Colour categories in a stone-age tribe

The Dani of Irian Jaya are a stone-age Melanesian people who have provided an empirical basis for the study of cross-cultural perception and cognition[1–3]. Although they had only two terms for describing colour, the Dani memory for colour seemed to be much like that of modern English speakers. We have investigated another stone-age culture, the Berinmo of Papua New Guinea, for the way in which they categorize colours, but the results do not support the idea that colour categories could be universal.

According to the linguistic relativity hypothesis[4,5], which is still influential, we construct our understanding of the world through language. Whorf[4] famously argued that, to an Eskimo, it would be unthinkable to use the same word for all types of snow because of its wide range of types and different uses.

We investigated colour in a remote, previously unstudied, hunter-gatherer tribe, the Berinmo, which lives on the upper reaches of the Sepik River in Papua New Guinea. When Berinmo subjects were asked to name the 160 colours in the standard Munsell array, thay used five basic colour terms[6]. The range and boundaries of these terms showed good intra-subject concordance, and can be seen in Fig.1 alongside the eight basic chromatic terms in English.

We replicated the Dani experiment with the Berinmo. The accuracy with which they remembered colours bore a striking similarity to the Dani; both groups of Melanesian subjects were very poor at this (9.6 and 7.7 out of 40, respectively). However, statistical analysis showed that, for both studies, the best statistical fit (that with the lowest stress value) was between Melanesian naming and Melanesian memory (Table 1a). This finding is consistent with the linguistic relativity hypothesis, but not with the interpretation of the original study.

The differences between English and Berinmo allow a further critical test of the contrast between colour universals and linguistic relativity. Berinmo does not mark the distinction between blue and green, but it has a colour boundary (between 'nol' and 'wor') in a position that does not exist in English. We investigated categorical effects[7,8] across both the blue–green and the nol–wor boundaries. We asked subjects to remember a colour over an interval of 30 seconds[1,2] and then select the same colour from a pair of similar alternatives. Sometimes the incorrect choice was from the same colour category and sometimes from a different one. We also added a 5-second-interval condition for the Berinmo as they had difficulty remembering blue–green samples for 30 seconds.

English subjects showed the expected advantage for cross-category blue–green decisions but not for nol–wor decisions; Berinmo subjects showed exactly the opposite pattern. The Berinmo showed no sign of a cross-category advantage for blue–green stimuli, but maintained their cross-category advantage for nol–wor stimuli both at 30 seconds and at 5 seconds. These results indicate that categorical perception occurs, but only for speakers of the language that marks the categorical distinction, which

