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Research Article

Effects of landscape variables and weather conditions on the seasonal arrival and population abundance of the green peach aphid *Myzus persicae* in sugar beet

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ABSTRACT

Understanding the ecological drivers of plant diseases and insect pests is essential for developing sustainable management strategies as chemical control options become increasingly limited. In European sugar beet production, the 2018 ban on neonicotinoids has led to a resurgence of viral yellowing, mainly vectored by the green peach aphid (*Myzus persicae*). Yield losses of up to 50% underscore the urgent need to understand the environmental factors shaping *M. persicae* dynamics to improve aphid vector forecasting and virus management. We collected aphid count data over three consecutive growing seasons from more than 100 fields across Belgium (Europe). A comprehensive modeling approach was used to identify key landscape, weather, and local factors influencing the arrival and abundance of alate and apterous *M. persicae*. To evaluate scale effects, analyses were performed at three spatial scales (300 m, 500 m, 1 km). Landscape factors did not show detectable effects on the arrival timing of alate or apterous *M. persicae*. In contrast, warmer winters and earlier sowing dates were associated with earlier aphid arrival and higher aphid abundance. The area of semi-natural herbaceous habitat had a positive effect on the abundance of both alate and apterous *M. persicae*. While this effect was mainly observed for the alate morphotype at the 500 m scale, it had a similar effect across all spatial scales for the apterous morph. The edge density of semi-natural woody habitat and urbanization area favored the abundance of alate and apterous *M. persicae* in a scale-dependent manner, respectively. Although the effect was limited, increasing arable land area reduced alate *M. persicae* abundance while increasing apterous abundance. These insights can help predict aphid arrival and abundance in sugar beet and support decisions on field selection, sowing time, and better management strategies to reduce aphid outbreaks and virus transmission.

Introduction

A better understanding of agricultural systems and the ecological interactions that occur within them is key to developing effective pest and disease management strategies (Dent & Binks, 2020). Agroecological approaches can be strengthened by identifying key landscape and weather factors that drive pest infestations (Brewer & Elliott, 2023). The wide geographic range of many pest species creates complex interactions with landscape features that can disrupt synchrony between pest dispersal and natural control (e.g., by natural enemies) (Haan et al., 2020; Lehmann et al., 2020). The effects of landscape heterogeneity on natural pest suppression vary across spatial scales and pest species, and are influenced by regional landscape composition (i.e., amounts of habitat) and configuration (i.e., spatial arrangement of habitat) (Xie et al., 2023; Zhang et al., 2020). Semi-natural habitats such as grasslands and hedgerows are known to support natural enemies by providing food, breeding sites and shelter (Holland et al., 2017; Perrot et al., 2021). However, the effect of semi-natural habitats on pest prevalence is largely influenced by pest traits, trophic interactions, and environmental conditions (Courson et al., 2022; Delaune et al., 2021; Veres et al., 2013).

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Moreover, interactions between crop fields and their margins are widely recognized as key to enhancing beneficial species and biodiversity, thereby promoting more environmentally sustainable pest control and supporting multiple agricultural functions (Crowther et al., 2023; Marshall, 2004). Crop phenology can also strongly influence early-season pest dynamics, as early-colonizing migrant pests could benefit from nutrient-rich young plants that provide optimal feeding and high levels of nutrients and defensive metabolites (Cao et al., 2018; Schop et al., 2022), promoting rapid population establishment. At the same time, biological control may be reduced if natural enemies exhibit lower phenological plasticity than the target pest, potentially leading to a temporal mismatch between predator activity and pest abundance (Fuchs et al., 2017; Reed et al., 2011).

Pest infestations are largely influenced by location-specific and seasonal weather patterns, with temperature, rainfall, humidity, and wind commonly used in pest models (Olatinwo & Hoogenboom, 2014). In many systems, mild winters increase pest survival, leading to early field arrival and a rapid increase in insect populations during the following growing seasons (Schneider et al., 2022). Conversely, high summer temperatures can increase pest mortality and limit dispersal in species with low heat tolerance (Mech et al., 2018; Schneider et al., 2022). Although several studies have shown the significance of landscape and weather factors on the dynamics of pest populations (Alignier et al., 2014; Perrot et al., 2021; Santos et al., 2018; Schneider et al., 2022; Wu et al., 2020), only a few have investigated the combined effects of multiple weather and landscape variables at different temporal and spatial scales (Courson et al., 2022; Luquet et al., 2023; Rakotoarinia et al., 2022).

In this study, we investigated factors influencing the arrival and abundance of the green peach aphid *Myzus persicae* (Sulzer) (Hemiptera: Aphididae) in sugar beet. *Myzus persicae* is a polyphagous aphid species, with a host range of more than 400 species from 50 plant families (Ali et al., 2021). Its rapid life cycle and short generation time allow an exponential population increase, causing significant crop losses through feeding damage, honeydew production and associated development of sooty molds, and virus transmission (Ali et al., 2023; Bass et al., 2014). In sugar beet, *M. persicae* is the most efficient vector of yellowing viruses, which include beet yellows virus (BYV), beet mild yellowing virus (BMYV), and beet chlorosis virus (BChV) (Hossain et al., 2021). These viruses cause yellowing, brittleness, and stunted growth in sugar beet, reducing root yield, sugar content, and extractability, with losses of up to 50 % (Wintermantel, 2005). With no resistant cultivars available, virus control has primarily relied on controlling the aphid vectors by neonicotinoid seed treatments (Elbert et al., 2008). However, following their EU ban (Bass & Field, 2018) aphid control relies mainly on foliar insecticides, which often fail to provide sufficient protection (Dewar & Qi, 2021). Furthermore, the availability of chemicals effective against aphids in sugar beet is limited, with many species, including *M. persicae*, having developed resistance to these substances (Bass et al., 2014; Mota-Sanchez et al., 2008). With limited alternatives for managing *M. persicae*, understanding outbreak drivers in sugar beet is essential to develop appropriate pest management strategies.

To investigate the main factors driving *M. persicae* population dynamics in sugar beet, we collected aphid count data over three consecutive seasons from more than 100 fields across Belgium (Europe). Using landscape metrics at multiple scales, weather data, and local variables (location, sowing week, field size), we identified key drivers influencing the arrival and cumulative abundance of alate and apterous *M. persicae*, their overall importance across spatial scales and the relative strength of their effects. We hypothesized that (i) aphid populations respond differently across spatial scales to landscape structure, with simplified and fragmented landscapes expected to support higher aphid densities due to weaker biological control; (ii) warmer winters result in earlier aphid emergence and increase aphid abundance reflecting the influence of climatic conditions on aphid phenology; and (iii) earlier sowing and larger fields favor aphid establishment by ensuring high-quality host plants during migration and reducing the impact of border-mediated biological control.

Materials and methods

Field survey

From 2021 to 2023, annual field surveys were conducted in collaboration with local sugar beet growers in Belgium. Over 100 sugar beet fields were sampled each year, with different fields surveyed in each successive year, following standardized guidelines established by IRBAB-KBIVB. This protocol has been used to collect data on aphid populations and viral yellowing in sugar beet fields for many years, and farmers are continuously trained and advised on data collection. Fields were monitored weekly from sugar beet emergence until canopy closure. At each monitoring point, 40 sugar beet plants per field were examined for alate and apterous *M. persicae*, with individuals classified morphologically. The black bean aphid, which occurred in most fields, along with other aphid species that were only occasionally observed, were excluded from this study as the survey targeted only the principal vector of yellowing viruses in sugar beet. First aphid observations and cumulative abundance were selected as descriptors of aphid population dynamics, following previous studies on aphid dynamics in sugar beet (Luquet et al., 2023; Phélippé-Guinvarc'h & Cordier, 2024; Qi et al., 2004). The weeks of first observation (WFO) of alate and apterous *M. persicae* were determined for each field by counting the number of weeks from January 1st until the week when each morphotype was first recorded. In addition, the cumulative abundance (CAb) of each morphotype was calculated as the sum of the weekly counts per site (Table S1). Information on crop variety and pesticide applications for the surveyed fields is summarized in the metadata file provided in the Supplementary Material. As all sugar beet varieties were underrepresented and field-level metadata were limited, these parameters were not included in the statistical analyses.

Environmental data

Landscape data

A land cover and land use (LCLU) map of Belgium (Fig. 1A) was developed in QGIS v.3.26.3 (QGIS Development Team, 2023) using regional data collected from the Flemish biological valuation map (INBO, 2020), the Wallonia land occupation and use map (SPW, 2020a), and the maps of Flemish and Wallonia agricultural land-use parcels (LV, 2020; SPW, 2020b). Field coordinates were mapped on the LCLU map, and areas calculated using QGIS. After excluding fields without a defined area or with fewer than four monitoring points, 318 study sites were included in the analysis (84 % of all monitored fields): 111 in 2021, 118 in 2022, and 89 in 2023. The landscape around each field was classified into six classes as described in Daelemans et al. (2023): arable land, urban areas, agricultural grasslands, semi-natural herbaceous habitat (SNH), semi-natural woody habitat (SNW) and orchards. Landscape composition (total class area) and configuration (class edge density) were calculated for each class within 300 m, 500 m, and 1 km buffers (Fig. 1B, Figures S1-S3). While total area quantifies the availability of resources provided by each landscape class, edge density captures the spatial arrangement of patches, reflecting their complexity and degree of fragmentation, which can influence species movement, interactions, and the distribution of organisms within the landscape. Areas within the buffers consisting of sea or land from another country were excluded from the calculations. Landscape metrics were calculated using the R packages *sf* v.1.0–15 (Pebesma, 2018; Pebesma & Bivand, 2023) and *landscapemetrics* v.2.1.1 (Hesselbarth et al., 2019).

