

Joint Bayesian inference of risk variants and tissue-specific epigenomic enrichments across multiple complex human diseases

Yue Li^{1,2,*} and Manolis Kellis^{1,2,*}

¹Computer Science and Artificial Intelligence Lab, Massachusetts Institute of Technology, 32 Vassar St, Cambridge, Massachusetts 02139, USA

²The Broad Institute of Harvard and MIT, 415 Main Street, Cambridge, Massachusetts 02142, USA

*Correspondence to liyue@mit.edu or manoli@mit.edu

Contents

| | | |
|----------|---|------------|
| 1 | Supplementary Figures | 3 |
| 2 | Supplementary Tables | 476 |
| 3 | Supplementary Text S1: HMC method details and RiVIERA algorithm outlines | 477 |
| 3.1 | Hamiltonian Monte Carlo (HMC) sampling for w_{kd} , w_{0d} , μ_d , ϕ_d | 477 |
| 3.2 | RiVIERA inference algorithm | 478 |
| 4 | Supplementary Text S2: GWAS simulation | 480 |
| 4.1 | Simulating genotypes | 480 |
| 4.2 | Simulating epigenomic enrichments | 480 |
| 4.3 | Simulating GWAS summary statistics | 481 |

List of Figures

| | | |
|----|--|-----|
| S1 | Simulation pipeline to generate genotypes. | 3 |
| S2 | Credible set calibration | 4 |
| S3 | Model performance on loci harboring multiple causal variants | 4 |
| S4 | Spearman correlation between estimated and simulated fold-enrichment | 5 |
| S5 | Enrichments on permuted data | 5 |
| S5 | Fine-mappng visualization | 474 |
| S6 | Gene ontology enrichments across the 9 immune traits | 475 |

List of Tables

| | | |
|----|--|-----|
| S1 | Full enrichment results for the 848 epigenomic annotations (Excel) | 476 |
| S2 | Credible SNPs and related functional genomic information (Excel) | 476 |
| S3 | Functional enrichments of credible SNPs (Excel) | 476 |
| S4 | Gene ontology enrichment results using credible genes (Excel) | 476 |
| S5 | Enrichments for eQTL of multi-trait model (Excel) | 476 |
| S6 | Credible SNPs inferred from the multi-trait model on the 9 immune diseases and related functional genomic information (Excel) | 476 |
| S7 | Gene ontology enrichment results using credible genes from cross-trait model (Excel) | 476 |

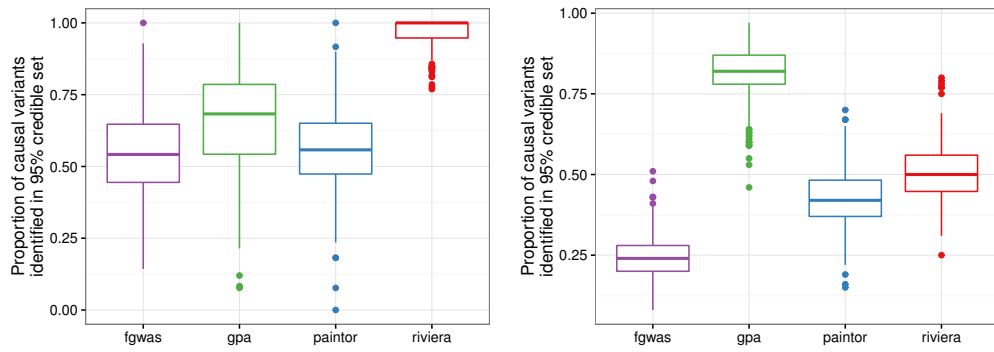


Fig. S2: Credible set calibration on simulated datasets with one variant per locus (left) and more than one causal variants per locus (right).

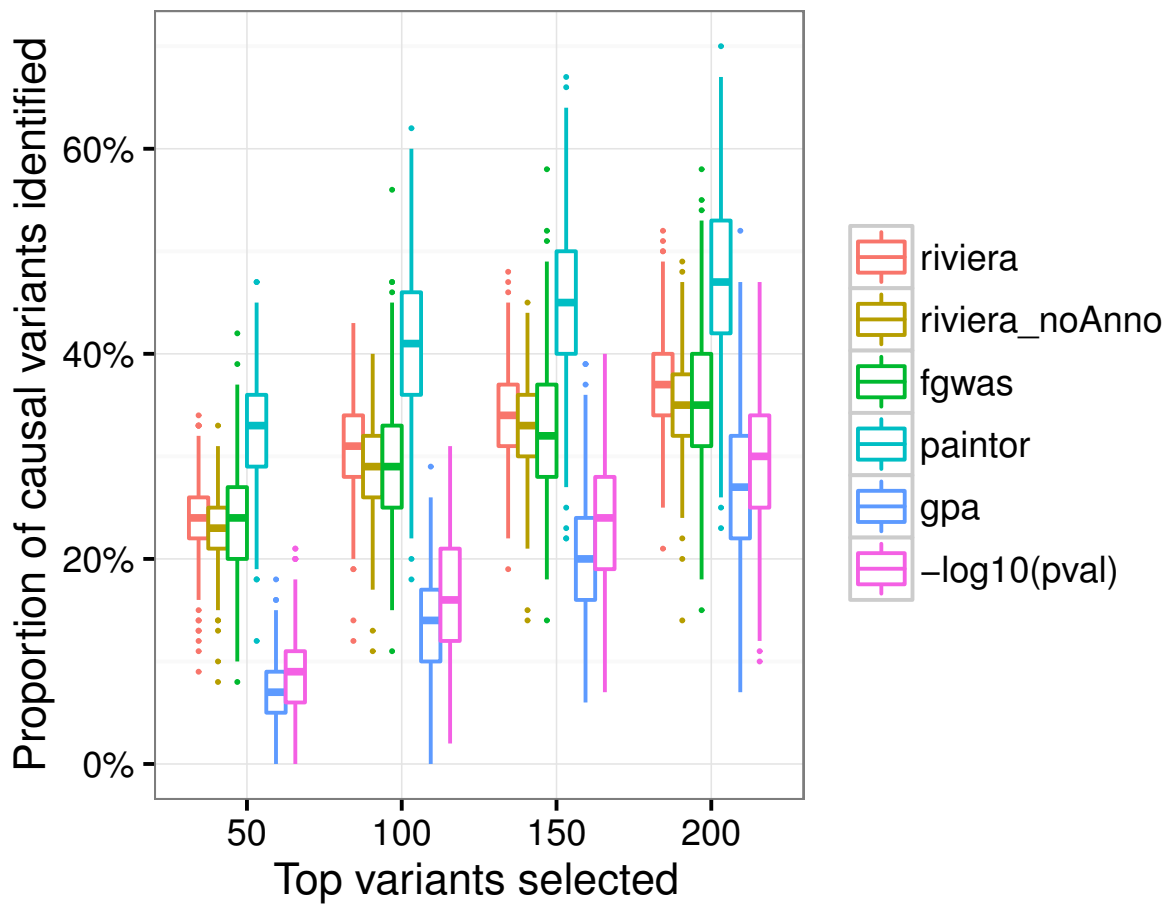


Fig. S3: Model performance on loci harboring multiple causal variants

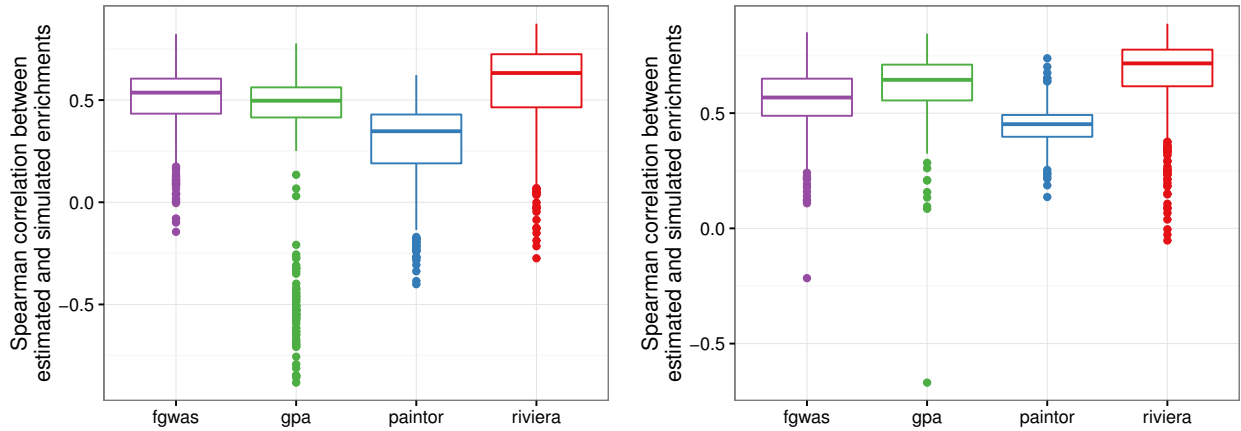


Fig. S4: Spearman correlation between estimated and simulated fold-enrichment. Left: single-causal variant per locus; Right: one or more causal variant per locus

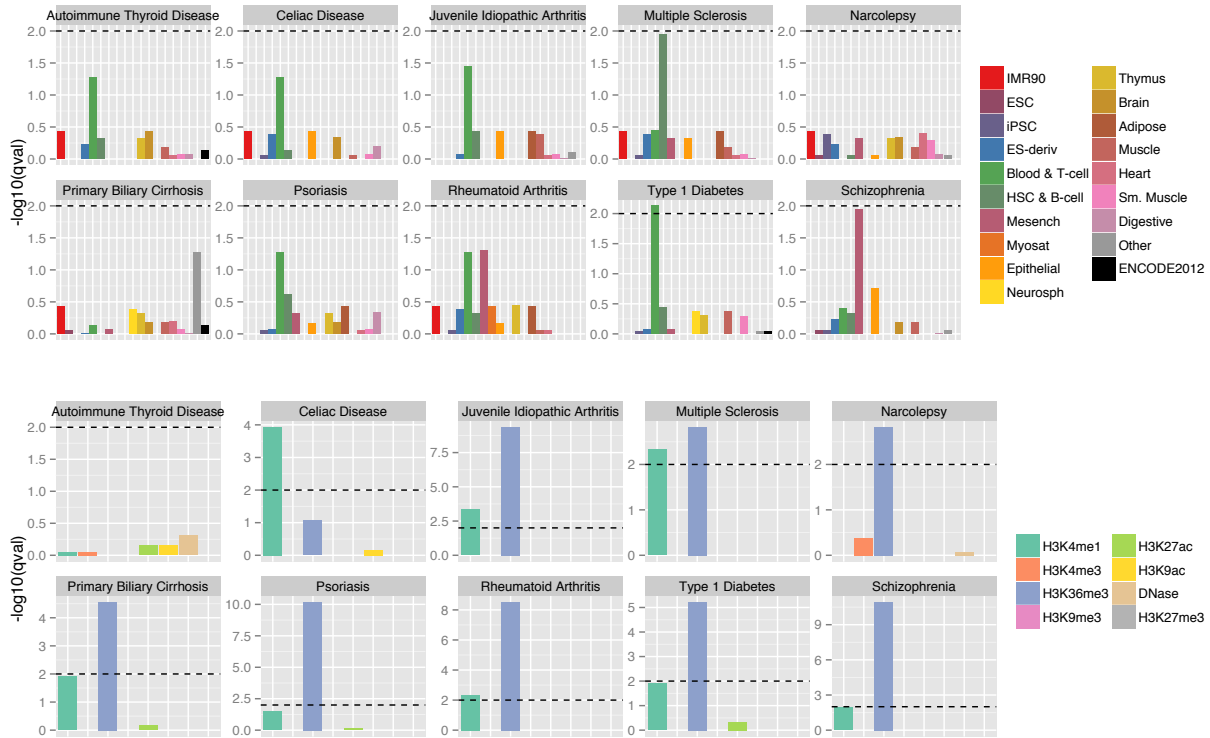
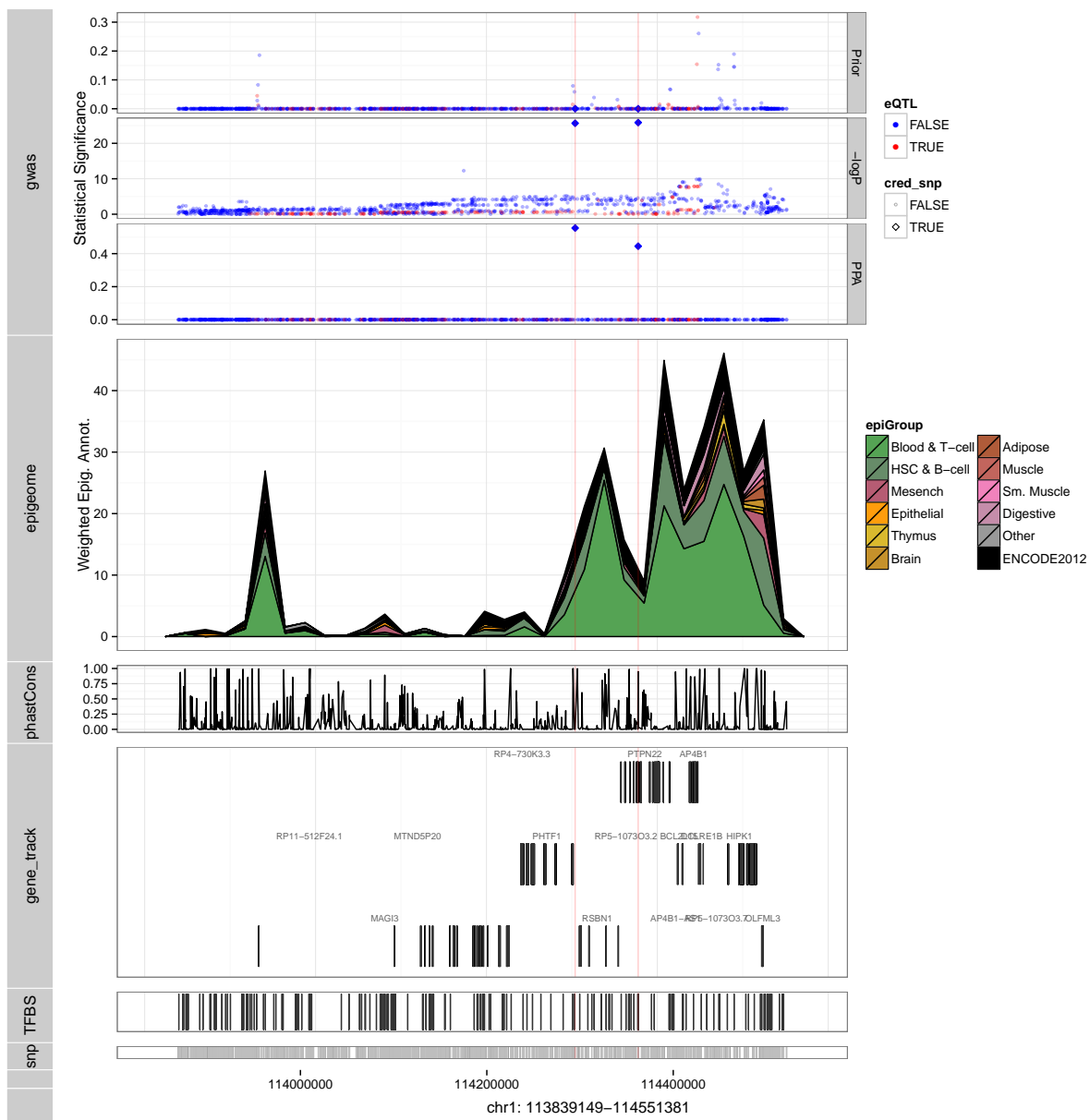
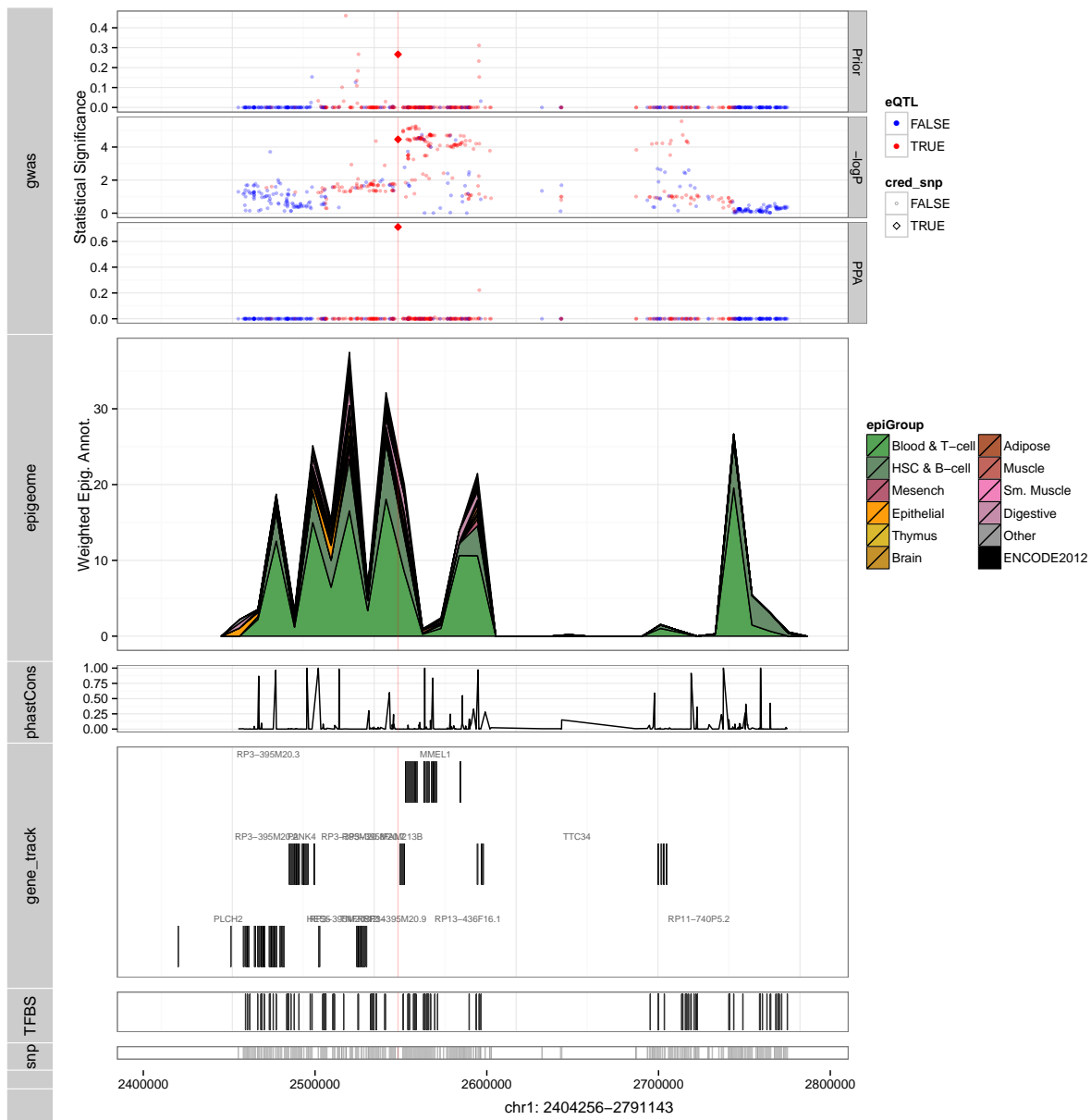


Fig. S5: Enrichments on permuted data. To further ascertain the enrichment results observed in Fig. 3, we permuted the data by randomly shuffling the SNPs and annotations and repeating the same enrichment tests on 19 tissue groups (upper panels) and 8 epigenomic marks (lower panels). Please refer to Fig. 3 for more details.

