Species Conservation on a Working Landscape: The Joint Production of Wildlife and Crops in the Yolo Bypass Floodplain

Cloé Garnache and Richard E. Howitt

Department of Agricultural and Resource Economics
University of California, Davis

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2011 AAEA & NAREA Joint Annual Meeting, Pittsburgh, Pennsylvania, July 24- 26, 2011.

Abstract

California is facing a severe water crisis. Water resources allocation creates conflicts among urban users, farmers, and environmentalists. Large diversions of water for agriculture and urban uses restrict habitat for native fish species contributing to the fish population collapse in the Sacramento-San Joaquin Delta. Efficiently allocating water between water uses is a current policy priority.

The Yolo Bypass floodplain, located in the Delta, is at the center of the debate. It provides unique habitat to native fish species, agricultural production, and flood protection to the city of Sacramento. The seasonal flooding of Yolo Bypass provides critical habitat to Chinook salmon. Yet, it may conflict with agricultural production, in particular rice farming. Managing Yolo Bypass for the joint production of wildlife and crops is critical to achieve efficient water allocation and species conservation objectives.

We develop a model that captures the marginal benefit to the commercial Chinook fishery and the opportunity cost to Yolo Bypass agriculture. Habitat provision affects both the crop yields and the fish stock—through greater survival rate of the juvenile Chinook salmon that use the inundated floodplain. We explicitly model how these two activities are affected by the habitat and allow for feedback between the fishery and agricultural production models such that crop acreages and harvest are endogenous to the model. The question presents a unique challenge for economists because the spatial and temporal scales of these models differ widely. While economic models can be aggregated for estimation and are normally predicated on yearly cropping decisions, biological models are sensitive to habitat variation over short distances and weekly, if not daily, changes. Our model uses a calibration approach to formally model the opportunity cost to agriculture.

1 Introduction

California is facing a severe water crisis. Water scarcity and environmental issues raise conflicts among urban users, farmers, and environmentalists over the allocation of water resources. Urban and agricultural demands for water are increasing, exerting greater pressure on an already strained system (Bay Delta Conservation Plan, Steering Committee, 2010). At the heart of California water debate is the Sacramento-San Joaquin Delta that provides water to about two-thirds of the population and millions of acres of irrigated farmland. Yet, the Delta's ecology is collapsing as the large quantities of water diverted have led to substantial habitat loss and imminent extinction of native fish species (Lund et al., 2007; Sommer et al., 2007).

The Yolo Bypass floodplain, located in the Sacramento-San Joaquin Delta, has recently received increasing attention as a potential solution. Appropriately managed floodplains, in general, provide multiple benefits to society in a synergistic way. In addition to their intrinsic ecological values, they support agriculture and commercial and recreational fishing, and supply substantial quantities of water for irrigation and urban use (Sommer et al., 2001a; Schluter et al., 2009). Studies suggest that more flooding of the Yolo Bypass increases benefits to native fish species, in particular juvenile Chinook salmon that use the floodplain as nursery habitat (Sommer et al., 2001a,b; Feyrer et al., 2006).

The Sacramento River Chinook salmon contributes to large commercial and recreational fisheries. Yet, Chinook populations have dramatically declined (California Department of Fish and Game, 2011). Winter-run Chinook are listed as endangered, spring-run as threatened, and fall- and late-fall run as Species of Concern under the federal Endangered Species Act. California fisheries rely on the fall-run. It is the most abundant of the Sacramento River runs as a result of its large hatchery component. Yet, the Sacramento fall-run Chinook recently collapsed and the California and Oregon fisheries closed in 2008 and 2009 triggering $170 million in federal disaster payments

(Upton, 2010). The National Marine Fishery Service identified unfavorable ocean conditions as the primary cause of the Sacramento fall Chinook population decline. However, it also found that the stock was more susceptible to poor ocean conditions because of freshwater habitat degradation.

The Yolo Bypass floodplain (Yolo County, California) is an ideal case study to analyze the tradeoffs among the joint production of multiple ecosystem services. It is a working landscape that contributes to crop production and habitat provision to juvenile Chinook salmon. When flooded in the winter Yolo Bypass provides valuable seasonal aquatic habitat to native fish species that forage and spawn on the submerged vegetation (Sommer et al., 2001a,b). Yet, late flooding may cause farmers to adjust their cropping program, shift to shorter season agriculture or reduce farmland.

The 24,000-hectare leveed floodplain was designed in the early 1930s as part of the Sacramento Flood Control Project (Sommer et al., 2001a). The state of California has authority on the flooding of the Yolo Bypass. When the flow exceeds some threshold in the Sacramento River, water is diverted into the Yolo Bypass at the Fremont Weir, north of Sacramento (the floodwaters then drain back into the Sacramento-San Joaquin Delta). About 75% of Yolo Bypass is privately owned while the rest is part of the Yolo Bypass Wildlife Area, which is managed by the California Department of Fish and Game. Two-thirds of the floodplain is used for agriculture in the spring and summer while the rest is mostly wetlands. Land in the Yolo Bypass is restricted by easements that grant the state the right to inundate it with floodwaters. These easements also prevent landowners from building structures or growing vegetation that would significantly obstruct flow conveyance. The state does not provide compensation to private landowners or the Wildlife Area for losses due to flooding. Yet, the state objective is to manage the flooding of the Yolo Bypass to maximize welfare, in particular for Yolo Bypass farmers and California Chinook fishers.

Based on the principle of co-equal goals defined by Bay Delta Conservation Plan, Steering Committee (2010), we allocate land between habitat provision and another economic activity equates the marginal benefits from conserving a unit of land for habitat to its opportunity cost.

The species that use this habitat generate benefits to economic activities such as hunting or fishing.[1] The habitat provision in turn affects the returns to both activities. Policy-makers interested in designing habitat conservation policies should jointly consider conservation, wildlife harvesting, and other activities that may depend on this area—for example agriculture (Bulte and Horan, 2003). Previous studies have called for the need to better integrate the disciplines of ecology and economics to gain understanding about the interdependencies that characterize human-dominated environments and to help policy-makers make more informed decisions about how to efficiently protect the environment (Settle et al., 2002; Shogren et al., 2003). Settle et al. (2002) find that omitting the feedback between economic and ecological models may lead to erroneous results and inefficient policies.

Optimal floodplain management requires the joint analysis of agricultural production and native species population dynamics. We develop a model that models the marginal benefit to the Chinook fishery and the opportunity cost to the Yolo Bypass agriculture. Increased habitat provision reduces the yield potential of the crops grown in Yolo Bypass but increases the adult fish stock—through greater survival rates of juvenile Chinook salmon. We explicitly model how the two economic activities are affected by habitat provision in Yolo Bypass and allow for feedback between the fishery and agricultural production models such that crop acreages and harvest are endogenous. The question presents a unique challenge for economists because the spatial and temporal scales of these models differ widely. While economic models can be aggregated for estimation and are normally predicated on yearly cropping decisions, biological models are sensitive to habitat variation over short distances and weekly, if not daily, changes.

The current literature on habitat conservation and wildlife harvesting typically specifies individual private agents who decide whether or not to conserve habitat on their land—e.g., Bulte and Horan (2003)—or a single agent or group that decides how much habitat to conserve—e.g.,

[1]These species may also have an existence value. Yet, this paper focuses on use values.

Skonhoft (1999). Our paper combines these two approaches. A social planner chooses the habitat level that balances the benefits of wildlife harvesting and cost to agriculture, while individual agents—farmers and fishers—maximize their profit given the habitat constraint.[2]

Previous literature on habitat provision and species conservation typically focuses on the optimal spatial allocation of land to either habitat for species conservation or another economic activity. We extend the literature by studying a landscape that is managed for mixed uses where the timing of allocation to these different land uses is critical to both activities. In the Yolo Bypass the question becomes where and when to switch land use between habitat and agriculture instead of restricting the decision to how much land to conserve for habitat. We use a calibration approach to estimate production functions for crops and fish that are functions of daily flooding decisions such that policy-makers can choose the time allocation to habitat and agricultural production that equates marginal benefit to marginal cost. This framework may be applied to other working landscapes where habitat has a seasonal component such as habitat for migratory bird or anadromous fish species.

Most of the literature on species conservation considers the landscape as either protected or unprotected with the assumption that only protected areas contribute to meeting conservation targets. This approach to conservation planning ignores the substantial contribution of non-protected land uses. Yet, recent studies have moved beyond that binary approach and looked at working landscapes that contribute simultaneously to production and species conservation (Nalle et al., 2004; Polasky et al., 2005; Wilson et al., 2007; Nelson et al., 2008; Wilson et al., 2010). Nalle et al. (2004); Polasky et al. (2005) analyze the joint production of wildlife and marketed commodity in the Willamette Basin, Oregon. They find that higher level of species conservation can

[2]This is an externality problem where habitat provision in Yolo Bypass generates a positive externality on fishers but negative on farmers. In theory, fishers and farmers would trade units of habitat until the marginal benefit of the last unit of habitat to the fishery equates its marginal cost to agriculture. However, because the state of California is in charge of the Fremont Weir operation for flood protection control, we consider a social planner approach.

be cost-effectively achieved compared to the reserve-site approach. Wilson et al. (2010) find that conservation planning that includes the contribution of production landscapes in East Kalimantan (Indonesian Borneo) can achieve biodiversity conservation goals more cost-effectively than traditional planning approaches. Our paper contributes to the literature on the conservation benefits of working landscapes. These landscapes are common in human-dominated environments and managing them for mixed uses may cost-effectively contribute to both production and species conservation objectives.

