REPLACEMENT TEXT 1:

Classical multi-state models are closely related to closed population SCR models. In particular, keeping with the notion of having a discrete state variable and going back to the shad example from Section 16.3.1.1, instead of having a Markovian state-transition model, we imagine that each fish has a "home area", and the observation state is conditioned on that (constant) home area, . We can express that model as

where (a discrete state) is the current location of fish *i*, and (also a discrete state) is its home area. We could imagine that the state-transition probability vector, , is related in some fashion to distance between possible observation states and home area. In this model, the current state, , is not Markovian as it is in classical multi-state models but, rather, an independent sample from a distribution indexed by . We see that, by letting the number of possible states increase to infinity, the model morphs into a continuous space SCR model, except can take on any value in the state-space (this type of “search-encounter” model was discussed in Chapter 15). If we restrict the potential observation locations to some prescribed subset of the state-variable , e.g., trap locations, then the model is precisely an SCR model for a fixed trap array. Therefore, SCR models can be viewed as multi-state models, but with a continuous state-variable (instead of discrete) – “space” - and with independent transitions between states in successive times (instead of Markovian).

REPLACEMENT TEXT 2:

In the above example on American shad, we lost a lot of information (about movement) by using a two-state model. As already mentioned, we could have used a seven-state model that would have allowed us to use the encounters at each antenna. However, as the number of states increases, so, too, does the number of parameters, particularly the number of transition parameters. It stands that highly parameterized transition probability matrices require huge amounts of data, which are often not available. Information is also lost in that we must reduce the encounter histories to be binary (“captured” or not during each sample occasion). In our shad example, fish can pass an antenna multiple times within a sample occasion but this information is typically not used in multi-state models. And finally, one other issue that multi-state models have not rectified is being in more than one state at a time. Again, in our shad example, we must decide what to do with a fish that is detected at more than one antenna. By reducing our example to two states of upstream and downstream, we reduced this problem to just a few cases. However, within the dataset, many fish are detected at two or more antenna during a week. This can be addressed sometimes by creating additional "states", but again, the number of states can grow quickly.

These issues are directly resolved by using a fully spatial CJS model in continuous space. We've established many times that various observation models allow for multiple detections in a given occasion, analogous to closed SCR models, so that information is not lost by having to create binary encounter histories. Additionally, by not defining a distinct state, spatial CJS models directly address the issue of individuals only being able to be in one state at a time. The formulation as an SCR model also resolves the problem of estimating large transition probability matrices, by allowing us to essentially parameterize the whole matrix by “distance” and therefore reduce the dimensionality of the problem to just 1 or a few parameters.

To achieve a fully spatial CJS model, we build on the state-space and multi-state CJS models, but explicitly incorporate individual movement as an individual covariate (Royle, 2009a). With this in mind, we need only make a few changes to the model. We will not have discrete states and thus the biggest difference is that individuals do not “transition” between a finite set of states, but instead are allowed to move in continuous space.

We may consider the same basic encounter models as described previously (i.e., Poisson, Bernoulli, or multinomial). In particular, let indicate the observed encounter data of individual *i* in trap *j*, during interval (secondary period or sub-sample) and primary period *t*. We note that in some cases we may have only one interval ), which correspond to the design underlying a standard CJS or JS models, whereas the case corresponds to the “robust design” (Pollock, 1982). The Poisson observation model, specified conditional on , is:

where is the baseline encounter rate and is the detection model as a function of distance. If the individual is not alive ), then the observations must be fixed zeros with probability 1. Remember that in the CJS formulation, we condition on first capture which means that will be 1 when *t* is the first primary period of capture. As before in the non-spatial CJS model, we can denote this as where indicates the primary occasion in which individual *i* is first captured.

Modeling time-effects either within or across primary periods is straightforward. For that, we define and then develop models for as in our closed SCR models (we note that trap-specific effects could be modeled analogously).

We follow the same model for survival as described in the non-spatial version of the CJS (Section 16.3.1). In that version, we did not allow for survival to be time specific. However, it is easy to do so by allowing to vary with each time step:

Under this model or the one in Section 16.3.1, there is still no recruitment and therefore once an individual leaves the population (i.e., ), it cannot return.