Nutrient Demand, Risk and Climate change: Evidence from historical rice yield trials in India

Dr. Sandip K. Agarwal & Dr. Ali Saeb

Indian Institute of Science Education and Research, Bhopal (IISERB)

Research Objectives

- Model the stochastic production function for the rice conditional on input and weather.

- Estimate the average yields of rice and risk through the moments of the rice yield distribution.

- Identify the marginal effects of nutrient and climate change on the rice yield distribution.

- Simulate the demand for nutrients and insurance under scenarios of climate change, consistent with economic rationales of profit maximization and utility maximization.

Data

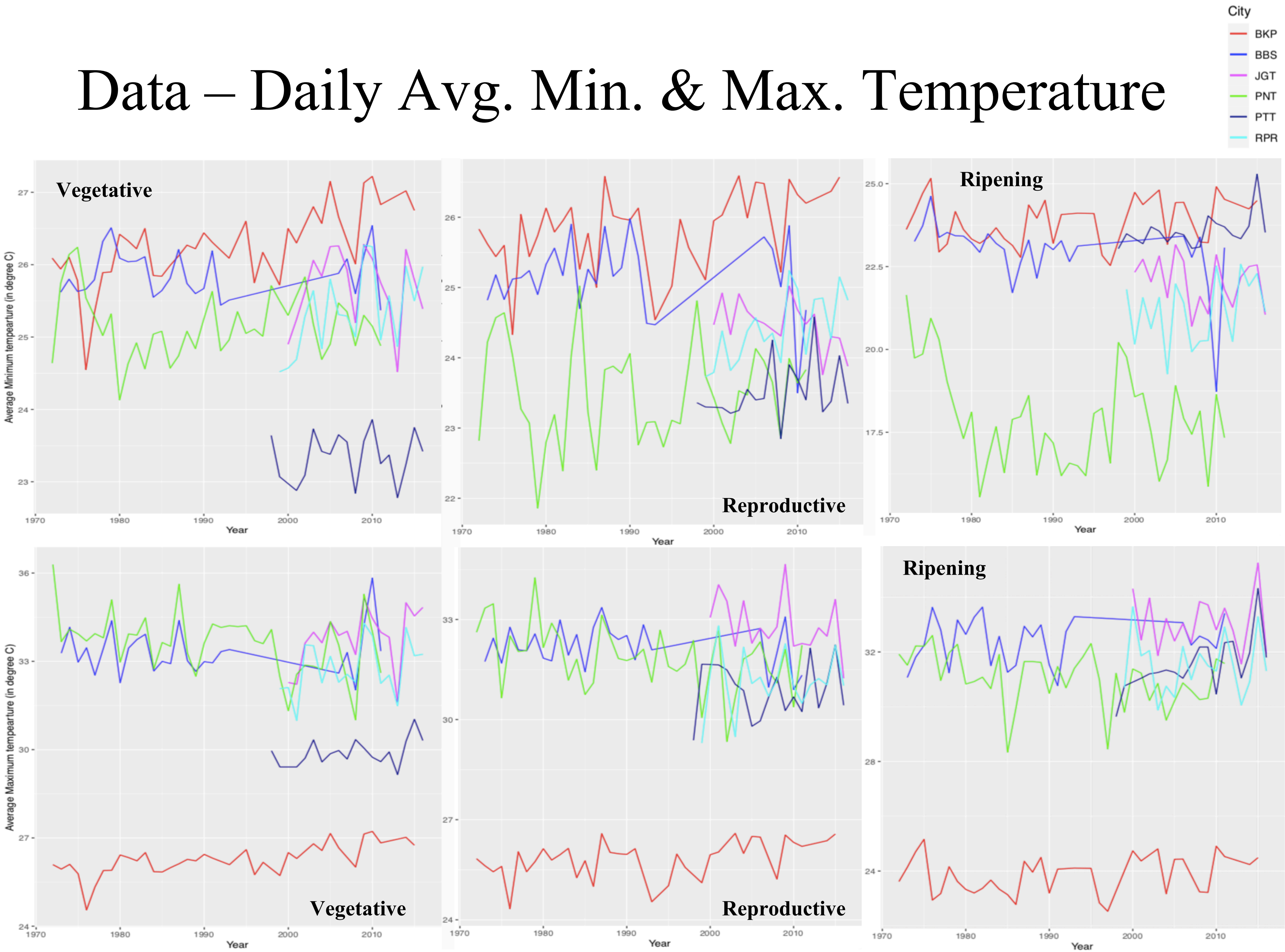
- Rice yield data is sourced from the Indian Institute of Soil Science (IISS), Bhopal, which is part of Long Term Fertilizer Experiments (LTFE)

