**Appendix 2: The statistical methods**

***1. Multiple autoregressive state systems (MARSS)***

To combine the time series of multiple pheromone traps, we fitted a Multivariate Autoregressive State-Space Modeling (MARSS) to the time series (specifically, see Chapter 15 of Holmes et al. 2012). The sampled blocks varied at the FREC across the years and no single block was sampled continuously from 1984 to 2016. Due to the gaps in data due to winter, we fitted the MARSS separately for each year. We only fitted the MARSS model for years when there were three or more blocks. For years with only two traps, we found that one trap had more consistent catches while the other trap had very few moths captured (see: 1985-1998 excluding 1986 in Figure S3).

The general MARSS model is shown below with a hidden state process and an observation ( model:



Here are the parameters that are estimated through maximum likelihood. The true population size is represented by the state with B describing the interactions between the different processes and describing the mean trend. Assuming there are traps per year, we first test if the time series can be combined in that there is one state process model to describe the population. We first we modify the matrix which is a matrix with each element describing which individual block time series is associated with what trajectory. For example, if there are three blocks (A, B, C), we can test multiple hypotheses: the three blocks can be represented by one state-process model, the three blocks have to be represented by three state process models, A and B are more similar to each other and can be represented by one state process model while C is different and must be described with another model, etc.   
  
We assume that all the blocks have the same observation variance and that the errors are i.i.d (). Therefore, we assume that is a diagonal matrix with equal variance .

(3)

Finally, the are the scaling parameters and represent the bias between the block and the total population. The first element in the will be fixed at 0 and the multiple time series are scaled against each other. After creating different hypotheses, we chose the model with the lowest AICc. We are then able to get the estimated underlying states and if there are more than two states, we chose the one with more sites across 33 years.

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**Figure S1:** Log-transformed time series of adult *Cydia pomonella* captured in pheromone traps across multiple blocks at the Fruit Research Extension Center from 1984 to 2016.

1. ***Circular variance***

Circular variance is a useful measure of dispersion in periodical. The important summary statistics consist of angular observations where *n* represents the total number of individuals. The mean resultant length is the average vector length when individuals are distributed on a circle.

(4)

The circular variance is then calculated as

(5)

Calculating the circular variance assumes that we know where the individuals are in the state of development, yet in our simulation we only know what stage and subcompartment they are in. We assume then that the number of individuals is evenly distributed in each subcompartment. We modify equation 4 then by integrating over the integral of each subcompartment.

(6)

is the mean density at each subcompartment with being the total number of individuals at the subcompartments.

(7)

By taking the integral, the final form of this equation is

(8)

References

Holmes, E. E., E. J. Ward, and K. Wills. 2012. MARSS: Multivariate autoregressive state-space models for analyzing time-series data. R Journal 4:11–19.