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How community forest management performs when REDD+ payments fail

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Abstract

The reduced emissions in deforestation and degradation (REDD+) initiative uses payments for ecosystem services as incentives for developing countries to manage and protect their forests. REDD+ initiatives also prioritize social (and environmental) co-benefits aimed at improving the livelihoods of communities that are dependent on forests. Despite the incorporation of co-benefits into REDD+ goals, carbon sequestration remains the primary metric for which countries can receive payments from REDD+, but after more than 10 years of REDD+, many site-specific programs have failed to complete the carbon verification process. Here, we examine whether the REDD+ social co-benefits alone are sufficient to have slowed deforestation in the absence of carbon payments on Pemba, Tanzania. Using satellite imagery (Landsat archive), we quantified forest cover change for the period before (2001–2010) and after (2010–2018) the launch in 2010–2011 of Pemba island's REDD+ readiness project. We then compared rates of forest cover change between *shehia* (administrative units) that were part of REDD+ readiness intervention and those that were not, adjusting for confounding variables and the non-random selection of REDD+ *shehia* with a statistical matching procedure. Despite considerable variation in forest outcomes among *shehia*, the associated co-benefits with the Pemba REDD+ project had no discernible effect on forest cover change. Likewise, we did not detect an effect of socioecological covariates on forest cover change across all *shehia*, though island-wide human population growth since 2012 may have played a role. These findings are unsurprising given the failure to secure carbon payments on Pemba and indicate that co-benefits alone are insufficient to reduce deforestation. We conclude that better oversight of all-involved parties is needed to ensure that REDD+ interventions satisfactorily conclude the process of securing a mechanism for carbon payments, if slowing deforestation is to be achieved.

1. Introduction

Globally, approximately 5 million ha of forest are lost annually to human activity (Curtis *et al* 2018), with adverse consequences for biodiversity, ecosystem services, community livelihoods and climate change (Barraclough and Ghimire 1995, van der Werf *et al* 2009, Thompson *et al* 2012). To mitigate climate change, the reducing emissions from deforestation and forest degradation (REDD+) initiative was introduced in 2007 at the 13th Conference of Parties and subsequently extended to include

safeguards, incentives and co-benefits (Den Besten *et al* 2014). Though different site-specific REDD+ initiatives took different institutional forms, the central goals remained constant: incentivize developing countries to protect and manage their forests through the issuance of payments for added carbon storage, as well as to improve conservation and sustainable forest management. With a financial incentive scheme built into forest protection, consistent positive outcomes were anticipated, and REDD+ attracted considerable funding (90% of which comes from the public sector; Streck 2012, Sunderlin *et al* 2015).

An evolving feature of REDD+ interventions has been the provision of 'non-carbon' social and environmental co-benefits. Often aligned with the UN Sustainable Development Goals (Milbank *et al* 2018), such co-benefits are typically aimed at reducing poverty, improving forest governance, empowering women, enhancing sustainable small-scale enterprise and protecting biodiversity (Duchelle *et al* 2019). Social co-benefits are increasingly emphasized in REDD+ interventions, both to safeguard communities against obvious abuses to economic and social wellbeing (e.g. Brown 2013, Frewer 2021) and to compensate for costs to communities associated with reduced forest clearance (Duchelle *et al* 2017). Although there is no precise theory of change as to how social co-benefits are expected to yield reduced deforestation (and enhanced carbon storage (Martius *et al* 2018)), plausible pathways include users incentivized to protect their forests by security of property rights, control of elite capture, community engagement and empowerment, improved livelihoods and broader environmental justice (Lawlor *et al* 2013, Salerno *et al* 2021), acting, in Duchelle *et al*'s (2017) sense, as 'carrots', or positive incentives for behavioral and institutional change.

To achieve social co-benefits outlined in REDD+, many projects adopt or expand upon pre-existing community forest management (CFM), and include communities in the design and implementation stages of REDD+ (Vijge *et al* 2016, Sharma *et al* 2017, Erbaugh *et al* 2020). With the addition of co-benefits, REDD+ has the potential to produce triple-wins for climate, forests and forest-dependent communities.

Despite the emphasis placed on REDD+ co-benefits, international-level payments currently issued by REDD+ are primarily associated with carbon sequestration (Turnhout *et al* 2017). However, the acquisition of carbon-related payments is not straightforward. Throughout the 2010's, carbon demand and prices in world carbon markets remained low, making it difficult to sell, though values grew substantially in 2018 and 2019 (Berntsen *et al* 2020). In addition, the measurement, reporting and verification process of REDD+ outcomes present challenges such as technical complications, data limitations, particularly for baseline information, and the lack of institutional capacity for data collection in

certain countries (Turnhout *et al* 2017). As a result, many REDD+ initiatives have failed to secure payments (Seymour and Busch 2016, Vatn *et al* 2017, Borgerhoff Mulder *et al* 2021). As of 2018, only one third of REDD+ projects had successfully been sold in the voluntary carbon market (Simonet *et al* 2018).

As monetary payments for REDD+ fall short, it is critical that we assess whether co-benefits alone are sufficient to achieve the primary goal of the REDD+ program—maintain forest protection to mitigate climate change. Here, we examine outcomes which, as noted above, could result from the co-benefits of REDD+ interventions, which include community engagement, improved livelihoods, control of elite capture and broader environmental justice, incentivizing protection even in the absence of carbon payments. We ask whether REDD+ has slowed forest loss in the absence of carbon revenue, with a focus on a REDD+ program on Pemba island, Tanzania, that has failed to provide carbon payments (Andrews *et al* 2020). By using Pemba as a model system, we respond to Borner *et al*'s (2016) suggestion to move away from estimating average effects of multiple, undifferentiated conservation initiatives, and focus on the absence of a specific element (payments) in one REDD+ readiness program.

