AI implementations for Dutch water management: a literature study

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Executive summary

This executive summary is intended and formulated for readers from the Ministry of Infrastructure and Water Management, for the CDIB/DGWB substrates. It is provided in Dutch.

IenW, en DGWB in het bijzonder, wil de inzet van datagedreven beleidsvoering verbeteren. Een belangrijk stuk van deze puzzel is het modelleren met Artificiële Intelligentie (AI) ter optimalisatie van huidige vraagstukken of zelfs voor het oplossen van geheel nieuwe vraagstukken. Deze literatuurbeschouwing onderzoekt de intersectie tussen drie soorten AI-toepassingsmethoden en zeven beleidstaken van DGWB, en bepaalt vervolgens voor ieder onderwerp de meerwaarde voor het DG op basis van huidige onderzoeksmaturiteit, verwachte onderzoeksgroei op korte termijn, en impact voor het DG. Dit literatuuronderzoek identificeert een aantal technologische ontwikkelingen op het gebied van AI die lenen zich goed voor inzet door DGWB. Deze onderwerpen zijn in essentie kansen die kunnen helpen met de transitie naar meer datagedreven beleid. De drie voornaamste kansen zijn als volgt:

1) AI en simulatie voor overstromingen

Bij het maken van simulaties over overstromingsgevaren in Nederland kan AI worden ingezet voor zowel het creëren van een digitale 3D-ruimte op basis van satelliet- en luchtfoto's als het laten voorspellen van de gedraging van water tijdens een overstroming, ter verbetering van het overstromingsbeleid.

2) AI en monitoring voor leidingnetwerken

De inzet van sensoren bij een leidingnetwerk maakt het mogelijk om met behulp van AI de status van het netwerk zeer nauwkeurig te monitoren. Door bijvoorbeeld te meten hoe de stroomsnelheid en -richting of de interne akoestiek zich gedragen, kunnen lekken of verstoppingen snel worden opgespoord voor minimale schade en/of waterverlies.

3) AI en netwerkoptimalisatie voor planning

Het plannen van de bouw van nieuwe gesloten waternetwerken, zoals riolering, kan worden geoptimaliseerd door middel van AI-gebaseerde netwerkmodellen. Voorbeelden zijn het verhogen van de algehele kostenefficiëntie of de robuustheid van een systeem wanneer er een segment niet naar behoren functioneert.

Abstract

This thesis consists of a literature review on how three types of Artificial Intelligence (AI) method applications may be used for improving data-driven decision making in the context of Dutch governmental water management, for the Directorate of Water and Soil. Water management officials may utilize the possibilities brought by recent developments in the field of AI. The literature review distinguishes three AI method applications in relevant works: (1) network planning and optimization, (2) monitoring and anomaly detection, and (3) simulation and prediction. These method applications are individually described according to a state-of-the-art benchmark, and then combined with the domains of seven governmental tasks of the Directorate of Water and Soil. Each intersection is assessed based on research maturity, expected research growth, and level of policymaking impact. As such, this literature review identified three key intersection fields for the Directorate of Water and Soil to further investigate: firstly, monitoring and anomaly detection intersected with pipeline construction and maintenance. Secondly, network planning and optimization intersected with waterway safety and flooding. Thirdly, simulation and prediction intersected with waterway safety and flooding. Further research on many intersection fields is suggested, but especially regarding the aforementioned three.

Keywords: Artificial Intelligence (AI), Dutch water management, Water infrastructure, Water policymaking

1 Introduction

Artificial Intelligence (AI) models often involve data optimization or prediction and may assist individuals or institutions with decision making. Recent research has shown that AI-driven models are a successful contributor in many fields working with large amounts of data (O'Leary, 2013; Zeiler & Fergus, 2014), and that its presence in the field of data science is only expected to increase (Liu et al., 2018; Surya, 2012). With the increase in availability of data and computing power for AI-driven models (Hwang, 2018), departments of national governments may join in with this technology. One such department is the Dutch Directorate of Water and Soil, a substrate of the Ministry of Infrastructure and Water Management. This literature research aims to identify trends in the academic field of AI that may be utilized for the successful execution of the tasks bestowed upon this Directorate. The introduction will provide context to this study by discussing the technical and political background, followed by the research problem and its objective, its significance, and its limitations respectively.

In the field of data science, AI models are a common tool for problem solving or formulating objectives (Russel & Norvig, 2020). A significant amount of currently deployed AI is in the form of machine learning, a computational method that utilizes experience to improve performance or make predictions (Mohri et al., 2018), where this experience refers to previous information in the form of data available to the learner itself. AI-driven algorithms appear to be considerably more effective as the size and complexity of data increases, and as such, excel in tasks that are beyond the capability of manual model engineering (Mohri et al., 2018), with language models as well-documented examples (Brown et al., 2020; Devlin et al., 2019). As such, AI-driven models may be used to solve problems previously deemed too complex, or used to improve the efficiency of existing problems.

With this literature review, these AI-driven models are researched within the context of The Dutch Ministry of Infrastructure and Water Management (*"Ministerie van Infrastructuur en Waterstaat",* henceforth *"the Ministry"*), which is the Netherlands' national department concerned with policymaking and the managing of any public infrastructure and water. Its policymaking substrate regarding water is the Directorate of Water and Soil (*"Directoraat-Generaal Water en Bodem"*), which is tasked to create and amend the policies and legislations regarding water management execution by both the ministry's own Directorate of Public Works and Water Management (*"Rijkswaterstaat"*), as well as the country's 21 regional Water Boards (*"Waterschappen"*) (*Organogram MinIenW*, 2022). As the policymaking substrate, the Directorate of Water and Soil (henceforth "*the Directorate*") decides the direction of water management in the Netherlands.

In 2019, the directorate set as a goal to improve its policymaking through data-driven decision making, making use of data labs present in the executive branches of the same ministry to deploy AI models (Harthoon & Ouwersloot, 2019). Additionally, the Directorate, along with the other policymaking directorates at the ministry, agreed to write an internal vision document on their prospective use of data in the short to medium term (Schouwenburg, 2019), further signifying their interest in data-driven problem solving and optimalisation. Research into these solutions is in most cases still in early developmental stages (Harthoon & Ouwersloot, 2019).

The relevance of this literature review for the Directorate of Water and Soil is to aid with their goal of using data-driven problem solving and optimalisation using AI models. As AI-driven algorithms can handle complex and large datasets and problems, they may prove useful for the Directorate to deploy. Hence, this literature review describes the current landscape of academic advancements in the field of AI-driven models relevant to the governing tasks of the

Directorate to assist it with their planned transition to more data-driven policymaking: *"Which AI-driven solutions contribute to Dutch water management?"*

Besides its relevance for the Directorate, this literature review may be utilized by future academic reviews to apply to different departments of the Dutch government with similar goals (Schouwenburg, 2019), other nations' governments, or international institutions.

The research scope of this literature review is defined by three decisions: firstly, the chosen framework is the set of policymaking tasks of the Directorate of Water and Soil, as well as the advancements of AI-driven models in data science. Secondly, the search methodology is limited to a specific publication database as well as specific query keywords (See section 2). Thirdly, this research focuses on the on the technical possibilities of AI-driven models; other aspects may have been omitted for the purpose of this research.

