Simulating tick bites in the Netherlands using agent-based modelling

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PREFACE

As part of the master's program Geographical Information Management and Applications, I present to you my final thesis titled *Simulating tick bites in the Netherlands using agent-based modelling*.

Completing this research would not have been possible without the help from some people to whom I would like to express my gratitude.

First of all, I would like to thank my supervisor Ellen-Wien Augustijn for all her guidance, valuable feedback, enthusiasm and support. Secondly, I would like to thank Tatjana Kuznecova for all her tips, feedback and help with the development of the agent-based model. Finally, I would like to thank my family, fellow students and friends for their advice and feedback during this process.

I hope you will enjoy reading this thesis.

SUMMARY

The number of people getting a tick bite and the number of people diagnosed with Lyme disease is increasing every year in the Netherlands. The number of people with Lyme disease in 2017 was 27 000. Because this is a high number and it is still increasing, research on ticks and tick bites needs to be done to gain more insight into the factors that influence the number of tick bites. Most studies so far have been focusing on the environmental factors that are of influence, while human factors are of equal weight. That is why this research considers both environmental and human factors.

With this research, an agent-based model has been developed to simulate tick bites in three different areas in the Netherlands: the Bilt, Ede and Schiermonnikoog. The Bilt is an urban area, Ede a forested area and Schiermonnikoog as Wadden Sea Island a coastal area. With a literature study, the factors influencing tick bites were found, and related to either hazard or exposure, which together determine the risk of getting a tick bite. Environmental factors determine the hazard, and the factors included in this model are vegetation type and weather. Human factors relate to exposure, and the model includes the factors accessibility, age and activity type. For this model, blanket-dragging data and VGI from Tekenradar, a Dutch platform where people can report their tick bite, have been used.

The model consists of four sub-models. First, the tick dynamics model. This model simulates tick abundance per land-use type (urban, forest, sand, other), based on blanket-dragging data. The tick abundance varies per month. Second, the human population model. The population consists of residents and tourists. The number of residents stays constant, but the number of tourists varies per week, considering the different stay periods of tourists. Third, the activity model. Activities (walking, gardening, playing, other) are assigned to all residents and tourists, related to the age group they belong to. Tourists move randomly every day as long as they are in the model, and residents move out of the urban area only on Saturday. The movements of the residents and tourists are limited by an accessibility layer, including National Landscapes and Natura 2000 areas, and precipitation. Fourth, the tick bite model. Getting a tick bite is calculated per resident/tourist and is based on the residents'/tourists' hazard * exposure values. With calibration, the output of the model has been matched to the Tekenradar data.

The output of the model is best when using risk = hazard * exposure. Here the resulting patterns of tick bites in the three case study areas are most comparable to reality. There are some differences between the case study areas. The risks assigned to the different activities in Ede and at Schiermonnikoog are the same, but these are different in the Bilt model. Also, all case study areas have a different threshold value at which people get a tick bite. However, the model clearly shows that tick bites are not only influenced by environmental factors, but also by human factors.

There are some limitations to the developed model. Assumptions have been made due to lack of data. Future research should focus on gathering more data that can be used as input for the model, such as detailed tourist information and more detailed tick abundance data per land-use type. Besides, some factors are missing, such as individual factors, including for example protection against ticks, and no-risk activities. The model developed with this research is a first step to gain insight into the factors influencing tick bites and future research can improve the model.

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1 INTRODUCTION

Between 1994 and 2009, there has been a huge increase in the number of general practitioner (GP) consultations for tick bites and GP-diagnosed erythema migrans, a rash indicating the beginning of Lyme disease, in the Netherlands. The numbers tripled resulting in 564 tick bite consultations per 100.000 inhabitants in 2009 and 134 erythema migrans diagnoses per 100.000 inhabitants (Hofhuis, Harms, van den Wijngaard, Sprong, & van Pelt, 2015). In 2014, there were some signs of a stabilization of the number of erythema migrans diagnoses and a decrease in the number of tick bite consultations (figure 1.1, (Hofhuis et al., 2016). However, the total number of people diagnosed with Lyme disease in 2017 was 27.000 whereas this number in 2014 was only 25.000 ((National Institute for Public Health and the Environment (RIVM), 2018). Besides that, in 2014 there were 482 tick bite consultations per 100.000 inhabitants compared to 535 tick bite consultations per 100.000 inhabitants in 2017. This means that there was still an increase last years in the number of GP tick bite consultations and GP-diagnosed Lyme disease.

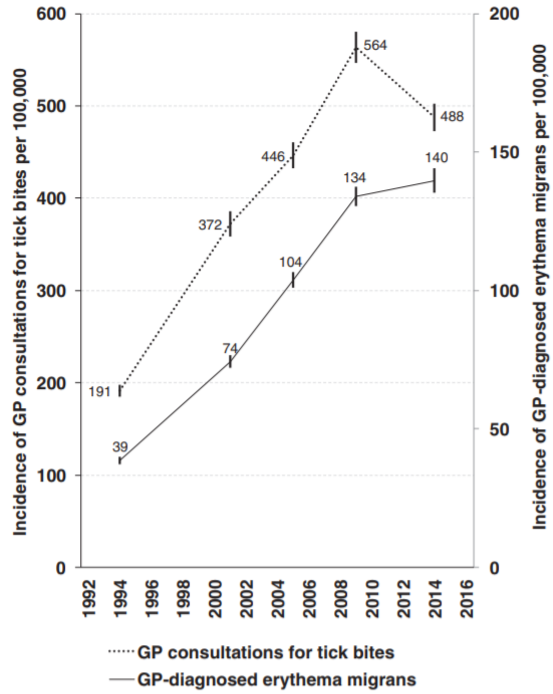


Figure 1.1 Incidence of GP tick bites consultations and erythema migrans diagnoses per 100.000 inhabitants in the Netherlands between 1994 and 2014 (Hofhuis et al., 2016)

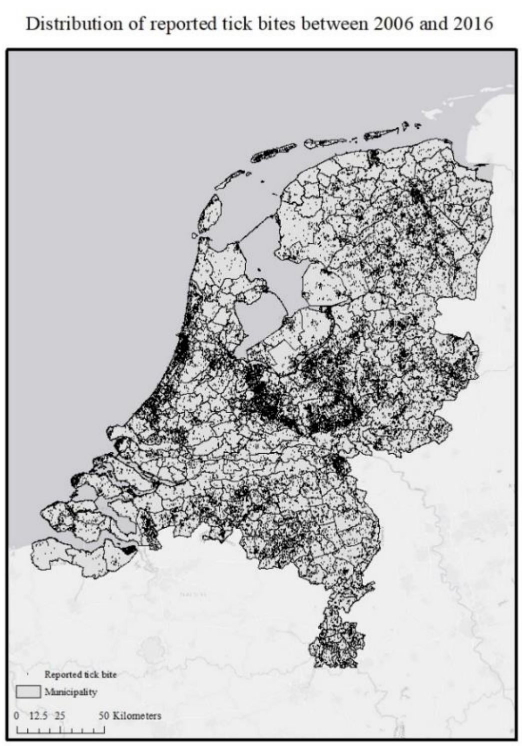


Figure 1.2 Distribution of reported tick bites between 2006 and 2016 (Tekenradar, 2018)

Ticks are bloodsucking parasites that live in close association with their hosts (Randolph, 1998). They mostly feed on mammal hosts, but they can also feed themselves with the blood of humans. They can cause diseases, such as Lyme disease, in humans when they are not removed in time (Randolph, 1998). Ticks wait and search in vegetation for a host to come by to attach themselves to and feed themselves with its blood. In the Netherlands, tick bites can be voluntary reported on the website of Tekenradar, a Dutch citizen science website, providing information and data about ticks in the Netherlands (Garcia-Martí, Zurita-Milla, van Vliet, & Takken, 2017). Between 2006 and 2016, almost 47.000 tick bites have been reported. The distribution of these reported tick bites is shown on the map in figure 1.2, clearly showing that some parts of the Netherlands experience more tick bites than others.

Several studies have been done on ticks and tick bites in the Netherlands. These try to find the factors that influence the presence of ticks and their dynamics. Environmental factors as well as human factors seem to influence the number of ticks and tick bites (Garcia-Martí, Zurita-Milla, Swart, et al., 2017; Gassner et al., 2011; S. Mulder, van Vliet, Bron, Gassner, & Takken, 2013). However, there is need of more clarity about which factors are mostly influencing the tick bites phenomenon. More knowledge about these factors can help decrease the number of tick bites and the amount of people with Lyme disease in the Netherlands. Therefore, this research investigates which factors mostly influence the tick bites phenomenon by developing an agent-based model (ABM), including several factors with a focus on human behavior, to discover spatial differences between the number of tick bites in different areas and to identify the best strategy to reduce the number of tick bites in the Netherlands.

1.1 RESEARCH OBJECTIVES

The main objective of this research is to investigate which factors influence tick bites in the Netherlands. This will be investigated by developing an agent-based model, including (1) tick distribution and activity and (2) human activity and mobility. This model will be calibrated with VGI from Tekenradar. This agent-based model for tick bite risk can hopefully help discover spatial differences in the number of tick bites in different areas and contribute to the decrease in the number of tick bites and people with Lyme disease in the Netherlands.

1.1.1 Research questions

To reach the main objective of this research, the following research questions will be answered.

1) What environmental and human factors influence the number of tick bites in the Netherlands?
2) How can these environmental and human variables be formalized in a framework suitable for agent-based modelling?
3) How should this framework of variables be implemented in an agent-based model?
4) What (spatial) differences in tick bite distribution are there between the case study areas resulting from the model?
5) To what extent does this model contribute to indicating tick bite risk and reducing the number of tick bites in the Netherlands?

1.1.2 Approach

The result of this research is an ABM that can be used at different locations. The model must be generic so that the values of the different sub-models can be changed easily which makes it possible to run the whole model at different locations. To come to this ABM, different steps need to be taken. The workflow of this research consists of four steps. It starts with a literature study and data analysis. The literature study results in a theoretical background, explaining the factors that influence ticks and tick bites more in depth and explaining what agent-based modelling is. The data analysis analyzes environmental data and the Tekenradar data, resulting in the variables that should be modelled. Step 1 constitutes the framework for step 2. Based on the literature study and data analysis, a conceptual model is set up and the variables that are of influence on the different sub-models are formalized. Step 3 is the implementation of the model and the analysis of the model, such as the verification of the model and a stability check. Step 4 is the analysis of the results of the model running in different areas with different experiments.

1.1.3 Relevance

The scientific relevance of this research is that it can show how important agent-based modelling is for exploring which factors influence the spread of diseases, in this case Lyme disease spread by tick bites. Based on the VGI data that will be used within this model, the factors that influence tick bite risk the most can be discovered. The societal relevance of this research is that the model can help reduce the number of tick bites and thus the number of people with Lyme disease. This also means that less money needs to be spent on healthcare for people with a tick bite or Lyme disease.

1.1.4 Constraints and limits

This research will only use the volunteered data of Tekenradar. However, this data has been put together with data from Nature Today [De Natuurkalender] which leads to misalignments. The information people must fill in on the questionnaire of Tekenradar when reporting a tick bite differs from the questionnaire of Nature Today. This leads to some tick bite reports including vegetation type and activity and other tick bite reports without this information. Besides that, volunteered data always have a bias. Correcting for this bias, for example more reporting when tick bites received media attention, is not an objective in this study. A lot of activities are included in the Tekenradar data but not all of them will be included in the agent-based model. Only recreational activities will be modelled, such as hiking and gardening. Next to that, hosts are an influencing factor on the number of tick bites, but this factor is not modelled due to the lack of data. There is no detailed data available about host populations in the Netherlands which makes this factor impossible to model within this research. The model does not run for the whole Netherlands but is more generic so that it can run for different areas. In this study, the model runs for some well-chosen regions, which are interesting for example because of their number of tick bites or their recreational areas.

1.2 OUTLINE

The outline of this research follows the workflow described in section 1.1.2. Chapter 2 presents the theoretical background about ticks, factors influencing tick and tick bites, and agent-based modelling. Chapter 3 presents the methodology of this research and chapter 3 presents the data analysis of environmental data, such as temperature and precipitation, and of the Tekenradar data, analyzing in what way factors, such as age and activity, influence the number of tick bites. Chapter 5 gives the model description. The verification of the model and the stability check are described in chapter 6. Chapter 7 then gives the analysis of the results following the experiments in the three case study areas. The research ends with a conclusion, discussion and recommendations.

2 THEORETICAL BACKGROUND

In this chapter, a framework for the agent-based modelling of tick bites is presented. This chapter is a literature review of climate (section 2.2), landscape (section 2.3) and behavior (section 2.4), all influencing the number of tick bites. Besides that, this chapter gives a literature review of agent-based modelling (2.6) and complex systems (2.7).

2.1 INTRODUCTION

2.1.1 Tick life cycle

The life cycle of a tick consists of four stages and the interstadial developments happen during different seasons (CDC [Centers for Disease Control and Prevention], 2017). At every stage, ticks need blood from hosts to survive. It can take three years before ticks completely fulfill their life cycle. Ticks can become infectious at two stages in their lifecycle. Either as a nymph, developing form larva and feeding themselves with infected blood, or as an adult, developing form nymph and feeding themselves with infected blood (Sharareh, Sabounchi, Roome, Spathis, & Garruto, 2017).

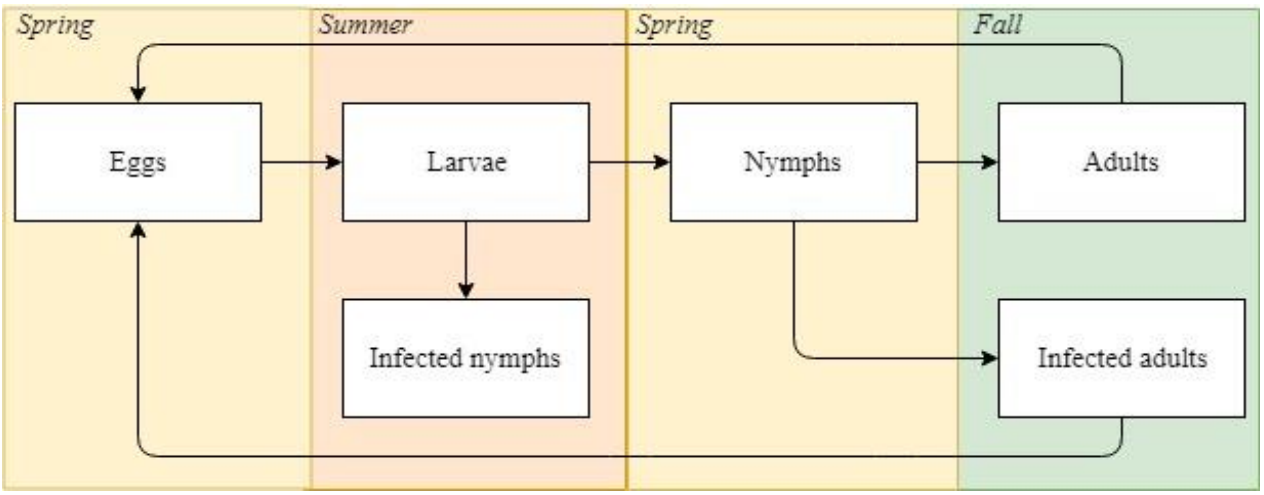


Figure 2.1 Tick life cycle model (adapted from Sharareh et al., 2017)

2.1.2 Influencing factors

The number of tick bites and the number of Lyme diagnoses in the Netherlands has been increasing since the 90s (Hofhuis et al., 2015). Figure 2.2 shows the number of reported tick bites per Dutch municipality, mapped as a percentage of the total amount of reported tick bites in the whole country. The total number of reported tick bites is 46.831 and figure 2.2 clearly shows which municipalities experience most of them. Based on past studies, these numbers of reported tick bites could relate to environmental factors or human factors (Garcia-Martí, Zurita-Milla, Swart, et al., 2017; Gassner et al., 2011; S. Mulder et al., 2013). Some studies only mention environmental factors that influence tick bites (Gassner et al., 2011; S. Mulder et al., 2013), while others state that human factors are of most influence (Garcia-Martí, Zurita-Milla, Swart, et al., 2017).

Figure 2.3 gives an overview of all the risks that need to be considered (Braks, Mulder, Swart, & Wint, 2016). Risk analysis is a framework for the assessment, management and control of the danger posed by the disease threat; in this case, Lyme disease (Sedda et al., 2014). For many infectious diseases, environmental factors have been used as strong predictors of risk. However, human factors are as of even importance as well, maybe of even more importance. Swart et al. (2014) predicted tick presence by environmental risk mapping. Their model could predict tick bite incidence independently but a high variability in the prevalence of tick bites remained unaccounted for by the presence of ticks only. To reduce the high variability, their model should be extended by human factors such as human activities. Thus, this chapter explores climate, landscape and behavior, all influencing tick bites (figure 2.3).

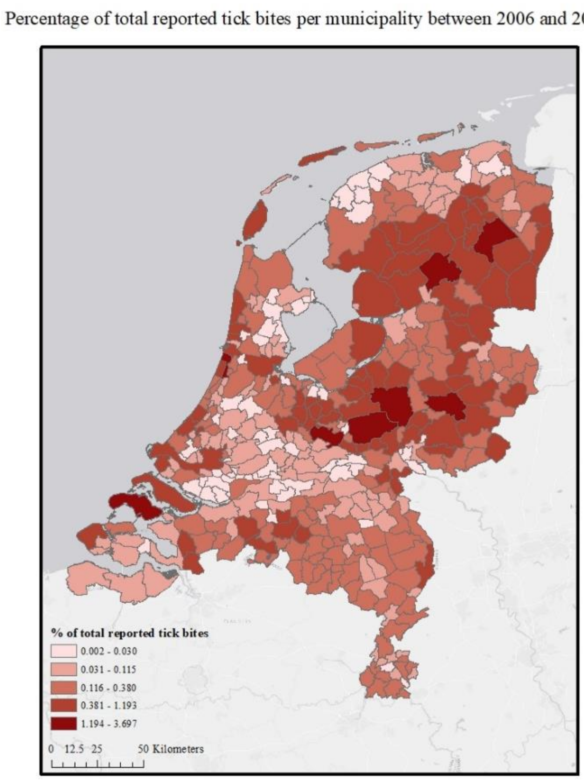


Figure 2.2 Percentage of total reported tick bites between 2006 and 2016 (Tekenradar, 2018)

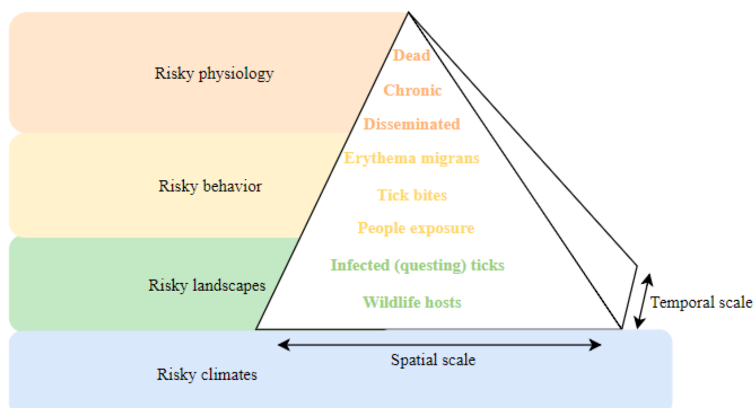


Figure 2.3 Risks and factors influencing tick bites (adapted from Braks, Mulder, Swart & Wint, 2016.)

2.2 CLIMATE

2.2.1 Past studies

Several studies have been done on ticks and tick bites in the Netherlands. Gassner et al. (2011) studied the geographic and temporal variations in population dynamics of ticks on 24 different Dutch sites. High densities of ticks were found in summer and low densities in winter. According to their study, the number of ticks depends on vegetation (according to their study is forest the most attractive to ticks), climate and host abundance. Although they found most ticks in summer, climate change is now contributing to a shift in the seasonal dynamics of tick populations, resulting in more ticks in winter (Gassner et al., 2011). These findings are partly like the findings of the study of Garcia-Martí, Zurita-Milla, Swart, et al. (2017). They found the following variables as determining tick presence and dynamics: temperature, precipitation, soil moisture, air humidity and vegetation type.

2.2.2 Temperature

Temperature affects the whole life cycle of ticks, which consists of four different stages. Depending on the ambient temperature, the development of a tick to a next stage takes weeks, months or years (Randolph, 2004). Figure 2.5 shows what parts of a tick population model are influenced by temperature. Temperature affects the stage development and the probability of ticks actively questing for hosts. Temperature has most influence on the development from larva to nymph and less influence on the development from nymph to adult. At a temperature of 18°C, the daily rate of interstadial development from larva to nymph is 0.25 and from nymph to adult 0.15 (Kaiser, Sutherst, Bourne, Gorissen, & Floyd, 1988). Larvae mostly live during summer while nymphs live during spring and adults during fall. Studying ticks in the United Kingdom has shown that under such sea-climatic conditions, which are comparable to the weather conditions in the Netherlands, a cohort of each stage of ticks is recruited each year in autumn and survives for one year until they have fed or died of fat exhaustion (Randolph, 2004). Something that should be considered is the diapause of ticks, a period of suspended development, typically during unfavorable environmental conditions. Temperature change is one of those environmental conditions that have an important influence (Gray, Kahl, Lane, Levin, & Tsao, 2016). Ticks prefer oviposition and molting occurring in summer because of the higher temperatures, so their perception of the change from long days to short days induces their behavioral and developmental diapause. Figure 2.4 shows a graph determining when ticks of a certain life cycle stage are active. The dips in the graph starting around July indicate the diapause of the different life cycle stages. The first curves end in overwintering in behavioral diapause (not seeking for hosts), the second curves in overwintering in developmental diapause (not developing into next stage) and the dotted curves end in development from the previous stage that fed in spring/summer. This graph clearly shows in what season the ticks of different life cycle stages are active and when they go into their diapause, resulting in most active infectious ticks during summer, caused by temperature changes per season (Gray et al., 2016).

Ticks avoid questing hosts at unfavorable times of the year, for example in mid-summer when the temperatures are too high or in winter when the temperatures are too low (Gray et al., 2016). As figure 2.5 shows, temperature is one of the determining factors of the probability of ticks actively questing for hosts. According to a study on ticks in Poland there is a positive correlation between air temperature, soil temperature and saturation deficit, and nymphal and adult questing activity (Kiewra, Kryza, & Szymanowski, 2014). Another study on ticks in Belgium got comparable results, showing that increasing temperatures lead to increasing questing ticks (Li, Heyman, Cochez, Simons, & Vanwambeke, 2012).

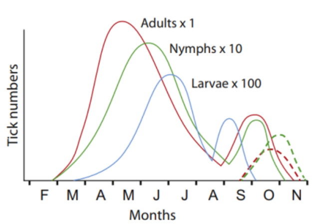


Figure 2.4 Graph representing the activity of the different tick life cycle stages (Gray et al., 2016, p. 995)

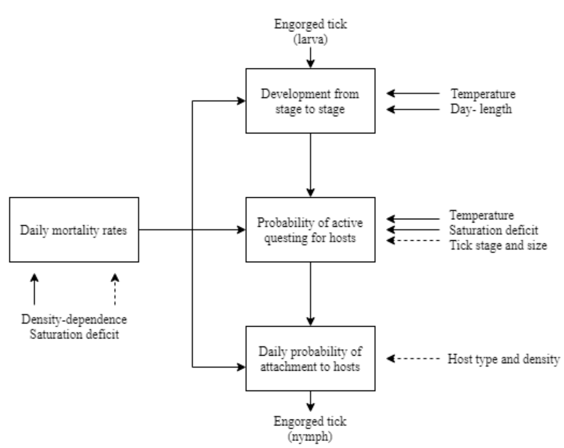


Figure 2.5 The structure of a tick population model with influencing abiotic (solid arrow) and biotic (dotted arrow) factors (Randolph, 2004, p. 38)

2.2.3 Precipitation

Multiple studies mention precipitation as an important environmental factor to consider when studying tick activity and incidence of Lyme disease (Burtis et al., 2016; Gage, Burkot, Eisen, & Hayes, 2008; Hornik et al., 2003). Precipitation has the most influence on active host seeking by ticks (Gage et al., 2008). A study into increased Lyme disease incidence in southern Sweden showed that an increase of 1 mm of the mean monthly summer precipitation decreased the Lyme disease summer incidence rate by 8%. One of the reasons why ticks seek less actively for hosts when it is raining more is because the dampness may inhibit their ability to climb vegetation (Bennet, Halling, & Berglund, 2006).

Precipitation is a key factor to predict tick presence. Hornik et al. (2003) studied tick-borne disease risk in Italy using GIS. They found that the accumulated winter precipitation before the year of sampling was one of the most important variables to predict tick presence. This is possibly because it influences the quantity of surviving larvae regarding the previous year. More winter precipitation means fewer larvae surviving, which results in less (infectious) nymphs in the following summer (Hornik et al., 2003). However, hot and dry weather does not automatically have strong demographic effects, but it does strongly affect the questing behavior of ticks, resulting in fewer ticks seeking for a host because of the hot and dry weather (Burtis et al., 2016).

Like temperature has precipitation influence on the life cycle of ticks. As mentioned above, winter precipitation affects the number of surviving larvae (Hornik et al., 2003). Late spring/early summer precipitation influences the tick life cycle as well. Heavy late spring/early summer precipitation leads to breaking larval diapause and eclosion (Daniel & Dusbabek, 1994). This precipitation may also contribute to the increased number of questing and surviving nymphs (Jenkins et al., 2001). Due to heavy rainfall is the moisture content of the forest floor higher, which favors tick survival.

2.3 LANDSCAPE

2.3.1 Vegetation type

Forest is, according to multiple studies, the optimal habitat for ticks (Garcia-Martí, Zurita-Milla, Swart, et al., 2017; Lindström, Gustav, & Jaenson, 2003; S. Mulder et al., 2013). According to a study into tick distribution in southern Sweden is there a greater abundance of nymphs in forested areas than in open vegetation areas (Lindström et al., 2003). A reason for this is that forest vegetation works as a buffer against weather extremes, with less differences in humidity and temperature in comparison to open vegetation.

Research into tick density in three parks in the United Kingdom found what kinds of vegetation experience the most ticks (Dobson, Taylor, & Randolph, 2011). This research took two years where every three weeks the different vegetation types were sampled using the method of blanket dragging (blankets picking up ticks). Ticks were found in all types of vegetation, but the density differed per type. The vegetation types with the highest tick density are wood, heather & Vaccinium (blueberry) and bracken wood. It was also found that tick activity started earlier in shrub and woodland than in grassland and heather (Dobson, Taylor & Randolph, 2011). This research clearly shows that ticks prefer woodlands, but the question remains if ticks only prefer wood or that they prefer vegetation types with undergrowth. Ticks prefer thick undergrowth because of sufficient browse, cover and humidity (Süss, 2003). In Belgium, ticks were studied in different forest understory vegetation types. These were bracken fern, bilberry, purple moor-grass and short grass. Larvae, as well as nymphs and adults, were found most in short grass. They were all found least in bracken fern (Tack et al., 2011). This study indicates that ticks prefer different kinds of undergrowth and not specifically forested areas.

Figure 2.6 shows three maps showing the distribution of tick bites in the Netherlands for the vegetation types garden and forest and the amount of forested area in 2015. Comparing these maps to figure 2.1 shows that the amount of forested area does not automatically explain the high percentages of tick bites. For example, the municipality in Zeeland with a relatively high percentage of tick bites does not have a lot of forested areas. The same counts for the Wadden Sea Islands and the dune areas alongside the North Sea. The amount of tick bites in gardens in these areas of the Netherlands is high which makes it likely that tick prefer undergrowth in general and not forest specifically.

