

Utility and reliability of the southern pine beetle prediction system

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The SPB prediction model (Appendix 1) generates a family of predictions for each administrative unit (usually county, parish, or Ranger District) in each year. “Spots” refer to local infestations of SPB that typically begin with 10 – 30 trees in the initial wave of SPB attacks during late spring.

- Probability of any SPB spots
- Approximate spots to expect if there are spots
- Probability of greater than 20 spots: *Prob(>20 spots)*
- Probability of greater than 50 spots: *Prob(>50 spots)*
- Probability of greater than 150 spots: *Prob(>150 spots)*
- Probability of greater than 400 spots: *Prob(>400 spots)*
- Probability of greater than 1000 spots: *Prob(>1000 spots)*

The predictions are all correlated, as one would expect. The probability of >50 local infestations (spots) in an administrative unit seems to be a reasonably intuitive metric that captures the overall predictions pretty well. Figure 1 shows how *Prob(>50 spots)* is related to the range of possible outcomes (number of spots). See [here](#)¹ for why we chose 50 spots. See [here](#)² for considering effects from the size of administrative units.

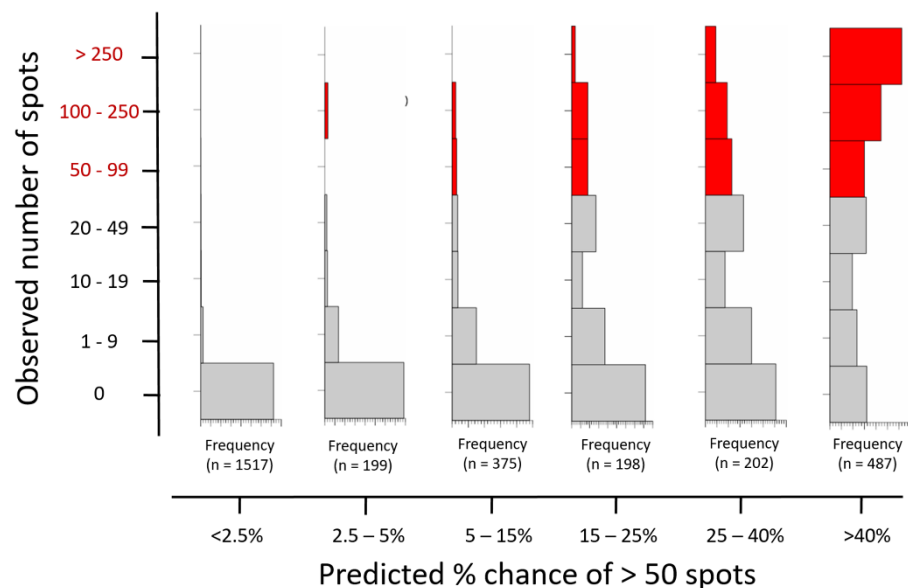


Figure 1. Increases in the predicted chance of an SPB outbreak are associated with changes in the distribution of possible outcomes. See the progression of frequency distributions from left to right above. At left: in 1517 cases where the predicted chance of an outbreak was < 2.5%, there has never been an outbreak. At right: an outbreak materialized in more than half of 487 cases where the predicted chance of an outbreak was > 40%. We encourage forest managers to interpret predictions from the SPB model as representing these distributions of possible outcomes.

¹ The structure of the model makes it simplest to generate predictions for discrete numbers of spots (that are powers of the base of the natural logarithms - 1, e^1-1 , e^2-1 , ...): i.e., 0, 1, 6, 19, 54, 17, 402. Of these, 54 spots (≈ 50 spots in a county) is similar to the threshold for an SPB “outbreak” of one spot / 1000 host acres that has been suggested previously. In this case, *Prob(>50 spots)* from the model predictions is roughly interpretable as the probability of an SPB outbreak.

² How does the size and host acres of administrative units affect model predictions and interpretations? We assume that larger counties with more host habitat tend to have more SPB spots during outbreaks. The model takes this into account by using the numbers of spots in the previous two years. We have thus far been unable to uncover any further statistical relationships between number of spots and size or host acres of administrative units. So the size of the unit seems to matter less than one might think. We will continue evaluating the effects of unit size as data accumulate. In any case, user can expect that the potential number of spots during an outbreak is higher in large administrative units and lower in smaller units. Users with smaller administrative units, where 50 spots would be more consequential than in a larger unit, may wish to use a lower action threshold for preparation (Figure 2).

