

Czynniki wpływające na występowanie wybranych inwazyjnych obcych gatunków roślin wzdłuż dróg w Polsce

Factors affecting the occurrence of selected invasive alien
plant species along roads in Poland

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Rozprawa doktorska

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Kraków, 2022

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SPIS PRAC

- I. Kotowska, D., Pärt, T., & Żmihorski, M. (2021). Evaluating Google Street View for tracking invasive alien plants along roads. *Ecological Indicators*, 121, 107020. DOI: 10.1016/j.ecolind.2020.107020. (IF = 4.958, 140 pkt MEiN)
- II. Kotowska, D., Pärt, T., Skórka, P., Auffret, A. G. & Żmihorski, M. (2022). Scale dependence of landscape heterogeneity effects on plant invasions. *Journal of Applied Ecology*, 59(5), 1313–1323. DOI: 10.1111/1365-2664.14143. (IF = 6.528, 140 pkt MEiN)
- III. Kotowska, D., Skórka, P., Pärt, T., Auffret, A. G. & Żmihorski, M. Spatial scale matters for predicting plant invasions along roads – maszynopis (wysłany do recenzji w *Ecology*).

FINANSOWANIE BADAŃ

Badania wchodzące w skład rozprawy doktorskiej finansowane były przez Narodowe Centrum Nauki w ramach grantu PRELUDIUM 2016/21/N/NZ8/01286 oraz stypendium ETIUDA 2019/32/T/NZ8/00343.

STRESZCZENIE

Inwazje gatunków obcych uznawane są za jedno z najpoważniejszych zagrożeń dla różnorodności biologicznej na świecie. Mimo, że problem ten dotyka obecnie blisko jednej piątej powierzchni Ziemi, a zasięg występowania i liczba nowych introdukcji obcych gatunków wciąż rośnie, mechanizmy biologiczne determinujące inwazje nie są w pełni poznane. Szczególnie istotnym zagadnieniem, którego nie udało się do tej pory wyjaśnić, jest wpływ struktury krajobrazu na występowanie obcych inwazyjnych gatunków roślin. Niewystarczająca jest również wiedza na temat relatywnej roli, jaką w procesach inwazji tych gatunków odgrywa szereg innych czynników, takich jak np. wpływ działalności człowieka, uwarunkowania klimatyczne i glebowe czy interakcje biotyczne między obcymi gatunkami. W konsekwencji, opracowanie skutecznych metod ograniczania negatywnych skutków rozprzestrzeniania się inwazyjnych obcych gatunków roślin i zapobieganie nowym inwazjom jest w znacznym stopniu utrudnione.

Celem badań było określenie zależności między wybranymi czynnikami środowiskowymi i antropogenicznymi a występowaniem inwazyjnych gatunków roślin w Polsce. Jako gatunki modelowe wykorzystano północnoamerykańskie nawłocie: kanadyjską (*Solidago canadensis*) i późną (*S. gigantea*), które są szeroko rozpowszechnione w krajobrazie rolniczym Europy i istotnie oddziałują na lokalną bioróżnorodność. W związku z tym, że jednym z kluczowych korytarzy ich rozprzestrzeniania się są drogi, w celu przeprowadzenia ich inwentaryzacji w dużej skali przestrzennej zastosowano nowatorską metodę wykorzystującą panoramiczne zdjęcia poboczny dróg dostępne w usłudze Google Street View. Ponieważ metoda ta nie została dotychczas empirycznie zweryfikowana, w pierwszym etapie prac dokonano jej walidacji na podstawie obserwacji terenowych, zakładając, że zdjęcia Google Street View będą wiarygodnym i użytecznym źródłem informacji o rzeczywistym występowaniu badanych gatunków. Następnie, wykorzystując tę metodę, przeprowadzono inwentaryzację inwazyjnych nawłoci wzdłuż 1347 losowo wybranych transektów w Polsce i zbadano zależność pomiędzy liczebnością badanych gatunków a heterogenicznością krajobrazu charakteryzowaną przy pomocy dwóch miar: konfiguracji i kompozycji. Spodziewano się, że te dwa komponenty mogą w różny sposób wpływać na inwazje nawłoci oraz że relacje te mogą być dodatkowo zależne od rozpatrywanej skali przestrzennej. W celu weryfikacji tych hipotez parametry opisujące strukturę krajobrazu określono w różnych skalach przestrzennych (w buforach o promieniu od 0,25 km do 5 km od badanych lokalizacji). Przewidywano ponadto, że wzorce rozmieszczenia inwazyjnych gatunków mogą być równocześnie kształtowane przez szereg innych czynników środowiskowych i antropogenicznych, których znaczenie również zmienia się wraz ze skalą przestrzenną. Wykorzystując dostępne dane geoprzestrzenne i algorytmy uczenia maszynowego, przeanalizowano więc relatywną rolę blisko 50 czynników charakteryzujących badane lokalizacje w przewidywaniu obecności inwazyjnych nawłoci w różnych skalach przestrzennych.

Weryfikacja metody wykorzystującej zdjęcia Google Street View do badania obecności inwazyjnych nawłoci na poboczach dróg potwierdziła jej wysoką skuteczność, umożliwiając tym samym jej zastosowanie w zasadniczej części badań. Wykazano, że stopień

heterogeniczności krajobrazu, zarówno pod względem konfiguracji, jak i kompozycji, wpływa pozytywnie na wskaźnik liczebności inwazyjnych nawłoci, jednak wielkość tego efektu uzależniona jest od skali przestrzennej: heterogeniczność kompozycyjna ma największe znaczenie dla występowania badanych gatunków w dużej skali, natomiast odwrotną zależność zaobserwowano w przypadku heterogeniczności konfiguracyjnej. Stwierdzono również, że lokalne wzorce rozmieszczenia inwazyjnych nawłoci determinowane są przez szereg czynników, spośród których najważniejsze są parametry charakteryzujące wpływ działalności człowieka, uwarunkowania klimatyczne i glebowe oraz struktura krajobrazu. Podobnie jak w przypadku miar heterogeniczności krajobrazu, wykazano, że rola innych charakterystyk w przewidywaniu występowania inwazyjnych nawłoci zmienia się wraz ze skalą przestrzenną.

Przeprowadzone badania demonstrują, w jaki sposób dostępne zasoby danych przestrzennych można wykorzystać do poszerzenia wiedzy na temat wielkoskalowych zjawisk ekologicznych, takich jak inwazje biologiczne. Walidacja metody umożliwiającej śledzenie rozmieszczenia inwazyjnych gatunków roślin na podstawie analizy zdjęć Google Street View pozwala na jej późniejsze zastosowanie w innych badaniach roślinności poboczy dróg. Uzyskane wyniki przybliżają zrozumienie mechanizmów inwazji biologicznych zachodzących w krajobrazie rolniczym oraz roli, jaką w tym procesie odgrywa struktura krajobrazu. Pozytywna relacja między miarami heterogeniczności krajobrazu a wskaźnikiem liczebności inwazyjnych nawłoci ma istotne praktyczne implikacje. Wynik ten sugeruje, że realizacja strategii ochrony różnorodności biologicznej ukierunkowanych na wspomaganie wysokiej heterogeniczności krajobrazu rolniczego, która obecnie jest wdrażana m.in. w Unii Europejskiej, może równocześnie wspierać wnikanie obcych inwazyjnych roślin. W związku z tym, kontrola populacji tych gatunków wydaje się szczególnie ważna w krajobrazach o najbardziej zróżnicowanej strukturze. Uzyskane wyniki pokazują też, jak ważny w badaniu procesów inwazji jest kontekst przestrzenny. Ponieważ, jak wykazano, różne czynniki potencjalnie wpływające na inwazje obcych gatunków roślin działają w różnych skalach przestrzennych, wykrycie i właściwa interpretacja relacji między badanymi zmiennymi a występowaniem inwazyjnych gatunków wymaga uwzględnienia odpowiedniej skali. Przeprowadzone badania pokazują również, że procesy inwazji biologicznych są w znacznym stopniu złożone, a na sukces gatunków inwazyjnych może wpływać równocześnie wiele czynników. Zrozumienie mechanizmów inwazji i ustalenie priorytetów w zarządzaniu obcymi gatunkami wymaga zatem kompleksowego podejścia, uwzględniającego wiele czynników i skal przestrzennych.

SUMMARY

Invasions of alien species are considered one of the most serious threats to global biodiversity. Despite this problem currently affects nearly one fifth of the Earth's surface, and the range and number of new alien species introductions continue to grow, the biological mechanisms determining invasions are not fully understood. A particularly important issue that has not yet been clarified is the effect of landscape structure on the occurrence of invasive alien plant species. Also, there is insufficient knowledge regarding the relative role played by a number of other factors in the invasion processes of these species, such as human impacts, climatic conditions, soil properties, or biotic interactions between alien species. As a result, the development of effective methods to reduce the negative effects of the spread of invasive alien plant species and prevent new invasions is considerably difficult.

The aim of the study was to determine the relationships between selected environmental and anthropogenic factors and the occurrence of invasive plant species in Poland. As model species, two North American goldenrods were used: the Canadian goldenrod (*Solidago canadensis*) and the giant goldenrod (*S. gigantea*). These plants are widespread in European agricultural landscapes and significantly affect local biodiversity. Given roads are one of the key corridors for their spread, a novel method using panoramic images of roadsides available in Google Street View was applied to perform a large-scale inventory of the studied species. Since this method has not been empirically verified so far, in the first part of the study it was validated by field observations, assuming that Google Street View images would be a reliable and useful source of information on the actual occurrence of the studied species. Next, using this method, an inventory of invasive goldenrods was conducted along 1347 randomly selected transects in Poland and the relationship between the abundance of studied species and landscape heterogeneity characterized by two measures: configuration and composition was examined. It was expected that these two components may have different effects on goldenrod invasions, and that these relationships may be further dependent on the spatial scale considered. To verify these hypotheses, parameters describing landscape structure were determined at different spatial scales (i.e., buffers with a radius ranging from 0.25 km to 5 km of the study locations). Moreover, it was predicted that distribution patterns of invasive species may be simultaneously shaped by a number of other environmental and anthropogenic factors, which also change in importance with spatial scale. Therefore, using available geospatial data and machine learning algorithms, the relative importance of nearly 50 factors characterizing the study locations in predicting the occurrence of invasive goldenrods at different spatial scales was analyzed.

The verification of the method using Google Street View images to study the occurrence of invasive goldenrods at roadsides confirmed its high effectiveness, thus allowing for its application in the main part of the study. The level of landscape heterogeneity, both in terms of configuration and composition, was shown to have a positive effect on the abundance index of invasive goldenrods, but the size of this effect depended on the spatial scale: compositional heterogeneity was the most important for predicting the occurrence of the studied species at large scales, whereas an opposite association was observed for

configurational heterogeneity. It was also found that local distribution patterns of invasive goldenrods are determined by a number of factors, among which those describing human impacts, climatic conditions, soil properties and landscape structure are the most important. Similarly to measures of landscape heterogeneity, the role of many other characteristics in predicting the occurrence of invasive goldenrods was shown to change with spatial scale.

The study demonstrates how the available geospatial data resources can be used to advance our knowledge of large-scale ecological phenomena, such as biological invasions. The validation of the method that enables tracking of invasive plant species distributions based on the analysis of Google Street View images allows for its subsequent use in other roadside vegetation studies. The obtained results provide a better understanding of the mechanisms of biological invasions occurring in agricultural landscapes and the role that landscape structure plays in this process. The positive association between measures of landscape heterogeneity and abundance index of invasive goldenrods has important practical implications. This result suggests that the implementation of biodiversity conservation strategies aimed at supporting high levels of heterogeneity in agricultural landscapes, which is currently being applied e.g. in the European Union, may simultaneously support the spread of invasive alien plants. Consequently, controlling populations of these species seems especially important in the most diverse landscapes. The research also demonstrates the importance of spatial context in studying invasion processes. Since different factors potentially affecting invasions of alien plant species were shown to operate at different spatial scales, detecting and properly interpreting the associations between studied variables and distribution of invasive species requires consideration of an appropriate scale. Moreover, the study shows that the processes of biological invasions are highly complex, and multiple factors can simultaneously influence the success of invasive species. Therefore, understanding the mechanisms of biological invasions and setting priorities for alien species management requires a comprehensive approach that incorporates multiple factors and spatial scales.

WSTĘP

Inwazje biologiczne jako rosnące zagrożenie dla przyrody i ludzi

Wielkie przemiany cywilizacyjne mające miejsce w ostatnich stuleciach przyniosły intensywny rozwój międzynarodowego handlu, transportu i turystyki. Pociągnęły za sobą nie tylko wzrost mobilności ludzi, ale umożliwiły również wielu gatunkom roślin i zwierząt pokonywanie barier geograficznych i pojawianie się poza naturalnym zasięgiem występowania (Hulme, 2009). Część z nich odnalazła w nowych lokalizacjach odpowiednie warunki do rozwoju stabilnych populacji i stała się inwazyjna (Blackburn i in., 2011), stanowiąc tym samym poważne zagrożenie dla różnorodności biologicznej w wielu miejscach na świecie (Vitousek i in., 1997; IPBES, 2019; Blackburn i in., 2019). Obce gatunki inwazyjne, dzięki specyficznym cechom, takim jak wysokie zdolności reprodukcyjne, szybki wzrost czy znaczna plastyczność względem warunków siedliskowych, mogą skutecznie konkurować z rodzimymi gatunkami (Elton, 1958). Tym samym mogą silnie oddziaływać na wiele komponentów ekosystemów, które kolonizują (np. wykorzystując dostępne zasoby, zmieniając warunki glebowe i wodne, modyfikując obieg pierwiastków; Richardson i in., 2000). W konsekwencji, inwazje gatunków obcych mogą prowadzić do spadku bogactwa gatunkowego rodzimych taksonów (Hejda i in., 2009a), ekstynkcji gatunków rzadkich oraz homogenizacji zbiorowisk roślinnych w wielu skalach przestrzennych (Wilcove i in., 1998; Schwartz i in., 2006).

Efekty tych niekorzystnych zmian środowiska powodowanych przez gatunki obce dotykają także ludzi. Inwazje obcych gatunków mogą prowadzić do utraty lub redukcji usług ekosystemowych (Kumar Rai i Singh, 2020), powodować spadek wydajności produkcji rolnej (Paini i in., 2016), oddziaływać negatywnie na istniejącą infrastrukturę (Booy i in., 2017), wreszcie stanowić istotne zagrożenie dla zdrowia ludzi (Neill i Arim, 2011). Konsekwencją rozprzestrzeniania się gatunków inwazyjnych są zatem znaczne straty ekonomiczne, które na świecie sięgają rocznie 26 mld dolarów (Diagne i in., 2021). Obecnie, w wyniku wielu celowych introdukcji i przypadkowych zawleceń, blisko jedna piąta powierzchni Ziemi narażona jest na negatywne konsekwencje wynikające z wnikania obcych gatunków inwazyjnych (IPBES, 2019). Przewiduje się, że zjawisko to będzie się stopniowo nasilało wraz z postępującymi zmianami klimatu i innymi antropogenicznymi przekształceniami naturalnych ekosystemów spowodowanymi przez działalność rolniczą, urbanizację i rozwój sieci dróg (Early i Sax, 2014).

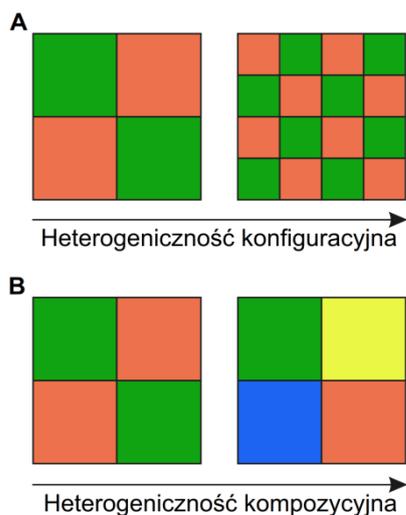
Czynniki kształtujące procesy inwazji obcych gatunków roślin

Tematyka inwazji biologicznych, a w szczególności inwazji obcych gatunków roślin, skupiła uwagę naukowców w ostatnich dziesięcioleciach, czego wynikiem było stworzenie licznych modeli teoretycznych i dokumentacja empiryczna tych procesów w wielu miejscach na świecie (Pyšek i in., 2020). Jednak złożoność zjawisk inwazji biologicznych sprawia, że mimo intensywnych badań, procesy te nie są w pełni poznane, przez co pozostają jednym z największych wyzwań współczesnej ekologii. Czynniki wpływające na sukces gatunków inwazyjnych związane są zarówno z wielkoskalowymi uwarunkowaniami geograficznymi,

takimi jak klimat, konfiguracja kontynentalnych mas lądowych czy łączność ekologiczna między poszczególnymi obszarami, jak również lokalnymi i efemerycznymi cechami i zjawiskami, takimi jak interakcje biotyczne czy krótkotrwałe i małopowierzchniowe zaburzenia środowiska.

Pośród wielu czynników mogących oddziaływać na występowanie inwazyjnych obcych gatunków roślin, rola struktury krajobrazu wydaje się być szczególnie istotna (Vilà i Ibáñez, 2011; González-Moreno i in., 2013). Może ona wpływać na szereg parametrów ważnych z perspektywy ekologii inwazji, takich jak: dostępność i stopień izolacji siedlisk preferowanych przez gatunki obce czy obecność potencjalnych dróg dyspersji. Niestety, rola struktury krajobrazu w przebiegu procesów inwazji jest równocześnie zagadnieniem szczególnie słabo zbadanym (With, 2002), zatem eksploracja relacji między krajobrazem a obecnością inwazyjnych gatunków roślin ma duży potencjał do istotnego poszerzenia dotychczasowej wiedzy z zakresu ekologii inwazji.

Struktura krajobrazu najczęściej opisywana jest przy pomocy miar jego zróżnicowania, czyli heterogeniczności. Ta cecha krajobrazu jest coraz powszechniej wskazywana jako czynnik szczególnie ważny dla rozmieszczenia i liczebności występujących w nim organizmów (np. Šálek i in., 2021). Ma ona zatem istotny wpływ na kształtowanie wzorców przestrzennych różnorodności biologicznej (Fahrig i in., 2011; Sirami i in., 2019; Martin i in., 2020). Dotychczasowe badania dotyczące zależności pomiędzy heterogenicznością krajobrazu, a jego podatnością na inwazje prowadzą jednak do niejednoznacznych wniosków wskazując, że charakter tych relacji może być pozytywny bądź negatywny (Williamson i Harrison, 2002; With, 2002; Hastings i in., 2004; Davies i in., 2005; Melbourne i in., 2007). Część badań sugeruje, że różnorodny krajobraz może hamować inwazje z uwagi na wysokie bogactwo rodzimych gatunków, które konkurują z gatunkami obcymi o dostępne zasoby (Melbourne i in., 2007), a rozdrobniona struktura siedlisk uniemożliwia im rozprzestrzenianie się (Alofs i Fowler, 2010). Niektóre prace dowodzą jednak, że wysoki stopień heterogeniczności krajobrazu może wspomagać inwazje obcych gatunków roślin, m.in. w związku z większą sumaryczną ilością dostępnych zasobów, a zatem większą dostępnością nisz ekologicznych dla gatunków inwazyjnych oraz większym udziałem siedlisk brzegowych (ekotonów) ułatwiających im efektywną dyspersję (McDonald i Urban, 2006). Ważnym aspektem w poszukiwaniu przyczyn tych sprzecznych przewidywań i wyników jest fakt, że heterogeniczność krajobrazu może być mierzona w różny sposób. Pojęcie heterogeniczności krajobrazu może się odnosić do jego konfiguracji lub kompozycji, a te dwie cechy, przynajmniej teoretycznie, mogą być całkowicie niezależne. Heterogeniczność konfiguracyjna opisuje przestrzenny układ (stopień rozdrobnienia) różnych typów pokrycia terenu, natomiast ich udział charakteryzuje heterogeniczność kompozycyjna (Ryc. 1; Fahrig i in., 2011). Te dwa komponenty heterogeniczności krajobrazu mogą być potencjalnie w różny sposób związane z występowaniem inwazyjnych obcych gatunków roślin, jednak brakuje obecnie empirycznej oceny ich relatywnego znaczenia w procesach inwazji.



Ryc. 1. Dwa komponenty heterogeniczności krajobrazu: konfiguracja (A; przestrzenny układ/rozdrobienie różnych typów pokrycia terenu) i kompozycja (B; udział różnych typów pokrycia terenu).

Poza strukturą krajobrazu, sukces obcych gatunków roślin w nowym siedlisku może być determinowany przez szereg innych czynników. Najważniejszym spośród nich jest bezpośredni wpływ działalności człowieka, która może kształtować wzorce występowania obcych gatunków na wszystkich etapach procesu inwazji. W początkowej fazie, działalność człowieka przyczynia się do transportu gatunków poza ich rodzime zasięgi, prowadząc do celowych lub przypadkowych introdukcji (Hulme, 2009; Lenda i in., 2014). W kolejnych etapach, obecność antropogenicznych zaburzeń w naturalnych ekosystemach wspomaga rozwój i rozprzestrzenianie się obcych gatunków roślin, które często wykazują preferencje do tego typu siedlisk (Hejda i in., 2009b). Coraz silniej oddziałującym czynnikiem wpływającym na sukces obcych gatunków jest również klimat (Diez i in., 2012). Introdukowane przez człowieka gatunki roślin mogą stać się inwazyjne wraz ze zmianą klimatu w kierunku bardziej korzystnych uwarunkowań termicznych lub wilgotnościowych (Bellard i in., 2018). Zarówno zmiany klimatyczne, jak i zmiany sposobu użytkowania gruntów związane z działalnością człowieka, prowadzą do modyfikacji dostępnych zasobów siedliskowych, takich jak np. właściwości glebowe, które mogą wpływać na inwazje obcych gatunków roślin (Schroeder i in., 2021). Ważną rolę w tych procesach mogą też odgrywać interakcje biotyczne. Na przykład negatywne oddziaływanie inwazyjnych gatunków roślin poprzez konkurencję o zasoby lub allelopatię może lokalnie redukować bogactwo gatunków rodzimych (Lenda i in., 2019), lecz inwazyjne gatunki mogą też konkurować o zasoby między sobą (Gioria i Osborne, 2014). Z drugiej strony, uznaje się, że gatunki inwazyjne kolonizując nowe ekosystemy zmieniają je w sposób ułatwiający osiedlanie się kolejnych gatunków obcych, co może sprzyjać kolejnym inwazjom i potęgować ich negatywny wpływ (Simberloff i Von Holle, 1999). Relatywne znaczenie tych wszystkich czynników dla występowania inwazyjnych obcych gatunków roślin jest jednak słabo poznane.

Dobrym poligonem do prowadzenia badań dotyczących znaczenia różnych czynników dla rozmieszczenia gatunków inwazyjnych są obszary użytkowane rolniczo. W związku z tym, że są to środowiska w mniejszym lub większym stopniu zmienione przez działalność człowieka, są one szczególnie podatne na wnikanie obcych gatunków (Chytrý i in., 2009). Ich niekontrolowane rozprzestrzenianie się w krajobrazie rolniczym może powodować wymierne szkody ekonomiczne oraz zanik rodzimej różnorodności biologicznej odpowiedzialnej za

usługi ekosystemowe, takie jak zapylenie czy kontrola tzw. „szkodników” upraw (Rosin i in., 2011). Wysoki stopień heterogeniczności krajobrazu rolniczego uznaje się za cechę kluczową dla ochrony różnorodności biologicznej, podczas gdy homogenizacja krajobrazu postrzegana jest jako jedna z głównych przyczyn jej utraty (np. Matson i in., 1997; Tschamtkke i in., 2005). Kluczowe pozostaje jednak pytanie: w jaki sposób wysoki stopień heterogeniczności krajobrazu rolniczego – cecha pożądana, bo sprzyjająca bioróżnorodności – wpływa na inwazje, stanowiące dla tej bioróżnorodności zagrożenie. Empiryczne badania dotyczące inwazji obcych gatunków roślin wydają się zatem szczególnie ważne na obszarach związanych z działalnością rolniczą.

Kontekst przestrzenny w badaniu procesów inwazji obcych gatunków roślin

W rozważaniach nad znaczeniem różnych czynników środowiskowych i antropogenicznych w przebiegu procesów inwazji szczególnie istotne wydaje się uwzględnienie kontekstu przestrzennego. Może mieć on kluczowe znaczenie dla identyfikacji predyktorów inwazji biologicznych, ponieważ różne czynniki wpływające na prawdopodobieństwo inwazji działają w różnych skalach przestrzennych (Czarnecka-Wiera i in., 2020). Można się spodziewać, że w dużej skali przestrzennej wpływ klimatu i działalności człowieka będzie największy (Shi i in., 2010), gdyż cechy te determinują występowanie gatunków inwazyjnych na poziomie całych regionów. Wraz ze zmniejszaniem skali cechy krajobrazu (np. udział różnych typów pokrycia terenu, gęstość sieci drogowej, dystans do cieków wodnych) mogą nabrać większego znaczenia ze względu na ich potencjalny wpływ na tempo i możliwość kolonizacji danego obszaru przez gatunki inwazyjne z populacji źródłowych. Natomiast wpływ czynników lokalnych, takich jak interakcje biotyczne, jest prawdopodobnie najbardziej widoczny w małej skali przestrzennej (Catford i in., 2009; Milbau i in., 2009). Stąd, w zależności od rozpatrywanej skali, znaczenie różnych czynników sprzyjających inwazjom obcych gatunków roślin, może być różne (Ricklefs i Jenkins, 2011). Uwzględnienie wymiaru przestrzennego w badaniu procesów inwazji może być zatem niezwykle ważne. Dotychczas większość badań empirycznych dotyczących czynników determinujących inwazje koncentrowała się jednak na jednej skali przestrzennej (ale patrz: Czarnecka-Wiera i in., 2020; Dyderski i Jagodziński, 2016).

Trudności w badaniu przestrzennych wzorców inwazji obcych gatunków

Rosnące zagrożenie ze strony inwazyjnych gatunków obcych niesie za sobą pilną potrzebę opracowania metod ograniczania negatywnych skutków tego zjawiska i zapobiegania nowym inwazjom w przyszłości. W tym celu niezbędne jest zrozumienie biologicznych mechanizmów inwazji, w tym przede wszystkim identyfikacja czynników środowiskowych i antropogenicznych kształtujących procesy inwazji gatunków obcych w różnych skalach przestrzennych. Właściwe zrozumienie procesów inwazji biologicznych oraz skuteczne zarządzanie inwazyjnymi gatunkami obcymi może być jednak utrudnione przez niewystarczającą dostępność odpowiednich danych dotyczących aktualnego rozmieszczenia, liczebności oraz dynamiki inwazji poszczególnych gatunków (Bradley i in., 2018). Szczegółowe informacje przestrzenne dotyczące występowania gatunków inwazyjnych są zwykle ograniczone do małych obszarów z uwagi na wysokie koszty ich pozyskania

i czasochłonność badań terenowych, a te, które są pozyskiwane w wyniku inwentaryzacji lub monitoringu przyrodniczego, szybko się dezaktualizują. W regionach mniej intensywnie eksplorowanych przez specjalistów, obecność i ekspansja gatunków inwazyjnych może w ogóle zostać niezauważona. W efekcie tego ograniczonego stanu wiedzy na temat inwazji obcych gatunków, budowanie wiarygodnych modeli statystycznych identyfikujących czynniki środowiskowe i antropogeniczne warunkujące inwazje jest utrudnione.

Mającą jednak miejsce w ostatnich latach intensywny wzrost zastosowania technologii cyfrowych w różnych dziedzinach stwarza szansę na pozyskiwanie danych dotyczących gatunków inwazyjnych z nowych, często niekonwencjonalnych źródeł. Przykładem może być usługa Google Street View (GSV), która jest dostępna w popularnych aplikacjach komputerowych Google Earth i Google Maps. Stanowi ona darmowe, otwarte źródło milionów georeferowanych i wysokorozdzielczych panoramicznych zdjęć cyfrowych pobocza setek tysięcy kilometrów dróg w Polsce i w wielu innych krajach na świecie. Jakość tych zdjęć pozwala na identyfikację wielu gatunków, szczególnie roślin oraz ich siedlisk (np. Hardion i in., 2016). Jest to zatem potencjalnie dobre źródło danych ale dotychczas prawie niestosowane w ekologii, a metoda ta została do tej pory wykorzystana jedynie w kilku publikacjach naukowych dotyczących biologii (np. Olea i Mateo-Tomás, 2013; Rousselet i in., 2013; Collette i Pither, 2015).

Zdjęcia poboczny dróg dostępne w Google Street View wydają się zatem szczególnie obiecującym źródłem informacji o występowaniu i szlakach dyspersji inwazyjnych obcych gatunków roślin, ponieważ to właśnie drogi należą do głównych korytarzy umożliwiających im rozprzestrzenianie się (np. Pauchard i Alaback, 2004; Christen i Matlack, 2009). Z obecnością dróg wiąże się występowanie zaburzeń (wynikających z użytkowania poboczy i ruchu samochodowego) sprzyjających wnikaniu obcych gatunków roślin. Drogi jako liniowe obiekty przecinają naturalne i przekształcone ekosystemy, łączą izolowane płaty siedlisk i mogą zwiększać przenikalność krajobrazu dla roślin (Forman i in. 2003). Dodatkowo, ruch samochodowy aktywnie transportuje ich nasiona (np. w bieżnikach opon, lub poprzez kierunkowy podmuch powietrza towarzyszący poruszaniu się samochodów). Mimo potencjalnej użyteczności zdjęć Google Street View do śledzenia inwazji obcych gatunków roślin, dotychczas metoda ta nie została poddana formalnej walidacji w oparciu o empiryczne dane terenowe. Możliwość jej wykorzystania do badania inwazyjnych gatunków roślin oraz szerszego zastosowania w badaniach ekologicznych jest zatem ograniczona.

CEL BADAŃ

Głównym celem badań było określenie wpływu różnych czynników środowiskowych i antropogenicznych w wielu skalach przestrzennych na występowanie wybranych inwazyjnych obcych gatunków roślin w krajobrazie rolniczym Polski. Jako gatunki modelowe wykorzystano inwazyjne północnoamerykańskie nawłocie (*Solidago canadensis* i *S. gigantea*). Są one szeroko rozpowszechnione na obszarach użytkowanych rolniczo, a jednym z istotnych korytarzy ich dyspersji, podobnie jak w przypadku wielu innych gatunków obcych, są drogi (np. Pauchard i Alaback, 2004, Christen i Matlack, 2009). Rozmieszczenie badanych gatunków w skali całego kraju określono przy pomocy nowatorskiej metody wykorzystującej panoramiczne zdjęcia poboczy dróg dostępne w usłudze Google Street View. Badania prowadzono w oparciu o trzy cele szczegółowe, których realizacja została opisana w trzech pracach naukowych:

Cel 1: Walidacja metody wykorzystującej panoramiczne zdjęcia dostępne w usłudze Google Street View do badania obecności inwazyjnych nawłoci na poboczach dróg (praca I).

Pierwszym celem było opracowanie i weryfikacja skuteczności metody inwentaryzacji gatunków inwazyjnych roślin przy pomocy panoramicznych zdjęć dostępnych w usłudze Google Street View. W ramach jego realizacji porównano dane dotyczące występowania inwazyjnych nawłoci zgromadzone przy pomocy analizy zdjęć pozyskanych z GSV z obserwacjami terenowymi. Przewidywano, że te dwa zestawy danych są ze sobą pozytywnie skorelowane, dlatego postawiono hipotezę, że metoda oparta na GSV prawidłowo identyfikuje obecność badanych gatunków na poboczach dróg. Ponieważ spodziewano się, że wiarygodność tej metody może zależeć od skali, jej skuteczność testowano w oparciu o dane o różnej rozdzielczości przestrzennej. Dodatkowo weryfikowano, jak na stopień podobieństwa między wynikami obu metod wpływają parametry, takie jak, czas, jaki upłynął między badaniem terenowym a wykonaniem zdjęcia, szerokość drogi, koszenie poboczy. Wreszcie, wykorzystując oba zestawy danych, przeanalizowano zależność między obecnością nawłoci a wybranymi cechami środowiska (obecnością nieużytków). Przewidywano, że w obu przypadkach asocjacje te będą pozytywne, a wielkość efektu podobna, co potwierdzałoby użyteczność metody GSV nie tylko do określania obecności inwazyjnych nawłoci, lecz również do konstruowania statystycznych modeli ekologicznych tłumaczących tę obecność w oparciu o cechy środowiska.

Cel 2: Określenie zależności między stopniem heterogeniczności krajobrazu rolniczego (charakteryzowanym przy pomocy wskaźników kompozycji i konfiguracji w różnych skalach przestrzennych) a liczebnością inwazyjnych nawłoci (praca II).

Walidacja metody (cel 1) umożliwiła realizację kolejnego etapu badań, który miał na celu określenie zależności pomiędzy dwoma komponentami heterogeniczności krajobrazu (konfiguracją i kompozycją), a liczebnością inwazyjnych nawłoci w krajobrazie rolniczym Polski. Testowano hipotezę zakładającą, że liczebność nawłoci wzdłuż dróg jest pozytywnie związana z poziomem heterogeniczności konfiguracyjnej otaczającego krajobrazu (tzn. jest większa w krajobrazach bardziej pofragmentowanych, a tym samym bardziej zasobnych

w potencjalne drogi dyspersji dla inwazyjnych gatunków roślin). Nie sformułowano natomiast przewidywań w odniesieniu do efektu heterogeniczności kompozycyjnej, ponieważ w oparciu o dotychczasową wiedzę trudno było *a priori* założyć, czy większa liczba typów użytkowania gruntów zwiększa, czy zmniejsza dostępność siedlisk preferowanych przez nawłocie. Ponieważ heterogeniczność krajobrazu i związane z nią wzorce przestrzenne w występowaniu gatunków i siedlisk są silnie zależne od skali, w której są badane (np. Wu i in., 2000), sprawdzono, jak wraz ze skalą przestrzenną zmienia się siła związku pomiędzy występowaniem badanych roślin a heterogenicznością kompozycyjną i konfiguracyjną krajobrazu.

