## Agriculture, Forestry and Other Land Use (AFOLU)

The process for estimating emissions in agriculture and land are quite different for a number of reasons. Agricultural emissions are estimated based on activity data (e.g. livestock population or nitrogen fertiliser consumption) which is not spatially explicit and which is mostly obtained from agricultural statistics reports. CH4 and N2O emission factors are then applied to the activity data to estimate emissions. Land emissions require land cover and land use change data and soils data which is spatially explicit. These areas are then multiplied by carbon stock change data. In addition, agriculture includes CO2, CH4 and N2O emissions, while the land emissions and removals are CO2. Calculations for Land are quite complex due to the spatial nature of the data and spreadsheets can become large. For all of these reasons it is easier to create two separate models which have a few links where they overlap, and then combine them to create the overall estimates and projections for the AFOLU sector.

The emissions in both the agriculture and land models are modelled following the IPCC 2006 guidelines, as is the case with the 2017 GHG inventory. The spreadsheets are set up with various tabs (IPCC categories, drivers, constants, variables, intermediate calculations, activity data, emission factors, emissions, emission summaries and mitigation drivers) to make it easy to navigate. The land sector model has mitigation scenarios and these can be selected separately to show individual impacts, or all can be selected to show overall outputs.

### Agriculture model

The main drivers for this agriculture baseline model are population (per capita) data and GDP data. Population data is obtained from the UNDP and the GDP data is modelled output from UCT’s SATIM model.

#### General emission model methodology

The agriculture model is set up following the IPCC 2006 guideline methodology as in the 2017 inventory. The basic method is the multiplication of the activity data (livestock data, manure inputs, nitrogen inputs, etc) with an emission factor. The emission factors are consistent with those from the inventory, with some being IPCC default values and other country specific data. In some cases the inventory has more detailed categories and in these cases weighted average emission factors were applied.

#### Baseline model methods and assumptions

#### Livestock (3A)

Livestock population data is the activity data to be projected. South Africa’s population is increasing and therefore the demand for food is increasing (BFAP, 2019). In addition, as the population becomes wealthier so the demand for meat will increase as the population moves away from more staple foods (Meissner et al., 2013a). Population and income are, therefore, important drivers of consumption which in turn impacts livestock populations. The relationship between population, income and consumption (meat, milk and egg) was determined from historical data (from Abstracts of Agricultural Statistics (AAS) (DAFF, 2019)) and then projected using population and income data from the SATIM model. Consumption rates were compared to the literature (BFAP, 2019; Fischer &Tramberend, 2019). Production is related to consumption, with historical data providing information on the number of livestock to produce the required amount of product. The total number of each type of livestock was divided into commercial and subsistence categories by applying the commercial to subsistence ratio given in the inventory.

Other cattle population data was determined slightly differently due to the beef feedlots. Meat consumption is determined from demand as for other livestock. Meat production is produced from feedlot and other commercial and subsistence cattle. The amount of meat produced from feedlots is determined first (based on the variables provided in the table below) and the remainder of the meat produced is assumed to come from commercial and subsistence cattle.

Horse and mule populations are not related to meat consumption. Horse population was found to have a good correlation with GDP per capita and are thus modelled using these drivers. Mule population estimates are lacking, but FAO data (FAOSTAT, 2018) indicates the population to be fairly stable. The model *assumes a constant mule population*. Mules and horses contribute very little to the agricultural GHG emissions so more detailed analysis would not yield any significant changes in the outputs.

