

Høgskolen i Innlandet





Crowdsourcing citizen-science for diversification and adaptation in agriculture: evidence from three continents

Kauê de Sousa

What is the problem we want to

solve?



Challinor et al. (2016) *Nat. Clim. Change* **6**:954-958 Tollenaar et al. (2017) *Nat. Clim. Change* **7**:275-278 Deutsch et al. (2018) *Science* **361**(6405):916-919

What is the problem we want to

solve?



What is the problem we want to solve?

- We need diverse, location-specific and scalable solutions for a climate adapted agriculture
- But current methods cannot address these solutions...

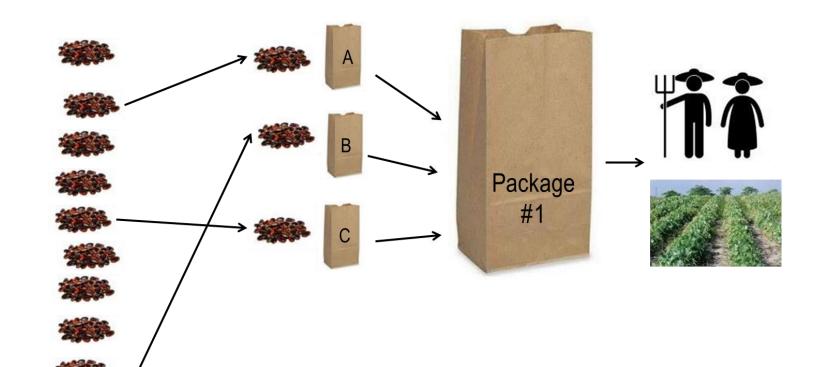
A new agricultural research paradigm

Centralized trial Decentralized trial Centralized trial (Collaborating farmers' field) (Research station) Managed by Managed by Managed by researchers and researchers many farmers one farmer



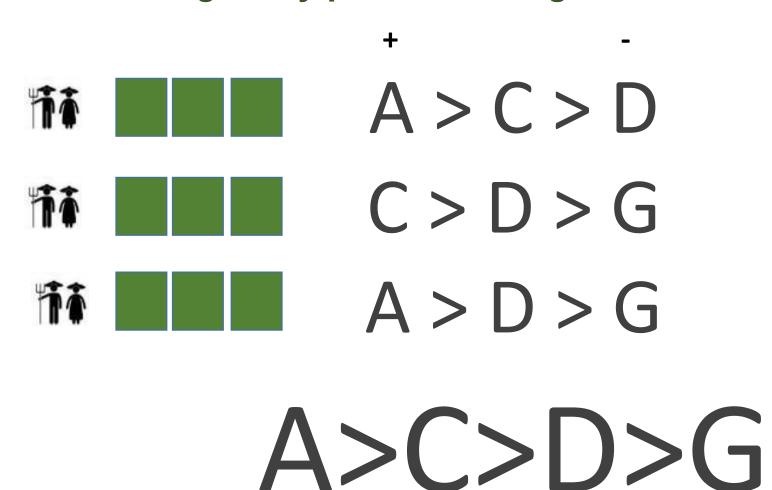
Crowdsourcing for climate adaptation

- A blind set of 3 varieties
- A randomization scheme
- Real farm conditions
- Farmers rank the varieties





Combining many partial rankings for the full picture







Crop variety management for climate adaptation supported by citizen science

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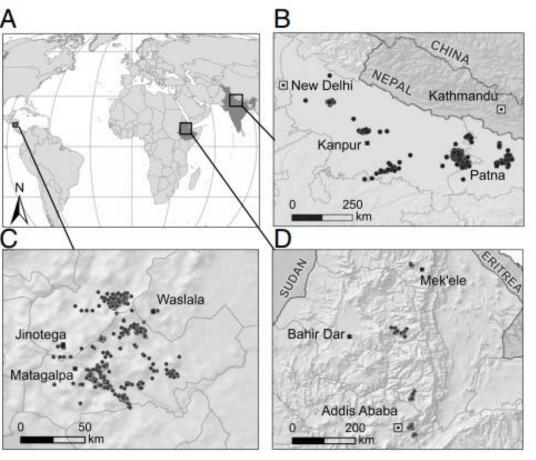
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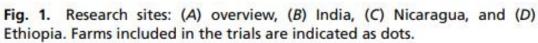
variety introduction accompanied by recommendations to help approaches to generate these recommendations lack scalabil-

Crop adaptation to climate change requires accelerated crop to local climate adaptation. This local focus is a strength as well as a limitation. Scaling is constrained by the resource-intensive farmers match the best variety with their field contexts. Existing nature of current participatory experimental methods and the incompatibility of datasets across different efforts (9). The result-

12,409 trial plots







What we found...

This approach can improve variety recommendations in four aspects:

- 1. Reduction of climate bias
- 2. Incorporation of seasonal climate forecasts
- 3. Risk analysis
- 4. Geographic extrapolation



Reduction of climate bias

Table 1. Goodness of fit (pseudo- R^2) of PLTs determined with 10-fold cross-validation

PLT model	Nicaragua	Ethiopia	India
No covariates	0.1484	0.3947	0.0381
Design	0.1869	0.4709	0.0721
Climate	0.1978	0.4870	0.0882
Climate + geolocation	0.1977	0.4720	0.0872

The model with only climate covariates has the best fit in all cases (indicated in bold).

