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LONG-TERM CHANGE IN VILLAGE-SCALE ECOSYSTEMS IN CHINA USING LANDSCAPE AND STATISTICAL METHODS

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Abstract. Densely populated village ecosystems in subsistence agriculture regions cover a global area equivalent to two-thirds of that of tropical rainforests. Measuring long-term anthropogenic changes in these regions presents methodological challenges for ecologists, because ecosystem processes must be measured and compared under preindustrial vs. contemporary conditions within highly heterogeneous anthropogenic landscapes. In this study, we use landscape classification and observational uncertainty analysis to stratify, estimate, and compare changes in landscape structure caused by the transition from traditional to modern management within a single village in China's Tai Lake Region. Contemporary data were gathered on-site during 1993–1996 using aerial photography, field surveying, local knowledge, and household surveys, while traditional period estimates, ~1930, were obtained using interviews, back estimation, and historical sources. A hierarchical landscape classification scheme was used to stratify village landscapes into 35 fine-scale landscape components with relatively homogeneous ecosystem processes. Monte Carlo simulation and data quality indexing were used to calculate and compare village and component areas and their changes. Using this approach, we observed significant long-term declines in the proportion of village area covered by paddy (−12%), fallow, and perennial areas (−8%), and increases in areas under buildings and infrastructure (+7%). Aquatic and wetland areas increased by nearly 40% from 1930 to 1994. Significant declines in fallow and perennial vegetation and increases in constructed and heavily trafficked areas indicate overall increases in human disturbance. Our methods for observational uncertainty analysis, anthropogenic landscape classification, and the linking of imagery with field, household, and other local data are powerful tools for detecting and monitoring long-term ecological changes within anthropogenic landscapes.

Key words: agroecology; anthropogenic ecosystems; China; data quality; ecological history; ecotope; Geographic Information Systems; land use; landscape classification; Monte Carlo uncertainty analysis; research synthesis; traditional agriculture.

INTRODUCTION

Recent anthropogenic changes in biodiversity and biogeochemical cycling are a matter of serious global concern (Simpson et al. 1977, Vitousek et al. 1997). In pristine and recently disturbed ecosystems, anthropogenic changes are readily detected by comparing the current state of ecosystems with that prior to extensive human alteration (Matthews 1983). In ancient agricultural regions however, the state of ecosystems prior to human alteration is too far in the past to be useful in measuring recent anthropogenic change. Change detection in these regions therefore requires comparison of ecosystems in their preindustrial (''traditional'') and contemporary states.

Subsistence agriculture villages still feed, clothe, and house nearly half of Earth's human population (Marsh and Grossa 1996:11). In densely populated agricultural regions of Asia, 1×10^6 km^2 have been cultivated for so long that natural vegetation patterns are unknown (Matthews 1983). Based on Whittlesey (1936), we estimate the 1930s global area of intensive subsistence agriculture to be $\sim 8 \times 10^6$ km^2, two-thirds the global area of tropical rainforests or nearly half the current global area of cultivated land (Matthews 1983). Subsistence villages have covered large areas since prehistoric times, yet we expect that recent changes in population density and agricultural technology have profoundly altered traditional patterns of village land use and ecosystem management. Further, we believe it unlikely that recent changes in village ecosystem structure and function can be detected using methods developed for global-, national-, or regional-scale landscape classification and ecological change detection.

To measure recent anthropogenic changes in subsistence agriculture regions, the traditional and contemporary state of ecosystems must be compared across

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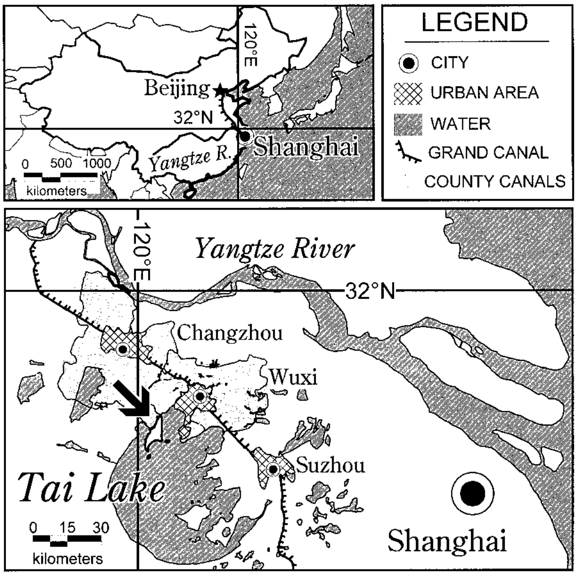

FIG. 1. Location of the village research site in the Tai Lake Region of Jiangsu Province. Latitude and longitude lines are the same in both map windows. The arrow in the lower map points to the location of Xiejia Village (31.5° N, 120.1° E). The lower map shows county boundaries and county-level canals for Wujin and Wuxi counties only. Changzhou (capital of Wujin County), Wuxi, and Suzhou cities are labeled to the right of their urban areas (see legend).

entire village landscapes. Intensive village management creates heterogeneous landscapes with ecosystem processes controlled as much by social as by environmental factors. Long-term, village-scale comparisons therefore require an anthropogenic approach for stratification of village landscapes into relatively homogeneous components based on stable differences in ecosystem processes and robust statistical methods that can integrate field, household, and landscape-scale data to measure change across landscapes. By aggregating landscape component measurements of biodiversity, nitrogen cycling, or other ecosystem properties, village and regional changes in globally important ecosystem properties, such as carbon and nitrogen sequestration, can be estimated. In this article, we measure changes in village landscape structure caused by the transition from traditional (~1930) to modern (~1994) management in the Tai Lake Region of China, an ancient agricultural region with growing environmental problems (Fig. 1; Ellis and Wang 1997, Ma 1997). In our subsequent article, we combine these measurements with soil data to estimate long-term, village- and regional-scale changes in soil and sediment nitrogen sequestration (Ellis et al. 2000).

Comparing village-scale ecosystems across long time periods is an uncertain enterprise. Even now, it is difficult to obtain high quality village-scale data, and for historical periods, data are often nonexistent, requiring subjective reconstruction from outside evidence. Moreover, all measurements of long-term change useful for decision making must precisely answer two questions: how likely are the changes observed and how reliable is the evidence? By combining probabilistic and qualitative indicators of uncertainty, we have developed an observational uncertainty analysis system that answers these questions in a form useful across disciplines.

METHODS

The study site

Xiejia Village of Xueyan Township, Wujin County, Jiangsu Province was chosen for field study in October 1993 after two field tours in the Tai Lake Region (Figs. 1 and 2). The site represents a typical floodplain rice/wheat (*Oryza sativa*/*Triticum aestivum*) subsistence village separated from urbanized areas and free of atypical developments such as special government programs. Human settlement in the village likely predates the Northern Song Dynasty (960–1126 AD), as it does in Xueyan Township, 2 km away (Zhu and Xu 1988: 97). The village is constructed on low-lying floodplain land reclaimed from wetlands near Tai Lake, and ranges from 2.5 to 5 m above sea level (Zhu and Xu 1988: 146). All village terrestrial soils were classified as ''Huangnitu'' paddy soils by national experts using field profiles and by reference to the Wujin County soil map (Wujin County Soil Survey Office 1986). We estimate traditional period management based on the average state of Xiejia Village ~1930, defined as the period between 1924 and 1935. Contemporary estimates are for 1994, defined as the period between January 1993 and December 1995.

Landscape classification

We stratify village surface area into ''ecotope'' landscape components using a four-stage classification scheme based on the hierarchy: landscape → management → biota → group. Ecotopes are defined as the smallest homogeneous ecosystem units within landscapes (Klijn and Udo De Haes 1994, Golley 1998:90), in our case, those recognizable by aerial photography or on the ground using a standardized classification system for at least two years in a row in the same location. The basic ecosystem factors we used for classification are soil class, sedimentary process, hydrology (periodicity and management), disturbance (type, intensity, and frequency), vegetation cover, and human and animal residence. By design, higher levels of the classification are larger in area and more stable over time than lower levels.

