Natural Capital Model: towards status A for pest control and pollination

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This document contributes to the body of knowledge which will be incorporated in more policy-oriented publications such as the National Nature Outlook and the Assessment of the Human Environment, and thematic assessments.

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Natural Capital Model: towards status A for pest control and pollination

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Abstract

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As part of the Status A quality trajectory for models within the Natural Capital Model, analyses have been conducted for the ecosystem service models pest control and pollination. For the pest control model, we performed a sensitivity analysis, uncertainty analysis, and validation using field data. These analyses aimed to identify the key model parameters, evaluate the influence of parameter uncertainty on model outcomes, and validate the predicted results against empirical field data. For the pollination model, both a sensitivity analysis and an uncertainty analysis were conducted to assess the robustness of the model in relation to variation in input parameters and their impact on prediction accuracy. We have fully adopted the structure of Status A (including the 22 criteria) to facilitate future audits and ensure that all necessary information is consolidated in one place. The results of these analyses are important steps towards the granting of Status A and contribute to the further enhancement of the reliability of the Natural Capital Model in supporting policy and decision-making processes related to ecosystem services.

Keywords: natural capital model, uncertainty, sensitivity, validation, pollination, pest control

In het kader van het kwaliteitstraject Status A voor de modellen van het Natuurlijk Kapitaal Model zijn analyses uitgevoerd voor de ecosysteemdienstenmodellen plaagonderdrukking en bestuiving. Voor het plaagonderdrukkingsmodel hebben we een gevoeligheidsanalyse, onzekerheidsanalyse en validatie met velddata uitgevoerd. Deze analyses waren gericht op het identificeren van de belangrijkste modelparameters en het evalueren van de invloed van parameteronzekerheid op de modeluitkomsten, evenals het valideren van de voorspelde resultaten met empirische velddata. Voor het bestuivingsmodel hebben we zowel een gevoeligheidsanalyse als een onzekerheidsanalyse uitgevoerd, waarbij de robuustheid van het model is geëvalueerd in relatie tot variatie in invoerparameters en hun invloed op de nauwkeurigheid van de voorspellingen. We hebben de structuur van Status A (met de 22 onderdelen) integraal overgenomen om de audits later gemakkelijker te maken en om ervoor te zorgen dat alle benodigde informatie op één plek is verzameld. De resultaten van deze analyses zijn belangrijke stappen voor de verlening van Status A en dragen bij aan de verdere verbetering van de betrouwbaarheid van het Natuurlijk Kapitaal Model in de ondersteuning van beleids- en besluitvormingsprocessen met betrekking tot ecosysteemdiensten.

Trefwoorden: Natuurlijk Kapitaal Model, onzekerheid, gevoeligheid, validatie, bestuiving, plaagonderdrukking

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Preface

The Dutch Environmental Assessment Agency (PBL) has, together with WOT-WUR, the legal task to inform policy on status and future trends in environment and nature. One of the key topics is the status and trends of ecosystem services. Scientific robust models are needed to inform policy on the current situation and the effects of policy plans. With the technical description of the ecosystem service models for pollination and pest control in the Natural Capital Model in this report, we aim to take an important step in quantifying the valuable goods and services that nature provides, thereby supporting the integration of ecosystem services into Dutch decision-making. As we work towards achieving Status A for these models, the Natural Capital Model is being applied in an increasing number of policy relevant studies. We will continue to collaborate with various partners to further enhance its scientific quality and practical applicability for future policy development and on-the-ground decision-making.

Project leader
Bart de Knegt

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Summary

Models and data sets used as part of WOT for the Netherlands Environmental Assessment Agency (PBL) must meet the status A quality requirements. Status A ensures the quality of the models through a systematic approach based on seven criteria and 22 subcriteria. This includes the description of the model and its technical implementation, the evaluation of the model (sensitivities, uncertainties and validation), the development and organization of the model, and the interpretation and use of the model's results. Work is underway to achieve Status A for the Natural Capital Model (NKM), which is essential for its application by PBL and the WOt. A self-assessment has been conducted based on the checklist with 22 subcriteria for all the models in the NKM, which has led to a focus on aspects that still need improvement.

The previous report on the NKM was structured according to these Status A criteria to give a comprehensive overview of the total results for the Status A auditors. Since then, efforts have been made to improve those aspects that did not yet meet the requirements, particularly in the areas of sensitivity analysis, uncertainty analysis, and validation. Work has begun with the pollination and pest control models, for which a quantitative method has been developed with WUR Biometris. This method can also be applied relatively easily to other ecosystem service models within the NKM. The results of this work are presented in this report, along with an updated overview of the status of all 22 Status A subcriteria and NKM ecosystem service models. To make the work of the Status A auditors easier and to maintain an overview, the chapters on pollination and pest control have been described in full.

During this project and the consultation with the Status A auditor group, it was concluded that the current quantitative approach—described in this report—for addressing uncertainty, sensitivity, and validation is deemed sufficient to meet the requirements for Status AA. To achieve Status A for the other ecosystem services within the Natural Capital Model, the necessary steps can be taken through a thorough expert assessment by the modelers and domain experts themselves, particularly by conducting a qualitative evaluation of uncertainties and validation aspects. However, for the sensitivity analysis, a quantitative assessment remains a requirement to obtain Status A. The quantitative approach adopted in this report has led to important insights that may not have emerged through expert judgement alone. For instance, it was found that the proximity of semi-natural grasslands plays a critical role in the final pollination indicator, while for pest control, the width of forest edges proved to be a key factor. It is recommended that these parameters be re-evaluated and calibrated in future updates of the model.

Samenvatting

Modellen en datasets die worden gebruikt als onderdeel van WOT voor PBL moeten voldoen aan de status A-kwaliteitsvereisten. Status A waarborgt de kwaliteit van de modellen via een systematische aanpak op basis van zeven criteria en 22 subcriteria. Deze omvatten de beschrijving van het model en de technische implementatie ervan, de evaluatie van het model (gevoeligheden, onzekerheden en validatie), de ontwikkeling en organisatie van het model en de interpretatie en het gebruik van de modelresultaten. Een zelfevaluatie is uitgevoerd op basis van de checklist met 22 subcriteria, wat heeft geleid tot een focus op aspecten die nog verbeterd moeten worden.

Het vorige rapport over het Natuurlijk Kapitaal Model (NKM) was gestructureerd volgens de Status A-componenten om een overzicht te geven van de totale resultaten voor de Status A-auditors. Sindsdien zijn inspanningen geleverd om de aspecten te verbeteren die nog niet aan de eisen voldeden, met name op het gebied van gevoeligheidsanalyse, onzekerheidsanalyse en validatie. Er is gestart met de modellen voor bestuiving en plaagbestrijding, waarvoor een kwantitatieve methode is ontwikkeld in samenwerking met WUR Biometris. Deze methode kan op relatief eenvoudige wijze ook worden toegepast op andere modellen voor ecosysteemdiensten binnen het NKM. De resultaten van dit werk worden gepresenteerd in dit rapport, samen met een bijgewerkt overzicht van de status van alle 22 Status A-subcriteria en ecosysteemdienst-modellen van het NKM. Om het werk van de status A-auditeurs gemakkelijker te maken en het overzicht te behouden zijn de hoofdstukken over bestuiving en plaagonderdrukking integraal beschreven.

Tijdens dit project en de consultatie met de Status A-auditorgroep is geconcludeerd dat de huidige kwantitatieve aanpak, zoals beschreven in dit rapport, voor onzekerheid, gevoeligheid en validatie voldoende wordt geacht om te voldoen aan de eisen voor Status AA. Om Status A te bereiken voor de overige ecosysteemdiensten van het Natuurlijk Kapitaal Model, kunnen de nodige stappen worden gezet door gebruik te maken van een grondige beoordeling door de experts van de modelleurs en deskundigen zelf, bijvoorbeeld door een kwalitatieve beoordeling uit te voeren voor met name onzekerheden en validatie. Voor het behalen van status A is voor de gevoeligheidsanalyse wel een kwantitatieve analyse vereist. Door de kwantitatieve aanpak in dit rapport zijn belangrijke inzichten verkregen die waarschijnlijk niet door expertbeoordeling aan het licht zouden zijn gekomen. Zo bleek bijvoorbeeld dat voor bestuiving de nabijheid van halfnatuurlijke graslanden van groot belang is voor de eindindicator van bestuiving, en dat voor plaagbestrijding de breedte van bosranden een cruciale factor is. Het wordt aanbevolen deze parameters te heroverwegen en te kalibreren in toekomstige updates van het model.

1 Introduction

Achieving scientific credibility and ensuring the reliability of models is crucial when integrating ecosystem services into decision-making processes. Within this context, we strive to obtain Status A certification for all the models of the Natural Capital Model. We start by obtaining status A for the pollination and pest control models. Status A represents a high standard of quality assurance, demonstrating that the models have undergone rigorous testing, validation, and documentation to meet scientific and technical benchmarks and that they are used correctly.

The ecosystem services of pollination and pest control play a vital role in maintaining agricultural productivity and ecosystem health. However, quantifying these services and incorporating them into policy and planning requires robust models that accurately reflect ecological and socioeconomic complexities. By striving for Status A, we are committed to ensuring that these models not only provide reliable estimates but also withstand scientific scrutiny and support evidence-based decision-making.

Our approach to attaining Status A involves a systematic process, including sensitivity and uncertainty analyses, validation with empirical field data, and adherence to the 22 components outlined in the Status A framework. Through these efforts, we aim to strengthen the scientific foundation of the models, increase transparency, and enhance their applicability for diverse stakeholders.

Achieving Status A for the pollination and pest control models is an important step towards integrating natural capital considerations into policy and practice, reinforcing the credibility and utility of these tools in supporting sustainable land use and conservation strategies.

2 Status A Self-assessment summary for all ES of the Natural Capital Model

Quality Assurance

Models and data sets used as part of WOt for PBL and other products must meet the status A quality requirements (Houweling and Voorn, 2015). This includes the description of the model and its technical implementation, the evaluation of the model (sensitivities, uncertainties and validation), the development and organization of the model, and the interpretation and use of the model's results (Table 2.1). This report describes the aspects of status A for the ecosystem service models of pollination and pest control, as we did a quantitative analysis on uncertainty, sensitivity and validation. The 8 aspects falling under 'Development & Organisation' (DO.5 & DO.6) and 'Interpretation & Use' (IU.7) apply to the Natural Capital Model (NC-Model) as a whole and are described by De Knegt et al. 2022.

The model has been validated at national and regional scales, and we aim to achieve Status A at the national level. At finer scales (e.g. land parcels), the outcomes are more uncertain. Coarse-resolution data such as soil and groundwater maps limit reliability at these smaller scales.

Table 2.1 *Overview of the 22 aspects of a status A assessment. Each criteria is described in separate sections of chapters 3 and 4 for the pollination and pest control model.*

Criterium	Part	Aspects	Reference in this report
Science & Technology			
ST.1	The model/dataset is described		
1,1	There is a general description of the model/dataset	purpose * area of application * theoretical framework * paradigms	per ecosystem service
1,2	The conceptual and formal model are documented	explicitly documented * assumptions * simplifications * embedded in literature	per ecosystem service
ST.2	The technical implementation of the model/dataset is documented		
2,1	The implementation is documented	Basic structure * flow diagram	per ecosystem service
2,2	The technical environment is documented	Language * IDE * settings * limitations	per ecosystem service
2,3	The model/dataset is tested	Tests documented * protocol * untested components named	per ecosystem service
ST.3	The parameters, variables, inputs to and output of the model/dataset are described		
3,1	The parameters and variables of the model/dataset are documented	Quantities * units * default values * default source * description	per ecosystem service
3,2	Calibration of parameters is described	Procedure * results discussed	per ecosystem service
3,3	The input and output is described	Structure * format * quantities * units * precision * description * link variables & parameters * version echo	per ecosystem service
3,4	The origin of input data is described	Data preparation pipeline * source * scripts tested	per ecosystem service
ST.4	The functioning of the model/dataset is evaluated		
4,1	A sensitivity analysis is performed	Tailored to model/dataset type * documented * discussed	per ecosystem service
4,2	An uncertainty analysis is performed	Qualitative discussion	per ecosystem service
4,3	The model/dataset is validated	Discussed * non-validated components named	per ecosystem service
4,4	The use of the model/dataset is monitored	Example studies listed	per ecosystem service
4,5	There is a general assessment of model/dataset quality	Relate goal to: test * sensitivity * uncertainty * validation * use	per ecosystem service
Development & Organisation			
DO.5	The development of the model/dataset is planned		
5,1	There is a development plan	List of plans * progress reported * based on evaluation	Chapter 19.1 of De Knegt et al. 2022
5,2	A version control system is in place	Documented * acceptance criteria * (WUR) central archiving	Chapter 19.1 of De Knegt et al. 2022
DO.6	The organisation around the model/dataset is planned		
6,1	The metadata of the model/dataset is available	Domain appropriate format	Chapter 19.2 of De Knegt et al. 2022
6,2	There is a management plan	Responsiblities: content * technical * next-in-line * ownership * financial cover	Chapter 19.2 of De Knegt et al. 2022
6,3	Dependencies are discussed	Datasources * (third-party) use	Chapter 19.2 of De Knegt et al. 2022
6,4	External use is formalised	Conditions for use * User support	Chapter 19.2 of De Knegt et al. 2022
Interpretation & Use			
IU.7	User documentation is provided		
7,1	Interpretation guidance is provided	Goal * area of application * theoretic framework * summary of evaluations * general public	Chapter 19.3 of De Knegt et al. 2022
7,2	There is a user manual	Operation instructions * installation guide * summary of technical documentation * minimal system requirement * format of input & output * contact information	Chapter 19.3 of De Knegt et al. 2022

Status-A progress

The Natural Capital model has not yet achieved Status A. Progress toward this goal is assessed by scoring all relevant Status A categories through a self-evaluation conducted by the model's developers and users. The results of this evaluation were reviewed by independent auditors from the Status A audit team. Table 2.2 presents an updated version of the Status A progress table previously published by De Knegt et al. (2022) and serves as the first official self-assessment.

Table 2.2 provides an overview of the Status A progress for the Natural Capital Model (NCM), which includes 13 models, a graphical user interface (GUI), and a land use map. Based on a self-assessment it evaluates progress across the seven core Status A categories, including model description, technical implementation, and model functioning. The table uses a three-part scale to classify progress: complete (green), partly complete (orange), and missing (red).

From this self-assessment we conclude that for most of the models the criteria for status A and AA are met. The criteria sensitivity, uncertainty analyses and validation are still missing for most models. These aspects are however tested against the status AA requirements. These areas are critical for ensuring the reliability of model predictions under varying conditions.

Besides an overview of the current status of the total NCM, this report describes all relevant status A categories of 2 of the 13 ecosystem services of the NCM: namely pollination and pest control. These two models were chosen as test cases to allow for the development of robust methodologies for key aspects like sensitivity and uncertainty analysis, which can then be applied to the other ecosystem service models. Furthermore, we choose these models due to their complexity and importance to agricultural productivity and ecosystem health. By refining these approaches, we aim to establish a framework to ensure that all NCM services meet the standards of Status A.

Table 2.2 *Progress of Status A quality assurance per criterion for each of the models, GUI and land use map (green = complete, orange = partly (in)complete, red = incomplete).*

		Drinking water production	Wood production	Biomass for energy production	Soil fertility (hydrology)	Prevention of heat islands	Water purification	Pest control	Pollination	Carbon sequestration	Air quality regulation	Water retention	Outdoor recreation	Natural heritage	Graphical User Interface	Land use map
ST.1 Description of the model	general description	green	green	green	green	green	green	green	green	green	green	green	green	green	green	green
	conceptual & formal description	green	green	green	green	green	green	green	green	green	green	green	green	green	green	green
ST.2 Technical implementation	implementation	green	green	green	green	green	green	green	green	green	green	green	green	green	green	green
	environment	green	green	green	green	green	green	green	green	green	green	green	green	green	green	green
	test	green	green	green	green	green	green	green	green	green	green	green	green	green	red	green
ST.3 Parameters, in-, output	parameters	green	green	green	green	green	green	green	green	green	green	green	green	green		green
	calibration	green	green	green	green	green	green	green	green	green	green	green	green	green		
	in-/output	green	green	green	green	green	green	green	green	green	green	green	green	green	green	green
	source	green	green	green	green	green	green	green	green	green	green	green	green	green		green
ST.4 Model functioning	sensitivity	red	red	red	red	red	green	green	green	red	red	red	green	green		
	uncertainty	red	red	red	red	red	red	green	green	red	red	red	red	green		
	validation	red	orange	red	red	red	red	green	green	orange	red	red	orange	green		red
	monitoring of use	orange	orange	orange	orange	orange	orange	orange	orange	orange	orange	orange	orange	green	red	red
	general assessment	red	red	red	red	red	red	green	green	red	red	red	red	green		green
DO.5 Management- and exploitation plan	development plan	green													orange	red
	version control	green													orange	red
DO.6 Organisation	metadata	green													orange	red
	managment plan	green													orange	red
	dependencies	green													orange	red
	external use	green													orange	red
IU.7 Interpretation & use	interpretation	green													green	red
	user manual	green													green	red

3 Pollination

This chapter provides all the necessary information required for a Status A audit of the pollination model. It details the theoretical foundations of the model including its general description, conceptual framework, and technical implementation. Additionally, this chapter describes input, output, parameters, and variables. What is new compared to the previous report (De Knegt et al. 2022) are descriptions of the model's functionality, covering key aspects such as sensitivity analysis, uncertainty analysis, validation, and a general assessment of model quality.

The focus of this chapter is on the ecosystem service pollination which is critical for food crop production. Approximately 75% of global food crops depend on animal pollination, primarily by insects such as honeybees, wild bees, bumblebees, and hoverflies. The model utilizes the concepts of supply (ecosystems that provide habitat for wild pollinators) and demand (pollination dependence of specific crops) to estimate the contribution of wild pollinators to crop production in the Netherlands. While the model produces detailed, high-resolution spatial maps of pollination services, it is designed to be applied and interpreted at a national scale, ensuring its utility for policy development and large-scale environmental assessments. Examples of the model's application are the Natural Capital Indicator (De Knegt et al. 2014, 2020) and in scenario studies (De Knegt et al. 2024, PBL, 2023).

By examining the pollination model in detail, this chapter aims to not only assess its functionality but also establish methodologies that can be applied to other ecosystem service models within the NCM framework. The findings from this analysis will help enhance the model's robustness and ensure that it meets Status A requirements.

3.1 Theoretical rationale of the model

3.1.1 General description of the model

The pollination model assesses how wild insect pollinators such as wild bees, bumblebees, and hoverflies contribute to crop production by estimating the avoided loss in yields due to pollination. The model evaluates the suitability of habitats for pollinators, their movement across landscapes, and the degree to which crops rely on pollination. Although designed for the Netherlands, the model can be adapted for other temperate regions.

Habitat Suitability
The model begins by evaluating habitats for their ability to support pollinators, scoring them on a 0–100 scale. High-quality habitats, like natural grasslands or hedgerows, receive high scores (80–100), while cropland and built-up areas are scored as unsuitable (score 0). These scores are based on floral resources (pollen and nectar availability) and nesting conditions (e.g. tree cavities or soil substrates).
This step identifies where pollinators are likely to thrive and establishes a base for estimating pollinator supply.

Visitation
Using the habitat suitability data as estimation of pollinator density, the model calculates how pollinators disperse in the landscape and travel to crop fields. Larger pollinators like bumblebees can forage up to 1750 meters, while smaller ones, like solitary bees, stay within a few hundred meters. The likelihood of visitation decreases with distance, based on an exponential decay function derived from studies, where the visitation rate halves at around 1300 meters. Fields closer to high-quality habitats benefit from higher visitation rates.

Pollination %
The percentage of pollination fulfilled is calculated based on the visitation rates. Pollination increases with more visits, but only up to a certain point. Beyond this threshold, additional visits do not significantly improve crop fertilization. For example, crops receiving sufficient visitation rates (e.g. equivalent to a visitation rate of 20%) achieve maximum pollination rate, set at 100%.

Pollination Dependence
The model incorporates crop-specific reliance on pollinators, categorized from "essential" (>90% dependence, e.g. courgettes) to "minimal" (5%, e.g. beans). This reflects the proportion of crop yield that would be lost without pollination. For example, sunflowers with moderate dependence (25%) will experience limited avoided loss compared to highly dependent crops.

Avoided Loss %
The model combines the pollination percentage and crop dependence to estimate avoided production loss. For example, a crop with a 50% pollination rate and 90% dependence would see a 45% avoided loss in yield. The results provide two key outputs: the average avoided loss across all fields and a weighted value emphasizing crops with higher pollination dependence, ensuring the importance of high-value pollination-dependent crops is reflected in the results (figure 3.1).

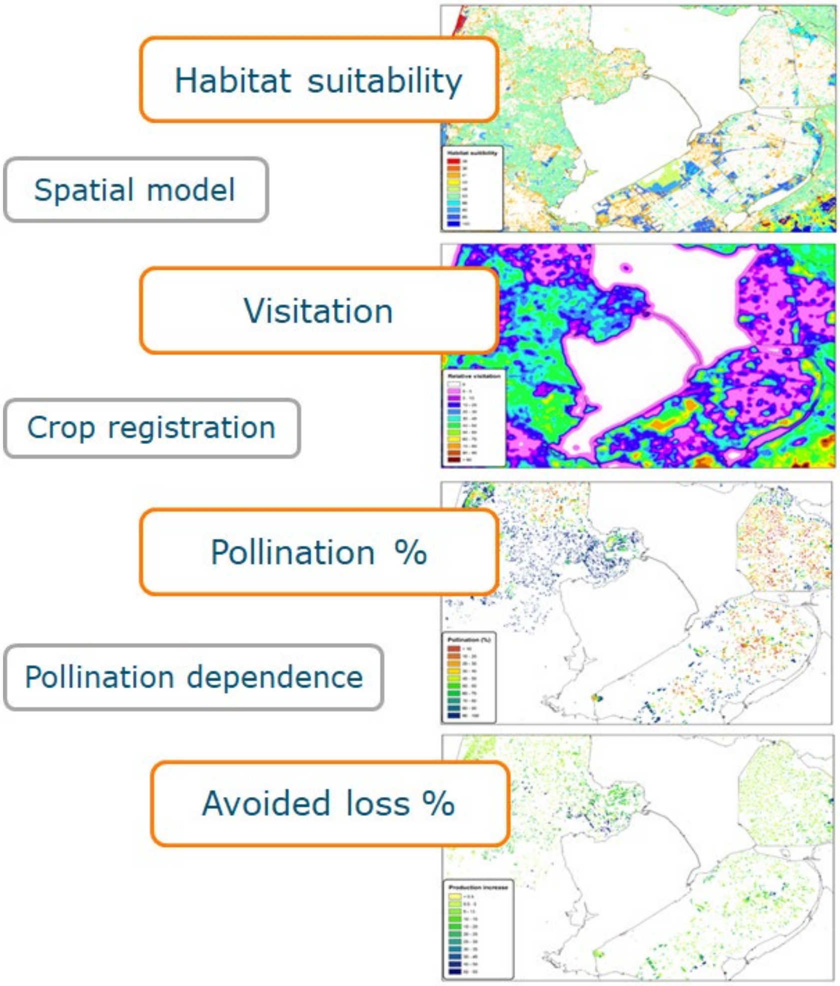

Figure 3.1 *The figure illustrates the sequential steps of the pollination model. (1) Habitat suitability: Ecosystem types are assessed for their ability to support pollinators, with higher suitability scores assigned to habitats like natural grasslands and hedgerows. (2) Visitation: Pollinator movement is modelled, with visitation rates decreasing exponentially with distance from source habitats. (3) Crop registration: Spatial data on crop fields is integrated, combining their location with their specific pollination dependence. (4) Pollination percentage: Pollination levels are calculated, linking visitation rates to crop-specific thresholds. (5) Avoided loss percentage: The avoided production loss due to pollination services is determined, highlighting the preservation of crop yields facilitated by wild insect pollinators.*

3.1.2 Conceptual and formal model

The conceptual diagram of the pollination ecosystem services model is presented in figure 3.2.

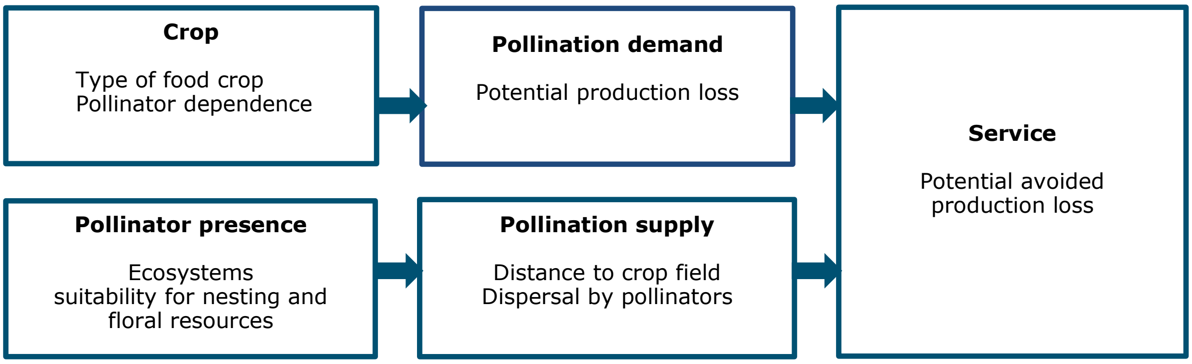

Figure 3.2 *The conceptual diagram of the pollination ecosystem services model. The top line shows the demand for pollination by food crops of which, to a certain extent, the production depends on insect pollination, while the bottom line shows the supply of pollination by ecosystems that vary in their suitability to provide nesting habitats and food sources for pollinators. Comparing the supply and demand results in the percentage of the potential production loss avoided by pollinators nesting in the local landscape.*

Pollinator presence
Ideally, pollinator presence would be based on spatial maps on pollinator density however these maps are currently not available. Therefore, it is assumed that suitability of habitats for pollinators, assessed by the presence of floral resources and nesting availability, can be used as a proxy for pollinator presence. Kennedy et al. (2013) show that the proxy for pollinator distribution based on the suitability of the surrounding land cover for nesting and floral resources, and assuming that nearby resources contribute more than distant resources, is a good predictor of pollinator density in crop fields.

To assess pollination supply, the following data are needed: a land use/land cover map with the spatial delineation of ecosystem types and information on the suitability of these ecosystems for pollinators based on the quality of the ecosystem for nesting and the availability of floral resources (table 3.1). The suitability of the ecosystems for pollinators is based on the qualitive assessment of habitat types by Kennedy et al. (2013).

To estimate the percentage pollination, the relationship between pollinator visitation and pollination is modelled as a linear function with a plateau and is expressed as:

$$pollination = MIN(100, 5 * visitation) \qquad \text{(Eq 3.1)}$$

This implies that pollination increases linearly with visitation rates up to a maximum of 100%, which is reached when the visitation rate equals or exceeds 20 (*visitation* ≥ 20).

Table 3.1 *Lookup table for an indicator of combined nesting suitability and floral resource availability for ecosystem types in the Netherlands, on a 0 - 100 scale, with 100 indicating most suitable, and 0 unsuitable (based on Kennedy et al., 2013).*

Description ecosystem types	Total nesting and floral suitability
Heath	100
Forest; deciduous	89
Natural grassland, bushes and hedges bordering fields, dunes with permanent vegetation	80
Forest; mixed	66
River flood basin, freshwater wetlands	48

Description ecosystem types	Total nesting and floral suitability
Tree lines	45
Forest; coniferous	44
Public green space, other unpaved terrain	41
Salt marsh	36
Meadows (grazing)	26
Beach, coastal dunes, inland dunes	26
Built-up, infrastructure	0
Water	0

Pollinator supply

Different species of pollinators can travel different distances. Large pollinators such as bumble bees forage over long distances (up to 1750 m; Walther-Hellwig and Frankl, 2000), while small pollinators such as solitary bees forage over shorter distances (up to several hundred meters). In their meta-analysis of 13 studies in temperate biomes, Ricketts et al. (2006) found that visitation rates of pollinators declined to half its maximum at 1308 m distance between the nesting sites and the crop. The optimal model for visitation rate (scaled 0 – 1, with 1 the maximum visitation rate) in temperate biomes is exp(-0.00053d) where d, is distance between the nesting sites and the crop in meters (Ricketts et al. 2006). This model includes species that forage over long distances and those that remain close to their nesting site. We assume that pollinators from all suitable habitats in the local landscape contribute to pollination. To obtain the relative visitation rate (scaled 0 -100) in a crop in map unit c (Lonsdorf et al., 2009) we calculate (Eq 3.2), where S_h represents the relative pollinator abundance (scaled 0 – 100, where 100 marks maximum suitability)

$$v_c = \sum_{h=1}^{H} S_h \frac{e^{-0.00053 d_{hc}}}{\sum e^{-0.00053 d}} \qquad \text{(Eq 3.2)}$$

in map unit *h* (based on the suitability for nesting and foraging for pollinators of the habitat in map unit *h*), d_{hc} is the distance between map unit *h* and the crop in map unit *c*. This is implemented by taking the convolution of the pollinator distribution (based on habitat suitability) and the negative exponential, with decay rate a = 0.00053 m^{-1} (Ricketts et al., 2006).