Meteorological data

Weather data were collected using the WOW-BE platform (KMI, 2023). Available weather stations were mapped on the LCLU map

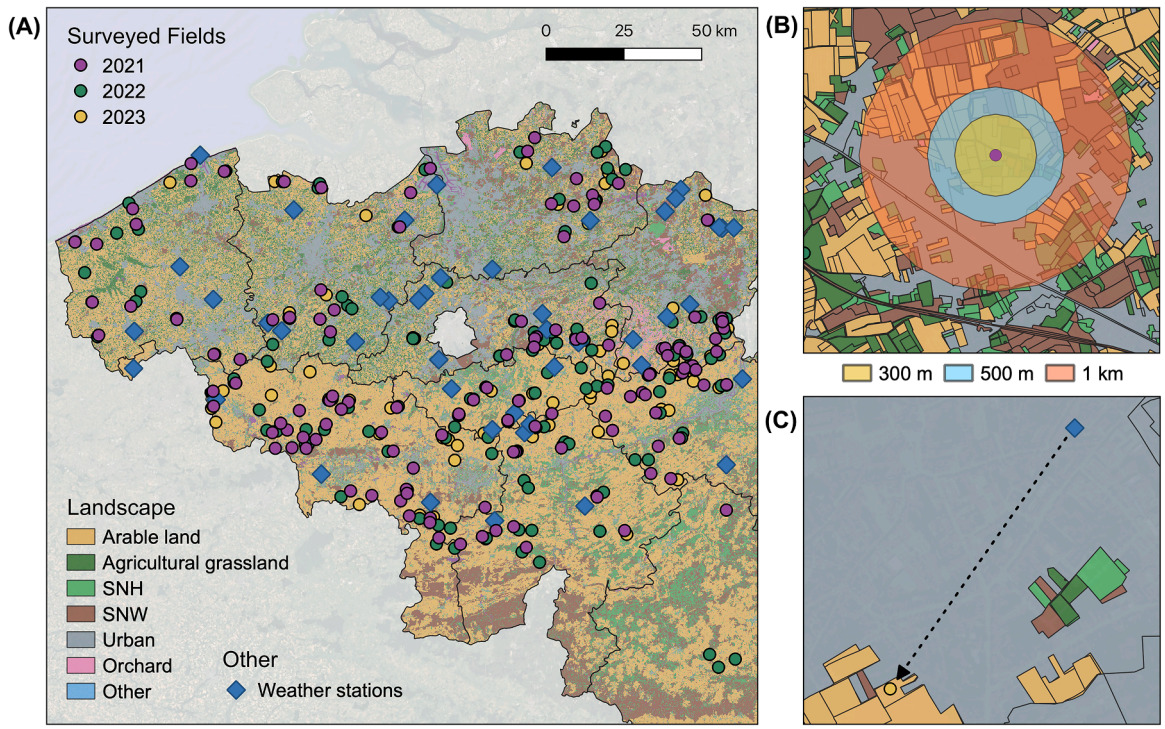


Fig. 1. (A) Land cover and land use (LCLU) map of Belgium displaying the location of surveyed fields and reference weather stations from the WOW-BE platform (KMI, 2023) for three consecutive growing seasons (2021–2023). (B) Visualization of the spatial scales used for the calculation of landscape metrics. (C) Weather station assignment.

(Fig. 1A), and each field was assigned to the nearest weather station (Fig. 1C). Subsequently, weather time series data from the assigned stations were used to calculate weather descriptors over different critical time windows that have been previously used to forecast virus yellows and the seasonal flight of *M. persicae* prior to the growing season (Luquet et al., 2023; Qi et al., 2004). The daily mean temperatures were averaged from January 1st to February 14th (TJF14), while cumulative degree-days (T; base temperature of 0 °C, without an upper threshold), precipitation (R), relative humidity (RH), wind speed (WS) and wind direction (WD) were computed as the mean daily values from November 1st to February 14th, commonly the deadline for selecting sugar beet varieties in the sector (Table S4).

Statistical analysis

Generalized linear models (GLMs) were built for each spatial scale using key landscape and weather variables to explain the first observation week and cumulative abundance of alate and apterous *M. persicae*. A total of 22 variables were initially tested (Table 1, Figures S1-S5). Poisson GLMs were applied to the week of first observation (WFO), and negative binomial regressions were used for abundance (CAb) to account for overdispersion. To minimize multicollinearity and identify relevant parameters across scales, the methodology described in Martin et al. (2016) was adapted for model selection. Given the large number of predictors, instead of fitting all possible combinations, forward model selection was performed separately at each spatial scale, guided by minimizing the second-order Akaike Information Criterion corrected for small sample sizes (AICc). Candidate predictors were added stepwise, each time selecting the variable with the greatest improvement in model fit (lowest AICc) over the intercept model. This process continued until no further improvement was achieved. The best models with $\Delta AICc < 2$ ($AICc_{model} - AICc_{best\ model}$) were selected at each scale for each response. For these models, Akaike weights (AICw) were calculated in two ways: (1) within each scale (AICw within), representing the relative weight among models at the same scale, and (2) across all scales (AICw across), representing the relative weight among all models at all scales (Rusch et al., 2011). The importance of each explanatory variable across scales was quantified as the sum of AICw across ($\sum$AICw across scales) for all models at all scales containing that variable, providing a measure of its contribution to explaining the response (Martin et al., 2016). Variables with $\sum$AICw across scales > 0.1 were considered key variables.

The model with $\Delta AICc = 0$ was selected as the best model at each spatial scale. To evaluate potential group-level structure arising from interannual variability, the random effect "Year" was added to the best models and compared with the corresponding fixed-effects-only models. Including "Year" did not improve model fit (as indicated by higher AIC values), the estimated variance component was negligible ($< 1 \times 10^{-8}$), and residual diagnostics showed no evidence of year-related structure (Table S2). Therefore, "Year" was not retained in the final models, and the selected models included only fixed effects to identify the main factors influencing the response.

Spatial autocorrelation in model residuals was assessed using Moran's I. Residuals from each of the best models were linked to sampling coordinates and projected to a metric coordinate system. Spatial weights were then generated using k-nearest neighbor networks (k = 2–8, Figure S6), and Moran's I was computed for each k to evaluate spatial dependence. No significant spatial autocorrelation was detected in model residuals (Table S3). A weak, localized clustering ($I \approx 0.2$ at low k) was observed for apterous cumulative abundance; however, the effect was limited to the smallest neighborhood scales and did not persist at broader spatial scales and was therefore assumed to be negligible for model interpretation.

The relative effect size of predictors in the best models was assessed using partial standardized coefficients (Luquet et al., 2023). The partial standardized coefficient for every predictor was obtained by standardizing the model coefficient with the standard deviation of the response variable and the partial standard deviation of the predictor (Cade, 2015). Partial standardized coefficients of fixed effects represent the direct effect of each predictor, with larger positive values indicating a stronger positive effect on the response variable when other predictors

Table 1
Variables used in the construction of GLMs explaining the arrival and cumulative abundance of alate and apterous *M. persicae* in sugar beet.

Category	Variable	Variable Description
Response variables		
Calculated for alate and apterous *M. persicae*	CAb	Cumulative abundance. Sum of the weekly counts per site.
	WFO	Week of first observation. Number of weeks since the first Monday of January until the first observation.
Predictive variables		
Landscape Calculated over three buffer areas of 300 m, 500 m, 1 km radius	$Crops_{CA/ED}$	Total class area (CA, ha) / class edge density (ED, m/ha) of arable land.
	$Urban_{CA/ED}$	Total class area (CA, ha) / class edge density (ED, m/ha) of urban landscape.
	$Grassland_{CA/ED}$	Total class area (CA, ha) / class edge density (ED, m/ha) of agricultural grassland.
	$SNH_{CA/ED}$	Total class area (CA, ha) / class edge density (ED, m/ha) of semi-natural herbaceous habitat.
	$SNW_{CA/ED}$	Total class area (CA, ha) / class edge density (ED, m/ha) of semi-natural woody habitat.
	$Orchard_{CA/ED}$	Total class area (CA, ha) / class edge density (ED, m/ha) of orchards.
Weather Calculated from November 1st to February 14th – Except TJF14	TJF14	Mean daily temperature (°C) from January 1st to February 14th.
	T	Cumulative degree-days (CDD, base temperature = 0 degrees Celsius, no upper threshold).
	WS	Mean wind speed (km/h).
	WD	Mean wind direction (°).
	R	Mean of daily rainfall (mm/h).
	RH	Mean relative humidity (%).
Local	C_{lat}	Field latitude (decimal).
	C_{long}	Field longitude (decimal).
	FA	Field area (ha).
	SW	Sowing week (# weeks since the first Monday of January).

are held constant.