Landscape classes categorize terrain, soil, and hydrologic factors (Table 1). Aquatic and wetland landscape classes are differentiated by sedimentary process and potential for emergent vegetation, defined as a maximum seasonal water depth <1 m, separating ''depths'' from ''margins'' of water bodies >1 m deep. Margins are limited to the slopes of canal and pond

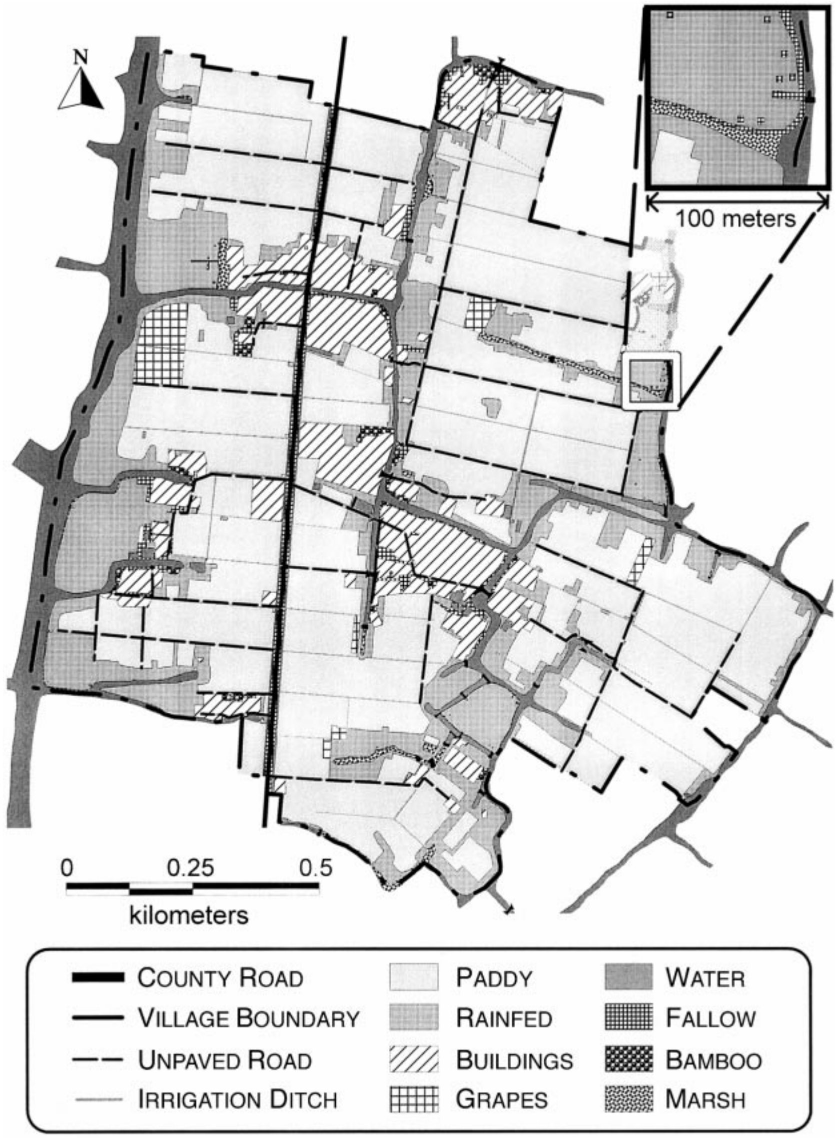

FIG. 2. Land use map of Xiejia Village, 1994. Land use types are based on aerial photography. The exploded view is a 10× magnification of a single hectare, illustrating detail not visible at lower resolution. Areas outside village borders are cleared, except for canals and the main road. The rainfed land use type refers to rainfed upland cropping systems. The county canal forms the west border of the village.

banks because there is a perched water layer <1 m below the soil surface most of the year. The ''marsh'' class is anthropogenic, representing canals and ponds filled with sediment or trash to a maximum seasonal water depth <1 m.

Management classes differentiate enduring site management factors influencing hydrology (irrigation, flooding) and disturbance (construction, cultivation, and grazing) (Table 2). Biota classes distinguish human, animal, and vegetation residence within landscapes resulting from long-term management interventions (Table 3). Groups stratify consistently observable patterns of land management, vegetation cover, and animal management that vary little over periods of a few years (Table 4). Perennial plant species that cover more than one hectare of village area are classified into separate ecotopes. Wherever possible, ecotopes overlap with standard systems of vegetation and land use classification (United Nations Educational Scientific and Cultural Organization 1973, Food and Agriculture Organization of the United Nations 1995). Table 5 lists all ecotopes classified within Xiejia Village.

Statistics

Strategy.—We estimate village-scale changes by combining measured, approximated, and calculated variables derived from household surveys, aerial photography, county records, village elder interviews, and

TABLE 1. Landscape classes for hierarchical ecotope classification.

Code	Name	Soil type	Sediment flux	Hydroperiod†	Landform†	Elevation (m)‡
T	terrestrial plain	Huangnitu paddy soil	erosion	saturated	flat	+5 to 0
M	marsh	sediment	accumulation	seasonally inundated	basin	+5 to −1
PM	pond margin	sediment	erosion and accumulation	seasonally inundated	slope	+5 to −1
CM	canal margin	sediment	erosion and accumulation	seasonally inundated	slope	+5 to −1
PA	pond	sediment	accumulation	permanently inundated	basin	<−1
CA	canal, village	sediment	accumulation and slow transport	permanently inundated	channel <30 m wide	<−1
CB	canal, county	sediment	accumulation and rapid transport	permanently inundated	channel >30 m wide	<−1

† Categories from Semeniuk and Semeniuk (1995).
‡ Elevation relative to annual maximum monthly mean surface water level.

other sources. To quantify observational uncertainty across all of these estimates and variables, we use probability distributions that describe our ''degree of belief,'' or betting odds, for the mean of each estimate (Box and Tiao 1992:14). To accomplish this, we first describe our degree of belief in those variables measured directly (measured variables) or estimated by subjective methods (subjective variables), by parameterizing probability distribution functions (PDFs) as outlined below and described in detail together with the estimation method of each variable. We then use Monte Carlo methods to derive probability densities for variables calculated as a function of other variables, such as bamboo areas calculated from household and census data and changes in area over time. To facilitate reliable comparisons between estimates that range from subjective to well sampled to somewhere in between, we use a standardized ''data quality pedigree'' index based on Costanza et al. (1992), so that the state of observations on each estimate is quantified and made explicit.

Measured variables.—We prepare PDFs for measurements on discrete variables, like the number of surveyed households with bamboo plots, using the Normal approximation of the Binomial distribution (Snedecor and Cochran 1980:117). PDFs for sampled measurements on continuous variables, such as areas and distances, were selected by fitting sample data to PDFs using Levenberg-Marquardt optimization (Palisades Corporation 1995). When Normal distributions were not rejected by Anderson-Darling or Kolmogorov-Smirnov fitting tests at $\alpha = 0.05$ (Law and Kelton 1991: 387–393), the sample mean and standard error (SE) were used to parameterize Normal (mean, SE) PDFs (note: we use a $f(\mu, \sigma)$ formulation instead of the conventional $f(\mu, \sigma^2)$). When Normal PDFs were rejected, we selected other open-form PDFs (Lognormal, Gamma, Pearson V, Weibull, Gumbel) based on fitting tests and probability plots (Law and Kelton 1991:331–340, 374–379). When no open-form PDF fit to sample data, we chose a Normal or other open-form PDF that best approximated the sample mean, median, variance, and range (maximum–minimum).

We used sample standard deviation (SD) instead of SE in PDFs for nonrandom samples and samples that were not identical with the variable to be estimated, such as regional samples used in place of village samples. We prepared PDFs for subsamples from nonrandom samples using Normal or Lognormal PDFs using the subsample mean and σ = subsample mean $\times$ sample SD/sample mean. For nonsampled direct measurements, such as geographic information systems (GIS) areas or village household count, we prepared PDFs using specific methods described along with their measurement, below. When positive rational number variables such as area or mass were described by PDFs

TABLE 2. Management classes for hierarchical ecotope classification.

Code	Name	Water management	Livestock	Cultivation
C	constructed	sealed or compacted surface	common	cleared
P	paddy crops	seasonal complete flooding	some	annual cropping
A	aquatic crops†	annual complete flooding	some	aquatic cropping
I	irrigated crops	seasonal partial flooding	none	annual and perennial cropping
R	rainfed crops	rare or infrequent low volume watering	rare	annual and perennial cropping
L	livestock	variable	intensive	grazed
V	mixed	variable	variable	variable
F	fallow	usually none	some	minimal, infrequent vegetation harvesting

† We combine this class with the ''rainfed crops'' class for analysis.

TABLE 3. Biota classes for hierarchical ecotope classification.

Code	Name	Vegetation	Domestic animals
r	residential, human	minimal	common
l	animals, large scale	minimal	intensive
f	aquatic animals†	variable	common
s	sealed infrastructure	minimal	rare
e	earthen infrastructure	some	rare
a	annual	annuals	rare
p	perennial	perennials	rare
m	mixed	variable	variable

† We combine this class with the ''animals, large scale'' class for analysis.

with a small likelihood of a negative value (<5%), we used a truncated PDF bounded at zero and the mean × 100 (Palisades Corporation 1996). If this likelihood was >5%, we chose instead a Lognormal or other positively bounded PDF.

Subjective variables.—When direct measurements are impossible, as for many 1930s variables, or are too costly or otherwise infeasible, we use methods similar to those for parameterizing subjective prior distributions in Bayesian statistics to describe our degree of belief in the mean of the variable (Berger 1980:63). We selected PDFs with mean, median, coefficient of variation (CV), shape, and range that best characterized our degree of belief across the entire range of possible

TABLE 4. Group classes for hierarchical ecotope classification.

