Public contributions to early detection of new invasive pests

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Abstract
Early detection of new invasive pest incursions enables faster management responses and more successful outcomes. Formal surveillance programs—such as agency-led pest detection surveys—are thus key components of domestic biosecurity programs for managing invasive species. Independent sources of pest detection, such as members of the public and farm operators, also contribute to early detection efforts, but their roles are less understood. To assess the relative contributions of different detection sources, we compiled a novel dataset comprising reported detections of new plant pests in the US from 2010 through 2018 and analyze when, where, how, and by whom pests were first detected. While accounting for uncertainties arising from data limitations, we find that agency-led activities detected 32–56% of new pests, independent sources detected 27–60%, and research/extension detected 8–17%. We highlight the value of independent sources in detecting high impact pests, diverse pest types, and narrowly distributed pests—with contributions comparable with agency-led surveys. However, in the US, independent sources detect a smaller proportion of new pests than in New Zealand. We suggest opportunities to further leverage independent pest detection sources, including by citizen science, landscaping contractors, and members of the public.

KEYWORDS
active surveillance, biological invasions, biosecurity, early detection, general surveillance, invasive species management, passive surveillance, pest surveys, public detection

1 INTRODUCTION

Invasive pests cause significant damages to economic and ecological systems, including to agriculture, biodiversity, and ecosystem service provisioning. Estimates of total annual damage and control costs for invasive species in the United States exceed $160 billion (2019 USD) (Pimentel, Zuniga, & Morrison, 2005). With increasing trade, changing climate, expanding source distributions of non-native pests, and increases in difficult-to-manage invasion pathways (such as ecommerce), rates of invasion and costs likely will continue to expand (Epanchin-Niell, McAusland, Liebhold, Mwebaze, & Springborn, 2021; Essl et al., 2015).

Efforts to avoid or reduce impacts from invasive pests include offshore and border prevention activities, as well as post-introduction efforts aimed at eradicating or controlling invasions. For invasive species that become
established in a new region, detection is critical to initiating eradication and control responses. Earlier detection can lead to better outcomes and lower long-term costs, as smaller invasions generally are easier and less costly to control and adaptation measures can be initiated sooner (Epanchin-Niell, Brockerhoff, Kean, & Turner, 2014; Liebhold et al., 2016; Lodge et al., 2006; Pyšek & Richardson, 2010).

Early detection of pests can arise from multiple sources (Hester & Cacho, 2017). Active surveillance by government agencies for early detection of new pest incursions, which we refer to as agency detections, involves programs at various government levels. Agency detections often include high-risk site surveillance and commodity- and pest-specific surveys (e.g., Acosta et al., 2020; Arndt, Robinson, Baumgartner, & Burgman, 2020; USDA, 2019). A second broad source of detections is local extension specialists or researchers, who may encounter pests during their routine activities or more systematic survey efforts (e.g., Hester & Cacho, 2017); we term these research/extension detections. A third broad source consists of members of the public and farm and nursery operators, which we refer to as independent sources. These detections, particularly those by members of the public, are often viewed by agencies as fortuitous, because they contribute to achieving biosecurity objectives but are not the direct outcome of planned investments in surveys (Hester & Cacho, 2017).

Our classification of detection sources is similar to previous pest detection categorizations, which generally are described as spanning from active to passive (e.g., Hester & Cacho, 2017; Pocock, Roy, Fox, Ellis, & Botham, 2016; White, Marzano, Leahy, & Jones, 2019). However, we employ the term independent instead of passive, in recognition that detections by operators or members of the public may be either passive (i.e., unintentional) or active (e.g., resulting from routine private activities to monitor landscaping or crop health), while nonetheless occurring independently from agency survey efforts.

Independent sources contribute to detecting new incursions and to monitoring spread of established invasions. For example, the Asian longhorned beetle (*Anoplophora glabripennis*), a major threat to hardwood trees in the US, was first detected and reported in 1996 by a Brooklyn resident who observed damage to street trees (Haack, Law, Mastro, Ossenburgen, & Raimo, 1997). Subsequent incursions of this species were also first reported by the public, often in private residential gardens (EPPO, 2011; Haack, Hérard, Sun, & Turgeon, 2010; Straw, Fielding, Tilbury, Williams, & Inward, 2015). Other examples in the US include the Asian shore crab (*Hemigrapsus sanguineus*) detected by a college student on a field trip and more recently the Asian giant hornet (*Vespa mandarinia*) discovered by a citizen on their front porch (Baker, 2020; McDermott, 2004). Independent sources have been prevalent and critical to early invasive species detection and management in other countries as well, see examples from New Zealand and Australia in Bleach (2019) and Hester and Cacho (2017).

