**Materials and Methods**

**Data Sets**

In this paper, we present the annotation and analysis of the pseudogene complement in human, worm, and fly, leveraging functional genomics data available from the ENCODE and modENCODE consortia. The human pseudogene annotation is based on the GENCODE 10 release. For worm and fly, we curated pseudogene annotation sets extending beyond WormBase WS220 and FlyBase 5.45. For mouse and macaque we used PseudoPipe automated pseudogene assignments based on the Ensembl 72 genome annotations. For zebrafish, we used pseudogene assignments from the Vega 53/Ensembl 73 manual annotation.

**Pseudogene Annotation**

Pseudogene annotation was conducted using a combination of manual annotation and in silico pipelines. The annotation files are available online at psicube.pseudogene.org for GRCh37 and GRCh38 (upon release).

*(a) Manual Annotation*

We manually annotated human pseudogenes on the basis of their homology to protein data from the UniProt database. The protein data were aligned to the individual bacterial artificial chromosome (BAC) clones that make up the reference genome sequence using BLAST [1]. We created gene models based on these alignments using the ZMAP annotation interface and the Otterlace annotation system [2]. Alignments were navigated using the Blixem alignment viewer [3]. We used visual inspection of the dot-plot output from the Dotter tool [3] to resolve any alignment with the genomic sequence that was unclear in, or absent from, Blixem. We defined a model as *pseudogene* if it possessed one or more of the following characteristics, unless there was evidence (transcriptional, functional, publication) showing that the locus represented a protein-coding gene with structural/functional divergence from its parent (paralog): (i) a premature stop codon relative to parent CDS, which could be introduced by nonsense or frame-shift mutation; (ii) a frame-shift in a functional domain - even where the length of the resulting CDS was similar to that of the parent CDS; (iii) a truncation of the 5' or 3' end of the CDS relative to the parent CDS; (iv) a deletion of an internal portion of the CDS relative to the parent CDS. Pseudogene loci lacking disabling mutations were annotated as “*ambiguous pseudogene”* when they lacked locus-specific transcriptional evidence. We note that the manual annotation pipeline checks every model for read-through stop codons coding for selenocysteine and for known genes with programmed frameshifts. If any transcriptional, functional, or publication evidence is found in support of such cases, the pseudogene model is discarded.

Fly pseudogenes were annotated in a similar way to human with two notable differences. First, while UniProt proteins were used to support the pseudogene annotation, we also used the CDS sequences of the parent gene loci predicted by PseudoPipe and/or FlyBase to build pseudogenes. Where the parent CDS was not clear, homologs of the pseudogene sequence were identified using BLAST. Secondly, where a parent CDS was used to investigate a pseudogene it was aligned to the genome using Exonerate [4] before being assessed using Blixem and Dotter.

Worm pseudogenes were annotated in a similar fashion using a combination of automated (PseudoPipe) and manual annotation (WormBase [5]). The PseudoPipe pseudogene set was intersected with the manually annotated one. All pseudogenes passing a threshold of 80% sequence overlap between the two data sets were selected as part of the high confidence data set. Further, we manually validated biotype annotations.

*(b) Automatic Annotation*

PseudoPipe is an automatic pseudogene annotation tool that uses protein homology data to identify pseudogenes. PseudoPipe uses six-frame translational BLAST to search all known protein sequences from Ensembl. Pseudogene disablements were determined through sequence alignments to functional genes. The pseudogene parents (functional gene paralogs) were identified on the basis of sequence similarity.

