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Title: Agricultural land-use change in Kerala, India:

Perspectives from above and below the canopy

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30 **Abstract** – Despite the availability of a wide range of tools,
31 measuring and explaining changes in land cover and land
32 use in tropical regions can be extremely challenging. Kerala,
33 India, is a biodiversity hotspot with a high population density
34 and a long history of complex agricultural land-use patterns.
35 Some reports suggest that agriculture in Kerala, which
36 historically is rice paddy-wetland and agroforestry-based, is
37 on the decline. However, the evidence is often anecdotal,
38 especially with regards to smallholding homegarden
39 agriculture. In this study we employ mixed methods,
40 including remote sensing, quantitative household surveys,
41 and semi-structured interviews, to unravel the complex land-
42 cover and land-use changes occurring in Kerala.

43 Results indicate that, from a land-cover change perspective,
44 agroforests are in dynamic equilibrium with other land
45 covers, being cleared for roads and new buildings, but offset
46 by the expansion of younger, less diverse agroforests into
47 paddy wetlands. Yet beneath the canopy, agroforests are
48 undergoing rapid land-use change not discernible using
49 remote sensing. These changes include a reported decrease
50 in the cultivation of 80% of Kerala's primary crop species
51 during 2003-2013, alongside a dramatic decline in chickens
52 (from 12.5 to 2.6 per homestead on average) and cows
53 (from 1.7 to 0.8). Over this period, no crop increased in
54 cultivation. According to farmers, the primary drivers of this
55 shift were declining profitability of agriculture in Kerala,
56 labour shortages, unreliable weather, unfamiliar pests and
57 diseases, and government policy.

58 Despite the undeniable move away from agricultural activity
59 in homegardens, we conclude that these ecologically and
60 culturally important systems are not disappearing, but rather
61 evolving to meet the needs of a less agricultural Kerala. Our
62 research highlights the value of using mixed methods for
63 characterizing land-use and land-cover histories in tropical
64 regions.

65 **Keywords:** homegarden; land-use management; tropical
66 agriculture; mixed methods; agroforestry

67 **1. Introduction**

68 Changes in land use and land cover are an important
69 manifestation of human interactions with the environment,
70 with manifold consequences for ecosystems and human
71 livelihoods (DeFries et al., 2007; Foley et al., 2005). There
72 has been a rapid rise in scholarship over the last two
73 decades aiming to understand the ecosystem service
74 tradeoffs related to land-use practices (DeFries et al., 2004;
75 Nair et al., 2009; Tomscha et al., 2016). How best to
76 manage landscapes to balance human needs and
77 environmental conservation has become a key focus of
78 research and policy debate (Benton, 2007; DeFries and
79 Rosenzweig, 2010; Green et al., 2005).

80 Yet land use must be accurately measured before it can be
81 effectively managed. Various quantitative and qualitative
82 methods have been developed to identify and measure
83 changes in land use and cover (Lambin et al., 2003;
84 Luyssaert et al., 2011; Munsi et al., 2010; Veldkamp and
85 Verburg, 2004). These include, but are not limited to,
86 classification of remotely sensed imagery, physical field

87 measurements, consulting government records, and
88 interviewing land users or occupants.

89 Measuring land-use/cover change (LUCC) is complicated by
90 the dynamic nature of human-managed landscapes, which
91 experience changes at multiple scales, and not necessarily
92 at the same time. This is especially true of tropical
93 landscapes in developing countries, in which agricultural
94 land holdings tend to be both small and diverse in style of
95 agriculture. Agricultural landscapes in these regions range
96 from subsistence- to commercial-based and tend to exhibit
97 high spatiotemporal variability in crop selection, which can
98 be based on markets, available technologies, government
99 incentives, pest prevalence, investment potential, and so on
100 (Altieri, 2009; Wrigley, 1971).

101 Kerala, a tropical state in South India, is an example of a
102 region with a dynamic history of land-use change that has
103 not been particularly well-documented. Archaeological
104 evidence suggests that Kerala participated in global
105 agricultural markets for at least 2000 years, trading spices
106 first with the Romans, and later with Portuguese, Dutch, and
107 British merchants (Jeffrey, 2001). In addition to spices such
108 as black pepper (*Piper nigrum*) and cardamom (*Elettaria*
109 *cardamomum*), Kerala has been a major producer and

110 exporter of rice (*Oryza sativa*) and coconut (*Cocos nucifera*)
111 (Kumar, 2005). Traditionally, much of Kerala's agricultural
112 activity has centered on homegardens. According to (Kumar
113 and Nair, 2004), homegardens are "intimate, multi-story
114 combinations of various trees and crops, sometimes in
115 association with domestic animals, around homesteads."
116 Homegardens, which are the result of generations of
117 successive crop intensification, are renowned for their
118 species richness, multifunctionality and sustainability (Kumar
119 et al., 1994; Kumar and Nair, 2004). As such, it is important
120 to differentiate between homegardens, which are the places
121 – houses and farms – where people live, and agroforestry,
122 which is a land cover category. Agricultural land in a
123 homegarden is primarily agroforest, in which plantation crops
124 such as coconut, banana, or rubber (*Hevea brasiliensis*) are
125 either well integrated, or in which plantation-style cultivation
126 constitutes a limited proportion of homegarden area.
127 Agroforests, on the other hand, consist of not only
128 homegardens but also mixed agroforests not associated with
129 a homestead. The vast majority of Kerala's rural homesteads
130 contain homegardens, yet these farms are quite small, and
131 other forms of agriculture such as plantations and paddy
132 land also exist.

133 Rapid agricultural land-use changes have occurred in Kerala
134 since the 1970s. In particular, local land-use scholars have
135 noted a shift towards monoculture and conventional cash-
136 crop agroforestry, at the expense of traditional, species-rich
137 homegardens (Kumar, 2005; Peyre et al., 2006). While a
138 shift towards monoculture-style agriculture would be
139 consistent with shifts observed in other developing regions, it
140 would be at odds with the fundamental cultural importance of
141 tropical agroforestry to rural Keralites (Kumar and Nair,
142 2004). Furthermore, observations of this transition have
143 been mostly anecdotal, as land-cover data collected by the
144 state fail to account for the complexity of Kerala's agricultural
145 landscapes (Kumar, 2005). In addition to the alleged shift
146 from traditional to monoculture-style agriculture, another
147 important land-use change has been the recent conversion
148 of paddy land into simple agroforests and other agricultural
149 crops (Guillerme et al., 2011). It is important to note that new
150 agroforests are often fundamentally different than traditional
151 homegarden agroforests, as the latter are, by definition,
152 intensively managed, more complex, and much older.

