Authors would like to recognize the thoughtful comments provided by the Reviewer which led to several important changes in our approach. We clarified the goals of this study, we focused on tower infrastructure currently measuring CH_4, and we better explained how we are measuring representativeness.

Reviewer 1:

This study aims to present a representative assessment of network infrastructure for improving our understanding of methane emissions across the US. I respectfully believe that the authors do not present the appropriate analysis for clearly addressing this goal. The authors present a relatively simple way to generate (ecological) clusters and then they list how many sites are in these clusters and evaluate their distance from the medoids. Arguably, the clusters were produced with variables that are relevant for any ecological process and they are not specifically designed to represent drivers of CH4 fluxes (as claimed by the authors). Representativeness is assessed based on the distance of the locations of the current study sites to the medoid, which is arguably a flawed approach as there are underlying assumptions that do not consider spatial heterogeneity of importance for CH4 fluxes. Finally, this study is more associated with a generic network representative analysis of AmeriFlux or GLEON and the authors present a lengthy discussion about limitations of CH4 measurements that are not directly related to the results.

Reviewer 1 highlights the need for greater detail in the approach taken to measure representativeness and our overall goal. In response to this comment we increased the level of detail in the methods section and provide here a summarized response.

The primary goal of this work is to determine key regions where we need CH_4 infrastructure within the US. We do this by identifying the gaps in active research infrastructure and evaluating where infrastructure can be adapted to include CH_4 measurements. To address this goal, we used a combination of climate data and dominant land cover types to guide the scientific community on how we can develop a distributed observing network for the US and provide a template for the development of similar networks in other regions. We focus here on EC flux towers because they are essential for a bottom-up framework that bridges the gap between point-based chamber measurements and airborne platforms and are therefore a useful basis for identifying gaps in the current network of CH_4 observations. Although we initially focused on all tower infrastructure, we now focused on the towers measuring CH_4 (n=100) and we distinguished between towers providing data to Ameriflux (yes =49, no = 51) and tower activity (active = 70; inactive = 30).

To understand the landscape representativeness across geographic clusters, we measured dissimilarity (previously called distance to the medoid) based on climate and land cover type. It is important to note that at the ecosystem scale a tower is representative of the ecosystem type and the region where it is stationed (Desai, 2010; Jung et al., 2011; Xiao et al., 2012; Chu et al., 2021); however, the landscape representativeness analysis done here uses a coarser classification of land cover classes that are more emblematic of regional disturbance regimes, resource availability, and factors that influence how ecosystems function, not the specific ecosystem type where the tower is situated. Chu et al., 2021 examined the land-cover composition and vegetation characteristics of 214 AmeriFlux tower site footprints. They found that most sites do not represent the dominant land-cover type of the landscape and when paired with common model-data integration approaches this mis-match introduces biases on the order of 4%–20% for EVI and 6%–20% for the dominant land cover percentage (Chu et al. 2021), making it essential to consider landscape characteristics in the design and evaluation of network infrastructure. Tower representativeness at the landscape scale is indicative of the capacity to upscale information by climate and the dominant ecosystems of locations within a landscape. We also calculate cluster representativeness by the towers' vegetation type to understand the sampling intensity of each vegetation type within a cluster, which is also an essential component of scaling CH_4 fluxes (Knox et al., 2019). In this analysis we used the reported International Geosphere-Biosphere Programme (IGBP) vegetation type classes that are listed for each tower in the Ameriflux data base, where we also checked to ensure towers were currently active and providing data to the network.

Main comments

I strongly recommend separating the results from the discussion section. The results are very limited, and the discussion is beyond what is presented. Separating these sections will bring transparency and clarity about what was done and how is proposed to be interpreted.

Authors agree with Reviewer 1 and have separated the results and discussion and increased the level of detail in both sections.

The authors claim that the MDA was used to define the state space into ecological clusters using information that is important for capturing patterns in CH4 (lines 208-225). That said, it is unclear how climate, ecotype and location (lat/long) are specific information relevant for CH4 and not for any other ecological process. It seems to me that this is a generic analysis and then the authors are interpreting this for CH4. I respectfully believe that there is a disconnection between this approach and the overarching goal of the study.

