Assessing climatic benefits from forestation potential in semi-arid lands

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Abstract
Forestation actions are a major tool for both climate-change mitigation and biodiversity conservation. We address two weaknesses in this approach: the little attention given to the negative effects of reduced albedo associated with forestation in many regions, and ignoring the potential of drylands that account for 40% of the global potential land area for forestation. We propose an approach to identify suitable land for forestation and quantify its ‘net equivalent carbon stock change’ over 80 years of forest lifetime (NESC), accounting for both carbon sequestration and albedo changes. We combined remote-sensing tools with data-based estimates of surface parameters and with published climate matrices, to identify suitable land for forestation actions. We then calculated the cumulative (over 80 years) ‘net sequestration potential’ (∆SP), the ‘emission equivalent of shortwave radiation forcing’ (EESF) due to changes in surface albedo, and, in turn, the combined NESC = ∆SP − EESF, of planting forests with >40% tree-cover. Demonstrating our approach in a large climatically diverse state (Queensland), we identified 14.5 million hectares of potential forestation land in its semi-arid land and show that accounting for the EESF, reduces the climatic benefits of the ∆SP by almost 50%. Nevertheless, it results in a total NESC of 0.72 Gt C accumulated by the end of the century, and 80 years of forestation cycle. This estimated NESC is equivalent to 15% of the projected carbon emissions for the same period in Queensland, for a scenario of no change in emission rates during that period. Our approach extends restoration efforts by identifying new land for forestation and carbon sequestration but also demonstrates the importance of quantifying the climatic value of forestation in drylands.

1. Introduction
Forests are key players in climate-change mitigation strategies in two ways: (a) by contributing to ‘source reduction’, preventing deforestation, in addition to limiting the global fossil fuel-based energy use (IPCC 2018). (b) By ‘carbon-sink enhancement’, e.g. carbon sequestration programs (Griscom et al 2017, Lewis et al 2019). To achieve the 1.5 °C target of the Paris climate agreement (Lewis 2016), through ‘source reduction’, global emissions need to be reduced by almost 50% of the 2010 levels by 2050 (Robiou Du Pont et al 2016). This will require dramatic and immediate policy changes. Therefore, the combination of avoided emission and active sequestration will be required (Rockström et al 2016).

Forestry strategies of carbon sequestration programs may play an important role in climate-change mitigation programs (Dixon et al 1994, Gullison et al 2007, Canadell and Schulze 2014, Griscom et al 2017, Ussiri and Lal 2017, Bastin et al 2019, Lewis et al 2019). These forestry strategies include reforestation (restoring forests in previously forested areas) and afforestation (planting forests in areas that did not have forests before), as well as minimizing deforestation, and improving forest management. The clean development mechanism (CDM) of the Kyoto Protocol allows governments and business
organizations to gain a fraction of their emission reduction credits from forestry (CDM-AR) projects in developing countries (Aslam 1999). Another initiative is the Bonn Challenge, which is a global effort to restore 350 Mha of the degraded forest by 2030 (www.bonnchallenge.org/). However, there is a clear lack of high-resolution quantitative estimates of the actual contribution of such potential projects to climate mitigation. Moreover, most previous studies focused on tropical, boreal, and temperate forests, neglecting the potential areas of the transition from humid to drylands. This is even though 40% of the global restoration opportunities, identified by the ‘Global Restoration Initiative’ occur in drylands (Potapov et al 2011).

The biogeochemical process of removing CO₂ from the atmosphere via carbon sequestration in forests, and its potential in limiting the radiative forcing (RF) of global warming is well-recognized (Dixon et al 1994, Pan et al 2011). However, forestry activities also modify land surface properties which in turn alter important surface biophysics, including albedo, thermal emission, and surface roughness (Betts et al 2007, Rotenberg and Yakir 2010, Arora and Montenegro 2011, Zhao and Jackson 2014). Forests generally have a lower albedo (the fraction of incident sunlight reflected back to space) than that of the ecosystem they replace (Betts 2007, Bright et al 2017, Hirsch et al 2018). The decreasing albedo results in higher absorption of solar radiation and exerts a positive RF on climate (i.e. warming). Forests can alter other biophysical properties including forest surface roughness, which has a strong impact on the exchange of water and energy between the land surface and atmosphere (Bonan 2008, Bright et al 2017) and may alter also local temperature (Breil et al 2020, Novick and Katul 2020). An increase in surface roughness can enhance turbulent-energy exchange between the land and atmosphere, and decrease the outgoing-longwave radiation, which may be important in dry areas (Rotenberg and Yakir 2010, Banerjee et al 2017, 2018).

The contrasting biogeochemical and biogeophysical effects of forestation on climate is increasingly recognized in the climate change and terrestrial ecosystems research community (Betts 2000, Bala et al 2007, Bonan 2008, Anderson et al 2011, Zhao and Jackson 2014, Bright et al 2015), yet it has not been implemented into climate policies for climate-change mitigation programs (Duveiller et al 2020). These effects vary largely among regions and forest types, but quantification of these contrasting effects in specific locations is still missing, particularly in dry regions (Bright et al 2015).