- Rice yield for 6 stations - Barrackpore (BKP), Bhubaneshwar (BBS), Jagtial (JGT), Pantnagar (PNT), Pattambi (PTT) and Raipur (RPR).

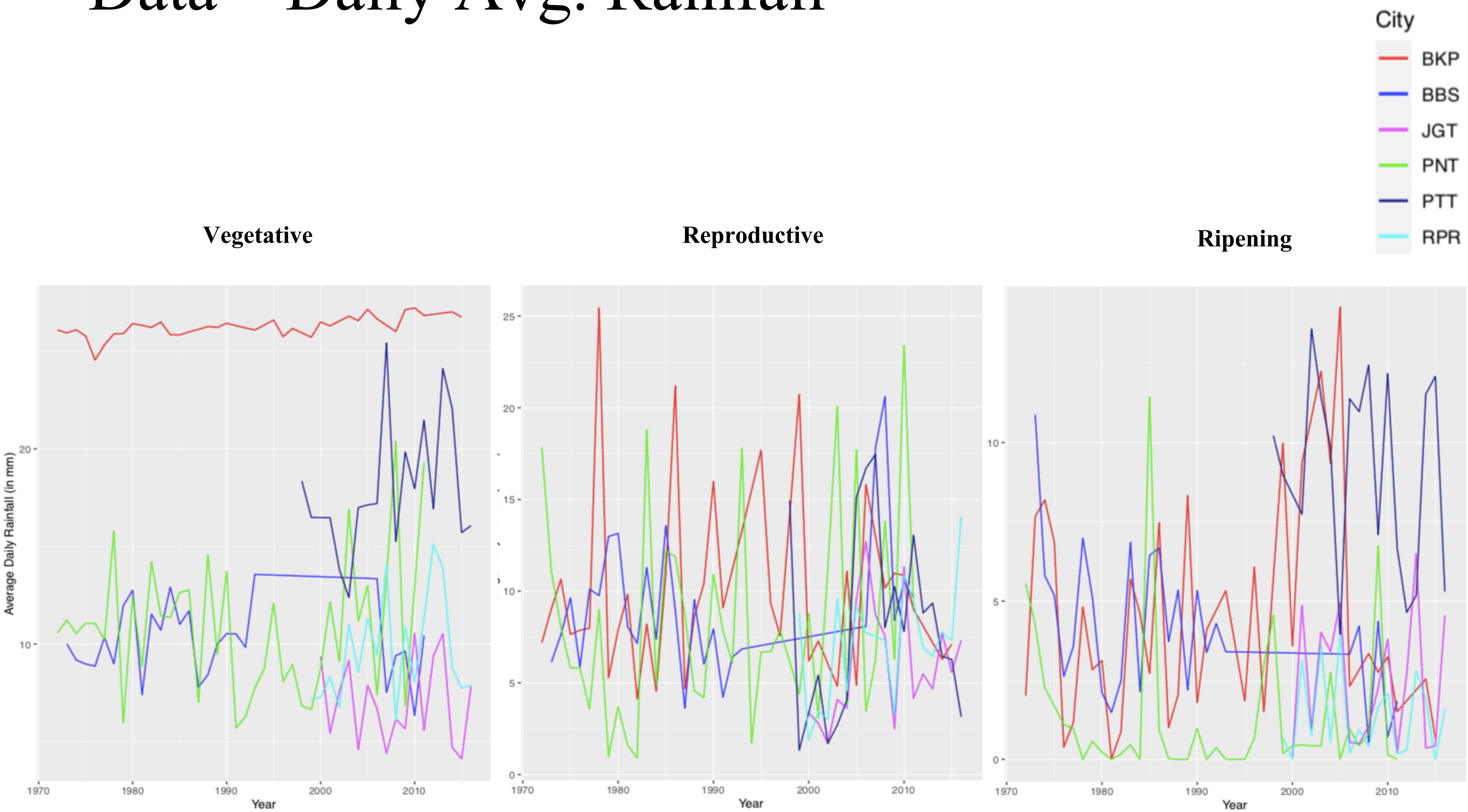
- Yield data is for the period between 1973-2016.

