A review of spatio-temporal modelling of quadrat count data with application to striga occurrence in a pearl millet field

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ABSTRACT

This paper describes how spatial statistical techniques may be used to analyse weed occurrence in tropical fields. Quadrat counts of weed numbers are available over a series of years, as well as data on explanatory variables, and the aim is to smooth the data and assess spatial and temporal trends. We review a range of models for correlated count data. As an illustration, we consider data on striga infestation of a 60 × 24 m^2 millet field in Niger collected from 1985 until 1991, modelled by independent Poisson counts and a prior auto regression term enforcing spatial coherence. The smoothed fields show the presence of a seed bank, the estimated model parameters indicate a decay in the striga numbers over time, as well as a clear correlation with the amount of rainfall in 15 consecutive days following the sowing date. Such results could contribute to precision agriculture as a guide to more cost-effective striga control strategies.

INTRODUCTION

In semi-arid and sub-humid tropical countries in Africa and parts of Asia, *Striga hermonthica* (Del.) Benth. (commonly known as witch weed) is an economically important parasitic weed that severely attacks cereal crops including pearl millet, sorghum and maize. In fact, it has been called the major biological threat to cereal crops in Africa [Ejeta *et al*, 1993], and has infested large portions of cereal production regions. The striga problem is particularly severe in areas with erratic rainfall and relatively poor soils; the greatest damage occurs in the Sahelian and Savannah zones. Due to the withdrawal of water, minerals and organic compounds from their hosts, and to putative phytotoxic effects, parasitic weeds have a very strong negative effect on both the quality and the quantity of the grain and straw yield. Recent trends away from traditional fallowing practices towards continuous mono cropping to meet the increasing population pressure have intensified the striga problem [Parker & Riches, 1993].

Striga control is very difficult. A contributing factor is early underground development during which time much of the damage to the susceptible host plant is done. The use of herbicides has several drawbacks. Firstly, herbicides are as likely to influence the host plant as the striga, and may damage other crops in the system. Secondly, as the farmers on the striga infested soils are generally poor, herbicides may not be affordable. Thirdly, the farmers do not immediately observe the results of their actions, as most of the harm has been done before control measures could be taken, and many seeds remain dormant in the soil, thus causing problems in the next growing season. Therefore, striga control requires a form of integrated crop management, where measures focused on the prevention of striga seed production and exhaustion of the supply of seeds in the soil [Hausmann *et al*, 2000] are implemented over a range of years.

At the moment, it is not fully understood what factors determine the number and distribution of emerged striga. It has been recorded that additional use of nitrate may increase the crop quality and reduce the striga damage [Boukar *et al*, 1996]. Moreover, a positive correlation was found between crop yield and striga occurrence [Manu *et al*, 1991], suggesting that a healthy, well fed host may be able to tolerate more emerged striga plants than an unhealthy one, so that striga is more likely to be found in the more fertile parts of a field. Striga seed are spread by wind, rainfall, through animal and human activities as well as contaminated crop seed [Hess & Haussmann, 1999]. Preseason rainfall serves to precondition striga seed for germination. Heavy showers with runoff are also likely to spread the striga laterally towards adjacent fields, and beyond. Nevertheless, patterns of weed spread have been little studied and are poorly understood, and stochastic models aimed at explaining covariate effects, as well as spatial and temporal variation, are useful.

The plan of this paper is as follows. We first describe a data set on the occurrence of striga in a millet field collected at the ICRISAT Sahelian Centre. We review statistical models for spatially correlated longitudinal count data, and finally illustrate one such model on the data mentioned before.

