Bridging World Heritage Management with Climate Change Adaptation in the Netherlands using Artificial Intelligence

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Abstract

UNESCO World Heritage (WH) properties are increasingly vulnerable to challenges caused by climate change, which requires them to balance the needs of heritage management with sustainable urban growth and climate change adaptation (CCA). CCA strategies are being developed by stakeholders at all levels. It is, however, not customary to generalise strategies developed in one property to another, since they are assumed to be highly localised. This paper takes the WH properties in the Netherlands as an example and showcases that topics relevant to CCA, such as climate change challenges and water management strategies, are being shared among properties in their heritage management plans, aiming to safeguard their Outstanding Universal Value. Sentence embeddings computed with cutting-edge Natural Language Processing models are used to retrieve similar topics among the properties and evaluate their associations. Common challenges (such as low groundwater level) and strategies (such as coastal dunes and dykes) are found to be mentioned in different properties. The methodological framework proposed in this paper, bridging CCA with WH management, can be repeated in other countries, and eventually at the global level, providing a generalisable integrated knowledge system beneficial and easily applicable in heritage properties from broad geographical and cultural contexts.

1. Introduction

Under global climate change, UNESCO World Heritage (WH) properties are increasingly challenged by needs in heritage management, climate change adaptation (CCA), and regional development (Sesana et al., 2021, Chen et al., 2024). UNESCO's list of *World Heritage in Danger* highlights the pressing need for coordinated international response to heritage threats. WH shows evidence of maintaining social resilience to climate change in the past thousand years (Yang et al., 2024). They are the perfect references to look at for climate resilience from the perspectives of past experiences, current actions, and future prospects. The 2023 *Policy Document on Climate Action for World Heritage* adopted by the General Assembly of State Parties specifically pointed out four main World Heritage Climate Action Goals towards 2030 (UNESCO, 2023). Among all the state parties, the Netherlands has been a world leader in CCA, particularly in water management and flood risk reduction (Stead, 2014). The Cultural Heritage Agency of the Netherlands' policies emphasise adaptive reuse strategies for heritage properties, promoting climate resilience in urban historic areas (Janssen et al., 2014). By involving public-private partnerships and multi-level governance, the Netherlands' approach ensures the conservation of WH properties while supporting sustainable tourism and community engagement, serving as a model for other nations facing similar challenges.

One significant challenge in adapting WH to climate change impact (Fatorić and Biesbroek, 2020), however, is a lack of universal adaptation policies that are known to and understood by all. It is largely unknown, for both local municipalities and international organisations, how the CCA challenges and solutions in one city apply to other cities. Strategies are heavily localised, even though similar issues might have been addressed elsewhere. The lack of generalizable knowledge and theories is therefore causing the "*wheels to be repeatedly reinvented*", leading to waste in resources and delay in decision-making for similar scenarios. Due to the massive volume of information and language barriers (in both senses of literal language and domain-specific jargon), it is challenging to analyse and integrate the policy documents, case studies, and local conservation records with traditional resource-intensive manual methods. Cutting-edge Artificial Intelligence (AI)-assisted methods such as Natural Language Processing (NLP) and information retrieval have played a vital role in assessing the cultural significance of WH properties (Bai et al., 2021) and CCA policies (Webersinke et al., 2021, Sietsma et al., 2023, Wright et al., 2023, de Rijke et al., 2025) at a large scale. However, they are mainly conducted separately, and few studies have explored their intersection. The language barriers mentioned above complicate matters further, making it especially hard for stakeholders to mobilise existing knowledge and inform decision-making. With its scalability and generalizability, NLP offers unprecedented opportunities to bridge the two jargon-heavy fields of heritage management and climate adaptation. This study aims to show the cross-case associations of WH management strategies addressing CCA in the Netherlands. It presents a methodological framework integrating WH studies, climate science, and computational data science, which can be further scaled up globally with the help of AI.

2. Methodology

2.1 Data

This study selected all 12 UNESCO WH properties (both cultural and natural) from the Kingdom of the Netherlands[1] (except for Willemstad in Curaçao) as the case study. Table 1 lists the name of all properties, their respective year of inscription

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[1] https://whc.unesco.org/en/statesparties/nl/, accessed March 14 2025.

to the UNESCO WH List, and the codes that they will be referred to throughout this paper. The openly accessible heritage management policy documents, i.e., *Statement of Outstanding Universal Value* (SOUV), the *Protection and management requirements* and the *Management Plan* (MP) of each property were collected and qualitatively coded into topics that are presumably relevant to the issue of CCA. In total, 74 topics were obtained from the documents (e.g., stakeholder collaboration as a potential strategy, legislation as a current strategy). The topics were further structured hierarchically into Management Strategies (past, present, and future ones), Operational Considerations (challenges and management considerations), and key aspects mentioned in SOUV (built structure, cultural landscape, environmental component, and resilience factors) (Cheang et al., 2025). For each property, the documents addressed a selection of topics among the 74 identified. Relevant scattered sentence quotes on these topics were extracted and aggregated into text blocks, resulting in a textual dataset $\boldsymbol{\mathcal{D}} = \{\mathcal{D}_{i,j}\}$, where i is the index of WH properties, j the index of topics, and $\mathcal{D}_{i,j}$, if not empty, would be a text block comprised of sentences, separated with a '⟨SEP⟩' token.

