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Synthetic Flows for Engineered Systems with Nonstationary Parameters: Study of Maui's Wailoa Ditch

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ABSTRACT: Water flow through engineered channels is important for decision making given its close ties to availability for allocation. However, planners often rely on estimates for natural streamflow, then use stream-by-stream assumptions and aggregation to estimate allocatable flows rather than directly assessing flows through engineered channels. Further, synthetic flows based on historical records can be unreliable when parameter nonstationarity due to effects like climate change is likely. This case study of the Wailoa Ditch, a major engineered surface water supply system on Maui, Hawaii, uses a natural experiment based on Maui's declining rainfall to demonstrate and validate that both problems can be addressed. For Wailoa, synthetic and actual flow characteristics differ by less than 5% when historical records are adjusted to reflect changing rainfall. Direct simulation of Wailoa's flows reproduces modern conditions more accurately than stream-by-stream approximations. Precipitation-based scenario analysis suggests that under the influence of both decadal oscillations and climate change, Maui is far more likely to experience water supply shortages on its main engineered system in the future than in the past.

(KEY TERMS: climate change, scenario analysis, drought, rainfall-runoff, water resource planning, synthetic streamflow, irrigation systems, ditch flow)

INTRODUCTION

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Global water stress is increasing (Vörösmarty et al 2010), putting pressure on water managers to be more sophisticated in planning not only for historically observed variability of supply but also for less predictable variability related to issues like climate change (UNDP 2014), groundwater depletion, and long-cycle shifts that might not be reflected in human records. Planners seek to address a fundamental question of how future conditions will affect the amount of water available for allocation among uses like agriculture, drinking water, and environmental flow restoration. Often, addressing this question relies on a second question: how much will it rain? While rainfall is a relatively easy parameter to measure and record, understanding rainfall scenarios alone is often insufficient. Planners also need to understand how rainfall ultimately contributes to the amount of water that enters human-managed systems from surface and groundwater sources in order to answer questions like whether more storage should be built in a given area, whether a permit for water abstraction should be issued, or whether a treatment facility is prepared for high and low flow events. Often, the ultimate flows of interest are those in engineered channels like pipes, canals, and irrigation channels, not those in natural channels like streams and rivers. However, most modeling attention is devoted to relating rainfall to natural channel flows—a crucial relationship for ecosystem management and other tasks—that planners must then evaluate for their contributions to the allocatable resource.

This multi-step process relating rainfall to first natural, then human-managed engineered flows requires assumptions about capture, flow relationships, and others that increase the complexity of modeling potential effects of major external forcers like climate change. Developing models that directly relate rainfall to flows in engineered channels enables scenario planning and direct investigation of water availability for human use from engineered systems. This research asks whether such model development might proceed by adapting rainfall-runoff models developed for natural channels to modeling flows through engineered systems, particularly when climate parameters are expected to be nonstationary. In particular, this case study uses a well defined case study with a natural experiment useful for validation to investigate the Wailoa Ditch, a major engineered supply channel on Maui Island, Hawaii.

Maui's Wailoa Ditch as Case Study. Maui is a bellwether for the types of planning challenges that many other global regions are likely to face. Maui is already experiencing possible economic water scarcity (see e.g. County of Maui 2012; Freedman 2007) due to both supply (Bassiouni and Oki 2013) and demand changes, including a substantial decline in precipitation (Chu and Chen 2005; Diaz and Giambelluca 2012; Elison Timm *et al* 2011; Elison Timm *et al* 2015; Timm and Diaz 2009; Zhang *et al* 2016), and it faces complex water demand profiles that are not easily resolved in a scarcity context (Grubert 2011). Maui is small enough to model fairly completely but large enough to host the kinds of climatic and use case diversity usually seen on national scales, particularly because of the extreme climatic differences between its sea level plains and high mountain regions (Giambelluca *et al* 1986). As an island, Maui has easily defined boundaries, and its long history of water management and allocation means it has long-term historical flow records for both natural and engineered systems. Crucially, these flow records span a period with a major decline in rainfall similar in magnitude to the kind of structural shift that might be seen with climate change, which allows for model validation via a natural experiment that tests whether models based on pre-shift data can accurately replicate observed post-shift conditions.

On Maui, most surface water available for human use is delivered through engineered channels called ditches that do not behave like natural streams. Maui's ditches ring the island, running perpendicular to and diverting the island's many mountain streams at multiple elevations

(Fig. 1). While Maui's water is abundant, it is not well co-located with demand, so users either rely on highly energy intensive (and thus expensive) sources or on high quality, low energy intensity surface water that is delivered by gravity through the ditch systems (Grubert 2015). The largest of these systems is the Wailoa Ditch, which forms the backbone of the East Maui Irrigation System (EMI) with a capacity of 195 million gallons per day (mgd; 8.5 m^3/s) (Wilcox 1996). Wailoa has a capacity larger than any river or stream in the State of Hawaii (Wilcox 1996), and EMI is the largest privately built and operated water system in the United States (HC&S 2014). For context, the California State Water Project—the largest built water conveyance system in the United States—is less than 20 times the size of EMI, despite serving about 250 times as many people and 23 times as much agricultural land (California Department of Water Resources 2011).

Wailoa and other ditches play important roles in Maui's human-influenced hydrology, in particular by artificially connecting streams. Most of the island's streams run mauka to makai (mountain to ocean), with few tributaries and rare interconnections among streams (Fig. 1). The ditches thus serve to connect and comingle waters that would not otherwise meet and would not otherwise reach the flat, sunny Central Plain region between Maui's two major volcanoes where agriculture and urban settlements exist. Wailoa is important enough to Maui's human water supply that daily mean flows measured and published by the USGS are available for dates between 1922 and 1987, an exceptionally long record that enables Wailoa's use as a validation case for modeling an engineered system (U.S. Geological Survey, National Water Information System. Accessed May 2010 – August 2011, http://waterdata.usgs.gov/nwis: unless otherwise noted, all historical streamflow data are from this source).