REDD+ programs were launched at multiple Tanzanian sites in 2010/11 (Burgess *et al* 2010, 2017) to counter forest loss along the coast, and to build upon several decades of decentralized CFM (Blomley *et al* 2008, Newton *et al* 2015). In Pemba, despite some indications of successful project implementation and preliminary outcomes (Caplow *et al* 2014, Sutta and Silayo 2014, Yakub 2016, Blomley *et al* 2017, Andrews and Borgerhoff Mulder 2018), the carbon agent failed to complete the Verified Carbon Standard process (Terra Global Capital 2014, Yocum 2016). With remaining international partners unable to complete the process, and no revenue from the sale of carbon, the project terminated at its end date and Pemba joined a roster of other discontinued REDD+ projects common in Tanzania (Lund *et al* 2017, Massarella *et al* 2018) and globally (Sunderlin *et al* 2015). Nevertheless, the Pemban forestry department (Department of Forestry and Non-Renewable Natural Resources (DFNRNR)) has attempted to continue support of REDD+ sites with limited resources (Borgerhoff Mulder *et al* 2021), thus offering the opportunity to evaluate the effects of the provision of REDD+ co-benefits on changes in forest cover in the absence of carbon payments.

Remote sensing is increasingly used to monitor forest cover change and assess the performance of conservation programs (Godoy *et al* 2012, Kukkonen and Kayhko 2014, Williams *et al* 2018, Oldekop *et al* 2019, Vancutsem *et al* 2021). Here, we use satellite imagery to first determine to what extent forest cover has altered for all *shehia* (ward-level administrative unit) across Pemba between pre- and post-project

intervention (2001–2010 and 2010–2018). Second, we ask whether any socio-ecological factors (e.g. rainfall, human density) other than REDD+ readiness status stand out as predictors of forest cover change. Third, we test for the possibility of the 'residual reserve' phenomenon (Margules and Pressey 2000); areas with pre-existing low levels of anthropogenic disturbance are chosen for protection (e.g. Giudice *et al* 2019), by examining the statistical evidence for non-random selection of *shehia* for participation in the REDD+ readiness program. Finally, using a matching procedure to create statistical quasi-controls for REDD+ *shehia*, we examine whether forest cover change at the *shehia* level is measurably related to the REDD+ readiness treatment absent of carbon payments. If co-benefits in the absence of payments are sufficient to incentivize forest protection, a plausible pathway exists whereby we would expect the REDD+ *shehia* forests to have improved rates of forest cover change to those of control *shehia* forests. Pre- and post-REDD+ measurements of forest cover, along with matched control *shehia* selected from Pemba, establish spatial and temporal baselines of condition that permit characterization of the effect of REDD+ on forests (Pressey *et al* 2015). Thus, we build on the most appropriate methodology for assessing an intervention that has no perfect control (Borner *et al* 2016, Ferraro *et al* 2019).

2. Methods

2.1. Study area
This study was conducted across the 920 km^2 oceanic island of Pemba, on the eastern coast of Tanzania (figure 1). The forest types on Pemba consist of coral rag forest, mangrove forest and high tropical forest (Siex 2011). A number of isolated forest patches are recognized as part of the threatened Coastal Forests of Eastern Africa Hotspot (CEPF 2010). Pemba also contains three long-standing government-managed Forest Protected Areas in the northern part of the island.

Historically, Pemba is estimated to have experienced roughly 95% forest loss in the last 200 years (Siex 2011, Punwong *et al* 2013). Clove production, starting in the early 19th century, converted tracts of terrestrial high forests to a patchwork agroforestry/scrub matrix (Sheriff 1987, Conte 2019). More recently, further losses of Pemba's mangrove, coastal and high forests have resulted from agricultural land conversion, timber harvesting, non-timber forest products (e.g. fuelwood), and local extraction industries (salt, sand, stone), all linked to population increase and rapid urbanization (Siex 2011, Fagerholm 2012, Fagerholm *et al* 2013, Terra Global Capital 2014).

The HIMA (*Hifadhi ya Misitu ya Asili ya Jamii*) REDD+ readiness program on Pemba was a collaboration among the DFNRNR, Royal Norwegian Embassy, Care International, the carbon agent Terra Global Capital, and a local NGO (*Jumuiya ya Uhifadhi wa Misitu ya Asili-Zanzibar*). The program entailed support for: (a) securing Community Forest Management Agreements (CoFMAs), thereby consolidating community forest tenure rights; (b) identifying high-priority forest areas for protection; (c) establishing *Shehia* (ward-level administrative unit) Conservation Committees responsible for planting, restoration, patrol and outreach; (d) administering trial motivation payments; and (e) funding small-scale community enterprise (improved cook stoves, honey production, etc.). Each component was aimed at contributing to the ultimate goal of making communities eligible for carbon payments, and to increase community engagement (Andrews *et al* 2020). Field visits (2015–2019) to each of the REDD+ readiness sites found active tree planting initiatives, woodlot establishment, mangrove regeneration, honey and beeswax production, forest monitoring and fining protocols. Eighteen of the 121 *shehia* on Pemba (figure 1) were selected for participation in the REDD+ readiness program on the basis of two primary criteria—a high per cent of forest cover and rapid perceived rates of forest loss—and all agreed to participate (Andrews *et al* 2020).

