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Modelling pathways to a carbon neutral Queensland beef sector through policy and investment to drive transition from deforestation to reforestation

Final Report

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Abstract

Adapting to a carbon constrained world is necessary for the future of the global livestock industry. In Australia, livestock grazing covers half of the continent and contributes over AUD$19 billion to the economy per year, with most of that value (over $14 billion) derived from beef cattle. The largest beef cattle herd in Australia occurs in Queensland, where beef is the most significant agricultural commodity but is also responsible for up to 25% of the state's annual greenhouse gas emissions. The Australian red meat sector has committed to an industry-wide carbon neutral target by 2030, and previous work has identified reduced deforestation in Queensland beef-producing regions as the most promising mitigation option for the sector as a whole.

This project aims to model pathways to carbon neutrality for the Queensland beef sector by 2030. The Full Carbon Accounting Model (FullCAM) is used to simulate biophysical changes in carbon stocks that would occur under different vegetation management regimes, and quantifying the potential emissions abatement delivered by avoiding clearing or restoring native vegetation. As the relative strength of regulatory settings under the Queensland *Vegetation Management Act 1999* (VMA) has historically been a significant driver of emissions in the land sector, we model how the emissions abatement task would vary under three counterfactual scenarios between 2020 and 2030: (1) strengthened policy settings, (2) current policy settings, and (3) relaxed policy settings. We develop these counterfactual scenarios by calculating historical changes in forest and sparse woody vegetation extent across 32 beef-producing Local Government Areas (LGAs, 95% of grazing land in Queensland) using nationally consistent data.

We find that under current policy settings, a carbon neutral Queensland beef sector would need to avoid or sequester 33 Mt CO2-e per year via changed vegetation management practices between 2020 and 2030. Under strengthened or relaxed policy settings, the abatement task varied between 13 and 41 Mt CO_2-e per year, respectively. In absence of targeted action to curb emissions, six LGAs (Cook, Murweh, Maranoa, Balonne, Central Highlands and Isaac), are predicted to collectively contributed 49 – 68% of the total emissions from vegetation management, depending on the assumed counterfactual. Where policy or incentives exist to avoid or sequester emissions, a maximum of 145 Mt CO_2-e per year can be sequestered between 2020 and 2030 – largely via avoided clearing of forest (68%), or management of sparse vegetation to become forest (avoided thinning or suppression, 16%).

Our results show that the relative strength of vegetation management regulatory settings has a material impact on the size of the Queensland beef sector's carbon neutral abatement task. Our findings can assist in identifying where the greatest potential exists for carbon abatement that is additional (above and beyond what would happen in absence of sector wide action to curb GHGs) and cost-effective.

Acknowledgements

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1. Introduction

1.1 Background

The global food system is a major source of greenhouse gas emissions (~ 30% [1]), which must be reduced to achieve the 1.5° and 2°C climate change targets under the Paris Agreement [2]. Livestock production directly contributes ~8-9% of global emissions [3,4], particularly through deforestation and clearing of land for pasture, and enteric fermentation. There is increasing pressure from both consumers and governments to reduce the emissions intensity of livestock production, such as through deforestation-free beef [5]. The rangeland systems that support livestock grazing – and the livelihoods of rural and regional communities – are in turn highly vulnerable to climate change [6,7]. Adapting to a carbon constrained world is therefore necessary for the future of the global livestock industry.

In Australia, livestock grazing covers half of the continent [8] and contributes over AUD$19 billion to the economy per year, with most of that value (over $14 billion) derived from beef cattle [9]. The Australian red meat sector has committed to an industry-wide carbon neutral target by 2030 [10], and is taking steps to improve its overall sustainability, such as through the Australian Beef Sustainability Framework [8]. Emissions from the Australian red meat sector have decreased by 55% since 2005 [11], but more work is needed to achieve carbon neutrality. Recent work [11,12] identified reduced deforestation as the most promising mitigation option for the Australian red meat sector as a whole.

Within Australia and internationally, beef cattle grazing is particularly carbon intensive [13,14]. The largest beef cattle herd in Australia occurs in Queensland, where beef is the most significant agricultural commodity ($5.7 billion in 2016–17 [15]) but is also responsible for up to 25% of the state’s annual greenhouse gas emissions (~ 40 Mt CO_2e out of ~170 Mt CO_2e in 2018 [16]. To achieve a sector- and nation-wide carbon neutrality target by 2030, the Queensland beef sector must be a major focus.

Research is needed to determine how a 2030 carbon neutrality goal could be operationalized for the Queensland beef sector. Such an analysis would most usefully be spatially explicit and consider factors that influence emissions abatement at a regional scale, including the area of land managed by the beef sector, historical rates of forest and sparse woody vegetation clearing and regrowth, and typical practices used to manage vegetation.

1.2 Objectives

The project aims to model pathways to carbon neutrality for the Queensland beef sector by 2030 through changes in vegetation management. The Full Carbon Accounting Model (FullCAM) is used to simulate biophysical changes in carbon stocks that would occur under different vegetation management regimes, and quantify the potential emissions abatement delivered by avoiding clearing or restoring native vegetation.

As the relative strength of regulatory settings under the Queensland *Vegetation Management Act 1999* (VMA) has historically been a significant driver of emissions in the land sector, we model how the emissions abatement task would vary under three counterfactual (policy) scenarios between 2020 and 2050: (1) strengthened policy settings, (2) current policy settings, and (3) relaxed policy settings.

The specific aims of the project were to:

(1) Develop, through desktop review and stakeholder consultation, a series of counterfactual (policy) scenarios that represent the future conditions in which beef cattle enterprises in Queensland would need to account for in a transition to carbon neutrality.

(2) Quantitative modelling of the maximum biophysical change in carbon stocks that may occur through a combination of avoided deforestation, reforestation, and regeneration (not necessarily reaching forest cover) for scenarios where land managers had incentives to undertake different land practices, where the aim is to reach sector-wide carbon neutrality by 2030 and maintain it thereafter.

(3) Summarise these findings in a written report and evaluate the implications of different incentives and policy scenarios for carbon sequestration outcomes.

2. Methods

2.1 Overview of methods

This project drew on multiple sources of data to model pathways to a carbon neutral Queensland beef sector.

To identify viable pathways to carbon neutrality by 2030, we first need to establish an estimated scenario of emissions from the Queensland beef sector *in absence of* sector-wide action to curb greenhouse gas emissions (GHGs). This ‘without action’ scenario is commonly termed the *counterfactual* [17]*,* and must be identified to quantify the GHG abatement requirement for carbon neutrality.

Past work by Mayberry et al. [11,12] identified counterfactuals for the Australian red meat sector by estimating historical emissions in 2005 and 2015.

In this study, we instead develop counterfactuals that are:

(1) spatially explicit and consider factors that influence emissions abatement at a regional scale across Queensland, and

(2) based on data-driven predictions of the future, rather than comparing to historical emissions at a single time point.

This allows us to understand how potential future impacts of changing regulatory regimes on vegetation management, which is a significant driver of emissions in the land sector [18,19], might influence the beef sector’s carbon abatement task up to 2030.

To do this, we translate the Queensland-scale policy scenarios of Butler and Fensham [20] into quantitative predictions of deforestation and reforestation at the Local Government Area (LGA) scale up to 2030, using historical data from the National Carbon Accounting System (NCAS) [21].

These data, combined with interview data on regional-scale information on vegetation management practices, are used to inform quantitative modeling of the maximum biophysical change in carbon stocks at the LGA level using the Full Carbon Accounting Model (FullCAM) [22].

From the FullCAM outputs, it is possible to establish LGA-level predictions of GHG abatement potential under three future counterfactual scenarios. This information can be used to inform policy and investment to drive transition from deforestation to reforestation.

2.2 Study area

To model the Queensland beef sector’s requirements for carbon neutrality by 2030, we first require an understanding of how much land the sector manages for grazing cattle at a regional scale. We estimated this using the most recent national land use dataset [23].

The ‘Grazing native vegetation’ subclass of the Australian Land Use and Management (ALUM) classification considers areas grazed by domestic stock on native vegetation where there has been limited or no deliberate attempt at pasture modification, and there is greater than 50 per cent dominant native species. We assumed that all ‘Grazing native vegetation’ land in Queensland was grazed by beef cattle.

We removed locations of recently designated protected areas not identified in the ALUM classification using the Protected Areas of Queensland layer [24]. We chose Local Government Areas (LGAs) as spatial units of analysis due to their relatively small size, which would enable greater differentiation in modelling outputs than what could be possible at a State or Natural Resource Management (NRM) Region scale (Figure 1).

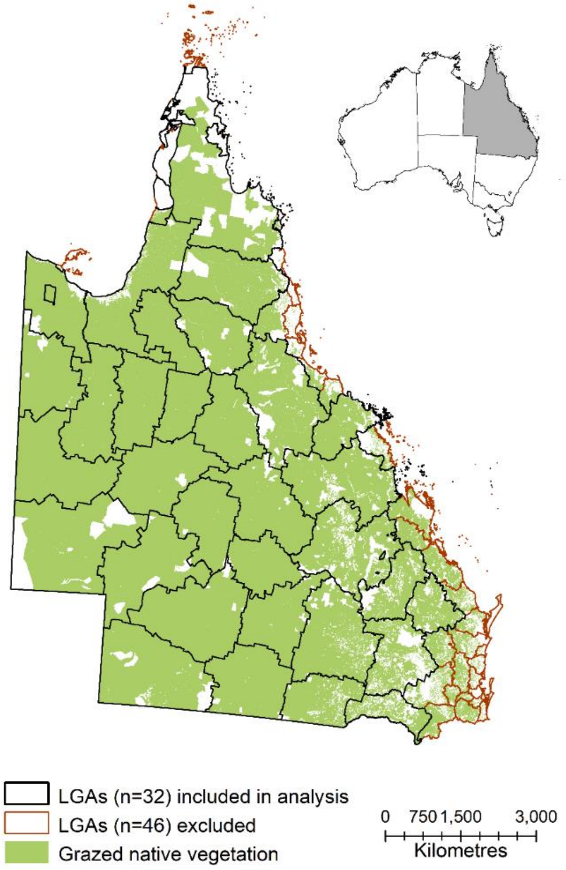


Figure 1. Study area, including Local Government Areas (LGA) included and excluded from analysis, and area of grazed native vegetation in Queensland.

To keep the size of the analysis manageable, we selected 32 out of the 78 LGAs in Queensland for modelling [22]. Each of these 32 LGAs contain at least 700,000ha of grazing land, and collectively make up 95% of total area of grazed native vegetation in Queensland (Figure 2).

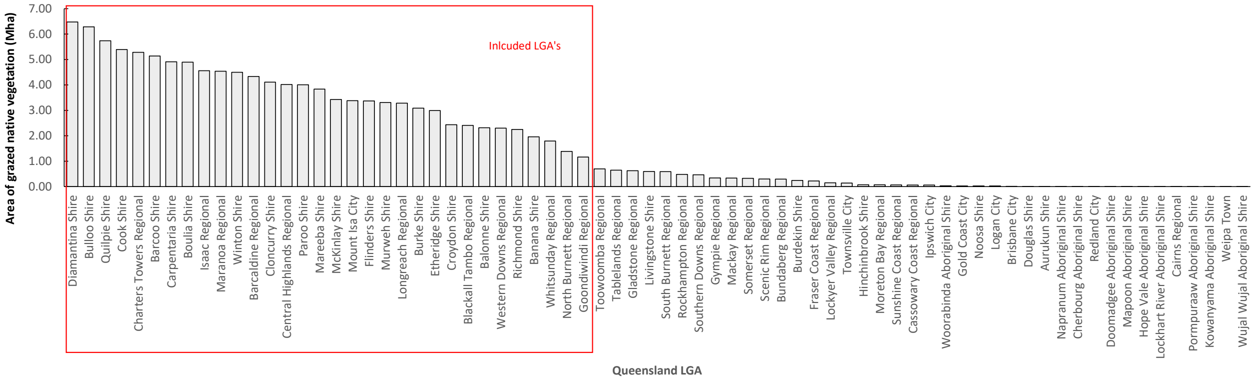


Figure 2. Area of grazed native vegetation (Mha) in each of the local government areas (LGA) across Queensland. The red box indicates the 32 LGA’s (each with with >0.7 Mha of grazed native vegetation) that were included in this study.

2.3 Counterfactual scenarios

2.3.1 Historical rates of change in forest and sparse woody vegetation cover at the LGA scale

To generate LGA-level counterfactual scenarios – that is, predictions of the future – we used the most recent nationally consistent data on forest and sparse woody vegetation extent [21] to estimate historical rates of change at the LGA scale.

The National Carbon Accounting System (NCAS) is used by the Australian Government to quantify stocks and flows of GHGs from the land sector, and so is consistent with emissions reported in the national inventory (Appendix 1) and with the use of FullCAM carbon accounting model (Section 2.4).

The NCAS uses over 7000 Landsat MSS, TM and ETM+ images to map forest and sparse vegetation extent at a 25-m resolution across the Australian continent. Note that the three-class classification version used in this analysis [21] discriminates between forest, sparse woody and non-woody land cover across a time series from 1988 to 2019. The superseded two-class classification excluded ‘sparse’ native vegetation types which do not meet the ‘forest’ thresholds of minimum 20 per cent canopy cover, at least 2 metres high and a minimum area of 0.2 hectares as defined by Furby [25]. The Australian Government began to estimate and report emissions on changes in the extent of sparse woody vegetation cover in addition to forest for the second commitment period under the Kyoto Protocol [26].

We followed Evans [27] and Evans et al. [28] by using the ‘raster’ package [29] in R Statistical software [30] to summarise forest and sparse vegetation extent and change at the LGA level from 1988 to 2019 (additional information and R code provided at Appendix 2 and [31]). In doing so, we were required to make two key simplifying assumptions.

First, we assumed that the area of forest **and** sparse vegetation in the earliest epoch (1988) in the was representative of the area of land with “forest potential”. This was done in absence of a spatial layer indicating the area of forest potential in 1972 in the publicly available data package [21]. We therefore assumed that any sparse vegetation in the 1988 epoch had the potential to become forest. The impact of this assumption on FullCAM predictions will be relatively small. This is because FullCAM is ‘blind’ to the definition of ‘sparse’ and ‘forest’ as it predicts sequestration of carbon in accordance with the input layer of site productivity potential.