Pollination percentage

Based on 39 studies, Rader et al. (2016) found a relationship between visitation variation and fruit set variation. Variation in fruit set could be calculated for 14 crops. They found that bee (not including honeybees) and non-bee pollinators had a positive relationship between fruit set and pollination. Furthermore, studies showed more pollen being deposited than needed for successful fruit set, with 10 - 40 times more pollen reported by Sáez et al. (2014) and Pfister et al. (2017). Therefore, we model the pollination level (p) as a linear function of the visitation rate (v), expressed as

*p = min(100, 5 * v)* (Eq 3.3)

This means that pollination increases linearly with visitation rates up to a maximum of 100% which is reached when the visitation rate equals or exceeds 20 (v ≥ 20). While this approach assumes a straightforward relationship, it serves as a starting point and does not account for potential differences between crop types.

The mean pollination percentage across all pollination-dependent crops, perc_poll, is calculated as:

perc_poll = (SUM(pollination in cells with pollination-dependent crops) / COUNT(cells pollination-dependent crops)) (Eq 3.4)

This value provides a general measure of how well pollination-dependent crops are pollinated across the entire landscape.

Pollination demand

To assess pollination demand, data on the spatial location of crops are needed in combination with the percentage of the potential crop production that depends on insect pollination (pollination dependence; table 3.2). In the Netherlands, the basic registration of crop fields (BRP, "basis registratie gewaspercelen") can be used for the spatial location of crops, or a land use map that distinguishes several crop types based on their dependence on pollination. The BRP contains the location of each crop field and the type of crop cultivated. In the model, a raster containing different crop types is combined with the pollination need of these crop types to determine the potential production loss in absence of insect pollinators. The measure used for pollination dependence per crop is based on a review article by Klein et al. (2007) on the positive impact by animal pollination on crop production per crop type. This impact (or dependence) is divided in five classes for the need of animal pollination, essential (> 90% of the production is lost without animal pollination), great (40 – 90% production loss), modest (10 – 40% production), little (>0 – 10% production loss), no increase (0 % production loss). The mean value of each class is taken for the pollination ecosystem services model: essential 95%, great 65%, modest 25%, little 5%, and 0%. The model assumes that all varieties of a certain crop are similarly dependent on animal pollination (e.g. there is no variance in how varieties of a crop depend on pollination).

Table 3.2 *Lookup table for pollination demand of pollination-dependent crop classes in the basic crop registration in the Netherlands (Basisregistratie Gewaspercelen). Based on the classification used for the pollination requirements for the Atlas Natuurlijk Kapitaal (ANK) and the classification by Klein et al. (2007).*

BRP Crop Code	BRP Crop Name	Description	Pollination Demand (%)	Crop Group
241	Capuchins (grey peas)	Capuchins	5	Green beans
242	Beans	Beans	5	Green beans
244	Peas (green/yellow)	Peas	5	Green beans
308	Peas (dry harvest)	Peas	5	Green beans
853	Broad beans (dry harvest)	Broad beans	5	Green beans
854	Broad beans (green harvest)	Broad beans	5	Green beans
2747/2748	Peas (production/seeds)	Peas	5	Green beans
2751/2752	Runner beans (production/seeds)	Runner beans	5	Green beans
2779/2780	Stem green bean	Stem green bean	5	Green beans
2781/1782	String bean	String bean	5	Green beans
311	Field beans	Field beans	25	Field beans
258	Alfalfa	Alfalfa	5	Other crops (alfalfa_soybeans)
663	Lupine (non-bitter)	Lupine	5	Other crops (alfalfa_soybeans)
665	Soybeans	Soybeans	5	Other crops (alfalfa_soybeans)
515	Sunflower	Sunflower	25	Other crops (strawberry_rapeseed)
1922	Oilseed rape, winter	Oilseed rape	25	Other crops (strawberry_rapeseed)
1923	Oilseed rape, summer	Oilseed rape	25	Other crops (strawberry_rapeseed)
2700-2703	Strawberries (open ground)	Strawberries	25	Other crops (strawberry_rapeseed)
2704-2707	Strawberries (on racks)	Strawberries	25	Other crops (strawberry_rapeseed)
428	Yellow mustard	Yellow mustard	65	Other crops (rapeseed_cucumber)
655	Black mustard	Black mustard	65	Other crops (rapeseed_cucumber)
664	Rapeseed	Rapeseed	65	Other crops (rapeseed_cucumber)
2729/2730	Cucumber (production/seeds)	Cucumber	65	Other crops (rapeseed_cucumber)
2731/1732	Gherkin (production/seeds)	Gherkin	65	Other crops (rapeseed_cucumber)
666	Linseed (oilseed, not fibre flax)	Linseed	5	Summer barley
1095-1096	Apple	Apple	65	Apple/pear fruits
1097-1098	Pear	Pear	65	Apple/pear fruits
1099	Grapes	Grapes	65	Apple/pear fruits
1100	Stone fruits	Stone fruits	65	Apple/pear fruits
1869	Blueberry	Blueberry	65	Apple/pear fruits

BRP Crop Code	BRP Crop Name	Description	Pollination Demand (%)	Crop Group
1870	Plum	Plum	65	Apple/pear fruits
1872	Sour cherry	Sour cherry	65	Apple/pear fruits
2326	Raspberries	Raspberries	65	Apple/pear fruits
2327	Blackberries	Blackberries	65	Apple/pear fruits
2328	Sweet cherry	Sweet cherry	65	Apple/pear fruits
1873	Blackberry	Blackberry	25	Rubus berries
1874	Other small fruits (e.g. gooseberries)	Other small fruits	25	Rubus berries
2325	Red berries	Red berries	25	Rubus berries
2723/2724	Courgette (production/seeds)	Courgette	95	Other crops (courgette_pumpkin)
2733/2734	Melon (production/seeds)	Melon	95	Other crops (courgette_pumpkin)
2735/2736	Pumpkin (production/seeds)	Pumpkin	95	Other crops (courgette_pumpkin)

Avoided production loss
The model combines the crop dependence and pollination percentage to estimate avoided production loss. For example, a crop with a 50% pollination rate and 90% dependence would see a 45% avoided loss in yield. The avoided production loss (APL) in presence of pollinators can be calculated as:

*APL = PPL * pollination (%)/100* (Eq 3.5)

where PPL is the potential production loss which is equal to the dependence on pollination or pollination demand. The avoided production reduction represents the use of the pollination service by the crops.

The mean percentage of production loss avoided (PPLA) is calculated over all cells with pollinator-dependent crops, as:

*PPLA = (SUM(APL) / SUM(dependence)) * 100* (Eq 3.6)

This value provides a weighted mean of APL, where crops with higher PPL have a greater influence on the result than those with lower PPL.

In the model output, two values are calculated based on the APL:
“perc_APL” is the mean value for APL in all crop fields.
“perc_PPLA” is the mean PPL avoided due to pollination, calculated as the sum of the APL in the crop fields divided by the sum of the PPL in the crop fields, multiplied by 100. In essence, “perc_PPLA” is a value for the weighted mean pollination, where the APL in crops with a higher PPL have a higher weight than crops with a lower PPL.

3.2 Technical implementation

3.2.1 Implementation model

Main model
The pollination model is written in python, with a yml file containing the environment needed to run the model stored in a repository online (https://git.wur.nl/roelo008/bestuiving). The model calculates the APL due to insect pollination. The calculation can be divided in two main branches.

In the top branch (Figure 3.3) the pollination demand is calculated by first reading in a raster with crop classification data as a spatial array. Followed by combining that spatial array with information on crop fields with a lookup table on crop dependence on insect pollination. This results in a spatial array with values for the dependence of crop production on insect pollination.

In the lower branch (Figure 3.2) the pollination supply is calculated in 3 steps:

1. First the land use raster is read in as a spatial array and combined with a lookup table containing values for habitat suitability for the supply of pollinators (ranging from 0 – 100). This results in a spatial array with habitat suitability.
2. Then habitat suitability is used as a proxy for pollinator supply by the ecosystem types. In the function calculate dispersal, the distribution of pollinator visitation is calculated (Eq.3.2) by taking a convolution between the pollinator supply (e.g. habitat suitability array) and a kernel describing the redistribution of the pollinators based on observed visitation rates for pollinators (Ricketts et al., 2008). Based on the analysis of Ricketts et al. (2008) the redistribution kernel is a negative exponential with decay rate ɑ. To calculate the redistribution kernel the function calculate dispersal furthermore needs the pixel size of the raster (in m), to ensures the decay factor (ɑ = 0.00053 (Eq. 3.2) (Ricketts et al, 2008)) is applied over correct distances. To make the calculations more efficient, the dispersal is calculated in areas of a fixed size. If the study area is smaller than this size no adjustments are needed, otherwise the calculate dispersal function divides the entire study area (e.g., the Netherlands or a province) into smaller sections. However, since crop fields within these boundaries are also visited by pollinators outside these borders, it is necessary to include a buffer zone around each section. This buffer (specified in meters) ensures that pollinator visitation from neighbouring areas outside the smaller section is accounted for in the calculations. The function uses this buffer to calculate an array representing pollinator visitation, ensuring that the results near the edges of each section are accurate and do not underestimate visitation due to the artificial division of the study area.
3. Next, in function 1, the percentage pollination is calculated for all the cells with crops that depend on pollination (i.e. dependence >0) based on percentage visitation (Eq. 3.3).
   Subsequently, in function 2, the pollination service in the crop fields is calculated (Eq. 3.5). This service is defined as the avoided production loss (APL) and is calculated based on what percentage of the crop production depends on pollination and the percentage pollination received.

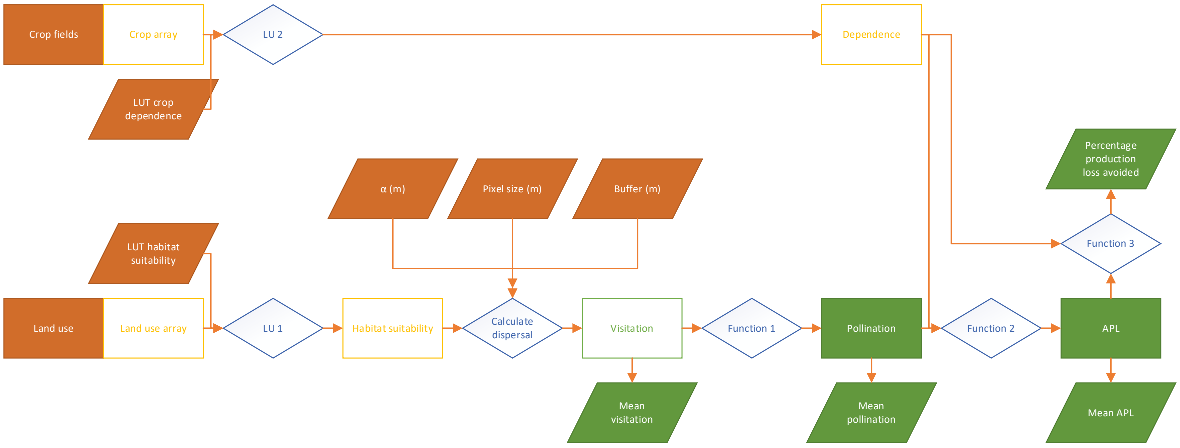

Figure 3.3 *Flow diagram of the pollination model. The filled orange boxes are input raster files. The filled orange parallelograms are input variables or lookup tables that are stored in one excel file (https://git.wur.nl/roelo008/bestuiving/-/blob/master/tests/dat/params_pollination.xlsx). The orange/white boxes are intermediate arrays. The green filled boxes are output arrays/rasters from the model. The filled green parallelograms are output values, these are written to an output file: model_result.ini, which also stores the paths of all input files. The green/white boxes are output arrays that are not written to an output raster. LU1 (bottom) combines the land use array with the lookup table with habitat suitability of the land use class for pollinators, based on the flower resources and the nesting suitability. LU2 (top) combines the crop array with the lookup table with dependence of the crop production on pollination. "Calculate dispersal" is a function that performs a convolution of the habitat suitability array and the dispersal kernel of the wild bees. This dispersal kernel is a 2D negative exponential kernel with decay rate α in meter. Function 1 calculates pollination in each 10x10m cell with a crop that depends on pollination (i.e. dependence array >0) based on the visitation array. pollination = MIN(100, 5*visitation) (Eq. 3.3). Function 2 calculates the avoided production loss (APL) in percentage in each 10x10m cell with a crop that depends on pollination (i.e. dependence array >0). APL = dependence*(pollination/100) (Eq. 3.5). Function 3 calculates the percentage of production loss avoided (PPLA) over all cells with pollinator dependent crops. PPLA = (sum(APL)/sum(dependence))*100 (Eq. 3.6).*

3.2.2 Technical environment

The model is programmed in Python (Python 3.7.9). An environment.yml file available in git (https://git.wur.nl/roelo008/bestuiving/-/blob/master/environment.yml) can be used to reproduce the exact environment in the simulations. The model has to run on a computer with an Intel Xeon W-2133 3.6 GHz processor and 16.0 GB RAM. Due to memory limitations, variables are stored as float32.

3.2.3 Testing set

A test dataset was prepared with the first version of the model to verify whether changes in the model affect the outcome and to test whether the model works as expected when run after a new installation. The dataset is from a small part of the Netherlands, therefore the test can be run in a few minutes. The municipality of Borsele was chosen as the pollination service there is much lower than the demand, making it sensitive to variation. More comprehensive testing, like testing for extreme input values or verification with field measurements has not been conducted. The results for the current situation and for a future scenario (Breman et al., 2022) have been judged by experts on plausibility.

3.3 Input and output, parameters and variables

3.3.1 Parameters and variables

The parameters are stored in an Excel file at:
https://git.wur.nl/roelo008/bestuiving/-/blob/master/tests/dat/params_pollination.xlsx

Parameters:
- The dependence on pollination per crop type/group; a value between 0-100 indicating how much the production is reduced in absence of insect pollinators. See 'afh' sheet in the parameter Excel file.
- The suitability of the habitat for pollinators; a value between 0-100 indicating the relative suitability of the habitat for pollinators based on floral resources and nesting availability (Kennedy et al., 2013) See 'habsuit' sheet in the parameter Excel file.
- The decay rate of the negative exponential function used to calculate pollinator visitation ('alpha_m') given in meters. See 'params' sheet in the parameter Excel file.
- The width of the buffer for calculation of pollination visitation in meters ('buffer_m'). `See 'params' sheet in the parameter Excel file. This is linked to the decay rate; for strong decay a smaller buffer can be used.
- The pollination efficiency ('eff_poll'), unitless. See 'params' sheet in the parameter Excel file. This value can be used to calculate the expected percentage pollination (range 0-100) based on the relative visitation (range 0-100).
- Pixel size of the input rasters ('px') in meters, constant. See 'params' sheet in the parameter Excel file.

The Excel file with the parameters is an input variable of the simulation. It is therefore possible to use a copy of the Excel file with alternative parameter values as an input file.

3.3.2 Calibration

The model was calibrated using parameters and parameter values derived from the literature. In addition, the spatial outputs were thoroughly evaluated to ensure alignment with ecological knowledge. This evaluation involved a collaborative review of maps generated at the national scale by the group of authors. The maps revealed logical spatial patterns, with higher pollination levels in complex landscapes featuring abundant (semi)natural elements, and lower levels in simpler, more homogenous landscapes. These patterns aligned with established knowledge of pollinator flight distances, further validating the model.

Moreover, the results were consistent with reported cases of pollination deficiencies documented in the literature and highlighted by experts. These findings reinforced the reliability and trustworthiness of the model outputs.

3.3.3 Input and output

Input
The model consists of four mandatory and seven optional variables.
Mandatory variables:
1. land_use: Geospatial raster (.tif) showing land use following LCEU (Land Cover and Ecosystem Unit) categories (see Knegt et al. 2022)
2. nvk_scen: Geospatial raster (.tif) with crop fields, following NVK categories for crop fields. The same folder also has a .tif.vat.dbf file with the same name as the .tif file containing the Description of the NVK categories_the format first defined by NVK (see Annex 3 in Breman et al 2022). It contains the raster and dbf file of crops susceptible to pests (demand for pest control)
3. params: Excel sheet with lookup tables and model parameters and constants
4. scenario: Name of the calculated scenario is used in the names of the output files

Optional variables:
1. --out_dir: output directory
2. --write_rasters: write geospatial output rasters to output directory
3. --reporting: write a text file with key outcomes
4. --test_input: verify model initialization; do nothing else
5. --test: verify model with test set; do nothing else
6. --service: Calculate contribution of ecosystems to avoided production loss (APL)
7. --env_proj_path Path of proj folder in python environment

Output
Output values:

1. perc_APL: mean percentage APL in pollination dependent crops
2. perc_poll: mean pollination percentage in pollination dependent crops
3. perc_PPLA: percentage of PPL prevented by received pollination
4. perc_visit: mean visitation by pollinators in pollination dependent crops

These output values are written in model_result.ini in the output directory

Optional output:
1. pollination.tif Geospatial raster showing percentage pollination in pollination dependent crops (optional, --write_rasters) (see Figure 3.4 for example for the current situation)
2. avoided_production_loss.tif Geospatial raster showing percentage avoided production loss in pollination dependent crops (optional, --write_rasters)
3. poldienst.tif Geospatial raster showing the contribution of ecosystems to the APL (optional, --service)
4. zs_poll_eu.csv CSV file with a table with per ecosystem type, the area in m2, the mean and standard deviation of the service and the sum of the contribution. Currently this is in percentage APL, but it is possible to link this to ton/ha or euro/ha.

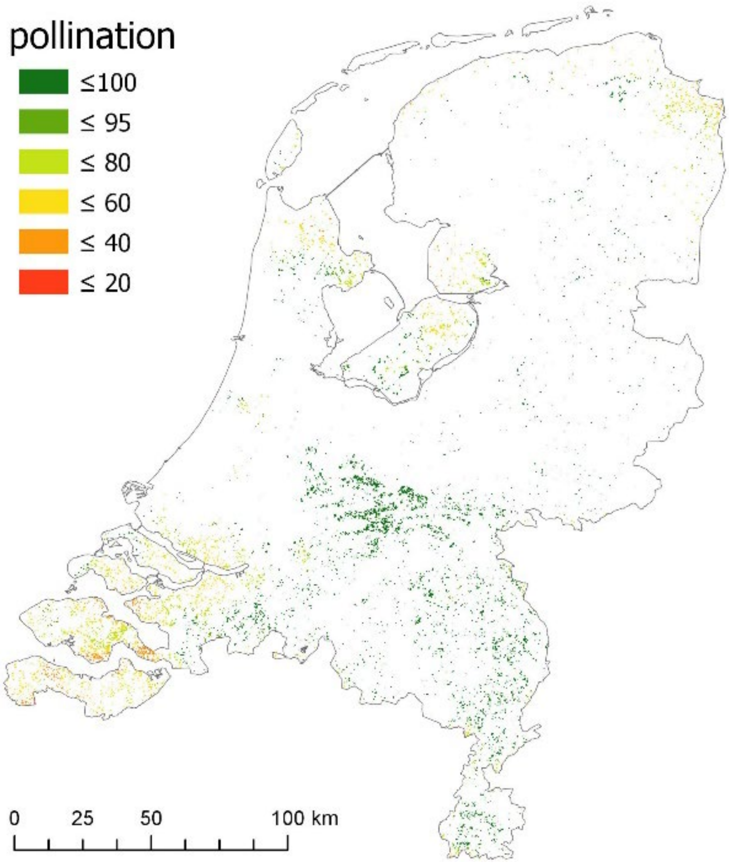

Figure 3.4 *Example of an output file (percentage pollination in pollination dependent crops for the current situation).*

3.3.4 Standard indicators

The model provides three indicators:
Supply: Supply of natural pollinators by ecosystems.

Demand: Pollination of (all) pollination dependent agricultural crops.

Combination of supply and demand: % APL of pollination dependent crops by natural pollinators (%PPLA).

The units of supply and demand are both in kg/ha.

3.4 Evaluation of model functioning

3.4.1 Sensitivity analysis

3.4.1.1 Introduction

This section outlines the sensitivity analysis conducted on the pollination model as part of the NCM. The model uses parameter values that represent the most likely values for a median situation. The sensitivity analysis evaluates how variations in each parameter influence the model's outputs, quantifying the relative contribution of each parameter to the overall variability in the model's predictions.

3.4.1.2 Method

Distribution and sampling of input parameters

The first step in the sensitivity analysis involved sampling values from hypothesized distributions of the model parameters. While the input maps remained fixed, only the model parameters were allowed to vary. Distributions of parameter estimates around their median values were empirically estimated by the authors informed by expert knowledge about the parameters' limits, most likely values (medians), and, where available, their variation (standard deviation) (Table 3.3).

The next step was to identify candidate distributions that could appropriately describe these inputs. Depending on their most likely behaviour, model parameters were sampled from uniform, beta, or other distributions. In many cases, a uniform distribution was assumed as all values within a specified range were considered equally likely. A beta distribution was used for parameters with defined limits, allowing for flexible shapes (symmetric, left-tailed, or right-tailed). The beta distribution always generated values between 0 and 1, which in some cases were re-scaled and shifted to match the parameter's range and behaviour. Annex 1 provides a summary of the distributions used to generate the input parameters, including re-scaling and shift factors.

Table 3.3 *Estimated distributions of each model parameter used in the sensitivity analysis (median, standard deviation, minimum and maximum).*

Parameter group	Parameter	Description	median_habsuit	SD	min	max
Dispersal	**alpha_m**	alpha (m)	0.00053		0.0004	0.0009
	alpha_m_short	alpha short (m)	0.0014		0.001	0.0019
	alpha_m_long	alpha long (m)	0.0002		0.0001	0.0003
Effectiviness	**eff_poll_unif**	effectiviness pollination (uniform distribution)	5		1	10
	eff_poll_norm	effectiviness pollination (normal distribution)	5.5	1.5	1	10
Ecosystem type	**1**	Non-perennial plants	0	0	0	0
	2	Perennial plants	0	0	0	0
	3	Greenhouses	0	0	0	0
	4	Meadows(grazing)	26	29	0	100
	5	Bushes and hedges bordering fields ("faunarand")	80	34	0	100
	6	Farmyards and barns	0	0	0	0
	11	Dunes with permanent vegetation	80	34	0	100
	12	Active coastal dunes	26	29	0	100
	13	Beach	26	29	0	100
	20	Bomenrij	89	39	0	100
	21	Deciduous forest	89	39	0	100
	22	Conferous forest	44	31	0	100
	23	Mixed forest	66	48	0	100
	24	Heath land	100	30	0	100
	25	Inland dunes	26	29	0	100
	26	Fresh water wetland	48	38	0	100
	27	(semi) natural grassland	80	34	0	100
	28	public green space (Mixed vegetation)	26	29	0	100
	28	public green space (Deciduous forest)	89	39	0	100
	29	Other unpaved terrain	41	33	0	100
	31	River flood basin	48	38	0	100
	32	Salt marsh	36	35	0	100
	41	Residential area	0	0	0	0
	42,43,45,46,47,48	Built-up, other	0	0	0	0
	44	Infrastructure	0	0	0	0
	51	Sea	0	0	0	0
	52	Lakes and ponds	0	0	0	0
	53	Rivers and streams	0	0	0	0
	0, 255, 999	No data	0	0	0	0
Crop groups	**89**	Apple, pear, fruit	65		40	89
	90	Rubus-berries	25		10	39
	91	Other crops, alfalfa & soy beans	5		1	9
	92	Other crops, strawberry & oil seed rape	25		10	39
	93	Other crops, rape seed & cucumber	65		40	89
	94	Other crops, courgette & pumpkin	95		90	100
	95	Green beans	5		1	9
	96	Field beans	25		10	39
	97	Summer barley	5		1	9

"Eff_poll" corresponds to "perc_poll" (see paragraph 3.3.3).

For the model input eff_poll (effectiveness of pollination), it was unknown what distribution (uniform or normal) would be most appropriate. We therefore considered two different distributions, uniform and normal, with the normal distribution as default, and the uniform distribution to check effects on the sensitivity. Thus two sets of input samples were generated for eff_pol.

Latin hypercube sampling (LHS) (Loh, 1996) was performed in R with function randomLHS from R package *lhs*. Two hundred hypercubes were sampled. The distribution of each input parameter was partitioned into 10 bins with equal probability, with each hypercube containing 10 samples, one from each of the 10 bins. Each hypercube was independently generated.
The resulting 2000 sampled input values (200 hypercubes) were then fed into the simulation model. In the first set of 1000 samples (100 hypercubes), eff_poll was normally distributed, while in the second set eff_poll was uniformly distributed. The two sets of 1000 samples were independent (not paired), and each covered the whole parameter space.

Two independent sets of 1000 outputs were obtained. The two sets were analysed separately.

Sensitivity analysis

Sensitivity analysis aims at assessing and quantifying the relative importance of each input parameter on each model output. It helps modellers identify important parameters and helps them optimize research to improve the most sensitive parameters. We used the Regression-Based global Sensitivity Analysis method (Jansen, 1999; Jansen, 2005; Becker, 2018; Ridolfi and Mooij, 2016). It is an approach for quantitative, variance-based, sensitivity analysis of mathematical models used for design purposes. We used a simple linear model to predict output y from input parameters $x=(x_1 \ldots x_k)$ as approximation to y=f(x), where f is a complex function (usually non-linear). In other words, we applied a simpler linear model to each output y as an approximation to a complex model f(x).Using this approach, we aimed to quantify the sensitivity of y to each parameter x_i.

We used the following quantities for each output y:

1. <u>The total variance of y</u>, V_{tot}, which depends on the distribution of inputs and on the model:
   $V_{tot} = V(y)=V[f(x)]$

   where f is the original model, and $x=(x_1 \ldots x_k)$ are the inputs with distribution D, x~D.

2. The top marginal variance, also known as first-order index, of each input xi, TMVi, measures the relative contribution to Vtot of varying the xi alone, and is defined as:
   $TMV_i = V[E(y|x_i)]$ (Eq 3.7)

   This measure corresponds to the effect of knowing x_i, averaged over all possible combinations of all other inputs. TMV_i can be expressed as a fraction of V_{tot}, calculated as R^2, the percentage of variance of output y accounted for by x_i, from a simple least squares model:
   $y=a+b_i\, x_i$.

   The TMV measure does not account for interactions of x_i with other inputs.

3. <u>The bottom marginal variance</u>, also known as total effect index, of each input x_i, BMV_i, is defined as:
   $BMV_i= \{V_{tot} - V[E(y|x_{-i})]\}$ (Eq 3.8)

   where $V[E(y|x_{-i})]$ is the variance of y when x_i is known, conditional on all inputs except x_i, $x_{-i} =(x_1 \ldots x_{i-1}, x_{i+1} \ldots x_k)$. BMV_i can be calculated as the decrease of variance accounted for when x_i is removed from a linear model that contains all inputs. Therefore BMV_i can account for interactions of x_i with other inputs. As with TMV, BMV can be expressed as a fraction of V_{tot}.

Linear models used

TMV (Eq 3.7) and BMV (Eq 3.8) were estimated for each output y, in different steps, with a series of linear models:

Model A: Model with all inputs x:
$y = a + \Sigma_j\, b_j\, x_j$

Model B: Model only with x_i:
$y = a + b_i\, x_i$

Model C: Model with all inputs except x_i:
$y = a + \Sigma_{-i}\, b_j\, x_j$

Procedure

1. In a first step, we considered the total percentage variance accounted for by model A for each output. If the total percentage of variance accounted for by model A (R^2) was < 90% of V_{tot} , then more elaborate linear models would be fitted until 90% of V_{tot} could be explained by each model.

2. In step 2, model B was fitted to output y and each input x_i, and the amount of explained variance, given by R^2, was taken as a measure of TMV_i for y.
3. In step 3, model A in step 1 was fitted to y, but excluding input x_i. BMV_i was calculated as the difference in R^2 between model A and model C,
   $BMV_i = R^2(A)-R^2(C)$.