2.2. Forest cover change
To quantify forest cover change within each *shehia* between 2001 and 2018, corresponding to 9 years before and 8 years after initiation of the Pemba REDD+ readiness program, we analyzed a collection of Landsat satellite images in Google Earth Engine (Gorelick *et al* 2017). We produced 2 year composite images to represent three time periods of interest: 2001 (May 2000–May 2002) and 2010 (October 2009–October 2011) from a combination of Landsat 5 and 7 imagery, and 2018 (January 2017–January 2019) from Landsat 8 imagery. Landsat imagery was used because it is open source, spans the entire temporal period of the study, has a high spatial resolution (30 m)^2, and has bi-weekly data availability (Cohen and Goward 2004). Due to the different protection status of forests within the government forest protected areas, these areas were masked out and excluded from spatial analysis (see S1 available online at stacks.iop.org/ERL/17/034019/mmedia for details on images and methods for collecting training data).

Images were classified as forest or non-forest for 2001, 2010, and 2018 using a *Random Forest* (Breiman 2001) supervised classification in Google Earth Engine (Gorelick *et al* 2017). We randomly assigned 70% of the training data locations to train the Landsat 5, 7 (2001; 2010) and Landsat 8 (2018) composite data, and used the remaining 30% for post-classification accuracy assessment (Stehman 1997; S1). Overall accuracy reported in the confusion
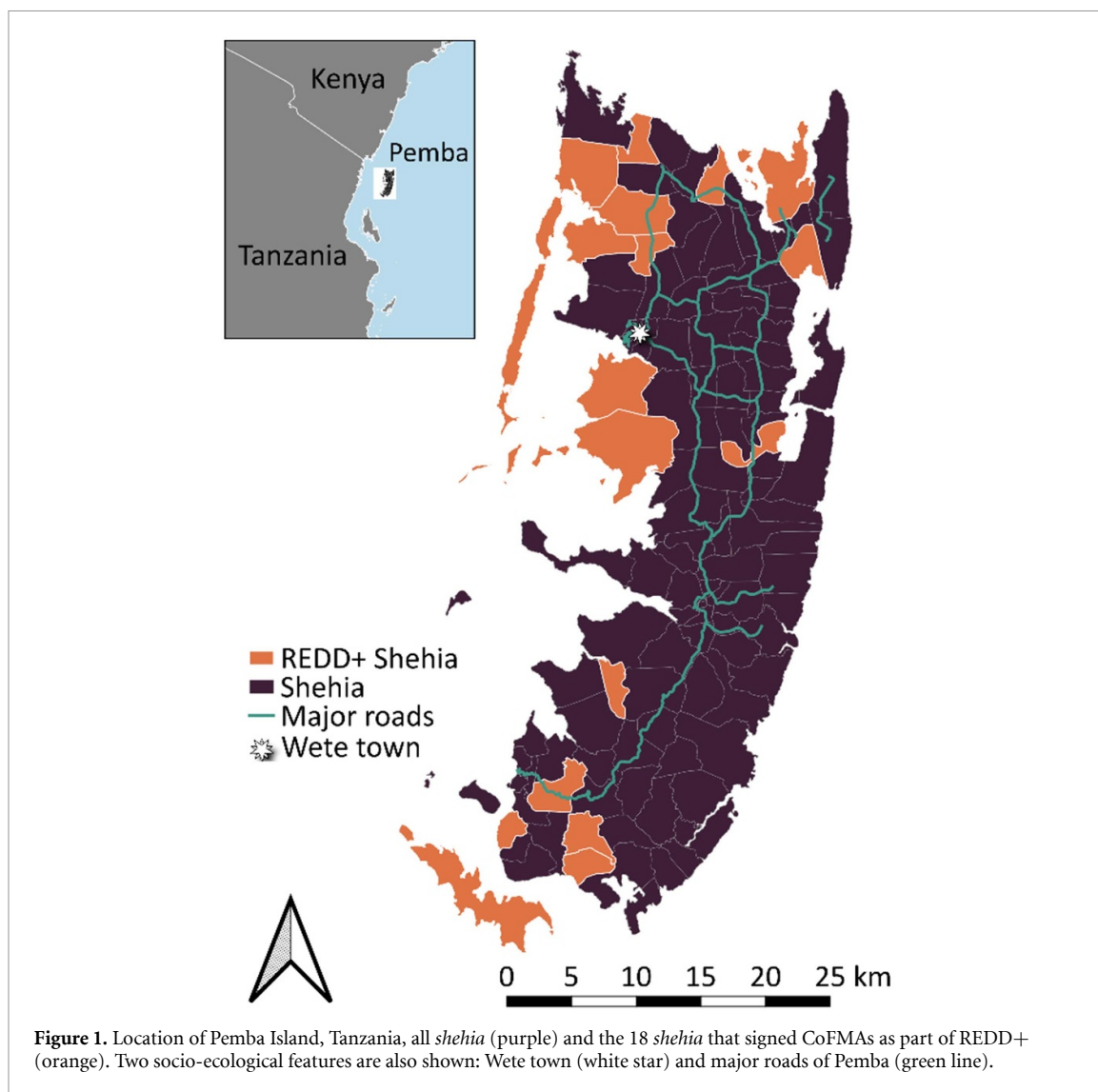
Figure 1. Location of Pemba Island, Tanzania, all *shehia* (purple) and the 18 *shehia* that signed CoFMAs as part of REDD+ (orange). Two socio-ecological features are also shown: Wete town (white star) and major roads of Pemba (green line).

matrix of the classified images was >90% for all images and demonstrated excellent agreement with the kappa coefficient (table S1), supporting the suitability of this approach. Potential sources of error in classifications may be attributed to distortion of satellite imagery from cloud cover, Scan Line Corrector error on Landsat 7, and similar spectral pattern of forest and non-forest classes, such as plantations.