Modeling for Water Management. Modeling potential future conditions using empirical historical data is a common approach to managing the inherent uncertainty of water supply (for example, see Fiering and Jackson 1971; Govindaraju and Rao 2010; Hirsch 1979; Srikanthan and McMahon 2001; Stedinger and Taylor 1982a and 1982b; and You *et al* 2014). Two major types of models used to model flows are rainfall-runoff models and synthetic flow models, both of which are almost always applied to natural systems like rivers and streams rather than engineered systems like canals and pipes. Rainfall-runoff models link rainfall to flow by explicitly accounting for specific, modeled mechanisms, such as basin shape, land cover, or elevation, while synthetic flow models use the statistical characteristics of the population of historical flow records to draw repeated samples that can be used for probabilistic analysis. That is, while rainfall-runoff models isolate specific mechanisms to estimate flow at the cost of possibly excluding an important determinant, synthetic flow models incorporate all mechanisms present in the historic record at the cost of not being able to isolate the effect of a particular mechanism. One reason this inability to isolate mechanisms is important is that synthetic streamflow models specifically do not account for the possibility that the underlying statistical structures present in the historic record do not accurately reflect actual conditions, which means that issues like short historical records, changes in climate or watershed conditions, and unmodeled periodicities can severely reduce their usefulness (Matalas 1997; Xu and Singh 2004; Vogel *et al* 1999). This condition of shifting historical parameters is called nonstationarity and poses a major challenge to planners seeking to address questions like how climate change might affect their systems and what levels of severe droughts and flooding might be experienced in the coming decades.

Nonstationarity on Maui and a Natural Experiment. This effort to model flows on engineered systems while accounting for the types of questions planners wish to answer—like how nonstationary parameters might affect the water system—benefits from a natural experiment that allows for model validation. Specifically, precipitation on Maui is nonstationary, having declined by approximately 15% (Chu and Chen 2005) since the period of record for widely-used long-term average (1916-1983) precipitation figures (Giambelluca *et al* 1986). Coincidentally, long-term USGS historical flow records (1922-1987) for the Wailoa Ditch cover a period similar to that for the long-term precipitation averages, which means that synthetic flow models for Wailoa based on historical data are vulnerable to precipitation nonstationarity. Independent flow records reflecting modern conditions exist and can be used to validate modeling results attempting to correct for this nonstationarity, presenting an opportunity for a natural experiment testing whether synthetic flow models can be adequately adjusted for nonstationarity by integrating relationships from rainfall-runoff models with synthetic flow models.

This natural experiment possible for Maui's Wailoa Ditch is important largely because it enables validation of a technique—adjusting historical flow statistics based on different levels of a parameter like precipitation—that can then be used for scenario analysis useful for water availability and drought planning. That is, if a model adjusted to reflect current precipitation conditions produces accurate estimates of current flow conditions on the Wailoa Ditch, planners can feel more comfortable using the adjusted model to test many different scenarios for future precipitation to evaluate likely water availability and drought risk. Simulations of engineered system flows can be a direct link between common hydrologic parameters like rainfall and inputs to social and economic analyses that require information about water availability. This study thus adds to the water management literature by addressing two main questions using Maui's Wailoa Ditch as a case study:

1) Can parameter relationships from rainfall-runoff models be used to compensate for nonstationarity in synthetic flow models?
2) Can models designed for natural channels effectively be applied to an engineered system to directly assess water availability, including drought risk?

In particular, this work joins the existing literature on rainfall-runoff modeling, synthetic flow modeling, nonstationarity, scenario analysis, and drought assessment, adding a perspective focused on an engineered system.

METHODS

This analysis demonstrates the usefulness of modeling water availability from engineered systems by generating scenario-based synthetic flows for those engineered systems directly, rather than by assessing flows in natural channels and making assumptions about their relationship to water availability. The analysis first validates the method using a natural experiment to confirm that rainfall nonstationarity can be addressed, then presents results of a drought risk assessment. Generation and analysis of scenarios linking rainfall to flows on the Wailoa Ditch uses four steps (Fig. 2):

1) Select rainfall scenarios for analysis based on the literature;

2) Apply rainfall-runoff relationships to scale historical flow data for scenario analysis;

3) Use scaled historical flow to generate synthetic flows for chosen scenarios;

4) Validate synthetic flows using independent data and assess major implications for water availability, primarily drought.

Step 1: Select future rainfall scenarios for analysis based on the literature

This drought case study examines three levels of rainfall that Maui might observe in the future:

a) A control scenario using historical 1916-1983 rainfall levels ("100%") as published in the 1986 Rainfall Atlas of Hawai'i (Giambelluca *et al* 1986), which were used to develop the regression equation used here (Gingerich 2005);

b) A validation scenario using estimated current rainfall levels, approximately 85% of the 1986 historical values ("85%," Chu and Chen 2005), as the basis of a natural experiment to be tested against measured modern flows; and

c) An inquiry scenario using estimated future rainfall levels based on ensemble means and application of multiple linear regression to six IPCC AR4 climate models, forecasting a 5-10% decline in winter (October – April) rainfall and a 5% increase in summer (May – September) rainfall versus present day values (Timm *et al* 2009; Elison Timm *et al* 2011). For this analysis, the more conservatively dry value of a 10% decline in winter rainfall is used. Since current rainfall is about 85% of historical values, anticipated rainfall under climate change is estimated at 77% of historical values for winter (90% of 85% of the 1916-1983 average) and 89% of historical values for summer (105% of 85% of the 1916-1983 average) when both the recently observed decline in rainfall and the expected seasonal effects of climate change are taken into account. Further background and analysis of additional future rainfall scenarios using a wider range of rainfall-runoff response parameters can be found in Grubert (2011).

Step 2: Apply rainfall-runoff relationships from regression equations to scale historical ditch flow for scenario analysis

Once rainfall scenarios are selected in step 1, the historical ditch flow record is scaled using the rainfall-runoff relationship implied by a regression equation that applies to the streams that feed the ditch, with an output (like median flow) that can be related to flows in the engineered channel. Regression equations link an output of interest, like streamflow, with easily measurable parameters, like basin size. Streamflow characteristics are often log-normally distributed (Oki *et al* 2010), and so streamflow regression equations frequently take the generic form

$$Q = k \times \prod_{i=1}^{n} X_i^{b_i} \qquad (1),$$

where Q represents flow, k is an empirical parameter, and X_i represent independent basin characteristics like area or elevation (Oki *et al* 2010). The exponent of each parameter indicates the sensitivity of median streamflow to that parameter. Larger exponents indicate higher sensitivity, with exponents greater than one indicating that flow will change proportionally faster than the parameter of interest.

Ditch characteristics cannot themselves be used to parameterize a regression equation developed for natural channels, as ditches have fundamentally different channel shape, orientation, and water input profiles from Maui's streams. Thus, in order to apply a rainfall-runoff relationship from a regression equation calibrated with natural channels to flow in an engineered system, a link must be established between the streamflow predicted by the regression equation and the desired type of flow in the engineered channel. In some cases, engineered channels might be capacity constrained by channel size (capturing all water up to some cumulative value), pipes (capturing all water from an individual stream up to some value), or other physical or operational constraints. For Wailoa, given a long-term record of mean flow in the engineered channel, it is necessary to find some relationship between mean ditch flow and one of the types of flows related to precipitation by a rainfall-runoff relationship. To establish this link, it is necessary to consider the physical relationship between the engineered channel and its inputs—here, the flow from many streams, not rainfall.

