Enhancing the Normalized Difference Water Index for Improved Urban Flood Detection

Author:

Abdulrhman Almoadi

Affiliation:

King Abdulaziz City for Science and Technology (KACST),

Institute of Earth and Space Science, Riyadh, Saudi Arabia.

Email:

aalmaadi@kacst.gov.sa

Submission Status:

This is a non-peer-reviewed preprint submitted to EarthArXiv. This is its first submission.

Mastodon:

(Not registered yet)

Enhancing the Normalized Difference Water Index for Improved Urban Flood Detection

Abdulrhman Almoadi

King Abdulaziz City for Science and Technology (KACST), Institute of Earth and Space Science, Riyadh, Saudi Arabia.
aalmaadi@kacst.gov.sa

Abstract: Accurate urban flood detection is crucial for effective disaster management and urban planning. Traditional indices like the Normalized Difference Water Index and Modified Normalized Difference Water Index often produce inaccurate results due to spectral confusion in urban areas and sensitivity to shadows. Moreover, MNDWI's reliance on the Shortwave Infrared band limits its use with certain sensors and UAVs. To overcome these limitations, this study introduces the Enhanced Normalized Difference Water Index, which incorporates a ratio of green band reflectance to NDWI to minimize urban noise. We tested ENDWI using satellite datasets from Landsat, Sentinel-2, WorldView-4, and Pleiades-Neo during and after flood events in two urban areas. The results demonstrate that ENDWI significantly improves the delineation of water bodies, wetlands, and non-water areas by reducing noise from urban structures. Unlike NDWI and MNDWI, ENDWI values center near zero, potentially enabling automated thresholding for water extraction. While shadows from tall buildings remain a challenge, these findings highlight ENDWI's potential for automated urban flood detection, offering valuable insights for flood management and urban planning. Further research is recommended to refine its application and address the remaining challenges.

Keywords: NDWI; MNDWI; Urban Flood; Spectral confusion; ENDWI; Flood management.

1. Introduction

Urban flooding is a significant challenge faced by many cities worldwide, exacerbated by climate change, rapid urbanization, and inadequate drainage systems. The effective detection and monitoring of water bodies during flood events are crucial for timely disaster management and urban planning. Remote sensing technology, particularly through the use of satellite imagery, has proven to be an invaluable tool in this regard. Among the various remote sensing indices developed for water detection, the Normalized Difference Water Index (NDWI) is one of the most widely used. NDWI exploits the spectral reflectance of water bodies to distinguish them from terrestrial features[1].

However, traditional indices such as NDWI often encounter spectral confusion, particularly in urban environments where built-up areas and shadows can distort the reflectance values. This issue can lead to inaccuracies in water detection and hinder effective flood monitoring[2]. The Modified Normalized Difference Water Index (MNDWI) was introduced to address some of these limitations by incorporating the Shortwave Infrared (SWIR) band, which helps to mitigate the effects of built-up areas and enhance water detection[3]. However, the effectiveness of MNDWI is often constrained by the limited availability of SWIR data in certain satellite sensors and Unmanned Aerial Vehicles (UAVs), reducing its applicability across diverse contexts[4].

In response to these challenges, this study introduces the Enhanced Normalized Difference Water Index (ENDWI), a novel approach designed to improve urban flood detection. The ENDWI leverages the ratio of green band reflectance to the NDWI, aiming to reduce the influence of urban features and provide a clearer distinction between water bodies, wetlands, and non-water areas. This new method is evaluated using satellite data from Landsat, Sentinel-2, and WorldView-4, focusing on two urban areas during and after flood events.

Preliminary results indicate that ENDWI not only minimizes noise from urban structures but also enhances the overall accuracy of water detection. Histograms of ENDWI values demonstrate a distribution centered around zero, in contrast to the clustering above zero observed in NDWI and MNDWI, suggesting its potential for automated thresholding and masking to effectively extract water bodies and wetlands in urban settings. Despite these advancements, challenges remain, particularly related to shadow effects from high buildings. Nevertheless, the findings from this study highlight the significant potential of ENDWI as a tool for automated urban flood detection, offering valuable insights into flood management and urban planning.

The objectives of this study are twofold: (1) to assess the performance of ENDWI in comparison to NDWI and MNDWI for urban flood detection, and (2) to explore its potential for automated thresholding to streamline flood detection processes. By advancing remote sensing techniques for urban flood detection, this research aims to provide valuable insights into disaster management and urban planning.

2. Study Areas and Data:

This study focuses on two urban areas that experienced significant flood events, analyzed using high-resolution satellite datasets (Table 1). All Study area located along Coastline of The Red Sea (Figure 1a), The first study area is Aleith City (Figure 1b), situated in southwestern Saudi Arabia. A flood event impacted the city on the evening of November 23, 2018. Floodwater moved westward through populated neighborhoods towards the Red Sea, inundating residential areas and causing widespread damage. Based on reports from the local Civil Defense, the flood affected 517 homes and 129 vehicles, necessitating the evacuation of 57 families, though no fatalities were reported. Data from two sensors were analyzed: WorldView-4 (spatial resolution 0.35m) acquired on November 27, 2018 (three days after the flood), and Sentinel-2 (spatial resolution 10m) acquired on November 28, 2018 (four days after the flood). These datasets were used to detect waterbodies and wetlands formed by the flood.