Within each *shehia*, total area (m²) of forest and non-forest was quantified for the 3 years of interest (2001, 2010, 2018) by *zonal statistics* in QGIS (QGIS Development Team 2018). Forest area was divided by total area (forest + non-forest) to obtain a percent of the *shehia* that was forest for each year (table S2). To calculate the annual rate of forest cover change before (2001–2010) and after (2010–2018) the implementation of CoFMAs, we used the compound interest law, as per the Food and Agriculture Organization of the United Nations (MacDicken *et al* 2016; table S2). Calculations are completed within RStudio V1.1.3 (RStudio Team 2015, R Core Team 2020).

2.3. Socio-ecological factors associated with forest cover change

To test whether factors other than REDD+ readiness participation were related to the rate and/or direction of forest cover change on all Pemba *shehia* (the *socio-ecological model*), we collected socio-ecological data at the *shehia* level associated with: (a) forest productivity potential and (b) remoteness and opportunity cost of forest clearance (table 1; figures S1(a)–(i); See S2 for details on sources and methods; Geist and Lambin 2002, Jones and Lewis 2015). Areas that are highly productive and fertile could impact forest cover change either positively, by promoting tree growth and regeneration, or negatively, by encouraging farmers to remove native forest and plant crops. Remote areas may incur high travel costs (opportunity costs) by vehicle or boat for distribution of harvested timber, which could disincentivize local communities to extract resources, with positive implications for forest cover change. Conversely, remote areas may lack, or be perceived to lack, enforcement and patrolling, with

Table 1. Socio-ecological factors associated with forest cover change.

Category	Covariate
Forest productivity potential	Median precipitation for the wettest month on Pemba (April)
	Elevation
	Slope
	Soil type
Remoteness and opportunity cost of forest clearance	*Shehia* area
	Human population density (2012)
	Human population growth rate (2002–2012)
	Distance to road (figure 1)
	Distance to coast
	Distance to the city of Wete—the central location for Pemba's forestry department and law enforcement (figure 1)
	Forest area in 2010 relative to *shehia* area

negative implications for forest cover change where timber harvests and/or forest clearance are illegal.

To investigate the relationship between forest cover change after REDD+ establishment (2010–2018) and covariates measuring remoteness or productivity, we fit a spatial autoregressive model (the *socio-ecological model*) using the *stsls* function in the *spdep* package (Bivand and Wong 2018). We opted to use a spatially explicit model to account for effects such as spatial clumping of high- (or low-) performing *shehia* producing positive autocorrelation, or source/sink dynamics among neighboring *shehia* producing negative autocorrelation. A list of *shehia* and their associated neighboring *shehia* can be found in the supporting data.

2.4. Evidence of non-random selection of REDD+ *shehia* and matching analysis

To examine the statistical evidence for non-random selection of REDD+ *shehia*, and to enable an appropriate match of REDD+ *shehia* to control *shehia*, we conducted covariate matching using all socio-ecological covariates (table 1; Jones and Lewis 2015, Schleicher *et al* 2019). We first removed control *shehia* that contained zero forest in 2010 ($n = 2$) and any control *shehia* that were urban ($n = 16$), as all REDD+ *shehia* were rural. The resulting dataset had 103 *shehia* total, of which 85 were control *shehia*, which served as a pool of possible matches for the 18 REDD+ *shehia* (table S2). We then matched each REDD+ *shehia* to five control *shehia* based on their covariate similarity ('covariate matching') via the *matchIt* package (Ho *et al* 2017). Propensity score matching is an alternative to covariate matching, but the small number of REDD+ *shehia* in the present sample made fitting a logistic model, which is typically part of the propensity score matching procedure, undesirable.
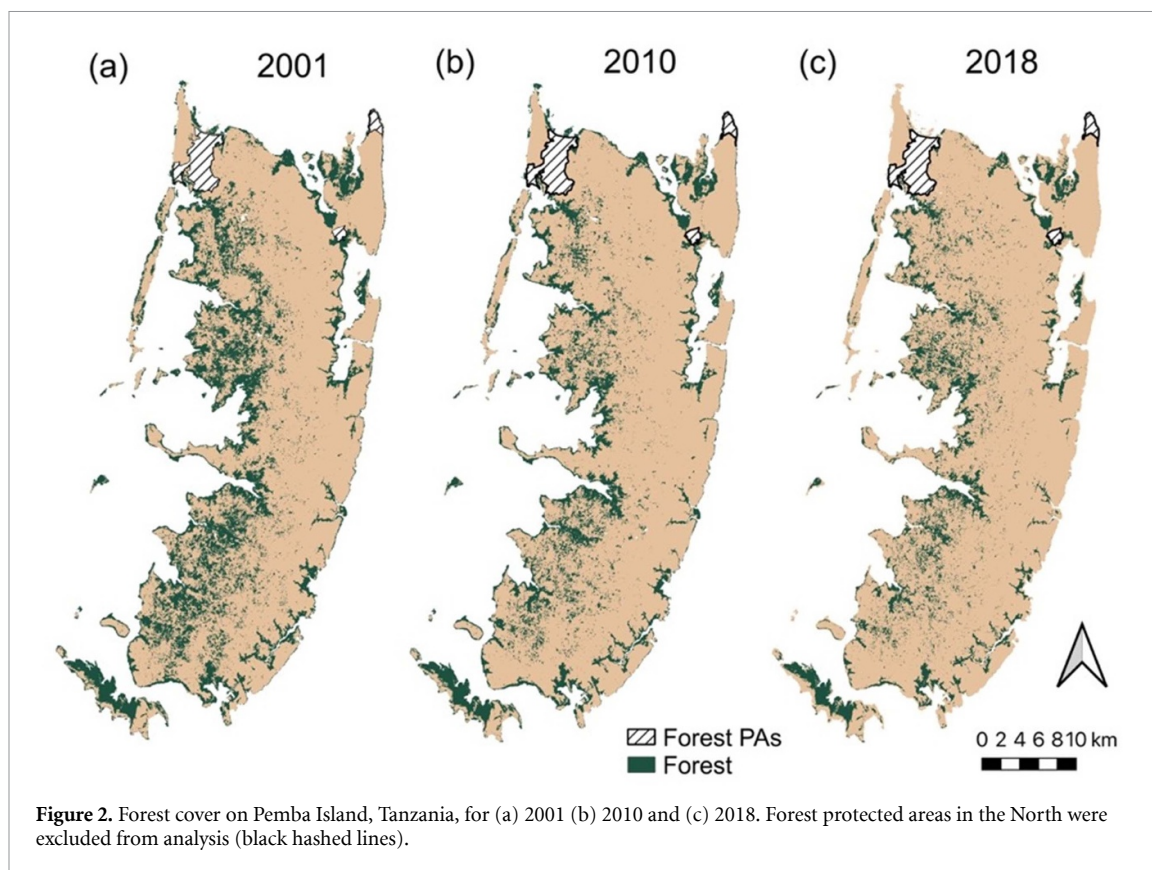
For the categorical covariate soil type, the matching procedure required an exact match between REDD+ *shehia* and control *shehia*. This is appropriate given the very distinct agroecological zones of Pemba long recognized by administrators and agricultural specialists (figure S1(d); Ali *et al* 1995). Once *shehia* were matched based on one of three soil categories, within each soil category, Mahalanobis distances (McCune *et al* 2002) were calculated using the set of continuous covariates (see socio-ecological data above). The Mahalanobis distance is a standard distance metric for multivariate, continuous observations accommodating covariates of different scales, as well as pairwise correlations between the covariates.

