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Costello, Christopher and Ward, Michael B.

UC Santa Barbara, The Australian National University

2007

Online at <https://mpra.ub.uni-muenchen.de/26527/>

MPRA Paper No. 26527, posted 09 Nov 2010 10:24 UTC

Search, bioprospecting and biodiversity conservation

Christopher Costello

Donald Bren School of Environmental Science & Management
UC Santa Barbara
Santa Barbara, CA 93106, USA
costello@bren.ucsb.edu

Michael B. Ward

Crawford School of Economics and Government
The Australian National University
Canberra, ACT 0200, Australia
michael.ward@anu.edu.au

This is a pre-print. The final peer-reviewed version of this paper is published in
Journal of Environmental Economics and Management
Volume 53, Issue 2, March 2007, Pages 158-179
[doi:10.1016/j.jeem.2006.04.001](https://doi.org/10.1016/j.jeem.2006.04.001)
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Abstract

To what extent can private-sector bioprospecting incentives be relied upon for the protection of biological diversity? The literature contains dramatically different estimates of these incentives from trivial to quite large. We resolve this controversy by isolating the fundamental source of the discrepancy and then providing empirically defensible estimates based on that analysis. Results demonstrate that the bioprospecting incentive is unlikely to generate much private-sector conservation. Thus, other mechanisms are likely required to preserve the public good of biodiversity.

Keywords: Bioprospecting, biodiversity, conservation, efficient search, information

1 Introduction

To what extent can the private-sector be relied upon for the protection of biological diversity? Bioprospecting, the search for valuable products such as pharmaceuticals in biological organisms, is one incentive mechanism that has received much recent attention (see, e.g. Polasky et al. (1993), Polasky and Solow (1995), Koo and Wright (1999)). An important controversy has emerged from this literature. Simpson et al. (1996) argue that bioprospecting incentives are likely vanishingly small, less than \$21/ha. In contrast, Rausser and Small (2000) argue that bioprospecting incentives are likely quite large, perhaps \$9,177/ha, because information facilitates a more efficient search process. This latter result suggests that perhaps we can rely on the private-sector for biodiversity conservation and has received a great deal of attention from subsequent academic and practitioner literatures (for example see Kassas and Lasserre (2004), Day-Rubenstein and Frisvold (2001), Nigh (2002), Firm (2003), and South Asian Network for Development and Environmental Economics (2003)).

This controversy is important for two reasons. First, the practical implications for biodiversity conservation are enormous. Second, the *cause* of the discrepancy in final estimates is of great consequence itself. If information fundamentally changes conservation incentives, then re-allocating scientific resources to provide such information may be the most efficient way to induce private conservation.

This paper makes three contributions. First we show, contrary to the conclusions of Rausser and Small, that information has only a trivial effect on conservation values in this important application.

Second, we carefully examine the two models to illuminate the true source of the discrepancy in estimates of private-sector conservation incentives. We find that the main source is simply different parameter choices. However, the key parameter choices are not defended in this literature. Third, we close this gap by assembling a defensible range of model parameters from a review of the scientific literature, biodiversity databases, government reports, and laboratory interviews. Based on these parameters, we resolve the outstanding question of the private-sector conservation incentives from bioprospecting.

2 Impact of an “organizing scientific framework”

Simpson et al. (SSR) couple a clever analytical argument with an empirical case-study, to argue that land in biodiversity hotspots has a bioprospecting marginal value of less than \$21/ha — far too small to offset the opportunity cost of development. The authors further argue that the values would always be small, regardless of the probability that any given species will lead to a new product. Under low probability searches, any research “lead” is unlikely to produce a successful innovation, and therefore has low value. But under high probability searches, research leads are redundant, so scarcity rent is decreased, and any given lead has low value.

The subsequent estimate of \$9,177/ha by Rausser and Small (RS) was therefore surprising — especially since it was based on the same data used by SSR. The high values accruing to infra-marginal leads illustrates RS’s theoretical point that scientific information lowers search cost and thus increases value. An “organizing scientific framework” allows a collection of leads to be searched in the most efficient order, rather than in effectively random order, as in SSR. Under informed search, rents accrue to the most promising leads because searching these first may allow researchers to avoid future, less productive searches. Efficient search, RS suggest, is responsible for the dramatic increase in marginal values. If the large discrepancy between results does, in fact, derive from efficient search, one would expect random (or otherwise inefficient) search to obtain values similar to those in SSR.

RS theoretically analyze the value of optimally ordered sequential search of a collection of research leads of differing quality. For each lead tested, a cost c is incurred. Lead k yields a success worth

R with probability p_k . The key theoretical distinction from the approach of SSR is in allowing the probabilities p to differ across leads, reflecting prior information about lead quality.

In this search model, the value of a collection of research leads is

$$\sum_{i=1}^N a_i(p_i R - c), \quad (1)$$

where $a_i = \prod_{j=1}^{i-1} (1 - p_j)$. Here, the term $p_i R - c$ represents expected return from searching lead i . The term a_i is the probability of searching lead i , or equivalently of failing to find an earlier success. The marginal value of a research lead, k , is simply the difference between the value of the ordered collection containing lead k and the value of the same collection excluding lead k . RS derive an iterative formula to calculate the marginal value of a research lead via backwards induction. That formula can equivalently be expressed as

$$\nu_k = \underbrace{Ra_{N+1} \frac{p_k}{1 - p_k}}_{\text{Revenue Component}} - c \underbrace{\left[a_k - \frac{p_k}{1 - p_k} \sum_{j=k+1}^N a_j \right]}_{\text{Cost Component}}. \quad (2)$$

In their bioprospecting example illustrating this theory, RS treat each area of land in a biological hotspot as a research lead.¹ To calculate a net present marginal value per hectare of land, RS multiply (2) by the number of tests per year, discount, and divide by 1000 (to convert the value per kilohectare to a value per hectare), yielding the final marginal value formula:

$$mv_k = \nu_k \frac{\lambda(1+r)}{1000r} \quad (3)$$

where λ is the number of tests per year and r is the discount rate. Note, in particular, that the marginal value formula depends on the order in which a lead is searched (via the a terms).

