Understanding RIOS sensitivities, strengths, and weaknesses

A demonstration in the Coyote Creek watershed

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The Natural Capital Project

http://www.naturalcapitalproject.org

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Preface: Using sensitivity and robustness analysis to assess the strengths and weaknesses of RIOS

Models are imperfect representations of reality, and even their imperfect representations can require specifying very large numbers of inputs whose values are not known with high degrees of confidence. Exploring how a model responds to changing parameters (sensitivity analysis), and how input uncertainty and model structure affect the precision and robustness of findings (uncertainty analysis), are therefore important parts of any model application. They help ensure that a modeling effort adequately captures the system behavior of interest, and also help in determining the level of confidence that can be placed in model outputs. This document illustrates such assessments, with a focus on the Natural Capital Project’s Resource Investment Optimization System (RIOS) and Sediment Delivery Ratio (SDR) model.

The goal of this document is to describe findings of sensitivity and uncertainty analysis conducted in the Coyote Creek watershed, but also to illustrate what can be learned by applying different sensitivity and uncertainty analysis techniques. Because ecosystem service provision is highly dependent on unique landscape characteristics, it is not generally possible to make a priori statements regarding which particular model inputs are most important – the important factors may vary from context to context. Therefore, while this document does illustrate findings of sensitivity and uncertainty analysis, it is equally important to consider the procedures that can be followed to generate spatial and non-spatial summaries of robustness and sensitivity, the interpretation of those outputs, and their implications for action (where action may include implementation decisions or additional modeling and data collection).

The first goal of the analysis described in this document is to show how users can avoid inferring greater precision and accuracy of model outputs than is merited. Meeting this goal is based on the idea that a thorough exploration of model parameters can illuminate the plausible range of outcomes that users should be prepared to consider (assuming that the structure of the model is considered generally valid). As an example, if varying parameters across a wide range of plausible values leads to very similar conservation investment portfolios, this provides more confidence in the recommendation than a case where small variation in uncertain parameters leads to very different arrangements for interventions. However, if there is doubt about the structure of the model, such insensitivity might instead highlight unrealistic model behavior that can be further investigated.

In the high variation case described above, the second goal of sensitivity analysis helps identify which input variables drive the results. This can then help identify where data or other information-gathering should be prioritized to improve the reliability of the modeling outputs. In the context of RIOS, some parameters correspond to measurable constructs (eg, activity cost), while others (eg, factor weights) reflect relative importance among variables, but not a measurable physical value. Improved data can be collected on measurable costs, and one can consult local experts, additional literature, or external modeling efforts to inform adjustments to non-physically based parameters like factor weights.

This document focuses on the use of RIOS as part of a broader effort to prioritize conservation investments. It therefore assumes familiarity with the general structure of RIOS, including types of parameters (eg, factors, factor weights, objective-transition scores). Attempts are made here to provide memory-refreshing context, but users should plan to refer to the RIOS user guide [link] for authoritative definitions (Vogl et al, 2015). Where relevant, we may also assume some familiarity with InVEST models. The reader is not assumed to have a pre-existing familiarity with methods of sensitivity analysis.

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1 It is possible that study of model structure and/or assessment of sensitivities across multiple environments will lead to rough generalizations depending on context, eg “in this type of landscape, factors A, B, and C will tend to be more important, while factors D, E, and F will matter less.” However, running a site-specific sensitivity assessment will be far more reliable, though it will take additional computational time.

2 The most recent version is linked to from this page: [link]
A companion document, currently in preparation, focuses on the details of implementing the types of sensitivity and robustness analysis described in this document, with the modeler/analyst as the intended audience. While this document focuses on the particular models RIOS and SDR, much of the “computational infrastructure” developed to support uncertainty analysis with RIOS (described here, and in the companion document) also extends to other modeling that may be done using substitutes for RIOS or in conjunction with RIOS.

To implement the procedures described in this document, the analyst will need RIOS (and possibly InVEST) set up on their computer, and the ability to call batch runs from a terminal window. As of August 2015, scripts exist to generate the analysis described in this paper, but are evolving with the interim goal that that users will only need to be able to make minor edits to R and Python code. The analyst should not need to actually “know” R or Python, because the scripts will have been set up so that only text editing of file paths and variable names will be required. It is currently thought that over the long term, many of the features and diagnostics described in this document may be incorporated into the user-interface distributions of RIOS and InVEST – but as of writing, it is still too early to make an estimate for when that may happen. Contact Benjamin Bryant (bpbryant@stanford.edu) for the latest set of code and associated guidance.
Applying RIOS in the Coyote Creek Watershed

Background: Promoting ecosystem services in the Coyote Creek Watershed

The Coyote Creek watershed is the largest watershed in Santa Clara valley, encompassing approximately 350 square miles from the eastern part of the Silicon Valley floor into the Mount Hamilton range and draining to the San Francisco Bay. Much of the uplands are protected areas and rural lands, with primarily agriculture in the Coyote Valley and urban Silicon Valley further north. Its water supplies are managed by the Santa Clara Valley Water District (SCVWD), which provides water to residents through groundwater and reservoirs filled by a mix of local and imported water.

In early 2014, the Open Space Authority (OSA) engaged the Natural Capital Project (“NatCap”) to help understand how protection and stewardship of natural capital can improve the health and sustainability of the Coyote Creek watershed. To do this, NatCap’s RIOS tool is being tested to see whether and how it can assist land managers in targeting restoration and conservation activities to provide the greatest benefit to water quality and quantity, and foster collaboration between management groups. RIOS does this by asking stakeholders to consider which ecosystem services (called objectives in RIOS) are of particular interest for improvement, which best management practices (called activities in RIOS) may be done to cause these improvements, and how much money will be spent on implementation. It then uses a variety of spatial biophysical information about the landscape, such as soils, topography and climate (called factors in RIOS) to locate the places where implementing these best management practices/activities are likely to lead to the greatest improvement in the ecosystem services (objectives) of interest, given stakeholder preferences and available budget. RIOS provides two main outputs: 1) score maps that combine biophysical factors to rank the landscape in terms of how important it is to do different activities, and 2) activity portfolios that show which specific activities should be done and where, given the biophysical scoring, stakeholder preferences and budget constraints.

