UTRECHT UNIVERSITY

MASTER THESIS

Mapping *Plasmodium falciparum* between 2000 and 2013 in Uganda on a 30 meter spatial resolution scale using environmental and spatial dependencies of malaria transmission

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Abstract

Many mapping efforts have been made to decrease the malaria burden on the world's population. High resolution spatial knowledge of malaria could increase the effectivity of malaria control and prevention which is especially useful for resource limited countries. In this study, 30 meter resolution malaria transmission suitability maps and exposure changes from 2001 to 2013 in Uganda are computed by using 6 predictor variables representing water proximity, water depth, water extent, temporal water, population density and air temperature. The latter four predictor variables show the strongest relations with malaria incidence rates. Furthermore, decreases in exposure to malaria over time have been noted. The decrease is associated with the urbanization in Uganda. While many agree that an increase in population causes a decrease in malaria transmission intensity, questions about the roles of wealth, institutions and population density remain and have to be addressed in future research.

Acknowledgements

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Chapter 1

Introduction

Malaria places a high burden on the world's past and current population. Since 2002 an unprecedented campaign against malaria has tried to control the disease in sub-Saharan Africa. Insecticides treated bed nets (ITN's), indoor residual spraying (IRS), artemisinin-based combination therapy (ACT), habitat removal and other malaria control practices reduced the incidence of clinical disease with 40% between 2000 and 2015 (Bhatt et al., 2015). While the reduction is considerable, the disease still remains and continuous efforts must be made to further reduce malaria prevalence.

Mapping malaria contributes to the spatio-temporal distribution knowledge of malaria and also increases effectivity of malaria control practices. To map malaria, knowledge is needed about the spatial dependencies of malaria transmission. Environmental factors that are known to influence malaria include temperature, humidity, surface water, vegetation, predators, pathogens and nutrient availability (Smith, Macklin, and Thomas, 2013). Population density, urbanization and resources for malaria prevention and control are some socio-economic factors that influence malaria transmission (Hay et al., 2005). Sometimes proxies for the mentioned factors are used. For instance, precipitation is often used in models to predict the state of surface water in time and space (Craig, Snow, and Sueur, 1999). Others try to map pools of water empirically or try to derive pools from hydrological processes (Bomblies, Duchemin, and Eltahir, 2008). The factors mentioned above contribute to the heterogeneous nature of breeding sites of the malaria vectors. As a result, hotspots of transmission can be spatially diverse throughout a region or country.

The usage of many variables and the complexity of their relations to transmission increase computation time which contribute to having either medium resolution global maps (e.g., (Craig, Snow, and Sueur, 1999; Gething et al., 2011; Tompkins and Ermert, 2013) have a 30 km, 5 km and 10 km resolution, respectively) or high resolution local maps (e.g., (Bomblies, Duchemin, and Eltahir, 2008) has a 10 m resolution). Medium resolution maps are able to show spatio-temporal patterns while high resolution maps can show hotspots (which are usually smaller than 1 km^2 (Bousema et al., 2012)). High resolution global maps, however are not yet present. These global high resolution maps could provide spatial and temporal knowledge of transmission hotspots in regions where thorough malaria prevalence studies are too costly, hence, reducing the costs of malaria control.

The knowledge of spatio-temporal dynamics of hotspots is of importance to successfully predict future hotspots but also to investigate the effectivity of current malaria controls (e.g., if malaria controls are applied to a village will malaria

hotspots shift to another village?). Especially in developing countries, where economic resources are limited, knowledge of the locations of these hotspots are of importance to implement effective and cost efficient control measures (Bousema et al., 2013; Bousema et al., 2010; Ernst et al., 2006).

Maps of malaria prevalence are in general, mapped as transmission of malaria: transmission suitability (a value between 0 and 1, 0 has the lowest probability of transmission and 1 the highest) (Craig, Snow, and Sueur, 1999), *Plasmodium falciparum* endimicity (Gething et al., 2011), malaria transmission (Bomblies, Duchemin, and Eltahir, 2008) and entomological inoculation rates (Tompkins and Ermert, 2013). Please note that *Plasmodium falciparum* is the main parasite which causes malaria in humans in Africa.

In health geography, exposure can be interpreted as both individual exposure and population exposure (Watson, Bates, and Kennedy, 1988). In the case of malaria, individual exposure can be defined as the biting rate of malaria vectors (mosquitoes) an individual experiences (Govella, Okumu, and Killeen, 2010). The population exposure is the exposure for a group of people which is aggregated (Watson, Bates, and Kennedy, 1988). Population and individual exposure to transmission is used to quantify the severity of malaria transmission in relation to population present at that location. Therefore it is a valuable asset in computing the spatio-temporal patterns of the impact of malaria.

The remainder of this thesis starts with the objectives and research questions. This is followed by the literature review, methodology, results and discussion. Finally, the conclusion is presented and recommendations for future research will be given.

Chapter 2

Objectives and research questions

The objective of this study is to investigate the change in exposure to *Plasmodium falciparum* (i.e., the malaria parasite) on a 30 m spatial resolution between 2000 to 2013 in Uganda. In this thesis, global datasets will be used to enable mapping at a global scale in future studies. Uganda will be used as study area to develop and validate the model due to the availability of survey data, strong spatial differences in malaria prevalence and the small size of the area, which reduces computation time. From the objective, the main research question is defined as:

How does the exposure to *Plasmodium falciparum* in Uganda change over time (2000 to 2013)?

Sub questions:
• Which environmental and socio-economic factors influence *Plasmodium falciparum* transmission? And how are their (spatial and temporal) characteristics related to *Plasmodium falciparum*?
• What is the malaria transmission suitability in Uganda and how does it change between 2000 to 2013?
• Does the *Plasmodium falciparum* transmission suitability map explain the empirical data of malaria incidences and how can we explain the differences?
• What is the exposure of the population to malaria in Uganda and how does it change over 2000 to 2013?

Chapter 3

Literature review

3.1 The malaria transmission cycle

Malaria is caused by the *Plasmodium* parasite and mainly uses vectors (mosquitoes) of the genus *Anopheles* to transmit the parasite. The malaria transmission cycle has three stages: development of the vector, the gonotrophic cycle and the sporogonic cycle. Transmission is part of the gonotrophic cycle of a vector. The gonotrophic cycles consist of feeding on hosts and reproducing (mating and oviposition). A vector could become infected when it feeds on an infected host. If infected, the sporogonic cycle starts which is the multiplication of the parasites inside of a vector. Finally the vector will be able to disperse the parasite to other hosts as part of the feeding section of the gonotrophic cycle. The development of vectors occurs after oviposition. When fully matured, these vectors will start their own gonotrophic cycle.

In general, the development of the vectors, gonotrophic cycle (reproductive and feeding) and sporogonic cycle (the parasites multiplication in the vector) are dependent on the factors stated in figure 3.1.

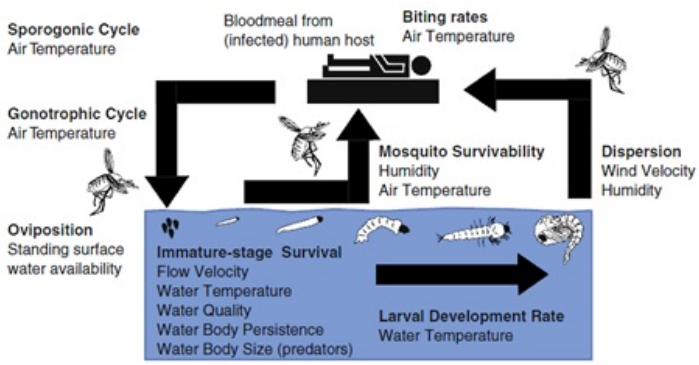

FIGURE 3.1: The malaria transmission cycle (Smith, Macklin, and Thomas, 2013).

3.2 Environmental and social dependencies

The type of *Plasmodium* parasite and especially the type of vectors determines the social and environmental dependencies of the transmission. Table 3.1 provides the three most prominent malaria vectors of malaria in Africa and observations of habitats and oviposition sites. Generalizations in preferences of vectors can be complicated (Muirhead-Thomson, 1951). This is a result of the adaptibility of the *Anopheles*

species complex (Fillinger et al., 2004), they are able to reproduce in any available water. Vectors however, do show slight breeding preferences (Holstein, 1954) as can be seen in table 3.1.

Table 3.2 presents an overview of the environmental and social dependencies of oviposition site selection and hence malaria transmission. Which are in fact the underlying factors of the preferences stated in table 3.1 .These factors or dependencies are further discussed in this literature review. Oviposition site selection and the spatial characteristics of malaria transmission are connected by the dispersion capacity of vectors. The dispersion is therefore of importance and is further elaborated in this section.

3.2.1 Air temperature

The survivability of vectors, the speed of the gonotrophic and sporogonic cycle and development of the vectors are mainly dependent on temperature and humidity (Bayoh, 2001). Water and air temperature and humidity influence the speed of development and the survivability of adult mosquitoes. In ideal circumstances, adult mosquitoes could survive up to 45 days (Bayoh, 2001). The parasite *Plasmodium falciparum* has a different relation on temperature than its vector, therefore a trade-off has to be made between vector survival and parasite development (sporogonic cycle) within the vector for adequate transmission (Hay et al., 2000; Gething et al., 2011).

The development into an adult mosquito takes about 16 days (1 day egg, 10 days larvae, 1 day pupae, 4 days of drying) with an average temperature of 24 degree Celsius (Niaz Arifin, Davis, and Zhou, 2010). Furthermore, sporogony can take 6 days at high temperatures (approximately 35 degrees Celsius) up to 28 days at low temperatures (approximately 20 degrees Celsius) with sufficient vector survival (5.9% at low temperatures and 29% at high temperatures)(Hay et al., 2000). Finally, after being developed in a full grown adult, the *An. gambiae* female looks for a mate, seeks a bloods meal, digests the blood meal and lays her eggs. This gonotrophic cycle takes typically 2 to 3 days. This period decreases with a temperature increase (Hay et al., 2000). Leaving humidity aside, this promotes that transmission is plausible if a temperature of 20 to 30 degrees Celsius is sustained for at least 24 days after egg placement. The thermal range for the *An. gambiae s.l.* is 18 to 34 degrees Celsius. Outside of this range no adult vectors will emerge (Bayoh and Lindsay, 2004).

3.2.2 Water, predators and nutrients

Figure 3.1 indicates that water is needed for oviposition and the development of new vectors. Observations of oviposition sites state that *An. arabiensis* and *An. gambiae s.s.* both prefer small, temporary habitats which are sunlit (no vegetation) whereas the *An. funestus* has a preference for larger, more permanent water with aquatic vegetation table 3.1. It seems that the main preferences regarding water consist of temporal continuity of water and size of the pools (i.e., depth and extent). These preferences are further elaborated in this section.

Temporal water characteristics

The time span of existence of pools or other forms of water can be of influence on the productivity of a site. The longer the water is present, the higher the negative influence of predators, disease and nutrient competition on the productivity (Depinay et al., 2004). The length of the presence of pools of water is dependent on the season (either wet or dry, warm or cold) and the sub surface. A high temperature can cause strong evaporation. Combined with a porous sub surface and little precipitation this can lead to a shorter time span of water availability. Vice versa, a non-porous subsurface, low temperatures and high precipitation can cause a longer time span of water availability.

Seasonal water characteristics

Water availability and malaria incidence rates change throughout the year. In the dry season, some rivers obtain a low flow rate. If this flow rate drops below a certain threshold, it will become a viable breeding habitat. The drying out phase of habitats just after the wet season also appears to play a critical role. Larvae retreat to places where an adequate amount of water is present, hence retreating to paleo channels, ephemeral river channels and spring fed ponds in the dry season (Smith, Macklin, and Thomas, 2013). Therefore it is expected that malaria incidences near rivers will come to a rise when transitioning from the wet season to the dry season. In the wet season itself the malaria incidence will be high due to a high amount of precipitation events. Therefore in the wet season and the transition of the wet and dry seasons, transmission is expected to be higher than during the dry season (since then, there is no water present).

Observations confirm the rationale. In the Sahel, seasonal effects of malaria are especially present due to the brief but heavy rainfall. In Niger, ephemeral pools, which are bound to precipitation events, are usually used as breeding sites (Bomblies, Duchemin, and Eltahir, 2008). It has also been shown that the number of vector larvae in water-retaining alluvial deposits along the Gambia peaks one month after the peak rains (Bøgh et al., 2003). Others also report that malaria breeding habitats will peak after a precipitation event (Hardy et al., 2013; Gimnig et al., 2001). Furthermore, Tanzanian lowland transmissions are perennial with a significant peak in the rainy season after the long rains in May, when vectors densities were high (Bødker et al., 2003).

Finally, a significant decrease in malaria transmission throughout Uganda at the end of the dry season was found (Okello et al., 2006). Just after a drought period however, the *An. gambiae* population sizes rises to a peak (Service, 1997). The alternation of wet season to dry season and dry season to wet season, as well as light precipitation events are pronounced causes for increased vector populations.

While most vectors prefer a small time span that water is present, the *An. funestus* forms an exception and prefers permanent water (Gillies and De Meillon, 1968). Also, other malaria vectors (*An. gambiae s.l.)* were found in more permanent waters (Fillinger et al., 2009; Fillinger et al., 2004). These permanent waters usually consist

of swamp rice cultivation fields or other man-made habitats as cemented-lined pits.

Concluding, the beginning and end of the wet season and the wet season itself seems to have the strong vector density rates whereas the end of the dry season has the lowest vector density rates. Some vectors (*An. funestus*) will sustain throughout the year. And other vectors will sustain throughout the year only in man-made habitats.