Drylands are defined based on their ‘aridity index’, which is the ratio between mean annual precipitation (MAP) and potential evapotranspiration (MAE; Zomer et al 2008):

\[ \text{AI} = \frac{\text{MAP}}{\text{MAE}} \]  

Areas with AI below 0.65 are considered drylands and are commonly divided into sub-regions of hyper-arid (AI < 0.05), arid (0.05 < AI < 0.2), semi-arid (0.2 < AI < 0.5) and dry-subhumid (0.5 < AI < 0.65).

Drylands cover ~40% of the earth’s terrestrial land (Safriel et al 2005) and this area is expected to increase by 23% by the end of this century (Huang et al 2016, Kouttroulis 2019). A recent study estimated the area of drylands forests as over 1000 million hectares, with 70% of the forests characterized as closed forests (Bastin et al 2017). Despite the large area of drylands, these regions were largely overlooked when forestation was considered (e.g. Nilsson and Schopflauer 1995, Betts 2000, Arora and Montenegro 2011). Some exceptions include, for example, Australia where Fensham and Guymer (2009) examined carbon accumulation from ecosystem recovery in Australia. They indicated a large area of potential land for restoration in Queensland, supporting both carbon sequestration and nature conservation. A more recent study demonstrated a positive feedback loop from the restoration of Australian woody-savannas as a result of an increase in evapotranspiration followed by an increase in cloud formation and precipitation, providing additional soil moisture for vegetation growth (Sytktus and McAlpine 2016). Note that these studies focused mostly on reforestation and ecosystem restoration, and less on the potential for forestation action in previously unforested areas. Other studies indicated that the increase in evapotranspiration rates after forestation can result in a decrease in water yield (Rohatyn et al 2018) and depletion of groundwater (Adane et al 2018). These findings indicate the need to keep a broad perspective in considering the sustainability of forestation in dry regions, without the precipitation enhancement mentioned above. Moreover, low water availability which results in suppressed latent-heat flux, combined with high radiation load in these conditions, can result in enhanced sensible-heat fluxes. This effect was previously demonstrated for dryland forest in what is termed a ‘convector effect’ (Rotenberg and Yakir 2011, Banerjee et al 2017).

A spatial explicit quantification of the areas suitable for forestation in the semi-arid regions, and its climatic impact is still missing. Such an approach is critical to achieving effective policies for both climate mitigation efforts, and as an integral consideration in biodiversity conservation based on forestation. Here we develop a simple method to assess the expected value of forestation actions as a strategy for climate-change mitigation, considering both carbon sequestration and albedo effects. We use the semi-arid region of Queensland (~80 Mha) as a case study.
2. Methods

2.1. Overview
The entire workflow of the study method is illustrated in figure 1. First, we generated a high-resolution (1 km) map with suitable land for forestation actions. Next, each grid from the resulting map was tested for its potential value for climate mitigation (if it is forested). Biogeochemical and biogeophysical factors were quantified using equations based on expected changes in vegetation structure and physiology, forest density, and species composition. These traits were translated to sequestration rates and albedo values.

Forestation albedo and carbon values were derived from nearby-existing forests, using remotely-sensed information and available model-based products (table 1).

2.2. Land suitability analysis
We conducted a spatial analysis in order to generate a map of geographically-based forestation potential (green boxes, figure 1). A set of suitability criteria based on biological and land-cover factors were used to identify areas with a forestation potential (Zomer et al 2008). The biological criteria were aridity-index threshold, excluding areas with AI < 0.2 (dataset 1, table 1), and areas above the timberline (based on warmest-month mean temperature <12 °C; Körner and Paulsen 2004; dataset 2, table 1). The biological criterion of AI > 0.2 is defined here to include the full range of semi-arid land as potential land for forestation actions, which is the focus of the current study. This threshold is based on the expectation that the limiting factor for forest establishment over previously unforested land in this range is the seedling...
Table 1. Descriptive information on dataset and products used for all variables in the current study. Including references to the relevant method section.

