Optimal Determination of Locally Variable Herbicde Application Rates in Presence of Uncertainty

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Weed competition can be a significant impediment to crop yield and profit. Herbicide is applied to reduce weed populations, minimize crop loss, and maximize profit. Complete and deterministic knowledge of the weed distribution would allow the farm manager to calculate the "correct" application rate. This correct rate would be locally variable, that is, more herbicide would be applied in areas of high weed density and a reduced amount would be used where there are few weeds. This locally varying treatment is an environmentally and economically sound approach to weed control.

The major problem facing farm managers is the unavoidable uncertainty in the spatial distribution of weeds in any particular field. Deciding on the optimal locally-varying rate of application in this case is more problematic. We propose a methodology for establishing optimal herbicide application rates using geostatistical models of uncertainty in weed density combined with principles from decision making.

A case study with data from a field near Saskatoon, Saskatchewan, Canada illustrates this methodology. Weed control is achieved with a significant reduction in herbicide. Herbicide requirements may not always go down; however, we can be sure that the herbicide is being applied at the right locations rather than uniformly over the entire field.

Introduction

If left uncontrolled, weeds reduce crop yield and significantly affect profits. Weed control is expensive and also affects profitability [16]. Herbicides are applied to more than 60% of the cropped acres in western Canada representing about 30% of the total cost of crop production. In addition to affecting profitability, Herbicides have a significant effect on the environment. Optimizing herbicide application rates would reduce environmental impact of unneeded herbicide while maximizing crop yield and profit.

Intense competition in the farming industry has sparked interest in precision farming techniques to manage costs and increase profits. Advances in technology such as global positioning systems have allowed the agricultural industry an opportunity to implement site specific herbicide application on farm equipment. Consequently, technology is available to assist farm managers in managing the spatial variability of weeds. Quantifying risk associated with weed distributions would provide an opportunity to implement locally variable optimal herbicide rates.

Therefore, the objective of this study is to propose a methodology for deriving "locally varying herbicide application rates" (LVHAR).

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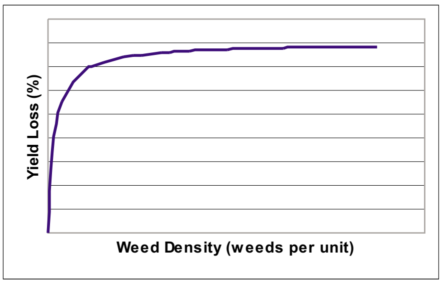

Figure 1: A conceptual figure of increasing weed density to decreasing crop yield.

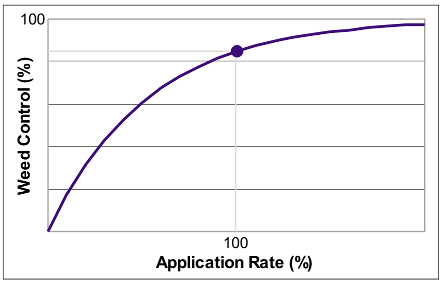

Figure 2: A conceptual map of herbicide application rate compared to % weed control.

Problem Setting

Weeds are a problem because they compete with crops for light, nutrients, and moisture [4]. Consequently, crop growth is affected and lower yields are realized. The crop loss is proportional to weed density [1], see Figure 1.

Weeds are rarely homogenous in their distribution. The spatial distribution of weeds in fields has been studied and found to be "patchy" [2, 3, 6, 12, 13]. It makes good sense to consider locally-variable herbicide rates that target these patches to minimize off-target application and reduce the total amount of herbicide applied.

Herbicides have long been used to optimize crop yield and mitigate economic loss [15]. Herbicides improve crop yield and have positive economic results. Traditionally, farm managers apply a uniform herbicide application rate. There are a number of reasons for this traditional approach (1) spraying is done early in the morning or late at night when the wind has died down, (2) the tractor speed is quite fast making it difficult to visually identify weed populations and dynamically adjust the rate, and (3) there has been no procedure to balance the risks associated with under- and over- spraying.

When herbicides are applied to crops at recommended label rates, they are legally required to control 85% of a weed population in Canada. Rates below the recommended label rate can decrease economic costs but may result in undesirable consequences such as poor herbicide performance and ineffective weed control [17, 9, 6]. Figure 2 illustrates the idea that below 100% of the recommended application rate, the expected efficacy decreases. Of course, not all locations in a field require *full* weed control, motivating the need for LVHAR.