Among all covariates, we expect those measuring relative forest area and forest cover change during the pre-REDD+ period to strengthen the comparability of REDD+ *shehia* with their matched controls, as these covariates were implicitly used for REDD+ selection (Andrews *et al* 2020). The closest five control *shehia* to each REDD+ *shehia*, in Mahalanobis distance, were then identified using a nearest neighbor method (table S3). Matching was performed with replacement, therefore a given control *shehia* may be matched to more than one REDD+ *shehia*.

2.5. Average effect of REDD+ status

To examine whether REDD+ status had an effect on forest cover change, we used matched REDD+ *shehia* and control *shehia* to estimate the *average treatment effect on the treated* (ATET; Jones and Lewis 2015). The ATET could, in concept, be formed by contrasting the forest cover change (2010–2018) in each REDD+ *shehia* with the average forest cover change of its matched controls, then subsequently averaging these contrasts over all REDD+ *shehia*s. However, this simple matching estimator has been shown to contain a conditional bias term, arising as a purely mathematical consequence of matching on a set of covariates (Abadie and Imbens 2006). We corrected for this bias by producing an alternative outcome for forest cover change (2010–2018) in each REDD+ *shehia* under the scenario of an absence of REDD+ management. To predict alternative outcomes based on the controls, we fit a second spatial autoregressive model (*stsls* function, *spdep* package; (Bivand and Wong 2018)) for the rate of forest cover change for 2010–2018, as a function of the socio-ecological covariates listed above (see table S4 for model estimates).

We then estimated the bias corrected ATET by use of an estimator that combines matching with regression (Abadie and Imbens 2011, section 5.8: Imbens and Wooldridge 2009), contrasting average rates of forest cover change of REDD+ *shehia* with average rates that potentially would have occurred, had they remained untreated (see supplementary material S3 for methods and expressions). To overcome the small number of REDD+ *shehia* ($n = 18$), we employed a bootstrapping method of Otsu and Rai (2017) based

Figure 2. Forest cover on Pemba Island, Tanzania, for (a) 2001 (b) 2010 and (c) 2018. Forest protected areas in the North were excluded from analysis (black hashed lines).

on covariate matching to obtain upper and lower confidence limits for ATET (S3). We additionally carried out two *post-hoc* analyses demonstrating other approaches for estimating the treatment effect (S4).

3. Results

3.1. Forest cover change
Overall forest extent on Pemba (excluding the Forest Protected Areas) was 260 km^2 in 2001 (25% of the island area absent protected areas), 190 km^2 in 2010 (18%), and 154 km^2 in 2018 (15%) (figure 2). The median forest cover change among *shehia* was −3.1% yr^{-1} for 2001–2010, and −3.4% yr^{-1} for 2010–2018. *Shehia*-level rates of forest cover change were generally negative, with 89% of *shehia* experiencing a reduction in forest area during 2001–2010 and 75% during 2010–2018 (table S2).

