Appendix 1: Modeling methods and additional results

Wetland diversity modeling

We mapped all emergent wetlands > 5×5 m within our study area. This minimum mapping unit included virtually all wetland patches in the study area and was less than the size of the smallest breeding home range we measured for Black Rails (0.16 ha; S.R. Beissinger, unpublished data). Areas covered by hydrophytes (*Typha* spp., *Scirpus* spp., *Juncus effusus*, *Leersia oryzoides*, or various sedges) were considered wetland. We included hydrophytes that dried seasonally; if green vegetation was present along the wetland-upland transition zone, we buffered 5 m around it. Open water and rice were excluded. If imagery was ambiguous, we used Google Earth imagery from adjacent years to help distinguish if a wetland was present. Patches were considered separate wetlands if they were >100 m from another patch of wetland, had different water sources, or were different management units (e.g., separate ponds).

We classified the water sources of the 623 wetlands on the properties of survey respondents (see *Social sampling*) using historical (1947–2015) aerial photographs of the landscape under different irrigation regimes to determine if natural springs or creeks existed before the addition of irrigation water. We also assessed all 222 wetlands on public lands and the remaining 16 rice fringe, 10 irrigation ditch, and 4 waterfowl impoundment wetlands on non-respondent properties to give us a comprehensive sample of these groups. We were able to gain property access to conduct field surveys of 271 wetlands (59 of which were newly assessed wetlands opportunistically added), supplementing our aerial interpretation with visual site inspections and interviews with landowners about water sources.

To determine the total number and area of wetlands supported by each water source, we estimated the number and total area of the remaining 826 (47% of all wetlands) privately owned fringe, slope, and fluvial wetlands that were supported by each water source. We first calculated the percent and areal percent of each of the three types of wetlands supported by each water source in our n = 934 known-source wetlands. We then multiplied these percentages by the total number and area of unknown-source wetlands in each of these categories, and then added them to the known-source wetlands in those categories. For example, for the number of spring-fed slope geomorphology wetlands (using only data from private lands):

$$\text{\# spring -slope wetlands} = \text{\# known spring slope} + \text{\# unknown slope} \times \frac{\text{\# known spring slope}}{\text{\# known slope}}$$

Confidence intervals were calculated based on the original proportions and then multiplied by the total number or area of unknown-source wetlands.

We fit Tobit regressions (Tobin 1958) in the R package *censReg* (v0.5.26) to estimate the expected percent wetness of wetlands during each period. We used Tobit regression censored at 0 and 1 and with a random effect for site, which was suitable for percent wetness data because wetlands could experience additional drying below 0% percent wetness (i.e., changing firm mud to cracked dry ground), while large inflows of water could cause flooding beyond 100% of the polygon saturated. We analyzed a model set that included water source (a factor; natural-only, irrigation-only, or both-source), wetland area (ln hectares), and interactions between these and each sampling period. For wetlands whose size varied annually (i.e., experienced changes in extent of hydrophyte cover) we used the maximum area (measured from aerial imagery) and corrected wetness estimates by multiplying the field-estimated percent wetness times the percent of the maximum area filled by the current area. We selected the best model via Akaike information criterion (AIC; Table A1.1). Impoundments (large, intensively managed waterfowl hunting wetlands found only in the Central Valley) were excluded from this analysis because they had complex management cycles of water drawdowns, planting, and re-flooding.

Social diversity modeling

Principal components analysis has been used to identify landowner types based on land management actions in Ireland and Switzerland (Howley 2013, Grêt-Regamey et al. 2019), and Kumer and Štrumbelj (2017) employed cluster analysis to identify different goals and values for small-scale private forest owners in Slovenia. We took the approach of Ferranto et al. (2013) and Sorice et al. (2014), who used factor analysis to identify landowner typologies in California and Texas rangeland based on ownership motivations, respectively.

We used our wetland mapping to count the number of natural-fed wetlands, irrigation-fed wetlands, ponds, and irrigated pastures on respondents' parcels in 2013. We fit generalized linear models in R (v3.2.2) to test for differences in number of each of these water features. Distributions were skewed (Figure A1.2), so we tested Poisson, quasi-Poisson (base package *stats*), negative binomial (package *MASS* v7.3), hurdle negative binomial, and zero-inflated negative binomial models using (package *pscl* v1.5). Standard errors, observed vs. expected zero counts, and maximum likelihood were used holistically to assess fit, and we determined a negative binomial fit best.

