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Research article

Developing reliable and valid measures for evaluating collaborative governance and adaptability: An example from the Collaborative Forest Landscape Restoration Program

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ABSTRACT

In recent decades, there has been an increased emphasis on, and application of, collaborative and adaptive forms of environmental governance as a means to address complex social-ecological problems that cannot be achieved alone and support sustainable resource management. However, the majority of research in the collaborative governance and adaptability arena has relied on individual or small-n case studies. This has led to a multitude of definitions, indicators, and indices, which limits our ability to make inferences across cases and contexts. Relatedly, most research lacks formal tests of assumptions related to the dimensional structure and validity of constructs thought to represent collaborative dynamics and adaptability. There is a need for systematic and cross-case assessments situated within robust statistical frameworks to further our understanding of the forces and factors that cultivate collaborative governance and adaptability. We developed and administered a standardized survey assessment, grounded in the theory and practice of collaborative governance and adaptability, to fifteen collaborative projects funded under the Collaborative Forest Landscape Restoration Program (CFLRP) in the United States. We then used confirmatory factor analysis to test the dimensional structure, reliability, and validity of our theoretically and empirically grounded measures. Results indicate the components of collaborative governance and adaptability comprise six dimensions – principled engagement, shared motivation, leadership, resources, knowledge and learning, and institutional arrangements. As expected, several dimensions were significantly related, and the pattern of inter-factor relationships aligned with theoretical and empirical assumptions. We also found that the six dimensions represent statistically reliable, valid, and distinct measures that may be used to evaluate collaborative governance and adaptability. While our focus was on the CFLRP, the assessment can be adapted in other collaborative environmental governance contexts and used as a foundation for addressing key research gaps, including relating collaborative environmental governance processes to social-ecological outcomes and collaborative adaptation and resilience through time. This is a critical line of work given the increased emphasis and reliance on long-term collaborative arrangements to achieve sustainability goals.

1. Introduction

In recent decades, there has been an increased emphasis on, and application of, collaborative and adaptive forms of environmental governance as a means to manage conflict, reduce uncertainty, address complex social-ecological problems that cannot be achieved alone, and increase sustainable resource management (Emerson et al., 2012; Emerson and Gerlak, 2014; Folke et al., 2005; Gupta et al., 2010; Ulibarri, 2019; Wondolleck and Yaffee, 2000). Here, we refer to collaborative governance as "the processes and structures of public policy decision making and management that engage people across the boundaries of public agencies, levels of government, and/or the public,

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private for-profit, and civic spheres to carry out a public purpose that could not otherwise be accomplished" (Emerson et al., 2012, p. 2). We refer to adaptability, or adaptive capacity, as "the ability of the CGR [collaborative governance regime] to alter its internal processes or convert structural elements as a response to experienced or expected changes in the societal or natural environments" (Emerson and Gerlak, 2014, p. 770).

There are a number of claimed benefits of collaboration, including enhanced efficiency and effectiveness when compared to top-down or centralized governance approaches, increased trust and legitimacy, shared understanding and support for locally relevant decisions, and enhanced social learning, all of which have the potential for spillover effects to other venues (Agranoff, 2006; Emerson et al., 2012; Koontz and Thomas, 2006; Pahl-Wostl, 2009; Struthers et al., 2023; Wondolleck and Yaffee, 2000). As a result, federal land management agencies in the United States, like the U.S. Department of Agriculture Forest Service (Forest Service hereafter), have increasingly invested in collaboration to accomplish wildfire and forest management goals (Butler and Schultz, 2019; Cheng and Sturtevant, 2012). Notable examples include the Healthy Forests Restoration Act of 2003, the Forest Landscape Restoration Act of 2009 that authorized the Collaborative Forest Landscape Restoration Program (CFLRP), the Joint Chiefs' Landscape Restoration Partnership, and the Shared Stewardship Strategy (Aldworth and Schultz, 2023; Butler and Schultz, 2019; Kee et al., 2023; Kooistra et al., 2021; Schultz et al., 2012, 2018).

These programs have attracted the attention of social and ecological science, and increasing evidence suggests that these programs have promoted positive social, economic, and ecological outcomes (e.g., Barrett et al., 2021; Butler and Schultz, 2019; McIver and Becker, 2021). Still, a number of research gaps remain, which, if addressed, could support the above-mentioned programs and other collaborative initiatives in evaluating progress and performance towards desired goals. The majority of research in the collaborative governance and adaptability arena has relied on individual or small-n case studies (Ansell and Gash, 2007; Siders, 2019; Ulibarri et al., 2020). Individual case studies are necessary as they provide local, nuanced information, which cannot be garnered by larger-n comparative assessments, and they are useful for theory-building (Conley and Moote, 2003; Douglas et al., 2020a; Emerson et al., 2012). Several case studies have developed measures of collaborative governance and adaptability for internal assessment purposes. While important for evaluating local efforts, this has led to a multitude of definitions, indicators, and proposed factors (i.e., latent, unobserved variables or constructs), which limits our ability to make inferences across cases and contexts (Conley and Moote, 2003; Emerson et al., 2012; Koontz et al., 2015; Siders, 2019). There is no consensus on the number and configuration of, and relationship between, factors that comprise collaborative governance and adaptability. Studies often employ these factors assuming they represent reliable, valid, and discrete constructs, but most research to date lacks formal tests of assumptions related to the dimensional structure and validity of factors thought to represent collaborative governance dynamics and adaptability (c.f., Lockwood et al., 2015). Therefore, there is a need for systematic and cross-case assessments situated within robust statistical frameworks to further our understanding of the components and elements that cultivate collaborative governance and adaptability (Douglas et al., 2020a; Emerson et al., 2012; Koontz et al., 2020).

