Hydrologic Resilience from Summertime Fog and Recharge: A Case Study for Coho Salmon Recovery Planning

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Research Impact Statement: Coastal fog and recharge strongly influence late summer instream hydroclimate conditions critical to coho and help to identify watersheds least vulnerable to future warming.

ABSTRACT: Fog and low cloud cover (FLCC) and late summer recharge increase stream baseflow and decrease stream temperature during arid Mediterranean climate summers, which benefits salmon especially under climate warming conditions. The potential to discharge cool water to streams during the late summer (hydrologic capacity; HC) furnished by FLCC and recharge were mapped for the 299 subwatersheds ranked Core, Phase 1, or Phase 2 under the National Marine Fisheries Service Recovery Plan that prioritized restoration and threat abatement action for endangered Central California Coast Coho Salmon evolutionarily significant unit. Two spatially continuous gridded datasets were merged to compare HC: average hrs/day FLCC, a new dataset derived from a decade of hourly National Weather Satellite data, and annual average mm recharge from the USGS Basin Characterization Model. Two use-case scenarios provide examples of incorporating FLCC-driven HC indices into long-term recovery planning. The first, a thermal analysis under future climate, projected 65% of the watershed area for 8–19 coho population units as thermally inhospitable under two global climate models and identified several units with high resilience (high HC under the range of projected warming conditions). The second use case investigated HC by subwatershed rank and coho population, and identified three population units with high HC in areas ranked Phase 1 and 2 and low HC in Core. Recovery planning for cold-water fish species would benefit by including FLCC in vulnerability analyses.

(KEYWORDS: planning; rivers/streams; hydrologic cycle; geospatial analysis; meteorology; coastal fog; recharge; temperature; fish; climate variability/change.)

INTRODUCTION

In 2012 the National Marine Fisheries Service (NMFS) developed a Recovery Plan for Central California Coast (CCC) Coho Salmon Evolutionary Significant Unit (henceforth the Recovery Plan) for the endangered CCC coho salmon (Oncorhynchus kisutch, henceforth coho) (NMFS 2012c). The Recovery Plan prioritized watersheds for recovery but did not include the frequency of coastal fog or low cloud cover in a watershed as attributes for prioritization of watersheds because data at the landscape level were not available. In this paper we explain why coastal fog is important to coho recovery planning and provide methods to reexamine Recovery Plan prioritization to using data that have become available.

The introductory section describes coastal fog as a climatological feature, the effect of coastal fog on watershed hydrologic capacity (HC), and provides background on the Recovery Plan into which we suggest, the impacts of coastal fog need to be examined.
Coastal Fog and Low Clouds

Meteorologically, fog is a low cloud with <1-km visibility, in contact with the Earth's surface. Colloquially, the term fog also describes the overcast condition under low clouds. Coastal fog and low clouds (CFLC) are a regular climatological feature of coastal California. They affect fish habitat by altering watershed dynamics, especially during the arid Mediterranean summer season (Madej et al. 2006; Woodward et al. 2014). Many variables influence the formation and evolution of CFLC and its subsequent pattern across the landscape and hydrologic impact. To better discuss the ecohydrologic alterations induced by CFLC and impact of future climate conditions on CFLC, we present a brief description of CFLC dynamics.

CFLC layers begin offshore as marine stratus or stratocumulus then advect onshore pushed by the prevailing northwest (NW) winds common along the eastern Pacific basin during the summer or the local sea-breeze circulation that forms on warm summer days due to the inland-coastal temperature differential. The extent of CFLC formation, daily and seasonal spatiotemporal persistence, and its distinct spatial pattern across watersheds depend on a stable atmospheric inversion of warm dry air descending on cooler air, wind-driven cold ocean currents from polar regions or vertically upwelled from the deep ocean, and advection across complex coastal topography (Iacobellis and Cayan 2013). The base of the cloud is usually 400–600 m above the ocean surface where the temperature of the ascending air mass lowers enough for condensation to occur. As the cloud swells from added marine moisture, and remains trapped under the atmospheric inversion, it expands horizontally toward land often with an added push from sea breezes. If the atmospheric inversion is lower in elevation than the topographic barrier of the coastal mountain range, the clouds stay on the ocean side of ridges, but often orographically creep up and spill over the ridgetop then evaporating once past the crest. Advecting CFLC flows through mountain gaps penetrating into low-lying valleys. Fog and low clouds will commonly reach inland 75 km through valleys (Figure 1), which is much further inland than the < 10 km measure of coastal impact commonly used as a “distance to coast” proxy for the effect of coastal fog (Barbour et al. 2014; Parish et al. 2016; Torregrosa et al. 2016). The spatiotemporal pattern of CFLC includes a multiday cycle controlled by relaxation of the large-scale atmospheric inversion and a diurnal cycle controlled by land surface solar insolation and the difference in heat capacity between the ocean and land. Increased condensation occurs at night within the cloud layer as the top of the cloud loses heat. The expansion of the CFLC layer, still trapped under the inversion, moves the base of the cloud closer to the Earth. (Eastman and Warren 2014; Schwartz et al. 2014; Clemesha et al. 2016, 2017). The complex spatiotemporal pattern of CFLC results in a distinct distribution of vegetation communities such as coastal redwood forest and maritime chaparral that are commonly associated with the “fog belt zone” (Barbour et al. 2007; Mooney and Zavala 2016).

Hydroclimate Impacts from Fog and Low Clouds

Fog and low cloud cover (FLCC) modify the amount of water and energy received by watersheds, which changes coastal hydrology through multiple pathways (Figure 2). The components of HC, defined here as the relative amount of cool water available for discharge to streams in late summer, is influenced by FLCC directly by increasing the water available to become streamflow and reducing plant water demand, as well as indirectly by reducing the energy loading that decreases air temperature and evapotranspiration (ET) (Figure 2). Below we describe the components of (1) fogdrip, (2) energy loading as shortwave radiation (SW), (3) the interaction of moisture and energy on ET, recharge (RCH) and discharge (DCH), and (4) the impact of air temperature ($T_a$) and DCH on stream temperature ($T_s$).

Fogdrip. The amount of water delivered through fogdrip depends on the duration of the fog event and the characteristics of the fog droplets: density, liquid water content, and aqueous chemistry. Fog droplets are typically 1–50 µm water-laden aerosol particles 100 times smaller than rain drops. Nuclei for fog water droplet condensation are diverse. Cloud condensation nuclei (CCN) can be gaseous molecular clusters, sea spray aerosols, evaporated salts and organics, biotic microfragments, dust, and many other types of particles that make good hydrophilic CCN (Hudson and Svensson 1995; Andreade 2013). Fog droplets, too light to precipitate, remain suspended in the air mass as it advects onshore or transitions from low cloud to fog. The droplets can aggregate into larger drizzle droplets that also get carried along with sufficiently strong wind. Fog droplets impact on surfaces such as redwood or pine needles, coalesce, and drip. Volumetric collection efficiency of surfaces varies and depends on impaction dynamics, relative wind, aerosol chemistry, surface hydroscopic characteristics, and fog droplet size (de Dios Rivera 2011; Regalado and Ritter 2016; Fernandez et al. 2018). Fog water deposition is an important source of water to coastal ecosystems, constituting 30%–40% or more of total water input for redwood forests (Harr 1982; Burgess and Dawson 2004), up to
44% for Bishop pine forests (Fischer et al. 2009), and during summer drought, 28%–66% for coastal prairie grasses (Corbin et al. 2005). The chemical composition of fog droplets includes ions that impact the nutrient status and biochemistry of the coastal ecosystems. The specific composition and relative concentration is determined by the CCNs and subsequent complex aqueous and photochemical reactions that occur as the droplets advect (Martinsson et al. 1992; Collett et al. 2002; Berkowitz et al. 2011; Montero-Martinez et al. 2014). Studies have documented fog-based ecosystem enrichment of nitrogen, calcium, potassium, and other ions through wet-deposition (Clayton 1972; Weathers et al. 2000; Collett et al. 2002; Ewing et al. 2009; Templer et al. 2015).

