Deltares

Assessment of the Nourishment Efficiency Using a Bayesian Modelling Approach

Case study: North Holland

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Summary
In this study, a Bayesian probabilistic model has been implemented to assess the effects of nourishments on a number of coastal indicators using, as input, data defined at Jarkus transect level for the North Holland coast. As indicators for short- and medium- term safety, probability of failure, MKL, and MDL have been selected.

The Bayesian network has proved to be a useful tool to point out the positive effects of different types of nourishments built in the past, as well as interrelations between different indicators and the related uncertainties. Moreover, by training the network using information derived from the past, the network can be used as predictive tool i.e. to plan a nourishment in order to reach a predefined objective (e.g. average seaward migration of MKL of a predefined distance).

Nevertheless, the strength of the correlation between variables was found to be highly dependent on data availability. On top of all, the fact that several transects have never been nourished or not been nourished for several years, strongly influence some of the results. As a matter of fact, these transects can not provide information on the effects of nourishments. However, they provide valuable information on the natural morphological evolution of the not-nourished stretched of coast. This problem could be partly overcome by using synthetic data derived by numerical models to partly fill up the missing information.

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	nov. 2012	Dr. Alessio Giardino	AG	Kees den Heijer	CH	Tom Schilperoort	
		Dirk Knipping		Dr. Maarten-Jan Kallen			

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1 Introduction

1.1 Background project State of the Coast

The Netherlands is a low-lying country where, approximately, 27 per cent of the territory is located below mean sea level and 55 per cent is prone to flooding. Protection against flooding is traditionally the primary objective of coastal policy in the Netherlands. However, since 1990 coastal policy has been subject to a number of modifications, and new objectives have been added to cope with the structural erosion problems of the Dutch coast. To fulfil these new objectives, the yearly volume of sand for nourishments was first increased to 6 millions m^3 of sand in 1990 and then to 12 millions m^3 in 2001. Even higher volumes might be necessary in the future to cope with the more severe sea level rise scenarios predicted.
On the other hand, the effect of the global economic crisis is pushing coastal managers to the development of optimal efficient and cost-effective nourishment strategies. Deltares has been commissioned by Rijkswaterstaat Waterdienst to develop knowledge needed to carry out an effective nourishment strategy (spatially and temporally). Deltares organised this project *Kennis voor Primaire Processen – Beheer en Onderhoud van de kust* (Knowledge for Primary Processes - Coastal Management and Maintenance) in a number of sub-projects. In order to link the project results to the actual nourishment practice of Rijkswaterstaat, the subprojects focus on the validation of a number of hypotheses on which the present nourishment strategy is based. "Toestand van de Kust" (State of the Coast) is one of the sub-projects of this multi-year program, with the aim of identifying the impact of nourishments on a number of indicators along the Dutch coast. During this first year, the analysis has focused on the North Holland coast (Giardino et al., 2012) and is being extended to the entire Dutch coast.

The following hypothesis were identified for the project Toestand van de Kust:

Hypotheses project State of the Coast
1) The nourishment strategy of the past years had lead to a positive (seaward) development of a number of "indicators" along the Dutch coast.
2) As a consequence, nourishments contribute to an increase of the safety level through a seaward shift of the erosion point.

The objective of project State of the Coast is two-fold:

- *To support the Waterdienst in determining where to nourish.*
  This is achieved by indicating on which spots along the coast the sediment buffer is limited. This buffer does not only concerns sediment volumes, but a wider range of coastal indicators. On spots that encounter limited buffers, the morphological development can be examined. If the buffer tends to get lower than a reference buffer and a (natural) increase in sediment volume is not expected on a short term, the Waterdienst can consider to nourish this part of the coast. In case financial state of affairs makes prioritizing urgent, the state of the coast can contribute to the prioritization process.
- *To advise the Waterdienst on the most efficient nourishment strategy.*
  This is achieved by deriving the effect of the previous nourishment strategy (1990 till present). Learned lessons from the past can be used to improve future nourishment strategies.

1.2 Motivation and Objectives

The motivation for applying the Bayesian network approach within the State of the Coast project is two-fold:

1. A Bayesian network is a useful tool to evaluate cause and effects (e.g. nourishment and effects on coastal indicators).
2. A Bayesian modeling approach gives an intuitive representation of the physical processes involved. The use of nodes and arrows makes directly visible which variables play a role and how they are correlated.
3. A Bayesian network is a probabilistic method and therefore allows to account for uncertainties.

The ultimate goal of this work is the development of a tool in support to decision makers for the design and evaluation of nourishment effects. In order to meet this goal, the model should enable the decision maker to:

1. Identify cause-effect relationships between nourishment volumes and change in trend in indicators.
2. Identify relationships between the different indicators.

These two aspects are investigated within this study with priority on indicators on short- and medium- term safety.

1.3 Set up of the study

The network set up within this study focuses on the North Holland coast. Nevertheless, the methodology applied is generic and the study could be easily extended to other coastal areas.

In Chapter 2, a brief overview on Bayesian modelling is given, with more detailed information on the variables used in the current network and how they are interrelated. Chapter 3 contains a number of practical examples that have been implemented to address some of the underlying hypothesis of this project (Section 1.1), and to show the usefulness of Bayesian networks for nourishment designs. The main conclusions of this study are summarized in Chapter 4, while a number of recommendations to improve the current work are given in Chapter 5.

2 Bayesian Network

2.1 Introduction

A Bayesian network is a method of reasoning using probabilities, where the *nodes* represent variables and *arrows* represent direct influence between the nodes. The advantage of using this approach is that by combining multiple parameters, makes it possible to make robust forecasts.

In general, the Bayes rule is expressed as:

$$p(F_i \mid O_j) = p(O_j \mid F_i)\, p(F_i) \,/\, p(O_j) \,,$$

where the left-hand term is the updated conditional probability (or 'posterior probability') of a forecast F_i, given a particular set of observations, O_j.

The best way to understand the Bayesian network is to illustrate it with an example. Here, the example of the European soccer championship will be used. Suppose the probability that the Netherlands will win the finals is 20% ($p(F_i)$). The first match of the Netherlands ($p(O_j)$) will affect the prior probability of event *($p(F_i)$)*. After this first match (loss against Denmark), one can update the prior probability of event *($p(F_i)$)* which will become conditioned or constrained by event O_j. Now the probability that the Netherlands will win the cup given the first los is just 5% and will be defined as $p(F_i \mid O_j)$. New information changes your degree of belief of a certain event.

Bayesian statistics are not new and they have been applied in different fields. In the field of coastal engineering Bayesian statistics have been used for example to predict coastal cliff erosion (Hapke and Plant, 2010), to predict wave height evolution in the surf zone given very sparse boundary conditions (Plant and Holland, 2011a), and to predict offshore wave heights and depth estimates given limited information from an onshore location (Plant and Holland, 2011b). Den Heijer et al. (2012) and Knipping (2012) have used a Bayesian network approach to predict the impact of extreme storm events on dune erosion along the Dutch coast. Moreover, several applications for Bayesian modelling related to environmental modelling are recently also being explored (Aguilera et al., 2011).

2.2 Set up of a network

The set up of a Bayesian network involves three main steps: *construction*, *training* and *validity check* (Knipping, 2012). These steps are illustrated in details in Appendix B with specific reference to the North Holland case.

Constructing the network means first defining the main variables that play a role in describing the process to study. For our application, the following variables have been selected: nourishment type and nourishment volume (Section 2.2.1), a number of coastal indicators (MKL, probability of failure and MDL; Section 2.2.2), a number of sub-areas with homogeneous characteristics (Section 2.2.3), three time intervals with similar nourishment strategy (Section 2.2.4), and a number of time horizons at which nourishment efficiency will be evaluated (Section 2.2.5). The selected variables are represented by nodes in the Bayesian network.

A correlation between two variables in a Bayesian network is illustrated with a directed arrow. In a Bayesian network, correlation means direct influence, or also called dependency using a statistical term. The process of defining nodes and designing arrows involves a good understanding of the physical processes underlying the network.

The feeding of information to the Bayesian network in order to construct the conditional probability tables is called *training*.

Finally, an evaluation or *validity check* of the model is made. In other words, is the Bayesian network capable to cover a representative sample of the behaviour domain to be measured and is the Bayesian network able to scientifically answer the questions is intended to answer?

2.2.1 Nourishment type and nourishment volume

The nourishment policy has been undergoing several modifications in the last 20 years. Before 1990, nourishments were not yet a common practice and usually they were built on the beach or on the dunes, eventually combined with hard structures (Giardino et al., 2010). After 1990, nourished volume was increased to about $6*10^6$ m^3/year for the all Dutch coast. Moreover, besides beach nourishments, more economically attractive shoreface nourishments started becoming common practice. In 2001 the volume was further increased to $12*10^6$ m^3/year to compensate for sediment loss due to sea level rise within the Coastal Foundation (Mulder et al., 2011).
A nourishment database has been set up at Deltares in close collaboration with the Waterdienst within the project Toestand van de Kust. Nourishments are available for all years and defined by volumetric values in m^3/m for different types of nourishment (beach, shoreface and dune). This database, which is provided by Open Earth (Van Koningsveld et al., 2010) via:

http://opendap.deltares.nl/thredds/dodsC/opendap/rijkswaterstaat/suppleties/suppleties.nc.html

was used to set up the network.

2.2.2 Coastal Indicators

A Bayesian network is based on measured or pre-computed data only. This means no calculations are executed within the Bayesian network. Prior to the study, a number of coastal indicators namely MKL, Probability of Failure and MDV were defined and pre-computed to evaluate the effects of a nourishment along the shore and in dune area (Table 2.1). The MKL indicator was selected to represent the volume in the cross-shore profile, from approximately the dune foot down to the -5 m line; the MDV describes changes in dune volume between the dune foot and the erosion point of 1990 and it is described in Arcadis (2011). The probability of failure serves as an overall indicator for safety and was computed with the model PC-ring ($HKV_{\text{Lijn in Water}}$, 2011).

The coastal indicators are available on the OPeNDAP server:

https://svn.oss.deltares.nl/repos/openearthrawdata/trunk/rijkswaterstaat/

Table 2.1 Description of the coastal indicators chosen for the analysis

Indicator		**Description**
Momentary Coastline Position	MKL	Volume of sand between dune foot and mean low water
Momentary Dune Volume	MDV	Volume of sand between dune foot and erosion point (afslagpunt) 1990.
Probability of Failure	Pf	Probability of failure of the first dune row (output of PC-ring model)

The different Matlab functions used to build the input file containing the value of the indicators (*.cas file) are described in Appendix A.

2.2.3 Sub-areas

A number of sub-areas were defined in Giardino et al. (2012) for the North Holland coast and characterized by a homogeneous nourishment strategy and autonomous trend (Figure 2.1). The same sub-areas are used within the Bayesian network.