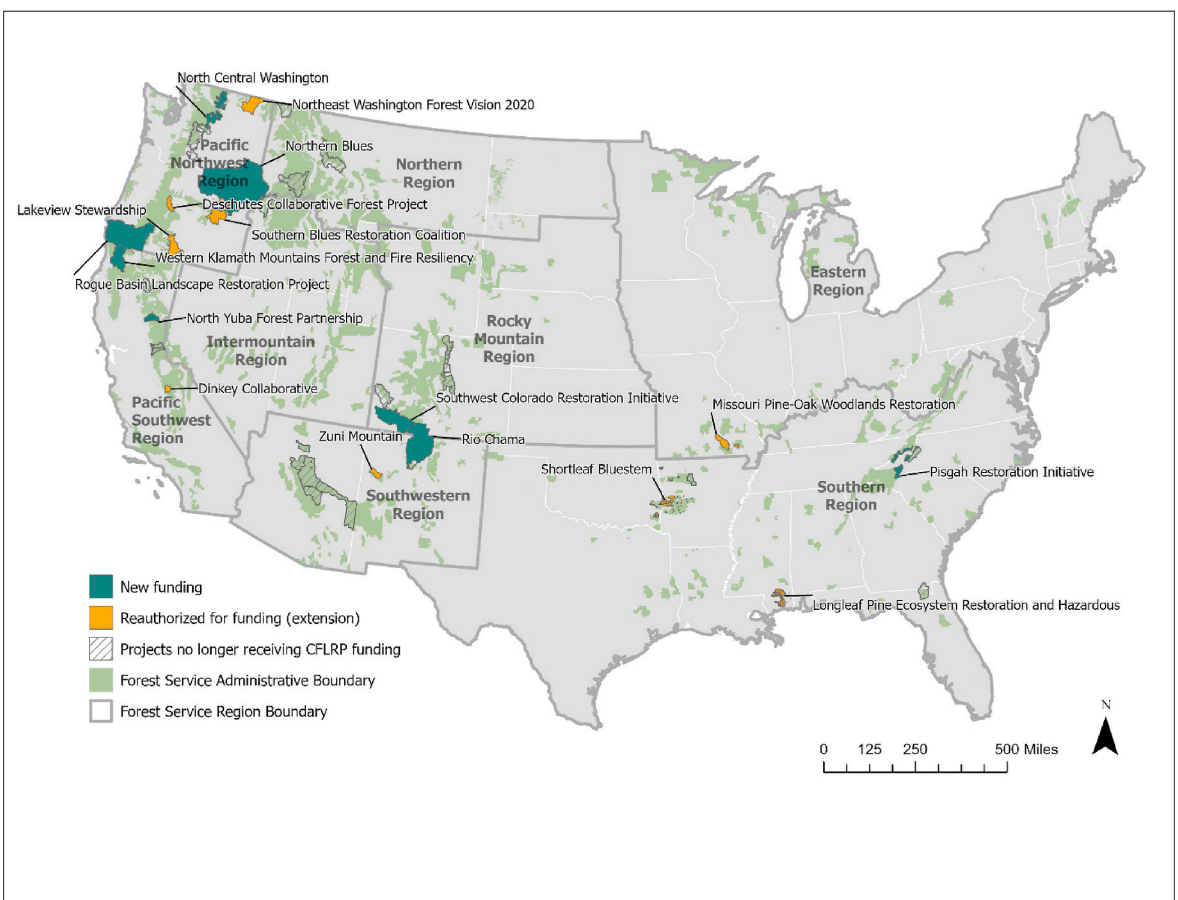

Fig. 1. Map of CFLRP projects. Newly authorized and extension projects are depicted in green and orange, respectively. These projects are the focus on this study. Projects no longer receiving funding (hatched) first received funding in 2010–2013 for 10 years. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

We developed and administered a standardized survey assessment, grounded in the theory and practice of collaborative governance and adaptability (Cinner and Barnes, 2019; Emerson et al., 2012; Emerson and Gerlak, 2014; Folke et al., 2005; Gupta et al., 2010), to the flagship CFLRP and its 15 authorized projects across the United States (Fig. 1). We used confirmatory factor analysis (CFA) to test the structure set forth by Emerson et al. (2012) and expounded on by Emerson and Gerlak (2014). Our two objectives were to:

1. confirm the number and configuration of factors that comprise collaborative governance and adaptability; and
2. evaluate the reliability and validity of our collaborative governance and adaptability measures.

Our study offers a starting point to address key research gaps in the understanding of collaborative governance and adaptability, which ultimately could support collaborative initiatives in evaluating collaborative progress and performance relative to project and program goals.

1.1. A brief history of collaboration in the Forest Service

Beginning in the 1960s, national-level legislation emerged to protect natural resources and allow for more public engagement and transparency around public forest planning and actions, including the Wilderness Act of 1964, the National Environmental Policy Act of 1969, the Endangered Species Act of 1973, and the National Forest Management Act of 1976. By the 1980s, some actors used this legislation as a mechanism to challenge forest management actions in courts, and by doing so, prompted a significant reduction in timber harvests on federally-managed lands and fundamental changes in land use in these systems (Beier et al., 2009; Sousa and Klyza, 2007; Trosper, 2003).

By the 1990s, a shift to collaborative governance approaches in public land management agencies, like the Forest Service, emerged in direct response to this litigation and other legal, regulatory, and bureaucratic challenges (Cheng and Sturtevant, 2012; Koontz et al., 2020; Schultz et al., 2021; Wondolleck and Yaffee, 2000). Abrams (2019) traced this transition towards collaborative governance and related it to three key factors: 1) the decline in the Forest Service's organizational legitimacy, autonomy, and discretion; 2) the decline in agency capacity as a function of lost political support among powerful timber interests, ballooning fire suppression budgets without concomitant increases for other activities, and loss of timber revenue due to the restructuring and downsizing of the timber industry; and 3) the need for innovation. This period of time was characterized by the ecosystem-based management revolution, where there was increasing emphasis on management for linked ecological, economic, and social sustainability goals (Abrams, 2019; Abrams et al., 2017; Cheng and Sturtevant, 2012; Wondolleck and Yaffee, 2000).

The emergence of collaborative governance regimes in U.S. federal forest management was the result of both ground-up, grassroots movements and top-down policy direction. Grassroots, community-led collaboration occurred as a last result to address social, economic, and ecological issues that were important to communities but could not be addressed by the Forest Service. Local communities recognized they needed to work together to achieve shared goals or minimize common risks, such as wildfire (Cheng and Sturtevant, 2012; Nie and Metcalf, 2016; Wondolleck and Yaffee, 2000). Top-down processes spurred collaboration during this time as well. In 1998, Congress required service contracts administered by the Forest Service use a multi-party monitoring and evaluation process (Nie and Metcalf, 2016). Further, following the disastrous 2000 wildfire season, the National Fire Plan reshaped fire policy in the U.S., with the recognition that government agencies, non-government organizations, and local communities needed to work together to address the wildfire problem and mitigate social and ecological risks to wildfire (Fleeger, 2008).

1.2. The emergence and status of the CFLRP and multi-party monitoring

The Omnibus Public Land Management Act of 2009 included the Forest Landscape Restoration Act (FLRA), which authorized the CFLRP, the purpose of which was to "encourage the collaborative, science-based ecosystem restoration of priority landscapes" (PL111-11, Section 4001). The FLRA authorized the CFLRP until 2019, and between 2010 and 2019 23 projects were funded under the CFLRP (Fig. 1). Congress reauthorized the CFLRP under the Agricultural Improvement Act of 2018. Funding for the CFLRP was also authorized in the 2021 Infrastructure Investment and Jobs Act (IIJA). In 2020, the Forest Service issued a request for proposals for funding new and existing projects for up to 10 years. Seventeen CFLRP projects currently receive funding, including eight new and nine extension (projects previously authorized for funding) projects (Fig. 1, Table 1). The focus of this paper is on 15 newly funded and extension projects that were authorized since 2020 (Table 1;

Table 1
Project characteristics and response rate.

Project Name	New or reauthorized	State(s)	Forest Service Region (s)	N	Response Rate
Deschutes Collaborative Forest Project	Reauthorized	Oregon	6	34	40%
Dinkey Collaborative	Reauthorized	California	5	22	14%
Lakeview Stewardship	Reauthorized	Oregon	6	15	25%
Longleaf Pine Ecosystem Restoration and Hazardous Fuels Reduction	Reauthorized	Mississippi	8	–	–
Missouri Pine Oak Woodlands Restoration	Reauthorized	Missouri	9	15	41%
North Central Washington	New	Washington	6	20	38%
North Yuba Forest Partnership	New	California	5	23	40%
Northeast Washington Forest Vision 2020	Reauthorized	Washington	6	9	15%
Northern Blues	New	Oregon; Washington	6	33	32%
Pisgah Restoration Initiative	New	Tennessee	8	–	–
Rio Chama	New	Colorado; New Mexico	2, 3	38	19%
Rogue Basin Landscape Restoration Project	New	Oregon; California	6	18	32%
Shortleaf Bluestem	Reauthorized	Arkansas; Oklahoma	8	25	26%
Southern Blues Restoration Coalition	Reauthorized	Oregon	6	21	13%
Southwest Colorado Restoration Initiative	New	Colorado	2	28	26%
Western Klamath Mountains Forest and Fire Resiliency	New	California	5	25	24%
Zuni Mountains	Reauthorized	New Mexico	3	15	17%

the Longleaf Pine and Pisgah CFLRP projects were awarded funding after we had completed survey recruitment and administration).