The RIOS analysis framework

To understand the analysis presented here, it is important to understand the relationship between the RIOS concepts of objectives, transitions and activities. As noted above, objectives are ecosystem services which a watershed manager is trying to improve. RIOS currently supports the objectives of erosion control, nitrogen and phosphorus retention, groundwater recharge enhancement, baseflow enhancement and flood mitigation. Transitions are general types of landscape changes that lead to an improvement in the chosen objectives. In RIOS the supported transitions are keeping native vegetation, assisted revegetation, unassisted revegetation, agricultural vegetation management, ditching, fertilizer management, and pasture management. Activities are the actual on-the-ground practices (such as purchasing easements, reforesting, fencing out cattle, cover cropping...) that will be implemented, with the intention of causing desired landscape transitions, to help improve particular objectives. Since there is a vast array of different activities that

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4 In this context, “supporting” an objective means that RIOS includes pre-identified factors (landscape data) that are expected to influence that objective, which the user is expected to provide, which feed the calculations to prioritize pixels for different activities. This is not the same as having an explicit biophysical model of the process.
may be used in different places and contexts, instead of trying to support them all, RIOS supports a fixed set of transitions instead, and each activity must map to one or more transitions.

Some additional detail on how RIOS works is given in relevant sections of this document, but it is not within this scope to fully explain how RIOS works. More detail is provided in the RIOS User Guide footnoted in the preface.

In the initial round of the analysis, the whole Coyote Creek watershed was considered (except urban areas), and a set of 6 activities/best management practices selected that could be used to improve multiple objectives/ecosystem services – erosion control, phosphorus and nitrogen retention, flood mitigation, groundwater recharge and augmentation of baseflow. Discussion of this initial analysis led to a decision to investigate RIOS sensitivities more deeply to understand its strengths and limitations, as well as inform the process for choosing of parameters.

For the sensitivity analysis, we simplified the analysis to focus on a smaller area of interest in the upper part of Coyote Creek (shown at right), so that procedures and results would be simpler and clearer. Only two objectives were considered, erosion control and baseflow augmentation. Three representative activities were included: easements (which protect existing native vegetation and were estimated to cost $6000/acre), restoration (where native planting is done, with a cost of $600/acre) and cover cropping (which represents improved agricultural practices and had a cost of $200/acre). Since user-defined activities must map to RIOS-supported transitions, easements were mapped to the transition “keep native vegetation”, restoration to “assisted revegetation” and cover cropping to “agricultural vegetation management.” For most runs, a one million dollar implementation budget was used, which by default was allocated equally between the three activities. More detail on the objectives, factors, and the activity and transition relationships is captured in tables in the next section.

These following sections illustrate sensitivity and robustness analysis techniques by walking through them in more detail. We describe what was done, why, and what the results suggest, what questions they raise, and how some of those questions could be answered by additional analysis. We first examine how the resulting RIOS activity portfolios respond to changing input parameters (sensitivity), then consider how stable these activity portfolios are as we change many input parameters (robustness), and finally turn to understanding how RIOS parameters translate into sensitivity of an actual ecosystem service.

Sensitivity analysis of RIOS portfolios

Sensitivity analysis illustrated on RIOS factor weights
This section focuses on understanding how sensitive RIOS portfolios are to varying factor weights. In RIOS, factors are biophysical datasets such as soil type, climate, topography and land cover, given as spatial raster layers, whose values (such as millimeters of soil depth or meters of elevation) are defined by individual “pixels” covering the landscape. There are also factors that are generated by RIOS which combine several spatial layers. The generated factor “upslope source” is a measure of how much erosion, nutrient or water may potentially come onto a pixel from the contributing area upslope. Similarly, “downslope retention” indicates how much potential erosion, nutrient or water retention exists
downslope of a pixel, between it and a stream. “Riparian continuity” looks specifically at retention and continuity along the riparian corridor. Factors specific to each objective are combined using weighted sums to estimate the objective score, or the ability of a pixel to contribute to a particular objective if it undergoes a certain land management transition. Higher objective scores indicate places where conservation or restoration activities have the greatest potential to improve a particular objective/ecosystem service.

To calculate an objective score as a weighted sum, individual factor weights must be specified by the user. RIOS provides default values for these factor weights, but provides users the flexibility to change them based on expert knowledge of local conditions. While the factor weights do not correspond to physically measurable parameters in a process-based model, increasing the weight of one factor relative to others implies that the factor plays a greater role in determining how well an objective can be met. Each objective’s factor weights are specified per transition type, so that, for example, a precipitation factor may play a more (or less) important role in determining where to site agricultural activities like cover cropping versus where to site assisted revegetation activities like reforestation. This also means that there is one factor weight for every combination of factor, objective and transition.

In RIOS, factors are grouped into four key processes that influence the effectiveness of landscape transitions in a given location – upslope source area and magnitude, on-site source, on-site retention, and downslope retention. The default factor weights in RIOS give equal influence to each process, each receiving a weight of 1, while the weights of factors within a process sum to 1. For example, in the sediment retention objective four factor inputs make up the on-site source component (USLE C factor, rainfall erosivity, soil erodibility, and soil depth), therefore the default factor weight for each component is 0.25.

Table 1 - Objectives considered in this RIOS analysis -- the coded terms are used in some tables and charts where the full name is not feasible to show.

<table>
<thead>
<tr>
<th>Coded term</th>
<th>Full Name</th>
<th>Brief Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>bf</td>
<td>Baseflow</td>
<td>Ability of the landscape to capture and store water and facilitate its slow release into streams</td>
</tr>
<tr>
<td>sed</td>
<td>Sediment Retention</td>
<td>Preventing excessive landscape erosion in the form of sheetflow, rill and gully and bank erosion</td>
</tr>
</tbody>
</table>

Table 2 - Transitions considered in this RIOS analysis, and the associated activities. The coded terms are used in some tables and charts.

