Testing the potential of Multiobjective Evolutionary Algorithms (MOEAs) with Colorado water managers

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Highlights

- Structured workshop effectively provided managers with hands-on tradeoff experience
- Interactive MOEA tradeoffs aided in creation of decision dominance structure

- Increasing tradeoff info often resulted in revised and divergent portfolio choices
- Managers suggested opportunities and challenges to using MOEAs for planning

Abstract

Multiobjective Evolutionary Algorithms (MOEAs) generate quantitative information about performance relationships between a system's potentially conflicting objectives (termed tradeoffs). Research applications have suggested that evaluating tradeoffs can enhance long term water utility planning, but no studies have formally engaged with practitioners to assess their perceptions of tradeoffs generated by MOEAs. This article examines how practitioners interact with MOEA tradeoffs and reports their ideas for how their agencies could use MOEA results. We hosted a group of Colorado water managers at a charrette, or structured investigatory workshop, where they directly interacted with tradeoffs, discussed how they used the information, and linked their workshop experiences to opportunities for MOEAs to enhance their agencies' planning processes. Among other interesting results, we found that managers' portfolio preferences diverged as tradeoff information increased and that structured information about the relationships between decision levers and performance would be beneficial for interpreting tradeoffs.

Keywords

participatory modeling; workshop; multiobjective evolutionary algorithm (MOEA); decision-making; long term planning; tradeoffs

1 Introduction

Decision making is a process; when a choice is available to be made, deliberation must occur if an agent desires an outcome and is able to take action (Aristotle, 1920). In most decision making processes, preferences are constructed based on problem framing, previous experience, and available information, time, and resources (Payne et al., 1992; Roy, 1999; Slovic, 1995; Tsoukias, 2008). In combination, these factors help decision makers develop what Montgomery (1983) terms a "dominance structure". A dominance structure is a set of cognitive rules that serve to create advantages for certain alternatives or neutralize disadvantages of others. Such a framework is necessary when there is no strictly-optimal option. The dominance structure is iteratively built up in stages using mechanisms that help decision makers assess relative merits of alternatives and/or alter their internal representations of situations until one alternative becomes dominant. This process of creating arguments for and against alternatives develops a justification, or basis for reasoning that can be conveyed to others. Justifiability is a cornerstone of deliberate human decision making (Connolly and Reb, 2012; Payne et al., 1992; Slovic, 1975; Tversky, 1972), and studying this in technology-based decision support is warranted.

Multiobjective Evolutionary Algorithms (MOEAs) have been researched and applied as tools to aid decision making processes concerning complex systems for which there are multiple conflicting performance measures. MOEAs seek to optimize system performance in multiple performance objectives, efficiently searching through thousands of alternatives to develop a set that quantitatively characterizes the approximate best tradeoffs between those objectives. These quantified tradeoffs reveal how much performance in one objective must be forfeited to get better performance in another. In the context of developing a long term water resources plan, MOEAs test thousands of alternative portfolios of new sources, new infrastructure, and new operations in order to balance between performance objectives such as maximizing supply reliability and minimizing environmental impact.

Several studies have applied MOEAs to long term water resources planning problems. Long term plans are essentially overarching decisions about pursuing a set of actions over an extended time horizon. Three recent academic examples are Matrosov et al.'s use of an MOEA to develop long term planning portfolios for London, balancing cost, energy use, resilience and environmental objectives (2015); Zeff et al (2016) optimization of long and short term risk triggers to develop adaptation strategies and support regional cooperation between utilities in North Carolina; and Wu et al.'s application of multiobjective optimization to identify portfolios of traditional and alternative water sources for Adelaide in consideration of cost, emissions, reliability, and the environmental impacts of water and wastewater reuse (2017). These studies demonstrate that MOEAs can produce informative tradeoffs for multiple aspects of planning in a variety of geographic contexts which could inform agencies' planning decisions. However, none of these examples have undertaken a structured exploration of how a practitioner or agency employing an MOEA would interact with or perceive tradeoffs, and thus have not determined whether or how they actually aid decision making.

To study whether the quantitative information found in MOEA tradeoffs contributes to the creation of defensible dominance structures that help water managers construct preferences and justify decisions, researchers need to be able to observe, interrogate, and analyze practitioners' usage of tradeoffs. Accomplishing this necessitates an interface between practitioners and researchers designed specifically around the type of information that results from MOEA-assisted optimization. Here, we can draw on an approach called a "charrette" which is used in non-academic settings to achieve a high level of public awareness and input on the design or vision of a community project or plan (US EPA, 2014). Charrettes are also used by researchers in the fields of construction management and safety. Research charrettes are structured workshops that bring together industry professionals and academics in a relatively short but intensely productive session in order to generate discussion and feedback about newly-created products or practices intended for industry use (Gibson and Whittington, 2010). Charrettes combine the advantages of surveys, interviews, and focus groups in an accelerated time frame, overcoming the difficulties of undertaking these methods individually (e.g. low response rates, time commitments from both researchers and practitioners, access to data, etc.). Results from applying these mixed methods to technical research topics have shown that charrettes can offer both short and long term benefits to participating industry professionals and improved validity and reliability of research outcomes (Abowitz and Toole, 2010; Green et al., 2010).

This paper presents the content, methods, and results of a research charrette through which our transdisciplinary research team engaged with Front Range, Colorado, water managers over the use of MOEA tradeoff information for long term water utility planning. The workshop was designed to discover how practitioners used tradeoff information to make decisions, and whether and how the managers perceived the information to be useful in their agencies' planning processes. The goals of the workshop were to expose practitioners to an emerging tool and use the collected data to hone future MOEA research agendas and target new applications.

The charrette that we focus on in this paper is the culmination of a larger study that introduced and applied the Participatory Framework for Assessment and Improvement of Tools (ParFAIT) (Smith et al., 2017). The following section briefly introduces MOEAs and presents work from the previous phases of our ParFAIT efforts that pertain to this final step in the framework. In Section 3, we describe the methods and content from our workshop. Next, we describe the results, and in Section 5 offer concluding remarks.

2 Background

2.1 MOEA-assisted optimization for long term water utility planning

For water utilities, planning for long term, sustainable water security is a critical task and a major undertaking. Technical staff review alternative planning portfolios and iteratively discuss goals, needs, and strategies with Board- or council-level decision makers (CSU, 2017a; MWD, 2015), and, increasingly, the public as well (WUCA, 2015). They generally do not find a perfect plan due to the conflicts between the financial, social, and environmental factors that utilities must navigate (Elkington, 2004), but utilities strive to make smart, responsible, and justifiable decisions that allow their systems to meet the communities' chosen demand reliability policies in combination with community values.

Multiobjective Evolutionary Algorithm (MOEA)-assisted optimization has been studied (Matrosov et al., 2015; Mortazavi et al., 2012; Smith et al., 2018; Wu et al., 2016) and applied (Basdekas, 2014; CSU, 2017a) as a method to help utilities develop long term plans. While a traditional planning process compares the performance of a handful of planning portfolios, MOEA-assisted optimization efficiently designs and tests thousands of potential portfolios. This extensive search and evaluation produces quantitative information about the system's performance in multiple objectives and the tradeoff relationships between those objectives.

Performing MOEA-assisted optimization requires a simulation model (already developed by most utilities), a problem formulation, an MOEA, and tradeoff visualizations. The problem formulation is a set of decision levers, objectives, and constraints that the MOEA uses to construct and compare planning portfolios. Decision levers are a utility's options to modify its system, e.g. building a reservoir or enacting conservation; the set of chosen decision levers makes up a portfolio. Objectives are measures of system performance that are quantified representations of a system's goals or purposes, e.g. minimizing frequency of lawn watering restrictions or maximizing water in storage. Constraints are numeric limits to acceptable performance, e.g. if a portfolio cannot meet 100% of indoor demand at all times it is not considered a valid planning approach.

MOEA-assisted optimization is carried out through many cycles of a computational loop. The MOEA generates an initial population of portfolios and feeds each one to the simulation model, which tests the portfolio over one or more future scenarios. At the end of the simulation, values for objectives and constraints are reported back to the MOEA. This loop iterates thousands of times, during which the MOEA intelligently evolves new "generations" of portfolios through both systematic and random recombination and mutation of the high-performing portfolios of previous generations. This results in a set of nondominated portfolios in which performance improvement in one objective is only achieved by sacrificing performance in another; thus, the portfolios "trade off" levels of performance. Analyzing the tradeoffs requires careful analysis including visualization techniques, and these are the final component of MOEA-assisted optimization. More information about tradeoff visualization is presented in Section 3.1.

Water utility planning is a complex process which may benefit from new technologies. Increased public scrutiny, greater mandates to protect social and environmental interests, and heightened awareness of future uncertainty all suggest that extensive portfolio search and explicit performance tradeoff information would be useful to the agencies.

2.2 Participatory Framework for Assessment and Improvement of Tools (ParFAIT)

Many research applications of MOEA-assisted optimization have established the ability of MOEAs to generate tradeoff information about water supply systems and produce innovative portfolios that can outperform plans developed with human expertise or previously-established operational approaches (Maier et al., 2014; Nicklow et al., 2010). While Colorado Springs Utilities and Melbourne Water are two notable examples (CSU, 2017b; Kularathna et al., 2015), instances of this promising tool being applied in real-world planning studies are rare. To understand and potentially overcome the limited uptake of MOEA-assisted optimization, researchers must consider the factors that lead industries to adopt tools and consciously seek to create usable science. That is, researchers must undertake intentional, iterative interaction with practitioners to understand their needs, transmit research, and co-produce relevant future research directions (Díez and McIntosh, 2009; Dilling and Lemos, 2011; Sarewitz and Pielke, 2007; Smits, 2002).

The Participatory Framework for Assessment and Improvement of Tools (ParFAIT) is a research process designed to bring academics and practitioners together in a structured way (Smith et al., 2017). ParFAIT is a four-phase research sequence that can be summarized as follows:

Step 1: Choose a promising research tool and a practical use for it that is supported by academic literature and knowledge of the proposed industry;

Step 2: Hold Workshop 1 to solicit input from practitioners that will inform development of a tool testbed. (A testbed is a platform on which the tool can be demonstrated to practitioners.);

Step 3: Build the tool testbed, iterating with practitioners as necessary to ensure relatability and relevance to real-world tool application context;

Step 4: Hold Workshop 2, a research charrette, to solicit practitioner feedback on the testbed results (i.e. results representative of what they could expect if their agencies adopted the tool).

