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RESEARCH ARTICLE

Going with the grain: scalar conservation easement dataset comparison

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Abstract
Context Private land conservation maintains global biodiversity while securing areas for biome shifts. Conservation easements (CEs) are the dominant form in both the US and increasingly, globally.
Objectives We illustrate the differences in the National Conservation Easement Database (NCED) and a fine-scale curated collection of CEs, the Granular Conservation Easement Datasets (GCED), which fills an imperative gap in the CE literature. We assessed each dataset's utility for different research objectives.
Methods The GCED represents a comprehensive baseline of the CEs placed between 1997 and 2008/2009 in twelve counties in six US states. We empirically compared GCED and NCED spatial geometries and related attributional data with qualitative and quantitative analyses.
Results NCED completeness varies geographically and categorically over time, lacking historical information about CE amendments. GCED comparison with the NCED subset with a year of CE establishment revealed a consistently higher CE count in the majority of GCED counties. CE spatial configurations also diverged between the GCED and the NCED. Spatial statistical analysis outcomes differed; for each dataset, CEs are generally clustering (Ripley's K) but Global Moran's I and Average Nearest Neighbor results diverged to varying degrees.
Conclusions The NCED creates a double-edged sword for researchers as the *only* nationally and

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publicly accessible compilation of CE data with evident omission bias. Landscape management and planning studies rely on the NCED but its incompleteness hinders its utility as a tool for CE tracking, oversight, planning, and research. Broad-scale geographic coverage and fine-scale accuracy are a tradeoff; future scholarship should understand the shortcomings of a particular dataset at a particular scale.

Keywords Conservation easements · Datasets · Broad-scale geographic coverage · Fine-scale accuracy

Introduction

There is a significant and growing reliance on privately conserved lands to maintain global and national (United States) biodiversity protection (McDonald et al. 2007; Rissman et al. 2007; Chapman et al. 2023), with immediate and projected climate change impacts and species extinction (Kamal et al. 2015). Conservation easements (CEs) are a proliferating mechanism on private lands, particularly with ideological shifts to support biodiversity conservation in the United States (US) (Manfredo et al. 2021). Employed nationally and increasingly globally, CEs realize land conservation and reduce land use conversion without the expense of purchasing the entire parcel (Fisher and Dills 2012; Kamal et al. 2015; Owley and Rissman 2016; Lacher et al. 2019). The original owner remains on and owns the parcel that is now theoretically diminished by the value of the foregone uses. CEs are private, contractual relationships between the landowner and the CE holder with no legal obligation to disclose the process or the CE location (Fairfax et al. 2005; Olmsted 2011; Pidot 2011). But public transparency manifests through the CE filing requirement in the county recorder's office as a legal encumbrance that runs with that parcel, generally—but not always—in perpetuity (Cheever 1996; McLaughlin 2005; Korngold 2007). The broader public has invested in the tool through the tax deductions available for the value of the foregone uses if the CE is a qualified conservation contribution (26 US Code §170(h) 2024) or through governmental (federal, state, or local) funding for direct CE purchase. Following the trend of neoliberalism and public–private partnerships, CEs are a hybrid of public investment and private autonomy, including the relative publicity of their existence on a property (Morris 2008).

The reasons for CE ubiquity are variable and contextual, but can be attributed, in part, to governmental support of the instrument in lieu of other land conservation options. The American Bar Association drafted the Uniform Conservation Easement Act (UCEA) between 1978 and 1980 (Burnett 2013; McLaughlin 2018), which at least 27 states have subsequently adopted, and the remainder of states have used as a model for their own CE enabling acts (Olmsted 2011). Since 1981, the US federal government has supported CEs through growing tax incentives, and they have become a dominant form of conservation on private lands (Rissman et al. 2007; Lacher et al. 2019). In the late 2000s, a burgeoning academic movement emerged to acknowledge the tool's lack of transparency in the landscape fabric, which Olmsted (2011) refers to as "the invisible forest... [that are] forest lands—and, for that matter, any other land types—protected by a perpetual CE, the existence and location of which are concealed from the public, whether deliberately or because of the opaque nature of the easement process" (p. 51). Others have documented and expressed concern about the lack of information and problems with CE collection and accounting in county recorders' offices, whether geospatial or the CE instruments themselves (Morris and Rissman 2009; Rissman et al. 2017; Overby et al. 2022). According to Olmsted (2011), "despite the efforts of some states and conservation organizations to compile CE data for public consumption, there are few functional systems that comprehensively track and provide easy access to CE data" (p. 51).

In 2009, scientists and representatives from non-governmental organizations (NGOs,) academia, and the federal government generated the first national database of CEs in the US. Known as the National Conservation Easement Database (NCED), it is a voluntary cooperative endeavor by a consortium that is privately and publicly funded. Conceived and initiated through the US Endowment of Forestry and Communities, the Trust for Public Lands (TPL) curates the publicly held CEs and Ducks Unlimited (DU) does the same for privately held CEs. It is unclear whether this effort was a response to the academic discussion, but the effect is to address an acknowledged gap in the location of CEs in the US landscape matrix. The NCED was first publicly released through the Protected Areas Database-United States (PAD-US) in November 2012, and continues to be intermittently updated. For a complete list of the variable schema, please see Supplementary Information Figure (SIF) 1 (NCED Schema 2023).

NCED participation is entirely *voluntary*, which leads to recognized data deficits. TPL and DU periodically solicit and assemble data from land trusts (LTs) and other CE holders, but do not mandate a formal process for CE spatial and substantive amendment. Their general protocol is to replace polygons and attributes with new ones, filling in spatial data gaps with old data. TPL and DU acknowledge the potential for differential amendment treatment depending on the public and private nature of the CEs; for nonprofit holders, substantive changes such as a CE transfer from one holder to another are annotated in the comments section. The date of CE establishment is maintained as the date on which the CE was created (Personal communication with authors 2019). Both TPL and DU estimate the NCED completeness, and both the PAD-US and the NCED websites acknowledge the deficiencies (geographic omissions, variable levels of completeness, voluntary participation, etc.), with caveats about the data's use. TPL and DU estimate that the NCED contains 90% of the CEs held by LTs and nonprofits, and 49% of the CEs held by governmental agencies. The lack of data from CE holders who do not want or have limited capacity to participate (Rissman et al. 2017, 2019) likely results in a systematic bias in the types of CEs contained within the NCED (Williamson et al. 2021). Hence, the NCED creates a double-edged sword for researchers as the *only* nationally and publicly accessible compilation of CE data with apparent omission bias. Several studies have relied on the NCED with variable acknowledgement of its shortcomings and correction attempts, potentially leading to flawed generalizations from the results.

The NCED's incompleteness hinders its utility as a tool for CE tracking, oversight, planning, and research. Historically, independent researchers lacked comparable data for empirical NCED assessment. To meet this need, we used CE data systematically compiled from the recorders' offices of twelve counties to generate finer-grained CE datasets, the Granular Conservation Easement Datasets (GCED), for unique empirical comparison with the NCED's spatial geometries and related attributional data. The GCED represents the most complete baseline which was reasonably possible to compile for the chosen counties and study timeframe. Our research objective was to comparatively analyze the utility and circumstances under which each dataset would best fit particular types of analyses (e.g., fine-scale versus broad-scale) and to illustrate their advantages and shortcomings so that researchers and practitioners can be cognizant when designing their projects with a particular dataset.