Predators, disease and carrying capacity

Predators, nutrients and disease decrease the productivity of an oviposition site. Predators and pathogens are a major factor of mortality (Service, 1997). It can be seen in table 3.3, that the highest amount of deaths attributable to predators is present in the pupae stage.

Service (1997) also found that in pools where predator density was low, 15.9% of the *An. gambiae* were infected with pathogens and parasites which eventually caused mortality. Hence development is limited with an increase of both predator pathogens and predators. Service (1997) noted that in temporary water, predators and pathogens will increase pre-adult mortality with a certain time lag and about 37% of the deaths of pupae are related to predators.

The larvae stage of a mosquito is associated with nutrient uptake. If the carrying capacity of a habitat is exceeded, pupae will use cannibalism to increase their own chances of survival (Hoek, 2015; Depinay et al., 2004). Therefore the carrying capacity of a certain habitat is also a limiting factor in the development of vectors. As a result of pathogens, predators and nutrient competition, only 10% of the eggs develop into adult mosquitoes (Costantini et al., 1996).

Predators, diseases and nutrients limit productivity in oviposition pools, however they are not present when a pool has just been formed or when it is cleaned by humans (Fillinger et al., 2004). Furthermore, it is found that younger habitats, that were cleaned every 10 days had 1.7 times more larvae than habitats that were cleaned every 30 days (Munga, Vulule, and Kweka, 2013). According to Fillinger et al. (2004) predators have a 20 day time-lag after the emergence of a new water source for predators to reach full capacity. Moreover, carrying capacity is not reached in the early stages of the pools. Hence, the shorter the timespan of the pools, the higher the productivity.

Water depth and extent

Water depth and extent influence the flow rate (due to wind) and temperature of the pools. Oviposition sites are preferred to have a relatively high temperature (for an increased speed of development of vectors (Bayoh and Lindsay, 2004) and a low flow rate. Therefore, the depth and extent of pools are mostly found to be small (table 3.1).

Consensus of preference of small pools is not present in observations. The *An. gambiae s.l.* breeds in both small waters (like cattle wallows, wheel tracks and domestic container) but also river margins, rice fields and seepage plains (Carter, Mendis, and Roberts, 2000). In Kenya, 80% of all *An. gambiae* in swamp marches and roadside ditches (Minakawa et al., 2004). Human-made larval habitats such as cement-lined pits were also important in malaria proliferation (Girardin et al., 2004). Furthermore, in The Gambia, floodplains are used as swamp rice cultivations which produced the vast majority of breeding sites (Fillinger et al., 2009). Bomblies et al. (2008) presents that in the Sahel, pools containing vectors are in the order of 10 m in diameter. An example where *An. gambiae* still breeds is rice fields, which are usually large water pools of relatively low depth (Klinkenberg et al., 2003). Rice fields have a large surface area but plants disrupt water velocity contributing to vector growth (Fillinger et al., 2009). According to Gillies and De meillon (1968) the *An. funestus* also breeds on the edges of the Wellcome dam in Kenya (13000 m^2).

Observations differ from human-made habitats to natural habitats and from an extent of the Wellcome Dam to the extent of a cattle's wallow. The depth, however, does not vary significantly. The depth of pools is usually less than 1 m (Paaijmans et al., 2010). Breeding sites in larger pools or lakes can also be located at inlets that have a low water velocity and shallow water depth (Tompkins and Ermert, 2013). High soil moisture in these inlets can also boost the breeding capacity of such an area (Bøgh et al., 2007). Therefore it is likely than *An. funestus* breeds in shallow waters on the edges of the Wellcome dam in Kenya. Hence, the influence of water depth has a higher priority in the vectors' choice of oviposition sites than the extent of pools. In general pools with a large extent will decrease the oviposition suitability of a site. A large water depth will decrease this suitability even more.

3.2.3 Anthropogenic influence

Humans have two ways of influencing malaria transmission. The first is the creation of strong oviposition sites; second is the necessity of humans for the transmission of malaria.

Studies present that human-made depression are strong foci for vectors in villages. This is due to the large period of time that the water is maintained but also because of the high quality of the water. Nutrients are therefore maintained throughout time. Human made depressions consist of cattle wallows, wheel tracks and domestic containers (Carter, Mendis, and Roberts, 2000; Girardin et al., 2004; Fillinger et al., 2004). These human-made depressions are especially important in small human settlement like villages.

The second way of influencing malaria transmission is the necessity of human host in the transfer of malaria from one vector to another (figure 3.1) (Beier, 1998). This is due to the fact that vectors can only obtain the parasite by feeding on a human host.

The distance of humans towards oviposition sites is therefore of considerable importance in multiple ways for transmission. Many studies find increases of malaria incidences of villages near lakes or rivers (Bomblies, Duchemin, and Eltahir, 2008). Usually the smaller the proximity of water to villages the higher the incidence rates

(Van Der Hoek et al., 2003; Oesterholt et al., 2006; Mutuku et al., 2006; Gu and Novak, 2009).

While a small increase in population may increase breeding sites and malaria transmission possibilities (Minakawa et al., 2004), urbanization will actually decrease infection of people due to elimination (concretization) of breeding sites and increasing pollution of the remaining sites (Hay et al., 2005). The studies presented above (Van Der Hoek et al., 2003; Oesterholt et al., 2006; Mutuku et al., 2006; Gu and Novak, 2009) are conducted in villages and not in highly urbanized area. Therefore the urbanization effect on oviposition sites is not visible. The urbanization effect is visible in figure 3.2, which states that the annual infected bites per person decreases with an increase of urbanization.

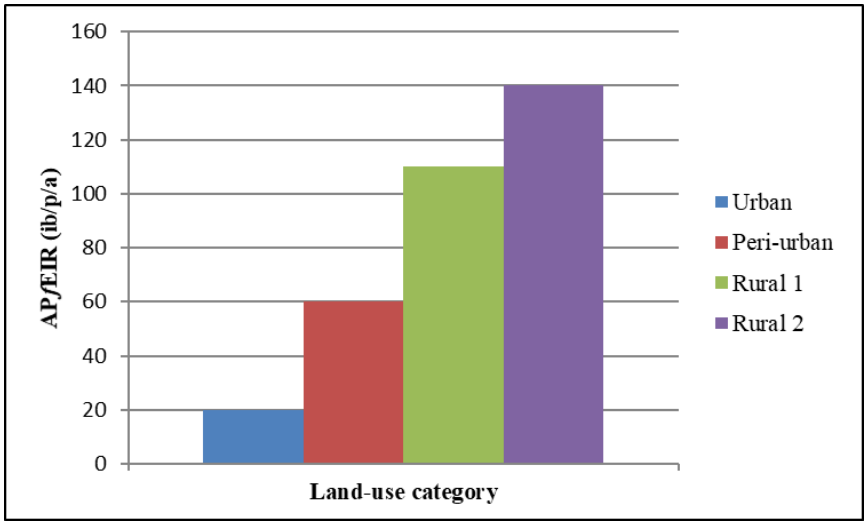

FIGURE 3.2: A declining APfEIR (Annual infected bites per person) with increasing urbanization (Hay et al., 2005).

3.3 Vector dispersion capacity

Oviposition locations are not only dictated by site preferences and temporal characteristics of these sites, but distance towards human settlements is also a contributing factor. Service (1997) reviewed these appetential (active) flights of vectors in literature. In general, the conclusion is that while some vector species could fly large distances (25 km (Hocking, 1953)), most of the vectors will not fly these distances if this is not needed. Malaria incidence rates will be highest near breeding places. However, flight distances can be over multiple kilometers if oviposition sites and hosts are widely separated. Wind speed and the kind of species can influence the flight distance (Service, 1997). Studies confirm that malaria incidences rates increase with a decreasing proximity towards breeding sites (Van Der Hoek et al., 2003; Gu and Novak, 2009; Midega et al., 2007; Costantini et al., 1996). For the *An. gambiae s.l.* it is often recommended that a 2 km barrier should be considered when practicing malaria control programs (Service, 1997). There are however cases in which there are differences in flight distances of vectors (Carter, Mendis, and Roberts, 2000). Therefore, is could be said that for vector dispersion capacity a 2 to 3 km range would be appropriate. Food shortage and adequate wind speeds may allow these vector to fly

out of this range (Carter, Mendis, and Roberts, 2000).

TABLE 3.1: An overview of observations of habitats and oviposition sites of different Anopheles species.

References	*An. gambiae s.s.*	*An. arabiensis*	*An. funestus*
(Ayala et al., 2006; Minakawa et al., 2002; Girardin et al., 2004; Holstein, 1954; Minakawa et al., 1999; Van Der Hoek et al., 2003)	Proximity to human settings	Proximity to human settings	Proximity to human settlements
(Bøgh et al., 2003)	Alluvial deposits in flood plains	Rice nurseries	
(Bombies, Duchemin, and Eltahir, 2009; Bomblies, Duchemin, and Eltahir, 2008)	Small ephemeral pools, temporary water, near human habitation	Small ephemeral pools, temporary water, near human habitation	
(Muirhead-Thomson, 1951)	Small, temporary, clean, sun-exposed water	Small, temporary, clean, sun-exposed water	
(Fillinger et al., 2009)	High water temperature and turbidity low conductivity, presence of algae and absence of tidal water		
(Gimnig et al., 2001)	Small, temporary habitats with algae and not vegetation	Small, temporary habitats with algae and not vegetation	Large, semi-permanent bodies of water containing aquatic vegetation
(Gillies and De Meillon, 1968)	Sunlit pools	Sunlit pools	Permanent water bodies
(Imbahale et al., 2011)	Both temporary and permanent human-made habitats	Both temporary and permanent human-made habitats	
(Klinkenberg et al., 2003)	Rice fields in early growing stages	Rice fields in early growing stages	
(Munga et al., 2006a)	Farmland habitats	Farmland habitats	
(Munga et al., 2006b)	Little predators and competitors	s Little predators and competitors	
(Mutuku et al., 2006)	Soil burrow pits, streambeds	Soil burrow pits, streambeds	
(Emosairue, Ogharanduku, and Nmor, 2015)	Open, sunlit and undisturbed habitats for oviposition	Open, sunlit and undisturbed habitats for oviposition	
(Sattler et al., 2005)	Small, highly organic polluted breeding sites	Small, highly organic polluted breeding sites	Small, highly organic polluted breeding sites
(Minakawa et al., 2012)		Man-made pools and lagoons	Vegetated habitats in lagoons

TABLE 3.2: An overview of the environmental and social dependencies of the transmission of malaria.

Dependency	Description	References
Air temperature	· The speed of development (of vectors) and sporogonic cycle of malaria of the vectors are dependent on temperature. · Air temperature partly determines the speed of which the first transmission could occur after a new aquatic oviposition site is created.	(Bayoh, 2001; Hay et al., 2000; Gething et al., 2011)
Temporal water	· The time that an aquatic habitat is present has an effect on the productivity of vectors (malaria transmission)(temporal water). · The vector productivity of a temporal aquatic site is further dependent on predators, disease and carrying capacity and seasonal water characteristics	(Depinay et al., 2004; Smith, Macklin, and Thomas, 2013; Service, 1997)
Water depth and extent	· The depth and extent of an aquatic habitat will influence flow rate (the smaller the pool, the less wind-related waves) and also the temperature of the water (the smaller the pool, the stronger the increase in temperature when exposed to the sun).	(Service, 1997; Paaijmans et al., 2010; Klinkenberg et al., 2003)
Population	· People are necessary for malaria transmission. · Urbanization however will decrease malaria transmission due to concretization and pollution.	(Carter, Mendis, and Roberts, 2000; Hay et al., 2005; Beier, 1998)

TABLE 3.3: Percentages of deaths attributable to predators (Depinay et al., 2004).

	Stage duration (days)	With predators	Without predators	Attributable to predators
Larvae	9.98	90.9	79.58	11.34
Pupae	1.79	73.49	35.63	37.86
Total	11.77	97.6	86.85	0.11

Chapter 4

Data and study area

4.1 Data

To maintain the possibility of mapping malaria suitability at a global scale, (most) datasets used are globally available. Furthermore, high resolution datasets are required due to the fact the high spatial variety in malaria transmission. The data is presented in table 4.1. The soil texture information was only provided once in 2012. The malaria incidence map consists of multiple surveys throughout Uganda from 2000 to 2015. This data set was only provided once.

TABLE 4.1: Datasets used in this study.

Dataset	Reference	Spatial extent	Spatial coverage	Temporal resolution
Open surface water	(Pekel et al., 2016)	Global	30 meter	monthly
(Linard et al., 2012; Worldpop, 2018)	Population	Global	100 meter	5 years
Digital elevation model	(RCMRD, 2018)	80 percent	30 meter	once
Precipitation	(Funk et al., 2015)	50°S to 50°N	5 km	Monthly
Temperature	(Karger et al., 2017)	All earth surfaces	1 km	Monthly
Evaporation	(Martens et al., 2017)	All earth surfaces	27 km	Monthly
Ground Texture	(Batjes, 2012)	All earth surfaces	10 km	Once (2012)
Malaria incidence observations	(Bhatt et al., 2015)	Multiple countries	point observations	Once (2000-2015)

4.2 Study area

Since mapping malaria globally is time consuming due to high computational demand, Uganda is used as study area. Global datasets are used to enable mapping at a global scale in future studies. Uganda is chosen due its differences in malaria prevalence (figure 4.1). The average annual temperature in Uganda is 26 degrees Celsius. From March till May and October till November it is the rainy season and in between the dry seasons, except for some light rains in November and December

(Okello et al., 2006). The effect of rainfall on malaria will vary with season and geography (Briët et al., 2008). This effect contributed to the variation in malaria prevalence in Uganda. This is confirmed by Okello et al. (2006) who did a prevalence study of *Anopheles* species at different locations in Uganda throughout 2002. The heterogeneity in the effect of rainfall on malaria prevalence is clear. The only spatial homogeneous trend occurs at the end of the dry season (in January), when transmission is observed to be lowest at all locations in Uganda. Okello et al. (2006) observed strong spatial differences in *Anopheles* biting rates throughout Uganda. Apac, a village located in a savannah grassland with extensive swamps near lake Kyoga has the highest biting rates (190 bites per man per month) whereas in villages located in hilly grassland, like Mubende only low biting rates (36 bites per night) are observed (appendix A). The figures below present the observations of *Plasmodium falciparum* in Uganda from 1984 to 2016.