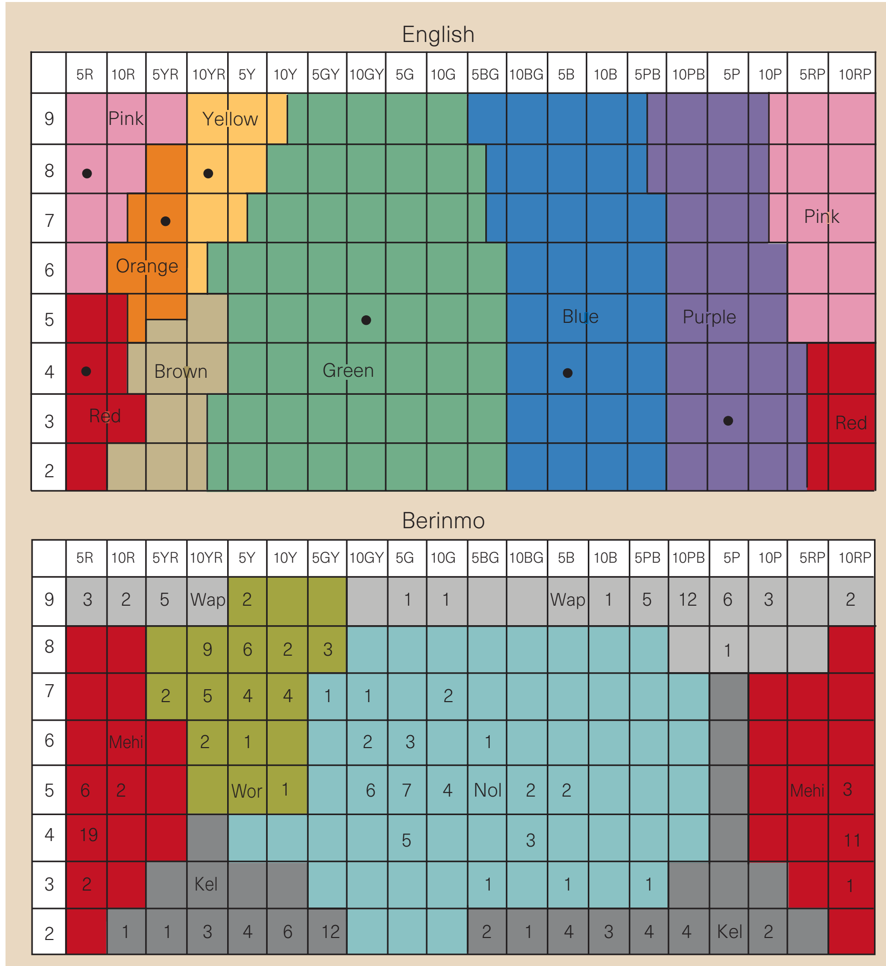

Figure 1 Distribution of English and Berinmo colour names. The Munsell system provides equally spaced samples in three dimensions, but is shown here as a Mercator projection of hue (horizontal axis) against lightness (vertical axis). The colours used to denote colour categories on these Mercator projections are for illustration only. Eight colour terms for English and five for Berinmo are shown. Dots on English naming data represent the position of focal colours[2]. Numbers on the Berinmo naming data represent the number of subjects who designated that colour as best example of the category. R, red; Y, yellow; G, green; B, blue; P, pink.

Table 1 Statistical analysis of language data

a Goodness of fit for multidimensional scaling solutions

Dani naming	versus	Dani memory	0.126
Dani memory	versus	US memory	0.161
Berinmo naming	versus	Berinmo memory	0.158
Berinmo memory	versus	English memory	0.256

b Mean trials to criteria in colour-categorization tasks

	Blue vs green	Green1 vs green 2	Nol vs wor	Yellow vs green
English speakers	3.2	5.9	3.8	1.4
Berinmo speakers	11.43	10.57	2.2	3.6

a, Measures of stress (departure from goodness of fit) are shown for comparison of naming and memory data. Low values indicate high goodness of fit. Data for comparisons between US naming and US memory are from ref. 1 and are compared with those from Berinmo and English subjects. In both cases, the fit between naming and memory is better than the fit between memory across language groups. b, Mean number of blocks to error-free performance. Categorizations are achieved more rapidly if they are consonant with distinctions made in the language of the subject.

is consistent with the linguistic relativity hypothesis.

If categories always form around natural fault lines in perceptual colour space, it should be relatively easy to learn another language's colour categories. To test this version of the universalist position, we asked English speakers to learn the nol–wor distinction and Berinmo speakers to learn the blue–green and yellow–green distinctions. For comparison, subjects were also asked to categorize stimuli in a manner consonant with the colour names of their own language. In addition, subjects learned a distinction not marked in either language: that between two types of green ('green 1' and 'green 2'). All tasks were made non-trivial by presenting only one stimulus at a time and by the inclusion of marginal examples of each category.

Berinmo subjects found learning to divide colours into green 1 and green 2 no harder than dividing them into blue and green; English speakers found the blue–green task easier. Berinmo subjects found the nol–wor task easier than the yellow–green task, whereas English subjects found the reverse. Tasks in which subjects divided stimuli varying in hue, lightness and saturation into two colour categories are performed better if the division corresponds to a linguistic, rather than a supposed universal, distinction (Table 1b).

Our results from these experiments are consistent with there being a considerable degree of linguistic influence on colour categorization, and place constraints on the type of neuron likely to underpin it. Neurons have been discovered in monkeys that are highly selective to wavelength[9], to combinations of wavelength and brightness[10] and to colour constancy[9], but it is unlikely that there are neurons that respond to all examples of a colour category unless their operation is susceptible to linguistic modification.

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Why biodiversity surveys are good value

Article 8 of the Convention on Biological Diversity obliges contracting parties to establish protected areas for conservation. This can be achieved in smaller networks of reserves if their design is based on how well different sites complement one another biologically, rather than on more commonly used criteria, such as species richness or simple availability for acquisition[1,2]. However, this increase in efficiency[3] requires species lists for each candidate site, and obtaining such data can be expensive; for example, a detailed survey of five taxa across 15,000 km^2 of forest in Uganda took nearly 100 person-years and cost about US$1 million[4,5]. Here we ask whether investing in such surveys makes economic sense, or whether conservation agencies would be better advised to continue following more traditional reserve selection procedures, at the cost of having to conserve larger reserve networks.