| ID | Data | Description | Period | Source/Reference | Use in current study                                                                 | Method section |
|----|------|-------------|--------|-----------------|--------------------------------------------------------------------------------------|----------------|
| 1  | AI   | Global Aridity Index | Multiyear annual mean from 1970 to 2000 | (Trabucco and Zomer 2019) | Suitability analysis - Identify semi-arid regions 0.2 < AI < 0.5                    | 2.1            |
| 2  | Temp.| Global monthly temperature | Multiyear monthly mean from 1970 to 2000 | (Fick and Hijmans 2017) | Suitability analysis - Temperature threshold. Temp. of the warmest month above 12 °C | 2.1            |
| 3  | LC   | ESA Climate Change Initiative—Land Cover project | 2015 (most updated published version) | http://maps.elie.ucl.ac.be/CCI/viewer/ | Suitability analysis—Mapping of potential forestation land and identification of forested area with above 40% cover | 2.1            |
| 4  | Rivers | Global rivers central line | — | — | — | — |
| 5  | $R_{SW}^i$ | Incoming shortwave radiation on a sloping surface | Multiyear monthly mean from 1981 to 2006 | (Gallant et al 2014) | Calculating radiative forcing changes due to changes in albedo (equation (2)) | 2.2            |
| 6  | $\alpha_s$ | Surface albedo lookup maps | Multiyear monthly mean from 2001 to 2011 | (Gao et al 2014) | Calculating the change in albedo after forestation actions (equation (2)) | 2.2            |
| 7  | CFC  | Fractional cloud cover from polar-orbiting satellites of CLARA-A1: CM SAF | The monthly average for 1982–2009 | (Karlsson et al 2012) | Calculating surface albedo from albedo lookup maps | 2.2            |
| 8  | IGBP | MODIS-IGBP land cover maps | 2007 | (Friedl et al 2002) | Calculating surface albedo from albedo lookup maps | 2.2            |
| 9  | NEP  | Net ecosystem productivity | Annual sums from half-hourly fluxes for 2002–2015 | (The ESDC developer team 2016) | Calculating the multiyear average of Net ecosystem productivity (NEP) | 2.3            |
Table 2. Summary of parameters and variables for the study equations, including a description of the parameter, units of use, the constant value from the literature or mean values in the estimated variables, the purpose of use, and reference to the relevant equation. # indicate unitless values.

| Description                                                                 | Unit          | Value (range)  | Purpose of use                                      | Equation |
|----------------------------------------------------------------------------|---------------|----------------|----------------------------------------------------|----------|
| AI Aridity Index—the ratio between mean annual precipitation and mean annual potential evapotranspiration | # 0.2–0.5     | Mapping semi-arid land for forestation actions     | 1        |
| Δαs Change in surface albedo after forestation action                       | # 0.04 (0–0.07) | Calculating changes in radiative forcing due to changes in albedo | 2        |
| Rs ↓\text{SW} Incoming short-wave radiation                               | W m⁻²         | Calculating changes in radiative forcing due to changes in albedo | 2        |
| Ts ↑\text{SW} Atmospheric transmittance factor                             | # 0.854       | Converting the results from the surface to the top of the atmosphere | 2        |
| RF\text{T oA}∆αs Radiative forcing at the top of the atmosphere as a result of changes in surface albedo after forestation action | W m⁻² 7.72 (0–16) | Metric for estimating the climatic effect of changes in surface albedo | 2        |
| NEP Long term average of net ecosystem productivity of existing forest     | gC m⁻² yr⁻¹ 187 (60–310) | Applying NEP in the carbon growth model for forest and non-forest scenarios | 3        |
| RE Radiative efficiency—net change in Earth’s radiative forcing (RF) due to change in the concentration of a greenhouse gas | W m⁻² 5.35 | Conversion of RF units into carbon equivalent | 4        |

*In the brackets are the ranges of estimated values for 90% of the data after excluding margins of 3% at the lowest and highest range.*

establishment, which can be overcome by initial supplement seedling irrigation during the first year(s), a common practice for afforestation in drylands (Bainbridge 2012).

Land-cover criteria included the exclusion of areas covered by water bodies, rivers with a buffer of 1 km, urban area, agriculture areas (cultivated land, but not pasture), as well as areas with woody cover (trees and shrubs) above 15% (datasets 3 + 4, table 1).

We first analyzed the full climatic gradient of Queensland, from semi-arid (0.2 < AI < 0.5) to dry-subhumid (0.5 < AI < 0.65) and humid (0.65 < AI). After identifying small opportunities for forestation actions in the dry-subhumid and humid areas, we continued to the next step of the analysis, which we applied to the semi-arid areas only. The predicted planted semi-arid forest characteristics were then extracted from nearby existing semi-arid forests, with >40% forest cover (dataset 3, table 1). We used a moving-window averaging method to calculate the expected carbon and albedo values of the potential forest in each cell. These values were the average values extracted from existing closed forests (>40% cover) within a distance of ~200 km. The size of the moving window was determined to satisfy a tradeoff between the benefits of small windows (representing actual local forest traits) and the benefits of large windows (using large forests, rather than few small patches, reduces the effects of error). Note that ~70% of Queensland’s closed forests are in drylands and ~20% of these forests have AI of 0.2–0.3 (See figure S3 available online at stacks.iop.org/ERL/16/104039/mmedia). This finding supports the assumption that dryland areas are relevant for potential forestation, if not excluded by other land-cover criteria.

