

Forecasting environmental change: modeling thermal refugia and brook trout abundance

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Objective	Input data	Region	Scale	Model	Benefits	Limitations
Modeling groundwater influence on stream temperature	Air/water temperature data	Shenandoah National Park	Stream reach	Multiple linear regression	Computationally simple; uses commonly collected data; provides index of groundwater effect	Requires local stream temperature data
Modeling seasonal climate influence on brook trout abundance	3-pass backpack electrofishing data; 33 years; 3204 samples; Mostly state agency fish data sources; PRISM climate data	PA to GA	Stream reach	Hierarchical Bayesian Models; MCMC	Flexible; Inference from posterior distributions; accounts for detection probability	Processing speed; requires external validation
				Boosted Regression Trees	Internal cross- validation; can model nonlinear responses; partials effects of individual vars	Requires large datasets

Modeling groundwater influence on stream temperature





Groundwater affects thermal habitat for stream fishes



Variation in groundwater influence



Stream temperature models





2-term linear models for stream temperature

 Mean daily air temperature (MDA)
Accumulated degree days (ADD): groundwater indicator

Improvements in model performance when including groundwater term (ADD).





Index of groundwater vs. air temperature controls ratio of standardized model coefficients

As much variation within HUC12 watersheds as between them



Unsuitable habitat



Modeling brook trout abundance





Interannual variation with spatial synchrony



Importance of flow for YOY abundance



















Modeling brook trout abundance: Hierarchical Bayesian Models (N-mixture) in JAGS/R

Process model:

N[*i*,*t*,*j*] ~ Poisson(λ) for *i* sites, *t* years, and *j* age classes across efishing passes

λ ~ seasonal climate covariates + mean effect (μ) + random effect (ε)

Detection model:

y[i,t,j] ~ Binomial(N[i,t,j], p)

p ~ sampling day-of-year effect + prior 7-d precip effect



Year (1982-2014)



Effects of seasonal climate variation on abundance

For 95% Credible Intervals excluding zero:

	Precipitation			
	YOY	Adult		
Fall	Positive	-		
Winter	Negative	-		
Spring	Negative	Negative		
Summer	-	-		

	Temperature			
	YOY	Adult		
Fall	Negative	Positive		
Winter	Positive	Negative		
Spring	-	_		
Summer	Positive	-		

Inferences

YOY abundance generally more responsive to seasonal climate variation than adult abundance Highest YOY abundance scenario: wet/cold fall + dry/warm winter + dry spring + warm summer Lowest YOY abundance scenario: dry/warm fall + wet/cold winter + wet spring + cold summer Highest adult abundance scenario: warm fall + cold winter + dry spring Lowest adult abundance scenario: cold fall + warm winter + wet spring Some seasonal climate effects have opposite effects on YOY and adult N: fall and winter temperature

Observed vs estimated abundance

1F003



Year (1982-2014)

Observed vs. estimated N: 10% hold-out validation



Observed

Boosted Regression Trees

- Library "gbm" in R and scripts from Elith et al. (2008)
- Internal cross-validation for model fitting
- Requires optimization for learning rate and tree complexity (interactive effects)
- Variables including density-dependent parameters (re: predation and competition) and density-independent parameters (re: temperature and precipitation)

Modeling brook trout abundance: adults



Modeling brook trout abundance: YOYs





Observed





Positive effects of YOY abundance on adult abundance in following year



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