- Weather data – daily rainfall, minimum and maximum, temperatures; Primarily used the Indian Meteorological Department (IMD) data, and partly the National Oceanic and Atmospheric Administration (NOAA).

Data – Daily Avg. Min. & Max. Temperature



Data – Daily Avg. Rainfall



Methodology

- OLS regression and Beta Regression

- OLS regression: $log(Y_i) = \Sigma_{k=1}^{K} \beta_k X_k$

- Beta regression: $g(\mu_i) = \mathbf{x_i}\beta, \qquad h(\varphi_i) = \mathbf{w_i}\delta$

$$\mu = \frac{exp(\mathbf{X}\beta)}{1 + exp(\mathbf{X}\beta)}, \qquad \varphi = exp(\mathbf{Z}\delta)$$

- Beta density: $f(y, \omega, \nu) = \frac{\Gamma(\omega + \nu)}{\Gamma(\omega)\Gamma(\nu)} \cdot y^{\omega - 1} \cdot (1 - y)^{\nu - 1}.$

$$\varphi = \omega + \nu, \qquad \omega = \mu\varphi, \qquad \nu = (1 - \mu)\varphi, \qquad V(y) \equiv \sigma^2 = \frac{\mu(1 - \mu)}{(\varphi + 1)}$$

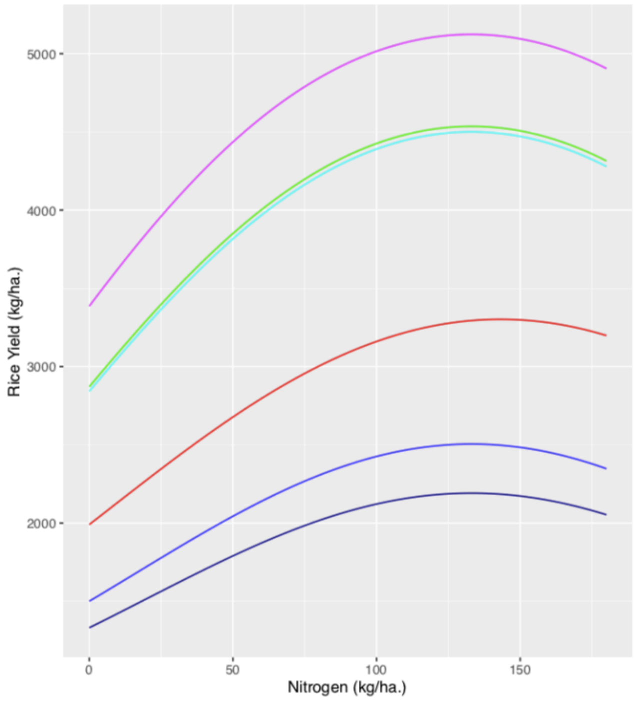
$$E[y] \equiv \mu = \frac{\omega}{\omega + \nu}, \qquad V(y) \equiv \sigma^2 = \frac{\omega\nu}{(\omega + \nu)^2(\omega + \nu + 1)}$$