This work lies at the intersection between terrestrial and marine economic activities. For example, Bulte and Horan (2003); Skonhoft (1999) analyze agriculture, hunting and habitat conservation. Bulte and Horan (2003) develop a theoretical model of optimal allocation of land among habitat conservation and agricultural expansion. Individual agents allocate their time between wildlife extraction and agricultural production. The opportunity cost of time allocated to farming is the foregone returns from harvesting wildlife, and reciprocally; it is therefore endogenous to the model. Skonhoft (1999) study the optimal allocation of land between habitat provision and agriculture in East Africa where a group of agents jointly decide on the optimal levels of harvesting of terrestrial species and cattle grazing. Other studies focus on habitat conservation and its effect on fisheries or fish population dynamics. Sanchirico and Springborn (2011) develop a bioeconomic model of a coral reef-mangrove-seagrass system to analyze the tradeoffs between conserving mangrove for fish species and clearing the mangrove for development. Their ecological model nests facultative and obligate species-habitat associations where the size of the mangrove habitat affects juveniles survival. Using a social planner approach, they solve for the optimal paths of fish catch and mangrove conversion that maximize the net present value from fishing, mangrove development, and storm protection benefits. Newbold and Siikamäki (2009) use reserve site selection based on cost-effectiveness criterion to prioritize conservation activities in the upper Columbia River basin. We model two economic sectors: fishery and agriculture, that are connected through the nursery habitat that the Yolo Bypass provides to juvenile Chinook salmon.

Furthermore, we argue that the opportunity costs of habitat conservation may not be constant. Newbold and Siikamäki (2009) and Sanchirico and Springborn (2011) assume fixed opportunity costs. In this example timing, not area, is the driving variable. It is likely that flood timing affects crop yields non-linearly. In addition, we believe that the behavioral response of farmers in the Yolo Bypass may allow them to minimize the marginal cost of early floods, however, late flood policies can be very costly. For example, farmers may respond to early floods by adjusting their cultural practices and switching to shorter growing crops and thus face relatively small and constant marginal cost. However, farmers may not have any ways to mitigate late floods—facing large and rising marginal costs.

This paper analyzes the joint management of the California commercial Chinook fishery and farming in the Yolo Bypass subject to flood protection control. In addition to specifying the crop acreages and harvest as endogenous, we also allow feedback on the fishery regulation such that the total allowable catch (TAC) is a function of the escapement.

This paper contributes to the understanding of the tradeoffs between habitat provision, flood protection, agriculture and fishery management on working landscapes. We investigate how managing these two economic activities jointly may increase welfare.

2 Bioeconomic model

We develop an optimal control model to analyze the tradeoffs between agriculture and habitat provision to a native fish species: the Sacramento River fall-run Chinook salmon (*Oncorhynchus tshawytscha*). Our study focuses on the habitat benefits accrued to the commercial Chinook fishery. Assuming a social planner manages the Yolo Bypass floodplain to maximize the joint profits of agriculture in the bypass and its contribution to the California Chinook commercial fishery, we solve for the last day of inundation, crop mix and acreages, and fish catches. The last day of inundation implicitly determines the lengths of the flooding and agricultural seasons because it marks the cut-off date when the flooding season ends and the agricultural season begins. Bay Delta Conservation Plan, Steering Committee (2010) finds that flows between 3,000 and 10,000 cubic-feet per second (cfs) between February and early June provide the most benefits to native fish populations. The flow entering Yolo Bypass at Fremont Weir determines the area inundated. Figure 4 in the appendix shows the area inundated for flows ranging from 1,000 to 10,000 cfs. The area inundated for the recommended flows at or above 3,000 cfs does not vary substantially between 3,000 and 10,000 cfs (25,000 and 30,000 acres, respectively). The difference in the number of agricultural fields that are affected by flows of 3,000 relative to 10,000 cfs represents less than 5% of the total number of fields included in the 10,000 cfs region. Because farmers make their cropping decisions at the field level, the results would not vary much by developing a spatially-explicit model for the 10,000 cfs region. The flow entering Yolo Bypass affects agriculture mostly through a temporal component rather than a spatial component. Therefore, we work with the 10,000 cfs region and develop a model that captures the temporal effect of the amount of flow that enters the floodplain.[3]

2.1 Agricultural production model

We develop an agricultural production model that solves for the acreages x_i for crop i maximizing the regional agricultural profit $\Pi_{ag}(\mathbf{x}, y)$ in Yolo Bypass as a function of the last day of inundation y. The region that is inundated at 10,000 cfs flow covers about 30,000 acres. We focus on the six crops the most widely grown in this region: rice, safflower, processing tomato, corn, sunflower,

[3] Yet, the height of the water column on the fields is a function of the flow and it controls how long the fields take to drain—flows of 10,000 cfs may take 3 additional weeks to drain relative to flows of 3,000 cfs. Thus, the larger the flow the more delayed planting may be and the higher the potential impact on agriculture. In our next model extension, we will allow for the flow to have various lags on the planting date and quantify the effects of flow on juvenile Chinook survival.

and irrigated pasture. These crops cover an average of 26,000 acres over 2005-2009 (Pesticide Use Reports).

The most disaggregated available yield data is at the county-level. However, Yolo Bypass soils differ from the soils that characterize the rest of the county because of its proximity to the Sacramento River and frequent flooding. As a result, Yolo Bypass yields are generally different from the average county yields.[4] Therefore, we have to use Yolo Bypass specific-yield data to accurately analyze the tradeoffs between agriculture and habitat provision for juvenile Chinook. In addition, we are interested in estimating the yield response to changes in flooding conditions to predict farmers' crop mix decisions. We decide to use the agronomic model DAYCENT to simulate Yolo Bypass specific-yield data and estimate the yield response to flooding and delayed planting.[5] The DAYCENT model is currently not calibrated for irrigated pasture. As a result, we use farmers reported yield for an average field in Yolo Bypass.

Generating Yolo Bypass specific-yield data

The DAYCENT model is the daily time step version of the well-known CENTURY biogeochemical process model. It was developed to simulate the major processes that affect soil organic matter, such as plant production, water flow, nutrient cycling and decomposition (Parton et al., 1998). Besides detailed soil and climate data, the two key inputs needed to accurately simulate yield are water and nitrogen application rates. We use the water input reported in the cost and returns studies of the University of California Cooperative Extension and recover the nitrogen rate such that the DAYCENT model's average yield at the county level matches the yield from the Agricultural Commissioner reports for Yolo County. We assume yields vary spatially across the county because of climate and soil conditions but we assume that management practices are constant across the

[4] Yolo Basin Foundation (2001, chap 2) points out that yields are lower in Yolo Bypass because of heavier soil and colder microclimate relative to the rest of the county.

[5] The DAYCENT model has been used for studies in Yolo County (De Gryze et al., 2009; Howitt et al., 2009).

county. Thus, we use the DAYCENT model to simulate Yolo Bypass specific-yields using the county average water and nitrogen application rates that are consistent with the average yields reported for Yolo County. The model typically generates lower yields for Yolo Bypass relative to the average county yields, which is consistent with farmers' observations.

The 31 flood scenarios simulated with the agronomic model DAYCENT, in terms of the last day if inundation and total number of days of inundation over the flood season, are presented in table 4 in the appendix. There may be multiple flood events during the flood season. The last day of inundation corresponds to the last day of inundation of the last flood event of the flood season. The flood season typically starts in December. However, we do not focus on the beginning of the flood season because the tradeoffs between agriculture and fall-run Chinook salmon occur over February-June. We simulate scenarios with variable total number of days of inundation in the flooding season to measure the effect of the number of flood days on agronomic yields. For a given last day of inundation we simulate between one and four flood events with equal number of days and uniformly distributed between January 1st and the last day of inundation.

We generate crop yield data for each field in the 10,000 cfs region using the DAYCENT model. The area consists of 162 agricultural fields. However, we aggregate adjacent fields that show similar soil characteristics because the DAYCENT model does not generate yield variation for fields with identical conditions. As a result, we run the DAYCENT model on 33 agronomic fields. The model is run over the period 1984-2009 and uses crop rotations commonly observed in the Sacramento Valley. Because rice is grown in continuous rotation, we allocate 11 fields to rice production, while the other crops are grown in rotations on the remaining 27 fields. We assume that all crops are grown conventionally and according to the management practices reported in the cost and return studies of the University of California Cooperative Extension. We use this panel dataset to recover the average yield for each crop over the period 2005-2009.

Estimating the agricultural production functions

We estimate crop-specific agricultural production functions using the Yolo Bypass yield data generated with the DAYCENT model. Our hypothesis is that yield responds to the land input, the last day of inundation and the total number of days of inundation during the flood season. The amount of land brought into the production of a given crop may reduce its yield as less productive land may become farmed. The last day of inundation can reduce yield as it may shorten the growing season for a crop. It is particularly important for rice since it is a crop with a long vegetative growth period such that the grain filling period generally occurs in September and cannot be delayed due to insufficient degree days in the fall. The net effect of the total number of days of inundation on crop yield is ambiguous. On the one hand, it may contribute to soil moisture and prevent potential water stress to the plant, but on the other hand, it may lower yields by favoring anaerobic conditions in the soil and thus limiting the availability of nitrogen to the plant during the growing season.

To capture the effect of bringing less productive farmland into the production of a given crop, we aggregate fields in decreasing order of yield. This results in 27 acreage data points for corn, safflower, sunflower and processing tomato and 11 acreage data points for rice—from the most productive field to all fields combined. By construction, yield shows decreasing returns to acreage and the production function is concave. Plotting these yield data against the last day of inundation shows that the yield response to the last day of inundation is highly non-linear, see figure 1. Crops have very different responses to the last day of inundation. The yields of rice, safflower, corn, processing tomato, and irrigated pasture (in animal unit months—AUM) are not affected by flooding until a crop-specific threshold. After that threshold, their yield dramatically drops (to zero for safflower, rice and corn). Yet, sunflower's yield shows a relatively small and smooth response to the last day of inundation.

We specify crop-specific fixed-proportion production functions $q_i = yld_i x_i$ such that yield for crop i is

$$yld_i = \alpha_i x_i^{\delta_i - 1}.$$

Parameter α_i is the scale parameter and δ_i is the returns to scale. Because we do not observe variation in input use, all inputs are set in fixed proportions with the land input. Note, therefore, that we only look at the extensive margin adjustment.