Operational utility of southern pine beetle predictions

When SPB predictions become available in late spring, an operational decision for many forest managers is whether or not to prepare for the possibility of an outbreak during the summer. Here we evaluated the actual outcomes for 2978 cases from 1988 - 2019 using two different thresholds in $Prob(>50 \text{ spots})$ for outbreak preparation. In both scenarios, we classified cases as actual outbreaks if more than 50 spots developed that year in the administrative unit (usually county or parish, sometimes Ranger Districts). The general patterns and conclusions should be about the same even with different criteria for what constitutes an outbreak.

Scenario 1. Prepare if estimated risk of an outbreak is 10% or more [$Prob(>50 \text{ spots}) > 0.10$]

- 94% Percentage of 399 historical outbreaks that would have occurred after preparation.
- 6% Percentage of cases with outbreak but no preparation (Fig. 2, upper)
- 64% Percentage of cases with preparation but no outbreak (Fig. 2, lower)
- 35%/65% Percentage of all cases ($n = 2978$) where preparation would/would not be recommended.

Scenario 2. Prepare if estimated risk of an outbreak is 20% or more [$Prob(>50 \text{ spots}) > 0.20$]

- 86% Percentage of 382 historical outbreaks that would have occurred after preparation.
- 14% Percentage of cases with outbreak but no preparation (Fig. 2, upper).
- 56% Percentage of cases with preparation but no outbreak (Fig. 2, lower).
- 26%/74% Percentage of all cases ($n = 2978$) where preparation would/would not be recommended.

In Scenario 1 compared to Scenario 2, there were more years with preparation but no outbreak (64% vs. 56% of cases), but outbreaks that come as a surprise (outbreaks without preparation) would be rare under Scenario 1 (6%). Even with the relatively careful approach of Scenario 1 (preparing for the possibility of an outbreak even when there is only a 10% chance), Scenario 1 would still have allowed most forests in most years (64%) to spare the expenses of preparing for an SPB outbreak in any given year. In Scenario 2 compared to Scenario 1, there would be fewer years where preparation was called for, and fewer cases of preparation for an outbreak that did not happen, but more cases of outbreaks without preparation (14% vs. 6%).

In choosing between these and other possible scenarios, managers will probably wish to consider the costs of preparing for outbreaks that do not happen vs. the costs of not preparing for outbreaks that do happen. In general, having a lower threshold for preparation will mean fewer unfortunate surprises, and higher threshold will mean fewer cases of preparing for events that do not happen (Figure 2). It would be easy and natural to use different action thresholds for different responses that are more or less challenging to implement. Improvement of the model (e.g., by taking advantage of the new outcomes that are added each year) will improve the reliability and utility of predictions by weakening trade-offs between “precision” and “recall” (https://en.wikipedia.org/wiki/Precision_and_recall).

