



Leibniz Institute of Agricultural Development
in Transition Economies

The role of smartphone-based weather information on climate change perception accuracy: Cross-country evidence from Kyrgyzstan, Mongolia and Uzbekistan

Begaiym Emileva, Lena Kuhn, Ihtiyor Bobojonov and Thomas Glauben

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Drought is one of the major natural hazards causing significant damage to agriculture, the economy and the environment (Mishra and Singh, 2010).

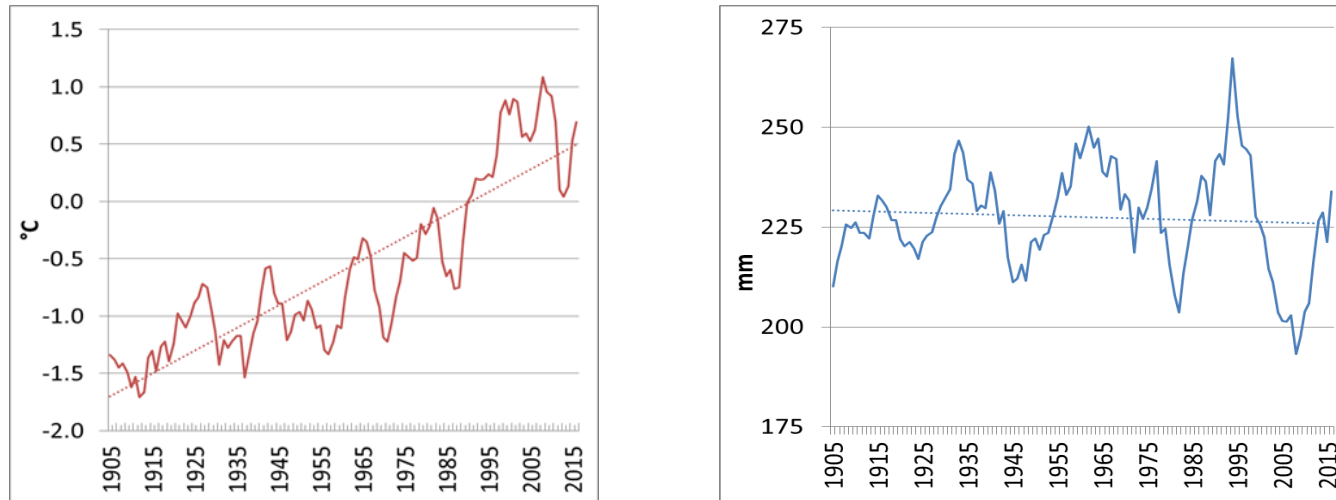


Figure 1: Changes in average temperatures and annual precipitation between 1906-2015 (5-year average) in Central Asia

- **Climate risk perception** is a **precondition for adaptation** measures (Howden et al. 2007).
- Access to **reliable, timely** and **relevant information** can help to reduce farmers risk and uncertainty (Mittal and Mehar, 2012).

Research gap

- Individual perception of climate risk not necessarily in line with objective risk (Hasan and Kumar, 2019).
- Role of online weather information yet is not fully researched.

Research questions

- Is farmers' perception of meteorological drought changes in Central Asia in line with actual drought changes?
- What is the role of smartphone-based weather information on drought perception accuracy?

Survey data

- Primary cross-sectional survey dataset (n= 2830) from Kyrgyzstan, Uzbekistan and Mongolia collected in 2021.
- A multi-stage cluster sampling procedure on grain farming households.
- Information on subjective experience of drought changes in the past ten years.

Meteorological data

- Satellite-based precipitation and temperature data from CHIRPS and GLDAS between 2010 to 2020.

Drought index

- Standardized Precipitation Evapotranspiration Index (SPEI);
SPEI value < -1.5 (severe & extreme dryness) on a weekly scale.