Bootstrap analysis
To measure the accuracy of TMV_i and BMV_i, bootstrap samples were drawn from the complete sample of inputs and outputs. This involved generating 100 bootstrap samples by random resampling (with replacement) from the original dataset of inputs and outputs. For each bootstrap sample, the Top Marginal Variance (TMV, Eq 3.7) and Bottom Marginal Variance (BMV, Eq 3.8) indices were recalculated. Confidence intervals (2.5% and 97.5%) for TMV and BMV indices were derived from these bootstrap results, providing a robust measure of the accuracy in sensitivity estimates. The variation in TMV and BMV values across bootstrap samples was typically around 10%, demonstrating that the sensitivity indices were stable.

3.4.1.3 Results
The model was run a total of 2000 times on two versions for Eff_poll; samples 1-1000 were run for Eff_poll normally distributed, and samples 1001-2000 were run for Eff_poll uniformly distributed.

Summary statistics of model inputs
The summary statistics of input parameters can be found in Annex 2, after applying the distributions in Annex 1, along with re-scaling and shifting for some parameters. These distributions represent the likely behaviour of the input parameters based on available knowledge and expertise. Since these parameters can have different scales, we reported and compared their coefficients of variation (CV), defined as CV=100*sd/mean. Coefficients of variation of inputs ranged between 5% and 45%. Coefficients of variation for normally distributed Eff_poll were 27% and 38% for uniformly distributed Eff_poll.

Model outputs
We then inspected model outputs; their summary statistics are shown in Table 3.4. Coefficients of variation of model outputs are between 10%-30% for Eff_poll Normally distributed, and between 15%-40% for Eff_poll Uniformly distributed (Annex 4). These coefficients of variation are within the range of those of the corresponding input parameters.

Detailed outputs
Annex 4 summarizes the model outputs for the two distributions of Eff_poll. Key outputs include:

1. Percentage of Potential Production Loss Avoided Due to Pollination (perc_ppla):
   - Shown in blue, this output quantifies the effectiveness of pollination services in reducing potential crop production losses.

2. Percentage Visitation by Bees in Crop Fields:
   - -Shown in green, this metric evaluates pollinator activity in crop fields across the study areas.

3. Standard Set of Output Indicators (SSI):
   - Shown in orange, the SSI consists of:
     - Demand (ssi_vraag): Pollination demand in the landscape.
     - Supply (ssi_aanbod): Pollination supply from the ecosystem.
     - Percentage of Demand Met (ssi_combi): The proportion of demand met by supply, equivalent to the national perc_ppla value.

Each of these outputs was calculated for:
- The Netherlands (NL).
- Three municipalities representing varying landscape complexities:
  - Borsele in Zeeland (ZL)
  - Horst aan de Maas in Limburg (LI),
  - Dronten in Flevoland (FL),

with ZL and FL being the least complex and LI the most complex. Additionally, outputs were reported for three pollinator dispersal distances: short (dispersal distance for smaller bees like Andrena species), long (dispersal distance for large bee species like bumble bees), and the default model setting (population mean distance).

Table 3.4 *Summary statistics of model outputs, for Eff_poll normally distributed; results for the uniform distribution are provided in Annex 4.*

outcome_Eff_poll_normal	min	mean	median	max	sd	var	cvpct	q025	q975
NL_perc_ppla_short	21	77.6	80.8	98.8	13.3	177.7	17.2	42.7	95.1
ZL_perc_ppla_short	13.3	56.9	57.4	98.4	14.9	223	26.2	26.9	85.2
LI_perc_ppla_short	26.8	92.8	97.9	100	11.9	140.6	12.8	56.5	100
FL_perc_ppla_short	10.7	49.5	49.3	93.4	13.9	193.1	28.1	22.7	78.9
NL_perc_ppla	23.6	81.3	84.2	99.7	12.6	158	15.5	47.1	96.9
ZL_perc_ppla	12.7	56.3	55.8	98.5	16.1	258.1	28.5	25.6	88
LI_perc_ppla	32.2	96.4	100	100	9.4	88.6	9.8	66	100
FL_perc_ppla	14.1	60.3	59.7	100	16.9	284	28	27.6	94.8
NL_perc_ppla_long	21.9	79.6	82.6	99.6	12.8	164.2	16.1	44.3	96.5
ZL_perc_ppla_long	10.4	48.8	47.6	100	15.6	243	32	21.5	86
LI_perc_ppla_long	24	94.2	100	100	12.5	155.9	13.3	55.2	100
FL_perc_ppla_long	17.7	76.1	77.6	100	18	325.2	23.7	36.6	100
NL_perc_visit_short	11.8	17.3	16.9	29.9	3.1	9.6	17.9	12.6	24.5
ZL_perc_visit_short	7.5	10.8	10.6	17	1.5	2.3	14	8.4	14.4
LI_perc_visit_short	17.7	23.6	23.3	34.7	2.8	8	11.9	18.8	29.7
FL_perc_visit_short	6.1	9.4	9.2	15.9	1.6	2.7	17.5	6.8	12.9
NL_perc_visit	13	18.5	18.1	30.9	3.1	9.4	16.6	14	25.5
ZL_perc_visit	6.9	10.4	10.2	16.8	1.5	2.3	14.5	7.9	13.8
LI_perc_visit	20.4	26.3	26	37.2	2.7	7.5	10.4	22.1	32.1
FL_perc_visit	8	11.8	11.6	20.8	1.9	3.5	15.8	9	16.3
NL_perc_visit_long	11.2	17.5	17.2	30.4	2.9	8.3	16.5	13.1	24.1
ZL_perc_visit_long	6	8.9	8.7	14.8	1.4	2	15.8	6.6	12.1
LI_perc_visit_long	14.1	22.8	22.8	35.6	3.4	11.4	14.8	16.3	29.4
FL_perc_visit_long	11.6	15.9	15.6	24.6	2.1	4.4	13.1	12.6	20.4
ssi_vraag	2368902	5887904	5698457	10591158	1958111	3.83E+12	33.3	2943448	9481554
ssi_aanbod	1168853	4779362	4640674	9916886	1758215	3.09E+12	36.8	2055865	8234647
ssi_combi	23.6	81.3	84.2	99.7	12.6	158	15.5	47.1	96.9

Conclusion on choosing normally or uniformly distributed Eff_poll
We chose to use the normal distribution for Eff_poll in the analysis as it better reflects a realistic scenario where values cluster around a typical mean, with fewer extreme cases. For example, the mean value of ssi_combi (percentage demand met, equivalent to NL_perc_ppla) was 81.3% under the normal distribution compared to 80.8% under the uniform distribution, showing a small difference in central tendencies. The 2.5th and 97.5th percentiles for ssi_combi were 47.1% and 96.9% respectively for the normal distribution, compared to 39.9% and 98.5% for the uniform distribution, indicating slightly wider variability with the uniform distribution.

Correlations
We then looked at correlations. Figure 3.5 shows correlations between model outputs (given for the output of Eff_poll with a normal distribution); the correlations were similar for the two sets of outcomes. All outcomes correlated positively with one another (no negative correlations). Highest correlations were observed between the same type of outcomes in different regions.

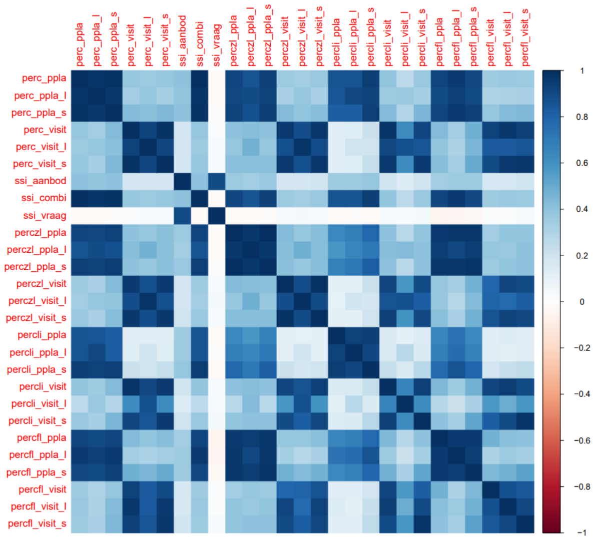

Figure 3.5 *Correlations between model outputs for the samples with Eff_poll normally distributed.*
While the uniform distribution introduced greater variability (e.g. coefficients of variation for ssi_combi were 15.5% for normal and 20.8% for uniform), the normal distribution aligned better with empirical expectations, offering robust outputs without overemphasizing extreme values. This made the normal distribution a more suitable choice for this analysis.

Sensitivity analysis
Sensitivity analysis was performed as described earlier. A full additive model with all inputs was fitted to each outcome (Model A, see section 2). For most outcomes, this additive model had an R^2 of more than 90%, where a single input explained more than 75% of the variation of y for the national level, as shown in Table 3. For outcomes perc_ppla (overall) and percli_ppla (Limburg), the full additive model explained less than 90%. Consequently we fitted complex models with interactions until the model explained more than 90% of the total variation of y (table 3.5 and Annex 5).

Table 3.5 *Sensitivity analysis indices per outcome y. Vtot is the variance of the outcome, Vtot=V(y); R2_all is the percentage of variance of y explained by Model A that contains all the explanatory variables; TMV is the percentage of variance of y explained by Model B that only contains the variable of interest; BMV is the difference R2_all – R2(Model C, that contains all the variables, except the variable of interest). Results are shown for eff_poll normally distributed, the results for the uniform distribution of Eff_poll are shown in Annex 5.*

	Effpol Normal				Effpol Normal	
output	**Vtot**	**R2_Add**	**R2_nonAdd**	**largest contributor**	**TMV**	**BMV**
NL_perc_ppla_s	177.7	86	97	eff_poll	65	62
ZL_perc_ppla_s	223.0	98		eff_poll	79	76
LI_perc_ppla_s	140.6	63	97	eff_poll	55	52
FL_perc_ppla_s	193.1	98		eff_poll	70	66
NL_perc_ppla	158.0	83	98	eff_poll	68	65
ZL_perc_ppla	258.1	98		eff_poll	79	76
LI_perc_ppla	88.6	44	98	eff_poll	40	38
FL_perc_ppla	284.0	98		eff_poll	75	72
NL_perc_ppla_l	164.2	85	99	eff_poll	70	66
ZL_perc_ppla_l	243.0	98		eff_poll	75	72
LI_perc_ppla_l	155.9	54	97	eff_poll	46	43
FL_perc_ppla_l	325.2	92		eff_poll	79	76
NL_perc_visit_s	9.6	100		P4	91	87
ZL_perc_visit_s	2.3	100		P4	78	73
LI_perc_visit_s	8.0	100		P4	72	67
FL_perc_visit_s	2.7	100		P4	80	76
NL_perc_visit	9.4	100		P4	92	87
ZL_perc_visit	2.3	100		P4	78	72
LI_perc_visit	7.5	100		P4	80	73
FL_perc_visit	3.5	99		P4	75	72
NL_perc_visit_l	8.3	98		P4	78	75
ZL_perc_visit_l	2.0	98		P4	66	63
LI_perc_visit_l	11.4	96		alpha_m_long	49	49
LI_perc_visit_l	11.4	96		P4	34	33
FL_perc_visit_l	4.4	98		P4	85	79

Table 3.5 displays sensitivity indices Top marginal variance, or first-order index (TMV) and bottom marginal variance, or total effect index (BMV), for the most relevant inputs for each output (see also Annex 6 and 7). The sensitivity analysis shows that the parameter eff_poll (effectiveness of pollination) was the largest contributor for perc_ppla (percentage of potential production loss avoided due to insect pollination) in all regions and for all distances, at between 35% and 75% (TMV and BMV indices). The bootstrap analysis confirmed the sensitivity results by recalculating TMV and BMV indices for 100 bootstrap samples. Confidence intervals for TMV and BMV indices showed a variation of approximately 10%, confirming that sensitivity indices in Table 3.5 are consistent and stable across resampled datasets (Table 3.6).

Table 3.6 Bootstrap-based indices of sensitivity analysis per outcome y in the first columns, and inputs x, in the second column. TMV is the top marginal variance (the R2 of the model containing only the variable of interest), BMV is the bottom marginal variance (the difference between the R2 of the full model and the model with all the variables except the variable of interest), lower refers to the 25% quantile and upper to the 97.5% quantile of the bootstrap samples.

		Eff_poll_Normal						Eff_poll_Unif					
output	**input**	**TMV.025**	**TMV.5**	**TMV.975**	**BMV.025**	**BMV.5**	**BMV.975**	**TMV.025**	**TMV.5**	**TMV.975**	**BMV.025**	**BMV.5**	**BMV.975**
NL_perc_ppla_short	eff_poll	61	65	68	70	76	81	73	76	77	79	82	86
ZL_perc_ppla_short	eff_poll	76	79	82	70	74	79	86	88	89	76	80	84
LI_perc_ppla_short	eff_poll	52	55	58	83	88	92	60	63	65	87	90	93
FL_perc_ppla_short	eff_poll	65	69	73	59	64	69	78	81	83	70	74	78
NL_perc_ppla	eff_poll	65	68	70	76	81	86	74	76	78	81	85	88
ZL_perc_ppla	eff_poll	77	79	82	69	74	79	88	89	91	77	82	85
LI_perc_ppla	eff_poll	37	40	44	89	93	96	46	50	53	89	92	94
FL_perc_ppla	eff_poll	72	75	79	65	70	75	83	85	87	74	79	82
NL_perc_ppla_long	eff_poll	67	70	72	76	81	86	76	77	79	82	86	89
ZL_perc_ppla_long	eff_poll	72	75	79	65	70	75	85	86	88	74	80	83
LI_perc_ppla_long	eff_poll	42	46	49	84	87	91	52	54	57	87	90	93
FL_perc_ppla_long	eff_poll	77	79	81	69	74	78	84	85	87	75	79	82
NL_perc_visit_short	P4	90	91	93	80	84	88	91	92	93	83	86	90
ZL_perc_visit_short	P4	75	78	82	65	71	75	75	78	81	69	73	78
LI_perc_visit_short	P4	69	72	76	60	65	69	67	72	75	63	67	72
FL_perc_visit_short	P4	78	80	82	70	74	78	78	81	84	71	75	79
NL_perc_visit	P4	91	92	93	80	84	88	91	92	93	82	86	90
ZL_perc_visit	P4	75	77	81	64	69	74	73	77	79	68	73	77
LI_perc_visit	P4	77	80	82	66	70	75	73	77	80	69	72	77
FL_perc_visit	P4	73	75	78	66	70	74	72	76	78	64	69	73
NL_perc_visit_long	P4	75	78	81	68	73	77	75	78	81	70	74	78
ZL_perc_visit_long	P4	62	66	69	56	61	66	61	66	69	58	62	66
LI_perc_visit_long	alpha_m_l	45	49	52	45	48	53	46	50	54	45	48	54
FL_perc_visit_long	P4	84	85	87	72	76	80	82	84	86	76	79	83

In table 3.6, the parameter, eff_poll, translates visitation to effectiveness of pollination in the field (% pollination = eff_poll * % visitation), and the percentage pollination is directly linked to the APL. Therefore we also expected it to be the largest contributor. The parameter P4 (habitat suitability of meadows for grazing) was the largest contributor for perc_visit in all regions except in Limburg for long distance (percli_visit_l), where alpha_m_long contributed most. The substantial contribution of meadows to visitation was initially unexpected due to their relatively low habitat suitability score. To investigate further, we performed a detailed spatial analysis (textbox), revealing an ecological explanation. The high contribution of meadows is due to their large spatial extent and proximity to crop fields making them a critical resource for pollinator visitation, despite their lower suitability per unit area.

Spatial Analysis of Meadows (P4) and Pollinator Visitation

Additional sensitivity analysis on spatial distribution ecosystem types in input map

Table 3.5 shows that meadows for grazing (P4) are the largest contributor for percentage of visitation by pollinators in all regions except in Limburg for long distance flying pollinators. Percentage visitation in crop fields depends on the total area of suitable habitats in the surrounding landscape combined with the level of suitability of those habitats.

To separate the effect of level of suitability from the effect of the total area near to crop fields that depend on pollination, we calculated the mean visitation of crop fields that depend on pollination (perc_visit) for each of the vegetated ecosystem types separately, assuming 100% suitability. The distance based mean visitation rates in Table 3.7 show that meadows potentially contribute the most (except for annual crops assumed to have 0 contribution in the model), as they constitute a large area often situated close to the crop fields needing pollination. The latter can also be deducted by the larger visitation rates of short distance dispersing pollinators compared to the long distance dispersing pollinators. For mixed forests, long dispersing pollinators have higher visitation rates than short dispersing pollinators, indicating that mixed forests are, on average, further away from the crop fields.

Even though the habitat suitability of meadows is relatively low, their presence close to the crop fields results in their being the largest contributor for percentage of visitation by pollinators. Depending on the most present ecosystem type near crop fields that need pollination, regional differences can occur regarding which ecosystem contributes most.

Table 3.7 *Individual contributions of ecosystem types to visitation, for simulations with one ecosystem set at 100% habitat suitability and all others at 0% suitability*.

Ecosystem type	Area	Mean visitation (area based)			Mean visitation (area & suitability based)	
	1000 ha	Short dispersal	Medium dispersal	Long dispersal	Habitat suitability	Mean visitation medium dispersal
Annual crops	806.8	39.1	32.5	24.8	0	0
Perennial crops	44.7	6.6	4.1	2.6	0	0
Meadows (grazing)	1113.9	22.6	22.2	19.9	26	5.8
Dunes with vegetation	19.8	0.1	0.1	0.1	80	0.1
Active coastal dunes	10.8	0.0	0.0	0.0	26	0.0
Beaches	2.2	0.0	0.0	0.0	26	0.0
Tree lines	13.4	0.4	0.4	0.3	45	0.2
Deciduous forest	175.0	3.7	3.9	3.6	89	3.5
Coniferous forest	82.8	0.9	1.1	1.2	44	0.5
Mixed forest	162.8	1.7	2.0	2.3	66	1.3
Heathland	51.4	0.3	0.4	0.5	100	0.4
Inland dunes	6.3	0.0	0.1	0.1	26	0.0
Fresh water wetlands	18.4	0.2	0.2	0.3	48	0.1
(Semi) natural grasslands	165.5	3.3	3.8	3.6	80	3.1
Public green spaces	70.7	0.9	1.2	1.3	41	0.5
Other unpaved	268.8	6.1	6.3	5.8	41	2.6
River flood basin	0.8	0.0	0.0	0.0	48	0.0
Saltmarshes	12.4	0.2	0.3	0.3	36	0.1

3.4.1.4 Overall conclusions of the sensitivity analysis for the Netherlands

With this analysis, we provide insights in the sensitivity of parameters for the results of the model, guiding future research, and informing strategies to enhance pollination services.

1. Eff_poll is the most important factor for outcomes
   - Outputs from the uniform distribution of Eff_poll show greater variability compared to the normal distribution, reflecting the broader range of sampled values.
   - However, central tendencies for most outputs are similar, making the normal distribution a better fit for realistic scenarios.
   - The effectiveness of pollination (Eff_poll) is the largest contributor to the variation in perc_ppla (percentage of potential production loss avoided) across all regions and dispersal distances, accounting for 35–75% of the total variance.
   - It is important to reassess and check the parameterizing of Eff_poll, as it directly translates visitation rates into pollination effectiveness and avoided production loss.
   - More empirical data are needed for Eff_poll to refine its parameterization, particularly for crop-specific (pollinators) and regional variations.
   - As Eff_poll is independent of the spatial configuration, this will be the most important factor for outcomes in other countries.

2. P4 (Meadows) are relatively important for the outcomes
   - P4 (habitat suitability of “meadows for grazing”) is an important factor influencing multiple outcomes of the model, including perc_visit (percentage visitation) and, indirectly, perc_ppla (percentage of potential production loss avoided).
   - The importance of meadows lies in their large spatial extent and proximity to pollination-dependent crop fields, which increases their contribution to pollinator activity and the delivery of pollination services, even though their habitat suitability per unit area is relatively low.
   - Given the significant role of meadows in the model outcomes, future research should focus on reassessing the P4 parameter through site-specific studies that evaluate actual habitat conditions, such as floral richness, nesting resources, and spatial configuration relative to crop fields. A more precise, localized understanding of meadow suitability will improve the accuracy and applicability of the model across diverse regions and landscapes.

3. Regional landscape variation matters
   - The dominant ecosystem type contributing to visitation varies by region. For example, in Limburg, alpha_m_long (a parameter affecting long-distance dispersing pollinators) plays a significant role for long-distance dispersers.
   - This emphasizes the need to account for regional landscape composition (these vary greatly in the Netherlands) when interpreting model results.

4. Long-distance pollinators in fragmented landscapes
   - Long-distance dispersers contribute more in fragmented landscapes, as observed in Limburg for long dispersal distances.
   - This highlights the ecological importance of maintaining connectivity between fragmented habitats to support pollination services.

5. National aggregates vs. spatial differentiation
   - While a few parameters, such as Eff_poll and P4, explain most of the variation in aggregated national-scale indicators, the spatial differentiation of outcomes can be influenced by a broader range of parameters, including pollinator dispersal distances (alpha_m_long), habitat suitability for other ecosystems, and the spatial configuration of habitats relative to crop fields. This underscores the importance of considering the combined effects of all parameters when interpreting spatial patterns, even if their influence on national-scale outputs is smaller.

3.4.2 Uncertainty analysis

Uncertainty analysis examines how uncertainties in a model's inputs affect its outputs. Its primary goal is to quantify the range and distribution of the model's outputs, considering the variability or estimated probability distributions of the inputs.

3.4.2.1 Method

The approach for uncertainty analysis builds on the distribution and sampling of input parameters described in Section 3.4.1.2, which is relevant to both sensitivity and uncertainty analyses. We calculated summary statistics for each output (y) to provide an understanding of the variability in outputs as a result of input variation. Annex 2 shows, for each model output (y), the minimum, maximum, mean, median, standard deviation, variance, coefficient of variation (CV), and quantiles (2.5% and 97.5%) to represent the 95% confidence interval. Additionally, we plotted histograms of the outputs (Annex 3) to provide a visual representation of their distributions. These visualizations helped to identify key characteristics, such as skewness, spread, and the presence of outliers. They also enable a comparison of the effects of different input parameter distributions, such as normal versus uniform for Eff_poll, on the model outputs. This descriptive approach ensures transparency, validates the sampling methodology, and improves the interpretability of the model results.

3.4.2.2 Results

In figure 3.7 the uncertainty around the mean is shown for the most important standard indicator used at the national scale "potential production loss avoided" (perc_ppla) (see section 3.3.4, Eq. 3.6).

The empirical confidence intervals were obtained for most relevant inputs (Annex 2), as well as for the outputs (Table 3.4).

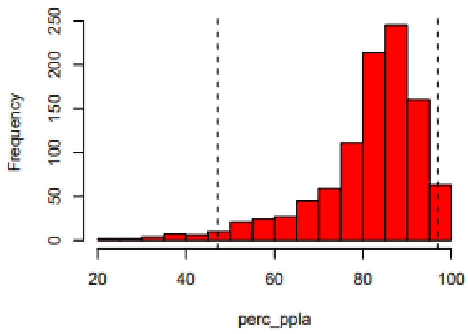

Figure 3.7 *Normal distribution of perc_ppla around te mean (80.5). Dashed lines indicate the 2.5th and 97.5th percentiles, representing the range that encompasses 95% of the output values.*

3.4.2.3 Overall conclusions of the uncertainty analysis

The uncertainty analysis confirms that the model outputs are robustly influenced by input variability and provides clarity on the range and distribution of key outputs.

The uncertainty analysis reveals that the national-scale standard indicator, "potential production loss avoided" (perc_ppla), has a mean of 80.5, with a 95% confidence interval ranging from approximately 47.1% to 96.9% under a normal distribution of Eff_poll (Table 3.4). The standard deviation is 12.6. The histogram shows a positively skewed distribution, indicating that most outcomes cluster closer to higher values, with fewer lower values.

3.4.3 Validation

We based our model on one that calculates visitation of pollinators based on habitat suitability and compares outcomes to field data on received pollen (Ricketts et al., 2008), however the model has not yet been validated for the Netherlands.

Earlier research on the decline of pollinators and their impact on yields by Holland et al. (2020) who compared open-pollinated and hand-pollinated flowers across 105 fields in Europe, shows an average yield reduction of 2.8% due to pollination limitations, with higher reductions in sunflowers (8%) and one oilseed rape region (6%). However, variations in insect visits to flowers did not directly correlate with pollination limitations, suggesting that other factors also influence crop yields.

The results from our model align well with these findings, capturing similar trends in pollination effectiveness and its contribution to reducing potential yield losses. However, to strengthen the credibility of the model and improve its applicability for decision-making, further research should prioritize validating its predictions through targeted field experiments. This would involve comparing model outputs with observed pollinator activity, crop yields, and other relevant ecological factors under controlled and natural conditions.

3.4.4 General assessment of model quality

General assessment of model quality

The combined evaluations of the model—sensitivity and uncertainty analyses, validation, and practical application—demonstrate its general "fitness for purpose" as a policy-support tool. Sensitivity analysis revealed that Eff_poll (effectiveness of pollination) and P4 (habitat suitability of meadows) are the most influential parameters affecting national-scale indicators like percentage visitation and potential production loss avoided. These findings underscore the need for improved empirical data, particularly site-specific studies, to refine these critical parameters and address regional variability.

The uncertainty analysis further confirmed the robustness and consistency of the model outputs, showing predictable distributions and stability across different input scenarios. Validation efforts aligned model predictions with observed trends in pollination limitations and crop yields from the literature, though additional field-based validation would strengthen confidence in its predictions.

Spatial analyses highlighted the importance of considering regional differences in landscape composition, emphasizing the need for more detailed, localized data on ecosystem contributions to pollination (flower richness for instance). While the model is well-suited to informing national-scale policy, targeted improvements in parameterization and validation will enhance its applicability across diverse landscapes and ecological contexts. Overall, the model provides a good foundation for supporting decisions on pollination and ecosystem services at a national level, with room for further refinement to improve its reliability and precision.

Model Assumptions, Simplifications, and Uncertainties
The model's utility and accuracy are influenced by several sources of uncertainty. First, the assumptions underlying the model may not always align with real-world conditions. For example, the assumption of uniform habitat suitability across certain ecosystem types overlooks potential site-specific variability, such as differences in floral richness or nesting resources. This can lead to overgeneralizations, particularly in heterogeneous landscapes, potentially introducing moderate to high impact uncertainties for localized applications.

Simplifications in the model such as linear relationships between visitation rates and pollination effectiveness reduce complexity but may fail to capture nuanced ecological interactions. These simplifications could result in low to moderate impact uncertainties, particularly if the model is applied to crops or regions where these relationships differ significantly from the assumed averages.

Uncertainty in data sources such as land-use and habitat suitability maps is another critical factor. Variability in map resolution, outdated data, or misclassification of land cover types can affect the accuracy of input layers, with moderate to high impact on model outputs, especially in regions where detailed spatial data is lacking.

Applying the model for purposes beyond its original scope such as evaluating novel ecosystem services or applying it to different ecological or policy contexts introduces additional uncertainties. These contextual shifts could lead to high impact uncertainties if the model's assumptions and parameterizations are not validated for the new applications.

Finally, parameter uncertainty, as quantified in the uncertainty analysis, reflects variability in key inputs like Eff_poll and P4. While this has been analysed, the impact of parameter uncertainty remains moderate to high, particularly for aggregated national indicators where these parameters are dominant.

3.5 Summary model quality and wishes for the future

Communication, Reliability, Completeness and Status-A progress
Ideally, reliability is communicated directly as part of the results. However, the current Status A framework does not yet fully provide for this. We propose introducing a standardized approach to communicate the reliability of results for each ecosystem service, using a 3-part scale (e.g., from "very high" to "low"). Additionally, the completeness of the indicators (using a 3-part scale) and the progress toward achieving Status A (scored across all criteria) should be explicitly reported. This section provides an overview of the quality status of all the criteria of the NC-Model, including the updates for pollination and pest control.

3.5.1 Reliability

Method
The reliability of the numerical data is presented according to the system used in the Environmental Data Compendium; this concerns our ability to model the ecosystem service. On the one hand, this pertains to how much we know about an ecosystem service, how well we understand the control variables that

determine the delivery of the service and, on the other hand, how good the data is to be able to make a reliable estimate of the ecosystem service. The reliability of the models is determined on the basis of expert judgement:

- Category A (high)
- Category B (moderate)
- Category C (low)

Result
B: moderate.

The model's theoretical and conceptual framework for pollination is well-developed and provides detailed descriptions of habitat suitability, pollinator visitation, and crop dependence. However, its precision is limited by significant assumptions and simplifications such as linear relationships and its reliance on proxies like habitat suitability for pollinator presence. While the input data, including land-use maps and crop classifications, are generally reliable, they are subject to variability in resolution, temporal consistency, and classification errors. Empirical validation remains limited, particularly for pollinator and crop-specific parameters like the effectiveness of pollination, Eff_poll, and regional variations. Although sensitivity and uncertainty analyses provide confidence in the model's robustness, the reliance on expert judgement for parameter ranges underscores gaps in empirical data that prevent the model from achieving the highest reliability category.