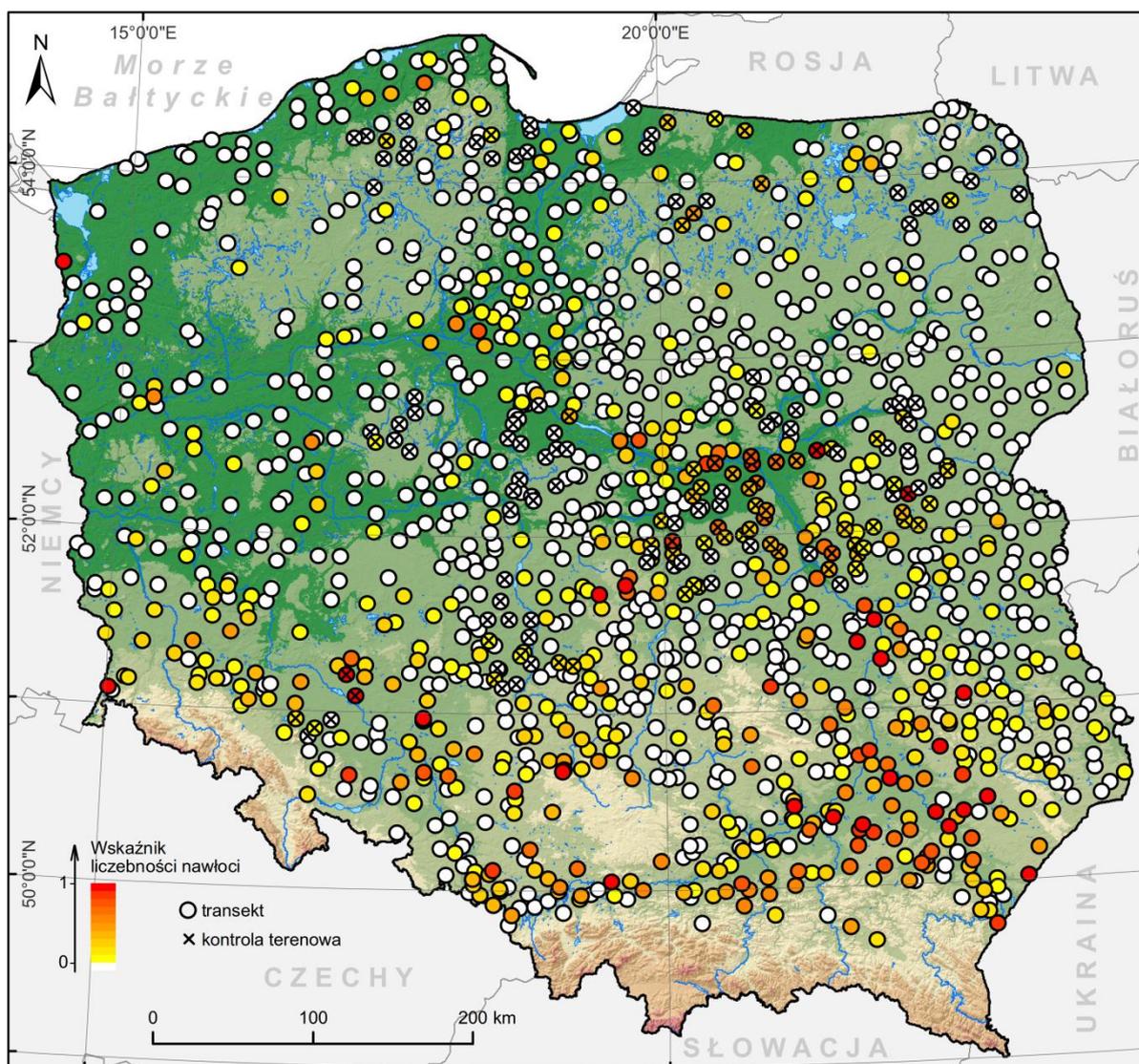
Cel 3: Identyfikacja głównych czynników determinujących obecność inwazyjnych nawłoci w Polsce w różnych skalach przestrzennych (praca III).

Prace realizowane w ramach drugiego celu badawczego zostały rozszerzone w ostatnim etapie badań, który miał na celu określenie relatywnej roli czynników potencjalnie wpływających na występowanie inwazyjnych nawłoci wzdłuż dróg w Polsce. W związku z tym, że procesy inwazji są w znacznym stopniu złożone, przewidywano, że obecność badanych gatunków determinowana jest przez wiele zmiennych środowiskowych i antropogenicznych, których znaczenie może się zmieniać w zależności od rozpatrywanej skali przestrzennej. W tej części badań testowano więc, w jaki sposób na lokalne wzorce inwazji nawłoci wzdłuż dróg wpływa blisko 50 różnych czynników charakteryzujących zarówno badane lokalizacje (np. parametry dróg, obecność innych obcych gatunków roślin mogących wchodzić w interakcje z nawłociami), jak i ich otoczenie (np. struktura krajobrazu, uwarunkowania glebowe, klimat, wskaźniki socjoekonomiczne) oraz jak relatywne znaczenie tych czynników zmienia się wraz ze skalą przestrzenną.

METODY

Badania nad czynnikami wpływającymi na występowanie inwazyjnych nawłoci prowadzone były w krajobrazie rolniczym Polski niżowej, wzdłuż 1347 losowo wybranych przydrożnych transektów (Ryc. 2) o długości 500 m każdy. Przy wyborze ich lokalizacji posłużono się otwartymi zasobami danych geoprzestrzennych (m.in. Numerycznym Modelem Terenu, bazą Corine Land Cover, danymi Open Street Map, zasobami Banku Danych Lokalnych Głównego Urzędu Statystycznego, panoramicznymi zdjęciami Google Street View). Ich wykorzystanie umożliwiło rozmieszczenie transektów wzdłuż dróg różnych klas (od autostrad po drogi lokalne), przecinających różnorodne siedliska rolnicze. Badane lokalizacje położone były w krajobrazach różniących się znacznie pod względem struktury i intensywności użytkowania gruntów. Były to zarówno duże, intensywnie użytkowane pola, pastwiska i łąki, jak i heterogeniczne krajobrazy, stanowiące mozaikę małych pól z różnymi typami upraw, ekstensywnie użytkowanych pastwisk i innych półnaturalnych siedlisk otwartych, sadów, nieużytków oraz lasów. Wybrane transekty reprezentowały gradient klimatyczny od klimatu suboceanicznego w północno-zachodniej Polsce do kontynentalnego we wschodniej i południowo-wschodniej części kraju (Kożuchowski, 2011). W wylosowanych lokalizacjach przeprowadzono wirtualną inwentaryzację inwazyjnych nawłoci przy pomocy zdjęć dostępnych w usłudze Google Street View, podczas której dla każdego transektu podzielonego na odcinki określano występowanie i wskaźnik liczebności badanych gatunków (Ryc. 2).

Do walidacji zastosowanej metody (**praca I**), spośród 1347 transektów wylosowano 160 lokalizacji (Ryc. 2). Przeprowadzono w nich wirtualne kontrole na podstawie zdjęć GSV oraz wizyty terenowe, podczas których rejestrowano obecność inwazyjnych nawłoci wzdłuż 500-metrowych transektów, odnotowując wyniki osobno dla 25-metrowych odcinków. Ponadto, w trakcie wirtualnych kontroli transektów gromadzono informacje o parametrach, które mogą mieć wpływ na prawdopodobieństwo wykrycia badanych gatunków (m.in. data wykonania zdjęcia GSV, szerokość drogi, koszenie poboczy). Aby określić skuteczność metody wykorzystującej GSV do inwentaryzacji inwazyjnych roślin wykonano trzy typy analiz. Do przetestowania zależności pomiędzy rezultatami wizualnej analizy zdjęć GSV i kontroli w terenie w skali odcinków oraz transektów zastosowano uogólnione modele liniowe. Ponieważ prawdopodobieństwo wykrycia badanych gatunków może być zależne od tego, czy pobocze drogi zostało wcześniej skoszone, analizę wykonano również dla podzbioru odcinków i transektów, na których roślinność była w pełni wykształcona (nie była koszona). Dokładność tych predykcji określono przy pomocy walidacji krzyżowej *'leave-one-out'*. Posłużono się również uogólnionymi modelami addytywnymi, aby określić, które czynniki wpływają na prawidłową klasyfikację transektu lub odcinka transektu jako zajętego (lub niezajętego) przez nawłoc. Ponadto wykorzystano uogólnione mieszane modele liniowe, aby porównać wpływ wybranych cech środowiska na obecność nawłoci w zależności od zastosowanego zestawu danych o występowaniu badanych gatunków (tj. danych terenowych lub zdjęć GSV).



Ryc. 2. Rozmieszczenie 1347 transektów, wzdłuż których przeprowadzono inwentaryzację inwazyjnych nawłoci przy pomocy zdjęć Google Street View i 160 transektów, wzdłuż których wykonano kontrole terenowe oraz wskaźnik liczebności nawłoci w badanych lokalizacjach (proporcja odcinków, na których podczas zdalnej analizy zdjęć stwierdzono występowanie nawłoci).

W celu określenia zależności między stopniem heterogeniczności krajobrazu a liczebnością inwazyjnych nawłoci (**praca II**), sąsiedztwo każdego z 1347 transektów zostało scharakteryzowane przy pomocy miar heterogeniczności konfiguracyjnej i kompozycyjnej. Jako wskaźnik heterogeniczności konfiguracyjnej wykorzystano zagęszczenie granic działek ewidencyjnych, natomiast heterogeniczność kompozycyjną opisano na podstawie udziału różnych typów użytkowania terenu w sąsiedztwie transektów przy pomocy wskaźnika różnorodności Simpsona. Oba komponenty heterogeniczności krajobrazu określone zostały w pięciu różnych skalach przestrzennych, tj. w promieniu: 250 m, 500 m, 1000 m, 2000 m i 5000 m od wyznaczonych transektów. Wpływ dwóch miar heterogeniczności na liczebność nawłoci w różnych skalach przestrzennych analizowano przy pomocy uogólnionych modeli addytywnych.

Do identyfikacji głównych czynników wpływających na występowanie nawłoci w Polsce (**praca III**) wykorzystano dostępne zasoby danych przestrzennych (m.in. biblioteki danych przestrzennych NASA, zobrazenia satelitarne Landsat 8, dane klimatyczne WorldClim, bazę Corine Land Cover, dane Open Street Map, zasoby Banku Danych Lokalnych Głównego Urzędu Statystycznego, wektorowe warstwy dostępne w Bazie Danych Obiektów Ogólnogeograficznych GUGiK). Każdy z 1347 transektów scharakteryzowano na podstawie szeregu zmiennych środowiskowych i antropogenicznych przypisanych do siedmiu kategorii. Niektóre charakterystyki określone były wyłącznie lokalnie, tj. wzdłuż transektu (parametry dróg, parametry kontroli, liczebność i różnorodność innych obcych gatunków roślin), jednak większość mierzono w sąsiedztwie badanych lokalizacji w różnej skali przestrzennej, tj. w promieniu: 250 m, 500 m, 1000 m, 2000 m i 5000 m od transektu (wpływ działalności człowieka, klimat, uwarunkowania glebowe, struktura krajobrazu). Wykorzystując zgromadzony zestaw danych zbudowano modele statystyczne oparte na algorytmie lasów losowych, opisujące zależność pomiędzy występowaniem nawłoci a 47 czynnikami potencjalnie wpływającymi na lokalne wzorce ich rozmieszczenia. Analizy te wykonano dla różnych skal przestrzennych (od 0,25 km do 5 km od badanych transektów) i na podstawie otrzymanych wyników określono relatywne znaczenie każdej z wykorzystanych zmiennych objaśniających dla przewidywania obecności nawłoci wzdłuż badanych dróg. Skuteczność modeli w przewidywaniu występowania nawłoci oceniono przy pomocy przestrzennej 10-krotnej walidacji krzyżowej. Aby sprawdzić, czy znaczenie rozpatrywanych czynników różni się pomiędzy skalami przestrzennymi i kategoriami zmiennych, wykorzystano uogólniony mieszany model addytywny. Dodatkowo, charakter zależności pomiędzy relatywnym znaczeniem każdej z 47 rozpatrywanych zmiennych i skalą przestrzenną określono przy pomocy współczynnika korelacji Spearmana. Rozkład uzyskanych współczynników korelacji porównano następnie z modelem zerowym (współczynniki korelacji dla randomizowanych zmiennych).

WYNIKI

W pierwszej pracy (I) zweryfikowano skuteczność metody wykorzystującej panoramiczne zdjęcia GSV do inwentaryzacji roślinności poboczy dróg. Obserwacje inwazyjnych nawłoci zgromadzone przy pomocy GSV i badań terenowych porównano ze sobą i stwierdzono istotną pozytywną zależność pomiędzy obecnością nawłoci określoną na podstawie wirtualnej analizy zdjęć GSV a rzeczywistym występowaniem badanych gatunków w terenie, zarówno w skali całych transektów, jak i ich odcinków. Obserwowany efekt był podobny dla podzbioru danych uwzględniającego jedynie transekty i odcinki, na których roślinność była w pełni wykształcona (nieskoszona). Dokładność metody wykorzystującej zdjęcia GSV do wykrywania obecności inwazyjnych nawłoci wynosiła (dla różnych zestawów danych) 72-85%. Ponadto wykazano, że parametry, takie jak szerokość drogi, pora roku czy czas, jaki upłynął od wykonania zdjęcia, nie wpływają na korelację pomiędzy rezultatami dwóch porównywanych metod inwentaryzacji (tj. wizualnej analizy zdjęć GSV i kontroli w terenie). Stwierdzono również, że asocjacje między obecnością nawłoci a wybranymi cechami środowiska (obecnością nieużytków) były pozytywne, a wielkość tego efektu podobna, niezależnie od tego, jakie źródło danych o występowaniu inwazyjnych nawłoci wykorzystano w analizach. Uzyskane wyniki potwierdziły zatem przydatność metody wykorzystującej zdjęcia GSV do śledzenia rozprzestrzeniania się inwazyjnych nawłoci wzdłuż dróg.

Pozytywna weryfikacja skuteczności metody inwentaryzacji gatunków inwazyjnych przy pomocy GSV umożliwiła jej zastosowanie do realizacji zasadniczej części badań. W drugiej pracy (II) przeanalizowano zależności pomiędzy liczebnością inwazyjnych nawłoci a stopniem heterogeniczności krajobrazu rolniczego Polski. Stwierdzono, że zarówno stopień heterogeniczności kompozycyjnej jak i konfiguracyjnej jest pozytywnie związany z lokalną liczebnością nawłoci, jednak wielkość tego efektu zależy od skali przestrzennej. Asocjacje pomiędzy liczebnością nawłoci a heterogenicznością kompozycyjną były najbardziej wyraźne w największej skali przestrzennej (tj. w buforze 5000 m od badanych lokalizacji), natomiast odwrotny wzorzec zaobserwowano w przypadku heterogeniczności konfiguracyjnej (najsilniejszy związek w promieniu 250 i 500 m od transektów).

Temat znaczenia różnych czynników potencjalnie determinujących występowanie inwazyjnych nawłoci kontynuowano w trzeciej pracy (III). Analiza zależności pomiędzy występowaniem inwazyjnych nawłoci a 47 czynnikami środowiskowymi i antropogenicznymi pokazała, że wzorce rozmieszczenia badanych gatunków kształtowane są przez szereg zmiennych, z których największe znaczenie ma wpływ działalności człowieka, uwarunkowania klimatyczne, glebowe i struktura krajobrazu. Lokalne czynniki, takie jak parametry drogi czy obecność innych obcych gatunków roślin mogących wchodzić w interakcje biotyczne z nawłociami, mają natomiast mniejsze znaczenie. Relatywny udział różnych charakterystyk w przewidywaniu występowania inwazyjnych nawłoci zmieniał się jednak wraz z rozpatrywaną skalą przestrzenną. Znaczenie większości cech krajobrazu (np. udziału terenów podmokłych, siedlisk półnaturalnych i lasów) rosło wraz ze skalą, podczas gdy wpływ takich czynników, jak np. gęstość zaludnienia, stopień intensyfikacji rolnictwa, ilość promieniowania słonecznego był coraz mniejszy.

WNIOSKI

Przeprowadzone badania pokazały, w jaki sposób rosnące zasoby otwartych geoprzestrzennych danych środowiskowych mogą być wykorzystane do pogłębienia wiedzy na temat zjawisk ekologicznych. Uzyskane wyniki (**praca I**) sugerują, że zdjęcia Google Street View, publicznie dostępne dla wielu dróg na całym świecie, mogą stanowić cenne, dodatkowe źródło danych o rozmieszczeniu inwazyjnych obcych gatunków roślin. Ponieważ metoda oparta na GSV pozwala na znaczną redukcję wysiłku próbkowania, umożliwia ona śledzenie procesów inwazji w dużych skalach przestrzennych przy relatywnie niskich kosztach. Ponadto, w związku z tym, że biblioteka zdjęć GSV jest stale uzupełniana i aktualizowana, narzędzie to może być użyteczne w badaniu zmian rozmieszczenia gatunków roślin, wynikających ze zmian klimatu i środowiska. Jego wykorzystanie może także przyczynić się do dalszego rozwoju bardziej efektywnych metod stosowanych w badaniach ekologicznych (np. wykorzystujących algorytmy uczenia maszynowego do identyfikacji gatunków roślin).

Zdalna analiza zdjęć GSV umożliwiła lepsze zrozumienie zjawiska inwazji obcych gatunków roślin wzdłuż dróg oraz roli, jaką w tym procesie odgrywa struktura krajobrazu rolniczego (**praca II**). Stopień heterogeniczności krajobrazu jest wyraźnie skorelowany z potencjałem inwazyjnym nawłoci, przy czym gatunki te występują generalnie częściej w bardziej heterogenicznych środowiskach. Co istotne, zależność siły tego związku od rozpatrywanej skali przestrzennej oznacza, że może on zostać przecoczony, jeśli badania skupiają się tylko na jednej skali przestrzennej. Uzyskane wyniki pokazują, że wybór miary heterogeniczności i skali przestrzennej badanego krajobrazu jest kluczowy dla wykrycia i interpretacji powiązań między występowaniem inwazyjnych obcych roślin, takich jak nawłocie, a heterogenicznością krajobrazu. Tym samym, ustalenia te powinny być brane pod uwagę przy identyfikacji czynników wpływających na rozprzestrzenianie się inwazyjnych roślin na obszarach użytkowanych rolniczo. Za jedną z ważnych metod ochrony różnorodności biologicznej w tego typu środowiskach uznaje się wspomaganie lub odtwarzanie heterogeniczności krajobrazu (m.in. w ramach mechanizmów Wspólnej Polityki Rolnej Unii Europejskiej, takich jak program rolno-środowiskowo-klimatyczny, obszary *Ecological Focus Areas*). Rezultaty przeprowadzonych badań sugerują jednak, że wysoki stopień heterogeniczności krajobrazu może sprzyjać wnikaniu obcych inwazyjnych roślin, co stoi w sprzeczności z pierwotnymi celami strategii ukierunkowanych na ochronę rodzimych ekosystemów. W związku z tym, wdrażanie regularnego użytkowania i realizacja programów eliminacji inwazyjnych obcych gatunków roślin wydają się szczególnie ważne w najbardziej heterogenicznych krajobrazach.

Kontekst przestrzenny ma również istotne znaczenie w przypadku wielu innych czynników potencjalnie wpływających na wzorce występowania inwazyjnych obcych gatunków roślin (**praca III**). Przeprowadzone badania pokazują, że zjawisko inwazji obcych nawłoci wzdłuż dróg jest w znacznym stopniu złożone – na jego przebieg wpływa równocześnie wiele zmiennych środowiskowych i antropogenicznych. Jednak, ich znaczenie w przewidywaniu rozmieszczenia nawłoci zmienia się w zależności od rozpatrywanej skali przestrzennej. Oznacza to, że różne czynniki wpływające na występowanie badanych

gatunków działają w różnych skalach przestrzennych. Podczas gdy większość działań mających na celu zwalczanie inwazyjnych gatunków roślin realizowana jest w skali lokalnej, uzyskane wyniki sugerują, że najbardziej znaczącą rolę w kształtowaniu wzorców rozmieszczenia nawłoci odgrywają wielkoskalowe czynniki. Z tego względu opracowanie strategii o większym zasięgu przestrzennym, np. na poziomie krajobrazu, może być ważne dla skuteczniejszego zwalczania problematycznych gatunków, takich jak nawłóć. Właściwe zrozumienie mechanizmów kształtujących przebieg procesów inwazji wymaga uwzględnienia relatywnej roli wielu czynników, wspólnie kształtujących wzorce rozmieszczenia inwazyjnych gatunków obcych w różnych skalach przestrzennych. Zastosowanie podejścia opartego na wielu zmiennych i skalach przestrzennych może być kluczowe w wyznaczeniu priorytetów w zarządzaniu populacjami inwazyjnych obcych roślin, a tym samym opracowaniu bardziej efektywnych strategii mających na celu ich zwalczanie oraz zapobieganie nowym inwazjom.

LITERATURA

- Alofs, K. M., Fowler, N. L. (2010). Habitat fragmentation caused by woody plant encroachment inhibits the spread of an invasive grass. *Journal of Applied Ecology*, 47(2), 338–347. <https://doi.org/10.1111/j.1365-2664.2010.01785.x>
- Bellard, C., Jeschke, J. M., Leroy, B., Mace, G. M. (2018). Insights from modeling studies on how climate change affects invasive alien species geography. *Ecology and Evolution*, 8(11), 5688–5700. <https://doi.org/10.1002/ece3.4098>
- Blackburn, T. M., Bellard, C., Ricciardi, A. (2019). Alien versus native species as drivers of recent extinctions. *Frontiers in Ecology and the Environment*, 17(4), 203–207. <https://doi.org/10.1002/fee.2020>
- Blackburn, T. M., Pyšek, P., Bacher, S., Carlton, J. T., Duncan, R. P., Jarošík, V., Wilson, J. R. U., Richardson, D. M. (2011). A proposed unified framework for biological invasions. *Trends in Ecology and Evolution*, 26(7), 333–339. <https://doi.org/10.1016/j.tree.2011.03.023>
- Booy, O., Cornwell, L., Parrott, D., Sutton-Croft, M., Williams, F. (2017). Impact of Biological Invasions on Infrastructure. *Impact of Biological Invasions on Ecosystem Services* (s. 235–247). Springer International Publishing. https://doi.org/10.1007/978-3-319-45121-3_15
- Bradley, B. A., Allen, J. M., O'Neill, M. W., Wallace, R. D., Barger, C. T., Richburg, J. A., Stinson, K. (2018). Invasive species risk assessments need more consistent spatial abundance data. *Ecosphere*, 9(7), e02302. <https://doi.org/10.1002/ecs2.2302>
- Catford, J. A., Jansson, R., Nilsson, C. (2009). Reducing redundancy in invasion ecology by integrating hypotheses into a single theoretical framework. *Diversity and Distributions*, 15(1), 22–40. <https://doi.org/10.1111/j.1472-4642.2008.00521.x>
- Christen, D. C., Matlack, G. R. (2009). The habitat and conduit functions of roads in the spread of three invasive plant species. *Biological Invasions*, 11(2), 453–465. <https://doi.org/10.1007/s10530-008-9262-x>
- Chytrý, M., Pyšek, P., Wild, J., Pino, J., Maskell, L. C., Vilà, M. (2009). European map of alien plant invasions based on the quantitative assessment across habitats. *Diversity and Distributions*, 15(1), 98–107. <https://doi.org/10.1111/j.1472-4642.2008.00515.x>
- Collette, L. K., Pither, J. (2015). Modeling the potential North American distribution of Russian olive, an invader of riparian ecosystems. *Plant Ecology*, 216(10), 1371–1383. <https://doi.org/10.1007/s11258-015-0514-4>
- Czarniecka-Wiera, M., Szymura, T. H., Kaćki, Z. (2020). Understanding the importance of spatial scale in the patterns of grassland invasions. *Science of the Total Environment*, 727, 138669. <https://doi.org/10.1016/j.scitotenv.2020.138669>

- Davies, K. F., Chesson, P., Harrison, S., Inouye, B. D., Melbourne, B. A., Rice, K. J. (2005). Spatial heterogeneity explains the scale dependence of the native–exotic diversity relationship. *Ecology*, 86(6), 1602–1610. <https://doi.org/10.1890/04-1196>
- Diagne, C., Leroy, B., Vaissière, A. C., Gozlan, R. E., Roiz, D., Jarić, I., Salles, J. M., Bradshaw, C. J. A., Courchamp, F. (2021). High and rising economic costs of biological invasions worldwide. *Nature*, 592(7855), 571–576. <https://doi.org/10.1038/s41586-021-03405-6>
- Diez, J. M., D’Antonio, C. M., Dukes, J. S., Grosholz, E. D., Olden, J. D., Sorte, C. J., Blumenthal, D. M., Bradley, B. A., Early, R., Ibáñez, I., Jones, S. J., Lawler, J. J., Miller, L. P. (2012). Will extreme climatic events facilitate biological invasions? *Frontiers in Ecology and the Environment*, 10(5), 249–257. <https://doi.org/10.1890/110137>
- Dyderski, M. K., Jagodziński, A. M. (2016). Patterns of plant invasions at small spatial scale correspond with that at the whole country scale. *Urban Ecosystems*, 19(2), 983–998. <https://doi.org/10.1007/s11252-015-0524-y>
- Early, R., Sax, D. F. (2014). Climatic niche shifts between species’ native and naturalized ranges raise concern for ecological forecasts during invasions and climate change. *Global Ecology and Biogeography*, 23(12), 1356–1365. <https://doi.org/10.1111/geb.12208>
- Elton, C. S. (1958). *The Ecology of Invasions by Animals and Plants*. Methuen, London.
- Fahrig, L., Baudry, J., Brotons, L., Burel, F. G., Crist, T. O., Fuller, R. J., Sirami, C., Siriwardena, G. M., Martin, J.-L. (2011). Functional landscape heterogeneity and animal biodiversity in agricultural landscapes. *Ecology Letters*, 14(2), 101–112. <https://doi.org/10.1111/j.1461-0248.2010.01559.x>
- Forman, R. T. T., Sperling, D., Bissonette, J. A., Clevenger, A. P., Cutshall, C. D., Dale, V. H., Fahrig, L., France, R., Goldman, C. R., Heanue, K., Jones, J. A., Swanson, F. J., Turrentine, T., Winter, T. C. (2003). *Road Ecology: Science and Solutions*. Island Press.
- Gioria, M., Osborne, B. A. (2014). Resource competition in plant invasions: Emerging patterns and research needs. *Frontiers in Plant Science*, 5, 501. <https://doi.org/10.3389/fpls.2014.00501>
- González-Moreno, P., Pino, J., Carreras, D., Basnou, C., Fernández-Rebollar, I., Vilà, M. (2013). Quantifying the landscape influence on plant invasions in Mediterranean coastal habitats. *Landscape Ecology*, 28(5), 891–903. <https://doi.org/10.1007/s10980-013-9857-1>
- Hardion, L., Leriche, A., Schwoertzig, E., Millon, A. (2016). Species distribution 2.0: An accurate time-and cost-effective method of prospection using street view imagery. *PLoS One*, 11(1), e0146899. <https://doi.org/10.1371/journal.pone.0146899>
- Hastings, A., Cuddington, K., Davies, K. F., Dugaw, C. J., Elmendorf, S., Freestone, A., Harrison, S., Holland, M., Lambrinos, J., Malvadkar, U., Melbourne, B. A., Moore, K., Taylor, C., Thomson, D. (2004). The spatial spread of invasions: new developments in theory and evidence. *Ecology Letters*, 8(1), 91–101. <https://doi.org/10.1111/j.1461->

0248.2004.00687.x

- Hejda, M., Pyšek, P., Jarošík, V. (2009a). Impact of invasive plants on the species richness, diversity and composition of invaded communities. *Journal of Ecology*, 97(3), 393–403. <https://doi.org/10.1111/j.1365-2745.2009.01480.x>
- Hejda, M., Pyšek, P., Pergl, J., Sádlo, J., Chytrý, M., Jarošík, V. (2009b). Invasion success of alien plants: do habitat affinities in the native distribution range matter? *Global Ecology and Biogeography*, 18(3), 372–382. <https://doi.org/10.1111/j.1466-8238.2009.00445.x>
- Hulme, P. E. (2009). Trade, transport and trouble: managing invasive species pathways in an era of globalization. *Journal of Applied Ecology*, 46(1), 10–18. <https://doi.org/10.1111/j.1365-2664.2008.01600.x>
- IPBES. (2019). *Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services*. E. S. Brondizio, J. Settele, S. Díaz, and H. T. Ngo (red.).
- Kożuchowski, K. (2011). *Klimat Polski. Nowe Spojrzenie*. Wydawnictwo Naukowe PWN, Warszawa.
- Kumar Rai, P., Singh, J. S. (2020). Invasive alien plant species: Their impact on environment, ecosystem services and human health. *Ecological Indicators*, 111, 106020. <https://doi.org/10.1016/j.ecolind.2019.106020>
- Lenda, M., Skórka, P., Knops, J. M. H., Moroń, D., Sutherland, W. J., Kuszewska, K., Woyciechowski, M. (2014). Effect of the Internet Commerce on Dispersal Modes of Invasive Alien Species. *PLoS ONE*, 9, e99786. <https://doi.org/10.1371/journal.pone.0099786>
- Lenda, M., Skórka, P., Knops, J., Żmihorski, M., Gaj, R., Moroń, D., Woyciechowski, M., Tryjanowski, P. (2019). Multispecies invasion reduces the negative impact of single alien plant species on native flora. *Diversity and Distributions*, 25(6), 951–962. <https://doi.org/10.1111/ddi.12902>
- Martin, A. E., Collins, S. J., Crowe, S., Girard, J., Naujokaitis-Lewis, I., Smith, A. C., Lindsay, K., Fahrig, L. (2020). Effects of farmland heterogeneity on biodiversity are similar to—or even larger than—the effects of farming practices. *Agriculture, Ecosystems and Environment*, 288, 106698. <https://doi.org/10.1016/j.agee.2019.106698>
- Matson, P. A., Parton, W. J., Power, A. G., Swift, M. J. (1997). Agricultural intensification and ecosystem properties. *Science*, 277(5325), 504–509. <https://doi.org/10.1126/science.277.5325.504>
- McDonald, R. I., Urban, D. L. (2006). Edge effects on species composition and exotic species abundance in the North Carolina Piedmont. *Biological Invasions*, 8(5), 1049–1060. <https://doi.org/10.1007/s10530-005-5227-5>
- Melbourne, B. A., Cornell, H. V., Davies, K. F., Dugaw, C. J., Elmendorf, S., Freestone, A. L., Hall, R. J., Harrison, S., Hastings, A., Holland, M., Holyoak, M., Lambrinos, J., Moore,

- K., Yokomizo, H. (2007). Invasion in a heterogeneous world: Resistance, coexistence or hostile takeover? *Ecology Letters*, *10*(1), 77–94. <https://doi.org/10.1111/j.1461-0248.2006.00987.x>
- Milbau, A., Stout, J. C., Graae, B. J., Nijs, I. (2009). A hierarchical framework for integrating invasibility experiments incorporating different factors and spatial scales. *Biological Invasions*, *11*(4), 941–950. <https://doi.org/10.1007/s10530-008-9306-2>
- Neill, P. E., Arim, M. (2011). Human Health Link to Invasive Species. *Encyclopedia of Environmental Health* (s. 116–123). Elsevier. <https://doi.org/10.1016/B978-0-444-52272-6.00528-6>
- Olea, P. P., Mateo-Tomás, P. (2013). Assessing species habitat using Google Street View: a case study of cliff-nesting vultures. *PLoS One*, *8*(1), e54582. <https://doi.org/10.1371/journal.pone.0054582>
- Paini, D. R., Sheppard, A. W., Cook, D. C., De Barro, P. J., Worner, S. P., Thomas, M. B. (2016). Global threat to agriculture from invasive species. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(27), 7575–7579. <https://doi.org/10.1073/pnas.1602205113>
- Pauchard, A., Alaback, P. B. (2004). Influence of elevation, land use, and landscape context on patterns of alien plant invasions along roadsides in protected areas of South-Central Chile. *Conservation Biology*, *18*(1), 238–248. <https://doi.org/10.1111/j.1523-1739.2004.00300.x>
- Pyšek, P., Hulme, P. E., Simberloff, D., Bacher, S., Blackburn, T. M., Carlton, J. T., Dawson, W., Essl, F., Foxcroft, L. C., Genovesi, P., Jeschke, J. M., Kühn, I., Liebhold, A. M., Mandrak, N. E., Meyerson, L. A., Pauchard, A., Pergl, J., Roy, H. E., Seebens, H., Kleunen, M., Vilà, M., Wingfield, M. J., Richardson, D. M. (2020). Scientists' warning on invasive alien species. *Biological Reviews*, *95*(6), 1511–1534. <https://doi.org/10.1111/brv.12627>
- Richardson, D. M., Pyšek, P., Rejmanek, M., Barbour, M. G., Panetta, F. D., West, C. J. (2000). Naturalization and invasion of alien plants: concepts and definitions. *Diversity and Distributions*, *6*(2), 93–107. <https://doi.org/10.1046/j.1472-4642.2000.00083.x>
- Ricklefs, R. E., Jenkins, D. G. (2011). Biogeography and ecology: Towards the integration of two disciplines. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *366*(1576), 2438–2448. <https://doi.org/10.1098/rstb.2011.0066>
- Rosin, Z. M., Takacs, V., Baldi, A., Banaszak-Cibicka, W., Dajdok, Z., Dolata, P. T., Kwiecieński, Z., Łangowska, A., Moroń, D., Skórka, P., Tobółka, M., Tryjanowski, P., Wuczyński, A. (2011). Koncepcja świadczeń ekosystemowych i jej znaczenie w ochronie przyrody polskiego krajobrazu rolniczego. *Chrońmy Przyrodę Ojczystą*, *67*, 3–20.
- Rousselet, J., Imbert, C.-E., Dekri, A., Garcia, J., Goussard, F., Vincent, B., Denux, O., Robinet, C., Dorkeld, F., Roques, A., Rossi, J.-P. (2013). Assessing Species Distribution Using Google Street View: A Pilot Study with the Pine Processionary Moth. *PLoS One*,

8(10), e74918. <https://doi.org/10.1371/journal.pone.0074918>

- Šálek, M., Kalinová, K., Daňková, R., Grill, S., Žmihorski, M. (2021). Reduced diversity of farmland birds in homogenized agricultural landscape: A cross-border comparison over the former Iron Curtain. *Agriculture, Ecosystems & Environment*, 321, 107628. <https://doi.org/10.1016/j.agee.2021.107628>
- Schroeder, H., Grab, H., Kessler, A., Poveda, K. (2021). Human-Mediated Land Use Change Drives Intraspecific Plant Trait Variation. *Frontiers in Plant Science*, 11, 592881. <https://doi.org/10.3389/fpls.2020.592881>
- Schwartz, M. W., Thorne, J. H., Viers, J. H. (2006). Biotic homogenization of the California flora in urban and urbanizing regions. *Biological Conservation*, 127(3), 282–291. <https://doi.org/10.1016/J.BIOCON.2005.05.017>
- Shi, J., Luo, Y. Q., Zhou, F., He, P. (2010). The relationship between invasive alien species and main climatic zones. *Biodiversity and Conservation*, 19(9), 2485–2500. <https://doi.org/10.1007/s10531-010-9855-4>
- Simberloff, D., Von Holle, B. (1999). Positive interactions of nonindigenous species: Invasional meltdown? *Biological Invasions*, 1(1), 21–32. <https://doi.org/10.1023/A:1010086329619>
- Sirami, C., Gross, N., Baillod, A. B., Bertrand, C., Carrié, R., Hass, A., Henckel, L., Miguet, P., Vuillot, C., Alignier, A., Girard, J., Batáry, P., Clough, Y., Violle, C., Giralt, D., Bota, G., Badenhausser, I., Lefebvre, G., Gauffre, B., Vialatte, A., Calatayud, F., Gil-Tena, A., Tischendorf, L., Mitchell, S., Lindsay, K., Georges, R., Hilaire, S., Recasens, J., Solé-Senan, X. O., Robleño, I., Bosch, J., Barrientos, J. A., Ricarte, A., Marcos-Garcia, M. Á., Miñano, J., Mathevet, R., Gibon, A., Baudry, J., Balent, G., Poulin, B., Burel, F., Tschardtke, T., Bretagnolle, V., Siriwardena, G., Ouin, A., Brotons, L., Martin, J. L., Fahrig, L. (2019). Increasing crop heterogeneity enhances multitrophic diversity across agricultural regions. *Proceedings of the National Academy of Sciences of the United States of America*, 116(33), 16442–16447. <https://doi.org/10.1073/pnas.1906419116>
- Tschardtke, T., Klein, A. M., Kruess, A., Steffan-Dewenter, I., Thies, C. (2005). Landscape perspectives on agricultural intensification and biodiversity–ecosystem service management. *Ecology Letters*, 8(8), 857–874. <https://doi.org/10.1111/j.1461-0248.2005.00782.x>
- Vilà, M., Ibáñez, I. (2011). Plant invasions in the landscape. *Landscape Ecology*, 26(4), 461–472. <https://doi.org/10.1007/s10980-011-9585-3>
- Vitousek, P. M., D'Antonio, C. M., Loope, L. L., Rejmanek, M., Westbrooks, R. G. (1997). Introduced species: A significant component of human-caused global change. *New Zealand Journal of Ecology*, 21, 1–16.
- Wilcove, D. S., Rothstein, D., Dubow, J., Phillips, A., Losos, E. (1998). Quantifying Threats to Imperiled Species in the United States. *BioScience*, 48(8), 607–615. <https://doi.org/10.2307/1313420>

- Williamson, J., Harrison, S. (2002). Biotic and abiotic limits to the spread of exotic revegetation species. *Ecological Applications*, 12(1), 40–51. [https://doi.org/10.1890/1051-0761\(2002\)012\[0040:BAALTT\]2.0.CO;2](https://doi.org/10.1890/1051-0761(2002)012[0040:BAALTT]2.0.CO;2)
- With, K. A. (2002). The Landscape Ecology of Invasive Spread. *Conservation Biology*, 16(5), 1192–1203. <https://doi.org/10.1046/j.1523-1739.2002.01064.x>
- Wu, J., Jelinski, D. E., Luck, M., Tueller, P. T. (2000). Multiscale analysis of landscape heterogeneity: scale variance and pattern metrics. *Geographic Information Sciences*, 6(1), 6–19. <https://doi.org/10.1080/10824000009480529>

PODZIĘKOWANIA

Dziękuję promotorom, dr hab. Piotrowi Skórcie i dr hab. Michałowi Żmihorskiemu za podjęcie się (niełatwego) zadania sprawowania opieki merytorycznej nad przygotowaniem niniejszej rozprawy doktorskiej. Przede wszystkim za cierpliwe motywowanie do myślenia, godziny owocnych (i bezowocnych) dyskusji, wyjątkowo celną i konstruktywną krytykę, cenne wskazówki, dobre (i trochę gorsze) rady, nieustającą gotowość do pomocy i zadziwiający entuzjazm.