This trade-off is shown in Fig. 1. Using a simple reserve selection rule (such as buying relatively intact land as it becomes available[1]) results in an inefficient reserve network, whose cumulative representation of biodiversity rises only slowly with increasing area. But if a complementarity-based algorithm is used instead, the network needed to achieve a particular conservation goal is reduced by an area a. The greater cost of conserving the less efficient network has a present value equal to $[a(x+y/r)]$, where x is the mean purchase cost of a unit area of land for conservation, and y is the mean cost per unit area of effective maintenance, discounted into the future at an annual rate r. In contrast, conducting a high-quality survey costs zA, where A is the total area of all the candidate sites surveyed, and z is the survey cost per unit area. It follows that investing in surveys is good value provided that $zA<[a(x+y/r)]$ or alternatively that $z<[(a/A)(x+y/r)]$. This therefore sets the upper limit of cost-effective surveys for reserve selection.

There are few published data with which to parametrize this simple model. Conservatively, we suggest that a/A (the relative saving in reserve area achieved by tackling complementarity) is commonly at least 5%; it will often be far higher[1]. Estimates for x and y, obtained from a diverse range of sources and expressed in 1990 US$, are summarized in Table 1. Using appropriate values for r (from 5% to 20%), we can then estimate $[(a/A)(x+y/r)]$. Marked variation in land prices[6] and labour costs means that this upper limit of cost-effective surveys varies enormously but, wherever data are available, this greatly exceeds the likely cost of high-quality surveys. For instance, in Uganda, at $r=10\%$, $[(a/A)(x+y/r)]\approx\$800$ per km^2, whereas the true value of z is less than one-tenth of this, at $58 per km^2. Reversing this calculation, detailed inventories would have to yield area savings of less than 0.4% — that is, $a/A<z/[x+y/r]$ — for them not to be worthwhile. This condition is extremely unlikely to be met[1]. So, in Uganda, detailed biodiversity inventories represent a very good conservation investment.

In other developing countries, the costs of detailed surveys for reserve selection are similar ($z\approx\$65$ per km^2 in Sri Lanka[7], and $z\approx\$135$ per km^2 in Yemen; A. Miller, personal communication), and far less than corresponding values for $[(a/A)(x+y/r)]$, which range from several hundred to a few thousand dollars per km^2 (Table 1). In developed countries, $[(a/A)(x+y/r)]$ is typically much higher (Table 1) and, although the labour costs of surveys are also high, these are generally offset by the greater availability of existing inventory data. As a result, in the United Kingdom, $z\approx\$1{,}500$ per km^2 (M. Drake and R. Porley, personal communication), which is much less than $[(a/A)(x+y/r)]$. In Australia, on average, $z\ll[(a/A)(x+y/r)]$, at just $5 per km^2 (ref. 8). As in some other countries, the Australian mean value masks huge local variation in all costs; nevertheless, in arid areas

Table 1 Estimates of the costs of buying and maintaining nature reserves

	Cost of land purchase, x ($ per km^2)	Cost of effective maintenance, y ($ per km^2)	Present value of maintenance, y/r ($ per km^2) $r=5\%$	$r=10\%$	$r=20\%$	$(a/A)(x+y/r)$ (assuming $a/A=5\%$) ($ per km^2)
Uganda	12,628	383	7,660	**3,830**	1,915	**823**
Ghana[12]	45,215	236	4,720	**2,360**	1,180	**2,379**
South Africa[13]	21,896	1,600	32,000	**16,000**	8,000	**1,895**
Brazil[12,14]	10,776	169	3,380	**1,690**	845	**623**
Belize[12,15]	14,087	350	7,000	**3,500**	1,750	**879**
UK	100,523	6,443	**128,860**	64,430	32,215	**11,469**
USA[12]	78,730	2,053	**41,060**	20,530	10,265	**5,990**
Australia[8,12]	385	359	**7,180**	3,590	1,795	**378**

Figures are in 1990 US$ and often mask considerable local variation. Figures in bold are based on r÷10% for developing countries and r÷5% for developed countries, but our conclusions are robust for $5\%<r<20\%$. Data were generously provided by T. Butynski, P. Howard, the African Wildlife Foundation, Conservation International, Fauna and Flora International, Kwa Zulu Natal Nature Conservation Service, Royal Society for the Protection of Birds, the Nature Conservancy, and the Western Australia Department of Conservation and Land Management, and cited sources.