

International trade and the risk of biological invasions

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Abstract

International trade is widely accepted as the primary conduit for unintentional introductions of non-indigenous species. But biogeographic heterogeneity, and differences in historical trade exposure across trade partners suggests that not all imports are equally risky. We develop an analytical model linking exotic species introductions and discoveries to trade volumes, and use historical data to estimate region-specific parameters of an import-invasion-discovery process. This approach allows us to empirically disentangle the different stages of the introduction process, from exposure to successful invasion to eventual discovery. These estimates form the basis for predicting invasion risk from future trade based on the regions from which imports originate. Our results suggest that many regions that have caused extensive damage in the past are unlikely to create future problems; instead it is from burgeoning trade partners that most non-indigenous species will arrive in the future.

1 Introduction

Economies develop in accordance with the endowments of the natural environment; it is precisely differences in these endowments that generate a basis for international trade. Shocks to the natural environment, therefore, can significantly impact economic activity. The scale of pecuniary and ecological costs associated with unintentional introductions of nonindigenous species (NIS), facilitated primarily by international trade, is substantial. In 1993 the Office of Technology Assessment (OTA) estimated that the annual cost to the United States from NIS was between \$4.7 and \$6.5 billion. Pimentel et al. (2000) later revised that figure upward to \$136 billion.¹ Perhaps because of the magnitude of these damage estimates, NIS introductions have received significant recent attention. For example, 750 prominent scientists and over 100 citizen's groups signed in December 2004 the following *Call to Action on Invasive Species* addressed to the United States Congress and President Bush:

We the undersigned scientists, resource managers, agricultural officials, and other experts call upon the U.S. Congress and the President to immediately take action to

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¹The figure cited by Pimentel et al. (2000) should be viewed carefully. On one hand, it does not include the difficult-to-quantify costs of species loss arising when NIS displace native species. Williamson (1999) argues that competition from NIS is the second most important cause of species loss worldwide; the leading cause is habitat loss. On the other hand, the figure does include the costs of dealing with harmful NIS that have been present in the United States for centuries—including rats and feral pigs—and so cannot be used as a measure of the marginal cost from introductions of new NIS.

drastically slow the introduction and spread of invasive species and to counteract the severe environmental, economic, and other harm these species cause. These actions would be invaluable and long-lasting gifts to the nation.

This paper addresses both theoretically and empirically the link between international trade and unintentional species introductions, where NIS introductions are facilitated by the trade process itself. Though economic activity is a clear driver of such introductions, our economic understanding of the linkages is in its infancy. For example, folk wisdom in the scientific community holds that the rate of introductions is growing over time. Given that the volume of trade has grown at about 6% per year over the past several decades, and trade is the primary conduit for unintentional NIS introductions, at first glance this assumption seems reasonable. But upon closer inspection we will reveal that the actual relationship between trade and introduction rates is much more complex.

To begin with, the higher a region's level of cumulative trade then the greater its exposure to NIS in the past. Correspondingly, the greater a region's past exposure, the greater the number of invasions it should have experienced already. This means there will be a smaller number of *new* NIS that can pose a risk in the future. Thus, for trade between two fixed regions, we expect to see the rate of NIS introductions decreasing in cumulative trade volume, the latter of which is growing over time.

But of course, not all trade is equal. Goods imported from countries with little biogeographic similarity to the importer pose little risk of carrying NIS that will be successful invaders; this is true even if imported goods are highly contaminated. Conversely, even when the hitchhiking rate is low, if the exporting and importing countries are very similar in terms of climate and geography, then the success rate of introduced species may be high. Accordingly, each trade partner carries a unique risk of infecting the importing region; this risk depends both on geographic (e.g. climate) and economic variables (e.g. phytosanitary standards). In short, invasion risk will vary according to the region from which imported goods originate.

What does this mean for current and future introduction rates? Imports from regions with which we have an established history of trade may pose little future risk, even if those regions are biogeographically quite similar to the importing region. The same may not be true of emerging suppliers. To the extent that new trade partners host unique organisms, then trade with newly-industrializing economies may herald exposure to new pools of potential NIS invaders, and high future risk.

We build an analytical model which takes into consideration the important role played by cumulative trade volumes and biogeographic characteristics of an importer's trade partners. We use this model to characterize the link between import volumes and the introduction rate of NIS. Before taking this model to the data, however, we must also take into account the fundamental difference between NIS introductions and *discoveries* of those introductions. As Costello and Solow (2003) argue, the discovery record is a poor proxy for actual introductions because it reflects a combination of both the introduction and discovery process. While the former depends on trade patterns, the latter depends on a variety of endogenous factors, not least of which is effort allocated to detecting established NIS in the host region.

We therefore employ a model of NIS discoveries which allows for a baseline marginal arrival rate (per unit of imports) to attenuate as a function of cumulative trade, while permitting the delay

between arrival and discovery of a species to vary based on observational effort and population growth.

Parameters of the model, including the baseline arrival rate and the speed of attenuation over cumulative trade, are estimated using data on NIS discoveries and a novel data set we have collected for foreign trade volume into the San Francisco Bay area. This is a region in which more than 232 NIS have been discovered and cumulative imports to date exceed 500 million tons. Trade data include yearly import tonnage via ocean vessel through the San Francisco Bay area for years 1856 through 1994, broken down by foreign country of origin. NIS discovery data for years 1853 through 1994 are taken from Cohen and Carlton's (1995) case study of the biological invasions to the San Francisco Bay.

Since our measures of trade and NIS include region of origin, we are able to calculate region-specific estimates. Combining those estimates with others' estimates of future trade volumes allow us to make region-specific predictions of future invasions. This is an important step because as cumulative trade varies by region, so will the attenuation of the base arrival rate per unit of trade.

These estimates have clear and immediate policy relevance. For example, a better understanding of region-specific introduction rates could inform the optimal mix of tariffs and inspections. Furthermore, if the U.S. were in a position to discriminate in its trade policies based on *anticipated* invasive species damages, all other things equal, it would be advantageous to increase trade with countries having low infectedness and high cumulative trade and to decrease trade with countries with the inverse. Finally, if a country imposes a selective tariff on the premise of NIS damage, our model applied at the regional level may aid in discerning whether or not such a tariff is justified or simply disguised protectionism. Overall, making trade-offs between trade-induced welfare gains and damages from NIS, within the context of international agreements, will benefit from a sharper picture of trade-driven NIS introductions.

Although we regard this paper as making two distinct contributions—it identifies and models the relationship between different components of the trade-introductions relationship, and offers policy-relevant predictions as to which trade regions will pose the greatest future risk of introducing additional NIS into San Francisco Bay—our central objective in this paper is to develop a framework for empirically disentangling the different elements in the trade-introductions-discoveries process. Accordingly, we allocate the majority of the pages in this early draft to developing our methodology. Moreover, we admit that, at this early stage in the life of this paper, the empirical predictions remain somewhat imprecise. Having offered these caveats to the reader, we now describe the layout of the rest of the paper. Section 2 provides a brief overview of NIS as an economic problem. In section 3 we develop our theoretical model that links trade, NIS introductions, and discovery of those species, and then apply the model empirically in section 4 to a novel data series. Based on trade forecasts and our estimates of the species introduction process, we make in section 6.2 region-specific forecasts of future invasions. Section 7 concludes.

