APPENDIX 1 Methods

Description of land-use scenarios – supporting information We developed four land-use scenarios relevant for Ka'ūpūlehu and pasturelands in the broader Kona region based on discussions with the land-owner Kamehameha Schools and the local Ka'ūpūlehu community (Table A1.1).

In scenario 1—*pasture*—the area continues to be managed as pasture. This scenario was based on current land cover as defined by a commonly utilized land cover map in Hawai'i (LANDFIRE 2012).

In scenario 2—*native forest restoration*—all pasture within the ahupua'a is restored to native forest. Ka'ūpūlehu is home to one of the most successful community-based dry forest restoration projects with has spurred interest in forest restoration for multiple environmental, educational, and socio-cultural benefits (Cordell et al. 2008). Based on the current distribution of native forest in Ka'ūpūlehu, areas above 1000 m were restored to Hawai'i montane subalpine mesic forest; areas below 1000 m with greater than 750 mm mean annual rainfall (MAR) to Hawai'i lowland mesic forest; and areas below 1000 m with less than 750 mm MAR to Hawai'i lowland dry forest. We assumed restoration was not feasible below 350 mm based on current and historical distribution of forest in Hawai'i (NatureServe 2011).

Scenario 3—*agroforestry*—combines culturally and economically important native species and Polynesian introduced plants, and the more recently introduced agricultural tree crop, fig (*Ficus carica*). Agroforestry was historically practiced in the region and across Hawai'i, but there there is currently no traditional agroforestry practiced in or near Ka'ūpūlehu. Estimates of species richness and diversity were developed for a potential agroforestry scenario (see biodiversity methods below and table A12). These were based on expert knowledge of agroforestry systems practiced in similar environments elsewhere in the Pacific Islands, as well as what might be economically and environmentally viable in Ka'ūpūlehu currently. Figs were included as 10% of the management area, and we assumed they do not require irrigation beyond establishment (Andersen and Crocker 2016), a factor important to the landowner.

Finally, in scenario 4 *-coffee*-pasture is converted to coffee within coffee's suitable climate zone. Coffee was limited to areas with mean annual temperatures greater than 15[°]C and less than 22.8[°]C (Bittenbender and Smith 2008) which constrained coffee to 13.6 km^2 in the current climate and to 8.9 km^2 under climate change (Table A1.1; Fig. 1). We assumed no import of water to meet irrigation needs, so negative water yield values in coffee areas indicate a water deficit in certain areas that needs to be supplied from groundwater (or catchment).

Table A1.1. Land-use scenarios developed for the current pasturelands of Ka'ūpūlehu, Hawaiʻi.

Methods to assess cultural ecosystem services: supporting information The cultural values work represents one site among three in a larger research project examining place-based and indigenous values on cultural ecosystem services across Hawai'i (Pascua et al. 2017). This research builds on a two-year collaborative research project on local knowledge and adaptation to change (Ka'ūpūlehu Community et al. 2014) where the community participants played a central role in determining methods, collecting and analyzing data, and creating an array of products. Methods included qualitative, in-depth interviews, focus groups, and workshops (see McMillen et al. (2016) for a full description of methods).

Our research in Ka'ūpūlehu followed culturally appropriate protocols for interacting with this community including thoughtfully engaging community elders and opening the workshop with a genealogical chant to demonstrate respect for both people and place (see Pascua et al. 2017). This process of building relationships, understanding, and trust between outside researchers and community members was fundamental to conducting our work in ways that respected and honored community perspectives and resonated with their priorities and goals.

Methods to assess groundwater recharge as a function of land-use and climate change *scenarios: supporting information*

Fog capture:

We employed a method developed by Engott (2011), where fog interception is calculated as:

 $F = P \times FIR \times FCE$

Where $F = fog$ interception; P = precipitation (as rainfall); $FIR = fog$ interception ratio; and $FCE = fog-catch$ efficiency.

Ka'ūpūlehu falls within fog interception zone 1 on Hawai'i Island (Engott 2011). This fog interception zone assigns a fog interception ratio between 0-1 (as the fraction of precipitation that represents fog interception in addition to mean annual precipitation) based on elevation.