Smith et al. (2017) introduced ParFAIT, including the detailed steps and methodology, the supporting theory behind the process, and the results of Workshop 1 (briefly summarized below). The ParFAIT purpose and process distinguish the study presented in this paper from previous MOEA research studies which either applied the tool to a stylized system without input from practitioners or worked with water managers to inform its application to a real system. This study instead seeks to create a context and platform through which practitioners from many agencies can gain experience using MOEA tradeoffs and provide their feedback to researchers. Here, we present results from our application of ParFAIT, including a charrette with utility managers to understand their engagement with tradeoffs and the overall usability of MOEAs for long-term decision making.

2.2.1 ParFAIT Workshop 1

Workshop 1 of our ParFAIT process took place in February, 2015. It brought together water managers from six Front Range, Colorado, utilities[1] and our research team which was made up of engineering, social science, and climate science researchers as well as water utility practitioners. Through targeted but free-form group discussions, managers shared their experiences of Front Range management challenges and provided feedback and suggestions to inform the elements needed to create an MOEA-assisted optimization testbed: supply and demand decision levers, performance objectives and constraints, future supply and demand scenarios, and important features for a generic but relevant hypothetical water supply simulation model.

Creating a relatable testbed is crucial for the successful application of ParFAIT because it is the basis for generating representative results, and also because its components must be recognizable to participants in the second ParFAIT workshop. This enables them to quickly grasp the testbed and focus on engaging with the results. Based on the information we generated through Workshop 1 and iteration with practitioners on our research team, we developed the problem formulation (decision levers, objectives, and constraints) and water supply simulation model that make up the Eldorado Utility Planning Model testbed.

2.2.2 ParFAIT testbed: The Eldorado Utility Planning Model and case study

To demonstrate MOEA-assisted optimization, we used the context of a hypothetical water utility, called "Eldorado Utility," undertaking a long term planning process. The Eldorado Utility Planning Model and

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[1] City of Aurora, City of Boulder, Colorado Springs Utilities, Denver Water, City of Fort Collins, and Northern Water

case study generically capture management context relevant to utilities on the Front Range of Colorado as well as other regions in the western U.S. The rest of this section will briefly describe Eldorado Utility's supply system and problem formulation, the model, and minimal pertinent Front Range context. Technical details about the optimization problem are included in the Appendix. For more Front Range context, refer to Smith et al. (2017), and for in depth discussion about the model and case study results, refer to Smith et al (2018).

Much of the western U.S. is severely water-limited and tightly regulated by the prior appropriation legal doctrine, or "first in time, first in right" (Hobbs, 2004). One practical outcome of these factors is that, as cities grow, they obtain a variety of types of water rights (e.g. storage rights and streamflow diversion rights), each with different temporal priorities, and which may be sourced from multiple geographic locations. To represent this, Eldorado's hypothetical system includes: two reservoirs on two different rivers with junior priority dates; three direct diversion streamflow rights on a nearby river – one senior, one mid-seniority, and one junior; one junior diversion right on a distant river that requires the diverted water to be conveyed under a mountain range in order to be stored closer to the utility; and 10,000 shares of a water wholesale company that Eldorado takes directly from a reservoir owned and operated by the wholesaler.

In many years, junior right holders do not all get their full allotments (Caulfield Jr. et al., 1987; P. O. Abbott, 1985); e.g., a reservoir does not necessarily fill or a streamflow right does not always get to divert. Streamflow and competition for water on different rivers varies, however, and this means that utilities' water supplies strategically span entire regions. The Eldorado Utility Planning Model encompasses 5 basins and 12 water users besides Eldorado. The other users with senior water rights often limit the yields from most of Eldorado's sources, but some also provide opportunities for the utility to acquire more reliable supplies.

The Eldorado Utility is a relatively small water provider and, like much of the western U.S., is expecting rapid population growth (State of Colorado, 2017). The utility has a set of 13 decision levers it can use to modify its system to meet growing demands. The levers fall into three general categories: pursuing "new" water, building new storage, and altering management of reusable water. The first category includes decisions about leasing strategic space in other agencies' reservoirs and obtaining the right to move reusable water around the region for more efficient access. Pursuing "new" water refers to decisions to acquire rights from regional agricultural or industrial users, or buying shares from water wholesalers. Conservation is also considered new water because it frees up water that would have otherwise not been available to meet growing demands. Building new storage includes decisions about whether and how much to expand an existing reservoir and whether to build a new one either upstream, downstream, or both.

Eldorado has defined five[2] performance objectives on which to evaluate potential portfolios. They are qualitatively described here and also summarized in Table 1. The first objective, "Years in Restriction 1" seeks to minimize how frequently Eldorado goes into Level 1 restrictions, which occurs when the utility's storage drops below 75% of average annual demand[3]. Eldorado's reliability policy dictates that the utility should not enact these restrictions more than 5 times in 25 years. The next objective captures the utility's desire to minimize missed opportunities, i.e. inability to use available water ("Missed Op Water"); this measures how much of certain types of water that Eldorado had access to but could not use due to incompatible demand timing, lack of storage, etc. Next, Eldorado seeks to minimize "New Supply"; this means minimizing the average annual volume of water over the course of the simulation that Eldorado acquires through decisions such as buying rights or shares or conserving water (i.e. freeing up water to meet new demands). While Eldorado does need more water for a growing population, this objective is minimized because drawing more water than necessary away from other users creates social and economic disruption in their communities. The "New Storage" objective minimizes the volume of newly-built storage within a portfolio because adding infrastructure is expensive, uncertain, and environmentally problematic. Finally, measuring "April 1 Storage-to-Demand" is another way for Eldorado to evaluate the reliability of their system; this objective seeks to maximize the *lowest* April 1st storage volume over the course of the simulation (i.e. it measures how much water is left in storage at the end of the winter drawdown season).

The single constraint included in the problem formulation was that all portfolios had to meet 100% of indoor demand (demand remaining after outdoor water use is prohibited by Level 3 restrictions).

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[2] The full optimization problem had two additional restrictions-based objectives that were not presented in the workshop but which are described in the Appendix.

[3] When storage drops below 50% of annual demand, more severe restrictions are triggered but those were not presented in the workshop (see the previous footnote).

Table 1. Summary of performance objectives.

Objective	**Description**
Years in Restriction 1	Minimize frequency of Level 1 restrictions over 25 years
Missed Op	Minimize average annual volume of the sum of: return flows that Eldorado could have captured and reused, forfeited Wholesaler shares, and forfeited Ag2 shares
New Supply	Minimize average annual new water created by either conserving or acquiring right and shares
New Storage	Minimize the volume of newly-built storage in a portfolio
April 1 Storage-to-Demand	Maximize the lowest April 1st storage-to-annual demand ratio during the 25-year simulation

The Eldorado Utility and regional system are modeled using the RiverWare platform (Zagona et al., 2001). The optimization was performed on a 25-year simulation horizon with a monthly timestep using the Borg MOEA (Hadka and Reed, 2013). Optimizations were performed in three different hydrologic scenarios: historic, streamflow resulting from a 1°C-perturbed future (qualitatively named “Very Warm” for workshop purposes), and streamflow resulting from a 4°C-perturbed future (referred to as “Very Hot” in the workshop). These temperatures were based on a previous climate change study in which all of our Front Range utilities participated; more information about the choice of these scenarios can be found in Woodbury et al (2012) and a description of their generation is in Smith et al (2018).

3 Methods

3.1 Interactive tradeoff visualization workbooks

To explore and understand the quantitative tradeoffs contained within a set of nondominated portfolios produced by MOEA-assisted optimization, users need to be able to see the complex relationships between the portfolios. This is facilitated by visualizing multiple portfolios at a time in several objectives, or dimensions. Being able to see relationships across all dimensions simultaneously provides the greatest opportunity to see tradeoffs, since only seeing a subset of the objectives can obscure higher-dimensional relationships (Kollat and Reed, 2007). Understanding and exploring a large dataset in many dimensions requires advanced visualization techniques called visual analytics (Keim et al., 2006; Liu et al., 2017; Thomas and Cook, 2006; Woodruff et al., 2013).

This study uses parallel axis plotting. The plots use a series of vertical axes to represent as many dimensions as desired (Fleming et al., 2005; Herman et al., 2014; Inselberg, 1985; Watson and Kasprzyk, 2017). Studies have shown that if parallel plots are interactive, first-time users can learn to use them effectively with 5-10 minutes of training (Johansson and Forsell, 2016; Siirtola and Räihä, 2006). Previous research has assessed whether users can evaluate multiple dimensions to complete a closed-form task with the plots, e.g. “Which one of the cars manufactured in 1982 has the slowest acceleration?” (Siirtola and Räihä, 2006). Our workshop differs in that we asked participants to use the information from the plots to make their own choices, so our results will reflect how practitioners used parallel plots to weigh tradeoffs and make judgements.

To enable the water managers to use parallel plots for subjective analyses, we created plots that supported extensive browsing, multiple selections, and comparisons between portfolios and across workshop activities. We used Tableau, a commercially-available business analytics program (Jones, 2014), to create a series of interactive worksheets on which participants could: hover over portfolios to get full decision and performance information, select one or more portfolios to highlight them, and enter portfolio IDs that changed the colors of those portfolios to register their choices for the activities described below. Critically, the workbooks allowed us to save their choices which both recorded them for later research analysis as well as allowed us to show managers how their choices changed (or did not change) over the course of the workshop.

Example results from optimizing the Eldorado Utility case study are presented in Figure 1. Briefly discussing the example results will facilitate readers’ understanding of the information that water managers used during the charrette (described in the next section). As demonstrated below, we showed charrette participants the objectives and decisions together to provide all information about the portfolios and enable them to evaluate tradeoffs between different objectives while simultaneously exploring decision preferences.