2 Species introductions: Damage and policy response

There has been substantial empirical work concerning the impacts of trade liberalization on industrial emissions associated with producing traded goods; see, for example, Grossman and Krueger (1993), Gale and Mendez (1998) and Antweiler et al. (2001). Damages arising from biological

invasions by NIS, however, are examples of externalities associated with consumption—as with the escape and establishment of exotic plants from nurseries—or movement of traded goods, as with invasions arising from discharge of contaminated ballast water; there has been considerably less economic research on these types of trade-related externalities. Exceptions include work on emissions associated with automobiles, lorries and fuel consumption, and damage from invasive species. Regarding the latter, theoretical works include Horan et al. (2002), Perrings (2002), Costello and McAusland (2003), McAusland and Costello (2004), and Olson and Roy (2003). Empirical economic research on trade and invasive species is limited to Dalmazzone (2000), discussed further below, and Fernandez (2004), who uses data on ballast emissions and biofouling to determine the magnitudes of subsidies, taxes, and liability rules ports might use to reduce marine invasions from intra-coastal shipping traffic.

Internationally, there are numerous vectors by which NIS enter a country. New species can be introduced intentionally², as is the case with many food crops and livestock. They may also be introduced unintentionally, resulting from import of goods that themselves are contaminated, such as fruit infested with medfly, or arrive in packing materials or on pallets that are contaminated. A third conduit for unintentional introductions is contaminated transport itself, such as when hulls fouled by exotic mollusks arrive in domestic ports, and/or incoming ships discharge ballast water—often infested with aquatic vertebrates, invertebrates, and algae—in coastal waters. This paper focuses on unintentional introductions of NIS, as these are more likely to be harmful than are intentionally introduced exotic species.³ Our empirical application focuses on the last of these conduits, contaminated shipping traffic.

As indicated in the discussion above, the general consensus⁴ amongst ecologists is that international trade is the primary conduit for unintentional introductions of NIS. The earliest empirical test of the trade-invasions relationship was provided by Dalmazzone (2000), who used cross-country data to assess whether economic openness links to biological invasions. Dalmazzone finds that neither tourism, trade (as a share of GDP), nor aggregate merchandise imports are statistically significant explanatory variables for biological invasions, but does find a statistically significant relationship between invasions and import duties.

Ecologists have taken a different tack. Ruiz et al. (2000) create an inventory of invasions into coastal marine communities in North America. They assume that primary introductions exhibit exponential growth over time and use data on first discoveries of NIS to estimate that the invasion-time relationship is “ $y = 7.08^{(0.017x)}$, $r^2 = 0.976$; where y is the number of new invasions and x is time in 30 [year] intervals, indicated as the first year of the 30y interval.” (Ruiz et al. p.492) They recognize, however, that the “patterns” present in their inventory reflect numerous sources of bias. For example, they acknowledge that reported invasions are not equivalent to actual invasions, and there is likely bias in reporting. They also point out that different host regions will have different abiotic resistance to invasions: “tropical species arriving in polar ecosystems may experience very

²See Thomas and Randall (2000) for an economic analysis of pre-emptive policy regarding intentional introductions.

³According to the OTA (1993) report, this is only true for a subset of phyla: “Far more unintentional introductions of insects and plant pathogens have had harmful effects than have intentional introductions. For terrestrial vertebrates, fish, and mollusks, however, intentional introductions have caused harm approximately as often as have unintentional ones, suggesting a history of poor species choices and complacency regarding their potential harm.” (OTA 1993 p.6)

⁴See, for example, OTA (1993) and Convention on Biological Diversity (2002).

poor survival compared to those arriving in temperate or tropical ecosystems.” (p. 511).

Drake and Lodge (2004) similarly focus on invasions of marine systems. Attempting to identify global hotspots of invasion, they estimate invasion rates using data on the number of ships visiting 243 ports worldwide in 2000. They first use a gravity model to estimate the number of vessel trips between each of the port pairs, then, using network flows analysis, identify the ports that contribute most to inter-region exchange of NIS. In their analysis, Drake and Lodge assume a constant per-ship-call probability of initiating invasion ($p = 4.4 \times 10^{-6}$), and recognize that, once infected, a host can itself become a source country, acting as a stepping-stone for secondary invasions in other regions.

Levine and D’Antonio (2003) depart from the earlier ecological literature and explicitly allow for attenuation in the trade-introductions relationship: “Each new container ship does not bring with it a whole new set of species; instead, each ship brings samples from regions already sampled by previous ships. Thus, as import volume increases, the per-ship probability of transporting a new introduction declines.” (p. 323) They account for this by employing three variants of the species-area curve, in which known invasions are an increasing, concave function of volume of aggregate imports into the United States. They then assume a 6% rate of growth for US imports in order to predict future invasions; their most conservative estimates predict invasions by 115 new insect species and 5 new plant pathogens between 2000 and 2020. They acknowledge that their “relationships would ideally be derived for the different biogeographic sources of exotic species” (p. 325), but do not use disaggregated trade data on the grounds that “the requisite data were unavailable.” (p. 325)

Finally, the present paper builds on earlier work by Solow and Costello (2004), who develop a statistical model of the invasion and discovery process. They posit that discoveries (observed invasions/introductions) depend on both actual introductions and “observational” effort. They estimate that “the mean rate of introductions [into San Francisco estuary] increase[d] from 0.3 introductions in 1850 to 2.3 introductions in 1995.” (p. 1822)

In summary, the ecological and economic literature to date has provided several empirical analyses of the trade-invasions link, but none has yet incorporated all of the key facets of the relationship. Ruiz et al. (2000) account for invasion risk that varies with characteristics of the host region but not the source; Dalmazzone (2000) and Levine and D’Antonio (2003) link invasions to trade volumes but neither distinguishes risk based on the source region; Drake and Lodge (2003) model both the source and host regions, but assume that infection risk is constant; Levine and D’Antonio (2003) allow for attenuation in the trade-invasions relationship, but do not distinguish between discoveries and actual invasions. Solow and Costello (2004) allow for attenuation and distinguish between discoveries and actual invasions, but do not directly link the invasions to trade nor distinguish between source regions. The present paper builds all of these important features into a single framework—attenuation of the trade-introductions relationship, discoveries versus actual introductions, and region-specific risk—providing the first estimates of current risk from trade related invasions on a region-by-region basis.

