Estimating trading partner exposure risk to new pests or diseases

Technical Report for CEBRA project 190606

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1. Executive summary

Commonly, trade restrictions and border inspection rates for goods susceptible to high threat pests or diseases are made based on the current distribution of a pest or disease. Specifically, if a country is known to have the threat, it will typically experience greater border inspection rates and/or be required to meet additional obligations (e.g. treatments or other restrictions) before the susceptible goods are accepted by a recipient country. While this approach is useful for allocating border surveillance for pests or diseases that have static or slow moving distributions, it is highly problematic for emerging threats that are fast spreading and may not be immediately detected by exporting countries.

Here, we propose a novel and pragmatic method that integrates border interceptions, trade data, pest occurrence records and climate suitability models to estimate the exposure risk of potential and current trading partners obtaining an established population of a new high threat pest or disease. The purpose of the model is to estimate country-level establishment exposure of such pests/diseases as a function of known risk commodities imported from infected countries. The output of this model is intended to be used with other risk analyses conducted by the Australian government to inform risk-based allocation of border screening resources. The model focuses solely on risk associated with trade, it does not account for other high risk pathways such as hitchhikers on passenger luggage, mail, air-cans, illegal trade, or natural dispersal across country borders. We illustrate this method using brown marmorated stink bug (BMSB; *Halyomorpha halys*) and Australian interception data as a case study.

We found that, irrespective of whether the model was parameterised using BMSB-specific interception or general contamination (i.e. presence of any organism) data, the United Kingdom, the Netherlands, Poland, Mexico and Sweden were amongst the countries most exposed to incursion and subsequent establishment of BMSB. Furthermore, our model identified the BMSB vulnerable tariff codes that are likely to introduce the greatest number of hitchhikers into Australia. For BMSB specifically, the highest risk tariffs were HS codes 9401 (seats), 8609 (containers) and 8701 (tractors), while for general contaminations (i.e. the presence of any foreign organism) codes 0810 (fresh fruit), 7318 (screws and bolts) and 8708 (motor vehicles) pose the greatest risk.

We believe this model is a substantial improvement over others that are currently available to biosecurity practitioners. First and foremost, our model was designed with the end-users (biosecurity practitioners) in mind. As a consequence, the analytical workflow aims to maximise the use of internally collected border surveillance data (e.g. interception records) and integrate these data with other publicly available data (e.g. trade data and climate data). Second, the workflow is applicable to any plant pest or disease that is predominately spread via international trade of commodities. Third, relative to standard pathway models that focus on identifying risk pathways of entry into an individual country, our model is both inwards and outwards focused, such that it estimates exposure risk within Australia as well as among countries. Finally, and perhaps most importantly, our method explicitly integrates pathway analysis with climate suitability modelling. This effectively means our model attempts to account for two fundamental geographic barriers to establishment of a pest or disease: 1) the ability of the pest/disease to reach a location; and 2) the suitability of the climate at the destination. This enhances standard pathway analyses, which generally ignore climatic suitability, and is also contrary to standard invasive species distribution modelling (sometimes termed risk maps in the invasive literature), which tend to focus on modelling climate suitability without accounting for pathways of entry and subsequent post-border movement of propagules.

2. Introduction

Changing climate and increasing globalisation of human movement and trade has dramatically increased the exposure of countries to new pests and diseases that can have devastating economic, environmental and social impacts. We need only look at the recent COVID-19 pandemic to see how quickly an emerging threat can spread and cause large-scale impacts to both social values and global economies. The difficulty faced by governments, industry and environmental practitioners is how to develop a strong and efficient border biosecurity system that can mitigate the risk of new pests and diseases entering, establishing and spreading while also allowing for increased global trade and human movement.

As inspection and surveillance resources are finite, governments and other biosecurity practitioners have used a variety of risk-based tools to help inform decisions of how and where to allocate resources. Most notable among these have been: 1) pest and disease prioritisation tools such as the "Weed Risk Assessment" (e.g. Pheloung *et al.*, 1999); 2) pathway analyses for identifying high risk modes of transport and points of entry (Douma *et al.*, 2016; Tingley *et al.*, 2018); and 3) risk maps, commonly in the form of suitability maps (Venette *et al.*, 2010; Elith, 2017; Venette, 2017), but sometimes also other components (Camac *et al.*, 2019, 2020), for informing post-border surveillance. While these tools have been critical for providing risk-based measures for allocating resources among species and pathways, and across space, a need remains for a pragmatic method that can estimate the establishment exposure to a new emerging pest or disease due to interactions with existing and potential trading partners.

Commonly, trade restrictions and border inspection rates for goods susceptible to high threat pests or diseases are based on the current distribution of the relevant pest or disease. Specifically, if a country is known to have the threat, it will typically experience greater border inspection rates and/or be required to meet additional obligations (e.g. treatments or other restrictions) before the susceptible goods are accepted by a recipient country. While this approach is useful for imposing trade restrictions and allocating pathway risk mitigations for pests or diseases that have static or slow moving distributions, it is highly problematic for emerging threats that are fast spreading and may not be immediately detected by exporting countries, thereby posing a secondary risk to to other countries.

Brown marmorated stink bug (BMSB; *Halyomorpha halys*) is one such pest. It is a highly polyphagous (>100 hosts) plant pest, that is not only a significant household nuisance pest (Rice *et al.*, 2014; Fraser *et al.*, 2017; Horwood *et al.*, 2019), but also poses a substantial threat to horticulture worldwide (Rice *et al.*, 2014). Over the last two decades, it has rapidly spread from its native range in East Asia (China, Japan, the Korean Peninsula and Taiwan) into Europe, North America and Canada, and in doing so, has caused significant agricultural losses (Rice *et al.*, 2014; Valentin *et al.*, 2017).

Currently, Australia is free of BMSB despite large regions estimated to be climatically suitable (Zhu *et al.*, 2012; Fraser *et al.*, 2017; Kriticos *et al.*, 2017). However, maintaining this pest-free status is becoming increasingly difficult as Australians import larger quantities of potentially contaminated goods from an expanding list of countries; ultimately increasing the risk posed to Australia's billion dollar horticultural industry.

Interception data coupled with expert opinion indicate that for both Australia and New Zealand the number of BMSB arrivals and the likelihood of establishment will be greatest when the pest overwinters in the Northern Hemisphere. This is because when BMSB overwinters, it aggregates in large numbers in both residential and industrial buildings. As a consequence, BMSB is a common stowaway in passenger luggage and imported bulk freight, cargo and vehicles (DAWR, 2017; Ormsby, 2018). Moreover, these stowaways can be found in large numbers, thereby rendering it more likely to establish on arrival as it can more easily overcome possible founder effects that inhibit the successful establishment of many other pests (DAWR, 2017).

Australia and New Zealand have both attempted to minimise their exposure to BMSB introductions by imposing higher inspection rates and additional phytosanitary restrictions for countries with known established populations (DAWR, 2017; Ormsby, 2018). However, the effectiveness of this additional risk mitigation strategy at reducing the exposure of Australia and New Zealand to BMSB incursions, or other fast spreading pests/diseases, will ultimately depend on the accuracy and speed with which risk countries are identified.

A major difficulty in identifying countries that that may contain an established population of a high threat pest, is that monitoring and reporting is not uniform among countries. This uneven effort could be due to a variety of reasons such as lack of taxonomic expertise and/or surveillance infrastructure, countries actively withholding information to maintain market access or misidentification of a threat as a similar endemic species. The consequence is that a pest or disease may go unreported until populations become large and impacts high, by which time other countries may have become unwittingly exposed to the new threat. For example, in many countries, BMSB populations have not been detected and reported until they formed large overwintering aggregations (DAWR, 2017), by which time Australia and New Zealand would have begun receiving imports from those countries that could potentially contain large numbers of BMSB (DAWR, 2017; Ormsby, 2018). As such, in order to enhance border screening activities of imported goods to detect fast spreading, high threat pests, a risk-based tool is required to estimate the country-level exposure to establishment as a function of international trade between known infected and uninfected countries.

Here, we propose a pragmatic method that integrates border interceptions, trade data, pest occurrence records and climate suitability models to estimate the exposure risk of potential and current trading partners obtaining a new high threat pest or disease. The purpose of the model is to estimate country-level establishment exposure of such pests/diseases as a function of known risk commodities imported from infected countries. The output of this model is intended to be used with other risk analyses conducted by the Australian government to inform risk-based allocation of border screening resources. The model focuses solely on risk associated with trade, it does not account for other high risk pathways such as hitchhikers on passenger luggage, mail, air-cans, illegal trade, or natural dispersal across country borders. We illustrate this method using brown marmorated stink bug (BMSB; *Halyomorpha halys*) and Australian interception data as a case study.

3. Methods

Our objective was to develop a method that can readily used by biosecurity agencies for estimating the exposure of current and potential trading partners to emerging high threat pests and diseases. In order to achieve this, we created a work flow that integrates pest interception data commonly collected by government biosecurity agencies and integrate these data with publicly available data on trade flows, pest occurrence records, human population and long-term climatic data (Fig. 3.1).

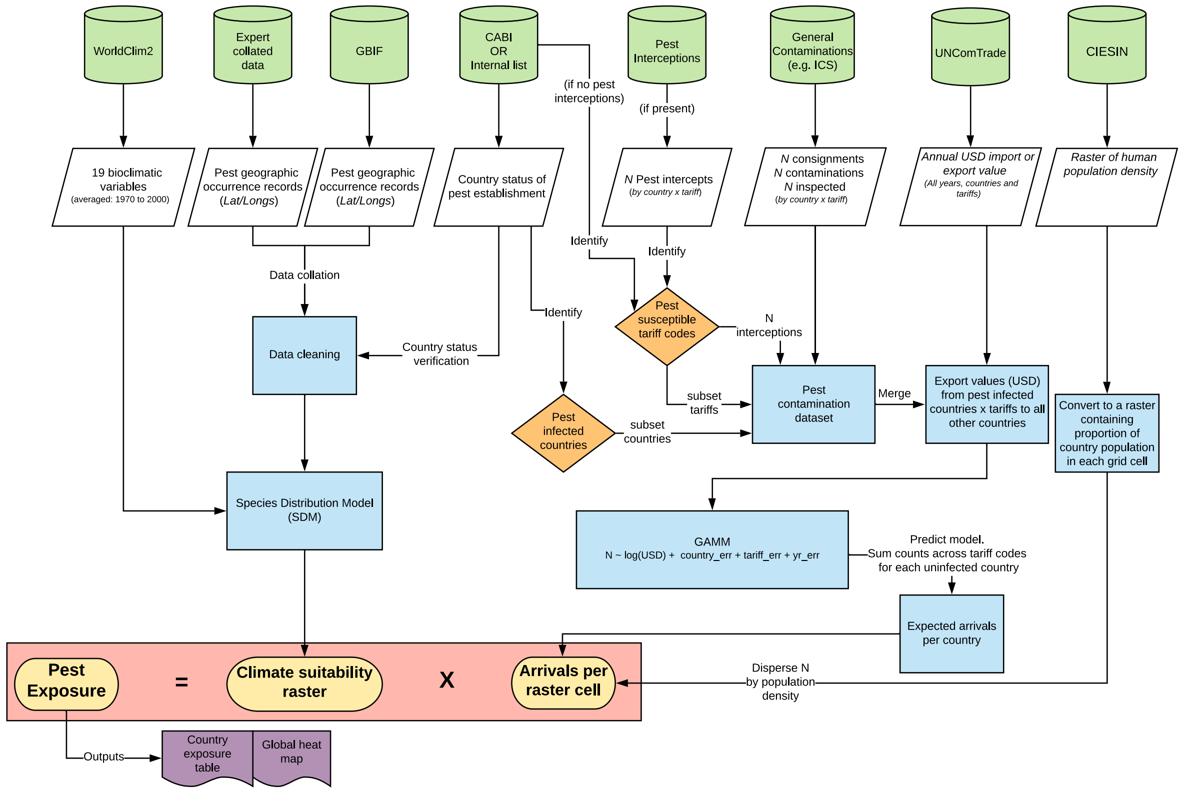

Figure 3.1.: Workflow for estimating trading partner exposure risk for high threat pests or diseases

At its foundations, the work flow is based on the principle that for a pest to successfully establish it must first overcome at two geographic barriers (Catford *et al.*, 2009), namely:

1. can it reach the location of interest (i.e. contamination rates)?
2. are the abiotic conditions suitable (e.g. climate suitability)?

In the ideal case, there should also be a third barrier – the suitability of the biotic environment (e.g. presence of host/food). However, measures of biotic suitability will vary considerably among species and are typically difficult to source at the appropriate resolution and extent required for this analysis. As such, our work flow focuses on the first two barriers and implicitly assumes that biotic suitability is uniform across geographic space, while acknowledging that this is unlikely to be the case in most circumstances.

In the following sections we outline the data sources and statistical models used to estimate both arrivals and climatic suitability. We then explain how these pieces of information can be integrated to derive a measure of exposure risk for each potential trading partner currently believed to be uninfected by BMSB.

3.1. Estimating climate suitability

For most pests, climate is likely to be the major abiotic barrier to establishment upon arrival, especially at large spatial scales (Thuiller *et al.*, 2005; Araújo & Rozenfeld, 2014; Higgins & Richardson, 2014). The geographic distribution of suitable climate can be estimated using a wide variety of approaches including climate matching algorithms (e.g. CLIMATCH, CLIMEX's climate matching algorithm; Crombie *et al.*, 2008; Kriticos *et al.*, 2015), environmental convex hulls and Range Bagging (e.g. Drake, 2015), correlative species distribution models (e.g. Maxent Phillips *et al.*, 2006), physiological models (e.g. NicheMapper; Kearney & Porter, 2017), semi-mechanistic models (e.g. CLIMEX; Kriticos *et al.*, 2015), or when data are poor, expert-derived suitability maps (e.g. Martin *et al.*, 2015). Many tools exist, and there are diverse opinions on how to use them, but there remains no strong evidence of a single *best* approach for predicting an invasive species' potential distribution (Barry *et al.*, 2015; Elith, 2017). As a consequence, our work flow is agnostic as to how abiotic suitability is estimated. The only condition required is that the output of your climate suitability model must be assumed to be proportional to the probability of establishment given a viable pest population is present at that location. We strongly recommend users consult Camac *et al.* (2020) to obtain practical guidance on how to robustly estimate a species' climatic suitability.

The potential distribution of brown marmorated stink bug (*Halyomorpha halys*) has been approximated using a variety of methods such as CLIMEX (Kriticos *et al.*, 2017), Maxent (Zhu *et al.*, 2012; Fraser *et al.*, 2017), Random Forests (Fraser *et al.*, 2017), Support Vector Machines (Fraser *et al.*, 2017) and ensembles of multiple of these methods (Fraser *et al.*, 2017). While some models exhibit some similarities (e.g. Eastern USA is almost always classified as suitable) substantial differences also exist between models (e.g. Appendix Fig A.1). This is particularly obvious when examining the distribution of suitable climate in Australia predicted by the different models. In the CLIMEX model, much of the central and north-east coast of Australia is estimated to be highly suitable. By contrast, the Maxent models compiled by Zhu *et al.* (2012), and to a lesser degree those reported by Fraser *et al.* (2017), suggest that the south-east and south-west of Australia are most optimal. Again, there are numerous reasons for such discrepancies, including differences in the choice of covariates or constraining factors, differences in the data sources used for parameterisation and validation, and varying assumptions underlying the models.

As there was little consistency in covariates used among published models, we estimated the geographic distribution of climate suitability for this species using a recently proposed method known as range bagging (Drake, 2015). Range bagging is an algorithm that uses presence-only data to estimate the environmental limits of species' habitat by subsetting the multidimensional environments (to user-defined levels of dimensionality), and then using convex hulls to estimate boundaries in each subset of environmental dimensions. Range bagging repeatedly fits models to a random assortment of occurrence samples (and covariate choices) and averages the outcome by using votes (how often a given environment occurs inside niche boundaries) on the ranges of convex hulls obtained from bootstrap samples across all the environmental dimensions. Effectively, its output is the proportion of models that consider a given location has suitable climate. For example, a suitability score of 0.1 would indicate only 10% of the estimated convex hulls ensembled deemed that location suitable. By contrast, a score of 0.9 would indicate that 90% of estimated convex hulls deemed that location climatically suitable.

The approach has seen recent applications to invasion biology, and appears promising in the context of biosecurity. Part of the appeal for this approach is that no absences or background data are required – presence data are sufficient (Camac *et al.*, 2020). This in turn removes a number of subjective decisions required in the modelling process and instead focuses solely on the data that we do have – presence locations. The method may also reduce inaccuracies that can arise from projecting to novel environmental conditions. This is because, unlike some other methods (e.g. Maxent), the method does not attempt to estimate response curves, but rather defines convex hull boundaries in environmental space based on known occurrences, whereby everything within the hull is considered suitable and everything outside it is deemed unsuitable. Another major advantage of range bagging is that it can readily be used to deal with uncertainty in covariate selection. This is done by specifying low dimensionality (e.g. 2-dimensions) and allowing the algorithm to randomly select from among a suite of possible covariates – effectively resulting in an ensemble of hundreds of competing models.

Here, we used the range bagging algorithm with dimensionality set to 2 (meaning only two covariates are fitted at a time), the number of bootstrapped models set to 100 and the proportion of occurrence records used per model set at 0.5. We allowed the algorithm to sample from all 19 WorldClim 2 (Fick & Hijmans, 2017) bioclimatic parameters (i.e. BIO01 to BIO19) derived from the published 2.5 minute (approximately 5 km resolution) raster layers. We used ensembles of "simple" two-dimensional models in order to minimise biases associated with model over-fitting and collinearity, and thus, maximise the model's transferability into novel environments (Camac *et al.*, 2020). Work by Breiner *et al.* (2017) has found that using ensembles of small models, each with only two variables, often outperforms standard SDM methods.

We used occurrence records of *Halyomorpha halys* collated by Kriticos *et al.* (2017). Prior to running the range bagging algorithms we first cleaned these occurrence records by using cleaning routines in the recently published `CoordinateCleaner` R package (Zizka *et al.*, 2019). Specifically, we removed records that:

1. had equal latitude and longitudes or within 0.5-degrees radius of coordinates 0,0;
2. were within a 5 km radius of a capital city;[1]

[1]In databases such as GBIF, if a record does not have accurate coordinates, sometimes coordinates are entered as centroids of either the country of detection or nearest capital city. While such coordinates are useful for providing information on the country or province of the record, they will be too coarse when estimating the climatic suitability of a species.

3. were within a 10 km radius of the centroid of a country or province;

4. were within 1-degree radius around the GBIF headquarters in Copenhagen, Denmark;

5. were within 100 m radius around known biodiversity institutions;

6. were located in the ocean;

We also removed duplicate records and thinned occurrence records to one point per 2.5 arc-minutes (the spatial resolution of the WorldClim 2 climate data). Following this, we removed all occurrence records that were outside known countries of establishment as verified by the Australian Government (Table 3.1). This ensured that the remaining occurrences were most likely from established populations, and thus suitable for inclusion in the range bagging analysis[2].