Methods

We generated spatial and CE instrument datasets using selection criteria to meet a larger project. Accordingly, we amassed a database of information on CE location and characteristics in rapidly urbanizing areas of the US. To select our study counties, we first assessed states around the country for those with the highest numbers of acres preserved in CEs (without normalizing by urbanized areas), which are within each Census region of the US. We chose two counties in each of the states that exhibited urbanization pressures (i.e., an increasing population growth rate higher than the US median from 2000 to 2010 based on US Census data from 2000 to 2021) to address potential state-level influences on CE use. Multiple counties didn't meet the growth criteria by Census region. We also narrowed the county selection with these additional criteria: volume of CEs by county (the greater the better, but at least more than 25 for statistical viability), an exurban character and Level 1 ecoregion exemplification. We used the "exurban" definition as a guiding but not entirely definitive principle (i.e., greater than 0.15 people/ha (0.06 people/acre) but less than 3.86 people/ha or "exurban" housing density as 0.68–16.18 ha per unit) (Theobald 2001). This allowed us to capture residential land use beyond the urban–suburban fringe, comprising parcels or lots that are generally too small to be considered productive agricultural land use. For the Level 1 ecoregion exemplification, we chose the ecoregions with the most acreage in each US Census region and greatest representation in the contiguous US, which are: Marine West Coast forest, Western forested mountains, Mediterranean California, North American deserts, Great Plains, Eastern temperate forests, and Tropical and Subtropical coniferous forest. Ecoregions in the US are spatially hierarchical, by Level, with Level 1 as the largest and closest to the concept of biome (Bailey 1995). We also sought to maintain a balance of states with state easement enabling laws that mandate some form of land use planning principles/public oversight in CE placement (Richardson and Bernard 2011). These criteria were tempered by data availability, including cost per CE document page and the format (i.e., whether something could be digitized and mapped in GIS). Our final study counties include: Sonoma and Sacramento in California; Boulder and Mesa in Colorado; Douglas and Washington in Minnesota; Lebanon and York in Pennsylvania; Charleston and Greenville in South Carolina; and Albemarle and Loudoun in Virginia. We attempted to gather all of the CEs possible for the timeframe from the county recorders' offices, which is the required repository that is technically publicly available (not voluntarily submitted, per the NCED). There are admitted problems with the county recording process (Morris and Rissman 2009); please see Overby et al. (2022) and Dyckman et al. (2024) for further descriptions of the dataset construction process, its challenges, and our attempts to triangulate to address them.

We collected 2823 CEs (electronically and in paper form) from the study counties, seeking all CEs filed (or amended) between 1997 and 2008/2009 (depending on the county). We developed a CE coding instrument with sections related to CE disposition, holder typology, public access, and other nominal variables for analysis. We developed our CE coding instrument independently from the NCED categories, using an iterative process for the CE purposes as they emerged during the coding process. See Self et al. (2024) and Dyckman et al. (2024) for a more detailed description of the GCED coding process. For the NCED, in addition to the spatial polygons of the CEs, the required CE characteristics most relevant to our study are the CE purpose coding (nine categories), the holder typology (ten categories), public access (four categories), duration (whether held in perpetuity or not), as well as the optional categorization of the CE from a biological perspective (i.e., GAP status and IUCN category). Once the GCED datasets were complete, we utilized three primary approaches to comparatively evaluate the NCED against them (SIF 2).

First, we sought to understand the ways in which the NCED is currently employed in peer-reviewed, published research. To do so, we conducted a systematic review of the CE literature that engages spatial analysis and GIS to capture the emergence of the use of the NCED. We searched Google Scholar, Web of Science, and Ebsco's Academic Premier with the following search terms: "national conservation easement database;" "conservation easements" and "spatial;" "conservation easements" and "GIS;" and "conservation easements" and "PAD-US."

We finished the search in January 2022 and began coding them in the following categories: publication year; whether they used NCED data; other data sources; year(s) of data source(s); study geographic coverage; type(s) of analysis; audience discipline(s); aspects of NCED data evaluated (spatial, purpose, holder, access, etc.); temporal with CE dates; and mitigation for shortcomings of NCED (SIF 3). In January 2025, we added another round of coding to catalog the studies' spatial analysis typologies using three coders for intercoder reliability. The journal review could be longitudinally updated, but this is a sufficient coverage to establish an understanding of NCED and CE spatial data usage.

Second, we created three subsets of the NCED for our counties. The first, NCED subset A, required physically (spatially) matching the GCED polygons with those present in the NCED for our study counties. To do so, a team of three coders visually inspected each GCED polygon to determine if there was an apparent match in the NCED, validating by acreage calculations in GIS. Our data matching criteria included whether there was a similarly sized polygon in proximity to the expected location based upon the size and location of the GCED polygon, and any attributional data match (i.e., year CE added and CE holder information, if available). We coded each GCED CE into one of three discrete categories with respect to the geometry matching to address the multiplicity issue: a GCED CE had *one* unique match in NCED subset A; a GCED CE had *no match* in NCED subset A; or a GCED CE matched with *more than one* CE in NCED subset A (i.e., the NCED had multiple polygons per one GCED polygon, which we labelled a *one to two* match). The resulting matching polygons from the NCED formed NCED subset A.

NCED subset B consisted of NCED subset A narrowed further to include only NCED CEs that contained attribute data on the year the CE was established. The final NCED subset included all NCED CEs for the GCED counties (NCED subset C). The GCED timeframe (1997–2008/2009) constrains NCED subsets A and B, while the NCED subset C contains CEs in each county from all years, given the inability to select the NCED data by year CE established since that attribute was consistently absent. Please see Supplementary Information Fig 4: Relationship of NCED subsets to visually convey our clipping approach (SIF 4).

It is important to note that the multiplicity issue when comparing GCED to NCED subset A also exists when comparing NCED subset A to the GCED; the NCED subset A CEs have *one* unique match in the GCED, *no match* in the GCED, or a *one-to-two* match in the GCED. This problem highlights the comparability challenge (i.e., apples to oranges, rather than apples to apples). Additionally, the datasets treat amendments to their CEs differently. Understanding that some of the GCED CEs were amended during our study period, in the analysis approaches described below, we evaluated all CEs that were either materially amended or added between 1997 and 2008/2009, depending on the county, selecting by our variable "YearCEEnd" as greater than 2009. This variable indicates the year that a CE terminates and/or is replaced by an amendment if that event occurred during the 1997–2008/2009 timeframe; a CE continues to exist as it was originally placed (no amendments) if the variable is greater than 2009. This selection approach would capture all CEs but not double count amendments on the GCED side.

