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Well pad-level geospatial differences in the carbon footprint and direct land use change impacts of natural gas extraction†

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Thorough accounting of the climate change impacts of natural gas is crucial to guide the energy transition towards climate change mitigation, as even decarbonization roadmaps project continued natural gas use into the future. The climate change impacts of natural gas extraction have not previously been assessed at the well pad level, accounting for a multitude of geospatial differences between individual pads. Well pads constructed across a varied landscape lead to a range of well pad areas, earth flattening needs, well pad lifetimes, total gas production, and direct land use change (DLUC) effects such as loss of original biomass, soil organic carbon loss, change in net primary productivity, and altering the surface albedo of the site. Using existing well pad data, machine learning techniques, and satellite imagery, the spatial extents of thousands of well pads in New Mexico were delineated for site-specific data collection. A parametric life cycle assessment (LCA) model of natural gas-producing well pads was developed to integrate geospatial differences and DLUC effects, yielding scenario analysis results for each identified well pad. The DLUC effects contributed a median of 14.4% and a maximum of 59.0% to natural gas extraction carbon footprints. The use of well pad-level data revealed that the carbon footprint of natural gas extraction ranges across orders of magnitude, from 0.016 to 46.4 g CO_2eq per MJ. The results highlight the need to quantify the climate change impacts of establishing a well pad and extracting natural gas case-by-case, with geographically specific data, to guide new installations towards lower emissions.

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1. Introduction

Natural gas use has been increasing in the United States despite efforts to mitigate climate change by reducing fossil fuel consumption. In recent years, production of electricity by natural gas-fired power systems has experienced the highest growth rates among all other technologies in the electricity sector, including renewable energy technologies.[1] Natural gas increased from 22% of total utility-scale US electricity generation in 2008 to 43% in 2023, while overall electricity generation in the US has remained relatively stable.[1,2] Natural gas use is projected by the US Energy Information Administration (EIA) to continue for at least the next few decades,[3] as even state decarbonization roadmaps such as California's 2022 Scoping Plan account for natural gas consumption into the future.[4] Reliance on natural gas will persist under the pretexts of eventually integrating it with carbon capture systems, phasing in biogas sources, or maintaining this capacity primarily for energy security purposes.

With natural gas remaining a key primary energy source, effective climate change mitigation planning will require comprehensive assessments of the greenhouse gas (GHG) emissions of natural gas energy systems from cradle to grave. The life cycle GHG emissions of electricity generated from natural gas in conventional power plants have been generally estimated to be approximately 470 g CO_2eq per kW h from life cycle assessment (LCA) harmonization research[5] (in contrast, coal GHG emissions are $\sim$980 g CO_2eq per kW h[6]). However, our understanding of the carbon footprint of natural gas is still evolving with recent research. Measurements of fugitive methane emissions at various life cycle stages of natural gas show high uncertainties.[7] Technologies and practices in the natural gas sector are changing as well, which can affect their life cycle GHG emissions. Furthermore, there may be additional climate change impacts that have yet to be quantified from direct land use change effects and short-lived climate forcers associated with natural gas. Recent advancements in computational

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capabilities and higher data quality and quantity provide an opportunity to improve analyses by reevaluating the climate change impacts of natural gas systems to include these complexities.

Notably, the contributions of direct land use change (DLUC) towards climate change through disrupting surface land, like removing original biomass, have been mostly overlooked in previous LCAs of natural gas energy systems, despite their documented influence on the carbon footprints of other energy systems such as multiple types of bioenergy feedstock production. Similar consequences may result from the DLUC associated with the expansion of natural gas extraction. A previous study reported that the potential future carbon sequestration in biomass that was lost through land transformation by new oil and gas extraction in North America from 2000 to 2012 amounts to ∼4.5 Tg.[8] Still, the contributions of DLUC to climate change include multiple factors in addition to this loss of future net primary productivity (NPP), which is a measure that represents vegetation's net carbon accumulation rate over time.[9] DLUC effects on disturbed land also include carbon emissions from loss of the original aboveground and belowground biomass carbon[10–12] and reductions in soil organic carbon (SOC), which is carbon stored in the soil that originates from organic matter.[13,14] Additionally, changes in surface albedo may be caused by new installations that affect the reflective properties of the land surface.[12] Albedo is a coefficient that describes the ability of a surface to reflect shortwave radiation.[15] While the other, carbon-related DLUC effects of new natural gas infrastructure would lead to overall increases in climate change impacts, the surface albedo change effects have indeterminate net consequences which should be examined on a site by site basis. Previous assessments of albedo change impacts of bioenergy systems, for example, have demonstrated both climate change impact reductions and increases, depending on the characteristics of the original land cover and the new land use.[16]

The natural gas industry is an enormous system with a wide range of components, facilities, and infrastructure, including storage facilities, buildings and structures for processing treatment, pipelines, compressor stations, well pads, and natural gas-fired power plants. For most of these components, equipment replacements or facility retrofits at the end of their operational lifetimes are likely to occur on the same land as their original infrastructure, leading to the DLUC effects being spread across longer lifespans on the same land. In contrast, most gas wells only have an efficient operational lifetime of 20 to 30 years,[17] and the limited extractable natural gas resources at a site necessitate new well pad areas to be constructed and drilled in new locations. Well pads and other land use during the natural gas extraction stage in the Western US occupy up to 49% of land occupied by components of the gas industry.[18] The area required for constructing a well pad can vary from 1000 to 20 200 square meters, depending on factors such as the number of drilled wells in each pad (up to 16 wells in a single pad), existing and surrounding vegetation, and ground elevation.[19] Along with pipelines, well pads render more frequent change and land expansion than other natural gas infrastructure like power plants, and thus present an opportunity for siting improvements that can be enacted more rapidly. Still, almost all environmental evaluation studies in the gas industry have ignored GHG emissions from this massive manipulation of grounds.

The amount of carbon originally present in multiple forms on these lands may vary substantially by land cover type (Fig. 1). Globally, the amount of carbon stored in above- and belowground biomass can range from 0 to 3481 and from 0 to

Fig. 1 Examples of natural gas well pads on lands with different types of vegetation (images sourced from Google Maps).

2078 metric tons per hectare, respectively.[20] Because well pads could replace various types of vegetation surfaces that include forests and shrubland, this variation would subsequently affect the relative contribution of DLUC to the carbon footprint of natural gas by site. Previous analyses that have included a measure of DLUC estimated generalized conditions for DLUC-related land characteristics instead of assessing site-specific data[19,21,22] (Table S1, ESI†), using instead a range of values for each parameter without categorizing them by case beyond overall conditions in a basin[23] or in a state or province.[21] These previous analyses concluded that DLUC from land disturbance for fossil fuels is a small percentage contribution to their overall life cycle GHG emissions,[19,21] but they did not account for interrelated DLUC conditions by well pad and so do not provide a precise accounting of the range of GHG emissions from DLUC for active gas wells.

The state of New Mexico serves as an ideal case study to investigate the contributions of DLUC effects and geographically variable factors to the life cycle climate change impacts of well pads. New Mexico is one of the top ten highest natural gas extraction states in the US.[24] In addition to conventional geologic sources of natural gas, New Mexico has access to shale gas plays including the Permian Basin,[25] a shale play that has experienced a rapid increase in oil and gas extraction in recent years.[26] Almost 47 000 well pads have been constructed for extracting natural gas (both with and without co-production of crude oil) in New Mexico.[25] The state maintains publicly available and comprehensive data on its wells, including their location coordinates, depths, production rates, ages, and other characteristics.[25] Furthermore, New Mexico's diverse geography includes multiple types of land cover and ecoregions[27] (Fig. S1 and S2, ESI†) across which its well pads are located, representing a broad range of original land conditions.

Extracting site-specific spatial data for thousands of gas wells from maps, satellite imagery, and satellite data products requires techniques that are less manually intensive than shape delineation by traditional geographic information system (GIS) analysis.[28] Machine learning methods such as instant segmentation, which involves identifying and delineating features on satellite images by image processing approaches, can be employed, but their application requires case-specific development of training datasets and careful assessment of the outputs to avoid unintended misidentification, missing features, or other errors. As well pads are established in areas of varying spatial characteristics, some past analyses that utilized machine learning for well pad identification have resulted in substantially lower numbers of delineated sites than expected.[18]

This study combines geospatial analysis, life cycle assessment (LCA), and machine learning to investigate the contributions of DLUC effects and other geospatial factors to the climate change impacts of natural gas extraction. The differences in climate change impacts from loss of original biomass carbon, loss of soil organic carbon, loss of net carbon uptake by biomass, and changes in surface albedo are determined for various sets of original land conditions and well characteristics using active gas wells in New Mexico. The relative scales of these impacts are compared to the GHG emissions of other processes from well pad development through natural gas extraction, and also evaluated for differences by land cover and ecoregion.

