Enhancing Cost Forecasting Accuracy for Flood Protection Projects

Predicting pricing of future dike reinforcements using Regression Weighted Reference Class Forecasting for the Flood Protection Programme

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Preface

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Preface

Integrating different topics and domains has always been of great interest to me. The freedom to choose a thesis topic has been both a challenging and an advantageous opportunity. Combining my interest for data-driven approaches, predictive modeling, and project cost estimation in infrastructure projects has been an insightful journey. Writing this thesis has significantly enhanced my understanding of the complexities involved in accurately predicting project costs and the importance of an integrated, data-driven approach in developing effective solutions. Also this process has taught me that data alone does not tell the story completely and it has pitfalls of its own. I hope to apply this understanding throughout my professional career, encountering and overcoming similar or entirely new challenges.

First and foremost, I would like to thank my supervisors from Delft University of Technology, Marcel Hertogh and Martijn Leijten. Your combined expertise allowed me to leverage a variety of methods and approaches. Your guidance and critical feedback throughout the process have challenged and stimulated me to elevate my work. It has inspired me to explore beyond my initial understanding of project cost estimation and predictive modeling.

Additionally, I would like to express my gratitude to Laurens Lancee and Allard Horstman from AT Osborne. Your constant support and invaluable guidance throughout the project have been instrumental. Our regular conversations provided profound insights into the subjects you are working on and your endeavors to enhance project outcomes. This experience has been a critical link between research and practice, underscoring why this connection is so vital.

I also extend my heartfelt thanks to Linda Kamphuis from HWBP. Your insights and support have greatly contributed to the depth and applicability of this research. The collaboration with you and your organization has been enriching, providing a practical perspective on the topics explored.

Furthermore, I would like to thank all the individuals I interviewed. Your perspectives have offered a fascinating view of the practical relevance of this topic and how we currently consider project cost estimation. These conversations revealed the diverse ways stakeholders perceive and approach project costs, highlighting the importance of understanding different drivers. Your interest and enthusiasm have been immensely motivating.

Lastly, I am incredibly grateful to my girlfriend, family and friends who have supported me throughout this entire process. Your critical remarks and encouragement have been invaluable. I would also like to thank my colleagues and fellow interns, I had a lot of fun thanks to you.

I hope you find this report insightful and engaging!

Matthijs W. Bodt

Brummen, December 2024

Executive Summary

The Netherlands, with over 3,500 km of primary flood defences managed by Rijkswaterstaat and regional water boards (Rijkswaterstaat, 2022), faces significant flood risks due to its low-lying geography (Haasnoot et al., 2020). Historical floods, such as the devastating 1953 flood that claimed over 1,800 lives (Van Alphen et al., 2011), highlight the importance of robust flood defences. Initiatives like the HWBP ensure compliance with safety standards mandated by the Water Act, requiring all dike sections to meet legal safety standards by 2050 (Delta Programme Commissioner, 2019). As sea levels rise, the responsibilities of the HWBP and Waterboards become increasingly expensive and complex to predict. By utilising Reference Class Forecasting enhanced with refined success factors, this research provides more accurate cost predictions, aiding the PD HWBP in planning and financing essential flood protection measures more effectively for the decades ahead.

This thesis explores the application of success factors in combination with Reference Class Forecasting (RCF) to improve cost predictions for dike reinforcement projects under the Dutch Flood Protection Program (HWBP). Accurate forecasting is critical for managing infrastructure budgets, especially as the Netherlands faces increasing demands on flood protection. Traditional cost estimation approaches are often hampered by optimism bias and limited ability to capture unique, project-specific variables. By analysing key factors like location, soil type, and environmental constraints, the study aims to refine RCF for improved accuracy.

This research aims to enhance RCF methodology by integrating success factors relevant to dike reinforcement, assessing the model's predictive power, and providing actionable insights for future applications in infrastructure project management. The study aims to address the following main research question:

To what extent can Reference Class Forecasting combining success factors make an accurate price prediction for the financial programming of HWBP's dike reinforcements until 2050?

Methodology

To develop a refined cost estimation model, this study employed an approach, combining literature review, expert interviews, and statistical modelling with a case study. This study evaluates the impact of incorporating success factors into a Reference Class Forecast (RCF) to improve cost prediction accuracy for dike reinforcement projects. The research scope focuses on HWBP-2 projects, which serve as the reference class, ensuring consistency and comparability. This study analyses dike reinforcements and therefore excludes rebuilds in order to maintain data homogeneity.

The research is structured into three main phases. In the first phase, literature reviews explore state-of-the-art forecasting methods and identify key cost-driving factors. Semi-structured interviews with experienced practitioners validate these factors. In the second phase, data is collected and analysed using SPSS software, with correlation and regression analyses determining the significance and impact of identified variables. In the third phase, the effectiveness of the improved RCF model is tested against the traditional method, comparing predictive accuracy and reliability.

A case study of 43 HWBP-2 projects forms the foundation for the analysis. These projects are matched with 28 new HWBP projects to test the improved RCF model's accuracy. The study highlights key cost-driving factors like geographic location, soil type, and regulatory conditions, ensuring methodological rigor and practical relevance. The findings contribute to refining forecasting methods critical for the HWBP's financial programming and broader flood protection planning.

State-of-the-art cost forecasting models

First the research started by evaluating three state-of-the-art cost prediction models in the infrastructure sector: Traditional Cost Estimating, Probabilistic Estimating, and Reference Class Forecasting (RCF). Each method has distinct strengths and limitations. Traditional Cost Estimating produces detailed, component-specific estimates and is flexible for repeatable and predictable projects but struggles with complexity, often underestimating costs for unique projects and being prone to bias. Probabilistic Estimating excels in managing uncertainty by quantifying risks and providing a range of possible cost outcomes but requires high-quality data, sophisticated statistical tools, and reliable baseline estimates, making it resource-intensive. RCF, tailored for complex or high-stakes projects, mitigates optimism bias by using historical data from similar projects to provide realistic outcome-based estimates. However, it relies heavily on the availability and relevance of a robust reference class and lacks detail on specific project components.

These models vary in their focus on detail, uncertainty management, and realism. Traditional cost estimating prioritises component detail but lacks reliability in uncertain scenarios, while Probabilistic Estimating excels in risk quantification but is resource-heavy. RCF balances realism and complexity but requires meticulous selection of comparable projects. Ultimately, the effectiveness of these methods depends on the quality and relevance of the underlying data, underscoring the importance of robust data collection and maintenance for accurate cost predictions. RCF is the most suitable method for forecasting the costs of dike reinforcements due to the availability of a general reference class and financial data that lacks the precision required for traditional cost estimating or probabilistic estimating methods.

Factors influencing costs

To refine cost predictions, eight key success factors were identified through literature review and validated via expert interviews. These factors include project location (urban, rural, or Natura 2000 areas), soil type, proximity to buildings, compliance with national safety standards, and the managing water authority. Using data from 43 HWBP-2 projects, a correlation and regression analysis quantified the impact of each factor on costs. Key factors like soil type, proximity to urban areas, and N2000 designation emerged as significant predictors, offering valuable insights into cost dynamics. This analysis enhances the ability to forecast costs accurately and supports resource-efficient planning for future dike reinforcement projects.

Results regression weighted reference class forecasting (RWRCF)

The findings reveal that the integration of success factors into the RCF model suggests a measurable increase in prediction accuracy. The following key findings have been measured:

- Standard Deviation of Errors:

  The RWRCF model demonstrated significantly lower variability in prediction errors (2.92 per km and 3.54 for total costs) compared to the traditional RCF (5.58 per km and 6.40 for total costs). This reflects a more stable and dependable forecasting method.

- R-Squared and Adjusted R-Squared:

  The RWRCF model achieved higher R-squared values (0.45 per km and 0.52 for total costs) than traditional RCF (0.23 per km and 0.34 for total costs), indicating a better fit to the data. Adjusted R-squared values reinforced these findings, with RWRCF avoiding unnecessary complexity while maintaining strong predictive alignment.

- Median Absolute Error and sMAPE:

  The RWRCF model consistently delivered smaller typical errors (Median Absolute Error of 1.67 per km and 2.10 for total costs versus traditional RCF's 4.20 per km and 5.05 for total costs). It also achieved substantially lower sMAPE values (20.35% per km and 18.90% for total costs), nearly halving the errors of the traditional RCF (55.68% per km and 48.75% for total costs).

- MASE (Mean Absolute Scaled Error):

  RWRCF achieved MASE values near the naive benchmark (1.20 per km and 1.15 for total costs), while traditional RCF showed far poorer performance (2.45 per km and 2.67 for total costs), indicating towards the RWRCF model's efficiency.

This study aimed to measure the potential value of integrating success factors into RCF for cost forecasting in complex infrastructure projects. By achieving greater accuracy in prediction, the model can help infrastructure managers and policymakers avoid costly overruns, ensure more effective use of resources, and improve the reliability of budget forecasts. The findings are particularly relevant for the HWBP, where enhanced cost prediction can support better planning and resource allocation in response to evolving flood protection needs.

The research concludes with several recommendations for future research and recommendations for practice. First, it is suggested to incorporate the success-factor-enhanced RCF model into routine project cost estimations for HWBP to improve cost predictability. Therefore, it advocates for the creation and maintenance of a comprehensive historical project database, as this is essential for the continued refinement and validation of RCF models. Third, it recommends expanding the model's application to other infrastructure sectors with similar cost estimation challenges, such as road construction, water management, and environmental restoration projects. This cross-sector applicability could further validate the model's effectiveness and provide insights for other types of public infrastructure forecasting. Another key finding of the research is that the current model seems to predict total costs of a portfolio of projects better than the costs of individual projects. Therefore it is recommended that future research focusses on improving the uncertainty of the model for individual projects, possibly making the developed method better suited to predict portfolios and individual projects.

In conclusion, this thesis indicates that incorporating success factors into RCF significantly enhances its predictive accuracy, making it a valuable tool for cost management in flood protection and potentially other infrastructure areas. By aligning with empirical data and context-specific variables, the RWRCF model offers a more objective framework for project cost estimation, aligning well with both theoretical research and practical needs within public infrastructure management.

Table of contents

List of figures

List of tables

1. Introduction

This chapter highlights the importance of sufficient dike protection and importance of predicting the costs of the projects in the Netherlands. Moreover, the research questions are discussed. First, in section 1.1, the relevant background information on the research topic is discussed. Second, in section 1.2, the identified problem description will be discussed. Subsequently, in section 1.3, the research questions of this study will be presented. Finally, the research relevance, including the scientific as well as practical relevance, will be discussed in section 1.4.

1.1 Background information

This report is written for my graduation thesis, to obtain a master's degree in Construction, Management and Engineering with the track Engineering & Systems. This research is conducted at AT Osborne and at the Programme Direction of the Flood Protection Programme (Hoogwaterbeschermingsprogramma, PD HWBP), with supervision of the University of Technology Delft. The focus of this research is on the prediction of prices of dike reinforcements using Reference Class Forecasting. The research of this master thesis is executed with the support of the company AT Osborne and PD HWBP. Their contribution is in the form of providing data, guidance and professional experience. The results of this research contributes to the field of knowledge on making price predictions for infrastructure projects, this is achieved by answering the following research-question:

'*To what extent can Reference Class Forecasting combining success factors make an accurate price prediction for the financial programming of HWBP's dike reinforcements until 2050?*'

As climate change is causing the sea-level to rise, and increasing the flow of water through the rivers, it is vital for the Netherlands to protect herself for the future. To ensure that the Netherlands is protected, a large number of dikes need to be reinforced. In order to complete the dike reinforcements, it is necessary to have an accurate financial planning. The research aims to assess whether Reference Class Forecasting (RCF) is a viable option to use for the HWBP programme and aims to use several factors in combination with the RCF to create a more accurate prediction.

In section 1.2, the problem description will be set out in which the reason for this topic and research are elaborated upon. Moreover, within this chapter the scientific and practical relevance are described. In section 1.3, the research goal will be explained in which main question of this research, the sub-questions and the structure to arrive to the answer on the main question will be elaborated upon. Additionally, the expected results will be discussed.

1.2 Problem description

Reference Class Forecasting (RCF) is a systematic forecasting methodology that uses historical data from similar past projects—the "reference class"—to improve the accuracy of predictions for future projects. Initially developed by Daniel Kahneman and Bent Flyvbjerg, RCF aims to counteract biases such as optimism bias and strategic misrepresentation, both of which frequently lead to project cost overruns and schedule delays (Flyvbjerg, 2006; Kahneman & Tversky, 1979). In contrast to traditional forecasting methods, which rely on subjective expert judgment or detailed models of individual projects, RCF offers a statistical approach by comparing a new project with a defined class of past projects. This data-driven method allows planners to base their estimates on observed outcomes rather than theoretical expectations (Flyvbjerg, 2009).

The methodology has gained traction in large-scale infrastructure projects, where the stakes are high and cost overruns are common. RCF has been shown to provide more accurate forecasts by incorporating a wide range of potential outcomes drawn from historical data (Love et al., 2019). Despite its growing acceptance, however, there are significant barriers to its effective implementation. Research suggests that several critical success factors are not consistently applied in practice, which diminishes the potential benefits of the methodology (Cantarelli et al., 2012).

One key issue lies in the selection of the reference class. The reference class is the set of similar projects that are used to forecast a project that still needs to be completed, and where more information is desired on for example the costs. The accuracy of RCF is highly dependent on the quality and relevance of the reference class chosen. A study by Cantarelli et al. (2010) highlighted that many project managers face difficulties in assembling a sufficiently large and appropriate reference class, often due to a lack of comparable projects or insufficient data. Furthermore, there are often discrepancies between historical projects and current projects in terms of scale, context, and external conditions, which can result in inaccurate forecasts (Love et al., 2019). In addition, researchers such as Budzier and Flyvbjerg (2013) point out that RCF does not inherently account for qualitative factors such as stakeholder influence, political environments, or technological changes, which can have substantial effects on project outcomes.

Although RCF provides a statistically grounded forecast, its utility is limited by the quality and comprehensiveness of the underlying data. Recent studies indicate that the absence of a robust database of historical project performance leads to suboptimal implementation of RCF (Van Oorschot et al., 2016). Flyvbjerg (2014) noted that this issue is particularly acute in developing countries, where data collection practices may be inconsistent or underdeveloped. As a result, RCF may not always capture the full complexity of the project environment.

Despite these challenges, the potential of RCF remains significant, particularly when combined with complementary methods. However, research by Love et al. (2019) demonstrates that many organizations have yet to integrate RCF fully into their project management frameworks. They argue that RCF is often applied as a standalone tool rather than as part of a broader risk management strategy, which limits its effectiveness in mitigating the full range of uncertainties encountered in large-scale projects.

This thesis will explore the current state of RCF in both theory and practice, with a focus on identifying the gaps between the ideal implementation of the methodology and its real-world application. Through a review of scientific literature and case studies, this research will assess how key success factors affect the accuracy of the forecasting abilities of RCF.

The challenges of implementing Reference Class Forecasting are not merely theoretical; they emerge in real-world applications, especially in large-scale infrastructure projects where accurate forecasting is essential. A notable example is the Flood Protection Programme for dike reinforcements in The Netherlands. This case study was specifically chosen due to the high level of comparability among projects, a key requirement for effective Reference Class Forecasting, as successful RCF relies on selecting a set of reference projects that are sufficiently similar in scope and context (Flyvbjerg, 2006; Lovallo & Kahneman, 2003). Additionally, it is uncommon to have a single program oversee such a large number of large-scale infrastructure projects, which enhances both data quality and availability.

Every year, flooding is a major natural hazard that affects the lives of 520 million people, takes around 25,000 lives, and causes between €50 and €60 billion in damages across the globe (Van Alphen et al., 2011). As a result of this, it is crucial to tackle flood management head-on. The Netherlands, with its unique geography, is particularly at risk a large area of the country is actually below sea level,see figure 1.2.1, making it prone to flooding (Haasnoot et al., 2020). In the history of the Netherlands, several floods occurred. The 1953 flood was particularly devastating, hitting the southwest of the Netherlands hard, leading to over 1,800 deaths and widespread damage (Van Alphen et al., 2011).

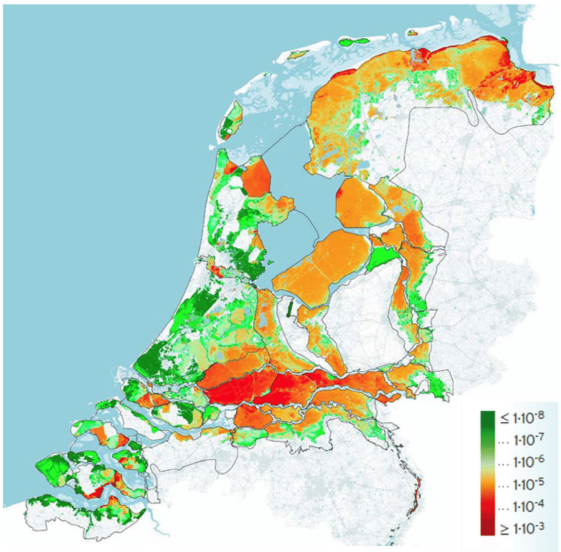

Figure 1.2.1: estimated individual risk for flooding for the Netherlands (Rijkswaterstaat, 2015)

The flood of 1953 was a turning point for the protection of vulnerable areas in the Netherlands. The Dutch government realised the importance of robust flood defences and started upgrading dikes, locks, and dunes. They also made the strategic decision to close off most tidal outlets, except for a few key channels that kept Rotterdam and Antwerp's ports accessible (Hall, 2015). On top of that, they recognised that some dikes weren't up to the necessary standards and decided to improve them to meet safety standards (Delta Programme Commissioner, 2019). To address these challenges, the Netherlands launched several initiatives under the Delta Programme, including the Room for the River and the Flood Protection Program (HWBP).

Nowadays, the Netherlands has approximately 3,500 km of primary flood defences. These primary defences are managed by the Directorate-General for Public Works and Water Management (Rijkswaterstaat) and the water boards (Rijkswaterstaat, 2022). In 2017, new water safety standards were introduced, shifting the focus from the probability of exceeding levels per dike ring to the risk of flooding per dike section. This means that since then, primary defences have been divided into dike sections. The Water Act stipulates that by 2050, all dike sections must meet legal standards. Thus, dike sections are also referred to as standard sections (AT Osborne, 2020).

From 2017 to 2023, all primary flood defences in the Netherlands were assessed by the dike managers in the first national assessment round (LBO1). The assessment determined whether the primary flood defences met the legal standards as set in the Water Act by the prescribed date, December 31, 2022, and if not, to what extent they deviate from these standards. The results identified the need for reinforcements in the flood protection programme in the Netherlands. The evaluation system is designed to be cyclical. By 2050, dike managers will conduct two more assessment rounds: from now until 2034 and from 2035 to 2046. This means that new insights can emerge from each assessment round, potentially leading to changes in the reinforcement requirements.

The PD HWBP controls the financial agenda of the dike reinforcement programme in the Netherlands. The HWBP funds 90% of the expected costs to the regional water authorities that have the task to execute the project they need funding for. In 2023 AT Osborne together with Witteveen+Bos conducted a study in which they provide the PD HWBP with a rough estimate of the costs of dike reinforcements until 2050. The estimation predicts prices ranging from 15,7 billion up to 32,9 billion euros. (AT Osborne & Witteveen+Bos, 2023) This is a wide range and it does not provide the PD HWBP with sufficient knowledge on how to plan the dike reinforcements over the years. Therefore, this research will contribute to knowledge on the most important factors that cause the prices of dike reinforcements in the past and will extrapolate these results into the future using Reference Class Forecasting to provide the PD HWBP with a narrower range of the expected costs of the dike reinforcements.

1.3 Research questions / development statement

This section contains the main research question, along with the sub-questions. The research questions follow from the problem statement. . In section 1.3, the expected results will be described. Chapter 2.2 will describe how the answers to the sub-questions contribute to answering the main research question

1.3.1 Research questions

'*To what extent can Reference Class Forecasting, combining success factors make an accurate price prediction for the financial programming of HWBP's dike reinforcements until 2050?*'

Sub-questions:

1. *What are the state-of-the-art models used to forecast prices in the infrastructure sector?*
2. *Is Reference Class Forecasting a viable way to predict prices for dike reinforcements?*
3. *What are the most important factors that can be used to predict the prices for dike reinforcements in the Netherlands?*
4. *How can the factors enhance the reference class forecast model?*
5. *What is the uncertainty of the price prediction?*

1.3.2 Expected Results

After completing this research, the expected result is that there is a clear overview of the most important factors determining the price for dike reinforcements. Moreover it is expected that the price prediction gives a more accurate view on the costs of the dike-reinforcements that need to be completed. Another outcome of the research could be that several conditions are found that need to be fulfilled before the impact of success factors can be concluded.

1.4 Scientific relevance

In traditional project management practices, forecasts are often based on deterministic cost estimates that do not fully account for variability and risk inherent in large-scale projects. Reference Class Forecasting (RCF) provides a probabilistic approach that overcomes this limitation by generating cost distributions from historical data, allowing for a realistic and data-driven assessment of cost uncertainty. By expanding RCF with success factors relevant to dike reinforcement, such as project scale, complexity, environmental conditions, and technological factors, this research aims to enhance the precision of cost predictions specifically for dike infrastructure projects, which are critical in flood defence.

The scientific relevance of this research lies in advancing the accuracy and reliability of project cost forecasting within large-scale, long-term infrastructure programs. The study specifically addresses the research question: "To what extent can Reference Class Forecasting combining success factors make an accurate price prediction for the financial programming of HWBP's dike reinforcements until 2050?"

This question not only holds importance for the financial programming of the High Water Protection Program (HWBP) but also contributes significantly to the broader fields of project management, risk assessment, and infrastructure finance by refining methodologies used to manage cost uncertainties in complex, long-term projects.

This study's combination of RCF with success factors aligns the forecasting model more closely with the unique conditions and variables that influence dike reinforcement projects. Success factors in this context serve as modifiers that capture the specific cost-driving characteristics of individual projects. Incorporating these factors into the forecasting process allows the model to provide more detailed predictions, which can significantly reduce the risk of budget overruns that have historically plagued similar projects. By calibrating RCF with these tailored factors, the research seeks to answer whether such a model can deliver an improvement in forecasting accuracy for the HWBP's long-term programming.

1.5 Practical relevance

The results of this research will aim at giving clarity for the HWBP on the future investments that are needed to protect the Netherlands from rising tide and increasing flow from rivers such as the Ijssel and Rijn, giving them an opportunity to enhance their financial planning for the future. And moreover gain insights into the most impactful factors that determine the costs for specific projects. The practical relevance of this research lies in its potential to improve cost management and strategic financial planning for long-term, high-stakes infrastructure projects, specifically within the HWBP aimed at reinforcing the Netherlands' flood defence. Accurate forecasting for such projects is essential given the substantial investments required, the risk of budget overruns, and the critical role of dike infrastructure in protecting communities from flood risks. By exploring how Reference Class Forecasting (RCF), combined with project-specific success factors, can refine cost predictions, this study offers practical insights for improving the financial programming of HWBP dike reinforcements up to 2050.

Beyond its implications for the HWBP, the RWRCF RCF approach with success factors has broader practical applications for similar infrastructure programs, both within the Netherlands and internationally. Large-scale infrastructure projects in transportation, urban development, and environmental protection share many characteristics with dike reinforcement projects: high costs, long timelines, and significant exposure to financial risk. By demonstrating a method to incorporate tailored success factors into reference class forecasts, this research provides a replicable model that can be adapted to other projects. For infrastructure stakeholders, this research could offer a practical tool to better manage the financial complexities of public projects, leading to more efficient use of resources and ultimately delivering greater value to the public.

2 Methodology

Various perspectives can be used to examine the impact of success factors on a Reference Class Forecast. This chapter outlines the structure and approach chosen for this study, while also detailing the scope and methodology. Section 2.1 defines the research scope, establishing the boundaries of the research. Section 2.2 focuses on the research setting and methodology, describing the methods employed in this study. Section 2.3 addresses how the literature review will answer each research sub-question. Section 2.4 focusses on how the interviews are conducted. After that section 2.5 will discuss the data-analysis methodology. In 2.6 the case study is discussed and lastly, in section 2.7, the outline of the research is shown.

2.1 Research Scope

This research aims to evaluate the impact of incorporating success factors into a Reference Class Forecast (RCF), using dike reinforcement projects as a focused case study. This section outlines the specific parameters that have been set to define the research scope and maintain clarity throughout the study.

First, the analysis will be limited to dike reinforcement projects that have been completed under the HWBP-2 programme. This is de predecessor to the current Flood defence programme. The decision ensures consistency in the reference class by focusing on projects that share common characteristics and were executed under similar organizational and regulatory conditions. By restricting the study of the reference class to HWBP-2 dike reinforcements, the research can draw upon reliable, comparable historical data to construct the reference class needed for an effective RCF.

Secondly, the research will emphasize the total costs of these dike reinforcement projects. This focus is necessary for providing a comprehensive assessment of the financial outcomes and ensures that all relevant cost components are considered when analysing the impact of success factors. By centring the analysis on total costs, the research can produce more holistic and practical insights into the financial implications of using success factors in RCFs.

Another important distinction is between dike reinforcements and rebuilds. Dike reinforcements are projects where existing structures are strengthened or improved, whereas dike rebuilds often involve entirely new constructions or significant redesigns. Including rebuilds could introduce significant variability due to differing project scopes and complexities, potentially skewing the reference class and making the analysis less reliable. Thus, this research will limit its scope to reinforcement projects to ensure that the data within the reference class remains as homogeneous as possible.

Lastly, the projects used for prediction purposes will be those completed under the HWBP program. This criterion reinforces the relevance of the study by ensuring that the forecasting methods being assessed are directly applicable to the current and future activities within the HWBP. By selecting completed projects, the research can use actual cost data to compare predicted outcomes with real-world results, allowing for a robust evaluation of the accuracy and effectiveness of RCF with success factors.

In summary, the projects in the reference class are from the HWBP-2 database, these projects will be used to predict the prices of projects from the new HWBP programme. By establishing these boundaries, the research maintains a clear and focused approach, enabling a detailed examination of the impact of success factors on RCF accuracy for dike reinforcement projects. These parameters help ensure that the findings are applicable and relevant to similar infrastructure forecasting needs within the HWBP and potentially beyond.

2.2 Research Setting and Methodology

This section discusses the methodologies and setting in which the research was conducted are explained. The research can be split into three main phases. Figure 2.2 gives an overview of how the research is split up and what steps are taken in each phase. Within the first phase of this research, an overview of other price predicting methods have been researched. Moreover, a literature review has been conducted to understand the gaps in existing academic literature on the impact of success factors on a Reference Class Forecast. Finally, a literature study has been conducted to identify the most influential factors on prices for dike reinforcements. In the second phase of the research, semi-structured interviews have been conducted to validate the factors found in the literature-review. Furthermore, data has been collected for each project to score the projects based on the factors found in phase 1 and 2.

In the third phase of the research, the impact of the factors on the price of the dike-reinforcements has been determined by using a data-analysis programme SPSS. This step is taken to ensure that the factors that have been identified are significant and have an impact on the total price of the dike reinforcements. At last a Reference Class Forecast is conducted to compare the accuracy of the new model compared to the traditional method. This gives insight into the impact of the success-factors on a traditional Reference Class Forecast.

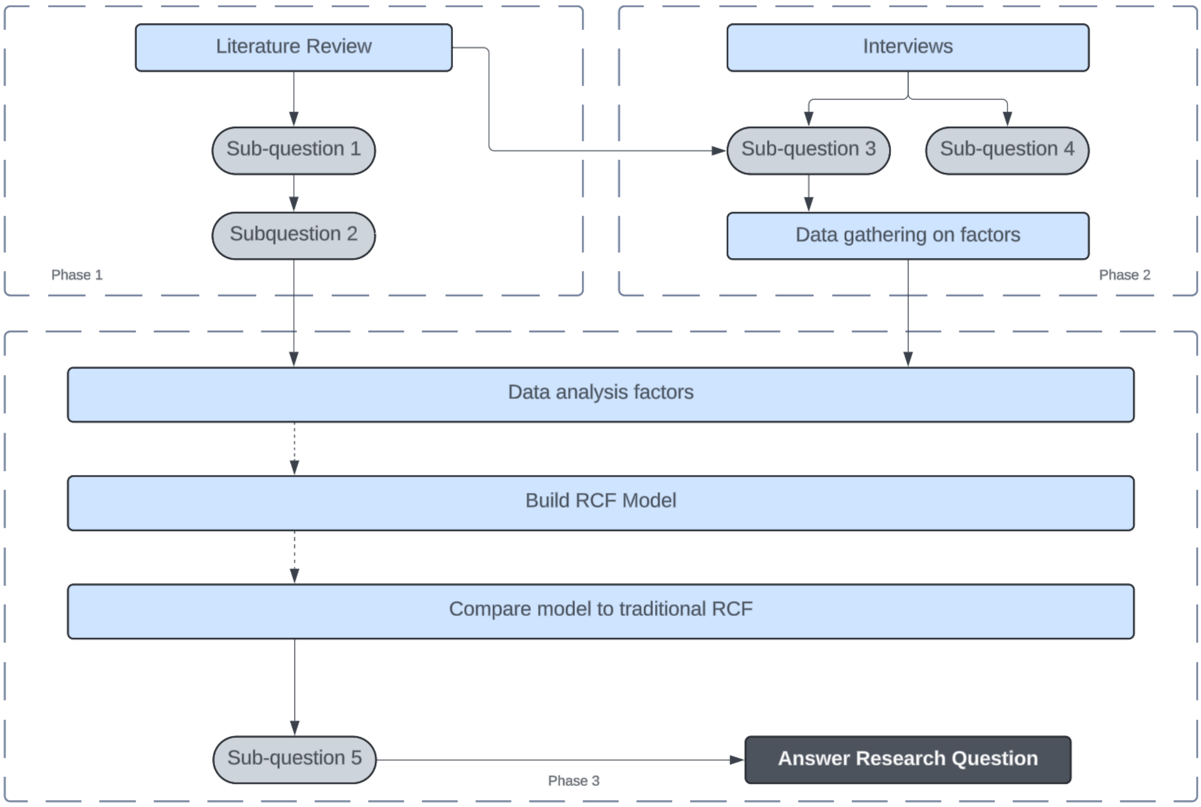

Figure 2.2: Methodology (author's image)

2.3 Literature review methodology

The first method for the research is a literature review. Webster & Watson (2002) argue that an effective and well-conducted literature review creates a firm foundation for advancing knowledge and facilitating theory developments. Snyder (2019) states that a literature review can identify knowledge gaps within the literature. Moreover, the paper states that a literature review can address research questions with a power that no single study has as it integrates findings and perspectives from many empirical findings.