Base code	Name	Extended code	Description†	Vegetation‡	Domestic animals
b	built-up	b1	dwellings and sealed dwelling infrastructure	minimal: SR	common
		b2	public and commercial buildings	minimal: SI	rare
		b3	paved roads and transport infrastructure	minimal: ST	none
		b4	impermeable irrigation and agriculture infrastructure	minimal: SI	rare
		b5	unpaved roads and access	minimal: ST	none
		b6	permeable irrigation	minimal: SI	rare
		b7	bare earth and permeable agricultural infrastructure	minimal: SR	none
a	domestic animals	a1	chickens, broilers, medium-scale confinement	minimal: SI	intensive
f	aquatic animals	f1	fish, herbivorous, small-scale	minimal: HI	intensive
c	annual crops	c1	annual crops	crop: AA4	rare
p	perennial crops	p1	orchard trees, peaches (*Prunus persica*) dominant	crop: AT1/AT2	rare
		p2	vineyard, *Vitis* sp. dominant	crop: AT3/AT4	rare
		p3	mulberry, *Morus alba* dominant	crop: AT3	rare
r	hydromorphic crops	r1	double cropped rice paddy, rice/wheat dominant	crop: AA5	rare
		r2	rice transplanting paddy, rice dominant	crop: AA5	rare
		r3	nonrice rooted wetland crops	crop: AA5	rare
		r4	floating and submergent crops	crop: AA5	rare
v	annual vegetation	v1	weeds, larger patches	VC/VD	rare
		v2	field borders, soybean (*Glyxine max*), broad bean (*Vicia faba*), annual weeds dominant	VC/VD	rare
g	tall graminoids	g1	tall grass, *Miscanthus sinensis* dominant	VA5	none
		g2	bamboo thicket, *Phyllostachys nigra* dominant	bamboo thicket	rare
t	perennial vegetation	t0	brush and weeds	IVB3	rare
		t1	medium trees, saplings and scrub	IIIB3	rare
		t2	mature trees, closed canopy, mainly deciduous	IIB2	rare
		t3	grave vegetation	VD2/IIIA/IIIB	rare
		t4	public planted trees, *Metasequoia glyptostroboides* dominant	crop: FP	rare
h	hydromorphic annual vegetation	h1	rooted, floating leaf and floating vegetation	VE1	some
		h2	floating and submergent vegetation	VE2	some
m	mixed management	m1	mixed: hydromorphic and mesomorphic vegetation, animal management	VE1/VC/VD	common

† Where unspecified, vegetation or crops are mesomorphic.
‡ Minimal and crop classes are from the Food and Agriculture Organization of the United Nations (1995:62); other vegetation classes are from page 63 of the same source.

TABLE 5. Xiejia Village ecotope key.

Code†	Label‡	Description	Area (ha)§ 1930	Area (ha)§ 1994
TCrb1	dwellings	residential buildings, including outbuildings	3.5 (1.7, 5.7)	11 (9.0, 14)
TCla1	chicken house	confined chicken production, medium scale	···	0.046 (0.02, 0.087)
TCsb2	public buildings	industry, government, education, and commerce buildings	···	2 (1.4, 2.8)
TCsb3	roads, paved	paved roads and covered transportation infrastructure	···	1.2 (1.1, 1.3)
TCsb4	irrigation, sealed	sealed irrigation ditches and agricultural infrastructure	···	0.13 (0.10, 0.20)
TCeb5	roads, unpaved	unpaved roads, paths, and unsealed access areas	1.7 (0.81, 3.8)	1.6 (0.74, 3.5)
TCeb6	irrigation, unsealed	unsealed earthen irrigation ditches	0.023 (0.002, 0.062)	1.2 (0.53, 2.5)
TCeb7	bare earth	bare, compacted earthen agricultural infrastructure	1.8 (0.79, 3.0)	0.43 (0.059, 1.1)
TPar1	paddy, double crop	rice paddy, double cropping	106 (91, 120)	75 (70, 80)
TPar2	paddy, transplanting	rice paddy, transplanting area, often single cropping	···	11 (9.7, 12)
TIpp1	orchard, irrigated	irrigated orchard, peaches dominant	···	5.7 (3.5, 8.3)
TIpp2	vineyard, irrigated	irrigated vineyard, *Vitis* sp. dominant	···	2.3 (2.1, 2.5)
TRav2	field borders	paddy field borders, soybean, broad bean, annual weeds dominant	1.9 (0.62, 4.8)	3.9 (2.3, 5.9)
TRac1	crops, rainfed	rainfed annual crops, small-scale	2.9 (1.5, 4.8)	22 (18, 25)
TRpp1	orchard, rainfed	rainfed orchard, peaches dominant	0.036 (0.012, 0.069)	2.6 (1.6, 3.9)
TRpp2	vineyard, rainfed	rainfed vineyard, *Vitis* sp. dominant	···	0.41 (0.28, 0.58)
TRpp3	mulberry	rainfed mulberry cropping	18 (12, 25)	···
TFav1	annual weeds	annual weeds, larger patches	2.4 (0.52, 6.7)	2.2 (0.68, 5.6)
TFpg1	tall grasses	tall grass thicket, *Miscanthus sinensis* dominant	1.8 (0.76, 3.3)	0.43 (0.13, 1.2)
TFpg2	bamboo	bamboo thicket, *Phyllostachys nigra* dominant	1.8 (0.76, 3.4)	0.95 (0.84, 1.1)
TFpt0	brush and weeds	brush and weeds	0.64 (0.088, 2.2)	0.50 (0.11, 1.6)
TFpt1	trees, medium	medium trees, saplings and scrub	1.6 (0.44, 4.1)	1.1 (0.36, 2.8)
TFpt2	trees, mature	mature trees, closed canopy, mostly deciduous	2.9 (0.40, 8.6)	1.1 (0.18, 3.3)
TFpt3	graves	grave vegetation, perennials and annuals	3.0 (1.6, 5.4)	0.11 (0.048, 0.20)
TFpt4	public trees	roadside area, government planted *Metasequoia glyptostroboides* saplings, crops and annual weeds	···	0.80 (0.73, 0.86)
MAar3	wetland crops	lentic wetland: nonrice rooted emergent and floating leaf crops	0.41 (0.04, 1.4)	0.36 (0.095, 0.63)
MFah1	wetland vegetation	lentic wetland: rooted, emergent and floating leaf vegetation	···	0.63 (0.35, 0.91)
PMVmm1	pond margins	pond margins: variable vegetation and livestock	0.009 (0.002, 0.022)	0.55 (0.43, 0.74)
PALff1	fishponds	pond depths: fish, herbivorous, small-scale	0.054 (0.024, 0.11)	0.55 (0.35, 0.79)
PAAar4	pond, crops	pond depths: nonrooted, floating crops	···	0.024 (0.006, 0.046)
PAFah2	pond, fallow	pond depths: floating and submergent vegetation	···	0.82 (0.53, 1.1)
CMVmm1	canal margins	canal margins: variable vegetation and livestock	1.3 (0.34, 2.9)	2.5 (2.1, 2.83)
CAAar4	canal, crops	village canal depths: nonrooted, floating crops	0.43 (0.18, 0.84)	0.42 (0.32, 0.54)
CAFah2	canal, fallow	village canal depths: floating and submergent vegetation	3.3 (0.92, 6.7)	3.4 (2.9, 4.0)
CBFah2	county canal, fallow	county canal depths: floating and submergent vegetation	2.8 (1.5, 5.1)	2.7 (2.5, 2.9)

† Codes are constructed from hierarchical ecotope classification classes in Tables 1–4.
‡ Labels used in charts.
§ Median and 90% credible interval (CIN in parentheses) of ecotope area estimates.

TABLE 6. Pedigree matrix for observational uncertainty analysis (adapted from Costanza et al. 1992).

Score	Statistical quality	Empirical quality	Methodological quality
4	excellent fit to a well-known statistical model (Normal, Lognormal, Binomial and soon)	controlled experiments and large sample direct measurements ($n \geq 50$)	approved standard in well-established discipline
3	good fit to a reliable statistical model by most fitting tests, but not all	historical/field data, uncontrolled experiments, small sample direct measurements ($n < 50$)	reliable method, common within discipline
2	fitting tests not significant, model not clearly related to data, or model inferred from similar data	modeled data, indirect measurements, handbook estimates	acceptable method, but limited consensus on reliability
1	no statistical tests or fitting, subjective model	educated guesses, very indirect approximations, ''rule of thumb'' estimates	unproven methods, questionable reliability
0	ignorance model (uniform)	pure guesses	purely subjective method

values for the variable (Carlin and Louis 1996:27–28). We compensate for the tendency to underestimate uncertainty by increasing our initial range estimates for subjective variables by at least 20% (Morgan and Henrion 1990, Cooke 1991). In all cases, we ensured that subjective variables had spreads 4 to 100 times larger than those typical for measured variables by setting their CVs 2 to 50 times larger than typical for sampled measurements on the same variables. Estimates for traditional period variables were always given larger CVs than contemporary estimates for the same variable except when contemporary and past variables were equally unknown. Though traditional period estimates were limited to indirect data, where possible we combined estimates made by different methods to improve data quality for this period.