Subsequently, models were fitted and then projected globally at 2.5 minute resolution. The outcome of this approach (Fig 3.2) was a suitability map that appeared to be in between the CLIMEX model and the Maxent model produced by Kriticos *et al.* (2017) and Zhu *et al.* (2012), respectively (See Appendix Fig A.1), with highest suitability in Europe, western Russia, eastern and central USA, South Africa, northern Argentina and eastern and south-western Australia.

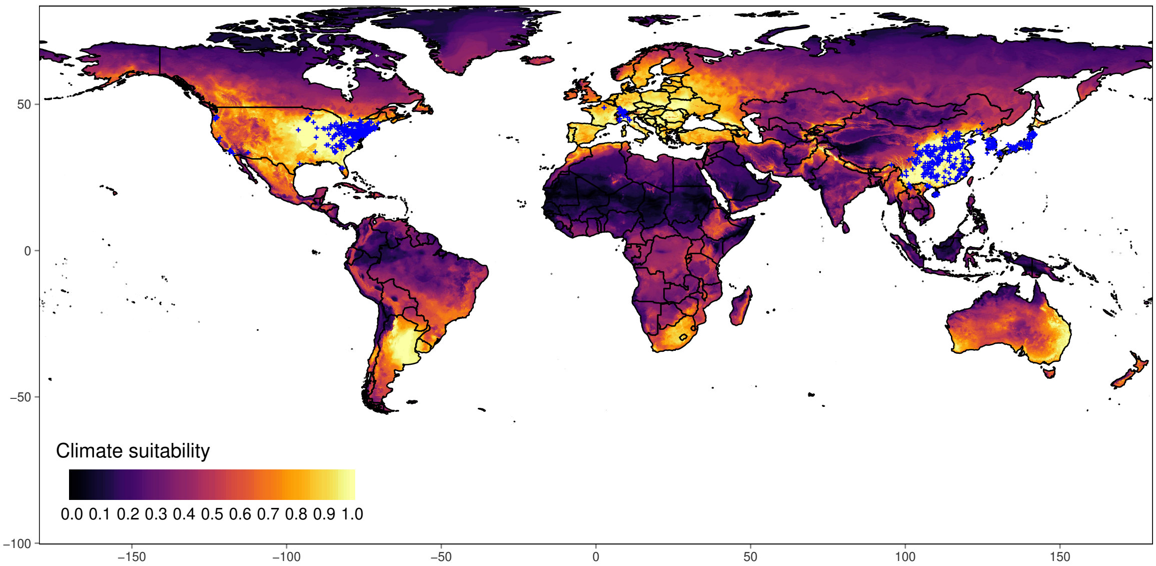

Figure 3.2.: Estimated climate suitability for brown marmorated stink bug. Suitability is the proportion of ensembled convex hulls that identify a location as climatically suitable across bootstrapped combinations of environmental variables.

[2]Note that, if such an internal list of infected countries is not available, one can use country statuses defined in CABI.

3.2. Estimating the number of pest arrival events for each trading partner

3.2.1. BMSB interceptions & general contamination data

To estimate the number of BMSB arrival events for current and potential trading partners we integrated three datasets collated and supplied by the Australian Department of Agriculture, Water and Environment (DAWE). The first of these was an internally reviewed and verified list of all countries known to contain established BMSB populations (Table 3.1). This list was used to identify 30 potential BMSB source countries. The second dataset contained 560 BMSB border interceptions that occurred between 2004 and 2018. Here, each record identified the consignment type as defined by HS code (i.e. Harmonized Commodity Description and Coding System; see Table A.1) and the likely country of origin. Some information was also available on the number and status (alive/dead) of bugs detected, however, this these details were not always recorded and varied significantly in how they were reported (i.e. counts estimated quantitatively or qualitatively). As such, for the purposes of this analysis, a BMSB interception included the detection of any bugs (alive and dead) on imported consignments. Invariably this meant that our model does not differentiate between interceptions containing few individuals relative to those containing hundreds, with the latter more likely to result in a viable established population.

Apart from providing us with BMSB interceptions, the dataset was also used to identify 95 BMSB susceptible tariffs (i.e. any HS codes with at least one BMSB interception). The third dataset was derived from the Integrated Cargo System (ICS) for the period between 2013 to 2018. This dataset contained annual counts of the total number of consignments imported into Australia, the number of border inspections and the number of detected contaminations for all 4-digit HS tariff codes (i.e. Harmonized Commodity Description and Coding System) and most BMSB source countries. These data were used to estimate the proportion of consignments inspected at the border. However, for some countries we were unable to source ICS data (Table 3.1), and where this occurred the proportion of consignments inspected was approximated using the median inspection rate across BMSB source countries for the relevant HS code/year [3]. In addition to this, for countries where we had ICS data, we also extracted the general contamination counts. Here, contamination refers to the presence of any organism in a consignment and not just those associated with BMSB. We included contamination counts because they provide a secondary measure from which to model pest arrivals. This can be particularly useful where there are few or no species-specific interceptions (e.g. new pest or disease), or in situations where species-specific interceptions are considered unreliable or not representative (e.g. biased inspection effort).

The final integrated dataset contained BMSB interceptions and general contaminations as well as the proportion of consignments inspected for each HS code by source country. Preliminary examination of the data between 2013 and 2018 revealed that BMSB had been intercepted 159 times on goods coming from 9 countries with known infestations. Italy, the USA and China had the highest numbers of recorded BMSB interceptions, followed by Japan and Romania, and lastly Canada, Russia, France and

[3] We deemed the median appropriate because for many cases, the variability in inspection rates for a high-risk tariff in a given year across infected countries was small. Moreover, sample sizes within tariff by year combinations were too small <4 to use reliably use imputation methods.

Germany, who each had 1 interception. Similarly, Italy and the USA also had the highest general contamination counts and were among the countries that traded the greatest numbers of BMSB-susceptible tariffs (Table 3.1).

Table 3.1.: Potential source countries with total counts of BMSB interceptions and contaminations (i.e. the presence of any organism in a consignment) observed between 2013 and 2018. N tariffs refers to the number of BMSB-susceptible HS codes exported to Australia. Contamination refers to the number of consignments that contained a presence of any organism. Missing refers to countries for which we were unable to source appropriate ICS data. Dem. People's Rep of Korea (i.e. North Korea) is included as a source country but does not officially export goods.

Country	Range	N tariffs	Interceptions	Contaminations
Italy	Invaded	93	78	1533
USA	Invaded	95	44	2849
China	Native	95	25	Missing
Japan	Native	88	6	1575
Romania	Invaded	71	2	12
Canada	Invaded	91	1	Missing
Russian Federation	Invaded	73	1	9
France	Invaded	93	1	297
Germany	Invaded	93	1	1461
Rep. of Korea	Native	92	0	Missing
Belgium	Invaded	91	0	Missing
Czechia	Invaded	84	0	Missing
Chile	Invaded	69	0	Missing
Bulgaria	Invaded	61	0	Missing
Malta	Invaded	47	0	Missing
Kazakhstan	Invaded	45	0	Missing
Bosnia Herzegovina	Invaded	32	0	Missing
Rep. of Moldova	Invaded	5	0	Missing
Austria	Invaded	87	0	9
Greece	Invaded	74	0	9
Slovenia	Invaded	73	0	9
Turkey	Invaded	85	0	56
Spain	Invaded	92	0	499
Serbia	Invaded	58	0	4
Hungary	Invaded	70	0	34
Croatia	Invaded	60	0	3
Switzerland	Invaded	88	0	22
Slovakia	Invaded	66	0	122
Georgia	Invaded	13	0	0
Dem. People's Rep. of Korea	Native	0	NA	NA

3.2.2. Trade data

To get a global and standardised measure of trade flow of BMSB-susceptible material between source countries and all other countries we extracted export statistics from the United Nations Comtrade database (UN Comtrade; https://comtrade.un.org). This database is the largest publicly accessible repository of international trade data, with over 3 billion records of import and export trade statistics collated since 1962. Specifically, we extracted the annual value (in USD) of exports of each of the 95 HS tariff codes from all BMSB source countries to each of their importing partners.

Trade value statistics relevant to Australia between 2013 and 2018 were then merged with the general contamination dataset such that each susceptible tariff code imported from a BMSB source country now had an estimated annual trade value. However, as imported consignments varied in inspection rates and because we did not have data on values of inspected consignments, we multiplied the trade value by the proportion of consignments inspected. This effectively gave us an estimate of the trade value inspected by Australian border authorities. While this is the best we had available, it invariably introduces a strong assumption that all consignments from a particular tariff-country-year combination are of equal value/size. After removing country by tariff combinations with zero border inspections – for which we cannot infer exposure risk – our final dataset contained 4306 rows of BMSB interception and general contamination count data.

3.2.3. Count model

Next we built Bayesian Generalised Additive Mixed Models (GAMMs) that modelled annual counts of BMSB interceptions and general contaminations, y_{ijt}, for each combination of country of origin, i, by tariff, j, by year, t, as a function of the logged trade value (USD) with random intercept effects for country of origin, ε_i, tariff code, ε_j, and year, ε_t:

$$y_{ijt} = \alpha + \text{USD}_{ijt} + \varepsilon_i + \varepsilon_j + \varepsilon_t. \tag{3.1}$$

We included random effects for four critical reasons: 1) they provide a convenient method for appropriately accounting for the non-independent structure of observations within years, country of origin and tariff codes; 2) they allow us to estimate group-level effects without substantially increasing the degrees of freedom; 3) they allow estimation of group-levels with few observations through a method referred to as "partial pooling" (Gelman & Hill, 2007) whereby low observation groups are estimated closer to the mean across groups, but are also more uncertain relative to groups with many observations; and most importantly 4) they provide a means for making predictions to new group-levels not included in model fitting (e.g. infected country or high risk tariffs not imported into Australia) (Gelman & Hill, 2007).

Models were fit using the R package `rstanarm` (Goodrich *et al.*, 2020) and the function `stan_gamm4` with a weakly informative prior specified on the intercept ($\mathcal{N}(0, 10)$). We ran the models using 4 chains, sampling 2000 iterations for each. Chain convergence was assessed using the Brooks-Gelman-Rubin convergence diagnostic (Brooks & Gelman, 1998). As BMSB interceptions and general contaminations are relatively rare events, there was a considerable proportion of zeros in both sets of data (0.98, 0.72, respectively). As such, to assess for possible over-dispersion in the count data, models were sampled using both Poisson and negative binomial distributions. A combination of posterior predictive checks on the proportion of predicted zeros and 10-fold cross validation was used to determine the most appropriate distribution to use. For the BMSB interception model, no discernible difference in predictive capacity was found between the Poisson and negative binomial models (Fig A.2). Furthermore, posterior predictive checks highlighted that the Poisson model accurately predicted the observed proportion of zeros (Fig A.3); as such, for this response we used the Poisson distribution. By contrast, for the general contamination response, both cross-validation (Fig A.4) and posterior predictive checks (Fig A.5) revealed that the negative binomial model was substantially better at prediction. We also considered the inclusion of other predictors associated with BMSB source countries such as whether the country was within the endemic range, and using the climatic suitability layer, the mean climatic suitability, the summed climatic suitability and the sum of climate suitability scaled by human population. However, in all cases, 10-fold cross-validation revealed that the inclusion of these additional predictors did not improve predictive capacity and they were therefore omitted (Fig A.6). While the models did a good job at predicting zeros and low BMSB/ general contamination counts, they each tended to underestimate the rare events where high counts of BMSB interceptions or general contaminations were recorded from particular country by tariff combinations (Fig A.7).

Once the final set of models was trained on the integrated dataset, we took 1000 draws from the posterior and used these to make posterior predictions of expected counts of both BMSB interceptions and general contaminations arriving at all countries as a function of imports of the 95 susceptible tariffs originating from the 30 identified BMSB countries. Predictions were made using 2018 (the latest year with complete data) trade value data extracted from the UN Comtrade database. For country-tariff combinations not present in the training dataset, posterior predictions were made by marginalising over the relevant predictor variables. In order to account for the uncertainty on the count model, we extracted three prediction quantities: the median and the lower and upper bounds of 95% credible intervals (roughly interpretable as the expected, best case, and worse case scenarios). As predictions were for each importing country, k, by susceptible tariff, j, and country of origin, i, we summed the expected counts to derive a median, lower and upper estimate of the total arrivals for each importing country:

$$\hat{y}_k = \sum_{i,j} \hat{y}_{ijk}. \tag{3.2}$$

3.3. Estimating country-level establishment exposure

As imported goods are assumed to be dispersed, and subsequently opened within a country as a function of population counts, we obtained a 2.5 arc-minute (approximately 5 km) resolution raster of expected human population counts for 2020 developed by Columbia University's Center for International Earth Science Information Network (CIESIN; 2018; Fig. 3.3). We deemed this an appropriate spatial resolution because: 1) it was a resolution that has been released and validated for both climate data and human population counts, and thus, meant we were using the original validated datasets as supplied with minimal GIS post-processing; and 2) it was a spatial scale that was not too fine that it would lead to computational issues (e.g. RAM exhaustion), or too coarse such that climate suitability in small countries, or those with complex terrain would be over or under-represented.

Using the human count raster, we distributed the expected (median), best (2.5% credible interval) and worst (97.5% credible interval) scenario estimates of expected BMSB interceptions and general contamination counts within each country, k, as a function of human population present in each cell l:

$$N_{kl} = \frac{\text{population count}_{kl}}{\sum_l \text{population count}_{kl}} \times \hat{y}_k. \tag{3.3}$$

We then weighted these expected arrivals in each grid cell, l, by the estimated climatic suitability of that location:

$$N_{\text{weighted}_{kl}} = N_{kl} \times \text{Climate suitability}_l, \tag{3.4}$$

where climate suitability is bounded between zero and 1 (i.e. the raw output from range bagging).

Finally we estimated the median, lower and upper country-level exposure to pest establishment, Exposure_k, by summing the climate weighted counts for each country:

$$\text{Exposure}_k = \sum_l N_{\text{weighted}_{kl}}. \tag{3.5}$$

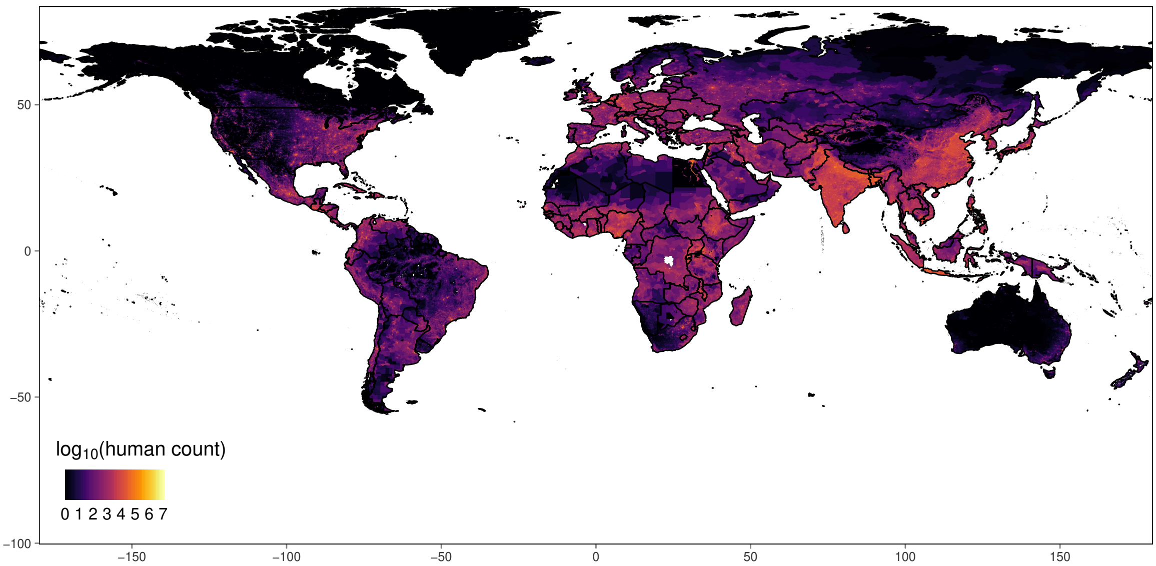

Figure 3.3.: $\log_{10}$ Human population counts. Raster derived from Columbia University's Center for International Earth Science Information Network (CIESIN 2018)

3.3.1. Exposure rankings

Biosecurity practitioners may require countries to be ranked relative to their exposure score for allocating finite border surveillance resources. In order to provide them with such ranks, we ranked countries in descending order of exposure risk. However, as we had three separate estimates of exposure (expected, best and worst case), we provided four ranked sets. The first three are simply the rank order associated with each of the three scenarios. By contrast, the fourth ranking, which we refer as the *overall rank*, attempts to account for rank order changes among the three scenarios. Here, we encapsulate those changes by summing the rank positions across the three scenarios, and then ranking the summed output in ascending order – whereby countries with lower sums have higher exposure risk. This was done using both BMSB interception data and general contamination data.

4. Results

Our analysis revealed that exposure to BMSB establishment as a function of interception data was greatest for Australia, the United Kingdom, the Netherlands, Poland, Hong Kong, Mexico, South Africa, Sweden and Denmark (Fig 4.1A, Table 4.1). Broadly, similar patterns were also found when using exposure scores estimated from general contamination data (Fig 4.1B, Table 4.2 – the most notable being that both models estimated that the United Kingdom and the Netherlands were within the top three most exposed out of 222 countries/territories. However, discrepancies in country ranks were evident, with Hong Kong[1], for example, being ranked 5th based on BMSB interception data and 13th based on general contamination data (See Tables A.2 and A.3 for full lists of ranks, or A.4 and A.5 for full lists of exposure scores). Australia ranked highly because by the nature of how the model was built, it had high coverage of susceptible tariffs being imported from infected countries, and contained suitable climate in regions where these goods would most likely be dispersed (i.e. eastern coast).