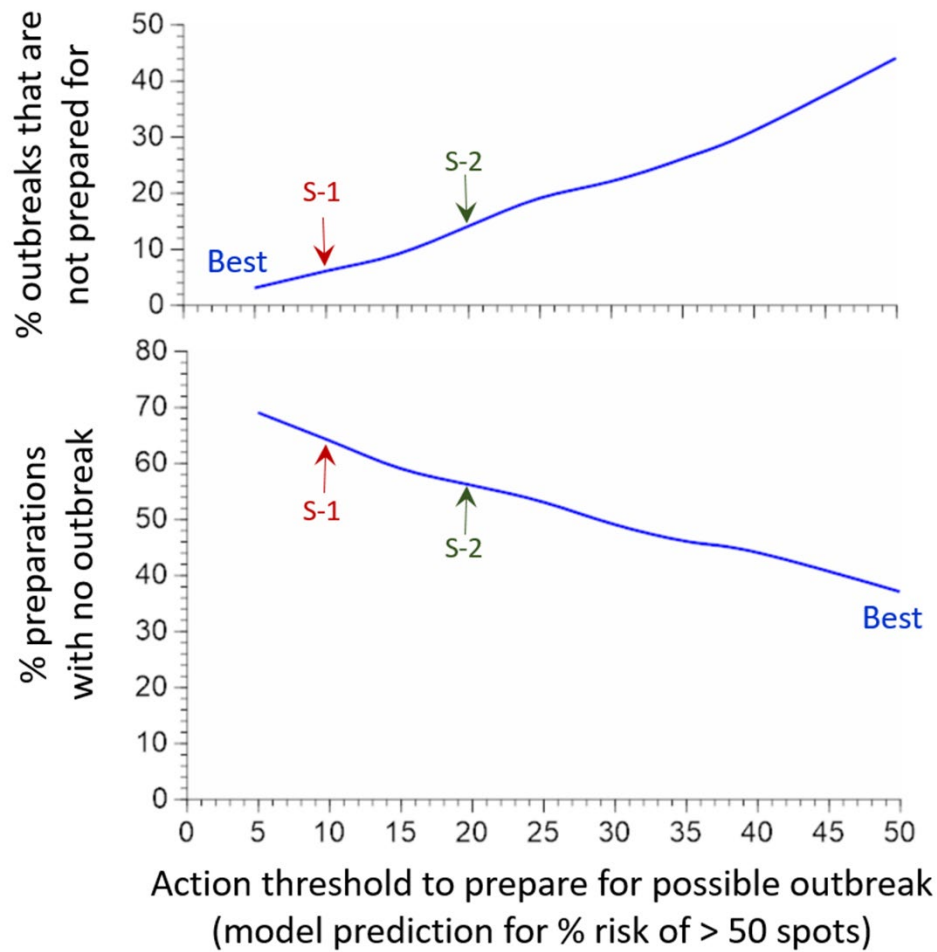


Figure 2. The effects of action threshold for preparation on the percentage of outbreaks that happen without preparation (upper) and the percentage of preparations in which no outbreak occurred. Lower action thresholds will minimize the unfortunate surprises (an outbreak that was not prepared for) while higher action thresholds reduce the cases where preparations are made without being needed. Scenarios 1 and 2 are indicated as S-1 and S-2. Based on 2978 cases from 1988 - 2019.

Model success in predicting the start of new outbreaks (needs to be updated to include 2011-2017 – including ranger districts)

How well has the model performed in predicting new outbreaks? Southern pine beetle population abundance tends to be either low or high (Fig. 3), and to stay low or high for years at a time. The best time to stop a potential multiyear outbreak is at the start of a new outbreak while abundance is still moderate. The SPB prediction system can provide several additional months of preparation time to forest managers who are at risk of a rising outbreak. Using data points for outbreaks only when they were **new** outbreaks in that year in that administrative unit, we consider outcomes from the scenario where preparation occurs if the estimated risk of a new outbreak is 10% or more.

Scenario 1. Prepare if estimated risk of a new outbreak is 10% or more [$Prob(>50 \text{ spots}) > 0.10$]

- 91% Percentage of 180 new outbreaks that would have occurred after preparation.
- 9% Percentage of cases with new outbreak but no preparation
- 82% Percentage of cases with preparation but no new outbreak
- 57%/43% Percentage of cases ($n = 1590$) where preparation would/would not be recommended.

With an action threshold of 10% in $Prob(>50 \text{ spots})$, there would have been preparation in advance of almost all new outbreaks (91%) and there would still have been 43% of cases (where a case equals one administrative unit in one year) where managers would not be called upon for SPB preparation. Less desirably, this management scenario would also involve preparation for plenty of cases where no outbreak occurs: 82% of cases with preparation would not have experienced a new outbreak.

