AJG

Article

Developing Integrated Modelling and Mapping Techniques for Calculating Plastic Leakage to The Waterway for The National Action Plan

Aprilia Nidia Rinasti*[1], Angsana Chaksan[1], Indradhi Faisal Ibrahim[1], Khin San Hlaing[1], Kavinda Gunasekara[1], Makoto Tsukiji[2], Ohnmar May Tin Hlaing[3], Thammarat Koottattep[1]

[1]Asian Institute of Technology, P.O. Box 4, 58 Moo 9, KM. 42, Paholoyothin Road, Pathum Thani, 12120, Thailand

[2]Institute of Global Environmental Strategies, 2108-11, Kamiyamaguchi, Hayama, Kanagawa, 240-0115, Japan

[3]Environmental Quality Management Co. Ltd., No.233, Block 23, Sayee Pin Lane, Thuwunna, Thingungyun, Yangon, Myanmar

*Corresponding author: A. N. Rinasti <aprilianidia@ait.ac.th>

Received: November 10, 2023; Accepted: May 15, 2024; Published: May 24, 2024

ABSTRACT

Plastic leakage models are compiled to provide baseline data. The critical elements in this working phase are systematically delivering current management, assisting survey-based condition judgements, and holistic calculations in the spatial context. Leakage modelling incorporated survey results, material flow, and spatial analyses, including proximity and hydrological analyses and weighting calculations. Mapping included global-scale data in a socioeconomic context, optical and thematic remote sensing, and geocoded features, with expected outcomes defined as a hotspot map using ModelBuilder, a designated toolbox for leakage modelling. The results were validated against satellite imagery. The capital city leaked up to 70 t per year into the main river; a small town with major water infrastructure leaked 45 t; and a small town with less waterway access leaked 1.8 tons annually. Plastic accumulation sites accounted for more than 200 items in these cities. The measurement was enhanced by using rough approximations with a container of known capacity, and the plastic exposure in the open environment was estimated to be approximately 220.38 L. Open land, newly developed areas, outskirts, and areas connected to neighbouring cities are vulnerable areas, and their management requires collaboration with neighbouring cities.

Keywords: Plastic waste, Material flow analysis, Hydrology, Mobile-app, Socio-economic

1. INTRODUCTION

1.1 Background

Plastic waste has become a major concern, and an integrated and strategic approach has been adopted to deliver preferable decision-making baselines. Plastic waste is ubiquitous in amounts that overwhelm the open environment. Here, the spatial-scale context was introduced to enhance the current leading solutions. Developing national-scale action plans for plastic waste management requires addressing gaps in plastic waste monitoring systems. The policy brief of the National Action Plans in plastic lacks the support of effective, consistent monitoring (March et al., 2023). Consequently, coordinated and maintained action plans are one of the keys to robustness in addressing the plastic waste issue.

Consistent plastic monitoring has been achieved using geographical modelling to incorporate data sharing into plastic waste management (The World Bank, 2021). Several regional approaches to geospatial information have been implemented in waste management. For example, plastic monitoring has been compiled in the water cycle and hydrological contexts (González-Fernández et al., 2021; Nihei et al., 2020; van Emmerik et al., 2022), encompassing the demographic context of behavioural waste management (González-Fernández et al., 2021; Jambeck et al., 2015; Sakti et al., 2021; Schuyler et al., 2021), and seasonal monitoring of plastic discharge (Rinasti et al., 2023; van Emmerik et al., 2019). Most approaches have been coupled with the local policy context (National Plastic Action Partnership, 2020); however, they lack advocacy for the central government as a national action plan.

This study defined the best-fit and replicable workflow for a plastic waste model, covering a city's demographic, natural setting, and waste management hierarchy. The model and mapping incorporate data input from fate analysis based on waste management assessment, survey-based input, and spatial-numerical modelling. The plastic that ends up in an open environment due to both intentional and inadvertent disposal is referred to as "plastic leakage" in our definition of the workflow. The workflow was developed to be replicable and scalable and can be updated to deliver consistent monitoring.

1.2 Overview

In modelling and mapping plastic waste with the aim of an integrative approach, the workflow identifies different fates, such as land, waterways, and marine environments (Rinasti et al., 2020). End-fate is a clear definition that stakeholders agree upon under the Global Definition of the Plastic Treaty (Castillo et al., 2023). To address this, calculations in the model are required to include waste management statistics and the Earth's phenomenon quantification model (Royle et al., 2022). Plastic waste is strongly correlated with demographic information, including population density, location of settlement areas, and land use in a social context (Tran-Thanh et al., 2022). Several studies have implemented urban area models, and satellite-detected night-time light (Levin et al., 2020) has become an accepted representation of the demographic context, where integration is needed with scenario implementation using slum context modelling (Kuffer et al., 2016). Therefore, the indicative fate can be derived from the population model.

Modelling the plastic fate requires the elaboration of its natural setting to incorporate monitoring. Plastics are lightweight, and monitoring their fate requires an understanding of controllable and uncontrollable measures in the environment. The model was developed at a hydrological scale to address the baseline information of rainfall (van Emmerik et al., 2019), storm surges, floods, and slope failures, which are common in Southeast Asia (Feeny et al., 2022). Flooding events are commonly modelled using morphometric analysis to include water flow (Abdel-Fattah et al., 2017), compliance with hydrologic models, and monitoring at floodgates. Flooding can cause plastic to scatter and block (Honingh et al., 2020), so it is desirable to monitor precipitation and flood-prone models based on flood records for a certain period (van Emmerik et al., 2023). The model's construction in the local context is compromised by plastic debris and obstructions that result in flooding.

2. MATERIAL AND METHODS

2.1 Data Collection

We collected data through stakeholder consultations, field surveys, and records. The first three methods were incorporated into primary data collection. To compile the data requirements, we were supported by local partners to obtain primary and secondary data.

2.1.1 Data Requirements

Data categories were set according to a previous study (Tran-Thanh et al., 2022), where plastic leakage was identified in the Lower Mekong River Basin. The data categories were grouped into static, dynamic, and natural indicators, which explained that the status of the city as static, compiled with time-stamp data as dynamic data, and incorporated with the natural indicators, such as natural-setting condition records. The following data requirements were adapted from the Guidelines for the Monitoring and Assessment of Plastic Litter in the Ocean (GESAMP Joint Group of Experts on the Scientific Aspects of Marine Environmental Protection, 2019), where the focus of identification was macroplastics (> 5 mm). The data requirements are listed in Table 1.

