Chapter 11

# Other Topics

- Prediction – surplus production example.
- Non-standard distributions – zero/one tricks.
- A simple model too hard for WinBUGS .
- ADMB (Automatic Differentiation Model Builder) demonstration.



# Prediction: Surplus prodn example

The population dynamics equation was

$$B_t \;=\; (B_{t-1} + rB_{t-1}(1 - B_{t-1}/K) - C_{t-1})\, e^{u_t}\;, \quad t > 1\;,$$

and this can be used (given the catch levels) to generate the posterior-predictive distribution of future biomass.

The example implements this from BRugs.

# Non-standard distributions

In some circumstances, we might need to use a distribution (for the data, or as a prior) that is not implemented in WinBUGS. For example:

- Cauchy
  - Recommended by Gelman (2005) as a prior for variance components. Not implemented in WinBUGS.
- Negative binomial
  - The WinBUGS implementation of the negative binomial only permits integer values of the overdispersion parameter.
- Reference prior
  - E.g., the Jeffreys' prior for the Beverton-Holt stock recruit curve (Millar, 2002).



# Non-standard distributions

It may be possible to generate the desired distribution as a function of other distributions.

- Cauchy
  - Gelman (2005) generates the Cauchy prior as the ratio Z/s, where Z is a standard normal and s is the square-root of a chi-square with 1 d.o.f.
- Negative binomial
  - The negative binomial can be generated as a gamma mixture of Poisson distributions.

# Non-standard distributions

More generally, WinBUGS can be coerced into handling non-standard distributions by using the zero/one tricks.

Essentially, we want to introduce a term $g(y,\theta)$ into the joint density.

We tell WinBUGS a little white lie, namely, that we observed a datum, 0, from a Poisson distribution with mean $-\log(g(y,\theta))$ . (If $g(y,\theta)$ can exceed unity, then we use mean $-\log(g(y,\theta))+C$, for some suitably big $C$.)

NOTE: For a Poisson($\mu$) distribution, the probability of a zero is $e^{-\mu}$. So, for a Poisson( $-\log(g(y,\theta))$ ) distribution, the probability is $g(y,\theta)$.



# Example: Modelling Cauchy data

Assume $$f(y\,|\,\theta) = \frac{1}{\pi}\frac{1}{1+(y-\theta)^2}$$

Using the zero trick:

```
model {
#Using the zero trick
  theta ~ dnorm(0.0,1.0E-6)
  for(i in 1:n) {
    zeros[i] <- 0
    phi[i] <- log(1+pow(y[i]-theta,2))
    zeros[i] ~ dpois(phi[i])
  }
}
#Data;
list(n=9, y=c(-0.774,0.597,7.575,0.397,
              -0.865,-0.318,-0.125,0.961,1.039))
#Inits;
list(theta=0)
```

# Too hard for WinBUGS

WinBUGS can handle large and sophisticated models, with hundreds of parameters. However …

The observation-error-only surplus production model is problematic for WinBUGS because the full conditional distributions for the parameters are massively non-linear and high-order. This model does not compile.



# ADMB software

The Automatic Differentiation Model Builder maximizes the joint posterior, and then uses adaptive Metropolis Metropolis-Hastings to sample from it.

ADMB demonstration: Observation-error-only surplus production model of the tuna data.

# ADMB vs WinBUGS

ADMB advantages:

- More powerful and flexible.
- Faster.
- Finds posterior mode:
  - Useful for approximation of Bayes factors.
  - Alternative to $D(\bar{\theta}) = D\left(E_{\theta|y}[\theta]\right)$ in calculation of DIC.
- Easily switch-able between classical and Bayesian.



# ADMB vs WinBUGS

ADMB disadvantages:

- Much, much, much harder to use.
- Not as well documented.
- Smaller group of users.
- Not as much fun!
- Lacking in exploratory tools and diagnostics.
- Difficult to interface to R.
- Non-free.