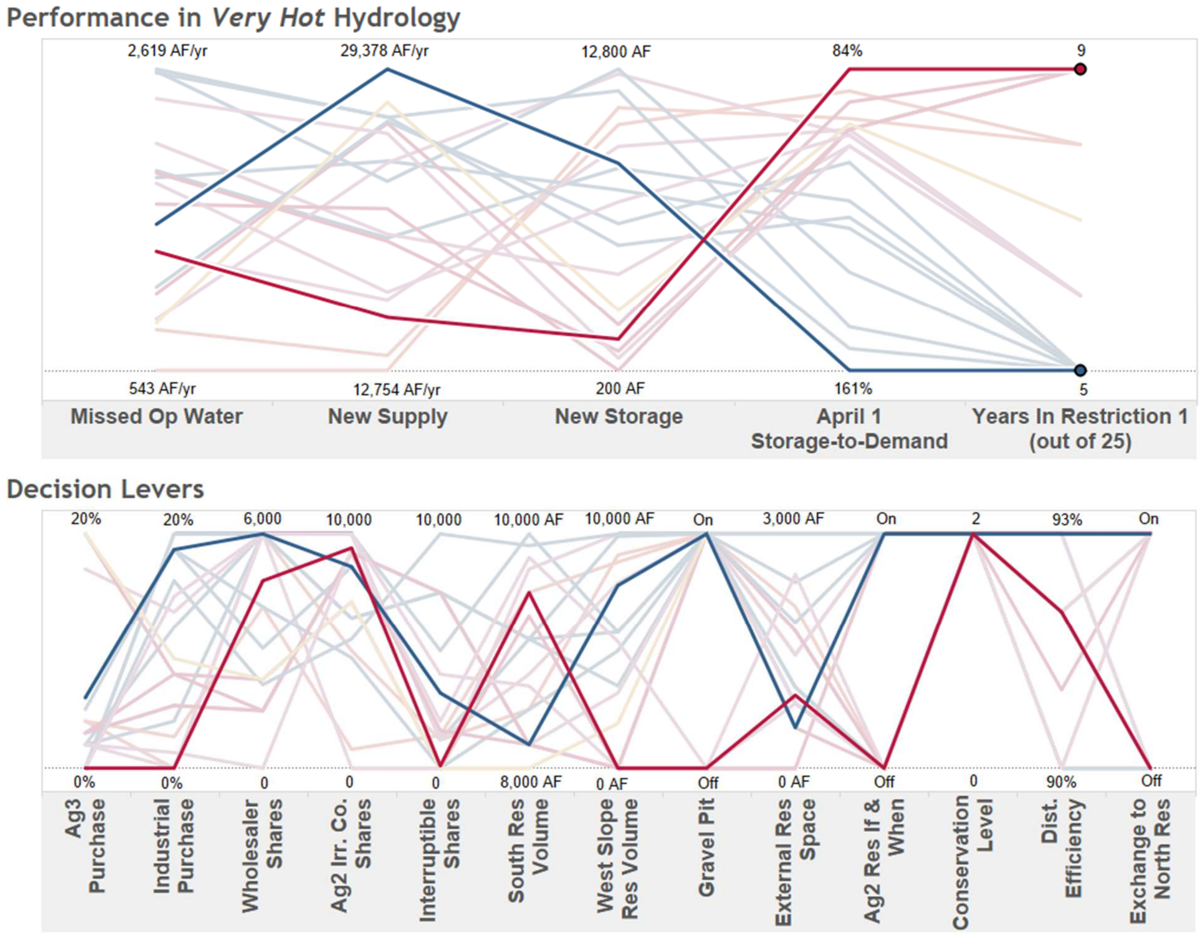

Figure 1. A screenshot of a Tableau worksheet that corresponds closely with what participants used in the charrette. Two portfolios are highlighted to demonstrate tradeoffs.

The plots in Figure 1 show 20 portfolios[4] that resulted from optimizing the Eldorado Utility case study using hydrology generated for a 4˚C-warmer (or "Very Hot") future. The top plot has five vertical axes- one for each performance objective. Each of the lines connecting the axes is a portfolio. The vertical position at which a portfolio line crosses an objective axis denotes its performance, where lower intersection is better. (Note that the objectives and decision levers all have different numerical scales and we have normalized the values so that each dimension fully spans its axis.) The portfolios are colored based on how many years of Level 1 restrictions they produced (i.e. the performance on the rightmost axis); blue lines all have five years in restriction, red lines all have nine years. Two portfolios

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[4] The full tradeoff sets produced by the Eldorado Utility optimizations included approximately 1000 portfolios each (Smith et al., 2018). In order to make the most of limited workshop activity time, we only showed participants 20 predetermined alternatives that were hand-selected by researchers such that the subset captured a wide range of performance for each objective and clearly presented the system's performance tradeoffs.

are highlighted to demonstrate the tradeoffs presented in the plot. The blue portfolio has the best possible performance in April 1 Storage-to-Demand and Years in Restriction 1, has medium-poor performance in New Storage and Missed Op Water, and the worst possible performance in New Supply. These levels indicate the tradeoffs between reliability measures on the right two axes and other system performance considerations. Conversely, the red portfolio performs the worst in April 1 Storage-to-Demand and Years in Restriction 1 but better, sometimes much better, than the blue portfolio in the other three objectives. Depending on Eldorado's preferences and priorities, they might choose portfolios with different performance characteristics.

The bottom plot shows decision lever attributes using a vertical axis for each of the 13 levers. As in the objectives plot, the lines connecting across axes are portfolios, and the position at which they intersect an axis denotes "how much" of a decision is included in the portfolio. The lower a portfolio line crosses, the "less" of that lever is present. Each portfolio line in the objectives plot has a corresponding line in the decision levers plot, so we can compare a few of the decisions led to the contrasting performance of the two highlighted alternatives described above.

3.2 MOEA research charrette: June, 2016

Step four of our application of ParFAIT, a research charrette, provided water managers with hands-on experience with MOEA-assisted optimization results. Our goals for the workshop were to:

1. provide exposure for the emerging tool;
2. observe managers' analyses of tradeoff information;
3. understand how managers relate the tradeoff information to their current needs and practices;
4. get feedback about what potential uses and barriers managers see in the tool;
5. learn about the general process of utilities adopting a new tool; and
6. report any opportunities for future research to meet the needs of practice.

Nine total participants from six Front Range utilities attended the workshop. The utilities represented a wide range of system sizes, and the individuals themselves also spanned a range of experience levels: 4 managers had over 16 years of experience in Front Range water management; 1 had between 11 and 15 years; 1 had between 6 and 10 years; and 3 had 0 to 5 years of experience. We also had participants with different roles within their respective agencies: four were at a management level and five were technical staff. This variety was helpful in getting different perspectives, and the presence of both technical and managerial practitioners was especially encouraging since having advocates at multiple levels of administration increases the likelihood of innovation uptake (Daniell et al., 2014).

3.2.1 Charrette development

Intense preparation and attention to charrette form, function, and sequencing made it possible for both participants and our team to approach the actual experience as a fun day of learning. Once we produced tradeoffs for the Eldorado system in multiple future scenarios (completed approximately three months prior to the charrette), we began the process of developing content and activities that could effectively introduce new concepts and provide an engaging hands on experience. To accomplish this, we undertook trials of content with unaffiliated water professionals and water researchers to learn about how MOEA novices reacted to various levels of information and visualization complexity. These dry runs helped shape the presentation of MOEA and testbed information, choices of activities, timing to complete them, and design of the Tableau workbooks.

The nine practitioner attendees were divided into three groups of three and seated at different tables. Each table had a facilitator, and the facilitators were chosen based on their familiarity with workshops and water management so that they could prompt and guide discussions in a neutral and knowledgeable way. Members of the core research team floated between groups to clarify technical or procedural questions. Each manager was given a laptop with the Tableau workbooks pre-loaded so that they could complete charrette activities independently. They then reflected on their individual efforts in small group discussions which are described in the Results section.

Data from this workshop includes the portfolio choices that managers made as well as discussions about the MOEA testbed tradeoffs, managers' analytical processes, utilities' planning approaches, tool adoption, potential for MOEAs overall, and workshop content. As such, we made sure to capture participants' portfolio choices but also took audio recordings and notes of each small group of managers. Having three types of information allowed us to ensure accuracy and produce results that synthesized both qualitative and quantitative responses. Additionally, post-workshop surveys recorded participants' overall perceptions of the usefulness of MOEA-assisted optimization.

The charrette used a detailed format, custom computer workbooks, and concrete tasks associated with the activities, all of which guided information flows between participants and researchers. Compared to our first ParFAIT workshop, which relied on free-form discussions about targeted topics to inform the direction of the overall project, this workshop was a relatively formal participation mechanism (Newig et al., 2008; Smith et al., 2017). However, the facilitated small group discussion sessions built into each activity captured open discussion and impressions from participants and allowed us to access subtleties of how utilities plan and operate and how managers relate to their systems. After the workshop we electronically surveyed participants about their perceptions of MOEA usefulness. This mixture of methods is fundamental to the success of charrettes (Gibson and Whittington, 2010). The incorporation of focus group-type activities and discussions was particularly useful for bridging the gap between researchers and practitioners because these interactions "provide a clear view of how others think and talk" (Morgan, 1993).

3.2.2 Training and support materials

In order for participants to fully engage in the workshop and provide researchers with thoughtful, relevant feedback about using the tool, they needed to be able to

1. understand why MOEA-assisted optimization has been proposed as a useful tool for water planning;
2. understand the concept of performance tradeoff sets;
3. have sufficient understanding and acceptance of the hypothetical utility, its supply and demand context, and its policies to be able to focus on tradeoffs;
4. understand and relate to the problem formulation and planning scenarios; and
5. effectively operate the Tableau workbooks and interact with parallel plots.

We covered these topics in a 90-minute introductory presentation. After explaining and taking questions about MOEAs and the testbed (content similar to that found in the Background section of this article), we held an interactive parallel plot training session.

In order to introduce parallel plots and tradeoff analysis, we created a simple multiobjective grocery shopping problem. Each participant used a Tableau worksheet set up identically to those that they would see in later activities that showed plots of performance and decision levers. We defined three conflicting objectives – minimize cost, maximize nutrition, and maximize pleasure – through which to optimize a set of eleven potential shopping items such as apples, ice cream, eggs, etc. As a group, we went through incremental closed-form exercises finding the least expensive shopping list, the most nutritious list, etc. The exercises required participants to analyze both the decision and objective plots and learn their interactive functions. The total training time was approximately 10 minutes. Questions were encouraged throughout, and no participants expressed any prolonged difficulty in interpreting the worksheets.

To support the managers in the day's activities, we gave them printed packets that included a diagram of the Eldorado Utility Planning Model, current and future utility demands, utility policies, descriptions of the decision levers and objectives, and descriptions of the different hydrologic scenarios. The diagram, reproduced in Figure 2, conveys the spatial and temporal complexity of the system using icons, colors, dates, and arrows.