The remainder of this document is structured as follows: three AI method applications were chosen in the methodology (Section 2) as a categorization dimension (Section 2.3), crossing with seven different governmental tasks of the Directorate (Section 2.4). The results section (Section 3) discusses the three AI method applications and their intersections with governmental task, with a set structure: starting with a description of the state-of-the-art benchmark for that method application, followed by an assessment of each intersection of the governmental task and the method application including an opinionated recommendation, and ending with a succinct overview of the task recommendations for that method application. The review is followed by the general discussion section (Section 4), which quantifies the level of research maturity, expected growth, and level of impact for the directorate to assess its overall usefulness. Additionally, it includes a limitations section, which assess the validity of this literature review study in general. Lastly, the conclusion (Section 5) summarizes the key points from the discussion analysis.

2 Methodology

2.1 Initial exploratory research

As a first step, I performed a broad literature search for studies containing the keyword 'AI' and variations as well as five keywords related to Ministry of Infrastructure and Water Management, intended as explorations of the current AI research landscape in potentially relevant areas. These keywords were encountered in the 2020 strategy document publications of the Ministry (*Beleidsagenda IenW*, 2020). Queries were exclusively performed in the Scopus database, to ensure that the sources were recognized by scientists (i.e., in contrast to Google Scholar results which can also produce non-peer-reviewed articles). In addition, I limited the search by publication date (2000 and onwards), to get an overview of recent developments. Six queries procured 562 results (Table 1).

Table 1: Initial exploration query keys, including found articles and query date.
**NB: (ai*) = ((artificial AND intelligence) OR ai)*

Query key	# Articles	Date
TITLE ((ai*) AND (sustainability OR sustainable OR sustain))	99	April 5, 2021
TITLE ((ai*) AND (circular AND economy))	7	April 12, 2021
TITLE ((ai*) AND (mobility))	28	April 13, 2021
TITLE ((ai*) AND (infrastructure))	48	May 5, 2021
TITLE ((ai*) AND (iot OR (internet AND of AND things)))	380	May 18, 2021
Total	*562*	

Subsequently, all results were screened according to a protocol where elements title, keywords and abstract were read by the researcher. At this stage, the scope of the research question was considerably broader, and included any AI method applications and responsibilities that the Ministry performed. As such, the screening protocol was used to check whether any of the contents of these three elements identified a relevance to two questions, both subjectively judged by the researcher:

- Does this publication include information directly applicable or potentially applicable to the responsibilities of the Dutch Ministry of Infrastructure and Water Management?
- Does this publication include detailed information on a specific Artificial Intelligence method application beyond a strictly abstract point of view?

In the case that both criteria were fulfilled, the article was included. Through this method, a more limited number of relevant articles remained (161 of 562 initial hits, or 28.6%).

With the goal of further exploration of the landscape, the journals that occurred at least 10 times in the selection of the 161 post-screening articles were marked (7 journals, Table 2). On June 4th, 2021, for each of these journals, I reviewed a list of the 50 most recent publications of each journal to identify whether there might be other relevant articles (and associated keywords) that I had not initially detected with the original keywords However, none of the recent publications in any of the journals had any relevance to AI deployment for governmental responsibilities, and I assumed that the high frequency of different topics of publications through many of these journals is cause for this.

Table 2: Most frequently encountered journals (descending).

Journal	# Articles
Sustainability (Switzerland)	22
IEEE Internet of Things Journal	16
Advances in Intelligent Systems and Computing	15
IEEE Access	14
ACM International Conference Proceeding Series	11
Lecture Notes in Computer Science	10
Journal of Self-Governance and Management Economics	10
Studies in Computational Intelligence	10
Other	53
Total	*161*

Due to the still very wide range of governmental responsibilities of the Ministry of Infrastructure and Water Management present in the themes of the screened selection of 161 studies, I decided in consultation with my supervisors of the Ministry and the University to narrow my scope to one specific domain of responsibilities: the tasks of the Directorate of Water and Soil. This domain was chosen as it was both a domain that occurred frequently as a subject in the post-screening articles and the first domain that was further explored.

2.2 Research development

Following the initial exploratory research, the literature research goal converged to a more precise research question, and subsequently distinguished the literature landscape along two categorical dimensions based on the exploratory research: AI method applications (Section 2.3) and governmental tasks of the Directorate (Section 2.4). These dimensions were used to create a quantification based on the intersection of these two dimensions. New queries were used in SCOPUS to create a contemporary benchmark of the AI method applications (Section 2.3.1), subsequently followed by querying and screening articles related to the governmental tasks.

2.3 AI Method applications

In this literature review, one of the categorization dimensions is defined as list of some, though not all, AI method applications. This categorization was chosen as a series of applications of AI-driven models rather than the mathematical models themselves and emerged as pragmatic choices as they appeared most distinctly in the exploratory research, subjectively judged by the researcher, and further discussed in the limitations (section 4.2). Furthermore, these method applications are considered as well-established applications within the field of AI (see references).

(1) Network planning and optimization: a classical computational problem (Tutte, 1947) with various optimization approaches and added depth in the form of complex networks (Albert & Barabási, 2002; Newman, 2003).
(2) Monitoring and anomaly detection: the overall monitoring of a system or network of systems, where the detection of anomalies may alarm the provider or cause the system to act autonomously (Chandola et al., 2009).
(3) Simulation and prediction: a method application ranging from simple prediction-based decision-making systems to the full implementation of a digital space of a real-life system, where predictions are made based on both earlier estimations and real-time monitoring, which allow intermediate updating of the simulation system (Davison et al., 2007; Snavely et al., 2008).

Further explanations and benchmarking of these AI method applications can be found in their respective subsections of the literature review section.

2.3.1 Benchmarking

For each of the AI method applications, a contemporary state-of-the-art 'AI benchmark' of each method application was established through new Scopus query searches on that AI method application. The addition of such a benchmark provided a method of comparison of the intersectional studies to the more general AI method application studies. In other words: the benchmark helps establish whether the general state-of-the-art of the method application is also the state-of-the-art that is used in the domain of the specific governmental task, or there is a discrepancy.

For this benchmarking, a screening protocol was used to check whether any of the contents of title, abstract and keywords of a publication answers the following question:

- Does this publication include thorough explanations of AI models used in this AI method application?

In the case that the criterion was fulfilled, the article was included (Table 3).

Table 3: AI method application benchmark query keys and number of found articles.
**NB: (ai*) = ((artificial AND intelligence) OR ai)*

AI application	Query key	# Articles
Common key	TITLE-ABS-KEY (ai*) AND …	
Network planning & optimization	… ((network OR graph) AND optimization)	6
Monitoring & anomaly detection	… ((anomaly AND detection) OR monitoring)	16
Simulation & prediction	… ((simulation OR modeling) AND real-time) OR (prediction OR optimization)	3+
Total		25+

2.4 Governmental Tasks

The second dimension for categorization is defined by governmental tasks. The two main branches of the Directorate of Water and Soil have each a set of 6 water management tasks, for a combined set of 12 (Organisatie- En Mandaatbesluit Infrastructuur En Waterstaat, 2021). This legal document provided some basis for this dimension, although it was defined insufficient due to various tasks being incompatible with the usage of AI (such as pushing for policy innovation), being too region specific (such as regulation of a particular coastal area) or being unrelated to water management (such as soil and underground). As such, I subjectively defined a new categorization based on seven concrete mentions within these tasks, listed below.