LVHAR may be included in an integrated weed management program due to environmental considerations [14]. We all recognize that unnecessary loading of herbicide in the environment could have severe long-term consequences including contamination of water supplies.

A key to LVHAR will be to identify the locations of high and low weed density. Weed sampling can be conducted to characterize the spatial and temporal variability. Our idea is to perform "some" sampling to determine the weed density and to supplement this limited sampling with geostatistical models of uncertainty. It would not be practical to sample everywhere in the field - it would be too laborious and expensive. The subject of optimal sampling density and procedures is important and not addressed in this paper.

There is a single true distribution of weeds for each field which is a result of complex environmental and biological processes. Unfortunately, it impossible to establish that unique true distribution without exhaustive sampling. Therefore, numerical models which describe some of the significant physical and biological features for a weed are created to address the limitations of sparse sampling.

Uncertainty exists because of our lack of knowledge about the true distribution of weeds; major decisions have to be made in the presence of this uncertainty about the weed distribution's extent, its density and what herbicide to apply. The goal of many farm managers is to make decisions in such a fashion that strikes a optimal balance between input costs and expected profit.

LVHAR, given uncertainty, can be defined as those herbicide rates that maximize expected profit per hectare. To determine LVHAR, requires a numerical model representing a weed distribution. A quantitative measure of profit depends on the revenue from the crop minus the costs of herbicide and its application. Thus, LVHAR are those rates that minimize crop yield loss while at the same time maximizing weed control for maximize profit at a particular location.

Methodology

The subject area of geostatistics provides the tools to numerically model phenomena correlated in space and time [5, 7, 10, 11]. Spatial correlations of weed distributions can be quantified and inferences drawn about weeds at other unsampled locations. Geostatistical tools can be used to model weed distributions, integrate different types of weed data measured at different scales, and assess and quantify uncertainty in a spatial context.

A case study using weed density data from a 35 ha field near Saskatoon, Saskatchewan, Canada was analyzed using geostatistical tools. All weed species were identified and counted at the 3-4 leaf stage in 1/4 m^{-2} quadrats 50 m apart in a grid for 1995. Wheat (*Triticum aestivum*) was grown. All weeds were counted and identified in 1996 on two 1 m grids which was used to account for the small scale variation in the 1995 data set. For this case study, weed species were grouped into broadleaf and grass categories since correlations between different species of weeds was almost zero (ρ=0.02). Finally, declustering revealed no appreciable differences and this data set was assumed to be representative of the entire study area.

The location and density of broadleaf weeds for 1995 is described in Figure 3 and illustrates significant variability throughout the field. Weed density is indicated by the same graph used in Figure 1 for all other graphs. A histogram of weed density for the 137 sample locations indicated a range of 1 to 408 broadleaf weeds per m^{-2} with a mean of 70.8, in Figure 4. The broadleaf weed distribution was highly skewed due to the absence or low frequency of weeds at 30% of the sample locations.

Modeling spatial distribution of weeds requires a quantitative measure of spatial variability; the most commonly used tool is the semivariogram [5, 7, 10, 11]. The spatial variability of weed density from the example data is illustrated in the variogram of Figure 5.

Broadleaf weeds are modelled as a continuous variable throughout the field. The short scale variability was quantified with a small grid of samples collected in 1996. This shows a low nugget effect of 0.05, that is, the weed density is very continuous over short scales. The direction of maximum continuity for 1995 is in the $N90^oE$ direction. A water way that transverses the southeast corner of the field may have influenced broadleaf weed distribution in 1995 accounting for the anisotropy.

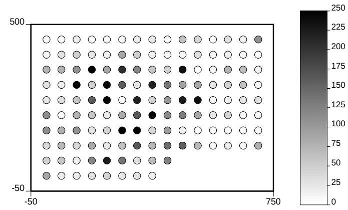

Figure 3: A map showing the total number of weeds at each of 137 sample locations.