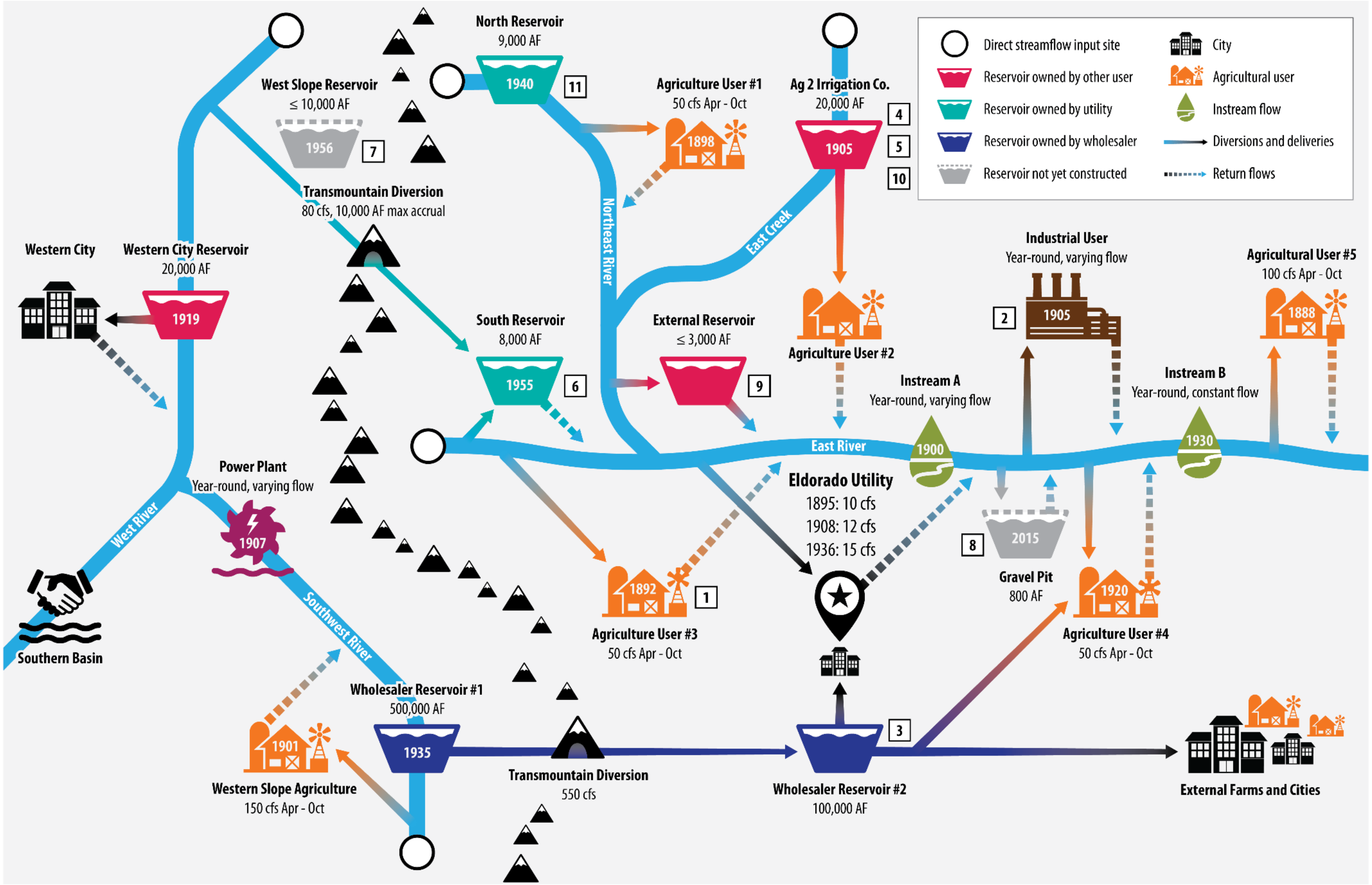

Direct streamflow input site
Reservoir owned by other user
Reservoir owned by utility
Reservoir owned by wholesaler
Reservoir not yet constructed
City
Agricultural user
Instream flow
Diversions and deliveries
Return flows
North Reservoir
9,000 AF
1940
11
West Slope Reservoir
≤ 10,000 AF
1956
7
Transmountain Diversion
80 cfs, 10,000 AF max accrual
Agriculture User #1
50 cfs Apr - Oct
1898
Ag 2 Irrigation Co.
20,000 AF
1905
4
5
10
Northeast River
East Creek
Western City
Western City Reservoir
20,000 AF
1919
South Reservoir
8,000 AF
1955
6
External Reservoir
≤ 3,000 AF
9
Agriculture User #2
Industrial User
Year-round, varying flow
1905
2
Agricultural User #5
100 cfs Apr - Oct
1888
Instream A
Year-round, varying flow
1900
Instream B
Year-round, constant flow
1930
East River
Eldorado Utility
1895: 10 cfs
1908: 12 cfs
1936: 15 cfs
Power Plant
Year-round, varying flow
1907
West River
Southwest River
Southern Basin
Gravel Pit
800 AF
2015
8
Agriculture User #3
50 cfs Apr - Oct
1892
1
Agriculture User #4
50 cfs Apr - Oct
1920
Wholesaler Reservoir #1
500,000 AF
1935
Western Slope Agriculture
150 cfs Apr - Oct
1901
Transmountain Diversion
550 cfs
Wholesaler Reservoir #2
100,000 AF
3
External Farms and Cities

Figure 2. Diagram of the Eldorado Utility Planning Model given to charrette participants in their supporting materials packets. Icons, colors, arrows, and dates all convey spatial and temporal relationships between water users.

3.2.3 Tradeoff activities

The core of the charrette was organized into four main activities to test behavior with the tool in four different situations of increasing complexity. During each activity managers were given 10-15 minutes to independently explore tradeoffs presented in Tableau workbooks and apply their own logic (or dominance structure) to choose two portfolios.

The purpose of Activity 1 was to establish initial preferences and create a basis for managers to compare decision making with and without tradeoff information. The participants chose one of three portfolios developed heuristically by an expert "consultant" (researcher familiar with the model and case study). Each portfolio was characterized by its constituent decisions and its firm yield in historical hydrology, but no performance tradeoff information was offered. The chosen portfolios from this activity were brought back in Activity 4.

The Activity 2 sequence was designed to ease the managers into evaluating tradeoffs in complex plots, to create space for analyzing tradeoffs without the dominant influence of reliability (Smith et al., 2017), to have managers be able to explicitly compare their use of different amounts of information, and to do all of this without considering the likelihood or implications of climate change on Front Range supplies. In Activity 2, Exercise 1, participants were shown performance of 20 algorithm-optimized portfolios in a two-objective tradeoff (along with a plot of all of the portfolios' decisions) and asked to select two "portfolios of interest." The portfolios resulted from optimizing for historical hydrology, and were constrained to meet Eldorado's restrictions-based reliability policy. This was made clear to managers so they knew they did not have to worry about reliability in this first activity. In Activity 2, Exercise 2, managers were shown the same set of 20 portfolios as in Exercise 1, but now were given performance information in a four-objective tradeoff plot (along with the decisions plot). In Activity 2, Exercise 3, participants were shown the choices they made from Exercises 1 and 2 in one plot to compare the preferences they expressed with different amounts of tradeoff information.

Activity 3 introduced the *frequency of Level 1 restrictions* objective and perturbed hydrology. The exercises allowed researchers to probe how the presence of the Level 1 restrictions objective influenced participants' perceptions of other tradeoffs and added hydrologic challenges to their decision calculations. In Exercise 1, participants were shown 20 algorithm-optimized portfolios that resulted from optimizing in a 1°C warmer (Very Warm) future. To understand the implications of the different hydrology, managers referred to the informational packets where plots showing a slightly lower magnitude of peak runoff, slightly earlier peak timing, and similar regional flow variability. They were again asked to choose two portfolios and had to directly trade off reliability policy performance with the other four objectives from Activity 2. Exercise 2 was identical to Exercise 1 except that the 20 portfolios were from a set produced by optimizing for a 4°C warmer (Very Hot) future. This scenario had a much lower peak runoff magnitude, much earlier peak timing, and lower variability due to lower magnitude high-flow years.

Activity 4 was designed to emphasize to participants that portfolios developed for or optimized under specific futures may not be acceptable if the future is different than they planned for. Managers saw the exact same set of portfolios from Activity 3, Exercise 2, but now their performance in a set of *varied* hydrologic traces was shown (i.e., in a supply scenario that they were not optimized for). The set of 10 traces were drawn from all other scenarios, so performance reflected the portfolios' average performances in a wide set of futures. They were again asked to make two choices from this set, and while making the choices they could see how each portfolio performed in varied as well as 4°C hydrology (so they had two parallel plots of objectives and one plot of decision levers). Managers were also shown how their hand-crafted solution from Activity 1 performed in both scenarios and asked to reflect on how they felt about those portfolios, which were developed using historical hydrology.

Table 2. Summary of charrette activities.

Exercise	# Objectives	Hydrology	Description
Activity 1	0	Historic	Choose 1 of 3 handmade portfolios
Activity 2, Exercise 1	2	Historic	Choose 2 portfolios based on 2 objectives
Activity 2, Exercise 2	4	Historic	Choose 2 portfolios based on 4 objectives
Activity 2, Exercise 3	4	Historic	Compare choices from 2- and 4-tradeoff exercises
Activity 3, Exercise 1	5	1°C	Choose 2 portfolios while evaluating explicit tradeoffs between reliability and other objectives
Activity 3, Exercise 2	5	4°C	Choose 2 portfolios while evaluating explicit tradeoffs between reliability and other objectives
Activity 4	5	Varied, 4°C	Choose 2 portfolios with knowledge of how they perform in both varied and extreme (4°C) hydrology; reflect on choices from Activity 1.

At the workshop, the managers played the roles of engineers at the hypothetical Eldorado Utility who were evaluating a new tool for its potential to enhance their upcoming long term planning process. Asking them to play a fictional role and use hypothetical (but realistic) tradeoff results helped participants to engage more candidly by distancing them from physical, social, and political pressures of their own systems. Similarly, for each activity, we asked the managers to choose two portfolios "to subject to further analysis" to avoid comparisons with the real-world, complex process that a utility undertakes to actually decide on one plan. It was important, however, to ask them to make individual choices; this forced them to really grapple with tradeoffs and to use some logical process, and thus created a more defined experience for them to discuss with researchers and each other.

For each exercise (except for Activity 2, Exercise 3 during which participants just compared two sets of portfolio choices), the group facilitators asked three main questions to prompt discussion:

A. What objective performances or tradeoffs made the two portfolios you chose interesting to you?

B. What decision lever attributes made the solutions interesting to you?
C. Based on the objectives' performance, as a manager at your utility, do you think you would have chosen the same solutions to investigate further? Why or why not?

Questions A and B were designed to separate the ways that performance and decision levers impacted choices, and question C was designed to emphasize that we wanted the managers to choose freely but also provide as much real-world decision making context as they could.

