	17.6	8.5 ↓	None *
Water	Low	4.92	5.58	0.66 ↑	Slight **
	Medium	43.6	51.7	8.1 ↑	Slight **
	High	25.4	31.7	6.3 ↑	Slight **
Human	Low	11.8	10.9	0.9 ↓	Slight **
	Medium	66.6	68.2	1.6 ↑	Slight **
	High	21.6	21.0	0.6 ↓	None *

(Impact classification: *= None; **= Slight; ***=Major).

Figure 6(a) and (b) show the backcasting step in which changes in input variables are influenced by adjustments in the average production level. Two different probability levels of production were chosen to illustrate this point. The first case (Figure 6a) involved a desired level at medium production of 59% (*while high* at 18.3%) and the second case (Figure 6b) where medium production of 33% (while high at 53.6%). In Figure 6 (a) the combined medium to high production level was at 77.3%, while this was at 86.6% in (b) indicating a 9.3% difference. The lack of financial and technical resources coupled with a relatively high percentage of low soil fertility level (Figure 6a) appear to be the major reasons for such medium agricultural production level. On the other hand, for a desirably high agricultural production level (Figure 6b), disruptive interventions in terms of increase in soil fertility levels as well as in water and technical resources would be needed. It appears, disruption through application of skilled human labor and access to financial resources did not increase agricultural production significantly. On sales and marketing derived directly from agricultural production, the summed probability values (medium and high) in Figure 6a, was 88.4% while this was 79.9% in (b) showing a 9.5% difference. Though not significantly different, this was contrary to normal expectations, where high production necessarily translated into high market sales (Benfica *et al.*, 2014). It shows that market sales are independent of production levels which have their own dynamism that are subject to external economic forces (size and structure of market, type of crop etc.). In either case, the level of production directly correlated with the values for processing as well as sales and marketing.

STRENGTHS, LIMITATIONS AND OPPORTUNITIES

Identification and choice of input variables: This is particularly critical since the extent and level of agricultural production as shown in the BBN model is contingent on the numbers and interactions of all input variables. A clear distinction of those primary variables that are indispensable for agricultural production (human, water and land resources) with secondary variables (improved technology, financial resources) are necessary. Modelling the different distribution probabilities and determining the best combinations for agricultural production would therefore require prior expert knowledge of, or empirical data on the level and extent of these input variables. Assessment of some variables may be more subjective and qualitative in nature, for example use of qualified human labor force, assessing the fertility status of the soil from vegetation growth, while for others that may be more objective, for example estimating the amounts of financial or water resource resources applied. Therefore, an accurate approximation of all input variables would give better distribution probabilities. However, such prior expert knowledge of input variables will require incorporating temporal as well as spatial or regional peculiarities and differences. This means, input variables or disruptions have spatial-temporal relevance and validity and therefore, cannot be used for extremely large areas all the time, or rather are not a panacea for all times under any agricultural production environments. These variables, will need to be updated, adjusted and tailored during modelling to the local needs of the area under study in order to forecast a more realistic approximation of agricultural production.

The software NETICA as compared to other similar BBN tools offers unique advantages of backcasting. This method allows the backward approximation of input variables (*parents*) from a specific and determined value (*child node*) during modelling.

Probability distribution of production under different scenarios

Table 2 and 3 were used to illustrate the impacts of scaling up of marginal probabilities on agricultural production of the different discrete random variables for the worst- and best-case scenarios respectively. The conditional probability, here in the form of agricultural production, is a function of both joint probabilities of all discrete variables in the domain. Using calibrated value of cowpeas at 50% CPD (Lomeling and Huria, 2020) as 700 kg ha^{-1}, the BBN forecasted value for *worst case* scenario was about 692.9 kg ha^{-1}. Scaling up the marginal probabilities of both financial resources and agrotechnology from 0.015 to 0.003 (*50% increase*) and 0.025 to 0.1 (*40% increase*), respectively, while keeping other variables constant increased agricultural production to 783.14 kg ha^{-1}, a 12% increment. For the *worst-case scenario* (Table 2), poor agricultural production was ≥ 263% higher than the desired medium to higher production, whereas this was ≤ 11% for *best-case scenario* (Table 3). It is evident therefore, that upscaling access to financial resources and to modern agrotechnology increased agricultural production, even as other discrete variables were kept unchanged. The significance of each input variable in overall agricultural production is also shown in both tables, e.g. a scaleup in agrotechnology from 17.5 to 71.76 kg ha^{-1} (a 24.4% increment) while for scaleup in financial resources from 10.5 to 21 kg ha^{-1} (a 50% increment).