Methodology

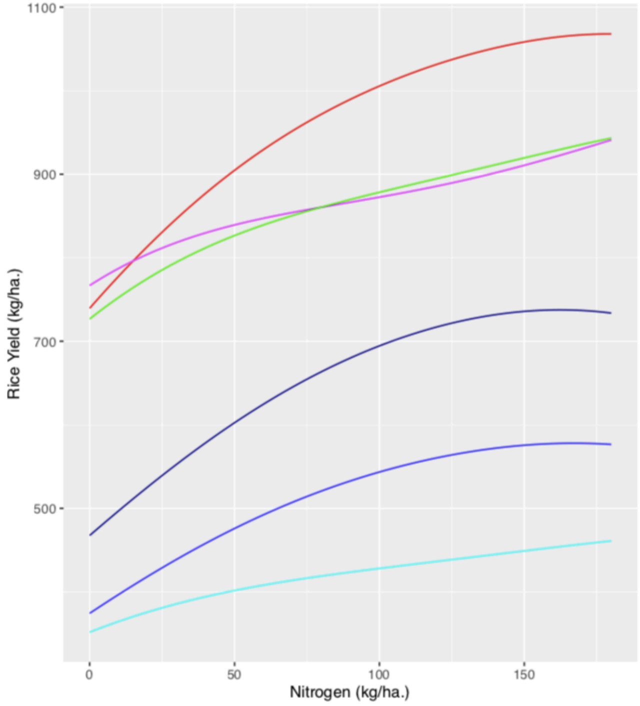
- Dependent variable: log(Yield) & Normalized Yield
- Independent variables: Nutrients, Weather, Station Fixed Effects
- Nutrients: N, P & K treatment levels with (with their quadratic term)
- Weather variables organized yearly as 3 growth stages: vegetative (Jun. – Aug.), reproductive (Sep.) and ripening stage (Oct.)
- Weather variables are averages of rainfall, min. and max. temperatures along with their standard deviation, skewness, and percentiles to account for weather distribution.