The CFLRP was a unique policy instrument within the United States for several reasons. It established a competitive selection process, provided a flexible 10-year funding commitment, focused investments in priority landscapes on Forest Service-managed lands, and required projects to develop a multi-party monitoring plan and establish funding for monitoring for 15 years (Schultz et al., 2018). The FLRA also required collaboration during planning, implementation, and monitoring phases. However, collaboration was not defined, and the FLRA or CFLRP did not provide prescriptive guidelines for collaborative engagement and participation. This ambiguity provided flexibility for projects to establish collaborative structures and processes that fit local social, historical, and political contexts (Schultz et al., 2019).

Research suggests that the CFLRP has led to positive social and ecological outcomes, including restoration outcomes that align with desired conditions and objectives; increased landscape-scale and cross-jurisdictional planning; more efficient planning and diverse accomplishments; increased trust, relationships, and legitimacy; and minimized conflict and litigation (Barrett et al., 2021; Butler and Schultz, 2019; Cannon et al., 2018; McIntyre and Schultz, 2020; McIver and Becker, 2021; Schultz et al., 2018). However, the CFLRP was not without challenges. Frequent turnover, varied commitment and capacity to engage in ways that met collaborative members' expectations, resource constraints, and a lack of clarity with regards to the allowable decision space and accountability in some cases led to diminished trust and challenges in getting work done on the ground (Beeton et al., 2022; Butler, 2013; Butler and Schultz, 2019; Christenson and Butler, 2019; Coleman et al., 2020).

In the first round of authorization (2010–2019), projects were required to develop and implement multi-party monitoring plans, which must involve multiple partners in the monitoring process. Multi-party monitoring was, and continues to be, critical for supporting social learning and trust-building (Schultz et al., 2014). Yet, there were also challenges, including varied capacity and expertise to develop and implement monitoring, limited landscape-scale monitoring, and a lack of common monitoring protocols and metrics deployed across projects, all of which led to difficulty assessing restoration outcomes across the CFLRP (Esch and Waltz, 2019; Forest Service, 2022; Schultz et al., 2014). To address these challenges, the Forest Service Forest, Range Management, and Vegetation Ecology staff partnered with Forest Service regions, CFLRP projects, and subject-matter experts to co-produce a common monitoring strategy (Forest Service, 2022). The strategy includes a core set of thirteen social, economic, and ecological monitoring questions that largely mirror the desired outcomes set forth in the FLRA. All newly authorized or reauthorized projects are required to address these questions. The intention is to institutionalize a rigorous, standardized monitoring program to monitor outcomes at the landscape scale and program-wide.

The common monitoring strategy includes evaluation of collaborative governance, in recognition that the collaborative health and resilience of projects can affect the pace and scale of implementing restoration actions on the ground and desired social and ecological outcomes. Tied to this component, the Forest Service asked the authors to develop a CFLRP-wide longitudinal assessment of collaborative governance and adaptability. Specifically, partners identified the need to monitor collaborative health, function, resilience, and perceived social, economic, and ecological progress.

2. Literature review: collaborative governance and adaptability

We situated our assessment within the collaborative governance and adaptability literature (Ansell and Gash, 2007; Emerson et al., 2012; Emerson and Gerlak, 2014; Folke et al., 2005; Gupta et al., 2010), relying largely on the integrative collaborative governance framework advanced by Emerson et al. (2012) and expanded on by Emerson and Gerlak (2014) in their assessment of adaptability in collaborative governance, to frame our survey instrument. Emerson et al.'s (2012) integrative framework for collaborative governance is a useful framework within which to situate our assessment for a number of reasons. First, it synthesizes current theory, prior research, and practice of collaborative governance from many fields (e.g., conflict management, public administration, environmental governance, planning) (Ansell and Gash, 2007; Bentrup, 2001; Daniels and Walker, 2001; Innes and Booher, 1999; Milward and Provan, 2006; O'Leary et al., 2006, and the special issue therein). Second, the framework: 1) acknowledges that change is a fundamental property of the system; 2) recognizes the iterative and adaptive nature of collaborative processes and outcomes; and 3) aligns the collaborative governance and adaptability literatures (Emerson and Gerlak, 2014). Third, the framework includes testable propositions related to the composition of, and causal linkages between, components, which have largely been untested in the literature.

As our assessment is concerned with the structure and function of collaborative governance and adaptability, we specifically focus on the three factors (referred to as components in Emerson et al. (2012)) of collaborative dynamics in the framework – principled engagement, shared motivation, and capacity for joint action – to orient this literature review. *Principled engagement* is grounded in the concepts of transparent, inclusive, and civil communication and negotiation, where "safe" or "neutral" venues are created for discussing controversial issues. Principled engagement is comprised of an iterative process of discovery, definition, deliberation, and determination, where partners identify shared values and concerns and jointly agree on the problems, strategies to address problems, and the collective purpose (Emerson et al., 2012). Engaging the "right" people, i.e., interested and affected parties, is a critical consideration for principled engagement.

Shared motivation includes the concepts trust-building, mutual understanding, legitimacy, and commitment. It is also referred to as social capital in the adaptability literature (Folke et al., 2005; Pelling and High, 2005). Social capital is often considered the "glue" for adaptive capacity (Folke et al., 2005, p. 451), and trust, in particular, is considered "the grease that allows the gears of collaboration to turn" (Ansell et al., 2020, p. 572). Social capital is facilitated by repeated interactions and investments in relationship- and legitimacy-building, and is often strengthened by mutual commitment (Emerson et al., 2012; Folke et al., 2005; Pelling and High, 2005).

Capacity for joint action includes concepts related to collaborative capacity and adaptive capacity in the collaborative governance and adaptability arenas, respectively (Emerson and Gerlak, 2014). Capacity for joint action includes the following sub-components: knowledge and learning; leadership; resources; and institutional arrangements. In a collaborative setting, knowledge and information should be co-created and shared equally among all members of the group, and information should be used to inform adaptive management processes (Emerson et al., 2012; Emerson and Gerlak, 2014). Adaptive governance emphasizes the role of social learning and flexibility, through which participants test, monitor, evaluate, and reflect on ecological trends (e.g., cause and effect of ecological disturbance), management action impacts, and broader assumptions related to problem framing, goals, values, and norms (Baird et al., 2014; Folke et al., 2005; Lebel et al., 2010; Pahl-Wostl, 2009; Sharma-Wallace et al., 2018). Flexibility in this context refers to the ability of groups to absorb social learning, improvise, and try out alternative actions in the face of uncertainty and change (Cinner et al., 2018; Gupta et al., 2010). Leaders can be convenors, facilitators, and/or sponsors, among others, and their roles may shift over time (Emerson and Nabatchi, 2015). Leaders are critical for linking people and entities to develop and accomplish shared goals, manage conflict, build trust, help steer collaborative direction, and maintain a collaborative vision and transparency (Ansell and Gash, 2007; Emerson et al., 2012; Flye et al., 2023; Folke et al., 2005; Olsson et al., 2006). Effective collaboration relies on sharing resources and the flexibility to mobilize them when needed, including funding, personnel, technical support, and facilitation (Cinner and Barnes, 2019; Emerson and Gerlak, 2014; Gupta et al., 2010). Institutional, or structural, arrangements are the processes and protocols (e.g., charters, decision rules) that guide collaborative engagement, participation, and decision-making. Institutional arrangements should be codified within and across organizations (e.g., within collaboratives and between collaboratives and agencies) (Emerson et al., 2012) and should be fair and equitable, transparent, responsive, and accountable (Emerson and Gerlak, 2014; Gupta et al., 2010; Lockwood, 2010).

The integrative framework of collaborative governance proposed by Emerson et al. (2012) and expanded on by Emerson and Gerlak (2014) offers a useful heuristic to categorize collaborative governance dynamics and adaptability and provide a foundation for testing theory. However, despite over two decades of research on these topics, relatively little is known about how the factors influencing collaborative governance and adaptability interact and reinforce each other (Ulibarri et al., 2020). Thus, a necessary direction for guiding future applications of the framework is to empirically test its dimensional structure in terms of the factors that comprise collaborative governance and adaptability.