153 Understanding LUCC in complex landscapes requires a
154 multi-faceted approach (Lambin et al., 2003; Veldkamp and
155 Verburg, 2004). Using Kerala as a case study, we explored

156 the use of a mixed-methods approach to gain a more
157 complete understanding of LUCC at multiple scales. First,
158 using high-resolution satellite imagery, we estimated broad-
159 scale land-cover changes in three of Kerala's environmental
160 and agricultural zones. We then zoomed in to the scale of
161 the homegarden to conduct quantitative household surveys
162 and semi-structured interviews with farmers. While the
163 remote sensing analysis aimed to identify changes in the
164 areal extent of land cover, the farm-scale component of the
165 study aimed to identify the individual land-use changes that
166 were occurring, as well as the drivers of these changes.
167 Finally, we synthesized the disparate data sources to
168 develop a coherent explanation of agricultural LUCC
169 changes in Kerala over the last decade.

170 **2. Methods**

171 **2.1 Study area**

172 Despite its small size (38 863 km²), Kerala is topographically
173 and ecologically diverse, consisting of a mix of coastland,
174 wetlands, and plains to the west, and rolling hills and the
175 Western Ghats mountain range to the east. Crop choice
176 depends primarily on topography and elevation, but also on
177 crop profitability, soil type, availability of irrigation, and public

178 policy (Guillerme et al., 2011; Kannan and Pushpangadan,
179 1990; Narayanan, 2006). The most common crops grown in
180 Kerala are rice in the lowlands; tea (*Citrus sinensis*), coffee
181 (mostly *Coffea arabica* and *C. canephora*), and spices in the
182 uplands; and banana (various species), coconut and
183 arecanut palms (*Areca catechu*) nearly everywhere (Kumar,
184 2005). Common homegarden food crops include jackfruit
185 (*Artocarpus heterophyllus*), mango (*Mangifera indica*), curry
186 tree (*Murraya koenigii*), and banana, among many others.
187 Yet Kerala's crop composition has experienced considerable
188 shifts since the 1950s, characterized by declines in rice and
189 increases in coconut and rubber (Kumar, 2005).

190 In addition to being biophysically, ecologically, and
191 agriculturally diverse, Kerala is socially, culturally, and
192 economically diverse, and is distinct from the rest of India.
193 Kerala has the highest Human Development Index (0.825 in
194 2015;(United Nations Development Program, 2015) and
195 highest literacy rate (93.91%; (Government of India, 2011) of
196 any state in India. Kerala's universal social services have
197 resulted in a healthy, highly educated population that often
198 travels abroad to find gainful employment (Prakash, 1998). It
199 is estimated that one person works overseas for every five
200 people employed in Kerala, with foreign remittances

201 accounting for roughly 25% of the state's economy
202 (Zachariah and Rajan, 2012). This mass exodus of skilled
203 and unskilled workers has come hand-in-hand with labour
204 shortages since the 1970s, which are generally assumed to
205 have contributed to the decline in paddy cultivation and a
206 rise in agroforestry in the 1980s and 90s (Kannan, 1998).

207 We conducted land-cover analyses in three panchayats (the
208 smallest political administrative unit in Kerala): Avinissery,
209 Kalikavu, and Poothrikka (Figure 1). Panchayat choice was
210 based on the availability of high-quality archival satellite
211 imagery as well as to best represent Kerala's diverse natural
212 environments and varied population density. Avinissery is a
213 densely populated, low-elevation panchayat consisting
214 primarily of homegardens and paddy rice. Kalikavu is close
215 to the Western Ghats, has low population density, larger
216 farm size, and produces large amounts of tree crops such as
217 rubber, coconut and arecanut. Poothrikka, which produces
218 rice, rubber, and homegarden crops (e.g. mango, jackfruit,
219 and bananas), is between Avinissery and Kalikavu with
220 regards to elevation and population density. We selected five
221 additional panchayats for landholder surveys and interviews,
222 using the same environmental and demographic criteria as
223 described for the first three (Figure 1).

224
 225 Fig. 1. Study area in Kerala, India. We conducted quantitative
 226 surveys and semi-structured interviews in 8 panchayats (black),
 227 representing 8 districts (dark gray) across the state. [Land-cover](#)
 228 classification and [change detection](#) were conducted using [satellite](#)
 229 [imagery](#) acquired from panchayats C, E, and F. The districts
 230 (panchayats in parentheses) labeled are: A: Kozhikkode
 231 (Thamarassery); B: Wayanad (Vengappally); C: Malappuram
 232 (Kalikavu); D: Palakkad (Kadampazhipuram); E: Thrissur
 233 (Avinissery); F: Ernakulam (Poothrikka); G: Idukki (Kattappana);
 234 H: Alappuzha (Thiruvandoor). The inset map is of peninsular
 235 India.

236

2.2 Remote sensing & land-cover change

For each of Avinissery, Poothrikka, and Kalikavu, we acquired an IKONOS-2 image from early 2000 and a GeoEye-1 image from 2012 (Table 1). We selected the imagery using the following criteria: 1) high-quality images with low cloud cover (<5%); 2) sufficient spatial overlap between paired images to encompass the entire panchayat; 3) paired images as close as possible to 10 years apart; 4) image pairs for each panchayat comprised a temporally coincident 10-year period; and 5) minimal seasonal variation between images in a pair. We collected ground control points between June and November 2013 and used them to georeference GeoEye-1 images. GeoEye-1 images were then used for co-registration of IKONOS-2 images, and all products were orthorectified using a 30 m ASTER DEM and subsequently pan-sharpened. We used ENVI version 5.1 (ENVI, 2013) and ArcGIS version 10.3 (ESRI, 2011) for all preprocessing.

Table 1. Satellites and imagery used to quantify [land-cover](#) changes in selected Panchayats of Kerala state, India.

