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Comparing and Combining Landsat Satellite Imagery and Participatory Data to Assess Land-Use and Land-Cover Changes in a Coastal Village in Papua New Guinea

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Abstract In regions lacking socio-economic data, pairing satellite imagery with participatory information is essential for accurate land-use/cover (LULC) change assessments. At the village scale in Papua New Guinea we compare swidden LULC classifications using remote sensing analyses alone and analyses that combine participatory information and remotely sensed data. These participatory remote sensing (PRS) methods include participatory land-use mapping, household surveys, and validation of image analysis in combination with remotely sensed data. The classifications of the swidden area made using only remote sensing analysis show swidden areas are, on average, two and a half times larger than land managers reported for 1999 and 2011. Classifications made using only remote sensing analysis are homogeneous and lack discrimination among swidden plots, fallow land, and non-swidden vegetation. The information derived from PRS methods allows us to amend the remote sensing analysis and as a result swidden areas are more similar to actual swidden area found when ground-truthing. We conclude that PRS methods are needed to understand swidden system LULC complexities.

Keywords Swidden · Land-use/land-cover · Participatory data · Village scale · Papua New Guinea

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Introduction

Satellite imagery has improved spatial and temporal estimates of land changes, yet even high-resolution imagery can result in poor enumeration and an oversimplification of land changes (Hett *et al.* 2012; IPCC Core Writing Team 2001; Ziegler *et al.* 2011). To better understand the drivers of land change ancillary data have been paired with satellite imagery to support observations. For example, logging exports in board lengths are used to estimate the amount of forest cleared (Mather 2005; Kohl *et al.* 2015). However, compiling and incorporating ancillary data for all types of land change remains a challenge, as the drivers of change are often complex. Recognizing this, it is important to utilize ancillary data to create the most accurate land-use and land-cover (LULC) analysis possible if land change data are to be used to inform policy, develop conservation strategies, and create the best management plans.

Participatory information derived from local knowledge is an important type of ancillary data that provides essential information to link observed patterns and trends of land-cover from remotely sensed data to ground-level land-use activities (Rindfuss *et al*. 2003; Herrmann *et al*. 2005; Leisz and Rasmussen 2012). Integrating spatial and social sciences is a way to comprehensively explore the human-environment interface and identify the driving forces causing changes in livelihood decisions and LULC (Herrmann *et al*. 2014; Rindfuss *et al*. 2003). Recent research demonstrates that more comprehensive understanding of local environmental and livelihood dynamics is achieved when stakeholders are included in research efforts (Ostrom 2009; McCall and Dunn 2012; Wakie *et al*. 2016). Stakeholders are those who have social or economic interests in the research results as it can influence their livelihoods or objectives (Estrella *et al*. 2000; Ramanath and Gilbert 2004). Stakeholders can include indigenous people, land-managers, community and development organizations, and policy makers.

In LULC change studies participatory research is conducted in collaboration with local land-managers and provides the means to assemble and quantify local peoples' environmental perspectives, knowledge, and resource use through discussions, interviews, and various activities (e.g. resource mapping, resource use ranking). This type of integrated research provides an opportunity to discuss past trends and future perspectives of change that may not be available in other empirical datasets. Participatory information and local knowledge can be made spatially explicit by using remote sensing imagery and geographical information systems (GIS) to provide further conceptualization of linear and non-linear connections between resource decisions and LULC changes (An 2012). These methods are broadly categorized as participatory GIS (PGIS). However, when the focus is to improve LULC classifications from satellite imagery we believe that a more accurate description is participatory remote sensing (PRS) because the participatory contributions are focused on the validation of LULC analyses and pairing satellite image analysis with resource maps. The advantage of PRS is that local land managers' spatial knowledge of the LULC can be recorded and explored in greater detail with the use of spatially explicit imagery and participatory maps (PPM). Also, the local land managers are included in and contribute to data analysis.

Participatory methods have produced intriguing changes in the representation and validation of LULC and changes therein (Dunn 2007; Voinov and Bousquet 2010; Lynam *et al.* 2007; Fritz *et al.* 2012; Matthews *et al.* 2007; McCall 2003). This interdisciplinary framework has also improved results (Voinov and Bousquet 2010; Lynam *et al.* 2007) and shows that detailed land-use knowledge can refine remote sensing LULC classifications and change detection (Schmidt-Vogt *et al.* 2009; Leisz and Rasmussen 2012). There are many examples of participatory research being used in LULC analyses, and some of the more recent include sea grass changes in the Solomon Islands (Lauer and Aswani 2010), coastal management in Hawaii (Levine and Feinholz 2015), vegetation changes in the Sahel (Herrmann *et al.* 2014), invasive species management strategies in Kenya (Wakie *et al.* 2016) and swidden agricultural changes in Vietnam (Leisz and Rasmussen 2012; Laney and Turner 2015).

Swidden agriculture systems (also referred to as slash-and-burn agriculture and shifting cultivation) are usually part of a subsistence livelihood system. Swidden land-uses and land-covers are dynamic and heterogeneous and pose many challenges when land-cover maps are based on satellite image analyses alone. This is because swidden shifts between cultivated and fallow periods, where tree cover is cut, dried, burned, crops planted and harvested, and fields fallowed for a length of time so that natural vegetation regenerates until it is bush or tree cover again, at which point it is cleared for agriculture. Across the globe over 300 million people employ some form of swidden (Mertz *et al.* 2009). As a result, land-cover associated with swidden systems is highly diverse. The diversity stems from the heterogeneity of climatic and environmental variables (e.g. precipitation, temperature, topography, hill slope, and soil nutrients), cultures, and techniques used (e.g. amount of time under crop or fallow, plot sizes, terracing, and crop selection; Fox *et al.* 2009). Also, swidden plots often follow natural contours, have swaths of natural vegetation between and within plots, and are selected to maximize crop production (Padoch 1986; Conklin 1961).

The variation found in swidden systems challenges our capabilities to accurately map it. Within a 100-m radius a large number of swidden land-uses can exist at one time (e.g. newly cleared land, cultivated land with young crops, recent fallow used for pasture, older fallow used for collecting non-timber forest products, etc.) and each could have a different land-cover. In this small area, multiple land-covers exist as well and can include a recently cleared plot with new crop sprouts, an early fallow plot that is dominated by young grass and herb growth, a cultivated plot with a mix of fruit trees, ground cover crops, and bush-like crops (i.e. cassava), and areas of woody growth that include mature trees. In addition to spatial variability, swidden land-covers are also temporally variable, meaning land-covers are not permanent and can change over relatively short time scales (e.g. after a few months, annually). The spatial and temporal dynamics of swidden land-covers are influenced by local conditions and management decisions. Another aspect that makes swidden difficult to assess is that tree cover on older fallow land and tree cover of natural forest areas are nearly indistinguishable in satellite imagery due to spectral similarities.

