SOCCJ Soil & Water Research Summary

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1 Introduction & Data

s The survey is taken once a year from 2020 to 2025. And there are 1858 observations, individuals, and each observation contains 1402 variables. The individuals are consistent across all years, while certain individuals are not observed in some years. And we focus on the variable recording whether using a method of production, Cover crops, for each individual in each year, leveled from 1 to 4, with 1 as not used last year and will not plan to use it, 2 as not used last year and not planning to use it within 3 years but open to use in future, 3 as not used last year but intend to use within 3 years, and 4 as already used last year. The data is blocked into 3 groups (time period), (2020, 2021), (2022, 2023), (2024, 2025). And we may assume data from different year blocks share some of the variables, that is part of the variables from year 2020, 2022, and 2024 are shared, but some are different. This is similar for year 2021, 2023, and 2025. The "cover crops", individual choices of method of production, is recorded in year 2021, 2023, 2025. And there is a group of other substitution methods of production also recorded as same 4 level variables in year 2021, 2023, 2025 together with "cover crops".

1.1 Scientific Questions

For this project, we focus on answering following questions:

(1) Which factors contributed to the individuals' choice of using "cover crops" from year (2020, 2021) to (2022, 2023);

(2) Which factors contributed to the individuals' choice of using "cover crops" from year (2022, 2023) to (2024, 2025);

After the investigation of the scientific questions (1) and (2) and based on the result we have from question (1) from year 2021 to 2023, we have an expectation, prediction, of the expected proportion of usage of "cover crops" in year 2025 given information in year block (2022, 2023), but the actual proportion of usage of "cover crops" in year 2025 is different from our expectation, prediction. Thus, the second part of scientific questions is

(3) what factors contribute to the differences between our expected, predicted, proportion of usage of "cover crops" in year 2025 and the actual proportion of usage of "cover crops" in year 2025.

2 Notation & Data Processing

- Individuals (i=1,. . . ,N) (about 1000).
- Years ($t \in 2020, \dots, 2025$).
- Blocks:
  - Block 1: (2020, 2021)
  - Block 2: (2022, 2023)

- Block 2: (2024, 2025)

- Ordered adoption state of cover crops (4 levels) in year ($t \in 2021, 2023, 2025$):

$$Y_{it} \in 1, 2, 3, 4$$

(1 = no use & no plan, …, 4 = already used last year).

- Let

$$S_i^{(1)} = Y_{i,2021}, \quad Y_i^{(1)} = Y_{i,2023}, \quad S_i^{(2)} = Y_{i,2023}, \quad Y_i^{(2)} = Y_{i,2025}$$

be the "start" and "end" states for blocks 1→2 and 2→3.

- Covariates:
  - (X_{it}^{even}) for even years (2020, 2022, 2024) – "production / structural" covariates.
  - (X_{it}^{odd}) for odd years (2021, 2023, 2025) – attitudes, plans, etc.

  Some of these are shared across blocks (same conceptual variable re-asked).

- Other methods of production (substitutes) are also 4-level variables ($Z_{it}^{(k)}$).

- Panel attrition & refreshment → nonresponse indicators (R_{it}) and design weights (d_{it}). Ultimately we'll work with analysis weights (w_{it}) that combine design + nonresponse adjustments (IPCW + imputation based on PMM).

- PCA was applied to a selected subset of survey variables to reduce dimensionality and summarize their joint variation into a smaller number of orthogonal components. The number of components retained was determined using parallel analysis based on imputed data, ensuring that only components explaining more variance than expected under random noise were kept. Then, we use summation scales of variables, in original non-imputed data, grouped based on loadings as low-dimensional representations of the original variables for further analysis.

3 Analytical Framework

3.1 Step A. Construct transition datasets for the two periods

- Dataset A (2021 → 2023) Covariates:

$$\mathcal{X}_i^{(1)} = \big(X_{i,2020}, X_{i,2021}, X_{i,2022}, X_{i,2023}, Z_{\cdot,2021}, Z_{\cdot,2023}\big),$$

possibly with engineered lags/changes (e.g., ($X_{2023} - X_{2021}$)).

- Dataset B (2023 → 2025) Covariates:

$$\mathcal{X}_i^{(2)} = \big(X_{i,2022}, X_{i,2023}, X_{i,2024}, X_{i,2025}, Z_{\cdot,2023}, Z_{\cdot,2025}\big),$$

remembering that some 2025 questions refer to 2024.

Keep weights ($w_i^{(1)}$) and ($w_i^{(2)}$) to account for design + attrition.

3.2 Step B. Q(1) & (2): model "transition behavior" and drivers

Objective: for each block (b=1,2), estimate

- Transition kernel

$$p_{k\to m}^{(b)}(x) = \Pr\left(Y^{(b)} = m, \middle|, S^{(b)} = k,\ \mathcal{X}^{(b)} = x\right),$$

- upward-movement risk

$$u_k^{(b)}(x) = \Pr\left(Y^{(b)} > S^{(b)}, \middle|, S^{(b)} = k,\ \mathcal{X}^{(b)} = x\right).$$

From these we can:

- describe transitions (Sankey-style) conditional on covariates;
- identify factors associated with more upward movement (from SHAP, partial dependence, or regression coefficients);
- optionally embed this in a causal estimator later (DML/TMLE) for selected modifiable factors.

3.3 Step C. Q(3): expected vs realized 2025 adoption

The analytical framework of this section is currently under development and has not yet been decided.

We want to compare:

- Expected 2025 adoption using only information up to block 2, what we would have predicted for 2025 if the world in 2024–2025 behaved like 2020–2023.
- Actual 2025 adoption with all later changes, including new covariate values in 2024–2025.

Possible set up:

- Fit a model for transition structure using block 1→2 (dataset A):

$$g^{(1)}(s, x_{\text{pre}}) \approx \mathbb{E}\left[Y^{(2)} \mid S^{(2)} = s,\ \mathcal{X}_{\leq 2023} = x_{\text{pre}}\right]$$

  trained only on variables available by 2023.

- Apply $(g^{(1)})$ to the 2023 population (with 2022 and 2023 covariates) to obtain a predicted distribution $(\hat{Y}_{2025}^{\text{pred}})$ and its proportion $(\hat{\pi}_{2025}^{\text{pred}})$.
- Compare with realized 2025 adoption proportion $(\hat{\pi}_{2025}^{\text{obs}})$ (using directly 2025 data).

Define the gap

$$\Delta = \hat{\pi}_{2025}^{\text{obs}} - \hat{\pi}_{2025}^{\text{pred}}.$$

Fit a full model $(g^{(2)})$ on block 2→3 with more covariates $(\mathcal{X}^{(2)})$ (including 2024/25 covariates), then investigate

$$d_i = g^{(2)}(S_i^{(2)}, \mathcal{X}_i^{(2)}) - g^{(1)}(S_i^{(2)}, \mathcal{X}_i^{\text{pre}})$$

explained by new covariates.

4 Theoretical Models & Estimands

4.1 Transition Boosting for Q(1) & Q(2)

4.1.1 Multiclass transition model (focusing on transition kernel)

For each block $b \in \{1, 2\}$ and individual $i \in \{1, \ldots, N\}$, we observe an origin state $S_i^{(b)} \in \{1, 2, 3, 4\}$ and a destination state $Y_i^{(b)} \in \{1, 2, 3, 4\}$, together with a covariate vector $\mathcal{X}_i^{(b)}$. We model the transition probabilities $p_{k \to m}^{(b)}(x) = \Pr(Y^{(b)} = m \mid S^{(b)} = k, \mathcal{X}^{(b)} = x)$ using a multiclass gradient-boosted tree model.

We form a feature vector

$$x_i^{(b)} \equiv \left(S_i^{(b)},\ \mathcal{X}_i^{(b)}\right), \tag{1}$$

where $S_i^{(b)}$ is included as a categorical predictor (implemented via one-hot indicators in the model matrix; e.g., `Y_from1`, ..., `Y_from4`).