Panchayat	Satellite ^a	Bands ^b	Resolution ^c (m)	Coverage (km ²)	Date	Cloud (%)
Avinissery	IKONOS-2	4 + Pan	3.2 (0.8)	27.06	2-Apr-2001	0
Avinissery	GeoEye-1	4 + Pan	2.0 (0.5)	42.84	10-Dec-2012	5

Panchayat	Satellite ^a	Bands ^b	Resolution ^c (m)	Coverage (km ²)	Date	Cloud (%)
Kalikavu	IKONOS-2	4 + Pan	3.2 (0.8)	34.81	22-Sep-2003	0
Kalikavu	GeoEye-1	4 + Pan	2.0 (0.5)	34.81	13-Jan-2012	0
Poothrikka	IKONOS-2	4 + Pan	3.2 (0.8)	44.88	13-Apr-2002	0
Poothrikka	GeoEye-1	4 + Pan	2.0 (0.5)	44.88	1-Feb-2012	0

257 a

258 IKONOS-2: launched 29/09/1999, Global Average
 259 Georeferenced Horizontal Accuracy: 15 m; GeoEye-1:
 260 launched 06/09/2008, Global Average Georeferenced
 261 Horizontal Accuracy: <4 m.

262 b

263 Spectral band wavelength range (in nm) for IKONOS-2:
 264 Panchromatic – 526 to 929, Blue – 445 to 516, Green –
 265 506 to 595, Red – 632 to 698, NIR – 757 to 853; GeoEye-
 266 1: Panchromatic – 450 to 800, Blue – 450 to 510, Green –
 267 510 to 580, Red – 655 to 690, NIR – 780 to 920.

268 c

269 Presented: multispectral (panchromatic).

270 Preliminary pixel-based classification yielded insufficient
 271 accuracy for the purpose of this study. While supervised
 272 classification has been successfully used for land-cover
 273 analysis in numerous contexts (e.g. Fretwell et al., 2012;
 274 Goetz et al., 2003; Gutierrez and Johnson, 2012; Mumby
 275 and Edwards, 2002), Kerala's rural landscapes are a
 276 complex mosaic of wetlands, tree plantations, and
 277 agroforests with large spectral variability. Furthermore, built
 278 surfaces such as houses and roads are often obscured by

279 overhanging trees or tree shadows, which led to an
280 overestimation of tree cover and underestimation of built
281 surfaces. We next attempted object-oriented classification,
282 but encountered the same issues with overhanging trees
283 and shadows.

284 We therefore opted for a manual classification approach
285 (although we used supervised classification to guide our
286 analysis as described in the next paragraph). Overhanging
287 trees and shadows were clearly visible to the naked eye, but
288 mischaracterized by both pixel-based and object-based
289 classification. Manually digitizing land-cover polygons by
290 hand is often more accurate, as shape, texture, and context
291 can be employed, in addition to spectral characteristics
292 (Lillesand et al., 2014; Lu and Weng, 2007). Manual
293 classification, or a combination of manual and object-based
294 image classification (OBIA), has been the preferred choice
295 for classifying complex tropical landscapes (Gibbs et al.,
296 2010; Ramdani and Hino, 2013).

297 The major shortfall of manual classification is the necessary
298 time investment. Because classifying all 6 images in their
299 entirety was too time consuming (Achard et al., 2012;
300 Shimabukuro et al., 2014), we adopted a systematic
301 unaligned sampling approach (Bellhouse, 1977). For each of

302 the three panchayats, we divided image pairs into 8 equal-
303 area sections, generated two random points for each
304 section, and used these 96 points to generate square 0.75
305 ha sample areas in ArcMap. We conducted maximum
306 likelihood supervised classifications using ENVI to ensure
307 that image samples were representative of the overall
308 image. Land-cover variability between samples and parent
309 images ranged from 0.2 to 7.9%.

310 We manually classified all 96 sample images into five land-
311 cover classes: agroforests, bare ground, built environments,
312 water, and wetlands. Agroforests in Kerala are the dominant
313 land-cover class, and typically consist of mixed tree crop
314 species around homesteads, and in some areas
315 monoculture plantations (especially rubber). In this study we
316 did not differentiate between monoculture agroforestry
317 (a.k.a. silviculture) and polyculture agroforestry because: 1)
318 the two exist along a continuum with no clear point of
319 demarcation, and 2) our remote sensing approach could not
320 differentiate between these two sub-categories. Wetlands,
321 which are often the lowest-lying regions in Kerala, occupy
322 the remainder of the agricultural land, and are used primarily
323 for the cultivation of rice. However, following paddy fields,
324 natural wetlands, and other non-tree wetland crops (e.g.

325 tapioca) are also considered in the wetland class. In this
326 study, all agriculture was classified into either wetland
327 (mostly rice paddy) or agroforestry, as these cover the
328 overwhelming majority of the landscape. It is important to
329 note that this land-cover classification is a broad
330 simplification of a highly complex landscape. Furthermore,
331 while non-treed dryland agriculture does exist in Kerala (e.g.
332 cassava), it is effectively absent from our selected study
333 regions.

334 Land-cover polygons were manually delineated and
335 classified if at least one of their axes was longer than 5
336 metres. Linear features were ignored if they were fewer than
337 3 pixels in width, because they could not otherwise be
338 reliably identified. In the rare case that an object could not be
339 identified by the user, images were opened in eCognition
340 Developer 8.8 so that the objects could be first isolated with
341 an appropriate segmentation, and then compared using
342 texture, shape, and spectral characteristics.

343 Land-cover change was assessed by subtracting one
344 classified image from the other (Singh, 1989), and first-order
345 Markov models were used to correct for variable image
346 acquisition dates (Urban and Wallin, 2002).

347 We could not validate the land-cover classification from this
348 study with ground truth points because image acquisition
349 dates ranged from one to twelve years prior to fieldwork.
350 Given the rapid change in Kerala's landscape, any validation
351 conducted using recent field data would be highly
352 inaccurate. Furthermore, our GPS measurements would not
353 have provided a reliable validation, because we could not
354 make use of differential correction in most panchayats due to
355 their remoteness. But given the distinct textural, structural,
356 topological and spectral characteristics of Kerala's
357 landscapes, the features digitized for this study were easily
358 discernable with the naked eye. In fact, scholars frequently
359 use both IKONOS-2 and GeoEye-1 imagery for validation of
360 lower resolution imagery (Huang et al., 2009; Potapov et al.,
361 2014; Wickham et al., 2013), and here we used them directly
362 to classify land cover.