To assess response diversity we used survey-based methods that provided respondents different stimuli in hypothetical situations to which they are asked to state their preferences and hypothetical decision. Stated preferences and conjoint analysis are two popular forms of survey-based methods with a well-established literature (Louviere et al. 2010, Johnston et al. 2017). These methods estimate a function where the probability of a specific hypothetical action or answer depends on one or several stimuli variables. When a stimulus is a specific dollar amount to be paid that is randomly varied among the sample of respondents according to a pre-specified vector of values, an associated willingness to pay measure can be estimated. In our study, we adapted these methods by using potential water allocation cutbacks during drought as the stimuli and different potential land-based actions to be taken by the landowners as the response. As some of the presented actions are not mutually exclusive, we were able to generate a probability model for each action separately. While the social dimension of our study is based on hypotheticals, it was the best available approach for understanding potential landowner actions when facing further water cutbacks. An alternative would have been to monitor land-use decisions in response to actual stimuli, but that would require a long time horizon, and we would not have control over the variables. Moreover, it is extremely challenging to monitor individual landowner actions within their properties at a landscape scale.

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Our survey included a question asking landowners how they would respond to hypothetical water cutbacks of 20, 50, or 100% (each landowner was randomly asked about one of these cutback levels). We used logistic regressions (NLOGIT v5.0) to analyze landowner responses to hypothetical water cutbacks by modeling the probability of a landowner taking adaptive actions that would negatively impact wetlands (e.g., reducing irrigation) or a landowner's livelihood (e.g., ceasing livestock rearing; see Table A1.2 for details). Response options to cutbacks that we presented in the survey were based on preliminary interviews. A write-in option was available but rarely used, indicating the provided choices captured the likely responses. Aside from typology, we included cutback amount, property size, and household income as variables. The final model is in Table A1.2. Because of the inclusion of these non-random responses, we report results on the respondents rather than the population; the proportion of landowners in each typology was similar between respondents and full population estimates (3.5% mean absolute difference).

Black Rail occupancy modeling

We assessed the impact of water source diversity on the Black Rail metapopulation by fitting a multi-season occupancy model (MacKenzie et al. 2003) using Program PRESENCE v11.7 (Appendix 1). Potential covariates for probabilities of initial occupancy (ψ), colonization (γ), and extinction (ε) we assessed were water source and three nuisance variables: area (natural log of hectares + 1), isolation (an autoregressive 7 km buffer radius measure obtained from Hall et al. (2018), and year (a set of dummy variables; not included on initial occupancy). Detection (p) only included year as a covariate. Continuous variables were standardized.

We implemented our occupancy modeling in two phases. First, to reduce the size of the model set we carried out a backwards model selection exercise for the three nuisance covariates. Water source was included in all models and AIC was used to assess model fit. The lowest AIC model included area as a covariate on ψ, γ, and ε, and year as a covariate on γ (Table A1.3). Unlike previous studies in this system (Risk et al. 2011), there was only weak support (>3 ΔAIC) for isolation influencing occupancy dynamics during this time period, possibly due to very low colonization rates during the drought. In the second phase we retained the nuisance variables from the best model and then ran a full model set of all possible water source combinations (Table A1.4). For both phases, covariates were included for initial occupancy if they were included for either colonization or extinction.

Finally, we used AIC weights of the water source model set to calculate model-averaged estimates of occupancy in each year for an average wetland with each of the three water sources. Because area of wetlands significantly differed among water sources, we used the median area in our black rail sample for each category: 0.076 ha for natural-only, 0.168 ha for irrigation-only, and 0.284 for both-source. We used 95% confidence intervals calculated via the delta method to assess significant differences.

Appendix 1: Modeling methods and additional results

WNV modeling

From June–October 2012–2014, we trapped mosquitoes at 63 wetlands (size range 0.03–6.7 ha) for 1,201 total site visits. We sampled 50 wetlands for one year and 13 wetlands in all three years. We visited each wetland weekly and set up four Center for Disease Control traps baited with dry ice, distributed along the wetland edge at ≥100 m intervals to capture spatial variation in mosquito densities; at some very small wetlands, shorter intervals needed to be used. The same trap locations were used at each visit. All mosquitoes caught were identified to species using morphological keys (Darsie and Ward 1981). For each wetland, we estimated the abundance of the main mosquito WNV vectors as the mean number of *Culex* mosquitoes caught per trap/night (from 4,710 trap/nights).