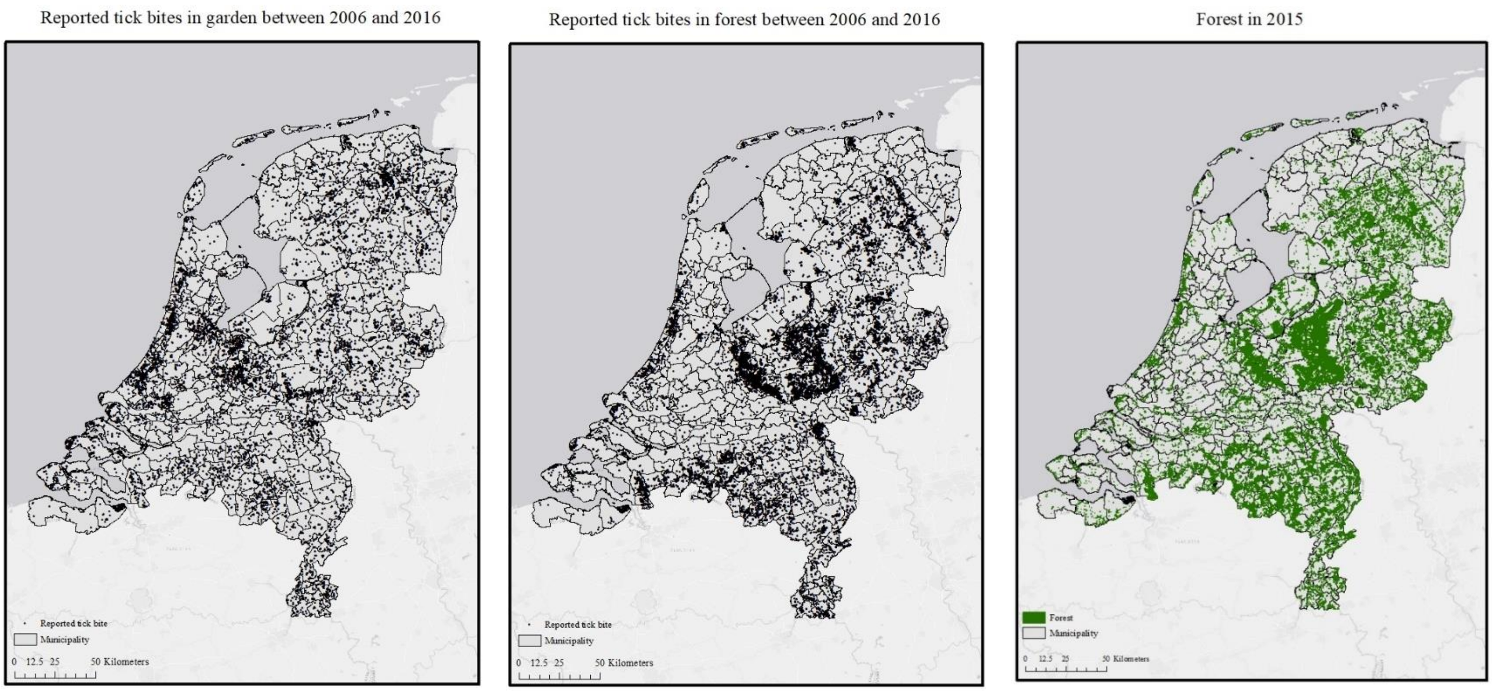


Figure 2.6 Maps showing tick bites in gardens and forests between 2006 and 2016 compared to the amount of forest in 2015 (Tekenradar, 2018)

2.3.2 Hosts

Ticks depend on the availability of hosts because ticks need their blood to survive. Ticks feed on many different hosts, for example, small rodents, lizards, wild boar, squirrels and livestock (Medlock et al., 2013). The presence of hosts for ticks is thus an influencing factor. Studies in Slovakia and the Czech Republic found that increasing numbers of available hosts, in this case rodents and deer, contributed to increasing numbers of ticks (Medlock et al., 2013). Also, studies in the UK and Denmark found that the expansion of host populations resulted in the presence of ticks in areas where they had never been before. The number of questing ticks increases when the number of hosts increases because increasing numbers of hosts make it easier for ticks to find a host (Pugliese & Rosà, 2008). However, immature stages of the tick life cycle can feed on all kinds of hosts but mature ticks feed more exclusively on larger hosts. Larger hosts are therefore essential for tick populations to survive. That is why humans are hosts for ticks as well, especially when other host populations are minimal (Medlock et al., 2013). Ticks need hosts to survive and their surviving population depends on the availability of host populations to suck blood from.

2.3.3 Environmental risk map

As mentioned before, Swart et al. (2014) made a first attempt to predict tick presence by environmental risk mapping. They created an environmental risk map based on tick suitable grids. These were calculated by classifying all their sampling coordinates into either presence or absence. These grids were combined with data of roe deer densities, soil moisture and satellite images.

This resulted in the environmental risk map shown in figure 2.7. Green means no risk, red means maximum risk and white means no prediction. Map A has the white pixels censored and map B shows all predictions (Swart et al., 2014). When comparing figure 2.7 with figure 2.6, there seems to be a relation between forest and environmental risk, but that does not count for the whole country. For example, Flevoland does not have a lot of forested areas but the environmental risk in this province is high. Also, the maps of figure 2.7 give a reliable overview of tick presence at a rough scale, but they do not yield insight in the drivers of tick presence (Braks et al., 2016).

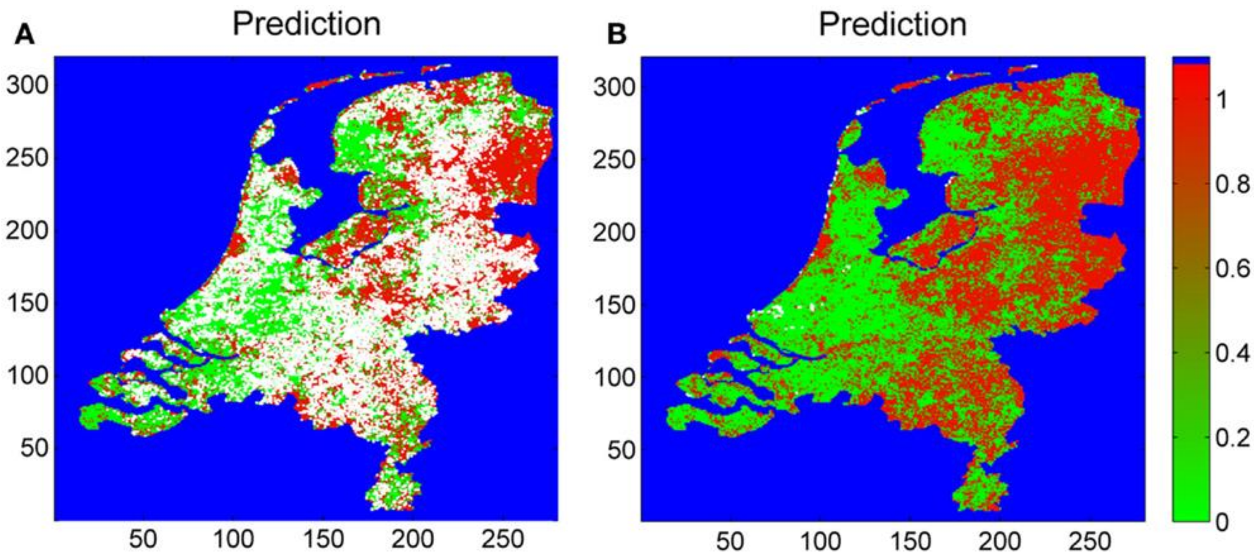


Figure 2.7 Environmental risk map (Swart et al., 2014)

2.4 BEHAVIOR

2.4.1 Past studies

As mentioned in section 2.2.1 have several studies been conducted on ticks and tick bites. However, most of them have focused on environmental factors and not on human factors. According to Garcia-Martí, Zurita-Milla, Swart, et al. (2017) are human-related factors of more influence than environmental factors. Tick bites are the result of tick abundance and human presence, and environmental features on their own do not seem to be enough to explain the tick bites phenomenon. As figure 2.3 shows, human behavior is of influence on tick bites and relates to human exposure.

2.4.2 Activity

The activities, which people are doing, are influencing the risk of getting a tick bite. Land use determines human presence at certain locations, such as forested areas or urban areas, and is thus related to human exposure to ticks (Linard et al., 2007). The interaction of people with certain kinds of land uses influences the chances of being bitten by ticks. For example, hiking in the forest or gardening are activities where people can get bitten by ticks easily because they interfere with the vegetation types which are the most attractive habitats for ticks.

A study into the determinants of the geographic distribution of Lyme borreliosis infections in Belgium found some positively linked factors to the Lyme borreliosis incidence rate (Linard et al., 2007). Forest cover is one of these factors but also the proportion of people living in separated houses.

Linard et al (2007) thus suggest that:

> Heterogeneous landscapes with a fragmented land use mixing forests and houses are more at risk. In areas with a high proportion of separated houses, people are more likely to have gardens and thus spend time outdoors. The presence of forests nearby further favors human-vector contacts. Peri-urbanization could thus be one of the major causes of the recent increase in Lyme borreliosis infection.

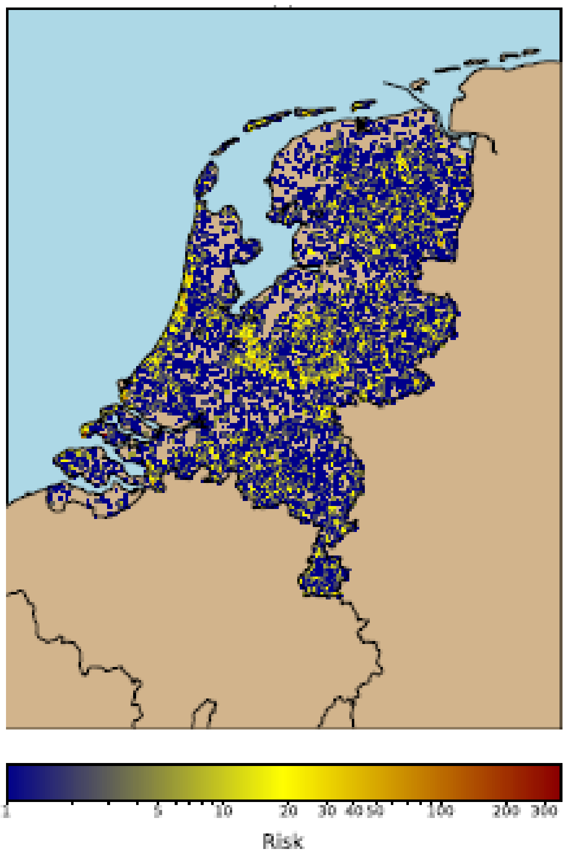
This indicates that forested areas and gardens are locations where people do activities which come together which a higher risk of getting a tick bite. As mentioned in section 2.4.3 are activities also closely related to the different age groups since people of different ages do different types of activities.

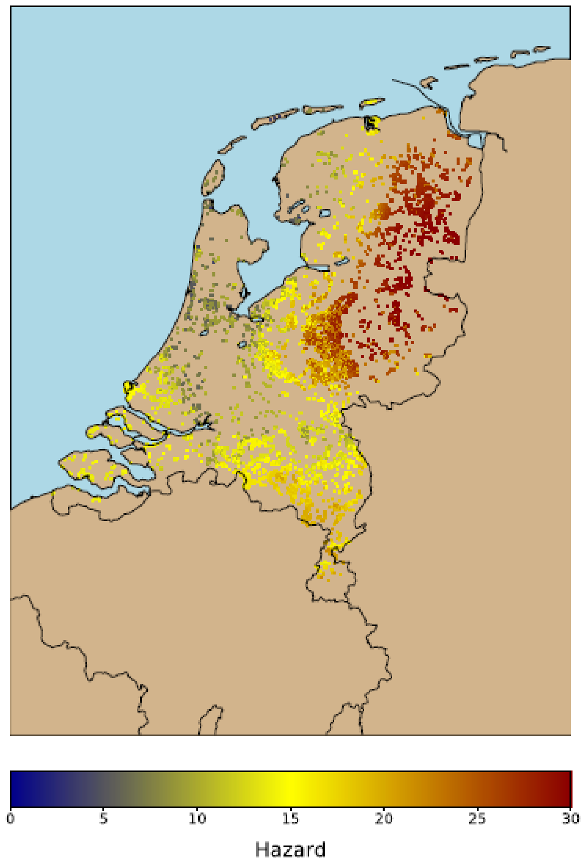
2.4.3 Age

The distribution of tick bites differs per age group. Mulder et al (2011) studied tick bites in the Netherlands using data of Nature Today. The highest numbers were found among the groups 0-9, 50-59 and 60-69. The lowest numbers were found among teenagers, 20-29 and elderly people. There are several reasons to explain these differences per age group. First, the type of activities done by each age group differs. Whereas children play outside a lot, do people from 40-60 walk a lot in the forest and do elderly people work a lot in their gardens. These differences per activity type are explained in section 2.3.3. Second, knowledge of ticks and access to the internet also influence the differences in tick bites per age group. Different age groups have different knowledge of ticks, prevention behaviour and use of the internet. People without access to the internet and people younger than 55 were less informed about ticks and tick bites than people with access to the internet and people older than 55. This means that not only activity type but also knowledge of ticks, awareness and access to the internet indicate the risk of getting a tick bite per age group.

2.4.4 Exposure

Multiple studies have focused on quantifying tick hazards, as Swart et al (2014) did on a national level. However, to predict or simulate tick bite risk, exploring exposure to ticks is necessary as well. According to Mulder, Snabilie & Braks (2016), who mapped tick bite risk on a local scale, are there several exposure parameters: accessibility (of ticks), recreational activity and different types of exposure (temporary, stationary). This kind of parameters needs to be considered when mapping or simulating tick bites (risk) (A. C. Mulder, Snabilie, & Braks, 2016). Instead of focussing on quantifying tick hazards, Garcia-Martí, et al. (2018) focused on quantifying human exposure. To calculate human exposure, risk and hazard need to be calculated first. They derived risk from the Tekenradar data and hazard from a tick activity model they developed in their previous work. Human exposure is then the result of combining the results of calculating risk and hazard. Figure 2.8 shows the three resulting maps of these calculations. The results show that well-known places for recreational activities as Utrechtse Heuvelrug and the dunes experience high human exposure. However, not only areas with vegetation types suited for recreational activities experience exposure, but also residential areas do. This suggests that the exposure to tick bites are driven by two types of users, recreational and residential (Garcia-Marti, Zurita-Milla, Harms, & Swart, 2018). Another result is that the risk of getting a tick bite increases when exposure to ticks increases but the hazard remains constant when exposure to tick increases.





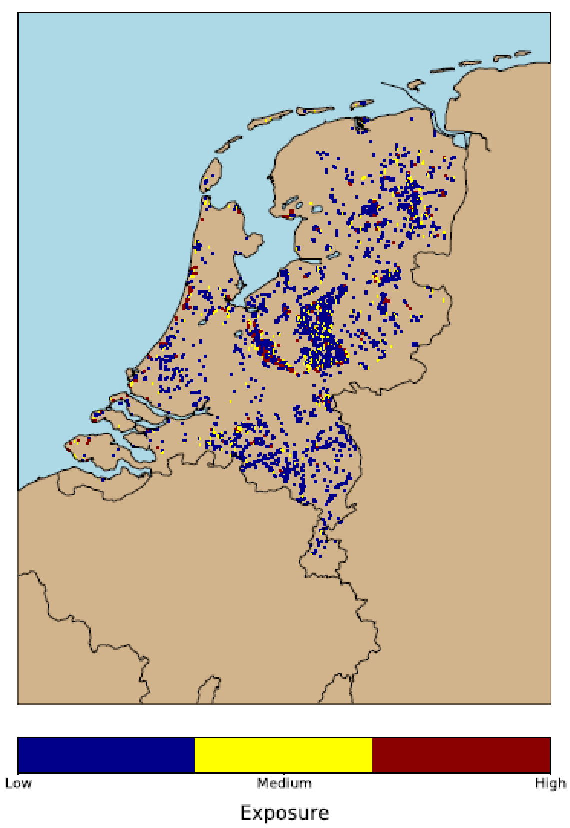


Figure 2.8 Maps showing the risk of getting a tick bite, the hazards for getting a tick bite and the human exposure to ticks in the Netherlands (Garcia-Martí, Zurita-Milla, Harms & Swart, 2018)

A comparable study was done in Sweden. For this research, the following variables were included: animal species, forest, landcover, accessibility and scenic beauty (Zeimes, Olsson, Hjertqvist, & Vanwambeke, 2014). Accessibility increases the touristic value and was based on (the length of) roads, inside the forest and the roads to enter the forest, the presence of holiday houses, relating to more outdoor activities, and the distance to Stockholm, referring to more frequent outdoor recreation. The scenic beauty of landscape features was based on the distance to water features, the proportion of broad-leaved forest and the mean three height, all factors contributing to the scenic beauty of landscape (Zeimes, Olsson, Hjertqvist, & Vanwambeke, 2014). These two factors influence exposure to ticks because they relate to more people doing recreational activities. According to Zeimes et al. (2014) can the risk of getting a tick bite be calculated by the following formula: R (risk) = H (hazard) * E (exposure).

2.5 SHORT SUMMARY

As discussed in this chapter, authors of past studies on tick bites make several statements, which can be used as a starting point for the data analysis in the following chapter. These statements are about where and when people have the highest risk of getting a tick bite and about the characteristics of people that get a tick bite. Besides that, statements about environmental factors are included. The most useful statements are listed below per factor.

Climate

a) Higher number of ticks in summer (Gassner et al., 2011);
b) Number of ticks depends on vegetation, climate and host composition (Gassner et al., 2011);
c) Temperature and precipitation determine tick presence and dynamics (Garcia-Martí, Zurita-Milla, Swart, et al., 2017);

Vegetation

d) High infection risk in forests and dune areas (Gassner et al., 2011);
e) Number of ticks depends on vegetation, climate and host composition (Gassner et al., 2011);
f) People mostly get a tick bite in forests or gardens (Mulder et al., 2013);
g) A forest is the optimal habitat for ticks (Mulder et al., 2013);
h) Tick bites are clustered in forested areas (Garcia-Martí, Zurita-Milla, Swart, et al., 2017);

Behavior

i) People aged 50-69 and children under 10 are bitten by ticks most (Mulder et al., 2013);
j) People above 60 mostly get a tick bite when gardening (Mulder et al., 2013);
k) Chances of being bitten by a tick depend on human exposure and interaction with land-use (Garcia-Martí, Zurita-Milla, Swart, et al., 2017);
l) Human-related factors are more important to modelling tick bites than environmental factors (Garcia-Martí, Zurita-Milla, Swart, et al., 2017).

All three of the studies clearly state that forested areas are the optimal habitat for ticks, which has already been discussed in section 2.3.1. For some Dutch municipalities, the amount of forested area can explain the number of ticks (figure 2.6) but that is not the case for every municipality. That is why variables such as type of activity when getting a tick bite or the age of people getting a tick bite should be analyzed, which is done in the following chapter.

2.6 AGENT-BASED MODELLING

2.6.1 Structure

According to De Smith, Goodchild, Longley & Associates (2018, p.489) does an ABM 'refer to the use of computational methods to investigate processes and problems viewed as dynamic systems of interacting agents'. They involve bottom-up modelling and seek macro-level understanding based on micro-level processes (De Smith, Goodchild, Longley, & Associates, 2018). The basic principle of an ABM is tracing and observing the behavior of an agent over time (Barnes & Chu, 2010). An ABM typically has the following three elements:

1) A set of agents, their attributes and behaviors;
2) A set of agent relationships and methods of interaction: an underlying topology of connectedness defines how and with whom agents interact;
3) The agents' environment: agents interact with their environment in addition to other agents (Macal & North, 2010).

These three elements are used to build a virtual model of a real-world system. This model represents components of the real-world system and keeps track of the behavior of the agents over time. An ABM does not only represent individual entities (the agents) but also the environment in which these individuals are living. Every agent has its own state and exhibits an explicit behavior. An agent can interact with other agents as well as with its environment. Figure 2.9 represents the structure of a typical ABM, showing that an agent interacts with its environment and other agents.

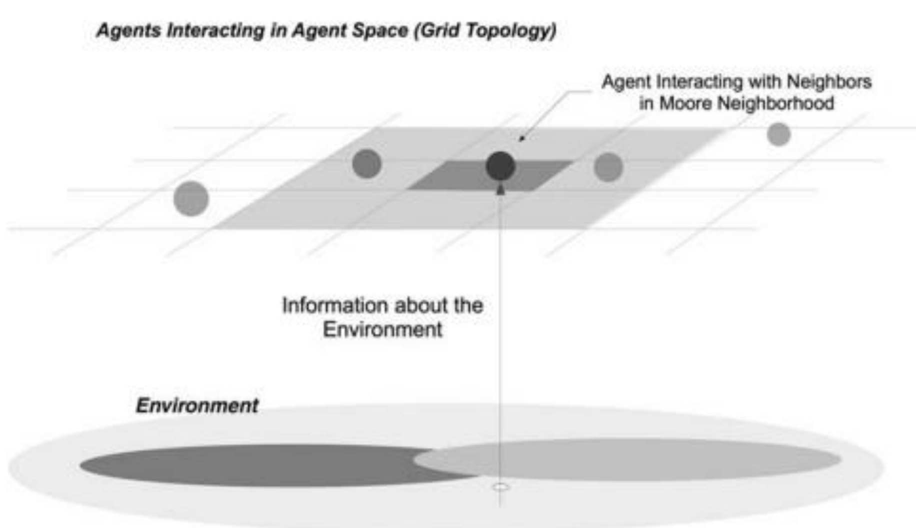


Figure 2.9 The structure of a typical ABM (Macal & North, 2010)

2.6.2 Agents

As mentioned above, agents are one of the elements of an ABM. There is no precise definition of an agent but there are some essential characteristics common to most agents:

1) Autonomy: an agent is autonomous and can act independently, without influence of centralized control;
2) Heterogeneity: every agent is a uniquely identifiable individual and groups of agents can exist but the development of an agent is autonomous;
3) Active: agents exert independent influence in a simulation, being pro-active (having goals to achieve) or reactive (having a sense of their surroundings);
4) Bounded rationality: agents can have knowledge of their environment, but this knowledge is constrained, resulting in agents making inductive and adaptive decisions;
5) Interactive: agents communicate with each other and their environment;
6) Mobility: agents can go through the space in which they are situated and interact with it;
7) Adaptation: agents may have the ability to learn and adapt its behavior based on past experiences, having some kind of memory (De Smith et al., 2018; Macal & North, 2010).

Agents always have some attributes, for example name or age, which can be static or dynamic. Besides attributes, they possess some behaviors, indicating how they interact with other agents and their environment (Macal & North, 2010).

2.6.3 Relationships

Relationships are the second element of an ABM. These are defined to link agents to each other or to their environment. These relationships can be pro-active or reactive. When a relationship is pro-active, an agent is goal-directed and needs to achieve goals in respect to its behavior. A reactive relationship means that an agent has some form of awareness or sense of its surroundings, for example because the agent is supplied with prior knowledge but has no particular goal to achieve (De Smith et al., 2018). The methods of interaction, defining how and with whom agents interact, are employed within the framework of relationships.

2.6.4 Environment

Originally, ABM's were implemented in the form of cellular automata, where agents move from one cell to another and one agent occupies one cell at a time. Nowadays, there are several kinds of environment. In the network topology, links and nodes are determined and in the Euclidian space model, agents move in two, three or higher dimensional spaces (Macal & North, 2010). In the GIS topology, agents roam in a realistic geo-spatial landscape, from patch to patch, providing information on the spatial location of an agent in relation to the location of other agents.

2.6.5 The ODD protocol

Earlier, ABM's have been criticized because they were so poorly described that the models could not be evaluated (Lorek & Sonnenschein, 1999). To overcome this problem of poor description, the ODD protocol (Overview, Design concepts, Details) was created (Grimm et al., 2010). This protocol exists of seven elements, which are shown in table 2.1. This protocol will be used to describe the ABM of this research.

Table 2.1 Elements of the ODD protocol (adapted from Grimm et al., 2010)

	ODD protocol element	**Description**
Overview	Purpose	Objectives of the model
	Entities, state variables, scales	Agents with attributes and behaviors, spatial units, environment
	Process overview, scheduling	Order of model's processes
Design	Design concepts (basic principles, objectives, learning etc.)	Rules of agents and their behavior
Details	Initialization	Initial state of the model world
	Input data	Data from external sources or other models
	Sub-models	Sub-models that represent the processes

2.7 COMPLEX SYSTEMS

An ABM often represents a complex system. Complex systems are characterized by interrelations between agents, discontinuous non-linear relations and feedbacks (Gell-Mann, 2002). For complex systems, ABM specifies rules for agents and the way they interact with each other. In that way, patterns can be observed which can give useful information (Galea, Riddle, & Kaplan, 2010).

According to Rea, Brown & Sing (2006) are living organisms better understood as 'complex adaptive systems characterized by multiple participating agents, hierarchical organization, extensive interactions among genetic and environmental effects, nonlinear responses to perturbation, temporal dynamics of structure and function, distributed control, redundancy, compensatory mechanisms, and emergent properties'. It has become clear that predicting the function of complex adaptive systems involves properties of the whole system and not only the properties of individual component agents (Rea, Brown, & Sing, 2006). When modelling epidemiologic systems, multilevel causes of health and their patterns of feedback and interaction need to be taken into account (Galea, Riddle & Kaplan, 2010). When it comes to tick bites and Lyme disease, spatial variables that influence vectors, hosts and their interactions can be categorized in three different scale levels; local-scale (vegetation type), meso-scale (landscape composition) and large-scale (macroclimate) (Killilea, Swei, Lane, Briggs, & Ostfeld, 2008). It is very essential to assess all these multi-scale impacts when modelling Lyme disease. For the management and prevention of Lyme disease it is of big importance to understand the causes of the spatial variation of the disease. Only in that way, the burden of this disease on our society can be reduced (Killilea et al., 2008).

2.7.1 Lyme disease

Ostfeld (2010) has written a whole book about Lyme disease, about the ecology of a complex system. Questions are what increases Lyme disease risk, what decreases it, why are there hotspots and bad years and why is it spreading? Several influencing factors have been studied such as the type of tick hosts (deer or mice) and the weather. However, finding the most influencing factors seems to be very hard. Lyme disease is influenced by several complex systems such as food webs, biodiversity and ecosystem functioning (Ostfeld, 2010). This makes it hard to point out the most influencing factors which cause the rapid spreading of the disease.

Schauber, Ostfeld & Evans (2005) did a study into the best predictor of annual Lyme disease incidence, comparing weather, mice and acorns. They found that not one variable outperformed the others. Their results ´highlight the difficulties in extracting rigorous causal inference from short-term observational data subject to spatial and temporal autocorrelation' (Schauber, Ostfeld, & Evans, 2005). Discovering one simple explanation for Lyme disease fluctuations will not be possible. Since Lyme disease is such a complex system, it is likely that both biotic and abiotic factors influence Lyme disease fluctuations which need to be incorporated both when modelling the disease in a reliable way.

3 METHODOLOGY

3.1 INTRODUCTION

The methodology of this research is divided into four steps (figure 3.1). Step 1 is the constitution of the theoretical background based on the literature study, presented in the previous chapter. The analysis of the Tekenradar data follows in chapter 4. With this step, the most influencing environmental and human factors are determined, which can be used as parameters in the agent-based model. Step 2 is the model development in NetLogo and the model description following the ODD protocol. When the model has been developed and implemented, it needs to be verified and calibrated with the Tekenradar data. After that, the model can run with different scenarios and the results of these scenarios need to be analyzed to identify how the model gives output most comparable to reality and if there are differences between the three case study areas. The model developed in this research can be used for further research in modelling tick bites with other influencing factors and modelling Lyme disease in the Netherlands.

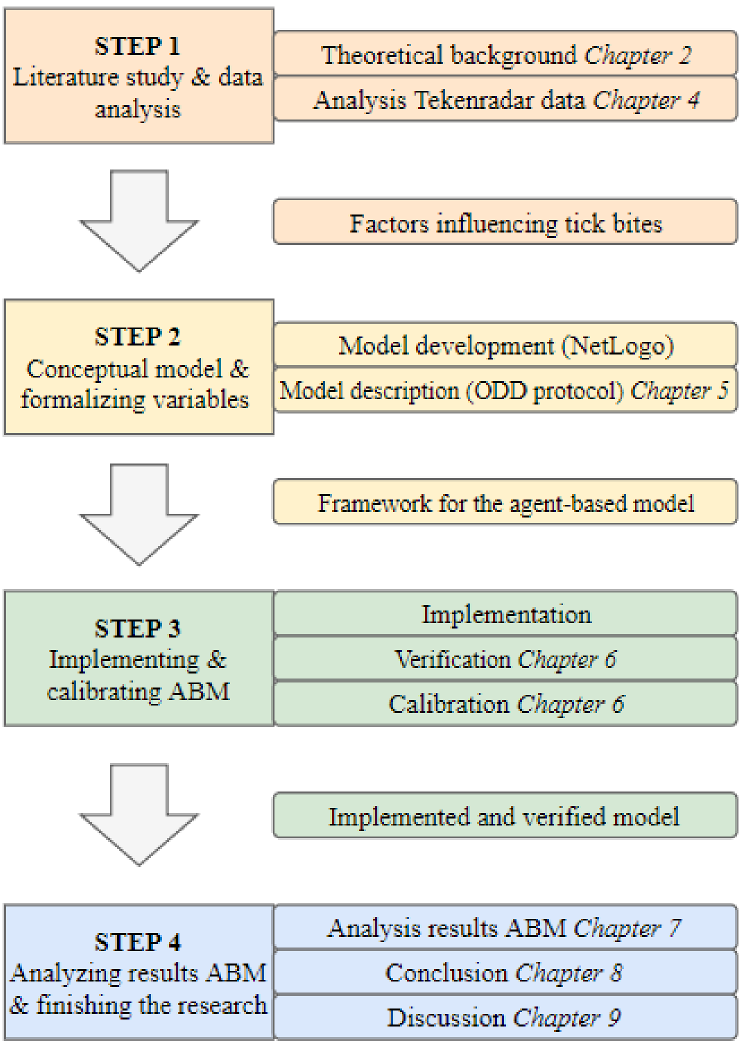


Figure 3.1 Methodology of this research

3.2 STEP 1

3.2.1 Theoretical background

Through a literature study, an insight into the environmental and human factors influencing the number of ticks and tick bites will be obtained. These factors are divided in three groups, either climate, landscape or human behavior. Agent-based modelling and complex systems will be studied, explaining the methodology of this research and showing that tick bites and Lyme disease are a complex system which needs to be modelled considering multi-scale factors. Only then, the system can be modelled reliably.

3.2.2 Analysis Tekenradar data

Besides the literature study, a first data analysis of the Tekenradar will be conducted. With this data analysis, the same factors as with the literature study are studied. Temperature and precipitation data from KNMI will be used to compare these with the number of tick bites, on a yearly basis and a monthly basis for the years 2012-2016. For the vegetation types the relationships between vegetation type and tick bites will be explored. The same accounts for the factors age and activity type, but these two are also linked to each other, showing that activity type differs per age group. As last, a framework will be created to show all the influencing factors and how these influence each other.

3.3 STEP 2

3.3.1 Model development (NetLogo)

The ABM of this research is developed in NetLogo. The development of the model is based on a conceptual model, which is the result of the literature study and data analysis. Because there are no other agent-based models created in the past simulating tick bites in the Netherlands, the model of this research is developed from the very first start.