To address the first sub-question, "*What are the state-of-the-art models used to forecast prices in the infrastructure sector?*" comparison is drawn from an extensive review of existing literature, highlighting the practical applicability and effectiveness of RCF relative to traditional inside-view methods (Flyvbjerg, 2006; Flyvbjerg, Garbuio, & Lovallo, 2009). This analysis considers both strengths and limitations, supporting a balanced evaluation of the current state-of-the-art price forecasting methods. (Van Wee & Rietveld, 2013).

The second sub-question, "*Is Reference Class Forecasting a viable way to predict prices for infrastructural projects?*", is tackled by comparing RCF with other established price prediction methods (Love, Sing, & Ika, 2019). a comprehensive literature review is conducted to gain an in-depth understanding of the methodology, including its capabilities and constraints (Flyvbjerg, 2006; Kahneman, 2011). This review will provide the foundational knowledge needed to assess the strengths and weaknesses of Reference Class Forecasting (RCF) as a predictive tool (Locatelli, Mancini, & Romano, 2017).

To answer the third sub-question, *"What are the factors that can be used to predict the prices for dike reinforcements in the Netherlands?"*, the research involves both a literature review and expert interviews. The literature review identifies key factors—such as material costs, labour expenses, project duration, environmental conditions, and regulatory requirements—that significantly impact the cost of dike reinforcement projects (Babbie, 2020; Saunders, Lewis, & Thornhill, 2019). Expert interviews provide qualitative insights that help validate and expand on these findings (Pallant, 2020). By combining literature-based evidence and practical insights from interviews, a comprehensive set of predictive factors is compiled.

Fourth, the sub-question, "*How can the success factors enhance the reference class forecast model?"* is answered by comparing the model using success factors to the traditional reference class forecast model. For this comparison the results will be analysed using several key indicators, such as the standard deviation of errors, the percentage error of the model.

Finally, the fifth sub-question, *"What is the uncertainty of the price prediction?"*, is answered by developing the RCF model and validating its predictions against the actual costs of completed HWBP projects (Flyvbjerg, 2008). The data analysis process employs SPSS software to conduct correlation analysis and multiple regression analysis, providing quantitative insights into how various factors influence total project costs (Field, 2018; Pallant, 2020). Correlation analysis assesses the strength and direction of relationships between independent variables (e.g., material costs, project complexity) and the dependent variable (project price) using Pearson's correlation coefficient (Hair, Black, Babin, & Anderson, 2019).

2.4 Semi-structured Interviews

Based on the literature review, interviews with different relevant actors will be conducted to answer sub-question 3: '*What are the most important factors that can be used to predict the prices for dike reinforcements in the Netherlands?*'.

Young et al. (2018) mention that interviews allow an in-depth analysis from a relatively small sample size and place the focus of research on the views of participants. Stakeholders such as financial controllers of the HWBP, financial controllers of the regional water authorities, and project managers will be approached for the interviews. For this, contacts of AT Osborne and the project managing board

(PD HWBP) will be used. The interviews will be of a semi-structured form as this gives the opportunity to expand the interviewee's responses (Rubin & Rubin, 2005).

In order to identify the most important factors, interviews have been sent to numerous practitioners of which 4 responded and had time to conduct an interview. All interviewees have several years of experience in the field of dike reinforcements.

Table 1: Overview of interviewees

Interview	*Company/Institution*	*Function*	*Date of interview*	*Duration of interview*
1	HWBP	Project Engineer	1st of August	01:04:38
2	Self employed	Cost expert	1st of August	01:14:05
3	Waterschap Limburg	Project Manager	6th of August	00:50:16
4	Self employed	Consultant	19th of August	00:51:20

2.5 Data analysis

The data obtained from the literature reviews, interviews and data provided by the HWBP needs to be analysed. The Literature review and interviews will provide the necessary data that is needed to answer sub-questions 3. The conclusions and data that will come from sub-questions 1 and 2 will provide the necessary means that are required to complete the rest of the research.

To answer the research question, "*To what extent do the factors impact the prices of dike reinforcements?*", a thorough data analysis process was conducted using the SPSS software. This process aimed to identify and quantify the relationship between various factors—such as material costs, project duration, labour expenses, environmental conditions, and regulatory requirements—and the price of dike reinforcement projects. SPSS, a powerful statistical analysis tool, was employed to determine the correlation and variance between these factors and the total costs, providing insights into the key drivers influencing price variations.

2.5.1 Correlation Analysis

The first step in the data analysis involved conducting a correlation analysis using SPSS. This analysis helps assess the strength and direction of the relationship between the independent variables (factors such as material costs, labour costs, and project complexity) and the dependent variable (price of dike reinforcement) (Field, 2018). By using Pearson's correlation coefficient, SPSS provides a clear picture of how changes in one factor are associated with changes in price (Pallant, 2020). A positive correlation would indicate that as a factor increases, the price tends to increase, while a negative correlation would suggest that an increase in a factor leads to a decrease in price (Dancey & Reidy, 2017).

For example, if a strong positive correlation is observed between material costs and total project price, it would suggest that rising material costs are a significant contributor to price increases. Conversely, if the project duration has a weak or negative correlation with price, it may indicate that project time is not a major cost driver compared to other factors (Hair, Black, Babin, & Anderson, 2019).

2.5.2 Regression Analysis

To model the relationship between multiple factors and the price of dike reinforcement projects, a multiple linear regression analysis was performed in SPSS (Field, 2018). This method enables the examination of how several independent variables collectively influence the dependent variable (price). By running a regression model, the analysis identifies which factors are statistically significant predictors of price and quantifies their relative impact (Pallant, 2020).

SPSS calculates the R-squared value to determine how much of the variation in project price can be explained by the included factors (Tabachnick & Fidell, 2019). Additionally, regression coefficients are used to understand the extent to which each factor contributes to price variations (Hair et al., 2019). For instance, the analysis might reveal that material costs have a stronger effect on prices than labour costs, or that projects in certain regions require more expensive dike reinforcements due to environmental considerations (Saunders et al., 2019).

2.5.3 Interpretation and Insights

The results from these statistical analyses in SPSS provide a comprehensive understanding of how each factor influences the overall price of dike reinforcement projects (Field, 2018; Hair et al., 2019). By identifying strong correlations, significant variances, and key predictors, the analysis helps to highlight the most influential cost drivers. These insights are a key step in the research, as the most important factors will be used in the model that aims to predict the prices of future dike reinforcements.

2.6 Case Study

In order to assess the impact of success factors on a Reference Class Forecast, a case study has been leveraged. Case studies have the advantage that they allow for the measurement of qualitative variables and allow for the incorporation of complex relations (Bennett, 2004). Moreover, Cronin (2014) praises case study research as a very legitimate research method that enables dealing with interconnected difficulties. The results of using the case study helps to answer the main research question: "'*To what extent can Reference Class Forecasting combining success factors make an accurate price prediction for the financial programming of HWBP's dike reinforcements until 2050?*'

The purpose of this case study is to explore the key factors affecting the prices of dike reinforcement, assess the quality of available data for Reference Class Forecasting (RCF), and evaluate the uncertainty of price predictions for these critical projects.

The data for this case study is primarily sourced from the *Projectenbank Dijkversterkingen* (PD HWBP), a database that tracks historical project data from dike reinforcement efforts across the country. This data is crucial for applying Reference Class Forecasting (RCF), a method that uses historical project outcomes to make more accurate predictions about future projects by comparing them to a "reference class" of similar past projects. To assess the sufficiency and reliability of the data provided by PD HWBP for conducting RCF, several aspects were considered:

1. **Completeness of Data:** The PD HWBP contains detailed information on cost components, project timelines, and key variables for a significant number of past dike reinforcement projects. However, gaps in data completeness, such as missing data for certain projects or incomplete information on cost overruns and delays, can reduce the reliability of predictions.

2. **Relevance of Reference Class:** The accuracy of RCF depends on the extent to which the reference class of past projects reflects the conditions of future projects. For the HWBP-2 and HWBP programmes, the diversity of past projects in terms of location, scale, and environmental conditions is generally adequate, though some unique projects may not have suitable comparisons in the database.

3. **Data Quality and Consistency:** Consistency in data collection methods over time is critical for reliable forecasting. If data collection standards have varied between projects, this could lead to inconsistencies that affect the accuracy of price predictions. In the case of PD HWBP, there are concerns regarding the standardization of cost data across different projects, particularly in older records, which may affect the quality of RCF.

2.6.1 Case Study HWBP

The case study focuses on dike reinforcement projects undertaken as part of the Dutch Flood Protection Program (Hoogwaterbeschermingsprogramma, HWBP). These projects are essential components of the Netherlands' national strategy to protect its population and economy from the increasing risks of flooding due to rising water levels and climate change. As a country renowned for its water management expertise, the Netherlands continually seeks to optimize its flood defense infrastructure. This research aims to evaluate whether an improved reference class forecasting (RCF) method provides greater accuracy and reliability in predicting project costs compared to the traditional RCF method.

The analysis centers on 43 completed dike reinforcement projects from the HWBP-2 program, which serve as the reference class for this study. These projects were managed by various regional water boards (waterschappen), each bringing distinct administrative practices and operational approaches. Key project variables, such as geographic location, soil type, environmental restrictions, and administrative management, are analysed to identify their impact on cost. Notably, this study excludes projects involving integrated opportunities for spatial or environmental enhancements. This decision ensures that the analysis focuses exclusively on standard dike reinforcement projects, avoiding potential confounding factors that could arise from additional objectives or benefits unique to integrated projects.

To ensure consistency and comparability across projects completed in different years, all costs are indexed to 2024 using the Grond-, Weg- en Waterbouw Index (GWW index). This indexing adjusts for inflation and fluctuations in construction costs over time, creating a standardized framework for evaluating and comparing project expenses. By normalizing the data, the study provides a clear and unbiased understanding of cost patterns and their relationship with key project variables.

The insights derived from the HWBP-2 projects are not only used to understand cost-driving factors but also form the foundation for predicting costs in 28 additional dike reinforcement projects from the newer HWBP program. These 28 projects represent the forecasted dataset used to test the accuracy of the improved RCF method. By matching projects in the HWBP dataset with their most comparable counterparts in the HWBP-2 reference class, the improved RCF method aims to deliver more precise cost predictions. The effectiveness of this enhanced approach is then evaluated by comparing its predictions to those generated using the traditional RCF method, providing a direct assessment of the improved methodology's benefits.

This case study is integral to addressing the overarching research question of whether the improved RCF method enhances the accuracy of cost predictions for dike reinforcement projects. By systematically analysing the relationships between project variables and costs, and by testing these findings within a structured forecasting framework, this study ensures methodological rigor and practical relevance.

Through its detailed examination of 43 HWBP-2 projects and their application as a reference class for forecasting, this case study highlights the complexities of cost dynamics in dike reinforcement. It not only enhances our understanding of these dynamics but also sets the stage for evaluating and refining forecasting methodologies that are crucial for addressing the challenges of flood protection in a changing climate. In figure 2.6.1, an overview of dike reinforcement projects that are under construction can be seen.

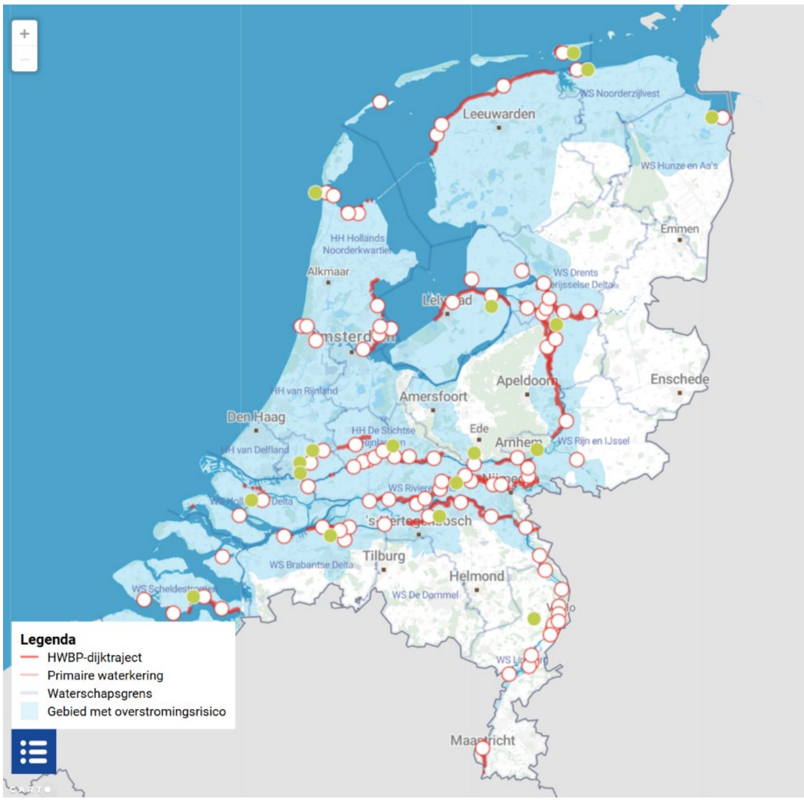

Figure 2.6.1: overview of dike reinforcements currently in construction (HWBP, 2024)

2.7 Outline Research

In this section, the outline of the research is summarised in Figure 2.7.1 in which the different stages of the study can be seen. First, in the reviewing part, the existing literature and state-of-the-art models are discussed. After those sections, in the assessment part, a study on Reference class forecasting is conducted and success factors in dike-reinforcements will be discussed. Subsequently in the validating stage, the data analysis is conducted and the new model is explained and results will be shown. After that discussion, limitations and strengths of the new method will be discussed. In the final two parts of the research the conclusion & recommendations are shown. This will answer the research questions and will give recommendations for future research.

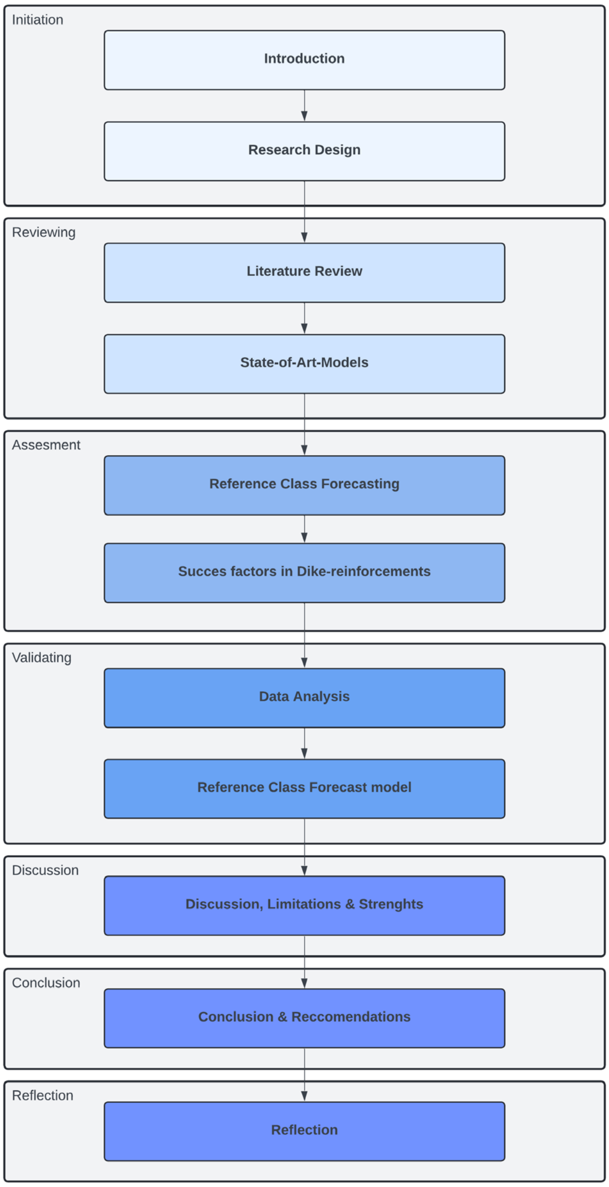

Figure 2.7.1: outline research (authors image)

3 Literature study

Getting a good understanding of literature is crucial in research. Therefore, this chapter will review various methods to predict pricing of dike reinforcements, an extensive review of the method Reference Class Forecasting and its limitations. Finally, price determining factors are reviewed.

3.1 Dike reinforcements

Dikes, or levees, are critical infrastructural elements in flood defence systems, particularly in low-lying areas like the Netherlands, where a significant portion of the population and infrastructure is below sea level. Dike reinforcements are necessary when existing structures no longer meet safety standards due to natural aging, increased water levels, or changes in environmental conditions. The purpose of reinforcing dikes is to ensure their resilience against flooding caused by river overflow, storm surges, or rising sea levels due to climate change. The process of dike reinforcement involves strengthening the structure of existing dikes by increasing their height, broadening their base, or using modern materials and engineering techniques to improve their capacity to withstand extreme weather events (Schielen & Gijsbers, 2021). Dike reinforcement techniques vary depending on several factors, such as the type of water the dike is protecting against (sea, river, or lake), the location's geology, and the urban or rural environment. Different methods will be discussed below.

3.1.1 Heightening and Broadening

One of the most traditional and widely adopted methods for reinforcing dikes is heightening and broadening. Heightening involves adding vertical layers to the dike to ensure that it can accommodate higher water levels during extreme weather events and high tides. This method is particularly effective for counteracting rising sea levels and increasing the dike's capacity to hold back surging waters during storms (de Vries et al., 2020). Broadening, on the other hand, involves extending the base of the dike to enhance its overall structural stability. By expanding the dike's footprint, engineers reduce the risk of lateral displacement and increase resistance to hydraulic forces that could cause collapse or breaching. This method is often employed in areas where space permits expansion, making it a suitable approach for rural dikes with available surrounding land (de Vries et al., 2020).

3.1.2 Slope Protection

Slope protection is crucial for preserving the long-term integrity of a dike, particularly in areas exposed to constant wave action or swift water currents. Erosion can weaken the slopes of a dike, eventually leading to breaches. To counteract this, engineers use various protective materials, such as concrete blocks, asphalt, or synthetic revetments. These materials are designed to absorb and deflect the energy of waves and prevent the surface material from being washed away (Schielen & Gijsbers, 2021). Concrete blocks, for example, offer durability and high resistance to wave impact, making them ideal for sea-facing dikes, while asphalt layers provide a flexible, water-resistant cover that adapts well to both river and coastal environments. Advances in material science have also led to the use of composite materials and synthetic revetments that combine strength with lightweight properties, improving the ease of installation and maintenance.

3.1.3 Use of Geosynthetics

The integration of geosynthetic materials has become increasingly common in modern dike reinforcement projects due to their superior properties compared to traditional reinforcement materials. Geosynthetics, such as geotextiles and geomembranes, enhance the dike's strength, stability, and resistance to water penetration (Koerner & Koerner, 2015). These materials are particularly advantageous in areas with poor soil quality or where high water pressures threaten to undermine the dike's foundation. Geotextiles can be used to separate soil layers, provide filtration, and reinforce the structure, while geomembranes create an impermeable barrier that helps prevent water from seeping through the dike (Koerner & Koerner, 2015). The lightweight nature of these materials, combined with their ease of transport and installation, makes them a cost-effective solution for large-scale projects or sites with limited access.

3.1.4 Underground Barriers

In locations where seepage poses a significant risk to dike stability, underground barriers are employed to prevent water from infiltrating beneath the structure. Techniques such as installing sheet piling or constructing deep cutoff walls are used to block water pathways under the dike, thereby maintaining the dike's structural integrity and preventing potential weakening (Van Duin et al., 2016). Sheet piling involves driving vertical steel or composite sheets deep into the ground to form a continuous barrier, ideal for preventing seepage in permeable soils. Deep cutoff walls, made from concrete or bentonite, offer a more permanent solution for areas with high groundwater levels. These underground barriers can be combined with surface-level reinforcement strategies to provide comprehensive protection against both over-topping and under-seepage.

3.1.5 Environmental Integration

The concept of "building with nature" has gained traction in recent years, emphasizing sustainable and eco-friendly dike reinforcement approaches. This method involves incorporating natural elements, such as planting vegetation or creating secondary floodplains, to enhance the dike's resilience while promoting ecological benefits (van Loon-Steensma & Vellinga, 2019). Vegetation, for instance, helps stabilize the soil on the dike's surface and reduce erosion by dissipating wave energy. Root systems anchor the soil and prevent washout, creating a natural defence mechanism that complements engineered structures. Additionally, secondary floodplains can act as buffer zones, absorbing excess water during high-flow events and reducing the hydraulic load on the dike. Such nature-based solutions provide dual benefits: reinforcing the dike and fostering habitats for wildlife, contributing to biodiversity and the overall health of the ecosystem (van Loon-Steensma & Vellinga, 2019).

3.1.6 Conclusion

In conclusion, dike reinforcement techniques are varied and must be carefully selected based on the specific conditions and characteristics of the location they are intended to protect. The choice of reinforcement strategy depends not only on the type of water body—be it sea, river, or lake—but also on the geological properties of the site and whether it is in an urban or rural environment. Each method has its unique advantages and limitations that must be considered to ensure both structural integrity and cost-effectiveness.

Heightening and broadening remain fundamental approaches for increasing a dike's capacity to withstand extreme water levels and improve overall stability. These methods are effective where space allows for expansion, particularly in rural settings. Slope protection is essential for areas exposed to significant wave action or fast water currents, where materials like concrete, asphalt, and synthetic revetments provide durable, erosion-resistant barriers. The use of geosynthetics introduces a modern dimension to reinforcement, offering enhanced strength, stability, and water resistance, particularly in locations with poor soil conditions or high water pressure.

For sites where seepage poses a major risk, sheet piling and cutoff walls provide critical protection by preventing water infiltration beneath the dike. These methods are particularly beneficial in locations with permeable soils or high groundwater levels. Lastly, environmental integration techniques, such as planting vegetation or creating secondary floodplains, exemplify the modern approach of "building with nature." This method not only strengthens the dike but also offers ecological benefits, fostering wildlife habitats and improving biodiversity. Ultimately, the choice of techniques must balance structural needs and environmental considerations, ensuring that dike reinforcement projects are effective, sustainable, and adaptable to site-specific challenges.

3.2 Factors Influencing the Cost of Dike Reinforcement

Besides the methods of reinforcement. the costs of dike reinforcement projects can vary widely depending on several factors, each contributing to the final project budget. This section will discuss the most important factors according to literature.

3.2.1 Material Costs

The choice of materials plays a major role in the overall cost of dike reinforcement. For traditional techniques, the availability and cost of raw materials such as clay, sand, and rock are significant determinants of the budget. However, the integration of modern materials like geosynthetics or advanced construction methods (such as sheet piling) can add to the cost (Koerner & Koerner, 2015). Furthermore, the availability of these materials locally versus the need for importation significantly impacts the project cost (de Vries et al., 2020).

3.2.2 Labour Costs

Labor represents another major expense in dike reinforcement projects. Skilled labourers, including engineers, construction workers, and specialists, are needed to execute the complex designs and construction processes involved in modern reinforcement techniques (Flyvbjerg, 2007). Additionally, labour shortages or fluctuations in labour market conditions can significantly affect project timelines and costs (Love et al., 2019).

3.2.3 Project Size and Complexity

Larger and more complex projects tend to require more resources, both in terms of materials and labour. Additionally, complex projects often involve specialized techniques or equipment, which can drive up costs. The dike's location also plays a significant role in determining the complexity of the project. Dike reinforcement in urban areas, for instance, may require additional logistical considerations, such as rerouting traffic or minimizing the impact on local populations (PBL Netherlands Environmental Assessment Agency, 2016).

3.2.4 Environmental and Regulatory Compliance

Strict environmental and regulatory requirements also contribute to the cost of dike reinforcement projects. These regulations may include mandatory environmental impact assessments, ensuring compliance with sustainability goals, or securing permits for construction near sensitive ecological zones (Hoes et al., 2019). Dike projects are also subject to the EU's Water Framework Directive, which aims to promote sustainable water management, often adding further regulatory complexity (European Commission, 2015).

3.2.5 Risk and Uncertainty

Every construction project is associated with uncertainty and risk, but dike reinforcement projects face heightened risks due to unpredictable environmental factors like climate change, rising sea levels, or extreme weather events. These uncertainties are often mitigated by increasing the robustness of the dike design, which can inflate costs. Additionally, contingencies must be built into budgets to account for potential delays or unforeseen challenges (Flyvbjerg, 2014).

3.2.6 Geotechnical Conditions

The geological conditions in the area where dike reinforcement is required have a significant influence on cost. Weak or unstable soil can require additional measures, such as deep foundations or soil stabilization techniques, to ensure the dike's effectiveness and longevity. This adds substantial expense to the project, as specialized equipment and techniques are needed (van Duin et al., 2016).

3.2.7 Conclusion

Dike reinforcement projects are critical to ensuring the long-term flood safety of vulnerable regions, particularly in low-lying areas like the Netherlands. These projects are complex and costly, with prices determined by multiple factors such as materials, labour, project size, environmental regulations, and geotechnical conditions. The use of modern techniques, such as geosynthetics and environmental integration, can increase the project’s effectiveness but may also add to costs. Understanding these factors and employing accurate forecasting methods like RCF are essential for effective project management and cost control in large-scale infrastructure projects.

3.3 Research into state-of-the-art price prediction models

In this section, several methods for predicting project costs will be explored, each with distinct approaches, strengths, and limitations. Accurate cost estimation is crucial in project management, particularly for large-scale infrastructure projects where the consequences of underestimating costs can be significant and for smaller projects grouped in a portfolio. Traditional cost estimating, probabilistic estimating, and Reference Class Forecasting (RCF) are three widely recognized methods, each suited to different project types and levels of complexity. This section will introduce these methods, discuss how they are applied in practice, and highlight the conditions under which each is most effective.

3.3.1 Traditional Cost Estimating:

Traditional cost estimation methods heavily rely on historical cost data, which involves using records from previously completed projects to forecast the costs of new ones. This approach assumes that past costs are reliable indicators of future expenses under similar conditions. However, this assumption is often flawed due to several factors.

One of the primary strengths of traditional cost estimation is its simplicity and ease of implementation. These methods do not require sophisticated tools or systems, making them accessible to a wide range of organizations. For example, small businesses or firms operating with limited resources often rely on traditional methods because they do not require significant upfront investments in technology or advanced training (Reddy, 2023). By utilizing straightforward processes, such as deriving costs from historical data or relying on expert insights, these methods allow project managers to quickly develop initial cost forecasts, which can be crucial during the early stages of project planning.

Another significant strength lies in the reliance on historical cost data. Historical data provides a tangible and often proven foundation for cost estimation. When past projects share similarities in scope, scale, and context with current undertakings, the use of historical data can provide accurate and reliable benchmarks (Project Management Institute, 2004). For instance, in industries like construction, infrastructure, or manufacturing, where processes and material costs are often predictable, historical cost records serve as a valuable reference for developing reasonable estimates. This ability to draw on past performance data makes traditional methods particularly effective for recurring or routine projects.

Additionally, the use of expert judgment in traditional cost estimation methods is another notable strength. Experts bring years of experience and domain-specific knowledge to the table, allowing for nuanced and context-sensitive evaluations of project costs. This is especially valuable in situations where quantitative data alone may fail to capture project-specific complexities or localized factors. For example, experts can account for regional differences in labour availability, regulatory requirements, or site-specific challenges, which can significantly influence project costs. The qualitative insights provided by experts complement historical data and help project managers make more informed decisions (Reddy, 2023).

Traditional cost estimation methods also align well with established accounting practices and regulatory frameworks, which adds to their reliability and compliance benefits. Organizations in industries with strict financial reporting and regulatory requirements, such as government-funded infrastructure projects, often favor traditional methods for their familiarity and alignment with these standards (Project Management Institute, 2004). This compliance ensures that cost forecasts meet external audit and reporting criteria, providing a layer of accountability.

Despite these strengths, traditional cost estimation methods are not without limitations. One significant limitation is the availability and quality of historical data. Many projects suffer from incomplete or inconsistent historical records, making it challenging to find truly comparable data. This scarcity of comprehensive historical data can lead to inadequate reference classes, compromising the accuracy of the estimates. Additionally, changes over time in factors such as inflation, material prices, labour costs, and technological advancements can render historical data less relevant for current projects. As a result, relying on outdated data can lead to significant inaccuracies in cost predictions (Flyvbjerg, Holm, & Buhl, 2002).

Another cornerstone of traditional cost estimating is expert judgment, where seasoned professionals use their knowledge and experience to forecast project costs. While expert judgment adds valuable insights, it is not without its pitfalls. Expert judgment is inherently subjective and can be influenced by personal biases and experiences. One common issue is optimism bias, where experts tend to underestimate costs and overestimate benefits due to their confidence in project success. This bias can lead to significant cost overruns as initial estimates fail to account for potential challenges and complexities (Flyvbjerg et al., 2002). Moreover, the variability in opinions among different experts can result in inconsistent estimates, adding to the uncertainty of project costs.

Traditional cost estimation methods often fall short due to their reliance on subjective opinions and incomplete data. The subjectivity inherent in expert judgment can lead to significant deviations from actual costs. Experts' biases and varying experiences introduce a level of inconsistency and unpredictability in the estimates. Furthermore, historical data used in these methods is frequently incomplete or not entirely relevant to the current project context. As projects evolve over time, the historical context may not align with current conditions, leading to inaccurate estimates. This reliance on potentially outdated data increases the risk of cost overruns, as initial forecasts fail to capture the true scope and scale of the project (Cantarelli et al., 2012).

Numerous studies have highlighted the limitations of traditional cost estimation methods. Flyvbjerg et al. (2002) conducted an extensive review of infrastructure projects and found that inaccurate cost estimates were prevalent, often due to the reliance on historical data and expert judgment without sufficient empirical backing. Their research underscores the need for more robust, data-driven forecasting methods to improve accuracy and reduce the risk of cost overruns. Similarly, Cantarelli et al. (2012) examined large-scale transportation infrastructure projects and identified that traditional forecasting methods often fail to account for project-specific variables, leading to significant cost discrepancies. Their findings suggest that incorporating empirical data and modern analytical techniques can substantially enhance the accuracy of cost predictions.