In response to such challenges, numerous remote sensing methods have been developed to identify and classify the diversity of swidden land-covers worldwide. A review by Li *et al.* (2014) describes techniques used in Southeast Asia and these include integrating spectral classification (optical and radar), phonological (morphological and physiological responses), statistical (binomial logistical regressions, machine learning), and landscape ecology (land-cover composition patterns).

In Papua New Guinea (PNG) identifying and classifying swidden LULC changes have received little to no attention. However, such analyses are vital in a country where approximately 85% of the population depends on swidden to fulfill subsistence and livelihood needs. An analysis of forest cover change at the national level cited swidden as one of the leading causes of forest degradation and loss, after timber extraction (Shearman *et al.* 2009). Based on the assessment that 85% of the population relies on swidden, their analysis uses population growth to extrapolate the expansion of swidden and therefore, population growth equals growth in swidden area. Using population growth estimates, Shearman *et al.* (2009) speculate that swidden expansion will continue to be a major cause of forest degradation and losses. However, since 2000 the land-cover change literature has conclusively shown that such simplistic use of population as a driver of land-cover change is not valid (Geist and Lambin 2002). Recent reviews of swidden and forest interactions worldwide, further show that LULC dynamics are not so simple (Lambin *et al.* 2001; Schmidt-Vogt *et al.* 2009; Fox *et al.* 2000; Mather and Needle 2000; van Vliet *et al.* 2012).

The Shearman *et al.* (2009) study is at the national level and LULC change assessments that focus on swidden at the national or regional level are challenging due to the extensive data collection required and the necessity to aggregate the data at this coarse scale (Li *et al.* 2014). Rindfuss *et al.* (2004) show that a relationship between population growth and deforestation found at a national level is an artifact of scale and when data are disaggregated to sub-national or local levels the relationship can be lost. To accurately understand drivers of deforestation and the role that population growth does or does not play, it is necessary to link remote sensing land-cover observations to ground level activities at the local or village level. In PNG, this means that a large sample of village level case studies is vital to identify the true drivers of land-cover change in the country. Such case studies should incorporate livelihood and swidden system management decisions and the associated influences on LULC trends. A literature search of peer reviewed articles at the village scale resulted in three LULC studies in PNG and these were conducted in a single region, the Highlands, a densely populated region in the central mountains (Ohtsuka 1994; Umezaki *et al.* 2000; Umezaki *et al.* 2002). Other articles found assess livelihood changes in response to major resource extraction from oil palm (Koczberski and Curry 2005; Koczberski *et al.* 2009; Koczberski *et al.* 2012) and mining (West 2006).

Goals and Objectives

As noted above, remote sensing methods alone are not sufficient to assess the dynamic nature of swidden. Therefore, the goal of this paper is to examine the difference between LULC assessment results obtained from using remote sensing data analysis alone and those obtained from using a multidisciplinary approach that integrates participatory data into remote sensing analysis. This study is conducted at the village scale and uses participatory and Landsat satellite data for 1999 and 2011. Using the results we aim to discuss land-cover changes at the village and compare these to a national level study by Shearman *et al.* (2009).

Methods

Study Area

The study village is a coastal community approximately 60 km south-southeast from the second largest city in PNG, Lae (Fig. 1). The customary territory contains diverse flora and fauna in both the terrestrial (330 km^2) and marine (170 km^2) habitats (Bein *et al.* 2007; Longenecker *et al.* 2011). Customary land tenure governs how land is used in the livelihood system, which is subsistence based and includes land-use activities (swidden, forest, animal husbandry, and hunting) and marine resources (ocean and reef). Swidden is the primary means of subsistence production. The main swidden area is located 5 km north of the village in a river delta. Some smaller swidden plots are scattered around the village. Seasonal deposits of rich fluvial sediments from rainy season floods replenish soil fertility and allow for shorter fallow periods. As a result, the fallow periods are typically five to seven years and have not been longer than 10 to 12 years throughout the village history. Because of the fertile soils and the large expanse of the delta, cultivation has remained contained in the flat land of the delta area. The crops include sago palm, root crops (cassava, taro, sweet potato, yam), fruit trees (betel nut, mango, coconut, banana, papaya), melons, pineapple, cucumbers, sugar cane, pit-pit (wild cane), and leafy greens.

There are many reasons that this village is an ideal site to assess land-cover changes within a swidden system. First, swidden in this village is located atop a fertile delta and, while this is locally unique, McAlpine and Freyne (2001) report that 4% of the PNG land surface are littoral and alluvial fans and support approximately 19% of the population. Therefore, it is representative of swidden areas that are depended upon by a fifth of PNG's population. Second, the village's land has not experienced any major logging or other resource extraction to date, which limits village resource degradation and losses. The lack of such resource extraction also eliminates the possibility of confounding land-cover classifications between logging and swidden, which is common in tropical regions. Third, there is no road access to the village (access is by boat only) so additional pressure on resources from an influx of migrants is limited. Last, the population growth rate between 1980 and 2011 in the village is 6% per year, higher than the national average of 4.5% per year. Therefore, if there is a relationship between population growth and swidden expansion, it should be more evident in this village.