Factors that need to be included in the model are selected based on the results of the literature study and the data analysis. Tick hosts like rodents are not part of the model because no data of these populations is available for the Netherlands. The focus of the model is on human behavior and how this relates to the number of tick bites. The model runs at three different locations; a residential area, a forested area and a coastal area. These areas cover different types of vegetation and population groups with different types of behavior. This is because it is then possible to discover spatial differences.

3.3.2 Model description (ODD protocol)

The description of the model follows the ODD protocol, which is described in section 2.5.5. Following this protocol ensures that the model can be developed in the same way by others. The ODD protocol aims to provide a generic structure and format for the documentation of ABMs, making them easier to understand and replicate.

3.4 STEP 3

3.4.1 Implementation

Now that the model is developed and described, it can be implemented ensuring that the model works right. This is followed by some analyses that test if the model works as expected.

3.4.2 Verification

The model needs to be verified before the sensitivity analysis can be conducted. In this research, the location of the turtles needs to be verified to check if the model acts correctly. This means that the turtles can only move to the patches inside the accessibility layer. If this is correct, the model acts as expected. The same counts for the resident and tourist distribution, age group distribution and precipitation threshold value, all parameters which will be verified.

3.4.3 Calibration

Two aspects of the model need to be calibrated. It is unclear what the probability of exposure is during the different activities included in the model. It is also unclear what the threshold value is above which exposure will lead to a tick bite. Both aspects will be addressed in this calibration.

3.5 STEP 4

3.5.1 Analysis results ABM

3.5.1.1 Experiments

To answer the research questions, several experiments will be conducted. The experiments are shown in table 4.1 with their variable settings and their output. These experiments explore the distribution of the tick bites and which factors influence the number of tick bites.

Table 4.1 Experiments with their settings and output

Experiment	Variable settings	Output
1) Only H	E = 1	Plot
2) H * E	Default	Plot
3) Residents vs tourists	Default; count residents and tourists separately	Graph
4) Location of tick bites	Default	Map
5) Accessibility	Accessibility layer on and off	Table
6) Weather	Precipitation layer on and off	Table

The first and second experiment explore the patterns of tick bites over time. Experiment 1 only uses H to indicate the number of tick bites and experiment 2 uses H * E. These experiments show how E influences the tick bites pattern.

The third experiment explores the distribution of the tick bites over the residents and the tourists. This experiment gives insight into the distribution of the tick bites over the two population groups and could find the cause of this distribution.

The fourth experiment explores the relationship between accessibility of areas and the number of tick bites. The fifth experiment explores the influence of precipitation on the number of tick bites. Precipitation influences the abundance of ticks (Gage et al., 2008) but also the activities of people and the clothes they are wearing. Protective clothing can reduce the risk of getting a tick bites (Stefanoff et al., 2012).

On wet days, the risk of getting a tick bite is lower and when there is heavy rainfall the risk is 0 because turtles do not move. This experiment explores how precipitation influences the number of tick bites and what happens with this number if precipitation does not limit the risk and movements of the turtles.

3.5.2 Conclusion and discussion

This research ends with a conclusion and discussion. In the conclusion chapter the research questions are answered. In the discussion chapter the limitations of the model and the research are discussed. Recommendations are also made for further research.

4 DATA ANALYSIS

4.1 INTRODUCTION

This study uses the Tekenradar dataset. The Tekenradar data is a volunteered geographic dataset, founded by RIVM in collaboration with Wageningen University. Tekenradar is a platform where citizens can report their tick bites and where they can learn about ticks and Lyme disease in the Netherlands. The website of Tekenradar also provides a tick expectancy for the following ten days, indicating in which regions in the Netherlands the nymphs are active. From 2006 on citizens could report their tick bite on the website of Nature Today. The website of Tekenradar got released in 2012 and from then on citizens could report their tick bite on that website. For the analysis in this chapter the years 2006-2016 were used because the data of these years was available to use. For the more in-depth analysis of the relationship between climate factors and tick bites the years 2012-2016 were used because in 2012 the website of Tekenradar got released with media attention, resulting in more people reporting their tick bites.

An initial analysis of the data will be performed based on the factors identified in the literature review (chapter 2). The idea behind this exploratory data analysis is to determine which of the factors mentioned in literature are valid of the Netherlands and can be detected in the dataset (s) and should be used in the ABM. As explained in chapter 2, tick bites can be predicted via the formula R= H * E.

In chapter 2 two types of hazard (H) were discussed, the vegetation type and climate factors. Several factors were discussed related to exposure (E) including the age of the person and the activity the person was conducting. The rest of this chapter analyzes hazard and exposure factors using the Tekenradar data.

4.2 CLIMATE

4.2.1 Temperature and precipitation

As stated in section 2.2.2 and 2.2.3, temperature and precipitation are two environmental factors that relate to tick presence and dynamics (Garcia-Martí, Zurita-Milla, Swart, et al., 2017). In previous studies, most tick bites have been reported during summer (Gassner et al., 2011). This can be caused by two drivers; (1) the higher temperature in summer and less precipitation causes ticks to be more active or (2) in summer people take part in more outdoor activities – and are therefore more exposed. The study of Perret, Guigoz, Rais & Gern (2000) found that ticks were always present when the temperature was above 10°C and never present when the temperature was under 1.9°C. This indicates that ticks like higher temperatures which relates to more ticks in summer (Perret, Guigoz, Rais, & Gern, 2000). In summer, people do more outdoor activities (García-Marti, 2017), resulting in more exposure to ticks and higher risks of getting a tick bite. Figure 4.1 shows the percentage of reported tick bites per month, clearly indicating that most tick bites have been reported in summer (30.717;65,59%). The peak months for tick bites is July, and tick bites are reported in all months including the winter (December, January and February). The average temperature per month over these years is included in the graph as well (Royal Netherlands Meteorological Institute (KNMI), 2018), showing that the higher temperature the more tick bites reported.

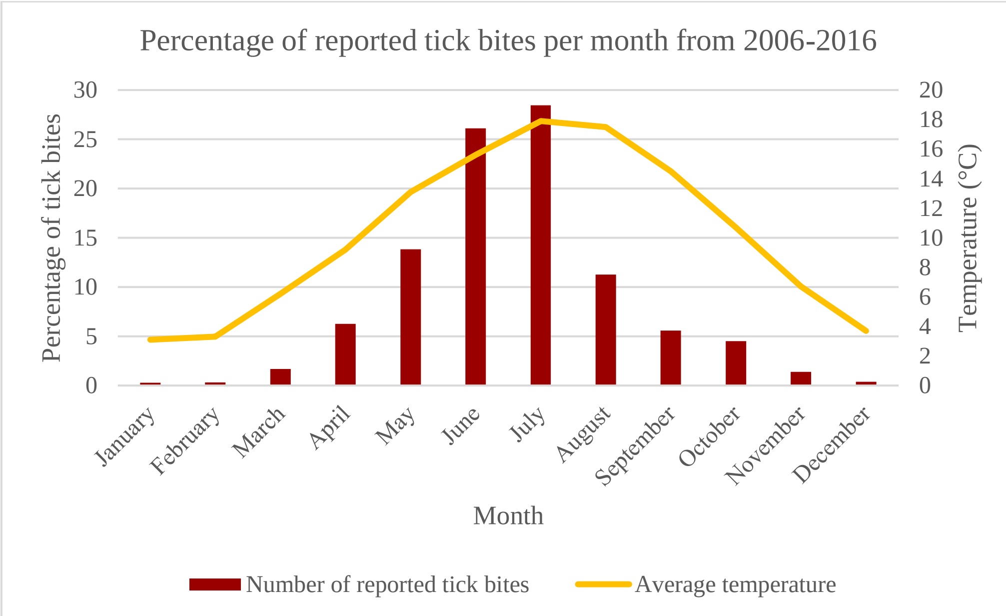


Figure 4.1 Percentage of reported tick bites per month (Tekenradar, 2018)

Figure 4.2 and 4.3 show the number of tick bites together with average temperature or precipitation per year. When looking at the last 4-5 years (when Tekenradar got media attention), there seems to be no clear relationship between high temperature or less rainfall and the number of tick bites. For example, the year 2014 had a high average temperature and less precipitation but the number of reported tick bites is quite low. The opposite occurs in the year 2015, the average temperature was lower and there was more rainfall, but the number of reported tick bites is very high.

Appendix I shows the graphs of 2012-2016 with average temperature, minimum temperature and average precipitation. These graphs give a more detailed look at the relationship between temperature and tick bites, and precipitation and tick bites. This is because there are delayed effects concerning surviving and questing ticks. As mentioned in section 2.2.3, heavy early spring precipitation influences the number of questing nymphs (Daniel & Dusbabek, 1994) and heavy winter precipitation the number of surviving larvae (Hornik et al., 2003). As found by Subak (2003), early summer Lyme disease incidence correlates with the June moisture index of two years previously. This means that temperature and precipitation have a delayed effect on the number of tick bites which can be discovered two years later (Subak, 2003). However, the analysis of the temperature and precipitation data (appendix I) does not show a clear linear relationship between temperature and precipitation and tick bites, it varies a lot per year. The only relationship that is valid for every year is that most tick bites are reported in summer (June and July) and these are the months with the highest temperatures. However, the question is if this is because of the warmer temperatures or people doing more recreational activities. That is why behavior factors are analyzed in section 3.4.

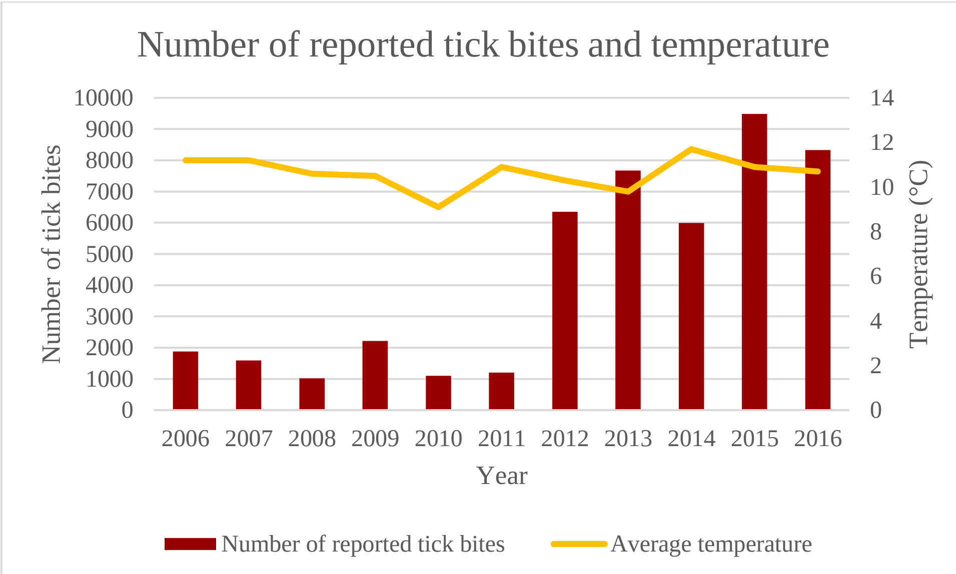


Figure 4.2 Number of reported tick bites and average temperature per year (Royal Netherlands Meteorological Institute (KNMI), 2018; Tekenradar, 2018)

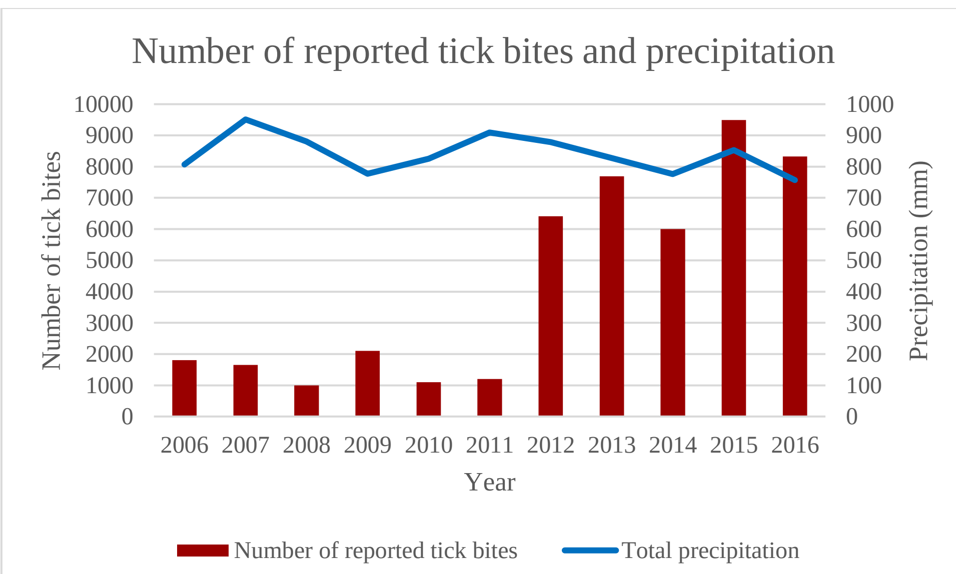


Figure 4.3 Number of reported tick bites and total precipitation per year (Tekenradar, 2018; KNMI, 2018)

4.3 LANDSCAPE

4.3.1 Vegetation type

Forest management is one of the critical drivers of the change of the geographical distribution of ticks in Europe (Medlock et al., 2013). This is because forest management leads to reforestation, which results in more suitable habitats for ticks in Europe since ticks and their hosts, such as rodents and birds, mostly live in forested areas. Figure 4.4 shows the percentage of reported tick bites per vegetation type.

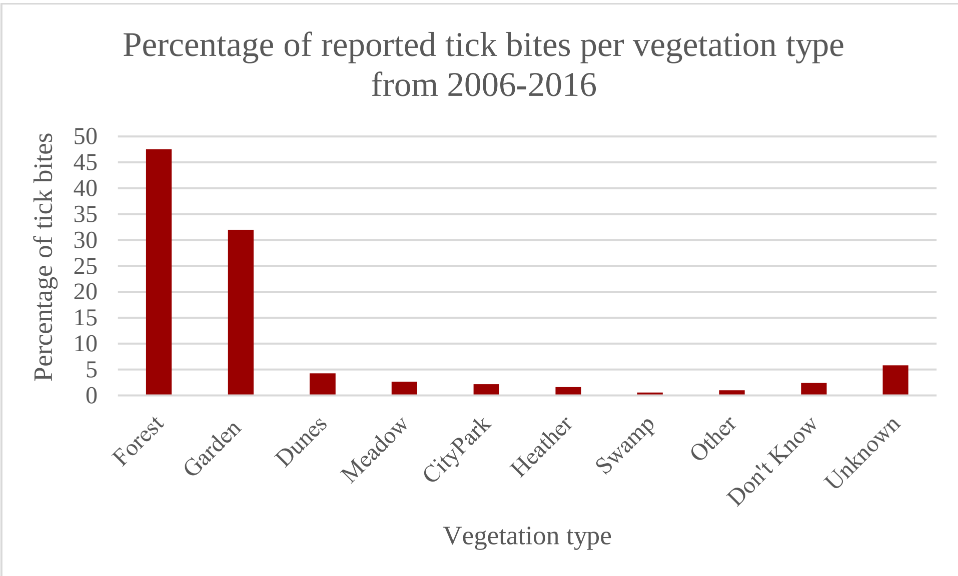


Figure 4.4 Percentage of reported tick bites per vegetation type (Tekenradar, 2018)

Almost half of the reported tick bites (47.52%) has been reported in a forest. However, also nearly one-third of the reported tick bites (31.96%) has been reported in a garden. According to Mulder et al. (2013), people who live in a forest or dune area have a higher risk of getting a tick bite in their garden. This is because in their study the high percentages of tick bites in forests or dunes corresponded significantly with the high percentages of tick bites in gardens.

4.3.2 Hosts

As mentioned in section 2.3.2, hosts influence tick presence because ticks feed themselves with blood from their hosts. However, due to lack of data of host presence in the Netherlands, it is not possible to analyze this factor and it is not part of the resulting ABM of this research.

4.4 BEHAVIOR

4.4.1 Activity type

Human behavior is closely related to environmental factors, such as weather, which makes these factors interesting to analyze because environmental factors, as well as human factors, are of influence on tick bites (Garcia-Martí, Zurita-Milla, Swart, et al., 2017). Figure 4.5 shows the percentage of tick bites per activity type. People apparently get most tick bites while walking (or hiking; 36.62%) or gardening (17.84%). This corresponds to the results of the analysis of the different vegetation types (figure 4.4) since people get the most tick bites in a forest or garden. However, the percentage of tick bites during playing is also high (12.44%) which does not automatically correspond to a vegetation type. The rate of tick bites per activity type differs per age group because people of different ages act differently.

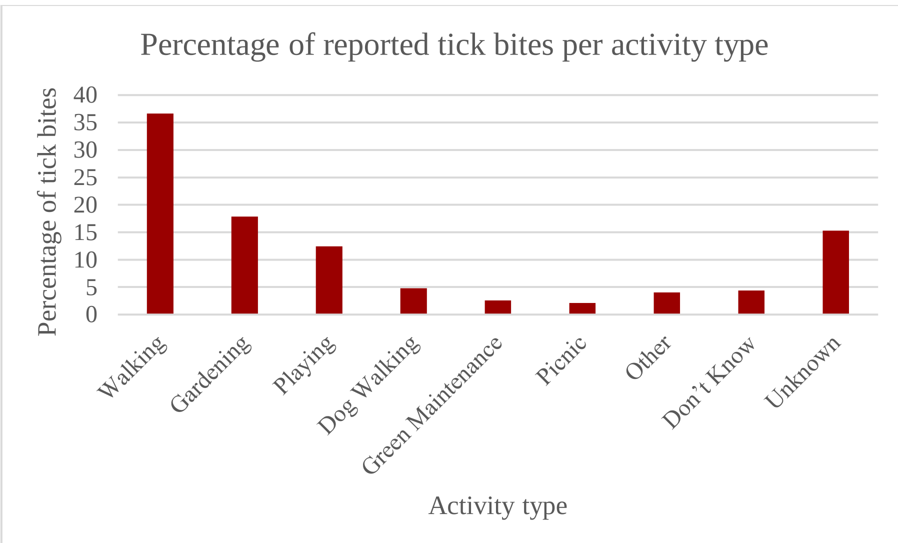


Figure 4.5 Percentage of reported tick bites per activity type (Tekenradar, 2018)

4.4.2 Age

Mulder et al. (2013) state that children under 10 and people between 50 and 69 get the most tick bites. This correlates with the average distribution of Lyme disease where the first maximum occurs in children between 5 and 9 years and the second maximum in people between 50 and 64 years (Lipsker & Jaulhac, 2009). They also state in their study that people above 60 get most tick bites when gardening while younger people are mostly bitten during walking (or hiking). Figure 4.6 shows that the first statement is not right in this case. Besides children under 10 and people from 50-69 (7,10%;22.67%), teenagers (10-19), people from 40-49 and people from 70-79 also get many tick bites (10.58%;11.03%;7.64%).

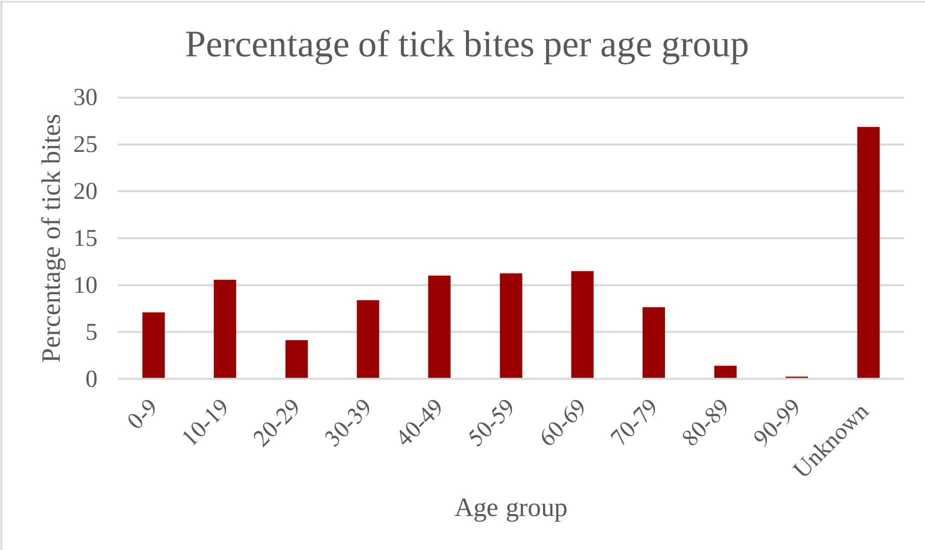


Figure 4.6 Percentage of tick bites per age group (Tekenradar, 2018)

Figure 4.7 shows that also the second statement is not right in this case. People above 70 get most tick bites during gardening but people between 60 and 69 get the most ones while walking (or hiking). People under 20 get the most tick bites during playing and walking, where the younger children will get a tick bite while playing and the older children while walking, and people between 20 and 59 during walking (or hiking) or other (dog walking, green maintenance, picnic, other). This figure clearly shows that the number of tick bites per age group differs and that different age groups get tick bites during different activities.

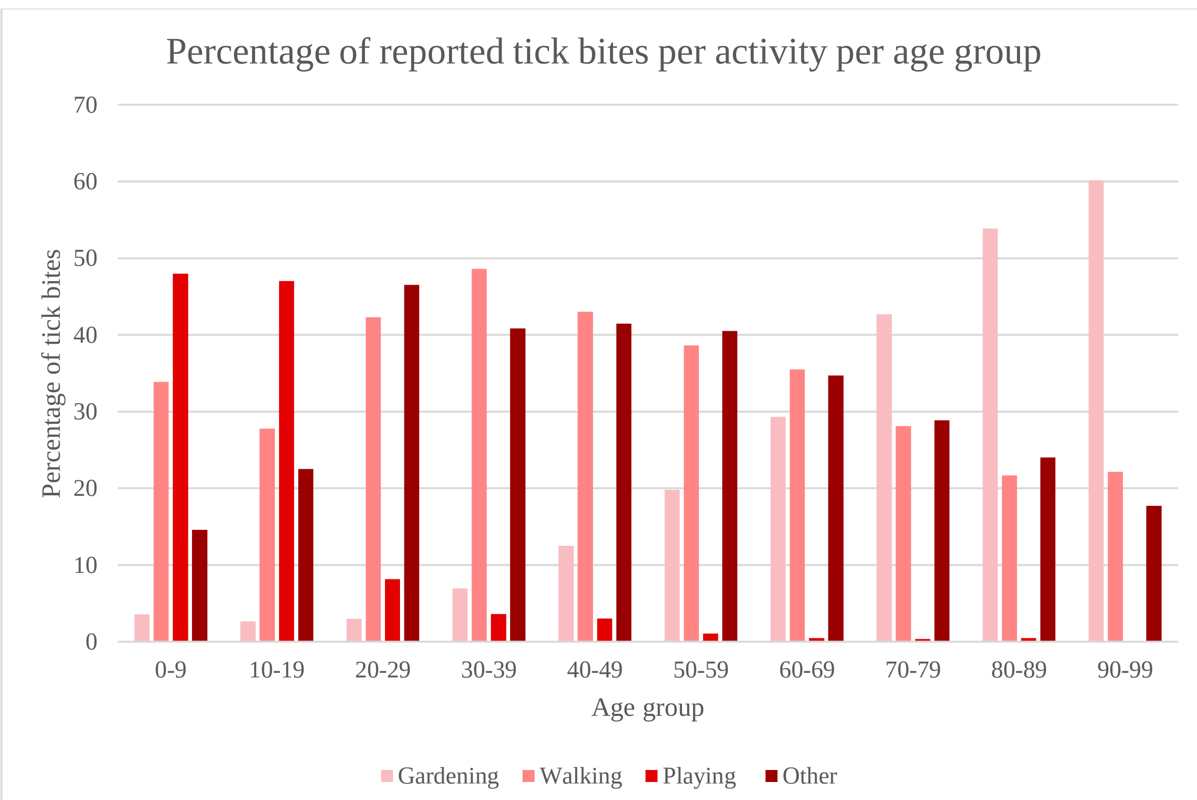


Figure 4.7 Percentage reported tick bites per activity per age group (Tekenradar, 2018)

4.5 ALL INFLUENCING FACTORS

All influencing factors described and analyzed in chapter 2 and 4 are shown in figure 4.8. The factors belonging together have been grouped, either exposure hazard, referring to figure 2.3.

The first group is exposure which relates to human behavior. As described, scenic beauty, accessibility, activity age and weather (Zeimes, Olsson, Hjertqvist & Vanwambeke, 2014; Garcia-Martí, Zurita-Milla, Harms & Swart, 2018) all relate to the chance of being exposed to ticks and thus the chance of getting a tick bite. Age and activity relate to the type of activity humans are doing, whereby different kinds of activities come with varying chances of getting a tick bite. Especially during walking/hiking, gardening and playing people have high chances of getting a tick bite. However, this chance differs per age group which is why age needs to be considered as well (figure 4.7).

The second group is hazard, which relates to landscape and climate. Vegetation is important to the amount of ticks because they prefer landscapes with a thick undergrowth (Süss, 2003). Hosts relate to ticks because ticks need to feed themselves with their blood. As described, increasing populations of hosts lead to increasing numbers of ticks (Pugliese & Rosà, 2008). Temperature and rainfall influence the abundance of tick as well. With too heavy rainfall ticks are not able to climb vegetation to get high enough to bite their hosts and ticks get active when temperatures are above 5°C (Bennet et al., 2006; Duffy & Campbell, 1994).

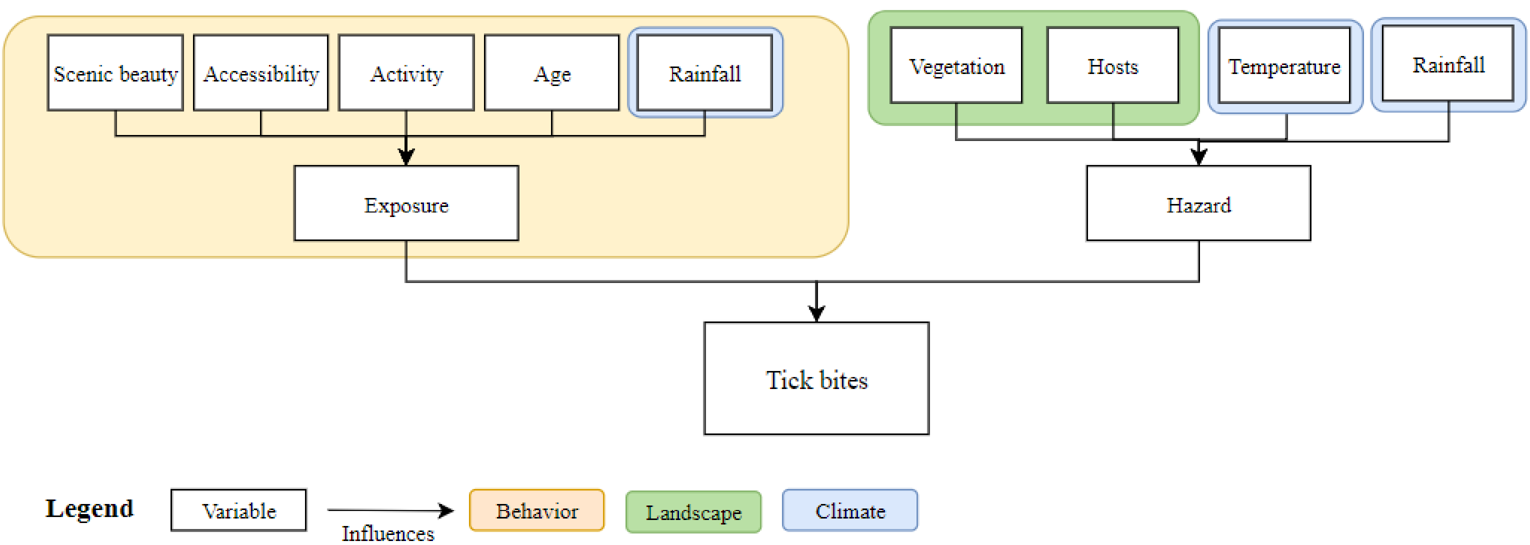


Figure 4.8 Scheme representing all influencing factors together, showing how they influence each other

4.6 CASE STUDIES

The model of this research runs at three different locations so that it is possible to discover spatial differences. These three areas are a residential area, a forested area and a coastal area. These three areas are interesting to simulate because they experience a different number of tick bites and people do different activities in these areas.

4.6.1 Forested area: municipality of Ede

Forests are the optimal habitat for ticks (Garcia-Martí, Zurita-Milla, Swart, et al., 2017; Lindström et al., 2003; S. Mulder et al., 2013). Forests can have a thick undergrowth and ticks can easily climb the vegetation to search for hosts. Besides that, forests are a great buffer against weather extremes, giving ticks a high chance of surviving (Lindström et al., 2003). A dense forested area in the Netherlands is the municipality of Ede. Almost half of the area of the municipality is covered by forest (figure 4.9), which makes it an interesting case study. Figure 4.10, showing the percentage of reported tick bites per vegetation type for the selected case study areas, clearly shows that most people in Ede get a tick bite while they are in a forest. Figure 4.11 shows that most tick bites in Ede are contracted during walking/hiking. The municipality of Ede is situated next to the national landscape 'Hoge Veluwe' which makes the area attractive for outdoor recreational activities.