4 Results

Throughout the day managers engaged with tradeoffs, facilitators, and each other. They took the purposes of the workshop seriously and combined openness to the activities with reflections about their own agencies' planning contexts. As we prompted them with specific concepts, they each interpreted and applied them differently. A result of this was that, across nine managers, the portfolio selections often varied widely and sometimes the processes they used to make them also varied significantly. Rather than report each individual's choices and processes, below is a description of common themes and examples of how logic changed over the course of the day.

4.1 Managers' use of tradeoffs

Within this section about how managers used tradeoff information, there are four subsections. The first discusses findings from Activity 2, which presented managers with first two, then four objectives to analyze. Brief synopses of two managers' decision processes and how they relate to dominance structuring are included. The second subsection of results is based on Activity 3, which introduced a fifth objective (Level 1 restrictions) and two new, more hydrologically challenging scenarios. Subsections three and four present findings that emerged throughout all four activities.

4.1.1 Tradeoffs in two objectives vs. in four objectives

In Activity 2, Exercise 1, where participants saw tradeoffs in two objectives, three general strategies emerged for choosing portfolios of interest. Five managers weighted performance in the objectives equally, two performed cost-benefit analyses between the two objectives, and two managers prioritized performance in one objective over the other. Figure 3 shows the results of Manager B4's cost-benefit analysis. The manager started by picking the portfolio with the least storage, then worked incrementally up the New Storage axis to find out how much better the performance in Missed Opportunity could get. The manager ultimately tried to find the portfolios where the tradeoff was "reasonable"- where the

Fig. 1

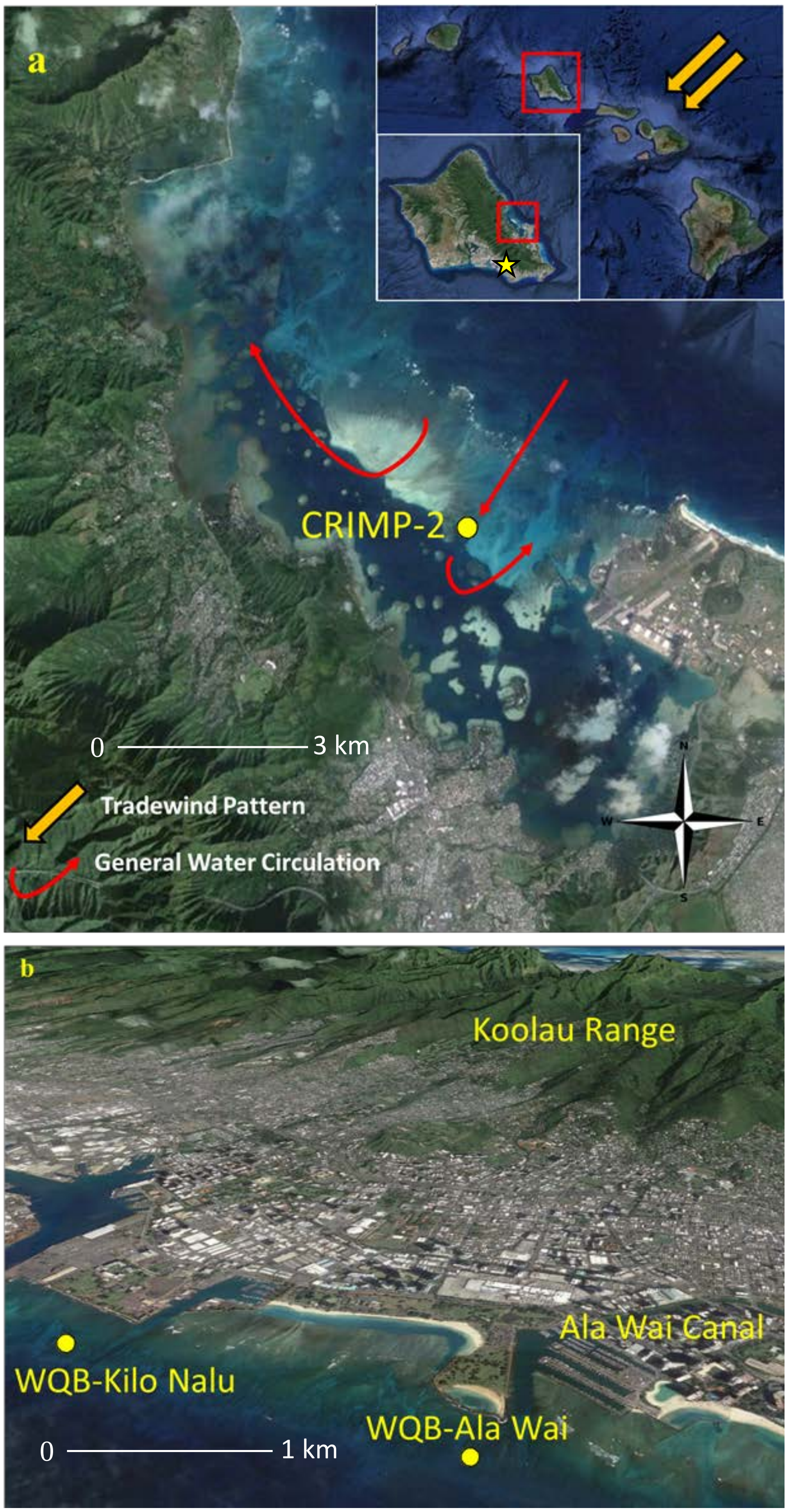

a
CRIMP-2
0
3 km
Tradewind Pattern
General Water Circulation
N
W
E
S
b
Koolau Range
Ala Wai Canal
WQB-Kilo Nalu
WQB-Ala Wai
0
1 km

Fig. 2

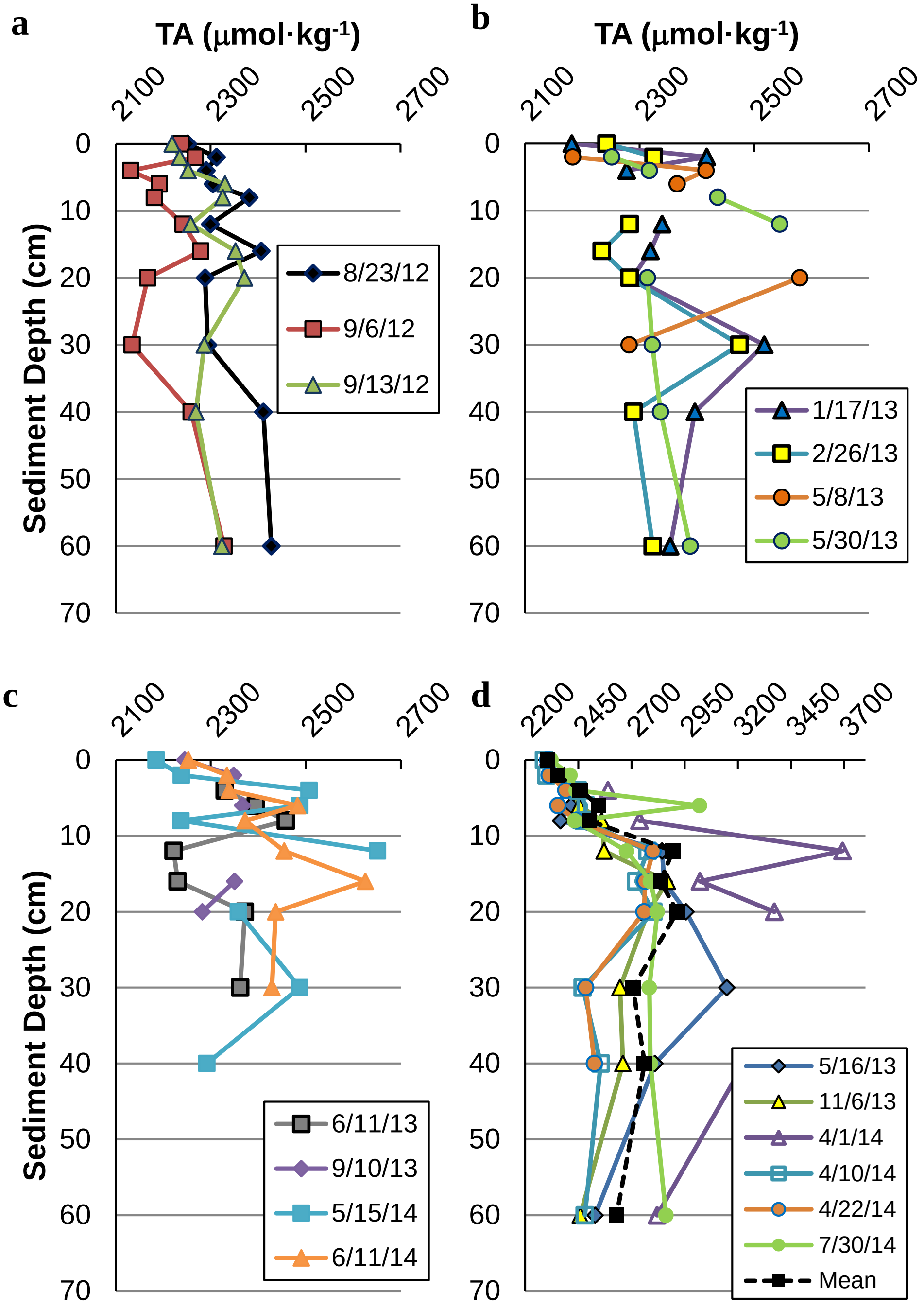

a
TA (µmol·kg-1)
2100
2300
2500
2700
Sediment Depth (cm)
0
10
20
30
40
50
60
70
8/23/12
9/6/12
9/13/12
b
TA (µmol·kg-1)
2100
2300
2500
2700
1/17/13
2/26/13
5/8/13
5/30/13
c
2100
2300
2500
2700
Sediment Depth (cm)
6/11/13
9/10/13
5/15/14
6/11/14
d
2200
2450
2700
2950
3200
3450
3700
5/16/13
11/6/13
4/1/14
4/10/14
4/22/14
7/30/14
Mean

