# 3 Concurrent green initiatives in the USA

With several essential issues in concurrent green initiatives—concurrent payments for environmental services in particular—identified and reviewed, this chapter turns to two specific concurrent green initiatives in the USA. On the one hand, we intend to show empirical evidence for spillover effects between the two initiatives. On the other hand, we provide some technical details (e.g., models, procedures) for how we arrive at the conclusion for the purpose of classroom teaching or education.

## 3.1 Two major green initiatives

The Conservation Reserve Program (CRP), authorized by the 1985 Farm Security Act and operated by the US Department of Agriculture (USDA hereafter), aims to retire environmentally sensitive land from agricultural production for 10–15 years (Riley, 2004). Such sensitive land is mainly located in highly erodible places. The central agri-environmental policy in the USA before 2002 used funds to pay retired farmers and low-income farmers (Claassen et al., 2008). The CRP has successfully reached its aims of preserving soil, water, and wildlife. For instance, the CRP has led to decreased cultivated acreage from 26% of the land area to 8% in Goodwin Creek, Mississippi. Perennial grasses established through the CRP have significantly improved infiltration and soil quality relative to conventional cropping systems at the Mark Twain Lake/Salt River Basin, Missouri. Substantial cropland area has been converted to grass or forest through the CRP at Yalobusha River and Topashaw Creek, Mississippi (Richardson et al., 2008). The CRP also benefits wildlife and fish (Gray & Teels, 2006).

The Environmental Quality Incentives Program (EQIP) was created in 1996 (via the 1996 Farm Bill) by consolidating several programs related to cropland and grazing land. Administered by Natural Resources Conservation Service (NRCS), the EQIP intends to pay agricultural producers to adopt environmentally friendly practices on their farmlands—i.e., lands that remain in production. So the EQIP is a working-land program and has cost-sharing for specific conservation practices (Ogg & Keith, 2002). Recent years, however, have witnessed increases in funding for working-land programs (e.g., EQIP) relative to land retirement programs (e.g., CRP). EQIP and CRP are concurrent payments for environmental

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services (PES) programs according to the 2018 Farm Bill amendments, which explicitly "allow[s] land enrolled in CRP during the last year of the CRP contract to be enrolled in the Environmental Quality Incentives Program" (Federal register, 2019). In this situation, there exists a substantial potential for spillover effects between CRP and EQIP.

## 3.2 Potential spillover effects between CRP and EQIP

As CRP and EQIP are large US agri-environmental programs, we searched the Web of Science under the keyword in this format "((Conservation Reserve Program or CRP) and (Environmental Quality Incentives Program or EQIP))" while selecting "All fields" (this is the most comprehensive choice compared with other alternatives such as "Title" and "Topic"). Then, we reviewed the abstracts and keywords of all the selected papers from this search: if both "Conservation Reserve Program" (or its acronym CRP) and "Environmental Quality Incentives Program" (or its acronym EQIP) occur in the abstract or keyword list, we consider it a potential paper addressing EQIP–CRP spillover effects. Otherwise, we skip it. Then, for all possible papers, we downloaded and read them in search of evidence of spillover effects.

We found 76 papers with publication dates ranging from 2000 to 2021 as of December 30, 2021. Of these 76 papers, 16 met a high standard for potentially addressing spillover effects. Out of the 16 articles, three suggest spillover effects—at least concurrency—between multiple green initiatives. First, Mishra and Khanal (2013) mention that a landowner can explicitly enroll in both programs, implying that EQIP and CRP meet our concurrent PES definition. Another paper indicates explicitly that in the Topashaw Canal watershed, USA, "interest in and sign-up for CRP began again in 1997 but dwindled to less than 2000 ha (4,942 ac) with payments of S20,000 per year once EQIP was initiated in 2002" (Wilson et al., 2008), indicating an offsetting spillover effect from EQIP to CRP. The third paper (Rossi et al., 2021) states that "Additional field experiments could reveal if these stated beliefs reflect the true motivations for farmers' enrollment in both programs," which implied that farmers have enrolled in both programs. We also found an implicit statement: "working-land and land retirement programs play complementary roles to reduce the environmental consequences of agricultural production" (Lambert et al., 2007), yet we found no discussion of their complementarity. However, no systematic work has been devoted to exploring such spillover effects.

Below are all 16 papers that potentially address EQIP–CRP spillover effects:

Claassen, R., Cattaneo, A., & Johansson, R. (2008). Cost-effective design of agri-environmental payment programs: U.S. experience in theory and practice. *Ecological Economics*, *65*(4), 737–752.

Rossi, G. D., Hecht, J. S., & Zia, A. (2021). A mixed-methods analysis for improving farmer participation in agri-environmental payments for ecosystem services in Vermont, USA. *Ecosystem Services*, *47*, 101223.