**Solar Radiation.** The finely dispersed aerosolized droplets of FLCC reflect incoming SW reducing solar energy by 80 W/m² (Matus and L’Ecuyer 2017) to 113 W/m² (Iacobellis and Cayan 2013). Low clouds scatter much more SW than they absorb (Haynes et al. 2013). Some SW absorbed by the cloud is re-emitted as longwave radiation (LW; i.e., thermal infrared) to the surface of the earth which is important for the heat budget that influences river temperatures. Re-emitted LW from the earth surface is reflected back by the cloud. Even counting all the re-emitted LW, the net radiative effect of low clouds is to cool the watershed (Chen et al. 2000). Highly controlled measurements of pavement under low clouds show temperature reductions up to 10°C (Walker and Anderson 2016). The temperature difference between coastal locations under fog and adjacent sunny inland locations commonly exceeds 10°C (Historical Weather for Bodega Bay and Santa Rosa, Weather Underground. Accessed February 13, 2018, https://www.wunderground.com/history). In addition to reducing the thermal loading to the land surface, the FLCC barrier amplifies the hydrologic impact of fogdrip on watersheds. The reduced energy input reduces the vapor saturation deficit (Thorntwaite and Holzman 1939; Thorntwaite 1940; Flint and Flint 2008) — commonly expressed in terms of vapor pressure.
ET, Recharge, and Discharge. Subsurface recharge occurs when (1) there is more water in the soil than used by plants on any given day, and (2) materials below the plant rooting depth are not restricted by impeding layers. The cooling effect of FLCC combined with the increase in relative humidity of the air mass lowers VPD. In general, hot dry days cause increased VPD, leading to increased water vapor diffusion (transpiration) through plant stomata (Urban et al. 2017). The fog induced decrease in VPD reduces evaporative demand, which leads to reduced plant ET. In a San Francisco peninsula watershed, FLCC reduced ET by 25% (Chung et al. 2017), in a coastal Atlantic laurel forest by 30% (Ritter et al. 2009), and under multi-year drought conditions, the rate could be higher still (Williams et al. 2018). Reduced LW reduces ET leaving more water in the subsurface, with the potential for enhanced recharge and baseflow.

Water from fogdrip combined with FLCC-mediated reduction of ET slows the steady baseflow recession that results in decreased streamflow during the arid California summer. Sawaske and Freyberg (2014, 2015) used baseflow recession analysis to quantify summertime FLCC effects on low flowing streams (<1.4 L/s/km²) by comparing the effects among three coastal basins in the Santa Cruz Mountains during July to September. During August, the hottest and driest month, fog events with typical fogdrip rates of 375 mm/month increased streamflow by 100% during the fog event and up to 200% after a lag of 2–6 days. Streamflow increases during the fog event were associated with fog-suppressed ET, whereas increased flow in the 2- to 6-day lag period was associated with baseflow augmented by fogdrip events. The duration of the lag period was a function of watershed size, with larger watersheds having longer duration lags (Sawaske and Freyberg 2014; Sawaske and Freyberg 2015). Fogdrip-derived baseflow increase is critically important for stream ecosystems in late summer. Fogdrip helps to provide critical summer coho refugia by sustaining pools that would otherwise dry out in late summer.

Depending on the depth of the soil layer, the permeability of the underlying bedrock, and the thickness of the unsaturated zone, seasonally recharged water can serve as a resilient source of baseflow to streams through the dry season. If the subsurface bedrock is highly fractured, the recharge can provide year to year sustaining flows that dampen the impacts of drought (Markovich et al. 2016). Subsurface physical structure and composition help to define the recharge of a watershed and its hydrogeologic buffering capacity. For example, in the case of two adjacent watersheds, both experiencing the same climatic conditions of precipitation, FLCC, and temperature, the watershed with highly fractured bedrock will have markedly higher annual recharge and late August discharge compared to one with high fractions of impervious clay content. Examples of these conditions for prioritized watersheds within the Recovery area are described in the results section. The hydrogeologic processes that dictate stream recharge at the reach scale occur at various spatiotemporal scales (Scanlon et al. 2002; Sophocleous 2002) and can be aggregated to show relative difference in recharge among watersheds using a hydrologic basin characterization model (BCM) run for multiple decades that incorporates parameters for topography, geology, soils, climate, and land surface features that drive ET such as the United States (U.S.) Geological Survey (USGS) BCM (Flint et al. 2013).

Air and Discharge Temperature Determine Stream Temperature. Stream temperature is an aggregate of conductive, convective and advective fluxes between water column, stream bed, hyporheic zone, groundwater, seeps of varying origin, shade and substrate type (Webb and Zhang 1997; Johnson 2004; Guenther et al. 2014; Fullerton et al. 2015). The dominant process influencing stream temperature is solar loading (Brown 1969; Torgersen et al. 2001; Mayer 2012; Dugdale et al. 2017; Dugdale et al. 2018; Loicq et al. 2018). A barrier to solar loading such as riparian vegetation or topographic shading reduces stream temperature (Bond et al. 2015; Kalny et al. 2017; Wawrzyniak et al. 2017). The strong correlation between air and stream temperature is commonly used to derive relatively accurate estimates of stream temperature modeled from air temperatures (Caldwell et al. 2015). However, in some cases when subsurface water discharges into streams, air and stream temperature trends diverge. Subsurface water tends to be cooler than water flowing on the surface in late summer (Middleton et al. 2016). In these situations, in addition to the reduction of SW, FLCC increases subsurface discharge into stream channels (Sawaske 2014; Sawaske and Freyberg 2015) thereby decreasing stream temperature (Bosch and Hewlett 1982; Jackson et al. 2000; Széles et al. 2018). Empirical modeling indicates that FLCC and the corresponding reduction in solar radiation and VPD correlates well with reductions in maximum daily stream temperature (Flint and Flint 2008).

Taken together the hydroclimatic result of FLCC in a watershed is a change in HC, defined as the relative potential of a watershed to discharge cool water into streams during late summer. In California coastal watersheds, HC results from static landscape
features: geology, geomorphology and topography, and climate variables that vary on a daily, seasonal, and interannual basis: precipitation, temperature, FLCC. The HC of a watershed increases when FLCC is the summertime norm for a watershed. Underlying landscape heterogeneity, defined by geomorphic and geologic features that change slowly, is increasingly important for identifying hydrologic refugia (Mclaughlin et al. 2017) and for selecting conservation areas threatened by climate change (Theobald et al. 2015).

Climate Change and the Recovery Plan

Warming due to climate change has exacerbated the ongoing decline of salmonids by rendering stretches of instream habitat thermally unsuitable (Isaak et al. 2012; Lawrence et al. 2014; Ward et al. 2015; Schoen et al. 2017). The CCC coho is one of the salmon species in precipitous decline, in danger of extinction (NMFS 2012c; Katz et al. 2013), and highly sensitive to water temperature and streamflow (Grantham et al. 2012; Arismendi et al. 2013; Flitcroft et al. 2016). Instream temperatures above $18^\circ$C–$20^\circ$C decrease growth rates of coho in juvenile stages. Temperatures above $21.5^\circ$C can be lethal (Brungs and Jones 1977; Bjornn and Reiser 1991; Richter and Kolmes 2005; Ebersole et al. 2009). In 1996 coho were listed Federally as threatened and in 2005 listed as endangered (61 FR 56138 and 70 FR 37160), thereby requiring a Recovery Plan under the Federal Endangered Species Act (ESA). In 2012 NMFS issued the CCC coho Recovery Plan and prioritized watersheds for threat abatement actions and restoration activities. Subwatersheds were assigned one of three priority action levels: Core (High), Phase 1 (Medium), and Phase 2 (Low) (Figure 3) (NMFS 2012a,2012b). Core subwatersheds required immediate action to protect existing coho populations. The subwatersheds in which coho were rarely observed despite suitable instream habitat and where action is less urgent were prioritized as Phase 1 areas. Restoration to improve Phase 1 areas would provide for coho population expansion, which is currently at critically low population numbers. Expanding suitable habitat decreases the risk of CCC coho extinction. Watersheds that have no coho sightings and are typically more degraded than Core or Phase 1 areas are in Phase 2. Improving Phase 2 areas will serve to improve overall long-term riparian system resilience (NMFS 2012b,2012c). Multiple factors were used to compare and prioritize the watersheds: coho population structure and viability, intrinsic potential (IP) ratings for stream reaches, instream conditions, hydrologic processes, human activities, cost, and feasibility (NMFS 2012a,2012b,2012c). Coastal fog was not one of the prioritization factors, even though FLCC strongly influences both elements of late summer hydrometeorological conditions, streamflow, and temperature.

Under the ESA, a Status Review is mandated for a listed endangered species at least every five years to assess the population viability of the species using updated or new scientific information. The last Status Review for the CCC coho populations (NMFS 2016) found all 28 populations remained below the recovery threshold and recommended no change to the endangered status for the species. The Status Review cited increasing negative impacts from climate change (Williams et al. 2016) and noted that the greatest temperature shifts from climate change are expected in the summer. The movement of water from fogdrip through baseflow is critically important to coho in late summer when disconnected pools scattered along the stream can dry out (Woodward et al. 2014; Hwan et al. 2017; Woelfle-Erskine et al. 2017). Juvenile coho in small pools are subject to high rates of mortality due to overheating, higher predation exposure, and reduced instream habitat (Sawaske 2014). We argue that the benefits to coho from FLCC will continue even under future scenarios of climate change (Kawai et al. 2018).