Results – Moments of Yield density

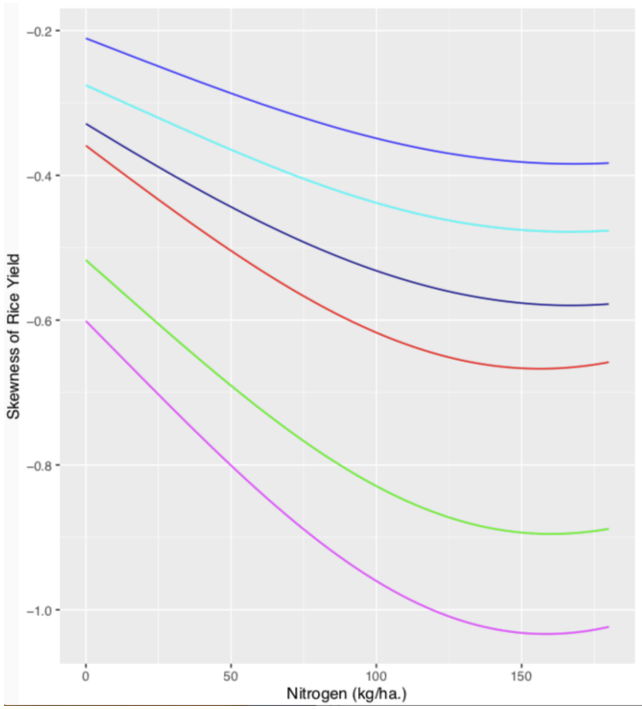
Yield Mean



Yield Standard deviation



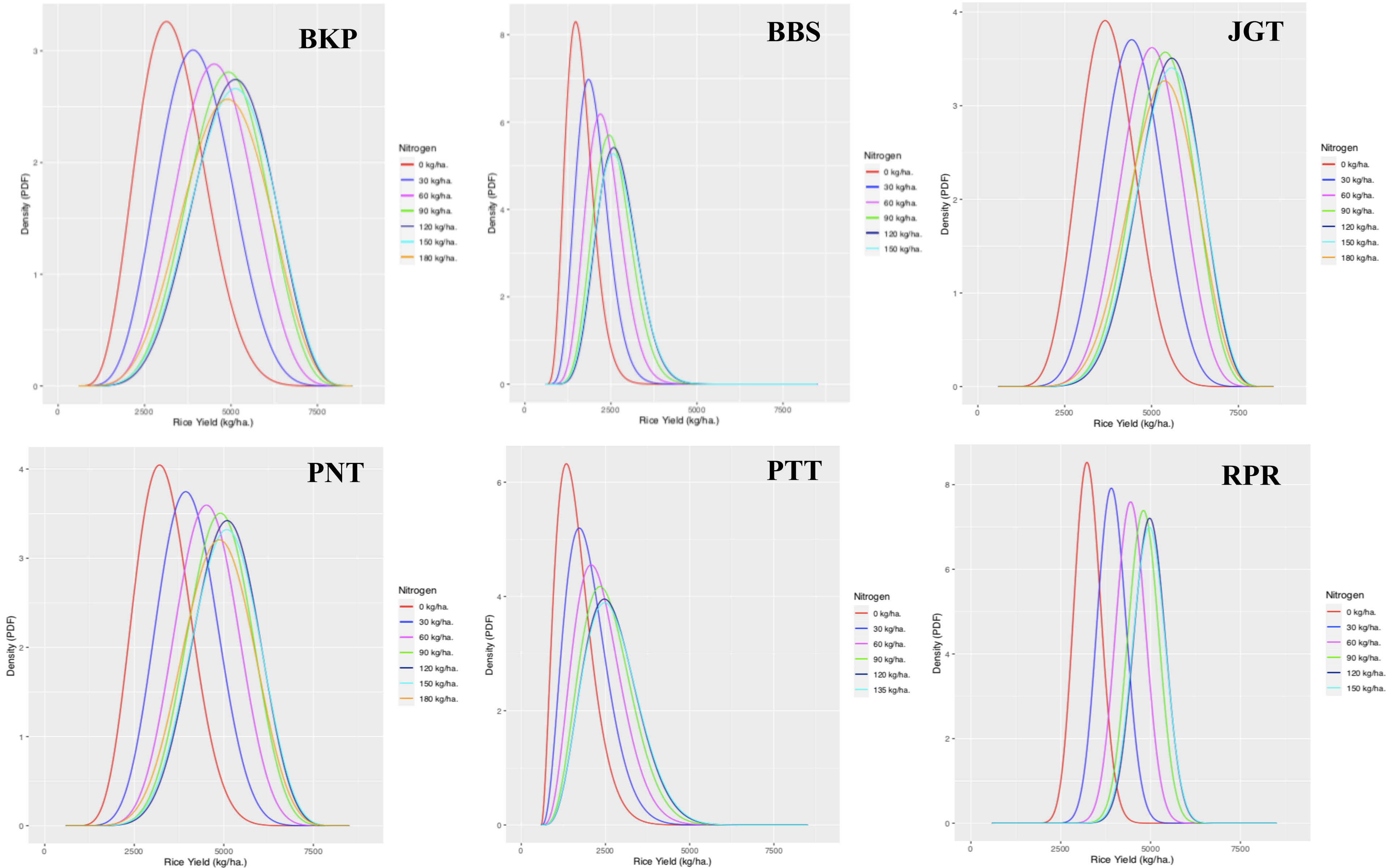
Yield Skewness



- N increases the yield and the yield variability

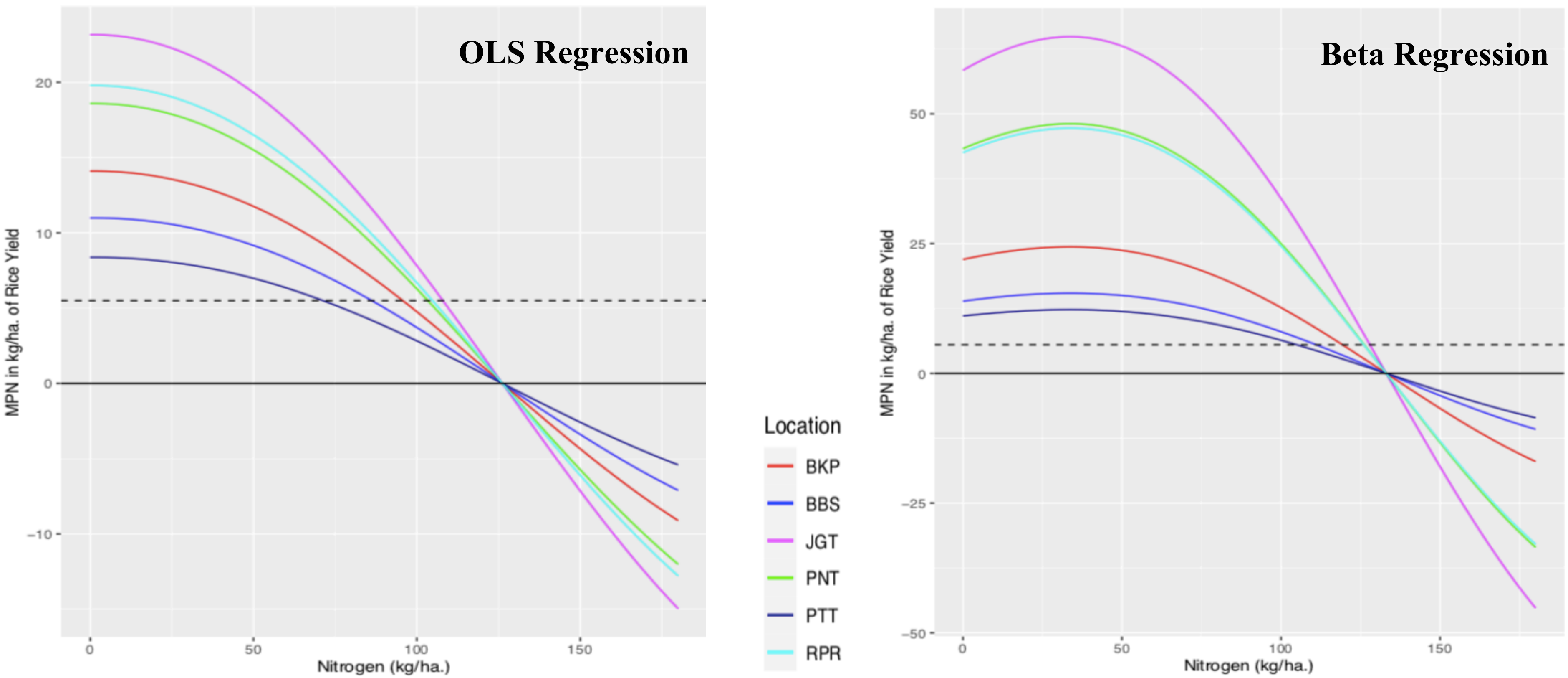
- Yield skewness falls (i.e. becomes more negative)

Results – Yield density



Results – Marginal Productivity of Nitrogen

- Marginal Prodcuitvity of Nitrogen (MPN) as consistent with economic rationale of profit maximization is used to find N demand: MPN = Price of nitrogen.



Results

- Rice yields are most sentisitve to rising temperatures during the vegetative and the reproductive stages.

- Rainfall during the ripening stage adversely affects the yield, and can be severe, if increase in average rainfall is contributed by lower percentiles of rainfall distribution.

Ongoing:

- Effect of weather changes on the yield distribution and the productivity of the nutrients.

- Simulating the changes in the demand for nutrient and insurance as a result of weather changes

References

- Agarwal, S. K. (2017). Subjective beliefs and decision making under uncertainty in the field.
- Babcock, B. A., & Hennessy, D. A. (1996). Input demand under yield and revenue insurance. *American journal of agricultural economics*, *78*(2), 416-427.
- Barnwal, P., & Kotani, K. (2013). Climatic impacts across agricultural crop yield distributions: An application of quantile regression on rice crops in Andhra Pradesh, India. *Ecological Economics*, *87*, 95-109.
- Lobell, D. B., Bänziger, M., Magorokosho, C., & Vivek, B. (2011). Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nature climate change*, *1*(1), 42-45.
- Luo, Q. (2011). Temperature thresholds and crop production: a review. *Climatic Change*, 109(3-4), 583-598.
- Pattanayak, A., & Kumar, K. K. (2014). Weather sensitivity of rice yield: evidence from India. *Climate Change Economics*, *5*(04), 1450011.
- Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. Proceedings of the National Academy of sciences, 106(37), 15594-15598.
- Welch, J. R., Vincent, J. R., Auffhammer, M., Moya, P. F., Dobermann, A., & Dawe, D. (2010). Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. *Proceedings of the National Academy of Sciences*, *107*(33), 14562-14567.