We prepared PDFs for well-understood variables, like areas sampled in 1994 but not in 1930, using PDF families typical for measurements on the variable, like Normal and Lognormal, with σ equal to our estimated range/4, with the range increased by 20% of the mean to compensate for overconfidence. In cases where little was known about a variable, as was the case for many village elder estimates, we generated PDFs by the method above but with truncated Normal or Lognormal PDFs to eliminate negative values, or by specifying a symmetric Beta ((Beta(α, α) -0.5) $\times$ range + average), a BetaSubjective with mean, minimum, maximum, and mode adjusted to give an appropriate CV and shape (Palisades Corporation 1996), by describing a histogram that was then fit to a PDF (Carlin and Louis 1996: 27–30), or by a method described along with the estimate in the methods below.

Combining multiple estimates on a single variable.—When multiple estimates on the same variable were made using independent methods, we averaged them by one of two methods, depending on whether they were measured directly. Multiple subjective estimates were combined using equal weighted averaging. All other multiple estimates were averaged using normalized inverse variance weights (W_i) calculated by the equation

$$W_i = \frac{\sigma_i^2}{\sum_{1}^{m} \sigma_i^2} \quad (1)$$

where σ_i^2 is the variance of the ith variable and m = the total number of estimates (Scheffé 1959:174).

Calculations using Monte Carlo methods.—We characterized probability densities for variables calculated from other variables using frequency distributions from 10 000 Latin Hypercube Simulation iterations (LHS) in @RISK software for Microsoft Excel; this was sufficient to stabilize all mean and SD estimates (LHS is an advanced form of Monte Carlo simulation; Morgan and Henrion 1990:204, Palisades Corporation 1996, Microsoft 1997*a*). We use medians instead of means to present our best estimates for calculated variables and describe the range of most likely values using 90% credible intervals (CIN), in the form: (5 percentile, 95 percentile; Morgan and Henrion 1990:84). When LHS yielded negative values for variables that could not be negative, such as area and length, we used conditional functions to invert the sign of negative values when $P(x < 0) < 0.2$, and to set them equal to zero when $P(x < 0) > 0.2$. This removed unrealistic values without large changes in mean, median, or variance. Separate PDFs were used to eliminate correlation between duplicated estimates.

Data quality pedigree.—We use a data quality pedigree modified from Costanza et al. (1992) to represent the statistical (stat), empirical (emp), and methodological (meth) quality of each variable based on three subjectively chosen ordinal scores from 0 to 4 as described in Table 6. Statistical quality scores describe our choice of statistical model, with higher scores given to PDFs fitted to sample data and lower scores to those chosen by more subjective methods. Empirical quality represents the degree to which we used direct observations to measure the variable. Methodological quality ranks our perception of the acceptance that peer review within the relevant discipline would give to the methods used for measurement. Pedigree scores are expressed using the notation {stat, emp, meth} or as a grade, normalized from zero to one, equal to: (stat + emp + meth)/(4 + 4 + 4) (Costanza et al. 1992). Variables with pedigrees less than {2, 2, 2} (grade < 0.5) can be considered subjective, and those above, directly measured.

We use a Visual Basic program (Microsoft 1997*b*) to compute pedigrees for variables that were calculated from other variables, based on principles outlined by Costanza et al. (1992; see Supplementary Materials). Pedigrees for the sum of added variables were calculated as the mean weighted average of the input pedigrees (MWA):

$$\mathrm{MWA} = \sum_{i}^{n} \left(P_i \times \frac{\bar{X}_i}{\sum_{i}^{n} \bar{X}_i} \right) \qquad (2)$$

where P_i = pedigree of the *i*th variable, $\bar{X}_i$ = mean of the *i*th variable, and n = the total number variables to be added. For multiplication and division we used the minimum pedigree of all input variables. Pedigrees for subtraction and weighted averaging depend on the degree to which the spread of the input variables ($S, = 2\sigma$) was similar to the difference between them (D).

When the difference between variables is much greater than their spread, as indicated by $D/S > 5$, Costanza et al.'s (1992) rule of thumb, we used MWA pedigrees for the results of subtraction and averaging. When $D/S < 5$, the difference between variables is similar to their spread, so subtracting them yields an estimate with greater uncertainty than the original variables. Pedigrees for these subtracted variables were reduced to $0.5 \times$ MWA when $D/S < 2$, and to $(1 - (5 - D/S) \times 0.5/3) \times$ MWA when D/S was between 2 and 5 (Costanza et al. 1992). When multiple estimates on a variable differ significantly less than their spread, i.e., $D/S < 5$, we increase our confidence in their average estimate by increasing its weighted average pedigree (WA, = MWA or equally weighted average, as described above) by $0.5 \times (\{4, 4, 4\} - \mathrm{WA})$ when $D/S < 2$ and by $(5 - D/S) \times 0.5/3 \times (\{4, 4, 4\} - \mathrm{WA})$ when D/S was between 2 and 5. For all averaged variables, we increased pedigrees by adding $0.05 \times$ (number of variables) to the WA, slightly increasing pedigrees whenever multiple independent method estimates were averaged. We limited pedigree increases to +{1, 1, 1} when averaging measured variables (weights from Eq. 1), and to half as much +{0.5, 0.5, 0.5} when subjective estimates were combined (equal weights). In keeping with their subjective nature, pedigrees are expressed as ordinals in the text. Using these methods, pedigrees of subtracted variables are revised downward whenever their differences are more uncertain than their original values, and the pedigrees of averaged estimates are always greater than single estimates, with significant increases (≤ 1) when multiple measurements on the same variable agree.

1994 village land use mapping

We prepared a nongeoreferenced, land use geographic information system (GIS) for Xiejia Village using MapInfo software (MapInfo 1995) based on a xerographic copy of a 1:10 000 scale aerial photograph taken in May 1991 (Fig. 2). Land use (LU) boundaries and features were traced for digitizing, limiting linear accuracy to 3.5 m, similar to the digitizer error (3.4 m). In November 1994, discrepancies and details >50 m^2 in size were field-verified, corrected, and redrawn on 1:1000 scale GIS printouts and redigitized, correcting the GIS. Village boundaries were field-verified with village leaders based on a 1:10 000 scale Xueyan Township map.

No significant distortion was observed when 48 standard land reform paddy field widths were compared in six locations across the photograph (one-way ANOVA $P = 0.4$; Snedecor and Cochran 1980:215). Skewing was also nonsignificant when field-surveyed and GIS-estimated distances were compared across 11 larger paddy areas. However, surveyed lengths were shorter than those from GIS (paired difference t test $P = 0.024$; Snedecor and Cochran 1980:85). Because this scaling error was <2% and was marginally significant, we did not apply a correction factor but instead compensate for this uncertainty by setting the minimum CV for all GIS estimates equal to 2%.

All GIS estimates were parameterized using Lognormal PDFs, as these fit best to repeated GIS measurements. Areas were calculated by adding LU polygon areas and SDs were predicted from polygon areas using a regression equation of SD on the mean area of 15 LU polygons differing in shape and size, re-digitized five times ($\mathrm{SD} = 0.56 \times \mathrm{area}^{0.62}$, $R^2 = 0.93$, $P < 0.001$; SPSS 1995). LU area SDs were adjusted to the 2% minimum CV, and the canal LU area CV was set to equal the water LU CV (~5%), to compensate for the exceptional size and convolution of canal polygons.

Fallow recognition bias and fallow ecotope areas.—Patches of fallow land were frequently included within the building and rainfed crop LUs. To correct for this bias and to measure fallow ecotope areas, 15 widespread sample locations comprising 9% of total village area were chosen in 10 sites near rainfed crops (5 along canals, 5 not) and in 5 sites near buildings. We resurveyed each sample area, redrew LU areas on 1:1000 scale GIS printouts, redigitized them, and measured LU areas before and after surveying. During the resurvey, the percent cover of each ecotope was estimated visually for each fallow LU area. For each LU type observed in more than three sample sites, we calculated fallow recognition bias as the mean difference in each LU area before and after sampling, multiplied by the ratio of the total sample space to the mean sampled area. Bias was calculated separately for the ''near buildings'' and ''near rainfed crop'' sample spaces. Bias was added to LU areas and bias sample SDs were used in place of GIS SDs whenever they were greater.

Fallow ecotope areas were calculated as the product of ecotope area proportions and the fallow LU area. Ecotope area proportions were calculated from fallow area percent cover samples using Normal (mean, SE) PDFs corrected for area near buildings vs. rainfed crops, truncated at zero and 1, and normalized by dividing them by their sum. Because the bare earth ecotope was poorly sampled ($n = 3$), we parameterized its area directly using a truncated Normal with 300% CV.

