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Using a conceptual Bayesian network to investigate environmental management of vegetable production in the Lake Taihu region of China

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ABSTRACT

Vegetable farms are one of many nitrogen (N) sources adversely affecting Lake Taihu in eastern China. Given the lack of quantitative “cause and effect” relationships and data relating to these systems, we developed a conceptual Bayesian network to investigate and demonstrate causal relationships and the effects of different mitigation strategies on N exports from vegetable farms in the Lake Taihu region. Structurally, the network comprised one primary transport factor, one primary source factor and three post-mobilisation strategies, and three output factors.

In general the network suggests that N exports are more sensitive to transport factors (i.e. runoff volumes) than source factors (i.e. fertiliser application rates) although the cumulative effects of excessive fertiliser were not considered. Post-mobilisation mitigations such as wetlands and ecoditches appear to be particularly effective in decreasing N exports however their implementation on a regional scale may be limited by land availability. While optimising N inputs would be prudent, the network suggests that better irrigation practice, including improved irrigation scheduling, using less imported water and optimising rainfall utilisation would be more effective in achieving environmental goals than simply limiting N supply.

1. Introduction

Lake Taihu is in the lower Changjiang (Yangtze) river delta in eastern China (Fig. 1). As China’s third largest freshwater lake (2334 km^2 and depth of approximately 2 m), Lake Taihu is an important source of domestic, industrial and agricultural water, assists water quantity regulation and provides transport, aquaculture and tourism services to one of China’s most developed areas (Shen et al., 2000). Rapid industrial development and population growth in the second half of the twentieth century has turned the once oligotrophic Lake Taihu (Chang, 1995) eutrophic (Luo et al., 2007), with seasonal algal blooms limiting public and private amenity (Qin et al., 2007). Nutrients enter the lake through urban, industrial and agricultural wastes and wastewaters discharged into tributaries (Qin et al., 2007) and atmospheric deposition (Luo et al., 2011, 2007). Recent reductions in industrial inputs to Lake Taihu have focussed attention on domestic and agricultural sources of nutrients, particularly nitrogen (N) and phosphorus (P) (Qin et al., 2007).

Intensive vegetable production is one of many agricultural industries aiming to mitigate their contribution to the non-point source pollution, particularly N, entering Lake Taihu. While deterministic models such as SWAT (Gassman et al., 2007), LEACHMN (Sogbedji et al., 2001), EPIC (Gassman et al., 2004) and DRAINMOD (Salazar et al., 2009) have been used to simulate N exported from agricultural systems and minimise nutrient exports, in this instance

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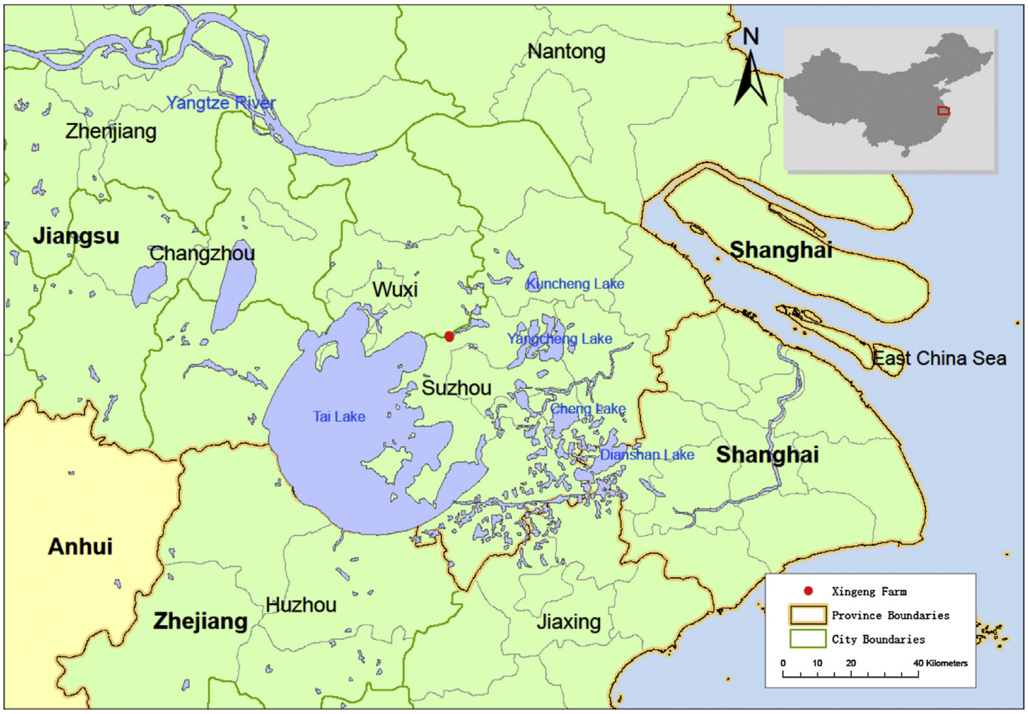

Fig. 1. The location of Xingeng Village Farm.

linking agricultural management to N exports and downstream effects is particularly difficult. There are few empirical relationships on which to base a deterministic model of N exports and there is a general lack of parametric information relating to the site specific characteristics.

Bayesian Networks (Pearl, 1988) are an alternative to conventional modelling that has been used extensively in natural resource sciences to examine complex relationships in data poor environments and for investigating multi-factor problems such as those associated with resource management (Aguilera et al., 2011; Alameddine et al., 2011; Ames, 2002; Ames and Neilson, 2001; Kragt et al., 2011; Nash and Hannah, 2011; Nash et al., 2013; Perez-Minana et al., 2012; Ticehurst et al., 2011; Varis, 1993, 1997; Varis and Kuikka, 1999; Young et al., 2011). Bayesian Networks are well reviewed elsewhere (Jensen and Nielsen, 2007; Korb and Nicholson, 2004; Pourret et al., 2008). In summary, Bayesian Networks provide a graphical representation of "cause and effect" relationships with the strength of the interdependencies (causal links) represented as conditional probabilities. The "nodes" represent variables with defined properties called "states" and directed links (also called arcs which pass from the parent node to the child node) are used to represent dependencies between variables. Dependencies are quantified in a Conditional Probability Table (CPT) associated with each node which considers all combinations of parent node states. Note that while variables may be discrete or continuous, in practice continuous variables are divided into discrete ranges for computational reasons.

Flexibility in data acquisition is a major benefit of Bayesian Networks. CPT's can be populated through direct data analyses (e.g. for probability of rainfall), elicitation of expert opinion, Monte Carlo simulations where deterministic relationships are known (i.e. points are drawn from distributions for inputs), and, where sufficient data are available, machine learning techniques. It is noteworthy that the method of data acquisition affects the structure of Bayesian Networks. For example, where expert opinion is used to populate CPT's the requirement that each CPT considers all combinations of the parent nodes and complexity that creates, places a natural limitation on the number of parent nodes and states.