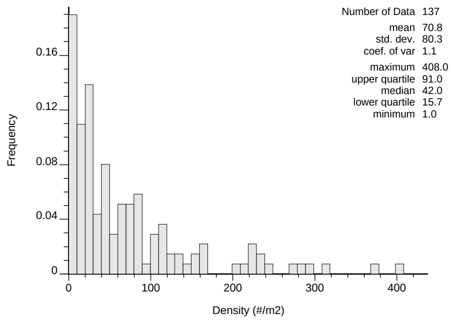

Figure 4: A histogram for weed density from a field near Saskatoon, Saskatchewan, Canada.

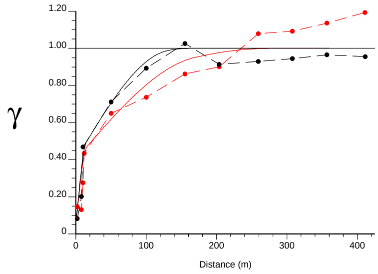

Figure 5: A semivariogram for weed density from a field near Saskatoon, Saskatchewan, Canada. The dashed line in the figure represents the experimental variogram while the solid lines represent the variogram model.

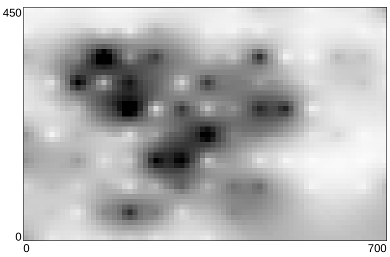

Figure 6: A kriged map of weed density for the field of interest near Saskatoon, Saskatchewan, Canada. The weed density is described in Figure 1.

A variogram provides critical input for modeling spatial uncertainty. This model of spatial correlation in Figure 5 was used for modeling at a 1 m^{-2} scale. The results were scaled up to a 10 m^{-2} block size for decision-making.

The true distribution of a weed species is unavailable given sparse sampling. Various geostatistical procedures have been devised to estimate the weed density at unsampled locations [5, 7, 10, 11]. Kriging was used to model weed density and this output served as a first input for a LVHAR program. The output of LVHAR is represented in Figure 6. Note that kriging is an interpolation technique that is not used for risk analysis and optimal decision making due to its smoothing feature [8, 11]. For this reason, the geostatistical method of simulation is used.

Simulation creates maps that honor the variogram and histogram [5, 7, 11]. Two realizations in Figure 7 differ from each other at any given location that was not sampled, but the overall histogram and variogram is the same. Thus, a simulated weed density map offers the advantage of characterizing variability at unsampled locations. One hundred realizations of the weed density were created and used for decision making. The first three realizations of 101 are shown in Figure 7. Small-scale variability of those realizations may conceal large-scale trends but the objective of simulation is to accurately reflect our state of incomplete knowledge in models for LVHAR. These models are used to perform risk-quantified decision-making.

An average of 101 realizations is shown in Figure 7, which is very similar to the kriged map in Figure 6.

Figure 8 illustrates a probability distribution of the weed density at one location on the map. Our determination of the LVHAR considers the uncertainty at each location. Although there is uncertainty at each location we must arrive at a single optimal application rate that can be mapped and applied in practice.

Herbicide application rate is determined by the weed density. The purple line in Figure 9 indicates the "cost" of herbicide application. The cost of herbicide product and application charge is described by the green line in Figure 9. Minimizing the crop yield loss in combination with the lowest herbicide rate to control a particular weed density will result in a minimal loss function. The minimum of this loss function becomes the optimal herbicide rate for that location in a field.

The "cost of yield reduction" function illustrated by the purple line in Figure 9 is displayed in Figure 10. In Figure 10, we see that larger weed density requires more herbicide that also costs more. This indicates that for a given weed density, herbicide rates can be optimized on a local basis.

The recommended herbicide rate is the optimal rate averaged over the uncertainty at a location in the field. There are several application rates illustrated in the diagram above the histogram in Figure 11. All these application rates are averaged from a distribution which becomes the mean of the LVHAR. This is represented by the black line in the histogram.