Thank You !

Table 1: Yield Regression

	Dependent variable:			
	OLS regression		Beta regression	
	log(Yield)		Normalized Yield	
	(1)	(2)	(3)	(4)
Nutrients				
N	0.0081***	0.0081***	0.0124***	0.0135***
	(0.0013)	(0.0013)	(0.0021)	(0.0023)
N^2	−0.00003***	−0.00003***	−0.00004***	−0.0001***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
P	0.0044***	0.0043***	0.0122**	0.0146**
	(0.0016)	(0.0016)	(0.0058)	(0.0063)
K	0.0020***	0.0020***	0.0082***	0.0075***
	(0.0005)	(0.0005)	(0.0027)	(0.0027)
K^2			−0.0001**	−0.0001*
			(0.00004)	(0.0001)
Vegetative				
$T_{min} : AVG$	−0.0841***	−0.1497	−0.0253	−0.1509***
	(0.0314)	(0.1113)	(0.0920)	(0.0549)
$T_{max} : AVG$	0.0236	−0.1105	0.0754	−0.0578
	(0.0316)	(0.0884)	(0.0466)	(0.0877)
$Rain : AVG$	0.0203***	0.0120	0.0517*	0.0350**
	(0.0077)	(0.0101)	(0.0312)	(0.0162)
$Days(T_{max} > crit.)$		−0.0075		−0.0083
		(0.0065)		(0.0077)
$T_{min} : SD$			−0.0916	
			(0.0813)	
$T_{max} : SD$	0.1041***		0.1902***	
	(0.0321)		(0.0620)	
$Rain : SD$	−0.0140***		−0.0267***	
	(0.0017)		(0.0094)	
$T_{min} : SK$			−0.0373***	
			(0.0129)	
$T_{max} : SK$	0.0854*		0.1916**	
	(0.0517)		(0.0964)	
$Rain : SK$	0.0502***		0.0766*	
	(0.0111)		(0.0417)	
$T_{min} : 75^{th}$		0.1076		
		(0.1124)		
$T_{max} : 5^{th}$		0.0499		
		(0.0363)		
$T_{max} : 75^{th}$		0.0473		0.0718
		(0.0329)		(0.0447)
$T_{max} : 95^{th}$		0.0688***		0.1029***
		(0.0078)		(0.0120)
$Rain : 5^{th}$		0.4161***		0.7189***
		(0.0800)		(0.1122)
$Rain : 25^{th}$		−0.1430**		−0.1601*
		(0.0616)		(0.0852)
$Rain : 75^{th}$				0.0117
				(0.0089)
$Rain : 95^{th}$		−0.0032		−0.0102**
		(0.0025)		(0.0049)
Reproductive				
$T_{min} : AVG$	−0.0802**	−0.1522***	−0.1083***	−0.4412***
	(0.0312)	(0.0142)	(0.0344)	(0.1241)
$T_{max} : AVG$	0.0580	−0.0807	0.1920*	0.3469***
	(0.0577)	(0.0638)	(0.1000)	(0.0635)
$Rain : AVG$	0.0104*	−0.0057	0.0363*	−0.0501***
	(0.0058)	(0.0046)	(0.0202)	(0.0175)
$Days(T_{max} > crit.)$	−0.0100		−0.0148	−0.0168
	(0.0111)		(0.0147)	(0.0174)
$T_{min} : SD$	0.0686***		0.1717**	
	(0.0234)		(0.0715)	
$T_{max} : SD$	−0.0747		−0.0870	
	(0.0635)		(0.1326)	
$Rain : SD$	−0.0052		−0.0201	
	(0.0057)		(0.0130)	
$T_{min} : SK$	0.0313		0.0491	
	(0.0292)		(0.0603)	
$T_{min} : 5^{th}$		0.0186**		0.0570
		(0.0092)		(0.0520)
$T_{min} : 95^{th}$		0.0694***		0.2255***
		(0.0154)		(0.0566)