[1]It should be noted that Hong Kong, and others such as Singapore, are major distribution centres of international trade. As such, it is possible they are being inappropriately assigned as the importing country in the Comtrade database when in fact they may act as an intermediary between two trading countries

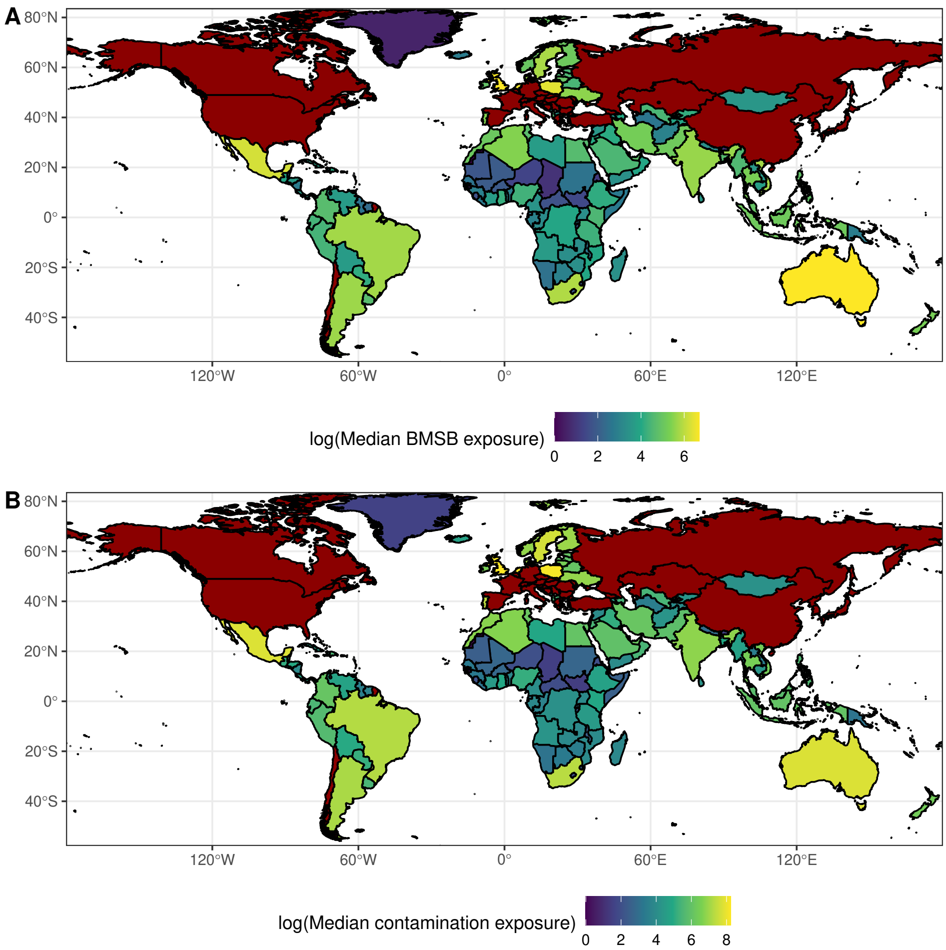

Figure 4.1.: Country-level exposure based on: A) BMSB interceptions; and B) General contamination records. Red = countries with known established BMSB populations. Note: While French Guiana and Alaska have no known BMSB populations, they are territories of France and the USA and as such have been masked red.

Table 4.1.: Exposure ranks of top 15 non-infected countries based on BMSB interception and trade data

Country	Overall rank	Median rank	2.5% rank	97.5% rank
Australia	1	1	1	4
United Kingdom	2	2	2	2
Netherlands	3	3	3	1
Poland	4	4	5	3
China, Hong Kong SAR	5	5	4	5
Mexico	6	6	6	6
South Africa	7	7	8	8
Sweden	8	8	10	7
Denmark	9	11	7	9
Viet Nam	10	9	9	12
Brazil	11	10	11	11
Argentina	12	12	13	14
India	13	13	12	15
Ukraine	14	14	17	10
Portugal	15	16	15	13

Table 4.2.: Top 15 non-infected countries with highest exposure ranks based on general contamination and trade data

Country	Overall rank	Median rank	2.5% rank	97.5% rank
United Kingdom	1	1	1	1
Netherlands	2	2	2	2
Poland	3	3	3	3
Mexico	4	4	4	5
Australia	5	5	5	4
Sweden	6	6	6	6
Portugal	7	7	8	7
South Africa	8	8	9	8
Brazil	9	9	7	9
Denmark	10	10	11	10
Argentina	11	11	10	11
Finland	12	12	13	13
China, Hong Kong SAR	13	13	14	14
India	14	16	12	16
Norway	15	15	15	15

While not a core objective, our model also estimated the establishment exposure for all BMSB-infected countries based on susceptible goods they import from other countries with BMSB populations. In examining these predictions (see Tables A.2 to A.5) we found that the USA, Germany and France were all ranked within the top four most exposed countries, irrespective of whether we used interception or general contamination data to parameterise our model.

The distribution of country exposure scores showed that in general, countries within the invaded or native range of BMSB had higher exposure scores relative to those with no known BMSB populations (Fig 4.2). This is mostly due to these countries both containing substantial areas of suitable climate and importing large quantities of goods from other BMSB-infected countries. The clear exception being North Korea, the outlier within BMSB's native range, which predominately only imports goods from China (Fig 4.2B). We also found that, at least according to the BMSB interception model (Fig 4.2A), the USA was a clear outlier – being the country most exposed to further BMSB incursions.

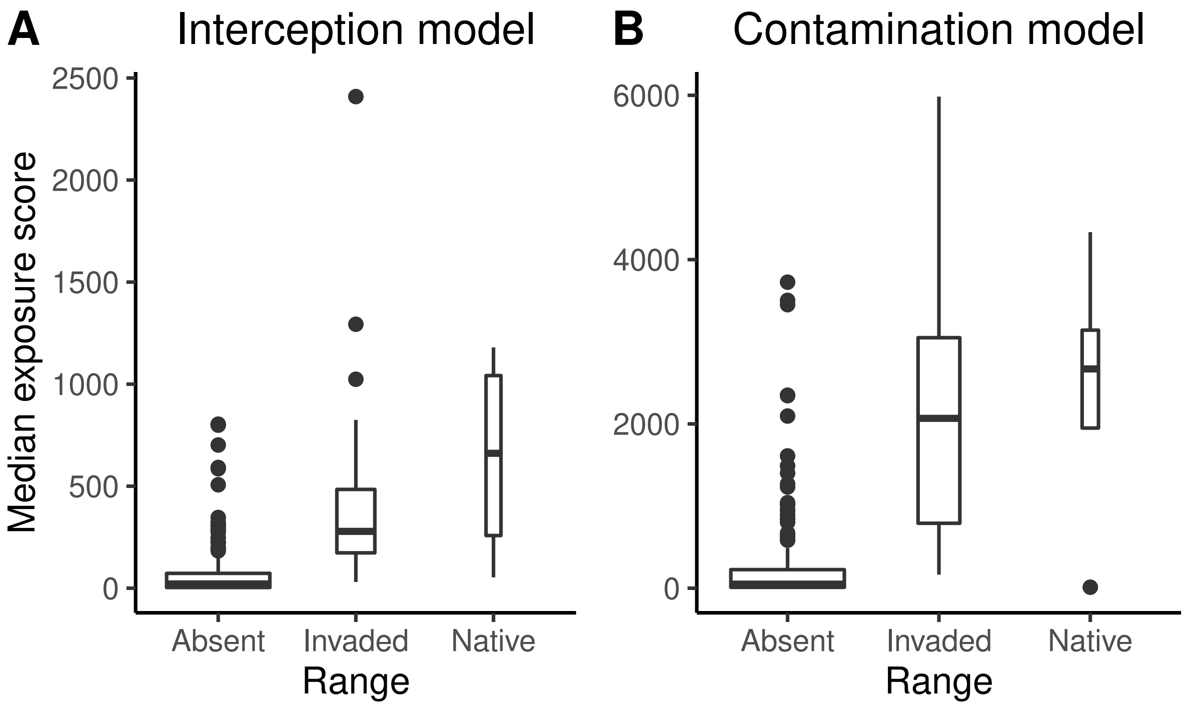

Figure 4.2.: Exposure scores by range status. Distribution of predicted median exposure scores based on the: A) BMSB interception model and B) general contamination model. The widths of box plots are proportional to the square-root of the number of observations in each range group.

Closer examination of the models revealed a strong non-linear relationship between the logged value (in USD millions) of imported susceptible goods from BMSB-infected countries. Specifically, we found that as the annual value of imported goods increased so did the risk of BMSB contamination, irrespective of whether BMSB interception or general contamination data were used. However, this relationship tended to be more uncertain for low-value imports – particularly for the interception model.

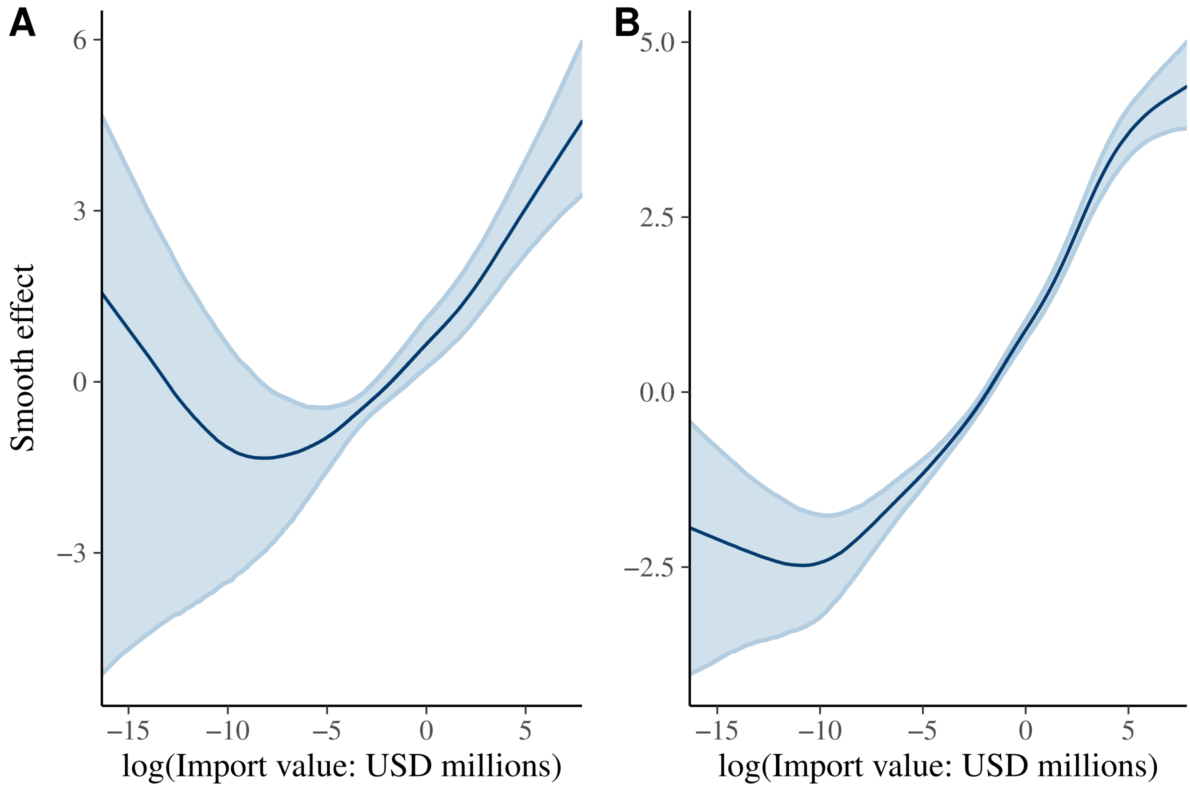

Figure 4.3.: Import value effects. Mean (± 95% credible intervals) effect of annual import value (in USD millions) on BMSB contamination using: A) BMSB interception data; B) General contamination data.

Examination of the additive source country effects revealed differential risk posed by BMSB-infected countries. According to the BMSB interception model, goods imported from China, Italy, Puerto Rico and Romania posed the most risk – each contributing significant positive effects to BMSB counts (Fig 4.4A). Italy and Puerto Rico were found to have the highest risk based on the general contamination model (4.4B). However, where country effects were estimated in both models, some differences existed. Goods imported from Spain, for example, were expected to be of higher risk in the general contamination model (i.e. positive effect) but considered much lower risk in the interception model. This difference is mostly due to the underlying general contamination data not being BMSB-specific but rather a general catch-all for any pest/disease interception or import document errors.

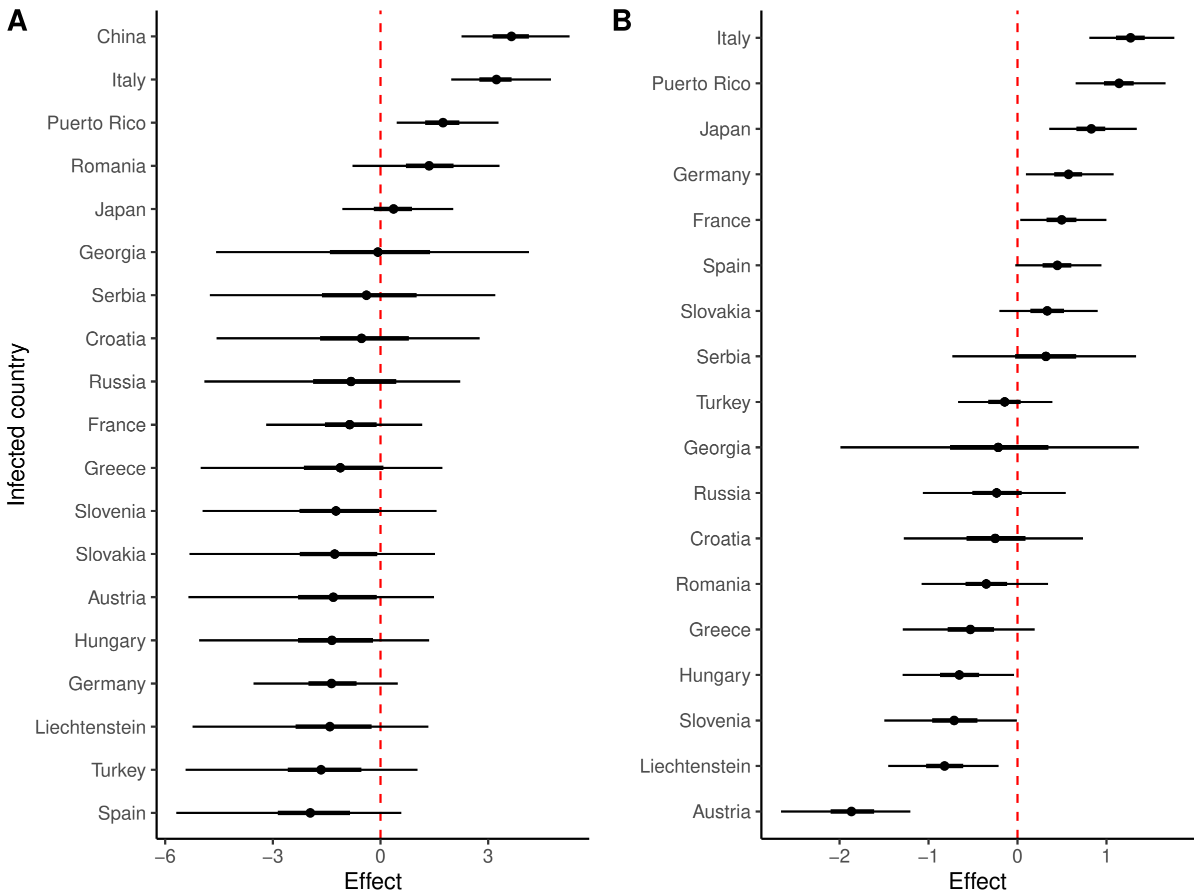

Figure 4.4.: Source country effects. Mean (± 95% & 50% credible intervals) source country effects using: A) BMSB interception data; B) general contamination data. Effects are interpreted as additive effects relative to the average intercept. Estimates above the red zero line are positive effects (i.e. increases counts) and those below it are negative effects (i.e. decreases counts). Note that countries such as China, South Korea and others (see Table 3.1) are missing from the general contamination dataset, and thus, the model is unable to estimate their observed effects.

Differential risk was also observed among the 95 BMSB-susceptible tariffs (Fig 4.5). In the BMSB interception model (Fig 4.5A) we found that HS codes 9401 (i.e. seats), 8609 (i.e. containers) and 8701 (i.e. tractors) posed the greatest risk (i.e. most positive effects). By contrast, the general contamination model indicated that 0810 (i.e. fresh fruit), 7318 (i.e. screws and bolts) and 8708 (i.e. motor vehicles) posed the most risk. As with the differences among country effects these discrepancies between models are mostly due to the underlying general contamination data not being BMSB-specific but rather a general catch-all for any pest/disease interception or import document errors. As such, BMSB-specific interventions are ignored in the general contamination dataset, which invariably manifests in differences in tariff risk profiles.

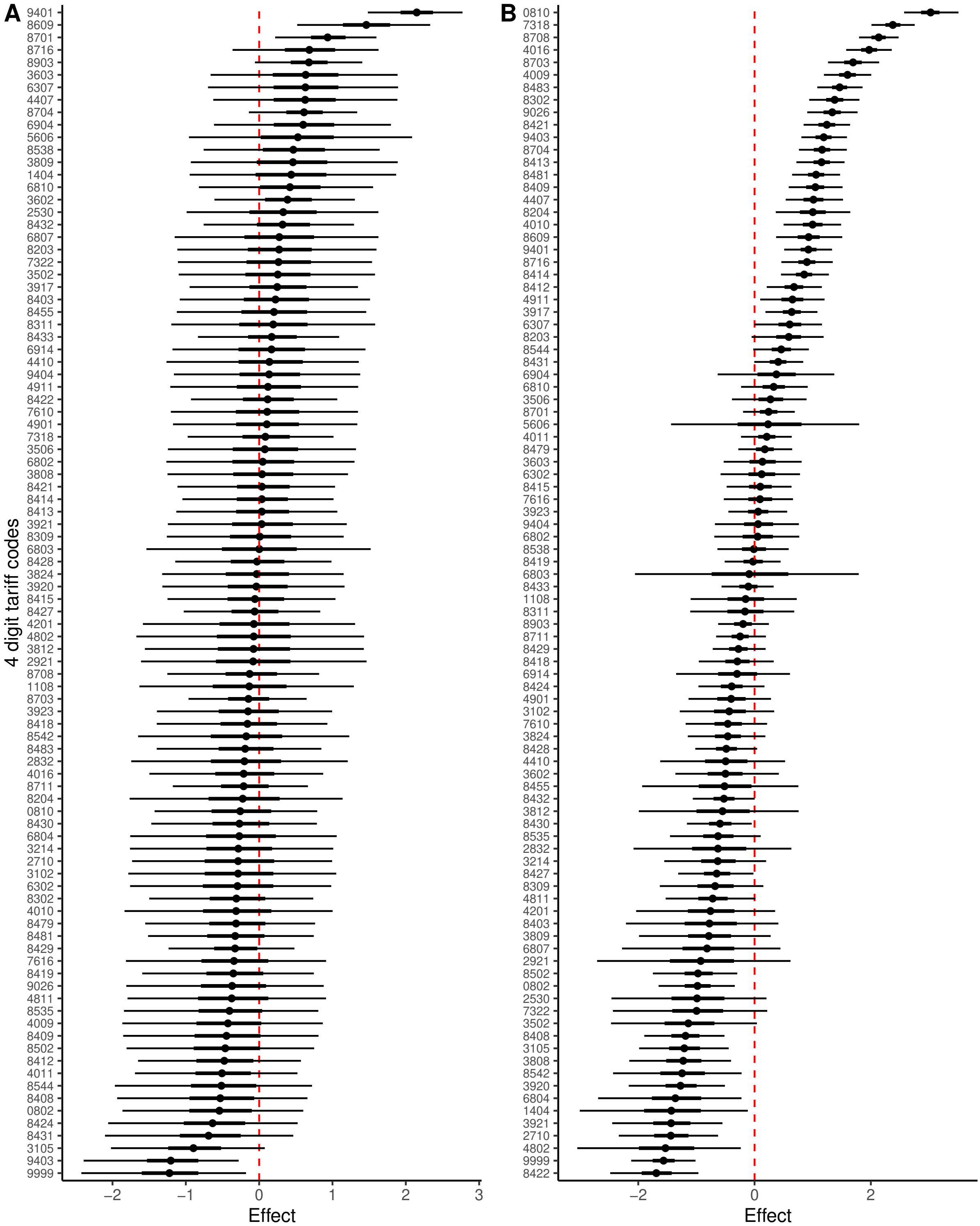

Figure 4.5.: Tariff effects. Mean (± 95% & 50% credible intervals) BMSB susceptible HS code effects using: A) BMSB interception data; B) general contamination data. Effects are interpreted as additive effects relative to the average intercept. Estimates above the red zero line are positive effects (i.e. increases counts) and those below it are negative effects (i.e. decreases counts).