3.5.2 Completeness

Method
CICES (Common International Classification of Ecosystem Services) provides definitions of ecosystem services. The CICES version 4.3 classification at the level of groups used by De Knegt et al. (2014) is compatible with the Dutch context and provides a logical and intelligible classification of ecosystem services. In 2018, the CICES classification was updated to version 5.1 (https://cices.eu/resources), with minor changes to version 4.3, so the previous classification and nomenclature can still be used. The classification used in this report is based on the level of groups.

The choice of which aspects are included often depends on data availability. For example, water pollution consists of many different pollutants and it is impossible to indicate the extent to which ecosystem services can filter individual substances from the environment. It was therefore decided to select the most important pollutants for water; phosphates and nitrates. During the purification of water by ecosystems, many other pollutants will also be filtered from the water. So indirectly, those substances are included in the ecosystem service. However, it is not known exactly how these processes work. For this reason, for each ecosystem service it is indicated – on the basis of expert judgement – how completely the chosen model covers the definition compared to the CICES 4.3 definition. Missing components in the model are indicated per model in the fifth section under the heading “Wishes for the future”.

- Category A (complete)
- Category B (contains the most important aspects)
- Category C (contains some aspects)

Results
B: contains the most important aspects.

Following the CICES system, in addition to agricultural crop pollination, the pollination of non-agricultural species is important. Seed dispersal is also mentioned in the CICES classification (“Pollination and seed dispersal”) but is not included here. Furthermore, CICES includes services about maintenance of source populations and habitat to protect their genetic diversity. This part is covered by the ecosystem services of natural heritage.

3.5.3 Status A progress

Status A progress legenda: **complete**, partly complete, missing

ST.1: Model description
- **General description**
- **Description conceptual and formal model**

ST.2: Technical implementation
- **Implementation**
- **Technical environment**
- **Testing**

ST.3: Description parameters, variables, input and output
- **Parameters and variables**
- **Calibration**
- **Input and output**
- **Origin Input data**

ST.4Model functioning
- **Sensitivity analysis**
- **Uncertainty analysis**
- Validation
- Monitoring of use
- General assessment

See for DO.5: model development, DO. 6: organisation and IU.7: user documentation De Knegt et al. 2022.

3.5.4 Future model development options

- The sensitivity analysis underscores the importance of reconsidering the visitation rate for sufficient pollination (eff_poll factor), particularly its threshold value, crop-specific variability, and alignment with pollinator efficiency and environmental conditions. Refining this factor could improve the model's accuracy in representing pollination dynamics and ecosystem services.
- The sensitivity analysis underscores the importance of reconsidering the general value assigned to meadow suitability as being supportive for pollinators. Specifically, it suggests reassessing the actual on-site value such as floral richness and site conditions, rather than relying on a uniform number for all of the Netherlands. This localized approach could better capture the true role of meadows in sustaining pollinator populations.
- Research highlights the importance of various habitats for pollinators such as protected areas and natural elements within agricultural landscapes, emphasizing the need to understand and quantify their specific contributions to supporting pollinator populations.
- Future research, including meta-analyses conducted in the coming years, should focus on the actual dispersal and foraging distances of different insect species from source habitats to agricultural crops recognizing that different insects pollinate different crops with varying efficiency. This would help refine the parameterization of key model components such as pollinator movement kernels and visitation rates. Additionally, promoting field studies to measure these distances directly for specific crop-insect interactions would provide essential empirical data to enhance model accuracy and ecological understanding.
- Research on the actual harvest losses or quality reductions in crops due to absent or insufficient pollination is needed. This could include meta-analyses to synthesize existing data and identify trends, as well as field studies to quantify crop-specific impacts and refine models of pollination dependence.
- Following the CICES framework, it is important to recognize that pollination is not only crucial for agricultural crops but also for non-agricultural species. A literature analysis could help determine the availability of information on this topic and identify knowledge gaps.

3.6 Literature

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4 Pest control

In this chapter, we provide all the necessary information required for a Status A audit of the pest control model. It details the theoretical foundations of the model including its general description, conceptual framework, and technical implementation. It also describes input, output, parameters, and variables, and explains the model's functionality, covering key aspects such as sensitivity analysis, uncertainty analysis, validation, and a general assessment of model quality.

The focus is on the ecosystem service of natural pest control, essential for maintaining agricultural productivity and reducing the reliance on pesticides. This service is provided by natural enemies of pests such as ground beetles, predatory bugs, and parasitic wasps, which help suppress pest populations in crop fields. The pest control model applies the concepts of supply (ecosystems that provide habitats and resources for natural enemies) and demand (the need for pest suppression in crop fields) to estimate the visitation of natural enemies to crop fields. While the model produces detailed, high-resolution spatial maps of pest control services, it is designed to be applied and interpreted at a national scale, ensuring its relevance for policy development and large-scale assessments. Applications include its use in the Natural Capital Indicator (De Knegt et al., 2014, 2020) and in scenario studies (Breman et al., 2022; De Knegt et al., 2024; PBL, 2023).

The pest control model estimates the contribution of ecosystems to pest suppression by assessing the suitability of natural habitats such as flower-rich margins, forest edges, and hedgerows, to support natural enemies and their movement toward crop fields. The model assumes no pesticides are used (no negative effects of pesticides on natural enemy species) and focuses on the potential contribution of natural pest control to agricultural productivity. We conducted sensitivity, uncertainty, and validation analyses using field data to evaluate the model’s performance and refine its estimates.

By examining the pest control model in detail, we aimed to validate its functionality and establish methodologies to be applied to other ecosystem services within the NCM framework. These findings will help refine the model's robustness and ensure it meets the stringent requirements of Status A, while offering insights into sustainable agricultural pest management strategies.

4.1 Theoretical rationale of the model

4.1.1 General description of model

Natural pest control is a regulating service defined as the ecosystem’s contributions to the prevention or reduction of effects of pests on crop production by providing shelter and alternative food sources to natural enemies of pest species. Currently, the model includes the contribution of natural enemies in the landscape to the visitation of the crop fields by arthropods, however the link to crop production has not yet been included. The pest control model has been developed for the Netherlands, but its extent is based on the input land use map. Therefore, with some adjustment of the parameters, it could potentially be used for other regions outside the Netherlands, or even other entire countries. The current parameterization, based on expert judgement, is valid for the Netherlands.

Natural enemies of insect pests require sufficient resources in the agricultural landscape. Ecosystems differ in the degree to which they can provide shelter and alternative food sources to natural enemies; this depends on the requirements of the natural enemies. The model assumes that arthropod natural enemies (primarily insects and spiders) are present in suitable habitats suitable (as actual nationwide observation data of the specific natural enemies are unavailable) and that they contribute to pest control in the crop fields. The model assumes that all crops in arable farming, fruit and vegetable cultivation and in open ground horticulture can profit from natural pest control. The model predicts the potential pest control level if no pesticides are applied. The contribution of the ecosystem types depends on the distance to the cultivated crop.

4.1.2 Conceptual and formal model

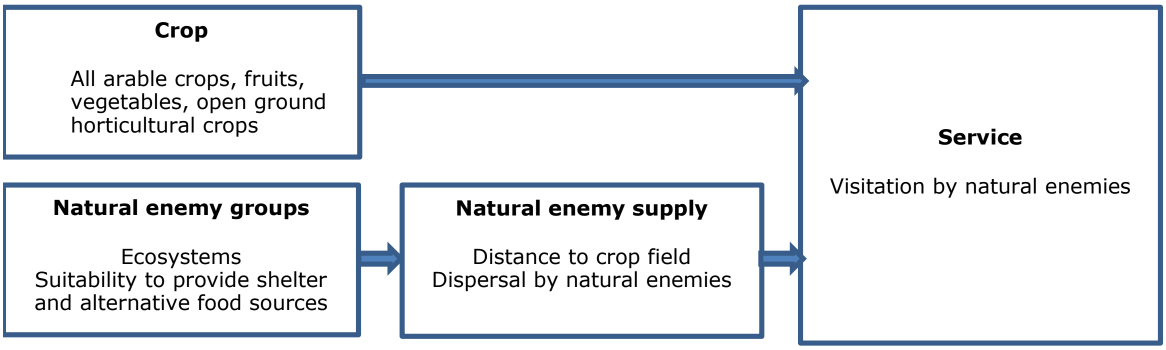

Figure 4.1 *The conceptual schedule of the natural pest control ecosystem services model. The model includes crops where production is potentially reduced due to damage by insect pests, and supply of natural enemies by ecosystems that vary in their suitability to provide shelter and alternative food sources for different groups of arthropod natural enemies.*

To develop a detailed understanding of natural pest control processes, we created a schematic overview of the model that illustrates how landscape configuration affects the supply and demand of pest control (Fig. 4.2). This model identifies the types of habitats that support pests' natural enemies and highlights the influence of landscape elements on pest control capacity.

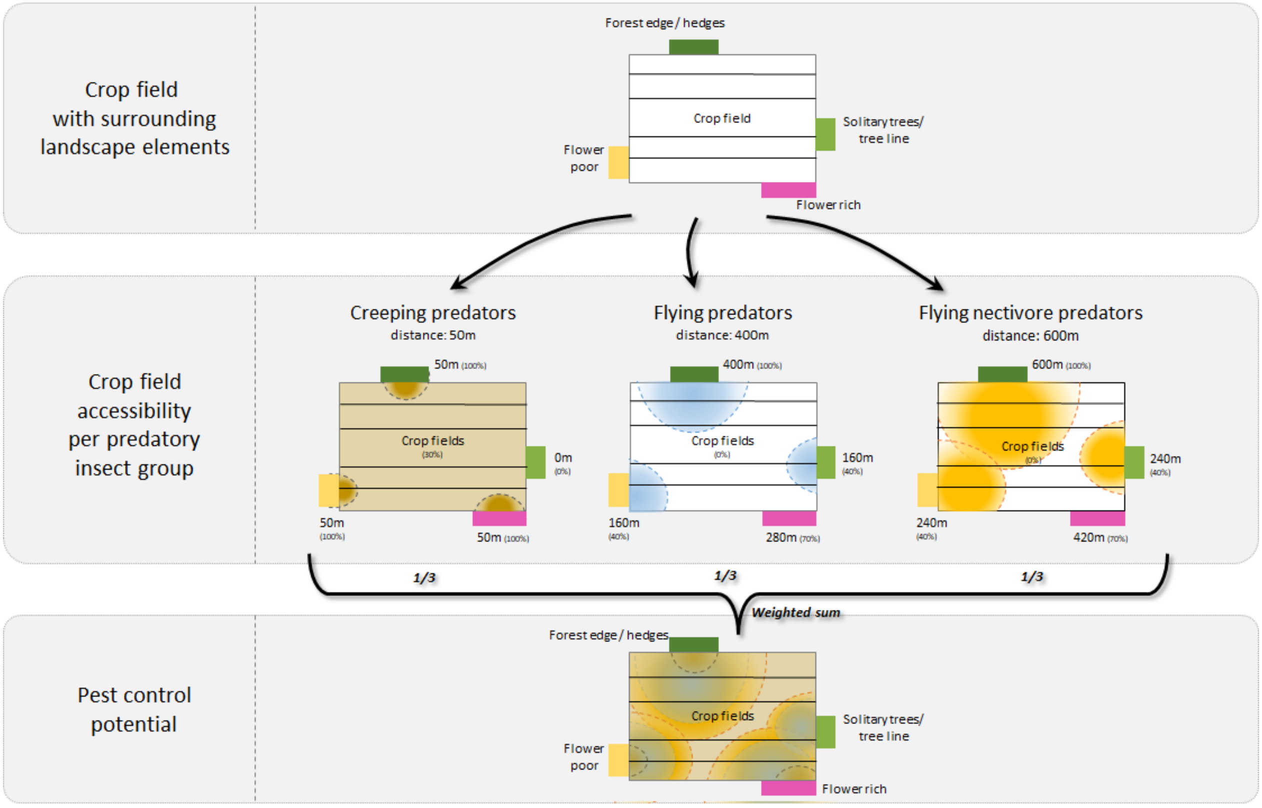

Figure 4.2 *Schematic overview of the natural pest control model, illustrating the demand and supply of natural pest control by three groups of predatory insects. The model integrates the suitability of source and flower habitats, the movement ranges of each predator group, and their combined impact on pest-susceptible crop fields.*

Potential pest control demand

It is assumed that all arable agriculture, fruit and vegetable cultivation, and open ground horticulture potentially require the same level of pest control. The basic registration of crop fields (BRP, "basis registratie gewaspercelen") (see: https://data.overheid.nl/dataset/10674-basisregistratie-gewaspercelen--brp-) can be used for the spatial location of crops. Currently, these crops are included in the harmonized land use map used for all ecosystem services (Annex 9). The BRP contains the location of each crop field and the type of crop cultivated.

Natural enemies

Three groups of natural enemies can be distinguished (Table 4.1) based on their dispersing ability and their dependence on landscape elements. The first group are ground-dwelling natural enemies (e.g. ground beetles and wolf spiders) with a limited dispersal ability. The second group are flying natural enemies (e.g. lady beetles and flowerbugs) with a larger dispersal ability than crawling natural enemies. The third group are flying natural enemies (e.g. predatory hoverflies and parasitoid wasps) that, as adults, require nectar and/or pollen as their main food source. These flying natural enemies generally have large dispersal abilities, but their level of pest control depends on floral resources close to the crop fields. Ideally, the distribution of the groups of natural enemies is based on spatial maps representing their population density. However, these maps are currently not available. Similar to the pollination model, it is assumed that the suitability of semi-natural habitats for the specific natural enemy groups and their proximity can be used as a proxy for natural enemy distribution. For pollinators, it Kennedy et al. (2013) show that the proxy for pollinator distribution based on the suitability of the surrounding land cover for nesting and floral resources and assuming that nearby resources contribute more than distant resources, is a good predictor for pollinator density in crop fields. For natural enemies, the composition of the landscape is also a predictor of their density and their effect on pest control (Goedhart et al., 2018); the amount of woody and herbaceous semi-natural habitats are especially important characteristics of the landscape (Chaplin-Kramer et al., 2011, Rusch et al., 2016, Dainese et al., 2019) as well as the amount of suitable floral resources (Ramsden et al. 2015; Woodcock et al., 2016; Van Rijn et al., 2019)

The natural pest control model divides the ecosystem categories in five habitat types (Table 4.2) based on their relationship of the three predator groups. These include two herbaceous types: flower-rich habitats like flower field margins, flower-poor habitats like roadsides or ditch banks in agricultural landscapes; two types of woody habitat: woody vegetation with a shrub layer including hedgerows, and solitary tree-lines without shrubs; and finally, habitats that do not contribute to pest control. Herbaceous habitat is considered flower-rich when expected to have a cover of at least 25% forbs (non-grasses) that potentially produce flowers suitable for natural enemies (Van Rijn & Wäckers, 2016). The first four habitat types that contribute to the pest control service provide input for the model. These maps are then linked with values for the suitability of these habitats for supporting each natural enemy group, ranging between 0 (unsuitable) and 100 (most suitable) (Table 4.3). These values are based on a literature review (e.g. Bartual et al., 2019) and expert judgement. Studies show that the length of the borders of semi-natural habitats are often more important than their area covered (Martin et al., 2019), therefore only the outer 30 meters of larger semi-natural habitats are considered source habitat. Additionally, a fifth input map was generated, including the cropland in the ecosystem type map. Annual cropland is considered a source habitat for ground-dwelling natural enemies only, as only ground and rove beetles can live year-round in and on arable land (Jowett et al., 2019).

Table 4.1 *Classification of natural enemies.*

Group	Mobility	Dependence on nectar	Examples
Crawling	Low	No	Carabid beetles, wolf spiders
Flying	Higher	No	Ladybirds, predatory bugs, rove beetles, hammock spiders
Flying nectivorous	Highest	Yes	Parasitic wasp, hover fly, lacewing

Table 4.2 *Classification of ecosystems.*

	Category	Examples
Herbaceous	flower rich	Perennial flower rich flower field margins, flower rich nature areas
	flower poor	Dunes, heathlands, flower rich meadows, ditch banks, roadsides, dykes
Woody	with shrubs	deciduous forest, coppice, thicket, wooded banks, hedges
	without shrubs	Avenue trees, coniferous forest
not functional elements		Water, arable land, grassland, streets, urban area

Supply of natural enemies

Different groups of natural enemies move at different distances so the groups are distinguished based on dispersal ability. Ground-dwelling predators have a low dispersal range, whereas flying natural enemies have a much greater dispersal range. The nectivorous flying natural enemies are expected to disperse from the sources habitats over even longer distances, but can only have an effect on pest control if they can survive and produce offspring, for which they need floral resources within a relatively short distance from the crop field (Van Rijn et al., 2013). Similar to pollinator dispersal, we assume that distribution from the suitable source habitats can be described with a negative exponential.

We use a negative exponential dispersal function to represent how visitation probability of natural enemies declines with distance:

$$P(d) = \exp(-\alpha d)$$

(Eq. 4.0)*

*For pollination, the same equation structure (Eq. 4.0) is used, with α=10.00053\alpha = \frac{1}{0.00053}α=0.000531, i.e., an effective distance of 0.00053 map units.

where P(d) is the relative probability of visitation at distance d, and α is a decay rate parameter (in m−1^{-1}−1) that depends on the mobility of the natural enemy group. This general equation underpins the calculation of relative visitation in the model (Eq. 4.1), and is parameterized separately per predator group (see Table 4.3).

We assume that natural enemies from all suitable habitats in the local landscape contribute to natural pest control. To obtain the relative visitation rate *v* (scaled 0-100) in a crop in map unit *c* and natural enemy group *p* we calculate,

$$v_{cp} = \sum_{h=1}^{H} S_{hp} \frac{e^{-\frac{1}{\alpha_p} d_{hc}}}{\sum e^{-\frac{1}{\alpha_p} d}} \qquad \text{(Eq.4.1)}$$

where V_{cp} is the relative visitation rate in a crop per natural enemy group, S_{hp} represents the relative predator abundance (scaled 0 – 100, where 100 marks maximum suitability) in map unit *h* (based on the suitability of the habitat in map unit *h* for natural enemy group *p*), d_{hc} is the distance between map unit *h* and the crop in map unit *c*. This is implemented by taking the convolution of the distribution of the natural enemy group p (based on habitat suitability) and the exponential decay function defined in Equation 4.0, using the predator-specific parameter α_p (see Table 4.3).

Flying natural enemies that depend on nectar require floral resources close to the crop fields. This is modelled with an additional spatial model that assumes that the effectivity of pest control is highest at the floral resources and decreases with distance from the floral resources following a 2D Gaussian distribution with an alpha of 100m (Table 4.3), with a range between 0 and 1, and multiplying this effectivity with the visitation rate (or density) of the flying nectivore natural enemy.

Two spatial models are applied to represent the ecological requirements of flying nectivorous natural enemies. The first uses a negative exponential kernel to capture their broader dispersal pattern from source habitats, ensuring general movement across the landscape is accounted for. The second employs a Gaussian distribution to emphasize the critical role of nearby floral resources, where pest control effectiveness peaks and decreases symmetrically with distance.

The model assumes that each natural enemy group contributes equally to pest control. The relative contribution of the three groups to pest control in the field is calculated based on the weights as presented in Table 4.3.

Table 4.3 *Influence of landscape elements on groups of natural enemies.*

Function landscape element:		**Source area**			**Nectar and pollen**
Group natural enemy		A. Crawling	B. Flying	C. Flying nectivorous	C. Flying nectivorous
Distance function (kernel)		Neg. exp.	Neg. exp.	Neg. exp.	Gaussian
Distance parameter, alpha (m)		50	400	600	200
Habitat value per grid cell (% of maximum)	Crop parcel itself (distance dependent)	5	0	0	0.02
	perennial, flower rich	10	70	70	1.0
	perennial, flower poor	10	40	40	0.6
	forest edge, hedges	10	100	100	0.7
	Solitary tree/line	2	50	50	0
Fraction of total		1/3	1/3		1/3

4.2 Technical implementation

4.2.1 Implementation model

The model calculates the relative visitation (%) of natural enemies of arthropods in the crop fields.

Figure 4.3 shows the flow diagram of the model. The filled orange boxes on the lefthand side are input raster files. The filled green boxes on the righthand side are output arrays/rasters from the model. The filled orange parallelograms in between are input variables; these are stored in one Excel file (https://git.wur.nl/lof001/plaagbestrijding/-/blob/master/tests/dat/pc_lut.xlsx). The orange/white boxes are intermediate arrays.

The input rasters/arrays on the lefthand side of Figure 4.3 are the crop fields, forest edge, flower rich edge, flower-poor edge, and tree-line edge. These last four can either be a direct input from the model when the optional parameter –area2border is set to *False*, or in the default setting where they are the result of a pre-processing calculation as depicted in Figure 4.4. The forest edge, flower rich edge, flower-poor edge and tree-line edge arrays are processed in Function 1 to serve as input for the allocation of the source habitats and nectar resources. The input is a 2.5x2.5 meter grid. For this grid the suitable values are summed into a 10 x 10 m grid. In this function the value can have a maximum of 16 (in case all 16 cells are forest edge/hedge). In the next step this is compared to a threshold ("thres_source") and all values equal or higher are considered source habitat and given value 1, where all others get value 0. The value of the array (0-16) stems from the number of 2.5 meter grid cells within the 10 meter grid cell.

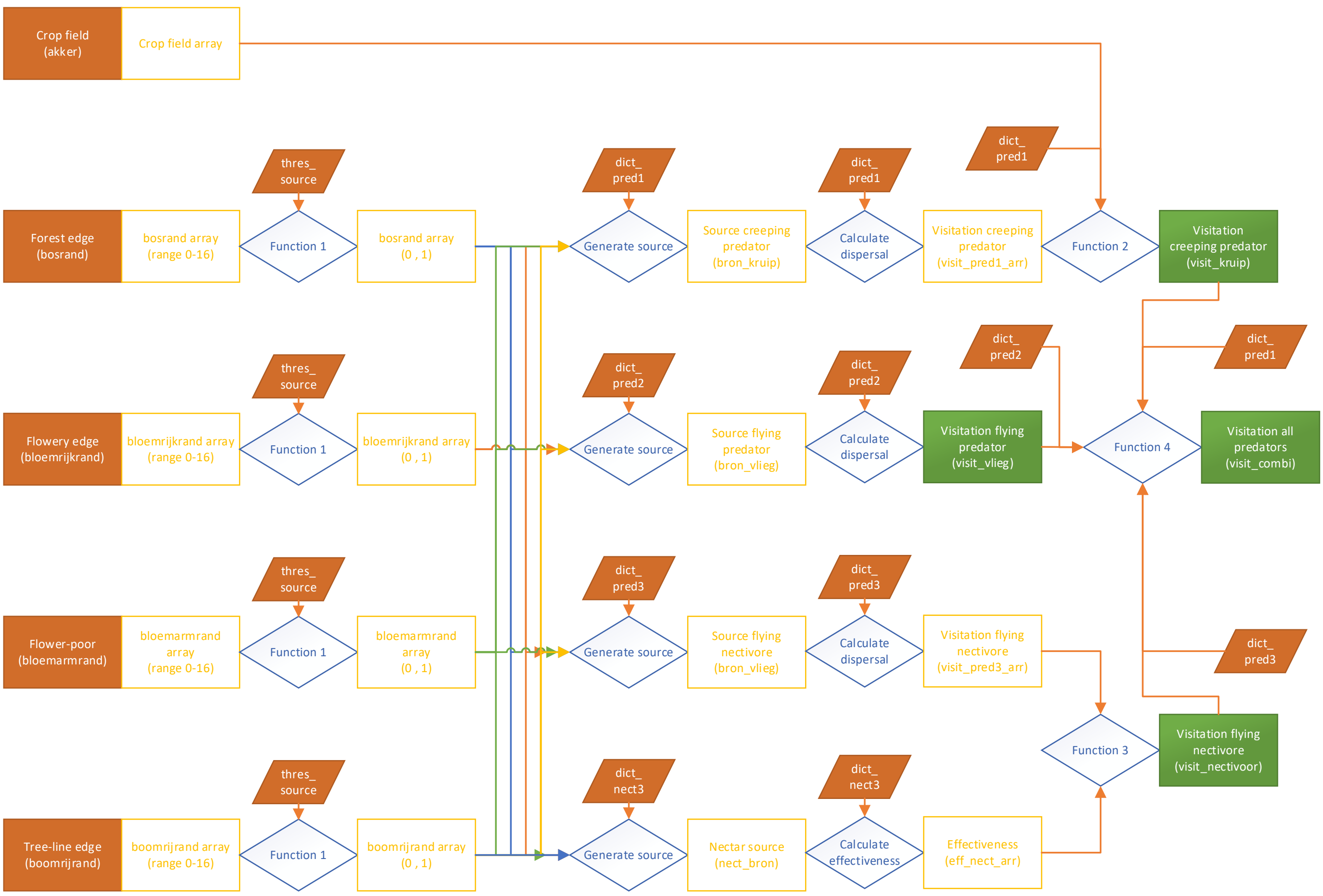

Figure 4.3 *Flow diagram of the natural pest control model.*

Overview of model functions

From each green box, the mean value in a crop field is calculated and written to an output file: model_result.ini, which also stores the paths of all input files.

- "Generate source" is a function that combines the "bosrand" (forest edge), "bloemrijkrand" (flower rich edge), "bloemarmrand" (flower poor edge) and "boomrijrand" (tree-line edge) arrays with the predator-specific habitat suitability as source habitat (stored in "dict_pred").
- "Calculate dispersal" is a function that performs a convolution of the predator source array and the dispersal kernel of the predator. This dispersal kernel is a 2D negative exponential kernel with a predator specific decay rate ɑ in meters (stored in "dict_pred").
- "Calculate effectiveness" is a function that performs a convolution of the nectar source array and Gaussian distribution kernel, based on parameters stored in "dict_nect3".

Details of key functions

- Habitat threshold
  In function 1, the value of the array (range 0-16) is compared to a threshold ("thres_source") and all values equal or higher are considered source habitat and given value 1; all others get value 0.
- Crawling predator visitation
  In function 2, in-field presence of crawling predators is added to the relative visitation by crawling predators from other sources. "visit_kruip" = min(100, "visit_pred1_arr" + "w_akker").
- Flying nectivores and effectiveness
  In function 3, the relative visitation of flying nectivores is multiplied with their effectiveness (based on availability of nectar sources). The suitabilities are constants and do not change, but effectiveness adjusts the contribution of nectar sources to predator visitation rates without altering habitat suitability. "visit_nectivoor" = min(100, "visit_pred3_arr" * "eff_nect_arr").
- Combined visitation
- In function 4, the combined relative visitation is calculated by adding the relative visitation of the three predator groups and correcting them for their relative weight in the final pest control. "visit_combi" = "frac_pred1"*"visit_kruip" + "frac_pred2"*"visit_vlieg" + "frac_pred3"*"visit_nectivoor", with "frac_pred1"+"frac_pred2"+"frac_pred3" = 1.

Predator source and nectar suitability

The four habitats are then combined in function "generate source" to a dictionary of the specific predator ("dict_pred") containing values for suitability as source habitat (range 0-100). This results in a spatial array with the predator source suitability. Source suitability is used as a proxy for predator supply by the ecosystem; a value of 100 indicates the highest predator density. As the flying nectivore also requires nectar, the function "generate source" is also used to combine the four habitats with a dictionary for the nectar resource ("dict_nect") containing values for suitability as nectar source (range 0-1). This results in a spatial array with the suitability as nectar source for flying nectivores. Nectar source suitability is used as a proxy to calculate effectiveness of the flying nectivores; a value of 1 indicates that all flying nectivores can effectively control pests.
It is assumed that the effectiveness of flying predators requiring nectar depends on the proximity to nectar sources. At the nectar source, pest control is optimal and it decreases with distance from the source following a Gaussian distribution. In the function "calculate effectiveness", the effectiveness of the flying nectivores is calculated by taking the convolution between the nectar source array and a Gaussian distribution kernel, with standard deviation "alpha_m" in meters. This results in the effectiveness array ("eff_nect_arr").