363 **2.3 Surveys, interviews, & farm-scale change**

364 2.3 Surveys, interviews, & farm-scale change

365 We conducted quantitative surveys and semi-structured
366 interviews at 115 homegardens between July and October of
367 2013. To maximize representation of Kerala's geographical
368 diversity, we visited farmers in one panchayat in each of

369 eight contiguous districts in central Kerala (Figure 1).
370 Numerous criteria were considered for the selection of
371 panchayats, including the availability of satellite data (see
372 Section 2.2), population density, and elevation, with the aim
373 of achieving the broadest possible representation of Kerala's
374 landscapes. In each panchayat, we randomly selected 15
375 farmers from household registries provided by local
376 governments, and included them in our sample if their
377 homegarden was at least 0.1 ha and contained at least 3
378 different cultivated tree species with a variety of understory
379 crops. In total, only one household failed to meet the
380 homegarden criteria, and two others chose not to participate.
381 In these cases, another homegarden was randomly selected
382 in order to keep samples sizes consistent between
383 panchayats. Due to logistical constraints, we were able to
384 visit only 10 homegardens in Wayanad.

385 We conducted both the quantitative surveys and semi-
386 structured interviews at the homes of the respondents. For
387 each of the 115 homegardens visited, we first conducted the
388 quantitative survey, which lasted approximately 30 minutes,
389 followed by the semi-structured interview, which lasted
390 anywhere between 30 and 90 minutes. All surveys and
391 interviews were conducted with a head of household, but in

392 many cases the entire family contributed. A translator from
393 Kerala Agricultural University was hired to assist in
394 communicating with respondents not fluent in English.

395 Our quantitative surveys were designed to elucidate land-
396 use histories by comparing the primary crops and livestock
397 produced on the homestead in 2013, and ten years prior, in
398 2003. Each survey consisted of a set of questions on
399 cultivation histories for 15 common crops (listed in Figure 4):
400 1) Do you grow this crop?; 2) Do you ever buy this crop?; 3)
401 Ten years ago, did you produce more, less, or the same
402 amount of this crop?; 4) Do you ever sell this crop?; 5) Ten
403 years ago, did you sell more, less, or the same amount of
404 this crop? We posed similar questions for livestock (cows
405 and chickens), asking farmers to estimate the number of
406 heads owned. In our quantitative surveys we also collected
407 location and size of homegardens using GPS (Trimble Juno
408 5 Handheld), and demographic data (e.g. size of family,
409 primary source of income). In analyzing crop and livestock
410 production, we controlled for changes in area by excluding
411 any homegardens that experienced changes in property size
412 between 2003 and 2013 ($n = 23$).

413 Our semi-structured interviews sought primarily to explore
414 the drivers of land-use change between 2003 and 2013. Our

415 leading question was: “Has agriculture on your land and/or in
 416 this panchayat decreased over the past 10 years?” Following
 417 this question, our interviews developed freely in various
 418 directions, but were guided generally by questions such as
 419 “What has caused agriculture to decrease on your
 420 homestead?” and “What has caused agriculture to
 421 decrease in Kerala”? We recorded answers on paper and
 422 digitized them using RQDA qualitative data analysis
 423 software, developing 99 codes and 14 themes from 115 files
 424 (Huang, 2012).

425 **3. Results**

426 **3.1 Current homestead characteristics**

427 Average homestead size ranged from 0.19 ha in
 428 Thamarassery to 0.67 ha in Vengapally, with a mean across
 429 all panchayats of 0.34 ha (Table 2). In general,
 430 homesteads were smaller in densely populated
 431 panchayats, which tend to be closer to the coast, and larger
 432 in less populated areas, usually closer to the mountains. Of
 433 the 115 farmers interviewed, 52% and 28% relied on farming
 434 as their primary and secondary sources of income,
 435 respectively, while 20% used their homesteads for only
 436 personal use (Table 2). Many respondents (64%) owned

437 additional agricultural land nearby that averaged 0.87 ha and
 438 was typically wetland (often in fallow) or plantation (Table 2).
 439 Duration of homegarden ownership was highly variable,
 440 ranging from 1-60 years with the current owner, and 1 year
 441 to “time immemorial” with the family (Table 2).

442 Table 2. Descriptive statistics for selected Panchayats of Kerala
 443 state, India.

Panchayat	n	Other Land			Ownership (years)		Agricultural Income		Family Size	
		Area (ha)	Percent Farmers ^a	Mean Area (ha)	With Family	Current Owner	Primary Source (%)	Secondary Source (%)	2003	2013
Avinissery	15	0.26	53	0.85	156	28	40	33	5.4	4.5
Kadampazhipuram	15	0.42	53	0.97	102	34	53	7	5.3	4.7
Kalikavu	15	0.23	60	0.81	43	26	60	27	7.6	6.7
Kattappana	15	0.37	53	1.85	39	21	80	13	5.4	5.4
Thiruvandoor	15	0.24	93	0.80	161	29	27	53	4.6	4.3
Poothrikka	15	0.33	40	0.19	118	35	40	27	6.1	4.9
Thamarassery	15	0.19	67	0.39	57	26	33	47	5.2	3.7
Vengapally	10	0.67	90	1.06	82	19	80	20	5.0	4.5
Total	115	–	–	–	–	–	–	–	–	–
Mean	–	0.34	63.63	0.87	94.75	27.25	51.63	28.38	5.58	4.84
St. Deviation	–	0.16	18.82	0.49	47.97	5.60	20.37	15.77	0.92	0.90

444

445 a

446 Percent of respondents in a panchayat who report owning additional
 447 land outside of the homegarden area.

448 Commercial crops such as areca and rubber were grown in
 449 most homegardens, though not all farmers were actively
 450 engaged in selling their crops (Figure 2a). In particular,
 451 coffee, cardamom, and pepper each had market
 452 engagement rates of just over 50%. Many commercial crops
 453 were highly geographically concentrated. Cardamom, for
 454 example, which was grown by only 20% of overall farmers in

our sample, was grown by 93% of farmers in Kattappana, a hilly panchayat in Kerala’s uplands. The most extensively planted food crops were coconut (present in 97% of homegardens), banana (94%), jackfruit (88%), and mango (87%; Figure 2b). Despite widespread on-farm production, over 99% of households needed to purchase food to meet domestic needs (Figure 2b). Fewer than 25% of farmers were engaged in the cultivation of rice, and even those who did grow rice explained that it was more sensible to sell rough rice for processing and use the profits to purchase rice from the store than it was for them to process the rice themselves. Of the 115 homegardens surveyed, only one claimed to be self-sufficient in the production of food.

Fig. 2. Major commercial (A) and food (B) crops grown, bought, and sold by homegardeners.