The model produces one real-valued *class margin* (score) for each destination level m:

$$f_m^{(b)}\left(x_i^{(b)}\right) \in \mathbb{R}, \qquad m = 1, 2, 3, 4. \tag{2}$$

The predicted transition probabilities are obtained through the softmax link:

$$\hat{p}_{im}^{(b)} = \Pr\left(Y_i^{(b)} = m \,\middle|\, x_i^{(b)}\right) = \frac{\exp\left(f_m^{(b)}(x_i^{(b)})\right)}{\sum_{r=1}^{4} \exp\left(f_r^{(b)}(x_i^{(b)})\right)}, \qquad m = 1, 2, 3, 4. \tag{3}$$

4.1.2 From leveled responses to multiclass training targets

For training, the original state and observed destination state $Y_i^{(b)} \in \{1, 2, 3, 4\}$ is represented by indicator variables $y_{im}^{(b)}$:

$$y_{im}^{(b)} = \mathbf{1}\{Y_i^{(b)} = m\}, \qquad m = 1, 2, 3, 4. \tag{4}$$

Given the softmax probabilities $\hat{p}_{im}^{(b)}$, the likelihood contribution of observation i can be written as

$$\Pr\left(Y_i^{(b)} \,\middle|\, x_i^{(b)}\right) = \prod_{m=1}^{4} \left(\hat{p}_{im}^{(b)}\right)^{y_{im}^{(b)}}. \tag{5}$$

We use analysis weights $w_i^{(b)}$ (design weights with attrition/nonresponse adjustments) in model training and in all summary estimands.

4.1.3 Loss function for training (weighted multiclass cross-entropy)

Let $\hat{p}_{im}^{(b)}$ be the softmax probabilities implied by margins $f_m^{(b)}(x_i^{(b)})$. The weighted multiclass negative log-likelihood (cross-entropy) optimized by XGBoost is:

$$\mathcal{L}^{(b)} = -\sum_{i=1}^{n_b} w_i^{(b)} \sum_{m=1}^{4} y_{im}^{(b)} \log \hat{p}_{im}^{(b)}, \tag{6}$$

equivalently

$$\mathcal{L}^{(b)} = -\sum_{i=1}^{n_b} w_i^{(b)} \log \hat{p}_{i, Y_i^{(b)}}^{(b)}. \tag{7}$$

4.1.4 Transition matrix estimation from fitted probabilities

After fitting the Transition Boosting model for block b, we compute fitted probabilities $\hat{p}_{im}^{(b)}$ for each observation. The weighted (model-based) transition matrix estimator is obtained by averaging predicted probabilities within each origin level k:

$$\widehat{T}_{k\to m}^{(b)} = \frac{\sum_{i:\, S_i^{(b)}=k} w_i^{(b)}\, \hat{p}_{im}^{(b)}}{\sum_{i:\, S_i^{(b)}=k} w_i^{(b)}}, \qquad k, m \in \{1, 2, 3, 4\}. \tag{8}$$

This provides an estimate of the transition distribution in the weighted target population, as presented in Table 1 and Table 2.

4.1.5 Covariate ranking by gain (loss reduction attributed to splits)

We rank covariates using the *gain* importance from XGBoost. Conceptually, gain measures how much a covariate contributes to reducing the training objective through splits in the fitted tree ensemble.

For block b, the model is trained by minimizing the weighted multiclass cross-entropy loss

$$\mathcal{L}^{(b)} = -\sum_{i=1}^{n_b} w_i^{(b)} \log \hat{p}_{i,Y_i^{(b)}}^{(b)}, \tag{9}$$

where $\hat{p}_{i,Y_i^{(b)}}^{(b)}$ is the fitted probability assigned to the observed destination level $Y_i^{(b)}$ under the softmax model.

During training, XGBoost grows trees by selecting splits that decrease the loss. For a candidate split s, define its (training) loss reduction as

$$\Delta\mathcal{L}^{(b)}(s) \equiv \mathcal{L}^{(b)}_{\text{before split } s} - \mathcal{L}^{(b)}_{\text{after split } s}. \tag{10}$$

A split is beneficial when $\Delta\mathcal{L}^{(b)}(s) > 0$.

Let j denote a feature (a column) in the model matrix. The gain importance for feature j is defined as the sum of loss reductions over all splits in the fitted ensemble that use j:

$$\text{Gain}^{(b)}(j) = \sum_{s:\, \text{split } s \text{ uses feature } j} \Delta\mathcal{L}^{(b)}(s). \tag{11}$$

Because categorical covariates and year-suffixed covariates can expand into multiple model-matrix columns, we aggregate gain to a base covariate (denoted B). Let $j \in B$ indicate that column j belongs to base covariate B. The aggregated gain is

$$\text{Gain}^{(b)}(B) = \sum_{j\in B} \text{Gain}^{(b)}(j). \tag{12}$$

We rank covariates by $\text{Gain}^{(b)}(B)$ to identify which base covariates most strongly improve prediction of transition outcomes in the fitted Transition Boosting model, as presented in Table 3 and Table 4.

4.1.6 SHAP decomposition of margins and weighted signed summaries (shap_dir)

For a fixed block b (time block) and a fixed destination class m, TreeSHAP provides an additive decomposition of the fitted margin:

$$f_m^{(b)}(x_i^{(b)}) = \phi_{0m}^{(b)} + \sum_{j=1}^{p_b} \phi_{ijm}^{(b)}, \tag{13}$$

where $\phi_{0m}^{(b)}$ is a baseline margin and $\phi_{ijm}^{(b)}$ is the SHAP contribution of feature j for observation i and class m.

To summarize SHAP at the base-covariate level, we aggregate SHAP values across model-matrix columns belonging to the same base covariate c:

$$\Phi_{icm}^{(b)} = \sum_{j\in c} \phi_{ijm}^{(b)}. \tag{14}$$

To align interpretation with transition rows, we compute origin-stratified, weighted signed averages of SHAP contributions (denoted `shap_dir` in outputs):

$$\text{shap\_dir}^{(b)}_{k,m}(c) = \frac{\sum_{i:\, S_i^{(b)}=k} w_i^{(b)}\, \Phi^{(b)}_{icm}}{\sum_{i:\, S_i^{(b)}=k} w_i^{(b)}}, \qquad k, m \in \{1,2,3,4\}. \tag{15}$$

The SHAP direction (signed SHAP) summaries are presented from Table 5 to Table 12.

4.1.7 Permutation impact tables on the probability scale

To present probability-scale directional effects aligned with the transition matrix, we compute permutation impact for each base covariate $c \in \mathcal{C}_b$. For a fixed origin level s, we permute the covariate block c within the stratum $\{i : S_i^{(b)} = s\}$ to break the association between c and the remaining covariates. Let π denote a random permutation over indices in this stratum, and define the permuted feature vector

$$x_i^{(-c)} \;=\; \big(x^{(b)}_{i,-c},\; x^{(b)}_{\pi(i),c}\big), \tag{16}$$

where $x^{(b)}_{i,-c}$ denotes all features except group c, and $x^{(b)}_{\pi(i),c}$ denotes the permuted value of group c.

For destination level m, define the (weighted) probability-impact estimand

$$\Delta^{\text{PI},(b)}_{s\to m}(c) \;=\; \mathbb{E}_w\Big[\hat{p}^{(b)}_{im}(x_i^{(b)}) - \hat{p}^{(b)}_{im}(x_i^{(-c)}) \;\Big|\; S_i^{(b)} = s\Big]. \tag{17}$$

Its empirical weighted estimator is

$$\widehat{\Delta}^{\text{PI},(b)}_{s\to m}(c) \;=\; \frac{\sum_{i:\, S_i^{(b)}=s} w_i^{(b)} \Big(\hat{p}^{(b)}_{im}(x_i^{(b)}) - \hat{p}^{(b)}_{im}(x_i^{(-c)})\Big)}{\sum_{i:\, S_i^{(b)}=s} w_i^{(b)}}. \tag{18}$$

Because permutation is random, we average over R independent permutations to obtain a stable estimate:

$$\overline{\Delta}^{\text{PI},(b)}_{s\to m}(c) \;=\; \frac{1}{R}\sum_{r=1}^{R} \widehat{\Delta}^{\text{PI},(b,r)}_{s\to m}(c). \tag{19}$$

The permutation impact tables are presented from Table 13 to Table 20.

