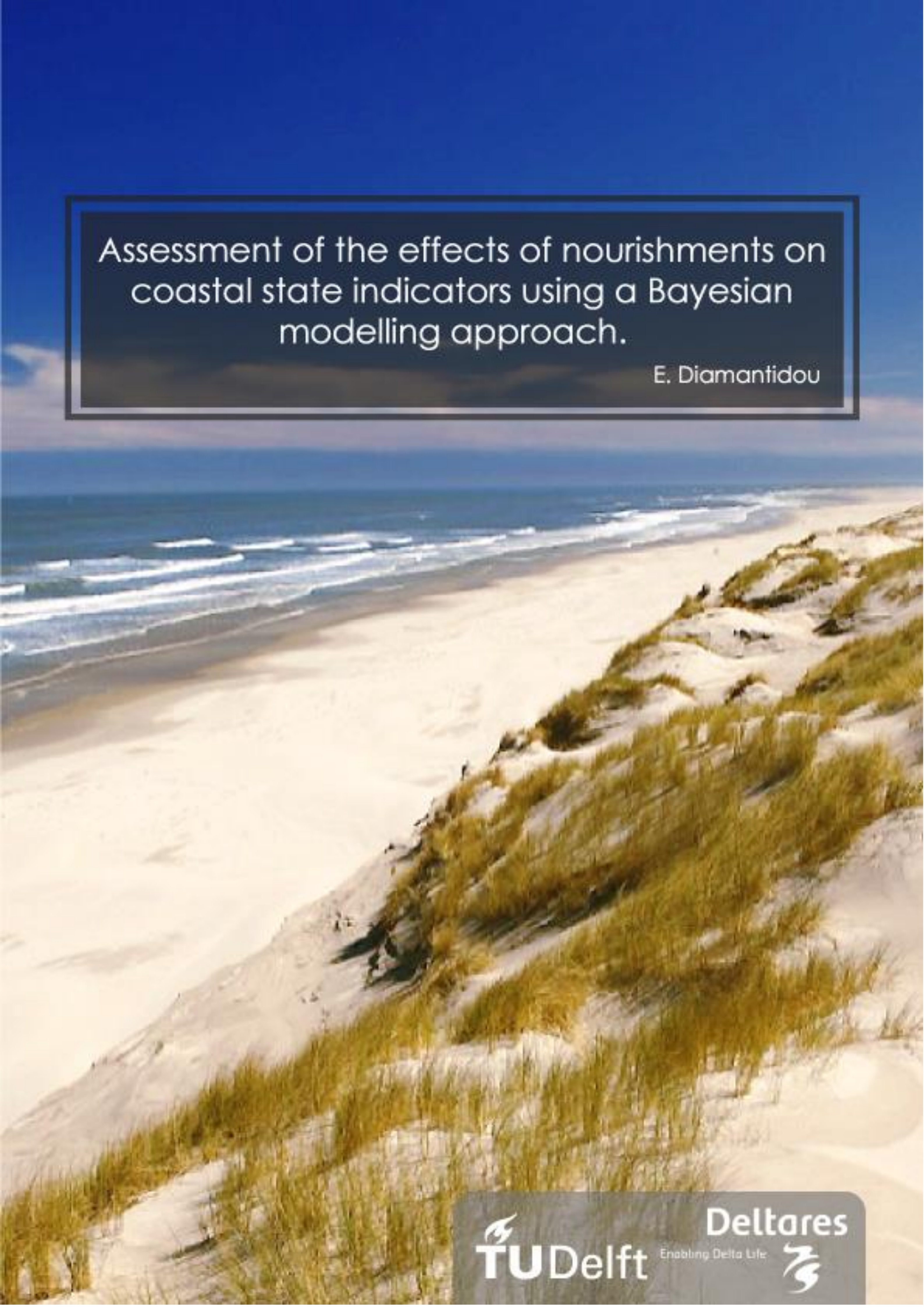
Assessment of the effects of nourishments on coastal state indicators using a Bayesian modelling approach.

E. Diamantidou



Assessment of the effects of nourishments on coastal state indicators using a Bayesian modelling approach.

by

Eleni Diamantidou

in partial fulfilment of the requirements for the degree of

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Front cover: Photo of coastal dune located at the Dutch coast. Downloaded from https://www.flickr.com

Preface

The present thesis concludes my Master of Science program in Hydraulic Engineering at the Faculty of Civil Engineering and Geosciences of TU Delft, The Netherlands. The study has been carried out at Deltares, in collaboration with TU Delft.

I would like to thank all the committee members for their contributions on this project. First of all, I would like to express my gratitude to Giorgio Santinelli and Alessio Giardino for giving me the opportunity to get involved in the *"KPP – B&O kust"* project of Rijkswaterstaat. I would like to thank Giorgio for his daily supervision and his continuous support through the whole process. Special thanks go to Alessio, whose experience and insightful comments were always valuable for the progress of my project. From the Dutch side, I would like to thank Sierd de Vries for always having a critical approach on my results and for his continuous feedback on my report. Finally, I would like to thank Saskia van Vuren and prof. Matthijs Kok for providing constructive feedback and recommendations during our meetings and for making me zoom out and consider practical aspects of my research.

Apart from my committee members, I would like to thank Stuart Pearson for his continuous enthusiasm on Bayesian networks and for his advices on the analysis and the use of the software. Moreover, I would like to thank Wiebke Jäger, who in a brief meeting managed to enlighten me on the mathematical background of the Bayesian inference. Finally, I would like to thank Nathaniel Plant for sharing his Bayesian Tools.

I owe many thanks to all the people I met in Deltares and in The Netherlands during these years. Thank you for your help, your advices and our great time we had together during this period.

Finally, I would like to express my gratitude to my parents and my sister for supporting me in my decision to start an MSc abroad and for motivating me during those years.

E.Diamantidou

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Abstract

The Dutch coast is affected by coastal erosion. In order to limit erosion and prevent inland migration of dunes, sand nourishments have been adopted as a common practice for the maintenance of the coast. The evaluation of the applied coastal erosion policy is achieved by the use of coastal indicators. Increased number of nourishments affects the coastal profiles and coastal indicators are used to describe those changes along the coastal zone. The present work intends to improve the definition of one of the indicators (dune foot position) by proposing a new methodology and to develop a Bayesian network in order to assess the effectiveness of nourishments on the coastal system. Coastal indicators, such as the Momentary Coastline and the dune foot position, are used in the Bayesian network in order to quantify those effects.

Available field measurements of the entire Dutch coastline (JARKUS morphometric database) are used in order to develop the methodology of the dune foot position detection. Taking into account the geometry of the profiles, the dune foot position can be detected by calculating the first and second derivatives of the measured points along the profiles. Comparison with visual, in-situ observations, constitute the validation method of the proposed methodology. Root mean square errors, with respect to visual observations, are used to compare the performance of two methods for the dune foot position detection; the proposed methodology and the current dune foot definition, which detects the dune foot at the most seaward crossing of the profile with the level of +3 m NAP. By looking at the performance of the methodologies at different areas, the results are diverse. However, the proposed methodology shows a general improvement of the detection. Moreover, the methodology is believed to be generic and applicable to other dune systems around the world, since it is purely based on the morphology of the profile.

A Bayesian modelling approach is used to assess the effectiveness of nourishments on coastal indicators for the Holland coast. The selection of the input and output parameters, the design of the network and the optimization of the structure are the main steps for the development of the model. Once the optimum configuration is chosen and the model is trained, the Bayesian network gives the possibility to investigate the relations between variables, by constraining the input nodes on a specific range of values and assessing changes on the indicators. By applying those constraints it can be found that nourishments have positive effects on the coastal indicators, since larger seaward displacement is observed compared to cases in which no nourishment has been implemented. Moreover, initial erosive trends of the dune foot position are constrained by the implementation of nourishments. In addition, the effects of nourishments at different time scales are investigated. To this end, time horizons of 1, 5 and 10 years after a nourishment implementation are chosen. Positive effects of nourishments are present at all the considered time horizons, with beach nourishment to have an immediate effect on the indicators, whereas shoreface nourishments reach a stronger effect 10 years after the implementation.

Finally, the Bayesian inference can be used as a decision support tool for coastal managers, since its user-friendly environment can lead to easy interpretation and use for coastal management purposes. The required sand volume can be estimated in order to achieve a specific magnitude of seaward displacement of the indicators or in order to preserve the coastline at the current state. The estimations concern large spatial scales.

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List of acronyms

Acronym	Description
BKL	Basal Coastline
BN	Bayesian Network
CPT	Conditional Probability Table
DF	Dune Foot
JARKUS	JAaRlijkse KUStmeting – Yearly coast measurements
LLR	Log Likelihood Ratio
MKL	Momentary Coastline
MLWL	Mean Low Water Level
MSL	Mean Sea Level
NAP	Normaal Amsterdams Peil – z reference
Pf	Probability of failure
RMSE	Root Mean Square Error
SLR	Sea Level Rise
TKL	Testing Coastline

Introduction

CHAPTER SUMMARY

The Dutch coast is affected by coastal erosion. Sand nourishments have become common practice in coastal management, since they have successfully limited erosion and prevented inland migration of dunes.

In order to better understand the effects of nourishments on the coastal system, a Bayesian network which uses coastal indicators, such as the dune foot position and the momentary coastline, is developed to describe coastal changes.

1. Introduction

1.1. Background information and problem description

Coastal erosion

Coastal erosion is a natural phenomenon, which influences and reshapes the European coastal landscapes (European Commission, 2004) and it has been a subject of a wide variety of research. Several studies have discussed the main factors that cause erosion. Sea level rise, change of storm climate and human interference are the three main factors that can possibly cause erosion according to Zhang et al. (2004). European Commission (2004) enumerates those factors. Waves, winds, tides, near-shore currents, storms, sea level rise, slope processes and vertical land movements are categorized as natural factors, whereas hard coastal defences, land reclamation projects, river water regulation works, dredging, vegetation clearing, gas mining or water extraction and ship waves are grouped together as human induced factors.

Coastal erosion in The Netherlands

A large part of the Dutch coast is affected by coastal erosion. Erosion is caused by the imbalance between sediment supply and demand. There is a large demand of sand, whereas there is only limited supply. Sea level rise leads to an increased sediment demand and, therefore, to retreat of the coastline and dune erosion (de Winter, et al., 2017). Besides the effects of sea level rise, large-scale interventions in the tidal basins influence this balance.

The Dutch coastline has a length of 432 km and it can be roughly divided into three areas with distinct morphological characteristics (from North to South): the Wadden Coast, the Holland Coast and the Delta Coast (Figure 1). The Wadden Coast consists of five main barrier islands. The dunes at the heads of the islands are not well-developed (Ruessink, et al., 2002). The Holland coast is gently curved with a long stretch of uninterrupted dune row. The dune system is interrupted by hard structures at the entrance of the Amsterdam Harbor at IJmuiden and at the discharging sluice of Katwijk (Van der Burgh et al., 2011). The Delta area consists of a large river delta.

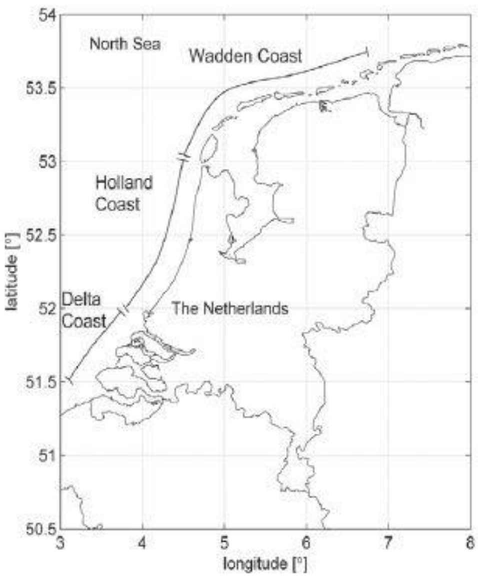

Figure 1 Three subareas of the Dutch coast (Source: Giardino et al., 2011).

It is important to prevent coastal erosion. In The Netherlands, the problem that could be encountered is the failure of the dune system, as a result of a single storm event and the potential flooding of the hinterland (European Commission, 2004). The Netherlands is threatened by floods, since as a low-lying country, 27% of the territory is located below mean sea level (Giardino, et al., 2011). Approximately 9 million people are living below sea level and 70% of the gross domestic product is being earned in those areas (Mulder, et al., 2011). Moreover, socio-economic development is present at the coastal area. Therefore, the protection and preservation of the coastal zone against coastal erosion has become a concern of growing importance.

1.2. Coastal policy

The coastal zone is preserved in order to ensure safety against flooding and protect the low-lying hinterland. The historical development of measures that were implemented, as well as the recent coastal erosion policy, are discussed in this section.

Coastal dunes, which approximately cover 59% of the Dutch coastline (Ruessink, et al., 2002), have a significant contribution to the protection of the hinterland, since they function as a natural barrier providing safety against flooding of the hinterland during extreme storms. However, the level of protection varies in time, since coastal dunes are dynamic (Van der Burgh, et al., 2011). In addition, their preservation is important for other reasons: they are used for recreational purposes, they provide drinking water and they are important in terms of ecology.

The first attempts to stabilize the dunes and to stop further structural erosion included “soft engineering” approaches, such as placement of sand fences and planting of marram grass. Nevertheless, those measures did not prevent the inland migration of the beach-dune system (Keijsers, et al., 2015). Since 1990, the Dutch government has implemented the “Dynamic Preservation Policy” which adopts the “hold-the-line” policy (MinV&W, 1989, as cited in Keijsers et al., 2015). This policy impose the maintenance of the coastline position to that of 1990. In 2000, the policy focuses on the preservation of the entire coastal zone and develops the concept of “Coastal Foundation”. The “Coastal Foundation” is defined as the area enclosed by the dune position and the -20 m depth contour (Giardino, et al., 2011). This led to an increasing total average yearly sand nourishment volume over time, from 6 millions m^3 in 1991 to a doubled value of 12 millions m^3 in 2001 (Mulder, et al., 2011).

Sand nourishment has two main advantages compared to other coastal protection measures. Firstly, nourishment is a relatively economical efficient method; the annual budget for management of the Dutch coastline is estimated to be 40 million Euros (European Commission, 2003). Secondly, sand nourishment does not cause negative consequences on the neighbouring areas of the implementation area, compared for instance to side effects due to a construction of a hard structure. On the contrary, those areas are positively influenced by the additional sand volume which is added to the system. Finally, nourishment does not interfere on the natural processes of the coast.

Based on annual coastal measurements and understanding of the coastal system, coastal managers take decisions concerning the time and place of a new nourishment implementation. Spatial distribution of sand nourishments along the Dutch coast for the period 1991-2006 can be found in Figure 2.

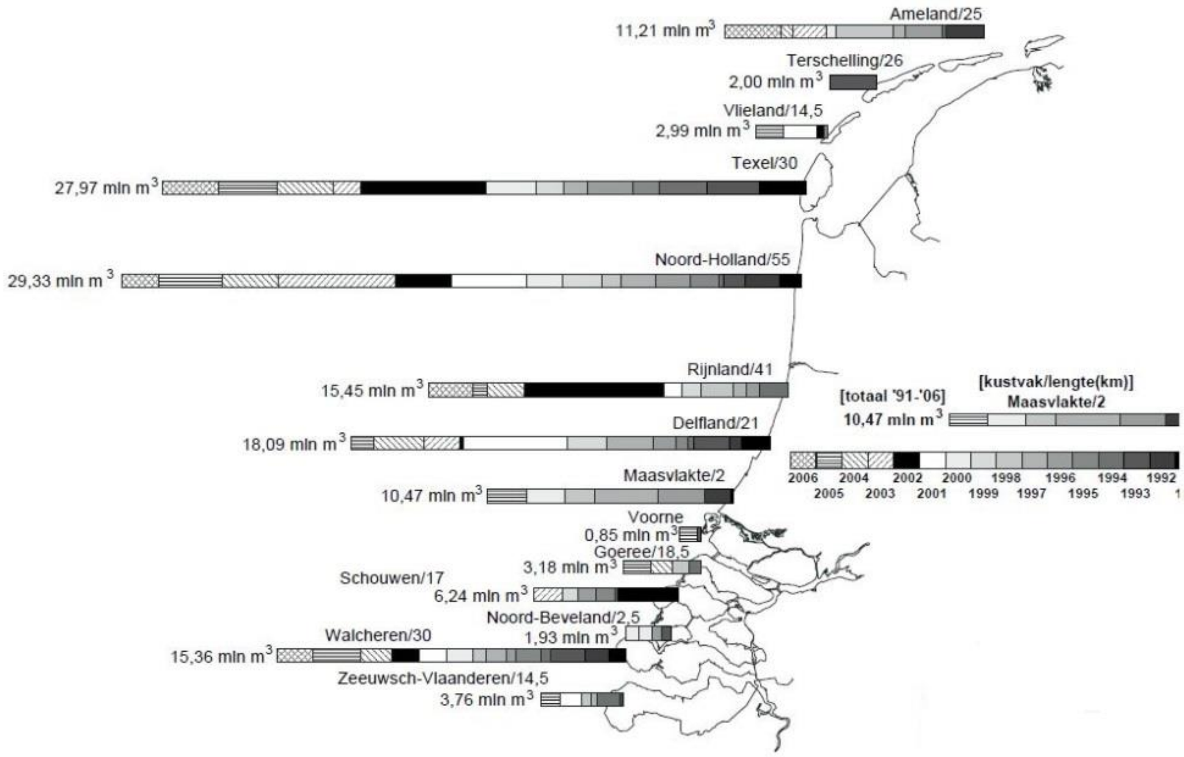

Figure 2 Sand nourishments along the Dutch coast between 1991 and 2006 (Source: Rijkswaterstaat nourishment statistics dated from 2007).

Dynamic preservation program

Initially, basic concepts and definitions are described in order to get a better insight into the current nourishment policy.

- Momentary Coastline (MKL)

The momentary coastline is located at a horizontal distance *B* from the dune foot position (Figure 3), where *B* is defined as the area shaded in gray, divided by *2H. H* is the vertical distance of the dune foot position from the mean low water level (MLWL). The area is defined by two horizontal planes (for any given cross-shore profile): the upper plane crosses the dune foot position and the lower is located at a distance 2*H* from the upper plane (van Koningsveld, et al., 2004).

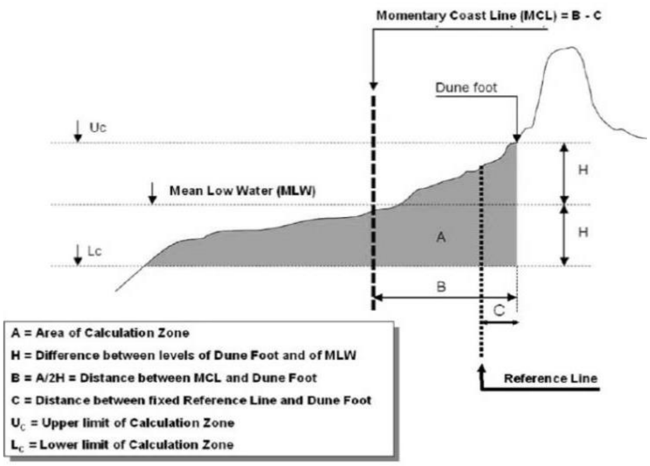

Figure 3 Definition of the Momentary Coastline (MKL) in a dune cross section (Source: Mulder, et al., 2011).

- Basal Coastline (BKL)

The Basal Coastline is defined as the coastline position of the year 1990. The BKL is located around MLWL (Ministerie van Infrastructuur en Milieu, 2016) and it has slightly changed its location after 1990, because of minor adjustments to the original definition.

- Testing Coastline (TKL)

The Testing Coastline is derived from a 10-year linear trend extrapolation of the MKL points which correspond to the previous 10 years. Therefore, the TKL describes the current state of the system. This method is chosen in order to account only for structural and not incidental erosion (van Koningsveld, et al., 2004). Figure 4 illustrates the method of the TKL extraction.

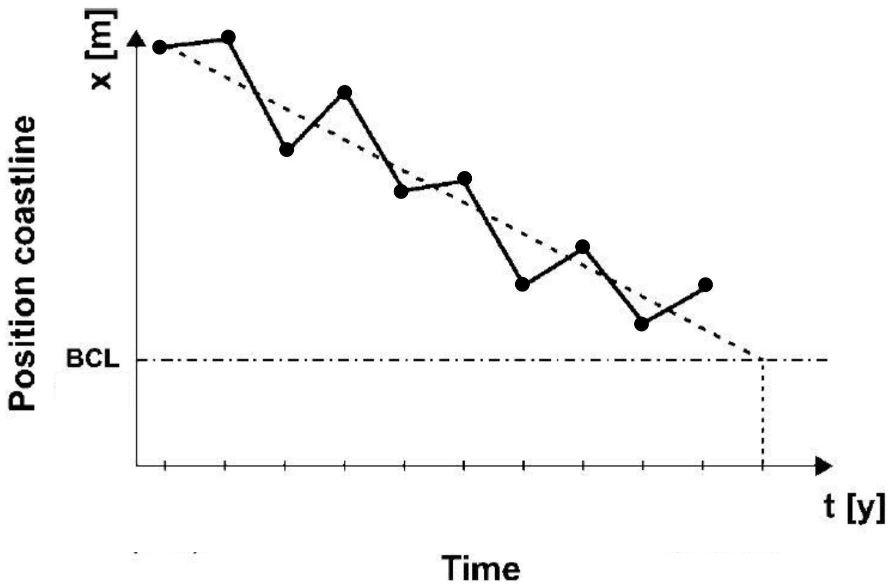

Figure 4 Graphical representation of the calculation of the testing coastline (Source: van Koningsveld and Mulder, 2004).

A comparison between the TKL and BKL determines whether a nourishment should be applied. By testing different profiles of the coast and comparing those two values, Rijkswaterstaat determines which locations need to be nourished.

1.3. Coastal indicators - Dune Foot position

The evaluation of the applied policy is achieved by the use of coastal indicators. Increased number of nourishments affects the coastal profiles and coastal indicators are used to describe changes along the coastal zone (Giardino, et al., 2014) and, in this way, evaluate the effects of nourishment on the coastal profiles. Therefore, well–defined indicators are essential and necessary for this evaluation.

The CoastView project defined the Coastal State Indicators as *"A reduced set of issue-related parameters that can simply, adequately and quantitatively describe the dynamic-state and evolutionary trends of a coastal system"* (Davidson, et al., 2007). Moreover, it was emphasised that the use of coastal indicators enhances the communication process between scientists, coastal managers and policy makers and decisions concerning coastal management are based on them (Van Koningsveld, et al., 2006).

The dune foot position is introduced in literature as coastal state indicator, which can be used to define erosional trends (Stafford, et al., 1971), to define the shoreline position (Battiau-Queney et al. (2003), Boak et al. (2005)) and to quantify changes related to system function (available space for nature and recreation) (Giardino, et al., 2014). Sediment management constitutes a primary approach to prevent inland dune migration and the dune foot position is used to calculate the MKL and, in extension, the required sand volumes (van Koningsveld, et al., 2004). The calculation of the MKL assumes that the dune foot is located at a fixed height above sea level, which is not always representative.

This section presents the use of the dune foot position in different studies related to dunes and dune dynamics and states the definitions that were adopted. Finally, it describes the current definition for the Dutch area and introduces an observed problem.

Dune dynamics

The coastal dunes and dune dynamics in The Netherlands have been a subject of a wide variety of research over decades. Arens et al. (1994) classified the Dutch foredunes in three major categories based on development, management and aeolian processes: progressive, stable and regressive foredunes. The classification can be used as a tool for calculation of sediment budgets. For this purpose, both aerial photographs from 1988 and the JARKUS-morphometric database of Rijkswaterstaat were used.

In dune foot dynamics, Ruessink et al. (2002) introduced a methodology which splits the dune foot dataset into a long-term trend and in variations around the trend (residual dune foot position). The residual position was then subdivided into an alongshore uniform and non-uniform component. A strong non-uniform behaviour is present, organised in sandwave-like patterns. Damsma (2009) investigated the influence of a mega nourishment on dune development. Bochev - van der Burgh et al. (2011) described the behaviour of managed coastal dunes over time intervals of decades, via the use of Empirical Orthogonal Function (EOF) analysis. A study on forecasting of beach volumes was conducted by Southgate et al. (2011). Sierd de Vries et al. (2012) used dune volume changes per year to find spatial and temporal variations in dune behaviour. A correlation between beach slopes and dune volume changes was found.

Shoreline evolution

Dune foot has been used in studies of erosion rates and shoreline changes around the world. Changes in dune foot line were used to indicate erosion rates along a part of North Carolina coast (Stafford, et al., 1971). Moreover, shoreline mobility was assessed by the use of the foredune foot for sandy beaches in the northern France (Battiau-Queney, et al., 2003). Furthermore, at the study of Castelle et al. (2017) dune foot was considered to quantify shoreline changes along a sandy coast in SW France. In addition, coastline evolution was quantified by the use of this indicator for beach-dune systems SW Spain (Del Rio, et al., 2013) and in Portugal (Ponte Lira, et al., 2016).

Previous and current definitions of dune foot position

Many definitions for the dune foot position are used in literature. Van de Graaff (1990) describes the dune foot line as the transition between the beach and the mainland. It is also defined as the position with a break in slope between the beach and the foredune. The definition corresponds to approximately 3 m above MSL. Moreover, Damsma (2009), Van der Burgh et al. (2011) and Ruessink and Jeuken (2002) used this definition for their studies. In addition, Quartel et al. (2008) described the dune foot (+3 m NAP) as the landward boundary of the beach. On the contrary, Guillen et al. (1999) developed a new definition for the dune foot position. At that study, the dune foot position was defined as the intersection of the +1 m NAP with the maximum slope of the profile between +1 and +5 m NAP, considering both morphological and sediment balance criteria. Moreover, a work related to a mega nourishment defines the dune foot at +5 m MSL (Hoonhout, et al., 2017). In The Netherlands, it is widely assumed that the dune foot is defined as the most seaward crossing of the +3 m NAP (Normaal Amsterdams Peil, i.e. the Dutch reference level, which is roughly located around mean sea level (de Vries, et al., 2012)).

The definition of +3 m NAP is widely accepted in The Netherlands, but it needs revision in order to represent reality more accurately. There are locations where the +3 m NAP definition results in a line far off the actual dune foot position. An example for a part of the Dutch coast can be found in Figure 5. The dune foot position is a parameter which is used in many studies for the calculation of beach widths and beach gradients (de Vries, et al., 2012), dune volumes (Van der Burgh, et al., 2011) and beach volumes. Furthermore, it is important for the nourishment policy, since the calculation of MKL is based on its position. In addition, dune foot position is essential for long term coastal management, since short term processes can be neglected (Guillen, et al., 1999). Hence, a well-defined indicator can lead to better monitoring of the evolution of beach and dune systems.

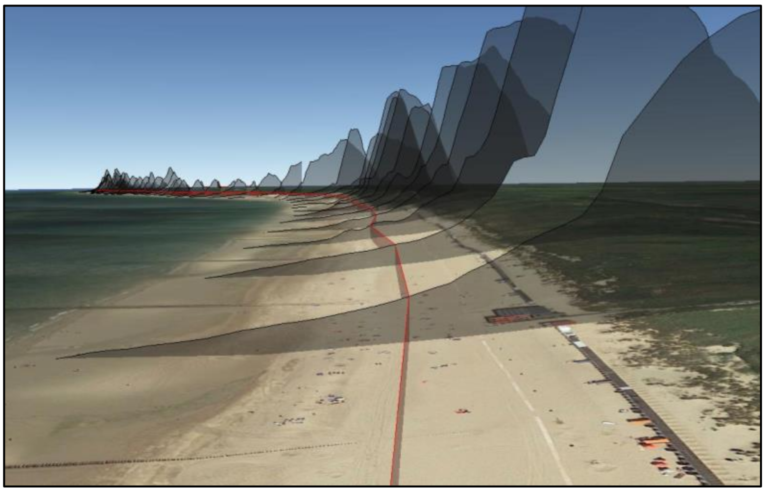

Figure 5 Observations in Walcheren (Google Earth Visualisation).

1.4. Research significance

The use of Bayesian networks offers many advantages to coastal engineering practice and one has been developed in this study in order to investigate the effectiveness of nourishments on the coastal system. Firstly, it is a fast and useful tool which can operate with large datasets and evaluate dependencies among the used parameters (Giardino, et al., 2012). Bayesian networks are highly useful in cases where measurements are prone to errors or they are not accurate enough. Incomplete data are also tolerated. In addition, they can make statistically robust forecasts, by combining multiple parameters and using probability relations to simulate complex interactions of a system. All the advantages mentioned above make the BNs a useful tool for this study.

Bayesian networks have applications in many fields and they are also very useful in coastal engineering. A Bayesian Network has been used to predict coastal cliff erosion (Hapke, et al., 2010). The network was successful in identifying areas with high probability of extreme erosion. Plant et al. (2011) used a Bayesian approach to predict and assimilate processes in the surf zone. Poelhekke et al. (2016) applied a Bayesian method to surrogate a process-based model within EWS in order to predict coastal hazards for sandy beaches. The study of Plomaritis et al. (2017) built upon the work of Poelhekke et al. (2016), by using a BN to evaluate different Disaster Risk Reduction measures. Jäger et al. (2017) developed a BN for decision making and coastal risk management, which estimates the percentage of affected receptors for different storm scenarios, taking into account their hazards and damages. At the study of Sanuy et al. (2017) a Bayesian network is used to link the forcing characteristics with expected consequences of coastal storm impacts for two sandy coasts at the Mediterranean.

Additionally, Den Heijer et al. (2012) predicted dune erosion due to extreme storm events and van Verseveld et al. (2015) used a BN to model multi-hazard hurricane damages on a part of New York, for the case of hurricane Sandy. Moreover, Bayesian networks have been used for studies of sea level rise vulnerability (Gutierrez, et al., 2011) and climate change impact assessment (Sperotto, et al., 2017). Finally, a Bayesian inference has been used for geomorphological predictions of a barrier island (Gutierrez, et al., 2015) and for predicting coastal flooding hazard on reef environments (Pearson, et al., 2017).

Despite the wide range of studies based on Bayesian networks in coastal engineering, two studies are available in which Bayesian networks have been used to investigate the effectiveness of nourishments on the coastal system. Giardino et al. (2012) developed a Bayesian network in order to assess the efficiency of nourishments on three coastal indicators; probability of failure of the first dune row, momentary dune volume and MKL. The network was based on measured data and the area of study was limited on North Holland. Later on, Giardino et al. (2013) developed a Bayesian network which was trained with a synthetic dataset; 297 nourishment scenarios were simulated by UNIBEST-TC at one specific transect. MKL and dune foot position were used for the assessment of the efficiency of nourishments.

Among the recommendations from Giardino et al (2012), the extension of the network to a broader area and the use of different indicators were suggested. This study tries to overcome the spatial limitations and assess the effects of nourishments on a large scale. MKL and dune foot position are the coastal indicators selected for the assessment. Furthermore, the study emphasizes on the way to optimize the network structure and identify the optimum connection among the variables. In addition, it investigates which variables should be included in the network. The training of the network is based on measured data. Then, the Bayesian Network can be used as a tool to indicate dependencies between nourishment characteristics and changes on the indicators (MKL, DF). By placing certain constraints on the parameters, the network provides the possibility to assess different scenarios (e.g. effects of a specific type of nourishment on dune foot displacement). Finally, possible applications of the constructed network on the coastal management practice are explored. Its user-friendly environment leads to easy interpretation and use by the coastal managers in the decision making process.

1.5. Scope and research questions

The main objective of this thesis work is to assess the effectiveness of nourishments on the coastal system, by using a Bayesian modelling approach. Coastal indicators, such as MKL and dune foot position, are used in the Bayesian network in order to quantify those effects, since they can describe changes along the coastal zone. Well defined indicators lead to better evaluation of the effects of nourishmnets. Therefore, a sub-objective of this study is to improve the method of the dune foot position detection.

The research questions that motivate this study are stated hereafter.

1.5.1. Bayesian modeling

How could the effects of nourishments on the coastal system, represented by coastal state indicators, be assessed by using a Bayesian modelling approach?

Answering this question will lead to the sub-questions below:

1. Which is the appropriate network design? Which variables should be included in the network?
2. Which are the effects of nourishments on coastal state indicators?
3. Which are the effects of different nourishment types on coastal state indicators?
4. What can be learned from the use of the Bayesian Network for coastal management purposes?

1.5.2. Dune foot position detection

How could the methodology for the detection of dune foot position be improved?

Answering this question will lead to the sub-questions below:

1. Could the methodology be generic and be based only on the geometry of the profile?
2. Could the methodology be applicable to dune systems in other countries?

1.6. Thesis outline

Chapter 1 includes background information relevant to the area of interest, provides the problem description and outlines the objectives and the research questions of this study.

Chapter 2 provides the methodology of this study. The approach that it is followed in order to fulfil the main objective and to answer the research questions above consists of 2 main phases; dune foot position detection and Bayesian modelling. Phase 1 is focused on the use of field measurements of coastal profiles in order to develop a new methodology for the dune foot detection. Phase 2 concerns the development of a Bayesian network in order to evaluate the effectiveness of nourishments on the coastal indicators; selection of the parameters used in the network, creation of the dataset for the training and optimization of the network structure are the required steps.

Chapter 3 presents the results of the two phases. Root mean square errors are calculated in order to relate the detected dune foot positions of the proposed methodology to actual dune foot positions. Then, the validity of the proposed methodology at other dune systems is tested by applying the methodology in a part of the Portuguese coast. Next, validation of the performance of the network is achieved by using confusion matrices. Finally, relationships and dependencies between the variables are identified and analysed. By placing certain constraints, different scenarios are developed in order to assess the effects on the indicators.

Chapter 4 provides a discussion over the assumptions which were used in the study, over the results of Chapter 3 and over the application of the constructed network in coastal engineering practice. Finally, Chapter 5 summarizes the main conclusions derived from this study and provides recommendations for future research.

Appendix A includes a number of graphs concerning the performance of the new methodology for the dune foot detection. Additionally, Appendix B concerns the way that information flows through the network. In Appendix C, information about the available data can be found. Appendix D includes alternative network layouts used for this study. Finally, Appendix E includes details of the results presented in Chapter 3.

Methodology

CHAPTER SUMMARY

The methodology applied in the study is explained at this chapter. Firstly, the new approach for the detection of the dune foot position is described. Then, the background on the theory behind Bayesian Networks is provided, followed by a discussion on the design of the Bayesian network. Assessment methods of the performance of different network configurations and the validation method of the optimum configuration are discussed.

