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Monitoring and Hotspots Identification of Invasive *Salvinia molesta* in Mwanza Gulf Using Remote Sensing Technique

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ABSTRACT

Invasive plants, such as aquatic macrophytes, pose environmental challenges that require immediate attention, as they can cause considerable economic and social-ecological damage if left to spread. The invasion of *Salvinia molesta (S.molesta)* along the Gulf of Mwanza, Lake Victoria, was recently reported. Thus, this study focused on detecting and monitoring its presence in the Gulf of Mwanza waters, quantifying the extent of infestation, monitoring its spatiotemporal distribution from 2020 to 2025, and identifying the hotspots. The study applied a remote sensing technique using multispectral imagery from Sentinel-2, a Support Vector Machine, coupled with freely available high-resolution imagery delivered by Google Earth Pro. Three classes, namely water, *S.molesta,* and built-up areas, were employed in the analysis, which yielded satisfactory findings with overall accuracy metrics consistently exceeding 98.5% and Kappa coefficients greater than 0.985, confirming the reliability of the methodology for the operational detection of *S.molesta* invasion along Lake Victoria. The results revealed an alarming increase in *S.molesta* infestation along the Gulf of Mwanza, with approximately 7.72 km^2 coverage portraying a 60.3% increase over the past five years. Moreover, the edges of the Kigongo-Busisi Bridge were identified as highly significant hotspot locations for *S.molesta* infestation. These hotspots were aligned with field observations, suggesting an existing link to potential nutrient-rich runoff originating from adjacent agricultural and residential areas. This study has generated vital information for the responsible authorities to institute management strategies geared towards combating the escalation of S. *S.molesta* invasion in Lake Victoria.

1. Introduction

Salvinia molesta (S.molesta) is an aquatic weed, free-floating fern that originates from Brazil and is grouped as a macrophyte, which is ranked second behind water hyacinth on a list of the most harmful aquatic weeds globally(Luque et al. 2014, Sigel et al., 2025). *S.molesta* is characterized by its rapid growth rate, and has been reported to invade many other freshwater areas, particularly warm freshwater around the world (Coetzee and Hill, 2020; Herbert et al., 2024; Johnson et al. 2010). Therefore, the South African government declared *S.molesta* molesta to be among the worst free-floating weeds in water during the 1960s, highlighting its annoying characteristics (Martin et al., 2018). *S.molesta* exhibits denser mats, rapid growth as biomass, and strong accumulation capabilities on water surfaces, such as lakes, rivers, and other waterlogged places (Chavula et al., 2023; Singh et al., 2021). *S.molesta* has intensive and highly invasive characteristics that have serious impacts on its economy, ecology, culture, and other long-term consequences (Lee, 2001; Woodley et al., 2025). Moreover, a denser mat of *S. molesta plants* creates a physical barrier above the water surface, blocking water transportation systems, restricting access to fishing sites, and disrupting recreational activities, thus negatively impacting tourism (Makhabu et al., 2024; Retnamma et al., 2023; Wahl et al., 2020). Similarly, water hyacinth, particularly *pontederia crassipes* (*pontederiaceae*), has been reported to hamper fishing activities for local communities in Lake Victoria in Uganda in 1989 (Mailu, 2001). Moreover, these species also threaten approximately 30 million people through the loss of fisheries, impeding water transportation and electricity production, coupled with reduced flows of other ecosystem services (Aloo *et al.*, 2013).

Denser mats of *S.molesta* block direct sunlight from reaching submerged native macrophytes, thereby hampering photosynthesis, which is essential for plant growth of these plants (Everitt *et al*., 2008). When submerged, native macrophytes cannot perform as much photosynthesis, leading to depletion of dissolved oxygen in the water (Andama et al., 2017; Lal, 2016) which influences the rise of carbon dioxide (CO_2) and hydrogen sulfide (H_2S) gas levels, resulting in a decrease in water pH (Van Driesche et al., 2010) This creates an unfavourable environment for the survival of other aquatic living organisms, particularly fishes (Dibble, 2009). Furthermore, the high affinity of *S.molesta* for sequestering nutrients leads to nutrient competition with native macrophytes, thereby disrupting their existence in the food web. In turn, this can negatively affect the food system and reduce habitat suitability for native invertebrates (Van Driesche et al., 2010). These changes in biochemical processes can create an unsuitable environment for native plants, leading to the death of native macrophytes, which in turn can eliminate the foundation for the native aquatic food web, with far-reaching direct effects on the survival of herbivores and predators (Van Driesche *et al.*, 2010).

A study by Andama *et al*. (2017) in Lake Kivu in Rwanda established a positive correlation between phosphate levels and the abundance of the invasive fern *S.molesta*. This research highlighted that eutrophication, driven by high nutrient loads of phosphorus and nitrogen, creates ideal conditions for the proliferation of invasive aquatic macrophytes. This situation is exacerbated by urbanization, the intensification of industrial production, and agricultural activities (Retnamma *et al*., 2023). These processes have been considered one of the main sources of pollution due to improperly treated wastewater and agricultural runoff, resulting in nutrient-enriched water bodies (Coetzee and Hill, 2012).

To contain the invasion of weeds into water bodies, the establishment of monitoring systems is of paramount importance for enhancing control and obtaining detailed knowledge of their local spatial distribution and temporal dynamics in terms of percent cover, rate of change, and dynamics. However, in large expanses of water bodies, such as those of Lake Victoria, implementing classification with hyperspectral data, ground inventory, and assessment is difficult, time-consuming, and expensive (Dao *et al*., 2021). For decades, remote sensing technology has offered timely, affordable, and reliable acquisition of remote-sensed datasets at generally lower costs than conducting ground surveys (Pottier *et al*., 2021).