**Classification & Evolution**

*(a) Classification*

Pseudogenes were classified as “processed” if they have lost their parental gene structures. Conversely, we classified pseudogenes as “unprocessed”/ “duplicated” if they retained the same exon-intron structure as their parent loci. In ambiguous cases we used other features to resolve the provenance of the pseudogene. Where the pseudogene represented a fragment of the parent, and the homology ended precisely at a splice junction the pseudogene was called “unprocessed” (“duplicated”). Conversely, where the fragment contained the fusion of two or more exons the pseudogene was called “processed”. If the parent had a single exon CDS, the presence of parent gene structure in the 5' UTR region (identified by alignment of mRNA and EST evidence) allowed the pseudogene to be called “unprocessed”/“duplicated”. Meanwhile, the presence of a pseudopoly(A) signal (the position of the parent poly(A) signal at the pseudogene locus) followed by a tract of A-rich sequence in the genome (indicating the insertion site of the polyadenylated parental mRNA) indicated a “processed” pseudogene. If there was no other evidence available to resolve the route by which the pseudogene was created, we used the position of the pseudogene relative to its parent. As such “processed” pseudogenes are reinserted into the genome with an approximately random distribution while “unprocessed”/“duplicated” pseudogenes tend to be more closely associated with the parent locus. Parsimony therefore suggests that pseudogenes that lie near to the parent locus are more likely to have arisen via a gene-duplication event than retrotransposition, and this was used as a tie-breaker in defining the pseudogene biotype.

*(b) Timeline*

Differences in the dynamics of genome evolution make it difficult to directly estimate pseudogene ages. We used sequence similarity to parent genes as an indicator of pseudogene age. Thus, young pseudogenes were defined by a high sequence similarity to their parents, while older, more diverged pseudogenes were characterised by a lower percent sequence similarity to parents. Next we binned pseudogenes by age. Given the large differences in the number of pseudogenes in the studied organisms, it was difficult to bin them consistently. Thus, we divided pseudogenes based on sequence similarities to their parents in 11, 11, 2 and 2 bins for mammals (human, macaque, and mouse), worm, fly and zebrafish respectively (Fig. 1B, S2). Consequently, in each mammal and worm bin there were on average 10% of the total number of pseudogenes. Due to the low numbers of pseudogenes in fly and zebrafish we chose a smaller number of bins, each containing on average 50% of the total number of pseudogenes.

*(c) Repeats*

We extracted genomic features such as CDS, UTR, and lncRNA for the human, worm and fly genome, leveraging existing available annotations (GENCODE 10, WormBase WS220 and FlyBase 5.45). We defined the genomic background as all un-gapped bases in the respective genomes. We used the repeat annotation for each genome from the UCSC Genome Browser, and extracted four major repeat classes: DNA, LINE (Long Interspersed Nuclear Elements), SINE (Short Interspersed Nuclear Elements) and LTR (Long terminal repeats). The repeat content for each annotation class or genome background was counted as the percentage of total nucleotides overlapping each of the repeat classes. Next, we analysed the sequence conservation using the PhastCons scores from the UCSC Genome Browser. For human, we used primate conservation scores; for worm, we used scores from alignments of *C. elegans* with 6 other worm strains; while for fly, we used scores from alignments of *D. melanogaster* with 14 different insects. For each annotation class or genome background, we calculated the average per nucleotide PhastCons score.

*(d) Disablements*

Analysing the sequence alignment between pseudogenes and parent genes obtained from PseudoPipe we identified three types of pseudogene disablements: insertions, deletions, and stop codons. We calculated the average defect density per pseudogene per megabase for each organism.

*(e) Selection*

Using the 1000 Genomes Project Phase 1 data we calculated the frequency of low coverage SNPs in pseudogene exons. As a proxy of the genomic average, we used the frequency of human low coverage SNPs in the upstream and downstream UTR exons of the pseudogenes. Overall, pseudogenes have a SNP frequency similar to the genomic average (Fig. S5).

Next we calculated the derived allele frequency (DAF) for each pseudogene (Fig. S11). Overall, pseudogenes are enriched in rare alleles (DAF < 0.05).