Second, we assumed that the change (measured in hectares) in forest and sparse vegetation extent between consecutive epochs (e.g between 2013 and 2014) can be attributed to human intervention, and specifically, to the beef sector. We used the modified ‘Grazing native vegetation’ layer (with recent protected areas removed, see Section 2.2) as a mask, so only changes in forest and sparse vegetation extent that occurred on land managed by the beef sector was captured by this analysis.

However, not all land use changes (e.g wildfires, drought) in these areas can be attributed to the beef sector. The Australian Government retains a version of the forest and sparse woody vegetation extent dataset [21] where changes between epochs are *attributed to human intervention* (as per the previous two-class classification version [32], as analysed by [27]). This dataset is unfortunately not publicly available, so the estimates of forest and sparse vegetation change presented in this report may represent overestimates of the changes attributable to the beef sector.

To ensure the accuracy of this data analysis, we cross-checked findings by aggregating the LGA-level data outputs up to all of Queensland, and compared to the numbers reported in the national inventory [21] (Appendix 3).

2.3.2 Translating Queensland-scale predictions to the LGA scale

Butler and Fensham [20] conceived four possible future policy scenarios for native vegetation clearing rates in Queensland at the state scale, according to the extent to which the *Vegetation Management Act* (VMA) 1999 may be strengthened or relaxed. Their analysis provides a framework from which to develop LGA scale counterfactuals that are necessarily hypothetical, but are informed by historical data and policy regimes.

For this analysis, we consider the first three scenarios to inform the development of three future counterfactual scenarios at the LGA scale (Table 2). We do not consider their fourth scenario in our analysis, which assumes the VMA is modified to enable new clearing for ‘high value agriculture’, as this is outside the scope of the beef sector.

Table 2. Three future counterfactual scenarios of native vegetation clearing rates in Queensland, adapted from Table 1 (pg 11) in Butler and Fensham [20]. For the purposes of this report we ignore the fourth scenario and have renamed the first three. *Note that [20] predicted a significant portion of primary forest conversation under the third scenario would occur via “thinning”, which is typically reported in the national inventory as sparse forest loss (sparse to non-woody classification; see Table S2)

This report scenario name	**Butler and Fensham (2021) scenario name**	**Butler and Fensham (2021) estimated total annual clearing in Queensland (k ha/year)**		**Butler and Fensham (2021) rationale**	**This report calculation to translate to LGA-level counterfactual scenario**	
		Forest primary conversion	**Forest re-clearing**		**Forest primary conversion**	**Forest re-clearing**
(1) Strengthened policy settings	1. Low clearing	20	70	First-time clearing approximately half of the average reported rates since 2010. Low re-clearing, around half of rates reported 2009-2013 under policies restricting regrowth clearing, which were relaxed in 2013.	50% of average rate from 2010-2018	50% of average rate from 2009-2013
(2) Current policy settings	2. Business as usual	40	210	First time clearing approximately half of the average of rates reported 2006-2018. Re-clearing comparable to average rate reported between 2006-2018.	50% of average rate from 2006-2018	Average rate from 2006-2018
(3) Relaxed policy settings	3. More grass	40* (plus 150 removed via “thinning”, equivalent to an additional 45 of primary conversion).	280	Both first-time clearing and re-clearing at higher end of range (upper quartile) reported under relatively permissive regrowth regulation policies. Comparable to reinstatement of regulatory relaxations implemented in 2013	Upper quartile (Q3) of annual rates from 2013-2018	Upper quartile of annual rates from 2013-2018

Here, we use the rationales put forward by Butler and Fensham [20] to inform the quantification of counterfactual scenarios at the Local Government Area (LGA) scale. We use the historical rates of forest clearing and regrowth at the LGA scale calculated in the previous subsection (2.3.1), and apply the calculation informed by Butler and Fensham [20]'s analysis to translate these historical estimates to LGA-level counterfactual scenarios (predictions of the future).

For example, Butler and Fensham [20] determined that if the existing VMA regulatory settings were to be maintained as they are up until 2030 ("Current policy settings"), the rate of first-time clearing would be approximately half of the average of rates reported 2006-2018. Therefore, to develop a "Current policy settings" counterfactual scenario, we calculated the predicted rate of first time clearing between 2020 to 2030 in each of our 32 LGAs (Figure 3) as 50% of the average rate observed between 2006 and 2018.

Rather than calculating the carbon abatement required to become carbon neutral according to a single historical timepoint (2005 or 2015) for all of Queensland, we draw on continuous historical data between 2006 and 2018, across 32 LGAs in Queensland, to develop three plausible future counterfactual scenarios. This approach facilitates a more nuanced and granular understanding of how the Queensland beef sector might achieve carbon neutrality by 2030, including which LGAs might offer more or less capacity for carbon abatement, depending on the strength of vegetation management regulatory settings in the future.

2.3.3 Regional vegetation management regimes

Within FullCAM, it is possible to simulate the effects of different vegetation management regimes to predict the effects on woody vegetation and soil biomass. To implement these simulations and quantify biophysical change in carbon stocks, we required information at the LGA level on the type and application frequency of different vegetation management practices.

Grazing landscapes in Queensland encompass a broad range of vegetation types, from the predominately tropical savanna woodlands of the north, to the open Mulga woodlands (*Acacia aneura*) of the central west, to the Brigalow (*Acacia harpophylla*) of the east. Vegetation management practices (including the use and timing of fire, mechanical or chemical clearing, and/or windrowing and burning of woody residues post-clearing) vary across these landscapes, and influence carbon sequestration outcomes in beef grazing systems across Queensland.

To capture this information at a regional scale, we undertook semi-structured interviews with a range of individuals familiar with vegetation management practices for livestock production in Queensland. Human Ethics Approval was granted under the Negligible or Low Risk pathway according to University of New South Wales policy (Approval no. HC200902).

Participant recruitment

We recruited participants familiar with typical land management practices for livestock production in Queensland. Collectively, we sought to identify participants who could speak to vegetation management practices that are typical of each of the twelve National Resource Management (NRM) regions in Queensland, such that these results could be extrapolated to our selected 32 LGAs.

To do this, we sought recommendations for participants from two key informants from the Queensland state government, and a peak industry body, respectively. We also individually contacted (via phone, email or both) the twelve NRM regional body offices with interview requests. Snowball sampling techniques were used [33], whereby interviewees were asked for their recommendations for potential participants at the conclusion of the interview.

All potential participants were emailed with a Participant Information Sheet and Consent Form (Appendix 3), and a list of questions (Table 3). In total, we contacted 23 potential participants, and completed interviews with 10.

Table 3. Interview guide used to identify vegetation management practices in beef grazing landscapes across Queensland. The guide was provided to participants prior to the interview and used as prompts for the conversation.

1. **Is fire management used to control woody vegetation, or is it mechanical or a mixture of both?**
    - **a.** If fire is used, how often would a typically land manager use that to control woody vegetation?
    - **b.** If mechanical clearing is used…also ask…
2. **When woody vegetation is cleared or pushed over, do land managers leave the vegetation on the ground or burn the residues?**
    - **a.** If residues are burnt, when and how is this done?
3. **When controlling woody vegetation to promote increased grass availability, does the woody vegetation re-sprout from remaining root stock, thereby requiring eventual re-clearing?**
    - **a.** If so, how many years before the cleared woody vegetation requires re-clearing?

Interview process

Prior to the commencement of the interview, participants were asked to provide formal consent (written or verbal). Interviews took approximately 30 minutes and were conducted over the phone or online video platform (participant's choice), at a time that suited the participant. Interviews were not digitally recorded, and the researcher took written notes only during the interview. The notes were written in MS Word and provided these notes to the participant to check for accuracy and edited where necessary. The final notes contained no information which could identify the participant and were uploaded to a secure OneDrive account accessible only to the research team.

Interview findings were summarized according to the NRM region(s) the participant indicated they were familiar with and referring to in their responses, and then extrapolated to our selected 32 LGAs depending on which NRM they primarily corresponded to (degree of overlap).

2.4 Modelling carbon pathways for each LGA

Modelling of the maximum biophysical change in carbon stocks (live and dead biomass and debris) was done using the Full Carbon Accounting Model, FullCAM (v 6.20.03.0827 [2020PR]); a carbon accounting model described in detail by Brack and Richards [34], and configured as a mixed (forest and agriculture) system simulating at monthly time-steps. FullCAM simulations were run from January 1700 to December 2050. All simulations commenced in 1700 to ensure that pools of soil carbon had reached an equilibrium level with respect to the site climatic conditions, maximum above-ground biomass (M), and fire regimes.

The vegetation simulated was grazed woodland or shrublands. In FullCAM, the ‘forest percentage cover’ input determines the predicted area available for grass to grow. Climate (rainfall, temperature, evaporation) and productivity were assumed to vary little within each LGA area. Since FullCAM is a point-based model, the location of simulation was selected as being a town near the centre of each LGA.

In FullCAM, predicted woody biomass (and hence, carbon inputs to other pools via turnover, mortality, clearing and fire) is highly influenced by the spatial input parameters for long-term maximum biomass potential of woody vegetation; M. The average M was therefore calculated spatially for the grazed native vegetation areas within each of the 32 LGAs.

2.4.1 Counterfactual and maximum abatement scenarios

Paul and Roxburgh [22] simulated biophysical change in carbon stocks under:

A. **Three counterfactual scenarios:** that is, what would happen *in absence of* sector-wide action to curb greenhouse gas emissions (GHGs)?

   (1) Strengthened policy settings.

   (2) Current policy settings

   (3) Relaxed policy settings

B. **Three corresponding maximum abatement scenarios:** whereby management actions are implemented to avoid the release of/increase sequestration of emissions through changed vegetation management practices:

   (1) Maximum abatement 1 (Max-1)

   (2) Maximum abatement 2 (Max-2)

   (3) Maximum abatement 3 (Max-3)

These simulations involved implementing 30 woody vegetation change scenarios (Table 4) under (A) the counterfactuals and (B) the maximum abatement scenarios, to calculate the consequences of management-induced changes from 2020 onwards, with woody vegetation cover in each LGA transitioning between either remnant forest (Fr), forest (F), sparse (S) or non-woody (N).

To simulate the three counterfactuals, Paul and Roxburgh [22] applied the average rates of change in forest and sparse woody vegetation cover (ha per year) in each LGA (calculated in subsection 2.3.2). For each LGA, the counterfactual rates of change from 2020-onwards were assumed to apply for 10 years (from 2020 to 2030) or 30 years (from 2020 and 2050). This was done for each LGA to attribute the number of hectares of grazed native vegetation under which the 30 scenarios were simulated.

However, there is a biophysical limit to the area available within each LGA. Therefore, for each area of grazed native vegetation of given combinations of F, S and N in 1988 and 2018, it was assumed that the annual changes assumed in each counterfactual would apply only up until the limit in available land is reached. This means that the 30-year simulation results are more uncertain that the 10-year results, as the simplifying assumption was made that there was **no re-clearing of previously cleared vegetation.** This assumption was made as there would be very high uncertainty around differing time-periods between clearing events in different beef producing regions.

For the corresponding management-induced changes that would maximise carbon abatement, changes in woody vegetation were simulated in FullCAM through the addition of FullCAM management events (described in detail: [22]).

For example, maximizing carbon abatement in woody vegetation change scenario 9 (F-S-N, Table 4) requires a management induced change from non-woody (N) in 2020-onwards under the counterfactual, to instead become forest (F). Information about regional vegetation management practices (Section 2.3.3) was incorporated into the modelling by simulating a greater amount of regrowth in LGAs where fire is used to manage woody vegetation when compared to those LGAs where clearing is either mainly mechanical or chemical.

Table 4. The 30 combinations of woody vegetation change scenarios applied for counterfactual and maximum abatement simulations of management-induced changes in the patterns of woody vegetation cover between 1988, 2018 and 2020 to 2030, with these transitioning between either remnant forest (Fr), forest (F), sparse (S) or non-woody (N). In the Maximum abatement scenarios, 'Forest*' indicates the scenarios where forest growth between 2020 to 2030 in the four LGA's with 'Mech & windrow' management regimes (Figure 5) was simulated using a combination of natural regeneration and reforestation with shelter belt plantings (50:50). When compared to the counterfactuals, the maximum abatement scenarios simulated were used to predict three types of emissions abatement as indicated in the different font colours: (i) avoided thinning or avoided suppression of natural regeneration; (ii) avoided clearing, and; (ii) regeneration that would have occurred anyway under the counterfactual scenarios

	Counterfactual				**Maximum abatement**			
Woody vege change scenario		**1988**	**2018**	**2020-2030**	**Woody vege change scenario**	**1988**	**2018**	**2020-2030**
1	Fr-Fr-Fr	Remnant forest	Remnant forest	Remnant forest	Fr-Fr-Fr	Remnant forest	Remnant forest	Remnant forest
2	Fr-Fr-S	Remnant forest	Remnant forest	Sparse	Fr-Fr-Fr	Remnant forest	Remnant forest	Remnant forest
3	Fr-Fr-N	Remnant forest	Remnant forest	Non-woody	Fr-Fr-Fr	Remnant forest	Remnant forest	Remnant forest
4	F-F-F	Forest	Forest	Forest	F-F-F	Forest	Forest	Forest
5	F-F-S	Forest	Forest	Sparse	F-F-F	Forest	Forest	Forest
6	F-F-N	Forest	Forest	Non-woody	F-F-F	Forest	Forest	Forest
7	F-S-F	Forest	Sparse	Forest	F-S-F	Forest	Sparse	Forest
8	F-S-S	Forest	Sparse	Sparse	F-S-F	Forest	Sparse	Forest
9	F-S-N	Forest	Sparse	Non-woody	F-S-F	Forest	Sparse	Forest
10	F-N-F	Forest	Non-woody	Forest	F-N-F	Forest	Non-woody	Forest
11	F-N-S	Forest	Non-woody	Sparse	F-N-F	Forest	Non-woody	Forest
12	F-N-N	Forest	Non-woody	Non-woody	F-N-F	Forest	Non-woody	**Forest***
13	S-F-F	Sparse	Forest	Forest	S-F-F	Sparse	Forest	Forest
14	S-F-S	Sparse	Forest	Sparse	S-F-F	Sparse	Forest	Forest
15	S-F-N	Sparse	Forest	Non-woody	S-F-F	Sparse	Forest	Forest
16	S-S-F	Sparse	Sparse	Forest	S-S-F	Sparse	Sparse	Forest
17	S-S-S	Sparse	Sparse	Sparse	S-S-F	Sparse	Sparse	Forest
18	S-S-N	Sparse	Sparse	Non-woody	S-S-F	Sparse	Sparse	Forest