How important is search order in the calculation of a research lead's value? The literature reviewed above suggests that search order is of paramount importance - randomly searching a collection yields a value of only \$21/ha, while efficient search increases this value to \$9,177. To test this expectation, we conducted a numerical experiment comparing expected marginal values under efficient search (in which leads are ordered in descending probability of success), random search (in which the search order is a random permutation of research leads), and maximally inefficient

¹SSR treat each species as a research lead, a difference to which we return.

Table 1: Marginal value of land in biodiversity hotspots under different assumptions about search order.

Biodiversity Hotspot	Incremental Value (\$/hectare)		
	Optimal	Random	Backwards
Western Ecuador	9,177	8,836	8,455
Southwest Sri Lanka	7,463	7,190	6,882
New Caledonia	5,473	5,277	5,056
Madagascar	2,961	2,863	2,751
W. Ghats of India	2,026	1,963	1,890
Phillippines	1,973	1,912	1,841
Atlantic Coast Brazil	1,867	1,809	1,744
W. Amazonia	1,043	1,012	977
Tanzania	811	787	760
C. Floristic S. Africa	632	614	593
Peninsular Malaysia	539	522	503
SW Australia	435	420	402
Ivory Coast	394	379	362
North Borneo	332	317	301
Eastern Himalaya	332	317	301
Colombian Choco	231	215	198
Central Chile	231	215	198
CA Floristic Province	0	-20	-43

search (in which leads are ordered in ascending probability of success). All parameter values are held constant at the RS levels across these search experiments.²

Table 1 reports the expected marginal values from engaging in optimal, random, and backwards search in each of the 18 biodiversity hotspots considered in SSR and RS. The optimal search column reproduces the results reported in RS. The backwards search column simply reverses the order in which research leads are searched. The random search column represents the expected marginal value over all permutations of the search order.³

The table reveals, surprisingly, that search order has a small percentage impact on marginal values. For example, searching in random order reduces the marginal value of a hectare in Western Ecuador only 3.7%, from \$9,177 to \$8,836 (not \$21 as in SSR), which is probably still sufficient to justify private-sector conservation.⁴ In fact, even conducting maximally inefficient search (last

² We apply Equation 3 using the following parameters: $R = 450e6$, $c = 485$, $r = .1$, $\lambda = 26.43$, $N = 74,640$, and $p_k = (1.2E - 5)e_k$ where e_k is the density of endemic species, per kilohectare, reported in RS.

³ In practice, this was calculated by 10,000 random permutations of the search order. The standard error of this approximation is $< 0.1\%$ of the reported marginal value, for all figures in the Table.

⁴ Note that the marginal values for the worst lead will be negative under inefficient search because RS set parameters such that the marginal value of CA Floristic Province would equal 0 under efficient search. If the researcher knew these marginal values would be negative under a less efficient search procedure they could be dropped from the queue. Doing so increases the remaining 17 marginal values by about 1% (e.g. Western Ecuador under random search

column of the table) reduces marginal values only slightly.

What accounts for the negligible impact of information in this example? In Equation 2 we separate the marginal value of a research lead into two additive components: a *Revenue Component* and a *Cost Component*. When using the RS parameters, the *Revenue Component* dominates; it is responsible for about 93% of the marginal value of a lead. Importantly, it is clear by inspection that the *Revenue Component* is independent of search order; it depends only on the term a_{N+1} , which is the probability of failure over the entire queue. On the other hand, the *Cost Component* does depend on search order. But because the empirical magnitude of the *Cost Component* is relatively small, the marginal value is not very sensitive to search order.⁵ Essentially, a lead has intrinsic value that relates to its ability to produce a success, regardless of the order in which it is searched. The results of the experiment presented in Table 1 suggest that something other than efficient search must account for the difference in estimates of conservation incentives. We next investigate in more detail the true source of the discrepancy.

3 The source of the discrepancy

One of the key practical differences between the SSR and RS models is in the treatment of research leads. SSR treat species as the relevant lead unit, and assume a constant success probability \bar{p} per tested lead. In contrast, RS treat hectares as the relevant lead unit. We suspect the reason for this divergence is to allow RS to embed heterogeneity of lead quality in a natural way. Since different regions have different species densities, a given hectare in a heavily biodiverse region is more likely to yield a success than a hectare in a less diverse region.

Given comparable parameterizations, this modeling change from species to land as research leads should be inconsequential. The failure probability in hotspot k using *land area* as the unit of analysis is: $(1 - \bar{p}e_k)^{N_k/e_k}$, where e_k is the density of species, $\bar{p}e_k$ is the probability of success per unit land

increases from \$8,836 to \$8,929).

