SIADS 697: Capstone
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What motivates farmers to implement climate mitigation measures?

Introduction

The climate crisis is one of the most urgent and pressing issues of our time. Emissions proceed with business as usual as temperatures rise and extreme weather events become more common. To curb these changes, we need to reduce and mitigate emissions. As of 2019, 31% of carbon dioxide emissions came from agri-food systems.[1] There is some good news, though, which is that farmers can implement mitigations on their farms to curb some of these emissions.

The question is, what motivates farmers to implement climate mitigation measures? That's exactly what researchers set out to answer with a 30-question survey run in 2019.[2] The survey collected information from 105 Swiss "farmers' individual concerns and perceptions of climate change, attitudes and goals, self-efficacy and locus of control, income satisfaction and social influences" as well as "risk preferences" and thirteen "climate change mitigation measures". The resulting dataset has 105 records with 227 columns including survey responses and external farm census data.

My goal is to understand farmer's motivations by using survey data to predict the proportion of mitigation measures implemented. My approach was three-fold. First, I tested hypotheses based on background research and the survey structure using an ordinary least squares (OLS) regression. Second, I generated hypotheses based on predictive features in the dataset using an explainable boosting machine (EBM) regression. Third, I compared my methods and findings from the dataset against an external analysis published by the survey designers.[3]

Phase 1: Hypothesis testing

Methods

Approach

My goal was to test six hypotheses I developed after a brief literature review about the thirteen mitigations and understanding the structure of the survey. Each section of the survey was designed based on existing research into the adoption of agricultural mitigations. I chose six sections to focus on because of personal interest in behavioral and social factors of the survey. I created six features that summarized each of these sections, then fit a OLS regression. I chose an OLS model because it is simple to train and the results are easy to interpret, which is necessary to understand the mechanisms underlying farmer's motivations.

Hypotheses

1. Environment minded: Farmers who prioritize greenhouse gas emission reduction, protection of environment, and preservation of biodiversity are more likely to implement climate mitigations.
2. Perceive weather change: Farmers who perceive changing weather patterns are more likely to implement climate mitigations.

3. Anticipate negative consequences: Farmers who anticipate negative consequences of climate change are more likely to implement climate mitigations.
4. Capable implement: Farmers who feel capable of implementing mitigation measures are more likely to implement climate mitigations.
5. Think measures effective: Farmers who perceive mitigation measures that are relevant to their farm as effective are more likely to implement climate mitigations.
6. Social connectedness: Farmers who are part of strong social networks are more likely to adopt innovations including climate mitigations.

Features

Each hypothesis was tested by taking the mean value of relevant survey features. For example, one survey question asks about the perception of severe weather events. This question has six sub-questions, each about a specific weather event (e.g., hail, drought, frost), with responses on a 5-point scale. In the dataset, there are six corresponding columns mapped to a 3-point scale. I took the average of these six columns to represent a single feature for hypothesis 2, which represents the average observation of changing weather. For additional details for the perception example, see Appendix I. For additional details of which columns in the raw dataset were combined into a feature for each OLS hypothesis, see Appendix II.

Outcome variable

The outcome variable was the proportion of applicable mitigations implemented. I calculated the variable based on the 13 mitigation measures from the survey. For each mitigation measure, the survey asked farmers to respond that they had implemented the measure, had not implemented the measure, or did not apply to their farm. I calculated the outcome variable as the number of implemented features divided by the number of applicable features, resulting a proportion from 0 to 1.

Unfortunately, the encoding of the mitigation columns in the codebook differs from the values in the dataset. The codebook encodes responses as 0 for not implemented, 1 for implemented, and NA for not applicable; the dataset has values of 1, 2 and 3. I emailed the author to clarify the values, but I have not yet received a response. Therefore, I had to assume which values represented which responses.

I assumed which value matched which response based on the following observations and assumptions.

- Observation 1: There are four types of farms reported in the dataset: Arable farms (which predominantly raise crops), Livestock farms (which predominantly raise animals), Specialized crops, and Other.
- Observation 2: There are categories for mitigation measures: Livestock and manure management, crop production, and energy use.
- Observation 3: Arable farms have few livestock. See Figure 1.
- Assumption 1: I assume that since most arable farms do not have livestock, most arable farms will consider livestock-specific mitigations not applicable.
- Assumption 2: I assume that the second most arable farms have a few livestock and will consider livestock-specific mitigations applicable but will not have implemented

them, because the payoff might not warrant the implementation effort at a small scale.

- Assumption 3: I assume that the least arable farms will consider livestock-specific mitigations have a few livestock, and will consider livestock-specific mitigations applicable, and have gone to the effort to implement them at a small scale.