Study Objectives

In this study we compare subwatersheds with differing spatiotemporal FLCC patterns to infer broad landscape scale differences in hydrologic impact and watershed hydrologic resilience. This study uses existing USGS data to compare the HC (Figure 2) of subwatersheds across the CCC coho habitat domain. We develop proxies for the FLCC-driven mechanisms that reduce stream temperature and increase streamflow (Figure 2). This work proposes to advance the NMFS Recovery Plan CCC coho watersheds assessment framework by providing spatially explicit measures of HC. Increased HC is a measure of hydrologic resilience to future warming. Using HC as an index we assess comparative watershed resilience under future climate conditions. Results are visualized within the Recovery Plan assessment framework of 299 subwatersheds grouped into 28 distinct coho population units (CPU) for two decision-use case scenarios.

DATA AND METHODS

This study used existing data and inputs from three sources: (1) NMFS Recovery Plan watershed
and stream reach data; (2) USGS Pacific Coastal Fog gridded data; and (3) gridded output for recharge and air temperature for historical and future projected time periods from the USGS BCM. The data and model outputs were combined to derive four indices of fog and recharge and two indices of HC (Table 1). The indices were used to explore watershed suitability for coho under two hypothetical decision-making use case scenarios.

**NMFS Recovery Plan Watersheds and Attribute Data**

The NOAA Fisheries Service identifies six recovery domains for salmon and steelhead evolutionarily significant units (ESU) in the Southwest region of the Pacific NW. This study encompasses one, the CCC. The CCC Technical Recovery Team (TRT) conducted extensive genetic and habitat analysis to identify the dependence and independence of 75 coho populations within the 21 main river systems of the CCC recovery domain and grouped them for recovery action purposes into 28 coho populations with distinct watershed boundaries. We call the group of watersheds with a distinct coho population a CPU. An individual CPU can consist of 1 to 62 level-10 hydrologic unit code (HUC) watersheds. The CCC river network contains more than 300 CalWater HUC 10 watersheds (available at http://frap.fire.ca.gov/data/frapgisdata-sw-calwater_download). For the Recovery Plan watershed prioritization, the TRT modified the CalWater delineated polygons by subdividing several watershed polygons to incorporate additional attribute information related to socioeconomic and ownership conditions that differ substantially on either side of the stream (the modified polygon layer is provided by NMFS upon request). The Recovery Plan uses the term subwatersheds to clarify the difference between CalWater watershed polygons and the Recovery Plan watersheds (henceforth subwatersheds). The polygon layer of 363 subwatersheds (attribute name: CCC_Core) provides drainage area, mapped boundaries for the defined coho populations, and the final prioritized rank.

**FIGURE 3.** Overview maps of recovery plan area. (a) six hydrologic basins (color coded) and 299 delineated subwatersheds (light black lines) grouped into 28 watershed units of distinct Central California Coast coho population. Labels indicate name of coho population unit (CPU) and the label line points to the watershed discharge location into the ocean. (b) color-coded Recovery Plan subwatershed priority rank.
assigned to each subwatershed. The analyses for this study used only the 295 subwatersheds prioritized by NMFS with Core, Phase 1, and Phase 2 (Figure 3b, introduction section has priority rank descriptions). The prioritization method is described in the Conservation Action Planning Key Attributes, Stresses, and Threats Report (NMFS 2012a,2012b). The unit of analysis for summary statistics in this study is the CPU aggregate of subwatersheds (CPUsW). The CPUsWs are listed north to south in summary tables. Some population units, such as the Caspar unit, inhabit only one subwatershed. Other CPUs, such as the Russian River unit, inhabit 62 subwatersheds.

We extracted subwatershed area-weighted IP and temperature attributes from the NMFS vector layer for each of nearly 52,000 stream reaches. IP is a measure of stream habitat quality for juvenile salmonids (Burnett et al. 2007) calculated (by NMFS) using historical coho population numbers and three persistent stream characteristics, mean annual discharge, stream gradient, and channel morphology (Burnett et al. 2007; Sheer et al. 2009). Temperatures for each stream reach were calculated by NMFS using 1961–1990 gridded PRISM (Daly et al. 2002) air temperature data at a 2 km resolution. Both polygon and vector files were provided by NMFS in ESRI shapefile format.

USGS Pacific Coastal Fog — FLCC Data

Gridded FLCC raster datasets (indices) were downloaded from the California Climate Commons online archives (http://climate.calcommons.org/datasets/summertime-fog). The indices were generated from frequency analyses of a 10-year archive of hourly day and night National Weather Satellite imagery (Torregrosa et al. 2016). Two of the summertime (June, July, August, and September) FLCC indices were used in this study, average hours per day of summertime FLCC 1999–2009 (FLCC_HRS, Figure 4a) and the coefficient of variation of all 1999–2009 summer months (FLCC_CV, Figure 4b). The FLCC HRS index provides a metric of relative cloud cover and FLCC CV provides a metric of the relative stability of the FLCC pattern across the landscape.

USGS BCM — Watershed Recharge

Geospatially continuous grid values for recharge, an output from the BCM, were downloaded from the California Climate Commons online archives (Accessed February 18, 2018, http://climate.calcommons.org/dataset/2014-CA-BCM) for historical (1981–2010) and future (2040–2069) time periods. The BCM is a monthly water balance model that has been well calibrated and is widely used for California (Flint et al. 2013). Inputs include gridded meteorological climate variables from PRISM (Daly et al. 2002,2008) that have been spatially downscaled to 270 m (Flint and Flint 2012), empirically measured landscape attributes including topography, soils, and underlying geology, and stream gauge data for calibration. The BCM calculates potential ET hourly using Priestly–

| Dataset      | Description of measure                        | Units       | Category breaks          |
|--------------|-----------------------------------------------|-------------|--------------------------|
| IP           | Area-weighted intrinsic potential (IP)         | Unitless    | Low < 52                 |
|              | reach values averaged for watershed           |             | Med 52–75                |
|              |                                               |             | High > 75                |
| FLCC_HRS     | Average summertime hours per 24 h period       | Hours per 24 h period | Low < 4 |
|              |                                               |             | Med 4–6                  |
|              |                                               |             | High 7–14                |
| FLCC_CV      | FLCC_HRS coefficient of variation             | Unitless    | Low > 0.2 (low stability) |
|              |                                               |             | Med 0.13–0.2             |
|              |                                               |             | High < 0.13 (high stability) |
| FLCC_Index   | FLCC_HRS × (1 – FLCC_CV)                      | Unitless    | Low < 0.3                |
|              |                                               |             | Medium 0.31–0.5          |
|              |                                               |             | High > 0.5               |
| BCM_Recharge | Annual 30-year climatological average         | mm/yr       | Low < 300                |
|              |                                               |             | Medium 300–600           |
|              |                                               |             | High 601–900             |
| HC(I)        | Sum of ordinated FLCC_HRS and BCM_Recharge indices | Unitless    | Low < 4                  |
|              |                                               |             | Medium 4–5               |
|              |                                               |             | High > 5                 |
| HC(II)       | Sum of ordinated FLCC_HRS, BCM_Recharge and FLCC_CV indices | Unitless    | Low < 6.3                |
|              |                                               |             | Medium 6.3–7.75          |
|              |                                               |             | High > 7.75              |

Notes: BCM, USGS Basin Characterization Model.

TABLE 1. Summary of index values with dataset source, description of measured value, units, and categorical breaks for each index.
Taylor equations and modeled solar radiation to incorporate topographic shading and cloudiness, aggregated to monthly timesteps, and calibrated for the State using all available California Irrigation and Management Information System stations. Recharge is calculated on a monthly timestep as the excess water from precipitation and potential ET that makes it into the soil profile and is left over after plants use the soil water for ET, occurring at the rate of bedrock permeability. Spatially distributed recharge rates were regionally calibrated for all mapped geologic types. Additional background information on the BCM algorithms that produce the recharge output and the downscaling techniques used on the Global Climate Models (GCM) input are available at http://climate.calcommons.org/article/featured-dataset-california-basin-characterization-model.

We used the climatological (30-year) average for recharge for midcentury, 2040–2069, from GCM representing the wettest and coolest projected conditions: Centre National de Recherches Météorologiques Circulation Model 5, France (CNRM) and the driest and hottest projected conditions: Model for Interdisciplinary Research on Climate, Earth System Model, Japan (MIROC). Both projections were developed using representative concentration pathways (RCP) 8.5. The recharge metrics used in this study include annual average mm/yr per raster cell (270 m²) and total annual mm/yr per subwatershed.