We made changes to the introduction and methods to clarify our objectives. The primary goal of this work is to identify the gaps in active research infrastructure by evaluating the location of ground-based research infrastructure that is and can be adapted to measure CH_4. This would provide guidance on how the research community could direct their resources to ensure the US can develop biogenic CH_4 budgets by targeting gaps in infrastructure. In addressing this goal, we used a combination of climate data and dominant land cover types along with a multidimensional cluster analysis to guide the scientific community on how we can develop a distributed observing network for the US and provide a template for the development of similar networks in other regions. Below we discuss in detail how we accomplished this goal.

Lines 236-245 – This section of the methods is unclear. Furthermore, I do not think that regions more similar to the medoid are more representative within given cluster, it may only mean that these regions are more similar to what the medoid is and have nothing to do with real representativeness. The authors assume that the medoid is more representative of the cluster but I think this is a misleading mathematical interpretation that is carried into interpretations of ecoregions and their representativeness. This issue is reflected in how the authors assess representativeness of 411 towers as they compare with their distance to the medoid under the (arguably) incorrect assumption that the closer to the medoid is better and that there is no relevant variability that is important for the representativeness of CH4 fluxes across a specific cluster.

Below we clarify what the medoid is and we adjusted how we measured tower representativeness of clusters in our work. The cluster analysis uses the k-medoids algorithm, which partitions data into k groups or clusters. Each cluster was represented by one of the data points in the cluster named the cluster medoid. The medioid has the lowest average dissimilarity between it and all other objects in the cluster. The medoid can be considered a representative example of the members of that cluster. The k-medoids algorithm requires the user to specify k, the number of clusters to be generated. A useful approach to determine the optimal number of clusters is the **silhouette** method. We fit an increasing number of clusters from 2 to 20 to construct a silhouette plot and choose the number of clusters that maximized the average silhouette width. Once we determined the number of clusters and the medoid of the cluster, we calculated the dissimilarity between every location within the cluster to the medoid to create a measure of how different each location was from the medoid condition of each cluster. We utilized the pointDistance function in the *raster* package, which provided a unit-less relative measure of dissimilarity that was determined by measuring the difference between the first and second dimensions produced by the isoMDS of each point in a cluster to the dimensions of the medioid. This analysis was repeated 10 times to ensure that the 20,000 pixel subsample would produce similar results in the dimensions and clustering. For simplicity, we show the results of the first analysis.

Climate, ecotype, and location (latitude/longitude) were used in a multivariate distance analysis to define the state space of the US (all 50 states & Puerto Rico) at the landscape scale and divide it into ecological clusters using information that is important for capturing continental patterns in biogeochemical cycles. Once we created a dissimilarity matrix, we used multidimensional scaling (MDS) to generate a two-dimensional ordination showing landscape dissimilarity with the *MASS* package in R (Venables WNRipley, 2002). The MDS makes it possible to evaluate dissimilarity in two dimensions, which is essential to our goal to evaluate representativeness. Knowing that regional patterns in climate and land cover will be important for scaling CH_4 to the regional and national scale, we divided the US into clusters to evaluate representativeness. This cluster analysis also allowed us to summarize our results within a geographical context, an approach that has been used to delineate spatial sampling domains, to assess the spatial representativeness of networks, and to suggest arrangements of study sites (Sulkava et al. 2011; Kumar et al. 2016). Once clusters were defined we utilized the pointDistance function in the *raster* package, which provided a unit-less relative measure of dissimilarity that was determined by measuring the difference between the first and second dimensions produced by the isoMDS of each point in a cluster to the dimensions of the medioid.

To understand representative of current CH_4 infrastructure, we defined clusters (Sulkava et al. 2011) and measured the dissimilarity between each location in a cluster to the medoid. We extracted the cluster and dissimilarity for all active tower sites measuring CH_4 that were distributed across the US and measured the tower cluster representativeness as the percent overlap between the range of dissimilarity sampled by the infrastructure ($r_{cluster}$) divided by the range of dissimilarity observed in the entire cluster (*r*; Eq. 1).

$$TR_{cluster} = (r_{cluster}/ r)*100 \qquad \text{Eq. 1}$$

We recognize that it is essential to capture the distribution of dissimilarity across an entire cluster to upscale ecosystem measurements. We also report the sampling intensity of the major ecosystem types within the cluster and report the ecosystem representativeness (R_{IGBP}) by the IGBP vegetation types of the towers (Eq. 2).

$$TR_{IGBP} = (r_{IGBP} / r)*100 \qquad \text{Eq. 2}$$

This approach allows the evaluation of representativeness that is not based on a specific research site, but on the dissimilarity of a location to other locations in the landscape and we use the range, which is indicative of a capacity to scale within a cluster.