According to the baseline case study of the city in a previous analysis (Rinasti et al., 2022), in which waste management assessment was deployed using a Waste Flow Diagram (Cottom et al., 2020), a gap analysis was used to develop a different scenario according to the data compiled from the local conditions. Gap analysis was conducted by reviewing the baseline data on the waste management conditions present in the city which were used in order to understand the leakage scenario calculation. The data used in the scenario mapping include plastic consumption, leakage from plastic manufacturing, and clean-up practices. The information for the scenario is included in the process of leakage quantification under the Waste Flow Diagram. Information was obtained through stakeholder consultation with the City Development Committee using a questionnaire regarding plastic waste management conditions, including the practices and management facilities in each township.

Table 1: List of data category required

Categories	**Data**	**Data Description**	**Collection Methods**
Static	Population density and residential types	Distribution of population density per area defined in the ward or village level. Dataset can be presented by using tabulate data.	(Primary) National population dataset; Population distribution dataset; (Secondary) WorldPop (global dataset population density)
	Nightlight imagery and gross domestic product	Distribution of nightlight in one city depicted in a raster dataset to approach the economic aspects in the area. The data combined from the remote sensing data (in raster) and local status regarded the income.	(Primary) Report or statistical data per ward according to the national statistics. (Secondary) Obtained from USGS (United States Geological Survey)
	Land use	Distribution of building area and land use area in the city at least consists of: — Residential area — Vegetation or plantation — Commercial area — Waterbodies	National mapping agency; Public housing authority

Categories	Data	Data Description	Collection Methods
	Waste generation	Average number of waste generation per ward in the city	Environmental service authority
	Plastic value chain	Data from the commercial activities include industry, food and beverage, tourism, accommodation, institutions, etc. The activities are referred to the common people gathered, opposite from the residential activities.	Point location of the facilities in GIS format (.shp); Statistical and open-source reports from respective companies
	Infrastructure area	Location of commercial area distribution along with the accessibility network dataset (road)	(Primary) National mapping agency; (Secondary) OpenStreetMap
	Municipal Solid Waste (MSW) facilities	Locations of facilities and waste management coverage areas sent to the respective facility	Environmental services authority
Dynamic	Population growth rate	The rate at which the number of individuals in the population increases during each period. The population growth rate's unit is a percentage per year.	Report or statistical data per ward according to the national statistics.
	Littering activities	Record of the field survey containing of plastic waste accumulation appearance in the environment. Data record must contain geolocation in order to map as the distribution.	Primary data collection from using Mobile Application for Macroplastic Survey
	Cleanup frequency	Existing regulated plastic waste reduction program and addressed area according to the report in statistics.	Primary data collection from using Mobile Application for Macroplastic Survey

Categories	Data	Data Description	Collection Methods
Natural	River network	The network of main river, stream, and the tributary in the watershed. Data should represent the distribution of delineated area (line or polygon) in GIS format (.shp).	(Primary) National mapping agency (Secondary) HydroSHEDS
	Meteorological stations and rainfall rate	Recorded rainfall rate (mm) in a daily basis from the station of meteorology in the city	(Primary) Meteorological authority (Secondary) CHIRPS v.2
	Soil erosion record	Recorded area of soil erosion (mainly in the riverbank area – close to the river) within period, extent to river catchment impact.	(Primary) National disaster management authority (Secondary) Global Soil Erosion
	Flood record	Recorded flooded area of flooding events, perpetually in the past 10-year period in the area.	Statistical data of flood record and map of flooded area from national meteorological agency.

2.1.2 Primary Data Collection

Primary data were collected via visual assessment using a mobile application for macroplastic surveys (Geoinformatics Center, 2023). Based on a previous study by Tran-Thanh et al. (2022), we identified the locations of plastic accumulation as artificial barriers, littering spots, and uncontrolled dumpsites. These locations imply that different types of plastic waste accumulate in open environments, including land- and water-based activities, at the city level.

The measurements were calibrated based on an estimate using a tape measure. Calculations were required to measure the accumulation length, width, and height of littering spots and uncontrolled dumps. The measurements of the artificial barrier types were estimated based on a 20 L water gallon container as calibrated measurements in the field.

2.1.3 Secondary Data

Secondary data were obtained from free open-source data and local partners in the respective cities. We prioritised open-source city-level data over national- and global-scale data. Most open-source data was compiled from geospatial data. Local partners contributed to delivering village-to-city-level data from local authorities.

The analysis integrated three approaches (local, global, and self-production) using 29 data sources. Local approaches refer to the data obtained and recorded at the city level. Local data were primarily obtained from local partners through national data portals or relevant authorities, such as the Myanmar Information Management Unit (MIMU), Department of Hydrology and Meteorology, and City Committee Development. Data were reordered from legacy data from 2010 to the most current data.

The global approach represents global-to national-level data, mainly accessible as open-source data. In this study, demographic and social distributions were represented by global-scale data using a combination of population density products (Kemper et al., 2021; Meta & CIESIN, 2019; WorldPop, 2020), which were combined with Land Cover and Global Land Analysis and Discovery Lab (GLAD) data from Esri (Esri, 2022; Potapov et al., 2022). To perform a detailed analysis of the type of settlement area, we used the Global Building Dataset (Maps, 2023) and compared it with the SEDAC Global Gridded Relative Deprivation Index (GRDI) v1 (Center for International Earth Science Information Network - CIESIN - Columbia University, 2022) to obtain dense population locations. The actual conditions were provided by the satellite images from the optical image Sentinel-2, and the economic approach was validated by the addition of nighttime light data from VIIRS (Ghosh et al., 2013).

Some indicators, such as dynamic and natural setting data, were collected in this study. We used the locations of waste management facilities, dumpsite areas, rainfall rate distributions, and disaster records. We used the advanced analysis, which included comparisons and data combinations, to determine the probability of slum areas, river network distribution, flooding and soil erosion, and drainage morphometry.

2.2 Hotspot Analysis

The source hotspots were defined based on the actual conditions of the city according to their spatial distribution. Leakage source hotspots were categorised from very low to very high levels following a previous approach (Tran-Thanh et al., 2022). A similar approach was adopted for plastic waste leakage source hotspots, in which the definition of a hotspot was improved to include the amount of waste leaked per tonne (Rinasti et al., 2022). For the final process in the initial analysis, the hotspot analysis concluded with a weighted overlay of spatial information.

Hotspot analysis was performed in three sequential steps: normalisation, weight calculation, and density calculation. Hotspots derived from the static data calculation included demographic information, accessibility, economy, plastic waste management, and regulations. Fuzzy analysis in ModelBuilder in ArcGIS was used to normalise the data between 0 and 1, referring to the membership assignment of static data from a previous study (Tran-Thanh et al., 2022). The ModelBuilder incorporated simplification for the scenario, data input, and leakage quantification. Consequently, the hotspot indicated an annual hotspot as a source hotspot.