Fig. 3

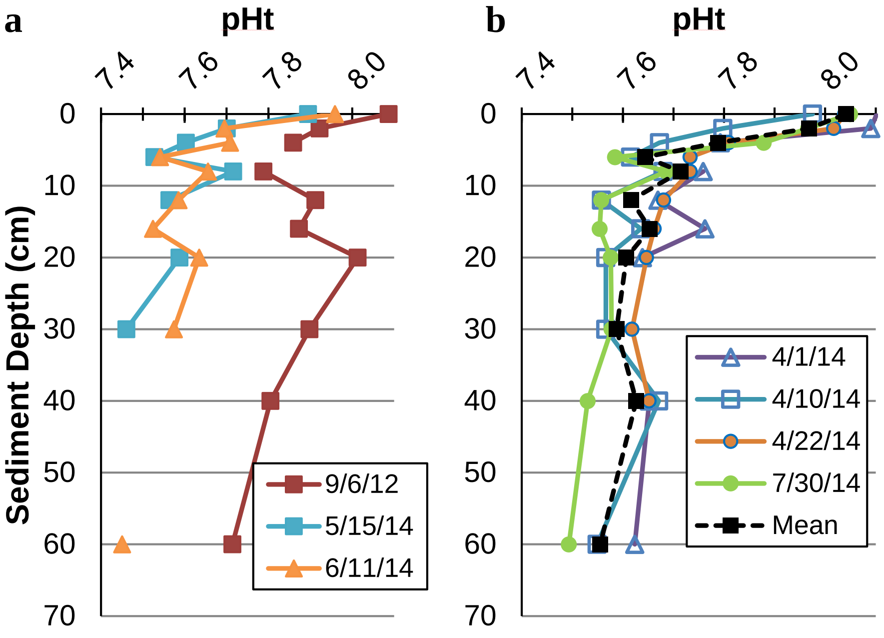

a
pHt
7.4
7.6
7.8
8.0
Sediment Depth (cm)
0
10
20
30
40
50
60
70
9/6/12
5/15/14
6/11/14
b
pHt
7.4
7.6
7.8
8.0
0
10
20
30
40
50
60
70
4/1/14
4/10/14
4/22/14
7/30/14
Mean

Fig. 4

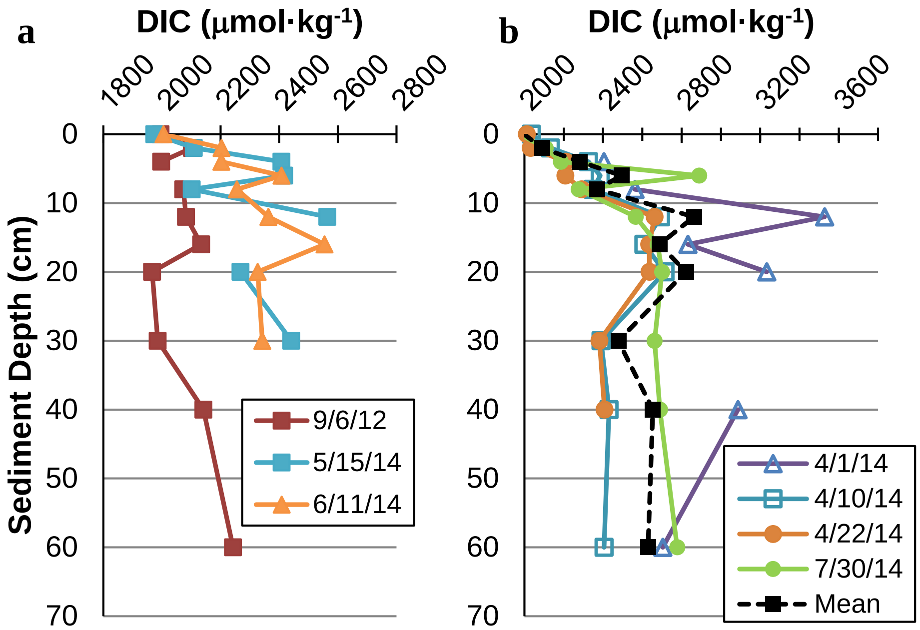

a
DIC (µmol·kg-1)
1800
2000
2200
2400
2600
2800
Sediment Depth (cm)
0
10
20
30
40
50
60
70
9/6/12
5/15/14
6/11/14
b
DIC (µmol·kg-1)
2000
2400
2800
3200
3600
0
10
20
30
40
50
60
70
4/1/14
4/10/14
4/22/14
7/30/14
Mean

Fig. 5

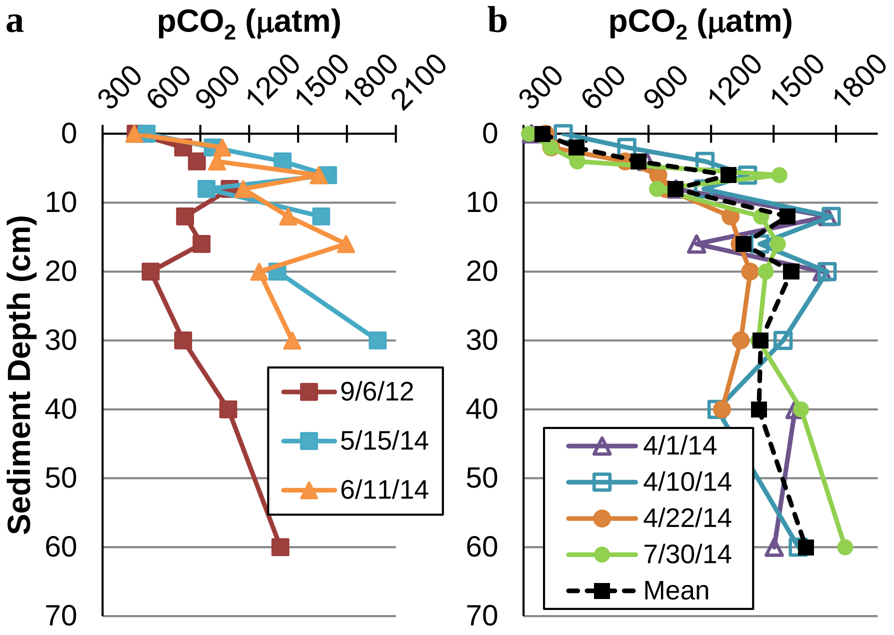

a
pCO$_2$ (μatm)
300
600
900
1200
1500
1800
2100
Sediment Depth (cm)
0
10
20
30
40
50
60
70
9/6/12
5/15/14
6/11/14
b
pCO$_2$ (μatm)
300
600
900
1200
1500
1800
0
10
20
30
40
50
60
70
4/1/14
4/10/14
4/22/14
7/30/14
Mean

Fig. 6

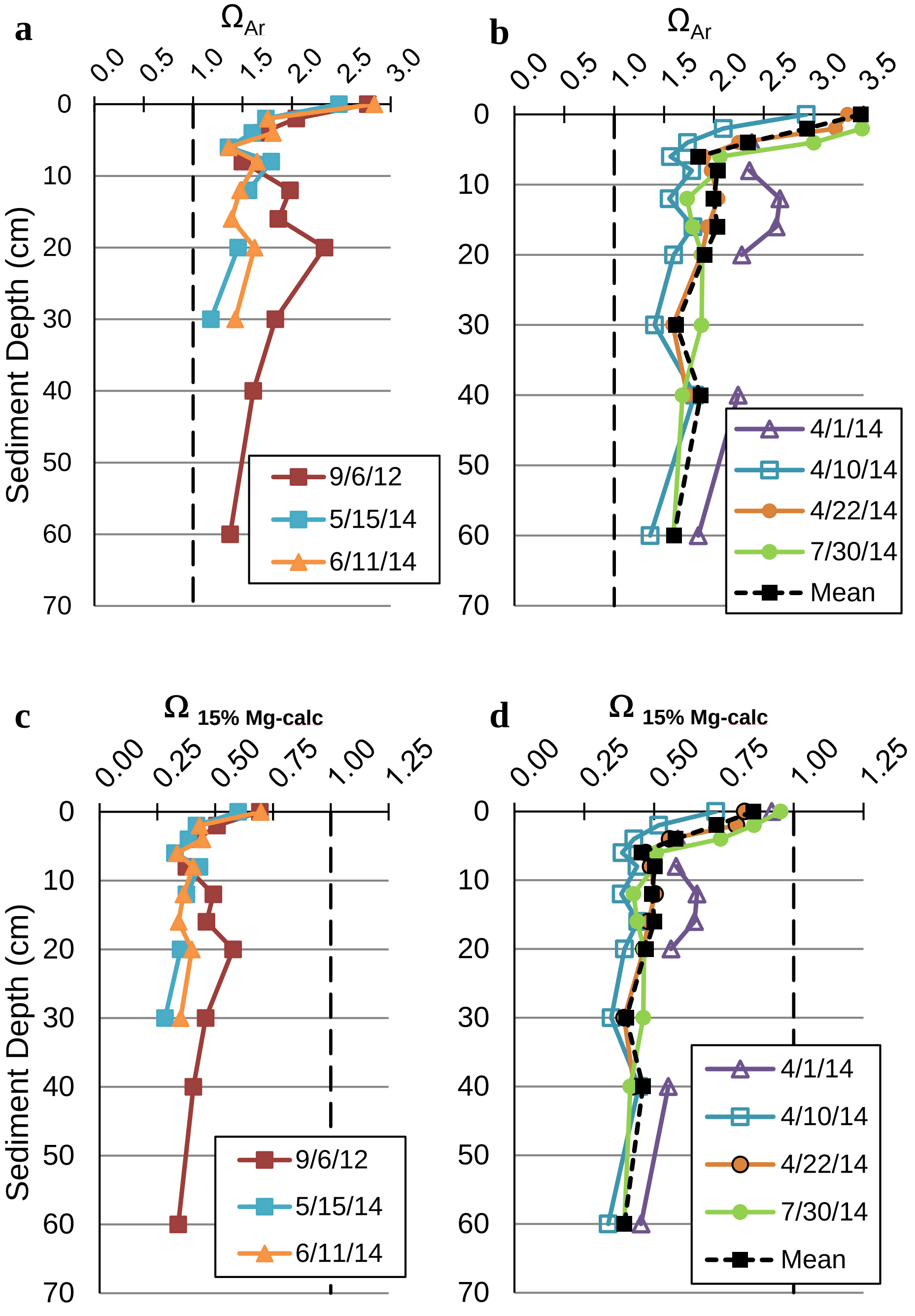

a
Ω_{Ar}
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Sediment Depth (cm)
0
10
20
30
40
50
60
70
9/6/12
5/15/14
6/11/14
b
Ω_{Ar}
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4/1/14
4/10/14
4/22/14
7/30/14
Mean
c
Ω 15% Mg-calc
0.00
0.25
0.50
0.75
1.00
1.25
Sediment Depth (cm)
9/6/12
5/15/14
6/11/14
d
Ω 15% Mg-calc
0.00
0.25
0.50
0.75
1.00
1.25
4/1/14
4/10/14
4/22/14
7/30/14
Mean