Seven regression equations linking precipitation to streamflow are identified for Maui, with two focused on mean flows (total mean flows for leeward and windward streams, Yamanaga 1972 *in* Verdin and Worstell 2008); three focused on median flows (total flow, Fontaine *et al* 1992; total and base flow, Gingerich 2005); and two focused on low flows (95 percent duration total and base flows, Gingerich 2005). Thus, if Wailoa Ditch flow can be related to mean, median, or low total or base flow for streams on Maui, a link enabling direct synthetic record generation for the ditch can be established.

A similar exercise considering available validation data and available relationships can be carried out in other settings with different results, but in the case of the Wailoa Ditch, the closest relationship is between median streamflows for the perennial Northeast Maui streams that feed Wailoa (Gingerich 2005) and mean ditch flow ($Q_{\text{ditch, mean}}$). The reason that median streamflows behave like mean ditch flow is because stream diversion structures, effectively gaps in the streambed that redirect water to the ditch system, tend to capture all low and medium flows: 100% of streamflow is captured roughly 70-80% of the time (Gingerich 2005). This capture is, on average, quite similar to median flows because of the flashiness of the streams, with very high infrequent flows that are not captured but tend to increase mean flow relative to median flow. The assumption that on average, annual median flows are diverted is supported by measurements taken at several streams (Gingerich 2005). Thus, mean ditch flows are approximated as aggregated median streamflows ($Q_{\text{ditch, mean}} \cong \Sigma Q_{\text{streams, median}}$), which provides the link between ditch flow data and a regression equation necessary to carry out validation of the natural experiment described in this work.

Details of the chosen regression equation, including original datasets, can be found in Gingerich 2005, summarized here. The equation (adapted here to SI units from the original, Gingerich 2005) estimates annual median streamflows in cubic meters per second for Northeast Maui streams given elongation ratio *ER* (a dimensionless measure of basin shape, where a higher *ER* represents a shorter, wider basin), maximum basin elevation E_{max} (meters), and annual mean rainfall *RF* (cubic meters per second, m^3/s, for the stream's drainage area):

$$Q_{\text{stream, median annual total flow}} = 27.48 \times ER^{-0.946} \times E_{\max}^{-1.366} \times RF^{1.338} \quad (2).$$

The regression equation provides the 50 percent flow duration of total flow (referred to as median flow henceforth) and is calibrated based on gaged daily-mean flow data adjusted to a 1914-2003 base period and annual rainfall data for 21 streams and their basins adjusted to a 1916-1983 base period (as published in Giambelluca *et al* 1986), converted to volume per second (Gingerich 2005). In both the flow and rainfall cases, adjustment to the base period required extrapolation of data due to limited records at some stations: complete records for the entire base period do not exist for all stations (Gingerich 2005). Applicable parameter ranges for Equation 2 are found in Table 1 (Gingerich 2005). The equation is considered applicable over roughly an order of magnitude in rainfall rate, from 0.2 to 1.4 m^3/s, which means it is valid for the range of rainfalls used for scaling in this work.

Scaling the historic ditch flow records by the rainfall-streamflow relationship that characterizes the ditch's inputs produces alternative scenario historical records that preserve statistical relationships but reflect different rainfall conditions. This adjusted record is important because it enables derivation of statistical structures like inter-trial correlations used to generate synthetic flow series in the next step. The scaled historical flows are not themselves used for drought analysis, but rather as the basis for generating synthetic flow records that are.

Scaling proceeds as follows. The relationship between streamflows and rainfall is isolated from the other regression equation parameters (e.g. basin size). That is, mean annual ditch flow can be related to mean annual rainfall by

$$Q_{\text{ditch, mean}} \propto RF^{b} \qquad (3),$$

where *b* is the exponent of rainfall in the regression equation – here, 1.338. Rainfall scenarios selected in step 1 are incorporated by noting that for future rainfall equal to *x* of current rainfall, the relationship is

$$Q_{\text{ditch, mean}} \propto x^{b} = \left(\frac{RF_{future}}{RF}\right)^{b} \qquad (4).$$

The factor in equation (4) is then multiplied by each monthly datum in the historical USGS monthly mean Wailoa Ditch flow records to produce an adjusted historical record that incorporates the effect of different rainfall scenarios.

Step 3: Use scaled historical flow to generate synthetic flows for chosen scenarios

Generating synthetic ditch flow sequences follows Fok and Miyasato (1976) in using a lag 1 Markov model, a time-varying stochastic model common in streamflow modeling (Fiering and Jackson 1971) for which the result of a trial depends only on the outcome of the trial directly preceding it.

Here, synthetic monthly flow sequences are generated for the Wailoa Ditch with this lag 1 Markov ditch flow model, which includes a random noise term, historical observed sample standard deviations, and a correlation coefficient that relates flows in one month to flows in the preceding month, based on historical or adjusted historical flow data. Let $Q_{i,j}$ be the flow in month j of year i. $Q_{i,j}$ is given as

$$Q_{i,j} = \bar{Q}_j + b_j\left(Q_{i,j-1} - \bar{Q}_{j-1}\right) + ts_j(1 - r_j^2)^{1/2} \quad (5),$$

where t is a random variate selected from a continuous probability distribution; s_j is the sample standard deviation of flows in month j; r_j is the correlation coefficient linking flows in month j to flows in month j-1, defined as

$$r_j = \frac{\sum_{k=1}^{p} x_{k,j}x_{k,j-1} - p\bar{x}_j\bar{x}_{j-1}}{s_j s_{j-1}(p-1)} \quad (6),$$

where p is the number of years of record (Fiering and Jackson 1971). If an initializing flow datum is missing, the sums are multiplied by $p/(p-1)$, as only $p-1$ terms are present. The regression coefficient b_j linking flows in month j to flows in month j-1 is defined as

$$b_j = r_j \times \left(\frac{s_j}{s_{j-1}}\right) \quad (7).$$

Here, the scaled historical flow data produced in step 2 are used to calculate the necessary coefficients for synthetic flow generation, summarized in Table 2.

In this case, t is selected from $N(0,1)$, the normal distribution with mean 0 and standard deviation 1, based on work by Fok and Miyasato (1976) extended by Grubert (2011) showing that the normal distribution is an appropriate fit for this type of analysis on the Wailoa Ditch, with 11 of 12 months passing a chi square test at 95 percent confidence with seven degrees of freedom (detail can be found in Grubert 2011). Given these relationships, the scaled historical record (65 flow-years) from step 2 is then used to calculate monthly correlation coefficients according to Equations 5-7. As the highest reported resolution on mean flows is daily, monthly data are considered reliable.