Fog-catch efficiency (FCE) is defined by vegetation type where fog interception only occurs in forest (all types, including agroforestry) $(= 1)$ and shrubs (including coffee) $(=.5)$. Grasslands, developed areas, and barren land covers are assigned an FCE of 0 (Engott 2011). The only modification made for climate change was changing rainfall as we did not have information on how FIR may change with climate change. FCE values were changed with land-use scenarios.

Actual evapotranspiration:

We estimated actual evapotranspiration (ET) under land-use and climate scenarios following (Wada et al. 2017) by creating linear regression equations with the annual latent heat flux equivalent (LE) of ET (W m⁻²) as a function of annual predictor variables: 1) air temperature; 2) net radiation; 3) relative humidity; 4) wind speed; 5) actual soil moisture; 6) leaf area index, canopy cover; and 7) vegetation height. We used a

database of 288,007 points across the Hawaiian Islands based on ET modeling at the hourly time step (Giambelluca et al. 2014). These ET estimates were validated with eddy covariance flux towers and modeled ET was highly correlated with direct measurements $(r^2=0.91)$ and bias and random errors were very low (MBE = 4 W m²and RMSE = 24 W \textsf{m}^2) (Giambelluca et al. 2014). A simplified modeling approach allowed us to run multiple land-use and climate scenarios at the annual time step.

We first tested for collinearity and removed variables with a VIF $>$ 5 (Zuur et al. 2009). We then incorporated spatial autocorrelation using the nlme package in R (Zuur et al. 2009) and selected the regression model with the lowest AIC value. We sub-setted larger land cover classes to 6463, the highest number of points in one land cover class that was able to run in R Studio without overwhelming the system. We maintained the points per island ratio in the subsets of larger land cover class. We used <1200 mm rainfall subset for two of the land cover classes (Hawai'i lowland mesic forest and Hawai'i lowland dry forest), which did not work well with the state data set. This was considered appropriate given that rainfall was <1200 mm in Ka'ūpūlehu.

LE values were used to obtain ET in water units (mm) by the equation:

$$
\frac{n}{\lambda * \rho_w}
$$

Where the $n =$ number of seconds in the relevant time period, $\lambda =$ the latent heat of vaporization of water (J kg⁻¹), and ρ_w =density of water (kg m⁻³) at the relevant temperature (Giambelluca et al., 2014).

ET model comparison with full ET model

We compared ET as estimated from the regression model to the full model estimates from Giambelluca et al. (2014) for each land cover type. Adjusted R^2 values were as follows: introduced perennial grassland (pasture): 0.91; Hawai'i subalpine mesic forest: 0.92; Hawai'i lowland mesic forest: 0.63; Hawai'i lowland dry forest: 0.66; coffee: 0.89; and introduced deciduous shrubland (used for fig): 0.99. Because adjusted R^2 does not account for the effects of spatial autocorrelation that we accounted for in the regression models, it is an imperfect, and likely conservative, measure of model fit. Within the Ka'ūpūlehu ahupua'a, the difference between the full model and regression model was <5% across all land cover types present.

Land-use and climate change scenario calculations:

Land-use changes were first accounted for by reassigning the appropriate regression equation for the new land cover. Coffee, pasture, and native forest were all modeled using the respective land cover classes in LANDFIRE (2012). We modeled agroforestry as 90% native forest cover—with adjusted leaf area index and vegetation heights (see below)— and as 10% introduced deciduous shrubland, a land cover class with a similar

stomatal conductance as fig (Giambelluca et al. 2014; González-Rodríguez and Peters 2010).

We changed annual vegetation height, LAI, and canopy cover to the median value for the given land cover in the Kona region as we did not find a relationship between these variables and rainfall. The 90% native agroforest LAI and canopy cover were calculated as an average of values for mixed agriculture and native forest. Vegetation height was calculated as $.7^*$ median height of forest+ $.3^*$ median height of mixed agriculture. This was based on the assumption that agroforestry would have 70% the density of trees. For the 10% fig, we used literature values for average height (Andersen and Crocker 2016) and used median values for canopy cover of another orchard crop (macadamia) for which spatial data on LAI and canopy cover was available.