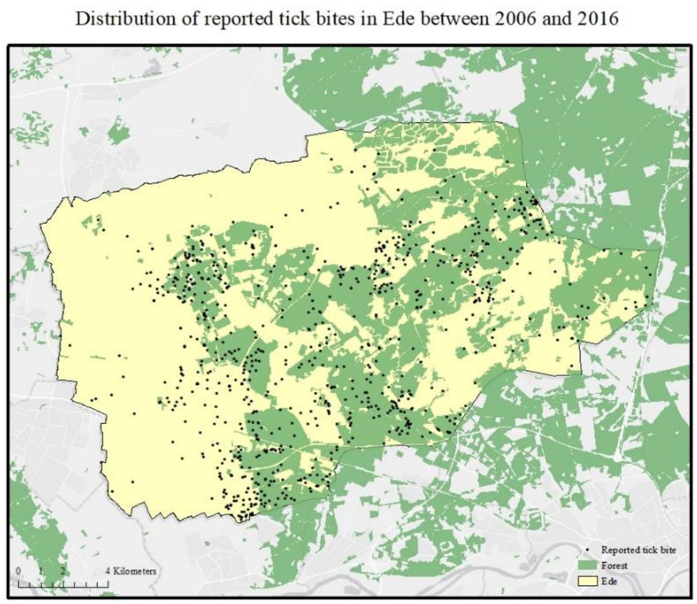


Figure 4.9 Tick bites in Ede (Tekenradar, 2018)

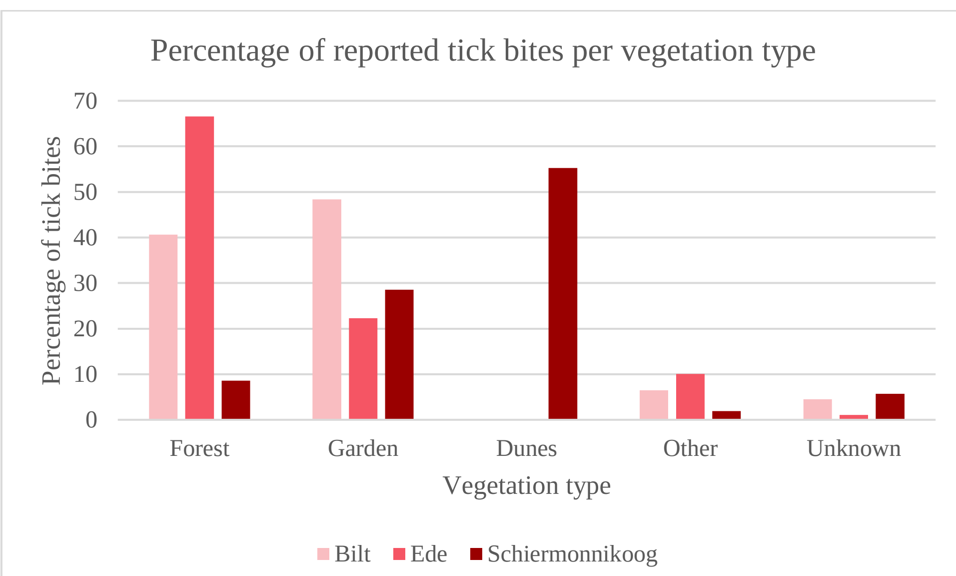


Figure 4.10 Tick bites per vegetation type per area (Tekenradar, 2018)

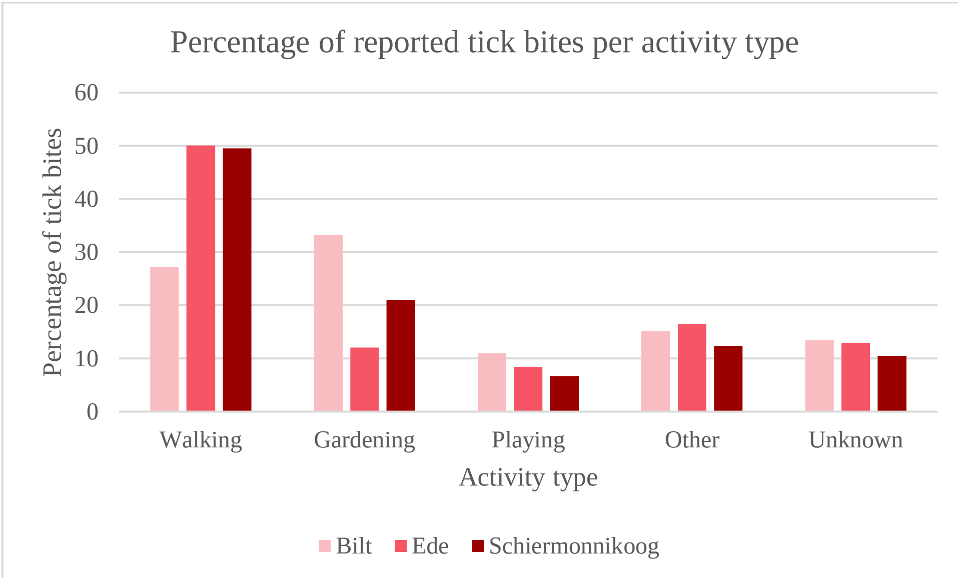


Figure 4.11 Tick bites per activity type per area (Tekenradar, 2018)

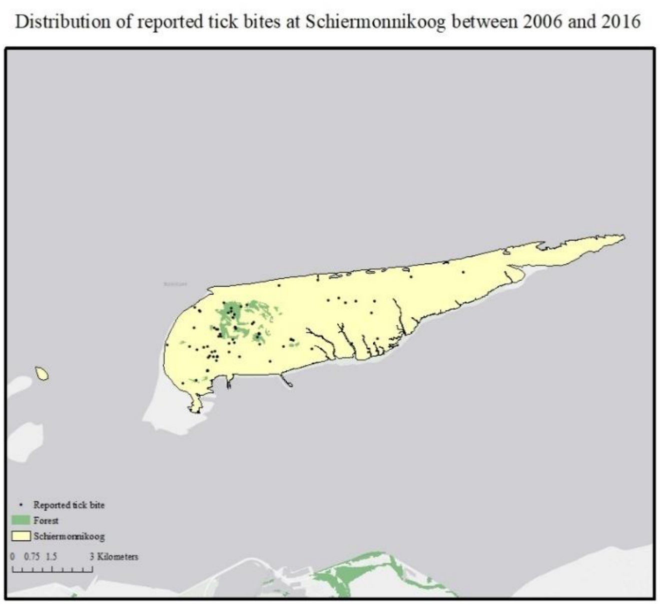


Figure 4.12 Tick bites at Schiermonnikoog (Tekenradar, 2018)

4.6.2 Coastal area: Wadden Sea Island Schiermonnikoog

Next to forested areas, coastal areas also experience many tick bites (S. Mulder et al., 2013). Dune grasses are a perfect habitat for ticks because they can easily climb it to start questing, waiting for a host (in this case mostly humans) to attach themselves to. The Wadden Sea Island Schiermonnikoog is a Dutch coastal area which is attractive to tourists (figure 4.12). Figure 4.10 clearly shows that most tick bites reported in Schiermonnikoog occur in dunes. Figure 4.11 reveals that these tick bites are most likely experienced during walking/hiking and other activities such as walking with the dog or having a picnic. This area is an interesting case study because it is a coastal area that experiences many tick bites and those bites are reported mostly in the dunes.

4.6.3 Residential area: municipality of The Bilt

A third interesting case study is a residential area. Tick bites are not only experienced in forests or dunes but also in gardens (S. Mulder et al., 2013). Human exposure to ticks is not only driven by recreational users but also by residential users (Garcia-Marti et al., 2018). A residential area in the Netherlands that experiences relatively many tick bites is the municipality of The Bilt (figure 4.13). In the Bilt, most tick bites are experienced in gardens (figure 4.10), mostly during gardening (figure 4.11) or other activities such as green maintenance. The municipality of The Bilt is an interesting case study because the tick bites are spatially distributed through the whole residential area. This relates to the statement that tick bites are driven by residential users as well (Garcia-Marti et al., 2018).

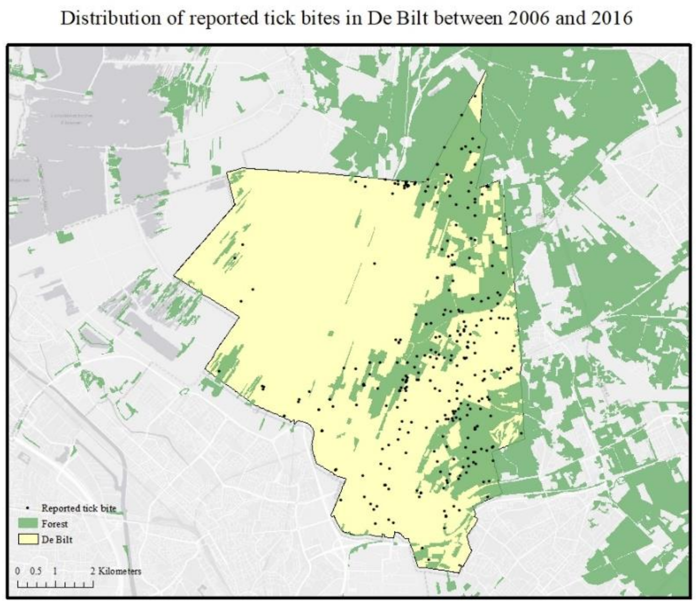


Figure 4.13 Tick bites in The Bilt (Tekenradar, 2018)

The result from the monthly analysis for the three case study areas is shown in figure 4.14. This figure shows that the tick bites in Ede and at Schiermonnikoog are similarly distributed. Most of the tick bites are reported in summer which makes sense because during summer more people are doing recreational outdoor activities. In The Bilt, the increase of the number of tick bites starts sooner and has its peak in May, June and July. This relates to spring being the best season to work in the garden.

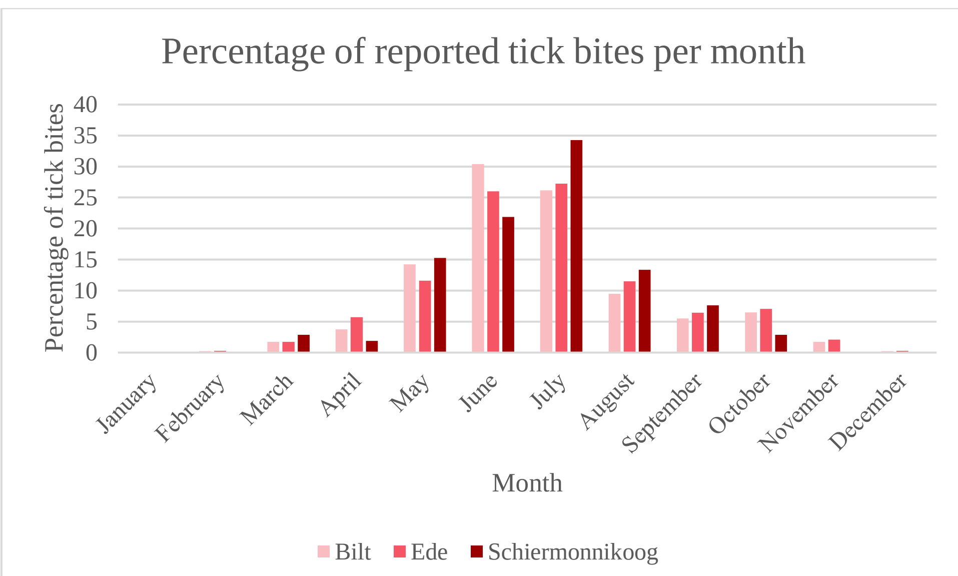


Figure 4.14 Tick bites per month per area (Tekenradar, 2018)

5 MODEL DESCRIPTION

5.1 OVERVIEW

5.1.1 Purpose

This agent-based model, simulating tick bite risk in the Netherlands, serves two purposes. First, it helps to find out which factors most influence tick bite risk. Its main purpose is to test the influence of human behavior on the number of tick bites. Secondly, it helps to identify differences between the three case study areas.

5.1.2 Entities, variables and scale

This model contains two types of agents. The agents of this model are the people involved in recreational and residential activities (residents and tourists). Table 5.1 provides and overview of the variables of these agents. The state variable of both agents is the infection (tick bite or no tick bite). The residents represent people living in the area, they have a home location and during the simulation they will not move out of the area, their number will remain constant (no births or deaths are simulated). Tourists have a stay period, which indicates the length of the stay in the area. Tourists are divided into the day, weekend and long stay tourists. New tourists are created during the simulation and after the stay period of the agent is over, the agent will leave. At the start of the simulation and when tourists enter the area, their infection status is zero (no tick bite).

Table 5.1 Agents and variables

Agent	Variable	Source
Tourists	Residence	Randomly assigned
	Stay-period	Based on municipality data
	Infection status	
	Activity	Tekenradar
Residents	Residence	In one of the urban areas
	Infection status	
	Activity	Tekenradar

This model contains a number of environments. Table 5.2 provides an overview of these environments.

The ticks are modelled as value of the land-use patches, indicating how high the tick abundance is per land-use type. There are four types of land-use in the model which have their own tick abundance. This abundance is based on the average monthly numbers of nymphs and adult ticks at the certain type of land-use. This sub-model is discussed in more detail in section 5.4.1.

Table 5.2 Environments and variables

Environment	Variable	Source
Land-use type	Tick abundance	Blanket-dragging data
Accessible areas	Binary layer indicating which areas are accessible and which areas are not accessible	

This model also contains a number of global variables. The climate data is loaded into the model at the start of every day. The model uses rainfall and temperature data.

The spatial scale of the model is municipality level. The three case studies are all different municipalities in different kind of areas in the Netherlands. The temporal resolution is one day, and the model is being run for a period of 1 year using the 2016 temperature data.

5.1.3 Process overview and scheduling

The focus of this ABM is on human behavior and how this influences the number of tick bites. The model has two different time lines, one for updating the tick abundance (one time per month) and one for resident and tourist activities and tourist creating and removal.

The ABM starts with the human population model, indicating if an agent is either a resident or a tourist (with a certain stay-period). The four different vegetation types (residential, forest, dunes/sand and other) are determined per patch and the model reads the amount of rainfall per day. As mentioned above, tick dynamics are modelled as percentage of ticks per patch per month. The activity of tourists and residents is based on the human population model, landscape and weather. Tourists do activities everyday while residents stay in the residential area during the week and do a recreational activity on Saturday. When there is heavy rainfall (above 50 mm) residents as well as tourists do not do any activities. All activities are based on the age group to which the turtle belongs.

The process overview of the human population and activity model is as follows:

1. Create new tourists
2. Determine day of the week and check if rainfall is low:
    a. Move tourists/residents
    b. Determine infection based on land-use type of the location, the weather (temperature) and the activity the tourist/resident is doing
    c. Return residents to their home location
    d. Remove tourists for which stay is over

The model needs to determine whether a turtle gets a tick bite or not. As mentioned in section 3.5 there are many factors influencing the risk of getting a tick bite. The research in Sweden about tick bites calculates the risk of getting a tick bite by hazard * exposure (Zeimes et al., 2014). In this study, hazard is defined by host species, forest and land cover and exposure by accessibility and scenic beauty. This research adopts this model and slightly adjusts it by adding personal factors incorporated in the exposure factor. The formula of this can be written down as follows:

$$R = H\ (L, T) * E\ (A, R, P) \tag{5.1}$$

where R = risk, hazard H is a combination of land-use and temperature, and exposure E is a combination of accessibility, rain influences and P representing personal factors which in this model is activity type.

In this research, hazard is determined by land cover (land-use type). Accessibility is defined by an accessibility layer which takes into account the National Landscapes and Natura 2000 areas in the case study areas. This layer defines where residents and tourists can move to and where they cannot move to. Weather is integrated as excessive rainfall leading to a stop of outdoor activities, and P represents personal factors including age and activity type.

The number of ticks in a certain land-use type varies over time as ticks are more active in warm summer months compared to cooler winter months. The tick abundance per land-use type was determined by blanket-dragging data. For every land-use type in the model (urban, forest, sand, other) was the tick abundance calculated by the number of nymphal land adult ticks. Larvae were left out because they do not bite people. These numbers (nymphal + adult ticks) were converted to percentages of the total number of nymphal and adult ticks in that month. The tick abundance is updated every month in the model, where the model reads at the first day of every month the new tick abundance per patch. This tick abundance also represents the risk of getting a tick bite per land-use patch.

Figure 5.1 shows the actual scheduling of the ABM. The first row of the figure shows the set-up procedures. The vegetation types are determined by GIS input which tells the model the vegetation type of every patch. Residents are already created in the set-up procedure because their number stays constant the whole run.

After the set-up is done, the model starts updating the tick abundance per land-use type every first day of the month. After this, tourists are created and the model reads rainfall data to indicate if a day experiences heavy rainfall or not, indicating whether residents/tourists will move or not. Together with the determined day and activity the residents/tourists will move (residents with gardening stay in the urban areas). When they have moved, the model calculated whether the resident/tourist gets a tick bite. After that, the residents move back to their homes (if it is a Saturday and they moved out of the urban area) and the tourist for which the stay is over are removed from the model.

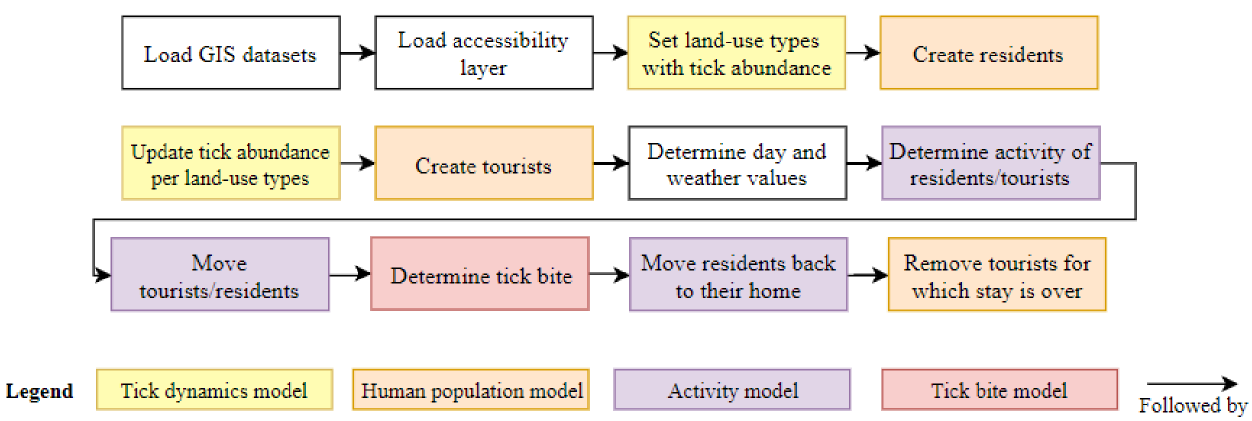


Figure 5.1 Scheduling of the ABM

5.2 DESIGN CONCEPTS

5.2.1 Interaction

In this model, the agents do not interact with each other. However, the agents interact with the environment of the model in a number of ways. The amount of rainfall changes every tick so, the probability of getting a tick bite based on the weather changes every day per agent. The chance of getting a tick bite based on the land-use type changes every time an agent moves because every land-use type has a different value. The movements of agents are random. These interactions change the number of agents getting a tick bite every tick.

5.2.2 Stochasticity

The model contains a number of stochastic elements. The activity type per agent is set randomly, so the number of agents performing a certain activity can change per run. The movements of the agents are random as well, which means that the value of getting a tick bite per land-use type is random too, linked to the agents' movements, and changes randomly every tick.

5.2.3 Observation

The key observations are the numbers of residents/tourists getting a tick bite per case study area. Besides that, the factors that influence the chance of getting a tick bite, such as weather and activity type, are observed as well, to find out which factors have the most influence.

5.3 DETAILS

5.3.1 Initialization

5.3.2 Input data

5.3.2.1 Tick dynamics model

Since 2006, groups of experienced volunteers familiar with ecological research have been collecting ticks at 24 different sites (figure 5.2) in the Netherlands. These groups collect the ticks by dragging a white cotton cloth ($1m^2$) over two marked transects of 100m (blanket dragging). The cloth is inspected at intervals of 25m for the presence of ticks (Gassner et al., 2011). The number of larvae, nymphs and adults are counted and removed at every interval. These blanket dragging data are the input for the tick dynamics model.

For this research, for each case study, the data from the blanket dragging locations closest to this site is used. Blanket dragging data from these three areas are available, and as mentioned in section 3.6, these three case studies all represent areas of different land use types which are interesting to model when studying tick abundance. Table 5.2 shows the numbers of larvae, nymphs and adults per case study area per year. For the case study Ede, the numbers of both Ede and Hoog Baarlo are calculated because these are both situated within the municipality of Ede. Appendix II shows the blanket dragging data of all sites from which data from every year were available. Only the numbers of nymphal and adult ticks were used because larvae do not bite humans.

Figure 5.2 Location of study sites blanket dragging (Gassner et al., 2011)

Table 5.3 Blanket dragging data per case study area per tick life cycle stage (…)

Larvae	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**Total**
Bilthoven	27	70	31	7	3	64	94	148	1,435	1,879
Ede & Hoog Baarlo	1819	2195	2,346	4,283	1507	2996	2413	5528	7060	30,147
Schiermonnikoog	22	156	154	112	412	340	110	64	609	1,979
Nymphs	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**Total**
Bilthoven	24	43	26	46	64	129	45	156	46	579
Ede & Hoog Baarlo	491	735	374	741	532	466	555	944	484	5,322
Schiermonnikoog	13	70	48	26	60	47	57	42	27	390
Adults	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**Total**
Bilthoven	6	14	20	11	37	19	18	6	7	138
Ede & Hoog Baarlo	24	76	37	84	70	55	54	94	99	593
Schiermonnikoog	8	22	17	21	32	30	18	15	13	176

5.3.2.2 Human population model

For the human population model, data about the numbers of residents and numbers of tourists per case study area were required. Data about the number of residents per case study were retrieved from the Central Bureau of Statistics Netherlands, shown in table 5.4.

Table 5.4 Number of residents per case study area in 2018 (CBS [Central Bureau of Statistics Netherlands], 2019)

Case study area	**Number of residents**
Bilthoven	42.846
Ede	114.682
Schiermonnikoog	932

Data about the number of tourists per case study area, shown in table 5.5. The information was retrieved from several sources, including the province of Utrecht and the province of Gelderland. The numbers of tourists were divided based on how many days tourists are staying in the area.

Table 5.5 Number of tourists per case study area (Provincie Utrecht, 2016; Ruimte & vrije tijd, 2017; Skylgenet, 2014; Visit Veluwe, 2017; WNL, 2018)

Case study area	**Stay period**	**Number of tourists per day**
Bilthoven (2015)	1 day	100.000
Ede (2017)	2 days	4.570.000
	5 days	2.870.000
	9 days	1.560.000
Schiermonnikoog (2017)	2 days	300.000

Because in winter the number of tourists is very low, the yearly numbers shown in table 5.4 were divided over 30 weeks (holiday season), which represent the period April-October. Only average annual data were available so the numbers of table 5.4 were calculated per week using the following formula:

$$y = B * g^{x} \tag{5.2}$$

In which y is the resulting number of tourists, β is the beginning value (which in this case is 0) and g is the exponential growth value. This formula represents exponential growth.

5.3.2.3 Bite model

The last sub-model of the ABM indicates whether a resident or tourist gets a tick bite or not. The used formula for this has already been discussed in section 5.1.3.

The probability of getting a tick bite per land-use was calculated based on tick abundance and was calculated per activity type based on the percentages of tick bites per type from the Tekenradar data. The values are shown in table 5.6.

Table 5.6 Probability of getting a tick bite per land-use and activity type per case study area (Tekenradar, 2018)

Case study area	% walking	% gardening	% playing	% other
The Bilt	27.18	33.17	10.97	28.68
Ede	50.09	12.04	8.42	29.45
Schiermonnikoog	49.52	20.95	6.67	22.86

The E in the formula is, next to the accessibility layer, determined by weather probability and activity. For activities are the assigned values shown in table 5.6. The values assigned to weather, in this case temperature, are adapted from a study on tick bites in Sweden (Lindgren & Gustafson, 2001). Added to these values was the one assigned to temperatures above 10°C because according to another study ticks were always present when temperatures were above 10°C (Perret et al., 2000).

The average temperatures per day are retrieved from KNMI (KNMI, 2019). Ticks are able to survive freezing temperatures but become really active when temperature rises above 4°C or 5°C (Duffy & Campbell, 1994). Table 5.7 shows the values assigned to the temperatures in the model.

Table 5.7 Probability values assigned to temperature (Lindgren & Gustafson, 2001)

Temperature (°C)	Value
< 5	0.1
≥ 5 and ≤ 10	0.6
> 10	1.0

5.4 SUB-MODELS

5.4.1 Tick dynamics model

The tick abundance is modelled using blanket dragging data as input. As mentioned before, because only nymphs and adults bite humans and can infect them with Lyme disease, larvae were not taken into account in the model. Figures 5.3 and 5.4 show the number of nymphal and adult ticks per case study area. Ede clearly experiences the highest numbers of ticks (1300 in June). In Ede and at Schiermonnikoog the most ticks were collected in June, whereas in Bilthoven the most ticks were collected in August. The number of adult ticks does not vary that much over the year, compared to the number of nymphal ticks. It is constant in Bilthoven at around 20 ticks, in Ede around 50 ticks and in Schiermonnikoog around 25 ticks.

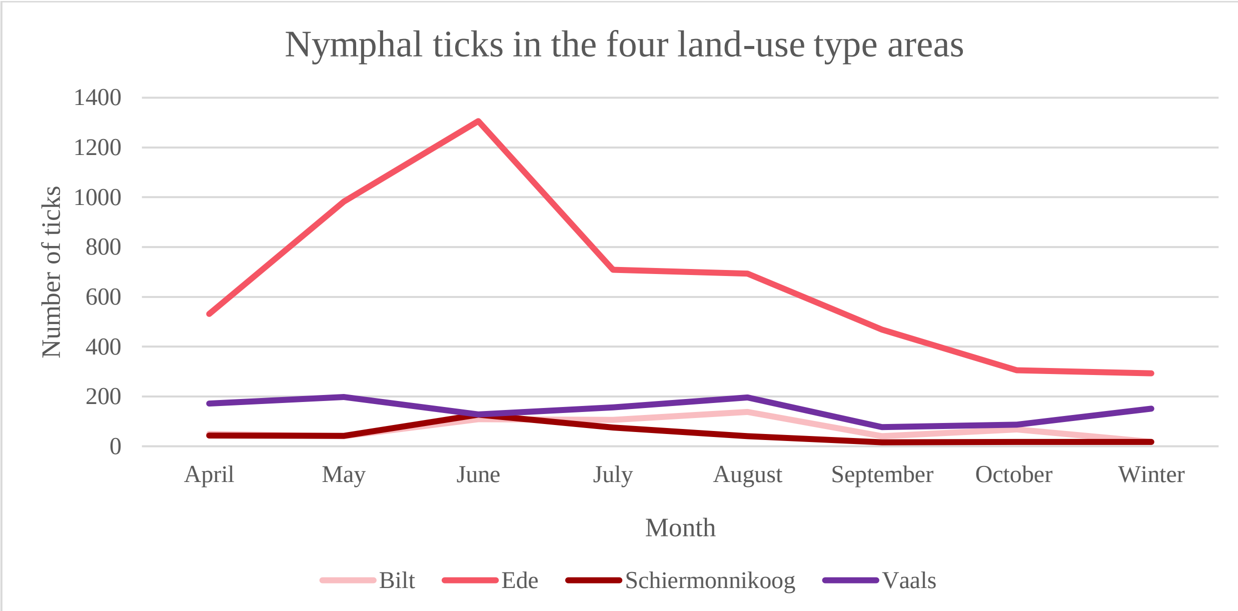


Figure 5.3 Nymphal ticks in the four land-use type areas

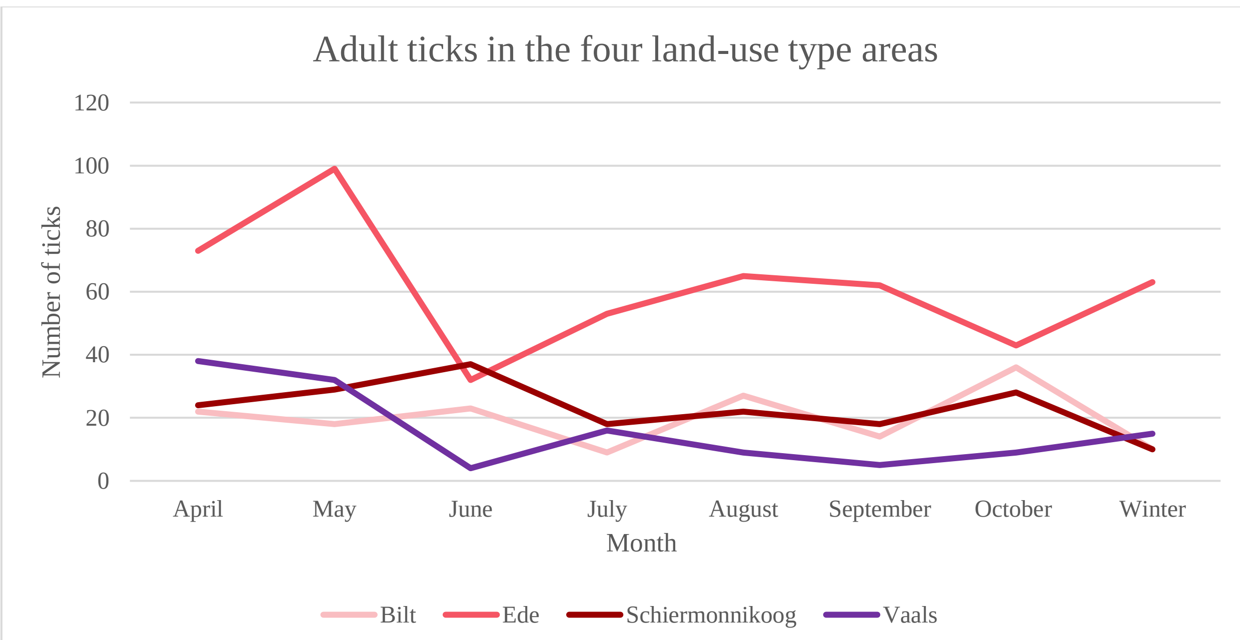


Figure 5.4 Adult ticks in the four land-use type areas

The model simulates forest, garden, dune and other vegetation types. As input for forest the numbers of Ede & Hoog Baarlo were used because these numbers represent the abundance in a forested area. The numbers of Bilthoven were used as input for garden and the numbers of Schiermonnikoog for dunes. The number of Vaals were used as input for other. Vaals was chosen as 'other' location because tick abundance was measured in an area with wood rush (Gassner et al., 2011). This is a suitable land-use type for other activities, besides hiking, gardening and playing, such as walking with the dog or having a picnic.