Generally, two conditional probability distributions of agricultural production as shown in Figure 6a and 6b can be compared. The slight difference between both outcomes lies in the qualification of medium and high production classifiers. As in Figure 6a, a 59% probability distribution (medium) of agricultural production appeared to be strongly influenced by both available human and water resources, but with less or hardly any financial and technical inputs and low soil fertility level. On the other hand (Figure 6b), the medium level of all input variables gave higher probability distribution of production levels (>53%), signifying the synergistic and complementary effect of all input variables. For sustainable agricultural production and a stable food security status, S. Sudan should on average ensure more access to financial and agrotechnical resources while maintaining a desirable soil fertility level, water resources even under the current deplorable state of unskilled human resources. Technical resources would be in terms of increased advisory and extension services to the farmers, provision of biofortified, hybrid and certified seeds as well as use of environmentally friendly organic chemicals for plant protection. The BBN model allows the probability adjustment of more or all discrete variables as desired to attain maximum conditional probability and hence possibilities for forecasting the highest agricultural production.

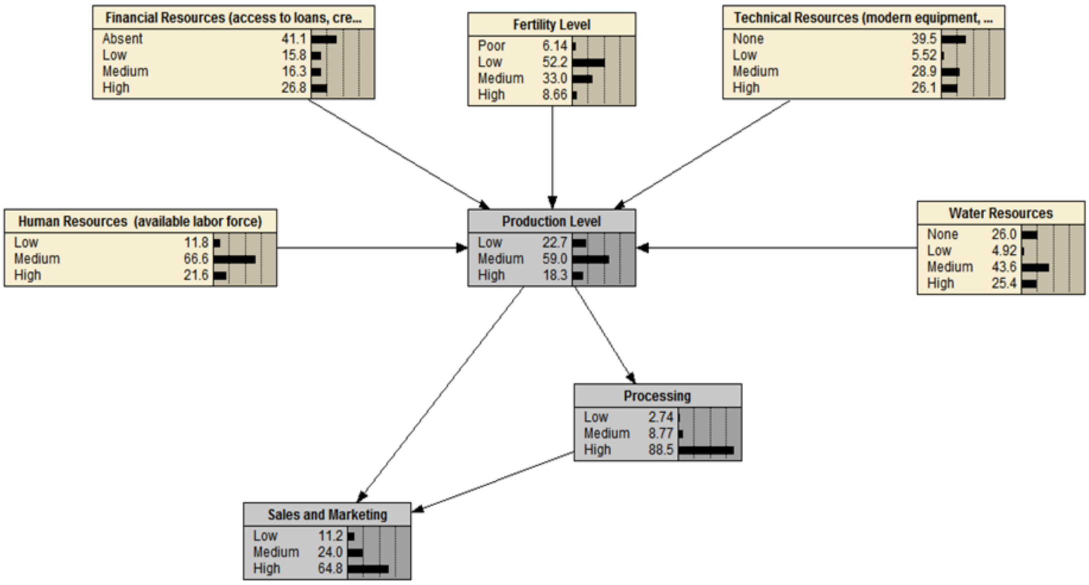


Figure 6(a). *A BBN showing variations in agricultural production level, processing, sales and marketing interlinkages prior to disruption.*