Frimpong, E. A., Lee, J. G., & Ross-Davis, A. L. (2007). Floodplain influence on the cost of riparian buffers and implications for conservation programs. *Journal of Soil and Water Conservation*, *62*(1), 33–39.
Gray, R. L., & Teels, B. M. (2006). Wildlife and Fish Conservation Through the Farm Bill. *Wildlife Society Bulletin*, *34*(4), 906–913.
Hess, G. R., Campbell, C. L., Fiscus, D. A., Hellkamp, A. S., McQuaid, B. F., Munster, M. J., Peck, S. L., & Shafer, S. R. (2000). A Conceptual Model and Indicators for Assessing the Ecological Condition of Agricultural Lands. *Journal of Environmental Quality*, *29*(3), 728–737.
Lambert, D. M., Sullivan, P., Claassen, R., & Foreman, L. (2007). Profiles of US farm households adopting conservation-compatible practices. *Land Use Policy*, *24*(1), 72–88.
Mishra, A. K., & Khanal, A. R. (2013). Is participation in agri-environmental programs affected by liquidity and solvency? *Land Use Policy*, *35*, 163–170.
Medina, G., Isley, C., & Arbuckle, J. (2021). Promoting sustainable agriculture: Iowa stakeholders' perspectives on the US Farm Bill conservation programs. *Environment, Development and Sustainability*, *23*(1), 173–194.
Mutandwa, E., Grala, R. K., Grado, S. C., & Munn, I. A. (2016). Family Forest Owners' Familiarity with Conservation Programs in Mississippi, USA. *Small-Scale Forestry*, *15*(3), 303–319.
Ogg, C. W., & Keith, G. A. (2002). New Federal Support for Priority Watershed Management Needs. *JAWRA Journal of the American Water Resources Association*, *38*(2), 577–586.
Reimer, A. P., & Prokopy, L. S. (2014). Farmer Participation in U.S. Farm Bill Conservation Programs. *Environmental Management*, *53*(2), 318–332.
Richardson, C. W., Bucks, D. A., & Sadler, E. J. (2008). The Conservation Effects Assessment Project benchmark watersheds: Synthesis of preliminary findings. *Journal of Soil and Water Conservation*, *63*(6), 590–604.
Riley, T. Z. (2004). Private-land habitat opportunities for prairie grouse through federal conservation programs. *Wildlife Society Bulletin*, *32*(1), 83–91.
Tumeo, M. A., Mauriello, D. A., Sadeghi, A. M., & Meekhof, R. (2000). Case Studies on the Application of Adaptive Risk Analysis to USDA's Resource Conservation Programs. In Y. Y. Haimes & R. E. Steuer (Eds.), *Research and practice in multiple criteria decision making* (pp. 492–509). Springer.
Tyndall, J. (2021). Prairie and tree planting tool—PT2 (1.0): A conservation decision support tool for Iowa, USA. Agroforestry Systems, 1–16.
Wilson, G. V., Shields, F. D., Bingner, R. L., Reid-Rhoades, P., DiCarlo, D. A., & Dabney, S. M. (2008). Conservation practices and gully erosion contributions in the Topashaw Canal watershed. *Journal of Soil and Water Conservation*, *63*(6), 420–429.

## 3.3 Empirical data collection and analysis

We obtained EQIP data in 2018 on a county basis from the USDA (USDA Farm Production and Conservation Business Center, 2020). We downloaded county-level CRP data in 2018 from the USDA Farm Service CRP program and statistics reporting portal (https://www.fsa.usda.gov/programs-and-services/conservation-programs/reports-and-statistics/conservation-reserve-program-statistics/index) on April 6, 2020. The income data were downloaded from the US

Census—SAIPE (Small Area Income and Poverty Estimates) and the related links (https://www.census.gov/data/datasets/2018/demo/saipe/2018-state-and-county.html and https://www.census.gov/programs-surveys/saipe.html). The farmland data were downloaded from the USDA—Farm Service Agency (https://www.fsa.usda.gov/news-room/efoia/electronic-reading-room/frequently-requested-information/crop-acreage-data/index). The population data were downloaded from the US Census Bureau (https://www.census.gov/data/tables/time-series/demo/popest/2010s-counties-total.html).