There are three gaps related to this point. First, there is no clear consensus on the number and configuration of factors that comprise collaborative governance and adaptability. For example, there is little understanding of whether the factors associated with collaborative governance and adaptability comprise distinct constructs (e.g., shared motivation), or represent dimensions of an underlying multi-dimensional construct (e.g., collaborative dynamics) (Emerson et al., 2012). Here, we use the term construct to refer to “the abstract idea, underlying theme, or subject matter that one wishes to measure” (Dew, 2008). Further, in the collaborative governance literature, Ansell and Gash (2007) postulate that institutional design (i.e., institutional arrangements), facilitative leadership, and informational work (i.e., knowledge and learning) are separate factors, whereas Emerson et al. (2012) considers them dimensions of capacity for joint action. Work in the adaptive capacity literature considers knowledge and learning, resources, leadership, and institutional arrangements separate but related factors (Cinner and Barnes, 2019; Engle and Lemos, 2010; Gupta et al., 2010; Lockwood et al., 2015). Second, and relatedly, studies employ these constructs assuming they are reliable, valid, and discrete, though this has largely been untested in the literature (see Lockwood et al., 2015 for an exception measuring the dimensions of adaptive capacity in the Australian agriculture sector). Third, many authors assert that the collaborative governance and adaptability factors are inter-related, meaning they reinforce one another, yet this also has not been rigorously tested (Ansell and Gash, 2007; Cinner et al., 2018; Cristofoli et al., 2022; Emerson et al., 2012; Sharma-Wallace et al., 2018; Thomson and Perry, 2006). These gaps helped inform the objectives and analysis presented herein.

3. Materials and methods

3.1. Data collection

We used Qualtrics, an online survey platform, to develop and administer a confidential survey to currently funded (as of December 2022) CFLRP projects (n = 15). The survey addressed the following four questions:

1. Do participants feel the collaborative exhibits characteristics generally associated with healthy, well-functioning, and resilient collaboration?
2. To what extent do participants feel the project is meeting process, socio-economic, and ecological goals?
3. What do participants need or recommend to improve the process?
4. What are the perceived challenges that affect collaborative performance and durability?

Here, we focus on the survey items related to the first question in order to develop and test collaborative governance and adaptability constructs. Survey items were developed based on a review of collaborative governance frameworks (Ansell and Gash, 2007; Biddle, 2017; Emerson and Nabatchi, 2015; Schultz et al., 2018; Ulibarri, 2015a) and literature on determinants of adaptive capacity (Cinner et al., 2018; Folke et al., 2005; Gupta et al., 2010). Survey item development was also informed by findings from the CFLRP (Beeton et al., 2020, 2022; Butler and Schultz, 2019; McIntyre and Schultz, 2020; Schultz et al., 2018). Additionally, items were adapted, where appropriate, from a variety of existing surveys in relevant peer-reviewed and grey literature (e.g., Biddle, 2017; Douglas et al., 2020a; Guariguata and Evans, 2020; Lockwood et al., 2015; National Forest Foundation, 2020; Plummer et al., 2017; Santo et al., 2020; Ulibarri, 2015a) (see supplementary material 1).

The collaborative dynamics section of the survey included subsections of indicators thought to measure the factors of principled engagement, shared motivation, and capacity for joint action. This section included 30 fixed-response items with a 5-point Likert response scale (strongly disagree to strongly agree). Respondents also had the option to select “don’t know/not applicable.”

Prior to administration, we piloted the survey with key members of the Colorado Front Range CFLRP (funded in 2012), the Northern Blues CFLRP (funded in 2021 and the first of the new cohort funded under the Agricultural Improvement Act of 2018), and CFLRP national program managers. This helped revise and refine the assessment. We then administered the survey to all members of the Northern Blues CFLRP and All-Lands Partnership in November 2021, and used responses and feedback from the CFLRP project members and coordinators to additionally refine the survey instrument.

After our initial pilot exercises, we engaged with and administered the survey to the remaining newly authorized and extension projects (n = 14). National and regional CFLRP coordinators helped convene introductory webinars (n = 4) in the fall of 2022 and spring of 2023 with project coordinators and members to review recruitment and administration protocols and identify the key points of contact from each project for follow-up engagement. For each CFLRP project, the authors coordinated several meetings with key contacts to determine appropriate timing for administration, target population for recruitment, and the administration protocol.

The target population for each project varied, and in some cases was quite dispersed, given that multiple entities and organizations at multiple levels were involved in projects (e.g., Forest Service unit-level staff, county commissioners, national environmental NGOs). Our goal was to conduct a complete census of participants involved in, and knowledgeable about, the project’s collaborative process to capture myriad experiences and perspectives of collaborative governance and adaptability (Bernard and Gravlee, 2015). We worked with CFLRP project coordinators to identify the target population, and project coordinators used participant listservs, or a listserv sub-set in the case where interested individuals and entities received emails about the project but were not active participants, for survey recruitment. The number of potential participants recruited by project varied considerably (n = 37–205). The survey was administered to projects between November 2022 and May 2023. For each project, we left the survey open for 4–10 weeks, depending on local needs. Periodic reminders were sent out to enhance response rate. In total, 405 people responded to the survey, and 341 responded to the collaborative dynamics section specifically, representing a 24% response rate. Response rate varied by project (13–41%; Table 1) and is aligned with similar online surveys in the literature (Grosso and Van Ryzin, 2011; Kapucu et al., 2013; Ulibarri, 2015a). The survey and administration procedures were approved by our university Institutional Review Board (protocol # 2679).

3.2. Data analysis

All survey items used in our analysis consisted of a 5-point Likert response scale (strongly disagree to strongly agree). Likert scales are robust to standard statistical procedures; i.e., the items can be treated as continuous variables (Vaske, 2019). All analyses were performed in R (R Core Team, 2022; version 4.3.1) and the Statistical Package for the Social Sciences (SPSS, IBM Corp., version 27).

3.2.1. Confirmatory factor analysis

We analyzed our data with confirmatory factor analysis (CFA). CFA assesses the relationships between indicators (i.e., survey items) and factors (i.e., latent variables, e.g., principled engagement) (Brown, 2015). CFA requires the pre-specification of all model parameters based on theory and previous empirical work (Brown, 2015; Vaske, 2019). We relied on existing theory and research regarding collaborative governance and adaptability to pre-determine indicator-factor relationships (see Section 2). CFA is an appropriate framework to confirm reliable scales and sub-scales, evaluate the presence of higher-order factors (i.e., a second-order model), and assess convergent and discriminant validity of constructs (Boateng et al., 2018; Brown, 2015). CFA was performed in R using the *lavaan* package (Rosseel, 2012).

We used maximum likelihood (ML) to estimate the CFA measurement model. Standard ML estimates assume the distribution of variables are multivariate normal. Data that departs substantially from multivariate normality requires the use of robust ML estimators, the most common of which are MLM (Satorra-Bentler scaled χ^2) and MLR (Yuan-Bentler T2* test statistic) (Satorra and Bentler, 1994; Yuan and Bentler, 2000). MLR has the added ability to estimate models that violate the assumption of multivariate normality and include missing data (Brown, 2015). There are many approaches to handling missing data. Direct ML, or full information ML, is considered the superior method in most cases to handle missing data, though it assumes the data is missing completely at random (MCAR) or missing at random (MAR) (Brown, 2015). Thus, to identify the appropriate estimator and method to handle missing data in our study, we conducted univariate and multivariate assessments of normality using the MVN package in R (Korkmaz et al., 2014) and a missing values assessment. Normality tests indicated our data exhibited multivariate non-normality (37.54, $p < 0.01$). Since our data departed from multivariate normality, we used the *MissMech* package in R to assess MCAR and MAR (Jamshidian et al., 2014), which is derived from the non-parametric test developed by Jamshidian and Jalal (2010). We found insufficient evidence to reject the assumption of MCAR or MAR ($p = 0.59$). Given our data can be assumed MCAR or MAR, we used the full information ML method to handle missing data, and we estimated the measurement model using the robust MLR estimator (Yuan and Bentler, 2000).