Therefore, I conclude that response 1 indicates implemented, response 2 indicates not implemented, and response 3 indicates not applicable. See Figure 2.

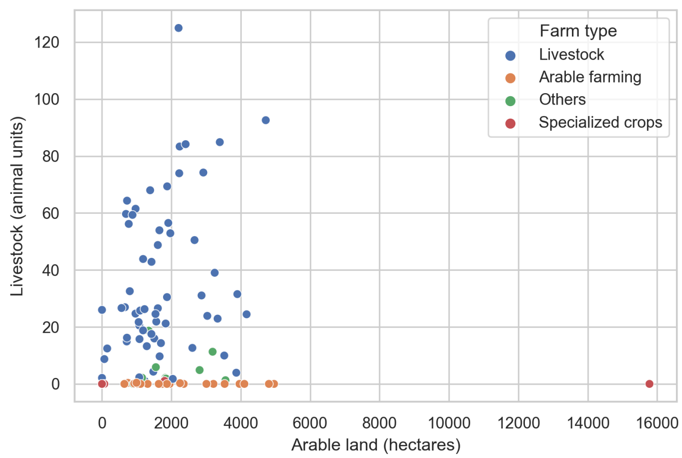

Figure 1: Arable land vs. livestock by farm type. The x-axis shows arable land in 0.01 hectares. The y-axis shows livestock in animal units, which is a way of quantifying different types of livestock into one unit. Hypothetical example: one beef cow may be considered 1 animal unit, and a sheep may be considered 0.3 animal units. Farm type is indicated by color, where blue is for livestock farms and orange is for arable farms.

Observations

- Livestock farms are spread along both axes, indicating a mix of arable land and livestock
- Arable farms are all along the x-axis, indicating a range of arable land but few livestock.

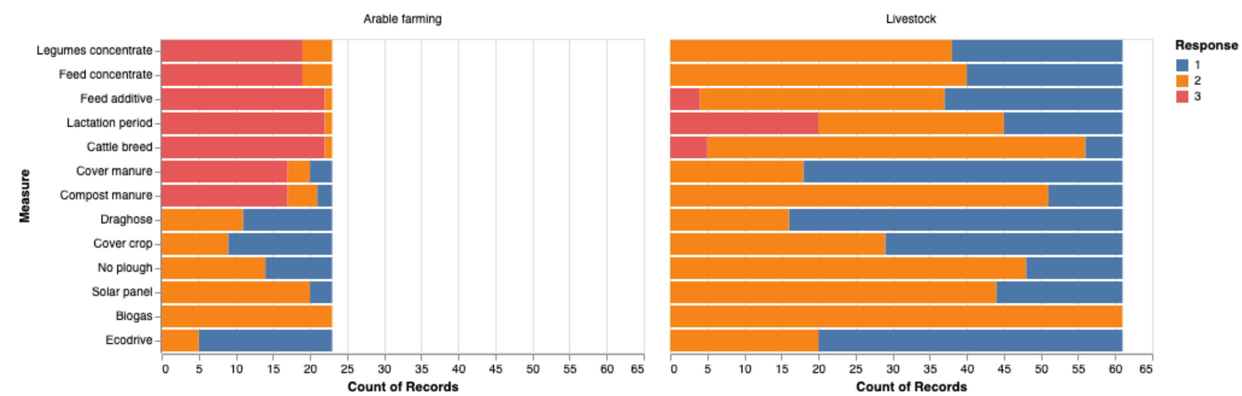

Figure 2: Mitigation response vs. mitigation measure. The x-axis shows the count of records is along the x-axis. The y-axis shows mitigation measure. The first seven measures (Legume concentrates to Compost manure) are all livestock mitigation measures. The next three measures (Draghose, Cover crop, and Solar panel) are crop mitigation measures. The last three measures are energy measures (Solar panel, Biogas, and Ecodrive). Color shows the survey response in order, where red is 3, orange is 2, and blue is 1. Arable farms are shown on the left, and Livestock farms are shown on the right.

Observations

- Most arable farms respond 3 to the seven livestock mitigation measures.
- The next most arable farms respond 2 to livestock mitigation measures.
- A few arable farms respond 1 to livestock mitigations that are related to manure (Cover manure and Compost manure).

Model

I fit an ordinary least squares regressor from the statsmodels library[4] with all of the data. I fit a model according to the equation below, where y is the proportion of applicable mitigations implemented, X is a hypothesized feature, alpha is a constant, beta are coefficients, and epsilon is an error term.

$$y = \beta X_{Environment\ minded} + \beta X_{Perceive\ weather\ change} + \beta X_{Anticipate\ negative\ consequences} + \beta X_{Capable\ implement} + \beta X_{Think\ measures\ effective} + \beta X_{Social\ connectedness} + \alpha + \epsilon$$

I checked four assumptions for the linear regression [5]. See Appendix III.