The invasion and rapid spread of aquatic weeds, such as *Salvinia molesta,* present a serious challenge to numerous sectors, creating a critical need for effective early detection and monitoring systems to guide control strategies. However, rapid detection and mapping of the distribution and status of *S. molesta* remains a significant challenge. This is often due to a lack of historical data, low resolution or poor quality of available data acquisition methods, and the highly dynamic nature of the plant itself. Recent reports have revealed a new invasion of *S. molesta* into the Mwanza Gulf of Tanzania, particularly along the Kigongo–Busisi area. This development underscores the urgent need for dedicated studies to establish the magnitude and extent of infestation.

Obtaining and maintaining up-to-date information on *S.molesta* distribution has been identified as one of the main challenges in *S.molesta* control. Over the past four decades, remote sensing has proven to be among the most appropriate technologies, and its methodologies have been well established for monitoring vegetation cover and other land use/cover (Abebe et al., 2022; Karanam et al., 2021; Wu et al., 2020). Monitoring vegetation and water bodies with complex optical properties requires high-resolution images which is currently achieved through use of Sentinel-2 imagery (Qing et al., 2021). On the other hand, Google Earth Engine has powerful algorithms for filtering and pre-processing satellite and multispectral images. Sentinel-2 imagery has also made remote sensing technology more useful for finding objects worldwide (Ragheb and Ragab, 2015; Yang et al., 2021; Zurqani et al., 2018). Performing classification detection and segmentation of objects requires algorithms such as Support Vector Machines (SVM). The SVM is an old method that has been extensively used for tuning machine learning models with outstanding performance and ease of use (Hamdi et al., 2022).

The objectives of this study were: 1) to quantify the spatiotemporal extent and spread rate of *Salvinia molesta* in the Mwanza Gulf within a 20 km buffer from 2020 to 2025 using Sentinel-2 imagery and remote sensing; 2) to identify and map persistent infestation hotspots through Getis-Ord Gi* spatial analysis, highlighting priority areas for targeted control.

2. Materials and Methods

2.1. The Study Area

The Gulf of Mwanza is one of the largest gulfs on the southern part of the Tanzanian side of Lake Victoria (Figure 1). It is approximately 60 km long and 2.5 to 11 km wide (Mabula et al., 2023). The Gulf is located in the vicinity of Mwanza City in northwest Tanzania. The Gulf of Mwanza was selected as the study site due to a recently reported case of S. *S.molesta* invasion. Furthermore, this area is considered to be the most ecologically important area of Lake Victoria (Mabula et al., 2023). On the other hand, the Kigongo-Busisi Bridge has been constructed along the Gulf of Mwanza, which connects the Misungwi and Sengerema Districts. This bridge may act as a barrier to restrict the flow of nutrients along the Gulf, thereby creating a conducive environment for the growth of *S.molesta.* The Gulf also hosts other socio-economic activities, such as agriculture, fish cage aquaculture, industries, and trade, which may influence the release of nutrients in the lake. The analysis for this study focused solely on the water-covered areas of the Gulf and was confined to the extending radius of 15 km from the centre of the Kigongo – Busisi Bridge. Therefore, the total coverage area under study was 31,655.96 ha.

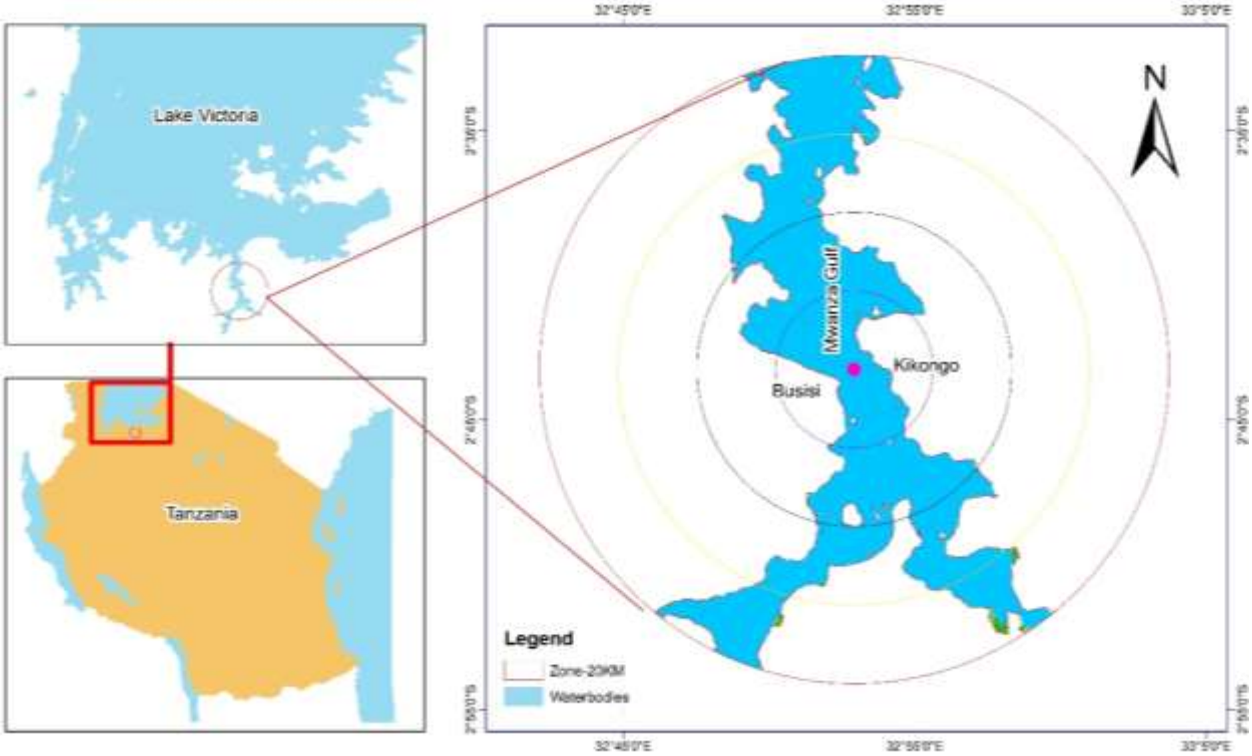

Figure 1: Map of Tanzania illustrating Gulf of Mwanza in Lake Victoria that connects Kigongo - Busisi Bridge. Source: Mabula *et al.*(2023).

