Statistical and Economic Techniques for Site-specific Nematode Management

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Abstract: Recent advances in precision agriculture technologies and spatial statistics allow realistic, site-specific estimation of nematode damage to field crops and provide a platform for the site-specific delivery of nematicides within individual fields. This paper reviews the spatial statistical techniques that model correlations among neighboring observations and develop a spatial economic analysis to determine the potential of site-specific nematicide application. The spatial econometric methodology applied in the context of site-specific crop yield response contributes to closing the gap between data analysis and realistic site-specific nematicide recommendations and helps to provide a practical method of site-specifically controlling nematodes.

Key words: nematode management, precision agriculture, site-specific techniques, spatial autocorrelation, spatial econometrics, yield response function.

Nematode infestations tend to be spatially clustered within agricultural fields and result in crop yield penalties in some areas but not in others (Evans et al., 2002; Wyse-Pester et al., 2002; Monfort et al., 2007). Nematode control in cotton is primarily dependent on the application of nematicides because of a lack of effective resistant cultivars (Koenning et al., 2004).

The relatively high cost of fumigant nematicides, the difficulty in their application, and environmental concerns with using fumigants has encouraged many cotton growers in the United States to consider ways to target specific zones within fields for nematicide application to minimize waste and expense (Mueller et al., 2011). The advent of "precision agriculture" technologies provides the possibility of site-specific nematode management rather than the "whole-field" approach that has historically been used. In order for a site-specific nematicide placement strategy to be utilized at the farm level, a clear indication of the potential for profitability as well as the efficacy of this approach must be perceived. Logically, estimation of profitability of site-specific nematode management and the development of application recommendations for individual fields must be based on the estimation of yield potential (penalty) where nematodes are yield-limiting. Site-specific crop yield data, as with most other agronomic data obtained at high resolutions within fields, are expected to be spatially structured, and failure to properly account for spatial structure of the yield data may result in inefficient parameter estimates for yield response functions. We review the spatial statistical techniques that model the correlation among neighboring observations and develop a spatial economic analysis to determine the potential of site-specific nematicide application from a theoretical and practical perspective. The spatial econometric methodology used to determine site-specific crop yield response is a necessary link between data analysis and site-specific recommendations that will help to provide a practical site-specific method of controlling nematodes.

STATISTICAL ANALYSIS PROBLEMS ASSOCIATED WITH PRECISION AGRICULTURE DATA

Recent advances in precision agriculture technologies provide farmers with the tools to determine the impact of nematode infestation and implement site-specific variable rate nematicide application (Mueller et al., 2011; Ortiz et al., 2012). Site-specific sensors that measure either soil electrical conductivity or electromagnetic induction provide continuous soil data over space so that models can be evaluated with a continuous covariate rather than discrete categories to explore the correlation between crop yield, nematode population density, and soil texture (Monfort et al., 2007; Ortiz et al., 2012). Global positioning systems (GPS) combined with yield monitors and variable rate fertilizer applicators have been used in conducting site-specific on-farm experiments (Griffin, 2009). However, difficulties experienced in the analysis of spatial crop data have been one of the key constraints to prevent the widespread adoption of site-specific technology (Anselin et al., 2004). Improving the precision of crop data analysis makes it possible to pinpoint geographic or environmental factors that affect nematode populations, and this, in turn, facilitates effective site-specific nematode management recommendations.

Omitted variables: Most precision agriculture data, including yield monitor data, contains thousands of observations. Generally speaking, statistically significant treatment effects would be expected with a large number of observations even with very small effects (Hicks et al., 1997). However, although many observations of the dependent variable exist, precision agriculture datasets tend to have few explanatory variables. This results in omitted variable problems or an under specification of the model. Ordinary least square estimates (OLS) are biased and generally inconsistent under omitted variables (Wooldridge, 2003) and OLS residuals

are expected to be spatially correlated when an important omitted variable has spatial structure (Bockstael, 1996; Bell and Bockstael, 2000). Additional spatial problems may also arise from measurement errors in attributes and location.