(1) 'Waterway construction planning' revolves around the planning phase and the construction phase of artificially engineered waterways (such as canals) or barricades (such as levies). Based on legal task a.2 ('instructing waterworks').

(2) 'Pipeline construction and maintenance' concerns the planning and construction of a pipeline network for freshwater and sewage water, as well as the maintenance of said network. Also based on legal task a.2 ('instructing waterworks').

(3) 'Surface water quality' includes the quality management of open waters that are not solely used as water reservoirs. Based on legal task b.1 ('quality & freshwater').

(4) 'Drinking water quality' describes similar control, though with water that is currently part of the closed piping network before it is consumed or contaminated by households and industry. Also based on legal task b.1 ('quality & freshwater').

(5) 'Reservoir management' focuses on the general supervision of water reservoirs. Based on legal task b.2 ('water supply and sewage').

(6) 'Waterway safety and flooding' incorporates the risks associated with water in the Netherlands from rivers, precipitation, and sea. Based on legal task a.1 ('water safety').

(7) 'Water supply and demand' concerns the problem of matching up the supplied quantity of drinking water with the demanded quantity. Based on legal task b.2 ('water supply and sewage').

To find relevant articles, several keywords were selected based on the name of the governmental tasks themselves, and a new search query was performed on the Scopus database. The screening protocol checked whether any of the contents of title, abstract and keywords of a publication answers two questions, judged subjectively by the researcher:

- Does this publication include information on a solution of a new or existing problem associated the respective governmental task?
- Does this publication include at least a moderate explanations of AI models used in this AI method application?

In the case that both criteria were fulfilled, the article was included (Table 4).

Table 4: Governmental tasks query keys and number of found articles.
**NB: (ai*) = ((artificial AND intelligence) OR ai)*

Task	Query key	# Articles
Common key	TITLE-ABS-KEY (ai*) AND …	
Waterway construction	… (canal OR waterway OR levy OR dike)	10
Pipeline construction	… ((water OR gas) AND pipe)	22
Surface water	… (surface AND water AND quality)	5
Drinking water	… ((drinking OR quality) AND water))	9
Reservoir management	… (reservoir AND water)	9
Waterway safety	… ((safety AND water) OR flooding)	20
Supply and demand	… ((supply OR demand) AND water)	11
Total		86

2.5 Discussion assessment process

2.5.1 Summarization

The overall summarization of the literature searches is put in a table at the start of the Results section (Section 3). This table provides an overview of the number of relevant studies found at the intersections between each AI method application and governmental task, as well as the number of relevant studies used for benchmarking each AI method application. For each cell, one of three scenarios may apply. The boundaries were based on the total amount of studies found.

1) None or very few (namely: 0-2) relevant studies have been found and successfully screened in this literature research at this specific intersection or benchmark. This result

may be interpreted in two ways, assuming the limitations of this literature study (Section 4.2): as a first option, no studies have been found due to the Method AI application being unfit or unimpactful with the dimensionality of problems related to the governmental task. As a second option, it is possible that possibilities of AI-driven solutions at this intersection have previously gone undiscovered. These intersections may signify a research gap.

2) A moderate number (3-6) of relevant studies have been found and screened in this literature research at this specific intersection of benchmark. In this literature review, this number is interpreted as the intersectional research being developed with a medium level of maturity. Additionally, this literature review assessed when the research was published. If most of the works were published in the last 5 years, then the field is considered being currently explored, with moderate level of expected new research in the upcoming short term (0-5 years). In contrast, a majority presence of dated (or 'historical') articles (2016 or earlier) with few or no newer publications could be an indication of a topic that no longer actively develops.

3) A high number (7+) of relevant studies have been found and screened in this literature research at this specific intersection or benchmark. It is interpreted that this intersection exhibits a high level of research maturity. Additionally, if an intersection contains a high number of recent articles (2017 or later), this literature review interprets the intersection to have a high current research 'momentum' and an additional high level of expected research in few upcoming short terms (0-5 years) due to its current popularity.

Following this summarization table, the Results section describes each benchmark and AI method application. Each intersection is finalized with a subjective recommendation based on one of the three scenarios and the potential level of impact for the government.

2.5.2 Analysis in discussion

Following the assessment of each intersection in the Results, the Discussion (Section 4) summarizes these recommendations in a quantifying overview. For each intersection, three subjective scores are given ranging from low (–) to moderate (±) to high (+). The scores are based on a subjective impression by the researcher regarding:

a) Level of research maturity, based on level of 'historical' (2016 or earlier) publications regarding AI method application in this intersection or in general (for benchmarking).
b) Level of expected growth in research, based on level of recent publications (2017 or later). A moderate or high level assumes a continuous trend of publications in the future.
c) Level of impact for the Directorate; based on a combination of the level of relevance of the application to the workings of the Directorate of Water and Soil as well as the level of improvement given by deploying said AI method application. For the level of assumed impact at every intersection, the level of relevance was sourced from a description of the Directorate's tasks (Organisatie- En Mandaatbesluit Infrastructuur En Waterstaat, 2021).

These scores are summed up in Table 6 in the discussion (Section 4.1). The benchmarking assessment of the method applications only pertain the first two scores, namely level of research maturity and level of expected growth.

3 Results

Through the summarization method described in the methodology, the following overview was obtained (Table 5). This table describes the number of articles found at each benchmark for AI method applications, and each intersection of method applications and governmental tasks.

Table 5: Number of articles found at each intersection, including benchmarks.

Governmental task	AI method application		
	Network planning and optimization	Monitoring and anomaly detection	Prediction and simulation
Benchmark	7	16	6
Waterway construction	4	-	6
Pipeline construction.	9	11	2
Surface water	-	5	-
Drinking water	1	4	6
Reservoir management	1	3	3
Waterway safety	1	4	14
Supply, demand	3	-	3
Total	26	42	40

Following, this results section will provide the literature review description and recommendations regarding the 108 found studies.

3.1 Network planning and optimization

The matter of network planning and optimization is quite thoroughly described in the field of graph theory as part of discrete mathematics and may be considered a classical mathematical problem (Tutte, 1947). Its relevant application for governmental water management lies, for example, in the building and maintenance of the underground water pipe grids throughout urban areas, as these are essentially networks with pipeline as edges and supply points, households, and industry as different types of nodes.

In the field of machine learning, network-type problems are currently often approached using Graph Neural Networks, which allows inference on graph-based descriptions (Abadal et al., 2022; Y. Li et al., 2016; Scarselli et al., 2009). Despite their common use in spacial problem solving, other models such as Convolutional Neural Networks fail to do this due to their partial pooling approach being incompatible with the topology of graphs, such as their arbitrary node distance (Abadal et al., 2022).

A slightly more dated, yet popular approach to this type of problem remains the Genetic Algorithm, which showed relative success over older, static algorithm approaches (Mirjalili, 2019). Historically, these static algorithms were used to optimize graph problems such as Nearest-Neighbor for traveling salesman-type problems or Branch-and-Price algorithm for coloring (Albert & Barabási, 2002), although these methods usually did not include the use of machine learning to improve their performance. More recently, general Deep Neural Networks have also been used for graph representation, albeit in novel phase (Cao et al., 2016). As such, this study considers Graph Neural Networks to be the current benchmark method of solving graph-type problems such as grid planning and network optimization.