471

472 **3.2 Land-cover and land-use changes**

473 LUCC results from the three methodological approaches

474 employed in this study were at times complementary and, at

475 other times, seemingly contradictory. Remote sensing

476 analysis, quantitative surveys, and semi-structured

477 interviews consistently showed a general decline in

478 agriculture across Kerala. Each of these methodological

479 approaches further suggested that the most prominent

480 change was a widespread increase in built surfaces in each

481 panchayat, accompanied by loss of wetland in all rice-

482 producing regions (Figures 3,4).

483

484 Fig. 3. [Land-cover](#) changes (in percentage gain or loss between
 485 images for each class) from [remote sensing](#) analysis for Avinissery
 486 (2001–2012), Kalikavu (2003–2012), and Poothrikka (2002–2012).

487

488 Fig. 4. Percent of home gardeners producing more (white), less
489 (black) or the same (gray) amount of common crops in 2013 as
490 compared with 2003 (n = 92). We removed respondents who did
491 not grow a given crop in 2003 (when reporting declines) and 2013
492 (when reporting increases), as well as respondents whose property
493 area changed during the 10-year period of investigation.

494 Source: quantitative surveys.
495

496 Remote sensing results suggested that total net agroforest
497 area remained constant, while quantitative survey results
498 and interviews seemingly contradicted these results by
499 pointing to a decline in the cultivation of agroforestry crops
500 (Figures 3, 4). Of the 15 crops we surveyed, 12 decreased in

501 production over a period of 10 years, while the remaining
 502 three remained constant, but did not increase (Figure 4).
 503 Rice, pepper, and cashew were the most heavily affected,
 504 with over 75% of respondents reducing production or
 505 abandoning cultivation altogether. The least changed crops
 506 were rubber, curry tree, and coffee, though none of these
 507 exhibited overall increases in production. Livestock
 508 ownership also declined, with the average number of
 509 chickens per homegarden dropping from 12.5 in 2003 to 2.6
 510 into 2013 and the average number of cows from 1.7 to 0.8
 511 (Figure 5).

512

513 Fig. 5. Average number of cows (A) and chickens (B) per
 514 homegarden for each panchayat in 2003 (black) and 2013 (white).
 515 Paired sign tests indicate that overall trends are significant for both
 516 chickens ($s = 4$, $p < 0.0001$) and cows ($s = 8$, $p < 0.0001$).
 517 Panchayat names are abbreviated to the first three letters.

518

519 Net agroforestry land area did not decrease as agroforests
 520 were in a state of dynamic equilibrium with wetlands (which
 521 were decreasing) and built surfaces (which were increasing;
 522 Table 3; Figure 6). Extensive net increases in built surfaces
 523 across all study sites came primarily at the expense of
 524 agroforests (70%) and bare ground (20%), but not from
 525 wetlands. Built surfaces were the land-cover class that saw
 526 the most growth; only half of those mapped in 2012 were
 527 present a decade prior. A remarkable 31% of farmers
 528 surveyed had built a new house on their property between
 529 2003 and 2012, and in almost every case the new
 530 construction came at the expense of agroforest. In
 531 interviews, farmers from all panchayats supported this result
 532 by making reference to increased rural construction
 533 threatening agroforests. The absence of new construction on
 534 wetlands in our land-cover analysis was also supported by
 535 our interviews; farmers explained that it was not advisable to
 536 build on wetlands due to state laws prohibiting new
 537 development in these areas.

538 Table 3. [Change detection](#) analyses for Avinissery, Poothrikka, and
 539 Kalikavu panchayats of Kerala state, India. For each [land-cover](#)
 540 pair, the top numbers are transition probability matrices that list the
 541 percent chance that a pixel of one land-cover class (rows) will
 542 change to a pixel of another class (columns) between 2002 and
 543 2012 (e.g. in Avinissery, 5.6% of the pixels on the landscape
 544 changed from agroforest in 2002 to built in 2012). Note that the

top numbers represent the percent of all transitions that occurred on the landscape (i.e. matrices sum to 100%). The numbers in brackets list the percent contribution of 2002 land covers to new land covers of 2012. For example, 66% of new built surfaces in Avinissery came from agroforest. The bottom number is the total area in square metres that transitioned from one land cover to another (e.g. in Avinissery, 22 207 m² of land transitioned from agroforest to built).

Avinissery			2012		
A	Agroforest	Bare	Built	Water	Wetland
	Agroforest	40.6	3 (43)	5.6 (66)	0 (0)
		143416	12063	22207	81
	Bare	4.2 (55)	2.5	1.9 (22)	0.1 (100)
		16748	6814	7709	323
2002	Built	1.9 (25)	0.2 (3)	5.4	0 (0)
		7558	804	18848	1
	Water	0.1 (1)	0 (0)	0 (0)	0.5
		386	0	36	1842
	Wetland	1.5 (19)	3.7 (54)	1 (12)	0 (0)
		5977	14535	3979	0
					97139
Poothrikka			2012		
B	Agroforest	Bare	Built	Water	Wetland
	Agroforest	64.6	2.6 (86)	2.1 (75)	0 (0)
		229855	9414	7570	0
	Bare	9.5 (73)	0.9	0.7 (25)	0 (0)
		33712	3320	2395	0
2002	Built	1.1 (8)	0.2 (7)	3.9	0 (0)
		4068	542	13735	0
	Water	0 (0)	0 (0)	0 (0)	0.2
		0	0	0	632
	Wetland	2.5 (19)	0.2 (7)	0 (0)	0 (0)
		8872	808	0	0
					39785
Kalikavu			2012		
C	Agroforest	Bare	Built	Water	Wetland
	Agroforest	83.4	3.3 (100)	2.7 (90)	0.3 (100)
		300686	10527	8817	808
	Bare	3 (91)	1.2	0.3 (10)	0 (0)
		9762	5639	1047	0
2002	Built	0.3 (9)	0 (0)	4.5	0 (0)
		906	146	16082	0
	Water	0 (0)	0 (0)	0 (0)	0.9
		120	0	41	3071
	Wetland	NA	NA	NA	NA

		0	0	0	0	0
	Mean			2012		
D		Agroforest	Bare	Built	Water	Wetland
	Agroforest	62.9	3 (59)	3.5 (70)	0.1 (100)	0.3 (100)
		224652	10668	12865	296	689
	Bare	5.6 (64)	1.5	1 (20)	0 (0)	0 (0)
		20074	5258	3717	108	0
	2002 Built	1.1 (13)	0.1 (2)	4.6	0 (0)	0 (0)
		4177	497	16222	0	0
	Water	0 (0)	0 (0)	0 (0)	0.5	0 (0)
		169	0	26	1848	1
	Wetland	2 (23)	2 (39)	0.5 (10)	0 (0)	19.4
		4950	5114	1326	0	45641

553

554

555 Fig. 6. Primary [land-cover](#) changes based on [aerial imagery](#) as a
556 percentage of total sampled area for Avinissery (A; 2001–2012),
557 Poothrikka (B; 2002–2012), and Kalikavu (C; 2003–2012). Arrow
558 weight represents magnitude of flow, and only changes exceeding
559 0.5% are reported.