The probability distributions defined in the CPT's are referred to as *prior* probabilities and relate to the general properties of the environment (i.e. region) and system (i.e. type of farm) to which the Bayesian Network applies. As evidence of state values is received for specific nodes (i.e. the attributes of specific farms are identified), they are added into the network by selecting the appropriate state value (i.e. giving that state a probability of 100%). The resulting *posterior* probability distributions for the remaining nodes in the network, in particular, for a set of query nodes (i.e. N exports), are computed based on basic laws of probability. Consequently, as evidence is added to a network in the form of node values (states), the possible outcomes that the network represents do not change, only the relative probabilities of those outcomes. The changes in the relative probabilities of states (and related mean estimates for nodes with numerical values) before and after evidence of state values is added to the network, reflect projected differences between specific systems and the expected "average" for the system under consideration. These projected differences from "average" can be used to compare and contrast a range of different scenarios for both the prognostic and diagnostic analyses. For example, McDowell et al. (2009) developed a farm scale Bayesian Network that related P exports to site characteristics and management in a data poor region of south-eastern Australia. The network was used to compare current management and best practice to poor management on three case study farms, demonstrating the utility of Bayesian Networks for targeting mitigation measures (McDowell et al., 2009). Nash et al. (2010) developed a field-scale Bayesian Network for N exports from high rainfall cropping in south-eastern Australia. The network was used to investigate the importance of various site factors related to N transport and source factors, especially fertiliser rates, on N exports (Nash et al., 2010).

The aim of this study was to develop a Bayesian Network that could be used to investigate and demonstrate causal relationships and the effects of different mitigation strategies on N exports from vegetable farms in the Lake Taihu catchment of eastern China using Xingeng Village farm as a case study. Given the lack of quantitative "cause and effect" relationships and data relating to these systems a relatively simple conceptual model and conceptually based mathematical equations, rather than experiential data, were used to populate the CPT's. This paper outlines; (a) the network development process; (b) the network and its attributes; and (c) the potential implications of the network output for Government initiatives aimed at mitigating N exports from intensive vegetable production systems and improving water quality in nearby Lake Taihu.

2. Materials and methods

2.1. Characteristics of vegetable growing areas of Xingeng Village Farm

Xingeng Village is located in Wangting town in the Xiangcheng district, in the northwest corner of Suzhou city (N 31°26′, E 120°28′). Being on the plains east of Lake Taihu, south of the Wangyu River and in a Level 1 protected area (refer Ministry of Environmental Protection, 2002), this farm is well located for demonstrating non-point source pollution mitigation measures.

Xingeng Village has a population of 5375 and covers an area of 480 ha, 330 ha of which is used for agriculture (Xingeng Village farm). The village is a modern agriculture demonstration area where the main crops are rice and vegetables. The village also produces mushrooms and grapes, and there are dairy and pig production facilities. This project addressed a 6.7 ha area used for organic vegetable production of which *c.* 4 ha was covered by poly-film greenhouses, *c.* 0.7 ha by multi-span greenhouses and *c.* 1 ha by insect nets, and *c.* 1 ha was exposed land.

The average annual temperature in Xingeng Village is 16 °C (the maximum is 38 °C and the minimum is 5 °C below zero) with 230 frost-free days annually (i.e. minimum temperature >0 °C) and more than 2000 h of non-cloudy weather. The annual rainfall is *c.* 1200 mm with the period between March and August accounting for about 65% of that total. In addition to rainfall, irrigation water sourced from the Wangyu river (Class 4 refer Ministry of Environmental Protection, 2002) is also used for growing vegetables.

Soils at Xingeng Village farm are described locally as "yellow mud" and "gleyed". Hand texturing suggests that the topsoil is a well-structured light clay/loamy clay *c.* 200 mm deep which overlies clay subsoils that have a compacted plough layer (Dr J. Shu, 12-10-11, *personal communication*). During site inspections there was little evidence of slaking or dispersion but there was evidence of mottling in soil brought to the surface through cultivation, suggesting elevated water tables for a substantial portion of the year. The pH value was reported to be between 7 and 7.5. Unfortunately, there is limited information regarding agronomic measures of soil fertility at this site. The use of composted organic materials may be contributing to the reportedly excellent soil structure and reportedly good soil fertility. Intermittent measurements of tail-water runoff on fifteen (15) occasions suggest drainage from the vegetable growing areas of Xingeng Village farm have an average total N (TN) concentration of 19.7 mg N/L (Range 9.6–39.6 mg N/L) and average total P (TP) concentration of 0.92 mg P/L (Range 0.57–1.85 mg P/L).

The main fertilizers used for agricultural production in Xingeng village are composted manure, a commercial organic fertilizer, urea and ammonium bicarbonate. In total approximately 1670 tons of fertiliser materials are applied to the farm annually. The vegetable growing area receives *c.* 650 kg N/ha and *c.* 220 kg P/ha annually through applications of composted manures and commercial organic fertilizer (2.2% N, 0.7% P) applied at annual rates of *c.* 50 and 190 tonnes, respectively.

2.2. Network development process

The process used to develop the Bayesian Network is presented in Fig. 2. The network development drew heavily on the processes used to develop similar networks for other industries (McDowell et al., 2009; Nash et al., 2010) and is consistent with recent guidelines (Chen and Pollino, 2012). To constrain intra-annual variation the network was conceptualised using an annual time-step. At Xingeng Village farm vegetable production areas are surrounded by drainage channels approximately 1 m deep. Consequently, while the network normalises data to the hectare scale, the network was conceptualised as applying at the "plot" scale, where a plot is defined as a hydrologically isolated production area. Using this definition plots on Xingeng Village farm varied between 0.024 and 0.288 ha in size.

Initial knowledge gathering involved two visits to Xingeng Village farm by the project team and extensive reviews of both Chinese and English literature. To address the geographical separation of some team members from the project site and ensure local knowledge was incorporated into project outcomes, a Steering Committee and a Working Committee were established. The Working Committee members dealing directly with farmers from Xingeng Village provided information to the project team at regular (generally bi-weekly) phone conferences. These knowledge gathering activities yielded limited empirical data and deterministic relationships on which the initial "cause and effect" diagram could be based. Consequently, the initial Bayesian Network was conceptualised as having transport and source factors responsible for nutrient generation, similar to P indices (Bechmann et al., 2005; Birr and Mulla, 2001; DeLaune et al., 2004a; DeLaune et al., 2004b; Elliott et al., 2006; Hooda et al., 2000), and post-mobilisation mitigations (i.e. wetlands, drainage re-use, ecoditches). However, unlike index systems, the Bayesian Network facilitated the incorporation of more complex "cause and effect" relationships.

The initial "cause and effect" diagram was developed using NETICA, version 4.08 (Norsys Software Corp., Vancouver, Canada) software. Where deterministic equations are used, NETICA uses forward Monte Carlo simulations to generate the probability distribution for the query nodes (i.e. *Total N Exports*) and was used for the entire model development and interrogation process.

The initial "cause and effect" diagram was reviewed at a specially convened workshop in Xingeng Village. The workshop was attended by the Steering Committee and Working Committee members in addition to four (4) farmers from Xingeng Village. At the workshop the assumptions underlying the diagram were discussed and evaluated. The workshop commenced with an introduction to "cause and effect" relationships and progressed to examine vegetable production. The initial diagram was presented and each node and link was examined in sequence and in detail. This examination comprised a two step process: (a) determining the appropriateness or otherwise of the "cause and effect" diagram's structure; and (b) collecting information regarding node values and relationships. All discussions were recorded on an audio tape and by a designated minute secretary.