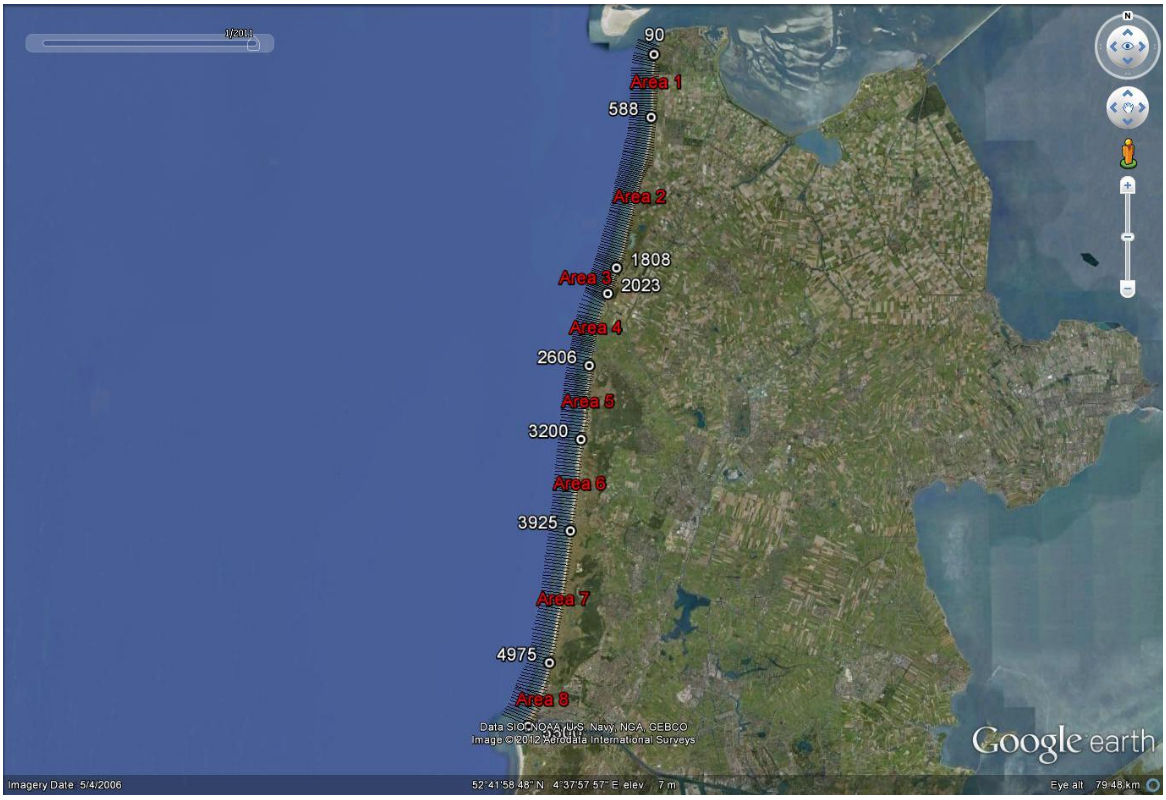

Figure 2.1 Definition of the locations of the different sub-areas (from Giardino et al. 2012). The white numbers indicate the Jarkus rays limiting the different sub-areas.

2.2.4 Time intervals

One of the characteristics of Bayesian networks is that they can not explicitly model time, since all data are treated in the network independently from the moment when the data was measured or computed. To assess the effect of nourishments at different times, a separate variable was created identifying three different time windows, corresponding to different nourishment policies:

1) 1965 – 1990: characterized by nearly no nourishment along the entire Dutch coast.
2) 1991 – 2000: characterized by a nourishment scheme of about 6 millions of m^3 of sand per year along the all Dutch coast.
3) 2001 – 2010: characterized by a nourishment scheme of about 12 millions of m^3 of sand per year along the all Dutch coast.

2.2.5 Time horizons

The efficiency of nourishments was evaluated for different time horizons: 1, 5, and 10 years. In this way, it was possible to compare the effect of beach nourishments (which usually have an instantaneous effect) against shoreface nourishments, which work on a longer time scale i.e. 5-10 years.

2.3 Assumptions related to the Bayesian network

A number of assumptions were made during the set up of the Bayesian network. Here an overview of those assumptions is given:

- Choice of using a specific Bayesian software package called “Netica”(www.norsys.com). Two implications derive from this choice:
  - Discrete variables.
    Because Netica uses discrete variables characterized by bins, continuous variables need to be discretized.
  - Learning algorithm.
    To quantify the relations between the variables a learning algorithm pre-defined in the software has been used.
- The selection of variables and relations to describe physical processes is subjective.
- Input data are available at transect level, once per year. No information is available between transects and/or different years.

3 Applications

3.1 Introduction

A number of applications have been described in this chapter. Table 3.1 gives an overview of the examples described in the following sections. For each example, one or different nodes were constrained to be certain (100% probability). Constraining is essentially the same as conditioning a variable in the network on a particular value i.e. we only look at transects where a nourishment has taken place (100% to find there a nourishment) and we assess the effects of only looking at those transects instead of considering them all. Nodes that are constrained appear in the network in grey colour, while a brown colour is used to identify nodes which are let free.

For each of the indicators, it is computed at how many transects (in %) there was a relative increase, decrease or negligible change with respect to the time window before, as well as the value of this relative change. Changes in MKL and MDL are defined as a difference between values at different years. For probability of failure, the ratio between the probabilities at different years is computed. We consider as negligible for a time period of 1 year, a change lower than 1 m in MKL, smaller than 1 m^3/m in MDV, and 0.01 in the ratio of probability of failure between two consecutive time windows.

Table 3.1 Description of the coastal indicators chosen for the analysis

Example	Question to evaluate
1) No nourishment *versus* nourishment	What is the effect of nourishments on the coastal indicators?
2) Nourishment strategy over time	How does the nourishment scheme change over time?
3) One year trend shoreface *versus* beach nourishment	What is the difference between short term (1 year) effect of a shoreface and a beach nourishment on the chosen indicators?
4) Ten year trend shoreface *versus* beach nourishment	What is the difference between long term (10 year) effect of a shoreface and a beach nourishment on the chosen indicators?
5) Relation MKL - Pf	What is the effect of a shift in MKL on the probability of failure?
6) Plan of a shoreface nourishment	What is the volume of a shoreface nourishment, necessary to reach a seaward shift of MKL between 0 – 25 m per year, for a ten year time window, and for one specific subarea (e.g. subarea 2)?

3.2 Overview of the Bayesian network – prior probabilities

The overview of the overall network, with the prior probability distribution for each variable, is shown in Figure 3.1. For each variable, represented by a box in the network, the probability distribution is given. These prior probabilities are computed after training the Bayesian network (Paragraph B.6).The average value of the distribution, with its standard deviation, is shown in the last line at the end of each box. Although average value and standard deviation give a useful information on the statistical significance of some of the indicators (e.g. probability of failure, MDV and MKL), they do not have any significance for some of the others. As an example, the binary variable *Nourishment executed in time horizon: yes/no* is also characterized by an average value of 0.228 and a standard deviation of 0.42 which is simply determined by the fact that a *0* value is automatically assigned to a *no* variable and a *1* value to a *yes* variable.

In general, the network can be described as a fault tree where a number of events at the top of the network leads to consequences in the nodes which come below in the tree. At the top of the tree, first appears the node *Time Horizon,* defining the time window which we want to analyse, and the node *Nourishment executed in the time horizon? No/Yes*, defining if we want to look at all the transects or only the ones which have been nourished. It is already clear from this figure that most of the transects (77.2% *no*; 22.8% *yes*) either have never been nourished, either have not experienced nourishments for several years, when al time horizons are considered together. As a consequence, if we want to look at the effect of nourishments based on a distribution with enough hits for each class, we will need to constrain this variable and only look at the nourished transects.
The nodes *Subarea* and *Time Interval* are defined below in the tree, the first describing what is the area of interest among the transects in North Holland and the latter which is the Time Interval of interest, corresponding to a certain nourishment strategy. Those nodes have a direct effect on the definition of the *Nourishment Type* and *Nourishment Volume,* given right below in the tree. The nourishment strategy is in fact different for different areas and for different time intervals. The nourishment strategy has then a direct effect on the indicators. This is defined first *as % of transects at which the indicators decrease, increase or stay the same*. Below in the tree, as *relative change* with respect to the time period before. Moreover, one of the underlying hypothesis of the project is that nourishments contribute to an increase of the safety level through a seaward shift of the erosion point. To prove this hypothesis, changes in values corresponding to the indicators MKL and MDV were linked with horizontal arrows to changes in the probability of failure.

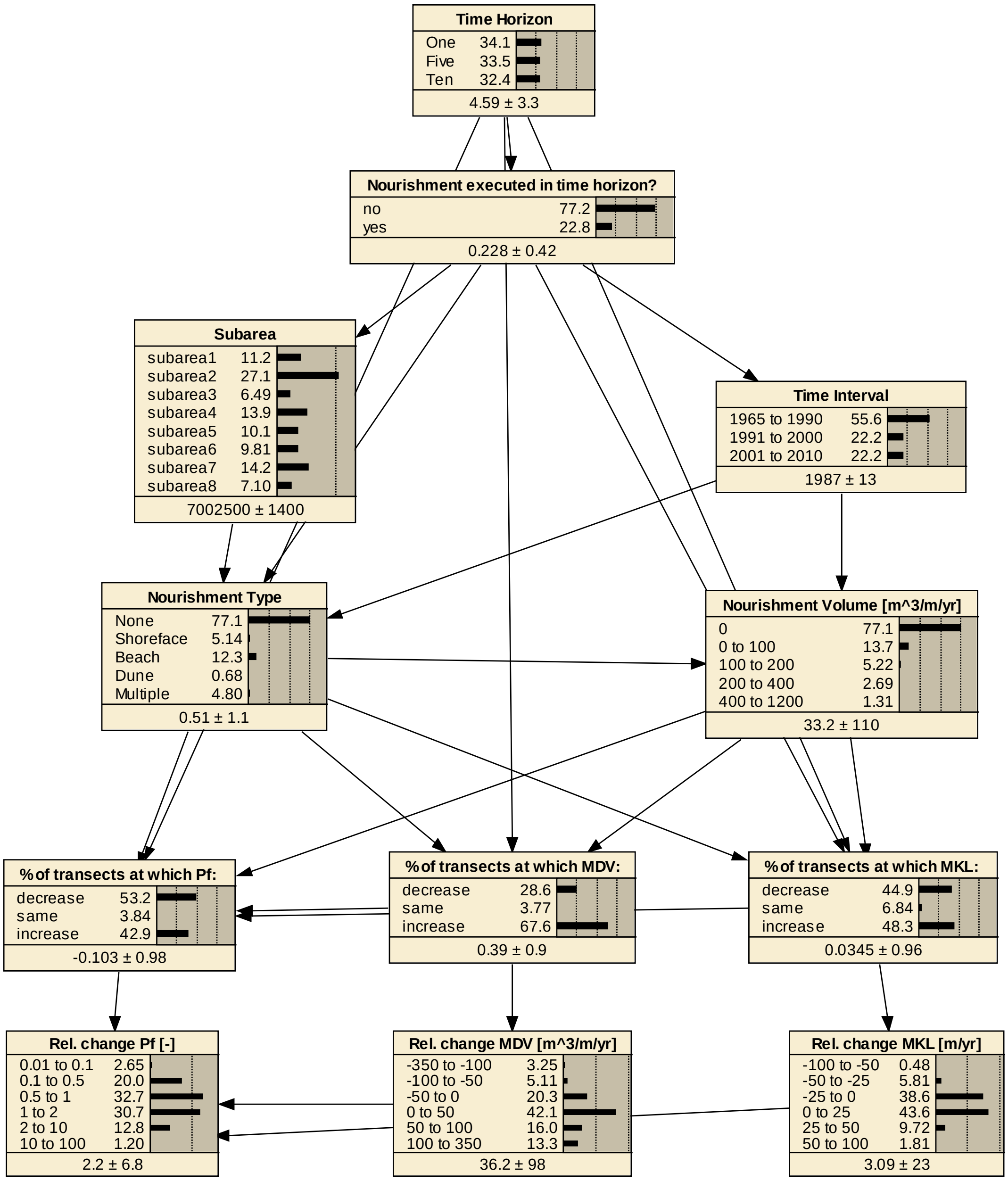

Figure 3.1 Bayesian network – prior probabilities

3.3 Example 1: no nourishment versus nourishment

To assess the general effects of nourishments, in Figure 3.2 and Figure 3.3 the node *nourishment executed in time horizon (no/yes)* has been respectively constrained. When we only look at transects which have been nourished (Figure 3.3), it is possible to see that all chosen indicators (*probability of failure Pf*, *MDV* and *MKL*) show an improvement with respect to the case *no* nourishment. This can be seen both, in an increase of the number of transects showing a trend towards a safer situation, as well as a relative improvement in the values of these indicators. As an example, when looking at transects which have never been nourished, only 45.4 % of them show a tendency towards an *increase* in *MKL*, while 48.8 % show a *decrease*. When we look at transects which have experienced at least one nourishment during the different time windows, the number of transects which have experienced an increase in MKL goes up to 58.1 %. The average relative change in MKL increases from 1.75 m up to 7.62 m.