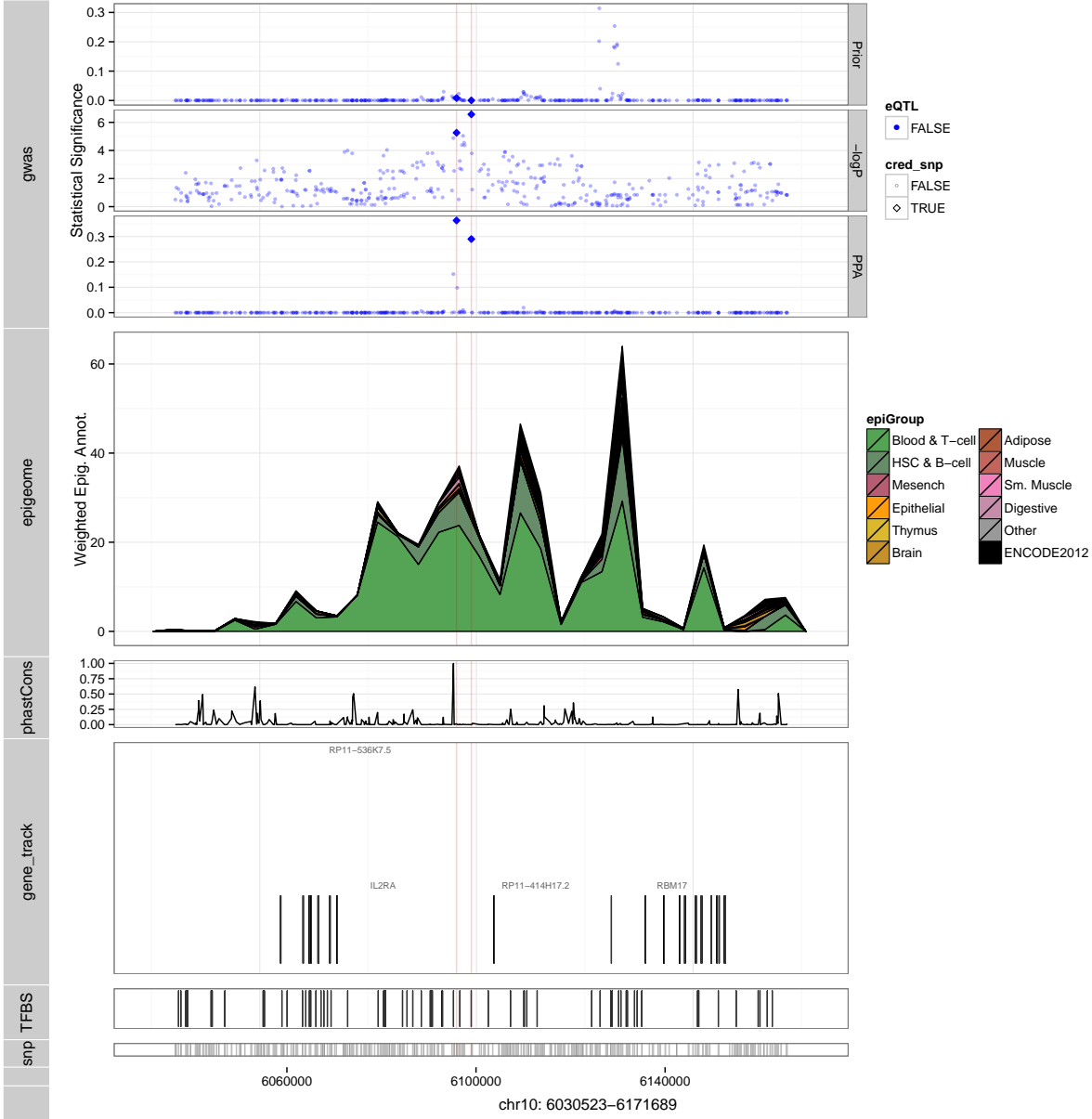
Autoimmune Thyroid Disease



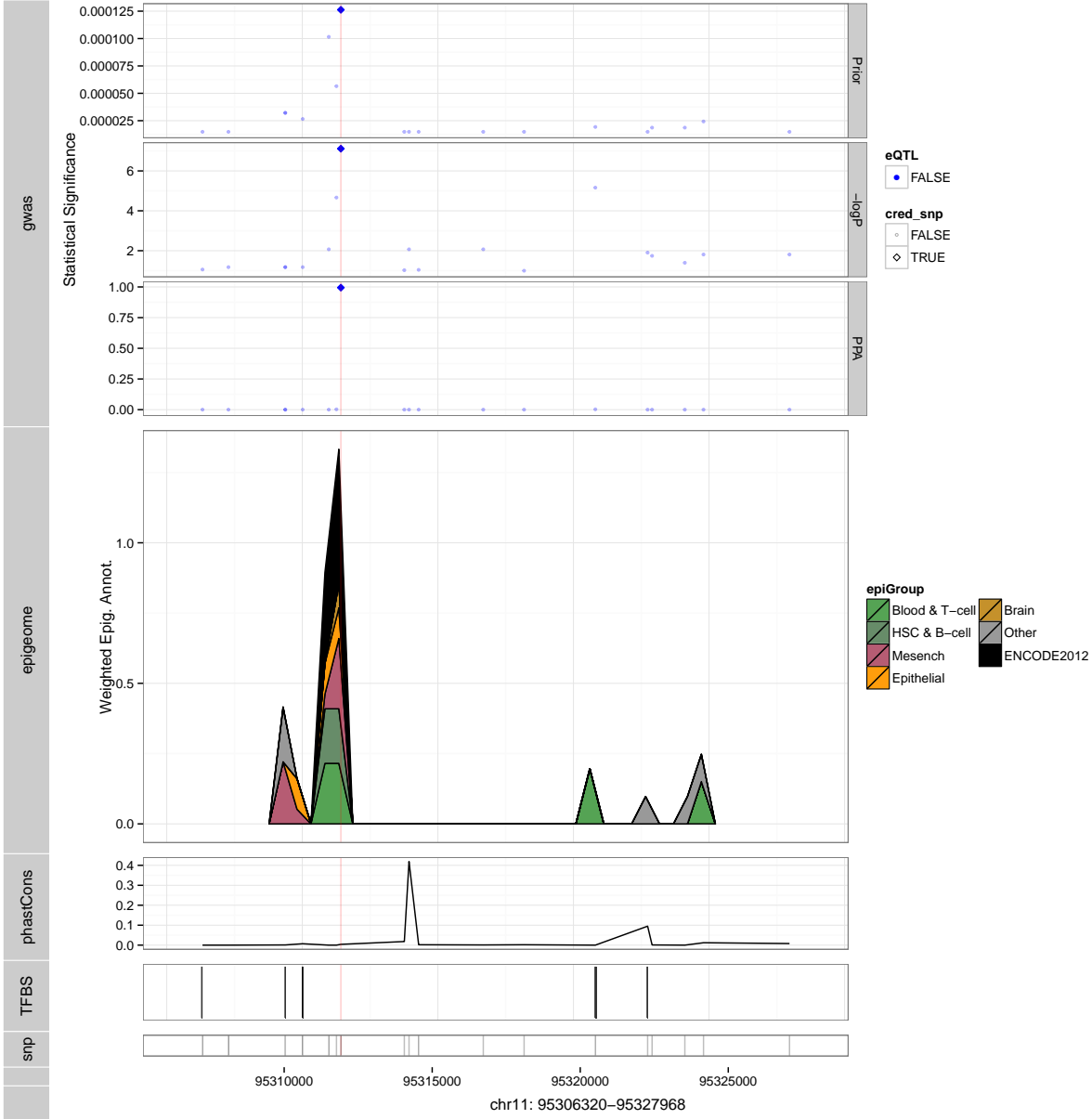
Autoimmune Thyroid Disease



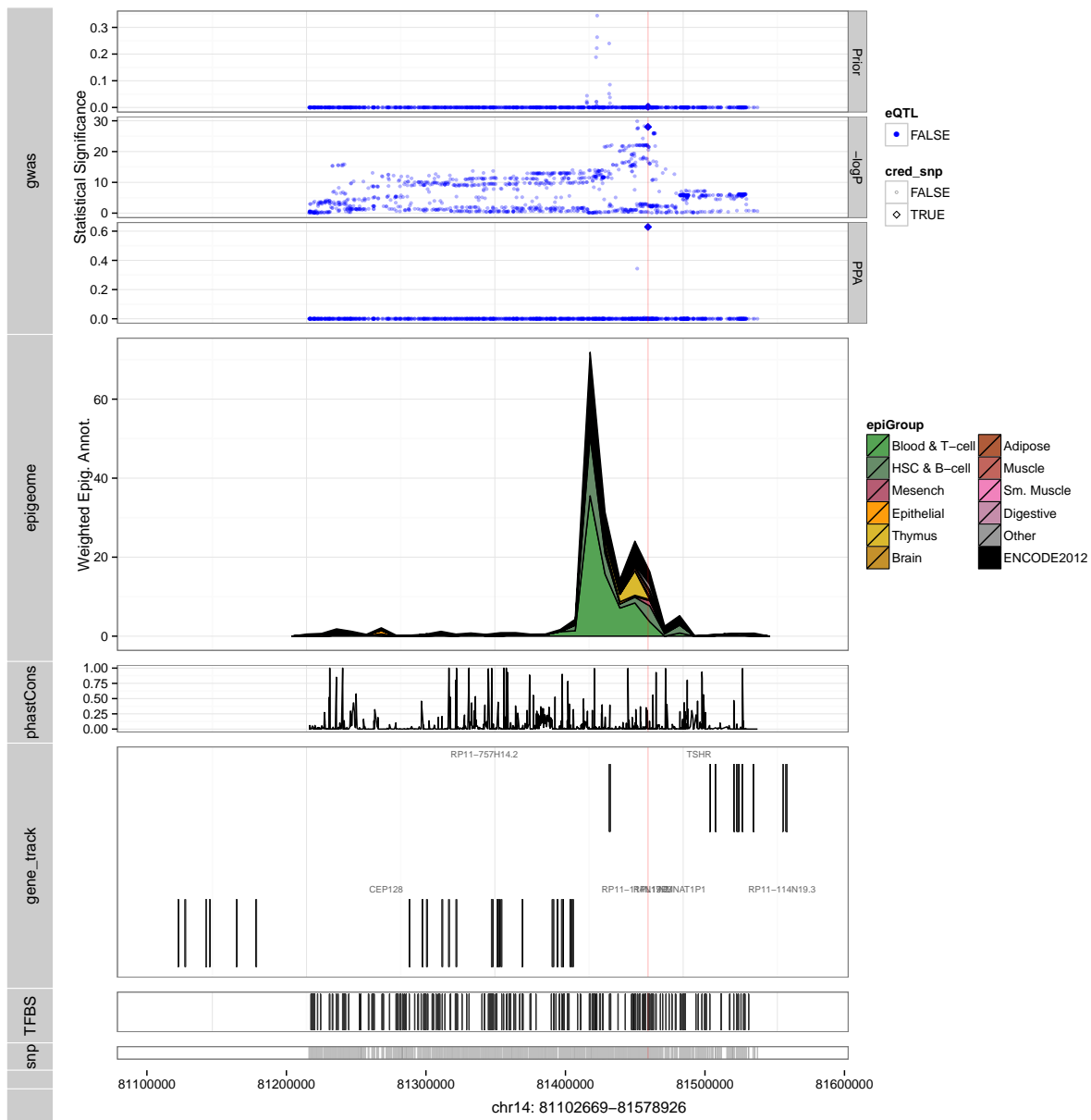
Autoimmune Thyroid Disease



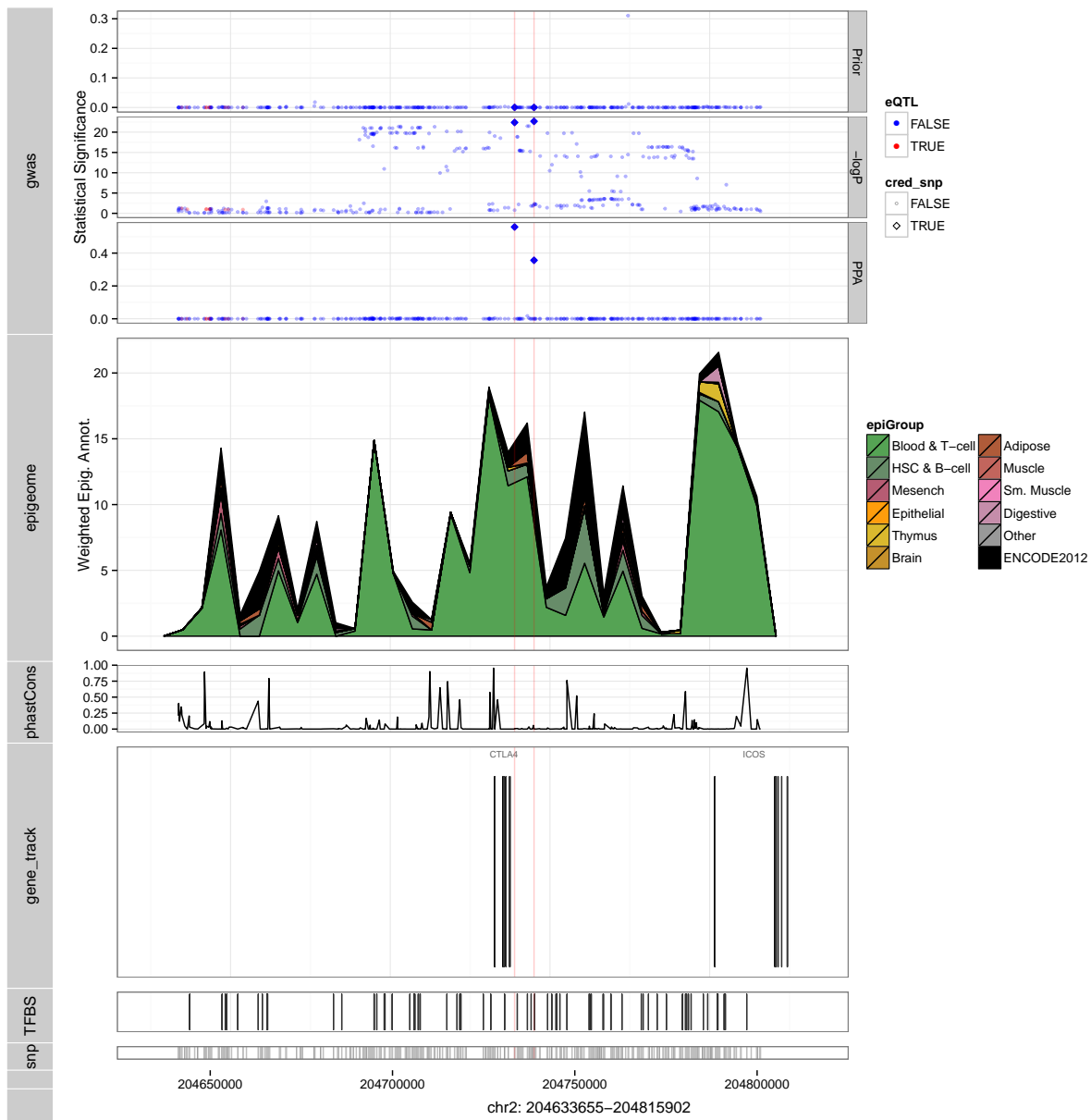
Autoimmune Thyroid Disease



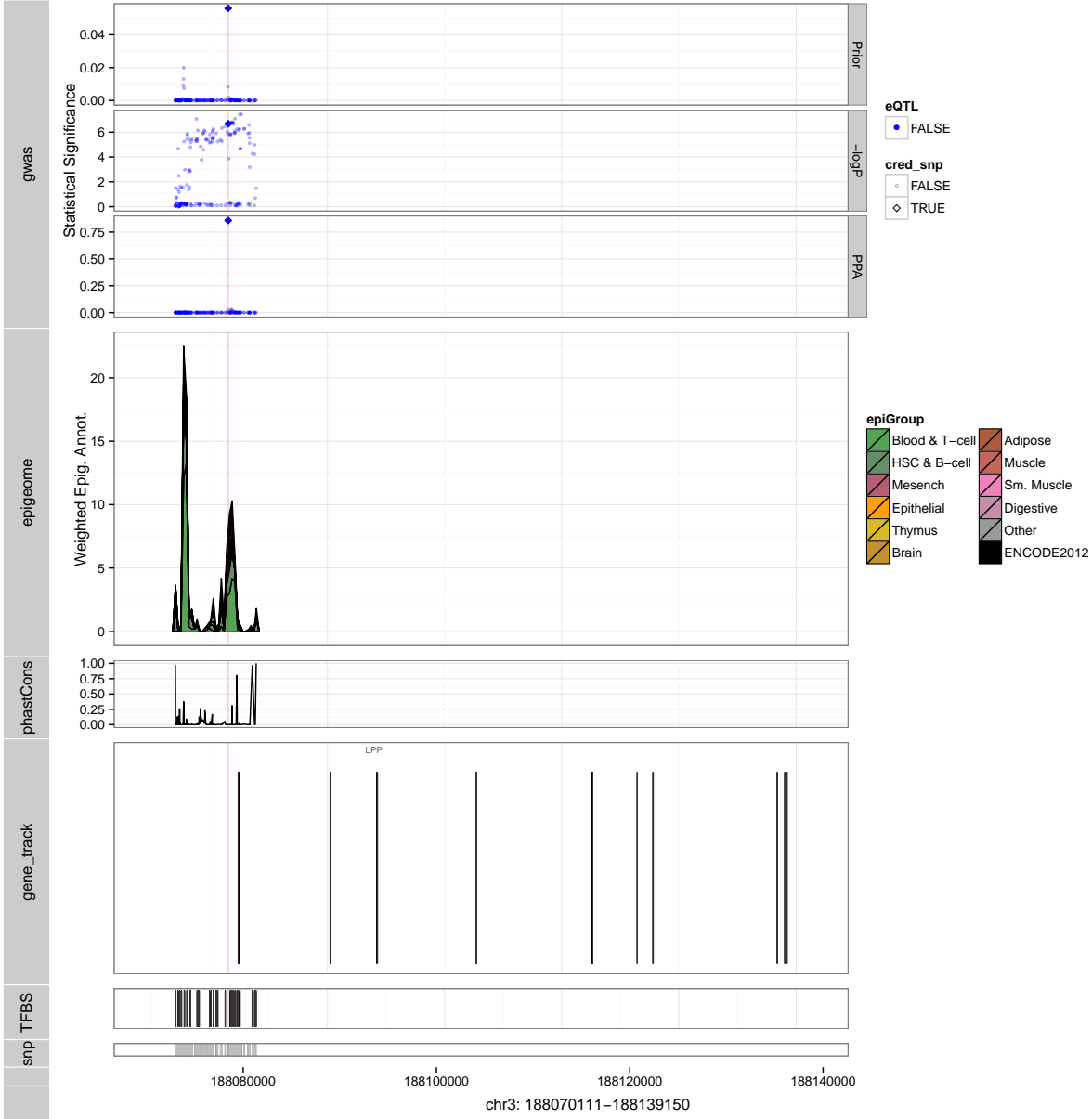
Autoimmune Thyroid Disease



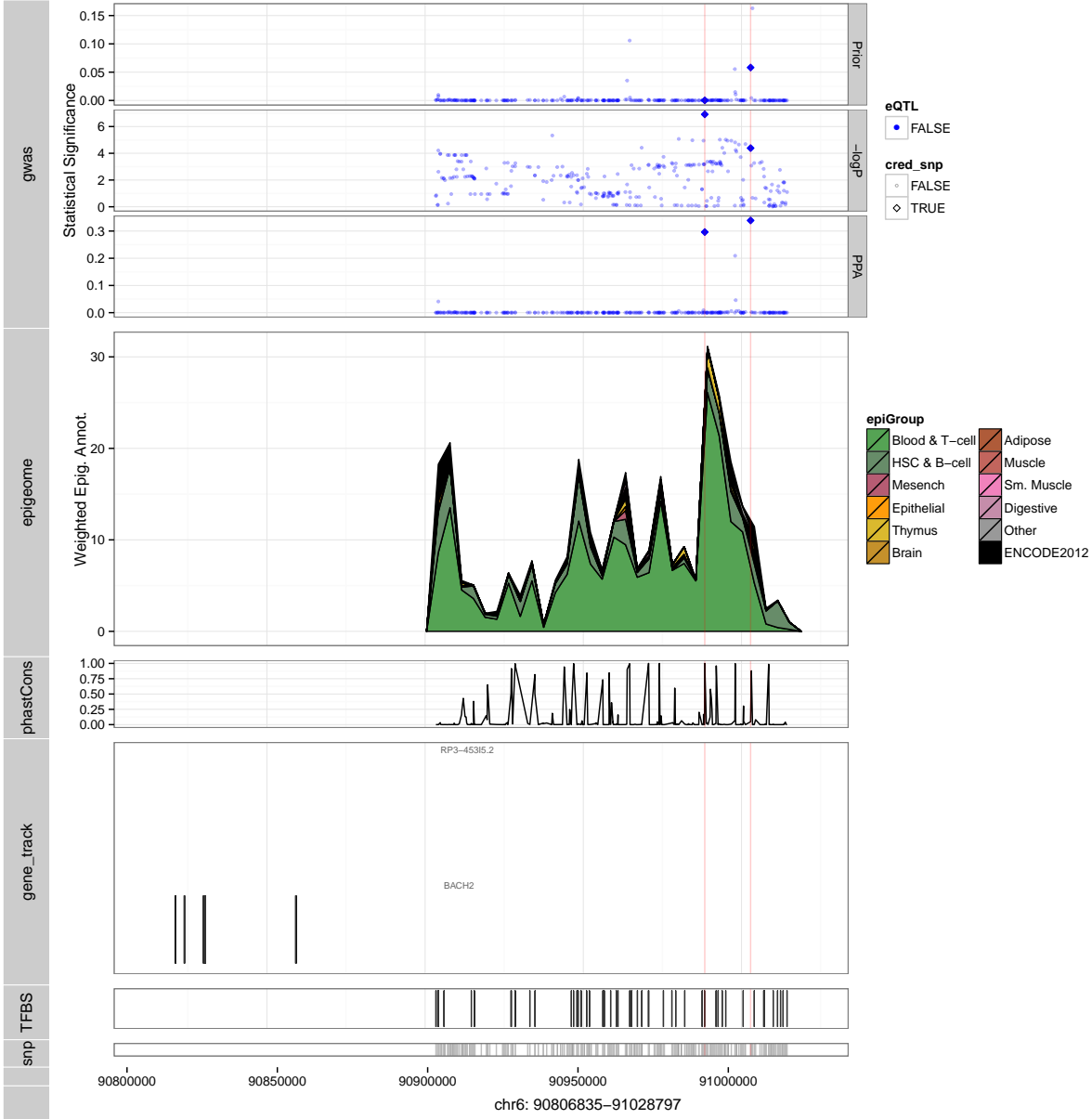
Autoimmune Thyroid Disease