Stationarity and heteroskedasticity: Spatial data, in general and precision agriculture data, in particular, results from spatial stochastic processes. Depending on assumptions regarding spatial stationarity, the unknown spatial stochastic process may result in spatial effects such as spatial heterogeneity and spatial dependence. These spatial effects occur in two-dimensional random fields generated by random processes in $\Re^2$ space that define the surfaces that are modeled (Cressie, 1993; Schabenberger and Gotway, 2005). Stationarity is concerned with the mean, variance, and covariance of the distribution. Spatial heterogeneity refers to structural instability across space, i.e., a nonconstant mean or variance (Anselin, 1988; Casetti, 1997; Anselin, 2001; Florax and Nijkamp, 2004). This instability across space can occur in functional forms or varying parameters or as heteroskedasticity. In general, heteroskedasticity is the lack of constant variance for random regression errors across all observations and is formally expressed as $\text{var}(\varepsilon_i) = \sigma_i^2$ where σ_i^2 differs for all i (Wooldridge, 2003). Spatial heteroskedasticity results from a non-stationarity process that links the variation in σ_i^2 to location of the observational units (Anselin and Griffith, 1988). Since spatial units such as agricultural plots may differ in some influential characteristics (e.g., soil texture, elevation, etc.), homoskedasticity, which is a strong assumption in classic statistical models, may not hold in applied spatial data analysis, such as site-specific nematode data. OLS estimates remain unbiased and consistent but are inefficient in the presence of heteroskedasticity, and therefore, aspatial estimators are inefficient with spatially heteroskedastic data.

Spatial dependence: On the other hand, the characteristics at proximal locations appear to be either positively or negatively correlated, which is called "spatial dependence." Spatial dependence leads to the spatial autocorrelation problem in statistics. Spatial autocorrelation is a weak stationarity process with nonzero covariance. Spatial autocorrelation occurs when observations are correlated with respect to distance—in other words, an observation is similar to, and can be partially predicted by, neighboring observations (Anselin, 1989). Positive spatial autocorrelation occurs when neighboring observations are more similar than observations further away, and this is anticipated in agricultural fields, analogous to Tobler's first law of geography (1970).

Spatial autocorrelation may occur in the error term, dependent variable, or in exogenous variables. Spatially autocorrelated residuals arise from omitted spatially autocorrelated variables (Bockstael, 1996; Bell and Bockstael, 2000), measurement error (Anselin, 1989), and specification error (Anselin, 1989). Because of

spatially autocorrelated data, a set of spatially dependent observations contains less information than independent observations of the same sample size (Anselin 1989; Florax and Nijkamp, 2004). Anselin (1989) states, "the loss of information that results from the dependence in the observation should be accounted for." The misspecification and measurement error leading to spatial autocorrelation may also cause spatial heteroskedasticity (Anselin and Griffith, 1988).

Spatial autocorrelation has traditionally been neutralized in agricultural field research by reducing experimental unit sizes until plot sizes could be assumed to be homogeneous (Montgomery, 2001). Replication, randomization, and blocking techniques can be combined with small plots to determine treatment differences. However, treatment effects are more efficiently estimated by modeling spatial autocorrelation than using the traditional approach of neutralizing spatial autocorrelation via randomization (Cressie, 1993). Spatial heterogeneity and spatial dependence jointly yield biased parameter estimates, which can be statistically misleading (Anselin and Griffith, 1988). However, site-specific measurements, spatial statistical modeling, and computation allow for new approaches to statistically valid inference.

SPATIAL STATISTICAL METHODS FOR SITE-SPECIFIC NEMATODE MANAGEMENT

Most agricultural data, including site-specific crop yield data, are expected to be spatially structured (autocorrelated and heteroskedastic), which violates the assumptions of classical statistics regarding independence of observations and homoskedastic error terms. Failing to account for spatial structure results in inefficient parameter estimates that bias the test statistics. The two most commonly used models that adjust for spatial dependence in site-specific agricultural data are spatial autoregressive error models and spatial autoregressive lag models. Either model can be estimated by maximum likelihood (ML), general method of moments (GM), instrumental variables (IV), and other classic estimators. A third extended spatial model is the spatial Durbin model, which addresses the concern over omitted variables.