All statistical analyses were performed in R v.4.3.2 (R Core Team, 2023), using the package *MASS* v.7.3–60 (Venables & Ripley, 2002) for GLMs, the package *spdep* v.1.4–1 (Bivand, 2022) for spatial autocorrelation analysis, the package *MuMIn* v.1.47.5 (Bartoń, 2023) for the calculation of partial standardized coefficients and the *ggplot2* v.3.4.4 (Wickham, 2016) package for data visualization.

Results

First detection and cumulative field abundance of M. persicae in sugar beet

Alate and apterous *M. persicae* were absent from 22 % and 15 % of surveyed fields, respectively (Table S1). Alate individuals were consistently detected earlier than apterous ones (Fig. 2; Table S1). Across the three monitoring seasons, first detections occurred between weeks 16 and 26 (mid-April to mid-June), with most fields recording initial aphid presence before mid-May. In 2022, both morphs appeared earlier and reached higher cumulative counts, particularly in fields where aphids emerged between mid-April and early May. Cumulative alate abundance varied across years, with 2.87 ± 5.11 in 2021, 8.67 ± 13.22 in 2022, and 6.16 ± 6.57 individuals in 2023. Alate numbers reached up to 50 individuals per field, except for two fields in 2022 where cumulative counts reached 108 and 62 individuals (Fig. 2A; Table S1). Apterous cumulative abundance showed a similar pattern, with 12.43 ± 15.58 in 2021, 28.42 ± 36.56 in 2022, and 16.62 ± 20.29 individuals in 2023. Apterous populations reached their highest densities in 2022, with the cumulative abundance exceeding 100 individuals in five fields and in one field in 2023 (Fig. 2B; Table S1)".

Factors affecting M. persicae arrival in sugar beet

For the time of arrival of *M. persicae*, the mean daily temperature between January 1st and February 14th (TJF14) and sowing week (SW) were consistently included in the selected models for both morphotypes (Fig. 3, Tables S4-S7). Latitude was included in a small fraction of the selected models for alate *M. persicae*, but with low variable importance across spatial scales (Fig. 3A; Tables S4, S6) and was not part of the best models (Fig. 3B). No landscape parameters had an important influence on the timing of aphid arrival (Fig. 3; Tables S6, S7), making the best models at all scales for both morphotypes the same (scale independent). Overall, the best models showed that later sowing consistently delayed aphid arrival ($p < 0.001$), while warmer winters (TJF14) led to earlier aphid occurrence ($p < 0.01$). The strength of the effect of both variables was comparable in the models for both morphotypes (Figs 3B, D).

Factors affecting M. persicae abundance in sugar beet

Landscape effects across scales

The cumulative abundances of both alate and apterous *M. persicae* were influenced by a selection of landscape variables across the spatial scales investigated (Figs 4, 5; Tables 2, 3; Tables S9-S11). The total area of semi-natural herbaceous habitat (SNH_{CA}) was the most important landscape predictor (Figs 4A, 5A; Tables 2, 3), positively influencing the abundance of both morphotypes (Figs 4B, 5B). For alate *M. persicae,* this effect was strong only at the 500 m scale (Fig. 4B; Table 2; $p < 0.001$). In contrast, the effect was strong and consistent across all spatial scales for apterous aphids (Fig. 5B; $p < 0.05$), appearing in all selected models (Table 3; Tables S9, S11). Urban landscape area ($Urban_{CA}$) positively influenced apterous *M. persicae* abundance primarily at 1 km (Fig. 5B; Table 3; $p < 0.01$), and was the second most important predictor across the different spatial scales (Fig. 5A) despite exclusion from the best models at 300 and 500 m. At the 1 km scale, total crop area ($Crops_{CA}$) had opposite effects on abundance of alate and apterous *M. persicae* (Figs 4B, 5B). However, its overall importance was less than half that of SNH_{CA} (Figs 4A, 5A; Tables 2, 3) with only the negative effect on alate *M. persicae* being statistically significant (Fig. 4B; $p < 0.05$). Edge density of semi-natural woody habitat (SNW_{ED}) positively affected alate *M. persicae* abundance at 300 m (Fig. 4B; Table 2; $p < 0.01$). Orchard area ($Orchard_{CA}$) had minor effects and was excluded from the best models (Fig. 4B; Table 2).

Weather and local effects

The mean daily temperature between January 1st and February 14th (TJF14) was included in all selected models across spatial scales for both alate and apterous *M. persicae* (Figs 4A, 5A; Tables S8-S11). For both morphotypes, TJF14 had a strong, consistent positive effect in the best models at all scales independent of other variables (Figs 4B, 5B; $p < 0.001$). Wind speed (WS) was also included in all models for alate *M. persicae* (Fig. 4A; Table S8, S10) negatively affecting aphid abundance (Fig. 4B; $p < 0.05$). Precipitation (R) was more important across scales for the abundance of the alate morphotype than most landscape variables except SNH_{CA} (Fig. 4A). However, its effect was predominantly at the 500 m scale (Tables S8, S10) and the negative effect on aphid abundance on the best model was small and not statistically significant (Fig. 4A; $p > 0.05$).

Sowing week (SW) was included in all models across scales for both morphotypes (Figs 4A, 5A; Tables S8-S11) and was the most important local factor affecting their abundance. Late sowing consistently reduced abundance regardless of landscape or weather variables (Figs 4B, 5B; $p < 0.001$). Field longitude (C_{long}) had high variable importance across scales for alate *M. persicae* abundance (Fig. 4A) but was only included in the best models at 500 m and 1 km, with a non-significant positive effect

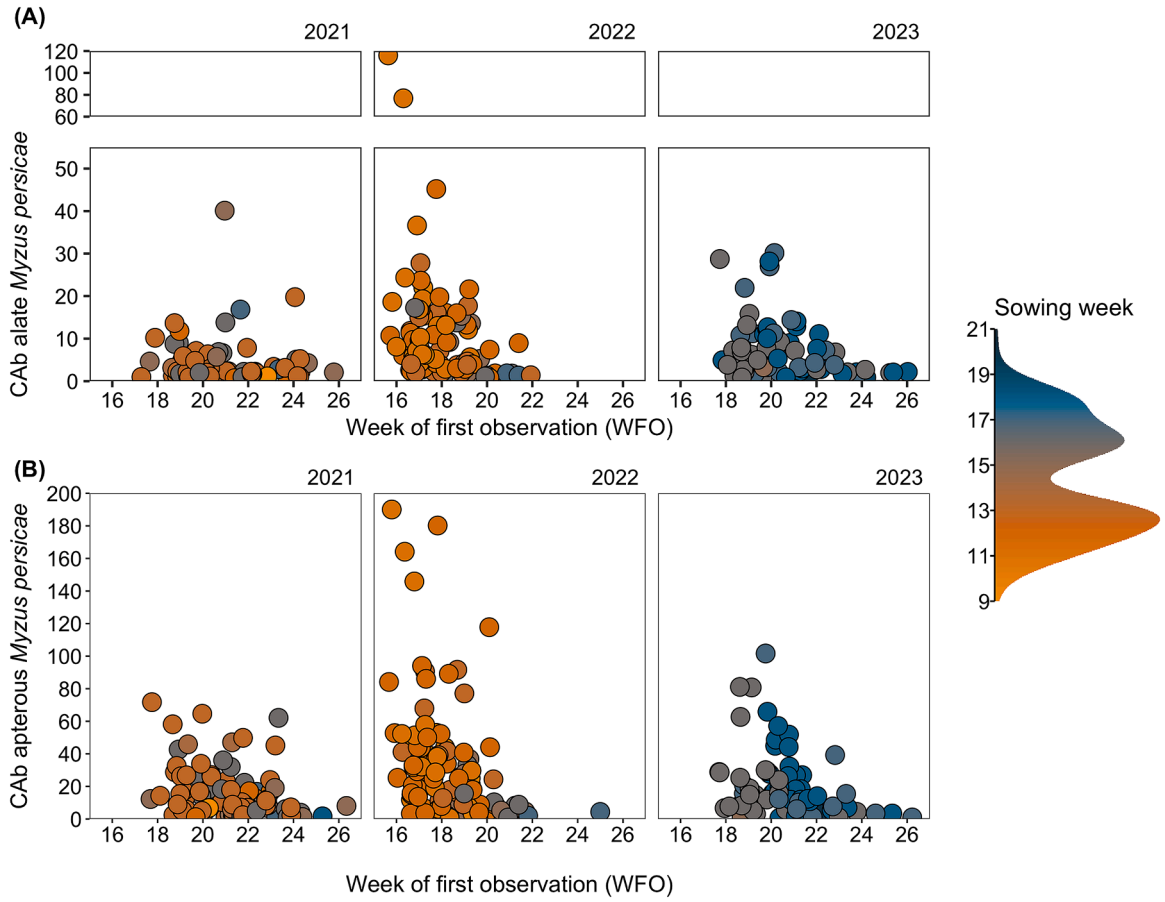


Fig. 2. Cumulative abundance (CAb) and week of first observation (WFO) of (A) alate and (B) apterous *M. persicae* in sugar beet over three consecutive growing seasons. Each point represents an individual field observation, with color indicating the sowing week for the corresponding field.