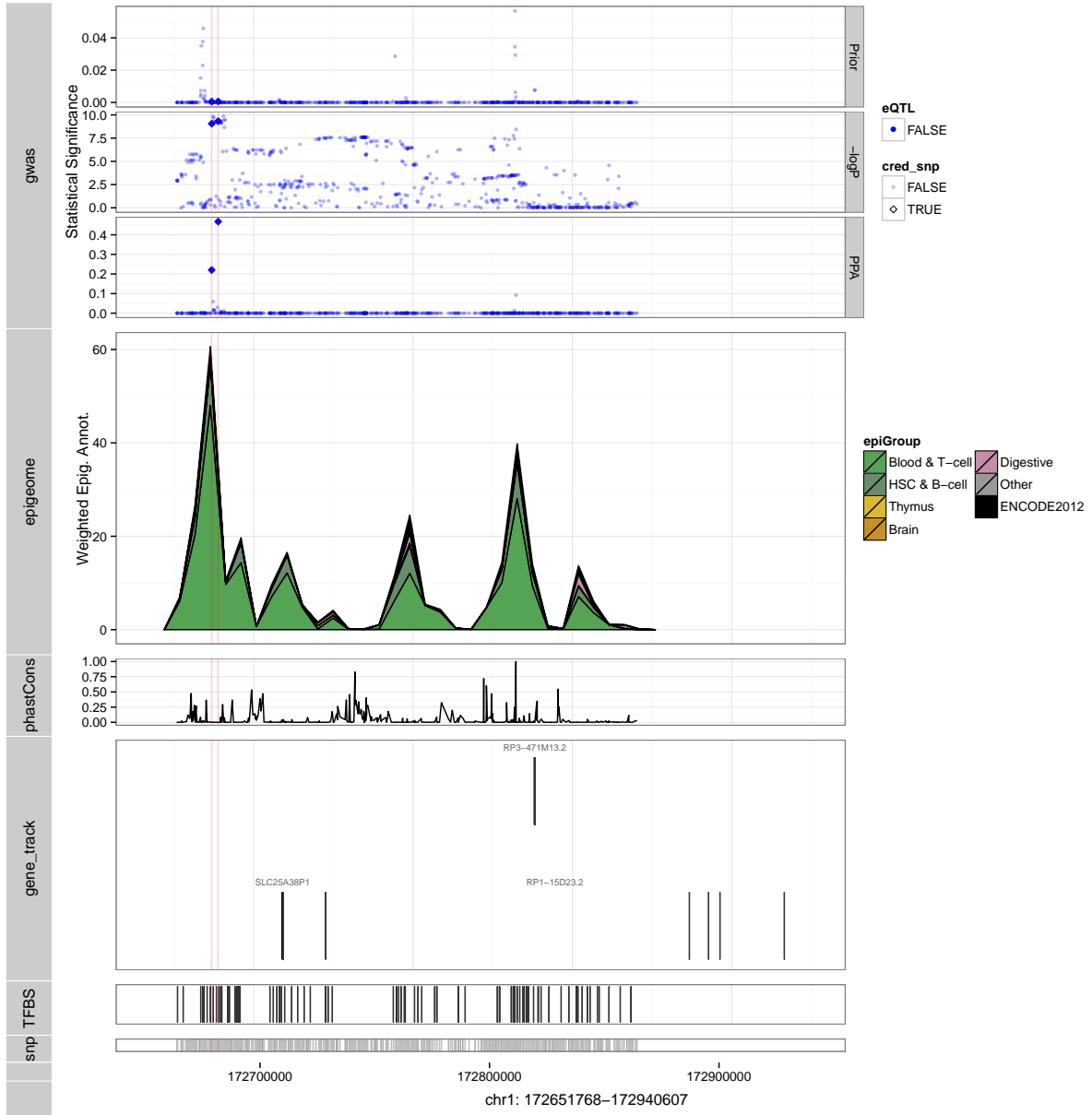
Autoimmune Thyroid Disease



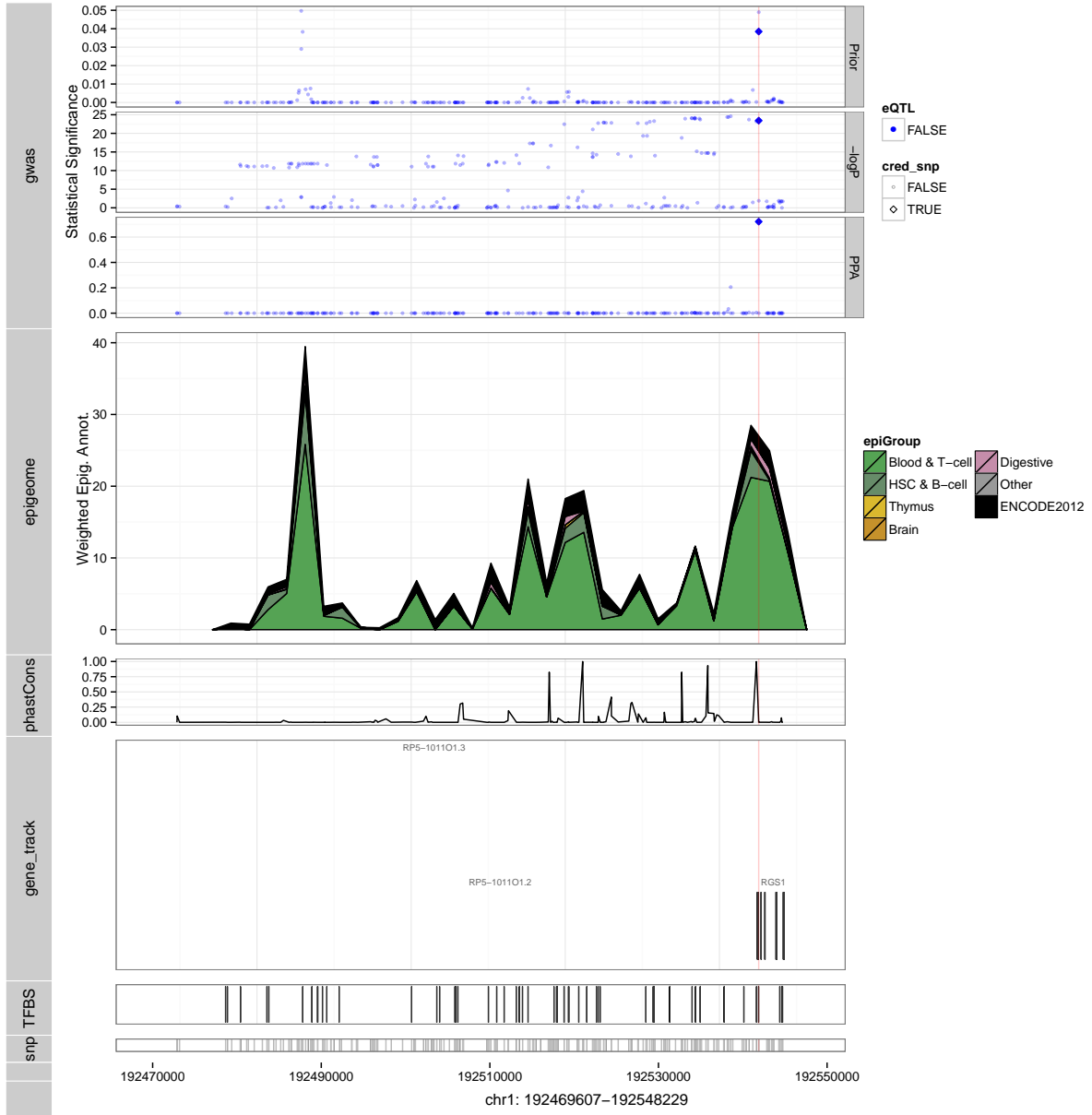
Autoimmune Thyroid Disease



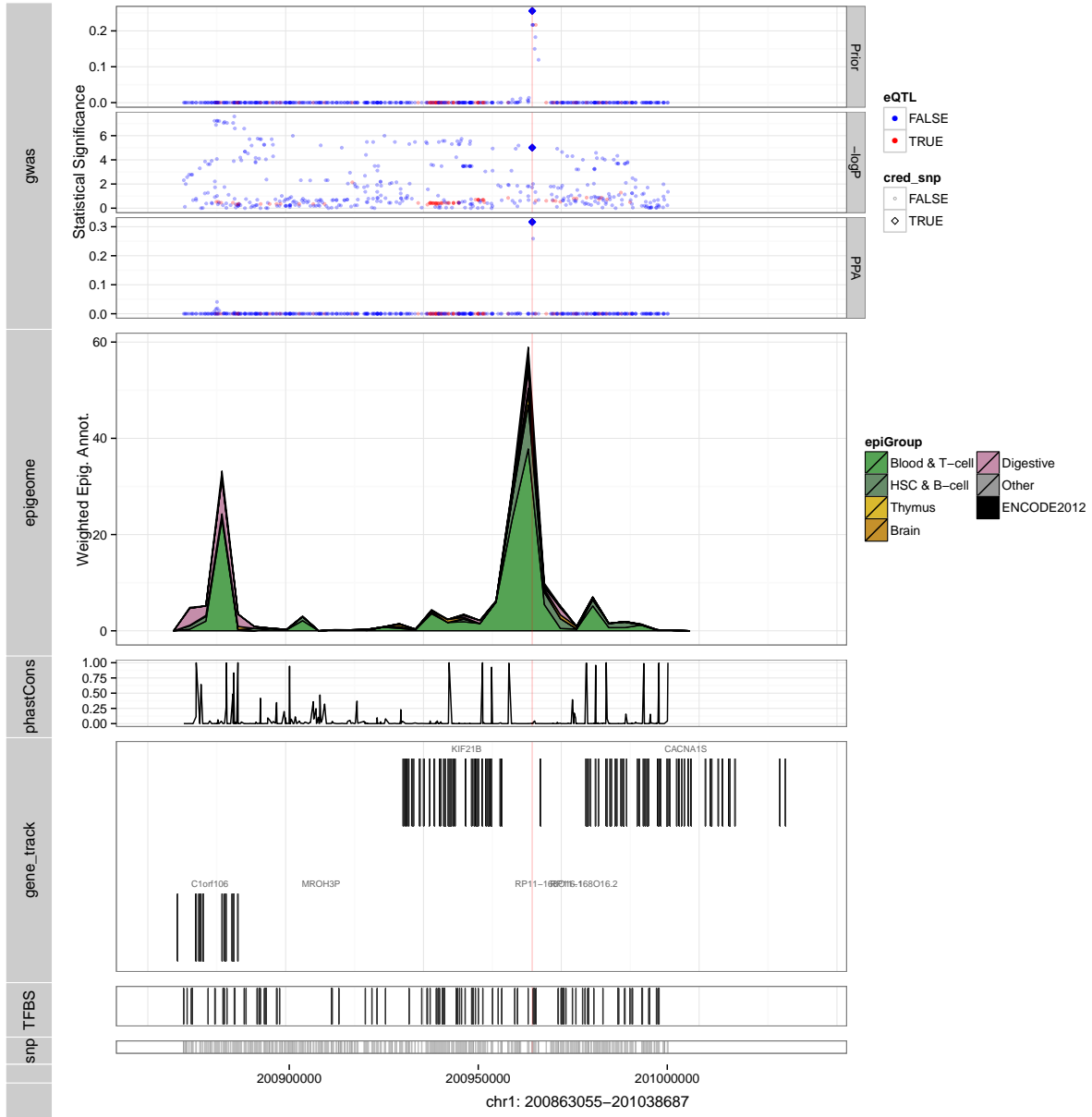
Celiac Disease



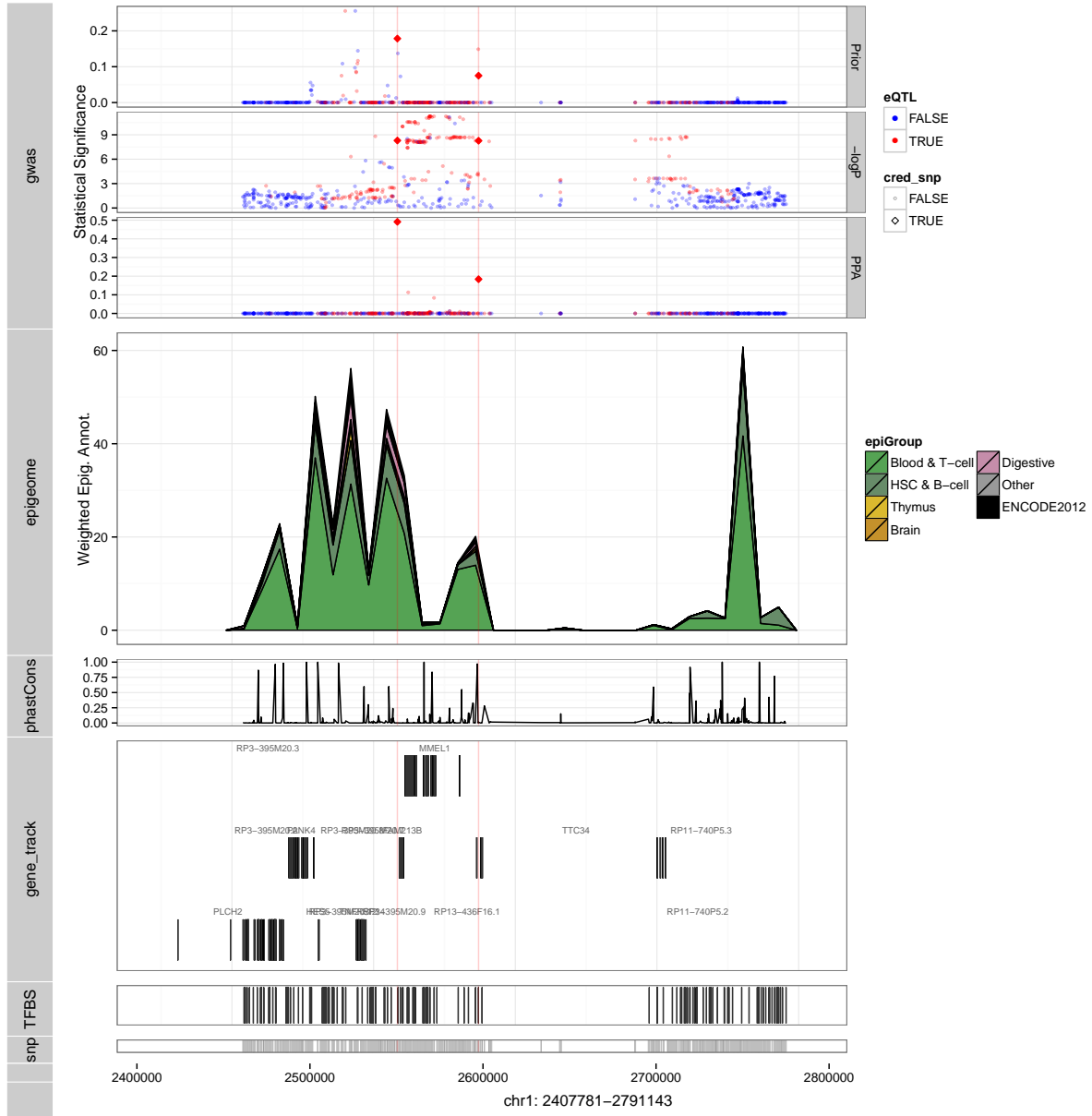
Celiac Disease



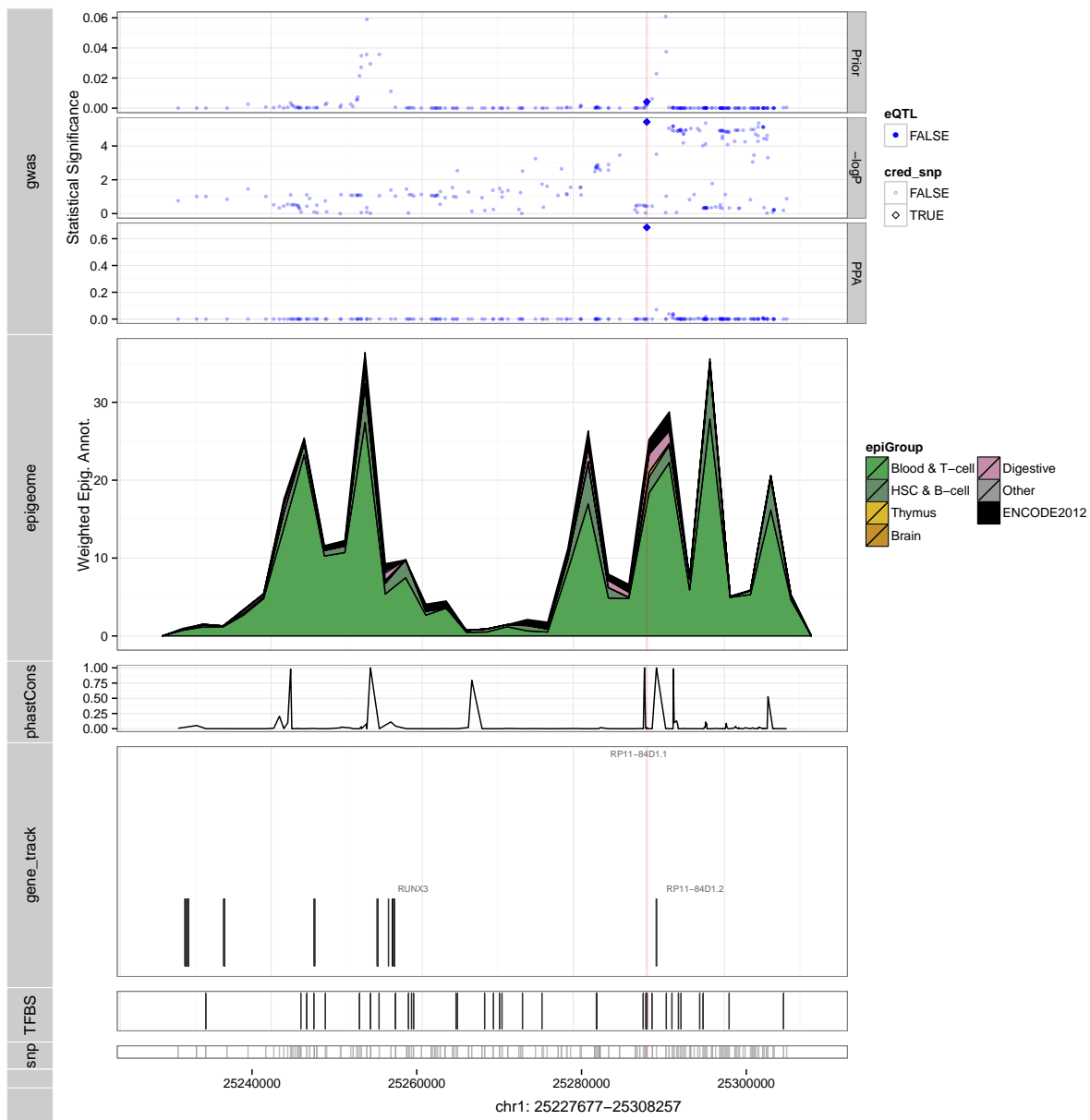
Celiac Disease



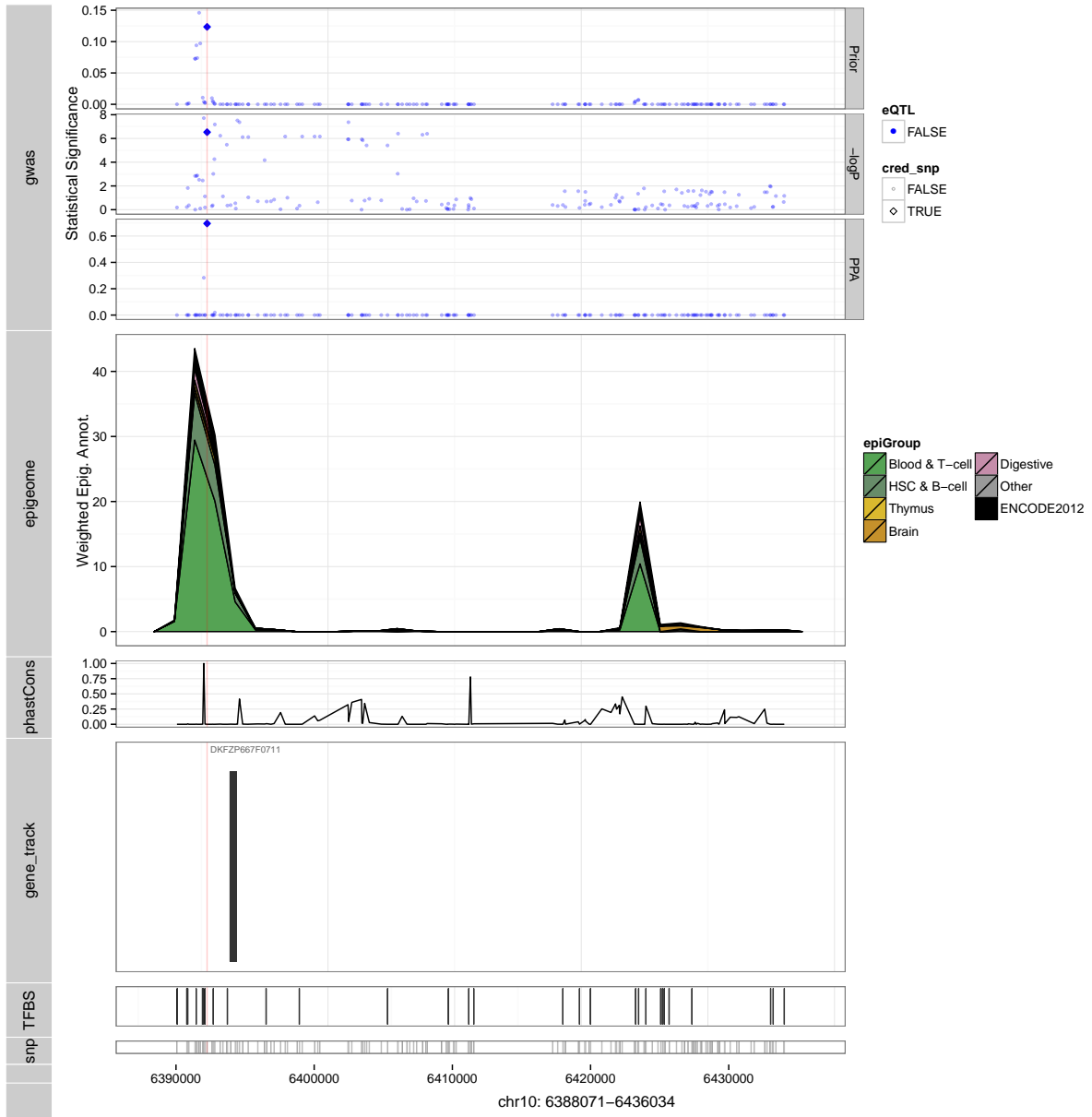
Celiac Disease



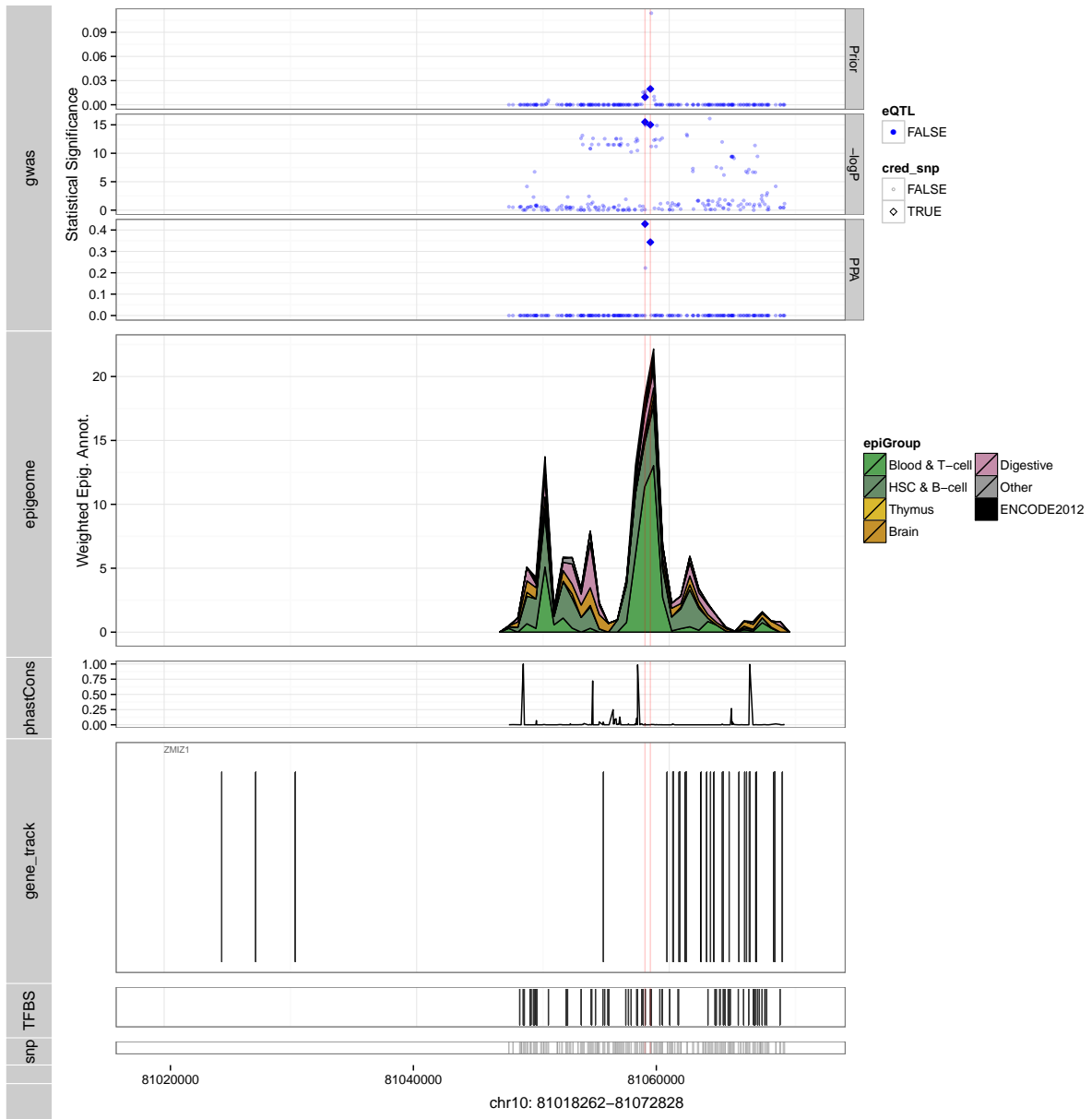
Celiac Disease