1. The outcome variable is normally distributed.
2. No predictors are correlated.
3. There are linear relationships between the predictors and outcome variable.
4. The model residuals have equal variance.

I evaluated the OLS model on four metrics. See Figure 3. I also visualized the actual values and predicted values of the outcome variable, which is the proportion of applicable measures implemented. See Figure 4.

- R-squared: the proportion of variance explained by the model. Higher is better, a higher R-squared means that the model explains more variance.

- Residual standard error (RSE): the standard error of the difference between model predictions and actual values in the outcome variable. Lower is better, lower RSE means that the model makes smaller mistakes in prediction.
- F-statistic and p-value: The likelihood that all coefficients of the model are actually 0. A lower p-value means it is unlikely that the model coefficients are 0.
- T-statistic and p-value: The likelihood that a single coefficient of the model is actually 0. A lower p-value means it is unlikely that the model coefficient is 0.

Results

	Dependent variable:prop_implemented
	(1)
anticipate_negative_consequences	-0.005
	(0.021)
capable_implement	0.052**
	(0.025)
const	0.172
	(0.152)
environment_minded	0.011
	(0.024)
perceive_weather_change	-0.106**
	(0.046)
social_connectedness	-0.009
	(0.032)
think_measures_effective	0.072***
	(0.027)
Observations	105
R^2	0.259
Adjusted R^2	0.213
Residual Std. Error	0.161 (df=98)
F Statistic	5.701*** (df=6; 98)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 3: OLS regression metrics.

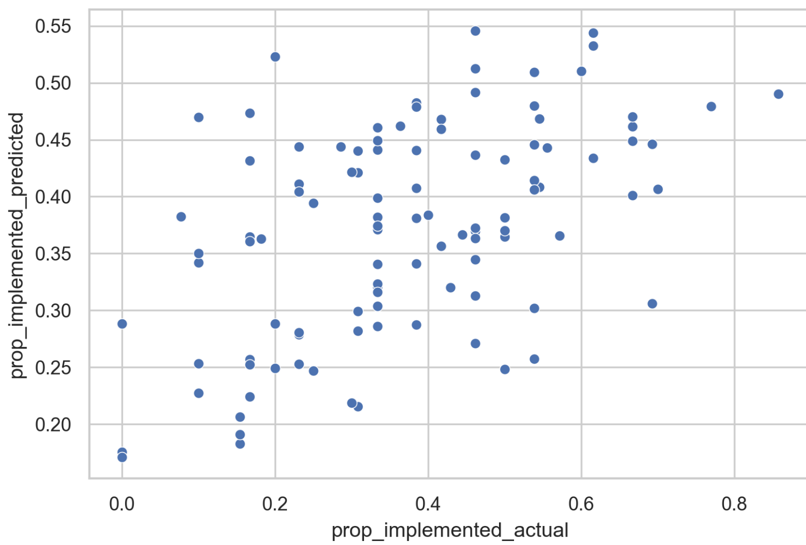

Figure 4: Actual values vs. predicted values of the outcome variable from OLS. The x-axis shows the actual values of the proportion of implemented measures. The y-axis shows the predicted values of the proportion of implemented measures.

Model

The adjust R-squared value is 0.213, which means that the model explains 21.3% of the variance. The RSE is 0.161, which means that the distribution of the difference between model predictions and actual values has a standard error of ±0.161 units, which is a ±16.1% difference in the proportion of implemented measures. The F-statistic has a $p<0.01$, indicating the results are highly significant. Overall, these metrics suggest that the model captures some meaningful variation in the data, but the model falls short on explaining much of the variation, and the predictions are not very accurate.

Coefficients

Three coefficients have statistically significant t-statistics.

Think measures effective has a highly significant coefficient of 0.072 (±0.027, $p<0.01$). This supports my hypothesis that thinking measures are effective is positively related to implementing more mitigations.

Capable implement has a significant coefficient 0.052 (±0.021, $p<0.05$). This supports my hypothesis that feeling capable of implementing a change is positively related to implementing more mitigations. That said, this feature is 64% correlated with the *Think measures effective* measure (see Appendix II), so these features may be capturing a similar relationship.

Perceive weather change has a significant coefficient of -0.106 (±0.046, $p<0.05$). This does not support my hypothesis that perceiving more extreme weather changes is positively related to implementing more mitigations; they are negatively related.

The remaining three coefficients did not have statistically significant t-statistics. *Anticipate negative consequences* had a coefficient of -0.005 (±0.021, $p>0.1$). *Environment minded* had a coefficient of 0.011 (±0.024, p>0.1). *Social connectedness* had a coefficient of -0.009 (±0.032, p>0.1).