Lastly, we found differential effects among years (Fig 4.6). In the BMSB interception model (Fig 4.6A), 2018 had more BMSB interceptions than other years, while 2016 had fewer than average. By contrast, the general contamination model (Fig 4.6B) indicated that both 2013 and 2018 had the fewest contaminations, while other years had average or slightly above average contaminations.

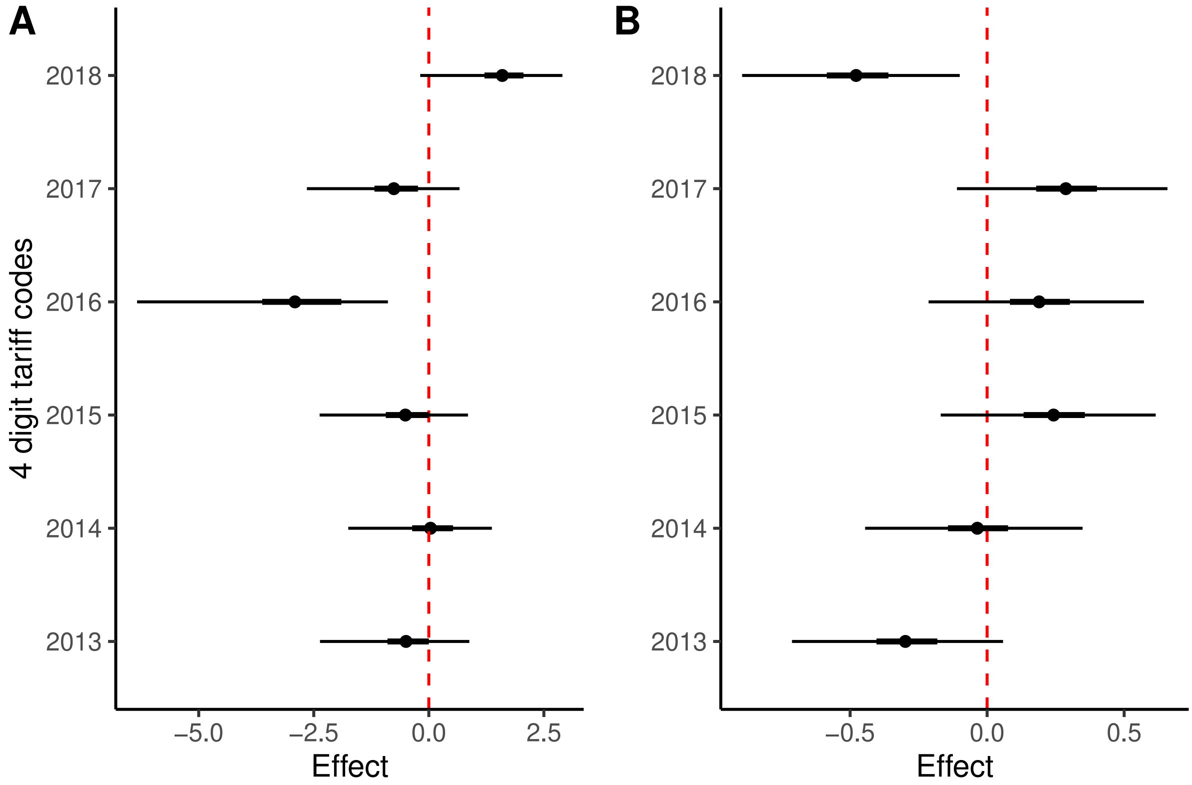

Figure 4.6.: Year effects. Mean (± 95% & 50% credible intervals) year effect using: A) BMSB interception data; B) general contamination data. Effects are interpreted as additive effects relative to the average intercept. Estimates above the red zero line are positive effects (i.e. increases counts) and those below it are negative effects (i.e. decreases counts).

5. Discussion

We developed a novel method that integrates border interceptions, trade data, pest occurrence records and climate suitability models to estimate the exposure risk of potential and current trading partners obtaining a new high threat pest or disease. We illustrate its implementation using Australian BMSB interception and general contamination data to model the exposure risk of brown marmorated stink bug (BMSB), a highly polyphagous plant pest that has rapidly spread across much of the Northern Hemisphere, and in doing so, caused significant agricultural losses (Rice *et al.*, 2014; Valentin *et al.*, 2017). We found that, irrespective of parameterising the model using BMSB-specific interception or general contamination data, the United Kingdom, the Netherlands, Poland, Mexico and Sweden were amongst the most exposed countries to BMSB incursions and subsequent establishment. This suggests that these countries, relative to others, not only import significant quantities of potential BMSB hitchhiker commodities from BMSB-infected countries, but are expected to have suitable climate in regions where these imported goods are likely destined (i.e. regions of high human population).

Comparing exposure scores between non-infected and infected countries also provided some measure of confidence in the model predictions (Tables A.2 –A.5. Germany, the USA, France and Italy – countries within BMSB's invaded range – were found to have some of the highest exposure scores. Assuming patterns in imported goods have not substantially changed over the last two decades, it is perhaps unsurprising that these countries were among the first to gain established populations of BMSB (CABI, 2020), and in some cases (e.g. USA and Italy), thought to have contributed to infestations elsewhere (Valentin *et al.*, 2017).

Lastly, in estimating country-level exposure to BMSB, our model also identified the BMSB-vulnerable tariff codes that are likely to introduce the greatest number of hitchhikers into Australia. For BMSB specifically, the highest risk tariffs were HS codes 9401 (i.e. seats), 8609 (i.e. containers) and 8701 (i.e. tractors), while for general contaminations (i.e. the presence of any foreign organism) codes 0810 (i.e. fresh fruit), 7318 (i.e. screws and bolts) and 8708 (i.e. motor vehicles) posed the greatest risk.

We believe this model is a substantial improvement over others that are currently available to biosecurity practitioners. First and foremost, our model was designed with the end-users in mind (biosecurity practitioners). As a consequence, the analytical workflow aims to maximise the use of internally collected border surveillance data (e.g. interception records) and integrate these data with other publicly available data (e.g. trade data and climate data). Second, the workflow is applicable to any plant pest or disease. For example, if one wished to apply the model to a pest thought to be highly tolerant of a wide range of climatic conditions, or that is a pest of stored food where ambient conditions matter little (e.g. Khapra beetle), then exposure would be estimated as the unweighted expected number of arrivals each country receives (Fig. A.8). Thirdly, relative to standard pathway models that focus on identifying risk pathways of entry into an individual country, our model is both inwards and outwards focused, such that it estimates exposure risk across all countries. Finally, and perhaps most importantly, our method explicitly integrates pathway analysis with climate suitability modelling. This effectively means our model attempts to account for two fundamental geographic barriers to pest establishment: 1) its ability to reach a location; and 2) the suitability of the climate at the destination (Catford *et al.*, 2009). This is contrary to standard pathway analyses, which generally ignore climatic suitability, or do not explicitly combine it with pathway information (Tingley *et al.*, 2018) – and is also contrary to standard invasive species distribution modelling (sometimes termed risk maps), which tend to focus on modelling climate suitability without accounting for pathways of entry and subsequent post-border movement of propagules (Venette *et al.*, 2010; Elith, 2017; Venette, 2017).

5.1. Model assumptions and decisions

While this method provides a pragmatic and transparent approach to quantifying trading partner exposure to new and emerging pests, the model relies on several assumptions that warrant careful consideration before using its findings to inform allocation of border surveillance resources.

5.1.1. Fundamental assumptions

Our model makes two fundamental assumptions based on pragmatic constraints associated with the available data. The first of these is that the interception or general contamination rates that Australia (i.e. our case study focal country) observes from each infected country by tariff combination is representative of 1) the propagule pressure and; 2) are consistent with trade going to other countries. This assumption is likely to be violated in some circumstances. However, without a global database in which each country is mandated to upload interceptions and the amount of surveillance effort they undertook, we believe this is likely the best data available to inform practical biosecurity decisions, and thus, an assumption we were willing to make.

The second major assumption is that the trade data used in this model are complete and accurately reflect the volume, country of origin and final destination of traded goods. Despite great effort in standardising and cleaning trade statistics held in the UN Comtrade database (United Nations Department of Economic and Social Affairs, 2017), inaccuracies, including in the documented country of origin and final destination, are likely still present. For example, countries such as Hong Kong and Singapore, which contain major shipping distribution centres, may be inaccurately documented as either the origin or final destination of goods, when in fact these countries may act as intermediaries where imported goods exchange hands, but are quickly exported elsewhere without containers being opened or moved outside the port.

The last assumption made was that detection rates were assumed to be perfect. Again this assumption is almost certainly untrue (Garrard *et al.*, 2008; Wintle *et al.*, 2012). However, given detection rates are expected to vary substantially among species (Garrard *et al.*, 2012; Martin, 2017) as well as other factors such as tariff types, points of entry, and the size and arrangement of consignments (which were not recorded), coupled with the lack of leakage survey data, estimating such rates is currently not practical without making additional strong assumptions.

In terms of our case study pest, brown marmorated stink bug, the assumption of perfect detection was less of an issue because the rate of detection of large aggregations capable of establishing a hitchhiking founder population – the detection quantity of concern to the Australian government (DAWR, 2017) – was expected to be high (McCarthy *et al.*, 2013). Furthermore, given Australia has one of the most comprehensive and stringent biosecurity systems in the world (Nairn *et al.*, 1996; Beale *et al.*, 2008; Craik *et al.*, 2017), we believe that the interception/ general contamination datasets collated by the Australian government are likely to represent the gold standard currently available for estimating country-level exposure risk.

5.1.2. Model decision 1: Pest-specific interceptions vs. general contamination?

A decision needs to be made as to whether the model is parameterised using pest-specific interceptions or general contamination data. While our analysis revealed that both data types resulted in similar risk profiles among countries, differences in rankings did occur. In most situations, pest-specific interception data are likely to be the gold standard and should be preferenced ahead of general contamination records. However, if the data are biased (e.g. border surveillance focused on particular countries or tariffs) or otherwise not considered representative of the entry pathway risk profile then the use of general contamination data may be more appropriate. A new and emerging pest or disease that has limited or no interceptions is one such example where general contamination data will be necessary. How well such data represents the focal species' risk pathways, however, will ultimately depend on how narrowly contamination data can be practically defined. For plant pests, for which this method is designed, we recommend that border-surveillance staff attempt to identify contaminations to at least taxonomic class, or in terms of functional type (e.g. sap sucking insects, fruit flies, etc.). Doing so should allow biosecurity analysts to subset contamination to the group that is expected to be most representative of the emerging threat.

5.1.3. Model decision 2: Susceptible tariffs

In our analysis, we identified susceptible 4-digit HS tariff codes that could support BMSB hitchhikers using border interception data. While this dataset is likely to represent the most comprehensive list of susceptible tariffs available for a country, it may not encompass the full list of susceptible commodities. For example, a susceptible commodity may be missing from the list if infected countries exported that commodity to other countries but not the country used to create the list. We attempted to reduce this possibility by running the analysis at the 4-digit HS code level as opposed to the 8-digit code level. Further HS code aggregation (e.g. to chapter level) could be undertaken; however, doing so may severely underestimate risk in some situations (e.g. where there is only one sub-chapter tariff susceptible to the pest). Moreover, further aggregation may diminish the model's ability to inform risk-based decisions at the level required for setting tariff-level border inspection rates. We recommend further research be undertaken to determine the most appropriate aggregation level to 1) adequately capture high risk tariffs; and 2) inform on-ground border inspection rates.

5.2. Future extensions

It is important to note that this model only considers exposure risk associated with trade. Currently the model does not account for exposure related to air passenger movement, illegal trade, air-can movement, natural spread, or other pathways of entry. Modelling natural spread is likely to be a difficult exercise as it requires precise GIS locations of known established populations coupled with accurate estimates of dispersal kernels – data that may not be easily sourced from all countries. By contrast, estimating the exposure related to air passenger movements may be achievable through the combination of passenger inspection data and global air passenger movement data, which is increasingly being made available (Mao *et al.*, 2015).

The model may also be extended by examining the potential risk posed to Australia from individual countries (e.g. UK to Australia) as a function of estimated exposure score derived from this model, estimates of likely contamination rates (potentially derived from known infected countries, or assumptions about expected population sizes) and the value/volume of goods imported exported from one country the other. The reason for conducting such an analysis is that it will provide decision-makers with a more nuanced understanding of which countries, beyond those known to be infected, contribute the greatest potential risk to Australia, and thus, where to invest border screening activities to mitigate this risk.

Lastly, the model can be extended in two important ways that will ultimately increase decision-makers' ability to forecast changes, and thus plan for the future. First, rather than estimating exposure risk as a function of historical trade data sourced directly from the UN Comtrade database, which is typically 1-year or more behind in terms of complete data (e.g. as of 6th June 2020 only only 74.61% of the data for 2019 are available – `https://comtrade.un.org/db/`), one could use data from the Global Trade Analysis Project (GTAP; Aguiar *et al.*, 2016) coupled with GTAP models (e.g. Van Ha *et al.*, 2017) to forecast changes in trade flow patterns under a range of potential future global-trade scenarios. The second extension is to estimate the potential distribution of a pest's suitable climate under various climate change scenarios. By implementing both extensions it should be possible to forecast temporal and spatial changes in exposure risk, and consequently, predict when and where incursions are most likely to occur.

5.3. Model validation

Models such as the one proposed in this report are notoriously difficult to validate due to the nature of the problem it attempts to estimate – rare events – coupled with there being very few independent datasets available to accurately test model predictive performance. While out of scope for this project, one possibility would be to examine how well historical temporal patterns of establishment align with hind-cast predictions from the model. This validation exercise would bring additional challenges in that it requires:

1. the pest/disease to have only spread among countries predominately as a function of international trade or in a way that is correlated with international trade;

2. a detailed understanding of the time line of incursions and which country they originated from;

3. estimates of how interception/contamination rates have changed among countries and tariff types over time;
4. an understanding of how effective each countries biosecurity system is at mitigating the pest entry and establishment; and
5. historical estimates of trade flows among countries

Compiling a dataset that would meet all of the above conditions to accurately test the model's predictive performance would be a substantial undertaking. However, with the increased use of DNA analyses coupled with more sophisticated collation of border surveillance statistics among World Trade Organisation member countries such a dataset may be much easier to produce in future.

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A. Appendix

A.1. Appendix Figures

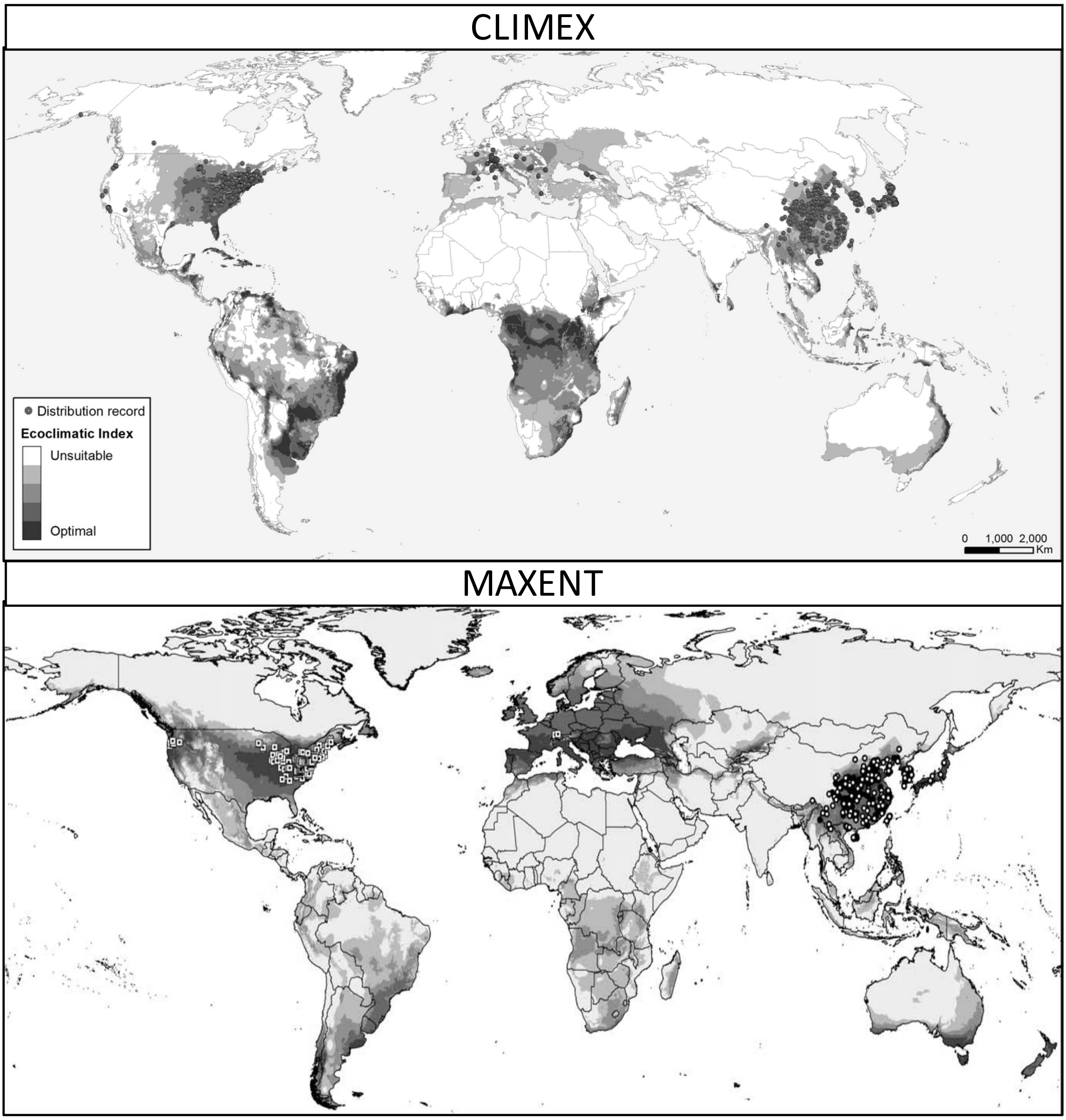

Figure A.1.: Published brown marmorated stink bug (*Halyomorpha halys*) CLIMEX (Kriticos *et al.*, 2017) and Maxent (Zhu *et al.*, 2012) distribution models. Darker shades indicate more suitable climate.