To capture the likely impacts of land-use and climate change on mean annual net radiation, we calculated annual net radiation as a function of rainfall and land cover class (divided into forest, shrub, grass, barren, and developed). We included spatial autocorrelation in the model to obtain the best fit model (Zuur et al. 2009). We used a Kona subset for net radiation predictions. To maintain the spatial variability, we adjusted net radiation for future climates and changes in land use using the marginal difference between modeled net radiation (as a function of precipitation and land cover type). The best model included spatial autocorrelation and did not include an interaction of land use and rainfall.

Following Giambelluca et al. (2014), we did not change available soil moisture with landuse change, with the exception of transitions to irrigated land covers (coffee). For coffee, we used the Kona area median 0.82 available soil moisture for coffee land cover and assumed irrigation to meet ET demand. To adjust available soil moisture under climate change we followed Giambelluca et al. (2014)'s method where:

 $y = 0.182 * ln(x) + 0.2632$

and where $y=$ soil moisture (percent) and $x=$ average of current and previous month mean rainfall (mm/day). We used statically downscaled estimates for wet and dry season rainfall (6 months wet season and 6 months dry season) to adapt the available soil moisture layer (Elison Timm et al. 2014) 1 . We followed IPCC RCP 8.5 mid-century projections by increasing temperature 1.4 degrees C across the study area (IPCC 2014). All scenario calculations were done in ArcMap raster calculator.

Uncertainty associated with groundwater recharge estimates:

We estimated the error of the modeled ET as the difference between the full ET model (Giambelluca et al. 2014) and the simplified regression model (as described above) (Wada et al. 2017). To do so, we computed the mean absolute and mean percent error

 1 2016 corrected projections were used.

(along with standard deviations) between the full model and the simplified regression model for each land cover class (at a 250 m pixel scale) within Ka'ūpūlehu. We used the following equations:

1. Mean absolute error for given land class=

$$
\frac{\sum_{i \in K} (ET1 - ET2)}{n}
$$

where $i = a$ pixel in land class k ; $n =$ number of pixels in land class k ; $ET1 =$ actual evaporation as calculated by regression model; and *ET2*=actual evapotranspiration as calculated by full model.

2. Mean percent error for given land class =

$$
\frac{\sum_{i \in K} \frac{(ET1 - ET2)}{ET2} * 100}{n}
$$

where $i = a$ pixel in land class k ; $n =$ number of pixels in land class k ; $ET1 =$ actual evaporation as calculated by regression model; and *ET2*=actual evapotranspiration as calculated by full model.

Where there were $n \geq 30$ pixels of a given land cover within the study ahupua'a, we used only pixels within the ahupua'a for comparison. However, in some cases land covers were not present in the ahupua'a 250 m map (but were present in the higher resolution 30 m map) or were in a scenario (e.g. coffee), but not in the current land cover map.

To characterize the uncertainty of land-use scenarios, we adjusted the ET estimates calculated using the regression equations as follows:

3. Adjusted $ET =$

$$
ET1/(1 - F1)
$$

Where $ET1 =$ actual evapotranspiration as calculated by regression model and $F1 =$ fraction underestimate of regression model compared to full model.

Error estimates are reported as one standard deviation around the adjusted AET in terms of percent difference between the regression model and the full model.

We used the following equations to calculate the change between scenarios:

4. Mean difference between scenarios =

$ET1adj - ET2adj$

Where ET1adj= bias adjusted AET scenario 1 and ET2 adj=bias adjusted AET scenario 2.

5. SD of difference $=$

$$
SQRT(SDET1adj^2 + SDET2adj^2)
$$

Where SDET1adj = standard deviation of bias adjusted AET scenario 1 and SDET2adj = standard deviation of bias adjusted AET scenario 2.

We used the following equations to translate this into percent change:

6. Percent change between scenarios =

$$
\frac{ET1adj - ET2adj}{ET1} * 100
$$

7. SD percent change $=$

$$
\frac{SD(ET1adj - ET2adj)}{ET1} * 100
$$

Scenarios were considered meaningfully or significantly different from each other when the difference in ET was greater than the SD of the difference.