We estimate a series of models to explain crop yield variation with acreage x_i, last day y and total number of days of inundation z as our independent variables. We find that the model that fits the data the best is one for which inundation affects yield through an inverse logistic scaling factor. We compare the goodness of fit of two nested models. The unrestricted model for crop i includes both last day y and total number of days of inundation z

$$yld_i = \frac{\alpha_i x_i^{\delta_i - 1}}{1 + e^{\gamma_{0i} + \gamma_{1i} y + \gamma_{2i} z}} + \epsilon_i \tag{1}$$

and the restricted model for crop i excludes the total number of days of inundation z

$$yld_i = \frac{\alpha_i x_i^{\delta_i - 1}}{1 + e^{\gamma_{0i} + \gamma_{1i} y}} + \epsilon_i \tag{2}$$

For rice, corn, safflower and sunflower, we cannot reject that $\hat{\gamma}_{2i}$ is not different from 0 (P-value>0.1) in model (1) using a post-estimation non-linear test and we cannot reject that the restricted model (2) is better than the unrestricted model (1) (P-value>0.1) using the likelihood ratio test. We also find that the AIC is lower for model (2) than for model (1). In contrast, for tomato we reject at the P-value=0.001 that $\hat{\gamma}_{2i}$ is not different from 0 in model (1), we reject at the P-value=0.001 that the restricted model (2) is better than the unrestricted model (1) using the likelihood ratio test, and AIC is lower for model (1) than for model (2). Therefore, we choose the unrestricted model (1) for tomato and the restricted model (2) for rice, corn, safflower and sunflower. Because we do not have field data or number of flood day variations for irrigated pasture we estimate $yld_i = (1 + e^{\gamma_{0i}+\gamma_{1i}y})^{-1}\alpha_i + \epsilon_i$ for the average yield reported by farmers for different last day of inundation, and assume the returns to scale δ_i is 0.96. Estimates of the agricultural production functions are presented in table 1. We are not interested in including the total number

Table 1: Estimated agricultural production functions. All estimates are significant at P-value$<$ 0.001. Standard errors are in parenthesis.

Crop	$\hat{\alpha}$ (se)	$\hat{\delta}$ (se)	$\hat{\gamma}_0$ (se)	$\hat{\gamma}_1$ (se)	$\hat{\gamma}_2$ (se)
Corn	11.18 (0.62)	0.92 (0.01)	-27.36 (2.57)	0.24 (0.02)	-
Sunflower	1.28 (0.03)	0.93 (0.00)	-4.70 (0.26)	0.03 (0.00)	-
Safflower	3.79 (0.17)	0.86 (0.01)	-11.63 (0.57)	0.12 (0.01)	-
Rice	5.64 (0.22)	0.96 (0.01)	-39.46 (3.10)	0.41 (0.03)	-
Tomato	57.56 (0.84)	0.96 (0.00)	-8.00 (0.20)	0.06 (0.00)	-0.004 (0.001)
Pasture	8.22 (0.23)	0.96	-5.37 (0.64)	0.05 (0.01)	-

of days z as a control variable because for a given last day of inundation y fish biologists determine the level of the variable z along with the number of flood events during the flooding season that maximize benefits to Chinook. In addition, the estimate $\hat{\gamma}_2$ is an order of magnitude smaller relative to $\hat{\gamma}_1$ and does not change the predicted yields. Therefore, for the rest of the analysis we fix the total number of days of inundation z to its value observed over 2005-2009 $\bar{z} = 14$ days.

Figure 1 shows the predicted yields for three levels of land in production: 10% and 50% of the most productive land for that crop in the region and 100% (all) of the land in the region.

Agricultural production model and calibration

Using the estimated agricultural production functions $q_i = y\hat{l}d_i x_i$ for all crop i, the regional agricultural production model is written

$$\max_{\mathbf{x}} \ \Pi_{ag}(\mathbf{x}, y) = \sum_i \frac{p_i \hat{\alpha}_i x_i^{\hat{\delta}_i}}{1 + e^{\hat{\gamma}_{0i}+\hat{\gamma}_{1i}y+\hat{\gamma}_{2i}\bar{z}}} - (c_i + \lambda_{2i})x_i - fc_{rice} \quad \text{subject to} \quad \sum_i x_i \leq \bar{L}$$

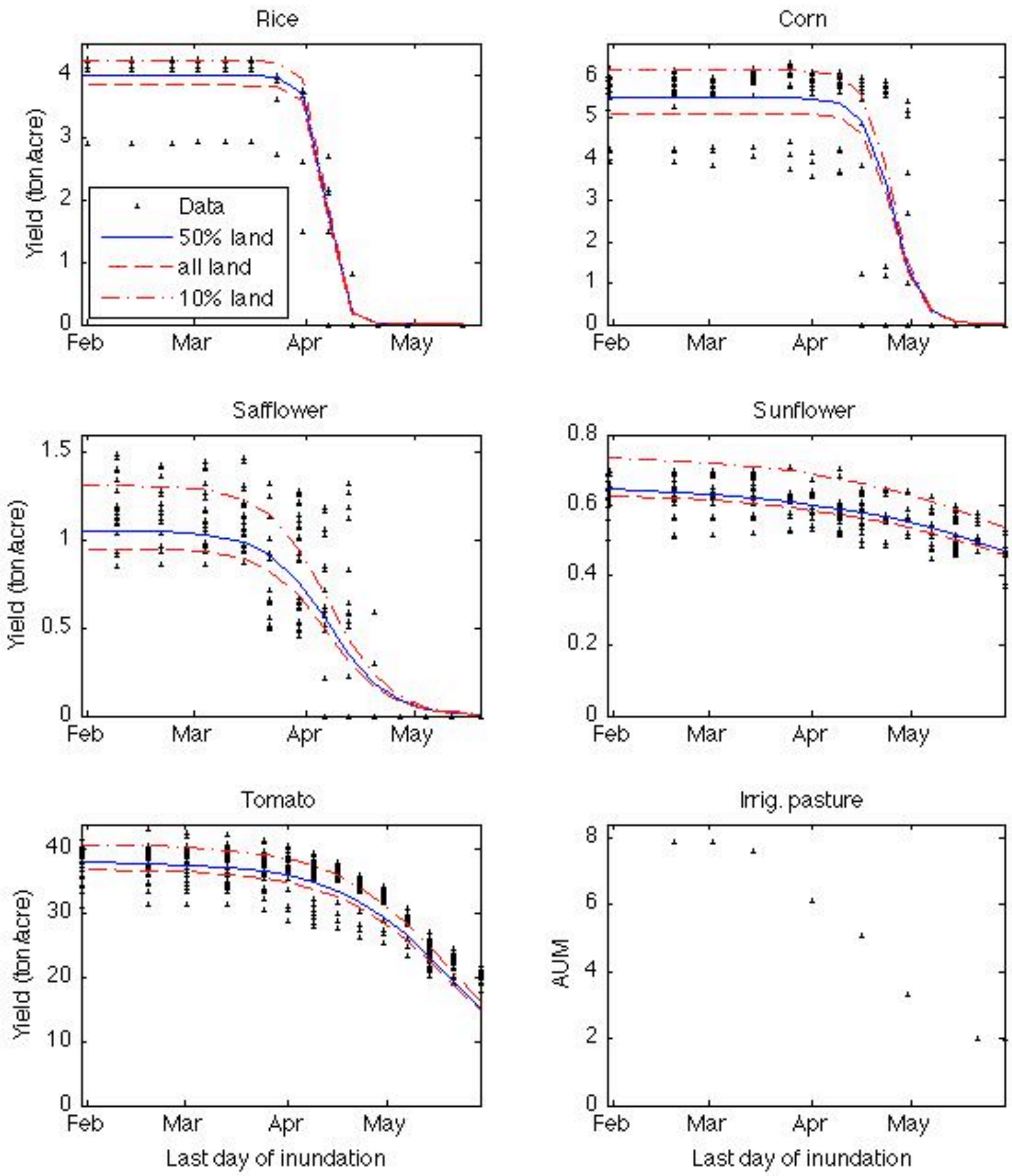

Figure 1: Crop-specific yield data and predicted responses to the last day of inundation and acreage in production

where p_i is output price, c_i is the per acre cost of activity i, $\bar{L}$ is the regional land constraint and λ_{2i} is a crop-specific adjustment cost term. $\hat{\gamma}_{2i}$ is set to zero for all crops but rice and tomato. fc_{rice} is a fixed cost from switching land from rice into field crop production.[6] We specify a quadratic switching cost $fc_{rice} = fc(\bar{x}_{rice} - x_{rice})^2$ if $\bar{x}_{rice} > x_{rice}$ ($fc_{rice} = 0$ otherwise) to reflect that converting a small amount of land out of rice may be common practice, however, because two-third of the farmland modeled in the region is currently in rice production switching a substantial amount of land out of rice may be prohibitively expensive—and potentially technically infeasible.

We calculate the 2005-2009 crop acreages in the 10,000 cfs region using field-level data from the Pesticide Use Reports. We use crop prices for Yolo County from the Agricultural Commissioner Reports and representative cost data for the Sacramento Valley from the cost and returns study of the University of California Cooperative Extension. We observed the last day of flooding from flow data collected by the California Department of Water Resources, see table 5 in the appendix. The last day of inundation was on average on March 1st over 2005-2009.

We calibrate the agricultural production model to the reference allocation 2005-2009 using positive mathematical programming (PMP), a widely used calibration method for agricultural production analysis (Howitt, 1995a,b). The term λ_{2i} ensures that the model exactly calibrates to the reference allocation in terms of acreages $\bar{\mathbf{x}}$: $\lambda_{2i} = p_i \hat{\delta}_i y \hat{l} d_i - (c_i + \lambda_1)$ for crop i where all variables are observed at the 2005-2009 allocation (Mérel et al.). The shadow price of land λ_1 is estimated during the first stage of PMP. Note that land is the only binding constraint in the region.