Code	Name of the Property	Year
AMS	Seventeenth-Century Canal Ring Area of Amsterdam inside the Singelgracht	2010
BEEMSTER	Beemster Polder	1999
COLONIES	Colonies of Benevolence	2021
DEFENCE	Dutch Water Defence Lines	1996
EISINGA	Eisinga Planetarium in Franeker	2023
FABRIEK	Van Nellefabriek	2014
KINDERDIJK	Mill Network at Kinderdijk-Elshout	1997
LGL	Frontiers of the Roman Empire – The Lower German Limes	2021
RIETVELD	Rietveld Schröder House	2000
SCHOKLAND	Schokland and Surroundings	1995
WADDEN*	Wadden Sea	2009
WOUDA	Ir.D.F. Woudagemaal (D.F.Wouda Steam Pumping Station)	1998

* The only natural heritage property

Table 1. Dutch UNESCO World Heritage Properties with their respective inscription year in alphabetic order

2.2 Embedding-based Textual Analysis

Text embedding is an essential idea in NLP, as well as the most recent large language models (LLM), which transforms raw texts (words, sentences, or paragraphs) into high-dimensional vectors using intermediate output layers of pre-trained language models on general tasks (Devlin et al., 2019, Li et al., 2020). The embeddings capture the essential semantic meaning of the texts and are aware of contextual nuances. They are widely used in downstream applications, including classification, semantic search, semantic textual similarity, and topic modelling (Reimers and Gurevych, 2019, Grootendorst, 2022, Korade et al., 2024). Using the state-of-the-art 'ALL-MPNET-BASE-V2' model[2] from the Sentence Transformer Python library (Reimers and Gurevych, 2019), the textual dataset $\boldsymbol{\mathcal{D}}$ is transformed into 768-dimensional vectorised sentence embeddings $\boldsymbol{E} = \{\boldsymbol{e}_{i,j} | \mathcal{D}_{i,j} \neq \varnothing\}$ of the non-empty text blocks of all WH properties mentioning all CCA topics. Pairwise cosine similarities $\boldsymbol{s}_{\text{combined}} = \{s_{i,j;i',j'} := f(\boldsymbol{e}_{i,j}, \boldsymbol{e}_{i',j'}) | \boldsymbol{e}_{i,j}, \boldsymbol{e}_{i',j'} \in \boldsymbol{E}, i \neq i'\}$ are computed between all pairs of text embeddings from different properties, where f represents the function computing cosine similarity of two vectors. Cosine similarities $\boldsymbol{c} = \{c_{i,j}\}$ are also computed between the embeddings of text blocks and a paragraph defining the concept of '*climate change adaptation*' from the United Nations Framework Convention on Climate Change (UNFCCC)[3] to filter topics that are semantically more relevant to CCA. Additionally, student's t-test is used to compare the distribution of $\boldsymbol{c}$ for text blocks whether or not detected as related to climate by the Climate BERT model (Webersinke et al., 2021) finetuned on the task of detecting climate-related paragraphs[4], to check the coherence of methods. The embeddings $\boldsymbol{E}$ are further aggregated at the row and column levels to obtain the overall embeddings of the WH properties and CCA topics: $\boldsymbol{E}_{\text{property}} = \{\boldsymbol{e}_i | \boldsymbol{e}_i = \sum_j \boldsymbol{e}_{i,j}/n_i\}$, $\boldsymbol{E}_{\text{topic}} = \{\boldsymbol{e}_j | \boldsymbol{e}_j = \sum_i \boldsymbol{e}_{i,j}/n_j\}$, where n_i, n_j are respectively the number of non-empty text blocks detected per WH property and CCA topic. These two aggregated embeddings are used to compute the pairwise cosine similarities among the WH properties and CCA topics, resulting in two square matrices: $\boldsymbol{S}_{\text{property}} = [S_{i,i'}]_{12\times12}, S_{i,i'} = f(\boldsymbol{e}_i, \boldsymbol{e}_{i'}), \boldsymbol{e}_i, \boldsymbol{e}_{i'} \in \boldsymbol{E}_{\text{property}}$, $\boldsymbol{S}_{\text{topic}} = [S_{j,j'}]_{74\times74}, S_{j,j'} = f(\boldsymbol{e}_j, \boldsymbol{e}_{j'}), \boldsymbol{e}_j, \boldsymbol{e}_{j'} \in \boldsymbol{E}_{\text{topic}}$.

After setting two thresholds $\alpha = .60$, $\beta = .25$ for $\boldsymbol{s}_{\text{combined}}$ and $\boldsymbol{c}$, a filtered data $\boldsymbol{\mathcal{D}}_{\text{filtered}} = \{(\mathcal{D}_{i,j}, \mathcal{D}_{i',j'}, s_{i,j;i',j'}) | s_{i,j;i',j'} > \alpha \text{ and } (c_{i,j} > \beta \text{ or } c_{i',j'} > \beta)\}$ can be obtained, containing the pairs of text blocks that are both similar to each other and relevant to the UNFCCC CCA concept. The total similarities of text blocks mentioning different topics from the same pairs of WH properties in the filtered dataset are counted as a square matrix $\boldsymbol{A}_{\text{filtered}} = [A_{i,i'}]_{12\times12}$, such that:

$$A_{i,i'} = \sum_{(j,j')} s_{i,j;i',j'}, \text{ for all } (\mathcal{D}_{i,j}, \mathcal{D}_{i',j'}, s_{i,j;i',j'}) \in \boldsymbol{\mathcal{D}}_{\text{filtered}}. \tag{1}$$

This becomes another similarity matrix of the WH properties representing the associations of their management strategies towards CCA. Spearman correlations are computed with the unrolled vectors of both similarity matrices $\boldsymbol{S}_{\text{property}}$ and $\boldsymbol{A}_{\text{filtered}}$.