<table>
<thead>
<tr>
<th>Coded term</th>
<th>Full Name</th>
<th>Brief Description</th>
<th>Caused by Activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>agmgmt</td>
<td>Agricultural Management</td>
<td>Increases in crop structure, coverage and/or diversity</td>
<td>Cover Crop</td>
</tr>
<tr>
<td>areveg</td>
<td>Assisted Revegation</td>
<td>Actively planting vegetation on bare or degraded lands</td>
<td>Restoration</td>
</tr>
<tr>
<td>keepnative</td>
<td>Keep Native</td>
<td>Retaining existing native or other types of desired vegetation, that would otherwise be degraded if not protected</td>
<td>Easement</td>
</tr>
</tbody>
</table>
### Table 3 - Factors relevant to the objectives considered in this RIOS analysis. Even when a factor is relative to two different objectives, there is a unique factor weight for each combination of factor, objective, and transition.

<table>
<thead>
<tr>
<th>Coded term</th>
<th>Full Name</th>
<th>Brief Description</th>
<th>Relevant Objectives</th>
</tr>
</thead>
<tbody>
<tr>
<td>uslope</td>
<td>Upslope source</td>
<td>Amount of erosion or water flow arriving on a pixel from its contributing area upslope</td>
<td>Baseflow, Sediment</td>
</tr>
<tr>
<td>dslope</td>
<td>Downslope retention</td>
<td>Erosion or water retention capability of the landscape between each pixel and the stream</td>
<td>Baseflow, Sediment</td>
</tr>
<tr>
<td>sdepth</td>
<td>Soil depth</td>
<td>Depth of soil to a restricting layer</td>
<td>Baseflow, Sediment</td>
</tr>
<tr>
<td>benef</td>
<td>Beneficiaries</td>
<td>People or other types of entities (fish, wetlands...) who benefit from an improvement in ecosystem services</td>
<td>Baseflow, Sediment</td>
</tr>
<tr>
<td>opsrc</td>
<td>On-pixel source</td>
<td>Amount of erosion being generated by the land cover type on the pixel itself</td>
<td>Sediment only</td>
</tr>
<tr>
<td>opret</td>
<td>On-pixel retention</td>
<td>Erosion retention capability of the land cover type on the pixel itself</td>
<td>Sediment only</td>
</tr>
<tr>
<td>eros</td>
<td>Rainfall erosivity</td>
<td>A measure of the kinetic energy of rainfall, such that heavier rainfall is more likely to detach soil particles</td>
<td>Sediment only</td>
</tr>
<tr>
<td>erod</td>
<td>Soil erodibility</td>
<td>How easily particles of a particular soil type detach and erode</td>
<td>Sediment only</td>
</tr>
<tr>
<td>ripcont</td>
<td>Riparian continuity</td>
<td>Retention ability and continuity of the riparian zone</td>
<td>Sediment only</td>
</tr>
<tr>
<td>aet</td>
<td>Actual evapotranspiration</td>
<td>The amount of precipitation that is lost to evaporation and use by plants</td>
<td>Baseflow only</td>
</tr>
<tr>
<td>annprecip</td>
<td>Annual precipitation</td>
<td>Total annual rainfall amount</td>
<td>Baseflow only</td>
</tr>
<tr>
<td>rough</td>
<td>Roughness</td>
<td>Land surface roughness related to the type of vegetation</td>
<td>Baseflow only</td>
</tr>
<tr>
<td>cover</td>
<td>Cover</td>
<td>Percent of the soil area covered in vegetation</td>
<td>Baseflow only</td>
</tr>
<tr>
<td>slope</td>
<td>Slope</td>
<td>Percent slope of the terrain, as defined by a digital elevation model</td>
<td>Baseflow only</td>
</tr>
<tr>
<td>stext</td>
<td>Soil texture</td>
<td>Soil property related to particle size that indicates how easily water infiltrates through the soil surface</td>
<td>Baseflow only</td>
</tr>
</tbody>
</table>

**Methods and metrics for testing factor weight sensitivity**

We implemented tests for factor weight sensitivity by running RIOS while independently varying each of 57 factor weights at three different levels relative to their default values. These 57 factor weights are mappings between the factors associated with a particular objective (as listed above) and the transitions that are being done to help meet that objective (in this case, keeping native vegetation, doing assisted revegetation and improving agricultural vegetation management). For the objective of Sediment there are 9 factors and 3 transitions, so $9 \times 3 = 27$ factor weights. Similarly, Baseflow has 10 factors x 3 transitions, giving a total of 57 factor weights being adjusted.
As an example of how these weights were varied, if we are considering a particular factor (e.g. soil depth) for the objective of erosion control, which has a default factor weight of 1, we set all other factors to their default value, and then:

1) Run RIOS once with soil depth factor weight set to zero,
2) Run it again with the same factor weight set to \( \frac{1}{2} \) the default value.
3) Run it again with the same factor weight set to 2x the default value.
4) Repeat steps 1-3 for all 57 factor weights relevant to the activities and objectives of the Coyote Watershed, creating a database of portfolios which we then analyze and extract statistics from.

To assess sensitivity of the RIOS activity portfolios, we first can examine the number of pixels whose recommended activity (including whether to do an activity at all) changes, for a given change in the factor weight. By this definition, RIOS output is more sensitive to factor weights that cause greater numbers of pixels to change. Table 4 below shows the number of pixel changes caused by the 10 most sensitive factor weights for each level of the factor weight multiplier (i.e., when the default factor weight is multiplied by zero, half and two). The column “Total # pixels changed” counts the number of pixels that are in some way different between the default portfolio and the altered portfolio. The column “Fraction of most sensitive” simply divides the “Total # pixels changed” value of a particular factor by the maximum change. Thus, the “slope” factor weight for the Base Flow objective and the Assisted Reveg transition (second row below), is 73% as sensitive as the most sensitive factor weight, which is riparian continuity as it relates to the ability of assisted revegetation transition to meet the sediment retention objective.
Table 4 - One-way sensitivities for the most sensitive factor weights, for different values of the factor weight multiplier. A unique factor weight is assigned to each combination of the first three columns. “Total # pixels changed” shows how many values are different from the default portfolio. “Fraction of most sensitive” shows how many pixels changed when a given factor weight was varied, relative to how many changed when the most sensitive factor weight was varied. “As fraction of default portfolio size” makes the same calculation, but relative to the total number of pixels in the portfolio. Highlighted rows are objective/factor/transition combinations that appear in the top 10 for all multipliers, which implies they are consistently important drivers of the portfolio.