Records are initialized with the mean flow for the first month, January in this analysis. The first 60 modeled months of synthetic data are discarded to reduce the signal of the initializing value. While negative flows are not commonly generated, the simulation is manually screened for negative values to eliminate negative flows from analysis where necessary. For this assessment, 1,000 model years of synthetic data are generated, a level at which basic statistical parameters are stable and rare events are detectable at a rate acceptable for a model that considers current conditions and a climate scenario through 2100.

Step 4: Validate synthetic flows using independent data and assess major implications for water availability, primarily drought

Validation. After synthetic flows for Wailoa Ditch are generated, two main aspects of the approach are validated using data external to those used to develop model relationships: namely, the hypothesized link between streamflows and ditch flows and the assumption that synthetic records for precipitation scenario analysis can be accurately produced by scaling the historical flow record. The validation process is illustrated in Fig. 3.

The first validation is a bottom-up approach that tests the assumption that mean ditch flows are approximately aggregated median streamflows ($Q_{\text{ditch, mean}} \cong \Sigma Q_{\text{streams, median}}$) by individually estimating Q_{median} for the 39 Northeast Maui streams that account for nearly all input to the EMI ditch system, then summing these flows for comparison to estimated $Q_{\text{EMI, mean}}$. The estimate is adjusted to reflect Wailoa's typical share of system flow to give an estimate of $Q_{\text{ditch, mean}}$ based on $\Sigma Q_{\text{streams, median}}$. If the estimate is similar to measured flow values for Wailoa, the validation succeeds.

For this bottom-up validation, the regression equation is applied to each of the 39 input streams using drainage basin characteristics at the highest-elevation point of diversion, which is usually the Wailoa diversion at about 400 meters of elevation. The streams, their basin characteristics as derived from StreamStats, a United States database, and the latitude and longitude of the delineation point for each stream can be found in Grubert (2011). StreamStats uses a 10-meter USGS Digital Elevation Model (DEM) to define elevations (Rosa and Oki 2010) and 1916-1983 rainfall averages (Giambelluca *et al* 1986).

Wailoa Ditch flow is estimated from measured EMI system flows based on data from USGS' NWIS database indicating that, on average, Wailoa Ditch accounted for about 68 percent of EMI system flows between 1931 and 1985 (the years with the most complete system gage records), with a standard deviation of 4 percent. This analysis assumes that Wailoa continues to account for 68% of EMI flows, with more background and analysis in Grubert (2011).

The second validation is a top-down test of the assumption that scaling the historical flow record using rainfall-runoff relationships enables the production of synthetic records that accurately replicate modern conditions by compensating for nonstationary precipitation. First, average synthetic flows from the control scenario are compared with historical records to ensure the model is working correctly. Average synthetic flows from the validation scenario (85%) are compared to measured flow data for EMI that are independent of the gage data underlying the estimate—specifically, flow data collected and reported by HC&S (CWRM 2010) rather than USGS (Fig. 3). Wailoa Ditch flow is again estimated by assuming that Wailoa accounts for 68% of EMI flow. If average synthetic flows roughly match recorded flows, the validation succeeds.

Drought assessment. Drought risk under lower rainfall futures is assessed by analyzing three flow-related parameters for each of three rainfall scenarios over 1,000 twelve-month periods of synthetic flow model data (Table 3). Extreme drought is defined as a month where mean Wailoa Ditch flow averages less than 0.9 m^3/s, a condition reached only once during the ditch's 65 year historical record (see Grubert 2011). This threshold is based on the system's emergency level: if EMI flows fall below 0.9 m^3/s (20 mgd in local units) flows are not adequate to simultaneously supply drinking water treatment plants at normal levels and provide adequate fire suppression water to a major local industrial facility (Hamilton 2008). Given Wailoa's major contribution to EMI flows (>70% during drought periods), a month with less than 0.9 m^3/s average flows on Wailoa is likely to contain periods of emergency on the EMI system generally.

RESULTS

Results are presented for validation of analytical decisions, then for drought analysis using synthetic flows for Wailoa Ditch generated via the validated procedure.

Validation

Bottom-up: Testing whether $Q_{\text{ditch, mean}} \cong \Sigma Q_{\text{streams, median}}$. Synthetic $Q_{\text{ditch, mean}}$ for Wailoa Ditch under the control precipitation scenario (i.e., replicating historical conditions) is 4.8 m^3/s (mean of 1,000 trials). For the 39 primary input streams, $\Sigma Q_{\text{streams, median}} = 4.7$ m^3/s, with historical measured $Q_{\text{ditch, mean}} = 4.9$ m^3/s. Thus, the control estimate is about 2% lower than observed flow and about 2% higher than $\Sigma Q_{\text{streams, median}}$, so the assumption that $Q_{\text{ditch, mean}} \cong \Sigma Q_{\text{streams, median}}$ is considered valid.

Top-down: Testing whether rainfall scaling compensates for nonstationarity. Synthetic $Q_{\text{ditch, mean}}$ for Wailoa Ditch flow under the validation precipitation scenario (i.e., replicating current conditions) is 4.0 m^3/s (mean of 1,000 trials). HC&S flow measurements indicate annual measured $Q_{\text{EMI, mean}}$ = 6.1 m^3/s (139 mgd) between 2003 and 2009 (CWRM 2010), which corresponds to estimated annual $Q_{\text{ditch, mean}}$ = 4.2 m^3/s for the Wailoa Ditch. Thus, the natural experiment succeeds, generating estimates within 5% of observations.

Drought assessment

For the control scenario using unscaled historical flow records, model results (sample size: 1,000 twelve-month trials) indicate a synthetic annual $Q_{\text{ditch, mean}}$ = 4.8 m^3/s, or 99% of historical flows. Extreme drought occurs in 74 of 12,000 months, for an incidence of 0.6%. Extreme droughts occur most frequently in September, for 24 out of 1,000 trials (2.4%) (Fig. 4). Annual synthetic $Q_{\text{ditch, mean}}$ are above the measured historical median $Q_{\text{ditch, mean}}$ in 48% of annualized trials, matching the expectation of 50% well. Monthly agreement is less good: for example, modeled January flows exceed historical median $Q_{\text{ditch, January mean}}$ in 60% of trials (Fig. 5).