2. Methodology

2.1. New methodology for dune foot detection

The methodology for the dune foot detection is described in this section. The purpose of the new methodology proposed in this thesis is the detection of dune foot position purely based on profile geometry. In this way, it can be generally applicable along the entire Dutch coast and it can be implemented to other sandy dune systems elsewhere.

First, a description of the study area and of the available data obtained throughout the years is given. Then, steps taken for dune foot position detection are described and two technical difficulties are discussed. Thereafter, two validation methods are explained, based on the use of visual observations and satellite images. Next, the use of heat matrices is introduced in order to assess the overall performance of the proposed methodology. Finally, an application to another dune system could indicate whether the use of the methodology is possible to areas beyond the Dutch coast.

2.1.1. Study area

The area of interest is the entire Dutch coast. Approximately 59% of the Dutch coastline is covered by dunes (Ruessink, et al., 2002). Only 10% of the Dutch foredunes are natural (without any human interference), and these dunes can be found mostly on the Wadden Islands (Arens, et al., 1994). The remaining foredunes have been stabilized or remodeled by human interventions. Deposition and erosion can be controlled by sand fences or by marram grass. The physical processes and the dune dynamics are also influenced by beach or dune nourishments.

2.1.2. Available data

The method for the dune foot detection is derived based on the JARKUS database of Rijkswaterstaat (Dutch Ministry of Transport, Public Works, and Water Management). The JARKUS[1] ("JAaRlijkse KUStmeting", Annual Coastal Measurement) survey was started in 1965 and data have been carried out annually between April and September. The data cover beach, dune and foreshore (de Vries, et al., 2012) and contain measurements of coastal profiles, which are taken with respect to a series of permanent beach poles along the coast (Van der Burgh, et al., 2011). Each profile has been measured for 52 years, from 1965 to 2016. The JARKUS database is available online[2] as open source software in the OpenEarth platform for coastal data and knowledge management.

[1] http://opendap.deltares.nl/thredds/dodsC/opendap/rijkswaterstaat/jarkus/profiles/transect.nc, http://opendap.deltares.nl/thredds/dodsC/opendap/rijkswaterstaat/MHW_MLW/MHW_MLW.nc

[2] hhttp://openearth.deltares.nl/

In cross-shore direction, the transects include the area from approximately the foredune to the -8 m contour (Giardino et al. (2014), Van der Burgh et al. (2011)) and there are records of elevation at every 5 m (Van der Wal, 2004). Moreover, the alongshore interval between two transects is 200-250 m. An example of a JARKUS profile over the years is given in Figure 6. Vertical distances are measured with respect to 0 m NAP and horizontal distances with respect to a permanent beach pole. The identification number of transects is defined by Rijkswaterstaat. The JARKUS dataset consists of two types of measurements: dry beach levels and nearshore underwater bed levels. Overlapping the measurements in the intertidal region (they were carried out near low and high tide respectively) enables them to be merged into a single data set (Southgate, 2011). This study focuses on the sub-aerial data. During the period of data gathering, the collection method has changed (de Vries et al. (2012), Van der Burgh et al. (2011)). Before 1977 dry beach measurements were gathered by means of leveling; afterwards, aerial photography was used until 1996. Thereafter, data were gathered by laser altimetry. Each technique has its own different accuracy; the accuracy is estimated to be 0.01 m for leveling, 0.1 m for photogrammetric measurements and 0.1 m for laser altimetry measurements (Van der Burgh et al., 2011).

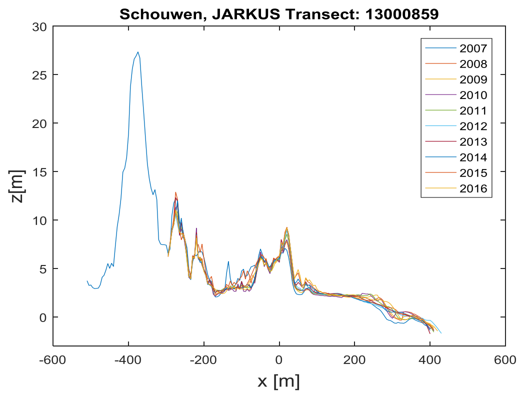

Figure 6 JARKUS profile measurements for one decade (Schouwen, Transect 13000859).

The JARKUS data are subdivided between different areas[3]. Those areas are listed in Table 1.

Sub-Areas	Area number according to Rijkswaterstaat
Schiermonnikoog	2
Ameland	3
Terschelling	4
Vlieland	5
Texel	6
Noord-Holland	7
Rijnland	8
Delfland	9
Voorne	11
Goeree	12
Schouwen	13
Walcheren	16
Zeeuws-Vlaanderen	17

Table 1 Areas of interest.

Finally, data for the mean high water level are used for the derivation of the new methodology.

[3] https://publicwiki.deltares.nl/display/OET/Dataset+documentation+JarKus

2.1.3. Dune foot position detection

Even if the JARKUS database is consistent, there are transects with missing information. Those data can lead to false and misleading conclusions. Incomplete parts of the data are identified and they are deleted in order to improve the quality of data. A complete transect in the JARKUS database consists of 1925 cross-shore measured points. The quality of the dataset could be represented by looking at the number of valid points for each transect. The number of valid points vary per transect. There are 23206 transects which have no valid points. Those transects are excluded from the calculations. The filtered dataset (80% of the transects) is used for the new methodology. For the transects used in the calculations, all the Not-A-Number (NaN) values are removed.

Two spatial constraints are defined in order to specify the area in which the detection will take place; a seaward and a landward constraint. By defining those constraints, the computation cost is small and errors at the detection can be avoided, since the detection will take place in a restricted area. As seaward constraint, the level of the intersection of the mean high water and the dune profile is chosen. In case of multiple crossings, the most seaward point is selected. For the landward constraint the peak height and the altitude of the points are taken into account. The steps which are taken are described below and they are depicted on the flowchart in Figure 7. First, among the multiple peaks which are observed along one transect, the peaks with heights larger than 2.4 m are selected. The value of 2.4 meters is assumed to be the critical height, above which a peak can be considered as dune peak and not as a secondary morphological feature. This value is derived after a series of tests for the Dutch coast. Then, the peak which is located at the most seaward position is considered to be the landward constraint. Finally, in cases the altitude of the peak is larger than +6 m NAP, the intersection of +6 m NAP height with the dune profile is found and it is assumed to be the landward constraint instead.

The new profile (testing profile, Figure 8), delimited by the two constraints, is used for the analysis. Transects with a small number of remaining valid points are removed from the dataset. The definition of the area of interest will follow the calculation of the first derivative. A threshold of 0.001 is used to set the first derivative to 0. Long sequences of zeros correspond to long flat stretches and they are removed. The second derivative is then found and a threshold of 0.01 is applied. The final step is to locate the most seaward position with a value larger than the threshold. The dune foot position corresponds to that point. This point is the transition of a constant slope to another one, having the meaning of a “break” in slope of the dune.

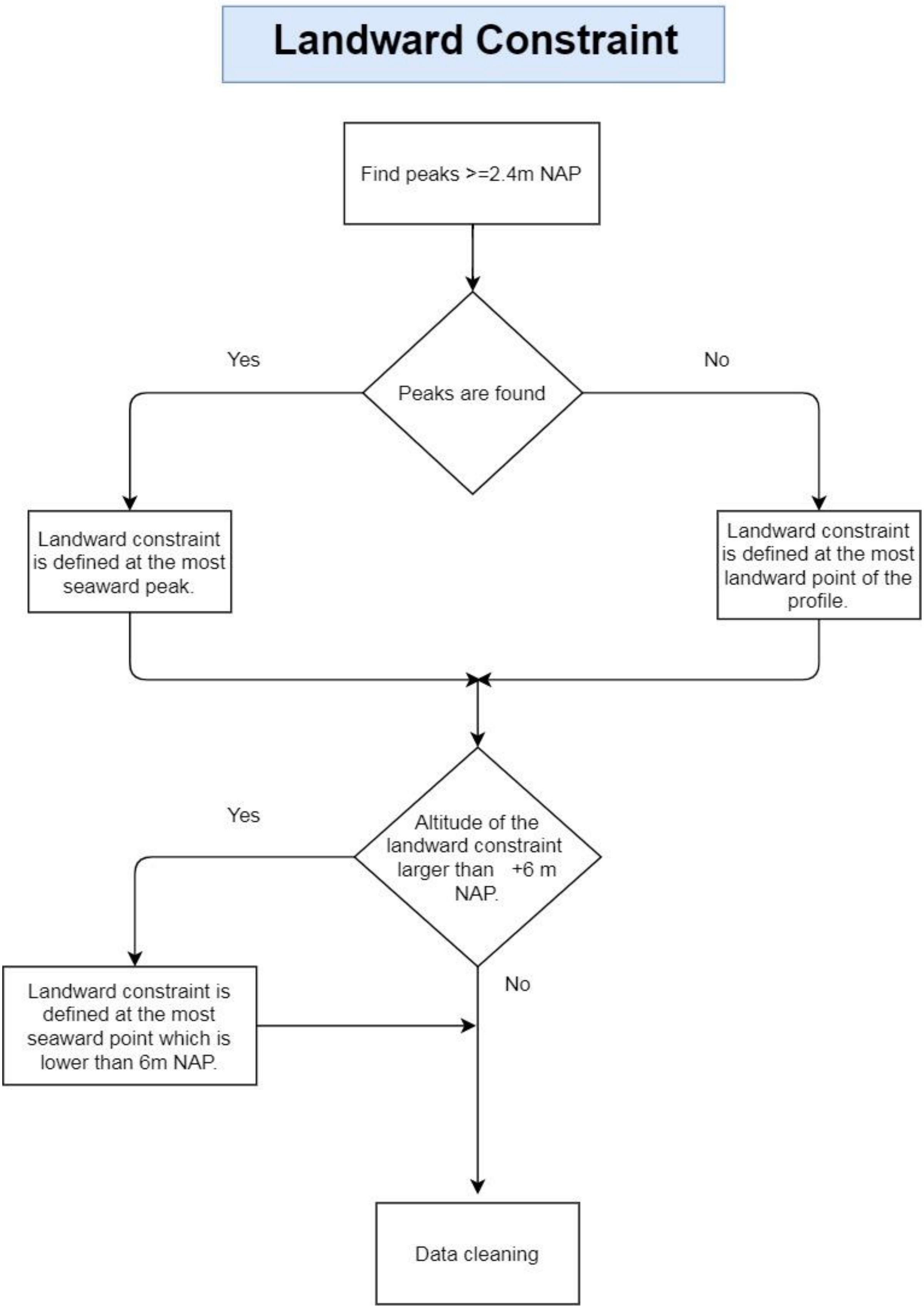

Figure 7 Steps taken for the calculation of the landward constraint, in order to define the "testing profile" for the detection of the dune foot position.

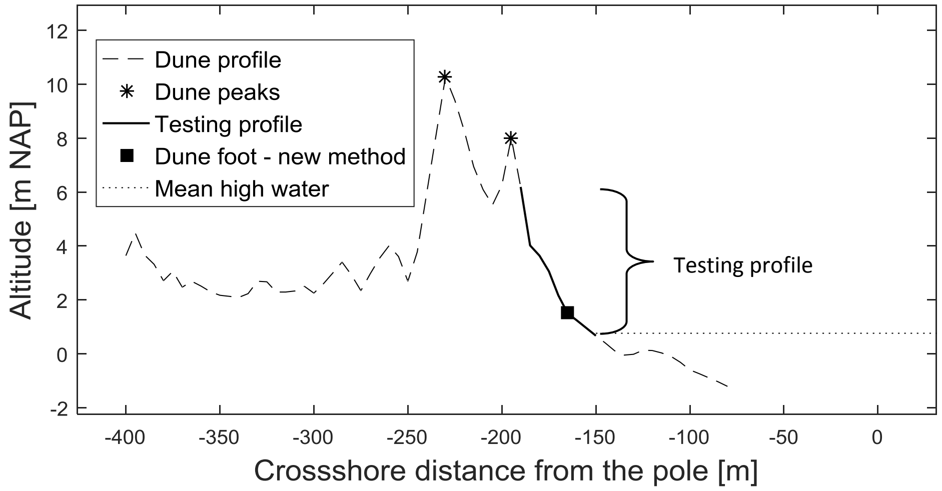

Figure 8 Testing profile of a cross shore JARKUS transect; Transect: 7003000, Year: 1979.

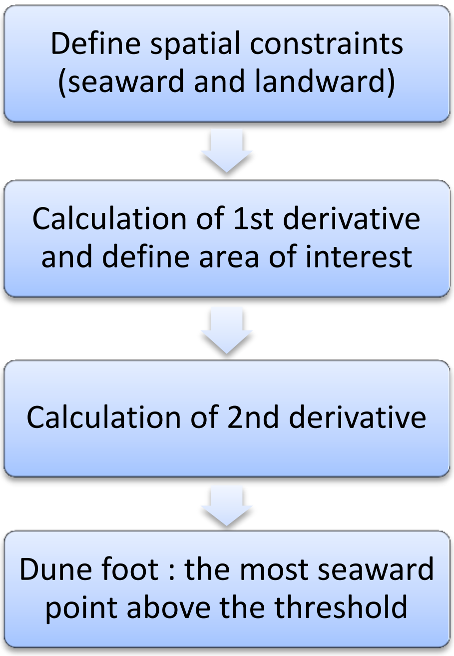

Figure 9 Steps taken for the dune foot detection.

The 1st and 2nd derivatives for two cross shore JARKUS transects can be seen in Figure 10 and Figure 11. Figure 10 shows a simple case, whereas Figure 11 shows a more complicated case, since there is more variability in the slope than in Figure 10. The calculation of the derivatives consists of two steps. First, derivatives are derived for the testing profile. Then, points with absolute values of the derivatives below the selected threshold are not taken into account. Dune foot position is the location of the most seaward point for which the value of the second derivative is above the threshold.

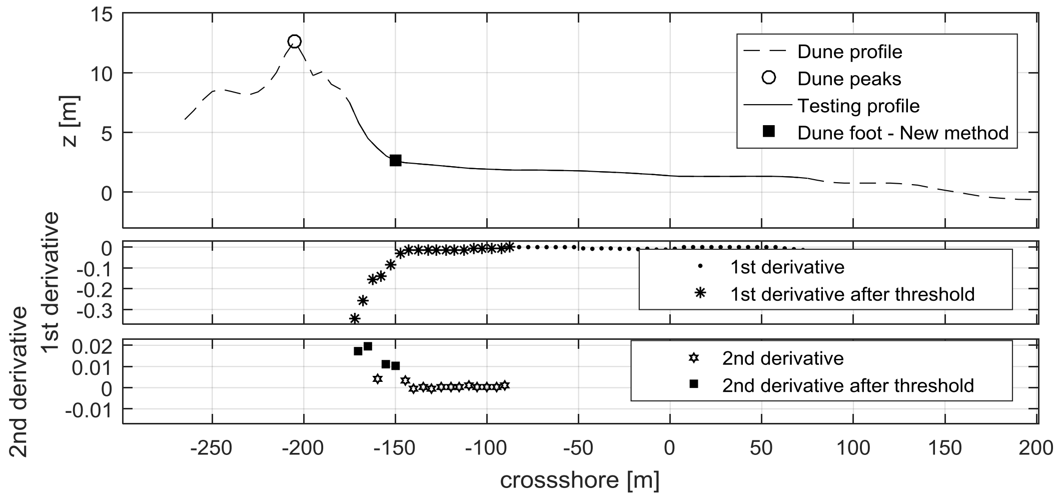

Figure 10 First and second derivatives; Transect 11000800, Year: 1981.

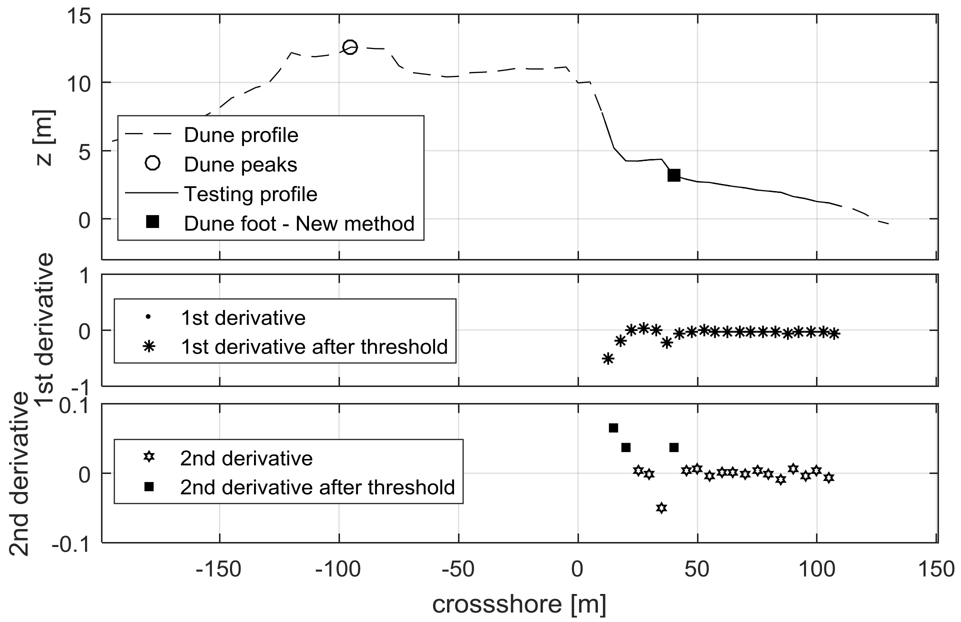

Figure 11 First and second derivatives; Transect 8006600, Year: 2000.

Technical aspects

Different values for the peak height were tested. A series of tests were carried out in order to define the value of the height and thresholds. The change of the height has large impact on the results and it is considered to be the most critical parameter. For each of those tests, the performance is estimated in comparison with visual observations and the dataset with the best performance is selected. The validation method and the dataset of visual observations are described at the next section.

The second constraint for the landward boundary (second decision node in Figure 7) leads to an increase in accuracy for the areas of Noord Holland and Rijnland. The implementation of this constraint leads to an increase in accuracy of 10% and 20% for the two areas respectively. The validation is achieved by comparing the results of the proposed methodology to visual observations.

By applying the above - mentioned constraint, it is possible to avoid two kinds of errors. At some transects, a flat area around the peak is present. Then, the algorithm deletes this part, and the dune foot location is predicted to be just landward of the start of this area (Figure 12). Secondly, transects with a high peak have constant slope for a large stretch, which results in zero 2^{nd} derivatives for that area of the dune. Thus, the dune foot is calculated to be located around the peak of the dune, which is highly deviated from the reality. By applying the +6 m NAP constraint, those errors can be avoided.

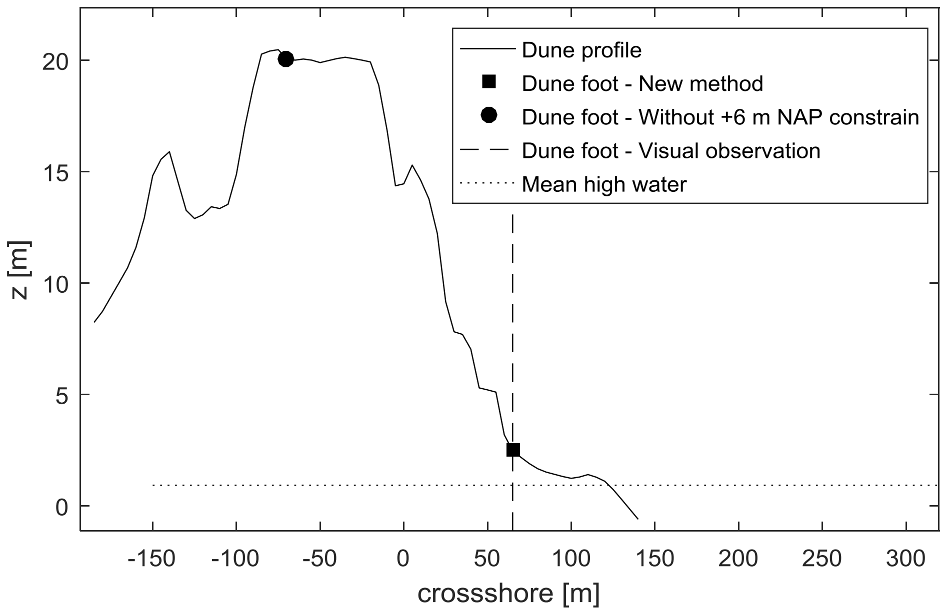

Figure 12 Dune foot detection with and without the +6 m NAP constraint; Transect: 8006400, Year: 1983.

Another challenge is the calculation of peak heights. An algorithm for the prominence of a peak is used for those calculations. "*The prominence of a peak measures how much the peak stands out due to its intrinsic height and its location relative to other peaks. A low isolated peak can be more prominent than one that is higher but is an otherwise unremarkable member of a tall range*"[4]. For some transects, the points which are considered the base of the peak are located far from the peak,

[4] https://nl.mathworks.com/help/signal/ref/findpeaks.html#buff2uu

which results in overestimation of the peak height. In Figure 13, the peak prominence *(h1)* of the most seaward peak is calculated from the local minimum at -20 m. In order to correct this overestimation some steps are taken to define an “endpoint” at the sea side. This point will be considered the reference level for the prominence calculation. In Figure 13, the final calculated prominence for the seaward peak is denoted as *h2*.

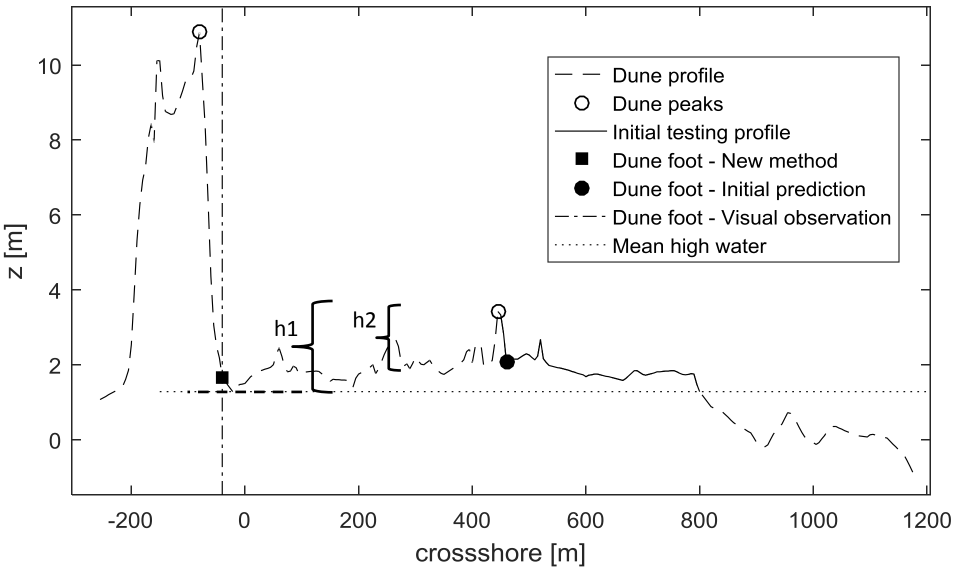

Figure 13 Correction for the peak height; Transect: 12000550, Year: 1979.

2.1.4. Validation methods

The proposed methodology is validated by the use of two methods; visual observations and satellite images. Those two methods are described in this section.

Visual observations

The visual observations are field measurements of the dune foot which have been conducted by Rijkswaterstaat annually. The dataset contains information about the dune foot position for the years 1843 until 1998. The measurements were taken based on the assumption that the dune foot is located at the break in slope between beach and dune. Moreover, the existence of vegetation might have contributed to the observations.

Root mean square errors

The RMSE is a statistical method which measures the deviation of a variable from another one. In this study, this method is used to quantify the deviation of the computed dune foot positions (based on the proposed methodology) from the dune foot positions derived from visual observations. Increasing values of RMSE indicate a larger deviation of the computed values from the visual observations.

The root mean square error can be expressed as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_{comp,i} - x_{vis,i})^2}{N}} \qquad [4]$$

Where:

- $x_{comp,i}$ is the cross shore distance of the computed dune foot position from the beach pole
- $x_{vis,i}$ is the cross shore distance of the dune foot position based on visual observations from the beach pole
- N is the sample size (number of transects that are considered)

RMSE are applied in two more cases. Firstly, they are used to compare the dune foot positions based on visual observations with the dune foot positions derived from the +3 m NAP definition. This definition is widely used in The Netherlands and it is desirable to compare its performance to the performance of the proposed methodology. Secondly, same comparisons are made for the assumption that the dune foot is located at the intersection of the coastal profile with the upper boundary used for the calculation of the MKL (Upper MKL).

Satellite images

The use of satellite imagery is the second method of validation of the developed methodology. The validation of the performance presented above is limited by the number of visual observations against which the new methodology can be compared. This is due to the limited time period during which the visual observations were held. Thus, there is a need to adopt another validation method for the following years.

Satellite images can be used to illustrate and assess the results of the proposed methodology. Images from SENTINEL-2 missions are freely available and they are used for this purpose. "*SENTINEL-2 is a polar-orbiting, multispectral high-resolution imaging mission for land monitoring to provide, for example, imagery of vegetation, soil and water cover, inland waterways and coastal areas*" (ESA, 2015). Two identical SENTINEL-2 satellites operate simultaneously. Sentinel-2A was launched on 23 June 2015 and Sentinel-2B followed on 7 March 2017.

2.1.5. Overall performance

An overview of the methodology can be achieved by the use of heat matrices. Heat matrices can be used to quickly gain insight into the data, and identify areas for further analysis, such as areas with no values or with high difference among the values. They are useful because they can allow for a given dataset to be easily summarized and understood at a glance.

2.1.6. Application to other dune systems

The proposed methodology is believed to be generic and applicable to other dune systems. The methodology is based on the morphology of the profile and certain parameters (i.e. height of the peaks) used in the calculations were derived based on a series of tests at the Dutch coast. In order to test whether the developed methodology is valid in other areas, tests are carried out for another dune system. A morphological dataset of a part of the Portuguese coastline (Aveiro, Figure 14) for the year 2011 is used. At those tests, the parameters remained identical. Thereafter, Google earth imagery is used to compare the results of the new methodology with the reality, since no field measurements for the location of the dune foot were carried out.

Figure 14 Location of Aveiro, Portugal (Image obtained from Google Earth).

2.2. Bayesian Network

At this phase of the study, a Bayesian network has been developed in order to assess the effectiveness of nourishments on the coastal system, which is represented (in the BN) by coastal state indicators. The aim of using the network is to identify dependences between nourishments and changes on coastal state indicators. This network aims to serve as a tool at the hands of managers or decision makers to help them assess the effects of nourishments on the coastal system for different cases and develop more efficient and cost-effective strategies.

First, a description of the study area and of the Bayesian inference is provided. Then, the input and output parameters are introduced. Thereafter, the network structure and the training process are described. Alternative network configurations are developed and log-likelihood ratio tests are proposed for the assessment and comparison of their performance in order to result to the optimum configuration. Moreover, confusion matrices are used for validation of the optimum configuration. Finally, the assessment of different scenarios developed by constraining parameters is proposed in order to explore dependencies between the parameters.

2.2.1. Case study

The study area for this part of the project is limited to the Holland Coast (Figure 15), which is located in the central part of The Netherlands, bounded by Den Helder in the north and Hoek van Holland in the south. The coastline is approximately 120 km and it has a slightly concave shape, with an orientation from 2° to 40° with respect to the North, in the northern part and southern part respectively (Giardino, et al., 2014). Hard structures are present, such as the entrance of the Amsterdam harbor and the discharging sluice of Katwijk, but it is mainly characterized by sand beaches and dunes. The Holland coast can be characterized as a wave dominated coast (European Commission, 2003). The average beach slope is between 1:35 and 1:60 (Giardino, et al., 2014).

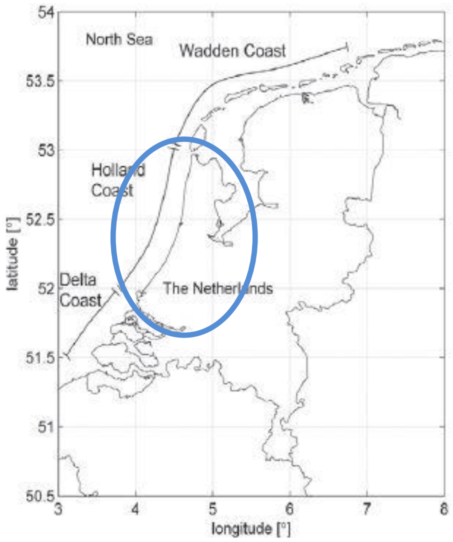

Figure 15 Map of The Netherlands (Source: Giardino et al., 2011)

The Wadden and Delta Coast are not considered in this part of the study. Those areas are governed by different morphological characteristics. Tidal channels and flats make the Wadden coast a complex system (European Commission, 2003). The effects of nourishments are difficult to be assessed at these complex environments. Alongshore sediment transport is considerable at those areas, which is in contradiction with the assumption made in this study, that the nourishment volume is only transported at the cross shore direction.

2.2.2. Bayesian Inference

A Bayesian Network is a probabilistic graphical model. It is used as a computational tool which describes a system using conditional probabilities. Bayesian inference is a statistical method to calculate how the degree of belief in something is modified due to new evidence or new information (Den Heijer, et al., 2012). The initial relation between the variables comes from prior knowledge about the system. This prior knowledge captures our understanding of the likelihood of particular outcomes (Plant, et al., 2011) and it is available before the network is updated with new observations. Bayes' rule is then used to update the probability of the variables that are linked with the new observation.

The development of a Bayesian Networks lies in an interpretation of Bayes' Theorem:

$$p(F_i|O_j) = \frac{p(O_j|F_i)\, p(F_i)}{p(O_j)} \qquad [1]$$

Where:

- $p(F_i|O_j)$ is the conditional probability of a particular forecast F_i given a set of observations O_j
- $p(O_j|F_i)$ is the conditional probability of the observations given a known forecast
- $p(F_i)$ is the probability of a particular forecast F_i, prior to any observation
- $p(O_j)$ is the probability of the observations (normalization factor)

The prior probability [$p(F_i)$] is useful for evaluating the quality of the data, since inconsistent data will result in very uncertain distributions and the last term [$p(O_j)$] is often responsible for large computational costs (Plant, et al., 2011).

Figure 16 illustrates a simple Bayesian Network consisting of 4 variables. Direct influence between the variables is represented by unidirectional arrows. Variables X2 and X3 influence directly the variables X4, whereas X1 is connected to X4 through the variable X2. Details about the flow of the information inside a network can be found in Appendix B. The Bayesian Network is a directed acyclic graph, or simply DAG, which means that there must not exist any directed cycles.

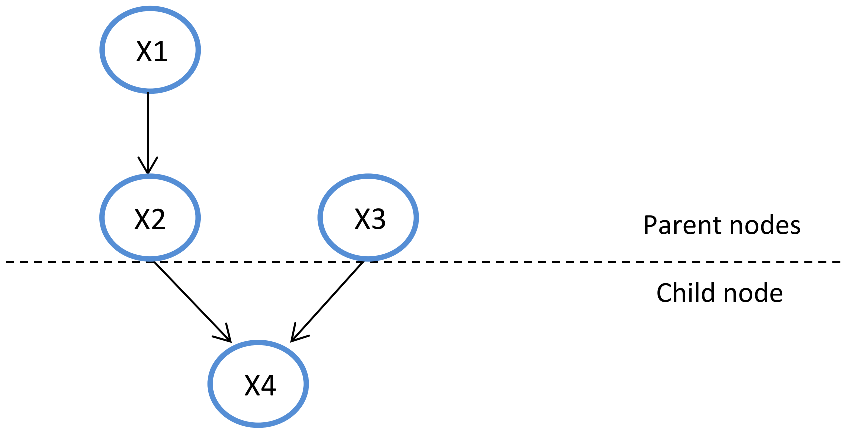

Figure 16 Simple Bayesian Network consisting of four variables.

Intermezzo:

Structure terminology (Korn, et al., 2004)*:*
In talking about network structure it is useful to employ a family metaphor: a node is a parent of a child, if there is an arc from the former to the latter. One node is an ancestor if another is it appears earlier in the chain, whereas a node is a descendant of another node if it comes later in the chain. Another useful concept is that of the Markov blanket of a node, which consists of the nodes' parents, its children and its children's parents. Any node without parents is called a root node, while any node without children is called a leaf node. Any other node (non-leaf and non-root) is called an intermediate node.

2.2.3. Bayesian network approach

For the present study the software Netica "6.02" (Norsys, 2003) is chosen, a widely used Bayesian network development software which is obtained from Norsys[5]. The decision to work with Netica was based on its performance options, the extensive supporting material provided and its successful use in several coastal applications.

Den Heijer et al. (2012) indicate four key steps in order to develop a Bayesian Network: data collection, building the network, training it, and validation. It is an iterative process, since the steps may be repeated in order to reach better results. Those steps are described below.

Parameter Selection / Node definition

It is essential for the network to find a balance between including enough variables to sufficiently represent the system and, on the other hand, constructing a simple model in order to reduce the simulation effort (Plant, et al., 2011) and maintain strong relationships between input and output. Marcot, et al. (2006) states that "*Deep models with many intermediate nodes may contain unnecessary uncertainty propagated from input to output nodes*" and suggests the use of four or fewer layers of nodes. Variables introduced in the network are described below and a simplified schematic is shown in Figure 17.

The input nodes

The input variables should sufficiently represent the system. A small description for each input node used in the BN will follow.

- **Time interval**: The reasoning behind this node is to represent different nourishment policies implemented with time. Before 1990 there was no nourishment policy, in 1990 the "Dynamic Preservation Policy" with the "hold-the-line" policy (MinV&W, 1989, as cited in Keijsers et al., 2015) was implemented and, finally, the "maintain-the-system" approach is in force from 2000. This resulted in an increasing total average yearly sand nourishment volume with the years.

- **Area**: The study area is the Holland coast. The area is divided into the subareas of Noord Holland, Rijnland and Delfland. All of the areas have an active nourishment policy but there are differences concerning the amount of volume that it is used. Later, in this section, those

[5] http://www.norsys.com

differences will be discussed in more detail. Furthermore, this node is included in order to enable the network to assess the nourishments on those areas separately.

- **Time horizon**: The aim of the implementation of this node is to investigate the effects of nourishments on different time scales. In case of beach or dune nourishments the effects are directly visible on the indicators. On the other hand, shoreface nourishments act at different time scale, since natural processes are expected to distribute an amount of sand towards the beach.