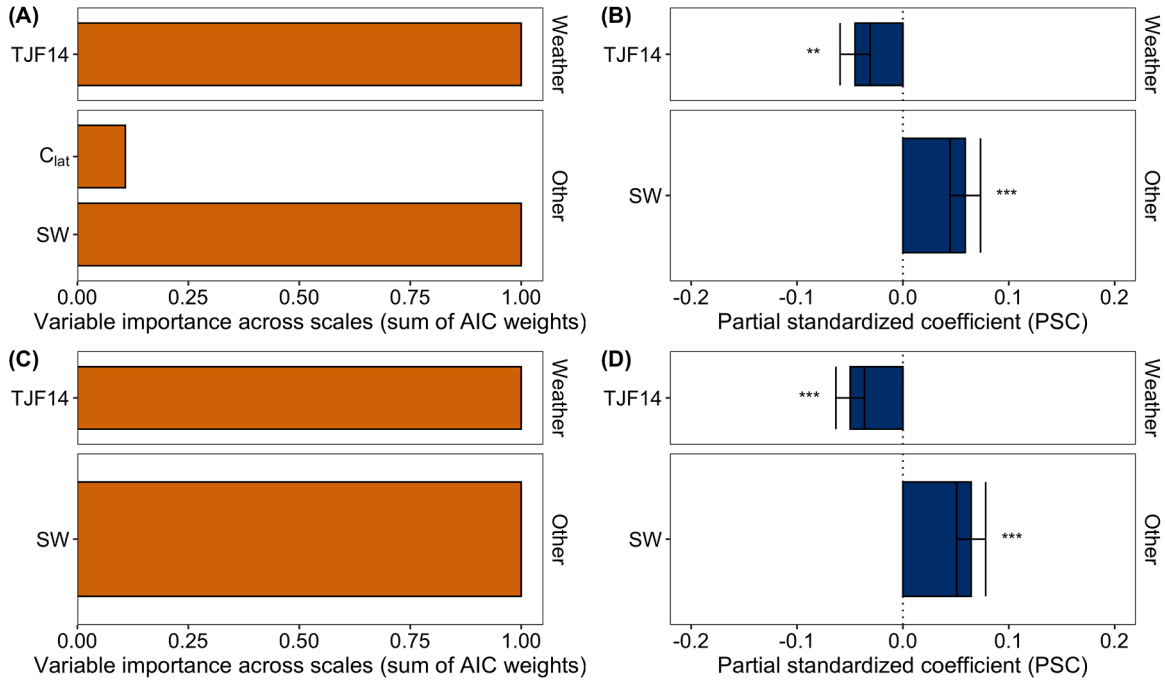


Fig. 3. Effect of key parameters on (A, B) alate and (C, D) apterous *M. persicae* first week of observation (WFO) in sugar beet. (A, C) Variable importance across scales as sum of AICc weights from selected models (ΔAICc < 2). (B, D) Partial standardized coefficients (estimate ± SE) from best models (ΔAICc = 0), describing the relative magnitude of the effects. Significant predictors are indicated by statistical significance codes: $^{**}p < 0.01$, $^{***}p < 0.001$. TJF14: Mean daily temperature (°C) from January 1st to February 14th. C_{lat}: Field latitude (decimal). SW: Sowing week corresponding to the number of weeks since the first Monday of January.

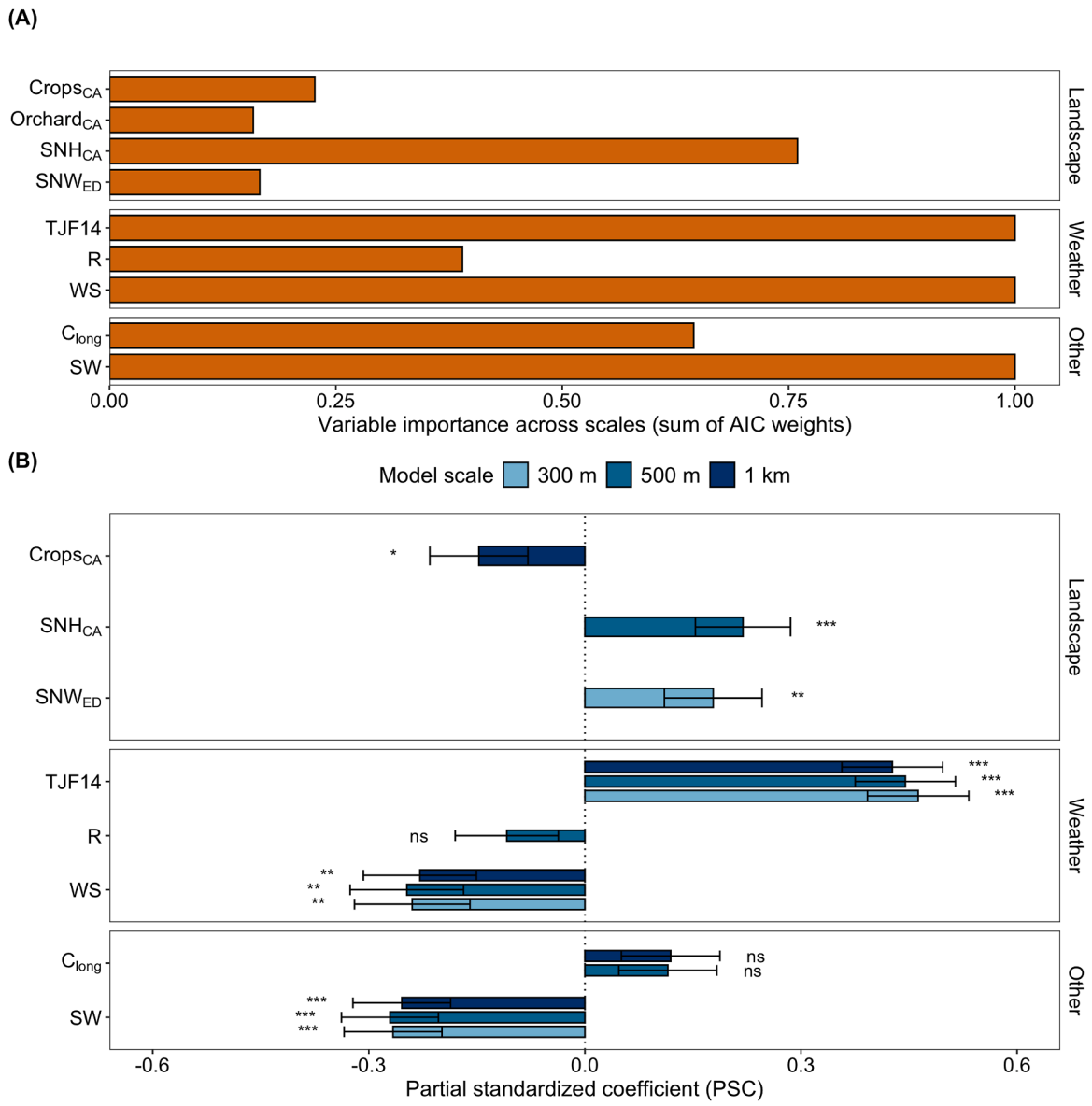


Fig. 4. Effect of key parameters on alate *M. persicae* cumulative abundance (CAb) in sugar beet. (A) Variable importance across scales as sum of AICc weights from selected models (ΔAICc < 2). (B) Partial standardized coefficients (estimate ± SE) from best models (ΔAICc = 0), describing the relative magnitude of the effects. Significant predictors are indicated by statistical significance codes: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, ns: non-significant. Crops$_{CA}$: Total class area (ha) of arable land. Orchard$_{CA}$: Total class area (ha) of orchards. SNH$_{CA}$: Total class area (ha) of semi-natural herbaceous habitat. SNW$_{ED}$: Class edge density (m/ha) of semi-natural woody habitat. TJF14: Mean daily temperature (°C) from January 1st to February 14th. R: Mean of daily rainfall (mm/h). WS: Mean wind speed (km/h). C$_{long}$: Field longitude (decimal). SW: Sowing week corresponding to the number of weeks since the first Monday of January. Weather parameters except TJF14 were calculated from November 1st to February 14th.

(Fig. 4B; $p > 0.05$). In contrast, field area (FA) was included in all models for apterous *M. persicae* abundance (Fig. 5A; Table S9, S11) and showed a consistent significant positive effect (Fig. 5B; $p < 0.05$). Overall, TJF14 and SW had the strongest effects on the abundance of both morphotypes across all spatial scales and landscape contexts, followed by WS for alate abundance, and SNH$_{CA}$ and FA for apterous abundance.