3 Estimating region-specific invasions from the discovery record

We model the first observation of a NIS as the combination of an introduction process and a discovery process. The introduction process captures *propagule pressure*, driven by the relationship between shipping and successful arrivals of NIS. Suppose that you start with N introducible species and that these species are introduced in a unit of shipping independently with probability p . The expected number of introductions in the k th unit of shipping is:

$$Np(1-p)^{k-1} \cong A \exp(-Bk) \quad (1)$$

Assuming that introductions follow a non-stationary Poisson process over cumulative shipping, (1) implies that the rate of arrivals, λ , follows

$$\lambda(S) = \beta \exp(-\gamma S) \quad (2)$$

where β and γ are non-negative parameters and S is cumulative shipping. The case where $\gamma > 0$ corresponds to saturation. Then, by a change of variables, the introduction process over time t is Poisson with rate function:

$$\lambda(t) = \beta s(t) \exp(-\gamma S(t)) \quad (3)$$

where $S(t)$ is cumulative shipping through time t and $s(t) = dS(t)/dt$ is the instantaneous shipping rate at t . The introduction rate per unit of shipping is therefore equal to a constant β which attenuates at the rate (over shipping) of γ .

Turning to the discovery process, assume that sightings⁵ of NIS follow a non-stationary Poisson process with rate function:

$$\mu(t) = \alpha \exp(\delta t) \quad (4)$$

where $\alpha > 0$ is a parameter. The parameter δ can be either positive or negative and is intended to capture in a rough way the effect of changes in discovery effort on discovery rate. Let $N(u, t)$ be the number of sightings in the interval (u, t) . Under this model, $N(u, t)$ has a Poisson distribution with mean:

$$E(N(u, t)) = \int_u^t \mu(t) dt = \frac{\alpha}{\delta} (\exp(\delta t) - \exp(\delta u)). \quad (5)$$

The event that a species that is introduced at time u is subsequently discovered (i.e., first sighted) at time t occurs when there is no sighting between u and t and a sighting at t . This occurs with rate:

$$f(u, t) = \exp(-E(N(u, t)))\mu(t). \quad (6)$$

Finally, the record of discoveries is also a Poisson process with rate function:

$$d(t) = \int_0^t \lambda(u) f(u, t) du. \quad (7)$$

Because we are working with annual data, it is necessary to specify a discrete-time analog to

⁵Note, a species may be “sighted” multiple times but can only be “discovered” once.

equation (7). We decompose the discovery rate d_t into the sum of all previous years' introduction rates, λ_u , each weighted by the probability, p_{ut} , that a species which arrives in year u is not discovered until year t :

$$d_t = \sum_{u=1}^t \lambda_u p_{ut}. \quad (8)$$

From the discrete-time analog of equation 3, the introduction rate is specified by:

$$\lambda_t = \beta s_t \exp(-\gamma S_t). \quad (9)$$

Let π_t equal the probability that a species which arrives in year u is observed in future year t . It follows that p_{ut} is given by the product of the probability that a species is *not* observed in previous years and the probability that the species is observed in year t :

$$p_{ut} = \pi_t \prod_{j=u}^{t-1} (1 - \pi_j) \quad (10)$$

It is reasonable to assume that π_t will vary over years t due to variation in factors such as observational effort. A model that accounts for this dynamic is the logit equation:

$$\pi_t = \frac{\exp(\pi_0 + \pi_1 t)}{1 + \exp(\pi_0 + \pi_1 t)} \quad (11)$$

where π_0 and π_1 are unknown parameters. A logistic transformation of π_t is linear in t , reflecting a monotonic trend in effort.

In section 5 below, we use the method of maximum likelihood to estimate parameters describing the introduction process. Given the discrete-time discovery rate function above, the log likelihood function is:

$$L(\theta) = \sum_{t=1}^T (y_t \log d_t - d_t) - T \log y! \quad (12)$$

where θ is a vector of parameters, y represents the record of actual discoveries (count per year) and T is the number of years on record. After describing the data, we estimate in section 5 the region-specific parameters of the NIS introduction-discovery process. When estimating the regional models, we assume that the discovery process parameters are identical across regions, but that the introduction process parameters (γ and β) are allowed to vary by region. The regional model log likelihood function is simply the sum of each regional log likelihood function.

4 An example from San Francisco Bay

In this section we estimate the parameters of the introduction process using data on shipping and introductions into a particular region, San Francisco Bay. The San Francisco Bay lies in central California at the confluence of the Sacramento and San Joaquin Rivers, draining 40% of the state's land surface area or approximately 153,000 km² (Nichols et al. 1986). The Bay and Delta system has undergone significant change in the past 150 years, leaving 95% of the original wetlands diked and filled and the fresh water flow cut in half via diversions to other regions of California. Also

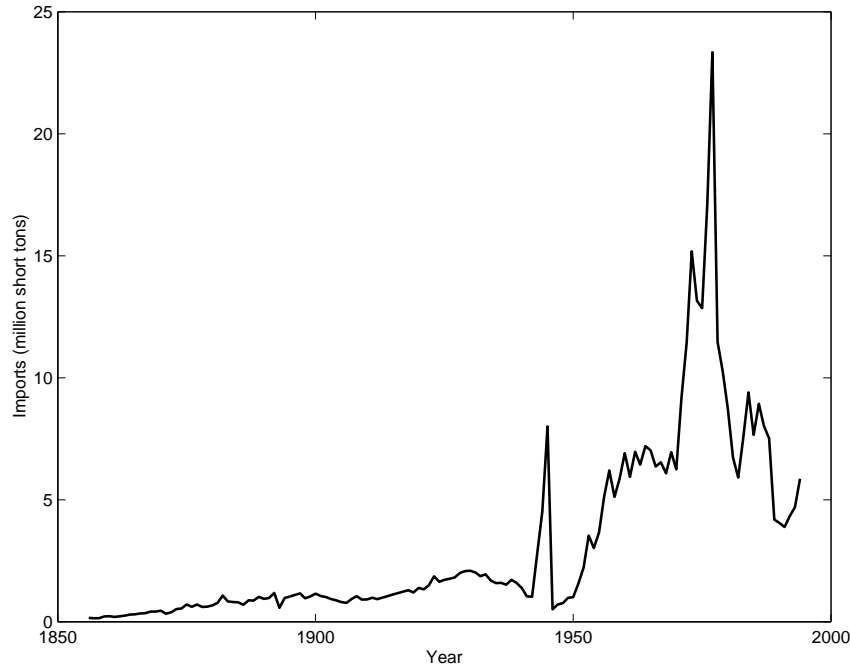


Figure 1: Yearly imports by vessel, San Francisco Customs District, 1856-1994

an important economic center and trade hub, the area had received over 436 million short tons of imported goods by the year 1994.