**Current and Future Temperature**

Temperature data for the analysis of present vs. future conditions are from PRISM (1981–2010) that have been spatially downscaled for BCM application (USGS, BCM. Accessed February 18, 2018, https://ca.water.usgs.gov/projects/reg_hydro/basin-characterization-model.html). Future estimates of average August air temperature were downscaled for BCM application from four GCMs for the 30-year midcentury period, 2040–2069. We used the same four models that were selected by Central California water managers participating in stakeholder-based workshops (Micheli et al.)
A kickoff goal of the workshop was to agree on and select a small representative set of GCMs that worked best for local and regional water resource planning and could be used as the set of common models across the board for interagency and multiple stakeholder decision making (Micheli et al. 2016). Three of the models are from the Coupled Model Intercomparison Project Phase 5 (CMIP5) that supported the 5th IPCC assessment and one is from CMIP3 supporting the 4th IPCC assessment (Meehl et al. 2007). The selected CMIP5 models, run under the 8.5-watt RCP (RCP 8.5) include: Community Climate System Model version 4.0, National Center for Atmospheric Research, U.S. (henceforth CCSM); CNRM; and the MIROC. One CMIP4 model was selected by managers to provide continuity with prior analyses that had been widely used by resource managers in prior years: NOAA Geophysical Fluid Dynamics Laboratory model, run under the moderate A-2 emissions scenario (henceforth GFDL-A2). The managers opted to have the CMIP5 models run with RCP 8.5 rather than RCP 4.5 because RCP 8.5 is closer to a business-as-usual scenario and better served their risk management need to address severe possible outcomes.

Hydrological Capacity Indices

Deriving HC indices involved four steps: reprojecting watershed polygon boundaries to match the raster layer projection to increase topological accuracy; summarizing metrics by subwatershed (299); categorizing each input to simplify the final combinatorial result; and categorizing values into a final three-category index to better visualize results for comparative analysis and planning discussions by fisheries managers and other stakeholders. The NMFS subwatershed polygon boundaries were reprojected from NAD83 UTM 10 into GCS84 Geographic to match FLCC rasters and into NAD83 California Albers Teale to match BCM raster layers. Metrics (e.g., hours FLCC/day, FLCC stability, and recharge) for each CCC coho subwatershed were calculated using the ArcGIS zonal statistics algorithm to average all raster cells of each subwatershed. Raster cells that straddled subwatershed boundaries were assigned to the subwatershed that contained the largest portion of the raster cell.

For comparative analysis, subwatersheds were assigned to low, medium, or high categories using indices of relative FLCC hours, FLCC interannual variability, recharge, and two versions of HC (Table 1). The categorical breaks of low, medium, and high for the FLCC hours index were based on visual identification using an overlay of FLCC on vegetation maps to select two contour lines, (i.e., one break between medium and high and one break between medium and low) to match published vegetation distribution patterns (Barbour et al. 2007; Vasey et al. 2014; Mooney and Zavaleta 2016) for vegetation types associated with fog-dominated environments such as maritime chaparral and coast redwood-Douglas fir forest patches (contour > 6) and vegetation associated with arid conditions (contour < 4). The categorical breaks for FLCC stability were based on overlays of FLCC hours and FLCC CV to identify values of FLCC CV associated with discrete landscape patches within areas of very high and very low FLCC hours. The categorical breaks for recharge were defined by the authors’ expert knowledge based on extensive personal experience of recharge rates for watersheds across California under a large range of climate conditions (Flint and Flint 2012; Flint et al. 2013; Thorne et al. 2015).

Two index combinations were used to derive maps of HC, the first combined FLCC hrs/day and average annual recharge. The second method adds a third index, FLCC CV a measure of the spatiotemporal stability of the FLCC pattern. The index value for each element, FLCC, recharge, and FLCC CV, was derived by first assigning a categorical value for low, medium, and high to each subwatershed as summarized in Table 1 and then applying Equation (1). Equation (1) provides the method to normalize and generate the indexed value.

\[ C + (V - V_{\text{min}})/V_{\text{range}}, \]

where \( C \) is the value of the category, low = 1, medium = 2, and high = 3, \( V \) is the value from the dataset (FLCC hrs/day; \( 1 - \) FLCC-CV; or recharge); \( V_{\text{min}} \) is the minimum value within the category; and \( V_{\text{range}} \) is the range between the minimum and maximum values within the category.

HC I (Equation 1) is the sum of FLCC_HRS index and recharge index. HC II (Equation 2) uses the product of FLCC_HRS and CV inverted to avoid inflating the value of FLCC stability in areas where the CV is low because FLCC is rarely present. Equation (2) provides the method to create an index value that is intuitively visualized.

\[ (\text{FLCC} \times (1 - CV)) + \text{recharge}. \]

HC (I and II) values were assigned low, medium, or high using natural breaks, a statistical mapping method developed by Jenks (1967) and implemented as a categorical classification option in ArcMap (ESRI 2017).

Use Case Scenarios

We developed two use case scenarios to explore methods for employing FLCC-driven HC as a measure
of watershed resilience. The first use case maps temperature across the landscape to assess coho vulnerability to current and future thermal stress for each CPUsW and explore the FLCC-related attributes that might mitigate the threat across coho CPUsWs. The second use case investigates the priority ranked subwatersheds to explore the FLCC-driven HC of each CPUsW subset targeted for immediate (Core) and subsequent (Phase 1 and 2) threat abatement and restoration actions by comparing the FLCC-related attributes for the CPUsW.

The first use case applied the NMFS air temperature threshold method (Agrawal et al. 2005) to identify thermally unsuitable areas. The vulnerability of each CPU to future temperature increases was derived as a percentage of the total coloh CPU above the 21.5°C threshold for 2040–2069 compared to the historical period 1981–2010. Areal averages were calculated using 30-year climatological average August maximum air temperatures extracted for each pixel from the historical climate (PRISM) and four future projections (CRNM, CCSM, MIROC5, GFDL-A2) described earlier.

The second use case compared the distribution of hydroclimate conditions across and within CPUsWs by priority rank (Core, Phase 1 and Phase 2) using IP, FLCC hours, recharge, and late summer HC II (LSHC) indices to explore whether any subwatersheds that ranked high in recovery priority had low HC and vice versa. To simplify the use case discussion, an average index value for all subwatersheds with the same priority rank is listed for each CPUsW in the analytic matrix. The matrix was color coded to identify subwatershed groups with high index value within each priority rank and to facilitate discussion of HC and long-term hydrologic resilience of the Recovery Plan populations under a warming climate.

RESULTS

HC: Inputs and Indices

The CPUsWs are listed north to south in the text and summary tables.

Fog and Low Cloud Cover. Average decadal summertime FLCC ranges from <2 hrs/day to more than 14 hrs/day among Recovery Plan subwatersheds (Figure 4a). The pattern of highest FLCC (6–14 hrs/day) at the coastal edge holds for most coho CPUsWs but diverges significantly for Gualala and Russian CPUsWs and CPUsWs south of Scott (Figure 4a) which have low (2–4 hrs/day) average summertime FLCC. The coarse three-category FLCC index (Figure 6a) simplifies the view of FLCC across the landscape and highlights the low FLCC conditions in the Gualala CPUsW area. Across the CCC area, there is a large spread in the variability in the monthly and interannual FLCC frequency (CV) during the 1999–2009 period (Figure 4), ranging from stable (0.02) to variable (0.44). The variability during this decade is similar to the high level of variability during the 1951–2007 period (Johnstone and Dawson 2010; Torregrosa et al. 2016). When both FLCC and FLCC variability are mapped and examined across the landscape (Figure 4a, 4b), there are distinct subwatershed areas with low (stable) FLCC CV and high FLCC, low FLCC CV and low FLCC, as well as less distinct patches with intermediate conditions. These patterns are more visible when the two indices are combined (Figure 6b). The FLCC index that includes FLCC CV (FLCC stability index) has less area categorized as high and medium than the FLCC index derived solely from FLCC hrs/day.

Recharge. Average annual BCM recharge values in the Recovery Plan subwatersheds for 1981–2010 range from more than 600 mm/yr in the northern CPUsW to <200 mm/yr in most of the CPUsWs south of the Gualala CPUsW (Figure 5a). Under the relatively wet projected future of CNRM, the average annual recharge of all subwatersheds increased except for a small portion of the eastern Gualala CPUsW subwatersheds that showed little change from current conditions. Under MIROC, the driest projected future, the average annual recharge for most populations decreased by 10–100 mm/yr with patches between Gualala and Redwood CPUsWs remaining close to historical recharge amounts. The coarse three-category recharge index (Figure 6c) reflects these patterns.