The second study area, Jeddah City (Figure 1c), located in western Saudi Arabia, experienced heavy rainfall on November 24, 2022. The resulting floodwaters caused extensive water accumulation, rendering two main roads and several streets unusable, disrupting transportation, and causing significant inconvenience to residents. For this event, Pleiades-Neo data (spatial resolution 0.30m) acquired on November 26, 2022 (two days after the flood), were analyzed. The dataset facilitated the detection of waterbodies and turbid water resulting from the flood event.

Figure 1. (a) Two study areas are located along the coastline of the Red Sea. (b) The first study area Aleith City was captured by WorldView-4 three days after the flood showing significant wetlands in the western and southern parts. (c) The second study area Jeddah City was captured by Pleiades-Neo two days after the flood when two main roads—one to the left and one at the bottom of the city—were rendered out of service result of water accumulation.

Table 1. Characteristics of Study areas and Dataset in this study.

Study area	Dataset (pixel in meter)	Date	Flood Timing	Water Type
Aleith City	Worldview-4 (0.35m)	27-Nov-2018	After 3 days for WV4, and 4 days for S2	Waterbody & Wetland
	Sentenal-2 (10m)	28-Nov-2018		
Jeddah City	Pleiades-Neo (0.30m)	24-Nov-2022	After 2 days	Waterbody & Turbid water

3. Methodology

This study introduces the Enhanced Normalized Difference Water Index (ENDWI) for urban flood detection, addressing the limitations of traditional water indices such as the Normalized Difference Water Index (NDWI) and Modified Normalized Difference Water Index (MNDWI). ENDWI aims to minimize the spectral confusion caused by urban features, such as built-up areas and shadows. To evaluate the effectiveness of this new index, we used satellite data from Landsat, Sentinel-2, and WorldView-4 for two urban flood events in Al-Leith and Jeddah, Saudi Arabia.

3.1. Data Collection

Satellite imagery for this study was collected from various sources including Landsat, Sentinel-2, WorldView-4, and Pleiades-Neo, to ensure comprehensive analysis of urban flooding across different spatial resolutions and temporal dynamics. Landsat imagery with a spatial resolution of 30 meters is renowned for its high-revisit time capturing data every 16 days[5]. This characteristic makes Landsat particularly valuable for long-term monitoring of land cover changes and water extent, especially in urban settings prone to flooding. The consistent revisit interval allows researchers to track the progression and recovery from flood events over extended periods facilitating the assessment of both immediate and long-term impacts on urban landscapes. Similarly, Sentinel-2 provides high-resolution data at 10 meters and boasts an even more frequent revisit time of approximately five days[6]. This enhanced temporal frequency allows for timely assessments of urban areas and their responses to flooding enabling the capture of rapid changes in water bodies and land cover. The frequent revisits are crucial for effectively monitoring flood events, as they provide the ability to assess changes in water extent and identify flooded areas soon after precipitation events.

During the recent flood events in Jeddah, Pleiades-Neo data with a spatial resolution of 0.30 meters, was utilized to capture detailed conditions. This high-resolution imagery provided critical insights into the immediate impacts of flooding on the urban landscape, allowing for precise assessments of water extent and distribution in affected areas. Pleiades Neo's ability to deliver high-resolution images shortly after the event makes it an invaluable tool for urban flood detection and management.

Furthermore, observations from Aleith City were conducted two days after the flood event, facilitating a comparative analysis of water recovery and the extent of flooding over time. The integration of WorldView-4 imagery with a spatial resolution of 0.35 meters further enhanced this analysis by enabling precise mapping of water bodies and urban features, providing a clearer picture of the flood's impact on infrastructure and land use.

3.2. Water Index Calculation

For the analysis, NDWI, MNDWI, and ENDWI were calculated using ArcPy by ArcGIS Pro to detect and compare flood extents. NDWI, introduced by McFeeters (1996) utilizes the green and near-infrared (NIR) bands to highlight water features:

$$\mathrm{NDWI} = \frac{\mathrm{Green} - \mathrm{NIR}}{\mathrm{Green} + \mathrm{NIR}}$$

While NDWI is effective for water detection, it is susceptible to spectral confusion from built-up areas and shadows in urban environments. To mitigate this Xu (2006) developed MNDWI which replaces the

NIR band with the Shortwave Infrared (SWIR) band providing better separation of water from built-up surfaces:

$$\text{MNDWI} = \frac{\text{Green} - \text{SWIR}}{\text{Green} + \text{SWIR}}$$

However, the availability of the SWIR band is often limited to satellite sensors and UAVs. To overcome this limitation, we proposed the Enhanced Normalized Difference Water Index (ENDWI). ENDWI applies a ratio of the green band reflectance to NDWI, to aim to reduce the spectral confusion associated with urban features such as roads, buildings, and shadows:

$$\text{ENDWI} = \frac{\text{NDWI}}{\text{Green}}$$

This formula adjusts the contribution of urban features to NDWI, enhancing its sensitivity to water bodies in densely populated areas.

