

Longitudinal modelling of crop root physiology as a breed-specific spatial response to environmental conditions



Grace S. Chiu,^{1,2,3} Anton P. Wasson,⁴ Alec B. Zwart⁵

¹ ANU Research School of Finance, Actuarial Studies and Statistics

- ² University of Washington, Department of Statistics
- ³ University of Waterloo, Department of Statistics and Actuarial Science
- ⁴ CSIRO Agriculture and Food
- ⁵ CSIRO Data61

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Outline

- Why model root architecture?
- 2 Data visualization
- 3 Inference approach: Pre-Chiu vs. Chiu
- ④ Key insights:
 - Multiresolution heritability
 - Root system's bulk vs. exploration



1. Why model root architecture?



Above ground. . .



Damage to bumper global wheat crop spurs use as animal feed



A combine drives over stalks of soft red winter wheat during the harvest on a farm in Dixon, Illinois, July 16, 2013. REUTERS/Jim Young/File Photo



Above ground. . .



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👿 Heritability - Wikipedia

Secure https://en.wikipedia.org/wiki/Heritability

Definition [edit]

Any particular phenotype can be modeled as the sum of genetic and environmental effects:^[4]

Phenotype (P) = Genotype (G) + Environment (E).

Likewise the phenotypic variance in the trait – Var (P) – is the sum of effects as follows:

$$Var(P) = Var(G) + Var(E) + 2$$

 $Cov(G,E).$



.

In a planned experiment Cov(G, E) can be controlled and held at 0. In this case, heritability is defined as:

$$H^2 = rac{\mathrm{Var}(G)}{\mathrm{Var}(P)} \ .$$

 ${\cal H}^{\!\!2}$ is the broad-sense heritability. This reflects all the genetic



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Q: What phenotypic features result in a high h^2 ?



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Age-old industry standard:

What above-ground phenotypic features result in a high h^2 ?



Getting to the ROOT of the issue. . .



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% http://people.csiro.au/W/A/Anton-Wasson

Nationa

Biography

Dr Anton Wasson is part of the Molecular marke by the GRDC (CFF00009). The project aims to ide phosphorus fertilizer that farmers have to apply Australia and the Riverina and South-West Slope Dr Wasson was previously part of the Root Phenotyping Project which developed cutting-edge field-based facilities to measure root performance and root architecture in the field

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Dr Wasson's focus is the improvement of the root structure of wheat to enhance water and nutrient uptake and use. This involves linking the outcomes of experiments in the laboratory and field.



Cutting-edge root system imaging



Article Navigation

A portable fluorescence spectroscopy imaging system for automated root phenotyping in soil cores in the field \Im

Anton Wasson 🖾, Leanne Bischof, Alec Zwart, Michelle Watt

J Exp Bot (2016) 67 (4): 1033-1043. **DOI:** https://doi.org/10.1093/jxb/erv570 **Published:** 29 January 2016



Cutting-edge root imaging

up/doi/10.1093/jxb/erv570

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Fig. 1.



Steps in the BlueBox methodology. (A) An operator root sampling with a 2 m long stainless steel coring tube with a tapered tip (not visible). The tube was driven into the ground by a tractor-mounted push press. (B) A soil core emptied into a cradle in a manual root-counting method. The core has been scored with a knife every 10cm to facilitate breaking. (C) The broken face of a soil core segment as seen by a human operator. The number of visible roots (highlighted with white arrows) is assessed in a few seconds. (D) The fluorescence imaging box (in the laboratory; for field use this would typically be mounted on a utility vehicle). The access panel at the front is ajar and a cassette is visible within. The digital SLR camera is operated remotely from the laptop. The battery on the left powers the LEDs, installed underneath the top cover. (E) View of the ceiling of the interior of the box. The central aperture is face of the digital SLR camera lens. The other apertures are UV-emitting LEDs (inactive in this photo) behind black light filter glass. (F) A visible image of the cassette containing the soil core segments. The cassettes were flipped so that both faces of the segment were photographed (the underside is visible here). (G) The fluorescence image of the cassette shown in F. The roots are fluorescing blue; larger roots are highlighted with white arrows.



Cutting-edge root imaging

ıp/doi/10.1093/jxb/erv570

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Fig. 3.