⁵ Take, for example, Western Ecuador, which is the most promising lead and has a marginal value of \$9,177 using the RS parameters and ordered search. The *Revenue Component* of that marginal value is about \$8,543. Again, this component is independent of the search order. The *Cost Component* makes up the remaining amount. If we were to order Western Ecuador *last* (i.e. in its worst possible position, rather than its best), the marginal value decreases to \$8,455, with *Revenue Component*=\$8,543 and *Cost Component*=\$88. Note, as was found by Rausser and Small, that the cost component can be positive or negative.

area⁶, and N_k is the number of species in hotspot k . Following SSR, the failure probability in hotspot k using *species* as the unit of analysis is: $(1 - \bar{p})^{N_k}$. To see that these failure probabilities are close, consider the following approximation:

$$(1 - \bar{p}e_k)^{N_k/e_k} \approx [(1 - \bar{p})^{e_k}]^{N_k/e_k} = (1 - \bar{p})^{N_k} \quad (4)$$

For this problem, the percentage difference between these two expressions is less than one one-thousandth of a percent. Similarly, all other parameters of the species approach of SSR can be constructed commensurately with the land approach of RS. However, care must be taken in the parameterization in order to provide a fair comparison of conservation incentives. RS intentionally selected their parameters to set the marginal value of the worst land to zero. This was intended to illustrate their theoretical point that information could increase the value of *infra*-marginal leads.⁷ Below we show that this reparameterization is responsible for almost all of the difference in marginal values.

To illuminate the source of the discrepancy between estimates, we adopt a strategy of sequentially transforming the parameters of the SSR model until they are comparable to those in the RS model. As we adjust each parameter in turn, we indicate by what multiplicative factor that adjustment changes the calculated marginal values. It turns out that each parameter difference increases the marginal value (w_i in equation 6 below) estimates of RS relative to those of SSR. In comparing the effect of parameter choices on marginal values, the order of parameter adjustment turns out to be irrelevant, as it does not change the reported factors. This comparison reveals that most of the difference in results between SSR and RS is explained simply by the use of incomparable parameter values rather than by efficient search. After all parameters are made comparable, we introduce lead heterogeneity. Finally, search efficiency accounts for the remaining (albeit small) difference between results.

⁶ As specified by RS

⁷ RS define the *information rent* of a lead as the amount by which its marginal value exceeds that of the worst lead. When the marginal value of the worst lead is reduced to zero, *all* rents are information rents under their definition. Note that the amount by which ordered search increases marginal value relative to random search is distinct from the RS concept of information rent, as our empirical example illustrates.

Following SSR, the marginal value of a species (in pursuit of a single product) is

$$v = (\bar{p}R - c)(1 - \bar{p})^N, \quad (5)$$

where \bar{p} is the constant probability of success, R is the revenue upon success, c is cost for each test, and N is the total number of leads. Note that Equation 5 is a special case of the marginal value of heterogeneous quality leads (Equation 2).⁸ Equation 5 has a simple interpretation. The marginal value of a species is the expected return in the event that the last species is sampled multiplied by the probability of needing to test the last species. To convert marginal value per *species* to marginal value per *hectare*, SSR employ a widely-accepted relationship between habitat area and species abundance, known as the “species area curve”. In hotspot i the number of species conserved with area A_i is: $n_i = \alpha_i A_i^z$, where α_i and z are parameters. The increase in species with an increase in area is the derivative, $\frac{dn_i}{dA_i} = z\alpha_i A_i^{z-1} = \frac{zn_i}{A_i}$. Denoting the density of species in hotspot i by $e_i = \frac{n_i}{A_i}$, the marginal contribution of area to species is ze_i . In the search for a single pharmaceutical product, the marginal value of land is then $w_i = vze_i$. If λ such searches are conducted per year, the marginal value of land in hotspot i for the purpose of bioprospecting in perpetuity is

$$w_i = (\bar{p}R - c)(1 - \bar{p})^N ze_i \lambda \delta \quad (6)$$

where δ is a discounting term that gives the net present value over an infinite horizon (typically $\delta = \frac{1}{r}$).⁹

We now compare the w_i values using the parameters in SSR and using the implied parameters in RS to show that most of the difference between the two sets of results derives simply from parameter choices.

- **Number of species (N): Factor of 12.5.** SSR assume a large pool of 250,000 plant species across the globe and value those species (and the land that supports those species) within global biodiversity hotspots. In the RS analysis, species outside the hotspots were not considered,

⁸ RS define the marginal value as the value of *dropping* a lead, while SSR define it as the value of *adding* a lead. To make Equation 5 a mathematically exact special case of Equation 2 therefore requires that Equation 2 be evaluated for the $k + 1$ species with a total of $N + 1$ species. This discrepancy is extremely minor quantitatively.

⁹ SSR use the following parameters: $\bar{p} = .000012$, $R = 450,000,000$, $c = 3600$, $N = 250,000$, $z = 0.25$, $e_i \in [.00009, .00875]$, $\lambda = 10.52$, $\delta = \frac{1}{r} = 10$. Inserting these into equation 6 (where $e = .00875$ for Ecuador) obtains the SSR result of \$21/ha.

leaving only 39,605 species. Reducing N to 39,605 increases marginal values by a factor of

$$\frac{(1-\bar{p})^{N_{RS}}}{(1-\bar{p})^{N_{SSR}}} = 12.5.^{10}$$

- **Ecological model parameter (z): Factor of 4.** SSR use the standard biogeography model called the species-area curve. The concave curve depicts the number of species on a landscape as a function of the area according to the equation $n_i = \alpha_i A_i^z$. The parameter z determines the degree of concavity. SSR assume $z = 0.25$. Given such a small value of z , the marginal contribution of new species by each additional hectare falls rapidly.

In contrast, RS do not explicitly specify a species-area curve. However, they assume that each hectare in a region has a fixed probability of producing a success. In other words, they specify a linear relationship between area and independent leads, $z = 1$. The value of the *marginal* hectare will differ since SSR stipulate a concave species-area relationship while RS implicitly use a linear relationship. Since z enters the marginal value calculation multiplicatively, the change in z from 0.25 to 1.0 increases values by a factor of $\frac{z_{RS}}{z_{SSR}} = 4$.