- **Maximum yearly water level**: This node represents the forcing of the system. Based on previous research, the maximum yearly water level is chosen as the most suitable storminess parameter, which influences the dune foot position (Giardino, et al., 2013). It is expected that an increase in maximum yearly water level will result to landward movement of the dune foot position.

- **Nourishment volume and nourishment type**: The amount of nourishment volume and the type (shoreface, beach and dune nourishment) are essential variables for the network, since they represent the nourishment strategy.

- **Nourishments**: This node separates transects that have been nourished at the year of interest from transects that they have not. It is used only for visualisation purposes.

Other variables were also investigated, such as wind conditions, sea level rise (SLR) and subsidence, but they are not included in the study. De Vries et al., (2012) concluded that there is no significant correlation between wind conditions and dune behaviour along the Dutch coast, based on the JARKUS measurements. Therefore, in this study it is assumed that the effects of wind on the indicators are negligible compared to the effects of nourishments. Finally, the effects of SLR and subsidence at this relatively short-term study are assumed to be negligible and they will not be further discussed.

The output nodes – The coastal state indicators

To quantify the effects of the nourishments, the changes of two morphological indicators are included in the network: the change of Momentary Coastline Position and the change of Dune Foot position. The coastal indicators can describe the morphological development of the coast (Giardino, et al., 2014). MKL and DF represent different functions and objectives. MKL gives information about the medium term safety, whereas DF is related to nature and recreation, as part of the "sustainable maintenance of the dunes" policy (Giardino, et al., 2012).

Data collection

Bayesian networks require a large amount of information in order to calculate the conditional probabilities between the variables. They are able to combine different data sources, such as field measurements, laboratory data and model simulations (Den Heijer, et al., 2012). At this study, available data concerning the parameters (input nodes and indicators) were obtained via field measurements. Datasets of nourishment recordings[6], MKL[7], DF[8] and maximum yearly water level[9] are used as input for training and validation of the network. A detailed presentation of the datasets can be found in Appendix C.

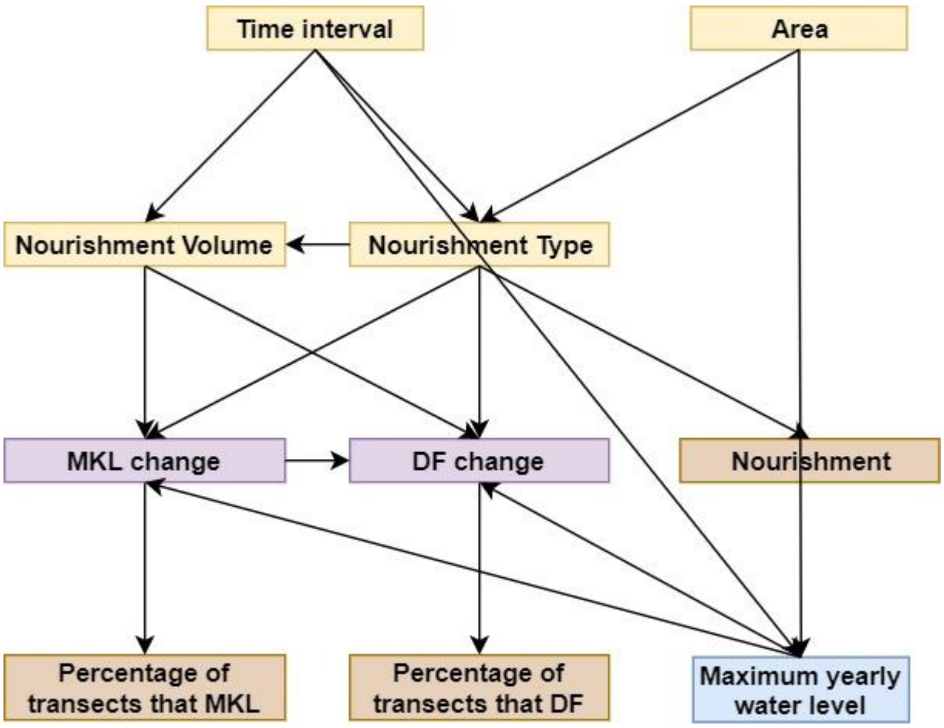

Figure 17 Simplified schematic of the network.

Network structure

Different variables in Netica are represented by nodes and direct influence between the nodes is represented by unidirectional arrows (See Figure 18). The use of nodes and arrows makes directly visible how one variable influences another. The graph is a directed acyclic graph, or simply DAG, which means that there must not be any directed cycles (Den Heijer et al. (2012), Korn et al. (2004)).

The software only allows for nodes with a limited number of realizations, which means that continuous parameters need to be discretized (van Verseveld, et al., 2015). Each node should be discretized into bins, with size of the bins optimized based on the following requirements. The intervals should be wide enough to minimize the computational effort and to contain large number of samples, but simultaneously they should be narrow and detailed enough to provide robust forecasts (Plant et al. (2011), Giardino et al. (2012)). Common types of values for nodes are: boolean

[6]http://opendap.deltares.nl/thredds/dodsC/opendap/rijkswaterstaat/suppleties/nourishments.nc.html
[7] http://opendap.deltares.nl/thredds/dodsC/opendap/rijkswaterstaat/BKL_TKL_MKL/catalog.html?dataset=varopendap/rijkswaterstaat/BKL_TKL_MKL/MKL.nc
[8] http://opendap.deltares.nl/thredds/dodsC/opendap/rijkswaterstaat/jarkus/profiles/catalog.html?dataset=varopendap/rijkswaterstaat/jarkus/profiles/transect.nc
[9] https://waterinfo.rws.nl/#!/kaart/waterhoogte-t-o-v-nap

values, which take the binary values true and false, ordered values (e.g. low, medium, high) and integral values (Korn, et al., 2004). The chosen values should represent the domain efficiently and address both the desired precision and the distribution of data. Hence, discretization requires careful consideration.

A histogram (Figure 18) is first used to get a sense of the distribution of the data. The distributions are used to guide the discretization process, by ensuring that the data are well captured. In the subplot of nourishment type, the values at the x-axis (0, 1, 2, 3, and 4) represent no nourishment, shoreface, beach, dune and multiple nourishments (more than one type) respectively. Data for beach and dune nourishments will be summed up into one bin for the Bayesian network. The nourishment volume is $0m^3$/year for approximately $3*10^4$ transects, but for illustration purposes of the remaining distribution, this value is not depicted in the graph. In the subplots of MKL and DF, the value "-1" represents landward movement, "0" represents no change and "1" represents seaward development.

The amount of bins for each node is essential for the network, since the performance of the network changes with the increasing number of bins. By comparing calibration and validation error rates, different studies found that 4 to 5 bins per input variable minimized those errors (Gutierrez et al. (2015), van Verseveld et al. (2015), Pearson (2016)). Calibration error rates are calculated by training and testing the network using the same dataset, whereas validation error rates are calculated by testing the network using data which were not used at the training phase. For the nodes of nourishment types, movement of the Dune Foot and MKL, the bins in the network represent the same discrete values as seen in Figure 18. The first assumption of the discretization of the nodes of dune foot change, MKL change and Nourishment Volume is shown in Figure 18 and it is chosen based on the original data distribution. Six bins for MKL and DF change were chosen. The bins which are the most probable are located around 0 and they have smaller width. Increased width is selected for values of bigger changes, since those values are rarer in the dataset.

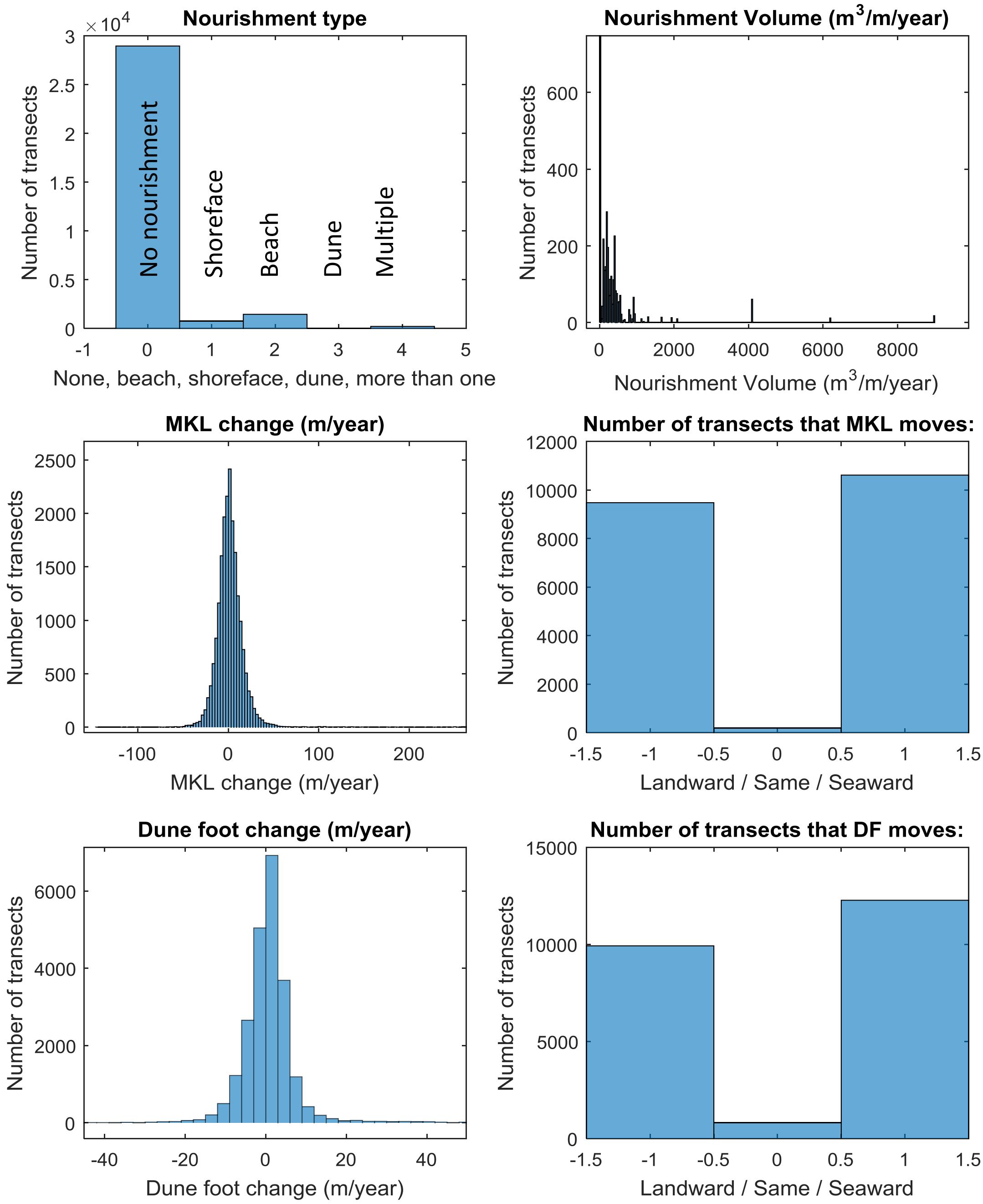

Figure 18 Data distribution for the different variables.

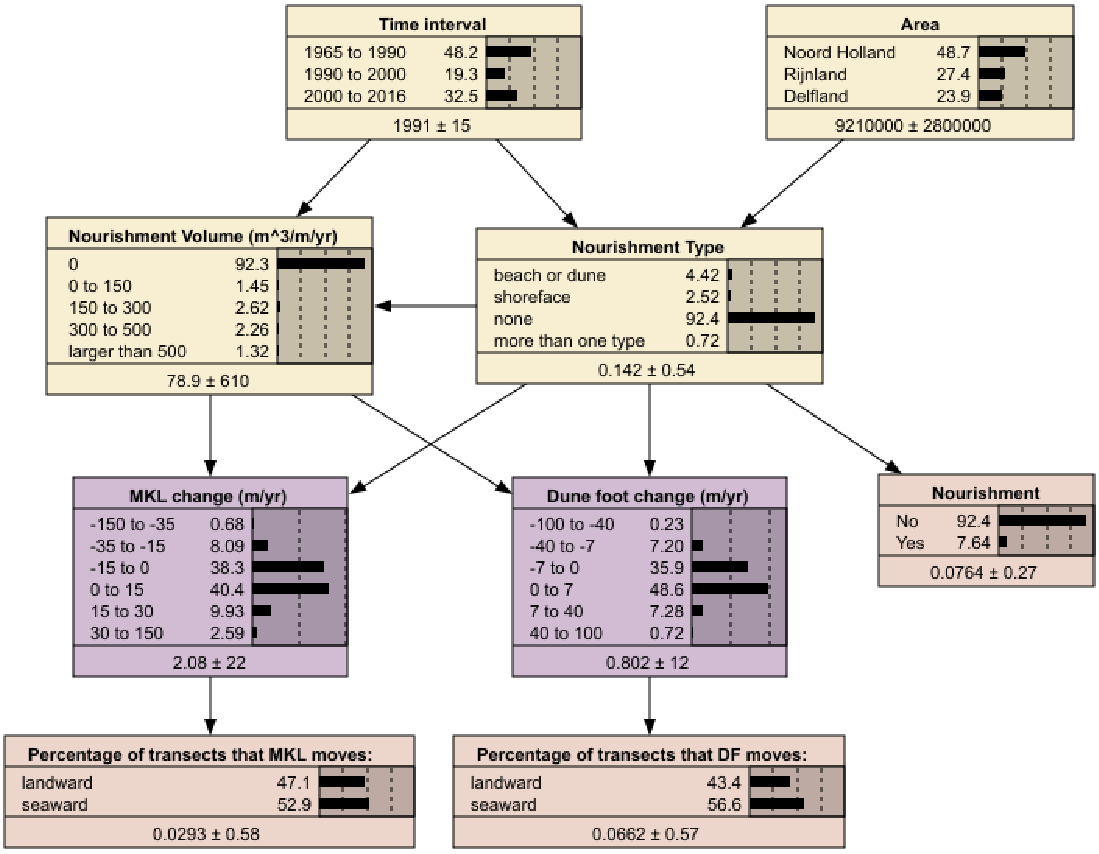

Figure 19 Bayesian network trained on all data (Configuration C). Nourishment characteristics and area are shaded in yellow, coastal indicators in purple and summarized nodes in brown.

Training of the network

Once the topology of the network is defined, the next step is to calculate the conditional probabilities for each node (Korn, et al., 2004) which are stored in discrete tables called Conditional Probability Tables (CPTs). In machine learning, datasets are typically divided into two sets from the beginning: a training set and a test set (Korn, et al., 2004). The former is used from the learning algorithm to calculate the conditional probability of the observation given a forecast. Once those likelihoods are learned, the network can be used for predictions. The test set is then used to assess how well the system is represented by the network. The test set is isolated from the learning process and is used strictly for testing after learning has completed (Korn, et al., 2004). In this study, 90% of the dataset is used for the training process and the remaining 10% of the dataset is used for the tests.

An example of how a conditional probability table could look like is presented in Table 2. The states of parent nodes “Time interval” and “Nourishment type” are denoted as intervals and as labels respectively. “Nourishment Volume” is the examined node and it is denoted by intervals from 0 to 6300 m^3/m/yr. The table contains the probabilities of the child node given each configuration of parents values (Norsys, 2003). For example, the probability of the nourishment volume to be at the interval of 0-150 $m^3/(m\ yr)$, given that the considered time interval is from 1965 to 1990 and there is beach or dune nourishment, is 36.93% (blue cell in Table 2).

$$P\begin{pmatrix} Nourishment\ volume = 0 - 150 \mid Time\ interval = 1965 - 1990, \\ Nourishment\ type = beach\ or\ dune \end{pmatrix} = 36.93\%$$

The CPTs are not always complete. In case of missing values, Netica assigns uniform distribution at the CPTs. This can be seen in case of shoreface nourishment type and for time interval of 1965 to 1990 (grey cells in Table 2). In fact, the first shoreface nourishment was implemented in 1997 in the area of Delfland. Netica has assigned the value of 20% for each state of the child node. The number results from the fact that the sum of the conditional probabilities in each row at the table must be 1. In addition, missing values are observed in case of a large number of bins or/and small intervals. The amount of data is a limiting factor in the modelling (Uusitalo, 2007), since it restricts the number of intervals.

Time interval	Nourishment type	0	0 to 150	150 to 300	300 to 500	500 to 6300
1965 to 1990	beach or dune	0.57	36.93	27.27	27.84	7.39
1965 to 1990	shoreface	20.00	20.00	20.00	20.00	20.00
1965 to 1990	none	99.97	0.01	0.01	0.01	0.01
1965 to 1990	more than one type	1.16	1.16	1.16	90.70	5.81
1990 to 2000	beach or dune	0.15	44.34	52.04	2.71	0.75
1990 to 2000	shoreface	1.79	1.79	1.79	44.64	50.00
1990 to 2000	none	99.92	0.02	0.02	0.02	0.02
1990 to 2000	more than one type	8.33	8.33	8.33	8.33	66.67
2000 to 2016	beach or dune	0.16	4.40	44.37	18.60	32.46
2000 to 2016	shoreface	0.14	8.72	20.84	53.95	16.35
2000 to 2016	none	99.95	0.01	0.01	0.01	0.01
2000 to 2016	more than one type	0.76	0.76	0.76	21.97	75.76

Table 2 Example of conditional probability table, node "Nourishment Volume"

Finally, the complexity of the network increases the size of the CPT and, by extension, the required data for the training of the network. Too much complexity (many nodes, discretization into many bins, many arrows) will lead to degradation of the quality of the prediction (Domingos, 2000 as cited in van Verseveld, 2015). This comes from the fact that distributions become weaker, since fewer data points are used per distribution (Uusitalo, 2007).

2.2.4. Alternative configurations

In this coastal application, it is not clear which variables should be connected to each other and which variables should be included in the network. Configurations with different connections among the nodes are assessed in order to conclude which is the optimum connection of the variables and which variables are the most important to improve the performance of the network. The way to assess the different configurations will be discussed at the section 2.2.5. The alternative configurations are presented below.

Connection of MKL and DF node

The momentary coastline and the dune foot position are variables which are not independent. This section investigates how the nodes which represent those variables must be connected in the network.

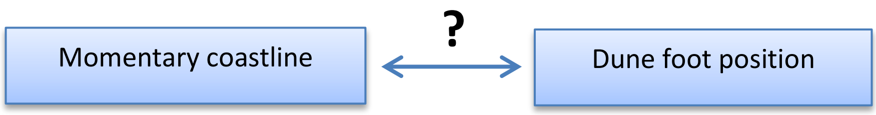

Figure 20 Connection between momentary coastline and dune foot position.

Bayesian inference suggests that in case that there is an influence between two nodes, then those two nodes should be connected by a directed arrow. The direction of an arrow influences the information flow in a network (see Appendix B). Momentary coastline is an indicator that is derived by taking into account the transect profile, therefore, it is based on dune foot position. Thus, an arrow should be directed from the DF-change node to the MKL-change node (Configuration B). On the other hand, the primary goal of the Government is to address the safety problems and the preservation of the MKL is of a primary importance. The network should be designed in such a way that it is possible to assess the effects of nourishments on the MKL. The link from MKL to dune foot could show which the benefits of the MKL change on the dune foot are (Configuration A). A configuration without this connection will be tested as well (Configuration C). The chosen configurations can be found in Appendix D.

Connection of time interval/area and indicators

"Time interval" node is not directly connected to the indicators at the configurations A, B and C, but the information is transferred through the intermediate nodes of "Nourishment Volume" and "Nourishment Type". In case that evidence in the middle nodes becomes available, information will not propagate from the "Time Interval" node to the indicators (see Appendix B). Therefore, a configuration which includes arrows directed from time-interval to the indicators will be tested (Configuration D). Following a similar line of reasoning, configuration E connects the "Area" node to the indicators and configuration F includes both types of connections (see Appendix D).

Natural forcing

The maximum yearly water level is considered to represent the natural forcing of the system. Therefore, configuration G includes this variable as a node. "Time interval" and "Area" are parent-nodes and the indicators are the child-nodes of this variable (see Appendix D).

2.2.5. Assessment of Bayesian performance

There are several well established methods for assessing the predictive skills of the network. Plant et al. (2011) suggested the use of the likelihood ratio to make this assessment. Other studies in literature used also the same method (Poelhekke et al. (2016), van Verseveld et al. (2015), den Heijer et al. (2012)). This method compares the prior probability of a Bayesian network with its updated probability. The log likelihood ratio can be determined by:

$$\mathrm{LLR} = \sum_{j=1}^{n} \log\left(p[F_i|O_j]_{F_i=O_j}\right) - \log\left(p[F_i]_{F_i=O_j}\right) \qquad [2]$$

Where $p[F_i|O_j]_{F_i=O_j}$ is the updated probability of a forecast F_i, given a subset of observations O_j and $p[F_i]_{F_i=O_j}$ is the prior probability for a forecast F_i. A positive log likelihood ratio means that the network has predictive skill since the updated prediction is better than the prior prediction. A positive ratio indicates improvement in the prediction and a negative value indicates that the updated prediction is worse than the prior prediction (Plant, et al., 2011).

By using the same method, it is also possible to compare the performance of two configurations with different structure, which were trained with the same dataset (Gutierrez et al. (2015), Poelhekke et al. (2016), Pearson (2016). In this way, we can determine the importance of certain links between the variables and identify which network structure is the optimum. This can be achieved by comparing the posterior probabilities of the two configurations based on the following equation:

$$\mathrm{LLR} = \sum_{j=1}^{n} \log\left(p[F_{1,i}|O_j]_{F_{1,i}=O_j}\right) - \log\left(p[F_{2,i}|O_j]_{F_{2,i}=O_j}\right) \qquad [3]$$

Where the first term at the right hand side represents the posterior probability of the first configuration and the second term represents the posterior probability of the second configuration. Positive score means that the first network performs better than the second.

In order to derive the LLR scores, the configurations are trained with 90% of the dataset (prior probabilities) and the remaining 10% is used for the assessment and the calculation of the posterior probabilities. At this assessment the output nodes “MKL change” and “DF change” are tested separately. For each case of the test dataset, beliefs of the input nodes are introduced to the trained configurations and predictions of the values of the output node are made. Then, the probability distributions of the output node are available. Finally, comparison is made among the probabilities of predicting the actual value (the value of the specific case), for the two configurations. The configuration which predicts the actual value with a higher probability is considered to be most reliable.

2.2.6. Confusion matrices

Once the network is constructed and the final configuration is chosen, confusion matrices are used as a validation method in order to assess the performance of the network. Poelhekke et al. (2016) and Pearson (2016) used confusion matrices to assess the performance of the developed networks. Predicted values derived from the network are compared to values (denoted as “actual” values) from the cases which were used to test the network. Since the dataset used to train and test the network is based on field observations, the "actual values" represent reality. The network is trained with 90% of the dataset and the remaining cases (10% of the dataset) are used for the testing.

2.2.7. Scenarios

A number of scenarios can be developed to analyse probabilistic relationships and dependencies between key variables. At this stage the network is trained with the entire dataset, in order to provide the maximum amount of cases. The development of the scenarios can be achieved by constraining nodes. Constraining is essentially the same as conditioning a variable in the network on a particular value (Giardino, et al., 2012), which makes possible to assess the effects of the specific option instead of considering the entire discretisation. For example, if the "type of nourishment" variable is discretised into "shore nourishment" and "beach or dune nourishment", it is possible to constrain the variable to one of those types and predict the effect of this specific type on the coastal indicators.

Results

CHAPTER SUMMARY

The results of the new methodology for the dune foot detection and the Bayesian network are presented at this chapter. First, the new methodology is compared to a dataset of visual observations for the Dutch coast and then to satellite images. An overview of the method's performance is shown and an application to another dune system is presented. Next, a fully-trained Bayesian network is presented and LLR scores are used to assess the performance of different configurations. Finally, the validation of the optimum network configuration and 5 scenarios are discussed.

3. Results

3.1. New methodology for the Dune Foot detection

This section presents the results of the dune foot detection method. First, the method is compared to visual observations and, next, to satellite images. Next, heat matrices are used to show the overall performance. Lastly, an application of the proposed methodology in a part of the Portuguese coastline is shown.

3.1.1. Visual observations for validation

A database of visual observations for the years 1843-1998 is available and it is used to validate the proposed methodology for the dune foot detection. In Figure 21, the dune foot positions based on visual observations are plotted against the dune foot positions derived from the new method for the entire Dutch Coast. The reference point (0 m) represents the position of the permanent beach pole for each transect. Measurements of coastal profiles and visual measurements are taken with respect to those beach poles (Van der Burgh, et al., 2011). Positive numbers refer to dune foot positions more seaward than the position of the beach pole.

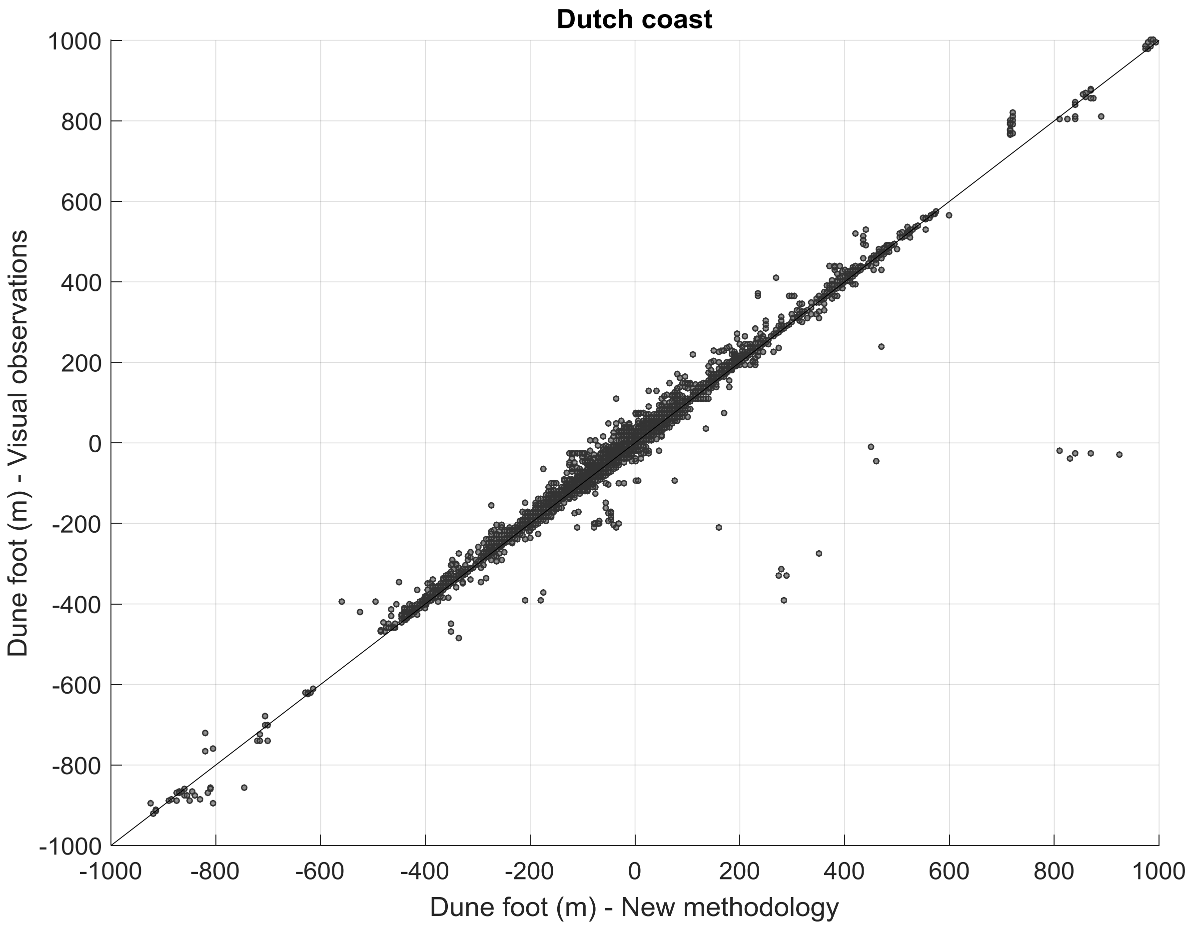

Figure 21 Scatter plot for the entire Dutch Coast. Dune foot positions based on visual observations are plotted against the dune foot positions derived from the new method. Cross shore distances from the beach pole are plotted for the dune foot as predicted based on the new methodology (x axis) against the dune foot based on visual observations (y axis).

Spatial visualisation

A spatial visualisation of the results is shown in Figure 22. At the x axis, the different transects are plotted. The value of "0" represents the northernmost point of the Dutch coast which is located at Schiermonnikoog. Larger values show ids of transects located in the south. At the y axis, the reference point (0 m) represents the position of the permanent beach pole for each transect. Positive numbers refer to dune foot positions more seaward than the position of the beach pole and negative numbers to more landward positions.

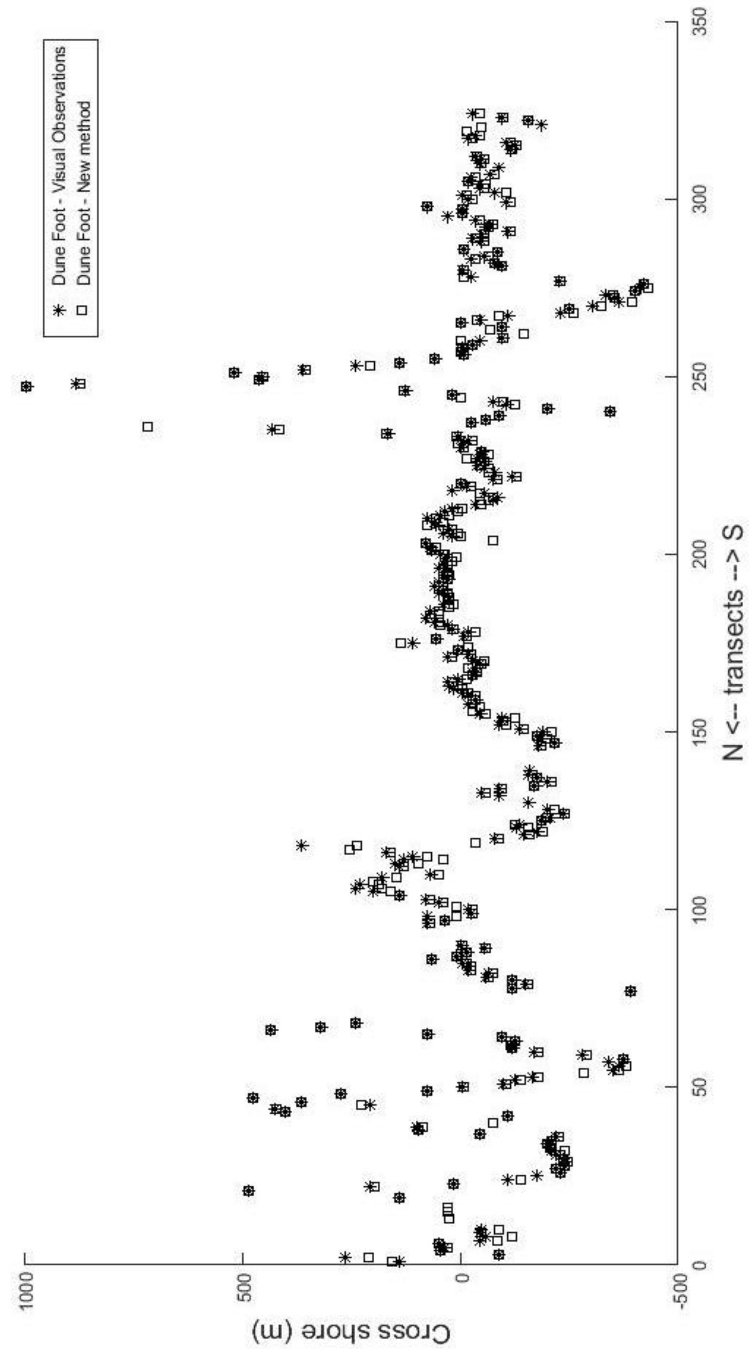

Figure 22 Spatial comparison of Dune foot position derived from the proposed methodology with the dune foot based on the visual observations for the entire Dutch coast in 1986. Cross shore distances are measured with respect to permanent beach pole for each transect.

Root means square errors

RMSEs are used to compare the performances of the three different methods; the proposed methodology, the +3 m NAP and the Upper boundary for the MKL estimation (Upper MKL). In Table 3, RMSEs are summarized for each area and for the three different methods. The Upper MKL performs worse than the other two methods. The comparison among the new methodology and the +3 m NAP definition, results in small differences, sometimes in favour of the new methodology and sometimes in favour of the +3 m NAP definition. A big difference in the outcome can be seen at Goeree, where the new methodology results in RMSE of 71.2579m, whereas the +3 m NAP definition to RMSE of 149.723m.

Areas	New methodology (m)	+3 m NAP (m)	Upper MKL (m)
Schiermonnikoog	26.0053	14.361	228.831
Ameland	17.7962	19.622	31.202
Terschelling	**48.7111**	**81.372**	28.871
Vlieland	9.3917	15.726	16.133
Texel	32.2327	18.021	23.824
Noord-Holland	14.7850	11.701	15.916
Rijnland	13.8180	10.217	10.216
Delfland	20.9501	10.816	11.114
Voorne	19.1631	21.682	127.648
Goeree	**71.2579**	**149.723**	**303.058**
Schouwen	21.6187	30.495	31.291
Walcheren	15.4671	10.791	9.576
Total:	**35.538**	**57.648**	**116.861**

Table 3 RMSEs (m) for the different methods for the dune foot detection compared with the visual observations.

RMSE for the entire Dutch coast

The RMSE is calculated for the entire Dutch coast, for the two methods; the new method and the +3 m NAP definition. The RMSE for the new method is 35.538m, whereas for the +3 m NAP definition is 57.648m. Therefore, the new methodology performs better over the entire area of the Dutch coast.

Sensitivity analysis

An important parameter for the methodology is the peak height, above which a peak is considered to be a dune peak. Heights from a range of 1 to 3 m were tested. For each case, a dataset is created and the RMSEs are calculated. The results are summarized in Figure 23. The dashed line represents the results from the +3 m NAP dataset. In cases when a small peak magnitude is chosen, such as peak height of 1 m, the method assigns the dune foot position more seaward than in reality. At the opposite cases, it assigns the dune foot position more landward.