DATA

In the appendix, we list counts of striga infestation in a 60 × 24 m^2 experimental field at the ICRISAT Sahelian Centre near Niamey (Niger). In 1985, the field was prepared for the cultivation of pearl millet (*Pennisetum glaucum* (L.) R. Br.), a drought resistant cereal crop adapted to light sandy soils [Dave, 1987]. Permanent metal stakes were placed at 1 m intervals around the field perimeter, in accordance with the recommended sowing density of pearl millet for the region. Debris was cleared from the field surface at the outset of the cropping season (May), and a basal fertiliser (15 kg per hectare each of N, P_2O_5 and K) was applied manually and incorporated by harrow. Millet of the variety *Composite Inter-Variétal de Tarna* (CIVT) was planted in hills at the grid points indicated by the stakes on the 18^{th} of June, following the first sizeable rainfall of the year [Sivakumar, 1982] (4.9 mm the day before and 19.4 mm on the sowing date). Many seeds were sown per hill, and thinned two to three weeks after sowing to a maximum of three plants per hill. Mechanical weeding was carried out two and four weeks after sowing. Subsequent weeding, if necessary to facilitate counts, was done by hand, taking care not to disturb emerged or emerging striga plants. Striga counts in quadrats of 1 × 1 m^2 around each hill were recorded at various stages of the growing season. In Table 1 we present summary statistics for the final count carried out after the millet harvest. The full data are listed in the appendix.

Since the striga were left untouched, seeds spread naturally, a phenomenon which may lead to the formation of localised seed banks causing spatial inhomogeneity. The native soil fertility also exhibits spatial variation [Manu *et al*, 1991]. Note that since millet is planted in a regular grid, no heterogeneity due to availability of hosts is caused. The resulting spatial pattern is given in Figure 1.

Finally, rainfall was measured at the central meteorological station of the Centre, as summarised in Table 2.

STATISTICAL MODELS FOR SPATIALLY CORRELATED COUNT DATA

In this section, we give an overview of stochastic models for spatially correlated count data arising from small area sampling of some underlying point process. Thus, the nature of the data collection process leads us into the realm of a missing data framework, and inference should be aimed at characteristics of the complete data (in our case the emerged striga pattern) based on the observations (here cumulative striga counts per hill).

TABLE 1: Quantiles, minimum, maximum and median of striga counts in 1 × 1 m2 quadrats in a 60 × 24 m2 millet field at the ICRISAT Sahelian Centre near Niamey (Niger) as observed 105 days after the sowing date (18 June 1985). Full data are listed in the appendix; for graphical representation, see Figure 1. The acronym DAS stands for days after sowing.

Year	*DAS*	*Min.*	*1stQu.*	*Median*	*Mean*	*3rdQu.*	*Max.*
1985	105	0	1	4.5	7.96	11	103

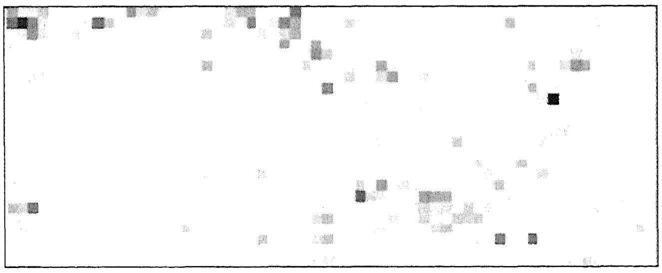

FIGURE 1: Striga counts in 1 × 1 m^2 quadrats in a 60 × 24 m^2 millet field at the ICRISAT Sahelian Centre near Niamey (Niger) as observed 105 days after the sowing date (18 June 1985). Low counts correspond to a white color; black is used for high values.

TABLE 2: Summary statistics for rainfall (mm) measured at the central meteorological station of the ICRISAT Sahelian Centre near Niamey (Niger) for the year 1985. The acronym DAS stands for days after sowing.

Year	*Sowing date*	*10 DAS*	*15 DAS*	*20 DAS*	*73 DAS*	*105 DAS*
1985	18 June	48.5	49.6	97.8	406.9	516.8

We shall begin by fixing some notation. Write I for the index set of quadrats, and denote by y_i the count in the quadrat C_i indexed by $i \in I$. Then, the data can be described by the vector $\mathbf{y} = (y_i)_{i \in I}, y_i \in \{0, 1, \ldots\}$.