To start our analysis using NCED subset A, we created a table of NCED attribute characteristics presence or absence by year of its existence as a datapoint in the NCED (2009–2020) per the elements of their coding schema that were relevant to the studies, assessing whether there were any omissions per the caveats on the PAD-US website (as well as the new NCED website) and our communications with the NCED administrators (SIF 5).

Next, we compared the relevant attribute content between the two kinds of datasets, matching the GCED and the NCED subsets A and C using geometry (i.e., the polygons) and comparing the count, size/acreage, CE holder, and first CE reason in two ways. With the multiplicity issue, we could conduct our counts in two ways: (1) count an NCED CE once for every time it matches a CE in the GCED, which means that if the same NCED CE matches with more than one GCED CE, that NCED CE is counted twice; and (2) only count an NCED CE once, even if it has more than one GCED match. For the analysis by CE holder type across the two datasets, we opted to count each attribute in the interest of maintaining relevant information. So if a GCED had two matches in the NCED subset A and those matches had the same holder type, it was counted once. If a GCED CE had two matches in the NCED and those matches had different holder types, each holder type was counted. The same principle was applied to the NCED when assessing matches in the GCED. This means that the CE holder type attribute results are higher than the total count of CEs in each dataset (GCED and NCED subset A) because they have more than one match in the other dataset but we do not lose any information. We conducted our analyses erring on the side of counting any time that we had a match, and regardless of whether the NCED subset A CEs had an establishment date.

We additionally visually compared the spatial geometry to assess the kinds of historic information being recorded in the NCED subset A versus the GCED, which might explain the differences in count (see Fig. 1). We compared the GCED CE holders and NCED CE holders by their respective typologies, using a combination of the NCED subset A and subset C. SIF 2 lists all of the analyses, the associated dataset(s), and the purpose(s) for the chosen approach(es).

We conducted univariate statistics for the GCED and the NCED subset A based on CE counts in our timeframe, by the total count over all of the years. We did the same for the CE size in acreage, and then used Welch's t-test with unequal variances between the CE acreage in the GCED and the NCED subset A. We also used NCED subset B to show the count of CEs added annually during our study period (SIF 6). To compare the volume of spatial distribution similarities, we used the Jaccard similarity coefficient (aka Jaccard index), which measures spatial overlap in the NCED subset and the GCED. As a measure of similarity, its "similarity coefficient" ranges from 0 (no

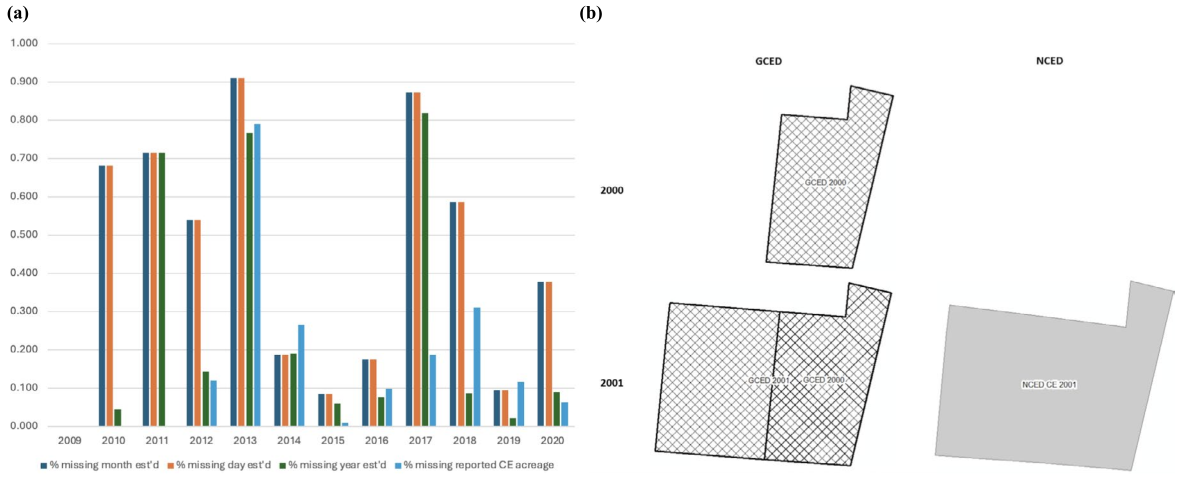

Fig. 1 Temporal and Spatial Illustration of NCED Data Loss. Fig 1(**a**) shows the yearly percentage of CEs from 2009 to 2020 that are missing the CE establishment month, day, and year data, and the reported CE acreage data, each of which are required NCED elements. Fig 1(**b**) shows the spatial manifestation of missing polygon data in the NCED

spatial similarity) to 1 (greatest spatial similarity). We converted vectors to rasters, set rasters at high resolution (10 m square) and used the Albers projection in GIS. We summed the area for all polygons in each county for the CE layers of each dataset, and then used the Intersect followed by the Union tools in GIS. We divided the Intersect results with the Union results to generate the Jaccard similarity coefficient, and then we measured the dissimilarity of the datasets by the Jaccard distance, which is 1 minus the Jaccard similarity coefficient. There is no rule of thumb for the amount of error in similarity of digitization in GIS, which is a shortcoming of this approach.

Third, we tested three analyses on each dataset to observe whether there was a trend in results' similarity or difference, determining whether outcomes differed based on the fine-scale versus the national-scale datasets. We ran three kinds of spatial statistics, Ripley's K function and Average Nearest Neighbor (ANN) on CE centroids and Global Moran's I on CE sizes, to assess CE clustering, using the last year (2008 or 2009) of each dataset (Self et al. 2023; Dyckman et al. 2024). These are global spatial statistical tests that analyze whether CEs cluster generally (Ripley's K), whether they cluster based on distance from feature to feature (ANN), and whether knowing the size of a CE provides information on the likelihood of nearby CEs being large or small (Global Moran's I). We estimated the null distribution of the Ripley's K function with 99 Monte Carlo permutations and used inverse distance weights for the Global Moran's I tests. We calculated the ANN using the distance between the CE centroids with the size of the study area equal to the convex hull of the centroids. We chose these tests because they are commonly used spatial statistical metrics, with Ripley's K as the standard approach for point data, Global Moran's I as the most widely used to examine relationships in aerial and point data, and ANN as a landscape ecology approach to test patch isolation or proximity on a landscape. Global Moran's I was the most frequent spatial hypothesis test (7.3%, 3 of 42 studies) in our literature review of the studies that employed NCED data in spatial analysis, followed by ANN and FRAGSTATS (edge contrast summed at class and landscape level; patch (core area) statistics from landscape metrics) (both 4.8%, 2 of 42 studies). We did not engage in a comprehensive comparison of spatial statistical test outcomes, which is a future line of inquiry. Instead, we used them to illustrate the potential outcome differentiation with the use of broad versus fine scale datasets.