This confirms both hypothesis 1 and 2 of this project, that nourishments lead to a positive (seaward) development of a number of chosen indicators and, as a consequence, of the safety levels (section 1.1).

Figure 3.3 also shows that the most common *Nourishment Type*, when the time interval is not constrained, is beach nourishment (53.7 % of the cases), followed by shoreface nourishments (22.3 %) and dune nourishments (2.67 %). In 20.8 % of the cases, different type of nourishment have been implemented (*Multiple* nourishments).

In most cases, nourishments have a volume between 0 and 100 m^3/m/year (59.4 %), some of them have a volume between 100 and 200 (22.6 %), and only few of them a volume between 200 and 400 m^3/m/year (11.6 %), and more than 400 m^3/m/year (5.62 %).

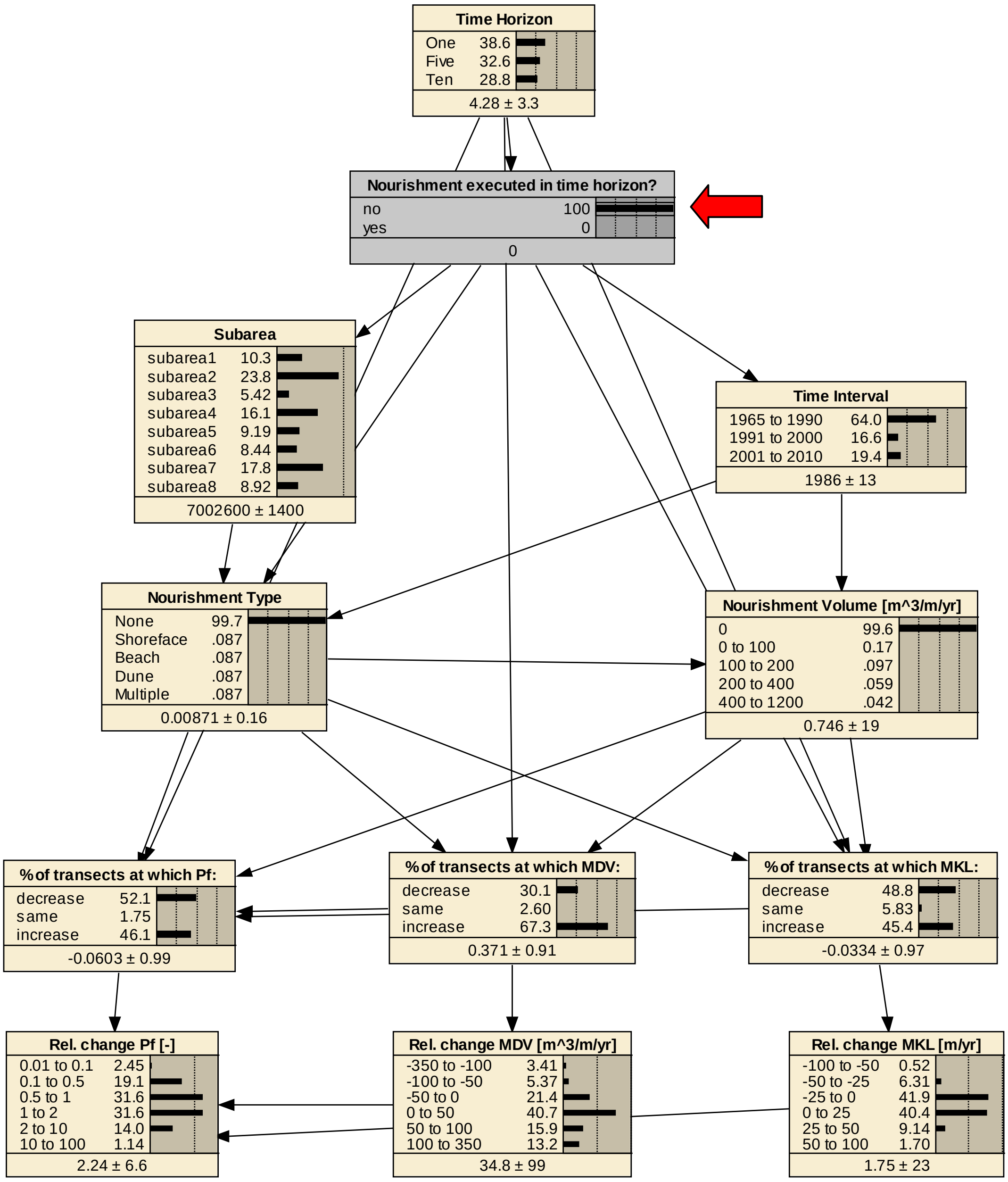

Figure 3.2 Example 1: no nourishment implemented

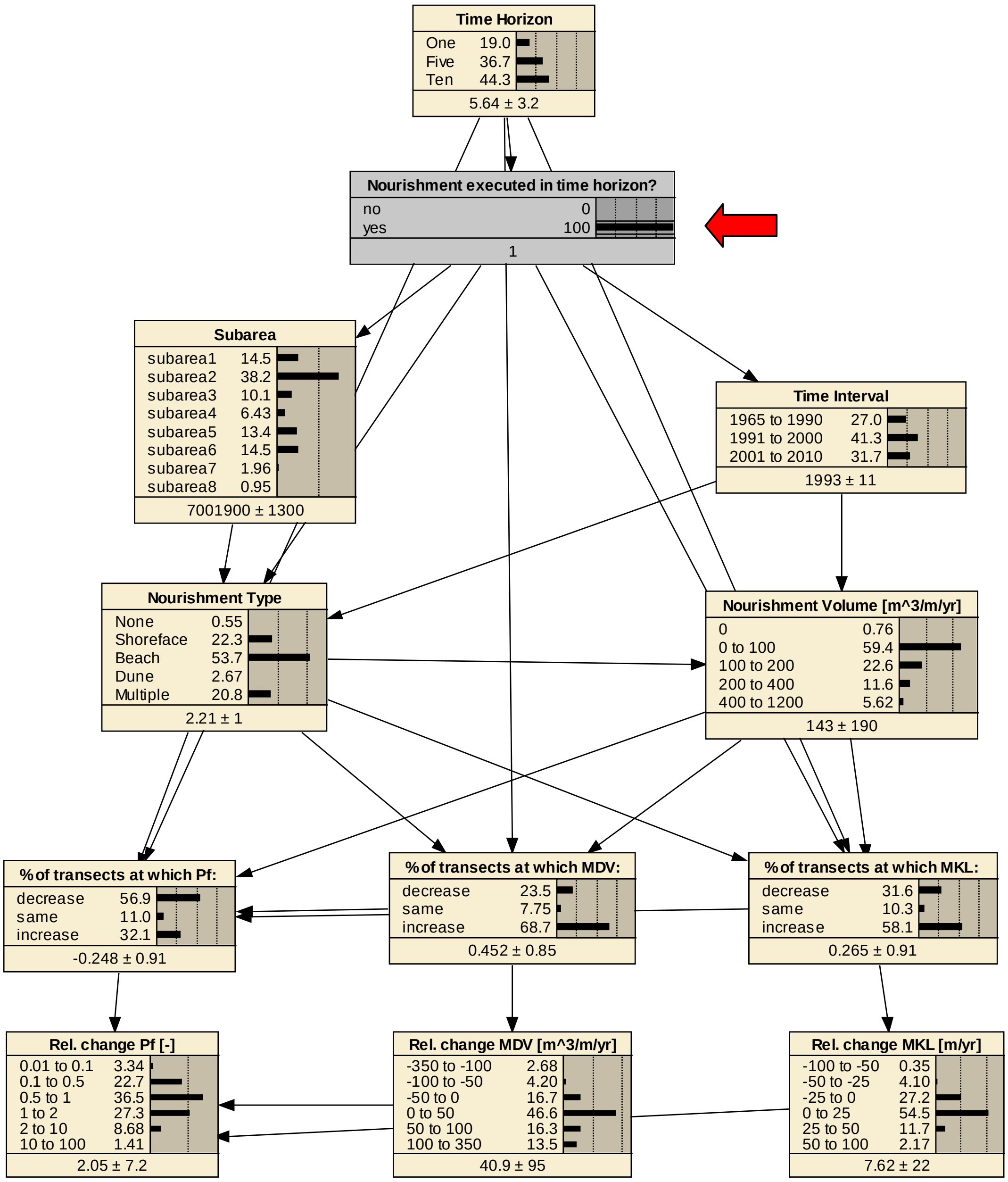

Figure 3.3 Example 1: only transects with nourishments

3.4 Example 2: Time interval 1965-1990 / 1991-2000 / 2001-2010

In this example, the relation between different time windows, nourishment schemes and change in indicators was assessed by constraining the node *Time Interval*. Figure 3.4 shows the values assumed by the different indicators for the time window 1965 and 1990. First of all, it is possible to see that most of the transects were not nourished (*Nourishment executed in time window*: *no* = 88.9%; *yes* = 11.1%). As a consequence, 46.8% of the transects had in *increase* in *MKL*, and 47.1% a *decrease* with an average relative seaward change of +2.34 m. Nevertheless, a large number of transects was already experiencing an increase in *MDV* (*increase* in 67.3% of the transects, decrease in 29.7% of the transects). Safety level represented by the probability of failure was also improving in 52.7% of the transects and worsening in 44.8 %.

In 1991-2000 nourishments started being widely applied (*Nourishment executed in time window*: *no* = 57.7%; *yes* = 42.3%) (Figure 3.5). In particular, nourishments were built in the form of beach nourishments (*Nourishment type*: *shoreface* = 5.43%; *beach* = 28.8%). The effect on the indicators was clear as all indicators showed a relative increase with respect to the previous situation. The *MKL increased* at 52.0 % of the transects with an average seaward shift of 4.4 m.

In 2001-2010 nourishments were also widely implemented (*Nourishment executed in time window*: *no* = 67.5%; *yes* = 32.5%) (Figure 3.6). However, in this time window nourishments were mainly built in the form of shoreface nourishments (*shoreface* = 17.3%; *beach* = 5.32%). The relative effect on the indicators was once again an improvement with respect to the previous time horizon, however slightly less clear than for the time window 1991-2000. As an example, MKL increased in 48.4% of the transects with an average seaward shift of 3.65 m.