After merging the datasets by county, we generated a dataset that contains the following variables: CRP2018 ($y$ for area enrolled in CRP; acres), EQIP_Area ($x_1$ for contracted land in EQIP; acres), Farm_Area ($x_2$ for total county farmland; acres), M_HH_inc ($x_3$ for county median household income in 2018; \$), and Pop2018 ($x_4$ for county population in 2018). As a preliminary initiative to handle spatial autocorrelation in the dataset, we first randomly selected 25% of the data out of 3,108 records, resulting in a dataset of 730 records for data analysis. According to the United Nations' Sustainable Livelihoods Framework, human, social, natural, physical, and financial capitals possessed by an entity (e.g., farm, household, community) play a crucially important role in relevant livelihood decisions. Using the acres of EQIP enrollment as dependent variable (y), we explain its variability using a set of variables that represent such capitals: the acres of CRP enrollment ($X_1$), total farmland ($X_2$, acres), median household income ($X_3$), and population size ($X_4$). The multivariate linear regression takes the following form (Equation 3.1):

$$y = b_0 + b_1 X_1 + \sum_{i=2}^{4} b_i X_i + e \tag{3.1}$$

where $b_0$ is the intercept, $b_1$ is the coefficient of $X_1$ (contracted land in EQIP; acres), and $b_i$ is the coefficient of the three control variables $X_i$ ($i$=2, 3, and 4) that contribute to explaining the variability in the dependent variable (land enrolled in CRP; acres). As shown later, the results indicate that under the control of county-level farmland area, income, and population size, EQIP land had a negative impact on CRP enrollment—each acre of EQIP land caused a loss of 0.28 ($p < 0.0001$) acre in CRP enrollment.

We further employed the eigenvector spatial filtering (ESF) method to handle potential biases in parameter estimates due to spatial autocorrelation (Chun, 2008; Griffith, 2000). Spatial autocorrelation refers to a situation where units that are geographically close to one another may have more similar values than those that are far apart, which is also known as Tobler's first law of geography (Tobler, 1970). If this type of autocorrelation is present in a regression model (e.g., in its residuals), then it violates a fundamental assumption in standard statistical analysis: regression residuals should be independent and identically distributed (i.i.d.). The violation may give rise to biased parameter estimates, e.g., an increase in type I error and falsely rejecting the null hypothesis of no effect.

Employing the ESF method, we tested various neighborhood sizes from the 1st- to the 20th-order Queen's neighborhood as we do not know precisely at what spatial scale(s) the residuals are spatially autocorrelated. At each neighborhood size, we generated the corresponding spatial weights matrix.

Following the relevant literature (An et al., 2016; Chun et al., 2016), we calculated the eigenvalues (ranked in descending order) and the corresponding eigenvectors under each neighborhood size (i.e., 1, 2 … up to 20). According to eigenvector selection literature (Hughes & Haran, 2013; Pace et al., 2013), a relatively small subset of top eigenvectors (e.g., top 50–100 for a dataset with 2,500 records; Hughes & Haran, 2013) should suffice as regressors for filtering out spatial autocorrelation. We name this procedure the "top *k* method" for illustration purposes, where it is essential to determine the value of *k*. One way to choose *k* is to select the top *k* eigenvectors corresponding to standardized eigenvalues greater than 0.7 (we name it the 0.7 rule; Hughes & Haran, 2013).

Alternatively, the top *k* eigenvectors can be determined by the "0.25 rule" (as described for illustration convenience; Chun et al., 2016), and the number thus chosen should be more than the subset defined by the 0.7 rule. Note that the 0.25 rule states that *k* can be determined if $EV_k/EV_{max} \geq 0.25$ for positive spatial autocorrelation, where $EV_{max}$ is the largest eigenvalue among all *n* eigenvalues (Chun et al., 2016). We show at each neighborhood size, the maximum eigenvalue, a quarter of the maximum eigenvalue (i.e., 0.25× maximum eigenvalue), and the number of eigenvectors with their eigenvalue greater than 0.25× maximum eigenvalue (Table 3.1). For instance, at neighborhood = 2 (the second-order neighborhood is chosen for eigenvector calculation), there are 290 eigenvectors with eigenvalues greater than 5.23 (here 5.23 = 0.25 × 20.91, where 20.91 is the maximum eigenvalue).

Therefore, we picked up the top *k* eigenvectors for the regression based on the 0.25 rule. The regression model is shown in Equation 3.2:

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4 + \sum_{g=1}^{k} c_g CEV_g + e \qquad (3.2)$$

Based on Equation 3.2, we calculated regression residuals, Moran's I value, and the associated Z score at each of the 20 neighborhood choices. Following Chun et al. (2016), we chose the appropriate model (corresponding to a specific neighborhood size) that (1) reduces spatial autocorrelation to an acceptable level (e.g., $|z|$ is less than 1.64 for alpha = 0.10) and (2) has the best (or close to the best) model fit in terms of, e.g., minimized AIC or maximized adjusted $R^2$. The first rule prevails if these two rules cannot be satisfied simultaneously. When multiple models (each for a unique neighborhood size) satisfy these two rules, we choose the one with fewer eigenvectors for higher degrees of freedom.

