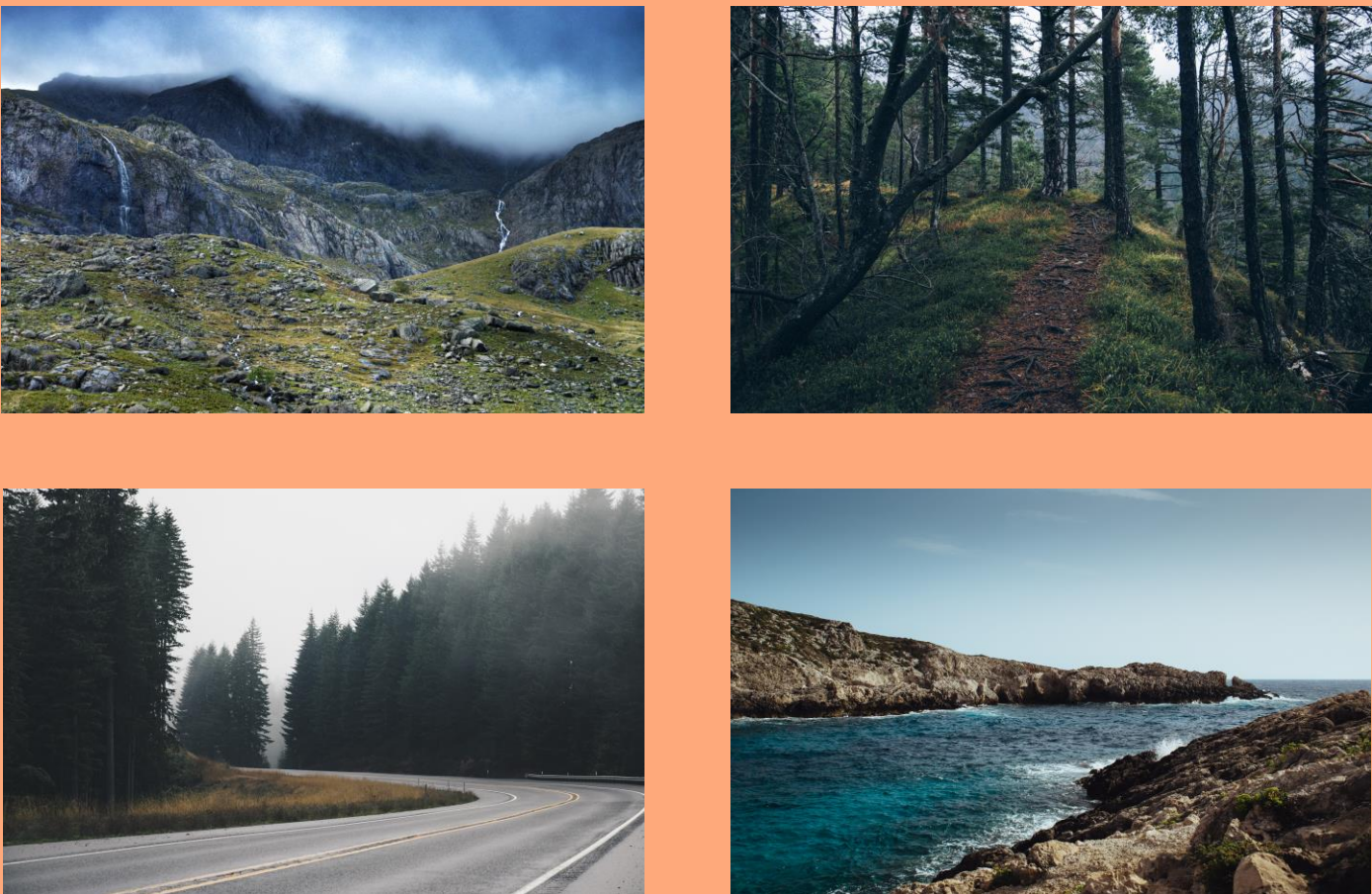


# Citizen Science and Land Cover Classification

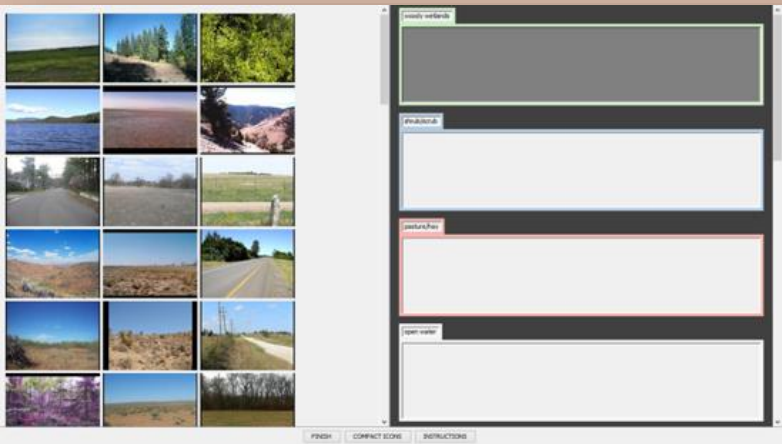
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With the recent availability of different types of earth observation data (e.g., high resolution aerial photos, ground-based photos), and the growth of citizen science and crowdsourcing, new opportunities have opened up for environmental monitoring and data creation from non-authoritative sources (i.e. novice citizens). If citizen science is to be used in the context of environmental research, there needs to be a rigorous evaluation of humans’ cognitive ability to interpret and classify environmental features. This research, with a focus on land cover, explores the extent to which citizen science can be used to sense and measure the environment and contribute to the creation and validation of environmental data.



Participants were asked to classify photos into one of 11 land cover classes. 5 experiments have been conducted, testing the influence of participant expertise, methodological design, and data input source/perspective (ground-based photos & aerial photos).



Experiments 1-3 used the methodological design seen to the left. This design tested lay participants, educated lay participants, and experts.



Experiments 4 & 5 used a different methodological design (seen above) from experiments 1-3. This design presented the participant with one photo at a time, allowing for the collection of confidence in each classification choice. Most importantly these experiments test the influence of aerial photos in the classification process, as seen in the design to the right.