Zooming into certain representative topic pairs (j, j') in $\boldsymbol{\mathcal{D}}_{\text{filtered}}$, the text blocks can be further disaggregated at the sentence level to obtain finer-grained topic-specific datasets $\{\boldsymbol{\mathcal{D}}^{(j,j')}\}$ with cases from various WH properties. Similar to Equation (1), pairwise cosine similarities can be computed at the sentence level and aggregated as topic-specific similarity matrices $\boldsymbol{A}^{(j,j')} = [A^{(j,j')}_{i,i'}]_{12\times12}$. Depending on the generality of topic pairs, a few columns and rows in $\boldsymbol{A}^{(j,j')}$ could be all zeros, meaning that for these WH properties, no similar sentences are found in other properties in this specific topic pair. In such cases, simplified similarity matrices with smaller dimensionality can be obtained by excluding these columns and rows. Three topic pairs (j, j') with high similarities $S_{j,j'}$ are selected as demonstrative examples: the diagonal pairs where both elements are '*CHALLENGE climate change*' and '*PRESENT/FUTURE STRATEGIES water management*', and the off-diagonal pair with these two topics as elements.

All the similarity matrices $\boldsymbol{S}_{\text{topic}}, \boldsymbol{S}_{\text{property}}, \boldsymbol{A}_{\text{filtered}}, \boldsymbol{A}^{(j,j')}$ are transformed into graphs as their weighted adjacency matrices, while the nodes are respectively the CCA topics and the WH properties. The graphs are visualised in Gephi with the Force

[2] https://huggingface.co/sentence-transformers/all-mpnet-base-v2, accessed June 8, 2025.

[3] https://unfccc.int/topics/adaptation-and-resilience/the-big-picture/introduction, accessed June 8, 2025.

[4] https://huggingface.co/climatebert/distilroberta-base-climate-detector, accessed June 8, 2025.

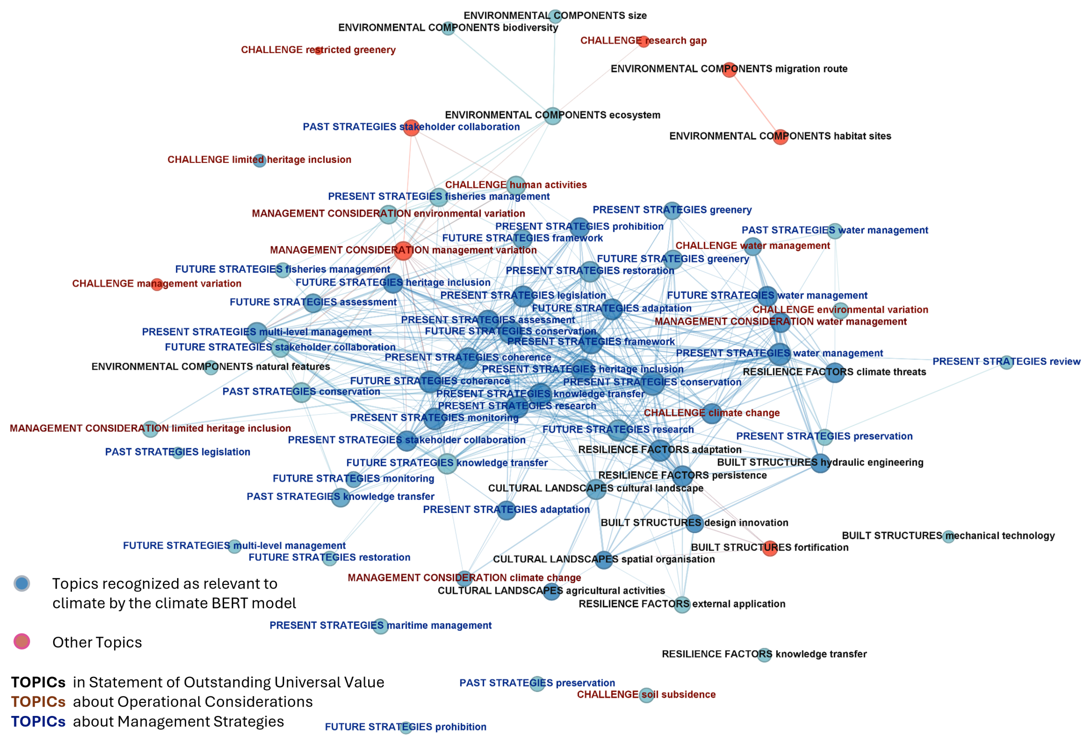

Figure 1. The pairwise cosine similarities $\boldsymbol{S}_{\text{topic}}$ of coded topics after aggregating the sentence embeddings of the properties using 'ALL-MPNET-BASE-V2' model. The thicker the links are and the closer the two nodes are positioned, the more semantically similar the two topics are according to the embeddings. Only links with a higher similarity of 0.6 are shown. Topics recognised as relevant to climate, based on the Climate BERT model, are coloured blue, and the others are coloured red. Text colours show the topic type.

Atlas algorithm based on the edge weights (Bastian et al., 2009, Jacomy et al., 2014). The inter-connection of WH properties and CCA topics reflected in the filtered dataset $\boldsymbol{\mathcal{D}}_{\text{filtered}}$ is visualised as a Sankey diagram using the Plotly Python library[5], where the flow sizes are continuously set as $s_{i,j;i',j'}$ for each flow connecting respectively (i, j, j', i) as nodes.

2.3 Sensitivity of Embedding Models

To check the robustness of the proposed methodological framework, the analysis described in Section 2.2 is repeated on two other embedding models from the Sentence Transformer library: 'MULTI-QA-MPNET-BASE-DOT-V1' model[6] and 'ALL-MINILM-L6-V2' model[7]. While 'MULTI-QA-MPNET-BASE-DOT-V1' model also provides 768-dimensional embeddings, 'ALL-MINILM-L6-V2' yields 384-dimensional ones. Spearman correlations are computed with the pairwise similarities $\boldsymbol{s}_{\text{combined}}$, the relevance with CCA concept embedding $\boldsymbol{c}$, and the unrolled similarity matrices $\boldsymbol{S}_{\text{topic}}, \boldsymbol{S}_{\text{property}}, \boldsymbol{A}_{\text{filtered}}$, all obtained from the three embedding models.