Spatial error model. The spatial error model is given as follows:

$y = X\beta + \varepsilon, \varepsilon = \lambda W\varepsilon + \mu$ or in reduced form as $y = X\beta + (I - \lambda W)^{-1}\mu$, where y is a $n \times 1$ vector of dependent variables, X is a $n \times k$ matrix of explanatory variables, β is a $k \times 1$ vector of regression coefficients, is an $n \times 1$ vector of residuals, λ is a spatial autoregressive parameter, W is an $n \times n$ spatial weights matrix, and μ is a well-behaved, nonheteroskedastic, uncorrelated error term (Anselin, 1988). When the spatial autoregressive term λ is 0, the spatial error model reverts to the aspatial model. The spatial error process can be characterized by the autoregressive (AR) or the moving average (MA)

error process resulting in global and local spillovers, respectively. The spatial error model has no substantive economic interpretation. When the spatial error model is appropriate, OLS estimates remain unbiased but are inefficient.

Spatial lag model: The spatial lag model is given as follows: $y = \rho W y + X\beta + \mu$ or in reduced form $y = (I - \rho W)^{-1}[X\beta + \mu]$, where ρ is the spatial autoregressive parameter and the others as previously defined (Anselin, 1988). Similar to the spatial error model, the spatial lag model reverts to the aspatial model when the spatial autoregressive term ρ is 0. Spatial lags result in global spillovers and have a substantive economic interpretation. Spatial lag models are sensitive to localized shocks influencing the whole system through the spatial multiplier $(I - \rho W)^{-1}$. The OLS estimator is inconsistent for purely spatial autoregressive processes (Lee, 2002).

Spatial Durbin model: Another model that can be used when there is concern about omitted variables for site-specific agricultural data is the spatial Durbin model. This model is equivalent to a mixed autoregressive model on a specification that includes spatially lagged dependent and exogenous variables. The spatial Durbin model is given as follows: $y = X\beta + \eta$, $\quad \eta = \rho W\eta + \varepsilon$, $\varepsilon = X\gamma + u$ or in reduced form $y = (I - \rho W)^{-1}[X\beta + WX\gamma + u]$, where η is an $n \times 1$ vector of a spatially correlated omitted variable following a spatial autoregressive process with autoregressive parameter ρ, and u is an $n \times 1$ vector of well-behaved independent identically distributed (i.i.d) random error terms. The omitted variable is correlated with X when $\gamma \neq 0$. The other terms are the same as previously defined. The spatial Durbin model assumes the dependent variable for each region depends on its own-region factors from the matrix X, plus the same factors spatially weighted averaged over the neighboring regions, WX, while accounting for the omitted variable not included in the model specifications. To empirically determine whether we need to apply a spatial model other than the standard aspatial model and to decide which spatial model, is more appropriate, spatial diagnostics such as Moran's I and Lagrange Multiplier (LM) tests of the OLS residuals provide insight into the underlying contagion.

The most common test for the existence of global spatial autocorrelation, which is the main motivation for applying a spatial statistical model, is the Moran's I test (Anselin, 1988) and it is given as follows:

$$I = \frac{n}{S_o} \frac{\mathbf{x}'\mathbf{W}\mathbf{x}}{\mathbf{x}'\mathbf{x}}$$

where $\mathbf{x}$ is an $n \times 1$ vector of a random variable as deviations from the mean, $\mathbf{W}$ is an $n \times n$ spatial weights matrix described earlier in relation to spatial process models, and S_o is the sum of the elements of $\mathbf{W}$ (Anselin, 1988). Moran's I is interpreted as a correlation coefficient (Anselin, 1988).

Positive values of Moran's I indicate that observations of a similar value occur as neighbors, whereas negative values signify that both high and low value observations occur as neighbors. A Moran's I value of zero signifies a random spatial distribution. A local indicator of spatial association (LISA) (Anselin, 1995) or the so-called local Moran's I, tests for local spatial autocorrelation. The LISA indicates significant spatial clustering and sums up proportional to the global Moran's I (Anselin, 1995). It is possible that a dataset could have significant local spatial clustering but no global spatial autocorrelation. Although Moran's I has power over spatially autocorrelated dependent variables and residuals including spatial lag and spatial error, respectively, additional misspecification tests are necessary to distinguish between the two. Five LM tests for spatial autocorrelation diagnostics are commonly conducted using OLS residuals including LM error (LM_λ), Robust LM error (LM_λ^*), LM lag (LM_ρ), Robust LM lag (LM_ρ^*), and LM Spatial Autoregressive Moving Average (SARMA) ($LM_{\lambda\rho}$). The LM_λ and LM_ρ tests are unidirectional tests with the spatial error and spatial lag models as alternative hypotheses, respectively. The LM_λ^* and LM_ρ^* tests take into account the potential presence of spatial lag or spatially correlated residuals. The LM_λ, LM_λ^*, LM_ρ, and LM_ρ^* asymptotically follow a χ_1^2 distribution. The $LM_{\lambda\rho}$ test is a multidirectional test that follows a χ_2^2 distribution.