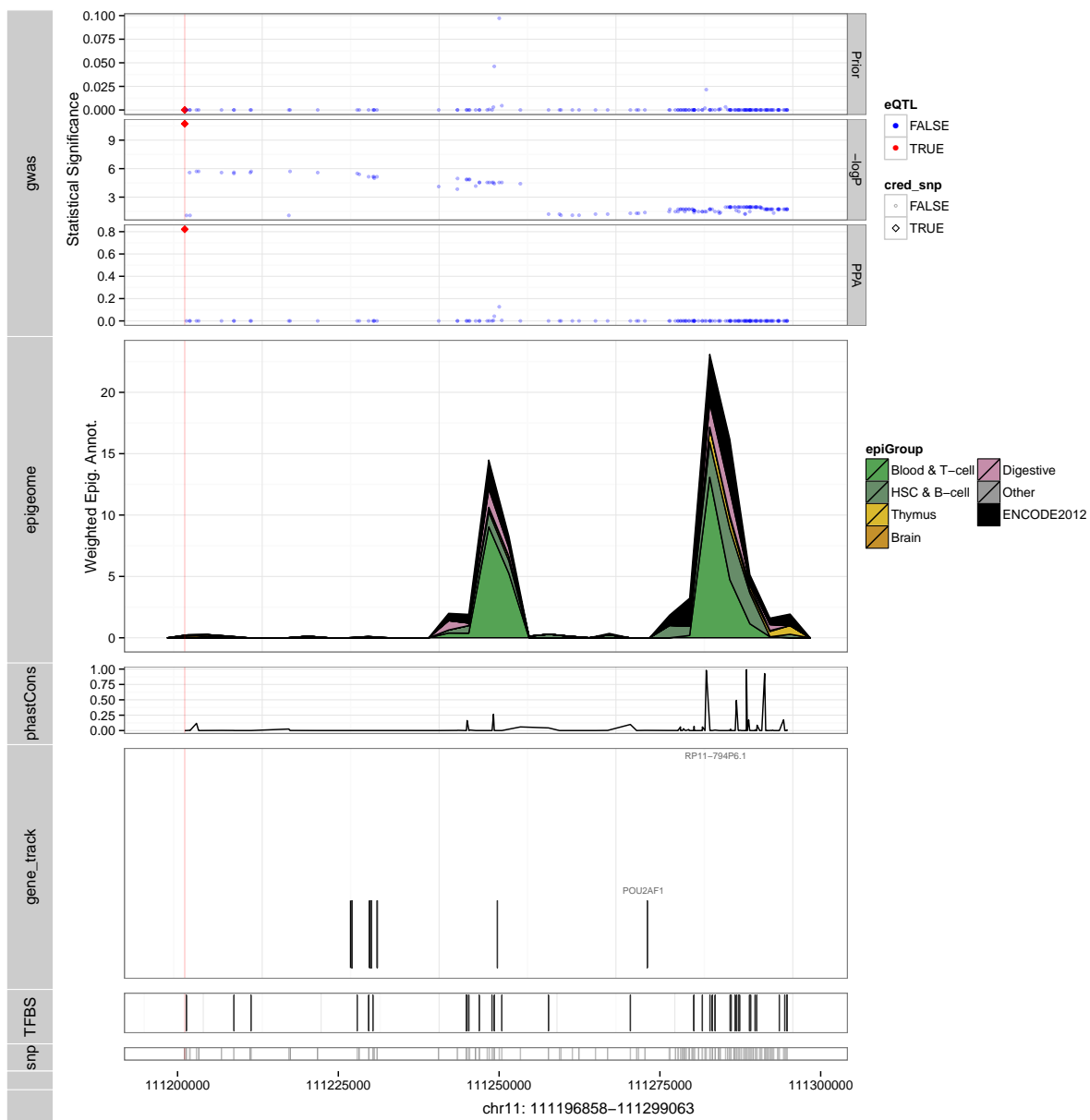
Celiac Disease



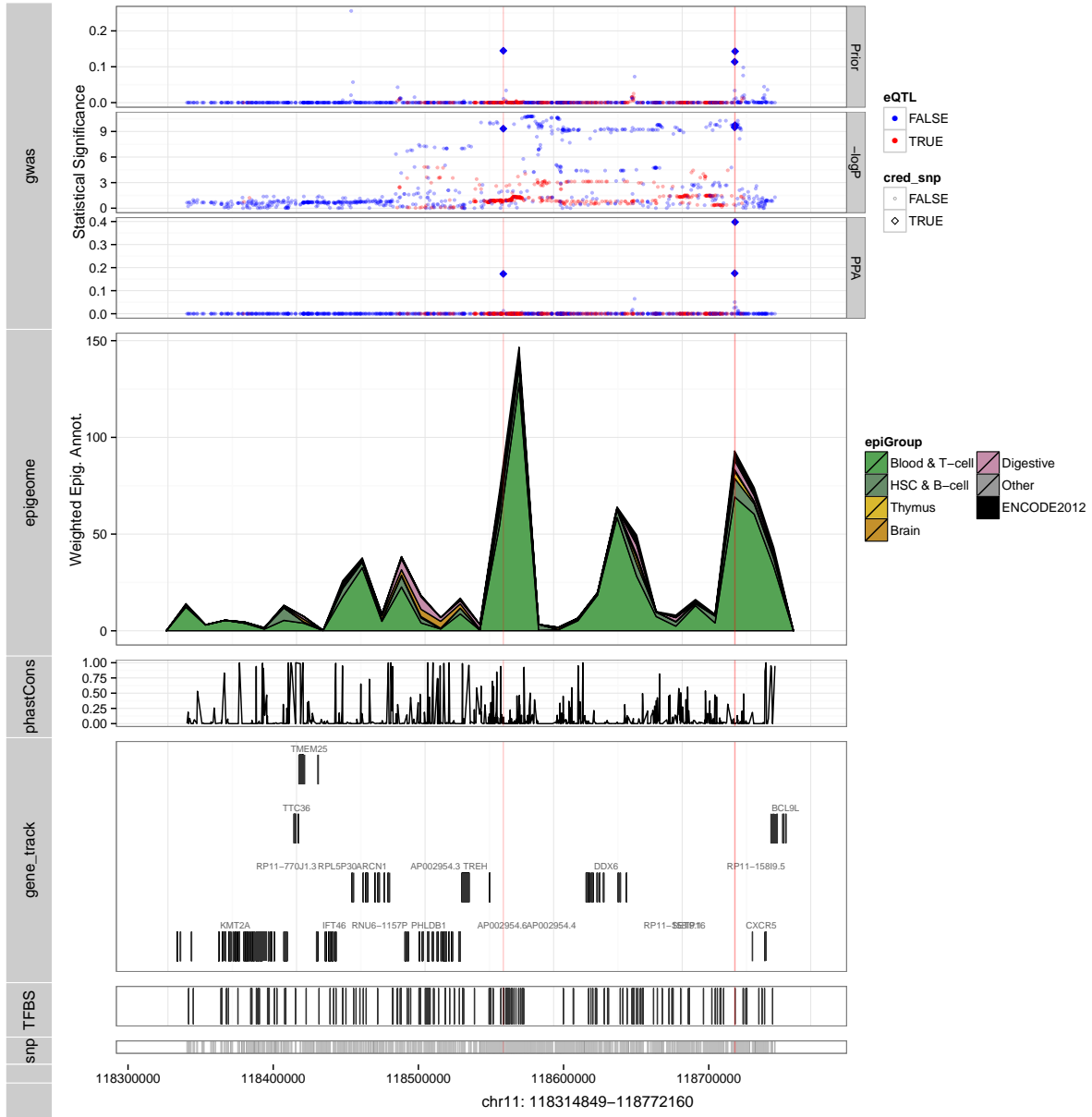
Celiac Disease



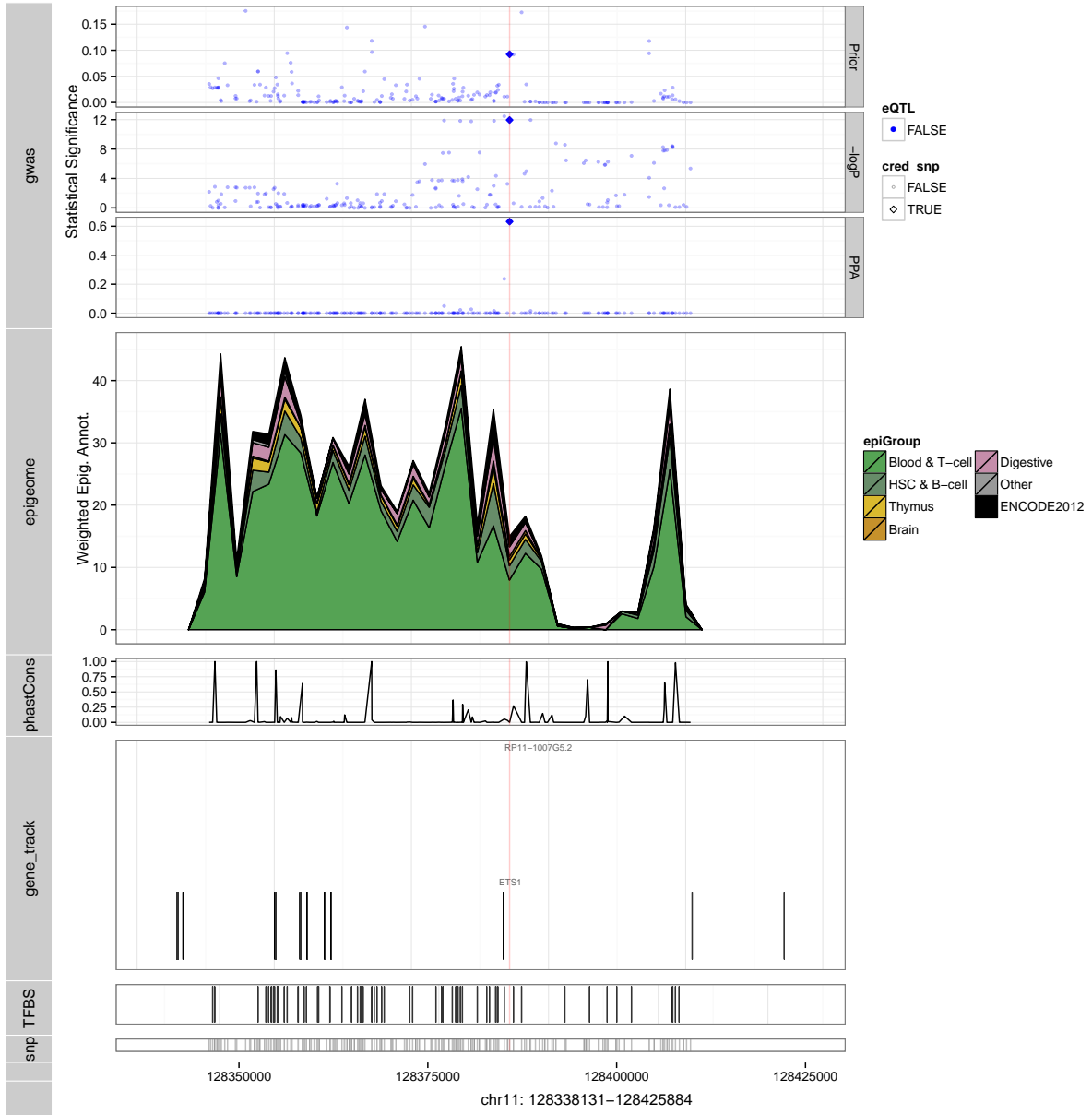
Celiac Disease



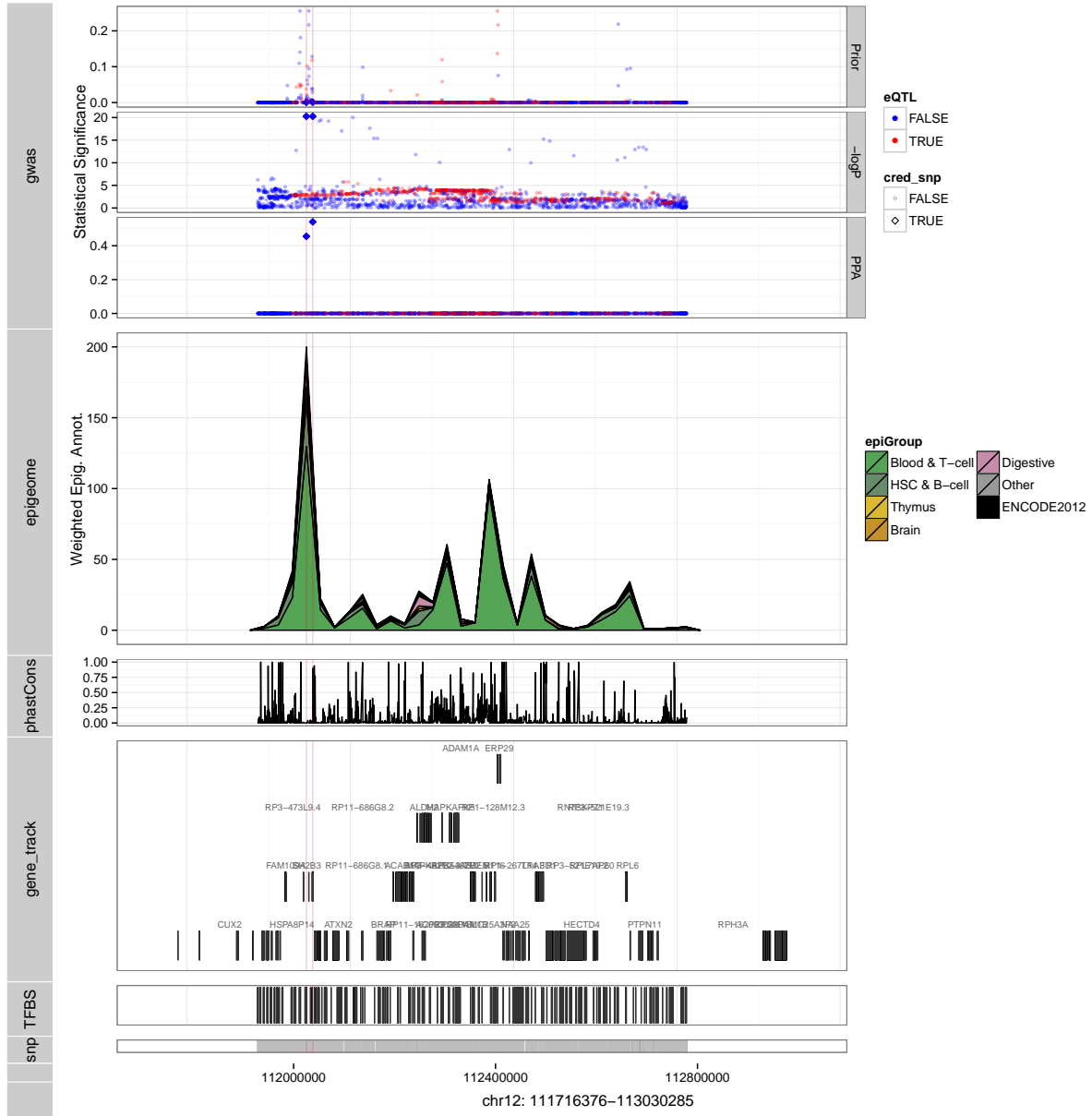
Celiac Disease



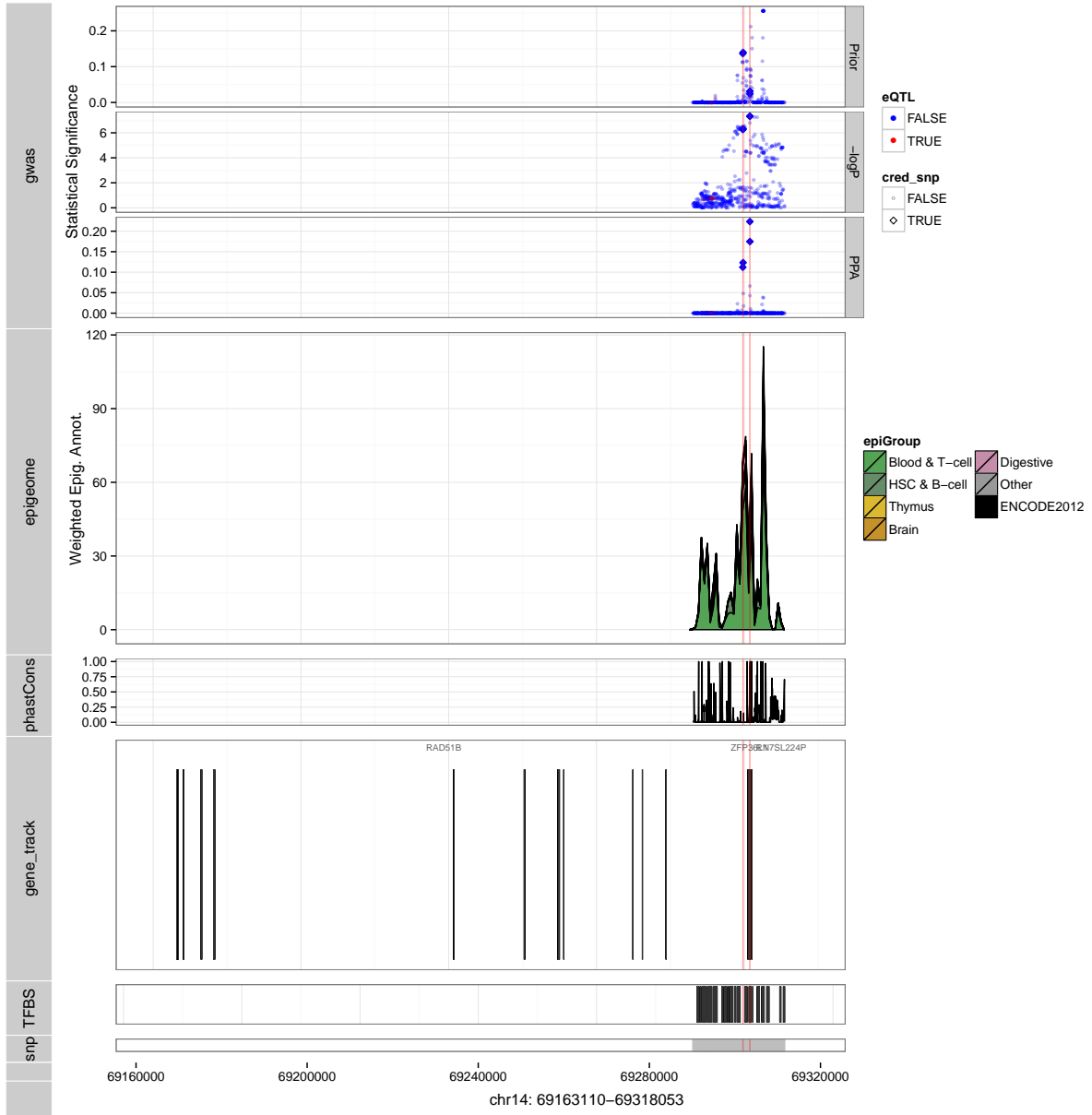
Celiac Disease



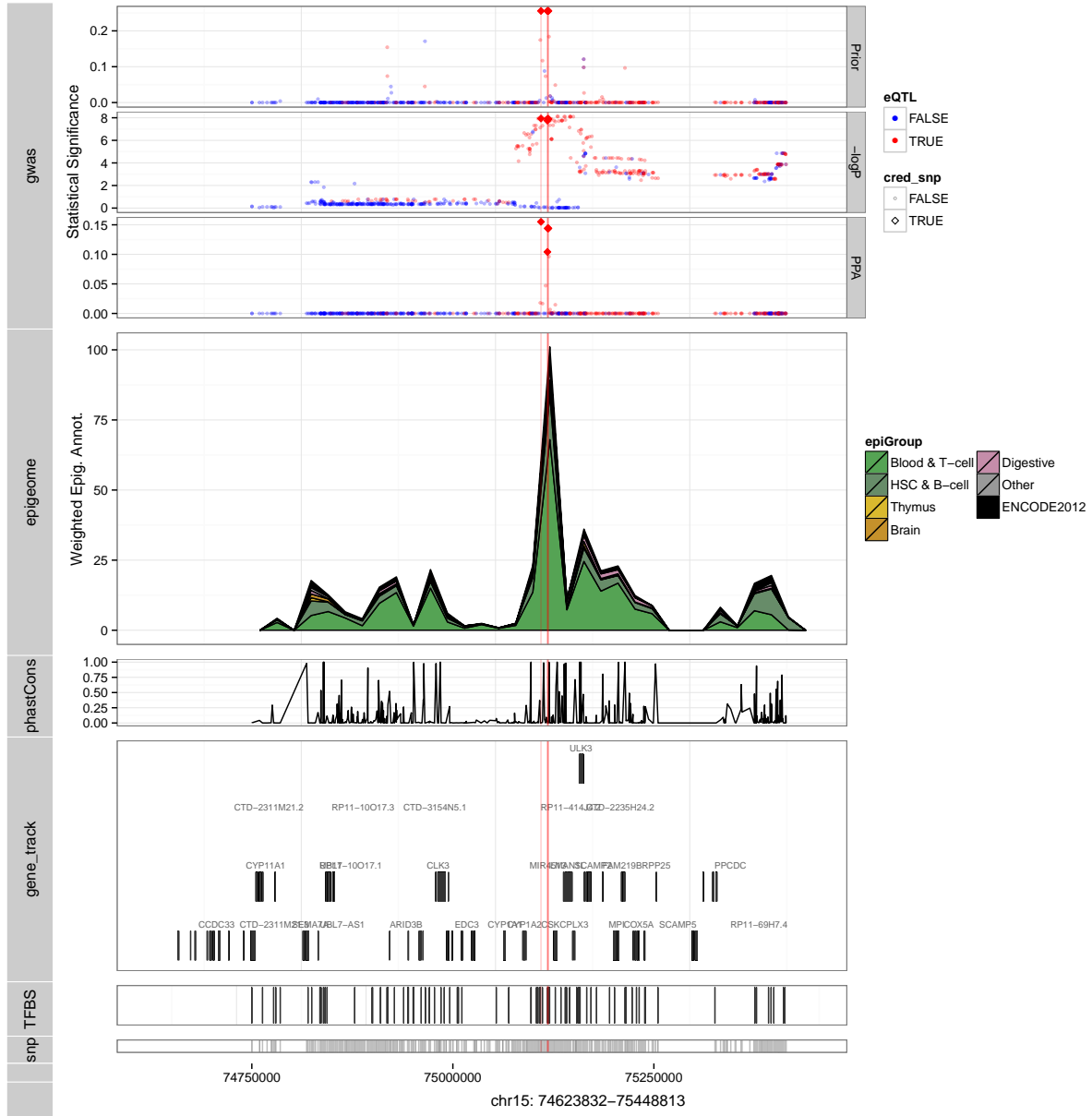
Celiac Disease



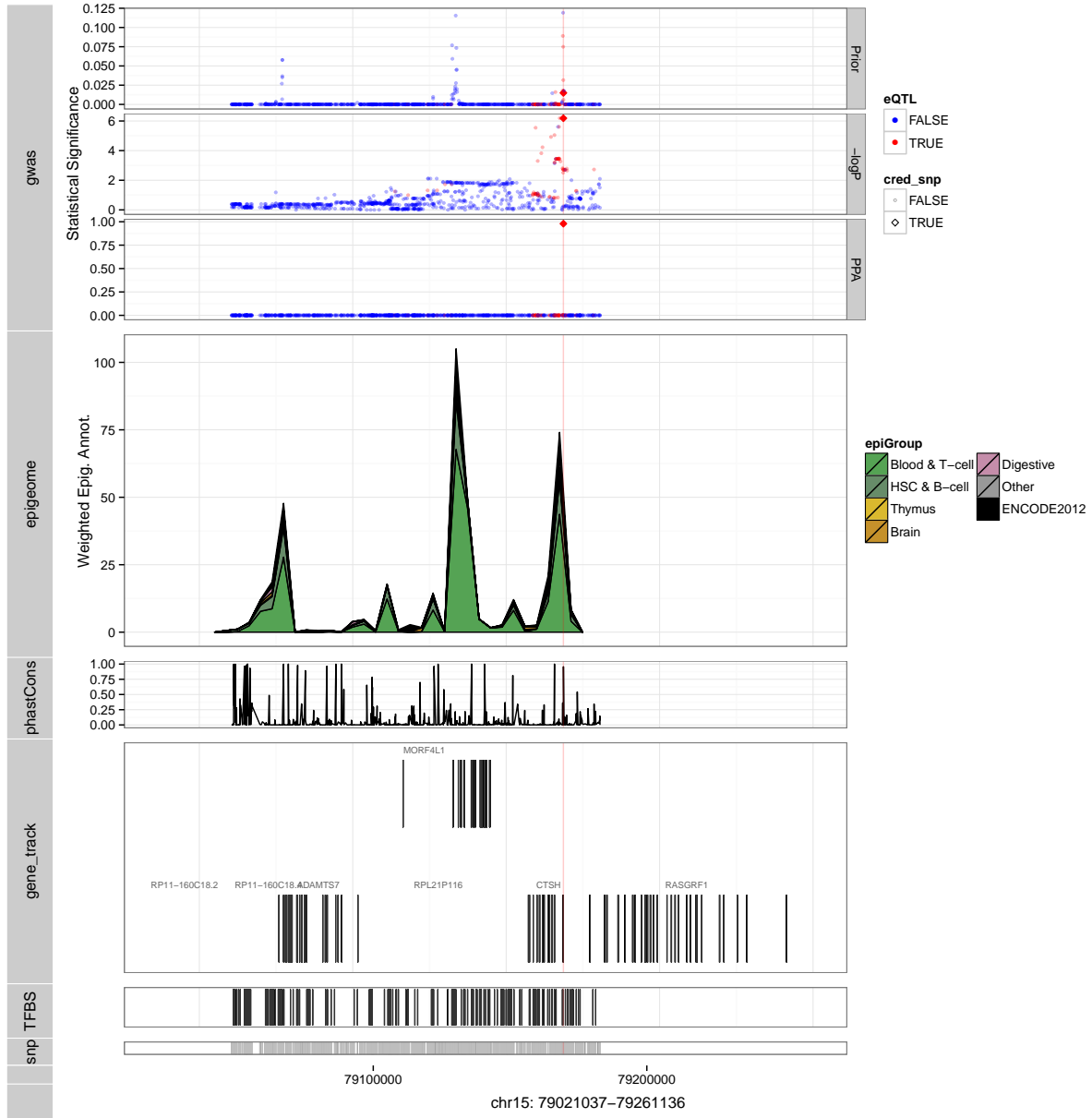
Celiac Disease



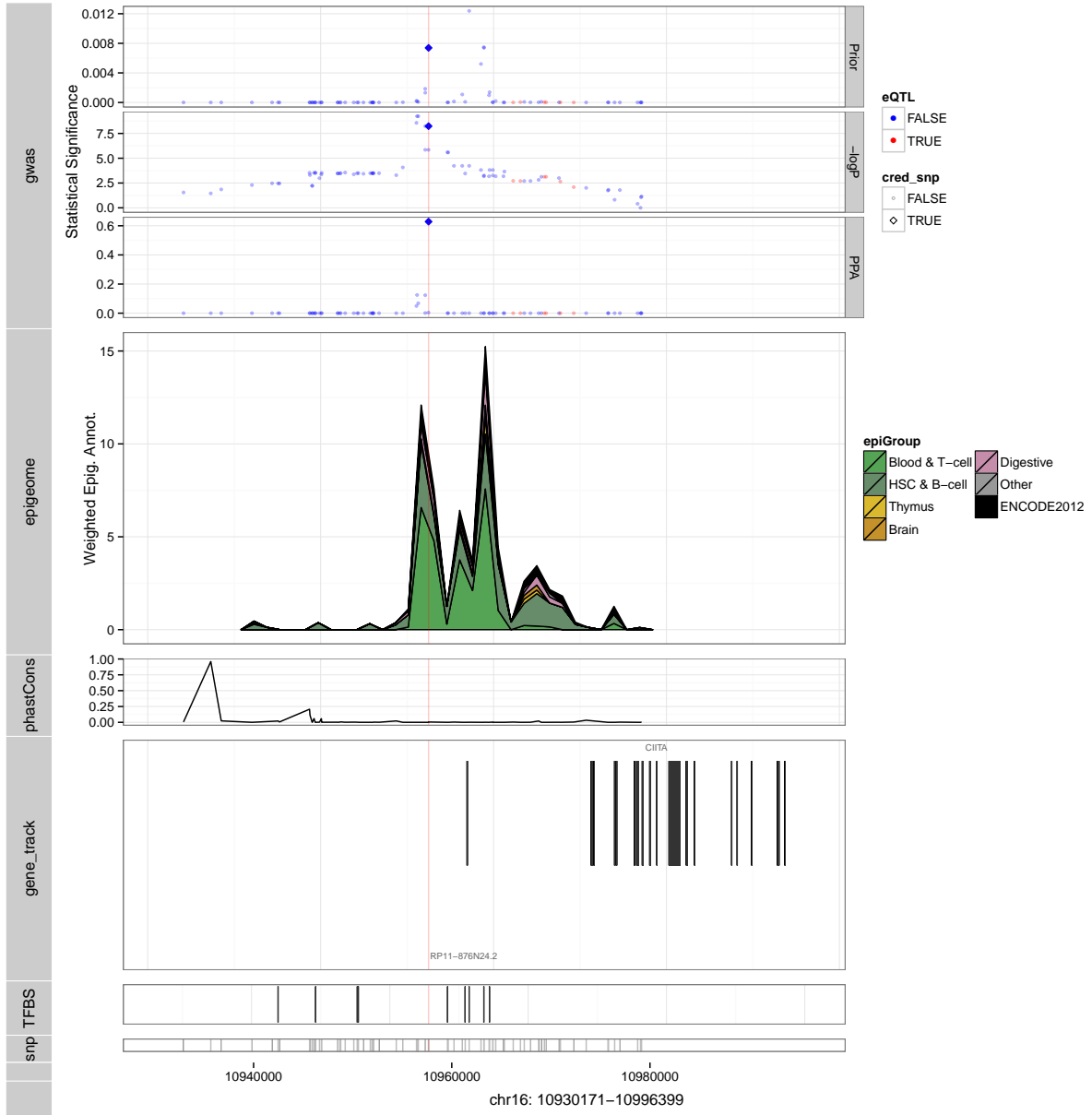