Methodological limitations

In the dataset comparisons, the GCED documents amendments to the CEs during its timeframe, since our CE coding indicated whether something materially changed in an attribute (e.g., CE size, CE holder, border adjustment, reason addition, etc.) that required a legal amendment. We could not determine the same in the NCED, as was acknowledged in our communication with the NCED administrators (Personal communication with authors 2019). We also do not have an explanation for the NCED's missing data (i.e., CE year established and reported acreage (SIF 5)). It is possible that these missing data were added later in a subsequent update to the NCED. A CE could also be aggregated and attributed to a different year; the NCED combines CEs into one or two instruments, while the GCED acknowledges the difference between material amendments (Fig. 1). We cannot comparatively assess the plausibility of these explanations, so we used the spatial geometry matching instead, which may create a bias toward greater count in the NCED subset.

Results and discussion

Reliance on the NCED

Our systematic literature review to find studies that used the NCED and/or PAD-US (with NCED as a component) revealed 64 articles published between 2007 and 2022 (SIF 3). Of those that matched our search terms, 42 used the NCED in some form in their studies, and most were published in the 2019–2021 range. The predominant aspects of the NCED data that they employed include: spatial relationships such as overlapping area analysis (66.7%), protected areas/CE area calculation through geospatial analysis of polygons (83.3%), and distance based analysis (edge to edge/feature)(31%); spatial hypothesis tests such as Global Moran's I (7.1%) and FRAGSTATS (edge contrast summed at class and landscape level; patch (core area) statistics from landscape metrics) and ANN (both 4.8%); GAP protection/management status (31%); and the CE holder typology (31%) (Table 1). The number of studies using the CE purpose was higher than the use of spatial hypothesis tests but low compared to the spatial relationships (only 19%, or 8 of 42), followed by the CE date added and public access (both 7.1%, or 3 of 42), as well as and the CE permanence (4.8%, or 2 of 42). This suggests that of the studies using the NCED during this time period, the majority focused on the CEs' spatial characteristics rather than the CE attributes. In the spatial analysis coding, we documented other kinds of analyses that may have a spatial component (e.g., spatial econometrics, a spatial variable derived from a polygon overlay as an input in a linear regression, etc.). But we coded conservatively, focusing solely on overt spatial testing of relationships and hypotheses.

Geographically, studies were predominantly national (co-terminus or a particular feature), rather than localized (state, regional, etc.). Despite the PAD-US completeness caveats, 57.1% both failed to acknowledge the NCED shortcomings and didn't rectify them through other data sources (i.e., recorder's office searches). Nevertheless, some generalized from their findings without this critical caveat. Only 9.5% of the studies acknowledged *and* rectified, while 33.3% noted the incompleteness. When further parsed to the 40 NCED studies that use *spatial analyses*, and within those, by study geographic coverage areas and analysis typologies such as connectivity, spatial hypothesis tests and spatial relationships, the regional studies had the greatest (62.5%) absence of shortcoming acknowledgement, followed closely by state studies (57.1%) (Fig. 2). None of the regional studies acknowledged *and* rectified. The spatial relationships, which rely on accuracy in the polygon shapes for overlapping analyses and protected area/CE calculation, had the highest absence of shortcoming acknowledgement in state-based studies (57.1% in both), followed closely by regional studies (37.5%). Spatial hypothesis tests such as ANN are also sensitive to area; the 2 studies using ANN were national in scale and did not mention the NCED shortcomings. Spatial and temporal data omissions and lack of mitigation will have an impact on the validity of any analysis, with the potential to skew and/or bias outcomes. But the effect may be more profound/stark in spatial relationships at finer scales (regional and state) than at the broader national scale, which could mask regional discrepancies through aggregation.

Spatial and content comparison

NCED attribute completeness

Our assessment confirmed the absence of information in the NCED, per the known shortcomings and caveats on the PAD-US website and the NCED

Table 1 Attributes of the 42 Studies Using the NCED

Aspects of NCED Evaluated (not mutually exclusive) (Percentage unless otherwise indicated)			Study geographic coverage (percentage)		Attempts to mitigate NCED shortcomings? (percentage)		Year article published (percentage)	
Spatial relationships	Data overlay	23.8	National (co-terminus	35.7	Yes, acknowledged and attempt to rectify	9.5	2014	4.8
	Distance Based Analysis (edge to edge/feature)	31.0	National (particular feature)	28.6	No, but acknowledged incompleteness	33.3	2015	11.9
	CE polygon raster grid conversion to point data	4.8	Regional (multiple states)	11.9	No mention	57.1	2016	9.5
	Overlapping Percentage/Area	66.7	State	16.7			2017	7.1
	CE Unit Count	21.4	Regional (within state)	7.1			2018	7.1
	Protected area/CE area calculation using geospatial analysis of polygons	83.3					2019	23.8
Spatial hypothesis tests	Global Moran's I	7.1					2020	23.8
	Hierarchical cluster analysis with fastcluster in R	0.0					2021	11.9
	Kernal density analysis	0.0						
	FRAGSTATS (edge contrast; patch (core area) statistics)	4.8						
	Ripley's K	0.0						
	Getis Ord General G	2.4						
	Average Nearest Neighbor	4.8						
Connectivity analyses	Connectivity modeling	4.8						
	Regional-scale connectivity models	2.4						
	Connectivity indices based on network theory	2.4						
Other kinds of tests and analyses	61 types, 80 uses	NA						
CE purpose		19.0						
CE holder typology		31.0						
GAP (protection/management) status		31.0						
Landowner type (landownership, CE and PAD-US)		23.8						
CE date/year added		7.1						
CE permanence		4.8						
Public access		7.1						

website. The subset of the NCED that matched our counties (NCED subset C) was missing critical and required attributes of relevance to the GCED. These included the year that the CE was established and the reported size of the CE (SIF 5). And yet, 83.3% of the 42 studies using the NCED involved analyses