For counts, it is natural to assume a Poisson law. However, the most straightforward route of specifying a Poissonian auto regression with the conditional mean of a particular quadrat depending on its neighbouring quadrats allows for negative correlation only [Besag, 1974], while in the present context the counts at neighbouring quadrats should be similar. Hence, we are led towards a Cox formulation where, conditional on the intensity, the counts are independent, and smoothness is taken into account by the intensity. Hence, the conditional distribution of the observed counts is

$$f(\mathbf{y} \mid \mu) = \prod_{i \in I} e^{-\mu(C_i)} \frac{\mu(C_i)^{y_i}}{y_i!} \qquad (1)$$

where μ denotes the complete data intensity. Note that the maximum likelihood estimator of $\mu(C_i)$ is equal to the observed y_i, and no smoothing is achieved. Consequently, we adopt a Bayesian point of view, and proceed to formulate a prior model for μ. As an aside, although agricultural applications have played a major role in the statistical literature from its beginning [*eg*, Fisher, 1928], most studies took a frequentist point of view, despite the obvious spatial correlation present in fields [Besag & Higdon, 1993; 1999]. Only recently, advances from spatial statistics and image analysis, which have both been predominantly Bayesian in nature, have spilled over to agriculture and other branches of statistics.

The prior distribution of the random intensity μ should reflect the spatial correlations between counts in different quadrats, as well as take into account covariates and quadrat geometry. For instance, Besag, York & Mollié [1991] propose a log linear Gaussian model of the form

$$\log \mu(C_i) = U_i + V_i + w_i + \log c_i \qquad (2)$$

where c_i is a base rate of expected counts (based on for instance the size of C_i), $U = (U_i)_{i \in I}$ is a smoothing random field capturing spatial structure, $V = (V_i)_{i \in I}$ is independent of U and captures any extra-Poisson variation, and $\boldsymbol{w} = (w_i)_{i \in I}$ incorporates the covariates. Commonly, $\boldsymbol{w} = A\theta$ for a known matrix A and parameter vector θ, or in other words $w_i = \sum_{j=1}^{k} A_{ij}\theta_j$. The field V is assumed to be Gaussian white noise, and U is an intrinsic auto regression [Künsch, 1987]

$$p(u) \propto \kappa^{-n/2} \sum_{i \sim j} \exp\left[-\frac{1}{2\kappa}\sum_{i \sim j}\left(u_i - u_j\right)^2\right]. \qquad (3)$$

where ~ is the neighbourhood relation on I and $\kappa > 0$. Sampling issues are considered in Knorr-Held & Rue [2000] and in Rue [2001]. Knorr-Held & Besag [1998] extend (2) to spatio-temporal observations as follows:

$$\log \mu_t(C_i) = \alpha_t + U_i + V_i + W_{t,i} \qquad (4)$$

where t is the time index, and $W = (W_{t,i})$ a linear model for the time-dependent effect of the covariates (as an approximation to binomial counts with logit as given above). The temporal trend α_t is modelled by a random walk with independent Gaussian increments. Similar ideas can be found in Mugglin *et al* [2000]. Diggle, Moyeed & Tawn [1998] consider a generalized linear mixed model as in (2), but ignore the V-field and employ a (continuous) stationary Gaussian process U with covariance structure of the form $\kappa\rho(u-u')$ for some $\kappa > 0$ and isotropic function ρ, *eg*, $\rho(u) = \exp\{-(\beta u)^\delta\}$ for some $0 < \delta < 2$ and $\beta > 0$. Link functions other than the logarithmic transformation could be considered as well. The same set-up is considered by Christensen, Møller & Waagepetersen [2000], who also discuss simulation. Omitting the covariates and base rate yields a log Gaussian Cox process [Møller *et al*, 1998].