The LM test with the highest χ^2 value, or alternatively the lowest p-value between LM_λ and LM_ρ, indicates whether the spatial error or spatial lag model is appropriate. Although $LM_{\lambda\rho}$ is distributed χ_2^2 rather than χ_1^2 as with the other four LM tests, a lower p-value indicates the higher-order model is appropriate. Since the LM tests do not distinguish between MA and AR processes, significant $LM_{\lambda\rho}$ indicate either SARMA or SARAR models. If none of the LM tests are significant, then the data can be analyzed aspatially rather than with spatial techniques. Similar to tests against spatial autocorrelation, LM tests may test against spatial heteroskedasticity. Besides the LM tests, some specification testing procedures, including likelihood ratio (LR) tests outlined by Elhorst (2010), Spatial Hausman test proposed by LeSage and Pace (2009) provides the possibility of a model with spatially-lagged independent variables (the spatial Durbin model).

Both the spatial error model (Anselin et al., 2004; Lambert et al., 2004; and Griffin et al., 2008) and the spatial lag model (Florax et al., 2002) have been used with site-specific yield data. The spatial Durbin model has not been widely used for spatial econometric applications. When a pathogen such as nematodes is the dependent variable, spatial contagion is expected to exist in the dependent variable, thus the spatial lag process model would be most appropriate. However, LeSage and Pace (2009) found that, when the spatially autocorrelated error terms (omitted variables) are correlated with explanatory variables, the coefficient estimates from the spatial error model are unbiased but

inefficient, and the spatial Durbin model is more appropriate.

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CASE STUDY OF ECONOMIC ANALYSIS FOR THE POTENTIAL OF SITE-SPECIFIC NEMATODE MANAGEMENT

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The clear establishment and precise estimation of yield potential (the yield penalty associated with nematodes) is essential to analyzing profitability and developing site-specific nematicide application recommendations. Function specification should reflect site-specific differences in yield response to nematicide application. Fumigant nematicides are spatially and temporally dynamic and their effectiveness depends on many factors including nematode population density, soil texture, and geographic characteristics. Model specification should account for the complexity of yield response. Improperly specified models are susceptible to omitted variable bias, which may be costly for site-specific or variable-rate nematicide application since prescriptions are based on the coefficient estimates from the yield response function. Moreover, failing to properly account for the spatial structure of the data could result in inefficient estimates for the site-specific yield response function and, in turn, affect the profitability analysis for the nematicide application.

Our case study applied spatial econometric methods to conduct an economic analysis of yield monitor data for the study of cotton response to nematicide application in Arkansas. On-farm experiments were conducted from 2001 to 2004 in a 6.07-ha production field in southeastern Arkansas. The field was subdivided into 512 plots (32 plots wide × 16 plots long). Each plot was approximately 0.012 ha consisting of four 30.5-m long rows (30.5 × 3.9 m). The geographic location of each plot was determined with a differential GPS receiver (Trimble, Sunnyvale, CA) accompanied by a GPS mapping software (Site-Mate, Farmworks, Hamilton, IN). The nematicide, 1,3-dichloropropene (Telone II, Dow Agrosciences, Indianapolis, IN), was applied 2 wk before planting in strips at rates of 0, 14.1, 29.2, or 42.2 l/ha in 2002. The experimental design for the trials was a randomized complete block design, and the treatments were replicated eight times. All plots were sampled for root-knot nematode (*Meloidogyne incognita*) population density each year before nematicide application (Mipre), at the time of planting (to represent the initial population after fumigation (Mipi)), at peak bloom (Mipm), and at harvest (Mipf). Yield files include data-point information about yields, latitude, longitude that were used to generate a geopositioned data file, and also soil texture (% sand fraction) and nematicide (Telone) application rate. The data for the 2002 crop season were used for the analysis. A queen contiguity spatial weight matrix (eight neighbors to each cell) was employed to capture the existing spatial structure.