Satellite Image Processing and Analysis

Landsat scenes from 1999 and 2011 were selected, as these scenes correspond to interview data. The 1999 image is a Landsat 5 TM image and 2011 is a Landsat 7 ETM+ image. Both scenes were captured during the dry season (September

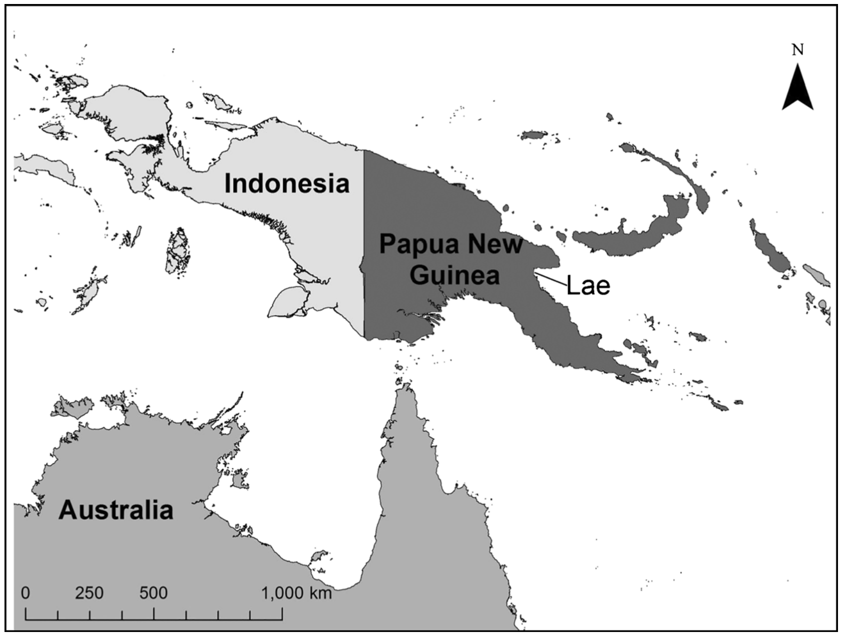

Fig. 1 Papua New Guinea and Lae, the second largest city in the country are identified.

– December) when the differences between land-covers are more spectrally distinguishable and land is more intensively cultivated. A single scene covers the entire village area. Image preprocessing included atmospheric corrections, georectification, and cloud masking. The classification process includes tasseled cap transformation, wetness –brightness difference index (Helmer *et al.* 2009), and K-means unsupervised classification. A binary classification of swidden and non-swidden land-covers was created (Table 1). A detailed description of image classification methods and accuracy assessments can be found in Hoover *et al.* (in review).

Independent, high resolution imagery (satellite imagery or aerial photos) is not available for the period of time when the 1999 Landsat scene was obtained for an accuracy assessment and therefore, visual interpretation of the raw imagery was used in combination with GPS ground-truth points from Bein *et al.* (2007) to assess the accuracy of the 1999 land-cover results. To conduct classification accuracy assessments for the 2011 Landsat image analysis, an independent image from the GeoEye satellite was available and captured in October 2010. The GeoEye image has a finer resolution (2 m) than the Landsat image (30 m) and is useful for visually interpreting land-cover accuracy for the 2011 classification results. Accuracy assessments are provided for the remote sensing analysis alone and for the PRS methods.

Participatory Data

We gathered information about land management and land-use from the local land-managers using participatory methods including semi-structured surveys, structured interviews (Chambers 1994), and participatory resource and land-use mapping (King 2002; Dunn 2007). The semi-structured surveys and discussions were conducted with knowledgeable community members to gain a comprehensive understanding of the framework of the customary land tenure system and swidden practices. Fieldwork was done in 2011 and 2014. Similar structured interviews conducted in 1999 by Bein *et al.* (2007) and Wagner (2002) to assess swidden land-use were referenced to add a temporal aspect to the study.

Surveys and Interviews

Through structured interviews we obtained information about household resource use. There were 32 randomly selected households and informants were divided equally between male and female. The interviews followed a list of questions that were consistent across informants and focused on swidden resources. Each informant described household swidden plots as the area currently cultivated. We observed that fallowed land is not reported by village land-managers as part of their swidden area. This is due either to the phrasing of interview questions or to how land-managers perceive swidden land. Numerical values obtained from the interviews (e.g. plot area) were averaged across the 32 households and scaled up to represent the village population. Qualitative information, such as perspectives about the drivers of resource use changes, typically fell into 3–4 categories and were generalized. To account for the total area utilized in the swidden cycle (cultivated swidden and fallowed swidden land), the cultivated swidden area is multiplied by the total time of the swidden cycle for 1999 (7 years; Bein *et al.* 2007) and 2011 (5.75 years).

Table 1 Land classification categories for swidden and non-swidden cover types

Swidden	Non-Swidden
• Cleared of vegetation	• Built structures
• Burned plots	• Forest
• Sparse crop cover (wide spacing or early growth)	• Riparian
• Denser crop cover	• Wetland
• Early fallow (weeds and grass)	• Water bodies
• Moderate fallow (grass, bushes, and small trees - 2-3 m in height)	• Sandy beach
• Late fallow (small and medium trees −5-6 m in height)	• Clouds
	• Shadows

Participatory Mapping of the Swidden Area

A hand-drawn participatory map (PPM) map of the village and swidden area was created. Ground-truthing of swidden plots was done with a GPS and tape measure to confirm plot location, size, orientation, and the phase (newly cleared, cultivated, or fallow). The PPM was digitized and georeferenced to the 2011 Landsat image. Reference points were added to a GeoEye image captured in 2010, as the finer resolution assists in comparing land-cover and the PPM in greater detail.

Participatory Remote Sensing and Data Validation

A critical component of participatory data collection, which is often skipped, is for researchers to incorporate and seek feedback from stakeholders before results are published (McCall 2003; Laituri 2011). The data validation process has been shown to facilitate additional discussions, information sharing, and collective learning among collaborators, and also improve resource and management negotiation and decision-making (Ruankaew *et al.* 2010; Laituri 2011). To validate our results we returned to the village in 2014. The results of PRS data analysis were presented to a 20-person group and the community as a whole. Posters were created and translated into Tok Pisin (national language) and each poster was presented orally and hung in the community center so that anyone could review and comment on the results. Everyone was encouraged to ask questions, discuss the results, and make edits to the posters. In the smaller 20-person group specific questions were posed, detailed notes taken, and map edits made to assure the accuracy of LULC classifications. Edits and corrections to the data and analyses were recorded and incorporated into final products. The remote sensing and participatory methods are processed independently and then paired for comparison and the summarization of results (Fig. 2).

Results

Accuracy Assessments

Accuracy assessments for the remote sensing analysis alone and PRS methods show that the inclusion of participatory data improves overall accuracy and the Kappa Statistic for 1999 and 2011 (Table 2). For both years, the omission error is higher than the commission errors for the swidden class, meaning non-swidden is inaccurately classified as swidden more often than swidden as non-swidden.