Using the data mentioned above means that the monthly numbers of nymphal and adult ticks, per vegetation patch are the same for every case study. The case study areas differ from each other because they all have different amounts of every vegetation type.

With these monthly numbers of ticks, the model simulates tick abundance per vegetation type per month, showing how tick dynamics fluctuates per month. Every month takes 30 days (30 ticks) in the model and at every first day of the month, the tick values change. Winter represents November, December, January, February and March. These were put together because the numbers of nymphal and adult ticks are very low during these months.

5.4.2 Human population model

The human population model makes a division between residents and tourists. Residents stay in the city during the week and move randomly outside of the city on Saturday. Tourists move randomly every day and have a certain stay-period. Tourists that stay one day are renewed every day. Tourists that stay two days stay the whole weekend. Tourists that stay five days arrive on Wednesday and leave on Sunday. Tourists that stay nine days arrive on Saturday and leave on Sunday the next week. The numbers of tourists are fixed, based on the input data discussed in section 5.3.2.2. However, a small change was made to the resulting numbers from the exponential growth formula. In May and October there are vacation weeks in the Netherlands. It is more realistic that more tourists will be in the case study areas in these weeks so that is why 5% of the number of tourists of every week has been added to the vacation week in May (week 19) and to the vacation week in October (week 42).

Where the residents and tourists can move to is defined by an accessibility layer. This layer represents the National Landscapes and Natura 2000 areas which are situated within the three case study areas. In the Bilt these are the Green Heart and the New Dutch Waterline, in Ede the Veluwe and at Schiermonnikoog the dunes, the North Sea zone and the Wadden Sea Zone. These are all attractive nature areas for recreation.

5.4.3 Activity model

As mentioned above, residents and tourists have different activity behaviors. Residents only leave the city on Saturday while tourists move randomly every day (as long as their stay-period). Their activities are influenced by the weather, in this model rainfall. The model reads rainfall values from a list every tick. This means that rainfall differs per day. The Ede model and Bilt model use the precipitation measurements from the weather station The Bilt and the Schiermonnikoog model uses the measurements from the station at Schiermonnikoog. Different measurements are used because the precipitation in the north of the Netherlands differs from the precipitation in the middle of the country. In case of heavy rainfall, which is above 50 mm in the Netherlands (KNMI, 2018), the residents and tourists do not move.

5.4.4 Bite model

This last sub-model indicates whether a resident or tourist gets a tick bite. As discussed in section 5.1.3, getting a tick bite is calculated with a formula considering all factors that influence the chance of getting a bite (formula 5.1). This formula calculates the chance of getting a tick bite per resident/tourist based on the patch on which the resident/tourist is every tick multiplied by the chance of getting a bite based on the temperature (which differs per tick), which represents the H, and this is then multiplied by the chance of getting a bite based on the activity a resident/tourist is doing, which represents the E (together with the accessibility layer and rainfall). This formula gives then a certain value per resident/tourist per tick and when this value is higher than the set threshold value (this will be discussed in section 6.2) the resident/tourist gets a tick bite.

6 MODEL ANALYSIS

6.1 VERIFICATION

This verification shows that the model behaves as expected. It verifies several parameters, such as the accessibility layer (section 6.1.1), the precipitation threshold value (section 6.1.2), the distribution of residents and tourists (section 6.1.3) and the division of the age groups (section 6.1.4). Because the three case study models are the same, the area of Schiermonnikoog has been used to do all the verifications. Only for the verification of the tourists with different stay-periods the Ede model has been used because there are only tourists with one type of stay-period in the Schiermonnikoog model. The stability check at the end shows after how many runs the output of the models gets stable.

6.1.1 Location turtles

The locations the turtles can move to are limited by the accessibility layer. Because all three case study areas are part of National Landscapes or Natura 2000 areas, these areas are used as accessible places for the turtles because such natural areas are attractive to tourists. The analysis below shows that the turtles indeed only move to accessible locations.

Figure 6.1 shows the distribution of turtles over all the patches during one simulation run for Schiermonnikoog. The figure clearly shows that the turtles can only move to the accessible parts of the municipality. Since the movement of the turtles is random, the patches are visited by different numbers of turtles. There are some outliers in the case study area, which are the white and black dots in figure 6.1. The black dot represents the urban path where the residents are situated. This patch is an outlier because the resident turtles stay at this patch six days a week so, that explains the high number of turtles at the residential patch during the run. The number of turtles at this patch is 87 162. The number of residents throughout the run is 250 * 360, which gives 90 000. The number of turtles at the patch is somewhat lower because all residents move away from this patch on Saturday, except the residents that have 'gardening' as activity because they do not move away from the residential patch on Saturday but stay on this patch. The other outlier is the patch where the tourists are created. They always enter the model at the same patch (-14, 7). The number of tourists that is in the model is 75 000. The number of turtles at the patch is 94 771. The number of turtles at the patch is higher than the total number of tourists in the model because when precipitation is above 50 mm, the turtles do not move and stay at their patch which automatically leads to a higher number of turtles at this patch.

Number of turtles per patch at Schiermonnikoog

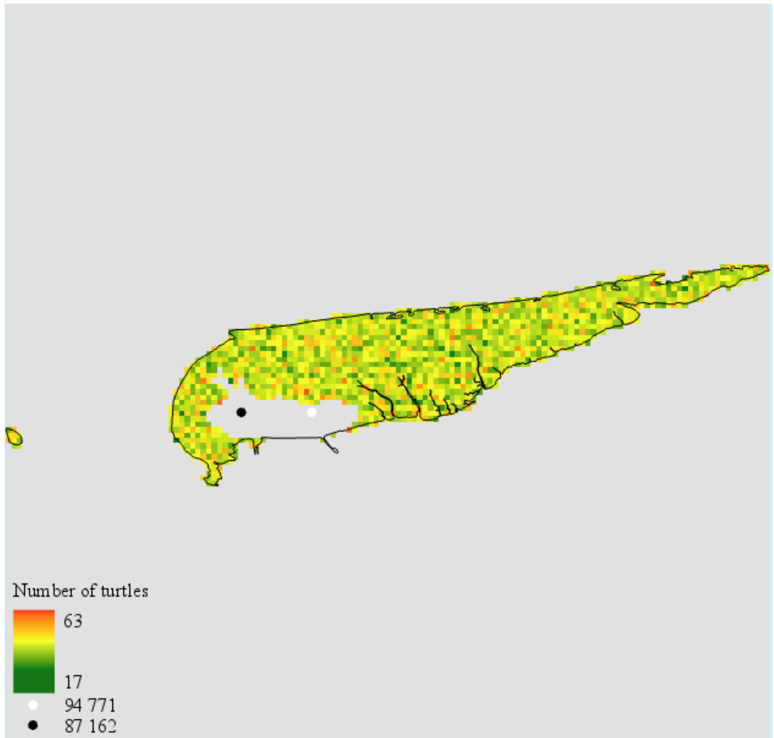


Figure 6.1 Number of turtles per patch at Schiermonnikoog

6.1.2 Precipitation threshold value

As discussed, when precipitation is more than 50 mm per day there is heavy rainfall. In the model this means that the turtles do not move because when it is raining heavily, people will not do any outdoor recreational activities. The Schiermonnikoog model has been used to verify if the model behaves as expected. Table 6.1 shows the amount of precipitation and the number of tick bites in January at Schiermonnikoog. The table shows that when precipitation is above 50 mm, there are no tick bites. There are also other days where precipitation is below 50 mm and no tick bites occur, but this relates to other factors such as the temperature because when temperature is low the weather probability of getting a tick bite is low. Table 6.1 verifies that indeed turtles do not get a tick bite when precipitation is above 50 mm. Because precipitation is implemented in the three case study models in the same way, this means that all the models behave as expected when concerning the precipitation threshold value.

Table 6.1 Verification precipitation and tick bites in January at Schiermonnikoog

Day	Precipitation	Tick bites		Day	Precipitation	Tick bites
1	0	228		16	56	0
2	21	220		17	0	0
3	11	222		18	0	0
4	53	0		19	30	0
5	0	0		20	12	15
6	1	218		21	0	0
7	99	0		22	31	224
8	1	224		23	3	221
9	12	220		24	5	227
10	0	0		25	0	220
11	56	0		26	43	225
12	47	220		27	32	219
13	55	0		28	3	225
14	46	0		29	109	0
15	72	0		30	31	221

6.1.3 Residents and tourists

The number of residents in the model stays the same throughout the year. The numbers of tourists vary, based on the exponential growth formula and the Dutch vacation weeks in May and October. Figure 6.2 is the verification of the number of residents and tourists at Schiermonnikoog. The figure shows that the model behaves as expected and that the number of residents is constant while the number of tourists is varying. The figure also shows that the tourists only stay 2 days and then leave, which is correct because there are only tourists with a stay-period of 2 days in the Schiermonnikoog model.

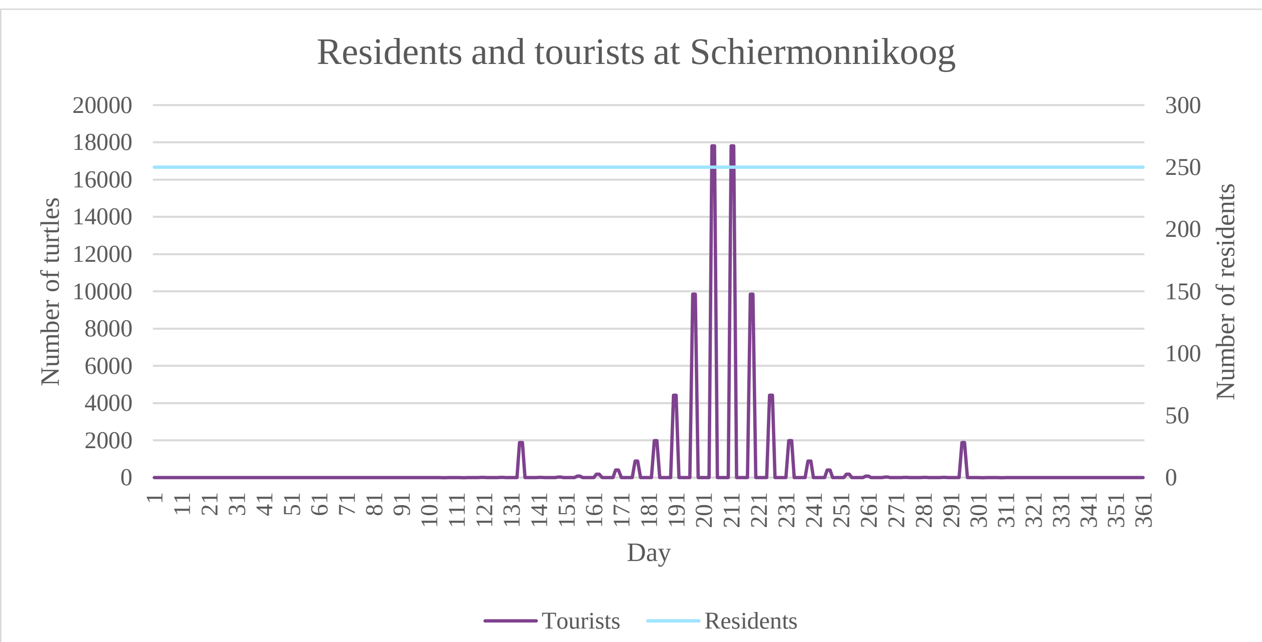


Figure 6.2 Residents and tourists at Schiermonnikoog

The Ede model has been used to verify the different types of tourists with their different stay periods. Figure 6.3 shows the three groups of tourists with varying stay periods. The stacked columns in the figure differ from each other because the tourists are removed from the model when their stay period is over. That is why some columns consist of all three types of tourists, some only of five-days and nine-days tourists and some only of nine-days tourists which stay in the model the longest. The figure shows that the distribution of the tourists is as expected with most of them in summer and peaks in May and October due to the vacation weeks.

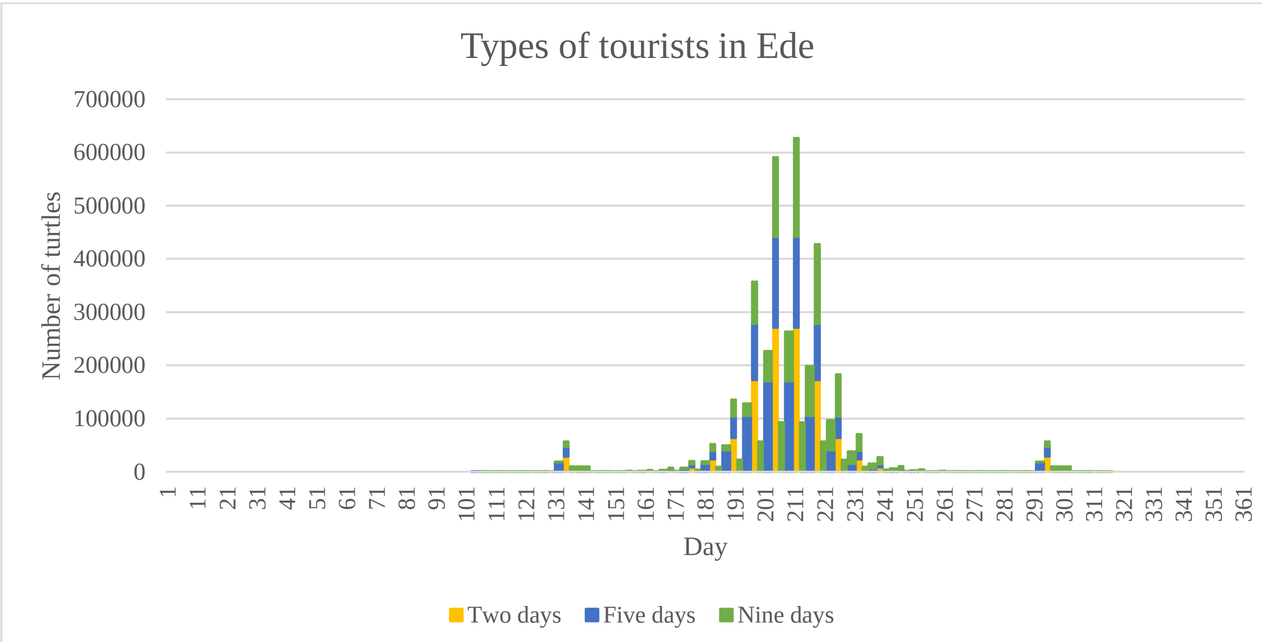


Figure 6.3 Types of tourists in Ede

6.1.4 Age groups

The final verification checks the distribution of the different age groups at Schiermonnikoog. These are determined by the percentages of residents and tourists in the certain age groups. Figure 6.4 shows the distribution of the age groups. The figure shows that the model behaves as expected and that the numbers of turtles per age group match the percentages. For example, on day 219, the Saturday of the week with the highest number of tourists, the distribution is as follows: 3083 children, 8676 adults and 6301 elderly. This means that 17.07% is child, 48.04% adult and 34.89% elderly. This matches the percentages of age groups for both residents and tourists together.

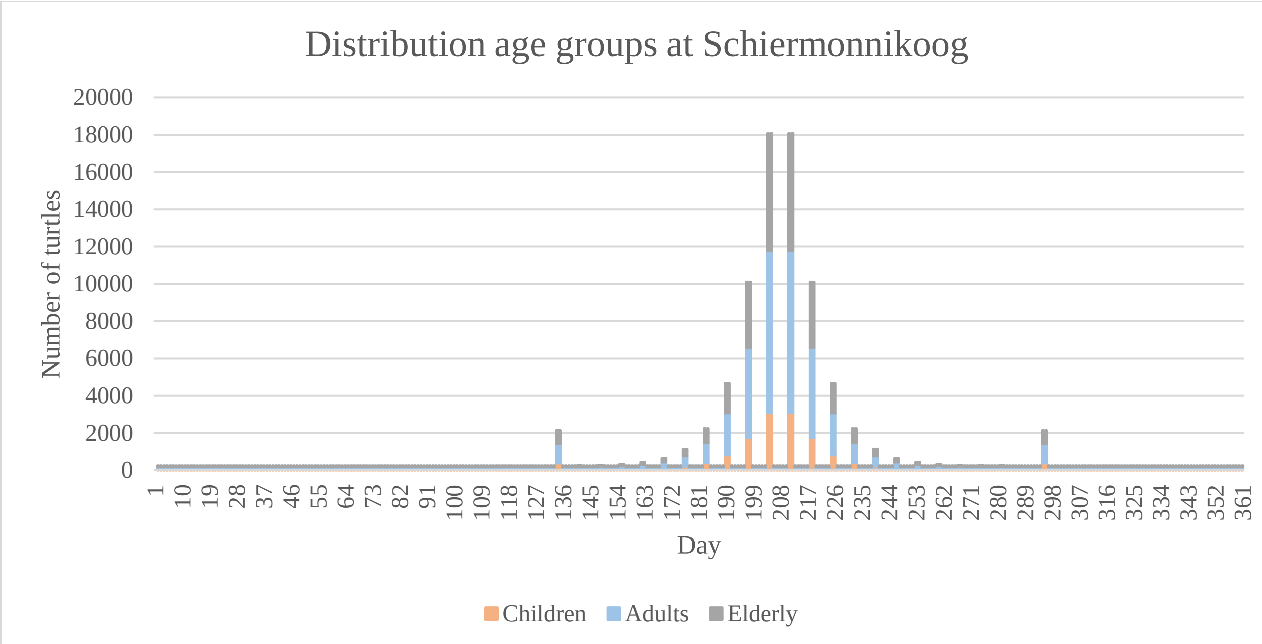


Figure 6.4 Distribution age groups at Schiermonnikoog

6.1.5 Stability check

The stability of the models is checked with two different methods. It is checked by plotting the average number of tick bites over an increasing number of runs. The resulting plot shows at which run the average number of tick bites becomes stable. The stability is also checked by using the method of the coefficient of variation, to determine after how many runs the number of tick bites gets stable. The coefficient of variation is defined as the ratio between the standard deviation of a sample and the mean of that sample (Lorscheid, Heine, & Meyer, 2012), resulting in the following formula:

$$Cv = \frac{\sigma}{\mu} \tag{6.1}$$

In this formula Cv is the coefficient of variation, σ the standard deviation of the sample and μ the mean of the sample. This formula is used to calculate the coefficient of variation for the runs with n = {5, 10, 25, 50, 100}. This wide range of runs gives a clear result of when the model becomes stable.

Figure 6.6 shows the average number of tick bites over an increasing number of runs at Schiermonnikoog. The figure shows that the model becomes stable after approximately 50 runs.

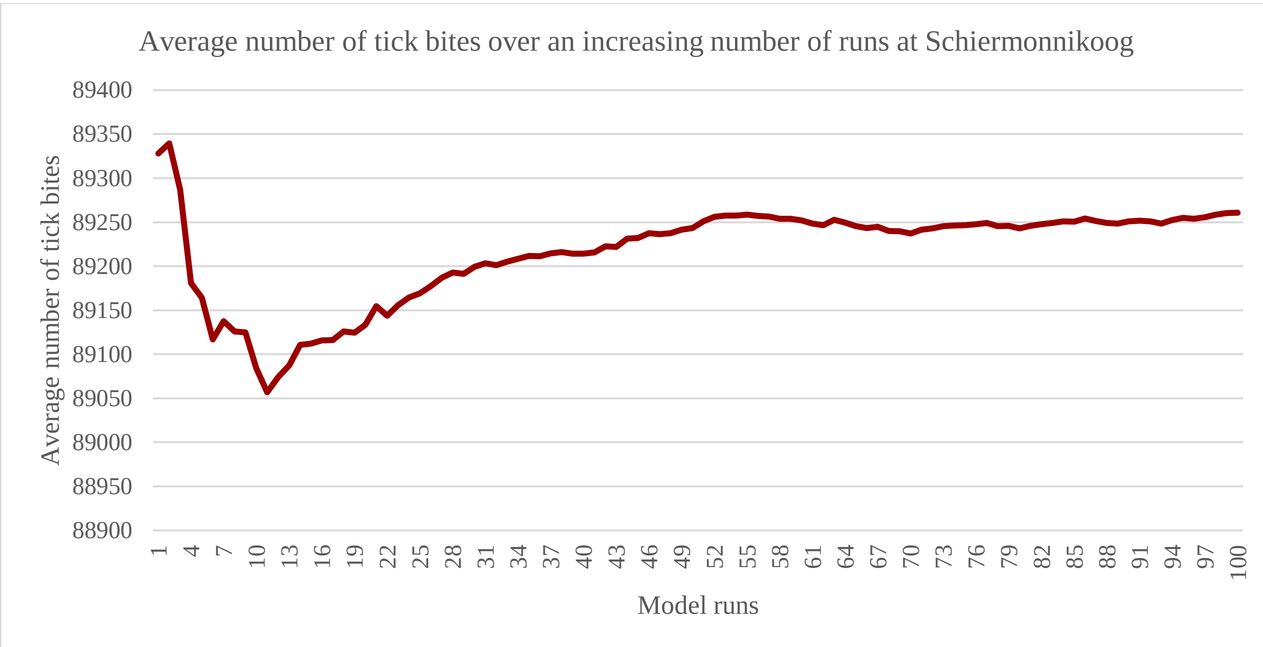


Figure 6.5 Average number of tick bites over an increasing number of runs at Schiermonnikoog

The results in table 6.2 show, next to the graph, that the model becomes stable after 50 runs. Conducting more runs is not necessary because it does not add to the stability of the model. This means that the minimum amount of runs for a stable result is 50.

Table 6.2 Cv runs Schiermonnikoog model

N	Cv
5	0.0022
10	0.0024
25	0.0024
50	0.0021
100	0.0021

6.2 MODEL CALIBRATION

Two aspects of the model need to be calibrated. It is currently unclear what the probability of exposure is during the different activities included in the model. It is also unclear what the threshold value is above which exposure will lead to a tick bite. Both aspects will be addressed in this calibration. The two factors are interrelated making it difficult to determine in which order the calibration should take place. Initially the activities will first be calibrated (6.2.1), followed by a calibration of the infection threshold (6.2.2.). In the last paragraph (6.2.3.) the two aspects will be calibrated together.

6.2.1 Calibration of the activities

As discussed in section 4.6, people in the three case study areas get their tick bites while doing different kinds of activities. Figure 6.6 shows the percentages of tick bites per activity type according to Tekenradar. In Ede and Schiermonnikoog most people get their tick bite while walking and in Bilt while gardening. The difference shows that the percentages are not identical for the study areas. This means that activities need to be calibrated for each case study area separately.

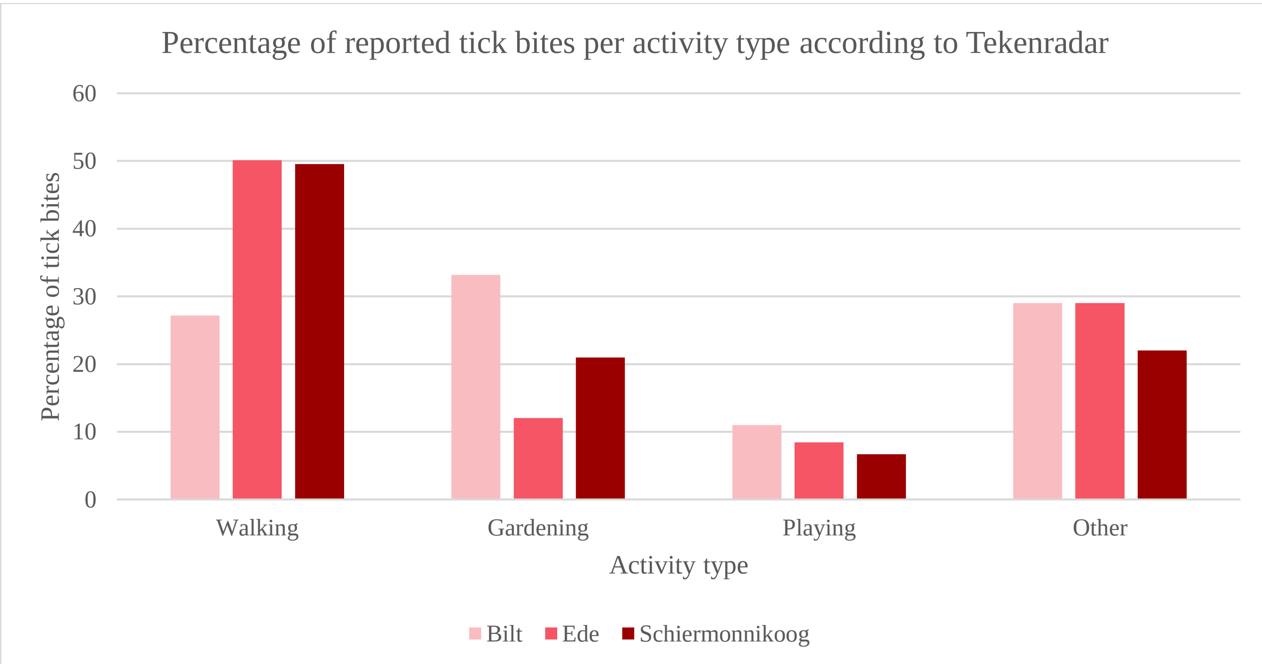


Figure 6.6 Percentage of reported tick bites per activity type according to Tekenradar (Tekenradar, 2018)

To get the same activity percentages as output from the models some changes have been made. It was assumed that the type of activity that people conduct, is partly determined by their age. Therefore, age groups were added to the model, for both residents and tourists. Sources about the age of tourists in Ede and Bilt were found, but not for Schiermonnikoog (see table 6.3). That is why the choice has been made to add the same age division for tourists in all the three case study areas, based on the sources about Ede and Bilt. Table 6.3 shows the percentages of each age group for residents and tourists per case study area.

Table 6.3 Percentages of age group per population group per case study area (Kenniscentrum gemeente Ede, 2019; Oozo, 2019; Toerisme Utrecht, 2016; Utrecht10, 2019; Visit Veluwe, 2017)

Population group	Age group	Bilt (%)	Ede (%)	Schiermonnikoog (%)
Residents	Children (0-18)	22	21	22
	Adults (19-64)	54	62	51
	Elderly (65+)	22	17	27
Tourists	Children (0-18)	17	17	17
	Adults (19-64)	48	48	48
	Elderly (65+)	35	35	35

The risk of getting a tick bite per activity is already different in the three models. The age groups are related to certain types of activities, as discussed in section 4.4.2. This means that in the models the age groups are related to the same types of activities. However, to get the activity percentages aligned with reality, there are some small differences in the three case study models. Table 6.4 shows which age groups do which activities in the three models. The table shows that in the Bilt elderly people do not walk and in Ede and at Schiermonnikoog adults do not garden. It would be more logical if the age groups and related activities would be the same in all three models. However, only with this distribution that slightly differs per case study area the output was closest to reality. That can indicate that using the same age group distribution of tourists in the three case study areas is not correct and that in reality this distribution differs per area. The threshold value for getting a tick bite was set at 0.005 for every case study area.

Table 6.4 Activities per age group per case study model

Area	Age group	Walking	Gardening	Playing	Other
Bilt	Children	X		X	
	Adults	X	X		X
	Elderly		X		X
Ede	Children	X		X	
	Adults	X			X
	Elderly	X	X		
Schiermonnikoog	Children	X		X	
	Adults	X			X
	Elderly	X	X		

With determining tick bites by H * E and the division of age groups and their activities as shown below are the percentages of tick bites per activity almost identical to reality. The output is shown in figure 6.7. this figure clearly shows that the percentages are almost identical to the percentages in reality. There are some differences of 3-4% but in general is the output of the models very comparable to reality.