560

561 Of the panchayats we investigated with remote sensing,

562 Avinissery experienced the most dramatic net increase in

563 built area (94%), and Poothrikka the lowest at only 29%
564 (Figure 3). Despite such massive development, net
565 agroforest land-cover area in Avinissery and Kalikavu did not
566 change, and Poothrikka even saw growth of 11%, which
567 coincided with net losses of wetland and bare ground (which
568 we suspect was, at that time, recently cleared agroforest).
569 While newly constructed areas in Avinissery and Poothrikka
570 came primarily from gross losses in agroforest (66% and
571 75%, respectively), these losses were mitigated by
572 encroachment of agroforests on wetlands and bare ground
573 (Table 3). Kalikavu, however, which is located in the
574 Western Ghats and does not have wetlands, witnessed a
575 52% increase in built land cover, 90% of which was at the
576 expense of agroforest (Table 3). Yet agroforests remained
577 mostly unaffected, due to very low initial levels of built area
578 in Kalikavu, which is relatively remote, combined with
579 extensive agroforests that cover nearly 90% of the
580 panchayat (Figure 3).

581 Widespread losses of wetland area in rice-growing regions
582 were almost entirely replaced by local gross increases in
583 agroforests and bare ground (Table 3; Figure 6). Among
584 panchayats, wetlands saw the least growth, with 97% of
585 2012 wetlands unchanged from 2002 (Table 3). Despite

586 dramatic increases in built surfaces across study regions,
587 little construction occurred on wetlands (10%; Table 3).
588 Change detection findings were consistent with interview
589 outcomes, in which respondents commented on how farmers
590 would plant trees on the periphery of wetland areas, thereby
591 gradually converting wetlands to agroforests (this process is
592 described in Guillerme et al., 2011).

593 Semi-structured interviews provided some insight to land-
594 use changes, and in doing so confirmed the quantitative
595 survey results. All but two farmers indicated that they had
596 observed a decline in agriculture on their property over the
597 same time period, as well as for the panchayat in general.
598 Most narratives of regional agriculture were consistent with
599 each other, pointing towards a widespread decline in both
600 garden-based and commercial farming, alongside an
601 increase in buildings and roads.

602 **3.3 Drivers of change**

603 Farmers provided numerous explanations for the decline of
604 agriculture in Kerala. The most common themes, from most
605 to least mentioned, were (percentage of respondents in
606 parentheses): 1) changing weather and climate (87%), 2)
607 decreased access to labour (80%), 3) declining profit

608 margins (60%), 4) poor access to pesticides and fertilizers
 609 (43%), 5) increased problems with pests and disease (43%),
 610 6) a stigma against agriculture (23%), and 7) construction
 611 competing for land use (17%). Using these primary themes,
 612 we present a conceptual organization of land use changes
 613 and drivers in Figure 7. In considering the themes together,
 614 one of the most widespread concerns was the increased
 615 financial risk associated with a combination of high
 616 investment costs alongside shrinking profit margins. Input
 617 costs such as labour, pesticides and fertilizers, which were
 618 deemed necessary by most farmers, have soared in recent
 619 years (Thomas and Devi, 2016).

620

621 Fig. 7. Conceptual organization of observed [land-use changes](#) and
 622 their drivers according to quantitative [household surveys](#) and semi-
 623 structured interviews. Arrows indicate direction of influence and
 624 black lines suggest a causal relationship between lower and higher-
 625 order drivers.

626 Sociological factors and government policy were also highly
627 cited drivers of agricultural decline. Many of the farmers
628 interviewed expressed uncertainty over the fate of their farm
629 should they grow too old to work. In most cases their
630 children were educated with university degrees and were
631 pursuing work in other sectors, often only finding such work
632 abroad. Several farmers considered Kerala's youth to be
633 over-educated, resulting in a shortage of white-collar jobs
634 and high levels of unemployment despite a serious shortage
635 in agricultural labour. The government was often criticized
636 for its inability to rectify Kerala's agricultural decline by
637 helping farmers in meaningful ways. Specific criticisms
638 included: 1) the implementation of welfare strategies, such
639 as the Mahatma Gandhi National Rural Employment
640 Guarantee Program, which may act as a disincentive for
641 labourers to work on farms (Gulati et al., 2014; Harish et al.,
642 2011), 2) not providing subsidies for expensive inputs and
643 technologies, and 3) not providing sufficient infrastructure to
644 connect farmers with regional and global markets.

645 Though it was mentioned less frequently than other drivers,
646 the increase in rural construction was identified by several
647 farmers as an important factor in the decline of agriculture.
648 Building new houses decreases agricultural production

649 locally because the new properties are typically erected on
650 what was agroforest. At the landscape scale, fragmentation
651 of properties as they are passed from one generation to the
652 next eventually results in agricultural holdings so small that
653 they cannot be farmed profitably. As farms become less
654 profitable, there is an increase in the relative value of real
655 estate as a land use compared to agroforest. The following
656 quote from a farmer in Kattappana highlights these
657 conflicting land uses (translated from Malayalam):

658 “The cost of labour is increasing, and the market price
659 for cardamom is decreasing. This year, the cost of
660 fertilizer and pesticide is double what it was last year.
661 Cardamom is like a child that requires too much care,
662 but no other crop is profitable. [...] We are planning to
663 build a lot of houses on this land for renting instead of
664 agriculture. We want to build a new house every year,
665 as they are a stable source of income.”

666 **4. Discussion**

667 **4.1 Land-use and cover changes**

668 A combination of remote sensing analysis, quantitative
669 surveys, and semi-structured interviews provided a
670 complementary means to paint a clear picture of land-use

671 and land-cover changes in Kerala between early 2000 and
672 2013. At the landscape scale, the remote sensing analysis
673 showed a pronounced increase in built area that coincided
674 with a decrease in wetlands. However, these coincided with
675 only negligible net changes in agroforestry land cover. But
676 below the canopy, at the household scale, we discovered
677 using quantitative surveys that all forms of agriculture
678 (wetland, garden, and commercial) are experiencing decline.
679 Semi-structured interviews provided narratives supporting
680 and enriching land-use and land-cover changes measured
681 using quantitative methods. The interviews provided
682 additional insights into the environmental, economic, social,
683 and political forces driving these changes.