Satellite Image Analyses

The maps in Fig. 3 show swidden and village land-cover for 1999 and 2011. The village area is composed of smaller swidden plots, fruit trees, and the village settlement (e.g. houses, schools). The northern arm of delta and land boundary changes over time, as it is influenced by the meandering river. Evidence of the river changing course can be observed between the scenes. Most of the non-swidden area between the two arms of the delta remains naturally vegetated because the soil is too moist to be successfully cultivated. This causes the swidden area to maintain a similar shape over time. There are two areas with notable increases in swidden area in the 2011 classification. First, swidden associated land-cover is wider along both arms of the delta. Second, swidden associated land-cover is more extensive in the area between the delta and the village.

Participatory Data

Structured Interviews

Data compiled from our 2011 interviews and the 1999 data from the Bein *et al.* (2007) and Wagner (2002) studies are presented in Table 3. Between 1999 and 2011 the population grew by 371 people and the number of households in the village increased from 80 to 128. The length of the swidden cycle (cultivated and fallowed) was 7 years in 1999 and 5.75 years in 2011. To accommodate these changes the duration of the cultivated

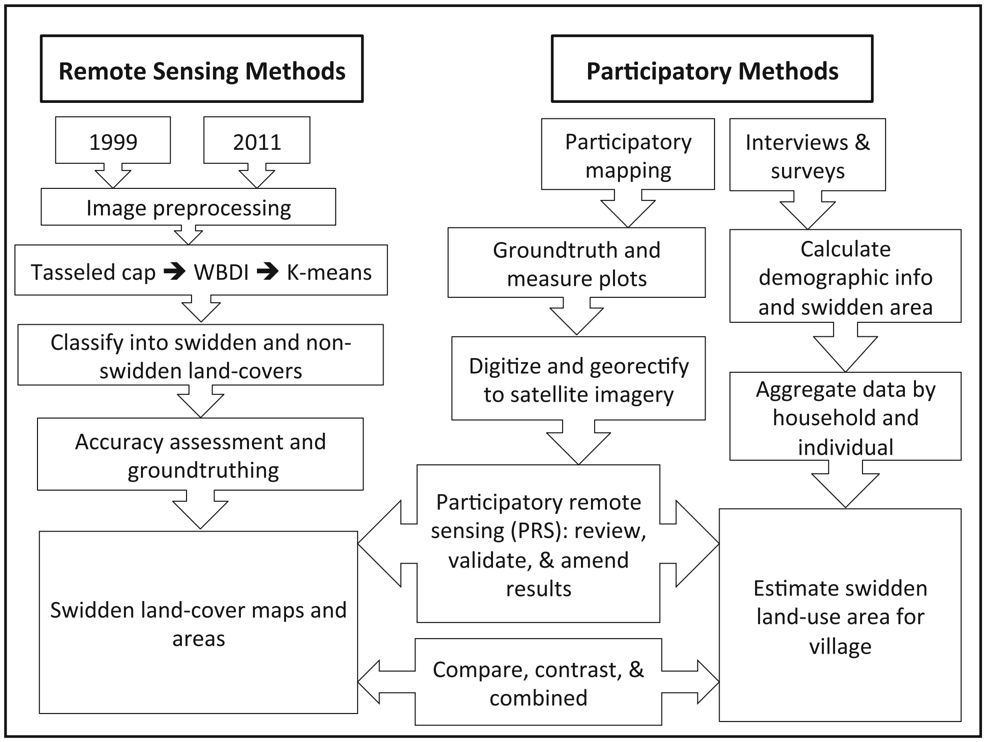

Fig. 2 Remote sensing and participatory methods are shown side by side to illustrate how data were merged for analyses and results

swidden lengthened from 1.2 to 2.75 years and the fallowed area shortened from 5.8 to 3 years. The average cultivated swidden area per household decreased from 0.404 ha (64 m^2) in 1999 to 0.323 ha (57 m^2) in 2011. While the number of cultivated swidden plots per household increased from 3.1 in 1999 to 3.8 in 2011, the average swidden area of a single plot decreased from 0.13 (36 m^2) to 0.095 (30 m^2) ha, respectively. Households maintained a greater number of smaller plots with the total area per plot decreasing over time.

Combining Participatory and Remote Sensing Datasets

Figure 4 shows the hand-drawn land-use map or PPM overlaid on the 2011 classified Landsat image. The subsets compare

Table 2 Accuracy assessment for the 1999 and 2011 classified scenes. Visual interpretation of the raw 1999 Landsat and 2010 GeoEye scenes were used for assessments. The remote sensing analysis alone and participatory remote sensing methods (in parenthesis) are both listed. The bold text shows where the correct classification was identified in the raw image and land-cover map.

1999 Landsat raw image						
1999 Landsat Land-Cover Map	Class	Non-swidden	Swidden	Row Total	Users accuracy	Commission error
	Non-swidden	**25 (27)**	5 (2)	30 (29)	83% (93%)	17% (7%)
	Swidden	13 (4)	**57** (67)	70 (71)	81% (94%)	19% (6%)
	Column Total	38 (31)	62 (69)	**82** (94)		
	Producers accuracy	66% (87%)	92% (97%)			
	Omission error	34% (13%)	8% (3%)			
	Overall Accuracy					85% (94%)
	Kappa Statistic					0.64 (0.86)
2010 GeoEye raw image						
2011 Landsat Land-Cover Map	Class	Non-swidden	Swidden	Row Total	Users accuracy	Commission error
	Non-swidden	**33 (44)**	6 (2)	39 (46)	85% (97%)	15% (4%)
	Swidden	16 (3)	**45 (51)**	61 (54)	74% (94%)	26% (6%)
	Column Total	49 (47)	51 (53)	**78 (95)**		
	Producers accuracy	67% (94%)	88% (96%)			
	Omission error	33% (6%)	12% (4%)			
	Overall Accuracy					78% (95%)
	Kappa Statistic					0.56 (0.90)