The Bay is one of only a small number of estuaries whose NIS populations have been thoroughly studied (Ray 2005). A particular advantage of focusing on this estuary is that early biological studies began at roughly the same time as the advent of major vectors of NIS introductions, reducing the possibility that early arrivals are mistaken for indigenous species (Ruiz et al. 2000). Recognized as perhaps the most invaded aquatic ecosystem in North America, the Bay has been profoundly altered by NIS introductions. For example, no shallow water habitat in the Bay remains uninvaded, and in some areas 100% of common species are exotic. Moreover, NIS species are the dominate force in ship and hull fouling, and introduced species are thought to have accelerated intertidal-region erosion (Cohen and Carlton 1995).

4.1 Historical Data

Our trade data set includes yearly import tonnage via ocean vessel through the San Francisco Customs District (SFCD) for years 1856 through 1994, disaggregated by foreign country of origin. Figure 1 shows aggregate imports over the period of study. We assembled the series from four different published sources, each of which are based on U.S. Department of Commerce (USDOC), Bureau of the Census records (see detailed data source description in Appendix A).⁶

⁶Data for war years of 1866, 1867 and 1913 through 1918 could not be located and were estimated using a linear step function between the pre- and post-gap four-year averages. Aggregate tonnage for years covered by digital data sources was checked against figures published by the U.S. Army Corps of Engineers (USACE 1986). Figures from both sources agree to within a few percent for each year except 1976 and 1977, when USDOC tonnage is 43% lower and 87% higher, respectively. USDOC data for both years was scaled to be consistent with the USACE figures because the USACE aggregate data trend was considered more plausible than the large yearly swing from

Region	NIS	Cumulative Imports (to 1994) (million tons)
Northeast Pacific	(NEP)	0
Southeast Pacific	(SEP)	1
Atlantic/Mediterranean	(ATM)	74
Southwest Atlantic	(SWA)	0
West Pacific	(WPC)	43
Southeast Atlantic	(SEA)	1
Indian Ocean	(ION)	3
Unknown	(UNK)	32

Table 1: NIS discoveries and cumulative imports by region

NIS discovery data for years 1853 through 1994 are taken from Cohen and Carlton (1995) case study of the biological invasions of the San Francisco Bay and Delta, an exhaustive compilation of all known NIS introductions in the region as reported by academic literature, periodicals, government agencies (e.g. California Department of Fish and Wildlife) and by the authors themselves. A minor update received directly from the authors was also appended. The data set includes (where known) the earliest discovery date, likely vectors of introduction and native region.

Over the 142-year period of study, 232 NIS were discovered in San Francisco harbor, for an average of 1.6 discoveries per year. Of these 232 species, 78 are thought to have arrived by some vector other than ocean vessel, and so we exclude these 78 species in our analysis. Thus, when we speak of NIS discoveries without qualifying the regions from which those NIS originally hail, we will be referring to a pool of 154 discovered NIS.

However in much of the analysis to follow we will instead prefer to focus on the NIS hailing from one region or another. For this analysis, we have divided up all possible source regions into seven groups, and assigned discovered NIS to these groups according to the native regions from which these NIS originally come. Unfortunately, we will lose some additional observations in this process. Of the 154 species believed to have entered San Francisco Bay via shipping traffic, 27 have native regions that are unknown, and 5 have multiple native regions. Thus, in our disaggregated pool, we exclude these 32 additional species, leaving 122 species upon which we can base our analysis at a region-by-region basis.⁷

The number of NIS discoveries and cumulative shipping trade by region of origin through 1994 is presented in Table 1. There is large variation in both NIS invasions and volume of trade over regions and it is readily apparent that invasions do not scale uniformly with trade. Differences may also stem from difficulty in classifying species as non-indigenous when their apparent ranges may be nearby. Mexico and Canada, for example, are part of the Northeastern Pacific region which has not been a certain source for any ship-borne invasions in our data set. For further discussion of San Francisco Bay NIS native origins, see Cohen and Carlton (1995).

In Figure 2 we plot cumulative discoveries against time; discovered NIS are decomposed by

1976 to 1977 observed in the USDOC data.

⁷A breakdown to the country level is not currently possible because species origins are not typically reported with that level of precision.

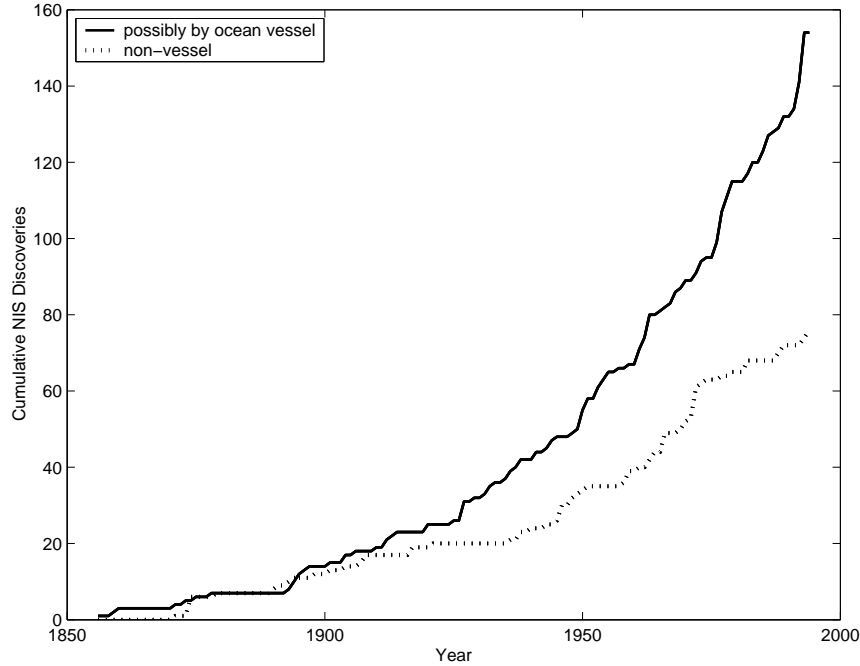


Figure 2: Cumulative NIS discoveries in San Francisco Bay over time and by vector: ocean vessel and other

the vector of believed introduction: “possibly arrived by ocean vessel” (in ballast water or in a ship’s seawater system, in solid ballast, in ship fouling or boring, and unknown) and “non-vessel” (all others, including intentional or accidental release by individuals and government agencies). It is on the basis of figures such as this that many researchers assume that NIS introductions are increasing at an increasing rate.

However, if we instead plot discoveries versus cumulative imports—see Figure 3—we see that the relationship between propagule pressure (proxied by shipping volume) and discoveries instead appears to be non-increasing, or possibly even declining. In the following section, our empirical estimates will confirm that the likeliest relationship between actual introductions and cumulative shipping is indeed concave.