2. Methodology

A multi-faceted approach was developed, incorporating LCA, GIS, machine learning, and data scraping, to comprehensively collect and process spatial data by well pad in order to investigate the geographic variability of the climate change impacts of gas wells. Machine learning was first used to identify the areal extents of well pads, which then facilitated geospatial analysis to be used for data collection for the site-specific input parameter values of the LCA model. A parametric LCA model was developed to calculate the cradle-to-gate climate change impacts of natural gas extraction, which were assessed for each well pad-level dataset of input parameter values. Machine learning through random forest was then used to conduct sensitivity analysis of the LCA results.

The methods were applied to active natural gas wells with over 0.5 Mcf of daily gas production[29] that were constructed between 1950 and 2020 in New Mexico, resulting in a selection of 24 991 active gas wells from over 47 000 gas wells that were drilled in the state during that time. Fig. S2 (ESI†) presents the point locations of the wells that were included in this study and the land cover types across the state, as informed by the 2019 US Geological Survey (USGS) National Land Cover Database 2001 (NLCD).[25,30]

2.1. Geospatial LCA goal and scope

This study involves geospatial LCA of natural gas well pads with a focus on geographic differences and DLUC effects. The goal of this study is to quantify the climate change impacts associated with the land transformation and land occupation of active gas wells in New Mexico using geographically specific data by well pad, to calculate the carbon footprint of natural gas extraction for individual well pads, and to determine how these impacts vary across ecoregions and land cover types. As natural gas use in the US has increased during the past 20 years,[1] the results of this geospatial LCA can be used to guide future natural gas extraction development by identifying locations leading to potentially lower GHG emissions from DLUC effects. The intended audience includes the scientific research community, policymakers, engineers involved in energy system planning, and natural gas industry investors and stockholders.

This geospatial LCA was conducted as a scenario sensitivity analysis, in which the characteristics of individual wells informed individual scenarios (n = 12 561 for this LCA after site identification and delineation *via* machine learning). The LCA was conducted using R software codes. Aligned with the goal of this study, the life cycle impact category of global warming potential was assessed using EPA TRACI 2.1 Midpoint.[31]

A functional unit of one megajoule (MJ) of energy released from the combustion of natural gas was selected for this LCA. An energy-based functional unit expressed in Joules is common across LCAs of fossil fuels and thus facilitates future comparisons of impacts among different studies providing the same function. The conversion from the volumes of natural gas per well to energy units assumed a heating value of 38.3 MJ m^{-3}, consistent with the average higher heating value reported by the US EIA for natural gas consumed in New Mexico between 2022 and 2024.[32,33] The heating value was assumed to be constant across the wells. In addition to scaling to a functional unit of 1 MJ, the impacts are presented scaled per well and per square meter for further investigation.

Coproduct allocation was applied to assign the shared impacts to oil and gas when extracted from the same well. This resulted in different coproduct allocation factors for each well pad as the produced quantities of oil and gas reported by individual well were used for this calculation. An energy-based allocation approach was deemed most appropriate to determine the allocation factors for the two fossil energy products.[34]

The system boundary was cradle-to-gate, including only the life cycle climate change impacts associated with establishing a well pad and extracting natural gas (Fig. 2). The "gate" is the point at which natural gas leaves the well; the delivery of natural gas to electric utilities or to industrial, commercial, or residential consumers is not included in this analysis. This study did not include new roads constructed to access natural gas well pad areas. However, land that was directly adjacent to the finished pads that had been altered to facilitate gas extraction activities was included within the scope of the study. The impact of the production of shared equipment like construction vehicles, well rigs, or compressors was not included in the LCA modeling because they are mutually used across several projects, accurate allocation of impacts is not possible, and the share of the total impact is expected to be nearly negligible as the equipment is used for several years and likely recycled at its end of useful life. Only the weight of this equipment was considered in order to calculate impacts for transporting the equipment.

2.2. Determination of lifetime natural gas production by well site

The well pads comprising this case study were constructed at different times throughout the last seven decades (Fig. S3, ESI†). Over this extended period, there have been considerable shifts and improvements in technologies and methods adopted to minimize environmental impacts. The assessment of the climate change impact by the exact technologies employed 70 years ago was not within the scope of this study. Instead, the climate impacts associated with current technologies were applied to older wells. Adopting this approach fit the focus on understanding the potential climate change impacts of future expansions of natural gas well pads. Still, land use changes observed over time from examining satellite data on early gas wells provided an overview of the changing patterns of direct land use alterations beyond the operational life cycle of the wells. While a limited number of well pads may be remediated after their operational lifespan, most are left without further human interventions;[35] therefore, the carbon stored in biomass and soils, plant productivity, and surface albedo can remain impacted by the original land transformation for an extended period until nature gradually restores the affected land.

Historical data on the fate of older well pads constructed before 1972 informed the projected future conditions for more recently established well pad areas. The range of lifetimes across the gas wells in New Mexico is broader than the 20 to 30 years assumed by other studies,[17] spanning from 5 to 120 years instead.[25] We observed that the average lifetime of ~11 000 plugged-on gas wells in NM was 29 years, and ~25 000

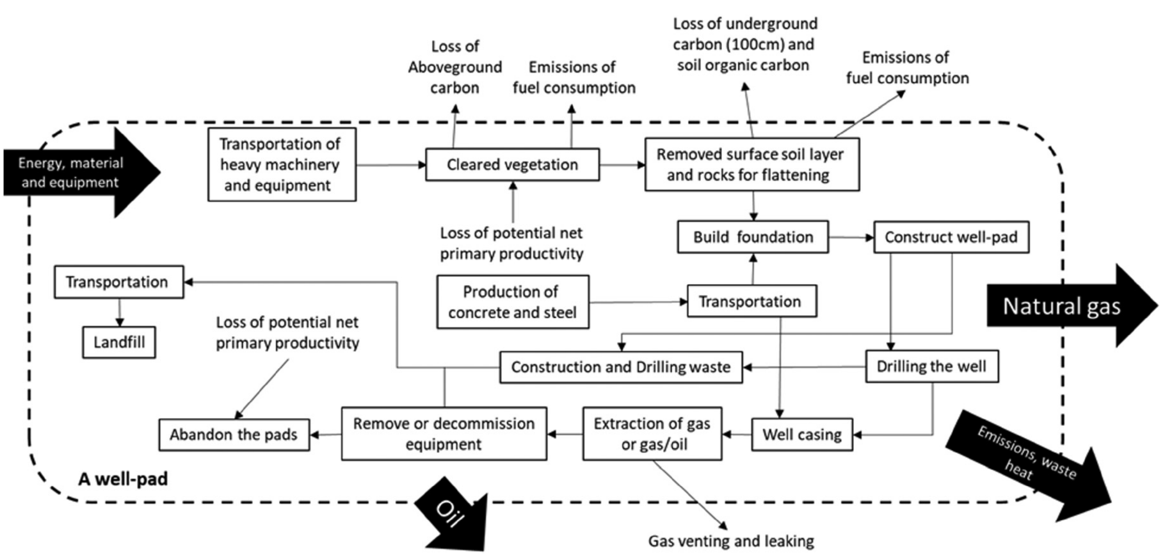

Fig. 2 System diagram of the processes included in the LCA model for extraction of natural gas (except for surface albedo change, which is not shown).

wells are still active and operating.[25] The average operating life of active gas wells with ages over 29 years in the 3 basins of studied wells was calculated at ~50 years. Thus, we selected 50 years as the average lifetime for the New Mexico natural gas wells.

For the active wells that began production before 1972, their lifespan from their spud year up to 2023 was assumed to be their lifetime, and the accumulation of yearly natural gas production up to 2023 was selected as their total production. For the rest of the well pads, their lifetime natural gas production was projected by determining descending lines-of-best-fit and exponential decline curves from their historical production over time, with a starting point of their average over the last four years. These wells' total production includes the extracted volumes up to 2023, plus this projected production up to a total lifetime of 50 years.[36] However, for cases in which the production curve dropped under 180 Mcf per year before 25 years from the spud year, we only included gas produced within those first 25 years.

2.3. Instant segmentation and machine learning set up

Because only the point locations of well pads were available, machine learning techniques were integrated into the workflow to delineate the full areas of thousands of well pads throughout New Mexico efficiently from aerial imagery. The gas wells were outlined with a deep learning model called Mask R-CNN (Region Convolutional Neural Network). This approach performs instant segmentation for detecting and delineating objects at the pixel level; thus, high-quality images are necessary to accurately detect objects.[37] High-quality aerial imagery with 3-meter resolution from the National Agriculture Imagery Program (NAIP) was employed.[38] To improve well pad identification ability across the varied land cover types iteratively, and considering the high computational analysis demands of this machine learning approach, we excluded the infrastructure components associated with well pads that were not within the well pads themselves, such as roads leading to the sites. Pads that contained more than one well were also excluded from this study.