The "cause and effect" diagram was modified to reflect comments from the Steering and Working Committees and farmers. While some of the suggested changes were cosmetic (i.e. name changes) there were some significant changes. For example, atmospheric N inputs to the farm had not been included in the cause and effect diagram. The final "cause and effect" diagram comprised one transport factor, one source factor and three post-mobilisation mitigation strategies (a) ecoditches; (b) wetlands; and (c) reuse of drainage water, and three output factors (a) *Nitrogen Concentration (mg/L)* (i.e. the N concentration of runoff from the plot); (b) *Export Efficiency (%)* (i.e. load of N leaving the plot relative to the *Potential N Load*); and (c) *Total N Exports (kg/ha/y)* (i.e. effective output from that area allowing for the effects of post-plot mitigations).

The first step in quantifying the network was to define the states. A full description of each node, its states and the sources of data used for compiling, calculating or estimating values used in the CPT's are presented in the Supplementary documentation accompanying this paper. For most nodes, states were represented as ranges rather than discrete numbers allowing for the uncertainty contained in a particular estimate to be included in the analyses (Fig. 3).

To develop the Bayesian Network, the relationships between parent (independent) and child (dependent) nodes and their states were documented in the CPT's that underpin the Bayesian Network structure (i.e. given each set of conditions in the parent nodes, what are the chances of each condition occurring in the child node?) (Cain, 2001). Where possible, quantitative data (i.e. rainfall records) and deterministic equations (i.e. generally derived from conservation of mass), were used. Deterministic equations were converted by the NETICA software to conditional probability tables and it was assumed that there was no uncertainty due to sampling (i.e. the sampling error was assumed to be part of the overall error of estimates). *Runoff* was estimated using standard methods (Allen et al., 1998) and the *Potential N Load* was estimated as the sum of *Total N Additions* (the sum of fertiliser and irrigation N inputs), *Carry Over N* and *Reapplied N in Reuse Water* minus *Gaseous Emissions* and *Crop N Removal* (Fig. 3).

Three important deterministic equations, not based on the "conservation of mass", related to *Wetland Efficiency*, *Gaseous Emissions* and *Nitrogen Concentration*. The *Wetland Efficiency* estimation is based on an equation adapted from Kadlec and Knight (1996) (Kadlec et al., 2000; Kadlec and Knight, 1996) for total Kjeldahl N with modification for local data (Lu et al., 2009). In the absence of sufficient data to develop statistical relationships, both *Nitrogen Concentration* and *Gaseous Emissions* estimations were conceptualised by technical specialists based on the "expected" rather than measured interactions between factors (Equation 1). *Runoff* and *Potential N Load* were the independent variables in the case of *Nitrogen Concentration*, and *Runoff* and nitrogen load (estimated as the sum of *Total N Additions, Carry Over N* and *Reapplied N in Reuse Water*, less *Crop N Removal*) in the case of *Gaseous Emissions*.

$$y = K_1 + K_2/(1 + \exp(-\eta)) \quad (1)$$

where y = Gaseous Emissions, Nitrogen Concentration (dependant variable); K_1 = Minimum value; K_2 = Maximum value; $\eta = K_3$*(Runoff $- K_4) + K_5$* $(x - K_6)$, K_3 = Estimated parameter; Runoff = Runoff (independent variable); K_4 = Estimated parameter; K_5 = Estimated parameter; K_6 = Estimated parameter; x = *Potential N Load* or nitrogen additions (independent variable).

Potential N Load and *Runoff* were assumed to be positively and negatively correlated to *Nitrogen Concentration* with the rate of change adjusted at the margins. As there was considerable uncertainty regarding parameter estimates and in view of the importance of the equation, the network was structured to enable changes in the

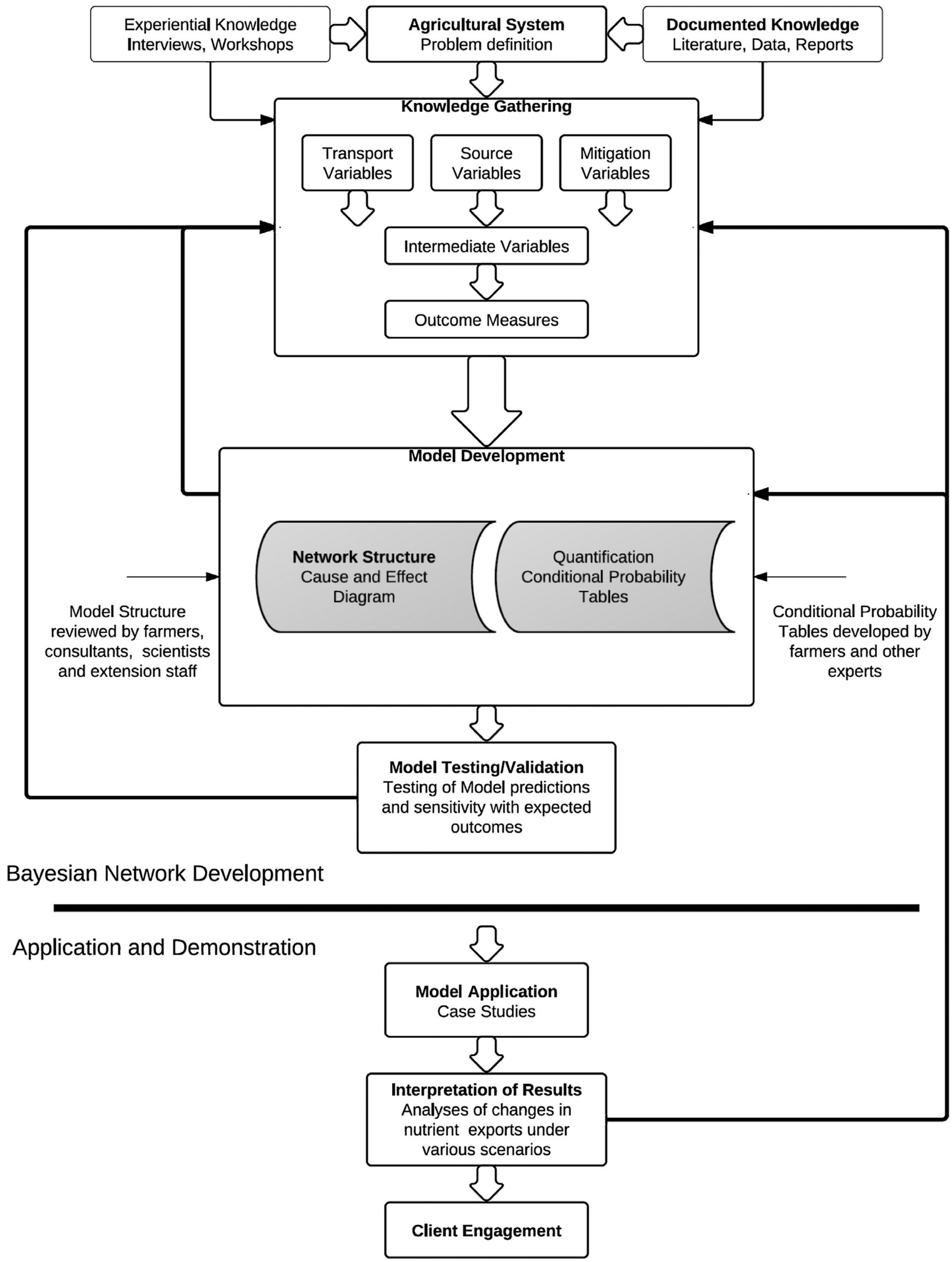

Fig. 2. Methodology for development of a conceptual model to describe nitrogen exports from the vegetable growing areas of Xingeng Village Farm (adapted from Nash et al., 2010).

equation parameters to be varied in order to assess the likely sensitivity of the outcomes to these factors. The upper and lower values were based on literature estimates of N concentration. *Gaseous Emissions* estimation was based on the "expected" relationship between *Runoff* (used as a surrogate estimate for soil water content) and nitrogen additions (estimated as the sum of *Total N additions, Carry Over N* and *Reapplied N in Reuse Water,* less *Crop N Removal*). Having a similar form to Eq. (1), *Runoff* and N additions were assumed to be positively correlated to denitrification and again the maxima and minima were based on literature estimates with input from a technical specialist (Prof. Deli Chen, 9-11-11, *pers. comm.*).