Discussion

Landscape parameters influencing M. persicae abundance

No landscape elements were found to influence the first observation of *M. persicae* in sugar beet fields, suggesting a clear dominance of weather patterns and local parameters in influencing aphid arrival and settlement. On the contrary, the abundance of *M. persicae* in sugar beet fields was strongly influenced by the surrounding landscape, consistent with previous studies linking landscape composition and configuration to arthropod pest dynamics through effects on dispersal, reproduction, survival, and natural enemies (Delaune et al., 2021; Veres et al., 2013). The abundance of the apterous morphotype was positively associated with the amount of semi-natural herbaceous habitat surrounding focal fields across all spatial scales, while the alate morphotype showed a weaker, scale-specific effect. These associations likely reflect the availability of secondary herbaceous hosts near sugar beet fields, which act as aphid reservoirs for *M. persicae*, a species known for its ability to feed and persist on a broad range of plant hosts. Such habitats may support genetically diverse *M. persicae* individuals produced through sexual reproduction on overwintering primary hosts and, under favorable conditions, also maintain parthenogenetic lineages persisting on herbaceous hosts from previous seasons or in greenhouses (Messelink et al.,

Table 2
Overall and scale-specific importance of key landscape parameters (∑AICw across > 0.1) included in the selected models (ΔAICc < 2) describing the cumulative abundance (CAb) of alate *M. persicae* in sugar beet. $Crops_{CA}$: Total class area (ha) of arable land. $Orchard_{CA}$: Total class area (ha) of orchards. SNH_{CA}: Total class area (ha) of semi-natural herbaceous habitat. SNW_{ED}: Class edge density (m/ha) of semi-natural woody habitat.

Parameter	% models[a]	Scale	% models per scale[b]	∑AICw within[c]	∑AICw across per scale[d]	∑AICw across scales[d]
		300 m	7.69	0.069	0.010	
$Crops_{CA}$	42.62	500 m	12.00	0.150	0.112	0.227
		1 km	95.65	0.958	0.105	
		300 m	7.69	0.111	0.016	
$Orchard_{CA}$	11.48	500 m	12.00	0.168	0.125	0.159
		1 km	13.04	0.157	0.017	
		300 m	7.69	0.071	0.010	
SNH_{CA}	44.26	500 m	100.00	1.000	0.746	0.760
		1 km	4.35	0.030	0.003	
		300 m	100.00	1.000	0.144	
SNW_{ED}	24.59	500 m	4.00	0.025	0.019	0.166
		1 km	4.35	0.030	0.003	

[a] Percentage of total models containing the parameter.
[b] Percentage of the total models per scale containing the parameter.
[c] AICw within was calculated using the subset of models at each corresponding spatial scale.
[d] AICw across was calculated using all models at all spatial scales (the sum corresponds to overall variable importance).

Table 3
Overall and scale-specific importance of key landscape parameters (∑AICw across > 0.1) included in the selected models (ΔAICc < 2) describing the cumulative abundance (CAb) of apterous *M. persicae* in sugar beet. $Crops_{CA}$: Total class area (ha) of arable land. SNH_{CA}: Total class area (ha) of semi-natural herbaceous habitat. $Urban_{CA}$: Total class area (ha) of urban landscape.

Parameter	% models[a]	Scale	% models per scale[b]	∑AICw within[c]	∑AICw across per scale[d]	∑AICw across scales[d]
		300 m	6.67	0.089	0.011	
$Crops_{CA}$	27.08	500 m	0.00	0.000	0.000	0.429
		1 km	57.14	0.581	0.418	
		300 m	100.00	1.000	0.123	
SNH_{CA}	100.00	500 m	100.00	1.000	0.158	1.000
		1 km	100.00	1.000	0.719	
		300 m	6.67	0.054	0.007	
$Urban_{CA}$	43.75	500 m	8.33	0.070	0.011	0.673
		1 km	90.48	0.912	0.656	

[a] Percentage of total models containing the parameter.
[b] Percentage of the total models per scale containing the parameter.
[c] AICw within was calculated using the subset of models at each corresponding spatial scale.
[d] AICw across was calculated using all models at all spatial scales (the sum corresponds to overall variable importance).

2021; Sanchez et al., 2013).

The abundance of the alate morphotype was positively associated with the edge density of semi-natural woody habitats, particularly within a 300 m radius. As the dispersal form, alates migrate from overwintering to secondary hosts, encountering diverse landscape features that can facilitate movement and settlement. Increased edge density likely reflected a greater number of habitat transitions, which may increase the availability of shelter sites and alternative aphid reservoirs. These conditions can support larger alate populations, consistent with findings by Thies et al. (2005), who reported an overall positive effect of structurally complex landscapes on aphid abundance. Moreover, Alignier et al. (2014) showed that forest edges had a positive effect on early aphid abundance through local dispersal, with predation pressures at the forest edges driving populations towards crop fields. However, they also observed a negative effect on early abundance at a large scale and on late abundance at a small scale, possibly due to the spillover of beneficial insects from woods to field crops. Studer et al. (2025) showed that forest cover had contrasting effects on aphid natural enemies in sugar beet. While it was positively associated with parasitic wasp abundance at smaller spatial scales, likely due to favorable microclimatic or resource conditions, it was negatively associated with hoverflies at broader scales, reflecting their preference for more open agricultural landscapes. While some alate individuals may have originated within the field, their production is generally linked to crowding, variable host quality, or natural enemy pressure (Müller et al., 2001; Sentis et al., 2019). In sugar beet, low population densities and scarce natural enemies favor the predominance of apterous morphs, suggesting that alates observed in the field are more likely associated with dispersal than with local population growth. However, the dynamics underlying alate production are complex and influenced by multiple interacting factors, which require further investigation. The positive association between total crop area and apterous *M. persicae* abundance aligns with findings of Cocu et al. (2005), who observed higher aphid densities in arable landscapes possibly due to greater food availability. Conversely, there was a negative correlation between arable land and the abundance of alate *M. persicae*. In this study, we used spatial scales that reflect the distances aphids typically travel during exploratory flights, characterized by repeated landings on host and non-host plants, and short migrations (Parry, 2013). At these scales, greater availability of suitable host plants may reduce alate production, as aphids are less likely to disperse in search of better food sources. However, the widely held assumption that wing induction is triggered by poor nutrition has been challenged (Müller et al., 2001).

Consistent with the positive influence of urban area on the population abundance of apterous *M. persicae* observed in this study, urbanization has been shown to benefit aphid populations by altering bottom-up and top-down processes in tri-trophic interactions (Butler & Trumble, 2008; Korányi et al., 2021; Turrini et al., 2016). Frequent exposure to pollutants such as SO_2, NO_2 and ozone could make plants better hosts for aphids, enhancing the development and survival of aphid populations, likely due to increased nutrient availability (Butler & Trumble, 2008). In addition, urbanization also fragments habitats and reduces natural enemy abundance, favoring mobile generalist species and weakening aphid control (Corcosid et al., 2019; Turrini et al., 2016). Urbanization affected apterous but not alate *M. persicae*, possibly because predators struggle to target dispersing aphids. However, since predator pressure can increase alate production (Sentis et al., 2019), urbanization may indirectly influence alate *M. persicae* in ways not captured here.

Weather conditions influencing M. persicae arrival and abundance

Warmer winters favored the early arrival and abundance of *M. persicae* in sugar beet fields across Belgium. This association may account for the earlier aphid observations and increased cumulative counts observed in 2022 relative to 2021 and 2023, potentially driven by the comparatively warmer winter months preceding the 2022 sugar

