MSc thesis in Civil Engineering

Testing linear regression to predict the influence of macro-scale parameters on micro-scale water quality parameters

Naomi Dommerholt

2023

TU Delft

MSc thesis in Water Management

Testing linear regression to predict the influence of macro-scale parameters on micro-scale water quality parameters

Naomi Dommerholt

October 2023

A thesis submitted to the Delft University of Technology in partial fulfilment of the requirements for the degree of Master of Civil Engineering

Picture Front Page: A suspension bridge above the Brantas near Kesamben, Kediri Residency, East Java (current day Kesamben, Blitar, East Java) (ca. 1922). (Unknown, 2022)

The work in this thesis was carried out with the help of:

Supervisors: Dr. ir. Maurits Ertsen
Dr. Saket Pande
Dr. Schuyler Houser

Preface

Dear reader,

This thesis report represents the culmination of my MSc programme in Water Management at Delft University of Technology. I have always had a vast interest in a wide area of things, so choosing a master's program was not easy. Selecting a master's program was a challenging decision, but reflecting on my past experiences, I found a recurring theme: Water. That is why I chose Water Management, and I can confidently say it was a choice I do not regret.

The journey continued as I faced the task of selecting a thesis topic, which proved to be no less challenging. Fortunately, after numerous discussions with Dr. Schuyler Houser, we found a topic that interested me. I extend my sincere gratitude to her for her guidance in this process.

My thanks also extend to Dr. ir. Maurits Ertsen and Dr. Saket Pande for their valuable assistance and willingness to answer my inquiries throughout this research journey.

In addition to my academic mentors, I must express my profound appreciation for my friends and family. Their unwavering support, encouraging words, and comforting hugs provided the emotional support that I needed to persist through the ups and downs of this journey.

As I prepare to embark on the next phase of my professional journey, I carry with me the knowledge I've acquired and the lessons I've learned during my time at Delft University of Technology.

Thank you,
Naomi Dommerholt
Delft, October 2023

Abstract

This study investigates the connection between macro-scale parameters (MSP) and micro-scale water quality parameters (MSWQP) in the Brantas River, employing a multivariate linear regression (MLR) modelling approach. The analysis reveals several critical insights into the complex dynamics of water quality in this river system.

Key findings indicate that high-quality input data, both in terms of quantity and measurement frequency, play a key role in the effectiveness of predictive models. Seasonality is a useful predictor and is recommended to be supplemented with rainfall data to better capture its influence on runoff and water quality. The study introduces the concept of basin accumulation and the implementation of buffer areas, demonstrating that these enhancements lead to improved model performance.

In conclusion, it can be said that relying just on macro-scale parameters is insufficient to generate an effective linear regression model. However, with the right optimizations and useful input data, it can be an insightful and valuable tool for water quality prediction.

Keywords: Multivariate Linear Regression, Dissolved Oxygen, Land cover, Macro-scale parameters, Micro-scale parameters, Water quality, Brantas River

Contents

List of Figures

List of Tables

List of Symbols

The next list describes several symbols that will be later used within the body of the document

β_i The regression coefficients

ϵ The error term, the part of y that the independent variables of y cannot explain

R^2 A statistical measure in a regression model that determines the proportion of variance in the dependent variable that can be explained by the independent variable

p-value Represents the probabilty

$\mathrm{x_n}$ The independent variables

y The dependent variable

Acronyms

1 Introduction

Water quality is often highly dependent on landscape characteristics. Deforestation for agriculture and an increasing population influence macro-scale parameters (MSP) and micro-scale water quality parameters (MSWQP). The influence of these MSP's, such as land cover and population, on MSWQP's has been analysed in a few studies but not for the Brantas River in Indonesia (Bostanmaneshrad et al., 2018). The surface water quality is below standards (Roosmini et al., 2018), and more research needs to be done on the origin of this pollution. Research that has been done, for example, by Fulazzaky (2009), suggests that water quality will decrease due to an increase in wastewater production as well as forests and land degradations resulting from population growth, urbanisation and economic and industrial developments. It is important to understand the influence of each land use in the basin compared to the water pollution to steer the agencies responsible for water quality towards the right policies. That is where research on the influence of MSP on the MSWQP can help show the different contributions of land use on the overall water quality in the Brantas River.

1.1 Multivariate linear regression

Numerous studies, such as those conducted by Chen et al. (2016), Wang et al. (2014), Wang and Zhang (2018), have explored the potential link between land cover and water quality using linear regression analysis. Multivariate Linear Regression (MLR) models are a straightforward and insightful method for investigating these relationships, making them an outstanding initial choice for gaining insights (Hope, 2020). Additionally, linear regression offers advantages in terms of computational efficiency, making it well-suited for smaller datasets and quick analyses. MLR models are transparent, providing clear visibility into the variables and coefficients integrated into the model. This transparency is valuable for identifying significant predictors and understanding their contributions to the outcome.

MLR proves effective when working with datasets featuring a limited number of observations or when the relationship between variables is expected to be relatively uncomplicated. Furthermore, MLR can serve as a valuable reference or foundational model compared to more intricate machine learning algorithms. It establishes a baseline against which to evaluate whether advanced models deliver substantial enhancements over a simple linear regression approach.

1.2 Multivariate linear regression in the Brantas

The Indonesian government aims to enhance water quality in the Brantas River. In pursuit of this goal, they need insight into the contribution of different pollution sources. While MLR is a known model, it should be noted that it does not automatically generate trustworthy results. Consequently, several tests and a critical evaluation are needed. Nonetheless, the MLR model for this purpose holds significance, as it offers a cost-effective and straightforward approach compared to the complexities of more elaborate Water Quality Index (WQI) models.

1.3 The objective

Hence, this research aims to test whether the water quality can be predicted by using a MLR model, by using MSP as independent variables and MSWQP as the dependent variable. A successful modelling of this relationship will generate valuable insights into the sources of pollution and their respective magnitudes. A helpful aspect of regression modelling for this purpose is its cost-effectiveness and relative simplicity, especially compared to the elaborateness of more complex WQI models.

1.4 Report set up

The report is set up as follows. In chapter 2, a more elaborate description of the study area will be given. In chapter 3, the methodology is described. In chapter 4, the results of the geographical analysis and the regression models are described. Chapter 5 evaluates and discusses the interesting findings. This is then followed by chapter 6 in which the conclusions are documented.

2 Study Area

This chapter aims to present the Brantas River Basin and its characteristics regarding water quality. Section 2.1 gives insight into the Brantas River and its relationship to water quality, including its climate. Section 2.2 describes the different agencies that monitor the water quality of the Brantas River. The last section gives an spatial analysis of the Brantas River basin.

2.1 The study area of the Brantas River

The Brantas hydrographic basin is situated in East Java, Indonesia. Stretching 320 kilometres, the Brantas River ranks as the second-longest river in East Java, draining an expansive area exceeding 11,000 square kilometres. Its primary water source originates from the Mount Arjuno water deposits, feeding its flow clockwise direction as depicted in Figure 2.1. (Mariyanto et al., 2019)

The upstream region is characterized by deforestation to make way for agriculture, which provides income but brings about issues such as erosion and a declining groundwater level. The downstream area faces water scarcity challenges, while businesses in this region rely on water originating from upstream sources. Managing water resources and maintaining water quality are key concerns for upstream and downstream communities to ensure economic growth and a high quality of life. (Blais, 2022)

A water quality assessment shows that the Brantas River has been classified as lightly and moderately polluted. The parameters that exceeded acceptable levels, listed from the most to the least, include Total Suspended Solids (TSS), Dissolved Oxygen (DO), Chromium (Cr6+), Total Dissolved Solids (TDS), and pH. These pollution issues are primarily attributed to wastewater and solid waste discharge from domestic sources and industries.(Roosmini et al. (2018); Arum et al. (2019); Marini and Weilguni (2003))

2.1.1 Seasonality and Climate

The region is in a predominantly tropical monsoon climate, characterized by March as the wettest month and August as the driest (Fujimoto, 2013). Annually, the area receives a precipitation range of 1100 to 3600 mm, with approximately 80 percent of this rainfall occurring during the monsoon season, which typically extends from November to March.

2.2 Water sampling and analysis

2.2.1 Water quality monitoring

Different agencies are monitoring the water quality of the Brantas. Amongst the different agencies, three key agencies measure constantly. The first of these three is Dinas Lingkungan Hidup Provinsi Jawa Timur (Environmental Protection Agency of East Java) or EPA. The second one is Balai Besar Wilayah Sungai Brantas (BBWS), or Grand Office of the Brantas

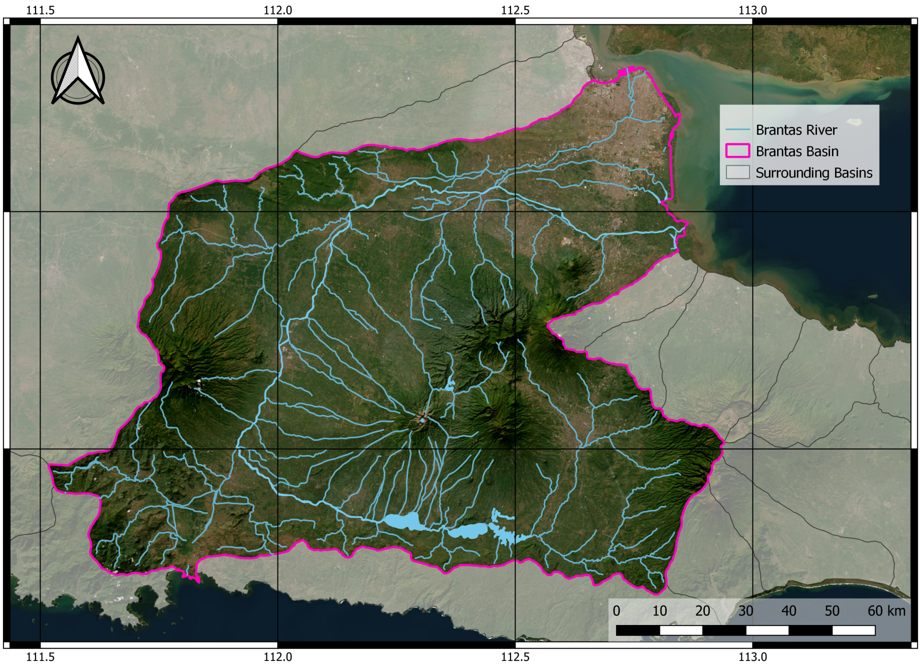


Figure 2.1: Map of the Brantas, based on data from WorldBank (2021)

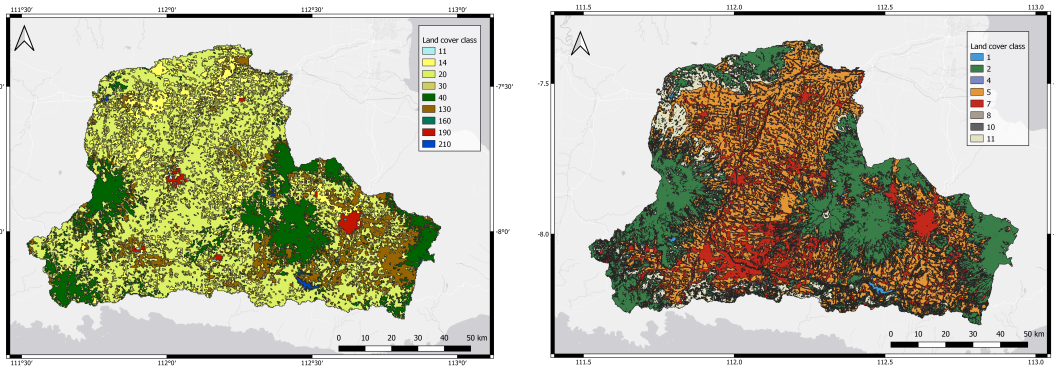
River Basin. The third is Perum Jasa Tirta I (Water Service Company 1) or PJT 1. All three have different goals and focuses. Willard (2022) describes the agencies as follows.

EPA has three main goals: control pollution, increase waste management services and increase the river's water quality. EPA does have the authority to enforce pollution standards, but the actual enforcement is relatively weak.

The main focus of BBWS is mostly on policies regarding water resources for both quantity and quality. However, the goals for water quality are unclear, and its main target to improve water quality throughout the Brantas River has no testable goals.

PJT 1 is a state-owned company that manages water resources in the Brantas. The primary responsibility is water allocation and maintenance of the water infrastructure. Furthermore, PJT 1 is directly involved in providing water supply services to both utilities and industries. However, this means significant expenses as it involves treating contaminated water to meet quality standards.

The three agencies are directly influenced by terrible water quality as they have to ensure that it is of good enough quality for industries and drinking water companies. Simultaneously, they possess limited authority and influence to improve water quality. While BBWS Brantas and PJT1 provide most water resource management functions related to development, utilization, irrigation, and flood control, their involvement in water quality control is relatively secondary. Provincial and municipal agencies provide many functions of water quality management, including water pollution control, spatial planning, development of wastewater treatment facilities and sanitation services, and solid waste management. (Houser et al., 2022)



(a) Globecover landcover map

(b) ESRI landcover map

Figure 2.2: Two different land cover maps

2.2.2 Water quality sampling

The three agencies measure in different parts of the Brantas and use different units for the same parameters. Table A.1 in Appendix A shows an overview of the different parameters. It should also be noted that the interval they measure is different. EPA measures monthly, BBWS quarterly and PJT also monthly. Willard (2022) ordered the agencies' data for his thesis, and the same data will be used for this research.

2.3 Spatial analysis

In 2004, East Java could be classified as densely populated, boasting a population density ranging from 500 to 1000 individuals per square kilometre (Statistik, 2009). When examining land cover maps, this high population density might not always be apparent. Figure 2.2 provides a comparison between two datasets: Figure 2.2 presents the Globcover dataset, illustrating the land cover for the year 2005 (Martucci, 2023). Figure 2.2bdisplays the ESRI land cover dataset, showcasing the land cover information for the year 2017 (Esri, 2022). A more detailed description can be found in Appendix 6.2 for both landcover maps. Both figures use the colour red to indicate urban areas. However, there is a notable contrast between the two datasets regarding urban coverage. In Figure 2.2a, urban areas occupy only 1 percent of the total area, whereas, in Figure 2.2b, they cover a significantly larger percentage, accounting for 25 percent of the landscape. In Chapter 4, this will be examined further as to where this difference comes from and how it could influence the results.

3 Method

This chapter aims to present the methodology used to analyze the data of the Brantas River in Indonesia to disclose if using multivariate linear regression is a good way of predicting water quality based on macro-scale parameters. Section 3.1 gives a brief explanation into using MLR for this study. The next section elaborates on the chosen parameters for the model. The last step before starting the model is mapping the land cover data. With the input clarified, section 3.4 describes how the model is constructed. Ìn the next section it is shown how the results are validated, after which the method for evaluating the results is shown. The last step in this chapter is to describe how the results are further optimized.

3.1 Using multivariate linear regression

Multivariate linear regression (MLR) is a statistical technique for modelling the relationship between multiple independent variables and a single dependent variable. It is an extension of simple linear regression, which deals with the relationship between two variables. In multivariate linear regression, the goal is to find a linear equation that best describes the relationship between the independent and dependent variables. For this research, the dependent variable is the micro-scale water quality parameter, and the independent variables are the macro-scale land cover parameters.

To do this for a river basin in which the dependent variable is measured at different points along the river, it is essential to delineate the sub-basins. Sub-basin delineation involves dividing the entire river basin into smaller, manageable sub-basins based on how rainfall would runoff into the river. The heterogeneity can be captured in both the micro-scale water quality and macro-scale land cover parameters by breaking down the river basin into sub-basins. This allows for a more precise analysis, as it recognizes that different parts of the basin may have unique characteristics that affect water quality differently. Water quality parameters may vary significantly along the length of a river due to various factors like urbanization, industrial activities, or natural landscape. Sub-basin delineation helps account for this spatial variation by segmenting the river into distinct sections. This ensures that the relationships between land cover and water quality are appropriately assessed within each sub-basin, considering local variations.

3.2 Choosing the water quality parameters

The three different agencies have measured different parameters in the past 15 years (see table in Appendix 6.2). Therefore, a lot of different data for different parameters is available. However, not all of these are measured consistently. Therefore, the same procedure for selecting the parameters was followed as described by Willard (2022) in his report.

The parameters that are considered for MLR model are:

- Temperature (Temp)
- Electrical Conductivity (EC)
- Dissolved Oxygen (DO)
- Total Suspended Solids (TSS)
- Biochemical Oxygen Demand (BOD)
- Chemical Oxygen Demand (COD)
- Ammonia (NH_3)
- Nitrite (NO_2)
- Nitrate (NO_3)
- Total Phosphorus (TP)

Generating satisfactory results with Multiple Linear Regression (MLR) proved more challenging than initially expected. It was therefore decided to streamline the approach by focusing solely on one key water quality parameter: Dissolved Oxygen (DO).

The choice for DO has several reasons. Firstly, it is a parameter for which data is consistently available from all three agencies, spanning multiple years of measurements. Secondly, Dissolved Oxygen levels can serve as an indicator of pollution linked to land cover and usage. For instance, reduced DO levels can be attributed to factors such as sewage (associated with urban landscapes) and agricultural runoff (Fitri et al., 2021).

3.3 Mapping the land cover data

3.3.1 Creating the (sub-)basins in the Brantas catchment

The MSPs are provided using different land cover maps in QGIS. For the land cover to be analysed and used in the MLR model, it must be divided into smaller subbasins within the Brantas Basin. First, the Brantas basin must be recreated based on a DEM to create the subbasins. This is done using Open Source Geographic Information System (QGIS) and the PCRaster tool following the instructions provided by van der Kwast et al. (2022).

The three agencies in this study have distinct measurement points, which are visually represented in Figure 3.1. As this study is an experimental setup, the approach involves examining each agency's data separately. The sub-basins have been delineated based on the measurement points and the DEM to facilitate this analysis. This means that if a water droplet descends and travels over the terrain, it will eventually reach the nearest measurement point, thus defining the boundaries of these sub-basins.

3.3.2 Analysing the geographical data focusing on land-use

Two maps are used within the QGIS software to analyse the complete land cover. These maps enable the visualization of land-use data within the Brantas catchment area. Subsequently, the area for each specific land cover type is calculated, measured in square kilometres. This analysis is performed individually for each sub-basin, allowing a better understanding of land cover distribution within distinct catchment regions.