The normalisation steps included rasterisation, fuzzification, and fuzzy analysis. Rasterisation was used to increase the reliability of the spatial distribution of the information contained in each dataset. The rasterisation method primarily concludes with the conditional actions of specific conditions. For example, there is a high probability of plastic waste generation in urban areas. We also included a multi-comparison analysis in which the conditions applied under the conditional actions were evaluated by simply unifying the supporting information. For example, the location of an urban area was compared with the locations of deprived settlement areas, building footprints, and average nighttime brightness to indicate the area prone to plastic leakage, as shown in Eq. (1).

$$y = y_0 - \left(\frac{X_1}{y_0} - \frac{X_2}{y_0} \ldots\ldots - \frac{X_n}{y_0}\right) - \left(\frac{Y_1}{y_0} - \frac{Y_2}{y_0} \ldots\ldots - \frac{Y_n}{y_0}\right) - \left(\frac{Z_1}{y_0} - \frac{Z_2}{y_0} \ldots\ldots - \frac{Z_n}{y_0}\right) \quad \ldots(1)$$

where

y = final probability of plastic leakage

y_0 = initial factors (e.g., urban area)

X_n, Y_n, Z_n = supporting factors (e.g., building footprints, night-time light brightness)

Based on the sample equations, comparisons were made to provide an actual representation of human factors influencing plastic waste generation. The equation was applied to all data inputs to improve the reliability of the data representation. The results were analysed using fuzzification to define hotspot levels.

Weight calculations were performed based on the area of interest (AOI) at the defined hotspot level during normalisation. We used zonal statistics, in which each pixel in the raster data input was calculated using the total value information based on the AOI. For example, the density of infrastructure locations in a hotspot area was calculated by comparing urban area hotspots and geocoded locations of plastic waste management facilities in terms of density. The weight calculation results indicated the source of plastic waste leakage according to static conditions.

Density calculation is the last step in determining the specific hotspots of plastic waste leakage. The initial results from the hotspot sources and weight distributions of the data input were converted to point locations, where each location was validated. We used optical imagery to validate the location and combined the analysis with land use data to estimate the urban area. To validate the plastic leakage area, we used the point locations of the macroplastic survey (Geoinformatics Center, 2023) as the sampling locations.

2.3 Leakage Analysis

2.3.1 Hydrologic Models and Factors

We used base assumptions to model the river morphology in the mathematical model. In the early stages of hydrological analysis, we generated the river as a waterway distribution by comparing the digitised data with the digital elevation model. The network distribution of the river was later analysed based on its morphology to understand each catchment area.

To be consistent with the underlying hydrological factors, we identified them based on rainfall records from weather stations and imaging observations over a four-year period. The purpose of analysing this trend was to identify the three peak months of rainfall for each monsoon in Myanmar, where the four years of rainfall maintained similar rates (Rinasti et al., 2023). According to a study on tropical climates, rainfall rates dominate the flux of water (Behara & Vinayachandran, 2016). Therefore, we analysed the rainfall using the catchment area obtained earlier.

We included the natural hazard of overflowing water using ten years of flood records obtained from several sources, such as local news, satellite analysis, and terrain modelling. Using a hydrologic scenario model with corresponding artificial boundaries like construction sites, bridges, and riverbanks, terrain-based flow modeling was carried out. Flood records were used to determine which areas were likely to flood frequently over the course of the year and which, given their topography, were more likely to experience flash flooding.

2.3.2 Riverine Analysis as Plastic Leakage Pathway

At this stage, the results included hotspot areas and hydrological models. Riverine analysis was the final analysis used to define plastic leakage input to the river. We combined the findings with proximity and morphometric analyses in accordance with the scenario given in a prior study (Tran-Thanh et al., 2022) and by gathering the hotspots of plastic leakage (Rinasti et al., 2022). Proximity was used to define the buffer area of the riverbank, and fuzzy membership assignment was used to quantify the probability leakage level.

The results obtained from leakage quantification based on the waste management assessment were used as input for this stage. By processing the field data (input using the mobile application) and using the material flow analysis from the previous phase of modelling, we accounted for the annual tons of leakage defined for each fate. The results from the mobile application were transformed into density to determine hotspots based on the accumulated evidence, which became the data input for hotspot detection.

Finally, we compiled information using the concept of spatial joining. The provisioning method for the spatial join improved the calculation of the surrounding probability, which was included in the statistical calculations. We used spatial joining and elaborated on the riverbank analysis by calculating the hotspots in each river catchment. In this study, we focused on river leakage according to riverbank zones compiled from buffered zone areas, based on the types of settlements nearby.

3. RESULTS AND DISCUSSION

3.1 Initial Assessment: Source Hotspot

Each hotspot level represents the vulnerability of the area to plastic leakage and ranges from low to high exposure. Hotspots are generally located in the centre of the city. The hotspots explained the development of human activity and the inclusivity of demographic values, as modelled in the priority list of the methodology. A hotspot indicates the probability of leakage in natural settings, where plastic leakage has not been identified.

The source hotspot shown in Figure 1 is explained similarly; however, the actual leakage was not detected. The resulting hotpot (Figure 1) is a classified area with a high probability of plastic waste generation, owing to its pattern of plastic consumption and notorious activities, including commercial and residential areas. The commercial area indicates economic growth, and the residential area emphasises plastic waste generation, both of which imply the development of plastic waste (Lebreton and Andrady, 2019; Nyberg et al., 2023). We used nighttime light indicators and population datasets to identify areas with higher economic growth (Ghosh et al., 2013).

Using the mobile application, we determined the factors affecting the actual hotspots of plastic leakage. The mobile application selects locations based on a survey. Approximately 370 sampling locations throughout the city were identified as plastic disposal accumulation sites. The results were incorporated as factors for hotspot detection. Figure 2 shows the distribution of accumulated plastics visualised as a heat map per kilometre (km).

The heatmap level indicates the dense location of the accumulation, according to the field survey. We limited the survey to one period during the dry season to ensure efficient data collection among the cities. The results indicated that litter spots were spread mostly in commercial zones, especially in busy areas of commercial zones. This implies that source hotspots can be evaluated using a sample of plastic waste accumulation based on the sampled locations.