A training dataset was generated from manually labeling the locations of 2500 wells on aerial imagery in ArcGIS, as a polygon shapefile. To build the training model, the labels were trained by testing several combinations of the batch, which represent the number of samples before each update, and epoch, the number of iterations the model works through in the data,[39] and 10% validation samples. A circle buffer with a radius of 150 m around the point location of gas wells limited the aerial imagery for the search in order to avoid capturing other human-made facilities in the search area. After investigating the probable causes of overfitting across multiple iterations, four classes of objects were identified to delineate the well pads: active sections, recovered areas, forest, and totally covered well pads. Active sections were gas well pad locations showing a clear separation from their surroundings. Recovered areas were locations adjacent to the active sections that were initially altered through well pad activities, but which had recovered over the years. Forested areas were well pads that were wholly surrounded by trees, and totally covered areas were active wells that were not easily observed due to vegetation, though the trace of their pad boundaries was recognizable. Ultimately, the output polygon shapefile from the best performing iteration of the object detection machine learning model was used to collect site-specific geospatial data like the well pad areas in square meters.

2.4. Data collection

Data was collected from multiple sources, both well pad-specific and generalized, as inputs to a parametric LCA model developed for systematic calculations of the cradle-to-gate GHG emissions of each identified and delineated well pad. The general data applied to all well pad scenarios included the weights of equipment and construction vehicles, fuel consumption rates of equipment, materials needed, and waste produced (Tables S2 and S3, ESI†). Well pad-specific features like vertical and horizontal well length, casing structure, cement and steel utilized in well casing, activation date, annual production of oil and gas, methods of gas extraction, and amounts of gas that were vented and flared were collected directly from a publicly available database on the official website of the New Mexico Energy Minerals and Natural Resources Department (EMNRD).[25] ArcGIS Pro and associated Python functions were used to calculate variables like the distance to the well owner's nearest warehouse and to dumping stations; the slope of the ground at the well pad location; the basin in which the well is located; and the areas of each well pad in m^2. The casing structure identified for each well was used to subsequently calculate fuel consumption in hydraulic fracturing and drilling, following the procedures described in Brandt *et al.* (2015) and El-Houjeiri *et al.* (2013).[40,41] The fuel use was not adjusted for vertical *versus* horizontal sections of the wells, but hydraulic fracturing was only calculated for the horizontal sections of shale gas wells. The Environmental Protection Agency (EPA) Ecoregion Level III data, which specified the ecological characteristics of each region in North America, and the United States Geological Survey (USGS) National Land Cover Database 2001 (NLCD) were used in conjunction to identify the original vegetation density and other land features in each location to determine the fuel required to clear the area of biomass and flatten it before construction of the pads.

We assume that the land occupied by well pads would have remained in its original land use if the well pads were not constructed on it. This assumption is fitting in this case, as most of the areas are remote and were not previously heavily disturbed by human activities given their original land cover types. To obtain the DLUC effects of losses of carbon or the emissions equivalent of albedo change, the values representing current conditions after conversion to a well pad were subtracted from the carbon stock or albedo conditions that characterize the land before the construction of pads. However, there are challenges in collecting data on original land conditions because satellite data from many decades ago is either not available or has low resolution that is incompatible with the dimensions of well pads. So, the average conditions within a 100-m radius circular buffer zone around the individual pads was used to inform the "before" conditions for the well pads, excluding the well pad areas themselves. The original land cover type for each well pad was identified by the majority land cover type of this buffer zone for each well using the 2001 NLCD satellite dataset, after removing specific land cover types that would misrepresent the original land conditions when present within the buffer zone of a well pad (Open Water, Developed Open Space, Developed Low Intensity, Developed Medium Intensity, and Developed High Intensity). The 25 well pads that did not result in a match were then assigned their appropriate NLCD land cover type from visual inspection of aerial imagery.

Relevant DLUC data was collected for both the well pad areas and their buffer zones. Surface albedo values over time were derived from Landsat Level 2 satellite images, which have a resolution of 30 meters and are available for a given location every two weeks.[42] To estimate the soil organic carbon (SOC) for several scenarios with various areas and slopes, the soil carbon contents at depths of 0.3, 0.5, 1.0, and 1.5 meters underground were collected for each well pad site from the United States Department of Agriculture (USDA) Gridded Soil Survey Geographic (gSSURGO) database, which presents this data primarily at a 10-meter resolution.[43] The SOC loss at each site was calculated by determining the depth and grade of soil disturbance and digging that was required to construct the well pad and the corresponding SOC values by depth, assuming that 30% of disturbed SOC would become CO_2 emissions during the lifespan of the well pad.[44] The aboveground biomass and belowground biomass data from a 300-m resolution raster developed by Spawn *et al.* (2020) were used to determine the average biomass carbon stock values on the original land of the well pads by land cover type, using only the areas within the 100-m radius buffer that were not the well pads themselves.[12,20,30] Then, well pad-specific aboveground and belowground biomass values were generated based on the fractions of this area by land cover type. It was assumed that the aboveground and belowground biomass contained a 45% carbon content and that this biomass would be either burned or decompose after its removal from the well pad site, converting the carbon to CO_2 emissions. Although CO_2 emissions arising from DLUC are biogenic, they were treated in the same manner as fossil CO_2 emissions in the LCA model because this carbon would have remained fixed in biomass if the well pad was not constructed on that area.

The University of Montana's Numerical Terradynamic Simulation Group has derived detailed estimates of net primary productivity (NPP) using Landsat 8 satellite imagery,[45] generating NPP data at a resolution of 30 m as the Landsat Productivity raster. One sixth of the NPP that would have occurred during the productive lifetime of each well is considered to be foregone carbon sequestration due to the removal of the biomass.[12] This reduction in carbon that would have been sequestered without the well pad is treated as a CO_2 emission in the LCA model. For many wells, the impact due to loss of potential NPP may continue after gas production ends, all the while accumulating year by year. Due to the uncertainty in post-production management and in natural recovery time, NPP loss beyond the end of the productive life of the well was not included in the impact calculations.

For well pads that were constructed on what was formerly Cultivated Crop land, the DLUC impacts arising from loss of aboveground and belowground biomass carbon and NPP loss were set as zero because the biomass carbon on the land is not permanent. The actual amount of carbon that had remained in biomass on the land throughout the year and across multiple years depends heavily on the type of crop, how much of the plant is harvested, how much of the remaining biomass after harvest would decompose (*e.g.*, agricultural residues left on a field) *versus* continue to hold carbon (*e.g.*, trees in orchards), and other environmental and human management factors. Inspection of historical aerial imagery confirmed that none of the gas well pads constructed on formerly cultivated croplands in this study had been orchards. Similarly, the biomass originally on any Developed type of land cover and its NPP were considered not permanent and were thus not included in the DLUC impacts, assuming that human development on the land would eventually occur if the well pads had not been constructed.

2.5. Sensitivity analysis

To determine the overall sensitivity of LCA results to the variability and uncertainty in input parameter values across all scenarios, random forest was employed. Random Forest is a machine-learning algorithm that obtains the outcomes of regression problems by averaging the results of several decision trees constructed from the primary dataset. It can determine the importance of an input variable by reviewing alterations of variances while separating out the decision tree.[46] We attempted different combinations of training and testing datasets from the LCA input parameters and results, using 90% of the data for training and 10% for testing. We report on the random forest result that showed the lowest mean squared error (MSE). This sensitivity analysis approach enabled simultaneous interpretation of all 12 561 well pad LCA scenarios for a holistic understanding of the influence of individual parameters on the carbon footprint of natural gas well pads.

3. Results and discussion

3.1. Results of well pad delineation by machine learning

Delineation of the well pad areas from satellite imagery was executed by applying instant segmentation methods coupled with Mask R-CNN machine learning techniques (Fig. S4 and S5, ESI†). Primarily due to the wide variety of pad shapes and conditions, we aimed to prevent overfitting and to train a more generalized model that can cover various situations as we tested several combinations of inputs. Consequently, the model was trained with approximately 2500 manually-labeled images, a batch size of 2, and an epoch value of 20. The Average Precision Scores for the model were as follows: 'Active Section' achieved a score of 0.6868, 'Partially Covered' scored 0.3022, 'Forest' recorded a score of 0.5305, and 'Totally Covered' had a score of 0.125. For instant segmentation, a confidence score of 70 was determined. Ultimately, 12 561 wells were delineated appropriately by this machine learning approach. We defined appropriate delineation from the model as showing complete data, not intersecting with other well pad areas, and showing a realistic size. This subset of 12 561 natural gas well pads was used in the subsequent steps of the analysis, serving as individual well pad-level LCA scenarios.