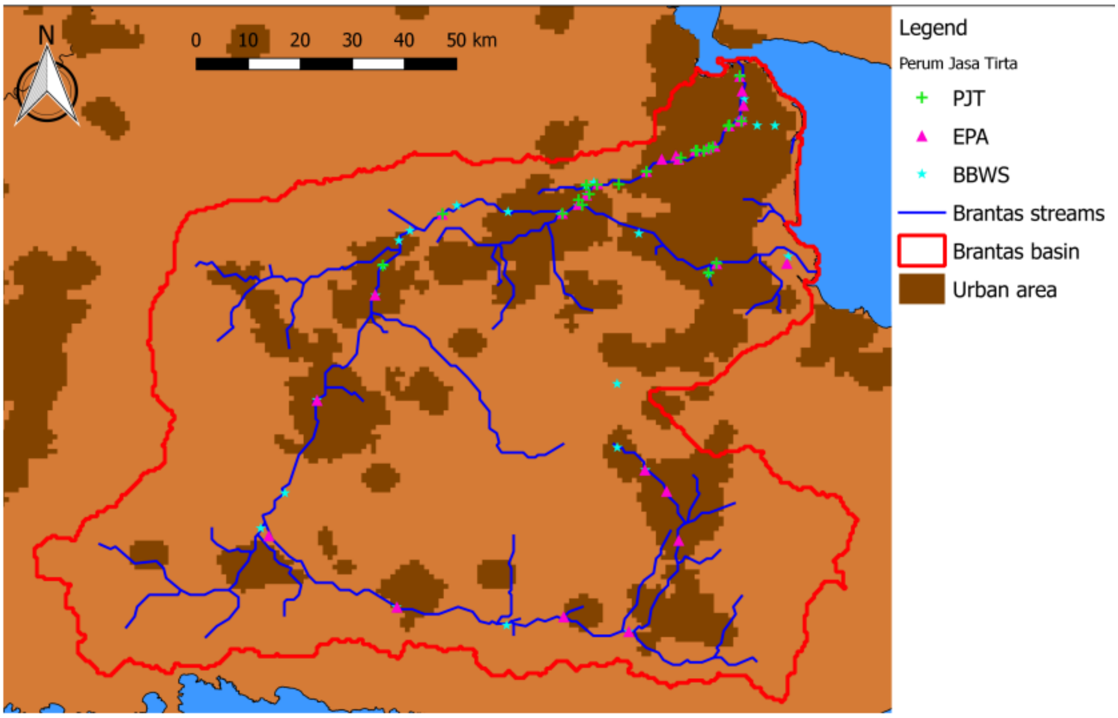


Figure 3.1: Water quality measurement locations of the three main agencies in the Brantas river basin. (Willard, 2022)

3.4 Setting up the multivariate linear regression model

Having completed the analysis of macro-scale parameters, the attention now turns to micro-scale parameters and their interactions with the MSP, using the multivariate linear regression model. The fundamental equation for Multivariate Linear Regression is expressed as follows (Holder, 1985):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \epsilon_i \tag{3.1}$$

where:

- y is the dependent variable (the variable that is being predicted or explained)
- x_1, x_2, ..., x_n are the independent variables (the independent variables that are used to predict the value
- $\beta_1, \beta_2, ..., \beta_i$ are the regression coefficients (the parameters that determine the slope of the regression line)
- ϵ is the error term (the part of y that cannot be explained by the independent variables) of y)

The standard error is a fundamental concept that quantifies the uncertainty and is calculated is depicted as:

$$\epsilon = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n-p}} \tag{3.2}$$

In this equation:

- ϵ represents the standard error of the regression.
- n is the number of observations.
- p is the number of predictors (independent variables) in the model.
- y_i is the actual observed value for the i-th observation.
- $\hat{y}_i$ is the predicted value for the i-th observation based on the regression model.

3.5 Validating the results

To validate the results, looking at the t-statistics, probability and R-squared is interesting. By examining and interpreting these measures, insight can be gained into the statistical significance of individual macro-scale parameters and the overall fit of the model. These validation techniques help ensure that the regression model provides meaningful and reliable insights into the relationship between the macro-scale and micro-scale parameters.

3.5.1 T-statistics

T-statistics are used in hypothesis testing to assess whether the coefficients of the predictor variables are significantly different from zero. The formula for the t-statistic is:

$$t = \frac{\text{Coefficient}}{\text{Standard Error of Coefficient}} \tag{3.3}$$

A higher absolute value of the t-statistic indicates greater evidence against the null hypothesis (that the coefficient is zero), suggesting a more significant impact of the coefficient on the water quality parameter.

3.5.2 Probability

Probability values, often called p-values, are used to determine the statistical significance of the coefficients of the macro-scale parameters in the regression model. Each coefficient represents the relationship between the independent (land cover) and the dependent (water quality) parameters. A low p-value (typically less than 0.05) indicates that the relationship between the dependent and independent parameters is statistically significant. A low p-value indicates a high statistical confidence in the relationship between the dependent and independent variables. It means the probability that the observed relationship between a given independent variable and the dependent variable is not only a random chance. In other words, a low p-value suggests a strong likelihood that there is indeed a meaningful and non-random connection between the independent and dependent variables. This is the probability that any given independent variable does not correlate. A low p indicates a high probability that there is a relationship between the independent and dependent variables.

$$p\text{-value} = P(|T| > |t_{\text{observed}}|) = 2 \cdot P(T > |t_{\text{observed}}|) \tag{3.4}$$

Where:

- p-value represents the probability.
- T is a t-distributed random variable.
- t_{observed} is the observed t-statistic associated with the coefficient.

3.5.3 R-squared and adjusted R-squared

R-squared is a measure that indicates the proportion of the variance in the response variable that is explained by the independent parameters of the model. It ranges between 0 and 1. An R-squared value closer to 1 indicates that the independent parameters account for a more significant proportion of the variability in the dependent parameter. However, R-squared doesn't consider the number of predictor variables, which can lead to overfitting.

$$R^2 = 1 - \frac{SSR}{SST} \tag{3.5}$$

Where:

- SSR is the sum of squared residuals
- SST is the total sum of squares

Adjusted R-squared addresses the limitation of the standard R-squared by considering the number of predictor variables in the model. It penalizes the addition of unnecessary predictor variables that might not contribute much to explaining the variance in the response. Adjusted R-squared provides a more balanced evaluation of model fit, helping to prevent overfitting. It is calculated using the following formula:

$$\text{Adjusted R-squared} = 1 - \frac{(n-1)}{(n-p)} \times (1 - R^2) \tag{3.6}$$

Where:

- n is the number of observations.
- p is the number of predictor variables.
- R^2 is the regular R-squared value.

3.6 Evaluating the results

The multivariate linear regression (MLR) model is optimized using the backward elimination method, where parameters with the highest p-values are iteratively removed until all remaining parameters have p-values below 0.05, signifying their significance. Subsequently, an evaluation is conducted by considering the impact of the buffer, aggregating macro-scale parameters, and assessing the influence of seasonality. This step is repeated after every step following the MLR.

3.7 Optimizing the results

Four additional steps are incorporated into the multivariate linear regression model to try and optimise the results. These improvements aim to account for the Brantas basin's unique characteristics and improve the prediction accuracy.

3.7.1 Implementing seasonality

Firstly, incorporating Seasonality, given that the Brantas basin experiences a tropical climate with distinct dry and monsoon seasons, seasonality is included as a factor in the model. The weather likely influences the water quality since the Brantas is in a tropical climate with a monsoon season. Research has shown that land use influence on water quality was greater during the wet season (Pak et al., 2021). The monsoon season in the Brantas basin is from November until March. The model incorporates the monsoon season by categorizing measurements during the monsoon season as '1' and those taken in the dry season as '0'.

3.7.2 Simplifying the land cover classes

Secondly, simplifying land cover categories will streamline the model and improve efficiency. Various land cover types are categorized into three broader categories: Natural Vegetation, Agricultural Landscape, and Urban Landscape. This simplification might help to reduce the complexity while retaining the essential characteristics of land use within the basin. The Urban Landscape was just the urban/built area category for both land cover maps. For the ESRI land cover map, the Natural Vegetation is the summation of Trees, Bare ground, Clouds and Rangeland. The Agricultural landscape is the summation of Flooded vegetation and Crops. For the GlobCover land cover map, the Natural Vegetation is the summation of Mosaic Vegetation, Semi Forest, Shrubland, and Forest. The Agricultural Landscape is the summation of Irrigated Cropland, Rainfed Cropland, and Mosaic Cropland.

3.7.3 Accumulating the sub-basins

Next, accumulating basin land cover types, instead of only looking at the sub-basin connected to the measurement point, all the upstream sub-basins are accumulated into one bigger sub-basin for that specific measurement point.

3.7.4 Generating the buffer area

Lastly, because not all precipitation within a sub-basin runs off to the river, the entire (sub)-basin is unlikely to influence the water quality. As the focus of this research is to see if a simple multivariate linear regression model can be used to predict water quality, the choice was made to generate a buffer around the river based on three different scales since the impact of land cover patterns and water quality differs on different spatial scales. The scale with the most significant impact on the river water quality is still a controversial issue (Peng and Li, 2021). For example, (Wang et al., 2017) found that the surface landscape pattern of the 4 km buffer zone has a solid descriptive ability for regional water quality in Aibi Lake, Xinjiang. However, the 100 m buffer zone is often considered the scale with the most significant impact on water quality (Huang et al., 2011). For this experiment, three distinct buffer area scales are selected: 4 kilometres, 500 meters and 100 meters. The 4 kilometres and 100 meters were determined based on the research. The 500-meter is an intermediary scale between the 4-kilometre and 100-meter buffers.

The buffer was created around the main channel. This can be seen in Fig. 3.2. Using the main channel as the basis for the buffer results in the loss of the two most upstream measurement points for both EPA and BBWS, as will later be shown in Chapter 4.3.

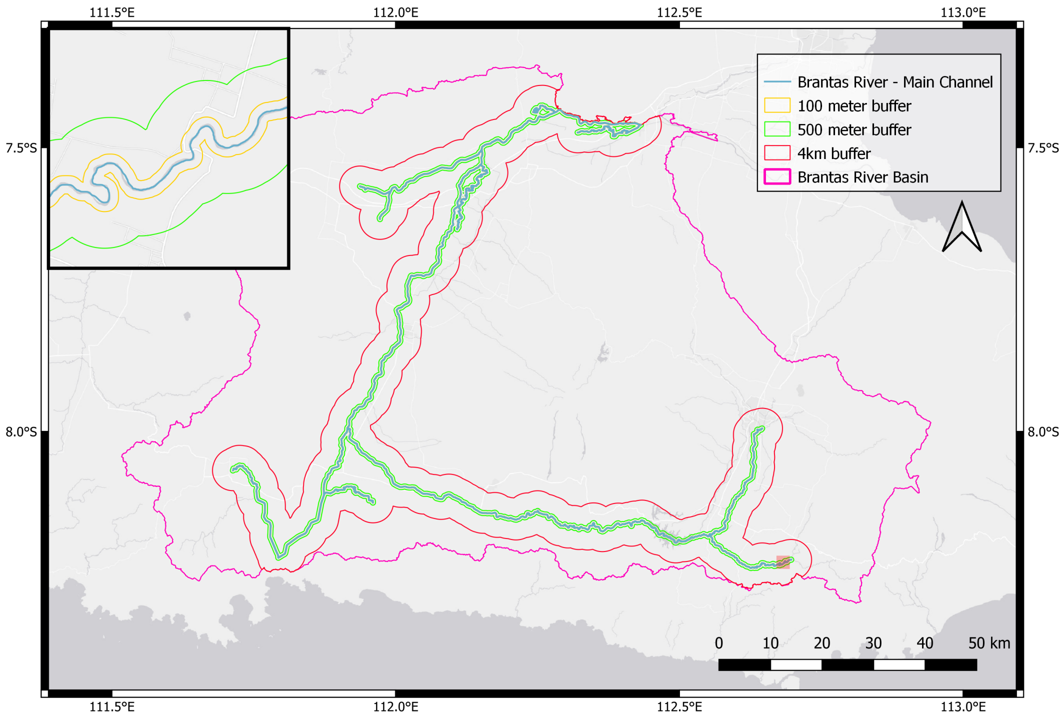


Figure 3.2: The Brantas River main channel and its corresponding buffers

4 Results

The research result of the method described in chapter 3 will be displayed and explained in this chapter. First, the selection of the water quality parameter will be presented in section 4.1 The outcome of mapping land cover using QGIS will then be presented in section 4.2. This will be followed by section 4.3 in which the creation of the sub-basins will be presented, followed by the accumulation of the sub-basins. Lastly section 4.4 presents the results of the multivariate linear regression model, including the results of the optimization steps.

4.1 Water quality parameter

As mentioned before, generating satisfactory results with Multiple Linear Regression (MLR) proved more challenging than initially expected. It was therefore decided to streamline the approach by focusing solely on one key micro-scale water quality parameter: Dissolved Oxygen (DO). Therefore, the dependent variable in all results mentioned below always remains DO.

4.2 Land cover maps

The two different landcover maps were introduced in section 2.3. The multivariate linear regression model incorporates the two distinct land cover maps to see if data input from the different map make sense. These maps generate the macro-scale parameters.

To briefly recap, the first map is sourced from ESRI (Esri, 2022), while the second is obtained from GlobCover (Martucci, 2023). The key difference between these maps is the classification of urban areas: ESRI's land cover classification designates approximately 25 percent of the region as urban, whereas GlobCover assigns only 1 percent of the Basin as an urban landscape. Appendix A.3 and A.4 have more details about the two maps.

Several factors contribute to this difference. Firstly, the data was collected 13 years apart, which can account for changes in urbanization. Secondly, the resolution differs significantly, with one map at 300 by 300 meters and the other at 10 by 10 meters. The coarser 300 by 300 resolution makes it easier to misclassify areas. Lastly, it remains somewhat unclear when a region is classified as urban; is it when a structure is present or when a certain percentage of land is paved? These reasons are not mutually exclusive and may produce the observed differences.

4.3 The (sub-)basin(s)

Creating a basin and sub-basin is essential to use the landcover data as the basis for macro-scale parameters. The initial step involves recreating the Brantas Basin, as illustrated in Figure 2.1. This requires using a DEM, which is then employed to delineate the basin and its main river network, determined by the Strahler Order.

Numerous attempts were made with different DEM's, but it proved impossible to generate the complete basin. The most satisfactory outcome can be observed in Figure 4.1. This representation is based on a DEM provided by Prof. O. Hoes, with a resolution of 8 by 8 meters. Consequently, the bifurcation of the river is not depicted, and data from Surabaya and measurements taken in Surabaya locations are not integrated into the MLR model.

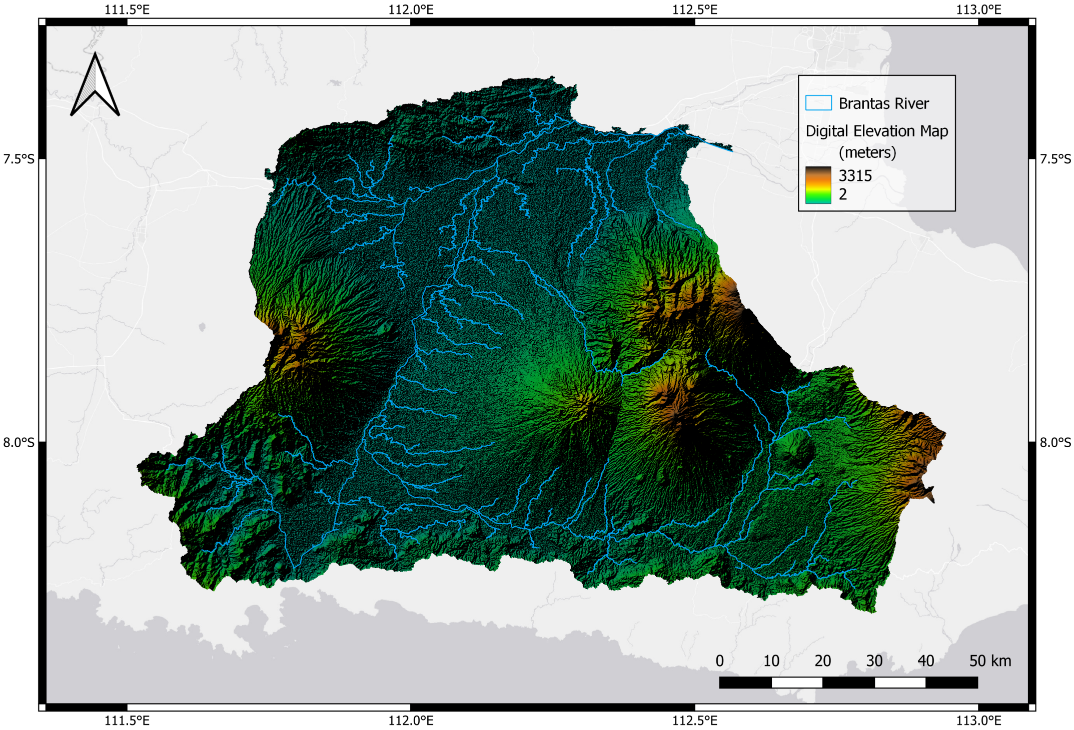


Figure 4.1: The Brantas Basin based on DEM with a resolution of 8 by 8 meters.

4.3.1 The sub-basins based on PJT measurement points

In the basin illustrated in Figure 4.1, the agency PJT has only three measurement points available. Given that the precision of the MLR model depends on the quantity of input data, the information from this agency is excluded from the scope of this research.

4.3.2 The sub-basins based on EPA measurement points

The EPA has collected data on DO from 11 measurement points, corresponding to the defined basins as illustrated in Figure 4.2.

In Figures 4.2a and 4.3a, the distribution of the macro-scale parameter within these basins can be observed. The four most dominant land cover types are range, built area, crops and trees for the ESRI land cover map. The GlobCover land cover map's biggest contributors are shrubland, semi forest, mosaic cropland and rainfed cropland.