Estimates from GIS.—GIS LU areas were direct estimates for the paved road, unpaved road, irrigated vineyard, and bamboo ecotope areas (Fig. 2, Table 5). We estimated management areas (sealed and unsealed irrigation, fishponds, water crops, roadside ponds, dammed canal ponds, concrete-bordered canals, and constructed ponds) and some ecotope areas (chicken house, public building, public tree, and wetland crops) by identifying them in the field and parameterizing them using GIS area PDFs. Perimeters from GIS were parameterized as Lognormal PDFs with CVs of 5% or greater.

Areas for the unsealed and sealed irrigation ecotopes were calculated by multiplying their GIS areas by the fraction of the irrigation LU area occupied by water channels. This fraction was calculated by dividing water channel area (GIS-estimated ditch length $\times$ sampled ditch width $\times$ the proportion of double-ditches $+ 1$) by irrigation LU area. We calculated field border ecotope area by adding the area of the irrigation LU not occupied by water channels to the area of paddy dikes (dike width $\times$ paddy LU area/paddy field width). We estimated double crop and transplant paddy ecotope areas from the paddy LU area (minus dikes) times the village standard ratio of transplanting to double crop area. Grave area was estimated by two methods: (1) rainfed crop area $\times$ grave to rainfed crop area ratio (field sample, $n = 8$), and (2) number of graves per household (surveyed, below) $\times$ total village households $\times$ individual grave area (field sample, $n = 42$). Irrigated orchard ecotope area was estimated from a 1980 village map. Irrigated grape area was calculated from the number of growers and their areas (village leader estimates). Fallow marsh ecotope area was calculated by subtracting wetland crop ecotope area from marsh LU area.

Household surveys

We define village households as families and dependents residing within a set of buildings with shared land management, cooking, and toilet facilities. A Xiejia Village household database was derived using this definition from the official village household list and the resulting household count was parameterized using a histogram fit to a Gumbel PDF.

A four page, cross-checking, Chinese survey schedule was developed using a nonrandom 22-household test survey. The schedule was then used to survey a 50-household random sample from the household database using structured interviews lasting approximately one hour in spring 1994. In summer 1995, a 20-household subsample was resurveyed using a more carefully cross-checked, seven page, three hour survey to collect more detailed information and test for bias. Households were paid for participation, questions were posed in Mandarin and local dialect, and survey coverage was 100%. Survey bias was calculated as the mean of the response differences between the original and subsample survey. Bias was added to the sample mean when the survey bias/SD ratio was >0.15 (bamboo, rainfed orchard, and grape ecotope areas) (Cochran 1977:14).

The proportion of surveyed households possessing a particular ecotope or other item was parameterized using the Normal approximation of the Binomial distribution whenever this proportion was <1 (Snedecor and Cochran 1980:117). Mean areas and amounts of items per household having the area or item were parameterized using Normal PDFs. Village-scale areas and amounts were calculated by multiplying PDFs for household means and proportions by the village household count. Residence-corrected persons per household was calculated from respondent-estimated annual residence proportions (days resident/365) for each household member. Village population was calculated by multiplying village household number by the residence-corrected persons per household; bias was nonsignificant.

Traditional period estimates

Village elder interviews.—Village data for 1930 were collected in 1995 using semi-structured, paid two-day interviews with three teams of two elder villagers, aged 72 to 85. Afterwards, four elders with clearest recall were regrouped to reach consensus on estimates. Informants estimated typical, minimum, and maximum 1930s areas by three methods: (1) recalling their own households, (2) estimating the state of ''typical'' village households, (3) estimating village areas as a proportion of 1994 areas, and (4) estimating village areas directly.

Data from methods 1 and 2 were aggregated to estimate areas of dwellings, paddy, mulberry, rainfed annual crops, graves, and threshing floors. Areas of dwellings, paddy, bamboo, wetland crops, rainfed orchard, unsealed irrigation, and total fallow land were calculated using method 3. Mulberry area in 1930 was estimated relative to 1994 paddy and irrigated orchard area. Fallow area was partitioned into ecotopes using 1994 ecotope area proportions with CVs increased by 50%, and with the relative proportions of bamboo and tall grass increased by 20%. Tall grass area was also estimated directly. Paved roads, public buildings, chicken houses, sealed irrigation, transplant paddy, irrigated orchards, grapes, public trees, fallow marshes, fallow ponds, and cropped ponds were not present in 1930. Village population and household number in 1930 were estimated directly and by aggregating estimates for ''natural villages'' (housing clusters); these were pooled to make Normal (average, range/4) PDFs.

Changes in water bodies, buildings, and roads recognized by village elders from our 1994 village GIS were used to ''backcast'' 1930s areas. Canals recalled as narrower and deeper in 1930 were modified and measured by buffering canal polygons by $-2/3 \times 1994$ canal margin width. The village covered almost exactly the same area in 1930 as in 1994, and was estimated as 1994 village area with a 5% CV.

Estimates from 1930s aerial photography.—A 1930s aerial photo of village landscapes <20 km from Xiejia (Buck 1937*a*:142, Photo 4) was digitized and size-referenced using houses, compost pits, and graves. The observed ratio of paddy dike length to paddy area was used to calculate field border area from elder-estimated 1930s paddy area and dike width. Small path area was calculated from observed path length to total area ratio × elder-estimated small path width × village area. Unpaved road area was calculated as small path area + main path area (1994 road length × elder-estimated 1930 width).

Historical data.—Xiejia 1930 household count was calculated from the 1994 count × the 1930 to 1994 county household ratio for Wujin and Wuxi estimated from the 1926–1934 averages for each county (Chang 1930, Bureau of Foreign Trade 1933, Zhu and Xu 1988, Tan 1994) and 1994 linear forecasts from 1980–1991 data (Village Socioeconomic Survey Team of the National Statistics Bureau 1989, 1993). Village population was estimated by the same method.

Household area of dwellings, threshing floors, paddy, rainfed crops, orchard, mulberry, and graves was estimated from 1930s surveys in Wujin and Wuxi (Buck 1930, Buck 1937*b*) and from county data (Chang 1930, Huang 1990). PDFs for different years and sources were parameterized separately and combined using equal weights; village area = area per household × village household count. Bare earth ecotope area = threshing floor area + nonthreshing floor bare area (1930 dwelling area × 1994 bare earth area/1994 dwelling area × 2/3).

Canal and pond areas

To partition canals and ponds into margin and depth ecotopes (Table 1), we surveyed cross sections of a nonrandom sample of 13 canals with varied widths across the village and in one pond in May 1995. A surveying tape was stretched across the tops of canal banks and a measuring rod was deployed from a boat to measure vertical distances from tape to water and sediment surface at 2-m intervals and at water margins. There were no significant differences between surveyed and GIS-estimated canal bank widths (random sample, $n = 117$) in terms of mean or variance (two-tailed t test $P = 0.6$; Levene's test $P = 0.2$; Snedecor and Cochran 1980:253). We therefore fit each canal cross section to a polynomial model by regression and graphical appraisal (2nd to 6th order, $R^2 > 0.97$), to generate samples of village canal dimensions for Normal sample PDFs.

Canal margin width was calculated by correcting cross section models for the difference between sampled (May) and annual maximum water depth (July), based on Tai Lake water levels (Zhu and Xu 1988:164). We approximate 1994 constructed pond margins as one-half canal margin width. Water areas and perimeters in 1930 are from the elder-corrected village GIS. Elders estimated canal and pond margin width as one-third the 1994 canal margin width. Margin areas were calculated as margin width × earthen perimeter length (concrete margin width = 0); depth areas = total water area − margin area.

Area normalization

When a set of ecotopes completely fills a larger region whose area can be measured independent of the ecotope areas, we normalized the sum of the ecotope areas to the area of the larger region using the equation

$$\mathrm{NA}_i = \mathrm{RA} \times \frac{A_i}{\sum_{1}^{n} A_i} \tag{3}$$

where NA_i = normalized ecotope area, RA = area estimate for the larger region, A_i = the ith independent ecotope area estimate, and n = the total number of ecotope areas in the larger region. This method limits variance in the sum of ecotope areas to the variance of the larger region. Ecotopes within the 1994 building and rainfed crop LUs were normalized using Eq. 3; no other ecotope/region estimates fit the criteria for normalization. After normalizing within LUs, complete sets of village ecotopes were normalized within village area estimates for 1930 and 1994.

RESULTS

Using observational uncertainty analysis to measure long-term change

We demonstrate our observational uncertainty analysis approach to long-term change measurement using bamboo ecotope area as an example, as illustrated by the statistics, probability densities, pedigrees, and boxplots in Table 7 and Fig. 3. Original variables in Table 7 are measured or estimated directly (*A*–*E*), while derived variables (*F*–*J*), such as household survey village

TABLE 7. Example of observational uncertainty analysis: change in bamboo ecotope area from 1930 to 1994.