Note that all log Gaussian models discussed above contain hyper priors that may be modelled by dispersed but proper distributions.

A disadvantage of the logarithmic transform is that it does not readily scale with respect to the quadrat size. For this reason, Wolpert & Ickstadt [1998] define

$$\mu(C_i) = \int_S k(C_{i,s})\, d\Gamma(s) \qquad (5)$$

to be a kernel mixture of a Gamma process $\Gamma(s)$ with shape measure $a(ds)$ and scale function $b(s) > 0$. The space S can be either continuous or discrete. For the mixture kernel, they propose

$$k(x,s) \propto e^{A\theta} \exp\left(\frac{-1}{2\kappa}\left|x - s\right|^2\right) \qquad (6)$$

It should be noted that the model is strictly speaking overparameterised (only the ratio $k(x,s)/b(s)$ matters) but since covariates only affect the kernel $k(.,.)$ the present formulation may be clearer.

To conclude our review, Green & Richardson [2000] suggest a Gamma mixture model

$$\mu(C_i) = c_i\, e^{w_i}\, \lambda_i \qquad (7)$$

where c_i and w_i are as in (2) and $\lambda_i = \lambda Z_i$ is a random allocation Z_i to one of k components $\lambda_1, \ldots, \lambda_k$. The allocation variables are smoothed by assuming $(Z_i)_{i \in I}$ to form a Potts model

$$p(\mathbf{z}) \propto \exp\left[\beta \sum_{i \sim j} 1\left\{z_i = z_j\right\}\right] \qquad (8)$$

with $\beta \geq 0$. The λ_j are independently Gamma distributed with shape parameter $a = 1$ and size parameter $b = \sum_{i \in I} c_i \sum_{i \in I} y_i$. More generally, the number of components may be random as well, *eg*, Stephens [2000].

RESULTS

To illustrate the developed methods, we return to the data on witch weed in a millet field discussed in the data section. For the classical Poisson/lognormal approach (1)-(2), the prior distribution of the smoothing field is improper. Here, we replace the intrinsic auto regression by a proper conditional auto regression [*eg*, Ripley, 1988], and examine the effect of its parameters. More specifically, recalling that rainfall is measured centrally, no specific fertility information is available, and all quadrats are of equal size, we set

$$\log \mu(C_i) = \log \beta + U_i + V_i \qquad (9)$$

Here β is the base rate, $V = (V_i)_{i \in I}$ a Gaussian white noise field with precision $\sigma > 0$, and $U = (U_i)_{i \in I}$ a Gaussian conditional auto regression smoothing field. The conditional mean is

$$E\left[U_i \mid U_j = u_j, j \neq i\right] = \frac{\gamma}{n_i} \sum_{j \sim i} u_j , \qquad (10)$$

the conditional variance

$$Var\left[U_i \mid U_j = u_j, j \neq i\right] = \frac{1}{n_i \tau}, \qquad (11)$$

for each $i \in I$. The quadrats C_i and C_j are neighbours $(i \sim j)$ if and only if they are horizontally or vertically adjacent, and n_i denotes the number of neighbours of the quadrat represented by index i (*ie*, $n_i = 4$ except at the borders). The parameter $\gamma \in (0,1)$ encourages near quadrats to have similar fertility and hence striga incidence, τ controls the precision.

Time could be taken into account by replacing log β by $\alpha_t = \theta w_t$ where w_t is the rainfall covariate (15DAS) in year t, and α_t the year effect.