Recommendation: due to the strong presence of historical publications and more recent studies, both this method applications' general benchmark research maturity and expected research growth is considered high.

3.1.1 Waterway construction planning

The use of AI-based network optimalisation for waterway planning has been suggested earlier (Ahuja et al., 1995), although this concept had not been worked out. More recent studies show that network planning may be used to calculate a cost-benefit model of levy construction based on the minimal height required to protect against flooding (Brekelmans et al., 2012; Zwaneveld et al., 2018). However, these approaches are very narrow, and few studies were found that primarily used network planning for the building of canals and levies. One recent study mentions the incorporation of a ‘water landscape’ in the shape of a network model to create an AI-based urban water environment overview (Xiang et al., 2021), and suggests the use of graph inference to motivate decision making by the model. However, like the paper by Ahuja et al. (1995), this example remains very exploratory in its description and is not a fully functioning model.

Recommendation: overall, little research regarding this topic was encountered during this literature study, possibly because waterway planning is rarely of such complex network nature that usage of AI-driven models of any kind is deemed necessary for its planning, and manual considerations were deemed sufficient. Due to a low number of older articles, the research maturity is interpreted as low, although the similarity of this problem to pipeline construction and maintenance (Section 3.1.2) is considered. A low-to-medium level of more recent articles exists, but mostly contain toy-world examples and little real-world implementations, and as such, no major growth in research is expected. Thirdly, its impact for the Directorate is uncertain, as most waterway projects appear to be manually worked out. Due to this, it remains to be seen whether the deployment of AI models will be worth the resource cost. Summarizing these three scores, it is not expected for novel methods to emerge soon with major implications, and thus, further research into this intersection is not necessarily recommended.

3.1.2 Pipeline construction and maintenance

As one of the oldest examples mentioned for grid planning and network optimalisation, pipeline construction was a common topic in 20th century graph theory works using classical algorithms (Ahuja et al., 1995; Goldberg & Kuo, 1985), although some already suggested the use of Genetic Algorithms for this problem (Dandy et al., 1996). In these studies, the typical goal was to minimize the amount of pipeline track necessary to reach every access point. In the years following, many more heuristic optimization methods to this problem were proposed (Da Conceição Cunha & Ribeiro, 2004; Da Conceição Cunha & Sousa, 1999; Xiang et al., 2021).

More recently, there exists an increase in suggested AI-based algorithms for this problem (Faulkner et al., 2020; H. Li et al., 2021), typically suggesting Genetic Algorithms to find cost-effective methods of deploying new grids of pipeline, like Dandy et al.'s (1996) earlier study, although these publications are exclusively theoretical and have not been found as applied in the real world.

Furthermore, this approach provides the opportunity to work with other goals, such as improving robustness in a network by making it less dependent on specific waterways in places where water security is of greater concern, such as in tectonically active regions (H. Li et al., 2021). This poses less of a problem for the Dutch pipeline grid, however, where cost efficiency is the main priority when new grids are built for residential or industrial areas. Notably, none of the found papers that discussed the intersection of AI-based grid planning and waterways suggested the usage of Graph Neural Networks, instead relying on Genetic Algorithms. Although several studies regarding this topic have existed for some decades, no records of governmentally deployed AI models were found within the searching scope of this literature study.

When considering the intersection of pipeline maintenance and grid planning, no standalone studies were found, although a conjunction may be drawn with monitoring and anomaly detection (Section 3.2.2).

Recommendation: for the intersection of network planning and pipeline construction, the research maturity is considered high. The abundance of recently published papers suggests a strong expected continued growth in this field, and the level of impact is similarly rated high due to the optimization of infrastructure construction being of key value for the Directorate. It should be noted, however, that there exists a gap between academic publications and real-world implementation: as such, this literature study strongly suggests that further scientific exploration of the benchmark model into this intersection may provide meaningful opportunities which could subsequently be used by the Directorate of Water and Soil.

3.1.3 Surface water quality

No studies were found at the intersection of surface water quality and network optimization. This may be attributed to the fact that the dimensions of the problem are different than the solutions provided by grid planning and network optimization. Even though it is not expected that surface water quality applications using AI network optimization will arise in the future by itself, there is a possibility for its use in conjunction with monitoring and anomaly detection (Section 3.2.4). Through monitoring a surface water quality at various points in a body of water, network optimization could theoretically be used to create a more efficient placement distribution of measuring sensors.

Recommendation: as the number of found scientific publications regarding this intersection were zero, it is scored is as follows. Both the maturity and expected growth of research is considered low. Similarly, the level of impact is found to be low due to the dimensionality problems. In conclusion, this literature study does not recommend an active pursuit of research into this topic.

3.1.4 Drinking water quality

Drawing similarities with surface water quality (Section 3.1.3), no studies were directly found at this intersection, although an ensemble method of monitoring and network optimization is possible in the shape of optimal sensor placement along a pipeline grid. Currently, sensor optimization methods are commonly used for wireless networks, but may also be used in discrete graph networks (Krause et al., 2008).

Recommendation: research maturity appears to be low, as well as expected growth due to a lack of currently existing research regarding this intersection. However, in contrast to the previous section, further research is considered of some additional value, as optimal sensor placement can significantly improve monitoring results without a necessity for additional sensors or other equipment, as mentioned in Krause et al. (2008). Furthermore, this sensor optimization method may be applied to different network contexts within the Directorate or even other directorates of the Ministry and is thus recommended as an opportunity for implementation.

3.1.5 Reservoir management

No studies were found to discuss the possibility of AI-powered grid planning for government deployment, with exception of one study by Alzu'bi et al. (2019), which mentions the usage of AI planning in the context of saltwater desalination plants in middle eastern regions where freshwater supply is scarce. Even though water desalination is not necessary for providing freshwater to households and industries in the Netherlands, as drinking water is sourced from underground reservoirs, the article provides a decision-making system for optimal locations to place water processing plants related to water reservoirs (Alzu'bi et al., 2019).

Recommendation: this intersection is a relatively unexplored field with a low research maturity and low level of expected growth. It is possible that this intersection might provide optimization solutions when planning new water treatment plants in the Netherlands, when more sophisticated models like Graph Neural Networks are used. However, it should be noted that the development of such a decision-making system may require a high number of resources (such as data gathering or model design and testing) relative to the frequency of need for such a model. Combined with the question of technical feasibility, its impact is considered low, and there is no recommendation to pursue more research into this intersection.

3.1.6 Waterway safety and flooding

AI-based solutions can be found at the intersection of network optimization and flooding evacuation. While research on this topic is scarce, it has been suggested that machine learning models may provide an evacuation plan of a region with imminent hazards, such as a water flood (Khalilpourazari & Pasandideh, 2021). This model was created as a decision-making system for helicopter rescue missions, although in a strictly theoretical setting. No practical examples were found.