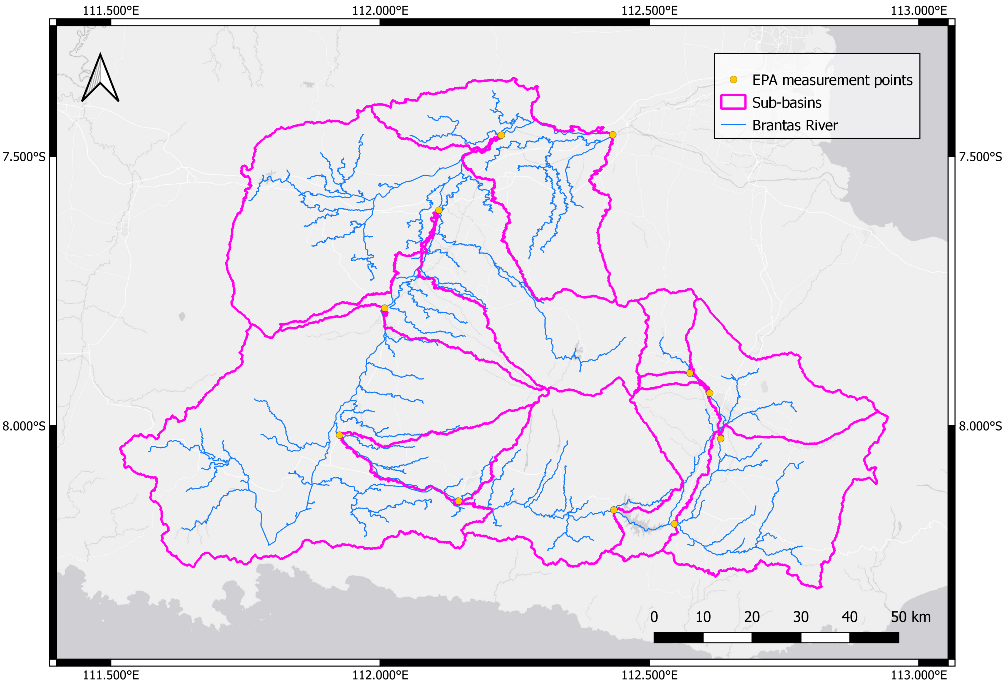
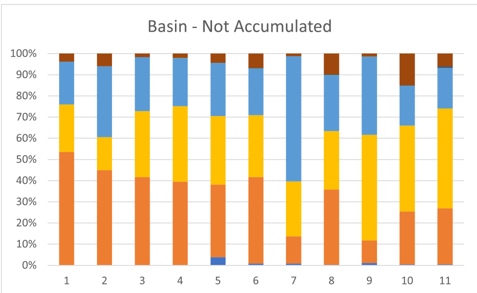
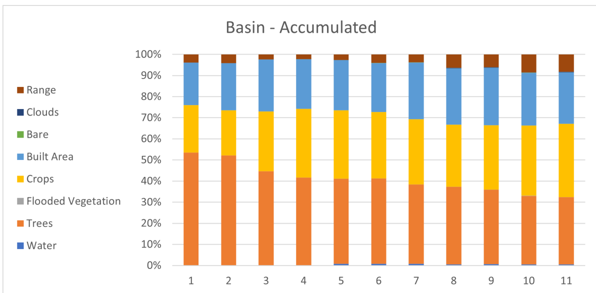


Figure 4.2: The sub-basins based on the 11 measurement points of EPA

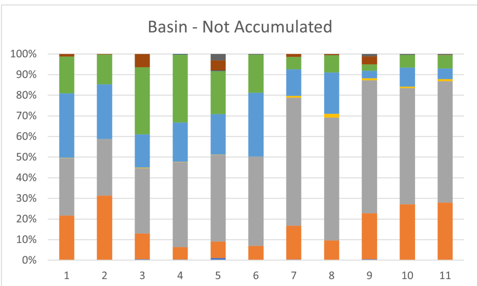


(a) ESRI not accumulated

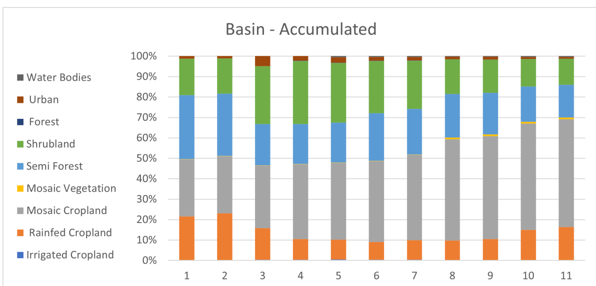


(b) ESRI Accumulated

Figure 4.3: Results ESRI EPA



(a) Glob not accumulated



(b) Glob Accumulated

Figure 4.4: Results Glob EPA

4.3.3 The sub-basins based on BBWS measurement points

The BBWS has collected data on DO from 16 measurement points, which correspond to the defined Basins as illustrated in Figure 4.5.

In Figures 4.5a and 4.6a, the distribution of the macro-scale parameter within these basins can be observed. The same as for the EPA measurement points, the four most dominant land cover types are range, built area, crops and trees for the ESRI land cover map. The GlobCover land cover map's biggest contributors are shrubland, semi forest, mosaic cropland and rainfed cropland.

4.3.4 Accumulating the sub-basins

The data from the subbasins is used in two different ways. From here on, the first is purely looking at the land cover within the subbasin, called the not accumulated data. In the second one, the land cover is accumulated. In the context of the EPA and BBWS, the accumulation of sub-basins occurs in a downstream manner. For EPA the sub-basins are numbered from one, representing the most upstream basin, to eleven, which signifies the most downstream basin. Sub-basin eleven is the cumulative sum of sub-basins one through eleven. BBWS follows a different accumulation pattern, see table 4.1. This is because BBWS measures before confluences, and EPA does not. This is one of the optimizations mentioned in section 3.7. The result of this accumulation is illustrated in Figures 4.2b, 4.3b, 4.5b and 4.6b. For both agencies and both land cover maps, this results in smaller differences between the subbasins.

Table 4.1: The accumulation pattern of BBWS, representing the sub-basins of Fig. 4.5

Basin number	Accumulation pattern
1	1
2	1-2
3	1-2-3
4	1-2-3-4
5	1-2-3-4-5
6	6
7	1-2-3-4-5-6-7
8	1-2-3-4-5-6-7-8
9	1-2-3-4-5-6-7-8-9
10	1-2-3-4-5-6-7-8-9-10
11	1-2-3-4-5-6-7-8-9-10-11-15
12	1-2-3-4-5-6-7-8-9-10-11-12-15
13	1-2-3-4-5-6-7-8-9-10-11-12-14-15
14	14
15	15
16	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16

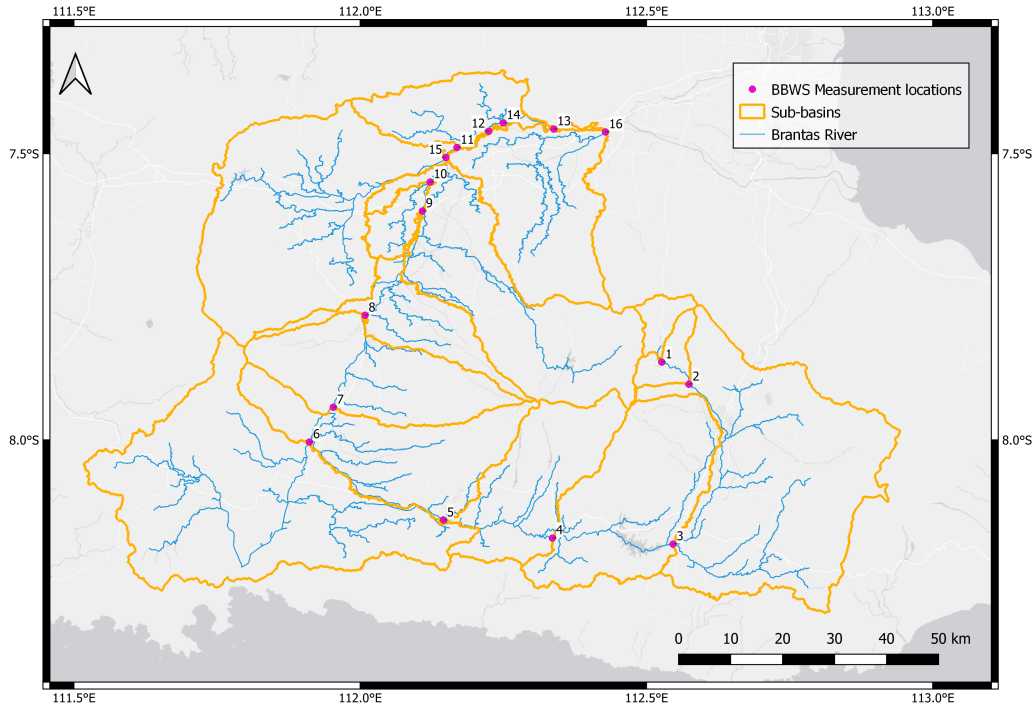
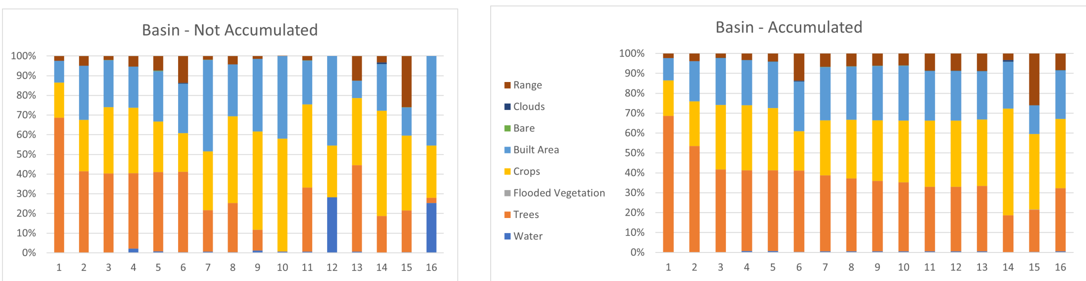


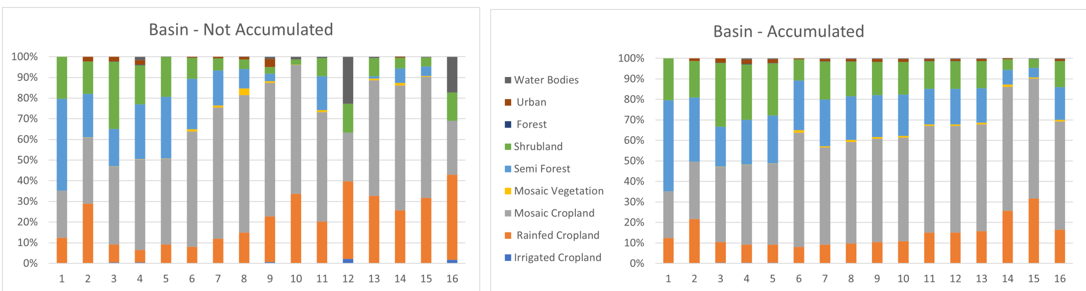
Figure 4.5: The sub-basins based on the 16 measurement points of BBWS



(a) ESRI not accumulated

(b) ESRI Accumulated

Figure 4.6: Results ESRI BBWS



(a) Glob not accumulated

(b) Glob Accumulated

Figure 4.7: Results Glob BBWS

4.3.5 The buffer area

The buffer is generated as mentioned in section 3.7.4. To recap, there are three distinct buffer area scales: 4 kilometres, 500 meters and 100 meters. However, because of the many tributaries, the choice was made to increase the Strahler order and focus more on the main channel. This makes the 4 km buffer effective because otherwise, it would still cover almost all of the basin. This resulted, however, in the two most upstream measurement points from both agencies being eliminated.

The same land cover distribution figures as mentioned above are also generated for the different buffer areas, land cover maps, and the accumulated and not accumulated basins for both agencies. The corresponding Figures B.2, B.3, B.4 and B.5 can be found in Appendix B. These visualizations provide insights into the entire basin and different buffer areas within the basins and the distribution of the macro-scale parameters.

4.4 Multivariate linear regression model

The presentation of this experimental research results follows best practices, where the weakest or least favourable results were excluded. However, it's important to note that no data was removed or eliminated at any analysis stage for a comprehensive comparison. All results, including those not mentioned below, can be found in Appendix B and are available for reference and comparison. In all the tables below, NS stands for not significant.

4.4.1 The first run

After running the first MLR model, four results were compiled on the two available land cover maps and the two different agencies. Two results were acceptable after validating the results by looking at R-squared and the probability, and these are the models connected to the EPA measurement points; see tables 4.2 and 4.3. The other two results had an R-squared so low that these independent variables could not explain the dependent variable. Both models had the input data for the dependent variables from BBWS.

Table 4.2: The results for the EPA measurement points and the ESRI land cover map.

R-squared		0.3491		n = 396
Adjusted R-squared		0.3408		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7.49	0.10	75.99	<0.01
Water	-0.18	0.01	-12.49	<0.01
Trees	0.00	0.00	-6.80	<0.01
Flooded Vegetation	4.35	0.40	10.95	<0.01
Crops				NS
Built				NS
Bare	2.10	0.28	7.55	<0.01
Clouds	0.25	0.04	6.61	<0.01
Range				NS

Table 4.3: The results for the EPA measurement points and the GlobCover land cover map.

R-squared	0.3423		n = 396	
Adjusted R-squared	0.3304			
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7.90	0.13	59.10	<0.01
Irrigated Cropland	-2.41	0.25	-9.48	<0.01
Rainfed Cropland	-0.01	0.00	-2.57	<0.05
Mosaic Cropland	0.01	0.00	5.54	<0.01
Mosaic Vegetation	-0.09	0.04	-2.45	<0.05
Semi Forest	-0.02	0.00	-7.05	<0.01
Shrubland				NS
Forest	2.45	0.35	6.97	<0.01
Urban	0.14	0.02	6.80	<0.01
Water Bodies				

4.4.2 Adding seasonality

The first optimisation step is applied to improve the MLR results, adding seasonality to the model. This improves the R-squared of all four of the initial results. Again, the most promising results were for the EPA measurement points. The ESRI landcover map had again the highest r-squared. This result can be found in table 4.4.

Table 4.4: The results for the EPA measurement points, the ESRI land cover map and seasonality added.

R-squared	0.3604		n=396	
Adjusted R-squared	0.3505			
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7.62	0.11	70.33	<0.01
Seasonality	-0.29	0.11	-2.61	<0.01
Water	-0.18	0.01	-12.58	<0.01
Trees	0.00	0.00	-6.85	<0.01
Flooded Vegetation	4.35	0.39	11.03	<0.01
Crops				NS
Built				NS
Bare	2.10	0.28	7.60	<0.01
Clouds	0.25	0.04	6.66	<0.01
Range				NS

4.4.3 Simplifying the land cover classes

The eight results generated in the previous steps are again trying to be optimized by simplifying the land cover classes. This did not generate satisfactory results. It always decreased the r-squared significantly. When keeping the same conditions as in table 4.4, the results are as follows, see table 4.5

Table 4.5: The results for the EPA measurement points, the ESRI land cover map, with seasonality added and simplified land cover classes.

R-squared		0.0468		n = 396
Adjusted R-squared		0.0396		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6.67	0.11	59.51	<0.01
Seasonality	-0.29	0.14	-2.15	<0.05
Natural Vegetation	0.00	0.00	-3.13	<0.01
Argriculturale Landscape	0.00	0.00	3.76	<0.01
Urban Landscape				NS

4.4.4 Accumulating the sub-basins

Accumulating the area of sub-basins for further optimization does not significantly improve R-squared, but it does make more macro scale parameters significant. This can be seen across almost all results that use the input from EPA for the dependent variable. When keeping the same conditions as in table 4.4, the results are as follows, see table 4.6

Table 4.6: The results for the EPA measurement points, the ESRI land cover map, seasonality added and the sub-basins accumulated.

R-squared		0.3660		n = 396
Adjusted R-squared		0.3529		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	8.10	0.17	48.14	<0.01
Seasonality	-0.29	0.11	-2.62	<0.01
Water	-0.11	0.02	-6.42	<0.01
Trees	-0.01	0.00	-7.62	<0.01
Flooded Vegetation	10.45	1.81	5.76	<0.01
Crops				NS
Built	0.00	0.00	2.46	<0.05
Bare	5.22	0.42	12.42	<0.01
Clouds	0.35	0.07	4.67	<0.01
Range	-0.02	0.00	-4.20	<0.01

4.4.5 Implementing the buffer

With the optimizations tested for the best result, the last step in improving the model is implementing the buffer size. This also slightly improves the R-squared value. The best result is generated using a 4 km buffer size. When keeping the same conditions as in table 4.6, the results are as follows, see table 4.7

Table 4.7: The results for the EPA measurement points, the ESRI land cover map, seasonality added, the sub-basins accumulated and the 4 km buffer implemented.

R-squared		0.3776		n = 324
Adjusted R-squared		0.3618		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	5.63	0.23	24.81	<0.01
Seasonality	-0.33	0.12	-2.68	<0.01
Water	-0.34	0.03	-10.38	<0.01
Trees	-0.09	0.01	-6.03	<0.01
Flooded Vegetation	-12.43	3.39	-3.67	<0.01
Crops	-0.01	0.00	-5.64	<0.01
Built	0.06	0.01	7.91	<0.01
Bare				NS
Clouds	-67.33	6.86	-9.82	<0.01
Range	0.29	0.03	8.58	<0.01

5 Evaluation and Discussion

In this chapter, the aim is to evaluate the different aspects of this study. In section 5.1, the discussion is started on the value of optimization. Next, in section 5.2, the actual results of the model are discussed to see if they make sense. Lastly, in section 5.3, the different input is discussed.

5.1 Assessing the value of the optimization

The results outlined in Chapter 4 do not readily lend themselves to straightforward categorization as good or bad outcomes. This ambiguity complicates whether employing Multivariate Linear Regression for predicting Dissolved Oxygen (DO) using macro-scale parameters is feasible. If this were a straightforward task, substantial resources wouldn't be invested in developing more complex models. Therefore, assessing the methodology used and exploring options for enhancement is required.

5.1.1 Seasonality

Seasonality consistently positively influences the model, as indicated by its ability to improve its fit, resulting in an improved R-squared value. The monsoon season consistently has a negative impact on Dissolved Oxygen (DO). This negative effect can be attributed to the monsoon season leading to an increased runoff, elevating the levels of suspended solids in the water. This increase in suspended solids tends to decrease the concentration of DO in the water (Fitri et al., 2021). To further enhance the accuracy of utilizing seasonal influence, it is advised to incorporate additional variables such as discharge and/or rainfall into the analysis.

5.1.2 Combining land cover

The initial idea behind combining the landcover classes into broader categories was to potentially mitigate the influence of small, specific classes that might disproportionately affect the results. The hope was that doing so would reduce overestimations of these smaller classes and, in turn, provide more accurate estimates for the larger, more general classes, effectively reducing noise in the analysis. However, this approach did not yield the expected results. It led to a significantly lower R-squared value than more detailed models.

This outcome suggests that the more detailed distinctions provided by the specific landcover classes are important for capturing the nuances in the relationship between land cover and DO. Therefore, the detailed classification of landcover classes appears crucial for a more accurate representation of the underlying dynamics in your analysis. This, in turn, shows the importance of the land cover data input.

5.1.3 Accumulation

The research conducted by Bostanmaneshrad et al. (2018) also uses the accumulation of basins, similar to the approach taken in the study. However, their paper lacks a clear explanation for the motivation behind the methodology. In this study, however, the same approach was chosen because of the interconnectedness of a river, where factors upstream can influence downstream parameters. The results indicate that while the accumulation of basins does not significantly improve the R-squared value, it does render several macro-scale parameters statistically significant. This suggests that including this method in the MLR model represents a useful step towards optimization.

5.1.4 Buffer size

For this specific area, the 4 km buffer stands out as a strong choice. Higher R-squared values indicate that it consistently outperforms the 500-meter and 100-meter buffers in most models. However, it's worth noting that the model coefficients showed unexpected and unusable magnitudes when using the smaller buffer sizes (500 meters and 100 meters). This suggests that using a buffer area is a good step in optimizing the MLR model. This is also suggested by Wang et al. (2017).

5.2 Assessing the realism of the results

Even though the steps above optimize the results in terms of R-squared, most of the results reveal a lack of consistency, with most parameter coefficients consistently showing a negative impact on DO. Occasional instances of parameters exhibiting a positive impact appear almost randomly. Given this inconsistency, it is reasonable to question the realism of these results.

Interestingly, most models indicate that natural vegetation has a negative effect, which seems counterintuitive given that natural vegetation should, according to other research, positively influence DO (Shi et al., 2017). This observation raises questions about the authenticity of the natural vegetation in this context.