Since for fixed initial base rate $\beta = \frac{1}{60 \times 24} \sum_{i \in I} y_i$ and smoothing parameters γ, σ and τ the log posterior density is concave in U and V, standard numerical procedures can be used to find the optimum [Besag *et al*, 1991]. Some results are given in Figure 2. It can be seen that an increase in γ leads to smoother $\mathbf{U}$; increasing the precisions τ and σ similarly yields smoother reconstructions, with less variation in both $\mathbf{U}$ and $\mathbf{V}$. Finally, the updated base rates

$$\sum_{i \in I} y_i \Big/ \sum_{i \in I} e^{u_i + v_i} \qquad (12)$$

are 7.90, 7.60, 7.93 and 7.56 for the parameter values considered in Figure 2 (from top to bottom).

A general pattern is observed in the smoothing field being a dark band from the top left towards a dark coloring in the central right part of the figures. Some details occur as well, where in particular the choice for

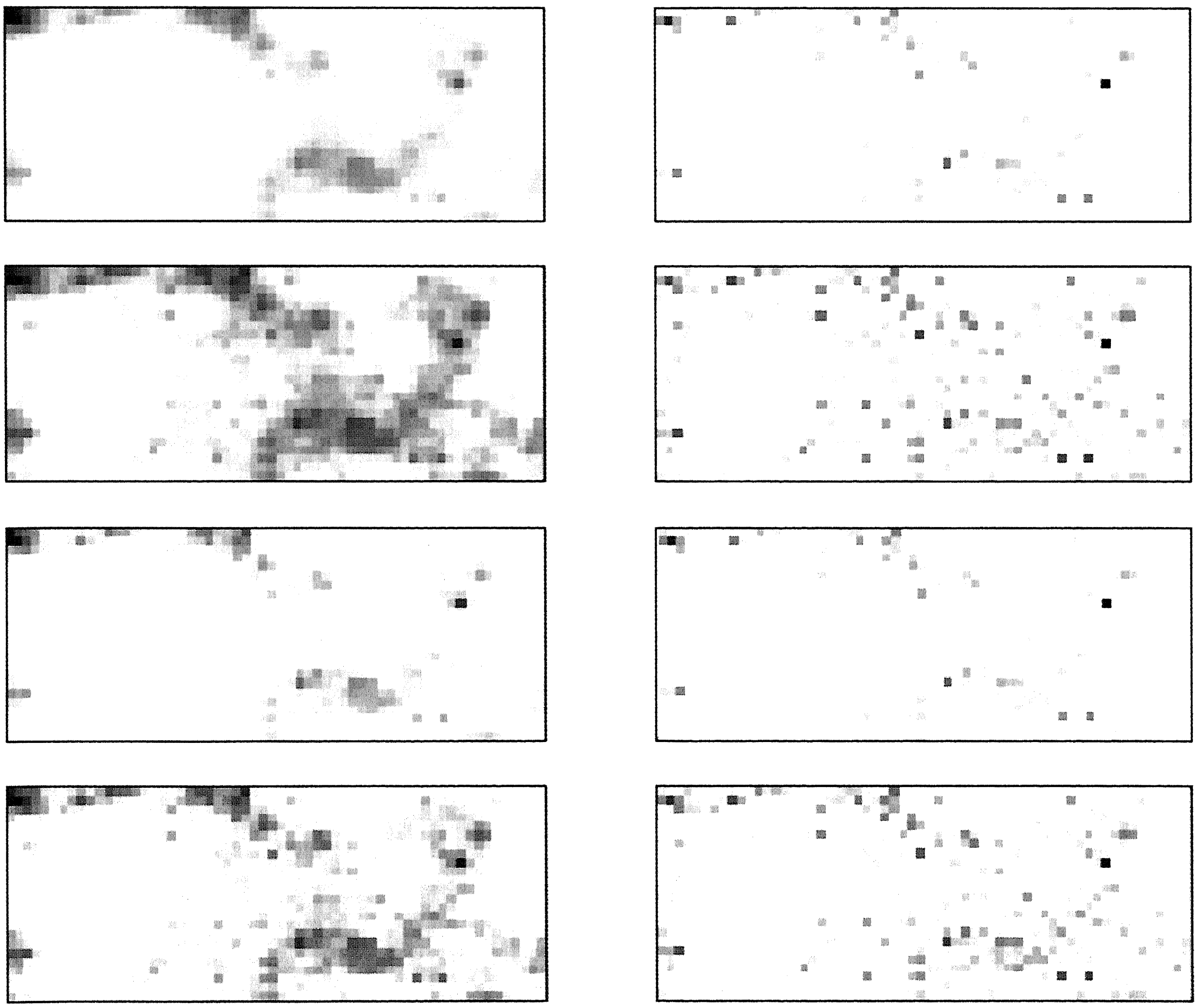

FIGURE 2: Maximum *a posteriori* estimates of the smoothing (left) and residual variation (right) fields given the data of Figure 1 for $\gamma = 0.9$ (top two lines) and $\gamma = 0.7$ (bottom two lines), $\tau = \sigma/4 = 100.0$ (odd lines) and $\tau = \sigma/4 = 10.0$ (even lines).

$\sigma=4\tau=100.0$ leads to a less noisy residual pattern than a choice for $\sigma=4\tau=10.0$. A choice for $\gamma=0.9$ also leads to more smoothness than a choice for $\gamma=0.7$. The noise, though, is largest where the pattern has the largest values. It can be concluded that the presence of seedbanks is identified by application of a spatial pattern analysis.

DISCUSSION

So far, we have focused on data obtained as a single image from one field in a single year, leading to a study of spatial variation on count data. However, data from within the same season as well as from different years are available as well. We aim to consider data collected over a range of years. In terms of modeling, we replace log β by $\alpha_t+\theta w_t$, where w_t is the rainfall covariate (15 DAS) in year t and α_t the year effect.

In several other studies, such an analysis may be interest, for example for the analysis of count data collected by a Geiger counter from the plane. An interesting example concerns the combination of the chemical elements Th, K and U [Schetselaar, 2000]. Related to such data collection and modeling is interpolation to obtain an even distribution of the data over an area of land. Observations along flight lines are relatively simple to collect, but spatial interpolation is not trivial, because the sampling pattern is very dense along the flight lines, but absent between them.