Please note, previously we measure representativeness by looking at the frequency of towers and comparing the distribution of dissimilarity (distance to the medoid) of tower locations to the distribution for the entire cluster. We have updated this approach by focusing on the range in dissimilarity.

Figure 2 – Are these regressions statistically significant? I doubt that that Fig2a is significant and Fig2b needs to be tested. If there is no statistical significance, please remove the line as it is a misleading graphic.

We originally included the regression lines to show (a) the lack of trend and (b) the trend between the % coverage of clusters and the frequenquency of towers within clusters for all tower infrastructure and infrastructure measuring CH_4. We removed this figure, as we no longer include all EC towers in this analysis and just focus on active CH_4 infrastructure.

Lines 298-307- Are these 411 towers actually active? It will be important to disclaim how many are active or if this is a network analysis of historical sites. Furthermore, not all sites may be relevant or would have equal weights for our understanding of CH4 fluxes. Sites were originally installed to measured CO2 and H2O fluxes but arguably they may not be relevant for regional CH4 fluxes. This question is not addressed in this study but is critical for assessment of the representativeness of a CH4 network.

We initially included all tower infrastructure to garner widespread support for instrumenting all towers. In response to Reviewer comments we focus this analysis on the towers measuring CH_4 (n=100) only and we distinguish between towers providing data to Ameriflux (yes =49, no = 51) and tower activity (active = 70; inactive = 30). There were 70 active EC towers measuring CH_4 distributed across forest (3 towers), grasslands (4 towers), shrublands (1), agriculture (19 towers), wetland (37 towers), barren (2 towers), and aquatic (4 towers) IGBP vegetation classes. Less than half of the active towers (43%) were providing data to the community through Ameriflux, limiting the development of CH_4 derived products. For this reason, we will first focus this analysis on the active towers providing data to Ameriflux. Although CH_4 EC tower infrastructure was not a part of a single organized network designed to be representative of the climate, landscape, and dominant IGBP vegetation classes that exist within the US, EC tower infrastructure that was providing data to Ameriflux was distributed across 8 of the 10 clusters (Table 3), with clusters NW and SE without any active towers providing data to the community. Tower representativeness of clusters range from 0 to 88%. The greatest $TR_{cluster}$ was for Eb and NEa and the lowest $TR_{cluster}$ was for NW and SE which had no towers. $TR_{cluster}$ was poor (<50%) for most clusters and high coverage was not associated with a higher frequency of towers. A high $TR_{cluster}$ representativeness was found in clusters where towers were dispersed across IGBP vegetation classes and where towers in wetlands, forests, or the arctic tundra (barren) were distributed across the state space of the cluster. Most clusters were substantially under-sampled (Table 3, Figure 4c) due to an insufficient number of towers measuring CH_4 and poor distribution across the cluster.