For the validation scenario approximating current conditions, synthetic annual $Q_{\text{ditch, mean}}$ = 4.0 m^3/s, or 80% of historical flows. Extreme drought occurs in 107 of 12,000 months, for an incidence of 0.9%. Extreme droughts again occur most frequently in September, for 28 out of 1,000 trials (2.8%). Annual synthetic $Q_{\text{ditch, mean}}$ are above the measured historical median $Q_{\text{ditch, mean}}$ in only 4% of annualized trials, and again, modeled January flows are relatively highest compared to actual data, with 34% of January trials showing $Q_{\text{ditch, mean}}$ above historical median $Q_{\text{ditch, mean}}$.

For the inquiry scenario approximating rainfall expected under anthropogenic climate change by 2100, assuming winter precipitation of 77% of 1916-1983 levels and summer precipitation of 89% of 1916-1983 levels, synthetic annual $Q_{\text{ditch, mean}}$ = 3.8 m^3/s, or 76% of historical flows. Extreme drought occurs in 129 of 12,000 months, for an incidence of 1.1%—nearly twice the rate simulated using 1916-1983 conditions. Here, October sees the largest incidence of extreme droughts, with 25 out of 1,000 trials (2.5%) (September has a 2.3% incidence). Annual synthetic $Q_{\text{ditch, mean}}$ are above the measured historical median $Q_{\text{ditch, mean}}$ in only 2% of annualized trials, with relatively higher flows in the summer as expected.

DISCUSSION

Validation

Validation indicates that the two major assumptions made in this work—$Q_{\text{ditch, mean}} \cong \Sigma Q_{\text{streams, median}}$ and that the historical record can be scaled using a rainfall-runoff relationship to reflect changed precipitation—are valid, with close agreement between simulated and actual flow statistics on an annual basis for both historical and current conditions. Assuming historical conditions, $\Sigma Q_{\text{streams, median}}$ is 4% lower than the long-term recorded annual $Q_{\text{ditch, mean}}$. Modeling mean ditch flow directly (assuming $Q_{\text{ditch, mean}} = \Sigma Q_{\text{streams, median}}$) produces an even more accurate estimate, only 2% lower than the long-term recorded annual $Q_{\text{ditch, mean}}$. The small underestimation is expected, as inputs from very small streams and high flow events are excluded. Actual $Q_{\text{ditch, mean}}$ would thus be expected to be slightly higher than the synthetic flows, confirmed by the data.

Notably for Maui, this validation further indicates that the EMI system essentially totally diverts annual median streamflows, as has previously been suggested (Gingerich 2005).

This study also validates the use of rainfall-runoff equations to compensate for nonstationarity in synthetic flow modeling for the Wailoa Ditch, reproducing basic annual statistics to within 5% of measurements (CWRM 2010) by generating synthetic records based on precipitation-scaled historical records. While this case study only addresses Northeast Maui, the result is a promising indicator that, given an appropriate regression equation, parameter scaling can enable accurate scenario analysis using synthetic flow generation methods. Many regions of the United States have fairly up-to-date regression equations available for linking climate parameters and streamflows (Verdin and Worstell 2008), and the higher geographic similarities across larger areas in the continental United States (Vogel *et al* 1999) suggest that high regression equation resolution is likely less important for other locations.

The model used here does not incorporate temperature effects, in part because model results indicate close agreement without the added complexity. Streamflows on Maui (and likely other volcanic islands) are likely to be less sensitive to temperature than other regions because Maui has almost no surface water storage, extremely flashy streams with low retention time, and no snowmelt input. A recent study on effects of climate change on streamflow on the Island of Hawaii also investigates links between streamflow and precipitation without incorporating a temperature parameter, noting a link between temperature and precipitation but not streamflow yield (Strauch *et al* 2015). Investigation of temperature effects on orographic rainfall at midlatitudes also shows this link (Siler and Roe 2014). Further, though Maui is getting warmer (Giambelluca *et al* 2008; Diaz et al 2014), temperatures at the elevations relevant to this study have been rising at less than half the global average rate (Fletcher 2010). Work in other basins indicates that rising temperatures tend to reduce streamflow (Fu *et al* 2007), suggesting the results presented here might conservatively underpredict drought. Issues like incorporating evaporation from water bodies, particularly given a rising temperature trend, might be more important elsewhere (Fu *et al* 2007), particularly where regression equations include a temperature relationship as a major parameter affecting flow (e.g. Vogel *et al* 1999).

Drought assessment

An implication of the regression equation's modeled relationship between rainfall and streamflow (Gingerich 2005, here translated to ditch flow) is that flows fall faster than rainfall: the exponent 1.338 implies that for every 1% fall in rainfall, flows will fall by 1.338%. This relationship is borne out in the modeled results for ditch flow response to rainfall: at 85% of rainfall, ditch flows are only 80% of their historical values, a 20% decline in flow for a 15% decline in rainfall as anticipated. The model behaves as expected and reflects the challenge that flows and thus water available for human use will fall faster than rainfall, in part because Maui's ditch-feeding streams have very little bank storage and highly porous beds.

The only recorded incidence of extreme drought as defined in this work occurred in October 1984, a 0.1% incidence in the 778 months of gage data between 1922 and 1987. The synthetic record generated assuming historical conditions suggests that extreme drought might be expected about six times as frequently over long periods of time, based on 1,000 model years of synthetic flows. This result could be a model artifact as the rainfall-runoff model does not capture the contributions of groundwater-derived base flows. Potential for some groundwater contribution likely means that the model overpredicts extreme drought, but it is worth noting that groundwater pumping activity has increased significantly since 1987, reducing the amount of groundwater available for inflow.

As expected, as rainfall declines, extreme droughts are expected to become more frequent, at about 0.9% under current rainfall conditions and 1.1% under conditions expected as a result of anthropogenic climate change (excluding the contributions of possibly threatened groundwater-derived base flows). Additional recent work on the effect of climate change on Maui's rainfall suggests that conditions could be considerably drier (Elison Timm *et al* 2015), making extreme drought even more likely. Modeled extreme periods tend to be more evident during the late portion of Maui's dry season (September – October) and the middle portion of Maui's wet season (January – February) (Fig. 4). While drought conditions at the end of the dry season make intuitive sense, the driver of mid-wet season droughts are less obvious: possibly, the fact that Maui's rainfall tends to come in a few large winter storms that might overtop diversions, resulting in the loss of floodwaters, is driving these conditions.

Overall, declining rainfall means less water is available for use from the Wailoa Ditch. Fig. 5 shows that the two low rainfall condition scenarios produce below-median mean flows in every month of the year: in fact, only 2-4% of years would be expected to reach median annual mean flows. The shape of the synthetic record based on historical conditions suggests that the model might be overpredicting flows in January-February, June, and September-October (Fig. 5); an alternative interpretation is that the small sample size that is the 65 year historic record has some characteristics that would not be observed over the long term.