Similarly, the influence of different land cover parameters seems to exhibit variability across various models. For instance, urban areas demonstrate a positive effect in some models, while in others, it appears negative. This variability poses challenges when arriving at definitive conclusions and comparing different models' outcomes.

5.3 Assessing the input

The lower R-squared values and the variability in coefficients mentioned above might indicate that the model's effectiveness is in question, even though some improvements are observed through optimization efforts. It is crucial to analyse the input variables to critically evaluate these results, as garbage in could lead to garbage out.

5.3.1 Water quality parameters

The choice for Dissolved Oxygen (DO) was made because it is a good indication of water quality. However, based on the results, DO can not simply be explained by only land cover. In other research, water temperature and pH were identified as the primary predictors of DO. (Ahmed and Lin (2021); Ouma et al. (2020)) Notably, upstream water temperatures typically tend to be cooler than downstream. Given that higher temperatures are associated with lower DO levels, it is reasonable that the temperature variations might influence the observed negative correlations with land cover parameters. This shows that using more than just macro-scale parameters for the model could eliminate much uncertainty in the results.

5.3.2 Land cover data

The ESRI land cover map is a better fit for these models than the GlobCover land cover map, with, for most models, a higher R-squared and adjusted R-squared. It is unexpected as the Globcover is timewise closer to the data. This might be explained by the lack of data on population density, as in the thirteen years between the two land cover maps, the population has increased at a different rate compared to the urban areas. This addition has the potential to yield improved results and a more comprehensive understanding of the factors affecting water quality, as is done in a similar study by Bostanmaneshrad et al. (2018)

It is worth noting that the ESRI land cover map provides yearly updated maps from 2017 onward. Therefore, if more recent water quality data becomes available in the future, it could be intriguing to incorporate yearly changing land cover data into the analysis to capture potential temporal variations.

5.3.3 Number of observations

In contrast to many other studies, the dataset used in this research has a notably larger number of observations, over 300 measurements. For instance, Bostanmaneshrad et al. (2018) worked with only 45 measurements collected from 15 stations over three seasons, while Wang et al. (2014) based their study on 40 measurements from 20 locations over two months. Despite the higher number of observations in this research, it is worth noting that some of these other studies achieved a higher R-squared value.

Notably, when setting up the model for this study, the average measurements per measurement point was used to test the model. This approach yielded results comparable to studies reporting an R-squared value exceeding 0.9. Consequently, a larger dataset can be challenging to directly compare the results with those of other studies due to variations in sample size and methodology, but it also questions the realism of the other studies.

Furthermore, it is important to consider studies Xu et al. (2020), which reported a relatively lower R-squared value of 0.4 despite having a limited dataset of 76 measurements gathered from 38 stations over two seasons. This example highlights that more observations do not necessarily guarantee more reliable or accurate results. Therefore, it is crucial to critically assess studies with lower observation counts, as the quality of the methodology and data collection processes may play a significant role in interpreting the findings.

5.3.4 Measurement points

The EPA measurement points demonstrate a better alignment with the models than the BBWS measurement points, as shown by the significantly higher R-squared and adjusted R-squared values. The EPA dataset also tends to yield more statistically significant land cover parameters in most models.

A notable contributing factor to this difference lies in the geographical distribution of measurement locations between the upstream and downstream sub-basins. In the downstream sub-basins based on BBWS measurement points, there are noticeable differences in the size and characteristics of the basins compared to the upstream sub-basins. This variation increases the influence of specific land cover types in the downstream regions, potentially explaining the consistently lower R-squared values observed for BBWS data across all the models.

5.3.5 Data input

The likely reason for the observed differences between the EPA and BBWS measurements could be the quarterly measurement schedule followed by BBWS compared to the monthly schedule followed by EPA. BBWS conducts measurements primarily in February, May, August, and November. This sampling strategy may introduce irregularities, particularly in the November measurements, due to the onset of the monsoon season. The beginning of the monsoon season can lead to fluctuations in both the timing and intensity of river processes, potentially affecting the data quality and consistency.

As is the case with all constructed models, it is crucial to recognize that the quality and quantity of input data substantially influence the model's outcomes. This principle holds for the data available for the Brantas River, where variations in measurement frequency and potential seasonal effects can impact the reliability and robustness of the models.

6 Conclusion and Recommendation

In this chapter, the key findings of this study on the relationships between macro-scale parameters (MSP) and micro-scale water quality parameters (MSWQP) in the Brantas River, as analyzed through a multivariate linear regression model, will be summarized. Additionally, recommendations will be provided for future research and actions based on the findings.

6.1 Summary of the findings

The research into the Brantas River's water quality dynamics using multivariate linear regression has yielded several insights. Notably, the following key findings have been identified:

- Importance of input data: High-quality input data is important, as the principle "garbage in, garbage out" holds true. When dealing with micro-scale water quality parameters, not only the quantity of observations matters, but also the interval between measurements is significant.
- Seasonality as a predictor: Seasonality is a good indicator, but it is proposed to integrate rainfall data into the model. Precipitation, particularly the amount of rainfall within a specific timeframe (e.g., daily or weekly preceding the measurement), should be considered. Rainfall can significantly influence river runoff, potentially increasing pollution and affecting dissolved oxygen levels.
- Combining macro-scale landcover parameters: Combining macro-scale landcover parameters does not yield favourable results and is not recommended for use in predictive models
- Accumulation for improved results: The accumulation of sub-basin data can enhance results, albeit with marginal improvements in R-squared values. However, it notably enhances the statistical significance of coefficients in nearly all cases.
- Implementing a buffer: Introducing a buffer area is a beneficial addition, leading to improved R-squared values.
- Dissolved Oxygen (DO) Prediction: Accurate prediction of DO levels based solely on macro-scale parameters is challenging. However, it is clear that macro-scale parameters have a significant influence on DO levels.

The objective of this research was to test whether the water quality can be predicted by using a MLR model, by using MSP as independent variables and MSWQP as the dependent variable. It can be concluded that relying just on macro-scale parameters is insufficient to generate an effective linear regression model. However, with the right optimizations and useful input data, it can be an insightful and valuable tool for water quality prediction.

6.2 Recommendations for future research

Based on the findings of this study, the following recommendations for future research are proposed:

- Fine-tuned sub-basin analysis: Conduct a more comprehensive analysis of sub-basins, with a focus on creating sub-basins of comparable size. This avoids overestimating certain parameters by selecting measurement locations based on the size of the sub-basin they represent rather than solely relying on available bridges for measurements.
- Precipitation Inclusion: Integrate rainfall data into the analysis, focusing on quantifying the amount of precipitation within defined time intervals. This will provide a more detailed understanding of the impact of rainfall on water quality, further optimizing the modelling framework.
- Expanded with micro-scale parameters: Expand the list of independent variables with micro-scale parameters and run linear regression with micro-scale parameters, including pH and temperature measurements, to enrich the model's capacity to predict DO levels.
- Population density: To enhance the urban landscape parameter's accuracy, consider incorporating population density data instead of only urban landscape. This addition will account for increased waste production in urban areas and improve the model's fit.

These recommendations should guide future research efforts to improve the understanding of the complex relationships between macro-scale parameters and micro-scale water quality parameters in the Brantas River. Ultimately, this will contribute to more effective water quality management and conservation initiatives.

Bibliography

Ahmed, M. H. and Lin, L.-S. (2021). Dissolved oxygen concentration predictions for running waters with different land use land cover using a quantile regression forest machine learning technique. *Journal of Hydrology*, 597:126213.

Arum, S. P. I., Harisuseno, D., Soemarno, S., et al. (2019). Domestic wastewater contribution to water quality of brantas river at dinoyo urban village, malang city. *Indonesian Journal of Environment and Sustainable Development*, 10(2).

Blais, S. (2022). Using forest restoration to address land degradation issues: The example of the brantas river basin in indonesia. Retrieved 19 January 2023 from https://nbi.iisd.org/savi-the-brantas-river-basin-indonesia/.

Bostanmaneshrad, F., Partani, S., Noori, R., Nachtnebel, H.-P., Berndtsson, R., and Adamowski, J. F. (2018). Relationship between water quality and macro-scale parameters (land use, erosion, geology, and population density) in the siminehrood river basin. *Science of the Total Environment*, 639:1588–1600.

Chen, Q., Mei, K., Dahlgren, R. A., Wang, T., Gong, J., and Zhang, M. (2016). Impacts of land use and population density on seasonal surface water quality using a modified geographically weighted regression. *Science of the total environment*, 572:450–466.

Esri (2022). Sentinel-2 10m land cover time series. Retrieved 12 December 2022 from https://data.apps.fao.org/catalog/dataset/f3f61bb2-78bf-4aba-a5ba-e708183336ec.

Fitri, A., Maulud, K. N. A., Rossi, F., Dewantoro, F., Harsanto, P., and Zuhairi, N. Z. (2021). Spatial and temporal distribution of dissolved oxygen and suspended sediment in kelantan river basin. In *4th International Conference on Sustainable Innovation 2020–Technology, Engineering and Agriculture (ICoSITEA 2020)*, pages 51–54. Atlantis Press.

Fujimoto, K. (2013). *Brantas River Basin Development Plan of Indonesia*. Palgrave Macmillan UK.

Fulazzaky, M. A. (2009). Water quality evaluation system to assess the brantas river water. *Water resources management*, 23(14):3019–3033.

Holder, R. (1985). *Multiple regression in hydrology*. Institute of hydrology.

Hope, T. M. (2020). Linear regression. In *Machine Learning*, pages 67–81. Elsevier.

Houser, R. S., Pramana, K. E. R., and Ertsen, M. W. (2022). Structuring the water quality policy problem: Using q methodology to explore discourses in the brantas river basin. *Frontiers in Water*, 4:1007638.

Huang, J.-L., Li, Q.-S., Hong, H.-S., Lin, J., and Qu, M.-C. (2011). Preliminary study on linking land use & landscape pattern and water quality in the jiulong river watershed. *Huan jing ke xue= Huanjing kexue*, 32(1):64–72.

Marini, G. and Weilguni, H. (2003). Hydrological information system based on on-line monitoring-from strategy to implementation in the brantas river basin, east java, indonesia. *Water science and technology*, 47(2):189–196.

Mariyanto, M., Amir, M. F., Utama, W., Bijaksana, S., Pratama, A., Yunginger, R., Sudarningsih, S., et al. (2019). Heavy metal contents and magnetic properties of surface sediments in volcanic and tropical environment from brantas river, jawa timur province, indonesia. *Science of The Total Environment*, 675:632–641.

Martucci, A. (2023). Land cover of indonesia - globcover (22 classes) - ”fao catalog”. Retrieved 25 June 2023 from https://data.apps.fao.org/catalog/dataset/f3f61bb2-78bf-4aba-a5ba-e708183336ec.

Ouma, Y. O., Okuku, C. O., and Njau, E. N. (2020). Use of artificial neural networks and multiple linear regression model for the prediction of dissolved oxygen in rivers: Case study of hydrographic basin of river nyando, kenya. *Complexity*, 2020:1–23.

Pak, H. Y., Chuah, C. J., Yong, E. L., and Snyder, S. A. (2021). Effects of land use configuration, seasonality and point source on water quality in a tropical watershed: A case study of the johor river basin. *Science of the Total Environment*, 780:146661.

Peng, S. and Li, S. (2021). Scale relationship between landscape pattern and water quality in different pollution source areas: A case study of the fuxian lake watershed, china. *Ecological indicators*, 121:107136.

Roosmini, D., Septiono, M., Putri, N., Shabrina, H., Salami, I., and Ariesyady, H. (2018). River water pollution condition in upper part of brantas river and bengawan solo river. 106(1):012059.

Shi, P., Zhang, Y., Li, Z., Li, P., and Xu, G. (2017). Influence of land use and land cover patterns on seasonal water quality at multi-spatial scales. *Catena*, 151:182–190.

Statistik, B. P. (2009). Statistik indonesia 2009 [statistical yearbook of indonesia 2009]. *Jakarta: BPS*.

Unknown (2022). Een kabelbrug over de rivier brantas bij kesamben, residentie kediri, oost-java. Retrieved 19 January 2023 from https://en.wikipedia.org/wiki/Brantas_River#/media/File:COLLECTIE_TROPENMUSEUM_Een_kabelbrug_over_de_rivier_Brantas_bij_Kesamben_residentie_Kediri_Oost-Java_TMnr_10007555.jpg.

van der Kwast, H., Menke, K., and Sherman, G. (2022). *QGIS for Hydrological Applications: Recipes for Catchment Hydrology and Water Management*. Locate Press.

Wang, G., Xu, Z., and Zhang, S. (2014). The influence of land use patterns on water quality at multiple spatial scales in a river system. *Hydrological Processes*, 28(20):5259–5272.

Wang, X. and Zhang, F. (2018). Multi-scale analysis of the relationship between landscape patterns and a water quality index (wqi) based on a stepwise linear regression (slr) and geographically weighted regression (gwr) in the ebinur lake oasis. *Environmental Science and Pollution Research*, 25:7033–7048.

Wang, X., Zhang, F., Li, X., Cao, C., Guo, M., and Chen, L. (2017). Correlation analysis between the spatial characteristics of land use/cover-landscape pattern and surface-water quality in the ebinur lake area. *Acta Ecol. Sin*, 37:7438–7452.

Willard, T. (2022). Water quality measurements in the brantas, indonesia: Constructing different perspectives with principal component analysis.

WorldBank (2021). Indonesia - Small Hydro GIS Database — Data Catalog - datacatalog.worldbank.org. Retrieved 25 June 2023 from https://datacatalog.worldbank.org/search/dataset/0042082.

Xu, S., Li, S.-L., Zhong, J., and Li, C. (2020). Spatial scale effects of the variable relationships between landscape pattern and water quality: Example from an agricultural karst river basin, southwestern china. *Agriculture, Ecosystems & Environment*, 300:106999.

A - Available data for the Brantas Basin

A.1 The measured parameters per agencie

Table A.1: The different parameters as measured by the different agencies

Agencies	EPA					BBWS					PJT
Year	2013	2014	2015	2016	2017	2009	2010	2011	2012-2014	2015-2019	2010-2019
Measurement Points	30	30	0	28	28	12	-	36	36	36	20
Temperature	-	Y	-	Y	Y	Y	-	Y	Y	Y	Y
pH	-	Y	-	Y	Y	Y	-	Y	Y	Y	Y
DO	Y	Y	-	Y	Y	Y	-	Y	Y	Y	Y
COD	Y	Y	-	Y	Y	Y	-	Y	Y	Y	Y
Turbidity	-	-	-	-	-	-	-	Y	Y	Y	Y
BOD	-	Y	-	Y	Y	Y	-	Y	Y	Y	Y
NO3	-	Y	-	Y	Y	Y	-	-	Y	Y	Y
NO2	-	-	-	Y	Y	Y	-	-	Y	Y	Y
Detergent	-	Y	-	Y	Y	Y	-	-	-	-	Y
NH3	-	Y	-	Y	Y	Y	-	-	Y	Y	Y
Oil and Grease	-	Y	-	Y	Y	Y	-	-	-	-	Y
Phenol	-	-	-	Y	Y	Y	-	-	-	-	Y
TP	-	-	-	-	-	Y	-	-	Y	Y	Y
Fecal Coli	Y	Y	-	Y	Y	Y	-	Y	Y	-	Y
Total Coli	Y	Y	-	Y	Y	Y	-	Y	Y	-	Y
Copper	-	-	-	-	-	-	-	-	-	-	Y
Chromium	-	-	-	-	-	-	-	-	-	-	Y
TSS	Y	Y	-	Y	Y	Y	-	Y	Y	Y	Y
TDS	-	Y	-	Y	Y	-	-	Y	Y	Y	Y
TP	Y	Y	-	Y	Y	-	-	-	-	-	Y
EC	-	Y	-	Y	Y	-	-	Y	Y	Y	Y
Free Chlorine	-	Y	-	Y	Y	-	-	-	-	-	Y
Cyanide	-	Y	-	Y	Y	-	-	-	-	-	Y
Hydrogen Sulfide	-	Y	-	Y	Y	-	-	-	-	-	Y
NH4	-	-	-	Y	-	-	-	-	-	-	-
Co	-	-	-	Y	Y	-	-	-	-	-	Y
Cd	-	-	-	Y	Y	-	-	-	-	-	Y
Cr	-	-	-	Y	Y	Y	-	-	Y	-	Y
Cu	-	-	-	Y	Y	Y	-	-	Y	-	Y
Fe	-	-	-	Y	Y	-	-	-	-	-	Y
Pb	-	-	-	Y	Y	-	-	-	-	-	Y
Mn	-	-	-	Y	Y	-	-	-	-	-	Y
Zn	-	-	-	Y	Y	-	-	-	-	-	Y
Fluoride	-	-	-	Y	Y	-	-	-	-	-	Y
SO4	-	-	-	Y	Y	-	-	-	-	-	Y

A.2 Creating the (Sub-)Basins

Different attempts to recreate the Brantas Basin as can be found on the world bank website (WorldBank, 2021) (the pink outline in figure A.1, called Brantas Basin) resulted in different results but never came close to generating the full Basin. The best result can be seen in Fig. 4.1

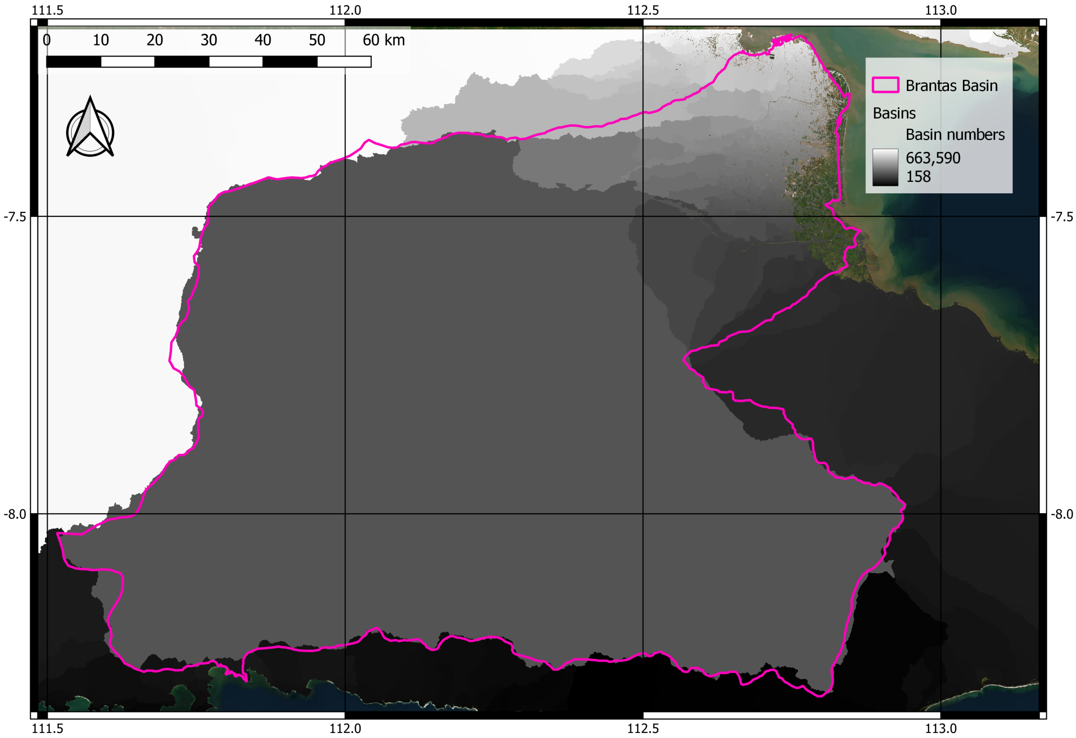


Figure A.1: The different subbasins based on an 8 by 8 meter DEM

A.3 ESRI Landcover

The land cover dataset from ESRI is generated with Impact Observatory's deep learning AI land classification model. This dataset, which depicts the year 2017 and has a resolution of 10 by 10 meters. (Esri, 2022). The land cover map can be seen in Fig. A.2. The explanation of the legend can be found in table A.2