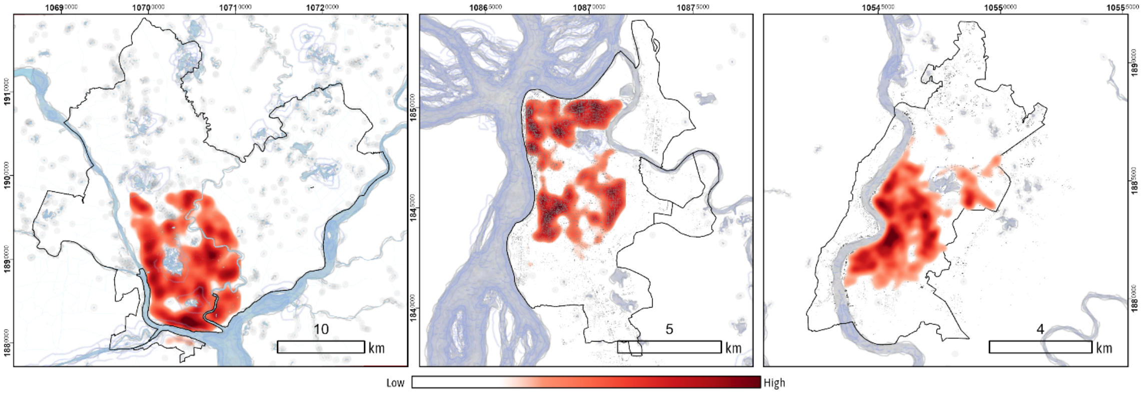

Figure 1. Source Hotspot Level of Plastic Leakage (left to right: Yangon, Mawlamyine, and Pathein, Myanmar)

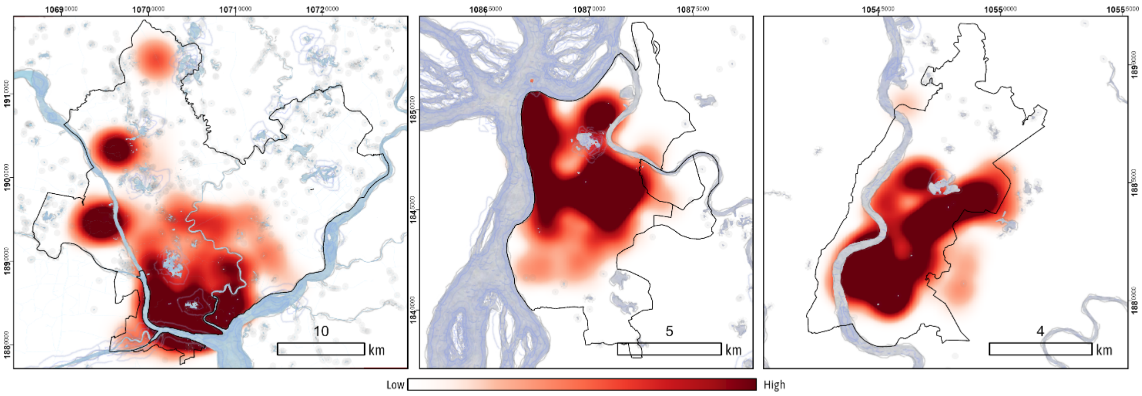

Figure 2. Heatmap of Accumulated Plastic based on Field Survey (left to right: Yangon, Mawlamyine, and Pathein, Myanmar)

3.2 Plastic Waste Accumulation from Survey

From the waste management assessment at the city level, we included a methodology using a Waste Flow Diagram, showing that approximately 25.8% of the leakage arose from mismanagement in disposal facilities. The waste flow is depicted in the Sankey Diagram in Figure 3, which provides an example of the plastic leakage flow assessment that forms the input for the actual hotspot detection.

Plastic waste leaked about 13,738 tons in Yangon, Myanmar, implying that more than 50% of the waste was retained on land. Plastic leakage identified from the collection, rejection from waste management facilities, and disposal of uncollected waste directly end up in an open environment. Here, we limited the identification of leakage based on the target area in land, water, and input to the drains to evaluate the unprocessed leakage to the environment. The results emphasised that 7,064 tons of plastic leaked into the land and 1,262–5,162 tons per year leaked into the waterway fate hotspots.

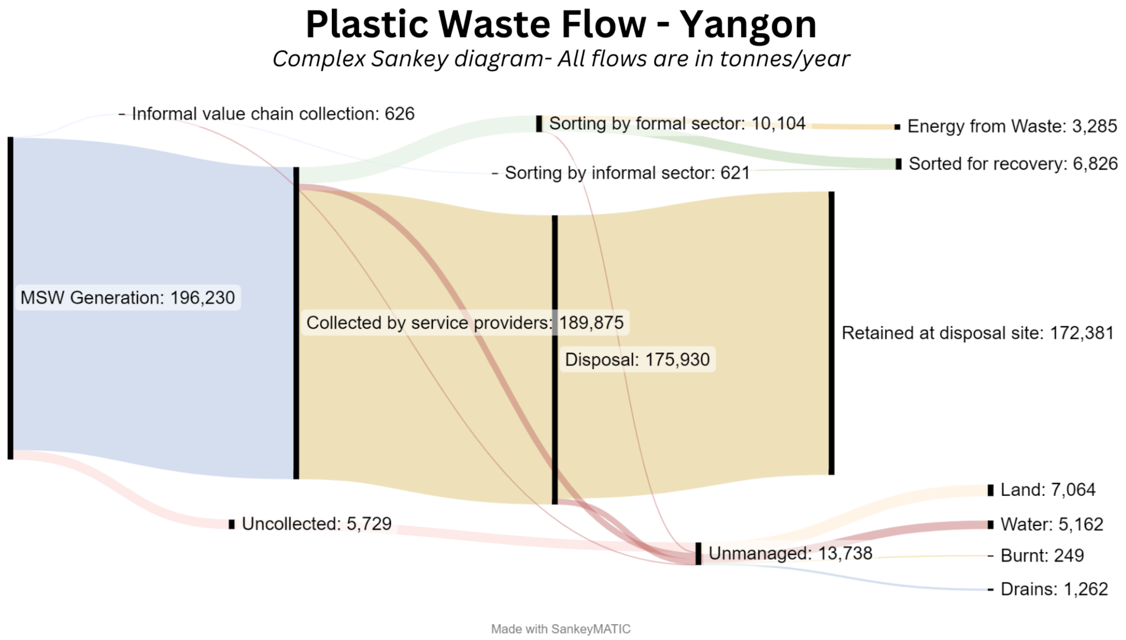

Figure 3. Sankey Diagram of Plastic Waste Flow in Yangon

Table 2. Survey on Plastic Waste Accumulation at each sampling site in Yangon

Survey location	Artificial barriers			Littering spots			Uncontrolled dumpsites		
	Point	%	Average vol. (L)	Point	%	Average vol. (m^3)	Point	%	Average vol. (m^3)
Yangon	26	15%	220.4	113	65%	1.3	34	20%	35.5
Dominant type of plastic	1. All 2. Food wrapper and sachet 3. Takeaway containers 4. Beverage bottle 5. Other plastic bags and sheets			1. Takeaway containers 2. All 3. Food wrapper and sachet 4. Beverage bottle 5. Other plastic bags and sheets			1. All 2. Food wrapper and sachet 3. Takeaway containers 4. Beverage bottle 5. Grocery bag		

The survey questions are available at https://arcg.is/1LbjqO. In this survey, we expected there to be more littering spots found in commercial areas due to the intensive activities around them. The mobile application for the macroplastic survey detected 370 locations in the three cities, with details of numerous plastics disclosed as leakages in the open environment. Table 2 presents the survey findings for Yangon. The amount of accumulated plastic waste was estimated based on the surveyors' findings.