5 Results

In this section we will apply the species discovery data and trade volume data described in section 4 to the likelihood-based model we developed in section 3. Our primary objective in this section is to obtain region-specific estimates of the historical introductions of NIS into San Francisco Bay. This will require disentangling the (observed) species discovery record from the (unobserved) species introduction record. The introduction model for NIS from trade region i is:

$$\lambda_{it} = \beta_i s_{it} \exp(-\gamma_i S_{it}) \quad (13)$$

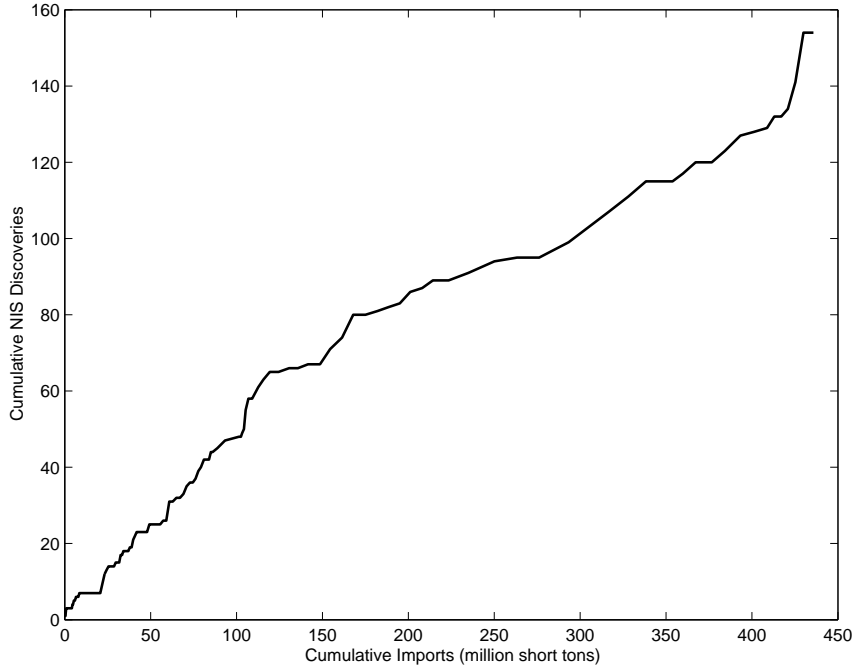


Figure 3: Cumulative NIS discoveries versus cumulative imports

Parameter	Trade Region	Estimate	p-value
β	ATM	3.27	0
	WPC	0.16	0
	ION	2.09	0
γ	ATM	0.04	0
	WPC	-0.01	.12
	ION	0.63	0

Table 2: Unrestricted parameter estimates, jointly estimated model

where s_{it} is the annual shipping volume from region i in year t and S_{it} is the cumulative shipping volume from that region up to, but not including year t . The discovery process is given by equations 10 and 11. We begin by estimating the model assuming a constant sighting probability, $\pi_t = 0.1$. This implies that each introduced species is observed about once every ten years; the time between introduction and the first sighting then is a geometric random variable. For example, the probability that a species is discovered (that is, observed for the first time) 5 years after its introduction is $(1 - \pi)^4 \pi = 7\%$ and the probability that the species is discovered *within* 5 years of introduction is 41%. In subsequent analysis we examine different assumptions about the discovery process.

Under this model, we allow for regional differences in both the base rate of invasions (β_i) and the attenuation rate (γ_i). We jointly estimate the parameters γ_i and β_i for the three regions for which we have more than one NIS discovery between 1856-1994. Those regions are Atlantic/Mediterranean (ATM), West Pacific (WPC), and Indian Ocean (ION). The unrestricted parameter estimates for the jointly estimated model are given in Table 2.

From the perspective of NIS introductions, an important characteristic of a trade partner is its inherent capacity to introduce NIS into San Francisco. At the beginning of a trade relationship, how infectious are the different partners? The infectiousness of a trade partner is based, as was previously discussed, on both the number of introducible species and on biogeographic similarities between regions. We can estimate the base rate of introductions by evaluating equation 13 at $S_{it} = 0$ and $s_{it} = 1$, which simply yields β_i . The parameter β_i can then be interpreted as the number of NIS introductions that would be expected to arrive with the first million short tons of trade. The maximum likelihood estimates of these parameters are 3.27 (for ATM) 0.16 (for WPC) and 2.09 (for ION), which are all statistically distinguishable from zero.

One question of interest is whether this baseline infectiousness could be equal across trade partners. We re-estimated the model under the restriction that $\beta_{ATM} = \beta_{WPC} = \beta_{ION}$. The maximum likelihood estimate of β is then 0.88, and the p-value from the likelihood ratio test is $p = 0$, so we can reject the hypothesis. Based on these results on β it is tempting to think that ATM is the most risky trade partner, followed closely by ION, and that WPC is a nearly riskless trade partner. That intuition would only be correct in the absence of attenuation of NIS introductions.

A central feature of our story about NIS introductions is the attenuation of intructions with respect to trade volume; in equation 13 we represent this attenuation via the parameter γ . Intuitively, we would expect that the more trade “experience” a country has with its partner, the less likely it is that new species will be introduced (and so $\gamma > 0$). The estimated attenuation rate in ATM is about 4% per million short tons of trade, and is statistically significant. The attenuation rate in WPC is estimated to be negative, but is not statistically different from zero. Consistent with the small number of introductions from ION, the attenuation rate in ION is much larger — it is very unlikely that new species will be introduced from ION to San Francisco. We tested the restriction that $\gamma_{ATM} = \gamma_{WPC} = \gamma_{ION}$ and obtained a p-value of 0, so this restriction can be rejected.

Based on the likelihood ratio tests above, we restrict $\gamma_{WPC} = 0$, and run the (otherwise unrestricted) model, maintaining the assumption that the sighting probability is $\pi_t = 0.1$. Under this model, we can derive both the fitted cumulative discovery record (from equation 8) and the cumulative introduction record (from equation 9), both over the period 1856-1994. These results are presented in Figure 4 which is organized as follows. The 3 rows correspond to regions ATM, WPC, and ION respectively. The first panel in each row plots cumulative species against trade volume, and the second panel in each row does so with time on the horizontal axis. Each row provides the cumulative discoveries (dotted lines) and fitted discoveries (solid lines).