19	S-N-F	Sparse	Non-woody	Forest	S-N-F	Sparse	Non-woody	Forest
20	S-N-S	Sparse	Non-woody	Sparse	S-N-F	Sparse	Non-woody	Forest
21	S-N-N	Sparse	Non-woody	Non-woody	S-N-F	Sparse	Non-woody	**Forest***
22	N-F-F	Non-woody	Forest	Forest	N-F-F	Non-woody	Forest	Forest
23	N-F-S	Non-woody	Forest	Sparse	N-F-F	Non-woody	Forest	Forest
24	N-F-N	Non-woody	Forest	Non-woody	N-F-F	Non-woody	Forest	Forest
25	N-S-F	Non-woody	Sparse	Forest	N-S-F	Non-woody	Sparse	Forest
26	N-S-S	Non-woody	Sparse	Sparse	N-S-F	Non-woody	Sparse	Forest
27	N-S-N	Non-woody	Sparse	Non-woody	N-S-F	Non-woody	Sparse	Forest
28	N-N-F	Non-woody	Non-woody	Forest	N-N-F	Non-woody	Non-woody	Forest
29	N-N-S	Non-woody	Non-woody	Sparse	N-N-F	Non-woody	Non-woody	Forest
30	N-N-N	Non-woody	Non-woody	Non-woody	N-N-F	Non-woody	Non-woody	**Forest***

All 30 woody vegetation change scenarios under the counterfactual, and the corresponding 30 under the maximum abatement scenario, were classified according to how emissions abatement would be generated (Table 4):

i. avoided thinning or avoided suppression of natural regeneration (Sparse vegetation in the counterfactual is managed to become Forest under the maximum abatement scenario)

ii. avoided clearing (Non-woody in the counterfactual is managed to become Forest under the maximum abatement scenario)

iii. regeneration that would have occurred anyway under the counterfactual scenario (Forest in the counterfactual is also Forest under the maximum abatement scenario).

2.4.2 Possible abatement under Emissions Reduction Fund (ERF) projects

Paul and Roxburgh [22] classified the management-induced changes under each of the 30 woody vegetation change scenarios according to whether it *may* qualify as a project under the Emissions Reduction Fund (ERF, Table 5). Only two ERF project-types were considered as possible achieve some of the maximum potential sequestration:

1. Human-induced Regeneration (HIR)
2. Reforestation (RF)

Although avoided clearing and soil carbon sequestration are also ERF methods, they were not considered here given there is currently negligible uptake of these methods in beef producing regions of Queensland- either due to remaining land being ineligible, and/or the method being not economically viable to implement.

The eligibility requirements for HIR project are that, **in the 10 years prior to the project, the land was non-forest**, with active management preventing forest cover being attained (such as grazing and/or clearing). The land must also be either N or S at the commencement of the project and must have the potential to attain F through natural regeneration (Table 5). However, as explained below, for the X-N-F scenarios where RF was also eligible, it was assumed that the land available was divided 50:50 to HIR and RF projects.

Other simplifying assumptions were:

(a) there had been no F cover within these scenarios during the 10-year period between 1988 and 2018, and

(b) all of the area allocated to these scenarios are indeed able to achieve F cover.

Table 5. The 30 woody vegetation change scenarios (outlined in Table 4) summarized according to the three types of emissions abatement and their potential eligibility under ERF projects of HIR and in some instances (as indicated by '*'), also RF.

Abatement type	**2020 to 2030**		**Potential ERF eligibility**
	Counterfactual	**Maximum abatement**	
Avoided thinning or suppression of natural regeneration due to grazing pressure. *X-X-S in absence of management,* *X-X-F with management*	X-S-S or X-N-S	X-S-F or X-N-F*	HIR or also RF*
	X-F-S	X-F-F	Not eligible
Avoided clearing *X-X-N in absence of management,* *X-X-F with management*	X-S-N or X-N-N	X-S-F or X-N-F*	HIR or also RF*
	X-F-N	X-F-F	Unlikely to be elgible for ERF method
Sequestration that would have occurred anyway under the counterfactual scenarios *X-X-F in absence of management,* *X-X-F with management*	X-F-F	X-F-F	Already forest cover – not eligible
	X-S-F or X-N-F	X-S-F or X-N-F*	HIR or also RF*

To calculate the maximum possible contribution RF may make to the total maximum abatement, maximum abatement simulations were considered that had: (a) N in 2020, and; (b) F by 2030 (X-N-F, Table 5).

For scenarios where RF was eligible, available land was divided 50:50 to HIR and RF projects, with 50% of the area under RF divided into 10% established with mixed species environmental plantings belts of high stocking density and 40% established with mixed species environmental plantings on land that was no longer used for grazing.

Only the four LGA's with histories of mechanical clearing and windrowing were considered to have potential for RF (e.g. Charter Towers, Banana, Whitsundays, North Burnett). The simplifying assumptions (a) and (b) above applied.

For all ERF project abatement calculations, the pools of carbon in soil and grass components were excluded.

3. Results

3.1 Counterfactual scenarios

3.1.1 Predicted rates of change in forest and sparse woody vegetation cover

Predicted rates of forest clearing and regrowth under three counterfactual scenarios are shown in Figure 3 (summarized across all 32 LGAs) and Figure 4 (for each individual LGA).

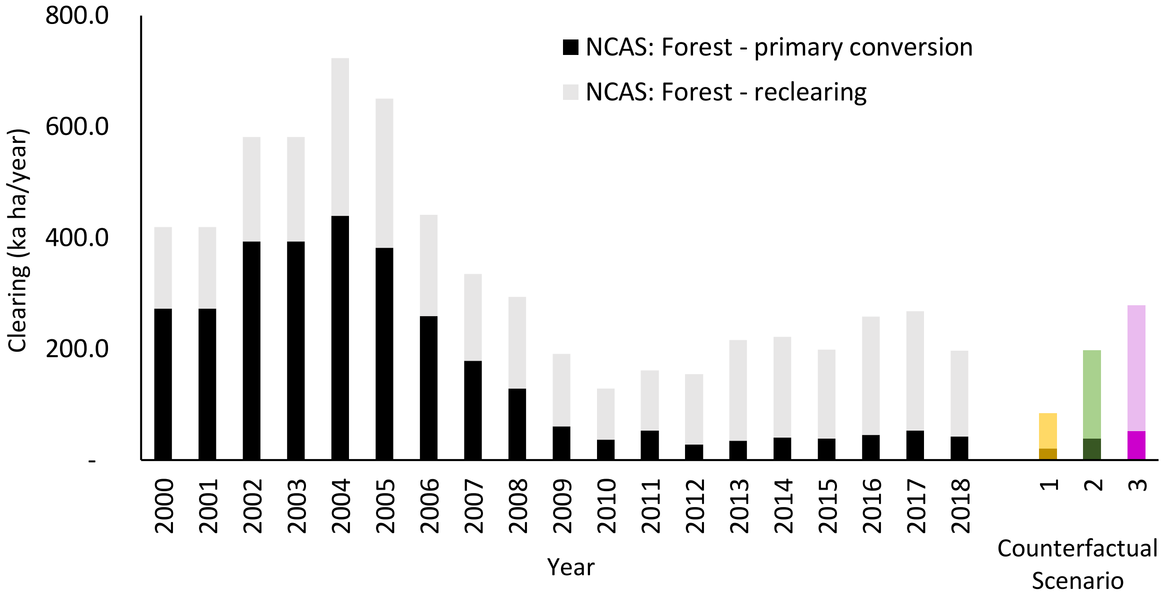


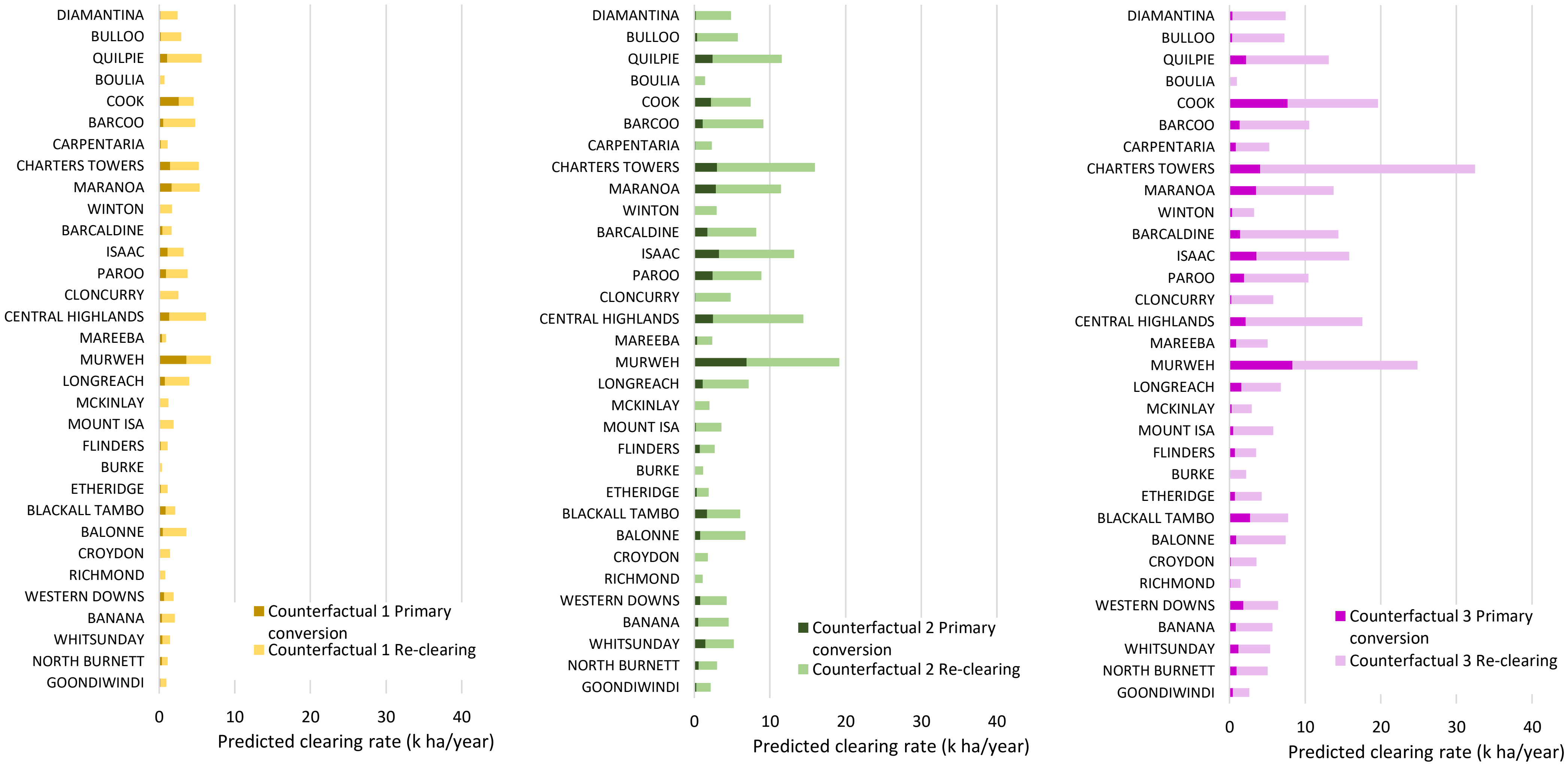
Figure 3. Primary forest conversion and reclearing estimates using NCAS data, 2000 to 2018 for 32 LGAs in Queensland (black and grey bars), and predicted annual rates of forest conversion and reclearing under three counterfactual scenarios: (1) Strengthened policy settings (yellow bar), (2) Current policy settings (green bar), and (3) Relaxed policy settings (purple bar).

Despite some differences identified between the NCAS and national inventory activity table ('NGGI') estimates (see Appendix 3), we find our predicted rates of forest and sparse woody vegetation clearing and regrowth broadly align with the estimates Butler and Fensham [20] derived using the NGGI (Table 6).

Table 6. Comparison between counterfactual estimates in this report and Butler and Fensham (2021)

Counterfactual	**Butler and Fensham (2021) predicted total annual clearing in Queensland (k ha/year)**		**This report predicted total annual clearing in 32 LGAs (k ha/year)**	
	Forest primary conversion	**Forest re-clearing**	**Forest primary conversion**	**Forest re-clearing**
(1) Strengthened policy settings	20	70	23	70.7
(2) Current policy settings	40	210	43	176
(3) Relaxed policy settings	40*	280	58	245

Figure 4. Predicted annual rates of primary forest conversion and re-clearing (k ha/year) according to three counterfactual scenarios, for 32 selected LGAs: (1) Strengthened policy settings (left, yellow bars), (2) Current policy settings (middle, green bars), and (3) Relaxed policy settings (right, purple bar). The y axis is ordered according to decreasing total area of grazed native vegetation in each LGA, as per Figure 2.



3.1.2 Regional vegetation management regimes

Our interview findings pointed to three broad regimes that are employed to manage native vegetation (where regulations permit it) on beef grazing land in Queensland (Figure 5):

- **Fire:** Vegetation is primarily managed using fire, which is dependent on rainfall in a region. Mechanical clearing only occurs around fence lines. There are six LGAs in Queensland that are predominately tropical savanna woodlands, where fire is the predominant management regime.
- **Mechanical (or chemical) clearing, and no burning of residues:** For the majority of LGAs (22 of 32), mechanical clearing is primarily used to control the extent of woody vegetation. Woody residues may either be left, or stick raked and left in piles, but burning “happens more regularly near the coast and on fertile land types” (Interviewee 7)
- **Mechanical clearing, and windrows burned:** In four LGAs, mechanical clearing is primarily used, with the woody residues mounded up in “windrows” and burnt. This occurs near more productive land near coast. Windrows might be burned every 3-4 years as it is expensive to do annually.