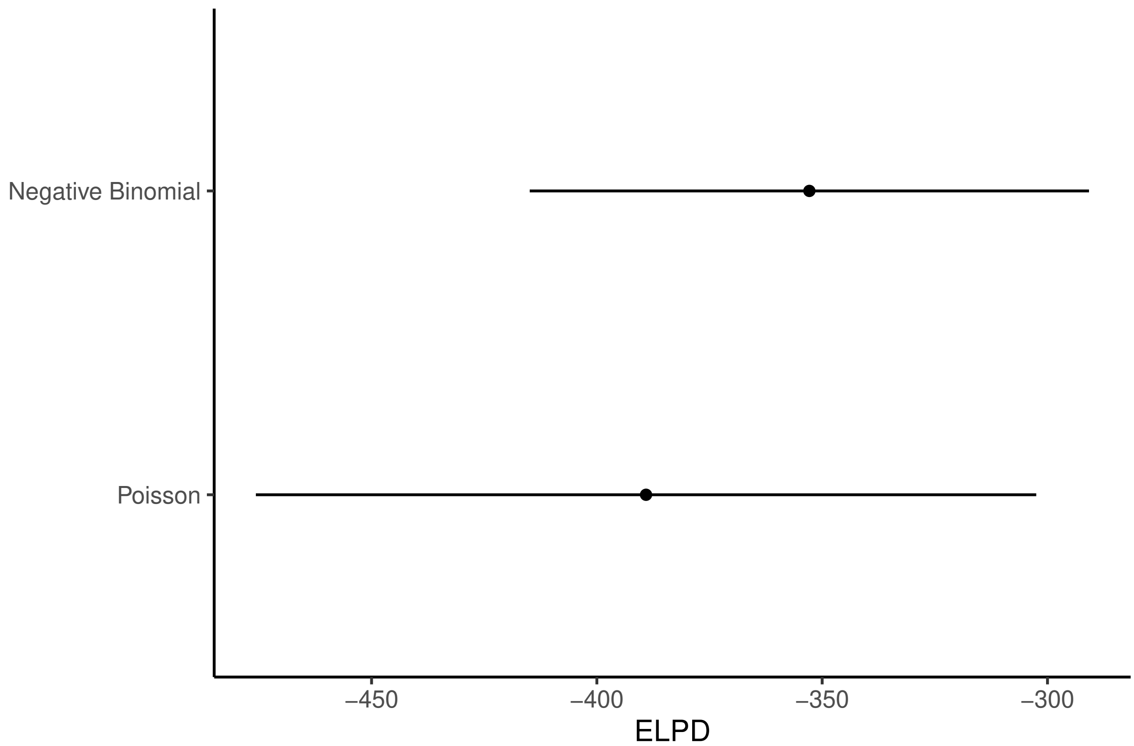

Figure A.2.: Cross-validation findings: Poisson vs negative binomial for interception model. Mean ($\pm$ 95% confidence intervals) Expected Log Predictive Density (ELPD) based on 10-fold cross-validation.

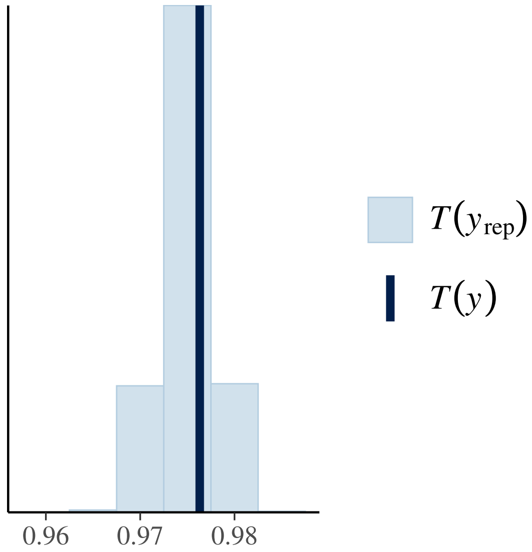

Figure A.3.: Posterior predictive check for interception model. Proportion of zeros predicted by model based on sample from posterior (T(y_{rep})) vs observed (T(y)).

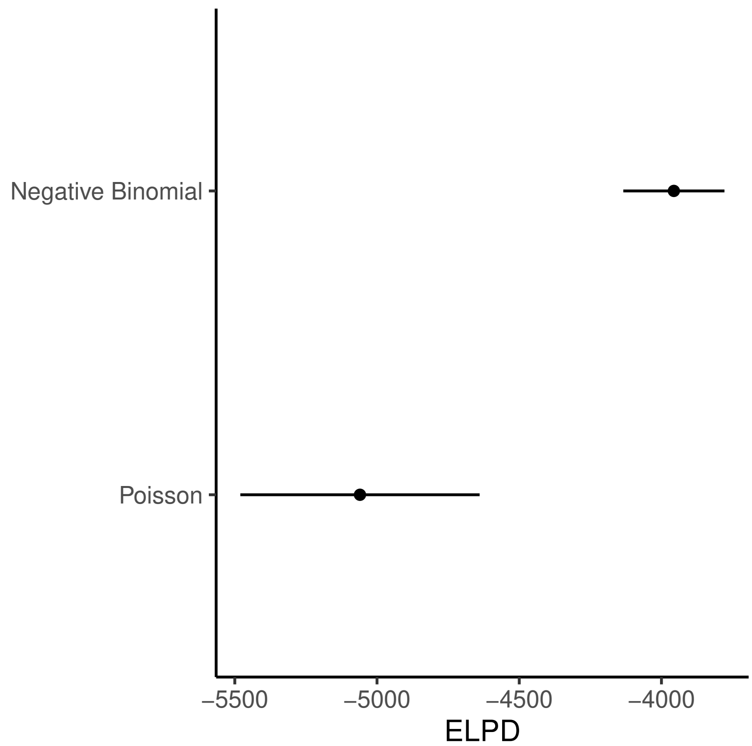

Figure A.4.: Cross-validation findings: Poisson vs negative binomial for general contamination model. Mean (± 95% confidence intervals) Expected Log Predictive Density (ELPD) based on 10-fold cross-validation.

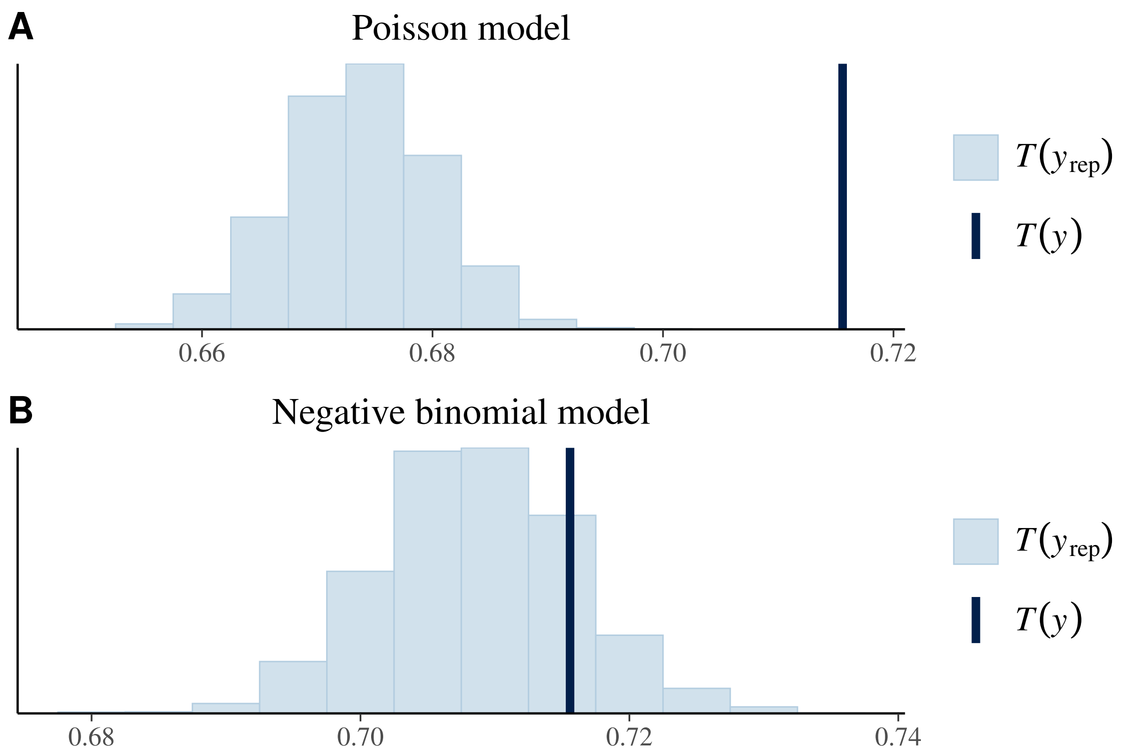

Figure A.5.: Posterior predictive check for general contamination model fitted with a: A) Poisson distribution; and B) a negative binomial. Proportion of zeros predicted by model based on sample from posterior (T(y_{rep})) vs observed (T(y)).

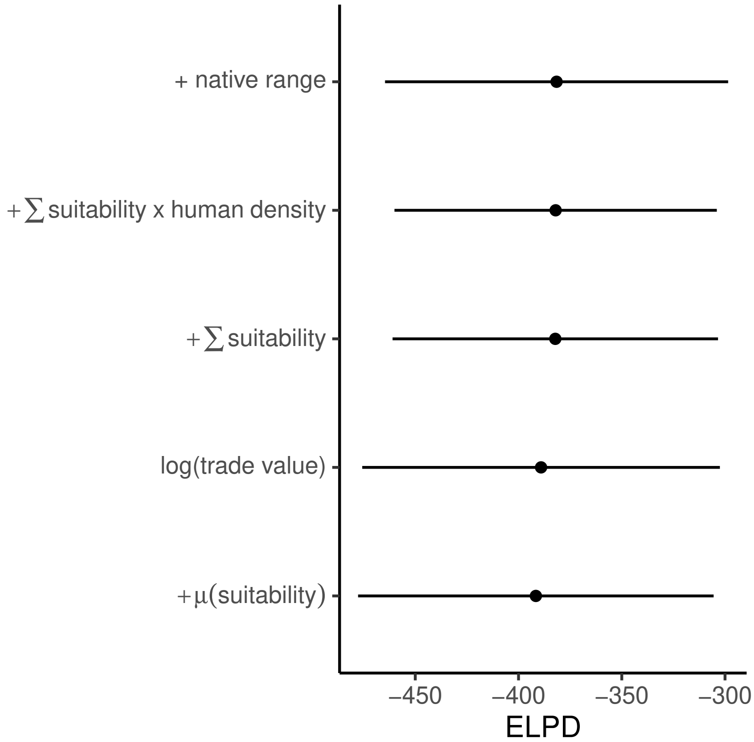

Figure A.6.: Cross-validation findings: additional covariates for interception model. Mean (± 95% confidence intervals) Expected Log Predictive Density (ELPD) based on 10-fold cross-validation.

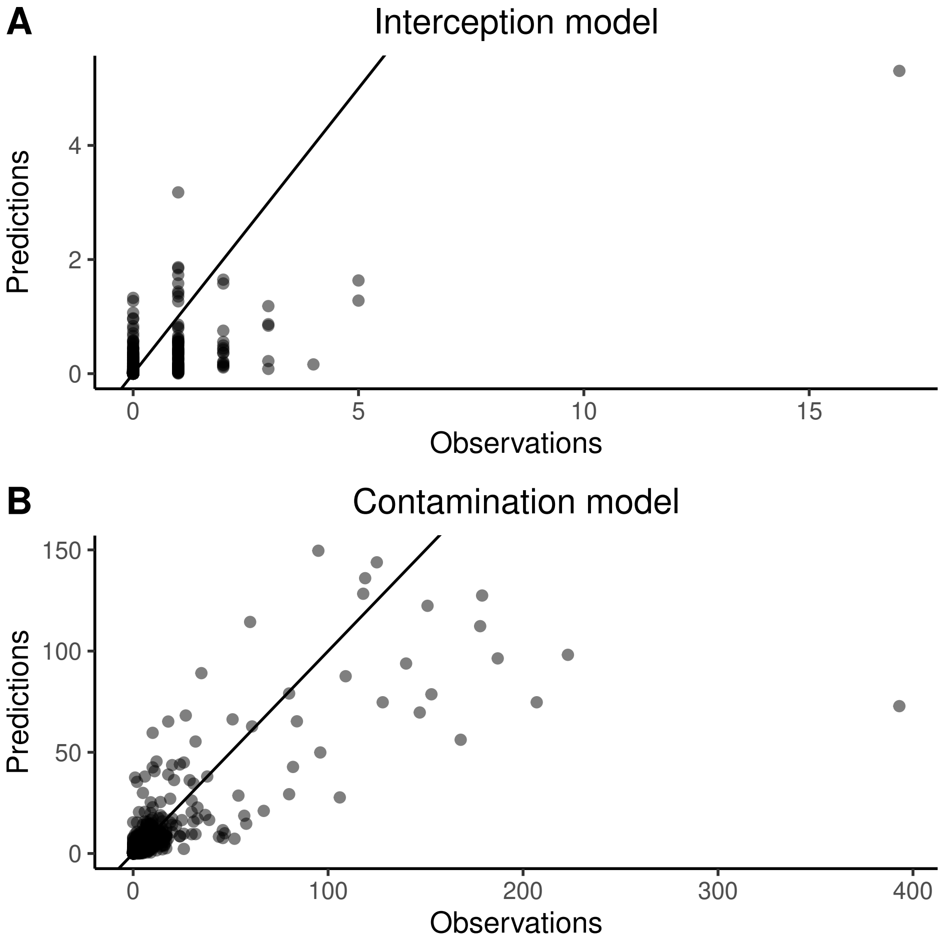

Figure A.7.: Model observations vs predictions. A) BMSB interception model; B) general contamination model. Solid line defines the 1:1 relationship.

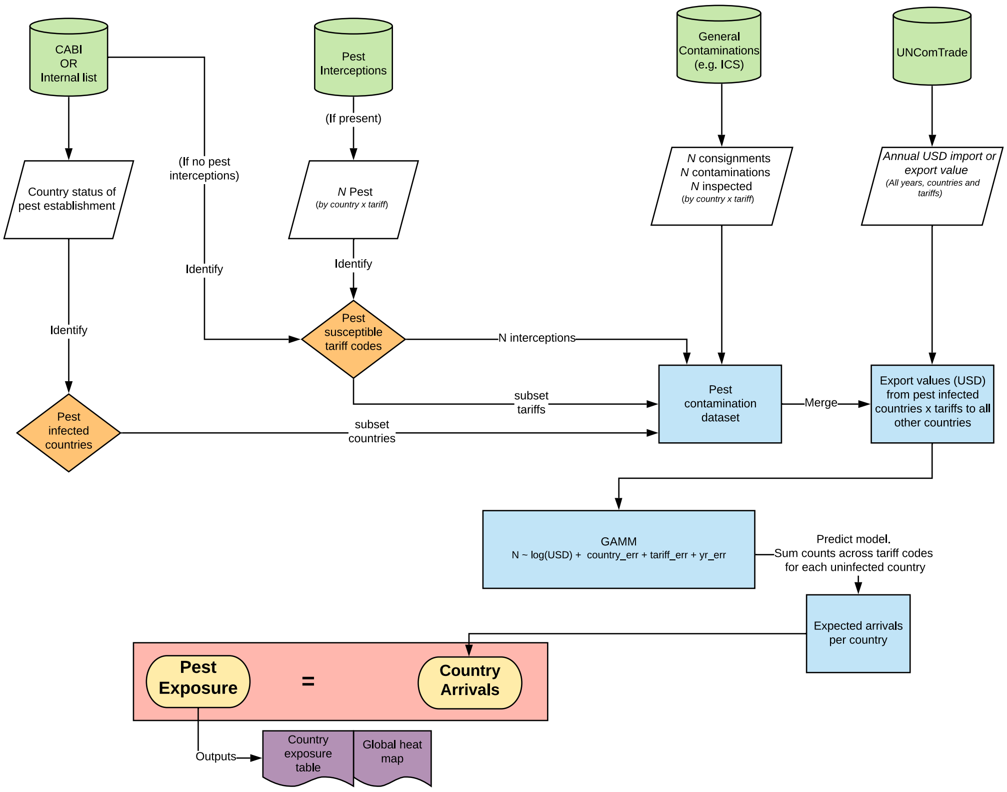

Figure A.8.: Workflow for estimating trading partner exposure risk for high threat pests or diseases that are presumed not to be limited by ambient climatic suitability.