Fig. 7

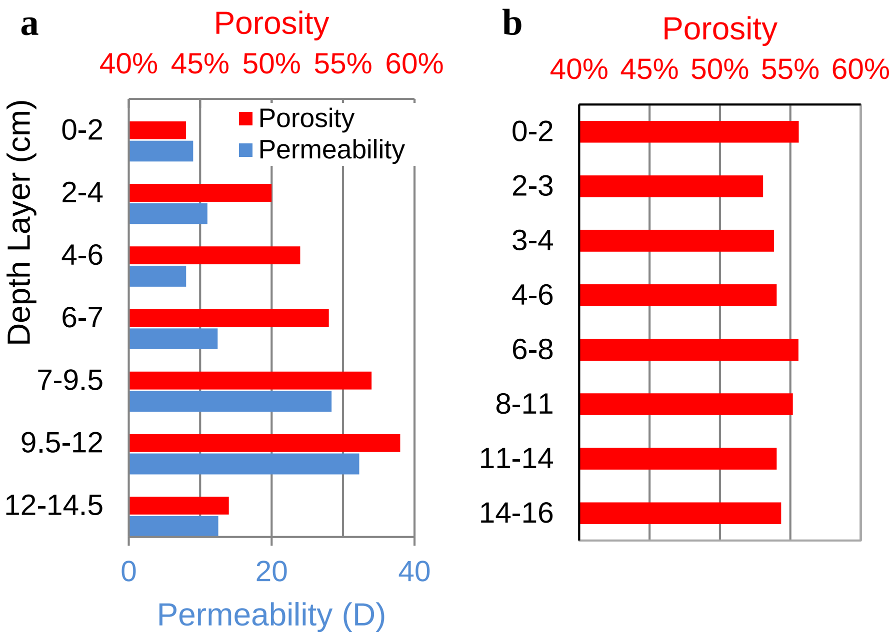
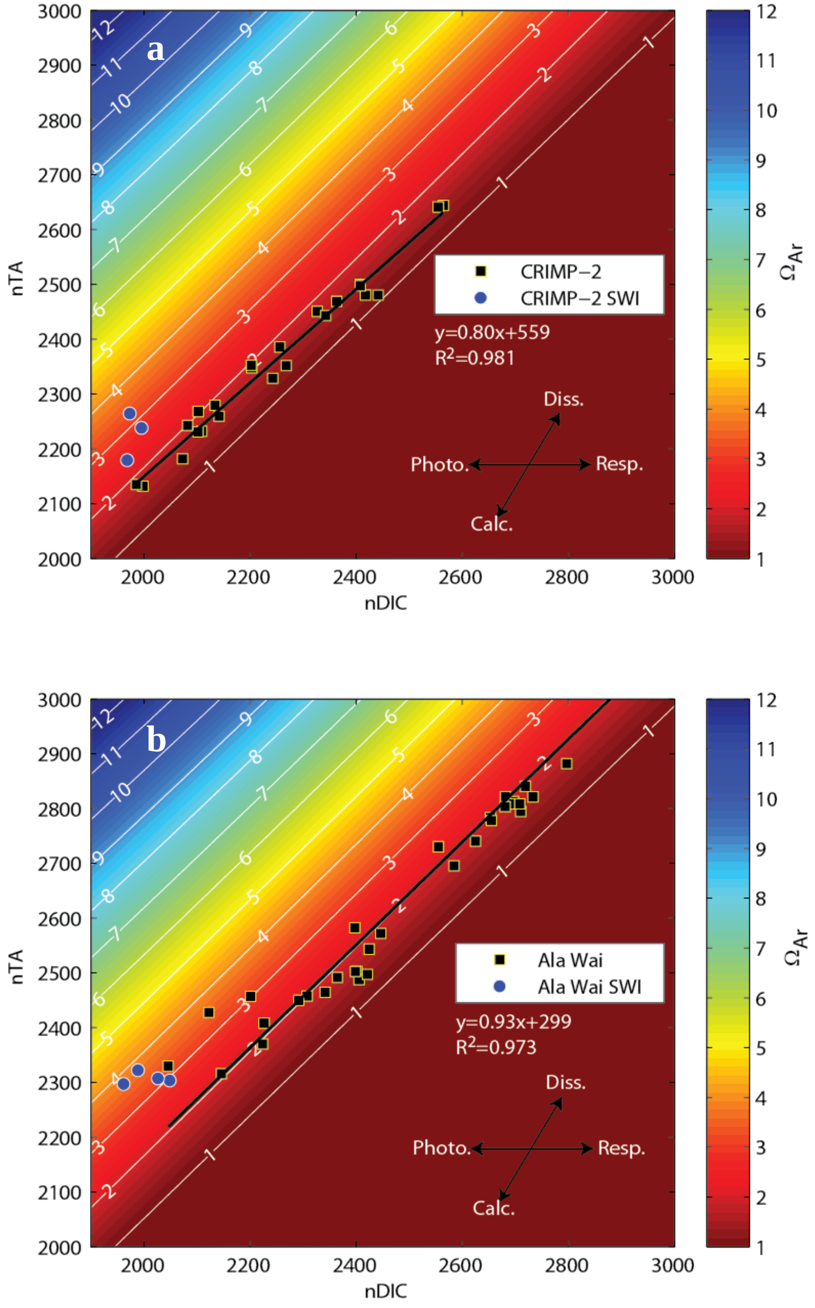
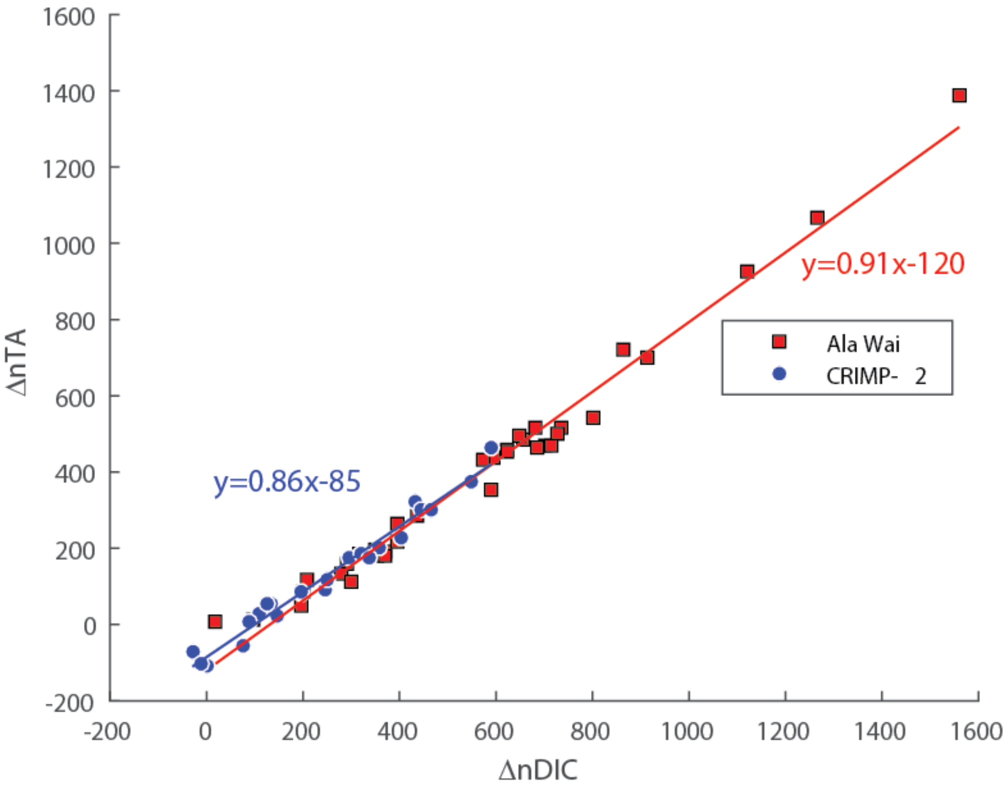

a
Porosity
40%
45%
50%
55%
60%
Depth Layer (cm)
0-2
2-4
4-6
6-7
7-9.5
9.5-12
12-14.5
🟥 Porosity
🟦 Permeability
0
20
40
Permeability (D)
b
Porosity
40%
45%
50%
55%
60%
0-2
2-3
3-4
4-6
6-8
8-11
11-14
14-16

Fig. 8



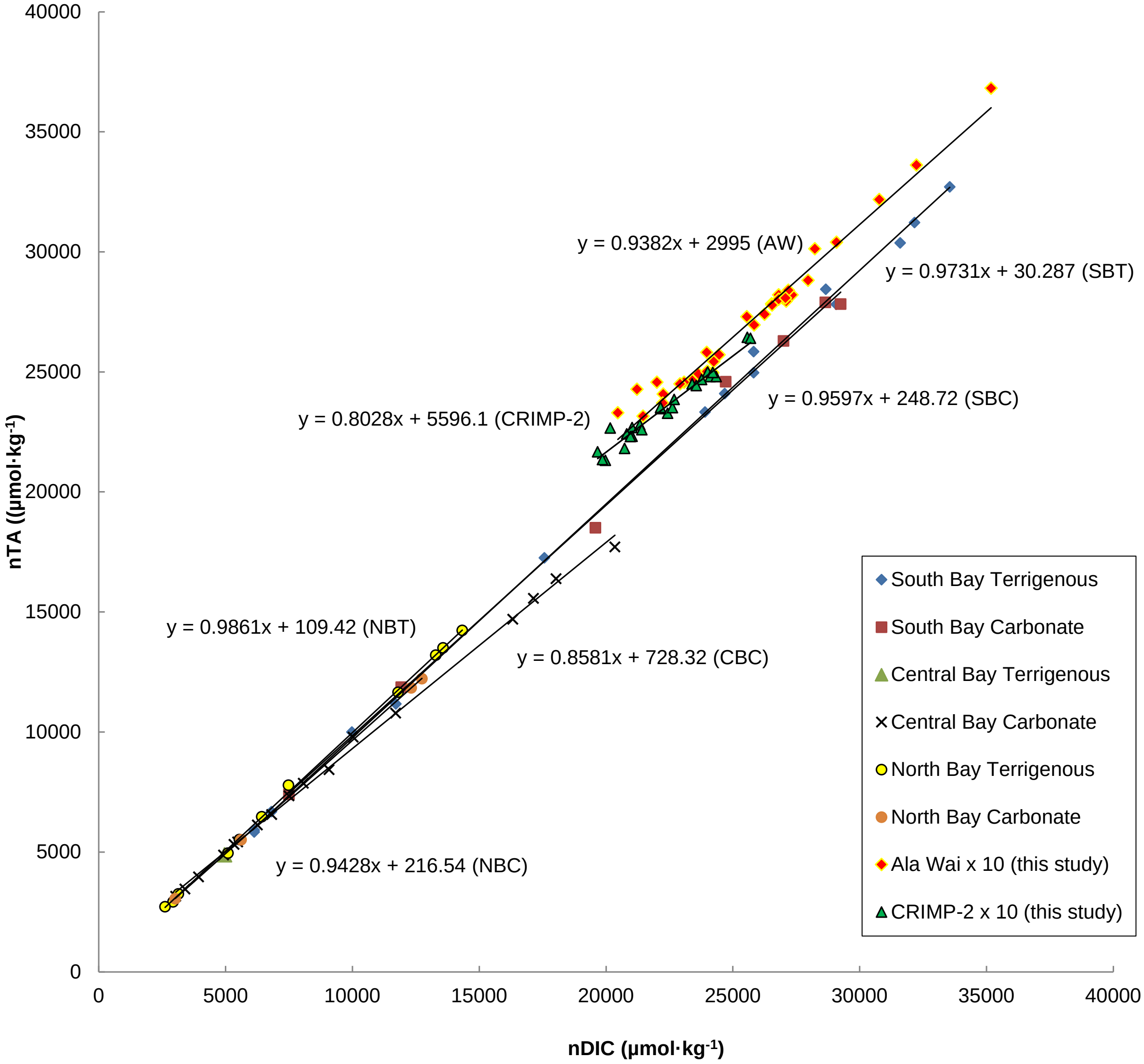
a
nTA
nDIC
CRIMP−2
CRIMP−2 SWI
y=0.80x+559
R^2=0.981
Diss.
Photo.
Resp.
Calc.
Ω_{Ar}
2000
2100
2200
2300
2400
2500
2600
2700
2800
2900
3000
1
2
3
4
5
6
7
8
9
10
11
12
b
Ala Wai
Ala Wai SWI
y=0.93x+299
R^2=0.973