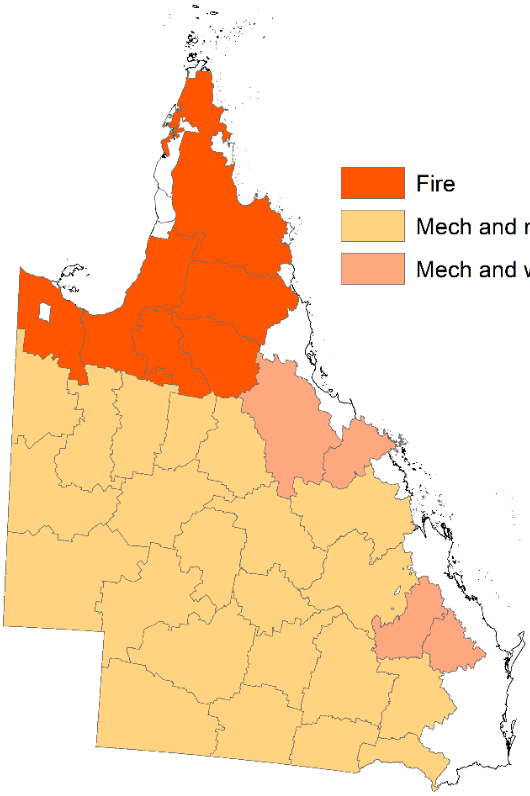


Figure 5. Distribution of three predominant vegetation management regimes across our study region. Further details, and information on how these regimes were modelled in FullCAM are provided in Paul and Roxburgh [21], Section 2.4.

3.2 Modelled carbon pathways

3.2.1 State-level results

Across the key beef producing areas of Queensland, it was predicted that *in absence of* sector-wide action to curb GHGs, and under current policy settings, a carbon neutral Queensland beef sector would need to avoid or sequester 33 Mt CO2-e per year via changed vegetation management practices between 2020 and 2030. (Figure 6a). Under strengthened or relaxed policy settings, the abatement task varied between 13 and 41 Mt CO_2-e per year, respectively. Over the full 10-year period (2020 to 2030), this equated to between 132 and 405 Mt CO2-e that would be released in absence of efforts to curb GHGs in the Queensland beef sector (Figure 6b).

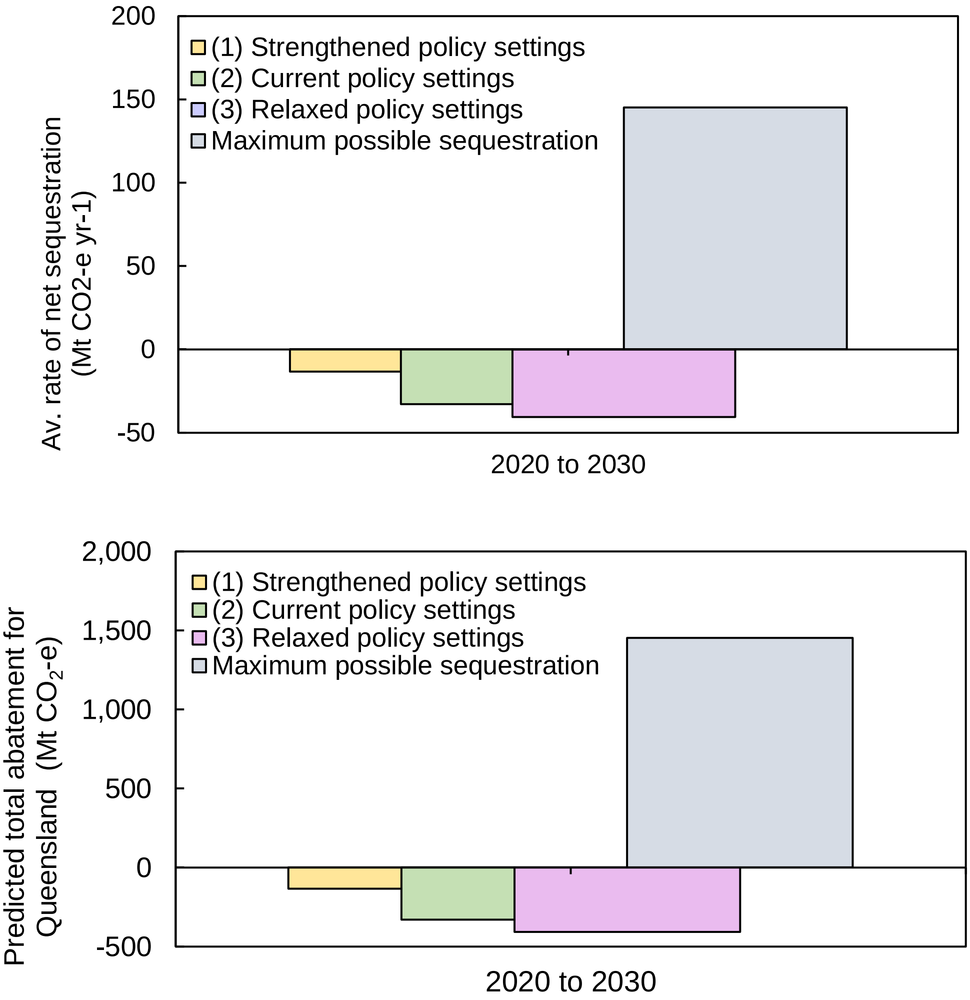


Figure 6. Average annual net sequestration (a) and total net sequestration (b) between 2020 and 2030 across beef producing areas in Queensland (32 LGAs, under three counterfactual scenarios and three corresponding maximum abatement scenarios. Note that the total maximum abatement was equivalent under all three maximum abatement scenarios.

Under the maximum abatement scenarios where management was implemented to promote forest cover on beef producing land across all 32 LGAs, it was predicted that a maximum of 1,452 Mt CO2-e could be sequestered. This equated to a predicted average rate of sequestration of about 145 Mt CO2-e yr-1 between 2020 and 2030 (Figure 6b). Note that this maximum abatement figure assumes that all beef grazing land is permitted to reach forest cover, which is not compatible with a functioning beef sector, and is over and above the abatement required to meet carbon neutrality.

The majority of abatement (68%) is predicted to occur through avoided clearing (98 to 101 Mt CO2-e yr-1) – that is, grazing land that would be Non-woody in absence of sector wide action to curb GHGs but is instead managed to become Forest under the maximum abatement scenario (Figure 7).

Sequestration from avoided thinning or avoided suppression of regrowth (Sparse vegetation in absence of management, that is managed to become Forest) ranges between 22 and 24 Mt CO2-e yr-1 (16%) depending on the counterfactual. Approximately 23 Mt CO2-e yr-1 of sequestration (16%) is predicted to occur regardless of any sector wide action to curb GHGs. Note that this “anyway” sequestration (that is, grazing land that would have retained Forest cover between 2020 and 2030 under both the counterfactual and maximum abatement scenarios) occurs as vegetation continues to mature and increase in woody biomass, though the rate of sequestration will taper off over time.

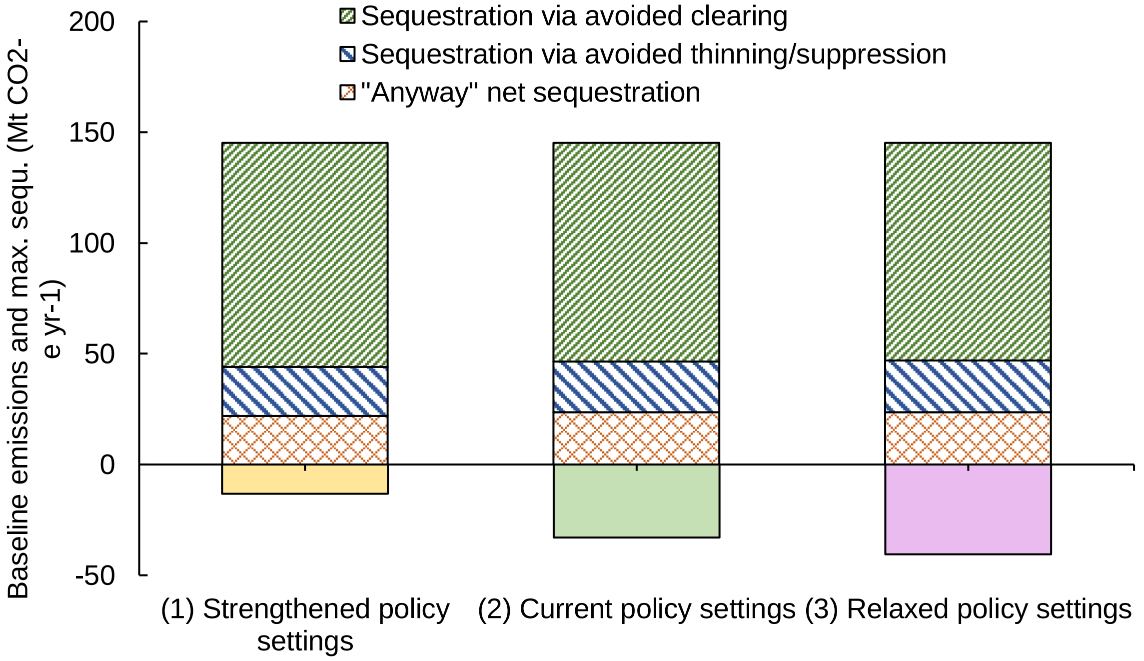


Figure 7. Average annual net sequestration under three counterfactual scenarios (as per Figure 6), and components of maximum abatement (Mt CO2-e yr-1, 2020-2030). Note that the “anyway” sequestration is already accounted for in the calculation of net emissions under the counterfactual (yellow, green and purple bars).

Paul and Roxburgh [22] also simulated changes in carbon stocks over a longer time period (2020 to 2050), by considering the rates of change in forest and sparse woody vegetation cover under just one counterfactual scenario, (2) Current policy settings. However, due to the model limitations outlined on page 19, any re-clearing of previously cleared vegetation was not simulated. This means that the assumption underpinning the 30-year findings is that **no re-clearing of previously cleared vegetation occurs,** and so cannot be directly compared to the 10-year results.

When considering these assumptions over 30 years (2050 – 2020), it was predicted that under the counterfactual, changes in total carbon stock would be 1,016 Mt CO2-e, or 34 Mt CO2-e yr-1, with the sequestration from regrowth being higher than the emissions from the initial clearing (a net sink) given no re-clearing was simulated during this period. However, if there were incentives to maximise abatement opportunities in these lands and thereby effectively promote F cover, it was predicted that the change in total carbon stocks would be equivalent to about 4,829 Mt CO2-e, or 161 Mt CO2-e yr-1. Most of this sequestration was attributable to either avoided clearing (49%) or avoided thinning or suppression due to grazing (34%). Only 17% of the maximum abatement potential over this longer timeframe was attributable to “anyway” sequestration.

3.2.2 LGA-level results

The change in total carbon stocks (expressed as Mt CO2-e yr-1 for 2020 to 2030) under each of the three counterfactuals are provided for each of the 32 LGAs in Figure 8. In absence of targeted action to curb emissions, six LGAs (Cook, Murweh, Maranoa, Balonne, Central Highlands and Isaac), are predicted to collectively contribute 49 – 68% of the total emissions from vegetation management, depending on the assumed counterfactual. Charters Towers is a high emitter under Relaxed and Current policy settings (10% and 7% of total emissions, respectively) and Blackall Tambo contributes 4% of the total under Strengthened policy settings.

Most LGAs are predicted to be a net source of emissions from vegetation management even under strengthened policy settings. However, some LGAs (e.g North Burnett, Carpentaria) are predicted to become a net sink of emissions under strengthened policy settings.

The maximum sequestration potential also varies substantially between LGAs. The highest potential sequestration rates were predicted to be in the LGAs that have the highest site productivity potentials, e.g. Banana, Central Highlands, Maranoa, North Burnett, Goondiwindi, and Western Downs.

Figure 9 shows the extent to which the maximum sequestration potential in each LGA is broken down according to the three broad types: avoided clearing, avoided thinning/suppression, and “anyway” sequestration. Figure 10 shows the combined annual sequestration potential from avoided clearing and avoided thinning/suppression ((Mt CO2-e yr-1, 2020-2030), averaged across maximum abatement scenarios (excluding “anyway” sequestration).

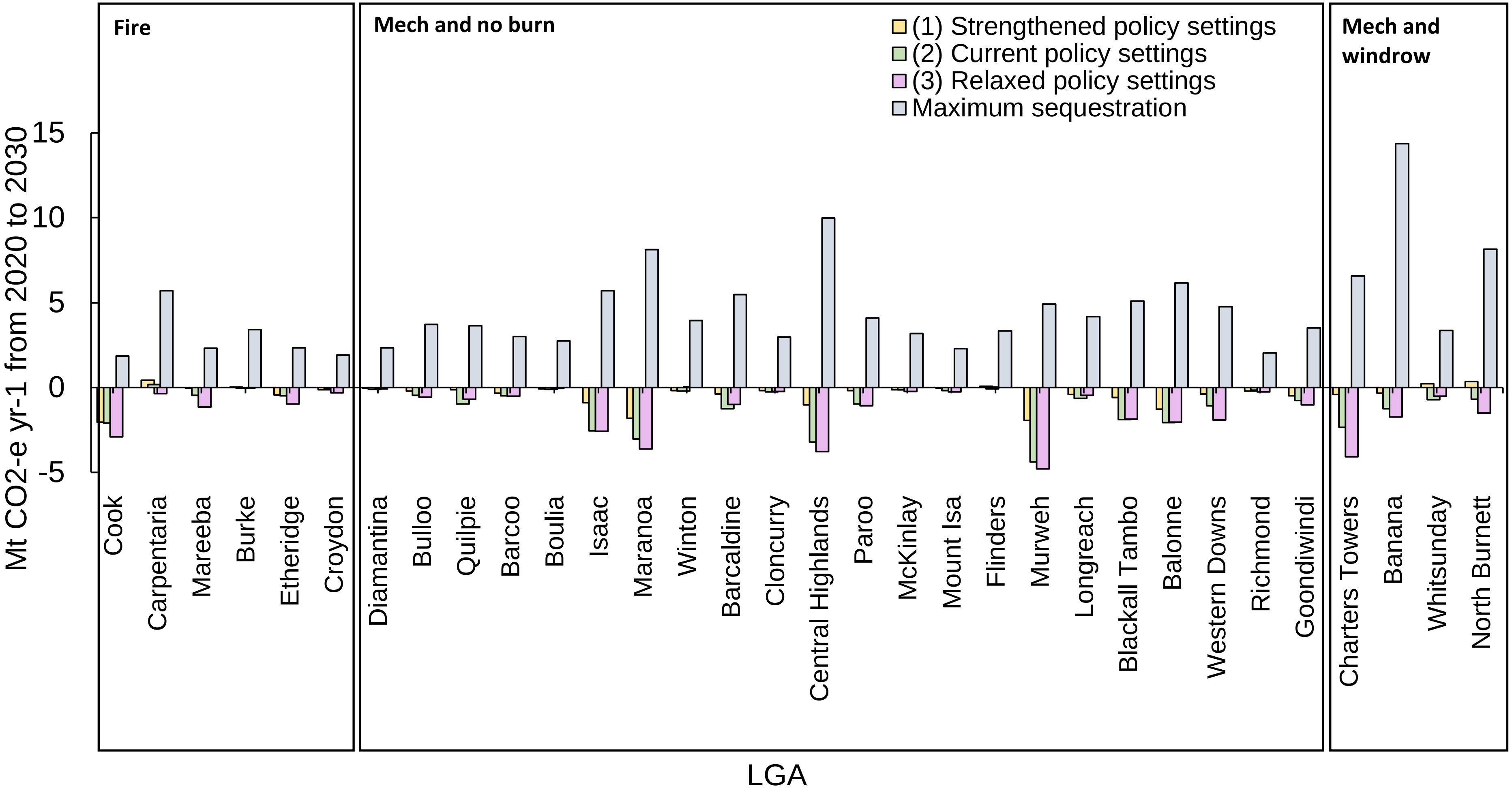


Figure 8. Average annual net sequestration between 2020 and 2030 for all 32 LGAs across beef producing areas in Queensland, under three counterfactual scenarios and the maximum abatement scenario.