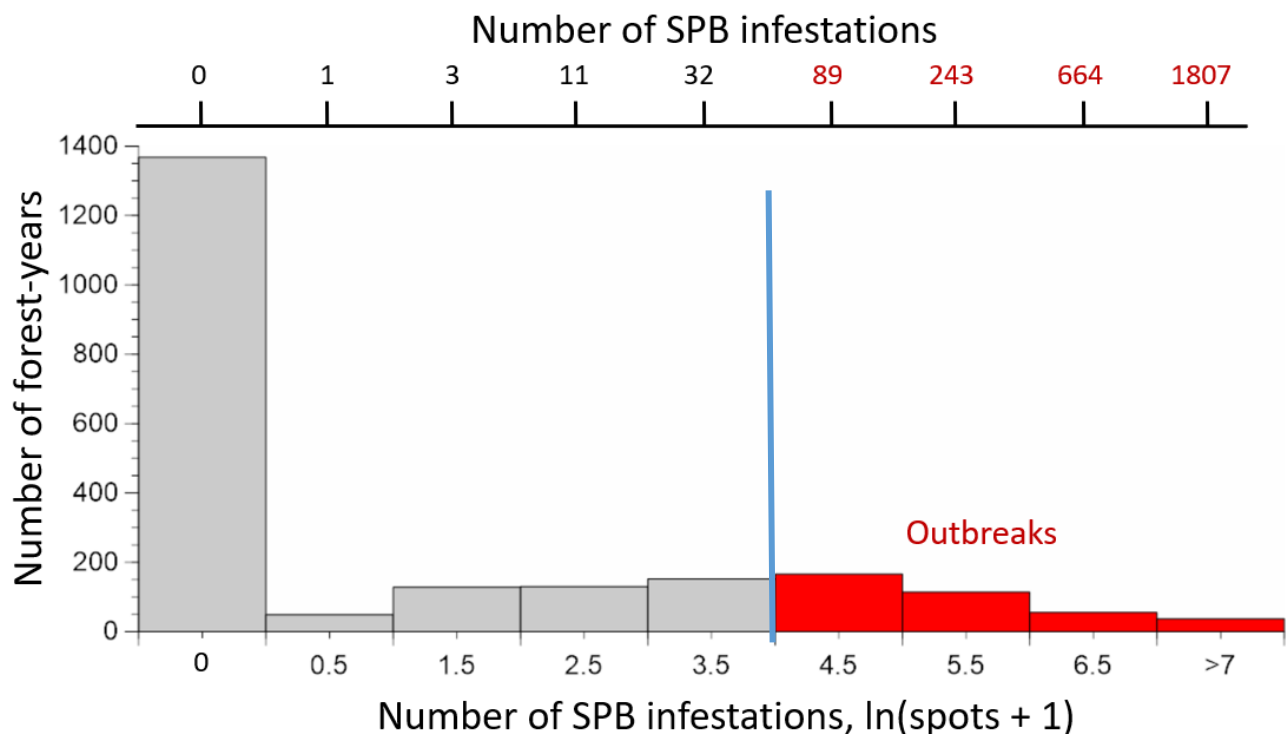


Figure 3. Southern pine beetles are rare (0 infestations) in most forests in most years (almost 1400 cases of 2199 forest-years from 1988 – 2019). However, when outbreaks occur they tend to be large and persistent. Red bars to the right indicate forest-years with 89 to > 1800 spots. See also [Martinson et al. 2013](#).

Appendix 1. Southern pine beetle prediction system as of 2017-2020

The current version of the model predicts risks of SPB impacts for each administrative unit (usually County, Parish, or Ranger District) based upon spring trapping captures of SPB (SPB_t), the number of spots last year ($Spots_{t-1}$), clerid trap captures the previous year ($clerids_{t-1}$), and the number of spots two years previously (SPB_{t-2}). The strongest effects on model predictions come from current year SPB captures and number of spots last year (Fig. A-1). The model is a next generation version of that which has been previously developed by Ron Billings, Texas Forest Service. The model structure is that of a zero-inflated Poisson (ZIP), which includes a binomial model and count model. It is specified below.

$$\pi = \frac{e^{\beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \dots}}{1 + e^{\beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \dots}} = \text{Probability of 0 spots from binomial element of Zero-inflated Poisson (ZIP).}$$

$$\mu = e^{\beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \dots} = \text{Mean of Poisson function that estimates number of spots (in log units) if there are spots}$$

Parameter		Binomial-model (π)	Count-model (μ)
intercept =	$B_0 =$	0.3021	0.9450
SPB =	$B_1 =$	-1.2839	0.2383
clerids.t1 =	$B_2 =$	0.3914	-0.0752
spots.t1 =	$B_3 =$	-1.1131	0.2411
spots.t2 =	$B_4 =$	-0.3992	

Prob(> 0 spots) considering binomial and count model
 $= 1 - (\pi + (1 - \pi) \cdot Z)$
 Where $Z = \text{Prob}(0 \text{ spots}) \text{ from count model} = \text{POISSON.DIST}(0, \mu)$