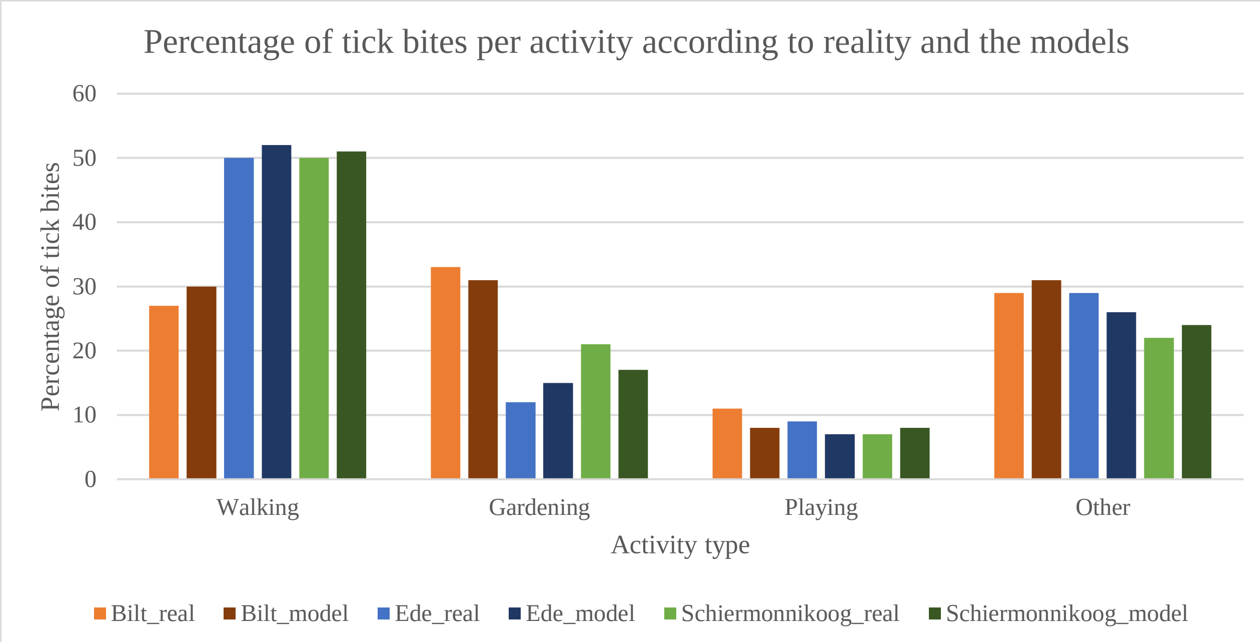


Figure 6.7 Percentage of tick bites per activity type according to reality and the models

6.2.2 Calibration of the number of tick bites

After calibrating the percentage of the activities, the total number of tick bites has to be achieved via calibration of the infection threshold. During the calibration of the percentages of activities, the resulting numbers of tick bites per case study area were very high. This means that the threshold value of 0.005, which was used in all three models for the activity calibration, is too low and results in too many tick bites. With the same settings as used for the activity calibration, meaning that the risk of getting a tick bite per activity is as described in table 5.3, the threshold values have been calibrated which should result in the right amount of tick bites. Every year people in the Netherlands experience approximately 1.3 million tick bites (RIVM, 2017). In 10 years, approximately 46 831 tick bites have been reported, which means that 0.4% of tick bites gets reported. Over 10 years, in the Bilt 401 tick bites have been reported, in Ede 1104 and at Schiermonnikoog 105. These numbers are thus 0.4% of the actual tick bites in these areas. So, the actual number of tick bites in the Bilt is 100 250, in Ede 276 250 and at Schiermonnikoog 26 250. These numbers have been used for the calibration because the models produce actual tick bites.

The calibration of the threshold value per case study model has resulted in the output shown in table 6.5. In the table the numbers of tick bites are already converted to the numbers of reported tick bites.

Table 6.5 Output of the tick bite threshold calibration per case study area

			Percentage per activity type (%)			
Area	**Threshold value**	**Reported tick bites**	**Walking**	**Gardening**	**Playing**	**Other**
Bilt	0.06	470	22	58	0	20
Ede	0.35	680	100	0	0	0
Schier	0.15	178	99.86	0.03	0	0.11

The numbers of tick bites are not exactly the same as the real numbers. In the Bilt and at Schiermonnikoog the numbers are too high while the number in Ede is too low. However, these numbers are the ones that get the closest to the real numbers. The threshold values differ greatly per case study area. The threshold in the Bilt is very low while the value in Ede is quite high.

When looking at the percentages of tick bites per activity type it is clear that these are not comparable to reality anymore. In both Ede and Schiermonnikoog, (almost) all the tick bites happen while walking. This can be caused by different factors. It can indicate that the risk of getting a tick bite while walking is lower than assumed now or too many age groups can do walking as activity (as described in table 6.4).

6.2.3 Calibration of the activities and the number of tick bites

The calibration of the activities and the calibration of the number of tick bites did not give the expected output of the model. Because this can be due to the assigned risks of the activities or the age groups doing certain activities are these factors now calibrated together with the threshold value of getting a tick bite. The output of this calibration, where both the percentages per activity and the total number of tick bites have been matched, is shown in the following tables. Table 6.6 shows the now assigned risk values to the activities and which age groups do which activities. Table 6.7 shows the output of these models as number of tick bites and percentages of tick bites per activities, and the used threshold value for getting a tick bite.

Table 6.6 Risk value and age groups per activity type per case study area (C = children, A = adults, E = elderly)

	Bilt		**Ede**		**Schiermonnikoog**	
Activity	**Risk value**	**Age group**	**Risk value**	**Age group**	**Risk value**	**Age group**
Walking	0.23	C, A, E	0.20	C, A, E	0.20	C, A, E
Gardening	0.36	A, E	0.20	E	0.20	E
Playing	0.37	C	0.20	C	0.20	C
Other	0.30	A, E	0.20	A	0.20	A

Table 6.7 Output of the calibration of activities and number of tick bites together (real values between brackets)

			Percentage per activity type (%)			
Area	**Threshold value**	**Reported tick bites**	**Walking**	**Gardening**	**Playing**	**Other**
Bilt	0.07	360 (401)	29 (27)	27 (33)	18 (11)	27 (29)
Ede	0.15	968 (1105)	50 (50)	9 (12)	9 (9)	32 (29)
Schier	0.06	356 (105)	50 (50)	19 (21)	9 (7)	23 (22)

As table 6.7 shows, the percentages per activity are comparable to the percentages in reality. Matching the right number of tick bites with these percentages per activity (almost) succeeded for the Bilt and Ede model but not really for the Schiermonnikoog model. The model produces 356 tick bites while the real number is 105. By increasing the threshold value by 0.01 the number of tick bites immediately drops to approximately 6 tick bites. The output shown in table 6.7 is as close to reality as the models can get.

Interesting to look at now is the distribution of the tick bites in time when using this calibrated model where both the number of tick bites and percentages per activity are comparable to reality. The distribution of the tick bites in the Bilt (figure 6.8) shows a small peak in summer but the real peak is in October. This could be due to the high value of tick abundance in gardens in October (0.19). Together with the high risk for gardening (0.36) this leads to many tick bites. In October and November, the tick abundance in ‘other’ vegetation is high as well (0.17;0.32), the land-use type that mostly covers the accessible parts of the municipality, which leads to many tick bites with the other activities as well.

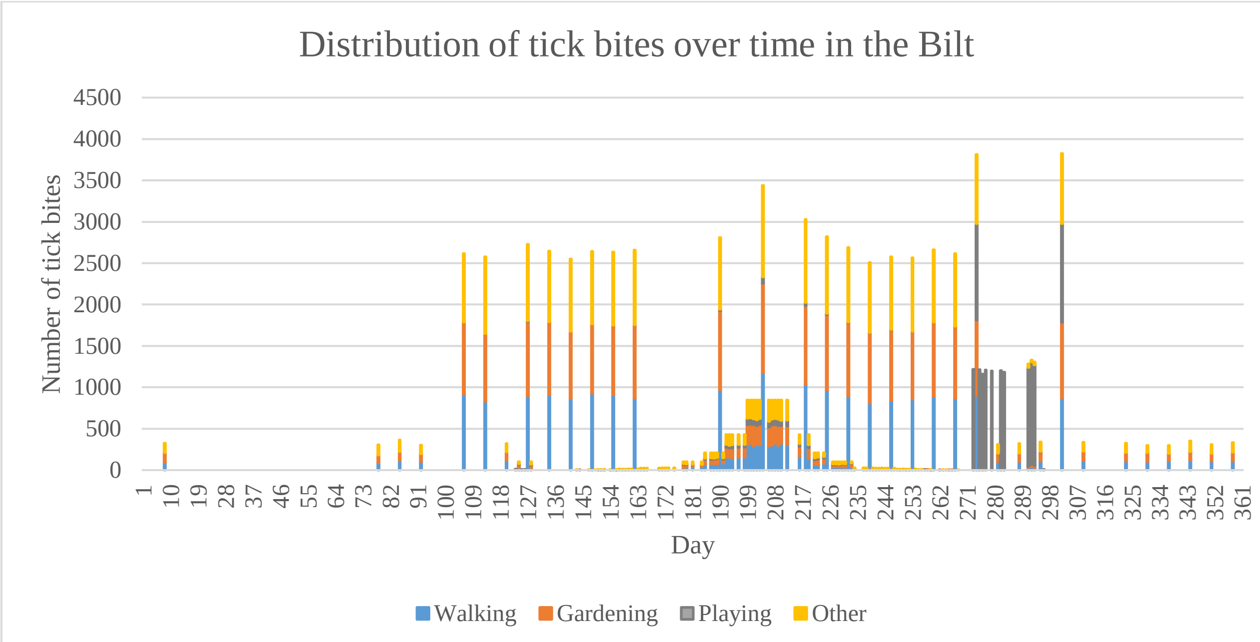


Figure 6.8 Distribution of tick bites over time in the Bilt with activity percentages and tick bites calibrated together

The distribution of the tick bites over time in Ede (figure 6.9) is different than expected. In reality most tick bites are experienced in summer (section 4.6.1). However, figure 6.9 shows that with the model where both activity percentages and tick bites number are calibrated most tick bites are experienced in spring. This could be due to the high tick abundance in the forest in spring (0.75). Because the accessible parts in Ede are mostly forest, this high tick abundance in the forest can lead to high numbers of tick bites.

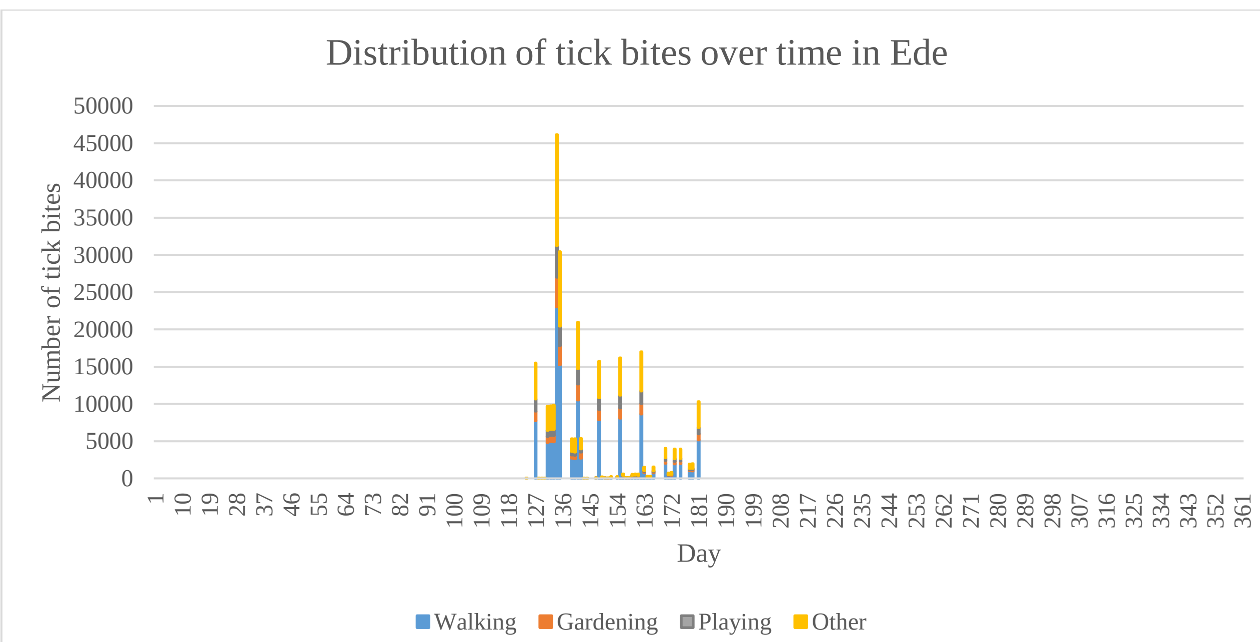


Figure 6.9 Distribution of tick bites over time in Ede with activity percentages and tick bites calibrated together

The distribution of tick bites over time at Schiermonnikoog is as expected. Most of the tick bites are experienced in summer and a small peak is there in the vacation in May as well.

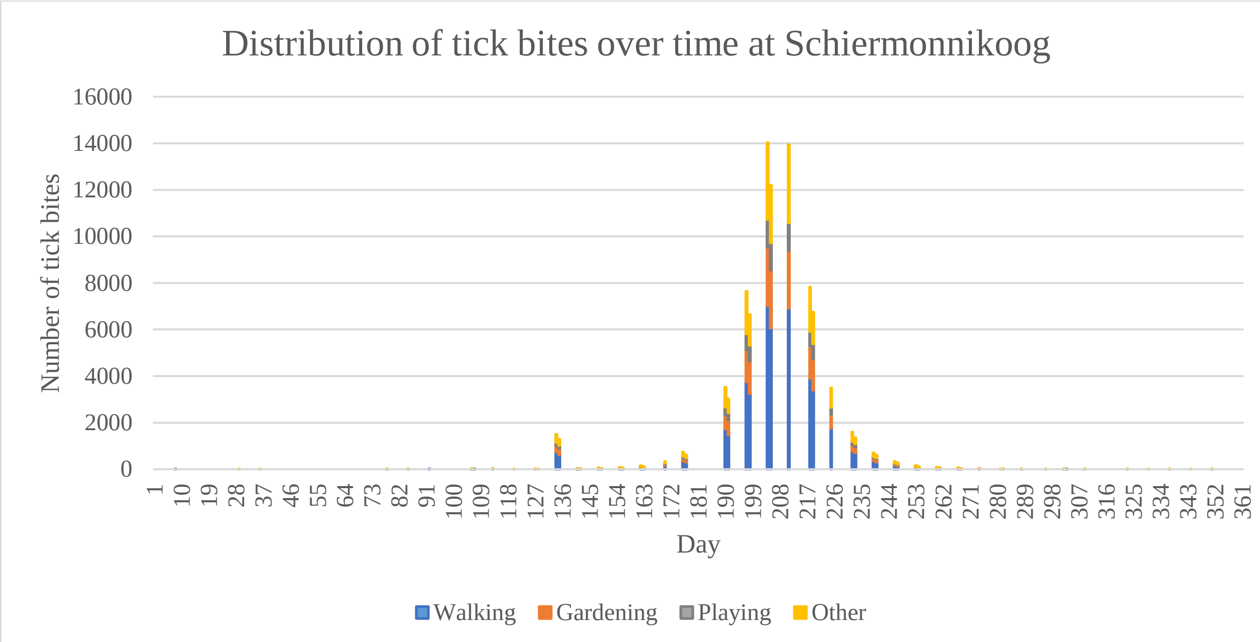


Figure 6.10 Distribution of tick bites over time at Schiermonnikoog with activity percentages and tick bites calibrated together

The model that will be used in the next chapter for the results of this research is the model where both activity percentages and number of tick bites are calibrated. This model comes closest to reality compared to the two other calibrated models. Concerning the distribution of the tick bites over time, this will be described in the results chapter as well and the factors that are missing in the models which could explain the output of the models or could improve the output of the models will be discussed.

7 RESULTS

7.1 EXPERIMENT 1: ONLY H

The three case study models have been run using only H as determining tick bites to check the tick bites pattern that results from the three case study models. This means that for this experiment E is assumed to be 1, which means that human activities have not been taken into account. This is to check to what extent the patterns of the tick bites in the three case study area can be explained based on only environmental and climate factors.

Figure 7.1 shows the real (reported) tick bites patterns of the three case study areas, according to Tekenradar. The patterns clearly show that the number of tick bites in winter (November-March) is low. Ede and Schiermonnikoog both have their highest percentage of tick bites in July while Bilt has its peak in June. In October there is also a small peak in Ede and Bilt while the percentage at Schiermonnikoog in October is still decreasing.

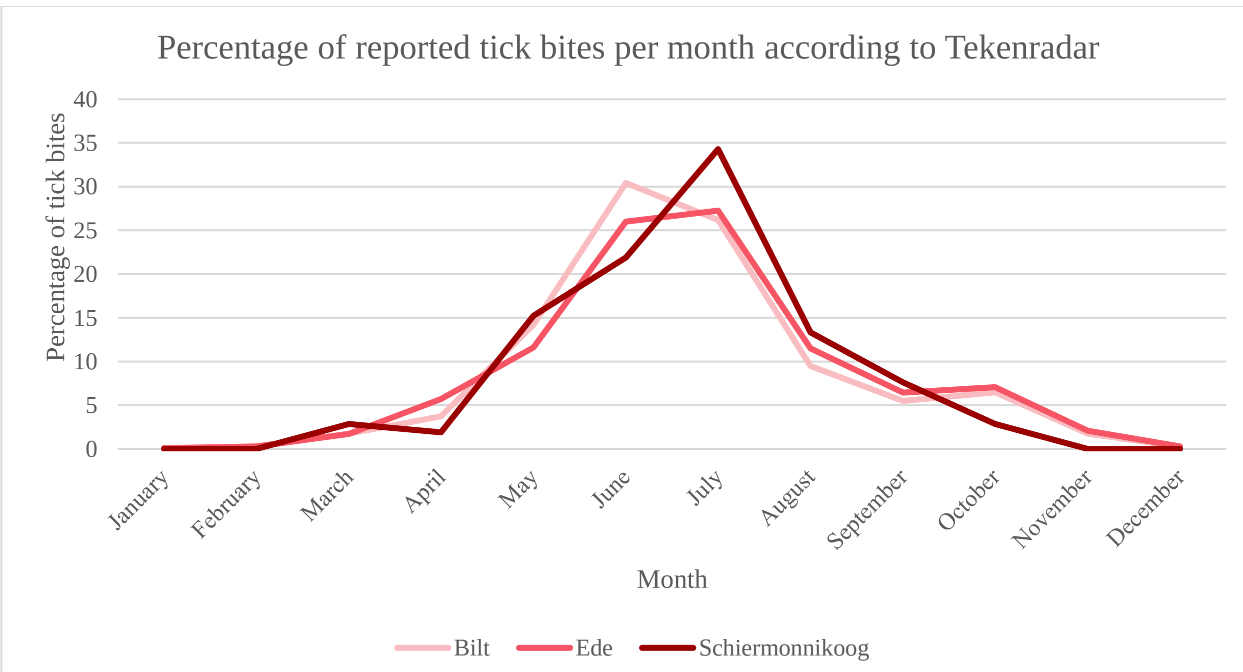


Figure 7.1 Percentage of reported tick bites per month according to Tekenradar (Tekenradar, 2018)

Figure 7.2 shows the patterns as simulated by the model. Ede and Schiermonnikoog both have their peak in July while there is a constant peak from June-October in Bilt. Ede and Schiermonnikoog also both have a small peak in October. This can be due to the vacation week in October which means that there is a higher number of tourists in the areas. The patterns for Schiermonnikoog and Ede are comparable to reality (figure 7.1). The peak of Bilt in June is missing in the resulting pattern of the model. The Bilt area differs from the other two case study areas in number of tourists. In the Bilt area, the number of residents outnumbers the number of tourists, and exposure is therefore expected to be more based on gardening then on recreational activities. The lack of the peak in the Bilt area, might indicate that when human activities are turned off, the gardening component is accountable for the missing peak.

When comparing the resulting patterns of the models and the number of nymphal and adults ticks in the three case study areas (section 5.4.1) there are some similarities as well. Ede and Schiermonnikoog experience most tick abundance in summer. The small peaks of adult tick abundance in the Bilt are in August and October, comparable to the output of the model.

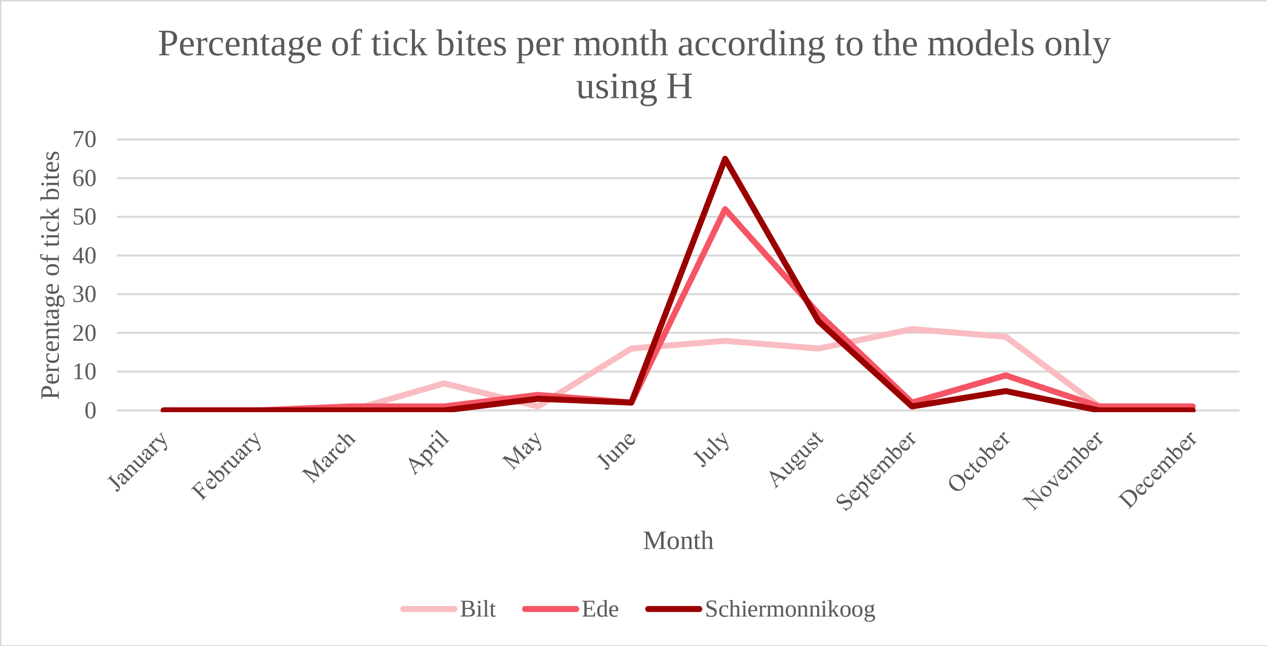


Figure 7.2 Percentage of tick bites per month according to the models only using H

7.2 EXPERIMENT 2: H * E

To determine the influence of E on the pattern of tick bites, this experiment uses H and E. As discussed in the previous section when only using H, especially the high peak in the Bilt in October seems to be odd. The patterns of the two other case study areas are more comparable to reality. Figure 7.3 shows the distribution of the tick bites over time in the three case study areas when using H * E. The pattern of Schiermonnikoog is quite the same but the patterns of the Bilt and Ede are quite different.

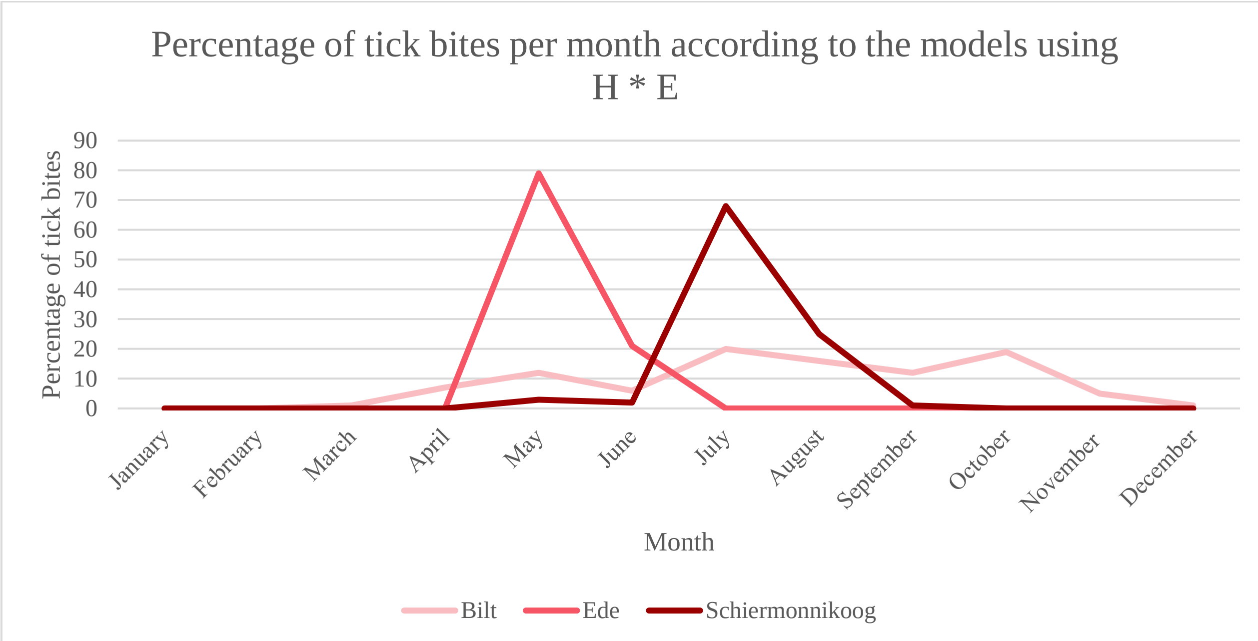


Figure 6.3 Percentage of tick bites per month according to the models using H * E

The Schiermonnikoog pattern looks like the pattern when only using H with most tick bites in July. The peak in Ede has shifted from July to May. This is an interesting shift that can be due to the influence of E. In Ede all activities have the same risk for getting a tick bite (see table 6.6; 0.20), to match the number of reported tick bites and the percentages of activities. In May the risk of getting a tick bite in the forest is very high (0.75) which apparently leads to most tick bites in this month and almost no tick bites in the rest of the year. Reducing the risk of getting a tick bite in the forest will shift the peak back. It can be concluded that the risk of tick bites in the forest is overestimated with the current values.

The pattern of tick bites in the Bilt has gotten more peaks divided over the year. Together with the higher calibrated risks for gardening, playing and other (0.36;0.37;0.30) and the higher risk of getting a tick bite at urban and other patches, H*E leads to these peaks in May, July and October. The peak in summer for the Bilt is still far too low. This can be due to an underestimation of the risk of getting a tick bite while gardening. It can also be due to residents only moving on Saturday. In summer and vacation weeks people will do more recreational activities because do not have to go to their work. Besides that, different age groups have different activity patterns. Adults need to work on week-days while for example children can play everyday (also outside the urban area).

7.3 EXPERIMENT 3: RESIDENTS AND TOURISTS

Because two population groups are integrated in the models (residents and tourists) is it interesting to see who gets the most tick bites. Figure 7.4 shows the percentages of tick bites per population group per case study area. In Ede and at Schiermonnikoog more tourists get a tick bite than residents. In Schiermonnikoog almost no residents get a tick bite. This seems to be logical because there are more tourists in the models than residents. Besides that, the residents only move on Saturday while the tourists move every day. This means that tourists have a changing risk of getting a tick bite more often than residents have because tourists go to different land-use patches more often.

In the Bilt more residents get a tick bite. This can be due to the high risk of getting a tick bite when gardening (0.36) together with the risk of getting a tick bite in urban areas where tourists not move to in the Bilt model.

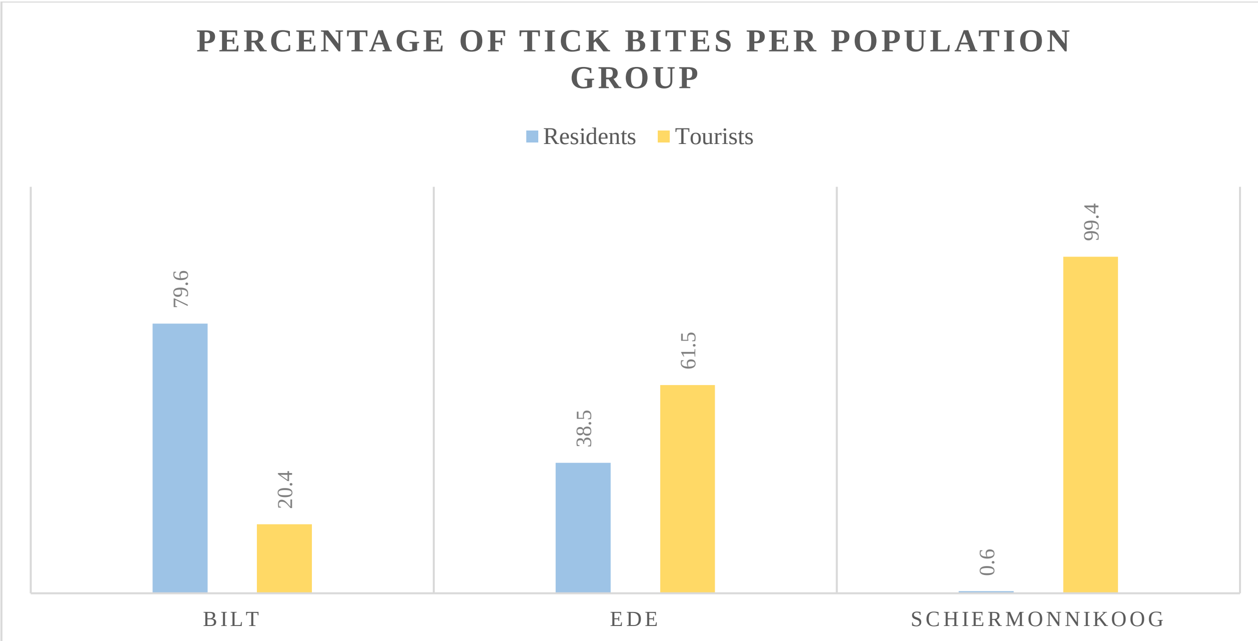
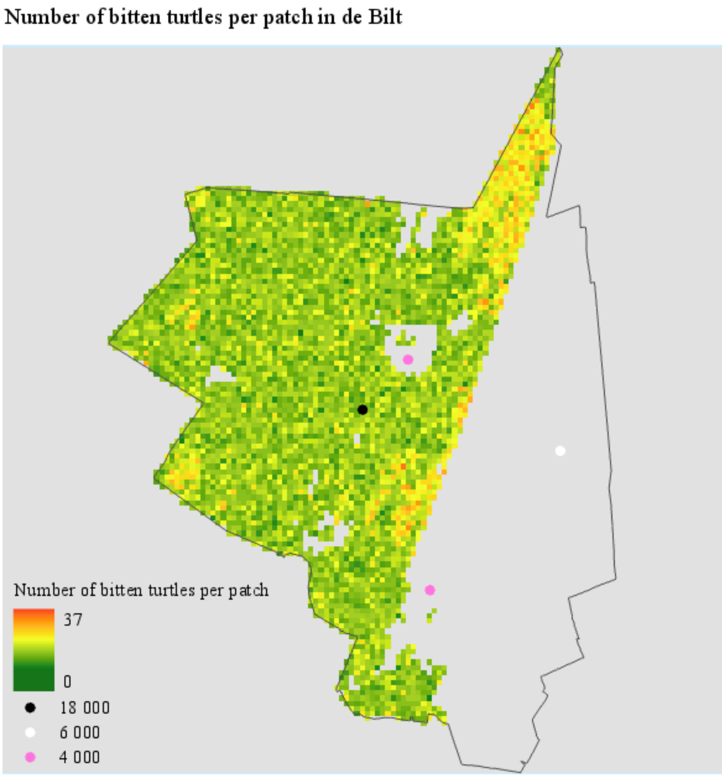


Figure 7.4 Percentage of tick bites per population group per case study area

There is one limitation of the model that is shown by this experiment. The limitation is the distribution of the activities. This distribution is now determined by the age groups only. However, in reality tourists do not garden while they do in the models. That explains why so few residents at Schiermonnikoog get a tick bite while 19% of the tick bites are experienced while gardening.