Recommendation: while previously considered only tangentially related to the Dutch water environment, the occurrence of a 2021 flood in the south-eastern part of the Netherlands proves that evacuation plans are of national interest. Total research maturity is low, considering the only publication found is a toy-world example. Despite this, the recent research does suggest a potential for moderate growth in this scientific landscape. AI-driven models are likely suitable for decision-making systems, as they could provide improved safety instructions during hazardous moments for relatively little developmental cost. This study considers this intersection of having a current reasonable level of impact, possibly increase to high level after more thorough implementation of real-time simulation models (Section 3.3.6) is performed by the Directorate.

3.1.7 Water supply and demand

While the water supply and demand question does concern the simulation of water flow in a given network (Altunkaynak et al., 2005; Zubaidi, Hashim, et al., 2020; Zubaidi, Ortega-Martorell, et al., 2020), no studies were found that performed any planning or optimization of the network itself. These studies used either a set of entirely independent variables or a static network model to simulate their predictions. The possibility of optimizing water pipeline supply networks while attempting to model supply and demand (Section 3.3.7) remains relatively unexplored but could considerably add to the improvement of said supply and demand models through this extra step of optimization.

Recommendation: while research maturity is low, current and expected research growth is considered moderate regarding this intersection. With a medium to high impact for incorporation of network optimization in sophisticated supply and demand models, this literature study suggests that further research on the conjunction of these topics may be investigated.

3.1.8 Network planning and optimization: overall summary

The AI method application of network planning and anomaly detection has a high degree of historic research maturity, as well as a high degree of expected continued research growth. Its impact as a method application is considered moderate (Section 3.1).

Within the intersection fields of network planning and optimization, there are various opportunities regarding network optimization and network planning, with high levels of assumed impact. Most notably, this study found both a significant presence of unused potential for Graph Neural Networks to assist in pipeline construction planning (Section 3.1.2), as well as potential expansion of supply and demand prediction models incorporating the use of network optimization as an extra layer of depth and complexity to the model (section 3.1.7). To a lesser degree, this literature review found potential for the optimization of water quality sensors placement along a network.

Waterway construction planning, surface water quality, and reservoir management were not considered potential opportunities for further research for the Directorate, due to their low level of expected research growth and low level of impact.

3.2 Monitoring and anomaly detection

A common purpose for AI-trained models is to monitor a set of real-time data to find and report any outliers within it. Its purpose to alarm the monitoring agent that a certain action is required. Well-known examples of where such systems are commonly used for detection are medical diseases (Cruz & Wishart, 2006; Jiang et al., 2017), credit card fraud (Islam et al., 2022; Ngai et al., 2011; Sharma et al., 2021), or seismic activity (Asencio-Cortés et al., 2018; Asim et al., 2017; Reyes et al., 2013). Many of these studies describe the earlier use of non-AI-based models or relatively ‘plain’ models such as k-nearest neighbors, or support vector machines. However, in more recent years, the usage of Deep Neural Networks has been steadily increasing due to their excellent results in these fields (Asim et al., 2017). Of particular interest for unsupervised anomaly detection is the Generative Adversarial Network (Schlegl et al., 2017), where two of these Deep Neural Networks compete for optimization. This approach recently featured in various highly cited studies and has been successful for a wide range of unsupervised anomaly detection (Fekri et al., 2019; D. Li et al., 2019; Lim et al., 2018; Schlegl et al., 2019).

For purposes of this literature review, the usage of Deep Neural Networks, and Generative Adversarial Networks in detail, is considered the current benchmark method for general AI-based monitoring and for unsupervised anomaly detection. However, no clear state-of-the-art benchmark could be established for supervised or semi-supervised anomaly detection, although functional examples of Convolutional Neural Networks and Hidden Markov Models were recently published (Shukla & Piratla, 2020; X. Wang et al., 2019). Furthermore, one study explicitly mentioned that an expansion on the monitoring capabilities of many systems requires substantial improvement to the measuring sensors, besides solely a state-of-the-art AI-based implementation (Rojek & Studzinski, 2019).

Recommendation: due to this literature finding some presence of historical publications and a very high presence of more recent studies, this method applications’ general benchmark research maturity is assessed as moderate, while its expected research growth is considered very high.

3.2.1 Waterway construction planning

No studies were found for waterway construction related to anomaly detection. This is attributed to the fact that during the planning phase of these works, there is no monitoring requirement, and therefore no anomaly detection requirement either. Considering the maintenance of these works, no studies were found.

Recommendation: due to no publications found, the maturity and expected growth are considered low. Despite no direct results, similar steps of AI-driven monitoring could be used, such as leakage detection (Section 3.2.2) or other forms of decay prediction (Section 3.3.2). By itself however, its impact for the Directorate is considered low since the waterway projects are largely manually planned, and thus AI model development may not be worth the time and cost investments.

3.2.2 Pipeline construction and maintenance

There were no examples of studies found at the intersection of the construction aspect of pipelines and monitoring. However, the maintenance aspect of pipelines was commonly discussed within the scope of this literature research, often concerning natural gas piping but with similar problems and opportunities. This section further draws parallels with drinking water quality (Section 3.2.4) as it is often measured in the same pipeline infrastructure, and water supply and demand (Section 3.2.7).

Pipeline maintenance monitoring is of crucial value to the instance that is responsible for this infrastructure, due to the need of a fully functioning drinking water and sewage network. Monitoring the infrastructure is possible due to placement of sensors along its various pipe edges to deduce the status of (a part of) the network. Two different trends of AI usage arose in the researched literature material. Firstly, the direct detection of leakages in pipelines (Karimian et al., 2021; Ozevin & Harding, 2012; Sebestyen et al., 2021; Tian et al., 2021), and secondly, the prediction of decay (Ren et al., 2018), which is further described in section 3.3.2, as it is more closely related to real-time simulation with anomaly detection elements.

As it was difficult to find studies related to water pipelines, most aforementioned publications describe the natural gas piping infrastructure. This study argues that the application is comparable to a high extent, as hidden leakage detection of natural gas piping has been applied to water piping successfully (Rojek & Studzinski, 2019; Zheng et al., 2021) and was theorized to work with Neural Networks several decades ago (Belsito et al., 1998). While older studies use simpler AI-driven models and less complex networks in general (Poulakis et al., 2003; Qu et al., 2010), Rojek & Studzinski's method incorporated feed-forward Neural Networks (Multilayer Perceptron Models) to predict where leakages were taking place within the network based on the flow speed at various measuring points.

An alternative method of finding anomalies is acoustic sounding, where any outliers in the audio response may correspond with outliers in the pipe casing (Liang et al., 2013; Ozevin & Harding, 2012). No papers using acoustic sounding mention the use of AI-based models, however.

Recommendation: with a high number of publications at this intersection, the research maturity is defined as high. The usage of the previously selected Generative Adversarial Network benchmark method at this intersection could provide substantial results; a recent preliminary study showed a high degree of success with this AI model for leakage detection, outperforming other Neural Network setups (Zheng et al., 2021). As such, the current and future research growth is also considered high. The potential level of impact for the directorate is thirdly considered high due to the country's massive water pipeline infrastructure, although more explorative research is suggested for water-specific piping.

3.2.3 Surface water quality

Historically, different approaches have been taken to the matter of quality monitoring of surface water in a region, although many studies suggest the use of sensors in combination with Geographical Information Systems to manually map the different compositions of water in a particular part of a waterway or lake (Sanders et al., 1983; Sokolova et al., 2022; Usali & Ismail, 2010). Only in very recent years, a study compares and assesses the impact of AI-driven models in this field in various locations in Canada, China, the Middle East, and Southeast Asia (Ighalo et al., 2021).