Methods to assess landscape flammability as a function of land-use and climate change *scenarios: supporting information*

We used a 20-year data set of burned area perimeters collected for the NW quadrant of Hawai'i Island by the Hawai'i Wildfire Management Organization to classify annual samples of random points across the landscape (N=150,000) as burnt or unburnt in a GIS. The dataset included the spatial extent of 91 fires ranging from 1 ha to >10,000 ha for the 3,000 km^2 landscape comprising the NW quadrant of Hawai'i Island. This binomial response was used to model the annual probability of fire occurrence per pixel as a function of (i) mean annual rainfall, (ii) mean annual temperature, (iii) land cover (Forest, Shrubland, Grassland, Agricultural, Developed, and Other from the 30m resolution 2012 LANDFIRE product), (iv) ignition density (derived from point-based wildfire records; (Pierce and Pickett 2014)), (v) aspect, and (vi) the annual rainfall anomaly (difference between annual and mean annual rainfall for the sample year) using generalized additive models (GAM; e.g. Brillinger et al. 2006). We fit models using all possible combinations of predictor variables, including an interaction between rainfall land cover, an interaction between rainfall anomaly and land cover, and sample

year as a random effect (Brillinger et al., 2006) and ranked these against the null model using Akaike's Information Criterion (AICc; Burnham and Anderson, 2013)

We used the top-ranked model (the global model; Akaike Weight >0.99; Explained Deviance=25.9%) and the Raster package in R (Hijmans and Van Etten, 2013) to predict the annual probability of fire occurrence across the Ka'ūpulehu watershed under current conditions (pasture), forest restoration, coffee and future changes in mean annual rainfall and mean annual temperature under the RCP 8.5 mid century scenario. The annual rainfall anomaly was set at zero for all predictions. The use of randomized, annual, point-based samples within 30x30m pixels (i.e. the resolution of land cover products) resulted in a model output that equates to the annual probability of fire occurrence per pixel. However, as the model response was derived from the annual extent of area burned over 20 years in the region, the per-pixel fire probabilities are best interpreted as the type of fire regime (e.g., high vs. low frequency) supported by the landscape and climatic features at each pixel, which we refer to as "landscape flammability." We explicitly excluded a spatial term in the model so that predicted fire occurrence probabilities were derived solely from landscape features and not weighted towards previously burned areas.

The predictors outlined above were selected based on data availability and the objective of assessing of how landscape features, and changes in those features, namely, land cover and climate, influence potential fire occurrence within the study area at Ka'ūpūlehu. Fire occurrence in Hawai'i is also driven by shorter-term temporal variability in weather conditions and human-caused ignitions, which were not captured in the model. The high uncertainty of these predictors and the lack of adequate temporal resolution in the annual fire history constrained the explanatory power of our best ranked model (see above). However, the predictors we used do capture the fundamental drivers of ecosystem fire occurrence $-$ climate, vegetation, ignition source, and topography (Pausas and Keeley 2009).

Methods to estimate biodiversity conservation values as a function of land use scenarios: supporting information

To assess biodiversity conservation value, we measured plant species richness and cover at field sites representative of the Ka'ūpūlehu scenarios. We focused only on plants, since with the exception of one species of bat, there are no native mammals in Hawai'i, nor native reptiles or amphibians; and over the elevation range of our study area, there are very few native bird species. We placed randomly located 10×50 m transects in pasture, restored native forest, and coffee monoculture land covers. Three transects were established in each of the forest and pasture land covers and were sufficient to capture most of the species richness of those land-uses based on species accumulation curves. Similarly, one transect was established in the coffee monoculture due to the homogeneity of the vegetation in this land use.

The restored native forest transects were established just across the border of an adjacent ahupua'a (Pu'u Wā'awā'a), due to the ability for us to easily monitor there. In terms of species composition, these were representative of the small area of restored native forest within Ka'ūpūlehu. Although the latter has been restored with more species, especially in the understory. Therefore our species richness estimates for the restored native forest scenario are likely underestimates. Within each transect, we established five adjacent 10 m x 10 m plots. In each 10 m x 10 m plot we identified and measured the height and diameter for all trees > 1.34 m tall and > 1 cm dbh. We also visually estimated percent canopy cover of tree species. We randomly selected a corner quadrat within each 10 m x 10 m plot to establish a nested 5 m x 5 m subplot. Within each 5 m x 5 m subplot we recorded the identity of all understory herbaceous and woody plant species $\left\langle \langle 1.34 \rangle \right\rangle$ and visually estimated percent cover by plant species, bare soil, rock, and dead wood. Samples were collected for all species not identified in the field. We identified a total of 56 species in the transects.