HC Indices. The two methods of combining FLCC metrics and recharge to derive HC show similar patterns across the Recovery Plan area with the highest HC in the northeast and lowest in the southern and central populations (Figure 7a, 7b). In most populations north of the Walker PUW, the addition of FLCC stability to the HC calculation reduced HC along the eastern subwatersheds with both high and medium recharge categories contracting westward. In those areas, under HC II, (which includes FLCC stability) high HC I values became medium and medium became low, although some exceptions are Navarro, Usal, and Cottaneva with little contraction of high category areas. The Russian River and Salmon CPUsWs were exceptions with expansion from low HC I values to medium values under HC II, a westward expansion. South of Salmon CPUsW most CPUsWs lose HC under HC II except for a portion of Pescadero CPUsW that changed to the high category.
**Current and Future Temperature.** Two 30-year temperature climatologies (1951–1980 and 1981–2010) and results from four models of projected future temperatures (2049–2017) (Figure 5c–5f) predicted progressive increase, for every CPU, in the proportion of the CPUsW area with average August maximum air temperature above the Recovery Plan threshold of $21.5^\circ$C. Temperature projections from the four representative GCMs vary (Figure 5c–5f); however, all show a warming trend. The upper Russian River basin began to have most of the CPUsW area above the August air temperature $21.5^\circ$C threshold by the end of the 20th Century. Although the absolute amount of CPUsW area above the threshold differed somewhat between models, the relative pattern of incursion toward the coast within CCC coho subwatersheds was similar among projections.

Under CRNM (Figure 5e), the coolest of the GCMs, the largest CPUsWs showed the greatest relative...
impact. Under MIROC conditions, the hottest of the four GCMs, very little of any of the CPUsW areas were below the August air temperature 21.5°C threshold. The width of the 20°C–21.5°C temperature band was thickest in the northern populations from Wages to Garcia and the more centrally located populations between the Russian and Walker CPUsWs. The 20°C–21.5°C temperature band is relatively thin for all other CPUsWs. Of the CPUsW areas larger than 100 km² only Albion, Walker, Lagunitas, San Gregorio had more than 50% of their area below the 21.5°C threshold under CRNM.
(Table 2). Under MIROC only four populations (Caspar, Redwood, Big Salmon, and Pudding), all small watersheds of <50 km², had most of the CPUsW area below 21.5°C.

Use-Case Scenarios

First Use Case: Temperature Analysis. The matrix in Table 2 aligns watershed attribute metrics by CPU, aggregated for all subwatersheds in the CPU, to compare FLCC impacts between CPU and against other CPUsW attributes. The total CPUsW area ranges from 1,644 km² (Russian) to 22 km² (Caspar). The smallest CPUs have one subwatershed (Cotteneva, Caspar, Pine Gulch, Gazos, and San Vicente) and the largest has 62 (Russian). Under 1981–2010 conditions, the percent of the CPUsW area above the Recovery Plan temperature threshold (average maximum August air temperature of 21.5°C) is negligible except for five CPUs with 6%–22% of their total area above the threshold, Navarro, Garcia, Gualala, Russian, and Scott. The percent of CPUsW area
above the threshold increased under two future temperature projections: “cool” CNRM and “hot” MIROC. Under CNRM only four CPUsWs (Pudding, Caspar, Albion, and Big Salmon) had negligible area above the threshold and eight had more than 65% of their CPUsW area above the threshold. Under MIROC, all CPUsWs had area above the threshold, 19 had more than 65% of their area above the threshold, and nine had more than 90% of their area above the threshold. Mirroring the mapped pattern of FLCC, most CPUsWs averaged at least four hours per day FLCC. Smaller CPUsWs had on average more hrs/day than larger CPUsWs although some medium-sized CPUsWs such as Pescadero had a population-wide summertime average of more than eight hours per day. Pescadero is also the CPUsW with the highest average IP score. Average annual recharge was highest in the northern CPUsWs. The largest CPUsWs (Navarro, Gualala, and Russian) had highest total recharge but when normalized by CPUsW area, Garcia had the highest recharge ratio (50.1) with Ten Mile close behind (41). The matrix is color coded as a visualization aid for group discussion about threat abatement and restoration options under future climate projections.

Second Use Case: Priority Rank Reexamination. To explore and compare the distribution of late summer hydrologic capacity (LSHC), among the three priority rank categories for each CPUsW a matrix was derived (Table 3) to group subwatersheds within each priority rank. IP = intrinsic potential index, FLCC = fog and low cloud cover index.

Notes: Values in the “high” index categories, FLCC and recharge > 2.9 and HC II > 7.75 are shaded blue and IP = 3 are shaded gray as visual aids during use-case scenario discussions.
Attributes are: Ntotal = total number of subwatersheds for the population unit; N = subset of subwatersheds within each priority rank. LSHC = late summer hydrologic capacity that includes FLCC stability.
[Corrections added on Dec 04, 2019, after first online publication: we have included revised table 3 in this proof.]
values (>7.75, Table 1) for subwatersheds with Phase 2 ranking. Two of these, Wages and Pescadero show high LSHC in Phase 1 or 2 and no subwatersheds ranked as CORE. Except for Pudding CPU, subwatersheds with LSHC > 9 are all ranked CORE. Noyo, Walker, and Soquel all have higher LSHC scores for their Phase 2 PRS than their CORE PRS (8.3, 8.0, and 8.3 vs. 7.4, 7.7 and 5.1 respectively). Except for High FLCC index values contribute to seven of the eleven high LSHC Core ranked PSAs. Four CPUs (Usal, Cottaneva, Wages and Ten Mile), all in the north CCC coho Recovery area, have high LSHC due solely to recharge. Noyo and Pescadero are the only CPUs with high IP (3, Table 1) and high LSHC.

DISCUSSION

Hydrologic Capacity

The synthesis of existing science on the impact of FLCC on watershed hydrology, described in the introduction, provides a strong basis for inferring that FLCC increases HC, a hydroclimate condition that provides needed instream habitat for juvenile coho. In Figure 2, elements outlined with a solid line have field measurements that have been cited in the introduction to anchor their relative contribution to HC whereas elements with a broken line do not. We lack data to fully quantify the relative contribution of FLCC to the hydroclimate of coho stream reaches within each subwatershed across the CCC coho Recovery Plan area. However, recognizing a positive impact on hydroclimate from FLCC, and based on the synthesis of published work describing the impact of FLCC to watersheds, we derived composite HC indices. The indices simplify the relationship of FLCC and HC using three broad categorical classes: low, medium, and high. Two assumptions underpin our use of an HC index to assess resilience in the face of increasing thermal stress that exacerbates the historical and climate change driven-variation in annual precipitation that can lead to extremely low late summer streamflow. The first assumption is that more FLCC results in more streamflow, which has been substantiated by field measurements (Sawaske and...
Freyberg 2015). The second assumption is that more FLCC results in lower stream temperatures, which has been indicated by many modeling studies as discussed in the introduction. We address the relationship of FLCC to stream temperature more fully in the Limitations and Future Work section. To generate matrices to compare the HC across CPUsWs and PSAs for two different use-case scenarios, we combined FLCC and recharge indices into composite HC indices without imposing a differential weighting scheme (Greco et al. 2019). Many categorical breaks could be used to classify the continuous variables into three-bin indices. We encourage users to recategorize the index values to fit their situation.

Fog and Low Cloud Cover. High FLCC values are not consistently found close to the coast. For example, close to the coast from the Wages to Garcia PUW (Figure 1, north of Cape Mendocino and Figure 4a) FLCC is high. Further south, close to the coast in the Gualala PUW, FLCC is low (Figure 1, south of Point Arena). The elevation of the coastal range is similar along both stretches of the coast but not topology (i.e., orientation of the coastline to prevailing winds or relative aspect of the elevation gradient of adjacent landforms) which differs. The coastal cape landform changes the eddy patterns of wind-driven movement of FLCC in areas south of the Garcia CPUsW during the predominant NW wind conditions and acts to reduce the amount of FLCC south of the cape. In contrast, FLCC moves inland through the low-lying San Francisco Bay, which is open to the NW winds. Incursions occur in other valleys aligned NW such as the area just north of the Gualala PUW. The predominant NW wind is a characteristic of the eastern Pacific basin and is part of the global circulation pattern and mechanism that gives rise to the dry Mediterranean climate summers of the region.

The variability and stability of FLCC measured by CV is associated with the same topological and topographic patterns that constrain the movement of FLCC across the landscape. During the 1999–2009 decade, the month-to-month and interannual FLCC variation was high (Torregrosa et al. 2016). Some years had relatively low FLCC frequency along the entire coast, whereas other years had locations showing summertime averages of 22 hrs/day. Despite the high variability, some areas of relative stability emerge where FLCC can be considered the summertime norm, even in years where the rest of the northern California coast had relatively low FLCC. The areas of lowest FLCC-CV: Pudding, Noyo, Caspar, and Pescadero PUW, also have very high FLCC. Even in years that have relatively few hours of FLCC these areas have above average summertime FLCC. Simplifying these relationships into categorical indices (Figure 7a, 7b) reduces the complexity of these relationships. When the variability in FLCC (Figure 4b) is added to the index map of FLCC (Figure 7a) less of the CPUsWs are FLCC dominated.