- **Number of tests per year (λ): Factor of 2.5.** Both papers make the assumption that multiple independent searches are conducted each year. SSR assume 10.52 tests per year, while RS assume 26.43 test per year. Since searches are independent, the number of tests per year simply scales up the value of a single search multiplicatively. The ratio of assumed number of tests is 2.5, so changing λ from 10.52 to 26.43 accounts for an increase by a factor of $\frac{\lambda_{RS}}{\lambda_{SSR}} = 2.5$ in values.

- **Search cost (c): Factor of 2.5.** The search cost in RS is \$485 per *kilohectare*. The search cost in SSR is \$3,600 per *species*. To make the units comparable, we need to translate the RS value to a cost per *species*. Searching all leads in RS would cost $74,640\text{kha} * \$485/\text{kha} = \36 million. With a total of 39,605 species, this is a cost of \$914 per species (the translation from species to area is linear because RS assume $z = 1$, see above). This adjustment of c from \$3,600 to \$914 yields a factor $\frac{\bar{p}R - c_{RS}}{\bar{p}R - c_{SSR}} = 2.5$ increase in marginal values.

¹⁰ Note that information that allowed the researcher to truncate a queue and only search the most promising leads may have considerable value and may significantly increase the value of remaining leads. This is distinct from rents accruing because a given collection of leads can be searched in a more efficient order.

- **Probabilities (\bar{p}): Factor of 1.** The scientific model RS used to assign heterogeneous probabilities is $p_k^{RS} = \bar{p}e_k$ where e_k is the density of endemic species at site k . By the approximation given in Equation 4 the failure probabilities in a region are numerically equivalent. The SSR and RS probability models are therefore already comparably parameterized, requiring no adjustment in \bar{p} .
- **Other parameters.** The remaining parameters are the same in the two models, so they should not generate a discrepancy. We do note however that a minor coding error was made by RS which leads to a practical difference in discounting between the two papers. Both authors assume a discount rate of 0.10. SSR obtain the NPV over an infinite horizon with a discounting term of $\delta = \frac{1}{r} = 10$. While RS intend to conform, they use in their computer code a discount term of $\delta = \frac{1+r}{r} = 11$. This causes an additional (though minor and unintended) discrepancy of a factor of 1.1.

We thus find that no single parameter difference is responsible for the discrepancy. Taken together these parameter adjustments result in an increase by a factor of 344 in the marginal value of a hectare in each hotspot region. That is, simply by choosing comparable parameter values would, by itself, increase the SSR marginal value in Western Ecuador from \$21 to \$7,095.

We have shown that simply reconciling the differences in parameters would account for most of the difference between the bioprospecting value estimates in this literature. But an additional difference between the two models is that RS assume that leads are of heterogeneous quality, while SSR assume that leads are of homogeneous quality. The final step in a fair comparison then, is to introduce heterogeneity in the quality of bioprospecting research leads. RS implement lead heterogeneity by assuming that the cost to test all species in a kilohectare is constant but the number of species per kilohectare, and thus the success probability, differs across regions. Alternatively, in keeping with the SSR approach of regarding species as the leads, one could allow costs per species to vary by region. Using this approach, comparable heterogeneous costs are calculated by $c_i = 485/e_i$.¹¹

¹¹ Neither RS nor SSR account for the case in which cost is heterogeneous. Doing so may require the search queue to be reorganized. This search theory problem is a special case of the general approach discussed in Weitzman (1979). Applying Weitzman's equation (7) to our problem, optimal search under heterogeneous costs and heterogeneous probabilities involves queuing leads in descending order of probability per unit cost (p_i/c_i).

Numerically, the two approaches yield nearly identical marginal values for any given search order ($\ll 1\%$ difference). Those regions with a low cost per unit success probability increase in marginal value, while more expensive regions decrease.

Numerical results for the heterogenous case are exactly those already presented in Table 1. A factor of about 1.2 for the highest marginal value results from the introduction of heterogeneity even under random search, increasing the marginal values from \$7,095 to \$8,836. The essential result on heterogeneity is that regions with a low cost per unit success probability have relatively high marginal values — *regardless of search order*. The difference in models to which RS attribute the discrepancy in results — search order — is responsible for the remaining difference: from \$8,836 to \$9,177 (a final factor of only 1.04).

Efficient search guided by improved information, the theoretical contribution of RS, is responsible only for 4% of the increased marginal value. Simply rectifying the (undefended) parameter differences between the two models accounts for the remaining 96%, even under random search.

4 Defensible parameter estimates

We have shown that the significant wedge between an early estimate of bioprospecting-derived marginal value (\$21/ha) and a more recent estimate (\$9,177/ha) cannot be attributed to efficient search. Instead, the difference can be attributed simply to different parameter assumptions. This result clearly raises the question: Which set of parameters is correct?

In fact, because these papers are intended to make primarily theoretical contributions, neither set of authors rigorously defends the parameters chosen. SSR choose some parameters to *maximize* the marginal value estimates (e.g. \bar{p}), and others are based on “generous estimates” (e.g. R). A reasonable interpretation of the SSR paper, then, is that \$21/ha is perhaps an *over*-estimate of the private-sector incentives.