Celiac Disease



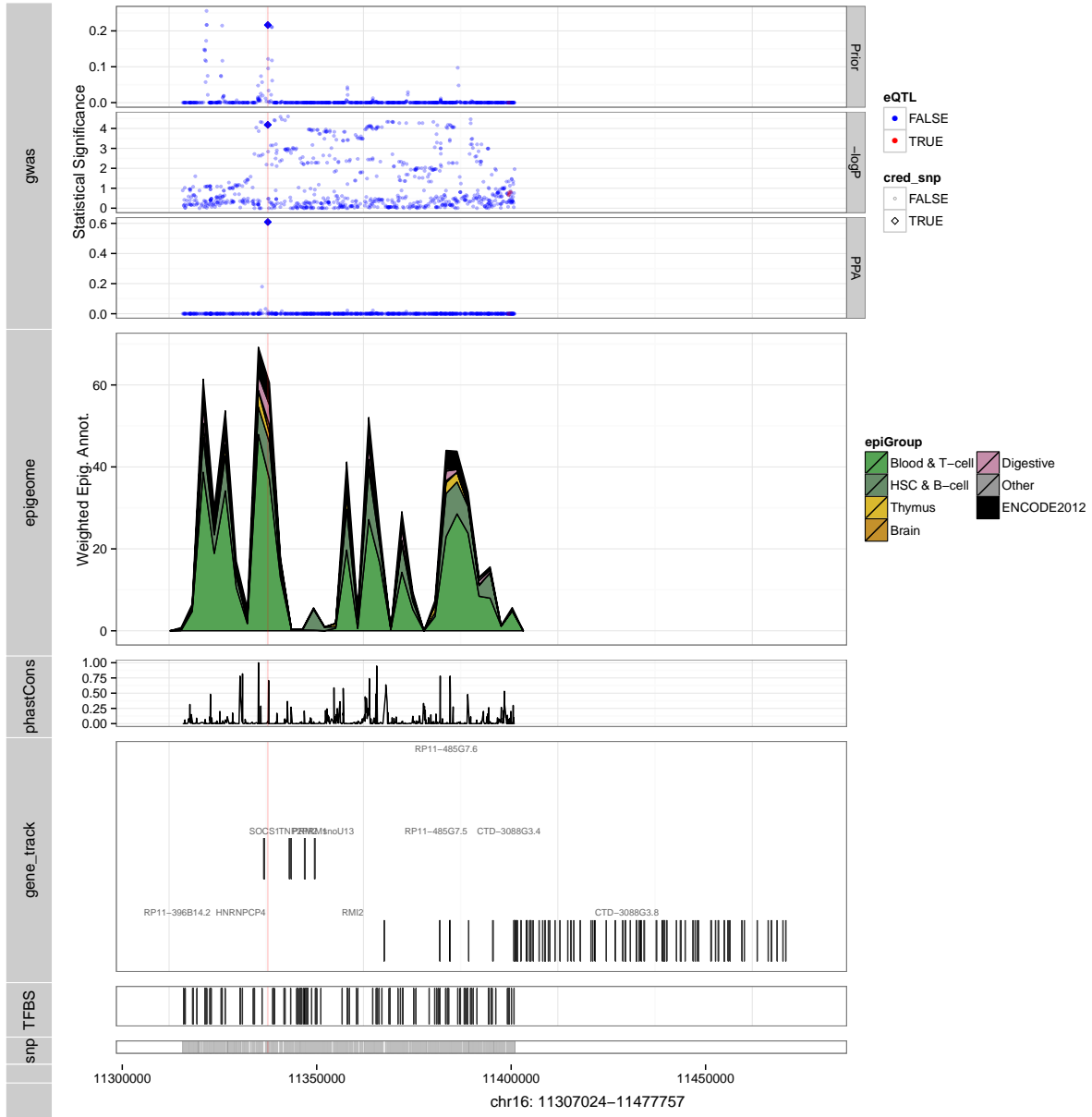
Celiac Disease



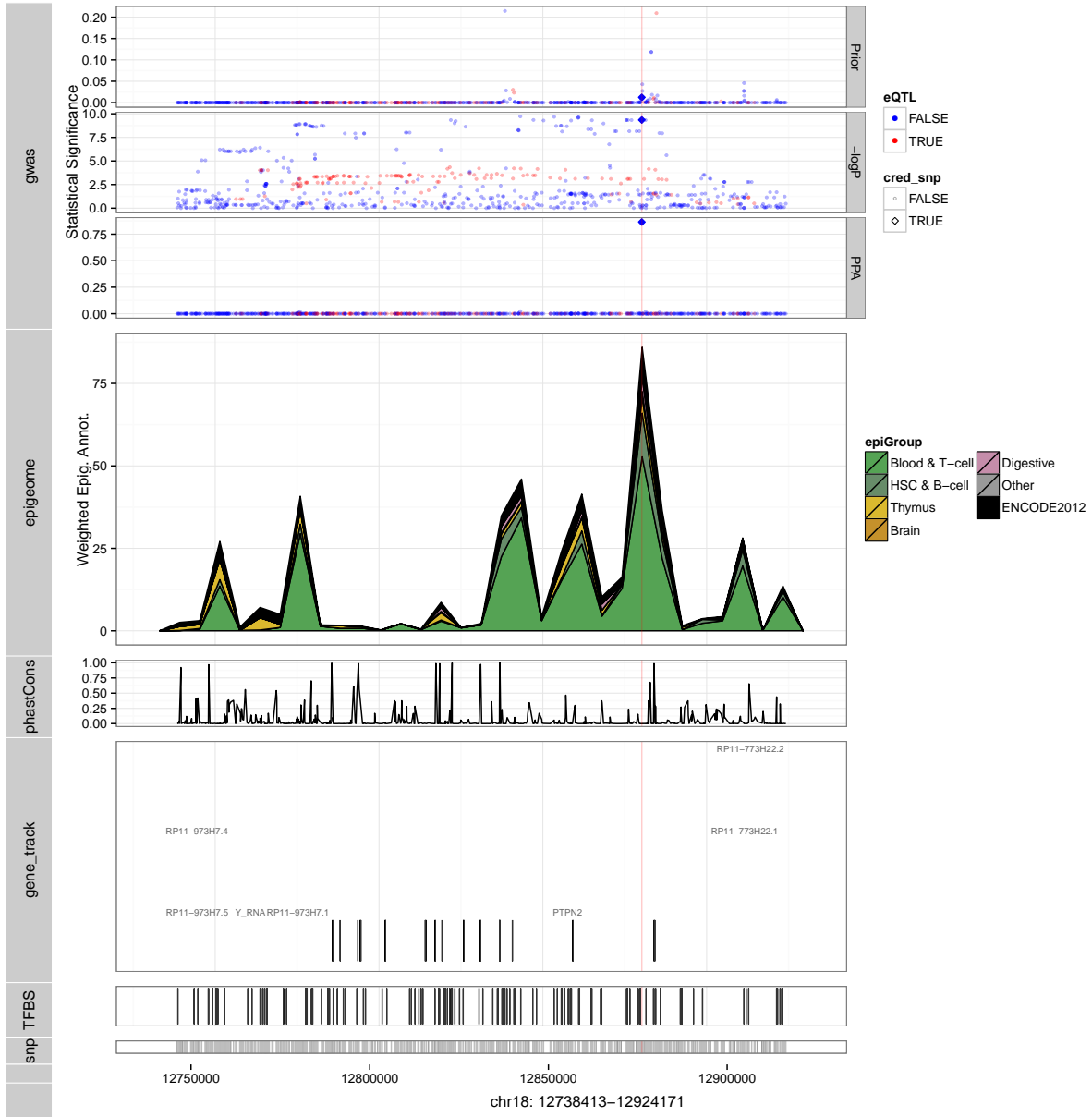
Celiac Disease



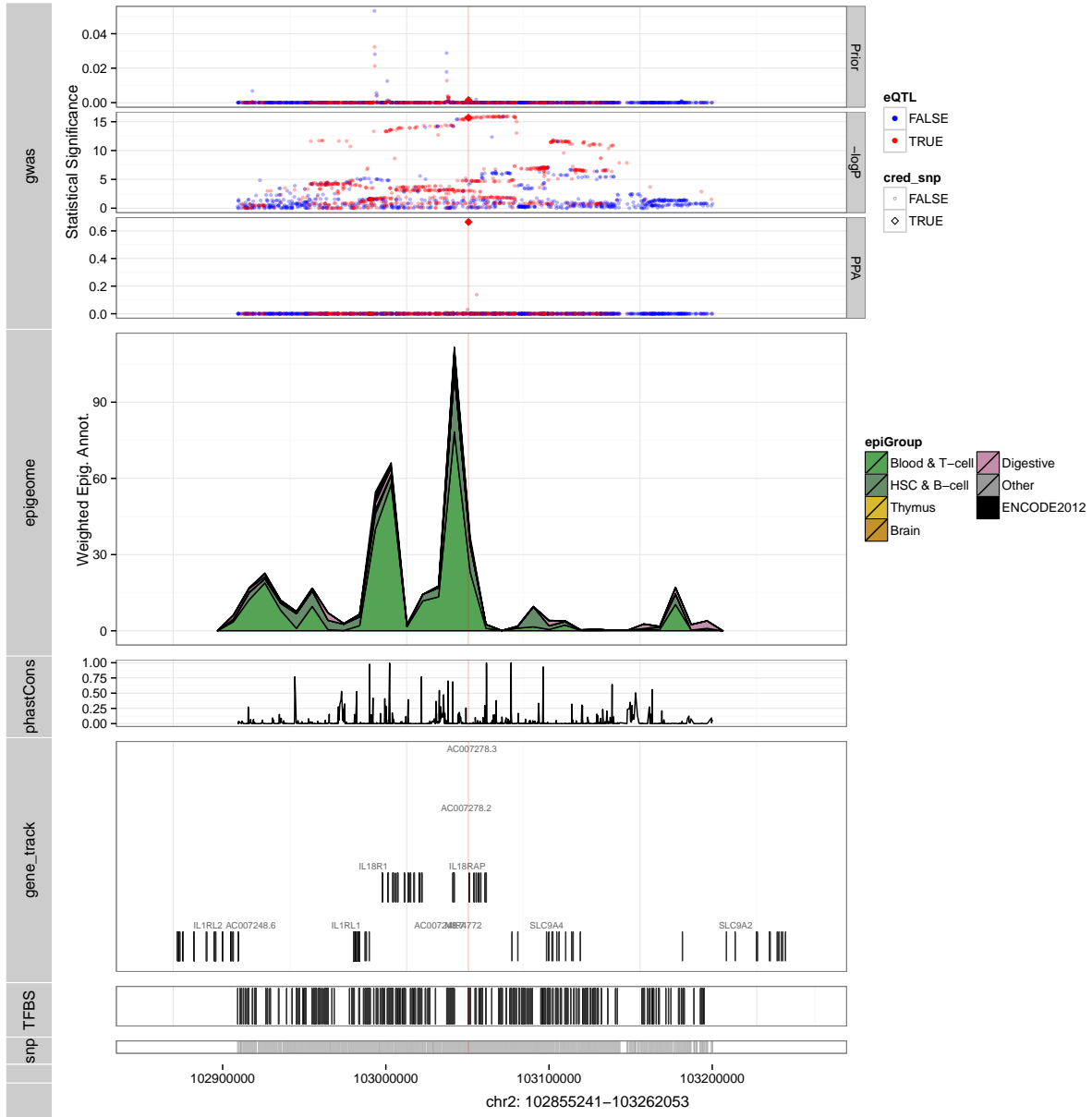
Celiac Disease



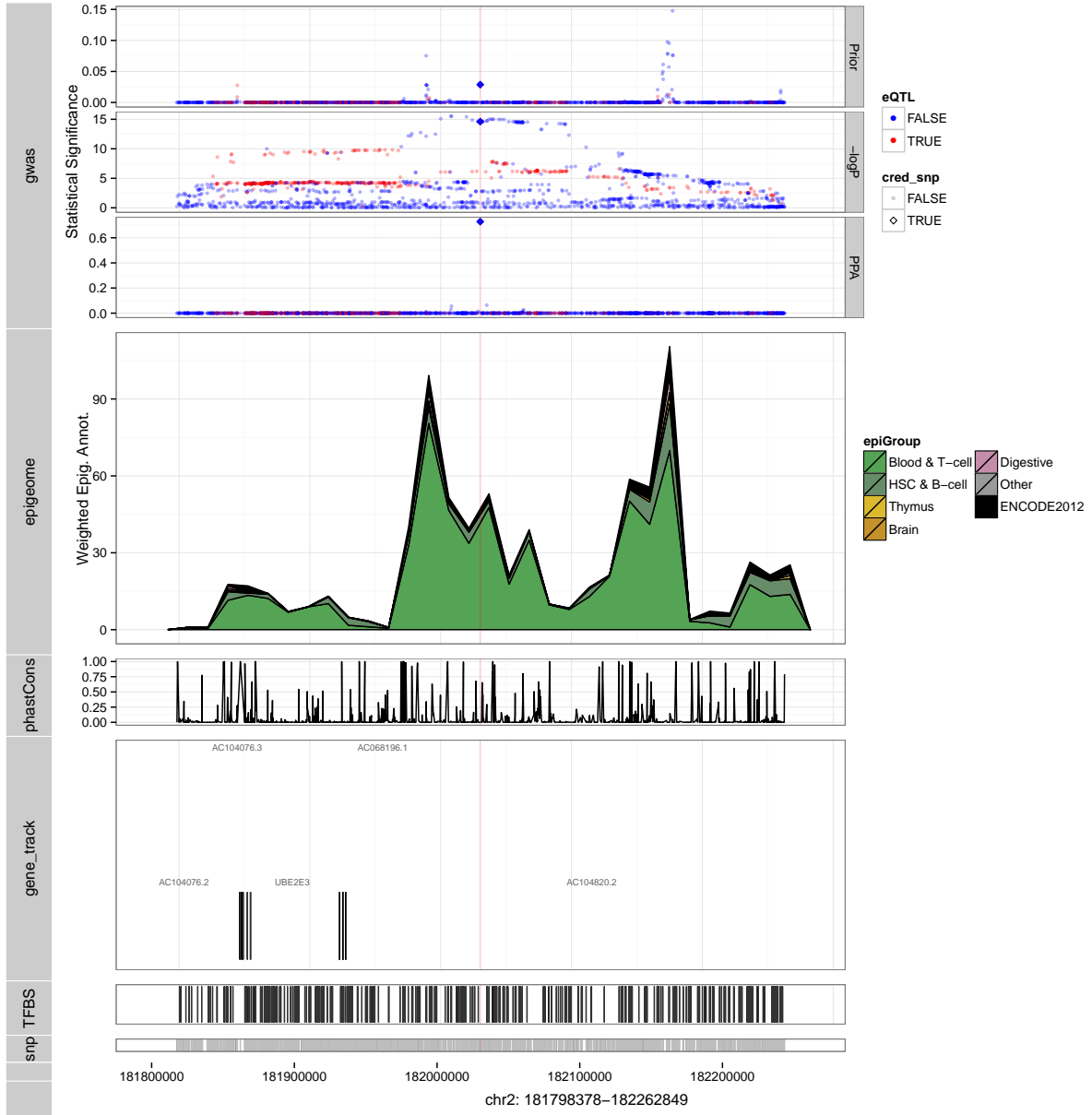
Celiac Disease



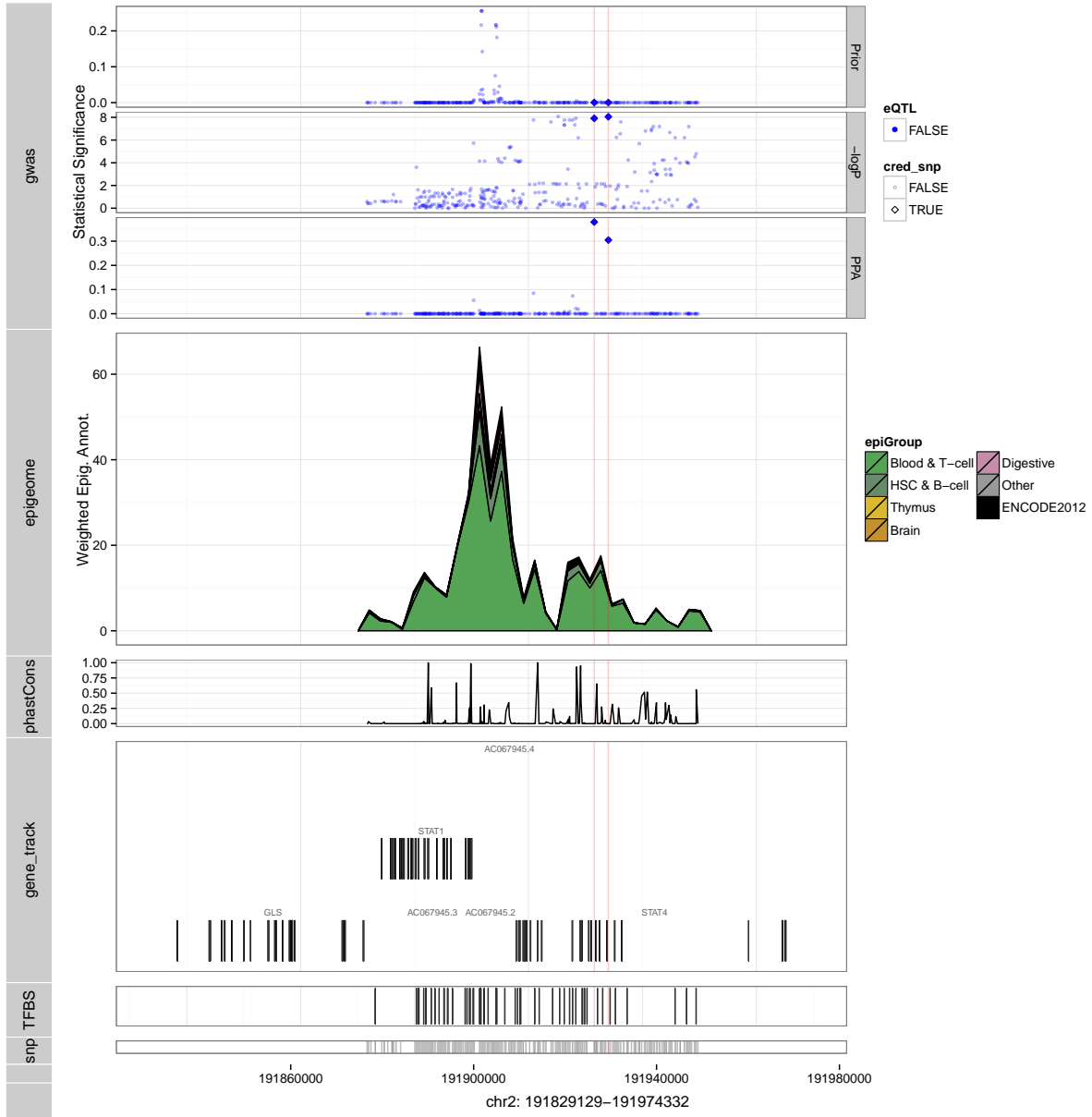
Celiac Disease



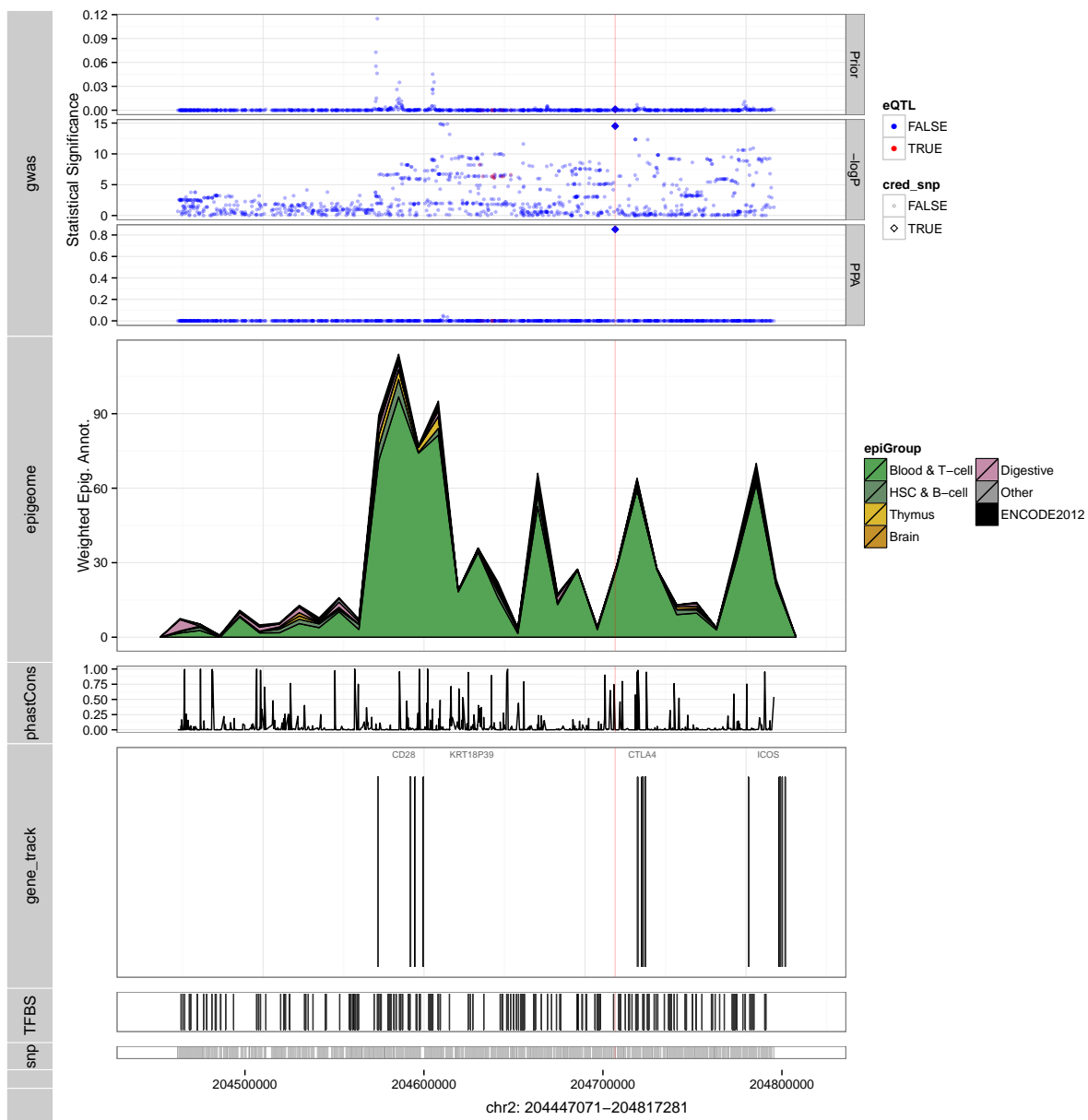
Celiac Disease



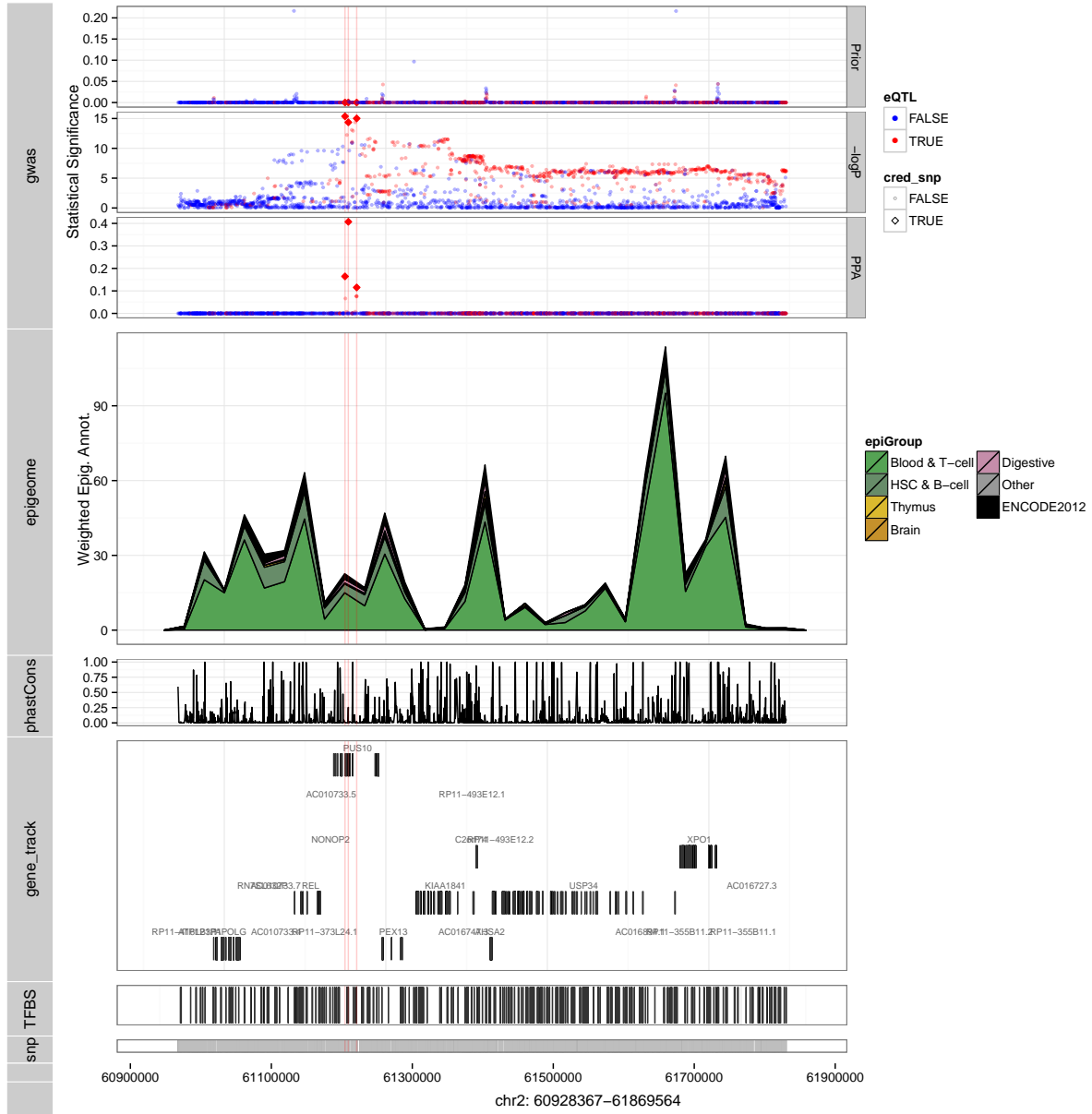
Celiac Disease