4.2 Markov Transition Model for Q(1) & Q(2)

4.2.1 Multiclass Markov transition model (transition kernel)

For each block $b \in \{1,2\}$ and individual $i \in \{1,\ldots,N\}$, we observe an origin state $S_i^{(b)} \in \{1,2,3,4\}$ and a destination state $Y_i^{(b)} \in \{1,2,3,4\}$, together with a covariate vector $\mathcal{X}_i^{(b)}$ and an analysis weight $w_i^{(b)} > 0$. We define the (covariate-dependent) transition kernel

$$p^{(b)}_{k\to m}(x) = \Pr\big(Y^{(b)} = m \,\big|\, S^{(b)} = k,\; \mathcal{X}^{(b)} = x\big), \qquad k, m \in \{1,2,3,4\}. \tag{20}$$

The goal of the Markov Transition Model (MTM) is to estimate $p^{(b)}_{k\to m}(x)$ and to identify covariates in $\mathcal{X}^{(b)}$ that are most predictive of transition behavior.

We fit a single pooled multinomial logistic regression for each block b by modeling the conditional distribution of $Y_i^{(b)}$ given $(S_i^{(b)}, \mathcal{X}_i^{(b)})$, using destination level 1 as the reference category. Define the feature vector

$$x_i^{(b)} \equiv \big(S_i^{(b)},\; \mathcal{X}_i^{(b)}\big). \tag{21}$$

For each destination level $m \in \{2,3,4\}$, the baseline-category logit model specifies

$$\log\left(\frac{\Pr(Y_i^{(b)} = m \mid x_i^{(b)})}{\Pr(Y_i^{(b)} = 1 \mid x_i^{(b)})}\right) = \eta_{im}^{(b)} = \alpha_m^{(b)} + \gamma_m^{(b)}\big(S_i^{(b)}\big) + \big(\mathcal{X}_i^{(b)}\big)^\top \beta_m^{(b)}. \tag{22}$$

Here:

- $\alpha_m^{(b)}$ is the intercept (baseline log-odds for destination m vs 1);
- $\gamma_m^{(b)}(S)$ is the initial-state effect (origin effect) for destination m vs 1;
- $\beta_m^{(b)}$ is the coefficient vector for covariates in $\mathcal{X}^{(b)}$ for destination m vs 1.

We treat S as a categorical predictor with reference level $S = 1$, so that

$$\gamma_m^{(b)}(1) \equiv 0, \qquad \gamma_m^{(b)}(k) \text{ is estimated for } k \in \{2,3,4\}. \tag{23}$$

Given the linear predictors $\eta_{im}^{(b)}$, the MTM implied transition probabilities are

$$\hat{p}_{im}^{(b)} = \Pr\big(Y_i^{(b)} = m \mid x_i^{(b)}\big) = \frac{\exp(\eta_{im}^{(b)})}{1 + \sum_{r=2}^{4} \exp(\eta_{ir}^{(b)})}, \qquad m = 2,3,4, \tag{24}$$

and for the reference destination

$$\hat{p}_{i1}^{(b)} = \Pr\big(Y_i^{(b)} = 1 \mid x_i^{(b)}\big) = \frac{1}{1 + \sum_{r=2}^{4} \exp(\eta_{ir}^{(b)})}. \tag{25}$$

Odds ratios. For a numerical covariate x_j (a component of $\mathcal{X}$), holding all other predictors fixed, a one-unit increase in x_j changes the log-odds of $Y = m$ vs $Y = 1$ by $\beta_{m,j}^{(b)}$, and the corresponding odds ratio is $\exp\big(\beta_{m,j}^{(b)}\big)$. For categorical covariates expanded into dummy variables, each dummy coefficient is interpreted as the log-odds difference relative to the baseline category (see below).

4.2.2 From leveled responses to multinomial likelihood targets

For training, define indicator variables for the destination class:

$$y_{im}^{(b)} = \mathbf{1}\{Y_i^{(b)} = m\}, \qquad m = 1,2,3,4. \tag{26}$$

Given the MTM probabilities $\hat{p}_{im}^{(b)}$, the likelihood contribution of observation i can be written as

$$\Pr\big(Y_i^{(b)} \,\big|\, x_i^{(b)}\big) = \prod_{m=1}^{4} \big(\hat{p}_{im}^{(b)}\big)^{y_{im}^{(b)}}. \tag{27}$$

We incorporate analysis weights $w_i^{(b)}$ in estimation to account for design and attrition/nonresponse adjustments.

4.2.3 Loss function for training (weighted multinomial log-loss)

Let $\theta^{(b)}$ denote the collection of MTM parameters $\{\alpha_m^{(b)}, \gamma_m^{(b)}(\cdot), \beta_m^{(b)}\}_{m=2}^{4}$. The weighted multinomial negative log-likelihood (weighted log-loss / cross-entropy) is

$$\mathcal{L}^{(b)}(\theta^{(b)}) = -\sum_{i=1}^{n_b} w_i^{(b)} \sum_{m=1}^{4} y_{im}^{(b)} \log \hat{p}_{im}^{(b)}(\theta^{(b)}), \tag{28}$$

equivalently

$$\mathcal{L}^{(b)}(\theta^{(b)}) = -\sum_{i=1}^{n_b} w_i^{(b)} \log \hat{p}_{i,Y_i^{(b)}}^{(b)}(\theta^{(b)}). \tag{29}$$

Thus, weights enter multiplicatively in the objective: observations with larger $w_i^{(b)}$ exert greater influence on the fitted transition model.

4.2.4 Transition matrix estimation from fitted MTM probabilities

After fitting the MTM for block b, we compute fitted probabilities $\hat{p}_{im}^{(b)}$ for each observation. The weighted (model-based) transition matrix estimator is obtained by averaging predicted probabilities within each origin level k:

$$\widehat{T}_{k\to m}^{(b)} = \frac{\sum_{i:\,S_i^{(b)}=k} w_i^{(b)}\,\hat{p}_{im}^{(b)}}{\sum_{i:\,S_i^{(b)}=k} w_i^{(b)}}, \qquad k, m \in \{1,2,3,4\}. \tag{30}$$

Each row sums to 1 by construction, and $\widehat{T}_{k\to m}^{(b)}$ is interpreted as the estimated (weighted) probability of transitioning from origin level k to destination level m in block b. The results of estimations of transition probabilities are presented in Table 21 and Table 22.

4.2.5 Covariate ranking by permutation importance on weighted log-loss (single fitted model)

To rank covariates by predictive contribution while keeping a single fitted MTM, we compute permutation importance using the weighted log-loss. Let $\hat{p}_{i,Y_i^{(b)}}^{(b)}$ denote the fitted probability assigned to the observed destination $Y_i^{(b)}$ under the original (unpermuted) predictors. Define the baseline weighted log-loss

$$\widehat{\mathcal{L}}_{\text{base}}^{(b)} = -\sum_{i=1}^{n_b} w_i^{(b)} \log \hat{p}_{i,Y_i^{(b)}}^{(b)}. \tag{31}$$

For a covariate unit c (defined below), we permute the values of c across individuals to break its association with $(S, \mathcal{X}_{-c})$ while keeping the fitted MTM parameters fixed. Let π be a random permutation of indices $\{1, \ldots, n_b\}$ and write the permuted predictor vector as

$$x_i^{(-c)} \equiv \big(x_{i,-c}^{(b)},\; x_{\pi(i),c}^{(b)}\big). \tag{32}$$

We then recompute the predicted probabilities under the same fitted MTM, obtaining $\hat{p}_{i,Y_i^{(b)}}^{(b),\pi(c)}$, and compute the permuted weighted log-loss

$$\widehat{\mathcal{L}}_{\pi(c)}^{(b)} = -\sum_{i=1}^{n_b} w_i^{(b)} \log \hat{p}_{i,Y_i^{(b)}}^{(b),\pi(c)}. \tag{33}$$

The permutation importance score is defined as the increase in weighted log-loss:

$$\text{Imp}^{(b)}(c) = \widehat{\mathcal{L}}_{\pi(c)}^{(b)} - \widehat{\mathcal{L}}_{\text{base}}^{(b)}. \tag{34}$$

In practice we average over $R = 5$ independent permutations:

$$\overline{\text{Imp}}^{(b)}(c) = \frac{1}{R}\sum_{r=1}^{R} \text{Imp}^{(b,r)}(c). \tag{35}$$

Larger $\overline{\text{Imp}}^{(b)}(c)$ indicates that permuting c degrades predictive performance more, so c is ranked as more important.