Recommendation: This type of research was notably absent for the Netherlands or surrounding countries within the search scope of this paper, although general research maturity in this intersection is moderate in other areas around the world. Ighalo et al. describe a multitude of AI implementations such as well-performing Artificial Neural Networks and Multilayer Perceptron Models (similarly present in Rojek & Studzinski (2019), see Section 3.2.2), no mention of Generative Adversarial Networks was made, and it remained the only publication found. Expected research developments are therefore considered low. Despite this, the proper monitoring of surface water quality is of key importance to the Dutch government due to its richness in surface water areas, as well as its dependence on it through drinking water, agricultural use, recreational use, and nature conservation. Therefore, its impact is considered high. Due to a low number of current development and a high potential level of impact, this literature review strongly suggests further research into this intersection.

3.2.4 Drinking water quality

Although drinking water quality is monitored in a similar capacity to surface water (Section 3.2.3), the key difference considered by this literature review is the monitoring of drinking water in a discrete pipe network rather than a continuous waterway or lake environment, and therefore, different studies may apply. Although no historical research regarding the intersection of water quality and monitoring was found within the search scope of this study, in recent years, AI-driven models have been successfully implemented for this purpose and provide excellent results (Al-Adhaileh & Alsaade, 2021; Mustafa et al., 2021; D. Wang et al., 2021). Furthermore, it has been suggested that some principles used in leakage detection (Section 3.2.2) could additionally be used for quality control of pipelines, such as when assessing pollution at specific access points (Poulakis et al., 2003).

Recommendation: the level of research maturity at this intersection started low, although there is an amount of recent relevant publications, which sets the expected growth to moderate. The importance of drinking water quality for the Dutch government is implied through safe and secure use for households, agriculture, and the industrial sector. As a government task with major stakes for a consistent clean water supply, the impact of potential AI-driven solutions is considered high. Therefore, this literature review already strongly recommends usage of this AI method application for increased implementation in its current form, while additionally taking future developments into account.

3.2.5 Reservoir management

No older publications at the intersection of monitoring and water reservoir management were found. In more recent years, the option for AI-driven open water reservoir management was only directly mentioned in one study (Mustafa et al., 2021). However, the concept of the AI model is not thoroughly worked out and would require considerably more exploratory research prior to real-world deployment. Two other studies found at this intersection search are the description of water quality monitoring using AI-driven models at the start of the supply chain (Zulkifli et al., 2018) as well as on the end of the supply chain at wastewater treatment plants (Kamali et al., 2021).

Recommendation: as no directly relevant publication was found by this review in historical context and solely one publication in more recent context, both research maturity and expected growth regarding this intersection are considered low. Furthermore, Dutch freshwater reservoirs do not take the form of open waters but are contained underground instead, and studies such as Mustafa et al.'s (2021) may not apply properly in the first place. Yet, proper monitoring and anomaly detection of freshwater supply seems to be of direct relevance for the Directorate, as much of the country's infrastructure is heavily dependent on it. Therefore, its impact is still set considered moderate, despite little academic research found. This literature review recommends further exploratory research into the monitoring of the Dutch freshwater reservoirs.

3.2.6 Waterway safety and flooding

The monitoring and anomaly detection of waterway safety and flooding scenarios is mentioned in a more dated study (Hunt, 2005), although the majority of the publication focuses on prediction-based systems rather than detection-based, and its contents may be more suitable for the simulation and prediction method application (Section 3.2.6). In recent years, AI-driven flooding detection models using monitoring sensors have been largely successful in both toy-world publications (Pyayt et al., 2011; Tabbussum & Dar, 2021) as well as real world case studies (Ke et al., 2020; Munawar et al., 2021), with Munawar et al. (2021) going as far as using image processing to monitor current water levels.

Recommendation: one historical publication was found at this intersection, and as such, its level of research maturity is considered low. In recent years, four publications provided a growth in research at the intersection of monitoring and flooding. Therefore, this literature review considers the expected growth to be moderate. Although there is a moderate level of information found on this intersection, this anomaly detection and monitoring may be considered an intermediary step for papers discussing the AI method application of simulation and prediction (Section 3.3.6). Both as an intermediary step and by itself, the impact of scientific development at this intersection for the Directorate is defined as high, due to water safety being one of their major goals.

3.2.7 Water supply and demand

No research at this specific intersection was found, potentially due to the monitoring and anomaly detection being only an intermediary step for prediction of the quantity of water supply and demand (Section 3.3.7).

Recommendation: research maturity and expected research growth at the intersection of monitoring and anomaly detection with water supply and demand are both considered low. Due to the use of this method application in formulating simulations or predictions, its impact is still defined as moderate for the Directorate. Further research regarding this task is therefore suggested when attempting to improve the aforementioned simulation and prediction.

3.2.8 Monitoring and anomaly detection: overall summary

While the relative level of research maturity in the AI method application field of monitoring and anomaly detection is only defined as moderate, its current level of development is considered very high, and further growth is expected (Section 3.2).

At the different intersections of the governmental tasks with monitoring and anomaly detection, various opportunities were defined with a potentially high level of impact. In particular, the task of pipeline construction and maintenance stood out with a high level of research maturity, expected growth, and level of impact (Section 3.2.2). Thus, it is strongly recommended by this literature review as a point of interest for the Directorate to further research. To a lesser degree, highly impactful tasks that could be improved using monitoring and anomaly detection were surface water (Section 3.2.3) and drinking water quality (Section 3.2.4), as well as water safety management (Section 3.2.6). Further exploratory research is suggested prior to large scale implementations due to the low to moderate levels of research maturity and current research growth for each of these tasks, however.

As a remainder, further research for the intersections of this method application with waterway construction, reservoir management, and water supply and demand are not strongly suggested due to their lack of research maturity, expected growth and relative low level of impact for the Directorate.

3.3 Simulation and Prediction

Using AI-driven models to predict outcomes or even simulate scenarios may help in preventive decision making or general analysis by the Directorate of Water and Soil. As the AI method application of simulation and prediction is a very broad term, its domain was confined by the search methodology.

The incorporation of AI in simulation models was relatively unexplored in the found literature, with only two dated studies that mentioned the possibility of increasing the complexity of simulations by using AI. The first study regarded this concept in an urban traffic model (Jávor & Szucs, 1998), and the second in the process simulation of supply chain logistics (Bruzzone & Orsoni, 2003). In more recent years (albeit falling under the category of dated articles in this literature review), predicting using AI-driven models has been very prominently developed (Jordan & Mitchell, 2015; Schmidhuber, 2015). Particularly interesting regarding the simulation side, a study showcased the capability of an AI model to geospatially simulate weather forecasting in an urban region (Shi et al., 2015). The authors stated that very few previous studies applied this specific AI-perspective to weather forecasting. A similar research gap was found for general descriptions of these full-scale implementations, as few studies were found in this search query that described overall simulation capabilities of AI-driven models. One exploratory study was found (Ahmad et al., 2016), but contained little depth regarding the AI implementation itself. Therefore, it was not possible for this literature review to establish an AI technique as the benchmark for this method application.