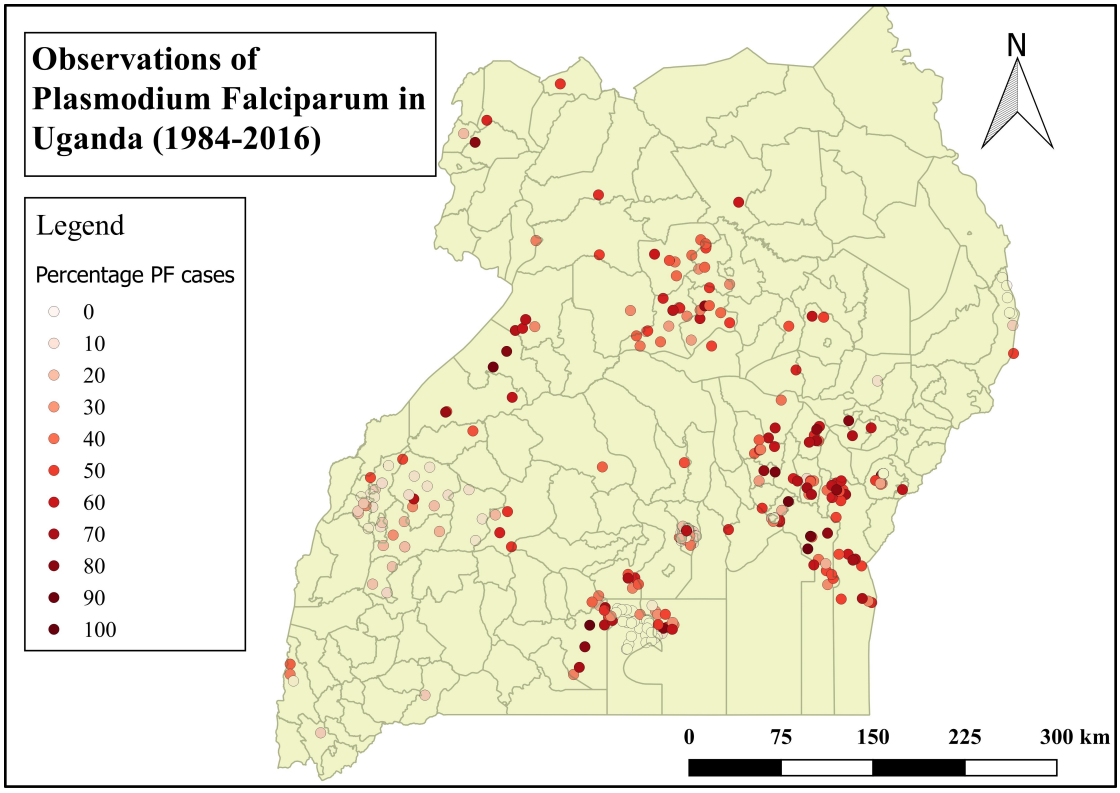

FIGURE 4.1: The percentage of *Plasmodium falciparum* cases out of the population in Uganda. The data is collected by the Malaria Atlas Project (Bhatt et al., 2015).

Within Uganda, multiple study areas are taken to increase the understanding of the reaction of the model on different areas. Areas near cities (Kampala), swamps (Kyoga), lakes (Victoria and George) are taken as is shown in figure 4.2.

As can be seen in figures 4.1 and 4.2, location, water content, population and incidences differ in these regions. Hence these regions have been chosen to explore the malaria transmission suitability in Uganda.

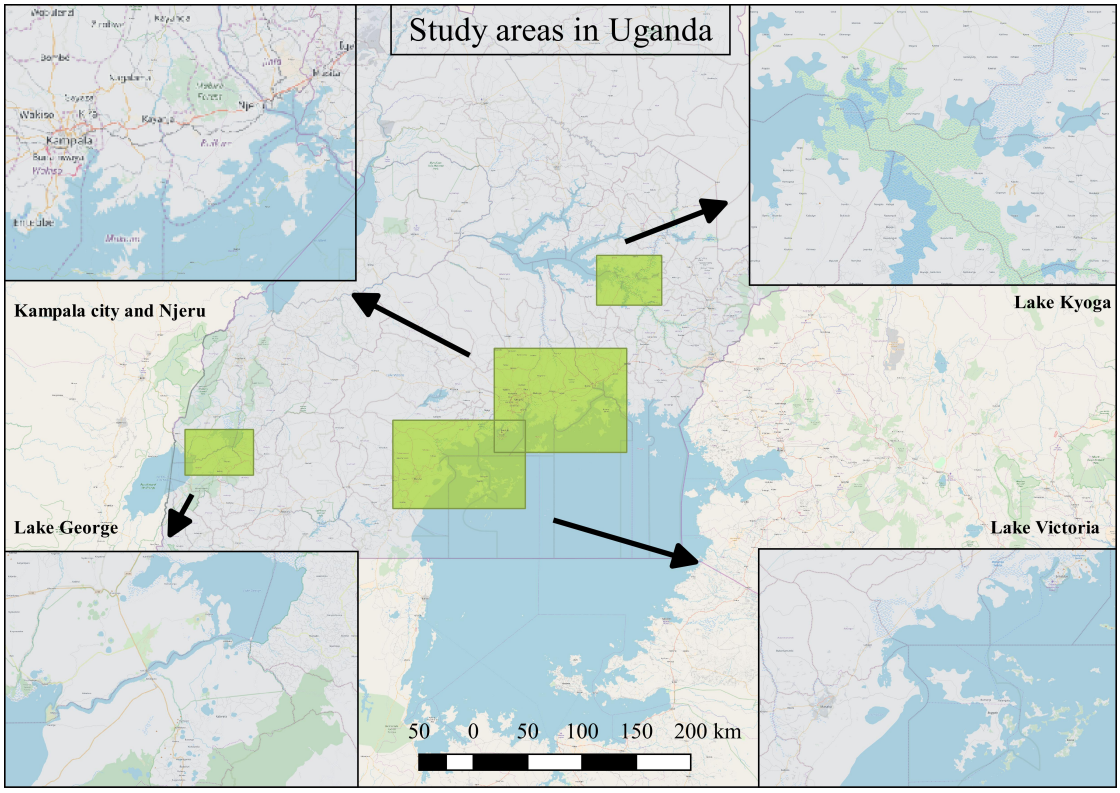

FIGURE 4.2: Multiple study areas within Uganda. The Kampala region, Lake George region, Lake Kyoga region and Lake Victoria region are presented in the left upper corner, left lower corner, right upper corner and right lower corner, respectively.

Chapter 5

Methodology

The transmission mechanisms and the weighted overlay to compute the malaria transmission map are presented first. This is followed by the methodology of the calibration and validation of the model. The section continues with the method for computing the exposure to transmission. Since the model tries to decrease the no data in the open surface water data set, the remainder of this section will described the methodology of this process.

5.1 The predictor variables for malaria transmission

The objective of this study is to map exposure to *Plasmodium falciparum*. Therefore the breeding sites of the most important vectors in Uganda are taken into account: *An. gambiae s.l.* and *An. funestus* (Okello et al., 2006). The location of oviposition sites and malaria transmission are dependent on the malaria determinants. The transmission mechanisms of malaria sites are derived from empirical data and literature research. Here, a short summary of these mechanisms are presented:

(i) Transmission risk increases with decreasing distance from open surface water.

(ii) Transmission risk increases with decreasing distance from population.

(iii) Transmission risk increases if temperatures are between 18 to 35 degrees for at least 24 days.

(iv) Transmission risk increases with more temporal variation in oviposition sites.

(v) Transmission risk increases with decreasing depth of water.

(vi) Transmission risk increases with decreasing extent of water.

In general the model to combine the malaria transmission rules to a malaria transmission map is static, with only a time component present in the water depth calculation (section 5.2.5). Variables that will change over space consist of temperature, population, evaporation and water. The constant components consist of infiltration capacity and the local drain direction.

5.2 Methods to represent transmission mechanisms

5.2.1 Predictor variable 1: Population density

The population density predictor connects malaria transmission suitability with population density in an area. Only in the large cities it is expected that malaria transmission is almost eradicated completely, while in villages and semi-urban areas,

concretization and malaria control is not yet at full capacity. Hence, it is assumed here that suitability of transmission increases in rural areas and decreases (slowly) in peri-urban until it reaches 0 in urban areas.

The following formula and figure are used to represent this in the model. Formula 5.1 is plotted in figure 5.1.

$$P_s = \begin{cases} \frac{1}{P_t} P_d & \text{for } P_d < P_t \\ \frac{1}{P_t - U} P_d & \text{for } P_d > P_t \end{cases} \tag{5.1}$$

Where U is the urbanization limit, P_s is the population density suitability, P_d is the density of population in square kilometers and P_t is the threshold for population. The value of P_t is 250 persons per square kilometer. This value indicates the difference between rural and sub-urbanized areas (Hay et al., 2005). Urbanized areas are defined by Hay et al. (2005) as more than 1000 people per square kilometer, hence this is used as the urbanization limit U in this function. Please refer to appendix B for an overview of the parameters used in this thesis.

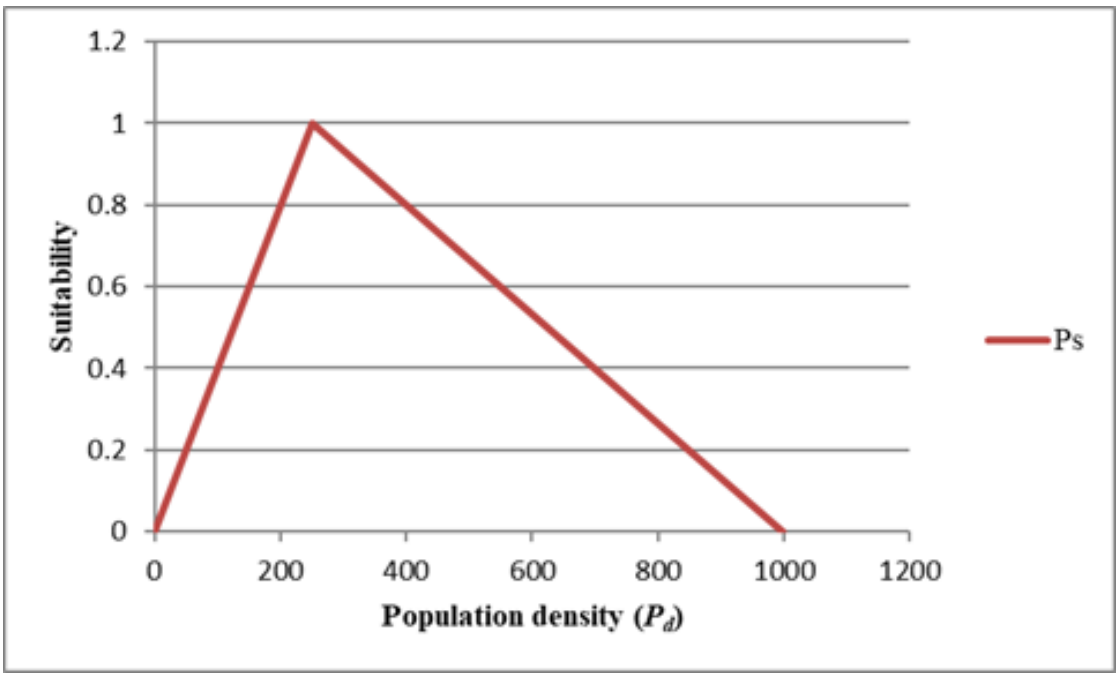

FIGURE 5.1: The population density suitability function.

5.2.2 Predictor variable 2: Surface water proximity

Rule 2 associates open surface water with transmission risk. In general, open surface water is associated with a high water table (or landscape depressions). People will use high water tables to create wells or use it for agricultural purposes. Therefore the likelihood of natural small ponding waters and anthropogenic surface water (pools smaller than 900 m^2 which cannot be seen in the open surface water dataset) being located around open surface water is higher than in other areas.

The surface water proximity transmission suitability is a distance decay function. Transmission risk is higher when being closer to breeding sites. Studies (Gu and Novak, 2009; Van Der Hoek et al., 2003; Midega et al., 2007; Costantini et al., 1996) show an exponential decrease of vectors the further it gets away from its habitat, here, an

exponential decrease is chosen as well. After a certain threshold distance, the change in suitability becomes almost zero due to the fact that little vectors will go further than that threshold distance. Equation 5.2 presents this in the model:

$$D_s = e^{D_c(-(\frac{D_i}{T_w}))} \tag{5.2}$$

Where D_s is the surface water proximity suitability, D_c is a coefficient that decreases the impact of larger distances on the suitability, D_i is the distance in meters to pixel i, and T_w is the surface water threshold in meters. While it is recommended that a 2 km barrier is used around breeding sites (Service, 1997), a flight distance threshold of 5 km is chosen here. This is because it is expected that some vectors, if needed, will pass the 2 km threshold as stated in Service (1997). With a relatively high value of 4 for the D_c, the emphasis of the suitability is placed on the shorter flight distances.