The filtered datasets $\boldsymbol{\mathcal{D}}_{\text{filtered}}$ obtained from all three models are first ranked with the similarity values $s_{i,j;i',j'}$. The top-n elements $\{(\mathcal{D}_{i,j}, \mathcal{D}_{i',j'}, s_{i,j;i',j'})\} \subset \boldsymbol{\mathcal{D}}_{\text{filtered}}$ are then aggregated to obtain the sets of top WH property pairs $\{(i, i')\}$, CCA Topic pairs $\{(j, j')\}$, and combined topic-property pairs $\{(i, j; i', j')\}$. Intersection over Union (IoU) values of these top-n sets between each pair of embedding models, as well as among all models, are computed to showcase the consistency of findings obtained from different models. Note that the IoU of three models is computed in two ways: 1) a *strict* version where the intersection of all three sets is used as the numerator; 2) a *loose* version where the union of pairwise intersections is used as the numerator instead.

3. Results

3.1 The Association among the CCA Topics

Figure 1 visualises the overall semantic relationship of the 74 topics coded from the heritage management documents in the Netherlands, based on their average textual embeddings. The centre of the graph is occupied by the various management strategies from the present, future, and past, showing their strong associations. The largest similarities appear between the present and future strategies of water management with a cosine similarity of .875, and among the present strategies of conservation, knowledge transfer, heritage inclusion, and legislation. The challenge of climate change, resilience factors of adaptation, persistence, the built structure of hydraulic engineering and design innovations, and the aspects of cultural landscape are positioned in the core of the semantic space, while the other topics from the categories of operational considerations and SOUV are scattered in the periphery. This suggests that the MP and SOUV are indeed describing the climate issues in heritage properties from different perspectives, both of which can be informative for CCA. 186 out of the 268 non-empty text blocks in $\boldsymbol{\mathcal{D}}$ coming from 66 out of 74 topics are

[5] https://plotly.com/python/sankey-diagram/, accessed June 9, 2025.
[6] https://huggingface.co/sentence-transformers/multi-qa-mpnet-base-dot-v1, accessed June 9, 2025.
[7] https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2, accessed June 9, 2025.

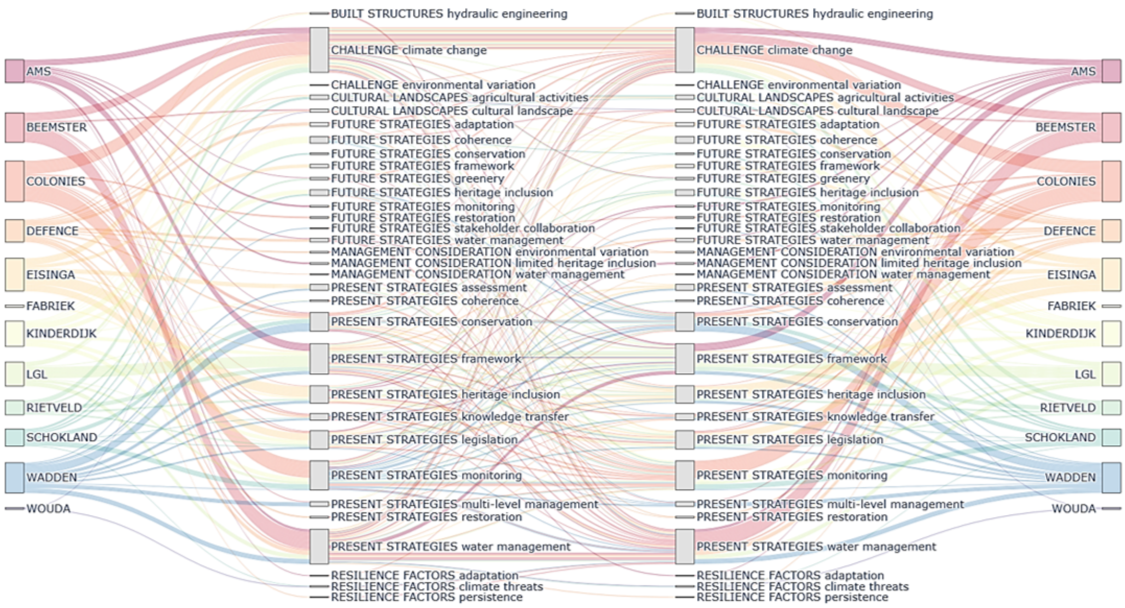

Figure 2. A Sankey diagram showing the associations of text blocks of coded topics in $\mathcal{D}_{\text{filtered}}$ that are relevant to climate change adaptation among twelve Dutch World Heritage properties. The thicker the flows, the more semantically similar text blocks are found.