To estimate WNV prevalence at each wetland, we first extracted RNA using RNeasy kits (Qiagen) followed by RT-PCR (Qiagen) on 2,551 pools of 1–50 *Culex* mosquitoes (Kauffman et al. 2003). We included at least one positive and negative control alongside each set of 40 reactions and all WNV-positive pools were run twice to confirm presence of WNV. In the few cases where a pool tested positive and then negative, we conducted a third test to determine WNV status. We then used bias-reduced generalized linear models using package *brglm* in R (v3.13) with a binomial distribution and an offset for mosquito pool size to estimate WNV prevalence using the presence/absence of WNV in 2,539 pools (mean 14.6 mosquitoes/pool). The full model included site, date, date^2, year, and interaction terms as predictors. The model with the lowest AIC (Table A1.5) was used to estimate WNV prevalence, the mean probability of a *Culex* testing positive for WNV at each wetland across all dates. Finally, we estimated WNV transmission risk at each wetland as the mean abundance of WNV-infected *Culex* mosquitoes (mean *Culex* abundance × mean *Culex* WNV prevalence).

We used analysis of covariance to test for effects of water source on the abundance of all mosquitoes, abundance of *Culex*, WNV prevalence, and WNV transmission risk, while controlling for the effect of wetland size (Fig. A1.1). We used a square root transformation on wetland size to equalize leverage and on all metrics involving mosquito abundance to maintain adequate homogeneity of variance.

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Table A1.1. AIC table for Tobit (censored 0–1) models of wetness of Sierra Nevada foothills wetlands, 2013–2016, with a random effect for site. Period is a factor representing 12 sampling time periods, source is a factor representing three water sources (natural-only, irrigation-only, both-source) and area was natural log of wetland size in hectares.

Model	AIC weight	ΔAIC	AIC	k
Period + source + source×period + area	0.766	0.00	294.95	45
Period + source + source×period + area + area×period	0.226	2.44	297.39	58
Period + source + source×period + area + area×period + source×area	0.005	10.26	305.21	60
Period + source + source×period + area + source×area	0.004	10.47	305.42	47
Period + source + source×period + area + area×period + source×area + source×area×period	0.000	25.63	320.58	86
Period + source + source×period	0.000	52.98	347.93	44
Period + source + area + area×period + source×area	0.000	61.65	356.60	32
Period + source + area + source×area	0.000	66.92	361.88	34
Period + area + area×period	0.000	74.11	369.06	30
Period + source + area + area×period	0.000	90.50	385.45	19
Period + source + area	0.000	93.50	388.45	21
Period + area	0.000	101.49	396.44	17
Period + source	0.000	139.21	434.16	18
Period	0.000	164.36	459.31	16

Table A1.2. Logistic regression coefficients (SE in parentheses) for Sierra Nevada foothills landowners' management actions in response to a hypothetical water availability cutback (either 20, 50, or 100%; included as a continuous covariate) from all sources (*n = 274)*. Asterisks (*, **, ***) denote significance at the 10, 5, and 1% levels.

Class	Wetland-impacting action[a]	Landowner-impacting action[b]
Intercept (investment-motivated)	-1.1503*** (0.3732)	-0.7160** (0.3385)
Profit-motivated	2.2133*** (0.5032)	2.0702*** (0.4937)
Tradition-motivated	1.1467** (0.4924)	0.7343 (0.4615)
Lifestyle-motivated	1.1178** (0.4763)	0.7979* (0.4474)
Environment-motivated	0.2088 (0.5165)	0.7538 (0.4597)
Recreation-motivated	0.1437 (0.4857)	-0.1673 (0.4572)
Water cutback (%)	-0.1934 (0.2690)	0.2178 (0.2590)
Household income ($ 2013)	0.7315*** (0.2781)	0.1301 (0.2662)
Property size (acres)	0.6822* (0.3935)	0.6105* (0.3666)

[a] Includes responses "Repair leaks in ditches, pipes, dams and/or ponds", "Recycle and/or reuse tailwater, irrigation or pond runoff", "Stop or use less water to irrigate pasture(s)" and "Reduce area of irrigated pasture".

[b] Includes responses "Stop or reduce growing crops or gardening", "Sell livestock or reduce stocking rate", "Find other grazing land", "Sell some or all the land", "Purchase water from outside (non-district) sources" and "Change to a different land use.

Table A1.3. Backwards stepwise AIC model selection table for a multi-season occupancy model for the Sierra Nevada foothills metapopulation of the California Black Rail (*Laterallus jamaicensis coturniculus*), 2012–2016. Starting with the full model (step 0), nuisance parameters (area, isolation, and year) were removed one at a time, and the lowest AIC was selected. The process was repeated until we found the lowest AIC (bold). Water source (natural, irrigated, or both; irrigated left out) was in all models.