Table 47 Model factors and assumptions for livestock

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **Value** | | | | **Data source** | **Assumption** |
| **2020** | **2030** | **2040** | **2050** |
| **Livestock production and consumption** | Based on historical data | | | | Abstracts of Agricultural Statistics (AAS) (DAFF, 2019) | Historical data shows efficiency improvements over the years; therefore the model assumes these efficiency improvements continue to 2050. |
| **Livestock category ratios** | TMR dairy cattle fraction: 0.35  Dairy pasture faction: 0.29  Commercial other cattle fraction: 0.53  Fraction commercial sheep: 0.87  Fraction commercial goats: 0.34  Fraction commercial swine: 0.88  Fraction commercial poultry: 0.96 | | | | 2017 inventory (DEFF, 2020) | Assumed that the fractions remain constant. |
| **Feedlot dressing faction** | 0.58 | | | | Spies, 2016 | Assumed to remain constant |
| **Fraction of total meat production produced in feedlot** | 0.73 | 0.76 | 0.80 | 0.83 | DAFF, 2011; DAFF, 2018a; FPMC, 2003; De Jager, 2016. | Reported values vary, but assumed fraction would increase over time. |
| **Days in a feedlot** | 120 | 120 | 120 | 120 | FPMC, 2003; Spies, 2016; Du Toit et al., 2013; Meissner et al., 2013. | For the baseline the value was assumed to remain constant. |
| **Livestock manure management data** | 2017 inventory data | | | | 2017 inventor (DEFF, 2020)y | Assumed to remain constant. |
| **Emission factors** | Based on 2017 inventory data | | | | 2017 inventory (DEFF, 2020) | Assumed to remain constant. |

#### Comparison of modelled livestock emissions with 2017 inventory

The modelled emissions match the inventory emissions very well when actual livestock population data is used. This is an indication that all the emission equations are correctly modelled and that the use of aggregated emission factors instead of herd emission factors does not have a significant effect on the emission outputs.

If the livestock populations are modelled (from 2012) there is a slight variation in the emission output (Table XX - XX below) as the model doesn’t show as much annual variation. In addition, the modelled data is about 10 % lower than the inventory. During the development of the baseline model it was found that the 2017 inventory was double counting dairy cattle. The inventory will be updated to reflect this. If these corrections are made then the model shows a good correlation with the inventory outputs.

Table 48 Comparison of enteric fermentation emissions between the current agriculture model, the original 2017 inventory and the proposed corrected inventory.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
| Enteric fermentation - model | 1 176.02 | 1 174.38 | 1 166.68 | 1 152.99 | 1 134.91 | 1 121.72 |
| Enteric fermentation – inventory (original) | 1256.16 | 1308.64 | 1302.46 | 1296.79 | 1240.57 | 1224.23 |
| Enteric fermentation – inventory (corrected) | 1183.63 | 1223.77 | 1223.46 | 1216.91 | 1161.26 | 1137.32 |
| Gg CH4 difference (model & inventory) | -80.14 | -134.26 | -135.78 | -143.80 | -105.66 | -102.51 |
| % difference | -6.38% | -10.26% | -10.42% | -11.09% | -8.52% | -8.37% |
| Gg CH4 difference (model & corrected inventory) | -7.61 | -49.39 | -56.78 | -63.92 | -26.35 | -15.60 |
| % difference | -0.64% | -4.04% | -4.64% | -5.25% | -2.27% | -1.37% |

Table 49 Comparison of manure management CH4 emissions between the current agriculture model, the original 2017 inventory and the proposed corrected 2017 inventory.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
| Manure management CH4 - model | 36.99 | 37.09 | 36.98 | 36.65 | 36.16 | 35.84 |
| Manure management CH4 – inventory (original) | 35.44 | 36.11 | 35.43 | 35.09 | 35.13 | 35.45 |
| Manure management CH4 – inventory (corrected) | 35.42 | 36.09 | 35.42 | 35.07 | 35.11 | 35.44 |
| Gg CH4 difference (model & inventory) | 1.55 | 0.98 | 1.54 | 1.56 | 1.03 | 0.39 |
| % difference | 4.38% | 2.71% | 4.35% | 4.44% | 2.92% | 1.10% |
| Gg CH4 difference (model & corrected inventory) | 1.57 | 1.00 | 1.56 | 1.57 | 1.04 | 0.41 |
| % difference | 4.43% | 2.76% | 4.40% | 4.49% | 2.97% | 1.15% |