A.2. Appendix Tables

Table A.1.: BMSB-susceptible commodities

HS code	Description
0802	Nuts (excluding coconuts, Brazils and cashew nuts); fresh or dried, whether or not shelled or peeled
0810	Fruit, fresh; n.e.c. in chapter 08
1108	Starches; inulin
1404	Vegetable products not elsewhere specified or included
2530	Mineral substances not elsewhere specified or included
2708	Pitch and pitch coke; obtained from coal tar or from other mineral tars
2710	Petroleum oils and oils from bituminous minerals, not crude; preparations n.e.c, containing by weight 70% or more of petroleum oils or oils from bituminous minerals; these being the basic constituents of the preparations; waste oils
2832	Sulphites; thiosulphates
2921	Amine-function compounds
3102	Fertilizers; mineral or chemical, nitrogenous
3105	Fertilizers; mineral or chemical, containing 2 or 3 of the elements nitrogen, phosphorus, potassium; other fertilisers; goods of chapter 31 in tablets or packages of gross weight not exceeding 10kg
3214	Glaziers' putty, grafting putty, resin cements, caulking compounds and other mastics; painters' fillings; non-refractory surfacing preparations for facades, indoor walls, floors, ceilings or the like
3502	Albumins (including concentrates of two or more whey proteins, containing by weight more than 80% whey proteins, calculated on the dry matter), albuminates and other albumin derivatives
3506	Prepared glues and other prepared adhesives, n.e.c. or included; products suitable for use as glues or adhesives, put up for retail sale as glues or adhesives, not exceeding 1kg net weight
3602	Prepared explosives, other than propellent powders
3603	Safety fuses; detonating fuses; percussion or detonating caps; igniters; electric detonators
3808	Insecticides, rodenticides, fungicides, herbicides, anti-sprouting products, plant growth regulators, disinfectants and the like, put up in forms or packings for retail sale or as preparations or articles
3809	Finishing agents, dye carriers to accelerate the dyeing, fixing of dyestuffs, other products and preparations, of a kind used in the textile, paper, leather or like industries, n.e.c. or included
3812	Prepared rubber accelerators; compound plasticisers for rubber or plastics, n.e.c. or included; anti-oxidising preparations and other compound stabilisers for rubber or plastics
3824	Prepared binders for foundry moulds or cores; chemical products and preparations of the chemical or allied industries (including those consisting of mixtures of natural products), not elsewhere specified or included
3917	Tubes, pipes and hoses and fittings thereof (for example, joints, elbows, flanges), of plastics
3920	Plastics; plates, sheets, film, foil and strip (not self-adhesive); non-cellular and not reinforced, laminated, supported or similarly combined with other materials, n.e.c. in chapter 39
3921	Plastic plates, sheets, film, foil and strip n.e.c. in chapter 39
3923	Plastic articles for the conveyance or packing of goods; stoppers, lids, caps and other closures of plastics
4009	Tubes, pipes and hoses, of vulcanised rubber (other than hard rubber), with or without their fittings (e.g. joints, elbows, flanges)
4010	Conveyor or transmission belts or belting, of vulcanised rubber
4011	New pneumatic tyres, of rubber
4016	Articles of vulcanised rubber other than hard rubber, n.e.c. in chapter 40
4201	Saddlery and harness for any animal (including traces, leads, knee pads, muzzles, saddle cloths, saddle bags, dog coats and the like) of any material
4407	Wood sawn or chipped lengthwise, sliced or peeled, whether or not planed, sanded or end-jointed, of a thickness exceeding 6mm
4410	Particle board, oriented strand board (OSB) and similar board (e.g. waferboard) of wood or other ligneous materials, whether or not agglomerated with resins or other organic binding substances
4802	Uncoated paper and paperboard, used for writing, printing or other graphics, non perforated punch-cards and punch tape paper, in rolls or rectangular sheets, of any size, other than paper of heading 4801 or 4803; hand-made paper and paperboard
4811	Paper, paperboard, cellulose wadding and webs of cellulose fibres, coated, impregnated, covered, surface-coloured, decorated or printed, rolls or sheets, other than goods of heading no. 4803, 4809, or 4810
4901	Printed books, brochures, leaflets and similar printed matter, whether or not in single sheets
4911	Printed matter, n.e.c., including printed pictures and photographs
5606	Yarn and strip and the like of heading no. 5404 or 5405, gimped (other than those of heading no. 5606 and gimped horsehair yarn); chenille yarn (including flock chenille yarn); loop wale-yarn
6302	Bed linen, table linen, toilet linen and kitchen linen
6307	Textiles; made up articles n.e.c. in chapter 63, including dress patterns
6802	Monumental or building stone, worked (except slate) and articles thereof (not of heading no. 6801) mosaic cubes etc., of natural stone including slate; artificially coloured granules of natural stone
6803	Slate, worked; and articles of slate or of agglomerated slate
6804	Millstones, grindstones, grinding wheels, etc without frameworks, for grinding, sharpening, polishing, etc and parts thereof, natural stone, agglomerated natural or artificial abrasives or of ceramics
6807	Asphalt or similar material; articles (e.g. petroleum bitumen or coal tar pitch)
6810	Cement, concrete or artificial stone; whether or not reinforced, articles thereof
6904	Ceramic building bricks, floor blocks, support or filler tiles and the like
6914	Ceramic articles; n.e.c. in chapter 69
7318	Screws, bolts, nuts, coach screws, screw hooks, rivets, cotters, cotter-pins, washers (including spring washers) and similar articles, of iron or steel
7322	Radiators for central heating, not electrically heated and parts thereof, of iron or steel; air heaters, hot air distributors not electrically heated, with motor fan or blower
7610	Aluminium; structures (excluding prefabricated buildings of heading no. 9406) and parts (e.g. bridges and sections, towers, lattice masts, etc) plates, rods, profiles and tubes for structures
7616	Aluminium; articles n.e.c. in chapter 76
8203	Tools, hand; files, rasps, pliers (including cutting pliers), pincers, tweezers, metal cutting shears, pipe cutters, bolt croppers, perforating punches and similar
8204	Tools, hand; hand-operated spanners and wrenches (including torque meter wrenches but not including tap wrenches), interchangeable spanner sockets, with or without handles
8302	Base metal mountings, fittings and similar articles for furniture, doors, staircases, windows, trunks, chests etc, castors with mountings of base metal, automatic door closers of base metal
8309	Stoppers, caps, lids (including crown corks, screw caps, pouring stoppers); capsules for bottles, threaded bungs, bung covers, seals and other packaging accessories, of base metal
8311	Wires, rods, tubes, plates, electrodes of base metal or metal carbides; of a kind used for soldering, brazing, welding; wires and rods for metal spraying
8403	Central heating boilers; excluding those of heading no. 8402
8408	Compression-ignition internal combustion piston engines (diesel or semi-diesel engines)
8409	Parts suitable for use solely or principally with the engines of heading no. 8407 or 8408
8412	Engines and motors; n.e.c. (e.g. reaction engines, hydraulic power engines, pneumatic power engines)
8413	Pumps; for liquids, whether or not fitted with measuring device, liquid elevators
8414	Air or vacuum pumps, air or other gas compressors and fans; ventilating or recycling hoods incorporating a fan whether or not fitted with filters

Table A.1.: *(continued)*

HS code	Description
8415	Air conditioning machines; comprising a motor driven fan and elements for changing the temperature and humidity, including those machines in which the humidity cannot be separately regulated
8418	Refrigerators, freezers and other refrigerating or freezing equipment, electric or other; heat pumps other than air conditioning machines of heading no. 8415
8419	Machinery, plant (not domestic), or laboratory equipment; electrically heated or not, (excluding items in 85.14) for the treatment of materials by a process involving change of temperature; including instantaneous or non electric storage water heaters
8421	Centrifuges, including centrifugal dryers; filtering or purifying machinery and apparatus for liquids or gases
8422	Dish washing machines; machinery for cleaning, drying, filling, closing, sealing, capsuling or labelling bottles, cans, boxes, bags, etc, machinery for aerating beverages
8424	Mechanical appliances for projecting, dispersing or spraying liquids or powders; fire extinguishers, spray guns, steam, sand blasting machines
8427	Fork-lift and other works trucks; fitted with lifting or handling equipment
8428	Lifting, handling, loading or unloading machinery; n.e.c. in heading no. 8425, 8426 or 8427 (e.g. lifts, escalators, conveyors, teleferics)
8429	Bulldozers, graders, levellers, scrapers, angledozers, mechanical shovels, excavators, shovel loaders, tamping machines and road rollers, self-propelled
8430	Moving, grading, levelling, scraping, excavating, tamping, compacting, extracting or boring machinery, for earth, minerals, or ores; pile drivers and extractors; snow ploughs and snow blowers
8431	Machinery parts; used solely or principally with the machinery of heading no. 8425 to 8430
8432	Agricultural, horticultural or forestry machinery for soil preparation or cultivation; lawn or sports-ground rollers
8433	Harvesting and threshing machinery, straw and fodder balers, grass or hay mowers; machines for cleaning, sorting or grading eggs, fruit or other agricultural produce, other than machinery of heading no 8437
8455	Metal-rolling mills and rolls therefor
8479	Machinery and mechanical appliances; having individual functions, n.e.c. in this chapter
8481	Taps, cocks, valves and similar appliances for pipes, boiler shells, tanks, vats or the like, including pressure-reducing valves and thermostatically controlled valves
8483	Transmission shafts (including cam and crank) and cranks; bearing housings and plain shaft bearings; gears and gearing; ball or roller screws; gear boxes and other speed changers; flywheels and pulleys; clutches and shaft couplings
8502	Electric generating sets and rotary converters
8535	Electrical apparatus for switching, protecting electrical circuits, for making connections to or in electrical circuits; for a voltage exceeding 1000 volts
8538	Electrical apparatus; parts suitable for use solely or principally with the apparatus of heading no. 8535, 8536 and 8537
8542	Electronic integrated circuits
8544	Insulated wire, cable and other electric conductors, connector fitted or not; optical fibre cables of individually sheathed fibres, whether or not assembled with electric conductors or fitted with connectors
8609	Containers; (including containers for transport of fluids) specially designed and equipped for carriage by one or more modes of transport
8701	Tractors; (other than tractors of heading no 8709)
8703	Motor cars and other motor vehicles; principally designed for the transport of persons (other than those of heading no. 8702), including station wagons and racing cars
8704	Vehicles; for the transport of goods
8708	Motor vehicles; parts and accessories, of heading no. 8701 to 8705
8711	Motorcycles (including mopeds) and cycles; fitted with an auxiliary motor, with or without side-cars; side-cars
8716	Trailers and semi-trailers; other vehicles, not mechanically propelled; parts thereof
8903	Yachts and other vessels; for pleasure or sports, rowing boats and canoes
9026	Instruments, apparatus for measuring or checking the flow, level, pressure of liquids, gases (e.g. flow meters, heat meters etc), not instruments and apparatus of heading no. 9014, 9015, 9028 or 9032
9401	Seats (not those of heading no. 9402), whether or not convertible into beds and parts thereof
9403	Furniture and parts thereof, n.e.c. in chapter 94
9404	Mattress supports; articles of bedding (e.g. mattresses, quilts, eiderdowns, cushions pouffes and pillows), fitted with springs or stuffed, whether or not covered
9999	Commodities not specified according to kind

Table A.2.: BMSB exposure ranks for all countries (including infected) based on interception and trade data.

Country	Range	Overall rank	Median rank	2.5% rank	97.5% rank
USA	Invaded	1	1	1	1
Germany	Invaded	2	2	2	2
Japan	Native	3	3	3	4
France	Invaded	4	4	4	3
Rep. of Korea	Native	5	5	5	8
United Kingdom	Absent	6	8	7	7
Netherlands	Absent	7	9	9	5
Australia	Absent	8	7	6	12
Canada	Invaded	9	6	8	13
Spain	Invaded	10	10	11	11
Poland	Absent	11	11	12	9
China, Hong Kong SAR	Absent	12	12	10	14
Italy	Invaded	13	16	13	10
Russian Federation	Invaded	14	15	14	16
Belgium	Invaded	15	13	16	17
Mexico	Absent	16	14	15	22
Switzerland	Invaded	17	18	17	19
China	Native	18	20	30	6
Turkey	Invaded	19	17	22	18
South Africa	Absent	20	19	19	27
Sweden	Absent	21	21	21	23
Czechia	Invaded	22	22	26	21
Romania	Invaded	23	23	27	20
Austria	Invaded	24	26	29	15
Denmark	Absent	25	27	18	28
Viet Nam	Absent	26	24	20	31
Brazil	Absent	27	25	23	30
Argentina	Absent	28	28	28	33
India	Absent	29	29	24	38
Slovenia	Invaded	30	33	35	26
Chile	Invaded	31	30	25	40
Ukraine	Absent	32	31	36	29
Hungary	Invaded	33	32	42	25
Portugal	Absent	34	35	32	32
Greece	Invaded	35	36	33	35
Slovakia	Invaded	36	39	49	24
Thailand	Absent	37	37	31	49
Croatia	Invaded	38	40	43	34
New Zealand	Absent	39	38	38	44
Algeria	Absent	40	34	46	42
Iran	Absent	41	41	37	53
Israel	Absent	42	44	39	48
Bulgaria	Invaded	43	42	53	37
Norway	Absent	44	48	45	43
Finland	Absent	45	46	52	39
Indonesia	Absent	46	43	34	61
Lithuania	Absent	47	50	50	41
Ireland	Absent	48	52	44	47
Morocco	Absent	49	47	54	46
Serbia	Invaded	50	54	62	36
Pakistan	Absent	51	45	51	59
Malaysia	Absent	52	51	40	69
Kazakhstan	Invaded	53	49	55	58
Philippines	Absent	54	53	41	68
United Arab Emirates	Absent	55	55	47	71
Georgia	Invaded	56	62	64	50
Latvia	Absent	57	65	60	51
Uruguay	Absent	58	58	59	62
Colombia	Absent	59	57	58	67
Tunisia	Absent	60	56	70	60
Albania	Absent	61	64	69	55
Singapore	Absent	62	61	48	80
Egypt	Absent	63	59	63	70
Estonia	Absent	64	69	74	54
Lebanon	Absent	65	66	61	74
Malta	Invaded	66	72	57	73
Saudi Arabia	Absent	67	68	56	84
Bangladesh	Absent	68	60	68	82
Uzbekistan	Absent	69	70	77	64
Belarus	Absent	70	71	88	52
Cyprus	Absent	71	76	66	72
Kenya	Absent	72	67	67	81
Myanmar	Absent	73	63	71	87
Peru	Absent	74	73	72	79
Ecuador	Absent	75	74	75	78
Nigeria	Absent	76	75	65	91
Luxembourg	Absent	77	89	99	45
United Rep. of Tanzania	Absent	78	77	73	90
Ghana	Absent	79	78	76	88
Jordan	Absent	80	84	79	83

Table A.2.: *(continued)*

Country	Range	Overall rank	Median rank	2.5% rank	97.5% rank
Bosnia Herzegovina	Invaded	81	97	92	57
Paraguay	Absent	82	80	94	76
Dominican Rep.	Absent	83	82	83	85
Guatemala	Absent	84	88	80	92
Iraq	Absent	85	83	82	97
Kyrgyzstan	Absent	86	79	108	77
Montenegro	Absent	87	112	87	66
Azerbaijan	Absent	88	85	122	63
Ethiopia	Absent	89	81	101	89
Mozambique	Absent	90	87	84	100
Oman	Absent	91	90	89	95
Panama	Absent	92	94	78	102
Dem. Rep. of the Congo	Absent	93	91	86	101
Cuba	Absent	94	93	96	94
TFYR of Macedonia	Absent	95	114	116	56
Rep. of Moldova	Invaded	96	110	113	65
Costa Rica	Absent	97	98	85	106
Dem. People's Rep. of Korea	Native	98	86	95	111
Côte d'Ivoire	Absent	99	99	91	103
Bolivia (Plurinational State of)	Absent	100	101	106	86
Tajikistan	Absent	101	92	111	93
Libya	Absent	102	96	110	96
Mauritius	Absent	103	103	102	99
Armenia	Absent	104	115	119	75
Mongolia	Absent	105	108	90	112
Angola	Absent	106	102	100	110
Honduras	Absent	107	104	112	98
Kuwait	Absent	108	106	98	115
Cambodia	Absent	109	95	107	118
Venezuela	Absent	110	100	128	104
Bermuda	Absent	111	124	81	128
Jamaica	Absent	112	113	114	107
Cameroon	Absent	113	111	104	120
Iceland	Absent	114	137	97	105
Sri Lanka	Absent	115	105	117	121
Madagascar	Absent	116	117	127	113
Syria	Absent	117	109	141	108
Qatar	Absent	118	122	103	134
Trinidad and Tobago	Absent	119	125	120	117
Lao People's Dem. Rep.	Absent	120	107	131	129
Zimbabwe	Absent	121	120	123	127
Zambia	Absent	122	121	118	132
Congo	Absent	123	123	125	123
Barbados	Absent	124	139	93	139
Bahamas	Absent	125	127	135	114
Nepal	Absent	126	119	136	122
Togo	Absent	127	126	129	124
Uganda	Absent	128	118	154	109
New Caledonia	Absent	129	142	121	119
El Salvador	Absent	130	128	124	131
Botswana	Absent	131	133	115	136
Yemen	Absent	132	116	143	130
Haiti	Absent	133	129	140	126
Afghanistan	Absent	134	132	153	116
Gabon	Absent	135	130	139	135
Benin	Absent	136	134	133	141
Cayman Isds	Absent	137	156	105	154
Br. Virgin Isds	Absent	138	152	109	155
Nicaragua	Absent	139	140	148	133
Bahrain	Absent	140	141	130	150
Djibouti	Absent	141	131	132	159
Maldives	Absent	142	138	137	148
Guinea	Absent	143	135	145	145
Malawi	Absent	144	147	138	143
French Polynesia	Absent	145	154	142	137
Somalia	Absent	146	143	126	165
Liberia	Absent	147	144	134	160
Guyana	Absent	148	150	151	140
Papua New Guinea	Absent	149	136	155	151
Equatorial Guinea	Absent	150	151	147	144
Rwanda	Absent	151	146	172	125
Fiji	Absent	152	145	146	156
Namibia	Absent	153	155	149	146
Suriname	Absent	154	157	152	142
Turkmenistan	Absent	155	148	173	138
Senegal	Absent	156	149	150	166
State of Palestine	Absent	157	159	156	153
Curaçao	Absent	158	164	159	152
Comoros	Absent	159	162	144	171
Belize	Absent	160	158	174	149

Table A.2.: *(continued)*

Country	Range	Overall rank	Median rank	2.5% rank	97.5% rank
Sudan	Absent	161	153	157	178
Aruba	Absent	162	169	160	167
Timor-Leste	Absent	163	161	158	179
Mali	Absent	164	163	162	176
Swaziland	Absent	165	166	175	161
Lesotho	Absent	166	167	176	163
Andorra	Absent	167	177	183	147
Burkina Faso	Absent	168	165	168	175
Burundi	Absent	169	172	178	158
Dominica	Absent	170	174	180	157
Brunei Darussalam	Absent	171	160	161	191
Antigua and Barbuda	Absent	172	173	179	162
Seychelles	Absent	173	180	164	174
Central African Rep.	Absent	174	170	177	173
Sierra Leone	Absent	175	171	167	184
Mauritania	Absent	176	168	166	189
Vanuatu	Absent	177	178	165	187
Saint Kitts and Nevis	Absent	178	179	184	169
Grenada	Absent	179	182	186	164
Tonga	Absent	180	175	181	185
Saint Lucia	Absent	181	185	188	170
South Sudan	Absent	182	176	182	186
Saint Vincent and the Grenadines	Absent	183	183	187	181
Marshall Isds	Absent	184	186	163	203
Solomon Isds	Absent	185	184	169	200
Niger	Absent	186	181	185	190
Gambia	Absent	187	187	170	199
Eritrea	Absent	188	188	189	182
Bhutan	Absent	189	193	194	172
Turks and Caicos Isds	Absent	190	191	192	180
Chad	Absent	191	189	190	194
Samoa	Absent	192	195	171	208
Greenland	Absent	193	196	196	183
Cook Isds	Absent	194	190	191	195
Cabo Verde	Absent	195	192	193	197
Sao Tome and Principe	Absent	196	197	197	188
Kiribati	Absent	197	194	195	198
San Marino	Absent	198	211	211	168
Anguilla	Absent	199	199	199	193
Faeroe Isds	Absent	200	201	201	192
Saint Pierre and Miquelon	Absent	201	212	212	177
Guam	Absent	202	203	203	196
Guinea-Bissau	Absent	203	198	198	207
Palau	Absent	204	200	200	206
Norfolk Isds	Absent	205	202	202	202
N. Mariana Isds	Absent	206	204	204	201
Nauru	Absent	207	205	205	205
Tuvalu	Absent	208	206	206	210
FS Micronesia	Absent	209	207	207	209
Wallis and Futuna Isds	Absent	210	208	208	212
American Samoa	Absent	211	209	209	215
Western Sahara	Absent	212	210	210	213
Montserrat	Absent	213	216	216	204
Pitcairn	Absent	214	213	213	214
Fr. South Antarctic Terr.	Absent	215	214	214	218
United States Minor Outlying Islands	Absent	216	215	215	219
Saint Helena	Absent	217	218	218	217
Falkland Isds (Malvinas)	Absent	218	221	221	211
Heard Island and McDonald Islands	Absent	219	217	217	220
Br. Indian Ocean Terr.	Absent	220	219	219	221
Niue	Absent	221	222	222	216
South Georgia and the South Sandwich Islands	Absent	222	220	220	222

Table A.3.: BMSB exposure ranks for all countries (including infected) based on contamination and trade data.