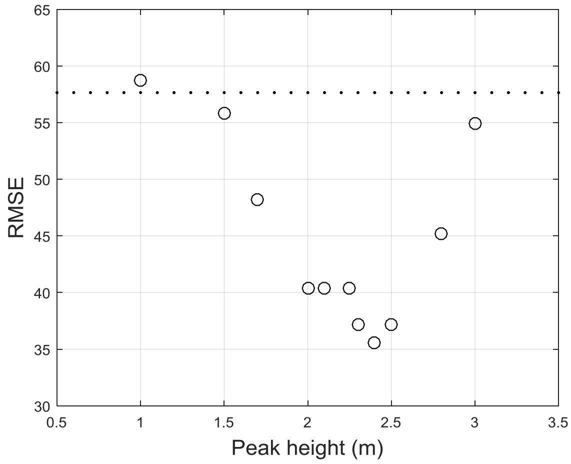

Figure 23 Sensitivity analysis of the magnitude of peak heights.

The height of 2.4 m results in smaller errors and this value is chosen for the method. This optimum value of the peak height is representative for the Dutch coast.

3.1.2. Satellite images

Satellite images (SENTINEL-2) are used to validate the methodology for the recent years, since the field measurements of the dune foot were carried out until 1998. Figure 24 and Figure 25 are parts of a satellite image which was acquired on 12th of March 2016. From the images we can conclude that the method detects a dune foot (blue pins in Figure 24) which is located in the area where the vegetation starts. This is only a qualitative measure, since the starting point of vegetation does not necessarily indicates the dune foot.

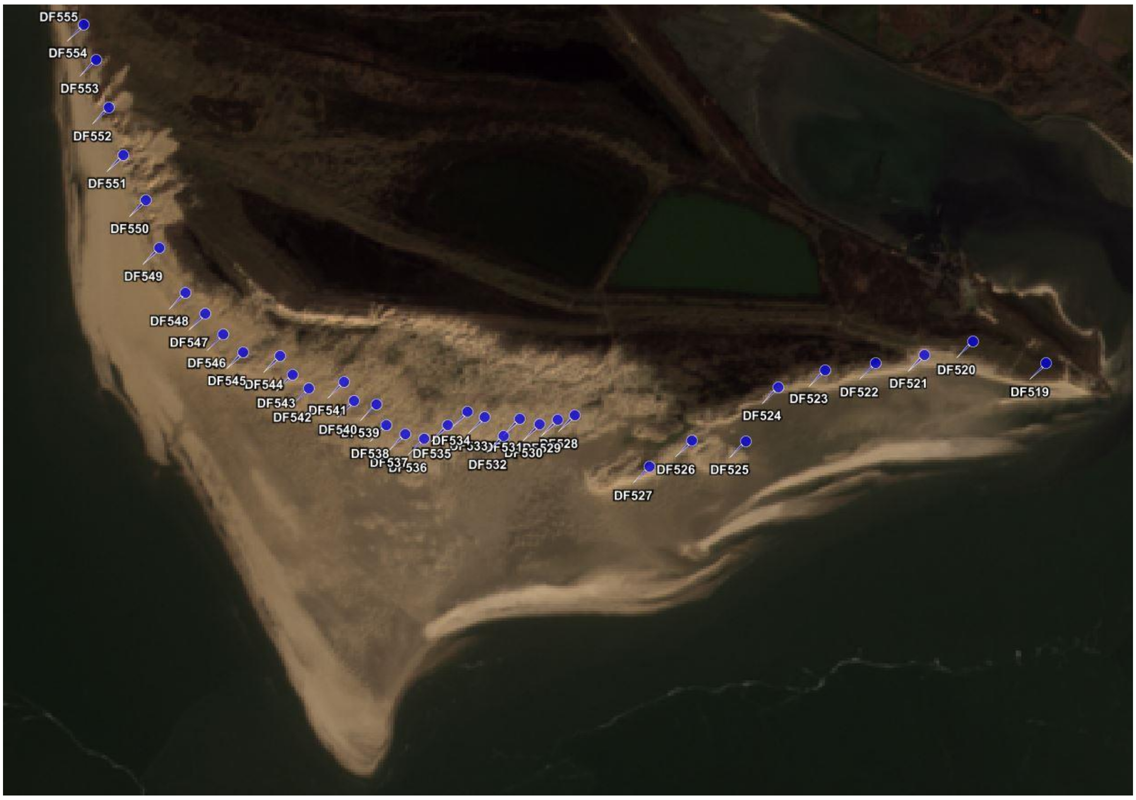

Figure 24 Dune foot detections based on the new methodology (blue spots) are imposed on a satellite image at the location of Texel.

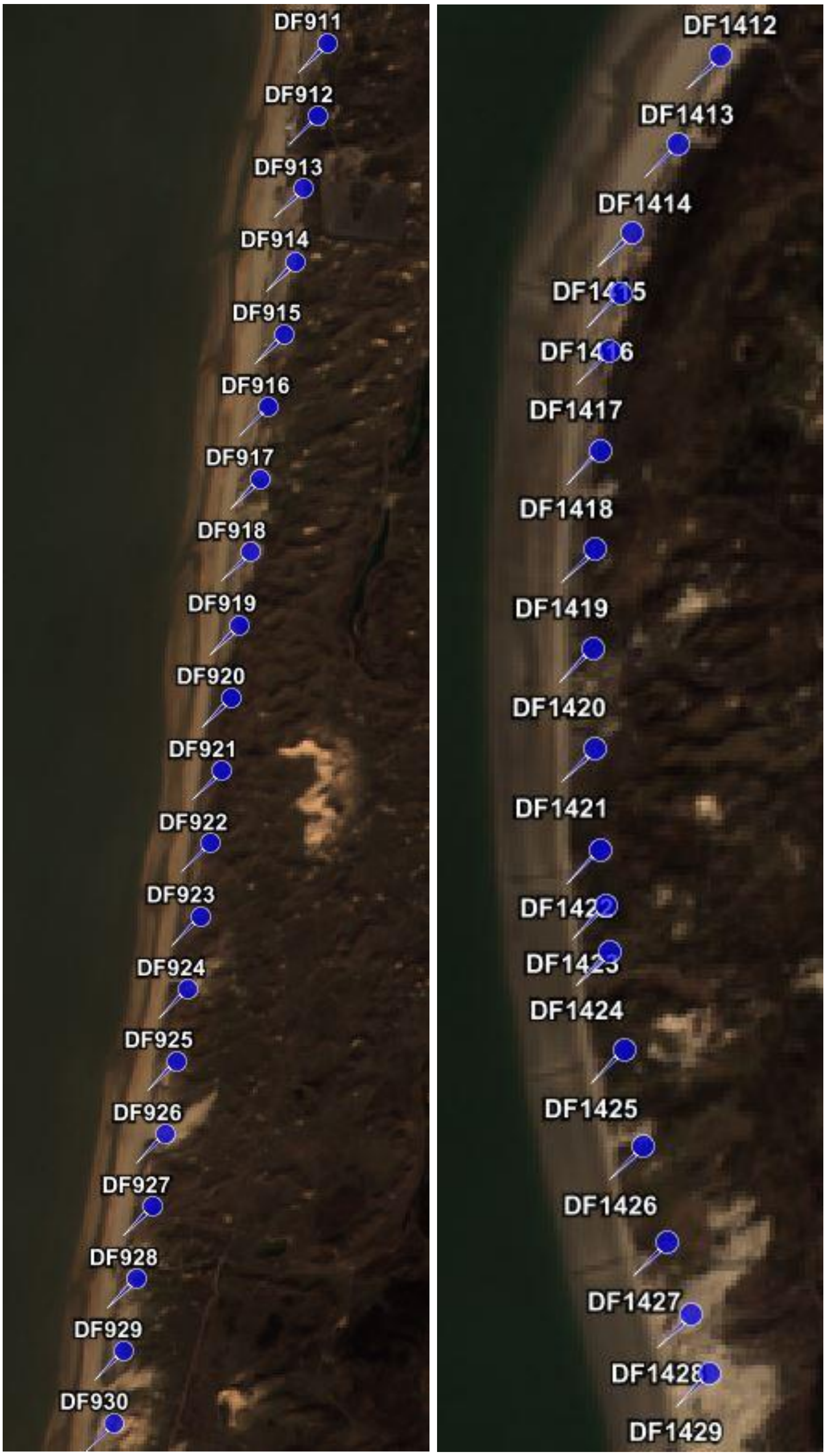

Figure 25 Dune foot detections based on the new methodology are imposed on satellite images; left: Holland Coast and right: Schouwen.

3.1.3. Overall performance

An overview of the methodology can be achieved by the use of heat matrices. In these matrices, the difference of the dune foot calculation with the visual observations can be seen for every year and for each transect. An example of the area of Ameland can be found in Figure 26. The matrices for the other areas along the Dutch coast are added in Appendix A.

The lowest negative value is displayed in red colour, whereas the highest positive value is displayed in green colour. Negative values indicate transects where the detection based on the new methodology results in a dune foot position more seaward than the actual (derived from visual observations), whereas positive values (displayed in green colour) indicate a dune foot position detected more landward than the actual. Pale colours represent very small differences between the visual observations and the dune foot predictions. Purely white cells represent predictions which coincide with the values of visual observations. Finally, yellow values represent transects which do not have any visual observation for the specific year, or cases for which the new methodology could not detect the dune foot. The separation of those two reasons is analysed further in Appendix A.

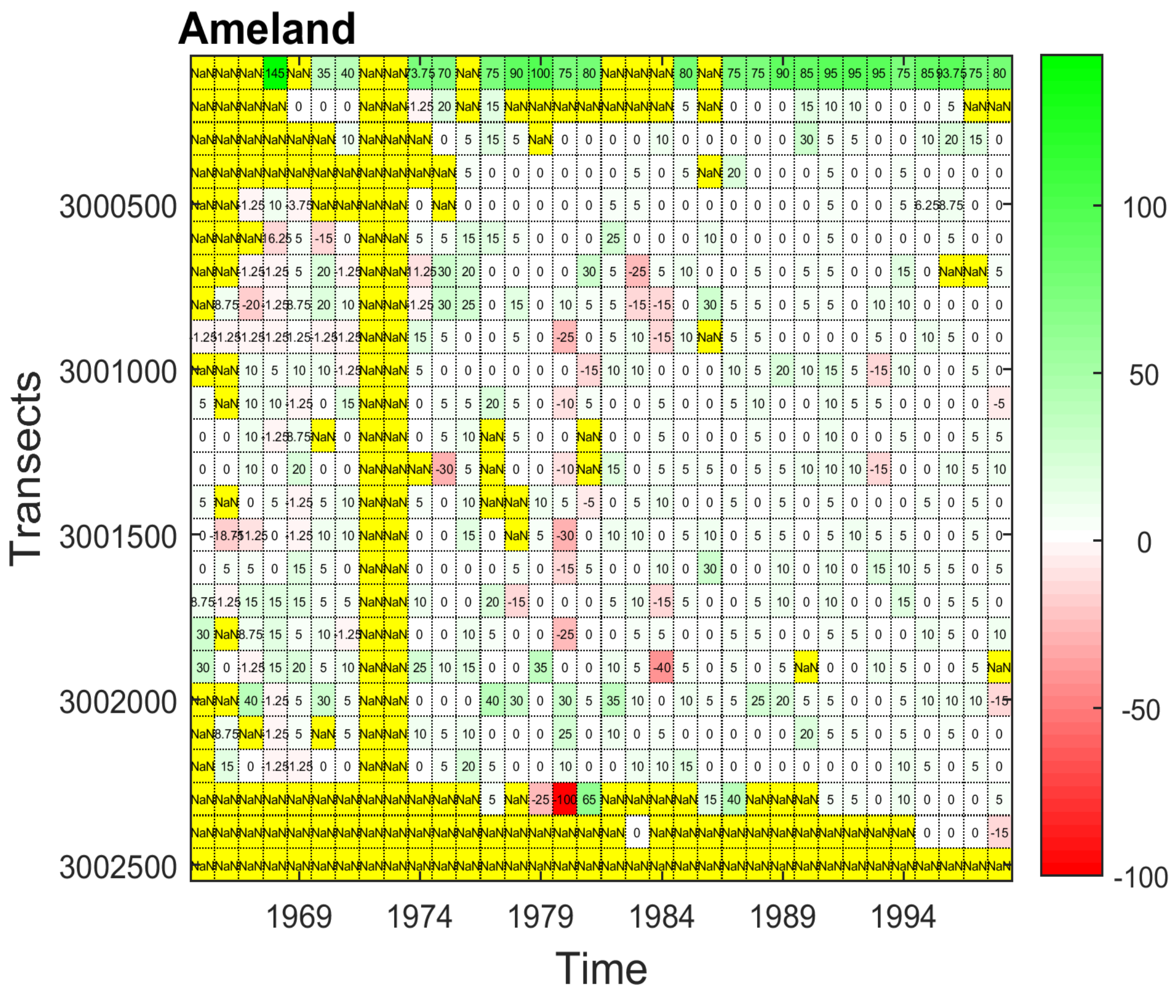

Figure 26 Cross shore differences of the predicted dune foot position with the dune foot position based on visual observations for the area of Ameland, for the years 1965-1998. Positive values (shaded in green colour) indicate a dune foot position detected more landward than the actual. Negative values (shaded in red colour) indicate a more seaward detection. Yellow values represent cases of missing values.

3.1.1. Application to other dune systems

The new methodology is applied at profiles along the coast of Aveiro and Google Earth images are used to compare the results with the reality, since no field measurements for the dune foot location were carried out. Figure 27 depicts the dune foot location derived from the proposed methodology (yellow marks) for four parts along the coast of Aveiro.

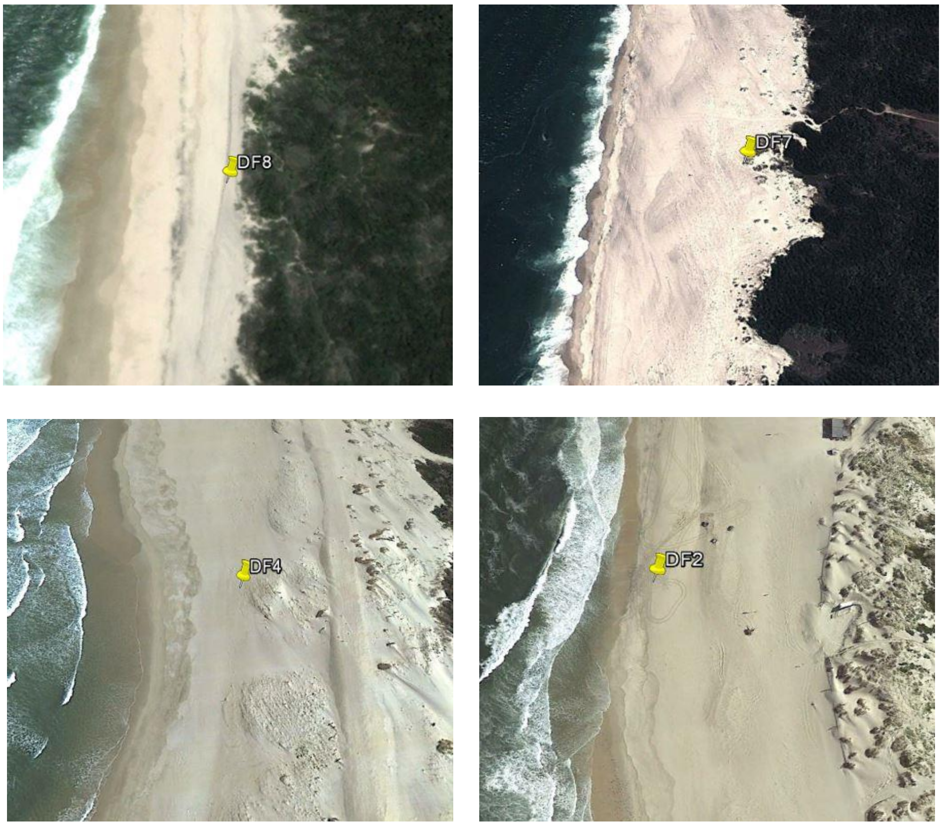

Figure 27 Dune foot detections based on the proposed methodology (yellow marks) in Aveiro are imposed on parts of Google Earth images.

Based on the comparison with the Google Earth images, it is difficult to conclude whether the methodology performs well, since not all the images were obtained in 2011 (year of profile measurements). Temporal variations of the profiles during this time, caused by accretion or erosion, might be present. The image of the upper right panel was obtained in 2011, the image of the upper left panel was obtained in 2012, while the image of the lower panels was obtained in 2013. Therefore, the deviation of the results for the lower panels might exist due to temporal changes of the profile. Moreover, concerning the lower left panel, new dunes seem to have been developed.

3.2. Bayesian network

This section presents the results of the Bayesian network approach. First, the trained network is presented and some relations are discussed. Thereafter, the performances of different configurations are compared. Variables and arrows necessary for the network are identified. Finally, a validation method and different scenarios for the optimum network are presented.

Trained network and node information

Figure 28 shows the full Bayesian network trained on all data. The data used for the training are described in Appendix C. Data from the THREDDS server are used for the dune foot position, since in case of Noord Holland, Rijnland and Delfland the proposed methodology results in larger errors (Table 3) compared to the current definition. The horizontal histograms in each node display the prior probabilities associated with the entire dataset.

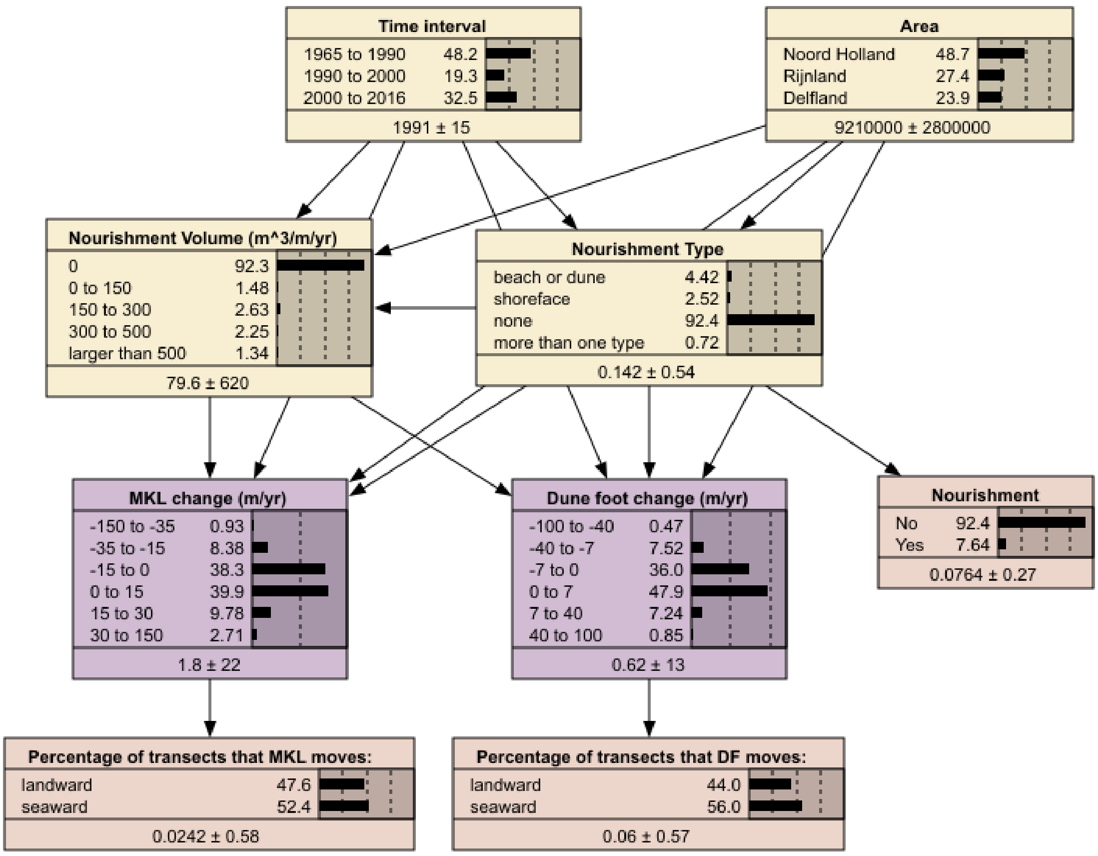

Figure 28 Bayesian network trained on all data (Configuration F). Nourishment characteristics and area are shaded in yellow, coastal indicators in purple and summarized nodes in light brown.

Here are some remarks about the structure and the meaning of the network (Figure 28 can be used as reference):

- Three groups of variables are visible in the network, represented by different colors. First, variables with yellow color represent nourishment policies and characteristics, as well as information about the areas of interest and time. Next, coastal state indicators are colored in purple. Finally, three nodes are used to summarize the information and they are colored in brown.

- The three bins at the "time interval" node represent different nourishment policies. From an absent nourishment policy during the first time window, through the 1990 first nourishment policy implementation, to a development of nourishment policy which implements volumes of 12 million of m^3/year at the third.
- "seaward" at the node of "percentage of transects that MKL moves" and "percentage of transects that DF moves" means that the indicators show a seaward movement from a year to another, which represents accretion with time. On the contrary, "landward" represents a landward movement of the indicators, or alternatively, erosion at the transect.
- 10% of the transects used in the network have never been nourished.

3.2.1. Log Likelihood ratio tests

Two series of tests are carried out by using LLR tests. The first part concerns the comparison among prior and posterior probabilities for a specific configuration. The second part concerns the comparison among the posterior probabilities of two different networks and the third part concerns configurations witch have one input node. For the tests, the dataset is randomly divided into 10 subsets. The configurations are trained with 9 of those subsets (90% of the entire dataset) and the remaining cases (10% of the entire dataset) are used for the calculation of the LLR scores.

LLR – Part 1: Performance of a configuration

Log-likelihood ratio tests were carried out in order to compare the posterior to the prior probabilities of the network. Prior probabilities represent the distribution of a trained network. Posterior probabilities are derived from the network if beliefs (based on a specific case) about the input nodes are introduced. Nathaniel Plant is the developer of the Matlab® scripts used for the LLR scores. Log-likelihood ratios are calculated for the chosen configurations (see Appendix E).

The final results for MKL and DF change for the entire set of configurations are visualised in Figure 29. In the figure, positive log-likelihood ratio values indicate that updated probabilities can more likely predict the actual value compared to the prior probabilities. Increasing values indicate better performance compared to the prior probabilities of each configuration.

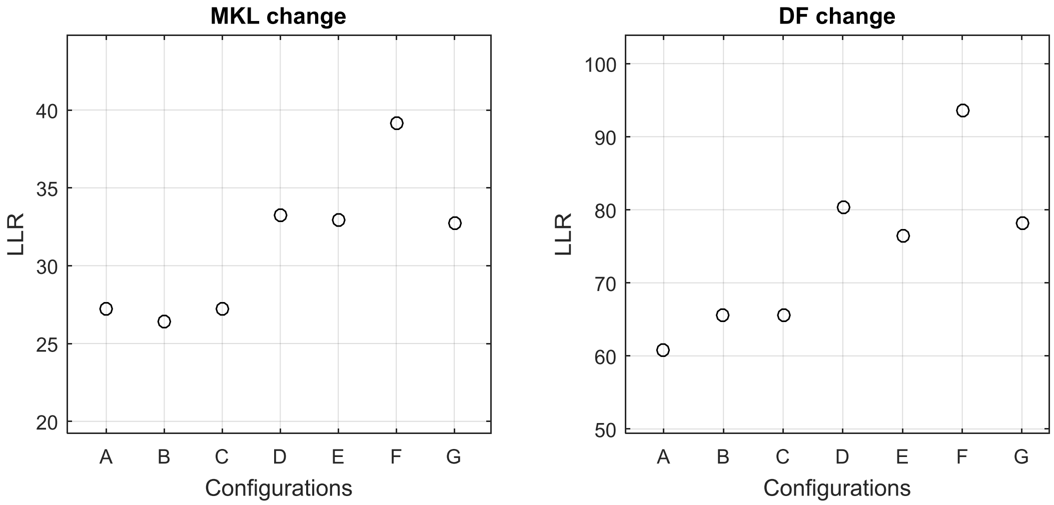

Figure 29 Log-likelihood ratios for the chosen configurations.

LLR – Part 2: Comparison among two configurations

In Table 4, comparison between two configurations (A vs B) results in positive values if the former configuration (A) performs better than the latter (B) and in zero values if there is no difference between the two configurations. Configuration C performs better than A, if the "DF change" node is under consideration, and their performance is equal for the "MKL change" node. Moreover, C performs better than B, if the "MKL change" is under consideration. Therefore, the nodes of MKL- and DF- change will not be connected (Configuration C), even if they are not independent.

Comparison	MKL change	DF change
A vs B	2.1602	-4.6277
A vs C	0	-4.6277
B vs C	-2.1604	0

Table 4 Log-likelihood ratios for configurations A, B and C compared to each other.

Negative values in Table 6 indicate that configuration E performs better than the remaining. Therefore, the input variables of "Time interval" and "Area" will be connected to the indicators.

Comparison	MKL change	DF change
C vs D	-6.1673	-15.3688
C vs E	-5.4439	-11.9402
C vs F	-11.4422	-29.0865
D vs E	0.7233	3.4285
D vs F	-5.2750	-13.7178
E vs F	-5.9984	-17.1464

Table 5 Log-likelihood ratios for configurations C, D, E and F compared to each other.

LLR – Part 3: "Single-input" networks

One of the objectives of this study is to examine which variables influence the network. For this purpose, log-likelihood ratio tests are carried out on networks with one input variable. Those tests can give insight about the importance of each variable in this assessment. The performance of the "single-input" networks is shown in Figure 30. It is obvious that "Nourishment Type" and "Nourishment Volume" perform better, whereas "Water Level" scores the lowest values. Here, "Water level" corresponds to the maximum yearly water level, as it was described before. Especially in case of "MKL change", water level LLR scores are around zero, which suggests that there is almost no improvement compared to the prior probabilities. Finally, in all cases the LLR scores fall below the dashed line, which represents configuration F. This analysis is only used to examine the importance of each variable separately and those networks will not be further discussed, since no useful outcome can be derived by using one input node.

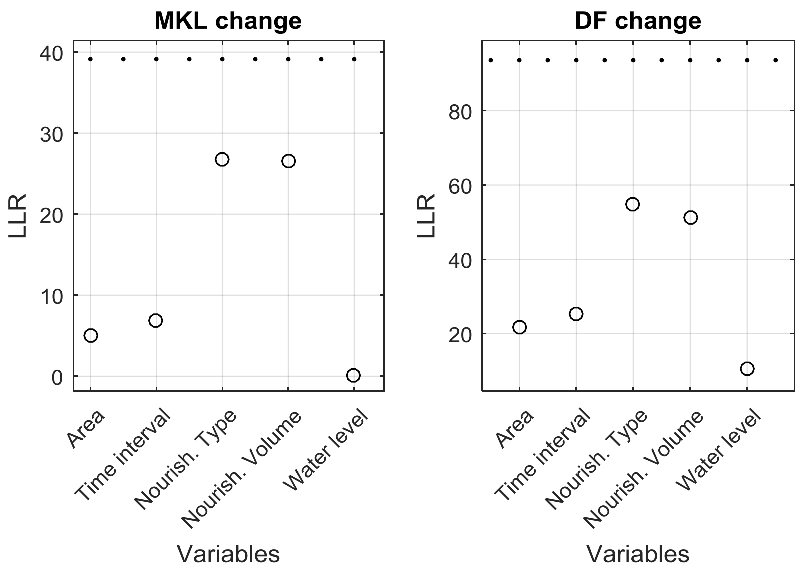

Figure 30 Log-likelihood ratio comparisons of networks with one variable as input.

3.2.2. Confusion matrices

The assessment with confusion matrices is the chosen validation method. Predicted values derived from the network are compared to values (denoted as "actual" values) from the cases which were used to test the network. Since the dataset that was used to train the network is based on field observations, the "actual values" represent reality. Table 6 and Table 7 show confusion matrices for MKL and DF change. Excellent performance is achieved in case of small changes of the indicators, whereas bigger changes are underestimated.

Overall, the Bayesian Network (Configuration F) estimates MKL change with an accuracy of **77.14%** and DF change with an accuracy of **86.57%**.

Predicted Values (m)						**Actual Values (m)**
-150 to -35	-35 to -15	-15 to 0	0 to 15	15 to 35	35 to 150	
0	0	13	0	0	0	-150 to -35
0	1	181	0	0	0	-35 to -15
0	2	767	0	0	0	-15 to 0
0	0	0	799	11	0	0 to 15
0	0	0	220	4	2	15 to 35
0	0	0	35	3	5	35 to 150

Table 6 Confusion Matrix for MKL change; Configuration F.

Predicted Values (m)						**Actual Values (m)**
-100 to -40	-40 to -7	-7 to 0	0 to 7	7 to 40	40 to 100	
0	0	9	0	0	0	-100 to -40
0	5	167	0	0	0	-40 to -7
0	1	833	0	0	0	-7 to 0
0	0	0	1073	23	3	0 to 7
0	0	0	93	48	0	7 to 40
0	0	0	7	2	7	40 to 100

Table 7 Confusion Matrix for DF change; Configuration F.

3.2.3. Constructed network – Scenarios

Different uses are possible with the Bayesian network. In this section 5 scenarios are shown. By constraining nodes we can develop scenarios in order to assess the effects of a specific option instead of considering the entire discretisation (Giardino, et al., 2012). Constrained nodes and values that are used for the assessment are emphasized with red boxes.

Scenario 1: Nourishment – No nourishment

The first scenario (Figure 31) is a simple application and it shows distributions if only cases where a nourishment has been implemented are considered. By constraining the "Nourishment" node, changes in the indicators are visible. Those changes are compared to the case when no nourishment is implemented. The probability of seaward movement of MKL is 73.4% and the probability of seaward movement of dune foot is 70.5%, with an average seaward displacement of 15 m and 7.98 m respectively. In the opposite case, if the network is constrained to transects which have not been nourished, the probabilities become 50.7% for seaward movement of MKL and 54.8% of dune foot. The average seaward displacement of MKL is 0.712 m and of DF is 0.0112 m. Therefore, as expected, nourishments have positive effects on the indicators.

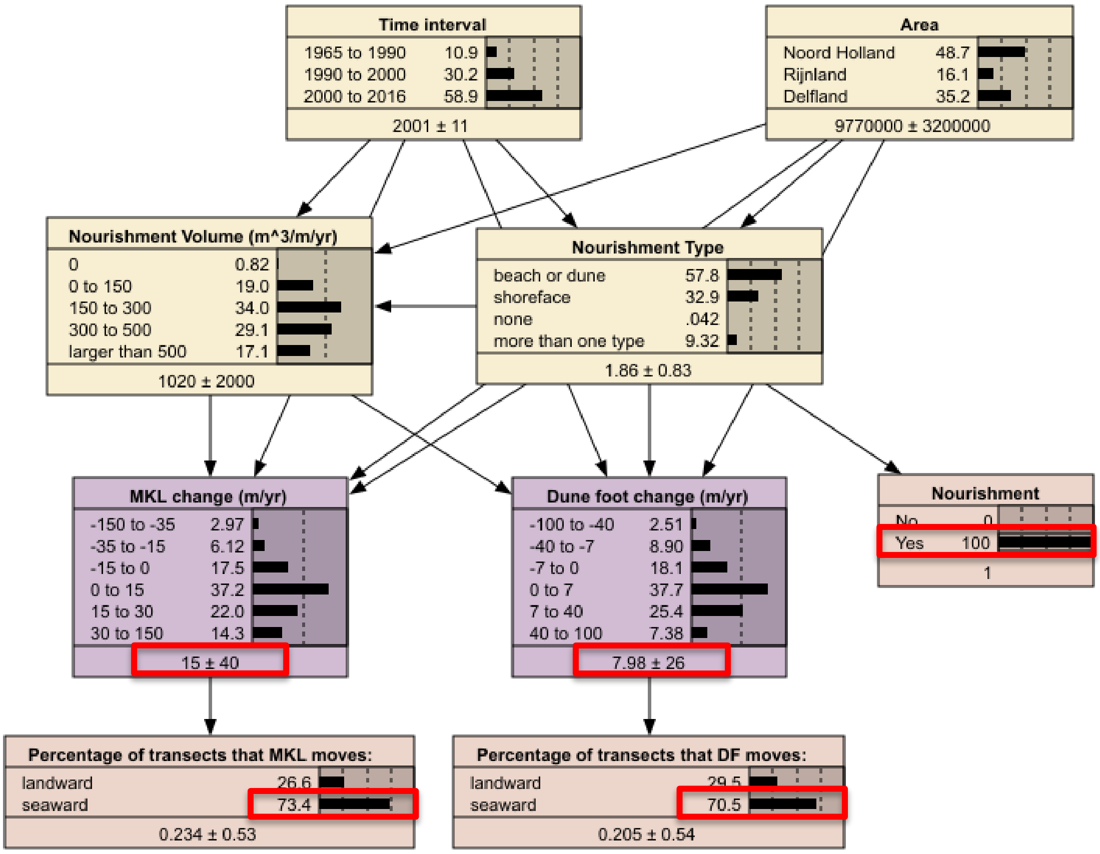

Figure 31 Configuration F constrained on cases where one or more nourishments have been implemented.

Scenario 2: Time interval and Area

In the next scenario, the effects of nourishments for the different time periods and different areas are discussed. First, by looking only in Noord Holland, the time interval will be constrained from 1965 to 1990, then from 1990 to 2000 and, finally, from 2000 to 2016. Moreover, this iteration will be executed for the areas of Rijnland and Delfland. In Figure 32, the time period is limited from 2000 to 2016 and the area is constrained in Delfland. The results for each combination are summarized in Table 11 and Table 12.