Equation 5.2 is plotted in figure 5.2.

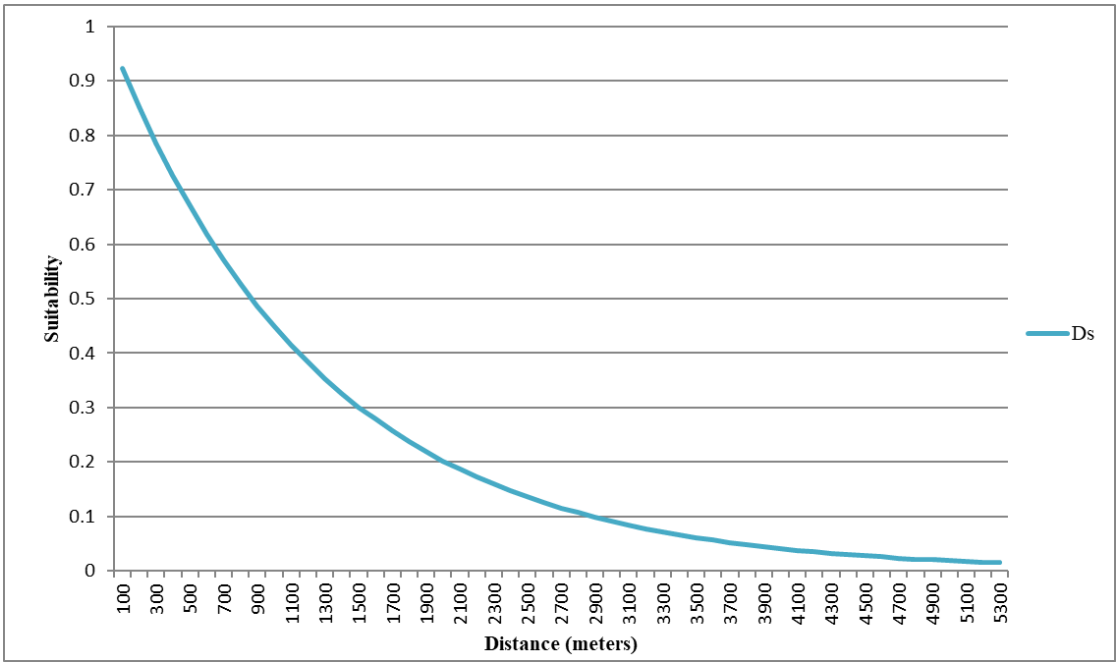

FIGURE 5.2: The water distance suitability function.

5.2.3 Predictor variable 3: Temperature

Rule 3 addresses the speed of development of the malaria parasites and their vectors, which is dependent on temperature. Temperatures in the suitable range will fluctuate; the highest suitability is given at temperatures of 30 degrees Celsius (highest vector survival (Hay et al., 2000)) and the lowest suitability is given towards the edges of the function, which are 18 to 35 degrees Celcius. These rules are only applied when these temperatures do not exceed a temperature range of 18 to 35 degrees Celsius for at least 24 days. Adult vectors will not be produced outside of the given temperature range (Bayoh and Lindsay, 2004). In general, 24 days is the fastest transmission possible after oviposition (section 3.3.1). Hence transmission is possible if a viable temperature is maintained for 24 days. Please note that it is known

that development speed in the aquatic stage is dependent on the water temperature, not air temperature. It is assumed here that air temperature forms an adequate representation of water temperature since water temperature is a derivative of air temperature. The suitability at a certain temperature will be given according to the following functions.

$$T_s = \begin{cases} (T - T_l)\frac{-1}{T_l - T_m} & \text{for } T_l < T < T_m \\ (T - T_m)\frac{1}{T_m - T_u} & \text{for } T_m < T < T_u \end{cases} \tag{5.3}$$

Where T_s is the air temperature suitability, T_l is the lower suitability limit temperature, T_m is the maximum suitability temperature and T_u is the upper suitability limit temperature and T is temperature in degrees Celsius.

5.2.4 Predictor variable 4: Temporal water

After the start of the formation of pools, water will reach its highest suitability due to strong nutrients and a lack of predators. It is assumed here that if all eggs in an oviposition site become adults, the suitability is 1. As presented in table 3, the total death of vectors that is attributable to predators is about 11% of the total pupae and larvae in an oviposition site. Hence it can be concluded that suitability decreases to 0.89 after 20 days, since then, predators will be on full capacity (Service, 1997). Then, pathogens and carrying capacity of the breeding spot will limit the suitability, linearly to 0.5. After four consecutive months the seasonal suitability will drop to 0.3, due to the fact that rice fields take up to four months from planting till harvesting. After harvesting, rice fields are not plausible oviposition sites anymore due to an increase of wind influence. After these four months the rice fields usually dry out as a result of the end of the wet season (Fillinger et al., 2009). If water is still present, it is considered to be permanent and hence only proper for the *An. funestus* species. The function is presented in figure 5.3. The temporal water suitability is defined as W_s.

5.2.5 Predictor variables 5 and 6: Water depth and extent

Water depth and water extent could be a potential proxy for water velocity, temperature and quality and subsequently for malaria transmission suitability. Ponding water and wet alluvial soil near rivers (Thomas and Lindsay, 2000; Bøgh et al., 2007; Smith, Macklin, and Thomas, 2013) could also be potential oviposition sites and are associated with local topographic depressions. While the presence and extent of water is dictated by the empirical dataset (Pekel et al., 2016), water depth is generated by a flow accumulation function.

Multiple factors play a role in the estimation of water depth. Precipitation is used as the starting point for calculating the water depth. Two other important factors, evaporation and infiltration are included here. Total infiltration capacity is estimated by the ground texture and the findings of Mangala et al. (2016) which relates texture to maximum infiltration capacity (Mangala, Toppo, and Ghoshal, 2016). Please note that these infiltration rates are used in a relative manner (i.e., actual infiltration rates are not used, only the knowledge that for example infiltration rates are higher in sand compared to clay). Infiltration is calculated according to the following formula:

$$I = P(\frac{I_c}{M_i}) \tag{5.4}$$

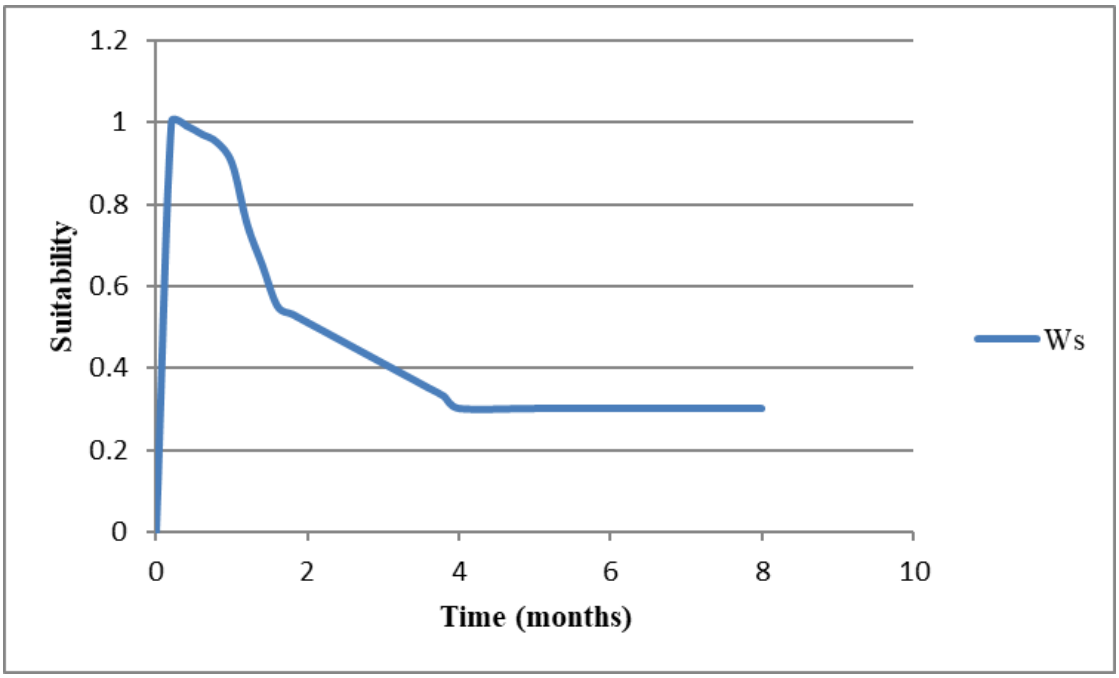

FIGURE 5.3: The temporal suitability function.

Where I is the monthly infiltration in milimeter (mm), P is the monthly precipitation in milimeter, I_c is the infiltration capacity in milimeter per hour and M_i is the maximum infiltration capacity in the study area. Infiltration is combined with evaporation of the GLEAM model (Martens et al., 2017) to form the main outflow.

The following function is used for calculating the water depth:

$$W_c = P - E - I \tag{5.5}$$

Where W_c is water depth change in mm per month, P is precipitation in mm per month, E is evaporation in mm per month and I is the infiltration in mm per month. Please note that lateral and ground water flow are not accounted for and that only overland flow is considered by equation 5.4.

A local drain direction map combined with the W_c as stated in equation 5.4 is be used to compute the water accumulated in the depressions of a digital elevation model (DEM). Please note that discharge is not included in equation 5.4 due to the fact that only W_c is calculated for depressions in the DEM. Hence it is assumed that the outflow of these depressions is mostly attributable to infiltration and evaporation and there is no or little outflow to rivers or larger water bodies.

The water changes of previous months will also be included to estimate the current water depth of the depressions. For that purpose, the following equation is used:

$$W(t) = W(t-1) + W_c(t) \tag{5.6}$$

Where *W(t)* is the water depth at a current time step, *W(t-1)* is the water depth of the previous time step, and *Wc(t)* is the change in water in the current time step.

The water body extents are calculated by equation 5.7:

$$E = \sum_{i=1}^{r} S * P_i \tag{5.7}$$

Where E is the extent of a water body, P_i is the presence of water in pixel i, S is the size (or resolution) of a pixel, r is the maximum radius of water bodies in which transmission is expected. The pixels that contain water are summed in a radius of 4000 m. After the radius of 4000 m it is expected that there is only little of transmission. While this is in contrary to the findings of Gillies and De meillon (1968) (malaria vectors on the edge of a large lake), it is thought that these findings will come forward in water depth and not water extent. In other words, water depth will be of more influence than water extent in regions of large lakes.

The distribution of water, within a pixel, is not heterogeneous. There may be high and low concentrations of water. As explained earlier, the range in water height for oviposition is 0 cm in wet soil to about 150 cm in rice fields (Paaijmans et al., 2010). Since very small pools (hoof prints, wells) cannot be noticed, it is assumed here that a low pool depth combined with a relatively small extent will have a high probability of having pools that are suitable for oviposition. The suitability averages are presented below. In the model, suitability is randomly picked within a normal distribution with a standard deviation of 0.025 and a mean that is dependent on the criteria presented in table 5.1. The randomness is incorporated due to the fact that the water extent ranges and the water depth ranges are of considerable size. A lower range is not possible due to restrictions of spatial resolution of the open surface water dataset and the possible errors in the DEM. Hence, it is unknown how the water extent and depth vary within these ranges as defined in table 5.1. Therefore randomness within a normal distribution is introduced here.

Water depth suitability is represented as H_s and water extent suitability is represented as E_s.

TABLE 5.1: The scores of the depth and extent transmission suitability function.

Transmission suitability	Suitability mean	H_s (m)	E_s (m^2)
Highest suitability	0.9	< 0.5	900
Medium suitability	0.6	0.5 - 1.0	900 - 2000
Low suitability	0.3	3 - 4	2000 - 4000
No suitability	0	> 4	> 4000

5.3 Predictor variable correlations

Different predictor may influence the malaria incidence observations (Bhatt et al., 2015) in different manners. Hence linear regressions between the malaria transmission predictors and the malaria incidence observations are made. The knowledge on the influence of the different predictors on the malaria incidences can be assessed using the regressions.

5.4 Missing data

The open surface water dataset of Pekel et al. (2016) has a considerable amount of missing data. The missing data can consist of snow, ice, cloud or sensor issues. It is expected that most of the no data in Uganda will come from sensor related issues and cloud cover. Figure 5.4 presents the number of scenes of Uganda which have a cloud cover of less than 20%. The figure shows that the number of scenes with less than 20% cloud cover increases over time. This would mean that the amount of scenes taken increases over time or that the missing data decreases over time. A spatial neighbourhood maximum method and a temporal continuity method have been designed and implemented to increase the usability of the dataset.