Country	Range	Overall rank	Median rank	2.5% rank	97.5% rank
Germany	Invaded	1	1	1	1
USA	Invaded	2	2	4	2
France	Invaded	3	3	3	3
China	Native	4	4	2	4
United Kingdom	Absent	5	5	5	6
Netherlands	Absent	6	6	8	7
Poland	Absent	7	7	10	8
Spain	Invaded	8	9	7	9
Canada	Invaded	9	10	6	10
Italy	Invaded	10	8	14	5
Belgium	Invaded	11	11	9	12
Austria	Invaded	12	12	12	13
Rep. of Korea	Native	13	13	13	14
Japan	Native	14	15	16	11
Czechia	Invaded	15	14	17	15
Switzerland	Invaded	16	16	15	17
Mexico	Absent	17	17	11	20
Australia	Absent	18	18	19	16
Turkey	Invaded	19	20	18	19
Hungary	Invaded	20	19	21	18
Sweden	Absent	21	21	20	23
Russian Federation	Invaded	22	23	22	21
Romania	Invaded	23	22	23	22
Slovakia	Invaded	24	24	25	24
Portugal	Absent	25	25	26	25
South Africa	Absent	26	26	27	26
Brazil	Absent	27	27	24	28
Slovenia	Invaded	28	28	28	27
Denmark	Absent	29	29	30	29
Argentina	Absent	30	30	29	30
Finland	Absent	31	31	32	32
China, Hong Kong SAR	Absent	32	32	33	33
Norway	Absent	33	34	35	35
Ukraine	Absent	34	33	42	31
Chile	Invaded	35	35	34	38
India	Absent	36	36	31	40
Bulgaria	Invaded	37	37	40	34
Greece	Invaded	38	38	37	36
Algeria	Absent	39	40	38	41
Morocco	Absent	40	39	39	42
Croatia	Invaded	41	41	46	37
Thailand	Absent	42	45	36	49
Serbia	Invaded	43	42	50	39
Lithuania	Absent	44	44	47	43
Viet Nam	Absent	45	47	44	44
Ireland	Absent	46	43	48	46
Israel	Absent	47	46	43	48
New Zealand	Absent	48	48	45	47
Luxembourg	Absent	49	49	51	45
United Arab Emirates	Absent	50	50	41	58
Tunisia	Absent	51	51	55	54
Iran	Absent	52	52	57	52
Colombia	Absent	53	53	52	59
Estonia	Absent	54	54	67	51
Egypt	Absent	55	56	56	60
Indonesia	Absent	56	57	53	62
Belarus	Absent	57	55	71	50
Saudi Arabia	Absent	58	60	49	68
Latvia	Absent	59	59	66	53
Kazakhstan	Invaded	60	58	70	55
Georgia	Invaded	61	63	63	57
Pakistan	Absent	62	61	62	61
Malaysia	Absent	63	62	59	70
Bosnia Herzegovina	Invaded	64	64	74	56
Peru	Absent	65	66	60	71
Singapore	Absent	66	65	54	79
Lebanon	Absent	67	67	65	69
Philippines	Absent	68	68	64	75
Dominican Rep.	Absent	69	69	58	81
Ecuador	Absent	70	70	72	74
Albania	Absent	71	71	83	64
Oman	Absent	72	75	61	82
Jordan	Absent	73	73	69	77
Malta	Invaded	74	76	77	76
Cyprus	Absent	75	79	78	73
Uruguay	Absent	76	72	103	65
Paraguay	Absent	77	81	79	80
Uzbekistan	Absent	78	77	98	66
Nigeria	Absent	79	82	73	87
Kuwait	Absent	80	80	68	96

Table A.3.: *(continued)*

Country	Range	Overall rank	Median rank	2.5% rank	97.5% rank
Guatemala	Absent	81	84	75	89
Azerbaijan	Absent	82	78	105	67
Kenya	Absent	83	92	80	84
Rep. of Moldova	Invaded	84	83	102	72
Iraq	Absent	85	85	90	86
Panama	Absent	86	87	76	99
TFYR of Macedonia	Absent	87	74	126	63
Honduras	Absent	88	88	82	94
Ghana	Absent	89	91	87	91
Bangladesh	Absent	90	90	99	88
Bolivia (Plurinational State of)	Absent	91	86	109	83
Costa Rica	Absent	92	95	81	102
Bahamas	Absent	93	89	94	101
Jamaica	Absent	94	97	84	103
Libya	Absent	95	94	104	92
Venezuela	Absent	96	100	88	104
Trinidad and Tobago	Absent	97	96	91	106
Myanmar	Absent	98	103	93	97
Qatar	Absent	99	99	86	111
Montenegro	Absent	100	93	127	78
Iceland	Absent	101	101	101	100
Cuba	Absent	102	98	113	93
Ethiopia	Absent	103	102	110	95
Cambodia	Absent	104	109	85	118
United Rep. of Tanzania	Absent	105	104	114	98
Andorra	Absent	106	107	92	117
Armenia	Absent	107	106	129	85
Afghanistan	Absent	108	113	100	110
Mauritius	Absent	109	108	111	105
Mongolia	Absent	110	116	97	116
Sri Lanka	Absent	111	115	96	120
Kyrgyzstan	Absent	112	112	131	90
Côte d'Ivoire	Absent	113	105	128	108
El Salvador	Absent	114	110	108	123
Yemen	Absent	115	122	95	125
New Caledonia	Absent	116	111	130	112
Uganda	Absent	117	125	112	119
Benin	Absent	118	131	89	136
Haiti	Absent	119	119	115	124
Dem. Rep. of the Congo	Absent	120	117	133	109
Angola	Absent	121	114	132	114
Tajikistan	Absent	122	121	135	107
Bahrain	Absent	123	120	106	138
Nicaragua	Absent	124	126	119	128
Cameroon	Absent	125	118	134	122
Syria	Absent	126	123	136	115
Mozambique	Absent	127	124	137	113
Togo	Absent	128	137	107	133
Zambia	Absent	129	128	120	131
French Polynesia	Absent	130	127	138	127
Lao People's Dem. Rep.	Absent	131	141	117	134
Madagascar	Absent	132	132	141	121
Bermuda	Absent	133	129	139	130
Cayman Isds	Absent	134	133	118	147
Gabon	Absent	135	130	140	129
Br. Virgin Isds	Absent	136	135	116	150
Guyana	Absent	137	138	121	142
Congo	Absent	138	134	142	126
Turkmenistan	Absent	139	140	145	135
Zimbabwe	Absent	140	142	146	132
Suriname	Absent	141	136	143	143
Barbados	Absent	142	139	144	144
Senegal	Absent	143	149	124	156
Botswana	Absent	144	145	149	137
Equatorial Guinea	Absent	145	144	148	141
State of Palestine	Absent	146	143	147	145
Guinea	Absent	147	147	151	146
Curaçao	Absent	148	146	150	149
Fiji	Absent	149	165	123	164
Rwanda	Absent	150	156	159	140
Nepal	Absent	151	157	160	139
Liberia	Absent	152	150	153	154
Papua New Guinea	Absent	153	151	154	152
Namibia	Absent	154	153	156	148
Aruba	Absent	155	148	152	159
Antigua and Barbuda	Absent	156	152	155	157
Belize	Absent	157	154	157	155
Maldives	Absent	158	158	161	153
Dominica	Absent	159	159	162	162
Guam	Absent	160	176	122	185

Table A.3.: *(continued)*

Country	Range	Overall rank	Median rank	2.5% rank	97.5% rank
Brunei Darussalam	Absent	161	172	125	187
Turks and Caicos Isds	Absent	162	155	158	172
Burkina Faso	Absent	163	160	163	165
Dem. People's Rep. of Korea	Native	164	169	171	151
Grenada	Absent	165	163	166	163
Swaziland	Absent	166	161	164	170
Djibouti	Absent	167	166	168	161
Mali	Absent	168	164	167	167
Saint Kitts and Nevis	Absent	169	162	165	173
Sudan	Absent	170	167	169	166
Saint Lucia	Absent	171	168	170	168
Malawi	Absent	172	174	175	158
Somalia	Absent	173	170	172	169
San Marino	Absent	174	177	177	160
Saint Vincent and the Grenadines	Absent	175	175	176	176
Burundi	Absent	176	178	178	171
Mauritania	Absent	177	173	174	181
Anguilla	Absent	178	171	173	188
Seychelles	Absent	179	182	182	175
Central African Rep.	Absent	180	183	183	174
Sierra Leone	Absent	181	179	179	183
Niger	Absent	182	180	180	184
Eritrea	Absent	183	181	181	182
Lesotho	Absent	184	184	184	177
Saint Pierre and Miquelon	Absent	185	185	185	179
Bhutan	Absent	186	189	189	178
Timor-Leste	Absent	187	187	187	186
Cabo Verde	Absent	188	186	186	192
Greenland	Absent	189	190	190	189
Comoros	Absent	190	195	195	180
South Sudan	Absent	191	192	192	190
Chad	Absent	192	191	191	193
Marshall Isds	Absent	193	188	188	202
Tonga	Absent	194	193	193	194
Gambia	Absent	195	194	194	196
Faeroe Isds	Absent	196	198	198	191
N. Mariana Isds	Absent	197	197	197	199
Montserrat	Absent	198	196	196	203
Vanuatu	Absent	199	200	200	195
Solomon Isds	Absent	200	199	199	201
Cook Isds	Absent	201	201	201	200
Kiribati	Absent	202	203	203	198
Sao Tome and Principe	Absent	203	204	204	197
Palau	Absent	204	202	202	204
Samoa	Absent	205	205	205	209
Guinea-Bissau	Absent	206	207	207	205
FS Micronesia	Absent	207	206	206	210
Nauru	Absent	208	209	209	208
Niue	Absent	209	208	208	213
Western Sahara	Absent	210	210	210	215
Wallis and Futuna Isds	Absent	211	212	212	211
American Samoa	Absent	212	211	211	216
Tuvalu	Absent	213	213	213	212
Pitcairn	Absent	214	214	214	214
Norfolk Isds	Absent	215	220	220	207
Fr. South Antarctic Terr.	Absent	216	215	215	218
Falkland Isds (Malvinas)	Absent	217	222	222	206
United States Minor Outlying Islands	Absent	218	216	216	219
Saint Helena	Absent	219	218	218	217
Heard Island and McDonald Islands	Absent	220	217	217	220
Br. Indian Ocean Terr.	Absent	221	219	219	221
South Georgia and the South Sandwich Islands	Absent	222	221	221	222

Table A.4.: BMSB exposure scores for all countries (including infected) based on BMSB interception and trade data. 2.5% and 97.5% refer to the lower and upper 95% credible limits.

Country	Range	Median	2.5%	97.5%
USA	Invaded	2408.97	370.01	22491.16
Germany	Invaded	1293.31	187.03	13370.20
Japan	Native	1179.75	176.91	7966.40
France	Invaded	1023.91	154.26	8815.45
Rep. of Korea	Native	996.17	145.95	5994.44
Canada	Invaded	824.64	103.73	4848.04
Australia	Absent	803.98	116.94	5221.56
United Kingdom	Absent	799.08	110.96	6407.40
Netherlands	Absent	701.80	92.98	7079.20
Spain	Invaded	635.56	74.62	5286.82
Poland	Absent	591.68	69.22	5975.96
China, Hong Kong SAR	Absent	585.46	81.80	4277.48
Belgium	Invaded	507.34	55.47	4000.74
Mexico	Absent	506.92	57.11	3571.25
Russian Federation	Invaded	484.69	59.12	4045.96
Italy	Invaded	482.26	60.51	5928.24
Turkey	Invaded	410.56	32.72	3874.19
Switzerland	Invaded	390.22	47.28	3714.52
South Africa	Absent	346.62	38.85	2587.14
China	Native	326.24	23.50	6425.11
Sweden	Absent	322.91	35.50	3455.46
Czechia	Invaded	319.94	26.52	3588.46
Romania	Invaded	310.21	25.93	3593.21
Viet Nam	Absent	307.76	36.30	2314.11
Brazil	Absent	305.49	32.58	2341.30
Austria	Invaded	299.46	23.58	4059.07
Denmark	Absent	288.89	39.36	2557.16
Argentina	Absent	287.43	23.63	2273.38
India	Absent	274.52	31.39	1922.37
Chile	Invaded	257.49	27.09	1802.51
Ukraine	Absent	247.75	19.64	2524.94
Hungary	Invaded	243.60	15.23	3384.98
Slovenia	Invaded	242.96	19.67	2772.75
Algeria	Absent	226.84	13.89	1766.79
Portugal	Absent	223.04	20.93	2276.46
Greece	Invaded	222.43	20.73	2159.86
Thailand	Absent	198.91	22.96	1331.39
New Zealand	Absent	194.49	18.39	1625.55
Slovakia	Invaded	190.23	11.41	3445.44
Croatia	Invaded	184.89	14.67	2242.02
Iran	Absent	183.27	18.62	1247.92
Bulgaria	Invaded	169.34	10.81	2083.93
Indonesia	Absent	163.83	20.59	1072.86
Israel	Absent	163.68	17.11	1367.03
Pakistan	Absent	163.66	11.31	1121.24
Finland	Absent	159.57	10.93	1835.94
Morocco	Absent	154.12	10.46	1490.50
Norway	Absent	145.12	13.89	1693.30
Kazakhstan	Invaded	142.97	10.06	1157.68
Lithuania	Absent	136.88	11.41	1780.76
Malaysia	Absent	133.43	16.52	894.00
Ireland	Absent	130.17	14.57	1379.16
Philippines	Absent	126.22	15.95	896.68
Serbia	Invaded	120.94	7.71	2146.07
United Arab Emirates	Absent	118.13	12.48	876.34
Tunisia	Absent	111.21	6.57	1101.37
Colombia	Absent	104.98	8.93	897.41
Uruguay	Absent	103.34	8.68	1037.52
Egypt	Absent	102.54	7.52	878.61
Bangladesh	Absent	101.03	6.69	677.31
Singapore	Absent	95.42	12.23	680.31
Georgia	Invaded	94.18	7.46	1317.21
Myanmar	Absent	93.11	6.29	564.36
Albania	Absent	92.97	6.61	1190.87
Latvia	Absent	91.05	8.41	1300.85
Lebanon	Absent	88.58	7.75	840.51
Kenya	Absent	88.16	6.77	678.99
Saudi Arabia	Absent	87.14	9.86	631.49
Estonia	Absent	85.80	5.72	1241.03
Uzbekistan	Absent	84.77	4.83	965.70
Belarus	Absent	83.64	3.62	1298.33
Malta	Invaded	80.70	9.41	843.09
Peru	Absent	79.31	6.18	704.32
Ecuador	Absent	77.64	5.65	721.15
Nigeria	Absent	74.79	7.22	533.88
Cyprus	Absent	72.26	7.03	851.75
United Rep. of Tanzania	Absent	71.82	5.76	541.98
Ghana	Absent	66.25	5.54	551.44
Kyrgyzstan	Absent	64.53	2.05	755.14
Paraguay	Absent	62.10	2.82	788.17

Table A.4.: *(continued)*

Country	Range	Median	2.5%	97.5%
Ethiopia	Absent	60.84	2.59	542.62
Dominican Rep.	Absent	58.90	4.18	601.49
Iraq	Absent	58.22	4.33	481.84
Jordan	Absent	57.44	4.61	659.72
Azerbaijan	Absent	54.67	1.54	966.37
Dem. People's Rep. of Korea	Native	53.32	2.81	342.50
Mozambique	Absent	51.96	3.93	422.32
Guatemala	Absent	51.08	4.46	509.02
Luxembourg	Absent	50.40	2.61	1497.16
Oman	Absent	50.29	3.45	486.01
Dem. Rep. of the Congo	Absent	49.82	3.71	413.13
Tajikistan	Absent	49.14	1.91	506.30
Cuba	Absent	46.48	2.79	494.02
Panama	Absent	44.79	4.69	402.66
Cambodia	Absent	41.67	2.08	327.58
Libya	Absent	39.06	2.00	482.24
Bosnia Herzegovina	Invaded	39.04	2.93	1165.08
Costa Rica	Absent	38.97	3.84	369.62
Côte d'Ivoire	Absent	38.52	3.00	397.52
Venezuela	Absent	38.14	1.29	393.75
Bolivia (Plurinational State of)	Absent	37.88	2.09	600.54
Angola	Absent	37.44	2.59	346.67
Mauritius	Absent	37.20	2.55	460.41
Honduras	Absent	36.39	1.89	460.97
Sri Lanka	Absent	34.25	1.68	306.22
Kuwait	Absent	34.21	2.69	333.17
Lao People's Dem. Rep.	Absent	33.25	1.16	266.97
Mongolia	Absent	33.03	3.16	340.61
Syria	Absent	32.32	0.86	353.54
Rep. of Moldova	Invaded	30.70	1.86	942.13
Cameroon	Absent	30.60	2.29	310.44
Montenegro	Absent	30.09	3.65	921.37
Jamaica	Absent	29.52	1.79	365.65
TFYR of Macedonia	Absent	28.89	1.70	1175.97
Armenia	Absent	28.36	1.67	813.06
Yemen	Absent	27.94	0.83	262.05
Madagascar	Absent	27.72	1.30	337.70
Uganda	Absent	27.04	0.48	352.17
Nepal	Absent	26.73	1.01	298.27
Zimbabwe	Absent	26.42	1.52	277.93
Zambia	Absent	25.87	1.68	253.10
Qatar	Absent	24.58	2.42	248.01
Congo	Absent	24.18	1.42	294.94
Bermuda	Absent	23.36	4.36	274.19
Trinidad and Tobago	Absent	23.23	1.60	328.65
Togo	Absent	21.83	1.23	284.76
Bahamas	Absent	20.33	1.02	334.61
El Salvador	Absent	19.78	1.52	259.40
Haiti	Absent	19.60	0.89	278.16
Gabon	Absent	18.36	0.98	243.06
Djibouti	Absent	18.20	1.15	144.13
Afghanistan	Absent	18.07	0.52	330.66
Botswana	Absent	17.64	1.75	240.73
Benin	Absent	17.33	1.14	188.69
Guinea	Absent	17.19	0.77	179.20
Papua New Guinea	Absent	15.66	0.47	164.22
Iceland	Absent	15.29	2.78	391.82
Maldives	Absent	15.19	1.00	170.22
Barbados	Absent	14.98	2.92	211.94
Nicaragua	Absent	14.95	0.71	248.97
Bahrain	Absent	14.51	1.22	164.95
New Caledonia	Absent	14.25	1.58	324.71
Somalia	Absent	14.15	1.34	123.70
Liberia	Absent	14.02	1.03	142.10
Fiji	Absent	13.53	0.77	147.86
Rwanda	Absent	13.45	0.00	282.04
Malawi	Absent	12.90	0.99	180.79
Turkmenistan	Absent	12.65	0.00	219.99
Senegal	Absent	12.24	0.67	119.42
Guyana	Absent	12.20	0.64	194.57
Equatorial Guinea	Absent	12.02	0.73	179.25
Br. Virgin Isds	Absent	11.97	2.03	150.61
Sudan	Absent	11.83	0.41	100.70
French Polynesia	Absent	11.63	0.86	234.89
Namibia	Absent	11.27	0.70	174.74
Cayman Isds	Absent	11.03	2.21	151.17
Suriname	Absent	9.57	0.59	185.38
Belize	Absent	8.39	0.00	168.65
State of Palestine	Absent	6.81	0.45	158.10
Brunei Darussalam	Absent	6.79	0.30	54.28