Limitations

Regression equations are empirical and highly specific to the conditions under which they are developed: thus, the most fundamental limitation of using regression equations for scenario analysis is the assumption that the underlying drivers of an empirical relationship do not change with the scenarios. One illustration of this problem is that the relationship between rainfall and streamflow (and thus, by extension, ditch flow) might change in response to climate change or other external factors like altered land use.

A specific example of how this relationship might not be independent of rainfall conditions is the situation where low rainfall leads to a higher contribution to streamflow by groundwater inputs. If rainfall declines, groundwater input (base flow) tends to become a larger relative contributor to total flow: if total streamflow is lower because of decreased rainfall but the groundwater contribution remains the same, the reduced total flow will be more dependent on groundwater. Thus, increasing rainfall by one percent might create a relatively smaller change to total streamflow than when more of the streamflow was due to rainfall, effectively decreasing the elasticity. Alternatively, if land use change causes more rainfall to become surface runoff rather than groundwater recharge, as might happen after deforestation (Idol 2003), rainfall would become a more significant contributor to total streamflow, and the elasticity would increase: more streamflow would result from the same increase in rainfall. Sensitivity testing using more rainfall scenarios and more regression equation relationships, including one developed for dryland streams, can be found in Grubert (2011).

Additionally, this analysis does not consider the potential effects of increased flow variability, which could be particularly relevant for drought assessment. However, evidence suggests that rainfall variability and streamflow variability might be declining or holding relatively stable for Hawaii and are not likely to be statistically significantly affected by climate change (Wetherald 2010; Elison Timm *et al* 2011).

CONCLUSIONS

This analysis of Wailoa Ditch flows on Maui, Hawaii integrates several well known tools to analyze surface water availability in engineered systems: regression equations characterizing parameter-runoff relationships; scenario analysis of potential future conditions to characterize ranges of outcomes and encourage resilient planning; and drought assessment with synthetic flow records, using observed parameters to simulate a large amount of statistically consistent data for analysis. In particular, this work demonstrates that when the relationship between natural and engineered channel flow is understood, generating synthetic flows for scenario analysis for engineered systems directly can produce accurate representations of reality.

While the particulars of this case study are not widely generalizable beyond volcanic islands with similar engineered channels, the broader insights are: focusing on engineered systems as targets for probabilistic assessment of water availability, drought risk, and other characteristics relevant to water management is useful, and using regression model relationships as the basis for scenarios testing nonstationarity in important parameters improves the value of synthetic flow modeling. Focusing directly on engineered systems can enable more accurate replication of real conditions on the systems most relevant to human use, as seen in the Wailoa example where a direct ditch flow estimate better reproduces measured flows than a more typical bottom-up estimate of streamflows that feed the ditch. The Wailoa Ditch presents a valuable opportunity to test direct generation of synthetic flows on engineered systems under different precipitation conditions because the system is large, isolated, and well characterized, with high quality data, a useful natural experiment that enables validation, and salience for socioeconomic decisions on Maui.

Accurately anticipating future surface water supplies has major implications for Maui and many other regions, including determination of agricultural viability, choices and investment in energy supply, and allocation of investment to various types of water infrastructure. Linking commonly-forecasted rainfall data to engineered system flows, which are an important indicator of water availability, is a useful way to link complex meteorological models to the water flow data that have the most actionable relevance for public and private decision makers. Further, focusing on engineered system flows helps to separate questions about immediate concerns like how much water is available given current conditions from longer-term questions about issues like how water is abstracted, diverted, and allocated. This Wailoa Ditch case study demonstrates that combining regression analysis, scenario analysis, and synthetic flow models to engineered systems can produce useful information for water planners by directly modeling the amount of water available to manage. Water managers like those on Maui already monitor and use data about flows on engineered systems because it is valuable. Being able to expand this information through direct modeling, which can be used in tandem with models of natural systems, grants flexibility and enables more direct communication about the biggest water management lever many planners have: the amount of water available and ready for allocation from engineered systems.

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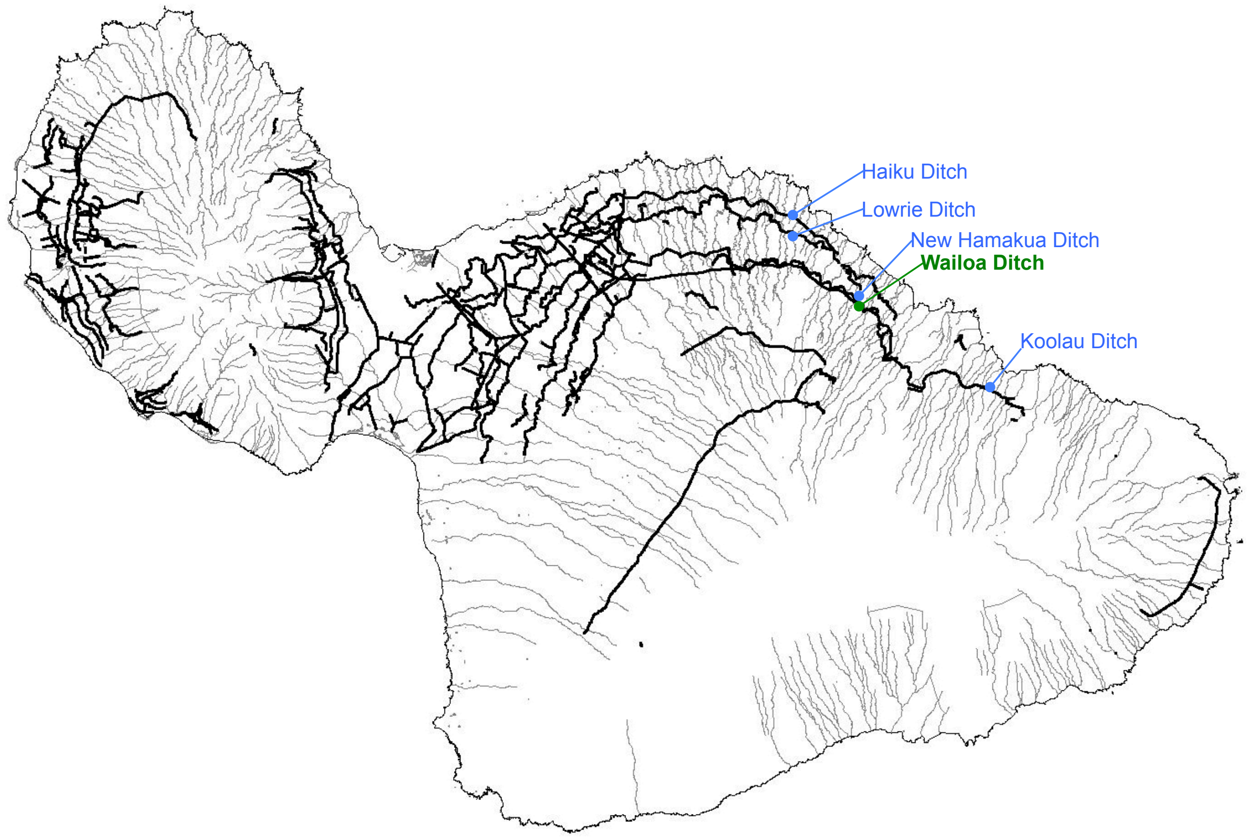
FIGURES

Fig. 1. This map shows Maui's natural (gray) and engineered (black) waterways, with Wailoa Ditch and other major East Maui Irrigation (EMI) ditches labeled.