The results based on Equation 3.2 indicate that at the tenth order, the spatial autocorrelation of residuals was nearly removed with $|z| = 0.54$ (Table 3.2). At this neighborhood size (i.e., the tenth order) with the least $|z|$ score, *k* was determined

*Table 3.1* The number of eigenvectors selected at each neighborhood size

| *Order* | *1* | *2* | *3* | *4* | *5* | *6* | *7* | *8* | *9* | *10* |
|---|---|---|---|---|---|---|---|---|---|---|
| Max value | 6.71 | 20.91 | 43.49 | 74.14 | 111.73 | 155.25 | 204.08 | 257.76 | 315.07 | 375.29 |
| 0.25 of max | 1.68 | 5.23 | 10.87 | 18.53 | 27.93 | 38.81 | 51.02 | 64.44 | 78.77 | 93.82 |
| Top # selected | >500 | 290 | 145 | 87 | 57 | 40 | 30 | 23 | 19 | 15 |
| *Order* | *11* | *12* | *13* | *14* | *15* | *16* | *17* | *18* | *19* | *20* |
| Max value | 437.38 | 500.07 | 562.59 | 624.13 | 683.70 | 740.56 | 793.92 | 843.20 | 887.87 | 927.47 |
| 0.25 of max | 109.35 | 125.02 | 140.65 | 156.03 | 170.93 | 185.14 | 198.48 | 210.80 | 221.97 | 231.87 |
| The last value | 13 | 10 | 9 | 8 | 7 | 7 | 6 | 5 | 4 | 4 |

*Table 3.2* Spatial autocorrelation of regression residuals for CRP and EQIP, USA

| *Neighborhood order* | *Under normality assumption* | | | *Under randomization assumption* | | |
|---|---|---|---|---|---|---|
| | *Moran's I*[a] | *p-value* | *Z score* | *Moran's I* | *p-value* | *Z score* |
| 1 | −0.0946 | 1.0000 | −8.9821 | −0.0946 | 1.0000 | −9.0694 |
| 2 | −0.0515 | 1.0000 | −8.6582 | −0.0515 | 1.0000 | −8.7351 |
| 3 | −0.0137 | 0.9994 | −3.2550 | −0.0137 | 0.9995 | −3.2843 |
| 4 | −0.0270 | 1.0000 | −8.5057 | −0.0270 | 1.0000 | −8.5746 |
| 5 | −0.0253 | 1.0000 | −9.8717 | −0.0253 | 1.0000 | −9.9512 |
| 6 | −0.0130 | 1.0000 | −5.9994 | −0.0130 | 1.0000 | −6.0484 |
| 7 | −0.0044 | 0.9877 | −2.2476 | −0.0044 | 0.9883 | −2.2657 |
| 8 | 0.0070 | 0.0000 | 4.6093 | 0.0070 | 0.0000 | 4.6472 |
| 9 | 0.0066 | 0.0000 | 4.9065 | 0.0066 | 0.0000 | 4.9455 |
| 10 | −0.0010 | 0.7033 | −0.5339 | −0.0010 | 0.7047 | −0.5380 |
| 11 | −0.0086 | 1.0000 | −7.2702 | −0.0086 | 1.0000 | −7.3251 |
| 12 | −0.0113 | 1.0000 | −10.5581 | −0.0113 | 1.0000 | −10.6381 |
| 13 | −0.0166 | 1.0000 | −17.0326 | −0.0166 | 1.0000 | −17.1610 |
| 14 | −0.0185 | 1.0000 | −20.6911 | −0.0185 | 1.0000 | −20.8460 |
| 15 | −0.0190 | 1.0000 | −22.9488 | −0.0190 | 1.0000 | −23.1202 |
| 16 | −0.0174 | 1.0000 | −22.5684 | −0.0174 | 1.0000 | −22.7360 |
| 17 | −0.0137 | 1.0000 | −18.9725 | −0.0137 | 1.0000 | −19.1124 |
| 18 | −0.0088 | 1.0000 | −12.9496 | −0.0088 | 1.0000 | −13.0441 |
| 19 | −0.0046 | 1.0000 | −6.9333 | −0.0046 | 1.0000 | −6.9840 |
| 20 | −0.0015 | 0.9829 | −2.1183 | −0.0015 | 0.9836 | −2.1336 |

Notes: [a] When calculating the spatial weights matrix, the few records (counties) in California were dropped as most counties in California did not have both CRP and EQIP implemented simultaneously, leaving few scattered counties in our dataset. Also in order to calculate Moran's I, counties without a residual were assigned the average of residuals of all residuals.

to be 15 based on the above 0.25 rule. Using these top 15 eigenvectors as spatial filters, the area of EQIP land had a negative coefficient of −0.2242 ($p < 0.0001$) (Table 3.3, the second model).

To examine whether the model based on a subset of 730 records (Table 3.3) can reduce the spatial autocorrelation to an acceptable level, we also calculated the Moran's I value of this model at four neighborhood levels, i.e., the 5th, 10th, 15th, and 20th. It turns out the residuals were still quite spatially autocorrected except at the 15th level (z = 1.5672; Table 3.4). This suggests that the subsampling method may not effectively reduce spatial autocorrelation.