While traditional cost estimating methods laid the groundwork for project forecasting, their inherent limitations—reliance on subjective opinions, incomplete data, and the inability to adapt to changing conditions—have led to significant inaccuracies and cost overruns in infrastructure projects. The evolution towards more empirical and data-driven methods, such as Reference Class Forecasting, addresses these shortcomings by providing more reliable and accurate cost estimates, thus better supporting the planning and execution of infrastructure projects.

3.3.2 Parametric Cost Estimating

Parametric cost estimating is a method that uses statistical relationships between historical data and other variables to predict the cost of a project. This approach is particularly useful in infrastructure projects where detailed information may not be available early in the planning stages. The method involves identifying key cost drivers, such as project size, duration, and complexity, and using these parameters to develop a cost model.

The core of parametric estimating lies in regression analysis, a statistical technique used to determine the strength and character of the relationship between one dependent variable and one or more independent variables. In the context of infrastructure projects, the independent variables could include factors such as geographical location, project type, and scale, while the dependent variable would be the project cost. Studies such as those by Ashworth (2004) and Jelen and Black (1983) have demonstrated the efficacy of this method in various sectors, including construction and engineering. These studies highlight the importance of selecting appropriate cost drivers and ensuring a robust dataset to improve the accuracy of the models.

Parametric cost estimating is particularly advantageous in the early stages of project planning when detailed designs are not available. It allows for quick cost assessments and scenario analysis. However, its accuracy is highly dependent on the quality of the historical data used and the relevance of the selected parameters. There is also a risk of over-reliance on past data, which may not fully capture unique aspects of the current project.

3.3.3 Reference Class Forecasting

Reference Class Forecasting (RCF) is a forecasting method grounded in behavioural economics and decision-making theory, aimed at reducing biases in project cost and time estimates. The theoretical foundation for RCF stems from the work of psychologists Daniel Kahneman and Amos Tversky, who developed Prospect Theory and won the Nobel Prize in Economics in 2002. Their research illustrated how cognitive biases—particularly optimism bias and strategic misrepresentation—often lead to overly optimistic estimates in project planning. RCF seeks to mitigate these biases by shifting from an "inside view" to an "outside view" of forecasting, relying on historical data from similar projects rather than individual judgment or subjective expectations (Kahneman & Tversky, 1979; Kahneman, 2011).

To counter these biases, Reference Class Forecasting shifts the focus from an "inside view" of forecasting—where project-specific knowledge, intuition, and judgment play a dominant role—to an "outside view." The outside view relies on empirical data from a "reference class" of similar projects. This reference class provides a historical baseline, using the actual performance of completed projects to generate realistic expectations for the current project. By grounding forecasts in real data rather than subjective predictions, RCF aims to provide a more accurate and bias-resistant estimation of costs and schedules (Kahneman, 2011).

Bent Flyvbjerg, a professor of project management and one of the leading figures in RCF, extended the theoretical work of Kahneman and Tversky into practical applications for large-scale infrastructure projects. His research in the early 2000s showcased how RCF could improve cost and schedule accuracy by comparing new projects to a "reference class" of completed projects with similar characteristics. In this process, RCF positions the current project within the historical performance distribution of past projects, generating forecasts based on empirical data rather than subjective assumptions. Flyvbjerg's work demonstrated that RCF could provide a more realistic prediction of project costs and timelines by accounting for the average performance of similar projects (Flyvbjerg, 2006; Flyvbjerg, 2008).

The traditional methods of cost estimation in infrastructure projects largely depend on historical data and expert judgment. This involves examining past projects that are similar in nature and scaling their costs to fit the current project. Key activities in traditional cost estimating include historical data analysis, expert judgment, analogous estimating, and bottom-up estimating. While these methods have provided a foundational framework, they are often criticized for their susceptibility to human biases and errors, leading to cost overruns and inaccurate forecasts.

Bent Flyvbjerg translated the theoretical insights of Kahneman and Tversky into practical applications with the development of RCF. Flyvbjerg's approach involves identifying a reference class of similar past projects, establishing a probability distribution for their outcomes, and using this distribution to predict the current project's outcomes. This method reduces the impact of individual biases by relying on empirical data rather than subjective estimates.

By comparing a new project with a carefully selected database of completed projects, RCF offers a distribution of outcomes rather than a single-point estimate. This probabilistic forecasting aligns with real-world project risks, where the future is uncertain and outcomes rarely follow the idealized projections set at the planning stage. Flyvbjerg's approach has been instrumental in making RCF an accepted practice in project management for public infrastructure. Notably, his work revealed that traditional cost estimates often miss the mark by wide margins, which leads to substantial budget overruns and project delays. By reducing these inaccuracies, RCF provides policymakers and planners with a more reliable tool to manage expectations and allocate resources effectively.

3.3.4 Conclusion

Traditional cost estimating methods have played a foundational role in project forecasting by leveraging historical data and expert judgment. However, these approaches are increasingly recognized for their limitations. The reliance on historical data assumes that past costs are reliable indicators of future expenses, an assumption that does not always hold true due to data quality issues, inflation, changes in labour and material costs, and technological advancements (Flyvbjerg, Holm, & Buhl, 2002). The incomplete or inconsistent nature of historical data can hinder the formation of adequate reference classes, thereby compromising estimate accuracy.

Expert judgment, although valuable for incorporating practical insights, is subject to personal biases, including optimism bias, where cost forecasts are underestimated due to overconfidence in project success (Flyvbjerg et al., 2002). This subjectivity, combined with the variability of expert opinions, leads to inconsistent and often unreliable cost predictions. The inability of traditional methods to adapt to evolving project conditions further exacerbates the risk of cost overruns, as noted in studies of large-scale infrastructure projects (Cantarelli et al., 2012).

Given these limitations, there is a growing emphasis on more empirical and data-driven approaches, such as Reference Class Forecasting and parametric cost estimating. These methods utilize broader datasets and statistical analyses, reducing the influence of individual biases and outdated data. By transitioning to such methodologies, project forecasting can achieve greater reliability and precision, providing essential support for the planning and execution of complex infrastructure projects. Because of the limitations of traditional cost estimating and the data requirements needed for parametric cost estimating, reference class forecasting will be further discussed and researched in the next section. An overview of the required data, strengths and weaknesses is shown in table 2.

Table 2: comparison between state-of-the-art cost forecasting mehtods

Method	Type of Data Required	Strengths	Weaknesses
Traditional Cost Estimating	Historical cost data for similar projects, expert judgment, project-specific parameters (e.g., materials, size)	- Provides detailed, component-specific estimates based on known project elements (Fleming & Koppelman, 2010).	- Prone to bias if unexpected factors arise, as it relies heavily on project-specific assumptions (Flyvbjerg, 2006).
Probabilistic Estimating	Baseline project estimates, risk data, statistical data on cost variability and probability distributions	- Accounts for uncertainty by providing a range of possible cost outcomes (Kwak & Ingall, 2007).	- Requires high-quality data and sophisticated statistical tools (e.g., Monte Carlo simulations) (Palisade Corporation, 2017).
Reference Class Forecasting (RCF)	Data on completed projects with similar characteristics (costs)	- Mitigates optimism bias by focusing on historical data from similar projects (Flyvbjerg, 2006).	- Relies on having a robust reference class; accuracy drops if comparable projects are lacking (Lovallo & Kahneman, 2003).

3.4 Reference class forecasting

As discussed in the section above there are several strengths and weaknesses, with each method. For this research reference class forecasting was chosen due to the availability of completed projects with similar characteristics. In this section reference class forecasting is further analysed.

Figure 3.4.1 shows the broader framework in which RCF fits within project management. At the top, is project management, which oversees the planning, control, and implementation of the project. Dynamic scheduling follows, which allows for adaptable timelines and resource allocation based on project progress.

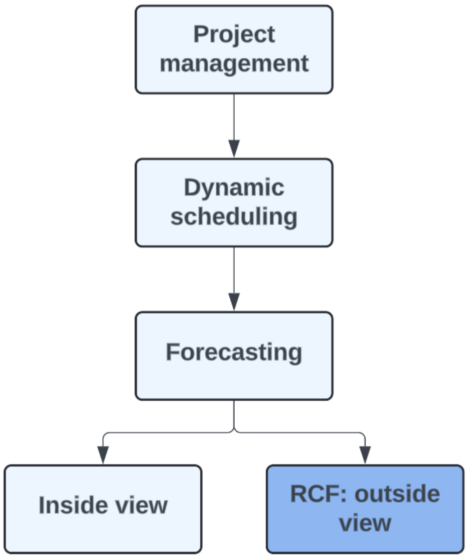

Figure 3.4.1: inside view vs outside view (authors image)

The forecasting stage divides into two approaches, inside View and outside View.

Inside View: The inside view focuses on the specifics of the current project, relying on project-specific details, expert judgment, and team knowledge to generate forecasts. This approach often leads to overly optimistic estimates due to optimism bias, where planners assume that the current project will avoid issues encountered in previous projects. Inside view forecasting is commonly used but tends to be vulnerable to biases like underestimating time and cost (Kahneman & Lovallo, 1993).

Outside View (RCF): Reference Class Forecasting represents the outside view. Instead of focusing on project-specific details, it compares the project with a database of similar past projects, using actual historical outcomes to establish a probability distribution for cost, duration, or other variables. By positioning the current project within this distribution, RCF predicts outcomes based on empirical data rather than individual or team assumptions. The outside view thus minimizes optimism bias by grounding predictions in past performance, which reflects average trends rather than idealized expectations (Flyvbjerg, 2014).

3.4.1 Strengths of Reference Class Forecasting

RCF has several strengths that make it a valuable tool in project management, particularly for large-scale infrastructure projects:

Reduction of Cognitive Biases: By taking an outside view, RCF addresses two major cognitive biases: optimism bias and strategic misrepresentation. Optimism bias leads project planners to overestimate positive outcomes, while strategic misrepresentation involves intentional underestimation or over-promise to secure project approval. Studies have shown that RCF can reduce the impacts of these biases by basing forecasts on historical data rather than subjective or politically motivated estimates (Flyvbjerg, 2006; Flyvbjerg, Garbuio, & Lovallo, 2009).

Reliance on Empirical Data: RCF relies on data from similar projects to generate forecasts, which allows for more realistic estimates. For instance, in infrastructure projects, Flyvbjerg and Stewart (2012) found that RCF could improve cost accuracy by 10–15% compared to traditional inside-view methods. By grounding predictions in actual project outcomes, RCF provides a statistically robust approach to forecasting.

Application Across Multiple Sectors: RCF has been successfully applied to a range of fields beyond infrastructure, including transportation, urban development, and IT projects. For example, in transportation projects, RCF has been shown to reduce cost overruns by adjusting for typical overestimations in travel demand forecasts, which often lead to underfunding of projects (Cantarelli, Flyvbjerg, & van Wee, 2010). The generalizability of RCF makes it a versatile tool for any project type with a substantial database of comparable historical projects.

Overall, Reference Class Forecasting provides a robust and data-driven approach to project estimation, addressing the limitations of traditional methods that rely heavily on expert judgment and historical data without empirical adjustments. By integrating historical distributions and specific project considerations, RCF supports more accurate, realistic, and adaptable forecasts for complex infrastructure projects (Touran, 2006; Flyvbjerg et al., 2002).

3.4.2 Limitations of Reference Class Forecasting

Reference Class Forecasting (RCF) is recognized for its capability to improve the accuracy of cost predictions for infrastructure projects by leveraging historical data from comparable projects. This method, however, is not without its limitations. Understanding these limitations is crucial for comprehensively assessing the uncertainty associated with RCF-based price predictions in infrastructure projects. In the sections below, the limitations of reference class forecasting are discussed.

3.4.2.1 Availability and Quality of Historical Data

RCF's effectiveness is significantly influenced by the availability and quality of historical data. Accurate forecasting relies on a substantial and well-documented dataset of past projects. When historical data is scarce or incomplete, the reference class may be inadequately formed, which can lead to less reliable predictions. The absence of comprehensive historical records limits the method's ability to produce robust forecasts, thereby increasing the uncertainty of the predicted outcomes () (ar5iv).

In addition to data availability, the quality of historical data is paramount. Data inaccuracies or biases can distort the reference class, resulting in misleading forecasts. Inaccurate data compromises the empirical foundation of RCF, amplifying uncertainty in the forecasts. Consequently, ensuring high-quality and comprehensive historical data is essential for minimizing prediction uncertainty (SpringerLink).

3.4.2.2 Selection of Reference Class

The selection of an appropriate reference class is critical for the success of RCF. The reference class must closely match the characteristics of the current project to produce accurate predictions. Misclassification, where non-comparable projects are included in the reference class, can skew the results, leading to higher uncertainty in forecasts. This issue is particularly pronounced in unique or innovative projects where comparable historical projects might not exist.

Moreover, the selection process can introduce biases if not conducted rigorously. Subjective judgments in forming the reference class can lead to biased selections, further increasing the uncertainty of the forecast. It is essential to establish transparent and systematic criteria for selecting reference classes to mitigate this risk (SpringerLink) (ar5iv).

3.4.2.3 *Homogeneity of the Reference Class*

For RCF to be effective, the projects within the reference class should be sufficiently homogeneous. Significant variations in project types, scales, geographic locations, or economic conditions can undermine the validity of the forecast. A highly heterogeneous reference class can lead to a broad and imprecise probability distribution, increasing the range of possible outcomes and thus the uncertainty. This makes it challenging to derive an accurate forecast.

Contextual differences between the reference class projects and the current project, such as variations in regulatory, environmental, or market conditions, can also lead to inaccuracies, thereby adding to the forecast's uncertainty. Ensuring homogeneity within the reference class is therefore crucial for reliable predictions (ar5iv).

3.4.2.4 *Static Nature of Historical Dat*

The static nature of historical data poses another significant constraint on RCF. Historical data reflects past conditions and may not account for future changes in technology, regulations, market conditions, or other dynamic factors. Infrastructure projects often span several years, during which significant changes can occur. Consequently, forecasts based solely on static historical data may become increasingly uncertain as these dynamic factors come into play.

Technological advancements and market shifts can further diminish the relevance of historical data, increasing the forecast uncertainty over time. Thus, while historical data provides a valuable foundation, it is essential to consider potential future changes to enhance forecast reliability (ar5iv).

3.4.2.5 *Over-Reliance on Quantitative Data*

RCF primarily focuses on quantitative data from past projects, potentially overlooking important qualitative factors such as stakeholder behavior, political influences, or unique project-specific risks. Ignoring these qualitative factors can lead to an incomplete assessment of potential risks and uncertainties, as these elements often play a crucial role in project outcomes.

Without considering qualitative aspects, unanticipated risks may arise, increasing the uncertainty and potentially leading to significant deviations from the forecasted outcomes. Therefore, integrating qualitative insights with quantitative data can provide a more comprehensive risk assessment and improve forecast accuracy (SpringerLink).

3.4.2.6 *Assumptions of Similarity and Predictability*

RCF operates on the assumption that future projects will follow similar patterns to past projects. This assumption can be problematic if future projects introduce new complexities or if past performance is not indicative of future outcomes. The assumption that past projects are fully representative of future ones can lead to overconfidence in the forecasts and underestimation of uncertainty. This is particularly true for innovative or unprecedented projects where historical precedents may be lacking.

Changes in industry standards, practices, and methodologies over time can also lead to discrepancies between past and future projects, further increasing forecast uncertainty. Recognizing and adjusting for these evolving standards is essential to maintaining forecast accuracy (ar5iv).

Despite its advantages, Reference Class Forecasting is not without limitations. Its effectiveness depends heavily on the availability and quality of historical data, as well as the appropriateness of the reference class selected:

1. **Dependence on Data Quality and Availability**: The accuracy of RCF forecasts is limited by the quality and relevance of the historical data. If data on past projects is incomplete, biased, or does not reflect current project conditions, the RCF method may produce misleading estimates. For instance, historical data might not capture recent advancements in technology or new regulatory standards that could significantly impact project costs. Additionally, for projects in emerging sectors or those with unique attributes, finding an appropriate reference class can be challenging, reducing RCF's applicability (Locatelli, Mancini, & Romano, 2017).

2. **Selection of the Reference Class**: One of the critical aspects of RCF is defining an appropriate reference class. The reference class must consist of projects that are genuinely comparable to the current project in terms of scope, complexity, and risk. However, selecting an adequate reference class can be subjective and may introduce biases if the chosen projects are not fully representative. For instance, if the reference class includes only projects completed under favorable economic conditions, it may underestimate the risks associated with the current project. This limitation introduces a potential for error in cases where the current project has unique characteristics not reflected in the historical data (Love, Sing, & Ika, 2019).

3. **Lack of Flexibility to Project-Specific Conditions**: While the outside view approach of RCF reduces bias, it also risks oversimplifying complex projects by focusing solely on historical averages. Projects with unique or innovative elements may face challenges that are not adequately represented by historical data. For example, a dike reinforcement project involving cutting-edge materials or construction techniques may have cost drivers not captured by past projects. RCF's reliance on past performance can overlook these unique factors, making it less accurate in such cases compared to a well-informed inside view (Flyvbjerg et al., 2009).

4. **Risk of Over-Reliance on Historical Trends**: RCF inherently assumes that historical data is a good predictor of future outcomes. This assumption may not hold in dynamic environments where external factors—such as policy changes, environmental conditions, or economic shifts—alter project outcomes significantly. For example, climate change is accelerating the need for flood defences, but past data on dike reinforcement projects may not fully account for the increased material costs or design requirements necessary for higher flood protection standards. Therefore, RCF may be less effective in contexts with high uncertainty or rapid change (Van Wee & Rietveld, 2013).

3.4.2.7 Practical Application and Cautions for Use

The image in section3.4 illustrates how RCF serves as a counterpoint to traditional inside view forecasting methods within the project management process. While dynamic scheduling and project management emphasize flexibility and responsiveness, forecasting with RCF offers a more stable, probability-based foundation grounded in empirical data. However, the effectiveness of RCF as an outside view method is contingent upon the careful selection of a reference class and the availability of high-quality historical data. Practitioners must also weigh the benefits of bias reduction against the risk of overlooking unique project conditions.

For optimal results, project managers should consider using RCF in tandem with inside view forecasting methods, particularly in cases where unique project-specific factors are relevant. Hybrid approaches that blend RCF with expert judgment allow for the benefits of empirical data while retaining flexibility to adapt to the particularities of individual projects. This balanced approach could enhance forecast accuracy by leveraging both the probabilistic strength of RCF and the contextual insight provided by inside view methods (Flyvbjerg, 2014).

Various scientific studies and publications endorse RCF as a superior method for project forecasting. Researchers argue that RCF's ability to bypass human biases and its reliance on empirical data make it a robust tool for accurate forecasting. By incorporating data from past projects, RCF provides a more objective basis for predicting costs, leading to more successful project outcomes (Love et al., 2016)

In contrast, traditional methods often fall short due to their inherent subjectivity and potential for bias. They may not adequately account for unexpected variables and changes in project scope, leading to significant deviations from initial estimates. Furthermore, without a systematic approach to leveraging historical data, traditional methods can miss out on valuable insights from past projects, resulting in repeated mistakes and underestimation of risks (Siemiatycki, 2009)

3.4.3 Conclusion

While Reference Class Forecasting offers significant advantages in reducing bias and providing data-driven predictions, its constraints highlight the inherent uncertainties in forecasting infrastructure project costs. The quality and selection of the reference class, the homogeneity of data, the static nature of historical information, and the exclusion of qualitative factors all contribute to the complexity and uncertainty of price predictions. Addressing these constraints is essential for improving the accuracy and reliability of RCF in infrastructure projects. By acknowledging these limitations and incorporating additional qualitative and future-oriented insights, practitioners can enhance the robustness of their forecasts and better manage the uncertainties inherent in infrastructure project planning.

3.5 How to perform a Reference Class Forecast

Figure 3.5.1 outlines a structured process for performing Reference Class Forecasting (RCF), a method rooted in behavioural economics and project management theory.

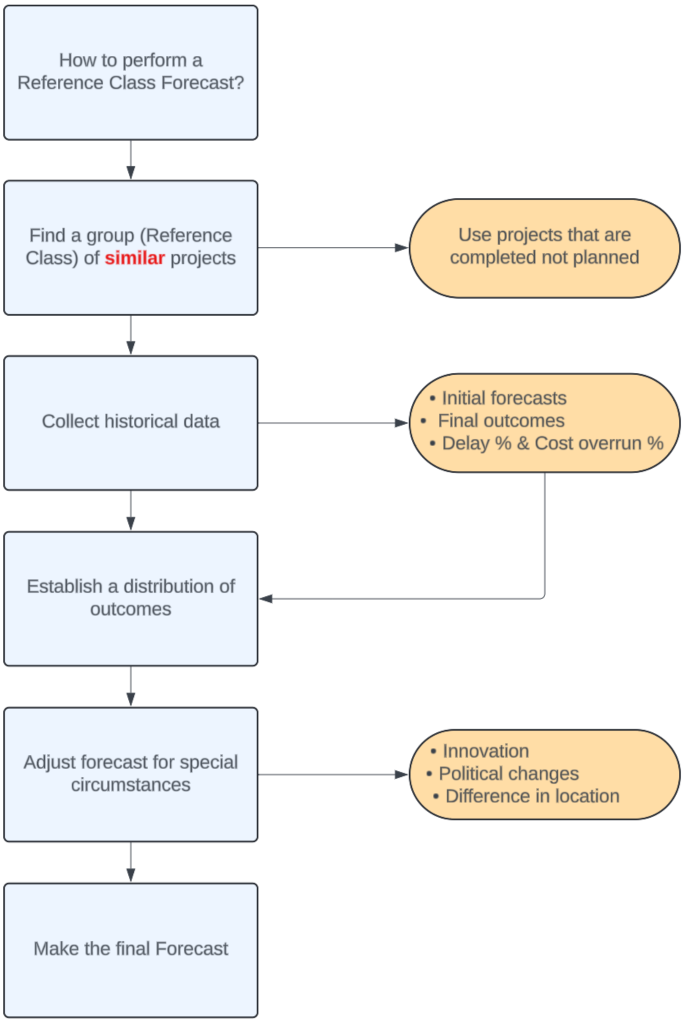

Figure 3.5.1: How to perform a reference class forecast (authors image)

The first step in performing RCF is to find a reference class of similar projects. Selecting an appropriate group of comparable, completed projects is crucial to ensure that the forecasting model is based on relevant and realistic data. Unlike planned projects, completed projects offer actual outcomes that can serve as a reliable baseline for predicting future performance. The choice of reference class must align with the current project's scope, complexity, and context to produce meaningful comparisons. Studies have shown that failing to select a truly comparable reference class can lead to skewed and unreliable forecasts (Flyvbjerg, Holm, & Buhl, 2002; Cantarelli et al., 2012).

Once the reference class is identified, the next step is to collect historical data from these projects. The data gathered should include initial forecasts, final project outcomes, and metrics such as delays and cost overrun percentages. This data is essential for assessing how closely initial predictions aligned with actual project results. By analysing this information, project planners can understand the range of potential deviations and prepare for more realistic forecasts. Historical data provides an empirical foundation that minimizes reliance on subjective opinions and enhances the objectivity of project cost and time predictions (Jelen & Black, 1983; Flyvbjerg, 2006).

With the collected data, the third step involves establishing a distribution of outcomes. This distribution illustrates the range and frequency of project costs and completion times within the reference class, providing a probabilistic view of what can be expected for similar future projects. Unlike single-point estimates, which often underrepresent variability, a distribution approach accounts for uncertainty and allows project managers to anticipate a broader spectrum of possible results. This step is critical for building forecasts that reflect real-world variability and are less prone to underestimation (Ashworth, 2004; Vose, 2008).

The fourth step in the RCF process is to adjust the forecast for special circumstances that may not be captured by the historical data. This adjustment ensures that the forecast remains relevant by incorporating unique aspects of the current project. Factors such as technological innovations, political changes, or site-specific conditions can significantly impact project outcomes. For instance, projects that involve the use of new technology may require adjustments to account for potential cost fluctuations or performance uncertainties (Chou, Cheng, & Wu, 2015; Kim, Kim, & Han, 2019). Additionally, political shifts or regulatory changes can alter project timelines and budgets, necessitating revisions to the baseline forecast (Cantarelli et al., 2012). Addressing these unique factors helps tailor the forecast to current circumstances, enhancing its reliability (Van Wee & Rietveld, 2013).

Finally, the process concludes with making the final forecast. This step synthesizes insights from the distribution of historical outcomes and adjustments made for special conditions. By combining empirical data with these tailored adjustments, the RCF approach delivers a balanced, evidence-based prediction. The final forecast is thus more resilient to common forecasting biases, such as optimism bias, and better equipped to anticipate potential deviations from initial project plans (Kahneman & Tversky, 1979; Flyvbjerg, 2006).

3.6 Implementing Success Factors in Reference Class Forecasting

Research into Reference Class Forecasting (RCF) has shown that incorporating project-specific success factors can significantly refine the method's accuracy. This body of work investigates how detailed variables related to individual projects can improve the predictive power of RCF, particularly for infrastructure projects.

3.6.1 Integration of Success Factors

A significant study by Love et al. (2015) delved into the effects of integrating success factors within RCF for construction projects. They identified key factors such as project complexity, stakeholder involvement, and environmental conditions. Their research indicates that these factors, when incorporated into the RCF model, provide a deeper understanding of potential risks and outcomes, thereby enhancing predictive accuracy.

3.6.2 Conclusion

The integration of success factors into Reference Class Forecasting has been empirically demonstrated to enhance the accuracy of cost predictions for infrastructure projects. By incorporating detailed project-specific variables, researchers have refined RCF, making it more reliable than traditional methods. These advancements build upon RCF's robust empirical foundation, combining it with modern analytical techniques to further mitigate biases and improve forecasting precision.

3.7 Most Relevant Cost-Driving Factors for Dike Reinforcement Projects

Literature shows several cost driving factors when reinforcing dikes. In Appendix The obstacles are of a technical, financial, institutional, or legal nature. Technical and financial aspects are self-explanatory: institutional aspects involve matters of an organizational nature, such as agreements between governments or having the right people in the right place. Legal aspects include obstacles arising from contracts and legislation. An obstacle can have multiple aspects. An overview of these cost driving factors can be found in Appendix D.

3.8 Selection of success-factors

The success-factors that emerged from the literature review were validated by interviewing several experts in the field of dike-reinforcements and financial modelling. The interviewees highlighted the following factors as the most influential on the price of a dike reinforcement, shown in table 3.

Table 3: Selected success-factors

Factor	Type of variable	Identified by interviewee
1 Is the project situated in a rural area?	Binary [yes/no]	1,2,3,4
2 Is the project situated in an urban area?	Binary [yes/no]	1,2,3,4
3 Is the project situated in a N2000 area?	Binary [yes/no]	1,2,3,4
4 Are there buildings close to the project?	Binary [yes/no]	1,2,3,4
5 What type of soil is situated at the project location?	String [sand, clay, sand & clay….]	1,2,3
6 What is the distance from the national standard?	String [A+, A, B, C, D]	1,2,3,4
7 Is the dike bordering a river or a sea?	Binary [Sea/River]	1,2,4
8 Which water authority managed the project?	String	3,4

An analysis was conducted on 43 dike reinforcement projects from the HWBP-2 programme using the factors mentioned above in table 3. Each factor was evaluated based on the type of variable it represented, such as binary or categorical, to assess the possible influences on the cost of these projects. For instance, factors like "Is the project situated in a rural area?" were scored as binary variables with values of "Yes" or "No," allowing for a straightforward categorization of the data.

To explore the relationships between these factors and the overall cost of the dike reinforcement projects, a correlation analysis and a regression analysis is performed. The correlation analysis helped identify the degree of association between each factor and the project costs. This provided insight into which factors might have stronger or weaker relationships with cost, revealing the most influential variables. For example, factors such as proximity to urban areas, soil type, and whether the project was situated in a Natura 2000 (N2000) area were tested for their potential correlation with the costs incurred.

Following this, a regression analysis is conducted to further quantify how much each of these factors could predict the cost of the projects. The regression model allowed me to assess the weight of each factor in contributing to the total cost, by estimating their predictive power when accounting for other variables. Factors like the type of soil, the presence of nearby buildings, and whether the dike bordered a river or sea were included as predictors in the model. The binary and categorical nature of the variables was appropriately handled through encoding techniques, such as dummy variables for binary factors, to ensure compatibility within the regression framework.

The combination of correlation and regression analysis not only helped to identify which factors were significantly correlated with project costs, but also provided insights into the relative importance and predictive capacity of each factor. This analysis was instrumental in understanding the underlying dynamics of cost variations across different dike reinforcement projects within the HWBP-2 programme. The findings can contribute to better forecasting and planning for future projects, where a clearer understanding of cost drivers is critical for optimizing resource allocation.

3.8.1 Definition of variables

In order to understand the success factors mentioned above, it is important to define said variables. In order to make an objective assessment on each of these variables for every project in the database it is important to define said variables very specific.

3.8.2 Rural and urban area

To determine the factor: “Is the project situated in a rural area? [yes/no]”, first it is important what the definition of a rural area is in the Netherlands. In the distribution system of the provincial fund, urban and rural areas are defined at the level of grid squares measuring 500 x 500 meters. The criterion used for this is the surrounding address density (SAD) of the relevant grid square. If the SAD is 1500 or more addresses per square kilometre, the square is classified as an urban area. If the SAD is less than 1000 addresses per square kilometre, it is considered a rural area.

Each year, at the request of the Ministry of the Interior and Kingdom Relations, Statistics Netherlands (CBS) calculates figures for each province regarding the number of inhabitants in rural areas for the provincial fund distribution system. This distribution system came into effect on January 1, 1998 (Dutch Official Gazette, 1997, 526).

This definition is the same when filling in the factor “urban area”. The reason why both the factors urban area and rural area are in the model is because sometimes a dike reinforcement project runs through rural areas and urban areas as well.