2.2. Data preparation

In this study, remotely sensed datasets of Sentinel-2 imagery, a medium-resolution (10m) satellite imagery, were used to classify objects within a Mwanza Gulf. All data collection procedures were conducted using Google Earth Engine (GEE). GEE is a cloud-based computing platform embedded with multiple data catalogues that archives diverse, consistent, and timely geospatial datasets, including the complete set of Sentinel-2 data (Zhang et al., 2021). The GEE allows users to prepare and test datasets before further analysis, and it allows the filtering of images based on date, band separability, pixel quality, cloud masking, and geometric collection under semi-automatic experiments (Adam and Heeto, 2018; Daldegan et al., 2019; Saah et al., 2019). Sentinel-2 imagery is freely downloadable data available in GEE (Pottier et al., 2021), which has a revisit time of five (5) days (Campos-Taberner et al., 2020) and has 10 years of operation. Based on these criteria, Sentinel-2 imagery is ideal for detecting *S.molesta* invasions in the Gulf of Mwanza. Therefore, a set of Sentinel-2 surface reflectance (Level-2A) images was obtained from the Copernicus Open Data Hub in GEE. The obtained Sentinel-2 dataset was filtered for cloud-free conditions, which was set as ≤ 10% cloud cover, and a specified temporal time was set between January 1st and March 30th, for all analysis years (2020, 2021, 2022, and 2025), and single-date imagery was avoided (Noi Phan et al., 2020), to ensure consistency and optimal classification accuracy. Subsequently, the images were clipped to the study area shapefile and visualized using a false-colour composite (Bands B8, B4, and B2) to highlight water and vegetation features. This procedure was processed within the Google Earth Engine and was tested before the final export for analysis in ArcGIS 10.8 (Zhang *et al.*, 2021). The collected images were then exported to the Google Drive Platform, which was then downloaded to proceed with further analysis in ArcGIS desktop version 10.8. Table 1 lists the datasets used in the study.

Table 1: Details of sentinel-2 imagery used for classification (2020-2025)

S/N	Year	Sensor	Acquisition Period	Cloud Cover Filter (%)	Resolution (m)
1	2020	Sentinel-2	Jan 1 - Mar 30	< 10	10
2	2021	Sentinel-2	Jan 1 - Mar 30	< 10	10
3	2022	Sentinel-2	Jan 1 - Mar 30	< 10	10
4	2025	Sentinel-2	Jan 1 - Mar 30	< 10	10

2.3. Training samples collection

One prerequisite for the collection of training samples is the selection of homogeneous objects that reflect similarly (Yang et al., 2021). Training samples are essential for supervised classification. Supervised classification requires a large amount of field data, which obtaining field data is time consuming and labour intensive, particularly when dealing with large study areas (Saah et al., 2019). Recent improvements in remote sensing and advancements in cloud computing technologies have overcome these challenges regarding the availability of high-resolution images (Saah et al., 2019). These platforms have facilitated the availability of homogeneous training samples from various sources (Yang et al., 2021). For example, recent interventions such as Open Foris (https://openforis.org/) have allowed users to collect training samples using high-resolution images and ancillary datasets, thereby reducing cost and time and releasing more reliable datasets worldwide (Koskinen et al., 2019). Similarly, platforms such as Google Earth Pro, Bing maps, and other open-source remote sensing platforms have enhanced users to collect and apply training samples for supervised classification (Koskinen et al., 2019; Ragheb and Ragab, 2015). Similarly, in this study, training samples were collected using multiple sources, such as Open Foris within Google Earth Pro and Sentinel-2 imagery, particularly when the Google Earth Pro updated image was found. All training samples were subsequently digitized and the saved Keyhole Markup Language (KML) files were exported to ArcGIS 10.8 for further processing (Cho and Ramoelo, 2019).

2.4. Validation analysis

The assessment of classified thematic maps is a difficult task because it involves the analysis of the model's validity and the accuracy of the results (Khaliq et al., 2023). According to Khaliq et al. (2023), statistical tests usually substantiate the randomly selected training samples used to classify thematic rasters and the produced raster values. The most trusted and standard statistical tests commonly applied for testing classification tasks are the metrics derived from the analysis of confusion matrices (Johnson and Jozdani, 2020; Tassi and Vizzari, 2020). The confusion matrix table is usually coupled with other metrics, including the Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA), and Kappa Coefficient (K), which can be applied to identify potential sources of error (Biondini and Kandus, 2006; Pan et al., 2021; Zomlot et al., 2017). In this study, only the Overall Accuracy (OA) and Kappa Coefficient (K) were adopted for classification validation analysis (Equations 1 – 4). The procedure for conducting validation analysis was performed to assess the Support Vector Machine (SVM)'s accuracy in classifying thematic maps for each study period (2020, 2021, 2022, and 2025) using 40% of the collected samples. A total of 300 validation points were involved in the validation process, which were equally distributed across three classes: 100 for water, 100 for *S.molesta* weeds, and 100 for built-up areas.

$$Overall\ Accuracy = \frac{Number\ of\ Correctly\ Classified\ Samples}{Total\ Number\ of\ Validation\ Samples} \ldots\ldots\ldots\ldots \quad (1)$$

$$Producer's\ Accuracy_{\ class\ i} = \frac{Number\ of\ Correctly\ Classified\ Samples\ in\ Class\ i}{Total\ Number\ of\ Validation\ Samples\ in\ class\ i} \ldots\ldots\ldots\ldots \quad (2)$$

$$User's\ Accuracy_{class\ i} = \frac{Number\ of\ Correctly\ Classified\ Sample\ in\ Class\ i}{Total\ Number\ of\ Validation\ Samples\ in\ class\ i} \ldots\ldots\ldots\ldots \quad (3)$$

$$K = \frac{P_0 - P_e}{1 + P_e} \ldots\ldots\ldots\ldots \quad (4)$$

Where:

K = Kappa coefficient, ranging from −1 to +1, where +1 indicates perfect agreement, 0 indicates no agreement beyond chance, and negative values indicate agreement worse than chance.