Numerical vs categorical (dummy) variables. For a numerical covariate x_j, the permutation unit c is the single column x_j, and permutation means replacing x_{ij} by $x_{\pi(i)j}$. For a categorical covariate C expanded into dummy variables $\{D_\ell\}$ (baseline level c_0), there are two valid choices:

- **Dummy-level permutation (per-dummy ranking).** Treat each dummy column D_ℓ as its own unit c and permute that 0/1 column across individuals; this produces importance scores for each dummy level separately.
- **Block permutation (category-level ranking).** Treat the entire set of dummy columns belonging to C as a group and permute them jointly (equivalently, permute the original factor C); this preserves valid one-hot structure and yields an importance score for the base categorical variable.

In either case, the weighted log-loss is computed identically; only the definition of the permuted unit c differs.
The results of covariate ranking by permutation importance are presented in Table 23 and Table 24.

4.2.6 Direction on log-odds tables (reference destination $Y = 1$)

To summarize the direction of association between covariates and transition outcomes on the log-odds scale, we construct "Direction on log-odds" tables from the fitted MTM coefficients with $Y = 1$ as the reference destination. For each destination $m \in \{2, 3, 4\}$, the MTM log-odds are

$$\log\left(\frac{\Pr(Y^{(b)} = m \mid S^{(b)}, \mathcal{X}^{(b)})}{\Pr(Y^{(b)} = 1 \mid S^{(b)}, \mathcal{X}^{(b)})}\right) = \alpha_m^{(b)} + \gamma_m^{(b)}(S^{(b)}) + \left(\mathcal{X}^{(b)}\right)^\top \beta_m^{(b)}. \tag{36}$$

Intercept row. The intercept entry in destination column m is $\alpha_m^{(b)}$, interpreted as the log-odds of $Y = m$ vs $Y = 1$ for individuals at the reference origin state $S = 1$ and with covariates at their reference/zero-coded values (baseline factor levels and 0 for numeric covariates as coded).

Initial-state effect rows. Because $S = 1$ is the reference origin level, we set $\gamma_m^{(b)}(1) = 0$ and report $\gamma_m^{(b)}(2), \gamma_m^{(b)}(3), \gamma_m^{(b)}(4)$ as log-odds shifts relative to $S = 1$:

$$\gamma_m^{(b)}(k) = \log\left(\frac{\text{odds}(Y = m \text{ vs } 1 \mid S = k, \mathcal{X})}{\text{odds}(Y = m \text{ vs } 1 \mid S = 1, \mathcal{X})}\right), \qquad k = 2, 3, 4. \tag{37}$$

Covariate rows: numerical variables. For a numerical covariate x_j, the table entry in destination column m is $\beta_{m,j}^{(b)}$. A one-unit increase in x_j changes the log-odds of $Y = m$ vs $Y = 1$ by $\beta_{m,j}^{(b)}$, and the corresponding odds ratio is $\exp\left(\beta_{m,j}^{(b)}\right)$.

Covariate rows: categorical variables (dummy variables kept separate). For a categorical covariate C with baseline level c_0 and dummy indicators $D_\ell = \mathbf{1}\{C = c_\ell\}$, $\ell = 1, \ldots, L$, we keep each dummy as its own row in the table (e.g., `C_level` in outputs). The table entry in destination column m is $\beta_{m,D_\ell}^{(b)}$, interpreted as the log-odds difference between level c_ℓ and baseline c_0 for $Y = m$ vs $Y = 1$, holding other predictors fixed.

Connection to transition probabilities. The direction tables summarize effects on the log-odds scale, while the transition matrix summarizes effects on the probability scale. Because probabilities are obtained through a softmax transformation, a positive coefficient $\beta_{m,j}^{(b)} > 0$ increases the log-odds of destination m relative to 1, but the resulting change in $\Pr(Y = m)$ depends on the full set of class scores $\{\eta_{ir}^{(b)}\}_{r=2}^4$.

The summary of directions of associations between covariates and transition outcomes on the log-odds scale are presented in Table 25 and Table 26.

5 Results

5.1 Transition Boosting

from\to	1	2	3	4
1	0.62	0.25	0.08	0.06
2	0.35	0.44	0.15	0.06
3	0.14	0.35	0.29	0.22
4	0.11	0.08	0.10	0.71

Table 1: The estimated transition distribution from year 2021 to year 2023. Rows correspond to the initial (origin) cover-crop level $S = s$ and columns correspond to the destination level $Y = k$; the entry $\widehat{T}_{s\to k}$ is the estimated (weighted) probability of transitioning from level s to level k, with each row summing to 1.

from\to	1	2	3	4
1	0.66	0.17	0.08	0.09
2	0.24	0.57	0.11	0.08
3	0.15	0.21	0.29	0.35
4	0.04	0.03	0.08	0.85

Table 2: The estimated transition distribution from year 2023 to year 2025.

	Covariates	Gain
1	Y_from4	0.16
2	Y23_20s	0.06
3	Y23_20v	0.06
4	Y23_20t	0.05
5	Y23_20_N_mgmt_prac	0.04
6	Y_from1	0.03
7	Y23_21_Econ_capacity	0.03
8	Y21_24i	0.02
9	Y21_24_CC_barriers	0.02
10	Y21_11_4R_Info_ag	0.02
⋮		

Table 3: Rank of covariates using the gain importance from XGBoost from year block (2020, 2021) to year block (2022, 2023). Each row corresponds to a (year-suffixed) base covariate; the reported gain is the total loss reduction attributed to splits using that covariate (aggregated across expanded model-matrix columns), with larger gain indicating greater predictive contribution to the transition outcome.

	Covariates	Gain
1	Y25_25b	0.20
2	Y_from1	0.09
3	Y25_27r	0.05
4	Y25_25c	0.05
5	Y25_27o	0.05
6	Y_from2	0.05
7	Y25_27h	0.03
8	Y25_27p	0.03
9	Y25_26_Compaction_mgmt_prac	0.02
10	Y24_3_Satisfaction	0.02
⋮		

Table 4: Rank of covariates using the gain importance from XGBoost from year block (2022, 2023) to year block (2024, 2025).