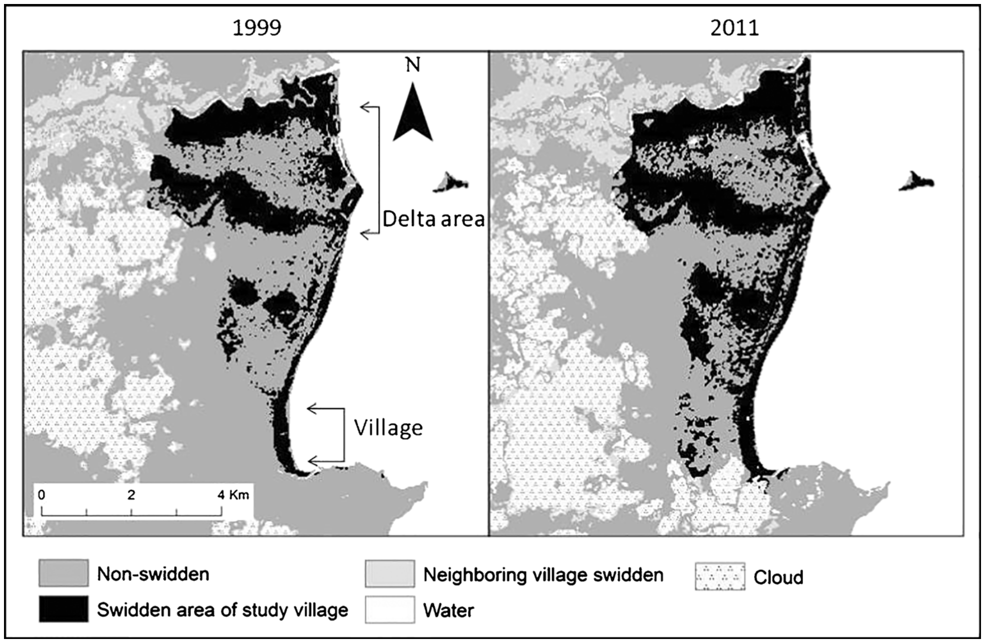

Fig. 3 Swidden land-cover using remote sensing data alone for 1999 and 2011

the output from remote sensing analysis alone and from the integrated PRS method for two locations, the main swidden (4a and 4b) and swamp (4c and 4d) areas. The swidden area in Subsets 4a and swamp land in Subset 4c show the land-cover classification using remote sensing analysis alone. Land managers reviewed these results during the PRS review and analyses decided that the swidden area in subsets 4a and 4c (remote sensing classifications alone) includes too much swidden land-cover. Therefore, Subsets 4b (swidden) and 4d (swamp) show the swidden land-cover area (dark grey) that should be merged with the non-swidden class. The dark grey land-cover will be referred to as the adjacent-non-swidden area. Land managers described that the adjacent-non-swidden area (Subset 4b) is made up of forest land-cover and is not used for swidden (cultivated or fallow). The PPM overlay further supports the land managers' perspectives, as the swidden plots in the PPM have a tighter fit within the swidden land-cover class in Subset 4b than in Subset 4a. Also, when the adjacent-non-swidden area is allocated to the non-swidden class, the blocks of natural vegetation that are scattered within the swidden area are identified. Land managers explain that these blocks of natural vegetation are common and can include fallow vegetation, groups of large trees (fruit trees, shade trees), natural fences, or vegetation on land not suitable for cultivation.

Subset 4c is dominated by swamp vegetation and land managers explained that this area is too wet for swidden,

Table 3 The 2011 data were collected during household structured surveys. Data in the 1999 column were derived from Bein et al. 2007. The equations in brackets show how the bolded categories are calculated

Summary of participatory data	1999	2011
Total population	479	850
Number of households interviewed	26	32
Approximate number of households in the village	80	128
Average people per household	6.1	6.4
Average cultivated & fallow swidden length (yr)	1.2 & 5.8	2.75 & 3
Total swidden cycle (yr)	7	5.75
Average cultivated swidden area of a single plot (ha)	0.13	0.095
Average number of cultivated plots per household	3.1	3.8
Average cultivated swidden area per household (ha)	0.404	0.323
[Average number of plots per household * average plot area (ha)]		
Total cultivated swidden area (ha)	32.3	41.3
[Average cultivated swidden area per household (ha) * the number of households in the village]		
Total swidden cycle area (cultivated and fallowed swidden)	225.4	237.5
[Total cultivated swidden area (ha) * Total swidden cycle length (yr)]		

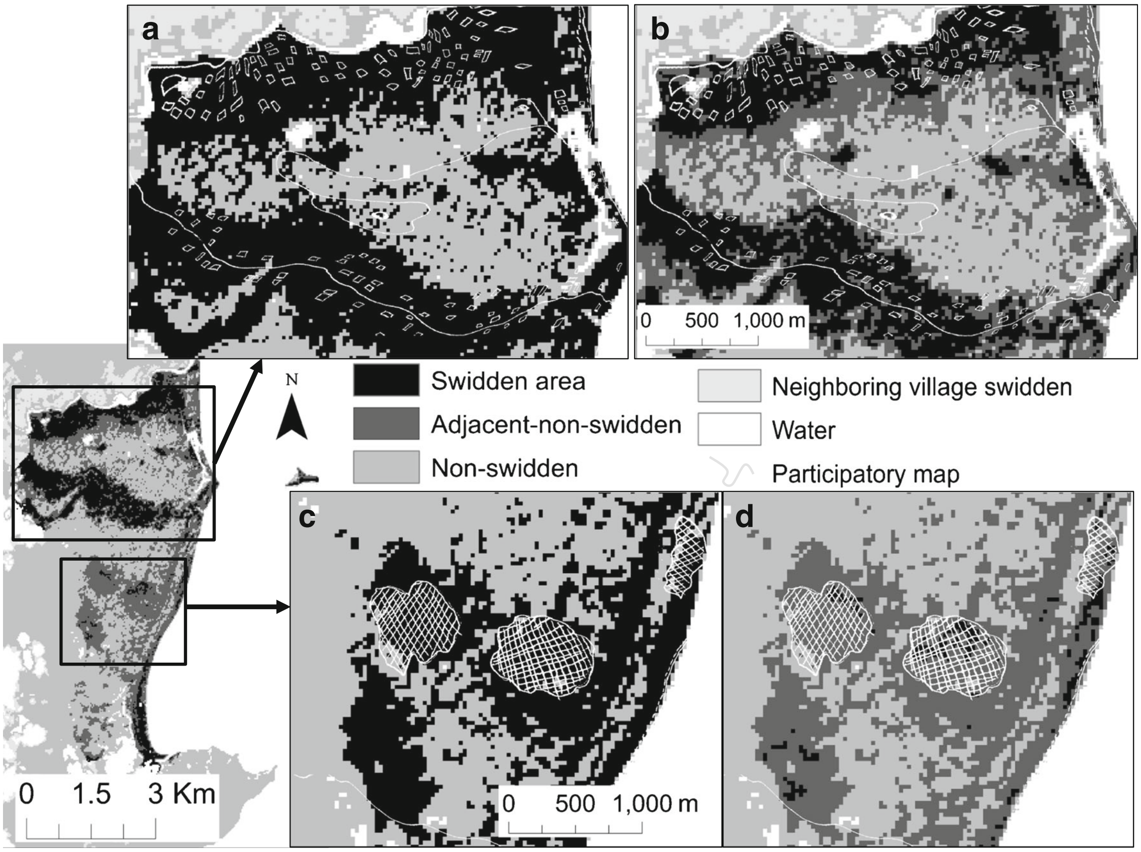

Fig. 4 The participatory map (PPM) of village and swidden land-use is overlaid with the 2011 Landsat classified image. Subsets a and b show the delta swidden area with individual plots identified (boxes) and subsets c and d show a swamp area (hashed areas). Subsets a and c are land-cover classifications using remote sensing analysis alone. Subsets b and d are the classifications after the land managers delineated misclassified swidden land-cover, shown in dark grey, and these areas should be merged with the non-swidden class