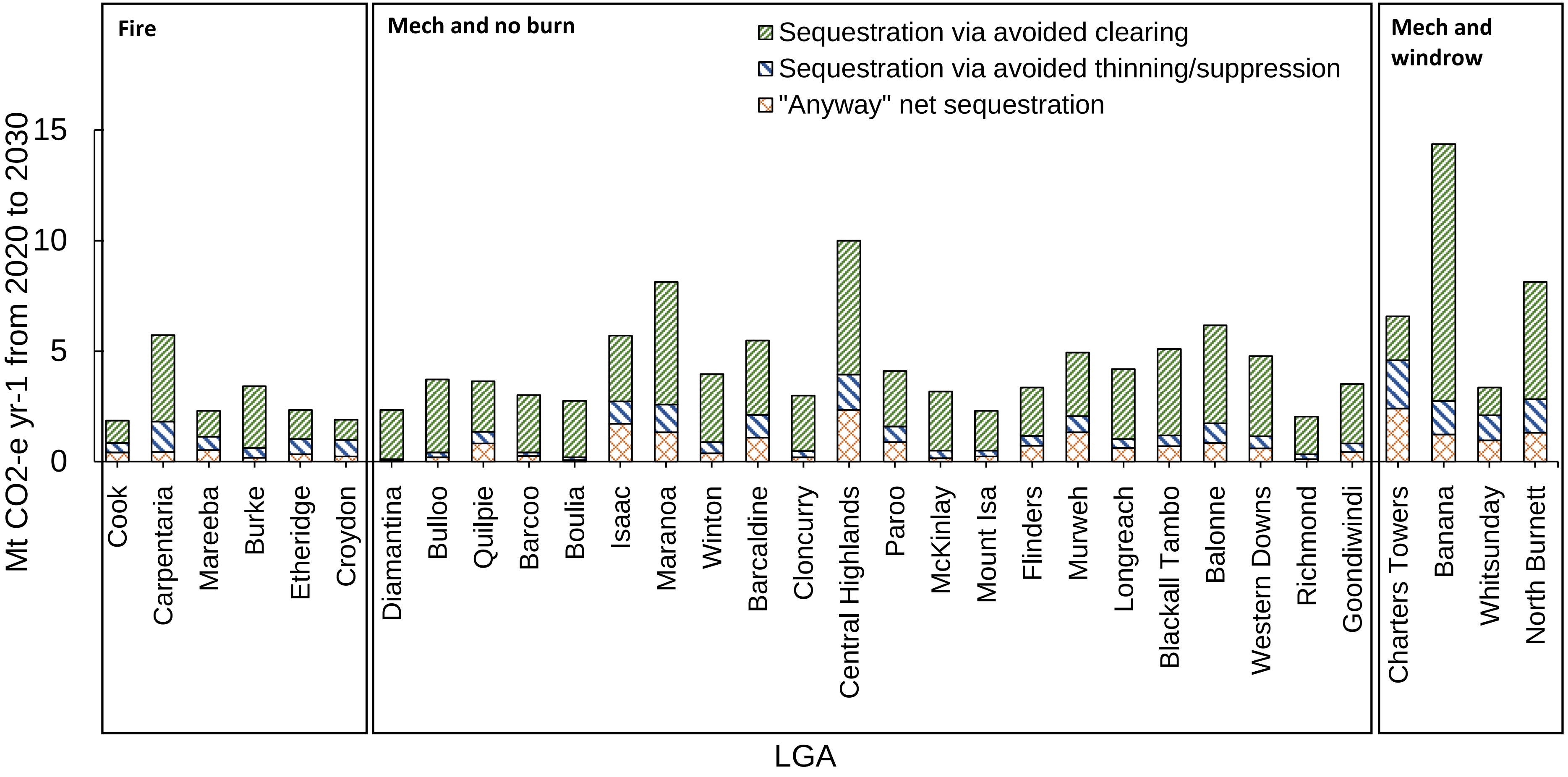


Figure 9. Average maximum abatement (Mt CO2-e yr-1, 2020-2030) within three types of sequestration for all 32 LGAs across beef producing areas in Queensland.

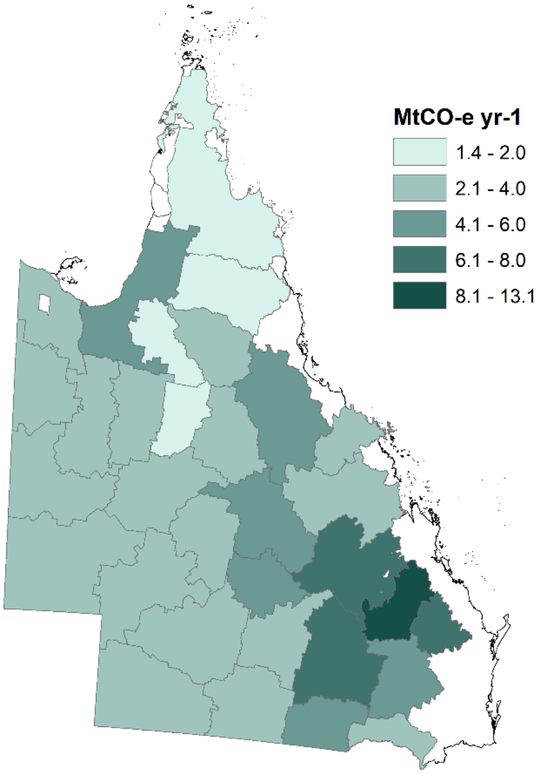


Figure 10. Average annual maximum abatement (Mt CO2-e yr-1, 2020-2030), for all 32 LGAs across beef producing areas in Queensland, combining the sequestration from avoided clearing and avoided thinning/suppression (excluding "anyway" sequestration), averaged across maximum abatement scenarios

3.2.3 Possible abatement under the ERF

Under the simplifying assumptions (a) and (b) outlined in Section 2.4.2[1], when compared to the maximum possible abatement possible (145 Mt CO2-e yr-1 between 2020 and 2030), the maximum possible contribution that HIR or RF projects may make under the ERF is 76% and 14%, respectively (Table 7). When all possible HIR and RF projects are considered together, the abatement is 91% of the maximum possible abatement.

However, we also find that 11% of the maximum sequestration potential that would have occurred anyway could also be eligible under the ERF. This result is reflective primarily of our inability to refine our assumptions (a) and (b) in the scope of this analysis. As such, our results here should be taken as highly uncertain, and likely a large overestimate of the potential sequestration eligible under the ERF.

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[1] The simplifying assumptions are (a) there had been no F cover within each of the 30 woody change scenarios (see Table 4) during the 10-year period between 1988 and 2018, and (b) all of the area allocated to these woody change scenarios are indeed able to achieve F cover.

Table 7. Contribution of possible ERF projects to the maximum abatement potential (145 Mt CO2-e yr-1 between 2020 and 2030) for all 32 LGAs across beef producing areas in Queensland. Note that values sum across columns and rows to sum to the values in **bold**

Abatement type	**% HIR**	**% RF**	**% maximum abatement potentiially eligible for ERF**
Avoided thinning or suppression of natural regeneration due to grazing pressure.	11	3	**14**
Avoided clearing	56	10	**66**
Sequestration that would have occurred anyway under the counterfactual scenarios	10	1	**11**
Total % max abatement potentiially eligible for ERF	**76**	**14**	**91**

4. Conclusions

4.1 Key findings

We find that under current policy settings, a carbon neutral Queensland beef sector would need to avoid or sequester 33 Mt CO2-e per year via changed vegetation management practices between 2020 and 2030. Under strengthened or relaxed policy settings, the abatement task varied between 13 and 41 Mt CO2-e per year, respectively. This result is broadly consistent with the findings of Mayberry et al. [11,12], though it should be noted that we did not calculate enteric emissions in this study which would likely contribute another 14-15 Mt CO2-e per year to our estimate of emissions abatement necessary to achieve carbon neutrality (Table S3).

Overall, our results show that the relative strength of vegetation management regulatory settings has a material impact on the size of the Queensland beef sector's carbon neutral abatement task.

Fortunately, there is significant capacity within Queensland's beef grazing lands to sequester carbon. We estimated that 145 Mt CO2-e yr-1 could be sequestered between 2020 and 2030. However, it should be noted that this figure assumes that all beef grazing land in Queensland is permitted to reach forest cover, which is not compatible with a functioning beef sector. As such, choices would need to be made about where and how emissions should be abated.

Most of the maximum potential abatement (68%) could occur through avoided clearing (98 to 101 Mt CO2-e yr-1), and 16% via avoided thinning or avoided suppression of regrowth (22 and 24 Mt CO2-e yr-1). Importantly, a further 16% of this potential abatement is predicted to occur "anyway" – that is, abatement that occurs both under both the counterfactual and maximum abatement scenarios. This finding must be taken into account when designing policy interventions, to ensure that emissions abatement delivered via incentives are additional to what would happen under the status quo.

We also find strong regional variation in the prediction emissions contributed by the beef sector across Queensland, and the maximum sequestration attainable in each LGA. Most LGAs are predicted to be a net source of emissions from vegetation management even under strengthened policy settings. However, some LGAs (e.g North Burnett, Carpentaria) are predicted to become a net sink of emissions under strengthened policy settings (Figure 8). These findings can assist in identifying where the greatest potential exists for carbon abatement that is additional and cost-effective.

Finally, our analysis suggests - under highly simplified assumptions – that up to 91% of the maximum possible abatement could be eligible as a carbon offset project under the ERF (76% and 14% as HIR and RF, respectively). However, this is likely an overestimate, and future work is needed to derive a more accurate figure.

4.2 Future work

As noted above, our analysis focused on predicted emissions and potential emissions abatement in Queensland beef producing regions and ignored enteric emissions from beef cattle. Future work could draw on LGA-level estimates of beef cattle herd numbers available from the Australian Bureau of Statistics [35] to estimate likely emissions under alternative cattle herd numbers and enteric emissions abatement technologies.

A more refined, spatially explicit analysis of where avoided clearing or reforestation could be eligible as projects under the Emissions Reduction Fund is also needed.

To improve estimates of emissions and abatement beyond beyond 10 years, more refined assumption regarding the X-S-F and X-N-F woody change simulations would need to take into account the likely rates of reclearing that may occur in the different LGAs. This will provide an improved understand how carbon neutrality can be maintained beyond 2030. Emissions abatement from avoided clearing and thinning cannot sustainably neutralize other emissions from the beef sector (e.g enteric), so other sources of abatement will need to come online in future.

Inclusion of other sources of emissions abatement not considered here. For example, silvopastural scenarios (maintaining widely spaced trees) may be applied in place of some of the X-S-N or X-F-N scenarios. Finally, future analyses could seek to include the soil carbon pool, which was not considered here.

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Appendices

Appendix 1: Historical emissions from Qld beef sector

Mayberry et al. [11,12] demonstrated that the vast majority of the Australian red meat sector's historical emissions were attributable to forest land, grassland and enteric fermentation (92 % in 2005, 86% in 2015; Table S1). This means we can be confident that our present analysis focused on these sources captures the majority of emissions from the Queensland beef sector.

Table S1. Underlined items are relevant for the Queensland beef sector. Note that Mayberry et al. [11,12] calculated emissions from processing, energy use, manure management and agricultural soils, which are calculated partly using the inventory but require some extrapolations and calculations that are not feasible in the scope of this current analysis.

Mayberry Table 5 Category	**Mayberry Table 5 Description**	**Description in Mayberry Appendix 9.2**	**2005**	**2015**	**Mayberry calculation**
Grassland	Deforestation	Land converted to grassland	75.01	29.86	Direct from inventory.
	Changes in pasture, grazing and fire management	Grassland remaining grassland	11.09	2.51	Allocation of grassland emissions to the red meat sector was calculated based on proportion of pasture used by different livestock, using animal intake as a proxy
		Subtotal	*86.10*	*32.37*	
Enteric fermentation	Enteric methane from beef cattle pasture, beef cattle feedlot, sheep meat and goats	Beef cattle Pasture	31.4	30.4	Direct from inventory
		Sheep meat	7.23	6.81	Corrected for meat-wool co-production
		Beef cattle Feedlot	1.39	1.57	Direct from inventory
		Goats	0.06	0.07	Direct from inventory
		Subtotal	*40.1*	*38.9*	
Forest land	Prescribed burning and wildfires	Forest land remaining forest land	2.87	-0.03	Calculates % of forests that are protected and assumes 68% of other native forests are available for grazing.
	Afforestation and revegetation	Grassland converted to forest land	-14.7	-12.5	Assumed that all emissions associated with conversion of grasslands to forest land were associated with the red meat industry. Values were reported directly from the inventory.
		Subtotal	*-11.8*	*-12.5*	
Total forest land, grassland and enteric emissions (Mt CO_2e)			*114.3*	*58.7*	
Total national red meat sector emissions (Mt CO_2e)			*124.1*	*68.6*	
% Total national red meat sector emissions attributable to forest land, grassland and enteric emissions			***92%***	***86%***	

We also used the data sources and methods of Mayberry et al. [11,12] to calculate the Queensland beef sector's LULUCF and enteric historical emissions. The Australian Greenhouse Emissions Information System (AGEIS) provides historical GHG emissions information by state/territory, and by source and sink category [16].