P_0 = Observed agreement (also called overall accuracy), representing the proportion of correctly classified samples in the confusion matrix. It is computed as: $P_0 = (\Sigma x_{ii}) / N$, where x_{ii} is the number of correctly classified samples for class i (the diagonal elements of the confusion matrix), r is the total number of classes, and N is the total number of samples.

P_e = Expected agreement by chance, calculated from the row and column totals of the confusion matrix. It is computed as: $P_e = \Sigma (x_{i+} \times x_{+i}) / N^2$, where x_{i+} is the total number of reference samples in class i (row total), and x_{+i} is the total number of classified samples in class i (column total).

2.5. Support Vector Machine (SVM) Classification

In this study, Sentinel-2 satellite imagery was classified using a Support Vector Machine (SVM) algorithm implemented in ArcGIS 10.8. SVM is a supervised machine learning classifier that is widely recognized for its robustness in handling complex, high-dimensional datasets and its ability to define nonlinear decision boundaries, thereby making it particularly suitable for diverse remote sensing classification tasks (Pottier et al., 2021; Qiao et al., 2020; Zhao et al., 2021). The classification process was conducted within ArcGIS 10.8 environment, which enabled the processing of satellite imagery and integration-referenced training datasets. The classifier was trained using 60% of the reference data, ensuring that the model was exposed to representative samples of each target land-cover category: open water, *Salvinia molesta*, and built-up areas. Four Sentinel-2 spectral bands, B2 (blue), B3 (green), B4 (red), and B8 (near-infrared), were selected as the input spectral bands for SVM classification. These bands were chosen because of their effectiveness in discriminating between aquatic vegetation, open water, and urban surfaces. The SVM algorithm was selected based on its proven capability to model complex nonlinear relationships between spectral responses and land-cover classes (Al-Najjar and Pradhan, 2021; Ge et al., 2020). Following the training phase and parameter optimization for each study year, the configured SVM model was applied to the respective pre-processed Sentinel-2 composite image covering the Mwanza Gulf. The procedure generated thematic classification maps delineating the spatial distribution of open water, *Salvinia molesta*, and built-up areas for 2020, 2021, 2022, and 2025.

2.6. Hotspot analysis

The Getis–Ord Gi* statistic was employed to identify statistically significant spatial clustering of *S. molesta* density within the Gulf of Mwanza. This spatial statistical method evaluates whether high or low values of a variable cluster in space are more than would be expected under a random distribution (Getis and Ord, 1992). The analysis was implemented using ArcGIS Desktop. The output included the GiZScore, GiPValue, N-Neighbours, and Gi-Bin for each grid cell representing *S. molesta* density. GiZScore is a standardized value that measures the intensity and direction of clustering. High positive scores indicated hot spots, whereas high negative scores indicated cold spots. GiPValue quantifies the probability that observed clustering occurs by random chance(Getis and Ord, 1992). This value provides a measure of statistical significance. The N-Neighbours field records the number of surrounding cells included in each local sum. This influenced the spatial context of the analysis. The Gi-Bin field classifies results into categories of statistical confidence. Scores of +3 and +2 indicate hotspots at 99% and 95% confidence levels, respectively. The scores of −3 and −2 indicate cold spots at the same confidence thresholds. Cells with a Gi-Bin value of 0 were considered to be not statistically significant, indicating that the spatial pattern could be random. Hot spots were defined as locations with *S. molesta* density significantly clustered at Gi-Bin levels of +2 or +3. Cold spots were defined as locations with Gi-Bin levels of −2 or −3 (Getis and Ord, 1992). This classification allowed for the identification of areas with the highest concentration of invasive weeds. This enabled further spatial interpretation of the invasion patterns within the Gulf of Mwanza.

3. Results

3.1. Temporal Dynamics of *S. molesta* Invasion (2020-2025)

The analysis of Sentinel-2 imagery using remote sensing classification techniques of a Support Vector Machine (SVM) has revealed distinct temporal trends of classified categories of *S.molesta aquatic* plants, water, and built-up areas within the Gulf of Mwanza between 2020 and 2025. The quantitative results of these classes (*S.molesta* , water, and built-up) detailing the area coverage in hectares (ha) and the corresponding percentage for each class are presented in Table 2, whereas the spatial distribution maps are presented in Figure 2. The overall results of this study revealed a noticeable increase in the area covered by *S.molesta* molesta. In 2020, *S.molesta* occupied 277 ha, representing 1.07% of the study area, while it increased to 291.88 ha (1.13%) in 2021 and 295.13 ha (1.14%) in 2022. This trend represents a total increase of 18.13 ha of *S.molesta* over the two (2) year monitoring period. Concurrently, the area classified as water showed fluctuations but an overall decrease by 2022. In 2020, water covered 25600.37 ha (98.74%), slightly increased to 25616.73 ha (98.80%) in 2021, and then decreased to 25482.43 ha (98.28%) by 2022, implying the overall decline between 2020 and 2022 was 117.94 ha. The area covered by built-up areas showed variability, ranging from 51 ha (0.20%) in 2020 to 150.81 ha (0.58%) in 2022. In the final year of analysis, the estimated area for the

S.molesta class in 2025 was 1651.74 ha, constituting 6.37% of the study area, indicating a dramatic acceleration of *S.molesta* invasion. The dramatic acceleration of the *S.molesta* invasion represents an estimated increase of 1356.61 ha from 2022 to 2025 alone, which is significantly larger than the total increase observed over the preceding two years (2020-2022). Moreover, the findings suggest an accelerating invasion rate, which is characteristic of invasive species entering an exponential growth phase under favourable conditions. Correspondingly, the analysed open water area in 2025 was estimated to decrease sharply to 24247.44 ha (93.52%). The analysed loss of 1234.99 ha of open water between 2022 and 2025 underscores the potential scale of habitat transformation driven by the *S.molesta* expansion. The built-up area results show a decrease to 29.19 ha (0.11%) in 2025 compared to 0.58 ha in 2022.