684 If agroforests aren't decreasing in areal extent, why are 95%
685 of farmers reporting a decline in homegarden crops? First,
686 new agroforests have mainly been consigned to infilled
687 wetlands, where fewer tree crops are able to grow
688 successfully. While banana, coconut, and areca can grow
689 with limited success in wetter soils, most other dominant
690 agroforestry species have trouble establishing due to poor
691 drainage and increased prevalence of flooding. These
692 conditions typically result in highly simplified post-wetland
693 agroforests (e.g. a mix of coconut with arecanut palms and

694 banana in the understory). Second, and contributing to the
695 same problem, wetlands are often further from homesteads
696 making intensive management less convenient. Farmers are
697 therefore less likely to grow medicinal, ornamental, or even
698 food crops intended for household use due to ease of
699 access and additional labour requirements. Finally, and
700 perhaps most importantly, mature agroforests often have
701 better developed cultivated species composition than newly-
702 planted agroforests, partly because slow-growing trees have
703 had time to establish, but also because older agroforests are
704 the product of generations of stewardship of culturally
705 important agricultural resources.

706 Are increases in building and road construction also driving
707 agricultural decline? At first glance, our remote sensing and
708 quantitative survey results appear to suggest that new
709 construction of built surfaces is driving a decline in
710 agroforestry, which is in turn expanding into, and thus driving
711 the decline of, less valuable wetlands (Raj and Azeez,
712 2009). While there is likely some validity to this
713 interpretation, semi-structured interviews and quantitative
714 surveys identified numerous other drivers of land-use
715 change (e.g. declining profitability, high levels of risk, etc.)
716 that convincingly supplant real estate and construction as

717 the primary causal agents of agricultural decline.
718 Furthermore, despite a surprising number of farmers (~30%)
719 reporting new construction on their property, far more (over
720 95%) reported a decline in agriculture.

721 We therefore propose that the high rates of building and
722 road construction reported in our study are not a driver of,
723 but rather an outcome of agricultural decline. Profitability,
724 and thus cultivation of paddy has dropped sufficiently and for
725 long enough in Kerala that farmers have allowed agroforests
726 to slowly encroach upon wetlands (Guillerme et al., 2011).

727 Agroforests, subject to the same economic and
728 environmental challenges as paddy (e.g. access to inputs,
729 climate, pests, etc.), albeit to a lesser extent, have become
730 attractive and affordable real estate for a population with
731 foreign money and an appetite for large, exurban houses.

732 Agroforests, while expanding into wetlands, are most
733 susceptible to new construction, given that houses cannot be
734 built on wetlands due to legal and logistical constraints.

735 According to this explanation, which is more in line with
736 farmers' perceptions, increased rural construction is not the
737 driver of agricultural decline, but rather an unfortunate
738 byproduct of a decade or more of unprofitable and unreliable
739 agriculture. This interpretation is also in line with research by

740 (Lambin et al., 2001), which suggests that drivers of land-
741 use and land-cover change are often primarily and
742 fundamentally linked to economic opportunities available at
743 the local level.

744 Some panchayat-specific results require brief consideration.
745 First, the unexpected 11% increase in agroforest measured
746 in Poothrikka is almost certainly related to the anomalous
747 62% decline in bare ground. We suspect that Poothrikka's
748 agroforests experienced a surge in clearing just prior to the
749 acquisition of the IKONOS-2 images used for this study in
750 April 2002. This surge could have happened for various
751 reasons, such as felling trees for timber, re-planting old and
752 depleted rubber and/or coconut plantations, or clearing for
753 construction. Therefore, the measured increase in agroforest
754 is more likely a regrowth event rather than agroforest
755 expansion.

756 A second point of consideration is the state of land-use
757 change in Kalikavu, as well as other upland regions of
758 Kerala that have little to no wetland. The 52% increase in
759 built surfaces measured in Kalikavu did not have a
760 considerable effect on absolute agroforest area, despite
761 arising almost exclusively at their expense, because the
762 initial proportion of built surfaces was relatively low (only 5%,

763 compared to 15% in Avinissery). However, if Kalikavu's
764 current rate of construction continues into the future, there
765 will be a disproportionate effect on agroforests. This is
766 because wetlands, which are absent in Kerala's uplands, are
767 unable to mitigate agroforestry losses as they do in other
768 parts of the state. This consideration will be important for
769 land-use management in the future, as the effect of building
770 and road development on agriculture in rural Kerala is a
771 product of both the presence of wetland and the relative
772 areal extent of remaining agroforest.

773 In recent years, homegarden researchers have raised the
774 concern that plantation-style agriculture in Kerala is
775 replacing more species-rich and culturally important
776 homegarden-style agriculture (Kumar, 2005; Peyre et al.,
777 2006). While our results cannot provide a conclusive or
778 detailed answer to this question, we can offer some insight.
779 While Kerala's homegardens have modernized considerably
780 over past decades (Peyre et al., 2006), our results fail to
781 support the hypothesis that they are being replaced by
782 plantation agriculture. None of the commercial or plantation
783 crops investigated in our study increased in production over
784 the ten year study period, which would be expected if non-
785 plantation crops were being replaced. Farmers were

undivided in their accounts of agricultural decline in general, whether with regards to homegarden, plantation, or wetland agriculture. As previously mentioned, the increase in construction, and in turn the number of homegardens, means a decrease in mean property size, and therefore a larger number of smaller homegardens. Smaller properties are less likely to have plantations, partly because new residents are less likely to be farmers, and partly due to spatial constraints (i.e. plantations benefit from economies of scale and are not profitable when too small). Furthermore, the growing number of households may even enhance regional crop species diversity, given that smaller homegardens in Kerala and Sri Lanka have been shown to exhibit higher cultivated species richness (Kumar, 2011; Mattsson et al., 2014).