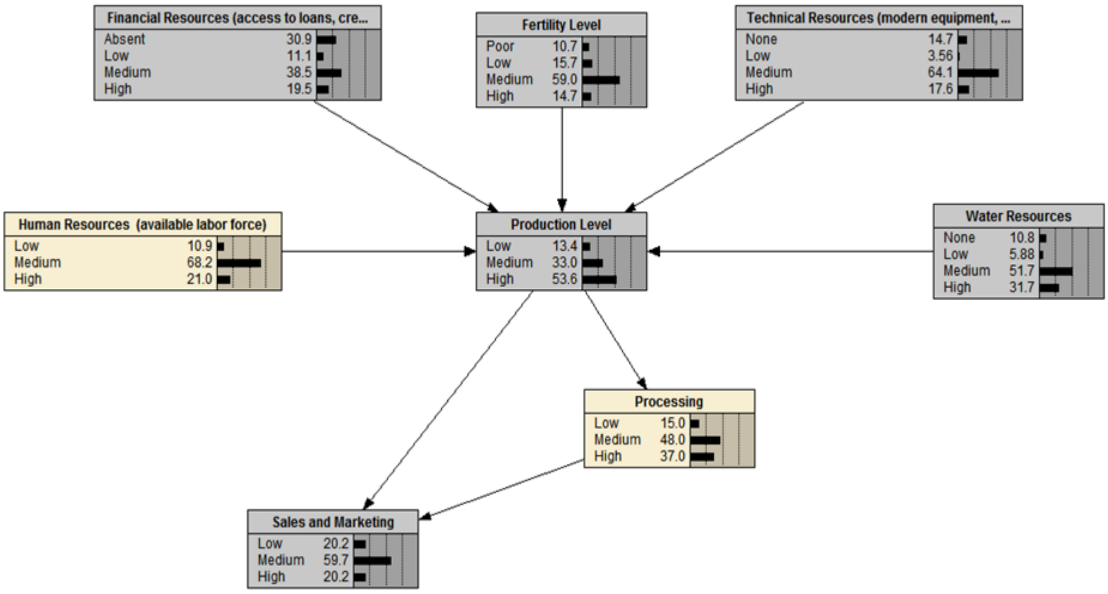


Figure 6(b). *A BBN showing variations in agricultural production level, processing, sales and marketing interlinkages after disruption.*

Conclusively, the BBN that incorporates both the fore- and back-casting approaches can be stated as an appropriate model in estimating the distribution probabilities of input disruptions on agricultural production. The possibility of applying either qualitative (*subjective, e.g. boolean*) and quantitative (*objective, e.g. real values*) input data to the model network reinforces the convenience of the approach. However, any real-life simulations using the model are contingent on the use of empirically generated data and, application of prior expert knowledge of the study area, while taking into consideration the spatial-temporal variabilities.

Parameter estimation, scalability and transferability

Understanding the inputs and processes of agricultural production are some of the main drivers of scalability (Woltering *et al.*, 2019). Moreover, the underlying reasons for scaling up, the timing of the needed innovative interventions and sustaining them over time are equally critical. As in the case illustrated herein, the five main input random variables for agricultural production in S. Sudan (*human, financial, water resources, land fertility and technology*) have different parameters with no specific metrics in quantifying and qualifying their individual impacts. As in Table 2, scaling up effects showed an increase in production level as triggered by increase in soil fertility status, water and technology use than for example, improved human or increased access to financial resources. Raising the probability distribution of certain input variables like; technology, human and financial resources to high values, had no overall scaling up effect on production level. Rather, maintaining this at medium or optimum level appeared to have had the desired scaling up effect on production.

On the other hand, technology is a generic term that may include anything from the use of on- and off farm machines and equipment, modern production methods to such input variables as biofortified and hybrid seeds. Challenges in calibration of scalability, may also be faced when trying to measure or quantify not only specific threshold values of each individual input variable, but also collectively of all input variables needed to offset the desired changes in production levels. This would require, assessing and measuring variables that have low probability distributions, but may have higher impacts on production levels and vice versa. After all, not all input variables have equal distributions and therefore uniform impacts on agricultural production. Similarly, scalability cannot under any circumstance be infinitely expanded without due consideration on the tradeoffs between environmental concerns and economic sustenance. Hereby, a breakpoint may be reached when scaling up of input variables becomes less profitable and environmentally unfriendly and may have to be reduced or, abandoned altogether. One other challenge is that, scalability within one given domain, or environmental and socio-economic set up is not transferable and replicable onto yet any other domain. Therefore, a blanket presumption that every, or all input variables irrespective of spatial-temporal variations are valid, is not only untenable but also economically unsustainable.

Conclusion

This study proposed a probabilistic-based Bayesian Belief Network model in forecasting the level of agricultural production $\mathbf{P}(Prod_{level}|\mathbb{D})$ in Juba County of South Sudan. The level of agricultural production was conceived as a joint probability determined to a larger extent by the joint probabilities of more than two or more input variables. The study showed that starting with known metric quantities of individual input variables a priori, (fertile soils, water resources, labor, financial resources, technology *etc.*) in the domain $\mathbb{D}$, their values could be adjusted, and production levels forecasted. Modeling disruptions of two input variable, e.g. improved agrotechnology and increased access of financial resources to smallholder farmers showed a more than 12% increase in production. Conversely, from the ideal and desired production level, the BBN backcasting method triggered an automatic change effect on almost all individual input variables. This way, a clear understanding on the role of each individual input variable and the corresponding quantity in the BBN model could be made. Further, the backcasting method also helped in delineating and prioritizing those individual input variables that had the highest probabilities and therefore significant impacts on agricultural production. Simulation of the various production scenarios (*from worst to best case*) by adjusting one or more input variables, the BBN model showed the magnitude of change and hence scalability. Therefore, simulating the various agricultural production scenarios through timely DATs interventions can help in making more informed decisions on scalability. This will not only increase agricultural production, but also transform agricultural production from subsistence level to a more market-oriented enterprise in Juba County and S. Sudan at large. The BBN model is an indispensable modeling tool that can be used to making informed decisions on scaling up input variables and hence agricultural production. However, much research using the BBN model is still needed on understanding how scalability in the absence of some, or presence of limited DATs interventions, higher probabilities in agricultural production can still be sustained.