2.3. Estimating changes in surface albedo and RF at the top of the atmosphere

One main climatic response to land-cover change (including forestation actions), is the change in monthly and annual ToA RF due to surface albedo changes (RF\text{T oA}∆αs), which can be calculated based on equation (2) (Bright et al 2015):

\[
\text{RF}\text{T oA}∆αs = \sum_{m=1}^{12} R_{\text{SW}} (t, m, i) \Delta α_s (t, m, i) T_{\text{SW}}^+ \cdot [W m^{-2}]
\]  

(2)
where $R_{SW}^i$ is the incoming shortwave radiation at the surface in W m$^{-2}$ (broadband of 0.3–5.0 µm; dataset 5, table 1). $\Delta \alpha_s$ is the change in the surface albedo. $T_{SW}^i$ is an upward atmospheric-transmittance term (0.854, as suggested in Bright et al. 2015), $m$ is the month, $i$ is the location, and $t$ is the analytical time step (1 year increments). $RF^{\Delta \alpha_s}_{t}$ was calculated first monthly ($m$), then summed over the year ($t$), to produce the annual mean value (see table 2 for parameters values).

Changes in surface albedo ($\Delta \alpha_s$) were estimated by combining values from global look-up maps (albedo LUM of Gao et al. 2014) with satellite (MODIS) IGBP land-cover maps (Friedl et al. 2002; Orange boxes, figure 1). This provided albedo values for both current and future conditions (based on existing forest values) for each grid cell in the study region. The LUM are at 0.05–0.1° resolution and include four different albedo types: black-sky, white-sky, snow-covered, and snow-free. In this paper, we used the highest resolution of 0.05° degree and a combination of the black-sky and white-sky of snow-free albedo. To combine white and black-sky albedo, the diffuse fraction was calculated based on clearness index which depended on sunshine/cloud fractions (dataset 7, table 1, for more information see supplementary section S8.1). Snow-covered albedo was not relevant for the specific area of research. Finally, we increased the LUM resolution of 0.05° by using land-cover maps with 1 km resolution and attributing each 1 km grid cell with the relevant albedo value from the albedo LUM (dataset 8, table 1).

2.4. Estimating the changes in carbon stock

The forests’ annual-carbon gain was evaluated from net ecosystem exchange (NEE), an output of the Earth System Data Cube (The ESDC developer team 2016; dataset 9, table 1), which is a temporal and spatial resampling of the eddy co-variance Fluxcom database (www.fluxcom.org). Note that below we use net ecosystem productivity, NEP, the positive carbon gain by the forest, which is identical to NEE, the negative carbon removal from the atmosphere.

The long-term (2020 until the end of the century; 80 years) forest-sequestration potential (SP) was then estimated using an adjustment of the general function proposed by Amiro et al. (2010) and further developed by Besnard et al. (2018) to express the development of net ecosystem productivity (NEP) with forest age, as follows:

\[
\text{NEP}_t = \text{NEP} \left(1 - \exp^{b \cdot t}\right), \quad \text{(kgC m}^{-2}\text{)} \tag{3}
\]

where annual carbon gain at time $t$ (NEP$_t$) is a function of multiyear average carbon gain (NEP, taken from NEP of existing nearby closed forests, table 2), growth rate ($b$), and years from initiating forestation action ($t$). Parameter $b$ is constant ($b = -0.17$) and is calculated based on the global analysis of Besnard et al. (2018), limiting the data for dryland flux sites only (for more details on the equation development see SI). $\Delta$SP was then calculated for each grid cell as the cumulative delta (over 80 years) between forested and non-forested NEP, simulations \( \sum_{t=1}^{t=80} \text{NEP}_{t, \text{forest}} - \sum_{t=1}^{t=80} \text{NEP}_{t, \text{non-forest}} \). In calculating $\Delta$SP, we assumed that non-forested carbon gain is equal to current vegetation NEP (multiyear average, table 2), and is constant throughout the whole simulated period. Finally, we excluded potential forest areas where NEP of current vegetation was higher than that of nearby existing forests.

We chose the study period of 80 years to be able to compare the results of our study with previous projections for climate mitigation and climate change by the end of the century (80 years for 2020–2100) and because it is well within the expected forest life cycle.

2.5. Estimating the combined carbon and albedo climatic effects

Finally, we used a similar approach to that of Betts (2000), and its terms, to compare the impact of changes in surface albedo, as emission equivalent of shortwave RF (EESF) at the top of the atmosphere, with the net sequestration potential (ASp) of the same forestation action, to produce the net equivalent stock change (NESC). We used an inverse version of the original equation by Myhre et al. (1998) with a simplification for small perturbations (Bird et al. 2008, Joos et al. 2013), based on Taylor series first approximation of the natural algorithm, resulting in the following equation (see parameters values in table 2):

\[
\text{EESF} = C_0 \cdot \frac{RF^{\Delta \alpha_s}_{t}}{RE \times A_E} \cdot \frac{k}{\zeta}, \quad \text{(kgC m}^{-2}\text{)} \tag{4}
\]

where $C_0$ is a reference atmospheric CO$_2$ concentration (410 ppm, the average atmospheric concentration for the past decade), $RF^{\Delta \alpha_s}_{t}$ is the annual multiyear average change in RF at the top of the atmosphere as a result of the change in surface albedo (W m$^{-2}$), RE represents the net change in Earth’s RF due to change in the concentration of greenhouse gas (5.35, W m$^{-2}$), $A_E$ is the Earth’s surface area (5.1 $\times$ 10$^{14}$ m$^2$), $k$ is a conversion factor, from ppm to kg C (2.13 $\times$ 10$^{12}$), and $\zeta$ is the airborne fraction (0.44).