We evaluated model fit using the recommendations from Brown (2015), which include assessing: 1) overall goodness-of-fit - we evaluated absolute (χ^2, χ^2/df, Standardized Root Mean Squared Residual [SRMR]), parsimony (Root Mean Square Error of Approximation [RMSEA]), and comparative (Comparative Fit Index [CFI], Tucker-Lewis Index [TLI]) fit indices; 2) localized areas of strain (standardized residuals and modification indices); and 3) interpretability, size, and statistical significance of the parameter estimates. This approach helped evaluate fit and consider options, if warranted based on theoretical and/or empirical grounds, for re-specification. We used standard thresholds to evaluate overall goodness-of-fit, including $\chi^2/df < 3$, SRMR and RMSEA ≤ 0.08, and CFI and TLI > 0.9 (Boateng et al., 2018; Brown, 2015). Only statistically significant parameters were included in the measurement model.

We compared relative fit among three nested models consistent with the gaps identified in section 2 (Fig. 2): 1) a first-order three factor model (i.e., principled engagement, shared motivation, capacity for joint action); 2) a first-order six factor model (i.e., principled engagement, shared motivation, leadership, resources, knowledge and learning, institutional arrangements); and 3) a second-order six factor model to test whether individual dimensions could be explained by a higher-order collaborative governance and adaptability construct (Emerson et al., 2012). Note it was not appropriate to test a second-order three factor model because the same number of parameters were estimated in the first-order three factor model, and thus the fit statistics were identical. Each model was compared using robust, scaled χ^2 values using the *SBSDiff* package in R (Mann, 2022), which is derived from the scaled χ^2 difference test developed by Satorra and Bentler (2010, 2001). We demonstrated fit using results of the scaled difference χ^2 test, CFA, TLI, SRMR, and Akaike Information Criterion and Bayesian Information Criterion (AIC and BIC, respectively).

3.2.2. Assessing reliability and validity of the measurement model within the CFA framework

We assessed the reliability and convergent, discriminant, and pre-

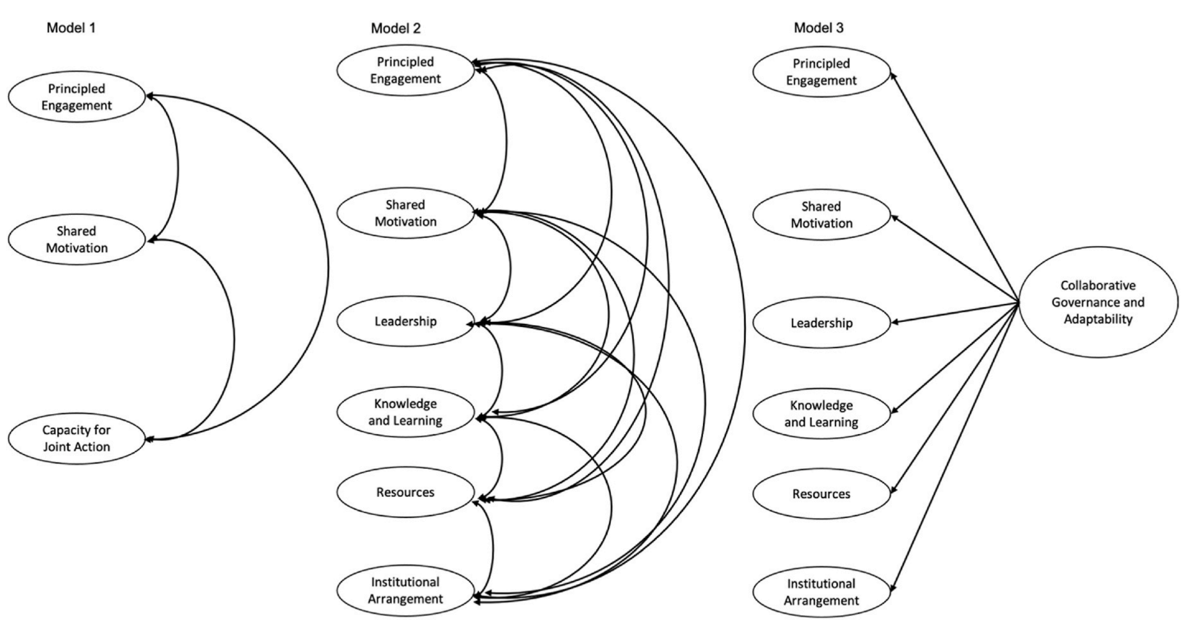

Fig. 2. Nested models for comparison.

dictive validity of factors that comprised the measurement model. We used the *SEMtools* package in R to evaluate composite reliability (CR). CR scores of ≥ 0.7 indicate a reliable scale for each factor in the measurement model (Nunnally and Bernstein, 1994). Convergent validity was evaluated using the following lines of evidence: standardized factor loadings (λ) ≥ 0.5, CR ≥ 0.7, and Average Variance Extracted (AVE) $\geq$ 0.5 (Fornell and Larker, 1981; Hair et al., 2014). We assessed discriminant validity by first evaluating correlations between factors – correlations ≥ 0.85 are considered potentially problematic in this context and require further testing. We supplemented the assessment of factor correlations with two nested model comparison methods, χ^2 (1) and χ^2(merge). χ^2 (1) is a nested model test where the correlation between two factors is fixed at 1 in a constrained model and compared to the original model, and χ^2(merge) refers to when two correlated factors are merged and then compared to the original model. These are appropriate approaches to assessing discriminant validity when theory and empirical research suggest higher inter-factor correlations, as is the case with the framework tested here (Rönkkö and Cho, 2022).

Next, we explored the predictive validity of our measures. Predictive validity, or the degree to which a measured concept accurately predicts scoring on a criterion measure, is useful for evaluating the practical utility of the concept (Murphy and Davidshofer, 2005; Manfredo et al., 2021; Teel and Manfredo, 2010). In a strict sense, predictive validity would be assessed by examining the extent to which the measured concept predicts an expected outcome in the future. An alternative, however, which can serve as an initial indication of the concept's predictive potential, is to test the association between the concept and a criterion of interest that is measured concurrently (i.e., at the same time). Taking the latter approach, we used correlation analysis (Spearman correlation, ρ) to assess: 1) the relationship between each factor and an index measuring perceived social process outcomes (CR = 0.89; AVE = 0.54, supplementary material 2); and 2) the relationship between each factor and an index measuring perceived ecological outcomes from collaboration (CR = 0.91; AVE = 0.585, supplementary material 2). We then evaluated the practical significance of correlation coefficients, with scores greater than or equal to 0.30 indicative of a moderate to large effect size (Cohen, 1988). We chose these outcome measures for our assessment on theoretical and empirical grounds. Scholars propose causal linkages between collaborative dynamics (e.g., principled engagement) and social and ecological outcomes (Emerson et al., 2012; Thomas and Koontz, 2011). Further, studies have demonstrated empirically the relationship between collaboration dynamics and both perceived and observed social and ecological outcomes (e.g., Biddle, 2017; Biddle and Koontz, 2014; Jager et al., 2020; Ulibarri, 2015a).