The data contributions of the public are an important ongoing area of research across a range of disciplines (Lukyanenko et al., 2020). Specifically, independent pest detection sources have received increasing attention in recent years from agencies and researchers (Bleach, 2018; Hester & Cacho, 2017). Most studies addressing the role of independent detections focus on contributions to monitoring pest spread or control efforts, rather than to early detection of new incursions (e.g., Cacho & Hester, 2011; Cacho, Spring, Hester, & Mac Nally, 2010; Keith & Spring, 2013; Poland & Rassati, 2019). For example, $1 million invested in public engagement activities as part of a fire ant (*Solenopsis invicta*) surveillance program in Queensland, Australia, was estimated to have achieved a level of detection that would have required $60 million in active (i.e., agency) surveillance (Cacho, Reeve, Trammel, & Hester, 2012; Hester & Cacho, 2017). The role of citizen science in augmenting biological monitoring efforts also has been extensively explored (Blackburn et al., 2020; Conrad & Hilchey, 2011; Crall et al., 2010; Dickinson, Zuckerberg, & Bonter, 2010; Johnson et al., 2014; Larson et al., 2020; McKinley et al., 2017). Empirical studies show that volunteer-based citizen science programs can significantly improve understanding of invasive species distributions (e.g., Crall et al., 2015; Delaney, Sperling, Adams, & Leung, 2008; Gallo & Waitt, 2011; Maistrello, Dioli, Bariselli, Mazzoli, & Giacalone-Forini, 2016; Meentemeyer, Dorning, Vogler, Schmidt, & Garbelotto, 2015; Pocock et al., 2016; Rothenberger et al., 2020; Scyphers et al., 2015). In addition, a recent analysis shows that species characteristics are significant factors in reporting probability, demonstrating that public contributions are not equally distributed across species types (Caley, Welvaert, & Barry, 2020). Many of the lessons drawn from these studies are broadly applicable to detection of invasive species by the public.

Recent research addressing the design and efficacy of surveillance programs for early detection of new pest incursions has largely addressed the questions of how much—and where—survey resources should be deployed to minimize long-term costs and damages (e.g., Epanchin-Niell, 2017; Epanchin-Niell et al., 2014; Epanchin-Niell, Haight, Berec, Kean, & Liebhold, 2012; Hauser & McCarthy, 2009; Holden, Nyrop, & Ellner, 2016; Horie, Haight, Homans, & Venette, 2013; Kaiser & Burnett, 2010; Moore & McCarthy, 2016; Yemshanov et al., 2015). While these studies have focused almost entirely on optimizing
targeted agency surveillance (e.g., trapping), sensitivity analyses in Epanchin-Niell et al. (2014) demonstrate that the background rate of invasion detection—in the absence of active surveillance—is an important factor in determining optimal surveillance investment. Specifically, in contexts where pests are unlikely to be detected by other means, the benefits of agency surveillance are greater, all else equal. Therefore, a better understanding of background detection rates can lead to more effective active surveillance program design.

Despite increasing recognition of independent sources for early detection, quantitative understanding of the public’s contribution to detection outcomes, as well as factors affecting detection likelihood, is limited. In New Zealand, Bleach (2018) finds that 63% of investigated detections of new pest incursions over one year were reported by the general public and an additional 10% had been reported by industry. This highlights the important role of independent detections in New Zealand, where residents have a legal mandate to report any pests they detect (Biosecurity Act 1993, Section 44). In Australia, Carnegie and Nahrung (2019) find that 36% of the 34 total forest pest detections over 20 years were by independent sources. The only similar study in the US, Looney, Murray, LaGasa, Hellman, and Passoa (2016), finds that 36% of new pest detections in Washington State over 24 years were by independent sources.

While studies have hypothesized factors likely to contribute to enhanced detection by independent sources, such as detections occurring on private lands or detections of highly conspicuous pests (Brown, van den Bosch, Parnell, & Denman, 2017; Cacho et al., 2010; Hester & Cacho, 2017; Looney et al., 2016; Pocock et al., 2016; Poland & Rassati, 2017), these have been largely untested. Understanding of the types of pests detected by various sources, where detections occur, and how quickly different sources detect pests is an informational gap that hinders effective accounting of independent sources of detection in biosecurity planning.

In this study, we develop and analyze a new dataset to explore detection sources responsible for intercepting and reporting new invasive pests in the United States. We classify detection sources based on the entities that detected and reported each new pest. For each pest detection, we also characterized the setting, geographic location, type of pest, anticipated impact of the pest, and estimated distribution of the pest within the United States when detected. We use these data to evaluate the relative contribution of each source in detecting new pests and to explore factors and circumstances influencing detection frequency across sources. In addition, we consider the potential that new pests could be detected even earlier through close monitoring of citizen science platforms such as iNaturalist. For this we compare the date of detection in our data with the first report date for each pest on iNaturalist to determine if any were reported earlier via that platform.