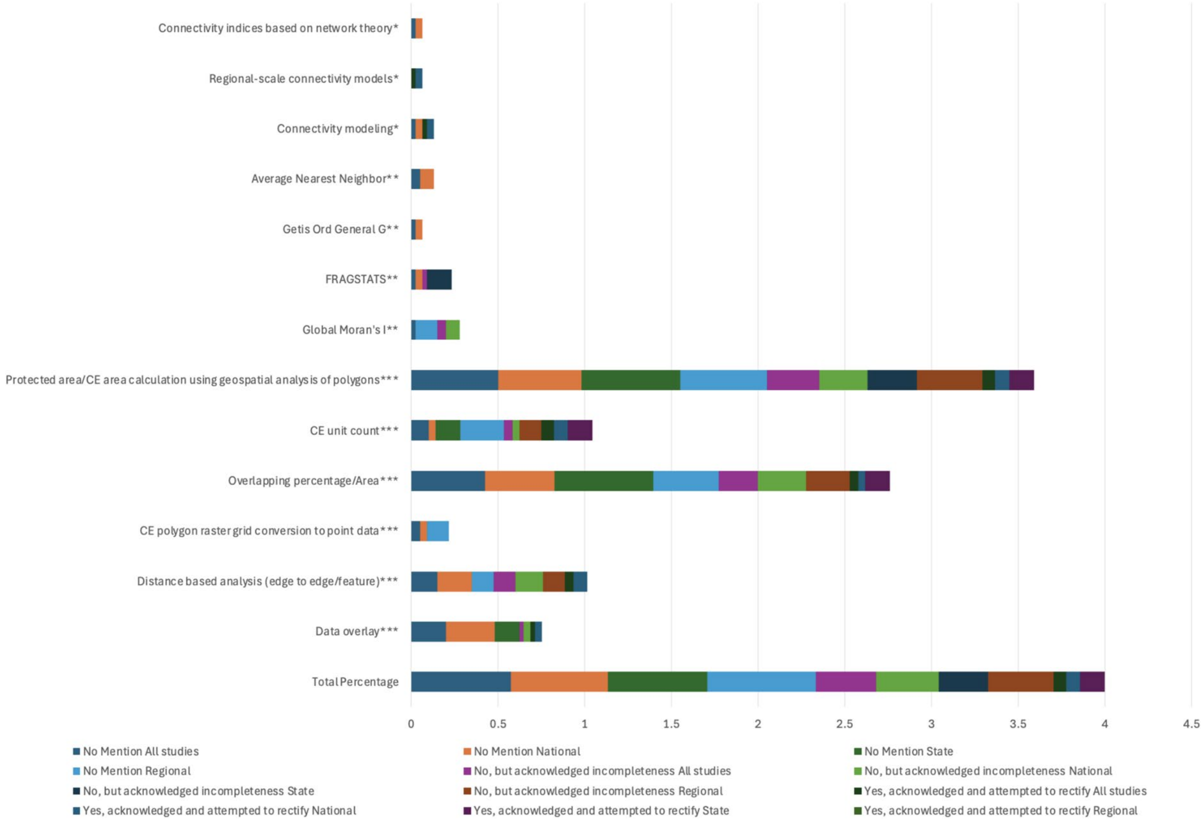

Fig. 2 Efforts to Mitigate NCED Shortcomings by Analysis Typology and Study Geographic Coverage in the 40 NCED Studies that used Spatial Analysis (Percent of spatial analysis studies within each geographic coverage that either acknowledged and mitigated, acknowledged but did not mitigate, or did not mention the NCED shortcomings). *Indicates Connectivity Analyses. **Indicates Spatial Hypothesis Tests. ***Indicates Spatial Relationships. Total counts for each geography: national = 25 studies; regional = 8 studies; state = 7 studies

with the protected area/CE area calculation (Table 1) and 48% of the 40 spatial NCED studies with national geographies that measured protected area/CE area did not mention the shortcomings (Fig. 2). NCED attribute completeness did not increase over time; rather, there are some spikes of greater absence in the CE size and year established variables in 2013–2014, and again in 2017 (SIF 5). Otherwise, these attributes are consistently absent each year from 2010 through 2020, with the following percentages of missing information in the NCED CEs added by year: CE year established (median: 8.83%; mean: 25.11%; standard deviation: 0.32) and reported acres (median: 10.74%; mean: 16.35%; standard deviation: 0.22). These omissions were not consistent within a year and lacked a temporal pattern, meaning that in some years, the CEs omitted the year established but included their reported acreage, while in other years, the omissions were reversed (SIF 5). Additionally, some year established information may have amended previous CEs which may or may not have included a year established when they were first reported in the NCED. So there is a risk of omission if year established is a variable in an analysis model.

Content comparison

The attribute categories between the GCED and the NCED are generally similar, assessing comparable topics. The GCED has more CE purpose subcategories with greater specificity than those in the NCED, while the NCED has information categorizing the level of use intensity through GAP status and the IUCN categories. Both have an assessment of CE permanence and of public accessibility with virtually the same subcategories. Although the count is the same (10 subcategories), the CE holder typology subcategories considerably diverge from one another, with similarity in only half (i.e., state, federal, joint, special district, and unknown) (SIF 7).

We compared the CE holder typology of the CEs mutually present in the GCED and NCED subset A based on the GCED subcategories, and then the NCED subcategories (Table 2). In most counties, the prevalent CE holder type was the same within the GCED subcategories or within the NCED subcategories but differed by counts. Within the GCED subcategories, there is a slight difference in two counties: Loudoun (county holder dominance in the GCED and LT dominance in the NCED), and Washington (city holder dominance in the GCED and state dominance in the NCED). Within the NCED subcategories, all CE holder predominance matched across the GCED and NCED subset A. Across the GCED and NCED subcategories, many counties matched CE holder types despite terminological differences; however, four counties (Lebanon, Loudoun, Washington and York) displayed disparity (Table 2). Despite the fact the NCED says that it has 90% of the CEs held by LTs and nonprofits, we found that the GCED CEs matched the NCED subset A CEs more often when the holders were governmental (e.g., state, county, city, etc.). The counties with a predominance of land trust CE holders had much lower matches between the GCED and the NCED, ranging from 28% to 88% (Table 2).

Acreage, count and spatial comparison

When comparatively evaluating the median CE size within the logged area of purpose categories that are consolidated into the same subcategories (SIF 7), there is more differentiation between the GCED and the NCED subset A (Fig. 3). There are mutually exclusive subcategories in the GCED, which includes agricultural viability/livestock, open space/scenic, recreation/education, and unknown that are absent in the NCED. Where the subcategories overlap (habitat/species protection, historic preservation, and other), the NCED consistently has higher median values of logged area by purpose, although the range is lower than in the GCED (Fig. 3).

CE acreage comparison using the CEs mutually present in the GCED and the NCED subset A shows discrepancy (Table 3). There is variability by county, with higher GCED acreage in seven counties and lower GCED acreage in five counties (Table 3). The GCED has a substantial volume of acreage that is not present in NCED subset A, ranging from 80.56 acres in York to 32,272.81 acres in Greenville. Albemarle is the only county in which the GCED does not have acreage that is absent in NCED subset A. Accordingly, it seemed unlikely that the two datasets would have equal variances in the acreage of their CEs. Welch's t-test results to check for equality in the mean CE acreage across the two datasets show that for all counties except Loudoun, we fail to reject the null hypothesis. Thus, while the total CE acreage differs considerably between the two datasets in most counties, the average CE sizes are similar in all counties except Loudoun (Table 3).

And yet, the overall count of CEs by county in both NCED subsets (C and A) and the GCED do not match. The GCED and NCED subset A are closer in count than NCED subset C, but the GCED count exceeds subset A in the majority of counties (seven) (Table 2). The NCED subset C counts are higher than either the GCED or the NCED subset A in ten of the twelve counties, while the GCED is higher than both NCED subsets in the other two counties (Table 2). On average, NCED subset A was missing 32% of the GCED CES, with a low of 0% missing (Albemarle) to a high of 96% missing (Washington) (Table 2). There were seven counties with greater than 75% of the GCED present in NCED subset A (Table 2). We also found that the NCED contained duplicate polygons of the same CE, inflating its count. Additionally, every county except Greenville and Washington had GCED CEs with more than one match in the NCED, ranging from a single one-to-two match in Sacramento to 52 in Boulder.