4. Results

4.1. Assessing the dimensional structure of collaborative governance and adaptability

Through evaluation of standardized factor loadings and significance, standardized residuals, and modification indices, the following actions were taken to respecify the models. First, we removed five items due to poor fit, which resulted in 25 remaining items. Two items in the shared motivation dimension, two in the resources dimension, and one in the institutional arrangements dimension were removed (Table 2). Second, modification indices and residual analysis suggested adding a path (i.e., correlated error) between two items in the principled engagement dimension (PE3 – *Participants agree about the problems that impact our landscape*; PE4 – *Participants agree about the strategies to solve problems*). Adding a correlated error between two items implies some covariation between items is explained by something other than the theoretical relationship between the indicators and the factor, such as when items are similarly worded, as was the case here. All models satisfied standard thresholds for goodness-of-fit (Table 3). The nested models were then

Table 2
Item means, standard deviation, standardized factor loadings (λ), composite reliability (CR), and average variance extracted (AVE) from CFA.

Factor (composite reliability; AVE)	Indicator	λ	*M*	*SD*
Principled Engagement	PE1. A representative cross-section of the individuals who have a stake in the issues and outcomes of this CFLRP project are involved.	0.64	4.1	1.11
(0.87; 0.56)	PE2. Participants work together to identify shared interests and concerns.	0.82	4.24	1.01
	PE3. Participants agree about key problems that impact our landscape.	0.70	4.03	1.04
	PE4. Participants agree about strategies to solve problems.	0.75	3.75	1
	PE5. Participants agree about the purpose of this CFLRP project.	0.77	4.2	0.99
	PE6. The collaborative process has created a neutral space to discuss controversial issues.	0.80	3.95	1.15
Shared Motivation	SM1. The collaborative process has helped participants build trust.	0.87	4.25	0.97
(0.91; 0.72)	SM2. The collaborative process has helped participants build personal and/or working relationships.	0.87	4.45	0.88
	SM3. The collaborative process has helped participants build mutual respect of others' positions and interests.	0.90	4.26	0.96
	SM4. Myself/my organization is committed to the CFLRP collaborative process.	0.69	4.64	0.75
	SM5. The US Forest Service is committed to the CFLRP collaborative process.[a]	–	–	–
	SM6. Other project participants are committed to the CFLRP collaborative process.[a]	–	–	–
Capacity for Joint Action				
Leadership	CJA1 (LD1). CFLRP project leaders have good skills for working with other people and organizations.	0.85	4.4	0.86
(0.89; 0.73)	CJA2 (LD2). CFLRP project leaders maintain and communicate a common collaborative vision and direction.	0.87	4.16	1.03
	CJA3 (LD3). CFLRP project leaders can motivate others to work together.	0.84	4.08	0.97
Knowledge and Learning	CJA4 (KNOW1). Participants co-generate knowledge and information to learn and solve problems.	0.81	4.11	0.95
(0.83; 0.56)	CJA5 (KNOW2). Knowledge and information is shared equally among CFLRP project participants.	0.70	3.84	1.15
	CJA6 (KNOW3). Project participants are committed to informing adjustments to management practices (i.e., adaptive management).	0.76	3.94	1.06
	CJA7 (KNOW4). Project participants have the flexibility to alter course when conditions change.	0.74	3.73	1.04
Resources	CJA8 (RES1). Our CFLRP project has adequate funds to carry out tasks and accomplish our work.[a]	–	–	–
(0.74; 0.59)	CJA9 (RES2). Our CFLRP project has adequate time to carry out tasks and accomplish our work.[a]	–	–	–
	CJA10 (RES3). Our CFLRP project has adequate technical expertise to carry out tasks and accomplish our work.	0.64	4.06	1.04

(continued on next page)

Table 2 (*continued*)

Factor (composite reliability; AVE)	Indicator	λ	*M*	*SD*
	CJA11 (RES4). Our CFLRP project has adequate skills to facilitate collaborative engagement activities.	0.88	4.09	1.04
Institutional Arrangements	CJA12 (IA1). Collaborative protocols are in place that promote accountability among CFLPR participants.	0.75	3.94	1.09
(0.89; 0.56)	CJA13 (IA2). Collaborative protocols are in place that promote accountability between the US Forest Service and CFLRP project participants.	0.74	3.69	1.15
	CJA14 (IA3). Collaborative protocols are understood by participants.	0.81	3.67	1
	CJA15 (IA4). Collaborative protocols are fair and equitable.	0.83	3.86	1.09
	CJA16 (IA5). Project participants clearly understand when and what collaborative input is useful to inform USDA Forest Service decisions.	0.72	3.54	1.1
	CJA17 (IA6). The US Forest Service is responsive to collaborative input.[a]	–	–	–
	CJA18 (IA7). The US Forest Service is clear about the decisions they make and why they make them.	0.63	3.75	1.13

[a] Removed from analysis due to poor fit. Model was respecified based on factor loadings, significance tests, standardized residuals, and modification indices.

compared to determine which model best fit the data while considering parsimony.

The three nested models we tested are illustrated in Fig. 2. The χ^2 difference test indicated that the more complex six factor model solution (model 2) was a better fit when compared to the first-order three factor model (model 1; $\Delta\chi^2 = 139.081$, $df = 12$, $p < 0.01$; Table 3). Further, when comparing the first-order models to the second-order six factor model (model 3), the second-order model significantly degraded model fit in both tests (Table 3; model 1 comparison - $\Delta\chi^2 = 67.17$, $df = 3$, $p < 0.01$; model 2 comparison - $\Delta\chi^2 = 50.83$, $df = 9$, $p < 0.01$). Thus, the second-order six factor model did not provide a more parsimonious fit to the data. The first-order six factor model (model 2) provided the best fit to our data. All measures of absolute, parsimony, and comparative fit indices support this conclusion (Table 3; $\chi^2/df = 1.77$; CFI = 0.951; TLI = 0.944; SRMR = 0.039; and RMSEA = 0.047).

4.2. Assessing reliability and validity

For the final six factor model, standardized factor loadings ranged from 0.63 to 0.90, CR coefficients ranged from 0.74 to 0.91, and AVE ranged from 0.56 to 0.73 (Table 2). Together, these findings provide evidence of strong internal reliability and convergent validity of our measures.

As expected, several factors exhibited high inter-factor correlations (Table 4). Four correlations exceeded the 0.85 cutoff typically associated with potentially problematic discriminant validity (Brown, 2015), including for: 1) principled engagement and shared motivation; 2) principled engagement and knowledge and learning; 3) leadership and knowledge and learning; and 4) institutional arrangements and knowledge and learning. Yet, there isn't consensus on a strict cutoff for assessing discriminant validity. The expected magnitude of correlation among factors to diagnose a problem should be assessed based on theoretical and empirical grounds specific to the concepts being measured (Rönkkö and Cho, 2022). Thus, we further evaluated discriminant validity using two nested CFA model comparison approaches appropriate for when factors are expected to be highly correlated. We first fitted a constrained model where the potentially problematic factor correlations were fixed to 1 and compared to our original model (i.e., model 2 from Fig. 2). We found that, for each factor pair, constraining the correlation to 1 significantly degraded model fit. In other words, the factor correlations of concern were significantly different from 1 ($\Delta\chi^2 = 8.09$–18.44, $df = 1$, $p < 0.01$; Table 5). Second, we fitted a constrained model where the indicators representing the potentially problematic factor pairs were merged into a single factor and compared to the original model (see supplementary material 3 for χ^2(merge) nested model comparisons for each of the 15 possible factor pairs from the six factor model). Similarly, merging factors significantly degraded overall fit of our measurement model ($\Delta\chi^2 = 33.83$–66.18, $df = 5$, $p < 0.01$; Table 5). Results of the nested model comparison provided evidence for discriminant validity between factors in our model. As a whole, these results provide evidence for convergent and discriminant validity, indicating that the components of collaborative governance and adaptability represent distinct constructs rather than dimensions of an underlying collaborative dynamics or adaptive capacity construct.