The algorithm is sensitive to the mathematical models used to quantify crop yield loss as a

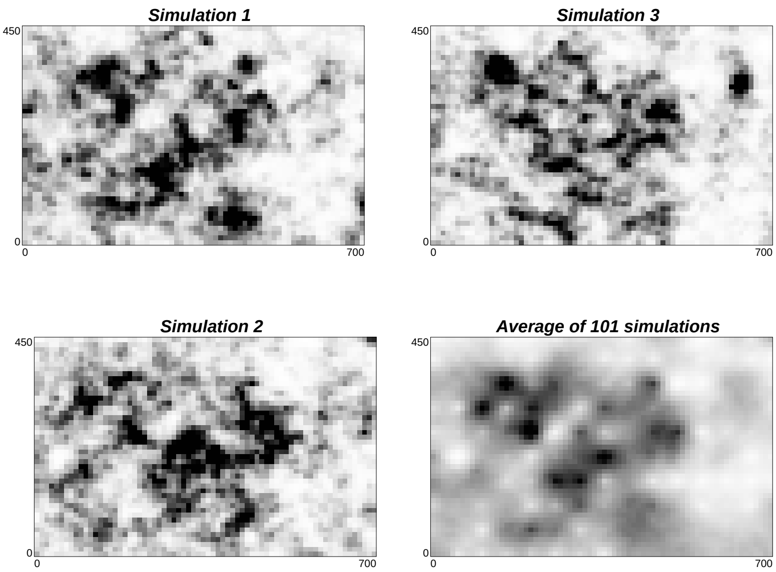

Figure 7: A simulated map of weed density for the field of interest near Saskatoon, Saskatchewan, Canada. The first three simulations are shown as well as an average of 101 simulations. The density is described in Figure 1.

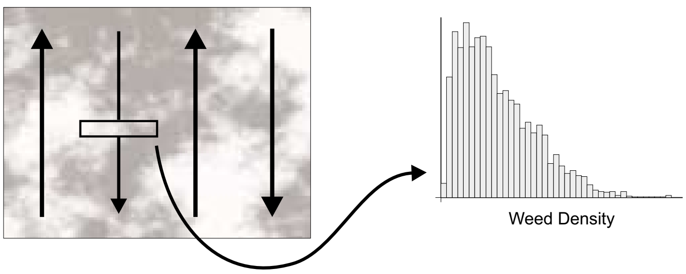

Figure 8: A map of weed density that can be used to create a probability distribution in a location in the field of interest.

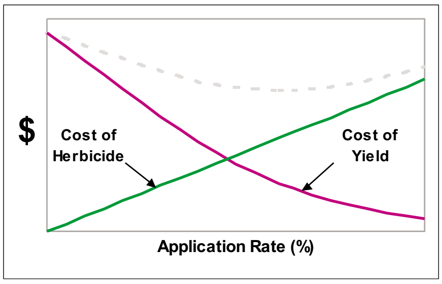

Figure 9: Application rate of herbicide compared to the crop yield loss. Also included is the cost of yield loss and cost of herbicide.

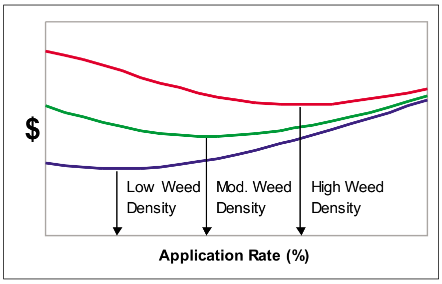

Figure 10: Varying herbicide application rates in response to different weed densities.

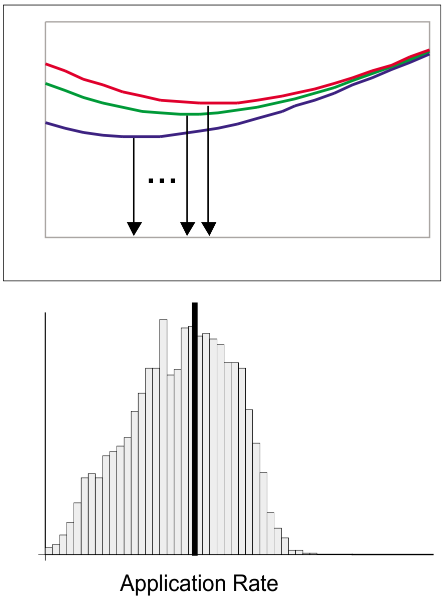

Figure 11: A map showing that as weed density varies, herbicide application rate will vary. The solid black line in the histogram represents a mean of the LVHAR.

function of weed density. The following model satisfactorily characterizes crop yield loss as a function of herbicide application rate:

$$W^{(l)} = 1 - exp(\frac{3h}{a})$$

$$Y^{(l)} = y_{wf}(1 + ad^b)$$

where y_{wf} is weed free crop yield, d is weed density, a is recommended application rate, h is maximum application rate and b is an arbitrary parameter, Y^l is % yield loss, W^l is weed loss and l is the number of realizations. Other models were evaluated and found to be less robust in describing this relationship especially at high weed densities.