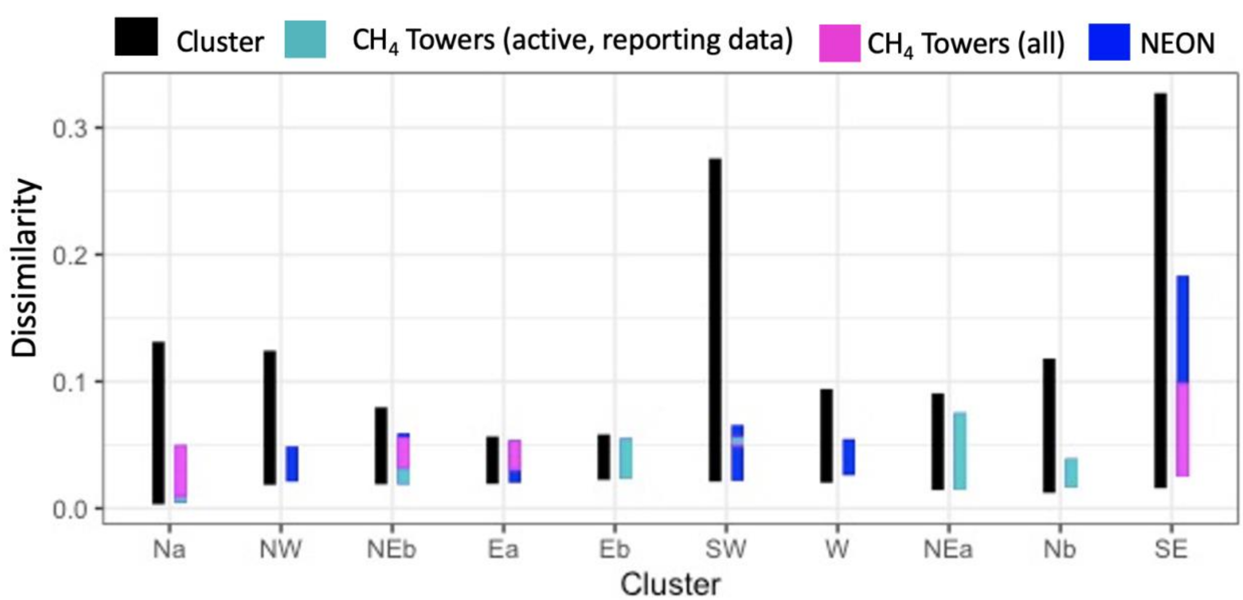

Figure 4. The range of dissimilarity for clusters, active CH_4 towers providing CH_4 data to Ameriflux, all active CH_4 towers, and for NEON towers.

Table 4. The $R_{cluster}$ for CH_4 towers that are active and providing data to Ameriflux, the $R_{cluster}$ for all active CH_4 towers and the $R_{cluster}$ for all active towers in addition to NEON towers.

Cluster	CH_4 Towers (Data Providing)	CH_4 Towers (All)	NEON Towers
Na	3.0	34.9	35.5
NW	-	0.1	26.3
NEb	19.8	60.6	65.9
Ea	0.01	63.1	89.4
Eb	88.1	88.1	88.1
SW	2.0	3.3	17.3
W	0.01	0.01	38.8
NEa	79.3	79.3	79.3
Nb	21.3	21.3	21.3
SE	-	23.6	50.8

There were important gains in $TR_{cluster}$ when considering all CH_4 towers regardless of if they were providing data to Ameriflux (Table 4 and Figure 4). The clusters with substantial gains in representativeness (> 10%) include Na, NEb, Ea, and the SE. The $TR_{cluster}$ of the NW, Ea, SW, W, and the SE would be enhanced by more than 10% with the addition of CH_4 instrumentation at NEON sites.

Lines 305-307 – I respectfully do not think that assessing the distance to a medoid is a good assessment of representativeness. If so, then we should place a few towers in these medoids and we will have a perfect representativeness for each cluster. We also know that clusters have similar ecological characteristics but there is much more diversity and heterogeneity that is not captured within a medoid. The last sentence of this paragraph is misleading as it implies that towers must be placed in the medoids that were calculated with generic variables that arguably are not specific for CH4 fluxes (as they are generic for any ecological process). Similar arguments can be done for the analysis and discussion presented in section 3.3. I respectfully do not think this is the proper way to assess representativeness of places where we need to be measuring CH4 fluxes.

We agree that although the medoid would be a good area to place towers within, to really enhance cluster representativeness towers need to be placed across the range of dissimilarity observed. We made changes to the text and included new estimates of tower representativeness to the cluster and for IGBP representativeness within a cluster.

Although CH_4 EC tower infrastructure was not a part of a single organized network designed to be representative of the climate, landscape, and dominant IGBP vegetation classes that exist within the US, EC tower infrastructure that was providing data to Ameriflux was distributed across 8 of the 10 clusters (Table 3), with clusters NW and SE without any active towers providing data to the community. Tower representativeness of clusters range from 0 to 88%. The greatest $TR_{cluster}$ was for Eb and NEa and the lowest $TR_{cluster}$ was for NW and SE which had no towers. $TR_{cluster}$ was poor (<50%) for most clusters and high coverage was not associated with a higher frequency of towers. A high TR $_{cluster}$ representativeness was found in clusters where towers were dispersed across IGBP vegetation classes and where towers in wetlands, forests, or the arctic tundra (barren) were distributed across the state space of the cluster. Most clusters were substantially under-sampled (Table 3) due to an insufficient number of towers measuring CH_4 and poor distribution across the cluster.