Destination level: 1

	Covariates	1	2	3	4
1	ϕ_0 (baseline)	0.75	0.75	0.75	0.75
2	Y23_20s	0.09	-0.07	-0.09	-0.05
3	Y23_20v	0.22	0.00	-0.26	-0.26
4	Y23_20t	0.13	-0.07	-0.16	-0.10
5	Y23_20_N_mgmt_prac	0.08	-0.04	-0.04	-0.06
6	Y23_21_Econ_capacity	0.01	-0.02	-0.02	-0.02
7	Y21_24i	0.00	0.01	0.00	-0.02
8	Y21_24_CC_barriers	0.00	-0.00	-0.01	-0.03
9	Y21_11_4R_Info_ag	0.00	0.00	-0.02	-0.01
10	Y20_14	0.01	0.00	-0.01	-0.02
⋮					

Table 5: SHAP direction (signed SHAP) summary for destination level 1, stratified by origin state, from year block (2020, 2021) to year block (2022, 2023). Columns 1–4 correspond to the initial (origin) cover-crop level $S = s$; each cell reports the weighted mean signed SHAP contribution of that covariate to the destination-1 margin $f_1(x)$ among individuals with $S = s$. The first row ϕ_0 is the SHAP baseline margin for class 1 (the intercept/reference score); each subsequent row is a covariate (year-suffixed base variable), with positive values indicating the covariate tends to increase the class-1 margin (and thus, all else equal, increase $\Pr(Y = 1)$) within that origin stratum, and negative values indicating it tends to decrease the class-1 margin. For example, for `Y23_20s`, a positive value in column $s = 1$ means this covariate pushes predictions toward destination level 1 for those starting at level 1, whereas negative values in columns $s = 2, 3, 4$ mean it pushes predictions away from destination level 1 for those starting at levels 2–4 relative to the baseline ϕ_0. And similar interpretations apply to the rest SHAP direction summaries.

Destination level: 2

	base	1	2	3	4
1	ϕ_0 (baseline)	0.43	0.43	0.43	0.43
2	Y23_20s	-0.37	-0.00	-0.01	-0.10
3	Y23_20v	0.00	0.02	-0.01	-0.06
4	Y23_20t	0.01	0.01	-0.00	-0.02
5	Y23_20_N_mgmt_prac	-0.15	0.01	0.03	0.00
6	Y23_21_Econ_capacity	-0.01	0.00	-0.01	0.01
7	Y21_24i	0.00	0.02	-0.01	-0.08
8	Y21_24_CC_barriers	-0.01	-0.00	0.00	-0.02
9	Y21_11_4R_Info_ag	-0.02	-0.01	0.01	0.00
10	Y20_14	0.00	0.00	-0.01	-0.02
⋮					

Table 6: SHAP direction (signed SHAP) summary for destination level 2, stratified by origin state, from year block (2020, 2021) to year block (2022, 2023).

Destination level: 3

	base	1	2	3	4
1	ϕ_0 (baseline)	0.10	0.10	0.10	0.10
2	Y23_20s	-0.04	-0.02	0.00	-0.00
3	Y23_20v	-0.07	-0.04	0.01	0.03
4	Y23_20t	-0.12	-0.03	0.02	0.03
5	Y23_20_N_mgmt_prac	-0.12	-0.03	-0.04	-0.00
6	Y23_21_Econ_capacity	-0.01	-0.00	-0.00	-0.00
7	Y21_24i	0.00	0.00	0.00	-0.01
8	Y21_24_CC_barriers	-0.00	0.00	-0.00	-0.02
9	Y21_11_4R_Info_ag	-0.01	-0.01	-0.02	-0.01
10	Y20_14	-0.00	-0.00	-0.00	-0.00
⋮					

Table 7: SHAP direction (signed SHAP) summary for destination level 3, stratified by origin state, from year block (2020, 2021) to year block (2022, 2023).

Destination level: 4

	base	1	2	3	4
1	ϕ_0 (baseline)	0.58	0.58	0.58	0.58
2	Y23_20s	-0.01	-0.00	-0.00	0.00
3	Y23_20v	-0.01	-0.01	-0.00	0.01
4	Y23_20t	-0.01	-0.00	0.00	0.00
5	Y23_20_N_mgmt_prac	-0.01	0.00	0.00	0.01
6	Y23_21_Econ_capacity	-0.03	-0.03	-0.01	-0.02
7	Y21_24i	-0.10	-0.13	-0.08	0.09
8	Y21_24_CC_barriers	-0.04	-0.06	-0.03	0.04
9	Y21_11_4R_Info_ag	-0.01	-0.01	-0.00	-0.00
10	Y20_14	-0.07	-0.06	-0.01	0.03
⋮					

Table 8: SHAP direction (signed SHAP) summary for destination level 4, stratified by origin state, from year block (2020, 2021) to year block (2022, 2023).

Destination level: 1

	base	1	2	3	4
1	ϕ_0 (baseline)	0.79	0.79	0.79	0.79
2	Y25_25b	0.01	0.02	-0.02	-0.13
3	Y25_27r	0.03	-0.12	-0.15	-0.15
4	Y25_25c	0.05	0.05	-0.04	-0.26
5	Y25_27o	0.04	-0.07	-0.08	-0.11
6	Y25_27h	-0.09	-0.08	-0.12	-0.13
7	Y25_27p	0.05	0.07	-0.12	-0.13
8	Y25_26_Compaction_mgmt_prac	0.06	0.01	-0.14	-0.22
9	Y24_3_Satisfaction	0.01	-0.01	-0.01	-0.02
10	Y25_27l	0.03	-0.04	-0.05	-0.06
⋮					

Table 9: SHAP direction (signed SHAP) summary for destination level 1, stratified by origin state, from year block (2022, 2023) to year block (2024, 2025).

Destination level: 2

	base	1	2	3	4
1	ϕ_0 (baseline)	0.42	0.42	0.42	0.42
2	Y25_25b	0.13	0.20	-0.03	-1.22
3	Y25_27r	-0.04	0.00	0.02	0.01
4	Y25_25c	0.01	0.01	-0.01	-0.06
5	Y25_27o	-0.15	0.04	-0.01	-0.00
6	Y25_27h	-0.04	-0.03	0.00	-0.01
7	Y25_27p	-0.01	0.00	0.00	-0.01
8	Y25_26_Compaction_mgmt_prac	-0.00	0.00	-0.00	-0.00
9	Y24_3_Satisfaction	-0.04	0.01	-0.04	-0.01
10	Y25_27l	-0.11	0.01	0.04	0.02
⋮					

Table 10: SHAP direction (signed SHAP) summary for destination level 2, stratified by origin state, from year block (2022, 2023) to year block (2024, 2025).

Destination level: 3

	base	1	2	3	4
1	ϕ_0 (baseline)	-0.18	-0.18	-0.18	-0.18
2	Y25_25b	0.02	0.03	0.02	-0.06
3	Y25_27r	-0.23	-0.07	0.07	-0.01
4	Y25_25c	-0.02	-0.02	0.01	0.05
5	Y25_27o	-0.03	-0.05	-0.02	-0.01
6	Y25_27h	-0.01	-0.00	0.00	-0.00
7	Y25_27p	-0.03	-0.04	-0.00	0.01
8	Y25_26_Compaction_mgmt_prac	0.01	0.00	-0.00	-0.04
9	Y24_3_Satisfaction	-0.00	-0.01	0.01	-0.00
10	Y25_27l	-0.01	-0.00	0.00	0.00
⋮					

Table 11: SHAP direction (signed SHAP) summary for destination level 3, stratified by origin state, from year block (2022, 2023) to year block (2024, 2025).

Destination level: 4

	base	1	2	3	4
1	ϕ_0 (baseline)	0.86	0.86	0.86	0.86
2	Y25_25b	-0.78	-0.95	-0.46	1.19
3	Y25_27r	-0.01	-0.00	0.00	-0.00
4	Y25_25c	-0.35	-0.40	-0.15	0.47
5	Y25_27o	-0.03	-0.03	-0.01	0.01
6	Y25_27h	-0.01	-0.00	0.00	0.01
7	Y25_27p	-0.05	-0.10	0.03	0.05
8	Y25_26_Compaction_mgmt_prac	-0.01	-0.01	0.01	0.01
9	Y24_3_Satisfaction	-0.00	-0.00	0.00	-0.00
10	Y25_27l	-0.01	0.00	-0.01	-0.00
⋮					

Table 12: SHAP direction (signed SHAP) summary for destination level 4, stratified by origin state, from year block (2022, 2023) to year block (2024, 2025).