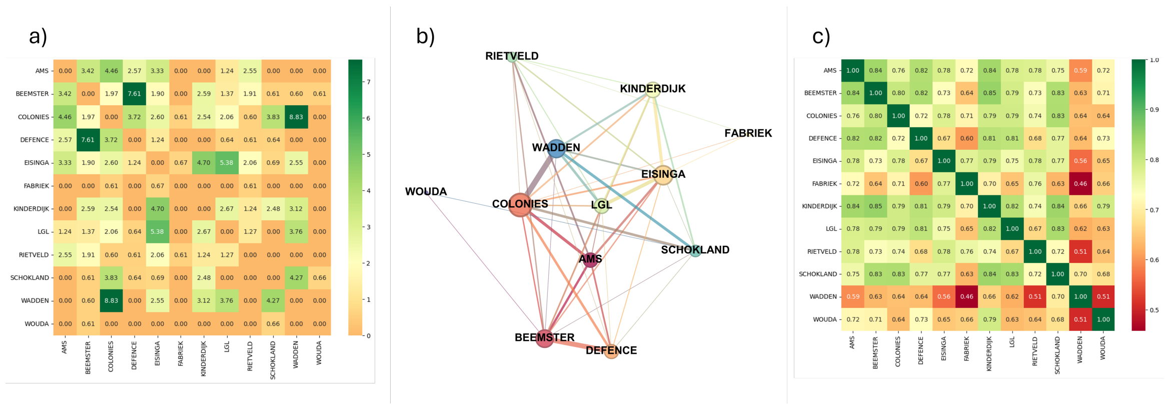

Figure 3. The associations among the twelve UNESCO World Heritage properties considering their relevance to climate change adaptation. a) the similarity matrix $\boldsymbol{A}_{\text{filtered}}$, where each entry shows the sum of all large pairwise cosine similarities among WH properties; b) the graph showing the association with $\boldsymbol{A}_{\text{filtered}}$ as link weights; c) the overall similarity matrix $\boldsymbol{S}_{\text{property}}$ among the WH properties, where each entry shows the cosine similarity of the aggregated embeddings of the text blocks from the WH properties.

detected as relevant to climate by the Climate BERT model (the blue nodes in Figure 1), for which the average similarity score $\boldsymbol{c}$ with the CCA concept is .210±.108, while for the ones not detected as relevant, the score is .118±.074. One-tailed t-test shows that the former is significantly larger than the latter, $T = 8.114, p < .001$. This suggests that the methods to filter CCA-related text blocks are consistent and that the selection of $\beta = .25$ as the threshold mentioned in Section 2.2 is reasonable.

In total, cosine similarities $\boldsymbol{s}_{\text{combined}}$ are computed for 64,732 pairs of sentence blocks from the 74 topics in all 12 properties, with a mean of .287 ± .133. Among them, 314 cross-property pairs that are semantically similar to each other from 32 CCA-relevant topics are kept in the filtered dataset $\mathcal{D}_{\text{filtered}}$, as demonstrated in Figure 2. The Sankey diagram showcases how the climate challenges and management strategies mentioned in one property are also related to other properties. *Colonies of Benevolence* and *Wadden Sea* have most semantically relevant texts written that are also to be seen in other Dutch WH properties, albeit the latter is the only natural heritage. *Van Nellefabriek* and *Ir.D.F. Woudagemaal (D.F. Wouda Steam Pumping Station)* show the most divergent MP and SOUV with the others in terms of CCA. The challenge of climate change and the present strategies of water management, framework, and monitoring are the dominant visualised topics, which are also strongly interrelated to each other. They can also be semantically related to far more topics, such as the built structures of hydraulic engineering, the management consideration of environmental variation, as well as many present and future strategies. Further examples will be given in Section 3.2 at the sentence level.

3.2 The Association of WH Properties under CCA

The semantic similarities of WH properties are shown in Figure 3 as heatmaps and graph. The two similarity matrices $\boldsymbol{A}_{\text{filtered}}$ and $\boldsymbol{S}_{\text{property}}$ demonstrate a moderate Spearman correlation of $\rho = .407, p < .001$, indicating that they capture two aspects of associations among the WH properties. While $\boldsymbol{A}_{\text{filtered}}$

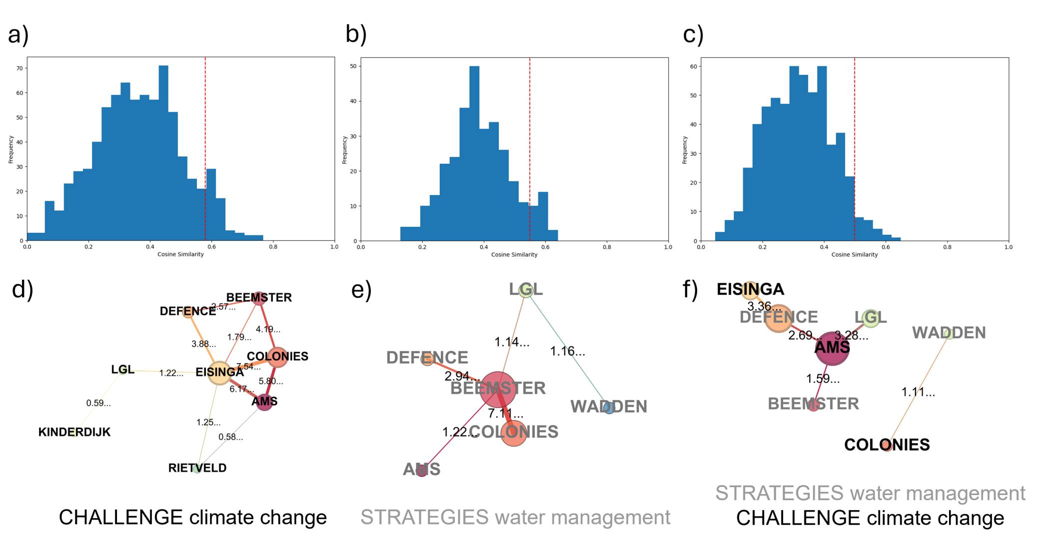

Figure 4. The sentence-level associations among the WH properties in specific topic pairs (j, j'), i.e., climate change challenge only, water management strategies only, and the interlink between the two. a)-c) The distributions of pairwise cosine similarities with sentences from each property mentioning certain topics; d)-f) The graph shows the similarities of properties that are found relevant in certain topics, where the link weight shows the sum of large pairwise cosine similarities $\boldsymbol{A}^{(j,j')}$ at the sentence level.