and any land-cover classified as swidden is incorrect. Therefore, nearly all of the land in this region is misclassified as swidden when only remote sensing analytical methods are used and should be non-swidden. The adjacent- non-swidden area in Subset 4d greatly reduces the amount of swamp land included in the swidden class. Both subset groups b and d show the portion of the swidden land-cover class that should be merged with the non-swidden class and this change reduces areas of misclassified swidden land-cover.

Figure 5 shows georeferenced swidden plots atop the classified Landsat (30 m) and raw GeoEye (2 m) images. The pixilated structure and different spatial resolution of these images shows how scale influences the interpretation of swidden LULC. Due to the difference in the fieldwork and capture dates of the GeoEye image, some of the listed LULCs have changed. In general, this figure better shows the complex and fragmented nature of swidden land-cover and why it is difficult to assess using remote sensing methods alone. First, swidden plots differ in orientation, size, and shape. Regardless of size, a swidden plot can be contained within a single Landsat cell or cross into multiple cells. Also, even though the georeferenced plots are rectangular, plots were often irregular in shape and often follow natural contours or features. Second, the land-covers do not always match the land-use and plots can have multiple uses and be classified as a single land-cover. Third, the newly cleared plots are easier to identify compared to plots with crop or fallow land-covers and can influence reflectance qualities disproportionally as bare soil has higher reflective qualities in some wavelengths.

Figure 6 compares the swidden area in hectares classified using remote sensing analysis alone and the PRS methods for 1999 and 2011. The remote sensing classifications without land manager inputs are 993 ha in 1999 and 1395 ha in 2011. The PRS method results in an output that includes two land-cover classes, swidden and adjacent-non-swidden. These two classes are combined for the 1999 and 2011 PRS methods to illustrate how much of the land-cover from remote sensing analysis alone is classified as adjacent-non-swidden by land managers. The amount of swidden area is 455 ha and 491 ha and the adjacent-non-swidden area is 537 ha and 905 ha for 1999 and 2011, respectively. The adjacent-non-swidden area accounts for 35% and 45% of the swidden land classified by remote sensing analysis alone.

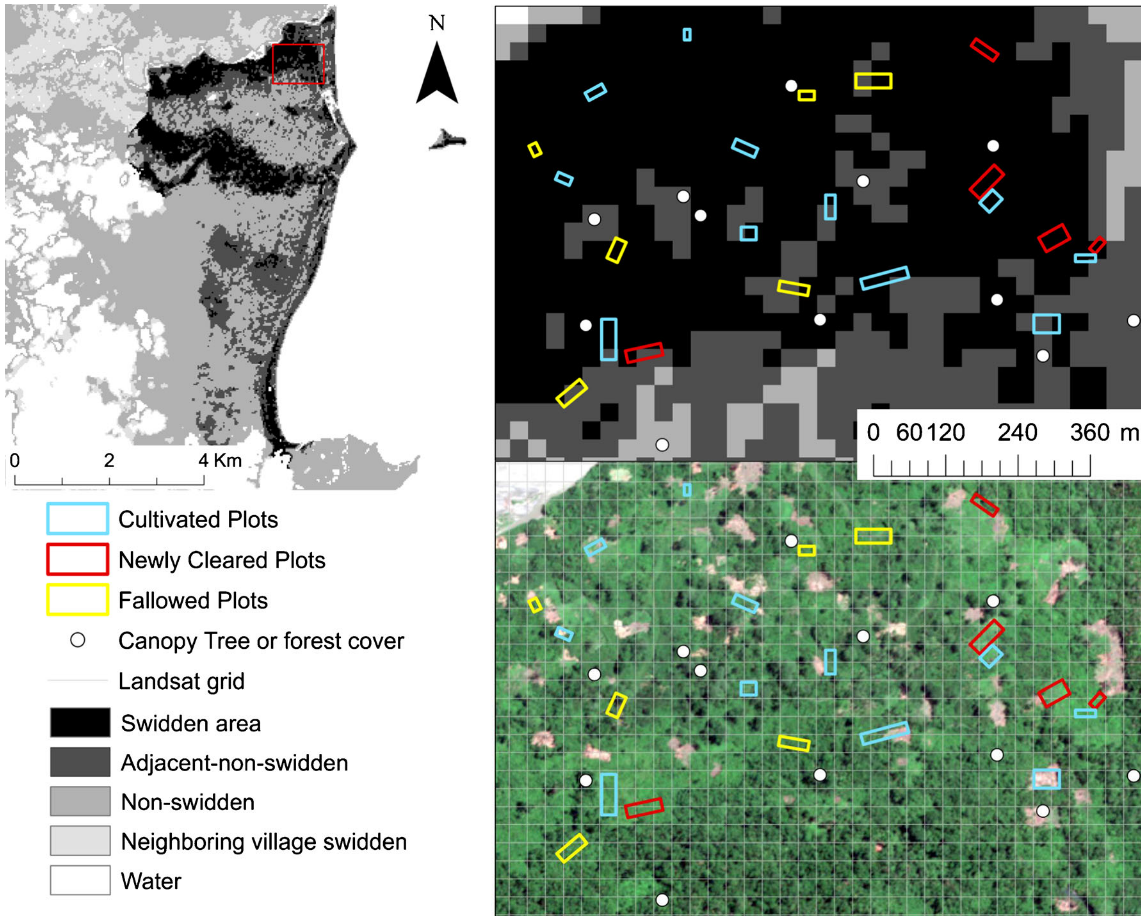

Fig. 5 The ground-truthed points and swidden plots shown are accurate area, location, orientation, and land-use and land-cover type. Some of the land-covers do not align with ground-truthed land-uses because there is a year separating the image capture and field data collection. A 30 m pixel grid is overlaid on the 2 m pixel resolution of the GeoEye image for resolution comparison

Each dataset in Fig. 6 shows an increase in swidden area over time. The larger increase in swidden area is for remote sensing analysis alone at 402 ha. The PRS swidden area increased by 35 ha between 1999 and 2011 when the adjacent-non-swidden area is not included in the total area. The percent increase over time for the remote sensing analysis alone is 40% and PRS is 8%.