Once again, this example helps confirming both hypothesis given in Section 1.1 that nourishments leads to a positive development of the indicators and as a consequence of the safety levels.

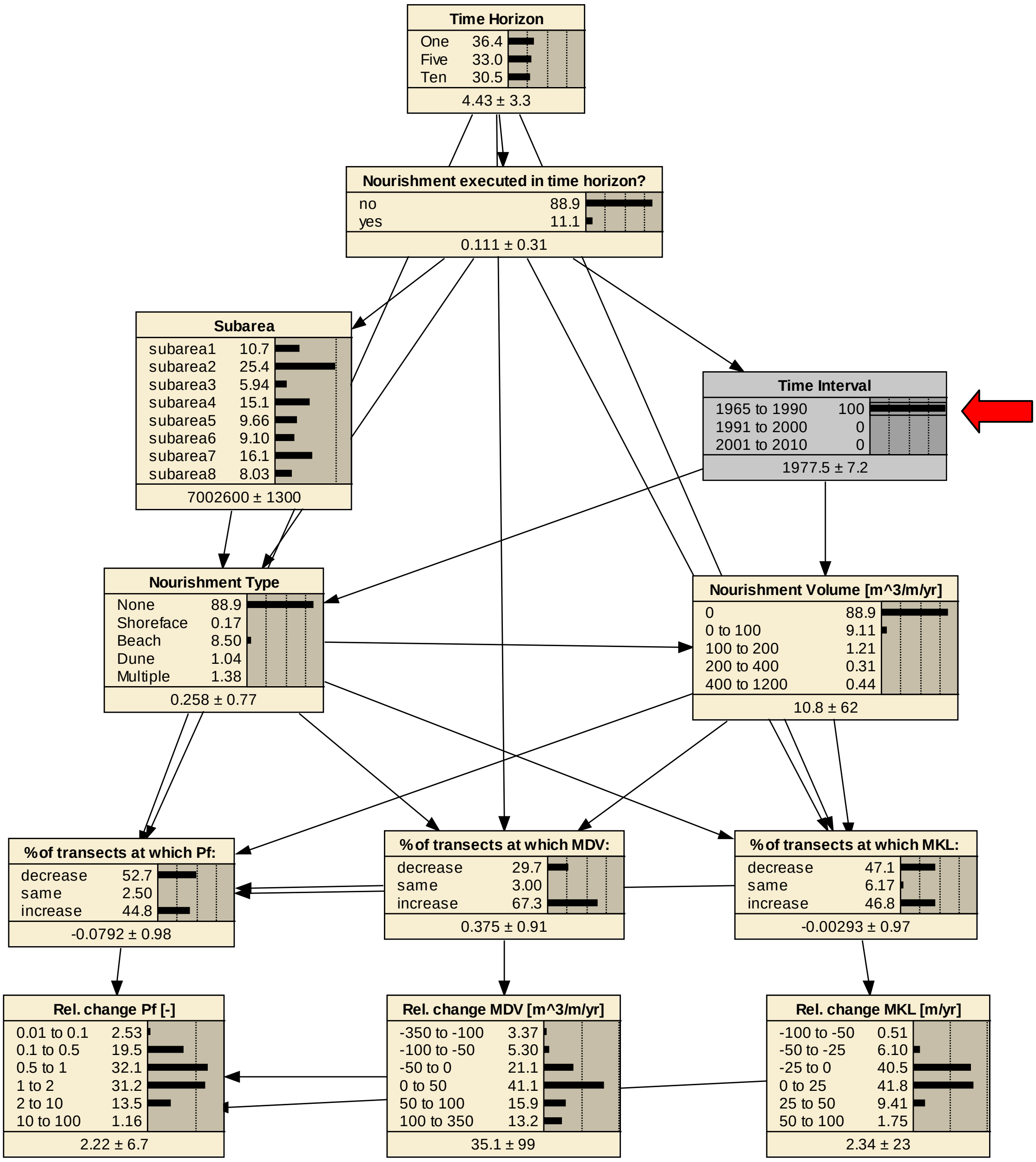

Figure 3.4 Example 2: time interval 1965 - 1990

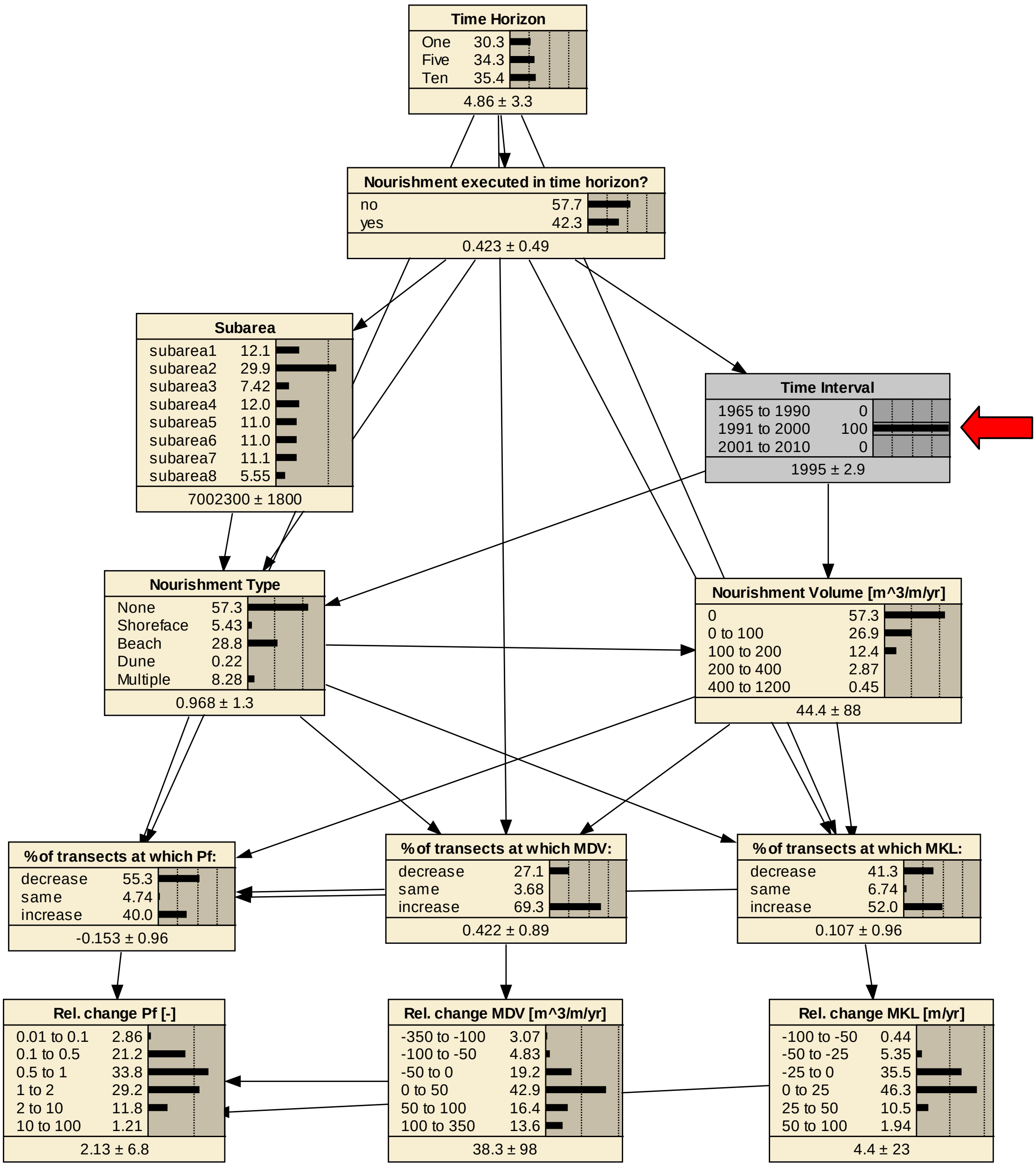

Figure 3.5 Example 2: time interval 1991 - 2000

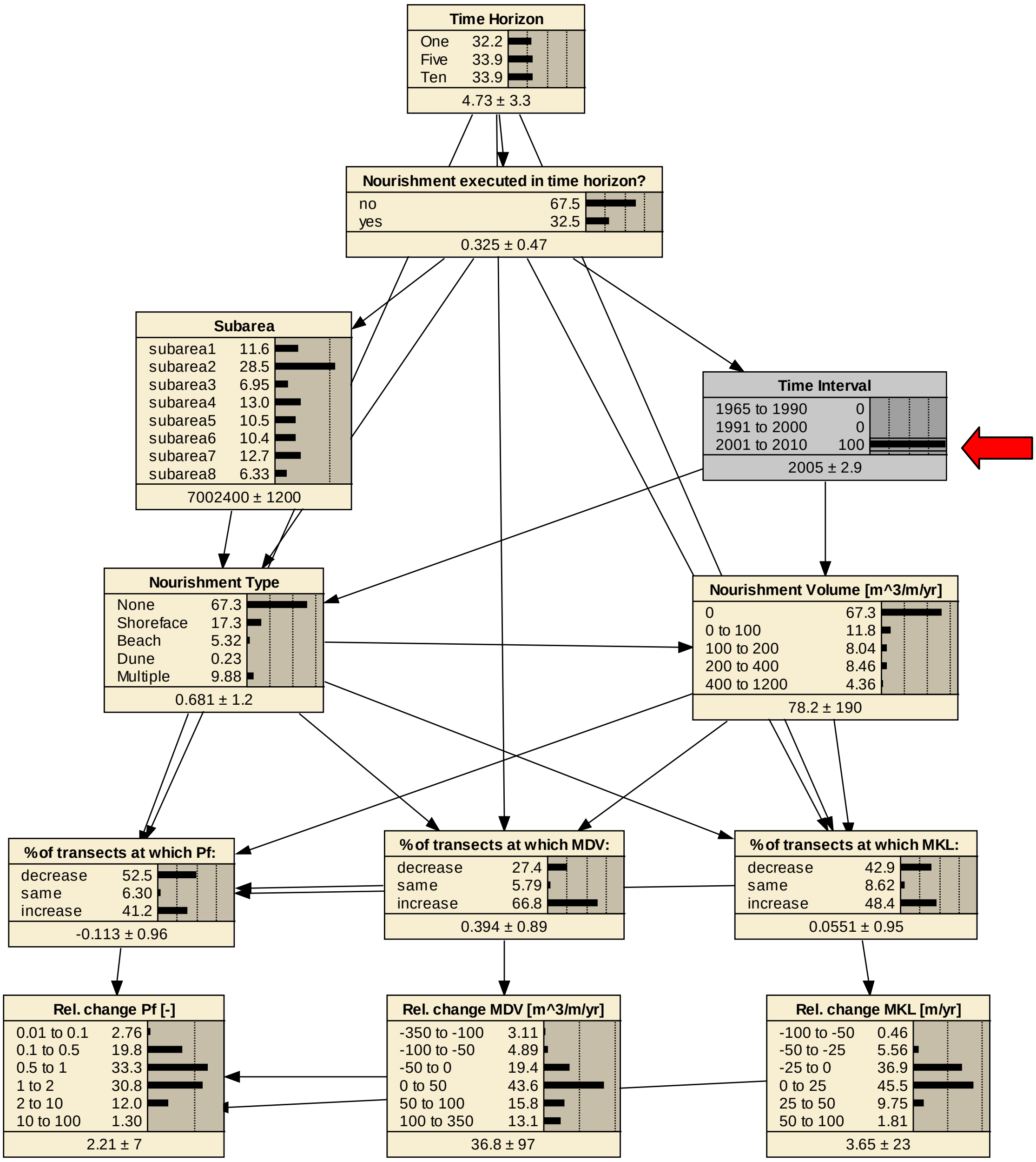

Figure 3.6 Example 2: time interval 2001 – 2010

3.5 Example 3: One-year trend shoreface versus beach nourishment

In this section, the instantaneous effect of shoreface and beach nourishments is compared by constraining the *Time Horizon* to *One* year, by selecting only transects at which *Nourishment is executed in time horizon* and respectively the Nourishment Type to *Shoreface* and *Beach*. In Figure 3.7, the effect of shoreface nourishments shows a general improvement of the indicators, which however becomes clearer in Figure 3.8, when the focus is on beach nourishments. As an example, 51.1 % of the transects at which a shoreface nourishment was applied show an *increase* in *MKL,* while beach nourishments leads to a seaward migration of the MKL at 61.1 % of the transects characterized by beach nourishments.