ID	Property	Topic	Sentence	Score
A.1	BEEMSTER	CHALLENGE climate change	*Water quantity management is mainly related to a different weather pattern caused by climate change with higher peaks in supply and longer periods of drought*	
A.2	DEFENCE	CHALLENGE climate change	*The most radical are the changes to be expected in the levels and distribution of precipitation over the seasons, and their effects on water management*	.715
B.1	AMS	CHALLENGE climate change	*The areas where the current groundwater level is already low may be particularly vulnerable to more extreme dry spells due to climate change*	
B.2	COLONIES	CHALLENGE climate change	*due to low precipitation figures in 2018 and part of 2019, a water shortage has arisen in the soil with potential drying out effects in the area*	.714
C.1	WADDEN	PRESENT STRATEGIES water management	*increase in activities for coastal flood defence and protection, such as dyke strengthening and sand nourishment.*	
C.2	LGL	PRESENT STRATEGIES water management	*In the Netherlands the coastal dunes and primary dikes protect against water levels which may occur with probabilities varying from 1/300 to 1/10,000 per year*	.581
D.1	AMS	CHALLENGE climate change	*The areas where the current groundwater level is already low may be particularly vulnerable to more extreme dry spells due to climate change*	
D.2	BEEMSTER	PRESENT STRATEGIES water management	*This reclamation has created the possibility of storing more water in the waterways and in the soil during heavy precipitation.*	.536
D.3	LGL	PRESENT STRATEGIES water management	*In the Netherlands the coastal dunes and primary dikes protect against water levels which may occur with probabilities varying from 1/300 to 1/10,000 per year*	.532

Table 2. Examples of sentences from different WH properties, of which the semantic meanings are found to be similar.

in Figure 3a) and b) focus on the count of high similarity text block pairs, $\boldsymbol{S}_{\text{property}}$ in 3c) shows the overall semantic similarity of text blocks in the WH documents. The largest number of similar text blocks appear between *Wadden Sea* and *Colonies of Benevolence*, as well as between *Beemster Polder* and *Dutch Water Defence Lines*, while the strongest overall similarity exists between *Beemster Polder* and *Mill Network at Kinderdijk-Elshout*. Whereas the *Wadden Sea* shows the lowest level of overall similarity with other properties in $\boldsymbol{S}_{\text{property}}$ probably because it is the only natural property, similar text blocks addressing relevant topics are found with other properties with certain natural attributes in $\boldsymbol{A}_{\text{filtered}}$. The *Van Nellefabriek* and *Ir.D.F. Woudagemaal (D.F. Wouda Steam Pumping Station)*, however, are less associated with other sites in both aspects.

Zooming into specific topic pairs, Figure 4 visualises three cases between the challenge of climate change and the (future and present) strategies of water management, and Table 2 gives a few concrete examples of sentence pairs in each case. Albeit the text blocks with sentences under the same CCA topic all originally have pairwise cosine similarities higher than .60, the finer-grained sentence-level similarities are again distributed in wide ranges with large number of unrelated sentence pairs. Thresholds were set respectively at .58, .55, and .50 to filter the highly similar sentence pairs. Besides the sentence pairs talking about the identical topics of climate change challenges and water management strategies, interrelated sentence pairs across topics and properties can be found. For example, sentence pair (A.1, A.2) in Table 2 both addressed the challenge of uneven distribution of precipitation over the years resulting in high peaks and drought, which is recognized by both *Beemster Polder* and *Dutch Water Defence Lines*. Sentences in (B.1, B.2) both discussed the vulnerability of water shortage in *Seventeenth-Century Canal Ring Area of Amsterdam inside the Singelgracht* and *Colonies of Benevolence*. In terms of water management as present strategies, *Wadden Sea* and *Frontiers of the Roman Empire – The Lower German Limes* both brought up the functioning of coastal sand dunes and dikes to

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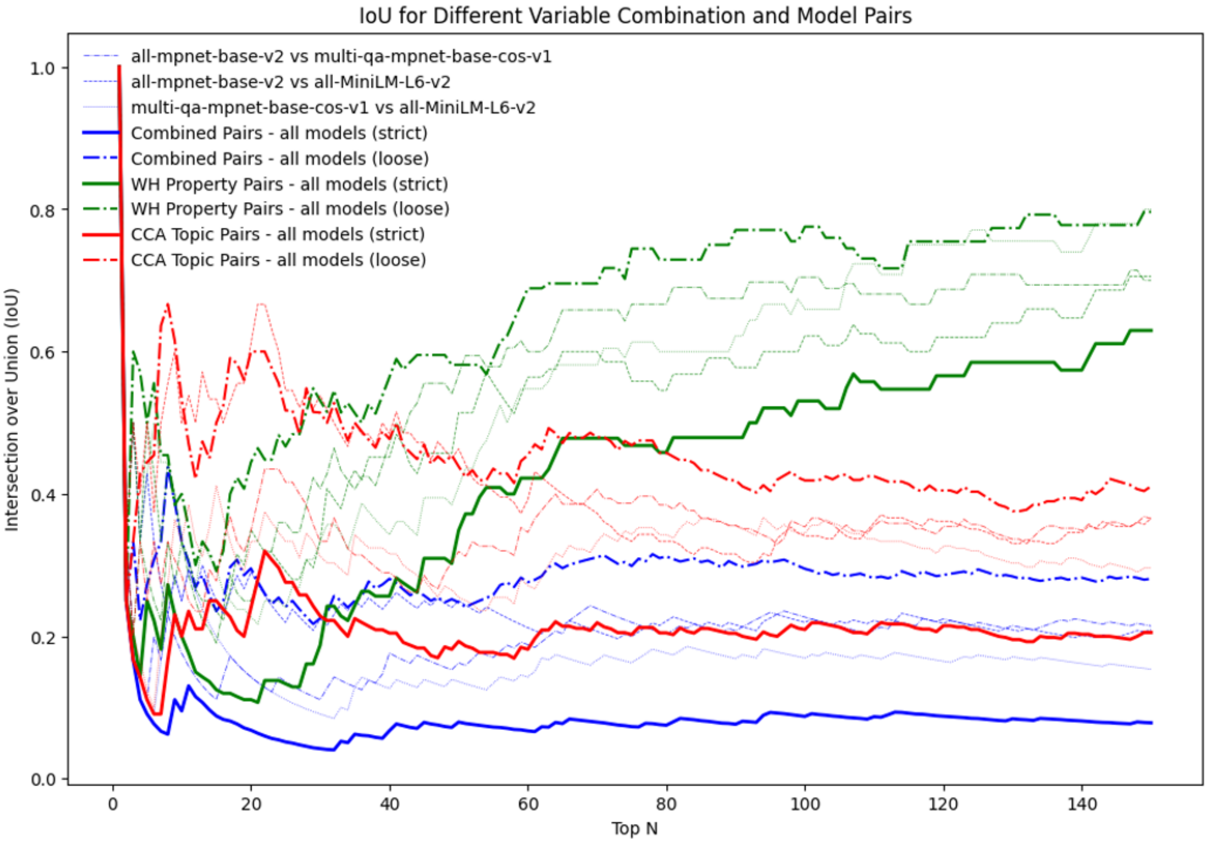