Recommendation: this literature review found a low presence of historical publications and moderate presence of more recent studies. (While technically falling under the 'dated' category, these studies all appeared in 2015, and are considered recent in this specific case). As such, this method applications' general benchmark research maturity is assessed as low, while its expected research growth is considered moderate.

3.3.1 Waterway construction and planning

At the intersection of simulation and prediction with waterway construction and planning, one mention is made in an historical work (Hunt, 2005), but does not provide in-depth exploration of possible scenarios. Later in time, Rabelo et al. (2015) published a real-world study regarding simulation modeling using AI (Rabelo et al., 2015), after which this literature review found multiple other papers. AI simulation models may be used for simulating and prediction of waterway bed depth (Kim et al., 2021; Pandey et al., 2021) or planning of water dams (Allawi et al., 2018), the latter of which could be similarly used for other waterworks such as levies. In fact, a similar prediction method was developed for predicting optimal levy construction heights (Zwaneveld et al., 2018).

Recommendation: while initial research maturity is considered low, there exists a recent surge in simulation and prediction at this intersection. Therefore, the expected research growth is considered high by this literature research. The level of impact for the directorate is considered similarly high, due to the Directorate's interest in optimization regarding waterway construction.

3.3.2 Pipeline construction and maintenance

This intersection search contained little literature found regarding AI-driven simulation (Mehmood et al., 2020). The examples mentioned in this publication are very exploratory in nature and do not cover any real-world scenarios. Regular prediction was encountered, albeit only once besides the aforementioned article (Mehmood et al., 2020; Sabour et al., 2021).

Recommendation: with a low level of research maturity and expected research growth, this intersection initially appeared with little potential. However, applying the high levels of maturity, growth and impact regarding the monitoring method application (Section 3.2.2), this literature review considers there to be a research gap where the monitoring data may be used to create AI-drive simulation models of pipeline networks. For example, these models may provide meaningful insights into the maintenance of current networks. Therefore, the level of potential impact is set to high, despite its low other scores. This literature review strongly suggests further exploration of this research gap.

3.3.3 Surface water quality

No studies were found at the intersection of simulation and prediction with surface water quality, for reasons unknown other than the confinement of the search scope.

Recommendation: with no associated research found, it is not possible to assess the level of research maturity and expected growth of this intersection as moderate or high for the Directorate. An example concept that was expected but not found withing the searching scope is the simulating of water pollution in a region over time, which could at least be of moderate impact for the Directorate. Exploratory research may provide a new perspective, but it is not expected.

3.3.4 Drinking water quality

This intersection was historically described in two studies, although solely as a suggestion for further implementation, and not as main topic itself (Msiza et al., 2008; Qu et al., 2010). In a similar fashion, recent studies assess drinking water quality solutions in the method application of simulation and prediction (Allawi et al., 2018; H. Li et al., 2021; Mehmood et al., 2020; Niu & Feng, 2021), but fail to provide a real-world solution or even a fully functioning toy-world solution.

Recommendation: research maturity remains low with only two tangentially related publications being found by this literature review. Despite a moderate presence of recent articles, none are of high quality concerning this governmental task, and thus, the expected research growth is considered similarly low. Thirdly, the level of impact is relatively low. Specifically, it is lower than the surface water quality assessment for this method application due to a smaller chance of external pollution occurring in a closed loop system.

3.3.5 Reservoir management

The management of reservoirs is thoroughly discussed historically, where one study provided an overview of AI-driven models for the sustainable use of groundwater in coastal aquifers (Sreekanth & Datta, 2011), in an exactly similar fashion to Dutch freshwater reservoirs. Namely, Sreekanth et al. (2011) thoroughly discuss the deployment of AI for prevention of saltwater intrusion into the aquifer. Another dated study provides thorough AI-driven examples regarding the water availability in a water reservoir (Mohaghegh, 2011), which take place in an open-water reservoir but might still be applied in a similar fashion to Dutch freshwater aquifers. Even in more recent years, the field of reservoir water availability continues to be researched (Guo et al., 2021).

Recommendation: research maturity is set to low due to the scarcity of found studies regarding this intersection. However, despite the low numbers of historical research and current research, the expected growth is of a moderate level due to the high quality and relevance of the studies found by this literature review. Its implied impact is of a high level for the Directorate of Water and Soil due to their interest in optimized and futureproof managing of the water reservoirs. As such, this literature review strongly suggests further research on simulation with water reservoir aquifers be performed.

3.3.6 Waterway safety and flooding

This intersection was found to contain many relevant publications. Historically, flood simulation models were based on manually crafted model regions (Ernst et al., 2010), such as coastlines (Hunt, 2005), rivers (Dutta et al., 2006; Hunt, 2005), or even more recently in urban areas (Babaei et al., 2018). Additionally, a study of water flooding damage was found regarding the Dutch population itself (Maaskant et al., 2009), unlike the other studies which were based on different examples in other parts of the world.

Studies of the implementation of AI into flood simulation models have recently increased in frequency, especially for spacial flood prediction (Arabameri et al., 2020; Costache & Tien Bui, 2019; Syifa et al., 2019; Tien Bui et al., 2016), most of which already implement high quality real-world examples, and one of which makes use of the automatic generation of 3D space based on satellite imaging (Syifa et al., 2019). General, non-spatial prediction research for waterway safety and flooding was also found to be published relatively recently (although some publications are technically considered ‘dated’ by this literature review methodology), such as for flood susceptibility of a region (Chapi et al., 2017; Pham et al., 2021), predicted estimations of flooding in certain areas (Aziz et al., 2017), and overall flood risk management (Munawar et al., 2021; Sayers et al., 2014).

Recommendation: Due to the number of dated publications relevant to this intersection, this domain appears as well-established in the field, and thus the level of research maturity is considered high. In a similar fashion, the level of recent publications is high, and the expected continued growth is therefore assumed as high by this literature review. The level of impact is additionally considered high due to the top priority of the Directorate of Water and Soil of providing safety from flooding against its citizens. Due to the high scorings, this literature review very strongly emphasizes the added value of direct deployment of models mentioned in this section and further research into the intersection by the Directorate.

3.3.7 Water supply and demand

Historically, at the intersection of simulation and prediction with water supply and demand, one manually engineered model was found for real-time simulation of water supply and demand of urban regions (Altunkaynak et al., 2005), although more recent studies do deploy AI-driven models in real-world examples (Zubaidi, Hashim, et al., 2020; Zubaidi, Ortega-Martorell, et al., 2020). Further improvement of these simulation models may be achieved through the implementation of network optimization models by adding complexity which further imitates the real-world factors regarding supply and demand (Section 3.1.7).

Recommendation: historical, established research at this intersection is scarce, and thus, the research maturity of this field is considered as low. While only a low amount of recently published works was found, further expected growth of this field is expected due to increasing levels of overall water demand, and consequently, the need for better water supply and demand matching exists. Similarly, the level of impact for the Directorate is set to moderate, and thus, further research into this intersection is suggested.

3.3.8 Simulation and prediction: overall summary

Currently, the relative level of research maturity in the AI method application of simulation and prediction is defined as relatively low, due to only the recent incorporation of AI into this application. Secondly, its current level of development is considered moderate: while few studies were found, further growth is expected. (Section 3.3).