The representativeness of IGBP vegetation types within clusters was poor for all vegetation types, excluding forests in the NEa. TR $_{IGBP}$ ranged from 0 to 79% and wetlands were the only IGBP class to be sampled across 8 clusters. Ideally, IGBP classes should be distributed both within and across clusters but there was not a single cluster with all 7 IGBP classes (forest, scrub, aquatic ecosystems, crops, wetlands, barren tundra, and grasslands).

Table 3. The total number of eddy covariance (EC) towers measuring CH_4 and providing data to Ameriflux. The tower frequency by dominant landscape type, the total cluster representativeness, and cluster representativeness by major ecosystem types are shown. For R $_{cluster}$ and R $_{ecosystem}$ values of 0.01 were assigned where a single tower is present.

Cluster	EC CH_4	Tower Frequency by Dominant Landscape Ecotype								TR $_{cluster}$ (%)	TR$_{IGBP}$ (%)						
		Forest	Scrub	Herb	Crop	Wet	Urban	Barren	AQ		Forest	Scrub	AQ	Crop	Wet	Barren	Grass
Na	4	2	1	-	-	1	-	-	-	3.0	0.01	0.01	-	-	0.02	-	-
NW	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
NEb	2	1	-	-	1	-	-	-	-	19.8	-	-	-	0.01	0.01	-	-
Ea	1	-	-	-	-	1	-	-	-	0.01	-	-	-	-	0.01	-	-
Eb	3	-	-	-	1	2	-	-	-	88	-	-	-	0.01	42.1	-	-
SW	7	-	-	1	3	2	-	1	-	2.0	-	-	-	0.14	2.0	-	0.01
W	1	-	-	-	-	-	-	-	1	0.01	-	-	-	-	0.01	-	-
NEa	7	4	-	-	-	3	-	-	-	79.3	79.3	-	0.02	-	13.4	-	-
Nb	8	-	2	4	-	2	-	-	-	21.3	-	-	0.01	-	21.3	6.3	0.01
SE	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Lines 381-390 – The authors assume that uncertainty is associated to poor data coverage, but this is never assessed. This paragraph essentially calls for more locations for measurements away from the medoid which will imply that representativeness (based on the method proposed by the authors) will be lower, as sites are away from the medoid. This is confusing and I strongly encourage the authors to revise the methods and the interpretation of the results.

We agree that changes in the methods and results are warranted to focus on the goals of this study and to clarify how representativeness is quantified. We also put the methods used in this study in the context of those used in other efforts to assess the representativeness of networks and infrastructure for current and future applications (Kumar et al. 2016; Lovett et al. 2007; Jongman et al. 2017; Villarreal et al. 2018; Chu et al. 2021; Novick et al. 2018). Representativeness studies discern when, where, and at what frequency networks are measuring ecological processes (Baldocchi et al. 2012; Jongman et al. 2017; Vaughan et al. 2001; Villarreal et al. 2018). Representativeness of research infrastructure is often described in terms of the extent to which the measurements collected at any given location and time represent the conditions at any other location and time, and this is often driven by ecological and climatic conditions (Sulkava et al. 2011; Chu et al. 2021). Representativeness is also measured across a landscape and studies have evaluated how tower infrastructure captures the variability observed within landscapes. All of these approaches are with the goal of understanding the representativeness of the measurements for a broader landscape, which is critical for upscaling point measurements to regional and global scales. Assessments inform the scientific community on how to increase their utility and are often designed to support network design, upscaling, and bias estimation (Chen et al. 2011; Ciais et al. 2014; Jongman et al. 2017; Schimel and Keller 2015; Villarreal et al. 2018; Kumar et al. 2016). There have been many attempts to assess the representativeness of existing flux tower networks for various purposes. To date, no study has focused on CH_4 infrastructure across the US, though many studies have used clustering and ecoregions (Sulkava et al. 2011; Hargrove et al. 2003), dissimilarity (Yang et al. 2008), and distance measures (Hargrove et al. 2003; Yang et al. 2008; He et al. 2015; Hoffman et al. 2013) on climatic (Novick et al. 2018) and vegetation type structure and function (Chu et al. 2021).

To understand representative of current CH_4 infrastructure, we defined clusters (Sulkava et al. 2011) and measured the dissimilarity between each location in a cluster to the medoid. We extracted the cluster and dissimilarity for all active tower sites measuring CH_4 that were distributed across the US and measured the tower cluster representativeness as the percent overlap between the range of dissimilarity sampled by the infrastructure ($r_{cluster}$) divided by the range of dissimilarity observed in the entire cluster (r; Eq. 1).