Figure 4 also plots *estimated introductions* (dashed lines) over the period 1856-1994. Recall from our earlier discussion that there is usually a lag between actual introduction of a new NIS species and the date when that new species is first sighted, and so the discovery record does not accurately reflect the true introduction process. Our model in section 3 accounts for this fact; the number of *undiscovered* species at any point in time can be estimated by:

$$\sum_{t=1}^{\tau} \lambda_t - d_t \tag{14}$$

which is visually observed as the vertical distance between the dashed and solid lines in Figure

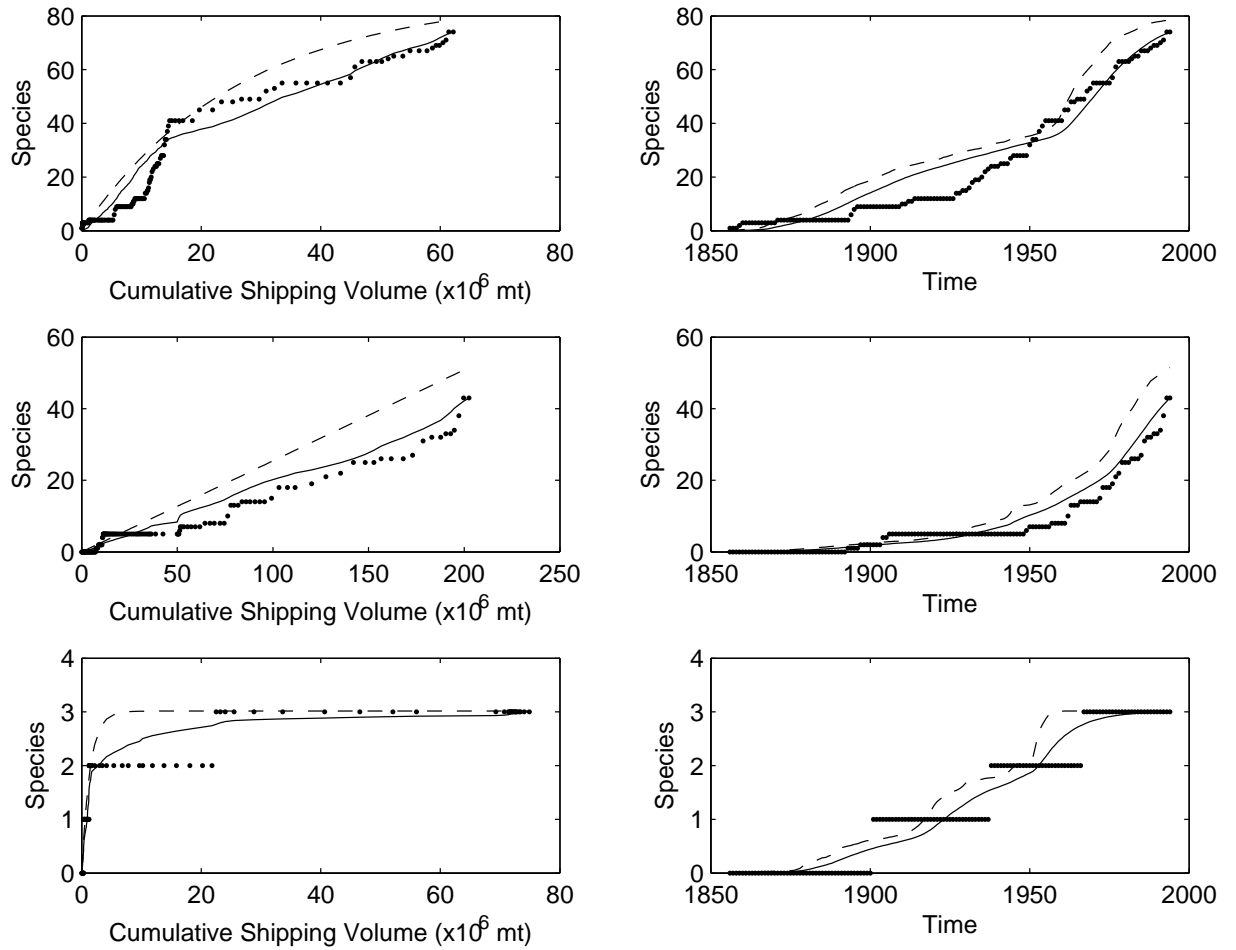


Figure 4: Cumulative discoveries (dots), fitted discoveries (solid), and fitted introductions (dashed) over the period 1856-1994. Top row is for ATM, middle row is for WPC, and bottom row is for ION.

Trade Region	# Discovered Species	# Introductions	# Undiscovered Species (1994)
ATM	74	78.57	4.57
WPC	43	51.47	9.47
ION	3	3.02	0.02

Table 3: Regional NIS discoveries and estimated introductions to 1994

4. Maintaining the assumptions above, we estimate the number of undiscovered species in 1994 attributable to each trade region. These results are presented in Table 3. According to the estimates above, about 5 yet undiscovered species from the ATM region are present in San Francisco Bay. About 10 such species exist from WPC, and none from ION. But these estimates may be sensitive to our assumption about the sighting probability, π_t . For example if $\pi_t = 1$, then there is no lag between introduction and discovery because all species that are present are observed every year. In that case, the number of undiscovered species would be zero. At the other extreme, take the case in which $\pi_t = 0.01$, so species are observed only about once every century. In that case, the estimate of the number of undiscovered species in 1994 rises sharply to 88.6 (for ATM), 125.9 (for WPC), and 1.8 (for ION). We are currently working on estimating π_0 and π_1 from the data directly, and so hope to be able to offer more concrete estimates of the number of undiscovered NIS in future drafts of this paper.

6 Predictions

Ultimately our objective is to predict future invasion risk from different trade regions. To do so we will first estimate the predicted number of new NIS, by region of origin, that will arrive in the next unit of trade. We will interpret this statistic as the “marginal invasion risk” of a trade partner. To accommodate changes in future trade patterns and volume we then attempt to predict the number of new NIS over the period 1995-2020 by incorporating partner-specific trade volume forecasts over the same period.

6.1 Forecast Trade Data

To ultimately predict future risk by region for the Bay we use forecasts of future imports into San Francisco district of lading (district 28) from Haveman and Hummels (2004); we are tremendously grateful to the authors for supplying us with the disaggregated projections. Their forecasted values are drawn from GTAP, the Global Trade Analysis Project⁸ using Walmsley et al. (2000) extension of the basic GTAP model.⁹

From the Haveman and Hummels data set we aggregated 2002 imports (actual values) and

⁸For more information on GTAP, see Hertel (1997), Dimaranan and McDougall (2002) or visit <http://www.gtap.agecon.purdue.edu>.

⁹According to Haveman and Hummels (2004), this extension “draws on World Bank forecasts of growth rates in gross domestic product, gross domestic investment, capital stocks, population, skilled labor and unskilled labor for each country. The model further assumes a set of trade policy changes, including the full implementation of Uruguay Round commitments, the implementation of China’s accession to the World Trade Organization, and the implementation of the agreement on textiles and clothing. It further assumes that, after the full implementation of the Uruguay Round commitments, there will be gradual tariff reductions commensurate with the rate of liberalization that has occurred in recent decades.” (p.76)

Region	2002 (actual)	2020 (forecasted)	Annual growth rate
Northeast Pacific	\$877	\$2,344	5.6
Southeast Pacific	147	240	2.8
Atlantic/Mediterranean	1,888	2,638	1.9
Southwest Atlantic	108	258	4.9
West Pacific	14,115	23,964	3.0
Southeast Atlantic	171	929	9.9
Indian Ocean	1,162	5,220	8.7
<i>Overall</i>	18,468	35,593	3.7

Table 4: Forecasted import volume growth rates based on forecasted trade values (millions of dollars)

2020 imports (forecasted values) by region. We then calculated the (constant) rate of annual import growth that would account for this predicted change. Imports, by region, into SF district of lading for 2002 and 2020 (predicted), as well as projected annual growth rates for imports from each region, are presented in Table 4.