We used the stepwise selection method to choose spatial filters (Chun et al., 2016; Chun & Griffith, 2011; Griffith, 2000) to verify the above results. Under this method, we used stepwise regression to select a subset of *s* significant eigenvectors (at alpha = 0.10) out of the top *k* eigenvectors. In our regression model (Equation 3.3), the top *k* eigenvectors—candidate spatial filters that were chosen based on the 0.25 rule—entered the stepwise procedure (note that $X_1$ through $X_4$ were forced to be included). These *s* eigenvectors were then used as spatial filters in the regression model that corresponds to a specific neighborhood size:

*Table 3.3* Regression results for the CRP and EQIP, USA

| *Variable* | *Model with n = 730 (669 used)* | | | | *Model with ESF (tenth-order neighborhood)*[a] | | | |
|---|---|---|---|---|---|---|---|---|
| | *Coefficient* | *t-score* | *p-value* | *Variance inflation* | *Coefficient* | *t-score* | *p-value* | *Variance inflation* |
| Intercept | 3713.7310 | 1.64 | 0.1010 | 0 | 8017.8357 | 5.18 | <0.0001 | 0 |
| EQIP_Area | −0.2823 | −5.39 | <0.0001 | 1.4413 | −0.2242 | −7.72 | <0.0001 | 1.3648 |
| Farm_Area | 0.0215 | 12.14 | <0.0001 | 1.4628 | 0.0174 | 13.67 | <0.0001 | 2.0796 |
| M_HH_Inc | 0.0061 | 0.14 | 0.8903 | 1.2393 | −0.0563 | −1.95 | 0.0509 | 1.4232 |
| Pop2018 | −0.0108 | −2.75 | 0.0061 | 1.2589 | −0.0033 | −2.11 | 0.0352 | 1.1620 |
| V1 | N/A | N/A | N/A | N/A | 210474 | 9.26 | <0.0001 | 1.7010 |
| V2 | N/A | N/A | N/A | N/A | 1087.7090 | 0.06 | 0.9523 | 1.0793 |
| … | | | | | | | | |
| V14 | N/A | N/A | N/A | N/A | −49285 | −2.82 | 0.0048 | 1.0208 |
| V15 | N/A | N/A | N/A | N/A | 9397.7823 | 0.52 | 0.6039 | 1.0417 |
| Model fit | $R^2$ = 0.2064, Adjusted $R^2$ = 0.2016 | | | | $R^2$ = 0.2253, Adjusted $R^2$ = 0.2201 | | | |

Note: [a] For eigenvectors, we only show the first two and last two for brevity. We chose to show results for regression with a subset of data ($n$ = 730) and with eigenvector spatial filtering (ESF; at the tenth-order neighborhood) for the case of CRP and EQIP, USA.

*Table 3.4* Spatial autocorrelation of regression residuals in the baseline model

| *Neighborhood order* | *Under normality assumption* | | | *Under randomization assumption* | | |
|---|---|---|---|---|---|---|
| | *Moran's I* | *p-value* | *Z score* | *Moran's I* | *p-value* | *Z score* |
| 5 | 0.0450 | 0.0000 | 17.9028 | 0.0450 | 0.0000 | 18.2122 |
| 10 | 0.0140 | 0.0000 | 11.3534 | 0.0140 | 0.0000 | 11.5468 |
| 15 | 0.0009 | 0.0616 | 1.5417 | 0.0009 | 0.0585 | 1.5672 |
| 20 | 0.0034 | 0.0000 | 6.5202 | 0.0034 | 0.0000 | 6.6235 |

Notes: The results are based on the baseline model with a subset of $n=730$ records but no eigenvectors, i.e., the first model in Table 3.2.

*Table 3.5* Regression results with the ESFs selected by stepwise regression

| *Variable* | *Coefficient* | *t-score* | *p-value* | *Variance inflation* |
|---|---|---|---|---|
| Intercept | 7,447.4780 | 5.23 | <0.0001 | 0 |
| EQIP_Area | −0.2240 | −7.90 | <0.0001 | 1.3000 |
| Farm_Area | 0.0172 | 14.02 | <0.0001 | 1.9338 |
| M_HH_Inc | −0.0440 | −1.65 | 0.0981 | 1.2138 |
| Pop2018 | −0.0035 | −2.26 | 0.0238 | 1.1413 |
| V1 | 212,815 | 9.59 | <0.0001 | 1.6214 |
| V6 | −75,696 | −4.27 | <0.0001 | 1.0488 |
| V9 | −66,165 | −3.71 | 0.0002 | 1.0308 |
| V10 | 62,279 | 3.60 | 0.0003 | 1.0308 |
| V11 | −96,370 | −5.43 | <0.0001 | 1.0373 |
| V12 | 45,740 | 2.58 | 0.0099 | 1.0247 |
| V14 | −49,891 | −2.86 | 0.0042 | 1.0182 |

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + \sum_{g=1}^{s} c_g CEV_g + e \tag{3.3}$$

where $x_i$ ($i=1$, 2, 3, and 4) are the four predictor variables defined in Equation 3.1, and $CEV_g$ and $c_g$ ($g=1, 2, 3, \dots s$; $s \le k$) are the eigenvectors that are chosen as spatial filters and the associated coefficients, respectively. Note that the $s$ chosen eigenvectors are not necessarily the top $s$ eigenvectors; therefore, $CEV_g$ in Equation 3.3 could differ from $CEV_g$ in Equation 3.2.