**Localization & Mobility**

*(a) Chromosomal localization*

We defined three chromosomal regions: the telomere (T), the body, and the centromere (C). We defined two telomeric regions: one at the 5’ end and one at the 3’ end, each representing 15% of the chromosome length. The centromeric region was defined as the middle 30% of the chromosome, by length, while the remaining 40% (2x20% between the inner ends of the telomeres and the respective edges of the chromosome centre) was labelled as the chromosome body. In the case of acrocentric chromosomes, we defined the centromeric region around the geometrical middle of the chromosome. We calculated the pseudogene frequency in the telomeric and centromeric regions for each chromosome in human, worm and fly. Based on these values, we calculated the average pseudogene frequency in the two regions for the entire genome (Fig. 2A). We used a two hypotheses binomial test to evaluate the statistical significance of the difference in the pseudogene frequency between the telomeric and the centromeric regions (Table S1). The first hypothesis is that the pseudogenes are equally distributed at the centromeric and telomeric regions. The second hypothesis describes the observed distribution of pseudogenes at in the centromeric and telomeric regions. As such, there are two options: “\*” – the centromere has more pseudogenes than the telomere; and “#” – the telomere has more pseudogenes than the centromere. The significance threshold p-value was set to 0.05.

*(b) Recombination*

We obtained recombination rate estimates for human, worm, and fly, from Nato *et al.* (2011) [6], Rockman and Kruglyak (2009)[7] and Comeron *et al.* (2012) [8] respectively. We applied a simple linear interpolation from these datasets to obtain recombination rates for each nucleotide. We used the Tajima’s D and Achaz’s Y values from Andersen *et al.* (2012) [9]. In order to replicate results from their publication, we used a local polynomial regression smoothing for all data-points, before applying linear interpolation to obtain recombination rates for all nucleotides in the genome.

Due to the fact that recombination rates can differ within genes, we calculated the average recombination rates for pseudogenes by averaging their recombination rates across the length of each element, and then averaging this value for all pseudogenes. Error bars represent standard errors (Fig. 2A).

*(c) Co-localisation tendency*

We evaluated the tendency of pseudogenes to reside on the same chromosome as their parent genes using a 2-by-2 contingency table “A” (Table S4), with elements *Ai,j,* where *i,j ={1,2}*:

· *A1,1* - the frequency of both the pseudogene and its parent residing on this chromosome;

· *A1,2* is the frequency of only the pseudogene residing on this chromosome;

· *A2,1* is the frequency of only the parent gene residing on this chromosome; and

· *A2,2* is the frequency of neither of the pseudogene or its parent residing on this chromosome.

We used Fischer’s exact test to analyse whether pseudogenes and their parents tend to reside on the same chromosome. Using the Bonferroni correction, the significance threshold was set to *0.05/n*, where *n* is the total number of tested chromosomes in this species.

*(d) Pseudogene mobility*

We inspected pseudogene exchange between different chromosomes, excluding the pseudogenes that reside on the same chromosome as their parents. We used a Poisson regression model to detect chromosomes that display significant pseudogene exchange.

We hypothesised that on a chromosome, the pseudogene export / import frequency follows a Poisson distribution with the mean and variance proportional to the number of coding genes / the chromosome size, respectively. Poisson regression was used to fit the pseudogene exchange frequency to the number of protein-coding genes / chromosome length. Any chromosome outside of the 95% prediction interval was considered to exhibit significant pseudogene exchanger (Fig. S12).

**Orthologs, Paralogs & Families**

*(a) Orthologs*

We defined pseudogenes as orthologous if they were located in syntenic regions and their respective parent genes were orthologous. We obtained human-mouse synteny information from the UCSC Genome Browser chain alignments files for human HG19 and mouse MM9. Parent protein-coding gene orthology information was downloaded from the Ensembl website. The human-worm-fly orthologous protein-coding gene set was obtained by combining the MIT prepared orthologous gene list [10] with that obtained from the Ensembl. This totalled about 28,000 orthologous gene triplets of which 1935 were in a 1-1-1 relationship.

The lists of orthologous genes and pseudogenes can be found in the Associated Data Files.

*(b) Paralogs*

We obtained the protein-coding gene paralogs of all pseudogene parent genes from the Ensembl website.