Although average (weighted by 2002 import values) import growth is predicted to be only 3.4% per year, region specific growth rates vary widely, running as low as 1.9% for San Francisco imports from the Atlantic/Mediterranean region, and as high as 9.9% and 8.7% from the Southeast Atlantic and Indian Ocean regions respectively.

One important caveat made by Haveman and Hummels (2004) in discussing their methods is the difference between desired port capacity and actual capacity. Their forecasts for imports into San Francisco by vessel reflect predicted demand for access to Bay area ports. However, as this demand represents a tripling of current trade volumes (including exports), it is unlikely that Bay area ports can accommodate this demand without future investments in port and road infrastructure. Like Haveman and Hummels (2004), we also assume that 2020 capacity at San Francisco ports equals forecasted demand, such that forecasted imports into the area are as described in Table 4.

6.2 NIS Introductions Forecasts

On the margin, predicting NIS introductions amounts to estimating the expected number of new NIS arriving in one more unit of trade from each region. This statistic can be conveniently estimated by evaluating equation 13 at $s_{it} = 1$ and $S_{it} = S_{i1994}$, using the region-specific parameter estimates for γ_i and β_i presented above. We will call this statistic the “marginal invasion risk” from region i . Using our parameter estimates, the marginal invasion risk from the three focal regions are: 0.33 (ATM), 0.25 (WPC), and 0 (ION), indicating that ceteris paribus, we would expect increased trade from ION to be relatively innocuous, four million short tons of trade from WPC to introduce about one species, and 3 million short tons of trade from ATM to introduce about one new species. Again allowing γ_{WPC} to be chosen by the likelihood estimation, we tested the non-linear restriction that the marginal invasion risk is equal across each of the three trade regions. With a p-value of 0, this hypothesis can be soundly rejected. We also tested the individual hypotheses that the marginal invasion risks were zero. We rejected the hypothesis that

Trade Region	Marginal Invasion Risk	Projected Imports	# New NIS
ATM	0.332	29.7	6
WPC	0.254	123.1	32
ION	0	181.8	0

Table 5: Predictions of new NIS invasions from estimated marginal invasion risk and forecasted import growth (millions of tons)

the marginal invasion risk from ATM is zero, and the hypothesis that the marginal invasion risk from WPC is zero. However, with a p-value of nearly 1.0, we were unable to reject the hypothesis that the marginal invasion risk from ION was zero. This result is consistent with the other findings in this paper that ION poses little invasion risk.

Combining the trade forecasts from above with the introductions model from equation 13, we are in a position to predict the number of new introductions from 1995-2020. Table 5 provides the estimates of the marginal invasion risk, the projected trade volume from 1995-2020, and the estimated number of new NIS introductions from each trade partner over the same period. The table tells a very interesting story. Focusing attention first on the marginal invasion risks of the three regions, it is clear that ATM is the most risky, followed closely by WPC, and ION is no risk at all. But if we are interested primarily in predicting the number of new NIS before 2020, we must account for the projected trade volume, which is substantially higher in WPC than in ATM. Once trade volumes are factored in, the predicted number of new NIS is much larger in WPC than in either of the other two regions. Importantly, trade with ION is projected to be the highest of the three regions (182 million short tons), but because the marginal risk is so low, we expect no new introductions from this substantial trade volume.

Accompanying Table 5 which presents the predicted number of new NIS introductions by 2020 is Figure 5 which shows the estimated cumulative number of introductions over both the data record (1856-1994) and the forecast time period (1995-2020). Consistent with the forecast estimates in Table 4, the slope of the NIS introduction process is flat for ION, relatively flat for ATM, and relatively steep for WPC.

All of the results above rely on the assumption that the sighting probability is approximately 10% per year. If the sighting probability were different, then the γ_i and β_i parameters in the introduction model would adjust to maximize the likelihood function. In turn, our predictions about the number of new NIS from 1995-2020 would change. How sensitive are our predictions of new NIS to our assumption about the sighting probability? To examine this question we re-estimate the expected number of new NIS from 1995-2020 attributable to each of the 3 focal trade regions under different assumptions about the sighting probability. Consistent with the results above, we find that our prediction of 0 new NIS from the Indian Ocean (ION) is insensitive to assumptions about π_t . Estimated species introductions from the other regions are somewhat more sensitive to assumptions about π_t ; the results for these two regions are graphed in Figure 6.

The estimated number of new introductions from ATM is somewhat insensitive to assumptions about π_t ; estimates range from about 12 new NIS introductions (if $\pi_t = 1$) to about 4 new NIS introductions (if $\pi_t = .01$). Provided the sighting probability is sufficiently large (above about $\pi_t = .05$, the result for region WPC is qualitatively similar) we can expect about 30 new

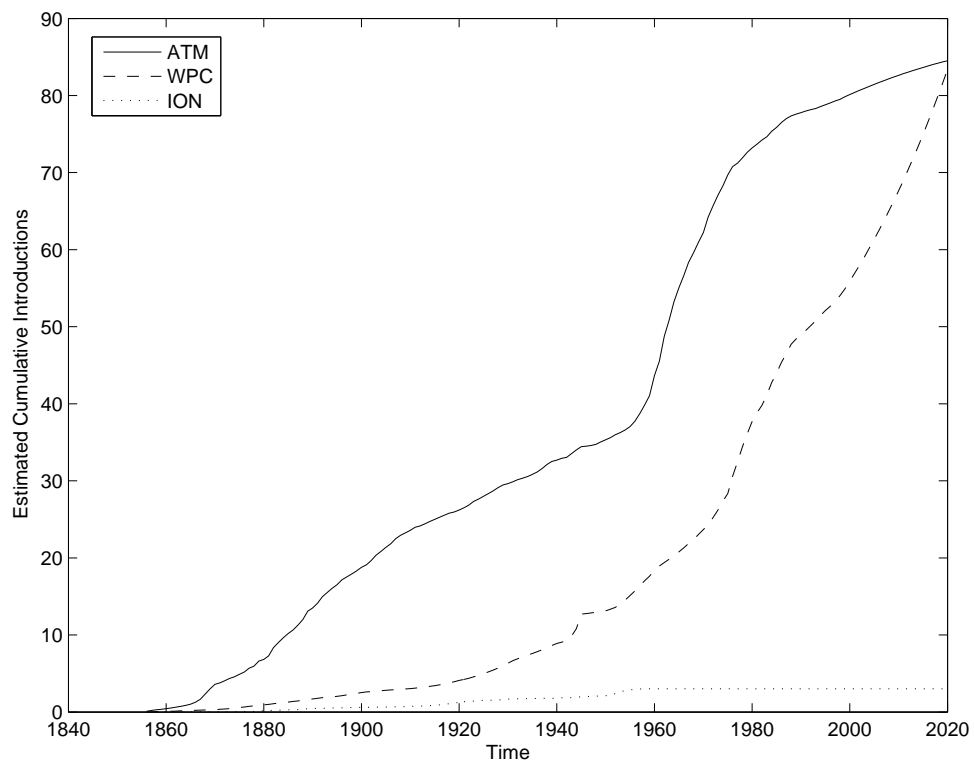


Figure 5: Estimated NIS introductions over the data record (1856-1994) and the forecast time period (1995-2020).