Predator dispersal and buffering

For the predators, in the function "calculate dispersal", the distribution of predator visitation is calculated by taking a convolution between the predator supply (e.g. predator source array) and a kernel describing the redistribution of the predators based on expert judgement. Similar to pollinator dispersal, the redistribution kernel is taken as a negative exponential with decay rate ɑ, stored in "dict_pred". To calculate the redistribution kernel, the function "calculate dispersal" requires the pixel size of the raster (in meters), which is stored in "dict_pred." For efficient computation, "calculate dispersal" divides the entire study area (e.g. the Netherlands or a province) into smaller sections when the area exceeds a pre-set number of cells. However, as predators can disperse beyond the boundaries of these smaller sections, the function incorporates a buffer zone (in meters) around each section. This buffer ensures that predator visitation from neighbouring areas outside the smaller section is accounted for in the calculations. Using this buffer, the function calculates an array representing predator visitation, ensuring accurate results near the edges of each section without underestimating visitation due to the artificial division of the study area.

Crawling and flying predator visitation

For the flying predator ("visit_vlieg") no further steps are needed.
It is assumed that crawling predators are always present in the crop fields. In function 2, the standard presence is added to the visitation array, taking into account that the maximum visitation is 100.
"visit_kruip" = min(100, "visit_pred1_arr" + "w_akker"). This results in the relative visitation rate of crawling predators ("visit_kruip"). The constant value for presence in the fields, "w_akker", is stored in "dict_pred1".
The presence of crawling predators in the crop fields may depend on management and pesticide use; this is currently not included in the model.

To calculate the effective pest control of the flying nectivores, in function 3 the relative visitation of the flying nectivores ("visit_pred3_arr") is multiplied with effectiveness to control the pests in the crop fields based on the nectar resources close to the fields ("eff_nect_arr"), taking into account that the maximum visitation is 100. "visit_nectivoor" = min(100, "visit_pred3_arr" * "eff_nect_arr"). This results in the relative visitation by flying nectivores ("visit_nectivoor").

Combined pest control visitation

Finally, in function 4, the combined relative visitation is calculated by adding the relative visitation of the three predator groups and correcting them for their relative weight in the final pest control; the relative weights "frac" are stored in the dictionaries of the predators and add up to 1. "visit_combi" = "frac_pred1"*"visit_kruip" + "frac_pred2"*"visit_vlieg" + "frac_pred3"*"visit_nectivoor", with "frac_pred1"+"frac_pred2"+"frac_pred3" = 1.

Output and pre-processing

For the output, the mean values of each of the output rasters ("visit_combi", "visit_kruip", "visit_vlieg", "visit_nectivoor") in the crop fields (i.e. cells where the value of the crop_field_array is equal or higher than the parameter "select_cropfields") is calculated.

By default it is assumed that the source rasters contain source areas. In the pre-processing module, the edges of these source areas are calculated (Figure 13.3). If these have already been calculated, they can be used directly as input; by setting the optional variable "area2border" to *False* the pre-processing module is skipped.

Pre-processing module overview

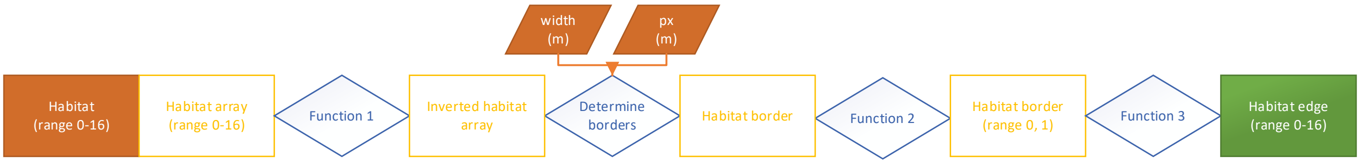

Figure 4.4 *Flow diagram pre-processing module of natural pest control model that selects the edges of source habitats.*

In figure 4.4, the filled orange box is an input raster file, the orange/white boxes are intermediate arrays and the filled orange parallelograms are input variables. These are stored in one Excel file (https://git.wur.nl/lof001/plaagbestrijding/-/blob/master/tests/dat/pc_lut.xlsx). The green filled box is the output array/raster of the module. Function 1 transforms the habitat array in an inverted habitat array. The original array has a range of 0-16 where the value represents the number of 2.5x2.5m cells in the 10x10m cell of that specific habitat type. In function 1, values higher than 2 are set to 0, and the other values (0,1,2) are set to 1, resulting in an inverted habitat where non-habitat cells have value 1 and habitat cells have value 0. Function "Determine borders", a moving window process where all cells within "width_m" from a non-habitat cell get value 1 and all others 0, is approximated with a convolution between the inverted habitat and a simple kernel; kernel = numpy.where(dist <= width_m, 1, 0), where dist is the distance from the centre of the kernel. In function 2, the resulting array "habitat border" is multiplied with the original habitat array (range 0-16); as a result non-habitat cells are set to 0 (because these are 0 in the original habitat array), edge cells have a value >=1, and habitat cells further than "width_m" away from the edge have a value 0 (because these are 0 in "habitat border"). The values of 1 and greater are then set to 1, resulting in the habitat border array with 0 for non-edge cells and 1 for edge cells. In function 3, the habitat border (0,1) array is multiplied with the original habitat array, and to include small-scale linear elements, the habitat cells with values (0,1,2) are included.

4.2.2 Technical environment

The model is programmed in Python (Python 3.7.9). An environment.yml file that can be used to reproduce the exact environment used in the simulations is available in git (https://git.wur.nl/lof001/plaagbestrijding/-/blob/master/environment.yml). The model requires a computer with an Intel Xeon W-2133 3.6 GHz processor and 16.0 GB RAM. Due to memory limitations, variables are stored as float32.

4.2.3 Testing

A test data set from a small area in the Netherlands can be used to quickly verify whether the model works as expected. This area, the municipality of Hoeksche Waard, is an area where the influence of field margins on pest control is being studied. More comprehensive testing, like testing for extreme input values or verification with field measurements, has not been done.

4.3 Input and output, parameters and variables

4.3.1 Parameters and variables

The parameters are stored in an Excel file which can be found at:
https://git.wur.nl/lof001/plaagbestrijding/-/blob/master/tests/dat/pc_lut.xlsx

Parameters
The Excel file contains two sheets; the first sheet "constant" contains the model constants:

- Pixel size of the input rasters ('px') in meters.
- Width of the borders taken into account as source or food habitat ('width_m') in meters. Natural enemies primarily overwinter in forest edges (up to 30m) therefore only the outer 30m of forest are taken into account in the calculations. The current version also only accounts for the outer 30m of the other habitat types.
- The parameters 'xmin', 'xmax', 'ymin' and 'ymax' can be used to set the extent of the area of interest; these are given in meters and based on an rDnew projection.
- A threshold for selection of crop fields ('select_cropfield') in the raster 'akkers'. This is used to select the area where crawling predators are present in the crop fields and for calculations of average values within the crop fields for the output. The default is set at 1, so if one of the 16 2.5 x 2.5 meter cells aggregated in the 10x10m cell contains a crop field, the 10x10m cell is assigned as crop field.
- A minimum threshold of number of 2.5x2.5m cells in the 10x10m cell that a habitat should contain to be included as source habitat. This threshold ensures that only habitats with sufficient spatial coverage are considered as source habitats, filtering out areas with sparse coverage that may not significantly contribute to pest control. The default value is set at 3.

The default values are currently set at:

key	value
px	10
width_m	30
xmin	10000
xmax	280000
ymin	300000
ymax	620000
select_cropfield	1
thres_source	3

The second sheet ”params_pred” contains the parameters related to suitability of the habitats for the three predator types and parameters related to their dispersal (see also Table 4.3). The parameters in the sheet are given per predator type (pred1=crawling predators, pred2= flying predators, and pred3=flying predators that depend on nectar). The last column (nect3) contains the parameters needed to calculate the range of the flying predators that need nectar with enough energy to control the pest.
The parameter 'alpha_m' is the decay rate of the negative exponential function used to calculate predator visitation given in meters. For the range where flying nectivores are effective, 'alpha_m' is the standard deviation of the gaussian function given in meters.

- The width of the buffer for calculation of predator visitation in meters ('buffer_m'). This is linked to the decay rate; for strong decay a smaller buffer can be used.
- The parameters that start with a 'w_' represent the relative weight of the habitats as source habitat (columns pred1, pred2 and pred3), range 0-100, and the relative suitability as nectar source (column nect3), range 0-1.
  - 'w_akker' gives the presence of crawling predators in the crop fields – input raster akkers.
  - 'w_bloemrijk1j' gives the suitability of annual flower rich habitats; these are currently not accounted for in the model
  - 'w_bloemrijk' gives the suitability of flowery habitats – input raster 'bloemrijk'
  - 'w_bloemarm' gives the suitability of flower-poor habitats – input raster 'bloemarm'
  - 'w_bosrand' gives the suitability of forest edges – calculated from input raster 'bos'
  - 'w_boomrij' gives the suitability of tree-lines and forest edges without shrubs as undergrowth – calculated from input raster 'boomrij'
- The parameter 'frac' is used as weight for the relative importance of the predator group (pred1, pred2 and pred3) in the delivered pest control. The values of these three groups should add up to 1. The value under nect 3 is a dummy value; this is not used.
- The parameter 'fact_nu' is currently not used. It is linked to a model where predators have a preference for certain habitats over other habitats.

The default values are set at:

key	pred1	pred2	pred3	nect3
alpha_m	50	400	600	200
buffer_m	1000	4000	6000	1000
w_akker (crop fields)	5	0	0	0.02
w_bloemrijk (flowery habitats)	10	70	70	1
w_bloemarm (flower-poor habitats)	10	40	40	0.6
w_bosrand (forest edges)	10	100	100	0.7
w_boomrij (tree lines)	2	50	50	0
frac	1/3	1/3	1/3	1

In the script, the column with the names (key) are linked to the values (pred1, pred2, pred3 or nect3) and stored in dictionaries (“dict_pred1”, “dict_pred2”,”dict_pred3” and “dict_nect3”).
The Excel file with the parameters is an input variable of the simulation. It is therefore possible to use a copy of this file with alternative parameter values as an input file.

Input variables
The model consists of eight mandatory and eight optional variables.

Mandatory variables:
1. land_use: Geospatial raster showing land use following LCEU categories
2. bos*: Geospatial raster met bos(randen) (forest edges)
3. boomrij*: Geospatial raster met bomenrijen (tree-lines)
4. bloemrijk*: Geospatial raster met bloemrijk(e randen) (flowery habitats)
5. bloemarm*: Geospatial raster met bloemarm(e randen) (flower-poor habitats)
6. akkers*: Geospatial raster met akkers (crop fields)
7. params: Excel sheet with lookup tables and model parameters and constants
8. scenario: Name of the scenario calculated; used in the names of the output files

The Geospatial rasters marked with '*' are aggregated rasters where the value represents the number of cells at 2.5mx2.5m in the 10m cell that contains the specific habitat, ranging from 0-16 cells. The 10x10m cell is included as a source or food habitat when the number of 2.5mx2.5m cells is equal or higher than the threshold number set by the parameter "thres_source". In this way, small linear features are also accounted for.

Optional variables:
1. --out_dir: output directory
2. --area2borders: reduce source area to only the borders/edges; default=true
3. --set_extent: use values from params to set extent, otherwise use extent of land_use map
4. --write_rasters: write geospatial output rasters to output directory
5. --reporting: write a text file with key outcomes
6. --test_input: verify model initialization; do nothing else
7. --test: verify model with test set; do nothing else
8. --env_proj_path: Path of proj folder in python environment

4.3.2 Calibration

The model has been calibrated using parameters and parameter values from the literature. Furthermore, the spatial results of the models have been critically assessed. The maps at national scales were discussed with the group of authors and adjustments of the kernels were made to get a more accurate prediction. Results from other experts and the literature show that our model is more or less in line with the European literature.

4.3.3 Output

Output
Output values:
1. perc_visit_combi: mean visitation by all predators in crop fields
2. perc_visit_kruip: mean visitation by crawling predators in crop fields
3. perc_visit_nectivoor: mean visitation by flying predators that need nectar in crop fields
4. perc_visit_vlieg: mean visitation by flying predators in crop fields

These output values are written in model_result.ini in the output directory.

The unit of perc_visit_combi and alike indicators is a percentage (%) representing the mean relative visitation of natural enemies in crop fields, scaled 0-100.

Optional output:
1. pred_all.tif: Geospatial raster showing predator visitation in crop fields (optional, --write_rasters)
2. pred_kruip.tif: Geospatial raster showing predator visitation in crop fields (optional, --write_rasters)
3. pred_nectivoor.tif: Geospatial raster showing predator visitation in crop fields (optional, --write_rasters)

4. pred_vlieg.tif: Geospatial raster showing predator visitation in crop fields (optional, --write_rasters)
5. bosrand16.tif: Geospatial raster containing forest edges, range 0-16, based on 'bos' raster (optional, --area2borders)
6. bloemrijkrand16.tif: Geospatial raster containing edges of flower rich areas, range 0-16, based on 'bloemrijk' raster (optional, --area2borders)
7. bloemarmrand16.tif: Geospatial raster containing edges of flower poor areas, range 0-16, based on 'bloemarm' raster (optional, --area2borders)
8. boomrijrand16.tif: Geospatial raster containing tree-line edges, range 0-16, based on 'boomrij' raster (optional, --area2borders)

Figure 4.5, shows the results for pest control in the Netherlands. Although the results are presented as national averages rather than spatially explicit data, they represent the model's output.

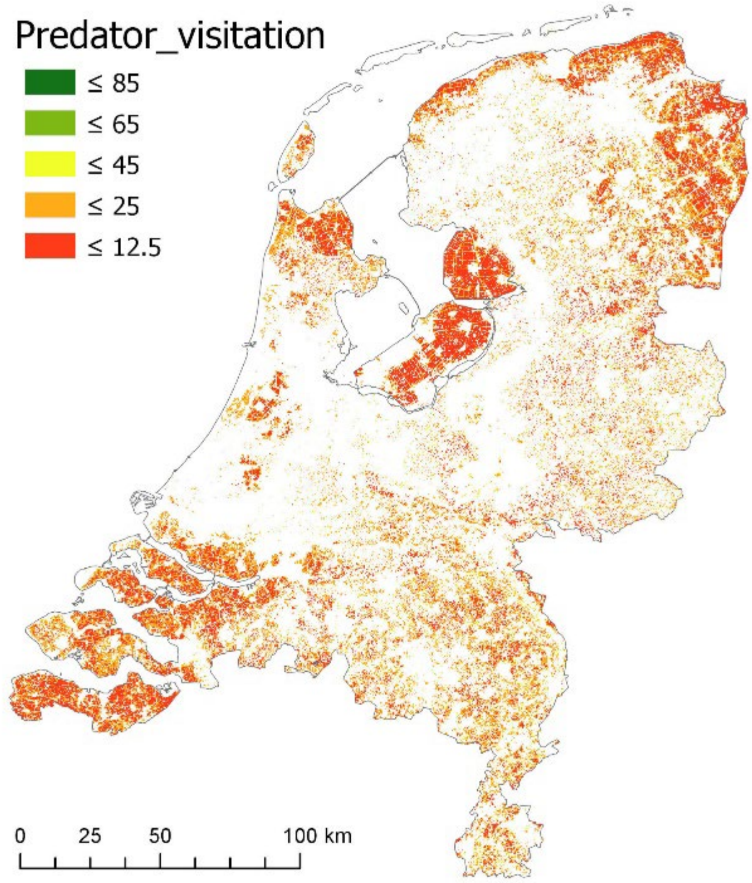

Figure 4.5 *Predator visitation in crops susceptible to pests.*

4.3.4 Standard indicators

The model provides three indicators:

- Supply: Supplies natural enemies of pests in agricultural crops.
- Demand: Demand for pest suppression of pest-susceptible agricultural crops to prevent loss of yield.
- Combination of supply and demand: Relative visitation of natural enemies in agricultural crops susceptible to pests (0-100).

The unit is a percentage (%) representing the mean relative visitation of natural enemies in crop fields, scale 0 - 100.

4.4 Evaluation of model functioning

4.4.1 Sensitivity analysis

4.4.1.1 Method

We follow the approach described by Jansen (1999), Jansen (2005), and Becker (2018).

Distribution and sampling of input parameters

The first step in uncertainty and sensitivity analysis is to sample values from hypothesized distributions of model inputs. Distributions of model inputs were empirically estimated by an expert on pest control, Dr. P.C.J.(Paul) van Rijn. The distributions were assumed to be either normally distributed if symmetric, or gamma distributed when right-tailed. The distributions of input parameters are shown in Table 4.4.

Simple Random sampling or Latin hypercube sampling (LHS) are both good options to sample values from distributions of inputs. In essence, an LHS involves dividing the cumulative density function (cdf) of a parameter into p equal partitions, and then randomly sampling n values from each partition. We used LHS to ensure having samples that cover the whole range of each input parameter. This method is widely used in uncertainty and sensitivity analysis of several models, e.g. MNP and can also be used for uncertainty analysis of other ecosystem services. LHS Sampling was performed in R with function randomLHS. For LHS the distribution of each input parameter was partitioned into p=10 partitions with equal probability and each partition was sampled n=100 times. This resulted in 1000 samples of each input parameter. The sampled input values were then fed into the simulation model. The simulation model was then run and a total of 1000 sets of outputs were obtained for four regions: the Netherlands (NL), and the provinces of Zuid-Holland (ZH), Noord-Brabant (NB), and Flevoland (FL).
The histograms of outputs were inspected to check whether any distributions were different from expected. The correlations between outputs were also examined to examine their relatedness; correlation of the measures between different types of predators was unexpected.

Table 4.4 *Ranges of input parameters; estimates from Paul van Rijn. The sampling distributions used were normal or gamma. Suffixes 1-4 refer to types of natural enemies (1=ground-dwelling , 2=flying , and 3=nectivorous, and to their nesting locations; 4 refers to the food location for nectivores).*

input NKM	*description*	*distribution (q2.5%-q50%- q97.5%)*	*LHS sampling*
alpha_m1	distance parameter (m)	30_50_80	10*gamma(shape=16,rate=3)
alpha_m2		250_400_700	100*gamma(shape=13,rate=3)
alpha_m3		400_600_900	100*gamma(shape=25,rate=4)
alpha_m4		100_200_300	normal(mean=200,sd=50)
wakker1	Suitability of Habitat : Annual cropland	3_5_8	gamma(shape=16,rate=3)
wakker2		0	const
wakker3		0	const
wakker4		0.01_0.02_0.03	0.01*normal(mean=2,sd=0.5)
wbloemrijk1	Suitability of Habitat : Flower-rich herbaceous habitats	7_10_15	gamma(shape=21,rate=2)
wbloemrijk2		50_70_90	normal(mean=70,sd=10)
wbloemrijk3		50_70_90	normal(mean=70,sd=10)
wbloemrijk4		1	const
wbloemarm1	Suitability of Habitat : Flower-poor herbaceous habitats	7_10_15	gamma(shape=21,rate=2)
wbloemarm2		20_40_60	normal(mean=40,sd=10)
wbloemarm3		20_40_60	normal(mean=40,sd=10)
wbloemarm4		0.4_0.6_0.8	0.01*normal(mean=60,sd=10)
wbosrand1	Suitability of Habitat : Woody habitat with shrub layer	7_10_15	gamma(shape=21,rate=2)
wbosrand2		100	const
wbosrand3		100	const
wbosrand4		0.5_0.7_0.9	0.01*normal(mean=70,sd=10)
wboomrij1	Trees without shrubs	1_2_3	normal(mean=2,sd=0.5)
wboomrij2		30_50_70	normal(mean=50,sd=10)
wboomrij3		30_50_70	normal(mean=50,sd=10)
wboomrij4		0	const
width_m	Width of border	P(10)=15%,P(20)=35%,P(30)=50%	multinomial
frac1	contribution to pest control	0.25-0.33-0.50	0.1*gamma shape=21, rate=6
frac2		0.25-0.33-0.50	0.1*gamma shape=21, rate=7
frac3		0.25-0.33-0.50	frac3=1-frac1-frac2

Sensitivity analysis

Sensitivity analysis aims at assessing and quantifying the relative importance of each input parameter on each model output. It helps modellers identify important parameters and helps to optimize research to improve the most sensitive parameters. We applied the Regression-Based global Sensitivity Analysis method (Jansen, 1999; Jansen, 2005; Becker 2018; Ridolfi and Mooij, 2016), an approach for quantitative, variance-based, sensitivity analysis of mathematical models used for design purposes. Our approach was based on linear models on output y with inputs x=(x1…xk) to approximate y=f(x), where f is the output of the model, by linear functions of x. In other words, we applied linear models to each output y as approximations to the complex model f(x).

We used the following quantities in this report, for each output y:

<u>The total variance of y</u>, Vtot, which depends on the distribution of inputs and on the model:

$V_{tot} = V(y)=V[f(x)],$

where f is the model, and $x=(x_1…x_k)$ are the inputs with distribution D, x~D.

<u>The top marginal variance</u>, also known as first-order index, of each input x_i; TMV_i measures the relative contribution to V_{tot} of varying the x_i alone, and it is defined as:

$TMV_i = V[E(y|x_i)].$ (Eq.4.3)

This measure corresponds to the effect of knowing x_i, averaged over all possible combinations of all other inputs. TMV_i can be expressed as a fraction of V_{tot}, calculated as R^2, the percentage of variance of output y accounted for by xi, from a simple least squares model:

$y=a+b_i x_i.$

The TMV measure does not account for interactions of x_i with other inputs.

The bottom marginal variance, also known as total effect index, of each input x_i, BMV_i, is defined as:

$$BMV_i = \{V_{tot} - V[E(y|x_{-i})]\}, \quad (Eq.4.4)$$

where $V[E(y|x_{-i})]$ is the variance of y when x_i is known, conditional on all inputs except x_i, $x_{-i} = (x_1 \ldots x_{i-1}, x_{i+1} \ldots x_k)$. BMV_i can be calculated as the decrease of variance accounted for when x_i is removed from a linear model that contains all inputs. Therefore BMV_i can account for interactions of x_i with other inputs. As with TMV, BMV can be expressed as a fraction of V_{tot}.

Linear models used

TMV (Eq.4.3). and BMV (Eq.4.4) were estimated for each output y, in different steps, with a series of linear models:

Model A: Model with all inputs x:

$$y = a + \Sigma_j b_j x_j$$

Model B: Model with x_i:

$$y = a + b_i x_i$$

Model C: Model with all inputs except x_i:

$$y = a + \Sigma_{-i} b_j x_j$$

Procedure

1. In a first step, the total percentage variance accounted by model A for each output y was considered. If the total percentage of variance accounted for by model A (R^2) was less than 90% of V_{tot}, then more complex models were fitted until 90% of V_{tot} could be explained by each model.
2. In step 2, model B was fitted to output y and each input x_i, and the amount of explained variance given by R^2 was taken as a measure of TMV_i for y.
3. In step 3, model A in step 1 was fitted to y, but excluding input x_i. BMV_i was calculated as the difference in R^2 between model A and model C
   $BMV_i = R^2(A) - R^2(C)$.

Bootstrap analysis

To measure the accuracy of TMV_i and BMV_i, bootstrap samples were drawn from the complete sample of inputs and outputs. TMV_i and BMV_i were recalculated for each bootstrap sample. Confidence intervals for these measures were estimated using the 2.5% and 97.5% percentiles of the bootstrap results.

4.4.1.2 Results

Summary statistics of model inputs

The summary statistics of quantitative model inputs are presented in Annex 8. These represent our most informed estimates of the likely behaviour of the input parameters based on the available knowledge and expertise. Since inputs can have different scales, we report and compare their coefficients of variation (CV), defined as CV=100*sd/mean. Coefficients of variation of inputs ranged between 15% and 27%. This means the order of the magnitude of the variation in the parameter values corresponds with the order of magnitude of the inputs, as expected.

Model outputs

We then inspected model outputs, their distributions and correlations. One of the outputs, 'SSI_vraag' is a constant (equal to 8.8E9) and therefore was excluded from the analysis. We were left with four types of outcomes: perc_visit_kruip, perc_visit_vlieg, perc_visit_nectivoor and perc_visit_combi, estimations for the Netherlands (NL) and a region in Zuid-Holland (ZH) Hoekse Waard, which comprises the municipalities (Korendijk, Oud-Beijerland, Binnenmaas, Strijen and Cromstrijen) and two municipalities within the Netherlands Mijerijstad in Noord-Brabant (NB) and Zeewolde in Flevoland (FL). This region and these municipalities were selected based on their spatial configuration of agricultural fields and semi-natural habitats, where Zeewolde (FL) has many large fields and relatively few semi-natural habitats, Hoekse-Waard (ZH) has smaller fields and more semi-natural habitats, and Mijerijstad (NB) has a heterogenous landscape with fields interspersed with semi-natural habitats. The empirical distributions of all outputs are shown in Annex 9. Histograms corresponding to perc_visit_combi are symmetrical. The histograms of perc_visit_kruip and perc_visit_nectivoor are lightly right skewed while the perc_visit_vlieg histograms are lightly left skewed.

Figure 4.6 shows correlations between model outputs. The strongest correlations occur between the same type of outcome in different regions. For example, perc_visit_kruip correlates well between regions. Outcomes perc_visit_combi correlate well with perc_visit_nectivoor, and less well with all other outcomes. Outcomes perc_visit_kruip correlate least with the other outcomes, as expected since the conditions for presence of ground-dwelling predators is different (mostly present in the field; move over short distances) from flying and nectivorous predators (mostly from outside the fields; disperse over longer distances).

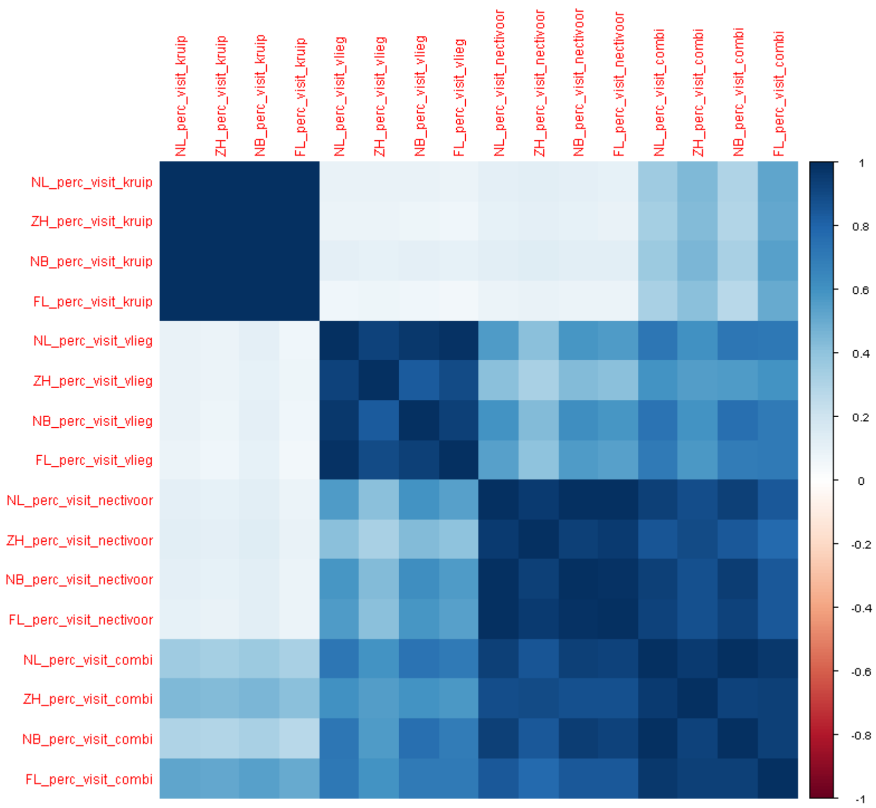

Figure 4.6 *Correlations between model outputs.*

Sensitivity analysis

For all outcomes, the additive model that included all inputs had an R^2 of more than 90%. All sensitivity measures described in the methods section were calculated for all outputs y and all inputs x. For most outputs, one or two inputs explained more than 90% of the variation of y, while all other inputs only had a small contribution to the variation of y. Table 4.5 displays sensitivity indices Top marginal variance, or first-order index (TMV) and bottom marginal variance, or total effect index (BMV), for the most relevant inputs for each output; Annex 10 shows the same sensitivity indices graphically. The TMV and BMV indices were similar in all cases, therefore we do not distinguish between them in the following comments (Table 4.5 and Figures in Annex 10).

For the mean occurrence of crawling predators in the field, *Perc_visit_kruip,* a simple regression model with input *wakker1* alone explained more than 97% of the total variation. This was observed for all regions. The parameter *wakker1* represents the initial occurrence of crawling predators in the crop field. This indicates that the mean occurrence of crawling predators in the field is mostly influenced by their initial presence in the field. Due to their limited dispersal capacity, crawling predators from the source habitats are often only present at the borders of the fields and therefore have a limited influence on the mean occurrence in the fields, but do affect the spatial distribution in the occurrence in the fields.