Destination level: 1

	base	1	2	3	4
1	transition prob	0.715	0.361	0.161	0.113
2	Y23_20s	-0.012	0.004	0.003	0.001
3	Y23_20v	0.006	0.015	0.008	0.021
4	Y23_20t	0.003	0.005	-0.002	0.001
5	Y23_20_N_mgmt_prac	-0.003	0.009	-0.003	0.007
6	Y23_21_Econ_capacity	0.001	0.002	-0.002	0.000
7	Y21_24i	-0.001	-0.000	-0.002	-0.000
8	Y21_24_CC_barriers	0.002	0.000	-0.001	-0.000
9	Y21_11_4R_Info_ag	0.002	0.001	-0.000	-0.000
10	Y20_14	-0.001	-0.002	-0.001	0.005
⋮					

Table 13: Permutation impact (probability-scale) summary for destination level 1, stratified by origin state, from year block (2020, 2021) to year block (2022, 2023). Columns 1–4 correspond to the initial (origin) cover-crop level $S = s$; the first row gives the baseline weighted transition probability $\widehat{T}_{s\to 1} = \mathbb{E}_w[\hat{p}_{i1} \mid S = s]$ from the fitted Transition Boosting model. Each subsequent row is a covariate (year-suffixed base variable), and each cell reports the estimated permutation impact $\Delta_{s,1}(b) = \mathbb{E}_w[\hat{p}_{i1} - \hat{p}_{i1}^{(-b)} \mid S = s]$, where $\hat{p}_{i1}^{(-b)}$ is computed after permuting covariate block b within the origin stratum. A positive value means the covariate helps predict destination level 1 in that origin group (permuting it reduces $\Pr(Y = 1)$), whereas a negative value means the covariate suppresses destination level 1 on average (permuting it increases $\Pr(Y = 1)$). For example, for `Y23_20s`, the negative entry in column $s = 1$ indicates that shuffling this covariate slightly increases the predicted probability of ending in level 1 among those starting in level 1, so its observed alignment acts (on average) against destination level 1 relative to the baseline transition probability. And similar interpretations apply to the rest permutation impact tables.

Destination level: 2

	base	1	2	3	4
1	transition prob	0.183	0.413	0.366	0.046
2	Y23_20s	0.021	0.005	0.001	-0.001
3	Y23_20v	-0.002	-0.011	-0.002	-0.005
4	Y23_20t	-0.001	-0.005	0.000	-0.001
5	Y23_20_N_mgmt_prac	0.005	-0.011	0.002	-0.002
6	Y23_21_Econ_capacity	-0.001	-0.002	-0.004	-0.000
7	Y21_24i	0.001	0.000	-0.000	0.002
8	Y21_24_CC_barriers	0.000	0.000	0.000	-0.002
9	Y21_11_4R_Info_ag	-0.001	-0.003	-0.001	-0.001
10	Y20_14	0.000	0.001	0.001	0.001
⋮					

Table 14: Permutation impact (probability-scale) summary for destination level 2, stratified by origin state, from year block (2020, 2021) to year block (2022, 2023).

Destination level: 3

	base	1	2	3	4
1	transition prob	0.060	0.172	0.274	0.120
2	Y23_20s	-0.006	-0.004	0.000	0.003
3	Y23_20v	-0.002	0.001	-0.002	-0.004
4	Y23_20t	-0.000	0.005	0.003	0.002
5	Y23_20_N_mgmt_prac	-0.001	0.005	0.003	-0.002
6	Y23_21_Econ_capacity	-0.002	-0.000	-0.001	0.001
7	Y21_24i	-0.000	-0.000	0.000	0.002
8	Y21_24_CC_barriers	-0.001	-0.000	-0.001	0.003
9	Y21_11_4R_Info_ag	-0.001	0.002	-0.000	0.002
10	Y20_14	0.000	-0.000	0.000	0.000
⋮					

Table 15: Permutation impact (probability-scale) summary for destination level 3, stratified by origin state, from year block (2020, 2021) to year block (2022, 2023).

Destination level: 4

	base	1	2	3	4
1	transition prob	0.042	0.053	0.199	0.720
2	Y23_20s	-0.004	-0.005	-0.004	-0.003
3	Y23_20v	-0.002	-0.005	-0.005	-0.012
4	Y23_20t	-0.002	-0.005	-0.002	-0.003
5	Y23_20_N_mgmt_prac	-0.001	-0.003	-0.002	-0.004
6	Y23_21_Econ_capacity	0.001	-0.000	0.007	-0.001
7	Y21_24i	0.000	0.000	0.001	-0.004
8	Y21_24_CC_barriers	-0.001	-0.001	0.002	-0.001
9	Y21_11_4R_Info_ag	-0.001	-0.000	0.001	-0.001
10	Y20_14	0.000	0.001	-0.000	-0.006
⋮					

Table 16: Permutation impact (probability-scale) summary for destination level 4, stratified by origin state, from year block (2020, 2021) to year block (2022, 2023).

Destination level: 1

	base	1	2	3	4
1	transition prob	0.664	0.239	0.155	0.039
2	Y25_25b	-0.007	-0.001	-0.010	-0.005
3	Y25_27r	-0.019	-0.002	0.007	0.002
4	Y25_25c	-0.002	0.002	-0.004	-0.001
5	Y25_27o	-0.021	0.009	0.014	-0.001
6	Y25_27h	-0.010	0.006	-0.000	-0.000
7	Y25_27p	-0.006	0.014	-0.004	-0.001
8	Y25_26_Compaction_mgmt_prac	0.005	0.000	0.014	0.002
9	Y24_3_Satisfaction	0.007	0.000	0.000	0.000
10	Y25_27l	-0.005	-0.001	0.001	-0.000
⋮					

Table 17: Permutation impact (probability-scale) summary for destination level 1, stratified by origin state, from year block (2022, 2023) to year block (2024, 2025).

Destination level: 2

	base	1	2	3	4
1	transition prob	0.170	0.570	0.209	0.035
2	Y25_25b	-0.004	0.003	-0.005	-0.016
3	Y25_27r	0.005	-0.005	-0.009	-0.003
4	Y25_25c	-0.001	-0.000	-0.002	-0.002
5	Y25_27o	0.017	-0.007	-0.006	-0.001
6	Y25_27h	0.003	0.000	-0.000	-0.000
7	Y25_27p	0.002	-0.003	-0.003	-0.000
8	Y25_26_Compaction_mgmt_prac	-0.001	0.001	-0.009	-0.001
9	Y24_3_Satisfaction	-0.004	0.001	-0.001	-0.000
10	Y25_27l	0.006	0.004	0.000	-0.001
⋮					

Table 18: Permutation impact (probability-scale) summary for destination level 2, stratified by origin state, from year block (2022, 2023) to year block (2024, 2025).

Destination level: 3

	base	1	2	3	4
1	transition prob	0.080	0.114	0.286	0.076
2	Y25_25b	-0.003	-0.000	-0.036	-0.013
3	Y25_27r	0.017	0.008	0.003	0.005
4	Y25_25c	-0.002	-0.001	-0.010	-0.004
5	Y25_27o	0.006	0.001	-0.006	0.003
6	Y25_27h	0.005	-0.004	-0.000	0.000
7	Y25_27p	0.002	-0.005	-0.005	-0.000
8	Y25_26_Compaction_mgmt_prac	-0.001	-0.000	-0.004	-0.000
9	Y24_3_Satisfaction	-0.002	-0.000	-0.000	0.001
10	Y25_27l	-0.000	-0.003	0.001	0.000
⋮					

Table 19: Permutation impact (probability-scale) summary for destination level 3, stratified by origin state, from year block (2022, 2023) to year block (2024, 2025).