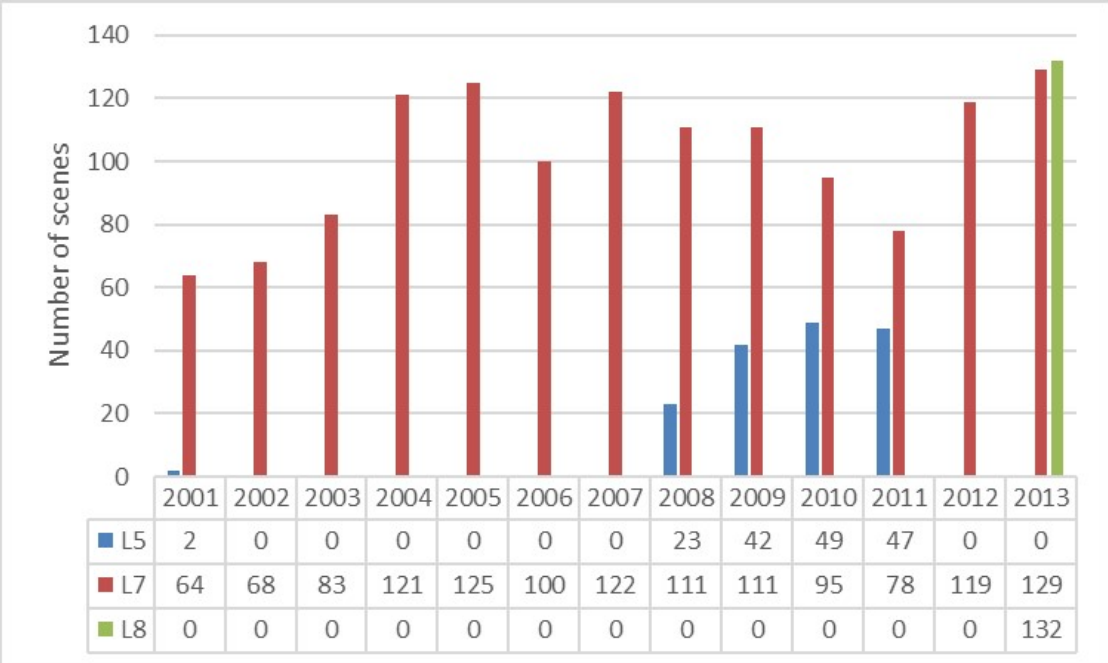

FIGURE 5.4: Landsat scences of Uganda with less than 20% cloud cover (CEOS, 2016).

The spatial neighbourhood maximum method computes the amount of land pixels and surface water pixels in the 8 pixels surrounding a missing data pixel. If more than half of the neighbourhood pixels is assigned water, the probability of having a lake in this area which also includes the pixel of interest is high. Hence, it is assumed that the pixel of interest is also water. If more than half of the neighbourhood pixels is land, then it is expected that the pixel of interest is also water. Especially the predictor variables water extent and water proximity are altered by this method. Hence this method is kept at a minimum.

The temporal continuity method looks at the time step before the current time step. If the previous time step shows surface water on a pixel that is no data in the current time step, the no data will become surface water. The same process is present for the land class. Due to that fact that this method will alter the temporal variable method, it is kept at a minimum as well.

The amount of time steps in the temporal continuity method and the amount of neighbourhood pixels used (defined as the radius from the pixel of interest) is dependent on the percentage of missing data in the current time step. The higher the percentage of missing data in the current time step, the higher the amount of time steps and neighbourhood pixels. Both methods are combined to derive the most optimum open surface water map.
Please refer to Busker (2017) for the visualization of the open surface water dataset by Pekel et al. (2015) .

5.5 Weighted overlay

The predictors are combined using a weighted overlay function. Different weights will be given to increase the influence of certain predictors on the total malaria transmission suitability. The influence of the weights will be defined with a calibration (section 5.6). The weighted overlay formula presented below.

$$S = \frac{P_s P_w + D_s D_w + W_s W_w + T_s T_w + E_s E_w + H_s H_w}{6} \tag{5.8}$$

The letters of formula 5.8 are explained in table 5.2.

TABLE 5.2: The description of the letters used in equation 5.8.

Variable	Predictors	Weights
Population density	P_s	P_w
Surface water proximity	D_s	D_w
Temperature	T_s	T_w
Temporal water	W_s	W_w
Water depth	H_s	H_w
Water extent	E_s	E_w
Total suitability	S	

5.6 Model calibration and validation

The suitability malaria map will be validated usings the malaria field survey data from the Malaria Atlas Project (MAP) (Bhatt et al., 2015). The survey data is also used to calibrate the weights of the predictor variables. For calibration the root mean square error (R) will be used as a goal function (equation 5.9). Calibration will start by using all the combinations for all weights in a range of 1 to 5, 5 to 10 and 10 to 15. Based on these results we will zoom in to find a lower rmse and hence a more accurate prediction capacity of the malaria transmission model. The objective function is stated in the following equation:

$$R = \sqrt{\sum_{i=1}^{r} \frac{(S_i - O_i)^2}{n}} \tag{5.9}$$

Where the R is the root mean square error, n is the number of observations S_i is the predicted value for observation i and O_i is the observed value for observation i. In this case, S_i will be the malaria transmission suitability average of 2013 and O_i is the percentage of malaria incidences in a field survey (Bhatt et al., 2015).

The quality of the datasets is highest in 2013 due to the fact that there is more no data present in older datasets. E.g., the open surface water map of January 1990 contain a considerable amount of no data whereas the map of January 2013 contains only little. Moreover, the temperature data set does not include years later than 2013. Hence, the data set is of the highest quality in 2013 and therefore used for calibration.

After calibration of the model, the malaria transmission suitability maps will be computed again. Then, linear regressions will be used to validate the malaria transmission suitability maps and the predictor variables. For the linear regressions, point observations of the malaria atlas project (Bhatt et al., 2015) will be used. Different years (not including 2013, since that year has already been used for calibration) and different areas are used for the validation.

5.7 Population exposure to malaria transmission

Once the malaria transmission suitability map has been made, the exposure is calculated. There are multiple definitions and multiple types of exposures. In this study, population exposure is derived from individual exposures. Individual exposure of malaria is defined as the number of bites by a vector infected with malaria (Govella, Okumu, and Killeen, 2010). While this study does not present a biting rate but transmission suitability, the transmission suitability is used as a proxy for biting rate. The higher the transmission suitability, the higher the probability of an increased amount of infected bites and hence the higher the individual exposure. In this way, only relative comparison between individual exposures is plausible.

According to the definition of Cardona et al. (2012), exposure refers to the inventory of elements in an area in which a hazard event may occur. I.e., if there are no people or elements, then there is no exposure. The population exposure distribution of the population in a certain study area is calculated according the following formula:

$$X_p = \frac{P_i}{P_t} \quad \text{for} \quad S_i > X_t \tag{5.10}$$

In which X_p is the exposure level the amount of people p above the exposure threshold X_t, S_i is the malaria transmission suitability (or exposure) in pixel i and $_t$ is the total amount of population in the study area. Multiple thresholds are made to derive an exposure distribution of the area.

Chapter 6

Results

In the following section the results will be described. First of all, the spatial and temporal variations of the malaria transmission predictor variables are shown. Second, the results of the robust calibration are presented. This is followed by the weighted overlay results of the malaria transmission suitability. Finally the results of the model validation and the exposure to transmission will be presented.

6.1 Spatial and temporal variation of the malaria transmission predictor variables

Figure 6.1 presents results of the spatial and temporal variation of malaria transmission. Only study areas are shown in which the predictor variables dictate the transmission suitability the most.

The changes in transmission suitability are given by the following formula:

$$C = \frac{(N - Y)}{N} \tag{6.1}$$

In which C is the change between two maps, N is the new map and Y is the old map. Hence, it is a rate of change based on the old map (e.g., the change from 2001 to 2006 till 2006 to 2013).

As is illustrated in figure 6.1 the change of temporal water transmission suitability varies strongly. The change from 2001 to 2006 till 2006 to 2013 shows decreases in temporal transmission suitability. In other words, it shows that pools do not have any change in occurrence (they stay present at the same spot for a longer time or are not present at all). The change in water proximity transmission suitability changes with the occurrence of water. Figure 6.1 shows some decreases in water proximity transmission suitability from 2001 to 2006 but especially from 2006 to 2013 near some large lakes. Further away from lakes, changes, both positive and negative, seem to be less strong as there is less water present. This also causes the large gradual changes in blue and orange. Finally, both water extent transmission suitability and water depth transmission decrease. The decrease in transmission suitability indicates either larger lakes which are unsuitable for malaria transmission or lack of water at a certain location.

Figure 6.2 shows that population increases in both the cities of Kampala and Njeru. The malaria suitability decreases due to the fact that urbanization increases in these cities. This occurs usually on the edges of cities or other urbanized places. Hence, there is a decrease in transmission suitability visible on the edges of the cities.

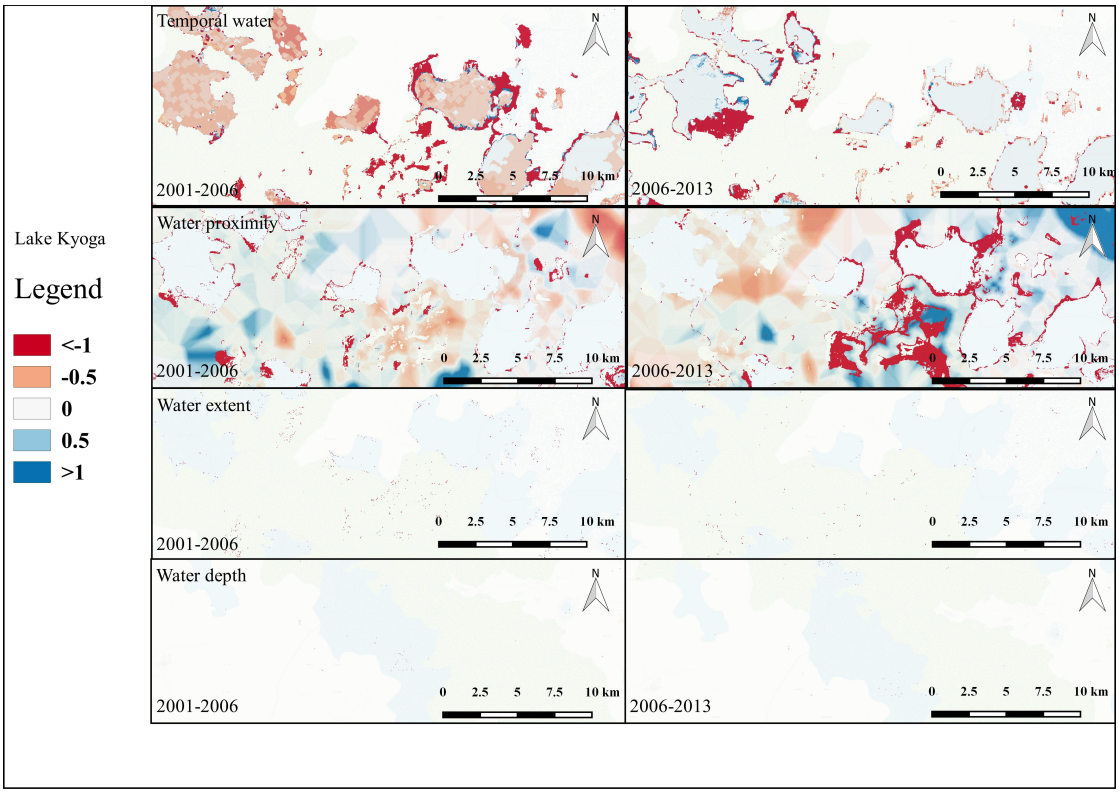

FIGURE 6.1: The changes in temporal water transmission suitability, water proximity suitability and lake extent suitability in Kyoga for the month December of 2001 to 2006 and 2006 to 2013. The change between maps is calculated by formula 6.1.

The temporal variation is described by a time series of the averaged yearly suitability of malaria transmission of the predictor variables. For the calculation of the averaged yearly suitability (table 6.1), the following formula is used:

$$A_{ya} = \frac{S_{yi}}{V_o} \tag{6.2}$$

Where A_{ya} is the yearly averaged and area averaged transmission suitability of predictor , S_{yi} is the yearly averaged suitability value of predictor transmission suitability for each pixel (i) and V_o is the total amount of data points per variable. The data points for temperature, population and water proximity are the total number of pixels on the map. The observation for temporal water, water depth and water extent are the amount of pixels where the variable is present (this is also shown in table 6.1).

Table 6.1 shows that the predictors water proximity, water depth and water extent change little between 2001 to 2013. The predictor variables temporal water, temperature and population density show larger changes. The temporal water predictor decreases in all years in all regions. The temperature predictor rises strongly in 2006 after which it decreases again in 2013. Furthermore, the population density shows a similar trend as the temperature predictor. A strong increase from 2001 to 2006 is present after which it decreases again from 2006 to 2013. The number of data points for water extent show a strong increase in 2006 in all regions. The observations of water depth seem strongly variable over time.