Discussion

It is intuitive to me that farmers who think measures are effective for mitigating climate change implement more measures. However, there are other reasons to implement climate mitigation measures, such as financial savings in terms of energy use, reduced cost of hauling out manure, and more productive crop, dairy, and meat production. It is interesting to know that the effectiveness of these mitigations for climate *specifically* is positively related to their implementation.

It is also intuitive to me that farmers who feel capable of implementing measures also implement more measures. It is hard to motivate yourself to do something that you don't feel capable of doing. This feature could be related to other important features that are not captured by the survey, such as the level of climate education a farmer has.

It is surprising to me that farmers who observe less severe weather changes also implement *fewer* measures. Personally, I have observed more severe weather events in my area and in reporting worldwide, that terrify me! And that feeling is motivating to reduce my own greenhouse gas emissions. One counter explanation could be that fear is also demoralizing rather than motivating, especially if farmers don't feel that their actions have an impact on climate change overall – there could be an interactive effect with other survey responses about whether a farmer's actions impact the climate. Another counter explanation could be that farmers may not link climate change and severe weather patterns at all, and they might not see these observations as a motivation for change.

Conclusions

The **main contributions** of this work are finding two significant relationships with the proportion of implemented measures:

- Farmers who feel capable of implementing measures often think measures are effective, and also implement more measures
- Farmers who perceive more extreme weather changes also implement fewer measures.

A major shortcoming of this model approach is that it enforces strong assumptions that the relationships are linear. An OLS model is very interpretable, but it is possible that these relationships are nonlinear in reality, and a more flexible and nonlinear representation may be more realistic.

Phase 2: Hypothesis generating

Methods

Approach

After developing a narrow set of hypotheses and testing them with an OLS regressor, I wanted to create a model that would be trained with as many features as possible, and surface important predictors. A useful predictor could hint at a driving motivator for farmers, which could be tested in follow up study. For this approach, I chose an Explainable Boosting Machine

(EBM) regressor because it claims state-of-the-art performance without sacrificing interpretability, which is necessary to understand the mechanisms underlying farmer's motivations.

Model

I fit an explainable boosting machine (EBM) regressor from the InterpretML library.[6] EBMs are generalized additive models that can capture pair-wise interactions and utilize machine learning techniques such as bagging and gradient descent in training.

I evaluated the EBM model on two metrics: R-squared and mean squared error (MSE) for the training and test data. Mean squared error is the average difference between model predictions and actual values. See Figure 5. I also visualized the actual values and predicted values of the outcome variable, which is the proportion of applicable measures implemented for the training and test data. See Figure 6. I also visualized the overall feature importance for the top 15 most important features for the model. See Figure 7.

Features

For this phase of the project, I included all complete features from the survey responses and external farm census data. I excluded columns from the census that lacked data for some farms, and I excluded survey responses that were optional and incomplete. The resulting feature dataset had 83 features. I used the scikit learn library [7] to preprocess data into training data (90%, n=94) and test data (10%, n=11). I encoded the categorical variable for the Swedish district of each farm into an ordinal numeric feature.

Outcome variable

I used the same outcome variable as phase 1, the proportion of applicable mitigations implemented.

Results

Model

The R-squared value for the test data is 0.205, which means that the model explains 20.5% of the variance. The MSE is 0.028, which means that the average squared difference between predicted and actual values is 0.028, which is a 2.8% difference in the proportion of implemented measures. See Figure 5. The model predictions for the test data could show a linear relationship, although it is tough to tell from the sparsity of points; the model predictions have a strong linear relationship with actual values for the training data. See Figure 6. Overall, these metrics suggest that the model has overfit to the training data, and it is capturing noise in the training data that does not generalize to the dataset overall. Despite this discrepancy, the EBM model is still capturing a similar amount of variance as the OLS model.

	Training data	Test data
R-squared	0.939	0.205

MSE	0.001	0.028

Figure 5: EBM regression metrics.