The regression results from Equation 3.3 also indicate that the tenth-order neighborhood is also acceptable with $|z|=1.4777$ ($p=0.0697$, not shown in a table), confirming the outcome regarding the tenth-order neighborhood by Equation 3.2. For the brevity purpose, we skip the Moran's I and other statistics for this method as we did for the top $k$ method (Table 3.1).

The coefficient for the area of EQIP land (EQIP_Area) is –0.2240 ($p < 0.0001$; Table 3.5), slightly different from that from Equation 3.2 (–0.2242; $p < 0.0001$; Table 3.3). Later we adopted the average of the two coefficients when calculating the impacts of EQIP on CRP: coefficient = [(–0.2242) + (–0.2240)]/2 = –0.2241, rounded to –0.22. When calculating the average coefficient, we did not include the coefficient from Equation 1, i.e., –0.2803 (i.e., the one from the $n = 730$ sample; Table 3.3), simply because we preferred a conservative estimate.

## 3.4 Potential reasons for the negative spillover effects

There is an offsetting spillover effect from EQIP to CRP, which can be explained as follows. First, we regard land scarcity as a top influential variable. The positive coefficient of total farmland (0.0172 with $p < 0.0001$; Table 3.5) indicates more enrollment in CRP in counties with more farmland. Second, land-use competition may also—at least partially—account for this offsetting impact. Both CRP and EQIP target farmland, sharing goals to preserve water, soil, and wildlife habitat—so increases in enrollment of one program may lead to decreases in that of the other.

Last but not least, facing two choices of CRP and EQIP that are competitive in many instances, landowners choose the more profitable one. As CRP participants must retire the enrolled land, the land then has no (or very little) agricultural income. The EQIP, instead of retiring the land, provides money to landowners for whatever environmentally beneficial practices they adopt. This operation implies that landowners still receive agricultural income. Furthermore, the EQIP pay rate was higher than that of the CRP, offering an additional incentive for landowners to participate in the EQIP rather than the CRP. All these factors may contribute to the declining CRP enrollment trend since 2007 (Figure 3.1) and explain why the 2018 CRP enrollment was far below the cap designated by the 2018 Farm Bill.

In 2018, 22 million acres of land were enrolled in CRP, far less than the cap of 27 million acres established by the 2018 Farm Bill (USDA Farm Service Agency,

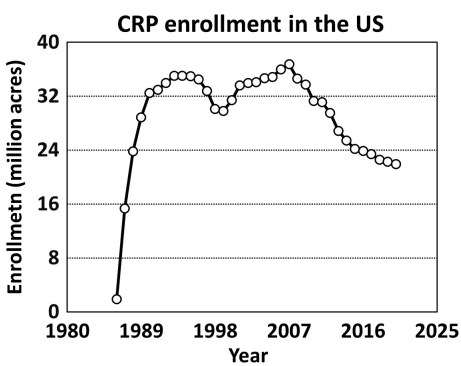


*Figure 3.1* Dynamics of CRP-enrolled acres in the USA between 1986 and 2018 (Data source is USDA Farm Production and Conservation Business Center, Economics and Policy Analysis Division, Data Services Branch, County-level CRP, and EQIP dataset in the USA, 2020).

*Table 3.6* Potential loss of CRP land area due to EQIP enrollment over time

| *Year* | *EQIP (million acres)*[a] | *Lost CRP (million acres)*[b] | *Soil erosion loss (billion)*[c] | *Carbon loss (million)* | *Cars back (million)* |
|---|---|---|---|---|---|
| 2009 | 23.1752 | 5.0985 | 2.0858 | 11.3558 | 2.0858 |
| 2010 | 24.1148 | 5.3053 | 2.1703 | 11.8163 | 2.1703 |
| 2011 | 22.4588 | 4.9409 | 2.0213 | 11.0048 | 2.0213 |
| 2012 | 24.3016 | 5.3464 | 2.1871 | 11.9078 | 2.1871 |
| 2013 | 24.4184 | 5.3721 | 2.1977 | 11.9650 | 2.1977 |
| 2014 | 19.4651 | 4.2823 | 1.7519 | 9.5379 | 1.7519 |
| 2015 | 18.6048 | 4.0930 | 1.6744 | 9.1163 | 1.6744 |
| 2016 | 15.7342 | 3.4615 | 1.4161 | 7.7098 | 1.4161 |
| 2017 | 17.0746 | 3.7564 | 1.5367 | 8.3665 | 1.5367 |
| 2018 | 17.7341 | 3.9015 | 1.5961 | 8.6897 | 1.5961 |
| 2019 | 18.0222 | 3.9649 | 1.6220 | 8.8309 | 1.6220 |
| 2020 | 17.6730 | 3.8881 | 1.5906 | 8.6598 | 1.5906 |
| Average | 20.2314 | 4.4509 | 1.8208 | 9.9134 | 1.8208 |