Figure 5. Comparison of behaviours of three embedding models in terms of the Intersection over Union (IoU) scores of the top topic, property, and combined topic-property pairs aggregated from text blocks in $\boldsymbol{\mathcal{D}}_{\text{filtered}}$ with top-n cosine similarities. The solid lines show the strict IoU scores from all models; the dashed-dotted lines show the loose IoU scores; and the thin lines show pairwise IoU scores.

protect the water levels in flood events in (C.1, C.2). Interestingly, although not necessarily directly applicable, the same challenge B.1 in *Amsterdam* about groundwater level was regarded as similar by the same water management strategy C.2 in *Lower German Limes* and another discussion D.3 about water storage in the waterways and soil to prevent water level changes in *Beemster Polder*. These commonalities can offer insights and inspirations, if not already workable solutions, from different properties under CCA, suggesting possible further synergies in making heritage management strategies under climate change.

3.3 Consistency of Results across Models

Despite the three tested embedding models are initially pretrained for different purposes: ‘ALL-MPNET-BASE-V2’ as the state-of-the-art version of Sentence Transformer providing assumably the best quality, ‘MULTI-QA-MPNET-BASE-DOT-V1’ for semantic searching and question answering, and ‘ALL-MINILM-L6-V2’ with half the embedding size for efficiency, they act consistently in the pipeline, as indicated with the generally high Spearman Correlation values in Table 3. Compared to the mean of $\boldsymbol{s}_{\text{combined}}$ by ‘ALL-MPNET-BASE-V2’ mentioned in Section 3.1, that of the other two models are slightly lower ($.235 \pm .120$ and $.214 \pm .121$, respectively). Therefore, a more tolerate threshold $\alpha = .50$ was used to filter the datasets and obtain $\boldsymbol{\mathcal{D}}_{\text{filtered}}$ of comparable sizes (390 and 454 pairs being kept in $\boldsymbol{\mathcal{D}}_{\text{filtered}}$, respectively). This change also slightly affects the composition of $\boldsymbol{A}_{\text{filtered}}$ and the connectivity strengths in the graphs visualised in Figure 3, as indicated by the moderate correlation values between .65 and .70 in Table 3.

Variable	Spearman Correlations ρ of Model Pairs*		
	Model Pair A-B	Model Pair A-C	Model Pair B-C
$\boldsymbol{s}_{\text{combined}}$	.836**	.810**	.802**
$\boldsymbol{c}$	.854**	.852**	.796**
$\boldsymbol{S}_{\text{topic}}$	.914**	.907**	.908**
$\boldsymbol{S}_{\text{property}}$	.927**	.931**	.944**
$\boldsymbol{A}_{\text{filtered}}$	.667**	.671**	.693**

* Model A - ‘ALL-MPNET-BASE-V2’; Model B - ‘MULTI-QA-MPNET-BASE-DOT-V1’; Model C - ‘ALL-MINILM-L6-V2’
** $p < .001$

Table 3. The Spearman correlations of different variables obtained from each pair of embedding models. For the matrices $\boldsymbol{S}_{\text{topic}}, \boldsymbol{S}_{\text{property}}, \boldsymbol{A}_{\text{filtered}}$, the correlations are computed with the unrolled vectors of their upper triangles.

Figure 5 further zooms into the consistency of the three models in their ordering of the highly similar property and topic pairs. The IoU scores evaluate how divergent the models are in picking up the top-n pairs. For example, a strict IoU score of .50 from all models means that 50% of all pairs independently picked up by each of the three models are jointly picked up by all three models. Yet a loose IoU score of .50 means that 50% of the pairs are jointly recognised by at least two models. The scores are influenced by both the overlapping pairs and the total number of pairs picked up by each model. Since there are fewer possibilities of WH property pairs than CCA topic pairs and combined topic-property pairs, it is also logical that the ranges of IoU scores also follow the same order, in reverse. The IoU scores are relatively high in the top-10 pairs, but they also fluctuate significantly since new pairs are frequently added. Remarkably, all three models picked up the same top 1 topic pair, i.e., the link between the challenge of climate change from different properties. As n grows larger, the IoU scores typically first drop and then rise before they gradually stabilise. The low score on the combined pairs suggests that instead of focusing on the rank of specific property-topic pairs $(i, j; i', j')$, the results can be more reliable when aggregated to the property and/or topic levels. This evaluation of the consistency of models also implies that by selecting a different embedding model, the order and appearance of elements in Figures 2, 3, and 4 might be slightly different, while the general trend will be consistent, which calls for careful interpretations.