Variable†	Description	Median	Mean	Credible interval‡	Units	CV (%)	Pedigree§	Function‖
Original variables								
1994								
A	bamboo area from village GIS	0.99	0.96	(0.93, 1.1)	ha	6	{3, 3, 3}	Lognormal
B	bamboo area per surveyed household	0.0032	0.0033	(0.0010, 0.0056)	ha/household	43	{4, 3, 2}	Normal
C	proportion of surveyed households with bamboo	0.48	0.48	(0.36, 0.60)	ratio	15	{4, 4, 2}	Normal
D	village household count	448	451	(429, 481)	households	4	{2, 3, 3}	Gumbel
1930								
E	bamboo area, informant estimate	1.8	1.9	(0.77, 3.4)	ha	42	{1, 1, 1}	BetaSubjective
Derived variables								
1994								
F	bamboo area, household survey estimate	0.69	0.71	(0.21, 1.3)	ha	45	{2, 3, 2}	$B \times C \times D$
G	bamboo area, average of survey and GIS estimates	0.98	0.95	(0.92, 1.1)	ha	6	{3, 4, 3}	$A \times W_1 + F \times W_2$¶
H	bamboo area, village normalized	0.98	0.98	(0.89, 1.1)	ha	6	{2, 3, 2}	Normalized (*G*)#
1930								
I	bamboo area, village normalized	1.8	1.9	(0.75, 3.5)	ha	45	{1, 1, 1}	Normalized (*E*)
Difference, 1994–1930								
J	Change in bamboo area	−0.81	−0.93	(−2.5, 0.24)	ha	92	{1, 1, 1}	*H–I*

† Uppercase letters denote identical variables in Fig. 3.
‡ 90% credible interval (CIN), bounding the region $0.05 < P < 0.95$.
§ Data quality pedigree ({statistical, empirical, methodological}; see Table 6).
‖ Probability distribution functions families are shown for original variables; derived variables are described as a function of original variables.
¶ Weighted average of multiple direct estimates with weights (W_i), calculated using Eq. 1.
# Ecotope area normalized to village area using Eq. 3.

bamboo area (*F*), are calculated from original variables using Monte Carlo simulation and the pedigree calculation algorithm. Derived variable pedigrees illustrate that a single low data quality estimate lowers data quality for any variable calculated by multiplication, and that the pedigree of differences between variables is very low when their difference is small and uncertain. The change in bamboo area from 1930 to 1994 is calculated as the difference between estimates for 1930 and 1994, *J*, with zero meaning no change and positive values representing an increase from 1930 to 1994.

Our 1994 estimated bamboo area (*H*) is lower than that for 1930 (*I*), indicating that bamboo area has decreased, as does the difference estimate, *J*, which is mostly below zero (Fig. 3). Moreover, our median estimate for the long-term change in bamboo area is −0.8 ha with a 90% credible interval (CIN) of (−2.5 ha, 0.2 ha) and an 87% probability that the change was negative: $P(J < 0) = 0.87$. We interpret this by saying that our evidence supports a net decrease in bamboo area with 87% probability (9:1 odds), most likely by 0.8 ha, though our evidence is weak, with a {1, 1, 1} pedigree, indicating a subjective estimate that will be much improved by further observations.

Village-scale changes in landscape structure

Though Xiejia Village covered roughly the same 162-ha area in 1930 as in 1994 (1994 area CIN = 156, 167; difference CIN = ±14 ha), modernization and population growth have altered the landscape substantially. The total village area of each ecotope in 1930 and 1994 is presented in Table 5, while Fig. 4 portrays ecotope and landscape class areas as a proportion of village area. Fig. 5 illustrates changes in ecotope and landscape class areas between 1930 and 1994. Ecotope estimates illustrate fine-scale changes, while broader changes are apparent in the landscape, management, and biota class estimates. Observational uncertainties are indicated using CVs, boxplots, and data quality pedigrees identical with those demonstrated in our bamboo

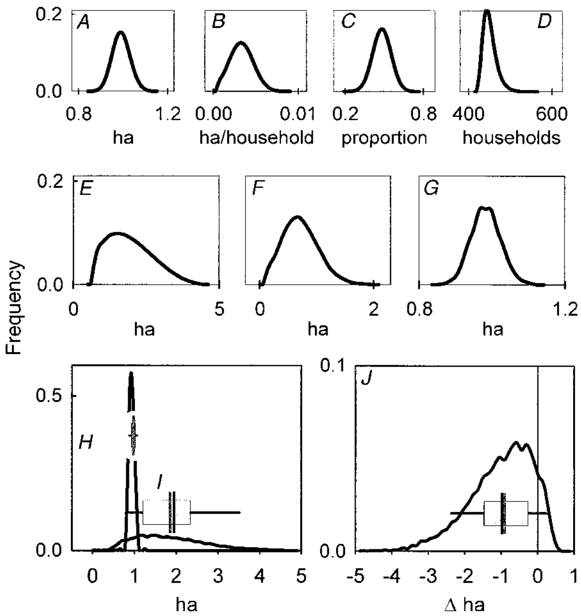

FIG. 3. Frequency distributions for variables in Table 7. Plot labels *A–J* correspond to variable labels in Table 7. Frequencies are charted on the *y*-axis, with ranges from 0 to 0.2 for plots *A–G,* and as marked for plots *H–J* (note that plots *H* and *I* are combined). A vertical line is drawn at $x = 0$ in *J*. Horizontal boxplots are drawn on plots *H, I,* and *J,* with a vertical black line depicting the mean, a vertical dark gray line for the median, a gray box bounding the interquartile range, and whiskers to the 5th and 95th percentiles.

area example, above (Table 7 and Fig. 3). In the boxplots of Figs. 4 and 5, estimates with interquartile ranges that do not overlap are different with ≥75% probability; this probability is >95% when their whiskers do not overlap.

Xiejia Village was dominated by just two ecotopes in 1930, paddy and mulberry, occupying 77% of total village area (Fig. 4). In 1994, the same proportion of village area was divided among the top five ecotopes. Between 1930 and 1994, the total number of ecotopes in Xiejia Village increased from 23 to 34, and of the 12 new ecotopes (mulberry was lost), four were constructed types, increasing the sealed surface area of the village (Fig. 4). Changes in irrigation infrastructure divided paddy land into double crop and transplanting ecotopes, so that paddy class area is a better indicator of long-term change than paddy ecotope areas. Large-scale irrigated grape and peach production, small-scale grapes, pond crops, fallow marsh areas, and public trees are other new additions to the landscape.

The most significant change in village landscape structure since 1930 is the net decline in paddy area from 65% to 53% of total village area in 1994 (Figs. 4 and 5). This 12% decrease (CIN = 3%, 22%) was caused by an 8% increase (3%, 13%) in the proportion of village area under irrigated and rainfed agriculture, a 7% increase (4%, 10%) in buildings and infrastructure and a 2% increase (CIN = −1%, 4%) in aquatic and wetland areas. Total agricultural area declined from ~81% of village area in 1930 to 77% in 1994, and fallow area also declined by 4% of total village area (CIN = −2%, 12%). Though the village's proportion of wetland and aquatic area increased by only 2%, this translates into a 38% (CIN = −10%, 110%) net increase in area of these ecotopes since 1930, a significant change. Village area under perennials decreased from 19% to 10% in 1994 (9% decline; CIN = 3%, 16%) as mulberry-fed silk production ceased, graves were eliminated, and fallow land was planted to annual crops.

Though landscape associations between ecotopes were flexible, we observed most fallow areas near canals and dwellings, and rainfed crops and dwellings were usually associated with canals. In 1930, graves were scattered throughout paddy and other agricultural land, and mulberry was most common near canals, according to elder informants and 1930s aerial photography. In 1994, concrete-edged canals were always near houses, and graves were usually within upland crop areas.

Population and land

Though village area did not change, village population nearly doubled between 1930 and 1994, from 960 (CIN = 719, 1238) persons in 210 (CIN = 159, 266) households in 1930, to 1735 (CIN = 1590, 1896) persons in 448 (CIN = 429, 481) households in 1994. Consequently, village population density increased from 5.9 (CIN = 4.4, 7.7) to 10.7 (CIN = 9.8, 11.8) persons per ha. Average paddy land per capita decreased even more, from 0.11 (CIN = 0.082, 0.15) ha in 1930 to 0.051 (CIN = 0.046, 0.055) ha in 1994, as did per capita agricultural land, which declined from 0.14 to 0.07 ha. Over the same period, village area under buildings and infrastructure increased to ~11%, up from 5% in 1930, mostly because per capita residential area increased from 37 m^2 in 1930 to 67 m^2 in 1994.

Corroboration and integration of estimates

Our 1994 estimates of village area, population, and paddy area agree with Xueyan Township statistics for Xiejia Village in 1993 (total area = 166 ha, population = 1802 persons, ''grain area'' = 89 ha). Though our household count was lower than the township statistic (503 households), this resulted mostly from differences in household definition, as village accountants recognized only 489 households and we corrected for emigration and cohabitation.