Table 50 Comparison of manure management N2O emissions between the current agriculture model, the original 2017 inventory and the proposed corrected 2017 inventory.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
| Manure management N2O – model | 5.23 | 5.30 | 5.33 | 5.33 | 5.29 | 5.28 |
| Manure management N2O – inventory (original) | 5.30 | 5.60 | 5.67 | 5.79 | 5.50 | 5.51 |
| Manure management N2O – inventory (corrected) | 5.13 | 5.38 | 5.47 | 5.58 | 5.31 | 5.30 |
| Gg N2O difference (model & inventory) | -0.07 | -0.30 | -0.34 | -0.46 | -0.21 | -0.23 |
| % difference | -1.35% | -5.41% | -5.99% | -8.01% | -3.73% | -4.10% |
| Gg N2O difference (model & corrected inventory) | 0.09 | -0.08 | -0.14 | -0.26 | -0.02 | -0.02 |
| % difference | 1.85% | -1.55% | -2.50% | -4.59% | -0.40% | -0.40% |

#### Aggregated and non-CO2 emissions on land (3C)

Aggregated and non-CO2 emissions on land includes biomass burning (3C1), lime application (3C2), urea application (3C3), direct N2O from managed soils (3C4), indirect N2O from managed soils (3C5) and indirect N2O from manure management (3C6). All of these categories are included in the model.

Biomass burning

Biomass burning shows high annual variability and there are really no good drivers for predicting this change. MODIS provides burnt area data for the years 2000 to 2017 for the inventory. Since it is difficult to predict the number of fires, a 10-year average (2007 to 2017) of the burnt area fraction was considered to be the best option for the model. The *10-year average burnt area fraction is assumed for all years*, and this reduces annual variability in the output. Biomass burning emissions are therefore modelled on the area of each land type (obtained from the Land model) together with the IPCC default emission factors and biomass stock data taken from the 2017 inventory. Due to the average values applied to the activity data some deviations from the inventory should be expected in the projected data for this category.

Lime application

Maize is South Africa’s most dominant crop, and it is cultivated for human consumption as well as for livestock feed. In the model maize area was the driver for lime consumption, and consumption of maize (by livestock and humans) was the driver of maize area. Maize consumption for feed was determined by applying livestock maize feed conversion factors and fraction of maize feed values (Table below) to the livestock production data. *These factors were assumed to remain constant*. Historical data from AAS is then utilised to determine the relationship between feed consumption and human consumption, consumption and production and lastly production and planted area. Based on historical data, and following IPCC methodologies, maize area was used as surrogate data to determine the lime consumption. IPCC 2006 default emission factors are applied.

Table 51 Maize feed conversion factors applied in the current agriculture baseline model.

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Maize feed conversion factor** | **Maize feed fraction** | **Data sources** |
| Dairy cattle | 1.5 | 0.6 | De Jager, 2016; DEA, 2018a |
| Beef cattle | 5.5 | 0.7 |
| Sheep & goats | 5.5 | 0.7 |
| Swine | 2 | 0.25 |
| Layers | 2 | 0.6 |
| Broilers | 1.6 | 0.65 |

Urea application

Urea application in the model is calibrated to inorganic fertiliser consumption. Due to high variability the relationship is not a strong one and an alternate driver needs to be considered in future. The IPCC 2006 default emission factor is applied.

Direct N2O from managed soils

Direct N2O emissions from managed soils includes emissions from inorganic and organic fertilisers, manure application to fields, urine and dung inputs in the pasture and range, as well as FSOM.

Inorganic N fertiliser consumption: Maize dominates the crop area and there is a good relationship between inorganic fertiliser consumption and maize area. Historic fertiliser consumption data and maize area (from AAS) is utilised to calibrate the model, with projected maize area changing with population and GDP. Current inorganic nitrogen application rates were assumed to remain the same in the future.

Organic N inputs: These include compost and crop residues. The amount of compost applied is estimated from the inorganic fertiliser consumption. The same *assumptions as provided in the inventory (5% of farmers apply compost as 33% nutrient requirement, 80% of compost is vegetative and 50% of crop residue which is included with crop residue inputs)* are applied. These *assumptions are assumed to remain constant*. Crop residue N input is projected based on the maize, wheat and sorghum area. The amount of crop residue N produced from these crops is determined from the factors provided in the table below. These three crops are *assumed to contribute 60% to the total crop residue N* (2017 inventory).

FSOM is projected based on land area and soil carbon changes from the land model. This is combined with IPCC default emission factors.