3.8.3 N2000 area

In order to determine whether a project is situated in a Natura 2000 area it is necessary to understand what a N2000 area is defined as. Natura 2000 is a European network of protected nature areas. In these Natura 2000 areas, certain animals, plants, and their natural habitats are protected to preserve biodiversity (species richness). Biodiversity has been under pressure in Europe for many years, and sustainable protection of flora and fauna is urgently needed. Since plants and animals are not restricted by national borders, it is important to approach nature conservation on a European scale. This helps prevent the natural environment in Europe and the Netherlands from becoming increasingly uniform.

In 1979, the Birds Directive was established, and in 1992, the Habitats Directive. These directives consist of two parts: species protection and habitat protection. All EU member states designate protected areas for specific (habitats of) (bird) species. The protected areas designated under both directives form the Natura 2000 network. To determine whether a project is located in or near a Natura 2000 area, a map developed by the Ministry of Agriculture, Fisheries, Food Security, and Nature was consulted.

3.8.4 Soil type

To determine the type of soil present at a project site, a 1:50,000 scale map developed by Atlas is consulted. This map classifies the soil into several categories: Sand, Loam, Clay, Peat, Sand & Loam, and Loam & Clay. The specific classification helps in understanding the soil's composition and properties, which are essential for planning construction, agricultural projects, or environmental assessments. Each type of soil has unique characteristics that influence its suitability for various types of land use.

For example, sand is known for its high permeability and poor nutrient retention, making it less suitable for intensive agriculture but ideal for drainage or certain types of construction projects. Loam (or Zavel in Dutch), on the other hand, is often considered a more fertile soil because it has a balanced mix of sand, silt, and clay, which allows it to retain water and nutrients better, making it ideal for farming. Clay soils, while rich in nutrients, tend to have poor drainage and can become waterlogged, which can pose challenges for construction but provide rich agricultural land for crops like rice in wetter regions.

Peat soils (Veen) are typically found in wetlands and are rich in organic material. However, they are often prone to subsidence and can be difficult to build on without special considerations. Finally, the mixed categories like Sand & Loam or Loam & Clay indicate areas where the soil is a blend, offering varying degrees of the properties of the individual components.

Understanding the soil type is critical for various industries, including construction, agriculture, and environmental conservation. Soil maps like the one provided by Atlas offer a crucial tool for land use planning by providing detailed information on the nature and composition of the land, allowing for more informed decision-making. Sources like the European Soil Data Centre (ESDAC) and national geological institutes often provide such detailed soil maps. These maps, along with modern digital mapping technologies, are crucial for planning sustainable development and ensuring that the land is used in ways that are compatible with its natural characteristics.

3.8.5 Assessment of dikes

In the Netherlands, dike safety assessments are rated using a grading scale that ranges from A+ to D, with each grade reflecting the condition and performance of a dike or flood defence system. These grades play an essential role in helping water authorities prioritize maintenance and reinforcement efforts. They indicate which dikes meet the required safety standards and which are vulnerable and in need of urgent attention.

The grading system from A+ to D is not only a tool for assessing the current state of dikes but also helps guide maintenance and reinforcement planning. Dikes with C and D ratings are typically prioritized for urgent attention, while those rated A or A+ may only require routine inspections and minor upkeep. This system ensures that resources are allocated efficiently to the most vulnerable areas, enhancing overall flood protection. Additionally, the ratings help authorities implement a risk-based approach to flood management. This means the areas at the highest risk of flooding, especially those protecting densely populated regions or critical infrastructure, receive the most attention. For example, dikes protecting major urban centres or vital economic zones may need to be reinforced even if they still meet basic standards to ensure they can handle future risks such as rising sea levels or increasingly frequent storms due to climate change.

To determine what score a project in the database has conform the LBO-1 safety assessment has, the website of waterveiligheidsportaal is consulted. The Waterveiligheidsportaal (Water Safety Portal) facilitates the exchange of information regarding the processes of assessment and reinforcement of primary flood defences in the Netherlands. At the core of this process is the Water Act of 2017, which provides the legal framework for managing water safety and flood protection throughout the country.

Various parties are involved in these processes. The dike managers, including the water boards (waterschappen) and Rijkswaterstaat (the national water authority), are responsible for maintaining and overseeing the primary water barriers. The Inspectorate of the Environment and Transport (ILT) plays a supervisory role, ensuring that the flood defences meet safety and regulatory standards. The High Water Protection Program (HWBP) is instrumental in coordinating and financing the reinforcement efforts, ensuring that flood defences remain strong and resilient. In addition, the Directorate-General for Water and Soil (DGWB) is responsible for setting policies and ensuring compliance with national water safety regulations.

Together, these organizations ensure that primary water defences across the Netherlands are regularly assessed and reinforced to safeguard the country from potential flooding, following the strict requirements laid out in the Water Act.

3.8.6 Proximity of buildings to the project

This factor determines whether the dike project is situated near existing buildings. It is a binary variable, with the possible outcomes being Yes or No. Proximity to buildings introduces additional challenges and constraints. When buildings are located close to the project site, construction activities may face restrictions due to concerns about noise, vibrations, or disruptions to local residents and businesses. Moreover, working near structures often requires specialized measures to prevent potential damage, such as monitoring for settlement or providing additional stabilization. These constraints can increase both the complexity and cost of the project.

3.8.7 Sea-dike or River-dike

This factor represents whether the dike project is located along a river or a sea. It is a binary variable with two possible outcomes: "Sea" or "River." The distinction between a river and a sea dike impacts various aspects of the project. Sea dikes are often subjected to more extreme tidal forces, saltwater corrosion, and storm surges, necessitating robust construction techniques and materials. In contrast, river dikes typically face challenges related to sediment transport, inland flooding, and variations in water levels. These differences in environmental conditions directly affect the technical requirements, cost, and complexity of reinforcement projects.

In the context of Reference Class Forecasting, this factor contributes to the classification of similar projects by ensuring that the chosen reference class includes projects with comparable environmental challenges. By incorporating this binary variable, the predictive model can account for the unique cost-driving characteristics associated with dikes bordering either rivers or seas, enhancing the accuracy of cost forecasts.

3.8.8 What water authority managed the project?

This factor identifies the specific water authority responsible for managing the dike reinforcement project. It is represented as a categorical variable, with the possible values being the names of different managing authorities. The managing water authority can influence various aspects of the project, including design preferences, regulatory requirements, and resource availability. Different authorities may adopt varying standards, operational practices, and approaches to risk management, which can impact the overall project costs. For example, some authorities might emphasize innovative construction techniques, while others may rely on traditional methods, leading to variations in cost structures and timelines.

Including this factor ensures that projects are grouped with others managed under similar conditions and by comparable authorities. This categorization helps account for regional or organizational differences that can significantly affect project outcomes, improving the accuracy and relevance of cost predictions. By recognizing the role of the managing authority, the forecasting model can better align reference classes with the unique characteristics of each project.

4 Data analysis of Success Factors

In this chapter, a systematic analysis of the collected data is conducted, forming a cornerstone of this research. The data analysis serves a dual purpose: it provides the empirical basis for addressing the research objectives and establishes a theoretical and methodological framework that supports subsequent analyses. This chapter focuses on understanding the relationships between various project characteristics and their impact on the costs per kilometer for dike reinforcement projects, indexed to the year 2024.

The purpose of this analysis is twofold. First, it identifies and quantifies the key factors influencing cost variations using robust statistical methods, including correlation matrices and regression modeling. These tools are used to determine the significance and strength of relationships between independent variables and project costs. Second, and most critically, the findings from this analysis underpin the matching method detailed in the following chapter. By examining the degree of comparability between projects within the HWBP-2 dataset and the HWBP dataset, the analysis provides the foundation for constructing reference classes essential to accurate cost prediction.

The analysis is integral to the functioning of the matching method. The matching method relies on the identification of patterns and relationships that allow projects to be paired with their most comparable counterparts. This pairing is essential to the development of a reference class forecasting model capable of producing reliable and precise cost estimates. Without a detailed understanding of the relationships between variables, such matching would lack the empirical rigor required for robust predictions.

This chapter is organized as follows. It begins with a Correlation Matrix Analysis, which explores the relationships between various project characteristics and provides initial insights into their impact on costs. The chapter then progresses to a detailed Regression Analysis, where the relative importance and predictive power of different variables are examined in depth. These sections collectively establish the statistical basis for the subsequent matching methodology discussed in Chapter 5.

By understanding the underlying factors that drive cost variations and grounding them in theoretical and empirical evidence, this chapter serves as a bridge between the raw data and the methodological innovations presented in the next chapter. Through its findings, it not only advances the understanding of cost dynamics in dike reinforcement projects but also lays the groundwork for methodological advancements that enhance the accuracy and reliability of cost forecasting models.

4.1 Correlation Matrix Analysis

The correlation matrix, table 4 provides an initial understanding of how different variables interact with each other. The full correlation matrix can be found in Appendix H. The table reveals a strong negative correlation between the variable indicating whether a project is located in a rural area (represented as Rural Area [1/0]) and Cost/km (2024), with a correlation coefficient of -0.457. This finding suggests that projects situated in rural settings tend to incur lower costs compared to those in urban settings. Conversely, the Urban Area [1/0] variable demonstrates a positive correlation of 0.432 with Cost/km (2024), indicating that urban projects are generally linked to higher costs. These insights highlight the geographical influence on project expenses.

Further examination of the correlation matrix reveals that the Year of costs variable exhibits a positive correlation of 0.160 with Cost/km (2024). This suggests that as the price level increases, the costs incurred per kilometre are likely to rise as well. Additionally, the presence of a Seadike or Riverdike is associated with lower costs, reflected by their negative coefficients in the matrix. This indicates that projects incorporating these types of dikes tend to be less costly to implement, underscoring the potential cost-saving benefits of utilizing specific infrastructure types.

In the analysis of the correlation between " Cost/km (2024)" (cost per kilometre in 2024) and other variables, several key relationships emerged that help explain the factors influencing project costs. One of the most significant correlations was found between cost per kilometre and the presence of buildings along the dike. Dikes located near built-up areas tend to have higher costs per kilometre, as reflected by the positive correlation (0.314, $p < 0.05$). The presence of infrastructure and construction along dikes adds to the complexity of reinforcement or construction projects. Urban areas require additional considerations, such as protecting existing buildings, utilities, and other services, which can significantly increase the cost and scope of the work involved.

A similar trend is observed when examining the correlation between costs per kilometre and the water boards responsible for the projects. For example, projects managed by the Hoogheemraadschap van Schieland en de Krimpenerwaard show a strong positive correlation with higher costs per kilometre (0.426, $p < 0.01$). This likely reflects the specific challenges faced in the regions under this water board's jurisdiction, such as more densely populated areas or difficult environmental conditions that require more extensive or sophisticated engineering solutions.

Another key finding is the relationship between urban and rural areas and project costs. Dikes located in urban areas (Stedelijk Gebied) exhibit a significant positive correlation with higher costs per kilometre (0.432, $p < 0.01$), while those in rural areas (Landelijk Gebied) show a strong negative correlation with costs (-0.457, $p < 0.01$). This makes intuitive sense, as urban environments tend to present more logistical challenges, including limited space, higher land value, and the need to minimize disruptions to human activities. In contrast, rural areas generally involve simpler projects, with fewer constraints and less complex terrain, leading to lower costs for reinforcement or construction.

Interestingly, while there is a weak negative correlation between costs per kilometre and sea dikes (Seadike) (-0.098), this relationship is not statistically significant. This suggests that, on average, there may not be a large difference in costs between sea dikes and other types of dikes, such as river dikes. Similarly, river dikes (Riverdike) exhibit a very weak and non-significant correlation with cost, indicating that the distinction between dike types (sea vs. river) does not strongly influence the costs associated with reinforcement projects.

In terms of environmental factors, Natura 2000 areas (N2000) show a weak and non-significant negative correlation with costs (-0.119). This suggests that being located near or within a Natura 2000 protected area does not have a strong impact on project costs. However, the restrictions in these areas could slightly limit the extent of construction or reinforcement activities, potentially reducing costs. As the researched dataset is from the HWBP-2 dataset, it is possible that these projects still had a construction exemption for nitrogen deposition. In other words, they did not account for it at that time. After the ruling by the Council of State, this construction exemption has been abolished, meaning that construction now needs to be emission-free or low-emission, which leads to high costs in the projects. This conclusion is drawn because at this moment the HWBP is specifically experiencing that Natura 2000 areas are leading to additional costs. (Linda Kamphuis, 2024)

Regarding the involvement of Rijkswaterstaat and various regional water boards (Waterschappen), the correlation with cost per kilometre varies. While Rijkswaterstaat projects show a slight negative correlation (-0.073), indicating marginally lower costs, this relationship is not statistically significant. Similarly, water boards like Waterschap Aa en Maas and Waterschap Scheldestromen exhibit small negative correlations with costs, though these relationships are weak and not significant, suggesting no major cost differences based on management by these entities.

Finally, there is a negative correlation between costs per kilometre and Afstand tot de norm (-0.287, p = 0.062), which is approaching statistical significance. This suggests that dikes further from their safety norm tend to have slightly higher costs per kilometre. This could be because urgent reinforcement projects, which are farther from the safety norm, may involve more complex and costly interventions, while projects closer to the norm might require less intensive work.

Table 4: Correlation Matrix

	Cost/km (2024)	Rural Area [1/0]	Urban Area [1/0]	Year of costs	Seadike	Riverdike	Development close to dike
Cost/km (2024)	1.000	-0.457	0.432	0.160	0.098	-0.098	0.314
Rural Area [1/0]	-0.457	1.000	-0.345	-0.210	-0.105	0.064	0.098
Urban Area [1/0]	0.432	-0.345	1.000	0.100	0.020	-0.061	-0.094
Year of costs	0.160	-0.210	0.100	1.000	-0.019	-0.009	-0.015
Seadike	0.098	-0.105	0.020	-0.019	1.000	-0.003	-0.004
Riverdike	-0.098	0.064	-0.061	-0.009	-0.003	1.000	0.001
Development close to dike	0.314	0.098	-0.094	-0.015	-0.004	0.001	1.000

4.2 Regression analysis

Following the correlation analysis, a regression model was used to quantitatively assess how well the independent variables predict Cost/km (2024). Regression analysis is widely used to explore relationships between variables and make predictions. Before the results are discussed in section 4.2.2, the assumption of linearity is discussed.

4.2.1 Assumption of linearity

A key assumption in this method is linearity, which posits a straight-line relationship between the dependent and independent variables. Ensuring this assumption is met is critical for the accuracy, reliability, and interpretability of the analysis. Ignoring non-linearity can lead to biased results, invalid inferences, and poor predictions. In this section, the assumption of linearity is checked for all variables that are not binary.

Non-linear relationships, if unaddressed, can result in biased parameter estimates and reduce a model's ability to represent the data accurately (Harrell, 2015). Moreover, statistical inferences, such as p-values and confidence intervals, rely on correctly specified models. Gelman and Hill (2007) note that patterns in residuals often indicate violations of the linearity assumption, compromising hypothesis testing and overall model validity.

Predictive performance also suffers when linearity is incorrectly assumed. A linear model cannot capture complex patterns, leading to underfitting or overfitting. Kuhn and Johnson (2013) emphasize that addressing non-linearity—through variable transformations, polynomial terms, or advanced modeling methods—can significantly enhance predictions. Additionally, preserving the interpretability of coefficients is only possible when the linearity assumption holds, as non-linear effects complicate the interpretation of regression outputs (James et al., 2013).

Table 5: Results of validating the assumption of linearity

Model variable	**P - value**
Year of costs	0,007
Year of costs ^ 2	**0,244**
Length [km]	0,085
Length [km] ^ 2	**0,728**
Afstand_tot_de_norm_encoded	0,527
Afstand_tot_de_norm_encoded ^ 2	**0,875**

Looking at table 5, the following can be concluded. The assumption of linearity is strongly validated for the Year of Costs (linear term), with a significant p-value of 0.007. This indicates that a linear relationship exists between the year of costs and the dependent variable, costs/km. Furthermore, the squared term of the year (p = 0.244) is not statistically significant, suggesting that a non-linear relationship is unnecessary. Together, these findings confirm that the linear form of the variable is sufficient to capture its effect on the dependent variable, validating the linearity assumption for this predictor.

For Length [km], the linear term shows a marginal p-value of 0.085, indicating potentially meaningful linear relationship with the dependent variable. The squared term, however, is highly insignificant (p = 0.728), providing no evidence of a non-linear effect. These results suggest that the linearity assumption is reasonable for this variable, though further exploration, such as variable transformations or interactions, might be warranted to fully validate its contribution to the model.

Finally, for Distance from the norm, both the linear term (p = 0.527) and its squared term (p = 0.875) are statistically insignificant, indicating no clear relationship—linear or non-linear—with kostenkm 2024. Despite this, the absence of a quadratic effect supports the assumption of linearity for this variable in its linear form, even if its overall influence on the dependent variable is minimal.

Concluding, all three non-binary variables fulfil the assumption of linearity and will be used in the regression model as such.

4.2.2 Results of the regression analysis

The regression results, summarized in Table 6, show an R-squared value of 0.764. This suggests that approximately 76.4% of the variability in project costs can be explained by the independent variables included in the model. Such a strong fit indicates that the selected factors are indeed meaningful predictors of costs.

To determine the relative importance of each predictor variable in influencing the target variable, Cost/km (2024) (cost per kilometre in 2024), a linear regression analysis is performed on the completed projects from HWBP-2. Linear regression is widely used in research for estimating relationships between variables and assessing the importance of predictors (Hastie et al., 2009). The regression model calculates coefficients for each predictor, representing its contribution to the variance in Cost/km (2024).

Table 6: Regression Results for Cost/km (2024)

Model variable	**Unstand. B**	**Stand. B**	**P - value**
(Constant)	-5502,295		0,007
Year of costs	2,752	0,495	0,007
Length [km]	-0,811	-0,350	0,085
Rural Area [1/0]	-15,120	-0,435	0,327
Urban Area [1/0]	16,604	0,481	0,310
N2000 [1/0]	8,643	0,235	0,263
Development close to dike	16,034	0,449	0,103
Riverdike	-6,674	-0,169	0,347
Regional Water Authority Hoogheemraadschap van Schieland en de Krimpenerwaard	24,834	0,367	0,075
Rijkswaterstaat	-9,874	-0,166	0,348
Water Board Aa en Maas	-33,381	-0,408	0,056
Water Board Groot Salland	-37,376	-0,327	0,096
Water Board Hollandse Delta	-20,599	-0,504	0,049
Water Board Noorderzijlvest	-24,478	-0,214	0,151
Water Board Rijn en Ijssel	-26,641	-0,233	0,214
Water Board Rivierenland	-9,434	-0,139	0,530
Water Board Scheldestromen	-10,679	-0,158	0,364
Water Board Vallei en Eem	20,365	0,178	0,436
Water Board Fryslân	-26,816	-0,539	0,013
Soil type – peat	2,687	0,033	0,844
Soil type – sand	-1,864	-0,044	0,837
Soil type – sand & loam	-19,477	-0,238	0,150
Soil type – loam	11,792	0,314	0,122
Soil type- loam & clay	26,373	0,490	0,072
Afstand_tot_de_norm_encoded	-1,641	-0,108	0,527
R-squared – 0.764			0.029

The regression model for explaining cost differences in dike reinforcement projects incorporates various statistically significant and theoretically justified predictors. With an R-squared value of 0.764, the model explains a substantial portion of the variance in project costs, and the overall model significance ($p = 0.029$) underscores that these predictors meaningfully relate to cost outcomes. In applied settings like engineering and environmental management, it is often advisable to retain variables that may not reach statistical significance if they hold theoretical importance, as literature and empirical practice underscore the complex, multi-faceted nature of cost dynamics in such projects (Wooldridge, 2016; Keith, 2019).

First, let's address the statistically significant and marginally significant predictors, which are retained in the model based on their clear contributions to explaining cost variability. The Year of Costs variable, significant at $p = 0.007$, shows a strong positive impact on cost, which aligns with known inflationary pressures and general cost escalations over time in infrastructure projects. Including Length of the dike in kilometers, which is marginally significant ($p = 0.085$), is also essential as it may account for economies of scale. According to economic theory, larger projects often benefit from reduced per-unit costs, making Length a theoretically robust predictor (Saha & Muro, 2020). Furthermore, organizations managing the projects—represented by variables such as water board Hollandse Delta and water board Fryslân—show statistically significant cost impacts. These variables reflect the administrative or managerial differences among organizations, which can influence project efficiency, funding allocation, and adherence to standards. Studies suggest that organizational management in public infrastructure projects can have notable effects on costs due to variations in expertise, project oversight, and resources (Love et al., 2015).

For non-significant predictors, we retain several based on their theoretical relevance and the potential for subtle, context-specific impacts on costs, even if their effects are not statistically significant in this particular sample. For instance, Rural Area and Urban Area variables capture geographic differences, potentially affecting costs due to variations in land value, accessibility, and regulatory requirements. While these variables are non-significant here, infrastructure projects in rural areas often have lower land acquisition costs, whereas urban projects may incur higher costs due to denser development and more stringent regulations (McGreal et al., 2012). Similarly, N2000, which likely represents proximity to protected areas under the European Natura 2000 program, is kept for its potential impact on construction restrictions. Environmental preservation requirements frequently impose cost premiums on projects in sensitive ecological zones, as documented by numerous environmental economics studies (Hanley et al., 2001).

Variables related to Beheerder (different managing organizations) are retained as they reflect potential managerial influences that can impact costs due to differences in organizational standards, funding, and resource allocation. Studies on public project management have shown that managerial differences among agencies or organizations can lead to cost variations, as some organizations may prioritize cost efficiency while others may focus on comprehensive quality standards, regardless of cost implications (Flyvbjerg et al., 2003). By including all Beheerder variables, the model provides a complete view of potential cost variability among management bodies, avoiding biases that might arise from selectively omitting certain organizations.

Soil types (Bodemtype variables), though not statistically significant, remain in the model due to their practical relevance in dike reinforcement projects. Soil composition (e.g., peat, sand, loam) can significantly impact the structural requirements and methods needed for reinforcement, affecting overall costs (Heathcote, 2010). For example, loamy or clay-rich soils might require additional reinforcement measures to ensure dike stability, thereby increasing costs. Including these soil types in the model ensures that important geotechnical factors are accounted for, even if their statistical effects are not prominent in this particular sample.

Finally, Afstand_tot_de_norm_encoded, representing proximity to regulatory standards, is retained due to its potential influence on cost outcomes, despite its high p-value. Proximity to engineering or safety norms could drive specific design decisions and adjustments that may impact cost. Engineering literature suggests that adherence to regulatory standards often results in additional costs, particularly in highly regulated fields like water management and infrastructure (Askar et al., 2021).

In conclusion, while statistical significance is a critical criterion in model-building, theoretical and practical considerations also play a vital role in applied contexts. Retaining variables that may not be statistically significant but are theoretically justified, such as management organization, environmental designations, soil types, and project geography, allows the model to align with established insights from infrastructure and environmental economics literature. This approach provides a balanced perspective, ensuring the model captures both statistically evident and theoretically grounded influences on dike reinforcement project costs.

Among the variables, Year of costs is a significant predictor with a p-value of 0.007, indicating that a later start of the projects is associated with increased costs per kilometre. Despite the robust findings, potential multicollinearity was noted among several predictors, which could affect the reliability of the coefficient estimates. Therefore, while the results provide valuable insights into the factors influencing Cost/km (2024), caution should be exercised in interpreting these relationships.

4.3 Conclusion

In conclusion, the cost per kilometre of dike projects in 2024 is most strongly influenced by whether the project is located in an urban or rural area, as well as the presence of construction and infrastructure along the dike. Urban areas and developed regions present greater logistical challenges, driving up the cost of reinforcement and construction projects. The specific water board managing the project also has an impact, with some regions exhibiting higher costs due to particular geographic or environmental challenges. However, factors such as soil type and proximity to Natura 2000 areas have little to no significant influence on the cost, based on the weak correlations observed. The regression model reveals several key insights into the factors influencing the cost per kilometre of dike projects. The most significant predictors include Year of costs, which shows that higher price levels are associated with increased project costs, and management by specific water boards such as Wetterskip Fryslân, which tends to reduce costs. Soil types, particularly zavel & klei, are also important in explaining cost variations. While some variables, like urban/rural location and buildings along the dike, exhibit expected relationships, their lack of statistical significance suggests the need for further investigation into how these factors interact with others in influencing project costs. The choice is made to keep insignificant variables into the model because of the theoretical en practical influence on the price of dike-reinforcements.

5 Regression Weighted RCF

In this section the model that has been developed will be discussed, this model will be called the "Regression weighted Reference Class Forecast model" or RWRCF. In chapter 4 an analysis is conducted on the importance of each factor on the costs/km of the dike reinforcements. This analysis forms the basis for selecting the right projects as a reference class for each project in in the HWBP database. Section 5.2 will explain further how projects are matched. The regression weighted reference class forecasting method uses several factors to create distinct reference classes for project cost predictions. In the traditional reference class forecasting method, a reference class would be selected of comparable projects. The forecast is then based on those comparable projects. The method researched in this thesis tries to establish which projects in the reference class are most suitable for forecasting the price of each individual project. When the reference class of each project is established, the model will use the average of the costs per kilometre of each reference class to predict the price for each project. In table 7, the differences between the RWRCF-model and the traditional RCF-model are highlighted.

Table 7: Characteristics of the RWRCF-model and the traditional RCF-model

	Regression Weighted RCF-model	**Traditional RCF-model**
General Approach	Utilizes the weighted similarity scores based on a set of predictor variables. This allows for more precise matching of projects by considering detailed characteristics and their relative importance. The RWRCF approach is based on techniques used in multi-criteria decision making. This provides a customized distance metric for each project (Zhang et al., 2006).	Selects a reference class based on general project similarities. The selection process is broader, focusing on overarching characteristics without a detailed analysis of individual factors. This method can overlook specific project nuances, leading to less precise predictions.
Factor importance	Importance of factors is derived from regression analysis. Each predictor variable is assigned a weight based on its relative impact on the target outcome (Cost/km), ensuring that the model prioritizes the most significant variables. The weights are normalized to allow for comparison across variables (James et al., 2013; Hastie et al., 2009).	Uses general factors without specific weighting. The traditional method does not quantify the relative importance of each predictor, leading to potential biases and less accurate matching. Factors are considered equally or based on subjective judgment.
Transparency	High transparency, as the model identifies exact-matched factors for each project pair. This allows decision-makers to understand the basis of each match and increases transparency in similarity-based recommendations. The method records specific factors that match exactly, enhancing interpretability (Li et al., 2018).	Lower transparency, as it does not provide specific factor matching. The traditional model relies on general project similarities without detailing which factors influenced the match, making it less clear how recommendations are derived.
	High accuracy due to the inclusion of detailed project attributes and their impact on costs. The regression-weighted model takes into account various specific characteristics, leading to more precise cost predictions and better alignment of projects (James et al., 2013).	Lower accuracy due to generalized criteria. The broader approach of the traditional model may not capture the specific influences on project costs, leading to less precise predictions and potential misalignments in project matching.
Data requirements	Requires detailed and specific data, including various predictor variables and their historical values. The need for comprehensive data ensures precise and reliable matching and predictions.	Requires less detailed data, focusing on broader project similarities. This simplicity can be an advantage when detailed data is not available but may reduce prediction accuracy.
Ease of application	More complex to implement due to the need for regression analysis and detailed data handling. This complexity can be a barrier to adoption but provides more accurate results.	Easier to implement, as it relies on general project similarities without the need for detailed data analysis. This simplicity can make it more accessible but at the cost of precision.

One important factor is year of costs, which adjusts for price indexation to account for inflation or changes in costs over time. Additionally, the location of the project plays a significant role, with distinctions made between projects in rural areas and those in urban areas. Whether the project is located within or near a Natura 2000 protected area is also considered, as these areas often have specific environmental restrictions that can influence project costs. The presence of buildings or infrastructure along the dike is another factor, which can increase project complexity and costs. The type of dike, specifically whether it is a river dike, is also used in determining the reference class.

The managing authority, such as Rijkswaterstaat or one of the various regional water boards, is taken into account, as different organizations may handle projects with varying approaches and resource allocations. The type of soil at the project site, including categories like sand, loam, peat, clay, and their combinations (such as loam & clay or sand & loam), is another important factor. Finally, the distance to the safety norm—which affects the urgency and complexity of the project—is also considered in the model. By combining these factors, the method enables more accurate matching of new projects with historical ones that share similar characteristics, leading to improved cost predictions.

5.1 Data usage

The model used in this research is built upon a database from the HWBP-2 programme, which consists of data on 43 dike reinforcement projects. These projects contain detailed information, including the finished and reported costs of each project. In order to allow for a direct comparison between projects completed in different years, the cost per kilometre for all projects has been indexed to the year 2024. This indexing is achieved using the GWW index sheet from the CBS, ensuring that inflation and changes in construction costs over time are accounted for.

Each of the 43 projects is evaluated based on a set of factors identified through literature review and interviews. These factors include various project-specific characteristics, such as length, soil type, and environmental constraints. The factors used in the model are significant, as they explain 76.4% of the variation in project costs. Rather than relying on a single reference class for cost predictions, the model generates multiple reference classes based on the unique combination of factors for each project. This allows for more accurate and tailored cost predictions for future projects.

The same HWBP-2 database is then used to predict costs for 28 completed projects from the newer HWBP programme. As with the earlier set of projects, the costs for these 28 projects have been indexed to 2024 using the GWW index sheet from CBS, ensuring consistency in comparisons across all projects. Each of the new projects is then scored on the same factors as the original 43 projects, ensuring that the model remains comparable and consistent in its application.

5.2 Methodology for Project Matching Based on Regression-Weighted Factor Importance

In this study, a data-driven approach to match dike reinforcement projects by using multiple predictor variables and their relative importance was developed. The primary objective was to find optimal project matches between two datasets, HWBP-2 (reference class dataset) and HWBP (forecasted projects). Using weighted factors derived from a regression analysis. This method aligns with techniques in predictive modelling and weighted similarity analysis, which are commonly used in fields such as recommender systems, machine learning, and multi-criteria decision making.

5.2.1 Normalizing Weights

The coefficients obtained from the regression analysis were converted into normalized importance weights by dividing the absolute value of each coefficient by the sum of all coefficients' absolute values. Normalizing the coefficients allows for a comparison of importance across variables on a unified scale, preventing any one variable from disproportionately affecting the match score due to differing units of measurement (James et al., 2013).