The Australian Greenhouse Emissions Information System (AGEIS) provides historical GHG emissions information by state/territory, and by source and sink category [16]. Following Mayberry, we attributed 100% of the carbon sink from Regrowth on deforested land (Table S2) to the beef sector in Queensland. We also attributed 100% of Grassland emissions to beef cattle.

Deviating from Mayberry, we ignored the Forest land remaining forest land and Cropland (feedlot) categories, as each of these categories had negligible impact on the overall emission profile [12]

Table S2. Justification for inclusion of national inventory components in calculation of historical beef sector emissions in Queensland

GREENHOUSE GAS SOURCE AND SINK CATEGORIES	**% attributed to beef sector**
3. Agriculture	
A. Enteric fermentation	
1. Cattle	
Dairy Cattle	0
Beef Cattle - Pasture	100
Beef Cattle - Feedlot	100
4. Land Use, Land-Use Change and Forestry	
A. Forest Land	
1. Forest land remaining forest land	0
2. Land converted to forest land	
Plantations and natural regeneration	0
Regrowth on deforested land	100
B. Cropland	
1. Cropland remaining cropland	0
2. Land converted to cropland	0
C. Grassland	
1. Grassland remaining grassland	100
2. Land converted to grassland	100

Based on the AGEIS data, emissions attributable to the beef sector in Queensland was 78.6 Mt CO_2e in 2005 and 34.8 Mt CO_2e in 2015 (from grassland, forestland, and enteric only), amounting to 63% and 51% of the total red meat sector emissions (Table S3).

Table S3. Total LULUCF and enteric emissions attributed to the beef sector in Queensland (kt CO$_2$e) according to the national inventory (AGEIS)

Category		**2005**		**2015**
Regrowth on deforested land	-	2,324	-	4,058
Grassland remaining grassland		10,602		5,799
Land converted to grassland		56,488		19,800
QLD Beef (grassland, forestland subtotal)		*64,766*		*21,541*
Enteric emissions (Beef - pasture)		13,879		13,232
Enteric emissions (Beef - feedlot)		737		889
Total QLD Beef (grassland, forestland, and enteric only)		**78,645**		**34,773**
Total National red meat emissions (according to Mayberry et al. 2018)		124,100		68,600
% total national red meat emissions		**63%**		**51%**

Considering only the Forest land, Grassland and enteric emissions categories from the State and Territories inventory [16], it is possible to identify a historical emissions trajectory for the beef sector in Queensland (Figure S1).

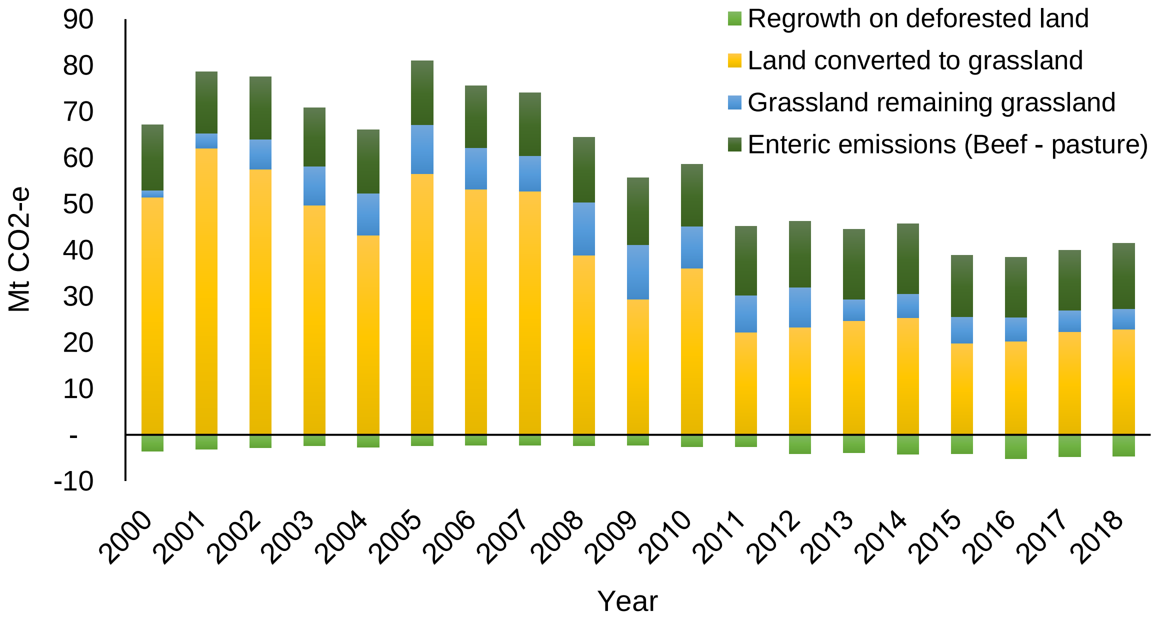

Figure S1. Historical beef sector GHG emissions in Queensland, considering only LULUCF and enteric emissions. Data taken directly from the State and Territories inventory of the Australian Greenhouse Emissions Information System (https://ageis.climatechange.gov.au/)

Appendix 2: Spatial data analysis

Step 1: Crop to Queensland only and create change layers

The National Forest and Sparse Woody Vegetation Data [21] is provided in a format whereby the Australian continent is split into a collection of mapsheets (or tiles, see Figure S2 below).

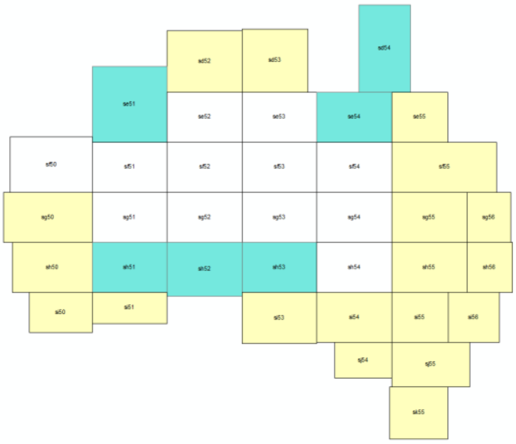

Figure S2: Map of available forest extent and change products. Areas shaded yellow are the intensive landuse zone. Areas shaded blue are termed priority rangelands for the National Inventory System. The remaining 12 white mapsheets are termed rangelands.

The following code uses a version of this dataset whereby the 37 available mapsheets (from sd52 to sk55) had been merged to form layers of forest and sparse vegetation extent for the whole Australian continent, for the 23 available epochs 1988 to 2018.

Note that annual forest extent and deforestation data are not available within the NCAS until 2005 [27,28]. Prior to then, data are instead captured within multi-year *epochs* (instances in time), with some epochs (e.g 1988) containing data for two consecutive years.

This code[2] does the following:

a) Crops the layer for each epoch (1988, 1991, …, 2018) to the Queensland border

b) Creates a new ‘change’ layer that represents the changes that occur between epochs. E.g the first ‘change’ layer is 1991, which represents the changes that occurred between 1988 and 1991. Change is encoded as per Table S4:

Table S4. Classification of changes between forest and sparse woody vegetation between epochs

0	No data/no change
1	Non-woody to sparse
2	Non-woody to forest
3	Sparse to forest
4	Sparse to non-woody
5	Forest to non-woody
6	Forest to sparse

---

[2] This code is also provided via OSF: https://osf.io/j237a/

```
# NCAS data analysis
# Code for slicing up national woody layer into Qld
# M Evans, 1/10/20
# Updated 8/01/21

# Need to conduct change analysis from earliest time point (1988)
# Also need to conduct remnant/regrowth analysis from earliest time point

#### load packages
library(sp) #classes and methods for spatial data
library(raster) #raster analysis
library(reshape2)
#library(rgdal)

## Set temporary directory
tempdir<-("C:/Users/z3530625/Rtemp/")
options(rasterTmpDir=tempdir)
options(rasterTmpTime = 1)
options(rasterMaxMemory = 1e10)

# Directories
directory<-("C:/…/")
datadirectory<-("C:/…/")

#################################################
# Import raster files

## LOCAL GOVERNMENT AREA LAYER
# 25m resolution
lga<-raster(paste(directory, "rasters/lgaqld.tif", sep=""))
crs(lga)<-"+proj=longlat +ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +no_defs"

# Extent of the QLD files
tex <-extent(lga)

####################
# IMPORT NCAS DATA #
####################
# First crop the national woody files to Qld extent
###############################################################################

# List the national files
woodyfiles <- list.files(path=paste(directory, "Vegetation/woody/", sep=""),
pattern = ".tif$")
#tiles_subset<-tiles[c(1,4)]
#tiles_subset<-woodyfiles

# Extract the years
#Remove sections of elements of the string which contain '.'
xdup<-gsub("\\..*","",woodyfiles)
#Remove duplicate entries
xyears <-unique(xdup)

# Get the tiles ordered by year
yrdf<-matrix(data=0, nrow=0, ncol=2)
for(f in 1:length(xyears)){

  # To get the year of the tile(s) in the correct order
  s<-strsplit(xyears[f],"y")[[1]]
  yr_num <-as.numeric(s[2])
  if(yr_num <= 20){
    yr_num<-yr_num+2000
  } else {
    yr_num<-yr_num+1900
```

```
    }

    yrdf_temp<-data.frame(woodytile=woodyfiles[f], yr=yr_num)
    yrdf<-rbind(yrdf,yrdf_temp)
  }

  yrdf_sort<-yrdf[order(yrdf$yr), ]

  # Now go through and get each woody tile and crop

  # Start analysis at year 1988
  for(y in 1:length(yrdf_sort[ ,1])){
    #Assuming that all files within a tile are of the same extent:
    ttile <- raster(paste(directory,"Vegetation/woody/",
  yrdf_sort[y,1],sep=""))

    #QLD tile
    woody_qld<-crop(ttile, tex,
  filename=paste(datadirectory,"woodyqld/",yrdf_sort[y,1], sep=""),
  snap="near",format="GTiff")

  }
  ############################################
  #CREATE CHANGE FILES
  ############################################
  # IMPORT QLD NCAS DATA #
  #######################

  # List the QLD files
  qldwoodyfiles <- list.files(path=paste(datadirectory, "woodyqld/", sep=""),
  pattern = ".tif$")

  # Start analysis at year 1998
  #yrsubset<-subset(yrdf_sort, yr>=1988)
  yrsubset<-yrdf_sort

  # Import
  # y=1 is 1988
  for(y in 2:length(yrsubset[ ,1])){
    #t=1
    ttile2 <- raster(paste(datadirectory, "woodyqld/", yrsubset[y,1],sep=""))
    #t=t-1
    ttile1 <- raster(paste(datadirectory, "woodyqld/", yrsubset[y-1,1],sep=""))

    ##Reclassify ttile2 (multiply by 100) then subtract tiles from each other
    changettile<- (ttile2*100)-ttile1

    ####Reclassify to correct values
    rescalechange <-matrix(c(0,100,200,-1,99,199,-2,98,198,
                             0,1,2,4,0,3,5,6,0), nrow=9, byrow=FALSE)
    ##Where
    #0 =   No data/no change
    #1 =   Non-woody to sparse
    #2 =   Non-woody to forest
    #3 =   Sparse to forest
    #4 =   Sparse to non-woody
    #5 =   Forest to non-woody
    #6 =   Forest to sparse

    #This shows the change in forest cover between t-1 and t1
    changettile_r<-reclassify(changettile, rescalechange)
    writeRaster(changettile_r,
  filename=paste(datadirectory,"c_woodyqld/",yrsubset[y,1],sep=""),
  format="GTiff")
    removeTmpFiles(h=0.5)}
```

Step 2: Identify remnant vs regrowth clearing events, and forest potential

The National Forest and Sparse Woody Vegetation Data [21] does not differentiate between first time (remnant) clearing, and re-clearing (regrowth clearing). Therefore, the following code was used to create a mask (used in Step 3) that enables the changes in forest or sparse vegetation extent occurring between epochs (as per Step 1) to be identified as first time clearing or re-clearing.

The code also uses the 1988 forest and sparse woody extent layer as a proxy for the area of forest potential.

As the ‘crosstab’ code in Step 3 can take a maximum of 3 layers, it was necessary to combine the remnant/regrowth and forest potential layers into one mask.

The final layer (for each epoch) is encoded as per Table S5.

Table S5. Classification of the remnant status and forest potential spatial layer. Note that a new layer is created for each epoch.