Special thanks to professor Tomas Pärt from the Swedish University of Agricultural Sciences for his valuable scientific advice, positive attitude and all the support I received, especially during my stay in his lab. Also, big thanks to Alistair Auffret for insightful comments, helpful suggestions and constructive discussions on this research.

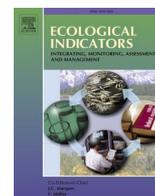
Za niezliczone konsultacje botaniczne dziękuję mgr Katarzynie Kotowskiej.

Serdeczne podziękowania dla koleżanek i kolegów z Instytutu Ochrony Przyrody PAN, przede wszystkim dla mgr Anny Misiewicz, mgr Sylwii Pustkowiak, mgr Aleksandry Splitt, mgr inż. Michała Bełcika i mgr Wojciecha Krztonia oraz dr Zuzanny Rosin z Uniwersytetu im. Adama Mickiewicza w Poznaniu za wesołe towarzystwo i życzliwe wsparcie na różnych etapach powstawania tej pracy.

Na końcu chciałabym szczególnie podziękować mojej rodzinie i znajomym za niebywałą wyrozumiałość.

ARTYKUŁ I

Kotowska, D., Pärt, T., & Żmihorski, M. (2021). Evaluating Google Street View for tracking invasive alien plants along roads. *Ecological Indicators*, 121, 107020. DOI: 10.1016/j.ecolind.2020.107020.



Evaluating Google Street View for tracking invasive alien plants along roads

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ARTICLE INFO

Keywords:

Agricultural abandonment
Farmland
Goldenrods
Invasive alien plants
Monitoring
Remote data collection
Road ecology
Roadside vegetation

ABSTRACT

Invasive alien plants are considered a major driver of global biodiversity loss. Therefore, there is a huge demand of spatial and temporal data on their distribution for investigating possible drivers of species invasions and for predictions of future distributions. We use Google Street View imagery (GSV) as a new source of spatial and temporal data. GSV provides millions of panoramic views along road networks worldwide allowing for the identification of many plant species, including invasive ones. Thus, GSV has a great potential to support ecological research in documenting species distribution, but reliable validation of its precision and accuracy is lacking. Here, we describe and evaluate an approach using GSV to visually track the spread of invasive alien plants, the North American goldenrods (*Solidago canadensis* and *S. gigantea*) occurring abundantly along road network in Poland (Central Europe). We determined presence/absence of the species along 160 randomly selected transects of a length of 500 m by visual inspection of GSV images and compared it with field surveys at the same transects. We show that the occurrence of goldenrods in GSV is a reliable predictor of their occurrence in the wild. Sampling parameters, like road width, season when GSV pictures were taken and number of months elapsed since taking the GSV pictures, did not change the correlation between outputs of the two methods (GSV and field sampling). Furthermore, both the occurrence of goldenrods observed in the field and their occurrence in GSV have similar relations to habitat characteristics investigated (the same direction of relationship and similar effect size). We suggest Google Street View images may be an additional tool to be used in the detection and tracking of the spread of invasive alien plants along roadsides. The approach may be useful in assessing temporal changes in roadside vegetation and managing problematic plant species across large spatial scales and may contribute to the further development of more efficient sampling methods in ecological studies.

1. Introduction

Global civilization changes taking place over the last centuries have brought an intensive development of international trade, transport and tourism (Mascie-Taylor and Krzyżanowska, 2017). These changes have not only resulted in an increased human mobility, but also enabled unintentional or intentional introductions of many plant species outside their natural ranges (Lenda et al., 2014; Lockwood et al., 2005). Once established, some of these alien plants have become invasive posing serious ecological problems to the native fauna and flora (Vitousek et al., 1997). Invasions of many species of alien plants have been identified as a major and growing driver of global biodiversity loss. They may inflict significant damages to native ecosystems through excessive use of resources, disruption of ecological processes and habitat modification (Richardson et al., 2000) thus, negatively affecting richness, diversity

and composition of native communities (Hejda et al., 2009), leading to the extinction of vulnerable indigenous species and homogenization of plant communities (Schwartz et al., 2006; Wilcove et al., 1998). Moreover, some species of invasive alien plants also may have an adverse impact on economy (e.g. by substantial production losses in agriculture or forestry) and human health (e.g. by causing allergies, including dermatitis, or accumulation and transferring toxins to human food; Neill and Arim, 2011; Pyšek and Richardson, 2010). It has been estimated that annual economic damages caused by invasive alien species in European Union are as high as 12 billion EUR and these costs are expected to rise (Shine et al., 2010). Therefore, a considerable legislative effort is currently being implemented to minimize the spread and negative impact of invasive plants on economy and environment (e.g. EU Regulation on Invasive Alien Species). Furthermore, numerous conservation initiatives are being taken to tackle threats from invasive alien plants to

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<https://doi.org/10.1016/j.ecolind.2020.107020>

Received 26 May 2020; Received in revised form 29 August 2020; Accepted 28 September 2020

Available online 10 October 2020

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biodiversity (e.g. projects co-funded by LIFE – the EU financial instrument supporting nature conservation).

Given the growing problem of invasive alien plants, there is an increasing demand of spatial data on invasive species for the purpose of monitoring and identifying drivers of species invasions. Such detailed spatial information are usually constrained to small scale inventories due to laborious and time-consuming surveys (but see atlas projects such as the Atlas Florae Europaeae; [Jalas and Suominen, 1972–1996](#)). Several studies used aerial photography and satellite remote sensing techniques to track alien plants (e.g. [Müllerová et al., 2013](#)) but usefulness of these methods is often limited because of the considerable financial costs of gathering high resolution images. However, recently, with the introduction of Google Street View (GSV) imagery, featured in Google Maps and Google Earth, a new source of georeferenced, open-access data has become available ([Anguelov et al., 2010](#)). GSV technology provides millions of vertical, panoramic views (i.e. photographic pictures) along the road network worldwide covering both urban and rural areas. It includes high quality images of the surroundings which allows for the identification of many plant species and habitats (see [Hardion et al., 2016](#)), as well as other structural or social features of neighborhood, such as buildings, sidewalks, road signs, aesthetics/disorder (e.g. graffiti) and pedestrian activity. Therefore, using GSV for virtual streetscape audits is an increasingly popular method of characterizing environment in the vicinity of roads for the purpose of urban planning or human health research (e.g. [Li et al., 2015](#); [Rundle et al., 2011](#); [Steinmetz-Wood et al., 2019](#)). GSV has also the potential to greatly support ecological studies in documenting species distribution. However, the possibility of its application in this field have been poorly evaluated so far. To date only few studies worldwide have used this source of data for identifying vulture habitats ([Olea and Mateo-Tomás, 2013](#)), monitoring the prevalence of the pine moth ([Rousselet et al., 2013](#)), and determining plant distribution: Russian olive ([Collette and Pither, 2015](#)), giant cane ([Hardion et al., 2016](#)), Persian hogweed ([Meier et al., 2017](#)), pampas grass ([Pardo-Primoy and Fagúndez, 2019](#)) and eucalypt ([Queirós et al., 2020](#)). [Rousselet et al. \(2013\)](#) and [Deus et al. \(2016\)](#) tested GSV as an alternative method to car surveys. However, reliable evaluation of precision and accuracy of GSV data needs to be investigated by comparisons to data collected in the field, but at present such validations are lacking.

Several studies have shown that one of the main corridors allowing invasive species to spread throughout different regions and environments are roadsides (e.g. [Christen and Matlack, 2009](#); [Pauchard and Alaback, 2004](#)). Roadsides are linear habitats that dissect landscape interior and generate disturbances related with traffic (light, noise, pollution with oil and salt) and management activities (e.g. regular mowing of roadside vegetation), and thus can mediate biological processes including dispersal through vehicle tires or air flow ([Forman, 2003](#); [Rew et al., 2018](#); [Speziale et al., 2018](#)). Presence of these dispersal vectors and linear character of the road network that connects isolated populations make roadsides crucial objects facilitating expansion of invasive alien plants ([Gelbard and Belnap, 2003](#); [Ibisch et al., 2016](#)). Thus, GSV imagery is a promising source of data covering dispersal pathways of many plant species and as such should cover highly relevant data to detect expanding populations of invasive species.

In this study we describe and evaluate a novel approach using GSV images to perform a large-scale inventory of two problematic plant species considered invasive in Eurasia: Canadian goldenrod (*Solidago canadensis*) and giant goldenrod (*S. gigantea*). These are highly competitive perennial herbs originated from North America which have spread across Europe and Asia as a result of intentional introduction for ornamental purposes. They have become one of the most successful invasive species in this region ([Weber, 2001](#)) due to their capacity for vigorous growth, rapid propagation by rhizomes, producing large number of small seeds spread by wind for long distances and because of an exertion of allelopathic effects on other plants. Consequently, the two goldenrod species may form dense stands outcompeting the native

plants ([Lenda et al., 2019](#)) and may have a negative impact on native pollinators ([Fenesi et al., 2015](#); [Moroń et al., 2009](#)), ants ([Kajzer-Bonk et al., 2016](#); [Lenda et al., 2013](#)) and birds ([Skórka et al., 2010](#)). In their alien range invasive goldenrods are especially abundant in disturbed ruderal environments such as roadsides, riverbanks as well as in agricultural fields, mostly abandoned fields or meadows ([Kabuce and Priede, 2010](#); [Weber, 2017](#)).

Here, we aim to validate the use of GSV by comparing data collected by virtual transect sampling using visual inspection of the vegetation on GSV images with corresponding transect data sampled in the field. We predict that these two datasets are positively correlated, and thus hypothesize that a GSV-based method properly identifies occurrences of the studied species along roads. As we expect that the reliability of GSV approach may be dependent on spatial scale, we used data on presence/absence of invasive goldenrods collected along: (1) c. 500 m-long transects and (2) c. 20 m-long sections of these transects. Moreover, we collected data on sampling parameters, such as time elapsed between the field survey and taking the GSV picture, width of the road and presence of road verge mowing, as we hypothesize that the degree of similarity between the two methods may be dependent on these variables (e.g. we expect that the larger the time lag between field survey and date of taking GSV picture, the higher dissimilarity and worse prediction of the goldenrod occurrence). Finally, we tested the usefulness of GSV data in addressing ecological questions. For this purpose, we compared whether GSV data and field survey data produced similar relationships to relevant environmental variables, in this case proportion of uncultivated areas (mainly abandoned fields and grasslands). We chose this variable because previous research found that uncultivated land is a main habitat of the goldenrods and may be their invasion pool ([Lenda et al., 2019](#); [Skórka et al., 2007](#)). Thus, we expect positive association between the goldenrod occurrence and cover of uncultivated land in the vicinity of transects, and that this association (the effect size) is similar between the two methods.

2. Materials and methods

2.1. Study area and transect selection

The study was conducted in agricultural areas of Polish lowlands where the two goldenrod species are widespread and still expand ([Tokarska-Guzik et al., 2012](#)). In this area we randomly selected 40 districts (average size: 1,030 km²) and chose all the 160 non-urban communes located within their boundaries. In each commune we randomly selected a point placed along road network ([Fig. 1](#)) using GIS tools and Open Street Map vector data in ArcGIS 10.4 software. The selected point was used to locate the beginning of a transect of about 500-m length. Each transect was subsequently divided into sections (see the following sub-chapter for details). If the transect was not covered by Google Street View imagery available in Google Maps web mapping service (as found on 10.05.2017) or intersected patches of forests, water bodies or urban areas (delineated basing on CORINE Land Cover database), it was rejected and the next randomly selected transect was used instead. The transect was also replaced by another one when it run along an unpaved road or was fenced with acoustic barriers. In total we selected 160 transects ([Fig. 1](#)) located along roads of different types in variable agricultural landscapes (both heterogeneous with a mosaic of small extensively managed fields, semi-natural and natural open habitats, forest patches and wastelands, and homogenous ones, i.e. with large fields intensively managed for crop production or large intensively grazed pastures). The spatial data processing was made with the use of ArcGIS 10.4 software.

2.2. Goldenrod survey using Google Street View

The selected 160 transects were remotely surveyed in Google Maps application with the use of GSV images taken between 2011 and 2014.

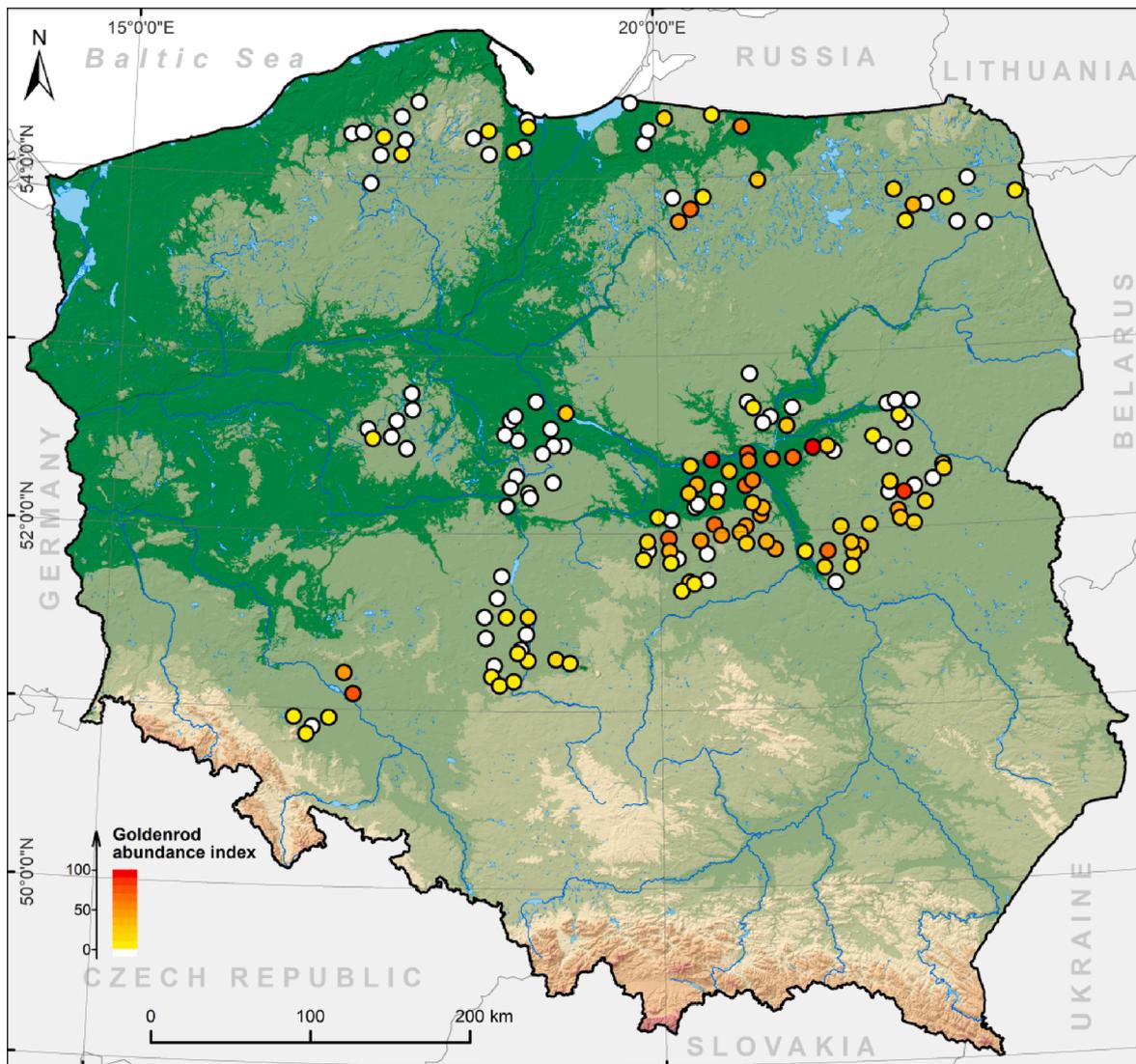


Fig. 1. Distribution of 160 transects surveyed for goldenrods in Poland and the goldenrod abundance index, i.e. share of transect sections (each about 20 m, c. 25 sections/transect) invaded by the goldenrods.

The vegetation was visually analyzed by virtual driving along the transects. As the GSV dataset consists of 360-degree images distributed unevenly along the Google vehicle's route, to keep the sampling effort equal among transects we considered two subsequent pictures located at a given transect line as a single transect section. The length of transect sections ranged between 10 and 61 m (at different roads images were taken at different distance intervals) with an average of 22 m and the mean number of sections per transect of 500 m length was 23 (range: 19–31). Using visual identification, for each transect section we manually determined the occurrence (i.e. presence/absence) of the two invasive goldenrods within 30 m (distance visually estimated) on each side of the road. Then, we used these data to obtain the occurrence of goldenrods at the transect level. As the surveyed species are superficially similar and often co-occur, we considered them together in the study (hereafter termed “goldenrods”). They were easily distinguished from other species by their characteristic shape, size and contrasting color of flowers (i.e. up to 2 m-tall aboveground shoots with numerous alternate single leaves on the stem, yellow inflorescences forming pyramidal panicles, often growing in clumps or dense stands). We also noted the date at which GSV pictures were taken and the coordinates of the picture using the ‘googleway’ (Cooley, 2018) and ‘httr’ (Wickham, 2018) packages in R (R Core Team, 2018). Since road managers in Poland are

obligated to maintain the roadside vegetation in a way that improves safety of road users, the road verges are mown ensuring proper visibility along the roadway. The vegetation is often cut twice a season (in June and August). However, the mowing frequency and time may vary depending on local conditions, type of road and its localization (urban vs. rural areas). Therefore, during the virtual data collection we also assessed the presence of road verge mowing (yes or no) within 30 m of each transect section on both sides of the road. The 30 m zone of the transect section line for a given side of the road was considered mowed if the visual inspection of the GSV picture indicated that the vegetation covering more than 50% of this area had been previously cut and was not yet fully re-grown in height.

2.3. Goldenrod survey in the field

To validate the GSV method we performed field sampling along the same set of 160 transects (separately for each transect section) previously used for remote data collection (GPS receiver was used to localize GSV sections in the field so potential mismatch should not exceed 5 m). The fieldwork was conducted during the vegetation season of 2017. Each transect was visited once, between July and September (i.e. the peak period of flowering). The observer walked along the road at a

constant pace of about 2 km per hour and noted the presence/absence of the goldenrods and whether mowing was applied within 30 m on both sides of the road for each transect section. The vegetation was classified as mowed using the same approach as in the GSV method. Analogous to the GSV method, the data on goldenrod occurrence along transect sections were subsequently used to determine the species occurrence at the scale of transects.

2.4. Transect characteristics

For each section of the transect we noted three characteristics. First, we calculated the share of uncultivated open area (i.e. abandoned arable land and grasslands) within 30 m on each side of the transect section using GIS tools based on analysis of freely available historical satellite imagery obtained from Google Earth. It was calculated both for the time when the GSV pictures were taken and for the time when the fieldwork was conducted. Second, based on the satellite images, we determined the width of the road as an average of three measurements taken in the start, middle and end point of the transect line (as it was not constant, however in all cases the difference between the three measurements was not larger than 1 m). Third, we calculated the length of the transect sections and the number of transect sections per transects using geographic coordinates of the GSV images. All the calculations were computed in ArcGIS 10.4 software.

2.5. Statistical analyses

To evaluate an approach using GSV for detection of invasive alien plants along roads we used generalized additive models (GAM), generalized linear mixed models (GLMM) and general linear models (GLM) implemented in ‘mgcv’ and ‘lme4’ packages (Bates et al., 2015; Wood, 2017) in R (R Core Team, 2018). We performed three types of analyses.

First, we tested whether GSV data predicts presence/absence of goldenrods in the field. For this purpose we performed GLMs with binomial error distribution and logit link in which the occurrence of goldenrods based on the field survey was a response variable (1/0) while the occurrence of goldenrods observed in GSV (termed “GSVSol”, see

Table 1
Description of explanatory variables used in the models.

#	Variable	Description	Model
1	GSVSol	Categorical. Presence (yes/no) of goldenrods detected by GSV method.	GLM1 _{ALL} , GLM1 _{UNMOWED} , GLM2 _{ALL} , GLM2 _{UNMOWED}
2	NSections	Continuous. Number of transect sections established along a given transect	GLM2 _{ALL} , GLM2 _{UNMOWED} , GAM2
3	GSVSeason	Categorical. Season of the year when the GSV pictures were taken: spring (May-June), summer (July-August), fall (September-October).	GAM1, GAM2
4	Length	Continuous. Length of the transect section in meters.	GAM1
5	WdthRoad	Continuous. Average width of the road in meters, computed using three measurements taken in the starting, middle and ending point of the transect line based on the satellite images.	GAM1, GAM2
6	MonthSinceGSV	Continuous. Number of months elapsing the GSV pictures and the field survey.	GAM1, GAM2
7	Uncultivated	Continuous. Share of uncultivated open area (abandoned arable land and grasslands) in the area of a given sampling unit.	GLMM1 _{GSV} , GLMM1 _{FIELD} , GLM3 _{GSV} , GLM3 _{FIELD}

Table 1 for list of variables) was an explanatory variable (1/0). As the accuracy of GSV method may depend on the spatial resolution of sampling units we fitted two models: using transect sections (GLM1_{ALL}) and transects (GLM2_{ALL}) as single data records. In all cases each side of the transect or transect section was treated independently, thus 160 transects resulted in 320 data records for the transect scale and 7426 for the transect section scale analyses. Moreover, as grass cutting on road verges may weaken the correlation between results of field survey and GSV, we repeated the two models only for transect sections without evidence of mowing both in GSV and field data (GLM1_{UNMOWED}, GLM2_{UNMOWED}, respectively). Additionally, in GLM2_{ALL} and GLM2_{UNMOWED} the number of transect sections per transect was used as a covariate (NSections; continuous variable).

We evaluated the performance of our four above GLM models by using “leave-one-out” cross validation approach (LOOCV). For each dataset we first selected all sampling units where the goldenrods were recorded in the field and the same number of random sampling units where they were absent, to keep presence to absence ratio equal (this is necessary to keep expected classification error as 50%). Among the selected data subsets a single observation *n* was excluded and used for validation, while remaining observations were used for model fit. Basing on this model, a prediction was made for the excluded observation *n*. The procedure was repeated for all data records in a given data subset. The ratio of number of correct predictions to the total number of predictions is an approximately unbiased estimate for the model classification accuracy (James et al., 2013). Moreover, we calculated two other model performance measures: sensitivity (proportion of sites correctly classified by the model as occupied by goldenrods) and specificity (proportion of sites correctly classified by the model as unoccupied by goldenrods). The described process (starting from the random selection of goldenrod-free sampling units) was replicated 10 times to include different sets of random sampling units in the validation and results of 10 replications were averaged.

Second, we aimed to determine factors that influence the correct classification of a transect or transect section as occupied or unoccupied by goldenrods based on GSV pictures (i.e. drivers of similarities and dissimilarities between outputs of GSV method and field survey). As mowing will affect these results for obvious reasons, we included in the analysis only the sections that were not mowed both in GSV and field data. To account for spatial autocorrelation in observations we fitted two binomial GAMs: for the transect section scale (GAM1) and the scale of transect (GAM2; note that transect length now varied among transects because of the removal of mowed sections). In both models the agreement between data on goldenrod occurrence obtained using the two methods was used as a response variable (1 – agreement, 0 – disagreement). The outputs of GSV method and field survey within a given sampling unit were considered as agreement if both methods detected the presence or both revealed the absence of goldenrods. The other cases were referred to as disagreement. In GAM1 one fixed categorical variable (GSVSeason) and three continuous variables (Length, WdthRoad, MonthSinceGSV) were explanatory variables. To account for spatial autocorrelation among adjacent transect sections, the transect section number (TransectSectionNo) was fitted with a spline with number of degrees of freedom set to 4. Moreover, the transect identity (TransectID) was introduced as a random factor. An analogous model using the same set of predictors was performed for the scale of transects (GAM2; with NSections instead of Length; see Table 1 for description).

Third, we compared estimates of the effect of uncultivated land for the goldenrod occurrence using datasets obtained with GSV and field survey (in both cases mowed sections were included) to test the usefulness of GSV method for predicting occurrence by environmental variables in the surrounding landscape. We computed two generalized linear mixed models (GLMM1_{GSV}, GLMM1_{FIELD}) for the scale of transect sections and two generalized linear models (GLM3_{GSV}, GLM3_{FIELD}) for the scale of transects. In all four models we used binomial error distribution with logit link function, goldenrod occurrence as a response

variable (1 – present, 0 – absent) and share of uncultivated land in the area of a given sampling unit (Uncultivated; continuous) as an explanatory variable. Moreover, in GLMM1_{GSV} and GLMM1_{FIELD} the transect ID was included as a random factor. As a result, we were able to compare parameter estimates of the uncultivated land effect between models using different sources of goldenrod occurrence.

3. Results

3.1. Goldenrod occurrence based on Google Street View and field data

At the transect sections scale, the field survey revealed goldenrods in 1081 out of 7426 sections (i.e. 14.5%, Table 2) and within 738 out of 3486 sections without mowing (21.2%; i.e. including only the sections that were not mowed both in the field and GSV). Figures based on Google Street View were lower and equaled to 8.6% sections occupied by goldenrods (12.3% without mowing). At the transect level, we observed goldenrods in 47.5% of the transects surveyed in the field (17.8% without mowing, i.e. including only the unmowed sections both in GSV and field data) while the corresponding figures for GSV data were 35% and 11.3% respectively (Table 2).

For each of the four datasets considered (i.e. transect sections and transects, with and without mowing), the occurrence of goldenrods based on field survey was significantly positively correlated with the GSV occurrence (Table 3). The models using goldenrod occurrence based on GSV method correctly classified 72–85% of sites surveyed in the field (as found by cross-validation, Table 3). All the models better predicted actual presences (ca. 94–97% of observed presences were classified correctly) than absences (ca. 64–78% of observed absences were classified correctly; Table 3).

3.2. Factors explaining similarities between Google Street View and field data

Similarity of information on goldenrod occurrence derived from the two compared methods (GSV and field survey) was hardly explained by the sampling characteristics. The season of the year when the GSV pictures were captured, width of the road and number of months elapsed since taking the GSV pictures did not affect the similarity between outputs of two sampling methods, both at the scale of transect section and transect (Table 4). Of considered explanatory variables, only the length of a transect section was negatively correlated with the probability of correct classification using GSV: the longer the transect section, the less similar are results of GSV method and field survey (Table 4). However, we did not find such association for the number of sections (i.e. reflecting average section length) at the scale of transects (Table 4).

3.3. Comparison of models using Google Street View and field data

The share of uncultivated land in the vicinity of transect section was a significant positive predictor of goldenrod occurrence as found in the

Table 2

Contingency table showing number of sampling units with and without goldenrod presence records based on GSV and field data in two spatial scales (transect sections and transects) and for two datasets (including all sections and only the sections that were not mowed both in the field and GSV).

	All sections		Unmowed sections	
	Field presence	Field absence	Field presence	Field absence
Scale: transect section				
GSV presence	497	144	381	70
GSV absence	584	6201	357	2678
Scale: transect				
GSV presence	110	4	21	5
GSV absence	42	164	20	184

Table 3

Summary of GLMs (parameter estimates followed by SE in parentheses) explaining the occurrence of goldenrods in the field survey in relation to goldenrod occurrence based on GSV images (GSVSol) along roads. Separate models were fitted for transect sections and transects as well as for full dataset and a subset of data without mowing. Significant effects are marked in bold. Significance levels (p-values) are indicated by asterisks, and are explained below the table. Performance of the models based on cross-validation (LOOCV) is given at the bottom.

Scale: Predictors	transect section		transect	
	GLM1 _{ALL} n = 7426	GLM1 _{UNMOWED} n = 3486	GLM2 _{ALL} n = 320	GLM2 _{UNMOWED} n = 230
Intercept	-2.36 (0.04)***	-2.02 (0.06) ***	-1.59 (1.40)	-2.10 (0.34) ***
GSVSol: yes	3.60 (0.10)***	3.71 (0.14)***	4.68 (0.54)***	3.70 (0.56)***
NSections	not included	not included	0.01 (0.06)	-0.02 (0.04)
LOOCV _{ACCURACY}	71.8%	74.4%	85.1%	74.0%
LOOCV _{SENSITIVITY}	95.1%	94.8%	96.9%	94.4%
LOOCV _{SPECIFICITY}	64.4%	66.8%	78.0%	66.5%

Statistical significance: *** < 0.001.

Table 4

Summary of GAMs (parameter estimates followed by SE in parentheses) explaining similarity between outputs of GSV method and field sampling at the scale of transect sections and transects in relation to sampling parameters. Significant effects are marked in bold. Significance levels (p-values) are indicated by asterisks, and are explained below the table.

Scale: Predictors	transect section	transect
	GAM1 n = 3486	GAM2 n = 230
Intercept	-0.10 (3.24)	7.09 (5.63)
GSVSeason: fall	0.22 (0.84)	-1.28 (1.27)
GSVSeason: spring	-1.20 (1.19)	-2.10 (1.46)
Length	-0.31 (0.08)***	not included
NSections	not included	-0.01 (0.07)
WdthRoad	-0.32 (0.36)	-0.33 (0.49)
MonthSinceGSV	0.06 (0.06)	-0.04 (0.10)

Statistical significance: *** < 0.001.

field (GLMM1_{FIELD}, Uncultivated effect: estimate = 0.70 (SE = 0.05), p < 0.001) and GSV (GLMM1_{GSV}, Uncultivated effect: estimate = 0.70 (SE = 0.04), p < 0.001). Similarly, the share of uncultivated areas positively predicted goldenrod occurrence in the transect scale for both field-based data and GSV data (GLM3_{FIELD}, Uncultivated effect: estimate = 0.96 (SE = 0.16), p < 0.001, GLM3_{GSV}, Uncultivated effect: estimate = 1.18 (SE = 0.21), p < 0.001, respectively; Fig. 2).

4. Discussion

We show that Google Street View can be used as an additional tool for surveying plant species at road verges and their immediate surroundings. As many invasive alien plants are occurring and dispersing along roadsides, GSV can be an important, effective tool for the future tracking of the spread of these species. More specifically, we showed that occurrence of goldenrods detected using GSV predicted their occurrence as observed in the field 3–5 years after GSV images were taken and this was true for both spatial scales considered (i.e. transects and transect sections). The GSV method performed especially well in predicting actual goldenrod presences. Sampling parameters, like presence of road verge mowing, road width, season when GSV pictures were taken and number of months elapsed since taking the GSV pictures, did not change the correlation between the two methods (except for transect section length suggesting a negative effect, most likely due to the difference in sampling effort between the two methods at longer sections). Finally, models based on GSV or field survey data produced very similar

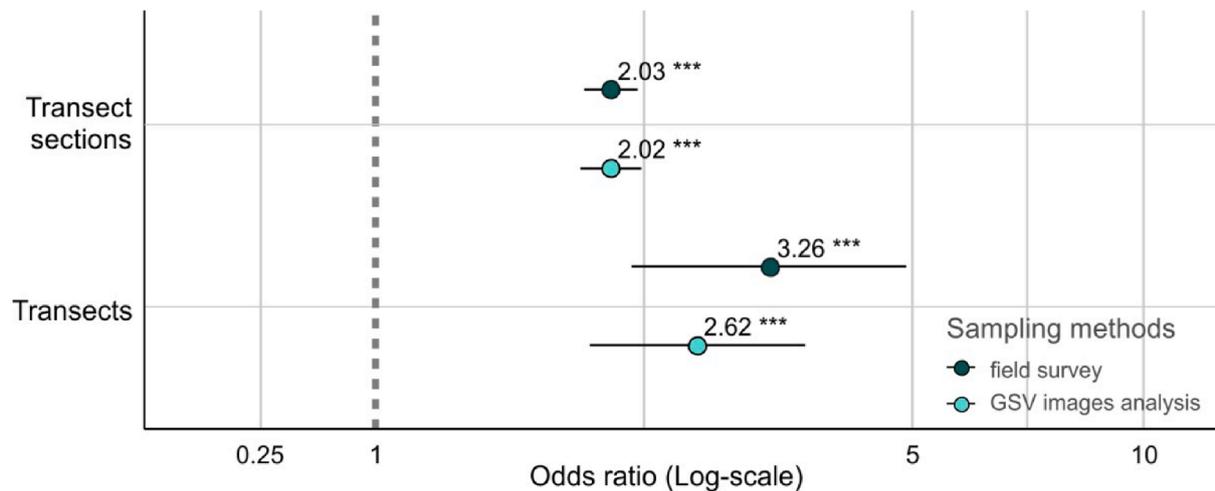


Fig. 2. Effect of share of uncultivated land on the occurrence of goldenrods (log odds with 95% CIs) from models using field survey and GSV image analysis in the scale of transect sections and transects.

estimates in the importance of the uncultivated land for the occurrence of goldenrods. Although these results are suggesting that GSV data appears to perform well in detecting and studying roadside vegetation, it may also have some limitations as discussed below.

GSV seems to be an effective tool for detecting species occurring in large numbers, being tall, having distinct shape or contrasting color. That is, species that are easily visually detected and easy to recognize at distance. For example, while browsing GSV for goldenrods, we noticed also the presence of several other invasive plant species: hogweeds (*Heracleum mantegazzianum* and *H. sosnowskyi*), knotweeds (*Reynoutria japonica*, *R. sachalinensis*, *R. × bohemica*), wild cucumber *Echinocystis lobata*, garden lupin *Lupinus polyphyllus*, box elder *Acer negundo*, black locust *Robinia pseudoacacia*, staghorn sumac *Rhus typhina* and black cherry *Prunus serotina*. However, as GSV was not intentionally designed for collecting plant data, some geometric distortions in the images could potentially affect both species detectability and mapping accuracy. Thus, smaller invasive species or species difficult to distinguish, like small-flower touch-me-not *Impatiens parviflora* or common beggar-ticks *Bidens frondosa*, commonly occurring along roadsides (Tokarska-Guzik et al., 2012), may be overlooked in GSV images.

