CHAPTER I

INTRODUCTION

1.1. Research Background

Rivers are essential for maintaining environmental balance. They're a key part of the Earth's water cycle and can greatly influence ecosystems, climate change, and human activities (Fan et al., 2022; Pappas et al., 2021; Yang et al., 2014). Because of this, many studies have focused on analysing and understanding river areas (Louis et al., 2024; Pugsee et al., 2024; Akter & Babel, 2012).

Mapping rivers is important for effective management. It helps track floods, monitor land cover changes, manage droughts, and analyse sedimentation and erosion. Regular mapping can also show changes over time, like shifts in river paths or signs of flooding and drought. So, it is clear that river mapping is both necessary and useful for protecting and managing water resources. However, conducting manual monitoring of river areas is time-consuming and labour-intensive, even on a small scale, making it increasingly impractical for large-scale global assessments. Therefore, with the advancement of satellite remote sensing technology, where we can collect the large-scale data remotely, it could make the river area mapping be done more easily while significantly reducing time constraints.

One commonly used type of remote sensing satellite is the Synthetic Aperture Radar (SAR) satellite. SAR is an active technology that uses microwave radar signals to capture images of the Earth. It sends radio waves to the surface and records the echoes that return (Conde & De Mata Muñoz, 2019). A key advantage of SAR is its ability to capture high-resolution images even through clouds. It can also work day and night, in any (Pappas et al., 2021; Goumehei et al., 2019; Ciecholewski, 2017), making it ideal for mapping river across the world is every area conditions.

Processing satellite data accurately for mapping and segmenting is really important because it forms the basis for making decisions. If the mapping is off or biased, it can mess up the analysis and lead to misunderstandings or solutions that don't fit the actual river problems. There are many ways to process satellite data, but Deep Learning stands out as one of the most effective and efficient methods. It's efficient because it can map or segment rivers quickly without starting over every time new data comes in. It's also effective because it can accurately match the segmentation to real field data.

Semi-automated and traditional machine learning methods, such as morphology, thresholding (Zhu et al., 2015), filtering (Yang et al., 2015), clustering (Liu et al., 2016), edge detection (Vignesh & Thyagharajan, 2017), band ratio, Support Vector Machine (Ciecholewski, 2017), Random Forest (Ko et al., 2015), and Maximum Likelihood (Goumehei et al., 2019) have significant limitations.

For instance, morphological operations can change the shape and size of rivers, making them look narrower than they actually are. Thresholding methods can misclassify other water bodies, like ponds and lakes, as rivers if their values are similar. These issues are even more common in medium- to high-resolution satellite images, where non-river features often appear. On top of that, semi-automated processes require reprocessing every time new data is added, making them time-consuming and inefficient.

This is where Deep Learning makes a big difference. It's not only faster but also more accurate. Deep Learning models can handle complex patterns in satellite imagery and match segmentation results closely with real-world data. They also save time by eliminating the need to start over whenever new data comes in. These advantages make Deep Learning one of the most effective methods for river mapping and segmentation.

In recent years, the use of deep learning in satellite remote sensing data has been widely applied in various fields (Tian et al., 2024; Singh et al., 2024; Ait El Asri et al., 2023). Deep learning architectures are advanced machine learning techniques that enhance computational performance and accuracy by increasing the number of layers, or the overall depth, in the network (Neupane et al., 2021). The method based on a convolutional neural network can complete the modelling process through automatic feature learning, avoiding the incomplete modelling process caused by early-stage human intervention (Fan et al., 2022).