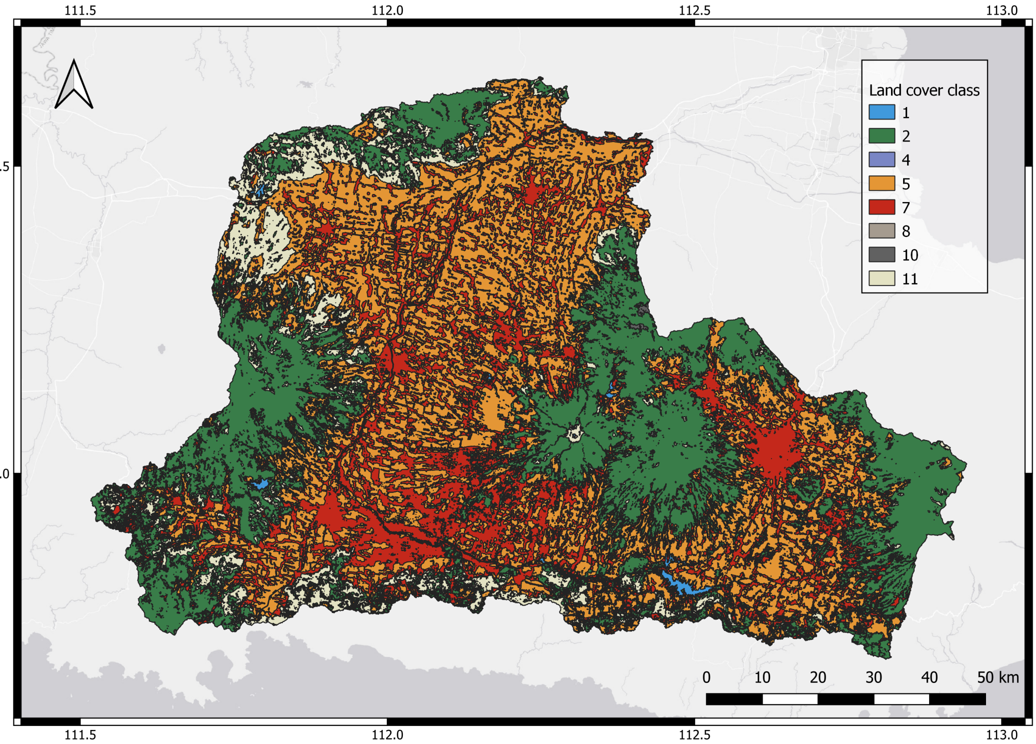


Figure A.2: The ESRI land cover map

Table A.2: Description of the legend as provided by Esri (2022)

Value	Name	Description
1	Water	Areas where water was predominantly present throughout the year; may not cover areas with sporadic or ephemeral water; contains little to no sparse vegetation, no rock outcrop nor built-up features like docks; examples: rivers, ponds, lakes, oceans, flooded salt plains.
2	Trees	Any significant clustering of tall (~15 feet or higher) dense vegetation, typically with a closed or dense canopy; examples: wooded vegetation, clusters of dense, tall vegetation within savannas, plantations, swamp or mangroves (dense/tall vegetation with ephemeral water or canopy too thick to detect water underneath).
4	Flooded vegetation	Areas of any type of vegetation with obvious intermixing of water throughout a majority of the year; seasonally flooded area that is a mix of grass/shrub/trees/bare ground; examples: flooded mangroves, emergent vegetation, rice paddies and other heavily irrigated and inundated agriculture.
5	Crops	Human planted/plotted cereals, grasses, and crops not at tree height; examples: corn, wheat, soy, fallow plots of structured land.
7	Built Area	Human made structures; major road and rail networks; large homogenous impervious surfaces including parking structures, office buildings and residential housing; examples: houses, dense villages / towns / cities, paved roads, asphalt.
8	Bare ground	Areas of rock or soil with very sparse to no vegetation for the entire year; large areas of sand and deserts with no to little vegetation; examples: exposed rock or soil, desert and sand dunes, dry salt flats/pans, dried lake beds, mines.
9	Snow/Ice	Large homogenous areas of permanent snow or ice, typically only in mountain areas or highest latitudes; examples: glaciers, permanent snowpack, snow fields.
10	Clouds	No land cover information due to persistent cloud cover.
11	Rangeland	Open areas covered in homogenous grasses with little to no taller vegetation; wild cereals and grasses with no obvious human plotting (i.e., not a plotted field); examples: natural meadows and fields with sparse to no tree cover, open savanna with few to no trees, parks/golf courses/lawns, pastures. Mix of small clusters of plants or single plants dispersed on a landscape that shows exposed soil or rock; scrub-filled clearings within dense forests that are clearly not taller than trees; examples: moderate to sparse cover of bushes, shrubs and tufts of grass, savannas with very sparse grasses, trees or other plants.

Table A.3: Land cover percentage within the Basin, based on the ESRI land cover map

Legend number	Area (km^2)	Percentage
1	55.509	0.57
2	3088.78	31.78
4	0.793	0.01
5	3384	34.82
7	2364.064	24.32
8	3.566	0.04
10	18.056	0.19
11	805.121	8.28

A.4 GlobCover landcover

The land cover dataset from GlobCover results from the European Space Agency's (ESA) initiative launched in 2004. This dataset, which depicts the year 2005 and has a resolution of 300 by 300 meters, was initially published in 2008. (Martucci, 2023) The land cover map can be seen in Fig. A.3 the explanation of the legend can be found in table A.4

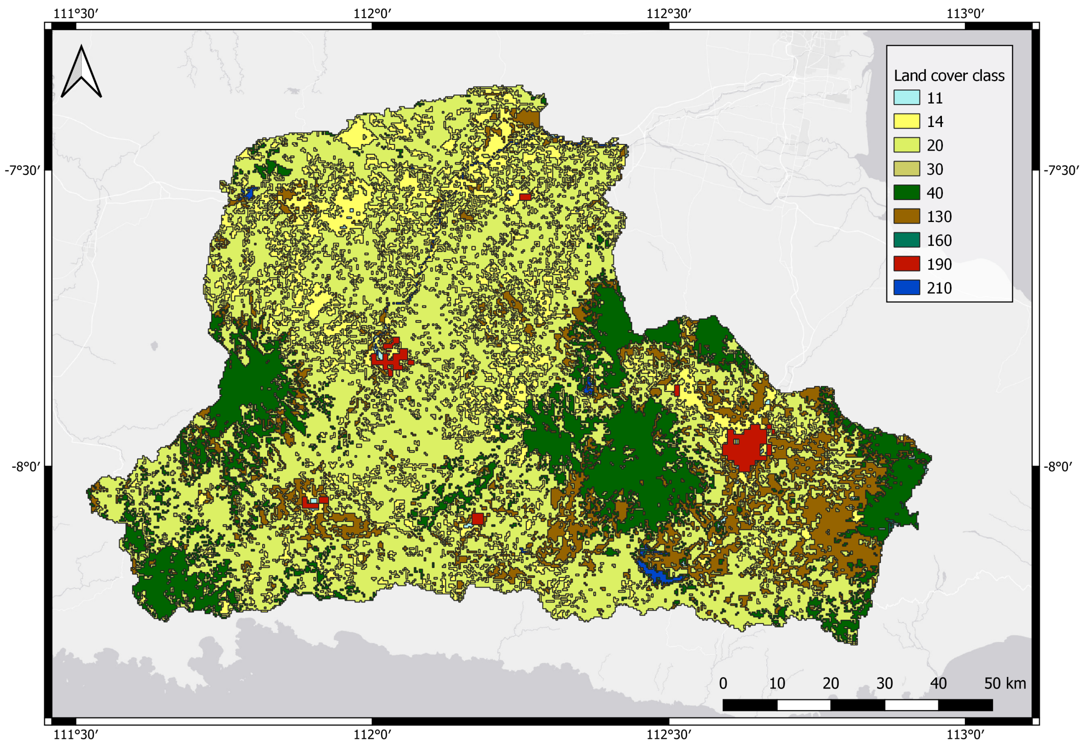


Figure A.3: The GlobCover land cover map

Table A.4: The legend of the GlobCover with the description as provided by Martucci (2023)

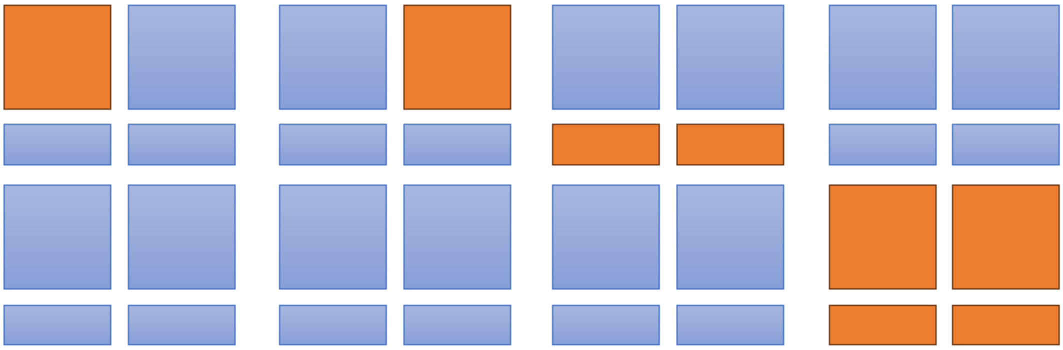
Number	Number Descriptions
11	Post-flooding or irrigated croplands
14	Rainfed croplands
20	Mosaic cropland (50-70%) / vegetation (grassland/shrubland/forest) (20-50%)
30	Mosaic vegetation (grassland/shrubland/forest) (50-70%) / cropland (20-50%)
40	Closed to open (>15%) broadleaved evergreen and/or semi-deciduous forest (>5m)
130	Closed to open (>15%) shrubland (<5m)
160	Closed (>40%) broadleaved forest regularly flooded, fresh water
190	Artificial surfaces and associated areas (Urban areas >50%)
210	Water bodies

Table A.5: Land cover percentage within the Basin, based on the GlobCover land cover map

Legend number	Area (km^22)	Percentage
11	23.336	0.24
14	1575.159	16.21
20	5125.52	52.73
30	81.213	0.84
40	1558.741	16.04
130	1231.328	12.67
160	5.267	0.05
190	87.601	0.90
210	31.338	0.32

B - Results

This appendix presents an overview of all the research results. It is divided into four subsections, each focusing on one of the two land cover maps in combination with one of the sub-basins based on the two agencies. Within each subsection, you will find four tables: one for the results obtained when considering the entire basin and three additional tables for different buffer areas. Each table contains information on the three optimizations, as illustrated in Figure B.1. Furthermore, four figures are included to visually depict the changes in land cover concerning the various buffer zones. Please keep in mind that the two most upstream measurement points have been excluded from the analysis due to the buffer's configuration and can not be found in the figures.



(a) First run (b) Seasonality (c) Simplifying (d) Accumulated

Figure B.1: Reading guide for the tables

B.1 EPA

B.1.1. ESRI Land cover map

Figure B.2: The division of the land cover types for the sub-basins of EPA, based on the ESRI land cover map. The x-axis is the number of the sub-basin

Table B.1: Results of the MLR, based on the EPA measurement points, the ESRI land cover map and the entire basin

Basin

Not Accumulated

R-squared		0.3491		
Adjusted R-squared		0.3408		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7.49	0.10	75.99	<0.01
Water	-0.18	0.01	-12.49	<0.01
Trees	0.00	0.00	-6.80	<0.01
Flooded Vegetation	4.35	0.40	10.95	<0.01
Crops				NS
Built				NS
Bare	2.10	0.28	7.55	<0.01
Clouds	0.25	0.04	6.61	<0.01
Range				NS

Not Accumulated + Seasonality

R-squared		0.3604		
Adjusted R-squared		0.3505		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7.62	0.11	70.33	<0.01
Seasonality	-0.29	0.11	-2.61	<0.01
Water	-0.18	0.01	-12.58	<0.01
Trees	0.00	0.00	-6.85	<0.01
Flooded Vegetation	4.35	0.39	11.03	<0.01
Crops				NS
Built				NS
Bare	2.10	0.28	7.60	<0.01
Clouds	0.25	0.04	6.66	<0.01
Range				NS

Not Accumulated + Combined

R-squared		0.0356		
Adjusted R-squared		0.0307		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6.55	0.10	67.24	<0.01
Natural Vegetation	0.00	0.00	-3.12	<0.01
Argriculturale Landscape	0.00	0.00	3.74	<0.01
Urban Landscape				NS

Not Accumulated + Combined + Seasonality

R-squared		0.0468		
Adjusted R-squared		0.0396		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6.67	0.11	59.51	<0.01
Seasonality	-0.29	0.14	-2.15	<0.05
Natural Vegetation	0.00	0.00	-3.13	<0.01
Argriculturale Landscape	0.00	0.00	3.76	<0.01
Urban Landscape				NS

Accumulated

R-squared		0.3548		
Adjusted R-squared		0.3432		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7.98	0.16	48.95	<0.01
Water	-0.11	0.02	-6.37	<0.01
Trees	-0.01	0.00	-7.57	<0.01
Flooded Vegetation	10.45	1.83	5.72	<0.01
Crops				NS
Built	0.00	0.00	2.44	<0.05
Bare	5.22	0.42	12.33	<0.01
Clouds	0.35	0.08	4.64	<0.01
Range	-0.02	0.00	-4.17	<0.01

Accumulated + Seasonality

R-squared		0.3660		
Adjusted R-squared		0.3529		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	8.10	0.17	48.14	<0.01
Seasonality	-0.29	0.11	-2.62	<0.01
Water	-0.11	0.02	-6.42	<0.01
Trees	-0.01	0.00	-7.62	<0.01
Flooded Vegetation	10.45	1.81	5.76	<0.01
Crops				NS
Built	0.00	0.00	2.46	<0.05
Bare	5.22	0.42	12.42	<0.01
Clouds	0.35	0.07	4.67	<0.01
Range	-0.02	0.00	-4.20	<0.01

Accumulated + Combined

R-squared		0.0204		
Adjusted R-squared		0.0154		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6.5743557	0.12	55.06	<0.01
Natural Vegetation				NS
Argriculturale Landscape				NS
Urban Landscape				NS

Accumulated + Combined + Seasonality

R-squared		0.0112		
Adjusted R-squared		0.0087		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6.83	0.09	77.12	<0.01
Seasonality	-0.29	0.14	-2.12	<0.05
Natural Vegetation				NS
Argriculturale Landscape				NS
Urban Landscape				NS

Table B.2: Results of the MLR, based on the EPA measurement points, ESRI land cover map and the 4km Buffer

4km Buffer									
Not Accumulated					**Not Accumulated + seasonality**				
R-squared		0,3634			R-squared		0,3776		
Adjusted R-squared		0,3493			Adjusted R-squared		0,3618		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	5,24	0,38	13,90	<0.01	CONSTANT	5,38	0,38	14,27	<0.01
Water	-0,24	0,02	-11,74	<0.01	Seasonality	-0,33	0,12	-2,68	<0.01
Trees	-0,09	0,01	-6,47	<0.01	Water	-0,24	0,02	-11,85	<0.01
Flooded Vegetation	-17,70	3,11	-5,70	<0.01	Trees	-0,09	0,01	-6,53	<0.01
Crops	-0,01	0,00	-2,62	<0.01	Flooded Vegetation	-17,70	3,08	-5,75	<0.01
Built	0,07	0,01	5,62		Crops	-0,01	0,00	-2,64	<0.01
Bare				NS	Built	0,07	0,01	5,67	<0.01
Clouds	-60,23	9,08	-6,63	<0.01	Bare				NS
Range	0,18	0,03	6,81	<0.01	Clouds	-60,23	9,00	-6,70	<0.01
					Range	0,18	0,03	6,88	<0.01
Not Accumulated + combined					**Not Accumulated + Combined + Seasonality**				
R-squared		0,0679			R-squared		0,0821		
Adjusted R-squared		0,0621			Adjusted R-squared		0,0735		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,29	0,12	52,37	<0.01	CONSTANT	6,43	0,13	47,68	<0.01
Natural Vegetation	-0,01	0,00	-3,29	<0.01	Seasonality	-0,33	0,15	-2,22	<0.05
Argriculturale Landscape	0,00	0,00	4,71	<0.01	Natural Vegetation	-0,01	0,00	-3,31	<0.01
Urban Landscape				NS	Argriculturale Landscape	0,00	0,00	4,74	<0.01
					Urban Landscape				NS
Accumulated					**Accumulated + seasonality**				
R-squared		0,3634			R-squared		0,3776		
Adjusted R-squared		0,3493			Adjusted R-squared		0,3618		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	5,49	0,22	24,62	<0.01	CONSTANT	5,63	0,23	24,81	<0.01
Water	-0,34	0,03	-10,28	<0.01	Seasonality	-0,33	0,12	-2,68	<0.01
Trees	-0,09	0,01	-5,97	<0.01	Water	-0,34	0,03	-10,38	<0.01
Flooded Vegetation	-12,43	3,42	-3,64	<0.01	Trees	-0,09	0,01	-6,03	<0.01
Crops	-0,01	0,00	-5,59	<0.01	Flooded Vegetation	-12,43	3,39	-3,67	<0.01
Built	0,06	0,01	7,83	<0.01	Crops	-0,01	0,00	-5,64	<0.01
Bare				NS	Built	0,06	0,01	7,91	<0.01
Clouds	-67,33	6,92	-9,72	<0.01	Bare				NS
Range	0,29	0,03	8,50	<0.01	Clouds	-67,33	6,86	-9,82	<0.01
					Range	0,29	0,03	8,58	<0.01
Accumulated + combined					**Accumulated + Combined + Seasonality**				
R-squared		0,0877			R-squared		0,1001		
Adjusted R-squared		0,082			Adjusted R-squared		0,0945		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	5,9728616	0,14	44,07	<0.01	CONSTANT	6,10	0,15	41,40	<0.01
Natural Vegetation				NS	Seasonality	-0,33	0,15	-2,25	<0.05
Argriculturale Landscape				NS	Natural Vegetation		0,00	5,54	<0.01
Urban Landscape				NS	Argriculturale Landscape				NS
					Urban Landscape				NS