Deriving a measure of FLCC stability to identify areas that maintained FLCC influence even during years of low FLCC was motivated in part by research that found fog frequency was reduced by 33% in northern California over the last century (Johnstone and Dawson 2010). The question of what will happen to coastal fog in the future is an area of active research and discussed further in the Limitations and Future Work section.

Recharge. The absolute amount of recharge changes significantly under different future projections (Figure 6b, 6c); however, across the landscape, the relative amount of recharge between subwatersheds remains similar because the factors that lead to differential recharge: bedrock permeability, topographic position, and soil storage remain static. When bedrock is highly permeable or fractured, higher recharge rates result. Bedrock with low permeability results in lower recharge rates and less water available late in late summer to maintain perennial streamflow. This difference in recharge-contributed HC is well demonstrated in Lagunitas, 1,279 mm/yr, and Pine Gulch, 352 mm/yr (Table 2, Figure 5). These two subwatersheds are adjacent to each other and receive similar precipitation (~ 900 mm/yr average for 1980–2010). The total area of the Lagunitas population subwatersheds, 226 km², is 10 times that of Pine-Gulch, 23 km², yet total annual recharge from Lagunitas subwatersheds is only 3.6 times greater than Pine Gulch. Each 270 m² grid cell recharges the Pine Gulch watershed with 352 mm/yr of the precipitated water, much more than the Lagunitas grid cell average of 128 mm/yr. The bedrock of Pine Gulch is porous sandstone, whereas Lagunitas has impermeable greenstone and claystone; they are on different sides of the San Andreas fault. These results illustrate that the Lagunitas subwatershed changes less under the varying future climate scenarios than Pine Gulch and therefore can be inferred to be more resilient to change.

The seasonal discharge and depletion of subsurface water, measured as baseflow recession, occurs sooner for watersheds with little water holding capacity. Ephemeral coastal streams that run dry before the winter precipitation events replenish baseflow do not support coho. Watersheds with FLCC have a sunshade barrier and increased moisture that increases HC (Figure 2), two critical late summer attributes for instream juvenile coho. Unlike future temperature projections that all trend in the same direction, some models project high future recharge, whereas others
project low recharge (Figure 6b, 6c). This is due to the projections for average annual precipitation that vary substantially, propagating low or high future recharge. The recharge projected in “wet” models such as CNRM contrasts strikingly from “dry” models such as MIROC; however, the relative pattern of recharge across the landscape is consistent across wet and dry projections. Those areas projected to have high relative recharge in wet models are the same areas that are projected to have high recharge in dry models (Figure 6a–6c).

The static patterns of recharge and FLCC across the landscape result from stable and geomorphically diverse conditions within the CCC recovery area. The geomorphologic conditions retain their pattern under varying climatic conditions. Identifying relatively stable patterns of geodiversity has become an important climate change adaptation planning method known as “conserving nature’s stage” (Anderson et al. 2015; Lawler et al. 2015; Pâtru-Stupariu et al. 2017).

We use the static nature of the landscape patterns associated with FLCC and recharge as a logical foundation that allows us to merge indices derived from different temporal periods (e.g., FLCC from hourly summertime data over a decade and 30-year annual BCM output derived from monthly climate inputs) into a metric of HC.

**HC Indices.** Adding the FLCC variability index, FLCC CV (Table 1), reduces the area of FLCC influence on HC II (Figure 6b) because it imposes the additional criterion of FLCC spatiotemporal stability that filters out some high FLCC grid cell with low CV. Using the Jenks optimization method to define categorical breaks the relative importance of FLCC CV (stability) becomes more important as it contracts across the landscape. The Jenks method clusters pixels in categories that minimize the cluster’s average deviation from the cluster mean while maximizing the deviation among clusters. This results in areas that have high FLCC and low CV (high stability) becoming a distinct “high” cluster propagating into the HC II index. An example of this is the unexpected westward expansion of high HC II in the Russian River and Salmon CPUsWs (Figure 8). In most other CPUsWs coastal areas already have high HC. Adding FLCC stability increases already high HC index values. Areas that had relatively low FLCC but high FLCC stability (low FLCC CV) are projected to have higher HC. The HC II index is well suited for use-cases that have long time horizons and address long-term processes or future threats such as increasing thermal burden from climate change or inquiries such as locating situations where coho populations may have evolved a genetic response (adapted) to highly variable stream temperature such as the Gualala PUW. The HC I version provides more discrimination among subwatersheds because the large range in FLCC values is not attenuated by the stability criterion.

**Temperature Threshold Analysis — Use Case 1**

Stream temperature is a limiting factor for coho; however, it is not a measure consistently available at the landscape-level. For the CCC Recovery Plan, Agrawal et al. (2005) developed a proxy for instream temperature specific to the CCC region based on air temperature. The proxy, average maximum August air temperature > 21.5°C, was derived after unexpected discrepancies were encountered while calculating CCC coho population viability curves for the CCC Recovery Plan area. For most of the 365 subwatersheds, the relationship between IP scores and coho records were as expected, high IP correlated with high coho density. The relationship did not hold for a cluster of 66 subwatersheds in the upstream reaches of the Russian River. Further investigation identified the temperature threshold (21.5°C average maximum August air temperature) that distinguished streams that did not have coho even though the IP scores suggested they should. These were identified as having thermally unsuitable instream habitat for coho in the CCC area. Based on the proxy, NMFS did not include those stream reaches (i.e., the cluster 66 subwatersheds) in the prioritization analysis they conducted as part of the Recovery Plan.

The use-case that assesses the thermal burden projected for coastal ecosystems by GCMs, differentiates subwatersheds based on their FLCC-conferred capacity to accommodate to future changes. The matrix in Table 2 provides the framework to explore watershed resilience under future warming conditions during late summer, the warmest temporal period of the coastal California year. Projections of widespread warming into the future show most of the CCC coho area surpasses the 21.5°C average maximum August air temperature threshold (Figure 5c–5f). None of the CMIP5 GCMs, which have a 100–200 km grid resolution, include local to regional atmospheric dynamics such as FLCC that occur on 0.1–100 km scales. The coastal to inland temperature gradient embedded in the meteorological record reflects the FLCC impact on temperature to some extent; however, meteorological stations are very sparsely located within the CCC coho Recovery area. Given the distinct and highly localized pattern of FLCC across the landscape and the recognition that this pattern is not captured by the meteorological station network, we used maps showing hourly FLCC zones to identify subwatersheds that benefit the most from FLCC protection that decreases August
temperatures. Subwatersheds are differentiated based on their relative vulnerability to an increased thermal burden due to higher solar loading to streams. Subwatersheds with more hours of FLCC, on average, are less vulnerable to thermal burdens than those with less average FLCC hrs/day. On average, all the coho CPUsWs have at least four hours per day FLCC except for Gualala, Russian, and San Lorenzo. These three populations would be more vulnerable to climate change and require additional adaptation strategies to maintain suitable instream habitat into the future. Conversely, populations in areas with high FLCC may have less solar loading and therefore lower temperatures than projected by downscaled GCMs that do not incorporate local meteorological phenomena such as FLCC.

The contraction of the thermally suitable temperature band (<20°C, dark blue on Figure 5) that occurred over the last two 30-year climate periods (1951–1980 and 1981–2010, Figure 5a and 5b) is projected to continue contraction into the future under all four GCM models (Figure 5c–5f). The increasing area of unsuitable thermal conditions (i.e., average maximum August air temperature > 21.5°C) squeezes the vulnerable thermal edge (the 20°C–21.5°C temperature band) closer toward the coast (light blue, Figure 5c–5f). Each GCM-derived projection shows an incremental westward contraction that impacts some subwatersheds more than others. Topography and local wind patterns drive the variability in width of the vulnerable 20°C–21.5°C temperature band. This thermal impact will also affect the inland to coastal temperature gradient, a gradient that is expected to increase into the future as more thermal load hits the inland land surface that heats more rapidly than the ocean surface. The same atmospheric and topographic conditions that lead to variations in the pattern of FLCC across the landscape (Figure 4a) are responsible for the patterns in the temperature bands visible across the landscape in Figure 5 maps. The width of the 20°C–21.5°C temperature band can be used as an indicator of vulnerability showing the spatial extent of the areas at the thermal edge of coho unsuitability. The width of the 20°C–21.5°C temperature band within the boundary of the CPUsWs could be considered the CPUsW’s thermal buffer. For example, the northern cluster of CPUsWs from Ten Mile to Navarro have a much wider 20°C–21.5°C temperature band than the neighboring Garcia or Gualala CPUsWs suggesting Garcia and Gualala CPUsWs are less buffered against unsuitable thermal burdens than Ten Mile or Navarro. This information could be useful for prioritizing subwatersheds based on thermal urgency within a recovery planning context that spans years to decades.