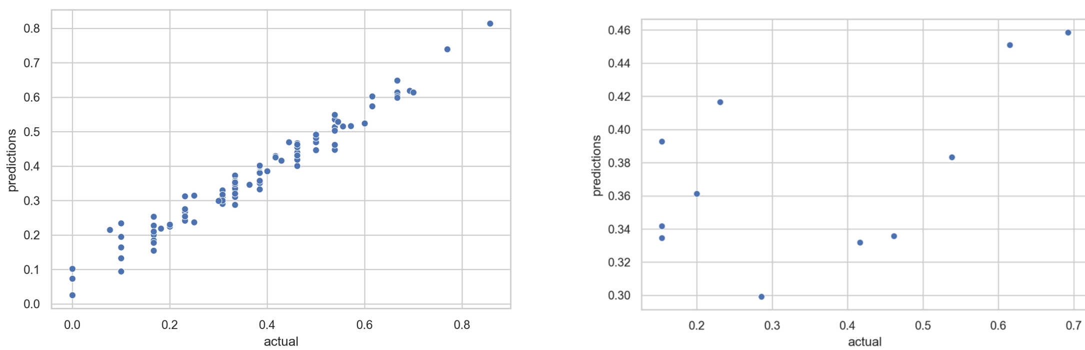

Figure 6: Actual values vs. predicted values of the outcome variable from EBM. The x-axis shows the actual values of the proportion of implemented measures. The y-axis shows the predicted values of the proportion of implemented measures. The left panel shows the training data, the right panel shows the test data.

Features

The mean absolute score of feature importance for all features is less than 0.01, which suggests that the model uses many features with low feature importance. See Figure 7. The top three important features with mean absolute scores > 0.008 are:

1. *soc_env*: On my farm, I want to produce more environmentally and climate-friendly than other farmers in my area. (5-point scale, 1 = strongly disagree, 5 = strongly agree)
2. *innov_pion*: I am a pioneer in climate change mitigation and implement appropriate measures, even if they involve economic risks. (5-point scale, 1 = strongly disagree, 5 = strongly agree)
3. *self_reduc*: I can do something about climate change on my farm by reducing greenhouse gases. (5-point scale, 1 = strongly disagree, 5 = strongly agree)

The most important pairwise interaction was *spec_crops x animal_unit*.

- *spec_crops*: total area of specialized crops (0.01 hectares)
- *animal_unit*: total animal units on the farm (livestock)

Three of the top fifteen features from EBM were included significant features from the OLS model. *Self_reduc* and *self_cap* columns were included in the *Capable implement* feature in OLS, and *percep_heavyrain* was included in the Perceive weather change feature in OLS. This suggests that despite having fewer features, the OLS hypotheses captured some features that drive variation in the entire dataset.

Another interesting feature from the EBM is *network*: the number of connections a farmer reported on the survey from 1 to 10. I created a feature to summarize *social connectedness* in the EBM, which took the average importance a farmer reported for the connections they did mention. *Network* was important to the EBM, while *social connectedness* was insignificant to the OLS. This may suggest that the size of a social network may be more useful measure for understanding farmer's motivations to implement mitigations than the average importance of all social connections.

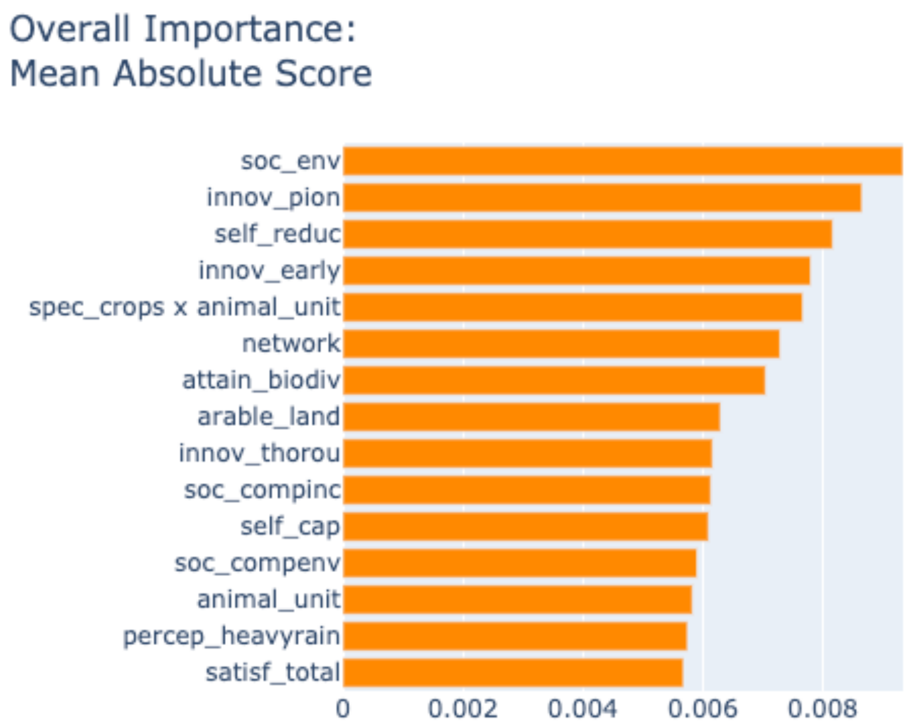

Figure 7: Feature importance for EBM regression. The x-axis shows the feature importance score, the y-axis shows the feature name in order from most to less important.