We hypothesize that crop yield penalties are a function of nematode population density (*Mipi02*, *Mipm02*, and *Mipf02*), nematicide application rate (*Telone*), and soil texture (*Zsand*). Since the evidence indicates a correlation between crop yield penalties, magnitude of infestation, and soil texture (Monfort et al., 2007; Mueller et al., 2011), some interaction terms, such as the soil texture interaction with nematode population and soil texture interaction with nematicide application rate, were included in the model to explore the potential relationship among soil properties, treatment application, and yield response. Then the empirical model estimated was expressed as follows:

$$Yield = f(Mipi02, Mipm02, Mipf02, Zsand, Telone,$$
$$Zsand : Telone, Mipi02 : Zsand, Mipm02 : Zsand,$$
$$Mipf02 : Zsand)$$

The estimation results for Standard (OLS), Spatial Lag (SAR), Spatial Error (SEM), and Spatial Durbin (SDM) models are summarized in Table 1. We interpreted the coefficient based on the best fit model, so we start explanation from the diagnostic tests conducted. Both Lagrange Multiplier (LM) Error test (LM-Error = 164.83, which is distributed as χ^2 with 1 degree of freedom) and LM Lag test (LM-Lag = 162.13, which is distributed as χ^2 with 1 degree of freedom) strongly reject the null hypothesis of no spatial autocorrelation at very high significance levels (p < 0.001). Also the spatial autoregressive parameter λ (Lambda) in the spatial error model and ρ (Rho) in the spatial lag model and spatial Durbin model are all highly significant at 1% significance level, which also indicates that spatial autocorrelation exists in the data, and the spatial model is more appropriate than standard aspatial model. Although Robust LM tests suggest a spatial error model as the proper alternative rather than a spatial lag model with higher statistic value, the spatial Hausman test rejects the null hypothesis and suggests the omitted variables are a problem and that the spatial Durbin model should be used in this situation (LeSage and Pace, 2009). The model fit improves when the spatial Durbin model is applied, as indicated by an increase in the log likelihood (from −3346 to −3314) and a decrease in AIC (from 6,843 to 6,670). In this site-specific nematode management case, spatially autocorrelated omitted variables (e.g., geographic characteristics) may influence the included explanatory variables (e.g., nematode population), so the local crop yield may not depend simply on local determinants, but also the neighboring plot's determinants. Thus, the spatial Durbin model is selected as the best fit model in this case study based on both empirical statistic diagnostics and theoretical considerations.

The signs of the coefficient estimates in Spatial Durbin model are the same as in the standard OLS model, with the exception of the significance level for some variables.

TABLE 1.   Coefficient estimates and diagnostic statistics.

	OLS	SAR	SEM	SDM
Variables				
(Intercept)	2161.000***	897.580***	2151.800***	348.560
Mipi02	-0.187*	-0.151*	-0.152*	-0.139
Mipm02	-0.019	-0.036**	-0.058***	-0.048***
Mipf02	-0.134**	-0.068	-0.038	-0.046
Zsand	-18.350***	-13.909***	-17.187***	-15.053***
Telone	-3.810	-3.531	-4.855**	-2.620
Zsand:Telone	0.118*	0.127**	0.169***	0.121**
Mipi02:Zsand	0.002	0.002	0.002	0.002
Mipm02:Zsand	0.0003	0.0006*	0.0011***	0.0008**
Mipf02:Zsand	0.003**	0.001	0.001	0.001
lag.Mipi02				0.167
lag.Mipm02				0.166***
lag.Mipf02				-0.382***
lag.Zsand				18.212**
lag.Telone				19.651*
lag.Zsand:Telone				-0.631**
lag.Mipi02:Zsand				-0.008
lag.Mipm02:Zsand				-0.003***
lag.Mipf02:Zsand				0.008***
Rho		0.818***		0.833***
Lambda			0.902***	
Measures of fit				
Log likelihood		-3346	-3340	-3314
AIC	6843	6717	6704	6670
Diagnostic tests	d.f.	Value	Prob	
Lagrange multiplier (error)	1	164.832	0.000	
Robust LM (error)	1	12.545	0.000	
Lagrange multiplier (lag)	1	162.133	0.000	
Robust LM (lag)	1	9.846	0.002	
Hausman test	10	93.748	0.000	

Significance is designated at $P = 0.01$, 0.05, and 0.10 by ***, **, and *, respectively.