The flagship example of a highly relevant intersection of AI-driven simulation and prediction with a governmental task is water safety and flooding (Section 3.2.6). Besides its high level of impact for Dutch water management, this field has a high research maturity and high expected research growth, making it an ideal opportunity to deploy or further research for the Directorate. Other high-impact governmental tasks identified in this literature review are waterway construction and planning (Section 3.3.1), pipeline construction and maintenance (Section 3.3.2), and reservoir management (Section 3.3.5), with moderate to high expected further growth in expected research, with exception of pipeline construction and maintenance. Further research into these areas is additionally strongly suggested.

To a lesser extent, surface water quality and water supply and demand are considered of moderate impact. Lastly, the intersection of general prediction of drinking water quality was scarcely researched and not considered of high impact: consequently, it is not recommended as an opportunity to pursue by the Directorate.

4 Discussion

4.1 Summary of results

Table 6 sums up the given scoring in the results (Section 3) ranging from low (–) to moderate (±) to high (+) regarding the three scores of research maturity, expected growth, and expected impact for the Directorate (Section 2.5.2).

Table 6: AI method impact assessment scoring of each intersection and benchmark.

AI method application	Governmental task	Scoring		
		Research maturity	Expected growth	Impact level
Network planning and optimization	Benchmark	+	+	
	Waterway construction	–	±	–
	Pipeline construction	+	+	+
	Surface water	–	–	–
	Drinking water	–	–	±
	Reservoir management	–	–	–
	Waterway safety	–	±	±
	Supply and demand	–	±	+
Monitoring and anomaly detection	Benchmark	±	+	
	Waterway construction	–	–	–
	Pipeline construction	+	+	+
	Surface water	±	–	+
	Drinking water	–	±	+
	Reservoir management	–	–	±
	Waterway safety	–	±	+
	Supply and demand	–	–	±
Simulation and prediction	Benchmark	–	±	
	Waterway construction	–	+	+
	Pipeline construction	–	–	+
	Surface water	–	–	±
	Drinking water	–	–	–
	Reservoir management	–	±	+
	Waterway safety	+	+	+
	Supply and demand	–	±	±

Across the three different AI method applications, several AI-driven models at intersections were identified in this literature review that strongly suggest further beneficial research outcomes or even direct implementation in their current form, all for the purpose of improved results for the Directorate of Water and Soil’s current data-driven solutions.

4.1.1 Network planning and optimization: discussion

With regards to the method application of network planning and optimization, the benchmarking showcased a high degree of research maturity and expected research growth. At the intersections, pipeline construction and maintenance stood out with a high score of research maturity, growth, and impact. Despite the pipeline construction and maintenance intersection and the benchmark having a high maturity score, all other governmental tasks scored low on this aspect, and low to moderate on expected growth. Yet, this literature review suggests further research into the intersections of this method application with the governmental task of supply and demand, and to a lesser extent the tasks of drinking water quality and waterway safety. Intersections not recommended for developmental pursuit by the Directorate are network planning and optimization in combination with waterway construction, surface water quality, and reservoir management.

4.1.2 Monitoring and anomaly detection: discussion

In the method application domain of monitoring and anomaly detection, a moderate degree of research maturity was found along with a high level of expected research growth. Concerning the seven intersections, pipeline construction and maintenance was assessed once more as having a high degree of all three aspects. Other governmental tasks scored low or moderate on the level of research maturity and the level of expected research growth in their respective field. This literature review does suggest further research into the intersections of this method application with the tasks of surface water quality, drinking water quality, and waterway safety, due to their defined high level of potential impact for the Directorate. To a lesser degree, the intersections of this method application with reservoir management and water supply and demand are considered opportunities due to their moderate level of impact. Waterway construction remains as a non-recommended intersection due to low to moderate level of maturity and expected growth, and low assessed level of impact.

4.1.3 Simulation and prediction: discussion

For the method application of simulation and prediction, a relatively low level of research maturity was encountered with a moderate level of expected research growth. Due to this, benchmarking was found to be infeasible.

The waterway and flooding intersection was most prominently available in literature and scored high on all three aspects, making it a prime example of an opportunity that should be further investigated by the Directorate. Other intersections were all assigned with a low level of research maturity, due to little historical articles found. Waterway construction and planning had a high degree of expected research growth, while the five remaining governmental tasks scored low to moderate on this aspect. Despite this, the literature review still suggests further research for all these tasks, with exception of drinking water quality, which scored low on every aspect in this AI method application.

4.2 Research limitations

This literature study is a theoretical exploration of technical possibilities within the field of AI to pursue in the short or medium term that could be deployed by the Directorate of Water and Soil directly by implementation or indirectly by enforcement through legislation. However, the suggestions made in this explorative theoretical literature review have been solely based on written articles in the academic field. The applicability of these suggestions may be limited for the Directorate due to various factors, such as ethical or legislative issues, a lack of readily available data, or heavy time or financial commitment. The presence of these various constraints has been omitted for this research as it was not included in its scope.

The research methodology included various ways to scope the research, which made the research feasible in a clear and explicit working frame, but also resulted in limitations to it. Querying was performed through the Scopus database, and certain deliberate keywords were used. It is possible that existing research on the subject has not been found due to it being indexed through different keywords, or that publications were not indexed in Scopus entirely; this is possible, as a multitude of academic databases exist. Nonetheless, exclusive usage of Scopus was a conscious decision in the making of this literature review, as its publications are peer-reviewed and generally considered of decent quality. Additionally, the screening protocols may have been subject to opinionated decisions, as it was difficult to provide a hard definition of relevance. Due to these factors, it is possible that valuable insights published in other studies remain undetected by this literature study. One such example is the problem with benchmarking the simulation and prediction method application; this literature review was unable to provide a technical benchmark, despite my suspected presence of studies detailing this.

Additionally, in the methodology section, this literature review identifies three existing AI method applications. Although seemingly most present in the found literature, it should not be considered a comprehensive list of all possible applications. While many different manners of categorizing the field of AI (and machine learning in particular) exist (Russel & Norvig, 2020), this study consciously chose these applications as part of the research scope.

Furthermore, the field of Artificial Intelligence has been strongly evolving since a few decades and will likely continue to do so in the coming years due to increased access to data gathering and computing power. As time passes, the actuality of the statements made in this research might diminish; it is suggested that future viewing of the study's suggestions should take caution and verify with the current benchmark in AI technology standards as well as contemporary moral considerations to deploy responsible state-of-the-art AI.

The reproducibility of this research is feasible to a limited extent, as the sources were accessed at a specific point in time. Due to the rapid evolution of the AI landscape, a steady increase in relevant study material may be found when searching at a later stage, which may be used to formulate a different yet plausibly improved review of opportunities.

5 Conclusion

This literature review identified several notable AI-driven model opportunities for the Dutch Directorate of Water and Soil to create new data solutions or optimize current ones. Flagship AI opportunities were found at three key intersection fields: firstly, monitoring and anomaly detection intersected with pipeline construction and maintenance. Secondly, network planning and optimization intersected with waterway safety and flooding. Thirdly, simulation and prediction intersected with waterway safety and flooding. Further research into the technical possibilities at these intersections is strongly suggested by this literature review. Additionally, it is suggested to perform research into the other factors that need to be considered, such as availability of data, technical feasibility, and legality of AI usage.

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