<table>
<tr><td>101</td><td>Non-remnant | Non woody 1988 (No forest potential)</td></tr>
<tr><td>102</td><td>Remnant | Non woody 1988 (No forest potential)</td></tr>
<tr><td>201</td><td>Non-remnant | Sparse 1988 (No forest potential)</td></tr>
<tr><td>202</td><td>Remnant | Sparse 1988 (No forest potential)</td></tr>
<tr><td>301</td><td>Non-remnant | Forest 1988 (Forest potential)</td></tr>
<tr><td>302</td><td>Remnant | Forest 1988 (Forest potential)</td></tr>
</table>

```
# NCAS data analysis
# Code for calculating whether vege is remnant or non remnant each year
# M Evans, 8/01/21

#### load packages
library(sp) #classes and methods for spatial data
library(raster) #raster analysis
library(reshape2)
library(rgdal)

## Set temporary directory
tempdir<-("C:/…/Rtemp/")
options(rasterTmpDir=tempdir)
options(rasterTmpTime = 1)
options(rasterMaxMemory = 1e10)

# Directories
directory<-("C:/…/")
datadirectory<-("C:/…/")

#############################################################################
###

# Get the year list
woodyfiles <- list.files(path=paste(directory, "Vegetation/woody/", sep=""),
pattern = ".tif$")
```

```r
# Extract the years
#Remove sections of elements of the string which contain '.'
xdup<-gsub("\\..*","",woodyfiles)
#Remove duplicate entries
xyears <-unique(xdup)

# Get the tiles ordered by year
yrdf<-matrix(data=0, nrow=0, ncol=2)
for(f in 1:length(xyears)){

  # To get the year of the tile(s) in the correct order
  s<-strsplit(xyears[f],"y")[[1]]
  yr_num <-as.numeric(s[2])
  if(yr_num <= 20){
    yr_num<-yr_num+2000
  } else {
    yr_num<-yr_num+1900
  }

  yrdf_temp<-data.frame(woodytile=woodyfiles[f], yr=yr_num)
  yrdf<-rbind(yrdf,yrdf_temp)
}

yrdf_sort<-yrdf[order(yrdf$yr), ]

############################################

# List the QLD woody files
# These show whether in each year, there is non-woody, sparse, or woody
qldwoodyfiles <- list.files(path=paste(datadirectory, "woodyqld/", sep=""),
pattern = ".tif$")

# List the QLD change files
# These show whether there has been a change between y and y-1
qldchangefiles <- list.files(path=paste(datadirectory, "c_woodyqld/",
sep=""), pattern = ".tif$")

####################################
### Forest potential layer
# Use 1988 (y=1) forest cover layer to indicate whether changes are
# occurring on land with forest potential
# Or maybe just use this 1988 layer as a multiplier

forest_poten<- raster(paste(datadirectory, "woodyqld/",
yrdf_sort[1,1],sep=""))

#Rescale so this 1988 forest_poten can be used as an addition for the rem vs
non-rem layer
rescalechange <-matrix(c(0,1,2,
                         100,200,300), nrow=3, byrow=FALSE)

##Where
#100 = Non woody 1988 (No forest potential)
#200 = Sparse 1988 (No forest potential)
#300 = Forest 1988 (Forest potential)

forest_poten_r<-reclassify(forest_poten, rescalechange)

##Write forest potential layer (1988)
writeRaster(forest_poten_r,
filename=paste(datadirectory,"forest_poten_r",".tif",sep=""), format="GTiff")
removeTmpFiles(h=0.5)

####################################
### Annual remnant cover layer
```

```
#First remnant layer is 1988
remtile<-forest_poten

#Rescale into
rescalechange <-matrix(c(0,1,2,
                         1,1,2), nrow=3, byrow=FALSE)

##Where
#1 =   Non-remnant
#2 =   Remnant

remtile_r<-reclassify(remtile, rescalechange)

##Write 1988 remnant layer
writeRaster(remtile_r,
filename=paste(datadirectory,"remvegcov/remvegcov",yrdf_sort[y,2],".tif",sep=
""), format="GTiff")

#Now add in the forest potential layer
forest_poten_r<-raster(paste(datadirectory, "forest_poten_r.tif",sep=""))
remtile_r<-raster(paste(datadirectory, "remvegcov/remvegcov1988.tif",sep=""))

rempottile<- remtile_r + forest_poten_r

##Where
#101 =   Non-remnant | Non woody 1988 (No forest potential)
#102 =   Remnant     | Non woody 1988 (No forest potential)
#201 =   Non-remnant | Sparse 1988 (No forest potential)
#202 =   Remnant     | Sparse 1988 (No forest potential)
#301 =   Non-remnant | Forest 1988 (Forest potential)
#302 =   Remnant     | Forest 1988 (Forest potential)

writeRaster(rempottile,
filename=paste(datadirectory,"rempottile/rempottile",yrdf_sort[y,2],".tif",se
p=""), format="GTiff")
removeTmpFiles(h=0.5)

#################
## Make annual set of remnant layers based on changes between years
#### Import change tiles
for(y in 3:length(yrdf_sort[ ,1])){

  #Import **previous year** remnant layer
  remtile<-raster(paste(datadirectory, "remvegcov/remvegcov", yrdf_sort[y-
1,2], ".tif",sep=""))

  #Import current year woody change file
  ctile <- raster(paste(datadirectory, "c_woodyqld/", yrdf_sort[y,1],sep=""))

  #CONSIDER ALL CLEARING EVENTS, INCLUDING 4, 5 AND 6
  ##Where
  #0 =   No data/no change    ->  No change in status
  #1 =   Non-woody to sparse  ->  New regrowth
  #2 =   Non-woody to forest  ->  New regrowth
  #3 =   Sparse to forest     ->  New regrowth. Sparse is by definition
regrowth
  #4 =   Sparse to non-woody  ->  Loss of regrowth
  #5 =   Forest to non-woody  ->  Loss of forest - potential change in status
if previously remnant
  #6 =   Forest to sparse     ->  Loss of forest - potential change in status
if previously remnant

  #NEED TO CONSIDER REGROWTH TOO. EITHER REGROWTH OR CLEARING INDICATES
  #IT IS NO LONGER REMNANT VEGETATION
```

```
  rescalechange <-matrix(c(0,1,2,3,4,5,6,
                           0,100,100,100,100,100,100), nrow=7, byrow=FALSE)

  ##Where
  #0   =   No forest change
  #100 =   Potential forest change

  changettile_r<-reclassify(ctile, rescalechange)

  #Now subtract change events from remnant layer
  remtile_c<-remtile-changettile_r

  ##Where
  #1    =   No forest change, no change in non-remnant status
  #2    =   No forest change, no change in remnant status
  #-98  =   Forest change, **change from remnant to non-remnant status**
  #-99  =   Forest change, no change in non-remnant status

  ####Reclassify to correct values
  remtile_change <-matrix(c(1,2,-98,-99,
                            1,2,1,1), nrow=4, byrow=FALSE)

  ##Where
  #1 =   Non-remnant
  #2 =   Remnant

  remtile_cc<-reclassify(remtile_c, remtile_change)
  writeRaster(remtile_cc,
filename=paste(datadirectory,"remvegcov/remvegcov",yrdf_sort[y,2],".tif",sep=
""), format="GTiff")

  #Now add in the forest potential layer
  forest_poten_r<-raster(paste(datadirectory, "forest_poten_r.tif",sep=""))

  rempottile<- remtile_cc + forest_poten_r

  ##Where
  #101 =   Non-remnant | Non woody 1988 (No forest potential)
  #102 =   Remnant     | Non woody 1988 (No forest potential)
  #201 =   Non-remnant | Sparse 1988 (No forest potential)
  #202 =   Remnant     | Sparse 1988 (No forest potential)
  #301 =   Non-remnant | Forest 1988 (Forest potential)
  #302 =   Remnant     | Forest 1988 (Forest potential)

  writeRaster(rempottile,
filename=paste(datadirectory,"rempottile/rempottile",yrdf_sort[y,2],".tif",se
p=""), format="GTiff")
  removeTmpFiles(h=0.5)
}
```

Step 3: Cross-tabulate clearing and regrowth events by LGA, epoch, and remnant/forest potential status

This code calculates the area of forest and sparse woody vegetation changes (see Table S4) occurring in each epoch and local government area (LGA), and also detects whether the change prompts a transition in remnant status (see Step 2).

Note that the LGA layer used here has been overlaid with a layer indicating the area of grazing land (see Figure 2 under section 2.2 Study area in main report), hence only forest and sparse woody vegetation changes that occur on land managed by the beef sector are counted in this analysis.

```
# NCAS data analysis
# Code for doing crosstab of woody change, LGA, potential forest and remnant
layers
# M Evans, 9/12/21

#### load packages
library(sp) #classes and methods for spatial data
library(raster) #raster analysis
library(reshape2)
library(rgdal)

## Set temporary directory
tempdir<-("C:/…/")
options(rasterTmpDir=tempdir)
options(rasterTmpTime = 1)
options(rasterMaxMemory = 1e10)

# Directories
directory<-("C:/…/")
datadirectory<-("C:/…/")

################################################
# Import raster files
## LOCAL GOVERNMENT AREA LAYER & GRAZING
lgagraz<-raster(paste(directory, "rasters/lga_graz_c.tif", sep=""))

# Extent of the QLD files
lgatex <-extent(lgagraz)

#######################################################
#Set up crosstab
lgaids <-read.csv(paste(directory,"R/LGAid.csv", sep=""), header=TRUE,
sep=",")
changeids<-read.csv(paste(directory,"R/changeid.csv", sep=""), header=TRUE,
sep=",")
#remcovids<-read.csv(paste(directory,"R/remcovid.csv", sep=""), header=TRUE,
sep=",")
remcovids<-read.csv(paste(directory,"R/rempotid.csv", sep=""), header=TRUE,
sep=",")


lgaids<-lgaids[,c(1,2)]

#Prepare final storage matrix for output
store<-matrix(data=0, nrow=0, ncol=10)
names<-c("Year", "LGAid", "LGA_NAME",
         "changeid", "changedesc", "changedesc2","changefreq", "changearea",
         "remcovid", "remcov")

colnames(store)<-names
```

```
#######################################################
#List the national files
woodyfiles <- list.files(path=paste(directory, "Vegetation/woody/", sep=""),
pattern = ".tif$")
#tiles_subset<-tiles[c(1,4)]
#tiles_subset<-woodyfiles

# Extract the years
#Remove sections of elements of the string which contain '.'
xdup<-gsub("\\..*","",woodyfiles)
#Remove duplicate entries
xyears <-unique(xdup)

# Get the tiles ordered by year
yrdf<-matrix(data=0, nrow=0, ncol=2)
for(f in 1:length(xyears)){

  # To get the year of the tile(s) in the correct order
  s<-strsplit(xyears[f],"y")[[1]]
  yr_num <-as.numeric(s[2])
  if(yr_num <= 20){
    yr_num<-yr_num+2000
  } else {
    yr_num<-yr_num+1900
  }

  yrdf_temp<-data.frame(woodytile=woodyfiles[f], yr=yr_num)
  yrdf<-rbind(yrdf,yrdf_temp)
}

yrdf_sort<-yrdf[order(yrdf$yr), ]

#yrsubset<-subset(yrdf_sort, yr>=2000)
yrsubset<-yrdf_sort

################################
# IMPORT QLD WOODY CHANGE DATA #
################################

qldwoodyfiles <- list.files(path=paste(datadirectory, "c_woodyqld/", sep=""),
pattern = ".tif$")

###############################
# IMPORT QLD REMNANT VEG COVER#
###############################

qldremvegcov <-list.files(path=paste(datadirectory,"rempottile/",sep=""),
pattern = ".tif$")

###############################
# CROSSTAB #
###############################

#For each year of data within this tile
#for(y in 1:length(yrsubset)){

#Start at the first change file, i.e 1989
for(y in 3:length(yrsubset)){

  yr<-yrsubset[y,2]

  #Prepare storage matrix just for this year
  tilestore<-matrix(data=0, nrow=0, ncol=10)
  names<-c("Year", "LGAid", "LGA_NAME",
```

```
           "changeid", "changedesc", "changedesc2","changefreq",
"changearea",
           "remcovid", "remcov", "cover1988", "forestpot")

  colnames(tilestore)<-names

  #Import woody change tile
  ttile <- raster(paste(datadirectory, "c_woodyqld/", yrsubset[y,1],sep=""))

  #Import remnant veg cover for the PREVIOUS year
  #remcovtile <- raster(paste(datadirectory, "remvegcov/remvegcov",
yrsubset[y-1,1], ".tif",sep=""))
  remcovtile <- raster(paste(datadirectory, "rempottile/rempottile",
yrsubset[y-1,2], ".tif",sep=""))

  #Multiple remcovtile by the forest potential layer

  cat("Calculating forest change for", yrsubset[y,1])
  # Create raster stack between woody change, remnant cover, and LGA-grazing
  x <-stack(ttile, remcovtile, lgagraz)

  #Crosstab will calculate the frequency of forest change for each epoch, LGA
and remnant forest status
  #This takes about 3 hours per tile
  #UNHASH AFTER TESTING
  vegfreq <-crosstab(x, digits=0, long=FALSE, progress="text")

  #Create a dataframe from the crosstab output
  vegfreq_df<-melt(vegfreq)
  vegfreq_df<-cbind(vegfreq_df,yr)

  names(vegfreq_df)<-c("changeid", "remcovid", "LGAid", "changefreq",
                       "Year")

  #Calculate area of forest/non-forest from frequency data
  cellha <- (23.9*27.9)/10000 #Albers projection
  vegfreq_df$changearea <-vegfreq_df$changefreq*cellha

  #Update LGA
  vegfreq_df<-merge(vegfreq_df, lgaids, by = intersect(names(vegfreq_df),
names(lgaids)))

  #Update change id
  vegfreq_df<-merge(vegfreq_df, changeids, by = intersect(names(vegfreq_df),
names(changeids)))

  #Update remnant id
  vegfreq_df<-merge(vegfreq_df, remcovids, by = intersect(names(vegfreq_df),
names(remcovids)))

  #Store data for next iteration
  vegfinal<-vegfreq_df[c("Year", "LGAid", "LGAname",
                         "changeid", "changedesc",
"changedesc2","changefreq", "changearea",
                         "remcovid", "remcov", "cover1988", "forestpot")]

  #tilestore<-rbind(tilestore, vegfinal)

  #Write progressive output for this tile
  write.table(vegfinal, file=paste(directory,"R/crosstab/c_woodyqld",
yr,".csv",sep=""),sep = ",", col.names = TRUE)

  cat("Completed calculations for", yr)
  #B <- A-proc.time()
  removeTmpFiles(h=0.5)}
```

Step 4: Compile crosstab output and annualise results

This final step is necessary to compile the crosstab output from each epoch (Step 3) into one dataframe, and to convert data from multi-year epochs into annualized estimates.

Annual forest and woody sparse vegetation change estimates (in hectares) were derived by average the estimate from an epoch over the number of years between it and the following epoch (Table S6), as per Evans [27] and previous advice from the Australian Government (S Reddy, pers comm).