3.2. Well pad-specific geospatial LCA results and discussion

The LCA model was performed for each of the 12 561 delineated well pads (Fig. 3). The range of the net DLUC impact is between −0.61 and 24.7 g CO_2eq per MJ, while the total impact is between 0.016 and 46.4 g CO_2eq per MJ. Across the individual well pad LCA results, the percentage of the total impact that is contributed by net DLUC effects ranges between −0.015% and 59.0% with a median share of 14.4% and an average overall DLUC share of 16.6% of the total impact. Across all well pads, the combined effects of soil carbon loss, biomass carbon loss, NPP loss, and albedo change led to a net negative climate change impact (cooling effect) for only 91 well pads. These well pads were located on five different land cover types and in six ecoregions. Similarly, there was no relationship to the land cover type or ecoregion determined for the 224 cases of positive albedo change impacts. As albedo change increased the climate change impacts in only 1.78% of the well pad scenarios, albedo change generally counteracts the carbon losses from the land, leading to a lower net DLUC impact, for most New Mexico active natural gas-producing well pads.

Still, the average contribution of the net DLUC impacts to the total climate change impact is 16.6% and can be as high as 59.0%. Raton (n = 655), one of the three New Mexico basins with a relatively high proportion of well pads on previously forested land (Fig. 4), shows the highest net DLUC contribution to the total impact, with an average of 35.4% and a range from 10.4% to 52.2% (Fig. 5). The San Juan basin (n = 8629) includes the well pads with both the highest and the lowest net DLUC shares across the dataset, while the Permian basin (n = 3277) depicts a slightly reduced range from 0.026% to 44.9% of the total impact, with an average of 12.6%. This illustrates that DLUC can provide a nonnegligible contribution to the life cycle climate change impact of natural gas extraction, and the variability even within 3 basins in the same state highlights the importance of including location-specific DLUC in LCAs involving well pad construction for oil and gas production.

Oil and gas productivity by well pad was examined as another possible driver for the differences in DLUC impacts by basin. A well pad with lower gas production during its lifetime would have higher DLUC impacts per MJ of natural gas extracted than another well pad that is identical to it otherwise. The New Mexico well pads with the highest DLUC impacts are located in the Raton basin, across which lifetime gas production is ∼725 600 Mcf per well on average, and ranges from 34 913 to ∼2 889 000 Mcf per well. By comparison, the average production by well pad in the New Mexico section

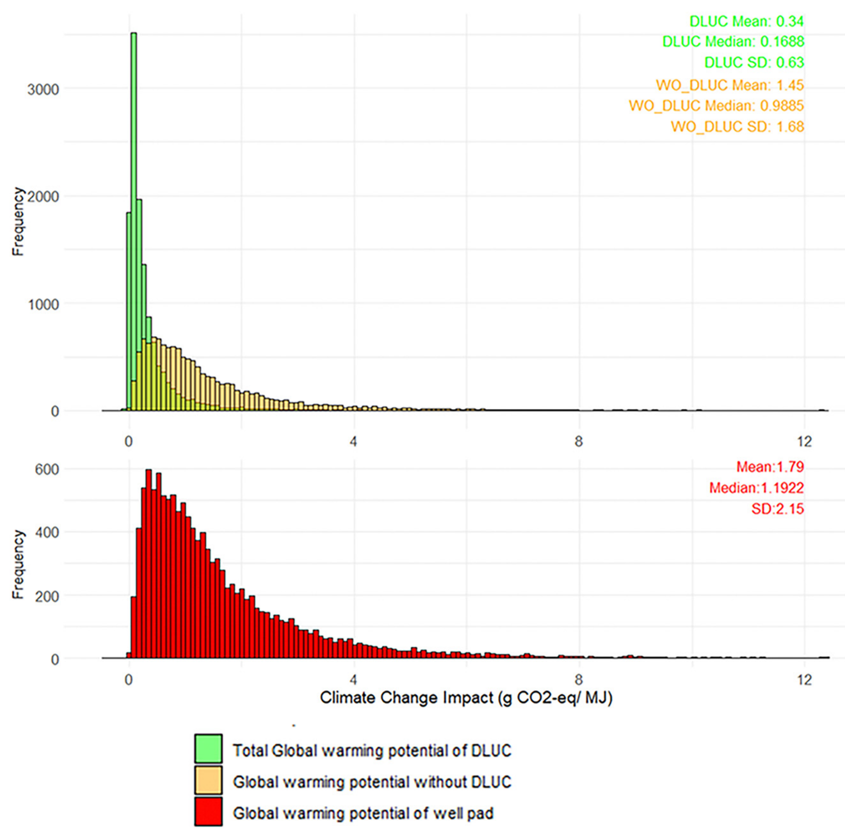

Fig. 3 Global warming potential due to direct land use change (DLUC) impacts and the global warming potential due to other processes (WO_DLUC) by well pad (top); total global warming impacts of the 12 561 gas well pads including all processes in the bottom histogram.

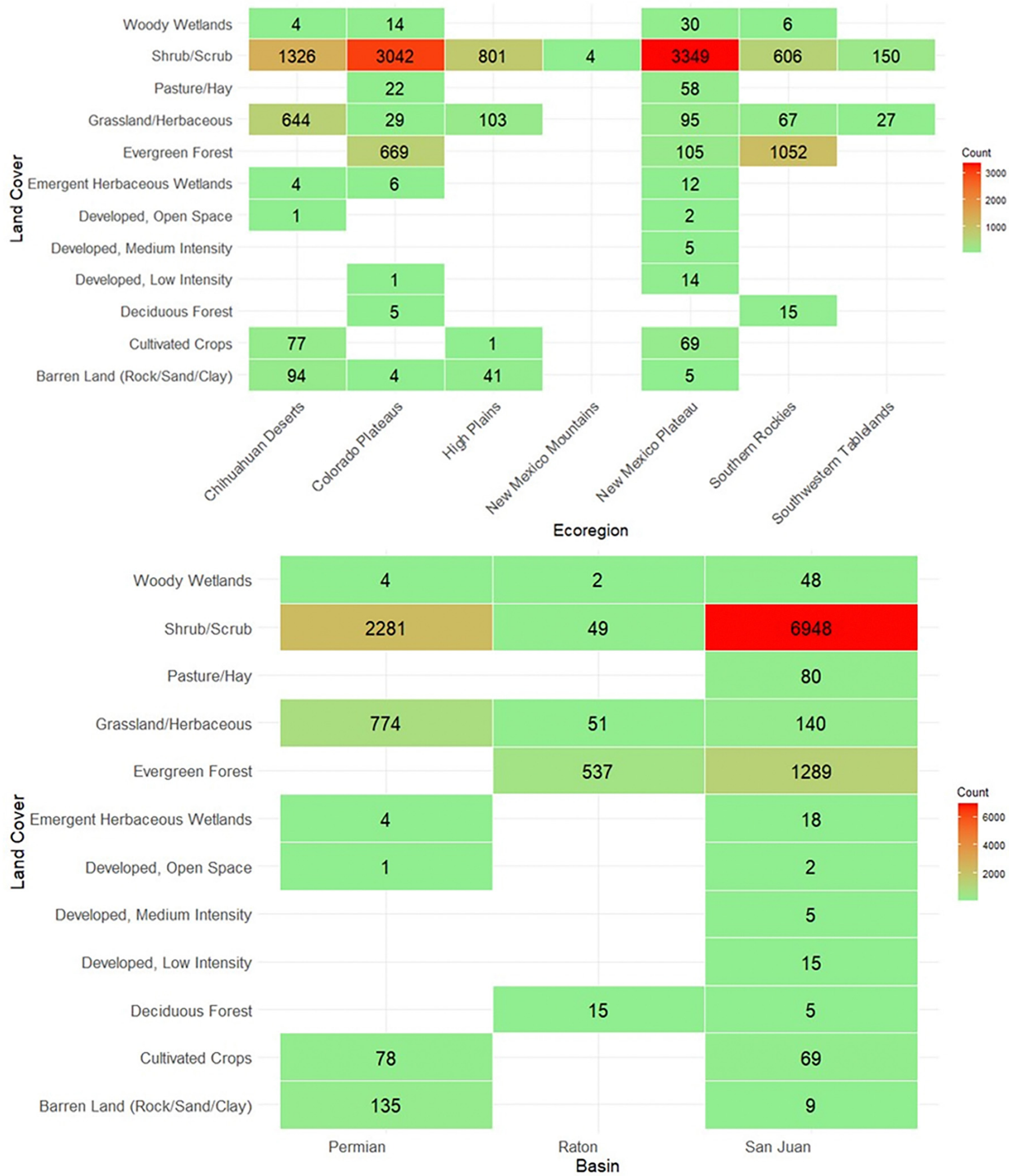

Fig. 4 The top heatmap illustrates the number of well pads in each combination of original ecoregion and land cover type. The bottom heatmap shows the abundance of well pads by land cover type and basin in the state of New Mexico, from the dataset in this study.

of the Permian basin is ∼413 900 Mcf per well, with a range from 25 946 to ∼2 278 800 Mcf per well; these 3277 wells tend to have lower natural gas production per pad than the 655 wells in the Raton basin. Thus, the higher DLUC impacts for Raton basin well pads are not primarily emergent from differences in natural gas productivity.