5.2.2 Calculation of Weighted Match Scores

For each project in the projects that need to be forecasted, a minimum of 2 matching projects in HWBP-2 dataset were found by calculating a weighted match score. This score was derived from the weighted sum of absolute differences between the values of corresponding predictor variables in HWBP-2 dataset and HWBP dataset. The match score computation followed the formula:

$$Weighted\ Match\ Score = \sum_{i=1}^{n} w_i * |x_{ij} - y_{ij}|$$

where w_i is the weight of the i^{th} variable, x_{ij} and y_{ij} are values of the i^{th} predictor for a project that is forecasted and for a project in the reference class, respectively, and n is the number of predictor variables.

5.2.2.1 Selection of Best Matches

After computing the weighted match scores, projects in the reference class were ranked for each project in database with forecasted projects. The project(s) with the lowest weighted match score(s) were selected as the best matches, indicating the highest similarity based on the weighted factors. This approach follows the principles of weighted nearest neighbour methods, which prioritize closer matches based on a customized distance metric (Zhang et al., 2006).

5.2.2.2 Identification of Matched Factors

To enhance interpretability, specific factors that matched exactly for each project pair were recorded. A factor was deemed matched if the absolute difference between values was zero, allowing decision-makers to understand the basis of each match and increasing transparency in similarity-based recommendations (Li et al., 2018).

5.2.2.3 Conclusion

In conclusion, this study developed a data-driven, weighted similarity approach to match dike reinforcement projects by leveraging predictor variables and their relative importance, allowing for optimal project comparisons between the HWBP-2 reference dataset and forecasted HWBP projects. This method combines insights from regression-derived weights with reference class forecasting. By normalizing the predictor weights, the analysis avoided the influence of variable scale discrepancies, a step crucial for achieving accurate similarity scores (James et al., 2013).

The calculated weighted match scores facilitated the identification of the most comparable projects for each forecasted project by ranking based on similarity, emulating weighted nearest-neighbour methods (Zhang et al., 2006). Through this process, the projects with the lowest scores were selected as optimal matches, thus enhancing project alignment based on empirical data rather than subjective selection. Additionally, identifying exact-matched factors for each project pair provides greater transparency, ensuring decision-makers can clearly assess the criteria driving each recommendation (Li et al., 2018). This structured, data-driven method lays a foundation for more robust predictive alignment in dike reinforcement and similar large-scale infrastructure projects, ultimately supporting better-informed cost estimations and project outcomes.

5.3 Calculation of weights

To effectively match projects based on multiple factors, we applied a weighted matching approach in which each predictor variable is assigned a weight based on its relative importance in predicting the cost per kilometre (Cost/km (2024). This weighting process allows us to prioritize variables that significantly impact the cost, ensuring that projects are matched based on the most relevant criteria. The following steps outline the calculation of these weights and the rationale for their use in our matching model.

5.3.1 Determining Factor Importance through Regression Analysis

The first step involved performing a linear regression analysis on the projects in the reference class to model the relationship between Cost/km (2024) (the target variable) and various predictor variables. Linear regression is widely utilized in econometric and predictive modelling applications to quantify the effect of multiple factors on a target outcome (Hastie et al., 2009). Here, we used the regression coefficients to estimate the influence of each predictor on project costs.

The regression model generated coefficients for each predictor variable, with each coefficient representing the estimated change in Cost/km (indexed for the year: 2024) for a unit change in the predictor, holding all other factors constant. The predictor variables included both categorical and continuous factors relevant to project characteristics, such as geographical type indicators (Rural Area [1/0], Urban Area [1/0]), environmental constraints (N2000 [1/0]), structural properties (Riverdike, Seadike), and soil types (Bodemtype variables).

5.3.2 Normalizing Regression Coefficients to Weights

To translate the regression coefficients into weights for the matching process, we used a normalization process that converts each coefficient into a proportion of the total absolute effect size across all predictors. This approach ensures that the sum of all weights equals 1, allowing us to compare factors on a consistent scale and effectively apply them in a matching algorithm.

The weight for each predictor iii was calculated as follows:

$$Weight_i = \frac{|Coefficient_i|}{\sum_{j=1}^{n} |Coefficient_j|}$$

where Coefficient_i is the absolute value of the regression coefficient for predictor i, and n is the total number of predictors. By using absolute values, we focus on the magnitude of each factor's effect on Cost/km (2024), regardless of direction, ensuring that both positive and negative influences are treated as indicators of importance (James et al., 2013).

This normalization yielded a set of weights that reflect each variable's relative importance in explaining the variability in project costs. The table in Appendix X summarizes the coefficients, normalized weight calculations, and final weights for each predictor.

5.3.2.1 Applying Weights in the Matching Score Calculation

Once the normalized weights were established, they were applied in the matching process. This formula is shown before in section 5.2.2. For each project in forecasted dataset, a weighted match score is computed with projects in the reference class dataset based on the sum of weighted absolute differences between corresponding predictor variables:

$$Weighted\ Match\ Score = \sum_{i=1}^{n} Weight_i * |x_{ij} - y_{ij}|$$

where:

- x_{ij} is the value of the i^{th} predictor for a project in the forecasted dataset.
- y_{ij} is the value of the i^{th} predictor for a project in the reference class dataset.

5.4 Conclusion

This study developed a data-driven approach that enhances Reference Class Forecasting (RCF) for dike reinforcement projects by incorporating multiple predictor variables and their relative importance, allowing for more accurate cost predictions. Traditional RCF often selects a reference class based on general project similarities, which can overlook specific factors that significantly impact project costs. By weighting predictor variables based on their calculated influence, this approach aligns with methodologies in predictive modeling and decision support systems, such as those described by James et al. (2013) and Hastie et al. (2009), ensuring that each variable's impact is proportionate to its cost significance.

The Regression weighted model integrates several factors like environmental constraints, project location, and soil type, weighted according to regression-derived importance scores. This factor-based approach in predictive modeling has been shown to improve accuracy by considering detailed project attributes, similar to the approaches in machine learning and multi-criteria decision-making (Zhang et al., 2006; Li et al., 2018). Additionally, the method's use of normalized weights ensures that all predictors are on a unified scale, enhancing the model's adaptability across various project contexts (James et al., 2013).

By using a weighted similarity score, this enhanced RCF model effectively identifies optimal historical project matches, a process akin to weighted nearest-neighbour methods (Zhang et al., 2006), improving both the accuracy and relevance of cost forecasts. The approach's ability to identify exact-matched factors provides increased transparency, supporting clearer insights into the rationale behind each prediction (Li et al., 2018). Overall, this refined RCF methodology offers a more accurate, objective, and transparent tool for cost estimation in dike reinforcement, potentially setting a foundation for improved prediction models in other large-scale infrastructure projects. The table with the weights for each variable can be found in appendix E, and the table that indicates what projects were used to predict the costs can be found in appendix F.

6 Results

This chapter presents a comparison between the forecasted costs from the Regression weighted reference class model and the actual costs for individual dike reinforcement projects. It evaluates how well the RWRCF model performs compared to the traditional Reference Class Forecasting (RCF) method in terms of accuracy, consistency, and ability to predict project costs. The chapter begins with a project-by-project comparison, looking at forecasted costs per kilometer alongside the actual costs. Next, the chapter examines the overall distribution of costs to see how closely the model's predictions align with the real costs, highlighting any patterns or differences. Key performance metrics, such as the standard deviation of errors, R-squared, MSLE, sMAPE, and MASE, are then used to give a clearer picture of how each approach performs.

6.1 Comparing both models to realised results for individual projects

In this section a comparison is made between the forecasted results generated by the developed model and the realised results.

6.1.1 Forecast results costs per kilometre (RWRCF)

Figure 6.1.1 presents a comparison between the realized (actual) costs and the forecasted costs per kilometre for 28 dike reinforcement projects. The blue bars represent the actual costs per kilometre in millions of euros, while the orange bars depict the model's cost predictions for each project. This comparison provides insight into the accuracy and consistency of the model's forecasts relative to the actual costs observed in the HWBP dataset.

Several key observations can be made from the chart. For many projects, the forecasted costs align closely with the realized costs, suggesting that the model is effective in providing reliable estimates for a substantial portion of the dataset. However, certain projects display noticeable discrepancies between the forecasted and realized costs. Notably, in projects 4, 5, 13, and 28, the model's predictions significantly differ from the actual costs, with some underestimations and overestimations evident. These deviations suggest that specific project characteristics may introduce complexities that the model does not fully capture, or they may indicate unique factors influencing the actual costs, such as unexpected challenges or variations in resource allocation.

Overall, the model demonstrates a reasonably good fit across most projects, with a tendency to maintain close proximity to the realized costs per kilometre. The alignment for the majority of the projects indicates the model's strength in handling typical cost drivers for dike reinforcements. However, the instances of larger variances highlight potential areas for model refinement, suggesting that further consideration of project-specific nuances could improve forecast accuracy. The RWRCF model predicted an average cost per kilometre of 7.950 million euros. While the average realised cost per kilometre is 8.079 million euros per kilometre. Indicating that the RWRCF model is in this form more fit to forecast costs on programme level in stead of individual level.

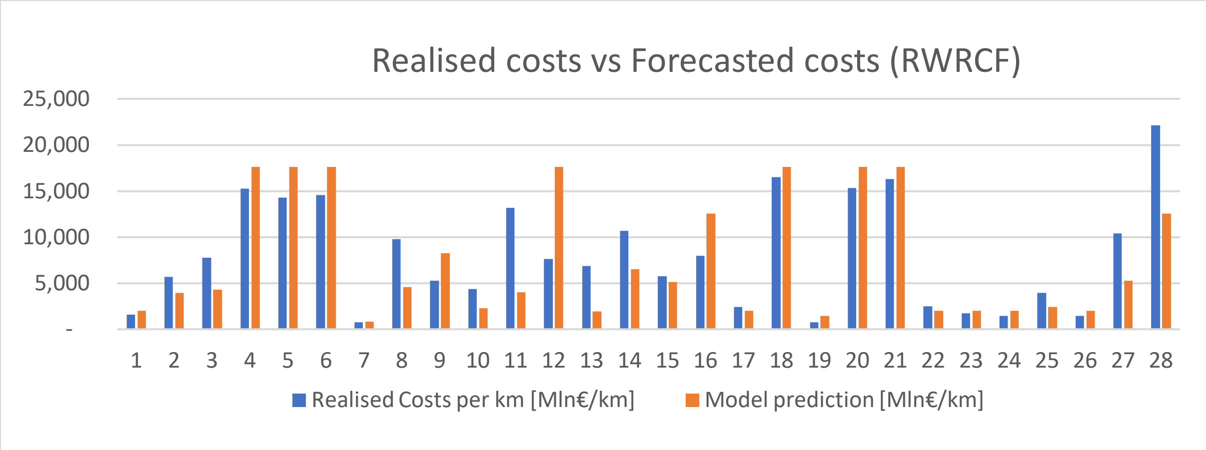

Figure 6.1.1: Realised costs vs forecasted costs per kilometre

6.1.2 Distribution of project costs per kilometre (RWRCF)

Following the initial comparison between realized and forecasted costs, the distribution of costs per kilometre, as shown in the Figure 6.1.2, offers additional insights into the characteristics of the model's predictions versus actual project costs. In this histogram, the orange bars represent the forecasted costs per kilometre for the projects, while the blue bars show the actual costs. The overlaid lines represent normal distribution fits for each dataset, with the red line indicating the distribution of the predicted costs and the blue line showing the actual costs. The x-axis represents cost categories in millions of euros, ranging from €0–€5 million up to €45–€50 million per kilometre. These categories define the cost ranges within which projects are grouped. On the primary y-axis (on the left), the frequency of projects within each cost category is displayed, indicating how many projects fall into each range. Meanwhile, the secondary y-axis (on the right) shows the relative probability density of costs, based on normal distribution curves for both predicted and actual costs.

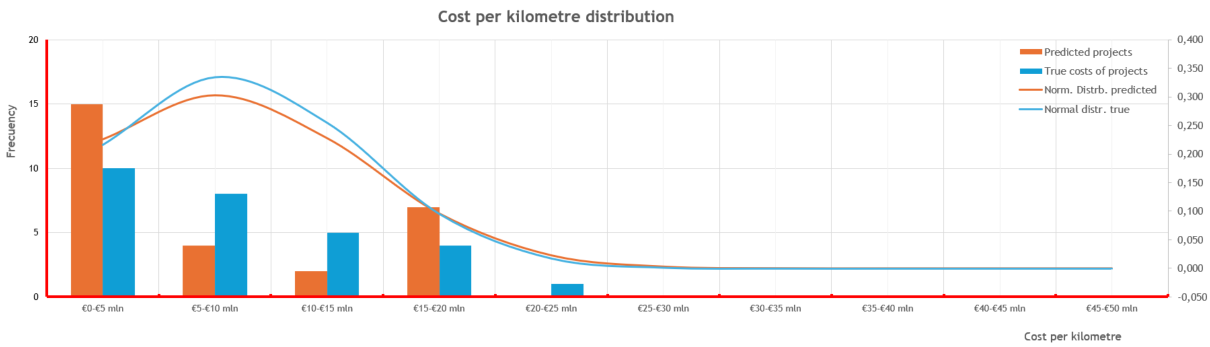

Figure 6.1.2: Cost per kilometre distribution, forecasted vs realised

From the distribution, we can observe that the forecasted and realized costs per kilometre have generally similar shapes, both displaying a right-skewed distribution. This suggests that while most projects cluster within lower cost ranges, there are a few projects with significantly higher costs per kilometre that extend the tail of the distribution. The alignment between the two distributions' shapes indicates that the model effectively captures the general pattern of cost variation across projects, even though there are some differences in specific cost ranges.

However, there are some noticeable differences in frequency within certain cost bands. For instance, the predicted costs show a higher concentration in the €0-€5M/km range compared to actual costs, which are more spread across the €5-€10M/km and €10-€15M/km ranges. This discrepancy suggests that the model may have a slight tendency to underestimate costs in certain cases, especially for projects with moderate to high complexity or unique characteristics that drive up costs per kilometre.

The normal distribution fit lines help in visualizing the alignment between predicted and realized costs further. The peak of the actual cost distribution appears to be slightly shifted toward higher costs compared to the predicted distribution. This shift highlights potential areas for improvement in the model, as it may not fully capture certain cost-inflating factors in specific project conditions, such as geographical, environmental, or regulatory constraints.

6.1.3 Percentage difference regression weighted reference class forecasting method

Figure 6.1.3 shows the percentage difference between the forecasted costs per kilometer from the RWRCF model and the realized costs. On the X-axis, the different projects are numbered. On the Y-axis, the percentage difference between the actual costs and the forecasted costs are shown. The data points are scattered, indicating variability in the model's accuracy across projects. Each data point, shown as a green dot, represents the percentage difference for a specific project. The position of the dot on the y-axis shows whether the RCF was higher or lower than the actual realized costs. In addition to the dots, error bars extend vertically from each point, representing the variability or uncertainty in the percentage difference. Wider error bars indicate greater uncertainty or variability in the data for that specific project.

While some predictions are close to the actual costs, as seen in points clustering around the 0% difference line, there are still several instances of under- or over-estimations. Although many variations remain within ±100%, this range of error suggests that the model's predictions could be improved. The model appears to incorporate project characteristics reasonably well, but the level of variability highlights the need for further refinement to achieve more consistent accuracy across different projects.

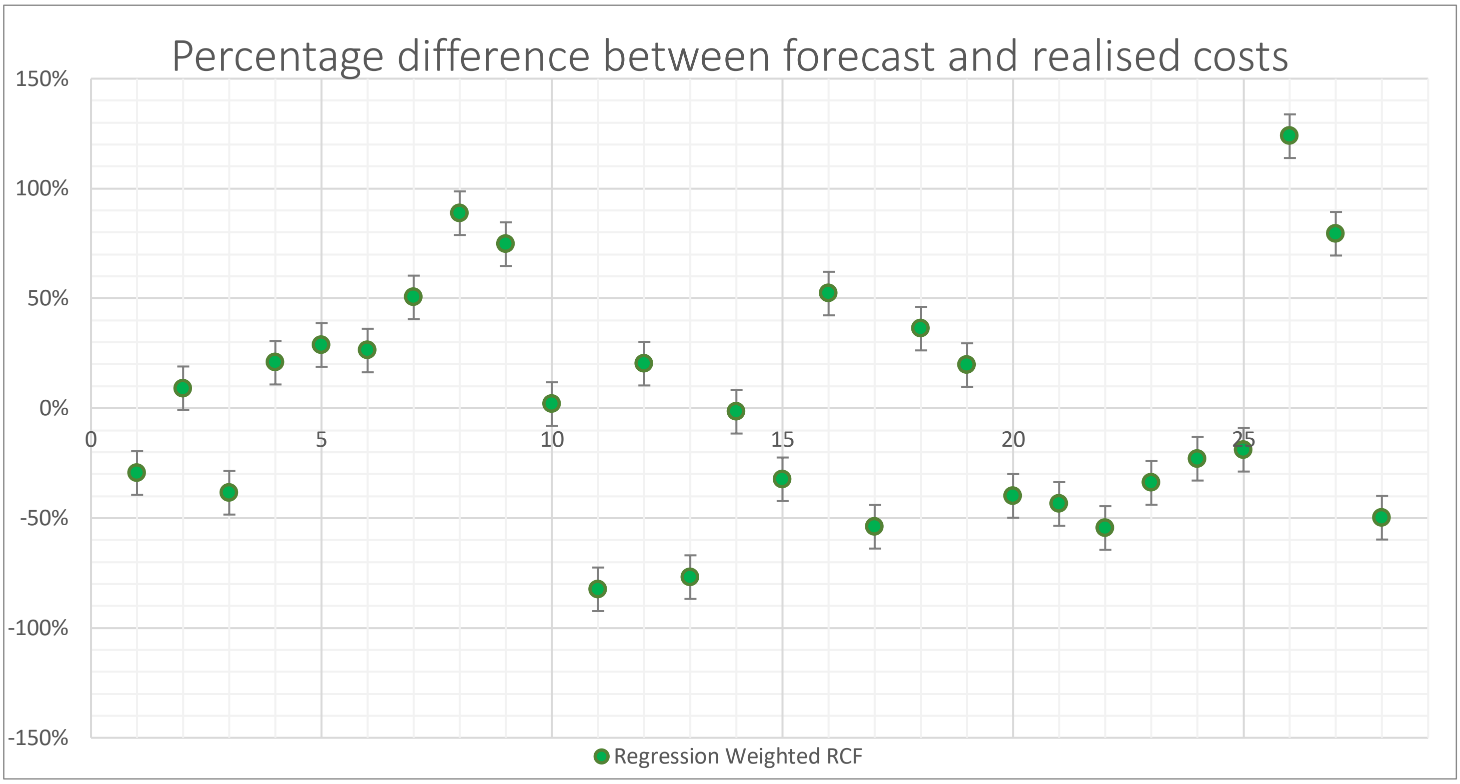

Figure 6.1.3: percentage difference between forecast/km and realised costs/km

6.1.4 Percentage difference traditional RCF method

In contrast, the second chart, which represents the percentage difference between the traditional RCF forecasts and realized costs, reveals significantly larger deviations. The red dots represent the percentage difference for each project, with their vertical position on the y-axis indicating the extent of overestimation or underestimation. Surrounding each red dot are error bars, which indicate the variability or uncertainty in the percentage difference for that specific data point. Wider error bars suggest a greater degree of uncertainty or variability in the data. Many data points show percentage differences well above 100%, with some even exceeding 1000%, indicating substantial overestimation in some cases.

From the figure, it is evident that there are extreme cases of overestimation by the traditional RCF, with some projects showing percentage differences exceeding 1400%. This suggests that for these projects, the traditional RCF significantly overestimated the realized costs. At the same time, other projects cluster closer to 0%, where the traditional RCF aligns more closely with the realized costs. A smaller number of projects exhibit negative values, indicating underestimation, although this is less frequent compared to overestimations. The error bars vary in size across projects, indicating differing levels of confidence in the accuracy of the calculated percentage differences.

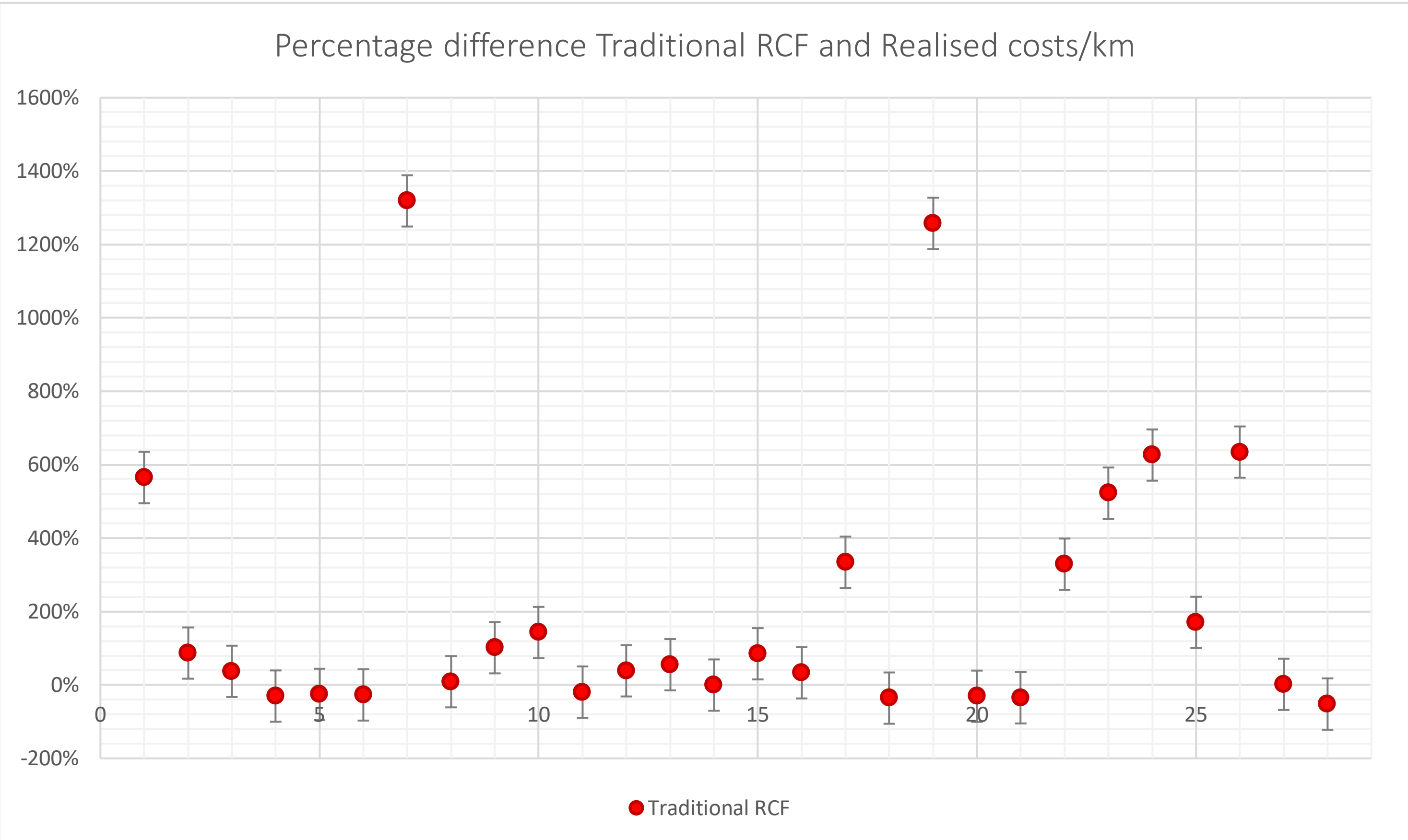

Figure 6.1.4: percentage difference traditional RCF and realised costs

In conclusion, Figure 6.1.4 highlights that traditional RCFs often overestimate project costs per kilometre, with some extreme outliers showing significant overestimations. While some projects align more closely with realized costs, the figure underscores the limitations of traditional RCF as a predictive tool, suggesting the need for more accurate and adaptive estimation methods.

This level of deviation highlights the limitations of the traditional RCF method when applied to dike reinforcement cost forecasting. The traditional RCF approach often relies on a broad, generalized reference class without specific project-level adjustments, which can result in predictions that are either too high or too low, failing to capture the unique characteristics of individual projects.

6.1.5 Interpretation of Results

The comparison between the two charts underscores the advantages of the RWRCF model over the traditional RCF approach in terms of both accuracy and reliability. The RWRCF model demonstrates tighter clustering around the 0% line, suggesting it is more effective in providing realistic estimates that are closely aligned with actual project costs. The traditional RCF method, on the other hand, shows substantial variability and significant overestimations for certain projects, which may stem from its generalized approach that lacks tailored adjustments for individual project factors.

Figure 6.1.5, titled "Comparison between RWRCF and Traditional RCF," compares the percentage differences between predicted project costs using Regression Weighted Reference Cost Factors (RWRCF) and Traditional Reference Cost Factors (RCF) against actual realized costs. This comparison is visualized through green and red dots, representing RWRCF and Traditional RCF, respectively, for various projects. The figure highlights how each method performs in estimating costs.

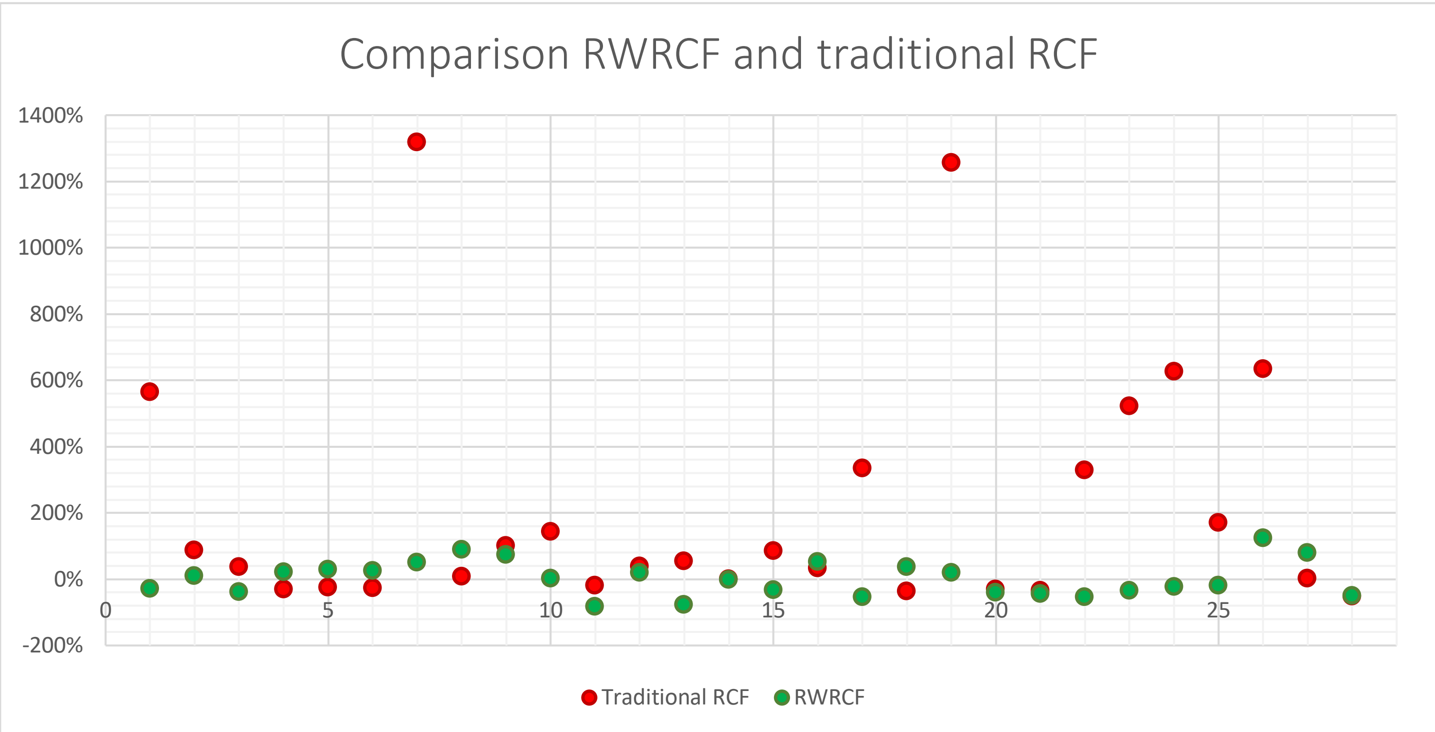

Figure 6.1.5: Comparison between RWRCF and traditional RCF in percentages

The x-axis represents a sequence of projects or data points, each corresponding to a specific project or category. The y-axis shows the percentage difference between predicted and realized costs, with values ranging from -400% to 1400%. Positive values indicate overestimation by the method, while negative values represent underestimation. The proximity of the dots to 0% indicates the accuracy of each method in predicting realized costs.

The green dots, which represent the Regression Weighted RCF, cluster more closely around the 0% line, showing that RWRCF predictions generally align better with realized costs. In contrast, the red dots, representing Traditional RCF, display much greater variability, with many projects showing significant overestimation of costs. For some projects, the red dots reach extreme outliers, exceeding 1000%, indicating that the Traditional RCF method substantially overestimated costs for those cases.

This analysis indicates that the RWRCF model provides a more precise and reliable method for predicting dike reinforcement costs compared to traditional RCF. By incorporating multiple weighted factors and dynamically adjusting the reference class based on project-specific characteristics, the RWRCF model offers a refined approach that reduces large deviations, as seen in the traditional method. This improvement in forecast accuracy supports the model's potential as a valuable tool for cost planning and budgeting in large-scale infrastructure projects, where precision is essential to manage resources effectively and minimize unexpected costs.

6.2 Comparing RWRCF to the traditional RCF

This section evaluates the performance of the RWRCF predictive model and the traditional Reference Class Forecasting (RCF) method in estimating project costs. The aim is to compare the two approaches across several performance metrics to assess their accuracy, consistency, and predictive power. Metrics such as standard deviation of errors, R-squared, Mean Squared Logarithmic Error (MSLE), Symmetric Mean Absolute Percentage Error (sMAPE), and Mean Absolute Scaled Error (MASE) each offer unique insights into the model's effectiveness. By analysing these indicators, the study highlights where the RWRCF model outperforms traditional RCF, showing improved reliability and precision.