Based on the survey and questionnaires administered to stakeholders, we found that the leakage of general types of robust plastics was profound. However, plastics in the environment are dominated by takeaway containers in relatively small areas of accumulation (i.e., littering spots), with an average volume of less than 1 m3. As shown in Table 2, littering spots accounted for 65% of the total plastic accumulation locations at the city level. The conclusions from the mobile app survey and the findings clarified the assessment of plastic waste consumption habits, which enlarged the scope of leakage modelling.

3.3 Riverine Plastic Leakage

Based on the leakage scenario and model input, we concluded that static riverine plastic leakage occurred within one year. A static period of one year was delivered based on the survey data input. The data were then summarised into a whole-year estimate. The input into the one-year prediction scenario included the city condition based on the results in Figure 1 and was developed in the pixel-based model shown in Figure 4. Thus, riverine plastic leakage provides indicative information on the possibility or scale of plastic leakage (e.g., 10 km of a river can leak approximately 2–5 tons per year).

A heat map was developed after applying the use case based on the actual waste management status of the city. The heatmap results refer to the volume composition shown in Table 2, where the sampled area was exposed to an accumulated amount of plastic waste. To distinguish between hotspots, Figures 5–7 depict the hotspots of each township and the extent to which the hotspot levels may be affected. The hotspot area describes the level of exposure to plastic leakage as a source of land-based activities, according to Tran-Thanh et al. (2022).

Plastic leakage occurred in different areas but was prevalent in the tributaries and mainstream areas. The representation of the mainstream was based on the hydrological factors modelled in the mainstream of the city, the hydrologic scenario in the mainstream areas, and the high dependency on increasing flow velocity in some regions, as shown in Figure 4.

The water surface and river depth were determined as the flow velocities that addressed the catchment area. The catchment area in the sub-basin (approximately 111 sub-basins in Yangon are plastic catchments) represents the plastic outflow to the water bodies. We highlight that the vast water flow in the northern part of the Yangon sub-basin may have caused a higher plastic flow to the city centre, as shown in Figure 5C.

We defined the main stream area as the general conclusion of a city's riverine plastic leakage state. According to the plastic leakage estimation by Alencar et al. (2022), robust detection can be achieved using the mainstream method. We conclude that the focus should be on deliverables with respect to leakage concentrations in mainstream areas.

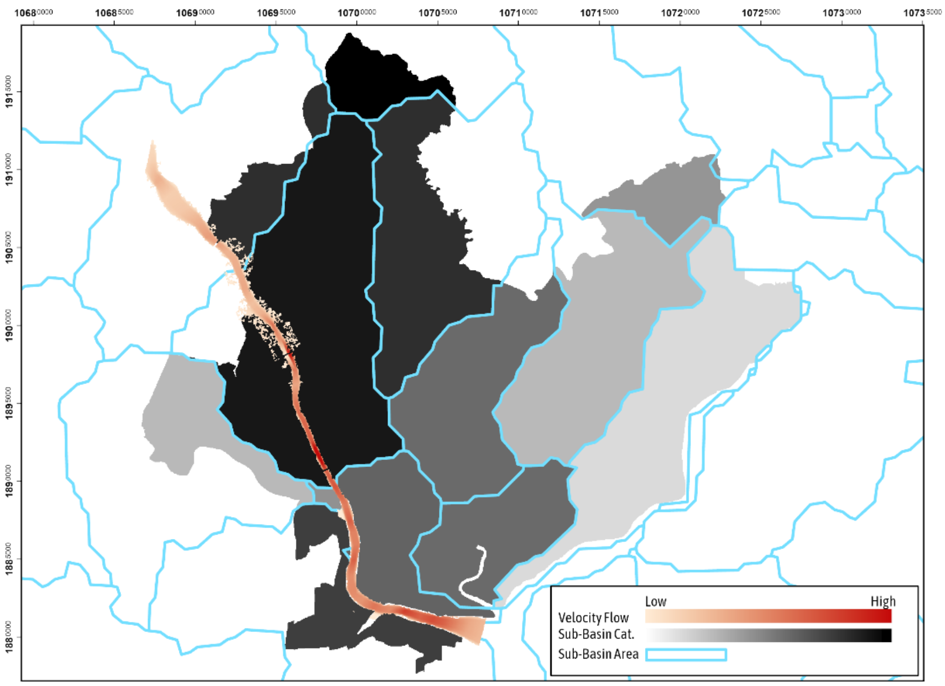

Figure 4. Increasing Flow Velocity in Yangon River Mainstream

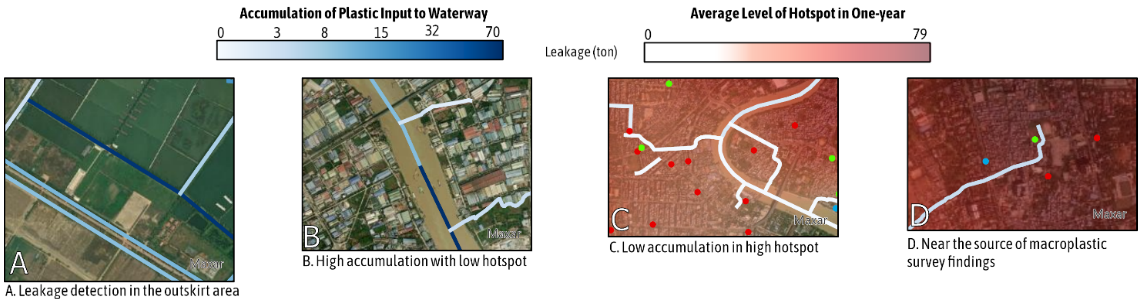

Figure 5. Highlighted Type of Leakage Pathway in the River: Yangon, Myanmar

3.4 Quest for Plastic Leakage Pathway in Different Cities

The plastic leakage findings in different cities varied based on the characteristics of each city. Defining the plastic leakage state improves additional analysis requirements and develops the state of each category. This study investigated the effects of Yangon, Mawlamyine, and Pathein.

3.4.1 Yangon

Yangon covers 598.75 km2 and has a population of more than 5.1 million. Yangon is the largest city in Myanmar and is highly likely to generate a significant amount of waste. Based on a survey of 33 townships, it was estimated that Yangon may experience up to 70 t of plastic leakage into its rivers annually. The riverine leakage map in Figure 5 shows different colours indicating the extent of the impact on the waterway, with darker shades indicating higher levels of leakage.

The details of the different types of leakage found in Yangon are as follows:

A. Leakage detection in the outskirt area
The outskirts of Dagon Township and newly developed areas in Yangon showed high levels of plastic leakage, but no nearby hotspots were detected. This implies that the leakage may have been caused by land-based hotspots outside of Yangon.