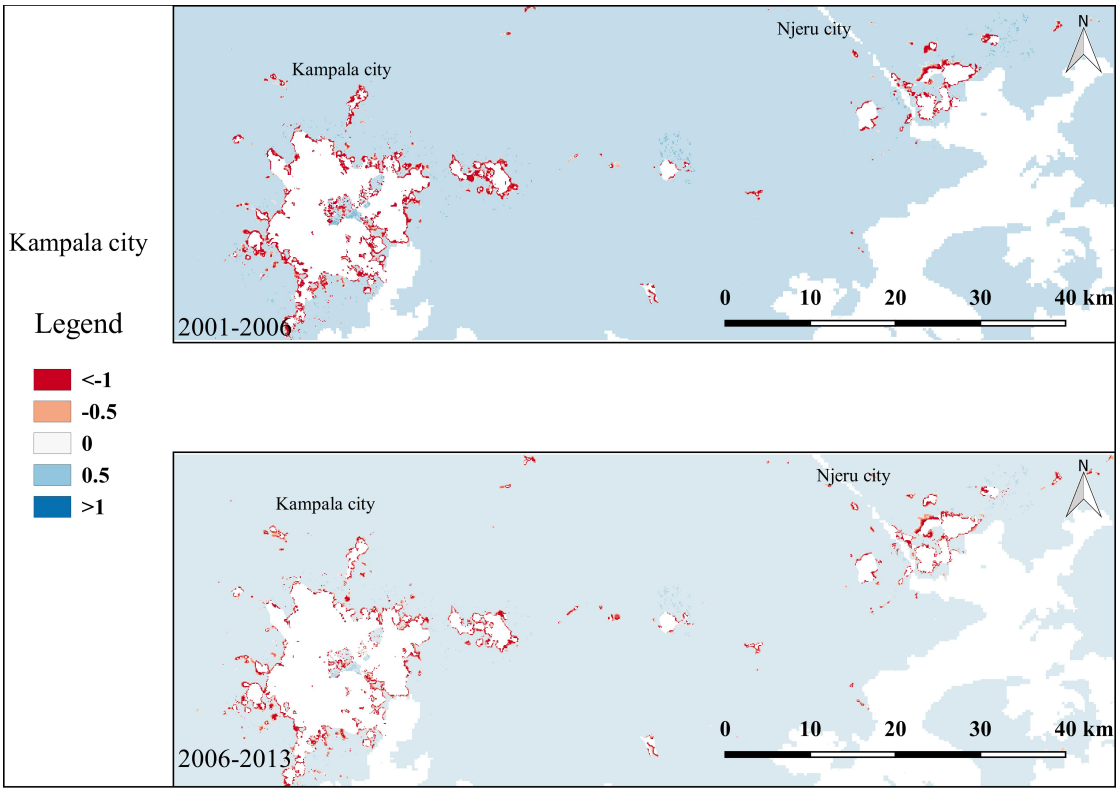

FIGURE 6.2: The changes in population density suitability in Kampala city for the month December for 2001-2006 and 2006-2013. The change has been calculated according to function 6.1.

6.2 Calibration results

Table 6.2 shows the root mean square error (rmse) results of different calibration runs. A general run was done for ranges between 1 and 15. The lowest rmse was obtained when all weights were ranging from 1 to 5. Particularly population density, temperature and water extent showed considerable differences in weights and therefore the following two runs were zoomed in on these variables. The weights (1.4 (population density), 1 (surface water proximity), 5 (temperature), 5 (temporal water), 1 (water depth), 5 (water extent)) had the lowest rmse score and was therefore used in the malaria transmission suitability model.

6.3 Malaria transmission suitability space-time mapping

In this section multiple study areas are shown to provide an insight of the malaria transmission model in Lake Kyoga, Lake Victoria, Lake George and Kampala city. Again changes are shown between 2001 and 2013.

Figure 6.3 indicates that in the Lake Kyoga area malaria transmission suitability decreases from 2001 to 2006 especially in the larger lakes (e.g., lakes in the north-east and south-west). From 2006 to 2013 it can be seen that malaria transmission suitability increases near the edges of the lakes. The figure also shows spots of suitability increases in the north-east from 2006 to 2013. These spots are also present in the change maps of the Kampala city area from 2001 to 2006 and 2006 to 2013 (south-west and west, respectively). These patterns are the result of either an increase in

TABLE 6.1: The yearly averaged and area averaged malaria transmission (A_{ya}) suitability for the predictors from 2001 to 2013 in the different study areas. The values are calculate using formula 6.2.

Area	George			Kyoga			Kampala			Victora		
Year	2001	2006	2013	2001	2006	2013	2001	2006	2013	2001	2006	2013
Temporal water	0.38	0.42	0.29	0.41	0.33	0.29	0.36	0.35	0.29	0.39	0.28	0.40
Temperature	0.51	0.59	0.56	0.63	0.64	0.61	0.39	0.45	0.40	0.39	0.47	0.42
Population density	0.12	0.12	0.10	0.24	0.24	0.23	0.30	0.29	0.26	0.18	0.18	0.17
Water proximity	0.20	0.22	0.19	0.33	0.33	0.31	0.10	0.10	0.11	0.11	0.11	0.10
Water depth	0.09	0.11	0.13	0.23	0.25	0.15	0.10	0.11	0.07	0.10	0.12	0.10
Water extent	0.07	0.13	0.07	0.08	0.10	0.08	0.08	0.08	0.07	0.08	0.06	0.06
Observations												
Water depth	328	402	522	602	741	1576	72	52	542	906	274	346
Water extent	2939	5555	2456	8232	2891	4960	2182	1089	2152	29717	12360	12729

population or an increase of water in these areas. In the Kampala area a decrease in malaria transmission suitability is seen at the edge of cities with a large population. Lake George shows increases in transmission suitability due to both an increase in population (blue spots) and temperature (north-west and south-east) from 2001 to 2006. From 2006 to 2013 a decrease of transmission suitability is seen near the edges of rivers and lakes.

Finally, the change from 2001 to 2006 at Lake Victoria was primarily positive, except for some areas around a bay (south) and a settlement (north). From 2006 to 2013 the general pattern is that transmission suitability keeps increasing.

Table 6.3 presents that the general trend from 2001 to 2006 is that malaria transmission suitability increases in all regions except for lake Kyoga. From 2006 to 2013 a sharp decrease is noted in all regions. The area of lake George decline only little compared to the areas of Lake Victoria, Lake Kyoga and Kampala city.

6.4 Model validation results and predictor correlations

6.4.1 Model validation

The validity of the model is checked by comparing the suitability model with empirical data from the Malaria Atlas Project (Bhatt et al., 2015). The areas around Lake Victoria and the city of Kampala contain these measurements. There were respectively 222 and 55 malaria incidences around Kampala and Victoria during 2000 to 2015. Hence comparison is only plausible in these areas. Comparison is done for the months December and November of 2001 and 2006.

TABLE 6.2: Calibration results of multiple runs. The lowest root mean square error (rmse) and the corresponding weights are presented in the table. The weights are shown in the following respective order: predictor 1 (population density), predictor 2 (surface water proximity), predictor 3 (temperature), predictor 4 (temporal water), predictor 5 (water depth) and predictor 6 (water extent). E.g., Weight 1: [predictor 1, predictor 2, predictor 3, predictor 4, predictor 5, predictor 6]

Weight ranges	stepsize	Lowest rmse	Weights
All weights: 10 to 15	1	0.71	(11,10,15,15,10,15)
All weights: 5 to 10	1	0.69	(6,5,10,10,5,10)
All weights: 1 to 5	1	0.65	(1,1,5,5,1,5)
Weight1: [1.1,1.3,1.5,1.7,1.9] Weight2: [1.0,1.0,1.0,1.0,1.0] Weight3: [4.1,4.3,4.5,4.7,4.9] Weight4: [5.0,5.0,5.0,5.0,5.0] Weight5: [1.0,1.0,1.0,1.0,1.0] Weight6: [4.1,4.3,4.5,4.7,4.9]	0.2	0.633	(1.1,1,4.5,5,1,4.3)
Weight1: [1.2,1.4,1.6,1.8,2.0] Weight2: [1.0,1.0,1.0,1.0,1.0] Weight3: [4.2,4.4,4.6,4.8,5.0] Weight4: [5.0,5.0,5.0,5.0,5.0] Weight5: [1.0,1.0,1.0,1.0,1.0] Weight6: [4.2,4.4,4.6,4.8,5.0]	0.2	0.631	(1.4,1,5,5,1,5)

TABLE 6.3: Total average malaria transmission suitability from 2001 to 2013 in the different regions. Calculations are done according to equation 6.2.

Year	Kyoga	George	Victoria	Kampala
2001	0.092	0.062	0.060	0.089
2006	0.089	0.063	0.067	0.090
2013	0.081	0.056	0.057	0.077

Table 6.4 shows that the transmission suitability model has little explanatory value (0.07 and 0.09) and negative regression coefficients. These linear regression are exemplary for the r^2 values and the regression coefficients of other regions.

6.4.2 Malaria transmission predictor correlations

The correlation between the malaria transmission predictors have been calculated and are shown in table 6.4.

The r^2 value in table 6.4 shows that temporal water suitability in December 2001 and December 2006 explains a significant part of the variance between the observations. Hence, indicating that this could be an important predictor variable. Furthermore, in December 2006, lake extent suitability also explains a considerable amount of variance which are present for both whole Uganda and the Kampala area. Furthermore, temperature and population density also have relatively high explanatory values. Please note that water depth, the transmission suitability model and distance to water have low explanatory values and hence are not included here.

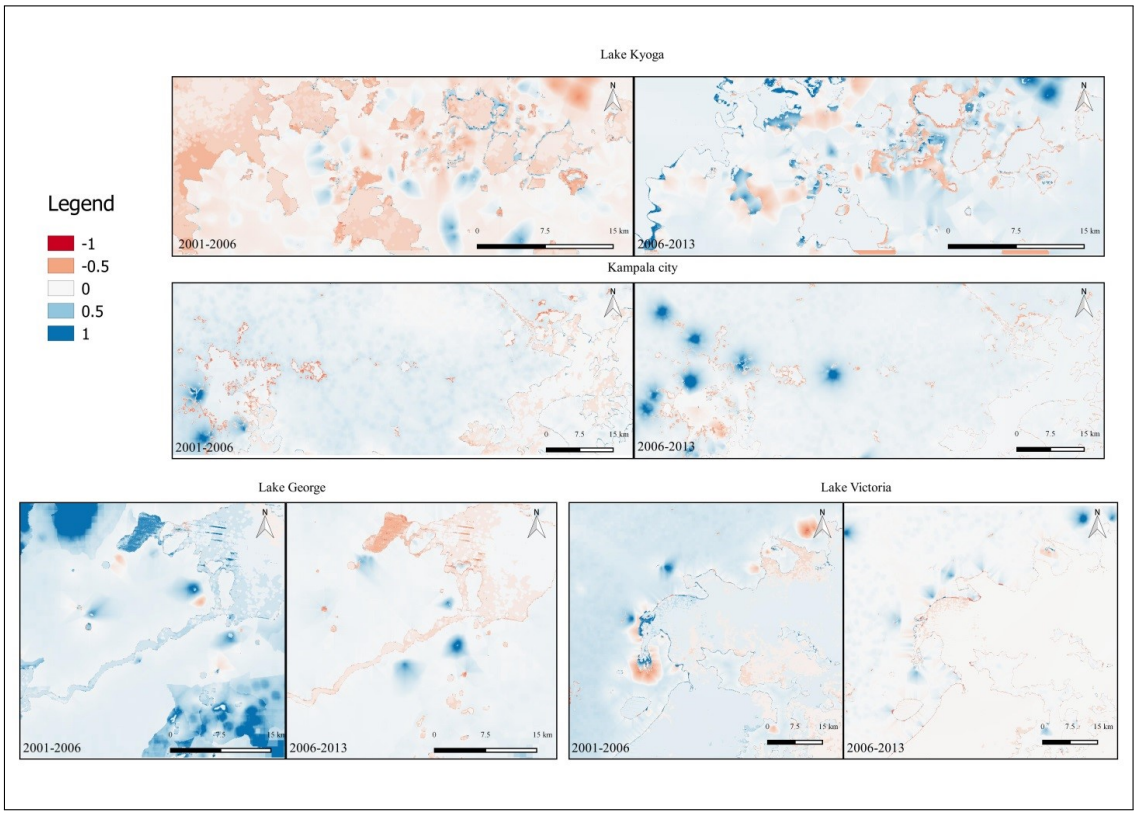

FIGURE 6.3: The changes in the transmission suitability of Lake Kyoga, Lake Victoria, Lake George and Kampala city for the month December of 2001 to 2006 and 2006 to 2013. Please note that the change between years has been calculated according to function 6.1.

6.5 Exposure to malaria transmission

Note that the proportion of the population that has a suitability above 0.15 is low. Hence, it is not considered here that it influences the main trend of the population of Uganda. In Kampala and Kyoga, the proportion of population experiencing a transmission suitability above 0.05, 0.1 and 0.15 decreases over time (Figure 6.4). The population proportion of December 2013 in Kyoga forms an exception as it becomes higher than the population proportion of 2006 at a threshold of 0.1. In the area of Lake George and Lake Victoria the population experiencing a low (0.05) threshold transmission suitability decreases steadily over time. This indicates that the proportion of population increases within the range 0 to 0.05 during 2001 to 2013. When looking at the population at the 0.1 threshold, however, the population of December 2001 drops below that of December 2006 and December 2013. While figure 6.4 shows this trend for December 2001, other years do not indicate similar trends. Figure 6.4 shows that in all years, Kyoga has the highest proportion of its population exposed to malaria transmission (threshold of 0.05). This is followed by Victoria, George and Kampala.