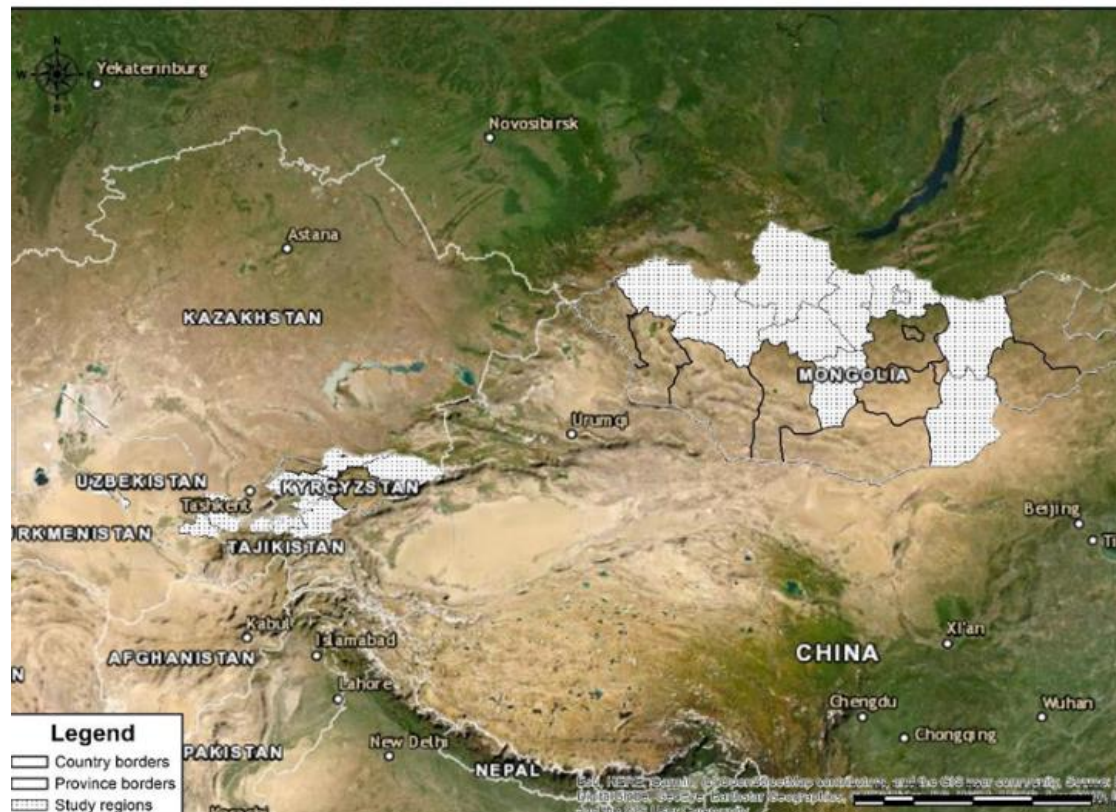


Fig. 2. Physical map of the study area

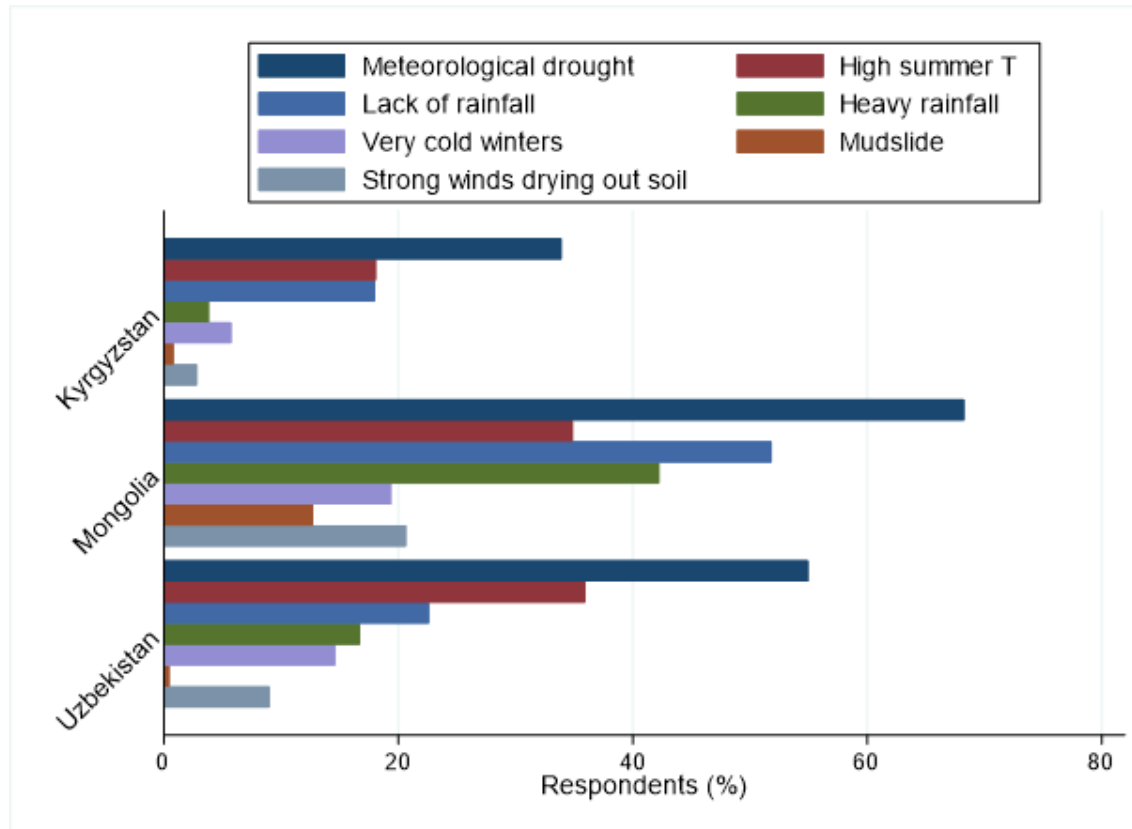


Fig. 3. Direct personal experience of extreme weather events in Kyrgyzstan, Mongolia and Uzbekistan

Tab. 1. Accuracy results: country specific and pooled

Country	Accurate perception %	Under estimation %	Over estimation %
Kyrgyzstan	51.00	37.74	11.26
Mongolia	31.73	-	68.27
Uzbekistan	56.53	10.11	33.36
Pooled countries	49.43	19.89	30.68

Endogeneous independent variable: Usage of mobile weather information („treated“)

Propensity-score-matching:

1. Estimation of logit model for the propensity of observations.
2. Nearest neighbour (NN); Kernel to find best match
3. Treatment effect: Average Treatment Effect on the Treated (ATT):

$$ATT_{(x)} = E [Y_1 | D = 1, X = x] - E [Y_0 | D = 0, X = x]$$

Tab. 2. Determinants of smartphone-based weather information acquisition: logit model estimates

Variable	Coefficient	Marginal effects
Age of household	-0.009 (0.00) ***	-0.002 (0.00) ***
Gender of the head of household	-0.072 (0.11)	-0.017 (0.03)
Education in agriculture	0.679 (0.12) ***	0.161 (0.03) ***
Attendance in extension services	0.086 (0.10)	0.020 (0.02)
Annual farm income	0.052 (0.04)	0.012 (0.01) ***
Agroecological zones	0.129 (0.08)	0.031 (0.02) ***
Attitude to online weather information reliability	-0.281 (0.05) ***	-0.067 (0.01) ***
Smartphone adoption	3.308 (0.28) ***	0.785 (0.07) ***
Districts	0.021 (0.00) ***	0.005 (0.00)
constant	-2.960	
Number of observations	2830	
Pseudo R2	0.241	
Chi2	918.8	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Test of equality of means of each variable before and after matching