Expected number of spots if there are spots = μ

Prob(> 18 spots) = $(1 - \pi) \cdot \text{PoissonCumdist}(\geq 3, \mu)$

Prob(> 53 spots) = $(1 - \pi) \cdot \text{PoissonCumdist}(\geq 4, \mu)$

Prob(> 147 spots) = $(1 - \pi) \cdot \text{PoissonCumdist}(\geq 5, \mu)$

Prob(> 402 spots) = $(1 - \pi) \cdot \text{PoissonCumdist}(\geq 6, \mu)$

Prob(> 1095 spots) = $(1 - \pi) \cdot \text{PoissonCumdist}(\geq 7, \mu)$

Prob(> 2979 spots) = $(1 - \pi) \cdot \text{PoissonCumdist}(\geq 8, \mu)$

The original units of SPB_t and $clerids_t$ are average captures per trap per two weeks in spring. Usually there are 1 - 3 traps per administrative unit that were monitored for six weeks during the time when SPB are dispersing to initiate new infestations. SPB_t is divided by 10 if endo-brevicommin was used to account for the greater attractiveness of traps relative to historical data. Prior to calculations, the independent variables are log-transformed [$\ln(x+1)$] and scaled to mean = 0 and SD = 1 relative to the historical data that were used to develop and parameterize the model. The model was fit using data for 1774 administrative units (usually counties, parishes, or Ranger Districts) from Texas to Virginia during 1988 – 2009).

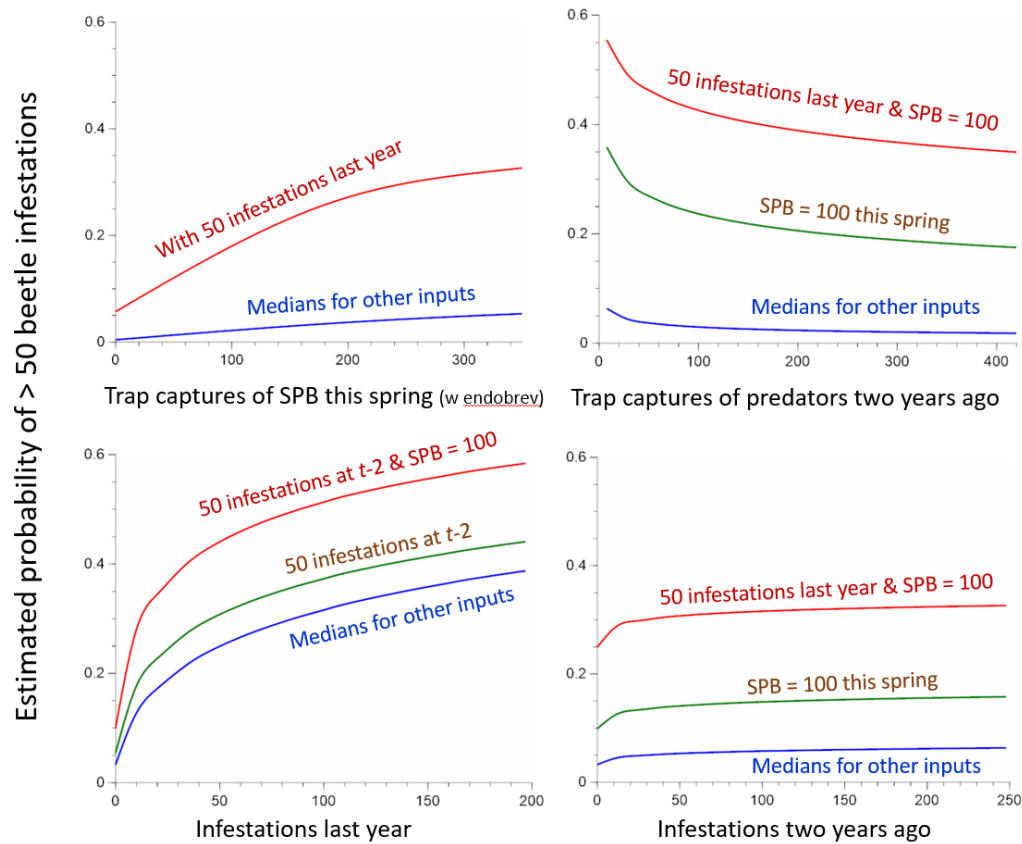


Figure A-1. The response of model predictions to varying levels of each input variable.

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