Step	Model	AIC weight	ΔAIC	AIC	k
3	Ψ(area, nat‡, both), γ(year, area, nat, both), ε(area, nat, both), p(.)	0.2199	1.32	1450.17	16
3	Ψ(area, nat, both), γ(year, nat, both), ε(year, area, nat, both), p(.)	0.0643	3.78	1452.63	18
3	Ψ(area, nat, both), γ(area, nat, both), ε(year, area, nat, both), p(.)†	0.0104	7.43	1456.28	16
2	**Ψ(area, nat, both), γ(year, area, nat, both), ε(year, area, nat, both), p(.)**	**0.4255**	**0.00**	**1448.85**	**19**
2	Ψ(area, iso§, nat, both), γ(year, area, iso, nat, both), ε(area, nat, both), p(.)	0.064	3.79	1452.64	18
2	Ψ(area, iso, nat, both), γ(year, iso, nat, both), ε(year, area, nat, both), p(.)	0.0404	4.71	1453.56	20
2	Ψ(area, iso, nat, both), γ(area, iso, nat, both), ε(year, area, nat, both), p(.)†	0.0033	9.73	1458.58	18
2	Ψ(area, nat, both), γ(year, area, nat, both), ε(year, nat, both), p(.)	0.0000	29.91	1478.76	18
1	Ψ(area, iso, nat, both), γ(year, area, iso, nat, both), ε(year, area, nat, both), p(.)	0.1171	2.58	1451.43	21
1	Ψ(area, nat, both), γ(year, area, nat, both), ε(year, area, nat, both), p(year)	0.0355	4.97	1453.82	23
1	Ψ(area, iso, nat, both), γ(year, area, iso, nat, both), ε(area, nat, both), p(year)	0.0077	8.03	1456.88	22
1	Ψ(area, iso, nat, both), γ(year, iso, nat, both), ε(year, area, nat, both), p(year)	0.0026	10.18	1459.03	24
1	Ψ(area, iso, nat, both), γ(area, iso, nat, both), ε(year, area, nat, both), p(year)†	0.0002	15.33	1464.18	22
1	Ψ(area, iso, nat, both), γ(year, area, iso, nat, both), ε(year, nat, both), p(.)	0.0000	32.02	1480.87	20
1	Ψ(area, iso, nat, both), γ(year, area, iso, nat, both), ε(year, nat, both), p(year)	0.0000	34.44	1483.29	24
0	Ψ(area, iso, nat, both), γ(year, area, iso, nat, both), ε(year, area, nat, both), p(year)	0.0091	7.68	1456.53	25
Null	Ψ(.), γ(.), ε(.), p(.)	0.0000	111.10	1559.95	4

† Models that did not include a year effect on γ could not estimate SE for natural because the beta estimate was infinitely negative

‡ Natural

§ Isolation

Table A1.4. AIC table for multi-season occupancy models for the Sierra Nevada foothills metapopulation of the California Black Rail (*Laterallus jamaicensis coturniculus*), 2012–2016, to assess the impact of water source on occupancy. All models except for the "true null model" have area as a covariate for Ψ, γ, and ε, and year dummy variables as covariates for γ and ε.

Model	AIC weight	ΔAIC	AIC	k
Ψ(natural, both), γ(natural, both), ε(natural), p(.)	0.3017	0.00	1447.35	18
Ψ(natural, both), γ(natural, both), ε(.), p(.)	0.2235	0.60	1447.95	17
Ψ(natural, both), γ(natural, both), ε(natural, both), p(.)	0.1425	1.50	1448.85	19
Ψ(natural, both), γ(natural, both), ε(both), p(.)	0.0895	2.43	1449.78	18
Ψ(natural), γ(natural), ε(natural), p(.)	0.0667	3.02	1450.37	16
Ψ(natural, both), γ(both), ε(natural), p(.)	0.0496	3.61	1450.96	17
Ψ(natural), γ(natural), ε(.), p(.)	0.0479	3.68	1451.03	15
Ψ(natural, both), γ(both), ε(natural, both), p(.)	0.0245	5.02	1452.37	18
Ψ(natural, both), γ(natural), ε(natural, both), p(.)	0.0236	5.10	1452.45	18
Ψ(natural, both), γ(natural), ε(both), p(.)	0.0156	5.93	1453.28	17
Ψ(both), γ(both), ε(.), p(.)	0.0098	6.86	1454.21	15
Ψ(both), γ(both), ε(both), p(.)	0.0039	8.72	1456.07	16
Ψ(natural), γ(.), ε(natural), p(.)	0.0008	11.81	1459.16	15
Ψ(natural, both), γ(.), ε(natural, both), p(.)	0.0003	13.84	1461.19	17
Ψ(both), γ(.), ε(both), p(.)	0.0000	17.78	1465.13	15
Ψ(.), γ(.), ε(.), p(.)	0.0000	17.84	1465.19	13
True null model	0.0000	112.60	1559.95	4

Table A1.5. AIC table for bias-reduced general linear models (binomial distribution and offsets accounting for differences in number of mosquitoes per pool) used to estimate West Nile virus prevalence at wetlands (*n* = 63) in the Sierra Nevada foothills.