TABLE 6.4: Linear regressions of the predictor variables and the malaria transmission observations by Bhatt et al. (2015). Here, only the relations with the highest r^2 values are shown

Regression coefficient	r^2 value	Year	Month	Predictor variable	Region
1.38	0.82	2001	12	Temporal water suitability	Kampala
1.51	0.81	2006	12	Temporal water suitability	Kampala
1.44	0.79	2006	11	Temporal water suitability	Kampala
31.19	0.79	2006	12	Water extent suitability	Uganda
-6.65	0.79	2006	12	Water extent suitability	Kampala
1.61	0.78	2001	11	Temporal water suitability	Kampala
193.41	0.34	2006	11	Water extent suitability	Uganda
15.89	0.33	2001	11	Temperature suitability	Victoria
17.00	0.28	2001	12	Temperature suitability	Victoria
0.27	0.11	2006	12	Population density suitability	Kampala
-3.33	0.09	2001	12	Malaria transmission suitability	Victoria
-2.81	0.07	2006	12	Malaria transmission suitability	Victoria
-2.9	0.06	2001	11	Malaria transmission suitability	Victoria

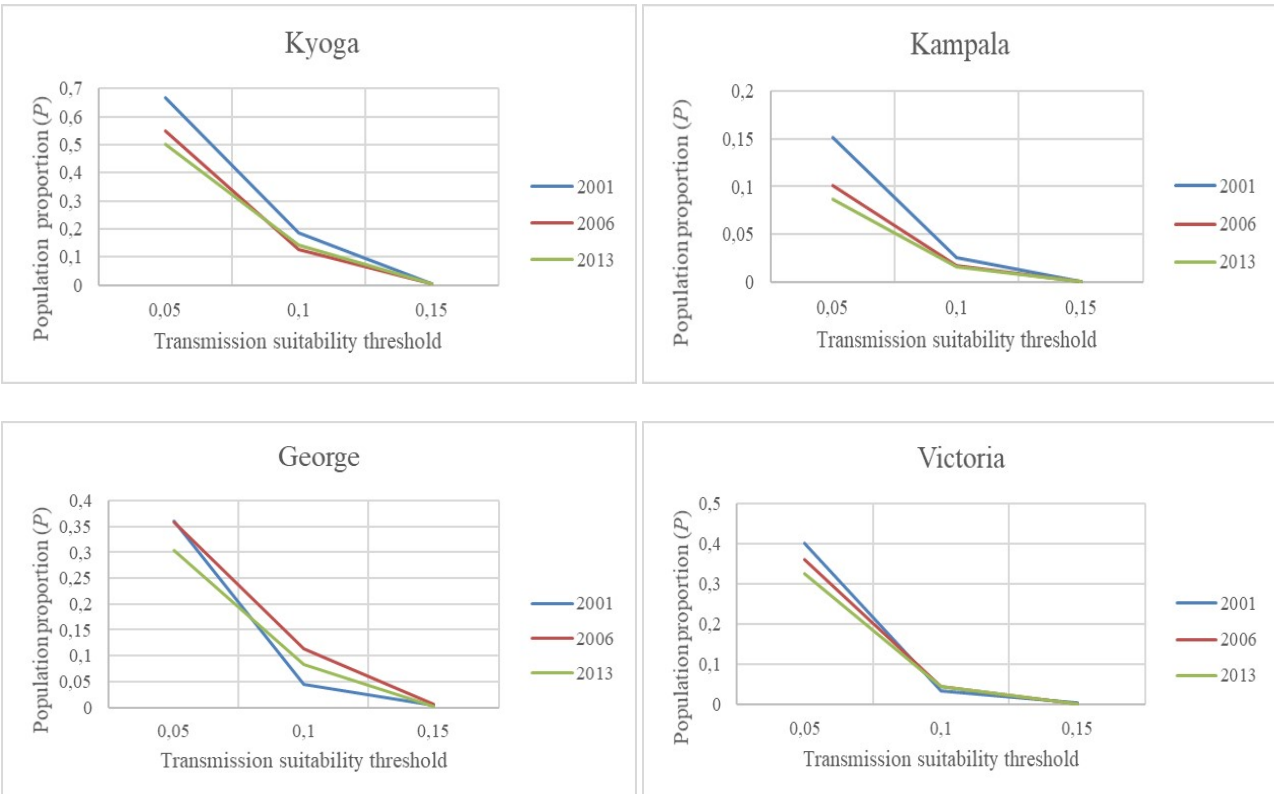

FIGURE 6.4: Transmission suitability thresholds and the corresponding population in December of 2001, 2006 and 2013 for the different study areas in Uganda. On the y-axis, the proportion of population is stated (equation 6.3) and on the x-axis the transmission suitability threshold is stated.

Chapter 7

Discussion

Mapping malaria at a high spatial resolution over multiple years could be used to increase the spatio-temporal knowledge of malaria transmission. In countries where resources are limited, this knowledge could increase the effectiveness of malaria controlling measures. In this study, multiple global data sets on a high resolution are used to derive a 30 m resolution malaria transmission suitability map. The malaria transmission suitability map is the result of a weighted overlay of 6 predictor variables. In this section, the outcome of the regressions of the predictor variables, calibration, the spatio-temporal transmission maps and the exposure distribution is discussed.

7.1 Significance and uncertainties of the predictor variables

The predictor variables have been validated using linear regressions. The results show that the temperature variable, the water extent variable, the temporal water variable and the population variable have considerable explanatory value for both November and December of 2001 and 2006. Similar results are also shown in the calibration results, where the temperature, temporal water and water extent have the highest weights (table 6.2). The calibrations also show that water depth and water proximity have the lowest weights. Moreover, water depth and water proximity have little to no explanatory value of the observations (Bhatt et al., 2015).

7.1.1 Population density predictor variable

Table 6.2 shows that the population predictor is more relevant for computation of the malaria transmission suitability map than water depth and water proximity. However, it has a lower influence than the temperature, water extent and temporal water variable. The population predictor however, does not provide the true susceptibility of people to malaria.

The population density predictor is able to distinguish between urbanized and non-urbanized areas. However, it is not a measure for health care and also not a measure for the prevention and control measures of a certain population. The general assumption is that a high economic status of an individual decreases the burden of malaria due to the ability to take prevention measures and access to better health care. A low economic status makes one more susceptible to malaria. While in general a higher economic status is associated with an increase in population, this may be not always the case. Especially in slums and rapidly urbanizing areas low income populations will be present and therefore they will be more susceptible to malaria. Hence, an increase in population density is not perfectly associated with an increase in malaria incidences.

The general trend of the relation of income and population density is shown in the result that population influences the malaria incidence suitability only little (table 6.2). Separation of income and population density could show a more accurate association of both variables to malaria.

7.1.2 Open surface water proximity variable

In this study, surface water was associated with a high water table of the surrounding region and hence a higher probability of malaria habitats. Smith, Macklin and Thomas (2013) noted that the possibility of breeding sites near rivers and other large water bodies is high. Hence the proximity to open surface water was used as a predictor variable. The calibration and validation results show little correlation of this predictor variable with the observations of malaria incidences. A reason for this could be that while vectors use open surface water to breed in, only specific pools are taken as its breeding site. Hence proximity to all open surface waters is not a strong malaria incidence predictor. It could be possible that the proximity to surface water with specific characteristics (as the other predictor variables) would be a stronger predictor.

7.1.3 Temperature predictor variable

Since the speed of the development of the vectors in the aquatic stage is dependent on the water temperature (Bayoh and Lindsay, 2004) and not on air temperature as is assumed in the model, uncertainties arise here. Larger water bodies require more energy to increase the temperature of that specific water body. Whereas in smaller water bodies little energy is required to increase the temperature. Therefore it is expected that there is an underestimation of water temperatures in larger water bodies when air temperature increases. An overestimation in smaller water bodies temperature is also possible when the air temperature increases (Morrill, Bales, and Conklin, 2005). For the non-aquatic stages of development of a vector, this is not relevant. For the aquatic stages however, this may form a considerable inadequacy. Hence the temperature predicator variable may increase in significance regarding the prediction of malaria incidences when a combination of water temperature and air temperature is used instead of air temperature only. Water temperature could be estimated with thermal infra-red imagery (Sentlinger, Hook, Laval, 1993) and air temperature (Heinz, Preud'homme, 1993).

7.1.4 Temporal water predictor

The temporal resolution of the study forms a limitation of the temporal predictor variable. According to Depinay et al. (2004) predators reach full capacity after 20 days. Since the current temporal resolution is one month, the transmission suitability has already decreased within the first time step. Hence, the variations in breeding site productivity within the first month are not accounted for. The current temporal water predictor variable has therefore not the optimal temporal resolution for describing malaria incidences. Finally, the temporal water predictor variable is altered by the no data handling of the open surface water dataset. Hence in months with considerable no data, this predictor variable has to be interpreted with caution.

7.1.5 Water depth predictor variable

Water depth had a relatively low weight in the calibration results and shows little explanatory value in the linear regressions. Many uncertainties are associated with the calculation of water depth. For instance, it is assumed that there is no discharge in the pools of water. Therefore the only outflow of the pool consists of infiltration and evaporation. This could lead to a discrepancy in the water depth due to a shortage in the outflow. Furthermore, infiltration is based on a pedotransfer function by Mangala et al. (2016). In this case, the soil average of 1 m of soil texture has been used to estimate the maximum infiltration capacity. Biological crusts, soil-moisture content, human activities on the soil surface and vegetation all form factors that could change the maximum infiltration capacity. These factors have not been taken into account when calculating the infiltration. Hence, water depth may not be accurately represented in this model. The water depth in this study is therefore not representative of the actual water depth.

7.1.6 Water extent predictor variable

Water extents show strong relations with the malaria incidence observations whereas water depth has little relations.

In this study, a water extent smaller than 900 m^2 and water depth smaller than 0.5 m promotes the highest suitable habitats for water extent and water depth, respectively. Many authors agree on this (Minakawa et al., 2004; Girardin et al., 2004; Bomblies, Duchemin, and Eltahir, 2008; Klinkenberg et al., 2003). However, there is also evidence that habitats smaller than 1 m^2 actually decrease the stability of habitats. Minakawa, Sonye and Yan (2005) found that the stability of habitats and pupal occurrence decrease when habitats were smaller than 1 m^3 . Flushing (Gimnig et al., 2001) and drying (as is the case during low water levels of Lake Victoria in 2006) are mentioned as possible causes. It is also said that occurrence of small habitats near large water bodies can increase the stability of small, temporary habitats through seepage. However, wave action near large lakes is able to reduce stability of habitats. Trees are able to reduce wave action and increase the stability of sites again (Minakawa et al., 2002).

This suggests that the productivity of very small habitats is dependent on the environmental factors (near lakes and vegetation) of the location. While drying of habitats is accounted for by the water depth predictor variable, flushing, wave action and seepage are not accounted for. Hence, the contribution of very small habitats, particularly in unstable regions, may be overestimated in this study and in general (Minakawa, Sonye, and Yan, 2005). Since water extents of 900 m^2 and lower includes many pools that are suitable breeding sites and not only those smaller than 1 m^2, the high transmission suitability that is given for these situations in the water extent predictor variable is still valid. However, the uncertainty and therefore the overestimation of transmission suitability, as stated above should be kept in mind. Please note that water extent is based on the open surface water dataset and that 2001 and 2006 have a considerable amount of no data. Hence the no data is expected to alter some of the results even while the spatial neighbourhood maximum method is used for handling no data (section 5.4).

7.2 Spatio-temporal variation of malaria transmission in Uganda

The results indicate that the malaria transmission model has little correlation with the observations of Bhatt et al. (2015). As explained in section 7.1, this could be due to the incorporation of inaccurate water depth representations and surface water proximity in the model but also due to malaria counter measures taken during these years. The malaria transmission model did not include malaria intervention and control procedures. The Roll Back Malaria initiative and the Millennium Development Goals of the United Nations enabled the large scale use of insecticide treated bed nets, indoor residual spraying and artemisinin-based combination therapy for clinical malaria cases (Bhatt et al., 2015). These malaria control and prevention projects caused a decrease in malaria incidence and thus, a difference between the malaria transmission model and the observations of incidence rates. While these differences exist, the outcome of the model still shows a possible path which the malaria transmission may have taken without the interventions between 2001 and 2013.

7.2.1 Spatial variation

The results show that from 2001 to 2013 high transmission suitability arises primarily in spots where either small populated areas increase in population (or new small villages form) or where new pools of water occur.

A spatial trend regarding water from 2001 to 2013 is visible to a small extent. While some malaria transmission spots sustain throughout the year, most regions have strong variation in transmission suitability along edges of large lakes and rivers. The location of the malaria transmission spots, near lakes and rivers, is also noted by other authors (Bøgh et al., 2003; Smith, Macklin, and Thomas, 2013) and was therefore expected.

Spatial variation near lakes and water are primarily influenced by water proximity and the temporal water variable. Since water proximity is given a low weight and temporal water is given a high weight, it is expected that temporal water has the primary influence in this area. Water extent of lakes will differ considerably depending on the amount of rainfall, evaporation and infiltration in the area. Since this varies, the extent of the lakes varies considerably, increasing the temporal malaria transmission suitability in this area. Since the results also show that water proximity has little relation with the malaria incidence observations (table 6.4), the emphasis on the temporal water is most likely rightful.

In general, the variable water extent shows high suitability values near rivers and in swamps (figure 6.1). Paleo channels and (flood plain) depressions form the main locations around the rivers and in swamps where water depth and water extent are suitable (Smith, Macklin, and Thomas, 2013)).

7.2.2 Temporal variation

It is observed that the water levels of lake Victoria have dropped strongly in 2006 and 2007 reaching a water level of 1.1 m below the 10 year average (Kull, 2006; Schwatke et al., 2015). Hereafter the lake levels increase again reaching stable levels in 2013. This is primarily attributable to increased evaporation and excessive discharge by the Owen Falls dams (Swenson and Wahr, 2009). A decrease in lake levels could infer a decrease of water levels and extents in multiple rivers and lakes in Uganda, contributing to an overall decrease in suitable habitats for malaria vectors.

Table 6.1 shows that lake extents and water depth both have a decrease over time in the amount of observations in water extent and water depth. More evaporation may empty small water bodies quickly, reducing the amount of overall suitable water bodies. Minakawa et al. (2008) noted that almost half of the breeding habitats sustained after the water level drop of Lake Victoria of the *Anopheles gambiae* species. Hence it is expected that the amount of observations or locations of both suitable water extent and water depth would decrease .

The amount of observations of water extent (table 6.1) (observations with a transmission suitability larger than 0) shows a considerable decrease in 2006. Hence, water extent does show a reaction to the increased evaporation. Water depth shows variable signs to the increase in evaporation. As mentioned before, the water depth as modelled here does not represent the actual water depth. This may be one of the factors contributing to the strong variance in water depth.