<table>
<thead>
<tr>
<th>Objective</th>
<th>Factor for Objective/Transition combination</th>
<th>Transition</th>
<th>Total # pixels changed</th>
<th>Fraction of most sensitive</th>
<th>As fraction of default portfolio size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sediment ripcont</td>
<td>Assisted Reveg</td>
<td>1634</td>
<td>1</td>
<td>0.159</td>
<td></td>
</tr>
<tr>
<td>Base Flow slope</td>
<td>Assisted Reveg</td>
<td>1192</td>
<td>0.729</td>
<td>0.116</td>
<td></td>
</tr>
<tr>
<td>Base Flow rough</td>
<td>Assisted Reveg</td>
<td>892</td>
<td>0.545</td>
<td>0.086</td>
<td></td>
</tr>
<tr>
<td>Base Flow dslope</td>
<td>Ag Mgmt</td>
<td>862</td>
<td>0.527</td>
<td>0.083</td>
<td></td>
</tr>
<tr>
<td>Sediment erod</td>
<td>Assisted Reveg</td>
<td>634</td>
<td>0.388</td>
<td>0.061</td>
<td></td>
</tr>
<tr>
<td>Sediment erod</td>
<td>Ag Mgmt</td>
<td>556</td>
<td>0.340</td>
<td>0.054</td>
<td></td>
</tr>
<tr>
<td>Base Flow annprecip</td>
<td>Assisted Reveg</td>
<td>556</td>
<td>0.340</td>
<td>0.054</td>
<td></td>
</tr>
<tr>
<td>Sediment erod</td>
<td>Ag Mgmt</td>
<td>552</td>
<td>0.337</td>
<td>0.053</td>
<td></td>
</tr>
<tr>
<td>Base Flow aet</td>
<td>Assisted Reveg</td>
<td>478</td>
<td>0.292</td>
<td>0.046</td>
<td></td>
</tr>
<tr>
<td>Base Flow stext</td>
<td>Assisted Reveg</td>
<td>390</td>
<td>0.689</td>
<td>0.037</td>
<td></td>
</tr>
<tr>
<td>Base Flow rough</td>
<td>Assisted Reveg</td>
<td>366</td>
<td>0.646</td>
<td>0.035</td>
<td></td>
</tr>
<tr>
<td>Sediment erod</td>
<td>Assisted Reveg</td>
<td>296</td>
<td>0.522</td>
<td>0.028</td>
<td></td>
</tr>
<tr>
<td>Sediment ripcont</td>
<td>Assisted Reveg</td>
<td>288</td>
<td>0.508</td>
<td>0.028</td>
<td></td>
</tr>
<tr>
<td>Sediment eros</td>
<td>Assisted Reveg</td>
<td>280</td>
<td>0.494</td>
<td>0.027</td>
<td></td>
</tr>
<tr>
<td>Sediment erod</td>
<td>Ag Mgmt</td>
<td>280</td>
<td>0.494</td>
<td>0.027</td>
<td></td>
</tr>
<tr>
<td>Base Flow annprecip</td>
<td>Assisted Reveg</td>
<td>276</td>
<td>0.487</td>
<td>0.026</td>
<td></td>
</tr>
<tr>
<td>Base Flow aet</td>
<td>Assisted Reveg</td>
<td>256</td>
<td>0.452</td>
<td>0.024</td>
<td></td>
</tr>
<tr>
<td>Sediment ripcont</td>
<td>Keep Native</td>
<td>250</td>
<td>0.441</td>
<td>0.024</td>
<td></td>
</tr>
<tr>
<td>Base Flow stext</td>
<td>Assisted Reveg</td>
<td>342</td>
<td>0.511</td>
<td>0.033</td>
<td></td>
</tr>
</tbody>
</table>
What do these tables tell us about...

**Which are the most important factor weights?** In this example, the factor weights associated with the assisted revegetation transition and base flow objective appear to be most important across the different factor weight multipliers.

**Does the sensitivity ranking for factors depend on how much the factor weight is varied?** Comparing across the tables (which can be done automatically with scripts), shows that seven factor weights appear in the top ten for each level of the factor weight multiplier. This type of analysis can be conducted for the top 5, top 10 or any number.

**Is the pixel change response proportional to how much a factor is varied?** Comparison across the different sub-tables for different levels of the factor weight multiplier shows that setting a factor weight to zero does cause notably larger differences than simply halving or doubling it. Doubling a factor weight versus halving causes a similar but slightly smaller number of transitions. This becomes clear if we look at the relative sensitivities in a different way, shown next.

**How sensitive are the factor weights?**

An alternative way to look at the same data is to plot it visually. We consider two related plots of the table data. Figure 3 orders the factors by most sensitive to least sensitive for given levels of the factor weight multiplier, and plots the sensitivity for all 57 factors. Figure 4 plots the most sensitive factors for a given factor weight multiplier, to allow us to “zoom in” to study the factors.

![Factor weight sensitivity](image)

*Figure 3 - Factor weight sensitivity, ordered from most sensitive to least sensitive, and grouped by the amount the default factor was multiplied by (the “Factor Weight Multiplier”). Sensitivities drop off rapidly after the top 10 or 20 variables.*
What do these sensitivity plots tell us about...

**How much the pixel response differs as a function of how much the factor weight is varied?** Figure 3 confirms that zeroing out factor weights always causes the most pixel change, as might be expected. Yet, even these changes are not that large – typically comprising less than a 10% change in where pixels are placed on the landscape.

**How does sensitivity fall off relative to the most important factor weight?** Figure 3 shows that sensitivities tend to be notably higher in the first 20 or so factors, but after that, most factors only cause a small percentage change in pixels, regardless of the factor weight multiplier. This means an analyst can safely focus on those top 20 for further consideration – specifically by ensuring they are a part of future sensitivity analyses going forward, and ideally consulting hydrologists or other local watershed experts to determine if any of these top factor weights should be adjusted based on their knowledge of the system.