Declaration of Competing Interest

The author declares that there is no known competing financial interest nor any personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

Anderson, K. (2001). Reconciling the electricity industry with sustainable development: backcasting – a strategic alternative. *Futures*, *33*, 607–623.

Attipoe, F. Y., Blay Jnr, J., Agyakwah, S., Ponzoni, R. W., Khaw, H. L., & Abban, E. K. (2013, October). Genetic parameters and response to selection in the development of Akosombo strain of the Nile tilapia (Oreochromis niloticus) in the Volta Basin, Ghana. In Proceedings of the International Symposium on Tilapia in Aquaculture, Jerusalem, Palestine (pp. 6-10).

Benfica, R., Boughton, D., Mouzinho, B., & Uaiene, R. (2014). Food Crop Marketing and Agricultural Productivity in a High Price Environment: Evidence and Implications for Mozambique. Research Paper 76E, Directorate of Economics, Ministry of Agriculture, Mozambique.

Bicking, S., Burkhard, B., Kruse, M., & Müller, F. (2019). Bayesian Belief Network-based assessment of nutrient regulating ecosystem services in Northern Germany. *PLoS ONE*, *14*(4), e0216053, https://doi.org/10.1371/journal.pone.0216053

Bonilla, C. C., Chamberlin, J., Guo, Z., & Hijmans, R. J. (2020). Spatial variation in fertilizer prices in Sub-Saharan Africa. *PLoS ONE 15*(1), e0227764, https://doi.org/10.1371/journal. pone.0227764

Clesensio, T., & George L. L. L. (2011). Post-conflict Development of Agriculture in South Sudan: Perspective on Approaches to Capacity Strengthening - Unpublished Report 22p.

Cooper, G., & Herskovitz, E. (1992). A Bayesian method for the induction of probabilistic networks from data. *Machine Learning*, 9, 309-347.

David, R. K., Marie-Hélène, S., Walter, E. B., José, E. B., Miguel, C., Achim, D., Bruno, F., Bruno, L., Mario, M., Cecilia, P., Rodrigo, S., María, E. S., & Juan, M. S. L. (2016). Translating the Sustainable Development Goals into action: A participatory backcasting approach for developing national agricultural transformation pathways. *Global Food Security*, 10, 71–79, http://dx.doi.org/10.1016/j.gfs.2016.08.002

Diao, X., Liangzhi Y., Vida, A., & Renato, F. (2012). Assessing Agricultural Potential in South Sudan – A Spatial Analysis Method. International Food Policy Research Institute (IFPRI), Washington DC, USA. http://dx.doi.org/10.5772/47938

Forioa, M. A. E., Landuyt, D., Bennetsena, E., Locka, K., Nguyena, T. H. T., Ambarita, M. N. D., Musongea, P. L. S., Boets, P., Everaert, G., Grandac, L. D., & Goethals, P. L. M. (2015). Bayesian belief network models to analyse and predict ecological water quality in rivers. *Ecological Modelling*, *312*, 222-238, http://doi.org/ 10.1016/j.ecolmodel.2015.05.025

Heckerman, D., Geiger, D., & Chickering, D. (1995). Learning Bayesian networks: combination of knowledge and statistical data. *Machine Learning*, *20*, 197–243.

IPC (2020) Source. Technical Manual, Version 1.1. http://www.fao.org/3/i0275e/i0275e.pdf

Jouanjean, M. A. (2019). Digital Opportunities for Trade in the Agriculture and Food Sectors. OECD Food, Agriculture and Fisheries Papers, No. 122, OECD Publishing, Paris.

Kanter, D. R., Schwoob, M. H., Baethgen, W. E., Bervejillo, J. E., Carriquiry, M., Dobermann, A., ... & de Lima, J. M. S. (2016). Translating the sustainable development goals into action: a participatory backcasting approach for developing national agricultural transformation pathways. *Global Food Security*, *10*, 71-79.

Kok, K., van Vliet, M., Bärlund, I., Dubel, A., & Sendzimir, J. (2011). Combining participative backcasting and exploratory scenario development: Experiences from the SCENES project. *Technological Forecasting and Social Change*, *78*(5), 835–851, https://doi.org/10.1016/j.techfore.2011.01.004

Krishnan, A., Banga, K., & Mendez-Parra, M. (2020). Disruptive technologies in agricultural value chains. Insights from East Africa. Working Paper 576, ODI, London.