Destination level: 4

	base	1	2	3	4
1	transition prob	0.086	0.078	0.350	0.851
2	Y25_25b	0.015	-0.001	0.051	0.034
3	Y25_27r	-0.003	-0.000	-0.000	-0.003
4	Y25_25c	0.005	-0.001	0.016	0.007
5	Y25_27o	-0.001	-0.003	-0.001	-0.001
6	Y25_27h	0.003	-0.002	0.000	-0.000
7	Y25_27p	0.002	-0.007	0.012	0.002
8	Y25_26_Compaction_mgmt_prac	-0.002	-0.001	-0.002	-0.001
9	Y24_3_Satisfaction	-0.002	-0.001	0.001	-0.000
10	Y25_27l	-0.001	-0.000	-0.002	0.001
⋮					

Table 20: Permutation impact (probability-scale) summary for destination level 4, stratified by origin state, from year block (2022, 2023) to year block (2024, 2025).

5.2 Markov Transition Model

from\to	1	2	3	4
1	0.68	0.18	0.05	0.09
2	0.35	0.41	0.14	0.09
3	0.11	0.35	0.29	0.25
4	0.15	0.06	0.13	0.66

Table 21: The estimated transition distribution from year 2021 to year 2023.

from\to	1	2	3	4
1	0.64	0.22	0.06	0.07
2	0.33	0.44	0.15	0.08
3	0.28	0.21	0.20	0.30
4	0.18	0.08	0.09	0.65

Table 22: The estimated transition distribution from year 2023 to year 2025.

	var	Δ_logloss_mean	Δ_logloss_sd	nperm
1	V_Y23_20_N_mgmt_prac__y2023	0.1501	0.0119	5.0000
2	V_Y23_20t__y2023	0.1065	0.0114	5.0000
3	V_Y20_12_Econ_capacity__y2020	0.0893	0.0147	5.0000
4	V_Y21_33__y2021	0.0747	0.0210	5.0000
5	V_Y20_3e__y2020	0.0689	0.0162	5.0000
6	V_Y21_24_CC_barriers__y2021	0.0674	0.0093	5.0000
7	V_Y20_4acde_scale__y2020	0.0650	0.0157	5.0000
8	V_Y21_13t__y2021	0.0616	0.0127	5.0000
9	V_Y21_13s__y2021	0.0614	0.0126	5.0000
10	V_Y21_8_Soil_health__y2021	0.0576	0.0046	5.0000
11	V_Y23_20u__y2023	0.0510	0.0158	5.0000
12	V_Y21_13v__y2021	0.0506	0.0077	5.0000
13	V_Y21_24_CC_benefits__y2021	0.0491	0.0125	5.0000
14	V_Y23_17__y2023	0.0482	0.0063	5.0000
15	V_Y20_11acdgi_scale__y2020	0.0477	0.0056	5.0000
16	V_Y23_21_Econ_capacity__y2023	0.0427	0.0116	5.0000
17	V_Y20_18__y2020	0.0422	0.0051	5.0000
18	V_Y23_18__y2023	0.0410	0.0128	5.0000
19	V_Y20_4b__y2020	0.0391	0.0070	5.0000
20	V_Y21_29__y2021	0.0380	0.0066	5.0000
21	V_Y21_26__y2021	0.0372	0.0099	5.0000
22	V_Y23_19__y2023	0.0365	0.0355	5.0000
23	V_Y20_34__y2020	0.0357	0.0103	5.0000
24	V_Y23_20s__y2023	0.0354	0.0114	5.0000
25	V_Y23_35__y2023	0.0338	0.0127	5.0000
26	V_Y20_23i__y2020	0.0333	0.0085	5.0000
27	V_Y20_13_Regulatory_motive__y2020	0.0316	0.0101	5.0000
28	V_Y23_16__y2023	0.0313	0.0108	5.0000
29	V_Y22_16_Private_entities__y2022	0.0305	0.0096	5.0000
30	V_Y20_13_Stewardship_motive__y2020	0.0303	0.0041	5.0000
31	V_Y23_33__y2023	0.0261	0.0084	5.0000
32	V_Y20_23abdl_scale__y2020	0.0249	0.0080	5.0000
33	V_Y23_20_EoF_prac__y2023	0.0247	0.0037	5.0000
34	V_Y21_11_4R_Info_ag__y2021	0.0241	0.0065	5.0000
35	V_Y23_21_Agron_efficacy__y2023	0.0235	0.0084	5.0000
36	V_Y20_12_Agron_efficacy__y2020	0.0226	0.0040	5.0000
37	V_Y20_6abcdefghijk_sum__y2020	0.0201	0.0093	5.0000
38	V_Y20_9__y2020	0.0199	0.0070	5.0000
39	V_Y20_3abcd_scale__y2020	0.0195	0.0063	5.0000
40	V_Y21_13u__y2021	0.0179	0.0075	5.0000
⋮				

Table 23: Rank of covariates using the permutation importance from year block (2020, 2021) to year block (2022, 2023). Permutation-importance ranking of covariates for the Markov Transition Model (MTM) from year block (2020, 2021) to (2022, 2023). Each row corresponds to one covariate `var`, evaluated by permuting its values across individuals (holding the fitted MTM fixed) and recomputing the weighted multinomial log-loss. The column Δ`logloss_mean` reports the average increase in weighted log-loss relative to the unpermuted baseline, $\Delta\mathcal{L} = \mathcal{L}_{\pi(\texttt{var})} - \mathcal{L}_{\text{base}}$, where larger values indicate greater predictive contribution of that covariate to transition outcomes. The column Δ`logloss_sd` is the standard deviation of $\Delta\mathcal{L}$ across `nperm` random permutations. Covariates are sorted in descending order of Δ`logloss_mean`; variables near the top are most influential for predicting cover-crop transition probabilities under the MTM.

	var	Δ_logloss_mean	Δ_logloss_sd	nperm
1	V_Y25_25b__y2025	0.7801	0.2080	5.0000
2	V_Y25_25e__y2025	0.0942	0.0188	5.0000
3	V_Y25_27r__y2025	0.0934	0.0187	5.0000
4	V_Y25_25d__y2025	0.0921	0.0217	5.0000
5	V_Y25_27o__y2025	0.0841	0.0186	5.0000
6	V_Y23_33__y2023	0.0821	0.0271	5.0000
7	V_Y25_27q__y2025	0.0774	0.0109	5.0000
8	V_Y25_26_Compaction_mgmt_prac__y2025	0.0774	0.0124	5.0000
9	V_Y25_25c__y2025	0.0601	0.0142	5.0000
10	V_Y25_26_Compaction_mgmt_tech__y2025	0.0578	0.0158	5.0000
11	V_Y23_18__y2023	0.0487	0.0144	5.0000
12	V_Y23_17__y2023	0.0472	0.0165	5.0000
13	V_Y23_35__y2023	0.0413	0.0183	5.0000
14	V_Y25_27a__y2025	0.0400	0.0076	5.0000
15	V_Y24_7_Stress__y2024	0.0381	0.0061	5.0000
16	V_Y25_27h__y2025	0.0381	0.0089	5.0000
17	V_Y25_27i__y2025	0.0348	0.0071	5.0000
18	V_Y23_19__y2023	0.0317	0.0086	5.0000
19	V_Y25_27p__y2025	0.0284	0.0052	5.0000
20	V_Y25_27f__y2025	0.0263	0.0050	5.0000
21	V_Y25_27m__y2025	0.0252	0.0056	5.0000
22	V_Y24_22_Conservation_advisor__y2024	0.0237	0.0024	5.0000
23	V_Y23_20_EoF_prac__y2023	0.0223	0.0031	5.0000
24	V_Y22_2_Opinion_leader__y2022	0.0222	0.0075	5.0000
25	V_Y25_27j__y2025	0.0215	0.0116	5.0000
26	V_Y23_20_N_mgmt_prac__y2023	0.0211	0.0105	5.0000
27	V_Y25_27l__y2025	0.0211	0.0065	5.0000
28	V_Y23_15__y2023	0.0199	0.0008	5.0000
29	V_Y24_6__y2024	0.0190	0.0060	5.0000
30	V_Y23_14__y2023	0.0187	0.0069	5.0000
31	V_Y24_21_NRS_support__y2024	0.0186	0.0104	5.0000
32	V_Y23_20v__y2023	0.0177	0.0033	5.0000
33	V_Y25_27g__y2025	0.0160	0.0059	5.0000
34	V_Y25_26_Compaction_concern__y2025	0.0160	0.0065	5.0000
35	V_Y22_17a_Trauma__y2022	0.0144	0.0058	5.0000
36	V_Y22_16_Private_entities__y2022	0.0134	0.0082	5.0000
37	V_Y23_20u__y2023	0.0129	0.0036	5.0000
38	V_Y24_21_NRS_barriers__y2024	0.0117	0.0059	5.0000
39	V_Y23_20t__y2023	0.0108	0.0057	5.0000
40	V_Y24_4__y2024	0.0087	0.0044	5.0000
⋮				