Final article available at: http://ascelibrary.org/doi/abs/10.1061/(ASCE)HE.1943-5584.0001468

Fig. 2. Synthetic flows for the Wailoa Ditch are generated for three precipitation scenarios using historical gage and precipitation data with scaled precipitation, then validated using modern flow records.

	Detailed steps	Data
Step 1: Select rainfall scenarios	• Choose control scenarios (1=historical) • Choose validation scenario (2=current conditions) • Choose inquiry scenario (3=climate change conditions)	• For $\phi = \frac{\text{scenario annual average}}{\text{historical annual average}}$: ○ $\phi_1 = 100\%$ ○ $\phi_2 = 85\%$ ○ $\phi_{3,\text{winter}} = 77\%$; $\phi_{3,\text{summer}} = 89\%$
Step 2: Scale historical flow	• Identify available relationships between nonstationary parameter (rainfall) and streamflow with elasticity α • Characterize relationship between ditch flow and stream flow • For each scenario, multiply monthly values in historical record by ${\phi_i}^{\alpha}$	• Regression equations (literature) ○ 1914-2003 USGS flow records (actual and extrapolated) for 17 Northeast Maui gages ○ 1916-1983 rainfall isohyets based on 18 Maui gages • Streamflow measurements up and downstream of ditch diversion structure
Step 3: Generate synthetic records	• Apply lag 1 Markov model to monthly-resolution scaled historical Wailoa record for each scenario	• Scaled 65 year (1923-1987) monthly mean flow record for Wailoa Ditch and derived parameters
Step 4: Validate outcomes for control and validation scenarios	• Bottom-up: derive median streamflow for 39 contributing streams using regression equations and scaling precipitation by ϕ_i • Top-down: take monthly means of measured ditch flow for historical (scenario 1) and present day (scenario 2) periods	• Bottom-up: ○ StreamStats: max elevation, drainage area (used for RF and ER), basin perimeter (used for ER), precipitation (used for basin RF, based on 1916-1983 isohyets), lat/long; scenario ϕ_i • Top-down: ○ Scenario 1: USGS 1922-1987 gaged flow data ○ Scenario 2: HC&S 2003-2009 flow data

Fig. 3. Modeled values for Wailoa Ditch flows are validated both bottom-up (by modeling inputs by 39 streams) and top-down (by comparing with independently measured flow data).

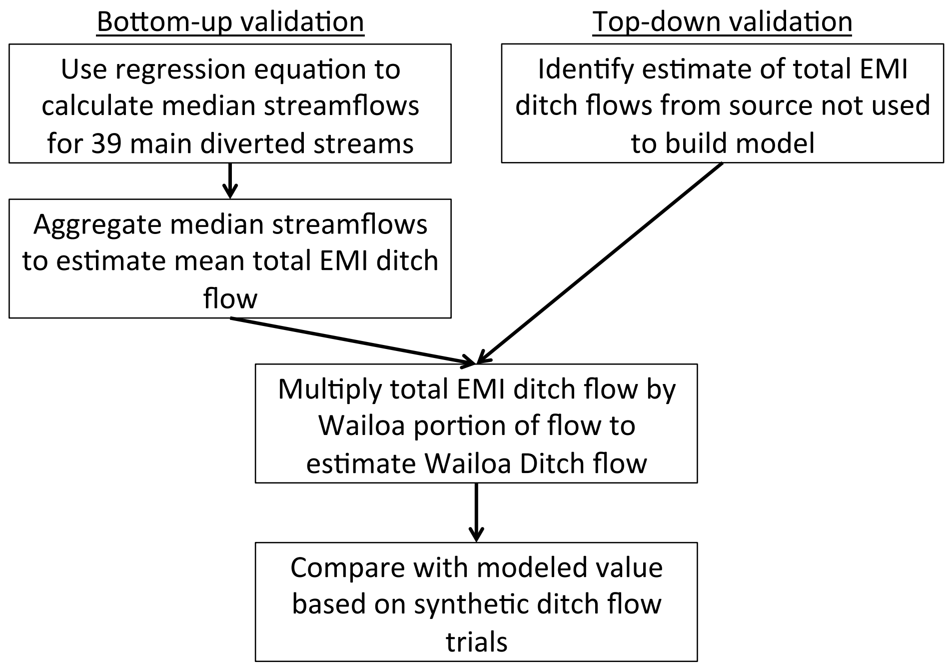
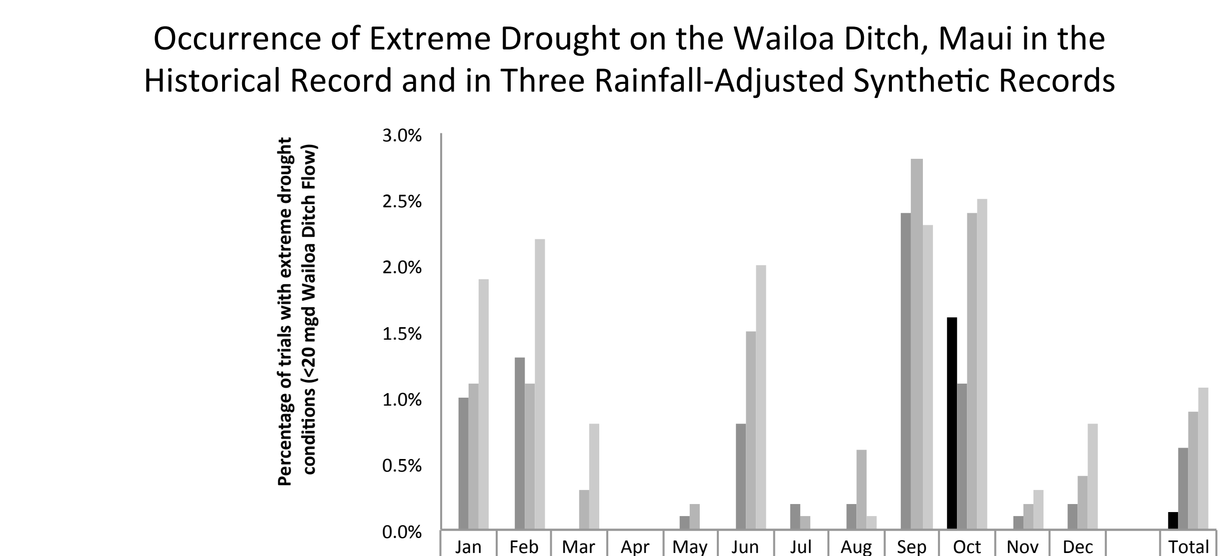
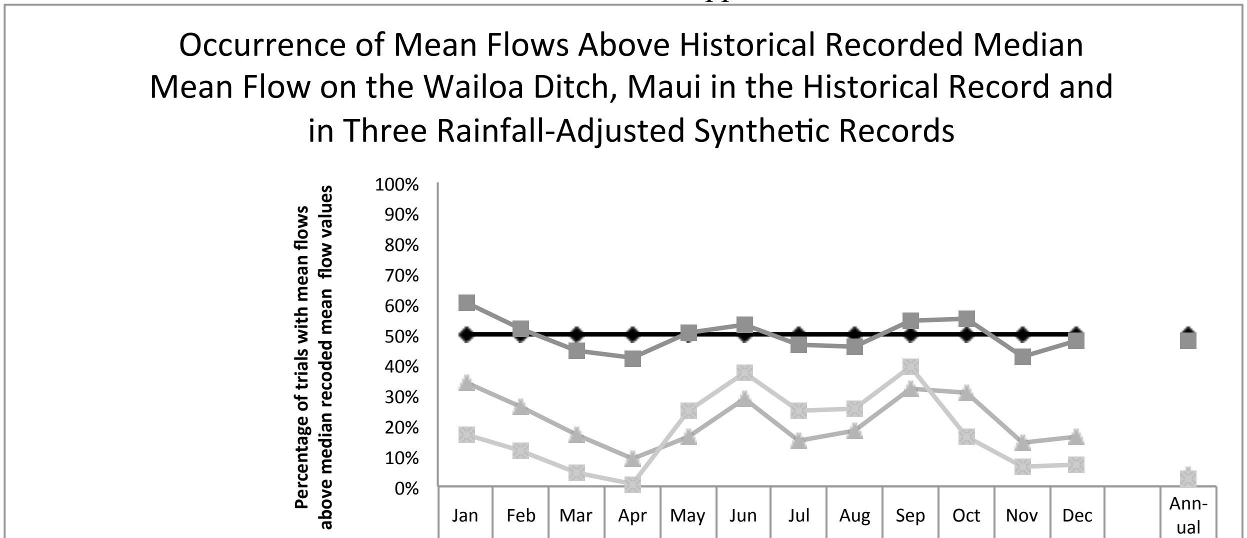