**Are there plateaus or thresholds in sensitivity?** Focusing within the top 20 most sensitive factors (Figure 4), it can be seen that for some levels of the multiplier there are groups of approximately equivalent sensitivity, followed by sharp drop-offs. For example, *bf_slope_areveg* (slope factor for the Baseflow objective, assisted revegetation transition) stands out as being the most sensitive to change, with soil texture (*bf_stext_areveg*) and surface roughness (*bf_rough_areveg*) forming the next-most-sensitive group, followed by a grouping of *sed_erod_areveg* through *sed_ripcont_keepnative*, etc. The analyst may wish to examine the factor weights and the associated factor input data to
confirm the behavior makes sense. Certainly part of the explanation is due to the fact that the default values for some factor weights are smaller than others, though this will not explain all the difference.

Alternative definitions of sensitivity: Activity switching

*Users may be more interested in knowing where pixels change from one activity to another, rather than simply whether there is any change at all. However, in this analysis the “where” question does not appear to be illustrative because most of the changes that occurred were changes in location, rather than from activity to activity switching.*

The tables and figures presented above used the definition of “any difference” in a pixel value. That is, simply counting the number of pixels where a portfolio has a different value compared to the reference portfolio. A user could instead focus on where activities switched from one to another, or only where pixels changed from doing or not doing an activity. In our analysis, the vast majority of changes occur from changing the location of pixels. It turns out this must happen when RIOS is run under the proportional allocation budget constraint, because the budgets for each activity essentially determine the number of pixels covered by that activity. However, we also re-ran the entire set of factor weight variations using a floating budget, which in theory should allow more switching – in general we found this did not happen, which was somewhat surprising. However, part of this may be due to the relatively small portion of the landscape being covered. One would expect that at higher budget levels with more of the landscape covered, there would be a greater amount of activity-to-activity switching. Other user-defined constraints may affect the switching rate. For example, if activities are only allowed on different sets of land cover types or if other prefer/prevent restrictions are in place that would result in few overlaps in allowed locations, then a greater budget would not necessarily result in more switching from one activity to another.

Alternative definitions of sensitivity: Prioritization scores (aka, suitability maps)

*A user can also assess sensitivity by looking at how prioritization scores change with different parameters. These scores will provide an indicator of sensitivity even when the recommended activity does not actually change within a certain level of parameter variation. They can be used to assess whether the best areas for specific activities are stable or sensitive.*

RIOS portfolios are maps with discrete values (i.e., the chosen activity for each pixel), that represent a selection from more comprehensive information captured in the “prioritization score” (the layer that feeds the activity selection algorithm). The prioritization score maps (which can also be thought of as “activity scores”) can be useful for understanding where on a landscape each activity would be more or less effective in meeting all of the stated objectives. An intermediate output of RIOS is the activity score map, which is reported both for the entire landscape and only for areas where that activity is feasible (based on the activity-transition table and any prefer/prevent inputs). Prioritization score maps can be viewed for each transition-objective combination (e.g., “what areas have the highest suitability for re-vegetation to improve baseflow?”) or for each activity (e.g., “what areas have the highest suitability for restoration to meet all my objectives?”). Prioritization score maps themselves may be used to identify hotspots or areas where programs may want to focus their activities, as an alternative to specifying a budget-limited portfolio of activities on specific pixels. In the context of sensitivity analyses, the response of the prioritization score may be considered as a way to gain a more refined and comprehensive understanding of how parameter changes could affect where different interventions make sense. Besides plotting them as maps, we can create a histogram of the relative change across each pixel. The wider the distribution of the histogram, the more sensitive the activity scores are to that parameter change. To rank sensitivities, take the mean or other summary statistic of pixel level changes above.

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5 Many are set to 1, but this is not always the case, and a good next step of the analysis is to reconstruct the same figures, but setting reference values for all factors to 1, rather than the defaults specified in the RIOS user’s guide.
Evaluating Robustness

The above analysis focused on understanding how RIOS portfolios changed as RIOS inputs changed. It is also useful to understand what aspects of RIOS output are stable as we change many input variables – since different combinations of parameters essentially capture different plausible ways the system might work, robustness across parameter combinations suggests that more trust can be placed in the RIOS outputs that remain stable, again, assuming general confidence in the model structure. Here, we examine two measures of robustness: modal portfolio frequency maps and breakeven maps.

How is RIOS being run to assess robustness?

One conception of robustness in the choice of activity is the range of possible states where the activity is chosen – if we use many model runs to vary all parameters simultaneously and over a wide range, and certain pixels are assigned an activity in nearly all of those parameter combinations, this suggests that the inherent landscape features make the activity a robust choice, regardless of the value of the parameters that turn out to most closely represent reality. To test whether this is the case, we use a “space-filling design” and run the model 57 times allowing factor weights to vary so that any factor could be up to 10 times as important as any other. The “space-filling” aspect refers to the idea that we want the parameter combinations to be as spread out as possible, rather than clustering near the center around the default values.

Robustness approach #1: Modal portfolio and frequency

When RIOS is run over the many parameter combinations described above, we can ask: “across all those variations, for each pixel, which activity was picked the most times?” We call this the modal portfolio. As a measure of robustness of the activities, we can also ask, on each pixel, how often was the modal activity picked? If this number is high (e.g. 90%) that means that we have more confidence that the activity chosen for that pixel is a good one, regardless of what the most appropriate parameter combination turns out to be. Figures 5 and 6 show the modal portfolio and frequency map for this set of 57 runs, for a zoomed in subset of the watershed.

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6 This is equal to the number of factor weights being varied, but it is not the same as doing “one run for each factor weight.” We use what is called a Latin Hypercube, and this type of analysis could be conducted with greater or fewer runs.
Figure 5 - Modal portfolio - each pixel shows the activity chosen most frequently across a large number of RIOS runs under widely varying parameter values.
Figure 6 - Frequency map for how often the activities in the modal portfolio were chosen. Numbers close to 1 (green) indicate the activities in the modal portfolio are very robust to variations in factor weight. A value of 1 would indicate that the activity was chosen for that location 100% of the time.

The prevalence of dark green in Figure 6 shows that most activities are quite robust, though there are some interesting areas cutting across the cover crop zone where the activity was chosen less frequently. A user could inspect landscape characteristics more closely to assess what may be driving that. In general, the cover crop interventions (which are cheapest) are far more robust than the restoration interventions, presumably in large part due to their low cost, but also possibly related to the landcover on which they can be undertaken.

