On-farm Strip Trials

going beyond small plot experiments (Part 2)

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Why Bayesian?

The adoption of Bayesian approaches simplifies the interpretation of the results and augments the inference [Che et al. , 2010].

Compared with REML, Baek, et al. [2019] demonstrate the advantages in terms of variation control and powerful inference.

It is a complementary approach to GWR.

Does the new model differ from GWR?

We rewrite the GWR model as:

$$y_i = \beta_0 + \beta_1 N_i + \beta_2 N_i^2 + (u_{0i} + u_{1i} N_i + u_{2i} N_i^2) + e_i, \quad (1)$$

where N_i is the nitrogen level at location s_i. The random term incorporates a spatial covariance matrix V_s such that

$$\Sigma_u = V_s \otimes V_u. \quad (2)$$

V_s could be $AR1(\rho_r) \otimes AR1(\rho_c)$, Gaussian random field, or nearest neighbour distance (similar to GWR).

What sampler should you use?

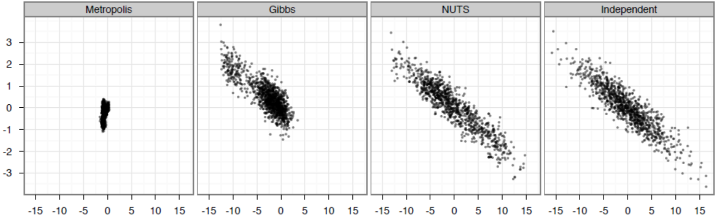
NUTS (No U-turn Sampler) [Hoffman et al. , 2014] is an extension to the Hamiltonian Monte Carlo method.

Compared with Gibbs sampling, NUTS has more effective sample sizes and lower autocorrelation that decreased at a faster rate.

When true heritability was low in the simulated data, the skewness of the marginal posterior distributions with the NUTS was smaller than that with Gibbs sampling [Nishio et al. , 2019].

The NUTS is implemented in the R-package: `rstan`.

Why NUTS?



Draws from a highly correlated 250-dimensional distribution (right)

	RW	Gibbs	HMC	NUTS
Conjugation	Yes	No	No	No
High dimension	Slow	Slow	Fast	Fast
Divergence risk	High	Medium	Low	Low
Sensitive to step size	High	Medium	Medium	Low

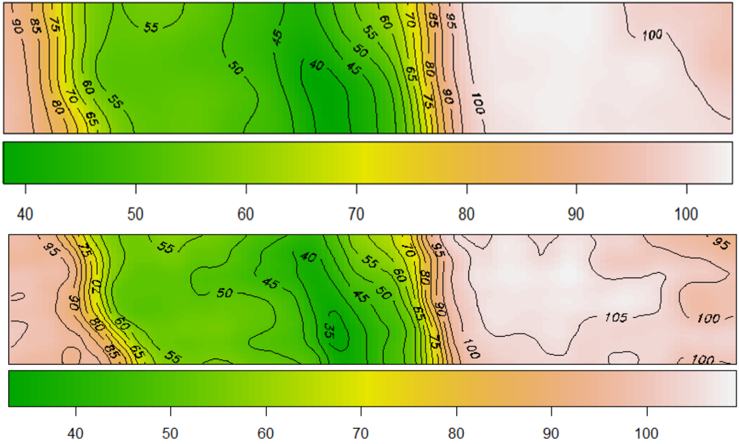
Is the Bayesian approach better than GWR?

One goal, two paths.

Each has its own advantages.

GWR	Bayesian SCRP
with neighbouring data	with all data
higher resolution	lower resolution
bandwidth selection	prior specification
maximise local log-likelihood	maximise global log-likelihood
t scores and p-values	credible intervals
	PP check and LOO PIT
	Pareto k diagnostic
	Bayesian R^2

Are the results different?



Predicted yield with medium nitrogen rate 75.4 kg/ha across the field by GWR (above) and Bayesian SCRP (below).

New research directions

On-farm large scale experiments can have great success in two important research directions, impacting Australian Grains Industry:

- assessment of trait stability; and
- assessment of performance across heterogeneous environment.

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