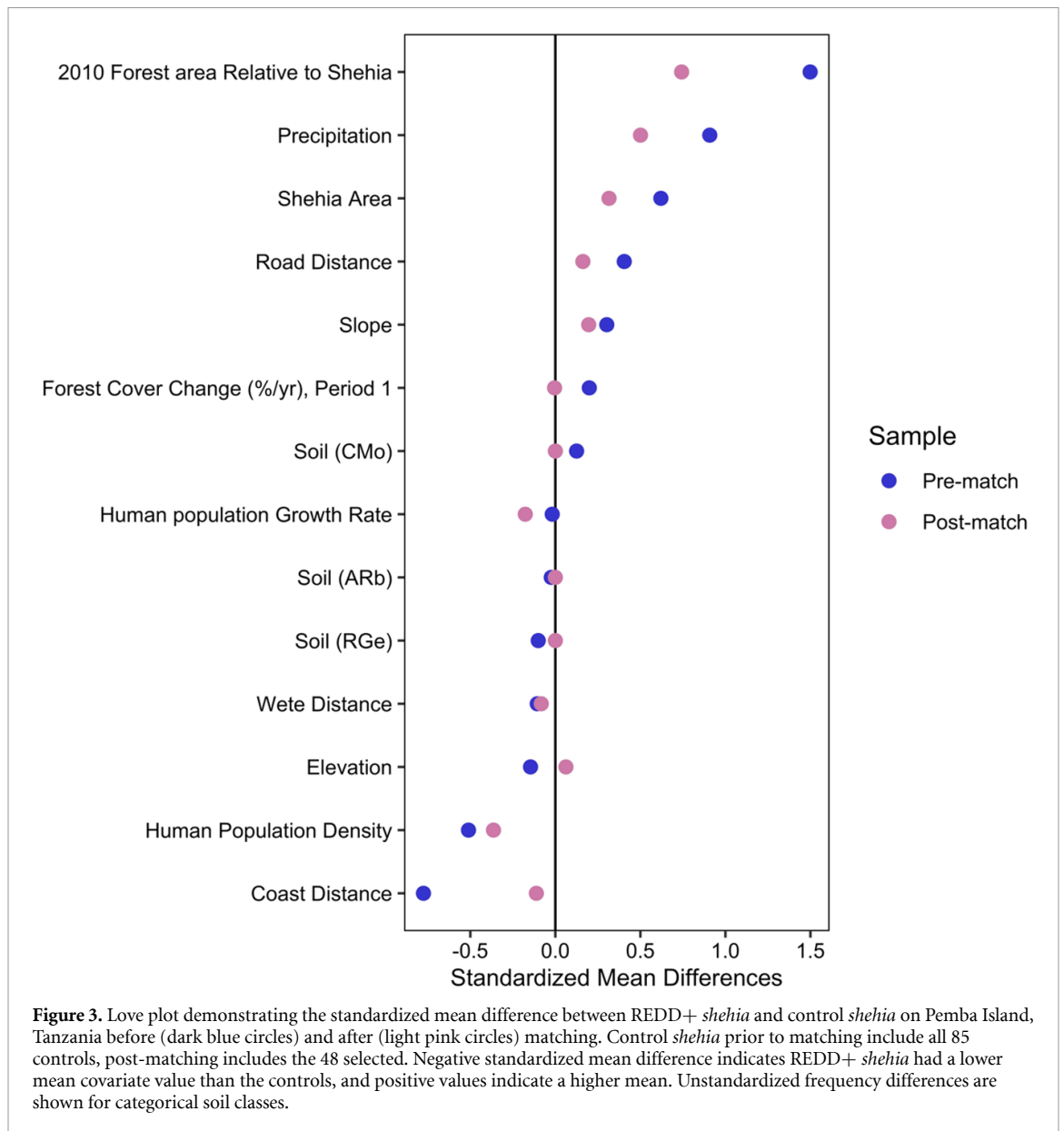## 3.2. Socio-ecological factors associated with forest cover change
None of the socioecological factors (table 1) stood out individually as significant predictors of forest cover change for 2010–2018. A low adjusted R^2 ($R^2 = 0.18$) and an absence of statistically supported socio-ecological effects (table S4) affirm the difficulty of explaining variation in forest cover change in these data. The estimated autoregressive parameter ($\rho_{\text{Lag}} = 0.09$) suggests modest spatial clustering of *shehia* with similar rates of forest cover change.

3.3. Evidence of non-random selection of REDD+ *shehia* and matching analysis
Prior to matching, the standardized mean difference of *shehia* that participated in the REDD+ readiness project versus control *shehia* was large for certain covariates: in particular, the ratio of forest to *shehia* area (figure 3; table S5). REDD+ *shehia* had a larger proportion of forested land than control *shehia*, suggesting that selection bias for *shehia* characteristics proxied by this variable played a part in targeting communities for REDD+ enrollment. Compared to the controls, areas chosen for REDD+ also had higher precipitation and greater total *shehia* area, although they did not differ substantively in forest cover change in 2001–2010. Areas chosen for REDD+ also tended to be closer to the sea and have lower population density. The post-match differences showed that matching brought the standardized mean difference closer to zero, and therefore brought the explanatory variables of the matched controls into greater concordance with those of the REDD+ *shehia*.

3.4. Average effect of REDD+ status
Finally, our analysis suggests that REDD+ *shehia* performed slightly worse on average than controls with regards to forest cover change, but uncertainty about the estimated effect is large compared to its magnitude ($\hat{\tau} = -0.2$% yr^{-1}, bootstrap 95% CI = −2.6, 2.3). Because the confidence interval for τ contains the null value zero, we are unable to rule out the possibility that control and REDD+ *shehia* were

Figure 3. Love plot demonstrating the standardized mean difference between REDD+ *shehia* and control *shehia* on Pemba Island, Tanzania before (dark blue circles) and after (light pink circles) matching. Control *shehia* prior to matching include all 85 controls, post-matching includes the 48 selected. Negative standardized mean difference indicates REDD+ *shehia* had a lower mean covariate value than the controls, and positive values indicate a higher mean. Unstandardized frequency differences are shown for categorical soil classes.

equivalent in their rates of forest change, or that REDD+ *shehia* performed somewhat better than controls. Figure 4 shows how REDD+ *shehia* and control *shehia* contribute individually to $\hat{\tau}$. The average treatment effect ($\hat{\tau}$) is a sum of weighted residuals (differences between observed and predicted values). REDD+ *shehia* sometimes performed better than predicted (above the line in figure 4), sometimes worse than predicted. The same is true for matched controls, though with greater variation in performance.