Model	AIC weight	ΔAIC	AIC	k
site + date + date^2 + year	0.501	0.0	1561.30	67
site + date + date^2	0.394	0.5	1561.78	65
site	0.075	3.8	1565.09	63
site + date	0.030	5.7	1566.95	64
site×date + date2 + year	0.000	76.9	1638.23	129
site×date + site×date^2 + year	0.000	183.1	1744.44	191
site×date + site×date^2 + site*year	0.000	207.4	1768.69	215

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Figure A1.1. Relationships between wetland size and three elements of West Nile virus transmission risk in the Sierra Nevada foothills. (a) Mean number of all mosquitoes caught per trap/night increased with wetland size ($abundance^{0.5} = 2.94 + 1.74 * size^{0.5}$, $r^2 = 0.27$, $p < 0.001$). (b) Mean number of *Culex* mosquitoes caught per trap/night increased with wetland size ($abundance^{0.5} = 2.31 + 0.81 \times size^{0.5}$, $r^2 = 0.12$, $p = 0.005$). (c) There was no relationship between mean West Nile virus prevalence in *Culex* and wetland size ($p = 0.671$).

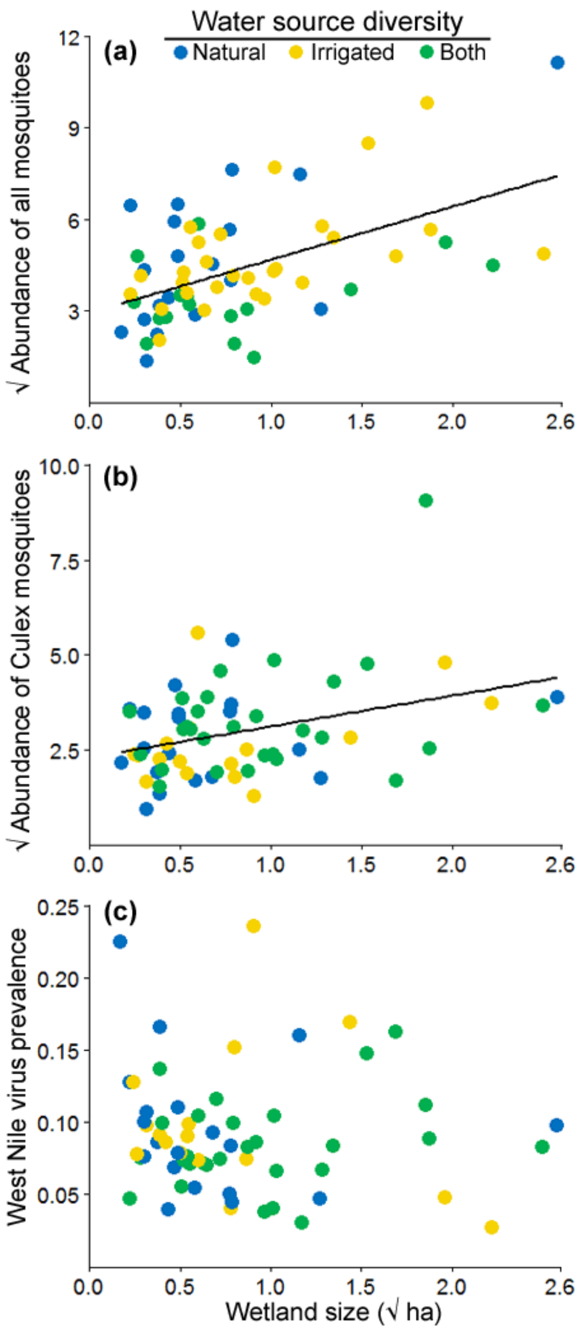

Figure A1.2. Histograms (15 bins) of the number of (a) natural-fed wetlands and (b) irrigation-fed wetlands on n = 351 landowner respondents' properties. One outlier recreation-motivated landowner with 138 irrigation-fed wetlands was excluded from panel b.