RS, on the other hand, choose one parameter in order to force the marginal value of the 18th hotspot to zero (c), and others are “based on those developed by Simpson et al. (1996)” (p.192). The only sensitivity analysis reported reveals an alternative estimate of \$11,000/ha. A reasonable

interpretation of the RS paper is that \$9,177 is perhaps an *under*-estimate. Despite the overwhelming attention that this literature has received by practitioners, it seems that the parameters used have never been scrutinized carefully. In this section we present and defend plausible values of these parameters.

We reviewed literature from economics, ethnobotany, ecology, genetics, and pharmacology to marshal a set of defensible, citable values for each of the 7 parameters of the model in equation 6. For each parameter, we identified several independent estimates from data in the published literature. We report below the range of values found in this literature search. It is intended to capture the full range of reasonable possibilities for each parameter. We then use these estimates to calculate the marginal values of land in biodiversity hotspots. This procedure provides the first defensible calculation of the true value of land in these biodiversity hotspots. The next subsection reviews the literature for each of the parameters in equation 6. The subsequent subsection provides the associated marginal value results, and relates those results to those obtained in previous literature.

4.1 Parameter estimates

We now briefly present the results of our search for defensible parameter values.

- **Number of species (N):** This is a measure of the total number of plant species on earth. There is widespread agreement among taxonomists that the number of *known* plant species is approximately 250,000 (Cronquist 1981; Farnsworth and Soejarto 1985). A more precise interpretation would account for both known, and as-yet undiscovered species. Several calculations discussed in Fabricant and Farnsworth (2001) estimate this number to be approximately 500,000. We therefore use a range for N of 250,000 – 500,000.
- **Ecological model parameter (z):** This parameter concerns the shape of the relationship between the total number of species on a landscape and the area of that landscape. The parameter tends to vary depending on the types of ecological communities under investigation. Kilburn (1966) reviews several such relationships, and finds that for plant species, they vary from $z = 0.26$ to $z = 0.43$. A seminal paper in this area is by Preston (1960), in which

$z = 0.27$. Keeley and Fotheringham (2003) estimate the parameter for plant species over 30 biogeographic regions. These estimates range from $z = 0.17$ to $z = 0.35$ with a mean of $z = 0.253$. We use a range for z of 0.17–0.43.

- **Number of tests per year (λ):** Following SSR, we can back-out the number of tests per year by acknowledging the probability of any given search being successful: $\lambda = \frac{S}{1-(1-\bar{p})^N}$, where S is the annual number of drugs approved per year that are derived from plants. The number of drugs approved by the United States Food and Drug Administration per year from 1996-2003 has ranged from 17 to 53, with an average approval of 31 drugs per year. Estimates of the percentage of total drug approvals that are naturally-derived also vary, but estimates range from 14% (Proudfoot 2002), to 40% (Butler 2004), but are typically around 25%. For the parameter S , we use a range of for S of 3–15. The values for λ itself are then calculated using the above equation and the parameter estimates for \bar{p} and N .
- **Search cost (c):** This parameter measures the actual cost of obtaining a plant tissue sample, transporting it to a laboratory, and testing that sample for active enzymes. Because these tests will be conducted to take advantage of economies of scale, the most significant portion of this cost is in the laboratory testing. We contacted several molecular laboratories that specialize in testing outsourced tissue samples to determine whether antibodies react in a particular way. When executed in bulk, these tests cost between \$4,000 and \$18,000 per species tested (e.g. Qualtek Molecular Laboratories, Santa Barbara, CA). We use a range for c of \$4,000– \$18,000.
- **Discount rate (r):** A special issue of *Journal of Environmental Economics and Management* (vol. 18, issue 2) was devoted to the empirical basis for discount rates. This series of articles provided theoretical and empirical guiding principles for identifying the correct r . Based on these articles, we use a range for r of 1%–10%. This range corresponds with the upper and lower 5% quantiles of estimates obtained in Weitzman’s solicitation of 2,160 economists’ opinions of the appropriate rate to be used for environmental applications (Weitzman 2001).

- **Probabilities (\bar{p}):** The probability that any given plant will lead to a commercial drug ranges considerably. The most optimistic estimate we encountered was 1-in-1,000 (Shackleton 2001). A more typical estimate is 1-in-10,000, and the most pessimistic value encountered was 1-in-40,000 (Onaga 2002). We therefore use a range for \bar{p} of .000025–.001.
- **Net Revenue upon success (R):** Upon discovery of a plant with promising chemical properties, a pharmaceutical firm must develop a commercially-viable drug and conduct three phases of FDA-observed clinical trials to determine dosage, efficacy, and side-effects prior to actually marketing that drug. Let \tilde{R} be the present value of the revenue stream from selling the drug, discounted to the time of drug approval. Now let \tilde{C} be the cost of clinical trials required to obtain approval to market a pharmaceutical product, also discounted to the time of drug approval. Then net revenue at the time of drug approval is given by $\pi = \tilde{R} - \tilde{C}$. The final calculation of R requires discounting π back to the time of plant discovery. DiMasi et al. (2003) estimate the mean time from the start of clinical trials to marketing approval is 90.3 months (7.5 years).

Grabowski and Vernon (2000) estimate the annual sales revenue, over a 20-year life of a drug, for a sample of 110 new drugs. To obtain \tilde{R} , we correct for inflation using the Consumer Price Index and discount back to the time of drug approval. For example, with $r = .10$, the estimate is $\tilde{R} = \$1.2$ billion. DiMasi et al. (1991) and DiMasi et al. (2003) estimate the expected cost of transitioning through the three phases of FDA clinical trials. These papers estimate the clinical trial cost per approved new drug, discounted to the time of drug approval, of $\tilde{C} = \$104$ million and $\tilde{C} = \$467$ million, respectively. We use the values given in Grabowski and Vernon (2000) to calculate \tilde{R} (which will depend on the discount rate). Our estimate of \tilde{C} falls in the range of \$104 million–\$467 million. The final calculation of $R = \frac{\tilde{R} - \tilde{C}}{(1+r)^{7.5}}$, then, depends on the rate of discount, and on which estimate of \tilde{C} is used. For example if $r = .10$ the implied values of R range from \$335 million–\$513 million.