We provide several contributions relative to the current literature. We present the first national-level analysis of sources of new pest detections in the United States, and compare our findings with those from a national-scale study in New Zealand (Bleach, 2018) and a state-level analysis from Washington in the United States (Looney et al., 2016). We also categorize and evaluate contextual variables about detections that have been suggested as relevant to understanding pest detection activities but have not previously been tested. Specifically, we meet calls for data collection on pest characteristics (Hester & Cacho, 2017; Looney et al., 2016) and detection contexts (Carnegie & Nahrung, 2019) to scrutinize assumptions typically made about the attributes of different sources of detection (Froud, Oliver, Bingham, Flynn, & Rowswell, 2008). We also outline opportunities to better leverage independent pest detection sources and data documentation and analysis needs to further enhance understanding of pest detection sources.

## METHODS

### 2.1 Data

Our analyses focus on first detections of pests that are new to the United States or to broad regions of the country and pose potential regulatory concern (e.g., because of ecological or economic consequences). Our data consist of detections of new, non-native pests in the United States over the nine-year period from January 2010 through December 2018 that triggered the preparation of a New Pest Advisory Group (NPAG) report by the US Department of Agriculture’s Animal and Plant Health Inspection Service (USDA-APHIS, 2021). Detections of several species with frequent introduction and routine eradication efforts, such as the Asian gypsy moth (Lymantria dispar asiatica) and Mediterranean fruit fly (Ceratitis capitata) do not trigger new NPAG reports and are therefore excluded. We also exclude species that are not yet in the United States, were detected only during international port inspections, or have only reassessments rather than completed NPAG reports.

We collected data for 169 pest detections by reviewing and extracting relevant information from their respective NPAG reports (USDA-APHIS, personal communication, April 3, 2019). We code the following categorical variables for each pest based on information...
in the report: initial detection source (Table 1); the anticipated economic sectors affected by the pest (horticulture, forest, agriculture); expected economic and environmental impacts from pest establishment (high or limited economic impact, environmental impact reported or not); regulatory classification (actionable/reportable, nonactionable/nonreportable); the distribution of the pest at the time of detection (occurrences in a single county, across multiple clustered counties, or across widespread counties); pest type; setting (e.g., nursery, farm, private residence). The final data set and details on how these variables were coded are provided in the Supporting Information (Tables S1–S6).

### Table 1  Pest detection source categories used in analyses

| Broad detection source categories | Intermediate detection source categories | Narrow detection source categories | Definition/description | Examples |
|----------------------------------|----------------------------------------|-----------------------------------|------------------------|----------|
| Agency: Agents and activities whose primary role is to detect and report non-native pests, such as pest detection surveys, inspections, and trapping activities | General agency monitoring | General agency monitoring | Pest detections by nontarget surveys and inspections conducted by federal and state agents | Routine monitoring and non-species-specific surveys by state and federal agencies (e.g., USDA, California Dept. of Food & Agriculture) |
| | Industry inspections | Industry inspections | Pest detections by state and federal agents through routine or targeted inspections of industry crops and plants | Plant inspectors, crop surveys, nursery and farm inspections |
| Commodity inspections | Commodity inspections | Pest detections during inspections of commodities traveling across state borders | Intercepted domestic mail, parcels, shipments |
| Trapping surveys | Trapping surveys | Pest detections during trapping surveys for non-native pests | Pest traps, target species trapping surveys |
| Research/extension: Extension agents and researchers, including individuals studying pests or agriculture | Research/extension | Researchers | Pest detections as a part of research or extension efforts by researchers or state extension officials | University researchers University extension specialists |
| Independent: Individuals who do not have a formal obligation to search for and report pests, such as homeowners or farm operators | Operators | Operators | Pest detections by farm and nursery operators managing plants in their fields and greenhouses | Nursery operators, farmers |
| | General public | Members of the public Citizen science Contractors | Pest detections by individuals who are not trained in or engaged professionally in detecting and reporting pests | Homeowners, gardeners BioBlitz, iNaturalist reports Pruning, tree-trimming services, private testing services |

#### 2.1.1  Detection source identification

We define the initial detection of a pest as the initial detection event that led to the pest being reported to the NPAG. We classified detections according to 10 narrowly delineated sources (“narrow detection source categories”), then aggregated these into intermediate and broad groupings for analysis (Table 1).

NPAG reports did not always describe a detection source, and some were ambiguous as to whether the documented source was for the initial detection or for a detection associated with subsequent confirmation or identification activities. We consulted archived NPAG documents at APHIS offices to further resolve sources.
and ambiguity. We were able to confirm initial detection sources for 62% (n = 105) of the 169 pests detected in our focal time period (“confirmed” hereafter). For 31% of observations, a detection source was identified but uncertainty remained as to its primacy (“unconfirmed” hereafter). We exclude from our analyses observations with entirely unknown detection source pathways (n = 12; 7%).

2.2 Analyses and hypotheses

Our analyses include statistical assessment of eight hypotheses (Table 2) regarding differences among detection sources, as well as a discussion of summary statistics. To transparently represent the uncertainty in the primacy of detection sources in our sample, we present two sets of results for each analysis, one using all pests with detection sources, both confirmed and unconfirmed initial detections (n = 157) and one using only data associated with confirmed initial detections (n = 105). All analyses were conducted in R (R Core Team, 2018).