Linear and nonlinear regressions were applied to explore whether a correlation exists between the DLUC impact by well pad and the gas well pad's construction year (Fig. S6, ESI†); no definite relationship to the spud year was determined, as both regressions showed a low R-squared value. This may imply a lack of clear difference in net DLUC impacts between horizontally drilled wells and vertical wells, as almost 95% of newer wells in the US are hydraulically fractured and horizontally drilled.[47]

The span of well pad areas by land cover type was also examined (Fig. S7, ESI†). The average area of active single-well pads constructed in New Mexico is 4800 m^2 and varies

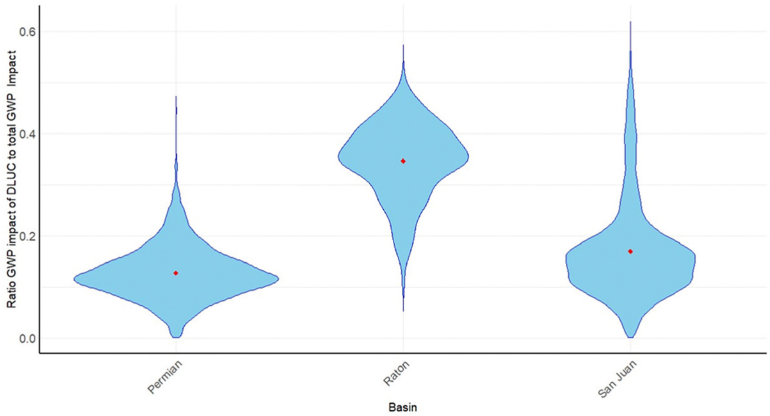

Fig. 5 Contribution of net DLUC impacts to the total impact calculated by well pad, categorized by basin in New Mexico.

significantly by land cover (p-value = 2×10^{-16}). However, the effect size was also small at 0.1, illustrating a significant but weak correlation, which may be due to the large sample size. The average area for conventional well pads in the entire US has been reported as 10 100 m^2, and the area for shale gas pads has been reported as 20 200 m^2;[23] this study's results also follow the same pattern of shale gas well pads having a larger area on average than conventional well pads (Fig. S8, ESI†). However, some of the shale gas extraction activities involved redrilling wells established in the 1960s, which may have limited ability to expand beyond their original well pad area; therefore, there is a wide range for the area of shale gas well pads.

Ultimately, a higher difference exists in well pad areas between land cover types than between conventional and shale gas wells (Fig. S9, ESI†). However, there is no significant relationship between land cover and the 436 shale gas well pads (p-value = 0.446). The well pad areas in the dataset range from 400 to 62 000 m^2, with the largest pads located in regions that were formerly shrubland and grassland. Shrubland was the most common land cover type upon which well pads were constructed, containing 73.9% of the well pads analyzed (Fig. 4). Well pad construction was not constrained to sparsely vegetated areas, however, as 15.1% of well pads were found to be constructed on former Evergreen, Deciduous Forest, and Woody Wetlands (Fig. 4). An increasing proportion of the well pads in this dataset were constructed in forested areas in recent years compared to prior decades (Fig. S6, ESI†). Upon further investigating differences by original land cover type, the GHG emissions due to direct land use change (which exclude albedo change impacts) from the implementation of well pads were found to be overall higher for well pads developed on more densely vegetated land like forests (Fig. S10, ESI†). The storage period of carbon in cultivated crops is distinct from other land types like forests, which preserve carbon for an extended period of time. Cultivated crops showed the lowest overall GHG-related DLUC impacts upon well pad construction, as only loss due to SOC disturbance was included in the calculations for wells on cultivated crop lands and no loss of biomass carbon.

Still, this assessment by land cover type may be affected by estimating original land conditions using the 2001 National Land Cover Dataset (NLCD) on surrounding land. Although this particular NLCD dataset is the oldest available version, around 7313 wells were established before 2001, for which the previous land cover type could have been different from the conditions represented by the 2001 NLCD data.

Original land cover conditions may be particularly important to appraise despite these uncertainties for older wells, maybe more so than the more careful validation of well pad areas. Comparison of Fig. S7 and S10 (ESI†) illustrates that the well pad area does not necessarily have the largest influence on the DLUC impact per well. For instance, for land that was previously evergreen forests, the range of area is similar to most other land cover types, but the range of impacts per well is higher than other land cover types. Relatedly, gas wells that were constructed on barren land and cultivated croplands occupied a higher average land area associated with lower DLUC impacts. Therefore, we also calculated the DLUC impact per unit area in each land cover type (Fig. S11, ESI†), which showed higher DLUC impacts per unit area for forested land cover types in general (Deciduous Forest and Evergreen Forest). However, there were fewer well pads established on land that was formerly Deciduous Forest (n = 20), and thus these ranges may not be representative of the possible span of impacts in practice. The Evergreen Forest results, on the other hand, were informed by hundreds of well pads (n = 1826). The DLUC impacts of forested lands being overall higher than those of non-forested land cover types were expected, as the aboveground and belowground biomass carbon in forested lands were both higher than in non-forested lands, on average, in this dataset.

When the difference in albedo from a well's spud year up to 2023 was converted to CO_2 equivalents per well pad to calculate albedo change impacts, albedo change was determined to be a non-negligible component of the climate change effects of establishing natural gas well pads (Fig. S12, ESI†). The median albedo change impact of the 12 561 studied wells is a cooling impact of −9500 kg CO_2eq per well, and these impacts range from −418 000 to +28 000 kg CO_2eq per well. The majority of well pads studied showed a cooling effect from albedo change instead of a contribution towards climate change. However, the average GHG emissions-based DLUC impacts (with surface albedo effects excluded) of approximately 2700 to 3 007 400 kg CO_2eq per well, with a median of 354 370 kg CO_2eq per well, indicate that the surface albedo change effect is generally smaller in magnitude than the effects of carbon sources of DLUC impacts (Fig. S13, ESI†). Only 91 well pads showed a larger contribution from albedo change than from carbon-based DLUC, and on average, albedo change impacts contribute 1.06% to the total impact. Still, 4011 well pads or nearly 32% of the scenarios showed a higher albedo change contribution than the average, reaching as high as 19.6% of the total impact originating from albedo change. These well pads were located across all three basins and all land cover types; statistical analysis indicated that the type of land cover does not significantly influence the impact due to albedo change, at a p-value of 0.973 (Fig. S14, ESI†). However, this may also be emergent from potential inaccuracies in identifying the original land cover types, or from differences in original land conditions across ecoregions for the same land cover types.

The contributions of net DLUC and albedo change effects to the total potential climate change impacts in g CO_2eq per MJ of natural gas extracted from each well pad were also compared by ecoregion (Fig. 6). The ecoregion delineation integrates many aspects, such as vegetation, land cover, geology, and soil features. Overall, well pads in the Southern Rockies ecoregion (n = 1747) showed the highest net contributions from DLUC to their total impacts, with an average of 30% DLUC and a median of 31%. In the Southern Rockies, 61.4% of well pads were located in previously forested land. All of the Raton basin well pads are within the Southern Rockies ecoregion, although most of the Southern Rockies well pads are in the San Juan basin. The Raton basin in northeastern New Mexico showed the highest overall climate change impacts for natural gas extraction among the three basins (Fig. 7). Well pads in the Southwestern Tablelands (n = 177) showed the lowest average and median net contribution from DLUC, both at 8%. All of the Southwestern Tablelands well pads are situated in shrubland or grassland, and all coincide with the Permian basin. Other ecoregions showed an average contribution from DLUC between 12–18% and median of 12–16%.