Although it is unlikely that new construction between 2001 and 2012 was a cause of the concurrent agricultural decline, increased built-area development may have other implications for agriculture in Kerala. Along with such development comes an increase in the rural population, which could contribute in other ways to the agricultural decline, most notably: 1) incoming landholders are less likely to be farmers because they often come from cities or are

809 returning from working abroad, in which case they have
810 alternative sources of income; they are also less likely to
811 enter into agriculture as they are dissuaded by low returns
812 on investment; 2) newcomers inject capital into local
813 economies, bringing with them (both directly and indirectly)
814 employment opportunities for those no longer drawn to the
815 high risk and low returns of agriculture; 3) high post-
816 secondary education attendance rates and narrowing social
817 boundaries between low- and middle-income classes have
818 produced a generation of young adults unwilling to take over
819 their parents' farms, fostering a stigma against agriculture
820 and other labour-based livelihoods; 4) new buildings are
821 constructed on partitioned land, and after a certain number
822 of partitions it becomes impossible to take advantage of
823 economies of scale. In other words, a minimum amount of
824 land is required for an agricultural operation to be profitable,
825 and Kerala's landscape is becoming increasingly
826 fragmented, consisting of smaller and smaller farms.
827 However, these potential impacts are speculative, and
828 further research would be required to monitor and identify
829 the effects of rural population growth and development on
830 Kerala's agricultural systems.

831 This increasing number of rural holdings might seem like a
832 worrying trend for conservationists, especially considering
833 Kerala's status as a biodiversity hotspot. But compared to
834 other developing hotspots, such as Southeast Asia and the
835 Amazon, where agricultural development of oil palm (in the
836 former), and pasture and soy (in the latter) have led to
837 massive deforestation (Barona et al., 2010; Koh and
838 Wilcove, 2008), Kerala's agricultural model holds some
839 promise. Homegardens as a form of intensive,
840 environmentally friendly agriculture are a working example of
841 a system in which high population density, agriculture, and
842 conservation interests can coexist (Galluzzi et al., 2010).
843 However, more research is required to assess the yield and
844 biodiversity potential of this wildlife-friendly farming model
845 (see Green et al., 2005).

846 **4.2 Mixed methods for LUCC research**

847 Taken together, the mixed methods employed in this study
848 worked in a complementary fashion to illustrate that
849 homegardens, the most common and widespread
850 agroforestry system in Kerala, may be declining in
851 agricultural importance, though not necessarily in extent,
852 numbers, or cultural importance. Each of the three methods
853 that we employed demonstrated distinct advantages and

854 limitations that, when considered together, paint a more
855 complete picture of LUCC. Remote sensing, which provides
856 a valuable means of consistently and relatively objectively
857 inferring large-scale changes in land cover over the historical
858 record, fails to capture more nuanced land-use changes and
859 is unable to probe the intangible experiences and knowledge
860 of those inhabiting the landscape. Semi-structured
861 interviews, which lack the relative objectivity of remote
862 sensing or quantitative surveys, introduce the nuance and
863 complexity of human experience, and allow for a rich
864 understanding not only of the causes of LUCC, but also of
865 the implications. Quantitative surveys can help to bridge the
866 gap between remote sensing and semi-structured interviews
867 by providing further evidence that helps to validate the links
868 researchers draw between above-canopy images and
869 below-canopy narratives. While quantitative surveys focus
870 on the human perspective, they do so by collecting data that,
871 when generalized from sample to population, may reveal
872 trends not evident to the subjects.

873 In this study, any conclusions that would have been drawn
874 from any individual method would have been deeply flawed.
875 While remote sensing analysis suggested that agroforests
876 were relatively healthy, sub-canopy investigations revealed

877 declining agroforestry despite constant areal extent. Neither
878 remote sensing nor quantitative surveys could have provided
879 the insight relating to the multiple LUCC drivers revealed in
880 the semi-structured interviews. Therefore, based on our
881 research, and in support of the ideas proposed previously by
882 Turner et al. (1994) and Lambin et al. (2003), we conclude
883 that land-use and land-cover change quantification and
884 identification of drivers in tropical regions is highly complex,
885 and warrants the adoption of a mixed-methods approach.
886 Given the inherent complexity of LUCC research, failure to
887 employ mixed methods at multiples scales could conceivably
888 lead to incomplete information and therefore inappropriate or
889 counterproductive policy outcomes.

890 **5. Conclusions**

891 We examined agricultural land use changes in Kerala using
892 a combination of remote-sensing, quantitative surveys and
893 semi-structured interviews. We found little support for the
894 hypothesis that plantations are replacing homegardens. On
895 the contrary, we found that homegarden extent is remarkably
896 stable. However, we documented a general decline in both
897 the production and importance of homegarden crops for the
898 average Kerala household, driven by changing
899 socioeconomic circumstances. Land use policy in Kerala

900 should address the broader shifts in the socioeconomic
901 landscape, rather than the physical landscape. Our study
902 demonstrates the value of a mixed-methods approach for
903 developing a richer understanding of land use changes.

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922

923

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Supplementary material

Preliminary pixel-based classification yielded insufficient accuracy for the purpose of this study. While supervised classification has been successfully used for land-cover analysis in numerous contexts (e.g. Fretwell et al., 2012; Goetz et al., 2003; Gutierrez and Johnson, 2012; Mumby and Edwards, 2002), Kerala's rural landscapes are a complex mosaic of wetlands, tree plantations, and agroforests with large spectral variability. Furthermore, built surfaces such as houses and roads are often obscured by overhanging trees or tree shadows, which led to an overestimation of tree cover and underestimation of built surfaces. We next attempted object-oriented classification, but encountered the same issues with overhanging trees and shadows.

We therefore opted for a manual classification approach (although we used supervised classification to guide our analysis as described in the next paragraph). Overhanging trees and shadows were clearly visible to the naked eye, but mischaracterized by both pixel-based and object-based classification. Manually digitizing land-cover polygons by hand is often more accurate, as shape, texture, and context can be employed, in addition to spectral characteristics (Lillesand et al., 2014; Lu and Weng, 2007). Manual classification, or a combination of manual and object-based image classification (OBIA), has been the preferred choice for classifying complex tropical landscapes (Gibbs et al., 2010; Ramdani and Hino, 2013).

The major shortfall of manual classification is the necessary time investment. Because classifying all 6 images in their entirety was too time consuming (Achard et al., 2012; Shimabukuro et al., 2014), we adopted a systematic unaligned sampling approach

(Bellhouse, 1977). For each of the three panchayats, we divided image pairs into 8 equal-area sections, generated two random points for each section, and used these 96 points to generate square 0.75 ha sample areas in ArcMap. We conducted maximum likelihood supervised classifications using ENVI to ensure that image samples were representative of the overall image. Land-cover variability between samples and parent images ranged from 0.2 to 7.9%.