When comparing the GCED CE counts with the NCED subset that has a year of CE establishment over time (NCED subset B), as would occur in any analyses that involve a temporal element, nine counties have a consistent and considerably higher count in any year compared with the NCED subset B (SIF 6).

GCED CE counts in three counties, Douglas, Lebanon, and Albemarle, are consistently almost comparable but just slightly higher over time than

Table 2 Relationship Between GCED and NCED subsets for Snapshot Year 2009 in Twelve Counties in the US

County	Total NCED subset C CE Count	Total NCED subset A CE Count	Total GCED CE Count	No. of GCED CEs Present in NCED subset A	Percent of GCED Present in NCED subset A	No. of GCED CEs Not Present in NCED subset A	No. of GCED CEs with One Match in NCED subset A	No. of GCED CEs with Two Matches in NCED subset A**	No. of instances where NCED subset A is missing information on original CE or amendment	GCED Dominant CE Holder by GCED Holder Typology (GCED CE count)	NCED Dominant CE Holder by GCED Holder Typology (NCED CE count in NCED subset A)***	GCED Dominant CE Holder by NCED Holder Typology (GCED CE count in NCED subset A)***	NCED Dominant CE Holder by NCED Holder Typology (NCED CE count in NCED subset A)
Albemarle*	562	349	343	343	100%	0	326	17	31	State (219)	State (213)	State (249)	State (222)
Boulder*	779	346	495	384	78%	111	332	52	60	County (331)	County (237)	LG (414)	LG(288)
Charleston	101	64	181	60	33%	121	53	7	8	LT (161)	LT (57)	NGO (64)	NGO (62)
Douglas*	330	69	64	63	98%	1	50	13	4	State (43)	State (40)	State (40)	State (44)
Greenville	39	24	99	28	28%	71	28	0	6	LT (54)	LT (24)	NGO (31)	NGO (24)
Lebanon*	205	108	107	101	94%	6	90	11	5	State (45)	State (42)	LG (84)	LG (86)
Loudoun	445	209	432	196	45%	236	183	13	12	County (219)	LT (89)	State (106)	State (99)
Mesa*	339	168	145	128	88%	17	84	44	19	LT (135)	LT (134)	NGO (147)	NGO (156)
Sacramento	102	38	65	38	58%	27	37	1	5	LT (27)	LT (23)	NGO (32)	NGO (30)
Sonoma*	388	120	124	115	93%	9	109	6	2	County (90)	County (87)	RA (90)	RA (93)
Washington	276	9	242	10	4%	232	10	0	3	City (172)	State (4)	LG (8)	LG (6)
York*	544	304	290	273	94%	17	237	36	9	State (132)	State (131)	LG (204)	LG (222)

Unless otherwise noted, datasets for analysis are the GCED for each county and the NCED matching spatialgeometryoftheGCED(NCEDsubset A) or all CEs in the NCED for the GCED counties (NCED subset C), to assess counts and matches. *LG* Local Government, *LT* Land Trust, *RA* Regional Agency, and *NGO* Nongovernmental Organization

*Indicates greater than 75% GCED present in NCED subset A

**GCED CEs with multiple NCED subset A matches were only counted once

***For these counts, if an NCED CE had two GCED matches and those GCED matches had the same holder type, it is counted once. If an NCED CE has two GCED matches and they have two differ holder types, each holder type is counted. The same principle applies to the GCED CEs when comparing the holder types in the NCED

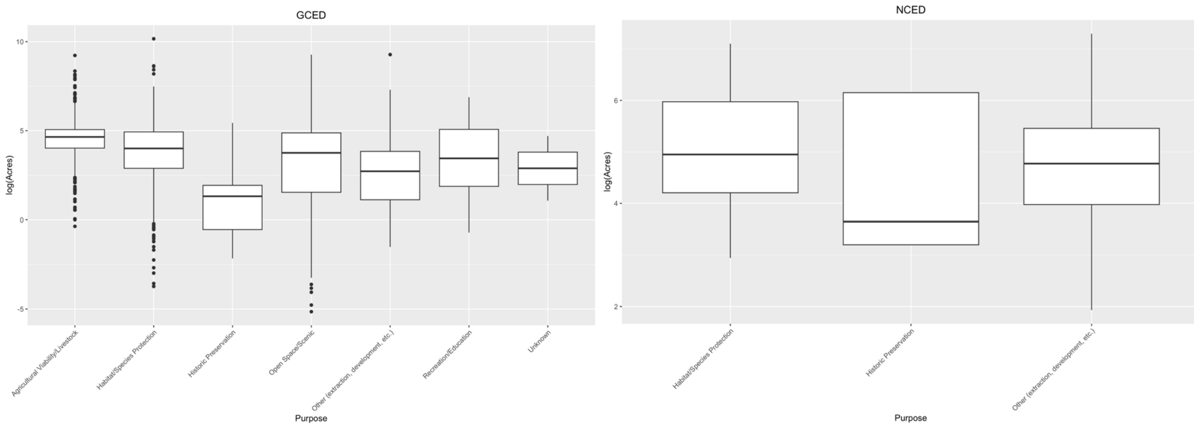

Fig. 3 Comparison of GCED and NCED Logged CE Area by First CE Purpose, using GCED for each county and the NCED subset A. For the GCED purposes, when a CE was amended (which would be the first CE purpose in the dataset), we used the second CE purpose that was substantive, not just an amendment

the NCED, while Mesa starts out higher but ends up lower in count than the NCED by the end of 2008 (SIF 6).

Beyond count, CE spatial configurations diverged between the GCED and the NCED subset A. For example, even with the matching CE count in Albemarle, there is an acreage discrepancy (69,652.41 in the GCED, 71,783.96 calculated in NCED subset A (Table 3)). The visual check of the spatial layers showed that the geometry differed between the two, illustrating both the issue with the total count incongruity and the physical differences. As Fig. 1 demonstrates, the NCED appears to overwrite the original CE data instead of maintaining a record of legal amendments to the CEs. In doing so, the NCED erases the record of the original polygon and attributes that would correspond to the original CE legal instrument, creating a one-to-many relationship between CE legal documents and CE geometry in the NCED, even if the CE geometry was materially changed through the amendment. In contrast, the GCED has a one-to-one relationship between the CE legal document and its geometry, differentiating the CE instruments by amendment and showing when and how a CE was placed and what it covered, both spatially (via different polygons) and conceptually (e.g., purposes, access, etc.). Figure 1 illustrates how the NCED does not differentiate the two CEs added in 2000 and 2001, respectively, in the GCED, treating them as the same instrument and polygon added in 2001. The number of instances where the NCED is missing information on a CE or its amendment ranges from 2 in Sonoma to 60 in Boulder (Table 2).

To further understand the extent of spatial configuration difference, the Jaccard similarity coefficient results for NCED subset A ranged from 0.05 (Greenville) to 0.94 (York) on a scale of 0 (no spatial similarity) to 1 (greatest spatial similarity) (SIF 8). Four counties had a Jaccard similarity coefficient score lower than 0.50. Curiously, Douglas had greater than 75% of the GCED CEs present in NCED subset A but its similarity score was lower than 50%. For the six other counties in which greater than 75% of the GCED CEs were present in the NCED, their Jaccard similarity coefficient scores were all between 0.63–0.94 (i.e., Albemarle, Boulder, Lebanon, Mesa, Sonoma and York).