Several factors may potentially weaken the observed high correlation between GSV and field data. First, some challenges may be linked to the frequency of GSV updates. The images used in our study were taken at different times (from morning hours until evening), months (from May to October), and years (2011 to 2014). Nevertheless, we did not find any effect of season on the probability of correct presence/absence detection of goldenrods, most likely because the studied species are relatively easily distinguishable all year round. However, in case of other species seasonal changes in vegetation growth will be more important. Furthermore, the differences between GSV and field data can also be driven by colonization and extinction events in the period between capturing GSV images and field survey, especially if the period extends to several years. Comparison of data from GSV and field survey (conducted 3–5 years after capturing GSV images) suggests an increase in goldenrod occurrence (see Table 2). However, with such an assumption one should expect a negative relationship between time elapsed since the GSV picture was taken and similarity between methods, which was not confirmed in our models (see Table 4).

Second, the probability of visual plant detection may be reduced by road verge mowing, and thus may substantially limit usefulness of GSV as a source of data. However, given there is some variation in the practice of road verge mowing, when using GSV one may also identify where mowing occurs and thus where the risk of establishment of invasive species is lower. Furthermore, mowing also reduces detection

of plants during field surveys, so this limitation is not exclusive for GSV method. Fortunately, it is relatively easy to detect recent mowing and account observed species occurrences for the mowing effect.

Finally, as highlighted in previous research (Rousselet et al., 2013), the image availability may be a crucial limitation for GSV-based sampling. GSV was primarily introduced in 2007 and covered major cities of North America. Since then it has been developed to include urban, suburban and rural areas from all around the world. Until now it has collected 170 billion Street View images captured along more than 16 million kilometers of roads across more than 220 countries and territories (Google, 2020). The GSV coverage is being successively enhanced, however there are still many places where GSV data is unavailable or its availability is limited (e.g. Africa, Central America, Middle East). Also, small gravel roads are excluded although they may be important habitats for many invasive plant species. Thus, the GSV method should be applied with caution as it may be biased by omission of some important areas.

Nevertheless, the great advantage of GSV method is that it appears to be more time- and cost effective and has much lower carbon footprint than collecting data in a traditional manner. Field sampling of vegetation usually is highly laborious (Hill et al., 2005). Given the large spatial scale of our survey, it required significant amounts of travel time. Hence, we managed to visit in the field on average six transects per day, while using GSV we were able to virtually sample the same area within an hour. We estimated that during the fieldwork an observer travelled by car a distance of about 7 700 km generating costs equaling 2 000 EUR and releasing 1.29 tons of carbon dioxide to the atmosphere. Sampling with GSV costed about 120 EUR and the estimated emission of carbon dioxide during virtual driving along transects was about 0.14 tons (see Appendix A for detailed calculations). Another future benefit of GSV data is that new GSV pictures are planned to be taken every several years, thus opening up for investigations of distributional shifts in plant species associated with climate and environmental change.

5. Conclusions

Being aware of the limitations discussed above, we conclude that Google Street View imagery, publicly available for substantial proportion of roads worldwide, is a valuable source of data on species distribution patterns. As the GSV-based method allows for considerable sampling effort reduction, it provides an opportunity to investigate some ecological phenomena (e.g. plant invasions) across large spatial scales with relatively low costs. Moreover, since the library of GSV images is permanently being updated, the tool has the potential to be used for

assessing temporal changes in roadside vegetation. We emphasize that utilization of GSV data for studying roadside environments (e.g. determining species distribution) should be further developed to include machine learning techniques for a fast identification of species and their occurrences. This would enable automatic detection of some objects (e.g. plant species) to open up for large scale analyses on the spread of invasive plant species across whole continents in order to identify new ways of how to manage these species in the future.

CRedit authorship contribution statement

Dorota Kotowska: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - original draft, Visualization, Project administration, Funding acquisition. **Tomasz Pärt:** Conceptualization, Writing - review & editing, Supervision. **Michał Żmihorski:** Conceptualization, Methodology, Software, Writing - review & editing, Supervision.

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.

Acknowledgements

The authors thank Piotr Skórka for helpful comments on the manuscript. The study was supported by the Polish National Science Centre grant: 2016/21/N/NZ8/01286 and the Polish National Science Centre doctoral scholarship: 2019/32/T/NZ8/00343.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecolind.2020.107020>.

References

- Anguelov, D., Dulong, C., Filip, D., Frueh, C., Lafon, S., Lyon, R., Ogale, A., Vincent, L., Weaver, J., 2010. Google street view: Capturing the world at street level. *Computer (Long Beach, Calif)* 43, 32–38. <https://doi.org/10.1109/MC.2010.170>.
- Bates, D., Mächler, M., Bolker, B.M., Walker, S.C., 2015. Fitting linear mixed-effects models using lme4. *J. Stat. Softw.* 67.
- Christen, D.C., Matlack, G.R., 2009. The habitat and conduit functions of roads in the spread of three invasive plant species. *Biol. Invasions* 11, 453–465. <https://doi.org/10.1007/s10530-008-9262-x>.
- Collette, L.K.D., Pither, J., 2015. Modeling the potential North American distribution of Russian olive, an invader of riparian ecosystems. *Plant Ecol.* 216, 1371–1383. <https://doi.org/10.1007/s10077-015-0514-4>.
- Cooley, D., 2018. googleway: Accesses Google Maps APIs to Retrieve Data and Plot Maps. R package version 2 (7), 1. <https://CRAN.R-project.org/package=googleway>.
- Deus, E., Silva, J.S., Catry, F.X., Rocha, M., Moreira, F., 2016. Google Street View as an alternative method to car surveys in large-scale vegetation assessments. *Environ. Monit. Assess.* 188 <https://doi.org/10.1007/s10661-016-5555-1>.
- Fenesi, A., Vágási, C.I., Beldean, M., Földesi, R., Kolcsár, L.-P., Shapiro, J.T., Török, E., Kovács-Hostyánszki, A., 2015. Solidago canadensis impacts on native plant and pollinator communities in different-aged old fields. *Basic Appl. Ecol.* 16, 335–346. <https://doi.org/10.1016/J.BAAE.2015.03.003>.
- Forman, R.T.T., 2003. *Road ecology : science and solutions*. Island Press.
- Gelbard, J.L., Belnap, J., 2003. Roads as Conduits for Exotic Plant Invasions in a Semiarid Landscape. *Conserv. Biol.* 17, 420–432. <https://doi.org/10.1046/j.1523-1739.2003.01408.x>.
- Google, 2020. Google Maps Blog. <https://www.blog.google/products/maps/> (accessed 1.20.20).
- Hardion, L., Leriche, A., Schwoertzig, E., Millon, A., 2016. Species Distribution 2.0: An Accurate Time- and Cost-Effective Method of Prospecion Using Street View Imagery. *PLoS One* 11, e0146899. <https://doi.org/10.1371/journal.pone.0146899>.
- Hejda, M., Pyšek, P., Jarošík, V., 2009. Impact of invasive plants on the species richness, diversity and composition of invaded communities. *J. Ecol.* 97, 393–403. <https://doi.org/10.1111/j.1365-2745.2009.01480.x>.
- Hill, D., Fasham, M., Tucker, G., Shewry, M., Shaw, P. (Eds.), 2005. *Handbook of Biodiversity Methods: Survey, Evaluation and Monitoring*, Handbook of Biodiversity Methods. Cambridge University Press. <https://doi.org/10.1017/cbo9780511542084>.
- Ibisch, P.L., Hoffmann, M.T., Kreft, S., Pe'er, G., Kati, V., Biber-Freudenberger, L., DellaSala, D.A., Vale, M.M., Hobson, P.R., Selva, N., 2016. A global map of roadless areas and their conservation status. *Science*. 354, 1423–1427. <https://doi.org/10.1126/science.aaf7166>.
- Jalas, J., Suominen, J. (Eds.), 1972-1996. *Atlas Florae Europaeae*. The Committee for Mapping the Flora of Europe and Societas Biologica Fennica Vanamo, Helsinki.
- James, G., Witten, D., Hastie, T., Tibshirani, R., 2013. *An introduction to statistical learning with applications in R*. Springer, New York. <https://doi.org/https://doi.org/10.1007/978-1-4614-7138-7>.
- Kabuce, N., Priede, N., 2010. NOBANIS – Invasive Alien Species Fact Sheet – Solidago canadensis. – From: Online Database of the European Network on Invasive Alien Species - NOBANIS. <https://www.nobanis.org> (accessed 1.22.20).
- Kajzer-Bonk, J., Szpilyk, D., Woyciechowski, M., 2016. Invasive goldenrods affect abundance and diversity of grassland ant communities (Hymenoptera: Formicidae). *J. Insect Conserv.* 20, 99–105. <https://doi.org/10.1007/s10841-016-9843-4>.
- Lenda, M., Skórka, P., Knops, J., Żmihorski, M., Gaj, R., Moroń, D., Woyciechowski, M., Tryjanowski, P., 2019. Multispecies invasion reduces the negative impact of single alien plant species on native flora. *Divers. Distrib.* 25, 951–962. <https://doi.org/10.1111/ddi.12902>.
- Lenda, M., Skórka, P., Knops, J.M.H., Moroń, D., Sutherland, W.J., Kuszewska, K., Woyciechowski, M., 2014. Effect of the Internet Commerce on Dispersal Modes of Invasive Alien Species. *PLoS One* 9, e99786. <https://doi.org/10.1371/journal.pone.0099786>.
- Lenda, M., Witek, M., Skórka, P., Moroń, D., Woyciechowski, M., 2013. Invasive alien plants affect grassland ant communities, colony size and foraging behaviour. *Biol. Invasions* 15, 2403–2414. <https://doi.org/10.1007/s10530-013-0461-8>.
- Li, X., Zhang, C., Li, W., Ricard, R., Meng, Q., Zhang, W., 2015. Assessing street-level urban greenery using Google Street View and a modified green view index. *Urban For. Urban Green.* 14, 675–685. <https://doi.org/10.1016/j.ufug.2015.06.006>.
- Lockwood, J.L., Cassey, P., Blackburn, T., 2005. The role of propagule pressure in explaining species invasions. *Trends Ecol. Evol.* 20, 223–228. <https://doi.org/10.1016/j.tree.2005.02.004>.
- Mascie-Taylor, C.G.N., Krzyżanowska, M., 2017. Biological aspects of human migration and mobility. *Ann. Hum. Biol.* 44, 427–440. <https://doi.org/10.1080/03014460.2017.131344>.
- Meier, S., Taff, G.N., Aune, J.B., Eiter, S., 2017. Regulation of the Invasive Plant *Heracleum persicum* by Private Landowners in Tromsø, Norway. *Invasive Plant Sci. Manag.* 10, 166–179. <https://doi.org/10.1017/inp.2017.11>.
- Moroń, D., Lenda, M., Skórka, P., Szentgyörgyi, H., Settele, J., Woyciechowski, M., 2009. Wild pollinator communities are negatively affected by invasion of alien goldenrods in grassland landscapes. *Biol. Conserv.* 142, 1322–1332. <https://doi.org/10.1016/J.BIOCON.2008.12.036>.
- Müllerová, J., Pergl, J., Pyšek, P., 2013. Remote sensing as a tool for monitoring plant invasions: Testing the effects of data resolution and image classification approach on the detection of a model plant species *Heracleum mantegazzianum* (giant hogweed). *Int. J. Appl. Earth Obs. Geoinf.* 25, 55–65. <https://doi.org/10.1016/J.JAG.2013.03.004>.
- Neill, P.E., Arim, M., 2011. Human Health Link to Invasive Species, in: *Encyclopedia of Environmental Health*. Elsevier, pp. 116–123. <https://doi.org/10.1016/B978-0-444-52272-6.00528-6>.
- Olea, P.P., Mateo-Tomás, P., 2013. Assessing Species Habitat Using Google Street View: A Case Study of Cliff-Nesting Vultures. *PLoS One* 8, e54582. <https://doi.org/10.1371/journal.pone.0054582>.
- Pardo-Primov, D., Fagúndez, J., 2019. Assessment of the distribution and recent spread of the invasive grass *Cortaderia selloana* in Industrial Sites in Galicia, NW Spain. *Flora Morphol. Distrib. Funct. Ecol. Plants*. <https://doi.org/10.1016/j.flora.2019.151465>.
- Pauchard, A., Alaback, P.B., 2004. Influence of Elevation, Land Use, and Landscape Context on Patterns of Alien Plant Invasions along Roadsides in Protected Areas of South-Central Chile. *Conserv. Biol.* 18, 238–248. <https://doi.org/10.1111/j.1523-1739.2004.00300.x>.
- Pyšek, P., Richardson, D.M., 2010. Invasive Species, Environmental Change and Management, and Health. *Environ. Resour. Rev. Environ.* 35, 25–55. <https://doi.org/10.1146/annurev-environ-033009-095548>.
- Queirós, L., Deus, E., Silva, J.S., Vicente, J., Ortiz, L., Fernandes, P.M., Castro-Díez, P., 2020. Assessing the drivers and the recruitment potential of *Eucalyptus globulus* in the Iberian Peninsula. *For. Ecol. Manage.* 466, 118147 <https://doi.org/10.1016/j.foreco.2020.118147>.
- R Core Team, 2018. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL <http://www.R-project.org/>.
- Rew, L.J., Brummer, T.J., Pollnac, F.W., Larson, C.D., Taylor, K.T., Taper, M.L., Fleming, J.D., Balbach, H.E., 2018. Hitching a ride: Seed accrual rates on different types of vehicles. *J. Environ. Manage.* 206, 547–555. <https://doi.org/10.1016/j.jenvman.2017.10.060>.
- Richardson, D.M., Pyšek, P., Rejmanek, M., Barbour, M.G., Panetta, F.D., West, C.J., 2000. Naturalization and invasion of alien plants: concepts and definitions. *Divers. Distrib.* 6, 93–107. <https://doi.org/10.1046/j.1472-4642.2000.00083.x>.
- Rousselet, J., Imbert, C.-E., Dekri, A., Garcia, J., Goussard, F., Vincent, B., Denux, O., Robinet, C., Dorkeld, F., Roques, A., Rossi, J.-P., 2013. Assessing Species Distribution Using Google Street View: A Pilot Study with the Pine Processionary Moth. *PLoS One* 8, e74918. <https://doi.org/10.1371/journal.pone.0074918>.
- Rundle, A.G., Bader, M.D.M., Richards, C.A., Neckerman, K.M., Teitler, J.O., 2011. Using google street view to audit neighborhood environments. *Am. J. Prev. Med.* 40, 94–100. <https://doi.org/10.1016/j.amepre.2010.09.034>.

- Schwartz, M.W., Thorne, J.H., Viers, J.H., 2006. Biotic homogenization of the California flora in urban and urbanizing regions. *Biol. Conserv.* 127, 282–291. <https://doi.org/10.1016/j.biocon.2005.05.017>.
- Shine, C., Kettunen, M., Genovesi, P., Essl, F., Gollasch, S., Rabitsch, W., Scalera, R., Starfinger, U., ten Brink, P., 2010. Assessment to support continued development of the EU Strategy to combat invasive alien species. Final Report for the European Commission. Brussels, Belgium.
- Skórka, P., Lenda, M., Tryjanowski, P., 2010. Invasive alien goldenrods negatively affect grassland bird communities in Eastern Europe. *Biol. Conserv.* 143, 856–861. <https://doi.org/10.1016/j.biocon.2009.12.030>.
- Skórka, P., Settele, J., Woyciechowski, M., 2007. Effects of management cessation on grassland butterflies in southern Poland. *Agric. Ecosyst. Environ.* 121, 319–324. <https://doi.org/10.1016/j.agee.2006.11.001>.
- Speziale, K.L., di Virgilio, A., Lescano, M.N., Pirk, G., Franzese, J., 2018. Synergy between roads and disturbance favour *Bromus tectorum* L. invasion. *PeerJ* 2018. <https://doi.org/10.7717/peerj.5529>.
- Steinmetz-Wood, M., Velauthapillai, K., O'Brien, G., Ross, N.A., 2019. Assessing the micro-scale environment using Google Street View: The Virtual Systematic Tool for Evaluating Pedestrian Streetscapes (Virtual-STEPS). *BMC Public Health* 19. <https://doi.org/10.1186/s12889-019-7460-3>.
- Tokarska-Guzik, B., Dajdok, Z., Zając, M., Zając, A., Urbisz, A., Danielewicz, W., Holdyński, C., 2012. Rośliny obcego pochodzenia w Polsce ze szczególnym uwzględnieniem gatunków inwazyjnych - Alien plants in Poland with particular reference to invasive species. Generalna Dyrekcja Ochrony Środowiska, Warszawa.
- Vitousek, P.M., D'Antonio, C.M., Loope, L.L., Rejmanek, M., Westbrooks, R.G., 1997. Introduced species: A significant component of human-caused global change. *N. Z. J. Ecol.* 21, 1–16.
- Weber, E., 2017. Invasive plant species of the world : a reference guide to environmental weeds. Cabi.
- Weber, E., 2001. Current and Potential Ranges of Three Exotic Goldenrods (*Solidago*) in Europe. *Conserv. Biol.* 15, 122–128. <https://doi.org/10.1111/j.1523-1739.2001.99424.x>.
- Wickham, H., 2018. httr: Tools for Working with URLs and HTTP. R package version 1.4.0. <https://CRAN.R-project.org/package=httr>.
- Wilcove, D.S., Rothstein, D., Dubow, J., Phillips, A., Losos, E., 1998. Quantifying Threats to Imperiled Species in the United States. *Bioscience* 48, 607–615. <https://doi.org/10.2307/1313420>.
- Wood, S.N., 2017. Generalized Additive Models : an introduction with R (2nd edition). Chapman and Hall/CRC.

Appendix A

Calculations of costs and emissions associated with field surveys and remote data collection in Google Street View.

The distance travelled by car during the fieldwork was calculated based on the observer's car GPS tracking history and was estimated to be about 7700 km. The field survey lasted for 29 days. Assuming that the daily allowance and accommodation in Poland is 17.5 EUR and the mileage rate is 0.1944 EUR per kilometer travelled, the total costs generated during the field survey were as high as about 2000 EUR (29 days * 17.5 EUR + 7700 km * 0.1944 EUR). Given the observer used a 7-year old compact car powered by a turbocharged diesel engine of the capacity of 1500 cm³, which consumes about 6 liters of fuel per 100 km travelled, the estimated emission of carbon dioxide during the fieldwork was 1.29 tons (based on the carbon footprint calculator available at <https://calculator.carbonfootprint.com>).

The remote data collection along 160 transects with Google Street View took 27 hours of work performed in 7 days. The total costs associated with virtual sampling included daily allowance and accommodation and equaled about 120 EUR (7 days * 17.5 EUR). The total carbon dioxide emission generated during remote surveys was about 0.14 tons and resulted from energy consumption (laptop computer: 50 Watts * 27 hours = 13.5 kWh = 0.01 tons CO₂, based on the carbon footprint calculator available at <https://calculator.carbonfootprint.com>, and website page views: 930 views * 160 transects * 0.89 g CO₂ = 0.13 tons CO₂, based on the website carbon calculator available at <https://www.websitecarbon.com>).

ARTYKUŁ II

Kotowska, D., Pärt, T., Skórka, P., Auffret, A. G. & Žmihorski, M. (2022). Scale dependence of landscape heterogeneity effects on plant invasions. *Journal of Applied Ecology*, 59(5), 1313–1323. DOI: 10.1111/1365-2664.14143.

RESEARCH ARTICLE

Scale dependence of landscape heterogeneity effects on plant invasions

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Funding information

Narodowe Centrum Nauki, Grant/Award Number: 2016/21/N/NZ8/01286 and 2019/32/T/NZ8/00343

Handling Editor: Rafael D. Zenni

Abstract

1. Invasive alien species are among the most concerning threats to native biodiversity world-wide, and the level of landscape heterogeneity is considered to affect spatial patterns of their occurrence and spread. However, as previous studies on these associations report contrasting results, the role of landscape heterogeneity on its susceptibility to invasions remains poorly understood. Landscape heterogeneity is usually described by two measures: configuration and composition. Both measures may differently affect invasive species and these impacts may be additionally scale dependent. Nevertheless, their relative contribution to invasion patterns is poorly known.
2. We investigated the effect of two landscape heterogeneity components: configuration (edge density) and composition (number and evenness of land cover types) measured at different spatial scales (from within 0.25 to 5 km of the studied locations) on the local abundance of one of the most invasive alien plant species in Europe, the North American goldenrods (*Solidago canadensis* and *S. gigantea*). Using publicly available geospatial environmental data and a novel method based on remote analysis of Google Street View images, we collected and analysed large dataset on goldenrod occurrence along 1,347 roadside transects in agricultural landscapes of Poland.
3. Both the compositional and configurational heterogeneity were positively associated with the local abundance of goldenrods, however, the effect size of these relationships was dependent on spatial scale. While abundance–heterogeneity associations were most pronounced at the largest spatial scale for compositional heterogeneity, the pattern was the opposite for configurational heterogeneity.
4. *Synthesis and applications.* Landscape heterogeneity is a clear correlate of plant invasion potential, with occurrences of invasive plants generally higher in more heterogeneous landscapes. However, scale dependence of this association means that researchers and practitioners may miss the association if only concentrating on a single spatial scale. While increasing heterogeneity of rural landscapes is widely introduced as a way to promote farmland biodiversity, we show that it may also support invasive plants, and thus conflict with original goals of biodiversity-oriented strategies. Therefore, we suggest implementing

regular management and eradication schemes in most heterogeneous landscapes. Finally, we demonstrate how remote analysis of plant invasions using existing imagery can advance our understanding of invasion biology.

KEYWORDS

biological invasions, farmland, goldenrods, Google Street View, landscape structure, Poland, roadsides, spatial scale

1 | INTRODUCTION

Along with significant human-induced environmental changes observed in the Anthropocene such as habitat destruction and climate change, invasions of alien species have become one of the most serious and growing threats to global biodiversity (Blackburn et al., 2019; IPBES, 2019). Invasive alien species can outcompete natives for available resources, induce habitat modifications or change biotic interactions within communities, and thus cause substantial native biodiversity declines and ecosystem degradation (Pyšek et al., 2012). They can also severely reduce services that native ecosystems provide to human beings (Kumar Rai & Singh, 2020) with negative effects on food security (Paini et al., 2016), human health (Pyšek & Richardson, 2010) and infrastructure (Booy et al., 2017). Thereby, invasive species, including plants, can adversely affect national economies leading to financial expenses exceeding 26.8 billion US\$ globally with an increasing trend (Diagne et al., 2021). About one fifth of the Earth's surface is now at risk due to biological invasions (IPBES, 2019) and the problem of invasive alien species is expected to accelerate under ongoing climate change and other anthropogenic disturbances in natural systems (Early & Sax, 2014). Therefore, it is important to improve our understanding of the circumstances under which invasive alien species, such as plants, establish and spread.

Landscape heterogeneity, that is, the spatial and temporal variation in structural and compositional complexity of the environment (Fahrig et al., 2011), is a simple, useful and easy to measure property of the landscape for ecology and conservation. It is also regarded as an important driver of biological invasions (González-Moreno et al., 2013; Vilà & Ibáñez, 2011). Since landscape heterogeneity strongly affects biodiversity, community composition and connectivity in plants (Gastauer et al., 2021; Lundholm, 2009), it is likely to be related to the occurrence patterns of invasive plants and to landscape invasibility in general (With, 2002). Heterogeneous landscapes may be less prone to invasions due to a high diversity of native species which efficiently utilize available resources, and thus limit successful colonization of alien plants through increased competition (Levine, 2000). Moreover, the fragmented structure of a heterogeneous landscape may hamper new plant incursions as available suitable habitat patches are scattered and isolated (Alofs & Fowler, 2010). In contrast, some research indicates that a heterogeneous landscape is more vulnerable to plant invasions because of increased amount of resources and ecological niches, and thus higher number of habitats suitable for invasive alien plants (Melbourne

et al., 2007). Furthermore, in a heterogeneous landscape there are more elements that facilitate the spread of these problematic species (e.g. ecotones, borders between land-use types, field verges, roads) and more animals that can be vectors of dispersal (Harrison et al., 2001). Yet, while landscape heterogeneity metrics improve performance of models describing the spatial patterns of alien plant species richness (Kumar et al., 2006), the role of landscape heterogeneity on its susceptibility to invasions is unclear because both positive and negative associations have been empirically confirmed (Hastings et al., 2004; Williamson & Harrison, 2002; With, 2002). It is, therefore, central to understand why different studies lead to contradictory conclusions.

Importantly, although the impact of landscape heterogeneity on invasive alien plants remains poorly understood, in many European countries conservation measures aim at increasing landscape heterogeneity to maintain farmland biodiversity and several studies recommend landscape management that promotes heterogeneity (e.g. Perović et al., 2015). Such measures are greatly supported by funding instruments available, for example, under the EU Common Agricultural Policy (e.g. implementing agri-environmental schemes or establishing Ecological Focus Areas, like fallow lands, field margins, hedges and trees). Costs of implementation of these conservation tools reach millions of EUR annually. However, assuming positive heterogeneity–invasibility association (Melbourne et al., 2007), biodiversity-oriented strategies promoting heterogeneity may increase the probability of plant invasions as a side effect, thus reducing effectiveness of their original goals.

It is possible that the discrepancies concerning the effect of landscape heterogeneity on its susceptibility to invasion may result from scale dependence. Davies et al. (2005) found that landscapes with more spatial heterogeneity in the environment sustained both more native and invasive species, leading to a positive correlation of native and alien plant diversity at large spatial scales. In contrast, most studies conducted at small spatial scales show that the more diverse native communities are the less likely they are to be invaded by alien plants (Davies et al., 2005; Gallien & Carboni, 2017). Thus, one can expect that a positive association between invasive plants and environmental heterogeneity will be stronger at larger spatial scales, perhaps because large-scale heterogeneity better reflects the availability of empty niches and dispersal corridors (Harrison et al., 2001; Melbourne et al., 2007), while heterogeneity at small spatial scales reflects increased levels of interspecific competition (e.g. Levine, 2000). Another important consideration is that landscape heterogeneity can be measured in different ways. Broadly

speaking, heterogeneity can be viewed as configurational (the spatial arrangement of land cover types and habitat edges) and compositional (the number and proportions of different land cover types, Fahrig et al., 2011). These two landscape heterogeneity components may potentially relate to plant invasions in different ways and this relationship may interact with spatial scale, but empirical evaluations of their relative contribution to invasion patterns are largely lacking at present.

Here, we aim to link two components of landscape heterogeneity (configuration and composition), measured at different spatial scales, to the distribution of common invasive alien plants along roads in agricultural landscapes of Poland. For this purpose, we applied a novel method using Google Street View (GSV; Kotowska et al., 2021) imagery to gather large-scale data on abundance of one of the most widespread invasive alien plants in this area, the North American goldenrods (*Solidago* spp.). Road verges constitute major dispersal conduits for alien plants world-wide, providing appropriate conditions for establishment of these opportunistic species and their expansion into new areas (Lázaro-Lobo & Ervin, 2019; McDougall et al., 2018). However, the colonization of roadsides by invasive plants may be altered by the heterogeneity of the surrounding environment, and here we test associations between abundance of invasive goldenrods along roads and heterogeneity of the nearby landscape. We hypothesize that local abundance of invasive goldenrods along roads is positively related to the level of configurational heterogeneity in a landscape (i.e. is higher in landscapes abundant in possible colonization routes for the species). In contrary, we had

no clear predictions concerning compositional heterogeneity effect as we cannot a priori assume whether higher number of land-use types increases or decreases availability of habitats preferred by goldenrods. Finally, to explore patterns in the data and to generate hypotheses about relationships between invasive plants and the surrounding landscape we compared effects of both configurational and compositional heterogeneities across different spatial scales.

2 | MATERIALS AND METHODS

2.1 | Study area and transect selection

The study was conducted in 1,347 roadside transects in rural landscapes across the country of Poland (Figure 1), where agricultural land uses cover about 50% of the country's area (Stacherzak et al., 2019). Out of a total of 2,478 local-authority areas ('communes') in Poland, we first selected all the 1,555 rural communes (i.e. those within which there are no cities, as defined by the Central Statistical Office for Poland). Next, based on the European Digital Elevation Model available through the Copernicus Land Monitoring Service (<https://land.copernicus.eu>), we excluded 195 communes located at an altitude of higher than 300 m a.s.l. (above 70% of the commune's area). This was done to limit the study area to lowland rural landscapes because the studied invasive species are mainly found in lowlands, while mountain areas are mostly covered by forests. Finally, using Google Street View (GSV) imagery available

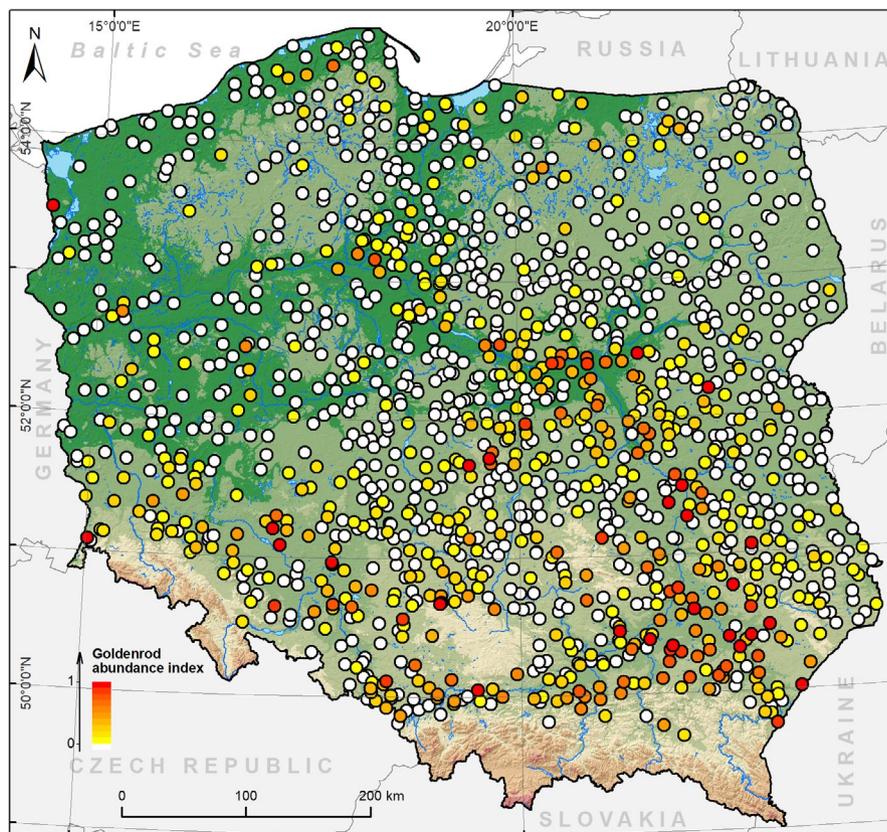


FIGURE 1 Distribution of 1,347 transects sampled for goldenrods in agricultural landscapes of Poland and the goldenrod abundance index recorded in the studied locations

in Google Maps web mapping service, we excluded 13 communes with no GSV coverage. This resulted in 1,347 communes, in which we randomly selected a transect of about 500 m length following the approach described in Kotowska et al. (2021). Using GIS tools and Open Street Map vector data, we placed in each commune a random point located along road network and subsequently used it as a beginning of a transect. If the transect was not covered by GSV imagery, was fenced with acoustic barriers or intersected by large patches of forests, water bodies or urban areas (as identified by the CORINE Land Cover database), it was rejected and the next randomly selected transect in the commune was used instead. As a result, the final 1,347 transects across Poland (mean nearest neighbour distance: 8,384 m, range: 990–32,685 m), covered a variety of agricultural habitats and represented a broad gradient of landscape heterogeneity. Landscapes included those that consisted of large arable fields or large intensively grazed pastures, as well as those with heterogeneous landscape mosaics containing small fields with different crops, low-intensity grazed pastures mixed with other semi-natural and natural open habitats, orchards, woodlands and wastelands. The spatial data processing was made with the use of ArcGIS 10.4 software.

2.2 | Model species

Canadian goldenrod (*Solidago canadensis* L.) and giant goldenrod (*S. gigantea* Aiton) are among the most successful invaders recorded in Central Europe (Carboneras et al., 2018). Once established, they form dense, extensive and single species stands, leading to a drastic reduction in native plant diversity (Moroń et al., 2009). Goldenrod expansion can negatively affect birds (Skórka et al., 2010), pollinators (such as bees, hoverflies and butterflies; Moroń et al., 2009; Lenda et al., 2019), beetles (de Groot et al., 2007) and ants (Lenda et al., 2013). Invasive goldenrods occur most abundantly in human-disturbed environments, such as roadsides, abandoned pastures and fields, ruderal habitats in urban areas and settlements, but also colonize riverbanks, forest edges, meadows and semi-natural grasslands (Perera et al., 2021). Both goldenrod species are widespread in Poland and their range is still expanding therein. Given the similarities between the two species in their morphology (reliable distinction is possible primarily by examining the presence of downy hairs on the upper third of the stem) and habitat preferences within their alien range, we consider them together in this study (and refer to them as 'goldenrods').

2.3 | Goldenrod sampling

To gather large-scale data on distribution of invasive alien goldenrods in Poland, we applied a novel method using Google Street View imagery to study roadside vegetation. This method allows

the study of a large number of sites across a suite of environments (from rural to urban) in many places throughout the globe with relatively low sampling effort, and shows high precision in relation to field inventory data (but see Kotowska et al., 2021 for discussion of its limitations, such as data availability, temporal variability in imagery or difficulties in detecting less conspicuous species). Each of the 1,347 transects was divided into (on average) 25 sections of around 20 m length (Figure 2b) and sampled for goldenrods by virtually 'driving' along the road and visually analysing GSV images. The remote data collection was performed using Google Earth application and was based on the panoramic views taken between 2011 and 2018. For each transect section, we determined the goldenrod occurrence (0/1) within 30 m of a transect line. To account for sampling bias resulting from roadside maintenance, we also assessed the presence of recent road verge mowing (0/1) within 30 m of the road. The 30 m zone was considered mown if the vegetation covering more than 50% of this area had been recently cut, as judged by not yet being fully re-grown in height. Additionally, we noted the coordinates of inspected GSV images. For each transect, we calculated a goldenrod abundance index as a proportion of transect sections invaded by the goldenrods. The information on road verge mowing along a transect was quantified as a proportion of transect sections considered mown. The study did not require any ethical approval.

2.4 | Landscape characteristics

We characterized the structure of the landscape in the vicinity of surveyed transects using measures of two landscape heterogeneity components: configuration and composition (as defined by Fahrig et al., 2011). To describe configurational heterogeneity, we calculated the edge density, that is, the density of land parcel borders based on the vector layers available from the Polish Head Office of Geodesy and Cartography. The higher the density, the more heterogeneously configured the landscape is, with many small and fragmented parcels. The compositional heterogeneity was computed using the modified Simpson's diversity index (Pielou, 1975; Simpson, 1949) of land cover types based on the CORINE Land Cover data (CLC; 29 land cover types in total, see Table S1). The higher the Simpson's diversity index, the higher the number of different land cover types and the proportional distribution of their area becomes more equitable. Both landscape characteristics were calculated at five scales, that is, buffer zones of 250, 500, 1,000, 2,000 and 5,000 m from the transect line (Figure 2a). While the Simpson's diversity index (i.e. compositional heterogeneity) increased with the buffer radius, the edge density (i.e. configurational heterogeneity) seemed to slightly decrease (Figure 3). Therefore, the values of two landscape heterogeneity indices were standardized (separately for each buffer zone), that is, scaled estimates (Figure 3), allowing for reliable result comparison across spatial scales and measures. The spatial analyses were performed using ArcGIS 10.4 software.