As it is logical to expect, when sand is put directly on the beach, this has an immediate effect on MKL, MDV and safety levels. The difference between shoreface and beach nourishments effects become smaller when looking at a Time Horizon of Ten years (Section 3.6).

In case of shoreface nourishments, the average seaward migration of MKL is equal to 7.72 m, while in case of beach nourishments it is equal to 6.85 m. Nevertheless, it is important to point out that the comparison between the two figures is between shoreface and beach nourishments with different volumes. The average volume of shoreface nourishments as shown by the variable *Nourishment Volume* is 205 m^3/m/yr, while the average volume of beach nourishments is 95.4 m^3/m/yr, since beach nourishments are usually smaller. The efficiency of beach nourishments on a time horizon of 1 year would be even more pronounced if the comparison was extrapolated to shoreface and beach nourishments with the same volume.

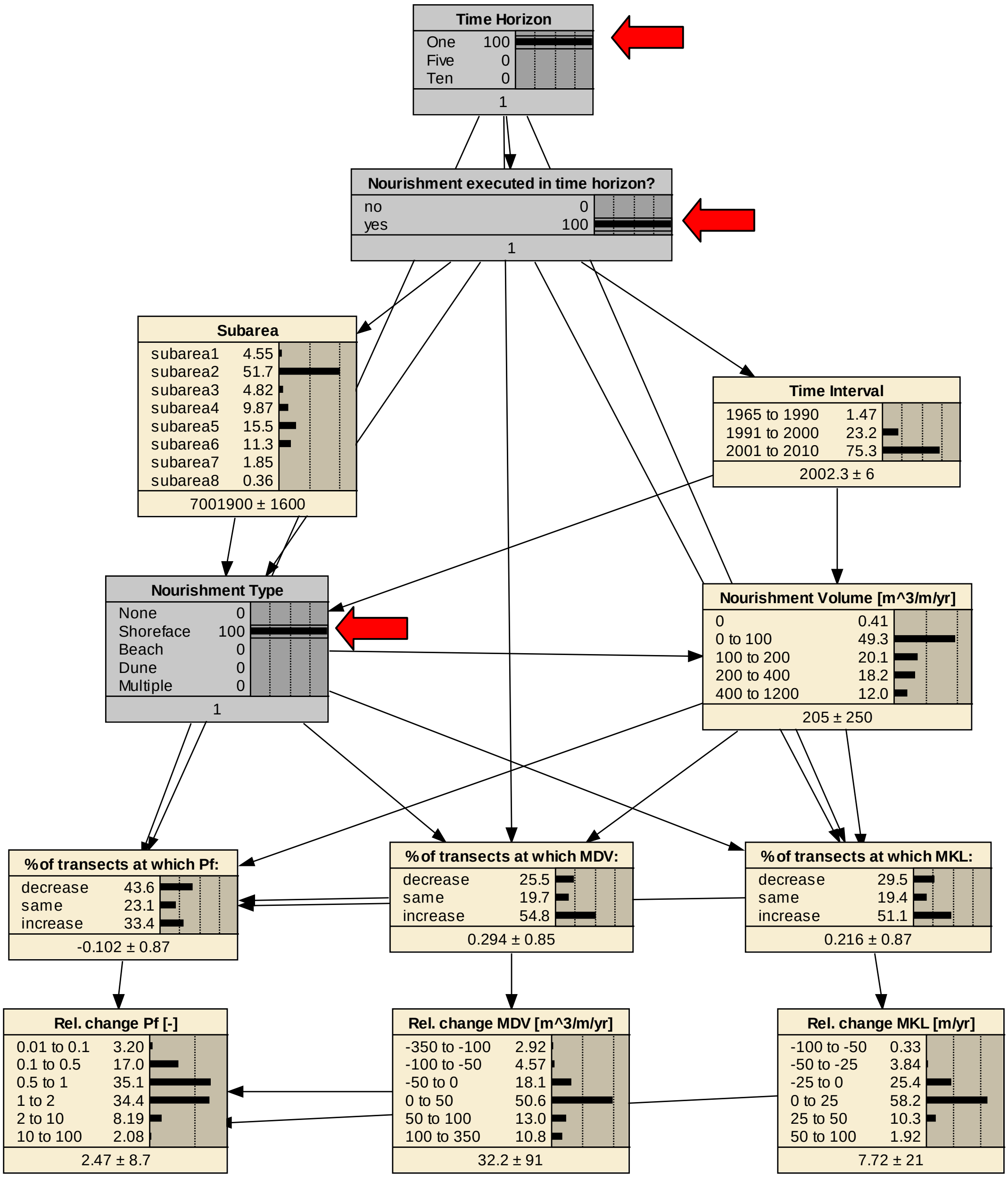

Figure 3.7 Example 3: One-year trend shoreface nourishment

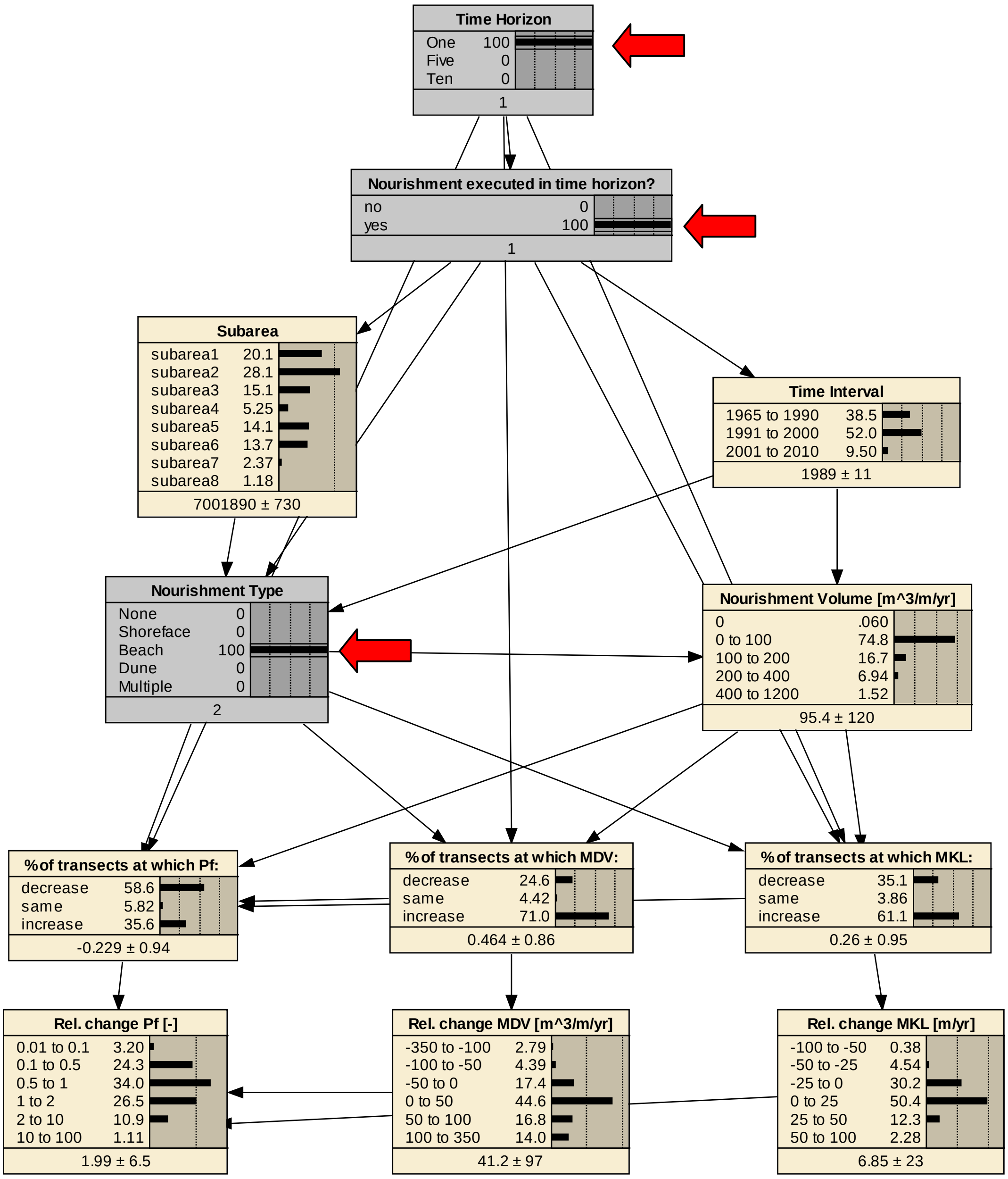

Figure 3.8 Example 3: One-year trend beach nourishment

3.6 Example 4: Ten-year trend shoreface *versus* beach nourishment

In this section, the long-term effect of shoreface and beach nourishments is compared by constraining the *Time Horizon* to *Ten* years and respectively the *Nourishment Type* to *shoreface* (Figure 3.9) and *beach (*Figure 3.10). In this case, the long term effects of beach and shoreface nourishments on Pf, MDL and MKL are comparable. As an example, MKL increases at 58.3 % of the transects in case of shoreface nourishments, and at 62.7 % of the transects in case of beach nourishments. This corresponds to a relative average seaward shift in MKL of 8.59 m in case of shoreface nourishment, against 8.23 m in case of beach nourishment. This behaviour supports the idea that shoreface nourishments do not have an immediate effect on the nearshore morphology (Section 3.5) but rather a delayed effect.