- **Density of endemic species (e_i):** Both SSR and RS use data collected by Myers (1988) and Myers (1990). We have updated these data with the most recent estimates of the density

of species in the 34 most biodiverse regions on earth (Myers et al. 2000; Conservation International 2005). These calculations consider the present area covered with vegetation, rather than the historical extent of vegetation in an area. Table 2 provides these updated hotspot locations, number of endemic plant species, area of vegetation cover, and density of endemic species.

The total number of known endemic species in these hotspots is 150,371. Note that the hotspots in Table 2 are ordered according to the density of endemic species (and therefore, by marginal value; see Figure 1 below).

Table 3 below summarizes the parameters used by Simpson et al. (1996), Rausser and Small (2000), and the range of values used in this study. In general, our derived parameter ranges accord with the values assumed by SSR.

4.2 New estimates of conservation value

For the 34 biodiversity hotspots shown in Table 2, we re-calculate the marginal value of land, using equation 6, based on the full range of parameter estimates discussed above. Under the assumption that the true parameter value is drawn from a uniform distribution over each range, and that these draws are independent across parameters, we are able to calculate a mean and upper and lower 5% quantiles for the marginal value of each hotspot. These results are illustrated in Figure 1.¹²

Using the least favorable combinations of parameters, the marginal values are < 0 because $\bar{p}R < c$; such searches would never be undertaken, so the bioprospecting value is 0. Our mean estimate for the most biodiverse region on earth is \$1.23/ha, and 95% of the estimates of the conservation value of this region are below \$1.69. If the most favorable set of parameter values is used, the conservation value for this hotspot could be as high as \$300/ha.¹³ The value of less-dense hotspots is commensurately smaller.

¹² We use 5 equally-spaced points over the stated range for each parameter, exhaustively enumerating all such combinations. We do not claim that the most reasonable subjective distribution is uniform. Rather, the assumption is intended to illustrate that it would require a *very* favorable draw of parameters within the reasonable range to imply non-negligible values. A more plausible subjective distribution, which placed greater weight in the range center, would be less generous.

¹³ This number is obtained by applying equation 6 using the parameters: $r = 0.01$, $p = 2.5E-5$, $c = 4000$, $z = 0.43$, $N = 250,000$, $R = 2.18E9$.

Table 2: Number of endemic plant species, current vegetation area, and species density in 34 biodiversity hotspots.

Hotspot	Area (x1000 ha)	# Endemic Species	Species density (spp/ha)
New Caledonia	512	2,432	0.0047
Cape Floristic Region	1,571	6,210	0.0040
Polynesia-Micronesia	1,002	3,074	0.0031
Philippines	2,080	6,091	0.0029
Caribbean Islands	2,296	6,550	0.0029
Madagascar and the Indian Ocean Isl.	6,005	11,600	0.0019
Mountains of Southwest China	2,100	3,500	0.0017
Sundaland	10,057	15,000	0.0015
Mediterranean Basin	9,801	11,700	0.0012
East Melanesian Islands	2,982	3,000	0.0010
Succulent Karoo	2,978	2,439	0.0008
Atlantic Forest	9,994	8,000	0.0008
Western Ghats and Sri Lanka	4,361	3,049	0.0007
Coastal Forests of Eastern Africa	2,913	1,750	0.0006
Indo-Burma	11,865	7,000	0.0006
Madrean Pine-Oak Woodlands	9,225	3,975	0.0004
Tumbes-Choc-Magdalena	6,590	2,750	0.0004
Tropical Andes	38,566	15,000	0.0004
Horn of Africa	8,297	2,750	0.0003
New Zealand	5,944	1,865	0.0003
Wallacea	5,077	1,500	0.0003
California Floristic Province	7,345	2,124	0.0003
Maputaland-Pondoland-Albany	6,716	1,900	0.0003
Southwest Australia	10,702	2,948	0.0003
Japanese Archipelago	7,470	1,950	0.0003
Eastern Afromontane	10,687	2,356	0.0002
Guinean Forests of West Africa	9,305	1,800	0.0002
Irano-Anatolian	13,497	2,500	0.0002
Himalaya	18,543	3,160	0.0002
Chilean Forests	11,914	1,957	0.0002
Mesoamerica	22,600	2,941	0.0001
Caucasus	14,382	1,600	0.0001
Cerrado	43,891	4,400	0.0001
Mountains of Central Asia	17,267	1,500	0.0001

Table 3: Comparison of parameter values used in SSR, RS, and the current paper.