Estimating the agricultural profit as a function of the last day of inundation

Using the calibrated agricultural production model we solve for the crop acreages that maximize the regional agricultural profit as an implicit function of the last day of inundation y. Figure 2

[6] This cost is important because farmers have to conduct a series of operations to make a rice field suitable for field crops, including removing the checks, discing the hard clay soil, and laser-leveling for furrow irrigation. This switching cost is estimated at $204-235 per acre based on the cost and returns studies.

shows the optimal crop mix and acreages, the regional agricultural profit, the opportunity cost and the incremental cost of flooding as a function of the last day of inundation y. Farmland represents

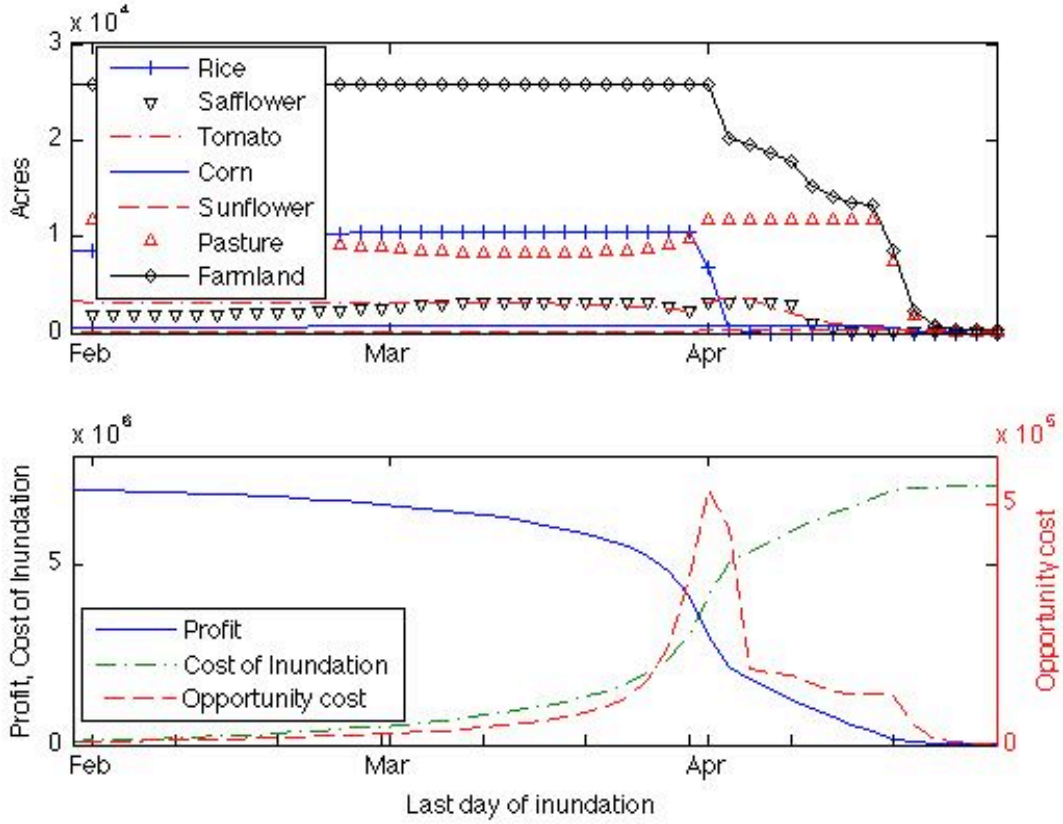

Figure 2: Optimal crop acreages, agricultural profit, opportunity cost and incremental cost as a function of the last day of inundation.

the acreage of the six crops modeled: rice, safflower, processing tomato, corn, sunflower and irrigated pasture. The opportunity cost is the marginal cost of an additional day of inundation on agriculture in Yolo Bypass. We also depict the incremental cost that shows the total cost of flooding on agriculture. When the last day of inundation occurs prior to March 1st, the agricultural production model predicts that farmers choose a relatively constant crop mix. Profit is relatively stable and the opportunity of flooding on Yolo Bypass agriculture is negligible. When the last day of inundation occurs between March 1st and April 10th, rice acreage increases—and corn acreage to a lower extent—because its yield is not affected by flooding, while the yields of safflower, sunflower, tomato and irrigated pasture have started to decline and, as a result, are relatively less profitable. This behavioral response does not offset the effect of flooding and profit steadily decreases while the opportunity cost increases. Between March 20th and April 14th, rice yield collapses to zero. Even though the acreages of pasture, corn, safflower and sunflower increase, profit drops dramatically and the opportunity cost rises exponentially. The opportunity cost peaks on April 2nd at about $530,000. Between April 2nd and May 1st, farmland decreases because the yields of corn, safflower, sunflower and pasture are too low to cover the variable costs. By May 1st farming in the Yolo Bypass stops being economically viable.

The regional agricultural profit is a strictly monotone function of the last day of inundation. Thus, for any last day of inundation there exists a one-to-one mapping between the profit function and the optimal crop mix and acreages. We estimate the regional agricultural profit response to the last day of inundation. The model that fits the best the data is

$$\Pi_{ag}(y_t) = \frac{\kappa_0}{1 + e^{\kappa_1 + \kappa_2 y}} + \epsilon.$$

Table 2 shows the results of the non-linear regression. Estimates are all significant at P-value$<$ 0.001. Standard errors are in parenthesis.

Table 2: Estimates of the agricultural profit $\hat{\Pi}_{ag}(y_t)$.

$\hat{\kappa}_0$ (se)	$\hat{\kappa}_1$ (se)	$\hat{\kappa}_2$ (se)
6.94 (0.03)	-14.98 (0.55)	0.17 (0.01)

The state of California currently manages the Yolo Bypass to provide flood protection to the city of Sacramento. The extent of the flooding required for flood protection purposes varies with the hydrologic year type (California Department of Water Resources, 1984-2009 data). Farmers in the Yolo Bypass currently make their cropping decisions in late winter-early spring based on their expectations on when the last day of inundation might be in a given year.

Now, let us assume that the state of California announces that it will operate the Fremont Weir to benefit juvenile Chinook salmon. Assuming that the state knows the Yolo Bypass farmers' opportunity cost to flooding, it will decide on the last day of inundation that maximizes the joint profit of the commercial Chinook fishery and farming in the Yolo Bypass. However, the state cannot choose a last day of inundation earlier than that which would have naturally occurred because its priority is to provide flood protection to the city of Sacramento. Therefore, the state faces a minimum flood constraint that is contingent on the hydrologic year type u, $y \geq y_{min}(u)$. Table 5 in the appendix shows the hydrologic year type and the observed flooding conditions of Yolo Bypass for 1984-2009. Table 6 shows the average last day of flooding at Fremont Weir and number of flood days contingent on the year type. Because the average last day of inundation is similar for dry and critically dry years, and normal and wet years, we aggregate hydrologic year types pairwise: dry-critically dry and normal-wet years. We assume $y_{min,u_t} \sim \mathcal{N}(\mu_{y,u}, \sigma^2_{y,u})$.

Assume the state announces to the farmers in the early winter—prior to when the cropping decisions are made—the chosen last day of inundation for the coming year. The farmers will now make their cropping decisions based on the last day of inundation announced by the state. This is a Stackelberg game where the state of California is the leader and the Yolo Bypass farmers act as the follower.

We use the estimated agricultural profit function $\hat{\Pi}_{ag}(y_t)$ for the last day of inundation announced by the state in the optimal control problem to solve for the last day of inundation and the fishery catches. This enables us to reduce the number of control variables since the optimal crop mix and acreages are implicitly determined by the last day of inundation in the agricultural production model.

In the next section, we model the population dynamics of Chinook salmon as a function of the last day of inundation. We assume that for a given last day of inundation the social planner can determine the number of flood days and their distribution within the flood season that maximize the benefits to juvenile Chinook salmon.

2.2 Chinook salmon population model

We develop a model of the Chinook population and of the commercial fishery. Salmon life-cycle spans from the small river tributaries to which mature adults migrate to spawning grounds to lay eggs, to freshwater habitats that juveniles use during their migration downstream to the ocean where they rear and mature before returning to the spawning grounds where they hatched. The number of smolts recruited in a given year is a function of the escapement, or number of spawners $x_{S,t}$, and the number of smolts released by hatcheries in the Sacramento River x_H. We assume that the smolts produced by the spawning stock follow a Beverton-Holt density-dependent recruitment function (Beverton and Holt, 1957). We assume that x_H is constant over the short-run because of technical constraints associated with changing production targets (Joint Hatchery Review Committee, 2001). Hatchery fish typically face higher mortality rate than natural-origin fish (Joint Hatchery Review Committee, 2001; Cavallo et al., 2011). We assume the relative lower survival rate of hatchery-origin smolts relative to their natural-origin counterparts occurs in the early life stage and we denote it s_H. The age-0 recruits or smolts $x_{0,t}$ in year t is

$$x_{0,t} = \frac{\beta_0 x_{S,t}}{1 + \beta_1 x_{S,t}} + s_H x_H$$

where $x_{S,t}$ is the spawning stock and $s_H x_H$ are the hatchery-origin smolts. Parameter β_0 represents the number of smolts per spawner at low escapement and $\frac{\beta_0}{\beta_1}$ is the maximum number of recruits in the population.

When inundated the Yolo Bypass floodplain provides an extensive habitat of shallow waters.

Sommer et al. (2001a,b); Jeffres et al. (2008) find that smolts grow faster in floodplains than in the main river stem because of higher primary and secondary productivity. As a result, the fish leaving Yolo Bypass are bigger and thus have a higher smolt-to adult survival rate relative to fish that do not use the floodplain. Smolts moving downstream in the river enter Yolo Bypass when floodwaters overtop the Fremont Weir north of the city of Sacramento. The ratio of smolts that enter Yolo Bypass during the winter and spring $\omega(y_t, u_t) \in [0, 1]$ is a function of the relative amount of flow that spills into the bypass and the number of smolts that are migrating in the river at the time. Smolt migration downstream the Sacramento River can be approximated with a gaussian distribution with a peak migration in April-May (Cavallo et al., 2011). We denote $\Phi(y_t) = Pr(Y \leq y_t)$ the cumulative distribution function of the normal distribution with mean on April 9th and standard deviation of 30 days. Perry et al. (2010) suggest that the fraction of smolts entering Yolo Bypass is proportional to the flow spilling into the Yolo Bypass.[7] Using 1984-2009 flow data from the California Department of Water Resources we find that the ratio of the flow that enters Yolo Bypass relative to the flow that stays in the Sacramento River on a given day is relatively uniformly distributed across the winter and early spring for a given flood season. We find that the average ratio of flow over a flood season is contingent on the hydrologic year type, see table 5. We specify the ratio of flow that enters Yolo Bypass in a given flood season contingent on the year type u_t such that $r_{u_t} \sim \mathcal{N}(\mu_{r,u}, \sigma^2_{r,u})$. When the state of California operates the Fremont Weir to jointly manage the fishery and agriculture, it chooses, in addition to the last day of inundation, the number and length of the flood events to maximize the benefits to juvenile Chinook salmon. In general, it will be able to let a larger ratio of flow enter Yolo Bypass than would have naturally