Where deterministic equations were used to derive conditional probability tables, the numerical ranges assigned to states potentially distorted subsequent probability distributions. For example, the NETICA software assumes that all values within a state (defined by upper and lower values) are equally likely to occur when in fact for non-linear equations values closer to the overall mean for that node may have a higher probability of occurrence. To accommodate the use of non-linear deterministic equations in the final network the number of states was often expanded in child nodes and the numerical ranges assigned to states were not uniform. The number of states and numerical ranges assigned to nodes depended on

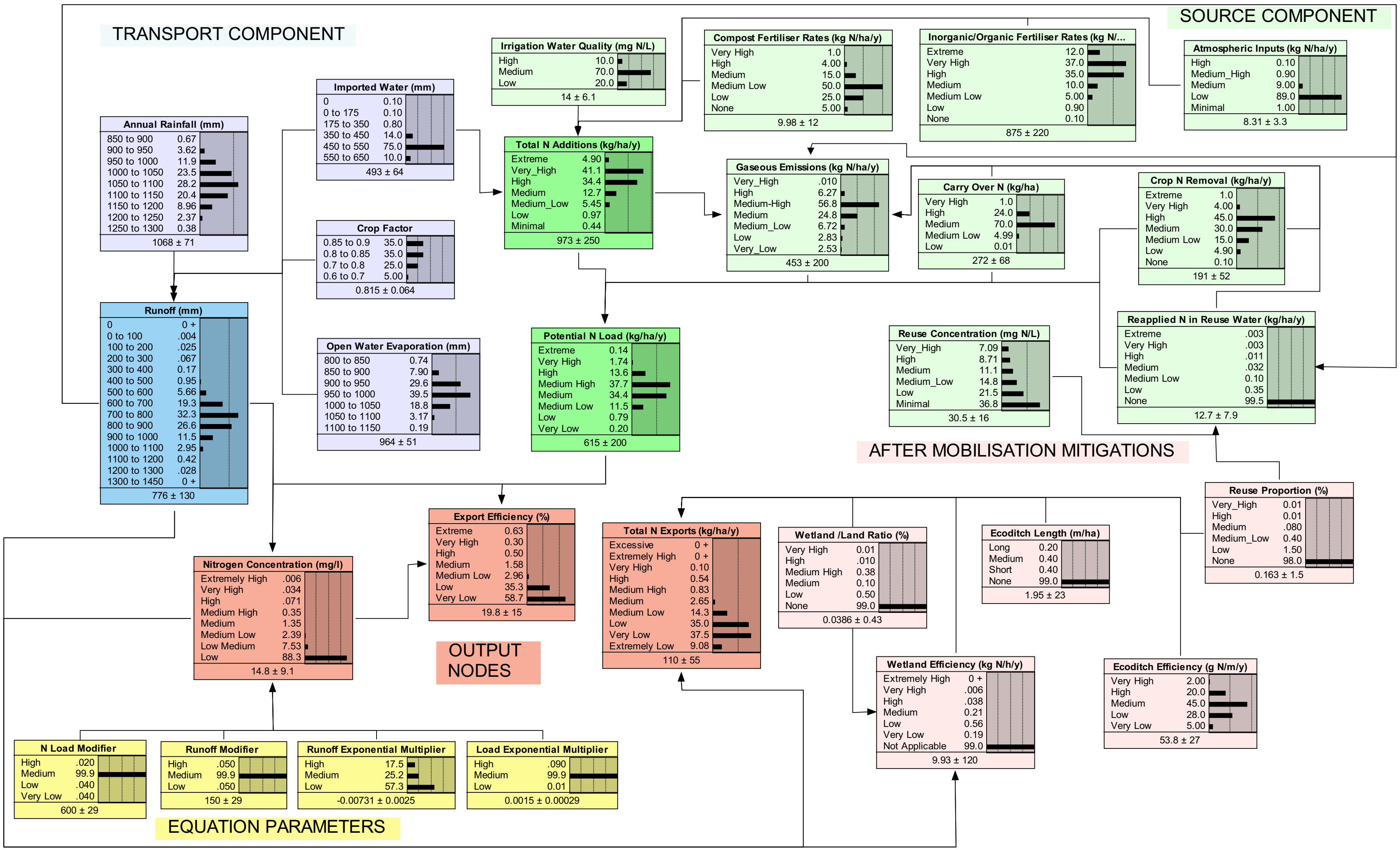

Fig. 3. A Bayesian Network of nitrogen exports from vegetable production on the Xingeng Village Farm.

the forms of the equations (i.e. log-normal) and the influence of the range choice on the estimated mean for the node.

The final network is presented in Fig. 3. In NETICA, the state descriptor for each node and the probabilities of each state can be represented both numerically and by the horizontal column graph. For continuous distributions, a mean estimate for that node, calculated as the sum of products of the mid points of the ranges and probabilities, is presented below the column graph along with the standard deviation. As noted above, the reliability of these estimates will depend on the form of the relevant distribution. As there was no comprehensive data set that could be used for formal validation, the network was assessed by examining a limited number of case studies, and comparing the network output with the expectations of experts familiar with these systems.

"Sensitivity to Findings" function of the NETICA software was used extensively as part of this quasi-validation process to examine specific relationships within the network and compare those with observed data and the assumptions used in their development (Korb and Nicholson, 2004).

3. Results and discussion

3.1. Network analyses and application

The primary network (i.e. with no specified *posterior* probabilities, Fig. 3) represents the "average" expectations for vegetable farms in the Lake Taihu region. The network suggests that *Total N Exports*, *Nitrogen Concentrations* and *Export Efficiency* are respectively (mean ± standard deviation), Medium-Low (110 ± 55), Low (15 ± 9) and Very-Low (20 ± 15) for those farms. The standard deviation being ≥50% of the estimated mean values for output, and many other key nodes, suggests that care needs to be taken when using the network. Importantly, the lack of quantitative information that could be used to develop the network, in addition to the error estimates, suggest that the network should be used primarily for analyses of general trends rather than absolute predictions of nodal values, especially at the margins (Nash and Hannah, 2011).