Notes:
[a] Data source: https://www.nrcs.usda.gov/Internet/NRCS_RCA/reports/fb08_cp_eqip.html.
[b] The lost CRP areas are estimated based on our modeled correlation, which is 22% of the total EQIP area. The data come from the dataset from the USDA (USDA Farm Production and Conservation Business Center, 2020).
[c] The news release from the USDA (USDA Farm Service Agency, 2019).

2019, p. 9). It is reported that all CRP land can generate a large amount of ecological benefits, including reduction of soil erosion (accumulative number) at the magnitude of 9 billion tons and sequestration of 49 million tons of carbon dioxide (equal to taking 9 million cars off the roads) (USDA Farm Service Agency, 2019). Our data show that between 2009 and 2020, the EQIP land was 20.2314 million acres (8.1874 million hectares) on average, which may have reduced CRP land by 4.4509 million acres (1.8012 million hectares) or 20.23% (100% × 4.4509 million/22 million) total CRP land. Given such data, the loss of CRP land due to its competitor EQIP (4.4509 million acres) is equivalent to increasing soil erosion by 1.8208 billion tons and carbon dioxide release by 9.9134 million tons. The increased release of greenhouse gas alone would be equivalent to putting 1.8208 million cars back on roads (Table 3.6).

## 3.5 Area-based conservation experiment

As discussed in Section 1.4, the conservation community has long established and maintained protected areas. Protected areas are considered an essential type of green initiative, which is credited to be the foundation of biodiversity conservation. The conservation community has recently started recommending area-based conservation measures for conservation purposes (Jonas et al., 2014; Maxwell et al., 2020).

We experimented to explore whether and how we can leverage the spillover effects to save costs while maintaining the total acres enrolled in CRP and EQIP.

We first convert various proportions of EQIP land located in areas eligible for both programs back to the CRP. The rationale is that some landowners may quit their land from the CRP—though more ecologically appropriate under this program—but enroll such land in the EQIP for its higher pay rate. The experiment begins with 22.0 and 18.02 million acres of CRP and EQIP enrollment in 2019, respectively, which stands as the baseline. Based on our finding in Section 3.3, each acre of EQIP land may lead to a reduction of 0.22 acre in CRP land, which suggests that 20.23 million EQIP lands (the average from 2009 to 2020) should have reduced CRP enrollment at the magnitude of 20.23 × 0.22 = 4.5 million acres.

Next, we consider five scenarios: zero (pre-pandemic, baseline), 25% (4.5 × 25% = 1.125 million acres reallocated from EQIP to CRP), 50%, 75%, and up to 100% restoration (all 4.5 million acres reallocated from EQIP to CRP; Table 3.7). As we move the same amount of EQIP acres to the CRP, the total acres in both programs remain the same, but the amount of total payment declines simply because the pay rate of CRP ($76.36/acre) is lower in comparison to that of EQIP ($137.98/acre). The results show that 2–7% of the total expenses would have been saved while still meeting the goal of constant acreage of both EQIP and CRP (Table 3.7).

If there are no spillover effects, the green efforts are invested in Figure 3.2A. However, our data analysis found that in areas with both CRP and EQIP eligible, a certain amount of land (22%, the dotted oval in Figure 3.2B), which is best for the CRP, has switched to the EQIP because of its higher pay rates and other benefits (Figure 3.2B). As a result, the total amount of land for CRP and EQIP remains unchanged, but the total ecological benefits will likely decrease, and the total payments for both programs will increase.

What is the application of this finding to landscape design and engineering? As we did in the China case (Section 6.6), we suggest changing the enrollment rules to some degree, such that some EQIP efforts in the middle section—the dotted circle—can be reallocated to EQIP-only areas (Figure 3.2C). As a result, the total area of both CRP and EQIP enrollment remains unchanged, but we get the effort (in the middle area) reallocated to the best ecological benefits. The other benefit is that through such a reshuffle of green efforts, we can allow a 2–7% budget cut for the whole USA but still keep the total area of both CRP and EQIP unchanged. Budget readjustments are particularly important at times of crisis, such as COVID-19.