First, we examine the distribution of initial pest detections across sources (H1); we test differences in the proportion of detections by each broad detection source using a chi-squared goodness of fit test and associated Bonferroni corrected pairwise tests. We compare how sources of detection in our study compare with those in previous empirical studies analyzing initial pest detections in Washington State (US) and New Zealand (H2; Looney et al., 2016; Bleach, 2018; Tables S7 and S8). We hypothesize that the proportional contributions of each broad detection source for pests in our study are more similar to those observed in the US study than those in the New Zealand study (H2). We test differences in the proportions of detections by each broad detection source in our data compared with the detection sources in Looney et al. (2016) and Bleach (2018) with two-tailed, two-proportion z tests.

| Hypothesis | Rationale |
|------------|-----------|
| H1. Relative to each of the other broad detection sources, more total and confirmed detections are made by agency sources. (S_{all}) | Agency sources are funded and targeted to detect pests and thus may be the most effective detection sources (Froud et al., 2008; Keith & Spring, 2013). But, nonagency sources contribute substantially to detections (Carnegie & Nahrung, 2019; Looney et al., 2016). |
| H2. Relative to other pest detection studies, the proportional contributions of broad detection sources in our data are more similar in the United States than in New Zealand. (S: the general public accounts for a lower proportion of detections in the United States relative to New Zealand.) | Bioscience policies differ across countries. For example, New Zealanders have a legal obligation to report organisms “not normally seen or otherwise detected” (Biosecurity Act 1993, Section 44). |
| H3. Relative to other broad detection sources, a higher proportion of agency detections are of high-impact pests (i.e., pests with anticipated environmental or economic impact). (NS) | Agency activities often target pests of economic or environmental concern. |
| H4. Relative to other broad detection sources, a higher proportion of agency detections will be of pests listed as reportable/actionable. (NS) | Agency surveillance generally focuses on economically or environmentally important hosts and therefore may detect a greater proportion of pests deemed reportable/actionable. |
| H5. Relative to other broad detection sources, a higher proportion of agency detections will be of pests with limited distributions at the time of detection. (NS) | Agency activities often target areas where pests have a higher expected probability of introduction (e.g., Epanchin-Niell et al., 2014; Froud et al., 2008; Poland & Rassati, 2019). |
| H6. Relative to other broad detection sources, a higher proportion of agency detections will be of high-value detections (i.e., detections of high-impact pests that are not yet widespread at detection). (NS) | Agency activities often target areas where pests have a higher expected probability of introduction (e.g., Epanchin-Niell et al., 2014; Froud et al., 2008; Poland & Rassati, 2019) and pests of high economic or environmental concern. |
| H7. Relative to other intermediate detection sources, a higher proportion of trapping-based detections will be of insects. (S_{all}) | Detection sources other than trapping detect a greater diversity of pest types, as traps generally are designed to target insects. |
| H8. Relative to other broad detection sources, a higher proportion of independent detections will occur in private settings, such as residential areas, farms, and nurseries. (S) | Independent detectors have greater access to private settings than other types of detectors (Cacho et al., 2010). |

*Study findings in parentheses. S: hypothesis supported with both all and confirmed detections; S_{all}: hypothesis supported based on all detections only; NS: hypothesis not supported by either data subset.
Next, we examine how detections of the following pest categories vary across sources: high-impact pests (H3), pests classified as actionable/reportable (H4), pests with limited distribution when detected (H5), and high-impact pests before they become widespread (H6). In addition, we look at the types of taxa detected across sources (H7) and the settings in which pest detections occurred across sources (H8). We assess H3-H4 by testing differences in proportions of each pest “type” (i.e., in terms of impact, actionable/reportable status, distribution, taxa, and setting) across sources using two-tailed Fisher’s exact tests and associated Bonferroni adjusted pairwise tests.

Finally, to assess the role that iNaturalist, a popular citizen science platform, could play in augmenting existing surveillance systems, we investigate whether any pests in our dataset that were detected January 1, 2015, or later (n = 67) were reported on iNaturalist before the detection date in the NPAG report.

3 | RESULTS

3.1 | Detection source contributions to pest detection (H1)

Across the 157 total detections in our dataset (confirmed and unconfirmed), agency sources account for 56%, independent sources for 27%, and research/extension sources for 17% (Figure 1; Table 3). A high number of agency detections are driven by general agency monitoring (27), industry inspections (24), and trapping surveys (24). All detections from commodity inspections, operators, and the general public were confirmed, but many detections from general agency monitoring, industry inspections, trapping surveys, and researcher/extension activities were unconfirmed (Figure 1a). Examining narrow source categories, members of the public (18) and operators (17) account for a substantial number of detections within the independent source category, while private contractors (6) and citizen science (1) detected fewer pests (Figure 1b). Focusing only on confirmed initial detections, agency sources account for 48%, research/extension sources account for 12%, and independent sources account for 40% (Figure 1; Table 3).