Analysis outcome differentiation

With the spatial analysis predominance in the studies using the NCED, we tested whether the differences in the datasets would manifest in analysis outcomes, depending on the choice of spatial statistical test. In all counties except Washington, the Ripley's K results showed significant CE clustering in both datasets, meaning that the CEs are generally clustering in each dataset. Washington's NCED Ripley's K results demonstrated insignificant dispersion at close distances and insignificant clustering at larger distances, likely attributed to the low CE count in

Table 3 Comparison of CE Acreage in the GCED and the NCED subset A

County	GCED baseline acreage 1997–2008/2009	NCED subset A acreage**	acreage of GCED CEs not present in NCED	acreage of GCED CEs with one match in NCED	acreage of GCED CEs with two matches in NCED***	Welch's t-test (no assumption of equal variances in acreage)							
						t statistic	degrees of freedom	p value (two-tail)	95% confidence interval (1)	95% confidence interval (2)	st'd error	mean of GCED	mean of NCED
Albemarle	69,652.41	71,783.96	0.00	65,409.78	4,242.62	− 0.14	689.34	0.89	− 41.01	35.18	18.96	203.07	205.68
Boulder	33,169.99	24,211.57	6,135.77	22,037.05	4,997.17	− 0.22	789.66	0.83	− 24.03	29.61	13.54	67.01	69.98
Charleston	33,883.33	18,516.09	19,159.42	11,937.54	2,786.38	− 1.05	70.07	0.30	− 301.07	91.50	96.95	187.20	289.31
Douglas	3,855.62	6,349.27	188.43	2,696.10	971.09	− 1.10	76.36	0.28	− 16.88	22.20	29.01	60.24	92.02
Greenville	34,311.37	2,027.19	32,272.81	2,038.56	0.00	1.00	99.17	0.32	− 286.18	758.74	262.83	346.58	84.47
Lebanon	12,056.46	12,169.87	533.63	10,206.63	1,316.20	0.00	212.38	1.00	− 19.32	12.71	7.99	112.68	112.68
Loudoun*	42,384.03	25,909.60	17,920.47	22,038.01	2,425.55	− 1.93	371.06	0.05	− 53.87	− 0.67	13.41	98.11	123.97
Mesa	61,370.63	53,291.90	2,941.46	30,771.77	27,657.39	1.01	244.36	0.31	− 70.79	340.72	105.25	423.25	317.21
Sacramento	24,052.07	16,555.02	5,576.83	18,166.73	308.52	− 0.33	74.78	0.74	− 516.52	339.51	198.93	370.03	435.66
Sonoma	58,408.67	65,244.49	738.98	54,857.77	2,811.91	− 0.32	215.84	0.75	− 862.51	500.58	226.98	471.04	543.70
Washington	3,669.12	339.08	3,309.66	359.46	0.00	− 1.87	8.39	0.10	− 50.12	5.10	12.07	15.16	37.68
York	34,405.94	36,475.77	80.56	27,205.43	7,119.95	− 0.15	579.32	0.88	− 35.81	2.61	9.14	118.64	119.99

Datasets for analysis are the GCED and the NCED matching spatial geometry of the GCED, including NCED CEs that lack establishment dates (NCED subset A)

*Indicates that the means of the populations' acreages are significantly different in the Welch's t-test

**These results count each NCED subset A CE once, even if it has multiple GCED matches, and it uses the NCED team's calculations of acreage as noted in the NCED

***These results use the GCED acreage calculated by the GCED team; if a GCED CE has more than one NCED subset A match, it is still only counted once the Washington NCED subset A. We did not display these findings, given the lack of differentiation. However, there were important differences in the Global Moran's I results (Fig. 4). Four counties showed a different outcome—whether significantly positive clustering or insignificant clustering—when using the GCED versus the NCED subset A. Eight counties manifested the same results across both datasets. The Global Moran's I results relate to the size of the CE and the likelihood of proximity to other similarly or differently (large or small) sized CEs; these results would be impacted if a CE were analyzed as one large CE versus two smaller CEs per Fig. 1. Two counties showed a different significance outcome in the ANN results.