Table S6. Assignment of woody forest and woody sparse vegetation change estimates from multi-year epochs into annual estimates

Epoch	**Time between epochs (yrs)**	**Assigned to years:**
1988 (early)	2	1988, 1989
1989 (end)	1	1990, 1991 (3 months)
1991 (early)	2	1991 (3 months), 1992 (3 months)
1992	3	1992 (9 months), 1993, 1994
1995	3	1995, 1996, 1997
1998	2	1998, 1999
2000	2	2000, 2001
2002	2	2002, 2003
2004	1	2004
2005	1	2005
…Annual until final epoch in dataset		
2018	1	2018

```
# NCAS data analysis
# Code for compiling results
# M Evans, 3/10/20
# Updated 14/10/20
# Updated 11-01-21

#### load packages
library(sp) #classes and methods for spatial data
library(raster) #raster analysis
library(reshape2)
library(rgdal)

## Set temporary directory
tempdir<-("C:/Users/z3530625/Rtemp/")
options(rasterTmpDir=tempdir)
options(rasterTmpTime = 1)
options(rasterMaxMemory = 1e10)

# Directories
directory<-("C:/…/")
```

```
datadirectory<-("C:/…/")

##############################################################################
###
# Create a loop to progressively import tiled data, compile onto single
dataframe

tiles <- list.files(path=paste(directory, "R/crosstab/", sep=""), pattern =
"c")

#Prepare final storage matrix for output
tilestore<-matrix(data=0, nrow=0, ncol=12)
names<-c("Year", "LGAid", "LGA_NAME",
         "changeid", "changedesc", "changedesc2","changefreq", "changearea",
         "remcovid", "remcov", "cover1988", "forestpot")

colnames(tilestore)<-names

for(i in 1:length(tiles)){
  tilestoretemp <-read.csv(paste(directory,"R/crosstab/",tiles[i],sep=""))
  tilestore<-rbind(tilestore, tilestoretemp)
}

#Write final output for all tiles in this version
c_woodyqld_allyears<-unique(tilestore)

write.table(c_woodyqld_allyears,
file=paste(directory,"R/crosstab/","c_woodyqld_allyears",".csv",sep=""),sep =
",", col.names = TRUE)

#######Need to create estimates for annual values
years_df_merge<-read.csv(paste(directory, "R/years_df_merge.csv",sep=""))

#### Woody change ###########
c_woodyqld_allyears_a<-c_woodyqld_allyears
c_woodyqld_allyears_a_m<-merge(c_woodyqld_allyears_a, years_df_merge,
                       by = intersect(names(c_woodyqld_allyears_a),
names(years_df_merge)))

# Get annual values
c_woodyqld_allyears_a_m$a_changearea<-
c_woodyqld_allyears_a_m$changearea/c_woodyqld_allyears_a_m$gapyrs

# Get rid of non-annual values
c_woodyqld_ann<-c_woodyqld_allyears_a_m[, c(2:12,14,15,17)]
# names(c_woodyqld_ann)<-c("STATE", "LGA_CODE", "lu_ten_id", "forestid",
#                          "changetype", "defortype", "deforest_type", "yrid",
"Year", "a_changearea")

# Sort according to Year
c_woodyqld_ann <- c_woodyqld_ann[order(c_woodyqld_ann$aYear), ]

# Remove zeros
#deforest_ann_pos<-subset(deforest_ann, area>0)

# Write out results
write.table(c_woodyqld_ann, file=paste(directory,
"R/crosstab/c_woodyqld_ann",".csv",sep=""),sep = ",", col.names = TRUE)

########
```

Appendix 3: Cross-check of NCAS and NGGI estimates

The national forest and sparse woody vegetation extent dataset (termed ‘NCAS’ here, Department of Industry, Science, Energy and Resources, 2020), provides higher clearing estimates than what is reported in the national inventory activity table (termed ‘NGGI’ here, Figure S3).

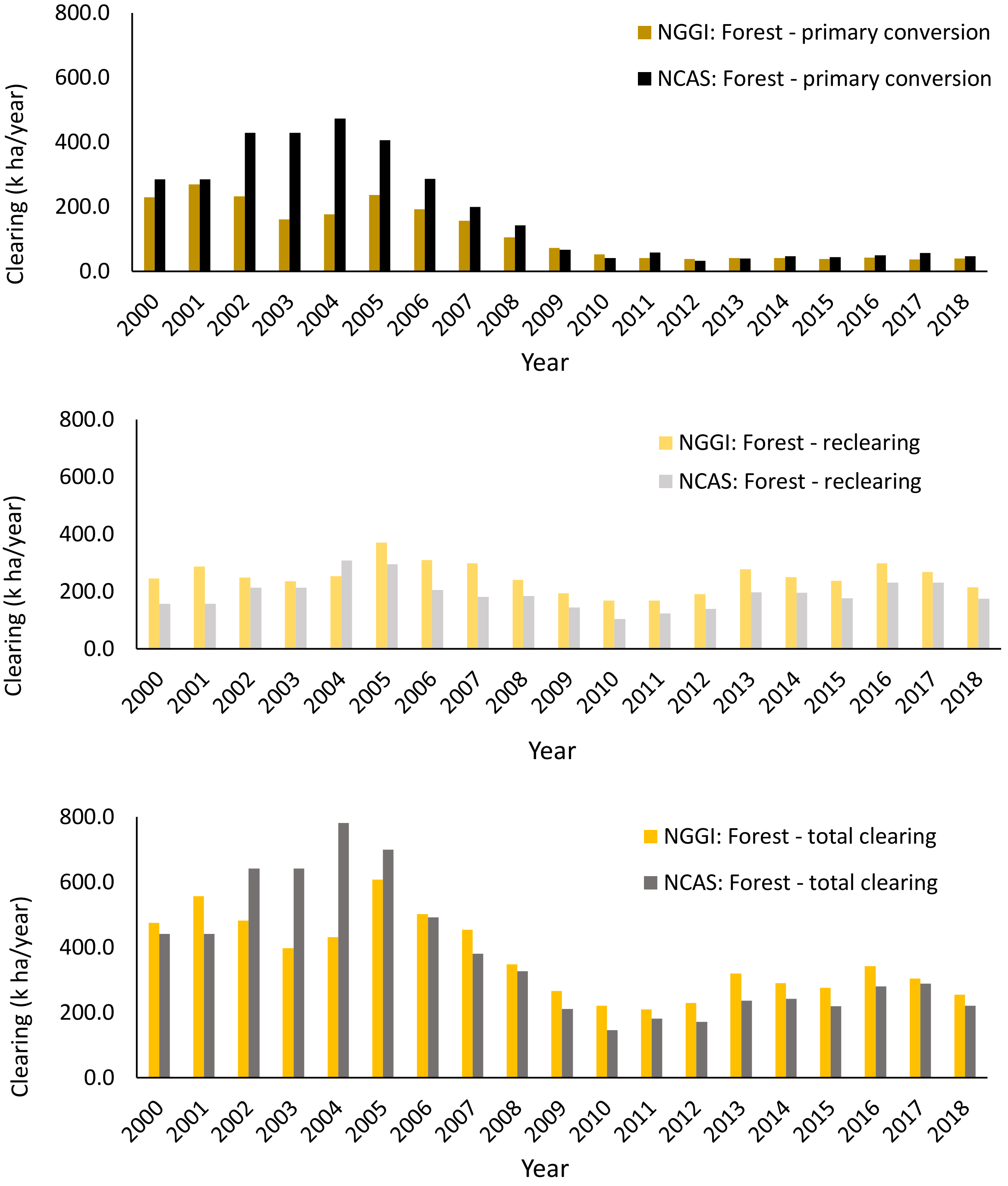

Figure S3. Comparison of primary forest conversion (top), forest re-clearing (middle) and total forest clearing (bottom) estimates from the NGGI and NCAS data sources.

The greatest disparity occurs between 2003 and 2006 in the primary conversion estimates (Figure S3, top). The opposite pattern is not seen over the same time period in the re-clearing estimates (Figure S3, middle), suggesting that the spatial data analysis used to distinguish between primary clearing vs re-clearing (Appendix 2, Step 2) is not the sole cause of the disparity. There is however an overall pattern of the NCAS re-clearing estimates being lower than what is reported in the NGGI (Figure S3, middle).

The disparity in primary conversion NGGI and NCAS estimates between 2003 and 2006 cannot be explained here. A plausible explanation are the additional steps the Australian Government takes to attribute forest conversion and re-clearing events to human intervention [32], that is not available as part of the dataset analysed here [21]. Nevertheless, we do not use data from 2003 and 2005 in our analysis to the impact of this disparity on our results is expected to be low.

Appendix 4: Participant information

Participant Information Sheet and Consent Form

Project Title: Modelling pathways to a carbon neutral Queensland beef sector

Researchers: Dr Megan C Evans, Dr Anna Lewis, Dr Keryn Paul, Dr Stephen Roxburgh

You are invited to take part in this research study. The research study aims to identify viable pathways to carbon neutrality by 2030 for the beef sector in Queensland.

1. What is the research study about?

We are seeking your input as we wish to understand the effects of different vegetation management method(s) (e.g mechanical, fire) on carbon sequestration outcomes in beef grazing systems across Queensland. The information you provide will be used to inform quantitative modelling that aims estimate carbon sequestration potential over time under a range of scenarios

2. Who is conducting this research?

The study is being carried out by the following researchers:

Dr Megan Evans (School of Business, UNSW Canberra) and Dr Anna Lewis (UNSW Canberra and University of Wollongong) and Dr Keryn Paul and Dr Stephen Roxburgh (CSIRO)

Research Funder: This research is being funded by WWF Australia, and is also supported by an Australian Research Council Discovery Early Career Researcher Award (Dr Evans, DE200100190)

3. Inclusion/Exclusion Criteria

Before you decide to participate in this research study, we need to ensure that it is ok for you to take part. The research study is looking recruit people who meet the following criteria:

Familiar with typical management practices of land management for livestock production in Queensland AND if you are speaking on behalf of an organisation or Department, that you are authorised to do so.

Participants who meet the following criteria will be excluded from the study:

Not familiar with typical management practices of land management for livestock production in your regions OR if speaking on behalf of an organisation or Department, that you are <u>not</u> authorised to do so.

4. Do I have to take part in this research study?

Participation in this research study is **voluntary**. If you do not want to take part, you do not have to. If you decide to take part and later change your mind, you are free to withdraw from the study at any stage.

If you decide you want to take part in the research study, you will be asked to:

- Read the information carefully (ask questions if necessary);
- Sign the digital consent form (page 4 of this form) **OR** provide verbal consent if you decide to participate in the study;
- Take a copy of this form with you to keep.

5. What does participation in this research require, and are there any risks involved?

If you agree to participate you will be asked to complete the following research procedures.

Interview: An online video or telephone interview, and you will be asked questions about typical management practices of land management for livestock production in your regions. You can return your consent form to the researchers prior to the interview commencing, or at the same time.

Alternatively, you may wish to respond to our questions by responding in an email (you will still need to provide us a signed digital consent form prior to, or at the same time as providing your responses)

Additional Costs and Reimbursement: There are no costs associated with participating in this research project, nor will you be paid.

6. What will happen to information about me?

By signing the consent form, you consent to the research team collecting and using information about you for the research study. The research team will store the data collected from you for this research project for:

- A minimum of 7 years after the completion of the research;

The information about you will be stored in an/a:

- Non-identifiable format where your identify will be unknown.

Your information will only be shared in a format that will not identify you.

- Information collected from you in an electronic format stored on a UNSW password protected OneDrive only accessible to the approved research investigators.
- Information collected from you using paper-based measures will be stored in the School of Business at UNSW Canberra (Building 27) and only the approved research investigators will have access to this information.

The information you provide is personal information for the purposes of the Privacy and Personal Information Protection Act 1998 (NSW). You have the right of access to personal information held about you by the University, the right to request correction and amendment of it, and the right to make a complaint about a breach of the Information Protection Principles as contained in the PPIP Act. Further information on how the University protects personal information is available in the **UNSW Privacy Management Plan**.

7. How and when will I find out what the results of the research study are?

The research team intend to publish and/ report the results of the research. All Information will be published in a way that will not identify you.

If you would like to receive a copy of the results you can let the research team know by inserting your email or mailing address in the consent form. We will only use these details to send you the results of the research.

8. What if I want to withdraw from the research study?

If you do consent to participate, you may withdraw at any time. You can do so by completing the 'Withdrawal of Consent Form' which is provided at the end of this document or you can ring the research team and tell them you no longer want to participate. Your decision not to participate or to withdraw from the study will not affect your relationship with UNSW Canberra, CSIRO or WWF. If you decide to leave the research study, the researchers will not collect additional information from you. You can request that any identifiable information about you be withdrawn from the research project.

9. What if I have a complaint or any concerns about the research study?

If you have a complaint regarding any aspect of the study or the way it is being conducted, please contact the UNSW Human Ethics Coordinator:

Complaints Contact

osition	NSW Human Research Ethics Coordinator
elephone	61 2 9385 6222
mail	umanethics@unsw.edu.au
C Reference Number	C200902

10. What should I do if I have further questions about my involvement in the research study?

The person you may need to contact will depend on the nature of your query. If you require further information regarding this study or if you have any problems which may be related to your involvement in the study, you can contact the following member/s of the research team:

Research Team Contact Details

Name	Dr Anna Lewis
Position	Research Fellow
Telephone	0412837295
Email	lewisa@uow.edu.au

Chief Investigator

Name	Dr Megan Evans
Position	Lecturer and ARC DECRA Fellow
Telephone	0418984248
Email	megan.evans@unsw.edu.au

Consent Form – Participant providing own consent

Declaration by the participant

☐ I understand I am being asked to provide consent to participate in this research study;

☐ I have read the Participant Information Sheet, or someone has read it to me in a language that I understand;

☐ I understand the purposes, study tasks and risks of the research described in the study;

☐ I provide my consent for the information collected about me to be used for the purpose of this research study only.

☐ I have had an opportunity to ask questions and I am satisfied with the answers I have received;

☐ I freely agree to participate in this research study as described and understand that I am free to withdraw at any time during the study and withdrawal will not affect my relationship with any of the named organisations and/or research team members;

☐ I would like to receive a copy of the study results via email or post, I have provided my details below and ask that they be used for this purpose only;

☐ I understand that I will be given a signed copy of this document to keep.

☐ I understand that the results of the research will be made available on the UNSW Canberra School of Business website.

☐ I would like to receive a copy of the study results via email or post, I have provided my details below and ask that they be used for this purpose only.

Name: ____________________________________
Address: __________________________________
Email Address: _____________________________

Participant Signature

Name of Participant (please print)	
Signature of Research Participant	
Date	

Declaration by Researcher*

☐ I have given a verbal explanation of the research study; its study activities and risks and I believe that the participant has understood that explanation.

Researcher Signature*

Name of Researcher (please print)	

Signature of Researcher	
Date	

[+]An appropriately qualified member of the research team must provide the explanation of, and information concerning the research study.

Note: All parties signing the consent section must date their own signature.