One of the deep learning method is Semantic Segmentation (Hao et al., 2020; Yu et al., 2018; Wang et al., 2018; Guo et al., 2018) that work by assigning a semantic label to each coherent region of an image. This research focuses on river area segmentation using semantic segmentation methods based on deep learning. The data used consists of Synthetic Aperture Radar (SAR) imagery from the Sentinel-1 satellite. Two model architectures applied in this study are U-Net and DeepLabv3+. The use of both architectures aims to compare performance and accuracy, enabling detailed analysis and evaluation of prediction errors in the models. U-Net architecture popular by its skip connections which link the encoder and decoder layers at corresponding levels that help retain high-resolution features and recover spatial information lost during down-sampling (Siddique et al., 2021) Navab et al., 2015). While DeepLabv3+ architecture leverages atrous (dilated) convolutions, which enable control over the receptive field without reducing the spatial resolution of feature maps, thus effectively capturing multi-scale contextual information (Vågen & Askevold, 2022).

The selection of U-Net and DeepLabv3+ architectures is based on previous studies, which have shown varying performance results in different case studies (Vågen & Askevold, 2022). Some studies reported that U-Net performed better, while others demonstrated the superiority of DeepLabv3+. Therefore, this research seeks to comprehensively explore the performance of both architectures to achieve more consistent and reliable results.

Several studies have used U-Net and DeepLabv3+ for river and/or waterbody segmentation. The results from these studies vary, with no clear consensus on which architecture performs better for river segmentation. In the thesis titled *Automated Mapping and Change Detection of Rivers and Inland Water Bodies by Semantic Segmentation of SAR Imagery using Deep Learning* (2022) by Renate Askevold and Mikael Vagen, both U-Net and DeepLabv3+ were employed, yielding different outcomes depending on the pixel size of the dataset. DeepLabv3+ with pre-trained weights performed better when tested on 512×512 pixels images, achieving a Jaccard Score of 0.856, compared to U-Net's score of 0.846. However, U-Net outperformed DeepLabv3+ when tested on full-sized images, with a Jaccard Score of 0.822, while DeepLabv3+ with pre-trained weights only achieved 0.250. This suggests that performance can vary significantly depending on the dataset resolution and architecture used (Vågen & Askevold, 2022) (Verma et al., 2021).

This research focuses on three main objectives: 1) creating a river segmentation dataset from SAR satellite data; 2) training a semantic segmentation model using a two deep learning architecture; and 3) compare the model performance for both deep learning architecture.

1.2. Problem Identification

Based on the background provided, the research problem can be identified and outlined as follows:

1. Manually river mapping is time-consuming work that need a lot of energy and resource as river is long and huge land cover and can across one area to another.
2. Traditional and/or semi-automated methods, such as morphological operations and thresholding, are inefficient when applied to river segmentation. These techniques require lengthy processes and cannot accurately segment rivers without additional steps. Those process also need to be repeated when mapping a new river area. As a result, more advanced approaches, such as deep learning, are needed to overcome these challenges.

1.3. Problem Scope

To address the previously identified issues, it is necessary to delineate the scope of the research to focus on the specific aspect that need to be solve. The following research limitation should be considered:

1. The creation of the dataset used in the modelling is included in this research
2. The study utilize Sentinel-1 C-Band Synthetic Aperture Radar (SAR) Ground Range Detected (GRD) imagery with Mekong River as the area of interest

3. Satellite data extraction is performed on the Google Earth Engine (GEE) platform for the period from January 2023 to December 2024, ensuring that there are no duplicate images for each month
4. In dataset creation, river area segmentation is measured from satellite images. If the satellite image does not clearly detect the presence of a river in a particular image, no river label is assigned to that specific data.
5. The polarization used in this research is Vertical transmits and Horizontal receive (VH) polarization
6. Two architectures, U-Net and DeepLabv3+ is employed for dataset modelling
7. The training and testing data is on PNG format and does not contain any coordinate system
8. Model evaluation is conducted using the Dice Coefficient while Testing Performance measured using Recall and Precision.

1.4. Research Problem Formulation

Based on the research background, the problem statements to be examined are as follows:

1. How to create river segmentation dataset using SAR imagery
2. How the performance model of U-Net architecture and DeepLabv3+ architecture

1.5. Research Objective

The objectives of this research are as follows:

1. Create river segmentation dataset using Sentinel-1 SAR satellite imagery
2. Train dataset using both U-Net and DeepLabv3+ architecture