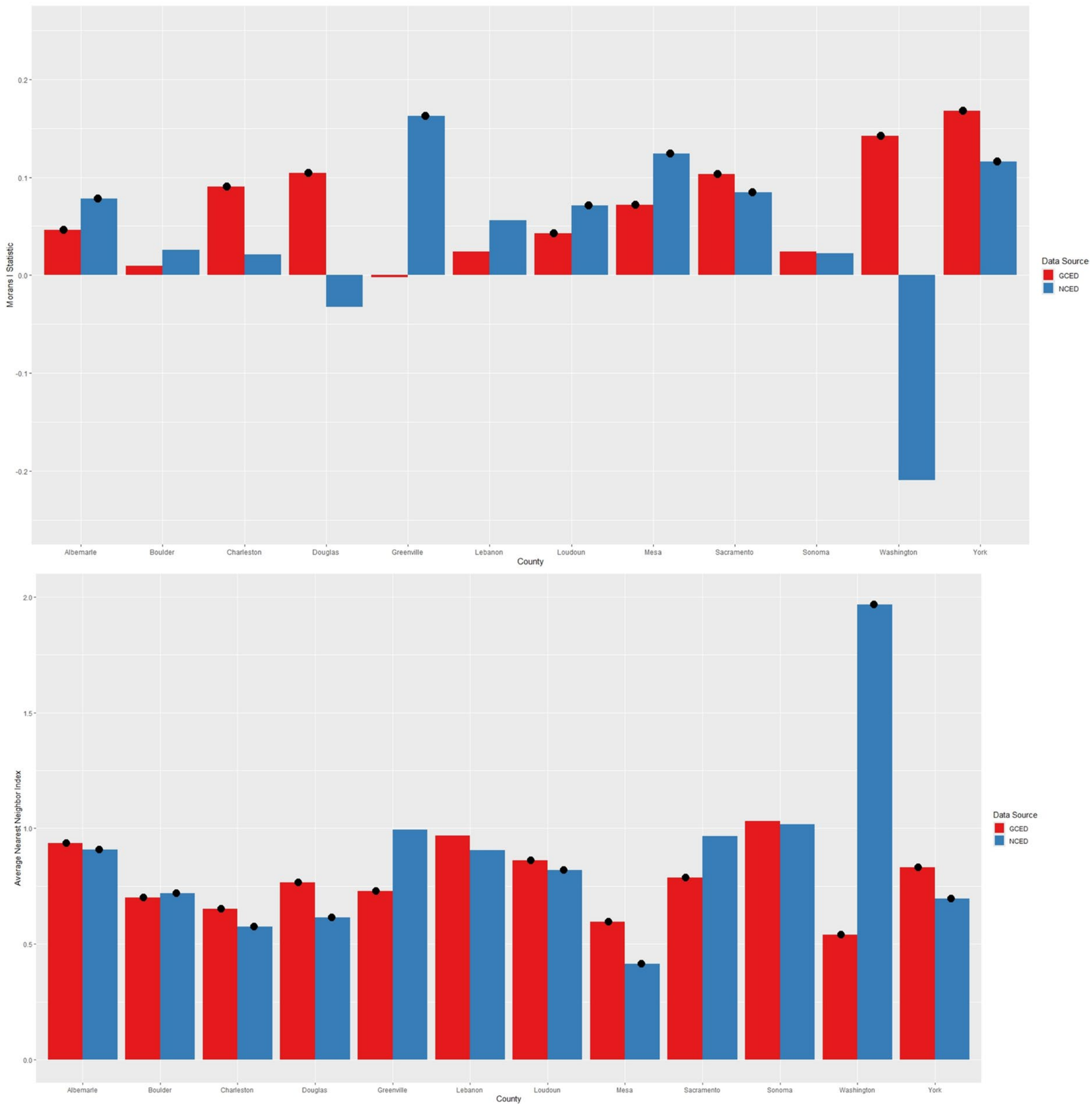

Fig. 4 NCED subset A versus GCED Global Moran's I and ANN Results by County. The Washington result may differ from the broader trend because of the low CE count (10) in the Washington NCED subset A. ● = p-value < 0.05, significant clustering

Conclusions

The combination of our qualitative and quantitative analyses revealed previously unidentified limitations and qualifications that should be considered in studies using the NCED and can be attributed, in part, to the NCED's acknowledged limitations. Other scholars have noted the NCED's recognized issues and corrected through occupancy models (Williamson et al. 2021) and local data supplementation (Graves et al. 2019). But our work reveals greater detail about the kinds of disparity in these data, including the absence of historical information related to CE amendments, and the ensuing implications with the ability to longitudinally analyze and determine accurate CE size, count, and outcomes of spatial statistical analyses related to CE size. It is apparent that there is disparity in NCED completeness both geographically and categorically over time. Regardless of NCED subset (whether matching by spatial geometry, subset A, or the more constrained version with the year of CE establishment, subset B), some counties' GCED CEs are almost entirely the same over time, some diverge consistently from the NCED, and the NCED has a "catch-up" with other counties, which matches the NCED curators' protocol (Personal communication with authors 2019). Our results reveal the issue of missing data, generally, with considerable variation depending on the county. Albemarle showed complete similarity in count across the two datasets (i.e., everything in the GCED showed up in the NCED subset A). But even with count comparability, these datasets did not perfectly match in acreage and associated population variances, in content (spatial, purpose, year established, etc.), and in similarity measured through the Jaccard indices. The typology of missing data is critical for the kinds of analyses documented in the literature; important and required attributes such as CE size and year established were missing in most years of the NCED subsets. Also, some of our GCED CEs appeared more than once in the NCED, begging the question of how something could be repeatedly present. As we demonstrated, the GCED CEs are more differentiated by material amendment (Fig. 1), which is a possible but not definitive explanation, and impacts the accuracy of CE count and acreage for spatial analysis.

Accordingly, we are concerned about complete generalizability from the available NCED data, as well as the tradeoff that occurs between broad-scale geographic coverage and fine-scale accuracy, as well as longitudinal analysis competence. If engaging in pre- and post-longitudinal policy analysis using the NCED, the omission of month, day and especially year established would generate unreliable outcomes. And this may be exacerbated by the particular geography/study area (e.g., Albemarle versus Washington, Table 2). Particularly, we sought to reveal and create awareness of potential issues in employing the NCED for fine scale analyses—and in the curation of researchers' datasets (e.g., the GCED). GCED construction time was considerable, onerous, and extremely expensive. But it provides as complete a CE population as possible within the study time period and the constraints of the county recorders' systems (Morris and Rissman 2009; Rissman et al. 2017; Overby et al. 2022).

Scale will matter for analysis outcomes. If engaging in a national-scale assessment, the NCED offers more coverage per time value than attempting to create individual datasets and may smooth any local biases. But if seeking accurate representation of the CEs over time in a more localized region, there is a need to either expend the energy to construct datasets similar to the GCED, or to augment the NCED, per Graves et al. (2019), Karieva et al. (2021), and Williamson et al. (2021). To generalize at a local scale from the NCED runs the risk of type I or II errors in statistical analysis. If CEs are missing completely at random, the reduced sample size diminishes the power of statistical tests, increasing the probability of type II errors. Systematic missingness can either create the appearance of spatial patterns resulting in type I errors or mask the existence of spatial patterns, resulting in type II errors. Consequently, it is impossible to determine if spatial tests using the NCED are overly conservative (i.e., prone to type II errors) or overly liberal (i.e., prone to type I errors), and there is likely a mix of the two phenomena. This combination of errors, different levels of voluntary data contributions by geographic location/entity (Table 2), the lack of verification other than researchers' own augmentation if/when they acknowledge omissions that affect the analysis outcomes depending on the research scale (Fig. 2), and the internal inconsistency within and by year in the types of data omissions (year established, reported acreage, etc.)(Fig. 1, SIF 5) converge on an inability to prescribe when, with what, and where researchers can have confidence in analysis outcomes using NCED data.

The NCED omission bias has the potential for differential outcomes depending on the academic and/or professional discipline using it. From a legal standpoint, the treatment of two adjacent CEs with different purposes and establishment dates (Fig. 1) as a single CE could obfuscate important attributes across the landscape. From a conservation biology perspective, treating two CEs as one even if they have different purposes could impact conservation efforts with an overestimation of landscape value, as the size and shape of conserved lands contribute to their conservation value (Chase et al. 2020; Williamson et al. 2021). Spatial analysis results could be skewed where size or CE centroids are used for spatial statistical tests. Testing policy effects through the NCED would be flawed, given the lack of longitudinal accuracy and the data updating process.

One must be a discerning dataset consumer, understanding their limitations and either correcting for or acknowledging their flaws. Analysis intent is impacted by reliance on incomplete data, and there is no geographic guidance in completeness of the NCED by region. Some problems are intractable (e.g., human error in recording, etc.), but our comparative work illustrates the consequences of the publicly acknowledged NCED limitations and reveals unacknowledged but equally critical issues that should inform future scholarship. This research corroborates previous work highlighting the need for an increased focus on generating more complete CE datasets, given their importance for land conversion and climate change (Morris and Rissman 2009; Olmsted 2011; Rissman et al. 2017; Overby et al. 2022; Dyckman et al. 2024).

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Author Contributions CD: wrote the manuscript. All authors conceptualized the analyses and comparative approaches. AO, CD, NF and SO: constructed the datasets. DW, SS, SO, AO, and CD: conducted analyses. All authors read, edited, revised, and approved the final manuscript.

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Data Availability These data will initially be made accessible, where county agreements do not preclude sharing, via a request to the authors. Within a year from publication, the datasets will be made available through a portal at Clemson University.

Declarations

Competing interests and Disclaimer The authors declare no competing interests. The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or US Government determination or policy.

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