Reexamining Subwatershed Priority Ranks — Use Case 2

Combining FLCC and recharge into one composite index of HC simplifies the complexity of contributions from FLCC to recharge, streamflow, and stream temperature for each watershed. The HC index that incorporates all three indicators, FLCC, FLCC stability, and recharge (HC II) is most useful for coho recovery planning as it provides a long-term view. California winters are prone to high variability in amount of total precipitation, and California summers are also prone to high hydrologic variability in amount of FLCC. Using the index that includes the FLCC stability indicator provides a way to identify watersheds that will more predictably experience FLCC during years of low-frequency FLCC. The last column of Table 3 identifies four CPUsWs with high values for late summer hydrologic capacity (LSHC, equivalent to HC II). The subwatersheds in the Noyo, Walker, Pescadero, and Soquel CPUsWs ranked with a Phase 2 priority have the higher LSHC index scores than either their respective Core or Phase 1 ranked subwatersheds. Certainly, there are many factors that go into the prioritization analysis for ranking; however, a reexamination that includes FLCC and recharge might show new options for effective long-term recovery actions.

There are also use cases that benefit from retaining the capacity to explore FLCC and recharge indicators individually to better explore options for addressing simultaneously the future threat of climate warming and groundwater extraction within priority watersheds. For example, two nearly adjacent CPUsWs, Ten Mile, and Noyo (Table 2), have similar total area and exposure to future thermal burdens but potentially different restoration options when their dissimilar FLCC and recharge conditions are taken into account. Ten Mile has less FLCC and more recharge than Noyo and could perhaps gain more benefit from planting riparian shade-trees. Additional tree planting in Noyo might add evaporative stress on groundwater reserves or reduce the already lower recharge (compared to Ten Mile) and therefore reduce discharge into the streams. In the latter case, other options that address water diversion or extraction would be of higher value. Coho Recovery planners have multiple sources of information about local use and extraction of subsurface water, some developed through long-term interactions with stakeholders on beneficial projects such as bank stabilization and erosion preventions (Deitch and Dolman 2017). Planners can incorporate water extraction and diversion information, FLCC and recharge indices, and add measurement and monitoring of on-site conditions, to better assess the relative
vulnerability of coho watersheds to surface and groundwater water extraction.

Surface and groundwater extraction continue to threaten coho habitat as described in the most recent 5-Year Status Review for the CCC Recovery Plan area (NMFS 2016) under Listing Factor A. In the Status Review the authors note the passage of the California Sustainable Groundwater Management Act (SGMA) with optimism stating "Recently signed California legislation may improve the existing over-allocation of the state's groundwater resources" while also explaining that "currently impaired streamflow and habitat conditions will generally persist across the ESU during at least the next decade" due to the "expected long delay (~20 years) in realizing tangible environmental improvement" from SGMA. Before SGMA, there was no regulatory connection between surface water and groundwater (Hebert 2016), a stark contrast to the physical connection that occurs through multiple pathways. Under SGMA, a groundwater management plan that does not achieve groundwater sustainability goals by 2040 — which includes no significant and unreasonable effects on beneficial uses, such as endangered coho — will result in mandated intervention by the State Water Resource Control Board to take over managing extractions and assessing fees. SGMA compliance cannot occur at the expense of reasonably protecting surface water beneficial uses (State Water Resources Control Board 2018). Application of FLCC and recharge HC indices could help identify groundwater basins that are influenced by FLCC thereby yielding better estimates of sustainable levels of water extraction under future climate warming.

When natural resource managers assessed and prioritized CCC coho watersheds for restoration and threat abatement, they did not have data and methods to incorporate coastal fog and recharge as part of the multi-criteria instream habitat evaluation. When the authors of the 5-Year Status Review (2016) identified climate warming as a threat, they likewise could not incorporate FLCC data to better assess long-term resilience. Coastal fog is a potential mitigating factor against the impacts of climate warming for several coho populations with high percentage of their total watersheds above the thermally unsuitable threshold (Table 2). By midcentury under the coolest future projection the Navarro coho population will have 80% of its subwatersheds thermally unsuitable; under the hottest GCM, 98% of the watershed area is projected to be thermally unsuitable. The addition of FLCC and recharge dynamics to the GCM results allows subregional climate factors to be incorporated into future projections. In the next section we discuss caveats to these results.

LIMITATIONS AND FUTURE WORK

The synthesis of existing science on watershed hydrologic modification due to FLCC, described in the introduction, provides a strong basis for inferring FLCC contributions to the HC of Recovery Plan sub-watersheds. The satellite and model-based approach we employed to differentiate FLCC-driven HC (FHC) among watersheds has strengths and limitations. The limitations of this approach provide considerable opportunity for future research. In this section we address three limitations and discuss the potential avenues for addressing each limitation with future work. Limitation 1 is the uncertainty in the FLCC to HC quantification. A method to address this limitation is to estimate the unmeasured elements in Figure 2. Limitation 2 is the uncertainty in landscape-wide correlation between FLCC impact derived from satellite data and on-the-ground impact. A method to address this second limitation is to conduct simultaneous measurements of satellite and ground FLCC characteristics. Limitation 3 is the uncertainty using historical FLCC patterns to project future FLCC states. A method to address the limitation of future patterns being markedly different from historical is to closely monitor atmospheric and climate change research by maintaining close links with colleagues in those science communities.

Coastal Fog Input Pathways to HC

The most uncertain pathways in the FLCC to HC quantification are shown in Figure 2 as pattern-filled arrows designating flows between FLCC and streamflow and temperature. Stream temperature impacts from FLCC are currently poorly quantified yet this relationship forms the basis for the temperature analysis in this work. Calculations of the impact of reduced SW using watt/min reductions from Jacobellis and Cayan (2013) and Matus and L'Ecuyer (2017) suggest at least a 3°C reduction from FLCC (100 watts = 3.2 Celsius heat units per minute), much less than the direct measurements of 10°C reductions (Walker and Anderson 2016) for roads under clouds. Measurements and models of impact from riparian shade (Rounds 2007; Bond et al. 2015; Kalny et al. 2017; Wawrzyniak et al. 2017; Sullivan and Rounds 2018) suggest stream temperature reductions from a solar loading barrier is significant. Although the precise amount of temperature reduction due to FLCC is lacking, a small amount (0.5°C) of reduction can be important, as discussed earlier with temperature bands of Figure 5. Acquiring high precision in the
temperature reduction in FLCC is complicated by the temporal variability in FLCC in a watershed and the continuous evaporation and condensation processes of the rising and descending moist air layer and the associated latent and sensible heat flux that complicates calculations. This study extrapolates FLCC summary statistics derived from an observational dataset of 26,000 hourly, three-band (visible, near infrared, and infrared) National Weather Service satellite images to differentiate watersheds using a three-category index. Our extrapolation sought to provide a new, scientifically defensible method for including FLCC in an endangered species recovery planning effort that does not have the luxury of time. The inferences laid out in Figure 2 are stronger for the streamflow pathway than the stream temperature pathway. More opportunities exist to reduce uncertainty in the fluxes of the temperature pathway. The temperature pathway in the schematic glosses over the complex relationships between FLCC, air, and stream temperature. Future work to measure uncertain elements within the FLCC to stream temperature pathway would reduce some limitations of this study. Madej et al. (2006) provide a preliminary effort using thermal infrared imaging and detail many of the challenges they faced that prohibited quantifying FLCC impact on stream temperature: temporal variability, unknown subsurface drainage patterns, and thermal stratification of surface water and deeper pools.

The effect of FLCC on streamflow, although well characterized for three sites in the Santa Cruz Mountains (Sawaske 2014), is poorly quantified across the landscape. Lacking baseflow recession analyses, we derived the FLCC impact on streamflow by linking FLCC with recharge capacity. Future work would test the method’s assumption through direct measurement of streamflow and FLCC in watersheds with different recharge capacities. Another important limitation to our method of calculating HC is the lack of groundwater extraction estimates and impacts of land use change on surface water inputs into the riparian systems. Adding estimates of groundwater extraction may become feasible with the stricter attention on measuring groundwater use that will come with SGMA. Adding landuse data at very high resolution such as what is now available through LiDAR acquisitions in Sonoma County, would provide input data for surface runoff models such as the USGS Precipitation Runoff Modeling System (PRMS). Several watersheds in the CCC area are being modeled using PRMS, adding higher resolution inputs to these models would help improve precision for better estimates of the effect of land cover and landuse change on the recharge portion of Figure 2.