B. Anomality of high accumulation in the waterway with low or no hotspot
A high probability of leakage was detected in the mainstream of Yangon, suggesting the presence of undetected leakage hotspots outside the coverage area flowing into the respective rivers. The lighter-coloured line indicates the possibility of leakage from suburban areas, which is estimated to be approximately 8–15 t annually.

C. Low accumulation at the indicated high hotspot area
The area displayed in Figure 5C is more prone to hotspots, owing to increased human activity and commercial spaces. Good management in the area may solve the lower categorised leakage to the identified waterway and reduce the pressure and amount of leakage to the nearby river. Figure 5C shows the high hotspot intensities based on the results of the macroplastic survey, which identified locations with high concentrations.

D. Leakage near the source of macroplastic survey using the mobile app
Different types of plastic waste were discovered through surveys conducted in this area. This area is an example of how hotspots contribute to the leakage of plastic waste into the main waterways.

3.4.2 Mawlamyine

The second city is a coastal island located in Mon State, close to the border with Kanchanaburi Province in Thailand. Mawlamyine has 223,017 inhabitants and is a town with an area of 72.69 km sq. Based on the conditions in Mawlamyine, high hotspot areas were identified primarily in the proximity of the main roads connecting other islands, towns, and regions. Calculations based on the Waste Flow Diagram estimated that Mawlamyine leaks 151 tons/year of plastic waste into the water system. The macroplastic survey identified 108 locations as accumulated points of plastic waste in the open environment, indicating a concentrated leakage area at the artificial barriers, where a general hotspot in coastal cities was identified. The relatively well-managed coastal area of Mawlamyine has different types of leakage.

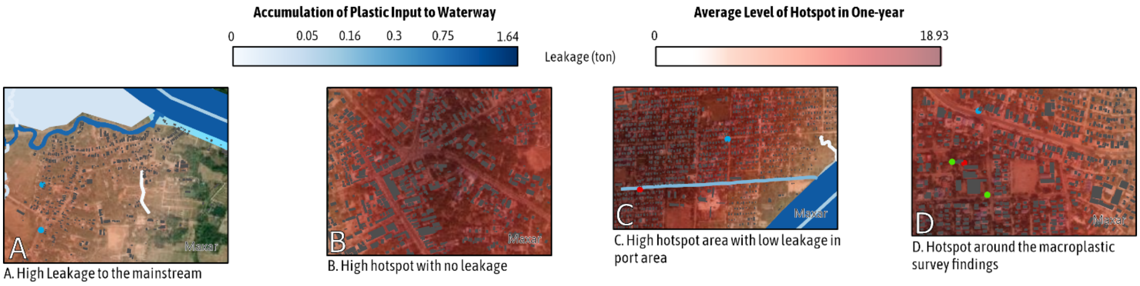

Figure 6. Highlighted Type of Leakage Pathway in the River: Mawlamyine, Myanmar

A. High leakage area to the mainstream

   Figure 6A shows the leakage flow into the Ataran River, which empties into the Thanlwin River. The leakage input was estimated to be from the tributaries of the Ataran River to its mainstream, up to 1.64 tons annually.

B. High hotspots with no leakage to the waterway were detected

   The area mapped in Figure 6B found about 18.93 tons/year of land-based leakage. In this area, the water body was unidentified, resulting in no leakage into the waterways. The accumulation of plastic leakage was not detected during the macroplastic surveys. The area shown in Figure 6B is well-managed, with a low chance of unsound disposal of plastic into the environment.

C. High-hotspot area with lower leakage in the port area

   Figure 6C depicts the high hotspots in the port area, indicating the locations of significant dynamic human activity throughout the years. The discovery of artificial barrier locations in field surveys confirmed this finding.

D. Hotspots and macroplastic survey findings

   Leakage mapping identified 10.7–14.3 tons/year leakage in the area shown in Figure 6D. Figure 6D shows the commercial zones crossed by main roads and bridges from other regions. The results for this area were consistent with the findings of field surveys and significantly contributed to the maximum leakage of Mawlamyines.

3.4.3 Pathein

Pathein is a densely populated urban area with a city centre at the mouth of the Pathein River. It has a main road connecting nearby cities, including Yangon, which is Myanmar's largest city. Based on the natural conditions in Pathein, a hotspot was identified near the Pathein River area in the city centre.

Owing to the extensive network of waterways throughout the city, Pathein is highly susceptible to plastic waste leakage, mainly as it flows into the mainstream (Figure 7D). According to calculations and proximity analyses based on waterway distribution, Pathein is estimated to leak approximately 45.1 tons of plastic waste annually, which is significantly higher than the plastic leakage in Yangon and Mawlamyine.

Despite its small size, the population density of Pathein was higher than that of Mawlamyine. Furthermore, it has been estimated that Pathein could leak up to 41.65 tons of plastic waste into land-based open environments.

A. Low leakage with no hotspot detected in the outskirt area

   The outskirts of Pathein, crossed by tributaries of the Pathein River in the eastern part of the city, developed an undetected leakage with no surrounding inhabitants (Figure 7A). According to this, hotspot detection typically yields the quantity determined in the areas under the jurisdiction of waste management authorities.

B. Hotspot within the main road

   A source hotspot was identified along the main road (Figure 7B), which significantly contributed to the leakage. The model estimated that approximately 16.27 tons of plastic waste leak annually from land-based activities along roads.

C. High leakage is detected and flows to lower hotspots

   The leakage findings suggest that plastic waste may flow through the waterway to hotspots lower in the catchment (Figure 7C). The map illustrates the correlation between the origin of the leakage and the intensity of the hotspot area in the city centre.

D. High hotspot near mainstream as the leakage input

   The leakage pathway accumulation map shows that the mainstream flow in Pathein is highly susceptible to plastic leakage. The hotspot located in its proximity, estimated to generate 32–41.6 tons/year, may significantly contribute to plastic waste entering the Pathein River.

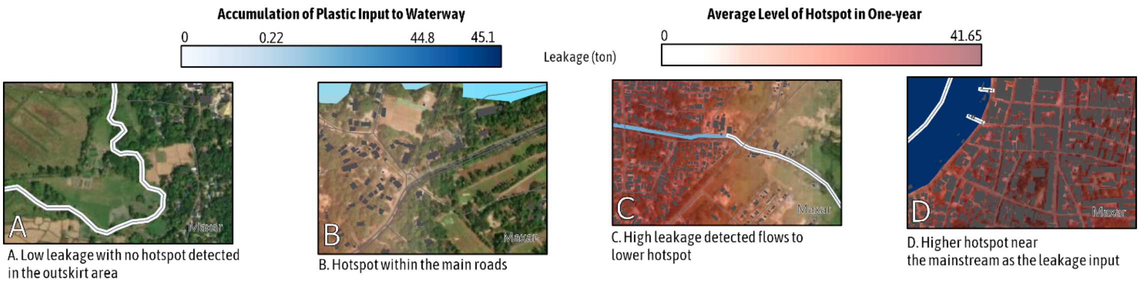

Figure 7. Highlighted Type of Leakage Pathway in the River: Pathein, Myanmar

4. CONCLUSIONS

Plastic leakage mapping helps monitor plastics and plan actions for cities. Our analysis focuses on the extent of geographical coverage and vulnerable areas with respect to compliance with national action plans. By improving the model at the city scale, the annual plastic leakage into rivers can be estimated.