*(b) Family Membership*

We grouped all pseudogenes into families according to their parents’ membership to a family in the Pfam database [11, 12]. We ranked the families based on the number of corresponding pseudogenes. We grouped the top families containing 25% of the total number of pseudogenes in each organism based on their biological relationship.

**Pseudogene Activity**

We defined pseudogene activity based on four features: transcription potential, presence of Polymerase II (Pol II) and Transcription Factor (TF) binding sites in the upstream region of the pseudogenes, and chromatin accessibility.

*(a) Transcription*

In order to determine the list of potentially transcribed pseudogenes, we determined the RPKM values of each pseudogene in human, worm and fly. Among the transcribed pseudogenes, we also identified those with discordant expression patterns with their parent genes, using the PseudoSeq pipeline. Methods are described below.

● *RPKM*

We quantified the transcriptional activity for each pseudogene annotation using the following workflow. (i) For each nucleotide we calculated a mappability index as *1/m,* where *m* is the number of matches found in the genome for the 75 bp sequence starting at that nucleotide position allowing up to 2 mismatches. A mappability index of 1 indicates unique mapping. (ii) We filtered out pseudogene regions with mappability lower than 1. (iii) We discarded any pseudogene regions shorter than 100 bp. (iv) We computed RPKM values for all unique pseudogene regions. (v) We set the human pseudogene RPKM selection threshold at 2. This value was chosen in agreement with previously published results [13, 14], which imply that on average 15% of human pseudogenes are transcribed. (vi) We evaluated the pseudogene RPKM selection threshold in worm and fly following the assumption that the transcription of protein-coding genes in human, worm and fly has a similar distribution. We applied quantile normalisation on the pooled “matched compendium” data for worm and fly, using human as a reference. This forces the transcription of protein-coding genes (but not the pseudogenes) to follow a similar distribution across the three organisms. (As a control, we also performed the normalisation on non-coding transcription instead of protein-coding genes and obtained consistent results.) (vii) We used the protein-coding gene normalisation to evaluate the RPKM selection threshold in worm and fly, obtaining 5.7 and 10.9 respectively. (viii) We used the calculated RPKM thresholds to obtain a list of transcribed pseudogenes in worm and fly respectively. For mouse, we used a similar approach following steps (i) to (vii) and obtained a RPKM selection threshold of 3.28. As a result we identified 878 transcribed pseudogenes in mouse.

● *PseudoSeq Pipeline*

PseudoSeq is a computational pipeline that makes use of RNA-Seq data from multiple tissues or developmental stages to compare the transcription of pseudogenes and their parents [14]. The pipeline maps RNA-Seq reads to the reference genome in conjunction with a splice junction library using Bowtie [15] and RSEQtools [16]. The signal tracks of the reads mapped to each pseudogene and its parent are generated across all the samples. Using this pipeline, we analysed pseudogene-parent expression correlation patterns. We found that pseudogenes may exhibit either concordant or discordant expression patterns with respect to their parents.

*(b) Additional Activity Features*

We defined the 2kb upstream of each pseudogene start site as the upstream region. We studied this region for the presence of Pol II and TF binding sites. The coordinates for Pol II and TFs were obtained from [17]. We annotated a pseudogene as Pol II active if at least 50% of the length of the Pol II binding site was included within the upstream region. Similarly, we annotated a pseudogene as TF active if at least 3 different TFs have at least 50% of their binding site within 2kb of the pseudogene start site.

Next, we analysed active chromatin in pseudogenes using chromatin segmentation for human (Segway [18]) and fly pseudogenes (9 State-Chromatin Segmentation [19]), and histone marks for worm pseudogenes. We analysed the distribution of the chromatin states along the pseudogene body. We annotated the human pseudogenes with an active chromatin label using a previously described model [14]. We compared the distribution of active and repressive marks in protein-coding genes. On average the ratio of the frequency of active to repressive chromatin marks for protein-coding genes is 5. Based on this analysis we developed a model for labelling pseudogenes with active chromatin. If the ratio of the frequency of active to repressive chromatin state marks was greater than or equal to 3, we labelled the pseudogene as having an active chromatin. The Segway active chromatin marks are GS (gene start), e/GM (enhancer, gene middle), GE (gene end), TSS (transcription start site). The Segway repressive chromatin marks are C (CTCF), R (repressive), F (FAIRE signal), L (low signal) and D (dead).