Table A.4.: *(continued)*

Country	Range	Median	2.5%	97.5%
Timor-Leste	Absent	6.65	0.40	95.97
Comoros	Absent	6.19	0.81	104.37
Mali	Absent	6.07	0.28	102.17
Curaçao	Absent	5.97	0.33	159.51
Burkina Faso	Absent	5.63	0.16	103.17
Swaziland	Absent	5.53	0.00	138.24
Lesotho	Absent	5.44	0.00	133.38
Mauritania	Absent	5.18	0.17	60.07
Aruba	Absent	5.05	0.32	118.22
Central African Rep.	Absent	4.50	0.00	103.35
Sierra Leone	Absent	4.34	0.16	82.76
Burundi	Absent	4.10	0.00	144.28
Antigua and Barbuda	Absent	4.04	0.00	137.97
Dominica	Absent	3.53	0.00	145.93
Tonga	Absent	3.44	0.00	70.79
South Sudan	Absent	3.28	0.00	70.57
Andorra	Absent	3.17	0.00	172.82
Vanuatu	Absent	3.07	0.20	60.84
Saint Kitts and Nevis	Absent	2.94	0.00	109.48
Seychelles	Absent	2.94	0.23	103.30
Niger	Absent	2.83	0.00	58.84
Grenada	Absent	2.82	0.00	128.91
Saint Vincent and the Grenadines	Absent	2.69	0.00	92.79
Solomon Isds	Absent	2.64	0.13	33.86
Saint Lucia	Absent	2.62	0.00	107.65
Marshall Isds	Absent	2.37	0.28	23.02
Gambia	Absent	2.10	0.08	37.05
Eritrea	Absent	2.06	0.00	91.84
Chad	Absent	1.54	0.00	47.21
Cook Isds	Absent	1.51	0.00	46.69
Turks and Caicos Isds	Absent	1.47	0.00	95.52
Cabo Verde	Absent	1.44	0.00	43.44
Bhutan	Absent	1.34	0.00	104.31
Kiribati	Absent	1.13	0.00	41.70
Samoa	Absent	1.05	0.06	15.45
Greenland	Absent	0.77	0.00	83.31
Sao Tome and Principe	Absent	0.76	0.00	60.13
Guinea-Bissau	Absent	0.72	0.00	16.07
Anguilla	Absent	0.66	0.00	49.43
Palau	Absent	0.61	0.00	16.63
Faeroe Isds	Absent	0.59	0.00	53.43
Norfolk Isds	Absent	0.57	0.00	23.32
Guam	Absent	0.28	0.00	44.38
N. Mariana Isds	Absent	0.27	0.00	24.11
Nauru	Absent	0.23	0.00	17.27
Tuvalu	Absent	0.14	0.00	5.25
FS Micronesia	Absent	0.12	0.00	7.34
Wallis and Futuna Isds	Absent	0.07	0.00	3.58
American Samoa	Absent	0.04	0.00	1.37
Western Sahara	Absent	0.00	0.00	1.98
San Marino	Absent	0.00	0.00	115.88
Saint Pierre and Miquelon	Absent	0.00	0.00	101.90
Pitcairn	Absent	0.00	0.00	1.70
Fr. South Antarctic Terr.	Absent	0.00	0.00	0.00
United States Minor Outlying Islands	Absent	0.00	0.00	0.00
Montserrat	Absent	0.00	0.00	20.25
Heard Island and McDonald Islands	Absent	0.00	0.00	0.00
Saint Helena	Absent	0.00	0.00	0.48
Br. Indian Ocean Terr.	Absent	0.00	0.00	0.00
South Georgia and the South Sandwich Islands	Absent	0.00	0.00	0.00
Falkland Isds (Malvinas)	Absent	0.00	0.00	4.80
Niue	Absent	0.00	0.00	1.03

Table A.5.: BMSB exposure scores for all countries (including infected) based on contamination and trade data. 2.5% and 97.5% refer to the lower and upper 95% credible limits.

Country	Range	Median	2.5%	97.5%
Germany	Invaded	5984.46	201.28	41357.73
USA	Invaded	4856.88	146.78	37495.32
France	Invaded	4571.20	161.06	30285.42
China	Native	4334.65	165.27	27158.98
United Kingdom	Absent	3725.64	134.07	24408.52
Netherlands	Absent	3503.82	111.06	24345.13
Poland	Absent	3451.41	108.37	23405.36
Italy	Invaded	3416.53	88.88	24713.54
Spain	Invaded	3198.37	113.84	21212.85
Canada	Invaded	3166.16	130.62	19628.33
Belgium	Invaded	3122.95	109.10	19481.91
Austria	Invaded	2829.04	90.45	18700.87
Rep. of Korea	Native	2744.07	89.36	18139.98
Czechia	Invaded	2678.96	79.56	17514.52
Japan	Native	2595.25	79.67	19514.60
Switzerland	Invaded	2492.22	87.88	16001.71
Mexico	Absent	2349.90	94.98	15113.85
Australia	Absent	2343.55	71.32	16109.36
Hungary	Invaded	2240.34	63.59	15426.62
Turkey	Invaded	2176.97	72.05	15344.39
Sweden	Absent	2095.70	66.96	14577.15
Romania	Invaded	2079.32	55.47	14852.23
Russian Federation	Invaded	2056.70	58.45	15080.88
Slovakia	Invaded	1776.72	46.56	13478.56
Portugal	Absent	1610.61	43.63	10590.51
South Africa	Absent	1489.61	41.96	10487.56
Brazil	Absent	1401.48	51.15	9586.75
Slovenia	Invaded	1336.26	37.33	10309.35
Denmark	Absent	1269.16	28.74	9368.07
Argentina	Absent	1232.50	32.70	8979.25
Finland	Absent	1041.19	24.75	7871.80
China, Hong Kong SAR	Absent	1013.97	24.52	7710.44
Ukraine	Absent	951.28	12.50	8182.93
Norway	Absent	945.33	21.51	6953.08
Chile	Invaded	928.49	22.66	6699.85
India	Absent	889.96	26.41	6425.45
Bulgaria	Invaded	856.15	15.31	7119.47
Greece	Invaded	849.06	16.70	6849.39
Morocco	Absent	844.16	15.32	6029.14
Algeria	Absent	801.27	15.33	6248.14
Croatia	Invaded	770.85	10.76	6786.36
Serbia	Invaded	729.99	9.64	6665.97
Ireland	Absent	672.05	10.12	5059.67
Lithuania	Absent	640.53	10.49	5813.48
Thailand	Absent	632.30	17.13	4619.21
Israel	Absent	622.11	12.46	4776.55
Viet Nam	Absent	616.18	11.93	5382.81
New Zealand	Absent	588.57	11.56	4834.03
Luxembourg	Absent	584.38	9.54	5094.93
United Arab Emirates	Absent	488.46	13.74	3432.24
Tunisia	Absent	472.88	7.89	3720.14
Iran	Absent	452.89	7.00	3923.11
Colombia	Absent	433.90	8.54	3328.36
Estonia	Absent	426.94	4.88	4090.31
Belarus	Absent	423.61	3.62	4181.54
Egypt	Absent	407.82	7.49	3222.68
Indonesia	Absent	404.36	8.37	3152.18
Kazakhstan	Invaded	397.14	3.69	3698.29
Latvia	Absent	377.28	5.06	3888.92
Saudi Arabia	Absent	370.75	10.04	2537.65
Pakistan	Absent	342.79	5.64	3156.02
Malaysia	Absent	316.63	6.60	2423.86
Georgia	Invaded	298.38	5.59	3444.92
Bosnia Herzegovina	Invaded	297.20	2.93	3468.15
Singapore	Absent	294.67	7.97	2052.87
Peru	Absent	288.03	6.18	2375.96
Lebanon	Absent	277.37	5.15	2511.77
Philippines	Absent	263.29	5.47	2215.88
Dominican Rep.	Absent	250.85	6.67	1983.21
Ecuador	Absent	242.80	3.22	2221.89
Albania	Absent	239.27	1.89	2903.65
Uruguay	Absent	234.46	0.87	2643.53
Jordan	Absent	234.36	4.13	2163.13
TFYR of Macedonia	Absent	231.54	0.00	2986.88
Oman	Absent	229.04	5.75	1712.06
Malta	Invaded	226.29	2.67	2164.19
Uzbekistan	Absent	225.61	1.07	2633.42
Azerbaijan	Absent	219.08	0.77	2613.85
Cyprus	Absent	217.41	2.54	2354.89
Kuwait	Absent	174.18	4.29	1276.26

Table A.5.: *(continued)*

Country	Range	Median	2.5%	97.5%
Paraguay	Absent	173.96	2.12	2032.77
Nigeria	Absent	169.97	3.02	1515.92
Rep. of Moldova	Invaded	165.61	0.91	2372.50
Guatemala	Absent	163.97	2.84	1471.56
Iraq	Absent	163.70	1.68	1531.68
Bolivia (Plurinational State of)	Absent	145.74	0.53	1659.15
Panama	Absent	143.86	2.81	1197.54
Honduras	Absent	143.65	1.89	1306.17
Bahamas	Absent	142.82	1.52	1140.40
Bangladesh	Absent	136.24	1.06	1502.96
Ghana	Absent	132.51	1.73	1434.86
Kenya	Absent	131.52	1.94	1628.65
Montenegro	Absent	131.28	0.00	2143.55
Libya	Absent	128.39	0.80	1361.33
Costa Rica	Absent	127.75	1.92	1117.93
Trinidad and Tobago	Absent	123.58	1.60	1068.41
Jamaica	Absent	122.35	1.79	1097.21
Cuba	Absent	117.84	0.46	1347.65
Qatar	Absent	113.94	1.75	879.41
Venezuela	Absent	112.28	1.71	1082.59
Iceland	Absent	110.28	0.93	1160.24
Ethiopia	Absent	107.65	0.52	1291.87
Myanmar	Absent	106.27	1.57	1274.76
United Rep. of Tanzania	Absent	86.01	0.44	1199.77
Côte d'Ivoire	Absent	85.71	0.00	1003.26
Armenia	Absent	82.57	0.00	1571.99
Andorra	Absent	76.85	1.58	783.71
Mauritius	Absent	76.68	0.51	1074.19
Cambodia	Absent	74.88	1.78	782.68
El Salvador	Absent	73.63	0.61	708.27
New Caledonia	Absent	72.81	0.00	873.99
Kyrgyzstan	Absent	70.34	0.00	1441.60
Afghanistan	Absent	69.17	1.03	886.68
Angola	Absent	68.55	0.00	809.04
Sri Lanka	Absent	66.33	1.20	767.10
Mongolia	Absent	63.05	1.15	785.93
Dem. Rep. of the Congo	Absent	61.35	0.00	913.67
Cameroon	Absent	56.49	0.00	735.09
Haiti	Absent	54.79	0.43	665.35
Bahrain	Absent	53.60	0.68	492.98
Tajikistan	Absent	51.69	0.00	1023.34
Yemen	Absent	50.26	1.25	633.39
Syria	Absent	50.20	0.00	792.00
Mozambique	Absent	49.74	0.00	833.32
Uganda	Absent	49.74	0.48	776.24
Nicaragua	Absent	49.66	0.36	604.67
French Polynesia	Absent	49.54	0.00	623.99
Zambia	Absent	48.04	0.34	591.50
Bermuda	Absent	47.97	0.00	594.46
Gabon	Absent	46.39	0.00	598.63
Benin	Absent	44.31	1.70	499.86
Madagascar	Absent	44.18	0.00	750.22
Cayman Isds	Absent	42.64	0.37	417.40
Congo	Absent	38.41	0.00	628.69
Br. Virgin Isds	Absent	37.33	0.41	358.81
Suriname	Absent	36.38	0.00	430.26
Togo	Absent	36.29	0.62	534.06
Guyana	Absent	34.99	0.32	438.94
Barbados	Absent	33.61	0.00	423.20
Turkmenistan	Absent	31.78	0.00	524.54
Lao People's Dem. Rep.	Absent	30.74	0.39	531.51
Zimbabwe	Absent	30.48	0.00	546.34
State of Palestine	Absent	28.61	0.00	422.57
Equatorial Guinea	Absent	28.41	0.00	440.17
Botswana	Absent	27.64	0.00	495.50
Curaçao	Absent	27.18	0.00	372.69
Guinea	Absent	27.04	0.00	421.11
Aruba	Absent	27.01	0.00	292.59
Senegal	Absent	26.84	0.10	306.73
Liberia	Absent	22.88	0.00	307.75
Papua New Guinea	Absent	22.65	0.00	330.83
Antigua and Barbuda	Absent	22.53	0.00	304.18
Namibia	Absent	22.18	0.00	376.62
Belize	Absent	21.97	0.00	307.62
Turks and Caicos Isds	Absent	20.27	0.00	210.55
Rwanda	Absent	18.29	0.00	476.44
Nepal	Absent	18.16	0.00	486.95
Maldives	Absent	16.94	0.00	329.89
Dominica	Absent	16.74	0.00	277.31
Burkina Faso	Absent	15.72	0.00	247.49

Table A.5.: *(continued)*

Country	Range	Median	2.5%	97.5%
Swaziland	Absent	15.20	0.00	220.40
Saint Kitts and Nevis	Absent	15.06	0.00	206.47
Grenada	Absent	14.49	0.00	256.89
Mali	Absent	14.35	0.00	234.70
Fiji	Absent	14.04	0.26	254.07
Djibouti	Absent	13.99	0.00	278.66
Sudan	Absent	13.95	0.00	235.18
Saint Lucia	Absent	13.08	0.00	229.59
Dem. People's Rep. of Korea	Native	12.16	0.00	336.93
Somalia	Absent	12.02	0.00	223.61
Anguilla	Absent	11.36	0.00	125.83
Brunei Darussalam	Absent	11.10	0.07	127.99
Mauritania	Absent	11.02	0.00	159.21
Malawi	Absent	10.92	0.00	295.95
Saint Vincent and the Grenadines	Absent	10.42	0.00	183.59
Guam	Absent	9.20	0.28	131.56
San Marino	Absent	8.99	0.00	285.63
Burundi	Absent	8.21	0.00	216.60
Sierra Leone	Absent	6.88	0.00	155.48
Niger	Absent	6.51	0.00	134.87
Eritrea	Absent	6.19	0.00	158.56
Seychelles	Absent	6.10	0.00	198.23
Central African Rep.	Absent	5.76	0.00	199.94
Lesotho	Absent	5.44	0.00	172.43
Saint Pierre and Miquelon	Absent	5.33	0.00	165.91
Cabo Verde	Absent	4.92	0.00	97.77
Timor-Leste	Absent	4.57	0.00	130.02
Marshall Isds	Absent	4.07	0.00	45.86
Bhutan	Absent	4.01	0.00	167.10
Greenland	Absent	3.85	0.00	111.39
Chad	Absent	3.51	0.00	90.36
South Sudan	Absent	3.28	0.00	105.09
Tonga	Absent	3.23	0.00	85.75
Gambia	Absent	3.03	0.00	68.85
Comoros	Absent	2.89	0.00	161.37
Montserrat	Absent	2.44	0.00	44.67
N. Mariana Isds	Absent	2.44	0.00	56.05
Faeroe Isds	Absent	2.06	0.00	99.44
Solomon Isds	Absent	1.89	0.00	48.46
Vanuatu	Absent	1.84	0.00	85.00
Cook Isds	Absent	1.51	0.00	48.98
Palau	Absent	0.90	0.00	27.04
Kiribati	Absent	0.84	0.00	57.18
Sao Tome and Principe	Absent	0.76	0.00	64.30
Samoa	Absent	0.70	0.00	19.31
FS Micronesia	Absent	0.54	0.00	12.03
Guinea-Bissau	Absent	0.40	0.00	24.66
Niue	Absent	0.26	0.00	5.16
Nauru	Absent	0.23	0.00	20.03
Western Sahara	Absent	0.17	0.00	3.31
American Samoa	Absent	0.12	0.00	3.02
Wallis and Futuna Isds	Absent	0.07	0.00	8.64
Tuvalu	Absent	0.07	0.00	5.25
Pitcairn	Absent	0.00	0.00	3.40
Fr. South Antarctic Terr.	Absent	0.00	0.00	0.00
United States Minor Outlying Islands	Absent	0.00	0.00	0.00
Heard Island and McDonald Islands	Absent	0.00	0.00	0.00
Saint Helena	Absent	0.00	0.00	0.89
Br. Indian Ocean Terr.	Absent	0.00	0.00	0.00
Norfolk Isds	Absent	0.00	0.00	23.31
South Georgia and the South Sandwich Islands	Absent	0.00	0.00	0.00
Falkland Isds (Malvinas)	Absent	0.00	0.00	23.52