Table B.3: Results of the MLR, based on the EPA measurement points, ESRI land cover map and the 500 m Buffer

500m Buffer				
Not Accumulated				
R-squared		0,3606		
Adjusted R-squared		0,3485		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,62	0,15	44,64	<0.01
Water				NS
Trees	-1,42	0,17	-8,13	<0.01
Flooded Vegetation	395,17	41,22	9,59	<0.01
Crops	0,02	0,00	4,46	<0.01
Built				NS
Bare	18,47	5,78	3,20	<0.01
Clouds	52,96	6,68	7,93	<0.01
Range	6,59	1,08	6,11	<0.01
Not Accumulated + seasonality				
R-squared		0,3747		
Adjusted R-squared		0,3609		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,76	0,16	43,38	<0.01
Seasonality	-0,33	0,13	-2,68	<0.01
Water				NS
Trees	-1,42	0,17	-8,21	<0.01
Flooded Vegetation	395,17	40,82	9,68	<0.01
Crops	0,02	0,00	4,51	<0.01
Built				NS
Bare	18,47	5,72	3,23	<0.01
Clouds	52,96	6,61	8,01	<0.01
Range	6,59	1,07	6,17	<0.01
Not Accumulated + combined				
R-squared		0,0574		
Adjusted R-squared		0,0544		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,23	0,11	57,66	<0.01
Natural Vegetation				NS
Argriculturale Landscape	0,02	0,00	4,43	<0.01
Urban Landscape				NS
Not Accumulated + Combined + Seasonality				
R-squared				
Adjusted R-squared				
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,37	0,12	51,17	<0.01
Seasonality	-0,33	0,15	-2,21	<0.05
Natural Vegetation				NS
Argriculturale Landscape	0,02	0,00	4,45	<0.01
Urban Landscape				NS
Accumulated				
R-squared		0,3573		
Adjusted R-squared		0,3472		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,23	0,18	35,07	<0.01
Water	-0,16	0,03	-6,30	<0.01
Trees	-0,39	0,06	-6,91	<0.01
Flooded Vegetation	169,59	29,07	5,83	<0.01
Crops				NS
Built	0,05	0,00	10,21	<0.01
Bare	64,43	6,78	9,50	<0.01
Clouds				NS
Range				NS
Accumulated + seasonality				
R-squared		0,3714		
Adjusted R-squared		0,3595		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,37	0,18	34,71	<0.01
Seasonality	-0,33	0,13	-2,67	<0.01
Water	-0,16	0,03	-6,36	<0.01
Trees	-0,39	0,06	-6,97	<0.01
Flooded Vegetation	169,59	28,80	5,89	<0.01
Crops				NS
Built	0,05	0,00	10,31	<0.01
Bare	64,43	6,72	9,59	<0.01
Clouds				NS
Range				NS
Accumulated + combined				
R-squared		0,0956		
Adjusted R-squared		0,0928		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	5,82	0,15	39,02	<0.01
Natural Vegetation		0,01	5,83	<0.01
Argriculturale Landscape				NS
Urban Landscape				NS
Accumulated + Combined + Seasonality				
R-squared		0,1097		
Adjusted R-squared		0,1042		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	5,96	0,16	37,12	<0.01
Seasonality	-0,33	0,15	-2,26	<0.05
Natural Vegetation		0,01	5,87	<0.01
Argriculturale Landscape				NS
Urban Landscape				NS

Table B.4: Results of the MLR, based on the EPA measurement points, ESRI land cover map and the 100 m Buffer

100m Buffer

Not Accumulated

Variable	Coefficient	Std. Error	t-Stastic	Probability
R-squared		0,3616		
Adjusted R-squared		0,3496		
CONSTANT	6,38	0,12	52,12	<0.01
Water				NS
Trees				NS
Flooded Vegetation	152,69	21,68	7,04	<0.01
Crops	0,07	0,02	3,02	<0.01
Built	0,27	0,05	5,45	<0.01
Bare	1110,68	99,97	11,11	<0.01
Clouds	280,36	25,20	11,12	<0.01
Range	-92,65	8,60	-10,77	<0.01

Not Accumulated + seasonality

Variable	Coefficient	Std. Error	t-Stastic	Probability
R-squared		0,3758		
Adjusted R-squared		0,362		
CONSTANT	6,52	0,13	49,42	<0.01
Seasonality	-0,33	0,12	-2,68	<0.01
Water				NS
Trees				NS
Flooded Vegetation	152,69	21,47	7,11	<0.01
Crops	0,07	0,02	3,04	<0.01
Built	0,27	0,05	5,50	<0.01
Bare	1110,68	99,01	11,22	<0.01
Clouds	280,36	24,96	11,23	<0.01
Range	-92,65	8,52	-10,88	<0.01

Not Accumulated + combined

Variable	Coefficient	Std. Error	t-Stastic	Probability
R-squared		0,0961		
Adjusted R-squared		0,0876		
CONSTANT	6,07	0,13	46,34	<0.01
Natural Vegetaion		0,06	2,73	<0.01
Argriculturale Landscape	0,14	0,03	5,41	<0.01
Urban Landscape		0,04	-2,54	<0.05

Not Accumulated + Combined + Seasonality

Variable	Coefficient	Std. Error	t-Stastic	Probability
R-squared		0,1102		
Adjusted R-squared		0,0991		
CONSTANT	6,21	0,14	43,09	<0.01
Seasonality	-0,33	0,15	-2,25	<0.05
Natural Vegetaion		0,06	2,75	<0.01
Argriculturale Landscape	0,14	0,03	5,45	<0.01
Urban Landscape		0,04	-2,56	<0.05

Accumulated

Variable	Coefficient	Std. Error	t-Stastic	Probability
R-squared		0,3554		
Adjusted R-squared		0,3432		
CONSTANT	6,13	0,19	32,56	<0.01
Water	-0,10	0,04	-2,38	<0.05
Trees				NS
Flooded Vegetation	206,02	33,76	6,10	<0.01
Crops				NS
Built	0,41	0,06	7,17	<0.01
Bare	1331,27	129,46	10,28	<0.01
Clouds	292,44	32,76	8,93	<0.01
Range	-101,14	10,47	-9,66	<0.01

Accumulated + seasonality

Variable	Coefficient	Std. Error	t-Stastic	Probability
R-squared		0,3696		
Adjusted R-squared		0,3556		
CONSTANT	6,27	0,19	32,37	<0.01
Seasonality	-0,33	0,13	-2,66	<0.01
Water	-0,10	0,04	-2,41	<0.05
Trees				NS
Flooded Vegetation	206,02	33,44	6,16	<0.01
Crops				NS
Built	0,41	0,06	7,24	<0.01
Bare	1331,27	128,24	10,38	<0.01
Clouds	292,44	32,45	9,01	<0.01
Range	-101,14	10,37	-9,75	<0.01

Accumulated + combined

Variable	Coefficient	Std. Error	t-Stastic	Probability
R-squared		0,0976		
Adjusted R-squared		0,0920		
CONSTANT	5,84	0,17	34,48	<0.01
Natural Vegetaion		0,04	2,12	<0.05
Argriculturale Landscape				NS
Urban Landscape				NS

Accumulated + Combined + Seasonality

Variable	Coefficient	Std. Error	t-Stastic	Probability
R-squared		0,1100		
Adjusted R-squared		0,1045		
CONSTANT	5,92	0,17	35,78	<0.01
Seasonality	-0,33	0,15	-2,26	<0.05
Natural Vegetaion		0,02	5,88	<0.01
Argriculturale Landscape				NS
Urban Landscape				NS

B.1.2. GlobCover Land cover map

Figure B.3: The division of the land cover types for the sub-basins of EPA, based on the GlobCover land cover map. The x-axis is the number of the sub-basin

Table B.5: Results of the MLR, based on the EPA measurement points, GlobCoverland cover map and the entire bassin

Basin

Not Accumulated

R-squared 0,3423
Adjusted R-squared 0,3304

Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,90	0,13	59,10	<0.01
Irrigated Cropland	-2,41	0,25	-9,48	<0.01
Rainfed Cropland	-0,01	0,00	-2,57	<0.05
Mosaic Cropland	0,01	0,00	5,54	<0.01
Mosaic Vegetation	-0,09	0,04	-2,45	<0.05
Semi Forest	-0,02	0,00	-7,05	<0.01
Shrubland				NS
Forest	2,45	0,35	6,97	<0.01
Urban	0,14	0,02	6,80	<0.01
Water Bodies				

Not Accumulated + seasonality

R-squared 0,3535
Adjusted R-squared 0,3401

Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	8,02	0,14	57,02	<0.01
Seasonality	-0,29	0,11	-2,59	<0.01
Irrigated Cropland		0,25	-9,55	<0.01
Rainfed Cropland	-0,01	0,00	-2,59	<0.01
Mosaic Cropland		0,00	5,59	<0.01
Mosaic Vegetation	-0,09	0,04	-2,47	<0.05
Semi Forest	-0,02	0,00	-7,10	<0.01
Shrubland				NS
Forest	2,45	0,35	7,02	<0.01
Urban	0,14	0,02	6,85	<0.01
Water Bodies				

Not Accumulated + combined

R-squared 0,1289
Adjusted R-squared 0,1222

Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,11	63,82	<0.01
Natural Vegetaion	0,00	0,00	2,33	<0.05
Argriculturale Landscape		0,00	-2,30	<0.05
Urban Landscape	-0,04	0,01	-6,59	<0.01

Not Accumulated + Combined + Seasonality

R-squared 0,1401
Adjusted R-squared 0,1313

Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,20	0,12	58,70	<0.01
Seasonality		0,13	-2,26	<0.05
Natural Vegetaion	0,00	0,00	2,35	<0.05
Argriculturale Landscape		0,00	-2,32	<0.05
Urban Landscape	-0,04	0,01	-6,62	<0.01

Accumulated

R-squared 0,3446
Adjusted R-squared 0,3310

Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	9,77	0,58	16,81	<0.01
Irrigated Cropland	-2,07	0,46	-4,45	<0.01
Rainfed Cropland	-0,06	0,01	-4,93	<0.01
Mosaic Cropland	0,04	0,01	5,62	<0.01
Mosaic Vegetation	-0,60	0,08	-7,19	<0.01
Semi Forest	-0,05	0,01	-4,20	<0.01
Shrubland	0,04	0,01	3,36	<0.01
Forest	-2,81	0,68	-4,15	<0.01
Urban				NS
Water Bodies	0,45	0,16	2,88	<0.01

Accumulated + seasonality

R-squared 0,3558
Adjusted R-squared 0,3408

Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	9,90	0,58	17,09	<0.01
Seasonality	-0,29	0,11	-2,59	<0.01
Irrigated Cropland	-2,07	0,46	-4,49	<0.01
Rainfed Cropland	-0,06	0,01	-4,97	<0.01
Mosaic Cropland	0,04	0,01	5,66	<0.01
Mosaic Vegetation	-0,60	0,08	-7,25	<0.01
Semi Forest	-0,05	0,01	-4,23	<0.01
Shrubland	0,04	0,01	3,38	<0.01
Forest	-2,81	0,67	-4,18	<0.01
Urban				NS
			2,90	<0.01

Accumulated + combined

R-squared 0,1699
Adjusted R-squared 0,1656

Variable		**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,14	53,18	<0.01
Natural Vegetaion				NS
Argriculturale Landscape		0,00	8,93	<0.01
Urban Landscape	-0,06	0,01	-8,79	<0.01

Accumulated + Combined + Seasonality

R-squared 0,1811
Adjusted R-squared 0,1748

Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,15	50,76	<0.01
Seasonality		0,13	-2,32	<0.05
Natural Vegetaion				NS
Argriculturale Landscape		0,00	8,98	<0.01
Urban Landscape	-0,06	0,01	-8,83	<0.01

Table B.6: Results of the MLR, based on the EPA measurement points, GlobCoverland cover map and the 4km buffer

4km Buffer

Not Accumulated

R-squared		0,3626		
Adjusted R-squared		0,3525		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	8,27	0,21	38,64	<0.01
Irrigated Cropland				NS
Rainfed Cropland	-0,01	0,00	-5,21	<0.01
Mosaic Cropland				NS
Mosaic Vegetation	0,77	0,11	6,79	<0.01
Semi Forest	-0,13	0,02	-7,01	<0.01
Shrubland				NS
Forest	-1,11	0,16	-6,82	<0.01
Urban	-0,12	0,02	-7,90	<0.01
Water Bodies				

Not Accumulated + seasonality

R-squared		0,3763		
Adjusted R-squared		0,3645		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	8,41	0,22	38,50	<0.01
Seasonality	-0,33	0,12	-2,64	<0.01
Irrigated Cropland				NS
Rainfed Cropland	-0,01	0,00	-5,25	<0.01
Mosaic Cropland				NS
Mosaic Vegetation	0,77	0,11	6,85	<0.01
Semi Forest	-0,13	0,02	-7,07	<0.01
Shrubland				NS
Forest	-1,11	0,16	-6,88	<0.01
Urban	-0,12	0,02	-7,97	<0.01
Water Bodies				

Not Accumulated + combined

R-squared		0,1774		
Adjusted R-squared		0,1697		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,12	54,37	0
Natural Vegetaion	0,00	0,00	5,54	<0.01
Argriculturale Landscape		0,00	-5,00	<0.01
Urban Landscape	-0,05	0,01	-4,17	<0.01

Not Accumulated + Combined + Seasonality

R-squared		0,1911		
Adjusted R-squared		0,1809		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,87	0,14	50,35	<0.01
Seasonality		0,14	-2,32	<0.05
Natural Vegetaion	0,00	0,00	5,58	<0.01
Argriculturale Landscape		0,00	-5,04	<0.01
Urban Landscape	-0,05	0,01	-4,20	<0.01

Accumulated

R-squared		0,3623		
Adjusted R-squared		0,3482		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	0,24	0,92	0,26	0,79
Irrigated Cropland	-2,35	0,24	-9,90	<0.01
Rainfed Cropland	0,02	0,00	8,71	<0.01
Mosaic Cropland	-0,35	0,18	-2,02	<0.05
Mosaic Vegetation	-0,21	0,03	-6,49	<0.01
Semi Forest	0,03	0,01	3,41	<0.01
Shrubland				NS
Forest	1,24	0,28	4,39	<0.01
Urban	0,49	0,07	7,35	<0.01
Water Bodies				NS

Accumulated + seasonality

R-squared		0,376		
Adjusted R-squared		0,3601		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	0,38	0,92	0,41	0,68
Seasonality	-0,33	0,13	-2,63	<0.01
Irrigated Cropland	-2,35	0,23	-10,00	<0.01
Rainfed Cropland	0,02	0,00	8,79	<0.01
Mosaic Cropland	-0,35	0,17	-2,04	<0.05
Mosaic Vegetation	-0,21	0,03	-6,55	<0.01
Semi Forest	0,03	0,01	3,44	<0.01
Shrubland	1,24	0,28	4,43	<0.01
Forest				NS
Urban	0,49	0,07	7,42	<0.01

Accumulated + combined

R-squared		0,1312		
Adjusted R-squared		**0,1258**		
Variable		**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,36	20,50	<0.01
Natural Vegetaion		0,00	5,32	<0.01
Argriculturale Landscape				NS
Urban Landscape	-0,08	0,02	-3,82	<0.01

Accumulated + Combined + Seasonality

R-squared		0,1449		
Adjusted R-squared		**0,1369**		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,36	20,72	<0.01
Seasonality		0,15	-2,26	<0.05
Natural Vegetaion		0,00	5,35	<0.01
Argriculturale Landscape				NS
Urban Landscape	-0,08	0,02	-3,84	<0.01

Table B.7: Results of the MLR, based on the EPA measurement points, GlobCoverland cover map and the 500m buffer

500m Buffer

Not Accumulated

R-squared		0,3600		
Adjusted R-squared		0,3540		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,82	0,11	64,04	<0.01
Irrigated Cropland				NS
Rainfed Cropland	0,01	0,01	2,63	<0.01
Mosaic Cropland				NS
Mosaic Vegetation				NS
Semi Forest				NS
Shrubland				NS
Forest	-2,34	0,21	-11,23	<0.01
Urban	-0,22	0,06	-3,72	<0.01
Water Bodies				NS

Not Accumulated + seasonality

R-squared		0,3737		
Adjusted R-squared		0,3659		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,95	0,12	59,14	<0.01
Seasonality	-0,33	0,12	-2,64	<0.01
Irrigated Cropland				NS
Rainfed Cropland	0,01	0,01	2,66	<0.01
Mosaic Cropland				NS
Mosaic Vegetation				NS
Semi Forest				NS
Shrubland				NS
Forest	-2,34	0,21	-11,33	<0.01
Urban	-0,22	0,06	-3,76	<0.01
Water Bodies				

Not Accumulated + combined

R-squared		0,1002		
Adjusted R-squared		0,0945		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,11	54,48	<0.01
Natural Vegetaion	0,02	0,00	5,55	<0.01
Argriculturale Landscape				NS
Urban Landscape	-0,28	0,07	-3,90	<0.01

Not Accumulated + Combined + Seasonality

R-squared		0,1139		
Adjusted R-squared		0,1055		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,37	0,13	49,24	<0.01
Seasonality		0,15	-2,22	<0.05
Natural Vegetaion	0,02	0,00	5,58	<0.01
Argriculturale Landscape				
Urban Landscape	-0,28	0,07	-3,93	<0.01

Accumulated

R-squared		0,3473		
Adjusted R-squared		0,3391		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	4,64	0,22	21,36	<0.01
Irrigated Cropland	0,44	0,12	3,62	<0.01
Rainfed Cropland				NS
Mosaic Cropland				NS
Mosaic Vegetation	19,93	2,13	9,36	<0.01
Semi Forest				NS
Shrubland	-0,05	0,02	-3,05	<0.01
Forest	-2,38	0,25	-9,35	<0.01
Urban				NS
Water Bodies				NS

Accumulated + seasonality

R-squared		0,3754		
Adjusted R-squared		0,3596		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	2,05	1,03	1,98	<0.05
Seasonality	-0,33	0,13	-2,63	<0.01
Irrigated Cropland	1,96	0,60	3,24	<0.01
Rainfed Cropland	0,04	0,02	2,39	<0.05
Mosaic Cropland	-0,06	0,02	-2,62	<0.01
Mosaic Vegetation	45,65	9,83	4,64	<0.01
Semi Forest	7,82	2,96	2,64	<0.01
Shrubland	-0,40	0,14	-2,92	<0.01
Forest	-13,17	4,07	-3,24	<0.01
Urban				

Accumulated + combined

R-squared		0,0958		
Adjusted R-squared		**0,0930**		
Variable		**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,12	52,39	<0.01
Natural Vegetaion		0,00	5,84	<0.01
Argriculturale Landscape				NS
Urban Landscape				NS

Accumulated + Combined + Seasonality

R-squared		0,1095		
Adjusted R-squared		**0,1039**		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,13	47,48	<0.01
Seasonality		0,15	-2,22	<0.05
Natural Vegetaion		0,00	5,88	<0.01
Argriculturale Landscape				
Urban Landscape				