Robustness approach #2: Breakeven prioritization scores
Another conception of robustness is how much things would need to change before a different decision is taken. If things need to change a lot, this implies high robustness. If a small change in a parameter changes the best course of action, this is not robust. We can focus on a particular portfolio and then answer the question:

How much would the prioritization scores for the chosen activities would have to change before each pixel switches to a different activity?
For the default portfolio, we can calculate the ratio of the prioritization score for the chosen activity relative to the prioritization score for the next best activity. The plotted value indicates how much (as a fraction) the prioritization score of the chosen activity would need to be reduced before the next best activity would be chosen. In the figure below, we can see that the cover crop interventions are highly robust (which may be due to its low price, and also due to the types of landcover on which cover cropping can be done) which also aligns with the findings of the modal portfolio analysis above. Values close to 1 mean the chosen activity is robust and has a prioritization score far above the next best activity, while values closer to zero mean very little would need to change.

One complication is that the statistics in this type of plot do not account for the potential of switching from one activity to the same activity in a different location. Rather, it represents the robustness relative to the next best activity on that pixel, assuming another activity would be chosen.

**Overall, the two robustness metrics tend to align well, and can be used together to assess where users can have confidence that different interventions make sense on the landscape. The robustness criteria may also be used to focus more detailed modeling efforts.**

**Coupling RIOS portfolios with an ecosystem service model to assess sensitivity of ES outcomes**

Ultimately, RIOS is used with the goal of cost-effectively implementing activities on the landscape to achieve a desired combination of ecosystem services provision. While we do not have ecosystem service models for all objectives (and understand the Santa Clara Valley Open Space Authority is also considering other models to assess and quantify...
potential service impacts), we do have an InVEST model for the sediment retention objective, and we use that here to illustrate a method of learning about relationships between RIOS parameters and resulting service provision, via the activity portfolios.

The InVEST Sediment Delivery Ratio (SDR) model is a fully distributed raster-based model that quantifies the relationship between land cover and average annual sediment export. By translating RIOS portfolios into scenario land cover maps, we can run these portfolio land cover maps through the SDR model to assess the effect of the activities on sediment export in the watershed. Below, we do this to test how sediment export changes as a function of activity costs, budget, and weight on the sediment retention objective.

**What was done?**

We generated RIOS portfolios under a variety of cost combinations, while steadily increasing the weight placed on the sediment retention objective relative to the baseflow objective. These portfolios were run through the InVEST SDR model, whose main output quantifies the amount of sediment eroding from the landscape that is exported to the stream. The results of this work are captured in Figure 8, where each curve represents a different cost combination. Here we do not delve into the different cost combinations, but instead just note the robustness of the general response across cost levels.

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Figure 8 - Response of sediment export to increasing weight on sediment objective under different assumptions of activity costs. The focus is less on the combinations of activity costs, but rather illustrates that the relationship is robust under many different parameter combinations. Such analysis could be repeated for other types of parameters besides costs.

The figure reveals a few interesting pieces of behavior:

- Sediment export decreases as weight on the sediment retention objective is increased, as expected.
- We also see that this response is robust to different cost combinations.
- The response to sediment objective weight diminishes as more weight is placed on the sediment objective (that is, the slope flattens out). This is true, with the exception of the green curves, which show a mild kink. This could be investigated further by looking at what changes to the portfolios are being made under those cost combinations. Since RIOS does not dynamically update landscape characteristics as each pixel enters the portfolio, it is possible it is choosing sediment retaining interventions in large clusters – when such clusters are run through SDR, the additional pixels make relatively less difference, since SDR accounts for the final landscape configuration.
- The changes due to cost combinations (or, equivalently, the budget) are as big as the changes on the objective weights. This means that setting objective weights in RIOS should depend heavily on whether stakeholders are interested in continuing to optimize tradeoffs between objectives, versus optimizing a particular objective subject to meeting a minimum performance level for another objective. In this example, if stakeholders are concerned primarily about increasing baseflow subject to a certain level of sediment retention, the analyst could run the model with all weight on the baseflow objective, as long as the budget was large enough.
Studying changes in more detail

Figure 8 above provides an overall view of the response, but additional insights can be gained by studying how the portfolios themselves change as the objective weights vary. The next series of figures shows two portfolios, and a highlighting of the difference between them. The first portfolio contains zero weight on the sediment objective and all weight on baseflow, while the second portfolio was generated with all weight on sediment objective. The third plot highlights the changes in a particular region.
Figure 9 – Portfolio results using default factor weights and all objective weight on baseflow (sediment objective weight = 0).
Figure 10 – Portfolio result using default factor weights and all objective weight on sediment retention (baseflow objective weight = 0).
Figure 11 - Change map between a portfolio targeting the baseflow objective and one targeting the sediment retention objective, zoomed in on NW corner of the watershed. “Act to SameAct” refers to places where the chosen activity did not change, “Act to Diff” indicates where one activity changed to another, while “NoAct” refers to transitions where a pixel changed status from being in or out of a portfolio.

The change map (Figure 11) shows that where there is change, it is change in location of activities, not change from one activity to another. As we shifted objective weights, we expected to see transitions from one activity to another in reflection of the better suitability – however, at least for relatively low budget values, the results and transition matrices we’ve examined suggest that, even with a floating budget, changes tend to occur by moving where activities take place, rather than switching between them. This could be due in part to the variation in cost-effectiveness on the landscape – particular activities are just particularly suited to certain landscape features which do not overlap much. Further study of prioritization score layers would help identify if this is the case. This issue can also be explored by running the same experiment with significantly higher (floating) budget levels and see whether transitions between activities occur.
How much more erosion reduction is achieved for a unit increase in budget?

We can answer this question by running the model under increasing budgets and considering the impact on sediment export. This is shown in Figure 12, where the y-axis represents the reduction in sediment export between implementing the RIOS portfolio and not implementing it. Even though we are talking about sediment *reduction*, a larger number means a bigger impact (ie, more reduction).