Thus, LVHAR are derived by simulating weed density, combining crop yield loss for those weed densities with herbicide costs to arrive at optimal application rates. Maps of weed density based on their associated uncertainty and the resulting optimal herbicide rates can be used to make risk-qualified decisions about what areas to spray in a field. This is illustrated in Figure 12 where the recommended rate of herbicide is represented by 100%. Variations in herbicide rate are described by a gray-scale where white represents no herbicide or a low rate while black indicates the highest rate of herbicide.

To determine LVHAR, assumptions are made for average crop yield, selling price and herbicide costs for this study. Crop yield was 3.0 t/ha selling for \$90/t which would gross \$300/ha. Herbicide costs are assumed to be \$50/ha which includes herbicide product at \$40/ha and \$10/ha for application cost. Maximum crop yield loss is assumed to be 40% while recommended herbicide application rate is 100% and maximum application rate is 200%.

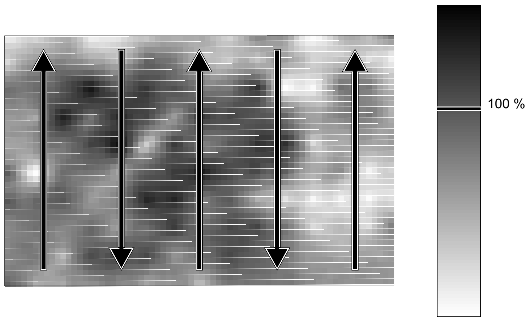

Figure 12: A map showing LVHAR with 100% as the recommended rate for this weed.

Results

To quantify the economics of optimal herbicide rates requires a suite of weed density realizations. These realizations can be used in a mathematical function which predicts application rate based on expected yield loss and herbicide costs at different locations. The mathematical function that will minimize the combined cost (C) of herbicide and crop loss for different rates at all locations $\mathbf{u}$ over all realizations is:

$$C_i(a = a') = \frac{1}{L} \sum_{l=1}^{L} C(a', w^{(l)}, w_{yl}, yl)$$

where a' is a recommended herbicide application rate, $w^{(l)}$ is the weed density for realization l, w_{yl} is the weed density causing yield loss, and yl is crop yield loss.

$$C(a', w^{(l)}, w_{yl}) = \%YL * E\{Y\} * E\{R\}$$

with $\%YL$ being the % yield loss, $E\{Y\}$ is the expected crop yield which is a constant, and $E\{R\}$ is the expected gross crop revenue of the crop which is a constant.

Assessing risk combines uncertainty and cost by considering i costs at location $\mathbf{u}$ for (a_i) herbicide application rates of w weed densities over many realizations, $C(\mathbf{u}; a_i, w)$. To determine the optimal herbicide rate for each realization at location $\mathbf{u}$, select the average rate of all L herbicide application rates:

$$a_{ave}(\mathbf{u}) = \{E\{a_i \mid min\{C(a_i, w^{(l)}(\mathbf{u})\}\}\}$$

Expected weed density from simulated distributions averaged 75.9 weeds/m^{-2} with a range of 3 to 356 weeds/m^{-2}. This histogram was more symmetrical compared to the original data in Figure 4.

A herbicide application map was created in Figure 13 using the expected weed density for the field of interest. Approximately 1% of the area is expected to be sprayed at above the recommended label rate of 100% while 48% of the area will receive 50% or less of the recommended herbicide rate.

The histogram in Figure 14 for this application map indicates a mean application rate of 50.4% with a range of 0 to 116%. Where weed density was high, higher rates of herbicide are applied compared to low weed density areas.

The cost of herbicide for this optimal application rate is $793 for the field compared to $1575 when the recommended rate is uniformly applied. Thus, herbicide treatment maps with a continuum of herbicide rates are optimized for cost and weed density resulting in an economic saving to farm manager. It is also expected that less off-target contamination will occur.