Table 24: Rank of covariates using the permutation importance from year block (2022, 2023) to year block (2023, 2025).

	term	2	3	4
1	(Intercept)	2.014	-4.670	1.060
2	S=2	1.441	1.815	1.207
3	S=3	2.123	3.674	3.419
4	S=4	0.648	3.287	5.875
5	V_Y23_20_N_mgmt_prac__y2023	0.607	0.783	0.760
6	V_Y23_20t__y2023	0.135	0.821	0.894
7	V_Y20_12_Econ_capacity__y2020	-0.371	-1.279	1.221
8	V_Y21_33__y2021_level2	-1.541	1.882	3.732
9	V_Y20_3e__y2020	-0.344	-0.488	0.636
10	V_Y21_24_CC_barriers__y2021	-0.524	-0.621	-2.145
11	V_Y20_4acde_scale__y2020	-0.330	-1.679	-1.686
12	V_Y21_13t__y2021	-0.022	-0.307	-0.842
13	V_Y21_13s__y2021	-0.378	-0.228	-1.047
14	V_Y21_8_Soil_health__y2021	-0.422	-0.705	1.186
15	V_Y23_20u__y2023	0.507	0.700	0.749
16	V_Y21_13v__y2021	0.475	0.295	0.813
17	V_Y21_24_CC_benefits__y2021	0.365	2.258	1.070
18	V_Y23_17__y2023_level1	0.190	0.207	1.700
19	V_Y20_11acdgi_scale__y2020	-0.529	-0.582	-1.764
20	V_Y23_21_Econ_capacity__y2023	0.280	1.064	0.569
21	V_Y20_18__y2020_level1	0.679	0.423	1.590
22	V_Y23_18__y2023	-0.061	0.395	0.249
23	V_Y20_4b__y2020	-0.064	0.061	-0.744
24	V_Y21_29__y2021	-0.047	0.356	-0.357
25	V_Y21_26__y2021	0.122	0.240	-0.562
26	V_Y23_19__y2023	0.073	-0.053	0.164
27	V_Y20_34__y2020	0.051	0.002	-0.536
28	V_Y23_20s__y2023	0.160	0.275	0.722
29	V_Y23_35__y2023	-0.053	-0.017	-0.020
30	V_Y20_23i__y2020	-0.414	-0.212	-0.823
31	V_Y20_13_Regulatory_motive__y2020	-0.187	-0.222	-0.707
32	V_Y23_16__y2023_level1	-0.694	-1.848	-1.468
33	V_Y22_16_Private_entities__y2022	0.492	0.605	0.754
34	V_Y20_13_Stewardship_motive__y2020	-0.049	0.072	0.394
35	V_Y23_33__y2023	0.020	0.008	0.005
36	V_Y20_23abdl_scale__y2020	-0.580	0.484	-0.651
37	V_Y23_20_EoF_prac__y2023	0.231	0.412	-0.304
38	V_Y21_11_4R_Info_ag__y2021	0.378	-0.038	0.171
39	V_Y23_21_Agron_efficacy__y2023	0.335	-0.205	0.905
⋮				

Table 25: Summary of the directions of associations between covariates and transition outcomes on the log-odds scale from year block (2020, 2021) to year block (2022, 2023). Direction on log-odds for the Markov Transition Model (MTM) with destination level $Y = 1$ as the reference category. Each row corresponds to a model term (`term`), including the intercept, initial-state indicators ($S = 2, 3, 4$; with $S = 1$ as the reference so its effect is 0), and covariates (with categorical covariates represented by separate dummy variables such as `_level`ℓ, relative to their baseline level). Columns `2`, `3`, and `4` report the estimated coefficients $\hat{\eta}_m$(`term`) in the baseline-category multinomial logit: $\log\{\Pr(Y = m \mid S, X)/\Pr(Y = 1 \mid S, X)\}$ for $m \in \{2, 3, 4\}$. A positive value in column m indicates that increasing the term (or being in that category/level) increases the log-odds—and hence the odds—of transitioning to destination level m relative to destination level 1, holding other predictors fixed; a negative value indicates a decrease. The odds ratio for a one-unit change in a numeric covariate (or for a dummy level vs baseline) is $\exp(\hat{\eta}_m)$.

	term	2	3	4
1	(Intercept)	-5.607	-10.749	-9.615
2	S=2	1.977	1.319	1.600
3	S=3	1.325	2.759	3.124
4	S=4	1.550	1.770	4.652
5	V_Y25_25b__y2025	-0.401	0.051	0.131
6	V_Y25_25e__y2025	-0.010	-0.092	-0.040
7	V_Y25_27r__y2025	0.594	0.927	1.094
8	V_Y25_25d__y2025	-0.019	0.012	-0.055
9	V_Y25_27o__y2025	-0.051	0.109	1.196
10	V_Y23_33__y2023	-0.017	0.010	0.020
11	V_Y25_27q__y2025	0.756	0.812	0.892
12	V_Y25_26_Compaction_mgmt_prac__y2025	1.775	2.404	3.810
13	V_Y25_25c__y2025	0.001	0.053	0.056
14	V_Y25_26_Compaction_mgmt_tech__y2025	-0.860	-2.438	-2.832
15	V_Y23_18__y2023	0.509	0.549	0.480
16	V_Y23_17__y2023_level1	0.412	2.224	-0.006
17	V_Y23_35__y2023	-0.011	-0.052	-0.052
18	V_Y25_27a__y2025	0.312	0.758	0.313
19	V_Y24_7_Stress__y2024	-1.040	-0.312	-0.874
20	V_Y25_27h__y2025	0.198	0.724	0.966
21	V_Y25_27i__y2025	0.491	0.047	0.484
22	V_Y23_19__y2023	-0.251	-0.318	-0.120
23	V_Y25_27p__y2025	0.090	0.571	0.506
24	V_Y25_27f__y2025	-0.243	0.448	0.196
25	V_Y25_27m__y2025	-0.003	0.801	0.551
26	V_Y24_22_Conservation_advisor__y2024	-0.701	0.089	-0.695
27	V_Y23_20_EoF_prac__y2023	-0.247	-0.524	0.325
28	V_Y22_2_Opinion_leader__y2022	0.110	0.141	0.999
29	V_Y25_27j__y2025	0.481	0.301	0.509
30	V_Y23_20_N_mgmt_prac__y2023	0.037	-0.341	-0.404
31	V_Y25_27l__y2025	0.361	0.227	-0.318
32	V_Y23_15__y2023_level1	0.431	-0.066	1.619
33	V_Y24_6__y2024	-0.337	-0.727	-0.312
34	V_Y23_14__y2023_level1	0.437	-1.182	-0.734
35	V_Y24_21_NRS_support__y2024	0.636	0.215	0.266
36	V_Y23_20v__y2023	-0.368	-0.378	-0.329
37	V_Y25_27g__y2025	-0.390	-0.192	-0.489
38	V_Y25_26_Compaction_concern__y2025	0.253	-0.036	-0.846
39	V_Y22_17a_Trauma__y2022	0.185	0.141	0.073
⋮				

Table 26: Summary of the directions of associations between covariates and transition outcomes on the log-odds scale from year block (2022, 2023) to year block (2023, 2025).