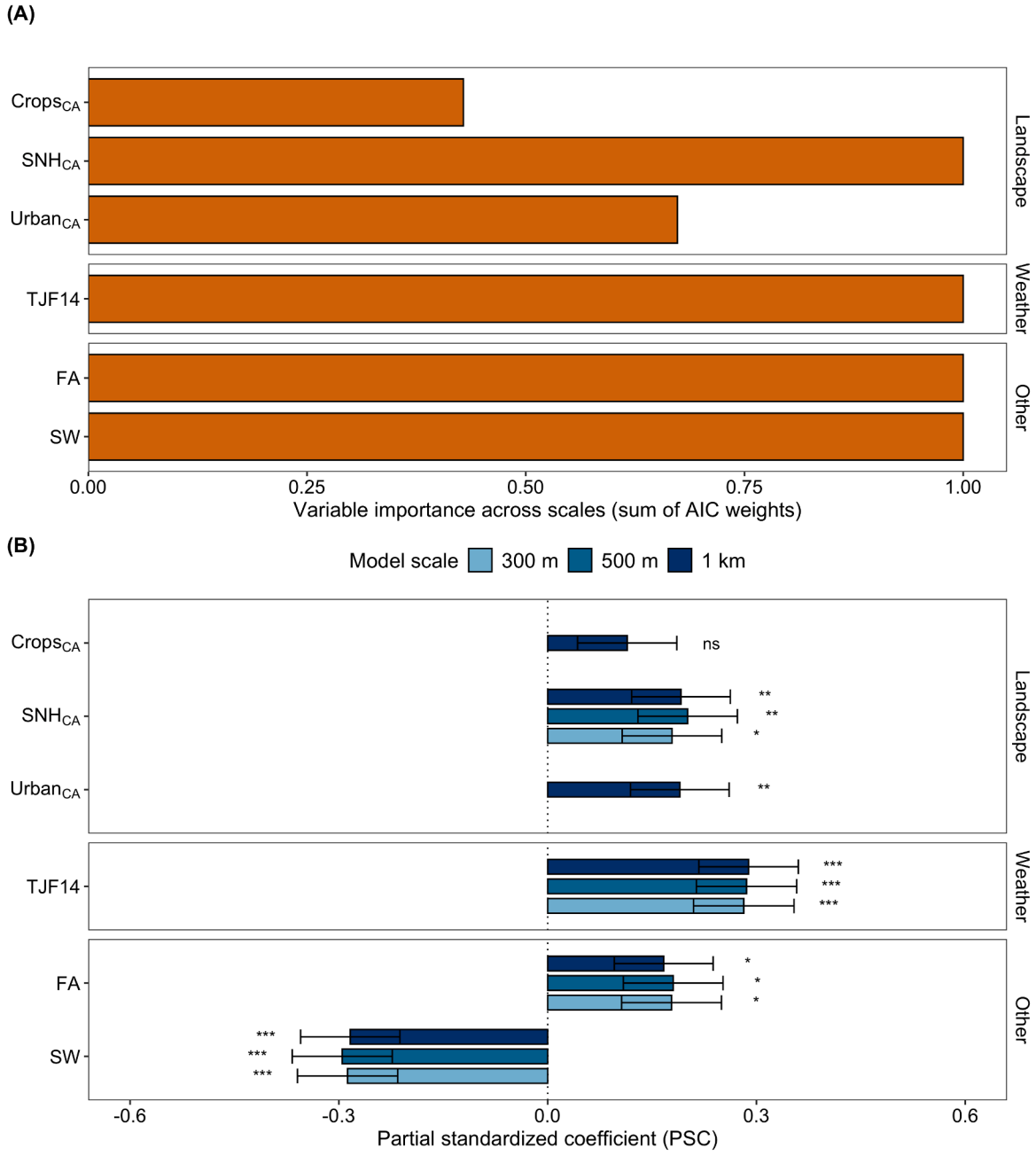


Fig. 5. Effect of key parameters on apterous *M. persicae* cumulative abundance (CAb) in sugar beet. (A) Variable importance across scales as sum of AICc weights from selected models (ΔAICc < 2). (B) Partial standardized coefficients (estimate ± SE) from best models (ΔAICc = 0), describing the relative magnitude of the effects. Significant predictors are indicated by statistical significance codes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$, ns: non-significant. Crops$_{CA}$: Total class area (ha) of arable land. SNH$_{CA}$: Total class area (ha) of semi-natural herbaceous habitat. Urban$_{CA}$: Total class area (ha) of urban landscape. TJF14: Mean daily temperature (°C) from January 1st to February 14th. FA: Field area (ha). SW: Sowing week corresponding to the number of weeks since the first Monday of January.

beet growing season. Similar findings in England (Dewar & Qi, 2021; Hemming et al., 2022) and France (Luquet et al., 2023) link earlier aphid flights to warmer winters, with global warming contributing to earlier and longer migratory periods (Wu et al., 2020). In addition, the broad host range of *M. persicae* and tendency for anholocyclic life cycles during warm winters (Cocu et al., 2005) may lead to higher overwintering and early spring populations. Moreover, thermal requirements for development and survival (Whalon & Smilowitz, 1979) support the positive impact of warm winters on both the time of arrival and abundance of *M. persicae* in sugar beet fields. Warmer winters may also disrupt the phenological synchrony between aphids and their natural enemies (e.g., aphid-parasitoid systems), as these organisms may respond differently to temperature changes (Le Ralec et al., 2010).

Wind speed negatively affected alate *M. persicae* abundance, consistent with reports that higher wind speeds hinder aphid migration by preventing departure from winter hosts or causing uncontrolled downwind low-altitude flights (Bell et al., 2023; Nemecek, 1993; Parry, 2013). Moreover, changes in migration routes due to habitat fragmentation can also significantly influence the spread of pests (Mazzi & Dorn, 2012) and modulate the effects of wind speed on aphid abundance. The abundance of alate *M. persicae* was also negatively influenced by rainfall, although the evidence for this effect was less conclusive than for wind speed. While rainfall can promote both the extent and distance of aphid movement, it has also been shown to increase aphid mortality, as

heavy rain can clear aphids from the air and kill newly established individuals on plants (Parry, 2013).

Local factors influencing M. persicae arrival and abundance

Late sowing consistently led to the late arrival and lower abundance of alate and apterous *M. persicae* in sugar beet fields, while the size of the field was positively correlated with the abundance of the apterous morphotype. Although *M. persicae* is a generalist, reproductive performance varies among plant species (Altesor & González, 2023; Hong et al., 2019). Thus, in fields with later sowing dates, early-spring migrants from overwintering hosts may have settled on alternative secondary herbaceous hosts, delaying or limiting their colonization of sugar beet, with later sowing also resulting in sugar beet host plants becoming available only later in the season. Moreover, in temperate regions, late sowing can sometimes lead to faster canopy closure when warmer and drier conditions favor rapid growth. In contrast, early sowing during wet, cool springs may result in poor emergence and slower development. Under such conditions, later sowing may shorten the period before canopy closure, limiting the time available for aphid population buildup on young plants. Earlier aphid arrival on early-sown fields may also lead to higher aphid abundance early in the season and create a temporal mismatch with natural enemies, potentially reducing biological control (Fuchs et al., 2017). Additionally, field margins can sustain natural enemies by offering floral and nutritional resources that enhance their survival and biocontrol activity (Crowther et al., 2023; Salat-Moltó et al., 2023). However, in large homogeneous sugar beet fields, the influence of these margins likely diminishes with increasing distance from the edges, reducing the influx and effectiveness of natural enemies in central areas. This reduced biological control pressure may explain the observed positive association between field area and apterous *M. persicae* abundance.

Implications for pest management

Our results clearly demonstrate that warmer winters promote earlier arrival and higher abundance of aphids, highlighting the increasing risk of aphid outbreaks under global warming. However, this climate-driven risk can be mitigated by considering landscape composition and structure, as these factors strongly influenced *M. persicae* abundance in sugar beet. Larger sugar beet fields and those in urbanized areas are at greater risk of aphid infestation, likely due to reduced natural enemy populations. The use of smaller sugar beet fields and delaying sowing in large fields, combined with management practices that support natural enemies could help mitigate these landscape-related risks, particularly in heterogenous landscapes containing multiple aphid reservoirs. Recent studies have shown that certain habitat manipulations can enhance early-season natural enemy communities in sugar beet systems. For example, Studer et al. (2025) showed that different types of flower strips and nearby landscape elements can increase natural enemy activity and reduce pest pressure. Other studies suggest that non-pest aphid species occurring on shrubs or flowering plants may provide alternative prey that help sustain natural enemies early in the season (Zytynska et al., 2021). Although our study did not directly assess these management approaches, they may represent promising complementary strategies to improve early biological control in sugar beet fields and could be explored in future work. In summary, by integrating information on weather conditions and landscape features, farmers can better anticipate aphid pressure and implement targeted pest management strategies, including strategic field selection, adjusted sowing dates, field margin design, and optimized insecticide application, to reduce aphid outbreaks and virus transmission while minimizing environmental impact.

Author contributions

NRP, AW, BL and HJ contributed to the study conception and design. Data collection and project administration was performed by AW. Data analysis was performed by NRP and HJ. The first draft of the manuscript was written by NRP, and all authors commented on previous versions of the manuscript and read and approved the final manuscript.

Data availability statement

The dataset and accompanying R script employed in the construction and analysis of the generalized linear models are available in the **Supplementary Material**.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Nicolas Rojas-Preciado: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **André Wauters:** Writing – review & editing, Project administration, Data curation, Conceptualization. **Bart Lievens:** Writing – review & editing, Supervision, Conceptualization. **Hans Jacquemyn:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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References

Ali, J., Bayram, A., Mukarram, M., Zhou, F., Karim, M. F., Mohammed, M., Hafez, A., Mahamood, M., Yusuf, A. A., Jie, P., King, H., Faheem Adil, M., Ma, Z., & Shamsi, I. H. (2023). Peach-potato aphid Myzus persicae: Current management strategies, challenges, and proposed solutions. *Sustainability, 15*(14), Article 11150. https://doi.org/10.3390/su151411150

Ali, M. Y., Naseem, T., Arshad, M., Ashraf, I., Rizwan, M., Tahir, M., Rizwan, M., Sayed, S., Ullah, M. I., Khan, R. R., Amir, M. B., Pan, M., Liu, T.-X., & Kavallieratos, G. (2021). Host-plant variations affect the biotic potential, survival, and population projection of Myzus persicae (Hemiptera: Aphididae). *Insects, 12*(5), 375. https://doi.org/10.3390/insects12050375

Alignier, A., Raymond, L., Deconchat, M., Menozzi, P., Monteil, C., Sarthou, J.-P., Vialatte, A., & Ouin, A. (2014). The effect of semi-natural habitats on aphids and their natural enemies across spatial and temporal scales. *Biological Control, 77*, 76–82. https://doi.org/10.1016/j.biocontrol.2014.06.006

Altesor, P., & González, A. (2023). Preference and performance of the generalist aphid Myzus persicae on closely and distantly related plant species. *Entomologia Experimentalis et Applicata, 171*(10), 754–764. https://doi.org/10.1111/eea.13341

Bartoń, K. (2023). MuMIn: Multi-model inference. https://CRAN.R-project.org/package=MuMIn.