![Figure 12 - Sediment export as a function of budget, broken out by whether there is equal allocation of budget across activities, or allowing activities to be chosen solely by cost-effectiveness ("floating budget"). In this case, there is minimal difference at high budgets, but significant difference for low budgets. The fact that the curve is downward sloping suggests that increasing budget is actually reducing the effectiveness of sediment retention, a counterintuitive result that may be genuine, or due to inadequacies in the modeling chain following RIOS portfolios.](image)

**The slope of this plot indicates how much more sediment export is reduced for each dollar added to the budget.** For example, when run with a floating budget (where RIOS is told to spend the whole budget in the most cost-efficient way, without allocating any budget to specific activities), each million dollars is associated with approximately 4000 ton change in average annual sediment export.

**But wait, why does it slope down?**

This plot is actually suggesting that spending more to implement more activities reduces the impact on sediment export – that is, it actually increases sediment to the streams. This highlights the importance of running portfolios through to service outcomes, and could be explained by several factors:

- Failure of the RIOS model to find the best locations – This could result from a sub-optimal portfolio selection by RIOS, due to the simplified heuristic prioritization approach (ie, the response shown is correct, because RIOS chose bad portfolios).
- Failure of land cover-based coefficients to accurately represent the potential sediment delivery from different land cover types – This could result from inaccuracies in land cover parameters associated with particular transitions, for example if restored forest parameters show more potential erosion than urban areas (ie, RIOS
chose well, but the coefficients associated with different land cover classes was problematic, so the modeled sediment retention is inaccurate.

- Failure of the sediment retention model to capture relevant behavior (ie, RIOS chose well, but the curve described is not correct because the model does not capture relevant processes in this area).
- Hidden tradeoffs with the baseflow objective (The response to the sediment objective is in fact changing as it should be, but that is masked because we have not modeled impacts on baseflow so we only “see” part of the story).

Re-running the modeling chain with the objective weight entirely on sediment retention would rule-out whether the cause is due to prioritization of the base flow objective at the same time. Inaccuracies in land cover parameters could be tested by reconstructing a biophysical table that shows restored vegetation as retaining more sediment than developed open space.

**Lessons learned, and implications for choosing RIOS over alternative approaches for prioritization**

**Big picture conclusions**

**RIOS should not be viewed as a means to produce a single portfolio that can be assumed “optimal.”** The illustrative modeling work on the Coyote watershed suggests that, as with any modeling or optimization approach, RIOS does not produce “the answer.” Instead, RIOS should be used to both constrain the areas where interventions are likely to meet objectives, and to help users gain an understanding of how the choice and placement of interventions is explained by factors on the landscape. Much of this understanding comes from delving into how RIOS outputs (including intermediate outputs) change in response to different parameters.

**RIOS was not highly sensitive to factor weights, but is sensitive to cost and objective weights.** Overall, we found that while factor weights are difficult to set, RIOS was also not particularly sensitive to them when varied one at a time. It is however, quite sensitive to both cost and objective function weighting. In general, where it is difficult to set parameters, the analyst should explore across a range of values, and the scripts we have developed make it easier to do this, as well as systematically summarize results, at varying levels of investigation and sophistication.

**The insights gained and confidence in the suitability of RIOS portfolios can be increased significantly if RIOS is paired with models which can be used to quantify the ecosystem services of interest.** As we saw in the response of sediment export to increasing budget, the actual response to an objective may not be what we expect, or may not be modeled as we expect. Instead of the InVEST SDR model, RIOS portfolios could potentially be used as inputs to MODFLOW if groundwater recharge is of interest, or HEC HMS for analyzing differences in rainfall-runoff. Regardless of the model selected, harmonizing assumptions and parameters across the optimization and service models is critical.

**RIOS versus other approaches to prioritization**

RIOS can be thought of as sitting in the middle of a spectrum, from rule-of-thumb based approaches to sophisticated spatial optimization approaches that utilize models of the services under consideration.

**Rules-of-thumb/expert knowledge:** If the ultimate goal is to cost-effectively achieve ecosystem service objectives, it is almost certain that RIOS would improve upon rule-of-thumb approaches and expert knowledge alone -- the main question is whether the improvement would be significant in terms of the ultimate portfolios chosen. The improvement is “almost certain” because the research that went into RIOS essentially embodies sophisticated and evidence-based rules of thumb (the importance of different factors to different objectives), but RIOS helps track and integrate those with extremely large amounts of data that is infeasible to sort through in an ad hoc manner. Thus many conclusions will align well (e.g., do cover crops where they are feasible), but when reaching the limits of scarce budgets, RIOS may point users to areas to consider that they may not have otherwise identified – that is, RIOS sorts through all the data
embodied in landscape rasters to identify specific areas that an expert user might not be able to pick out. Where budgets are high enough to cover large parts of the landscape, it may be that recommendations from RIOS and expert users largely overlap because there are only so many places to do interventions, and most of them are identified by either approach. However, while RIOS considers many factors simultaneously, expert knowledge may also identify where RIOS provides poor recommendations due to failure to account for certain interactions or contextual issues not recommended in the RIOS structure. Therefore, using RIOS in the recommended manner of generating candidate portfolios that can then be vetted with expert knowledge holds promise.

**Service-model based optimization:** The other extreme is optimization that is based on dynamically estimating the marginal gain in ecosystem services from changing the activity performed on each individual pixel. If it is the case that one has models for all services of interest, and one has the ability to translate land cover portfolios into parameters for those models, then it may be feasible and make more sense to utilize a spatial optimization algorithm. These algorithms will be more likely to produce truly “optimal” portfolios with respect to the service being modeled, but they also require more expert knowledge of optimization processes, and may also require more detailed data, and be generally less open to transparent stakeholder participation. By contrast, RIOS will not be quite as optimal, but the structure and intermediate outputs will help facilitate stakeholder discussion and building understanding of the reasoning behind a portfolio.

**Generalizing this analysis to service-based optimization**

Even if analysts choose to link an optimization routine with a service model rather than use RIOS, the tools and analytic approaches developed in this guidance will still be useful to gain an understanding of the model behavior and robustness of the portfolios generated. RIOS can be viewed as a special case of spatial optimization more broadly, where, in the case of RIOS, the objective function and portfolio selection algorithm are specified together. Factor weights may be thought of as analogous to parameters that feed ecosystem service models. The “objective-transition score” on a pixel may be thought of as an approximated estimate of the marginal value in service change associated with that activity/transition.