Practical consequences from an analysis as the current one can be large, in particular in relation to reduction in herbicide use. For optimal use of manpower and herbicides, smoothed maps showing the presence of seedbanks are usually of a larger benefit than the original maps, which show large incidental spatial variation that is difficult to handle. A quantitative analysis of these results, though, still has to be done. The smoothed map gives a good impression of how to apply these efforts for weed management in an optimal way, namely where the seed bank is present. This may lead to a better use of scarce resources.

CONCLUSION

This paper presents a review of spatial models of quadrat count data with possible extensions towards spatio-temporal modelling. It is based on an application to striga occurrence in a pearl millet field. We conclude that the presented models have interesting consequences for agricultural applications.

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RESUME

Cet article décrit comment des techniques de statistiques spatiales peuvent être utilisées pour analyser des occurrences de mauvaises herbes dans des champs tropicaux. Nous supposons que des comptages de mauvaises herbes par quadrant sont disponibles sur une série d'années, ainsi que des données sur des variables explicatives, et le but est de lisser ces données et d'estimer des tendances spatiales et temporelles. Nous passons en revue un choix de modèles pour des données de comptage corrélées. A titre d'illustration, nous considérons des données d'invasion de la striga d'un champ de millet de 60x24 m2 dans le Niger collectées de 1985 à 1991, modelées par des comptages indépendants selon Poisson et un terme d'auto régression à priori imposant une cohérence spatiale. Les champs lissés montrent la présence d'une banque de semis, les paramètres estimés du modèle indiquent un déclin dans les nombres de la striga à la longue, ainsi qu'une nette corrélation avec le montant de précipitation dans 15 jours consécutifs suivant la date des semailles. De tels résultats pourraient contribuer à une agriculture de précision comme guide pour des stratégies de contrôle de la striga plus rentables.