[7] Perry et al. (2010) develop a mark-recapture experiment in the Sacramento-San Joaquin Delta using acoustic telemetry to follow the movements of smolts through the Delta migration routes. They find that the proportion of juvenile Chinook that take a given migration route is equal to the proportion of flow. However, Perry et al. (2010) point out that because of the surface-biased distribution of smolts, juvenile Chinook may pass trough spillways in higher proportion than the flow. This suggests that the cumulative share of smolts entering Yolo Bypass may positively deviate from the ratio of flow spilling over Fremont Weir. Thus, $\omega(y_t, u_t)$ may be a conservative estimate of the fraction of smolts that actually use the Yolo Bypass.

occurred. Therefore, the cumulative fraction of smolts that enter Yolo Bypass is

$$\omega(y_t, u_t) = \Phi(y_t) r_{u_t}.$$

The fraction $1 - \omega(y_t, u_t)$ represents the smolts that move through the main river channel. Kjelson and Brandes (1989); Brandes and McLain (2001) use coded-wire tagging data of hatchery fish released near Sacramento and recaptured by the ocean fishery to estimate the Sacramento River fall-run Chinook smolt-to adult survival.[8] Their estimates range between 0.002 and 0.02 based on the year and river flow conditions. The fish are released near Sacramento in the Sacramento River channel adjacent to Yolo Bypass. Therefore, these estimates reflect the smolt-to adult survival rate when only using the river, denoted s_R. Because smolts that use Yolo Bypass grow faster, they have a survival rate s_B that is higher than the one for smolts that only use the river channel s_R with $s_B > s_R$.[9] The population-level survival rate of juvenile Chinook is driven by the survival rates specific to the migration route—Yolo Bypass or main-stem of the Sacramento River—and the proportion of the population using each migration route. We write the smolt-to adult survival

$$s(y_t, u_t) = s_B \omega(y_t, u_t) + s_R(1 - \omega(y_t, u_t)) + \theta_{u_t}$$

where θ_{u_t} is a stochastic term that is contingent on the hydrologic year type u_t. The smolt-to adult survival rate is affected by river flow conditions (Kjelson and Brandes, 1989; Brandes and McLain, 2001; Cavallo et al., 2011). We assume $\theta_{u_t} \sim \mathcal{N}(\mu_{\theta,u}, \sigma^2_{\theta,u})$ where the mean $\mu_{\theta,u}$ is positive for

[8] Survival rate studies are generally based on coded wire tag (CWT) release and recovery data from hatchery operations. The tagged individuals are recovered as adults some years after they were released from hatcheries as smolts. The resulting estimate of smolt-to adult survival rate is a product of freshwater, estuarine, and marine survival rate.

[9] Sommer et al. (2001b) find that more flooding increases Diptera (principally chironomids) and zooplankton production, which dominate juvenile Chinook diet. This suggests that the smolt-to adult survival rate when using Yolo Bypass may be increasing with the last day of inundation. However, because of the lack of data to estimate this relationship we assume s_B is constant.

normal and wet years and negative for dry and critically dry years. At the end of period t the stock of adults $x_{a,t}$, natural- and hatchery-origin fish, are subject to harvest H_t. The remaining adults $x_{a,t} - H_t$ escape and return to spawn. Therefore, escapement at the beginning of the next period $t+1$ is[10]

$$x_{S,t+1} = (s_B \omega(y_t, u_t) + s_R(1 - \omega(y_t, u_t)) + \theta_{u_t}) \left(\frac{\beta_0 x_{S,t}}{1 + \beta_1 x_{S,t}} + s_H x_H \right) - H_t.$$

Commercial fishery model

The Pacific Fishery Management Council (PFMC) regulates the total allowable catch (TAC) for the commercial and recreational fisheries based on expected escapement $x_{S,t+1}$. The PFMC escapement goal is of 122,000 to 180,000 spawners, natural- and hatchery-origin combined. In year t the fishing rate F_t is

$$F_t = \begin{cases} 0 \quad \text{if } x_{S,t+1} \leq \underline{x}_S \\ F_0 + F_1 ln(F_2 + x_{S,t+1}) \quad \text{if } \underline{x}_S \leq x_{S,t+1} \leq \bar{x}_S \\ \bar{F} \quad \text{if } x_{S,t+1} \geq \bar{x}_S \end{cases} \tag{3}$$

where $x_{S,t+1}$ is the expected escapement after the fishing season t.[11] When expected escapement is below $\underline{x}_S$ =122,000 fish, the fishery is closed and when it is above the threshold $\bar{x}_S$ =409,000 the fishing rate F is capped at $\bar{F}$=0.7, which represents the maximum annual catch limit. The TAC in fishing season t is $Q_t = F_t x_{a,t}$ and harvest cannot exceed the quota, $H_t \leq Q_t$.

The California Chinook salmon commercial fishery is a limited entry fishery, denote N the

[10] We choose to keep the model simple and do not develop an age-structured population model with individual cohorts because we do not think the nature of the results would change.

[11] The PFMC estimates future escapement based on the number of 2-year old, called jacks, that escape prematurely relative to the 3- and 4-year old adults.

number of fishers participating in the fishery. We assume the race to fish is moderate and capital investment has stabilized. This assumption is supported by the relatively long fishing season (50 days on average over the past 8 years) and the fact that the fishery does not systematically catch the TAC. Fisher n harvests $h_{nt} = qe_{nt}x_{a,t}$ where q is the catchability parameter, e_{nt} is fishing effort in number of vessel day, and $x_{a,t}$ represents the adult stock fish in the fishing season t. We assume that the fisher's variable fishing cost is a linear function of the fishing effort ve_{nt} and that he incurs a fixed cost f per vessel that participates in a given fishing season t. We assume fishers face the same variable cost v and fixed cost f. We use data from the 2006 cost study conducted by Hackett and Hansen (2008). Fisher n's profit is $\Pi_{Cn}(e_{nt}, x_{a,t}) = pqe_{nt}x_{a,t} - ve_{nt} - f$ where p is the market price of wild Chinook salmon. Substituting $e_{nt} = \frac{h_{nt}}{qx_{a,t}}$ into the profit expression, we have $\Pi_{Cn}(h_{nt}, x_{a,t}) = \left(p - \frac{v}{qx_{a,t}}\right) h_{nt} - f$. The industry harvest is $H_t = \sum_n h_{nt}$ and is a function of the total fishing effort $E_t = \sum_n e_{nt}$. Thus, the industry profit for the fishing season t is written $\Pi_C(E_t, x_{a,t}) = pqE_t x_{a,t} - vE_t - Nf$ or equivalently

$$\Pi_C(H_t, x_{a,t}) = \left(p - \frac{v}{qx_{a,t}}\right) H_t - Nf. \tag{4}$$

We assume that the state of California knows the Chinook industry profit function. Therefore, it chooses the harvest H_t and the last day of inundation y_t that maximize the joint profit of the fishery and farmers in Yolo Bypass subject to the maximum biological fishing rate F_t defined in equation 3. The fishery will exactly catch the allowed H_t announced by the state as H_t maximizes the industry's profit for the fishing season t.

2.3 Economic model

The infinite horizon optimal control problem of the social planner is

$$V = \max_{y_t, H_t} \sum_{t=0}^{\infty} (1+\rho)^{-t} \left(\Pi_C(H_t, x_{a,t}) + \hat{\Pi}_{ag}(y_t) \right) \tag{5}$$

$$\text{subject to} \quad x_{S,t+1} = (s_B \omega(y_t, u_t) + s_R(1-\omega(y_t,u_t)) + \theta_{u_t}) \left(\frac{\beta_0 x_{S,t}}{1+\beta_1 x_{S,t}} + s_H x_H \right) - H_t \tag{6}$$

$$H_t \le F_t x_{a,t} = \begin{cases} 0 \quad \text{if } x_{S,t+1} \le \underline{x}_S \\ \left(F_0 + F_1 ln\left(F_2 + x_{S,t+1}\right)\right) x_{a,t} \quad \text{if } \underline{x}_S \le x_{S,t+1} \le \bar{x}_S \\ \bar{F} x_{a,t} \quad \text{if } x_{S,t+1} \ge \bar{x}_S \end{cases} \tag{7}$$

$$y_{min,u_t} \le y_t \le y_{max},\ 0 \le x_{S,t+1} \tag{8}$$

$$y_{min,u_t} \sim \mathcal{N}(\mu_{y,u}, \sigma^2_{y,u}),\ \theta_{u_t} \sim \mathcal{N}(\mu_{\theta,u}, \sigma^2_{\theta,u}) \tag{9}$$

$$x_{S,t=0},\ u_{t=0} \tag{10}$$

where ρ is the discount rate and the escapement $x_{S,t+1}$ is equal to the current adult stock net of harvest $x_{a,t} - H_t$. $\hat{\Pi}_{ag}(y_t) = \frac{\hat{\kappa}_0}{1+e^{\hat{\kappa}_1 + \hat{\kappa}_2 y_t}}$ is the estimated agricultural profit in the study region in year t, see table 2. $\Pi_C(H_t, x_{a,t})$ is the fishery profit at the end of the fishing season t as defined in equation 4. Equation 6 is the equation motion controlling the change in escapement. Condition 7 determines the maximum catch based on estimated escapement. Condition 8 imposes the restriction that the state of California chooses a last day of inundation y_t such that flood protection to the city of Sacramento is satisfied. Condition 9 specifies that the flood and biological functions are stochastic and follow normal distribution contingent on the hydrologic year type.

A sequence of hydrologic year types u_t is not random but follows a pattern where a normal-wet year is more likely to be followed by a normal-wet than a dry-critically dry year and vice versa. We use data for 1984-2009 from the California Department of Water Resources to estimate the transition probability matrix associated with a Markov process of order 1.

2.3.1 Necessary conditions

The current value Lagrangian for problem 5 is

$$
\mathcal{L} = \Pi_C(H_t, x_{a,t}) + \hat{\Pi}_{ag}(y_t)
$$
$$
+\lambda_t \left(s(y_t, u_t) \left(\tfrac{\beta_0 x_{S,t}}{1+\beta_1 x_{S,t}} + s_H x_H \right) - H_t \right) + \underbrace{\Lambda \left(s(y_t, u_t) \left(\frac{\beta_0 x_{S,t}}{1+\beta_1 x_{S,t}} + s_H x_H \right) - H_t \right)}_{-x_{S,t+1} \leq 0}
$$

where λ_t is the current value shadow price of an additional unit of spawning stock and Λ is the Lagrangian multiplier on the state constraint.