Results of our predictive validity tests (Spearman correlation, ρ) showed that correlation coefficients between each factor and reported social process and ecological outcomes were all significant at the $p < 0.001$ level. Further, the strength of association for each correlation coefficient was moderate to strong (Table 6). Together these findings provide further empirical evidence for the validity of our measures.

Table 3
Nested model comparisons using scale-corrected chi-square difference test (Bryant and Satorra, 2012). See Fig. 2 for visual representations of models 1–3.

Model	Model 1	Model 2	χ^2 difference: model 1 and 2	Model 3	χ^2 difference: model 1 and 3	χ^2 difference: model 2 and 3
χ^2	822.58	597.24		667.92		
scaled χ^2	623.66	457.57		510.71		
scaling correction factor	1.319	1.305		1.308		
df	271	259		268		
parameters	79	91		82		
χ^2/df	2.30	1.77		1.71		
$\Delta\chi^2$			139.08		67.17	50.83
Δ *df*			12		3	9
p-value			<0.001		<0.001	<0.001
CFI	0.910	0.951		0.941		
TLI	0.901	0.944		0.934		
SRMR	0.047	0.039		0.045		
RMSEA	0.076	0.057		0.062		
AIC(BIC)	1880 (18,383)	17,879 (18,227)		17,931 (18,246)		

Table 4
Inter-factor correlations.

Factor	Principled Engagement	Shared Motivation	Leadership	Knowledge and Learning	Resources	Institutional Arrangements
Principled Engagement	–					
Shared Motivation	0.90	–				
Leadership	0.81	0.74	–			
Knowledge and Learning	0.89	0.80	0.91	–		
Resources	0.79	0.66	0.82	0.83	–	
Institutional Arrangements	0.78	0.70	0.77	0.86	0.74	–

Table 5
Discriminant validity nested model comparisons. $\Delta\chi^2$ (1) is a test where the correlation between two factors is fixed at 1 in a constrained model and compared to the original model, and $\Delta\chi^2$ (merge) refers to when two correlated factors are merged and then compared to the original model.

Factor Pair	χ^2 (1)			χ^2 (merge)		
	$\Delta\chi^2$	*df*	p-value	$\Delta\chi^2$	*df*	p-value
Principled Engagement ~~ Shared Motivation	8.09	1	<0.01	39.45	5	<0.001
Principled Engagement ~~ Knowledge and Learning	14.73	1	<0.001	53.72	5	<0.001
Leadership ~~ Knowledge and Learning	15.73	1	<0.001	33.83	5	<0.001
Institutional Arrangements ~~ Knowledge and Learning	18.44	1	<0.001	66.18	5	<0.001

5. Discussion

5.1. Implications

In this section, we summarize the implications of our findings for the theory and practice of collaborative governance and adaptability organized around our study objectives. First, there is little consensus on the number and configuration of factors that comprise collaborative governance and adaptability (Emerson et al., 2012; Koontz et al., 2015; Siders, 2019). Koontz et al. (2015) note that there are many frameworks and variables purported to cultivate collaborative governance and adaptability. Yet, differences in how they are defined, configured, and measured limits our understanding of their underlying relationship and our ability to test and advance theory. Similar critiques exist in the social learning literature (Gerlak et al., 2019; Gerlak and Heikkila, 2019), and more broadly in the adaptive governance and adaptive capacity literature (Biesbroek et al., 2017; Siders, 2019).

As a starting point for addressing these limitations, our first objective was to test the dimensional structure of the integrative framework for collaborative governance proposed by Emerson et al. (2012), and expounded upon by Emerson and Gerlak (2014) to link collaborative and adaptive capacity for joint action. Emerson et al.'s (2012) framework comprises three factors associated with collaborative governance dynamics – principled engagement, shared motivation, and capacity for joint action. In our study, we found that the principled engagement and shared motivation factors aligned well with the integrative framework for collaborative governance. However, our results suggest the capacity for joint action dimensions – leadership, knowledge and learning, resources, and institutional arrangements – represent related, but distinct, factors. In other words, in the context of the CFLRP, the four factors could not be considered part of the underlying construct capacity for joint action as proposed in Emerson et al. (2012). Additionally, our results indicated that a second-order model significantly degraded the model fit when compared to both the three and six factor models, which suggest that the factors could not be explained by a larger underlying construct of collaborative dynamics. These findings align with other frameworks and empirical work (Ansell and Gash, 2007; Douglas et al., 2020a; Gupta et al., 2010). Thus, our results confirmed the dimensional structure of our collaborative governance and adaptability measures comprised six dimensions – principled engagement, shared motivation, leadership, resources, knowledge and learning, and institutional arrangements.

Second, studies deploy collaborative governance and adaptability measures assuming they represent valid and discrete constructs, an assumption that has been largely untested. Here, we used several lines of evidence to test the reliability, as well as the convergent, discriminant, and predictive validity of our collaborative governance and adaptability measures. In this vein, it is widely suggested that the dimensions of collaborative governance and adaptability are interrelated, as they are said to be mutually-reinforcing (Ansell and Gash, 2007; Emerson et al., 2012; Folke et al., 2005; Pahl-Wostl et al., 2007). As expected, we found that the six dimensions of our measurement model were indeed interrelated. Four dimensions were highly correlated, and the pattern of inter-factor relationships aligned with theoretical and empirical work. Notably, principled engagement and shared motivation were highly correlated. Emerson et al. (2012) suggest outcomes of principled engagement can include increased trust, mutual understanding, and internal legitimacy, which are the key elements of shared motivation. Further, knowledge and learning were highly correlated with principled engagement, leadership, and institutional arrangements. This finding aligns with Pahl-Wostl et al.'s (2007) depiction of the relationship between social learning and other collaboration components. Social learning, according to Pahl-Wostl et al. (2007), shapes, and is shaped by, the relational components of collaboration. Social learning is thought to be effective under open venues for communication and negotiation, strong leadership, and clear ground rules for engagement.

Our measures of collaborative governance and adaptability exhibited strong internal reliability and convergent validity. While the measures were statistically related, they can be considered distinct constructs, as evidenced by our discriminant validity assessment. Further, we found preliminary evidence for predictive validity of our measures. Each of our measures were significantly related to perceived social process and ecological outcomes. Ulibarri (2015a) demonstrated that collaboration dynamics were related to perceived outcomes, and specifically were more strongly related to the more proximal social process outcomes when compared to ecological outcomes. The strength of associations between our collaboration dynamics scales and outcomes aligns with

Table 6
Predictive validity analyses for six collaborative dynamics dimensions.

	Principled Engagement	Shared Motivation	Leadership	Knowledge and Learning	Resources	Institutional Arrangements
Social process outcomes[a]	0.726[b]	0.672[b]	0.689[b]	0.751[b]	0.601[b]	0.725[b]
Ecological outcomes[a]	0.462[b]	0.339[b]	0.397[b]	0.469[b]	0.426[b]	0.484[b]

[a] Spearman's ρ correlation coefficient.
[b] $p < 0.001$.

this work. Overall, results suggest the six factors in our final model represent statistically reliable and valid measures that may be used to evaluate collaborative governance and adaptability.

5.2. Limitations of the present study and future work

A limitation to consider for this work is that the survey was developed for a specific context, the CFLRP. We developed measures that were grounded in the research and practice of the CFLRP and unique to collaboration in U.S. public land management to ensure measurement specificity and relevance (Conley and Moote, 2003). While our focus is on the CFLRP, we believe that the framework, survey instrument, and methods are applicable to other cross-boundary collaborative environmental governance contexts. However, the instrument could benefit from further refinement, adaptation, and testing in different cases and contexts to determine if the survey items are locally- and contextually-appropriate, and if the dimensional structure, pattern of factor relationships, and reliability and validity of measures remain consistent with results from this study. In particular, there may be room for refining items to reflect the unique ways in which Tribes engage with public lands management agencies. The Forest Service engages with Tribes who are distinctive rightsholders and sovereign nations; some Nations have chosen to engage through the CFLRP collaborative framework while others work directly with the Forest Service in government-to-government consultation. Future surveys in the CFLRP or other public lands management collaborative venues may require additional attention to these histories, differences, and relationships among interested entities and distinct rightsholders.