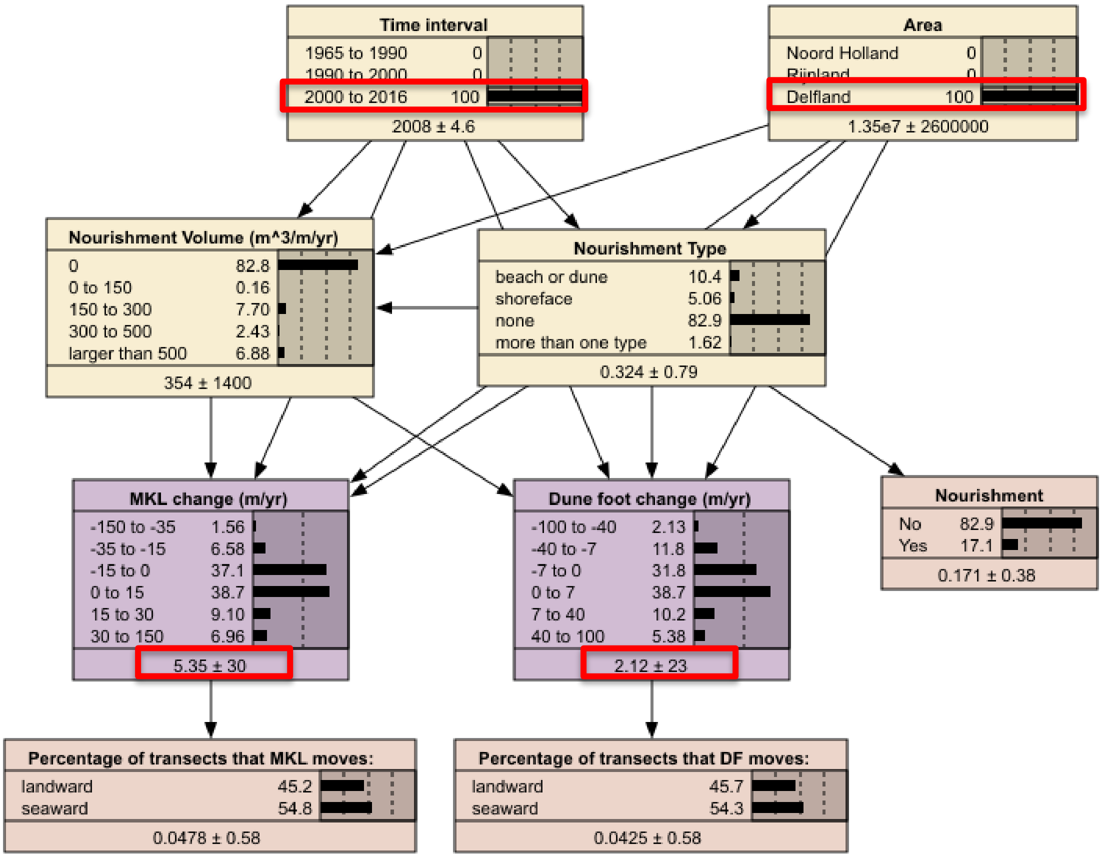

Figure 32 Configuration F constrained on time interval and coastal section (Cases for time interval 2000 – 2016 and area of Delfland).

Firstly, it is observed that the initial erosive trends of DF position are constrained by the nourishments that have been implemented. Then, it is expected that with increasing time interval, the magnitude of seaward movement of the indicators will be increasing, since more sand volume is implemented with time. In case of MKL change this positive trend is present in all areas (Table 11). Delfland is the area with the most positive effects and the largest nourishment volume. Moreover, in case of dune foot change, in Noord Holland and Rijnland, this positive trend is present.

On the other hand, in case of Delfland, DF is shifted on average seaward by -0.0414 m/year at the first time interval, by 2.31 m/year at the second and it is reduced to 2.12 m/year at the third (Table 12). In the third time interval there is indeed more nourishment volume, but this volume was applied mainly by shoreface nourishments. Therefore, by looking at yearly differences of the indicators, a smaller amount of sand volume implemented mainly by beach nourishments in the period 1990-2000 has higher effects on DF than a larger amount implemented by both beach and shoreface nourishments in the period 2000-2016.

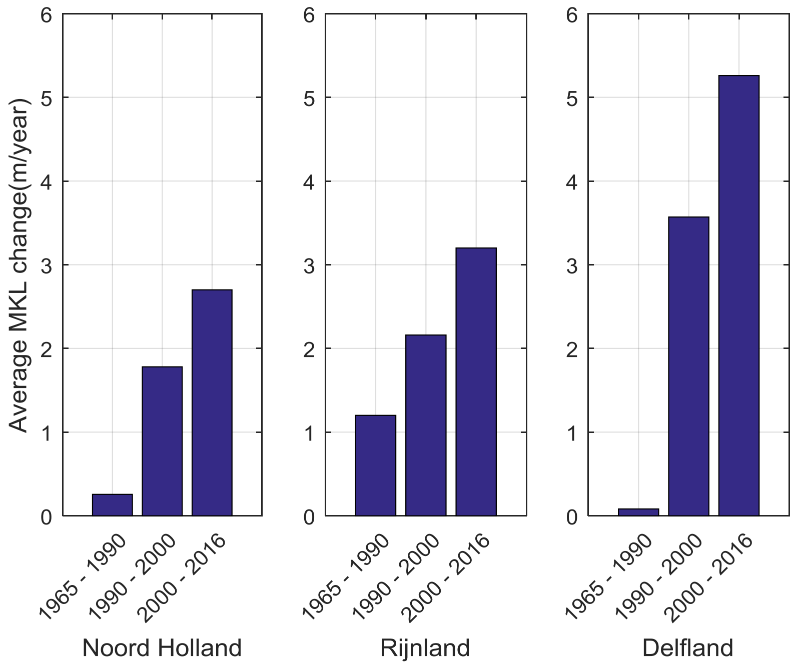

Figure 33 Average MKL change for different areas and time interval (m/year).

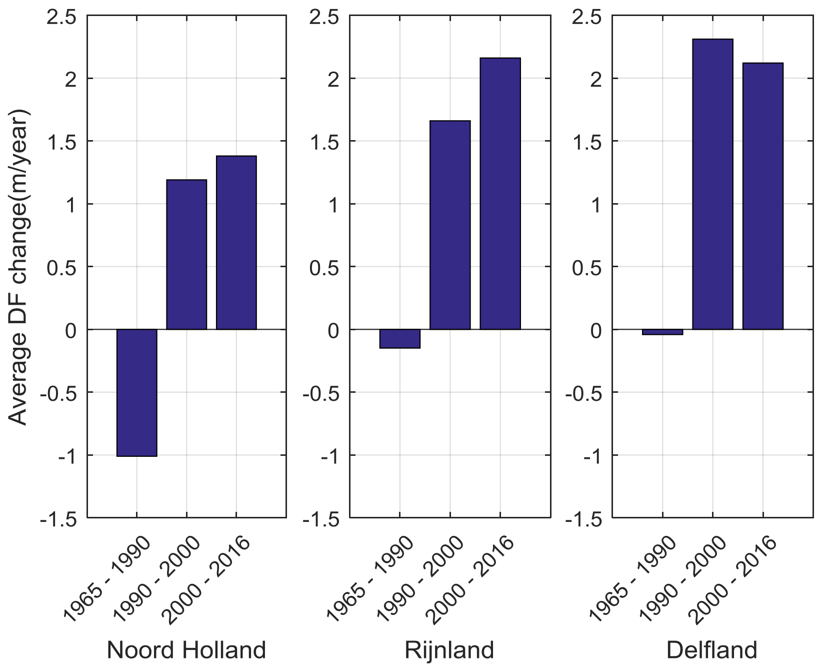

Figure 34 Average DF change for different areas and time interval (m/year). Positive numbers show seaward movement of the dune foot, whereas negative numbers show landward movement.

Scenario 3: Nourishment Volume

It is also insightful to know what the shift of the indicators is, when increasing sand volumes. Table 8 summarizes the results. A positive trend has been observed on MKL. By looking the values of average DF change, a transition from beach to shoreface nourishments can be noticed; there is an average decrease in the case of 300-500 m^3/m/year. The probability of the implementation of the sand by shoreface nourishments from 18.8%, when the nourishment volume is 150-300 m^3/m/year, increased to 58.7% in that case.

Nourishment Volume (m^3/m/year)	Average MKL change (m/year)	Average DF change (m/year)
0	0.71	0.01
0-150	11.6	3.61
150-300	11.5	8.4
300-500	12.9	7.43
Larger than 500	29.9	13.3

Table 8 Average MKL and DF changes for different Nourishment Volumes.

Figure 35 illustrates the network, constrained on the extreme scenario of nourishment volumes more than 500 m^3/m/year. In case of MKL change, two peaks are visible at the probability distribution. The first peak (0-15 m/year) is due to shoreface nourishments and the second due to beach or dune nourishments, which result in bigger displacement of the MKL. It is also visible in which areas and time this amount of volume is implemented.

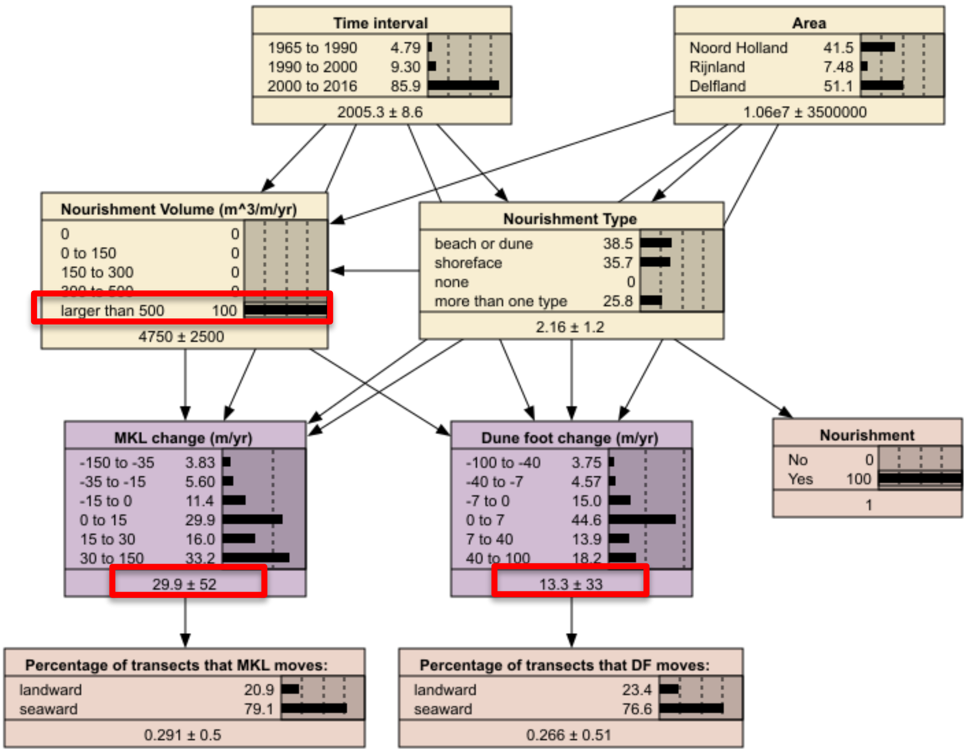

Figure 35 Configuration F constrained on Nourishment Volume.

Scenario 4: Beach-dune or shoreface nourishment

This scenario concerns the assessment of the effects of beach-dune or shoreface nourishments on coastal indicators. The average MKL change in case of beach/dune nourishment is 18.5 m/year and in case of shoreface nourishment is 6.08 m/year. The similar values for DF change are 10.9 m/year and 0.262 m/year for beach/dune and shoreface respectively. Those values are illustrated in Figure 36.

One observation is that nourishments have smaller effects on DF than on MKL, by looking at yearly differences. Moreover, effects of beach nourishments are directly visible and they result in seaward movement of the indicators of more than 10 m. However, effects of shoreface nourishments are visible on MKL, but on DF are not visible yet.

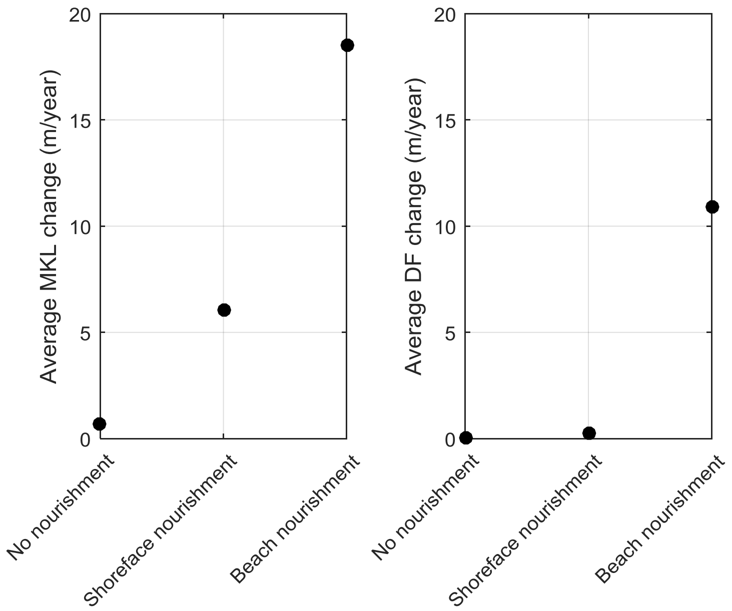

Figure 36 Average MKL (left panel) and DF (right panel) change in case of no nourishment, shoreface or beach nourishment.

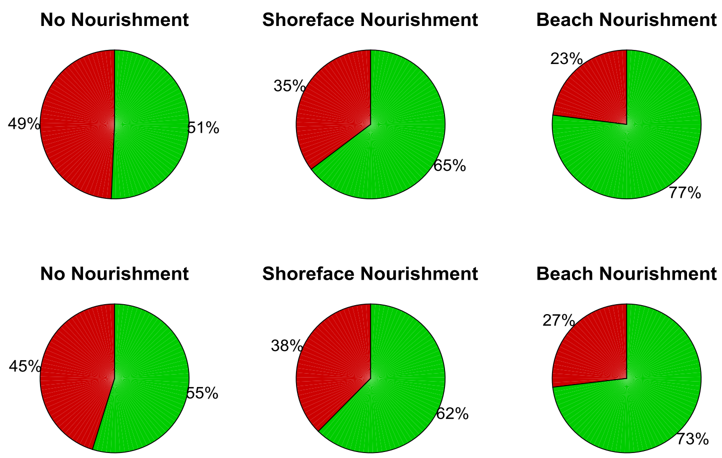

Figure 37 Displacement of MKL (upper panels) and DF (lower panels). Green colour represents probability of seaward displacement of the indicators, whereas red colour represents probability of landward displacement.

The assessment of the effects of beach-dune or shoreface nourishments can be done for each or the areas separately.

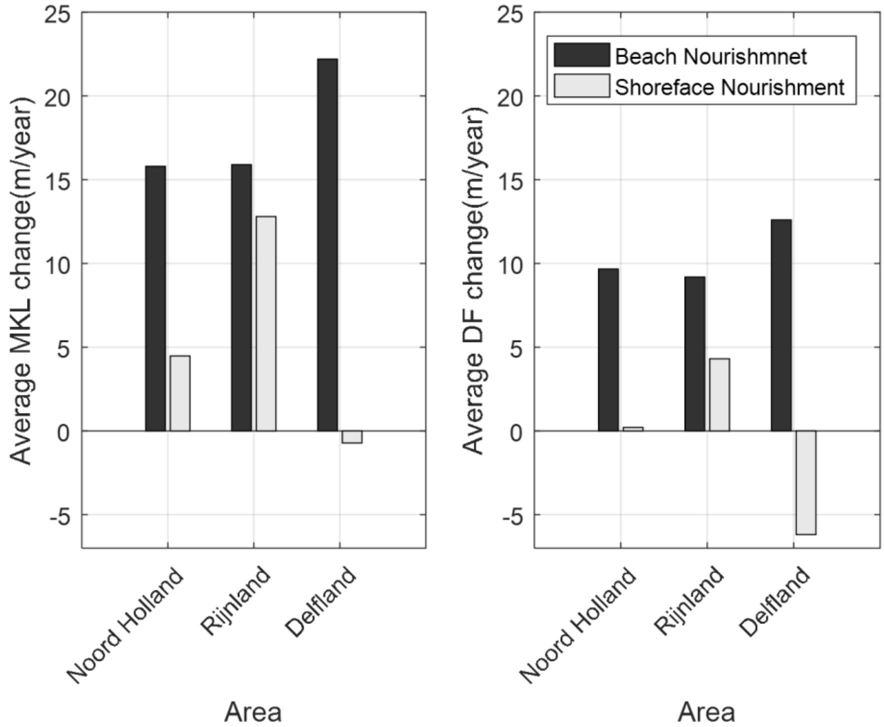

Figure 38 Average displacement of MKL (left panel) and of DF (right panel). Positive numbers show seaward movement of indicators, whereas negative numbers show landward movement.

A first observation from Figure 38 is that the effects of beach or dune nourishments are directly visible on the indicators and they have more positive effects than shoreface nourishments in all of the cases. Moreover, Delfland is the area where the most nourishment volume was applied. In case of beach nourishments the MKL is influenced directly and the average seaward movement is larger compared to the MKL movement of the other areas. However, in case of shoreface nourishments a negative trend is observed. This could be explained by the fact that transects that are selected to be nourished are transects which lack in sand volume and they have an erosive trend. This in combination with the fact that effects of shoreface nourishments are not directly visible, leads to those negative values.

Scenario 5: Time horizon

Scenarios 1-4 concern yearly changes of the indicators, whereas in this scenario, changes in a time horizon of 5 and 10 years are considered as well. Those changes are expressed in m/year in order to be comparable to each other. For this purpose, the network is trained with a dataset which contains differences between the position of the indicators at the current year and the position 5 or 10 years later, averaged over the chosen number of years. Figure 39 and Figure 41 show the probability that the indicators are displaced seaward (green colour) or landward (red colour). Figure 40 and Figure 42 show the mean displacement (m/year) of MKL and DF respectively.

In Figure 40 and Figure 42, it is visible that effects of beach nourishments are immediate and they fade away with time, whereas effects of shoreface nourishments appear from the first year, but they reach the maximum in time horizon of 10 years. This is observed for both of the indicators. Overall, the nourishments have a positive effect. In addition, Figure 39 and Figure 41 show that cases, in which no nourishment has been implemented, have a positive trend. This is due to the fact that nourishment volume is spreading and affects transects that have not been nourished.

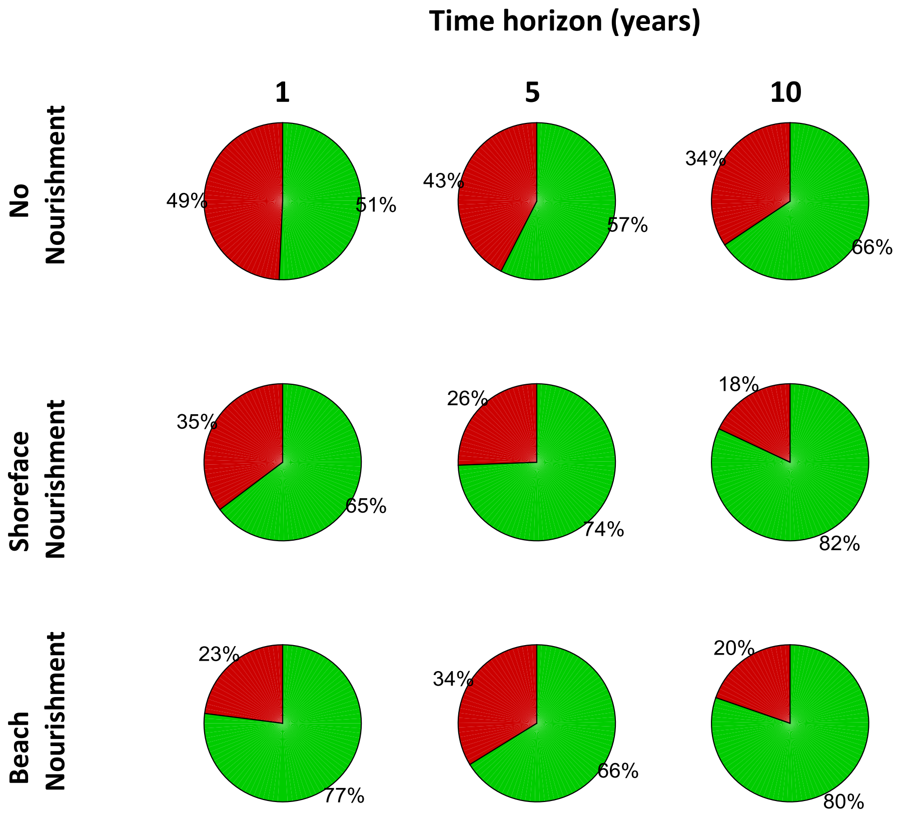

Figure 39 Displacement of MKL. Green colour represents probability of seaward displacement of the MKL, whereas red colour represents probability of landward displacement.

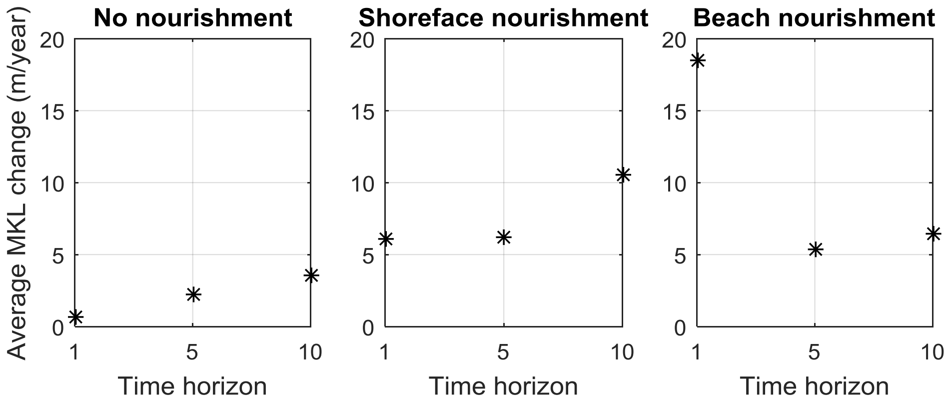

Figure 40 Average MKL change (m/year) in case of no nourishment, shoreface or beach nourishment, for 1, 5 and 10 years after the implementation.

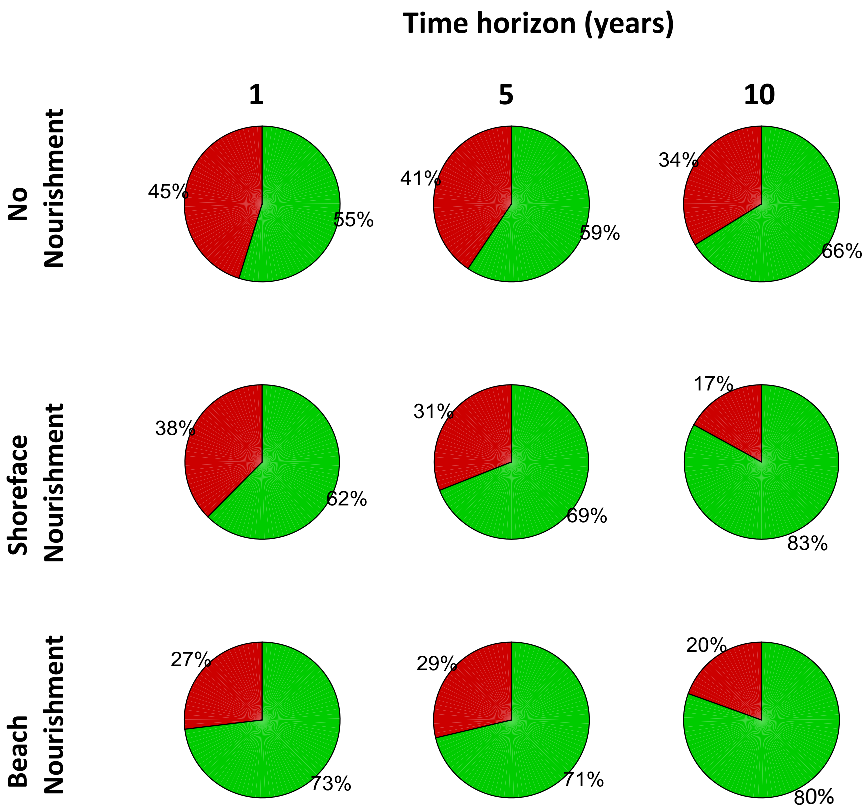

Figure 41 Displacement of DF. Green colour represents probability of seaward displacement of the DF, whereas red colour represents probability of landward displacement.

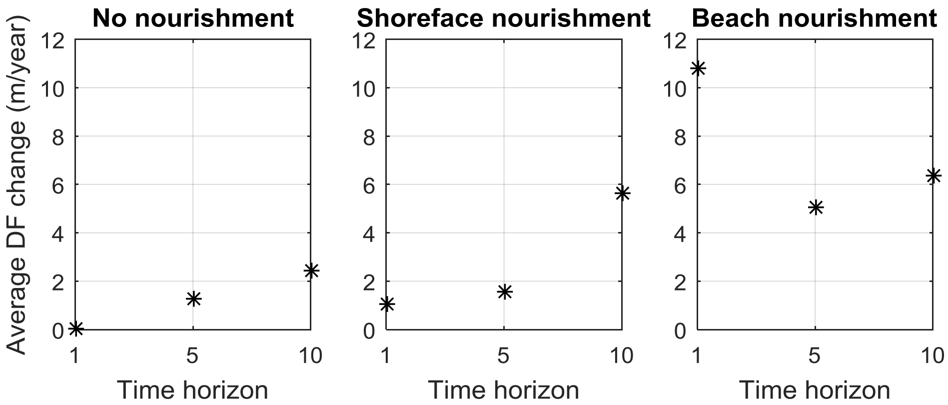

Figure 42 Average DF change (m/year) in case of no nourishment, shoreface or beach nourishment, for 1, 5 and 10 years after the implementation.

Annual changes of the coastal state indicators normalized by the nourishment volume

At this section the changes per year are normalized by the sand volume of the nourishment in order to be able to relate the changes of the indicators (results from scenario 5) to the applied nourishment volume. In this way, the effects of the two different types of nourishments (beach vs shoreface) on the coastal state indicators could be comparable. The Bayesian network enables to make this calculation by extending the network. *"MKL change / Nour. Volume"* and "*DF change / Nour. Volume"* (green nodes in Figure 43) are added at the existing configuration. The average values of those nodes by constraining the *"Nourishment Type"* at beach or shoreface nourishment, for the three different time horizons (1, 5 and 10 years) are plotted in Figure 44 and Figure 45.

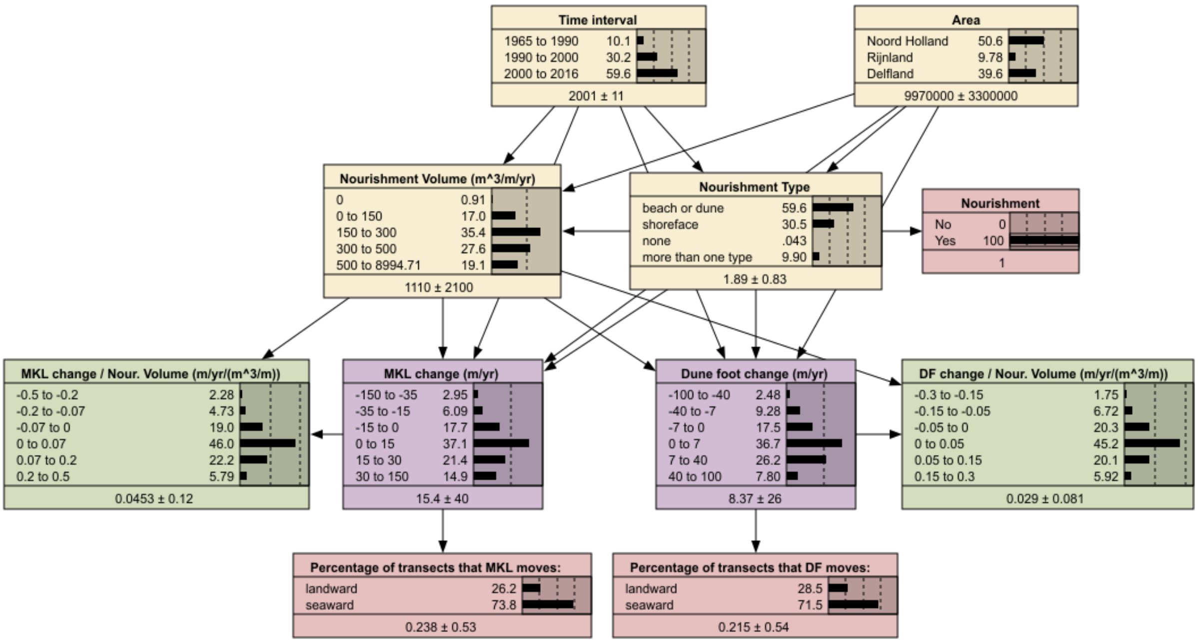

Figure 43 Configuration F with two extra nodes, which represent the annual change of the coastal indicators normalized by the nourishment volume (green nodes). The network is constrained at cases where a nourishment has been implemented.

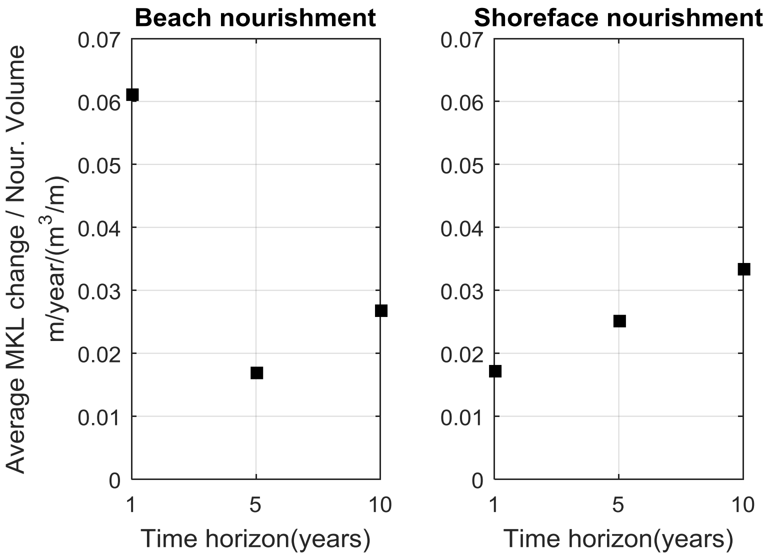

Figure 44 Average MKL change normalized by the nourishment volume for time horizon of 1, 5 and 10 years, in case of beach (left panel) or shoreface nourishment (right panel).

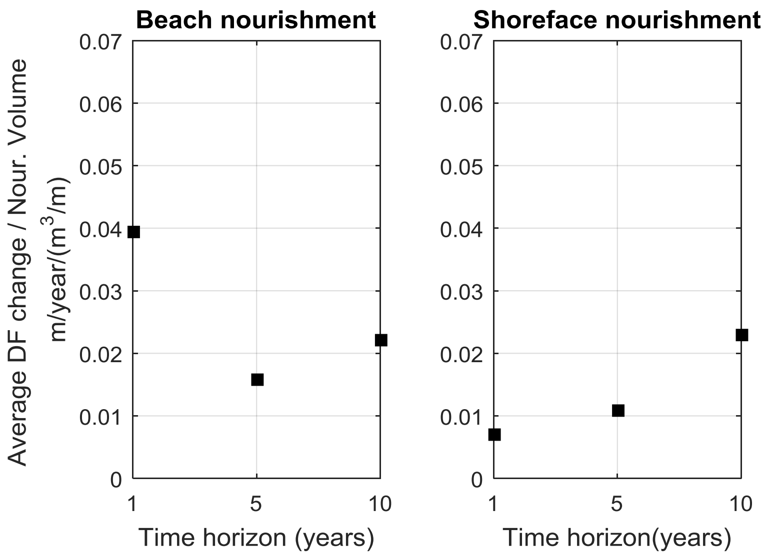

Figure 45 Average DF change normalized by the nourishment volume for time horizon of 1, 5 and 10 years, in case of beach (left panel) or shoreface nourishment (right panel).

The average change of the indicators normalized by the nourishment sand volume is estimated 1, 5 and 10 years after the implementation of the nourishment (Figure 44 and Figure 45). Firstly, immediate effects on the indicators one year after the implementation of the nourishment are present in case of beach nourishments. The effects of shoreface nourishments on the indicators are not directly visible, since more time is needed for the sediment to be transported onshore.

On the contrary, investigation of the changes 10 years after the implementation of the nourishment is meaningful in case of shoreface nourishments. Beach nourishments can remain in place for smaller intervals, since they have restricted lifetime. When a beach nourishment is implemented, a decrease in the magnitude of change is expected with time. The observed increase in MKL (or DF) seaward displacement is present due to the assumptions of the Bayesian model. The model accounts only for cross-shore sediment transport. In reality, the nourished sand is spreading at both cross-shore and alongshore direction. Therefore, the transects are affected by neighbouring nourishments. Moreover, the possibility of existence of more than one nourishment implementation during the examined time interval contributes to this increase.

Finally, comparison between the two types of nourishments can be achieved in case of 5 years after the implementation of the nourishment. MKL is influenced in a larger extent by shoreface than by beach nourishment (Figure 44), whereas DF is influenced in a larger extent by beach nourishment (Figure 45). However, even if it is possible to compare the magnitude of changes of the indicators, it is important to consider that each type of nourishment accomplishes different purposes and has different time-scale. Furthermore, environmental aspects and cost related issues should be taken into account for the final decision concerning the type of nourishment which should be implemented.

Discussion

CHAPTER SUMMARY

This chapter discusses the results presented in Chapter 3. Next, it presents the assumptions adopted in this study for the development of the Bayesian Network. Thereafter, it presents the differences of the use of the two different datasets for the dune foot parameter. Finally, it presents a possible application of the constructed network in order to accomplish coastal management purposes.

4. Discussion

4.1. Dune foot position detection

This study develops a methodology which detects the dune foot position based on the geometry of the profiles along the Dutch coastline, by calculating the second derivatives of the measured points along the profiles. At the Dutch dune system, this methodology shows a general improvement of the dune foot detection, compared to the current definition of +3 m NAP. The detected positions can indicate annual changes of the coastal profiles.

The methodology has been applied to sandy dune systems of the Dutch coast. An investigation has been done in order to evaluate the performance of the methodology in a dune system of another country. In this case, the methodology can be applied in the dune system. However, the validation method needs improvement, since no measurements of the dune foot were carried out and comparisons were conducted based on Google Earth images.

There are two limitations concerning the proposed methodology. Firstly, the dataset used in this study contains records of elevation at every 5 m. It is expected that decreased resolution will deteriorate the performance of the methodology. Secondly, a general expectation is that the methodology will not detect the dune foot position close to reality when anomalies are present around the actual dune foot position, since those anomalies will influence the results of the 2nd derivatives.

4.2. Log-likelihood ratio tests

The use of log-likelihood ratio tests provides insights about the structure of the network. Different configurations have been tested in order to find the optimum. Optimizing the structure of the network is difficult, since it is not always explicit which variables should be linked and in which way. For instance, dune foot and MKL are dependent variables. Nevertheless, at the optimum network those variables are not directly connected. Induced complexity, by having an extra parent node, leads to decrease in its performance.