The first-order necessary conditions are

$$
\frac{\partial \mathcal{L}}{\partial y_t} = \frac{\partial \hat{\Pi}_{ag}}{\partial y_t} + (\lambda_t + \Lambda) \frac{ds}{dy_t} \left(\frac{\beta_0 x_{S,t}}{1+\beta_1 x_{S,t}} + s_H x_H \right) \leq 0 \tag{11}
$$
$$
y_{min,u_t} \leq y_t \leq y_{max} \quad (y_t - y_{min,u_t})(y_{max} - y_t) \frac{\partial \mathcal{L}}{\partial y_t} = 0 \tag{12}
$$
$$
\frac{\partial \mathcal{L}}{\partial H_t} = \frac{\partial \Pi_C}{\partial H_t} - \lambda_t - \Lambda \leq 0 \quad 0 \leq H_t \leq F_t x_{a,t} \quad H_t(F_t x_{a,t} - H_t) \frac{\partial \mathcal{L}}{\partial H_t} = 0 \tag{13}
$$
$$
\frac{d\lambda_{xt}}{dt} = \rho \lambda_t - \frac{\partial \mathcal{L}}{\partial x_{S,t}} = \rho \lambda_t - \frac{\partial \Pi_C}{\partial x_{S,t}} - (\lambda_t + \Lambda) s(y_t, u_t) \frac{\beta_0}{(1+\beta_1 x_{S,t})^2} \tag{14}
$$
$$
x_{S,t+1} = (s_B \omega(y_t, u_t) + s_R(1 - \omega(y_t, u_t)) + \theta_{u_t}) \left(\frac{\beta_0 x_{S,t}}{1+\beta_1 x_{S,t}} + s_H x_H \right) - H_t \tag{15}
$$
$$
-x_{S,t} \leq 0 \quad \Lambda[-x_{S,t}] = 0 \quad \frac{d\Lambda}{dt} \leq 0 \quad [= 0 \text{ when } -x_{S,t} < 0] \tag{16}
$$
$$
\frac{\partial \mathcal{L}}{\partial \Lambda} = s(y_t, u_t) \left(\frac{\beta_0 x_{S,t}}{1+\beta_1 x_{S,t}} + s_H x_H \right) - H_t \geq 0 \quad \Lambda \geq 0 \quad \Lambda \frac{\partial \mathcal{L}}{\partial \Lambda} = 0 \tag{17}
$$

Condition 11 implies that when the fish stock is positive ($\Lambda = 0$) and the constraints on the last day of inundation are slack ($y_{min,u_t} < y_t < y_{max}$), the shadow price of the fish stock is equal to minus the ratio of the marginal cost of flooding to agriculture over the marginal benefit in additional number of fish. The higher the marginal cost or the lower the marginal benefit, the lower the shadow price of the fish stock. Condition 13 implies that, provided the fish stock is positive, when the harvest is positive and below the TAC ($0 < H_t < F_t x_{a,t}$), the shadow price of the fish stock is equal to the marginal profit from another unit of harvest ($\frac{\partial \Pi_C}{\partial H_t} = \lambda_t$). The more profitable the fishery, the greater the shadow price of the fish stock. The costate equation 14 represents the dynamics of the shadow price of the fish stock over time.

Assume an interior steady-state solution exists. Then, we have

$$\underbrace{\rho}_{\text{Discount rate}} = \underbrace{\frac{\frac{\partial \Pi_C}{\partial x_{S,t}}}{\frac{\partial \Pi_C}{\partial H_t}}}_{\text{Ratio of marginal benefit from stock to benefit from harvest}} + \underbrace{s(y_t, u_t)\frac{\beta_0}{(1+\beta_1 x_{S,t})^2}}_{\text{Marginal density-dependent cost}} \tag{18}$$

$$\underbrace{\frac{\partial \hat{\Pi}_{ag}}{\partial y_t}}_{\text{Marginal cost from flooding}} = \underbrace{\frac{\partial \Pi_C}{\partial H_t}\frac{ds}{dy_t}\left(\frac{\beta_0 x_{S,t}}{1+\beta_1 x_{S,t}} + s_H x_H\right)}_{\text{Marginal benefit from flooding}} \tag{19}$$

Equation 19 shows that the optimal level of flooding in Yolo Bypass is such that the marginal benefit to the fishery, in terms of increased catches and additional stock production, balances the marginal cost to agriculture. The more profitable the fishery or the less profitable agriculture in Yolo Bypass, the larger the optimal level of flooding at the steady state.

Yet, it is realistic that harvest is constrained by the TAC such that $H_t = F_t x_{a,t} = \frac{F_t x_{S,t}}{1-F_t}$, provided the fishery is profitable. Then, we have the corner solution

$$\underbrace{\rho}_{\text{Discount rate}} = \underbrace{\frac{\frac{\partial \Pi_C}{\partial x_{S,t}}}{\frac{\partial \hat{\Pi}_{ag}}{\partial y_t}} \frac{ds}{dy_t} \left(\frac{\beta_0 x_{S,t}}{1+\beta_1 x_{S,t}} + s_H x_H \right)}_{\text{Ratio of marginal benefit to cost from flooding}} + \underbrace{s(y_t, u_t) \frac{\beta_0}{(1+\beta_1 x_{S,t})^2}}_{\text{Marginal density-dependent cost}}$$

$$\underbrace{\lambda_t}_{\text{Shadow price of stock}} \geq \underbrace{\frac{\partial \Pi_C}{\partial H_t}}_{\text{Marginal benefit from harvest}}$$

3 Numerical analysis

Table 3: Ecological and economic parameters

Parameter	Description	Value
β_0	Slope at origin of Beverton-Holt curve (Worden et al., 2010)	60
β_1	Saturation parameter of Beverton-Holt curve	1.7e-6
x_H	Hatchery fish released each year (CDFG)	22e6
s_H	Hatchery fish survival at release (CDFG)	0.02
s_R	Smolt-to adult survival when only using river (Brandes and McLain, 2001)	0.02
s_B	Smolt-to adult survival when using Yolo Bypass[12]	0.03
p	Ex-vessel price of wild Chinook \$/fish (PFMC)	46
v	Variable fishing cost \$/vessel/day (CDFG)	276
f	Fixed fishing cost \$vessel/season	1,600
N	Number of vessels participating in the commercial fishery (PFMC)	477
q	Catchability parameter (PFMC)	3.06e-5
ρ	Discount rate	0.05

We solve problem 5 using the collocation method described in Miranda and Fackler (2002, p141-142). This method approximates an unknown value function using a linear combination of known basis functions at a set of collocation nodes spanning the solution space. It converts the optimal control problem into a parameter optimization problem where we solve for the coefficients of the approximating polynomial function. We use Chebychev basis polynomials in combination

[12]Sommer et al. (2001b) find that apparent growth rate of smolts that use Yolo Bypass is increased by 42% relative to smolts to stay in the river. We assume a linear relationship between growth and survival.

with Chebychev interpolation nodes as described in Judd (1998, p223) and Miranda and Fackler (2002, p119-123). This results in a well-conditioned interpolation equation and the Chebychev basis coefficients can be computed accurately and efficiently (Miranda and Fackler, 2002).[13] We then solve the transformed optimization problem using a constrained nonlinear programming algorithm. See Howitt et al. for more detail on the methodology used in this paper.

The following simulations use the parameter values displayed in table 3. We assume $\theta_{dry_t} \sim \mathcal{N}(-0.005, 0.005)$ and $\theta_{wet_t} \sim \mathcal{N}(0.005, 0.005)$. In addition, we suppose that the state of California faces minimum flood constraints to provide flood protection services such that $y_{min}(dry_t) \sim \mathcal{N}$(Jan-7,20) and $y_{min}(wet_t) \sim \mathcal{N}$(Apr-9,44) based on the Department on Water Resources data, see table 6. Figure 3 shows the results for the efficient provision of habitat in Yolo Bypass (denoted 'optimal') and for the current management—Yolo Bypass is managed for flood protection control and agriculture (denoted 'status quo'). The first hydrologic year is a normal-wet year and the following years are drawn from a Markov chain.

The stock of Chinook is generally larger and fluctuates much less under the optimal management than the current management. In particular, the PFMC conservation objective of a minimum escapement of 122,000 fish is typically satisfied under the optimal management.[14] We find that the shadow price of salmon is generally lower and more stable under the optimal management than the current management as would be expected.

Under optimal management the state of California may choose to prevent harvest even though the PFMC conservation objective of 122,000 fish is satisfied. This is because the state makes its decisions based on the probabilities of future hydrologic year types. Because a dry or critically dry

[13]Convergence of the non-linear constrained parameter optimization problem was met at 8e-5 using the CONOPT3 solver in GAMS.

[14]This is important because when escapement lies below this threshold for 3 consecutive years the fishery is declared overfished. Even if fishing is not the primary factor in the depression of the stock, the PFMC must act to limit the exploitation rate of the fishery so as not to limit recovery of the stock, or as is necessary to comply with ESA consultation standards. We do not consider the costs associated with the overfishing concern. As a result, we may underestimate the costs of the current management.