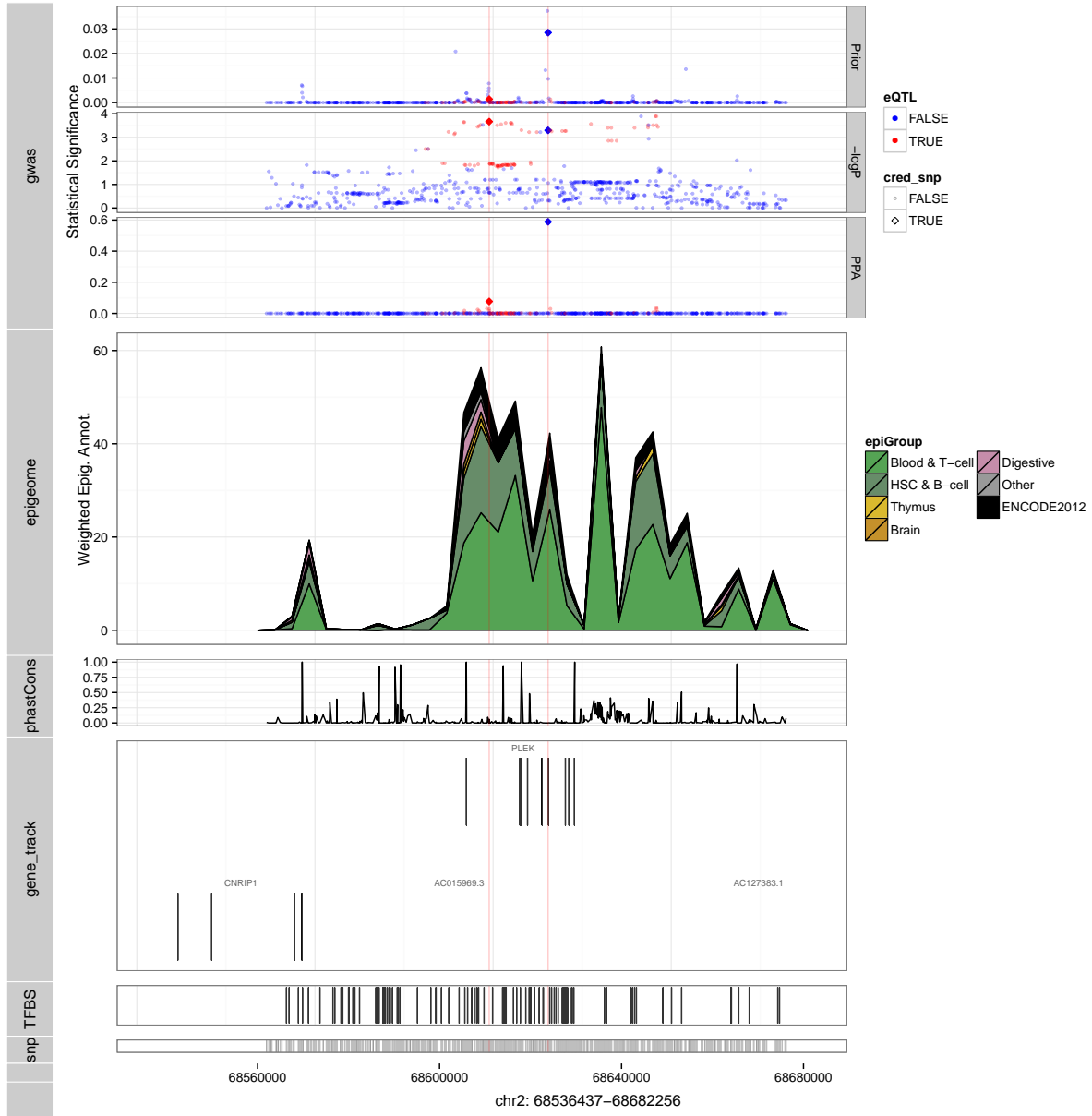
Celiac Disease



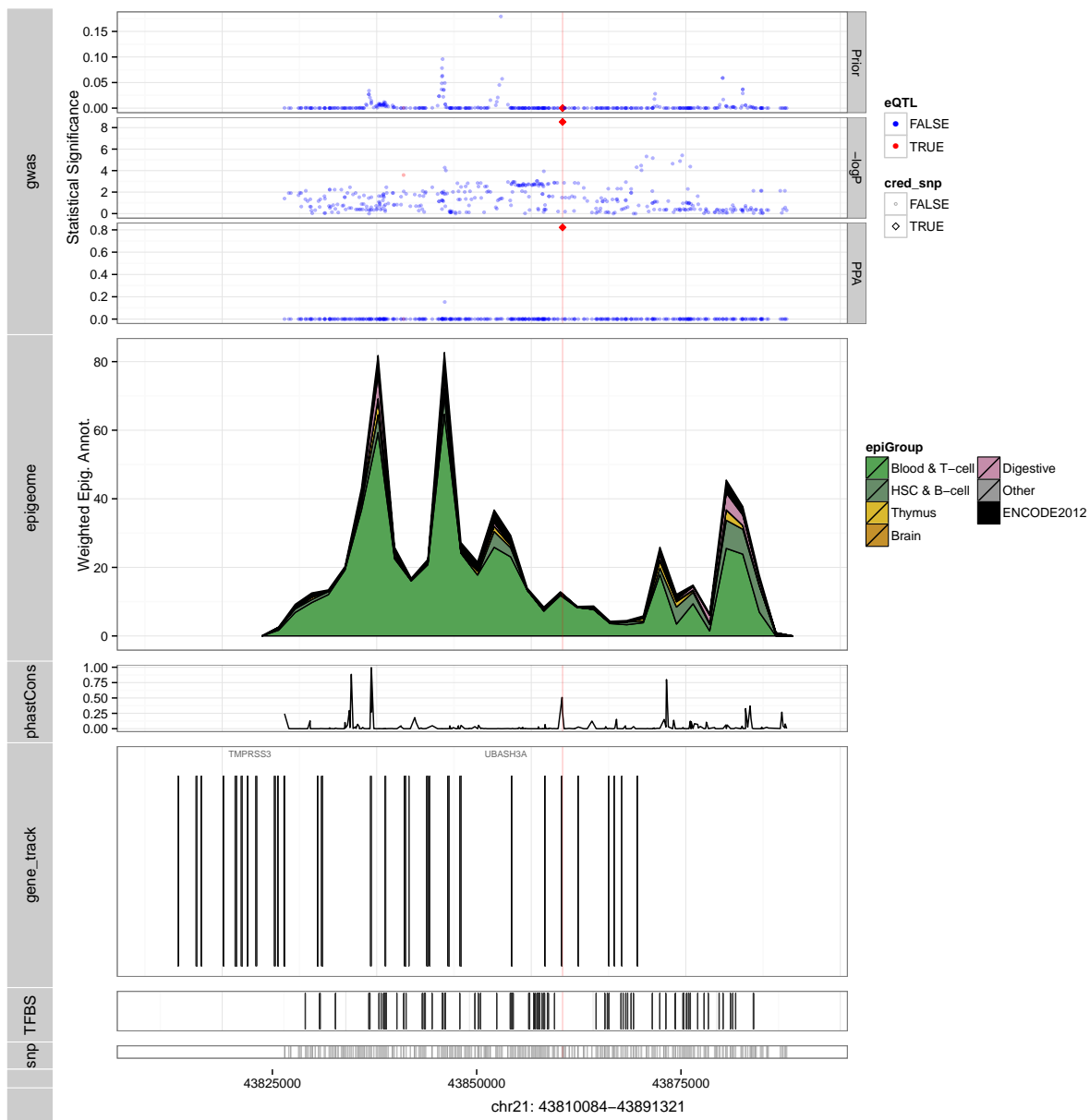
Celiac Disease



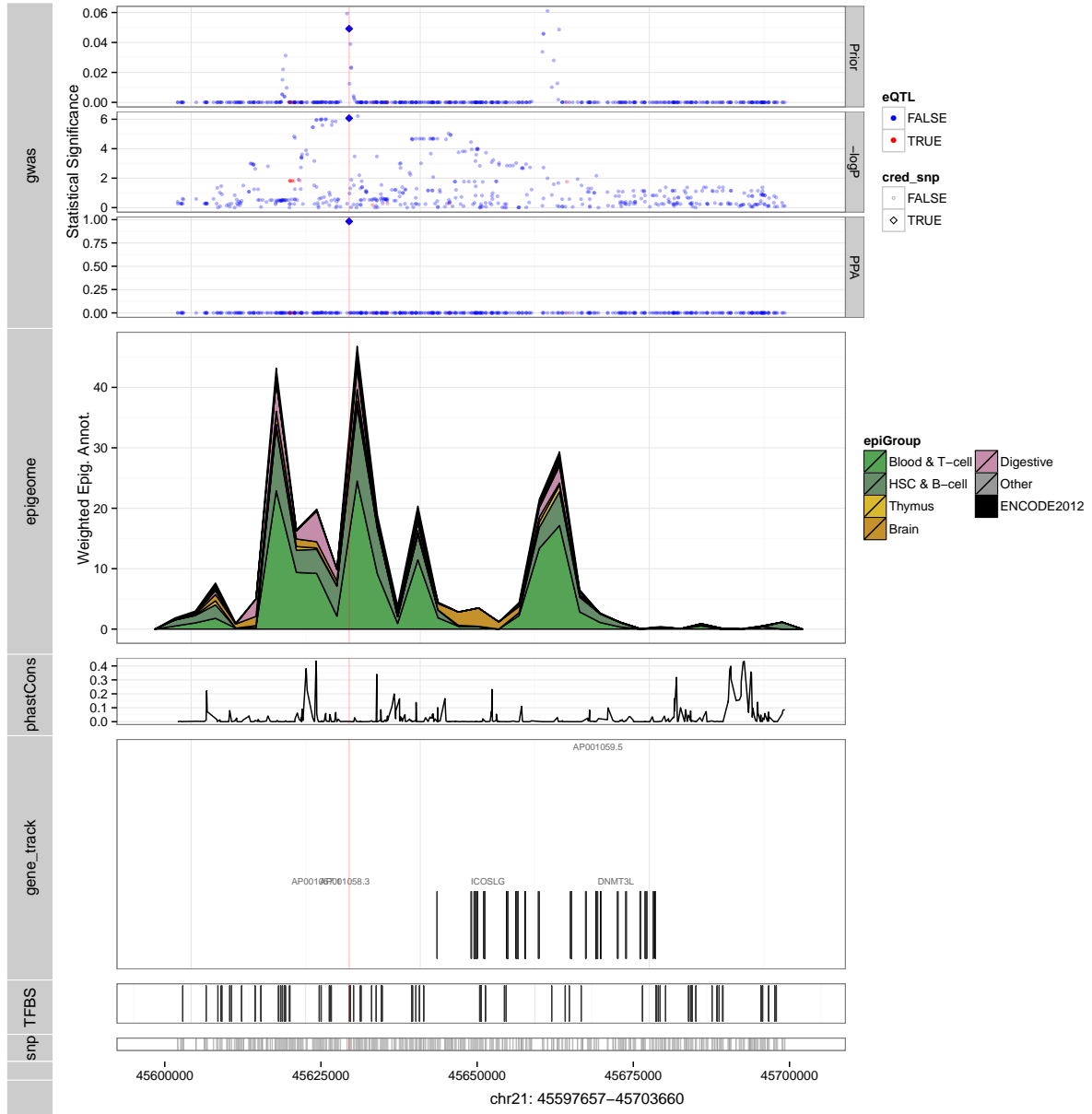
Celiac Disease



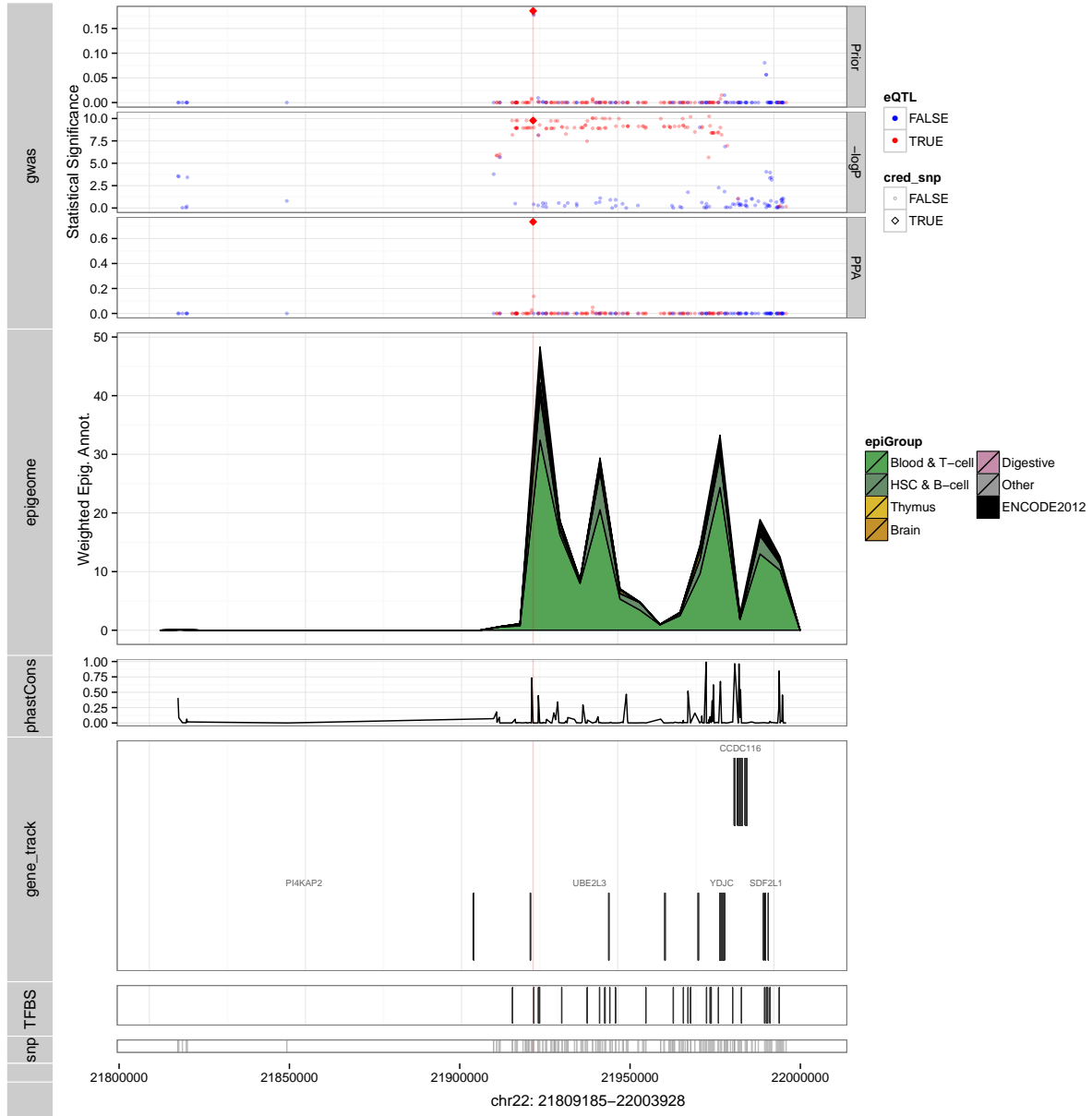
Celiac Disease



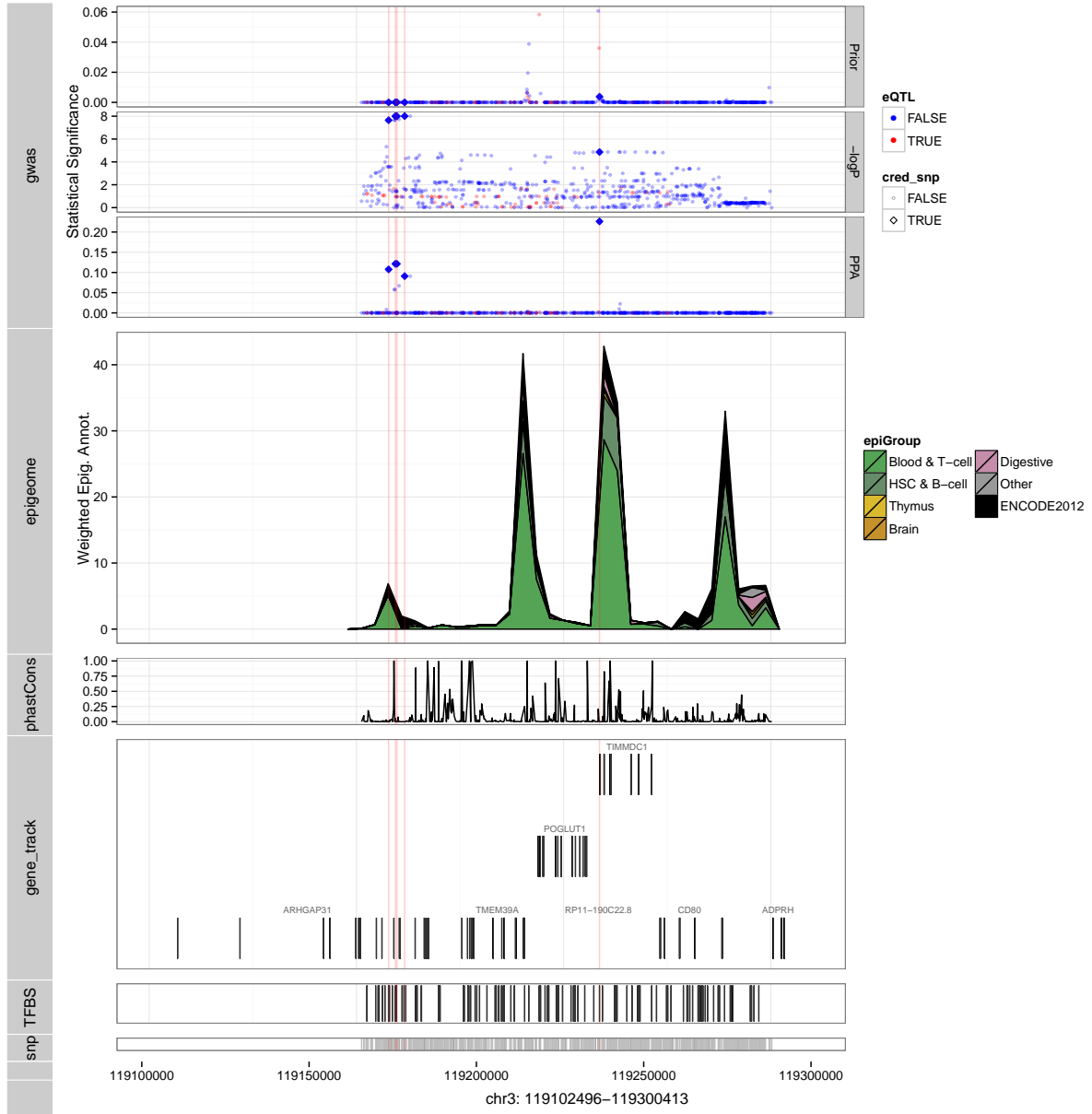
Celiac Disease



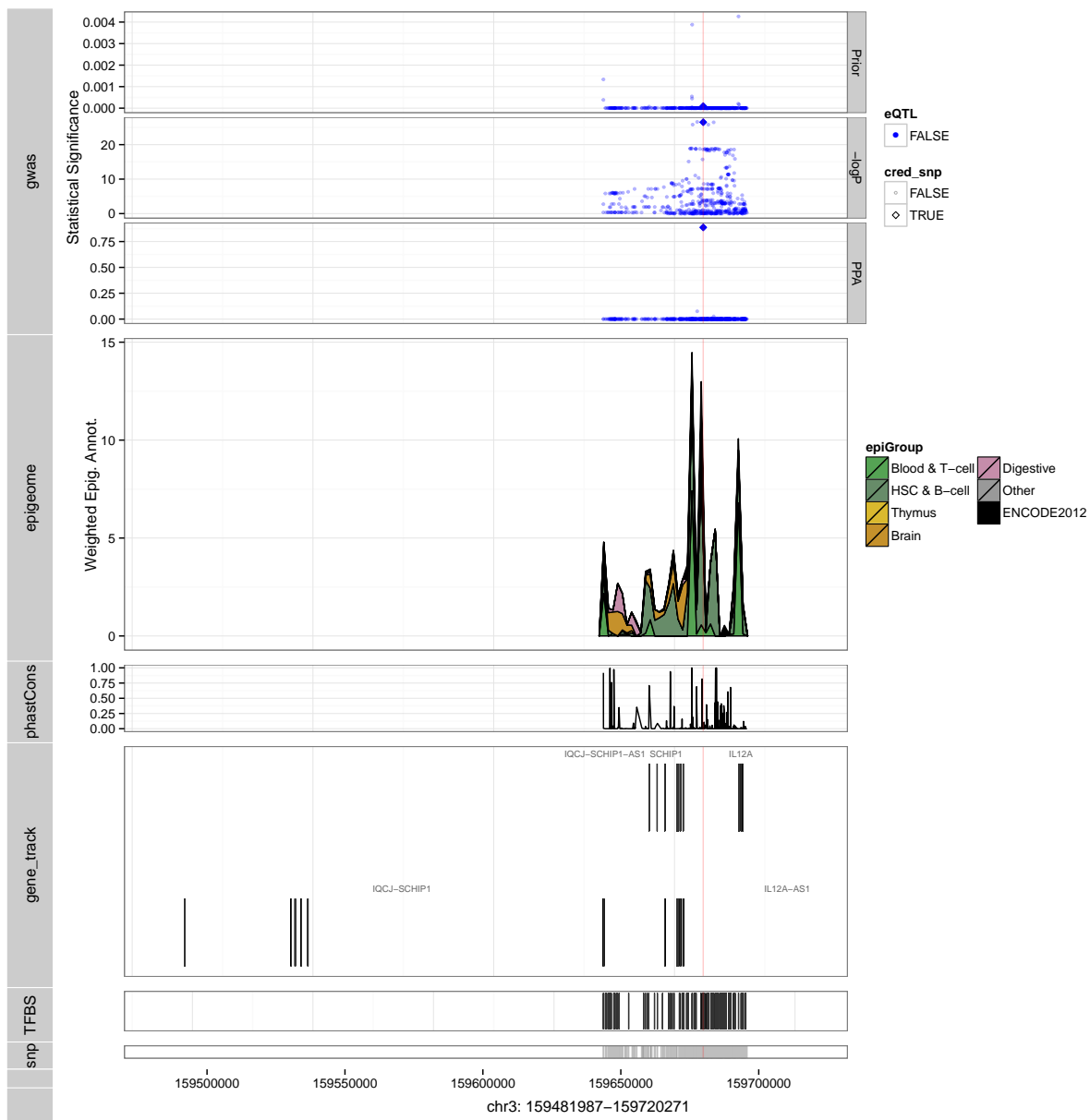
Celiac Disease



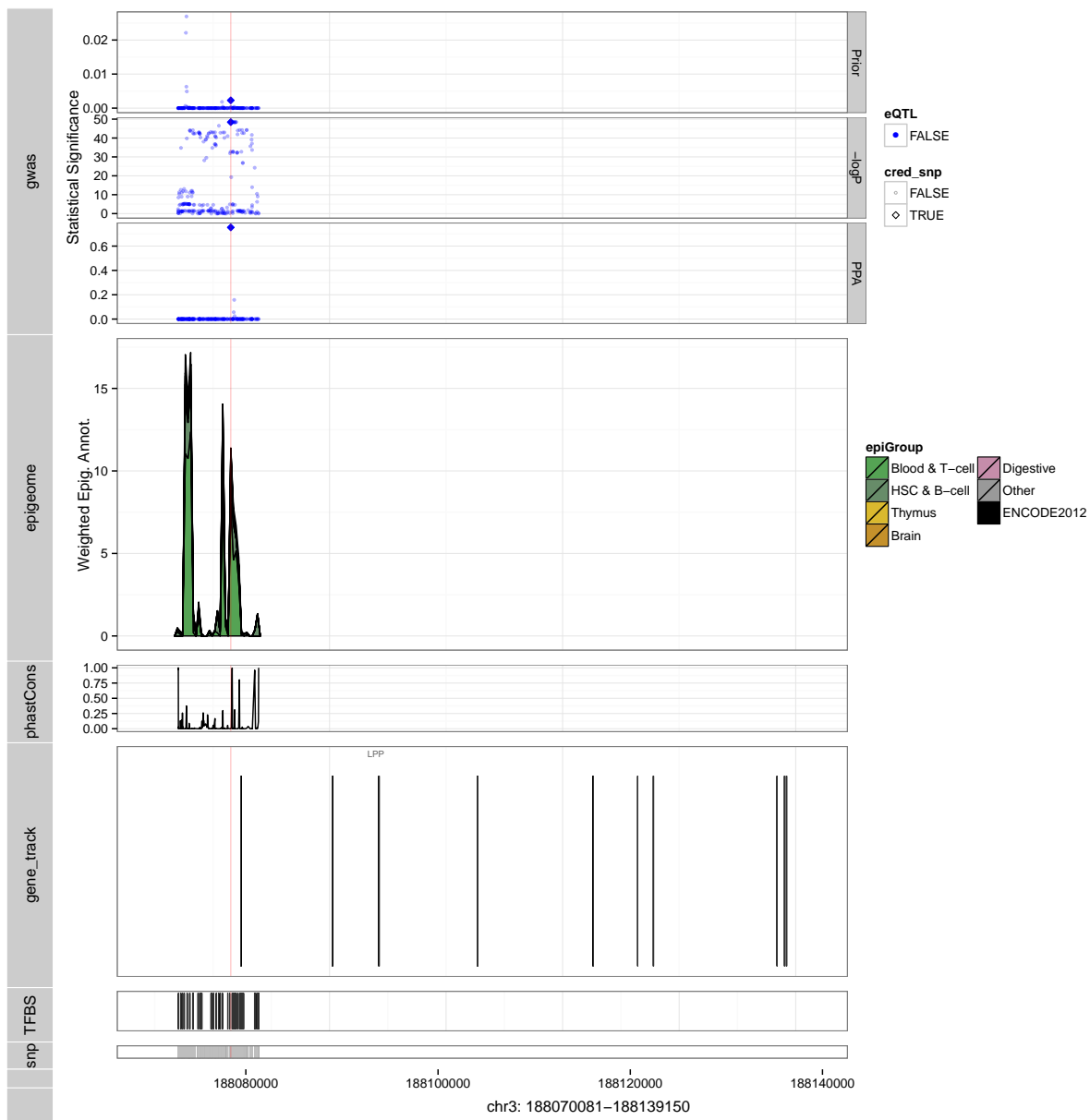
Celiac Disease



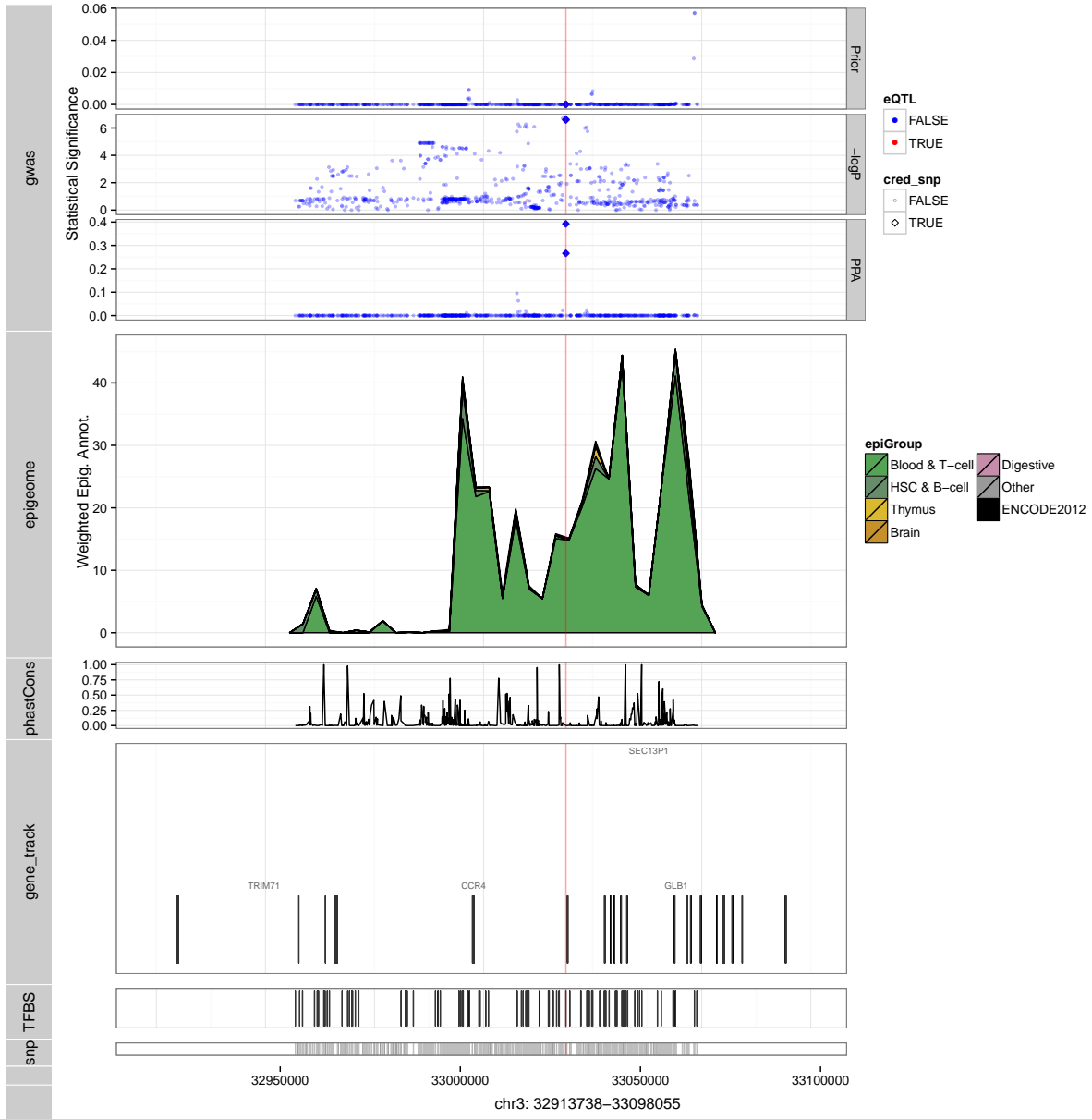