For the mean occurrence of flying predators in the field, *Perc_visit_vlieg*, the parameter *width_m,* the width of the edges of the semi-natural habitats included as source habitat, explained more than 70% of the variation in all regions except ZH, where it explained only 40%. Another input, *wbloemarm2,* the relative density of flying predators in semi-natural habitats with few flowers, explained between 10%-20% of the variation of *Perc_visit_vlieg*, in NL and in FL. In NB, *wbloemarm2* explained less than 10%, and *wboomrij2,* the relative density of flying predators in *tree-lines and hedgerows,* explained slightly more than 10% of the variation of *Perc_visit_vlieg*. Interestingly, in ZH, *wbloemarm2* helped explain around 40% of the variation in the *Perc_visit_vlieg,* whereas *width_m* only explained also around 40%, thus less than in other regions. The differences in the explained variation between the regions shows that the spatial configuration of the fields and the types of semi-natural habitats can affect the model outcomes for the flying predators.
Both alpha_m4, the parameter that influences the distance of the effect of nectar sources on the occurrence of flying predators that require nectar, and width_m explained roughly in equal amounts (42%-46%) the variation in the mean occurrence of flying predators that require nectar, perc_visit_nectivoor, except in ZH where alpha_m4 explained more (58%) than width_m (21%).

Input *width_m,* the width of the edges of the semi-natural habitats included as source habitat, explained more than 50% of the variation of *Perc_visit_combi,* the combined occurrence of the three predator groups in the crop fields, in all regions except ZH where it only helped explain 30% of the variation. The second most important input was *alpha_m4*, the parameter that influences the distance of the effect of nectar sources on the occurrence of flying predators that require nectar, explaining between 15%-25% of the variation in *Perc_visit_combi*, except in ZH where it explained more than 30% of the variation. In ZH and FL, wakker1, the parameter of the initial occurrence of crawling predators in the field, also helped explain roughly between 10%-20% of the variation in *Perc_visit_combi*.

Table 4.5 *Sensitivity analysis indices per outcome y in the first columns, and inputs x, in the second column. Vtot is the variance of the outcome, Vtot=V(y); R2_all is the percentage of variance of y explained by Model A; TMV is the percentage of variance of y explained by Model B; BMV is the difference R2_all – R2(Model C).*

outcome	***input***	***Vtot***	***R2_All***	***TMV***	***BMV***
NL_perc_visit_kruip	wakker1	1.8	99.9	98	96
ZH_perc_visit_kruip	wakker1	1.8	99.9	98	96
NB_perc_visit_kruip	wakker1	1.8	99.9	97	96
FL_perc_visit_kruip	wakker1	1.76	100.0	99	98
NL_perc_visit_vlieg	wbloemarm2	2.28	98.0	15	18
NL_perc_visit_vlieg	width_m	2.28	98.0	75	78
ZH_perc_visit_vlieg	wbloemarm2	1.26	93.8	40	44
ZH_perc_visit_vlieg	width_m	1.26	93.8	39	43
NB_perc_visit_vlieg	wboomrij2	3.22	98.3	12	10
NB_perc_visit_vlieg	width_m	3.22	98.3	82	82
FL_perc_visit_vlieg	wbloemarm2	1.01	98.0	14	18
FL_perc_visit_vlieg	width_m	1.01	98.0	71	75
NL_perc_visit_nectivoor	alpha_m4	16.22	95.0	46	42
NL_perc_visit_nectivoor	width_m	16.22	95.0	42	40
ZH_perc_visit_nectivoor	alpha_m4	9.63	93.8	58	54
ZH_perc_visit_nectivoor	width_m	9.63	93.8	21	21
NB_perc_visit_nectivoor	alpha_m4	25.57	95.0	44	40
NB_perc_visit_nectivoor	width_m	25.57	95.0	45	44
FL_perc_visit_nectivoor	alpha_m4	3.56	94.6	46	43
FL_perc_visit_nectivoor	width_m	3.56	94.6	41	40
NL_perc_visit_combi	alpha_m4	3.29	95.8	27	23
NL_perc_visit_combi	width_m	3.29	95.8	55	55
ZH_perc_visit_combi	alpha_m4	1.83	92.7	37	31
ZH_perc_visit_combi	wakker1	1.83	92.7	15	11
ZH_perc_visit_combi	width_m	1.83	92.7	31	31
NB_perc_visit_combi	alpha_m4	5.05	95.9	26	23
NB_perc_visit_combi	width_m	5.05	95.9	59	58
FL_perc_visit_combi	alpha_m4	1.01	96.5	21	17
FL_perc_visit_combi	wakker1	1.01	96.5	22	18
FL_perc_visit_combi	width_m	1.01	96.5	50	50

TMV and BMV indices were also evaluated for 100 bootstrap samples which yielded a TMV and BMV for each input-output combination. From the set of 100 bootstraps, TMV and BMV empirical confidence intervals were obtained for the most relevant inputs per output. See Table 4.6 and Annex 11 for the most relevant inputs for each output. The bootstrap TMV and BMV values agree with the pattern in Table 4.5. The variation observed due to bootstrapping ranged around 10% in most cases, with values close to those in Table 4.5.

Table 4.6 *Bootstrap-based indices of sensitivity analysis per outcome y in the first columns, and inputs x, in the second column. TMV is the top marginal variance, BMV is the bottom marginal variance, lower refers to the 2.5% quantile and upper to the 97.5% quantile of the bootstrap samples.*

outcome	*input*	*TMV_lower*	*TMV_med*	*TMV_upper*	*BMV_lower*	*BMV_med*	*BMV_upper*
NL_perc_visit_kruip	wakker1	97	98	98	91	94	96
ZH_perc_visit_kruip	wakker1	97	98	98	91	94	96
NB_perc_visit_kruip	wakker1	97	97	97	91	94	96
FL_perc_visit_kruip	wakker1	99	99	99	94	96	98
NL_perc_visit_vlieg	width_m	72	75	77	71	76	80
ZH_perc_visit_vlieg	wbloemarm2	35	41	45	39	43	47
ZH_perc_visit_vlieg	width_m	34	39	43	37	42	47
NB_perc_visit_vlieg	width_m	80	82	84	76	80	84
FL_perc_visit_vlieg	width_m	67	71	73	68	73	77
NL_perc_visit_nectivoor	alpha_m4	41	46	50	37	41	45
NL_perc_visit_nectivoor	width_m	36	42	46	34	39	44
ZH_perc_visit_nectivoor	alpha_m4	53	58	63	48	52	57
ZH_perc_visit_nectivoor	width_m	17	22	25	17	20	24
NB_perc_visit_nectivoor	alpha_m4	38	44	49	36	39	43
NB_perc_visit_nectivoor	width_m	39	45	49	37	42	47
FL_perc_visit_nectivoor	alpha_m4	41	46	51	38	42	47
FL_perc_visit_nectivoor	width_m	36	41	45	34	39	43
NL_perc_visit_combi	width_m	51	55	59	47	53	58
ZH_perc_visit_combi	alpha_m4	32	37	43	27	31	34
ZH_perc_visit_combi	wakker1	12	15	19	9	11	12
ZH_perc_visit_combi	width_m	25	31	35	25	30	33
NB_perc_visit_combi	alpha_m4	22	27	32	19	22	25
NB_perc_visit_combi	width_m	54	59	63	50	56	61
NL_perc_visit_combi	alpha_m4	23	28	33	20	23	26
FL_perc_visit_combi	alpha_m4	17	22	26	15	17	19
FL_perc_visit_combi	wakker1	19	22	27	16	18	20
FL_perc_visit_combi	width_m	45	50	54	43	48	52

4.4.1.3 Overall conclusions of the Sensitivity Analysis

This sensitivity analysis provides insights into how model parameters influence the results, guiding future improvements and informing strategies to enhance natural pest control services. The combined visitation of all predator groups (Perc_visit_combi) is the model's most comprehensive outcome (and a standard indicator for the national level), and the analysis highlights key factors affecting it:

1. Combined Predator Visitation (Perc_visit_combi)
   - The width of edges of semi-natural habitats (width_m) is the most critical parameter, explaining more than 50% of the variance in most regions, however in Zuid-Holland (ZH) its influence is only 30%.
   - Alpha_m4, which determines the effective distance of nectar sources for nectivorous predators, is the second most important factor, accounting for 15%-30% of the variance in most regions and over 30% in ZH.
   - Wakker1, the initial presence of crawling predators in crop fields also contributes 10%-20% to the variation in some regions, particularly in ZH and Flevoland.

2. In this combined analysis, the individual predator groups show distinct sensitivities:
   Crawling Predators (Perc_visit_kruip)
   - Their mean occurrence is primarily determined by wakker1, explaining over 97% of the variation across all regions.
   - Due to their limited dispersal capacity, crawling predators rely more on their initial presence in fields than on semi-natural habitat proximity.

   Flying Predators (Perc_visit_vlieg)
   - Width_m significantly influences flying predator visitation, explaining over 70% of the variance in most regions, however in ZH it only contributes around 40%.

- The suitability of flower-poor habitats (wbloemarm2) explains 10%-20% of the variation in most regions and up to 40% in ZH.

Nectivorous Flying Predators (Perc_visit_nectivoor)

- Alpha_m4 and width_m are equally critical, each explaining 42%-46% of the variance in most regions.
- In ZH, alpha_m4 becomes more dominant, explaining 58% of the variation compared to 21% for width_m.

3. Regional Variations
   - The analysis highlights how differences in regional landscape configurations such as the proportion, arrangement, and connectivity of semi-natural habitats shape the sensitivity of model outcomes to specific parameters. In Flevoland (FL) and Zuid-Holland (ZH), characterized by simpler landscapes with larger fields and fewer semi-natural habitats, parameters like width_m and alpha_m4 have a more pronounced impact as they determine the extent and effectiveness of source habitats. Conversely, Noord-Brabant (NB), with its complex and heterogeneous landscape of smaller fields interspersed with diverse semi-natural habitats, exhibits a more balanced sensitivity across multiple parameters. This reflects the broader and more evenly distributed contributions of its varied and well-connected habitats to pest control services.

4. Robustness of Results
   - The models used in the analysis explained over 90% of the variation in all results, showing that the sensitivity analysis is reliable.
   - Additional checks using bootstrap analysis confirmed that the sensitivity results are stable, with confidence intervals matching the observed patterns.

4.4.2 Uncertainty analysis

Uncertainty analysis examines how uncertainties in a model's inputs affect its outputs. Its primary goal is to quantify the range and distribution of the model's outputs, considering the variability or estimated probability distributions of the inputs.

4.4.2.1 Method

During one simulation run, a single combination of input parameters is evaluated and a single set of outputs is produced by the model. Section 4.3.1 gives the default input parameters used by the model. For the sensitivity analysis these parameters were allowed to vary according to their hypothesized distributions. The inputs vary in different combinations from run to run, yielding a distribution for each output.

In uncertainty analysis we observe the effect that uncertainty of input parameters $x=(x_1 \ldots x_k)$ has on the distribution of a model output y. This distribution can be characterized by measures of location and by measures of variation.
We summarized the distribution of each output y in terms of its minimum, maximum, mean, median, standard deviation, variance, cv, and quantiles 2.5% and 97.5% (95% confidence interval). Histograms of the outputs were also plotted.

4.4.2.2 Results

Uncertainty analysis

Table 4.8 shows the summary statistics for each outcome (outcome names in first column). The outcomes are the adequacy of habitat for predators of each type (ground-dwelling, flying, nectivorous, and all combined) per region (NL, ZH, NB, and FL). Per predator type, FL has smaller values (mean, median) than other regions, while NB has larger values. The coefficient of variation (cv%) ranges between 15% - 24% for most outcomes, comparable with the coefficients of variation of model inputs. For perc_visit_nectivoor, the coefficient of variation is around 40%, substantially higher than for other types of predators. The higher variance for flying nectivores is logical as the occurrence of flying nectivores (perc_visit_nectivoor) is determined by the combined effect of floral and source habitats, while the occurrence of other predator types is only determined by the presence of source habitats. Across different regions, the coefficient of variation is more or less similar for the same type of outcomes. We note a higher cv% in FL, which has a more monotone landscape with less floral and source habitat compared to the other regions. In this situation, small changes in the amount of suitable habitat have greater consequences than in more complex landscapes.

Table 4.8 *Summary statistics of model outputs.*

outcome	*min*	*mean*	*median*	*max*	*sd*	*var*	*cv%*	*q2.5%*	*q97.5%*
NL_perc_visit_kruip	3.1	6.4	6.3	11.3	1.3	1.8	21	4.1	9.4
ZH_perc_visit_kruip	3.2	6.4	6.3	11.5	1.3	1.8	20.9	4.2	9.4
NB_perc_visit_kruip	3.3	6.5	6.4	11.4	1.3	1.8	20.7	4.2	9.5
FL_perc_visit_kruip	2.7	5.9	5.8	10.7	1.3	1.8	22.6	3.7	8.8
NL_perc_visit_vlieg	3.9	8.3	8.5	11.9	1.5	2.3	18.2	5	10.6
ZH_perc_visit_vlieg	3.5	7.2	7.3	10.8	1.1	1.3	15.5	4.9	9.3
NB_perc_visit_vlieg	5.5	10.1	10.4	13.8	1.8	3.2	17.7	6.3	12.9
FL_perc_visit_vlieg	2.2	5	5.1	7.9	1	1	20	2.9	6.7
NL_perc_visit_nectivoor	1.5	9.5	9.1	23.2	4	16.2	42.5	2.8	18.3
ZH_perc_visit_nectivoor	1.5	8.5	8.4	18.7	3.1	9.6	36.4	3.1	15
NB_perc_visit_nectivoor	1.9	11.7	11.4	29.4	5.1	25.6	43.1	3.4	22.7
FL_perc_visit_nectivoor	0.6	4.2	4	10.3	1.9	3.6	44.5	1.2	8.5
NL_perc_visit_combi	4	8	8	13.6	1.8	3.3	22.5	4.7	11.8
ZH_perc_visit_combi	4.2	7.4	7.4	11.8	1.4	1.8	18.3	4.8	10.2
NB_perc_visit_combi	4.4	9.5	9.5	16.1	2.2	5.1	23.8	5.3	14
FL_perc_visit_combi	2.5	5	5	8.1	1	1	20	3.1	7.1

At a national level, the combined pest control indicator (perc_visit_combi) has a mean value of 8.0, with a range from 4.0 - 13.6 (minimum and maximum values), and an sd of 2.5 (figure 4.7).

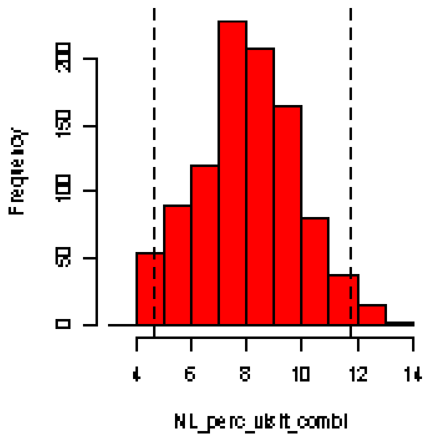

Figure 4.7 *Uncertainty around the mean (=8.0) of the combined indicator of percent visits of predators for pest control in the Netherlands. Dashed lines indicate the 2.5th and 97.5th percentiles, the range encompassing 95% of the output values.*

4.4.2.3 Overall conclusions of the uncertainty analysis

1. Range of Outputs
   - National-Level Results: At a national level, the combined pest control indicator (perc_visit_combi) has a mean value of 8.0%, with a range extending from 4.0 -13.6 (minimum and maximum values), and ab sd of 2.5. This distribution demonstrates moderate variability in pest control services across the Netherlands.

   - Regional Variability:

- Flevoland (FL): has the lowest mean values and highest variability across all predator groups, with perc_visit_combi (range 2.5 - 8.1_ reflecting the region's simpler landscape configuration and reduced semi-natural habitat availability.
- Noord-Brabant (NB): exhibits higher mean values (range 4.4 - 16.1) due to its heterogeneous landscape and well-connected habitats.
- Zuid-Holland (ZH): has intermediate mean values and variability (range 4.2 - 11.8) reflecting its smaller field sizes and moderate habitat diversity.

- Predator Groups: the occurrence of flying nectivorous predators (perc_visit_nectivoor) shows the highest variability across regions, with the lowest values in FL (mean of 0.6) and the highest in NB (11.7). This reflects the greater dependence of nectivorous predators on both source and floral habitats which are less prominent in simpler landscapes like Flevoland.

2. Bootstrap Validation of Sensitivity Results
   - The sensitivity indices for key parameters were recalculated using 100 bootstrap samples, confirming the robustness of the results:
   - Width of Source Habitats (width_m): this parameter consistently explained significant variance in the visitation rates of flying predators across all regions, with particularly strong influence in FL due to the importance of edge habitats in simpler landscapes.
   - Nectar Dependency (alpha_m4): this parameter showed higher influence in NB, where nectivorous predator populations are expected to be higher due to more abundant floral resources.

4.4.3 Validation

4.4.3.1 Method

We used data on predation rates of cabbage moth collected in 2003 by Bianchi et al. (2005), and parasitism rates on diamondback moth collected in 2006 by Bianchi et al. (2008) from organic farm plots in both simple and complex agricultural landscapes, considering the amount of natural elements within these landscapes.

Predation rates of cabbage moth (*Mamestra brassicae)* eggs were evaluated in Brussels sprout fields on 26 organic farms across diverse landscape complexities in the Netherlands, while excluding pesticide effects (Bianchi et al., 2005). Sampling occurred in 20 fields from August 18 to September 11, 2003. Egg batches were placed on filter paper cards and fixed under leaves on randomly selected plants. After two days, the cards were collected. Predation was assessed by comparing pre and post-exposure photographs, with empty, damaged, or removed eggs considered predated. Predation rates were calculated as the difference in egg numbers before and after exposure.

In July 2006, parasitism rates in diamond back moth (*Plutella xylostella*) larvae were assessed at 22 organic Brussels sprout farms across the Netherlands (Bianchi et al., 2008). In each field, ten larvae in the second or third instar were placed on eight Brussels sprout plants. After two days, the plants were collected, and the parasitism rate was determined by dissecting the larvae. In the Netherlands, cabbage moth caterpillars are primarily parasitized by wasps of the genus Diadegma (Bukovinszky et al., 2004). Female Diadegma can lay up to 800 eggs in a 25-day lifetime if a suitable sugar source is available. In the absence of honey or nectar, adults only survive 3-4 days.

A linear regression was performed on the predicted abundances of natural enemies at the locations where predation and parasitism data were collected (figures 4.8 and 4.9). Both the predation rates and the parasitism rates were strongly correlated with woody habitats and forest. We compared the area of woody habitats and forests collected in 2003 and 2006 in a 1km radius around the observations with the area of forest in the current ecosystem type map. Only points where the forest area differed less than 40% with the original area were included in the validation analysis. For the *Mamestra brassicae* egg predation data, 14 of the 20 quantified points were included; for the *Plutella xylostella* egg parasitism data, 13 of the 22 quantified points were included.

4.4.3.2 Results

The model predictions on abundance of all natural enemy groups combined were validated with the predation 2003 data of *Mamestra brassicae* eggs. The correlation between in the egg predation and the combined abundance of all natural enemy groups was assessed with both the Pearson and Spearman correlation test. The Pearson correlation was 0.822 (p=0.0003) while the Spearman rank correlation rho was 0.459 (p=0.10).

The parasitism of *Plutella xylostella eggs* 2006 data was used to validate the model predictions on abundance of flying nectivores, as their main parasitoid requires nearby nectar sources. The correlation between the egg parasitism of *Plutella xylostella eggs* and the abundance of the flying nectivores was also assessed with both the Pearson and Spearman correlation test. The Pearson correlation was 0.681 (p=0.01) while the Spearman rank correlation rho was 0.5 (p=0.08).

4.4.4 General assessment of model quality

The sensitivity analysis confirms that the model is responsive to input variations, effectively capturing the key drivers of pest control services. At the national level, the most important factors influencing outcomes are width_m (habitat edge width) and alpha_m4 (nectar-dependent predator dispersal). Regionally, additional factors such as wakker1 (initial predator presence) become significant, reflecting the varying influence of landscape composition and habitat connectivity on pest control outcomes.

The uncertainty analysis supports the model's reliability, with the variability in outputs aligning closely with input variability. For the national-level combined indicator (perc_visit_combi), the mean visitation is 8.0%, with a standard deviation of 2.5%. The 95% confidence interval ranges from 4.0% (2.5^{th} percentile) to 13.6% (97.5^{th} percentile). Regionally, variability is influenced by landscape configurations. For example, in FL, the mean visitation is 5.3% with an sd of 1.8%, while in NB, this is 10.3% with an sd of 2.2%. These differences highlight how regional availability of semi-natural habitats affects sensitivity and variability, emphasizing the need for nuanced interpretation at sub-national scales.

The validation results provide additional confidence in the model’s predictive capabilities. Comparisons with field data on predation and parasitism rates show strong correlations with predicted natural enemy visitation rates, particularly for landscapes with well-connected semi-natural habitats. While year-to-year variability in field data introduces uncertainty, the validation results suggest that the model provides reliable estimates of pest control services.

The use of the model in real-world applications, including national assessments and scenario analyses, demonstrates its practical utility. The model has been successfully applied for policy development and natural capital assessments to estimate pest control services, meeting the specifications for its intended use. However, its applicability at finer spatial scales (e.g. parcel-level assessments) requires further testing and validation to ensure accuracy.

In conclusion, the pest control model meets the specifications outlined in Sections 1.1–1.2 and is fit for its intended purpose at national and regional scales. While the model could potentially be simplified for national-scale assessments, its current complexity is essential for capturing spatial variations at finer scales. The robustness of the sensitivity and uncertainty analyses combined with validation against field data, ensures that the model provides reliable and actionable insights into pest control services. Further parameter refinements and additional field validations could enhance its accuracy and applicability in broader contexts.

Model Assumptions, Simplifications, and Uncertainties

The model's performance and applicability are shaped by several uncertainties:

Model Assumptions

The model assumes uniform habitat suitability across ecosystem types, which does not account for site-specific variability in factors like floral richness, structural complexity, or resource availability. In practice, these assumptions may not hold true, particularly in heterogeneous landscapes, potentially leading to moderate to high uncertainties in localized applications.

Simplifications
To simplify implementation, the model assumes linear relationships between predator visitation rates and pest suppression effectiveness, but may therefore miss complex ecological interactions like non-linear thresholds or predator group synergies. These simplifications introduce low to moderate uncertainties, particularly in diverse landscapes or for crops with pest control dynamics that differ from generalized assumptions.

Uncertainty in Data Sources
The model relies on input data such as land-use and habitat suitability maps which can vary in resolution, accuracy, and currency. Misclassifications, outdated datasets, or inconsistent map quality can introduce moderate to high uncertainties in regions with less detailed or reliable spatial data.

Use Beyond Original Scope
Applying the model outside its intended purpose such as for new ecosystem services, different geographic regions, or novel policy contexts, poses additional uncertainties. These high-impact uncertainties stem from potential misalignment of the model's assumptions, structure, or parameterization with the new applications.

Parameter Uncertainty
Key parameters like dispersal distances (alpha_m) and habitat suitability scores significantly influence model outputs, affecting visitation rates and pest control estimates. While the model reliably captures general trends, variability in these parameters introduces moderate to high uncertainty, particularly for national indicators like combined visitation (perc_visit_combi) and in regions with fragmented habitats. Refining these inputs is essential for accurate, context-specific applications.

4.5 Summary model quality and wishes for the future

Communication, reliability, Completeness and Status-A progress
Ideally, reliability is communicated directly as part of the results, however the current Status A framework does not yet fully provide for this. We propose introducing a standardized approach to communicate the reliability of results for each ecosystem service, using a 3-part scale (e.g. from "very high" to "low"). Additionally, the completeness of the indicators (using a 3-part scale) and the progress toward achieving Status A (scored across all criteria) should be explicitly reported. This section provides an overview of the quality status of all the NC-Model criteria, including updates for pollination and pest control.

4.5.1 Reliability

Method
The reliability of the numerical data showing how well we are able to model the ecosystem service is presented according to the system used in the Environmental Data Compendium. On the one hand, this pertains to how much we know about an ecosystem service, how well we understand the control variables that determine the delivery of the service and, on the other hand, how good the data are to be able to make a reliable estimate of the ecosystem service. The reliability of the models is determined on the basis of expert judgement:
- Category A (high)
- Category B (moderate)
- Category C (low)

Result
B: moderate.

The model has a well-developed theoretical and conceptual framework and provides detailed descriptions of control variables, including habitat suitability, predator visitation, and crop dependence. However, the model relies on significant assumptions and simplifications such as linear relationships between predator visitation and pest suppression, limiting its precision. Input data such as land-use maps and habitat classifications are generally reliable but subject to classification errors, spatial resolution variability, and temporal inconsistencies. Empirical validation is limited, particularly for region-specific parameters such as predator visitation rates and dispersal distances. The reliance on expert judgment for parameter estimates, while robust, highlights gaps in empirical data, preventing the model from achieving the highest reliability category.

4.5.2 Completeness

Method
CICES (Common International Classification of Ecosystem Services) provides definitions of ecosystem services. The CICES version 4.3 classification at the level of groups used by De Knegt et al. (2014) is compatible with the Dutch context and provides a logical and intelligible classification of ecosystem services. In 2018, the CICES classification was updated to version 5.1 (https://cices.eu/resources), with minor changes to version 4.3, so the previous classification and nomenclature can still be used. The classification used in this report is based on the level of groups.

The choice of which aspects are included often depends on data availability. For example, water pollution consists of many different pollutants. For individual substances it is impossible to indicate the extent to which ecosystem services can filter them from the environment. It was therefore decided to select the most important pollutants for water; phosphates and nitrates. During the purification of water by ecosystems, many other pollutants will also be filtered from the water. So indirectly, those substances are included in the ecosystem service. However, it is not known exactly how these processes work. For this reason, for each ecosystem service it is indicated – on the basis of expert judgement – how completely the chosen model covers the definition compared to the CICES 4.3 definition. Missing components in the model are indicated per model in the fifth section under the heading “Wishes for the future”.
- Category A (complete)
- Category B (contains the most important aspects)
- Category C (contains some aspects)

Results
B. contains most important aspect.

In the CICES system, natural pest control is broadly defined (Haines-Young & Potschin, 2013) and comprises pest and disease regulation in natural systems, agro-ecosystems (agriculture and livestock), and human populations. This includes the suppression of invasive species. The elaboration of this ecosystem service in this chapter focused on natural pest regulation in agricultural areas, especially on arthropods above ground. In this way, the criteria include the most important aspects, but are not comprehensive.

4.5.3 Status A progress

Status A progress legenda: **complete**, partly complete, missing

ST.1: Model description
- **General description**
- **Description conceptual and formal model**

ST.2: Technical implementation
- **Implementation**
- **Technical environment**
- **Testing**

ST.3: Description parameters, variables, input and output
- **Parameters and variables**
- **Calibration**
- **Input and output**

- **Origin Input data**

ST.4: Model functioning
- **Sensitivity analysis**
- **Uncertainty analysis**
- **Validation**
- Monitoring of use
- **General assessment**

See for DO.5: model development, DO. 6: organisation and IU.7: user documentation De Knegt et al. 2022.

4.5.4 Future model development options

- One of the most important wishes for the future is to translate the model results (pest density) to how this affects agricultural crop yields to answer the question of at what pest density the use of plant protection products can be omitted for the various crops. Recently, we were able to translate the model outcomes into their effects for crop yield for sugar beets, via the pests and the viruses they carry (De Knegt et al. in prep.), but this is just one of the many crops grown in the Netherlands.
- Furthermore, the pest density indicator is now expressed as a percentage; we recommend expressing this as the density of pest suppressors.
- As with pollination, the effect of pest suppression depends on the specific crop; different crops vary in their susceptibility to pests. In the future we should account for the different sensitivity of crops to pests, thereby accounting for the spatial effects of interactions between crop parcels..
- The input maps of those habitats that are flower rich and function as a source of floral food could be improved. For example in the Hoeksche Waard, much is known about the occurrence of flower richness of individual field margins, enhancing the explained variance of the model. However, information on flower richness/composition of field margins and other habitats is not currently available for the whole of the Netherlands. In the future, the estimates of this aspect of habitats need to be more accurate, perhaps with the use of AI.
- Further field data is needed to validate different aspects of the model results with field measurements, e.g. aphid growth rates and caterpillar parasitisation for the different groups of natural enemies.
- In the set up and parameterizing phase, the model focused heavily on suppressing aphids. However, many other types of pests cause damage to agricultural crops, as well as crop diseases such as viruses, fungi and bacteria. There is a need to include more types of pests and diseases in the model.
- The model now assumes pest suppression in the absence of pesticides. In the future, it should include the effects of using or not using pesticides on pests and pest suppressors.
- In the CICES system, natural pest control is broadly defined (Haines-Young & Potschin, 2013) and comprises pest and disease regulation in natural systems, agro-ecosystems (agriculture and livestock) and human populations. This includes the suppression of invasive species. The elaboration of this ecosystem service in this chapter focused on natural pest regulation of agricultural crops, especially above ground. In doing so, the criteria include the most important aspects, but these are not comprehensive.
- We recommend reconsidering those model parameters that are most important in the explanation of the variance (alpha_m4, width_m).