7.4 EXPERIMENT 4: WHERE DO PEOPLE GET THEIR TICK BITE

The following maps show where the people in the different case study areas get their tick bite. In the Bilt people get their tick bites distributed over all accessible parts of the municipality (figure 7.5). There are some outliers. The biggest outlier is the patch where all tourists enter the model. The other outliers are the residential patches where the residents are situated and where the residents stay on when they have gardening as activity because they do not move out of the city on Saturday.



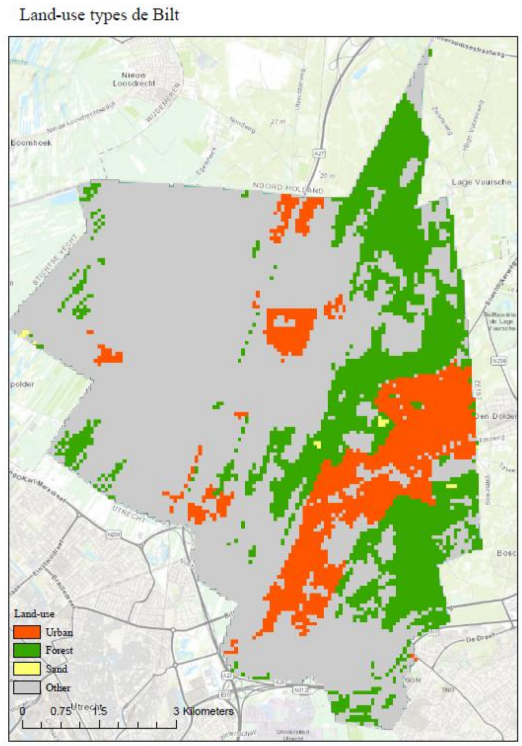
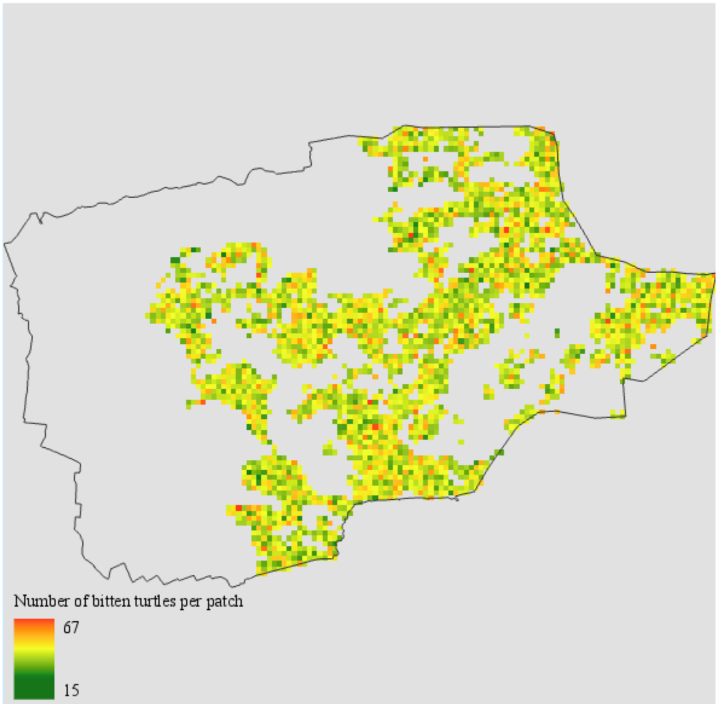


Figure 7.5 Number of bitten turtles per patch in the Bilt and land-use types

In Ede, all tick bites are experienced in the forested areas (figure 7.6). This again shows that the model needs to be adjusted so that the tick bites while gardening can only be experienced in the urban areas because now these are also experienced in the forest which is not realistic. Although the residents that have gardening as activity do not move out of the city on Saturday, no tick bites are experienced in the urban areas. This is because the threshold value for getting a tick bite in the Ede model is so high that a resident with the risk values of urban area and gardening can never exceed this value. This again shows that a more complex activity is necessary whereby only residents can garden and not the tourists too. At Schiermonnikoog the tick bites are experienced in the forest and 'other' areas (figure 7.7). This is not realistic because most of the reported tick bites at Schiermonnikoog are reported in the dunes (see section 4.6). No tick bites in the model in the dunes is due to the low tick abundance risk in the dunes. More data about the risk of getting a tick bites in the dunes could improve the model and give a more realistic distribution of the tick bites at the Island.

Number of bitten turtles per patch in Ede



Land-use types Ede

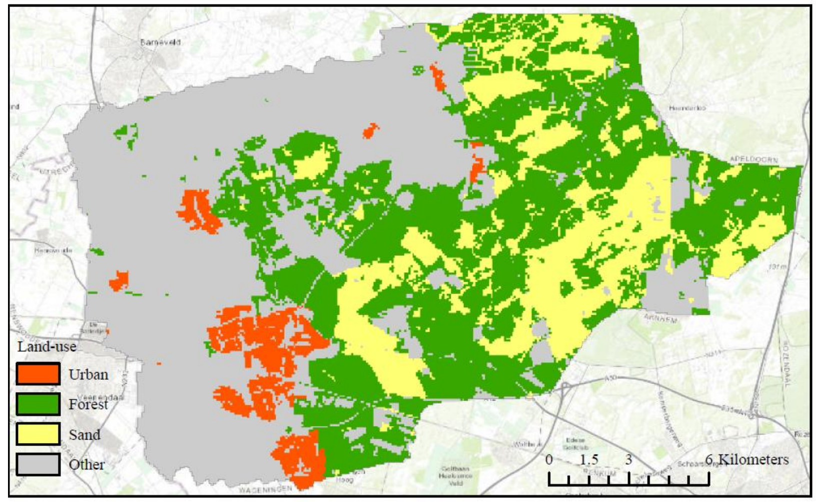
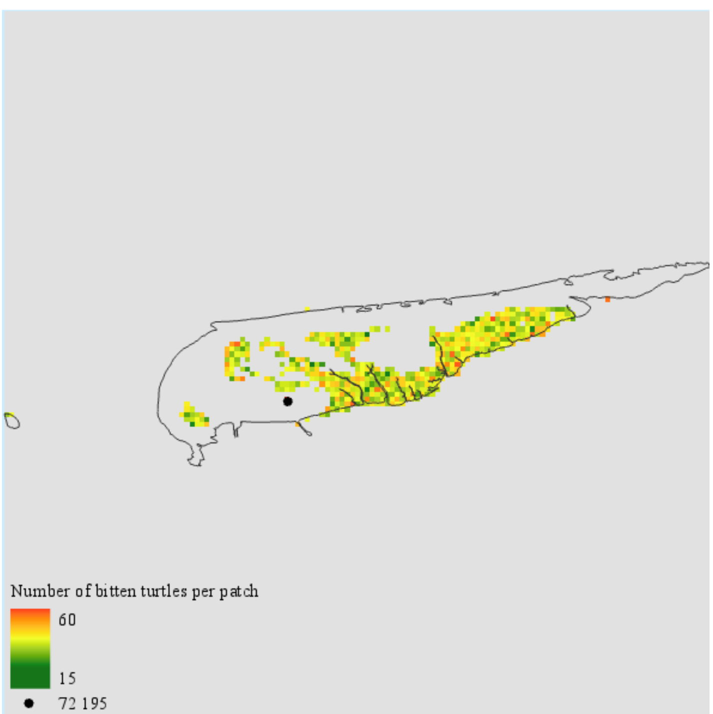


Figure 7.6 Number of bitten turtles per patch in Ede and land-use types

Number of bitten turtles per patch at Schiermonnikoog



Land-use types Schiermonnikoog

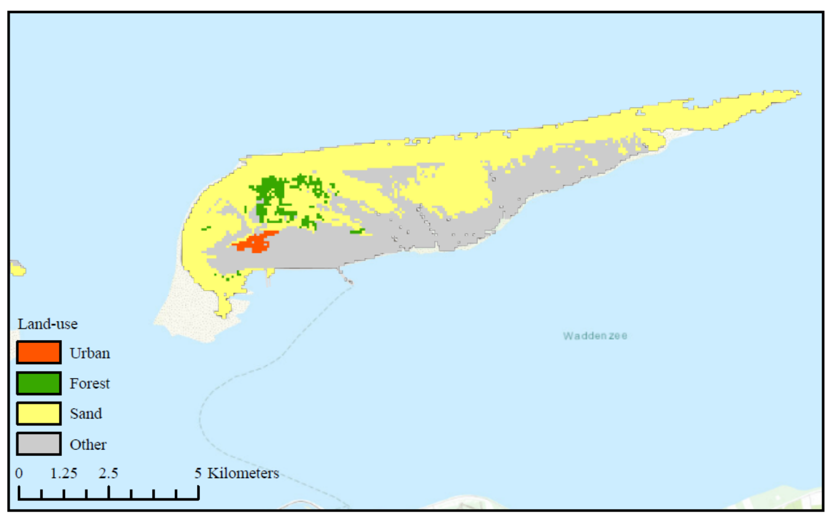


Figure 7.7 Number of bitten turtles per patch at Schiermonnikoog and land-use types

7.5 EXPERIMENT 5: ACCESSIBILITY

As previously discussed, the accessibility layer limits the parts of the municipality where residents and tourists can move to. Table 7.1 shows how turning off the accessibility layer influences the total number of tick bites. The number of tick bites in both the Bilt and Schiermonnikoog is hardly influenced. The number of tick bites in Ede clearly decreases. This is logical because now the residents and tourists can move to more patches with land-use type ‘other’ which has a relatively low tick abundance risk. This lower tick abundance risk leads to fewer tick bites.

Table 7.1 Number of tick bites per case study area with and without accessibility layer

Case study area	Accessibility layer	Number of tick bites
Bilt	On	89 389
	Off	89 951
Ede	On	241 894
	Off	159 411
Schiermonnikoog	On	89 124
	Off	92 362

7.6 EXPERIMENT 6: PRECIPITATION

The set precipitation threshold value limits the movements of residents and tourists and thus the chance of getting a tick bite. When residents and tourists do not move, they cannot get a tick bite. As expected, the number of tick bites in the Bilt and Ede increases when this precipitation threshold value is turned off (table 7.2). Without this threshold, residents and tourists can move more often to different land-use patches, which probably means that more residents and tourists move to forest patches where the tick abundance risk is high. Only at Schiermonnikoog the number of tick bites decreases when turning of the precipitation threshold value. This can be due to more movements for the residents and tourists to dune areas (sand patches) which have a low tick abundance risk, resulting in less tick bites. The model currently only applies a threshold for heavy rainfall, however, weather may have a more dominant impact on the activities tourists conduct. Only a bad weather forecast may already lead to less tourists, or less tourists in certain land-use types. Also, very high temperatures will influence the activities people perform (possibly leading to less risk). This is a factor that needs to be explored further.

Table 7.2 Number of tick bites with and without precipitation value per case study area

Case study area	Precipitation threshold value	Number of tick bites
Bilt	On	89 389
	Off	255 578
Ede	On	241 894
	Off	326 224
Schiermonnikoog	On	89 124
	Off	53 105

8 CONCLUSION

In this research, tick bites were modelled in three different areas (the Bilt, Ede, Schiermonnikoog) in the Netherlands using agent-based modelling to gain more insight in the environmental and human factors that influence tick bites. To do so, the following research questions were posed:

1) What environmental and human factors influence the number of tick bites in the Netherlands?
2) How can these environmental and human variables be formalized in a framework suitable for agent-based modelling?
3) How should this framework of variables be implemented in an agent-based model?
4) What (spatial) differences in tick bite distribution and influencing factors are there between the case study areas resulting from the model?
5) To what extent does this model contribute to indicating tick bite risk and reducing the number of tick bites in the Netherlands?

The first three research questions have been answered with a literature study, data analysis with data from Tekenradar, and the development of an agent-based model with NetLogo. Many factors seem to influence tick bites, and these relate to a combination of human behavior, landscape or climate. The factors that are included in the ABM determine either hazard or exposure which together determine the risk of getting a tick bite.

The factors resulting from literature and the data analysis that determine hazard are land-use types and temperature. Four different land-use types are included in the model: urban area, forest, sand/dunes and other. The risk of getting a tick bite differs per land-use type, where the risk is the highest in forested areas. Daily temperature is included in the model as well. Temperature influences tick abundance because ticks prefer warmer temperatures and start being active when the temperature is above 4°C-5°C.

The factors resulting from literature and the data analysis that determine exposure are rainfall, accessibility and activity type (which is partly determined by age). These factors all relate to human behavior. Rainfall influences human behavior because when it is raining heavily (50 mm according to KNMI) people will not do any outdoor recreational activities. Accessibility influences exposure because people go to areas that are easily accessible. An accessibility layer is added to the model to determine where people can move to. Activity influences the chance of getting a tick bite because the risk of getting a tick bite differs per activity. Four different activities are included in the model: walking, gardening, playing and other. These activities are related to age because people from different age groups do different activities.

To include all these factors in an agent-based model, four sub-models were developed. The first one is the tick dynamics model which simulates the tick abundance per land-use type. For this model blanket-dragging data was used as input, indicating the number of ticks at the different land-use types, converted to percentages of the total number of ticks. In the model these numbers are updated every month because the tick abundance differs per month, with most ticks in summer and the least number of ticks in winter. The second sub-model is the human population model. This model simulates two population groups; residents and tourists. The number of residents is constant, and the number of tourists gets updated based on an exponential growth formula, Dutch vacation weeks and the different stay periods of tourists.

The third sub-model is the activity model. All residents and tourists get assigned to an activity, based on the age group they belong to. Tourists move every day until they are removed from the model while residents stay in the urban area during the week-days, they move on Saturday and are back in the urban area on Sunday. There are some limitations related to the movements of the residents and tourists in the model. When the daily precipitation is above 50 mm both residents and tourists do not move and thus cannot get a tick bite. If residents have gardening as activity they do not move out of the urban area. The residents and tourists can also only move to the parts of the areas that are within the accessibility layer. This layer represents the National Landscapes and Natura 2000 areas which are situated within the three case study areas. The last sub-model is the bite model, indicating whether a resident/tourist gets a tick bite or not. Getting a tick bite is calculated with the following formula:

$$R = H\ (L,T) * E\ (A,R,P)$$

where R = risk, hazard H is a combination of land-use and temperature, and exposure E is a combination of accessibility, rain influences and P representing personal factors which in this model is activity type.

In this formula all the factors influencing the risk of getting a tick bite come together.

To get the most suitable model and because it was not clear what the exposure for the different activities was and what the threshold value for getting a tick bite was, the model was calibrated in three different ways using the VGI from Tekenradar. First, the activities were calibrated to get the percentage of tick bites per activity as in Tekenradar. Second, the number of tick bites was calibrated to the number of tick bites in Tekenradar. Third, both the activities and number of tick bites were calibrated together. The third calibration got closest to reality, so this was the model that was used for the different experiments. A result from the calibration was that the risk of getting a tick bite per activity type was the same for Ede and Schiermonnikoog but that it was different for the Bilt. The threshold value for getting a tick bite was almost the same for the Bilt and Schiermonnikoog but was different for Ede.

With different experiments, the models of the three case study areas were tested and compared. To get the pattern of tick bites over time closest to reality it is not enough to only use H to calculate tick bites risk. The patterns resulting from H * E are partly comparable to reality but there are some irregularities between the three case study areas. At Schiermonnikoog most tick bites are experienced in summer, which is comparable to reality. In Ede most tick bites are experienced in spring while in reality they are experienced in summer. This means that some parameters are not yet totally right or that parameters are missing. The same counts for the Bilt, the pattern resulting from the model is an equal distribution of the tick bites from April-November while in reality most tick bites are experienced in June. However, there are some small peaks in May and October which is comparable to reality, relating to people gardening in spring and autumn.

So, there are differences in the distribution of tick bites over time between the three case study areas. There are some other differences as well. In Ede and at Schiermonnikoog more tourists get a tick bite compared to residents while in the Bilt more residents get a tick bite compared to tourists. There are also some spatial differences. In Ede people get their tick bites in the forested areas, at Schiermonnikoog in forested areas and 'other' land-use areas and in the Bilt in the urban areas and 'other' land-use areas. Turning off the accessibility layer barely influences the number of tick bites in the Bilt and at Schiermonnikoog, but it does influence the number of tick bites in Ede because the number clearly decreases. By turning off the precipitation threshold value the number of tick bites in the Bilt and Ede increases while the number of tick bites at Schiermonnikoog decreases.

This model contributes to indicating tick bite risk because it is a first step to gaining more insight in the factors that influence tick bites. This research clearly shows which factors are important to consider and that human behavior is of big influence. When coming up with strategies to reduce the number of tick bites, such as starting campaigns or giving readings, these influencing factors should be taken into account and could be focused on. Also, the differences between areas in the Netherlands, such as land-use types or age groups in the areas, should be considered. By improving the model, that is developed with this research, tick bites in the Netherlands can be simulated even more comparable to reality, hopefully one day resulting in decreasing the number of people getting a tick bite and getting infected with Lyme disease in the Netherlands.

9 DISCUSSION

The model developed in this research, simulates tick bites in three different areas in the Netherlands. The most important aspect of this model are the factors that influence tick bites. Assumptions on factors were made with the greatest care, but some of them need to be discussed.

A first important assumption is made for the tick dynamics model. The data used for this sub-model comes from the blanket-dragging research. This research is done at 24 different sites in the Netherlands. However, from many sites a lot of data was missing, so there were only a few sites that had complete tick abundance data for every month from 2006-2014. The case study areas have partly been chosen because they were one of the sites with a complete dataset. The tick abundance values in the model were assigned based on the assumption that Schiermonnikoog represents a coastal area, Bilthoven an urban area, Ede a forested area and Vaals ‘other’ land-use type areas. These case study areas were chosen because they largely consist of a landuse type for which data is available. However, to get better tick abundance values per land-use type, blanket-dragging research should be conducted in areas with a range of different land-use types. In this study, all kinds of land-use types, besides urban, forest and sand, are put together in the ‘other’ category. This means that for different kinds of land-use types, such as grassland and swamp, the tick abundance is the same. Making a more detailed division between land-use types could make the model more realistic.

A difficult issue of the human population model was the distribution of the tourists in time. No data is available about the distribution of tourists over the months/weeks in the Netherlands. That is why an exponential growth formula has been used to calculate the distribution of the tourists over the touristic season from April-October with the highest number of tourists in summer. The number of tourists in the vacation weeks in May and October has been increased with 5% of the number of tourist in all the other weeks. This has been done because in vacation weeks the number of tourists in the case study areas will be higher than in other weeks. However, if data about the actual distribution of tourists over the year would be available to use the model could be improved. Besides that, the assumption has been made that the distribution of tourists over the different age groups is the same in all three case study areas. However, in reality, this will not be the case. For example, in Ede, most people visit the nature area ‘Veluwe’, an area that is probably most attractive to older people. Using a more realistic distribution of tourists over the different age groups per case study area would improve the model.

Some assumptions for the activity sub-model have been made as well. There are four types of activities which relate to different age groups. For now, both residents and tourists can garden while this is not realistic. A more complex activity model should ensure that only residents can garden. Activities are assigned to the residents and tourists, assuming that the residents and tourists do their outdoor recreational activities all year. This is not realistic because in winter, for example, people will not be gardening. The activities that are now used in the model are seasonal activities which will be mostly conducted in spring and summer. To improve the model, more activities should be added. Now all the activities in the model have a certain risk of getting a tick bite while it is more realistic that residents and tourists also do recreational activities where there is no risk, such as going to a museum. Besides activities where there is no risk, can activities on their own also have different risks. For example, walking has now one risk value while walking can be done in different ways. People can stay on the roads in the forest and do not get in touch with the vegetation, which has a low risk of getting a tick bite. People can also leave the roads in the forest and walk through the vegetation, maybe even climb the trees, which has a much higher risk of getting a tick bite, compared to staying on the roads has. The activities that are now included in the model all definitely have a risk of getting a tick bite but including no-risk activities and a more in-depth division of the activities could improve the model.

Residents only perform activities one time a week (Saturdays). However, different age groups have different weekly patterns leading to different levels of exposure. For example, elderly people may garden every day, and children play every day. Improving the activity patterns of residents may improve the patterns generated by the model.

The activities and their risk values have been discussed in the calibration part of this research. For the model that has been used for the experiments, both the activities and the number of tick bites were calibrated. One of the results was that the risk values for the activities in Ede and Schiermonnikoog were the same while the values for the activities in the Bilt were different. That indicates that when gardening in the Bilt people have a higher risk of getting a tick bite compared to gardening in Ede or at Schiermonnikoog. That seems to be a little odd. A more in-depth calibration is necessary to look further into the risk values assigned to the activities, finding out if the risk value per activity per area differs or it should be the same.

The movements of the residents and tourists in the model are limited by the accessibility layer. In the model, National Landscapes and Nature 2000 areas are included in this layer. Due to the lack of data availability, only natural areas attractive to tourists were included. However, it is not realistic that tourists only go to recreational areas. To make the models more realistic, data should be available about the touristic spots in the case study areas which are interesting for tourists to visit. These should be nature spots as well as urban spots since tourists also visit cities and not only nature areas.

Weather is included in the model, either limiting the movements of the residents and tourists (precipitation) or indicating the risk of active ticks (temperature). Precipitation is only limiting the movements of turtles at a certain kind of threshold value. However, this is not entirely comparable to reality. Rainfall does not only influence whether people go outside or not, but it also influences their kind of protection against tick bites. When it is raining, people will put on long pants and a jacket. This is automatically more protection against ticks because ticks will have problems trying to attach themselves to humans if they wear such clothes. Perhaps also smaller amounts of rainfall need to be considered to reduce the number of tick bite on rainy days. Besides that, the weather forecast can also influence the movements and choices of recreational activities of people. If bad weather is predicted, people will be more likely to go to the museum than go to the forest. The same applies to temperature. Temperature values in the model are now only used to determine if ticks are active. Temperature also influences the recreational activities people do and the clothes people are wearing, and thus indirect their protection level against tick bites. Further research could focus on the influence of weather on recreational activities and clothes people are wearing and how this is related to the risk of getting a tick bite. That can then be incorporated into the model to make it more realistic.

As mentioned above, clothes that people wear can increase or decrease the risk of getting a tick bite. Something that could be added to calculate the risk of getting a tick bite. Wearing certain kind of clothes could be included in this personal risk factor. Such a personal risk factor has not been added to the model in this research due to the lack of data availability. No data was found to what extent clothes can influence the risk of getting a tick bite. Another factor included in this personal risk factor could be how much people know about ticks. For example, it is possible that residents know about tick abundance in their surroundings while tourists do not know anything about this. It is also possible that people learn about ticks and consider the risk of getting a tick bite when they go outside because they have been bitten by a tick before. Such factors have not been included in the model yet, but further research in how more personal factors influence the risk of getting a tick bite could improve the model and make it more realistic.

The threshold value at which people get a tick bite has been calibrated. For the three case study areas, the threshold value was different. The value for the Bilt and Schiermonnikoog was almost the same but the value for Ede was very different.

It is questionable if the threshold value should be different per area or if the value should be the same for all areas. A more extensive calibration is necessary to find this out. This has not been done within this research because with the now used threshold value the percentage of tick bites per activity and the total number of tick bites were already calibrated. To gain more insight in the threshold value of getting a tick bite, because there is no literature or data about yet, a more in-depth calibration needs to be conducted.

Although there are some limitations to the developed model, as discussed above, this model is the first step to gaining more insight into the factors that influence the risk of getting a tick bite. As stated in the literature, most studies are now focusing on environmental factors that influence tick bites, but human factors are important or maybe even more important to focus on. This research does this and shows that human behavior is of influence on the risk of getting a tick bite. It is the first step to fill the gap of combining environmental and human factors to simulate tick bites.

It is recommended to focus further research on improving the developed model. As discussed in this chapter, there are some assumptions and limitations that need further research. A lot of data is lacking, such as the actual distribution of tourists through the year in the Netherlands or the age distribution of tourists in certain areas in the Netherlands, so more data availability could already improve the model. Further research should mainly focus on improving all the factors and parameters used in the model, which results in output of the model that is more comparable to reality. A new factor, the personal risk factor, should be added to consider how people protect themselves against tick bites, with for example long pants or special anti-tick socks. When the data and factors used in the model are improved, a more extensive calibration should be conducted to improve the model even more. When this has been done, the model can even better simulate tick bites in the Netherlands, and it could be used to come up with strategies to reduce the number of tick bites and the number of people being infected with Lyme disease. The model shows which factors are of influence and campaigns or readings could focus on these factors and learn people more about them.