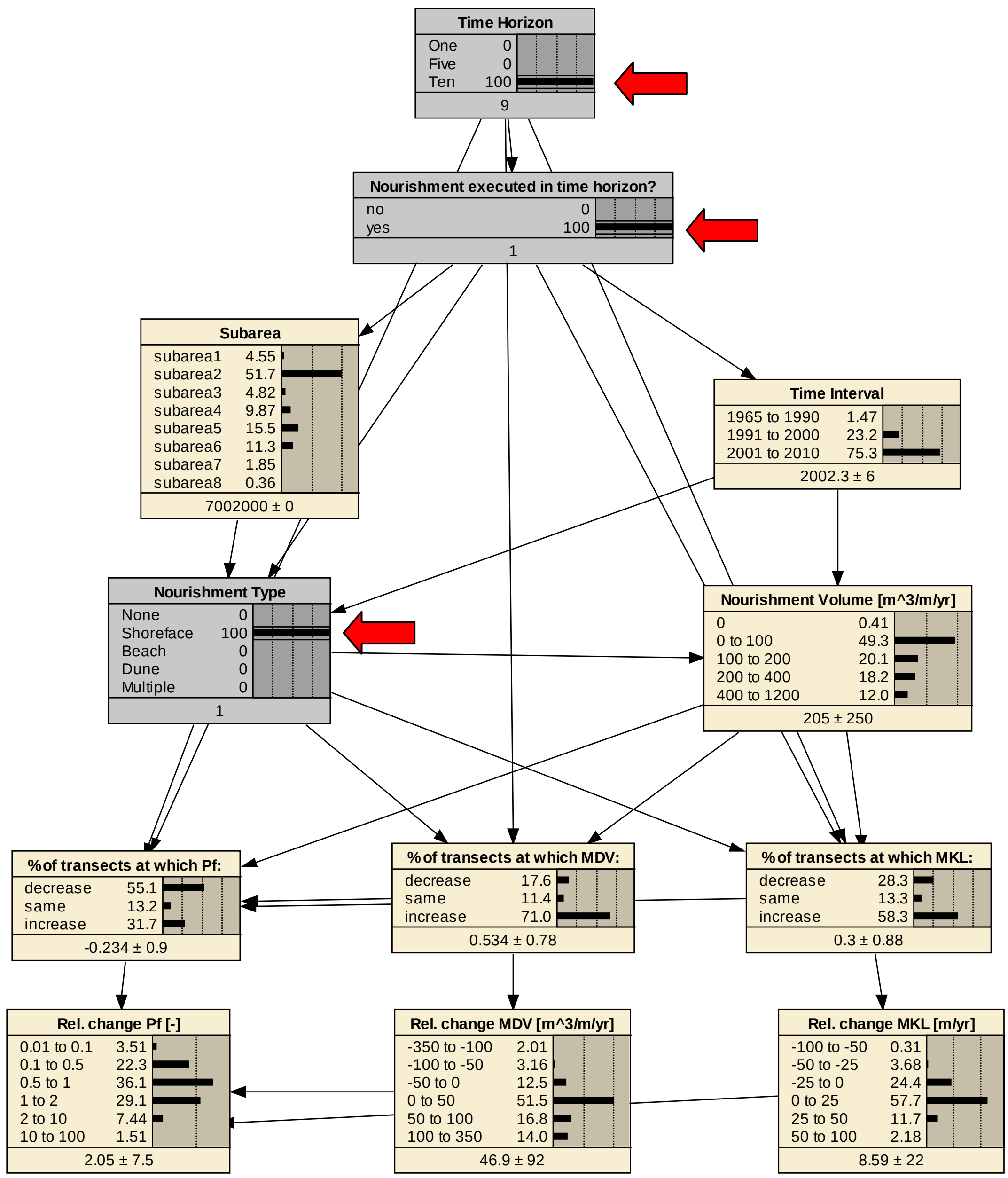

Figure 3.9 Example 4: Ten-year trend shoreface nourishment

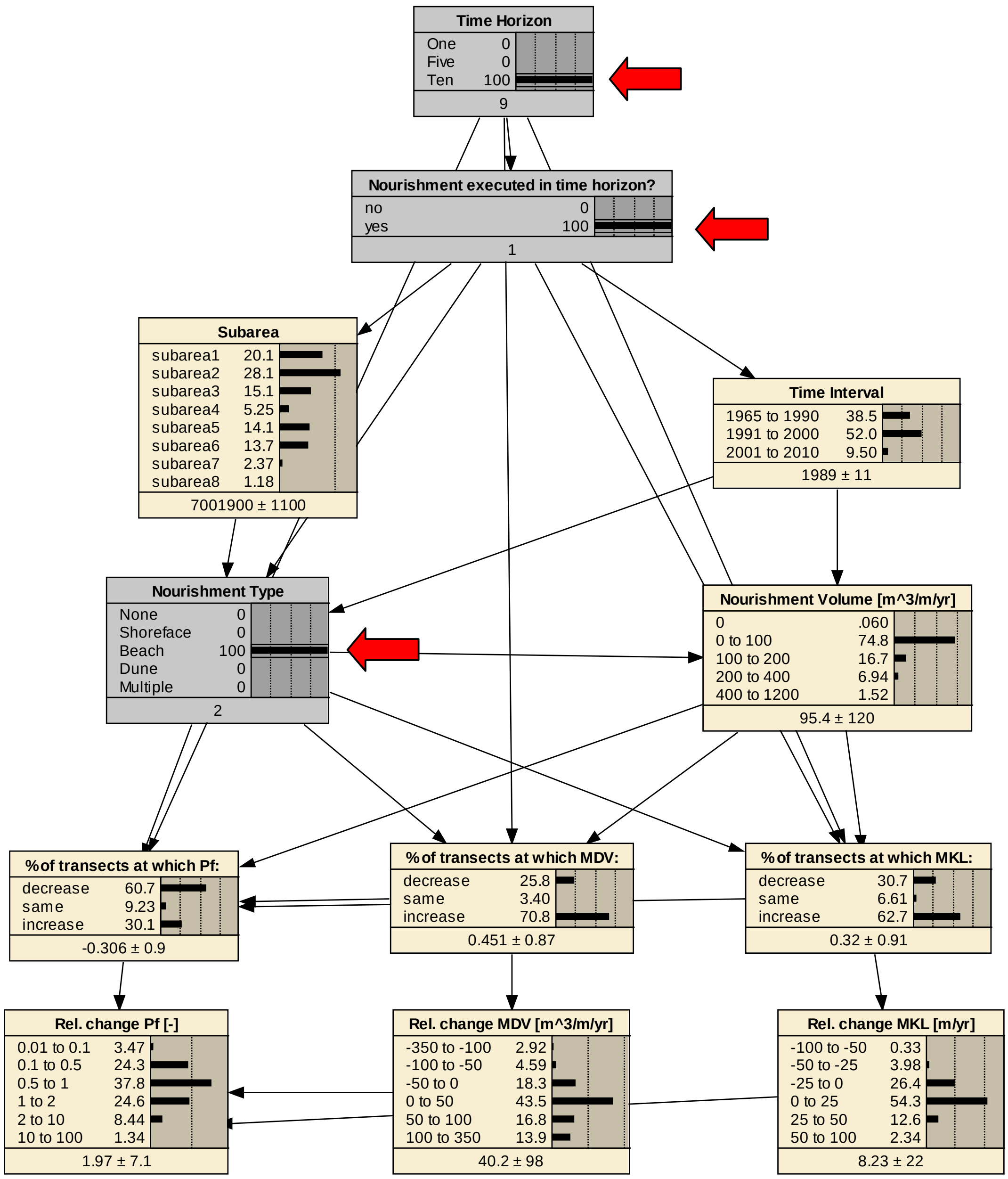

Figure 3.10 Example 4: Ten-year trend beach nourishment

3.7 Example 5: Relation between sand volumes in the MKL zone and probability of failure

In this section, the effects of a possible change of sand volumes in the cross-shore profile on the probability of failure are assessed by constraining the MKL value at first to an average change equal to -37.5 m (Figure 3.11) and then to an average change equal to +12.5 m (Figure 3.12). A negative change in MKL is representative for coastal erosion, while a positive change would represent accretion. In the first case, the landward MKL shift would lead to a pronounced peak in *Relative change of Pf* between 2 and 10, which means that at most transects the probability of failure will increase between 2 and 10 times. In the second case, the seaward MKL shift would lead to a peak in the distribution of *Relative change of Pf* between 0.5 and 1, meaning that at most transects the probability of failure will decrease to a value between half of the actual value and the actual value. This means that to an approximate shift in MKL equal to 50 m, a change in Pf equal to one order of magnitude can be expected. These results are in line with the prediction shown in Arcadis (2011) and Santinelli (2012), who predicted a change in Pf equal to one order of magnitude for a change in MKL equal to 42.2 m.

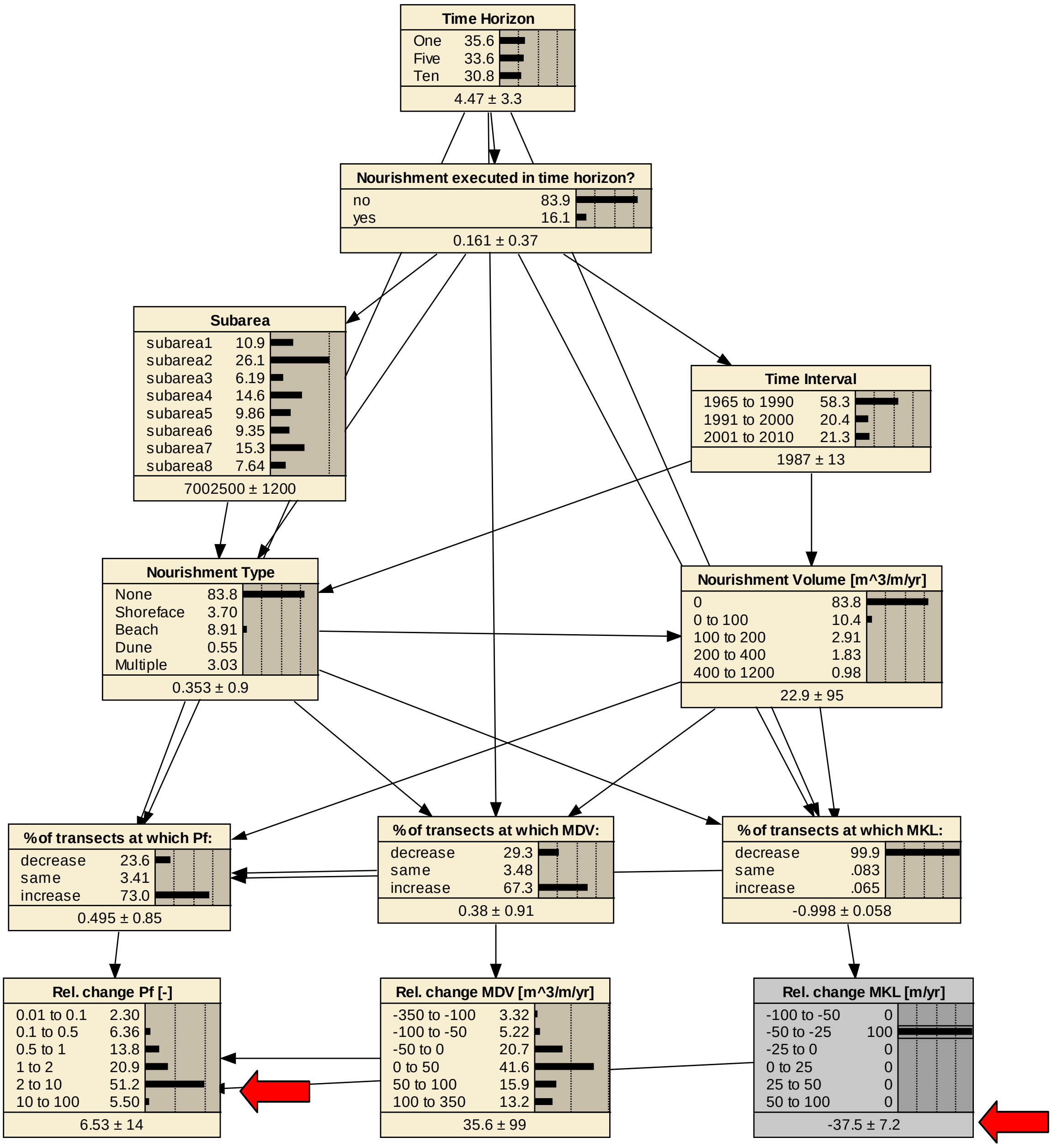

Figure 3.11 Example 5: Effect of landward shift in MKL on probability of failure Pf.