Fig. 9



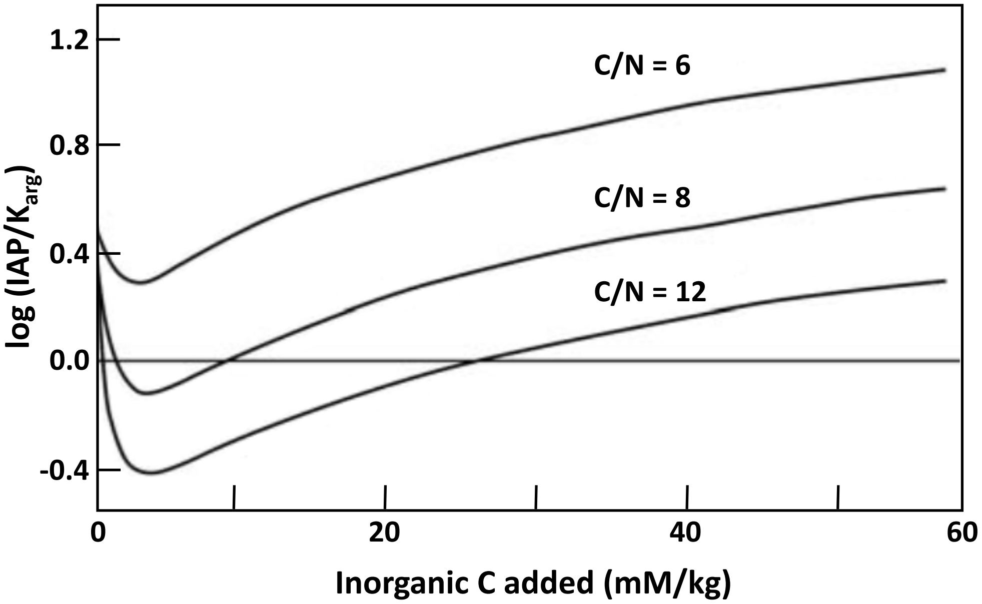
1600
1400
1200
1000
800
600
400
200
0
-200
ΔnTA
-200
0
200
400
600
800
1000
1200
1400
1600
ΔnDIC
y=0.91x-120
y=0.86x-85
🟥 Ala Wai
● CRIMP- 2

Fig. 10



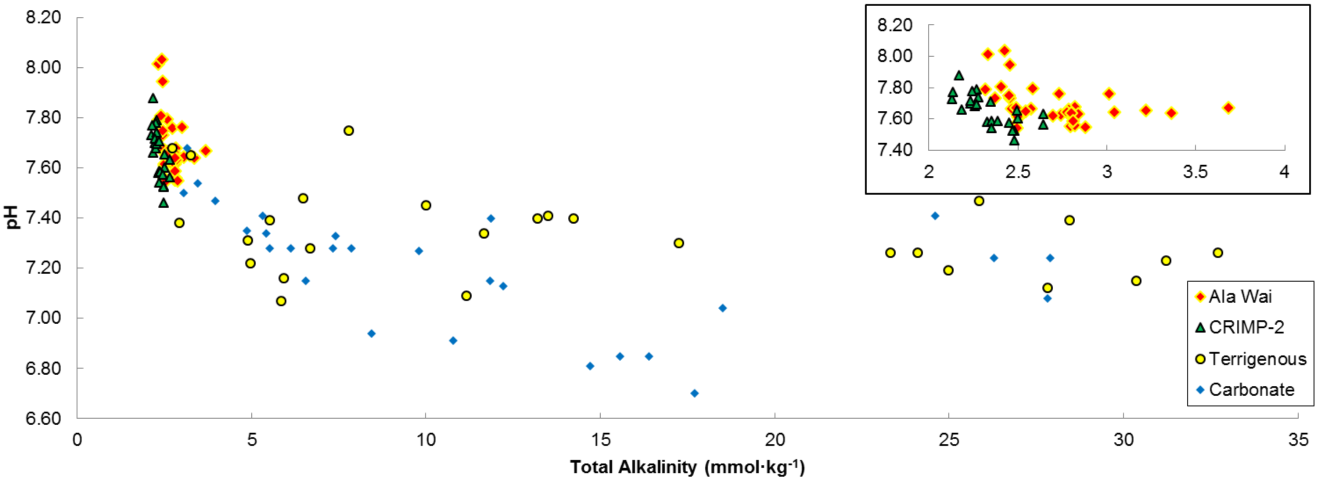
40000
35000
30000
25000
20000
15000
10000
5000
0
nTA ((µmol·kg-1)
0
5000
10000
15000
20000
25000
30000
35000
40000
nDIC (µmol·kg-1)
y = 0.9382x + 2995 (AW)
y = 0.9731x + 30.287 (SBT)
y = 0.9597x + 248.72 (SBC)
y = 0.8028x + 5596.1 (CRIMP-2)
y = 0.9861x + 109.42 (NBT)
y = 0.8581x + 728.32 (CBC)
y = 0.9428x + 216.54 (NBC)
◆ South Bay Terrigenous
■ South Bay Carbonate
▲ Central Bay Terrigenous
× Central Bay Carbonate
○ North Bay Terrigenous
● North Bay Carbonate
◆ Ala Wai x 10 (this study)
▲ CRIMP-2 x 10 (this study)

Fig. 11



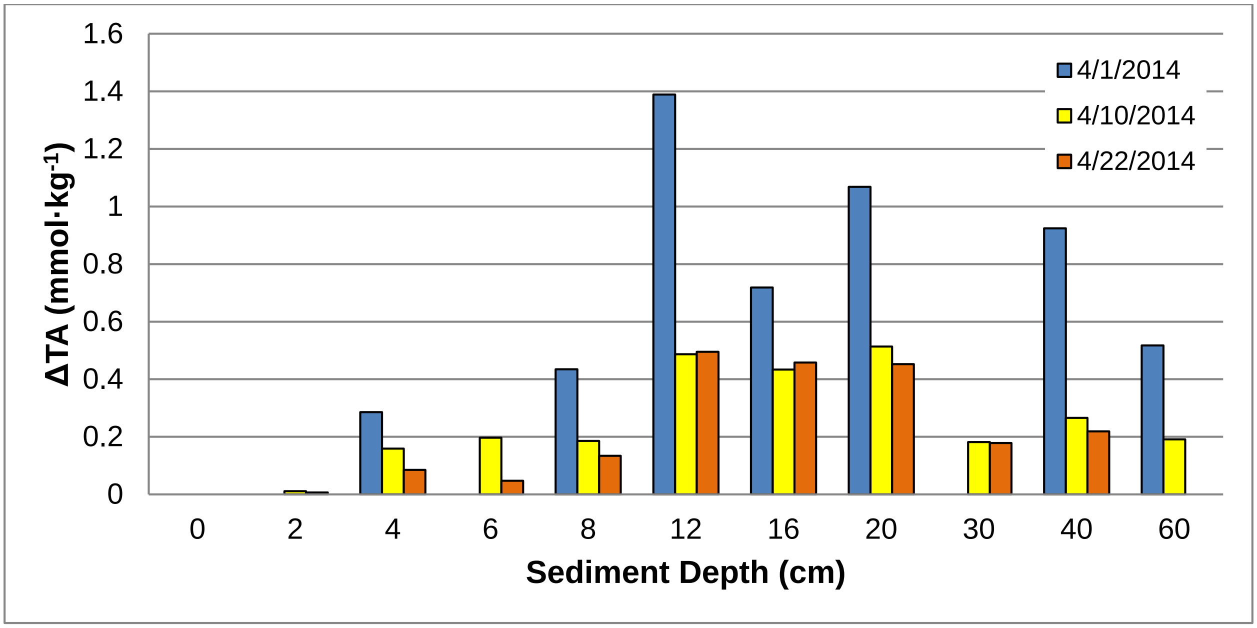
log (IAP/K$_{arg}$)
1.2
0.8
0.4
0.0
-0.4
C/N = 6
C/N = 8
C/N = 12
0
20
40
60
Inorganic C added (mM/kg)

Fig. 12



8.20
8.00
7.80
7.60
pH 7.40
7.20
7.00
6.80
6.60
0
5
10
15
20
25
30
35
Total Alkalinity (mmol·kg⁻¹)
8.20
8.00
7.80
7.60
7.40
2
2.5
3
3.5
4
Ala Wai
CRIMP-2
Terrigenous
Carbonate

Fig. 13


1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
ΔTA (mmol·kg-1)
4/1/2014
4/10/2014
4/22/2014
0
2
4
6
8
12
16
20
30
40
60
Sediment Depth (cm)