1) Model for the sea surface temperature

model {

trend[1]<-alpha+beta[1]\*cos(2\*pi\*JDAYS[1]/365)+beta[2]\*sin(2\*pi\*JDAYS[1]/365) # defining the first element of the series

for(i in 2 : N) { # N is the number of days

T[i] ~ dnorm(mu[i], tau) # T is observed temperature

mu[i] <- trend[i] + ar1 \* (T[i-1] - trend[i-1]) # including autocorrelation (AR1)

trend[i]<-alpha+beta[1]\*cos(2\*pi\*JDAYS[i]/365)+beta[2]\*sin(2\*pi\*JDAYS[i]/365) # seasonal trend

}

ar1 ~ dunif(-1.1,1.1) # Prior for autocorrelation parameters

alpha~ dnorm( 0 , 1.0E-6 ) # Prior for alpha

beta[1] ~ dnorm( 0 , 1.0E-6 ) # Prior for beta1

beta[2] ~ dnorm( 0 , 1.0E-6 ) # Prior for beta2

tau ~ dgamma( 0.001 , 0.001 ) # Prior for tau (tolerance for random variability around the expected temperature)

#derived

phi<-atan(beta[2]/beta[1]) # maximum

}

2) Model for the spawning probability

model {

#fish level

for (i in 1:N){ # number of fish sampled

gsi[i]~dgamma(mu.i[i],r.i[i]) # observed GSI

r.i[i]<-r[zz[i]] # parameter “rate” of the gamma of the individual (NOTE that it is conditional to the state of the individual, zz[i] (spawning or not)

mu.i[i]<-mu[zz[i]] # parameter “shape” of the gamma of the individual (NOTE that it is conditional to the state of the individual, zz[i] (spawning or not)

z[i]~dbern(pS[i]) # current state of the fish i

zz[i]<-z[i]+1 # trick for setting zz (either 0 or 1) from the output of the Bernoulli distribution (either 1 or 2)

logit(p.r[i])<-alpha+beta1\*cos(2\*pi\*JDAYS[i]/365)+beta2\*sin(2\*pi\*JDAYS[i]/365) # p.r is the probability of a female is at spawning state, given that it is sexually mature

pS[i]<-p.mad[i]\*p.r[i] # p.mad is the probability that a female is sexually mature (DATA; they are inferred from TL and morphotype, from empirical data)

}

#state level (spawning and non-spawning)

for (i in 1:2){ # 2 states; r and mu are the two parameters of a gamma distribution

r[i] ~ dunif(0,100)

mu[i] ~ dunif(0,100)

}

#Priors

alpha~ dnorm( 0 , 1.0E-6 ) # Prior for alpha

beta[1] ~ dnorm( 0 , 1.0E-6 ) # Prior for beta1

beta[2] ~ dnorm( 0 , 1.0E-6 ) # Prior for beta2

#derived

phi<-atan(beta2/beta1)

}

3) Model for the feeding index

model {

#fish level

for (i in 1:N){ # N fishes

gut[i]~dgamma(shape[MUESTREO[i]],rate[MUESTREO[i]]) # shape and rate

} # MUESTREO is a given haul/sample

for (i in 1:M){ # M hauls/samples

rate[i] ~ dunif(0,100) # Prior for rate

shape[i] <-mu[i]\*rate[i]

mu[i]<-alpha+beta1\*cos(2\*pi\*JDAYS[i]/365)+beta2\*sin(2\*pi\*JDAYS[i]/365) # trend

}

#Priors

alpha~ dnorm( 0 , 1.0E-6 ) # Prior for alpha

beta[1] ~ dnorm( 0 , 1.0E-6 ) # Prior for beta1

beta[2] ~ dnorm( 0 , 1.0E-6 ) # Prior for beta2

#derived

phi<-atan(beta2/beta1)

}

4) Model for the distance travelled (note that the model for the home range is identical)

model {

#fish level

for(i in 1:npeces){ # npeces is the number of fish

trend[1,i]<-alpha0+alpha[i]+beta[1]\*cos(2\*pi\*JDAYS[1]/365)+beta[2]\*sin(2\*pi\*JDAYS[1]/365)+beta[3]\*TL[i] # setting the value for the first element in the series

for(j in 2:M){ # nested loop within each fish: M are time periods (10 days)

trend[j,i]<-alpha0+alpha[i]+beta[1]\*cos(2\*pi\*JDAYS[j]/365)+beta[2]\*sin(2\*pi\*JDAYS[j]/365)+beta[3]\*TL[i]

mu[j,i]<-trend[j,i]+rho\*(D[j-1,i]-trend[j-1,i]) # adding autocorrelation

D[j,i]~dnorm(mu[j,i], tau)

}

}

#priors for fish (intercept random effects)

for(i in 1:npeces){

alpha[i]~dnorm(0,tau.alpha) # tau.alpha determines the between-fish variability in intercepts

}

#hyperpriors

alpha0~ dnorm( 0 , 1.0E-6 ) # Prior for the general intercept

for (i in 1:3){

beta[i]~dnorm(0, 1.0E-6) # Priors for betas

}

tau~dgamma(0.001,0.001) #

tau.alpha~dgamma(0.001,0.001) # Prior for tau.alpha (it determines the between-fish variability in intercepts)

rho~dunif(-1,1) # Prior for the autocorrelation term

#derived

phi<-atan(beta[2]/beta[1])

}

5) Model for catchability

model {

for (i in 1:N){ # N is the number of gear deployments

CAP[i] ~ dpois(mu.eff[i]) # CAP are captures (number of fish per fishing journey)

abundance[i]~dgamma(shape[i],rate[i]) # PRIORS for expected abundance (hidden, unobserved variable). Shape and rate are the gamma parameters and they are inferred from Pita (2011).

mu.eff[i]<-abundance[i]\*p[i] # expected catches, given abundance and p

logit(p[i])<-log(EFF[i])+alpha+beta1\*cos(2\*pi\*JDAYS[i]/365)+beta2\*sin(2\*pi\*JDAYS[i]/365)

} # seasonal trend for p

#Priors

alpha~ dnorm( 0 , 1.0E-6 ) # Prior for alpha

beta[1] ~ dnorm( 0 , 1.0E-6 ) # Prior for beta1

beta[2] ~ dnorm( 0 , 1.0E-6 ) # Prior for beta2

#derived

phi<-atan(beta2/beta1)