Table 2: Coverage of *S.molesta*, water, and built-up areas in hectares (ha) and percentage (%) from 2020 to 2025 in the Gulf of Mwanza.

	Year - 2020		Year - 2021		Year - 2022		Year – 2025	
Class Name	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
S.molesta	277	1.07	291.88	1.13	295.13	1.14	1651.74	6.37
Water	25600.37	98.74	25616.73	98.80	25482.43	98.28	24247.44	93.52
Built-Up	51	0.20	19.76	0.08	150.81	0.58	29.19	0.11
Total	**25928.37**	**100**	**25928.37**	**100**	**25928.37**	**100**	**25928.37**	**100**

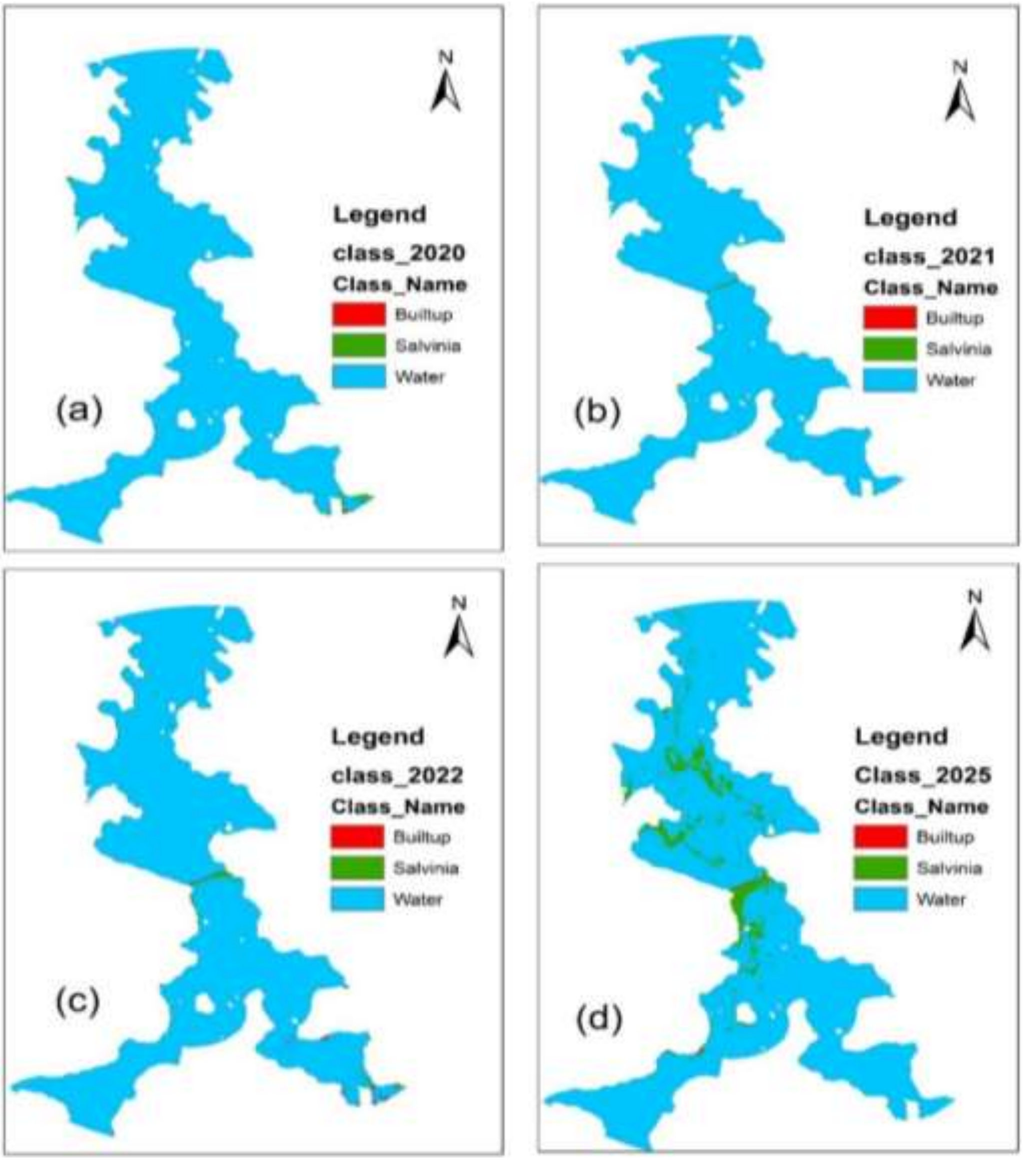

Figure 2: Spatial distribution of water, S.molesta and built-up areas in the gulf of Mwanza for (a) 2020, (b) 2021, (c) 2021, and (d) 2025, based on sentinel-2 SVM classification.

3.2. Spatial Distribution of *S.molesta* Hotspot for the year 2025

The Getis-Ord Gi* hotspot analysis revealed spatial clustering patterns of *Salvinia molesta* density across the Mwanza Gulf, as illustrated in the map in Figure 3. The overall distribution was predominantly random, with a majority of the areas showing no statistically significant clustering (Gi-Bin = 0). However, the analysis successfully identified distinct and localized areas of statistically significant high-density clusters (hotspots) and low-density clusters (cold spots), as shown in Table 3 and the analysed hotspots maps representing typical dense mats of *S.molesta* are presented in Figure 4. Two primary hotspots (Gi-Bin ≥ +2) were identified, indicating areas with a significant accumulation of *S. molesta*. The first and most concentrated hotspots were located at and near the edges of the Kigongo-Busisi bridge area, which exhibited the highest *S. molesta* density. A second hotspot forming a distinct linear pattern was identified directly along the main ferry transport route connecting Kigongo and Busisi.