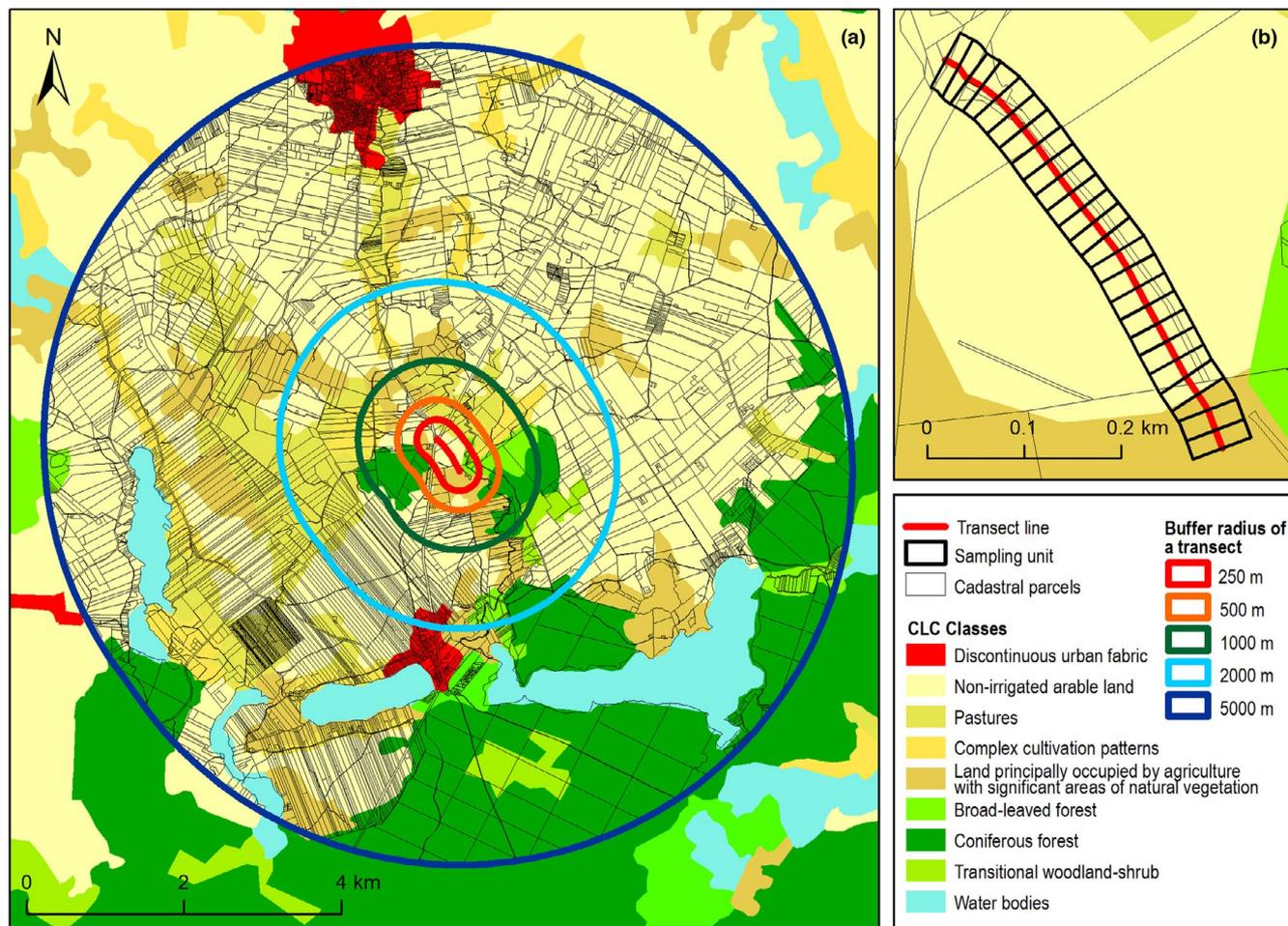


FIGURE 2 A study location; five spatial scales (i.e. buffer zones of a transect line) at which the landscape heterogeneity measures were calculated (a) and 25 sampling units surveyed for goldenrod occurrence within 30 m of a transect line (b)

2.5 | Statistical analysis

To link landscape heterogeneity to local abundance of goldenrods in Poland, we used generalized additive models (GAMs) implemented in `mgcv` package (Wood, 2017) in R (R Core Team, 2020). We fitted five binomial GAMs (GAM 1–5) with logit link, one for each of the spatial scales at which the landscape heterogeneity measures were calculated. In each model, we used the goldenrod abundance index (i.e. proportion of transect sections invaded by the goldenrods ranging from 0 to 1) as a response variable, each transect as a single data record (initially 1,347 transects, finally 1,153 transects were used, see below) and number of transect sections established along a given transect as a weight argument. In all GAMs, the two components of landscape heterogeneity (i.e. configuration and composition) were simultaneously considered as two explanatory variables (continuous variables fitted with parametric linear fit; both standardized prior to the analysis; Pearson's correlation coefficient between the two landscape heterogeneity components in five considered spatial scales was between 0.22 and 0.26). Moreover, as we presumed that roadside vegetation cutting may reduce the probability of visual plant detection, we included the proportion of

transect sections considered mown as a covariate (Mowing; continuous variable; parametric linear fit) in the models. Additionally, to control for spatial autocorrelation in observations, the longitude and latitude of the central point of a transect line were fitted with interaction of nonparametric splines and degrees of freedom fixed (to enable comparisons among different GAMs) to 30 (allowing for relatively complex fit, as explained in Wood, 2017). With this approach, the response variable is expected to vary in a nonlinear way across space, and part of this variation is explained by geographical location, thus reducing spatial autocorrelation in model residuals (Wood, 2017). The restricted maximum likelihood (REML) was used to avoid overfitting while estimating smoothing parameters. The spatial dependency in residuals of the five performed models was additionally checked by visual inspection of spline correlograms plotted with the `nCF` package in R (Bjornstad, 2020). As residuals of data records placed in close proximity were still not fully independent (positive spatial autocorrelation), among 194 pairs of transects located closer than 6 km from each other one transect was excluded from the original dataset while remaining 1153 data records were used for the final modelling. For all five GAMs performed on this subset of 1153 data records the spatial autocorrelation of residuals

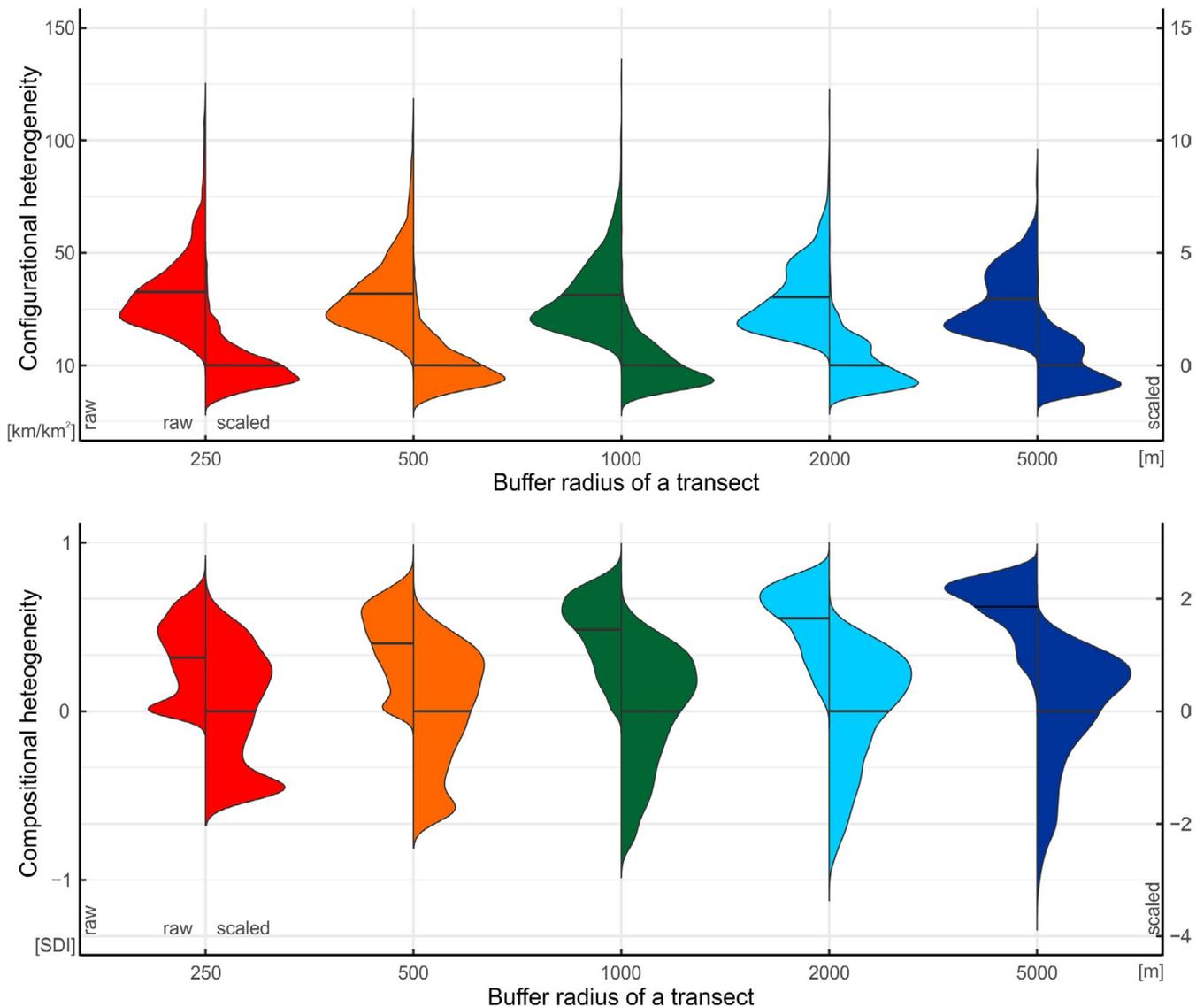


FIGURE 3 Landscape heterogeneity measures: configuration (edge density; upper panel) and composition (Simpson's diversity index of CLC classes; SDI; lower panel) in five spatial scales showed with kernel density and mean (horizontal thick line) separately for the original dataset (left polygons) and scaled values (right polygons)

was low (below 0.2) and not significant ($p > 0.05$, 95% confidence intervals largely overlapping zero, see [Figure S1](#)), indicating no further problem with spatial autocorrelation in our models.

We used odds ratio with a 95% confidence interval to compare the strength of associations (i.e. effect sizes) between goldenrod abundance index and the two components of landscape heterogeneity across the five spatial scales. Here, the odds is the ratio between the number of invaded transects (all sections along a transect invaded by the goldenrods) and the number of uninvaded transects (all sections goldenrod-free). The odds ratio measures the change in the odds when an explanatory variable changes by one unit. So, the ratio of the two odds (before and after the explanatory variable changes by one unit) indicates the importance of the variable in explaining the outcome of interest (i.e. proportion of transect sections invaded by the goldenrods). Odds ratio takes values between zero and infinity, where a value greater than one describes a positive

relationship, less than one implies a negative relationship, while one is interpreted as no relationship. The closer the odds ratio to one, the weaker the association.

3 | RESULTS

Goldenrods were recorded at 419 of 1,153 transects (36%), with abundance index ranging from 0 to 1 (mean = 0.10, SD = 0.21). The goldenrod abundance index was generally positively correlated with both compositional and configurational landscape heterogeneity. That is, transects with higher goldenrod abundance were generally surrounded by landscapes that had relatively more and evenly distributed land cover types, and that had a higher concentration of small land parcels and higher edge densities. Nonetheless, and despite the low variation in these metrics across scales ([Figure 3](#)),

the effects of compositional and configurational heterogeneity on goldenrod abundance were dependent on the spatial scale of the heterogeneity measure. At the local and medium scale (i.e. buffer zones of 250 m, 500 m, 1,000 m and 2,000 m of a transect line) the proportion of transect sections invaded by the goldenrods was positively linked to the level of configurational heterogeneity, while no such effect was found for the largest spatial scale ($r = 5,000$ m). Goldenrod abundance index was also positively related to compositional heterogeneity for all the five considered buffer zones. While the strength of the abundance–heterogeneity association reduced with increasing spatial scale for configurational heterogeneity, it increased with increasing spatial scale for compositional heterogeneity (Figure 4). These relationships held, even when controlling for the negative effect of recent mowing on goldenrod detection (Table 1, Figure 4).

4 | DISCUSSION

In line with our predictions, we found that goldenrod abundance was positively related to configurational landscape heterogeneity. This suggests that the spread of the invasive goldenrods is more likely in fragmented landscapes with higher edge density. Contrary to our predictions, we also found a clear positive association between compositional heterogeneity and goldenrod abundance, suggesting that a high number of different land-use types may benefit invasive goldenrods even when accounting for edge density (i.e. configurational heterogeneity). The effects of these two landscape heterogeneity components were strongly scale dependent: goldenrod abundance–configurational heterogeneity relationships were most distinct at smaller spatial scales, while the pattern was the opposite for compositional heterogeneity. Below we discuss possible mechanisms

driving the observed pattern and its possible applications for invasive plant management.

4.1 | Roadside invasions and landscape heterogeneity

Roadsides are disturbed linear habitats which often differ in soil characteristics and management practices from surrounding areas as a result of implementation of roadside maintenance activities (Forman et al., 2003). Hence, the vegetation that occurs in such environments tends to be more rich in disturbance-adapted species, including invasive alien species, than plant communities growing further away from the road (e.g. Gelbard & Belnap, 2003). Invasive plants occupying roadsides can often spread along this continuous habitat as a result of seed transport by vehicles (Von Der Lippe & Kowarik, 2007) and water flush via road drainage system (Christen & Matlack, 2009). However, the processes of dispersal and colonization of road verges by invasive plants can be also impacted by the characteristics of the surrounding landscape (Minor et al., 2009; Vilà & Ibáñez, 2011). We found that both the configuration and composition of farmland landscape adjacent to roads were related to the goldenrod abundance at road margins. This suggests that roadside colonization patterns are driven not only by an enhanced establishment through altered site conditions and car traffic facilitating dispersal, but also by species filtering processes operating at larger spatial scales than the roadside itself.

Our findings support previous studies suggesting a generally positive link between distribution of invasive alien plants and landscape heterogeneity level (Lázaro-Lobo et al., 2020; Vilà & Ibáñez, 2011; With, 2002). The positive goldenrod–configurational heterogeneity association is in line with previously reported conclusions that

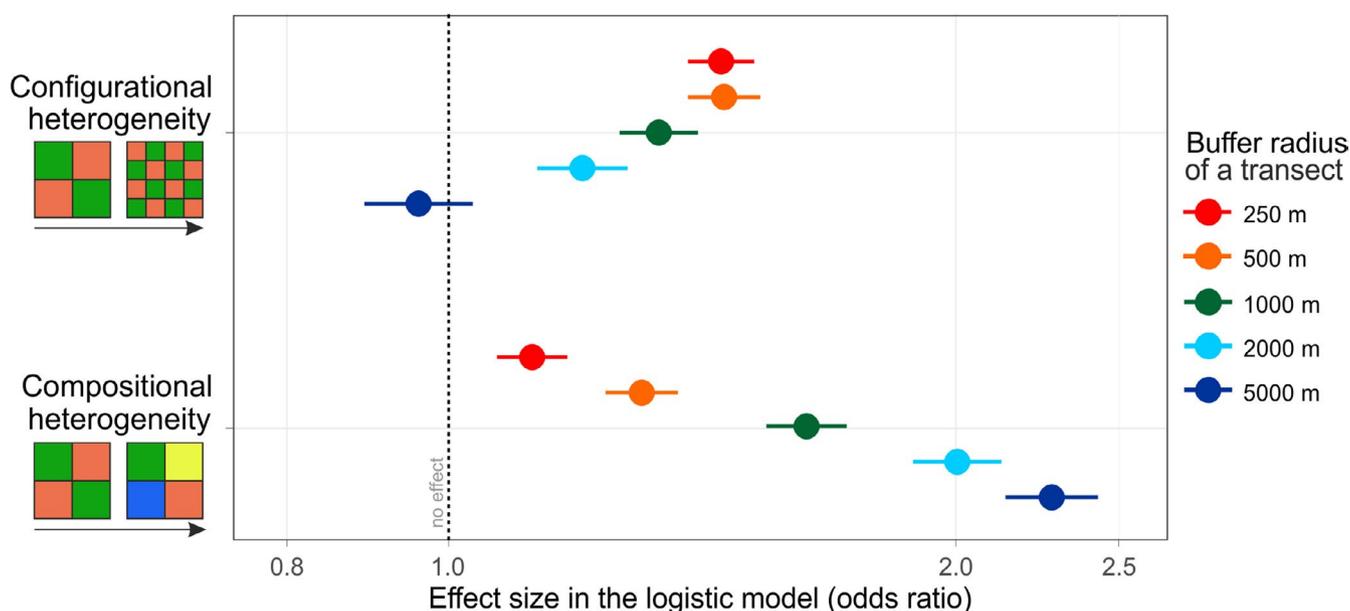


FIGURE 4 Effect of compositional and configurational landscape heterogeneity on the index of goldenrod abundance (odds ratio with 95% CIs) in five different spatial scales as found by GAMs summarized in Table 1

TABLE 1 Summary of five generalized additive models (GAMs) analysing abundance of invasive goldenrods at 1,153 transects established along roads in Poland, in relation to configurational and compositional landscape heterogeneity. The GAMs use different spatial scales, parameter estimates (*SE* in brackets) are given for linear fit and estimated degrees of freedom in case of spline fit. Significance levels are specified with asterisks

	GAM1	GAM2	GAM3	GAM4	GAM5
	<i>r</i> = 250 m	<i>r</i> = 500 m	<i>r</i> = 1,000 m	<i>r</i> = 2,000 m	<i>r</i> = 5,000 m
Linear fit					
(Intercept)	-2.87 (0.04)***	-2.89 (0.04)***	-2.93 (0.04)***	-2.99 (0.04)***	-3.03 (0.04)***
Configuration	0.37 (0.02)***	0.38 (0.02)***	0.29 (0.03)***	0.18 (0.03)***	-0.04 (0.04)
Composition	0.11 (0.02)***	0.26 (0.03)***	0.49 (0.03)***	0.70 (0.03)***	0.82 (0.03)***
Mowing	-0.14 (0.03)***	-0.15 (0.03)***	-0.16 (0.03)***	-0.17 (0.03)***	-0.18 (0.03)***
Spline fit					
<i>s</i> (<i>X</i> , <i>Y</i>)	29***	29***	29***	29***	29***
Dev.expl	34.0%	34.7%	35.9%	37.7%	39.0%
R^2_{adj}	27.9%	28.6%	30.3%	32.9%	35.3%

Statistical significance: *** <0.001.

edge habitats (e.g. field margins) may support the movement of invasive plant propagules across the landscape (Warren et al., 2013). The observed positive association between compositional heterogeneity and the abundance of goldenrods corroborate a hypothesis that a landscape with many land cover types can be more prone to the successful colonization by invasive plants possibly due to their superior ability to take advantage of variable disturbed environments as it is in agricultural areas (Davies et al., 2005; Melbourne et al., 2007). As a consequence, high availability of source habitats in the nearby heterogeneous landscape can support the colonization of roadsides by invasive plants. It should be noted, however, that rural landscapes are environments that are heavily influenced by human activity (i.e. agricultural management). The level of this impact across space and time plays an important role in the establishment and subsequent spread of invasive alien plants. It has been shown that post-agricultural lands usually have a greater abundance and diversity of invasive alien plant species (Lenda et al., 2019; Vilà & Ibáñez, 2011). Therefore, as generally greater agricultural abandonment results in higher environmental heterogeneity, the positive association between compositional landscape heterogeneity and abundance of invasive goldenrods reported in our study, may be an effect of increased proportion of wastelands in more heterogeneous areas. Unfortunately, there are no good data on abandoned land distribution to test this hypothesis directly.

4.2 | Spatial scale and choice of metric

At the local scale, the level of configurational landscape heterogeneity played a more important (positive) role in the distribution of invasive goldenrods than landscape composition (with the latter, however, still important). However, an increase in spatial scale coincided with an increase in the importance of compositional

heterogeneity and decrease in the effect size of configurational heterogeneity. Generally, our study confirms earlier findings on importance of spatial context for patterns of biological invasions (e.g. Czarniecka-Wiera et al., 2020). The two landscape heterogeneity measures we used can be considered as ecological filters determining the processes by which local-scale species assemblages (in our case: roadside vegetation) are derived from the species pools of larger scales (Aronson et al., 2016; Morin, 2011; Poff, 1997). The strength of the influence of different filters on local species composition is hypothesized to vary across spatial scales and the factors operating at smaller scales can be subordinate to large-scale factors (Milbau et al., 2009): at the larger scale, landscape features are important, while at the very local scale, biotic interactions, such as competition, can play a major role in determining the assemblage composition (Melbourne et al., 2007; Perović et al., 2015). It has been suggested that it is the landscape level, where the processes of invasive plant species establishment, population growth and further spread take place (Theoharides & Dukes, 2007). Nevertheless, the scale of landscape effects on biological processes can depend on the landscape variable that is measured (Patenaude et al., 2015), thus both the landscape composition and configuration may differently affect species distribution (Zhang et al., 2020). Our results are in accord with previous theoretical predictions suggesting that the scale of effect of habitat fragmentation (i.e. configurational heterogeneity) should be smaller than the scale of effect of habitat amount (i.e. compositional heterogeneity) (Miguet et al., 2016). A potential explanation for such pattern may be that compositional heterogeneity generally increases with spatial scale (Ben-Hur & Kadmon, 2019). This may increase number of available niches (Ben-Hur & Kadmon, 2019; Sirami et al., 2019), and, in line with our findings, might make a landscape more vulnerable to invasion. However, as landscape effects may interact with invasive plant species' traits

such as dispersal ability and habitat requirements, both the size and direction of landscape heterogeneity effects across different spatial scales may be species specific (Lázaro-Lobo et al., 2020; Martin et al., 2019; Perović et al., 2018). In any case, we argue that when identifying the drivers of the links between landscape structure and composition and the spread of invasive plants such as goldenrods we need to carefully choose the measure of heterogeneity and the spatial scale, relevant for the ecological process of interests, to properly understand the results obtained.

5 | CONCLUSIONS

Increasing landscape heterogeneity has been repeatedly suggested to halt the decline of farmland biodiversity as species richness often increases with increasing landscape heterogeneity (Benton et al., 2003; Fahrig et al., 2011; Martin et al., 2020; Sirami et al., 2019). Therefore, significant financial support has been allocated to increase heterogeneity in agricultural landscapes of Europe (e.g. under the EU Common Agricultural Policy instruments). However, when we increase landscape heterogeneity, we may also promote the establishment of invasive plant species with negative effects on the native fauna and flora as a result (e.g. Moroń et al., 2009; Skórka et al., 2010). Clearly, we need to find ways to promote the native biodiversity without promoting invasive species. Our results show, however, that the choice of heterogeneity metric and the spatial scale of the landscape studied is crucial for detecting and interpreting links between occurrence of invasive alien plants and landscape heterogeneity. This should be considered when identifying mechanisms linking invasions to landscape heterogeneity to produce further recommendations concerning invasive plant management while still benefiting native biodiversity. To reach such an aim we first suggest to prioritize the mapping of invasive alien plants especially in heterogeneous landscapes either by specific inventories or by the use of remote data collection (e.g. with GSV images). Second, we suggest conservationists in collaboration with road verge managers to implement regular road verge management and eradication schemes in these landscapes such that the invasive plant species are kept at lowest possible population levels at a regional scale. To reduce the total costs of invasive plant control one may allocate more resources to the most risky landscapes by, for example, repeated mowing during the growing season in heterogeneous landscapes.

ACKNOWLEDGEMENTS

We thank Zuzanna Rosin for helpful discussion on this paper. The study was supported by the Polish National Science Centre grant: 2016/21/N/NZ8/01286 and the Polish National Science Centre doctoral scholarship: 2019/32/T/NZ8/00343.

CONFLICT OF INTEREST

The authors declare no conflict of interest. Alistair G. Auffret is an Associate Editor of *Journal of Applied Ecology*, but took no part in the peer review and decision-making processes for this paper.

AUTHORS' CONTRIBUTIONS

D.K., M.Ž., P.S., T.P. and A.G.A. conceived the ideas, designed methodology and led the writing of the manuscript; D.K. collected and analysed the data. All authors contributed critically to the drafts and gave final approval for publication.

DATA AVAILABILITY STATEMENT

Data are available via the Dryad Digital Repository <https://doi.org/10.5061/dryad.ngf1vhhw3> (Kotowska et al., 2022).

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REFERENCES

- Alofs, K. M., & Fowler, N. L. (2010). Habitat fragmentation caused by woody plant encroachment inhibits the spread of an invasive grass. *Journal of Applied Ecology*, 47(2), 338–347. <https://doi.org/10.1111/j.1365-2664.2010.01785.x>
- Aronson, M. F. J., Nilon, C. H., Lepczyk, C. A., Parker, T. S., Warren, P. S., Cilliers, S. S., Goddard, M. A., Hahs, A. K., Herzog, C., Katti, M., La Sorte, F. A., Williams, N. S. G., & Zipperer, W. (2016). Hierarchical filters determine community assembly of urban species pools. *Ecology*, 97(11), 2952–2963. <https://doi.org/10.1002/ecy.1535>
- Ben-Hur, E., & Kadmon, R. (2019). Heterogeneity–diversity relationships in sessile organisms: A unified framework. *Ecology Letters*, 23, 193–207. <https://doi.org/10.1111/ele.13418>
- Benton, T. G., Vickery, J. A., & Wilson, J. D. (2003). Farmland biodiversity: Is habitat heterogeneity the key? *Trends in Ecology & Evolution*, 18(4), 182–188. [https://doi.org/10.1016/S0169-5347\(03\)00011-9](https://doi.org/10.1016/S0169-5347(03)00011-9)
- Bjornstad, O. N. (2020). 'Ncf': Spatial covariance functions. R package version 1.2-9. <https://CRAN.R-project.org/package=ncf>
- Blackburn, T. M., Bellard, C., & Ricciardi, A. (2019). Alien versus native species as drivers of recent extinctions. *Frontiers in Ecology and the Environment*, 17(4), 203–207. <https://doi.org/10.1002/fee.2020>
- Booy, O., Cornwell, L., Parrott, D., Sutton-Croft, M., & Williams, F. (2017). Impact of biological invasions on infrastructure. In *Impact of biological invasions on ecosystem services* (pp. 235–247). Springer International Publishing. https://doi.org/10.1007/978-3-319-45121-3_15
- Carboneras, C., Genovesi, P., Vilà, M., Blackburn, T. M., Carrete, M., Clavero, M., D'hondt, B., Orueta, J. F., Gallardo, B., Galdes, P., González-Moreno, P., Gregory, R. D., Nentwig, W., Paquet, J. Y., Pyšek, P., Rabitsch, W., Ramírez, I., Scalera, R., Tella, J. L., ... Wynde, R. (2018). A prioritised list of invasive alien species to assist the effective implementation of EU legislation. *Journal of Applied Ecology*, 55(2), 539–547. <https://doi.org/10.1111/1365-2664.12997>
- Christen, D. C., & Matlack, G. R. (2009). The habitat and conduit functions of roads in the spread of three invasive plant species. *Biological Invasions*, 11(2), 453–465. <https://doi.org/10.1007/s10530-008-9262-x>
- Czarniecka-Wiera, M., Szymura, T. H., & Kaćki, Z. (2020). Understanding the importance of spatial scale in the patterns of grassland invasions. *Science of The Total Environment*, 727, 138669. <https://doi.org/10.1016/j.scitotenv.2020.138669>

- Davies, K. F., Chesson, P., Harrison, S., Inouye, B. D., Melbourne, B. A., & Rice, K. J. (2005). Spatial heterogeneity explains the scale dependence of the native–exotic diversity relationship. *Ecology*, 86(6), 1602–1610. <https://doi.org/10.1890/04-1196>
- de Groot, M., Kleijn, D., & Jogan, N. (2007). Species groups occupying different trophic levels respond differently to the invasion of semi-natural vegetation by *Solidago canadensis*. *Biological Conservation*, 136(4), 612–617. <https://doi.org/10.1016/j.biocon.2007.01.005>
- Diagne, C., Leroy, B., Vaissière, A. C., Gozlan, R. E., Roiz, D., Jarić, I., Salles, J. M., Bradshaw, C. J. A., & Courchamp, F. (2021). High and rising economic costs of biological invasions worldwide. *Nature*, 592(7855), 571–576. <https://doi.org/10.1038/s41586-021-03405-6>
- Early, R., & Sax, D. F. (2014). Climatic niche shifts between species' native and naturalized ranges raise concern for ecological forecasts during invasions and climate change. *Global Ecology and Biogeography*, 23(12), 1356–1365. <https://doi.org/10.1111/geb.12208>
- Fahrig, L., Baudry, J., Brotons, L., Burel, F. G., Crist, T. O., Fuller, R. J., Sirami, C., Siriwardena, G. M., & Martin, J.-L. (2011). Functional landscape heterogeneity and animal biodiversity in agricultural landscapes. *Ecology Letters*, 14(2), 101–112. <https://doi.org/10.1111/j.1461-0248.2010.01559.x>
- Forman, R. T. T., Sperling, D., Bissonette, J. A., Clevenger, A. P., Cutshall, C. D., Dale, V. H., Fahrig, L., France, R., Goldman, C. R., Heanue, K., Jones, J. A., Swanson, F. J., Turrentine, T., & Winter, T. C. (2003). *Road ecology: Science and solutions*. Island Press.
- Gallien, L., & Carboni, M. (2017). The community ecology of invasive species: Where are we and what's next? *Ecography*, 40(2), 335–352. <https://doi.org/10.1111/ecog.02446>
- Gastauer, M., Mitre, S. K., Carvalho, C. S., Trevelin, L. C., Sarmiento, P. S. M., Meira Neto, J. A. A., Caldeira, C. F., Ramos, S. J., & Jaffé, R. (2021). Landscape heterogeneity and habitat amount drive plant diversity in Amazonian canga ecosystems. *Landscape Ecology*, 36(2), 393–406. <https://doi.org/10.1007/s10980-020-01151-0>
- Gelbard, J. L., & Belnap, J. (2003). Roads as conduits for exotic plant invasions in a semiarid landscape. *Conservation Biology*, 17(2), 420–432. <https://doi.org/10.1046/j.1523-1739.2003.01408.x>
- González-Moreno, P., Pino, J., Carreras, D., Basnou, C., Fernández-Rebollar, I., & Vilà, M. (2013). Quantifying the landscape influence on plant invasions in Mediterranean coastal habitats. *Landscape Ecology*, 28(5), 891–903. <https://doi.org/10.1007/s10980-013-9857-1>
- Harrison, S., Rice, K., & Maron, J. (2001). Habitat patchiness promotes invasion by alien grasses on serpentine soil. *Biological Conservation*, 100(1), 45–53. [https://doi.org/10.1016/S0006-3207\(00\)00206-8](https://doi.org/10.1016/S0006-3207(00)00206-8)
- Hastings, A., Cuddington, K., Davies, K. F., Dugaw, C. J., Elmendorf, S., Freestone, A., Harrison, S., Holland, M., Lambrinos, J., Malvadkar, U., Melbourne, B. A., Moore, K., Taylor, C., & Thomson, D. (2004). The spatial spread of invasions: New developments in theory and evidence. *Ecology Letters*, 8(1), 91–101. <https://doi.org/10.1111/j.1461-0248.2004.00687.x>
- IPBES. (2019). *Global assessment report on biodiversity and ecosystem services of the intergovernmental science-policy platform on biodiversity and ecosystem services*. E. S. Brondizio, J. Settele, S. Díaz, & H. T. Ngo (Eds.). Retrieved from <https://www.ipbes.net/global-assessment>
- Kotowska, D., Pärt, T., Skórka, P., Auffret, A. G. & Żmihorski, M. (2022). Data from: Scale-dependence of landscape heterogeneity effects on plant invasions. Dryad Digital Repository, <https://doi.org/10.5061/dryad.ngf1vhhw3>
- Kotowska, D., Pärt, T., & Żmihorski, M. (2021). Evaluating Google street view for tracking invasive alien plants along roads. *Ecological Indicators*, 121, 107020. <https://doi.org/10.1016/j.ecoli.2020.107020>
- Kumar Rai, P., & Singh, J. S. (2020). Invasive alien plant species: Their impact on environment, ecosystem services and human health. *Ecological Indicators*, 111, 106020. <https://doi.org/10.1016/j.ecoli.2019.106020>
- Kumar, S., Stohlgren, T. J., & Chong, G. W. (2006). Spatial heterogeneity influences native and nonnative plant species richness. *Ecology*, 87(12), 3186–3199. [https://doi.org/10.1890/0012-9658\(2006\)87\[3186:SHINAN\]2.0.CO;2](https://doi.org/10.1890/0012-9658(2006)87[3186:SHINAN]2.0.CO;2)
- Lázaro-Lobo, A., & Ervin, G. N. (2019). A global examination on the differential impacts of roadsides on native vs. exotic and weedy plant species. *Global Ecology and Conservation*, 17, e00555. <https://doi.org/10.1016/j.gecco.2019.e00555>
- Lázaro-Lobo, A., Evans, K. O., & Ervin, G. N. (2020). Evaluating landscape characteristics of predicted hotspots for plant invasions. *Invasive Plant Science and Management*, 13(3), 163–175. <https://doi.org/10.1017/inp.2020.21>
- Lenda, M., Skórka, P., Knops, J., Żmihorski, M., Gaj, R., Moroń, D., Woyciechowski, M., & Tryjanowski, P. (2019). Multispecies invasion reduces the negative impact of single alien plant species on native flora. *Diversity and Distributions*, 25(6), 951–962. <https://doi.org/10.1111/ddi.12902>
- Lenda, M., Witek, M., Skórka, P., Moroń, D., & Woyciechowski, M. (2013). Invasive alien plants affect grassland ant communities, colony size and foraging behaviour. *Biological Invasions*, 15(11), 2403–2414. <https://doi.org/10.1007/s10530-013-0461-8>
- Levine, J. M. (2000). Species diversity and biological invasions: Relating local process to community pattern. *Science*, 288(5467), 852–854. <https://doi.org/10.1126/science.288.5467.852>
- Lundholm, J. T. (2009). Plant species diversity and environmental heterogeneity: Spatial scale and competing hypotheses. *Journal of Vegetation Science*, 20(3), 377–391. <https://doi.org/10.1111/j.1654-1103.2009.05577.x>
- Martin, A. E., Collins, S. J., Crowe, S., Girard, J., Naujokaitis-Lewis, I., Smith, A. C., Lindsay, K., Mitchell, S., & Fahrig, L. (2020). Effects of farmland heterogeneity on biodiversity are similar to—Or even larger than—The effects of farming practices. *Agriculture, Ecosystems and Environment*, 288, 106698. <https://doi.org/10.1016/j.agee.2019.106698>
- Martin, E. A., Dainese, M., Clough, Y., Báldi, A., Bommarco, R., Gagic, V., Garratt, M. P. D., Holzschuh, A., Kleijn, D., Kovács-Hostyánszki, A., Marini, L., Potts, S. G., Smith, H. G., Al Hassan, D., Albrecht, M., Andersson, G. K. S., Asís, J. D., Aviron, S., Balzan, M. V., ... Steffan-Dewenter, I. (2019). The interplay of landscape composition and configuration: New pathways to manage functional biodiversity and agroecosystem services across Europe. *Ecology Letters*, 22(7), 1083–1094. <https://doi.org/10.1111/ele.13265>
- McDougall, K. L., Lembrechts, J., Rew, L. J., Haider, S., Cavieres, L. A., Kueffer, C., Milbau, A., Naylor, B. J., Nuñez, M. A., Pauchard, A., Seipel, T., Speziale, K. L., Wright, G. T., & Alexander, J. M. (2018). Running off the road: Roadside non-native plants invading mountain vegetation. *Biological Invasions*, 20(12), 3461–3473. <https://doi.org/10.1007/s10530-018-1787-z>
- Melbourne, B. A., Cornell, H. V., Davies, K. F., Dugaw, C. J., Elmendorf, S., Freestone, A. L., Hall, R. J., Harrison, S., Hastings, A., Holland, M., Holyoak, M., Lambrinos, J., Moore, K., & Yokomizo, H. (2007). Invasion in a heterogeneous world: Resistance, coexistence or hostile takeover? *Ecology Letters*, 10(1), 77–94. <https://doi.org/10.1111/j.1461-0248.2006.00987.x>
- Miguet, P., Jackson, H. B., Jackson, N. D., Martin, A. E., & Fahrig, L. (2016). What determines the spatial extent of landscape effects on species? *Landscape Ecology*, 31(6), 1177–1194. <https://doi.org/10.1007/s10980-015-0314-1>
- Milbau, A., Stout, J. C., Graae, B. J., & Nijs, I. (2009). A hierarchical framework for integrating invasibility experiments incorporating different factors and spatial scales. *Biological Invasions*, 11(4), 941–950. <https://doi.org/10.1007/s10530-008-9306-2>
- Minor, E. S., Tessel, S. M., Engelhardt, K. A. M., & Lookingbill, T. R. (2009). The role of landscape connectivity in assembling exotic