Table B.8: Results of the MLR, based on the EPA measurement points, GlobCoverland cover map and the 100m buffer

100m Buffer									
Not Accumulated					**Not Accumulated + seasonality**				
R-squared		0,3618			R-squared		0,3755		
Adjusted R-squared		0,3497			Adjusted R-squared		0,3616		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	2,40	0,60	3,98	<0.01	CONSTANT	2,54	0,60	4,23	<0.01
Irrigated Cropland				NS	Seasonality	-0,33	0,13	-2,63	<0.01
Rainfed Cropland	0,81	0,10	8,50	<0.01	Irrigated Cropland				NS
Mosaic Cropland		0,12	-7,67	<0.01	Rainfed Cropland	0,81	0,09	8,58	<0.01
Mosaic Vegetation		0,98	-5,05	<0.01	Mosaic Cropland		0,12	-7,74	<0.01
Semi Forest	2,24	0,28	7,93	<0.01	Mosaic Vegetation				NS
Shrubland				NS	Semi Forest	-4,92	0,97	-5,09	<0.01
Forest				NS	Shrubland	2,24	0,28	8,01	<0.01
Urban	5,89	1,00	5,89	<0.01	Forest				NS
Water Bodies	1,09	0,19	5,67	<0.01	Urban	5,89	0,99	5,94	<0.01
					Water Bodies	1,09	0,19	5,72	<0.01
Not Accumulated + combined					**Not Accumulated + Combined + Seasonality**				
R-squared		0,0801			R-squared		0,0137		
Adjusted R-squared		0,0744			Adjusted R-squared		0,0106		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,12	52,89	<0.01	CONSTANT	6,71	0,10	66,74	<0.01
Natural Vegetaion	0,07	0,01	5,03	<0.01	Seasonality		0,16	-2,11	<0.05
Argriculturale Landscape				NS	Natural Vegetaion				NS
Urban Landscape	-0,76	0,32	-2,36	0,0186364	Argriculturale Landscape				NS
					Urban Landscape				NS
Accumulated					**Accumulated + seasonality**				
R-squared		0,3627			R-squared		0,3764		
Adjusted R-squared		0,3486			Adjusted R-squared		0,3605		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	14,28	0,98	14,60	<0.01	CONSTANT	14,42	0,97	14,86	<0.01
Irrigated Cropland	-8,78	2,26	-3,88	<0.01	Seasonality	-0,33	0,13	-2,63	<0.01
Rainfed Cropland		0,09	-7,21	<0.01	Irrigated Cropland	-8,78	2,24	-3,92	<0.01
Mosaic Cropland		0,09	10,38	<0.01	Rainfed Cropland	-0,64	0,09	-7,28	<0.01
Mosaic Vegetation	-7,88	2,63	-3,00	<0.01	Mosaic Cropland	0,93	0,09	10,48	<0.01
Semi Forest	-12,83	3,62	-3,55	<0.01	Mosaic Vegetation				
Shrubland					Semi Forest	-7,88	2,60	-3,03	<0.01
Forest	-12,18	1,75	-6,97	<0.01	Shrubland				
Urban					Forest	-12,83	3,58	-3,58	<0.01
Water Bodies	1,12	0,25	4,48	<0.01	Urban	-12,18	1,73	-7,03	<0.01
								4,52	<0.01
Accumulated + combined					**Accumulated + Combined + Seasonality**				
R-squared		0,0952			R-squared		0,1089		
Adjusted R-squared		**0,0924**			**Adjusted R-squared**		**0,1033**		
Variable		**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,12	52,33	<0.01	CONSTANT		0,13	47,43	<0.01
Natural Vegetaion		0,00	5,82	<0.01	Seasonality		0,15	-2,22	<0.05
Argriculturale Landscape				NS	Natural Vegetaion		0,00	5,85	<0.01
Urban Landscape				NS	Argriculturale Landscape				NS
					Urban Landscape				NS

B.2 BBWS

B.2.1. ESRI Land cover map

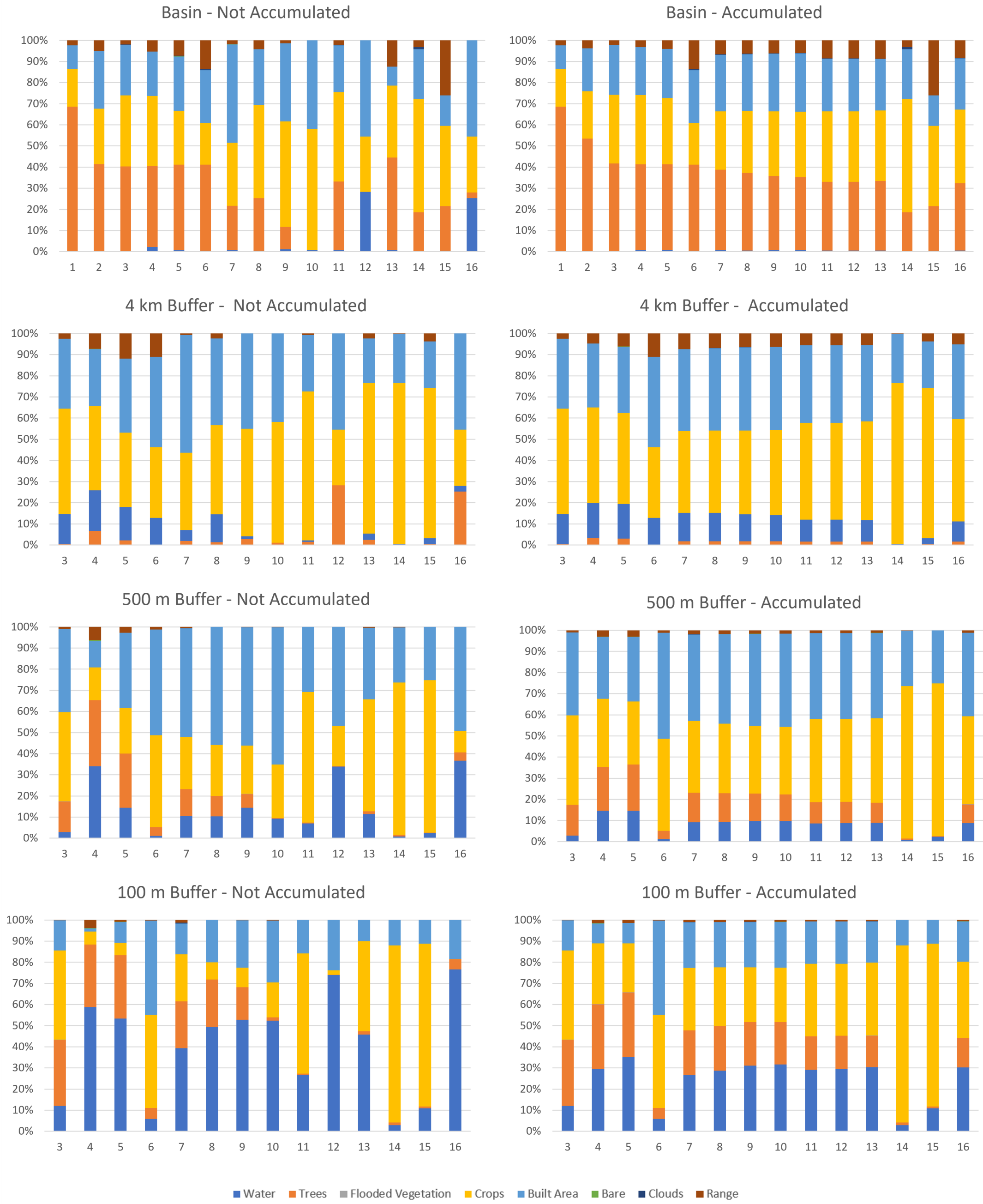


Figure B.4: The division of the land cover types for the sub-basins of BBWS, based on the ESRI land cover map. The x-axis is the number of the sub-basin

Table B.9: Results of the MLR, based on the BBWS measurement points, ESRI land cover map and the entire basin

Basin

Not Accumulated				
R-squared		0,0475		
Adjusted R-squared		0,0393		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,09	0,08	91,92	<0.01
Water		0,01	-2,49	<0.05
Trees				NS
Flooded Vegetation				NS
Crops				NS
Built	0,00	0,00	-2,53	<0.05
Bare	0,59	0,20	2,98	<0.01
Clouds				NS
Range				NS
				NS

Not Accumulated + seasonality				
R-squared		0,0774		
Adjusted R-squared		0,0668		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,26	0,09	79,24	<0.01
Seasonality	-0,31	0,09	-3,35	<0.01
Water		0,01	-2,53	<0.05
Trees				NS
Flooded Vegetation				NS
Crops				NS
Built	0,00	0,00	-2,56	<0.05
Bare	0,59	0,19	3,02	<0.01
Clouds				NS
Range				NS

Not Accumulated + combined				
		0,0141		
Adjusted R-squared		0,0113		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	**7,05**	**0,07**	**105,40**	**<0.01**
Natural Vegetation		0,00	-2,24	<0.05
Argriculturale Landscape				NS
Urban Landscape				NS

Not Accumulated + Combined + Seasonality				
Adjusted R-squared		0,0385		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	**7,22**	**0,08**	**85,99**	**<0.01**
Seasonality	-0,31	0,10	-3,31	<0.01
Natural Vegetation		0,00	-2,27	<0.05
Argriculturale Landscape				NS
Urban Landscape				

Accumulated				
		0,0165		
Adjusted R-squared		0,0108		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	**7,03**	**0,09**	**76,35**	**<0.01**
Water				NS
Trees	0,00	0,00	-2,37	<0.05
Flooded Vegetation				NS
Crops				NS
Built				NS
Bare	0,53	0,22	2,41	<0.05
Clouds				NS
Range				NS

Accumulated + seasonality				
		0,0464		
Adjusted R-squared		0,0382		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	**7,20**	**0,10**	**68,84**	**<0.01**
Seasonality	-0,31	0,10	-3,30	<0.01
Water				NS
Trees	0,00	0,00	-2,40	<0.05
Flooded Vegetation				NS
Crops				NS
Built				NS
Bare	0,53	0,22	2,45	<0.05
Clouds				NS
Range				NS

Accumulated + combined				
R-squared		-		
Adjusted R-squared		-		
Variable		**Std. Error**	**t-Stastic**	**Probability**
CONSTANT				NS
Natural Vegetation				**NS**
Argriculturale Landscape				NS
Urban Landscape				NS
Urban Landscape				NS

Accumulated + Combined + Seasonality				
R-squared		0,0299		
Adjusted R-squared		**0,0271**		
Variable		**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,11	0,07	100,53	<0.01
Seasonality	**-0,31**	**0,10**	**-3,29**	**<0.01**
Natural Vegetation				NS
Argriculturale Landscape				NS
Urban Landscape				NS
Argriculturale Landscape				NS
Urban Landscape				NS

Table B.10: Results of the MLR, based on the BBWS measurement points, ESRI land cover map and the 4km buffer

4km Buffer

Not Accumulated

R-squared		0,0388		
Adjusted R-squared		0,0325		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,73	0,09	72,19	<0.01
Water		0,05	2,59	<0.01
Trees				NS
Flooded Vegetation				NS
Crops				NS
Built				NS
Bare	-9,97	3,18	-3,13	<0.01
Clouds				NS
Range				NS

Not Accumulated + seasonality

R-squared		0,0741		
Adjusted R-squared		0,0649		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,92	0,11	64,49	<0.01
Seasonality	-0,35	0,10	-3,40	<0.01
Water		0,05	2,64	<0.01
Trees				NS
Flooded Vegetation				NS
Crops				NS
Built				NS
Bare	-9,97	3,13	-3,18	<0.01
Clouds				NS
Range				NS

Not Accumulated + combined

R-squared		0,0154		
Adjusted R-squared		0,0122		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	**6,97**	**0,06**	**109,68**	**<0.01**
Natural Vegetation		0,00	-2,19	<0.05
Argriculturale Landscape				NS
Urban Landscape				NS

Not Accumulated + Combined + Seasonality

R-squared		**0,0507**		
Adjusted R-squared		0,0445		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	**7,16**	**0,08**	**85,00**	**<0.01**
Seasonality	-0,35	0,10	-3,37	<0.01
Natural Vegetation		0,00	-2,22	<0.05
Argriculturale Landscape				NS
Urban Landscape				NS

Accumulated

R-squared		0,0221		
Adjusted R-squared		0,0157		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	**6,72**	**0,10**	**64,21**	**<0.01**
Water				NS
Trees				NS
Flooded Vegetation				NS
Crops				NS
Built				NS
Bare				NS
Clouds	-2,09	0,88	-2,38	<0.05
Range	0,01	0,00	2,60	<0.01

Accumulated + seasonality

R-squared		0,0574		
Adjusted R-squared		0,0481		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	**6,91**	**0,12**	**58,88**	**<0.01**
Seasonality	-0,35	0,10	-3,37	<0.01
Water				NS
Trees				NS
Flooded Vegetation				NS
Crops				NS
Built				NS
Bare				NS
Clouds	-2,09	0,86	-2,42	<0.05
Range	0,01	0,00	2,64	<0.01

Accumulated + combined

R-squared		-		
Adjusted R-squared		-		
Variable		**Std. Error**	**t-Stastic**	**Probability**
CONSTANT				NS
Natural Vegetation				**NS**
Argriculturale Landscape				NS
Urban Landscape				NS
Urban Landscape				NS

Accumulated + Combined + Seasonality

R-squared		0,0353		
Adjusted R-squared		**0,0321**		
Variable		**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,08	0,08	92,01	<0.01
Seasonality	**-0,35**	**0,10**	**-3,35**	**<0.01**
Natural Vegetation				NS
Argriculturale Landscape				NS
Urban Landscape				NS
Argriculturale Landscape				NS
Urban Landscape				NS

Table B.11: Results of the MLR, based on the BBWS measurement points, ESRI land cover map and the 500m buffer

500m Buffer

Not Accumulated

R-squared		0,0833		
Adjusted R-squared		0,065		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,79	0,12	56,20	<0.01
Water		0,07	3,62	<0.01
Trees	-0,17	0,07	-2,30	<0.05
Flooded Vegetation		24,37	2,67	<0.01
Crops		0,01	-3,53	<0.01
Built				NS
Bare	-38,84	9,21	-4,22	<0.01
Clouds				NS
Range	1,68	0,56	2,98	<0.01

Not Accumulated + seasonality

R-squared		0,1186		
Adjusted R-squared		0,098		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,98	0,13	53,39	<0.01
Seasonality	-0,35	0,10	-3,46	<0.01
Water		0,07	3,69	<0.01
Trees	-0,17	0,07	-2,34	<0.05
Flooded Vegetation		23,94	2,72	<0.01
Crops		0,01	-3,60	<0.01
Built				NS
Bare	-38,84	9,05	-4,29	<0.01
Clouds				NS
Range	1,68	0,55	3,04	<0.01

Not Accumulated + combined

R-squared		-		
Adjusted R-squared		-		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT				**NS**
Natural Vegetation				NS
Argriculturale Landscape				NS
Urban Landscape				NS

Not Accumulated + Combined + Seasonality

R-squared		**0,0353**		
Adjusted R-squared		0,0321		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	**7,08**	**0,08**	**92,01**	**<0.01**
Seasonality	-0,35	0,10	-3,35	<0.01
Natural Vegetation				NS
Argriculturale Landscape				NS
Urban Landscape				NS

Accumulated

R-squared		0,0480		
Adjusted R-squared		0,0354		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	**6,98**	**0,12**	**56,52**	**<0.01**
Water	0,19	0,05	3,55	<0.01
Trees				NS
Flooded Vegetation				NS
Crops				NS
Built	-0,04	0,01	-3,37	<0.01
Bare	-33,72	10,58	-3,19	<0.01
Clouds				NS
Range	0,87	0,32	2,73	<0.01

Accumulated + seasonality

R-squared		0,0833		
Adjusted R-squared		0,0681		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	**7,17**	**0,13**	**53,68**	**<0.01**
Seasonality	-0,35	0,10	-3,41	<0.01
Water	0,19	0,05	3,62	<0.01
Trees				NS
Flooded Vegetation				NS
Crops				NS
Built		0,01	-3,43	<0.01
Bare	-33,72	10,40	-3,24	<0.01
Clouds				NS
Range	0,87	0,31	2,78	<0.01

Accumulated + combined

R-squared		-		
Adjusted R-squared		-		
Variable		**Std. Error**	**t-Stastic**	**Probability**
CONSTANT				NS
Natural Vegetation				**NS**
Argriculturale Landscape				NS
Urban Landscape				NS
Urban Landscape				NS

Accumulated + Combined + Seasonality

R-squared		0,0353		
Adjusted R-squared		**0,0321**		
Variable		**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,08	0,08	92,01	<0.01
Seasonality	**-0,35**	**0,10**	**-3,35**	**<0.01**
Natural Vegetation				NS
Argriculturale Landscape				NS
Urban Landscape				NS
Argriculturale Landscape				NS
Urban Landscape				NS

Table B.12: Results of the MLR, based on the BBWS measurement points, ESRI land cover map and the 100m buffer

100m Buffer									
Not Accumulated					**Not Accumulated + seasonality**				
R-squared		0,0777			R-squared		0,9254		
Adjusted R-squared		0,0593			Adjusted R-squared		0,1130		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,68	0,12	54,13	<0.01	CONSTANT	6,87	0,13	51,61	<0.01
Water		0,07	3,09	<0.01	Seasonality	-0,35	0,10	-3,45	<0.01
Trees	-0,46	0,18	-2,60	<0.01	Water		0,07	3,14	<0.01
Flooded Vegetation				NS	Trees	-0,46	0,18	-2,65	<0.01
Crops				NS	Flooded Vegetation				NS
Built	-0,14	0,05	-2,88	<0.01	Crops				NS
Bare	-1173,50	364,97	-3,22	<0.01	Built	-0,14	0,05	-2,93	<0.01
Clouds	-310,62	98,18	-3,16	<0.01	Bare	-1173,50	358,51	-3,27	<0.01
Range	93,83	30,43	3,08	<0.01	Clouds	-310,62	96,45	-3,22	<0.01
					Range	93,83	29,89	3,14	<0.01
Not Accumulated + combined					**Not Accumulated + Combined + Seasonality**				
R-squared		-			**R-squared**		**0,0353**		
Adjusted R-squared		-			Adjusted R-squared		0,0321		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT				**NS**	**CONSTANT**	**7,08**	**0,08**	**92,01**	**<0.01**
Natural Vegetation				NS	Seasonality	-0,35	0,10	-3,35	<0.01
Argriculturale Landscape				NS	Natural Vegetation				NS
Urban Landscape				NS	Argriculturale Landscape				NS
					Urban Landscape				NS
Accumulated					**Accumulated + seasonality**				
R-squared		0,0316			**R-squared**		0,0668		
Adjusted R-squared		0,0220			Adjusted R-squared		0,0545		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	**6,60**	**0,11**	**57,72**	**<0.01**	**CONSTANT**	**6,79**	**0,13**	**54,03**	**<0.01**
Water				NS	Seasonality	-0,35	0,10	-3,38	<0.01
Trees				NS	Water				NS
Flooded Vegetation				NS	Trees				NS
Crops				NS	Flooded Vegetation				NS
Built				NS	Crops				NS
Bare	-351,87	130,16	-2,70	<0.01	Built				NS
Clouds	-106,12	38,70	-2,74	<0.01	Bare	-351,87	127,98	-2,75	<0.01
Range	27,06	9,77	2,77	<0.01	Clouds	-106,12	38,05	-2,79	<0.01
					Range	27,06	9,61	2,82	<0.01
Accumulated + combined					**Accumulated + Combined + Seasonality**				
R-squared		-			R-squared		0,0476		
Adjusted R-squared		-			**Adjusted R-squared**		**0,0413**		
Variable		**Std. Error**	**t-Stastic**	**Probability**	**Variable**		**Std. Error**	**t-Stastic**	**Probability**
CONSTANT				NS	CONSTANT	6,91	0,11	60,18	<0.01
Natural Vegetation				**NS**	**Seasonality**	**-0,35**	**0,10**	**-3,36**	**<0.01**
Argriculturale Landscape				NS	Natural Vegetation		0,01	1,98	<0.05
Urban Landscape				NS	Argriculturale Landscape				NS
					Urban Landscape				NS
Urban Landscape				NS	Argriculturale Landscape				NS
					Urban Landscape				NS