Table 8: performance metrics regression model vs traditional reference class model

Metric	**RWRCF/km**	**RCF/km**	**RWRCF (total costs)**	**RCF (total costs)**
Standard Deviation of Errors	2.92	5.58	3.54	6.40
R-Squared	0.45	0.23	0.52	0.34
Adjusted R-Squared	0.43	0.20	0.50	0.31
MSLE	0.02	0.05	0.03	0.08
Median Absolute Error	1.67	4.20	2.10	5.05
sMAPE	20.35%	55.68%	18.90%	48.75%
MASE	1.20	2.45	1.15	2.67

In evaluating the forecasting performance of both the RWRCF model and the traditional Reference Class Forecasting (RCF) method, several key metrics were analysed to assess accuracy, consistency, and overall predictive power. Each metric provides unique insights into the model's effectiveness and reliability compared to the traditional approach, highlighting areas where the RWRCF model offers notable improvements in prediction accuracy and consistency. Each metric will be tested on the performance of the model including success factors and on the traditional Reference Class Forecasting method. An overview is shown in table 8.

6.2.1 Standard Deviation of Errors

The standard deviation of errors indicates the consistency in forecasting performance across projects. For the RWRCF model, the standard deviation of errors was 2.92 per km and 3.54 for total costs, while the traditional Reference Class Forecasting (RCF) method showed higher deviations of 5.58 per km and 6.40 for total costs. This substantial difference implies that the RWRCF model’s predictions are more stable and generally closer to actual costs, reflecting a more reliable forecasting method. A lower standard deviation is typically preferred, as it shows that errors remain controlled and consistent, making the model more dependable for cost estimation (Jorgensen et al., 2009). In contrast, the higher standard deviation in the traditional RCF forecasts suggests broader variation, leading to less dependable cost predictions and increased risk of significant deviations from actual costs.

6.2.2 R-Squared and Adjusted R-Squared

R-squared values represent the proportion of variance in actual costs that each model can explain. Higher R-squared values indicate a better model fit. For the RWRCF model, R-squared scores were 0.45 per km and 0.52 for total costs, while the traditional RCF method showed lower values of 0.23 per km and 0.34 for total costs. This suggests that the RWRCF model better captures cost variability, indicating a stronger alignment with actual cost drivers. Adjusted R-squared values, which correct for model complexity, also supported these findings, with the RWRCF model achieving values of 0.43 per km and 0.50 for total costs compared to 0.20 per km and 0.31 in the traditional RCF method. Higher adjusted R-squared values demonstrate that the RWRCF model avoids unnecessary complexity, fitting the data effectively without overfitting, a common goal in predictive modelling (James et al., 2013).

6.2.3 Mean Squared Logarithmic Error (MSLE)

Mean Squared Logarithmic Error (MSLE) emphasizes how well each model handles underestimations, with a heavier penalty for under-prediction errors, which can be more problematic in cost forecasting contexts (Hyndman & Athanasopoulos, 2018). The RWRCF model achieved MSLE values of 0.02 per km and 0.03 for total costs, significantly lower than the traditional RCF method's 0.05 per km and 0.08 for total costs. This lower MSLE suggests the RWRCF model is better at avoiding severe underestimations, which can have costly consequences in infrastructure projects. The traditional RCF's higher MSLE indicates more frequent and pronounced underestimations, reducing its reliability in cases where under-prediction poses substantial risks.

6.3 Median Absolute Error

The median absolute error (MAE) is less affected by outliers, providing a stable measure of typical prediction errors (Zou et al., 2007). For the RWRCF model, the median absolute error was 1.67 per km and 2.10 for total costs, compared to the traditional RCF method's 4.20 per km and 5.05 for total costs. This indicates that, on average, the RWRCF model yields a smaller forecasting error, making it more reliable for typical project cost estimates. The lower median error for the RWRCF model suggests that most of its predictions are closer to the actual costs, while the traditional RCF model shows larger variations, indicating a tendency toward less accurate forecasts.

6.3.1 Symmetric Mean Absolute Percentage Error (sMAPE)

Symmetric Mean Absolute Percentage Error (sMAPE) provides a balanced view of the model's performance, treating over- and under-predictions equally. Lower sMAPE values are preferred, as they reflect closer alignment with actual values (Kim & Kim, 2019). The RWRCF model achieved sMAPE values of 20.35% per km and 18.90% for total costs, compared to the traditional RCF method's much higher values of 55.68% per km and 48.75% for total costs. These results indicate that the RWRCF model is significantly more accurate, with errors almost half that of the traditional RCF approach. The high sMAPE in the traditional RCF method underscores its struggle with large forecasting errors, while the lower sMAPE in the RWRCF model highlights its balance and accuracy.

6.3.2 Mean Absolute Scaled Error (MASE)

Mean Absolute Scaled Error (MASE) compares model performance to a naive benchmark, with values close to or below 1 indicating that the model performs as well as or better than a simple forecast based on historical averages (Hyndman & Koehler, 2006). The RWRCF model achieved MASE values of 1.20 per km and 1.15 for total costs, showing close alignment with the naive benchmark. In contrast, the traditional RCF method showed MASE values of 2.45 per km and 2.67 for total costs, far exceeding the benchmark. This result suggests that the traditional RCF method underperforms relative to a simple prediction approach. The near-benchmark MASE values of the RWRCF model indicate that it performs nearly as well as a basic historical average, while also benefiting from tailored, data-driven insights, making it a more effective tool for cost forecasting.

6.4 Conclusion

In summary, the analysis of these metrics demonstrates that the RWRCF model consistently outperforms the traditional RCF method across all key indicators. The RWRCF model's lower standard deviation of errors reflects more consistent and reliable forecasts. The higher R-squared and adjusted R-squared values indicate a better fit to actual data, while the lower MSLE, median absolute error, and sMAPE confirm that the RWRCF model provides more accurate predictions. The MASE scores further emphasize the effectiveness of the RWRCF model, showing that it performs comparably to a naive benchmark, whereas the traditional RCF method falls significantly short. Collectively, these results underscore the RWRCF model's superiority in forecasting project costs, providing a robust, accurate, and reliable tool for cost prediction that significantly enhances upon the limitations of the traditional RCF approach.

7 Discussion & Limitations

In this research, the effectiveness of enhancing Reference Class Forecasting by incorporating success factors has been analysed. The objective was to contribute to the understanding of the critical role of comparability when applying Reference Class Forecasting to project forecasting. The study aimed to provide deeper insights into how the integration of project-specific success factors could refine the accuracy and reliability of forecasts by ensuring that the selected reference class aligns more closely with the project under consideration.

This section presents a reflection on the research findings, discussing their implications and how they align with existing literature on forecasting methods. Additionally, it addresses the limitations of the study, exploring potential factors that may have influenced the outcomes and outlining areas where future research could build on these findings. By reviewing both the strengths and constraints of this work, the discussion seeks to provide a comprehensive overview of the research's contributions and its applicability to real-world forecasting practices in large-scale infrastructure projects.

7.1 Discussion

The primary goal of this research was to develop a method for predicting the future costs of the Flood Protection Programme up to 2050. To achieve this, an effective price prediction approach was required to equip the researcher with the necessary tools for accurate forecasting. While extensive studies have been conducted on Reference Class Forecasting, the literature remains unclear on the role of comparability in improving forecasting accuracy. This gap in the existing knowledge shifted the focus of this research towards investigating whether incorporating success factors can enhance the predictive capability of Reference Class Forecasting. And to what these success factors are in the context of dike-reinforcements.

7.1.1 Identifying success factors

Dike-reinforcements in the Netherlands, financed by the Flood Protection Programme are used as a case study because of the unique similarity and data availability that could be provided by the Flood Protection Programme. This is due to the fact that one programme oversees almost all dike reinforcements. This is something that in other areas of infrastructure is hard to find, and necessary when conducting a reference class forecast. The research aims to research whether the addition of success factors can enhance the forecasting abilities of a reference class forecast. In order to find the key factors for dike reinforcements, a literature review has been done. The literature review mostly highlighted technical aspects as cost factors as well as the geotechnical conditions, location and complexity of the reinforcement. To validate these findings several interviews were conducted with experts in the field of dike reinforcements, with years of experience. Four interviews were conducted, and although they mostly shared the same opinions on what factors have the biggest impact on costs, it could be that more experts need to be interviewed to gain a better understanding on what factors influence the price of a dike reinforcement the most.

7.1.2 Modelling

The quantitative part of the research consists of the data analysis and the model that has been developed. Initially, the selection of the Reference Class was performed by seeking an exact match between projects based on a strict set of factors. While matches were found, the model frequently relied on only one project as a reference, as it did not search further once a match was identified. This approach overlooked the potential for including multiple projects that could serve as suitable matches but differed by only one less matching factor. By failing to consider these near-matches, the model limited its predictive accuracy and robustness, resulting in high uncertainty and large standard deviations due to a reliance on a single project. Such reliance reduces the stability of predictions, as Flyvbjerg et al. (2003) suggest that a broader set of references enhances the reliability of project cost forecasts. Selecting additional projects as references could have introduced subjectivity, as the decision would depend on manual judgment rather than a consistent methodology.

To address these challenges, the methodology was refined by assigning weights to the factors and calculating a match score between projects. This adjustment allowed for a more nuanced matching process, where the most important factors exerted a greater influence on the selection of reference projects. By prioritizing certain factors, the revised approach enabled the model to identify multiple reference projects with varying degrees of similarity, rather than relying solely on exact matches.

The use of weighted factors brought two main advantages. Firstly, the most critical factors, based on their predictive strength as determined through regression analysis, had a stronger influence on the selection process. This shift ensured that key variables affecting costs, played a central role in matching. Weighted matching techniques are well-documented in predictive modelling, where more flexible matching criteria have been shown to improve the accuracy of predictions, especially in complex contexts (Gelman & Hill, 2007). Secondly, the revised methodology allowed for multiple projects to serve as reference points. By aggregating data from several similar projects, the model achieved greater predictive stability, reducing the standard deviation and uncertainty associated with cost estimates. Moreover, using a comparability-based approach ensures that the selection of projects is guided by data-driven matching criteria rather than subjective judgment, improving objectivity and consistency in the reference class selection.

The adjustment from an exact-match search to a weighted matching system has important theoretical implications for project cost prediction models, especially in fields where projects vary widely in context and scope. This approach aligns with the principles of reference class forecasting, as described by Flyvbjerg et al. (2009), which suggests that using broader and more flexible classes of reference data enhances the robustness of predictive models for infrastructure costs. By allowing certain factors to weigh more heavily, this approach aligns with the notion that key variables should reflect contextual sensitivity, a principle highlighted in institutional economics and infrastructure studies (Dewulf & Kivits, 2019; Ostrom, 2005). The ability to prioritize certain factors is also valuable in settings where some characteristics, such as regional management practices or land use types, disproportionately influence costs.

7.2 Limitations & Strengths

When reflecting on the used research design, methods and completeness of this research, the limitations and the strengths can be debated. In this section first the limitations will be discussed. Subsequently the strengths and added value to existing literature are highlighted.

7.2.1 Limitations

As with every master thesis, this research has its limitations. Due to time constraints the scope of the research had to be defined, and aspects had to be deliberately excluded from the scope.

7.2.1.1 Subjectivity in factor selection

One of the primary limitations of this study lies in the subjectivity involved in selecting the factors that influence the cost of dike reinforcements. The chosen factors were based largely on expert opinions, gathered through interviews with professionals who have years of experience in dike reinforcement projects. Although these four experts generally agreed on the key factors that impact costs, such as the location of the dike (urban vs. rural) and the presence of infrastructure nearby, it is possible that a broader range of perspectives could reveal additional or alternative factors. The relatively small sample size of experts consulted may not fully capture the complexity and diversity of opinions within the industry. Interviewing a larger number of stakeholders, including engineers, project managers, and policymakers across different regions, could yield a more comprehensive understanding of the variables that truly drive costs. Expanding the scope of expert consultations would likely improve the robustness of the factor selection process, potentially leading to a more nuanced and representative set of cost determinants.

7.2.1.2 Potential inaccuracy of relevant factors

Another limitation of this study is the potential for inaccurate effects of relevant factors. Specifically, the factor "afstand_tot_de_norm," which measures the condition of the dike relative to a national safety standard set by the First National Assessment round of primary flood protection (LBO-1), presents unique challenges. This standard was established after the completion of several projects in the dataset, meaning that its influence on costs is difficult to quantify retroactively. As a result, the accuracy of the weighted match scores, which are used to determine the best reference class for each project, may be affected. The omission or limited applicability of certain factors could lead to incomplete or less precise cost predictions, suggesting that the model could benefit from additional variables that reflect the evolving standards and conditions of dike projects. Or in a simplification in the amount of factors, this is suggested by the adjusted R-squared mentioned in chapter 4.

Another factors effect which measures whether a N2000 area is close to the project is potentially inaccurate. Because of legislative changes, projects used as a reference class did not have to take the effects of nitrogen deposition into account. This can lead to a skewed view on the effects of a N2000 area close to dike reinforcements.

7.2.1.3 Limitations of normalised weighing method

The method used to weigh the success factors in the model is another area of potential limitation. The study employed a weighting approach that, while validated in the literature, is one of many possible methods available for assigning importance to predictor variables. Different weighting techniques can yield different results, and the choice of method can significantly impact the final predictions. For example, alternative approaches such as machine learning algorithms or more sophisticated statistical techniques might better capture the relative importance of each factor, especially in complex, multi-factor models like this one. The reliance on a single weighting method without experimenting with others could introduce a degree of bias, as this chosen approach may not be the most suitable for this particular dataset or prediction context. By testing multiple weighting methods, the model could potentially achieve a higher level of accuracy and reliability in its cost predictions.

Another limitation of using a weighting method in combination with reference class forecasting is that the reference class gets divided into several smaller reference classes. This makes the individual forecasting ability less robust. In order to use this method, a much bigger reference class is needed than literature currently advises.

7.2.1.4 Inherent limitations of reference class forecasting

Reference class forecasting improves cost predictions by relying on historical data from similar projects, but it has key limitations. A major challenge is finding a truly comparable set of past projects, as unique characteristics in each project, such as specific location, environmental factors, or regulatory differences, can reduce accuracy. Additionally, by averaging past data, RCF may overlook project-specific nuances, potentially leading to over- or underestimations in complex cases.

RCF also assumes historical data is relevant to current conditions, which may not hold due to factors like inflation, technological changes, or new regulations. Finally, RCF is highly dependent on the quality of past data, which can limit reliability if records are incomplete or inconsistent. While RCF is valuable, its effectiveness depends on suitable reference data and can miss unique project risks.

7.2.1.5 Generalizability of findings

This model was specifically tailored to dike reinforcement projects, using the HWBP-2 dataset. The chosen factors—such as environmental and management-related variables—reflect the unique context of dike reinforcements and may not apply broadly to other types of infrastructure. Each water management region presents distinct characteristics that could affect cost factors differently, limiting the model's generalizability to other regions or dike projects.

However, the methodology developed, particularly the data-driven weighting approach, has potential for adaptation in other infrastructure domains. Applying similar methods to different project types could enhance cost forecasting in various fields. Further research should test the model with diverse datasets to confirm its robustness and explore its broader applicability.

7.3 Strengths

Despite its limitations, this research also possesses several strengths that contribute valuable insights to the literature. First, this study employs a rigorous approach by integrating literature review, expert interviews, and data analysis to identify and validate key cost factors for dike reinforcements. This validation process ensures that the factors are not only well-grounded in existing research but are also supported by expert insights and empirical evidence. By triangulating findings across these sources, the study enhances the credibility and reliability of the identified factors, lending a higher degree of rigor to the overall methodology. This robust approach reduces potential biases and reinforces confidence in the research's conclusions.

Secondly, the research delves into the impact of improving comparability between reference class projects and forecasted projects to try to achieve more accurate cost predictions. This focus on refining project matching is significant, as it suggests that better-aligned reference classes can enhance forecasting precision. This methodological improvement holds potential beyond the specific case of dike reinforcements, as it can be applied to other areas of infrastructure forecasting where tailored project matching could yield similar benefits. As such, the research contributes valuable insights for enhancing the generalizability and adaptability of reference class forecasting.

Third, the study’s use of mixed methods—combining qualitative insights from expert interviews with quantitative data analysis—provides a balanced and objective exploration of findings. This combination not only strengthens the research’s conclusions but also enables a more comprehensive understanding of the factors driving cost variations in dike reinforcement projects. By using both qualitative and quantitative methods, the study benefits from the depth of expert perspectives and the precision of statistical validation, offering a robust foundation for its recommendations and ensuring a more nuanced approach to infrastructure cost forecasting.

Finally, a strength of this study lies in its attempt to address the knowledge gap around "comparability" in reference class forecasting. By examining the specific factors that enhance comparability between the reference class and forecasted projects, this research goes beyond traditional reference class forecasting approaches, which often assume comparability without thoroughly defining or testing it.

Through a careful selection and validation of factors that impact cost differences in dike reinforcements, the study offers a more nuanced view of how project similarity can directly improve forecasting accuracy. This focus on comparability not only strengthens the reliability of cost predictions for dike reinforcements but also contributes a foundational understanding of how tailored project matching can enhance reference class forecasting across other types of infrastructure projects. In this way, the study provides a valuable contribution to the literature, setting a precedent for more precise and context-sensitive approaches to reference class forecasting.

8 Conclusion and Recommendations

In recent years, the costs of infrastructure projects have been steadily rising due to a combination of factors, including increasing labour and material costs, stricter regulatory requirements, environmental considerations, and growing project complexity. This trend has intensified the focus on forecasting methods with a practical approach to enhance the accuracy of project cost estimates. As infrastructure demands grow and become more complex, traditional cost estimation methods have proven limited in accommodating unexpected challenges and contextual variables. RCF is one of several methods that address these challenges in a systematic and data-driven way by using historical data and comparable project outcomes. This method has shown potential in refining cost predictions, especially in complex environments where precise estimates are crucial to avoid substantial financial and social costs.

The research used qualitative as well as quantitative methods to explore various subjects linked to the main research question. '*To what extent can Reference Class Forecasting, combining success factors make an accurate price prediction for the financial programming of HWBP's dike reinforcements until 2050?*'

8.1 Conclusion research sub-questions

Within this section, the four research sub-questions are answered. The sub-questions have cumulatively allowed to answer the main research question.

1) *What are the state-of-the-art models used to forecast prices in the infrastructure sector?*

In order to gain a good understanding of the available models currently used to predict prices in the infrastructure sector, three widely used models are assessed. Table 9 summarises the type of data required, strengths and weaknesses for each method.

Table 9: State-of-the-art models review

Method	Type of Data Required	Strengths	Weaknesses
Traditional Cost Estimating	- Historical cost data for similar projects	- Detailed, component-specific estimates - Flexible, can use various techniques for different project types - Well-suited for projects with predictable and repeatable characteristics	- Prone to bias if unexpected factors arise - Tends to underestimate costs for complex projects - Limited in accuracy for unique or highly complex projects
Probabilistic Estimating	- Baseline project estimates - risk data, - statistical data on cost variability - probability distributions	- Accounts for uncertainty by providing a range of possible cost outcomes Enhances decision-making by quantifying risk and cost contingencies - Provides a better understanding of risks, helping to manage budget overruns more effectively	- Requires high-quality data and sophisticated statistical tools - Can be complex and time-consuming to set up, especially for large projects - May still rely on baseline estimates that are subject to bias or error if initial assumptions are weak
Reference Class Forecasting	- Data on completed projects with similar	- Mitigates optimism bias by focusing on historical data from similar projects - Effective for complex or unique projects where traditional estimates may be unreliable - Provides outcome-based estimates that are generally more realistic in high-stakes projects	- Relies on having a robust reference class; accuracy drops if comparable projects are lacking - Less specific to project components, potentially lacking detail on individual cost drivers - Requires careful selection of the reference class to ensure similarity and relevance

Looking at table 10, each method has its own strengths and weaknesses. Traditional cost estimating is well-suited for projects that are predictable and repeatable, relying heavily on historical data to produce detailed, component-specific estimates. Its flexibility allows for various techniques to be applied across different project types. However, this method struggles with complexity and unpredictability, often underestimating costs for unique or highly intricate projects. It is also prone to bias, especially when unexpected factors arise.

Probabilistic estimating, on the other hand, excels at managing uncertainty by incorporating risk data and statistical tools to provide a range of possible cost outcomes. This approach enhances decision-making by quantifying risks and cost contingencies, offering a better understanding of potential budget overruns. Despite these strengths, it requires high-quality data and sophisticated statistical tools, which can make it resource-intensive and time-consuming. Additionally, it still relies on baseline estimates that can be prone to bias or errors if the initial assumptions are flawed.

Reference class forecasting stands out as a method tailored for complex or high-stakes projects or programmes. By focusing on historical data from similar projects, it effectively mitigates optimism bias and delivers realistic, outcome-based estimates. However, its accuracy depends on the availability and relevance of a robust reference class, and it may lack detail regarding specific project components. Careful selection of comparable projects is critical to its success.

Overall, these methods offer varying levels of accuracy and focus, with clear trade-offs between detail, uncertainty management, and realism. Their effectiveness ultimately hinges on the quality and relevance of the data used, making data an essential factor in any cost-estimating approach.

2) *Is Reference Class Forecasting a viable way to predict prices dike reinforcements?*

Reference Class Forecasting (RCF) emerges as a viable tool for predicting prices in dike reinforcement projects, with several key strengths that make it particularly suited for the infrastructure sector. By using an outside view, RCF reduces the optimism bias and strategic misrepresentation often inherent in traditional cost estimation methods. Grounded in empirical data from similar past projects, it allows for more realistic estimates that align with the actual outcomes of comparable infrastructure projects. This data-driven approach can significantly improve cost forecasting accuracy for dike reinforcements, where unique environmental and regulatory conditions often complicate traditional inside-view estimations.

However, the applicability of RCF for dike reinforcement projects also depends on certain conditions. The method's effectiveness is highly influenced by the availability, quality, and relevance of historical data. Accurate forecasts require a robust dataset of past projects that share key similarities with the current dike reinforcement context. Limitations arise when such data is either insufficient or when past projects do not adequately reflect new standards or changes in technology, materials, and regulatory requirements specific to modern dike reinforcements.

For this research, the availability of a robust dataset with comparable projects was a significant advantage, making it particularly suitable for applying Reference Class Forecasting (RCF). The dataset, sourced from the HWBP-2 programme, comprises projects completed under a single, uniform financing programme—the Flood Protection Programme (HWBP). This uniformity ensures consistency in the data collection process, as all projects adhered to similar organisational, regulatory, and financial guidelines. The HWBP's centralised structure reduces variability in how cost data is reported and categorised, creating a reliable foundation for constructing a reference class. This consistency is critical for RCF, as it relies on comparing projects with shared characteristics to predict future costs accurately. By leveraging this high-quality dataset, the research could confidently identify cost-driving factors and assess the effectiveness of the improved RCF model, ensuring the findings are both robust and practically applicable.

However, its effectiveness depends on the quality and availability of comprehensive historical data, as inaccuracies or incomplete records can compromise the forecasts. The selection of a suitable reference class is critical, requiring careful matching to the current project’s characteristics, as misclassification or biases during selection can skew results. Homogeneity within the reference class is essential to maintain forecast validity, as significant variations or contextual differences can increase uncertainty. However, RCF’s reliance on static historical data limits its ability to account for dynamic future changes, such as technological advancements or evolving market conditions, while its focus on quantitative data risks overlooking qualitative factors like stakeholder behavior or unique project risks. Despite these limitations, RCF offers robust, probability-based forecasts that can complement inside-view methods, making it a valuable tool when used alongside expert judgment for unique or complex projects.

Concluding, while RCF provides a valuable and often more accurate approach to predicting costs in traditional and complex dike reinforcement projects, its effectiveness is tempered by the quality and relevance of historical data and the challenge of ensuring an appropriate reference class. In contexts with adequate and relevant data, RCF has strong potential to improve budget estimations and project outcomes for dike reinforcements, though practitioners should remain aware of its limitations and consider hybrid approaches when unique project conditions warrant more flexible methods. Limitations such as data- availability and -quality, the selection of the reference class and the over reliance on quantitative data without to ability to properly account for changes in innovation and market conditions limits the method in its application for predictions on a larger timeframe.

3) *What are the most important factors that can be used to predict the prices for dike reinforcements in the Netherlands?*

Based on a literature review and interviews with experts, the most important factors for predicting the costs of dike reinforcements in the Netherlands were identified.

- Is the project situated in a rural area?
- Is the project situated in an urban area?
- Is the project situated in a N2000 area?
- Are there buildings close to the project?
- What type of soil is situated at the project location?
- What is the distance from the national standard?
- Is the dike bordering a river or a sea?
- Which water authority managed the project?

The factors include the project's geographical context (urban or rural location), proximity to existing infrastructure (such as nearby buildings), and the managing authority (specific water boards). Projects located in urban areas and those with nearby development tend to incur higher costs per kilometre due to increased logistical complexity, land value, and the need to manage potential disruptions to surrounding infrastructure. Conversely, projects in rural areas generally show lower costs, aligning with fewer spatial constraints and simpler logistical needs.

While some factors, like soil type and Natura 2000 area designation, were anticipated to impact costs significantly, they showed weaker correlations with cost per kilometre in this analysis, suggesting a more nuanced or minimal role in cost determination for dike reinforcements. However, given that certain factors (like proximity to safety norms) approached significance, further investigation may clarify how these interact with core cost drivers.

Another important factor is the time at which the costs are assessed, with a trend toward increasing costs over time, reflecting inflation and the rising expenses associated with dike reinforcement even though the prices have been indexed according to the national inflation rate for water-infrastructure. Additionally, the involvement of specific water authorities, has been shown to influence costs, potentially due to variations in regional management practices, local environmental conditions, or resource allocation.

4) How can the factors enhance the reference class forecast model?

The factors identified in this study can enhance Reference Class Forecasting for dike reinforcements by providing a more tailored approach to using the reference class, which addresses some of the traditional RCF method's limitations. Specifically, integrating factors such as urban/rural location, presence of nearby buildings, managing water authority, and soil type seems to allow for a more nuanced and relevant comparison of projects, improving forecast accuracy. In the Regression weighted RCF model, the importance of each factor was derived from regression analysis, where weights were normalized to reflect each factor's relative impact on costs per kilometre. By applying these weighted factors to calculate match scores, the study ensured that the reference class selected for each project aligns more closely with the project's unique characteristics. This refined approach mitigates the tendency of traditional RCF to rely on broader, less specific reference classes, which often results in high variability and inaccuracy.

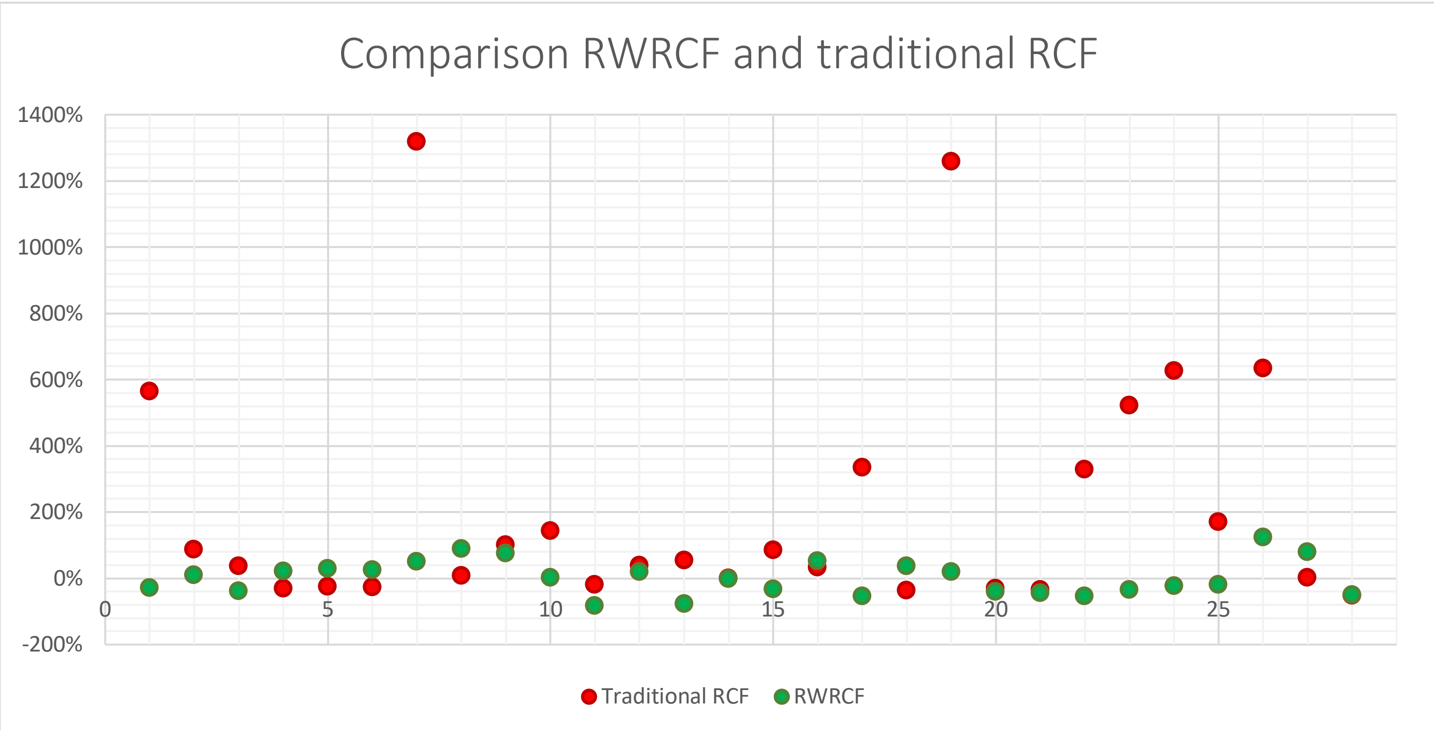

Figure 8.1.1: Comparison between RWRCF and traditional RCF in percentages

Figure 8.1 underscores the effect the factors have on the accuracy of the RWRCF model. It can be clearly seen that the green data points (RWRCF model) outperform the red data points (Traditional RCF model). This is concluded because the severeness of outliers is less high and the green data points generally lie closer to the 0% error margin line compared to the traditional model.