For fly, we looked at chromatin segmentation in 2 cell lines, S2 and BG3. If the ratio of the frequency of active chromatin marks to the frequency of repressed marks was larger than 2 in either of the cell lines, we labelled the pseudogene with an active chromatin tag. There are three active chromatin marks: Pro (promoter), Enh (enhancer) and Tnx (transcription); and three repressive marks: Rep (repressive), Het (heterochromatin) and Low (low signal).

Finally, we looked at the chromatin signatures of H3K4me3 and H3K4me1 in worm pseudogenes. We compared the signal intensities of these histone marks around the pseudogene body to coding gene signals. If the signals were of similar intensities, we labelled the pseudogene as having active chromatin.

 *(b) Upstream Sequence Analysis*

We examined upstream proximal regions within 2kb of the annotated start sites for all pseudogenes, parent genes and paralogs.

We calculated the sequence similarity of the upstream regions between pseudogenes and parents, and between paralogs and parents using ClustalW2.1 [20]. For this process, we used the default settings of this alignment tool. The fraction of identical total nucleotides was calculated as the sequence similarity.

For the study of upstream sequence activity, we used H3K27ac histone mark ChIP-Seq data [21] (uniformly processed signals with fold change calculated against control). The comparison is focused on protein-coding gene–pseudogene, 1-1 pairs where the parent gene does not have a corresponding gene paralog, and protein-coding gene–paralog 1-1 pairs where the protein-coding gene has one pseudogene.

In human, we analysed data from 15 cell lines: Dnd41, Gm12878, H1hesc, Helas3, Hepg2, Hmec, Hsmm, Hsmmt, Huvec, K562, Nha, Nhdfad, Nhek, Nhlf, Osteobl; in worm, we used data from three developmental stages (EE, L3, AD) while in fly we studied the EL and L3 developmental stages. For each upstream region, the normalised signal from each experiment was aggregated and averaged over the 2kb sequence. Using a threshold value of 1, we labelled regions as active if their signal values were higher than the set threshold in all the experiments considered. We labelled regions as inactive if their signal values were less than the defined threshold in all the experiments studied. For the parent-pseudogene-paralog trio set in Fig. 4C, the number of trios belonging to each of the four scenarios were counted.

**“Functional” Pseudogene Candidates**

*(a) Pseudogene-parent Coexpression*

To study pseudogene-parent co-expression patterns, we calculated Spearman correlations of expression levels (RPKM values in RNA-Seq) across different developmental stages or cell lines. In worm and fly, we used gene expression data across embryonic developmental stages (33 stages in worm, 30 stages in fly). In human, we used gene expression data across 19 human ENCODE cell lines.

*(b) Translation*

We used a proteo-genomic search to identify translated pseudogenes. (i) We generated putative peptides using 3-frame translation of annotated pseudogenes. (ii) We built a target peptide sequence database by merging the putative peptide and the complete human proteome datasets [22]. (iii) We used Peppy to map the target peptides against raw MS spectra (available from [23]) under the default search settings [24]. The peptide identification false discovery rate was set lower than 0.01 using a target-decoy method. (iv) We refined the peptide-spectra matches by eliminating all peptides matching known proteins or variants (according to UniProt). Also we retained only the unique peptides identified at least twice in our analysed cell lines. (v) We annotated a pseudogene as putatively translated if it had two or more unique peptide matches.

The putatively translated pseudogenes were evaluated in terms of RNA expression (RPKM value) in the corresponding ENCODE human cell lines. We labelled the pseudogene translation candidates as highly confident if they had a RPKM value greater than 2. We used BLASTP [1] to compare sequence similarity between the pseudogene peptides and those originating from their parent protein.

**References**

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