3.3. Influence of individual parameters and processes on natural gas LCA results

The relative contributions of individual steps and processes involved in the extraction of natural gas to the total cradle-to-gate carbon footprint were compared across the individual well pad scenarios (Fig. 8). The impacts related to steel production deliver the highest average contribution to GHG emissions among detailed processes, followed by concrete production and carbon sequestration loss due to foregone NPP, respectively. The other individual processes that contribute to DLUC impacts, such as aboveground carbon loss, belowground carbon loss, and soil organic carbon loss, produce considerable amounts of GHG emissions of similar magnitudes to the other processes, such as cement production for casing and transportation from the well pad to transfer extracted mud, dug earth, and construction waste to the local disposal site and to return equipment and other devices that are no longer needed (Fig. 8). Another location-specific process, the transportation of waste to a landfill, shows a notable contribution to the total impact, further indicating the importance of incorporating geospatial specificity in LCA. As for the individual steps leading to a functional well pad, the construction of the pad provides the highest contribution to the total impact. The DLUC impacts (aside from albedo change

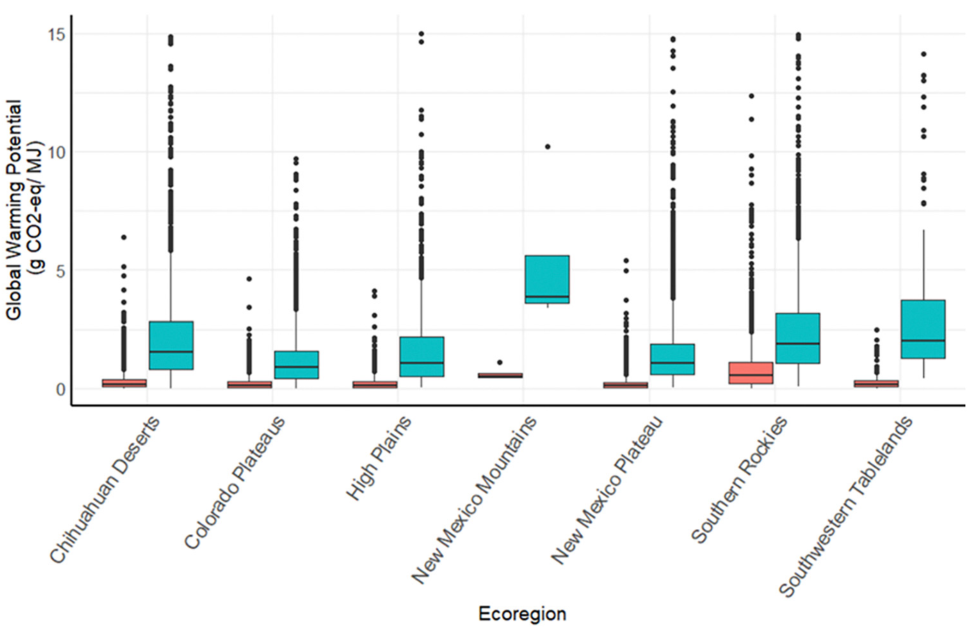

Fig. 6 Climate change impacts of active well pads in New Mexico by Level III ecoregion, depicting both the total impacts (teal) and the DLUC effects in isolation (pink).

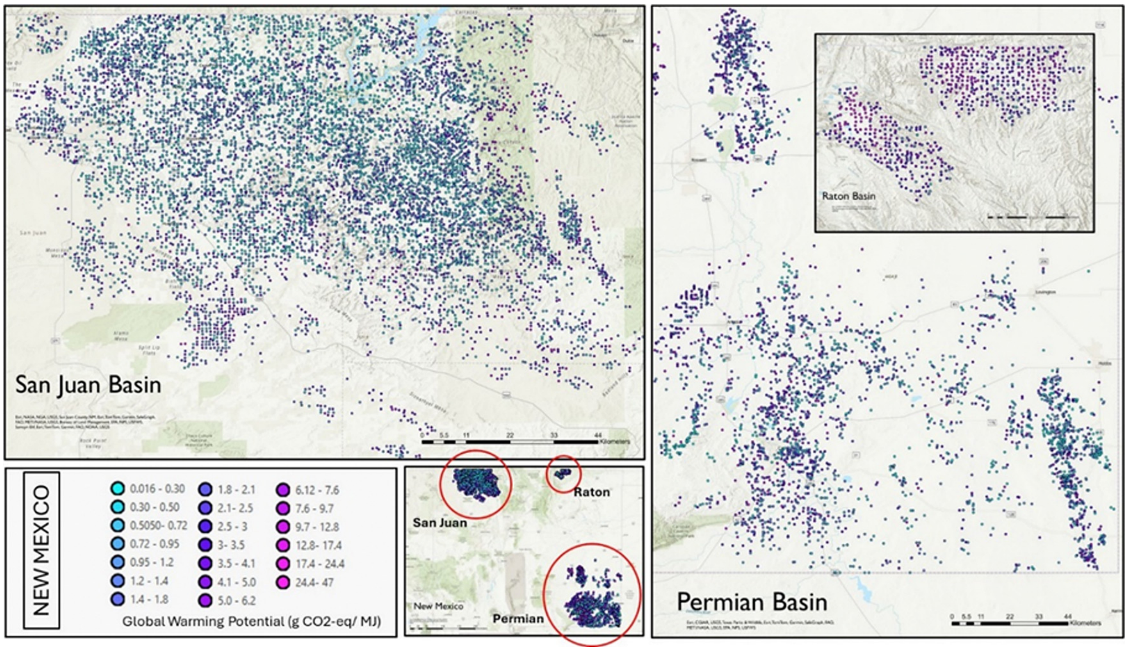

Fig. 7 Point density map of New Mexico illustrates the climate change impact of 12 561 active gas well-established between 1970 and 2020.

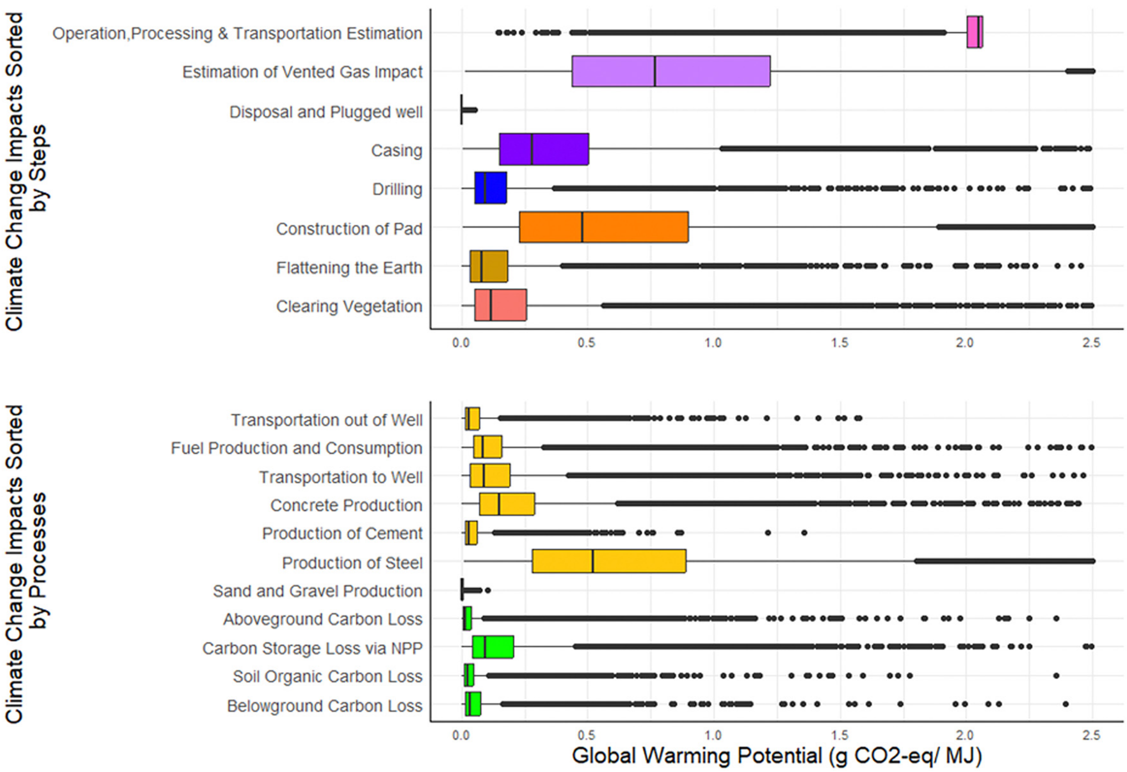

Fig. 8 Box plots of the GHG emissions of each process and each step across well pad scenarios, along with the additional estimated impacts from gas used for operation, processing, and transportation and the impact of vented gas. Albedo change impacts are not shown.

impacts) are included in the steps of clearing the vegetation and flattening the earth (Fig. 8). Approximately 0.5% of the well pad scenarios had a larger contribution from the cumulative DLUC effects than from other processes combined.

Some of the initial steps of gas removal and the energy required for gas extraction and CO_2 injection are included in the 'Operation, Processing & Transportation Estimation.' The other processes included in this step, like the energy required for the compressor to pressure the gas for transportation *via* pipeline, are also included in this section, as separation of these processes was not possible despite originally being outside the scope of this study. These impacts of compression are estimated for the lifetime of each gas well from data specific to 2022 and 2023, as this energy demand was only reported thoroughly for those years for these New Mexico wells. The same procedure was undertaken to quantify vented and flared gas, which were only reported for 2022 and 2023. The gas is usually vented during the maintenance of the system or sometimes flared at the site, and these releases can be intentional or unintentional. The values are estimated for the entire lifetime of gas wells and shown disaggregated from other impacts in Fig. 8. However, vented and flared gas impacts are not included in the total global warming potential in the other figures and among aggregated impacts due to a lack of available historical data and the possibility of substantial variation from year to year, as observed from the 2022 and 2023 data.