3.3. Thresholding Vs Classification

After computing ENDWI for the study areas, we noticed that the thresholding techniques automatically were applied to classify Flood-affected regions, especially in the High-resolution dataset. were NDWI and MNDWI Traditional thresholding needed for NDWI and MNDWI, based on previous studies that recommend fixed and dynamics thresholds to determine water bodies and wetlands[7], however, We observed that the histogram of ENDWI values centered on zero value, in contrast to NDWI and MNDWI, which tended to cluster towards to one, in this case, in statistical analysis in this study, Values of NDWI and MNDWI, not that much close to zero compared with the ENDWI in the mean, median, and stander deviation for all datasets. This clustering near zero facilitated automated thresholding, as it improved the separation between water and non-water areas in urban environments, reducing the spectral noise caused by buildings and other artificial structures. Especially, the roofs of houses and buildings

3.4. Visualizations and Statistical Analysis

Flood extent maps generated from the three indices provided initial insights into their performance. ENDWI exhibited a notable noise reduction caused by urban features compared to NDWI and MNDWI. To further support these visual findings, we conducted a statistical analysis using histograms to examine the distribution of index values across the flood-affected areas. ENDWI histograms showed clustering near zero, indicating a cleaner separation of water from non-water pixels, even in built-up regions. This clustering suggests that ENDWI may be better suited for automated thresholding, though further research is needed to confirm this observation. These results suggest that ENDWI has the potential to enhance urban flood detection, providing a more accurate representation of flood extents in complex urban environments.