Field sampling increased 1994 fallow land areas estimated by aerial photography from 1.7% to 4.5% of the total village area, while decreasing the area of buildings and rainfed crops by 1% and 1.5%, respectively. Though this method also increased CVs for these estimates, the field corrected areas are far more reliable than those directly from GIS. Still, the high variance

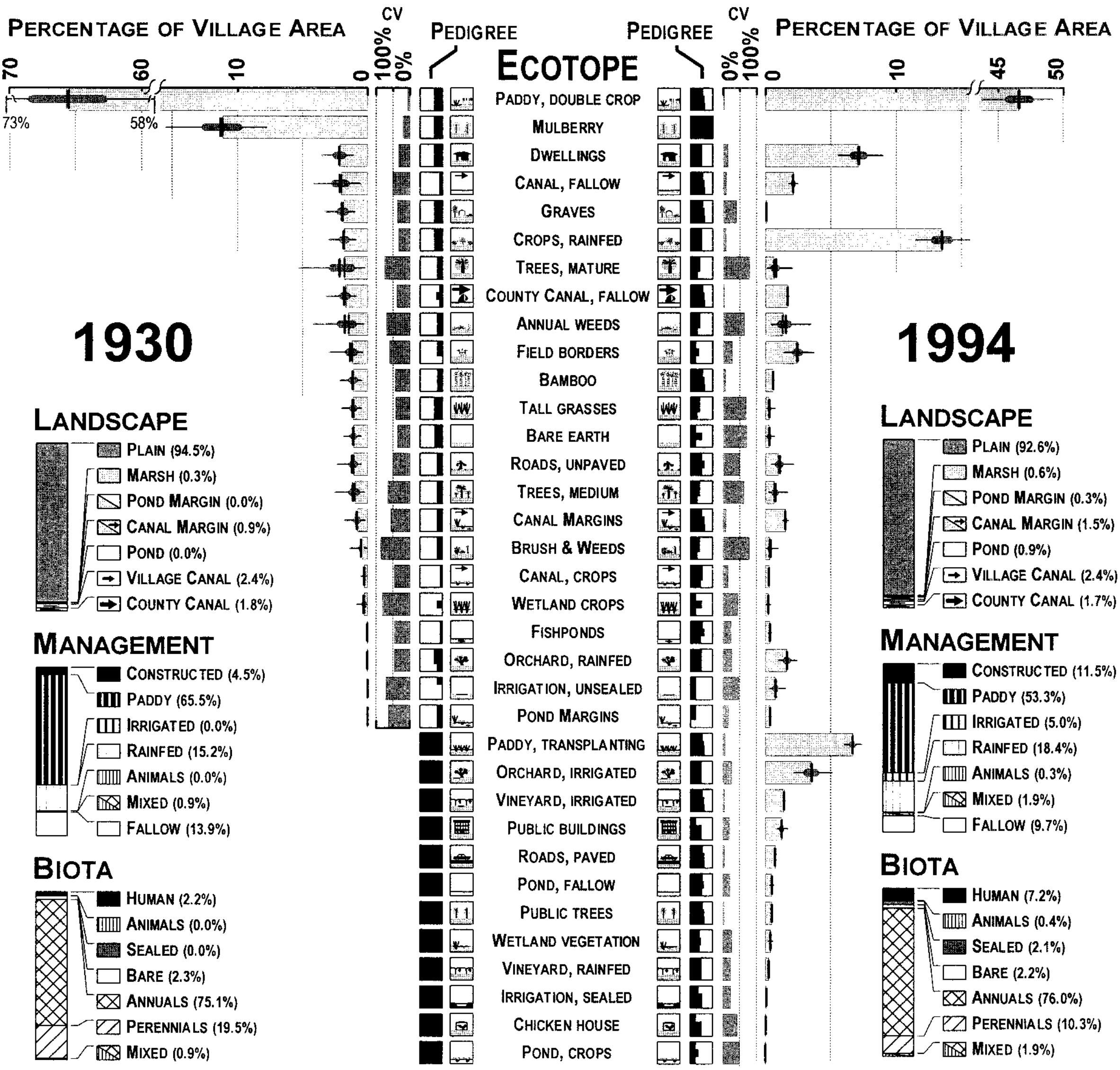

FIG. 4. Percentages of 1930 and 1994 Xiejia Village area in ecotopes and landscape classes. Ecotopes are sorted by 1930 median area percentage, largest to smallest, top to bottom, and then by 1994 median area percentages for ecotopes not present in 1930 (black pedigree boxes). Ecotopes are represented by unique pictographs with labels from Table 5. Pedigree boxes contain three black bars representing data quality pedigree scores for ecotope estimates (Table 6); CV bars depict the coefficient of variation. In the ecotope percentage chart, light gray horizontal bars represent medians; horizontal boxplots illustrate interquartile ranges using dark gray oval boxes; means and medians are vertical black and dark gray lines, respectively; and whiskers are drawn to the 5th and 95th percentiles. Bar charts at the bottom left and right of the figure illustrate the proportion of village area in landscape, management, and biota classes (Tables 1–3).

of fallow area and proportion estimates gave the fallow ecotope area estimates the highest CVs of all areas in this study (Fig. 4).

When added, ecotope areas within the 1994 building and rainfed crop LUs were 28% and 24% lower than the direct estimates for these LU areas, respectively. We corrected this by normalizing using Eq. 3; no other ecotope/LU area combinations were suitable for normalizing by this method. After normalizing ecotopes within the building and rainfed crop LUs, the sum of 1994 ecotope areas was only 0.2% greater than the total village area. When 1930 independent ecotope area estimates were added, their sum was 0.7% greater than the total village area, an excellent agreement considering that paddy, mulberry, and dwelling areas were estimated from historical sources and elder farmer interviews.

DISCUSSION

Observational uncertainty analysis of long-term change measurements

Measuring village areas and their long-term changes required combining data ranging in quality from recent

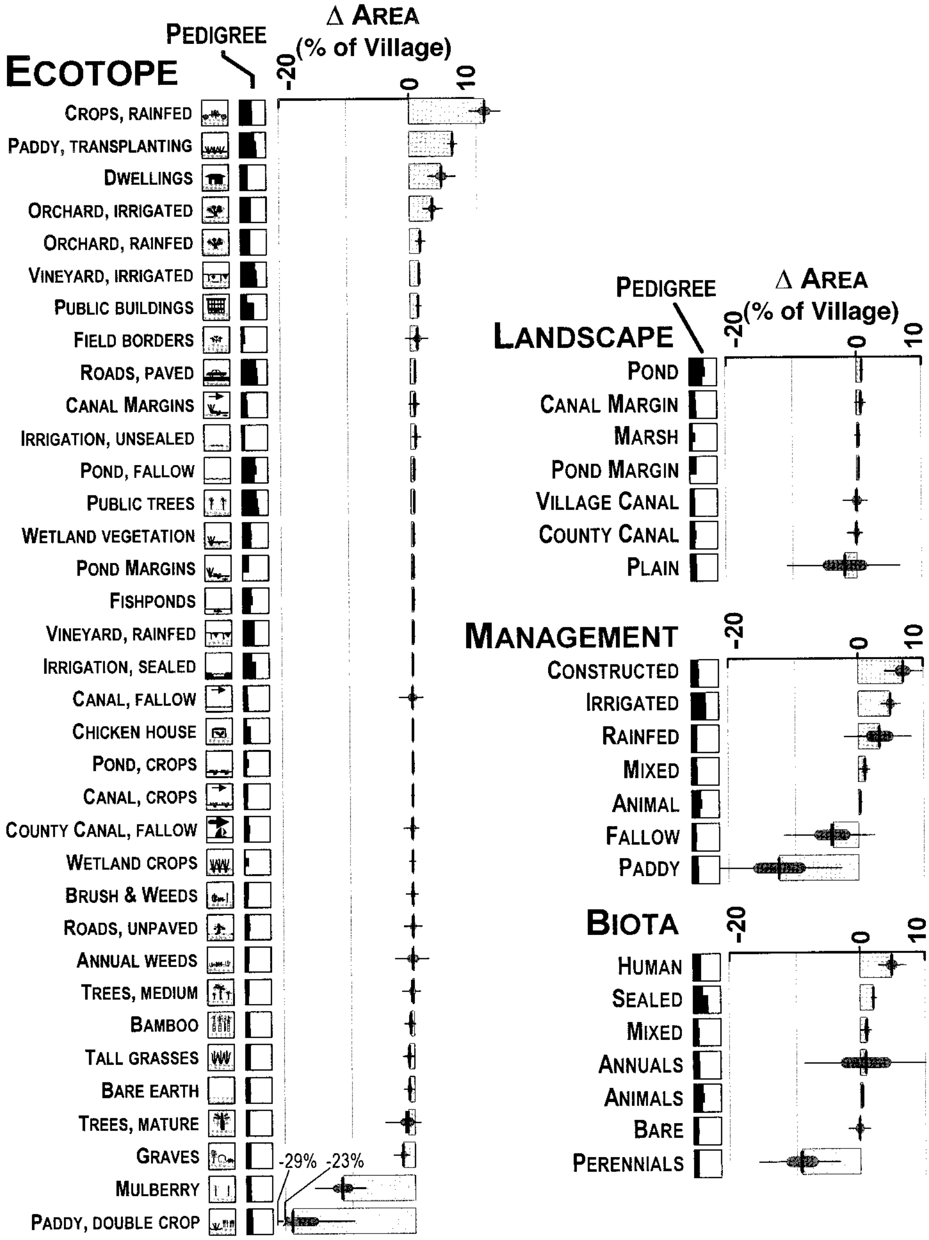

FIG. 5. Change in areas of ecotopes and landscape classes in Xiejia Village, 1930 to 1994, as a percentage of total village area. Positive values indicate increases since 1930. Ecotopes and classes are sorted by the median change, positive to negative, top to bottom. Ecotope changes are depicted on the left, charts on the right illustrate changes for landscape, management, and biota classes (Tables 1–3). The remaining graph components are identical to those described in Fig. 4.