Given that there is currently no traditional agroforestry practiced in or near Ka'ūpūlehu, estimates of species richness and cover were developed for a potential agroforestry scenario based on expert knowledge of agroforestry systems practiced historically in Ka'ūpūlehu and those currently in practiced in similar environments elsewhere in the Pacific Islands. We assumed that the richness and cover of understory non-native species would be the same in the agroforest as the restored forest, since both are managed to remove these weedy species but it is impossible to eliminate them.

We used Bootstrap estimates to estimate species richness for the pasture, coffee and restored forest sites. All analyses were done using the R package Vegan (Oksanen et al. 2013). Since the agroforest scenario was not based on empirical data, we did not generate error estimates for any of the richness or cover values we assigned.

We categorized species as invasive species based on the Hawai'i state list of noxious weeds and those categorized as dominant invaders by the South Pacific Regional Environment Programme (Shirley 2000).

Table A1.2. Species composition for Agroforestry scenario. The species list was developed based on the composition of Hawaiian agroforestry systems historically practiced in the region, and the abundance of native species in the study site that are currently culturally and economically important. It includes Fig, an economically important introduced species with a growing market, appropriate for the climatic zone. Threatened/Endangered species are based on U.S. Fish and Wildlife Service listed species believed to or known to occur in Hawai'i (U.S. Fish and Wildlife Service 2015).

Methods to estimate economic returns to landowners as a function of land-use scenarios: supporting information

Table A1.4. Annual revenue and costs for pasture/cattle ranching scenario

Table A1.5. Parameter descriptions and values for native forest restoration scenario

^aBased on Henahena cost estimates (personal communication, Elliott Parsons) ^bBased on Kaiholena cost estimates (personal communication, Shalan Crysdale) ^cBased on Puu Waawaa project data (personal communication, Elliott Parsons) ^dBased on Haena cost assumptions (personal communication, Kawika Winters)

Table A1.6. Annual revenue and costs for native forest restoration scenario

Table A1.7. Parameter descriptions and values for coffee scenarios

*Based on Kamehameha Schools trial density (8,000 trees/13 acres)

**http://www.ctahr.hawaii.edu/oc/freepubs/pdf/ab-11.pdf

***http://www.nass.usda.gov/Statistics_by_State/Hawaii/Publications/Sugarcane_and_ Specialty_Crops/201508coffee.pdf

Table A1.8. Annual revenue and costs for coffee scenario (current climate)

Table A1.9. Annual revenue and costs for coffee scenario (RCP 8.5 mid century)

Table A1.10. Parameter descriptions and values for Hawaiian agroforestry scenario

^ghttp://www.mama-kii.com/collections/all

 $^{\text{h}}$ Idol et al. (2007):

http://www.hawaiiforestinstitute.org/documents/journal_sept2007.pdf ⁱGoldstein et al. (2006): http://www.pnas.org/content/103/26/10140.abstract

Table A1.11. Annual revenue and costs for Hawaiian agroforestry scenario

Results

Groundwater recharge results: supporting information

Table A1.12. Mean Annual Rainfall (MAR), fog interception, evapotranspiration, and groundwater recharge in the study area in millions of liters per year (MLPY). Letters indicate significant differences in AET and groundwater recharge among land uses within each climate scenario.

Landscape flammability results: supporting information

Fig A1.1. The annual area burned for the NW quadrant of Hawaii Island from 1992 to 2011.

Fig A1.2. The probability of fire occurrence for grasslands, shrublands, and forest. Points indicate actual probabilities calculated as the proportion and standard deviation (error bars) of area burned binned across the rainfall gradient. Solid lines indicate model predictions and dashed lines indicate the upper and lower 95% confidence intervals. Rug plots below illustrate the distribution of mean annual rainfall across the Kaupulehu watershed under current conditions (black rug) and under the RCP 8.5 climate change scenario (gray rug).

Mean annual rainfall (mm)

Biodiversity value results: supporting information

Table A1.13. Species richness and vegetation cover by land-use scenario in Ka'ūpūlehu Hawai'i. Values represent means \pm 1 SE. The category "non-native" includes both introduced and invasive species. Species richness was estimated using a Bootstrap estimator, numbers in parentheses represent actual species counts from the transects.

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