RESUMEN

Este artículo describe como pueden utilizarse técnicas estadísticas espaciales, para analizar la distribución de malezas en campos tropicales. Asumimos que se dispone de contajes del número de malezas en áreas-muestra por una serie de años, así como de datos relativos a las variables explicativas, y que el propósito es de suavizar los datos y de evaluar las tendencias espaciales y temporales. Se revisa una gama de modelos para datos de contaje correlacionados. Como ilustración, tomamos en consideración datos sobre infestación de striga recolectados desde 1985 hasta 1991 en una parcela de mijo de 60x24 m2 en Niger. Los datos fueron modelizados por contajes independientes de Poisson y un término de auto-regresión previa para obtener coherencia espacial. Las parcelas suavizadas muestran la presencia de un banco de semillas, mientras que los parámetros estimados del modelo indican una disminución de los números de striga con el tiempo, así como una clara correlación con la cantidad de lluvias caída durante 15 dias consecutivos después de realizarse el sembrado. Estos resultados podrían contribuir a la agricultura de precisión, para guiar estrategias más efectivas en costo para el control de la striga.

APPENDIX

Striga counts in 1 × 1 m^2 quadrats in a 60 × 24 m2 millet field at the ICRISAT Sahelian Centre near Niamey (Niger) as observed 105 days after the sowing date (18 June 1985).

38	59	10	19	0	1	3	3	0	0	0	1	8	1	3	1	24	11	37	15	9	9	3	19
24	94	24	2	4	1	3	0	2	1	8	3	15	0	8	11	15	11	33	22	24	4	3	3
24	51	45	1	4	4	25	9	1	0	15	6	3	0	6	6	5	9	55	4	2	2	13	14
31	25	26	8	3	6	17	14	0	1	0	1	3	0	1	0	0	0	16	2	2	0	0	2
8	18	23	10	0	0	1	2	0	0	0	1	4	1	0	1	4	4	9	4	9	1	7	5
11	5	9	0	7	0	0	3	3	0	4	0	1	0	0	2	2	2	1	3	1	0	0	1
6	9	26	0	2	1	0	1	0	1	2	0	1	3	4	2	3	6	7	0	1	1	7	3
10	22	10	2	1	0	0	0	1	0	0	0	2	6	1	3	3	5	3	0	0	4	0	13
17	60	9	1	5	1	2	0	0	5	3	3	0	1	10	0	0	2	0	3	0	3	0	0
3	32	3	2	4	4	0	1	0	0	2	0	0	0	0	1	0	1	3	1	1	0	0	0
15	15	0	1	5	15	3	0	0	10	2	0	1	0	0	2	0	3	0	2	0	1	0	4
46	17	7	2	2	1	5	0	0	2	1	0	0	0	1	1	3	0	2	2	0	1	1	3
28	8	1	10	3	0	1	6	0	0	0	0	0	0	0	0	0	4	3	0	1	3	0	5
33	7	1	8	14	7	3	8	0	0	1	0	0	0	0	0	0	0	0	1	1	2	2	3
23	4	1	6	3	11	8	8	5	1	1	4	0	0	0	0	0	2	1	7	7	17	9	3
13	8	4	7	4	3	2	0	2	1	1	3	1	0	0	0	0	3	1	11	2	10	1	0
5	8	7	0	1	3	2	2	0	6	2	3	4	9	1	3	2	9	4	14	30	8	1	1
13	14	13	6	1	16	3	5	0	3	0	1	1	0	0	3	6	1	3	20	2	0	1	3
2	9	32	3	4	35	1	4	1	0	1	1	11	3	0	24	5	1	3	11	4	1	5	4
8	22	3	5	3	2	1	11	6	0	1	4	13	6	3	14	0	16	10	5	2	0	2	8
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7	0	4	0	0	0	0	0	0	0	1	6	6	5	0	0	5	22	20	13	18	3	9	8