The results (table 6.1) also show that the transmission suitability of water extent and water depth do not show a specific trend between 2001-2013. During 2006, larger water bodies should increase in transmission suitability due to a drop in water levels, whereas smaller highly suitable water bodies can disappear, thus decreasing the transmission suitability. Table 6.1 results show that while the water extent average suitability shows variable signs , the overall transmission suitability in 2006 for the areas of Kampala, George and Victoria does increase (table 6.2). The temperature suitability variable shows similar results. Since the temperature suitability predictor variable has a higher influence on the overall transmission suitability than water extent, it is expected that this is the main cause for the transmission suitability increase in 2006.

In all regions the population density predictor variable decreases, which is most likely due to urbanization. Small villages are abandoned which cause the population density predictor to decrease. Moreover, people move to urbanized areas in which the population density also decreases. Other sources also show considerable evidence that transmission suitability is low in large cities (Watts et al., 1990; Gardiner et al., 1984). Hence an overall decrease of the population density predictor occurs between 2001 to 2013.

7.3 Spatio-temporal exposure variation

The results show that the exposure in Kampala and Kyoga to malaria transmission of the population decreases over time. In Lake George and Lake Victoria the proportion of the population that had a transmission suitability of 0.05 and higher decreases over time as well. However, in December 2006 and December 2013 a higher proportion of the population had a transmission suitability higher than 0.1 compared to December 2001. This indicates that transmission above 0.1 had increased in the area of lake George and (to a lesser extent) in the area of lake Victoria during this period. The general decrease in exposure over time could be caused by multiple factors. Temperature changes, temporal water changes and population changes are most significant; therefore they are expected to have the highest influence from 2001 to 2013.

7.3.1 Urbanization and exposure to malaria

The decrease of exposure in all areas is most likely attributable to urbanization. In all areas the population increases while the population transmission suitability decreases between 2001 and 2013. The only possibility for this phenomenon to occur is that the population density rises above the 250 persons per square kilometers threshold. Above this threshold better health care and a decrease in oviposition sites due to concretization and a lack of open surface water decreases the malaria transmission suitability (Hay et al., 2005). Moreover an urban setting can increase opportunities for surveillance, control and prevention of infectious disease in general. Hence, it is expected that urbanization is the main cause of the decrease in the population exposure.

In literature the general trend is that urbanization causes a decrease in infectious diseases (Trape and Zoulani, 1987; Phillips, 1993; Hay et al., 2005). However not all agree. Gubler (2011) notes that major drivers of increased incidence of dengue in urban areas include lack of effective mosquito control and unplanned urbanization. Highly domesticated vectors can lay eggs in plastic containers and automobile tires. Unplanned urbanization such as slums of large urbanized cities can cause limited health care and vector control (Gubler, 2011). Moreover, a higher population density could also increase the probability of an epidemic. Piles of organic refuse and rainwater in containers also pose to be potential breeding sites for vectors. Therefore it cannot be assumed that an increase in population density causes a decrease in transmission suitability.

In a global context the relation between income and malaria is evident. Malaria causes a decrease in worker productivity, premature mortality and an increase in medical costs. Therefore malaria causes a lower economic growth of a country (Sachs and Malaney, 2002). Vice versa, poverty is not the main cause of malaria, but rather a consequence. High income countries have better health care and therefore are able to eradicate malaria. Low income countries do not have this ability and therefore, they are subjected to the burden of malaria (Gallup and Sachs, 2001). It is expected that in urbanized areas similar spatial differences will be present. In this study these spatial differences within urbanized areas have not been accounted for. For this reason, the decrease in exposure in urbanized areas could be overestimated. In the future, unorganized urbanization of low income will increase and hence this error is increased as well.

7.3.2 Temperature and temporal water in lake George

The exposure distribution of Lake George shows that higher exposures were present in 2006 compared to 2001. This evident in the exposure threshold value of 0.1. Table 7 shows that the temperature predictor rises strongly during 2006. The temperature transmission suitability combined with an increase in the temporal water suitability is expected to be the cause of the rise in exposure.

An increase in temperature transmission suitability is a result of an overall temperature increase. A temperature rise increased evaporation during this year. This is confirmed by Swenson and Whar (2009), whom noted increased evaporation near lake Victoria. High evaporation can cause small water bodies to disappear, decreasing the overall transmission suitability. However, table 7.1 shows that the amount of observations in the area of lake George does not decrease, but it increases.

In the open surface water data set of Pekel et al. (2015), clouds and sensor limitations are represented as no data. It is expected that strong evaporation will lead to

considerable cloud cover and thus a considerable amount of no data. The increase in cloud cover of whole Uganda is seen in figure 5.4. Busker (2017) shows that the area of George is also affected.

If the no data is either continuous or not present, no scattering of water occurs. However, if patches of no data exists, scattering of larger water bodies is more plausible. Usually, patches often occur when clouds are present. Scattering of large lakes occur more in 2006 than in 2001 or 2013. In both 2001 and 2013 continuous no data or non-presence of no data in this area is more present than in 2006. Scattering of large lakes into multiple smaller lakes (making them more suitable) due to patches of no data in 2006 could be one of the reasons for the increase in water extent observations. To observe the open surface water dataset, please refer to Busker (2017).

The increases in temporal water (table 6.1) during this 2006 can also be a consequence of a strong variability of the no data patches. Therefore, it can be said that the higher exposure was mainly caused by an increase in temperature, however, the exposure was also increased by the no data patches which influenced the water predictors.

The effect of a temperature increase (compared to 2001) is much more visible in 2013. Since there are less no data patches, the water predictors do not show strong variances when compared to 2001. Only the temperature transmission suitability increases (compared to 2001), which leads to an increase of the population that has an exposure of 0.1 and higher.

Chapter 8

Conclusion

A high spatial resolution malaria transmission map could increase the effectivity of malaria control measures, especially in resource limited countries. Multiple predictor variables were defined and used to compute the suitability and exposure of transmission to malaria for different study areas from 2001 to 2013 in Uganda.

In this study the predictor variables consisted of air temperature, the duration of existence of water (temporal water), water depth and extent, population density and water proximity.

Air temperature influences the speed of development of vectors and the speed of the sporogonic cycle. Water temperature however, must also be accounted for, to accurately represent the speed of development of the vectors. The productivity of a breeding site is dependent on the time that water is present. Predators, disease and carrying capacity will decrease the productivity with an increase in time period that a breeding site is present. Furthermore, small and shallow waters are suitable habitats as long as they have a stable environment with little influence of precipitation flushing, evaporation and wave action (when located near a large lake). Humans are able to create suitable breeding sites but are also necessary to transfer malaria from one vector to another. Furthermore, an increasing economic status of humans can decrease the probability of being a human host for malaria transfer due to increased malaria prevention and control.

Air temperature, water extent and temporal water are most correlated with the malaria incidence observations (r^2 of 0.331, 0.788 and 0.823, respectively). The water proximity and water depth predictors are not correlated with the observations. In general, the model itself does not show strong relations with the incidence observations as well (r^2 of approximately 0.1). This is mainly attributable to the large scale malaria control and prevention in Africa and Uganda, which are not accounted for in the model. Please note that each predictor (and the model itself) is separately correlated with the observation to show its own variance. Therefore, the r^2 of variables can be higher than the r^2 values of the model.

From 2001 to 2013 there is an overall decrease in exposure with a sharp increase in 2006. The increase in 2006 is thought to be caused by an increase in temperature. The increased temperature caused an increase in temperature suitability. Water predictors in some areas are shown to react on the change in evaporation. In other areas as lake George the water predictors show less response due to an increase of cloud cover over this area.

The decrease in transmission suitability and exposure over time is caused by urbanization. There may be, however, an overestimation of the decrease in transmission suitability due to the spatial variability of health care and malaria prevention and control within such urbanized areas. The current trend of exposure decreasing with urbanization that is seen in this model however, is most likely a valid one.

Chapter 9

Recommendation for future research

The following section presents manners to improve the model for higher accuracy of the malaria transmission model and also ideas for future research.

9.1 The predictor variables

The model consists currently of 6 predictor variables. Details and improvements for the rules and model in general found in this study can be used for an increase in accuracy for predicting transmission spots.

First of all, the probability of having malaria habitats near each pool or stream of water is low according to validation results. Hence, water proximity has to be left out of the model or has to be combined with other predictor variables. E.g., some locations are considered suitable for multiple predictors, the distance from that spot should be taken as a predictor. The population predictor has to be combined with the economic status of the population to increase the accuracy of predicting the transmission of malaria. Increased economic status of people causes better health care and a decrease in economic status can cause decreased health care and more puddles for malaria vectors to breed in. Research is needed to increase the knowledge on the quantitative relation of the economic status and malaria transmission.

Furthermore the temperature predictor should include both air temperature and water temperature, due to the fact that the differences between the two, which depends on the size of pools, can be substantial. The water depth function was not adequate in this model as a result of the missing discharge as part of the outflow. Moreover, biological crusts, soil-moisture content, human activities on the soil surface and vegetation are factors that have not been taken into account calculating the infiltration. In a future water depth predictor, these limitations should be accounted for calculating water depth. For an increase in the detail of the water extent and temporal water predictor variables, increases in spatial and temporal resolution would be adequate. For that purpose either different datasets or interpolation (or prediction) between pixels and time steps have to be calculated.

Finally, to improve the quality of the validation of the model a different study area should be used. The malaria occurrences should be only dependent on population and climate and not include malaria control measures.

9.2 Urbanization

The findings of this research confirms that urbanization decreases the exposure to malaria considerably. In a future research, a higher performance malaria transmission model could be acquired by investigating the quantitative and qualitative impact of urbanization, wealth and institutions. Many questions could be asked when investigating these factors: How does the speed of urbanization affect the degree of transmission? To what extent does the wealth of people moving to cities affect the relative malaria the incidence rates in the city? To what extent does population density still affect malaria transmission suitability after the malaria transmission suitability has been corrected for wealth? To what degree does an increase in wealth decrease malaria incidences? Is personal wealth more important than wealth of a whole population (cities, country, provinces)? Does the amount or quality of institutions matter in the control and preventions of malaria independent of the wealth of the country?

Future predictions of population and growth of wealth are, hopefully, able to show the most suitable areas of transmission in the future. With this spatial knowledge, policy makers are able to take malaria control and preventions methods in regions where it is needed the most and prevent future problems.

Appendix A

Malaria transmission intensity in Uganda

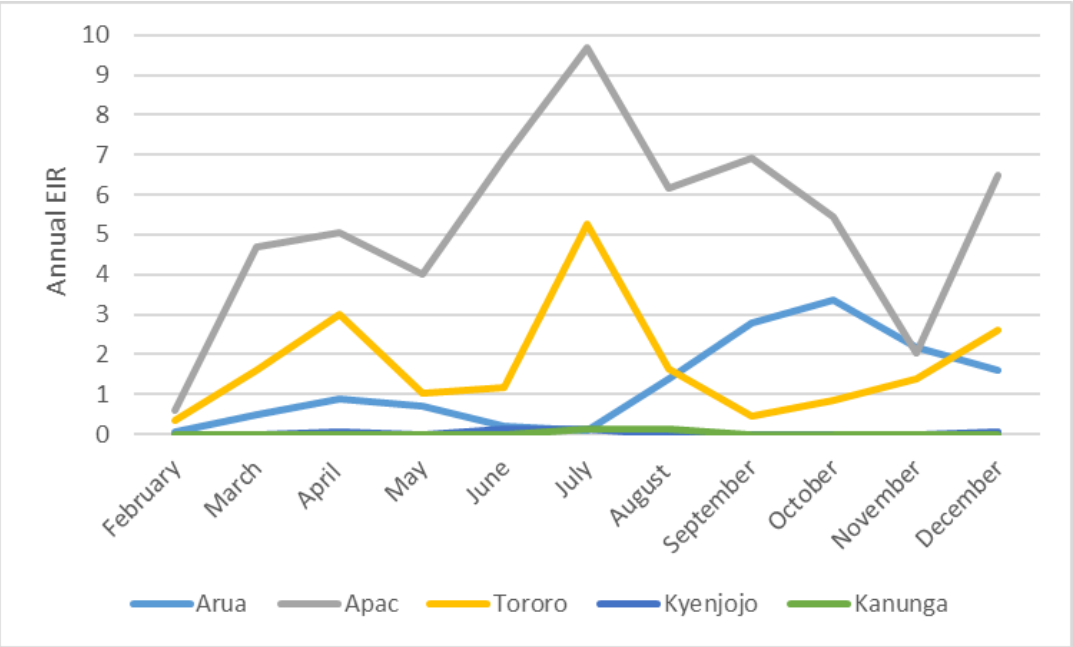

FIGURE A.1: The annual entomological inoculation rate (EIR) for different parts of Uganda (Okello et al., 2006).

For reference, Apac and Kyenjojo is located near lake Kyoga and lake George, respectively.

Appendix B

Parameters used in this study

TABLE B.1: The parameters used in the first three predictor variables of this study.

Equation	Parameter	Value	Description
6.1	Pt	250	Threshold population suitability in persons per square meters
6.1	U	1000	Urbanization limit in persons per square meters
6.2	Dc	4	The impact of large distances on the water distance suitability
6.2	Di	5000	maximum distance of malaria vectors in meters
6.3	Tl	18	Temperature lower limit in degrees Celsius
6.3	Tm	30	Temperature suitability maximum in degrees Celsius
6.3	Tu	35	Temperature upper limit in degrees Celsius

Appendix C

The global malaria transmission model

To access the scripts of the model, please click on the following link:

https://drive.google.com/open?id=15NlB6xlcwm4-l3KMw8byG2Ti81O_es4K

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