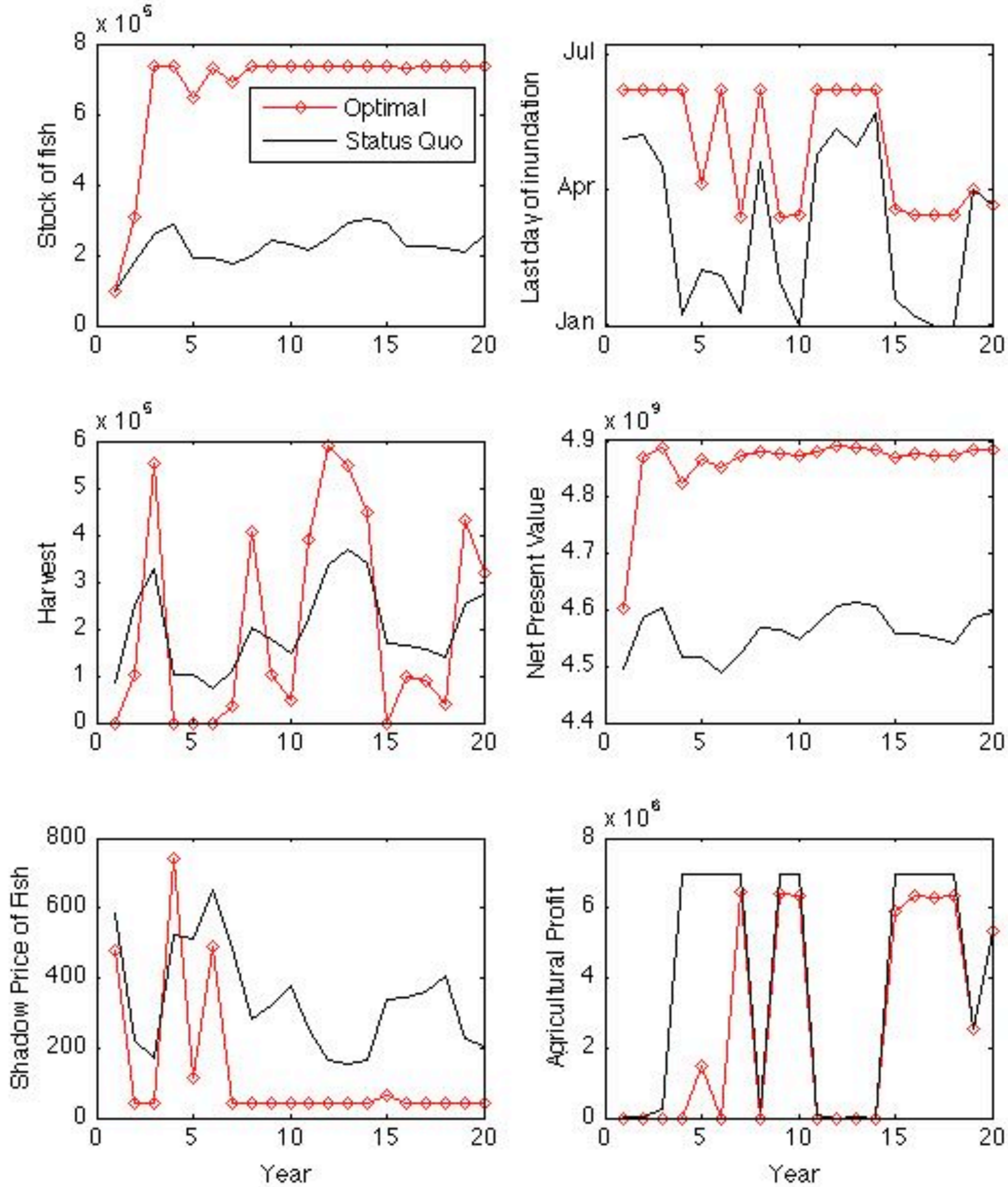

Figure 3: Optimal Chinook stock, harvest, last day of inundation, net present value, and shadow price of salmon.

year is likely to preface a cycle of several dry years, the state may limit fishing in anticipation of a negative shock on the Chinook population in the next years.

The last day of inundation under the current management is determined by the natural flooding that would happen with the Fremont Weir operating passively. It is almost perfectly correlated with the hydrologic year type such that on average it is inundated until January 7th in a cry-critically dry year and until April 9th in a normal-wet year. However, under the optimal management it is always optimal to choose to inundate at least until March 15th because until then the cost of flooding to agriculture is relatively small. In some years it is optimal to inundate after March 15th. In this case, because the opportunity cost to farmers decreases after April 2nd, we find that it is optimal to inundate Yolo Bypass for as long as possible (until June 8th). This results in inundation pulses: either the state chooses a short (March 15th) or long inundation season (June 8th).

We find that the optimal management typically generates larger net present value than the current management by 15%.

4 Conclusion

The Yolo Bypass floodplain is an example of a working landscape. It provides seasonal habitat to juvenile Chinook salmon, flood protection to the city of Sacramento, and is used for agriculture. There are conflicts among farmers and the salmon fishing industry because it is presumed that farm profits and habitat provision to juvenile Chinook are in competition at certain times. We find that there exist tradeoffs between the joint production of crops and salmon, and that the current management is inefficient. Managing fish and crop production jointly would increase welfare—with potential compensation from fishers to farmers—and contribute to achieving the PFMC conservation objectives.

Furthermore, as part of the Sacramento-San Joaquin Delta, the Yolo Bypass is at the center of the conflict over the water allocation in California between farmers, environmentalists, and urban users. Large water exports to agriculture and urban centers in Southern California are responsible for habitat degradation and the Delta's ecological crisis (Bay Delta Conservation Plan, Steering Committee, 2010). Achieving efficient water allocation among these uses is critical to solve the conflict.

Building on recent advances on modeling fishery-habitat linkages (Sanchirico and Springborn, 2011) and using agronomic models to calibrate agricultural production models, we develop a model that analyzes the tradeoffs between agriculture and a native fish species in a seasonally inundated floodplain. This work contributes to understanding the interactions between agriculture and population dynamics and extends the literature on species conservation on working landscapes. Our paper formally integrates an agricultural production model with a salmon population model. Explicitly modeling the crop yield response to shorter growing season allows us to predict the effect of more flooding on crop mix and agricultural profit in the Yolo Bypass floodplain. We find that assuming a fixed opportunity cost to agriculture is not realistic—in contrast to Newbold and Siikamäki (2009); Sanchirico and Springborn (2011). We develop a Chinook salmon model that allows juveniles to have a beneficial association with the floodplain. The model stochastically simulates the response of the salmon population to habitat provision contingent on year type. In addition, the state of California faces stochastic constraints on providing flood protection control to the city of Sacramento using historic flow conditions.

We find that managing Yolo Bypass to jointly provide habitat, flood protection, and crops leads to substantial gains in most of the years relative to the current management. In addition to welfare, the stock of salmon is larger and more resilient to dry or critically dry years. In general we find that the fishery profit is positive in a larger number of years while agricultural profit is smaller in some years under optimal management.

Future work will consider the effect of the amount of flow entering the Yolo Bypass on juvenile

Chinook salmon and agriculture. It is not yet clear how the flow affects juvenile survival, however, fields generally take longer to drain with larger flows potentially delaying planting—further work is needed to quantify these relationships. Furthermore, we will investigate the effect of uncertainty where the state of California has imperfect information on the response functions of farmers and fishers.

References

Bay Delta Conservation Plan, Steering Committee (2010). Bay Delta Conservation Plan. Progress Report.

Beverton, R. and Holt, S. (1957). *On the Dynamics of Exploited Fish Populations*. Fishery Investigations Series II Volume XIX, Ministry of Agriculture, Fisheries and Food.

Brandes, P. L. and McLain, J. S. (2001). Juvenile Chinook Salmon Abundance, Distribution, and Survival in the Sacramento-San Joaquin Estuary. *Fish Bulletin 179: Contributions to the Biology of Central Valley Salmonids*, 2:39–136. California Department of Natural Resources, Sacramento, California.

Bulte, E. H. and Horan, R. D. (2003). Habitat Conservation, Wildlife Extraction and Agricultural Expansion. *Journal of Environmental Economics and Management*, 45:109–127.

California Department of Fish and Game (2011). Fisheries Resources and Species Management. http://www.dfg.ca.gov/fish/Resources/Chinook/index.asp. Last visited: 04/29/11.

Cavallo, B., Bergman, P., and Melgo, J. (2011). The Delta Passage Model. Technical report, Cramer Fish Sciences.

De Gryze, S., Albarracin, M. V., Catala Luque, R., Howitt, R. E., and Six, J. (2009). Modeling Shows that Alternative Soil Management Can Decrease Greenhouse Gases. *California Agriculture*, 63(2):84–90.

Feyrer, F., Sommer, T., and Harrell, W. (2006). Importance of Flood Dynamics versus Intrinsic Physical Habitat in Structuring Fish Communities: Evidence from Two Adjacent Engineered Floodplains on the Sacramento River, California. *North American Journal of Fisheries Management*, 26:408–417.

Hackett, S. and Hansen, M. (2008). California Fleet Impacts Survey. Unpublished data.

Howitt, R., Msangi, S., Reynaud, A., and Knapp, K. Using Polynomial Approximations to Solve Stochastic Dynamic Programming Problems: or A 'Betty Crocker' Approach to SDP. University of California, Davis.

Howitt, R. E. (1995a). A Calibration Method for Agricultural Economic Production Models. *Journal of Agricultural Economics*, 46(2):147–159.

Howitt, R. E. (1995b). Positive Mathematical Programming. *American Journal of Agricultural Economics*, 77(2):329–342.

Howitt, R. E., Catala Luque, R., De Gryze, S., Wicks, S., and Six, J. (2009). Realistic Payments Could Encourage Farmers to Adopt Practices that Sequester Carbon. *California Agriculture*, 63(2):91–95.

Jeffres, C. A., Opperman, J. J., and Moyle, P. B. (2008). Ephemeral Floodplain Habitats Provide Best Growth Conditions for Juvenile Chinook Salmon in a California River. *Environmental Biology of Fishes*, 83:449–458.

Joint Hatchery Review Committee (2001). Anadromous Salmonid Fish Hatcheries in California. Technical report, California Department of Fish and Game and the National Marine Fisheries Service.

Judd, K. (1998). *Numerical Methods in Economics*. MIT Press, Cambridge, Mass.

Kjelson, M. and Brandes, P. (1989). The Use of Smolt Survival Estimates to Quantify the Effects of Habitat Changes on Salmonid Stocks in the Sacramento-San Joaquin Rivers, California. In Levings, C., editor, *Proceedings of the National Workshop on the Effects of Habitat Alteration on Salmonid Stocks. Canadian Special Publication of Fisheries and Aquatic Sciences*, volume 105, pages 100–15.

Lund, J., Hanak, E., Fleenor, W., Howitt, R., Mount, J., and Moyle, P. (2007). Envisioning Futures for the Sacramento–San Joaquin Delta.

Mérel, P. R., Simon, L., and Yi, F. A Fully Calibrated Generalized Constant-Elasticity-of-Substitution Programming Model of Agricultural Supply. American Journal of Agricultural Economics. Forthcoming.