B.2.2. GlobCover Land cover map

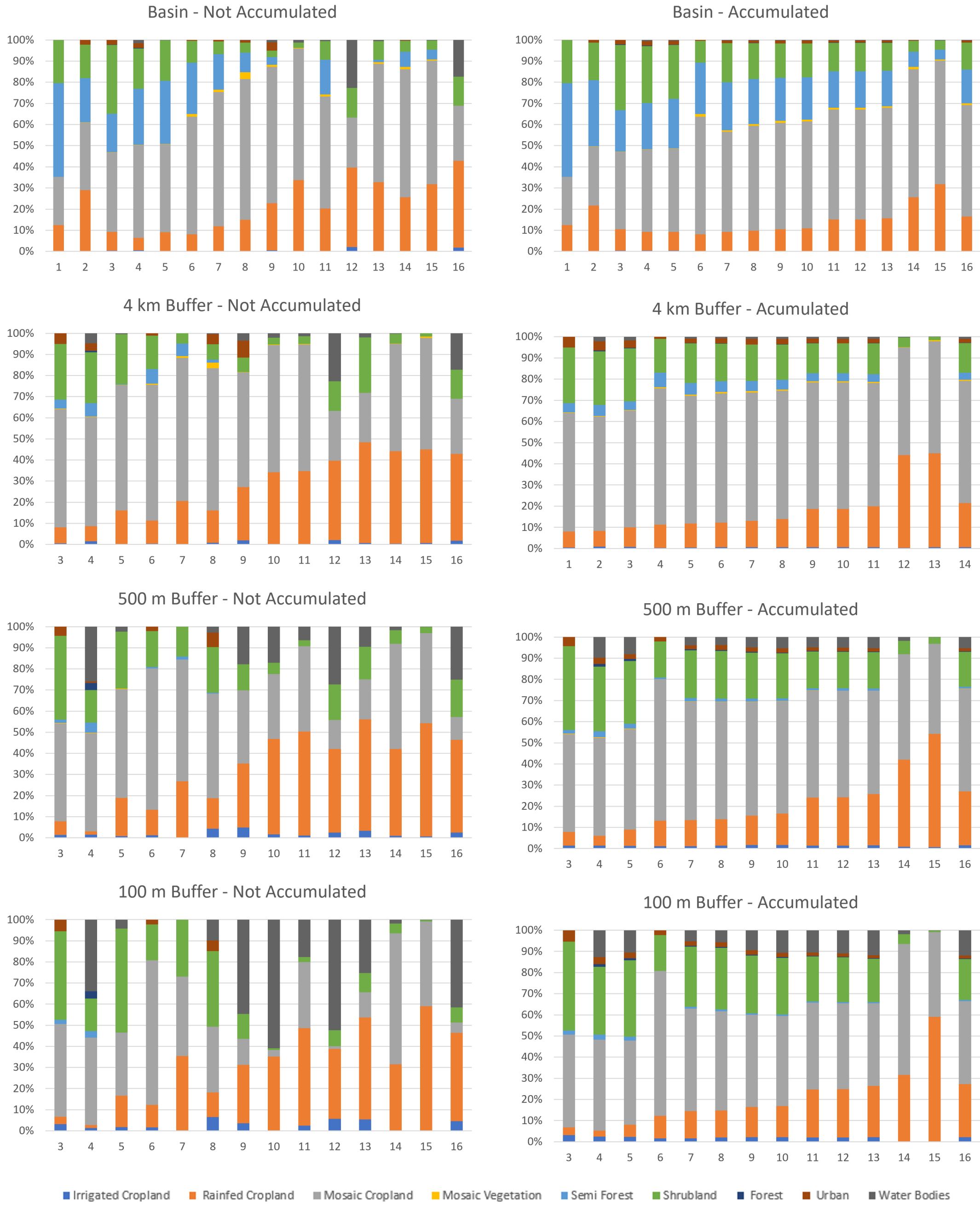


Figure B.5: The division of the land cover types for the sub-basins of BBWS, based on the GlobCover land cover map. The x-axis is the number of the sub-basin

Table B.13: Results of the MLR, based on the BBWS measurement points, GlobCover land cover map and the entire basin

Basin

Not Accumulated

R-squared 0,0893
Adjusted R-squared 0,0735

Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,99	0,09	81,99	<0.01
Irrigated Cropland		0,17	2,32	<0.05
Rainfed Cropland	0,00	0,00	3,13	<0.01
Mosaic Cropland		0,00	-4,01	<0.01
Mosaic Vegetation				NS
Semi Forest	0,00	0,00	2,85	<0.01
Shrubland	0,00	0,00	2,06	<0.05
Forest	-1,16	0,33	-3,52	<0.01
Urban				NS
Water Bodies				NS

Not Accumulated + seasonality

R-squared 0,1192
Adjusted R-squared 0,1013

Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,16	0,10	73,19	<0.01
Seasonality	-0,31	0,09	-3,42	<0.01
Irrigated Cropland		0,16	2,35	<0.05
Rainfed Cropland	0,00	0,00	3,17	<0.01
Mosaic Cropland		0,00	-4,07	<0.01
Mosaic Vegetation				
Semi Forest	0,00	0,00	2,89	<0.01
Shrubland	0,00	0,00	2,09	<0.05
Forest	-1,16	0,32	-3,58	<0.01
Urban				
Water Bodies				

Not Accumulated + combined

R-squared 0,0332
Adjusted R-squared 0,0304

Variable	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	0,06	116,93	<0.01
Natural Vegetaion	0,01	-3,47	<0.01
Argriculturale Landscape			NS
Urban Landscape			NS

Not Accumulated + Combined + Seasonality

R-squared 0,0449
Adjusted R-squared 0,0394

Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,25	0,09	79,81	<0.01
Seasonality		0,10	-3,31	<0.01
Natural Vegetaion		0,00	-2,34	<0.05
Argriculturale Landscape				
Urban Landscape				

Accumulated

R-squared 0,0891
Adjusted R-squared 0,0759

Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,82	0,09	76,19	<0.01
Irrigated Cropland	0,77	0,15	5,02	<0.01
Rainfed Cropland		0,00	5,30	<0.01
Mosaic Cropland		0,00	-5,73	<0.01
Mosaic Vegetation	0,01	0,00	5,26	<0.01
Semi Forest				NS
Shrubland				NS
Forest	-1,92	0,36	-5,38	<0.01
Urban				NS
Water Bodies				NS

Accumulated + seasonality

R-squared 0,1190
Adjusted R-squared 0,1037

Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,99	0,10	68,94	<0.01
Seasonality	-0,31	0,09	-3,42	<0.01
Irrigated Cropland	0,77	0,15	5,10	<0.01
Rainfed Cropland		0,00	5,38	<0.01
Mosaic Cropland	-0,01	0,00	-5,82	<0.01
Mosaic Vegetation		0,00	5,35	<0.01
Semi Forest				
Shrubland				
Forest	-1,92	0,35	-5,47	<0.01
Urban				

Accumulated + combined

R-squared -
Adjusted R-squared **-**

Variable	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT			NS
Natural Vegetation			NS
Argriculturale Landscape			NS
Urban Landscape			NS

Accumulated + Combined + Seasonality

R-squared 0,0299
Adjusted R-squared **0,0271**

Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,07	100,53	<0.01
Seasonality		0,10	-3,29	<0.01
Natural Vegetaion				NS
Argriculturale Landscape				NS
Urban Landscape				NS

Table B.14: Results of the MLR, based on the BBWS measurement points, GlobCover land cover map and the 4km buffer

4km Buffer

Not Accumulated

R-squared		0,0578		
Adjusted R-squared		0,0517		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,07	0,07	105,66	<0.01
Irrigated Cropland				NS
Rainfed Cropland				NS
Mosaic Cropland				NS
Mosaic Vegetation		0,04	-3,62	<0.01
Semi Forest				NS
Shrubland				NS
Forest	-0,25	0,10	-2,46	<0.05
Urban				NS
Water Bodies				NS

Not Accumulated + seasonality

R-squared		0,1098		
Adjusted R-squared		0,092		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,18	0,12	61,20	<0.01
Seasonality	-0,35	0,10	-3,45	<0.01
Irrigated Cropland				NS
Rainfed Cropland	-0,01	0,00	-1,98	<0.05
Mosaic Cropland		0,00	2,30	<0.05
Mosaic Vegetation		0,06	-3,79	<0.01
Semi Forest	-0,03	0,02	-2,00	<0.05
Shrubland				NS
Forest	-0,22	0,11	-2,01	<0.05
Urban				NS
Water Bodies				NS

Not Accumulated + combined

R-squared	0,0391		
Adjusted R-squared	0,0359		
Variable	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	0,07	107,06	<0.01
Natural Vegetaion	0,04	-3,53	<0.01
Argriculturale Landscape			NS
Urban Landscape			NS

Not Accumulated + Combined + Seasonality

R-squared		0,0743		
Adjusted R-squared		0,0683		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,22	0,09	84,66	<0.01
Seasonality		0,10	-3,41	<0.01
Natural Vegetaion		0,04	-3,59	<0.01
Argriculturale Landscape				NS
Urban Landscape				NS

Accumulated

R-squared		0,0525		
Adjusted R-squared		0,0400		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,71	0,11	58,76	<0.01
Irrigated Cropland				NS
Rainfed Cropland		0,00	-2,81	<0.01
Mosaic Cropland		0,00	3,67	<0.01
Mosaic Vegetation	-0,16	0,06	-2,49	<0.05
Semi Forest	-0,05	0,02	-3,16	<0.01
Shrubland				NS
Forest				NS
Urban				NS
Water Bodies				NS

Accumulated + seasonality

R-squared		0,0878		
Adjusted R-squared		0,0727		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,90	0,13	55,09	<0.01
Seasonality	-0,35	0,10	-3,42	<0.01
Irrigated Cropland				NS
Rainfed Cropland		0,00	-2,86	<0.01
Mosaic Cropland	0,01	0,00	3,73	<0.01
Mosaic Vegetation		0,06	-2,54	<0.05
Semi Forest	-0,05	0,01	-3,21	<0.01
Shrubland				NS
Forest				NS
Urban				NS
Water Bodies				NS

Accumulated + combined

R-squared	0,0226		
Adjusted R-squared	**0,0161**		
Variable	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	0,11	60,64	<0.01
Natural Vegetaion	0,05	-2,13	<0.05
Argriculturale Landscape	0,00	2,38	<0.05
Urban Landscape			NS

Accumulated + Combined + Seasonality

R-squared		0,0578		
Adjusted R-squared		**0,0485**		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,12	56,22	<0.01
Seasonality		0,10	-3,37	<0.01
Natural Vegetaion		0,05	-2,16	<0.05
Argriculturale Landscape		0,00	2,42	<0.05
Urban Landscape				NS

Table B.15: Results of the MLR, based on the BBWS measurement points, GlobCover land cover map and the 500m buffer

500m Buffer									
Not Accumulated					**Not Accumulated + seasonality**				
R-squared		0,0697			R-squared		0,1049		
Adjusted R-squared		0,0605			Adjusted R-squared		0,0931		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,96	0,06	115,03	<0.01	CONSTANT	7,15	0,08	88,27	<0.01
Irrigated Cropland				NS	Seasonality	-0,35	0,10	-3,46	<0.01
Rainfed Cropland				NS	Irrigated Cropland				NS
Mosaic Cropland				NS	Rainfed Cropland				NS
Mosaic Vegetation		1,67	3,68	<0.01	Mosaic Cropland				NS
Semi Forest				NS	Mosaic Vegetation		1,64	3,75	<0.01
Shrubland				NS	Semi Forest				NS
Forest	-0,96	0,23	-4,11	<0.01	Shrubland				NS
Urban	-0,32	0,09	-3,65	<0.01	Forest	-0,96	0,23	-4,18	<0.01
Water Bodies					Urban	-0,32	0,09	-3,71	<0.01
					Water Bodies				
Not Accumulated + combined					**Not Accumulated + Combined + Seasonality**				
R-squared		0,0453			R-squared		0,0795		
Adjusted R-squared		0,0390			Adjusted R-squared		0,0704		
Variable		**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,06	116,46	<0.01	CONSTANT	7,12	0,08	88,76	<0.01
Natural Vegetaion		1,74	2,93	<0.01	Seasonality		0,10	-3,36	<0.01
Argriculturale Landscape				NS	Natural Vegetaion		1,71	3,00	<0.01
Urban Landscape		0,17	-3,77	<0.01	Argriculturale Landscape				NS
					Urban Landscape		0,17	-3,78	<0.01
Accumulated					**Accumulated + seasonality**				
R-squared		0,0635			R-squared		0,0988		
Adjusted R-squared		0,0512			Adjusted R-squared		0,0839		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,62	0,12	57,26	<0.01	CONSTANT	6,81	0,13	53,91	<0.01
Irrigated Cropland		0,31	3,65	<0.01	Seasonality	-0,35	0,10	-3,44	<0.01
Rainfed Cropland				NS	Irrigated Cropland		0,30	3,71	<0.01
Mosaic Cropland				NS	Rainfed Cropland				NS
Mosaic Vegetation	9,87	2,45	4,03	<0.01	Mosaic Cropland				NS
Semi Forest				NS	Mosaic Vegetation		2,40	4,10	<0.01
Shrubland				NS	Semi Forest				NS
Forest				NS	Shrubland				NS
Urban	-0,76	0,20	-3,92	<0.01	Forest				NS
Water Bodies		0,07	-3,31	<0.01	Urban	-0,76	0,19	-3,99	<0.01
					Water Bodies		**0,07**	**-3,37**	<0.01
Accumulated + combined					**Accumulated + Combined + Seasonality**				
R-squared		0,0508			R-squared		0,0861		
Adjusted R-squared		**0,0414**			**Adjusted R-squared**		**0,0740**		
Variable		**Std. Error**	**t-Stastic**	**Probability**	**Variable**	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,11	61,67	<0.01	CONSTANT		0,12	57,16	<0.01
Natural Vegetaion		1,86	3,67	<0.01	Seasonality		0,10	-3,42	<0.01
Argriculturale Landscape		0,00	2,55	<0.05	Natural Vegetaion		1,83	3,74	<0.01
Urban Landscape		0,21	-3,34	<0.01	Argriculturale Landscape		0,00	2,60	<0.01
					Urban Landscape		0,21	-3,40	<0.01

Table B.16: Results of the MLR, based on the BBWS measurement points, GlobCover land cover map and the 100m buffer

100m Buffer

Not Accumulated

R-squared		0,0666		
Adjusted R-squared		0,0542		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,86	0,08	80,83	<0.01
Irrigated Cropland		0,67	2,07	<0.05
Rainfed Cropland				NS
Mosaic Cropland				NS
Mosaic Vegetation				NS
Semi Forest		1,73	3,53	<0.01
Shrubland				NS
Forest	-7,90	1,85	-4,28	<0.01
Urban	-2,53	0,65	-3,87	<0.01
Water Bodies				

Not Accumulated + seasonality

R-squared		0,1018		
Adjusted R-squared		0,0870		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,05	0,10	70,51	<0.01
Seasonality	-0,35	0,10	-3,44	<0.01
Irrigated Cropland		0,66	2,11	<0.05
Rainfed Cropland				NS
Mosaic Cropland				NS
Mosaic Vegetation				NS
Semi Forest	6,13	1,70	3,60	<0.01
Shrubland				NS
Forest	-7,90	1,81	-4,36	<0.01
Urban	-2,53	0,64	-3,94	<0.01
Water Bodies				

Not Accumulated + combined

R-squared		-		
Adjusted R-squared		-		
Variable		**Std. Error**	**t-Stastic**	**Probability**
CONSTANT				NS
Natural Vegetation				NS
Argriculturale Landscape				NS
Urban Landscape				NS

Not Accumulated + Combined + Seasonality

R-squared		0,0353		
Adjusted R-squared		0,0321		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	7,08	0,08	92,01	<0.01
Seasonality		0,10	-3,35	<0.01
Natural Vegetaion				NS
Argriculturale Landscape				NS
Urban Landscape				NS

Accumulated

R-squared		0,0532		
Adjusted R-squared		0,0407		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,80	0,12	55,70	<0.01
Irrigated Cropland				NS
Rainfed Cropland				NS
Mosaic Cropland				NS
Mosaic Vegetation	5,28	1,55	3,41	<0.01
Semi Forest	0,20	0,06	3,34	<0.01
Shrubland				NS
Forest	-8,06	2,44	-3,31	<0.01
Urban	-2,87	0,89	-3,24	<0.01
Water Bodies				

Accumulated + seasonality

R-squared		0,0884		
Adjusted R-squared		0,0733		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT	6,99	0,13	52,86	<0.01
Seasonality	-0,35	0,10	-3,42	<0.01
Irrigated Cropland				NS
Rainfed Cropland				NS
Mosaic Cropland				NS
Mosaic Vegetation		1,52	3,47	<0.01
Semi Forest	0,20	0,06	3,40	<0.01
Shrubland				NS
Forest	-8,06	2,40	-3,36	<0.01
Urban	-2,87	0,87	-3,30	<0.01
Water Bodies				

Accumulated + combined

R-squared		-		
Adjusted R-squared		**-**		
Variable		**Std. Error**	**t-Stastic**	**Probability**
CONSTANT				NS
Natural Vegetation				NS
Argriculturale Landscape				NS
Urban Landscape				NS

Accumulated + Combined + Seasonality

R-squared		0,0353		
Adjusted R-squared		**0,0321**		
Variable	**Coefficient**	**Std. Error**	**t-Stastic**	**Probability**
CONSTANT		0,08	92,01	<0.01
Seasonality		0,10	-3,35	<0.01
Natural Vegetaion				NS
Argriculturale Landscape				NS
Urban Landscape				NS

Colophon

This document was typeset using $\LaTeX$, using the KOMA-Script class `scrbook`. The main font is Palatino.