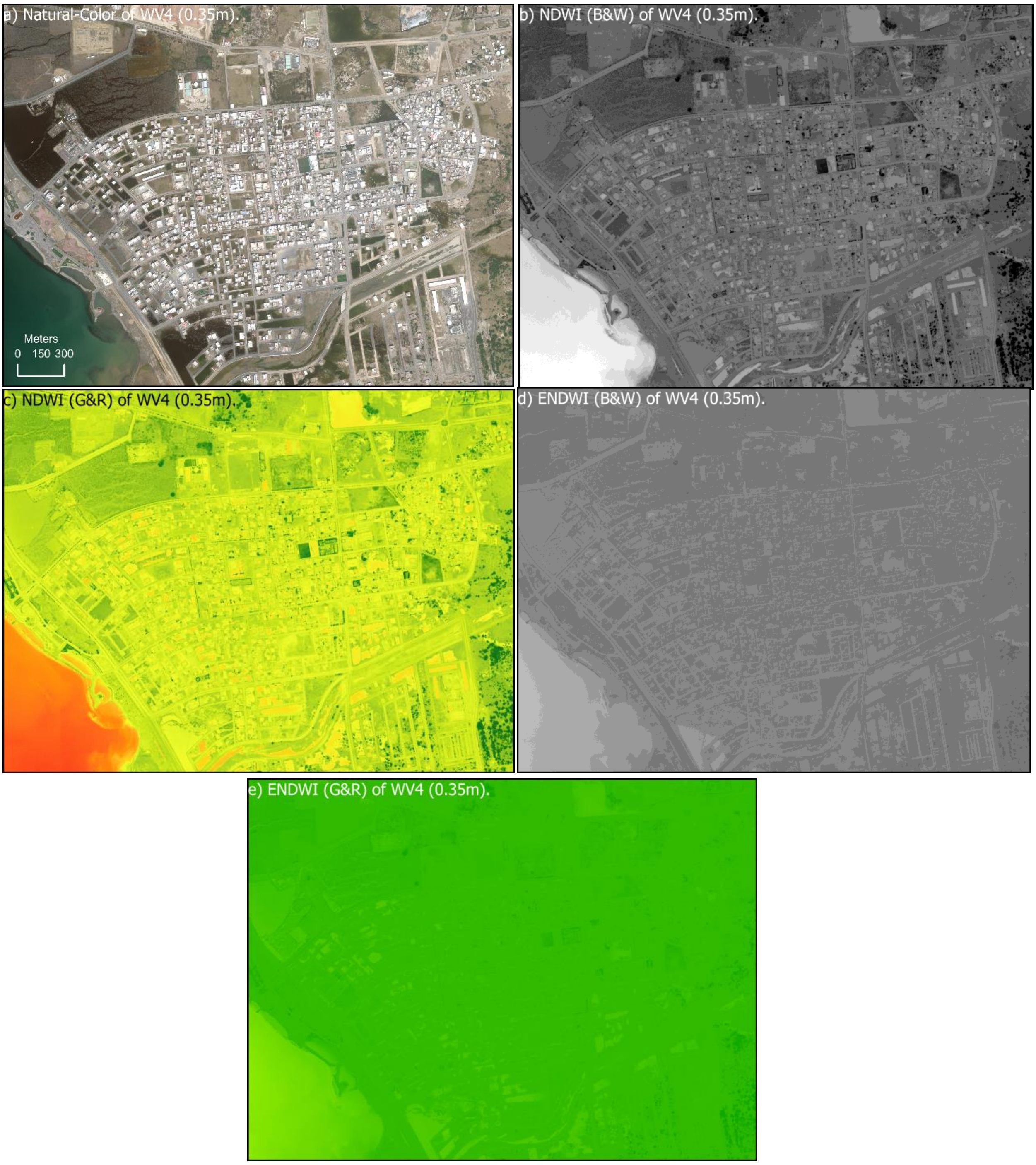
4. Results

The effectiveness of the Enhanced Normalized Difference Water Index (ENDWI) was evaluated against traditional indices, including the Normalized Difference Water Index (NDWI) and the Modified Normalized Difference Water Index (MNDWI), across the two study areas affected by flooding: Aleith City and Jeddah City, Saudi Arabia.

4.1. Flood Extent Mapping

Flood extent maps were generated for each index during the flood events, enabling a visual comparison of their performance in distinguishing water bodies from built-up areas. (Figures 2, and 3) present the flood extent maps produced using NDWI, MNDWI, and ENDWI for Al-Leith City, derived from WorldView-4 and Sentinel-2 datasets, respectively.

Figure 2. Visualization of Al-Leith City using WorldView-4 image: (a) Natural color composite, (b) Pure NDWI output displayed as a single band where white indicates more flood-affected and wetland areas, (c) NDWI classified into five classes, (d) ENDWI highlighting flooded and wetland areas in a single band, and (e) ENDWI classified into five classes.



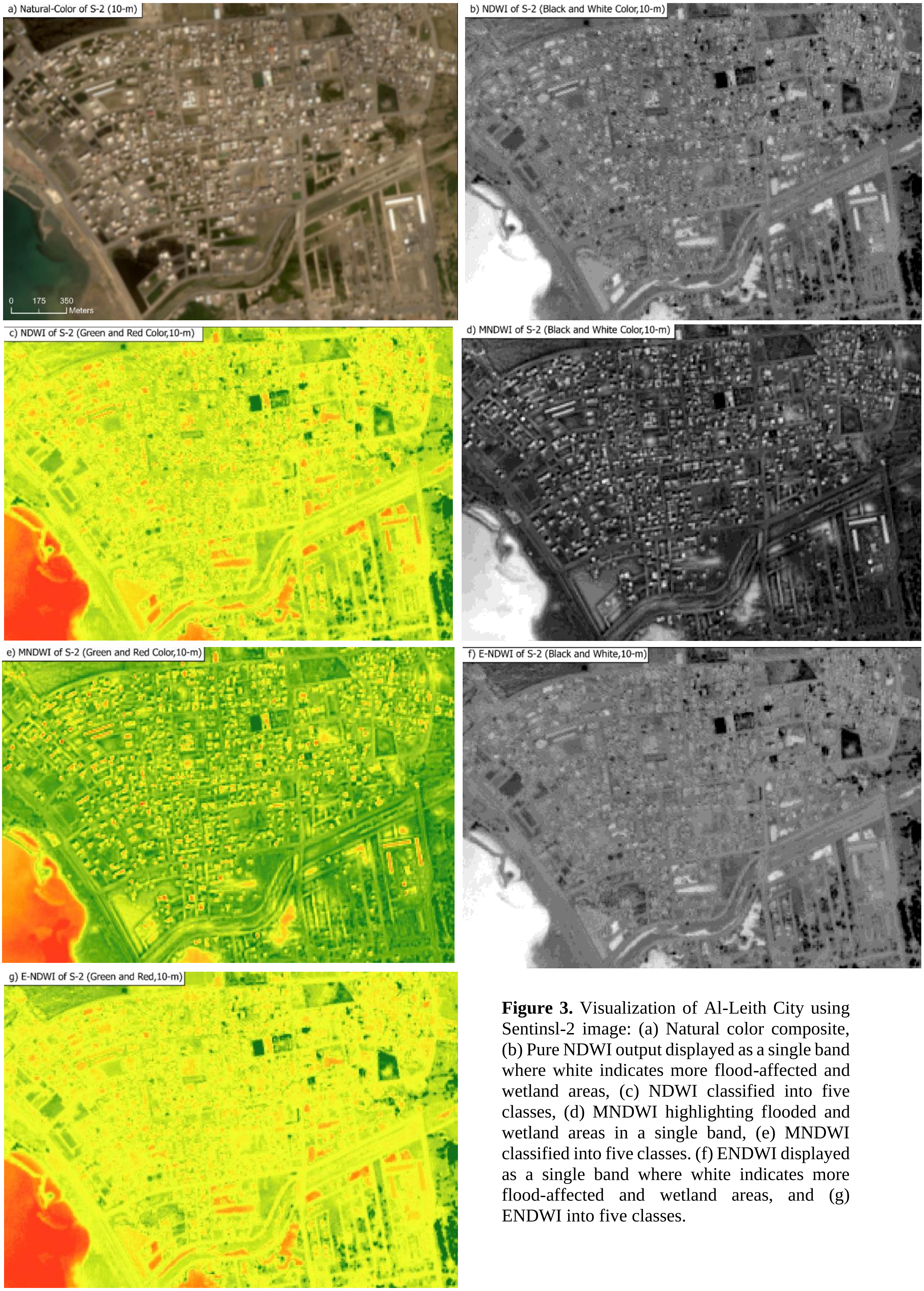


Figure 3. Visualization of Al-Leith City using Sentinsl-2 image: (a) Natural color composite, (b) Pure NDWI output displayed as a single band where white indicates more flood-affected and wetland areas, (c) NDWI classified into five classes, (d) MNDWI highlighting flooded and wetland areas in a single band, (e) MNDWI classified into five classes. (f) ENDWI displayed as a single band where white indicates more flood-affected and wetland areas, and (g) ENDWI into five classes.