Yield Regressions *(contd.)*

	(1)	(2)	(3)	(4)
$T_{max} : 5^{th}$		0.0530		
		(0.0331)		
$T_{max} : 75^{th}$				-0.1986^{***}
				(0.0631)
$Rain : 5^{th}$		0.2583^{***}		0.4360^{***}
		(0.0610)		(0.0485)
$Rain : 25^{th}$		-0.0406		
		(0.0253)		
$Rain : 75^{th}$				0.0150^{***}
				(0.0056)
$Rain : 95^{th}$		0.0017		0.0076^{***}
		(0.0013)		(0.0028)
Ripening				
$T_{min} : AVG$	0.0654^{**}	0.0195	0.0880^{***}	0.2228^{**}
	(0.0257)	(0.0157)	(0.0161)	(0.1046)
$T_{max} : AVG$				-0.4995^{***}
				(0.1327)
$Rain : AVG$	-0.0256^{**}	-0.0656^{**}	-0.0490	-0.0353^{**}
	(0.0112)	(0.0259)	(0.0506)	(0.0173)
$T_{min} : SD$	0.0299			
	(0.0405)			
$Rain : SD$			0.0053	
			(0.0137)	
$Rain : SK$			0.0503	
			(0.0308)	
$T_{min} : 25^{th}$				-0.0500
				(0.0420)
$T_{min} : 75^{th}$		-0.0339		-0.1160^{**}
		(0.0240)		(0.0544)
$T_{min} : 95^{th}$		0.0269^{**}		
		(0.0130)		
$T_{max} : 5^{th}$				0.0710^{*}
				(0.0389)
$T_{max} : 25^{th}$				0.1362^{**}
				(0.0688)
$T_{max} : 95^{th}$				0.2620^{***}
				(0.0750)
$Rain : 5^{th}$		-0.8283^{***}		-1.7752^{***}
		(0.1502)		(0.1815)
$Rain : 25^{th}$		0.2683^{**}		0.4474^{*}
		(0.1255)		(0.2399)
$Rain : 75^{th}$				-0.0200
				(0.0171)
$Rain : 95^{th}$		0.0082^{*}		
		(0.0043)		
$Intercept$	7.3846^{***}	8.9882^{***}	-9.6665^{**}	-3.0100
	(2.1243)	(1.9084)	(4.1064)	(2.9376)
$City(BBS/PTT)$	-0.3705^{***}			-0.6237^{***}
	(0.0210)			(0.0361)
		2		
$City(BBS)$		-0.3540^{***}	-0.5823^{***}	
		(0.0146)	(0.1183)	
$City(PTT)$		-0.1270		
		(0.1797)		
$City(JGT/PNT)$	0.2485^{***}		0.7884^{**}	
	(0.0308)		(0.3507)	
$City(JGT)$		0.2992^{***}		0.5461^{***}
		(0.0539)		(0.0834)
$City(RPR)$			0.5070	
			(0.4576)	
Observations	920	920	920	920
R^2	0.6858	0.7298	0.6159	0.6760
Adjusted R^2	0.6773	0.7194		
AIC	254.8	136	-1589.6	-1761.7

Note: *p<0.1; **p<0.05; ***p<0.01

Yield Regressions *(contd.)*

Precision sub-model	(3)	(4)
N	-0.0023^{**}	-0.0019^{*}
	(0.0009)	(0.0011)
$Intercept$	2.5818^{***}	2.7186^{***}
	(0.0955)	(0.1215)
$City(BBS/RPR)$	1.4826^{***}	
	(0.0360)	
$City(BBS)$		1.0787^{***}
		(0.0256)
$City(RPR)$		1.9004^{***}
		(0.0276)
$City(JGT/PTT/PNT)$		0.4308^{***}
		(0.0765)
$City(JGT/PTT)$	0.4328^{***}	
	(0.0330)	
$City(PNT)$	0.2094^{***}	
	(0.0180)	
Note:		*p<0.1; **p<0.05; ***p<0.01