As a first step to examining the properties of the network, the sensitivity of the two primary Output nodes, *Nitrogen Concentration* and *Total N Exports*, to other nodes, were investigated. The primary measure used to compare the sensitivity of the Output nodes to Transport, and Source nodes and After Mobilisation Mitigation nodes was variance reduction. The Output nodes are quantitative and have an initial distribution. When information is supplied about the state of a parent (e.g., *Runoff* or *Potential N Load*) node, this may shrink the Output node distribution towards more probable values, reducing its variance. The variance reduction then is simply the difference between the variances of the Output node distribution computed before and after information was supplied. A second metric, Belief variance, can also be used. Belief variance measures the expected squared change in class probabilities in the Output node distribution when information is supplied about the state of a parent. The variance reduction and belief variance are each averaged appropriately over the range of the parent node values. Both these metrics can be automatically computed from within the NETICA software. The sensitivity analyses are presented in Table 1.

Nitrogen Concentration was most sensitive to *Total N Exports* and *visa versa* reflecting the computational relationship between the two. *Runoff* and *Imported Water* were the next most important factors, presumably reflecting the direct relationship between transport factors and *Nitrogen Concentration*. The observation that *Potential N Load*, which was a parent node, had less effect on the *Nitrogen Concentration* than *Imported Water*, is important from a management perspective. It implies that management of imported water is the best way to optimise nitrogen concentrations given that *Annual Rainfall*, *Crop Factor* and *Open Water Evaporation*, which were the fifth, ninth and tenth most important factors affecting *Nitrogen Concentration*, are generally not amenable to management intervention. *Potential N Load* was the fourth and *Gaseous Emissions* the seventh most important factors affecting *Nitrogen Concentration*. In part the lower importance of source related factors can be attributed to their distance from the target

Table 1
Sensitivity analyses of the *Nitrogen Concentration* and *Total N Exports* nodes of the vegetable Bayesian Network.[a]

Nitrogen Concentration					*Total N Exports*				
Order	Node	Variance Reduction[b]	Percent	Belief Variance[c]	Order	Node	Variance Reduction	Percent	Belief Variance
0	Nitrogen Concentration	64.5	100	0.1170	0	Total N Exports	2845	100	0.5141
1	Total N Exports	39.5	61.2	0.0219	1	Nitrogen Concentration	1144	40.2	0.0134
2	Runoff	30.2	46.9	0.0170	2	Runoff	219	7.7	0.0043
3	Imported Water	12.2	18.9	0.0038	3	Export Efficiency	203	7.1	0.0016
4	Potential N Load	9.4	14.6	0.0077	4	Potential N Load	127	4.5	0.0007
5	Annual Rainfall	4.1	6.4	0.0057	5	Runoff Exponential Multiplier	113	4.0	0.0011
6	Export Efficiency	4.1	6.3	0.0070	6	Imported Water	41	1.4	0.0003
7	Gaseous Emissions	3.1	4.9	0.0027	7	Annual Rainfall	17	0.6	0.0005
8	Runoff Exponential Modifier	3.0	4.6	0.0077	8	Wetland Efficiency	14	0.5	0.0003
9	Crop Factor	1.5	2.3	0.0029	9	Wetland/Land Ratio	11	0.4	0.0002
10	Open Water Evaporation	1.3	2.0	0.0020	10	Total N Additions	8	0.3	0.0000
11	Wetland Efficiency	0.3	0.5	0.0001	11	Inorganic/Organic Fertiliser Rates	7	0.2	0.0000
12	Inorganic/Organic Fertiliser Rates	0.2	0.3	0.0003	12	Crop Factor	6	0.2	0.0003
13	Total N Additions	0.1	0.2	0.0003	13	Gaseous Emissions	3	0.1	0.0002
14	Carry Over N	0.0	0.0	0.0000	14	Reuse proportion	3	0.1	0.0000
15	Crop N Removal	0.0	0.0	0.0000	15	Open Water Evaporation	2	0.1	0.0001
16	Runoff Modifier	0.0	0.0	0.0000	16	Ecoditch Length	2	0.1	0.0000
17	Reapplied N in Reuse Water	0.0	0.0	0.0000	17	Reapplied N in Reuse Water	2	0.0	0.0000
18	Irrigation Water Quality	0.0	0.0	0.0000	18	Ecoditch Efficiency	1	0.0	0.0001
19	N Load Modifier	0.0	0.0	0.0000	19	Carry Over N	1	0.0	0.0000
20	Load Exponential Multiplier	0.0	0.0	0.0000	20	Crop N Removal	1	0.0	0.0000
21	Compost Fertiliser Rates	0.0	0.0	0.0000	21	Runoff Exponential Multiplier	0	0.0	0.0000
22	Atmospheric Inputs	0.0	0.0	0.0000	22	Irrigation Water Quality	0	0.0	0.0000
23	Ecoditch Length	0.0	0.0	0.0000	23	N Load Modifier	0	0.0	0.0000
24	Ecoditch Efficiency	0.0	0.0	0.0000	24	Load Exponential Multiplier	0	0.0	0.0000
25	Reuse Proportion	0.0	0.0	0.0000	25	Compost Fertiliser Rates	0	0.0	0.0000
26	Wetland/Land Ratio	0.0	0.0	0.0000	26	Atmospheric Inputs	0	0.0	0.0000
27	Reuse Concentration	0	0.0	0.0000	27	Reuse Concentration	0	0.0	0.0000

[a] For colour scheme refer Fig. 3.
[b] "Variance Reduction" is the average reduction in the variance of the target node (*Nitrogen Concentration* or *Total N Exports*) distribution when the state of parent/ancestor is known.
[c] The "Belief Variance" measures the corresponding change in the target node distribution

node. However, the low sensitivity of *Nitrogen Concentration* to *Total N Additions* compared to *Gaseous Emissions* highlights the potential importance of denitrification in these systems and warrants further investigation. As expected After Mobilisation Mitigations had negligible effect on the *Nitrogen Concentration* which is estimated at the plot scale.

Runoff was the second most important factor affecting *Total N Exports* with the other transport related factors *Imported Water, Annual Rainfall*, *Crop Factor* and *Open Water Evaporation* sixth, seventh, twelfth and fifteenth. *Potential N Load* was the fourth most important factor affecting *Total N Exports* with *Total N Additions* and *Inorganic/Organic Fertiliser Rates* and *Gaseous Emissions*, tenth, eleventh and thirteenth, respectively. While, *Total N Exports* was sensitive to wetland properties (i.e. *Wetland Efficiency* and *Wetland/Land Ratio* were the eighth and ninth most important factors), the effects of reuse (*Reuse Proportion* was the fourteenth most important factor) and ecoditches (*Ecoditch Length* and *Ecoditch Efficiency* were the sixteenth and eighteenth most important factors) were a little surprising. The low sensitivity of *Total N Exports* to the After Mobilisation Mitigation nodes compared to Source and Transport nodes results from them not being used on the majority of farms in the target region and that observation being reflected in the *prior* probabilities of the respective nodes (i.e. if a mitigation strategy only applies to a limited number of farms, regional scale N exports are relatively insensitive to that mitigation strategy). The Belief Variance results were generally consistent with the Variance Reduction results.