Finally, the net-equivalent change in carbon stock due to both the cooling effect of carbon sequestration and warming effect due to albedo change (NESC, Purple box, figure 1), was calculated by a simple subtraction:

\[
\text{NESC} = \Delta \text{SP} - \text{EESF}, \quad \text{(kgC m}^{-2}\text{80yr}^{-1}) \tag{5}
\]

where positive NESC is for net cooling effect when the net SP overcomes the albedo effect (EESF).

Note, that while both $\Delta$SP and EESF are positive, the first is referring to the uptake of carbon and the
second to emission. Moreover, while the change in SP is accumulated throughout the full period of simulation, the change in albedo is assumed to be a one-step change. This widely used simplification (Bets 2000, Myklebly et al 2017, Favero et al 2018) is justified by the focus of the study on the net result by the end of the simulation period (equation (5)), and the common assumption that the effect of albedo change on the RF is a one-time change that maximizes at an early canopy stage (partly since sun angle is usually not at the Nadir reducing the exposure of bare soil).

2.6. Data preparation

All data analysis and preparation, described in sections 2.1–2.5, were done using R 3.6.0 (R Core Team 2020). All layers for equations (1)–(5) were re-sampled in 30-arc seconds resolution (~1 km at the equator). All parameters were first calculated as multi-year monthly mean and then averaged (for albedo data) and summed (for carbon data) over a year. All datasets used in this paper analysis are described in table 1.

3. Results

The first stage of our analysis (see figure 1) was based on the ESA Climate Change Initiative—land-cover project and identified a total of 14.5 Mha (million hectares) of potential land for forestation actions in Queensland’s semi-arid region (figure 2, table 3), and less than 1 Mha of land in the dry-subhumid and humid area (not shown). This land consists of nearly 70% grasslands, and 30% sparse woody vegetation (land with <15% woody vegetation cover; table 3). In addition, within the semi-arid region in Queensland, there are 2.6 Mha of closed forest land (>40% tree cover), of which 90% are evergreen broadleaved forests, and 10% are deciduous broadleaf, and needle-leaf forests (see details in SI, and figure S4).

In terms of carbon uptake, our analysis of existing forests (based on dataset 9, table 1) revealed a large potential contribution of net carbon sequestration by the closed (>40%) forests of Queensland semi-arid land, with a mean annual NEP of 1.87 tC ha\(^{-1}\), and 90% of the area with annual NEP between 0.6 and 3.1 tC ha\(^{-1}\) (table 3, figure S5(b)). In contrast, in the potential forestation land, NEP was around zero (0.06 tC ha\(^{-1}\) yr\(^{-1}\)), reflecting averages values of 0.13 and –0.1 for the grassland, and sparse vegetation areas, respectively (table 3). We noticed a high spatial variability in current NEP, ranging between –0.5 and 0.7 tC ha\(^{-1}\) yr\(^{-1}\) over 90% of the area, with 55% being a small net carbon sink (positive NEP) and 45% being a small net carbon source (negative NEP), but with values near zero and with no clear pattern across Queensland (figure S7).

In terms of albedo change, the potential area for forestation was found to have an average albedo of 0.16 and 0.18, for the grassland and sparse vegetation, respectively (table 3). The albedo in the closed (>40%) forests was found to be relatively low, with an average value of 0.12, and ranging between 0.11 and 0.14 in 90% of the forest area (table 3, figure S5(a)). By applying forestation actions over this land, the surface albedo decreased on average by 25% in the grassland and 33% in the sparse vegetation, respectively. We found high spatial variability in current surface albedo across the potential forestation areas, ranging from 0.12 to 0.2 (figure S6(a)) and therefore high spatial variability also in the change in surface albedo, ranging from no change to –0.07 (figure S6(b)).

We simulated the combination of ∆SP and the albedo effect (EESF) over 80 years of forest development. We found a significant increase in the NESC (NESC; 45.3 tC ha\(^{-1}\) 80 yr\(^{-1}\)) over the entire area. Overall, 80% of the area was estimated to have a net positive climatic forcing (cooling), with an eventual increase in the net equivalent stock of 76.2 tC ha\(^{-1}\) for this area at the end of the simulated period (figure 2; NESC blue area). In contrast, 20% of the area was found to have a net negative climatic forcing (warming effect), expressed in a decrease in the net equivalent stock of –29.2 tC ha\(^{-1}\) 80 yr\(^{-1}\) (figure 3; NESC orange area).