Collaborative governance regimes are nested within broader social, political, economic, and ecological contexts, and the progress and performance of collaboration is impacted by both internal and external factors. While a great deal of research has described different components of collaboration, there is less understanding of the relationships between collaborative processes and social-ecological outcomes, and how different systems contexts and drivers affect collaborative process dynamics (Douglas et al., 2020b; Emerson and Nabatchi, 2015; Ulibarri, 2015a). Some notable research has started to address linkages between collaborative dynamics and outcomes (Baudoin and Gittins, 2021; Biddle and Koontz, 2014; Koontz et al., 2020; Ulibarri, 2015a, 2015b; Wang and Zhao, 2021). The framework we used to determine measures of collaborative governance and adaptability is a nested, systems-based framework that proposes causal linkages between system components (Emerson et al., 2012). It thus provides an opportunity to further contribute to our understanding of the relationship between external social-ecological contexts, drivers, dynamics, and outcomes. A fruitful line of inquiry lies in using methods like qualitative comparative analysis to characterize which and what configuration of collaborative process variables may lead to successful outcomes in different contexts (Avoyan, 2022a; Cristofoli et al., 2022; Douglas et al., 2020b).

Additionally, the majority of research linking collaborative dynamics to outcomes has focused on more proximal collaborative actions (e.g., development of management plans, monitoring, implementation) and process-related outcomes (e.g., minimize conflict, new relationships, process effectiveness). There are challenges, however, to measuring socio-economic and ecological outcomes of collaboration. In particular, actions taken by collaboratives are often temporally disjunct from outcomes on the ground and thus it is difficult to establish causality. Addressing this gap would require baseline and longitudinal research, which is relatively limited in the collaborative governance arena (Conley and Moote, 2003; Ulibarri et al., 2020; Ansell and Gash, 2007). There is a need to evaluate the impact of collaboration on the more distal social and environmental outcomes that collaboratives are asked to achieve (e.g., socio-economic stability, improved resource conditions) (Ansell and Gash, 2007; Baudoin and Gittins, 2021; Koontz et al., 2020). In this vein, intermediate process-related outputs and collaborative actions can determine the type and extent of outcomes and impacts. In other words, these actions, outcomes, and impacts are inextricably linked, occurring as a path-dependent trajectory of change (Koontz et al., 2020; Emerson et al., 2012). Evaluating the complex and causal linkages between collaboration dynamics and outcomes could be achieved using standardized frameworks and assessments like the one presented here or others (e.g., Newig et al., 2018), cross-case meta-analyses, or rigorous within-case methods like process tracing (Avoyan, 2022b; Koontz et al., 2020; Ulibarri, 2015b). Structural equation modeling, and path analysis in particular, may provide a useful approach for assessing the degree to which intermediate process-related outcomes and actions mediate the more distal outcomes and impacts of collaboration (Biddle and Koontz, 2014; Jager et al., 2020; Mosley and Park, 2022).

Collaboratives evolve and adapt their structures and processes as priorities, capacities, and the public value they provide change (Imperial, 2022; Imperial et al., 2016; Ulibarri et al., 2020). However, there is a limited understanding of how collaborative groups adapt collaborative structures, practices, and processes to maintain their progress and performance (Cheng et al., 2015; Imperial, 2022; Ulibarri et al., 2020). The limited research on collaboration over time has suggested that participation and engagement decrease through time (Heikkila and Gerlak, 2016; Hui et al., 2020). Some argue that trust and personal relationships (i.e., shared motivation) may be more important in the early phases of collaboration until the group is institutionalized (Imperial et al., 2016). Ulibarri et al. (2020) conducted an analysis of collaborative governance and evolution using the Collaborative Governance Database (Douglas et al., 2020a) and found that most of the collaboration dynamic variables peaked towards the mid-point; a focus on transparency and accountability was observed later in the collaboration life-cycle; and leadership tended to be concentrated early on, but more distributed in later phases of the collaborative life-cycle. Ulibarri et al. (2020) also found some evidence of the importance of conflict resolution (process outcome) at the beginning of the collaborative life-cycle compared to innovative solutions and effectiveness, for example, in later phases. Systematic, cross-case assessments through time can help document: 1) what collaboration governance dynamics are important and when; 2) what adaptations and outcomes occur over time; and 3) how collaborative processes and intermediate outputs influence social and ecological outcomes that may be temporally disjunct from the collaborative process.

The assessment presented here is part of the CFLRP common monitoring strategy. Newly authorized projects are required to address the common monitoring strategy for 15 years, thus offering a unique opportunity to study collaborative governance and adaptability through time and across projects within a natural experimental setting, where each project is situated within diverse social and environmental contexts, but all under the same policy instrument (Ansell and Gash, 2007). There are currently no gold-standard criterion variables from which to evaluate our scales, an oft-cited challenge to validity assessment (Boateng et al., 2018). Still, there is room for further testing of the predictive validity of our scales by assessing their association with observed social and ecological outcomes reported in the CFLRP common monitoring strategy. Further, mixed-methods research that pairs systematic quantitative analyses with in-depth case studies and qualitative inquiries would be particularly beneficial to gain sufficient depth and breadth in understanding collaborative governance and adaptability in the complex, social-ecological systems in which collaborative governance regimes are embedded (Ansell and Gash, 2007; Conley and Moote, 2003).

6. Conclusion

In conclusion, we administered a survey grounded in the theory and practice of collaborative governance and adaptability to fifteen projects authorized and funded under the CFLRP and administered by the Forest Service in the United States. We used confirmatory factor analysis to test propositions related to the dimensional structure, reliability, and validity of our collaborative governance and adaptability measures. Several of these assumptions had been largely untested in the literature. We confirmed the dimensional structure of our collaborative governance and adaptability measures comprised six reliable and valid factors. As anticipated, several factors were interrelated. Still, our discriminant validity assessment suggested the factors comprised distinct constructs. We argue that the results presented herein offer a set of robust collaborative environmental governance and adaptability measures that can be further refined, adapted, and tested. While our initial focus was on the collaborative groups funded under the CFLRP, the framework, survey instrument, and methods are applicable to other collaborative environmental governance arrangements. The assessment can be used in the future as a baseline with which to contribute to our limited understanding of how collaborative dynamics relate to social and environmental outcomes (Koontz et al., 2020) and how collaborative groups adapt collaborative structures, practices, and processes under change to maintain their progress and performance (Cheng et al., 2015; Imperial, 2022; Ulibarri et al., 2020). This is a critical line of work given the increased emphasis and reliance on long-term collaborative arrangements with multiple interested and affected parties to achieve sustainability goals.

CRediT authorship contribution statement

Tyler A. Beeton: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Tara L. Teel:** Writing – review & editing, Supervision, Methodology. **Melanie M. Colavito:** Writing – review & editing, Funding acquisition, Data curation. **Nicolena vonHedemann:** Writing – review & editing, Data curation. **Ch'aska Huayhuaca:** Writing – review & editing, Data curation. **Antony S. Cheng:** Writing – review & editing, Funding acquisition. **Benjamin Ghasemi:** Writing – review & editing, Methodology. **Adam J. Snitker:** Writing – review & editing, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

As per Institutional Review Board requirements, we are not able to share data associated with this article.

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Appendix A. Supplementary data

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