Bass, C., & Field, L. M. (2018). Neonicotinoids. *Current Biology, 28*(14), R772–R773. https://doi.org/10.1016/j.cub.2018.05.061

Bass, C., Puinean, A. M., Zimmer, C. T., Denholm, I., Field, L. M., Foster, S. P., Gutbrod, O., Nauen, R., Slater, R., & Williamson, M. S. (2014). The evolution of insecticide resistance in the peach potato aphid, Myzus persicae. *Insect Biochemistry and Molecular Biology, 51*, 41–51. https://doi.org/10.1016/j.ibmb.2014.05.003

Bell, J. R., Clark, S. J., Stevens, M., & Mead, A. (2023). Quantifying inherent predictability and spatial synchrony in the aphid vector Myzus persicae: Field-scale patterns of abundance and regional forecasting error in the UK. *Pest Management Science, 79*(4), 1331–1341. https://doi.org/10.1002/ps.7292

Bivand, R. (2022). R packages for analyzing spatial data: A comparative case study with areal data. *Geographical Analysis, 54*(3), 488–518. https://doi.org/10.1111/gean.12319

Brewer, M. J., & Elliott, N. C. (2023). Recent advances in agroecological research for increasing scope of areawide pest management of arthropods in cropping systems. *Current Opinion in Insect Science, 56*, Article 101019. https://doi.org/10.1016/J.COIS.2023.101019

Butler, C. D., & Trumble, J. T. (2008). Effects of pollutants on bottom-up and top-down processes in insect–plant interactions. *Environmental Pollution, 156*(1), 1–10. https://doi.org/10.1016/j.envpol.2007.12.026

Cade, B. S. (2015). Model averaging and muddled multimodel inferences. *Ecology, 96*(9), 2370–2382. https://doi.org/10.1890/14-1639.1

Cao, H.-H., Zhang, Z.-F., Wang, X.-F., & Liu, T.-X. (2018). Nutrition versus defense: Why Myzus persicae (green peach aphid) prefers and performs better on young leaves of cabbage. *PLOS ONE, 13*(4), Article e0196219. https://doi.org/10.1371/journal.pone.0196219

Cocu, N., Harrington, R., Rounsevell, M. D. A., Worner, S. P., & Hullé, M. (2005). Geographical location, climate and land use influences on the phenology and numbers of the aphid, *Myzus persicae*, in Europe. *Journal of Biogeography, 32*(4), 615–632. https://doi.org/10.1111/j.1365-2699.2005.01190.x

Corcosid, D., Cerrettiid, P., Caruso, V., Mei, M., Falcoid, M., & Marini, L. (2019). Impact of urbanization on predator and parasitoid insects at multiple spatial scales. *PLOS ONE, 14*(4), Article e0214068. https://doi.org/10.1371/journal.pone.0214068

Courson, E., Petit, S., Poggi, S., & Ricci, B. (2022). Weather and landscape drivers of the regional level of pest occurrence in arable agriculture: A multi-pest analysis at the French national scale. *Agriculture, Ecosystems and Environment,, 338*, Article 108105. https://doi.org/10.1016/j.agee.2022.108105

Crowther, L. I., Wilson, K., & Wilby, A. (2023). The impact of field margins on biological pest control: A meta-analysis. *BioControl,, 68*, 387–396. https://doi.org/10.1007/s10526-023-10205-6

Daelemans, R., Hulsmans, E., Laenen, E., Remy, S., Beliën, T., & Honnay, O. (2023). Direct and indirect effects of management and landscape on biological pest control and crop pest infestation in apple orchards. *Journal of Applied Ecology, 60*(1), 181–192. https://doi.org/10.1111/1365-2664.14319

Delaune, T., Ouattara, M. S., Ballot, R., Sausse, C., Felix, I., Maupas, F., Chen, M., Morison, M., Makowski, D., & Barbu, C. (2021). Landscape drivers of pests and pathogens abundance in arable crops. *Ecography, 44*(10), 1429–1442. https://doi.org/10.1111/ecog.05433

Dent, D., & Binks, R. H. (2020). *Insect pest management (3rd edition)*. CABI.

Dewar, A. M., & Qi, A. (2021). The virus yellows epidemic in sugar beet in the UK in 2020 and the adverse effect of the EU ban on neonicotinoids on sugar beet production. *Outlooks on Pest Management, 32*(2), 53–59. https://doi.org/10.1564/v32_apr_02

Elbert, A., Haas, M., Springer, B., Thielert, W., & Nauen, R. (2008). Applied aspects of neonicotinoid uses in crop protection. *Pest Management Science, 64*(11), 1099–1105. https://doi.org/10.1002/ps.1616

Fuchs, B., Breuer, T., Findling, S., Krischke, M., Mueller, M. J., Holzschuh, A., & Krauss, J. (2017). Enhanced aphid abundance in spring desynchronizes predator–prey and plant–microorganism interactions. *Oecologia, 183*(2), 469–478. https://doi.org/10.1007/s00442-016-3768-1

Haan, N. L., Zhang, Y., & Landis, D. A. (2020). Predicting landscape configuration effects on agricultural pest suppression. *Trends in Ecology & Evolution, 35*(2), 175–186. https://doi.org/10.1016/J.TREE.2019.10.003

Hemming, D., Bell, J., Collier, R., Dunbar, T., Dunstone, N., Everatt, M., Eyre, D., Kaye, N., Korycinska, A., Pickup, J., & Scaife, A. A. (2022). Likelihood of extreme early flight of Myzus persicae (Hemiptera: Aphididae) across the UK. *Journal of Economic Entomology, 115*(5), 1342–1349. https://doi.org/10.1093/jee/toac012

Hesselbarth, M. H. K., Sciaini, M., With, K. A., Wiegand, K., & Nowosad, J. (2019). landscapemetrics: An open-source R tool to calculate landscape metrics. *Ecography, 42*(10), 1648–1657. https://doi.org/10.1111/ecog.04617

Holland, J. M., Douma, J. C., Crowley, L., James, L., Kor, L., Stevenson, D. R. W., & Smith, B. M. (2017). Semi-natural habitats support biological control, pollination and soil conservation in Europe. A review. *Agronomy for Sustainable Development, 37*, 31. https://doi.org/10.1007/s13593-017-0434-x

Hong, F., Han, H. L., Pu, P., Wei, D., Wang, J., & Liu, Y. (2019). Effects of five host plant species on the life history and population growth parameters of Myzus persicae (Hemiptera: Aphididae). *Journal of Insect Science, 19*(5). https://doi.org/10.1093/jisesa/iez094

Hossain, R., Menzel, W., Lachmann, C., & Varrelmann, M. (2021). New insights into virus yellows distribution in Europe and effects of beet yellows virus, beet mild yellowing virus, and beet chlorosis virus on sugar beet yield following field inoculation. *Plant Pathology, 70*(3), 584–593. https://doi.org/10.1111/ppa.13306

INBO. (2020). Biologische waarderingskaart en natura 2000 habitatkaart. Datavindplaats Vlaamse Overheid. https://www.vlaanderen.be/datavindplaats/catalogus/biologische-waarderingskaart-en-natura-2000-habitatkaart-toestand-2020.

KMI. (2023). WOW-BE (Weather Observations Website – Belgium). https://wow.meteo.be/.

Korányi, D., Szigeti, V., Mezőfi, L., Kondorosy, E., & Markó, V. (2021). Urbanization alters the abundance and composition of predator communities and leads to aphid outbreaks on urban trees. *Urban Ecosystems, 24*, 571–586. https://doi.org/10.1007/s11252-020-01061-8

Le Ralec, A., Anselme, C., Outreman, Y., Poirié, M., Van Baaren, J., Le Lann, C. C., & Van Alphen, J. J. M. (2010). Evolutionary ecology of the interactions between aphids and their parasitoids. *Comptes Rendus Biologies, 333*(6–7), 554–565. https://doi.org/10.1016/J.CRVI.2010.03.010

Lehmann, P., Ammunét, T., Barton, M., Battisti, A., Uhd Jepsen, J., Kalinkat, G., Neuvonen, S., Økland, B., Terblanche, J. S., & Björkman, C. (2020). Complex responses of global insect pests to climate warming. *Frontiers in Ecology and the Environment, 18*(3), 141–150. https://doi.org/10.1002/fee.2160

Luquet, M., Poggi, S., Buchard, C., Plantegenest, M., & Tricault, Y. (2023). Predicting the seasonal flight activity of Myzus persicae, the main aphid vector of Virus Yellows in sugar beet. *Pest Management Science, 79*(11), 4508–4520. https://doi.org/10.1002/ps.7653

LV. (2020). Landbouwgebruikspercelen. *Datavindplaats Vlaamse Overheid*. https://www.vlaanderen.be/datavindplaats/catalogus/landbouwgebruikspercelen-lv-2020.

Marshall, E. J. P (2004). Agricultural Landscapes. *Journal of Crop Improvement, 12*(1–2), 365–404. https://doi.org/10.1300/J411v12n01_05

Martin, E. A., Seo, B., Park, C., Reineking, B., & Steffan-Dewenter, I. (2016). Scale-dependent effects of landscape composition and configuration on natural enemy diversity, crop herbivory, and yields. *Ecological Applications, 26*(2), 448–462. https://doi.org/10.1890/15-0856

Mazzi, D., & Dorn, S. (2012). Movement of insect pests in agricultural landscapes. *Annals of Applied Biology, 160*(2), 97–113. https://doi.org/10.1111/j.1744-7348.2012.00533.x

Mech, A. M., Tobin, P. C., Teskey, R. O., Rhea, J. R., & Gandhi, K. J. K (2018). Increases in summer temperatures decrease the survival of an invasive forest insect. *Biological Invasions, 20*, 365–374. https://doi.org/10.1007/s10530-017-1537-7

Messelink, G. J., Lambion, J., Janssen, A., & van Rijn, P. C. J. (2021). Biodiversity in and around greenhouses: Benefits and potential risks for pest management. *Insects, 12*(10), 933. https://doi.org/10.3390/insects12100933

Mota-Sanchez, D., Hollingworth, R. M., & Whalon, M. E. (2008). *Global pesticide resistance in arthropods*. CABI.