Table 3 summarizes the area-integrated NESC, as a result of the proposed forestation actions over 80 years in the semi-arid areas of Queensland. The two main land-cover types, grassland, and sparse vegetation cover differed in the carbon equivalent results. Although the EESF was higher by 20% in the sparse vegetation compared with the grassland (62 compared with 52 tC ha\(^{-1}\) 80 yr\(^{-1}\)), the ∆SP in the sparse vegetation land was smaller by 40% (115 compared to 70 tC ha\(^{-1}\) 80 yr\(^{-1}\)). As a result, NESC in the sparse vegetation was significantly lower than in the grassland (8.3 compared to 63 tC ha\(^{-1}\) 80 yr\(^{-1}\)). Finally, the total NESC for Queensland potential forestation in semi-arid lands was estimated to be 45 tC ha\(^{-1}\) 80 yr\(^{-1}\) on average, or 0.64 GtC over the entire period of simulation (table 3). By excluding potential forestation land with NESC < 0 (leaving 11.7 Mha of potential forestation land) the total NESC increased by 12% (up to 0.72 GtC 80 yr\(^{-1}\), table 3).

To demonstrate the importance of producing the results at high resolution (1 km, in this case study), we examined the sensitivity of the results to resolution. We computed the root square mean deviation (RSM) for different resolutions, ranging from our reference of 1 km to a low resolution of 100 km (figure S8). The results indicated a sharp increase in RSM by ~15 tC ha\(^{-1}\) 80 yr\(^{-1}\), which is 20% of the average NESC when shifting from a resolution of 1 km to 10 km. Errors were even higher at the lower resolution of 40 km (RSM of ~25 tC ha\(^{-1}\) 80 yr\(^{-1}\) which is 40% of the average NESC).
Figure 2. Queensland potential forestation land across a climatic gradient. Green is for potential forestation land, as resulted from the suitability analysis. The colored scale from orange to bright green is for the climatic gradient indicated by the aridity index. Inset shows the location of the Queensland region in red above the map of Australia.

Table 3. Summary of forest and potential forestation land results; multiyear averages of carbon (net ecosystem productivity, NEP) and surface albedo (αs) of existing forests (above 40% canopy cover) and potential forestation land (grassland and spare vegetation—below 15% cover). The results of forestation actions presented in ton carbon per hectare (tC ha⁻¹) of emission equivalent of shortwave forcing (EESF), and in tC ha⁻¹ 80 yr⁻¹ of the net sequestration potential (ΔSP = NEP_{forest} - NEP_{non-forest}), and net equivalent stock change (NESC = ΔSP - EESF). Last is the total NESC which is summed over all potential forestation land. The second and last rows are calculated over potential forest areas with positive NESC only. Note, that while both ΔSP and EESF are positive, the first is referring to the uptake of carbon and the second to emission.

| Unit         | Existing forests (>40% cover) | Potential forestation land |
|--------------|-------------------------------|-----------------------------|
|              | Grassland                     | Spare vegetation            | All             |
| Total area   | Mha                           | 2.6                         | 9.7             | 4.7             | 14.5           |
| Positive NESC area | Mha                      | 2.6                         | 9.1             | 2.6             | 11.7           |
| αs           | #                             | 0.12                        | 0.16            | 0.18            | 0.16           |
| NEP          | tC ha⁻¹ yr⁻¹                  | 1.87                        | 0.14            | -0.07           | 0.07           |
| ΔSP          | tC ha⁻¹ 80 yr⁻¹               | —                           | 114.7           | 69.7            | 100.1          |
| EESF         | tC ha⁻¹                      | —                           | 51.7            | 61.6            | 55             |
| NESC         | tC ha⁻¹ 80 yr⁻¹               | —                           | 63.0            | 8.3             | 45.3           |
| Total NESC   | GtC 80 yr⁻¹                   | —                           | 0.61            | 0.04            | 0.64           |
| Total positive NESC | GtC 80 yr⁻¹              | —                           | 0.62            | 0.10            | 0.72           |
4. Discussion

4.1. Expanding forestation into the semi-arid domain

The potential forestation area of 14.5 Mha identified in Queensland using our approach is much lower than the area of the potential restoration opportunities determined by two global restoration datasets: The ‘Global Restoration Initiative’ (GRI; Potapov et al. 2011), and the global tree restoration potential (Bastin et al. 2019). These two datasets estimated 34.7 Mha and 74.5 Mha for forest restoration in the semi-arid area of Queensland, respectively. This large difference may stem from the different assumptions used in the suitability analysis of the different studies. Generally, our approach aims to maximize the climatic-cooling effects of the forestation actions. This approach resulted in several key differences relative to the earlier studies. The major impact on the total area identified is because the two previous studies identified restoration opportunities in all non-forested areas, including dense shrublands and low-density forests (woody savanna and open forests) in areas previously forested. Our analysis (based on preliminary assessments) did not indicate a significant climate-related advantage in converting these vegetation types into forest of >40% cover. Our criteria, therefore, focused on relatively bare-land areas, having <15% vegetation cover of trees or shrubs. This shifted and extended the research to areas which were not previously considered, allowing both reforestation and afforestation actions in these sites.