The image processing steps in the analysis software. (A) Image of cassette template. (B) Circular 'Well' labels (each label is overlaid as a separate colour). (C) RGB image of cores in wells. (D) Detected 'Linear structures' mask (overlaid in green on blue channel). (E) 'Debris' mask (overlaid in green on original image). (F–J) All subsets shown with 'Well' labels as transparent overlays: (F) blue channel image; (G) 'Debris-excluded root' mask (in green); (H) 'Roots within wells' mask (in green), with arrows indicating excluded roots; (I) labelled 'Reconstructed roots' (In 'Well' label colour), with arrow indicating a reconstructed root; (J) labelled 'Filtered roots' (in 'Well' label colour), with arrow indicating a root filtered by hue. (K) Labelled 'Filtered roots' (overlaid in 'Well' label colour) in 'Well' label colour), with arrow indicating a root filtered by hue. (K) Labelled 'Filtered roots' (overlaid in 'Well' label colour), with arrow indicating a root filtered by hue. (K) Labelled 'Filtered roots' (overlaid in 'Well' label colour), with arrow indicating a root filtered by hue. (K) Labelled 'Filtered roots' (overlaid in 'Well' label colour), with arrow indicating a root filtered by hue. (K) Labelled 'Filtered roots' (overlaid in 'Well' label colour), with arrow indicating a root filtered by hue. (K) Labelled 'Filtered roots' (overlaid in 'Well' label colour), with arrow indicating a root filtered by hue. (K) Labelled 'Filtered roots' (overlaid in 'Well' label colour), with arrow indicating a root filtered by hue. (K) Labelled 'Filtered roots' (overlaid in 'Well' label colour), with arrow indicating a root filtered by hue. (K) Labelled 'Filtered roots' (overlaid in 'Well' label colour), with arrow indicating a root filtered by hue. (K) Labelled 'Filtered roots' (overlaid in 'Well' label colour), with arrow indicating a root filtered by hue. (K) Labelled 'Filtered roots' (overlaid in 'Well' label colour), with arrow indicating a root filtered by hue. (K) Labelled 'Filtered roots' (overlaid in 'Well' lab



2. Data visualization



"It's very important to see first hand how the data are collected. Like, the guy downstream sees a fish swoosh by, yells to the data entry guy 200 yards upstream: 'Fish! I think it was a G[???] Redhorse!' Could've been Greater or Golden or neither; data guy enters 'seahorse'."



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— (My dramatized version of) the greatest piece of advice from Peter Guttorp.

Soil coring at multiple field environments can directly quantify variation in deep root traits to select wheat genotypes for breeding $\frac{1}{2}$

A. P. Wasson 🗷, G. J. Rebetzke, J. A. Kirkegaard, J. Christopher, R. A. Richards, M. Watt

J Exp Bot (2014) 65 (21): 6231-6249. **DOI:** https://doi.org/10.1093/jxb/eru250 **Published:** 24 June 2014



Fig. 4 Root distributions by depth at Leeton Experimental Station 2011. The error bars show the standard error of the mean for four replicated observations. [...]

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Front. Plant Sci., 02 March 2017 | https://doi.org/10.3389/fpls.2017.00282

Differentiating Wheat Genotypes by Bayesian Hierarchical Nonlinear Mixed Modeling of Wheat Root Density



¹Commonwealth Scientific and Industrial Research Organisation (CSIRO) Agriculture & Food, Canberra, ACT, Australia
²Research School of Finance, Actuarial Studies and Statistics, College of Business and Economics, Australian National University, Canberra, ACT, Australia
³Commonwealth Scientific and Industrial Research Organisation (CSIRO) Data61, Canberra, ACT, Australia
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Differentiating Wheat Genotypes by Bayesian Hierarchical Nonlinear Mixed Modeling of Wheat Root Density

Anton P. Wasson^{1*}, 👤 Grace S. Chiu^{2*}, 👤 Alexander B. Zwart³ and 👤 Timothy R. Binns⁴

¹Commonwealth Scientific and Industrial Research Organisation (CSIRO) Agriculture & Food, Canberra, ACT, Australia
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My co-authors



My co-authors





Biography

Dr Anton Wasson is part of the Molecular markers for root hair traits and enhanced phosphorus use efficiency (PUE) in wheat project funded by the GRDC (CFF00009). The project aims to identify genes and traits in wheat that can reduce the amount of non-renewable phosphorus fertilizer that farmers have to apply to optimize the yield. Trials are being conducted in the Central Wheatbelt of Western Australia and the Riverina and South-West Slopes of New South Wales.

Dr Wasson was previously part of the Root Phenotyping Project which developed cutting-edge field-based facilities to measure root performance and root architecture in the field.

Dr Wasson's focus is the improvement of the root structure of wheat to enhance water and nutrient uptake and use. This involves linking the outcomes of experiments in the laboratory and field.





3. Inference: Pre-Chiu vs. Chiu





• collapse t:
$$w_{ij?} = f(y_{ij?1}, y_{ij?2}, ..., y_{ij?T})$$
, e.g., $f = \max$

• linear mixed model for w_{ij?}



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- y_{ijkt} longitudinal WRT t
 - ID spatial Poisson process!
 - \ast but obviously overdispersed \Longrightarrow



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random intensity curves $\theta_{ij}(t)$



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random intensity curves $\theta_{ij}(t)$

Spatial dependence not yet formally modelled.