Lomeling, D. (2015). Spatial Distribution of Food Poverty Incidence in Juba Town. A geostatistical Assessment. *Journal of Food Security*, 3(1), 11-24, http://doi.org/10.12691/jfs-3-1-3

Lomeling, D., & Huria S. J. (2020). Using the DSSAT-CROPGRO model to simulate gross margin and N-leaching of cowpea fertigated with human urine. *Archives of Agriculture and Environmental Science*, *5*(1), 1-10, http://doi.org/10.26832/24566632.2020.050101.

Matthew J. S. (2018). Getting value from artificial intelligence in agriculture. *Animal Production Science*, *60*(1), 46-54, https://doi.org/10.1071/AN18522

Mulder H., & Biesiot W. (1998). Transition to a Sustainable Society – A Backcasting Approach to Modelling Energy and Ecology. Ed: Edward Elgar, Cheltenham, UK.

Olympio A., Biplove C., & Nicholas J. (2014). An analysis of Government Budgets in South Sudan from a human development perspective Discussion Paper 08/2014, UNDP South Sudan.

Pachico, D., & Fujisaka, S. (2004). Scaling Up and Out: Achieving Widespread Impact Through Agricultural Research. CIAT Publication No. 340, pp 293.

Poppe, K. J., Wolfert, S., Verdouw, C., & Verwaart, T. (2013). Information and communication technology as a driver for change in agri-food chains. *Euro Choices 12*, 60-65.

Price, C. S., Moodley, D., & Pillay, A.,W. (2018). Dynamic Bayesian decision network to represent growers' adaptive pre-harvest burning decisions in a sugarcane supply chain. Proceedings of the Annual Conference of the South African Institute of Computer Scientists and Information Technologists, SAICSIT´18, pp 89–98, https://doi.org/10.1145/3278681.3278693

Rabbi, Md., Ali, S. M., Kabir, G., Mahtab, Z., & Paul, S. K. (2020). Green Supply Chain Performance Prediction Using a Bayesian Belief Network. *Sustainability*, *12*, (3), 1-19, http://doi.org/10.3390/su12031101

Robinson J., Burch S., Talwar S., O'Shea M., & Walsh M. (2011). Envisioning sustainability: Recent progress in the use of participatory backcasting approaches for sustainability research. *Technological Forecasting and Social Change*, 78(5), 756–768, https://doi.org/10.1016/j.techfore.2010.12.006

Rotz, S., Duncan, E., Small, M., Botschner, J., Dara, R., Mosby, I., Reed, M., & Fraser, E. D. G. (2019). The politics of digital agricultural technologies: a preliminary review. *Sociology Ruralis*, 59, 203-229.

Scanagatta, M., Corani, G., de Campos, C.P., & Zaffalon, M. (2018). Approximate structure learning for large Bayesian networks. *Machine Learning*, *107*, 1209–1227, https://doi.org/10.1007/s10994-018-5701-9

Scanagatta, M., Salmerón, A., & Stella, F. (2019). A survey on Bayesian network structure learning from data. *Progress in Artificial Intelligence*, 8, 425–439. https://doi.org/10.1007/s13748-019-00194-y

Sharma S. K., & Sharma S. (2015). Developing a Bayesian Network Model for Supply Chain Risk Assessment, Supply Chain Forum: *An International Journal*, 16(4), 50-72, http://doi.org/10.1080/16258312.2015.11728693

Trendov, N. M., Varas, S., & Zenf, M. (2019). Digital Technologies in Agriculture and Rural Areas: Status Report, Food and Agricultural Organization of the United Nations, Rome. https://datareportal.com/reports/digital-2020-south-sudan.

Woltering, L., Fehlenberg, K., Gerard, B., Ubels, J., & Cooley, L. (2019). Scaling – from "reaching many" to sustainable systems change at scale: A critical shift in mindset. *Agricultural Systems*, *176*, 1-9, https://doi.org/10.1016/j.agsy.2019.102652

World Bank: https://www.worldbank.org/en/country/southsudan/overview. Accessed on 02.04.2021.

Zhang, H., Liu, Y., Zhang, Q., Yan, C., & Xu, S. (2020). A Bayesian network model for the reliability control of fresh food e-commerce logistics systems. *Soft Computing*, *24*, 6499–6519, https://doi.org/10.1007/s00500-020-04666-5