To demonstrate this point, we conducted a re-analysis of the data in the two earlier studies by excluding areas with current shrub or tree cover above 15% and areas with restoration opportunities of vegetation cover below 40% cover from the potential restoration land and compared with our results. Such re-analysis of the two restoration studies resulted in only 1.3 and 6.3 Mha of potential dense reforestation land (GRI and Bastin et al. 2019, respectively) which are only 10%–50% of the 14.5 Mha potential land for forestation actions estimated here.

Another key difference between the present and the two previous studies is their attempt to restore different categories of vegetation cover, including closed forests, open forests, and woodland (>40%, 25%–40%, and 10%–25% vegetation cover, respectively). Here we applied a more radical approach, introducing only relatively closed forests of >40% cover, enhancing the $\Delta SP$ component. To demonstrate this particular point, we used our map of potential forest cover and reclassified based on the two previous studies. This resulted in the partitioning indicated in figure S9, which shows that our forestation action is more intensive, in terms of $\Delta SP$, than predicted by the two previous studies. This is because; (a) our map includes afforestation of area with no previous forest cover (not included in the previous studies), (b) limiting ourselves to reforestation with forest cover above 40% (in contrast to the earlier studies restoring forest with less than 40% cover). (c) Overlap with the previous studies in forestation intensity only in the part indicated in figure S9 as restoration.

While we are aware of the limitations in extending potential forestation land beyond the existing ‘dry timberline’, woody encroachment is well documented, such as in sub-Saharan Africa (e.g. Venter et al. 2018), and support our focus on maximizing the potential of forestation in dryland to mitigate global warming. Furthermore, as noted above,
large-scale afforestation actions beyond the 'dry timberline' already exist in areas with MAP > 300 mm, which is consistent with our threshold of AI > 0.2. Such extensions overcome the main limitation of seedling establishment by the use of supplement seedling irrigation during the first year(s) of forestation (Bainbridge 2012) and other water management techniques (Berthe 1997).

Based on the analysis above we argue, and demonstrate that, on the one hand, mapping the spatial restoration opportunities in itself may not reflect the full potential in forestation carbon sequestration and, on the other hand, the expected climatic effects of restoration projects must also be considered. We also note that to achieve efficient climate mitigation, afforestation opportunities, in addition to restoration and reforestation, should be considered.

4.2. Estimating the combined effects of changes in albedo and carbon storage
To calculate the predicted change in carbon and albedo due to our proposed forestation actions, we used forest characteristics derived from existing nearby forests as the reference for the potential forests. For this purpose, we identified almost 3 Mha of closed forests (>40% cover) in the semi-arid areas of Queensland. Although semi-arid forests are important for the carbon cycle and climate (Bastin et al. 2017), descriptions of their characteristics are relatively scarce (Poulter et al. 2014, Bastin et al. 2017, Qubaja et al. 2019, Fagan 2020). Here, we compared the annual results to the published data from an extensively studied semi-arid Aleppo pine planted forest in Israel, Yatir forest (Qubaja et al. 2019). The mean values of closed forests albedo and net ecosystem productivity estimated in the present study, based on data from existing semi-arid sites, was 0.12 and 1.87 tC ha$^{-1}$ yr$^{-1}$, respectively (table 3), which is in good agreement with the albedo and NEP values from the Israeli Aleppo pine forest, of 0.11 and 1.6 ± 0.32 tC ha$^{-1}$ yr$^{-1}$, respectively (Qubaja et al. 2019). We then compared the forest growth model using the same published data of long-term carbon stock change of the semi-arid Yatir forest (i.e. cumulative NEP over 50 years since forest establishment, $t = 50$) and found high agreement with previously published results (Qubaja et al. 2019), which showed agreement within ±10%.

The change in surface albedo due to forestation actions of 0.04, on average (table 3), was compared with the respective values in previous studies. It was found to be higher than earlier estimates for the same region (Syktus and McAlpine 2016), but lower than estimated for afforestation in similar conditions (Rotenber and Yakir 2010). The higher albedo change compared to Syktus and McAlpine (2016) can be related to the different scenarios in the two studies, with more intensive land-cover change in the current study (afforestation with dense forest instead of restoration of woody savanna), resulting in larger change in albedo. The smaller change compared with Rotenberg and Yakir (2010) can be related to the difference in soil type (Queensland’s red kandosols and tenosol soils are darker than the chalky soils of the Negev).