4. Discussion

We find the deforestation rates on Pemba in the first decade of this century have continued, marginally increasing (from 3.1% to 3.4% yr^{-1}; figure 2) through the following decade; a scale of deforestation documented in other oceanic islands (Harper *et al* 2007,

Asner *et al* 2016). Our results also show that HIMA, a site-specific REDD+ readiness program, in the absence of carbon revenues, has had no demonstrable effect on forest cover loss in Pemba *shehia* during the 8 years after initiation compared to matched controls during the same period. As such, community-managed forests motivated by co-benefits alone do not necessarily reduce forest loss (Somanathan *et al* 2009, Urech *et al* 2013, Kukkonen and Kayhko 2014, Pollini *et al* 2014, Benjaminsen 2017, Oldekop *et al* 2019). This does not imply that community forestry is ineffective. In fact, it is even possible that unfulfilled promises of payments might undercut (Fletcher *et al* 2016) the otherwise positive, non-carbon effects of CFM initiatives, an issue currently being examined in Pemba.

Given the failure to secure carbon payments, it is not surprising that rates of forest cover change on Pemba are seemingly unrelated to REDD+
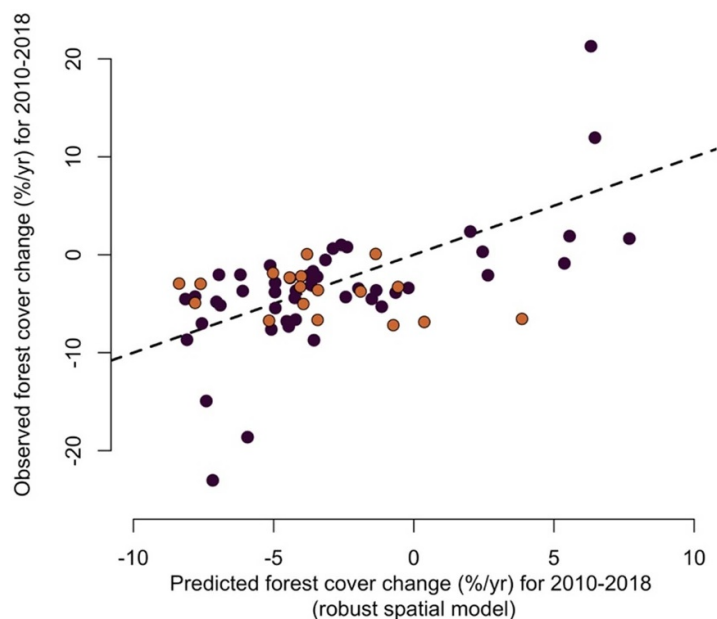
Figure 4. A comparison of predicted and observed forest change from 2010 to 2018 for REDD+ *shehia* (orange circles) and matched control *shehia* (purple circles) on Pemba Island, Tanzania. Predicted forest change is based on the spatial autoregressive model derived from control *shehia*. The line of equality (dashed black line) depicts *shehia* that would have an equal predicted to observed value. *Shehia* that performed better than predicted lie above the line of equality. The observed forest change in several matched controls departed noticeably from the predicted change (purple circles in the lower left and upper right of the figure area). The bias-corrected estimator ($\hat{\tau}$) is a sum of weighted residuals—differences between the observed and predicted value (vertical distances between each point and black dashed line)—across REDD+ *shehia* and their matched controls.

participation (we discuss the implications of incomplete interventions in 4.4). Even with incentive payments, improved forest cover is in no way guaranteed. Bos *et al* (2017) found 'overall minimal impact of REDD+ in reducing deforestation on the ground thus far' (see also West *et al* 2020). Nevertheless, our finding is cause for concern given the high proportion of REDD+ projects that continue to fail to produce carbon credits (Sunderlin *et al* 2015, Simonet *et al* 2018).

4.1. Factors contributing to the ineffectiveness of REDD+ readiness in slowing deforestation on Pemba

The magnitude of the average treatment effect is largely consistent with effects reported for similar studies and methods (Borner *et al* 2016, Oldekop *et al* 2019). In addition, similar to other analyses, spatial factors likely contribute to our finding that Pemba's REDD+ readiness project has had no demonstrable effect on forest cover change (Mertens and Lambin 1997, Kok and Veldkamp 2001, Käyhkö *et al* 2011, Kukkonen and Kayhko 2014). The extent of Pemba and the *shehia* contained within Pemba are small (figure 1). Therefore, relatively small levels of unregulated take or land use change have a large influence on the percent of forest cover within *shehia*. Furthermore, leakage (the shift in resource extraction to a location outside the focal area (Ewers and Rodrigues 2008, Wunder 2008)) is plausible, as it is relatively easy for people to travel across *shehia* boundaries

and extract unsanctioned resources from another *shehia*'s forest (Andrews and Borgerhoff Mulder 2018, Borgerhoff Mulder *et al* 2021). Accordingly, our spatial model suggests that neighboring *shehia* are slightly more likely to have similar rates of forest cover change than non-neighbors.

In considering covariates of forest cover change, we focused on factors that represented productivity potential and opportunity cost (table 1) but found that none stood out as particularly significant predictors. However, processes not measured sufficiently precisely in our study may have influenced forest removal. For example, we used *shehia*-level human population growth following the 2002 and 2012 population census, but with the next census results expected in 2022, growth rates since 2012 are unknown, and may have influenced forest cover change patterns we witnessed for 2010–2018. Likewise, Euclidean distance measures may have underestimated the inaccessibility of some areas. For instance, the three REDD+ *shehia* that had the most improved rates of forest cover change in comparison to their predicted values were small islands or tide-dependent peninsulas accessible primarily by boat (Kisiwa Panza; Mtambwe Kusini; Shumba Mjini). Boat access certainly does not inhibit deforestation, as seen on the north-western islands (figure 2), but it may complicate extraction by outsiders (leakage).