Table 52 Crop residue factors applied in the current agriculture baseline model.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Yield (t/ha)** | **Residue to yield ratio** | **Dry matter fraction** | **Fraction residue left in field** | **Carbon fraction** | **N:C ratio** |  |
|  |
| **Maize** | 4.2 | 1.5 | 0.87 | 0.48 | 0.5 | 0.015 |  |
| **Sorghum** | 2.8 | 1.4 | 0.89 | 0.12 | 0.5 | 0.015 |  |
| **Wheat** | 3.7 | 1.3 | 0.89 | 0.48 | 0.5 | 0.015 |  |

Indirect N2O from managed soils and manure management

Indirect N2O emissions are linked directly to the data from the direct N2O emissions and so these emissions are projected based on the outputs from the direct N2O and the IPCC default emission factors.

#### Comparison of modelled aggregated non-CO2 land emissions with 2017 inventory

There is some difference between the modelled aggregated emission outputs (see table XX) and the 2017 inventory outputs and the main reasons for this are:

* Corrections made to the livestock population data (mentioned in the livestock section above) affect the direct and indirect N2O from managed soils as well as the indirect N2O from manure management;
* Biomass burning data differs between the two data sets as the inventory shows high annual variability since fires are a natural disturbance. The model applies an average burnt area fraction which reduces the annual variability in the outputs;
* Urea and lime consumption data are also highly variable, particularly urea data, and the model does not show such high annual variability. The urea data for the inventory is obtained from SARS import data, whereas the model estimates it based on crop areas. The model estimates may be more accurate since it is looking at actual field application, whereas not all the SARS imported urea could be applied to soils in that year.

Table 53 Comparison between the modelled emissions and the 2017 inventory emission estimates for Aggregated and non-CO2 emissions on land.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
| Aggregated and non-CO2 emissions on land – model | 23 204.13 | 23 293.69 | 23 209.75 | 23 049.57 | 22 872.16 | 22 754.25 |
| Aggregated and non-CO2 emissions on land – inventory (original) | 24 218.92 | 25 582.98 | 25 675.49 | 24 749.30 | 23 164.45 | 23 447.11 |
| Aggregated and non-CO2 emissions on land – inventory (corrected) | 23 529.91 | 24 515.78 | 24 861.24 | 23 844.78 | 22 277.20 | 22 432.56 |
| Gg CO2e difference (model & inventory) | -1 014.79 | -2 289.28 | -2 465.74 | -1 699.74 | -292.29 | -692.86 |
| % difference | -4.19% | -8.95% | -9.60% | -6.87% | -1.26% | -2.95% |
| Gg CO2e difference (model and corrected inventory) | -325.78 | -1 222.09 | -1 651.48 | -795.21 | 594.96 | 321.69 |
| % difference | -1.38% | -4.98% | -6.64% | -3.33% | 2.67% | 1.43% |

### Land modelling

#### General emissions model methodology

The land category includes the emission and removal of carbon due to changes in land use. It covers the six land types identified by IPCC, namely Forest land, Cropland, Grasslands, Wetlands, Settlements and Other lands. Within each category carbon changes in land remaining in the same land category and also land converted to another category are included. All of these sub-categories (36 including conversion between all 6 classes) are included in the model, but carbon changes from wetlands are not estimated due to its complexity. This is consistent with the inventory. In addition, further sub divisions of these 6 categories, as provided in the 2017 inventory, are included.

Land areas and land change

In this model the 1990 area is the starting point and then the annual change data is applied to this area for the various conversions to determine the area in each land converted and land remaining category. Land area converted to a land type is accumulated for 20 years in the land converted category, after which it moves to the land remaining category.

The model has been set up with land change data from the 2017 inventory. This made use of the 1990-2014 national land cover change data (DEA, 2015b) and applied some corrections as discussed in the inventory. A 2018 land cover map has recently been produced for South Africa (DEA, 2019b), however the methodology and the vegetation classification for developing this map differed from the 1990 and 2014 maps. This makes it difficult to compare the two. A method for integrating the different maps, and any further future maps, will need to be developed going forward.