- plant communities: A network analysis. *Ecology*, 90(7), 1802–1809. <https://doi.org/10.1890/08-1015.1>
- Morin, P. J. (2011). *Community ecology*. Wiley.
- Moroń, D., Lenda, M., Skórka, P., Szentgyörgyi, H., Settele, J., & Woyciechowski, M. (2009). Wild pollinator communities are negatively affected by invasion of alien goldenrods in grassland landscapes. *Biological Conservation*, 142(7), 1322–1332. <https://doi.org/10.1016/j.biocon.2008.12.036>
- Paini, D. R., Sheppard, A. W., Cook, D. C., De Barro, P. J., Worner, S. P., & Thomas, M. B. (2016). Global threat to agriculture from invasive species. *Proceedings of the National Academy of Sciences of the United States of America*, 113(27), 7575–7579. <https://doi.org/10.1073/pnas.1602205113>
- Patenaude, T., Smith, A. C., & Fahrig, L. (2015). Disentangling the effects of wetland cover and urban development on quality of remaining wetlands. *Urban Ecosystems*, 18(3), 663–684. <https://doi.org/10.1007/s11252-015-0440-1>
- Perera, C., Szymura, T., Zajac, A., Chmolewska, D., & Szymura, M. (2021). Drivers of *Solidago* species invasion in Central Europe—Case study in the landscape of the Carpathian Mountains and their foreground. *Ecology and Evolution*, 11(18), 12429–12444. <https://doi.org/10.1002/ece3.7989>
- Perović, D., Gámez-Virués, S., Börschig, C., Klein, A.-M., Krauss, J., Steckel, J., Rothenwöhrer, C., Erasmí, S., Tscharntke, T., & Westphal, C. (2015). Configurational landscape heterogeneity shapes functional community composition of grassland butterflies. *Journal of Applied Ecology*, 52(2), 505–513. <https://doi.org/10.1111/1365-2664.12394>
- Perović, D. J., Gámez-Virués, S., Landis, D. A., Wäckers, F., Gurr, G. M., Wratten, S. D., You, M. S., & Desneux, N. (2018). Managing biological control services through multi-trophic trait interactions: Review and guidelines for implementation at local and landscape scales. *Biological Reviews*, 93(1), 306–321. <https://doi.org/10.1111/brv.12346>
- Pielou, E. C. (1975). *Ecological diversity*. Wiley.
- Poff, N. L. R. (1997). Landscape filters and species traits: Towards mechanistic understanding and prediction in stream ecology. *Journal of the North American Benthological Society*, 16(2), 391–409. <https://doi.org/10.2307/1468026>
- Pyšek, P., Jarošík, V., Hulme, P. E., Pergl, J., Hejda, M., Schaffner, U., & Vilà, M. (2012). A global assessment of invasive plant impacts on resident species, communities and ecosystems: The interaction of impact measures, invading species' traits and environment. *Global Change Biology*, 18(5), 1725–1737. <https://doi.org/10.1111/j.1365-2486.2011.02636.x>
- Pyšek, P., & Richardson, D. M. (2010). Invasive species, environmental change and management, and health. *Annual Review of Environment and Resources*, 35(1), 25–55. <https://doi.org/10.1146/annurev-envir-033009-095548>
- R Core Team. (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. Retrieved from <http://www.R-project.org/>.
- Simpson, E. H. (1949). Measurement of diversity. *Nature*, 163(4148), 688. <https://doi.org/10.1038/163688a0>
- Siramí, C., Gross, N., Baillo, A. B., Bertrand, C., Carrié, R., Hass, A., Henckel, L., Migué, P., Vuillot, C., Alignier, A., Girard, J., Batáry, P., Clough, Y., Violle, C., Giralt, D., Bota, G., Badenhausser, I., Lefebvre, G., Gauffre, B., ... Fahrig, L. (2019). Increasing crop heterogeneity enhances multitrophic diversity across agricultural regions. *Proceedings of the National Academy of Sciences of the United States of America*, 116(33), 16442–16447. <https://doi.org/10.1073/pnas.1906419116>
- Skórka, P., Lenda, M., & Tryjanowski, P. (2010). Invasive alien goldenrods negatively affect grassland bird communities in Eastern Europe. *Biological Conservation*, 143(4), 856–861. <https://doi.org/10.1016/j.biocon.2009.12.030>
- Stacherzak, A., Hájek, L., & Heřdak, M. (2019). Changes in the use of agricultural land in Poland and Czech Republic. *Journal of Ecological Engineering*, 20(7), 211–221. <https://doi.org/10.12911/22998993/109869>
- Theoharides, K. A., & Dukes, J. S. (2007). Plant invasion across space and time: Factors affecting nonindigenous species success during four stages of invasion. *New Phytologist*, 176(2), 256–273. <https://doi.org/10.1111/j.1469-8137.2007.02207.x>
- Vilà, M., & Ibáñez, I. (2011). Plant invasions in the landscape. *Landscape Ecology*, 26(4), 461–472. <https://doi.org/10.1007/s10980-011-9585-3>
- Von Der Lippe, M., & Kowarik, I. (2007). Long-distance dispersal of plants by vehicles as a driver of plant invasions. *Conservation Biology*, 21(4), 986–996. <https://doi.org/10.1111/j.1523-1739.2007.00722.x>
- Warren, R. J., Ursell, T., Keiser, A. D., & Bradford, M. A. (2013). Habitat, dispersal and propagule pressure control exotic plant infilling within an invaded range. *Ecosphere*, 4(2), 1–12. <https://doi.org/10.1890/ES12-00393.1>
- Williamson, J., & Harrison, S. (2002). Biotic and abiotic limits to the spread of exotic revegetation species. *Ecological Applications*, 12(1), 40–51. [https://doi.org/10.1890/1051-0761\(2002\)012\[0040:BAALTJ\]2.0.CO;2](https://doi.org/10.1890/1051-0761(2002)012[0040:BAALTJ]2.0.CO;2)
- With, K. A. (2002). The landscape ecology of invasive spread. *Conservation Biology*, 16(5), 1192–1203. <https://doi.org/10.1046/j.1523-1739.2002.01064.x>
- Wood, S. N. (2017). *Generalized additive models: An introduction with R* (2nd ed.). Chapman and Hall/CRC.
- Zhang, Y., Haan, N. L., & Landis, D. A. (2020). Landscape composition and configuration have scale-dependent effects on agricultural pest suppression. *Agriculture, Ecosystems and Environment*, 302, 107085. <https://doi.org/10.1016/j.agee.2020.107085>

SUPPORTING INFORMATION

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How to cite this article: Kotowska, D., Pärt, T., Skórka, P., Auffret, A. G., & Žmihorski, M. (2022). Scale dependence of landscape heterogeneity effects on plant invasions. *Journal of Applied Ecology*, 59, 1313–1323. <https://doi.org/10.1111/1365-2664.14143>

Supplementary materials

Figure S1. Spline correlograms (mean and 95% CI in color) showing dependency among residuals from GAM models fitted for five spatial scales and spatial distance (in km) among data records (x axis).

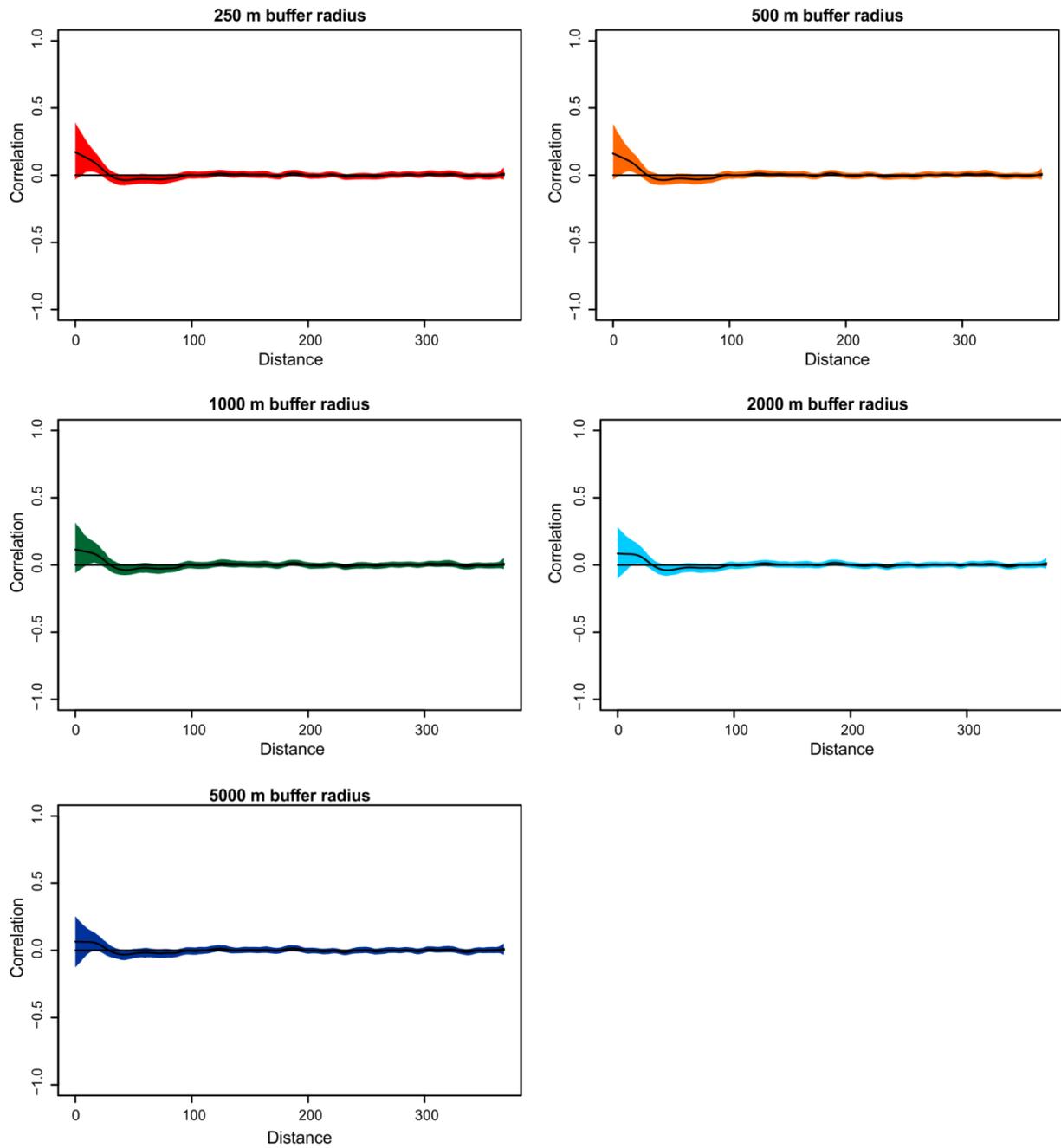


Table S1. Corine Land Cover (CLC) classes recorded within buffer zones of 250, 500, 1000, 2000 and 5000 m from studied transects

CLC code	CLC description	250m	500m	1000m	2000m	5000m
111	Continuous urban fabric				X	X
112	Discontinuous urban fabric	X	X	X	X	X
121	Industrial or commercial units	X	X	X	X	X
122	Road and rail networks and associated land	X	X	X	X	X
123	Port areas					X
124	Airports			X	X	X
131	Mineral extraction sites	X	X	X	X	X
132	Dump sites	X	X	X	X	X
133	Construction sites	X	X	X	X	X
141	Green urban areas				X	X
142	Sport and leisure facilities	X	X	X	X	X
211	Non-irrigated arable land	X	X	X	X	X
222	Fruit trees and berry plantations	X	X	X	X	X
231	Pastures	X	X	X	X	X
242	Complex cultivation patterns	X	X	X	X	X
243	Land principally occupied by agriculture, with significant areas of natural vegetation	X	X	X	X	X
311	Broad-leaved forest	X	X	X	X	X
312	Coniferous forest	X	X	X	X	X
313	Mixed forest	X	X	X	X	X
321	Natural grasslands			X	X	X
324	Transitional woodland-shrub	X	X	X	X	X
331	Beaches, dunes, sands			X	X	X
333	Sparsely vegetated areas			X	X	X
411	Inland marshes	X	X	X	X	X
412	Peat bogs	X	X	X	X	X
511	Water courses	X	X	X	X	X
512	Water bodies	X	X	X	X	X
521	Coastal lagoons			X	X	X
523	Sea and ocean			X	X	X
Total number of CLC classes		20	20	26	28	29

ARTYKUŁ III

Kotowska, D., Skórka, P., Pärt, T., Auffret, A. G. & Żmihorski, M. Spatial scale matters for predicting plant invasions along roads – maszynopis (wysłany do recenzji w *Ecology*).

Spatial scale matters for predicting plant invasions along roads

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Abstract

Biological invasions are one of the most serious global threats to biodiversity, with severe economic and social impacts. The complexity of this problem challenges effective management of invasive alien species as the contribution of many factors involved in the invasion processes across different spatial scales is not well understood. In this study, we identify the most important determinants associated with the occurrence of two invasive alien plants, the North American goldenrods (*Solidago canadensis* and *S. gigantea*), commonly found in agricultural landscapes of Europe. We applied a novel method based on remote analysis of Google Street View images to perform a large-scale inventory of goldenrods along 1,347 roadside transects across Poland. Using open access geospatial data and machine learning techniques, we investigated the relative role of nearly 50 variables potentially affecting the distribution of studied species at five spatial scales (from within 0.25 km to 5 km of the studied locations). We found that the occurrence of goldenrods along roadsides is simultaneously influenced by multiple drivers among which factors related to human impacts, climatic conditions, soil properties and landscape structure are the most important, while local characteristics, such as road parameters or abundance and diversity of other alien plants are less influential. However, the contribution of these variables in predicting goldenrod distribution changes across spatial scales. This suggests that different invasion drivers operate at different spatial scales and that some important associations may be overlooked when focusing on a single spatial context. Thus, understanding the processes of biological invasions requires considering the relative importance of different factors concurrently shaping the patterns of invasive alien species distribution across different spatial scales. We highlight that using multi-scale approaches involving a wide range of variables may enable setting priorities for the management of invasive alien plants, and thus developing more effective strategies aiming at preventing, eradicating, and controlling these problematic species.

Key words: alien plants; anthropogenic pressures; drivers of invasions; farmland; goldenrods; Google Street View; Poland; roadsides; spatial scale

1. Introduction

The phenomenon of biological invasions is a major fingerprint of the Anthropocene, contributing substantially to global human-induced environmental change and threatening both biodiversity and human welfare (Pyšek et al. 2012, Kueffer 2017, IPBES 2019). The spread of alien species has been shown to alter the structure and functioning of ecosystems (Levine et al. 2003, Hejda et al. 2009a), causing extinctions of indigenous fauna and flora (Blackburn et al. 2019) and reducing services that native ecosystems provide for human wellbeing (Kumar Rai and Singh 2020). These changes are difficult to reverse and have already caused serious economic damage (Diagne et al. 2021). Moreover, the adverse effects of biological invasions are predicted to become exacerbated as the climate, landscape and socio-economic factors are also rapidly changing across the globe (With 2002, Early and Sax 2014, Early et al. 2016). Therefore, an understanding of the different environmental and anthropogenic drivers of invasions is important to deliver guidance on how to manage invasive alien species and prevent new invasion events in the future.

Biological invasions are, by definition, caused by human activity. For several hundred years, the transfer of plant species outside of their native ranges has been driven by cross-border trade, leading to both intentional and accidental introductions (Hulme 2009). As such, the main predictor of invasion success has often been found to be the invasion pathway, that is, the method and frequency by which a species has been introduced (Wilson et al. 2009). Human activity is also a strong predictor of invasion processes following the introduction stage, because the establishment and subsequent spread of alien species is commonly associated with anthropogenic habitats (Hejda et al. 2009b). Furthermore, it has been recognized that plant invasions are also influenced by landscape structure (With 2002,

Melbourne et al. 2007), including the presence and configuration of human-modified landscape features such as roads, watercourses, built-up areas and abandoned agricultural fields (Lenda et al. 2012, Kotowska et al. 2021). Such land use and landscape characteristics represent not only suitable habitats for alien plants, but also potential source pools and pathways for further invasions (Vilà and Ibáñez 2011, Warren et al. 2013, Kotowska et al. 2022). By contrast, semi-natural habitats, such as grasslands and woodlands are usually more resistant to establishment of alien plant species (Chytrý et al. 2008).

Climate change is another, growing anthropogenic driver of biological invasions (Diez et al. 2012). Alien plants that have been introduced by humans may become invasive as the climate changes to provide more favorable temperatures, humidity, precipitation or solar radiation (Hulme 2017). Climate models generally predict invasive species to change their ranges in relation to spatial and temporal changes in climate (Hulme 2017, Bellard et al. 2018). Still, it is expected that human-mediated long-distance transport and anthropogenic habitat modifications are the major drivers of biological invasions (Hulme 2017). Also, human population density, income and various other socioeconomic indices have been shown to be positively associated with regional numbers of alien plants (Taylor and Irwin 2004, Pyšek et al. 2010).

Together, both climate change and human-related land-use alterations lead to modifications in the quality, availability, and configuration of habitat resources, and can thus influence plant invasions (Schroeder et al. 2021). Soil properties (e.g. high nitrogen content, acidity) may positively impact invasion of alien plants which, in turn, may also affect nutrient pools in the topsoil and the standing biomass, generally contributing to a homogenization of soil conditions (Dassonville et al. 2008, Vitti et al. 2020). This ‘ecosystem engineering’ can then act to facilitate further invasions, although interactions among potentially invasive species can also be an important determinant of whether multiple invasions occur (Lenda

et al. 2019). It has been suggested, for instance, that successfully-established non-native species may facilitate the establishment of other alien species, thus accelerating the invasion process (the so-called ‘invasional meltdown’ process; Simberloff and Von Holle 1999). However, the relative role of associations among alien plants, environmental drivers and human activity in supporting invasions of alien plants is not clearly understood.

The processes that regulate the introduction, establishment and spread of alien species are clearly highly complex and involve a multitude of factors (Catford et al. 2009, Heger et al. 2013). In addition to the many ways in which these different factors affect biological invasions, they also operate at different spatial scales (Czarniecka-Wiera et al. 2020). At large spatial scales (regional level), one expects the effect of climate and human impacts to be most prevalent (Shi et al. 2010). At intermediate (landscape) spatial scales, landscape characteristics may become more important, whereas the impact of local characteristics, such as biotic interactions are likely most pronounced at small, local spatial scales (Catford et al. 2009, Milbau et al. 2009). Hence, depending on the spatial context, the relative importance of different factors enabling/promoting establishment and distribution of invasive alien plants are likely to vary (Ricklefs and Jenkins 2011). Most empirical studies on the drivers of plant invasions, however, have focused on a single spatial scale (but see: Brown et al. 2008, Czarniecka-Wiera et al. 2020, Kotowska et al. 2022).

Given the number of factors and underlying mechanisms potentially involved in success of invasive alien plants, the pressing issue of predicting their distribution remains a challenge. Dealing with this problem requires an integrative approach (Barney and Whitlow 2008), but many studies are limited by the number of drivers that are covered and the joint and relative effects of multiple invasion drivers has rarely been examined (but see: Bazzichetto et al., 2018; Szymura et al., 2018). More comprehensive approaches accounting

for the simultaneous role of multiple drivers of invasions across different spatial scales are therefore needed.

Here, we investigate the relative importance of multiple factors associated with occurrence of common invasive alien plants across different spatial scales. We used invasive north American goldenrods (*Solidago* spp.) as model species and collected data on their occurrence along roadside transects in agricultural landscapes of Poland by applying a novel and reliable method based on remote analysis of Google Street View images (Kotowska et al. 2021). We tested how local roadside invasion patterns are influenced by multiple characteristics of the environment and its anthropogenic pressures by associating invasive goldenrod occurrences along roads with 47 variables potentially affecting their distribution. These were grouped into seven categories that included human impacts, landscape structure, climate characteristics, soil properties, abundance and diversity of other alien plant species, road characteristics and transect sampling parameters. As the impact of the considered invasion drivers was expected to be scale dependent, we tested their effect on the probability of goldenrod occurrence across different spatial scales, ranging from 0.25 km to 5 km of the studied locations.

2. Methods

2.1 Model species

Canadian goldenrod (*Solidago canadensis* L.) and giant goldenrod (*S. gigantea* Aiton) are two highly successful plant invaders of North American origin that have colonized a broad range of European landscapes (Weber 2001, Carboneras et al. 2018). Due to their high competitive ability with efficient seed production, rapid growth, prolific rhizome propagation and capacity to exert allelopathic effects on other plants, they can dominate native vegetation over vast areas forming dense, homogeneous stands (Kabuce and Priede 2010). Consequently, the

spread of these two goldenrod species can lead to a drastic reduction of native plant diversity (Moroń et al. 2009, Lenda et al. 2019) and can adversely affect birds (Skórka et al. 2010) and insects, including pollinators (such as bees, hoverflies and butterflies; Lenda et al., 2021, 2019; Moroń et al., 2021, 2009), beetles (de Groot et al. 2007) and ants (Lenda et al. 2013). Invasive alien goldenrods are found in a wide spectrum of habitats. They occur abundantly both in human-disturbed habitats, such as roadsides, railway embankments, abandoned agricultural lands and ruderal environments associated with built-up areas, as well as in semi-natural grasslands, meadows, forest edges and riverbanks (Kabuce and Priede 2010, Perera et al. 2021). Since both goldenrod species are similar in morphology and habitat preferences within their secondary range (Perera et al. 2021), we consider them together in this study (and refer to them as “goldenrods”).

2.2 Study area and transect selection

The study was conducted along roads in agricultural lowland landscapes across the country of Poland (Figure 1). The two goldenrod species are widespread throughout this area with locally high abundances (Moroń et al. 2009, Lenda et al. 2019). For the purpose of roadside transect selection, out of the total of 2478 local administrative units in Poland (‘communes’, the number is for as of 2017), we first chose all 1555 rural communes (i.e., those within which there are no cities, as defined by the Central Statistical Office for Poland). Next, to restrict the study area to lowland regions, we excluded 195 communes in which 70% of the commune’s area was at an altitude of over 300 m a. s. l., according to the European Digital Elevation Model (available through the Copernicus Land Monitoring Service; <https://land.copernicus.eu/>). Finally, using Google Street View (GSV) imagery via the Google Maps web mapping service, we excluded 13 communes with no GSV coverage. As a result, we selected a total of 1347 communes, in which transects of about 500 m in length were set following the approach described in Kotowska et al. (2021). In each commune, we randomly

selected a point along the road network using GIS tools and Open Street Map vector data, and then used it as the location to start a transect. If GSV images were not available for the transect, or more than 50% of the transect's length intersected patches of forest, water bodies or urban areas (as identified by the CORINE Land Cover database), it was discarded and the next randomly selected transect in the commune was used instead. The transect was also discarded and replaced when the visibility of roadside vegetation was reduced by e.g. presence of acoustic barriers. Consequently, the resulting set of 1347 transects established across Poland (mean nearest neighbor distance: 8384 m, range: 990-32685 m) included roads of different classes (from highways to minor roads), intersecting a range of agricultural habitats. The studied locations were surrounded by farmland landscapes differing greatly in their structure and level of land-use intensity, including large, intensively managed arable fields, pastures and meadows, as well as heterogeneous landscape mosaics composed of small-scale arable fields with different crops, orchards, meadows and low-intensity grazed pastures mixed with patches of other semi-natural and natural open vegetation, marshes, woodlands, wastelands and scattered farmsteads. The selected transects also represented a climatic gradient from suboceanic climate in north-western Poland to continental climate in east and south-eastern part of the country (Kozuchowski 2011). Spatial data processing was carried out using ArcGIS 10.4.

2.3 Alien plant species sampling

Large scale data on distribution of goldenrods and other alien plant species were gathered remotely using Google Street View images. This novel, time- and cost-efficient method for studying roadside vegetation has been proven to be reliable in relation to field inventory data and has been suggested as a tool for detecting invasive alien plants occurrences over large areas (but see Kotowska et al., 2021 for discussion of its limitations). Each of the 1347 transects was divided into (on average) 25 sections of around 20 m length (Figure 2B). Next,

using Google Earth, the transects were sampled for goldenrods and other alien plant species by virtually “driving” along the road and visually analyzing GSV images. The remote data collection was performed based on the panoramic views taken between 2011 and 2018. For each transect section, we determined the occurrence of goldenrods and other identified alien plants (0/1) within 30 m of a transect line. Since the maintenance of roadside vegetation may reduce the probability of plant detection, for each transect section we also assessed the presence of recent road verge mowing (0/1) within 30 m of the road. The 30 m zone was considered mown if the vegetation covering more than 50% of this area had been recently cut, as judged by not yet being fully re-grown in height. The information on road verge mowing along a whole transect was quantified as a proportion of transect sections considered mown. Additionally, for each transect, we noted the date at which GSV pictures were taken and the information on road surface material (asphalt/other). Based on the transect section-scale observations, we determined the goldenrod occurrence (0/1) and diversity of other alien plant species at each transect. Moreover, an abundance index of alien plants (other than goldenrods) that could be detected along a transect (e.g., box elder, black locust, Canadian horseweed; see Appendix S1: Table S1 for a full species list) was calculated as a proportion of transect sections occupied by each of the alien plant species.

2.4 Environmental and human activity-related data

Initially, we considered a set of 60 characteristics grouped into seven categories as explanatory variables potentially explaining goldenrod occurrence along roads in agricultural landscapes of Poland (not all of them were finally used in the analyses; see Statistical analyses section for explanations, Table 1 for a list of variables used in the models and Appendix S1: Table S1 for a full list of 60 initially considered characteristics). First, variables describing human impacts (i.e., socio-economic indices, human footprint index, agricultural intensity) were included, as the level of goldenrod invasion is generally mediated by human activity.

Second, characteristics of landscape structure (e.g., cover of land-use types, landscape heterogeneity indices, distance to watercourses, road density) were used as proxies of the amount of suitable habitat and potential dispersal corridors in the vicinity of the studied transects. Third, topsoil chemical properties (pH, content of calcium carbonates, phosphorus, potassium and nitrogen) were considered as parameters describing habitat conditions in the areas surrounding transect locations. Fourth, we considered climatic factors (i.e., mean temperature, precipitation, solar radiation and growing season length), as goldenrod occurrence may be more likely in areas characterized by warm temperatures, humid conditions and high solar radiation (Park et al. 2020). Fifth, since biotic interactions among alien plants may intensify their ecosystem impacts and/or promote secondary invasions by other species (Simberloff and Von Holle 1999), we considered indices describing the abundance and diversity of alien plant species other than goldenrods that were observed along the transects (13 species in total; the number of other alien plant species recorded along a transect ranged between 0 and 5). Sixth, we assumed that the importance of roadsides constituting major dispersal corridors for invasive alien plants (McDougall et al. 2018, Lázaro-Lobo and Ervin 2019) may be enhanced by certain road characteristics, such as, e.g., those related to high traffic volumes (Joly et al. 2011). Thus, we described several parameters of studied roads (i.e., road class, road width, road curvature, road direction, road surface). Finally, we also included transect sampling parameters (i.e., month and year when the GSV pictures were taken, number of sections established along a transect line and information on road verge mowing) to account for potential bias arising from remote data collection with GSV panoramas (Kotowska et al. 2021).

These variables were either determined based on the GSV data inspection or calculated using GIS tools based on open geospatial data available for the study area (such as satellite imagery, Open Street Map vector layers, Corine Land Cover database, WorldClim

database and other datasets mostly derived from national or European government agencies; see Appendix S1: Table S1 for the detailed description of variables and data sources). The characteristics that were site-specific, i.e., abundance and diversity of other alien plant species, road parameters as well as transect sampling parameters, were determined at the transect scale only (i.e., along or within 30 m of the road). Whereas large-scale variables (i.e., human impacts, landscape structure, soil properties and climatic conditions) were measured at five spatial scales, i.e., within buffer zones of 250, 500, 1000, 2000 and 5000 m of the studied transects (Figure 2A; except for two distance-based characteristics, see Table 1). The spatial data processing and calculations were performed using ArcGIS 10.4 software, Google Earth Engine platform, and packages: ‘raster’ (Hijmans 2022) and ‘sf’ (Pebesma 2018) in R (R Core Team 2020).

2.5 Statistical analysis

To determine the relative importance of the considered variables for the probability of goldenrod occurrence across different spatial scales we used random forest (RF) models implemented in ‘caret’ package (Kuhn 2022) in R. Prior to the analyses, the dataset was filtered to remove near zero variance predictors and highly correlated variables (i.e., those with Pearson’s correlation coefficient > 0.9 ; da Silva et al., 2020). Consequently, out of the total of 60 characteristics, 47 were used in the further analyses (see Table 1). We performed five RF classification models, one for each of the spatial scales at which the large-scale factors were measured. In each model, we used the goldenrod occurrence along a transect (1 – presence, 0 – absence) as the response variable and each transect as a single data record (1347 in total). In all models, we considered a set of 47 predictor variables which consisted of local factors (four variables describing the abundance and diversity of other alien plant species, four road parameters and four transect sampling parameters), two distance-based variables characterizing landscape structure, and large-scale factors calculated for a given

spatial scale (16 characteristics of landscape structure, eight indicators of human impacts, four descriptors of climatic conditions and five characteristics of soil properties). For each RF model, the number of decision trees was set to 2000 and the *mtry* parameter (i.e., the number of randomly selected features to be used at each tree node split) was tuned from the values: 2, 9, 16, 22, 28, 34, 40, 47 to find the best performing model.

Performance of each of the five RF models was assessed using 10-fold cross validation, repeated five times. Since the spatial structure in the data can lead to the underestimation of model prediction error, we used spatial blocking to account for this problem while validating our models (Roberts et al. 2017). In this approach, the k-fold cross validation procedure divides a dataset into k spatially separated folds based on a specified distance (cell size of the blocks; Valavi et al., 2019). Each fold is given an opportunity to be used as a held back test set, while all the remaining folds are used for model fit. The procedure is repeated k times and the mean performance based on k models evaluated on the k hold-out test sets is reported. The size of the blocks for the validation was chosen based on the range of spatial autocorrelation in the model residuals following Roberts et al. (2017). The blocks were constructed using ‘blockCV’ package (Valavi et al. 2019) in R. As the number of goldenrod presences and absences in our dataset was not equal, at each of the 10 resampling iterations in the cross validation the prevalent class in training set was randomly sub-sampled, so that the frequencies of goldenrod presence and absence matched. The process was replicated five times to include different sets of random transects in the validation of a model, and results of the replications were averaged. Consequently, 50 different hold-out datasets were used to assess the final model’s performance. We used the overall accuracy, kappa coefficient and confusion matrix-based measures (including specificity and sensitivity) as the model performance metrics.

The contribution of each predictor variable in explaining the goldenrod occurrence was measured using the variable importance score, which bases on the decrease in a model accuracy when a single variable is randomly shuffled (Breiman 2001). To visualize the mean marginal effect of each variable on the probability of goldenrod occurrence, we used partial dependence plots drawn with ‘pdp’ package (Greenwell 2017) in R.

To test whether the variable importance scores of different explanatory variables differ across the five spatial scales and seven variable categories, we fitted a generalized additive mixed model (GAMM) with gamma distribution and log link function using ‘mgcv’ package in R (Wood 2017). In this model we used the variable importance as a response variable (continuous, ranging from 0.7 to 29.9) and three explanatory variables: spatial scale (categorical with five levels: 250m, 500m, 1000m, 2000m and 5000m), variable category (categorical with seven levels: human impact, climate, alien species, landscape, road, soil, transect) and interaction of these two. Each variable importance calculated for a given spatial scale was treated independently, thus, the model was performed based on a total of 235 data records and the variable identity was introduced as a random factor (fitted with ridge penalty spline). As our primary interest in this analysis was to test the interaction between the spatial scale and variable category, the performance of this model was compared with a model without the interaction term, basing on the Akaike information criterion (AIC).

Finally, to examine scale-dependency in the variable importance scores of all predictor variables, we calculated the Spearman’s correlation between the importance score and the spatial scale, independently for all variables. The distribution of these correlation coefficients was then compared to the null model (i.e. distribution of coefficients obtained for correlations between permuted importance scores and spatial scale, repeated 100 times) using ‘sm’ package (Bowman and Azzalini 2021) in R.

3. Results

Goldenrods were recorded in 505 of 1347 sampled transects (37.5%). The species were widespread throughout Poland, with higher concentrations found in the southern part of the country (Figure 1). The performance of RF models explaining goldenrod occurrence was similar across the five considered spatial scales. The models predicted goldenrod occurrence with an overall accuracy of about 70-71% and achieved corresponding kappa coefficients of about 0.37-0.41, thus indicating moderate model performances. All the models predicted goldenrod absences slightly better than presences (c.a. 71-73% and 66-69% of absences and presences, respectively, were classified correctly; Table 2).

Human impacts, climatic conditions and soil properties were generally most important variable categories for predicting goldenrod occurrences in Polish roadsides at all spatial scales. These were followed by landscape structure, local characteristics of roads, transect sampling parameters and occurrence of other alien plants (Figure 3, Appendix S1: Table S1). Across all the considered spatial scales, the individual predictor variables: human population density, solar radiation and agricultural intensity were among the most contributing factors in explaining the probability of goldenrod occurrence, while the abundance and diversity of other alien plant species was of relatively low importance (Figure 5, Appendix S2: Figure S1 and Figure S2).

The importance of explanatory variables in predicting goldenrod occurrence was, however, scale dependent, as indicated by the GAMM model that included an interaction term between the variable category and spatial scale performing better (AIC=1126.6) than a model without this effect (AIC=1143.8). This was largely driven by the effect of increasing relative contribution of landscape variables with increasing buffer radius, while no such effect was found for the other categories of variables (Figure 3, Appendix S1: Table S2).

Scale-dependence was also confirmed for several single predictor variables (Figure 4A, Figure 5, Appendix S2: Figure S1 and Figure S2). The Spearman correlation coefficients between the spatial scale and the importance of variables in predicting goldenrod occurrence varied from positive, through none to negative (Figure 4A). Broadly speaking, landscape variables, such as coverage of wetlands and water bodies, semi-natural habitats and forests, were again shown to increase in importance with increasing spatial scale (Figure 4A, Figure 5). The influence of some other drivers of goldenrod occurrence decreased with the spatial scale: namely almost all human impacts as well as solar radiation, landscape configuration and two of the four road variables (Figure 4A, Figure 5, Appendix S2: Figure S1 and Figure S2). On the other hand, the importance of several predictors was not correlated with the buffer radius of a transect, including all the considered variables related to soil properties (Figure 4A, Appendix S2: Figure S1). The observed pattern in the associations between the spatial scale and variable importance was significantly non-random as indicated by the tests of equity ($p < 0.01$ in each of the 100 runs; Figure 4B). However, the direction of relationships between the occurrence of goldenrods and the examined variables was generally similar across the spatial scales as demonstrated by the partial dependence plots (Figure 5, Appendix S2: Figure S1 and Figure S2).