4.3. Configuration with Maximum Yearly Water Level

The maximum yearly water level was chosen to represent the natural forcing of the system and it was initially included in the network. Even if the final configuration does not include this parameter, its effects are shortly discussed here. The effects of this parameter on the two indicators were difficult to be observed. The magnitude of influence is smaller compared to the influence of the nourishments. The expected outcome would be that the MKL and DF move landward with increasing maximum yearly water level. However, this is not observed in the network, since the impact of the natural forcing on the indicators is weak, compared to the impacts due to nourishments. This comes in accordance with the conclusion of the research made by Giardino et al. (2014).

4.4. Developed scenarios

In order to investigate the effectiveness of nourishments, 5 scenarios have been developed. Scenario 1 investigates differences between profiles where nourishment has been implemented and profiles where it has not. Seaward displacement of the indicators proves the positive effects of the nourishments on the coastal zone. Scenario 2 concerns the effects by looking at each area separately, for the different time periods. Initial erosive trends of DF are constrained by the nourishments. Moreover, the seaward displacement of the indicators is highly influenced by the type of nourishment for each time period, even if in most of the cases the magnitude of the displacement is increasing with time. Next, the 3rd scenario examines the influence of the magnitude of the nourishment volume on the coastal indicators. Nourishment type influences the results, although, overall, a positive trend is observed for increasing nourishment volume. Thereafter, scenario 4 assesses the effects of different nourishment types. Beach nourishment appears to have stronger effects on both indicators than shoreface nourishment, considering annual changes of the indicators. Finally, different time horizons are investigated in scenario 5. Positive effects of nourishments are present at all of the considered time horizons, with beach nourishments to have an immediate effect on the indicators, whereas shoreface nourishments reach a stronger effect 10 years after the implementation.

4.5. Assumptions adopted for the Bayesian Network

4.5.1. Assumptions for data distributions – removed outliers

The distribution of annual differences of MKL and DF position (nodes of MKL-change and DF-change) contains few large values which were excluded from this study. It corresponds to a percentage of 0.36% of the whole dataset. Those values do not always have a physical meaning. For instance, large values of the dune foot change might exist due to the fact that one secondary peak is created in the foredune, and the detection of the dune foot results in a position highly different from the previous year.

By constraining the dataset, the Bayesian network becomes more reliable, since overestimations in calculation of mean values can be avoided. Outliers (large absolute values) are summed up at the outer bins of the nodes and they lead to an increasing width of those bins. The calculation of the mean value depends on the probability distribution and on the width of the bins, since it is calculated based on the following formula:

$$\mu = \sum_{i=1}^{N} p(x_i) * x_i \qquad [5]$$

Where N is the number of bins, p (x_i) is the probability of a specific bin and x_i is middle value of the bin. Usually the distribution, by constraining nodes, is skewed to positive numbers. Therefore, a large bin width would lead to a shift of the mean value to a higher number. On the other hand, the percentage of seaward or landward displacement of the indicators is not influenced by the existence of those outliers.

4.5.2. Only cross-shore effects are accounted

In this study, the effects of nourishments are examined, assuming that the sand volume is transported only at the cross shore direction. Alongshore sediment transport is not considered in the network. In reality, positive effects of the nourishments do not only influence the nourished transects, but they also influence neighbouring transects, since the sand volume is spreading in both cross-shore and alongshore direction. The effect of this limitation is visible in scenario 5 (Section 3.2.3), in case of investigating the effects of beach nourishments 10 years after the implementation.

Increase in magnitude of seaward displacement of the indicators is observed, when a decrease is expected, since the examined transects are influenced by nourishments applied on neighbouring transects.

4.5.3. Timing between field measurements and nourishments

The effects of nourishments can be detected based on yearly differences of the indicators, when field measurements of a transect (for the year of the nourishment) have been carried out before the implementation of the nourishment. For instance, in case of a beach nourishment implementation, the displacement of the indicators, caused by the nourishment, will be visible in the dataset, if the measurements were conducted in this chronological manner. However, the transects might have been measured before or after a nourishment, or the time of the measurements might be unknown. Cases in which the transects were measured after a nourishment are corrected by assigning the value of the preceding year for the current year of the nourishment. For cases in which the time of the measurements is unknown, it is assumed that the transects were measured before the implementation of the nourishment.

4.5.4. One nourishment is accounted at a time horizon

This sub-section refers to cases where the effects of nourishments on coastal indicators 5 or 10 years after the implementation are investigated (5 or 10 year time horizon). Nourishments might be more frequent than 5 or 10 years at the transect of interest. In these cases, only the nourishment applied at the first year of the examined period is taken into account, and is assumed that no other nourishment was implemented during that period. This assumption performs well in cases for which shoreface nourishments are not considered, since the effects on the indicators in a short period are expected to be negligible. However, in case of beach nourishments, the indicators will show a larger magnitude of seaward displacement than it would be expected (Scenario 5, Section 3.2.3). This assumption leads to overestimation of the magnitude of seaward displacement of the indicators for time horizon of 5 and 10 years.

Moreover, two additional methods were considered for the calculation of the nourishment volume applied during a specific time horizon. Firstly, one method takes all nourishments applied during the time horizon into consideration and assumes that they are implemented on the outset of the first year of the time horizon. In this case, trends and dependencies are very difficult to be identified. Secondly, cases where a nourishment was implemented during the first year of the time horizon and no extra nourishment was implemented at the transect until the end of the time horizon are considered. However, those cases are limited; 1123 cases for 5 years and only 222 for 10 year time horizon, which makes the performance of the network not reliable.

4.6. Comparison of the new and old database for the Dune Foot

The proposed methodology of the dune foot detection, which is derived at the first part of this study, shows a general improvement of the detection when the entire Dutch coast is considered. However, for the areas of the Holland coast; Noord Holland, Rijnland and Delfland, the +3 m NAP definition results in smaller root mean square errors with respect to visual observations. For this reason, the dataset which corresponds to +3 m NAP definition is used for the training of the Bayesian network. This sub-section compares and discusses the results of using those two different datasets.

Configuration F is trained with the two datasets; “F1” is the network trained with the dataset derived from the new methodology and “F2” the network trained with the dataset derived from the +3 m NAP definition. The prior probabilities for the two networks differ (See Appendix D). By looking the DF-change node of the network “F1”, the most probable result is in the range of 0 to 7m (51%) and the rest of the probabilities are almost equal distributed to the bins “-40 to -7”,-7 to 0” and “7 to 40”, whereas for the network “F2”, the probability distribution of the node approximates a normal distribution, with the most likely outcome to be estimated at the range of “0 to 7 m”.

Values of DF change (m/year) are different between the two datasets. In the case of deriving the dataset from the new methodology, it is observed that in many years the dune foot position remains the same. Due to resolution of the method, small differences result usually to zero. On the other hand, in the second dataset small values around zero are observed. Finally, the former dataset contains a larger amount of missing values than the latter.

In case of expansion of the study area at the entire Dutch coast, the use of the new dataset is recommended, since for some cases there is more than 50% reduction of the error compared to the +3 m NAP definition.

4.7. Reverse application – Use of the network for coastal management purposes.

The Bayesian network is a valuable tool for data management. The possibility to explore relationships and dependencies among the variables can provide better understanding of the data. Moreover, it can operate with large datasets in a fast and user-friendly way. Therefore, applications in large spatial scales can be succeeded by the use of a network. The constructed network can be used as a decision support tool for coastal managers. In this section two possible applications of the constructed network are presented.

In Bayesian Networks, the information flows both forward and backward. The scenarios in this study (Section 3.2.3) were developed by constraining input nodes and investigating the effects of each option on the indicators (forward inference). It is possible to assign constraints on the indicators (constrain to one range of seaward displacement values) and then estimate the required sand volume, in order to achieve this magnitude of seaward displacement. Applications of the network can be developed based on the backward flow of the information within the network.

Application 1- Consult about required nourishment volumes for a specific displacement of the indicators.

The network can be used to estimate the required volume for a specific MKL or DF displacement. The sand volume can be estimated for the different areas and for different nourishment types. An example can be seen in Figure 46. The time interval is constrained to 2000-2016, since this range represents the current policy. Red boxes represent constrained values and the green box shows the average nourishment volume that should be applied in order to fulfil the requirements. Therefore, for the area of Noord Holland, in order to have 7.5 m average seaward displacement of the MKL in one year, 322 m^3/m should be applied by means of beach nourishment.

The network can be used to advise coastal managers about the required nourishment volume on a large-scale. The overall average required volume for different magnitudes of the indicators’ seaward displacement can be estimated for the areas of Noord Holland, Rijnland and Delfland. Different nourishment types can be examined and the required sand volumes can be estimated for different time horizons. Finally, sand volumes, in combination with the nourishment type can be linked to the costs.

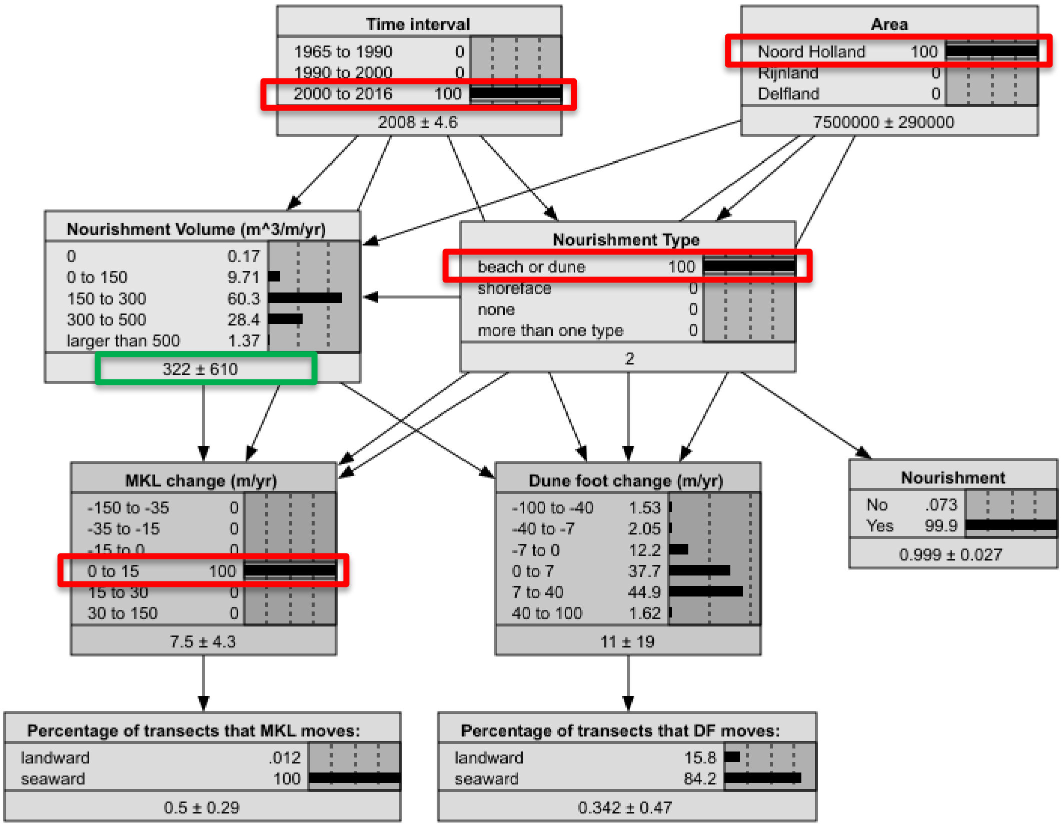

Figure 46 Backward inference of the Bayesian Network. The network is constrained on time interval, coastal region, type of nourishment and MKL change (red boxes) and it is trained for one year time horizon. The output of interest is the average nourishment volume (green box).

Application 2 - Consult about the preservation of the coast at the current state.

This application concerns the use of the Bayesian network for maintenance purposes. The Bayesian network provides the possibility to reshape the probability distribution of the nodes. The distribution for the coastal indicators is constructed in a way that decreases the standard deviation, by eliminating the bigger values and results in an average value of 0 m / year.

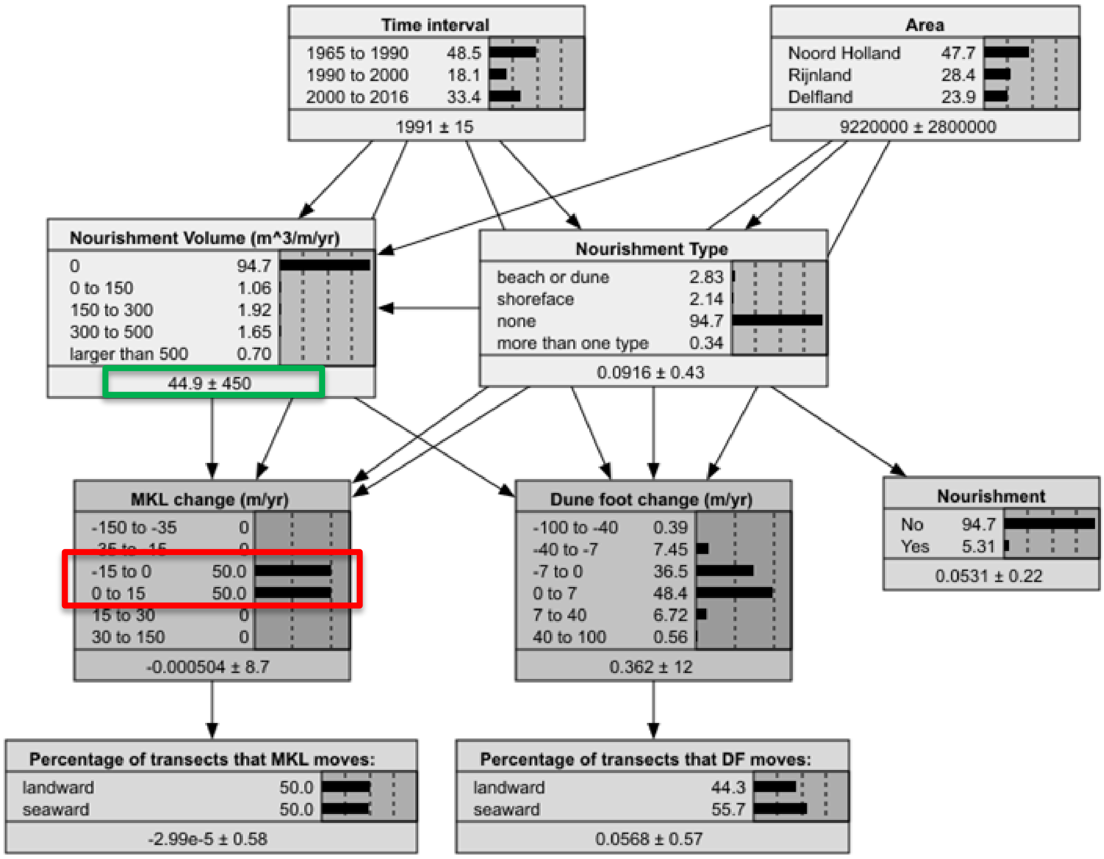

Figure 47 Backward inference of the Bayesian Network. The network is constrained on MKL change highlighted by the red box (0 average changes) and it is trained for one year time horizon. The output of interest is the average nourishment volume (green box).

Figure 47 shows the Bayesian network constrained on MKL change. The average change of MKL is 0 m / year with a standard deviation of 8.7 m / year. In order to maintain the MKL of the Holland coast, the Dutch government should implement around 45 m^3/m/year of sand at the Holland coast. Similar estimation can be achieved for the maintenance of the DF position. In this case, 52.5 m^3/m/year of sand are required.

This example of the application concerns the preservation of the entire Holland coast in case of annual predictions. Long-term predictions and discretization of the coastal area is possible by the use of the network.

Conclusions and Recommendations

CHAPTER SUMMARY

The main results of this study are summarized at this chapter. Answers are provided for the research questions posed in Chapter 1. Next, recommendations for further research are provided.

5. Conclusions and Recommendations

5.1. Conclusions

5.1.1. Dune foot detection

1. Could the methodology of the dune foot position detection be generic and be based only on the geometry of the profile?

It is possible to detect the dune foot position based on the geometry of the coastal profile, by calculating the first and second derivatives of the measured points along the profile. The stretch of the profile where the detection occurs is delimited by two constraints; a seaward and a landward constraint. The mean high water level is considered to be the seaward constraint and the highest point of the most seaward dune peak is considered to be the landward constraint. To this end, it is essential to determine which peaks along the coastal profile are considered to be dune peaks and which are secondary morphological features. Based on a series of tests for the Dutch coast, peaks above or equal to 2.4 m are assumed to be dune peaks. The point of transition from a constant slope to another one for the predefined stretch has a higher second derivative value compared to the neighbouring points and this is the position where the dune foot is detected.

2. Could the methodology be applicable to dune systems in other countries?

The methodology developed in this study is believed to be generic and applicable to other dune systems, since it is based on the morphology of the coastal profile. The mean high water level is used only as a boundary and it does not affect the detection of the dune foot position.

In order to verify this assumption, the proposed methodology is applied in a part of the Portuguese coastline. This coastal system consists of steeper profiles, compared to the Dutch profiles, and each profile has only one main dune peak and no secondary peaks. Therefore, the peak height of “2.4 m” selected based on the Dutch dataset does not influence the detection of the dune foot at this area. The spatial resolution of the measured points is comparable to the resolution of the dataset used for the Dutch coast. The results are compared to Google Earth imagery. At the majority of the examined cases the methodology detects the dune foot near the vegetation, which is considered to be a good detection. Nevertheless, it is advisable to adopt a better validation method or apply the methodology to areas where more data are available.

Main research question: How could the methodology for the detection of dune foot position be improved?

In addition to the previous description of the methodology applied to the Dutch coast, a general improvement of the dune foot detection was seen, compared to the current definition of the +3 m NAP. RMSEs computed with respect to visual observations are used to compare the performance of the two methods. The proposed methodology performs better in case that the entire Dutch coast is considered. By comparing the performance of the methodologies at different areas, the results are diverse. It can be noticed that the new methodology performs better in dynamic systems, such as the Wadden islands and the Delta area.

5.1.2. Assessment of the effectiveness of nourishments using a Bayesian Network

1. Which is the appropriate network design? Which variables should be included in the network?

The choice of the input and output variables and the way of connecting them are essential for the design of the Bayesian Network. Nourishment type, nourishment volume, time interval, coastal region (area) and maximum yearly water level were considered for this study. Moreover, changes on the indicators caused by wind, sea level rise and subsidence, are considered to be negligible compared to changes due to nourishments for the examined time horizon. Nourishment volume and type are proven to be the most important variables, followed by the time interval and then the area. On the contrary, the maximum yearly water level is not included at the final network, since it deteriorates its performance. MKL and DF are used as output variables. Finally, the use of LLR scores for the comparison among different network configurations indicates the optimum network structure.

2. Which are the effects of nourishments on coastal state indicators? Which are the effects of different nourishment types on coastal state indicators?

The use of a Bayesian network gives the possibility to investigate relations between variables, by constraining them. By constraining input nodes and assessing changes on the indicators, the following conclusions are drawn:

- Nourishments have positive effects on the coastal state indicators.
- Initial erosive trends of the DF are constrained by nourishments.
- Beach / dune nourishments have larger positive effects than shoreface nourishments in the short-term (yearly changes of the indicators).
- Comparisons are made for 3 different time horizons; 1, 5 and 10 years after the implementation of a nourishment. Positive effects of nourishments are present for all the considered time horizons, with beach nourishment to have an immediate effect on the indicators, whereas shoreface nourishments reach a stronger effect 10 years after the implementation. In case of no nourishment implemented at a transect, the mean seaward displacement of the indicators increases with increasing time horizon, since more sand volume is available at the coastal system.

3. What can be learned from the use of the Bayesian Network for coastal management purposes?

The Bayesian inference can be used to advise coastal managers about required sand volumes in large spatial scales. To this end, two possible applications of the constructed network have been discussed. Firstly, the required sand volume can be estimated in order to achieve a specific magnitude of seaward displacement of the indicators. Those estimations could concern different coastal areas or the entire Holland coast, and different nourishment types. Secondly, the network is capable of advising coastal managers about the required nourishment volume for preservation purposes (0 m displacement of the indicators).

Main question: How could the effects of nourishments on the coastal system, represented by coastal state indicators, be assessed by using a Bayesian modelling approach?

It is possible to find dependencies among variables and trends of a specific variable. By examining different scenarios, the mean seaward or landward displacement of the indicators can be estimated. Transects with nourishments can be compared to transects without. Moreover, effects of different types of nourishments can be assessed, as they have already been discussed in the sub-questions above.

5.2. Recommendations

1. Datasets for validation of the proposed methodology on other dune systems

The proposed methodology for the dune foot position detection was applied in another dune system. However, availability of field measurements for the validation of the applicability is limited in this case. Specifically, datasets which contain information about the actual dune foot position would be useful for validation purposes. In addition, more datasets from all around the world, which represent different dune systems with different characteristics, would be essential to verify the universal applicability of the method.

2. Dune foot position with respect to the vegetation

Satellite images were used as a supplementary method for validation of the proposed methodology of the dune foot position detection. The start of vegetation is assumed to approximately indicate the dune foot position. Further studies could investigate the correlation of the starting point of the vegetation with the actual dune foot position at the Dutch coast. The increasing use of remote sensing techniques on coastal engineering practice could provide more data available for research. However, seasonal variations of the vegetation and different coastal environments would lead to difficulties in developing a generic methodology.

3. Synthetic Dataset

A synthetic dataset constructed by the use of numerical software could also be used in future applications to produce data for different cases which will serve as input for the network. For instance, large nourishments can be simulated with a software package. Including more cases and larger sample of data, the network will increase its performance to those “extreme” inputs, which are not frequently present at the historical data.

4. Different indicators

Other indicators can be assessed. Giardino et al. (2012) selected the probability of breaching of the first dune row which serves an indicator for safety. The momentary dune volume (volume of sand between dune foot and erosion point 1990) was considered as well. In addition, the beach slope, which is significantly correlated to dune volume changes (de Vries, et al., 2012), can be considered.

5. Use of trends in time instead of differences for the indicators

In case of time horizon of 5 or 10 years, the changes of the indicators were expressed in m/year and they were calculated as the difference of the location of the indicator at the current year and the location after 5 or 10 years respectively, divided by the number of years. Another way to calculate those changes could be based on the trend in time, taking into account all the measured points during the chosen time horizon. In this way, impacts due to inconsistencies in the dataset could be reduced.

6. Considered area

This study concerns the area of Holland coast, which is subdivided into the areas of Noord Holland, Rijnland and Delfland. Future studies could extend the current model to investigate bigger or smaller areas. The three main areas could be divided to more subareas in order to assess the effects of nourishments in a smaller spatial scale. Moreover, the network could also be applied in areas of other countries with similar characteristics. In this case, the bin discretization should be reformulated. Finally, the extension of the network towards the Wadden and the Delta coast can be considered.

Discretization into smaller areas would be valuable for the future nourishment practice. In this study, required sand volumes can be estimated in large spatial scales, since the examined coastal regions are broad. Discretization to smaller areas would help coastal managers to decide on the sand volume required for each area. However, a balance should be found between the finer discretization and the data needed to train the network. The use of a synthetic dataset could contribute in solving this problem.

A configuration is proposed in case of discretization in finer areas (Figure 48). The network can be extended by one extra node, in order to achieve this discretization. At the example shown in Figure 48, the Noord Holland is discretized into 7 subareas. In addition, subarea 8 includes a part of Noord Holland and the coastal regions of Rijnland and Delfland. The discretization of the subareas proposed here, is based on the work of Giardino et al (2012). Smaller discretization can be considered and developed.

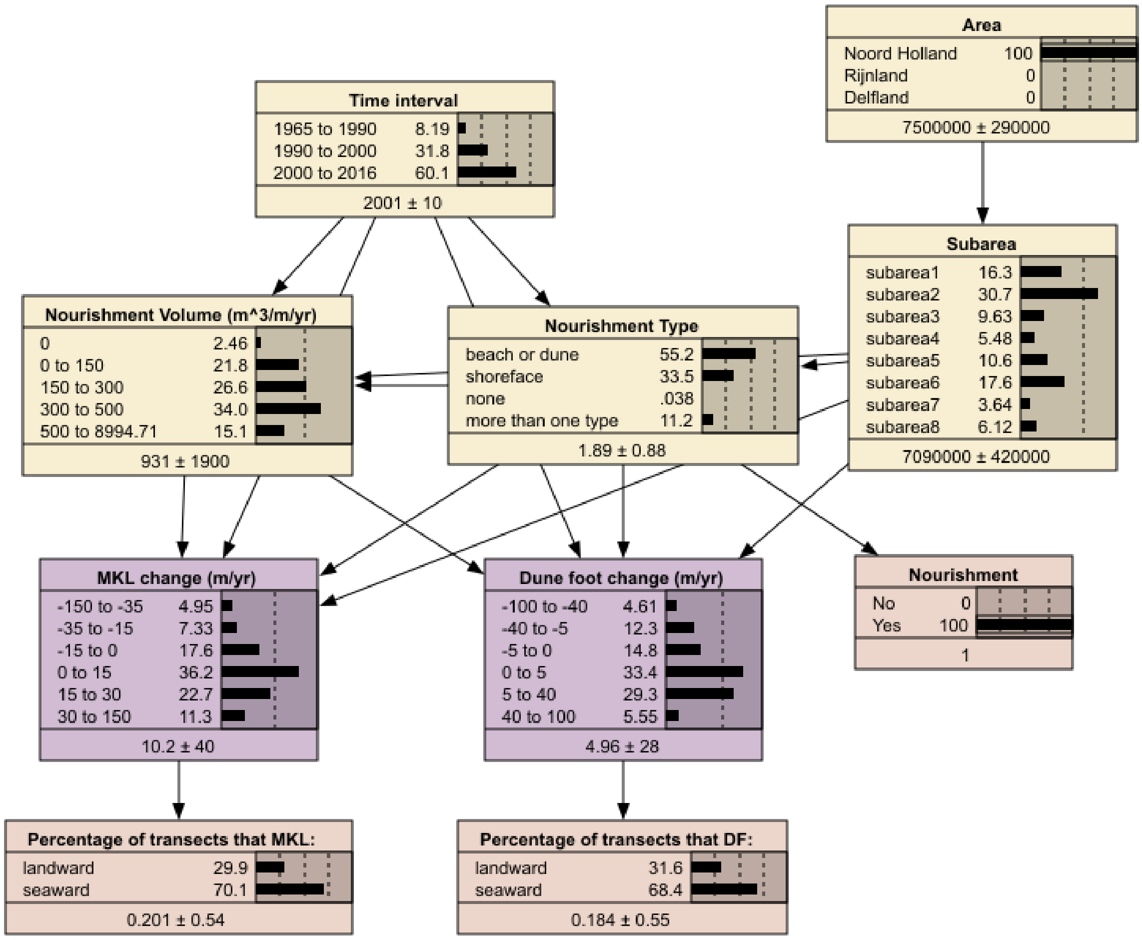

Figure 48 Network configuration proposed for the subdivision of the coastal areas.

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Appendices

A. Heat matrices

Negative values, displayed in red colour, indicate transects where the detection based on the new methodology results in a dune foot position more seaward than the actual (derived from visual observations), whereas positive values (green colour) indicate a dune foot position detected more landward than the actual. Pale colours represent very small differences between the visual observations and the dune foot predictions. Purely white cells represent predictions which coincide with the values of visual observations. Yellow values represent transects which do not have any visual observation for the specific year, or cases for which the new methodology could not detect the dune foot.

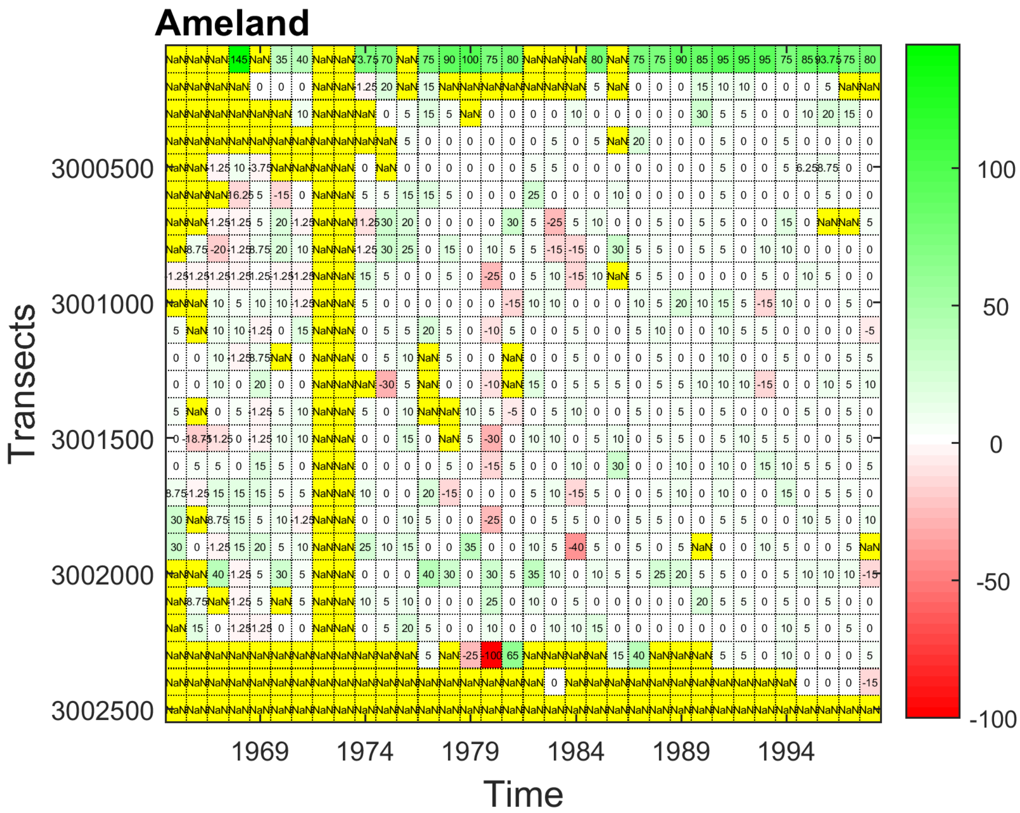

Figure 49 Heat matrix for the area of Ameland. The values represent the cross shore differences of the dune foot position based on the proposed methodology with the dune foot position based on visual observations. Values are plotted for the years 1965-1998.

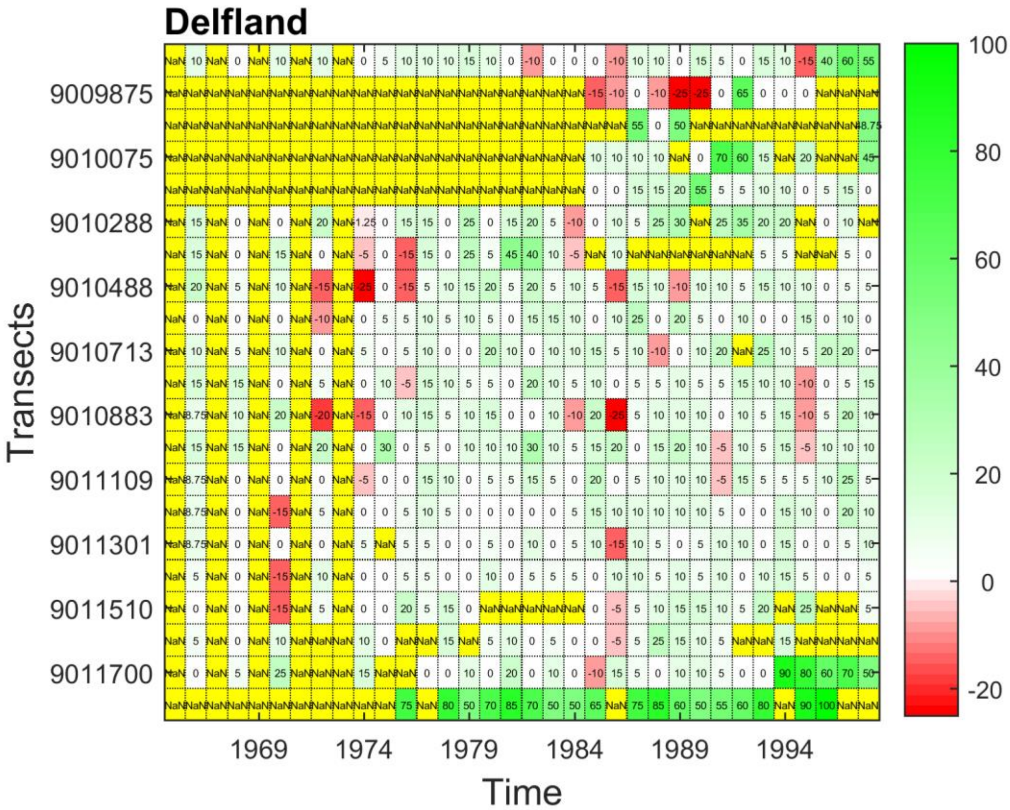

Figure 50 Heat matrix for the area of Delfland.

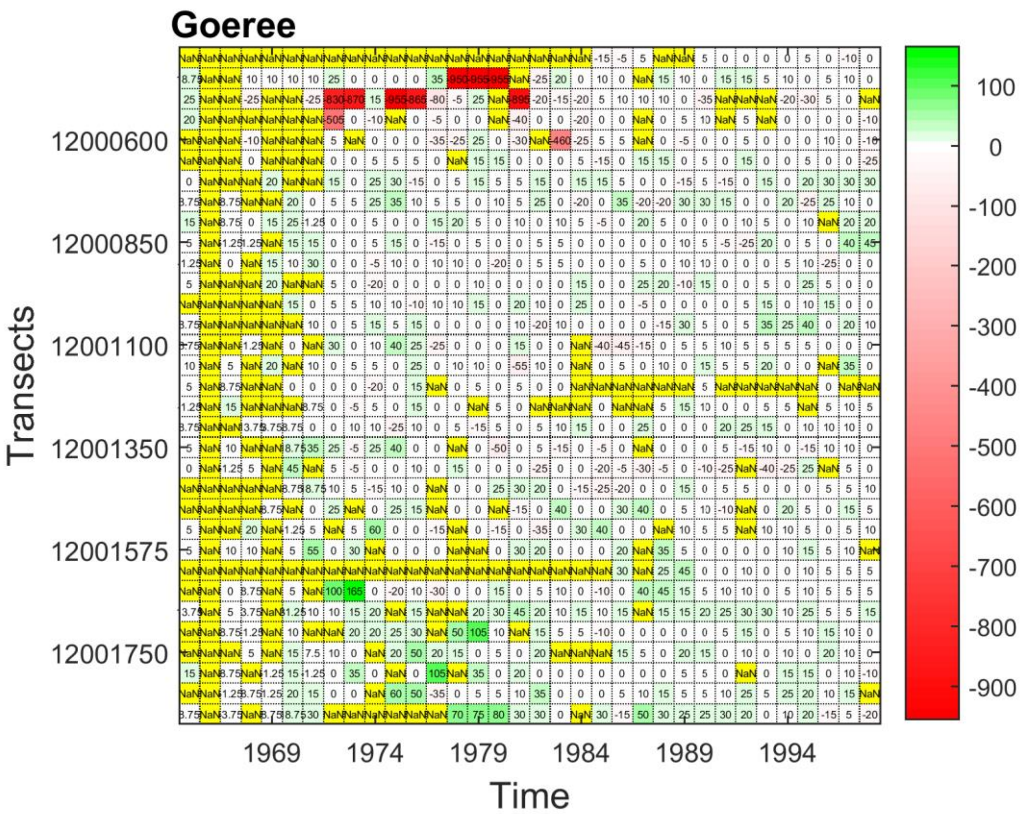

Figure 51 Heat matrix for the area of Goeree.