In the absence of alternative data, the Xingeng Village farm was used as a basis for a series of case studies to investigate the properties of the network and the effects of different farming systems, including potential mitigation measures. The results of those investigations are presented in Table 2. The network suggests that generally, water exiting plots on Xingeng Village farm has a Low-Medium *Nitrogen Concentration* (32 ± 9), the farm has Low *Export Efficiency* (25 ± 11), and Very-Low *Total N Exports* (47 ± 33) at the whole of farm scale (i.e. where After Mobilisation Mitigations are included). These figures are generally consistent with snapshot monitoring (mean 19.7 mg N/L mean and range of 9.6–39.6 mg N/L) while *Total N Exports* in particular compares favourably with other farms in the region (Table 2, No. 0). The conceptual equation relating *Runoff* and *Potential N Load* to *Nitrogen Concentration* also affects the performance of the network. Comparing current practice with the upper and lower limits that might be expected (Table 2, Nos. 1a, 1c and 1d) for a system similar to Xingeng Village farm suggests that the equation parameters have relatively minor effects on the states of the Output nodes.

Investigating the effects of mitigation strategies using a Bayesian Network is somewhat more difficult than with conventional process models. The relationships defined in the CPT's, which enable diagnostic as well as prognostic analyses, can easily lead to misinterpretation where the *posterior* probabilities of more than just the target node vary. Based on the CPT's, the network estimates the most probable combination of factors leading the particular state values entered. Consequently, it is important to check when comparing mitigation strategies by giving a particular state of a node a probability of 100% that only target node is altered. For example, comparing current practice on Xingeng Village farm with (Table 2, No. 1a) and without specifying a state value for *Wetland Efficiency* (Table 2, No 1b) counter-intuitively suggests that lower wetland efficiency may be associated with lower N exports (*Total N Exports* 47 ± 33 and 42 ± 33 respectively). The network specifies that *Wetland Efficiency* depends on hydraulic retention time, which is affected by the runoff volume. Consequently, specifying the state of the *Wetland Efficiency* node affects the *posterior* probabilities of other nodes including *Runoff*, *Gaseous Emissions* and *Potential N Load*. In such cases the comparison is between two farming systems (and combinations of climatic factors) rather than two mitigation strategies. Similarly, the network suggests that increasing the size of a wetland by 150% is likely to be associated with only marginally reduced *Total N Exports* (Table 2, No. 2a) and probably increases *Total N Exports* if that change is accompanied by improved *Wetland Efficiency* (Table 2, No. 2b). Again, specifying the state of the *Wetland Efficiency* node affects the *posterior* probabilities of other nodes. For an increasing area of wetlands, a more appropriate comparison is between current practice and the *prior* probability distribution of *Wetland Efficiency*. That comparison (Table 2, Nos. 1b and 2b) suggests, as one might expect, that increasing the proportional area of wetlands does not affect plot scale *N Concentration* but decreases farm scale *Total N Exports* from 47 ± 33 to 34 ± 27. When appropriately compared, the incremental reductions in *Total N Exports* attributable to higher *Wetland/Land Ratio* are similar to that which occurs with higher *Ecoditch Efficiency* (Table 2, No. 3).

Compared to current practice, the network suggests that an absence of After Mobilisation Mitigations (Table 2, No. 4) is likely to be associated with similar *Nitrogen Concentration* and *Export Efficiency*, but significantly increased *Total N Exports* (i.e. Medium-Low compared with Very-Low). The network suggests that 40–50% drainage reuse does not compensate for the loss of the other mitigations as there would probably be an increase in *Total N Exports* compared to current practice (i.e. Low rather than Very-Low, see Table 2, No. 5). The observation that the changes to *Total N Exports* were in proportion to the *Reuse Proportion* suggests that the additional N in reuse water has little overall impact on N exports. The network also suggests that a maximal *Wetland/Land Ratio* (10%) (Table 2, No. 6) has a similar effect on *Total N Exports* to 50% drainage reuse. This appears reasonable given that the reuse water is assumed on average to have a Low to Medium-Low N concentration (*c.* 30 mg N/L). Overall, the network suggests that ecoditches are the most effective of the After Mobilisation Mitigations (Table 2, No. 7). Ecoditches appear to be capable of achieving similar results to the current suite of reuse, wetland and ecoditch mitigations.

Source management is an alternative strategy that can be used to mitigate N exports. The network suggests that for farms similar to the Xingeng Village farm, reducing fertiliser applications from Medium (500–700 kg N/ha) to Low (0–300 kg N/ha) has a small effect on *Nitrogen Concentration* (i.e. Low as compared to Low-Medium, Table 2, No. 8) but is probably less effective than the After Mobilisation Mitigations in lowering *Total N Exports* (i.e. Low as compared to Very-Low). This is consistent with the relative insensitivity in the short term of the Output nodes to Source nodes as identified in the sensitivity analyses. However, being based on an annual time-step, it is noteworthy that this network does not consider the cumulative effects of nutrient inputs.

In complex farming systems it is rare to change only one aspect of the system. To demonstrate the utility of the Bayesian Network for assessing the cumulative impacts of management changes the combined effects of higher than usual *Inorganic/Organic Fertiliser Rates, Compost Fertiliser Rates*, *Carry Over N* and *Imported Water* were compared (Table 2, No. 9). The network suggests that these interventions will have little effect on *Total N Exports* but lower *Nitrogen Concentration* and *Export Efficiency* compared to the current situation. Again this could be considered counterintuitive but it is in keeping with the sensitivity analyses. The suggested outcomes are likely in years when there is increased *Runoff* (880 compared to 550 mm) which leads to dilution and increased *Gaseous Emissions* (Very-High compared to Low) as a result of increased N availability and water-logging. If *Gaseous Emissions* are

Table 2
Case studies of the vegetable Bayesian Network.