Müller, C. B., Williams, I. S., & Hardie, J. (2001). The role of nutrition, crowding and interspecific interactions in the development of winged aphids. *Ecological Entomology, 26*(3), 330–340. https://doi.org/10.1046/j.1365-2311.2001.00321.x

Nemecek, T. (1993). The role of aphid behaviour in the epidemiology of Potato Virus Y: A simulation study [ETH Zurich]. 10.3929/ethz-a-000909462.

Olatinwo, R., & Hoogenboom, G. (2014). Weather-based pest forecasting for efficient crop protection. *Integrated pest management* (pp. 59–78). Academic Press. https://doi.org/10.1016/B978-0-12-398529-3.00005-1

Parry, H. R. (2013). Cereal aphid movement: General principles and simulation modelling. *Movement Ecology, 1*, 14. https://doi.org/10.1186/2051-3933-1-14

Pebesma, E. (2018). Simple features for R: Standardized support for spatial vector data. *The R Journal, 10*(1), 439–446. https://doi.org/10.32614/RJ-2018-009

Pebesma, E., & Bivand, R. (2023). *Spatial data science: With applications in R*. Chapman and Hall/CRC. https://doi.org/10.1201/9780429459016

Perrot, T., Rusch, A., Coux, C., Gaba, S., & Bretagnolle, V. (2021). Proportion of grassland at landscape scale drives natural pest control services in agricultural landscapes. *Frontiers in Ecology and Evolution, 9*, Article 607023. https://doi.org/10.3389/fevo.2021.607023

Phélippé-Guinvarc'h, M., & Cordier, J. (2024). Actuarial implications and modeling of virus yellows on sugar beet after the EU's ban on neonics and climate change. *Smart Agricultural Technology, 8*, Article 100493. https://doi.org/10.1016/j.atech.2024.100493

QGIS Development Team. (2023). *QGIS geographic information system*. Open Source Geospatial Foundation Project. http://qgis.osgeo.org.

Qi, A., Dewar, A. M., & Harrington, R. (2004). Decision making in controlling virus yellows of sugar beet in the UK. *Pest Management Science, 60*(7), 727–732. https://doi.org/10.1002/ps.871

R Core Team. (2023). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/.

Rakotoarinia, M. R., Guillaume Blanchet, F., Gravel, D., Lapen, D. R., Leighton, P. A., Ogden, N. H., & Ludwig, A. (2022). Effects of land use and weather on the presence and abundance of mosquito-borne disease vectors in a urban and agricultural landscape in Eastern Ontario. *Canada. PLOS ONE, 17*(3), Article e0262376. https://doi.org/10.1371/journal.pone.0262376

Reed, T. E., Schindler, D. E., & Waples, R. S. (2011). Interacting effects of phenotypic plasticity and evolution on population persistence in a changing climate. *Conservation Biology, 25*(1), 56–63. https://doi.org/10.1111/j.1523-1739.2010.01552.x

Rusch, A., Valantin-Morison, M., Sarthou, J.-P., & Roger-Estrade, J. (2011). Multi-scale effects of landscape complexity and crop management on pollen beetle parasitism rate. *Landscape Ecology, 26*(4), 473–486. https://doi.org/10.1007/s10980-011-9573-7

Salat-Moltó, A., Caballero-López, B., Pérez-Hidalgo, N., Michelena, J. M., Ferrer Suay, M., Guerrieri, E., & Blanco-Moreno, J. M. (2023). Not all field margins are equally useful: Effects of the vegetation structure of margins on cereal aphids and their natural enemies. *Insects,, 14*(2), 156. https://doi.org/10.3390/insects14020156

Sanchez, J. A., La-Spina, M., Guirao, P., & Cánovas, F. (2013). Inferring the population structure of Myzus persicae in diverse agroecosystems using microsatellite markers. *Bulletin of Entomological Research, 103*(4), 473–484. https://doi.org/10.1017/S0007485313000059

Santos, L. A. O., Botelho Costa, M., Lavigne, C., Aparecido Fernandes, O., Bischoff, A., & Franck, P. (2018). Influence of the margin vegetation on the conservation of aphid biological control in apple orchards. *Journal of Insect Conservation, 22*, 465–474. https://doi.org/10.1007/s10841-018-0074-8

Schneider, L., Rebetez, M., & Rasmann, S. (2022). The effect of climate change on invasive crop pests across biomes. *Current Opinion in Insect Science, 50*, Article 100895. https://doi.org/10.1016/J.COIS.2022.100895

Schop, S., Kloth, K. J., Raaijmakers, E., & van der Vlugt, R. A. A (2022). The effect of mature plant resistance in sugar beet (Beta vulgaris spp. vulgaris) on survival, fecundity and behaviour of green peach aphids (Myzus persicae). *Bulletin of Entomological Research, 112*(5), 707–714. https://doi.org/10.1017/S0007485322000128

Sentis, A., Bertram, R., Dardenne, N., Ramon-Portugal, F., Louit, I., Le Trionnaire, G., Simon, J.-C., Magro, A., Pujol, B., Hemptinne, J.-L., & Danchin, E. (2019). Different phenotypic plastic responses to predators observed among aphid lineages specialized on different host plants. *Scientific Reports, 9*, 9017. https://doi.org/10.1038/s41598-019-45220-0

SPW. (2020a). Occupation du sol en Wallonie. *Géoportail de La Wallonie*. https://geoportail.wallonie.be/catalogue/47b348f1-6e7a-4baa-963c-0232a43c0cff.html.

SPW. (2020b). Parcellaire agricole anonyme. *Géoportail de La Wallonie*. https://geoportail.wallonie.be/catalogue/af3bbfca-02d8-454a-818b-188aaf0f91aa.html.

Studer, A., Näpflin, L., Jeanneret, P., & Jacot, K. (2025). Enhancing natural enemies in sugar beet fields: The impact of flower strip types and landscape elements. *Biological Control, 210*, Article 105879. https://doi.org/10.1016/j.biocontrol.2025.105879

Thies, C., Roschewitz, I., & Tscharntke, T. (2005). The landscape context of cereal aphid–parasitoid interactions. *Proceedings of the Royal Society B: Biological Sciences, 272*(1559), 203–210. https://doi.org/10.1098/rspb.2004.2902

Turrini, T., Sanders, D., & Knop, E. (2016). Effects of urbanization on direct and indirect interactions in a tri-trophic system. *Ecological Applications, 26*(3), 664–675. https://doi.org/10.1890/14-1787

Venables, W. N., & Ripley, B. D. (2002). Modern applied statistics with S (Fourth). https://www.stats.ox.ac.uk/pub/MASS4/.

Veres, A., Petit, S., Conord, C., & Lavigne, C. (2013). Does landscape composition affect pest abundance and their control by natural enemies? A review. *Agriculture, Ecosystems & Environment, 166*, 110–117. https://doi.org/10.1016/J.AGEE.2011.05.027

Whalon, M. E., & Smilowitz, Z. (1979). The interaction of temperature and biotype on development of the green peach aphid Myzus persicae (Sulz.). *American Potato Journal, 56*, 591–596. https://doi.org/10.1007/BF02853990

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. New York: Springer-Verlag.

Wintermantel, W. M. (2005). Co-infection of beet mosaic virus with beet yellowing viruses leads to increased symptom expression on sugar beet. *Plant Disease, 89*(3), 325–331. https://doi.org/10.1094/PD-89-0325

Wu, Y., Li, J., Liu, H., Qiao, G., & Huang, X. (2020). Investigating the impact of climate warming on phenology of aphid pests in China using long-term historical data. *Insects, 11*(3), 167. https://doi.org/10.3390/insects11030167

Xie, W., Men, X., Liu, S., Glaum, P., Li, R., Wen, Z., Yang, Q., Huang, B., Zhang, L., Zheng, H., Shen, Y., Yang, Y., & Ouyang, Z. (2023). Landscape composition and configuration relatively affect invasive pest and its associator across multiple spatial scales. *Frontiers in Sustainable Food Systems, 7*, Article 1114508. https://doi.org/10.3389/fsufs.2023.1114508

Zhang, Y., Haan, N. L., & Landis, D. A. (2020). Landscape composition and configuration have scale-dependent effects on agricultural pest suppression. *Agriculture, Ecosystems & Environment, 302*, Article 107085. https://doi.org/10.1016/J.AGEE.2020.107085

Zytynska, S. E., Eicher, M., Fahle, R., & Weisser, W. W. (2021). Effect of flower identity and diversity on reducing aphid populations via natural enemy communities. *Ecology and Evolution, 11*(24), 18434–18445. https://doi.org/10.1002/ece3.8432