Celiac Disease



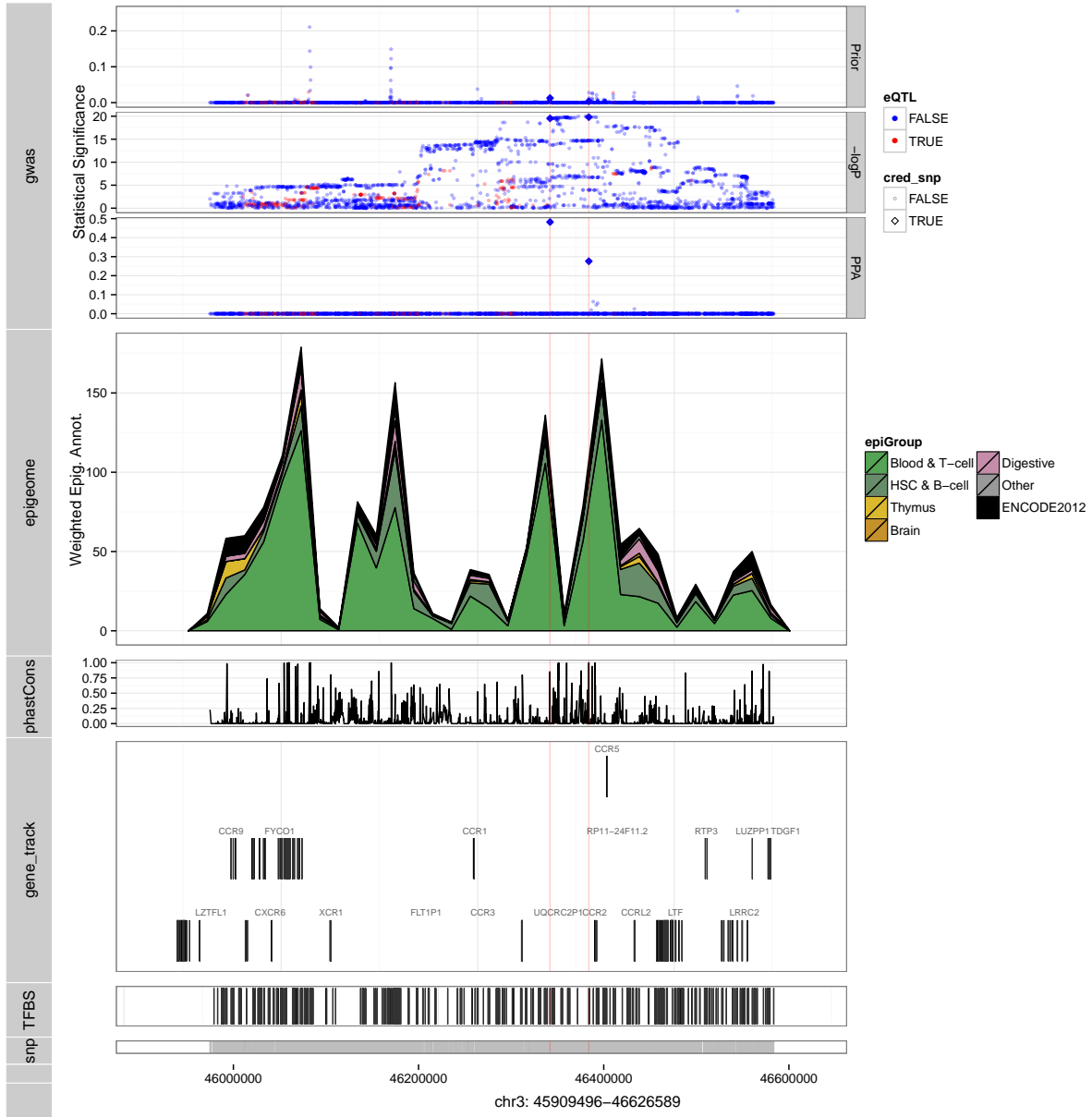
Celiac Disease



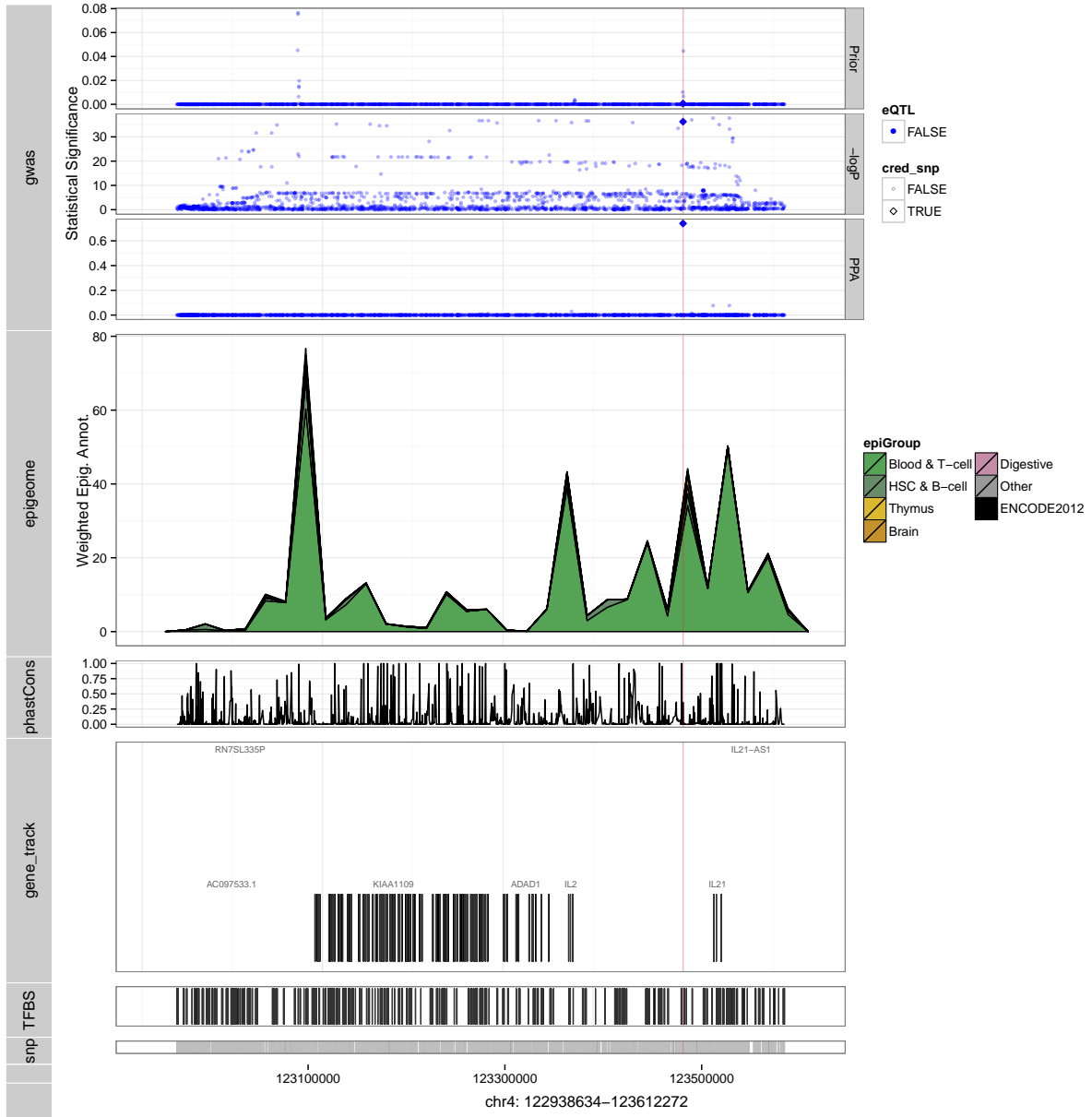
Celiac Disease



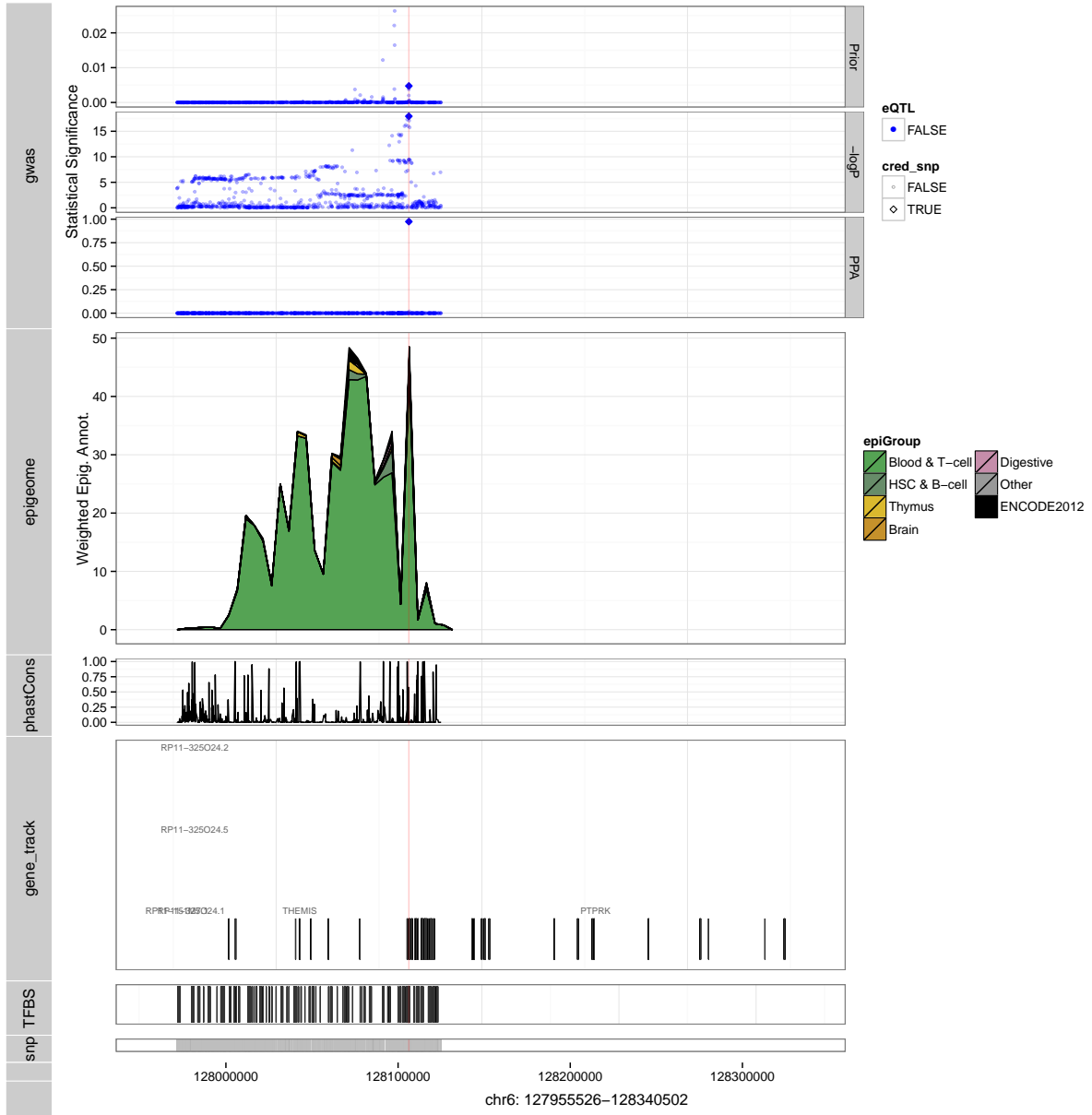
Celiac Disease



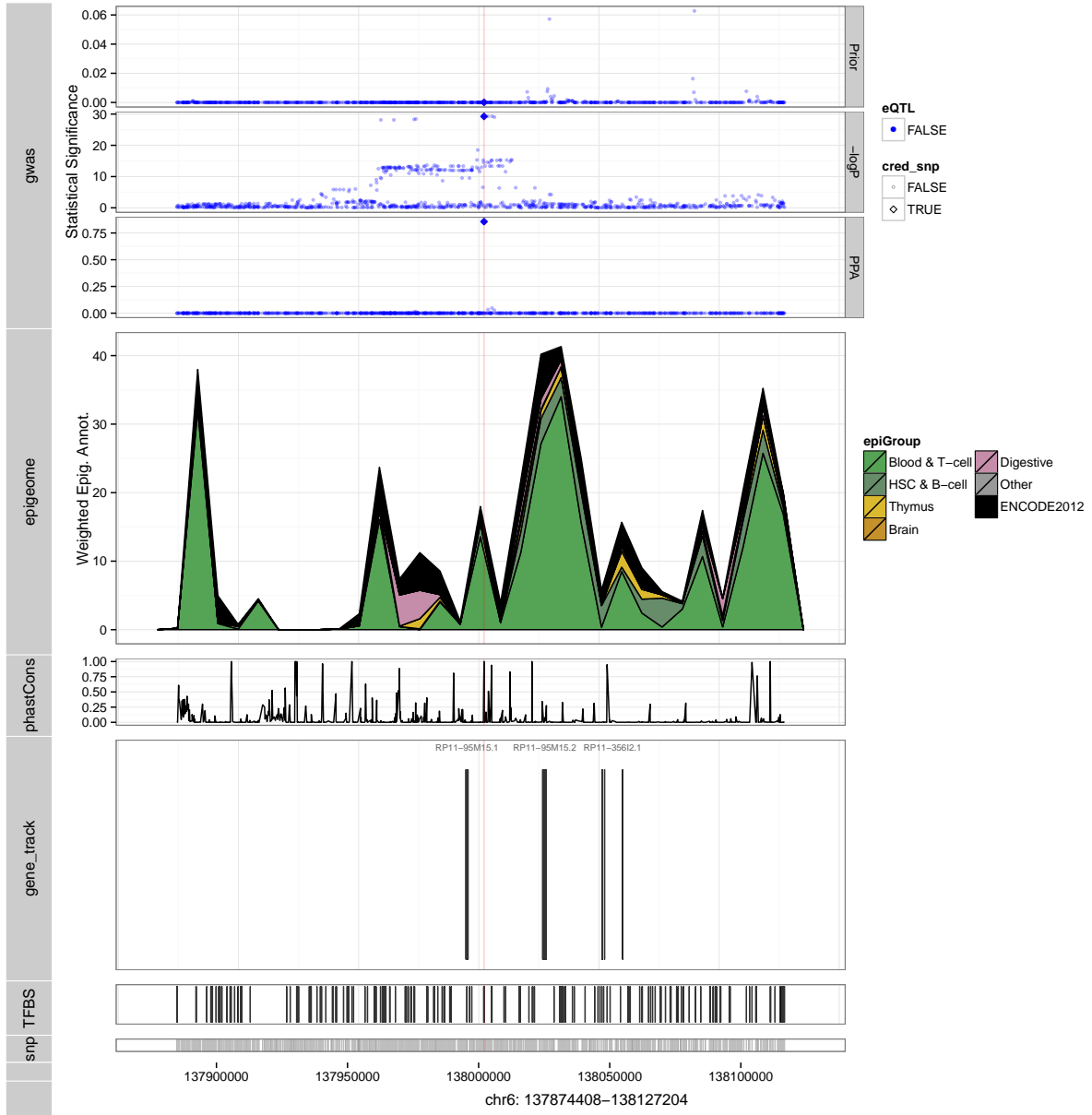
Celiac Disease



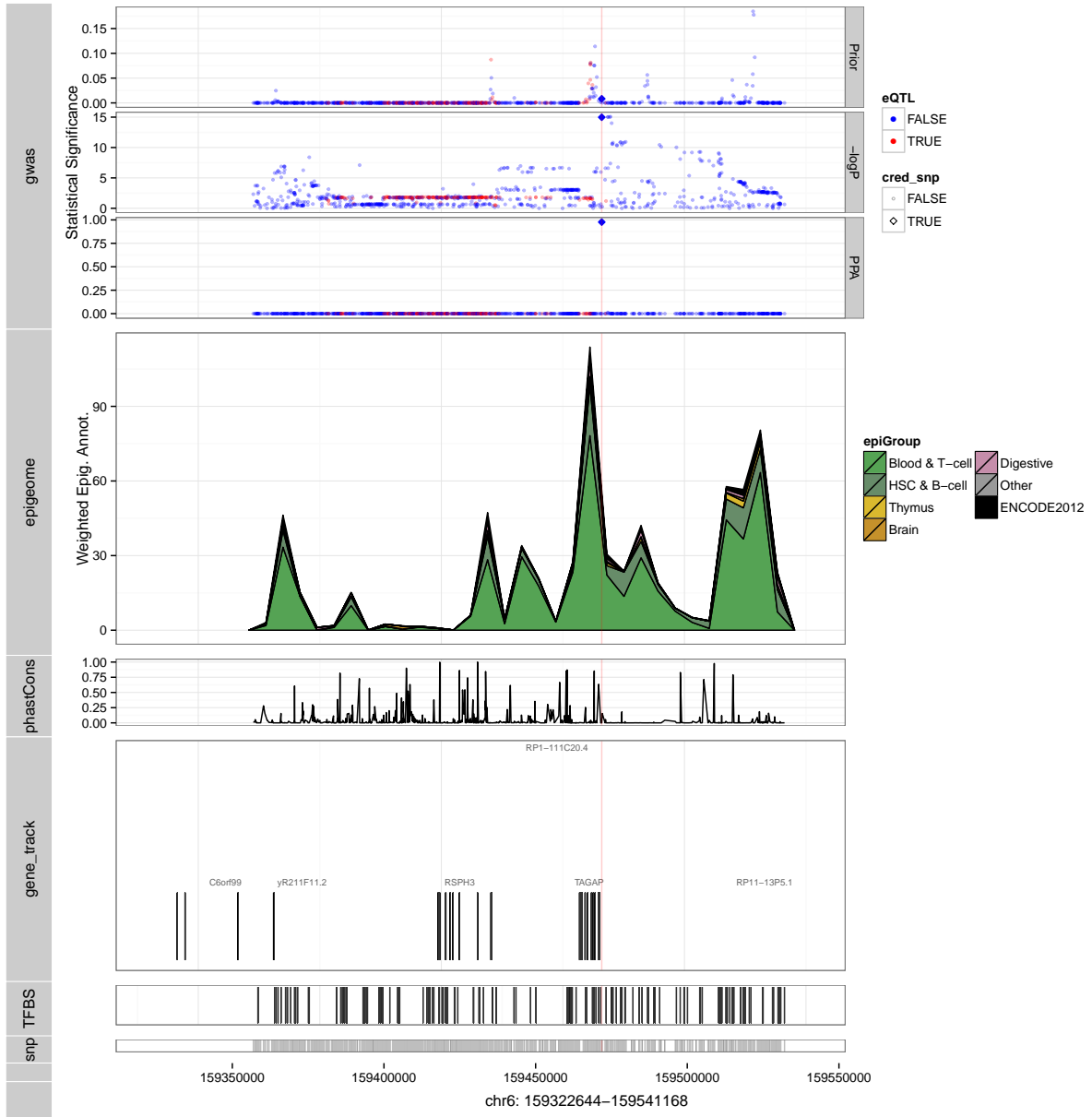
Celiac Disease



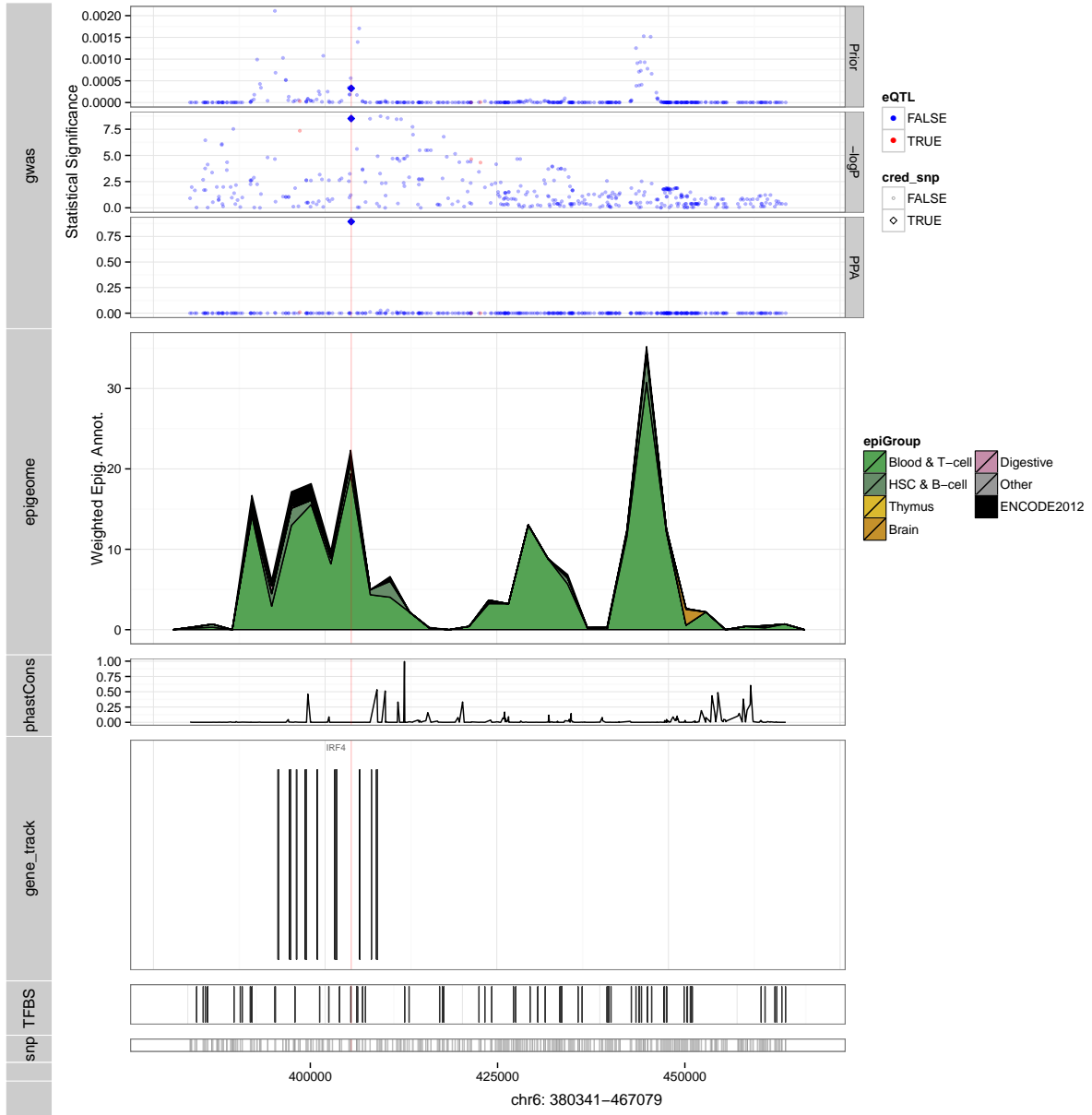
Celiac Disease



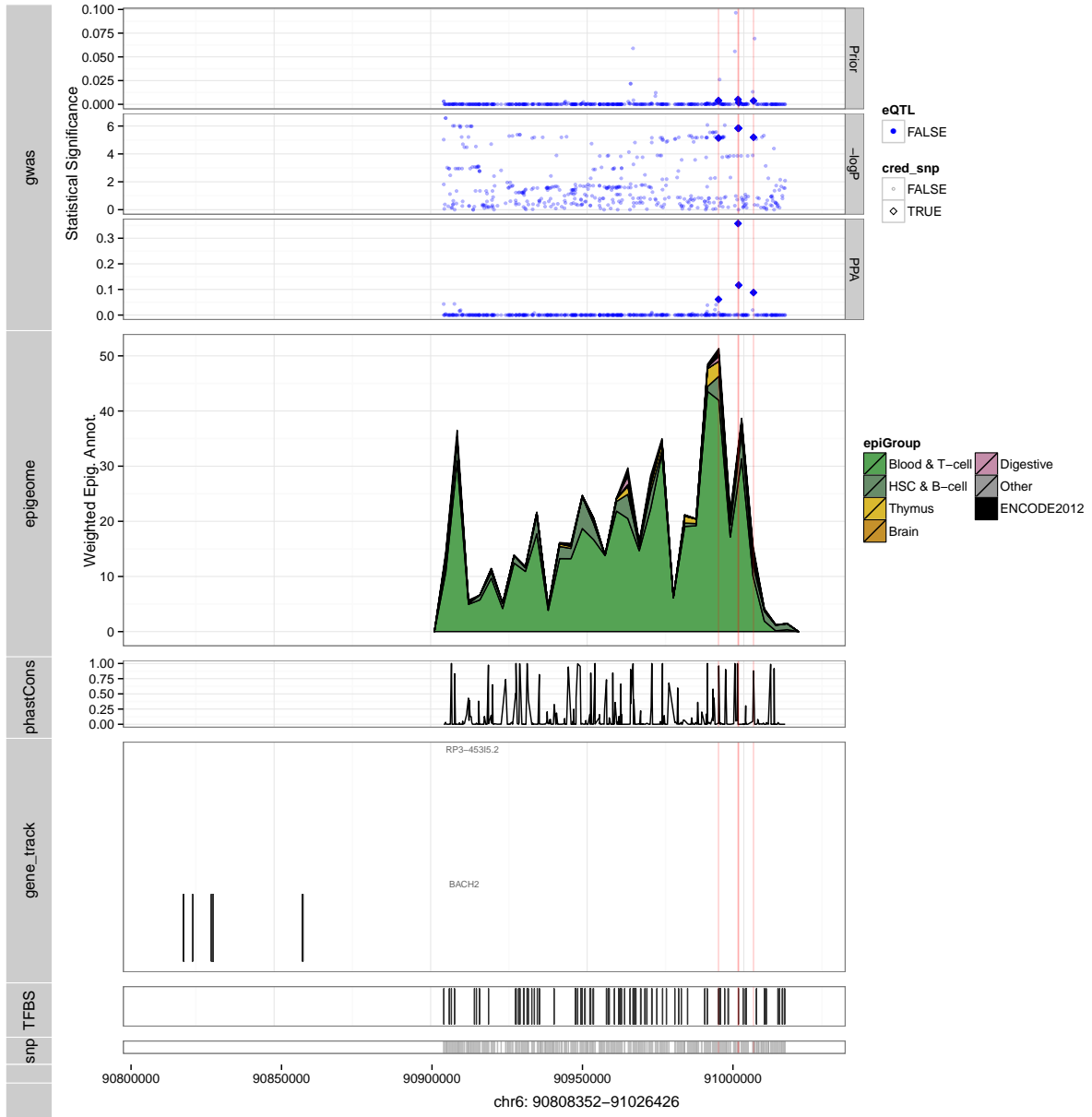
Celiac Disease