The results indicate the effectiveness of this enhanced RCF method, showing that the RWRCF model outperforms the traditional RCF approach across several key metrics. For example, the lower standard deviation of errors and higher R-squared values indicate that the RWRCF model achieves both consistency and a better fit with actual costs. Additionally, metrics like Mean Squared Logarithmic Error (MSLE) and Symmetric Mean Absolute Percentage Error (sMAPE) demonstrate that the RWRCF model significantly reduces forecast errors, especially in cases of under- or overestimations.

Concluding, by improving comparability between reference class and forecasted projects, the study shows that the Regression weighted model offers a viable enhancement to RCF, delivering a more accurate, relevant, and adaptable approach for forecasting dike reinforcement costs. This result should be considered as an indication that the Regression weighted method can improve the traditional method of reference class forecasting. As mentioned in chapter 5, the minimum amount of projects in the reference class should be 10 to 30, depending on which researcher answers the question. While there are 43 projects in the reference class for this case study, the chosen method has narrowed down the reference class for each project to a maximum of 3. This means that further research is necessary to conclude with certainty that this method does have the potential to enhance reference class forecasting.

5) What is the uncertainty of the price prediction?

The uncertainty in predicting costs for dike reinforcement projects varies depending on whether the regression weighted model is applied to individual projects or used to estimate average costs across multiple projects. For individual project predictions, the RWRCF model indicates improved accuracy and consistency over traditional Reference Class Forecasting (RCF), although certain limitations persist.

In table 10, the performance of the RWRCF model can be seen compared to the traditional model. The standard deviation of errors (SDE) for the RWRCF model, at 2.92 per kilometre, shows that predictions generally stay closer to actual costs, with less spread in errors than the traditional RCF method, which has a notably higher SDE of 5.58 per kilometre. This smaller deviation in the RWRCF model suggests more reliable predictions on an individual project basis, reducing some of the uncertainty that the traditional RCF method's greater variability introduces.

Additional metrics also indicate that the RWRCF model captures individual project costs more accurately. The R-squared (R^2) for individual projects is 0.45, meaning the model explains 45% of the variation in costs—a significant improvement over the RCF method's 23%, but still leaving substantial room for further refinement to capture unique, project-specific factors. Furthermore, the model's Mean Squared Logarithmic Error (MSLE) of 0.02 per kilometre highlights its effectiveness in avoiding large underestimations that could lead to budget shortfalls. In contrast, the traditional RCF method's higher MSLE of 0.05 per kilometre indicates more frequent and substantial underestimations, increasing uncertainty and risk for individual projects.

For forecasting the average cost per kilometre across multiple projects, the RWRCF model indicates even greater accuracy and stability. The Mean Absolute Scaled Error (MASE) score for the RWRCF model is close to 1 (1.20 per kilometre), indicating that its predictions nearly match the accuracy of a simple historical average, enhanced by the data-driven insights the model offers. The traditional RCF method's MASE of 2.45 per kilometre, however, shows that it underperforms relative to even a basic benchmark, underscoring its limitations in estimating average costs across projects.

In conclusion, the RWRCF model indicates to a more accurate and stable approach to forecasting both individual project costs and program-wide average costs for dike reinforcement projects. While some uncertainty remains, especially in the predictions of individual projects due to unique project-specific nuances, the model's improved alignment with actual costs indicates a notable advancement over traditional RCF methods. This balance between project-specific precision and reliability in program-wide estimates makes the RWRCF model a more effective tool for cost forecasting, supporting better-informed budgeting and resource allocation.

Table 10: performance regression weighted model vs traditional reference class model

Metric	RWRCF/km	RCF/km	RWRCF (total costs)	RCF (total costs)
Standard Deviation of Errors [Mln€]	2.92	5.58	3.54	6.40
R-Squared	0.45	0.23	0.52	0.34
Adjusted R-Squared	0.43	0.20	0.50	0.31
MSLE	0.02	0.05	0.03	0.08
Median Absolute Error	1.67	4.20	2.10	5.05
sMAPE	20.35%	55.68%	18.90%	48.75%
MASE	1.20	2.45	1.15	2.67

8.2 Conclusions main research question

This thesis had the aim to answer the following main research question:

'*To what extent can Reference Class Forecasting combining success factors make an accurate price prediction for the financial programming of HWBP's dike reinforcements until 2050?*'

To answer this question qualitative and quantitative methods have been applied. First an assessment of the state-of-the-art forecasting models was made through an academic literature review. Second, the viability of predicting prices for dike reinforcements with reference class forecasting has been studied through literature review and comparing the case study to the availability of data and data that is needed. Third a literature review and interviews were conducted to identify the most important cost-driving factors for dike reinforcements. Fourth, data analysis determined the importance of each variable and the combining explanation capacities of all factors combined. This was done via a correlation analysis and a regression analysis. Finally the model was constructed and compared to the true realised costs and the traditional reference class forecasting method.

The new regression weighted model demonstrates a greater predictive accuracy when estimating costs per kilometre compared to forecasting total project costs. This suggests that the model is more suitable for predicting the average costs/km over a larger number of projects. The findings also suggests that incorporating success factors enhances the effectiveness of the reference class forecasting method, making it a valuable addition to cost estimation strategies. This finding is not set in stone, due to the lack of comparable projects when using this specific methodology. In practice, the feasibility of this method is therefore quite difficult and an extensive database with a large number of projects is required to validate this methodology.

Currently, the Flood Protection Program (HWBP) predominantly relies on an inside view approach for cost forecasting. RCF, as an outside view method, provides a contrasting perspective that can complement the inside view approach. While HWBP's current error margin stands at 30%, this margin still outperforms the model developed in this research. Nevertheless, the model's predictions are, on average, 7% below the actual costs per kilometre, indicating it could add a level of refinement to current practices. The model's absolute average percentage difference is 39.32% for individual projects, the absolute average percentage error for the total costs of the projects is 31%. This signifies that while its individual project accuracy may be limited, RWRCF could be effective for forecasting costs at a programme level or for broader cash flow management. Given these findings, I recommend using this model as a supplement to the existing inside view forecasts rather than as a standalone prediction tool. This combined approach could enhance the robustness of HWBP's cost estimation framework, leveraging the strengths of both perspectives to support more reliable budgeting and decision-making in future dike reinforcement projects.

In conclusion, this thesis has demonstrated the potential enhancement of Regression weighted Reference Class Forecasting that incorporates success factors for predicting dike reinforcement costs. The findings show that the regression-weighted model improves predictive accuracy, particularly in estimating costs per kilometre, suggesting its utility for program-level cost forecasting and broader financial planning. However, the model's effectiveness is constrained by the limited availability of comparable project data, highlighting the need for an extensive database to validate its methodology fully. While HWBP's current cost forecasting methods achieve lower error margins, integrating the proposed model as a complementary tool can enhance the robustness of cost estimation practices. This combined approach of inside and outside view methodologies could provide HWBP with a more nuanced, reliable framework for budgeting and strategic decision-making, ultimately supporting the program's financial programming goals through 2050.

8.3 Scientific Recommendations

Looking back at the process, assumptions needed to be made and boundaries had to be set. This meant that certain aspects of this complex topic remain undiscussed. Within the following section, the recommendations for future research will be presented.

8.3.1 Conduct Additional Interviews to Identify Success Factors

To enhance the reliability of the model, conducting further interviews with stakeholders and experts could provide a deeper understanding of relevant success factors. Expanding the qualitative input may lead to a more comprehensive and accurate model that captures the nuanced influences on project costs.

8.3.2 Apply the Model to Other Infrastructure Sectors

To improve the robustness and predictive accuracy of the model, it is recommended to conduct further interviews with a broader range of stakeholders and experts involved in dike reinforcement projects. These interviews could help uncover additional success factors that may not have been initially considered, providing a more nuanced understanding of variables that influence project costs. Insights gathered from practitioners, project managers, and technical experts can add valuable qualitative data, which may reveal context-specific influences or project-specific challenges that quantitative data alone might overlook. By incorporating a more comprehensive set of success factors, the model could more accurately reflect the complexities and variances inherent in large-scale infrastructure projects, thereby improving its predictive power and reliability.

8.3.3 Explore Alternative Regression Methods

While linear regression was chosen for this study, exploring alternative regression methods could further enhance predictive accuracy. Advanced techniques such as non-linear regression, polynomial regression, or machine learning models (e.g., decision trees, random forests, or gradient boosting) may capture relationships in the data that linear regression cannot. For instance, non-linear models could accommodate complex interactions among variables, which may be especially useful for infrastructure projects with diverse, interdependent cost drivers. Additionally, machine learning techniques have the potential to identify latent patterns within the data and highlight unexpected relationships. By comparing the performance of these alternative models against linear regression, future researchers may identify a more suitable approach that yields higher accuracy and captures additional predictive factors.

8.3.4 Improve the Measurement of the Distance-to-Standard Factor

The "afstand_tot_de_norm" (distance-to-standard) factor currently lacks reliable impact measurement due to inconsistent tracking and variability in how project conditions are recorded at the outset. Inconsistent data recording practices mean that this factor's influence on costs remains underexplored. To enhance the model's precision, it would be valuable to develop a standardized protocol for assessing and recording project conditions uniformly across all projects at the time of initiation. This protocol could include periodic assessments to monitor a project's condition relative to established standards. By ensuring that the initial state of each project is consistently documented, future studies could more accurately measure the impact of distance-to-standard on project costs. This approach could provide insights into how initial project conditions correlate with costs, thereby enriching the model's accuracy for forecasting costs based on initial project assessments.

8.4 Recommendations for Practice

This section outlines key recommendations aimed at enhancing the Flood Protection Program's (HWBP) approach to cost prediction for dike reinforcement projects. Building on the findings of this research, the recommendations focus on three critical areas: improving data collection and maintenance, exploring simplified forecasting models, and investigating the impact of emerging regulatory factors. Each recommendation addresses specific gaps identified in the current practices and offers actionable insights to strengthen HWBP's financial programming and project planning capabilities.

8.4.1 Focus on Data Collection and Maintenance

It is recommended that the Flood Protection Program (HWBP) prioritises the establishment of a comprehensive system for collecting and maintaining data to fully enable the use of data-driven methodologies, such as Reference Class Forecasting (RCF). While initial steps have been taken in this direction, these efforts remain insufficient to support advanced predictive tools. Robust and structured data collection is essential for improving the accuracy of cost predictions for dike reinforcement projects. A well-maintained database would allow HWBP to better understand historical trends, identify cost-driving factors, and improve the comparability of projects, thus enhancing the reliability of financial programming.

Moreover, expanding data collection efforts is not solely about implementing RCF but about creating a foundation for identifying the most suitable method for cost prediction. With a rich and diverse dataset, HWBP could experiment with different forecasting techniques and evaluate their fit and performance against the unique challenges of dike reinforcements. Data is a critical enabler for informed decision-making, and investing in its collection and management will not only support forecasting accuracy but also drive innovation and improve project planning in the long term.

8.4.2 Investigate Simplified Models with Fewer Variables

It is recommended that HWBP pursue follow-up research to explore whether a model with fewer variables could achieve comparable or improved predictive accuracy. A simplified model would reduce complexity and may result in easier adoption across various organizational levels. By identifying a core set of influential factors, HWBP can ensure that forecasting remains both practical and effective. Simplified models are often less resource-intensive, require less specialized knowledge to implement, and could gain broader acceptance among stakeholders, ultimately making them more sustainable in the long term.

Testing simplified models would also provide valuable insights into the trade-offs between accuracy and usability. If a streamlined approach proves effective, it could serve as a stepping stone toward integrating data-driven forecasting methodologies into HWBP's standard practices. This process would enable the organization to refine its predictive tools incrementally, aligning them with operational capacities and stakeholder needs while still reaping the benefits of enhanced cost forecasting. By focusing on simplicity and accessibility, HWBP can ensure that forecasting improvements translate into tangible impacts on project execution and financial management.

8.4.3 Investigating the Impact of Emerging Regulatory Factors

It is recommended that the HWBP investigates the effects of distance from the safety norm and the Natura 2000 (N2000) factor on the costs of dike reinforcement projects. These factors were only enforced after the HWBP-2 dataset concluded, and their influence on project costs remains uncertain. As the current dataset does not include sufficient projects where these variables were consistently applied, there is a limitation in drawing reliable conclusions or integrating them into cost prediction models. Given the potential significance of these factors on project scope, regulatory requirements, and associated costs, a more detailed understanding is essential.

To address this gap, the HWBP should prioritise the systematic collection of data from projects where these factors are actively implemented. This could involve capturing specific costs linked to N2000 environmental regulations or adjustments required to comply with updated safety norms. By analysing this data, the HWBP can refine its forecasting models and enhance the accuracy of future cost estimates. Such an approach will ensure the programme adapts effectively to evolving regulations, supporting more robust financial planning for dike reinforcement projects.

It is recommended that the HWBP investigates what the effects are of distance from the safety norm and the N2000 factor. Both factors were only used after the year that the HWBP-2 dataset ended. A sound prediction/conclusion cannot be made on these variables as

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Appendix A informed consent form

U wordt uitgenodigd om deel te nemen aan een onderzoek genaamd *Impact of succes factors on Reference class forecasting*. Dit onderzoek wordt uitgevoerd door *Matthijs Bodt* van de TU Delft *In samenwerkuing met AT Osborne en het HWBP*.

Het doel van dit onderzoek is om inzicht te krijgen in welke factoren sterk van invloed zijn op prijsbepalingen van dijken en of dit kan leiden tot een nauwkeurigere financiële voorspelling en zal ongeveer 30-60 minuten in beslag nemen. De data zal gebruikt worden voor het behalen van de Master Thesis van Matthijs Bodt. U wordt gevraagd om uw professionele inkijk op het gebied van succesfactoren bij dijkversterkingsprojecten.

Zoals bij elke online activiteit is het risico van een databreuk aanwezig. Wij doen ons best om uw antwoorden vertrouwelijk te houden. We minimaliseren de risico's door de antwoorden van de data anoniem te verwerken, uw functie/werktitel zal wel gebruikt worden. De interviewdata zal na het afronden van mijn Afstuderen worden vernietigd (ongeveer eind oktober)

Uw deelname aan dit onderzoek is volledig vrijwillig, en u kunt zich elk moment terugtrekken zonder reden op te geven. U bent vrij om vragen niet te beantwoorden.

Matthijs Bodt

PLEASE TICK THE APPROPRIATE BOXES	Yes	No
A: GENERAL AGREEMENT – RESEARCH GOALS, PARTICPANT TASKS AND VOLUNTARY PARTICIPATION		
1. Ik heb de informatie over het onderzoek gedateerd [*05/08/2024*] gelezen en begrepen, of deze is aan mij voorgelezen. Ik heb de mogelijkheid gehad om vragen te stellen over het onderzoek en mijn vragen zijn naar tevredenheid beantwoord.	☐	☐
Separate 'yes/no' tick boxes allow you to make sure that your participant is actively affirming their consent. If the participant wants to tick the no box this allows you to clarify any points the participant is unsure about. ***If this is not applicable for your study, then remove the 'no' box.***		
2. Ik doe vrijwillig mee aan dit onderzoek, en ik begrijp dat ik kan weigeren vragen te beantwoorden en mij op elk moment kan terugtrekken uit de studie, zonder een reden op te hoeven geven.	☐	☐
This point should be modified accordingly where a legal guardian will be giving consent, and/or where a participant, outside the context of the research is in a dependent or subordinate position to the researcher.		
3. Ik begrijp dat mijn deelname aan het onderzoek de volgende punten betekent [*see points below*]	☐	☐
• *an audio-recorded interview, of which the text will be transcribed*		
4. Ik begrijp dat mijn deelname aan het onderzoek als volgt wordt gecompenseerd [*…*]	☐	☒
5. Ik begrijp dat de studie eind oktober eindigt.	☐	☐
Please add the anticipated timing or how the date will be determined		
B: POTENTIAL RISKS OF PARTICIPATING (INCLUDING DATA PROTECTION)		
6. Ik begrijp dat mijn deelname de volgende risico's met zich meebrengt. Ik begrijp dat deze risico's worden geminimaliseerd door de antwoorden anoniem te verwerken	☐	☐
7. Ik begrijp dat mijn deelname betekent dat er persoonlijke identificeerbare informatie en onderzoeksdata worden verzameld, met het risico dat ik hieruit geïdentificeerd kan worden [*…*]	☐	☐
8. Ik begrijp dat binnen de Algemene verordering gegevensbescherming (AVG) een deel van deze persoonlijk identificeerbare onderzoeksdata als gevoelig wordt beschouwd, namelijk [*zie onderstaande punten*]	☐	☐
9. Ik begrijp dat de volgende stappen worden ondernomen om het risico van een databreuk te minimaliseren, en dat mijn identiteit op de volgende manieren wordt beschermd in het geval van een databreuk []	☐	☐
anonymous data collection, (pseudo-) anonymisation or aggregation, secure data storage/limited access, transcription		

PLEASE TICK THE APPROPRIATE BOXES	Yes	No
10. Ik begrijp dat de persoonlijke informatie die over mij verzameld wordt en mij kan identificeren, zoals [*bijvoorbeeld naam, woonplaats*], niet gedeeld worden buiten het studieteam.	☐	☐
11. Ik begrijp dat de persoonlijke data die over mij verzameld wordt, vernietigd wordt op [datum overeen te komen]	☐	☐
Please add the anticipated timing or how the date will be determined		
C: RESEARCH PUBLICATION, DISSEMINATION AND APPLICATION		
12. Ik begrijp dat na het onderzoek de geanonimiseerde informatie gebruikt zal worden voor [...]	☐	☐
• *Master thesis rapport*		
13. *If you want to use quotes in research outputs then add extra question:* Ik geef toestemming om mijn antwoorden, ideeën of andere bijdrages anoniem te quoten in resulterende producten.	☐	☐
14. *If you want to use named quotes, then add extra question:* Ik geef toestemming om mijn naam te gebruiken voor quotes in resulterende producten	☐	☐
15. *If written information or other works are provided by the participants (e.g. in a reflection or other diary, or as images etc.) please check* https://www.tudelft.nl/library/copyright/c/what-is-copyright) *for information on copyright, and/or contact the Copyright Team for further information at* copyright-lib@tudelft.nl *and insert appropriate consent questions accordingly.*	☐	☐
D: (LONGTERM) DATA STORAGE, ACCESS AND REUSE		
16. Ik geef toestemming om de geanonimiseerde data (antwoorden op de interview vragen) die over mij verzameld worden gearchiveerd worden in [Impact of succesfactors of Reference Class Forecasting] opdat deze gebruikt kunnen worden voor toekomstig onderzoek en onderwijs.	☐	☐

Signatures

____________________	__________________________	01-08-2024___
Naam deelnemer	Handtekening	Datum

____

Ik, **de onderzoeker**, verklaar dat ik de informatie en het instemmingsformulier correct aan de potentiële deelnemer heb voorgelezen en, naar het beste van mijn vermogen, heb verzekerd dat de deelnemer begrijpt waar hij/zij vrijwillig mee instemt.

Matthijs Bodt___________	____________________	30-07-2024___
Naam onderzoeker	Handtekening	Datum

Appendix B: Interview

Interview opzet

Vraag 1: Kunt u wat vertellen over uw ervaring en werkzaamheden in het verleden?

Vraag 2: Wat zijn factoren die u vanuit uw ervaring hebt gezien die sterk van invloed zijn op de kosten/km van dijkversterkingsprojecten

Sub 1.1: Wat zijn de top 5 factoren?

Sub 2.1: Hoe zou u projecten scoren op basis van die factoren; ja, nee ; schaal 1-5 of 1- 10?

Vraag 3:

In hoeverre heeft de subsidieregeling invloed op de totale kosten/km van dijkversterkingsprojecten?

Sub 2.1: Zo ja heeft dit invloed op de 5 genoemde factoren?

Background Information:

- Ask the interviewee to briefly describe their role and experience related to dike reinforcement projects/ the institution they worked for.
- Gather context on their expertise and involvement in cost estimation or project management.

Project Scope and Specifications:

"Can you describe the typical scope of a dike reinforcement project?"

"What specific technical specifications are most important in determining the cost of these projects?"

Material Costs:

"What types of materials are commonly used in dike reinforcement?"

"How do the costs of these materials vary, and what factors contribute to these variations?"

Labor and Workforce:

"How does the availability and cost of skilled labour impact the price of dike reinforcement per kilometre?"

"Are there specific labour-intensive processes that significantly drive up costs?"

Design and Engineering:

"How does the complexity of the dike design influence overall costs?"

"What role do engineering assessments and environmental studies play in the cost structure?"

Geographical and Environmental Factors:

"How do geographical conditions (e.g., soil type, terrain) affect the cost of dike reinforcements?"

"What environmental considerations (e.g., impact on local ecosystems) need to be accounted for, and how do they influence costs?"

Regulatory and Compliance Costs:

"What regulatory requirements must be met during dike reinforcement projects?"

"How do compliance and permitting processes impact the overall cost per kilometre?"

Technology and Innovation:

"Are there any recent technological advancements that have affected the cost of dike reinforcements?"

"How do innovations in materials or construction techniques influence pricing?"

Project Management and Overheads:

"What project management practices are essential for controlling costs in dike reinforcement projects?"

"How do overhead costs, such as project management fees and contingency funds, factor into the overall price?"

External Factors:

"How do market conditions, such as supply chain disruptions or economic fluctuations, impact the cost of materials and labour?"

"What role do stakeholder engagements and community relations play in the cost dynamics of these projects?"

Case Studies and Examples:

"Can you provide examples of dike reinforcement projects where costs were particularly high or low? What were the key factors in those cases?"

"What lessons have you learned from past projects that could help in managing costs more effectively in future projects?"

Data HWBP

In hoeverre is de data die aan het hwbp wordt verschaft door de waterschappen betrouwbaar en wat zijn dingen waarop ik zou moeten letten? (Bijvoorbeeld; definitie verschillen)

Appendix C: strengths and weaknesses of cost estimating methods

Method	Type of Data Required	Strengths	Weaknesses
Traditional Cost Estimating	Historical cost data for similar projects, expert judgment, project-specific parameters (e.g., materials, size)	- Provides detailed, component-specific estimates based on known project elements (Fleming & Koppelman, 2010).	- Prone to bias if unexpected factors arise, as it relies heavily on project-specific assumptions (Flyvbjerg, 2006).
		- Flexible, can use various techniques (e.g., analogous, parametric) for different project types (AACE, 2020).	- Tends to underestimate costs for complex projects with unforeseen challenges (Merrow, 2011).
		- Well-suited for projects with predictable and repeatable characteristics (Fleming & Koppelman, 2010).	- Limited in accuracy for unique or highly complex projects (Flyvbjerg, 2014).
Probabilistic Estimating	Baseline project estimates, risk data, statistical data on cost variability and probability distributions	- Accounts for uncertainty by providing a range of possible cost outcomes (Kwak & Ingall, 2007).	- Requires high-quality data and sophisticated statistical tools (e.g., Monte Carlo simulations) (Palisade Corporation, 2017).
		- Enhances decision-making by quantifying risk and cost contingencies (PMI, 2017).	- Can be complex and time-consuming to set up, especially for large projects (Baccarini & Love, 2014).
		- Provides a better understanding of risks, helping to manage budget overruns more effectively (Williams, 2002).	- May still rely on baseline estimates that are subject to bias or error if initial assumptions are weak (Williams, 2002).
Reference Class Forecasting (RCF)	Data on completed projects with similar characteristics (e.g., costs, durations, scope); contextual data on outcomes	- Mitigates optimism bias by focusing on historical data from similar projects (Flyvbjerg, 2006).	- Relies on having a robust reference class; accuracy drops if comparable projects are lacking (Lovallo & Kahneman, 2003).
		- Effective for complex or unique projects where traditional estimates may be unreliable (Flyvbjerg et al., 2009).	- Less specific to project components, potentially lacking detail on individual cost drivers (Flyvbjerg, 2006).
		- Provides outcome-based estimates that are generally more realistic in high-stakes projects (Kahneman & Tversky, 1979).	- Requires careful selection of the reference class to ensure similarity and relevance (Lovallo & Kahneman, 2003).

Appendix D: Cost driving factors

No.	Obstacle Description	Technical	Financial	Institutional	Legal
1	Governance cross-sectoral opportunities are needed as an additional driver to make indigenous soil viable, but these do not easily fit within project frameworks (MIRT decision-making, Water Framework Directive, municipal council recreation, provincial contribution to additional nature development, etc.)			X	
2	Sustainability objective with indigenous soil is missing as a project objective. Alongside governance cross-sectoral opportunities, sustainability is a driver for using indigenous soil; if this is missing in the project objective, there is no trigger/reason to investigate it			X	
3	(Lower) physical soil quality of the existing soil does not match the technical requirements set by the water board; technical requirements remain leading	X	X	X	X
4	Frameworks and guidelines from available standards encourage standard solutions and do not challenge innovation or the use of indigenous soil	X			X
5	The effect of using non-standard materials on future management, maintenance, and the extendability of the water barrier is insufficiently clear	X			
6	Supply of indigenous soil from other projects and programs (both planning and physical/environmental quality) is unclear and thus seen as a risk for project duration and budget	X		X	
7	The contract, budget, and/or planning does not allow additional investigations in floodplains to map physical and environmental quality				X
8	Potential demand for soil within the project is seen as too limited to further explore possibilities	X	X		
9	Reward for achieving a project with indigenous soil is still missing in the Most Economically Advantageous Tender (MEAT) criteria				X
10	Interim storage is legally not possible, making it unfeasible to plan and exchange soil flows across projects	X	X	X	X
11	Excavation in the floodplain can lead to adverse effects on the safety of the dike, groundwater effects, and may bring risks and additional costs or risks of delay in procedures	X	X	X	
12	Lack of experience with all aspects surrounding the use of indigenous soil, leading to a culture within the team where this is seen more as a risk than an opportunity	X		X	

13	. Distance from the current situation to the standard. LBO-1 -> agree on technology	X			
14	. One or more failure mechanisms and required spatial requirements. + add type of failure mechanism	X			
15	Chosen structural solution (strength calculations, sheet piling, use of soil/peat).	X			
16	Number of structures (excluded) and presence of large underground infrastructure (e.g., gas pipelines).	X			
17	Number of required integration measures (relocation instead of reinforcement).	X			
18	Amount of required compensatory measures.	X			
19	Amount of required logistic measures.	X			
20	Required land or real estate costs.		x		x
21	Location (rural/urban area/Natura 2000 areas).	X		x	
22	Type of Dike: Whether it's an earthen embankment, rock-armored dike, or a concrete seawall.	X			
23	Height and Width: Higher and wider dikes require more materials and labour.	X			
24	Soil Stability: The type of soil (sand, clay, peat) and its stability affect the complexity and cost of construction.	X			
25	Groundwater Levels: High groundwater levels may require additional dewatering measures.	X			
26	Quality and Quantity of Materials: The amount and type of soil, rock, concrete, and other materials needed.	X			
27	Transportation Costs: Distance from material sources to the construction site.	X			
28	Project Duration (Completion time).	X			
29	Opportunities for Integration/Interfaces with Municipalities - separate business case.			X	
30	Contract Form (discussion).		X		
31	AHP method.				
32	Stakeholder involvement.			x	
33	One or more failure mechanisms and required spatial requirements. + add type of failure mechanism	X			

Appendix E: Normalised weights per success factor

PREDICTOR	COEFFICIENT	ABSOLUTE COEFFICIENT	NORMALISED WEIGHT CALULATION	NORMALISED WEIGHT
WATER BOARD FRYSLÂN	-0.539	0.539	$\frac{0.539}{6.229}$	0.076
WATER BOARD HOLLANDSE DELTA	-0.504	0.504	$\frac{0.504}{6.229}$	0.071
URBAN AREA [1/0]	-0.481	0.481	$\frac{0.481}{6.229}$	0.068
DEVELOPMENT CLOSE TO DIKE	0.449	0.449	$\frac{0.449}{6.229}$	0.063
RURAL AREA [1/0]	-0.435	0.435	$\frac{0.435}{6.229}$	0.061
WATER BOARD AA EN MAAS	-0.408	0.408	$\frac{0.408}{6.229}$	0.058
REGIONAL WATER AUTHORITY VAN SCHIELAND	0.367	0.367	$\frac{0.367}{6.229}$	0.052
WATER BOARD GROOT SALLAND	-0.327	0.327	$\frac{0.327}{6.229}$	0.046
SOIL TYPE - LOAM	0.314	0.314	$\frac{0.314}{6.229}$	0.044
SOIL TYPE – LOAM & CLAY	0.490	0.490	$\frac{0.490}{6.229}$	0.069
N2000 [1/0]	0.235	0.235	$\frac{0.235}{6.229}$	0.033
SOIL TYPE – SAND & LOAM	-0.238	0.238	$\frac{0.238}{6.229}$	0.034
WATER BOARD RIJN EN IJSSEL	-0.233	0.233	$\frac{0.233}{6.229}$	0.033
WATER BOARD NOORDERZIJLVEST	-0.214	0.214	$\frac{0.214}{6.229}$	0.030
WATER BOARD VALLEI EN EEM	0.178	0.178	$\frac{0.178}{6.229}$	0.025
RIVERDIKE	-0.169	0.169	$\frac{0.169}{6.229}$	0.024
RIJKSWATERSTAAT	-0.166	0.166	$\frac{0.166}{6.229}$	0.023
WATER BOARDSCHELDESTROMEN	-0.158	0.158	$\frac{0.158}{6.229}$	0.022
WATER BOARDRIVIERENLAND	-0.139	0.139	$\frac{0.139}{6.229}$	0.020
AFSTAND_TOT_DE_NORM_ENCODED	-0.108	0.108	$\frac{0.108}{6.229}$	0.015
SOIL TYPE - SAND	-0.044	0.044	$\frac{0.044}{6.229}$	0.006
SOIL TYPE - PEAT	0.033	0.033	$\frac{0.033}{6.229}$	0.005

LENGTH [KM]	0.495	0.495	$\frac{0.495}{6.229}$	0.079
YEAR OF COSTS MADE	-0.350	0.350	$\frac{0.350}{6.229}$	0.056