4. Discussion

4.1 Implication for Heritage Management

Up to now, there is insufficient awareness of the effects of climate change within the cultural heritage sector (European Commission, 2022, Ministry of Infrastructure and Water Management, 2023), and it remains challenging to offer climate-adaptive management strategies for WH to respond to climate change impacts (Fatorić and Biesbroek, 2020), due to the extremely large and complex nature of policy documents. This study is among the first examples to bridge WH management and CCA with the help of AI. It is a pilot exploration on how to extract, summarise, and organise textual information that falls in the intersection of CCA and WH management corpora, in order to form a generalisable, interdisciplinary, and global knowledge system eventually. The findings can offer policymakers insights into management strategies to be implemented in cultural and natural heritage sites other than WH properties.

The largest contribution of this study is that it offers a simple and reproducible methodological framework to evaluate the associations of WH properties in terms of their common challenges and shared strategies under climate change, and to extract similar texts from different properties addressing relevant CCA topics. The framework can be easily repeated in another country and has the potential to be further scaled up at the global level. Albeit still largely exploratory, the results hinted that properties in the Netherlands are facing similar challenges of flood and drought, the groundwater level change, uneven precipitation distribution, and extreme weather. These challenges are addressed through comparable water management strategies in different WH properties, such as coastal dunes and dikes to protect the water levels in flood events, and water storage in waterways and soil to mitigate drought. Arguably, each property is unique in its geographical, cultural, and historical context, with its own Outstanding Universal Value, meaning that it would be unreasonable and impractical to blindly copy the management strategies of one property to the other. Stakeholders, such as heritage managers, local communities, municipalities, state parties, and international organisations, however, can still gain inspiration from other case studies. It goes beyond the conventional branding of 'best practices' at local scales, where only carefully selected cases can be referred to and compared (Markham et al., 2016). All properties are potentially compared to all the other properties within a pool that are facing the same challenge and have drawn tailored solutions. The significance of the approach further grows as the pool gets larger and involves more geographically divergent regions. It might be possible for human experts to master all the sophisticated conditions, challenges, and solutions of a limited number of properties. But when the scale grows up to hundreds, thousands, and even more properties worldwide, the depth of knowledge also drops as a natural consequence. AI is then an effective and efficient bridge to bring in knowledge beyond the conventional networks of any single expert. Stakeholders such as policymakers and heritage managers will have more (previously unknown) materials and examples at hand when proposing climate-adaptive heritage management strategies. Strategies developed in one property can, after careful evaluation, justification, and localisation, potentially be applied in another property facing similar challenges, even from another continent. It will eventually encourage co-learning among different stakeholders around the world and promote the involvement of indigenous knowledge and traditional wisdom in the changing climate (Yang et al., 2024).

4.2 Limitations and Future Steps

The dataset used in the paper comes from an earlier study of qualitatively reviewing and annotating the heritage documents of the WH properties in the Netherlands (Cheang et al., 2025). The scope of this paper was, however, limited only to the SOUV and MP of the properties. According to the earlier study, only two properties (*Wadden Sea* and *Dutch Water Defence Lines*) were explicitly addressing CCA-relevant topics in their *State of Conservation Reports*. Based on the common climate change challenges found in this paper, stronger awareness would be expected. Future studies could apply the same steps to other heritage management and CCA policy documents, such as the *Periodic Reporting* submissions from UNESCO, the national *Environment and Planning Act*, *Climate Action Plans*, and *National Adaptation Strategy*, as well as the *National Communications* and *Nationally Determined Contributions* in UNFCCC, and the working group reports of IPCC (*Intergovernmental Panel on Climate Change*). As such, the bridge between heritage management and climate change adaptation can be approached from both directions with the help of AI, searching for intersections addressed in the two domains.

The currently highlighted CCA strategies emphasising water management can be a specific characteristic in the Netherlands and other similar coastal countries. The same methodological framework should be repeated in other countries and regions with different climate and geographical conditions to make the knowledge pool of CCA topics sufficiently diverse and inclusive. In order to scale up the analysis to multiple countries, and eventually to the entire World Heritage List, additional optimisations on the procedure are needed. In collaboration with expert knowledge, guided topic modelling and Retrieval-Augmented Generation (RAG) using LLM can be integrated into the early steps of retrieving and categorising CCA topics (Grootendorst, 2022, Chen and Hao, 2025). Semi-supervised classification models can be trained to classify texts into CCA topics using the current and future datasets. Since the embedding models may be influential to the results, as shown in Section 3.3, properly integrating them as an ensemble (Sagi and Rokach, 2018) can further improve the reliability of the proposed framework. Lastly, computing pairwise cosine similarities can get extremely expensive as the dataset gets bigger, which asks for optimisation algorithms for computation and storage.

5. Conclusions

This paper uses Artificial Intelligence, or more specifically, Natural Language Processing, to show that Climate Change Adaptation (CCA) topics are already prevalent in the management strategies of UNESCO World Heritage (WH) properties in the Netherlands. It brings cultural heritage closer to natural heritage in the Dutch context to understand how WH contributes to CCA. It further demonstrates the commonalities of CCA-relevant heritage management strategies in properties with divergent natures. It can be further extended to the entire WH list as a knowledge graph to map the commonalities, nuances, and complexity at the global level, advising cross-country collaborations in pursuit of sustainable development.

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