Discussion

Social comparison and innovativeness were important features to the EBM I excluded from the OLS. However, it makes sense that social comparison could be a powerful motivator to implement changes, and that a drive to innovate despite financial risks of implementing new measures would be related to implementing more changes.

I was surprised to see so few pairwise interactions in the most important features, because many of these features are strongly correlated; especially features that correspond to the same overall survey section. That said, it makes sense to me that some interaction of farm census data would impact how many measures farmers are implementing. For example, livestock mitigations may have a larger payoff for farms with more livestock; I was unsurprised to see this predictor ranked highly.

Conclusions

The **main contributions** of this work are finding three important features with relationships to the proportion of implemented measures:

- Farmers who want to produce more environmentally and climate-friendly than other farmers in their area
- Farmers who are pioneers in climate change mitigation, despite economic risk
- Farmers who believe they can change climate by reducing greenhouse gas emissions on their farm

One major shortcoming of this model approach is that it can only capture pairwise interactions at most, and many of these features may be correlated. It's possible that the abundance of features made it challenging for the model to sort out which were the most useful in training. An approach with dimensionality reduction, such as PCA, could improve prediction accuracy, and be inspected with InterpretML visualizations to determine where the most variation is in the dataset. Another approach could be training an elastic net, which performs well when there are more features than observations and features are highly correlated.[8]

Phase 3: Comparison to external study

After conducting my own analysis, I compared my approach and findings to another analysis published by the survey creators.[3] There are a few notable differences and similarities.

- Overall question: I wanted to know what motivates farmers to adopt climate mitigations in general. Since the experts are authors in the field and more informed, they had a much more targeted question than me. Their question was: How do non-cognitive skills influence farmer's mitigation behaviors?
- Hypothesis test: While I was interested in six specific factors, the authors were interested particularly in the non-cognitive skills of self-efficacy (whether a person believes they are capable of a particular task), locus of control (whether a person believes their abilities and efforts determine an outcome), and innovativeness (trying new technologies and organizations to enhance production). They posit a hypothesis that self-efficacy and locus of control determine mitigation behavior through the mediator of innovativeness.
- Model formulation: The authors tested 12 linear models. 10 models were OLS regressors, similar to my approach. Comparing our OLS formulations, the authors included models with and without control variables of farm characteristics and farmer demographics, which I did not try.
- Mediation: I did not have any hypothesized mediators. The authors include two of the 12 linear models that use a two-step method called sequential g-estimation to determine whether innovativeness is a mediator between non-cognitive skills (locus of control and self-efficacy) and mitigations implemented. First, a model is fit to account for innovativeness, and determine what proportion of mitigations would be implemented otherwise. Second, a model is fit using non-cognitive skills to predict the proportion of mitigations from step one. If the second model is not robust to the correction from the first model, than innovativeness is likely a mediator.

- Omitted variable bias: I did not account for omitted variables in my analysis. The authors also use the Oster bound approach to determine how much omitted variable bias there would need to be for their results to be null.
- Features: The authors collected related responses on the survey using means, same as I did, but they also used factor analysis for certain responses, and it's not clear what drove that modeling decision. My OLS feature of *perceive weather change* is comparable to their *climate change perception* control variable. My OLS feature of *Think measures effective* is the same as their *Perceived effectivity of measures* control variable.
- Outcome variable: The authors also used the proportion of applicable mitigation measures as the dependent variable for their model formulations.
- Findings: The authors find evidence that locus of control and self-efficacy have strong positive associations with implementing mitigations. The authors find some support that innovativeness is a mediator for this effect. The authors find that omitted variables would have to be three times as important as included covariates to change their model interpretations.

Although I am not a domain expert in this field, I uncovered some similar patterns in the dataset to the survey designers. The **main contribution** of this comparison is that my analysis supports domain expert findings that non-cognitive skills are an important covariate with the proportion of climate mitigation measures that farmers implement. I also learned two new methods to check for a mediator and determine how robust results are to omitted variable bias in observational data.

As the authors of this paper mention, though, these methods are not sufficient to interpret observational data in a causal way. I also found myself questioning the approach – did the researchers enter this survey design with this specific hypothesis? I know that pre-registration of analyses is not common in all domains yet, but I think it should be. I would have more confidence in these findings if I could see the hypotheses were developed and published before the data collection and analysis.

Conclusions

The biggest shortcoming in this analysis is an open question: How generalizable are these findings? This data is self-reported data from a survey of 105 Swedish farmers who self-selected to participate. These findings may not generalize outside of that context and cannot be interpreted causally.