A global application rate of 50% herbicide resulted in 5% more expected economic loss compared to the optimal herbicide application methodology. The maps comparing these two results are shown in Figure 15 and indicate higher losses in the areas of high weed density for the global rate of 50%.

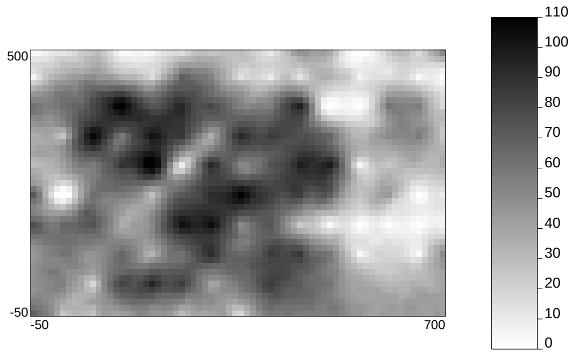

Figure 13: A LVHAR map.

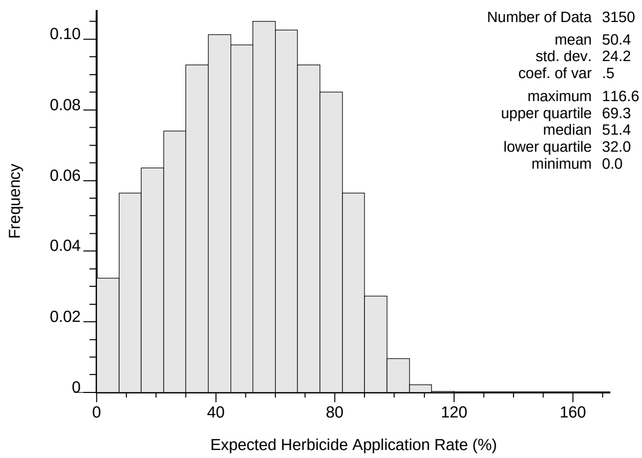

Figure 14: A histogram of herbicide application rates for the field of interest where 100% is the recommended rate.

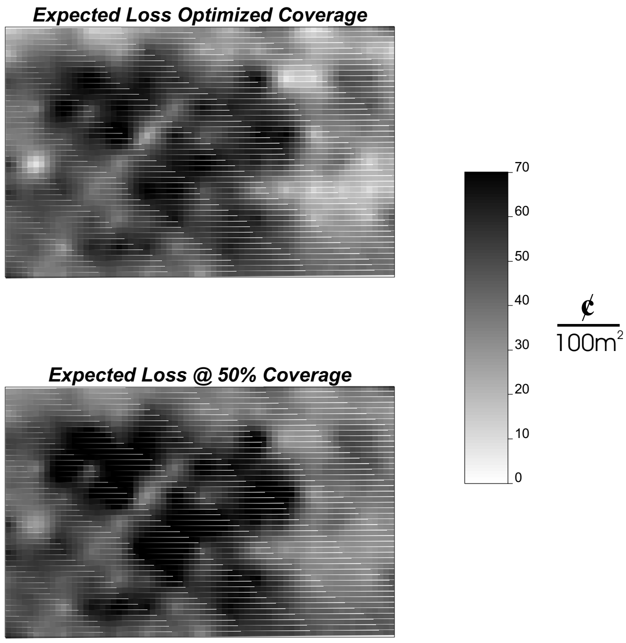

Figure 15: The optimized expected crop yield loss compared to the expected yield loss at 50% of recommended rate.

Discussion

The optimal sample spacing that balances time and labour costs with improved accuracy needs further study. Data from different sources needs to be considered for validating this methodology. Only one technique of weed control was examined while farmer managers usually have several options.

Variable rate information is limited, however weed response to herbicide rate was extrapolated from studies published in the literature. Consequently, we assumed knowledge of how weeds respond to varying herbicide rates. This requires verification under different environmental and cropping conditions.

Spatial statistics are useful to characterize the heterogeneity of weed distributions as well as quantify the uncertainty due to incomplete data. The LVHAR methodology attempts to incorporate risk along with the spatial distribution of weeds into a model for optimal herbicide rate application.

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