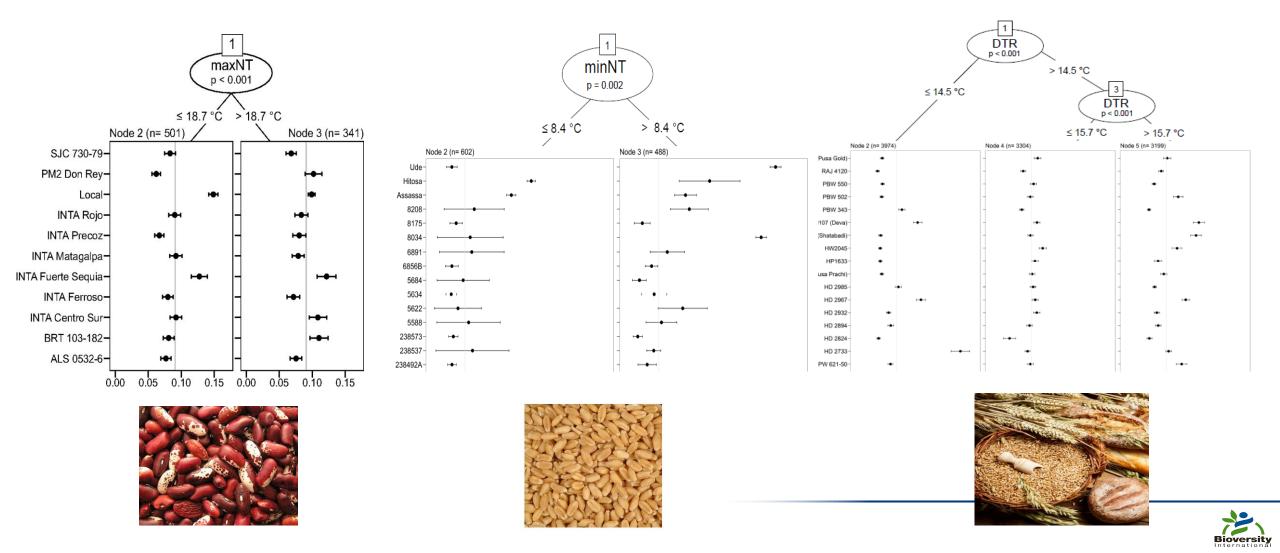
Table 2. Goodness of fit (pseudo- R^2) of generalizable PLT models

Model	Nicaragua	Ethiopia	India
No covariates	0.1533	0.4280	0.0611
Average season	0.1536	0.4290	0.0694
Perfect forecast	0.1749	0.4442	0.1065

Model average season corrects for climatic sampling bias by averaging predictions over a base period of seasonal climate data. Model perfect forecast uses observed climatic covariates in the predicted seasons. Values represent cross-validated pseudo- R^2 values averaged across blocks and weighted with the square root of the sample size of each block.



Incorporation of seasonal climate forecasts



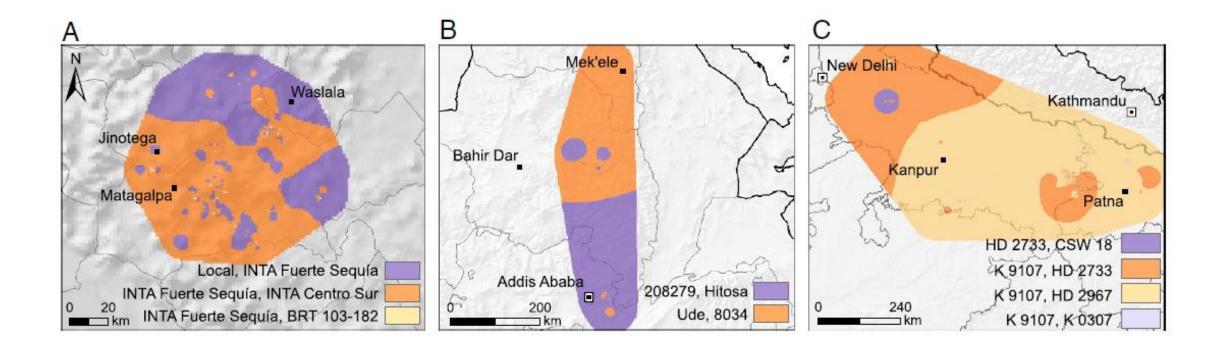
Risk analysis

Table 3. Expected probability of winning (average of all farms over the base period) and worst regret measures of a subset of the varieties

Case study and variety	Probability of winning	Worst regret
Common bean (Nicaragua)		
Local variety	0.130	0.023
INTA Fuerte Sequía	0.125	0.021
INTA Centro Sur	0.098	0.057
BRT 103-182	0.092	0.068
INTA Rojo	0.088	0.082
INTA Matagalpa	0.087	0.057
Durum wheat (Ethiopia)		
208279	0.059	0.062
Hitosa	0.049	0.035
208304	0.041	0.048
8034	0.030	0.053
Ude	0.025	0.063
222360	0.023	0.061
Bread wheat (India)		
K 9107 (Deva)	0.077	0.051
HD 2967	0.068	0.047
HD 2733	0.066	0.036
K 0307 (Shatabadi)	0.063	0.095
CSW 18	0.042	0.073
HI 1563 (Pusa Prachi)	0.041	0.093



Geographic extrapolation





Recap...

- Citizen science data revealed generalizable relations between seasonal climate variables and crop variety performance
- Climatic analyses of these data were shown to improve variety recommendations
- The approach can track climate trends as they manifest themselves on farms
- The findings can serve to create variety portfolios that diminish climate risk





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Thank you!

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