In addition to high-density clusters, the analysis also identified several statistically significant cold spots (Gi-Bin ≤ −2). These locations represent areas where the analysed density of *S. molesta* was significantly lower than the regional average.

Table 3: Hotspots values for GiP-Value, N-Neighbours, Gi-Bin values, and Giz-Score

Hotspots	GiP-Value	N-Neighbours	Gi-Bin values	Giz-Score
Class 1	0.0 – 0.570	1 – 11	0	-0.095 – 2.796
Class 2	0.571 – 0.957	12 – 24	1 – 2	2.797 – 13.173
Class 3	0.958 – 1.000	25 – 41	3	13.174 – 28.115

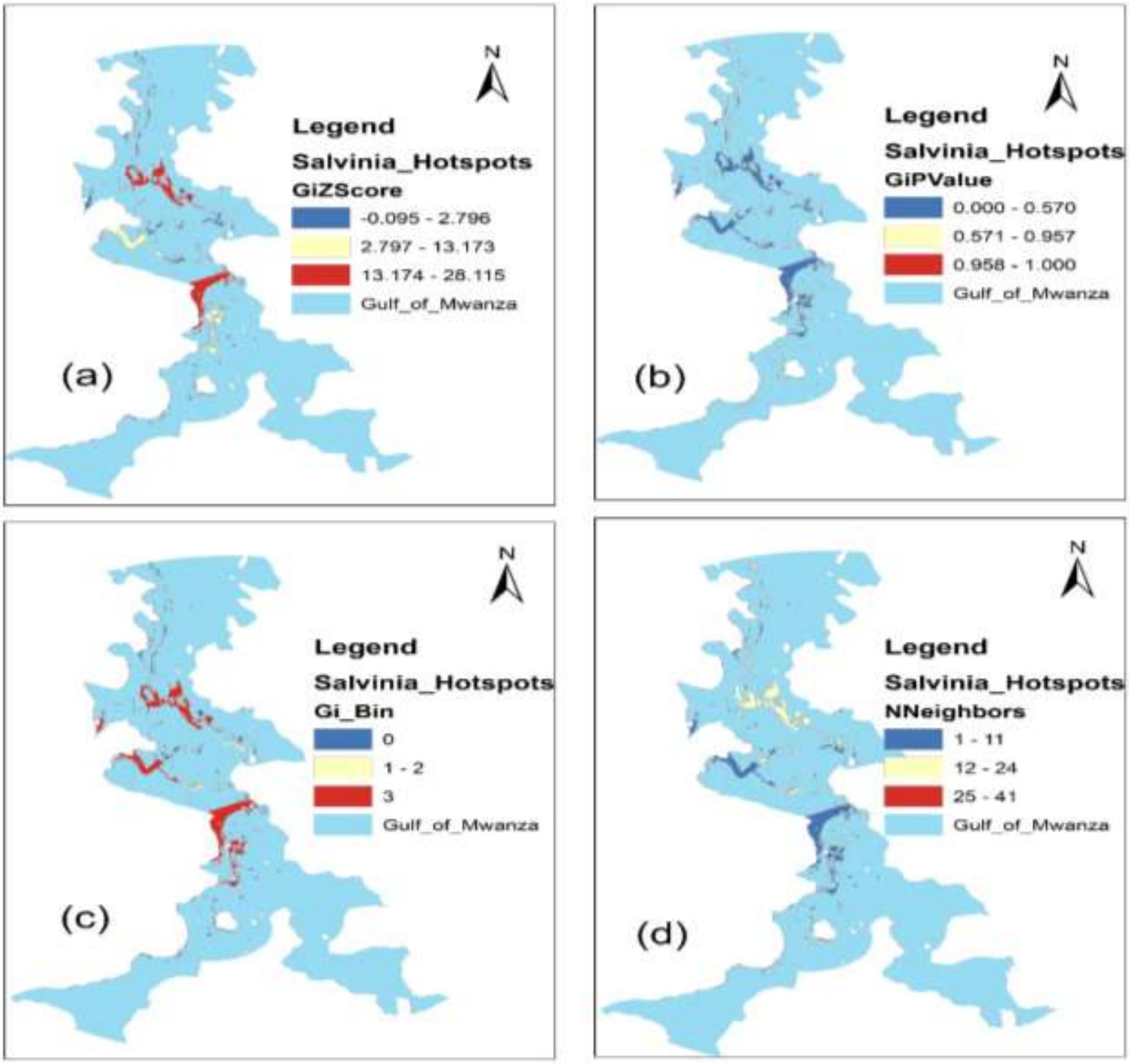

Figure 3: Analysed hotspots maps representing (a) GiZ-Score (b) GiP-Value, (c) Gi-Bin and (d) N-Neighbours values corresponding to areas identified as hotspots.

Figure 4: Field photographs illustrating typical dense mats of *S.molesta* observed in Gulf of Mwanza during (March 2025), corresponding to areas identified as hotspots or high-density infestations in the remote sensing analysis. (a) – (d) Extensive surface cover observed near the Kigongo-Busisi Bridge. (e) Indicates the removed *S.molesta* (f) A close-up showing the characteristic leaf structure and density of the mats of *S. molesta*.

3.3. Classification Accuracy

The study evaluated the SVM classification mode using overall accuracy and Kappa coefficient. The study revealed very high levels of accuracy for all study years. The overall validation accuracy ranged from 98.52% in 2020 to 99.98% in 2025. The corresponding kappa coefficients were consistently high, starting at 0.985 in 2020 and reaching 0.998 by 2025. These Kappa values signify almost perfect agreement between the classification results and validation data, according to established interpretation benchmarks (Khaliq et al., 2023; Long et al., 2021), confirming the high fidelity of the mapping results.