Using pairwise chi-squared comparisons, we find that the agency source category detected a significantly higher number of pests than either the research/extension (p < .01) or independent (p < .01) source category when analyzing all detections (Table S9). However, when running pairwise chi-squared tests for confirmed detections only, the agency source had a significantly higher number of detections than the research/extension source (p < .01), but not the independent detection source (p = 1.0) (Table S9). These tests support our hypothesis H1—that agency sources detect more pests than either extension/research or independent sources—for all detections, but not for the confirmed subset.

Independent detection sources may be underrepresented in our data because unconfirmed initial detections may include reports based on follow-up activities to an unidentified independent detection. We explore the implications of this in Table 3. The third row of Table 3 quantifies the maximum possible contribution of independent sources to pest detection, as well as the minimum contributions of agency sources, in our data, by presenting a scenario that attributes all unconfirmed detections to independent sources. Under this exploratory scenario, 60% and 32% of detections are attributed to independent and agency sources, respectively. These findings indicate that the actual contribution of independent sources to initial detection lies somewhere between 27% and 60% of detections, while agency sources were responsible for 32% to 56% of initial pest detections.

![Figure 1](https://example.com/figure1.png)

**Figure 1:** Number of confirmed and unconfirmed initial detections across (a) intermediate and (b) narrow detection source categories.
3.2 Comparison with pest detection sources in other contexts (H2)

We compare our national-scale US pest detection data to two similar datasets (Figure 2). We find no statistical difference between our data and Washington state-level data from Looney et al. (2016) (Figure 2a) in terms of the relative contributions of independent, agency, and research/extension sources for all detections ($p = .23, .37, .93$, respectively) and for confirmed detections ($p = .68, 1.00, .69$, respectively) (Table S10). These results support hypothesis H2 that the relative contributions of the broad detection sources US-wide are similar to those in Washington state.

When comparing our data to New Zealand data from Bleach (2018) (Figure 2b), we find statistically significant differences in the proportional contributions of the general public, agency, and research/extension detection sources, when considering all detections ($p < .01$) and confirmed detections only ($p < .01$) (Table S11). Specifically, the agency detection source accounts for a higher proportion of detections in the United States than in New Zealand, and the general public accounts for a lower proportion of detections in the United States. These results support hypothesis H2 that there are significant differences in the relative contributions of the broad detection sources in the United States and New Zealand.

3.3 Economic and environmental impact (H3)

When examining the economic sectors at risk from pests in our dataset, we find that the agricultural sector has the highest number of potential pests detected ($n = 80$), followed by the horticultural sector ($n = 62$). Twenty-five pests in our dataset affect multiple sectors. The forestry sector is affected by the least number of pests ($n = 21$).

The potential economic and environmental impacts of a new pest are major factors in determining the value of an initial detection. We found that 52% of pests are described in the NPAG reports as likely to be a major economic pest or to have environmental impact; we refer to these as high-impact pests. Another 18% are classified as having unknown potential impacts. The remaining 30% are classified as limited-impact pests (i.e., no indicated environmental impact and low anticipated economic impacts) (Figure 3a). The general public detected the highest number of high-impact pests across intermediate detection sources ($n = 17$). Contrary to our hypothesis H3, we find no differences in the proportion of high-impact pests detected by broad detection sources for all detections ($p = .43$) and for confirmed detections ($p = .69$) (Table S12).
FIGURE 3 Types of pests detected and context of detections across detection sources: (a) impact severity, (b) reported regulatory status, (c) estimated distribution of pest at detection, (d) value of detection (based on impact severity and pest distribution), (e) pest type, and (f) setting in which pest was detected. Results are shown for all detections (left column) and confirmed detections only (right column). See Tables S1–S6 for category definitions.
3.4 Agency actionability recommendations (H4)

When examining the recommended actionability status (actionable/reportable versus nonactionable/nonreportable), we find that all intermediate detection categories are detecting species of each recommendation status (Figure 3b). Contrary to our hypothesis H4, we find no difference in the proportion of pests that are actionable/reportable across broad detection sources for all detections (Fisher’s exact test, \( p = .84 \)) and for confirmed detections (Fisher’s exact test, \( p = .71 \)) (Table S13).

3.5 Pest geographic distribution (H5)

We examine the estimated geographic distribution of pests at their time of detection, dependent on their source of detection. General agency monitoring and the general public are the intermediate detection sources responsible for the highest percentages (21% each) of detected pests with limited distributions in their new range (Figure 3c). Contrary to our hypothesis H5, we find that relative to other broad detection sources, a higher proportion of detections by the independent source were of pests with a limited distribution when considering all detections (Fisher’s exact test, \( p < .01 \)) or confirmed detections (Fisher’s exact test, \( p < .01 \)) (Table S14).