This approach allows us to identify key regions where we need CH_4 infrastructure within the US. We agree that this analysis does not capture the heterogeneity of the conditions that drive CH_4 fluxes at the ecosystem scale. It is designed to evaluate the sampling intensity of research sites at the landscape scale. In the design of a network, this course resolution influences the capacity to scale ecosystem level results to the landscape, region, and to the national level, which is required for the development of budgets and emission strategies.

Lines 293-402 – This is a similar paragraph where the authors discuss about uncertainty from a narrative, but this was never quantified in the formal representativeness analysis presented in this study. This paragraph and most of the discussion section is an expert opinion and is not directly related to the analyses presented.

Thank you for this comment, we made changes to the text throughout to better connect the discussion to the goals of this work. While we are interested in reducing uncertainties in CH4 budgets and models, we refocused the discussion on evaluating the strengths and limitations of existing measurement infrastructure and the critical need for strategic augmentation to provide the most valuable information toward reducing uncertainties in future large-scale budget estimations. Our analysis complements previous studies based on climatic or vegetation characteristics (Hargrove et al. 2003; Yang et al. 2008; Villarreal et al. 2018), and identifies regions within the US where gaps are limiting the development of upscaling techniques. To accurately understand the impact of climate and land cover change on biogenic CH_4 emissions, we need a long-term, calibrated, and strategic continental-scale CH_4 observatory network. Current gaps in existing measurement infrastructure limit our ability to capture the spatial and temporal variation of biogenic CH_4 fluxes and therefore limit our ability to predict future CH_4 emissions. Maps of potential CH_4 emissions require land cover classification targeted at land cover types like wetlands that are important sources of CH_4 to the atmosphere. Aquatic ecosystems like streams and lakes as well as coastal ecosystems are significant and variable sources of CH_4 not well studied on a long-term basis. Through our analysis using climate, land cover, and location variables, we have identified priority areas to enhance research infrastructure to provide a more complete understanding of the CH_4 flux potential of ecosystem types in the US. For EC tower locations, dissimilarity coverage was lacking for clusters Na, W, and Nb, and currently clusters Na, W, Eb, and Nb are substantially under sampled. All aquatic sites are under sampled within each cluster. An enhanced network would allow for us to monitor both the response of CH_4 fluxes to climate and land use change as well as the impact of future policy interventions and mitigation strategies.

There are three related studies that assess the representativeness of the AmeriFlux network that may be of interest for the authors.

Chu, H., X. Luo, Z. Ouyang, W. S. Chan, S. Dengel, S. C. Biraud, M. S. Torn, S. Metzger, J. Kumar, M. A. Arain, T. J. Arkebauer, D. Baldocchi, C. Bernacchi, D. Billesbach, T. A. Black, P. D. Blanken, G. Bohrer, R. Bracho, S. Brown, N. A. Brunsell, J. Chen, X. Chen, K. Clark, A. R. Desai, T. Duman, D. Durden, S. Fares, I. Forbrich, J. A. Gamon, C. M. Gough, T. Griffis, M. Helbig, D. Hollinger, E. Humphreys, H. Ikawa, H. Iwata, Y. Ju, J. F. Knowles, S. H. Knox, H. Kobayashi, T. Kolb, B. Law, X. Lee, M. Litvak, H. Liu, J. W. Munger, A. Noormets, K. Novick, S. F. Oberbauer, W. Oechel, P. Oikawa, S. A. Papuga, E. Pendall, P. Prajapati, J. Prueger, W. L. Quinton, A. D. Richardson, E. S. Russell, R. L. Scott, G. Starr, R. Staebler, P. C. Stoy, E. Stuart-Haëntjens, O. Sonnentag, R. C. Sullivan, A. Suyker, M. Ueyama, R. Vargas, J. D. Wood, and D. Zona. 2021. Representativeness of Eddy-Covariance flux footprints for areas surrounding AmeriFlux sites. Agricultural and Forest Meteorology 301-302:108350.