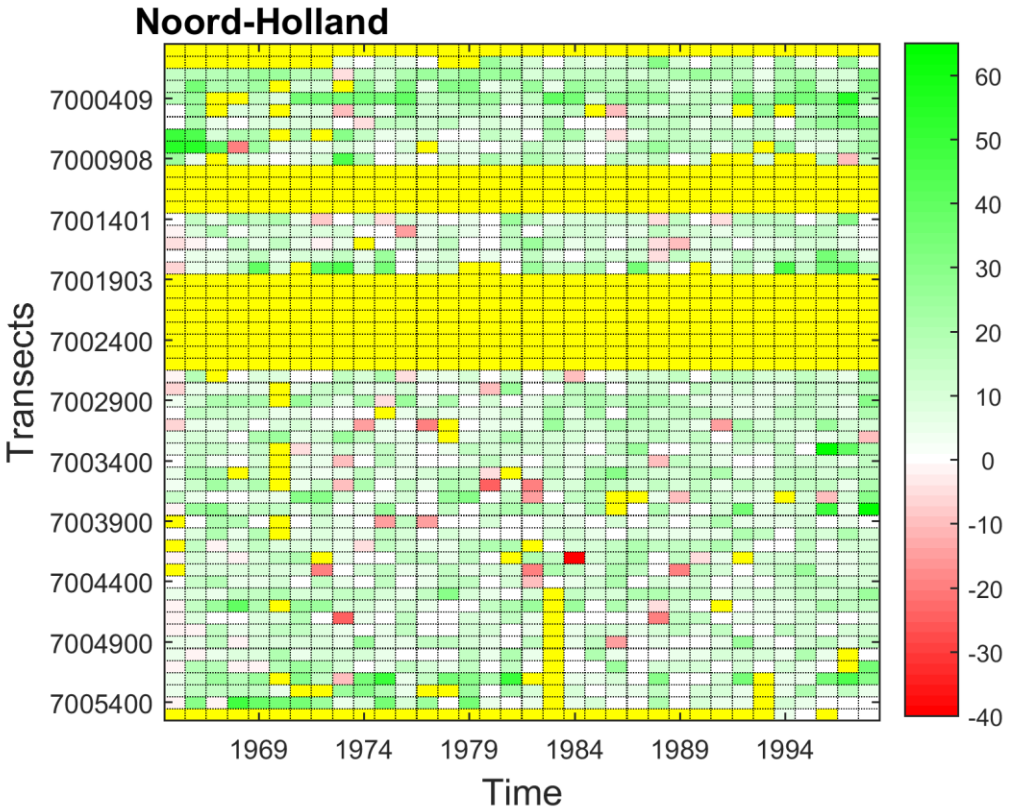

Figure 52 Heat matrix for the area of Noord Holland.

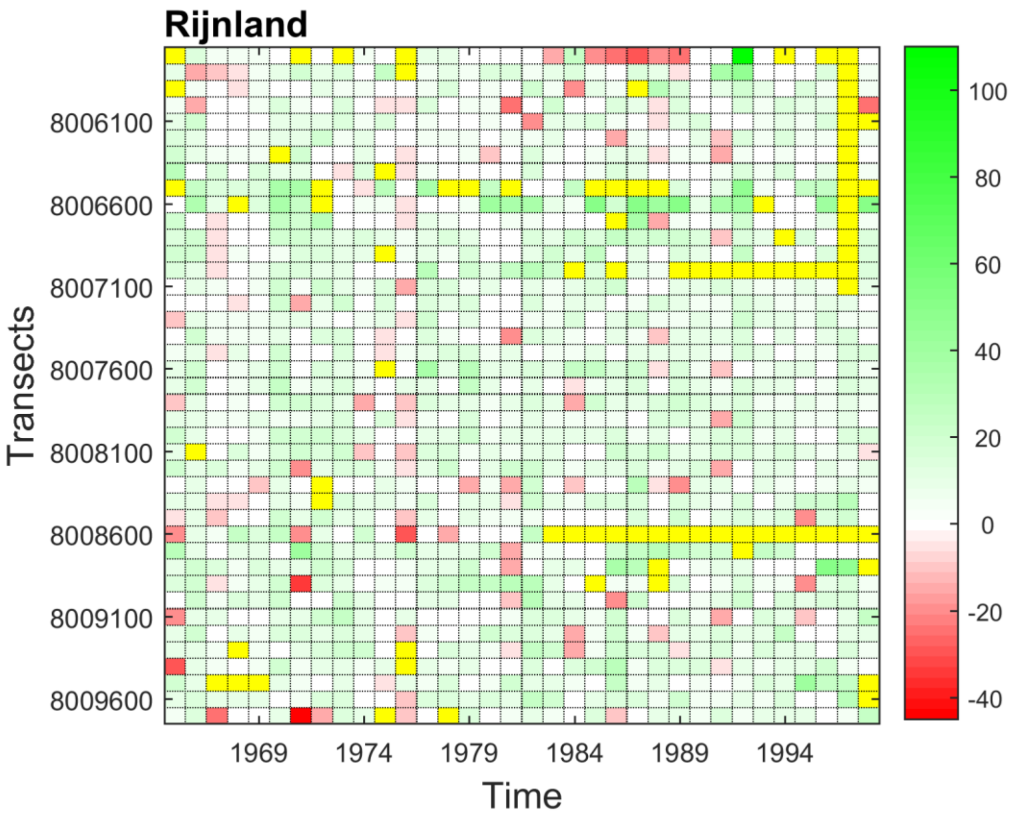

Figure 53 Heat matrix for the area of Rijnland.

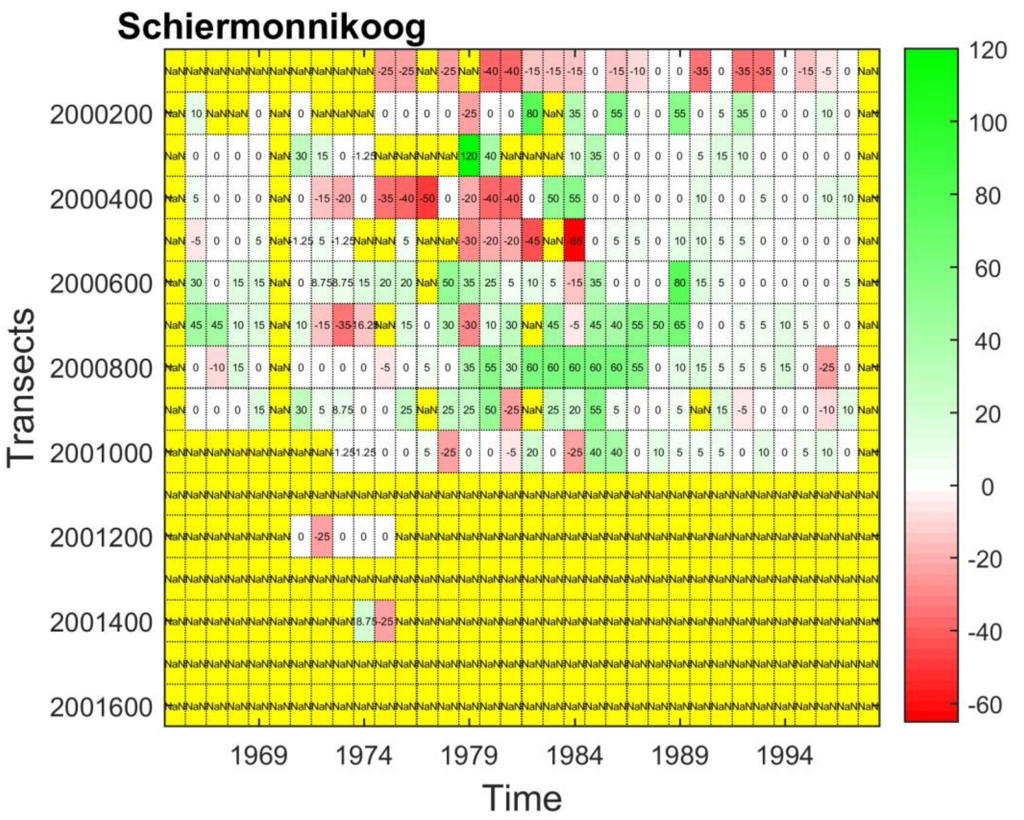

Figure 54 Heat matrix for the area of Schiermonnikoog.

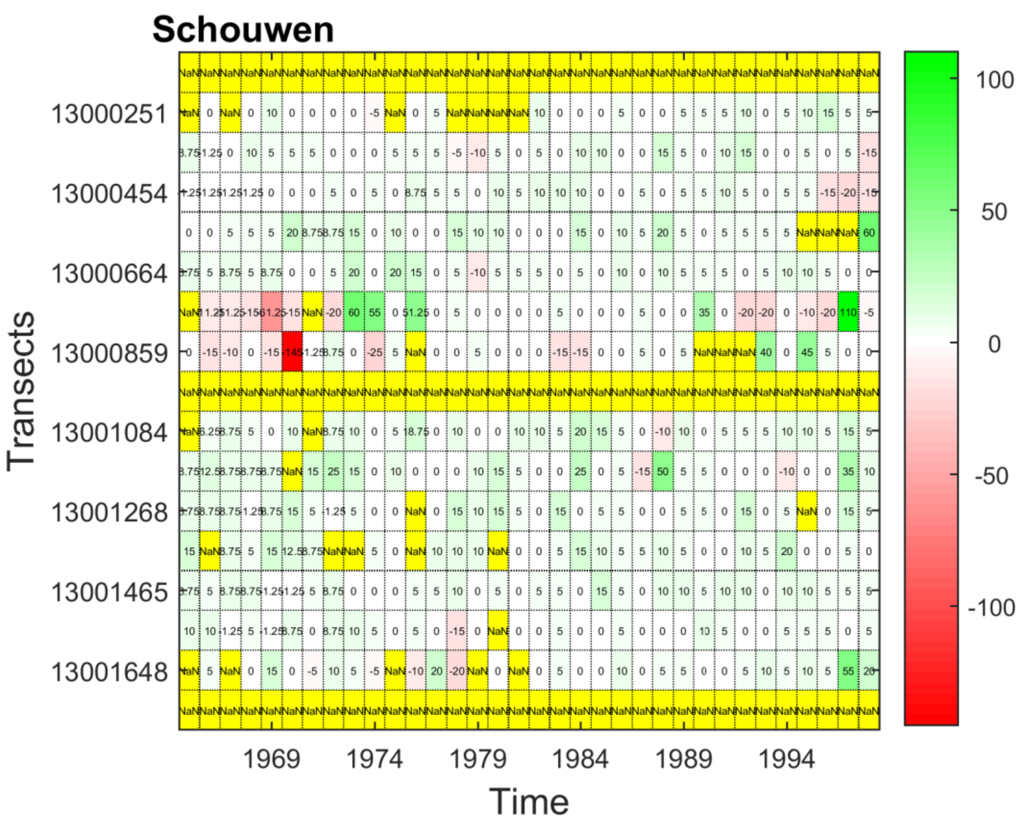

Figure 55 Heat matrix for the area of Schouwen.

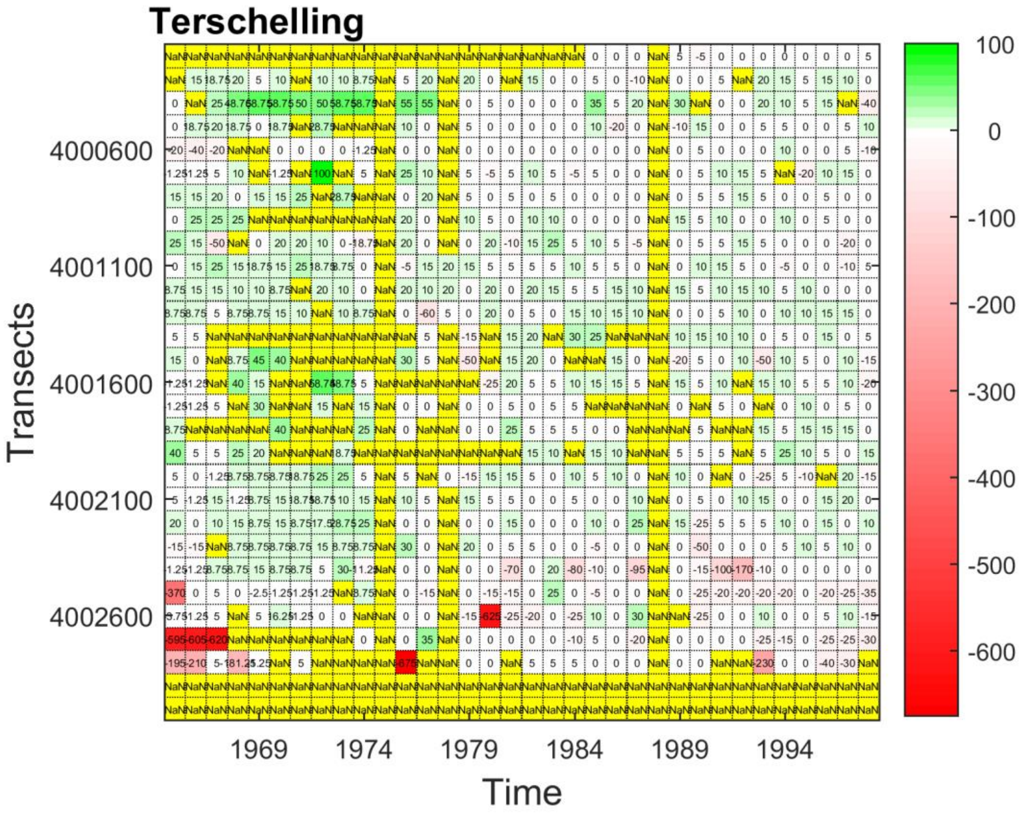

Figure 56 Heat matrix for the area of Terschelling.

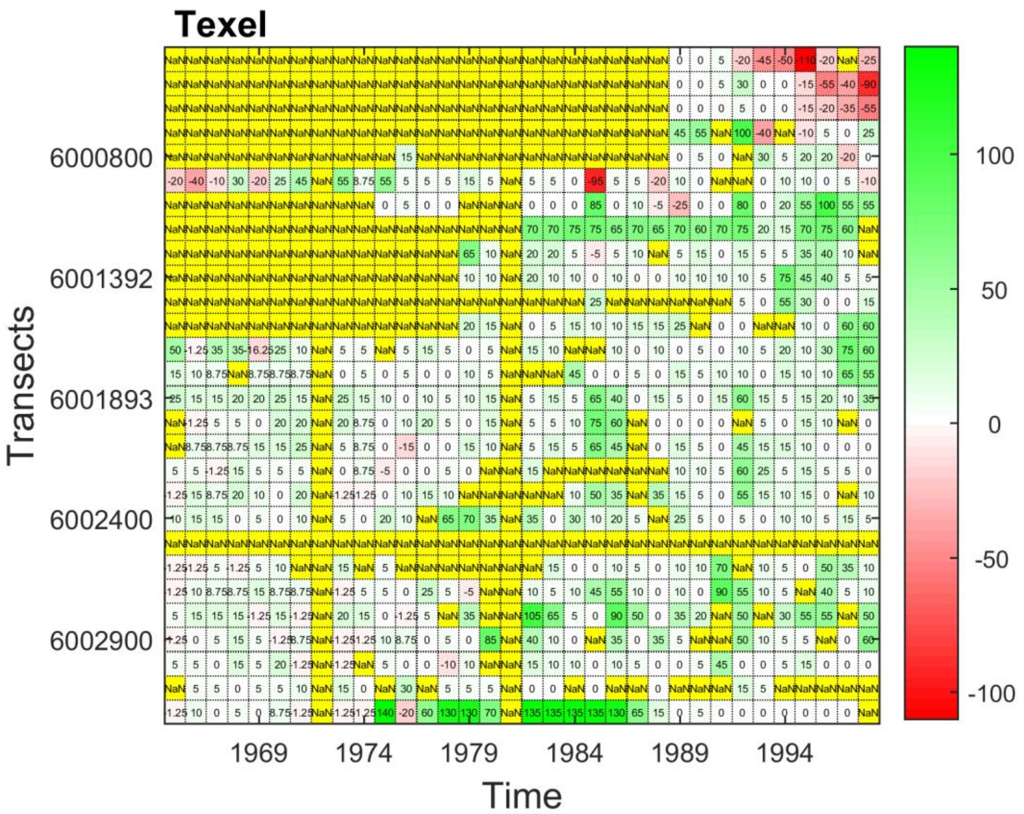

Figure 57 Heat matrix for the area of Texel.

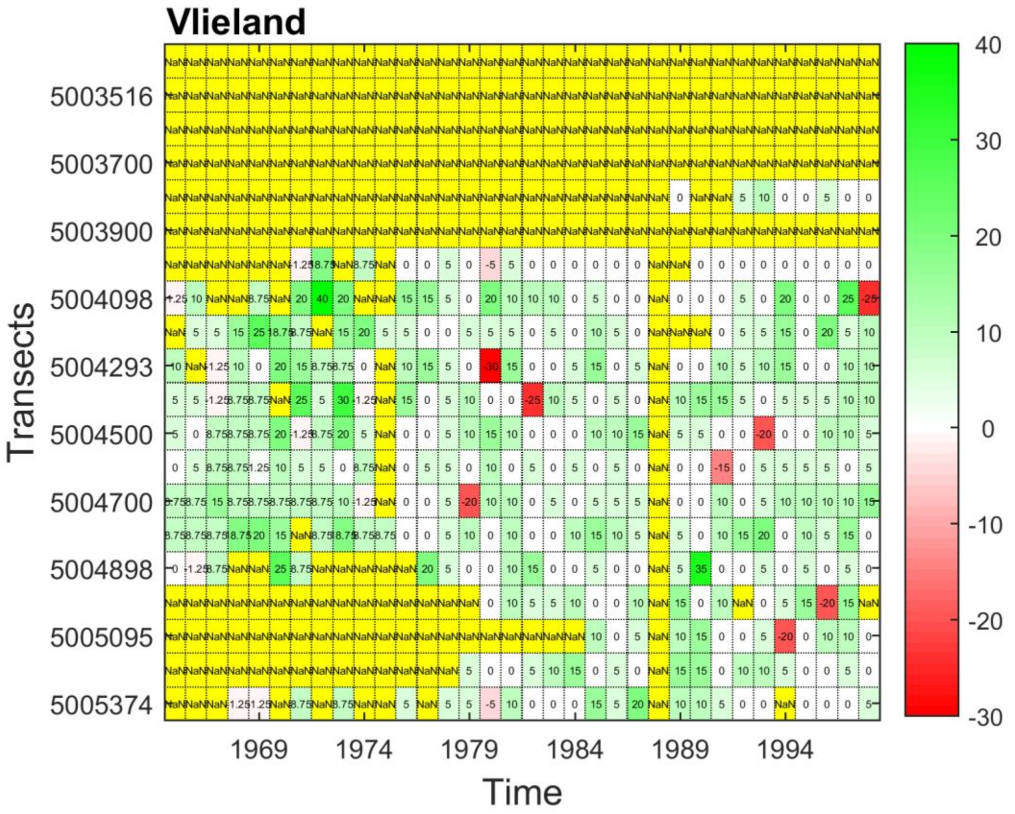

Figure 58 Heat matrix for the area of Vlieland.

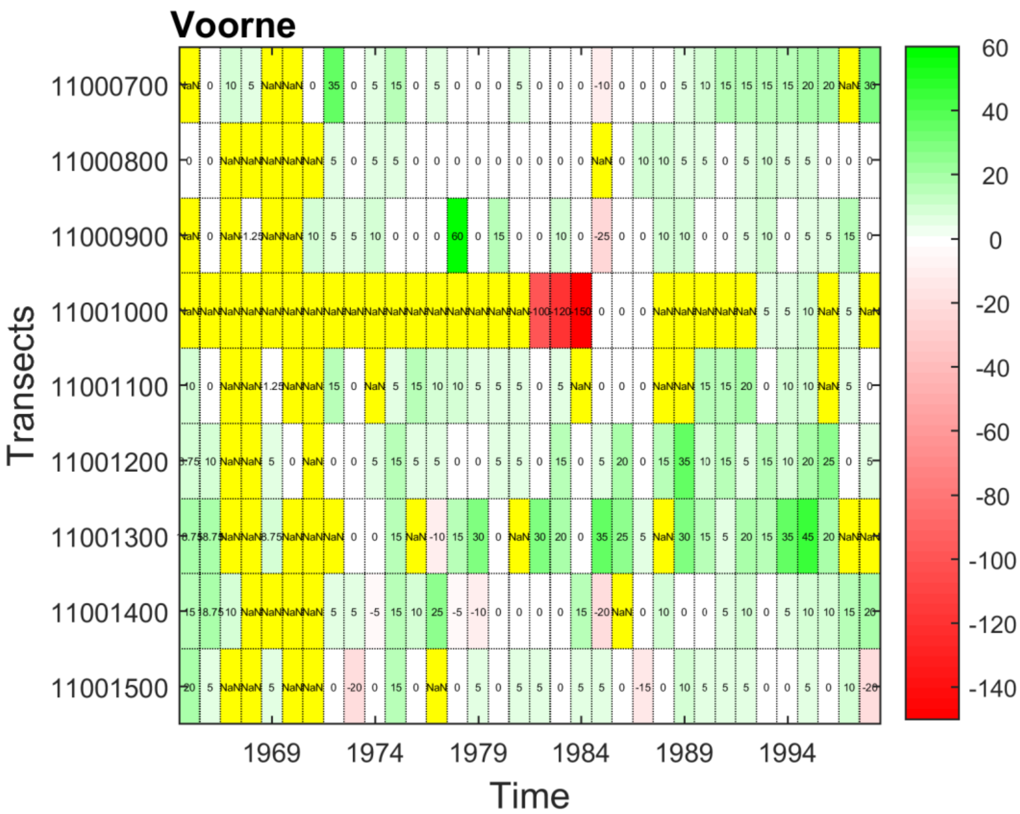

Figure 59 Heat matrix for the area of Voorne.

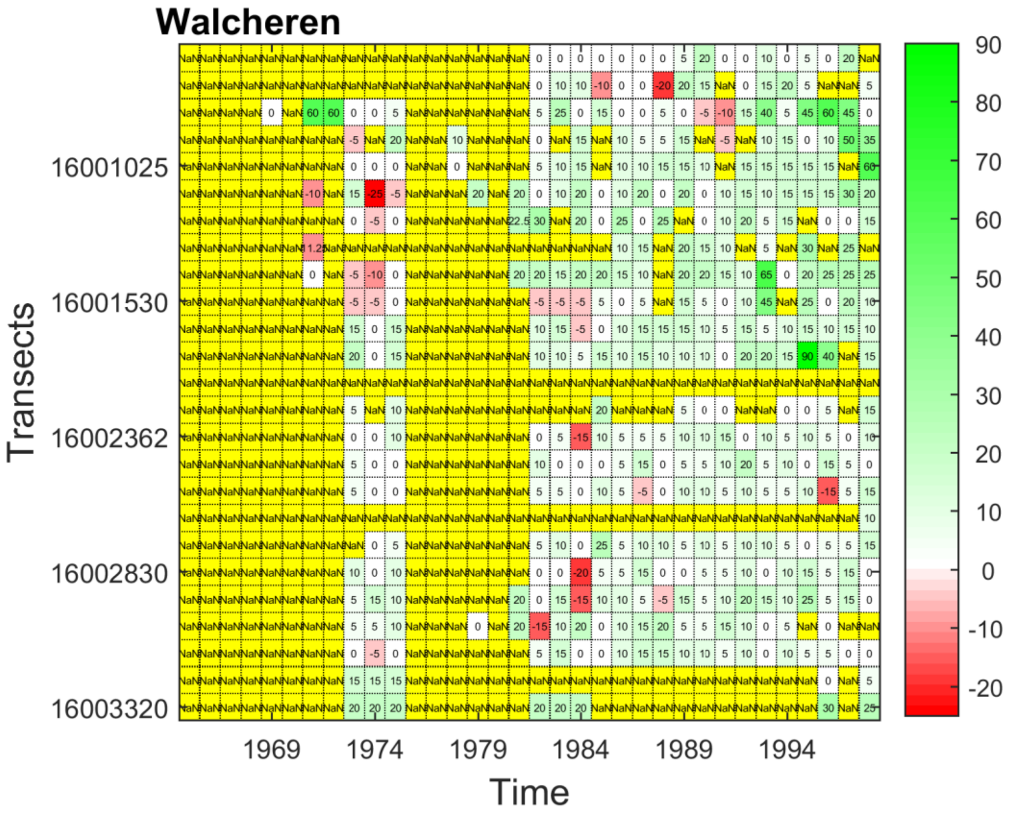

Figure 60 Heat matrix for the area of Walcheren.

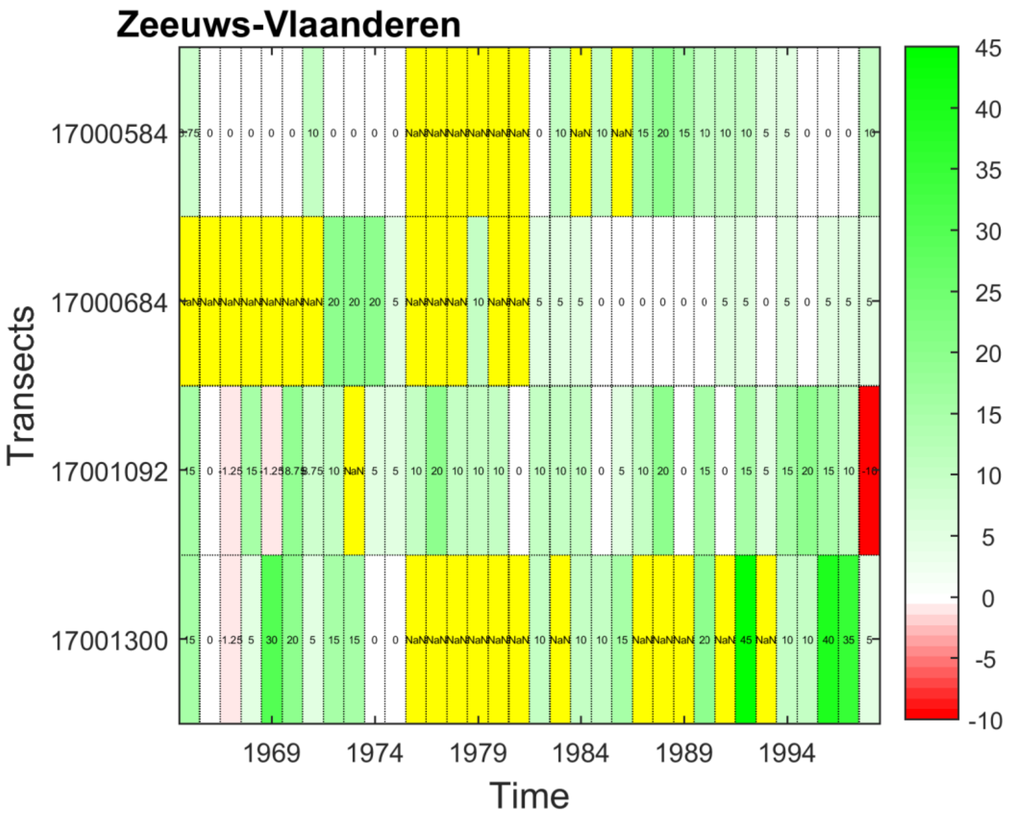

Figure 61 Heat matrix for the area of Zeeuws-Vlaanderen.

The purpose of the following matrices is to depict the coverage acquired by using the new methodology for the dune foot position detection. Cases for which the new methodology could not detect the dune foot position are displayed in red colour. Yellow colour represents transects which do not have any visual observation for the specific year. Finally, white cells represent cases for which the difference of the dune foot position derived from the new methodology with the dune foot position based on the visual observations can be calculated.

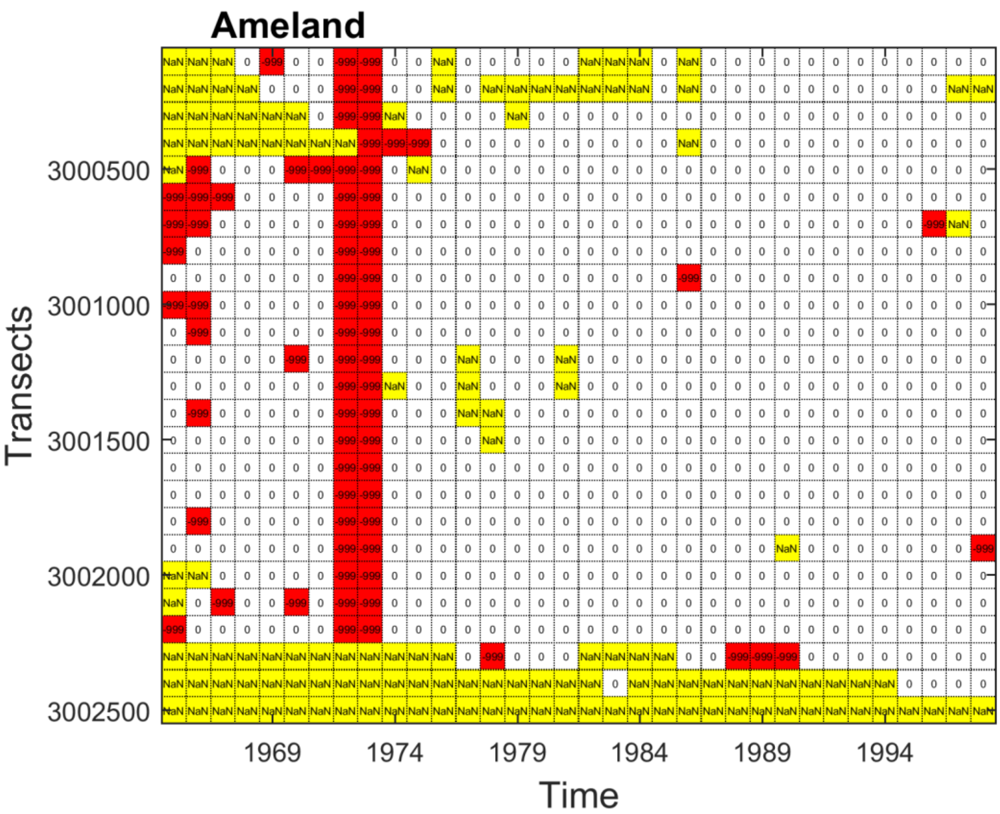

Figure 62 Coverage of the new dataset for the dune foot position detection. Area of Ameland, for the years 1965-1998.

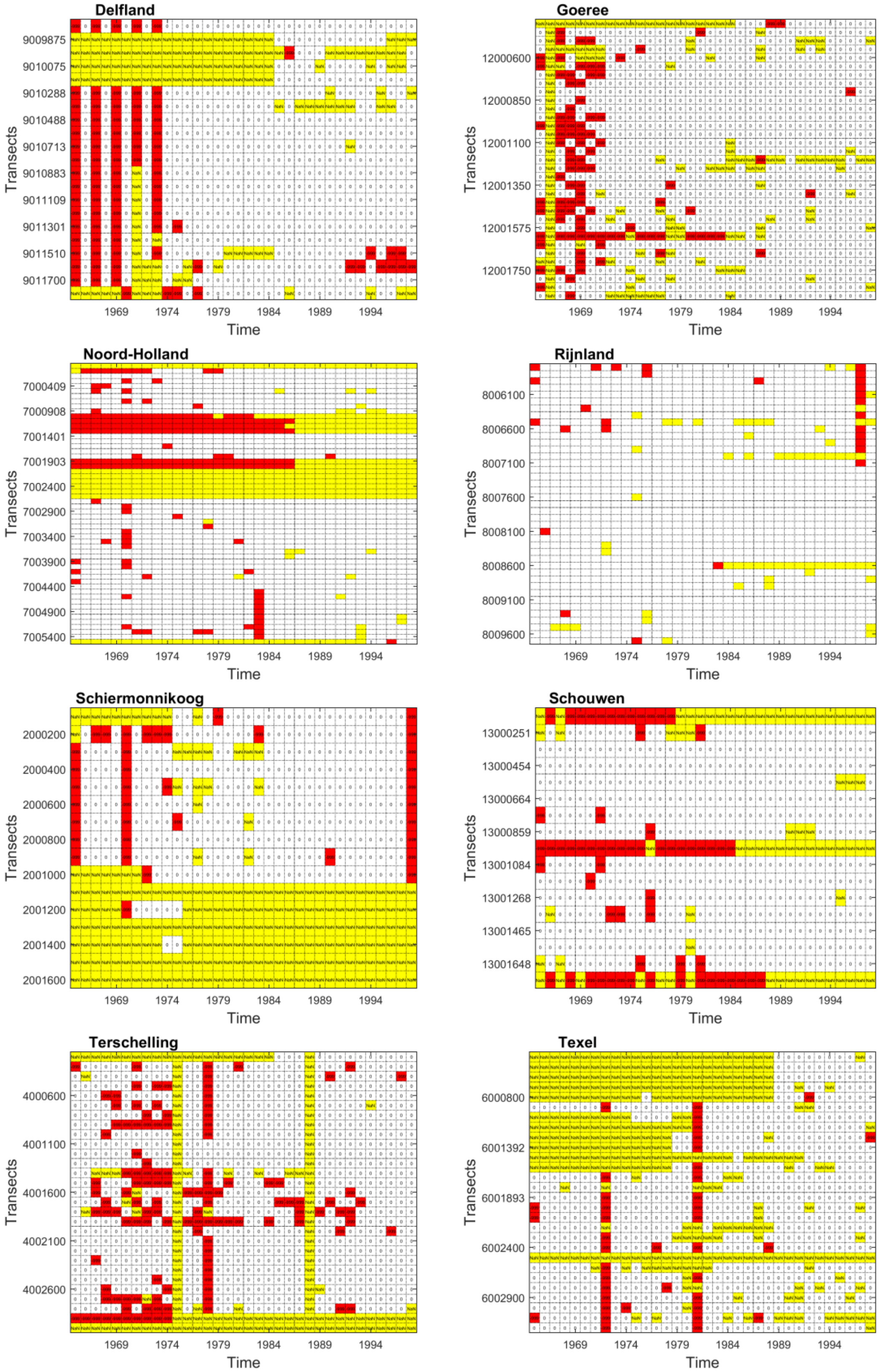

Figure 63 Coverage of the new dataset for the dune foot position detection. Areas of: Delfland, Goeree, Noord-Holland, Rijnland, Schiermonnikoog, Schouwen, Terschelling and Texel, for the years 1965-1998.

