

Discussion of ‘Environmental decision-making using Bayesian networks: creating an environmental report card’

Divergent indicator systems are commonly used in the field of industry, to monitor the environmental impacts and sustainability of the business (e.g. [1, 2]). Johnson *et al.* present an application for assessing the environmental health of a harbour. A Bayesian Network (BN) is utilized in integrating and categorizing information from different types of measurements, using their spatial variation as the source of uncertainty. The integration occurs on multiple levels: from measures to indicators, further on to indicator groups and finally to an environmental component of an even more holistic environmental reporting system. Aggregation of the message of multiple environmental indicators and assessment units is a very topical issue in Europe, where corresponding indicator approaches are adopted to assess the ecological status of aquatic systems, for example, by EU’s Marine Strategy Framework Directive (EC [3]) and Water Framework Directive (WFD, EC [4]). BNs have several advantageous characteristics for this type of analysis as demonstrated in this paper, as well as by, for example, Lehtikoinen *et al.* [5] and Moe *et al.* [6]. The present paper is a good demonstration of the properties of the method and one possible way to apply it in the indicator approach. The presented model is apparently made for the real use of managers, which makes the simplicity one important criteria for the model’s goodness. In the following, I discuss some potential further development ideas, covering both methodological and management oriented observations.

1. Sources of uncertainty

In the presented Bayesian Network (BN), the uncertainty arises only from the spatial variation of the measurements among the sites within one harbour zone (proportion of the monitoring sites that are assigned to a certain class). Rather than a probability distribution, I see this as a frequency distribution that shows the zone’s ‘level of belonging to a certain class’. Of course, given that the selection of sampling sites manages to represent the whole zone in a balanced way, we could think that this distribution tells us the probability of getting a certain result if we go to the area and take a random sample.

One of the criteria mentioned in the text for selecting the water and sediment quality measures composing an indicator was the amount of natural fluctuation, which impedes the detection of the signals of interest. With a BN, it would actually be relatively easy to sort out this type of ‘noise’ caused by randomly fluctuating external drivers, such as weather conditions, by including them in the modelled system ([5, 6]). Data on external driver at the moment of the measurements could be included in the data set, and its effect on the quality measures learned, for example, by using the expectation–maximization–algorithm, which enables estimating the conditional probability distributions based on a data set when only the graphical BN structure is given [7]. This would allow the model user to analyze whether an improved or impaired environmental status is likely resulting from human activities or is caused by some external drivers. Even the latter alternative may, in the long run, mean that the human activities need to be regulated to adapt to the potentially changing external conditions.

2. Acknowledging links between measures, indicators and zones

In the presented application, measures that in reality are highly correlated (such as nitrogen and phosphorus concentration and other water quality factors) are handled as independent of each other, meaning that there are no links between those variables in the BN structure. As the distribution of one quality measure represents variation in the observations among the sites of a zone, this means that the informative links between the observations from the same site, where the same background conditions are known to affect behind all the measures, is lost. In addition, neighboring zones are typically

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more correlated by their status than those with longer distance or physical barriers between them. As the presented BN application is used for aggregating divergent elements only, and not for diagnosing or manipulating the system, the existence of links do not affect the results. Including the links would, however, be an easy way to increase uses of the model, making it an even more versatile tool. It would enable making assessments despite some missing data, even for some data poor areas, as the observed measures would help in inferring the likely status of some unobserved variable. Similarly, the knowledge concerning the status of nearby areas would update our belief on the status of a data-poor area.

Another additional value gained by including the links in the BN structure, would be its use for the management planning purposes. For example, such a model could be used for evaluating how the management actions targeted to a certain zone would likely affect the state of the surrounding zones, or how management of some particular measures (e.g. nutrients) would likely affect the other measures. Also in this case, the quantitative dependencies between the nodes in the BN could be learned from data by using the expectation–maximization–learning algorithm.

3. Aggregation rules and the risk of misclassification

Aggregation of the information provided by several assessment units is an interesting topic as several alternative ways to do this exist. In the presented case, aggregation of the measures, indicators and the higher order units is based on averaging over the frequency distributions. To make end-user-friendly statements on the status of different units or components, the state with the highest probability is provided. In Lehtikoinen *et al.* [5], we compared probability distributions for the ecological status of coastal water areas, given different aggregation rules. The results showed that averaging by mean typically gives very positive aggregation result if compared with the one-out-all-out approach (OOAO), where the unit in lowest class defines the final aggregation result. The pessimism of OOAo arises from the fact that the more units we aggregate, the smaller is the probability of reaching the highest quality class ($P = 1 \div N_c^{N_u}$, where N_c is the number of status classes in the classification system and N_u the number of units to be aggregated). Recently, Probst [8] have presented an interesting idea of a probabilistic version of the OOAo, which can be used, with a pre-defined confidence level, to define the minimum number of units which should meet their assessment benchmarks so that the aggregation result can be considered as positive. Carriger *et al.* [9], in turn, demonstrate how BNs can be utilized in quantifying joint power of evidence provided by several measurements, something that could be applicable in the multi-indicator context too, when the confidence level of the joint classification result is of interest. In addition, it could help analyzing the risk of misclassification arising from different sources of uncertainty.

True status of an environmental indicator within a certain geographical area (here a zone of the port) is uncertain because of, for example, the spatial variation in the measurements and the external drivers causing noise to the system. Even the reference value of measure, typically used for statistically defining the class boundaries and thus having a remarkable role in the final classification result, is uncertain, thus forming an important additional element that adds the risk of misclassification. In their review of assessment methods related to the WFD in Europe, Birk *et al.* [10] pointed out that the majority of classifications are based on statistical approaches instead of ecological principles, thus the class boundaries may not correspond to biologically meaningful changes in ecosystems. Fernandes *et al.* [11] used long term data to study the probability to achieve the ‘good’ state simultaneously for nutrients (phosphorus and nitrogen) and chlorophyll-a concentration in the context of WFD objectives at the Gulf of Finland, Eastern Baltic Sea, finding a weak dependency between these closely connected metrics. They concluded this finding may result from a non-harmonized target-setting, which does not take into account dependencies, variability and uncertainty. Irvine [12], in turn, highlights that the fixed-boundary classification schemes are found to be insensitive to the realities of spatial and seasonal variance and calls for the incorporation of the risk of misclassification when designing and evaluating the results of WFD monitoring programmes. In Lehtikoinen *et al.* [5], we have suggested more comprehensive acknowledgement and analysis of different sources of uncertainty when it comes to the status classifications of the ecological indicators, which might be relevant also in the presented case by Johnson *et al.* Their model could even be further developed for analyzing the risk of misclassification because of the uncertainty that arises from the spatial variability in their monitoring data. All in all, it seems to me that BNs have a great potential for the development of advanced indicator assessment tools in various sectors, and I am glad that Johnson and co-authors have provided the present demonstration.

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