## Appendix: Moran's I calculation

We present a detailed description of how to calculate the Moran's I value at the various neighborhood definitions that are shown in Table 3.2. For data and related code, visit our website http://www.complexties.org/book/green_initiative, and go to this subfolder EQIP-CRP-data/Moran-I/. Readers without interest in such detail scan skip this section.

*Table 3.7* Payments saved due to policy redesign between CRP and EQIP

| | *Pre-pandemic* | | *During or post-pandemic* | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Baseline*[a] | | *25% restoration*[b] *(1.125 m. acre)* | | *50% restoration (2.25 m. acre)* | | *75% restoration (3.375 m. acre)* | | *100% restoration (4.5 m. acre)* | |
| | *Area* | *Pay* | *Area* | *Pay* | *Area* | *Pay* | *Area* | *Pay* | *Area* | *Pay* |
| CRP | 22.00 | 1,680 | 23.125 | 1,766 | 24.25 | 1,852 | 25.375 | 1,938 | 26.5 | 2,024 |
| EQIP[c] | 18.02 | 2,486 | 16.895 | 2,331 | 15.77 | 2,176 | 14.645 | 2,021 | 13.52 | 1,865 |
| Total | 40.02 | 4,166 | 40.02 | 4,097 | 40.02 | 4,028 | 40.02 | 3,958 | 40.02 | 3,889 |
| Change | N/A | N/A | 0 | −69 | 0 | −139 | 0 | −208 | | −277 |
| Change % | N/A | N/A | 0 | −2% | 0 | −3% | 0 | −5% | | −7% |

Notes:

[a] Based on 2019 data, we consider both area (million acres) and payment (million dollars).

[b] The base of restoration is 4.5 million acres (total lost CRP land due to EQIP).

[c] EQIP data from https://www.nrcs.usda.gov/Internet/NRCS_RCA/reports/fb08_cp_eqip.html.

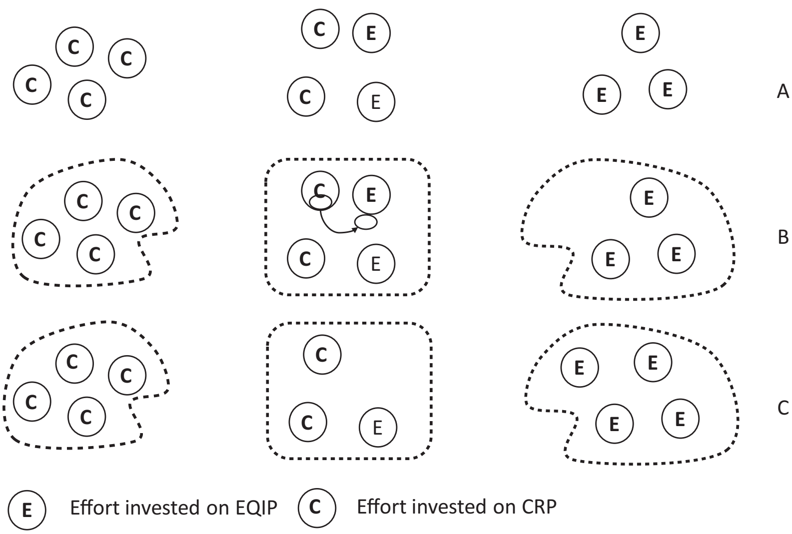


*Figure 3.2* Initiative efforts invested in EQIP and CRP if (A) there are no spillover effects, (B) there is a spillover effect, and (C) the influenced EQIP effort is relocated to EQIP-only areas. The left, middle, and right dotted areas represent CRP eligible only areas, CRP and EQIP simultaneously eligible areas, and EQIP eligible only areas.

Step 1: Data preparation

1.1 Create folders named **NonSpatial, Results, and Shapefiles**; move **Out_no_EV.csv** into the **Nonspatial** folder.
1.2 Import **out_data_1.csv** into ArcMap, join with county layer by FIPS_co. Extract the matching records as a new shapefile named **county_outdata.shp** under the Shapefiles folder.
1.3 Fill in missing residuals in each table from average of all residuals (Step 1 in MoranI.R)

Step 2: Calculate the neighborhood for each order specified in the table names (Step 2 in MoranI.R)

Step 3: Calculate Moran's I.

We calculate Moran's I values for regression residuals and related statistics (Step 3 in MoranI.R); two tables are found in the Results folder (**MoranI_nor.csv** for Moran's I under normality and **MoranI_ran.csv** for Moran's I under randomization).

Step 4: Prepare a table for non-spatial model (Step 4 in MoranI.R)

4.1: merge the non-spatial table with the full county layer (3,106 counties)
4.2: fill in missing residuals in each table from an average of all residuals

Step 5: Calculate Moran's I for regression residuals and related statistics (Step 5 in MoranI.R); two tables are found in the Results folder (**MoranI_Nsp_nor.cs**v for Moran's I under normality and **MoranI_Nsp_ran.csv** for Moran's I under randomization)

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