Appendix F: Matched projects and match scores

Project	Predictor	Match score	Matched factors	Cost/km [Mn €]
Oevererosie Klaphek	Markermeerdijk Marken, zuid- en westkade	0,0525	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 0,37
Oevererosie Klaphek	Wieringermeerdijk en Stonteldijk	0,0978	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Riverdike, Seadike	€ 1,51
Oevererosie Klaphek	Zimmermanpolder Zuid-Beveland	0,1286	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 4,08
Koppelstuk WIJD KoegrasSeadike	KoegrasSeadike	0,0690	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Bodemtype_zand	€ 6,70
Koppelstuk WIJD KoegrasSeadike	Dijkversterking Hellevoetsluis	0,0797	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Riverdike, Seadike, Bodemtype_zand	€ 4,58
Koppelstuk WIJD KoegrasSeadike	Pleijweg/Schaapdijk/Broekdijk te Arnhem	0,2186	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 0,57
Koppelstukken WIJD Dijkvakken	Onrustpolder Noord-Beveland	0,0000	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Afstand_tot_de_norm_encoded, Bodemtype_zand	€ 1,90
Koppelstukken WIJD Dijkvakken	Ameland, Waddenzeekering	0,0452	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Riverdike, Seadike, Afstand_tot_de_norm_encoded, Bodemtype_zand	€ 6,66
Spuihaven Schiedam	Havendam Lemmer	0,1034	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 2,35
Spuihaven Schiedam	Dijkversterking Krimpen	0,1034	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 48,24
Spuihaven Schiedam	Havendammen en steenbekleding Stavoren	0,1106	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 2,20
Ijsseldijk Gouda - Spoor 1 (real incl innovatiesubsidie)	Havendam Lemmer	0,1034	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 2,35
Ijsseldijk Gouda - Spoor 1 (real incl innovatiesubsidie)	Dijkversterking Krimpen	0,1034	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 48,24
Ijsseldijk Gouda - Spoor 1 (real incl innovatiesubsidie)	Havendammen en steenbekleding Stavoren	0,1106	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 2,20
Capelle Moordrecht	Havendam Lemmer	0,1034	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 2,35
Capelle Moordrecht	Dijkversterking Krimpen	0,1034	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 48,24
Capelle Moordrecht	Havendammen en steenbekleding Stavoren	0,1106	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 2,20
Maasboulevard Cuijk	Markermeerdijk Marken, zuid- en westkade	0,1042	Rural Area [1/0], Urban Area [1/0], Development close to dike, Riverdike, Seadike	€ 0,37
Maasboulevard Cuijk	Keent en Keent - Grave	0,1379	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Bodemtype_zavel & klei	€ 0,65
Maasboulevard Cuijk	Wieringermeerdijk en Stonteldijk	0,1494	Rural Area [1/0], Urban Area [1/0], Riverdike, Seadike	€ 1,51
Waterfront Dalfsen	Dijkversterking Hellevoetsluis	0,0861	Rural Area [1/0], Urban Area [1/0], Development close to dike, Riverdike, Seadike, Bodemtype_zand	€ 4,58

Waterfront Dalfsen	KoegrasSeadike	0,1658	Rural Area [1/0], Urban Area [1/0], Riverdike, Seadike, Bodemtype_zand	€ 6,70
Waterfront Dalfsen	Havendam Lemmer	0,2006	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 2,35
Lauwersmeerdijk	WaddenSeadike, Nieuwstad, Bocht van WatumD	0,0000	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Afstand_tot_de_norm_encoded, Bodemtype_zavel	€ 7,75
Lauwersmeerdijk	Veerhaven Kruiningen	0,0345	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Bodemtype_zavel	€ 15,76
Lauwersmeerdijk	WaddenSeadike, Friese kust	0,0452	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Riverdike, Seadike, Afstand_tot_de_norm_encoded, Bodemtype_zavel	€ 1,22
Zettingsvloeiing V3T Spijkernisserbrug	Havendammen en steenbekleding Stavoren	0,0690	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Bodemtype_zavel	€ 2,20
Zettingsvloeiing V3T Spijkernisserbrug	Havendam Lemmer	0,0761	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 2,35
Beesel (19P)	Dijkversterking Nieuwe Stadse Seadike	0,0588	Rural Area [1/0], Urban Area [1/0], Development close to dike, Riverdike, Seadike, Afstand_tot_de_norm_encoded	€ 3,30
Beesel (19P)	Dijkversterking Hoeksche Waard Zuid	0,0588	Rural Area [1/0], Urban Area [1/0], Development close to dike, Riverdike, Seadike, Afstand_tot_de_norm_encoded	€ 4,74
Blerick bij de oude Gieterij	Havendammen en steenbekleding Stavoren	0,0690	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Bodemtype_zavel	€ 2,20
Blerick bij de oude Gieterij	Havendam Lemmer	0,0761	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 2,35
Blerick bij de oude Gieterij	Dijkversterking Krimpen	0,0761	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 48,24
Heel (19I)	Boxmeer	0,0941	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 1,06
Heel (19I)	Wieringermeerdijk en Stonteldijk	0,1042	Rural Area [1/0], Urban Area [1/0], Development close to dike, Riverdike, Seadike	€ 1,51
Heel (19I)	Dijkversterking Nieuwe Stadse Seadike	0,1042	Rural Area [1/0], Urban Area [1/0], Development close to dike, Riverdike, Seadike	€ 3,30
Eemshaven-Delfzijl	WaddenSeadike, Friese kust	0,1984	Rural Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Bodemtype_zavel	€ 1,22
Eemshaven-Delfzijl	Veerhaven Kruiningen	0,2091	Rural Area [1/0], N2000 [1/0], Riverdike, Seadike, Bodemtype_zavel	€ 15,76
Eemshaven-Delfzijl	Terschelling, Waddenzeekering	0,2227	Rural Area [1/0], Development close to dike, Riverdike, Seadike	€ 2,59
Lauwersmeer Vierhuizergat (afgerond)	Houtribdijk	0,0000	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Afstand_tot_de_norm_encoded, Bodemtype_zand	€ 8,79
Lauwersmeer Vierhuizergat (afgerond)	IJsselmeer, kleibekleding en pipingmaatregelen	0,0345	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Bodemtype_zand	€ 2,49
Lauwersmeer Vierhuizergat (afgerond)	Zimmermanpolder Zuid-Beveland	0,1387	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Afstand_tot_de_norm_encoded	€ 4,08
IJsselpaviljoen Zutphen	Dijkversterking Hoeksche Waard Noord	0,0870	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 7,30

IJsselpaviljoen Zutphen	Markermeerdijk Hoorn - Edam - Amsterdam	0,0870	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 21,42
IJsselpaviljoen Zutphen	Flaauwe Werk	0,0941	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 8,84
Pannerden-Loo	Markermeerdijk Marken, zuid- en westkade	0,0525	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 0,37
Pannerden-Loo	Wieringermeerdijk en Stonteldijk	0,0978	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Riverdike, Seadike	€ 1,51
Pannerden-Loo	Zimmermanpolder Zuid-Beveland	0,1286	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 4,08
RIDS Fase 1 IJsselkade	Havendam Lemmer	0,1215	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 2,35
RIDS Fase 1 IJsselkade	Dijkversterking Krimpen	0,1215	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 48,24
RIDS Fase 1 IJsselkade	Havendammen en steenbekleding Stavoren	0,1286	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 2,20
Twentekanaal	IJsselmeer, kleibekleding en pipingmaatregelen	0,1551	Rural Area [1/0], Urban Area [1/0], Development close to dike, Riverdike, Seadike, Bodemtype_zand	€ 2,49
Twentekanaal	Markermeerdijk Marken, zuid- en westkade	0,1832	Rural Area [1/0], Urban Area [1/0], Development close to dike, Riverdike, Seadike, Afstand_tot_de_norm_encoded	€ 0,37
Vianen	Havendammen en steenbekleding Stavoren	0,1034	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Bodemtype_zavel	€ 2,20
Vianen	Havendam Lemmer	0,1106	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 2,35
Vianen	Dijkversterking Krimpen	0,1106	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 48,24
Vianen Hazelaarplein	Havendammen en steenbekleding Stavoren	0,1034	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Bodemtype_zavel	€ 2,20
Vianen Hazelaarplein	Havendam Lemmer	0,1106	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 2,35
Vianen Hazelaarplein	Dijkversterking Krimpen	0,1106	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 48,24
Wolferen-Sprok - De Stelt	Markermeerdijk Marken, zuid- en westkade	0,0525	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 0,37
Wolferen-Sprok - De Stelt	Wieringermeerdijk en Stonteldijk	0,0978	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Riverdike, Seadike	€ 1,51
Wolferen-Sprok - De Stelt	Zimmermanpolder Zuid-Beveland	0,1286	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 4,08
Burghsluis-Schelphoek	Markermeerdijk Marken, zuid- en westkade	0,0180	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Afstand_tot_de_norm_encoded	€ 0,37
Burghsluis-Schelphoek	Wieringermeerdijk en Stonteldijk	0,0633	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Riverdike, Seadike, Afstand_tot_de_norm_encoded	€ 1,51
Burghsluis-Schelphoek	Zimmermanpolder Zuid-Beveland	0,0941	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 4,08
Emanuelpolder	Markermeerdijk Marken, zuid- en westkade	0,0180	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Afstand_tot_de_norm_encoded	€ 0,37

Emanuelpolder	Wieringermeerdijk en Stonteldijk	0,0633	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Riverdike, Seadike, Afstand_tot_de_norm_encoded	€ 1,51
Emanuelpolder	Zimmermanpolder Zuid-Beveland	0,0941	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 4,08
Flaauwershaven-Borrendamme	Wieringermeerdijk en Stonteldijk	0,0180	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Afstand_tot_de_norm_encoded	€ 1,51
Flaauwershaven-Borrendamme	Dijkversterking Nieuwe Stadse Seadike	0,0870	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 3,30
Zierikzee-Bruinisse	Markermeerdijk Marken, zuid- en westkade	0,0071	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Afstand_tot_de_norm_encoded	€ 0,37
Zierikzee-Bruinisse	Wieringermeerdijk en Stonteldijk	0,0524	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Riverdike, Seadike, Afstand_tot_de_norm_encoded	€ 1,51
Zierikzee-Bruinisse	Zimmermanpolder Zuid-Beveland	0,0690	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Bodemtype_zavel	€ 4,08
Apeldoorns Kanaal	Versterking Eemdijk en Zuidelijke Randmeren	0,1316	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike, Afstand_tot_de_norm_encoded	€ 5,54
Apeldoorns Kanaal	Houtribdijk	0,2263	Rural Area [1/0], Riverdike, Seadike, Bodemtype_zand	€ 8,79
Apeldoorns Kanaal	Wieringermeerdijk en Stonteldijk	0,2437	Rural Area [1/0], Development close to dike, Riverdike, Seadike, Afstand_tot_de_norm_encoded	€ 1,51
Eemdijk - Spakenburg (deel Westdijk)	Dijkversterking Hoeksche Waard Noord	0,0690	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 7,30
Eemdijk - Spakenburg (deel Westdijk)	Markermeerdijk Hoorn - Edam - Amsterdam	0,0690	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 21,42
Eemdijk - Spakenburg (deel Westdijk)	Flaauwe Werk	0,0761	Rural Area [1/0], Urban Area [1/0], N2000 [1/0], Development close to dike, Riverdike, Seadike	€ 8,84

Appendix G: projects used as reference class to predict projects

Projects	Matched project 1	Matched project 2	Matched project 3
Oevererosie Klaphek	R2-061	W1-006	W2-031
Koppelstuk WIJD KoegrasSeadike	W2-080	WN-001	W2-089
Koppelstukken WIJD Dijkvakken	W2-019	W2-049	-
Spuihaven Schiedam	W2-021	W2-002	W2-013
Ijsseldijk Gouda - Spoor 1	W2-021	W2-002	W2-013
Capelle Moordrecht	W2-021	W2-002	W2-013
Maasboulevard Cuijk	R2-061	WN-012	W1-006
Waterfront Dalfsen	WN-001	W2-080	W2-021
Lauwersmeerdijk	W2-069	R2-022	W2-030
Zettingsvloeiing V3T Spijkernisserbrug	W2-013	W2-021	-
Beesel (19P)	W2-026	WN-008	-
Blerick bij de oude Gieterij	W2-013	W2-021	W2-002
Heel (19I)	WN-024	W1-006	W2-026
Eemshaven-Delfzijl	W2-030	R2-022	W2-045
Lauwersmeer Vierhuizergat	R2-006	W2-014	W2-031
IJsselpaviljoen Zutphen	WN-009	W2-004	WZ-007
Pannerden-Loo	R2-061	W1-006	W2-031
RIDS Fase 1 IJsselkade	W2-021	W2-002	W2-013
Twentekanaal	W2-014	R2-061	-
Vianen	W2-013	W2-021	W2-002
Vianen Hazelaarplein	W2-013	W2-021	W2-002
Wolferen-Sprok - De Stelt	R2-061	W1-006	W2-031
Burghsluis-Schelphoek	R2-061	W1-006	W2-031
Emanuelpolder	R2-061	W1-006	W2-031
Flaauwershaven-Borrendamme	W1-006	W2-026	-
Zierikzee-Bruinisse	R2-061	W1-006	W2-031
Apeldoorns Kanaal	W2-063	R2-006	W1-006
Eemdijk - Spakenburg (deel Westdijk)	WN-009	W2-004	WZ-007

Appendix H: correlation matrix

Correlations

		Prijspeil data	Lengte [km]	Landelijk gebied [1/0]	Stedelijk Gebied [1/0]	N2000 [1/0]	Bebouwing langs dijk	Zeedijk	Rivierdijk	kostenkm 2024	Beheerder_Hoogheemraadschap van Schieland en de Krimpenerwaard	Beheerder_Rijkswaterstaat	Beheerder_Waterschap Aa en Maas	Beheerder_Waterschap Groot Salland	Beheerder_Waterschap Hollandse Delta	Beheerder_Waterschap Noorderzijlvest	Beheerder_Waterschap Rijn en Ijssel	Beheerder_Waterschap Rivierenland	Beheerder_Waterschap Scheldestromen	Beheerder_Waterschap Vallei en Eem	Beheerder_Wetterskip Fryslân	Bodemtype_veen	Bodemtype_zand	Bodemtype_zand & zavel	Bodemtype_zavel	Bodemtype_zavel & klei	Afstand_tot_de_norm_encoded
Prijspeil data	Pearson Correlation	1	,483**	0,072	-0,029	0,229	0,116	0,034	-0,034	0,160	-0,185	0,119	0,029	-0,054	0,072	-0,054	-0,204	-0,097	-0,273	-0,005	0,161	0,243	0,058	0,207	-0,085	-0,221	-0,086
	Sig. (2-tailed)		0,001	0,646	0,852	0,140	0,458	0,829	0,829	0,305	0,235	0,445	0,854	0,729	0,645	0,729	0,190	0,538	0,076	0,977	0,302	0,117	0,710	0,183	0,588	0,154	0,585
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Lengte [km]	Pearson Correlation	,483**	1	0,088	0,026	0,198	0,253	-0,063	0,063	-0,037	-0,071	0,076	-0,080	-0,099	-0,106	-0,110	-0,070	-0,065	-0,169	,330*	0,010	0,286	-0,023	,322*	-0,204	-0,175	0,155
	Sig. (2-tailed)	0,001		0,577	0,868	0,202	0,102	0,688	0,688	0,815	0,652	0,630	0,611	0,527	0,497	0,484	0,655	0,681	0,279	0,031	0,947	0,063	0,883	0,035	0,190	0,262	0,320
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Landelijk gebied [1/0]	Pearson Correlation	0,072	0,088	1	-,911**	0,281	-,491**	0,200	-0,200	-,457**	-,308*	0,285	0,197	0,137	0,046	0,137	-0,173	-,308*	0,244	0,137	0,088	-0,248	0,112	-0,026	0,178	-0,116	0,189
	Sig. (2-tailed)	0,646	0,577		0,000	0,068	0,001	0,199	0,199	0,002	0,045	0,064	0,207	0,380	0,768	0,380	0,266	0,045	0,115	0,380	0,575	0,108	0,473	0,869	0,254	0,461	0,225
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Stedelijk Gebied [1/0]	Pearson Correlation	-0,029	0,026	-,911**	1	-,314*	,560**	-0,253	0,253	,432**	0,280	-,313*	-0,216	-0,151	0,013	-0,151	0,158	0,280	-0,268	0,158	-0,125	0,226	-0,160	0,005	-0,137	0,081	-0,144
	Sig. (2-tailed)	0,852	0,868	0,000		0,040	0,000	0,102	0,102	0,004	0,069	0,041	0,165	0,335	0,935	0,335	0,312	0,069	0,083	0,312	0,425	0,145	0,307	0,974	0,382	0,606	0,355
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
N2000 [1/0]	Pearson Correlation	0,229	0,198	0,281	-,314*	1	-,330*	0,180	-0,180	-0,119	-,394**	0,223	-,318*	0,107	0,148	0,107	0,107	-0,199	0,190	-0,222	-0,150	-0,082	0,235	0,153	0,133	-0,212	0,249
	Sig. (2-tailed)	0,140	0,202	0,068	0,040		0,031	0,248	0,248	0,446	0,009	0,152	0,038	0,494	0,345	0,494	0,494	0,200	0,222	0,152	0,337	0,600	0,128	0,326	0,395	0,171	0,107
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Bebouwing langs dijk	Pearson Correlation	0,116	0,253	-,491**	,560**	-,330*	1	-0,100	0,100	,314*	0,211	-,416**	-0,058	-0,200	0,196	-0,200	-0,200	0,211	-,356*	0,119	0,171	0,170	-,314*	0,170	-0,122	-0,171	-0,058
	Sig. (2-tailed)	0,458	0,102	0,001	0,000	0,031		0,523	0,523	0,041	0,175	0,006	0,710	0,197	0,208	0,197	0,197	0,175	0,019	0,448	0,273	0,276	0,041	0,276	0,436	0,273	0,710
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Zeedijk	Pearson Correlation	0,034	-0,063	0,200	-0,253	0,180	-0,100	1	-1,000**	0,098	-0,161	0,179	-0,129	-0,090	-,323*	0,263	-0,090	-0,161	0,049	-0,090	0,225	-0,129	,353*	0,124	0,078	-0,213	0,106
	Sig. (2-tailed)	0,829	0,688	0,199	0,102	0,248	0,523		0,000	0,532	0,304	0,250	0,408	0,564	0,035	0,088	0,564	0,304	0,757	0,564	0,146	0,408	0,020	0,430	0,618	0,171	0,497
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Rivierdijk	Pearson Correlation	-0,034	0,063	-0,200	0,253	-0,180	0,100	-1,000**	1	-0,098	0,161	-0,179	0,129	0,090	,323*	-0,263	0,090	0,161	-0,049	0,090	-0,225	0,129	-,353*	-0,124	-0,078	0,213	-0,106
	Sig. (2-tailed)	0,829	0,688	0,199	0,102	0,248	0,523	0,000		0,532	0,304	0,250	0,408	0,564	0,035	0,088	0,564	0,304	0,757	0,564	0,146	0,408	0,020	0,430	0,618	0,171	0,497
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
kostenkm 2024	Pearson Correlation	0,160	-0,037	-,457**	,432**	-0,119	,314*	0,098	-0,098	1	,426**	-0,073	-0,138	-0,083	-0,182	-0,035	-0,099	0,258	-0,125	-0,054	-0,203	0,003	-0,205	-0,042	0,083	0,036	-0,287
	Sig. (2-tailed)	0,305	0,815	0,002	0,004	0,446	0,041	0,532	0,532		0,004	0,640	0,379	0,598	0,242	0,826	0,529	0,095	0,425	0,730	0,192	0,982	0,186	0,791	0,595	0,820	0,062
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Beheerder_Hoogheemraadschap van Schieland en de Krimpenerwaard	Pearson Correlation	-0,185	-0,071	-,308*	0,280	-,394**	0,211	-0,161	0,161	,426**	1	-0,088	-0,060	-0,042	-0,151	-0,042	-0,042	-0,075	-0,075	-0,042	-0,110	-0,060	-0,141	-0,060	-0,180	-0,099	-0,156
	Sig. (2-tailed)	0,235	0,652	0,045	0,069	0,009	0,175	0,304	0,304	0,004		0,576	0,700	0,788	0,335	0,788	0,788	0,633	0,633	0,788	0,481	0,700	0,367	0,700	0,247	0,526	0,318
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Beheerder_Rijkswaterstaat	Pearson Correlation	0,119	0,076	0,285	-,313*	0,223	-,416**	0,179	-0,179	-0,073	-0,088	1	-0,071	-0,049	-0,176	-0,049	-0,049	-0,088	-0,088	-0,049	-0,129	-0,071	0,229	-0,071	-0,036	-0,116	0,077
	Sig. (2-tailed)	0,445	0,630	0,064	0,041	0,152	0,006	0,250	0,250	0,640	0,576		0,652	0,753	0,258	0,753	0,753	0,576	0,576	0,753	0,410	0,652	0,140	0,652	0,816	0,458	0,622
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Beheerder_Waterschap Aa en Maas	Pearson Correlation	0,029	-0,080	0,197	-0,216	-,318*	-0,058	-0,129	0,129	-0,138	-0,060	-0,071	1	-0,034	-0,122	-0,034	-0,034	-0,060	-0,060	-0,034	-0,089	-0,049	-0,114	-0,049	0,095	0,264	-0,191
	Sig. (2-tailed)	0,854	0,611	0,207	0,165	0,038	0,710	0,408	0,408	0,379	0,700	0,652		0,828	0,437	0,828	0,828	0,700	0,700	0,828	0,571	0,756	0,468	0,756	0,544	0,087	0,220
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Beheerder_Waterschap Groot Salland	Pearson Correlation	-0,054	-0,099	0,137	-0,151	0,107	-0,200	-0,090	0,090	-0,083	-0,042	-0,049	-0,034	1	-0,085	-0,024	-0,024	-0,042	-0,042	-0,024	-0,062	-0,034	-0,079	-0,034	-0,102	,425**	-0,133
	Sig. (2-tailed)	0,729	0,527	0,380	0,335	0,494	0,197	0,564	0,564	0,598	0,788	0,753	0,828		0,588	0,880	0,880	0,788	0,788	0,880	0,692	0,828	0,613	0,828	0,517	0,004	0,394
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Beheerder_Waterschap Hollandse Delta	Pearson Correlation	0,072	-0,106	0,046	0,013	0,148	0,196	-,323*	,323*	-0,182	-0,151	-0,176	-0,122	-0,085	1	-0,085	-0,085	-0,151	-0,151	-0,085	-0,222	-0,122	-0,148	-0,122	0,117	-0,200	0,011
	Sig. (2-tailed)	0,645	0,497	0,768	0,935	0,345	0,208	0,035	0,035	0,242	0,335	0,258	0,437	0,588		0,588	0,588	0,335	0,335	0,588	0,153	0,437	0,344	0,437	0,455	0,199	0,943
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Beheerder_Waterschap Noorderzijlvest	Pearson Correlation	-0,054	-0,110	0,137	-0,151	0,107	-0,200	0,263	-0,263	-0,035	-0,042	-0,049	-0,034	-0,024	-0,085	1	-0,024	-0,042	-0,042	-0,024	-0,062	-0,034	-0,079	-0,034	0,234	-0,056	-0,133
	Sig. (2-tailed)	0,729	0,484	0,380	0,335	0,494	0,197	0,088	0,088	0,826	0,788	0,753	0,828	0,880	0,588		0,880	0,788	0,788	0,880	0,692	0,828	0,613	0,828	0,130	0,721	0,394
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Beheerder_Waterschap Rijn en Ijssel	Pearson Correlation	-0,204	-0,070	-0,173	0,158	0,107	-0,200	-0,090	0,090	-0,099	-0,042	-0,049	-0,034	-0,024	-0,085	-0,024	1	-0,042	-0,042	-0,024	-0,062	-0,034	-0,079	-0,034	-0,102	,425**	0,003
	Sig. (2-tailed)	0,190	0,655	0,266	0,312	0,494	0,197	0,564	0,564	0,529	0,788	0,753	0,828	0,880	0,588	0,880		0,788	0,788	0,880	0,692	0,828	0,613	0,828	0,517	0,004	0,984
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Beheerder_Waterschap Rivierenland	Pearson Correlation	-0,097	-0,065	-,308*	0,280	-0,199	0,211	-0,161	0,161	0,258	-0,075	-0,088	-0,060	-0,042	-0,151	-0,042	-0,042	1	-0,075	-0,042	-0,110	-0,060	-0,141	-0,060	-0,180	,470**	-0,237
	Sig. (2-tailed)	0,538	0,681	0,045	0,069	0,200	0,175	0,304	0,304	0,095	0,633	0,576	0,700	0,788	0,335	0,788	0,788		0,633	0,788	0,481	0,700	0,367	0,700	0,247	0,001	0,127
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Beheerder_Waterschap Scheldestromen	Pearson Correlation	-0,273	-0,169	0,244	-0,268	0,190	-,356*	0,049	-0,049	-0,125	-0,075	-0,088	-0,060	-0,042	-0,151	-0,042	-0,042	-0,075	1	-0,042	-0,110	-0,060	0,083	-0,060	0,217	-0,099	0,167
	Sig. (2-tailed)	0,076	0,279	0,115	0,083	0,222	0,019	0,757	0,757	0,425	0,633	0,576	0,700	0,788	0,335	0,788	0,788	0,633		0,788	0,481	0,700	0,595	0,700	0,162	0,526	0,284
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Beheerder_Waterschap Vallei en Eem	Pearson Correlation	-0,005	,330*	0,137	0,158	-0,222	0,119	-0,090	0,090	-0,054	-0,042	-0,049	-0,034	-0,024	-0,085	-0,024	-0,024	-0,042	-0,042	1	-0,062	-0,034	-0,079	-0,034	-0,102	-0,056	0,276
	Sig. (2-tailed)	0,977	0,031	0,380	0,312	0,152	0,448	0,564	0,564	0,730	0,788	0,753	0,828	0,880	0,588	0,880	0,880	0,788	0,788		0,692	0,828	0,613	0,828	0,517	0,721	0,073
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Beheerder_Wetterskip Fryslân	Pearson Correlation	0,161	0,010	0,088	-0,125	-0,150	0,171	0,225	-0,225	-0,203	-0,110	-0,129	-0,089	-0,062	-0,222	-0,062	-0,062	-0,110	-0,110	-0,062	1	0,230	0,123	-0,089	0,027	-0,146	0,008
	Sig. (2-tailed)	0,302	0,947	0,575	0,425	0,337	0,273	0,146	0,146	0,192	0,481	0,410	0,571	0,692	0,153	0,692	0,692	0,481	0,481	0,692		0,138	0,433	0,571	0,863	0,350	0,958
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Bodemtype_veen	Pearson Correlation	0,243	0,286	-0,248	0,226	-0,082	0,170	-0,129	0,129	0,003	-0,060	-0,071	-0,049	-0,034	-0,122	-0,034	-0,034	-0,060	-0,060	-0,034	0,230	1	-0,114	-0,049	-0,145	-0,080	0,005
	Sig. (2-tailed)	0,117	0,063	0,108	0,145	0,600	0,276	0,408	0,408	0,982	0,700	0,652	0,756	0,828	0,437	0,828	0,828	0,700	0,700	0,828	0,138		0,468	0,756	0,352	0,610	0,977
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Bodemtype_zand	Pearson Correlation	0,058	-0,023	0,112	-0,160	0,235	-,314*	,353*	-,353*	-0,205	-0,141	0,229	-0,114	-0,079	-0,148	-0,079	-0,079	-0,141	0,083	-0,079	0,123	-0,114	1	-0,114	-,339*	-0,187	,415**
	Sig. (2-tailed)	0,710	0,883	0,473	0,307	0,128	0,041	0,020	0,020	0,186	0,367	0,140	0,468	0,613	0,344	0,613	0,613	0,367	0,595	0,613	0,433	0,468		0,468	0,026	0,231	0,006
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Bodemtype_zand & zavel	Pearson Correlation	0,207	,322*	-0,026	0,005	0,153	0,170	0,124	-0,124	-0,042	-0,060	-0,071	-0,049	-0,034	-0,122	-0,034	-0,034	-0,060	-0,060	-0,034	-0,089	-0,049	-0,114	1	-0,145	-0,080	0,102
	Sig. (2-tailed)	0,183	0,035	0,869	0,974	0,326	0,276	0,430	0,430	0,791	0,700	0,652	0,756	0,828	0,437	0,828	0,828	0,700	0,700	0,828	0,571	0,756	0,468		0,352	0,610	0,514
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Bodemtype_zavel	Pearson Correlation	-0,085	-0,204	0,178	-0,137	0,133	-0,122	0,078	-0,078	0,083	-0,180	-0,036	0,095	-0,102	0,117	0,234	-0,102	-0,180	0,217	-0,102	0,027	-0,145	-,339*	-0,145	1	-0,239	-0,255
	Sig. (2-tailed)	0,588	0,190	0,254	0,382	0,395	0,436	0,618	0,618	0,595	0,247	0,816	0,544	0,517	0,455	0,130	0,517	0,247	0,162	0,517	0,863	0,352	0,026	0,352		0,123	0,099
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Bodemtype_zavel & klei	Pearson Correlation	-0,221	-0,175	-0,116	0,081	-0,212	-0,171	-0,213	0,213	0,036	-0,099	-0,116	0,264	,425**	-0,200	-0,056	,425**	,470**	-0,099	-0,056	-0,146	-0,080	-0,187	-0,080	-0,239	1	-0,249
	Sig. (2-tailed)	0,154	0,262	0,461	0,606	0,171	0,273	0,171	0,171	0,820	0,526	0,458	0,087	0,004	0,199	0,721	0,004	0,001	0,526	0,721	0,350	0,610	0,231	0,610	0,123		0,107
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43
Afstand_tot_de_norm_encoded	Pearson Correlation	-0,086	0,155	0,189	-0,144	0,249	-0,058	0,106	-0,106	-0,287	-0,156	0,077	-0,191	-0,133	0,011	-0,133	0,003	-0,237	0,167	0,276	0,008	0,005	,415**	0,102	-0,255	-0,249	1
	Sig. (2-tailed)	0,585	0,320	0,225	0,355	0,107	0,710	0,497	0,497	0,062	0,318	0,622	0,220	0,394	0,943	0,394	0,984	0,127	0,284	0,073	0,958	0,977	0,006	0,514	0,099	0,107	
	N	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43