4. Discussion

We found that the occurrence of goldenrods along roadsides is associated with multiple factors, among which those describing human impacts, climatic conditions, soil properties and landscape structure are the most important. However, the relative contribution of these characteristics in predicting goldenrod distribution changed across spatial scales. Thus, our results clearly suggest that the effect of variables driving plant invasions can be dependent on the spatial scale examined. Below we discuss possible explanations of the mechanisms

causing the observed patterns and list potential limitations associated with the methods used. Last, we suggest possible applications of our results for invasive plant management.

4.1 Importance of environmental and anthropogenic variables

By including a wide range of invasion predictors, we were able to show that plant invasions are influenced by multiple drivers and their success cannot be described by a single measure. However, some of the considered variables appeared to be more important for the predictions of goldenrod invasion than others. As expected, measures of human activity, such as agricultural intensity, human population density and several other indicators of socio-economic conditions, were among the most influential determinants of goldenrod distribution. This is likely because these characteristics are surrogates of anthropogenic disturbances in natural systems and reflect the level of propagule pressure (Lockwood et al. 2005, Hulme 2009, Pyšek et al. 2010). It has been suggested that the impact of human activities on species invasions overwhelms the influence of climatic conditions (Pyšek et al. 2010, Dyderski et al. 2022). However, this has not been confirmed in our study as climatic characteristics, mainly thermal conditions (the amount of incoming solar radiation and average annual temperature), were also among the most important variables explaining goldenrod occurrence. These associations are in line with previous research describing the preference of the studied species to well irradiated areas characterized of relatively warm temperatures (Cao et al. 2018). Furthermore, the occurrence of goldenrods was clearly associated with soil properties, especially phosphorus content, although the mechanism behind this association needs further research. The distribution of studied species was also linked with the characteristics of landscape structure, for instance landscape configuration. The general importance of landscape structure for the outcomes of invasion processes has been already highlighted by several studies (Vilà and Ibáñez 2011, Kotowska et al. 2022). Our results suggest that the dispersal efficiency of alien plants, such as goldenrods, can be

positively related to the level of landscape configuration as a high concentration of edge habitats (e.g. ecotones, field margins) may facilitate the movement of invasive plant propagules across the landscape (Warren et al. 2013).

Factors related to road parameters were found to have little impact on the probability of goldenrod invasion. This suggests no substantial differences in goldenrod occurrence among different road types or classes or that the influence of local variables was too low to alleviate the effect of large-scale characteristics (Czarniecka-Wiera et al. 2020). Also, no clear associations between goldenrod presence and other alien plants may suggest that indices measured at the level of a roadside plant community are relatively less important. This is consistent with previous suggestions that the colonization of road verges by invasive alien plants and their further spread can be impacted by processes operating at larger spatial scales than the roadside. For example, invasion probability can be more influenced by the surrounding landscape (Minor et al., 2009; Vilà and Ibáñez, 2011), or it can be a reflection of the increased use of the roads in areas of high population density, which could promote spread of species to roadsides and surrounding habitats (Auffret et al. 2014). On the other hand, the low predictive power of other alien plants for the occurrence of goldenrods might be an indication that these species also relate to the same factors as goldenrods or that possible interactions between alien plants may occur on a very local scale (Lenda et al. 2019), smaller than the scale of a transect.

We considered a large set of factors potentially affecting goldenrod occurrence in order to capture the high complexity of the invasion process (Catford et al. 2009). While many existing studies concentrate on one specific type of variables, such as landscape structure (e.g. Andrew and Ustin 2010) or species traits (Van Kleunen et al. 2010), we tried to overcome this potential weakness by covering a variety of different categories that could reasonably be expected to influence invasion success. However, there may, of course, still be

important drivers that we did or could not cover in our study. For example, current invasion patterns may be better reflected by historical factors (such as, introduction history, historical land use changes) than contemporary processes (Essl et al. 2011, Mattingly and Orrock 2013), thus making the predictions about the present situation even more challenging. Moreover, biological invasions are dynamic phenomena, and different drivers are involved in this process at different stages along the invasion pathway (Theoharides and Dukes 2007). Since the geographic range of goldenrods in the study area is still expanding (Perera et al. 2021), our data likely included observations of the species at different invasion stages. Therefore, some of the considered determinants of goldenrod distribution may have been less informative than expected because their effect could have been site-specific.

4.2 Effect of spatial scale

We found that the effect of different factors associated with goldenrod occurrence changes across spatial scales, thus corroborating earlier suggestions on the importance of spatial context for understanding patterns in plant invasions (Milbau et al. 2009, Czarniecka-Wiera et al. 2020, Kotowska et al. 2022). Our results indicate that the probability of invasion of alien plants, such as goldenrods, is not only moderated by a multitude of drivers, but also that their role in the invasion process changes depending on the spatial scale considered. For example, the influence of human population density was more prevalent at small spatial scales suggesting that human activity-related factors may be responsible, for instance, for local introductions and dispersal of the studied plant (Lenda et al. 2014). Simultaneously, the importance of, e.g., road density was highest at the largest spatial scale, indicating that roads, being the dispersal corridors for goldenrods, may shape their distribution across wider areas. Similarly, the importance of multiple land use types was more pronounced at larger spatial scales, suggesting that the number of habitats available for invasive species may make the landscape more vulnerable (or resistant) to invasions. At the same time, landscape

configuration played a more important role for goldenrod distribution at smaller spatial scales, thus following previous conclusions that the scale of effect of habitat fragmentation (i.e. the level of landscape configuration) is smaller than the effect of habitat amount (Miguet et al. 2016, Kotowska et al. 2022). Our findings are generally in accordance with earlier suggestions that different invasion drivers operate at different scales (Vicente et al. 2019) and that small scale patterns may be constrained by larger scale factors (Levin 1992, Pauchard and Shea 2006). Although the presented effects may be species-specific and may be different depending on the considered range of spatial scales, our results highlight the need for multi-scale approaches in studying the mechanisms driving plant invasions.

Despite our important findings regarding both spatial scale and the effects of a variety of environmental and anthropogenic drivers of invasion, it is still true that the predictive accuracy of our models was not very high. One reason for this is that the considered explanatory variables were measured based on open spatial data acquired from different sources, so their quality varied in terms of accuracy, completeness and reliability. Thus, the performance of our models may have been influenced by some feature noise that could bias the learning process (Zhu and Wu 2004). Furthermore, we cannot exclude some errors introduced in the reference dataset as a result of remote data collection on goldenrod occurrence with Google Street View images. The method shows high precision in relation to field inventory data, however it also has some limitations (e.g., temporal variability in imagery, difficulties in detecting less conspicuous species or individuals) which may reduce the probability of visual plant detection (Kotowska et al. 2021), and thus deteriorate the data quality and, consequently, the model accuracy. Still, given these limitations, which largely only increase the uncertainty in our estimates of goldenrod occurrence – variable relationships, our study using open access environmental data shows the possibilities of

investigating species occurrence patterns in relation to multiple possible drivers at different spatial scales.

4.3 Management implications

Implementing effective measures aiming at preventing, eradicating, and controlling plant invasions is strongly limited by the resources (mostly financial) available for their management. Therefore, such efforts require setting priorities to identify invasion hotspots and to target the most important factors driving the success of invasive species (Ziller et al. 2020). Our study highlights how we can benefit from using the huge amounts of freely accessible environmental data and considering different spatial scales to better approach the full complexity of potential mechanisms underlying processes of biological invasions. Such a multiple variable and spatial scale approach opens up for the development of better and more efficient counter-measures to prioritize management attempts to the spatial scale at which the most important factors affecting plant invasions operate. While most strategies for controlling invasive species may focus on the site scale, our results show that local characteristics may be less important for plant invasion patterns as compared to, e.g., variables associated with landscape structure. Thus, the development of management initiatives at larger scales, e.g., landscape level, may be important for more effective control of invasive plants, such as goldenrods.

Acknowledgements

The study was supported by the Polish National Science Centre grant: 2016/21/N/NZ8/01286 and the Polish National Science Centre doctoral scholarship: 2019/32/T/NZ8/00343.

References

Andrew, M. E., and S. L. Ustin. 2010. The effects of temporally variable dispersal and

- landscape structure on invasive species spread. *Ecological Applications* 20:593–608.
- Auffret, A. G., J. Berg, and S. A. O. Cousins. 2014. The geography of human-mediated dispersal. *Diversity and Distributions* 20:1450–1456.
- Barney, J. N., and T. H. Whitlow. 2008. A unifying framework for biological invasions: The state factor model. *Biological Invasions* 10:259–272.
- Bazzichetto, M., M. Malavasi, V. Barták, A. T. R. Acosta, V. Moudrý, and M. L. Carranza. 2018. Modeling plant invasion on Mediterranean coastal landscapes: An integrative approach using remotely sensed data. *Landscape and Urban Planning* 171:98–106.
- Bellard, C., J. M. Jeschke, B. Leroy, and G. M. Mace. 2018. Insights from modeling studies on how climate change affects invasive alien species geography. *Ecology and Evolution* 8:5688–5700.
- Blackburn, T. M., C. Bellard, and A. Ricciardi. 2019. Alien versus native species as drivers of recent extinctions. *Frontiers in Ecology and the Environment* 17:203–207.
- Bowman, A. W., and A. Azzalini. 2021. R package “sm”: nonparametric smoothing methods (version 2.2-5.7) URL <http://www.stats.gla.ac.uk/~adrian/sm>.
- Breiman, L. 2001. Random forests. *Machine Learning* 45:5–32.
- Brown, K. A., S. Spector, and W. Wu. 2008. Multi-scale analysis of species introductions: combining landscape and demographic models to improve management decisions about non-native species. *Journal of Applied Ecology* 45:1639–1648.
- Cao, Y., Y. Xiao, S. Zhang, and W. Hu. 2018. Simulated warming enhances biological invasion of *Solidago canadensis* and *Bidens frondosa* by increasing reproductive investment and altering flowering phenology pattern. *Scientific Reports* 8:1–8.
- Carboneras, C., P. Genovesi, M. Vilà, T. M. Blackburn, M. Carrete, M. Clavero, B. D’hondt, J. F. Orueta, B. Gallardo, P. Geraldes, P. González-Moreno, R. D. Gregory, W. Nentwig, J.-Y. Paquet, P. Pyšek, W. Rabitsch, I. Ramírez, R. Scalera, J. L. Tella, P. Walton, and R.

- Wynde. 2018. A prioritised list of invasive alien species to assist the effective implementation of EU legislation. *Journal of Applied Ecology* 55:539–547.
- Catford, J. A., R. Jansson, and C. Nilsson. 2009. Reducing redundancy in invasion ecology by integrating hypotheses into a single theoretical framework. *Diversity and Distributions* 15:22–40.
- Chytrý, M., L. C. Maskell, J. Pino, P. Pyšek, M. Vilà, X. Font, and S. M. Smart. 2008. Habitat invasions by alien plants: a quantitative comparison among Mediterranean, subcontinental and oceanic regions of Europe. *Journal of Applied Ecology* 45:448–458.
- Czarniecka-Wiera, M., T. H. Szymura, and Z. Kącki. 2020. Understanding the importance of spatial scale in the patterns of grassland invasions. *Science of the Total Environment* 727:138669.
- Dassonville, N., S. Vanderhoeven, V. Vanparrys, M. Hayez, W. Gruber, and P. Meerts. 2008. Impacts of alien invasive plants on soil nutrients are correlated with initial site conditions in NW Europe. *Oecologia* 157:131–140.
- Diagne, C., B. Leroy, A. C. Vaissière, R. E. Gozlan, D. Roiz, I. Jarić, J. M. Salles, C. J. A. Bradshaw, and F. Courchamp. 2021. High and rising economic costs of biological invasions worldwide. *Nature* 592:571–576.
- Diez, J. M., C. M. D'Antonio, J. S. Dukes, E. D. Grosholz, J. D. Olden, C. J. Sorte, D. M. Blumenthal, B. A. Bradley, R. Early, I. Ibáñez, S. J. Jones, J. J. Lawler, and L. P. Miller. 2012. Will extreme climatic events facilitate biological invasions? *Frontiers in Ecology and the Environment* 10:249–257.
- Dyderski, M., J. Żarnowiec, A. Stebel, and D. Chmura. 2022. Propagule pressure and land-use are more important than climate for invasive bryophytes regional distributions. *Landscape Ecology*:1–14.
- Early, R., B. A. Bradley, J. S. Dukes, J. J. Lawler, J. D. Olden, D. M. Blumenthal, P.

- Gonzalez, E. D. Grosholz, I. Ibañez, L. P. Miller, C. J. B. Sorte, and A. J. Tatem. 2016. Global threats from invasive alien species in the twenty-first century and national response capacities. *Nature Communications* 7:1–9.
- Early, R., and D. F. Sax. 2014. Climatic niche shifts between species' native and naturalized ranges raise concern for ecological forecasts during invasions and climate change. *Global Ecology and Biogeography* 23:1356–1365.
- Essl, F., S. Dullinger, W. Rabitsch, P. E. Hulme, K. Hülber, V. Jarošík, I. Kleinbauer, F. Krausmann, I. Kühn, W. Nentwig, M. Vilà, P. Genovesi, F. Gherardi, M. L. Desprez-Loustau, A. Roques, and P. Pyšek. 2011. Socioeconomic legacy yields an invasion debt. *Proceedings of the National Academy of Sciences of the United States of America* 108:203–207.
- Greenwell, B. M. 2017. pdp: An R Package for Constructing Partial Dependence Plots. *The R Journal*, 9:421–436.
- de Groot, M., D. Kleijn, and N. Jogan. 2007. Species groups occupying different trophic levels respond differently to the invasion of semi-natural vegetation by *Solidago canadensis*. *Biological Conservation* 136:612–617.
- Heger, T., A. T. Pahl, Z. Botta-Dukát, F. Gherardi, C. Hoppe, I. Hoste, K. Jax, L. Lindström, P. Boets, S. Haider, J. Kollmann, M. J. Wittmann, and J. M. Jeschke. 2013. Conceptual frameworks and methods for advancing invasion ecology. *Ambio* 42:527–540.
- Hejda, M., P. Pyšek, and V. Jarošík. 2009a. Impact of invasive plants on the species richness, diversity and composition of invaded communities. *Journal of Ecology* 97:393–403.
- Hejda, M., P. Pyšek, J. Pergl, J. Sádlo, M. Chytrý, and V. Jarošík. 2009b. Invasion success of alien plants: do habitat affinities in the native distribution range matter? *Global Ecology and Biogeography* 18:372–382.
- Hijmans, R. J. 2022. raster: Geographic Data Analysis and Modeling. R package version 3.5-

15. <https://CRAN.R-project.org/package=raster>.
- Hulme, P. E. 2009. Trade, transport and trouble: managing invasive species pathways in an era of globalization. *Journal of Applied Ecology* 46:10–18.
- Hulme, P. E. 2017. Climate change and biological invasions: evidence, expectations, and response options. *Biological Reviews* 92:1297–1313.
- IPBES. 2019. Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. E. S. Brondizio, J. Settele, S. Díaz, and H. T. Ngo (Eds.). <https://www.ipbes.net/global-assessment>
- Joly, M., P. Bertrand, R. Y. Gbangou, M. C. White, J. Dubé, and C. Lavoie. 2011. Paving the way for invasive species: Road type and the spread of Common ragweed (*Ambrosia artemisiifolia*). *Environmental Management* 48:514–522.
- Kabuce, N., and N. Priede. 2010. NOBANIS – Invasive Alien Species Fact Sheet – *Solidago canadensis*. – From: Online Database of the European Network on Invasive Alien Species - NOBANIS. www.nobanis.org.
- Van Kleunen, M., E. Weber, and M. Fischer. 2010. A meta-analysis of trait differences between invasive and non-invasive plant species. *Ecology Letters* 13:235–245.
- Kotowska, D., T. Pärt, P. Skórka, A. G. Auffret, and M. Żmihorski. 2022. Scale dependence of landscape heterogeneity effects on plant invasions. *Journal of Applied Ecology* 59:1313–1323.
- Kotowska, D., T. Pärt, and M. Żmihorski. 2021. Evaluating Google Street View for tracking invasive alien plants along roads. *Ecological Indicators* 121:107020.
- Kożuchowski, K. 2011. *Klimat Polski. Nowe Spojrzenie*. (Climate of Poland: a new approach; in Polish). Wydawnictwo Naukowe PWN, Warszawa.
- Kueffer, C. 2017. Plant invasions in the Anthropocene. *Science* 358:724–725.

- Kuhn, M. 2022. caret: Classification and Regression Training. R package version 6.0-91. <https://CRAN.R-project.org/package=caret>.
- Kumar Rai, P., and J. S. Singh. 2020. Invasive alien plant species: Their impact on environment, ecosystem services and human health. *Ecological Indicators* 111:106020.
- Lázaro-Lobo, A., and G. N. Ervin. 2019. A global examination on the differential impacts of roadsides on native vs. exotic and weedy plant species. *Global Ecology and Conservation* 17:e00555.
- Lenda, M., P. Skórka, J. M. H. Knops, D. Moroń, W. J. Sutherland, K. Kuszewska, and M. Woyciechowski. 2014. Effect of the Internet Commerce on Dispersal Modes of Invasive Alien Species. *PLoS ONE* 9:e99786.
- Lenda, M., P. Skórka, J. M. H. Knops, D. Moroń, S. Tworek, and M. Woyciechowski. 2012. Plant establishment and invasions: an increase in a seed disperser combined with land abandonment causes an invasion of the non-native walnut in Europe. *Proceedings of the Royal Society B: Biological Sciences* 279:1491–1497.
- Lenda, M., P. Skórka, J. Knops, M. Żmihorski, R. Gaj, D. Moroń, M. Woyciechowski, and P. Tryjanowski. 2019. Multispecies invasion reduces the negative impact of single alien plant species on native flora. *Diversity and Distributions* 25:951–962.
- Lenda, M., P. Skórka, K. Kuszewska, D. Moroń, M. Bęcik, R. Baczek Kwinta, F. Janowiak, D. H. Duncan, P. A. Vesk, H. P. Possingham, and J. M. H. Knops. 2021. Misinformation, internet honey trading and beekeepers drive a plant invasion. *Ecology Letters* 24:165–169.
- Lenda, M., M. Witek, P. Skórka, D. Moroń, and M. Woyciechowski. 2013. Invasive alien plants affect grassland ant communities, colony size and foraging behaviour. *Biological Invasions* 15:2403–2414.
- Levin, S. A. 1992. The problem of pattern and scale in ecology: The Robert H. MacArthur Award Lecture. *Ecology* 73:1943–1967.

- Levine, J. M., M. Vilà, C. M. D'Antonio, J. S. Dukes, K. Grigulis, and S. Lavorel. 2003. Mechanisms underlying the impacts of exotic plant invasions. *Proceedings of the Royal Society B: Biological Sciences* 270:775–781.
- Lockwood, J. L., P. Cassey, and T. Blackburn. 2005. The role of propagule pressure in explaining species invasions. *Trends in Ecology and Evolution* 20:223–228.
- Mattingly, W. B., and J. L. Orrock. 2013. Historic land use influences contemporary establishment of invasive plant species. *Oecologia* 172:1147–1157.
- McDougall, K. L., J. Lembrechts, L. J. Rew, S. Haider, L. A. Cavieres, C. Kueffer, A. Milbau, B. J. Naylor, M. A. Nuñez, A. Pauchard, T. Seipel, K. L. Speziale, G. T. Wright, and J. M. Alexander. 2018. Running off the road: roadside non-native plants invading mountain vegetation. *Biological Invasions* 20:3461–3473.
- Melbourne, B. A., H. V. Cornell, K. F. Davies, C. J. Dugaw, S. Elmendorf, A. L. Freestone, R. J. Hall, S. Harrison, A. Hastings, M. Holland, M. Holyoak, J. Lambrinos, K. Moore, and H. Yokomizo. 2007. Invasion in a heterogeneous world: Resistance, coexistence or hostile takeover? *Ecology Letters* 10:77–94.
- Miguet, P., H. B. Jackson, N. D. Jackson, A. E. Martin, and L. Fahrig. 2016. What determines the spatial extent of landscape effects on species? *Landscape Ecology* 31:1177–1194.
- Milbau, A., J. C. Stout, B. J. Graae, and I. Nijs. 2009. A hierarchical framework for integrating invasibility experiments incorporating different factors and spatial scales. *Biological Invasions* 11:941–950.
- Minor, E. S., S. M. Tessel, K. A. M. Engelhardt, and T. R. Lookingbill. 2009. The role of landscape connectivity in assembling exotic plant communities: a network analysis. *Ecology* 90:1802–1809.
- Moroń, D., M. Lenda, P. Skórka, H. Szentgyörgyi, J. Settele, and M. Woyciechowski. 2009. Wild pollinator communities are negatively affected by invasion of alien goldenrods in

- grassland landscapes. *Biological Conservation* 142:1322–1332.
- Moroń, D., E. Marjańska, P. Skórka, M. Lenda, and M. Woyciechowski. 2021. Invader–pollinator paradox: Invasive goldenrods benefit from large size pollinators. *Diversity and Distributions* 27:632–641.
- Park, J. S., D. Choi, and Y. Kim. 2020. Potential distribution of Goldenrod (*Solidago altissima* L.) during climate change in South Korea. *Sustainability* 12.17:6710.
- Pauchard, A., and K. Shea. 2006. Integrating the study of non-native plant invasions across spatial scales. *Biological Invasions* 8:399–413.
- Pebesma, E. 2018. Simple Features for R: Standardized Support for Spatial Vector Data. *The R Journal* 10.1:439.
- Perera, P. C. D., T. H. Szymura, A. Zając, D. Chmolewska, and M. Szymura. 2021. Drivers of *Solidago* species invasion in Central Europe—Case study in the landscape of the Carpathian Mountains and their foreground. *Ecology and Evolution* 11:12429–12444.
- Pyšek, P., V. Jarošík, P. E. Hulme, I. Kühn, J. Wild, M. Arianoutsou, S. Bacher, F. Chiron, V. Didžiulis, F. Essl, P. Genovesi, F. Gherardi, M. Hejda, S. Kark, P. W. Lambdon, M. L. Desprez-Loustau, W. Nentwig, J. Pergl, K. Poboljšaj, W. Rabitsch, A. Roques, D. B. Roy, S. Shirley, W. Solarz, M. Vilà, and M. Winter. 2010. Disentangling the role of environmental and human pressures on biological invasions across Europe. *Proceedings of the National Academy of Sciences of the United States of America* 107:12157–12162.
- Pyšek, P., V. Jarošík, P. E. Hulme, J. Pergl, M. Hejda, U. Schaffner, and M. Vilà. 2012. A global assessment of invasive plant impacts on resident species, communities and ecosystems: the interaction of impact measures, invading species' traits and environment. *Global Change Biology* 18:1725–1737.
- R Core Team. 2020. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL <http://www.R-project.org/>.

- Ricklefs, R. E., and D. G. Jenkins. 2011. Biogeography and ecology: Towards the integration of two disciplines. *Philosophical Transactions of the Royal Society B: Biological Sciences* 366:2438–2448.
- Roberts, D. R., V. Bahn, S. Ciuti, M. S. Boyce, J. Elith, G. Guillera-Arroita, S. Hauenstein, J. J. Lahoz-Monfort, B. Schröder, W. Thuiller, D. I. Warton, B. A. Wintle, F. Hartig, and C. F. Dormann. 2017. Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography* 40:913–929.
- Schroeder, H., H. Grab, A. Kessler, and K. Poveda. 2021. Human-Mediated Land Use Change Drives Intraspecific Plant Trait Variation. *Frontiers in Plant Science* 11: 592881.
- Shi, J., Y. Q. Luo, F. Zhou, and P. He. 2010. The relationship between invasive alien species and main climatic zones. *Biodiversity and Conservation* 19:2485–2500.
- da Silva, V. S., C. A. Silva, M. Mohan, A. Cardil, F. E. Rex, G. H. Loureiro, D. R. A. de Almeida, E. N. Broadbent, E. B. Gorgens, A. P. Dalla Corte, E. A. Silva, R. Valbuena, and C. Klauberg. 2020. Combined Impact of sample size and modeling approaches for predicting stem volume in *Eucalyptus* spp. forest plantations using field and LiDAR data. *Remote Sensing* 12.9:1438.
- Simberloff, D., and B. Von Holle. 1999. Positive Interactions of Nonindigenous Species: Invasional Meltdown? *Biological Invasions* 1:21–32.
- Skórka, P., M. Lenda, and P. Tryjanowski. 2010. Invasive alien goldenrods negatively affect grassland bird communities in Eastern Europe. *Biological Conservation* 143:856–861.
- Szymura, T. H., M. Szymura, M. Zając, and A. Zając. 2018. Effect of anthropogenic factors, landscape structure, land relief, soil and climate on risk of alien plant invasion at regional scale. *Science of the Total Environment* 626:1373–1381.
- Taylor, B. W., and R. E. Irwin. 2004. Linking economic activities to the distribution of exotic plants. *Proceedings of the National Academy of Sciences of the United States of America*

101:17725–17730.

- Theoharides, K. A., and J. S. Dukes. 2007. Plant invasion across space and time: factors affecting nonindigenous species success during four stages of invasion. *New Phytologist* 176:256–273.
- Valavi, R., J. Elith, J. J. Lahoz-Monfort, and G. Guillera-Arroita. 2019. BlockCV: An R package for generating spatially or environmentally separated folds for k-fold cross-validation of species distribution models. *Methods in Ecology and Evolution* 10:225–232.
- Vicente, J. R., C. Kueffer, D. M. Richardson, A. S. Vaz, J. A. Cabral, C. Hui, M. B. Araújo, I. Kühn, C. A. Kull, P. H. Verburg, E. Marchante, and J. P. Honrado. 2019. Different environmental drivers of alien tree invasion affect different life-stages and operate at different spatial scales. *Forest Ecology and Management* 433:263–275.
- Vilà, M., and I. Ibáñez. 2011. Plant invasions in the landscape. *Landscape Ecology* 26:461–472.
- Vitti, S., E. Pellegrini, V. Casolo, G. Trotta, and F. Boscutti. 2020. Contrasting responses of native and alien plant species to soil properties shed new light on the invasion of dune systems. *Journal of Plant Ecology* 13:667–675.
- Warren, R. J., T. Ursell, A. D. Keiser, and M. A. Bradford. 2013. Habitat, dispersal and propagule pressure control exotic plant infilling within an invaded range. *Ecosphere* 4:1–12.
- Weber, E. 2001. Current and Potential Ranges of Three Exotic Goldenrods (*Solidago*) in Europe. *Conservation Biology* 15:122–128.
- Wilson, J. R. U., E. E. Dormontt, P. J. Prentis, A. J. Lowe, and D. M. Richardson. 2009. Something in the way you move: dispersal pathways affect invasion success. *Trends in Ecology and Evolution* 24:136–144.

- With, K. A. 2002. The Landscape Ecology of Invasive Spread. *Conservation Biology* 16:1192–1203.
- Wood, S. N. 2017. *Generalized Additive Models : an introduction with R* (2nd edition). Chapman and Hall/CRC.
- Zhu, X., and X. Wu. 2004. Class Noise vs. Attribute Noise: A Quantitative Study. *Artificial Intelligence Review* 22:177–210.
- Ziller, S. R., M. de S. Dechoum, R. A. Duarte Silveira, H. Marques da Rosa, B. C. Mello Oliveira, R. D. Zenni, M. S. Motta, and L. Filipe da Silva. 2020. A priority-setting scheme for the management of invasive non-native species in protected areas. *NeoBiota* 62:591–606.

Tables

Table 1. List of variables used in goldenrod occurrence modeling. Full description and data sources are given in Appendix S1: Table S1.

Category (scale)	Variables
Human Impact (within 250, 500, 1000, 2000 and 5000 m of a transect)	Human Footprint Index (HFI), Agricultural intensity index, Income per capita, Population density, Citizens>65, Proportion of women, Higher education rate
Climate (within 250, 500, 1000, 2000 and 5000 m of a transect)	Mean temperature, Precipitation, Solar radiation, Growing season length
Soil (within 250, 500, 1000, 2000 and 5000 m of a transect)	Soil pH, Soil CaCO ₃ content, Soil P content, Soil K content, Soil N content
Landscape (within 250, 500, 1000, 2000 and 5000 m of a transect)	Landscape composition, Landscape configuration, Artificial surfaces, Arable land, Pastures, Heterogeneous agricultural areas, Forests, Semi-natural habitats, Wetlands and water bodies, River density, Road density, Urban areas, Grasslands, Water and wetness, Wastelands, Normalized Difference Vegetation Index (NDVI)
(distance)	River distance, Urban distance
Road (along a transect)	Road width, Road curvature, Road direction, Road class
Transect (within 30 m of a transect)	Mown road verge, Transect sections, Year of GSV picture, Month of GSV picture
Alien species (within 30 m of a transect)	Box elder abundance, Black locust abundance, Canadian horseweed abundance, Diversity of alien plants (of a total of 13 species)

Table 2. Performance of five RF models explaining the occurrence of goldenrods at 1357 transects established along roads in Poland in relation to environmental and human activity-related characteristics in five spatial scales.

Scale [m]	Accuracy	Kappa	Sensitivity	Specificity
250	0.7045	0.3908	0.6931	0.7114
500	0.7023	0.3841	0.6812	0.7150
1000	0.6971	0.3712	0.6653	0.7162
2000	0.7038	0.3829	0.6653	0.7268
5000	0.7149	0.4077	0.6871	0.7316

Figure legends

Figure 1. Distribution of 1347 transects sampled for goldenrod occurrence in agricultural landscapes across Poland

Figure 2. An example study location; five spatial scales (i.e. buffer zones of a transect line) at which the plant invasion drivers were analyzed (A) and 25 transect sections surveyed for alien plant occurrence within 30 m of a transect line (B).

Figure 3. Average relative importance of seven variable categories for goldenrod occurrence in five spatial scales based on the RF models.

Figure 4. The Spearman rank correlation coefficients ($p < 0.05$ in red) between the importance of each variable and increasing spatial scale (A) and the distribution of observed (red curve) and permuted (black curves) correlation coefficients (B). A positive correlation indicates that the relative variable importance increases as the spatial scale increases, a negative correlation means that the relative variable importance decreases with increasing spatial scale. Variable names abbreviations are explained in Table 1 and Appendix S1: Table S1, variable color codes are given in Figure 3. Variables are ordered by decreasing correlation coefficient.

Figure 5. Changes in the importance of explanatory variables related to human impacts (left panel) and landscape structure (right panel) for predicting goldenrod occurrence in Polish farmland in five spatial scales based on the RF models. Partial dependence plots showing the mean marginal effect of these variables on the probability of goldenrod occurrence across five spatial scales are given as small inner panels. Each inner plot represents the effect of each variable while holding the other variables constant and different spatial scales are shown with a color gradient from pale (250 m) to dark (5000 m).