Sensitivity analysis for this LCA was performed using random forest, and we report on the result with the lowest MSE at 0.19. The single most influential variable affecting the total impact was determined to be the total production of natural gas for the entire lifetime of the well pad (Fig. S15, ESI†). This is primarily the result of the total gas production being a key component in scaling to the functional unit of 1 MJ of natural gas extracted, as well as a factor in the calculation of the allocation ratio which is used to scale shared well pad impacts between oil and gas produced. The other input variables with high influence on the total impact were identified using random forest techniques after filtering out the total gas production from the bar plot (Fig. 9). The area of the well pad, amount of concrete needed in constructing the pad, and the amount of steel used are the next most influential parameters overall across the 12 561 well pad LCA scenarios. These parameters vary site to site due to the accessibility and slope of the original land and the depth and horizontal length of the well. DLUC-related parameters such as the amount of carbon in belowground biomass and the reduction in carbon sequestration due to lost NPP are also prominent among influential factors. The ecoregion classification is ranked more highly than either the basin or the original land cover in the random forest results, suggesting that differences between ecoregions may affect the LCA results even for wells on the same land cover type and within the same basin. This may be due to the presence of different species and climatic factors, which subsequently affect the value distribution of DLUC and albedo-related parameters.

Complex and partial interconnections between the variables exist among the parameters analyzed, despite independent data collection for each variable in the uncertainty analysis. For example, while the mass of steel used in the wells is affected by the depth of the well for pipes and also the type of well structure for the casing form, other factors like the metal thickness,

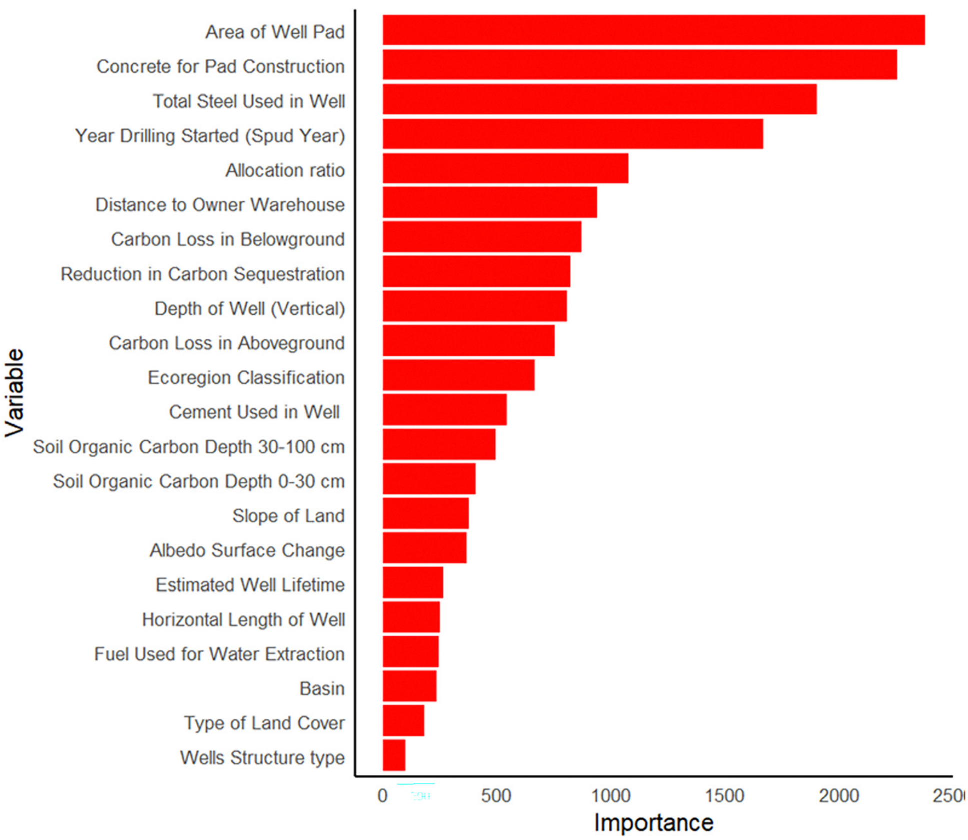

Fig. 9 Random forest analysis results depicting the relative influence of individual input parameters on the total carbon footprint of a well pad, with total gas production not shown.

pipe cross-sectional diameter, and kinds of steel can play essential roles in the weight of total steel used in the well. The same situation applies to cement in the well. Also, complex relationships affect the mass of the concrete relative to the total area of the gas extraction pad. In addition, the ecoregion classification was partially related to the original carbon present on the land, as was the land cover type. As this random forest approach isolates variables in each tree through bootstrapping, these connections may cause underemphasis or overemphasis on the importance of a certain variable. The effects can be reduced by increasing the number of trees; in this analysis, the number of trees was set to 1000.[48] In this case, there is a high possibility of overestimating the effect of the steel used in the well while underestimating the influences of the well's structure and vertical depth. Through this analysis, variables with complex connections are eliminated, and the model has only trained on the following variables: depth of well (vertical), year drilling started (spud year), horizontal length of well, distance to owner warehouse, area of well pad, ecoregion classification, type of land cover, slope of land, basin, wells structure type, estimated well lifetime, fuel used for water extraction, allocation ratio, and the total gas production volume (Fig. S16, ESI†). Eliminating some factors in the training model may overestimate the effect of included variables. Nevertheless, considering Fig. 5 and Fig. S16 (ESI†), the strong influence of some variables that are likely to be correlated with multiple others, like the area of well pads, was observed. After constructing the random forest model and identifying the importance of the area of pads, depth of wells, and total gas production, the marginal effect of these three highly influential variables on the climate change impact of extracting natural gas was illustrated using partial dependence plots (Fig. 10).[49] The marginal effect in the context of a partial dependence plot (PDP) means predicting or estimating the sensitivity of the outcome to an input variable when the other variables are constant, similarly to a local sensitivity analysis, which is common in LCA studies.

The PDPs as sensitivity analysis results illustrate that the impact increases sharply when the area of the gas well pad is increased up to between 12 000 and 15 000 m^2. It should be noted that these outcomes were obtained specifically for this study's New Mexico gas well pad selection, in which large-size

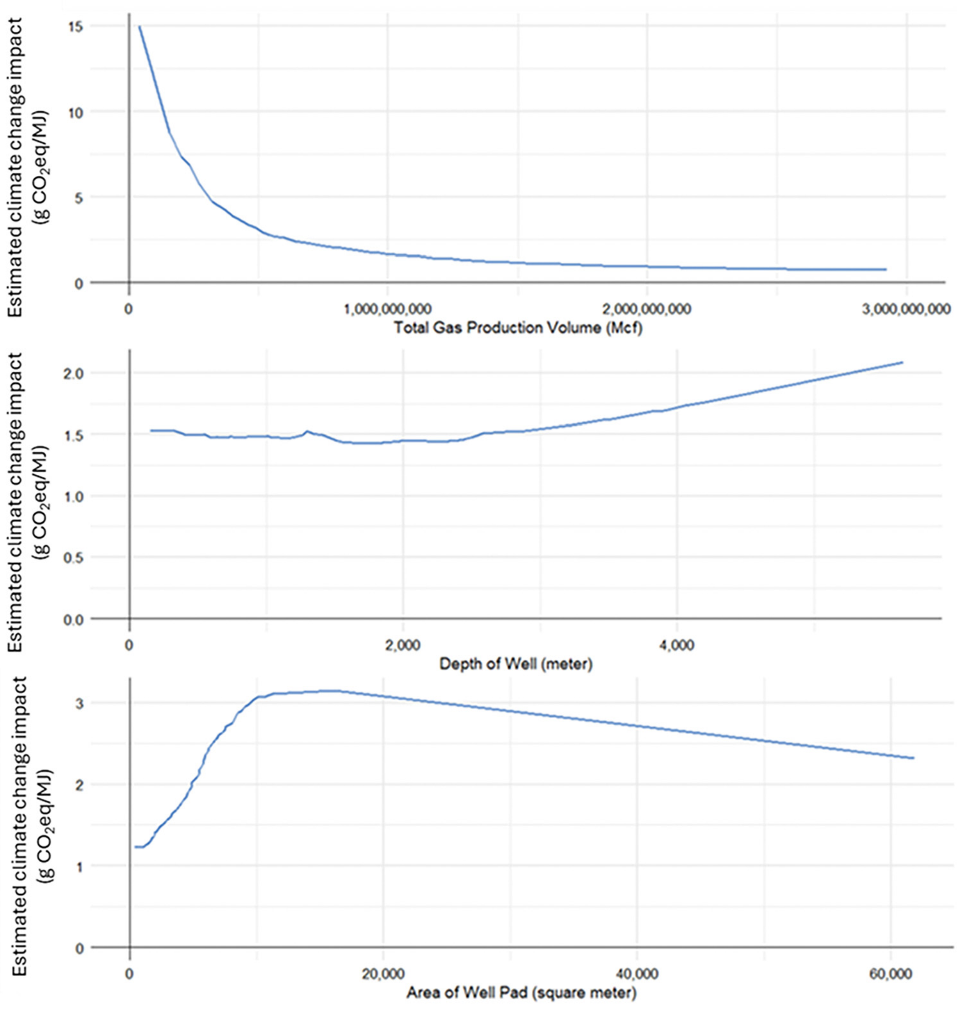

Fig. 10 The marginal effect of the three most influential factors for the climate change impact of extracting natural gas, depicted in partial dependence plots.

gas pads tended to be constructed in low vegetation regions, which explains the behavior of the area sensitivity curve beyond that point slightly above 12 000 m^2. Furthermore, the estimation accuracy of this sensitivity analysis approach is higher when the number of samples is large, and the vast majority of the areas were smaller than 10 000 m^2 (Fig. S7 and S9, ESI†).