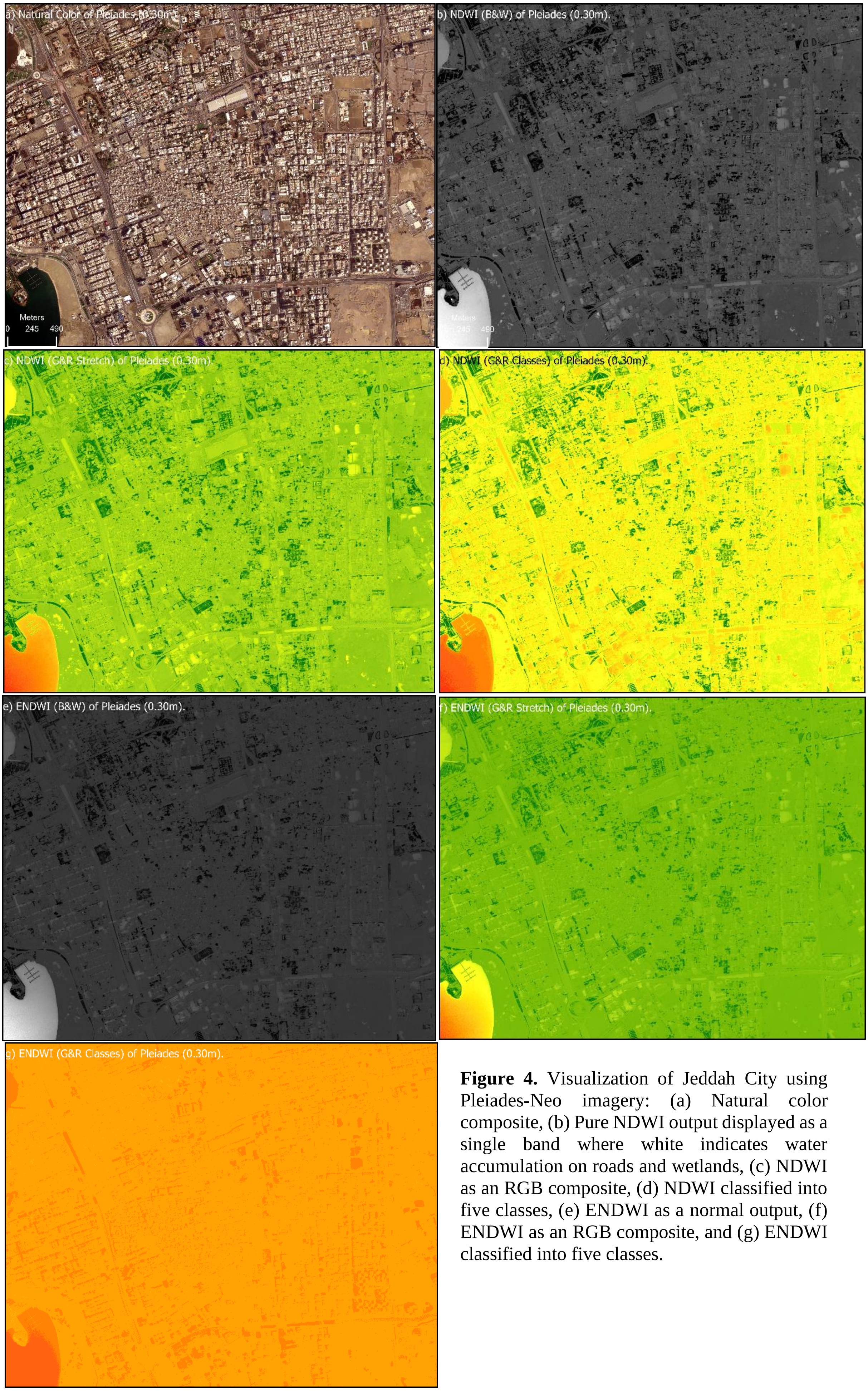


Figure 4. Visualization of Jeddah City using Pleiades-Neo imagery: (a) Natural color composite, (b) Pure NDWI output displayed as a single band where white indicates water accumulation on roads and wetlands, (c) NDWI as an RGB composite, (d) NDWI classified into five classes, (e) ENDWI as a normal output, (f) ENDWI as an RGB composite, and (g) ENDWI classified into five classes.