Figures

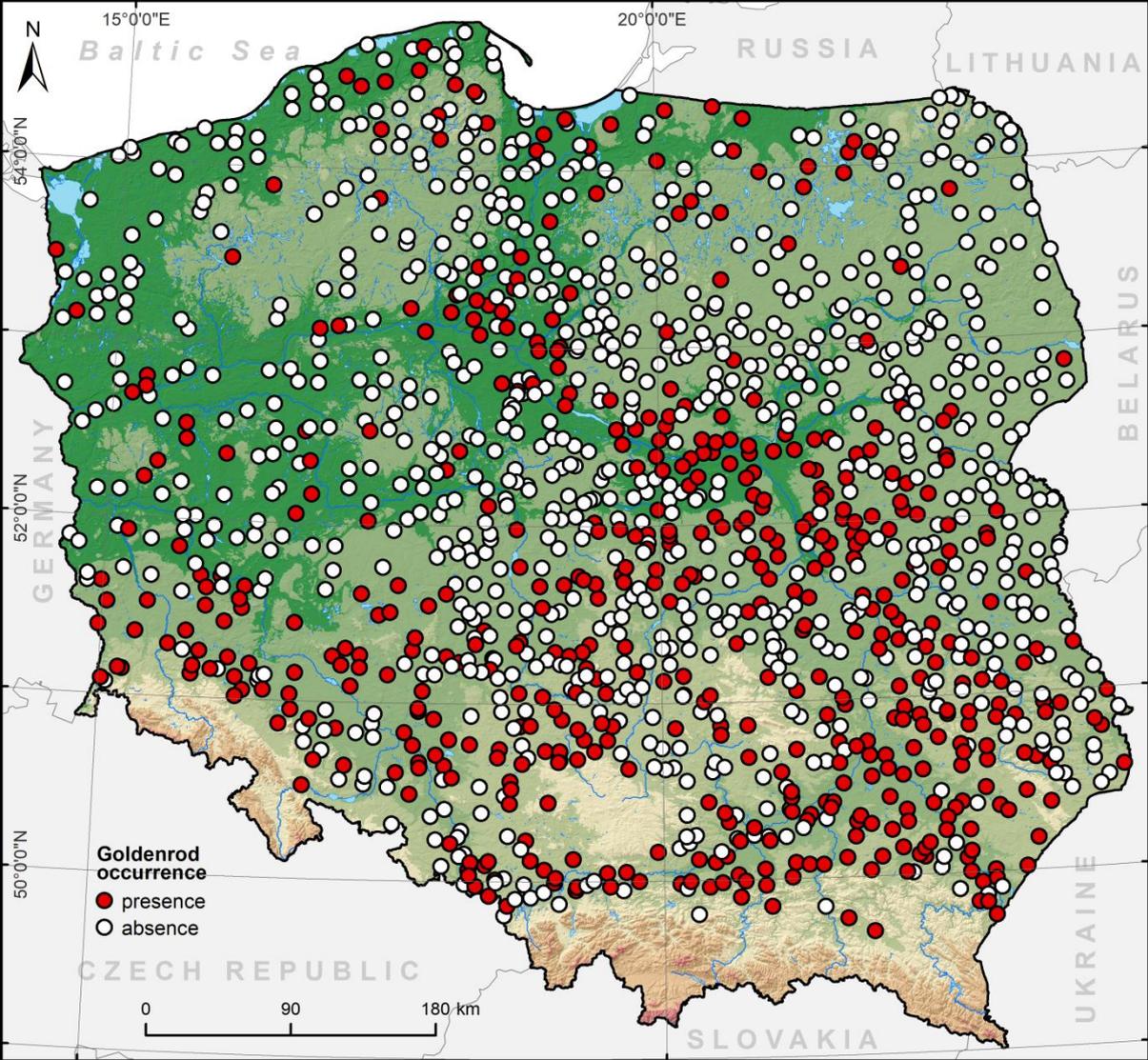


Figure 1

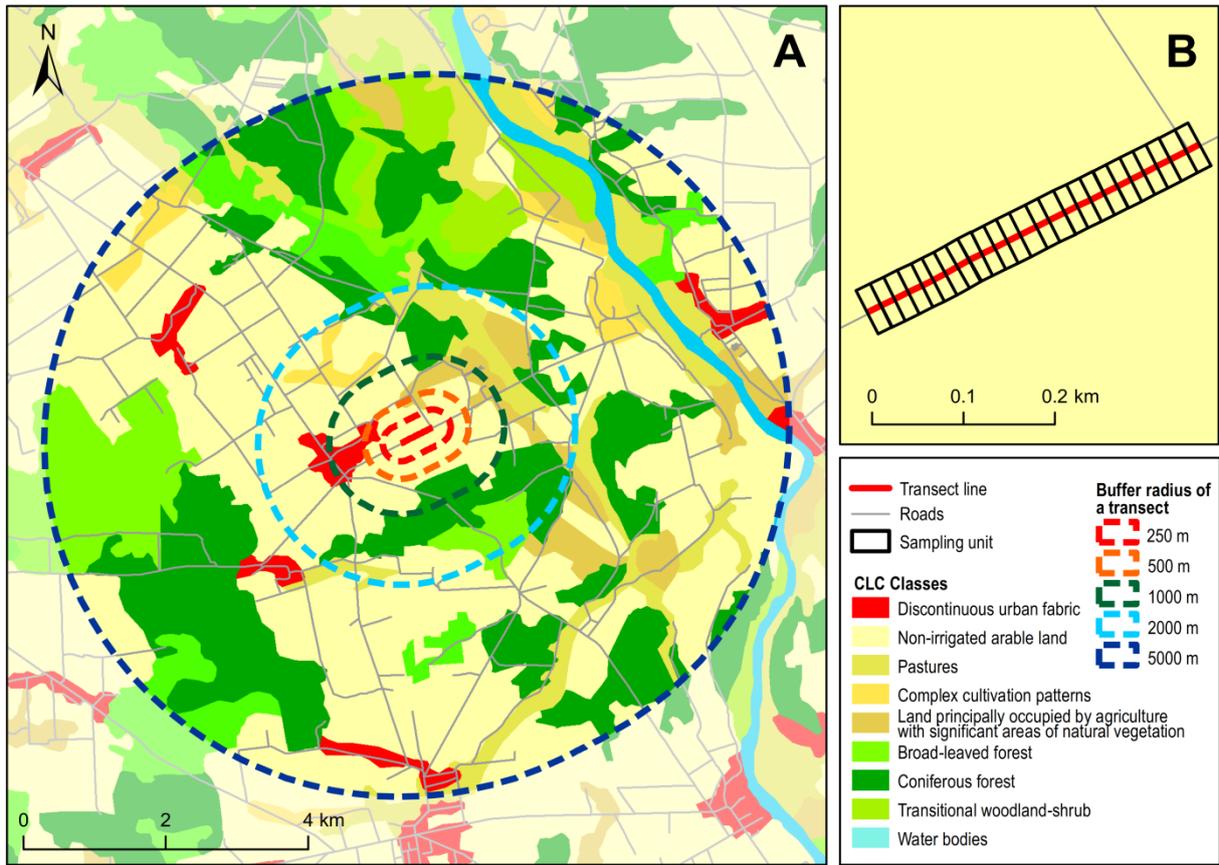


Figure 2

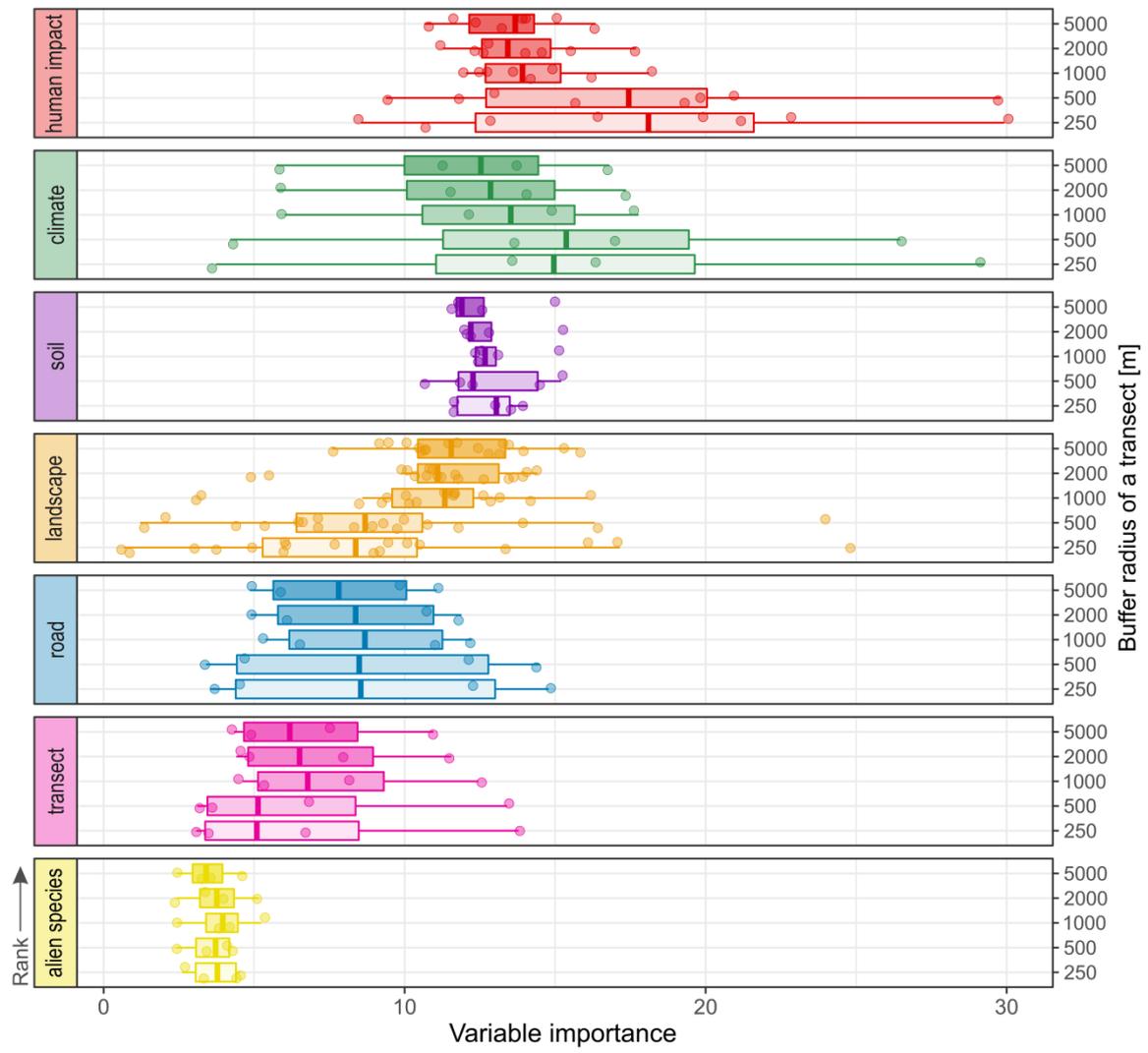


Figure 3

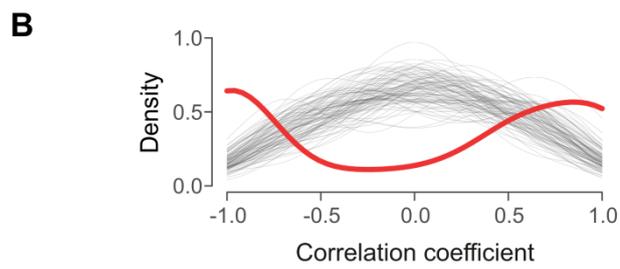
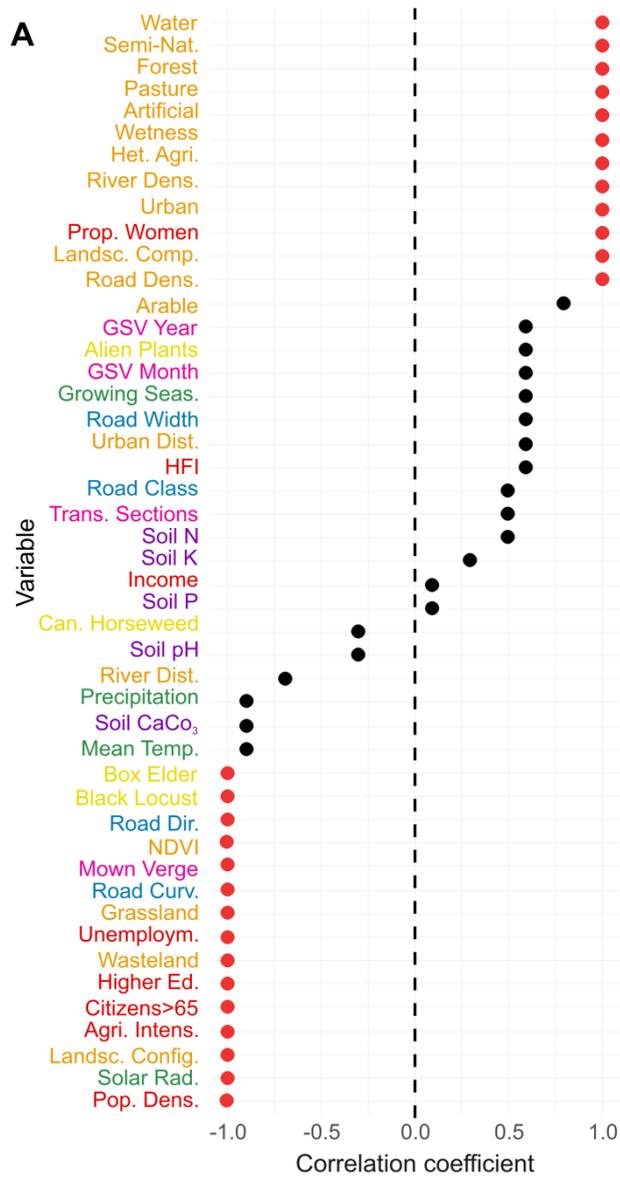


Figure 4

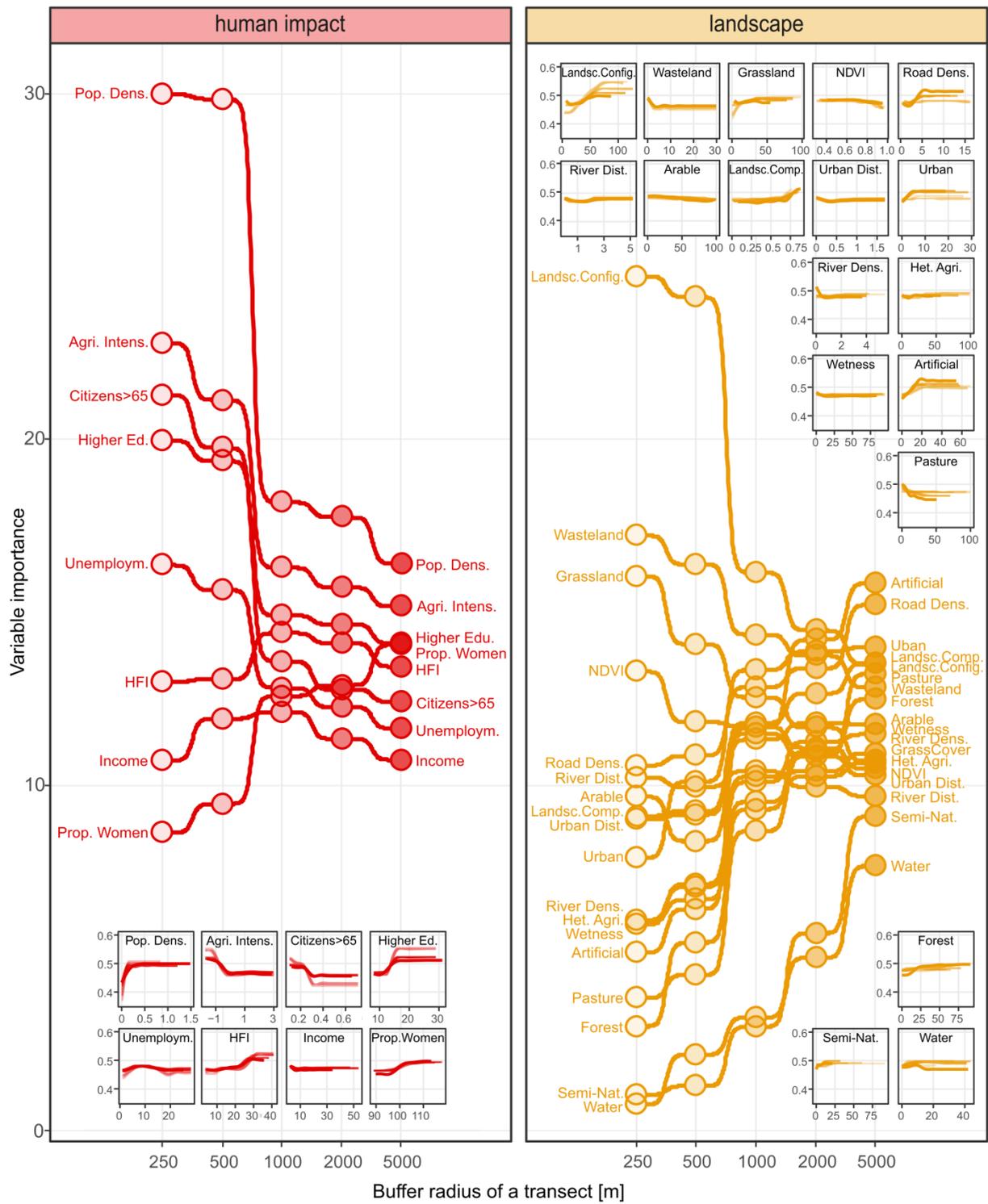


Figure 5

Appendix S1: Tables

Table S1. Explanatory variables considered as divers of goldenrod occurrence in five RF models. For each variable its abbreviation (in brackets), description and source of data is given (if applicable). The variables marked with an asterisk were not used in the final analysis.

VARIABLE	DESCRIPTION	DATA SOURCE	CATE GORY
<i>Variables measured within 250, 500, 1000, 2000 and 5000 m of the studied transects</i>			
Human Footprint Index (HFI)	Mean Human Footprint Index within a buffer, measuring the cumulative human pressure on the environment at spatial resolution of about 1km using information on built-up environments, population density, electric power infrastructure, crop lands, pasture lands, roads, railways, and navigable waterways	Venter et al., 2016, 2018	HUMAN IMPACT
Agricultural Intensity index (Agri. Intens.)	Composite agricultural intensity index calculated using the PCA, based on the share of farms larger than 10 ha and use of fertilizers in a commune (average weighted by the area of each commune within a buffer)		
Income per capita (Income)	Commune income per capita (average weighted by the area of each commune within a buffer) [PLN·10 ³]		
Population density (Pop. Dens.)	Population density in a commune (average weighted by the area of each commune within a buffer) [1000 people·km ⁻²]		
Citizens>65	Share of citizens older than 65 years in the total population of a given commune (average weighted by the area of each commune within a buffer) [%]	Local Data Bank database, Statistics Poland	
Proportion of women (Prop. Women)	Proportion of women; number of women per 100 men in a commune (average weighted by the area of each commune within a buffer)		
Unemployment rate (Unemploym.)	Share of registered unemployed in the total working-age population of a given commune (average weighted by the area of each commune within a buffer) [%]		
Higher education rate (Higher Ed.)	Share of higher educated citizens in the total number of economically active population (i.e. aged 15 and more) of a given commune (average weighted by the area of each commune within a buffer) [%]		
Mean temperature (Mean Temp.)	Annual mean temperature within a buffer [°C]	WorldClim Global Climate Data Version 2.0 (Fick and Hijmans, 2017)	CLIMATE
Precipitation	Annual precipitation within a buffer [mm]		
Solar radiation (Solar Rad.)	Average annual potential incoming solar radiation within a buffer [MJ·m ⁻² ·day ⁻¹]		
Growing season length (Growing Seas.)	Growing season length within a buffer, calculated as the number of days between the first 5-day period with average temperatures above 5°C to the first 5-day period with temperatures below 5°C [days]	Copernicus Land Monitoring Service	
Soil pH	Topsoil pH measured in water (mean value within a buffer)	Maps of Soil Chemical properties at European scale based on LUCAS 2009/2012 topsoil data (Ballabio et al., 2019)	SOIL
Soil CaCO ₃ content (Soil CaCO ₃)	Topsoil calcium carbonates content (mean value within a buffer) [mg·kg ⁻¹]		
Soil P content (Soil P)	Topsoil phosphorus content (mean value within a buffer) [mg·kg ⁻¹]		
Soil K content (Soil K)	Topsoil potassium content (mean value within a buffer) [mg·kg ⁻¹]		

Soil N content (Soil N)	Topsoil nitrogen content (mean value within a buffer) [g·kg ⁻¹]	
Landscape configuration (Landsc. Config.)	Density of land parcel borders within a buffer [km/km ²]	Polish Head Office of Geodesy and Cartography
Landscape composition (Landsc. Comp.)	Modified Simpson's diversity index of land cover types within a buffer based on CLC data. The higher the index, the higher the number of different land cover types and the proportional distribution of their area becomes more equitable	
Artificial surfaces (Artificial)	Coverage of artificial surfaces (CLC class 1), including: urban fabric; industrial, commercial and transport units; mine, dump and construction sites; artificial, non-agricultural vegetated areas [%]	
Arable land (Arable)	Coverage of arable land and permanent crops (CLC classes 21 and 22), including: non-irrigated arable land and fruit trees and berry plantations [%]	
Pasture	Coverage of pastures (CLC class 231) [%]	
Heterogeneous agricultural areas (Het. Agri.)	Coverage of heterogeneous agricultural areas (CLC class 24), including complex cultivation patterns and land principally occupied by agriculture, with significant areas of natural vegetation [%]	CORINE Land Cover (CLC) database
Forest	Coverage of forests (CLC class 31), including: broad-leaved forest, coniferous forest and mixed forest [%]	
Semi-natural habitats (Semi-Nat.)	Coverage of semi-natural habitats (CLC classes 32), including: natural grasslands and transitional woodland-shrub [%]	
Unvegetated areas* (Unveg.)	Coverage of open spaces with little or no vegetation (CLC class 33), including beaches, dunes, sands and sparsely vegetated areas [%]	
Wetlands and water bodies (Water)	Coverage of wetlands and water bodies (CLC classes 41 and 5), including: inland marshes, peat bogs, water courses, water bodies, coastal lagoons, sea [%]	
River density (River Dens.)	Density of watercourses within a buffer the vector watercourse layer [km/km ²]	General Geographic Objects Database (Main Centre of Geodetic and Cartographic Documentation in Poland)
Road density (Road Dens.)	Road density within a buffer based on the road vector layer [km/km ²]	Open Street Map
Urban areas (Urban)	Coverage of built-up areas based on the High Resolution Imperviousness raster layers of 10 m pixel resolution [%]	
Grassland	Coverage of grasslands based on the High Resolution Grasslands raster layers of 10 m pixel resolution [%]	
Tree cover density* (Trees)	Tree cover density based on the High Resolution Tree Cover Density raster layers of 10 m pixel resolution [%]	Copernicus Land Monitoring Service
Water and wetness (Wetness)	Coverage of water and wet surfaces based on the High Resolution Water and Wetness of 10 m pixel resolution [%]	
Wasteland	Share of wastelands in a commune (average weighted by the area of each commune within a buffer) [%]	Local Data Bank database, Statistics Poland

LANDSCAPE

Normalized Difference Vegetation Index (NDVI)	Mean Normalized Difference Vegetation Index within a buffer, calculated based on the Landsat 8 images using Google Earth Engine (30 m pixel resolution, max pixel value from the growing season in a given year). The higher the index, the more abundant and vigorous the vegetation.	Landsat 8 satellite imagery (United States of Geological Survey archive)	
<i>Distance-based variables</i>			
River distance (River Dist.)	Distance to the nearest watercourse based on the vector watercourse layer [km]	General Geographic Objects Database (Main Centre of Geodetic and Cartographic Documentation in Poland)	LANDSCAPE
Urban distance (Urban Dist.)	Distance to the nearest built-up areas, based on the building vector layer [km]	Open Street Map	
<i>Transect scale variables (measured along or within 30 m of the studied transects)</i>			
Road width	Road width measured using satellite images [m]	Google Earth	ROAD
Road curvature (Road Curv.)	Road curvature calculated as the ratio of the length of a transect and the straight-line distance between the end points of a transect, based on the road vector layer		
Road direction (Road Dir.)	Road direction determined as the absolute deviation from NS direction in degrees, based on the road vector layer	Open Street Map	
Road class	Road class: 1=primary, 2=secondary, 3=tertiary, 4=unclassified, 5=track; based on the road vector layer		
Road Surface*	Road surface: asphalt/other (cobblestone/dirt/gravel/setts/slabs)	Google Street View images	
Transect sections (Trans. Sections)	Number of sections established along a transect line	-	TRANSECT
Mown road verge (Mown Verge)	Proportion of roadside (i.e. area within 30 m a transect line) considered mown		
Year of GSV picture (GSV Year)	Year in which a GSV picture was taken	Google Street View images	
Month of GSV Picture (GSV Month)	Month in which a GSV picture was taken		
Box elder abundance (Box Elder)	Proportion of transect sections occupied by box elder <i>Acer negundo</i>		ALIEN SPECIES
Black locust abundance (Black Locust)	Proportion of transect sections occupied by black locust <i>Robinia pseudacacia</i>		
Canadian horseweed abundance (Can. Horseweed)	Proportion of transect sections occupied by Canadian horseweed <i>Conyza canadensis</i>	Google Street View images	
Hogweed abundance* (Hogweed)	Proportion of transect sections occupied by giant hogweed (<i>Heracleum mantegazzianum</i>) or Sosnowsky's hogweed (<i>H. Sosnowskyi</i>)		
Knotweed abundance* (Knotweed)	Proportion of transect sections occupied by Japanese knotweed (<i>Reynoutria japonica</i>) or giant knotweed (<i>R. sachalinensis</i>)		

Garden lupin* abundance (Lupin)	Proportion of transect sections occupied by garden lupin <i>Lupinus polyphyllus</i>
Staghorn sumac abundance* (Sumac)	Proportion of transect sections occupied by <i>Rhus typhina</i>
Black cherry abundance* (Black Cherry)	Proportion of transect sections occupied by black cherry <i>Prunus serotina</i>
Northern red oak abundance* (Red Oak)	Proportion of transect sections occupied by northern red oak <i>Quercus rubra</i>
Jerusalem artichoke abundance* (Jerus, Artichoke)	Proportion of transect sections occupied by Jerusalem artichoke <i>Helianthus tuberosus</i>
Japanese rose abundance* (Japan. Rose)	Proportion of transect sections occupied by Japanese rose <i>Rosa rugosa</i>
Wild cucumber abundance* (Wild Cucumber)	Proportion of transect sections occupied by wild cucumber <i>Echinocystis lobata</i>
Common milkweed abundance* (Milkweed)	Proportion of transect sections occupied by common milkweed <i>Asclepias syriaca</i>
Diversity of alien plants (Alien Plants)	Number of alien plant species (other than goldenrods) observed along a transect, ranging between 0 and 5; there were 13 species (or species groups) in total: box elder, black locust, Canadian horseweed, hogweeds (giant hogweed and Sosnowsky's hogweed), knotweeds (Japanese knotweed and giant knotweed), garden lupin, staghorn sumac, black cherry, northern red oak, Jerusalem artichoke, Japanese rose, wild cucumber, common milkweed.

Table S2. Summary of generalized additive mixed model (GAMM) explaining the importance of variables for predicting goldenrod occurrence in relation to spatial scale, variable category and their interaction. Parameter estimates, standard error (SE) and test statistics are given for linear fit and the estimated number of degrees of freedom (edf) and test statistics are given for spline fit. Significance levels are specified with asterisks.

	Estimate	SE	<i>t</i> value
Linear fit			
(Intercept)	2.83	0.16	17.73 ***
scale:500 m	-0.01	0.12	-0.10
scale:1000 m	-0.17	0.12	-1.45
scale:2000 m	-0.20	0.12	-1.70
scale:5000 m	-0.23	0.12	-1.93
category:alien species	-1.54	0.28	-5.56 ***
category:landscape	-0.84	0.19	-4.39 ***
category:climate	-0.27	0.28	-0.97
category:road	-0.80	0.28	-2.91 **
category:soil	-0.28	0.26	-1.09
category:transect	-1.09	0.28	-3.94 ***
scale:500 m × category:alien species	-0.03	0.21	-0.16
scale:1000 m × category:alien species	0.21	0.21	1.03
scale:2000 m × category:alien species	0.21	0.21	1.01
scale:5000 m × category:alien species	0.17	0.21	0.82
scale:500 m × category:landscape	0.08	0.14	0.59
scale:1000 m × category:landscape	0.48	0.14	3.34 **
scale:2000 m × category:landscape	0.61	0.14	4.28 ***
scale:5000 m × category:landscape	0.75	0.14	5.21 ***
scale:500 m × category:climate	0.01	0.21	0.07
scale:1000 m × category:climate	0.09	0.21	0.42
scale:2000 m × category:climate	0.07	0.21	0.35
scale:5000 m × category:climate	0.08	0.21	0.39
scale:500 m × category:road	0.00	0.21	-0.01
scale:1000 m × category:road	0.26	0.21	1.27
scale:2000 m × category:road	0.24	0.21	1.16
scale:5000 m × category:road	0.22	0.21	1.06
scale:500 m × category:soil	0.01	0.19	0.07
scale:1000 m × category:soil	0.20	0.19	1.03
scale:2000 m × category:soil	0.21	0.19	1.10
scale:5000 m × category:soil	0.21	0.19	1.12
scale:500 m × category:transect	0.01	0.21	0.05
scale:1000 m × category:transect	0.39	0.21	1.91
scale:2000 m × category:transect	0.37	0.21	1.79
scale:5000 m × category:transect	0.36	0.21	1.73
	edf	<i>F</i> value	
Spline fit			
s(variableID)	37.12	13.75 ***	
Dev.expl	85.3%		
R^2_{adj}	0.74		

Statistical significance: *** < 0.001; ** < 0.01

References:

- Ballabio, C., E. Lugato, O. Fernández-Ugalde, A. Orgiazzi, A. Jones, P. Borrelli, L. Montanarella, and P. Panagos. 2019. Mapping LUCAS topsoil chemical properties at European scale using Gaussian process regression. *Geoderma* 355: 113912.
- Fick, S.E. and R.J. Hijmans, 2017. WorldClim 2: new 1km spatial resolution climate surfaces for global land areas. *International Journal of Climatology* 37.12: 4302-4315.
- Venter, O., E. W. Sanderson, A. Magrath, J. R. Allan, J. Beher, K. R. Jones, H. P. Possingham, W. F. Laurance, P. Wood, B. M. Fekete, M. A. Levy, and J. E. Watson. 2018. Last of the Wild Project, Version 3 (LWP-3): 2009 Human Footprint, 2018 Release. Palisades, New York: NASA Socioeconomic Data and Applications Center (SEDAC). Accessed 05.01.2022.
- Venter, O., E. W. Sanderson, A. Magrath, J. R. Allan, J. Beher, K. R. Jones, H. P. Possingham, W. F. Laurance, P. Wood, B. M. Fekete, M. A. Levy, and J. E. Watson. 2016. Sixteen Years of Change in the Global Terrestrial Human Footprint and Implications for Biodiversity Conservation. *Nature Communications* 7:12558.

Appendix S2: Figures

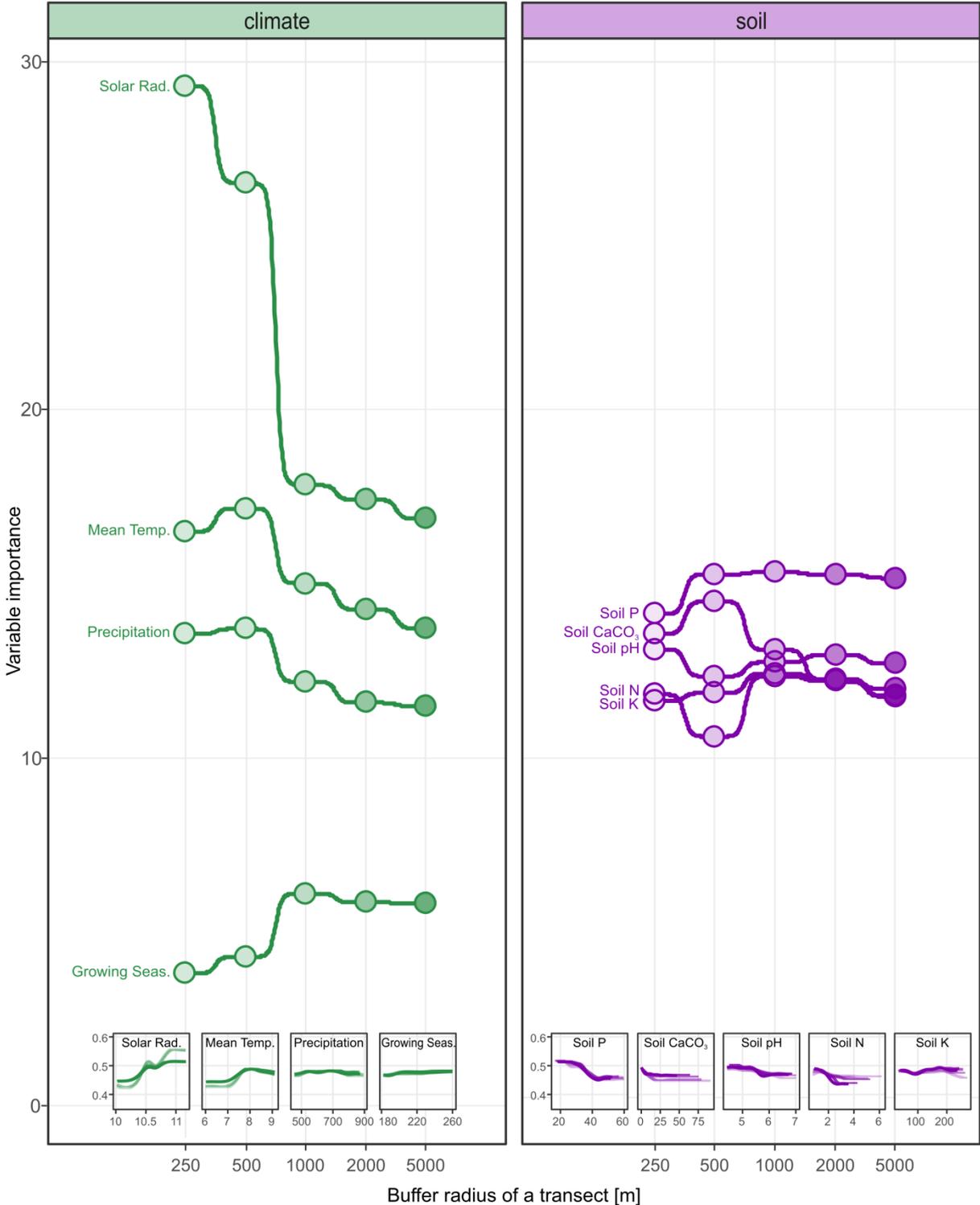


Figure S1. Changes in the importance of explanatory variables related to climatic conditions (left panel) and soil properties (right panel) for predicting goldenrod occurrence in Polish farmland in five spatial scales based on the RF models. Partial dependence plots showing the mean marginal effect of these variables on the probability of goldenrod occurrence across five spatial scales are given as small inner panels. Each inner plot represents the effect of each variable while holding the other variables constant and different spatial scales are shown with a color gradient from pale (250 m) to dark (5000 m).

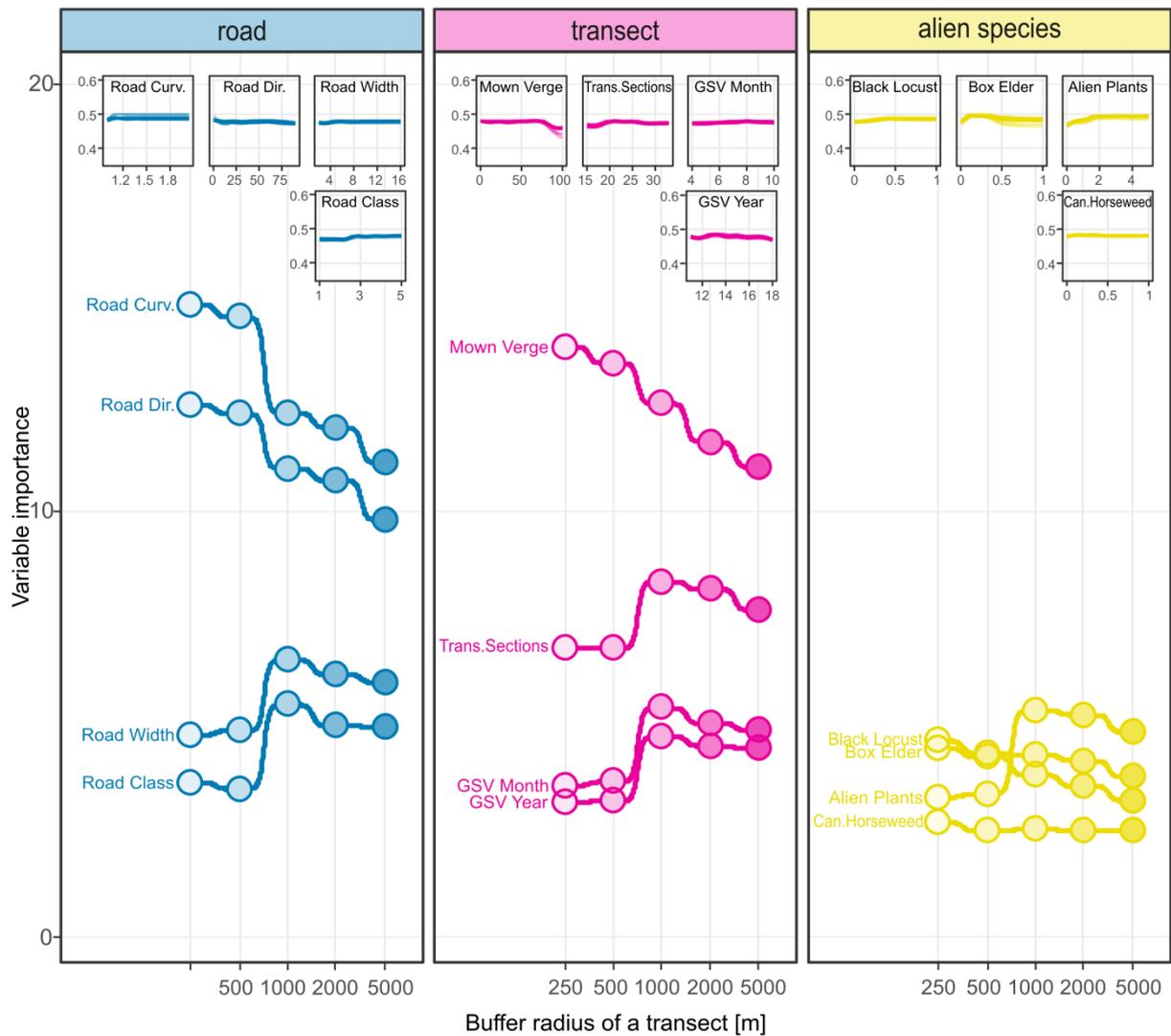


Figure S2. Changes in the importance of explanatory variables related to road characteristics (left panel), transect sampling parameters (inner panel) and biotic interactions among alien plants (right panel) for predicting goldenrod occurrence in Polish farmland in five spatial scales based on the RF models. Partial dependence plots showing the mean marginal effect of these variables on the probability of goldenrod occurrence across five spatial scales are given as small inner panels. Each inner plot represents the effect of each variable while holding the other variables constant and different spatial scales are shown with a color gradient from pale (250 m) to dark (5000 m).

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- zdalnej analizie zdjęć Google Street View;
- zbudowaniu baz danych;
- analizie statystycznej;
- interpretacji i wizualizacji wyników;
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- Contributing to conceiving the ideas
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- analizie statystycznej;
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- interpretacji i wizualizacji wyników;
- przygotowaniu tekstu maszynopisu.

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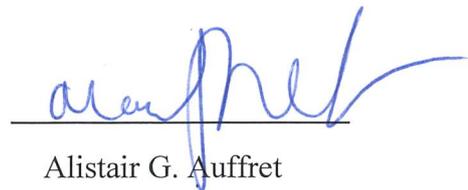
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