Fig. 4: Gamma probability density $\gamma_{\alpha,\beta}(t) \propto \theta_{\alpha,\beta}(t)$





Fig. 4: Gamma probability density $\gamma_{lpha,eta}(t)\propto heta_{lpha,eta}(t)$

- $\alpha \leftrightarrow \operatorname{root}$ system's bulk
- $\ \ \, \textbf{ } \hspace{0.1 cm} \beta \leftrightarrow \text{ root system's downward } \text{ exploration/penetration} \\$
- (α, β) bivariate

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 $egin{aligned} &y_{ijkt} \sim \mathsf{Poisson}(heta_{ij}(t)), \ & heta_{ij}(t) = \psi_{ij} ullet \gamma_{lpha_ieta_i}(t) ullet e^{\phi_{ijt}} \ & \psi_{ij} = e^{\psi_0+\kappa_j}e^{ au_i} \end{aligned}$



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Note: Smooth $\gamma(t)$ but jagged $\theta(t)$ due to ϕ_t



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Binns' internship:

- Zwart and Binns learned Bayesian inference (from me)
- prelim model implementation: Gelman et al.'s Stan

After Binns:

• final models in paper: Chiu & Zwart



4. Key insights



First, the punchline. . .



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"Our integrative approach can allow selective pre-breeding programs for root distribution and may facilitate the identification of genetic markers from field data."



On to the details. . .



Heritability is high!



Posterior mean intensity curves $\theta_{ij}(t)$ (Fig. 6):





Posterior mean idealized intensity curves $\psi_{ij}\gamma_i(t)$ (Fig. 5):





More formally:

$$\begin{split} \sigma_{\log \theta(t)}^2 &= \sigma_{\text{genes}}^2(t) + \sigma_{\phi}^2 \\ \sigma_{\text{genes}}^2(t) &= \sigma_{\tau}^2 + (\log t)^2 (e^{\sigma_{\alpha}^2} - 1) e^{2\mu_{\alpha} + \sigma_{\alpha}^2} + t^2 (e^{\sigma_{\beta}^2} - 1) e^{2\mu_{\beta} + \sigma_{\beta}^2} - \\ &\quad (t \log t) (e^{\rho\sigma_{\alpha}\sigma_{\beta}} - 1) e^{\mu_{\alpha} + \mu_{\beta} + (\sigma_{\alpha}^2 + \sigma_{\beta}^2)/2} \\ h_h^2(t) &= \frac{\sigma_{\text{genes}}^2(t)}{\sigma_{\text{genes}}^2(t) + \sigma_{\phi}^2} = \text{ depth-specific heritability of intensity function} \\ h_h^2 &= \text{heritability of overall architecture} \\ &= \text{harmonic mean of } h_h^2(t) \end{split}$$



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Multiresolution definition



 $h_{\alpha(-\beta)}^2$ = heritability of root bulk's location (and size) on log scale, ignoring its relation with penetration rate

$$= \text{harmonic mean of } \left\{ \frac{(\log t)^2 (e^{\sigma_\alpha^2} - 1) e^{2\mu_\alpha + \sigma_\alpha^2}}{(\log t)^2 (e^{\sigma_\alpha^2} - 1) e^{2\mu_\alpha + \sigma_\alpha^2} + \sigma_\phi^2} \text{ for } t > 1 \right\}$$

 $h_{\beta(-\alpha)}^2$ = heritability of root's decline rate of penetration on log scale, ignoring its relation with bulk location

$$= \text{harmonic mean of } \left\{ \frac{t^2(e^{\sigma_\beta^2} - 1)e^{2\mu_\beta + \sigma_\beta^2}}{t^2(e^{\sigma_\beta^2} - 1)e^{2\mu_\beta + \sigma_\beta^2} + \sigma_\phi^2} \right\}$$

 $h_{\tau}^2 = \frac{\sigma_{\tau}^2}{\sigma_{\tau}^2 + \sigma_{\phi}^2} =$ heritability of intensity function's intercept on log scale



Posteriors of heritability metrics (Fig. 7):



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Posteriors of heritability metrics (Fig. 7):





High heritability of bulking



"[It s]uggests that a breeding program could successfully alter the depth at which a root system proliferates."



Low τ -heritability



Low τ -heritability

"Sampling position [in the field] is likely to have a strong influence on the surface root counts."



Bulking up vs. Exploring



$0.9 \approx \text{median } P(\operatorname{cor}(\alpha_i, \beta_i) > 0 \mid \text{data})$



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• Tendency to explore downwards negates tendency to bulk up away from surface.



$0.9 \approx \text{median } P(\operatorname{cor}(\alpha_i, \beta_i) > 0 \mid \text{data})$

- Tendency to explore downwards negates tendency to bulk up away from surface.
- "[P]lants have evolved randomness and instability in their root system development (Forde, 2009). . . which may facilitate exploration. . . of the soil for cracks and pores. [O]ur model implies that more branching near the surface gives better access to the subsoil."



In closing



"If a paper uses a t test to solve an environmental research problem that no one else has been able to solve, we will publish it."

— Peter Guttorp in an *Environmetrics* Editorial Board Meeting as Co-Editor-in-Chief





Search for Grace S Chiu on Google Scholar or Research Gate.