Variable	Unmatched samples			Nearest-neighbor matching			Kernel matching		
	Treated N=1702	Control N=1128	Diff. P-value	Treated N=1697	Control N=1128	Diff. P-value	Treated N=1697	Control N=1128	Diff. P-value
Age	45.99	46.09	-7.49 ***	46.03	46.21	-0.52	46	46.15	-0.66
Gender	1.16	1.23	-4.42 ***	1.16	1.14	1.65	1.16	1.15	1.06
Education in agriculture	0.37	0.16	12.67***	0.37	0.36	0.7	0.37	0.33	2.18*
Extension service attendance	0.45	0.26	10.11***	0.44	0.49	-2.35	0.44	0.50	-2.95***
Annual farm income	4.42	3.09	20.59***	4.42	4.47	-0.85	4.42	4.47	-0.92
Agroecological zones	2.40	1.77	-0.62	2.39	2.32	2.81	2.39	2.33	2.27*
Attitude to reliability of online weather information	2.3	3.03	-19.4	2.30	2.33	-0.88	2.30	2.33	-0.93
Smartphone adoption	1.0	0.8	18.35	0.99	1.00	-1.73	0.99	0.99	-1.43
Districts	45.5	21.04	4.81***	45.38	45.83	-0.48	45.38	45.98	-0.64

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Tab. 6. ATT results for the impact of smartphone-based weather information on drought perception: Country specific

Meteorological drought perception	Treated households	Control households	ATT(NN) (SE)	ATT kernel (SE)
Kyrgyzstan	0.45 (0.02)	0.29 (0.02)	0.116 (0.03) ***	0.144 (0.05) ***
Mongolia	0.71 (0.02)	0.57 (0.05)	0.204 (0.07) ***	0.145 (0.07) ***
Uzbekistan	0.54 (0.02)	0.59 (0.03)	-0.045 (0.05)	-0.043 (0.05)

Tab. 7. ATT results for the impact of smartphone-based weather information on accurate drought perception

Outcome variable	Treated households (N=1699)	Control households (N=1128)	ATT(NN) (SE)	ATT kernel (SE)
Meteorological drought perception	0.56	0.48	0.080 (0.02) ***	0.075 (0.03) ***

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Tab. 4. ATT results for the impact of smartphone-based weather information on accurate drought perception: Country specific

Accurate meteorological drought perception	Treated	Control	ATT Nearest Neighbor (SE)	ATT Kernel (SE)
Kyrgyzstan	0.49	0.44	0.053 (0.04) ***	0.049 (0.03) ***
Mongolia	0.29	0.45	-0.146 (0.12)	-0.159 (0.04) ***
Uzbekistan	0.57	0.46	0.120 (0.06)	0.108 (0.06) ***

Tab. 5. ATT results for the impact of smartphone-based weather information on drought perception

Outcome variable	Treated (N=1702)	Control (N =1124)	ATT Nearest Neighbor (SE)	ATT Kernel (SE)
Accurate meteorological drought perception	0.48	0.50	-0.026 (0.4)	-0.013 (0.03)

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

- Online weather information increases the subjective perception of drought increase over the past ten years
- However: it only increased the accuracy of drought perception in Kyrgyzstan
- In Mongolia and in Uzbekistan, effect was negative or insignificant. There no contribution to ACCURATE drought perception in these countries.

Possible explanations

- Lower yield and more extensive farming systems in Mongolia
- Less dense distribution of weather stations in Uzbekistan and Mongolia
- Share of irrigated agriculture differently in these countries.
- Any other reasons?

Implications

- Smartphone weather information can improve climate risk perception
- But: More regional specific information, e.g satellite - based information.
- Age, education: smartphone apps should be simple and easily accessible
- Digital attitude: more digital trainings to increase digital literacy and acceptance.