Thank you for this comment. We agree that the work of Chu et al., 2021 is relevant to our goals and provides an important analysis of EC tower footprint-to-target-area mismatch. He showed that few eddy-covariance sites are located in a truly homogeneous landscapes when considering climate and land cover characteristics . Mis-match is limiting model-data integration approaches and introducing biases on the order of 4%–20% for EVI and 6%–20% for the dominant land cover percentage.

We considered the results of their analysis, which support the evaluation of dominant land cover types in the evaluation of representativeness. Chu et al., 2021 chose land cover type as the categorical characteristic because it is commonly used in modeling and upscaling studies. The land cover products used in this study include the 2001–2016 United States National Land Cover Dataset products (NLCD; https://www.mrlc.gov/)and 2010 Land Cover of Canada (https://open.canada.ca/). We used similar products as Chu etal., 2021, improved to provide more detail on aquatic systems due to their importance for CH_4. It is important that towers are representative of the landscapes they exist within, and this work proposed a simple representativeness index based on their evaluations that can be used as a guide to identify site-periods suitable for specific applications and to provide general guidance for data use.

Novick, K. A., J. A. Biederman, A. R. Desai, M. E. Litvak, D. J. P. Moore, R. L. Scott, and M. S. Torn. 2018. The AmeriFlux network: A coalition of the willing. Agricultural and Forest Meteorology 249:444–456.

Novick et al., 2018 is another great and relevant synthesis study that laid the foundation for our work. Novick et al. 2018, discusses representativeness in reference to the climate (MAT and MAP) of towers, noting the degree of overlap in network infrastructure. This overlap makes it possible to subsample from the AmeriFlux database to form site-clusters that experience similar climate conditions but different land cover types, enabling the disentangling of effects of climate and vegetation on fluxes. The dissimilarity measure across clusters is used here to measure the variation across clusters and we are interested in current CH_4 infrastructure in this landscape.

Villarreal, S., M. Guevara, D. Alcaraz-Segura, N. A. Brunsell, D. Hayes, H. W. Loescher, and R. Vargas. 2018. Ecosystem functional diversity and the representativeness of environmental networks across the conterminous United States. Agricultural and Forest Meteorology 262:423–43while we used the dominant landscape lcc.

Villarreal et al., 2018 assess the representativeness of AmeriFlux and NEON based on ecosystem functional diversity characterized by 64 EFT categories across CONUS. Their EFT analysis defined the prominent EFT for a location (EFTmode) and measured representativeness based on a) the number of different EFT categories (EFTmode) represented by each network, b) representativeness of the EFT inter-annual variability (EFTint; number of unique EFTs within each pixel during years 2001–2014), and c) the spatial representation of EFTmode and EFTint based on a maximum entropy approach (i.e., spatial functional heterogeneity).

We included these studies and more to put this work in the broader context of representative studies. “There is a pressing need to design different scientific approaches to assess the representativeness of networks and infrastructure for current and future applications (Kumar et al. 2016; Lovett et al. 2007; Jongman et al. 2017; Villarreal et al. 2018; Chu et al. 2021; Novick et al. 2018). Representativeness studies discern when, where, and at what frequency networks are measuring ecological processes (Baldocchi et al. 2012; Jongman et al. 2017; Vaughan et al. 2001; Villarreal et al. 2018). Representativeness of research infrastructure is often described in terms of the extent to which the measurements collected at any given location and time represent the conditions at any other location and time, and this is often driven by ecological and climatic conditions (Sulkava et al. 2011; Chu et al. 2021). Representativeness is also measured across a landscape and studies have evaluated how tower infrastructure captures the variability observed within landscapes. All of these approaches are with the goal of understanding the representativeness of the measurements for a broader landscape, which is critical for upscaling point measurements to regional and global scales. Assessments inform the scientific community on how to increase their utility and are often designed to support network design, upscaling, and bias estimation (Chen et al. 2011; Ciais et al. 2014; Jongman et al. 2017; Schimel and Keller 2015; Villarreal et al. 2018; Kumar et al. 2016). There have been many attempts to assess the representativeness of existing flux tower networks for various purposes. To date, no study has focused on CH_4 infrastructure across the US, though many studies have used clustering and ecoregions (Sulkava et al. 2011; Hargrove et al. 2003), dissimilarity (Yang et al. 2008), and distance measures (Hargrove et al. 2003; Yang et al. 2008; He et al. 2015; Hoffman et al. 2013) on climatic (Novick et al. 2018) and vegetation type structure and function (Chu et al. 2021)."