In Aleith City, NDWI and MNDWI struggled to accurately delineate flood-affected areas due to significant spectral confusion caused by urban structures and shadows. Many water features were misclassified as non-water, particularly in densely populated neighborhoods. Conversely, ENDWI demonstrated superior performance in accurately identifying water bodies, effectively minimizing the influence of urban features. The resultant flood extent map clearly depicted the flood-prone areas, revealing the true extent of water coverage in the urban landscape.

A similar trend was observed in Jeddah, where heavy rainfall caused extensive flooding. The flood extent maps indicated that while NDWI and MNDWI included numerous false positives, ENDWI provided a clearer delineation of water surfaces, accurately reflecting the accumulation of floodwater on the roads and in urban areas. The ENDWI map also indicated regions that were impacted by water accumulation that were not detected by the other indices, thus enhancing the overall flood detection capability.

4.2. Statistical Analysis of Index Values

Statistical analysis was conducted to evaluate the effectiveness of each index, with histograms generated for each study area to reveal distinct distributions of index values. Figure 5 shows the histograms for WorldView-4 and Pleiades-Neo datasets, illustrating NDWI and ENDWI values for both Al-Leith and Jeddah Cities. Figure 6 presents the histograms for Sentinel-2 data, showing NDWI, MNDWI, and ENDWI values for Al-Leith City. The mean, median, and standard deviation (STD) values were calculated for each index, helping to quantify the central tendency and spread of the data, which further informed the analysis of index performance in distinguishing water and non-water areas.

The NDWI histogram exhibited a bimodal distribution, with the mean and median values close to zero, indicating a significant overlap between water and non-water areas. This overlap, reflected in the standard deviation (STD), suggests that the NDWI index has a relatively high level of variability, which likely contributed to classification errors. The MNDWI histogram showed a similar pattern, with mean and median values near zero and a wide STD, highlighting the restricted effectiveness of this index in urban settings. These indices' performance in urban flood detection is limited due to this overlap, making accurate classification more challenging in densely populated areas.

In contrast, the ENDWI histograms presented a tighter distribution with values clustering around zero. The mean and median values of ENDWI were centered closer to zero, and the standard deviation was narrower, indicating a clearer separation between water and non-water areas. This tighter distribution enhances the reliability of automated thresholding methods for water detection. The clustering of ENDWI values around zero indicates its superior performance in distinguishing flood-affected areas, making it a more effective tool for urban flood monitoring and detection.

Figure 5. (**Top and Bottom Left**) Histograms of Jeddah and Al-Leith City using high-resolution imagery (WorldView-4 and Pleiades-Neo) for NDWI, showing the mean values close to zero. (**Top and Bottom Right**) Histograms for ENDWI, with the mean values more centered around zero.