4.6 Literature

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Justification

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Annex 1 Pollination: distribution of parameters

Hypothesized distribution of each input parameter (median, standard deviation, minimum and maximum), and the distribution used to generate the corresponding samples (distribution, corresponding parameters Par1 and Par2), and linear transformation needed to re-scale and shift samples when needed. Par1 and Par2 are either minimum and maximum (if Uniform distribution), mean and sd (if Normal distribution) or the two shape parameters of the beta distribution.

lceu	description	median_habsuit	SD	min	max	distribution	par1	par2	multiply	add	comment
alpha_m	alpha_m	0.00053		0.0004	0.0009	uniform	0.0004	0.0009	1		
alpha_m_short	alpha_m_short	0.0014		0.001	0.0019	uniform	0.001	0.0019	1		
alpha_m_long	alpha_m_long	0.0002		0.0001	0.0003	uniform	0.0001	0.0003	1		
eff_poll_unif	eff_poll_unif	5		1	10	uniform	1	10	1		this is a multiplication factor, not a percentage
eff_poll_norm	eff_poll_norm	5.5	1.5	1	10	normal	5.5	1.5	1		this is a multiplication factor, not a percentage
0	no_data	0	0	0	0	constant			1		
1	Non-perennial_plants	0	0	0	0	constant			1		
2	Perennial_plants	0	0	0	0	constant			1		
3	Greenhouses	0	0	0	0	constant			1		
4	Meadows_(grazing)	0.21	0.23	0	0.8	beta	2	10	125	0.06	
5	Bushes_and_hedges_bordering_fields/fau	0.64	0.27	0	0.8	beta	25	5	125	-0.2	
6	Farmyards_and_barns	0	0	0	0	constant			1		
11	Dunes_with_permanent_vegetation	0.64	0.27	0	0.8	beta	25	5	125	-0.2	
12	active_coastal_dunes	0.21	0.23	0	0.8	beta	2	10	125	0.06	
13	beach	0.21	0.23	0	0.8	beta	2	10	125	0.06	
20	Bomenrij	0.71	0.31	0	0.8	beta	50	5	62.5	-0.2	0.5*125 (0.5*deciduous_forest)
21	Deciduous_forest	0.71	0.31	0	0.8	beta	50	5	125	-0.2	
22	Conferous_forest	0.35	0.25	0	0.8	beta	5	15	125	0.1	
23	Mixed_forest	0.53	0.38	0	0.8	beta	20	12	125	-0.1	
24	Heath_land	0.8	0.24	0	0.8	beta	50	1	125	-0.2	
25	inland_dunes	0.21	0.23	0	0.8	beta	2	10	125	0.06	
26	fresh_water_wetland	0.38	0.3	0	0.8	beta	6	15	125	0.1	
27	(semi)_natural_grassland	0.64	0.27	0	0.8	beta	25	5	125	-0.2	
28	public_green_space_M	0.21	0.23	0	0.8	beta	2	10	125	0.06	0.75*Meadows_(grazing)+0.25*deciduous_forest
28	public_green_space_DF	0.71	0.31	0	0.8	beta	50	5	125	-0.2	0.75*Meadows_(grazing)+0.25*deciduous_forest
29	other_unpaved_terrain	0.33	0.26	0	0.8	beta	5	16	125	0.1	
31	river_flood_basin	0.38	0.3	0	0.8	beta	6	15	125	0.1	
32	salt_marsh	0.29	0.28	0	0.8	beta	3	10	125	0.07	
41	residential_area	0	0	0	0	constant			1		
42	built-up	0	0	0	0	constant			1		
43	built-up	0	0	0	0	constant			1		
44	infrastructure	0	0	0	0	constant			1		
45	built-up	0	0	0	0	constant			1		
46	built-up	0	0	0	0	constant			1		
47	built-up	0	0	0	0	constant			1		
48	built-up	0	0	0	0	constant			1		
51	sea	0	0	0	0	constant			1		
52	lakes_and_ponds	0	0	0	0	constant			1		
53	rivers_and_streams	0	0	0	0	constant			1		
999	no-data	0	0	0	0	constant			1		
255	no-data	0	0	0	0	constant			1		
89	welBA_plaaggevoellig_appel_peer_fruit	65		40	89	uniform	40	89	1		
90	welBA_plaaggevoellig_Rubus-bessen	25		10	39	uniform	10	39	1		
91	welBA_plaaggevoellig_overige_gewassen	5		1	9	uniform	1	9	1		
92	welBA_plaaggevoellig_overige_gewassen	25		10	39	uniform	10	39	1		
93	welBA_plaaggevoellig_overige_gewassen	65		40	89	uniform	40	89	1		
94	welBA_plaaggevoellig_overige_gewassen	95		90	100	uniform	90	100	1		
95	welBA_plaaggevoellig_sperziebonen	5		1	9	uniform	1	9	1		
96	welBA_plaaggevoellig_sperziebonen_(vel	25		10	39	uniform	10	39	1		
97	welBA_plaaggevoellig_zomergerst	5		1	9	uniform	1	9	1		

Annex 2 Pollination: summary statistics of model inputs

Annex 2A

Summary statistics of 1000 samples used as input in the pollination model, where eff_poll is distributed as N(5.5,1.5).

input	min	mean	median	max	sd	var	cv%	q2.5%	q97.5%
alpha_m	0	0	0	0	0	0	22.29	0	0
alpha_m_short	0	0	0	0	0	0	17.98	0	0
alpha_m_long	0	0	0	0	0	0	28.92	0	0
eff_poll_Normal	1	5.5	5.5	10	1.51	2.29	27.47	2.54	8.52
P4	8.22	28.4	26.02	82.88	12.97	168.27	45.67	10.25	60.31
P5	42.88	79.08	80.05	96.37	8.43	71.01	10.66	59.8	92.55
P11	44.47	79.1	80.1	98.06	8.46	71.5	10.69	60.39	92.45
P12	7.92	28.28	26	92.39	12.87	165.53	45.49	10.34	57.55
P13	8.24	28.39	26	73.21	13.02	169.56	45.87	10.32	61.24
P20	34.79	44.33	44.62	49.07	2.4	5.75	5.41	38.68	48.17
P21	68.42	88.6	89.27	98.66	4.89	23.93	5.52	77.18	96.38
P22	16.84	43.7	42.6	86.49	11.81	139.47	27.03	23.77	69.6
P23	33.67	65.65	65.92	94.43	10.56	111.48	16.08	43.85	85.87
P24	81.83	97.55	98.28	100	2.37	5.63	2.43	91.01	99.94
P25	7.64	28.35	25.99	98.11	13.02	169.61	45.93	10.17	59.5
P26	21.24	48.1	47.34	85.19	11.88	141.17	24.7	27.53	73.78
P27	45.76	79.18	80.11	96.73	8.36	69.88	10.56	60.71	92.99
P28	23.16	43.42	41.82	83	10.71	114.73	24.67	27.19	67.97
P29	15.95	42.3	41.21	84.39	11.45	131.2	27.08	22.75	68.24
P31	16.68	48.36	47.37	96.61	12.23	149.59	25.29	28.13	75.44
P32	10.77	37.67	35.83	93.62	14.07	198.1	37.36	16.2	69.03
P89	40.01	64.54	64.49	88.97	14.15	200.21	21.92	41.14	87.37
P90	10	24.47	24.5	38.98	8.36	69.83	34.15	10.54	38.18
P91	1.01	5.01	5	9	2.3	5.29	45.92	1.23	8.82
P92	10.06	24.48	24.48	39	8.36	69.91	34.15	10.71	38.32
P93	40	64.51	64.53	88.99	14.12	199.43	21.89	41.22	87.65
P94	90.01	94.98	95	99.98	2.89	8.35	3.04	90.27	99.69
P95	1	5.02	5	8.99	2.31	5.32	45.99	1.26	8.76
P96	10.04	24.51	24.51	38.98	8.43	71.12	34.41	10.56	38.33
P97	1.01	4.99	5	8.99	2.31	5.34	46.29	1.19	8.83

Annex 2B

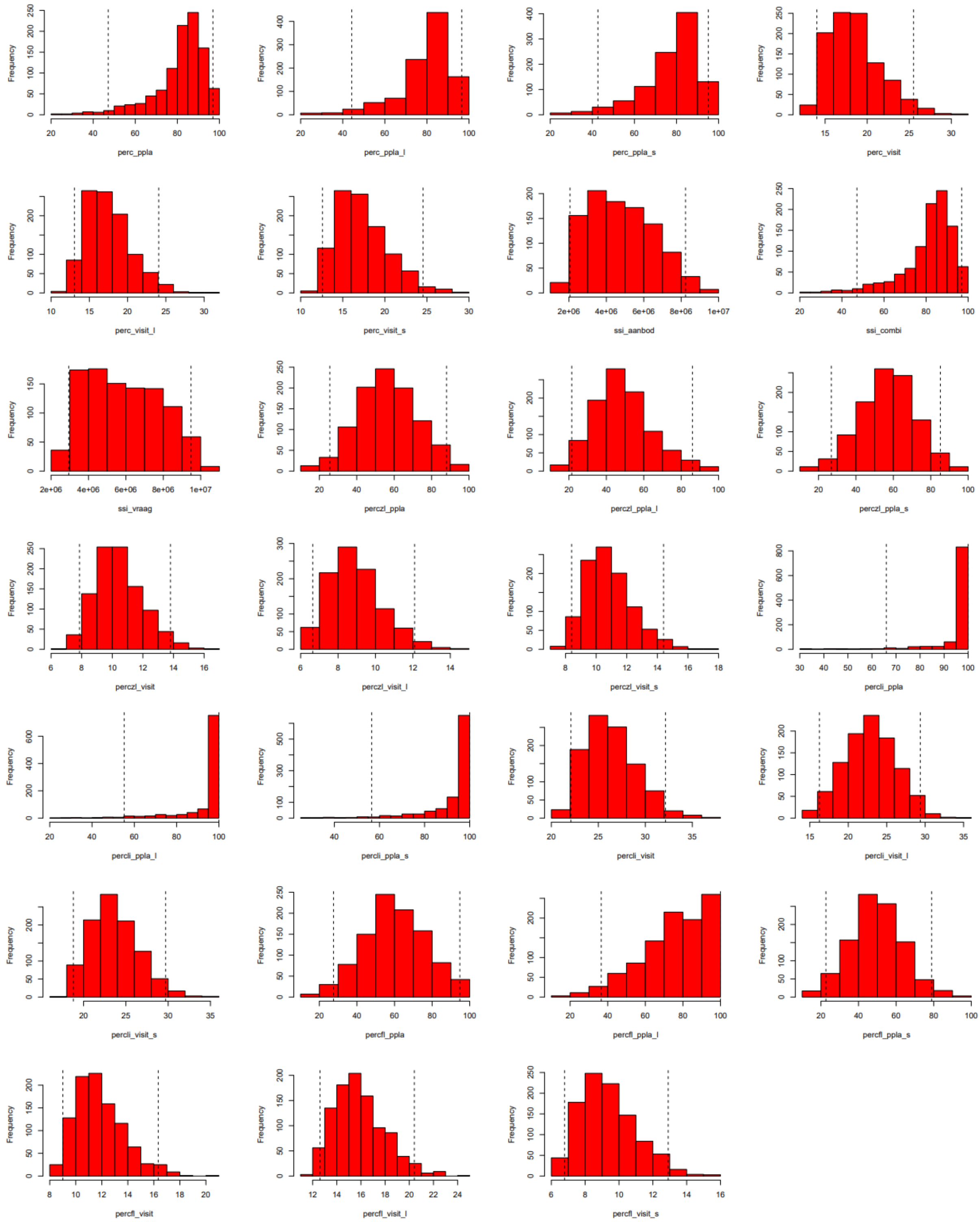
Summary statistics of 1000 samples used as input in the pollination model, where eff_poll is distributed as U (1, 10).

input_uniform eff_poll	min	mean	median	max	sd	var	cv%	q2.5%	q97.5%
alpha_m	0	0	0	0	0	0	22.31	0	0
alpha_m_short	0	0	0	0	0	0	17.8	0	0
alpha_m_long	0	0	0	0	0	0	28.74	0	0
eff_poll_Uniform	2	6.01	5.99	9.97	2.31	5.34	38.42	2.25	9.78
P4	8.31	28.39	25.98	78.49	12.96	168.05	45.66	10.51	58.92
P5	47.06	79.16	80.1	97.15	8.41	70.68	10.62	61.13	92.23
P11	47.4	79.14	80.11	96.59	8.39	70.36	10.6	60.06	92.49
P12	7.83	28.35	26.03	77.05	12.82	164.45	45.24	10.23	58.51
P13	7.99	28.31	25.93	82.84	12.71	161.6	44.9	10.48	56.8
P20	35.81	44.33	44.63	49.55	2.37	5.59	5.34	39.06	48.11
P21	70.4	88.61	89.25	98.9	4.87	23.7	5.49	77.23	96.18
P22	18.36	43.72	42.69	82.55	11.71	137.1	26.78	24.02	68.35
P23	20.87	65.58	65.92	96.99	10.75	115.64	16.4	44.34	86.13
P24	81.02	97.56	98.28	100	2.37	5.62	2.43	91.56	99.94
P25	7.8	28.35	26	93.08	13.02	169.51	45.93	10.57	58.88
P26	17.77	48.1	47.4	87.71	12.02	144.56	25	26.23	74.44
P27	44.66	79.17	80.09	97.29	8.42	70.87	10.63	61.38	92.63
P28	23.76	43.51	41.8	83.49	10.92	119.28	25.1	27.6	69.06
P29	16.56	42.23	41.19	81.5	11.19	125.15	26.49	23.17	65.97
P31	18.43	48.25	47.36	98.79	12.16	147.97	25.21	26.96	73.49
P32	12.57	37.64	35.81	89.55	13.92	193.85	36.99	17	70.03
P89	40.06	64.48	64.5	88.98	14.13	199.73	21.92	40.96	87.61
P90	10.01	24.51	24.54	38.98	8.37	70.04	34.14	10.73	38.24
P91	1	5	4.99	8.99	2.31	5.31	46.09	1.19	8.76
P92	10	24.48	24.48	38.98	8.4	70.61	34.33	10.62	38.1
P93	40.06	64.48	64.55	88.98	14.14	200	21.93	41.11	87.94
P94	90	94.99	94.99	99.97	2.89	8.33	3.04	90.26	99.75
P95	1.01	5	4.99	8.99	2.31	5.34	46.23	1.26	8.81
P96	10.03	24.51	24.51	38.96	8.37	70.12	34.17	10.84	38.24
P97	1	5	5.01	8.99	2.31	5.34	46.22	1.24	8.81

Annex 3 Pollination: histograms of model outputs

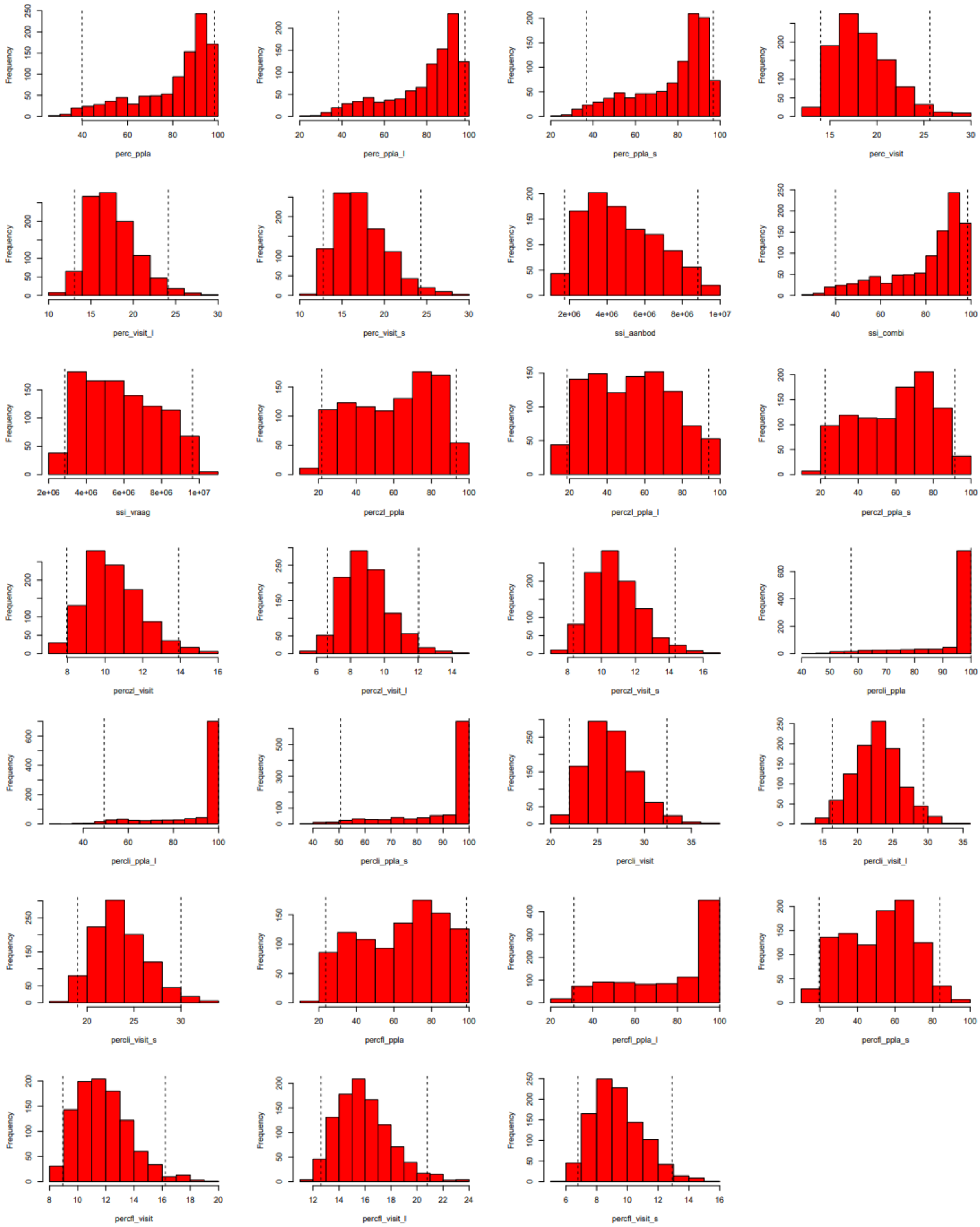
Annex 3A

Histograms of model outputs, where input eff_poll was normally distributed. Eff_poll mostly affected perc_ppla, in all regions and for all distances.



Annex 3B

Histograms of model outputs, where input eff_poll was uniformly distributed. Eff_poll mostly affected perc_ppla, in all regions and for all distances.



Annex 4 Pollination: summary statistics of model outputs, either for Eff_poll normally (left) or uniformly (right)distributed

outcome_Eff_poll_normal	min	mean	median	max	sd	var	cvpct	q025	q975
NL_perc_ppla_short	21	77.6	80.8	98.8	13.3	177.7	17.2	42.7	95.1
ZL_perc_ppla_short	13.3	56.9	57.4	98.4	14.9	223	26.2	26.9	85.2
LI_perc_ppla_short	26.8	92.8	97.9	100	11.9	140.6	12.8	56.5	100
FL_perc_ppla_short	10.7	49.5	49.3	93.4	13.9	193.1	28.1	22.7	78.9
NL_perc_ppla	23.6	81.3	84.2	99.7	12.6	158	15.5	47.1	96.9
ZL_perc_ppla	12.7	56.3	55.8	98.5	16.1	258.1	28.5	25.6	88
LI_perc_ppla	32.2	96.4	100	100	9.4	88.6	9.8	66	100
FL_perc_ppla	14.1	60.3	59.7	100	16.9	284	28	27.6	94.8
NL_perc_ppla_long	21.9	79.6	82.6	99.6	12.8	164.2	16.1	44.3	96.5
ZL_perc_ppla_long	10.4	48.8	47.6	100	15.6	243	32	21.5	86
LI_perc_ppla_long	24	94.2	100	100	12.5	155.9	13.3	55.2	100
FL_perc_ppla_long	17.7	76.1	77.6	100	18	325.2	23.7	36.6	100
NL_perc_visit_short	11.8	17.3	16.9	29.9	3.1	9.6	17.9	12.6	24.5
ZL_perc_visit_short	7.5	10.8	10.6	17	1.5	2.3	14	8.4	14.4
LI_perc_visit_short	17.7	23.6	23.3	34.7	2.8	8	11.9	18.8	29.7
FL_perc_visit_short	6.1	9.4	9.2	15.9	1.6	2.7	17.5	6.8	12.9
NL_perc_visit	13	18.5	18.1	30.9	3.1	9.4	16.6	14	25.5
ZL_perc_visit	6.9	10.4	10.2	16.8	1.5	2.3	14.5	7.9	13.8
LI_perc_visit	20.4	26.3	26	37.2	2.7	7.5	10.4	22.1	32.1
FL_perc_visit	8	11.8	11.6	20.8	1.9	3.5	15.8	9	16.3
NL_perc_visit_long	11.2	17.5	17.2	30.4	2.9	8.3	16.5	13.1	24.1
ZL_perc_visit_long	6	8.9	8.7	14.8	1.4	2	15.8	6.6	12.1
LI_perc_visit_long	14.1	22.8	22.8	35.6	3.4	11.4	14.8	16.3	29.4
FL_perc_visit_long	11.6	15.9	15.6	24.6	2.1	4.4	13.1	12.6	20.4
ssi_vraag	2368902	5887904	5698457	10591158	1958111	3.83E+12	33.3	2943448	9481554
ssi_aanbod	1168853	4779362	4640674	9916886	1758215	3.09E+12	36.8	2055865	8234647
ssi_combi	23.6	81.3	84.2	99.7	12.6	158	15.5	47.1	96.9

outcome_Eff_poll_uniform	min	mean	median	max	sd	var	cvpct	q025	q975
NL_perc_ppla_short	24	77.4	84.5	99.7	17.5	305.1	22.6	37	96.9
ZL_perc_ppla_short	15.8	59.5	63.2	99.3	20.2	409.5	34	22.5	91.3
LI_perc_ppla_short	35	90.4	99.5	100	15.1	227.9	16.7	50.6	100
FL_perc_ppla_short	13.2	51.8	54	99.6	18.3	335.9	35.4	19.5	83.9
NL_perc_ppla	27.2	80.8	87.4	99.8	16.8	283.3	20.8	39.9	98.5
ZL_perc_ppla	15	59.7	62.1	99.2	21.7	471.5	36.4	21.6	93.3
LI_perc_ppla	42.9	93.8	100	100	12.1	146.2	12.9	57.5	100
FL_perc_ppla	17.4	63.4	66.3	100	22.4	503.5	35.4	23.6	98.6
NL_perc_ppla_long	23.6	79.3	85.4	99.6	17.1	293.6	21.6	38.3	98.2
ZL_perc_ppla_long	11.6	53.1	53.1	99.8	21.7	469.7	40.8	18.7	94
LI_perc_ppla_long	28.8	91.2	100	100	15.7	247.6	17.3	49.3	100
FL_perc_ppla_long	22.6	77.4	86.2	100	23.3	541	30	31.1	100
NL_perc_visit_short	11.4	17.3	16.8	28.9	3.1	9.4	17.7	12.8	24.3
ZL_perc_visit_short	7.3	10.8	10.6	16.1	1.5	2.2	13.8	8.3	14.3
LI_perc_visit_short	16.9	23.6	23.3	33.6	2.8	7.6	11.7	19	30
FL_perc_visit_short	6	9.3	9.1	15.8	1.6	2.6	17.3	6.8	12.9
NL_perc_visit	12.9	18.5	18.1	29.8	3	9.2	16.4	14	25.6
ZL_perc_visit	7	10.4	10.2	15.6	1.5	2.2	14.2	8	13.9
LI_perc_visit	20.3	26.3	26	36.8	2.7	7.2	10.2	22	32.4
FL_perc_visit	8	11.8	11.6	19.6	1.9	3.5	15.9	8.9	16.2
NL_perc_visit_long	10.8	17.5	17.1	29.3	2.9	8.2	16.4	13.1	24.2
ZL_perc_visit_long	5.6	8.9	8.7	14.6	1.4	2	15.8	6.6	12
LI_perc_visit_long	13.7	22.8	22.8	35.5	3.4	11.2	14.7	16.4	29.4
FL_perc_visit_long	11.8	15.9	15.6	23.5	2.1	4.2	12.9	12.6	20.8
ssi_vraag	2330533	5880564	5679723	10789823	1979441	3.92E+12	33.7	2848299	9653046
ssi_aanbod	1088455	4764295	4444830	9760117	1947101	3.79E+12	40.9	1736357	8820729
ssi_combi	27.2	80.8	87.4	99.8	16.8	283.3	20.8	39.9	98.5

Annex 5 Pollination: sensitivity analysis of normal and uniformly distribution of Eff_poll

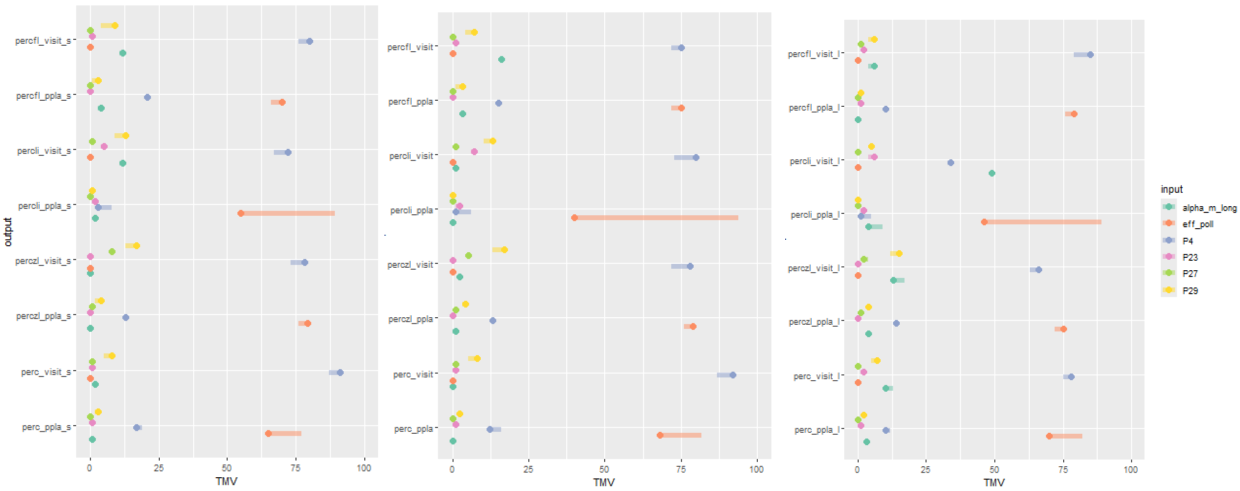
Sensitivity indices per output y. Vtot is the variance of the outcome, Vtot=V(y); R2_all is the percentage of variance of y explained by Model A; TMV is the percentage of variance of y explained by Model B; BMV is the difference R2_all – R2(Model C). Results are shown for eff_poll respectively normally, or uniformly, distributed.