Discussion

The land-cover datasets for PRS and remote sensing analysis alone present different information about swidden area and changes at the village scale. The PRS methods results show that when these data are paired a more in depth and comprehensive understanding of swidden area LULCs are achieved than when either data set are used alone. The integration of land-manager perspectives and knowledge via PRS methods offers a unique insight into local land-use.

The classification of swidden area land-cover using remote sensing analysis alone is over two and a half times larger than the results using PRS methods. In part, the differences in area are a result of transforming a continuous landscape into the discrete and categorical format of the imagery and analysis, respectively. While this is the

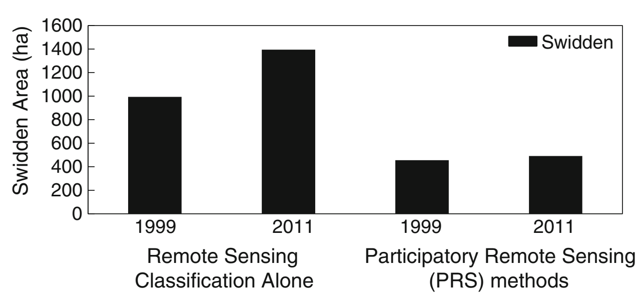

Fig. 6 Total swidden area classified using remote sensing analysis alone and PRS methods for 1999 and 2011

case in nearly all land-cover analyses, swidden areas are made up of highly complex land-covers and it proves more difficult to accurately classify swidden using Landsat data alone. The accuracy assessments and Kappa statistic quantitatively supports that swidden commission and omission errors are higher when remote sensing analyses alone are compared to PRS methods. The majority of these errors show swidden land misclassified as non-swidden, which is why the swidden area is larger in the remote sensing analysis alone.

All land-cover analyses are subject to mixed pixels because continuous landscapes are dissected into pixels and each assigned a single spectral number. However, in swidden landscapes this is extenuated due to the sub-pixel land-use characteristics. The georeferenced plots and finer resolution of the GeoEye image (Fig. 5) demonstrate the degree to which the swidden area is a patchwork of land-covers that have countless different land-cover combinations in one Landsat (30 m) pixel. Nearly every pixel has a different proportion of swidden, fallow, and natural vegetation land-covers because swidden plots are created in response to landscape and crop characteristics to maximize yields (Padoch 1986; Conklin 1961). We posit this creates a higher proportion of mixed pixels that results in the over estimation of swidden area using remote sensing analysis alone, as many of the mixed pixels have a spectral signature more similar to swidden land-cover.

The PPM overlay on the imagery also helps understand some of the classification errors. The PPM overlay shows areas that are actively cultivated swidden plots and the areas between the swidden plots are a combination of fallow and non-swidden (natural vegetation) land. As recommended by the land-managers during PRS methods, the additional adjacent-non-swidden class (dark grey; Fig. 4) is added to the land-cover classification to show how much land is misclassified. The area classified as swidden is consequently reduced and land managers agreed that merging the adjacent-non-swidden area with the non-swidden class is more representative of the land-covers found in the swidden areas and the fallowed and non-swidden natural vegetation are better identified. In addition, when the adjacent-non-swidden class is excluded the commission and omission errors are reduced and overall accuracy improves.

The increase in swidden area seen between 1999 and 2011 using PRS methods is 35 ha compared to 402 ha increases observed using remote sensing analysis alone (Fig. 6). The population grew from approximately 479 people to 900 people over the time frame (village elder, Wagner 2002). Both years have large areas misclassified as swidden when the remote sensing alone approach is used, with more area is misclassified in 2011. We posit that this is caused by local weather conditions that make natural vegetation and swidden land-covers more spectrally similar. For example, the delta and coastal area have a high water table and the annual precipitation regime influences soil moisture and vegetation growth, which can make the swidden and natural vegetation less distinguishable. Therefore, refining the remote sensing analyses with local land manager knowledge greatly improves the ability to distinguish these land-covers when classification methods cannot. The 35 ha increase in swidden land-cover over time could accurately represent swidden expansion over time, but we hesitate to make conclusive assessments with only two data points. Hoover *et al.* (in review), conducted a longer-term study between 1972 and 2015 with 40 Landsat scenes and identified that there was not a significant temporal trend in swidden land-cover change. Thus, the observed swidden area changes could be due to differences in swidden phase at the time of scene capture. For example, a larger proportion of recently burned plots are more spectrally distinct and would result in a larger swidden area detected in the imagery compared to more mature stages of crop cover, which is more spectrally similar to natural vegetation. Reflectivity differences within the swidden area could also be caused by changes in cultivars, changes in crop density, and more area cleared per season from shortened fallows, all of which were described by land managers Hoover *et al.*, (in review). Although, land managers recognize that shortening fallows to crop more continuously results in higher weed encroachment, increased pest infestations, and lower soil fertility over time, it is still done. The land mangers described that they have ample land for cultivation, but it is better to intensify cultivation on the more fertile delta area than expand on to less fertile land or the adjacent hillsides. This preferential selection is similar to results from the McAlpine and Freyne (2001) study conducted at the provincial scale across PNG.