Our study examined forest cover change as an outcome of REDD+ implementation in Pemba. Questions remain regarding the mechanistic pathway

that might drive such outcomes in REDD+ and CFM projects, particularly when payments fail, warranting further attention in future studies. Furthermore, this study examined only a single forest-related outcome—deforestation. Forest degradation is another feature of REDD+, and can occur under the dominant forest canopy (e.g. via grazing), effecting the overall carbon balance (Herold *et al* 2011, Houghton 2012). Though forest degradation is likely to occur on Pemba, degradation was not addressed in this study.

4.2. Techniques for assessing REDD+ and community forest management (CFM)

Our counterfactual-based study satisfies recent calls for methodologically rigorous assessments of REDD+ and CFM projects (Andam *et al* 2008, Bowler *et al* 2012, Borner *et al* 2016, Hajjar *et al* 2016, De Sy *et al* 2018, Hajjar and Oldekop 2018, Schleicher *et al* 2019, West *et al* 2020). Specifically, we incorporated four methodological improvements to the matching procedure. First, we adjusted for selection bias ('residual reserve' phenomenon) by matching on criteria used for REDD+ readiness selection (Schleicher *et al* 2019). Accordingly, we found evidence for the preferential targeting of *shehia* with large forest areas in 2010 relative to *shehia* area (figure 3). Second, in using *shehia*-level socio-ecological covariates to measure baseline conditions, we adjusted for other factors that could influence forest cover change—biophysical characteristics that could alter forest productivity, and social factors that represent the opportunity cost of forest clearance (Jones and Lewis 2015, Dezécache *et al* 2017, Oldekop *et al* 2019).

Third, we adopted a similar approach to that of West *et al* (2020) who used 'synthetic controls' matched to treated sites. Like West *et al*, and unlike the conventional approach ('crediting baselines') that uses as a counterfactual only historical levels of deforestation in the years preceding the project, our counterfactual (predicted) scenarios of deforestation were based on actual forest cover change observed in those matched controls during the period when the REDD+ readiness intervention had been initiated. In this way they reflect contemporary political and economic developments, such as the worldwide increase in clove prices. Fourth, we advanced methodological procedures for impact evaluation (Borner *et al* 2016) by implementing the bootstrap procedure of Otsu and Rai (2017). This study demonstrates a practical application of this bootstrap procedure, and in combination with the *post-hoc* analysis in S4, offers viable approaches for examining the efficacy of conservation programs when the number of treated units is small.

4.3. Individual heterogeneity

Our findings show that certain *shehia* had lower rates of forest cover loss than predicted, while others exhibited higher rates (figure 4). However, there is considerable heterogeneity among *shehia* regarding their implementation and experience of REDD+ readiness (Benjaminsen 2014). Though all *shehia* in the program received initial 'motivation' payments (Andrews *et al* 2020), the extent of outreach, training and co-benefits was inevitably variable. One Pemban *shehia* dropped out of the program in 2019 due to internal conflict (see also Benjaminsen 2014). Other *shehia* are even now cultivating their relationships with the Forestry Department to access further support for forest protection (Borgerhoff Mulder *et al* 2021). Understanding factors influencing forest cover change requires going beyond estimating average effects, and calls upon researchers to investigate specific cases with respect to both their precise institutional and spatial context (e.g. Kukkonen and Kayhko 2014, Massarella *et al* 2018). Other studies note that reporting average treatment effects alone can mask the idiosyncratic features associated with spatiotemporal variation in forest cover change (Chhatre and Agrawal 2009, Fernandes *et al* 2016, Lund *et al* 2018), and have reported on the high variability of forest cover change between communities (Blackman *et al* 2017, Santika *et al* 2017). Here, we highlight the significance of this point at a highly local level.

4.4. REDD+ without realized incentives

It is perhaps unsurprising we find no discernible effect on forest cover change resulting from an incomplete intervention. Although the selected and voluntarily participating sites benefitted from REDD+ readiness co-benefits, tenure security embodied in their CoFMAs, forest management capacity building, and small enterprise generation, they did not receive anticipated carbon payments. The Pemba REDD+ project is not unique in its lack of carbon revenue; many other site-specific REDD+ projects have faced similar fates (two thirds as of 2018), and future projects run the risk of carbon credits failing to materialize (Simonet *et al* 2018). Yet, in the face of considerable evidence of the effectiveness of payments for environmental services in protecting forests (Jayachandran *et al* 2017, Sharma *et al* 2017, Sills *et al* 2017, Oldekop *et al* 2019, Hajjar *et al* 2021), we are not claiming that our findings show REDD+ cannot work; rather that failure to complete project payments (unfortunately inherent in the field of international aid, Angelsen *et al* 2017, Turnhout *et al* 2017) seriously jeopardizes REDD+ outcomes, that co-benefits cannot fully compensate, and that better oversight is therefore needed at the national level to secure carbon credits (Fischer *et al* 2016, Angelsen *et al* 2017, Massarella *et al* 2018).

Though we must conclude that the presence of co-benefits alone was insufficient to reduce deforestation—the primary target of the REDD+ program—there is potential for yielding positive environmental and social outcomes. On Pemba,

it is emerging that CFM is expanding despite the absence of carbon payments, with multiple communities signing up to receive CoFMAs and the co-benefits (Borgerhoff Mulder *et al* 2021), interestingly as anticipated in the final report on Pemba's REDD+ program (Royal Norwegian Embassy 2015, see also Caplow *et al* 2014). To this end, in addition to the capacity for carbon sequestration, high-quality monitoring of other outcomes related to social and environmental co-benefits, including those not formally identified by the intervention, must be integral to the monitoring of REDD+ and CFMs (Miller *et al* 2017, Oldekop *et al* 2019, Hajjar *et al* 2021).

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: 10.25338/B8405M.

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