3.6 Detection value (H6)

We identified 62 detections as high-value, which we define as detections of pests whose distributions are not yet widespread at the time of detection and are high-impact. We identified an additional 26 potentially high-value detections, which we define as detections of pests whose distributions were not yet widespread when detected but whose potential impacts are unknown. General agency monitoring and the general public were responsible for a high number of high-value detections, with the general public accounting for a relatively greater proportion of high-value detections among confirmed initial detections (Figure 3d). However, we found no statistical difference in the proportion of high-value detections across our broad detection sources for all (Fisher’s exact test, \( p = .79 \)) and confirmed (Fisher’s exact test, \( p = .92 \)) detections (Table S15), thereby failing to support hypothesis H6.

3.7 Pest characteristics (H7)

We find that most sources detect many different types of pests (Figure 3e). The majority of detections across nearly all sources were insects, the most commonly detected pest type in our data (\( n = 76 \)). The general public detected pests representing all types except mollusks, of which there were only two detections. Confirming hypothesis H7, insects constitute a significantly higher proportion of detections by trapping surveys than detections by any other source for all detections (Fisher’s exact test, \( p < .01 \)), and by any source except research/extension for confirmed detections (Fisher’s exact test, \( p < .01 \)) (Table S16).

3.8 Detection settings (H8)

In analyzing the settings in which pest detections by different sources occurred, several patterns are revealed. Detections at inspection sites arise largely from commodity inspections, and detections at research sites occur largely through the research/extension source. The general public is responsible for the highest number of detections in residential areas, and operators discovered the highest number of new pests in nurseries (Figure 3f). We find statistically significant differences in the proportion of detections in private settings across broad detection sources, for all detections (Fisher’s exact test, \( p < .01 \)) and for confirmed detections (Fisher’s exact test, \( p < .01 \)). Associated pairwise comparisons show that independent sources detected a significantly higher proportion of pests in private settings than agency sources, for all detections (Fisher’s exact test, \( p = 1.3e^{-02} \)) and for confirmed detections (Fisher’s exact test, \( p < .01 \)) (Table S17), confirming our hypothesis H8.

3.9 iNaturalist detections

Of the 67 species in our dataset that were reported in 2015 or later, we find one case where a pest’s presence in the United States was reported on iNaturalist prior to the detection event that led to the NPAG report. In that case, the NPAG process was triggered by the pest’s detection in a trap in a residential area about 3 months after the initial iNaturalist report. The NPAG and iNaturalist detections occurred about 20 miles apart, and the species—an insect—was found to be distributed across several clustered counties at the time of the NPAG report.

4 DISCUSSION

A primary goal of pest surveillance is to detect pests early in the invasion process when they are less widespread and less costly to control. While the importance of
various detection sources for new pest introductions has been examined in several specific contexts (Bleach, 2018; Carnegie & Nahrung, 2019; Looney et al., 2016), they have not been examined at the US scale or compared across contexts. In this section, we discuss results and lessons from the first national-level analysis of detection sources for new pest incursions in the United States.

4.1  Key findings

We find that between 32% and 56% of new pest incursions were initially detected and reported by agency sources, such as agency monitoring, surveillance trapping activities, and industry inspections. Between 27% and 60% were detected by independent sources, such as by residential landowners and farm and nursery operators. Between 8% and 17% of detections were detected initially by research or extension personnel. The wide range for each estimate is due to uncertainties in distinguishing initial detection sources from detections arising from follow-up surveillance activities.

When comparing our results with similar data for Washington State (Looney et al., 2016), we do not find statistically significant differences in the relative contributions of each broad detection source. However, we find that independent detections play a larger role in New Zealand than in our US dataset. These findings may reflect New Zealand’s significant national investment in public pest awareness and reporting, as well as its regulatory mandate for members of the public to report potential pests (Bleach, 2018; Biosecurity Act 1993, Section 44).

Even though independent source contributions to pest detection appear to be lower in the United States than in New Zealand, they are nonetheless substantial and likely provide important economic value. For example, independent sources detected at least 31% of high economic or environmental impact pests in our data. The general public’s efficacy in detecting high-impact pests may arise from individuals’ inclination to report or inquire about pests that appear to be causing harm, a hypothesis that cannot be assessed with our data.

Independent sources also detected the highest number and proportion of pests with limited distribution. Specifically, of the 62 detected pests with limited distribution, operators detected 11 (18%) and the general public detected 13 (21%). This finding was contrary to our expectation that pests might spread quite far before being noticed and reported by independent sources, as compared with agency sources, which may target areas with high anticipated introduction rates. An important caveat is that ascertaining the distribution of pests first detected by independent sources may be more difficult and uncertain relative to those detected by agency sources, particularly if general or targeted surveillance is not available to evaluate pests’ wider potential extent. Thus, the likelihood of underestimating the distribution of pests detected by independent pathways may be greater and deserves additional study.