	Effpol Normal			Effpol Uniform				Effpol Normal		Effpol Uniform	
output	**Vtot**	**R2_Add**	**R2_nonAdd**	**Vtot**	**R2_Add**	**R2_nonAdd**	**largest contributor**	**TMV**	**BMV**	**TMV**	**BMV**
NL_perc_ppla_s	177.7	86	97	305	88	99	eff_poll	65	62	76	71
ZL_perc_ppla_s	223.0	98		410	98		eff_poll	79	76	88	83
LI_perc_ppla_s	140.6	63	97	228	68	98	eff_poll	55	52	63	59
FL_perc_ppla_s	193.1	98		336	98		eff_poll	70	66	80	76
NL_perc_ppla	158.0	83	98	283	86	99	eff_poll	68	65	76	71
ZL_perc_ppla	258.1	98		472	98		eff_poll	79	76	89	84
LI_perc_ppla	88.6	44	98	146	54	99	eff_poll	40	38	50	47
FL_perc_ppla	284.0	98		503	97		eff_poll	75	72	85	81
NL_perc_ppla_l	164.2	85	99	294	87	99	eff_poll	70	66	77	73
ZL_perc_ppla_l	243.0	98		470	98		eff_poll	75	72	86	82
LI_perc_ppla_l	155.9	54	97	248	60	98	eff_poll	46	43	54	51
FL_perc_ppla_l	325.2	92		541	91		eff_poll	79	76	85	81
NL_perc_visit_s	9.6	100		9	100		P4	91	87	92	89
ZL_perc_visit_s	2.3	100		2	100		P4	78	73	78	75
LI_perc_visit_s	8.0	100		8	100		P4	72	67	72	69
FL_perc_visit_s	2.7	100		3	100		P4	80	76	81	77
NL_perc_visit	9.4	100		9	100		P4	92	87	92	89
ZL_perc_visit	2.3	100		2	100		P4	78	72	77	74
LI_perc_visit	7.5	100		7	100		P4	80	73	77	74
FL_perc_visit	3.5	99		4	99		P4	75	72	76	71
NL_perc_visit_l	8.3	98		8	98		P4	78	75	78	76
ZL_perc_visit_l	2.0	98		2	99		P4	66	63	66	63
LI_perc_visit_l	11.4	96		11	96		alpha_m_long	49	49	50	50
LI_perc_visit_l	11.4	96		11	96		P4	34	33	34	33
FL_perc_visit_l	4.4	98		4	98		P4	85	79	84	81

Annex 6 Pollination: TMV and BMV

Annex 6A

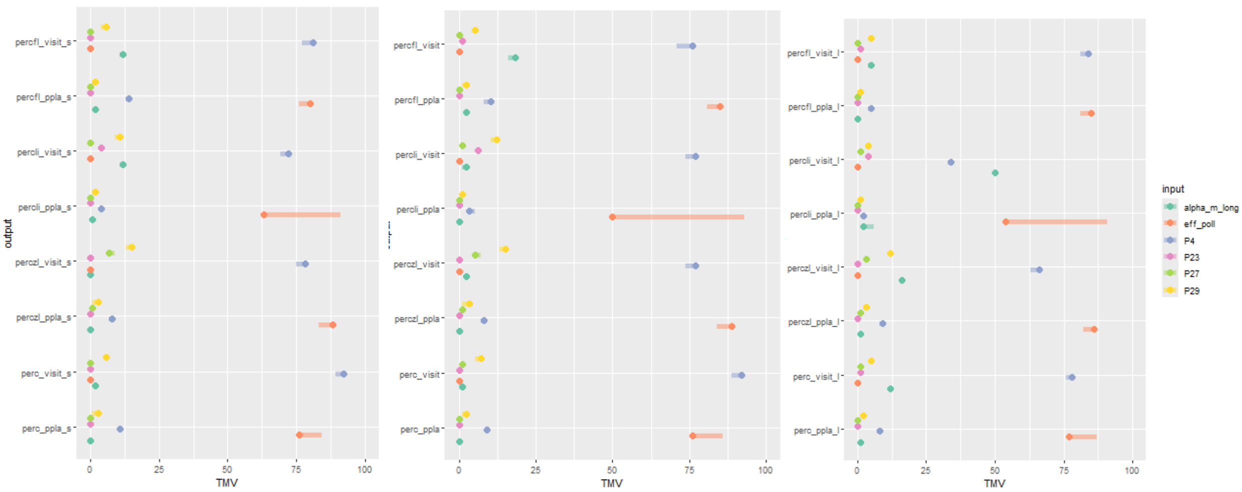
Top marginal variance or first-order index (TMV, Eq.3.7) and bottom marginal variance or total effect index (BMV, Eq.3.8) indices showing the contribution of the most important inputs overall (alpha_m_long, **eff_poll Normal**, P4, P23, P27, P29) for each outcome (rows in graphs). Dots are TMV, lines show distance to BMV (A: short distance, B: medium distance, C: long distance).



A B C

Annex 6B

Top marginal variance or first-order index (TMV, Eq.3.7) and bottom marginal variance or total effect index (BMV, Eq.3.8) indices showing the contribution of the most important inputs overall (alpha_m_long, **eff_poll Uniform**, P4, P23, P27, P29) for each outcome (rows in graphs). Dots are TMV, lines show distance to BMV (A: short distance, B: medium distance, C: long distance).

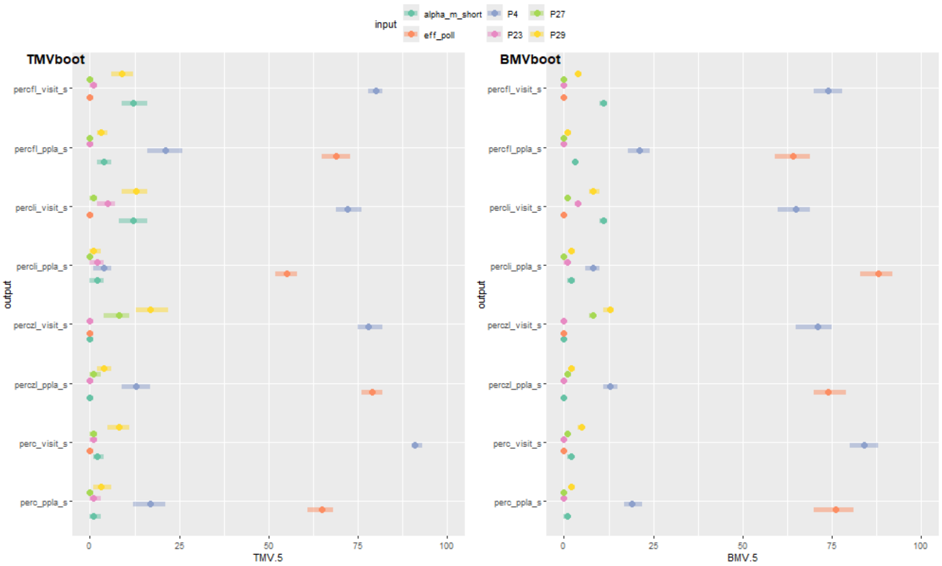


A B C

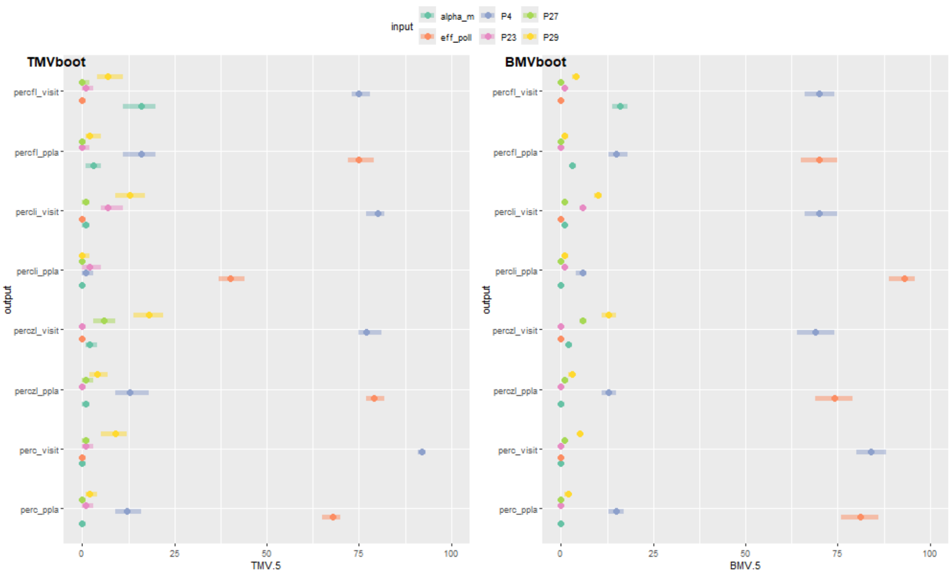
Annex 7 Pollination: bootstrap indices

Bootstrap indices: TMV (left figure) and BMV (right figure), showing the contribution of the most important inputs overall (alpha_m_long, **eff_poll Normal**, P4, P23, P27, P29) for each outcome (rows in graphs). Dots represent mean values, with empirical confidence intervals (A: short distance, B: medium distance, C: long distance).

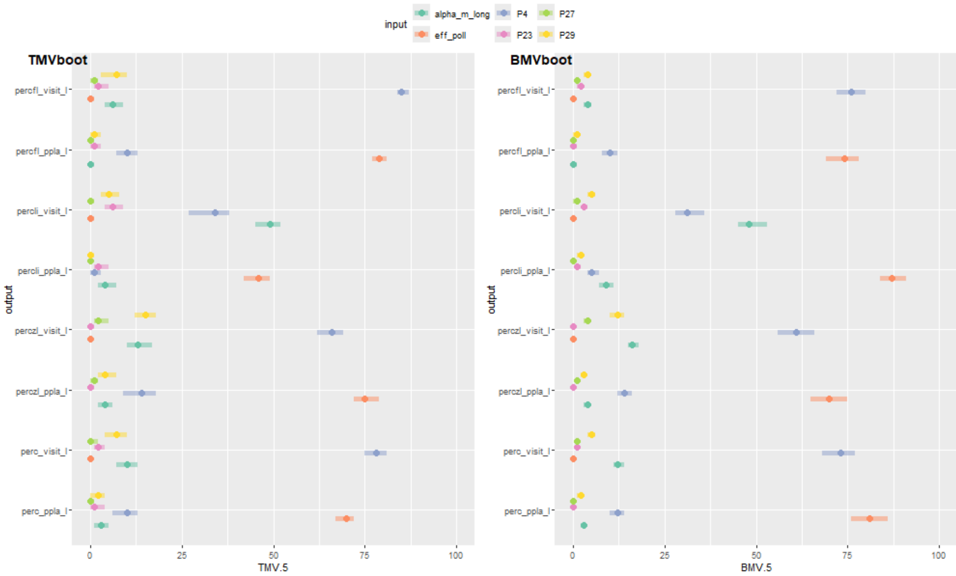
A



B



C


input
alpha_m_long
eff_poll
P4
P23
P27
P29
TMVboot
BMVboot
output
percfl_visit_l
percfl_ppla_l
percli_visit_l
percli_ppla_l
perczl_visit_l
perczl_ppla_l
perc_visit_l
perc_ppla_l
0
25
50
75
100
TMV.5
BMV.5

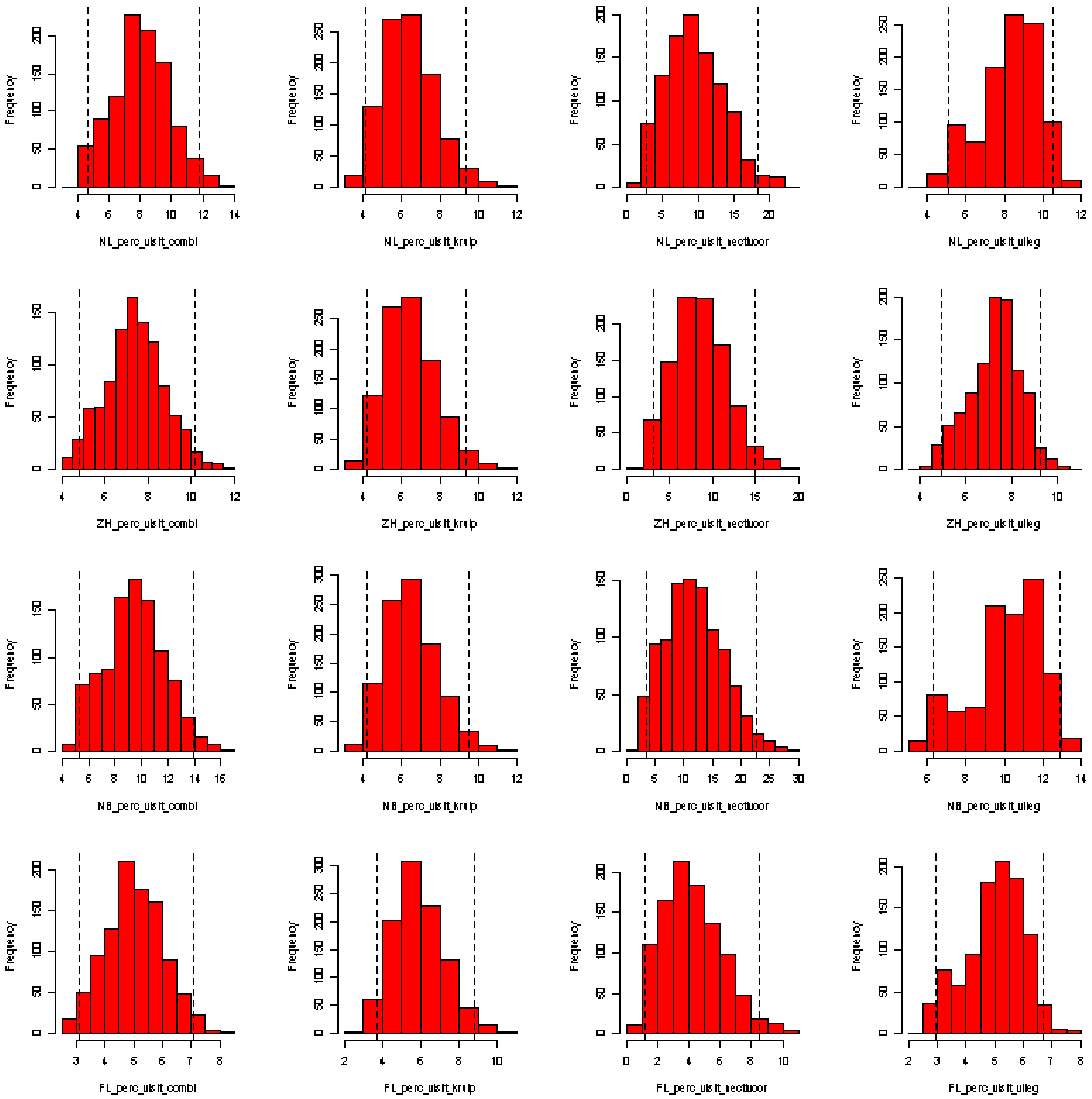
Annex 8 Pest control: summary statistics

Summary statistics of quantitative model inputs.

input	*min*	*mean*	*median*	*max*	*sd*	*var*	*cv%*	*q2.5%*	*q97.5%*
alpha_m1	20	53	52	104	13	175	25	31	85
alpha_m2	158	432	422	839	117	13693	27	225	678
alpha_m3	307	624	616	1011	123	15109	20	414	886
alpha_m4	49	200	200	356	51	2643	26	96	302
wakker1	2.2	5.3	5.2	10.0	1.3	1.8	24.8	3.1	8.3
wakker4	0	0.02	0.02	0.04	0.01	0	25.8	0.01	0.03
wbloemrijk1	4.6	10.5	10.3	20.5	2.3	5.3	21.8	6.7	15.6
wbloemrijk2	41	70	70	101	10	104	15	50	90
wbloemrijk3	39	70	70	104	10	104	15	51	90
wbloemarm1	4.6	10.5	10.3	20.6	2.4	5.7	22.6	6.3	15.7
wbloemarm2	5.7	40.0	40.0	72.8	10.5	109.5	26.2	19.1	59.9
wbloemarm3	9.0	40.0	40.0	81.9	10.2	103.6	25.5	19.3	58.7
wbloemarm4	0.29	0.6	0.6	0.97	0.1	0.01	17.19	0.4	0.81
wbosrand1	4.4	10.5	10.3	19.3	2.3	5.1	21.6	6.6	15.4
wbosrand4	0.37	0.7	0.7	1	0.1	0.01	14.7	0.5	0.9
wboomrij1	0.13	2	2	3.53	0.51	0.26	25.29	1	2.94
wboomrij2	19.7	50.1	50.0	80.2	10.3	106.5	20.6	30.0	71.4
wboomrij3	16.73	49.96	50	80.21	10.28	105.64	20.57	29.67	69.5

Annex 9 Pest control: histograms of model outputs

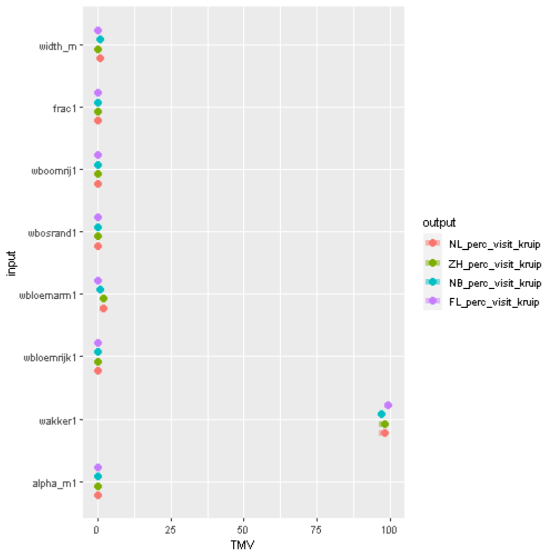
Histograms of model outputs. Per row the outputs per region (NL, ZH, NB, FL), and per column the different outcomes (perc_visit_combi, perc_visit_kruip, perc_visit_nectivoor, perc_visit_vlieg).



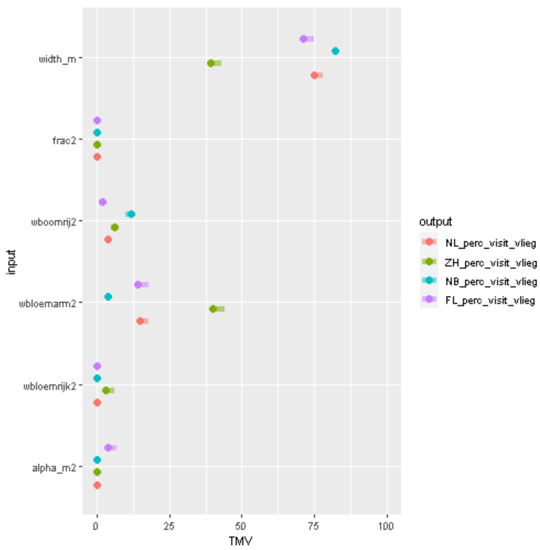
Annex 10 Pest control: TMV and BMV

Top marginal variance or first-order index (TMV) and bottom marginal variance or total effect index (BMV) indices shown for each input (rows in graphs) per type of outcome (A: perc_visit_kruip, B: perc_visit_vlieg, C: perc_visit_nectivoor, D: perc_visit_combi). Dots are TMV, lines show distance to BMV.

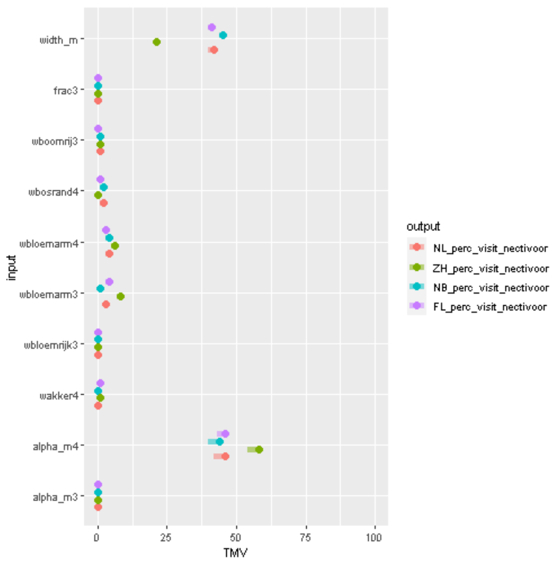
A



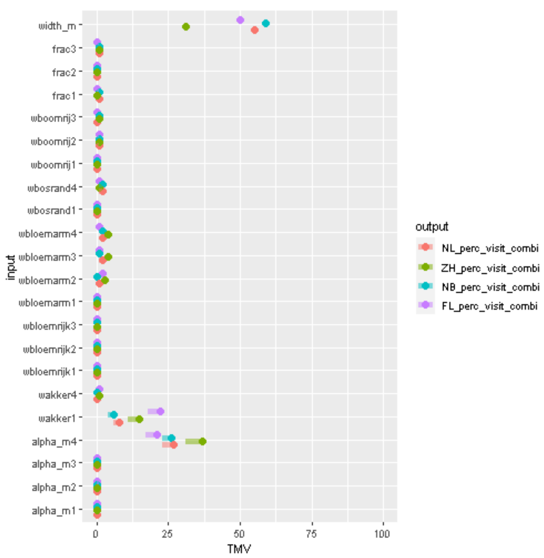
B



C



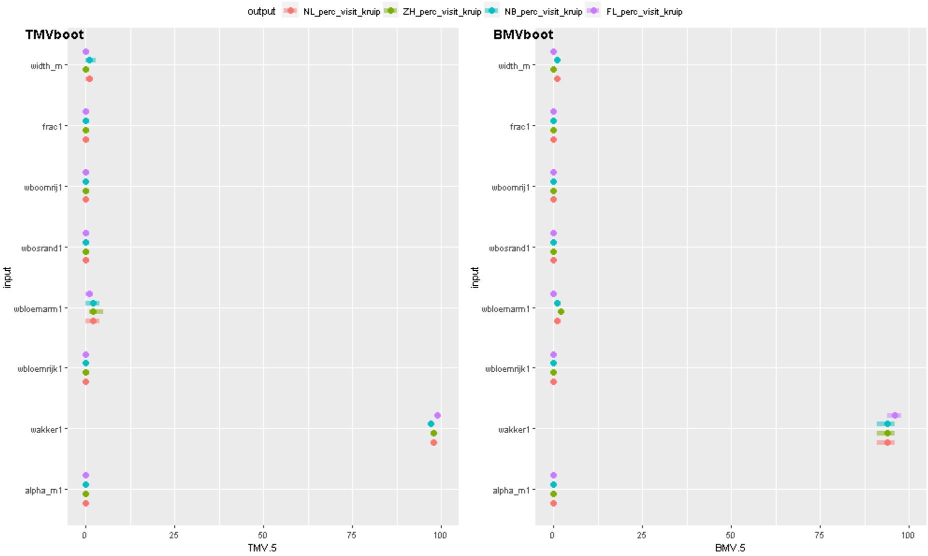
D



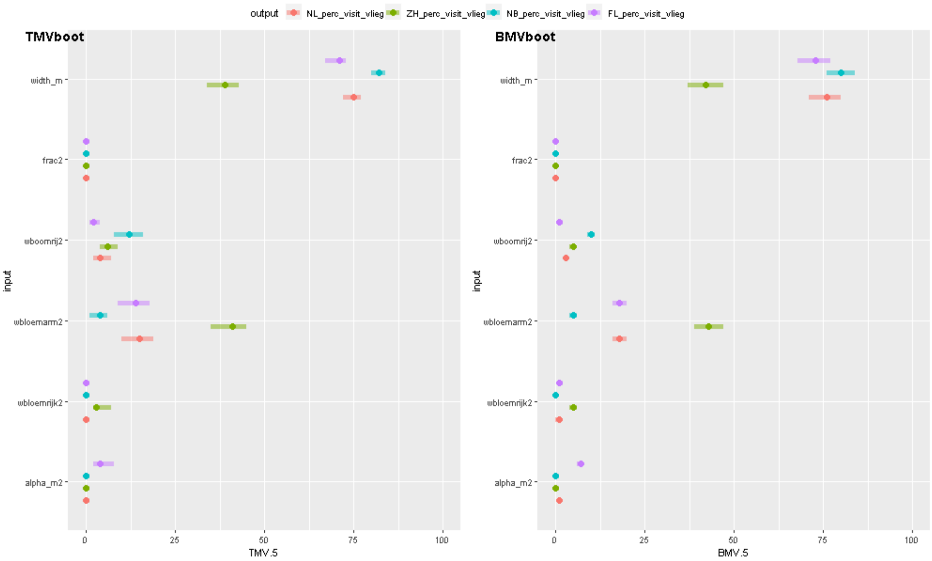
Annex 11 Pest control: bootstrap indices

Top marginal variance or first-order index (TMV) and bottom marginal variance or total effect index (BMV) indices shown for each input (rows in graphs) per type of outcome (A: perc_visit_kruip, B: perc_visit_vlieg, C: perc_visit_nectivoor, D: perc_visit_combi). TMV left hand graphs; BMV right hand graphs. Dots represent mean values, with empirical confidence intervals.

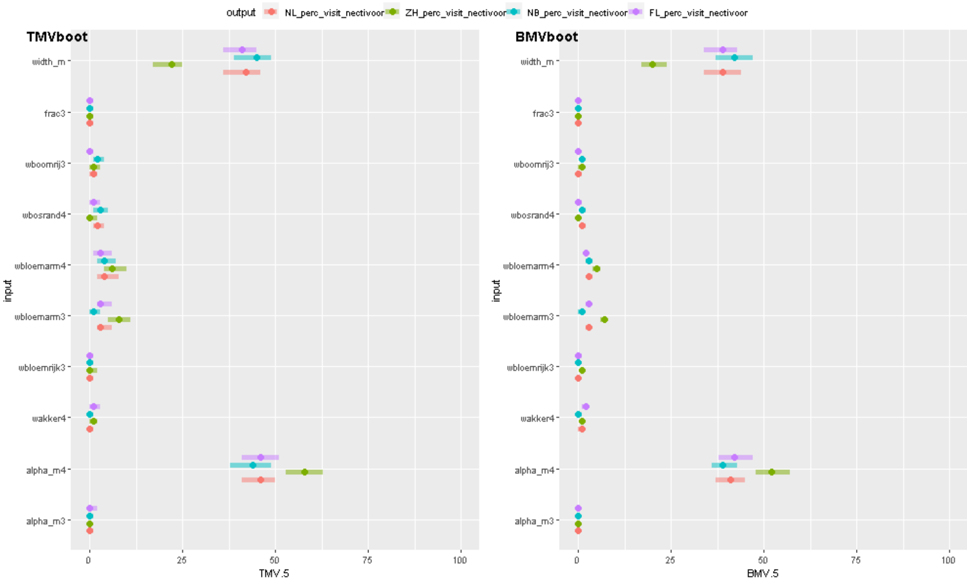
A



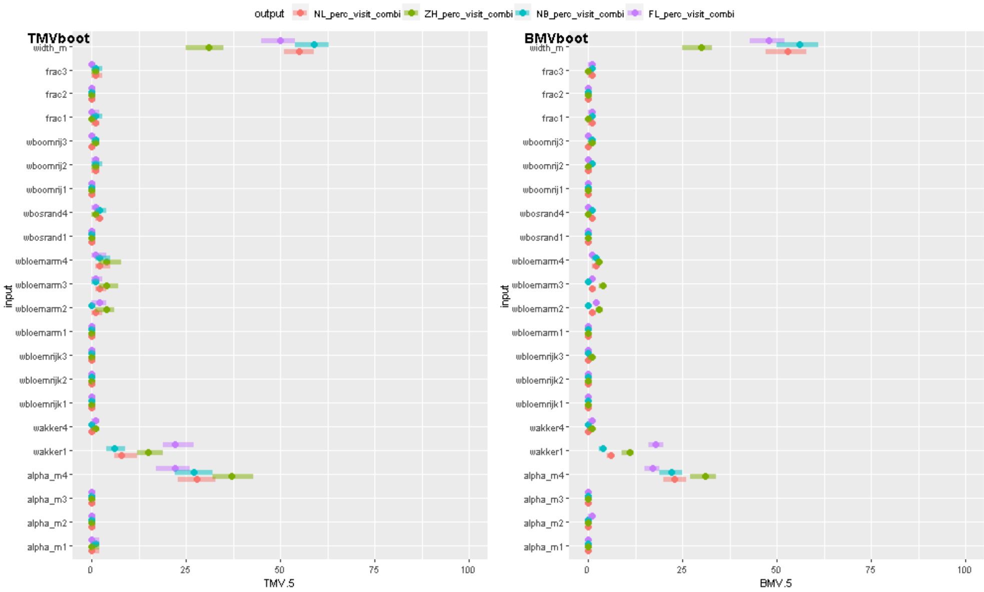
B



C


output
NL_perc_visit_nectivoor
ZH_perc_visit_nectivoor
NB_perc_visit_nectivoor
FL_perc_visit_nectivoor
TMVboot
BMVboot
width_m
frac3
wboomrij3
wbosrand4
wbloemarm4
wbloemarm3
wbloemrijk3
wakker4
alpha_m4
alpha_m3
input
0
25
50
75
100
TMV.5
BMV.5

D


output
NL_perc_visit_combi
ZH_perc_visit_combi
NB_perc_visit_combi
FL_perc_visit_combi
TMVboot
BMVboot
width_m
frac3
frac2
frac1
wboomrij3
wboomrij2
wboomrij1
wbosrand4
wbosrand1
wbloemarm4
wbloemarm3
wbloemarm2
wbloemarm1
wbloemrijk3
wbloemrijk2
wbloemrijk1
wakker4
wakker1
alpha_m4
alpha_m3
alpha_m2
alpha_m1
input
0
25
50
75
100
TMV.5
BMV.5

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