Miranda, M. J. and Fackler, P. L. (2002). *Applied Computational Economics and Finance*. MIT Press.

Nalle, D. J., Montgomery, C. A., Arthur, J. L., Polasky, S., and Schumaker, N. H. (2004). Modeling Joint Production of Wildlife and Timber. *Journal of Environmental Economics and Management*, 48:997–1017.

Nelson, E., Polasky, S., Lewis, D. J., Plantinga, A. J., Lonsdorf, E., White, D., Bael, D., and Lawler, J. J. (2008). Efficiency of Incentives to Jointly Increase Carbon Sequestration and Species Conservation on a Landscape. *Proceedings of the National Academy of Sciences*, 105(28):9471–9476.

Newbold, S. C. and Siikamäki, J. (2009). Prioritizing Conservation Activities Using Reserve Site Selection Methods and Population Viability Analysis. *Ecological Applications*, 19(7):1774–1790.

Parton, W. J., Hartman, M., Ojima, D., and Schimel, D. (1998). DAYCENT and its Land Surface Submodel: Description and Testing. *Global and planetary change*, 396:1–14.

Perry, R. W., Skalski, J. R., Brandes, P. L., Sandstrom, P., Klimley, A., Ammann, A., and MacFarlane, B. (2010). Estimating Survival and Migration Route Probabilities of Juvenile Chinook

Salmon in the Sacramento–San Joaquin River Delta. *North American Journal of Fisheries Management*, 30:142–156.

Polasky, S., Nelson, E., Lonsdorf, E., Fackler, P., and Starfield, A. (2005). Conserving Species in a Working Landscape: Land Use with Biological and Economic Objectives. *Ecological Applications*, 15(4):1387–1401.

Sanchirico, J. N. and Springborn, M. (2011). How to Get There From Here: Ecological and Economic Dynamics of Ecosystem Service Provision. *Environmental and Resource Economics*, 48(2):243–267.

Schluter, M., Leslie, H., and Levin, S. (2009). Managing Water-Use Trade-Offs in a Semi-Arid River Delta to Sustain Multiple Ecosystem Services: a Modeling Approach. *Ecological Research*, 24:491–503.

Settle, C., Crocker, T., and Shogren, J. (2002). On the Joint Determination of Biological and Economic Systems. *Ecological Economics*, 42:301–11.

Shogren, J. F., Parkhurst, G. M., and Settle, C. (2003). Integrating Economics and Ecology to Protect Nature on Private Lands: Models, Methods, and Mindsets. *Environmental Science and Policy*, 6:233–242.

Skonhoft, A. (1999). On the Optimal Exploitation of Terrestrial Animal Species. *Environmental and Resource Economics*, 13:45–57.

Sommer, T., Armor, C., Baxter, R., Breuer, R., Brown, L., Chotkowsli, M., Culberson, S., Feyrer, F., Gingras, M., Herbold, B., Kimmerer, W., Mueller-Solger, A., Nobriga, M., and Souza, K. (2007). The Collapse of Pelagic Fishes in the Upper San Francisco Estuary. *Fisheries*, 32(6):270–277.

Sommer, T., Harrell, B., Nobriga, M., Brown, R., Moyle, P., Kimmerer, W., and Schemel, L. (2001a). California's Yolo Bypass: Evidence that Flood Control Can Be Compatible with Fisheries, Wetlands, Wildlife, and Agriculture. *Fisheries*, 26(8):6–16.

Sommer, T., Nobriga, M., Harrell, W., Batham, W., and Kimmerer, W. (2001b). Floodplain Rearing of Juvenile Chinook Salmon: Evidence of Enhanced Growth and Survival. *Canadian Journal of Fisheries and Aquatic Sciences*, 58:325–333.

Upton, H. F. (2010). Commercial Fishery Disaster Assistance. Report for Congress RL34209, Congressional Research Service.

Wilson, K., Meijaard, E., S. Drummond, S., Grantham, H., Boitani, L., Catullo, G., Christie, L., Dennis, R., I. Dutton, I., Falcucci, A., Maiorano, L., Possingham, H., Rondinini, C., Turner, W., Venter, O., and Watts, M. (2010). Conserving Biodiversity in Production Landscapes. *Ecological Applications*, 20(6):1721–1732.

Wilson, K. A., Underwood, E. C., Morrison, S. A., Klausmeyer, K. R., Murdoch, W. W., Reyers, B., Wardell-Johnson, G., Marquet, P. A., Rundel, P. W., McBride, M. F., Pressey, R. L., Bode, M., Hoekstra, J. M., Andelman, S., Looker, M., Rondinini, C., Kareiva, P., Shaw, M. R., and Possingham, H. P. (2007). Conserving Biodiversity Efficiently: What to Do, Where, and When. *PLoS Biology*, 5(9):1850–1861.

Worden, L., Botsford, L. W., Hastings, A., and Holland, M. D. (2010). Frequency Responses of Age-Structured Populations: Pacific Salmon as an Example. *Theoretical Population Biology*, 78:239–249.

Yolo Basin Foundation (2001). A Framework for the Future: Yolo Bypass Management Strategy.

Appendix

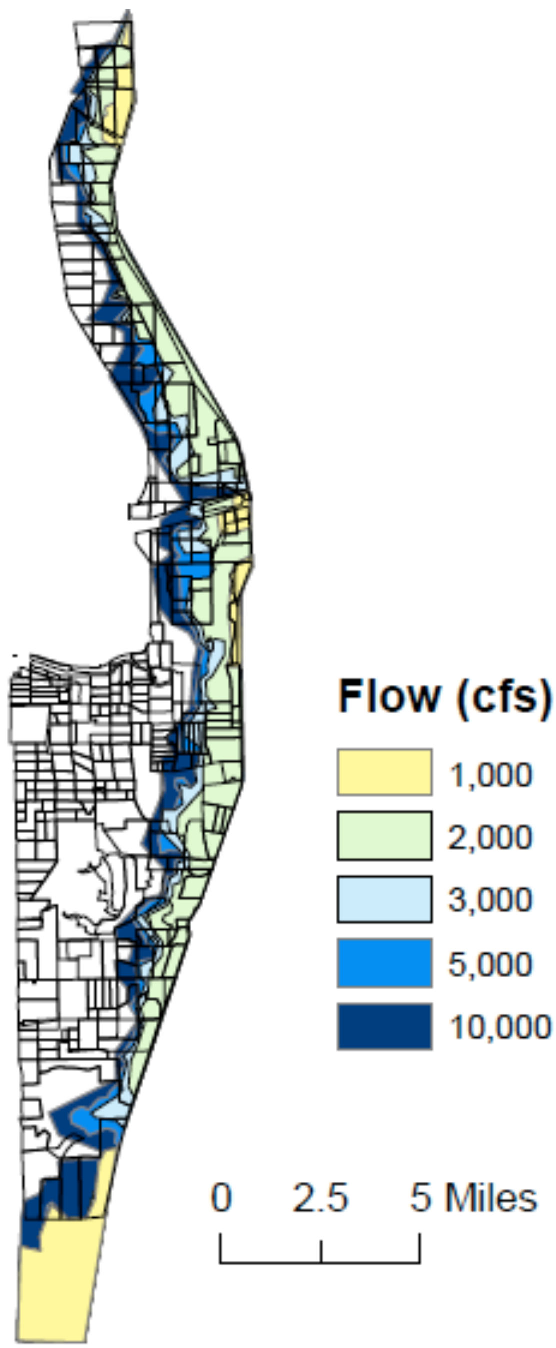

Figure 4: Area inundated in Yolo Bypass for various levels of flow entering at Fremont Weir.

Table 4: Flood scenarios simulated with the DAYCENT model.

Scenario	Last day of inundation	Total number of flood days
1	-	0
2	Jan-30	15
3	Feb-19	15
4	Feb-19	30
5	Mar-3	30
6	Mar-15	15
7	Mar-15	30
8	Mar-15	45
9	Mar-15	56
10	Mar-26	30
11	Mar-26	45
12	Mar-26	56
13	Mar-26	74
14	Apr-2	56
15	Apr-10	15
16	Apr-10	30
17	Apr-10	42
18	Apr-10	45
19	Apr-10	74
20	Apr-10	100
21	Apr-16	56
22	Apr-24	74
23	May-1	100
24	May-8	100
25	May-15	30
26	May-15	45
27	May-15	56
28	May-15	74
29	May-15	84
30	May-22	100
31	May-30	100

Table 5: Hydrologic year type and Yolo Bypass flood data (California Department of Water Resources (DWR)). N: denotes a normal year, W: wet year, D: dry year, and C: critically dry.

Year	Hydrologic year type	Last day of flooding at the Fremont Weir	Total number of flood days	Ratio flow Yolo Bypass/ Sacramento River
1984	W	11-Jan	11	0.15
1985	D	-	0	0
1986	W	25-Mar	38	0.83
1987	D	-	0	0
1988	C	-	0	0
1989	D	14-Mar	3	0.01
1990	C	-	0	0
1991	C	-	0	0
1992	C	-	0	0
1993	N	6-Apr	31	0.16
1994	C	-	0	0
1995	W	13-May	81	0.60
1996	W	24-May	51	0.29
1997	W	13-Feb	54	0.88
1998	W	8-Jun	82	0.70
1999	W	14-Mar	38	0.23
2000	W	17-Mar	33	0.43
2001	D	-	0	0
2002	D	10-Jan	7	0.06
2003	N	7-May	11	0.04
2004	N	10-Mar	23	0.28
2005	N	24-May	4	0.03
2006	W	5-May	102	0.75
2007	D	-	0	0
2008	D	-	0	0
2009	D	-	0	0

Table 6: 1984-2009 average flooding conditions in Yolo Bypass. Standard deviation in parenthesis.

Hydrologic year type	Last day of flooding	Number of flood days	Ratio of flow
C	-	0	0
D	11-Feb (26)	1 (3)	0.01 (0.02)
N	19-Apr (33)	17 (12)	0.13 (0.11)
W	5-Apr (49)	54 (29)	0.54 (0.27)
C-D	7-Jan (20)	1 (2)	0.01 (0.02)
N-W	9-Apr (44)	43 (30)	0.41 (0.30)