aerial photographs to estimates made by village elders for the 1930s. By integrating data quality pedigrees with credible intervals, CVs, boxplots, and betting odds, we give experts and nonexperts alike the information they need to evaluate the likelihood of specific area changes and to decide whether our evidence is sufficient for their needs. Moreover, our probabilistic estimates can serve in designing future studies with data quality pedigrees indicating the degree to which observations have already been made. For example, our 1994 estimate of unsealed irrigation ecotope area had an especially low pedigree and high CV (Fig. 4). This indicates that when new observations are available, the updated estimate should have lower uncertainty and higher data quality. The pedigrees of all our 1930s area estimates were below {2, 2, 2}, as were those for many of our area change estimates (Figs. 4 and 5). Though these low pedigree estimates are best regarded as subjective approximations (Table 6), we believe their quality is not unusually low for fine-scale estimates of long-term change.

Monte Carlo methods facilitate synthesis and long-term comparisons of landscape- and ecosystem-scale measurements because observational uncertainty can be computed for estimates calculated from any number and type of variables (Morgan and Henrion 1990:199). For example, our ecotope proportion estimates could be used to estimate long-term village-scale rates of denitrification or carbon sequestration by multiplying them by denitrification or carbon sequestration rates measured within each ecotope. Moreover, Monte Carlo sensitivity analysis can be used to identify the variables and sample sizes needed to decrease uncertainty in estimates at any scale by any given amount (Morgan and Henrion 1990:207).

Village landscape stratification

Intensive land management within the level floodplain terrain of Xiejia Village created fine-scale landscape features demanding specialized anthropogenic landscape classification and area measurement (Fig. 4). For example, field borders are heavily impacted by human traffic and occupied 2.5% of village area in 1994 (Fig. 4). Because of their narrow width (<30 cm) and insertion within paddy fields and irrigation systems, it was necessary to integrate field data with aerial photography to measure them. Patches of fallow land were dispersed among buildings and rainfed crops so that direct measurements from aerial photography underestimated their area by ~60% relative to field sampled estimates. Field verification of fluvial process was required for all village water bodies, because many apparent canals were closed to external flow and many seemingly enclosed bodies were connected to canals. Field surveys, local knowledge, and household surveys were also necessary to measure constructed areas, managed wetland and aquatic ecosystems, and large-scale animal confinement.

We stratified and measured anthropogenic wetland and aquatic areas using a hydrogeomorphic approach that expands on existing techniques (Brinson 1993, Semeniuk and Semeniuk 1995). Using canal cross-section measurements, we distinguished margin ecotopes with steep slopes and potential for emergent macrophyte growth from the deeper, flatter, depth ecotopes (Table 1). Though very narrow (~3 m), margin ecotopes occupied nearly 2% of village area in 1994 (Fig. 4) and are the anthropogenic equivalent of riparian ecotones, with diverse vegetation and dynamic biogeochemistry (Pollock et al. 1998).

In most landscape classifications, the fine-scale features we measured in Xiejia Village would be lumped into more generalized classes. For example, the entire village would be classified as rice paddy using imagery or other land use data with element size >1 km^2. Large-scale estimates across densely populated agricultural regions fail to consider the fine-scale impacts of human populations within the landscape and will likely fail in identifying long-term anthropogenic changes in ecosystem processes across these areas. Our observations demonstrate that measurement of long-term ecological change within subsistence agriculture regions requires anthropogenic landscape classification and the integration of field, household, and other local data with remote imagery. Though our current measurement techniques did not always yield georeferenced data, use of Geographic Positioning Systems and laser rangefinders should allow field mapping of all ecotopes within our classification system.

Ecological impacts

Though most of Xiejia Village remains a level plain managed as rice paddy, the village has experienced significant long-term declines in paddy and perennial area, increases in constructed area, and changes in wetland and aquatic ecotopes (Fig. 5). We believe these changes are typical of those across the fertile floodplains that cover >26 500 km^2 of the Tai Lake Region. Long one of the most developed and productive in China, the region is experiencing environmental problems caused by modernization and development before other regions (Ellis and Wang 1997).

As a whole, Xiejia Village was more impacted by human disturbance in 1994 than it was in 1930. In the 1950s, graves were eliminated from level land by national policy, removing fallow perennial vegetation from ~2% of the total village area. Disease and market forces ended mulberry production in the 1970s, eliminating yet another perennial vegetation from the village. Permanent paths and irrigation ditches doubled the area of field borders disturbed by human traffic since 1930, and the area covered by houses, roads, and other infrastructure has nearly tripled. In total, the perennial and fallow annual vegetation that covered 24% of the village in 1930 was reduced to only 16% by 1994, with a 60% decline in the area of mature trees and a 50% decline in overall perennial area (Figs. 4 and 5). Because fallow areas are generally more species-rich than those disturbed by construction, tillage, fertilization, herbicides, flooding, and human traffic, these changes have likely decreased biodiversity across the village (Matson et al. 1997).

The 7% increase in village sealed surface area (sealed + human biota class in Fig. 5) has likely increased surface runoff, concentrating nutrients from the region's nutrient-rich precipitation in wetlands and waterways (Ma 1997). Moreover, the region's paddy fields currently lose ~50 kg N·ha^{-1}·yr^{-1} to runoff (Ma 1997). If village wetland and aquatic areas trap 3 Mg N·ha^{-1}·yr^{-1} by sedimentation and denitrification, as do Swedish farm ponds (Jansson et al. 1994), the presence of one hectare of wetlands for every seven hectares of paddy in 1994 may help to buffer N losses to the region's surface waters. The 38% expansion of wetland area since collective canal management ended in 1980 has likely increased this nutrient trapping capacity over 1930s levels.

Land use changes we have observed are known to alter the albedo, surface roughness, water surface area, and evapotranspiration of landscapes, with likely effects on local climates (Stohlgren et al. 1998). Further, the conversion of paddy to rainfed crops and buildings has probably altered C and N sequestration in village soils (Cai 1996, Ellis et al. 2000). For biogeochemical processes with nonlinear responses to changes in environment and management, such as denitrification and carbon sequestration, averaging ecosystem processes across broad landscape classes is subject to large and unknown bias, casting doubt on the reliability of estimates made by these methods. By measuring village-scale changes in sample villages representing the ecological characteristics of farmed landscapes and integrating these with landscape estimates for other management regimes within bioregions, more reliable estimates of these processes at bioregional and national levels are possible.

Village food security

Even with doubled village populations since 1930, farm households still produce virtually all the rice they consume, with rice supplying ~75% of dietary calories (Ellis and Wang 1997). Population growth has now slowed and grain yields have outpaced population growth since 1930 (Ellis and Wang 1997). Nevertheless, further declines in paddy area could easily offset future gains in yield, notwithstanding new legal controls on conversion of paddy to other uses. In response to market forces, >3% of village grain area has been converted to commercial grape production since 1930, but this change is reversible, if necessary. More disturbing is the increased area under buildings and infrastructure that has rendered 7% of the village useless for grain production since 1930. Though these changes have increased living standards, continuing these trends will erode village food security, leaving the region vulnerable to external markets.

CONCLUSIONS

We measured ecologically significant anthropogenic changes in village landscapes by combining anthropogenic landscape classification with field and household measurements. Though others have studied land use change in subsistence agriculture villages (Ali 1995, Lawrence et al. 1998), our estimates are unique in both their detail and the degree to which their uncertainty has been characterized. Subsistence agricultural villages based on intensive paddy rice production cover $\sim 4 \times 10^6$ km^2 of the developing nations of Asia (Whittlesey 1936). By measuring and visualizing changes within these intensively managed anthropogenic landscapes, this study demonstrates methods for measurement and monitoring of long-term change across this area and the 4×10^6 km^2 of subsistence agriculture not based on rice (Whittlesey 1936). Our system for observational uncertainty analysis and measurements of long-term change in village landscape structure thus provide a strong foundation for estimating long-term, village-scale changes in biodiversity and biogeochemistry, such as soil nitrogen sequestration (Ellis et al. 2000).

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SUPPLEMENTARY MATERIALS

The data quality pedigree calculator is available in ESA's Electronic Data Archive: Ecological Archives A010-006.