The accuracy of the annual WFD

(Waste Flow Diagram) assessment significantly affects the leakage mapping results. Furthermore, by updating the data on the WFD assessment and mobile app surveys, for example, based on monthly surveys carried out using mobile apps, the accuracy of the leakage mapping can be improved.

We attempted to improve the mapping using several enhancements for the final assessment. A smooth validation workflow is required to improve the model, correct the sequence survey results, and develop a threshold model for the scenarios.

This study concludes that different regulations can be implemented under this model by modifying the toolbox and developing a scenario for waste management assessment. The model workflow can be incorporated into the forecasting of plastic waste reduction strategies (e.g., a plastic reduction of 10% in general). In future, waste management scenarios will undergo a comprehensive evaluation on a citywide scale.

ACKNOWLEDGEMENT

We express our greatest appreciation to the local partner in Myanmar (Environmental Quality Management - EQM) and the authority bodies of the City Development Committee in Yangon, Mawlamyine, and Pathein for providing the data requirement in this study. The analysis and algorithm are fully developed and conducted by the Geoinformatics Center of the Asian Institute of Technology. The work has been elaborated with the designated Mobile Application, which can be fully accessed from the link: https://plitter.org/mobile-dashboard. This manuscript has gone through the professional English Editing by the Editage.

DATA AVAILABILITY

The toolbox for processing the plastic waste leakage is published in (https://figshare.com/articles/journal_contribution/Plastic_Leakage_GIS_Toolbox_v_1/23977752). The tool can be tested in ArcGIS for the version 1 (v.1) compilation.

REFERENCES

Abdel-Fattah, M., Saber, M., Kantoush, S. A., Khalil, M. F., Sumi, T., & Sefelnasr, A. M. (2017). A hydrological and geomorphometric approach to understanding the generation of wadi flash floods. *Water*, 9(7), 1–27. https://doi.org/10.3390/w9070553

Alencar, M. V., Gimenez, B. G., Sasahara, C., Elliff, C. I., Rodrigues, L. S., Conti, L. A., Gonçalves Dias, S. L. F., Cetrulo, T. B., Scrich, V. M., & Turra, A. (2022). How far are we from robust estimates of plastic litter leakage to the environment? *Journal of Environmental Management*, 323, 116195. https://doi.org/10.1016/J.JENVMAN.2022.116195

Behara, A., & Vinayachandran, P. N.

(2016). An OGCM study of the impact of rain and river water forcing on the Bay of Bengal. Journal of Geophysical Research: *Oceans*, 121(4), 2425–2446. https://doi.org/10.1002/2015JC011325

Castillo, A. Del, Azoulay, D., & Bonacini, C. (2023). Compilation of Key Terms Relevant for the Negotiation of a Treaty to End Plastic Pollution. https://www.ciel.org/wp-content/uploads/2023/05/Compilation-of-Key-Terms-Relevant-for-the-Negotiation-of-a-Treaty-to-End-Plastic-Pollution_FINAL.pdf

Center for International Earth Science Information Network - CIESIN - Columbia University. (2022). Global Gridded Relative Deprivation Index (GRDI), Version 1. Palisades, New York: NASA Socio-economic Data and Applications Center (SEDAC). https://doi.org/10.7927/3xxe-ap97

Cottom, J., Zabaleta, I., Zurbruegg, C., Stretz, J., & Eschborn, B. S. (2020). User manual: Waste flow diagram (WFD): A rapid assessment tool for mapping waste flows and quantifying plastic leakage. In Deutscge Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH. https://www.giz.de/expertise/html/62153.html

Esri. (2022). Sentinel-2 10m Land Use/Land Cover. https://www.arcgis.com/apps/instant/media/index.html?appid=fc92d38533d440078f17678ebc20e8e2

Feeny, S., Trinh, T.-A., & de Silva, A. (2022). Detecting Disasters and Disaster Recovery in Southeast Asia: Findings from Space. *Natural Hazards Review*, 23(2). https://doi.org/10.1061/(asce)nh.1527-6996.0000532

Geoinformatics Center, A. I. of T. (2023). Mobile Application for Macro Plastic Survey. https://arcg.is/1rSHDm

GESAMP Joint Group of Experts on the Scientific Aspects of Marine Environmental Protection. (2019). Guidelines for the monitoring and assessment of plastic litter in the ocean. In *GESAMP Report and Studies:* Vol. no 99. http://www.gesamp.org/publications/guidelines-for-the-monitoring-and-assessment-of-plastic-litter-in-the-ocean

Ghosh, T., Anderson, S. J., Elvidge, C. D., & Sutton, P. C. (2013). Using nighttime satellite imagery as a proxy measure of human well-being. *Sustainability*, 5(12), 4988–5019. https://doi.org/10.3390/su5124988

González-Fernández, D., Cózar, A., Hanke, G., Viejo, J., Morales-Caselles, C., Bakiu, R., Barceló, D., Bessa, F., Bruge, A., Cabrera, M., Castro-Jiménez, J., Constant, M., Crosti, R., Galletti, Y., Kideys, A. E., Machitadze, N., Pereira de Brito, J., Pogojeva, M., Ratola, N., … Tourgeli, M. (2021). Floating macrolitter leaked from Europe into the ocean. *Nature Sustainability*, 4(6), 474–483. https://doi.org/10.1038/s41893-021-

00722-6

Honingh, D., van Emmerik, T., Uijttewaal, W., Kardhana, H., Hoes, O., & van de Giesen, N. (2020). Urban River Water Level Increase Through Plastic Waste Accumulation at a Rack Structure. *Frontiers in Earth Science*, 8(February), 1–8. https://doi.org/10.3389/feart.2020.00028

Jambeck, J. R., Geyer, R., Wilcox, C., Siegler, T. R., Perryman, M., Andrady, A., Narayan, R., & Law, K. L. (2015). Plastic waste inputs from land into the ocean. *Science,* 347(6223), 768–771. https://doi.org/10.1126/science.1260352

Kemper, T., Melchiorri, M., & Ehrlich, D. (2021). Global Human Settlement Layer. https://publications.jrc.ec.europa.eu/repository/handle/JRC126219