We further explored the value provided by detections across sources. The value of early detection generally increases with smaller distributions at detection and with higher anticipated impact if left uncontrolled (Epanchin-Niell, 2017). We defined high-value detections as those of pests that NPAG reports anticipated would cause high economic or environmental impacts and that were not yet widespread at the time of detection. We find similar proportions of high-value detections within each broad detection source, although agency sources detected a higher total number. We also find no difference across broad detection sources in the proportion of detected pests recommended for actionable/reportable regulatory status by USDA-APHIS, supporting that independent sources are similarly effective at detecting actionable pests.

Independent sources also detected a similar diversity of pest types as other broad sources, and the general public detected all pest types except mollusks (for which there were just 2 observations). Independent sources played a particularly prominent role in detecting pests in private settings, such as residential areas, which may be most accessible by independent sources. Detections by operators largely occurred in farm, orchard, and nursery settings, as expected, but a high proportion of pests detected by general agency monitoring and industry inspections also occurred in nurseries.

Of the 25 confirmed detections in our data by the public, 6 were by contractors (e.g., landscapers), 1 was through citizen science, and 18 were by the general public (e.g., residential landowners). Given the small percentage of the US population that are landscapers or similar types of contractors, 6 detections via this source appears substantial. Importantly, contractors may be particularly likely to encounter pests in their work, as they are often hired to address tree or landscaping damage.

4.2  Opportunities to further leverage independent detection sources

Our study highlights the diverse sources that detect new pests and the range of contexts in which detections occur in the United States. Our findings support the importance of independent sources in the United States for detecting a diversity of high-impact pests. However, the general public appears to contribute a smaller proportion of new
pest detections in the United States than in New Zealand, suggesting there may be opportunities to increase the sensitivity of these sources and augment their contribution to reducing risk. We highlight four key opportunities to increase the contributions by independent detection sources in the US.

4.2.1 | Leverage ethical and environmental attitudes to increase awareness and motivation among the general public

Alternative motivations for public reporting of invasive species (beyond private benefits, or legal obligations) include pro-environmental and ethical attitudes, as well as interest (Pocock et al., 2016; Rotman et al., 2012; Roy et al., 2012). Motivations for reporting invasive species can depend on perceptions of invasive species and their impacts, which are complex and have not been sufficiently studied (Kapitza, Zimmermann, Martín-López, & von Wehrden, 2019; Shackleton et al., 2019). Influencing perceptions through targeted informational campaigns can increase awareness and motivation, but a solid understanding of stakeholder values regarding potential invasive species is needed to craft an effective social marketing campaign (Dayer et al., 2020). Strategic messaging about invasive species management, framed in terms of stakeholder values and identity and delivered by trusted sources, may be more effective for incentivizing reporting than generalized outreach. Similarly, some stakeholders may be better motivated by appeals to consider the potential economic ramifications of invasive pests.

4.2.2 | Enhance invasive pest reporting channels to agencies

Significant opportunity exists for expanding clear and low-burden channels for reporting detections to agencies. Such channels include hotlines (e.g., Bleach, 2018; Carnegie & Nahrung, 2019), websites like Recording Invasive Species Counts (Roy et al., 2012), and apps like the Invasive Alien Species in Europe mobile app (Tsiamis et al., 2017). Strategic public awareness campaigns that include clear reporting channels can increase the likelihood that the general public will report particular species (e.g., Cacho et al., 2012; Roy et al., 2015). Similarly, citizen science networks such as Wild Spotter (2019) and Invaders of Texas (Gallo & Waitt, 2011) both educate the public and provide reporting channels. “Gamification” of reporting channels also has been suggested to motivate reporting (August et al., 2015; Nov, Arazy, & Anderson, 2014; Roy, Pocock, et al., 2012). This model is being implemented in Australia, where the Invasive Species Council recently partnered with the observation app Questagame (Herald, 2019).

Increasing engagement for the purpose of invasive pest management could have auxiliary benefits as well - public participation in citizen science has been shown to promote knowledge diffusion, environmental policy engagement, and behavioral change (Johnson et al., 2014; Lawrence, 2009).

4.2.3 | Integrate existing citizen science observations into agency and other surveillance activities

Integrating existing online citizen science platforms, such as iNaturalist and iSpot, into agency surveillance processes and early detection survey activities by land managers and natural resource contractors could augment both early detection and distribution information (August et al., 2015; Larson et al., 2020; Pawson, Sullivan, & Grant, 2020). As use of these citizen science platforms grows, agencies have an opportunity to utilize these collaborative databases by monitoring for posts of potential new pest detections, as well as for information on spread and distribution (e.g., Pocock et al., 2016). Citizen science platforms have already contributed to specific detections of new pests in Britain (iSpot, 2009; Turner, 2009) and Alaska (iNaturalist, 2019). We found that among the pest detections since 2015 in our dataset, one of the species had been reported 3 months prior on iNaturalist than its first reported NPAG detection.