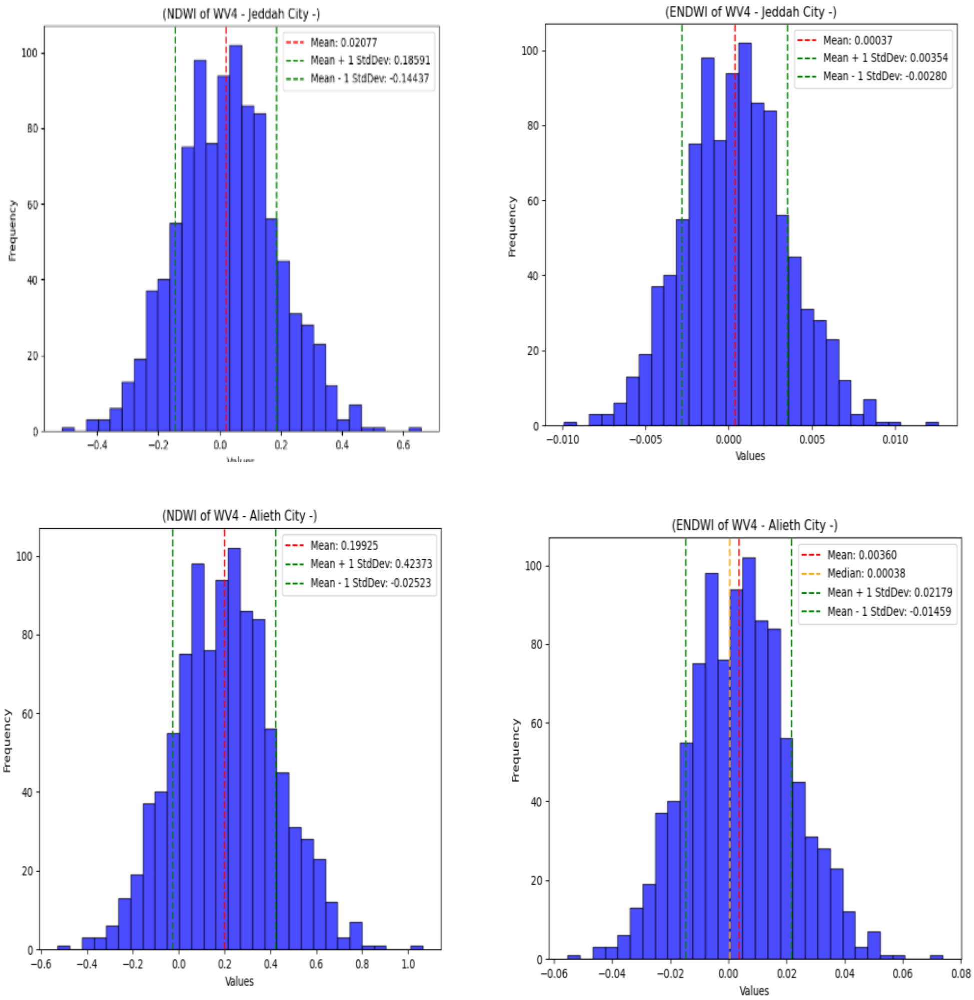
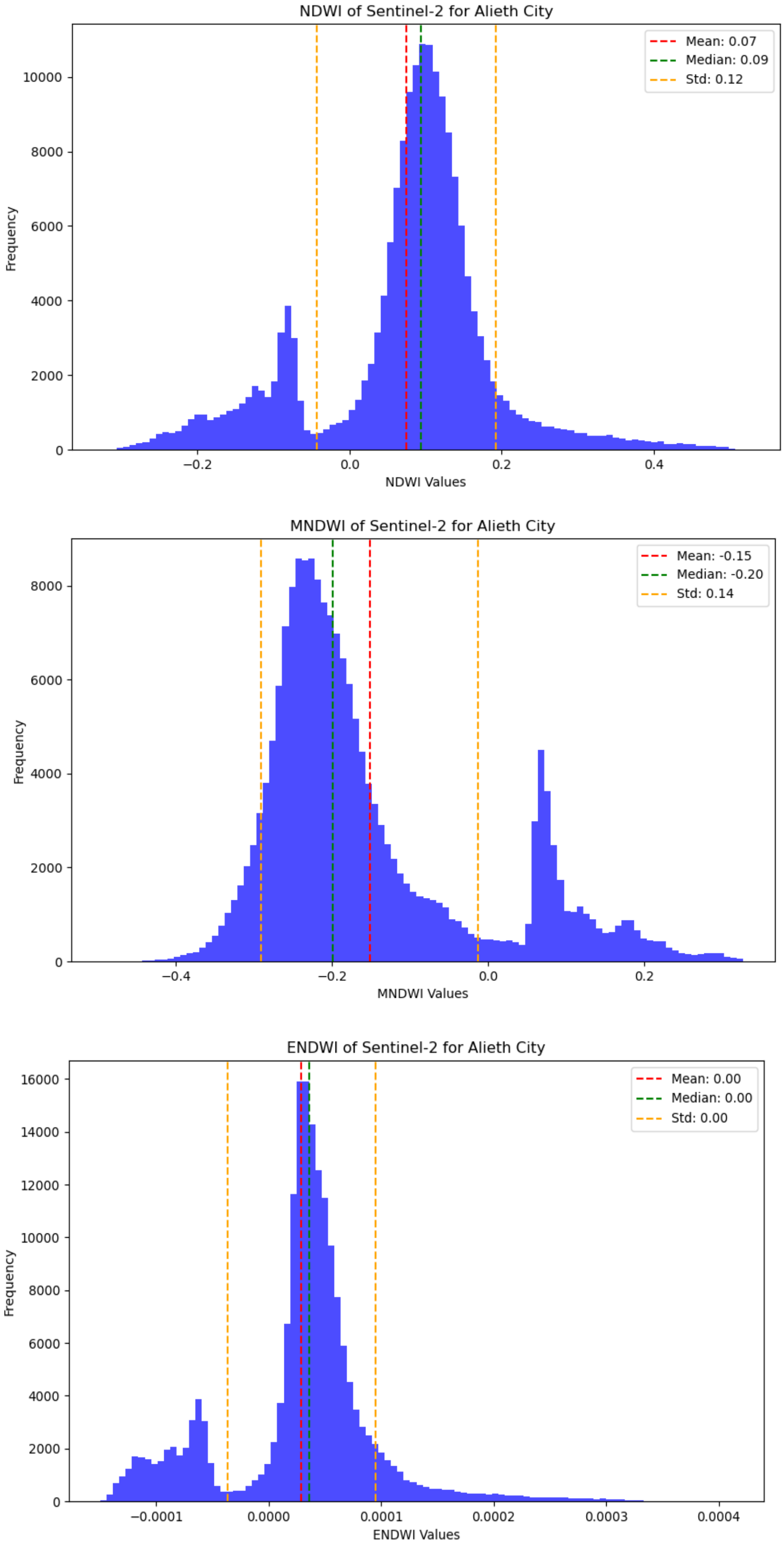


Figure 6. Histograms of Al-Leith City using Sentinel-2 imagery for NDWI, MNDWI, and ENDWI. The mean, median, and standard deviation values for NDWI and MNDWI **(Top and Middle)** are near zero, while the histogram for ENDWI **(Bottom)** shows these values more centered around zero.