Parameter	Simpson et al. (1996)	Rausser and Small (2000)	Range of new estimates
N	2.5E5 species	74,640 kha	[2.5E5,5E5] species
z	0.25	1	[0.17,0.43]
λ	10.52 tests/yr.	26.43 tests/yr.	[3,15.03] tests/yr.
c	\$3600 per species	\$485 per kha	[\$4000,\$18000] per species
r	10%	10%	[1%,10%]
p	1.2E-5 per species	[1.1E-6, 1.1E-4] per kha	[2.5E-5,1.0E-3] per species
R	\$4.5E8	\$4.5E8	[\$3.4E8,\$2.2E9]
e	[0.09, 8.75] species/kha	[0.09, 8.75] species/kha	[0.1,4.7] species/kha

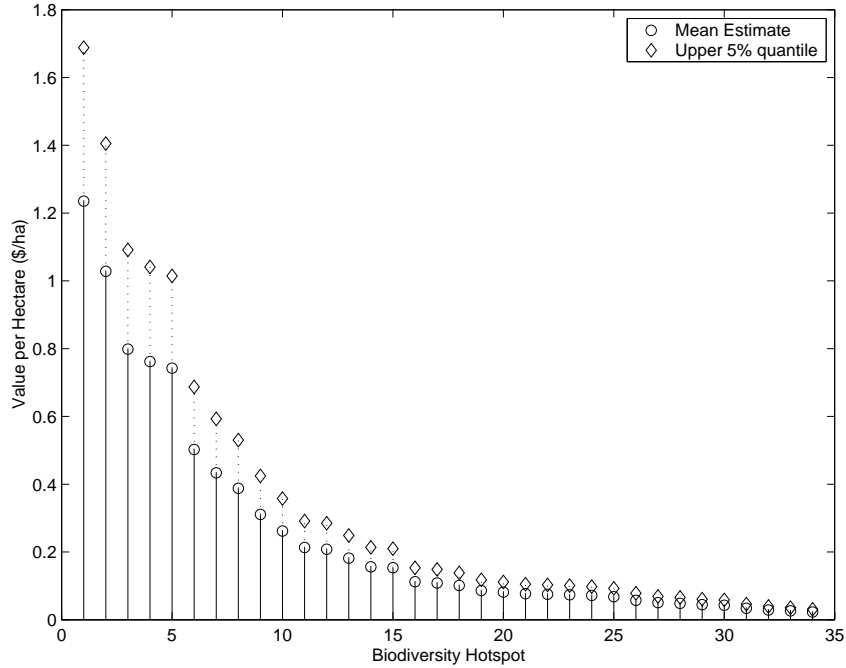


Figure 1: Marginal value of land in biodiversity hotspots world-wide

Rather than assuming a constant probability of success for each species, we could adopt a model in the spirit of Rausser and Small (2000), in which some species are known to be more likely to yield a success than others. To explore this, we introduce heterogeneity by assuming there are 34 groups of species differentiated by research promise. Each species within a group has the same success probability, but these probabilities differ between groups. The group sizes and probabilities are engineered to have heterogeneity commensurate with that under the RS approach.¹⁴ The bioprospector searches through these species in optimal order, exhausting the first group before moving to the second. Species of each quality are present in all biodiversity regions, so that destruction of habitat in any region destroys some members of each species group.

To explore the impact of ordered search under heterogeneity, we calculate the marginal value land in each region. The important difference between regions is in the number of species driven extinct

¹⁴ These probabilities are engineered to give the same degree of heterogeneity as would obtain under the RS device of using land as research leads, with probabilities determined by species density. The success probability for species group k is set so that the probability of a finding a pharmaceutical within that group is the same as a success with region k . Also, the same proportion of research leads is allocated to region k and species group k . This correspondence between groups and regions is simply a mathematical construct to ensure comparable heterogeneity; each group of species is distributed in equal proportion across all regions. The construction provides a generous degree of heterogeneity; the best research lead probability is over 50 times greater than the worst.

by destroying a set amount of habitat. Given this loss in species, the search must be conducted over fewer research leads of all types, leading to a reduction in bioprospecting value — this reduction is the marginal value of land. We calculate this marginal land value for the full range of defensible parameter values presented earlier in this section. We find that the marginal value of the most promising hotspots indeed increases under ordered search of heterogeneous leads, to \$14/ha (mean estimate) and to \$65/ha (upper 5% quantile estimate). While these numbers are significantly larger in percentage terms than those derived under homogeneous leads, they unfortunately still lie below what would likely be required for large scale private sector conservation via bioprospecting.

5 Conclusion

Can bioprospecting provide a sufficient incentive for private-sector biodiversity conservation? Previous work in this area has focused primarily on making conceptual contributions — perhaps at the expense of empirically reliable estimates. Nevertheless, dramatically different answers have been reported. The discrepancy has been attributed to efficient search guided by improved information. In contrast, we have demonstrated that the strength of the bioprospecting incentive hinges predominantly on the values chosen for several key parameters of the economic and biological models. Depending on the selected parameters, conservation incentives can be either trivially small or quite large. We have attempted to resolve the outstanding question of bioprospecting conservation incentives by providing a range of defensible estimates for each of the parameters in this model, and recalculating the marginal value of land for bioprospecting. For most parameter combinations within that range, marginal land values from bioprospecting are far too small to provide plausible conservation incentives.

Our results are consistent with the empirical evidence of private-sector biodiversity protection, where bioprospecting firms have been reluctant to invest in conservation for this purpose. Even perhaps the most celebrated bioprospecting venture - between Merck & Co. and Costa Rica's National Biodiversity Institute (INBio) has resulted in a <\$5 million investment by Merck; no major discoveries that have benefited both Merck and biodiversity have been made (Onaga 2002).

A very recent exception is the October, 2005 announcement that two products, an enzyme used in the manufacturing of cotton and a fluorescent protein used as a chemical marker, were developed from Costa Rican biodiversity. The products were developed by Diversa, an American biotechnology company, who has entered a profit-sharing agreement with INBio. This was the first such success in Costa Rica (INBio 2005).