- Focus on meteorological drought. Agricultural drought could provide different results.
- Future research should focus on more in-depth question concerning drought-accuracy.
- Higher-resolution satellite indices for higher precision
- Including winter precipitation for Mongolia

Conclusion

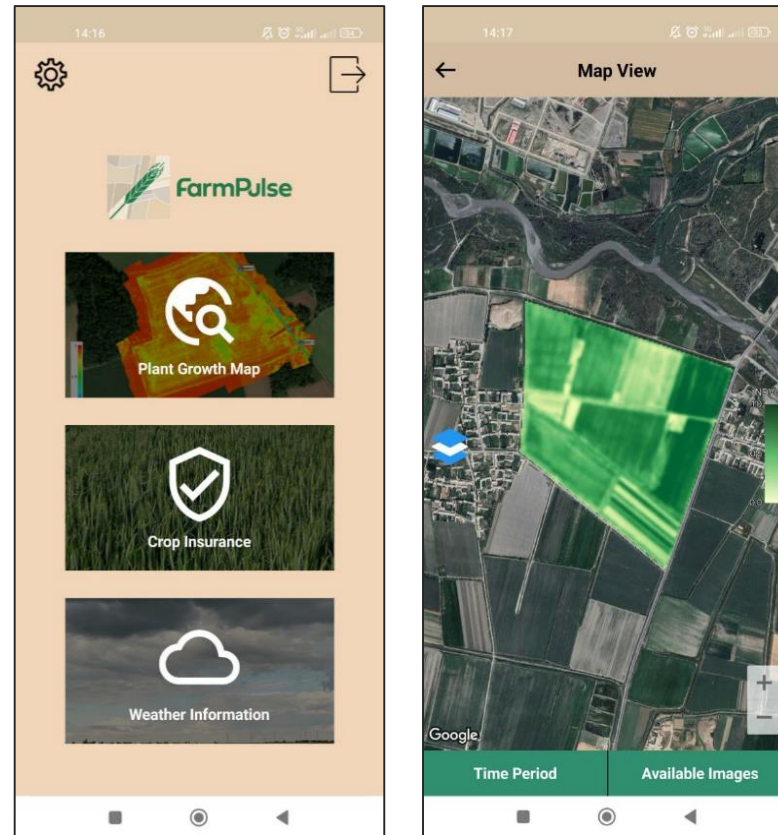


Fig.6. Example of Farm Pulse app



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Thank you for your attention!

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Tab. 8. Summary statistics of household characteristics and outcome variable

Variable	Value	Mean Std. Dev; Percentage (N = 2830)
Age of head of household	Mean (years)	47.29 (11.44)
Gender	Male	81.02
	Female	18.98
Education in agriculture	Yes	28.45
	No	71.55
Farmers extension service attendance	Yes	37.24
	No	62.76
Annual farm income in US dollar	Mean (1-6)	3.89 (1.81)
Farm location	(1 sub-humid; 2 semi-arid; 3 arid)	2.14 (0.84)
Attitude to the online weather information reliability	(1 strongly agree - 5 strongly disagree)	2.59 (1.05)
Smartphone adoption	Yes	91.66
	No	8.34
Country	Mean (1-3)	2.19 (0.74)

^[1] Annual farm income categories in US dollar: 1 = KG < 707; MN < 1753; UZ < 467.
 2 = KG 707.1 – 1769; MN 1753.1 – 8772; UZ 467.1 – 2341.
 3 = KG 1769.1 – 2948; MN 8772.1 – 17545; UZ 2341.1 – 4680.
 4 = KG 2948.1 – 4717; MN 17545.1 – 26316; UZ 4680.1 – 7017.
 5 = KG 4717.1 – 7076; MN 26316.1 – 35088; UZ 7017.1 – 9.357.
 6 = KG \$ >7076.1; MN \$ > 35088.1; UZ \$ > 9.357.1.