A 2018 South African National Land Cover Assessment was completed as part of the 2018 land cover mapping project to verify the natural land class changes between 1990/2014/2018. This assessment (DEA, 2019a) showed that most of the land changes between the natural classes were not real changes. It only indicated that there may be some loss of indigenous forest to grassland, loss of thicket to woodland, thicket to shrubland and shrubland to grassland. This information was incorporated into the land change matrix data by making some assumptions:

* The conversion areas where no conversion is considered to occur were reverted back to the 2014 land remaining land class;
* For thickets to woodlands, thicket to shrublands and indigenous forest to grasslands only small amounts of change were shown to be true changes, therefore a quarter of the change area from the land change maps was applied and the rest of the area was reverted back to the 2014 land class; and
* For shrublands to grasslands most of this was indicated to be real change therefore this area was left as is.

Carbon stock changes

The model applies carbon stock data, taken from the 2017 inventory (which is obtained from the National Terrestrial Carbon Sinks Assessment (DEA, 2015)), to the land areas to determine the carbon stock changes. Biomass, dead organic matter (DOM) and soil organic carbon (SOC) pools are included for each category.

In forest land biomass pool carbon gains and losses are determined as the gain-loss approach is followed which is consistent with the inventory. The gains are due to growth and losses are due to fire (all vegetation types), other disturbances (plantations), harvesting (plantations), and fuelwood removal (woodlands). Carbon gains in croplands, grasslands, settlements and other lands are modelled in a similar manner as for forest lands, with land area and biomass growth, however for annual crops and grasslands growth is only accounted for in the first year of conversion. After this a net zero balance is assumed (IPCC, 2006) as all gains and losses will be equal in annual systems. For carbon losses only losses due to fires are included for these land types and this is consistent with the inventory.

DOM, for all land types, only includes litter changes due to a lack of deadwood data. DOM (litter) changes are estimated from the area and average DOM stock values (2017 inventory) for each vegetation type. SOC is related to the soil carbon reference value and these are dependent on soil type and climatic conditions. In the inventory SOC data is determined for each land change type by overlaying the vegetation, soil and climate maps. IPCC SOC reference values and stock change factors are then applied. For modelling purposes an area weighted averages of soil carbon for each land and conversion type from the inventory overlays was determined and applied to the land areas.

Carbon stock changes are not determined for wetlands due to a lack of data. This is consistent with the inventory. Methane emissions from wetland are included by combining the wetland area with the IPCC emission factor of 0.044 kg CH4/ha/day.

#### Baseline model methods and assumptions

The activity data that needs to be projected is land area and this is projected based on the annual change data. The land areas increase and decrease based on the annual land change matrix data (which shows both conversions to and from the various land types). Converted land remains in the conversion category for the default 20 years before moving to the land remaining category. The total land area always remains constant. The following assumptions were made with regard to land area projections:

* For all land classes, except plantations and conversion of woodland to shrublands, it was assumed that the annual land change between 1990 and 2014 continues at the current rate;
* For plantations Forestry SA (FSA, 2020) indicate that plantations may expand by an additional 150 000 ha. Of this the 100 000ha in the Eastern Cape is listed as a PAMs so was excluded in the baseline model projection. Therefore only a 50 000ha was included for plantations between 2020 and 2030;
* Clearing of alien invasive species is carried out in order to improve ecosystem services and biodiversity. The conversion of shrublands to grasslands is already included in the land change maps, however it is assumed with the land degradation neutrality targets there will be additional clearing. The NRM branch of DEA has set targets for clearing grasslands and the AFOLU strategy (DEFF, 2020a) indicates that 70% of these targets are likely to be achieved. For grassland clearing this is 111 226 ha by 2030. In the baseline model it is assumed that 111 226 ha are cleared by 2030 (assumed this to be a conversion from woodland to grassland), and this is assumed to continue to some degree with the same area being cleared again by 2050;
* Targets have also been set for clearing forests and woodlands. As for clearing of grasslands, 70% of the NRM target (DEA, 2015; DEFF, 2020) was applied (76269 ha forest and 4423621ha woodland (including fynbos)) by 2030. Clearing was also assumed to continue at the same rate to 2050. Clearing of these land types was assumed not to be a land conversion but rather a loss of biomass carbon (due to the clearing process) and then a growth starting from the following year.