The nematode population at planting time (*Mipi*) and at harvest time (*Mipf*) are significant determinants for the cotton yield in the OLS model whereas the population density at the bloom time (*Mipm*) is highly significant for the yield variability suggested by the regression results from spatial Durbin model. The soil texture (percent sand fraction, *Zsand*) has significant impact on the crop yield across spatial and aspatial models. Nematicide application (*Telone*) is not a significant factor for the cotton yield variability, but it can have significant impact when interacting with the soil texture (*Zsand:Telone*), indicating that the yield response for the nematicide application varies with soil texture. The yield response for a given nematode population density is also different depending on soil texture (*Mipm02: Zsand*). The spillover effects of some explanatory variables from neighboring plots also significantly influence the local crop yield (*lag.Mipm02, lag.Mipf02, lag.Zsand, lag.Telone, lag.Zsand: Telone, lag.Mipm02: Zsand, lag.Mipf02: Zsand*) although some of the coefficient signs are different from the local effect signs since the spillover effects in the spatial Durbin model extend throughout the whole spatial system.

It should be noted that the magnitude of coefficients of the spatial Durbin model cannot be compared directly with coefficients from a model that does not contain a spatially lagged dependent variable since the autoregressive parameter interacts with the explanatory variables. To interpret the magnitude of the coefficient, we need to derive the marginal effects of a particular explanatory variable, which can be decomposed into direct, indirect, and total effects as illustrated by LeSage and Pace (2009).

The coefficient estimates suggested that the crop yield response for a given nematode infestation level or nematicide application rate differs by soil texture; therefore, site-specific nematicide application may be modestly profitable. The delineation of management zones for nematicide application decisions within fields can be evaluated based on nematode density and soil texture (percentage of sand, clay, silt, or electrical conductivity as a proxy). In this case study, because soil texture was the most useful factor for explaining variation in yield, management zone based on soil texture categories can be delineated as follows: (i) 0% to 30% sand, (ii) 30% to 45% sand, (iii) 45% to 65% sand, and (iv) 65% to 100% sand. The average return for the field was estimated as the weighted sum of returns in each management area, where the weights are the proportion of the area. Maximization of expected profit from variable rate application can be expressed as follows:

$$MaxE[\pi] = \sum_{i=1}^{4} Area_i * E[P_C * E(Yield) - P_T * T_i]$$

where E = expectation operator; π = total net returns over site-specific nematicide application ($ ha^{-1}); Area$_i$ = proportion of management area i (i = 1,...,4); Pc = price of cotton ($ kg^{-1}); E (Yield) = expected yield estimate from the yield response function estimated with the spatial Durbin model (kg/ha); P$_T$ = price of nematicide (Telone) ($ kg^{-1}); and T$_i$ = quantity of nematicide applied in area i.

We can also calculate the expected net return from uniform rate application. The difference of the net return from the variable rate application and uniform rate application can be viewed as the breakeven variable rate (VR) fee. On the other hand, we can estimate the VR application cost, which may include the equipment costs, staff training cost, etc. If the breakeven VR fee can cover the estimated VR application cost, then site-specific nematicide application would be profitable. This economic analysis provides an initial insight into the potential of site-specific nematode management.

Conclusions

The spatial statistical and economic analysis techniques offer an opportunity to develop more precise parameter estimates in a crop yield response function for site-specific nematicide application by exploiting spatial structure inherent in agricultural yield data. The precision of economic analysis related to yield, return, and profitability of site-specific nematode management can be improved based on the parameter estimates from the appropriate spatial statistical model. Successful adoption of the spatial econometric methodology requires more mature field-scale experimentation including experimental design, implementation, data collection, analysis, and interpretation. To use the site-specific response estimates in decision making more efficiently, spatial modeling applied for panel data, which accounts for both spatial and temporal heterogeneity and dependencies, should be given more attention in future research.

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