4. Discussion of the Results

4.1. Ecological and Socio-economic Implications of temporal and spatial dynamics of *S.molesta* Proliferation

The results of the temporal analysis indicated the status of *S.molesta* its invasion in the Gulf of Mwanza between 2020 and 2025. Overall, the results indicated a total increase in *S.molesta* in the study area during the study period. Moreover, the study highlighted a dramatic acceleration in *S.molesta* by 2025. This estimated exponential increase in detected *S.molesta* along the Gulf of Mwanza aligns with the known biological characteristics of other *Salvinia* species, such as those of *S. molesta* (Mailu, 2001; Ot et al., 2011). *S. molesta* is notorious for its rapid vegetative reproduction (Range, 2020). Under optimal conditions, often found in nutrient-rich tropical waters, such as Lake Victoria, *S. molesta* can double its biomass in as little as days (Martin et al., 2018), enabling it to rapidly colonize vast areas (Everitt et al., 2008). The analysed rate of expansion in the Gulf of Mwanza suggests that conditions are highly favourable for such rapid proliferation. *S. molesta* is globally recognized as one of the most problematic invasive aquatic plants, ranking second only to the water hyacinth (*Eichhornia crassipes*) in terms of negative impacts (Herbert et al., 2024). The successful invasion of diverse aquatic ecosystems across Africa, Asia, Australia, and the Americas serves as a stark precedent (Everitt et al., 2008; Martin et al., 2018). The formation of thick, impenetrable mats, sometimes exceeding a meter in depth, is a hallmark of severe infestation (Range, 2020). The analysed 2025 scenario for the Mwanza Gulf, with *S.molesta* potentially covering 6.37% of the study area, suggests a trajectory towards such mat formation. This represents more than just an increase in weed cover, signifying a potential ecological regime shift in the affected parts of the Gulf, transitioning from open-water systems to ecosystems dominated by a dense, floating invasive macrophyte layer (Range, 2020). Such shifts fundamentally alter ecosystem structure and function, with cascading consequences for biodiversity and ecological processes (Mayfeld III *et al.,* 2021).

The rapid timeline indicated by the analysis is a substantial increase anticipated within just three years (2022-2025), underscoring the critical importance of timely intervention. Reactive management strategies, often implemented only after impacts become severe, are likely to be overwhelmed by weed growth rate (Ruiz et al., 2021; Lee, 2001; Mailu, 2001; Timberlake and Chidumayo, 2004). The recent emergence and rapid spread reported in local news outlets further corroborate the urgency depicted in the results (Daily News, 2025; The Citizen, 2025).

The results revealed that the expansion of *S.molesta* in the Gulf of Mwanza has profound potential ecological and socioeconomic consequences. The results are consistent with impacts documented both at global and regional scales, including the Lake Victoria Basin itself (Mailu, 2001; Martin et al., 2018). Ecologically, the formation of dense surface mats drastically reduces light penetration into the water column (Everitt et al., 2008). This inhibits photosynthesis by phytoplankton and submerged native macrophytes, disrupting the base of the aquatic food web and leading to loss of primary productivity (Everitt et al., 2008). Furthermore, mats impede oxygen diffusion from the atmosphere into the water, while decomposition of the large plant biomass consumes dissolved oxygen (Everitt et al., 2008). This combination frequently leads to hypoxic or anoxic conditions(Crespo et al., 2020; Segurado et al., 2021), particularly beneath dense mats, which stress or kill fish and aquatic invertebrates (Herbert et al., 2024). Such conditions can also alter water chemistry, potentially lowering the pH (Friesen et al., 2021) and increasing the concentrations of substances such as hydrogen sulfide (Everitt et al., 2008). The overall result is a significant reduction in aquatic biodiversity, as native species are outcompeted, displaced, or unable to survive in altered habitats (Herbert et al., 2024).

The socioeconomic ramifications for communities around the Gulf of Mwanza are equally severe. Lake Victoria supports vital fisheries, provides transport routes, and supplies water for domestic and agricultural use (Mabula et al., 2023). *S.molesta* infestation directly threatens these services. Thick mats physically obstruct navigation, impeding fishing boats, transport ferries (as indicated by the ferry line hotspot), and access to water(Mabula et al., 2023; Mailu, 2001). Recent reports from Mwanza confirm that ferry services have already been affected (Daily News, 2025; The Citizen, 2025). Fisheries are particularly vulnerable; mats entangle fishing gear, block access to fishing grounds, reduce fish populations through habitat degradation and oxygen depletion, and can lead to significant reductions in catch and income for fishing communities (Daily News, 2025; The Citizen, 2025). Fish farming operations are also directly affected, with mats surrounding cages preventing feeding and potentially causing fish death due to poor water quality (The Citizen, 2025). While not directly toxic, mats can also create stagnant water conditions suitable for breeding disease vectors, such as mosquitoes, and harbour other hazardous organisms. The cumulative economic losses associated with *S.molesta* infestations, encompassing damage to fisheries, transport disruption, control costs, and impacts on tourism and water supply, can be substantial(Mailu, 2001). These impacts are likely to disproportionately affect local communities that depend directly on the lake's resources for their livelihood and sustenance (The Citizen, 2025). The combination of direct interference (gear entanglement, blocked access) and indirect effects (habitat degradation, oxygen depletion) creates a synergistic negative pressure on the Gulf of Mwanza fishery, threatening both the resource base and livelihoods dependent upon it (Daily News, 2025).

4.2. Spatial Patterns and Potential Drivers of Invasion Hotspots

The identification of statistically significant hotspots near Kigongo-Busisi and along the ferry line provides a crucial spatial focus for understanding and managing *S.molesta* invasion. The non-uniform distribution indicated by hotspot analysis suggests that specific local factors, rather than just broad-scale conditions, drive the most intense areas of infestation. Such factors could include surface wind, flowing water, leaf water accessibility, growth forms of *S. molesta*, and nutrient supply (Li et al., 2018). Understanding these drivers is the key to developing effective targeted interventions. Several factors, often acting in concert, are likely to contribute to hotspot formation.