#### Forest land (3B1)

Carbon gains in forest lands are projected by applying the forest carbon stock gain data from the inventory to the changing land area. Harvest losses for plantations are *assumed to be related to plantation area*. A 10-year rotation cycle dominates so wood harvested from plantations is modelled based on the plantation area 10 years prior. TUP area has been increasing since 1990, but for the last 10 years TUP area has been about 8% of plantation area (FSA, 2019). TUP area is therefore assumed to be 8% and this is assumed to remain unchanged in the baseline.

Fuelwood use is related to the number of households that use wood for heat, cooking and light. In the model projected fuelwood use is driven by the fuelwood component of the energy model, where household income is the driver. The population is divided into low, medium and high income households and the percentage of households in each group using fuelwood is assigned. Low income households are seen to be declining towards 2050, while middle and high income households are increasing. In terms of wood use, the percentage of wood used by low and middle income classes’ declines with time, while consumption in high income households remains the same (details can be found on the residential section under energy). An average household wood consumption value from the inventory (3.5 t/yr) is applied and this is assumed to remain constant until 2050.

The losses due to fires are calculated with the average burnt area fraction (as discussed under the section on biomass burning in the agriculture model), and this fraction is assumed to remain constant between 2020 and 2050. The application of an average burnt area throughout the time series reduces the annual variability in the output.

Carbon changes due to land conversions, DOM carbon changes and SOC changes are projected by applying the stock change factors from the inventory to the changing land areas.

#### Croplands (3B2), grasslands (3B3), settlements (3B5) and other lands (3B6)

Carbon gains for these land types are projected by applying the carbon stock data to the changing land areas. Only fire losses are included and these are projected assuming an average burnt area fraction which is kept constant throughout the time period, with the fraction then being applied to the changing land area.

#### Wetlands (3B4)

Wetland emissions are projected by applying a default per hectare emission factor, which is assumed to remain constant, to the changing wetland area.

#### Harvested wood products (3D1)

Harvested wood products is a small sink and is projected using the historical relationship between harvested wood and harvested wood product emissions.

#### Comparison of land model outputs with 2017 inventory

There is a large difference between the model output and the 2017 inventory data and there are various reasons for this:

* Additional assumptions, based on the land change assessment report (DEA, 2019a) about land changes in thicket to woodland, thicket to shrubland, and indigenous forest to grassland were incorporated into the land change matrix. These changes lead to a slower increase in forest land and slower decline in grassland. This in turn means a reduction in the sink compared to the 2017 inventory;
* The model applies an average burnt area fraction since modelling natural fire disturbance is very difficult. Applying this average value means that there is much less annual variability. The actual burnt area data used in the 2017 inventory shows a significant decline between 2012 and 2017 which meant that there was a decline in carbon removals from the land contributing to the increasing sink. With an average burnt area value removals remain constant and model outputs show a reduced sink compared to the inventory;
* Fuel wood losses are determined differently in the model compared to the inventory. The model uses outputs from the energy model which estimate wood use on population and income group. The data incorporated in the model is felt to be more detailed and accurate than the method applied in the inventory. Based on the new methodology the fuelwood use is shown to increase slightly over the period 2012-2017 instead of decline as shown in the 2017 inventory. The declining fuelwood use in the inventory contributes to the increasing sink, however in the model fuelwood losses are more constant and show a slow increase. This leads to increased losses from woodlands thereby reducing the sink. Modelled output shows a smaller sink than the inventory;
* Harvested wood is modelled on the plantation area, which again shows a smooth change and does not provide much annual variability. In the 2017 inventory wood harvest also declined over the years 2012-2017 which further contributed to the sink;
* The inventory calculation files are large and complex and in the process of developing this model a few errors were detected and it is suggested that these errors be corrected in the inventory.

The inventory shows a large increasing sink between 2012 and 2017 which is not shown in the model due to the reasons given above. The model shows a much more average land sink value and the projected data does not display the annual variability shown in the inventory. The model output provides estimates that are more consistent with inventory estimates for the period 1990 to 2010, with the increasing sink in 2017 appearing as a more unusual event. There is therefore a large amount of uncertainty around the land sink estimates, due partly to variance in natural disturbance that cannot be accounted for. If the minimum and maximum natural disturbance values are considered then the land estimates could be as much as 10 Mt CO2 higher or lower than the projected value in any given year.