3.4. Contextualization

The average impact of constructing well pads and drilling the wells in virgin land across ecoregions in New Mexico is 1.45 g CO_2eq per MJ without DLUC impacts, and the average impact rises to 1.79 g CO_2eq per MJ when DLUC impacts are included. When the estimated impact of vented and flared gas (shown in Fig. 8) is also integrated into the total impact to more closely align with the system boundaries of other natural gas extraction LCAs, the average impact determined across the 12 561 well pads increases from 1.79 to 3.05 g CO_2eq per MJ, and the maximum impact from 46.4 to 60.4 g CO_2eq per MJ (Fig. S17, ESI†). Because some additional processes are excluded in this study, such as the impact of using electricity at the well pads to run pumps and the water and gas injection processes, as well as energy needs for gas removal (initial processing), the actual average impact of these studied cases would be even higher. Despite this fact, the average impact of 3.05 g CO_2eq per MJ that includes DLUC effects is higher than previously calculated in other studies. The National Energy Technology Laboratory (NETL) provides a comprehensive technical report determining the average global warming potential of natural gas extraction in the US as 2.8 g CO_2eq per MJ,[19] while another detailed analysis concluded that the climate change impact of production of natural gas is 7.18 g CO_2eq per kW h or 0.893 g CO_2eq per MJ,[17] assuming that 0.21 m^3 of natural gas would be needed to generate 1 kW h, and that 1 m^3 of natural gas contains approximately 38.3 MJ m^{-3}.

Even without including vented and flared gas estimates, 7810 or 62.2% of the well pads in this study showed a higher impact than 0.893 g CO_2eq per MJ,[17] and these wells showed an average net contribution from DLUC of 18.1%. In comparison with the higher previously reported carbon footprint of 2.8 g CO_2eq per MJ,[19] 2159 well pads in this study (17.2%) were associated with a larger total impact; this subset showed an average net contribution from DLUC of 20.4%. Furthermore, 130 well pads incurred a total climate change impact higher than 10 g CO_2eq per MJ, and DLUC effects contributed 22.9% of their total impacts, on average. In this study, the well pads with higher climate change impacts for natural gas extraction were generally associated with greater contributions from DLUC than well pads with lower impacts.

The average estimation of life cycle GHG emissions for generating electricity from natural gas have been previously reported as approximately 58.43 g CO_2eq per MJ,[50] while the impact of only well pad construction through gas extraction including DLUC (with vented and flared gas impacts) can be as high as 60.5 g CO_2eq per MJ as calculated in this study. Still, even without accounting for vented and flared gas, this well pad-level analysis revealed that the carbon footprint of natural gas extraction ranges across orders of magnitude, from 0.016 to 46.4 g CO_2eq per MJ across the 12 561 New Mexico wells studied. The results illustrate the importance of considering DLUC effects and other geographically specific variables before selecting a well pad site in order to minimize cradle-to-gate GHG emissions, and also of taking appropriate measures to prevent releases of natural gas during the operation and maintenance of the system.

The DLUC impacts calculated in this study may also be more conservative than their actual extent, as the DLUC impacts of land converted for gas extraction beyond the well pad site itself were not included. Accounting for land disrupted for access roads and associated infrastructure to support the oil and gas industry close to the well pads would increase the DLUC impacts presented in this study. On the other hand, replanting and land reclamation efforts could decrease the magnitude of DLUC impacts at well pad sites, but these would not generally cancel their effects. For example, lost NPP during the years before replanting with the same native vegetation would not be regained, and the pulse GHG emissions from SOC loss and biomass carbon loss at the start of well pad construction would have still contributed to atmospheric GHG concentrations years before these efforts at mitigation. Additionally, the use of concrete at well pads limits the full area that can return to its previous or natural conditions.

The implications of this study extend beyond New Mexico, as ecoregions and basins do not follow state boundaries. The Raton Basin extends farther north from New Mexico into Colorado, and farther west from the existing well pads into protected forests. There are 3728 active oil and gas well pads in the Raton Basin across the two states.[51] The hundreds of gas well pads in New Mexico extracting gas from the Raton Basin were mostly constructed within a 10-year period on private forested land. Notably, 43% of forested land in New Mexico is privately owned.[52] Laws and best practices for private forests differ between states; in New Mexico, cutting or removing woody material from private lands requires simply written consent from the owner, and construction projects such as clearing for access roads do not require a harvest permit or an approved forest harvest practice plan.[53]

Tree removal can lead to utilization of wood products in regions with established and robust forestry industries and for wood species that have favorable characteristics. The forested land in the northeastern New Mexico region is dominated by pinyon-juniper and ponderosa pine trees. Pinyon is particularly resinous and its stands tend to have low tree density, limiting its uses and affecting the economic feasibility of its harvest.[54] High hauling costs and transportation access difficulties have been identified as major utilization challenges for pinyon wood in the Southwest.[54] New Mexico has also experienced a decline in wood processing capacity, which further contributed to prohibitively long distances between prospective harvest sites and mills.[55] Additionally, the most common approach to tree removal in pinyon-juniper woodlands in the Southwest is mastication, which shreds woody biomass and does not typically involve any collection or harvest, even in fuel reduction projects for wildfire prevention.[55] The dry climate and shorter growing season of the Southern Rockies ecoregion cause slow regeneration of trees after clearcut types of forest harvests, which further inhibits major forestry activities.[56] Overall, in New Mexico in 2019, tree removals accounted for less than 5% of tree biomass loss, as tree mortality from other causes dominated.[57] Thus, it is unlikely that the biomass cleared from the 160 hectares of gas well pad areas (which does not include any inactive/plugged wells, oil-only extraction sites, pads with multiple wells, or access roads) in the Raton Basin was wholly used beneficially. These natural, legal, logistical, and economic conditions further support the need to include location-specific data and DLUC impacts in calculating the climate change impacts of well pads, as the Raton Basin well pads in this study showed an average of 35.4% net DLUC contribution to their total impacts.

4. Conclusions

The results of this study illustrate that the climate change impacts associated with the loss of original biomass carbon, soil organic carbon loss, and change in net primary productivity caused by establishing a natural gas well pad should be quantified and included in life cycle assessments (LCAs) of natural gas. These direct land use change (DLUC) effects are highly variable by site, and their magnitudes can match those of individual process impacts. In locations with relatively high concentrations of organic carbon per unit area prior to construction, like forested lands, DLUC effects can have a particularly notable influence on the cradle-to-gate climate change impacts of natural gas. The carbon footprint of natural gas extraction was also found to be dependent on several parameters that vary geographically and by well pad in addition to DLUC effects, such as gas production, relative amount of coproduced oil, the well pad area, well depth, lifetime, and transportation distances. Although some parameters cannot be fully controlled or predicted, like the lifetime natural gas production of a well, the carbon footprint of new natural gas wells could be reduced by first assessing prospective installation sites for their potential DLUC impacts.

Overall, a total climate change impact difference ranging three orders of magnitude was observed across the 12 561 natural gas-producing well pads analyzed in this geospatial LCA study. The common values used for the impact of natural gas extraction in LCAs are thus not universally representative of the actual impact, which could only be determined through well pad-specific data that is not consistently available for LCAs of downstream products. In this study, we combined data collected with GIS methods, machine learning, and a dataset for wells in New Mexico with a level of detail that is unmatched in other states at the time of this writing. The accuracy of LCAs that include natural gas may depend on other states compiling and publishing well pad-level data and on extending this multilayered approach nationally.

Author contributions

A. S. completed the investigation and visualizations, and also wrote the original draft. A. S. was the lead in performing the formal analysis, with M.-O. F. in a supporting role. Both A. S. and M.-O. F. contributed equally to the methodology, data curation, software, and validation. M.-O. F. was the lead in the conceptualization of the study, with A. S. in a supporting role. M.-O. F. acquired funding and resources for the study, provided project administration and supervision, and reviewed and edited the writing.

Data availability

The data used for this study can be accessed in the Kaggle data repository at **https://doi.org/10.34740/KAGGLE/DSV/9527170**.

Conflicts of interest

There are no conflicts of interest to declare.

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