The **key contributions** from this analysis are

- Phase 1: <u>I determined three significant covariates for farmers implementing mitigations.</u>
    - Thinking measures effective
    - Being capable of implementing measures
    - Perceiving extreme weather changes
- Phase 2: <u>I surfaced additional possible predictors of farmers implementing mitigations.</u>
    - Social comparison as a motivator warrants future study in agriculture
    - Innovativeness warrants future study in agriculture

    - Being capable of implementing measures warrants future study in psychology
- Phase 3: <u>I supported one key finding of an independent external analysis.</u>
    - Locus of control was an important covariate in my OLS model
    - Locus of control and innovativeness were important features in my EBM model

These predictors could be used to survey prospective farmers for piloting new mitigation measures. I suggest a three-pronged approach to future work. First, further analysis of this dataset could be helpful. I suggest using different models for different types of farms and different types of mitigations. I also suggest fitting an elastic net model as a more appropriate model to surface useful predictors. Second, I suggest analyzing a complementary dataset. The survey authors collected and published a complimentary dataset on farmers social networks. Based on findings here that the number of connections and social comparison may play a role in mitigation uptake, an analysis of this data may complement these findings nicely. Third, I suggest a non-observational approach. A pseudo-experimental or randomized control trial design would be useful to causally interpret why farmers implement more mitigations than others. With a causal understanding, it would be clearer how to encourage farmers to further mitigate emissions on their farms, and partly address the climate crisis.

Statement of Work

This project was completed individually by Brooke Hawkins.

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Appendix I: Survey Details

The survey had seven sections.

1. Expected consequences and perceptions of climate change
2. Perceived self-efficacy and locus of control (non-cognitive skills)
3. Current implementation and expected effectiveness of mitigation measures
4. Education, personal preferences, goals, and innovativeness
5. Income satisfaction
6. Personal social networks and social comparison
7. Risk preferences, loss aversion and probability weighting (multiple price list)

The survey asked about 13 climate mitigation measures.

Category	**Shorthand name**	**Variable name**	**Survey question**
Livestock and manure management	Legumes	legum	I substitute some of the (imported) concentrates for my animals with native grain legumes (e.g., peas, lupines, field beans, European soya).
	Reduction concentrates	conc	I reduce the concentrate content to a maximum of 10 percent of the ration for my animals.
	Lactation	lact	I keep my cows for at least 5 lactation periods.
	Breed	breed	I keep cattle of a dual- purpose breed (for example, original brown cattle).
	Additives	add	I feed my cattle tannins, flaxseed or similar feed additives to reduce methane emissions from digestion.
	Cover manure	covman	The manure storage on my farm is covered.
	Compost manure	comp	I compost the farm manure.
Crop production	Draghose	drag	I apply the fertilizer close to the ground with a draghose or a similar technology.
	Cover crop	cov	I include cover or catch crops in my rotation.

	Ploughless	plough	I do not use the plough for tillage.
Energy production and use	Solar panels	solar	I have solar panels for energy production.
	Biogas	biog	Manure from my farm is fermented in a biogas plant.
	Ecodrive	ecodr	When working with the tractor I drive in eco-drive mode (fuel-efficient).

Here is an example of how a survey question was encoded in the dataset.

Survey question

Q2. How did you perceive the frequency of extreme weather events over the past 10 years on your farm?

	Strong increase 1	2	No change 3	4	Strong decrease 5
Hail events	☐	☐	☐	☐	☐
Continuous dry phases	☐	☐	☐	☐	☐
Frost in autumn and spring	☐	☐	☐	☐	☐
Heavy rain	☐	☐	☐	☐	☐
Long rainy periods	☐	☐	☐	☐	☐
High temperatures and heat waves	☐	☐	☐	☐	☐

Codebook entry

percep_hail	How did you perceive the frequency of extreme weather events over the past 10 years on your farm? [Hail]	1= no change, 2 = increase or decrease, 3 = strong increase or strong decrease
percep_drought	How often have you perceived extreme weather events over the past 10 years? [Drought]	1= no change, 2 = increase or decrease, 3 = strong increase or strong decrease
percep_frost	How often have you perceived extreme weather events over the past 10 years? [Frost in spring or autumn]	1= no change, 2 = increase or decrease, 3 = strong increase or strong decrease
percep_heavyrain	How often have you perceived extreme weather events over the past 10 years? [Heavy rain]	1= no change, 2 = increase or decrease, 3 = strong increase or strong decrease
percep_longrain	How often have you perceived extreme weather events over the past 10 years? [Prolonged rain periods]	1= no change, 2 = increase or decrease, 3 = strong increase or strong decrease
percep_heat	How often have you perceived extreme weather events over the past 10 years? [Heat waves]	1= no change, 2 = increase or decrease, 3 = strong increase or strong decrease

Five sample records

percep_hail	percep_drought	percep_frost	percep_heavyrain	percep_longrain	percep_heat
2	2	2	1	2	2
3	2	2	3	3	3
2	3	1	1	1	3
2	2	2	2	2	2
2	3	2	2	1	3

Appendix II: OLS Features

Here is how a feature was derived for each hypothesis in the ordinary least squares regression.