S.molesta thrives in nutrient-rich waters, particularly those high in nitrogen and phosphorus (Wahl et al., 2021). Hotspots may therefore coincide with areas receiving significant nutrient inputs from sources, such as agricultural runoff, discharge from settlements or industries, or inadequate waste management practices(Gherardi , 2007; Room, 1994). Reports from Mwanza explicitly link the current invasion to agricultural runoff and human activities near the shore (Daily News, 2025; The Citizen, 2025). The Kigongo-Busisi area, situated near the shoreline and potentially associated with significant infrastructure development (ferry terminal and bridge construction), could be particularly susceptible. Such locations often represent a confluence of potential drivers: land-based nutrient runoff, altered water flow or sheltered conditions created by shoreline modifications or structures, and increased human activity, including boat traffic (Daily News, 2025). Physical factors, such as water currents and wind, also play a crucial role in the distribution of free-floating plants, such as *S.molesta*(Martin et al., 2018; Wahl et al., 2020). Mats can be passively transported and accumulate in sheltered bays, eddies, or shorelines, potentially contributing to the high densities observed in the Kigongo-Busisi hotspot (The Citizen, 2025; Wanda et al., 2021). Wind direction is noted as a factor in the spread within the Gulf of Mwanza (Daily News, 2025; The Citizen, 2025). Human activity is another major driver, through both nutrient pollution and direct dispersal. Boat traffic is a well-documented vector for the spread *S.molesta* fragments (Everitt et al., 2008; Wahl et al., 2020). The hotspots identified along the ferry line strongly suggest such a mechanism. This may represent a 'vector corridor' where constant ferry movement not only transports fragments to new locations along the route, but also continuously fragments existing plants through propeller action, potentially creating ideal conditions for regeneration and maintaining high densities along this linear feature (The Citizen, 2025). The initial introduction points of the weed into the Gulf are likely linked to human activities, such as aquarium trade or accidental transport (Everitt et al., 2008; Wahl et al., 2020). may also influence the initial locations of the spread and the subsequent hotspot development.

5. Conclusion and Recommendations

5.1. Conclusion

This study employed remote sensing techniques and spatial analysis to assess the temporal dynamics and identify spatial hotspots of invasive *S.molesta* in the Gulf of Mwanza, Lake Victoria. The results revealed an accelerated trend of *S.molesta* expansion (2020 and 2022), with estimations indicating a dramatic increase in its coverage by 2025, implying a potential leading to significant displacement of open water habitats. The trajectory of *S.molesta* expansion has highlighted a rapidly escalating threat to the ecological integrity and socio-economic usability of the Mwanza Gulf, consistent with recent reports of weed emergence and impacts in the area.

Furthermore, the Getis-Ord Gi* hotspot analysis successfully identified statistically significant spatial clusters within the 2025 *S.molesta* distribution. Significant hotspots, indicating exceptionally high invasion density, were located near the edge of Kigongo-Busisi and along the main ferry line. These findings move beyond generalized concerns by providing quantitative, spatially explicit evidence of the invasion's potential scale and pinpointing specific high-priority areas where ecological impacts are likely most severe and intersect critically with human activities, such as transport and shoreline development. Therefore, implementing targeted management and continued monitoring efforts for. *S. molesta* invasion in the Gulf of Mwanza is paramount to mitigating its likely adverse consequences.

5.2. Recommendations

Based on the findings of this study, the following recommendations are proposed for management, monitoring, and future research to address the proliferation of S. molesta in the Gulf of Mwanza:

Implement Targeted Management in Hotspot Areas: The strategic allocation of management resources should be prioritized for the hotspots identified near Kigongo-Busisi and along the primary ferry route. A comprehensive, integrated control plan is crucial for these high-density areas to prevent further propagation and mitigate immediate impacts on navigation and aquatic ecosystems. Although mechanical removal is a viable initial response, as evidenced by recent efforts, this approach should be viewed as a component of a broader, more sustainable management strategy.

Assess Biological and Chemical Control Options: It imperative that a thorough feasibility study is conducted to introduce host-specific biological control agents. The Salvinia weevil (Cyrtobagous salviniae), which has a well-documented history of success in controlling infestations in other regions, is the primary candidate for consideration. However, this process must be preceded by a rigorous assessment of the potential non-target ecological impacts within the Lake Victoria ecosystem. Concurrently, the judicious use of approved aquatic herbicides should be evaluated for rapid response scenarios, provided there is strict adherence to all environmental and regulatory protocols.

Mitigate the Drivers of Proliferation: A sustainable, long-term solution necessitates addressing the underlying factors that contribute to hotspot formation, particularly nutrient pollution. Therefore, authorities should prioritize the identification and control of eutrophication sources such as agricultural runoff and untreated sewage effluent entering the lake. The enforcement of existing environmental policies, including the 60-meter buffer zone regulation, is paramount to reducing the nutrient loads that fuel the proliferation of invasive macrophytes.

Enhance Monitoring and Early Detection Systems: The continuation and enhancement of remote sensing-based monitoring programs are critical for tracking the spatial and temporal dynamics of S. molesta infestation. The consistent use of satellite data, such as those from the Sentinel-2 mission, facilitates frequent and broad-scale coverage of the study area. Furthermore, increasing the frequency of monitoring during peak growing seasons is essential to enable early detection and a rapid, evidence-based management response to new or expanding clusters.

Areas for Further Research: Future research efforts should focus on validating 2025 distribution projections and hotspot locations through direct field surveys. Detailed field studies should be conducted within hotspot and non-hotspot areas to definitively identify the primary environmental drivers (e.g., water nutrient concentrations, currents, and shoreline structure) of the observed spatial clustering. Finally, any consideration of biological control must be supported by rigorous, localized host-specificity testing and ecological risk assessment before any introductions are made.

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