The correlative relationship between the increase in population and swidden land expansion over time is overly simplistic and falls short in describing the multifaceted and complex drivers of land change (Bourke 2001; Filer *et al.* 2009; Boserup 1976; Lambin *et al.* 2003). However, at the national extent, Shearman *et al.* (2009) cites the growing population as the primary cause of expanding swidden areas. In a follow up study between 2002 and 2014 by Bryan and Shearman (2015) show the amount of land-cover changes attributed to swidden agriculture was nil, even though population growth followed the same trajectory. The lack of swidden expansion was described as intensification of current swidden areas and an economic shift to a cash economy. Although Shearman *et al.* (2009) and Bryan and Shearman (2015) performed ground-truthing and accuracy assessments for land-cover classifications, none of their methods included land manager information, which would have likely identified intensification strategies in both studies as McAlpine and Freyne (2001) found in their study. From this, we believe that it is highly likely that many swidden areas are over classified in the 1972–2002 Shearman *et al.* (2009) study. Another reason large changes in swidden area were observed between 1972 and 2002 is because Shearman *et al.* (2009) included two land-covers into the subsistence agricultural class that contributed to swidden area. First, forest cover changes caused by landslides were included in the swidden category and should be a class in and of itself due to the frequency and spatial extent of landslides in PNG. Second, land-cover adjacent to swidden areas and villages was classified as degraded forest because these areas could not be attributed to other causes of forest loss. This contrasts with information supplied by land managers in our study, as the land-cover adjacent to the swidden area was not used by land managers and was, in part, affected by mixed pixels. We argue that in regions where swidden is a major land-use, additional LULC classification strategies should be incorporated into land-cover classification processes, such as PRS. Also, swidden should be allocated as a separate LULC category at national and wider extents because there are a range of different LULC types and the ecological impacts among these differ (Rerkasem *et al.* 2009; Delang and Li 2013; Ziegler *et al.* 2011; Kremen and Miles 2012).

To improve the delineation of land-cover associated with swidden land-use systems at wider extents, a finer spatial resolution may help. Often such data are not available for longer time series, e.g. dates before 2000. Even with fine resolution data image analyses are still challenging in swidden landscapes and the inclusion of PRS methods would assist in refining land-cover classifications to more accurately distinguish among the different land-covers found in swidden landscapes. For large areas with coarse resolution data, land-cover classifications that rely on remote sensing analysis alone are likely to allocate more forest loss to swidden in regions where resource extraction (e.g. logging) because these land-cover changes can be confounded, especially if villages border logging concessions. For our study village LULC assessments and changes are not confounded by logging yet classifying swidden with remote sensing analysis alone still over classified swidden LULC. Collaborative PRS methods allow us to refine the land-cover classification and we identify multiple areas that were misclassified as swidden in the output of the remote sensing analysis alone.

Potential Sources of Error

A potential source of error from participatory data collection is that swidden plots could have been misestimated during the data collection phase when land-managers were asked to describe their plots in approximate length and width measurements. Although ground-truthing efforts measured plots and assured that estimates were accurate in area, all of the plots in the swidden area were not measured. Also, length and width area measurements do not account for natural and irregularly shaped plots, which are widespread in this swidden area (Fig. 4 and 5). While these methods capture the approximate area of a plot, it is likely that the true area slightly differs, which would affect cultivated and total swidden area calculations. As land-use results show, a large majority of the total swidden area is under fallow or natural vegetation, yet not much information was collected about the fallow periods aside from the duration. Simply multiplying the cultivated swidden area by the swidden cycle length may not be a good representative of total swidden area because land may be used and rotated in a different manner. In general, more information is needed about fallow and naturally vegetated areas and this is another area where land-cover information could be usefully paired with land-use information from local land managers to estimate how much land is devoted to the complete swidden-fallow cycle.

The second aspect that influences land-cover assessment is the resolution of the satellite imagery in relation to the mean swidden plot area. Land-managers described single swidden plots ranging from 12 m^2 to 105 m^2, with a mean of approximately 30 m2. The average plot size is equivalent to the area of one Landsat pixel but this does not account for the smallest identifiable object in an image (spatial resolution). To visually identify individual swidden plots multiple Landsat pixels are needed and we found that approximately 100 m^2 or just over a 3 × 3 pixel area is needed to identify a plot. Such a large area only accounts for larger plots and we surmise that the spatial resolution of Landsat data is too coarse to identify swidden plots on an individual basis. The finer resolution (2 m) of the GeoEye imagery allowed for smaller swidden plots to be identified, but deciphering the different land-uses and associated land-covers is still a challenge due to the mosaicked and varied landscape created by swidden land-use. While the GeoEye data have a finer resolution, it does not have the temporal or spatial coverage available from the Landsat archives, and thus Landsat data will continue to be used for time series analysis of swidden LULC changes in the future. This reality makes it imperative to find methods for using Landsat data to accurately classify land-uses and their associated land-covers, such as swidden, that many rural populations worldwide continue to make use of and rely upon for their livelihoods.

Conclusion

Overall, swidden landscapes are difficult to classify and more prone to mixed pixels than other agricultural land-uses and their associated land-covers. Although finer resolution satellite data may be better suited for swidden LULC detection and change analyses, these data are often costly and do not have the same historical extent as the Landsat archives. Therefore refining Landsat classifications of swidden LULC is vital, as many people in the world continue to rely upon swidden for their livelihoods.

Participatory data from local land-managers is important to incorporate into satellite data assessments as it improves accuracy assessments and provides additional details to better understand observed LULC trends. Therefore, in regions where swidden is the mainstay of subsistence livelihoods, the inclusion of participatory information is a valuable data source for accurate LULC assessments. We demonstrate that the information derived from participatory methods can be used with Landsat datasets to improve LULC assessments and understand temporal dynamics. Importantly, the assessment of swidden area from PRS methods is more accurate than that from remote sensing analysis alone.

PRS methods reveal the differences between Landsat analyses and land manager information. Landsat smoothes the fragmented landscape into pixels representing single land-covers and overestimates the swidden area by two and a half times compared to land manager land-cover descriptions. One reason these datasets differ is that land managers described swidden area as only actively cultivated land, whereas Landsat analyses include cultivated swidden, fallowed, and natural vegetation indiscriminately. When both datasets are used in tandem, the distinctions among actively cultivated swidden, fallow, and natural vegetation can be extracted. We suggest that the cultivated swidden area, as described by the land managers, could be subtracted from the total swidden area classified using Landsat to distinguish how much land is cultivated, fallowed, or under non-fallow natural vegetation.

In conclusion, if only LULC classifications from remote sensing analysis methods alone are used when assessing swidden LULC then people's swidden livelihood systems will continue to be misclassified and mischaracterized. This has arguably happened for land-cover change analysis in PNG at the national extent. We show at the village level how PRS methods, the combination of the remote sensing and participatory data, is one avenue of refining swidden LULC assessments to more accurately reflect the reality of swidden land-use and the associated land-covers.

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Compliance with Ethical Standards

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Conflict of Interest None.

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