Kuffer, M., Pfeffer, K., & Sliuzas, R. (2016). Slums from space-15 years of slum mapping using remote sensing. *Remote Sensing*, Vol. 8, Issue 6. https://doi.org/10.3390/rs8060455

Lebreton, L., & Andrady, A. (2019). Future scenarios of global plastic waste generation and disposal. *Palgrave Communications*, 5(1). https://doi.org/10.1057/s41599-018-0212-7

Levin, N., Kyba, C. C. M., Zhang, Q., Sánchez de Miguel, A., Román, M. O., Li, X., Portnov, B. A., Molthan, A. L., Jechow, A., Miller, S. D., Wang, Z., Shrestha, R. M., & Elvidge, C. D. (2020). Remote sensing of night lights: A review and an outlook for the future. *Remote Sensing of Environment*, 237. https://doi.org/10.1016/J.RSE.2019.111443

Maps, B. (2023). Global ML Building Footprints. https://github.com/microsoft/GlobalMLBuildingFootprints

March, A., Nieminen, L., Aurora, H., Walker, T. R., Shejuti, S. M., Tsouza, A., & Winton, S. (2023). Effectiveness of national action plans | Global Plastics Treaty Policy Brief. https://plasticspolicy.port.ac.uk/research/national-action-plans

Meta, & CIESIN. (2019). Data for Good at Meta. https://data.humdata.org/organization/facebook?q=high resolution population density&ext_page_size=100

National Plastic Action Partnership. (2020). Radically Reducing Plastic Pollution in Indonesia: A Multistakeholder Action Plan (Issue April). https://globalplasticaction.org/wp-content/uploads/NPAP-Indonesia-Multistakeholder-Action-Plan_April-2020.pdf

Nihei, Y., Yoshida, T., Kataoka, T., & Ogata, R. (2020). High-Resolution mapping of Japanese microplastic and macroplastic emissions from the land into the sea. *Water*, 12(4). https://doi.org/10.3390/W12040951

Nyberg, B., Harris, P. T., Kane, I., & Maes, T. (2023). Leaving a plastic legacy: Current and future scenarios for mismanaged plastic waste in rivers. *Science of The Total Environment*, 869, 161821. https://doi.org/10.1016/J.SCITOTENV.2023.161821

Potapov, P., Hansen, M. C., Pickens, A., Hernandez-Serna, A., Tyukavina, A., Turubanova, S., Zalles, V., Li, X., Khan, A., Stolle, F., Harris, N., Song, X.-P., Baggett, A., Kommareddy, I., & Kommareddy, A. (2022). The Global 2000-2020 Land Cover and Land Use Change Dataset Derived From the Landsat Archive: First Results. *Frontiers in Remote Sensing*, 3(April), 1–22. https://doi.org/10.3389/frsen.2022.856903

Rinasti, A. N., Gunasekara, K., Winijkul, E., Ninsawat, S., & Koottatep, T. (2023). Developing Scenario of Plastic Waste Leakage in the Jakarta Hydrology Environment Using Seasonal Data Conditions and Socio-economic Aspects. *Springer Geography*, 65–88. https://doi.org/10.1007/978-3-031-16217-6_5/FIGURES/6

Rinasti, A. N., Ibrahim, I. F., Gunasekara, K., Koottatep, T., & Winijkul, E. (2022). Fate identification and management strategies of non-recyclable plastic waste through the integration of material flow analysis and leakage hotspot modeling. *Scientific Reports*, 12(1), 1–14. https://doi.org/10.1038/s41598-022-20594-w

Rinasti, A. N., Sakti, A. D., Agustina, E., & Wikantika, K. (2020). Developing data approaches for accumulation of plastic waste modelling using environment and socio-economic data product. *IOP Conference Series: Earth and Environmental Science*, 592(1). https://doi.org/10.1088/1755-1315/592/1/012013

Royle, J., Jack, B., Parris, H., Elliott, T., Castillo, A. C., Kalawana, S., Nashfa, H., & Woodall, L. C. (2022). Plastic Drawdown: A rapid assessment tool for developing national responses to plastic pollution when data availability is limited, as demonstrated in the Maldives. *Global Environmental Change*, 72. https://doi.org/10.1016/J.GLOENVCHA.2021.102442

Sakti, A. D., Rinasti, A. N., Agustina, E., Diastomo, H., Muhammad, F., Anna, Z., & Wikantika, K. (2021). Multi-scenario model of plastic waste accumulation potential in indonesia using integrated remote sensing, statistic and socio-demographic data. *ISPRS International Journal of Geo-Information*, 10(7). https://doi.org/10.3390/ijgi10070481

Schuyler, Q., Wilcox, C., Lawson, T. J., Ranatunga, R. R. M. K. P., Hu, C. S., & Hardesty, B. D. (2021). Human Population Density is a Poor Predictor of Debris in the Environment. *Frontiers in Environmental Science*, 9.

https://doi.org/10.3389/fenvs.2021.583454

The World Bank. (2021). Plastic Waste Discharges from Rivers and Coastlines in Indonesia. In Marine Plastics Series, East Asia and Pacific Region. https://doi.org/10.1596/35607

Tran-Thanh, D., Rinasti, A. N., Gunasekara, K., Chaksan, A., & Tsukiji, M. (2022). GIS and Remote Sensing-Based Approach for Monitoring and Assessment of Plastic Leakage and Pollution Reduction in the Lower Mekong River Basin. *Sustainability*, 14(13), 7879. https://doi.org/10.3390/su14137879

van Emmerik, T. H. M., de Lange, S., Frings, R., Schreyers, L., Aalderink, H., Leusink, J., Begemann, F., Hamers, E., Hauk, R., Janssens, N., Jansson, P., Joosse, N., Kelder, D., van der Kuijl, T., Lotcheris, R., Löhr, A., Mellink, Y., Pinto, R., Tasseron, P., Vriend, P. (2022). Hydrology as a Driver of Floating River Plastic Transport. *Earth's Future*, 10(8). https://doi.org/10.1029/2022EF002811

van Emmerik, T. H. M., Frings, R. M., Schreyers, L. J., Hauk, R., de Lange, S. I., & Mellink, Y. A. M. (2023). River plastic transport and deposition amplified by extreme flood. *Nature Water*, 1(6), 514–522. https://doi.org/10.1038/s44221-023-00092-7

van Emmerik, T. H. M., Loozen, M., Van Oeveren, K., Buschman, F., & Prinsen, G. (2019). Riverine plastic emission from Jakarta into the ocean. *Environmental Research Letters*, 14(8). https://doi.org/10.1088/1748-9326/ab30e8

WorldPop. (2020). WorldPop Hub: Population Density. https://hub.worldpop.org/project/categories?id=18