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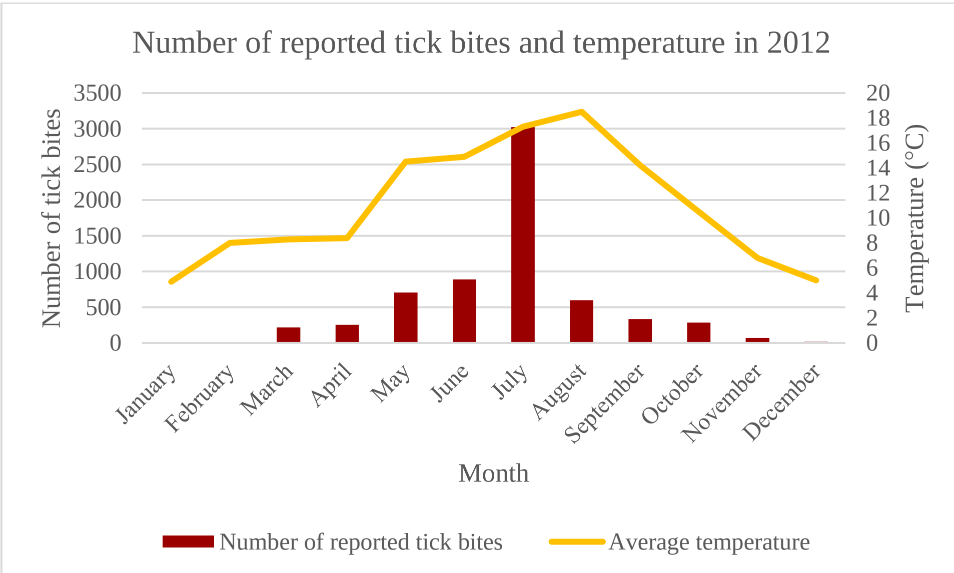
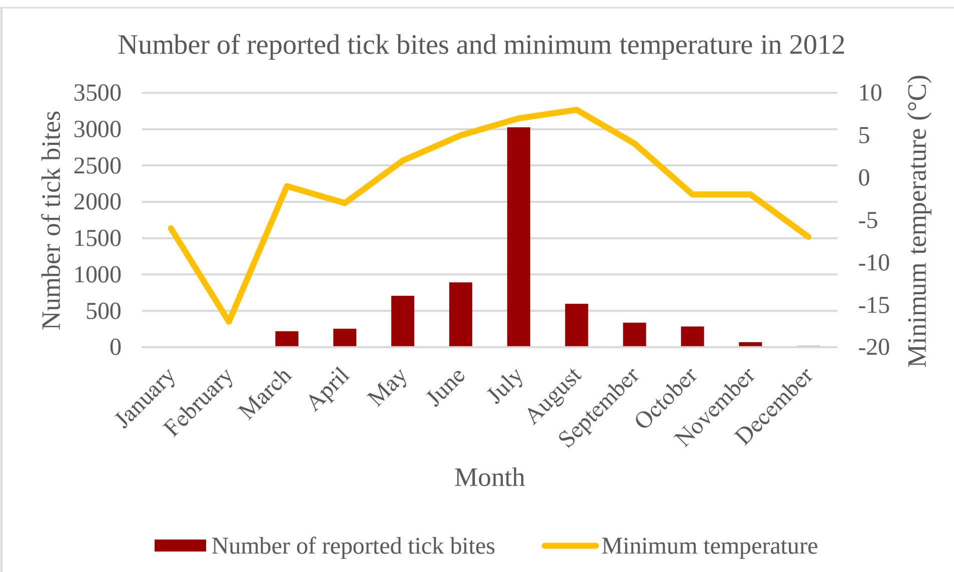
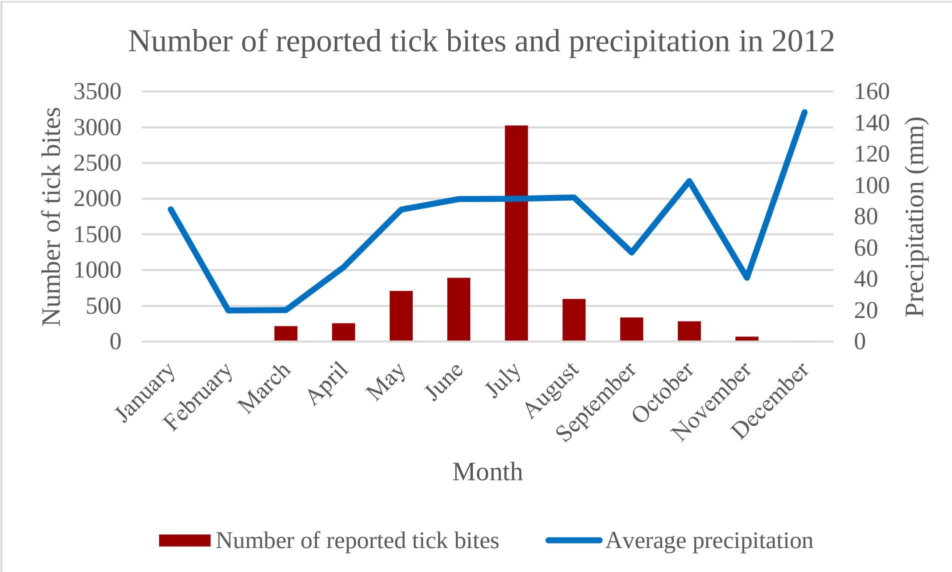
APPENDICES

APPENDIX I DATA ANALYSIS GRAPHS 2012-2016

2012

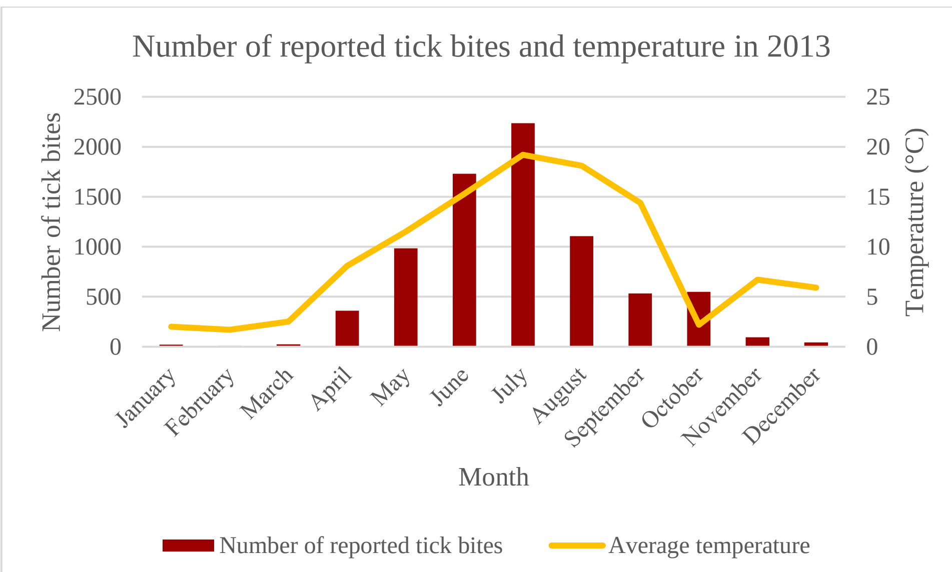




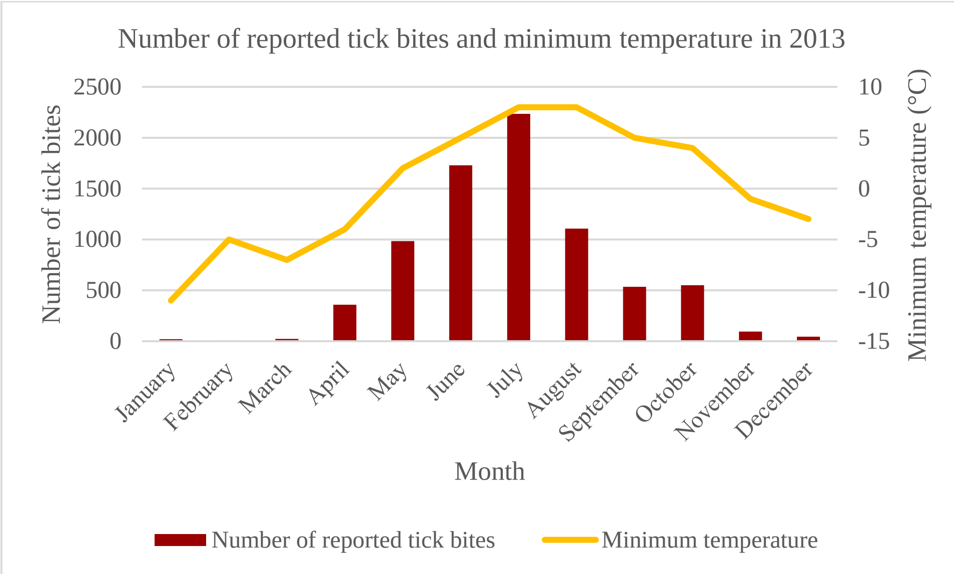


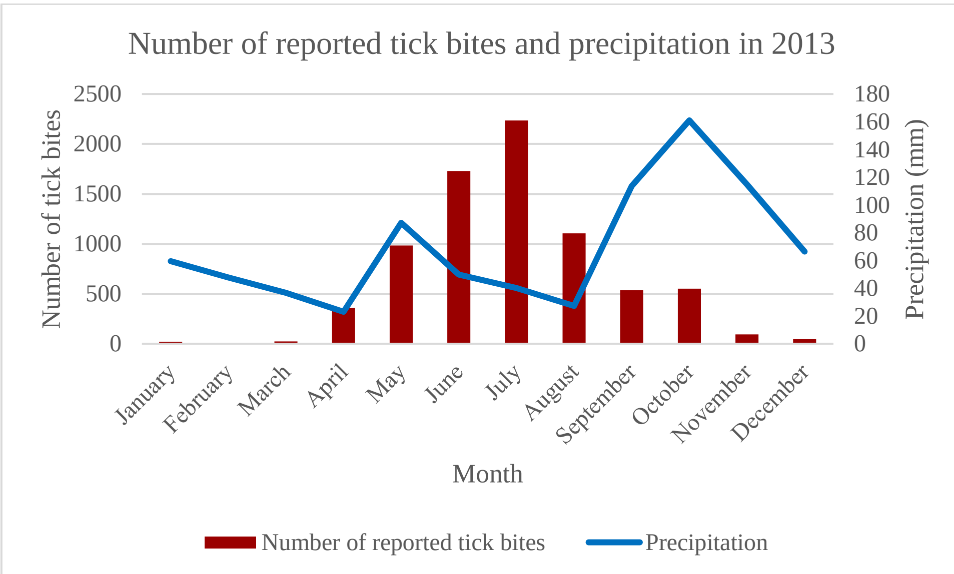
Number of reported tick bites and precipitation in 2012
Number of tick bites
3500
3000
2500
2000
1500
1000
500
0
160
140
120
100
80
60
40
20
0
Precipitation (mm)
January
February
March
April
May
June
July
August
September
October
November
December
Month
Number of reported tick bites
Average precipitation

2013

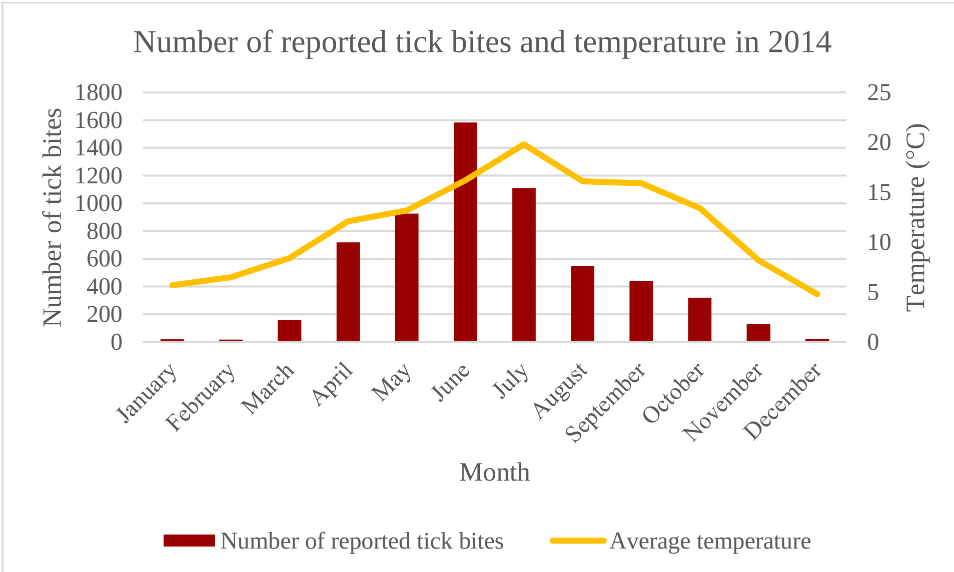


Number of reported tick bites and temperature in 2013
Number of tick bites
2500
2000
1500
1000
500
0
25
20
15
10
5
0
Temperature (°C)
January
February
March
April
May
June
July
August
September
October
November
December
Month
Number of reported tick bites
Average temperature

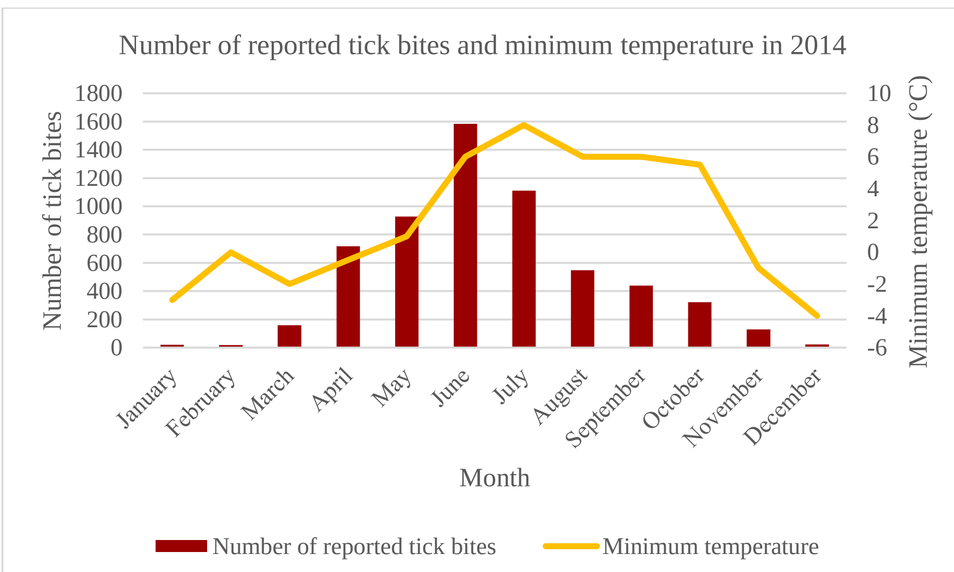

Number of reported tick bites and minimum temperature in 2013
Number of tick bites
2500
2000
1500
1000
500
0
10
5
0
-5
-10
-15
Minimum temperature (°C)
January
February
March
April
May
June
July
August
September
October
November
December
Month
Number of reported tick bites
Minimum temperature


Number of reported tick bites and precipitation in 2013
Number of tick bites
2500
2000
1500
1000
500
0
180
160
140
120
100
80
60
40
20
0
Precipitation (mm)
January
February
March
April
May
June
July
August
September
October
November
December
Month
Number of reported tick bites
Precipitation

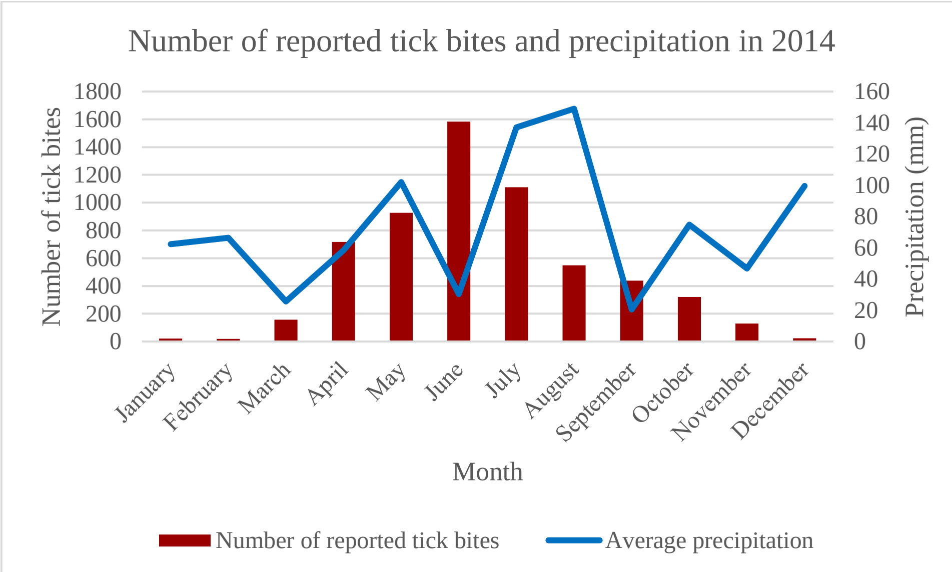
2014



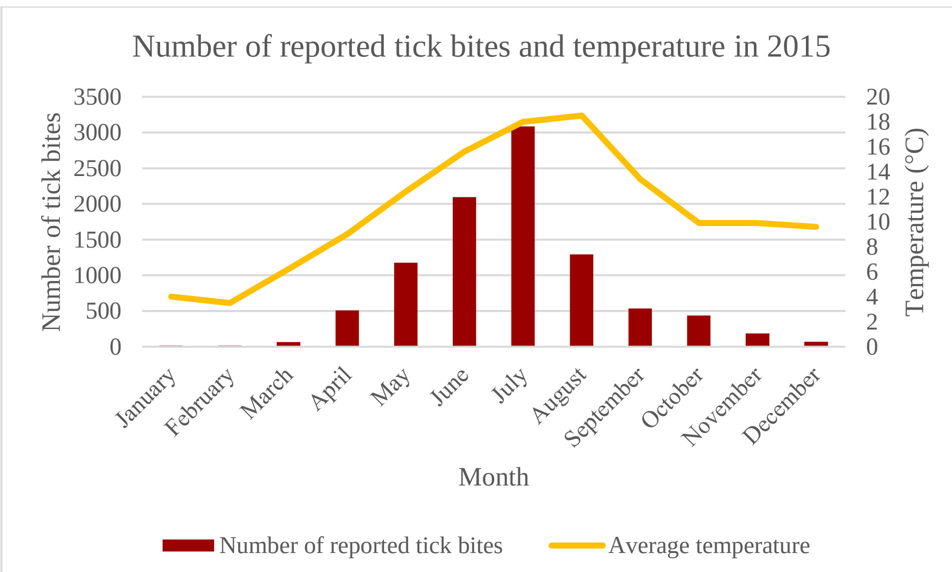
Number of reported tick bites and temperature in 2014
Number of tick bites
1800
1600
1400
1200
1000
800
600
400
200
0
25
20
15
10
5
0
Temperature (°C)
January
February
March
April
May
June
July
August
September
October
November
December
Month
Number of reported tick bites
Average temperature

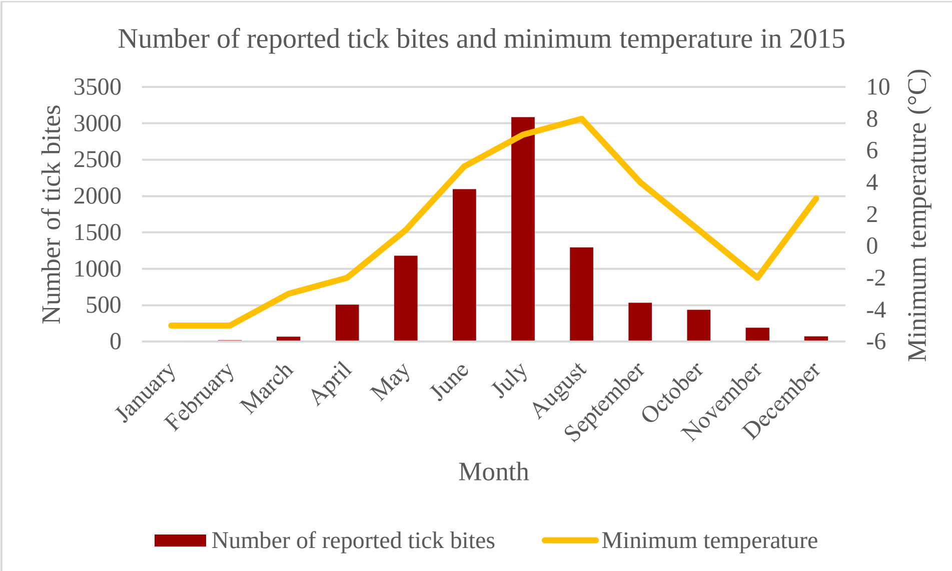


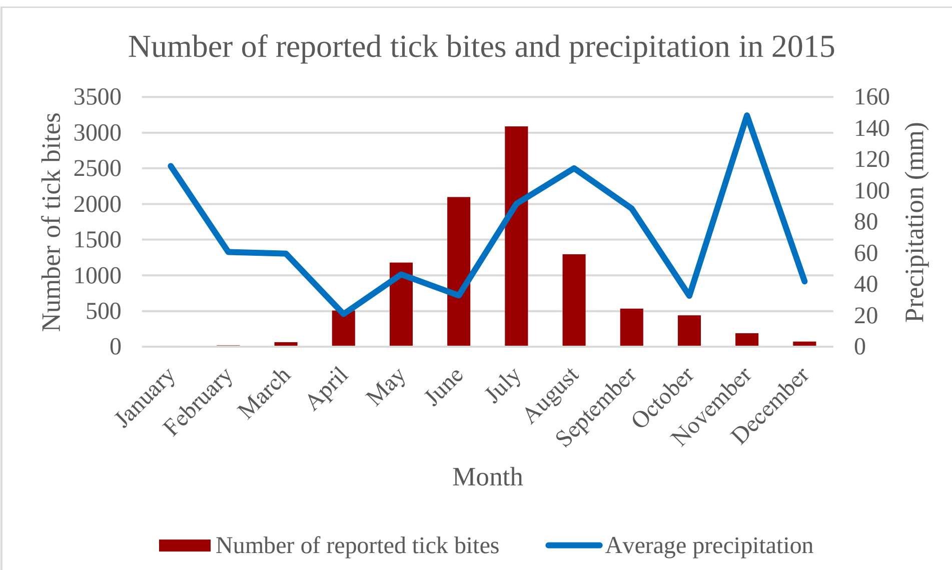
Number of reported tick bites and minimum temperature in 2014
Number of tick bites
1800
1600
1400
1200
1000
800
600
400
200
0
10
8
6
4
2
0
-2
-4
-6
Minimum temperature (°C)
January
February
March
April
May
June
July
August
September
October
November
December
Month
Number of reported tick bites
Minimum temperature


Number of reported tick bites and precipitation in 2014
Number of tick bites
1800
1600
1400
1200
1000
800
600
400
200
0
160
140
120
100
80
60
40
20
0
Precipitation (mm)
January
February
March
April
May
June
July
August
September
October
November
December
Month
Number of reported tick bites
Average precipitation

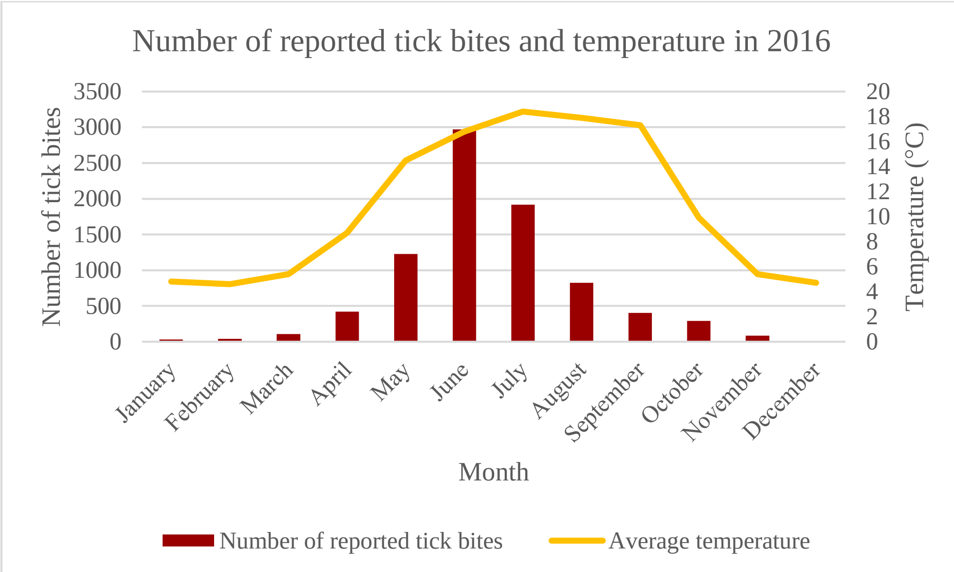
2015

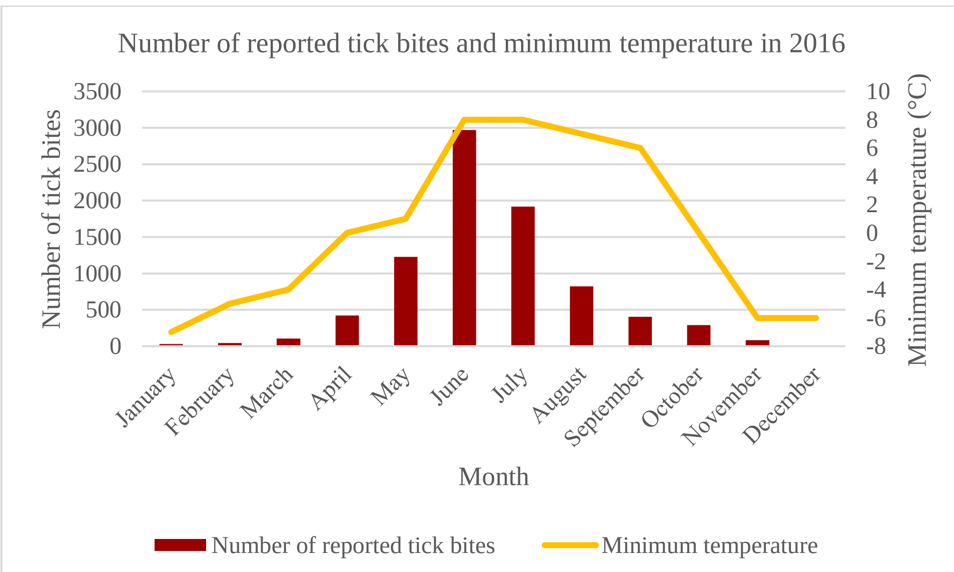

Number of reported tick bites and temperature in 2015
Number of tick bites
3500
3000
2500
2000
1500
1000
500
0
20
18
16
14
12
10
8
6
4
2
0
Temperature (°C)
January
February
March
April
May
June
July
August
September
October
November
December
Month
Number of reported tick bites
Average temperature

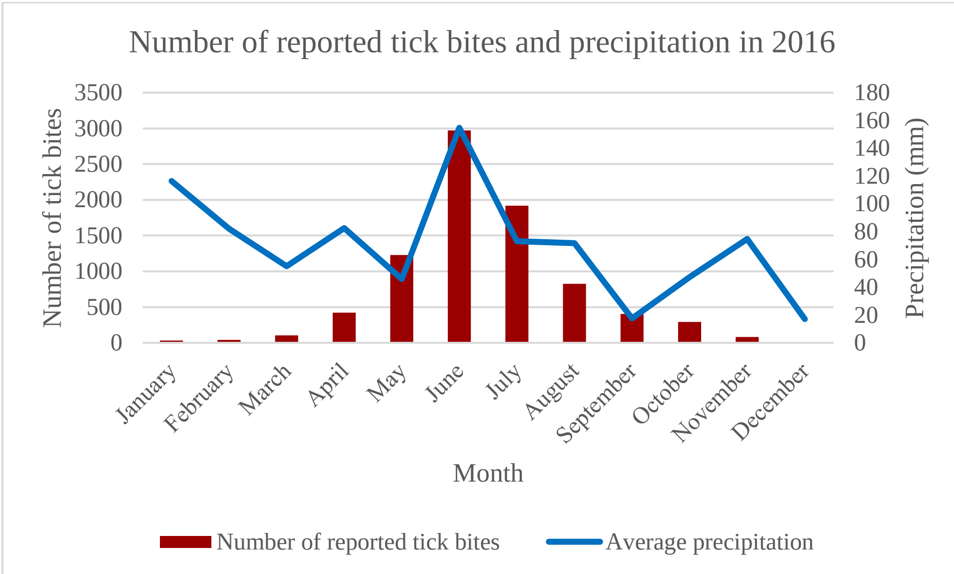

Number of reported tick bites and minimum temperature in 2015
3500
3000
2500
2000
1500
1000
500
0
Number of tick bites
10
8
6
4
2
0
-2
-4
-6
Minimum temperature (°C)
January
February
March
April
May
June
July
August
September
October
November
December
Month
Number of reported tick bites
Minimum temperature


Number of reported tick bites and precipitation in 2015
3500
3000
2500
2000
1500
1000
500
0
Number of tick bites
160
140
120
100
80
60
40
20
0
Precipitation (mm)
January
February
March
April
May
June
July
August
September
October
November
December
Month
Number of reported tick bites
Average precipitation

2016


Number of reported tick bites and temperature in 2016
Number of tick bites
3500
3000
2500
2000
1500
1000
500
0
Temperature (°C)
20
18
16
14
12
10
8
6
4
2
0
January
February
March
April
May
June
July
August
September
October
November
December
Month
Number of reported tick bites
Average temperature


Number of reported tick bites and minimum temperature in 2016
Number of tick bites
3500
3000
2500
2000
1500
1000
500
0
Minimum temperature (°C)
10
8
6
4
2
0
-2
-4
-6
-8
January
February
March
April
May
June
July
August
September
October
November
December
Month
Number of reported tick bites
Minimum temperature


Number of reported tick bites and precipitation in 2016
Number of tick bites
3500
3000
2500
2000
1500
1000
500
0
Precipitation (mm)
180
160
140
120
100
80
60
40
20
0
January
February
March
April
May
June
July
August
September
October
November
December
Month
Number of reported tick bites
Average precipitation

APPENDIX II BLANKET DRAGGING DATA OF ALL AVAILABLE SITES

Larva	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**Total**
Appelscha	0	2	0	50	165	7	4	60	116	404
Bilthoven	27	70	31	7	3	64	94	148	1,435	3,025
Ede	750	697	1,773	3,344	726	659	336	238	170	9,853
Gieten	120	1,257	1,255	2,424	1,799	5,783	3,577	4,192	1,090	24,269
Hoog Baarlo	1,069	1,488	573	939	781	2,337	2,077	5,290	6,890	24,849
Kwade Hoek	0	0	0	0	2	0	11	0	0	13
Montferland	71	467	660	517	86	233	71	135	813	3,288
Schiermonnikoog	22	156	154	112	412	340	110	64	609	2,005
Twiske	227	319	251	462	674	1,132	765	1,015	1,716	7,989
Vaals	0	256	136	199	278	61	67	122	241	1,371
Veldhoven	50	231	424	27	71	472	201	386	419	2,932
Wassenaar	10	78	168	983	259	791	218	529	749	4,163
Total per year	2,346	5,021	5,425	9,064	5,256	11,879	7,531	12,179	14,248	
Nymphs	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**Total**
Appelscha	23	65	0	94	216	234	43	30	31	736
Bilthoven	24	43	26	46	64	129	45	156	46	814
Ede	353	424	258	551	315	230	190	320	208	3,324
Gieten	91	194	90	334	327	1,116	739	908	445	5,146
Hoog Baarlo	138	311	118	190	217	236	365	622	276	2,925
Kwade Hoek	145	81	16	18	68	6	12	17	8	418
Montferland	43	215	190	385	411	282	132	485	185	3,119
Schiermonnikoog	13	70	48	26	60	47	57	42	27	436
Twiske	58	304	240	224	314	207	227	199	253	2,759
Vaals	13	166	116	144	131	211	105	120	152	1,469
Veldhoven	146	341	160	237	384	660	394	776	493	5,082
Wassenaar	26	173	217	355	501	567	541	581	652	5,016
Total per year	1,073	2,387	1,479	2,604	3,008	3,925	2,850	4,256	2,776	
Adults	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**Total**
Appelscha	6	33	0	18	48	54	23	11	18	211
Bilthoven	6	14	20	11	37	19	18	6	7	165
Ede	13	59	35	65	59	43	37	56	54	492
Gieten	12	19	14	19	29	100	64	98	34	442
Hoog Baarlo	11	17	2	19	11	12	17	38	45	191
Kwade Hoek	8	14	45	29	45	29	52	22	22	434
Montferland	1	6	10	31	18	47	22	8	18	221
Schiermonnikoog	8	22	17	21	32	30	18	15	13	196
Twiske	3	18	4	31	11	14	13	16	27	186
Vaals	1	14	10	16	9	15	6	26	14	146
Veldhoven	58	184	160	40	79	101	49	84	112	1,188
Wassenaar	1	15	25	36	22	27	55	13	10	245
Total per year	128	415	342	336	400	491	374	393	374	