The Satellite-Based Approach

This study uses high temporal resolution (hourly) satellite-derived measures of FLCC. This approach, a top-of-the-atmosphere view, will not resolve whether the FLCC layer is fog or low cloud, limiting precise quantification of the fogdrip pathway (Figure 2) which only occurs under foggy conditions. The use of ground-based cameras, in strategically placed locations, could provide the horizontal data or conjunctive use of ceilometer data. Both lack the extensive coverage of satellite imagery. Lacking data to quantify the relative amount of fog vs. low cloud and the contribution of each to HC — but recognizing that more FLCC and higher capacity for recharge will provide greater resilience to thermal stress and improve instream habitat quality — we derived FLCC indices using satellite imagery and broad categorical classes of high, medium, and low.

Precise quantification of fogdrip across the landscape is difficult because measuring fogdrip is difficult. Fog can be extremely patchy, heterogeneous in both horizontal and vertical dimensions. Fog can dissipate quickly but it can also last for weeks, which necessitates a high temporal resolution data set such as the hourly National Weather Service images used in this study. Fog can be very dense, becoming drizzle, or very sparse, becoming meteorologically mist. An alternative to the limited satellite-based approach is collecting fogdrip data directly and volumetrically. The advantage of this approach is improved quantification of the direct impact of fogdrip. Unfortunately, the heterogeneity and patchiness of fog limits extrapolating fogdrip measurements from single points to larger landscape areas and would therefore require many collection sites. Defining a sampling strategy and mapping how many sites would be needed, in which locations would also require better quantification of the spatiotemporal variability at streamflow relevant intervals.

Fogdrip is typically collected using an impacting surface such as a 1m² mesh in a stiff frame or threads on a cylindrical harp suspended above ground on top of a collecting trough funnelling fog water into a tipping bucket rain gauge (Goodman 1985; Fischer and Still 2007; Fernandez et al. 2018). Fogdrip is also collected using an arrangement of rain troughs radiating from a bucket positioned under a tree canopy (Sawaske and Freyberg 2015). Even under very similar conditions in the same general location with similar fog events, collection results differ by several orders of magnitude, 18 mm/month, 375 mm/month, and 4,000 mL/m²/night (Goodman 1985; Sawaske 2014; Chung et al. 2017, respectively). Comparing fogdrip collection results is also further complicated by differing measurement units,
volumetric (mL/m²), and meteorological (mm). Many variables influence the amount of fogdrip a watershed receives. Wind strongly affects impaction and coalescence of fog droplets (de Dios Rivera 2011; Frumau et al. 2011; Holmes et al. 2015) and the composition of aerosols influence the size of fog water droplets and therefore the liquid water content of the fog event (Hudson and Svensson 1995; Öström et al. 2000; Feingold and Chuang 2002; Degejie et al. 2015). The location within the watershed is also crucial, as forest edges receive more fog than the interior (Ewing et al. 2009). Other alternative methods of estimating fog and the density of water in fog, come from a completely different discipline, communication networks, and are in experimental stages. Fog affects wireless communication by altering the transmission between ground level commercial microwave cell towers. Algorithms have been developed to accommodate the degradation of the signal and improve cellular communications. Cell tower networks have been proposed for fog monitoring (David 2018) and monitoring precipitation (David et al. 2019).

**The Future of Coastal Fog**

Projecting a future trend for FLCC requires models that address the complex, interacting feedbacks of atmospheric processes at synoptic to local scales (Kaplan et al. 2017); teleconnections between oscillating ocean-atmosphere cycles (Li et al. 2016; McGregor 2016; Sun et al. 2017); rising cloud base due to urban heat effects (Williams et al. 2015); changes in advection strength in response to an increase in the inland to coastal temperature gradient, mentioned earlier (Wang and Ulrich 2018 although see Clemesha et al. 2017); fog droplet interaction with water scavenging aerosols, pollution, and urban metabolites (Klemm et al. 2005; LaDochy and Witiw 2012; Koračin et al. 2014; Sanchez et al. 2016; Gray et al. 2019); and the relationship of local scale upwelling dynamics to fog formation (Telford 2000; Robart 2013; Renault et al. 2016). To date, no model incorporates all these elements.

A regional dynamic simulation model of California coastal fog for 1900–2100 shows a long-term trend of 12%–20% reduction in coastal fog (O'Brien 2011; O'Brien et al. 2013); however, it does not include several feedbacks and processes that may be important for the future of fog, such as coastal upwelling and shifts in the center of summertime high-pressure zones. The interannual coastal fog frequency is closely tied to the relative latitudinal location of the descending branch of the Hadley cell that generates the Pacific high-pressure zone. When the high-pressure zone moves north, more fog is observed along the California coast, when it moves south less fog is observed (Johnstone and Dawson 2010). Black carbon and tropospheric ozone effects have been associated with the poleward widening of the descending branch of the Hadley circulation (Hu et al. 2018), which would increase summertime FLCC in northern California. The uncertainty associated with feedbacks complicates the picture. For example, an increase in inland temperatures could lead to a stronger coastal to inland temperature gradient leading to an increase in top-of-the-atmosphere turbulence. This could lead to either less fog due to additional entrainment of moisture into the dry subsiding layer, or more fog from the stronger advection of moist air inland.

In a study using CMIP5 atmospheric simulations and multimodel data, Kawai et al. (2018) found that most model simulations have marine fog consistently increasing in the eastern North Pacific in boreal summer. Kawai's results are consistent with shipboard observations that showed an increase in northern California coastal fog from 1950 to 2007 (Dorman et al. 2017). Other work suggests that the reductions in fog seen over the last century might be more strongly linked to basin wide ocean-atmosphere oscillations such as the Pacific Decadal Oscillation, other synoptic-scale cycles affected by the jet stream that can be expected to continue to oscillate (Johnstone 2011; Johnstone and Mantua 2014; Dorman et al. 2017) or air pollution (Gray et al. 2019). Might the increasing aerosol load from higher frequency fires in California fires have the unexpected result of more summertime FLCC?

The high variability in annual and monthly FLCC values observed from the 1999–2009 FLCC that were used for this study provide analogs to the future projections of FLCC except for a future with no coastal fog. A no fog future is simulated to happen if CO₂ levels rise to 1,200 ppb, four times current levels (Schneider et al. 2019). The uncertainty in cloud feedback under climate warming (Zelinka et al. 2017) and the interdisciplinary nature of fog research suggests that keeping in touch with discussions at meetings such as those of the American Geophysical Union, European Geosciences Union, and the International Conference on Fog, Fog Collection, and Dew are important venues for keeping abreast of research on future trends for coastal fog.

Chile, Peru, South Africa, and Canary Islands, like California situated on the eastern edge of ocean basins, also have dry season coastal fog that provides HC that facilitate biotic survival. The FLCC-based method described in this work can inform ecological resource management in these other regions that also face the challenge of prioritizing resources to restore watersheds and protect species.
CONCLUSION

Recently available datasets for FLCC were combined with modeled recharge to generate indices of HC. Maps of FLCC, recharge, and HC for the CCC coho Recovery plan area subwatersheds and population units were used to explore the spatial distribution of hydrologic resilience. Subwatersheds with high combined values for average FLCC, recharge, and relative stability of FLCC are the subwatersheds with the highest HC and resilience relative to the instream hydroclimatic needs of coho. Watersheds with higher capacity to provide cool water to streams during coastal California’s critical late summer period are more resilient in the face of a warming climate. Temperature projections from CMIP3 and CMIP5 GCMs show likely future thermal stress for coho in California streams. These GCM-derived temperature projections do not include subregional processes such as FLCC and recharge dynamics. Including FHC improves an understanding of coastal hydrodynamics and can help inform discussions about watershed resilience to future thermal burden and thereby improve coho recovery planning.

We structure the results presented in this article to be compatible with future status reviews for improved management of salmonid populations from several user perspectives, natural resource managers from federal, state, local organizations who need to coordinate with local watershed stakeholders to attain ESA goals and explore long-term solutions for coho recovery; local stakeholders who want to understand the relative importance of FLCC to streams on their property; and analysts charged with incorporating the latest science into status reviews. The results presented here can be used to refine watershed assessments for future status reviews, incorporate a long-term view of hydrologic resilience into the investment strategies embodied in the restoration and recovery efforts, and prioritize future research questions. The Recovery Plan is a multi-decade effort to save central California coho from extinction. With much of the Recovery Plan area in private ownership, successful threat abatement and restoration actions to stem the decline of coho populations will require high levels of stakeholder involvement and timely incorporation of new scientific information.

SUPPORTING INFORMATION

Additional supporting information may be found online under the Supporting Information tab for this article: GIS data files and spreadsheets for all analyses presented.

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