**Final lessons**

Below we list some of the lessons we have identified to date based on our model runs and analysis of the RIOS structure. (This references some of the above, but is not a pure recapitulation of issues already demonstrated.) We also include some other hypotheses that we anticipate being able to confirm with additional analysis.

- Being sensitive to a factor weight is not the same as being sensitive to quality of the factor raster data. They are linked, but showing that RIOS outputs are sensitive to a factor weight does directly correlate to the importance of having precise and accurate data for that factor. Testing alternative spatial inputs is a necessary but separate task that we did not undertake here.
- In general, RIOS sensitivity is both determined by relative scores for each activity on each pixel, but also by the budget. We suspect that the “best” pixels (ie, those with the highest prioritization scores) are likely to remain stable, while more change is likely to happen for pixels that have priority scores near the cutoff where adding pixels runs up against the budget constraint: Changes in parameters will cause “borderline” pixels to flip in or out of the set of activities.
- Running RIOS with activity-specific budget constraints alters the nature of sensitivities by enforcing the number of pixels for each activity – if there is no floating budget, pixels can only shift location in response to changing factor weights.
- RIOS is likely to be much more sensitive to activity cost data than to factor weights, though it will be relatively insensitive to cost increases in activities that are not chosen for very many pixels in the reference portfolio (ie where all factors and costs are assigned their original/default values). This is because if an activity is already chosen very little, increasing its cost will only reduce its likelihood of being chosen. For the same reason,
portfolios will also be less sensitive to cost decreases in the dominant activity, since they were already attractive options and will only look better as they become cheaper.

- Utilizing “prefer and prevent” areas for activities (see RIOS guidance) significantly decreases sensitivity to cost and factor weights within the preferred area -- and under some conditions, it becomes entirely insensitive.
- Summarizing the difference in the activity score for the chosen activity versus the next best activity can provide a good indicator of overall robustness -- eg, how much the cost would have to change or how much the activity score would have to change before that pixel flips to a different activity.
- RIOS assumes that any activity that can cause a particular transition on the landscape is assumed to be equally effective at doing so. If this is not the case, the cost-effectiveness metric that forms the basis of the prioritization score can be significantly skewed, and bias toward cheaper interventions even if those interventions have less likelihood of being effective. Users can currently work around this by increasing the effective costs as a proxy for lower transition effectiveness. However, if this approach is taken, users will need to make their own assessment of when the budget constraint is reached (because RIOS does not currently distinguish between effective cost and actual cost) -- fortunately this is a relatively straightforward raster calculation.
- Depending on the broader goals, RIOS should also be run recognizing the difference between costs borne by implementing agencies (ie, those costs that are subject to the budget constraint), and costs borne by others -- whether they are opportunity costs of putting land into certain uses, or maintenance costs that follow after an initial intervention.

While some applications of RIOS have including limited exploration of how portfolios change in response to changing inputs, the efforts described in this report constitute the first systematic analysis of RIOS behavior, and also helped develop tools to assess that behavior more easily. Overall, the analysis confirmed some predicted aspects of RIOS behavior while also highlighting areas where it appears to deviate from what might be expected or desired, in ways that may or may not be problematic, depending on the ultimate cause and application. We hope that this is just the first set of analysis in what will be a broader endeavor to explore RIOS behavior with an eye towards understanding its strengths and limitations in informing conservation planning and implementation.
Appendix: Potential additional analyses

This section describes additional runs and analyses that could be undertaken to better understand the behavior of RIOS as well as isolate the drivers of certain behaviors that have already been observed. It is motivated by and written assuming familiarity with the analysis above.

Re-run the budget variation analysis (as captured in Figure 12) all the way through to ROI calculations with all weight on the sediment objective. This would be a “more fair” test of the response to budget, since it is the only service outcome we can currently see. If the curve is still downward sloping, this eliminates the possibility that the downward response on sediment is due to competition with the base flow objective.

Re-run the budget variation analysis (and possibly others) all the way through ROI calculations using only weight on the sediment objective, and with altered biophysical table that includes adjusted usle_c parameters that may be causing the downward sloping ROI curve shown in Figure 12.

Re-run all designs (just to the portfolio stage) using both proportional and floating budget, and test whether there is increasing amount of activity to activity switching under different parameter combinations as budgets are increased. This should be done in conjunction with assessment of the activity-transition matrix and the land use classification table, to see how much changes are restricted by land cover type, versus how much stability in portfolios is due to superior cost-effectiveness.

Relating, conduct runs with all costs equal to more closely study the effect of the activity scores and whether that induces activity to activity transitions.

Do LHS runs with increasingly large numbers of runs to understand convergence of maximal extent (that is, how big does LHS need to be to stop adding pixels to extent of all portfolios?). This approach could also be taken to track portfolio extent on an activity-specific basis – i.e., what is the footprint of all places where a certain activity is recommended at a certain budget level?

Understand source of kink in concavity of sediment response to objective weight, under some cost combinations (as shown in Figure 8).

Assess drivers of plateaus in one-way sensitivities (as discussed around Figure 4).

Rerun under all factor weight defaults as 1, rather their sometimes fractional default values.

Analyze the cost-variation runs (which drop each cost by 50% relative to its default) and compare them to the one-at-a-time factor weight sensitivity analysis to confirm that portfolios are more sensitive to a given percent change in cost than to a given percent change in a particular factor weight.

Assess consistency between the modal portfolio frequency map and the breakeven score map approach to robustness by plotting and regressing them against each other, on a pixel-by-pixel basis.

Compare whether there are many significant differences between the modal portfolio and the portfolio generated using mean input values. If there are not, and if there is good agreement between the portfolio frequency and breakeven map, this implies a good robustness assessment can likely be had without generating many portfolios necessary for the modal frequency analysis.

Given that response of the sediment objective to increasing budget saw a convergence of the fixed and floating values, test whether the convergence in sediment response is driven by a convergence to similar portfolios, or whether two rather different portfolios produce similar sediment outcomes.

Conduct additional sensitivity analysis to assess sensitivity to different levels of raster aggregation at each stage of the process (RIOS inputs, portfolio and activity score outputs, and sediment outputs).

Compare factor weight sensitivity to the sensitivity of varying inputs with bias and noise (and generally systematically test sensitivity to varying factor inputs).