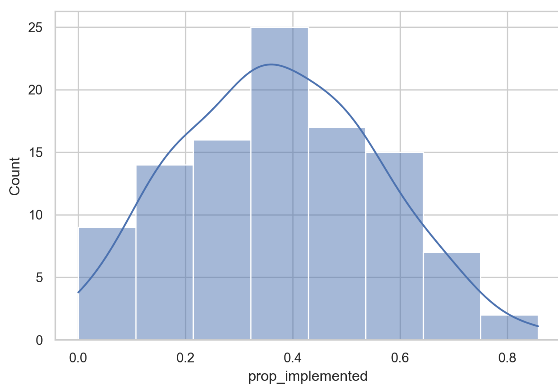
Feature	**Hypothesis**	**Calculation and Columns**
environment_minded	Farmers who prioritize greenhouse gas emission reduction, protection of environment, and preservation of biodiversity are more likely to implement climate mitigations.	= mean(GHG_goal, env_goal, biodiv_goal)
perceive_weather_change	Farmers who perceive changing weather patterns are more likely to implement climate mitigations.	= mean(percep_hail, percep_drought, percep_frost, percep_heavyrain, percep_longrain, percep_heat)
anticipate_negative_consequences	Farmers who anticipate negative consequences of climate change are more likely to implement climate mitigations.	= mean(cons_general, cons_farm)
capable_implement	Farmers who feel capable of implementing mitigation measures are more likely to implement climate mitigations.	= mean(self_reduc, self_act, self_cap, self_conf, self_not)
think_measures_effective	Farmers who perceive mitigation measures that are relevant to their farm as effective are more likely to implement climate mitigations.	= if applicable then mean(legum_eff, conc_eff, add_eff, lact_eff, breed_eff, covman_eff, comp_eff, drag_eff, cov_eff, plough_eff, solar_eff, biogas_eff, ecodr_eff)
social_connectedness	Farmers who are part of strong social networks are	= mean(net_name1_imp,

	more likely to adopt innovations including climate mitigations.	net_name2_imp, net_name3_imp, net_name4_imp, net_name5_imp, net_name6_imp, net_name7_imp, net_name8_imp, net_name9_imp, net_name10_imp)

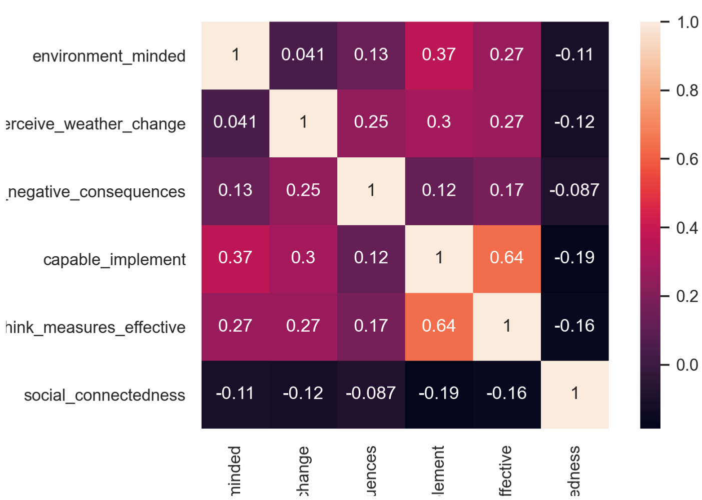
Appendix III: OLS Assumptions Check

See report 2 in the GitHub repository for statistical checks to accompany to these visualizations.

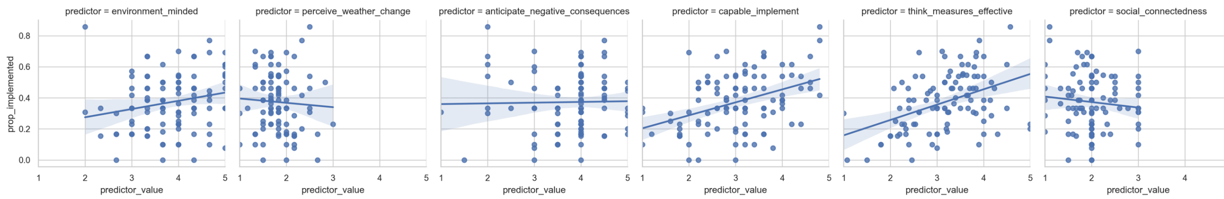
1. The outcome variable is normally distributed.



2. No predictors are correlated.



3. There are linear relationships between the predictors and outcome variable.



4. The model residuals have equal variance.