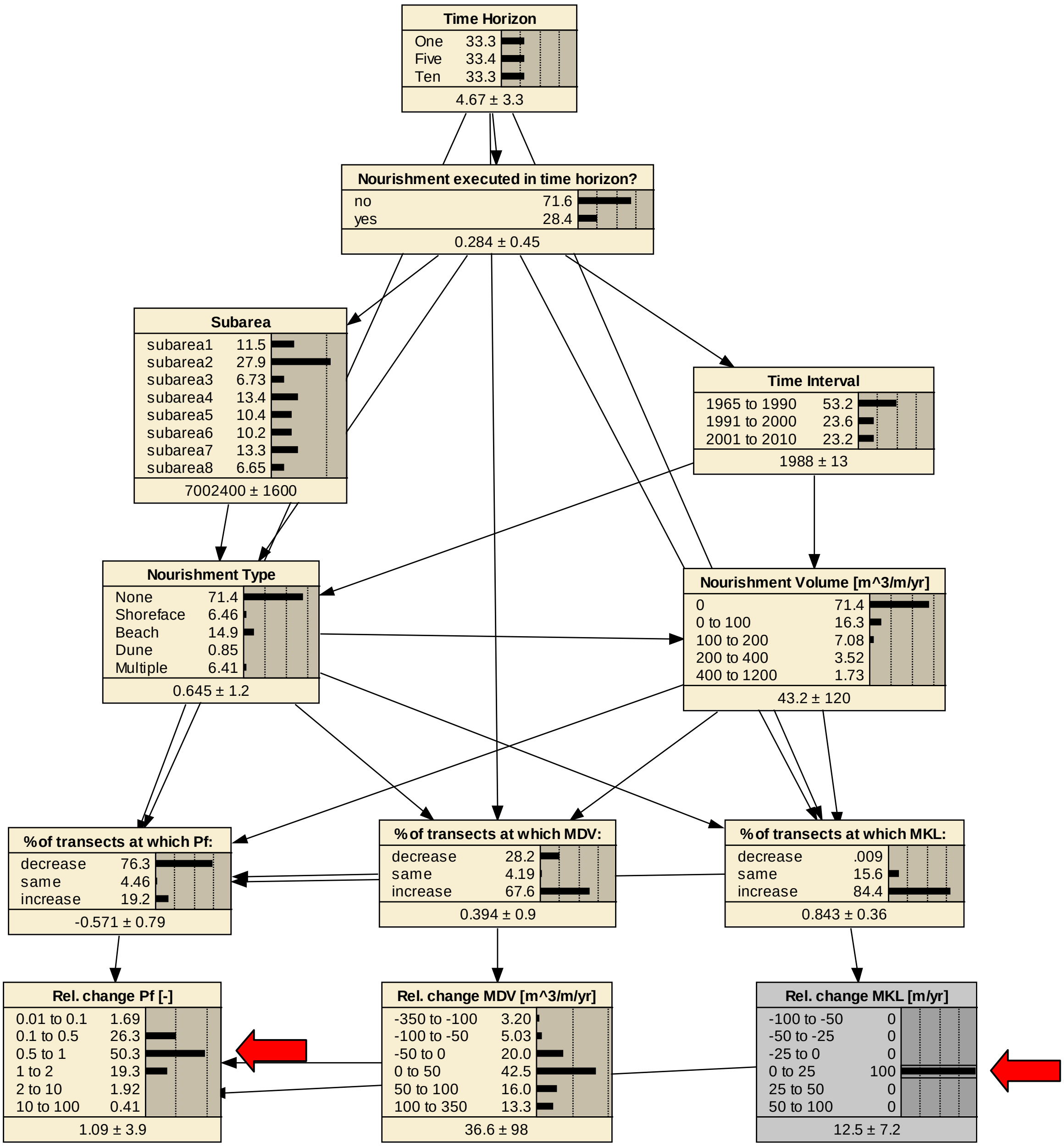

Figure 3.12 Example 5: Effect of seaward shift in MKL on probability of failure Pf.

3.8 Example 6: Plan of a nourishment strategy

In this section, the Bayesian network is used to plan a *Shoreface* nourishment, which should enable to reach a certain objective. The objective that is prescribed is reaching an average seaward shift of *MKL* between 0 and 25 m per year (in average 12.5 m per year), in *subarea 2* and looking at a *Time Horizon* of 10 years.
From the network it can be derived that the objective can be achieved by nourishing in average subarea 2 with 205 m^3/m/yr during the 10 year time window.

Besides the relative improvement in *MKL*, this nourishment strategy will lead to an average relative increase of *MDV* of 47 m^3/m/yr, and a probability of failure decreasing mainly to a value between half of the actual value and the actual value.

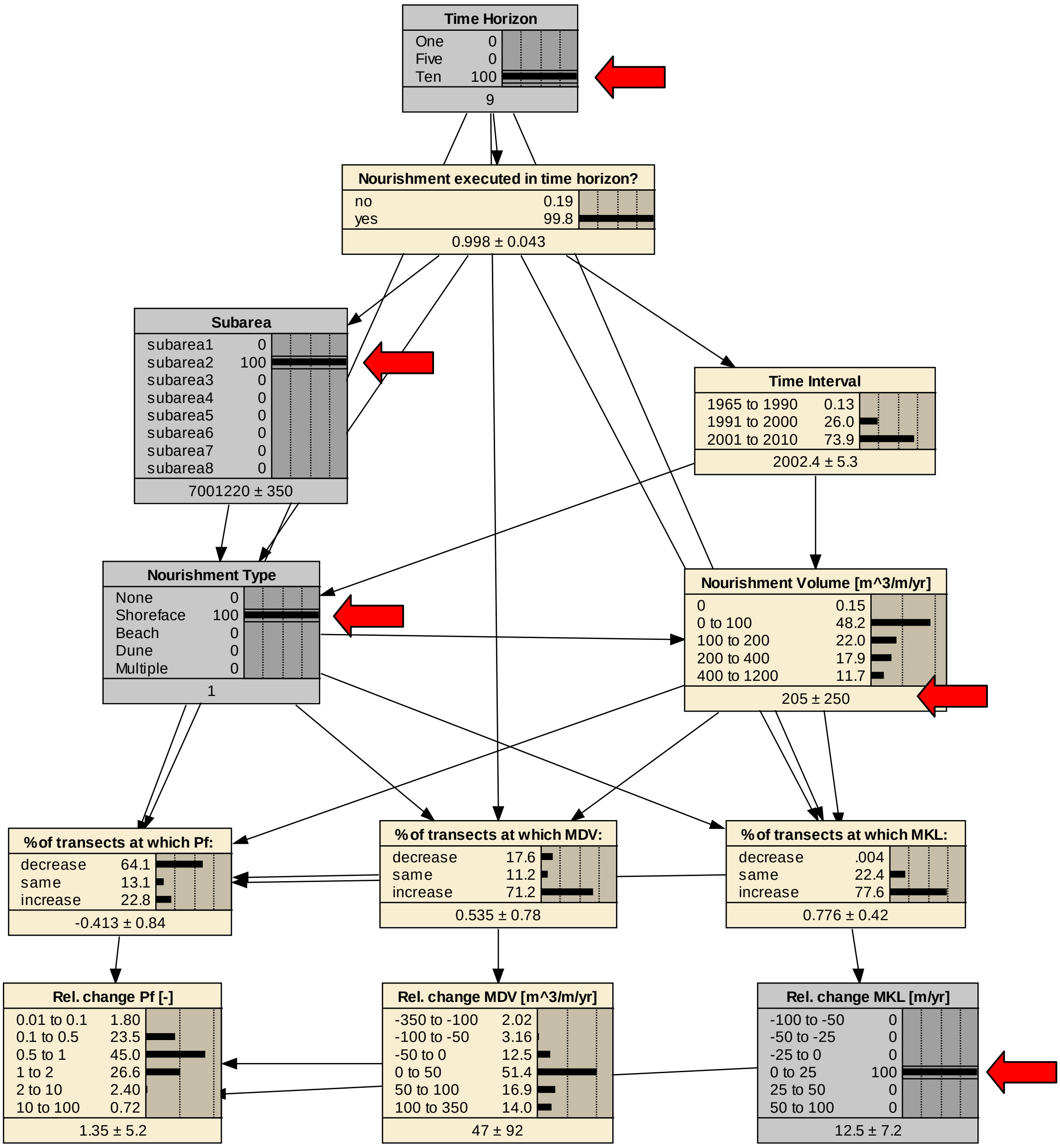

Figure 3.13 Example 6: Plan of a nourishment scheme to reach a pre-defined objective

4 Conclusions

In this study, a Bayesian network has been built to assess the effects of nourishments on a number of indicators using as input, data defined at transect level for the North Holland coast. The Bayesian approach is in fact very suitable to the application, since it can be easily used to evaluate cause and effects (e.g. nourishment and effects on coastal indicators). Moreover, being based on a probabilistic method, allows accounting for uncertainties. As indicators for short- and medium- term safety, probability of failure, MKL, and MDL have been selected.

A number of applications have been shown, supporting the idea that, in general, nourishments have lead to an improvement of the different indicators with respect to the non- nourishment case. This also confirms the starting hypothesis of the current project "Toestand van de Kust": nourishments have positive effect on different indicators. In particular, for short-term effects, beach nourishments are more effective than shoreface nourishments. However, in the long term (10-year time scale) the two effects become comparable.

Moreover, changes in volumes in the cross-shore profiles appear to influence directly the probability of failure of the first dune row. An average shift in MKL of 50 m, can lead to a change in probability of failure of about 1 order of magnitude.

The last example shows how the network can also be used to plan a nourishment strategy in order to achieve a certain objective (e.g. average improvement of MKL of 12.5 m/yr), defining types and volumes of nourishments which can be used to reach the objective.

5 Recommendations for Future Work

A number of recommendations for future studies are suggested in this chapter and can be used to improve the work presented in this report.

- Use of heterogeneous data (model + measurements) as input to the network. It is possible to use as input to the network synthetic data derived by running a model simulation (e.g. based on UNIBEST-CL or Delft3D). In this way, it could be possible for example to assess the effects of nourishments at transects where nourishments have never been executed. In the same way, the effect of very large nourishments, which are still limited in number, could also be evaluated.
- The study has only focused on the North Holland coast. The study can be extended to the rest of the Dutch coast. The effect of a nourishment derived using the network implemented for North Holland could be used for example as predictive tool for South Holland, which has similar morphological characteristics, and then verified once the new network is built.
- Additional indicators could be added to the network to describe other physical parameters e.g. storminess parameter, sloping factor... Also, if necessary, new relations could be implemented by adding additional arrows. However, it is important to keep in mind that adding new variables and arrows might complicate the network making it more difficult to define clear interdependences between variables.
- The discretization of variables is a necessary step to build the network, which however is subjective and can affect the results. Different discretisation procedures can be evaluated.
- The network is still under development and improvements are still needed to be able to use it as management tool. The interface for example could be improved to make it more user-friendly.