	BA	CC	AL	AO	EW	FO	OS	DW	PH	SS	WW		BA	CC	AL	AO	EW	FO	OS	DW	PH	SS	WW		BA	CC	AL	AO	EW	FO	OS	DW	PH	SS	WW		
BA	46.43	1.86	0	0	7.14	0.71	2.86	0	2.86	34.43	0.71		BA	42.14	0.71	0.71	0	7.14	0	0.71	2.14	0.71	45.71	0	BA	14.29	3.57	0	0	14.29	3.57	0	0	0	0	45.29	0
CC	9.29	37.14	0	2.14	2.86	0	14.29	0.71	11.43	1.14	0		CC	8.57	44.29	0	0.71	8.57	0	1.43	10	0.71	0.71	CC	0	67.86	0	0	0	0	0	0	0	25	7.14	0	
AL	0	0	57.86	30	0	0	7.86	0	2.86	1.43	0		AL	0	47.86	47.14	0	3.57	1.43	0	0	0	0	AL	0	3.57	78.57	10.71	0	0	0	3.57	0	0	0	7.14	0
AO	0.71	0	46.43	35.71	0.71	0	2.86	0	7.86	5.71	0		AO	0	37.86	57.86	0.71	0	2.14	0	1.43	0	0	AO	0	46.43	46.43	0	0	0	0	0	0	0	7.14	0	
EW	6.43	5	0	2.14	33.57	12.14	0	0.71	17.86	16.43	5.71		EW	3.57	1.43	0	0	9.29	34.29	6.43	0	20.71	17.14	7.14	EW	0	17.86	0	0	17.86	42.86	3.57	0	3.57	10.71	3.57	
FO	0.71	0.71	0	2.86	72.14	0	0	1.43	30	2.14	0		FO	1.43	0	2.86	0.71	4.29	79.29	0	1.43	5.71	8.29	FO	0	0	0	0	0	0	0	3.57	17.86	0			
OS	23.57	13.57	0.71	0.71	0	35	15	30	0.71	0	0		OS	15.71	14.29	0	0	0.71	0	0	0	13.57	13.57	0.71	OS	0	14.29	0	0	14.29	0	21.43	28.57	0	0	0	
DW	0	0	0	0	0.71	0.71	0.71	92.14	0	0	5.71		DW	0	0	0	0	0	0	0	93.57	0	0	0	DW	0	0	0	0	0	0	0	100	0	0		
PH	14.29	1.14	2.86	3.57	5.57	12.14	34.29	0	9.29	14.29	3.57		PH	12.14	4.29	2.86	1.43	6.43	10.71	32.86	0	11.43	17.86	0	PH	0	21.43	0	0	0	0	0	32	0	46.43	7.14	0
SS	45	0.71	0.71	0	0.71	0.71	30	0	3.57	33.14	1.43		SS	35.71	0.71	0.71	0	5	3.14	6.43	0	3.57	45.71	0	SS	17.86	0	0	0	0	0	0	17.86	0	60.71	0	
WW	0	1.43	1.43	0	1.43	74.43	0	0	0	7.14	17.14		WW	0	0	0.71	0.71	3.57	77.86	0	0	2.14	15	WW	0	0	0	0	0	0	0	82.86	0	7.14	0		