4.3. Visual Observations

Visual inspection of the flood extent maps corroborated the quantitative findings. ENDWI provided clearer visual representations of water bodies, with fewer artifacts from built-up features. The mapping results indicate that ENDWI is not only effective in detecting water bodies but also valuable for disaster management and urban planning efforts.

5. Discussion

The results of this study demonstrate that the Enhanced Normalized Difference Water Index (ENDWI) offers significant improvements in urban flood detection, particularly in reducing the spectral confusion typically encountered in densely built environments. One of the key findings is that the histogram of ENDWI values is centered around zero, in contrast to the positive skew seen in traditional indices like NDWI and MNDWI. This distribution indicates a more balanced classification of water bodies, wetlands, and non-water areas, making ENDWI especially effective in urban settings where traditional methods often struggle. Notably, ENDWI enhances the separation between water, wetland and non-water features, reducing false positives typically caused by the reflectance of built-up areas, such as roofs of buildings and houses.

The performance of ENDWI in distinguishing wetlands from man-made surfaces, like roofs, was particularly promising. In contrast to traditional indices, which tend to misclassify rooftops as water bodies due to their spectral similarities with water in certain bands, ENDWI's improved classification ensures more accurate detection of actual floodwaters and wetland areas. This refinement is particularly important in urban environments where complex land cover, including buildings and other infrastructure, often leads to significant misclassification. ENDWI’s ability to maintain a tighter distribution around zero values suggests that it is less likely to overestimate the presence of water on roofs, thus improving the overall accuracy of flood mapping. However, while ENDWI shows marked improvement, it is not without its challenges. The influence of shadowing effects, particularly from high-rise buildings, continues to complicate the distinction between rooftops and floodwater. Although ENDWI outperforms traditional indices in this regard, further research is needed to refine the index to better handle shadow effects. The incorporation of advanced machine learning techniques or multi-sensor fusion could potentially improve the accuracy of flood detection in areas affected by shadows, offering a pathway for addressing these residual issues.

6. Conclusions

This study introduces the Enhanced Normalized Difference Water Index (ENDWI) as a powerful tool for urban flood detection, demonstrating its significant advantages over traditional indices like NDWI and MNDWI. ENDWI effectively reduces spectral confusion caused by urban structures, leading to more accurate delineation of water bodies, wetlands, and non-water areas. The unique feature of ENDWI with its values centered around zero, minimizes the overestimation of water presence which is a common issue with traditional indices. This makes it particularly valuable in urban settings where rooftops and water bodies often exhibit similar spectral characteristics. The ability of ENDWI to distinguish between wetlands and rooftops in urban areas is a key advancement. It provides more reliable flood maps by reducing the misclassification of buildings as water bodies, ensuring that urban planners and disaster managers have a more accurate understanding of flood extents. Despite its success, challenges remain, particularly in handling shadow effects from high-rise buildings which continue to impact the accuracy of water classification. Future work should focus on enhancing the robustness of ENDWI to shadowing effects and exploring the integration of machine learning for automated classification.

In conclusion, ENDWI represents a significant step forward in urban flood detection offering a more reliable tool for disaster management and urban planning. Its ability to reduce false positives and accurately classify water bodies and wetlands makes it an invaluable asset for improving flood resilience. Continued research to refine ENDWI and address its limitations will be essential for maximizing its potential in various urban contexts ultimately supporting more effective flood monitoring, response, and resource allocation.

Acknowledgments

High-resolution data used in this study were provided by King Abdulaziz City for Science and Technology (KACST) for research purposes under governmental agreements. These data were employed to support the methodology presented herein. The author gratefully acknowledges KACST for their provision of these resources.

Funding

This research received no external funding.

References

[1] S. K. McFeeters, “The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features,” May 01, 1996, Taylor & Francis. doi: 10.1080/01431169608948714.

[2] C. Fen, X. Chen, T. V. de Voorde, D. A. Roberts, H. Jiang, and W. Xu, “Open water detection in urban environments using high spatial resolution remote sensing imagery,” Mar. 12, 2020, Elsevier BV. doi: 10.1016/j.rse.2020.111706.

[3] H. Xu, “Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery,” Jul. 07, 2006, Taylor & Francis. doi: 10.1080/01431160600589179.

[4] W. Jiang et al., “An Effective Water Body Extraction Method with New Water Index for Sentinel-2 Imagery,” Jun. 11, 2021, Multidisciplinary Digital Publishing Institute. doi: 10.3390/w13121647.

[5] M. Rättich, S. Martinis, and M. Wieland, “Automatic Flood Duration Estimation Based on Multi-Sensor Satellite Data,” Feb. 14, 2020, Multidisciplinary Digital Publishing Institute. doi: 10.3390/rs12040643.

[6] D. C. Mason, S. L. Dance, and H. Cloke, “Floodwater detection in urban areas using Sentinel-1 and WorldDEM data,” Feb. 23, 2021, SPIE. doi: 10.1117/1.jrs.15.032003.

[7] L. Ji, L. Zhang, and B. K. Wylie, “Analysis of Dynamic Thresholds for the Normalized Difference Water Index,” Nov. 01, 2009, American Society for Photogrammetry and Remote Sensing. doi: 10.14358/pers.75.11.1307.