Fig. 4. Lower rainfall leads to increased risk of extreme drought. Highest modeled drought risks occur in the late part of the dry season and during the middle of winter, when storm flows might not be able to be captured with existing infrastructure.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec		Total
Actual record (1922-1987), 778 months	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.6%	0.0%	0.0%		0.1%
Synthetic: 100% historical rainfall, 12,000 months	1.0%	1.3%	0.0%	0.0%	0.1%	0.8%	0.2%	0.2%	2.4%	1.1%	0.1%	0.2%		0.6%
Synthetic: 85% historical rainfall, 12,000 months	1.1%	1.1%	0.3%	0.0%	0.2%	1.5%	0.1%	0.6%	2.8%	2.4%	0.2%	0.4%		0.9%
Synthetic: 77% winter historical rainfall / 89% summer historical rainfall, 12,000 months	1.9%	2.2%	0.8%	0.0%	0.0%	2.0%	0.0%	0.1%	2.3%	2.5%	0.3%	0.8%		1.1%

Fig. 5. Lower rainfall leads to lower ditch flow. As rainfall drops, the proportion of years where mean flow is above the historical median mean value approaches 0.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec		Ann-ual
Actual record (1922-1987), 778 months	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%		50%
Synthetic: 100% historical rainfall, 12,000 months	60%	52%	45%	42%	51%	53%	47%	46%	55%	55%	43%	48%		48%
Synthetic: 85% historical rainfall, 12,000 months	34%	26%	17%	9%	16%	29%	15%	18%	32%	31%	15%	17%		4%
Synthetic: 77% winter historical rainfall / 89% summer historical rainfall, 12,000 months	17%	12%	4%	1%	25%	38%	25%	26%	39%	16%	6%	7%		2%

TABLES

Table 1: Parameter ranges for Gingerich equation for median streamflow, Northeast Maui

Parameter	Range	Mean
RF (rainfall, cubic meters/second)	0.19 – 1.4	0.79
E_{max} (maximum basin elevation, meters)	760 – 2,800	2,000
ER (elongation ratio, dimensionless)	0.17 – 0.34	0.26

Note: Converted to SI units (two significant figures) from the original in Gingerich 2005. The equation is considered valid for a wide range of rainfall values, which makes it valuable for rainfall scenario analysis.

Table 2: Lag 1 Markov model coefficients used to generate synthetic flows on the Wailoa Ditch

Coefficient	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
$Q_{avg, j}$	4.4	4.1	5.4	5.8	5.6	4.6	5.7	5.3	3.9	3.9	4.9	4.7
s_j	1.4	1.4	1.6	1.3	1.4	1.6	1.5	1.5	1.6	1.5	1.5	1.3
r_j	0.42	0.68	0.05	0.35	0.42	0.65	0.58	0.55	0.72	0.60	0.46	0.59
b_j	0.45	0.65	0.06	0.30	0.45	0.73	0.56	0.55	0.75	0.57	0.45	0.54

Note: Mean monthly flow Q_j and monthly standard deviation s_j are given in m^3/s;, correlation coefficient r_j and regression coefficient b_j are dimensionless.

Table 3: Rainfall scenarios and flow-related parameters used to assess drought risk on the Wailoa Ditch

Rainfall Scenarios	Flow-related parameters
Control (100% of historical)	Mean flow
Validation (85% of historical)	Frequency of extreme drought
Inquiry (Seasonal, with climate change)	Frequency of flows below historical median

Note: Rainfall scenarios are described in Step 1 of the Methods section.