	BA	CC	AL	AO	EW	FO	OS	DW	PH	SS	WW		BA	CC	AL	AO	EW	FO	OS	DW	PH	SS	WW		BA	CC	AL	AO	EW	FO	OS	DW	PH	SS	WW			
BA	21.43	0.71	0	0	14.29	5	1.43	0	2.14	55	0		BA	42.86	0	0	11.43	2.86	1.43	0	0.71	40	0.71		BA	0	0	0	0	0	0	0	0	0	0	0		
CC	43.57	64.31	0	0	4.29	0	22.86	0	16.43	4.29	0		CC	5.71	40	0	2.86	1.43	0	0	32.86	0.71	11.43	4.29	0.71	CC	0	0	0	0	0	0	0	0	0	0	0	
AL	0	0	62.86	30	0	0	2.86	0	0	0	0		AL	0	40	0	53.57	35.71	0	0	7.14	2.86	0	0	AL	0	0	0	0	0	0	0	0	0	0	0		
AO	0	0	45.71	42.14	0	0	2.86	0	9.29	0	0		AO	0	42.86	38.57	48.29	0	0.71	4.29	0	7.14	0.71		AO	0	0	0	0	0	0	0	0	0	0	0		
EW	0.71	2.14	0	0	17.14	30.71	5	15	22.14	7.14	0		EW	2.86	2.14	0	0	12.86	37.14	0	0	12.86	20.71	2.86		EW	0	0	0	0	0	0	0	0	0	0	0	
FO	0	0	0	0	2.86	62.86	0.71	0	0	9.29	4.29		FO	0.71	0	0	0	0	0	0	78.57	1.43	2.14	14.29	2.14		FO	0	0	0	0	0	0	0	0	0	0	0
OS	7.14	13.57	0	0	2.86	0	43.57	15.71	16.43	2.71	0		OS	12.14	11.43	2.71	0	3.57	39.29	0	0	0	0	0		OS	0	0	0	0	0	0	0	0	0	0	0	
DW	0	0	0	0	0.71	0	0	98.57	0	0.71	0		DW	0	0	0	0	0	0	0	0.71	0	0	0		DW	0	0	0	0	0	0	0	0	0	0	0	
PH	2.86	4.29	0	2.14	2.14	14.29	38.29	0	20	17.86	1.14		PH	2.14	5.71	0	5.71	3.57	2.14	42.86	0	3.57	17.86	1.14		PH	0	0	0	0	0	0	0	0	0	0	0	
SS	22.86	0	0	0	2.86	1.43	15	0	3.57	14.29	0		SS	32.86	0	0	1.43	0.71	15.71	15.71	0	7.86	41.43	0		SS	0	0	0	0	0	0	0	0	0	0	0	
WW	0	0	0	0	7.86	72.14	0	0	0	2.86	17.14		WW	0	0	2.14	0.71	0.71	45	0	0	0	0	0		WW	0	0	0	0	0	0	0	0	0	0	0	

Experts were not significantly different from educated lay participants, and the addition of aerial photos did not significantly increase participant agreement/classification accuracy.

**Conclusions:** These categorical land cover classification tasks are difficult. A possible explanation for why, is that this categorical classification design is generalizing land covers too much, and these classes are too low-level that subjectivity overrides objectivity. The earth’s surface is often complex and heterogeneous. Forcing this complexity into relatively low-level categorical classes is prone to errors and disagreements. When you allow for subjective interpretation of terms, the consistency and reliability of responses drop and the variety of unique responses increases. When using citizen science, making the task as objective as possible is critical for reliable and consistent responses.