No.	Description	Imported water (mm)	Rainfall (mm)	Runoff (mm)	Compost fertiliser rate (kg/ha/y)	Inorganic/organic fertiliser rate (kg/ha/y)	Gaseous emissions (kg N/ha/y)	Carry over N (kg/ha)	Wetland/land ratio (%)	Wetland efficiency (kg N/ha/y)	Ecoditch length (m)	Ecoditch efficiency (g N/m/y)	Reuse proportion (%)	Nitrogen conc. (mg/L)	Export efficiency (%)	Total N exports (kg/ha/y)
Regional estimates																
0	Prior probabilities only	493 ± 64[a]	1068 ± 71	776 ± 130	Medium-low (10 ± 12)	High (875 ± 220)	High (453 ± 200)	Medium (272 ± 68)	(0.04 ± 0.4)	(9.9 ± 120)	(2.0 ± 23)	(54 ± 27)	(0.2 ± 1.5)	Low (15 ± 9)	Very low (20 ± 15)	Medium-low (110 ± 55)
Xingeng Village Farm																
1(a)	Current practice	175–350[b]	1050–1100	527 ± 93	Medium (10–30)[c]	Medium (500–700)[d]	Low (78 ± 75)	Medium (200–300)[e]	Medium (4)[e]	Medium (1250–2000)[e]	Long (300–450)[e]	Medium (40–70)[e]	Medium (20–30)[f]	Medium-low (32 ± 9)	Low (25 ± 11)	Very-low (47 ± 33)
1(b)	Current practice *Wetland Efficiency* not specified	175–350	1050–1100	552 ± 100	Medium	Medium	Low (96 ± 91)	Medium[e]	Medium	Low 1240 ± 740	Long	Medium	Medium	Medium-low (25 ± 17)	Low (20 ± 13)	Very-low (42 ± 34)
1(c)	Current practice lower limit[g]	175–350	1050–1100	765 ± 110	Medium	Medium	Medium-low 270 ± 120	Medium	Medium	Medium	Long	Medium	Medium	Low (13 ± 6)	Very-low/low (20 ± 14)	Very-low (25 ± 17)
1(d)	Current practice upper limit[h]	175–350	1050–1100	649 ± 76	Medium	Medium	Medium-low 168 ± 110	Medium	Medium	Medium	Long	Medium	Medium	Medium-low (30 ± 8)	Low (35 ± 12)	Low (62 ± 38)
2(a)	Current practice[i] (1a) larger wetland	175–350	1050–1100	474 ± 73	Medium	Medium	Low (50 ± 44)	Medium	Very-high (10)	Medium	Long	Medium	Medium	Medium (57 ± 14)	Low (35 ± 10)	Very-low (43 ± 36)
2(b)	Current practice Larger Wetland *Wetland Efficiency* not specified	175–350	1050–1100	552 ± 100	Medium	Medium	Low (96 ± 91)	Medium	Very-high	Low 711 ± 480	Long	Medium	Medium	Medium-low (25 ± 17)	Very-low/low (20 ± 13)	Very-low (34 ± 27)
3	Optimum Ecoditch Efficiency *Wetland Efficiency* not specified	175–350	1050–1100	552 ± 100	Medium	Medium	Low	Medium	Medium	Low 1240 ± 740	Long	Medium	Medium	Medium-low (25 ± 17)	Very-low/low (20 ± 13)	Very-low (31 ± 25)
4	No after mobilisation mitigations	175–350	1050–1100	552 ± 100	Medium	Medium	Low (84 ± 80)	Medium	None (0)	Not-applicable	None (0–0)	Medium	None (0–0)	Low-medium (25 ± 17)	Very-low/low (20 ± 13)	Medium-low (128 ± 77)
5	Single reuse effect *Wetland Efficiency* not specified	175–350	1050–1100	552 ± 100	Medium	Medium	Medium-low (112 ± 100)	Medium	None	Not-applicable	None	Medium	Very-high	Low-medium (26 ± 18)	Very-low (19 ± 13)	Low (73 ± 48)
6	Single wetland effect *Wetland Efficiency* not specified	175–350	1050–1100	552 ± 100	Medium	Medium	Medium-low (84 ± 80)	Medium	Very-high	700 ± 470	None	Medium	None	Low-medium (25 ± 17)	Very-low/low (20 ± 13)	Low (63 ± 48)
7	Single Ecoditch Effect	175–350	1050–1100	552 ± 100	Medium	Medium	Medium-low (84 ± 80)	Medium	None	Not-applicable	Long	Very-high (100–215)	None	Low-medium (25 ± 17)	Very-low/low (20 ± 13)	Very-low (36 ± 32)
8	Single effect of lower fertiliser No after mobilisation mitigations	175–350	1050–1100	552 ± 100	Medium	Low (0–300)	Medium-low (26 ± 16)	Medium	None	Not-applicable	None	Medium	None	Low (17 ± 10)	Medium-low (42 ± 27)	Low (92 ± 50)
No after mobilisation mitigations																
9	High fertiliser, carryover N and imported water	550–650	1068 ± 71	883 ± 110	Very-high (60–100)	Very-high (900–1100)	Very-high (799 ± 140)	Very-high (400–800)	None	Not-applicable	None	Medium	None	Low (13 ± 6)	Low (15 ± 11)	Medium-low (117 ± 51)
10	High fertiliser and carryover N Medium *gaseous emissions*	327 ± 160	993 ± 71	434 ± 100	High	Very-high	Medium (200–400)	Very-high	None	Not-applicable	None	Medium	None	Medium-low (64 ± 38)	Low (21 ± 12)	Medium-high (254 ± 130)
Diagnostic analyses																
11	Very high *Nitrogen concentration* No after mobilisation mitigations	67 ± 110	1011 ± 66	210 ± 81	Medium (10 ± 13)	High (961 ± 170)	Low (56 ± 71)	279 ± 71	None	Not-applicable	None	Medium	None	Very-high (120–160)	Low (27 ± 12)	Very-high/high (300 ± 130)

(*continued on next page*)

Table 2 (*continued*)

No.	Description	Imported water (mm)	Rainfall (mm)	Runoff (mm)	Compost fertiliser rate (kg/ha/y)	Inorganic/organic fertiliser rate (kg/ha/y)	Gaseous emissions (kg N/ha/y)	Carry over N (kg/ha)	Wetland/land ratio (%)	Wetland efficiency (kg N/ha/y)	Ecoditch length (m)	Ecoditch efficiency (g N/m/y)	Reuse proportion (%)	Nitrogen conc. (mg/L)	Export efficiency (%)	Total N exports (kg/ha/y)
12	Extremely-high *Total N Load* No after mobilisation mitigations	357 ± 150	1002 ± 72	480 ± 130	Medium (11 ± 13)	Very-high (1060 ± 130)	Medium (284 ± 210)	298 ± 98	None	Not-applicable	None	Medium	None	Very-high (116 ± 31)	Medium-low (43 ± 10)	Extremely-high (600–800)

[a] State or most probable state, where a posterior probability is specified (i.e. one state given a value of 100%) the state range is specified in parenthesis the first time it is listed. Where the state Name is not numeric and a posterior probability has not been specified, the estimated mean and standard deviation is specified in parenthesis and the state Name reflects the estimated mean. State Names reflecting the estimated mean are not provided for some After Mobilisation Mitigations.

[b] Estimated from pumping figures at the reuse pond (500 mm/ha) and 50% overall reuse from the pond.

[c] Estimated as 50 tonnes applied over 6.7 ha with 10% dry matter and 30 g N/kg DM.

[d] Estimated as 190 tonnes applied over 6.7 ha at 2.2. %N local estimate.

[e] Local estimate.

[f] Estimated from pumping figures at the reuse pond (500 mm/ha) and 50% overall reuse from the pond.

[g] *N Load Modifier*, High; *Runoff Modifier*, Low; *Runoff Exponential Modifier*, High; *Load Exponential Modifier*, Low.

[h] *N Load Modifier*, Very Low; *Runoff Modifier*, High; *Runoff Exponential Modifier*, Low; *Load Exponential Modifier*, High.

[i] *N Load Modifier*, Medium; *Runoff Modifier*, Medium; *Runoff Exponential Modifier*, Low; *Load Exponential Modifier*, Medium, *Potential N Load*, Medium High.

then restricted to Medium (i.e. 200–400 kg N/ha) (see Table 2, No. 10), the network suggests that combination of *posterior* probabilities is likely to occur in years of significantly less runoff (i.e. 430 compared to 880 mm), that *Nitrogen Concentrations* and *Export Efficiency* will be similar to current practice, and *Total N Exports* significantly higher (i.e. Very-Low for current practice compared to Medium-Low and Medium-High for unrestricted and Medium *Gaseous Emissions*, respectively). While these examples demonstrate the utility of Bayesian Networks for investigating complex systems, it should be noted that there are artefacts of the discretisation process, especially at the margins, that may exaggerate mean estimates (Nash and Hannah, 2011) of states.