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A List of Matlab functions

A Bayesian network is a probabilistic graphical model based on data. Data is entered as cases to the Bayesian network. A case is a record in the database and represents an event. The input database is built as a matrix with, on every line, a unique case. For this study, five Matlab-scripts were used to organize a dataset that serves as input to the Bayesian network constructed in Netica (www.norsys.com) (Table A.1). The scripts, together with an example are available in the OpenEarth repository.
https://svn.oss.deltares.nl/repos/openearthmodels/trunk/deltares/CoastalState_Bayesian/

Table A.1 Lists of Matlab script used to construct the Bayesian network.

Name Matlab script/function	**Description**
csb_collect_data.m	Main script calls all the other functions.
csb_getIndicator.m	Obtain data of the indicators from the server.
csb_getNourishVol.m	Obtain nourishment data from the server.
csb_createDataMatrix.m	Organize the data in case-style (every row in the matrix is a unique case).
netica_write_case_file.m	Write data to an ascii file such that Netica can read the data.

A more detailed description can be found in the help of the functions.

B How to build a Bayesian network? Example North Holland Coast

This appendix aims to clearly describe the steps to make in order to construct a Bayesian network. As example, the Bayesian network described in the current study will be used. The procedure given in Table B.1 was followed and is explained step by step.

Table B.1 List of actions to construct a Bayesian network.

	Action	Description
1	Download Netica	Download Netica software package.
2	Create nodes	Select variables that play a role in the system.
3	Draw arrows between the nodes	Determine correlations between the variables of interest.
4	Discretize variables	Select bin ranges for the (continuous) variables in your network.
5	Train Bayesian network	Learn relations between the variables with the use of data and quantify the relations in conditional probability tables.
6	Update Bayesian network with (new) information	Pick a certain combination of variables (a so-called case) and evaluate the change of the variable of interest (here, coastal indicator).

B.1 Download Netica

The Bayesian network development software Netica (www.norsys.com) has been used within this project. There are several available Bayesian software packages (see wikipedia for a complete list). The choice for Netica has two main reasons. Firstly, Netica is widely used. Secondly, Netica is user friendly such that it is simple to build a Bayesian network from scratch. Netica is a free software package; however, the free version has a limitation to 15 nodes in the size of the network that can be built with it. However, in the OpenEarthModels a license key is available that allows to built networks larger than 15 nodes.

B.2 Create Nodes

After downloading the Netica software package, it is possible to start 'building' the network. The building part is divided into two actions: create nodes (this section) and connect nodes (next section).

In a Bayesian network, nodes represent variables. In this study, the effect of nourishment on coastal indicators is investigated. Therefore, the selected variables represent either causes (a nourishment) and effects (e.g. change in dune volume). Other variables were added to describe the spatial and temporal variations of the variables. The list of variables, as well as the objective which supported the choice of these variables, are shown in Table B.2.

Table B.2 List of nodes in the Bayesian network described in this study.

Index	Name	Description	Objective
1	Sub-area	Jarkus transect indices for different sub-areas in North Holland.	Evaluate the nourishment policy over space.
2	Time Interval	Years.	Evaluate the nourishment policy over time.
3	Time Horizon	Time frames.	Evaluate nourishment effects on the short-, medium-, and long-term.
4	Nourishment executed	Binary: yes or no.	Evaluate the effects of implementing a nourishment or not.
5	Nourishment type	It describes the type of nourishment implemented: shoreface, beach, dune, multiple (combination of different nourishments), and no nourishment.	Evaluate the effects of implementing different type of nourishments.
6	Nourishment volume	Nourished volume per year [m^3/m/yr].	Evaluate the effect of different nourishment volumes.
7	% of transects at which Pf [decrease, same, increase]	It describes at how many transects the probability of failure will decrease, stay the same or increase.	What will happen, in average, at the different transects to the probability of failure?
8	% of transects at which MDV [decrease, same, increase]	It describes at how many transects MDV will decrease, stay the same or increase.	What will happen, in average, at the different transects to the MDV?
9	% of transects at which MKL [decrease, same, increase]	It describes at how many transects MKL will decrease, stay the same or increase.	What will happen, in average, at the different transects to the MKL?
10	Rel. change Pf [-]	Order of magnitude of change in safety.	Relative change in probability of failure (order of magnitude).
11	Rel. change MDV [m^3/m/yr]	Order of magnitude of change in dune volume.	Relative change in dune volume (order of magnitude).
12	Rel. change MKL [m/yr]	Order of magnitude of change in MKL-position.	Relative change in MKL (order of magnitude).

How to add nodes?
In Netica, it is simple to add nodes to your network. Click on the yellow oval icon in the taskbar to add a nature node to your network. When double-clicking on the node, the node settings are open and node options can be set. The node settings used in the current study are shown in Table B.3.

Table B.3 Node settings used in the current study

Option	Setting	Useful information
Name	Variable dependent	Name of the node. Make sure this name is equal to the name of the column in your input dataset.
Title	Variable dependent	Title of the node as shown in the network.
Type	Nature	Variables used represent nature nodes.
Discrete/Continuous	Variable dependent	Use discrete in case of a fixed number of states, for example *yes* or *no* nourishment. Use continuous otherwise.
State	Variable dependent	A node is represented by states (bins). This process is called discretization and described in section B.4.

B.3 Draw arrows between the nodes

In a Bayesian network two nodes are directly correlated if there is an arrow between the nodes. This arrow is always directed, this means it is pointing from one node to the another one.

In a Bayesian network correlation means direct influence, also called *statistical dependency* indicating that the dependency does not need to be causal or physical. Here, an arrow is drawn when a physical relation exists according to our knowledge of the underlying processes.

How to add a link?

Click on the *arrow symbol* in the taskbar to connect two nodes and draw an arrow from the parent node to the child node. You can draw arrows between all nodes, however cycles (or loops) results in an error because a node is affecting itself.

B.4 Discretise variables

Because Netica works with categories instead of numbers, it is required to represent the continuous physical processes with a small number of discrete categories. This process hereafter referred as discretisation results in a number of bins, representing the estimated probability density distribution (i.e. histogram) for each variable (Figure B.1). With the discretisation process some information will get lost. For example a bin with an interval of [1; 2] cannot distinguish a value of 1.1 and 1.9 since both numbers fall in the same bin.

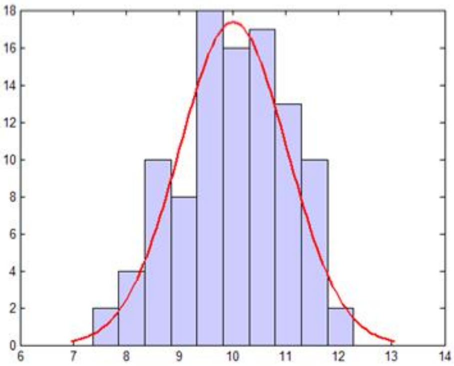

Figure B.1 Graphical representation of a discretisation procedure.

On the other hand, a very high number of bins will affect the dimensionality and complexity of the Bayesian network. Moreover, if there are too many bins relative to the size of the training data set, very few observations (or hits) will fall in some of the probable states and therefore they will not be well constrained. Too few bins, however, may not resolve the variability of the variables, blurring important information.

The choice made to discretise the nodes in this network is presented in Table B.4. As a general guideline, it is important to minimize the number of bins in such a way to obtain a statistically robust network but also computationally efficient.

Table B.4 List of variable with the related number of bins and the choice for the number of discretisation bins.

Variable	Continuous/ Discrete	#bins	Choice for discretization thresholds
Subarea	Continuous	8	Sub-areas within region North-Holland. Transects within each sub-region have a similar nourishment strategy and natural behaviour (see Giardino et al 2012).
Time Interval	Continuous	3	Three periods to distinguish between three nourishment strategies.
Time Horizon	Discrete	3	To evaluate short-, medium-, and long-term effects of a nourishment on the coastal indicators
Nourishment executed?	Discrete	2	Is there any nourishment executed in that given year in that subarea over given time interval?
Nourishment type	Discrete	5	To distinguish between all the type of nourishment and no nourishment.
Nourishment volume	Continuous	5	Nourishment volume per linear meter divided over the time horizon. Bin ranges flexible, maximum fixed to exclude low probability extremes that are physically not significant.
% of transects at which Pf:	Discrete	3	Increase/decrease in safety. Relatively small changes are filtered out and considered as similar.
% of transects at which MDV	Discrete	3	Increase/decrease in dune volume. Relatively small changes are filtered out and considered as similar.
% of transects at which MKL	Discrete	3	Increase/decrease in MKL position. Relatively small changes are filtered out and considered as similar.
Rel. change in probability of failure	Continuous	6	Definite magnitude representing the relative changes.
Rel. change in MDV	Continuous	6	Definite magnitude representing the relative changes.
Rel. change in MKL	Continuous	6	Definite magnitude representing the relative changes.

How to discretize variables in Netica?

Only continuous variables need to be discretized. For instance the variable ‘nourishment type’ contains five unique values, representing the five types of nourishment. In this case, the

number of bins equals five and represent the five nourishment types. For other variables discretization is necessary.
The option *discretization* can be selected above the dialog box, in the node settings. Type the discretization thresholds in this dialog box. Every line represents one threshold so press enter when adding one threshold. When ready press ‘okay’ and the node is discretised. Because at this phase there is still no data entered to the network, Netica does not know how the information is distributed between the nodes. Therefore, the different nodes are characterized by a uniform probability distribution. By default, the name of a state is defined by the range of the particular state. In the same way as selecting ‘discretisation’ one can select ‘states’. Type here the name of the specific bin as you want to be appearing in the network.

B.5 Train Bayesian network

After discretizing the Bayesian network, it is time to train the network with data. A training algorithm is used to learn the relations between the variables in the network. For a detailed description on how the training algorithm works see the Netica online help.
After training, the prior probabilities of the Bayesian network are shown. Basically, for every node a histogram is given for the data entered. For all the nodes also the mean and standard deviation is given in the last line of each box.

How to train a Bayesian network in Netica?
For this project, the training algorithm ‘Counting-Learning’ is used. To do so select, ‘incorp case file’ in the task bar ‘cases’. Select the dataset (with .cas extension) that serve as training set for your Bayesian network. First Netica will ask what the degree which is for learning. This is one by default and we advice to keep it like this. Than Netica will ask you what to do with the values that fall outside your outer bin ranges. In order to prevent Netica to extend your bin ranges press *disregard the values that fall outside the bin ranges.* After the learning phase the Bayesian network is trained, so the conditional probability tables are filled. To have an impression of how such a *cpt* looks like, select a node and press the green italic F in the task bar).

B.6 Update Bayesian network

Now that the Bayesian network is trained, it is possible to infer in the network. This can be done by adding new information (data) or constraining certain variables and evaluate what happens with the other variables. With the constraining, it is possible to simulate a (future) event and analyze what effect this will have. This effect is shown by a change in the probability distribution. Adding new data or constraining nodes, result in a change in the probability distributions, also called posterior distribution.

How to constrain nodes?
It is quite simple to constrain a node to one specific bin. Just click on the name of the bin, (so not the black bar itself), and the bin will be constrained. The ‘constrained’ node turns grey and the probability of selected bin turns into 100%. To ‘de-constrain’ a bin press on the bin name again.