Current private bioprospecting incentives are likely insufficient to induce significant investments in biodiversity. However, future incentives could grow as more species suffer extinction (i.e. N is reduced). For example if only those known endemic species in biodiversity hotspots were to survive a mass extinction (leaving 150,371 species), our mean estimate would climb to \$60/ha, and our upper 5% estimate would climb to \$268/ha.¹⁵ If both 3/4 of known species and *all* undiscovered species became extinct (leaving 62,500 species), the mean conservation value of the most biodiverse land would rise to \$700/ha and the upper 5% estimate would rise to \$3,000/ha. — perhaps large enough to offset the opportunity cost of development in some locations. Thus it might be that bioprospecting could serve as a backstop preservation incentive after a catastrophic mass extinction. While such an event may seem unlikely in the near term, this thought experiment raises some interesting questions about the dynamics of land conversion, species loss, and associated private-sector conservation incentives.

In summary, our results corroborate the pessimistic view of SSR that the bioprospecting conservation incentive is insufficient to offset development. These results accord with the view that the private-sector cannot, in general, be expected to efficiently provide public goods. To the extent that biodiversity is a public good, other incentive mechanisms will be required for its protection.

References

Butler, M. (2004). The role of natural product chemistry in drug discovery. *Journal of Natural Products* 67(12), 2141–2153.

Conservation International (2005). Conservation international biodiversity hotspots. <http://www.biodiversityhotspots.org/xp/Hotspots>.

¹⁵ This is analogous to the assumption in RS that only species inside biodiversity hotspots “count”. This is an unrealistic assumption because, in principle, any species (regardless of location) could provide a success. The question then is whether any given location is sufficiently dense in species to incentivize conservation. We have found, in general, that it is not.

- Cronquist, A. (1981). *An Integrated System of Classification of Flowering Plants*. New York: Columbia University Press.
- Day-Rubenstein, K. and G. Frisvold (2001). Genetic prospecting and biodiversity development agreements. *Land Use Policy* 18, 205–219.
- DiMasi, J., R. Hansen, and H. Grabowski (2003). The price of innovation: new estimates of drug development costs. *Journal of Health Economics* 22, 151–185.
- DiMasi, J., R. Hansen, H. Grabowski, and L. Lasagna (1991). Cost of innovation in the pharmaceutical industry. *Journal of Health Economics* 10, 107–142.
- Fabricant, D. and N. Farnsworth (2001, March). The value of plants used in traditional medicine for drug discovery. *Environmental Health Perspectives Supplements* 109(S1), 69–75.
- Farnsworth, N. and D. Soejarto (1985). Potential consequence of plant extinction in the united states on the current and future availability of prescription drugs. *Economic Botany* 39(3), 231–240.
- Firm, R. (2003). Bioprospecting – why is it so unrewarding. *Biodiversity and Conservation* 12, 207–216.
- Grabowski, H. and J. Vernon (2000). The distribution of sales revenues from pharmaceutical innovation. *Pharmacoeconomics* 18(Suppl. 1), 21–32.
- INBio (2005). Products generate resources for conservation. Press Release: <http://www.inbio.ac.cr/en/noticias01.htm#interactive>.
- Kassar, I. and P. Lasserre (2004). Species preservation and biodiversity value: a real options approach. *Journal of Environmental Economics and Management* 48(2), 857–879.
- Keeley, J. and C. Fotheringham (2003). Species-area relationships in Mediterranean-climate plant communities. *Journal of Biogeography* 30, 1629–1657.
- Kilburn, P. (1966). Analysis of the species-area relation. *Ecology* 47(5), 831–843.
- Koo, B. and B. Wright (1999). The role of biodiversity products as incentives for conserving biological diversity: some instructive examples. *The Science of the Total Environment* 240, 21–30.
- Myers, N. (1988). Threatened biotas: hot spots in tropical forests. *Environmentalist* 10(3), 187–208.
- Myers, N. (1990). The biodiversity challenge: expanded hot-spots analysis. *Environmentalist* 10(4), 243–256.
- Myers, N., R. Mittermeier, C. Mittermeier, G. da Fonseca, and J. Kent (2000). Biodiversity hotspots for conservation priorities. *Nature* 403, 853–858.
- Nigh, R. (2002). Maya medicine in the biological gaze. *Current Anthropology* 43(3), 451–477.
- Onaga (2002, May). Cashing on in nature’s pharmacy. *EMBO Reports*.
- Polasky, S. and A. Solow (1995). On the value of a collection of species. *Journal of Environmental Economics and Management* 29(3), 298–303.
- Polasky, S., A. Solow, and J. Broadus (1993). Searching for uncertain benefits and the conservation of biological diversity. *Environmental and Resource Economics* 3, 171–181.
- Preston, F. (1960). Time and space and the variation of species. *Ecology* 41, 611–627.
- Proudfoot, J. (2002). Drugs, leads, and drug-likeness: An analysis of some recently launched drugs. *Bioorganic and Medicinal Chemistry Letters* 12, 1647–1650.
- Rausser, G. and A. Small (2000). Valuing research leads: bioprospecting and the conservation of genetic resources. *Journal of Political Economy* 108(1), 173–206.
- Shackleton, C. (2001). Re-examining local and market-oriented use of wild species for the conservation of biodiversity. *Environmental Conservation* 28(3), 270–278.

- Simpson, D., R. Sedjo, and J. Reid (1996). Valuing biodiversity for use in pharmaceutical research. *Journal of Political Economy* 104(1), 163–185.
- South Asian Network for Development and Environmental Economics (2003, February). Sandee newsletter #6.
- Weitzman, M. (2001). Gamma discounting. *The American Economic Review* 91(1), 260–271.
- Weitzman, M. L. (1979). Optimal search for the best alternative. *Econometrica* 47(3), 641–654.