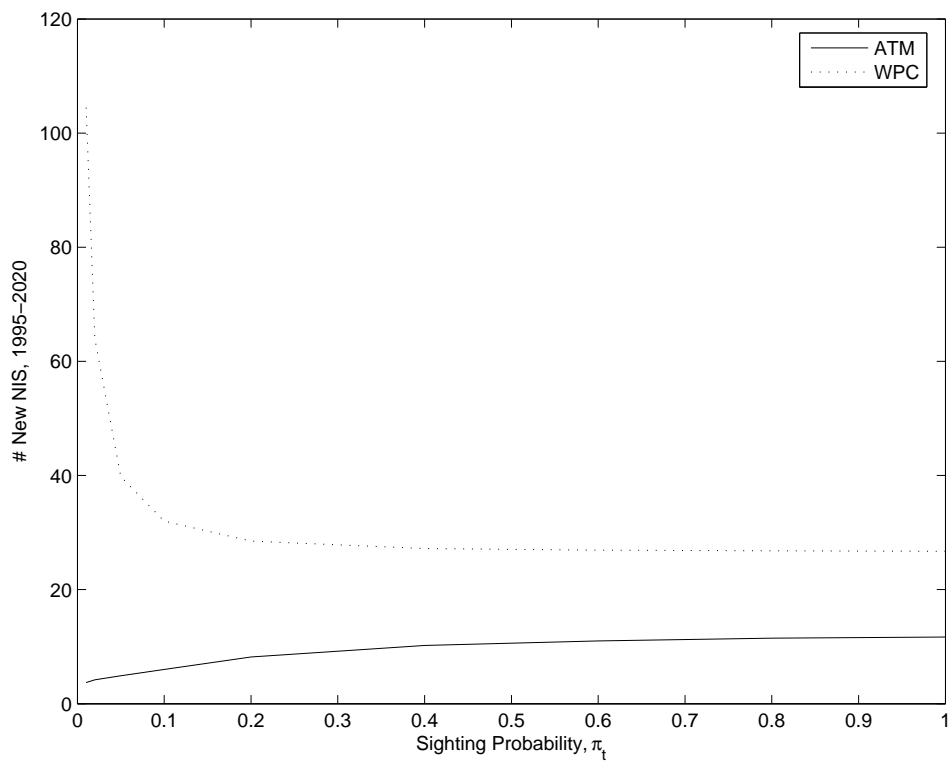


Figure 6: Estimated number of new NIS from 1995-2020 attributable to each trade region, under different assumptions about the sighting probability.

introductions regardless of the sighting probability. However, when π_t gets very low, the estimated number of new introductions from WPC rises sharply. This is a consequence of the re-optimized parameter estimates under the new assumption about π_t . For example, when $\pi_t = .01$, the new maximum likelihood estimate of $\beta_{WPC} = 0.83$ which is much larger than the same parameter estimate when $\pi_t = .1$ (in which case $\beta_{WPC} = .16$ when γ_{WPC} is unrestricted and $\beta_{WPC} = .25$ when $\gamma_{WPC} = 0$). Essentially what is happening is that to reconcile the discovery record with a very low sighting probability, the introduction rate must be very high.

7 Concluding remarks

Past biological invasions have been ecologically and economically significant, and international trade has played a major role in facilitating those invasions. Biologists have made considerable progress in identifying the variables important in the invasion process. For example, it is well understood that international trade and tourism are sources of propagule supply, that new introductions of NIS depend on that supply, but that risk of future invasions likely attenuates with cumulative exposure. Moreover, risk of future introductions also depends on the extent to which source and host regions exhibit biogeographic similarities, and there is often a lag between the introduction and discovery of new NIS. But accurately estimating the invasion risk by region of origin requires a more complete understanding of the trade-introduction-discovery process.

In this paper, we develop an analytical model of that process in which shipping volumes proxy propagule supply that fosters introductions of new species, and those introduced species are eventually discovered. We use the model to estimate the inherent infectiousness of trade with a variety of trade partners (aggregated into regional groupings) and estimate the rate at which infectiousness attenuates with cumulative exposure. Employing forecasts of future trade volumes and patterns, we then use our estimates to identify trade regions that are likely to be sources of substantial NIS introductions in the near future. Based on historic trade and invasion data, our estimates suggest that the San Francisco Bay region faces negligible risk from imports arriving from the Eastern Pacific, South Atlantic, and Indian Ocean regions, continued risk from the Atlantic/Mediterranean region, and explosive risk from the West Pacific region. Assuming a constant sighting probability of .10, we predict that by 2020, the San Francisco Bay and Delta area will receive introductions of 6 new NIS from the Atlantic/Mediterranean regions, and 32 new NIS from the West Pacific, relative to 1994.

Before concluding, we believe it important to clarify the limitations of this study. The spatial resolution of our model was hampered by uncertainty about the native range of many NIS. In estimation, we faced a tradeoff between geographic precision and bias introduced from exclusion of observations with broad native range designations. Perhaps demonstrations of the value of detailed source information, such as in this paper, will foster the allocation of additional resources for such NIS forensics. A limitation of our theoretical model stems from our assumption of regional independence, that is, the infectedness of one region does not affect that of another. It is likely that some number of NIS discovered in the Bay are secondary invaders, having used some port between their native range and the Bay as a “stepping-stone”. While this network effect is likely important, it is set aside in the current analysis in order to sharpen the understanding of two-way connections.

Appendices

A Import data sources

1855-1945: *Foreign Commerce and Navigation of the United States*, U.S. Department of Commerce (and Labor), Bureau of the Census (Statistics).

1946-1967: *Foreign Trade through the San Francisco Customs District*, published by: Board of State Harbor Commissioners for San Francisco Harbor (1946-1955), San Francisco Port Authority (1956), Port of San Francisco (1957-1959), Bank of America, Economics Department, Regional Research Station (1960-1967). All were compiled from Bureau of the Census records, Department of Commerce.

1968-1989: Annual Import Data Bank files, Records of the Division of Foreign Trade Statistics Machine-Readable Records, U.S. Bureau of the Census, U.S. Imports for Consumption and General Imports, TSUSA Commodity by Country of Origin, FT246, Washington, D.C.

1990-2000: U.S. Imports of Merchandise (CD-ROM). Published by the U.S. Department of Commerce, U.S. Census Bureau, Data User Services Division.

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