The resulting net $\Delta$SP of ∼100 tC ha$^{-1}$ 80 yr$^{-1}$, accumulated over the entire simulation period, is lower compared to the results of Qubaja et al. (2019). These differences can be due to higher pre-forestation sequestration rates in some parts of our study area, such as grasslands in the southeast, and river bands in the Northwest (figure S7: dark blue colored pixels). We show a significant increase in SP, but these results are limited to the end of the simulation period (80 years). Note that the approach used here assumes essentially constant NEP over this period (e.g. Besnard et al. 2018). Additionally, we observed linear carbon accumulation over nearly 60 years with no signs of change in the semi-arid afforestation at Yatir; (Qubaja et al. 2019). We consider potential changes in NEP over longer periods as too uncertain and beyond the scope of this study.

4.3. The potential climatic effect of semi-arid forestation actions—carbon vs. albedo
The importance of the carbon-equivalent model for assessing the combined effects of the carbon and albedo changes associated with forestation was already demonstrated by several previous studies (Betts 2000, Bird et al. 2008, Joos et al. 2013). Here, the warming effect due to forestation actions (55 tC ha$^{-1}$), is offset by the $\Delta$SP effects only 48 years after forestation, resulting in an ultimate net cooling effect (NESC) of 45 tC ha$^{-1}$ after 80 years of forestation. This climatically beneficial net-carbon gain is 55% lower than if only changes in carbon SP were considered. Around 20% of the potential forestation area was predicted to result in a net-warming effect after 80 years of simulations (NESC < 0, orange-colored pixels; figure 3), apparently due to their relatively high background albedo (0.18), and relatively low potential forest NEP (0.76 tC ha$^{-1}$ yr$^{-1}$).

As part of the 2015 Paris Agreement, Queensland committed to net-zero emissions by 2050. This requires immediate actions of both emissions reduction and offset of the residual emissions, such as by bio-sequestration through forest regrowth. The cumulative net $\Delta$SP over 30 years of simulation (until ∼2050), is estimated here as 0.47 GtC, summed across all of Queensland’s potential forestation areas. It is in agreement with the required bio-sequestration rate of 0.5 GtC for Queensland’s commitment to net-zero emissions by 2050 (Climate Works Australia and The Climate Institute 2016). However, this $\Delta$SP does not account for the climatically negative albedo effect (EESF), estimated here as equivalent to 0.8 GtC. Climate-change mitigation potential, rather than carbon sequestration per-se, should be...
the indicator of state and national commitments to address the threats of global warming. Here, we show that the potential net-carbon gain by implementing the potential forestation actions in Queensland is 0.72 GtC over 80 years (NESC, until 2100). In comparison, Queensland’s total GHG emissions over the same period, in the business-as-usual scenario, is 4.6 GtC (extrapolating the official estimate of 1.6 GtC until 2050; Climate Works Australia and The Climate Institute 2016). Combining these estimates, forestation potential NESC can balance ~15% of the projected carbon equivalent emissions of the business-as-usual scenario in Queensland by 2100.

Here, we account for two main consequences of forestation; change in RF due to change in surface albedo and change in atmospheric CO₂ due to changes in carbon-sequestration rates. Other effects of forestation actions were excluded from this analysis. For example, land-cover changes can alter local, regional, and global climate, depending on the scale of change. At the local scale, forests can be large consumers of water, increasing the evapotranspiration rate, and therefore reducing water availability for ecosystem services and human consumption (Filoso et al 2017, Rohatyn et al 2018). Regional-scale research in Australia (Syktus and McAlpine 2016) and the Sahel (Yosef et al 2018) indicated enhanced cloud formation above large-scale restored and afforested lands, respectively, increasing the overall net-cooling effect which would be estimated based only on carbon sequestration. In contrast, the negative climatic forcing of forestation can be associated with forest canopy cooling and the suppression of long-wave radiation emission, with a RF similar to that of the albedo effects (Rotenberg and Yakir 2010, Lee et al 2011). Forestation’s impact on the environment also includes possible negative effects on the local biodiversity (Pawson et al 2013, Veldman et al 2015, Anderegg et al 2020). Note that the effects mentioned here are mainly local, while our study focuses on the effect of local forestation actions on the global climate and therefore it is not the main focus of our study. However, we do propose that areas identified with potential climatic cooling (combined carbon and albedo effects), should also be examined for their local cooling (evapotranspiration) or warming (thermal radiation) effects.

This study reports a ‘case study’ as a basis for developing an approach to efficiently assess climatically relevant forestation potential in dryland areas. Such efforts should be extended to continental and global scales, which is currently underway. Notably, in a preliminary assessment based on the extension of the current regional ‘case study’ to the global scale, we could identify nearly 400 Mha of potential forestation area over semi-arid lands. This global potential together with the significance of the current study results demonstrate the importance of future research into forestation actions over drylands.

**Data availability statement**

The data that support the findings of this study are available upon reasonable request from the authors.

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**Author contributions**

Shani Rohatyn, Eyal Rotenberg, Dan Yakir and Yohay Carmel jointly planned and designed the research. All authors interpreted the results. S R wrote the first draft of the manuscript, and all authors contributed substantially to revisions.

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