To leverage online citizen science platforms, additional investments in quality assurance may be necessary, as online identifications cannot be validated in a laboratory setting (Dickinson et al., 2010; Roy, Pocock, et al., 2012). In addition, Caley et al. (2020) find through statistical analysis of online citizen science reports in Australia that these sources are relatively sensitive to conspicuous species and insensitive to nondescript species. Therefore, investments in these channels are most likely to be cost-effective in the context of distinctive, highly visible pests.

4.2.4 | Incentivize contractors who manage landscapes to report potential invasive pests

Contractors managing landscapes and treating potential plant hosts are uniquely positioned to detect new pests. Our findings show that this group already contributes importantly to pest detection, and these occupations are
well suited for training on invasive pest and damage identification. Promoting reporting among this group, perhaps through certifications or permitting and licensing requirements, might augment detection of novel pests at low cost. The Northwest Michigan Invasive Species Network’s “Go Beyond Beauty” program is an example of certification in the context of invasive plants.

Further leveraging independent sources for detecting new pest incursions offers a means to expand detection efforts across far larger areas than can feasibly be targeted by regulatory and agency programs, and seemingly at comparatively low costs. However, this general form of surveillance is likely to contribute a higher proportion of reports that turn out to be species that are native, pose insignificant impacts, or are already known to authorities (e.g., Bleach, 2018). Reports of these insubstantial detections can pose processing and identification costs, which should be considered when designing efforts to increase independent detections.

4.3 | Research needs and opportunities to improve data quality

Additional information about the relative efficacy of different sources for detecting pests would be valuable for surveillance planning (e.g., Caley et al., 2020; Pocock et al., 2016). However, estimating the probability of detection is not possible with available data because we lack information about where and when pests were initially established and the distribution of ongoing surveillance activities (Keith & Spring, 2013). Therefore, we cannot estimate the delay until detection or the exposure across space and time of pests to different sources of detection. Importantly, the probability of a pest being detected at a location depends not only on its being present at that location, but also on a source encountering, noticing, and reporting it. Another challenge in determining relative source efficacy is that factors influencing the likelihood of detection by independent sources also may influence the likelihood of introduction (e.g., both may be higher in locations with more people and susceptible resources). Hence, locations with a greater number of detections are not necessarily areas with greater efficacy of detection, and vice versa.

Our study lacks data on false positives, which pose costs. A better understanding of the frequency of false positives and factors affecting their prevalence would facilitate evaluation of the trade-offs associated with efforts to increase independent detections and would enable more careful design of strategies to leverage independent and other detection sources (Hester & Cacho, 2017).

While our findings substantially expand understanding of various sources of new pest detection, their precision is limited by variation in the availability of information about detection contexts for pests in our dataset. Only 62% of detections could be fully characterized from available information, suggesting that significant opportunity exists to enhance detection documentation and future analyses at minimal additional cost. Existing data collection frameworks for new pest detections should be augmented to include specific identification of the initial detection source and circumstances of the detection, such as how the pest came to be noticed. This information could provide insight into a source’s motives and which types of pests are more likely to be reported by certain stakeholders (Cacho et al., 2012; Carnegie & Nahrung, 2019).

A clear record of reporting pathways (i.e., how and to what entity the initial detection source reported the observation) would enable improved understanding of the roles of various entities in detection reports and allow for more robust analysis and program design. For example, we observe a significant proportion of detections occurring through local extension agents; knowing whether these originated with members of the public could provide valuable information for outreach resource allocation. Finally, background documentation on agency surveillance activities, especially whether they were implemented in response to specific reports, would allow detections to be traced to specific sources.

5 | CONCLUSIONS

Through compilation of a novel dataset, we have completed the first nationwide assessment of sources of new pest detections in the United States and empirically evaluated the role of contextual factors and species characteristics in detection of new pest introductions. Independent sources detected a wide diversity of pest types, including high-impact pests. Our findings support that independent sources play an important role in detection and complement agency surveillance activities, particularly in private settings. Lessons from our US case study can be applied in similar contexts, and our analytic framework can be used for other regions and data sources. Holistic consideration of the diverse sources of potential pest detection will facilitate the design of cost-effective surveillance programs, enhancing opportunities for early detection and rapid response to reduce impacts from new pest introductions.

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CONFLICT OF INTEREST
The authors have no competing interests.

AUTHOR CONTRIBUTIONS
Rebecca Epanchin-Niell conceived of and led the study. All authors developed conceptual framing and data collection methods. Tyler Treakle and Epanchin-Niell designed statistical analyses. Alexandra L. Thompson conducted literature review and collected primary qualitative data from APHIS archives. Tyler Treakle led data coding, managed and analyzed data, and prepared figures. All authors discussed and interpreted results and wrote the manuscript.

DATA AVAILABILITY STATEMENT
Data used in the analyses have been included as supplementary information.

ETHICS STATEMENT
The authors are not aware of any ethical issues regarding this work.

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**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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