Finally the diagnostic properties of the network were examined by investigating the combination of factors most likely to lead to a Very-High *Nitrogen Concentration* and Extremely-High *Total N Exports* (see Table 2, Nos. 11 and 12). The network suggests that Very-High *Nitrogen Concentration* is most likely to occur when *Runoff* is lower (i.e. 210 ± 81 mm compared to 776 ± 130 for the "average" farm) due to lower *Imported Water* (i.e. 67 ± 110 mm compared to 493 ± 64 mm), and the *Potential N Load* is higher (i.e. Very-High compared to Medium-High) due to Low as compared to High *Gaseous Emissions* in the primary analyses. The network suggests that Extremely-High *Total N Exports* will occur in years of less than average *Runoff* (i.e. 480 ± 130 mm compared to 776 ± 130 mm), when there is an Extreme *Potential N Load* as a result of Very-High or Extreme *Inorganic/Organic Fertiliser Rates* and slightly reduced *Gaseous Emissions* (i.e. Medium compared to High).

3.2. Concluding discussion

Nitrogen exports from vegetable production systems in the Lake Taihu region of China are an important local issue. Given the lack of quantitative "cause and effect" relationships and data relating to these systems, a Bayesian Network was developed, primarily based on a relatively simple conceptual model and conceptually based mathematical equations, rather than experimental or experiential data. The outputs from the network make sense and, with the possible exception of *Gaseous Emissions*, are generally consistent with the limited literature that is available from the target area (Table 3). Data regarding *Gaseous Emissions* is equivocal. Unfortunately, while it is relatively easy to measure nitrogen dioxide and di-nitrogen oxide, di-nitrogen gas is difficult to measure and can comprise a considerable portion of denitrification products especially under waterlogged conditions and at higher soil pH (Simek and Cooper, 2002; Stevens et al., 1998). Where drainage losses of N have been estimated (Table 3), conservation of mass would suggest that losses of gaseous N are significantly greater than that measured as nitrogen dioxide and di-nitrogen oxide. The conceptual equation relating *Runoff* and *Potential N Load* to *Nitrogen Concentration* is also important. However, comparing network estimations using the upper and lower parameter limits that might be expected (Table 2, Nos. 1a, 1c and 1d), suggests the equation parameters have relatively minor effects on the states of the Output nodes.

In terms of resource allocation, this study would suggest that After Mobilisation Mitigations are particularly effective in decreasing N exports. Given that water storages exist in many parts of the target area but there is limited availability of land, ecoditches and reuse systems appear useful ways to mitigate N exports and at the village scale may be integrated with wetlands and/or other agricultural pursuits (i.e. fish farming). However, as the network amply demonstrates, these are farming systems where consideration needs to be given to the interactions between the different components of the system. Factors such as

Table 3
Selected studies of vegetable production and the associated nitrogen transformations in the Lake Taihu region of China.

Site	Time period of study	Crops	Annual rainfall (mm)	Fertiliser rate (kg N/ha)	Additional N source (kg N/ha yr)	Gaseous losses (kg N/ha yr)	Leaching losses (kg N/ha yr)	Residual mineral N (kg N/ha)	Depth to groundwater (m)	Reference
Yixing, Jiangsu Province	April 2008–March 30, 2010	Tomato Sweet Corn Cucumber Celery		0–870			11–123	<1350 (0–0.1 m)	0.8	(Min et al., 2011a)
Yixing, Jiangsu Province	April 2006–March 2007	Tomato Cucumber Celery	1177	0–870	Wet deposition, 6	Unaccounted for N 28–134	62–172	151 (0–0.5 m)	0.8	(Min et al., 2011b)
Nanjing, Jiangsu Province	Sep. 4–Dec. 6, 2003	Chinese Cabbage		0–600		Total gaseous losses 20–46				(Bing et al., 2006)
Jiaxing, Zhejiang Province	Aug. 28–Dec. 17 2006	Cabbage Garlic Radish	1167	271 268 264		Total gaseous losses 3–31				(Pang et al., 2009)
Yixing, Jiangsu Province	May, 2009	Tomato Baby Bok Choi	*c.* 1100	<1400				335–1157 (nitrate, 0–0.2 m)		(Zhu et al., 2011)
Yixing, Jiangsu Province	June 2005–June 2006	Pokchoi Spinach Tomato	1048	1310			32% groundwater samples >50	256–832		(Shi et al., 2009)
Nanjing, Jiangsu Province	26 Nov. 2001–26 Jan. 2003	Radish Baby Bok Choy Lettuce Baby Bok Choi Celery		323 142 129 246 796		148 Whole of year flux denitrification (N_2O)				(Xiong et al., 2006)

water and soil pH, N concentration and N species (i.e. ammonium concentration) would be important in the development of such integrated systems.

At the plot scale, limiting N inputs is often seen as the simplest and easiest way to reduce N concentrations in drainage. However, the relationships between *Runoff* and other factors, especially *Gaseous Emissions*, and the high N requirements of vegetable crops suggests that such a simple solution, while helping mitigate N exports, may not be the best option as it ignores the complex interactions occurring in these systems. Better irrigation practice including improved irrigation scheduling, using less imported water and optimising rainfall utilisation, when coupled with nitrification inhibitors (Cui et al., 2011), may be more effective than simply limiting N supply in achieving environmental goals. This is not to argue that optimising N fertiliser application rates is unimportant. Rather, it is to argue that these are farming systems and, as the network suggests, the optimum combination of mitigation strategies will depend on the farm in question.

Vegetable production in the Lake Taihu region is not atypical of such systems elsewhere in China (Ju et al., 2004; Wang et al., 2008) or other countries (refer for example Wilkinson et al., 2009). A better understanding of the factors affecting N exports from these systems is needed to fully assess the potential value of Bayesian Networks and similar modelling technologies for system optimisation and policy development. That requires data. Based on this study it is possible to identify some relatively easy and useful data acquisition activities. *Runoff* is a key transport parameter. Topography in the Lake Taihu region necessitates the use of electric pumps for irrigation. Recording irrigation times, pump characteristics and energy consumption can provide useful data on water use. Water use data, when added to meteorological data, can be used to estimate evapotranspiration (Allen et al., 1998), estimate runoff volumes and guide iterative improvements in irrigation practice. Similarly, input and output data from plots (i.e. fertiliser rates, produce removed) can be manually recorded and when coupled with strategic water quality monitoring used to prepare a simple mass balance. Proprietary or purpose built rising stage samplers (Hawdon et al., 2007) and proprietary water test kits have made water testing more accessible and much cheaper. Such data collection activities can provide in the relatively short term (i.e. <5 years) sufficient data to increase the resolution of models such as the one developed in this project, particularly in respect to gaseous emissions.

From a policy perspective the Bayesian Network developed through this project has a range of potential applications. Firstly, the network could be used as part of a training programme. The complex interactions that lead to nutrient exports are not always intuitively apparent. Bayesian Networks such as the one developed in this project have been used in participatory learning programs for both technician and farmer participants (McDowell et al., 2009; Nash et al., 2010). Appropriate training will be important if irrigation management is to be considered an environmental as well as production issue. Secondly the network could be used to prioritise farms for mitigation of N exports. Such an application would require extension staff to visit and assess individual farms. While this would be time consuming, the data collected during those visits would be extremely useful in defining the *prior* probabilities in the network and therein regional norms against which individual farms should be assessed. Finally, an improved network based on better data could be used to develop individual solutions for specific farming enterprises. In so doing the network could potentially be used to quantitatively estimate the costs and benefits of particular on-farm solutions.

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Appendix A. Supplementary material

Supplementary material related to this article can be found at http://dx.doi.org/10.1016/j.envsoft.2013.03.008.

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