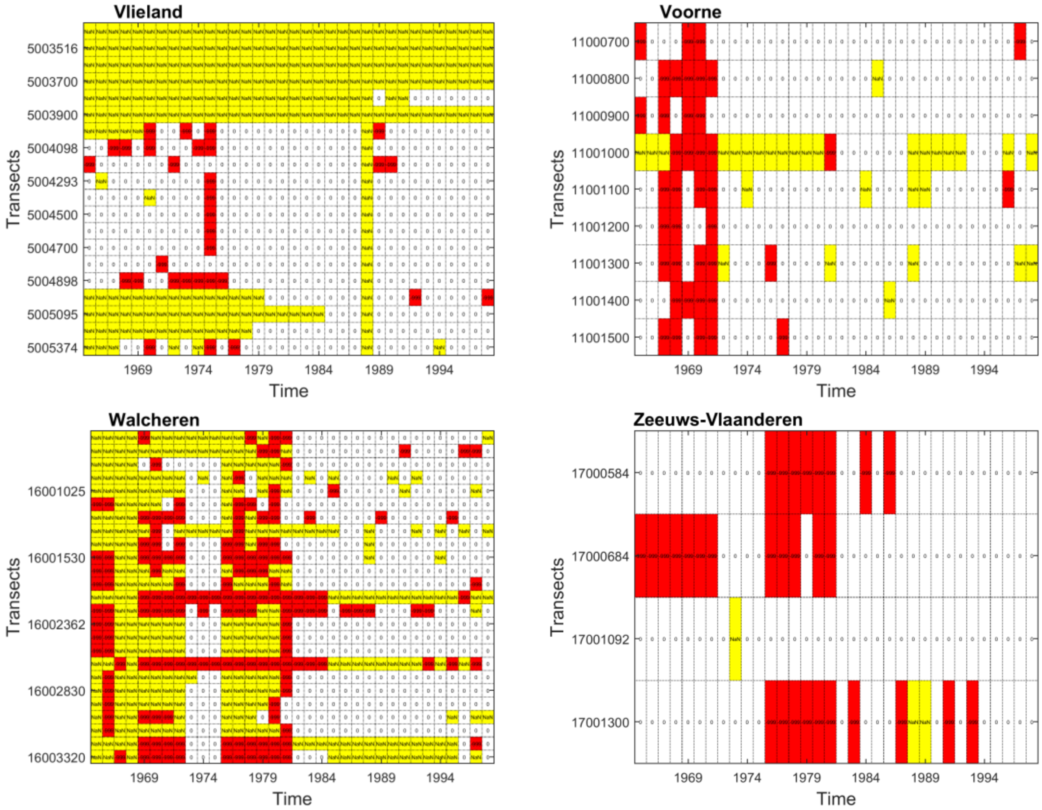

Figure 64 Coverage of the new dataset for the dune foot position detection. Areas of: Vlieland, Voorne, Walcheren and Zeeuws-Vlaanderen, for the years 1965-1998.

B. Information flow: Forward and backward inference.

One important aspect of the network development is how the information is propagated within the network. The type of connection and the existence or absence of evidence influence the flow of the information (Bromley, 2005). There are three possible ways of connections within a Bayesian network:

1. **Serial connection (A → B → C)**

Information can propagate from node A to node C, via node B and vice versa. In case that hard evidence becomes available for node B, information will not be able to propagate from node A to node C or vice versa.

2. **Diverging connection (A ← B → C)**

This type of connection follows the same rules as Serial connection. In case that no evidence becomes available for node C, the information can flow from node A to node C, via node B and vice versa.

1. **Converging connection (A → B ← C)**

This case comes in contrast with the already described connections. Information can flow from node A to node C, via node B only in case that hard evidence is available for node B. This connection is known as *v-structure*.

C. Available data

Bayesian networks require a large amount of information in order to calculate the conditional probabilities between the variables. They are able to combine different data sources, such as field measurements, laboratory data and model simulations (Den Heijer, et al., 2012). Available data concerning the parameters (input nodes and indicators) were obtained via field measurements and they are presented in this section. These data are used as input for training and validation of the network.

- Nourishment recordings

For this study, a nourishment database[10] is used to train the Bayesian Network. This database has been set up at Deltares in cooperation with Rijkswaterstaat. The database includes nourishments performed along the Dutch coast (2268 transects) in the period 1952-2016.

Figure 65 Visualisation of nourishments in Noord Holland (Image obtained from Google Earth). Orange boxes represent dune nourishments, yellow boxes represent beach nourishments and blue boxes represent shoreface nourishments, as they are defined in the dataset.

An example can be found in Figure 65. The figure shows nourishments for the period 1974-2002. More details such as the period when the nourishment took place, the volume of sand and the type are shown for one of the beach nourishments. Furthermore, the area where the nourishments are implemented is visible in the figure.

[10] http://opendap.deltares.nl/thredds/dodsC/opendap/rijkswaterstaat/suppleties/nourishments.nc.html

- MKL and DF measurements

Data for coastal indicators[11] are available on a THREDDS server. MKL and DF values are provided for the years between 1965 and 2016. There are values for each transect of the area of interest. This dataset is created based on field measurements. Transects are measured yearly, and the exact date of the measurement is available. The measurement date might refer to a time before, during or after that the implementation of a nourishment, for a specific transect and year. A measurement can fall "during" a nourishment, because the available data about the time of nourishment is the starting and ending time, and it concerns sometimes an entire area. Therefore, it is not clear if the nourishment was already applied on a specific transect. In those cases, it is assumed that the transects were measured before the implementation of a nourishment. Cases where the transects were measured after a nourishment are corrected by assigning the value of the previous year in place of the year of the nourishment. In this way, differences per year will show the effect of nourishment. In particular, for the MKL, out of 1998 cases that a nourishment has been implemented, in 1437 cases the profile was measured before the implementation, in 492 it was measured during and in 69 cases it was measured after. For the dune foot position the number of cases is 1543, 482 and 176 respectively.

- Maximum yearly water level

The parameter is derived using measurements from two stations; Den Helder and Hoek van Holland. Instant measurements of water level are available with 5 minutes interval. The locations of the stations can be seen in Figure 67. The numbers show the water level at the two stations at the moment when the picture was captured. The maximum water level was found for each year and then it was interpolated along the Holland coast in order to obtain a value at each JARKUS transect. At the station "Hoek van Holland", the maximum yearly water level is bigger compared to the station "Den Helder" for the majority of the years (Figure 66).

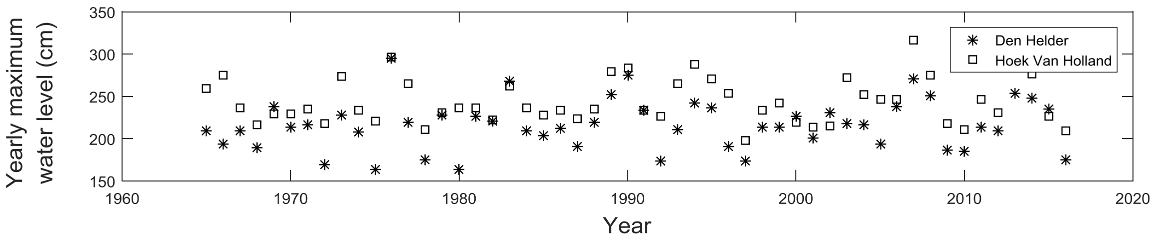

Figure 66 Yearly maximum water level for the stations Den Helder and Hoek van Holland for the years 1965-2016.

[11] http://opendap.deltares.nl/thredds/dodsC/opendap/rijkswaterstaat/BKL_TKL_MKL/catalog.html?dataset=varopendap/rijkswaterstaat/BKL_TKL_MKL/MKL.nc
http://opendap.deltares.nl/thredds/dodsC/opendap/rijkswaterstaat/jarkus/profiles/catalog.html?dataset=varopendap/rijkswaterstaat/jarkus/profiles/transect.nc,

Figure 67 Location of water level stations Den Helder and Hoek van Holland (https://waterinfo.rws.nl/#!/kaart/waterhoogte-t-o-v-nap/).

D. Alternative network configurations

This section shows the alternative network configurations which were used for LLR tests in order to find the optimum configuration. Configuration A includes a directed arrow from MKL to DF, Configuration B connects these two nodes by an arrow directed from DF to MKL and Configuration C does not include this connection (no arrow). Configuration D connects the time interval with the indicators. Configuration E connects the area with the indicators and Configuration F connects both time interval and area to the indicators. Finally, Configuration G includes the additional node of maximum yearly water level.

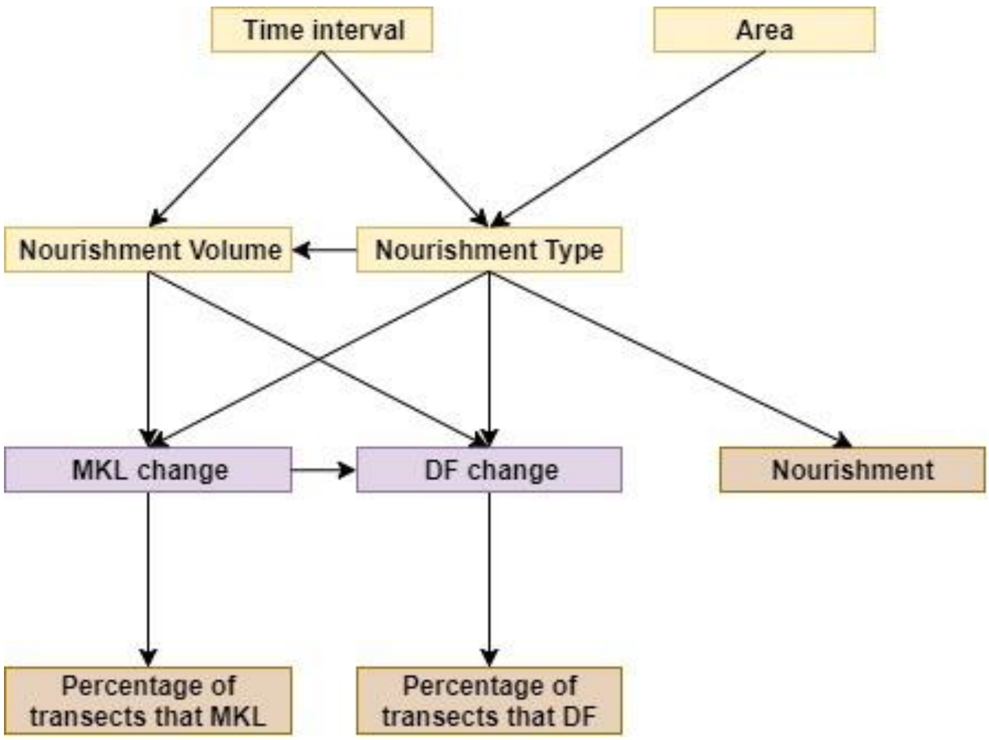

Figure 68 Simplified schematic of Configuration A. Nourishment characteristics and area are shaded in yellow, coastal indicators in purple and summarized nodes in brown.

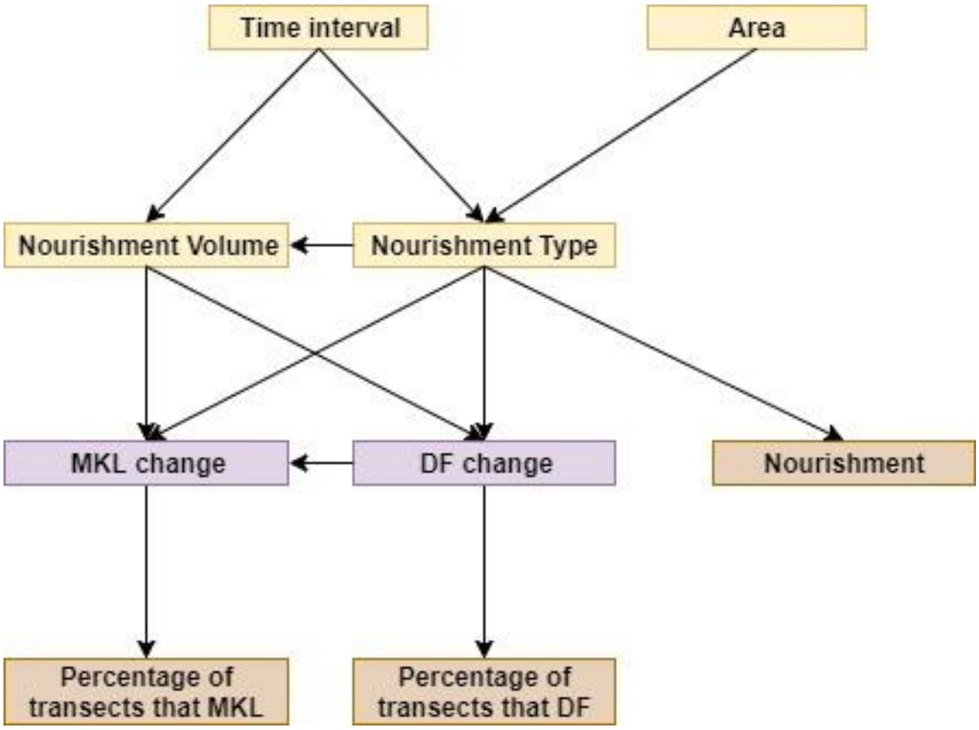

Figure 69 Simplified schematic of Configuration B.

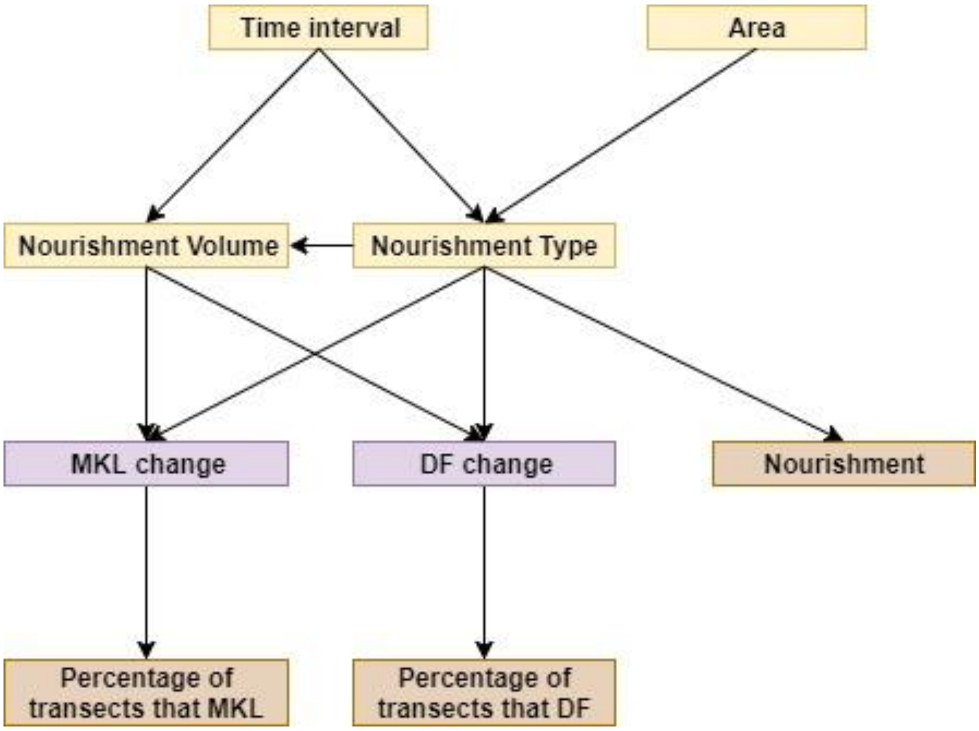

Figure 70 Simplified schematic of Configuration C.

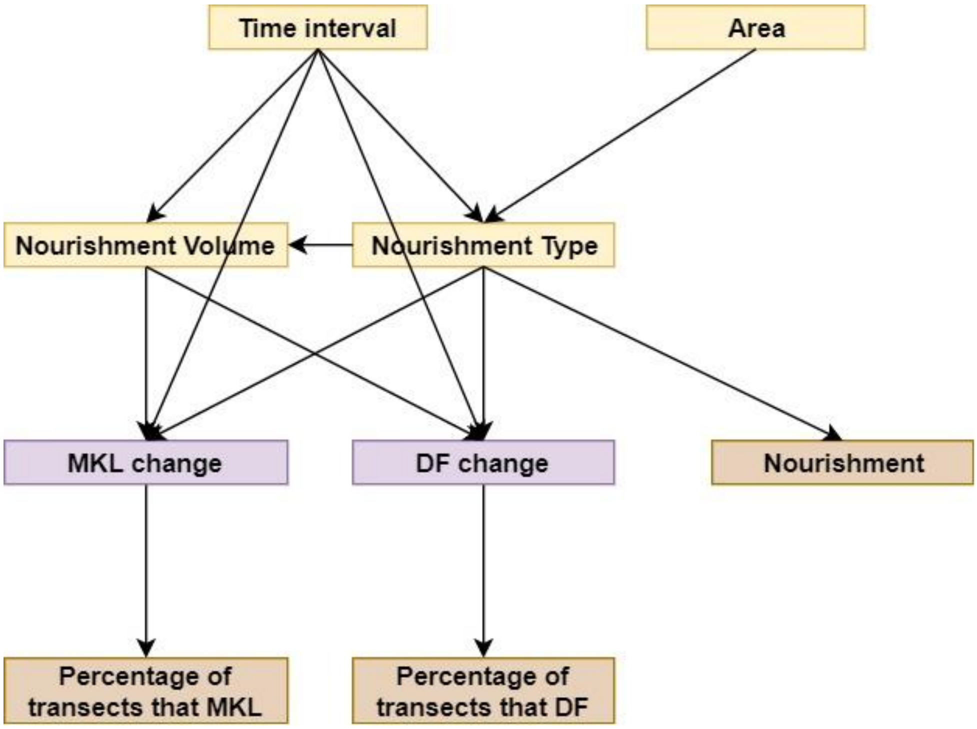

Figure 71 Simplified schematic of Configuration D.

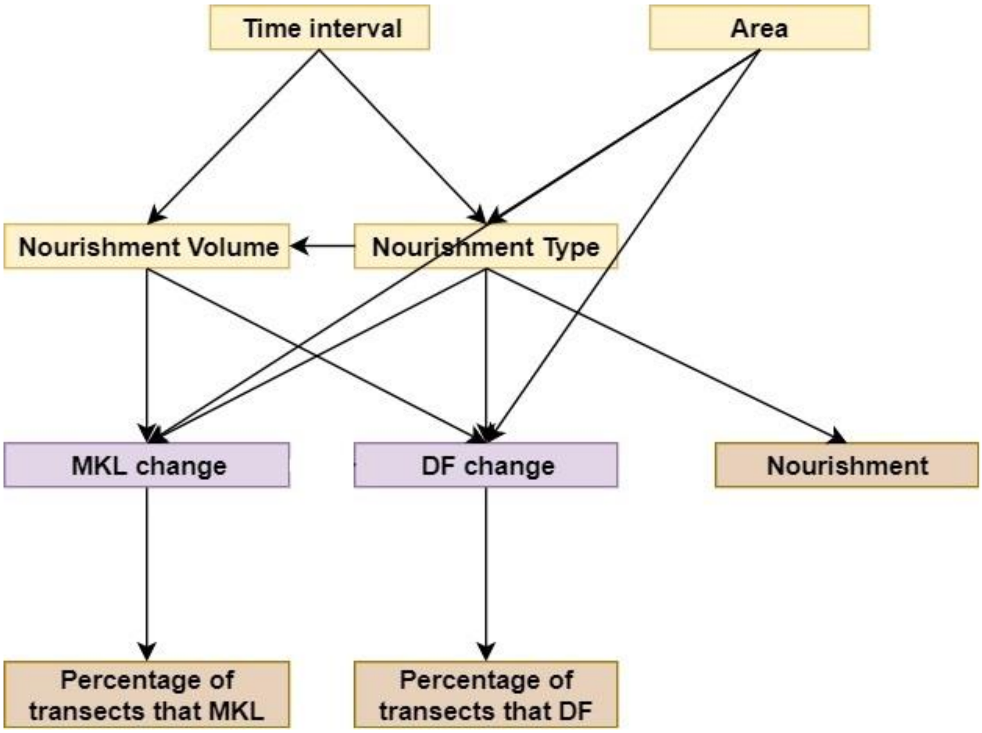

Figure 72 Simplified schematic of Configuration E.

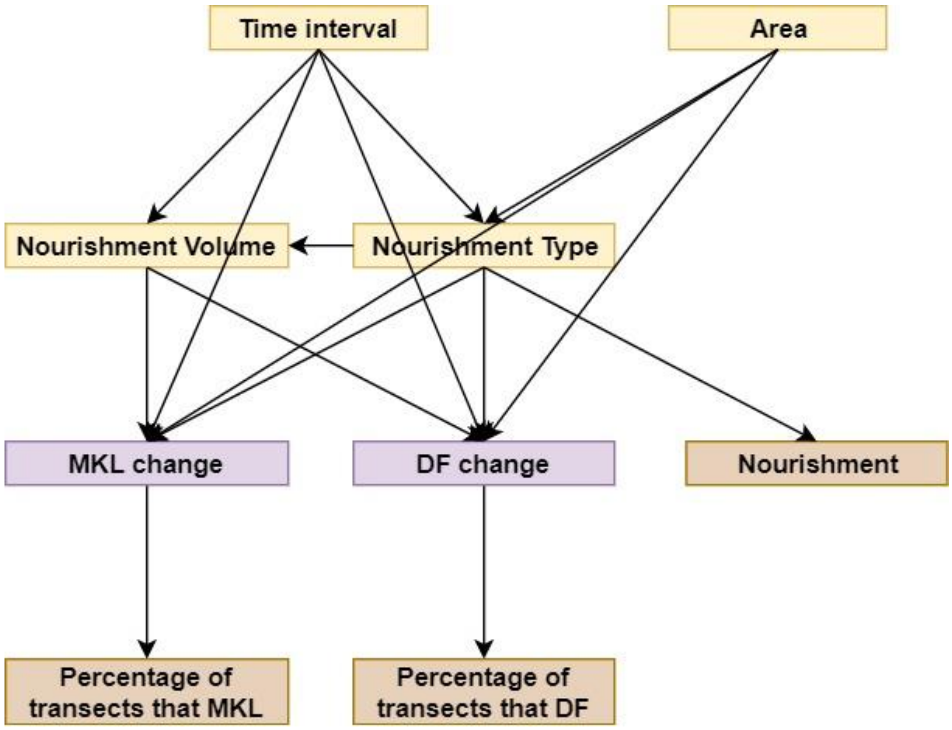

Figure 73 Simplified schematic of Configuration F

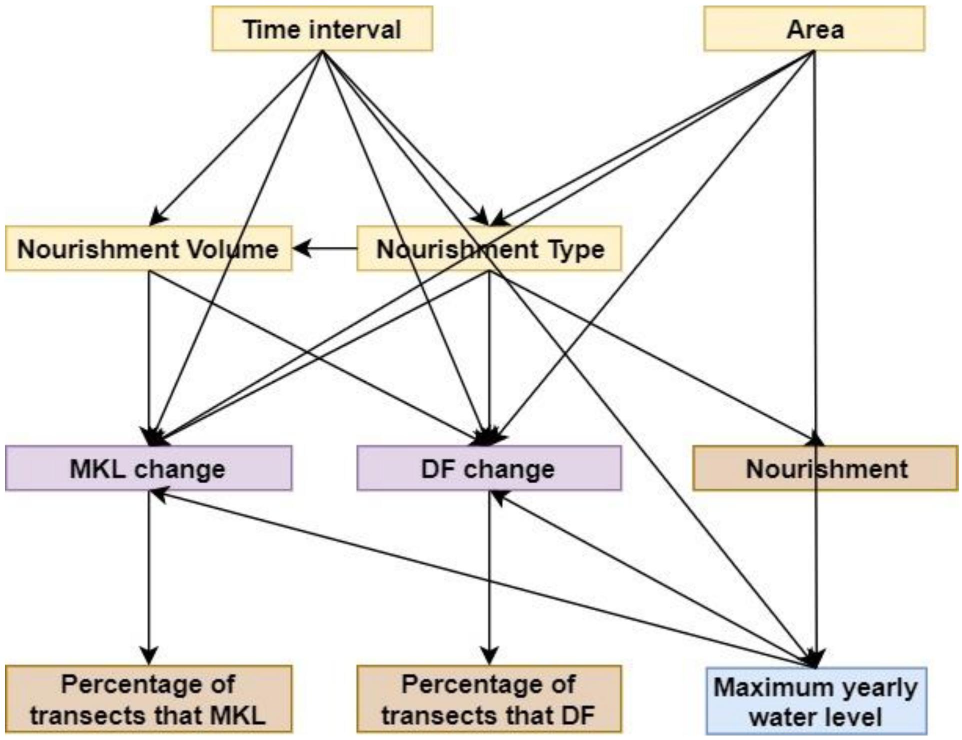

Figure 74 Simplified schematic of Configuration G. Nourishment characteristics and area are shaded in yellow, coastal indicators in purple, summarized nodes in brown and natural forcing in blue.

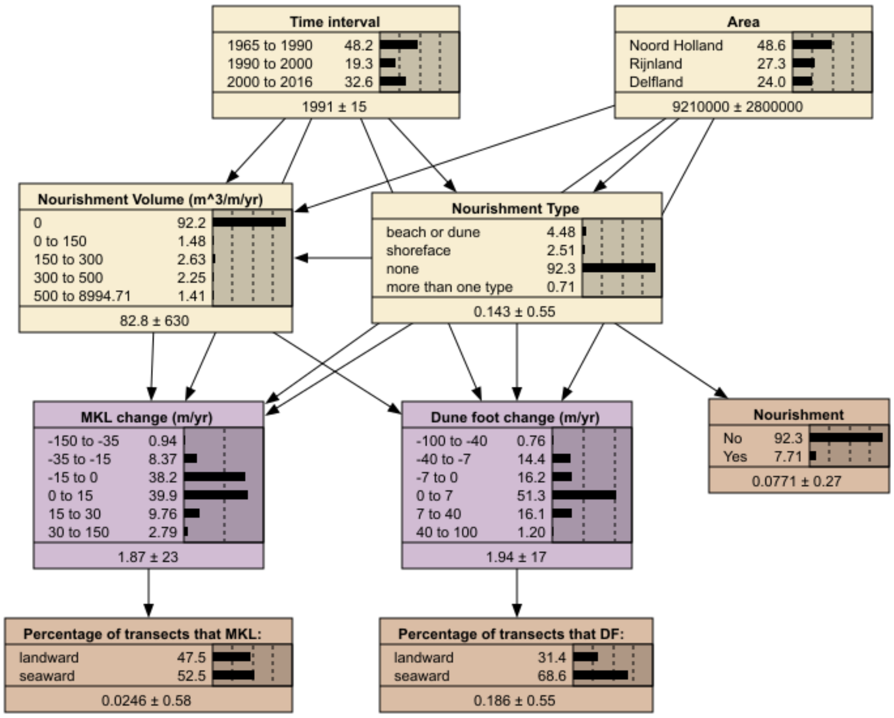

Figure 75 Configuration F1; the network is trained with the dataset which obtains dune foot positions derived from the new methodology.

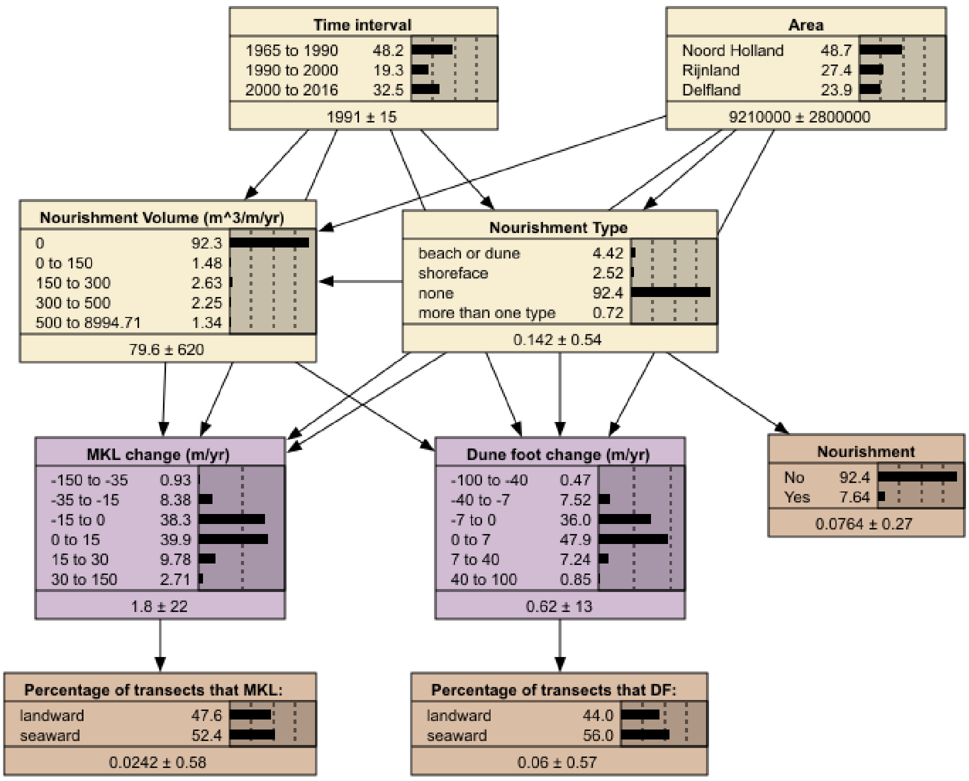

Figure 76 Configuration F2; the network is trained with the dataset which obtains dune foot positions derived from the +3 m NAP definition.

E. Bayesian network output

Log-likelihood ratio tests

This section contains the results which were used to derive the figures of section 3.2.1. The final results of comparison among the prior and posterior probabilities for the entire set of configurations are summarized in Table 9.

Configuration	MKL change	DF change
A	27.1920	60.8937
B	26.3902	65.5327
C	27.1920	65.5327
D	33.2361	80.3496
E	32.9169	76.4901
F	39.1276	93.6080
G	32.6908	78.0832

Table 9 Log-likelihood ratios (dimensionless quantities) for the chosen configurations tested against themselves.

The results of the configurations of one input node are summarized in Table 10. Prior probabilities are compared to the posterior for each configuration. This analysis is only used to examine the importance of each variable separately.

Input node	MKL change	DF change
Area	4.963	21.726
Time interval	6.793	25.514
Nourishment Volume	23.669	55.012
Nourishment Type	26.587	51.250
Maximum yearly water level	0.178	10.398

Table 10 Log-likelihood ratios (dimensionless quantities) for "single-input" configurations.

Scenario 2

This section summarises the results used for the formation of the figures of the scenario 2 in section 3.2.3. Table 11 and Table 12 correspond to 50Figure 33 and Figure 34 respectively.

Time Interval	Noord Holland	Rijnland	Delfland
1965 - 1990	0.256	1.2	0.082
1990 - 2000	1.78	2.16	3.57
2000 - 2016	2.7	3.2	5.26

Table 11 Average MKL change for different areas and time (m/year).

Time Interval	Noord Holland	Rijnland	Delfland
1965 - 1990	-1.01	-0.149	-0.0414
1990 - 2000	1.19	1.66	2.31
2000 - 2016	1.38	2.16	2.12

Table 12 Average DF change for different areas and time (m/year). Positive numbers show seaward movement of the dune foot, whereas negative numbers show landward movement.

Scenario 4

Table 13 and Table 14 summarise the results used for the formation of the figures of the scenario 4 in section 3.2.3.

Area	Beach nourishment	Shoreface nourishment
Noord Holland	15.8	4.48
Rijnland	15.9	12.8
Delfland	22.2	-0.715

Table 13 Average displacement of MKL (m/year).

Area	Beach nourishment	Shoreface nourishment
Noord Holland	9.67	0.213
Rijnland	9.19	4.31
Delfland	12.6	-6.19

Table 14 Average displacement of Dune Foot (m/year). Positive numbers show seaward movement of indicators, whereas negative numbers show landward movement.

Changes of the indicators normalized by the nourishment volume

Confusion matrices are used to validate the extending network in Section 3.2.3. Overall, the Bayesian Network (Figure 43) estimates *"MKL change / Nour. Volume"* with an accuracy of **85.71%** and "*DF change / Nour. Volume"* with an accuracy of **86.98%**. Table 15 and Table 16 show the confusion matrices for those nodes.

Predicted Values (m)						**Actual Values (m)**
- 0.5 to -0.2	-0.2 to -0.07	-0.07 to 0	0 to 0.07	0.07 to 0.2	0.2 to 0.5	
0	0	0	0	0	0	-0.5 to -0.2
3	3	2	0	0	0	-0.2 to -0.07
0	1	31	0	0	0	-0.07 to 0
0	0	0	75	1	0	0 to 0.07
0	0	0	9	21	0	0.07 to 0.2
0	0	0	0	6	2	0.2 to 0.5

Table 15 Confusion Matrix for MKL change / Nour. Volume.

Predicted Values (m)						**Actual Values (m)**
- 0.3 to -0.15	-0.15 to -0.05	-0.05 to 0	0 to 0.05	0.05 to 0.15	0.15 to 0.5	
0	0	0	0	0	0	-0.3 to -0.15
0	5	3	0	0	0	-0.15 to -0.05
0	0	33	0	0	0	-0.05 to 0
0	0	0	85	6	0	0 to 0.05
0	0	0	6	24	0	0.05 to 0.15
0	0	0	0	6	0	0.15 to 0.3

Table 16 Confusion Matrix for DF change/Nour. Volume.