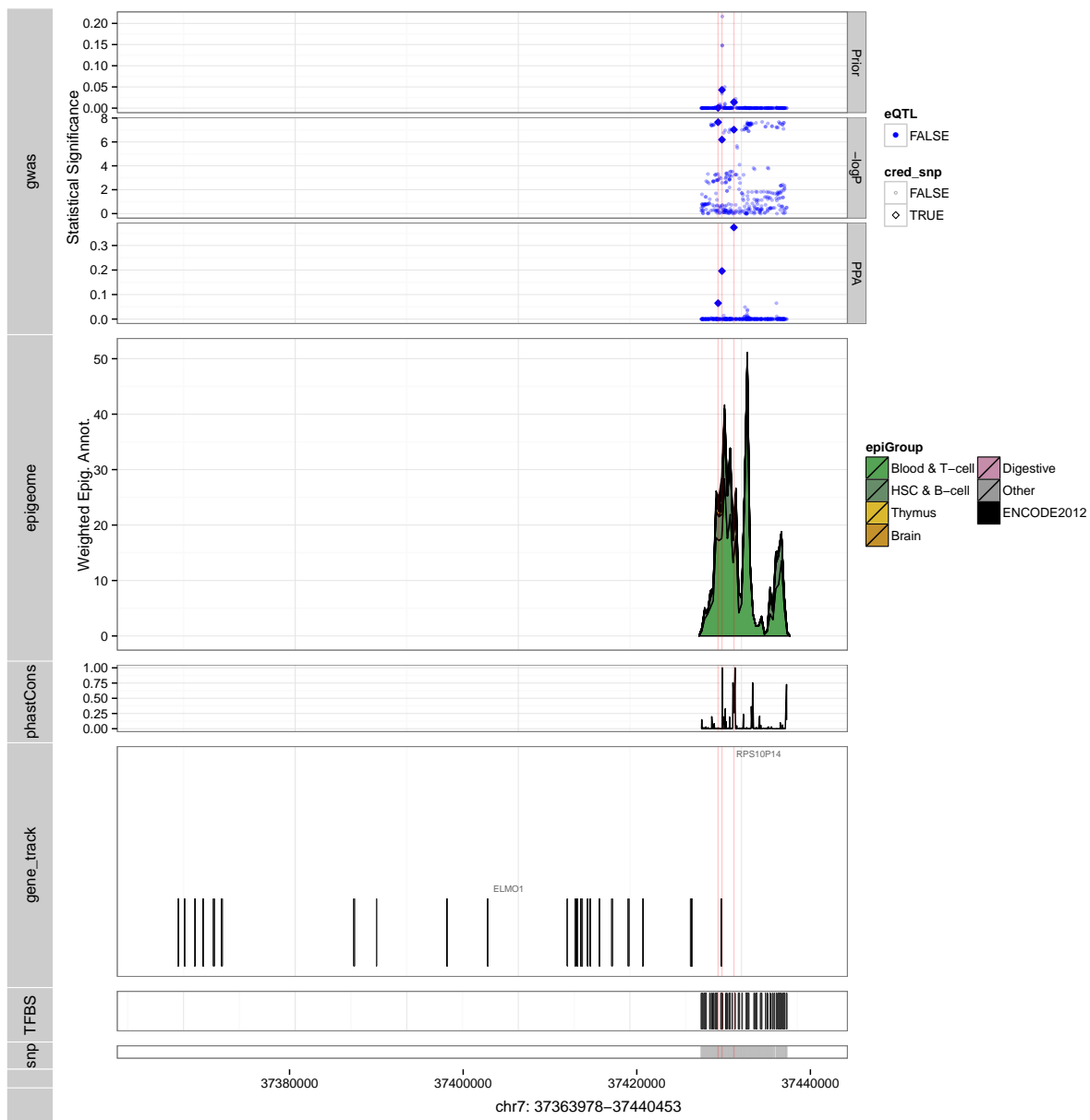
Celiac Disease



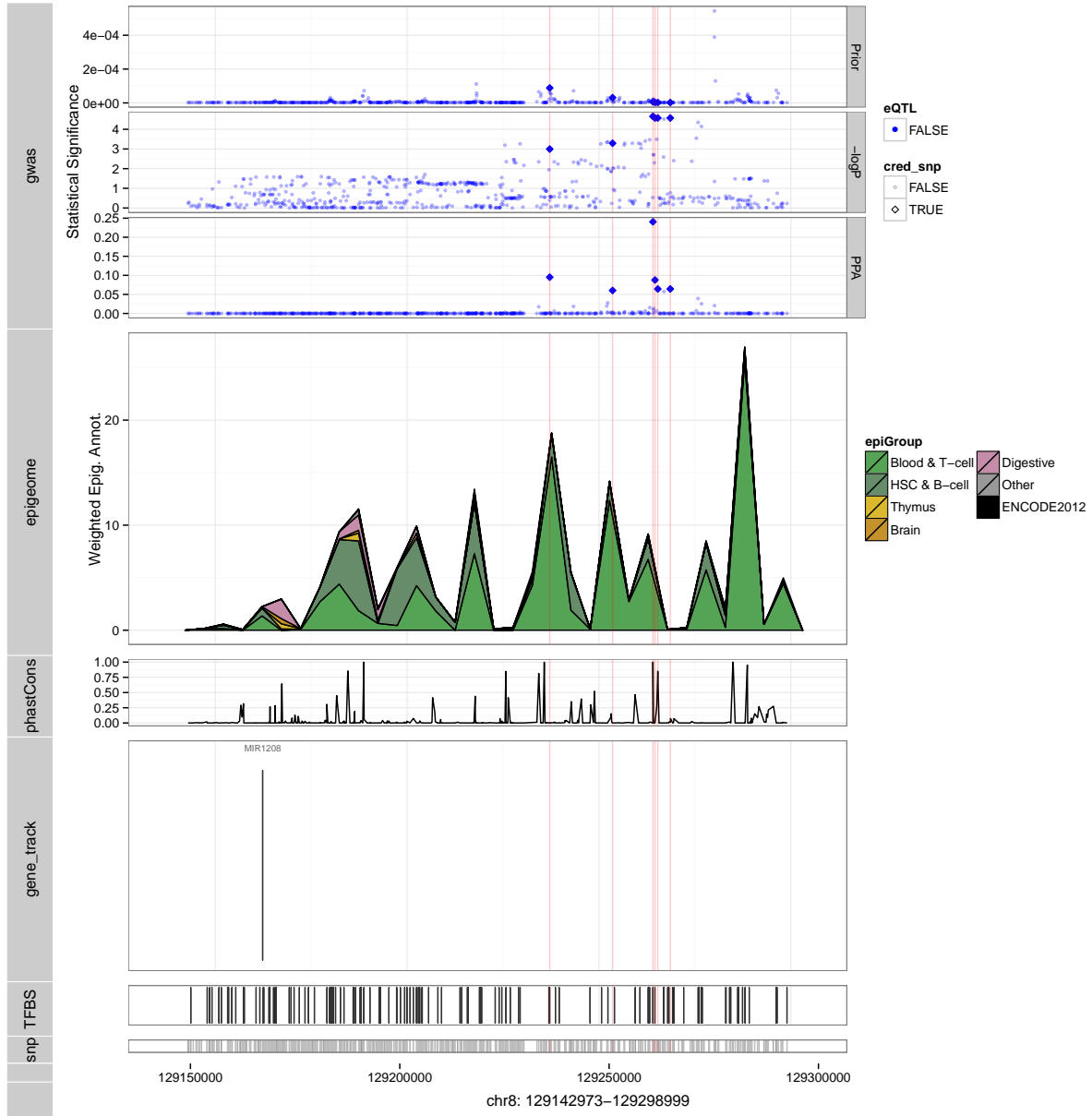
Celiac Disease



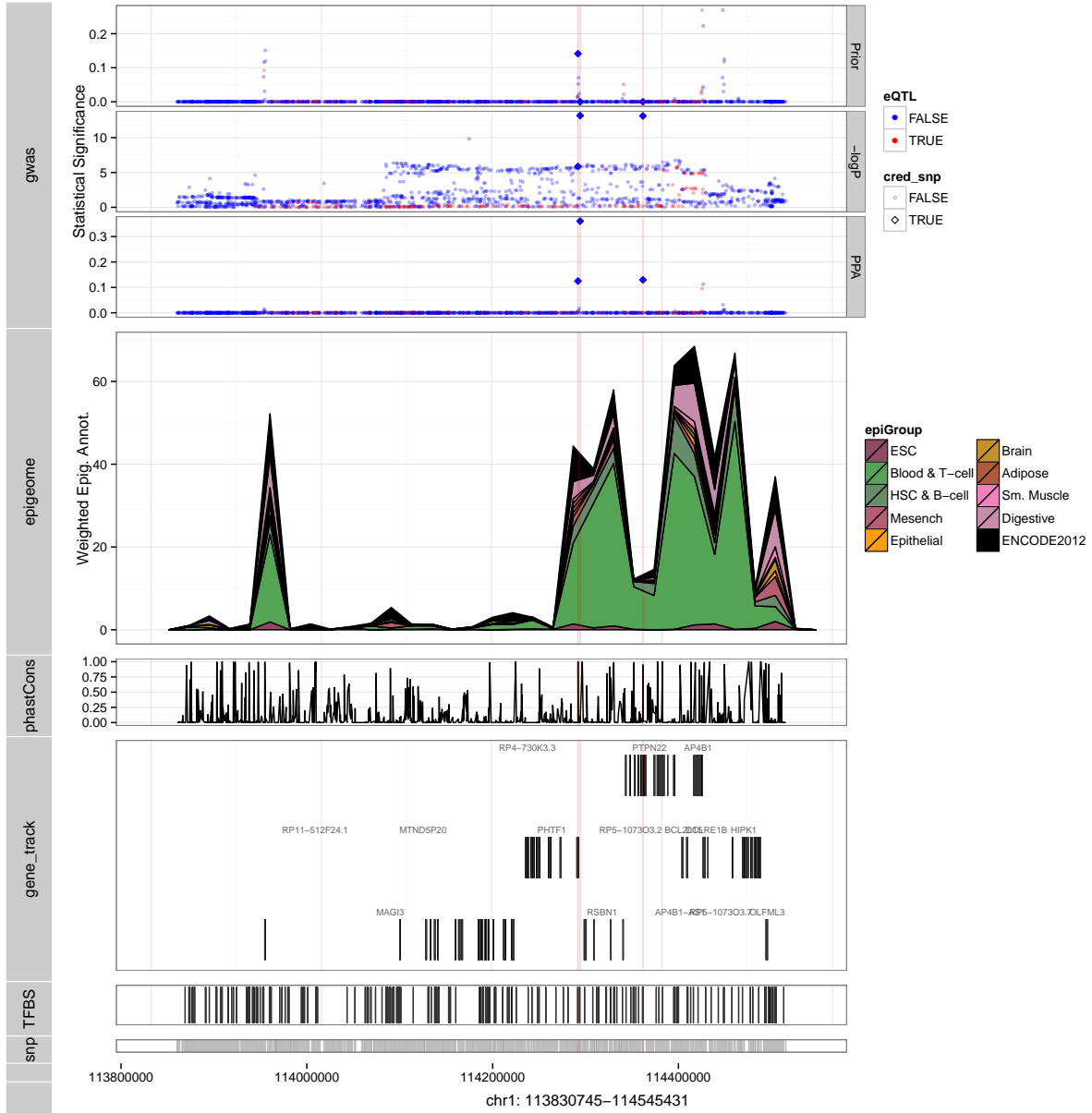
Celiac Disease



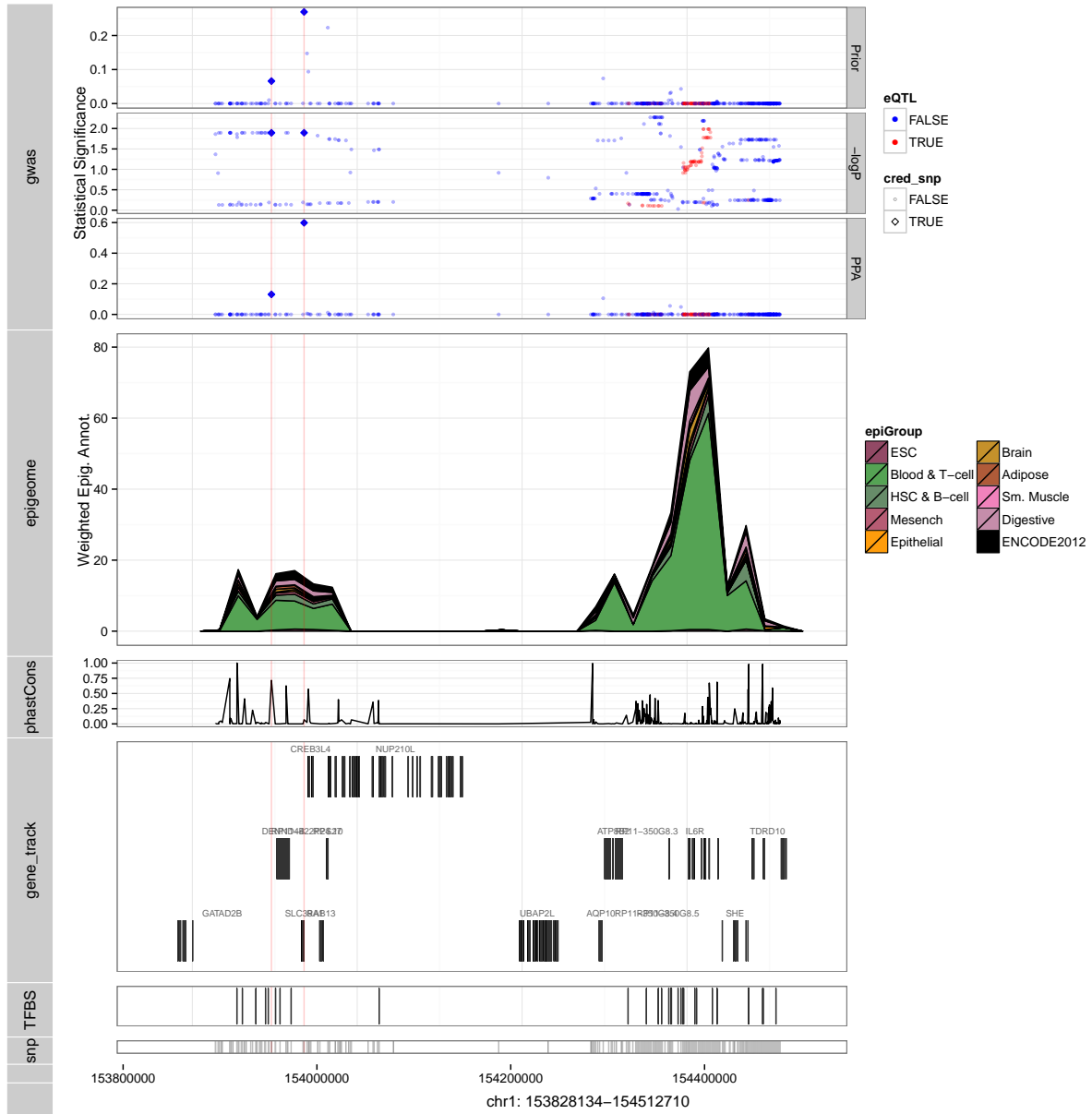
Celiac Disease



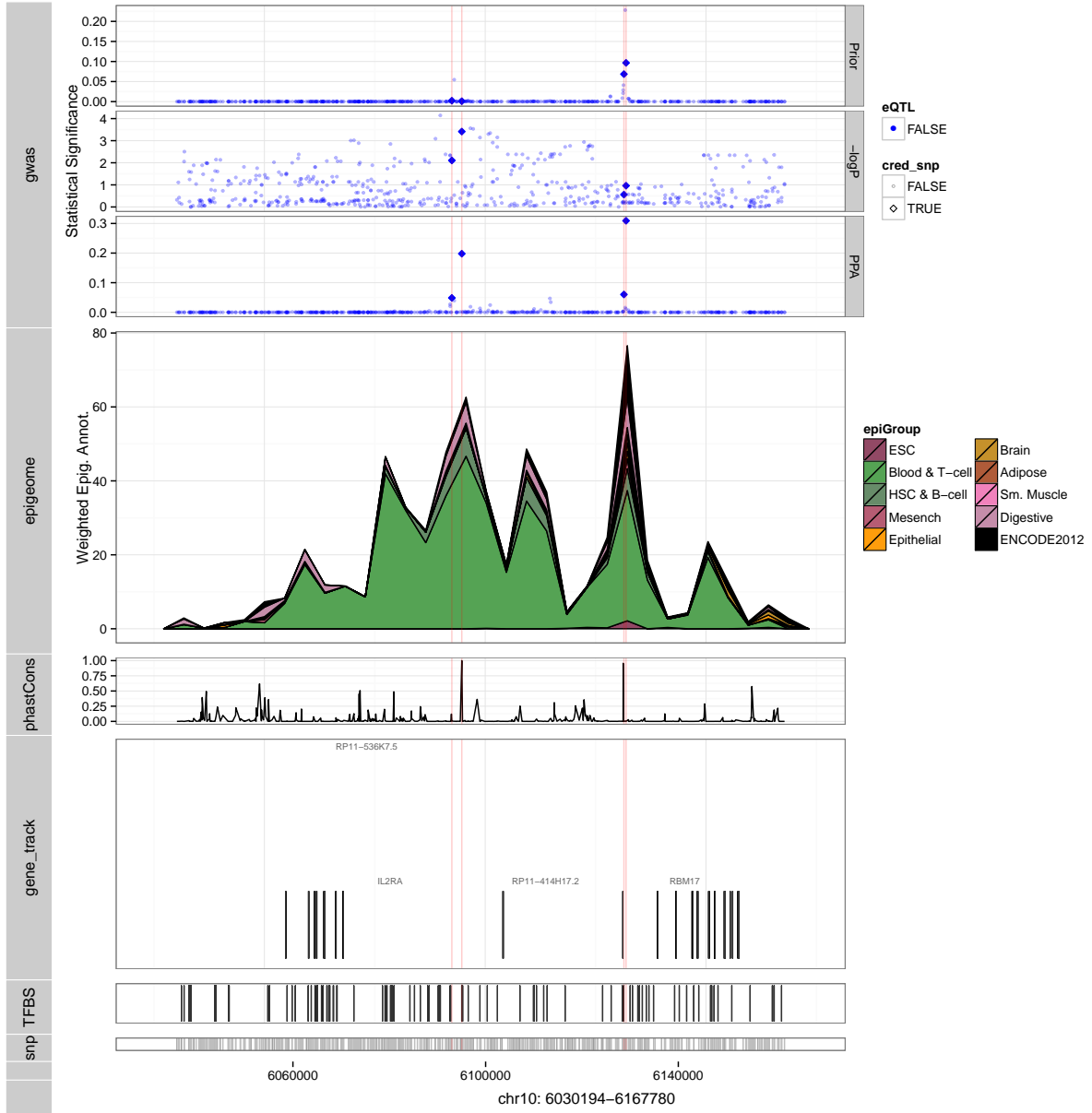
Juvenile Idiopathic Arthritis



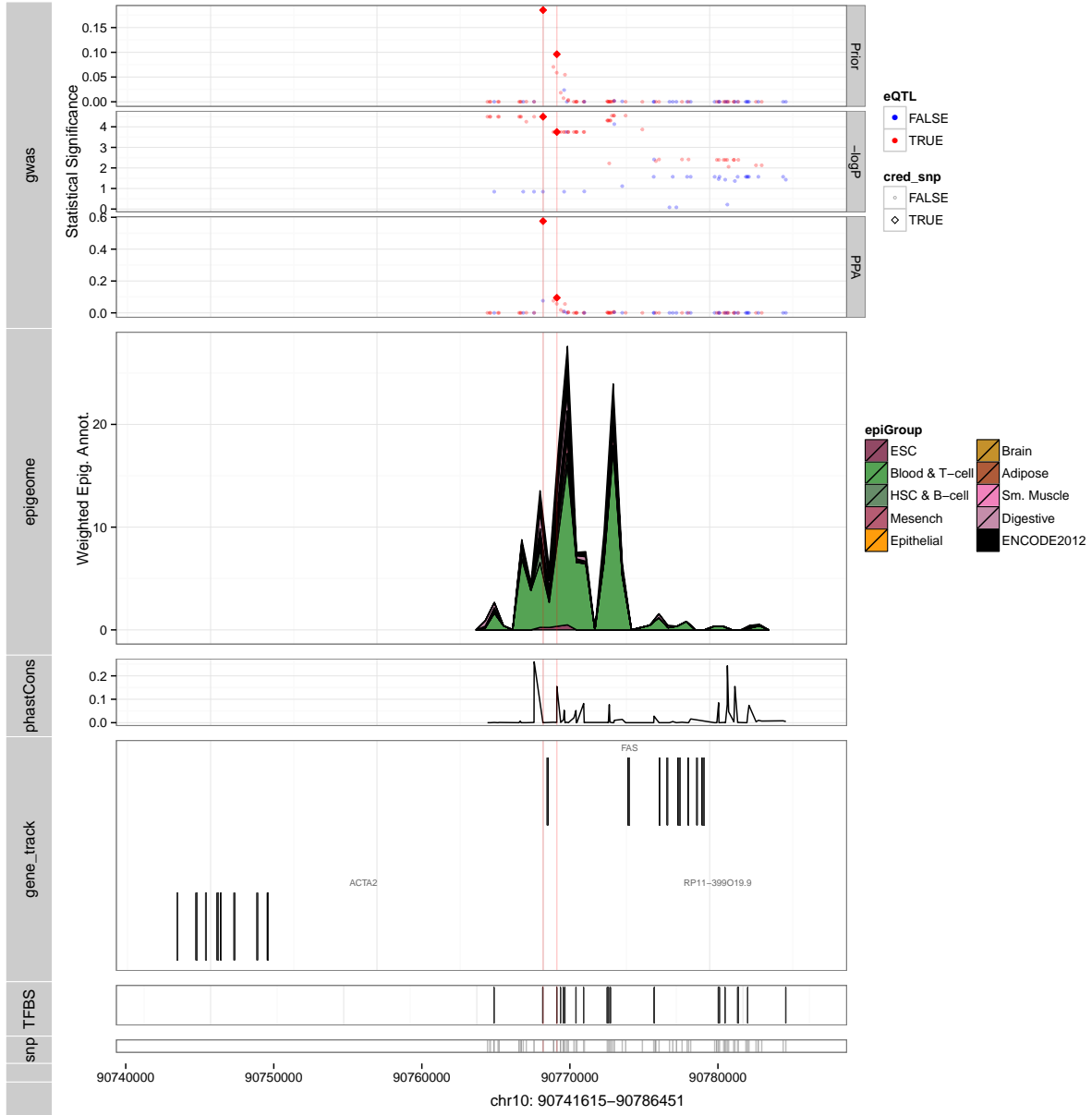
Juvenile Idiopathic Arthritis



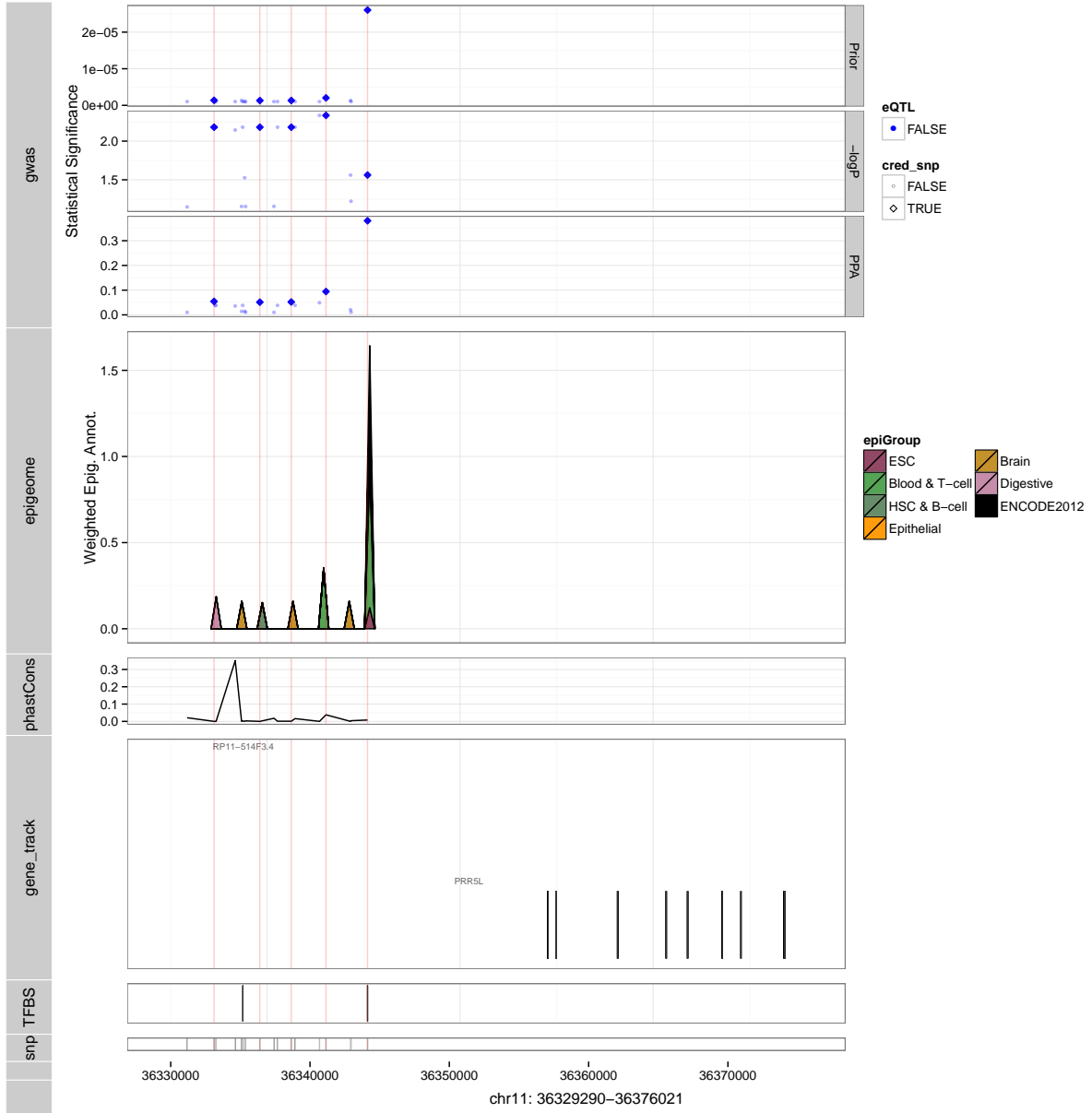
Juvenile Idiopathic Arthritis



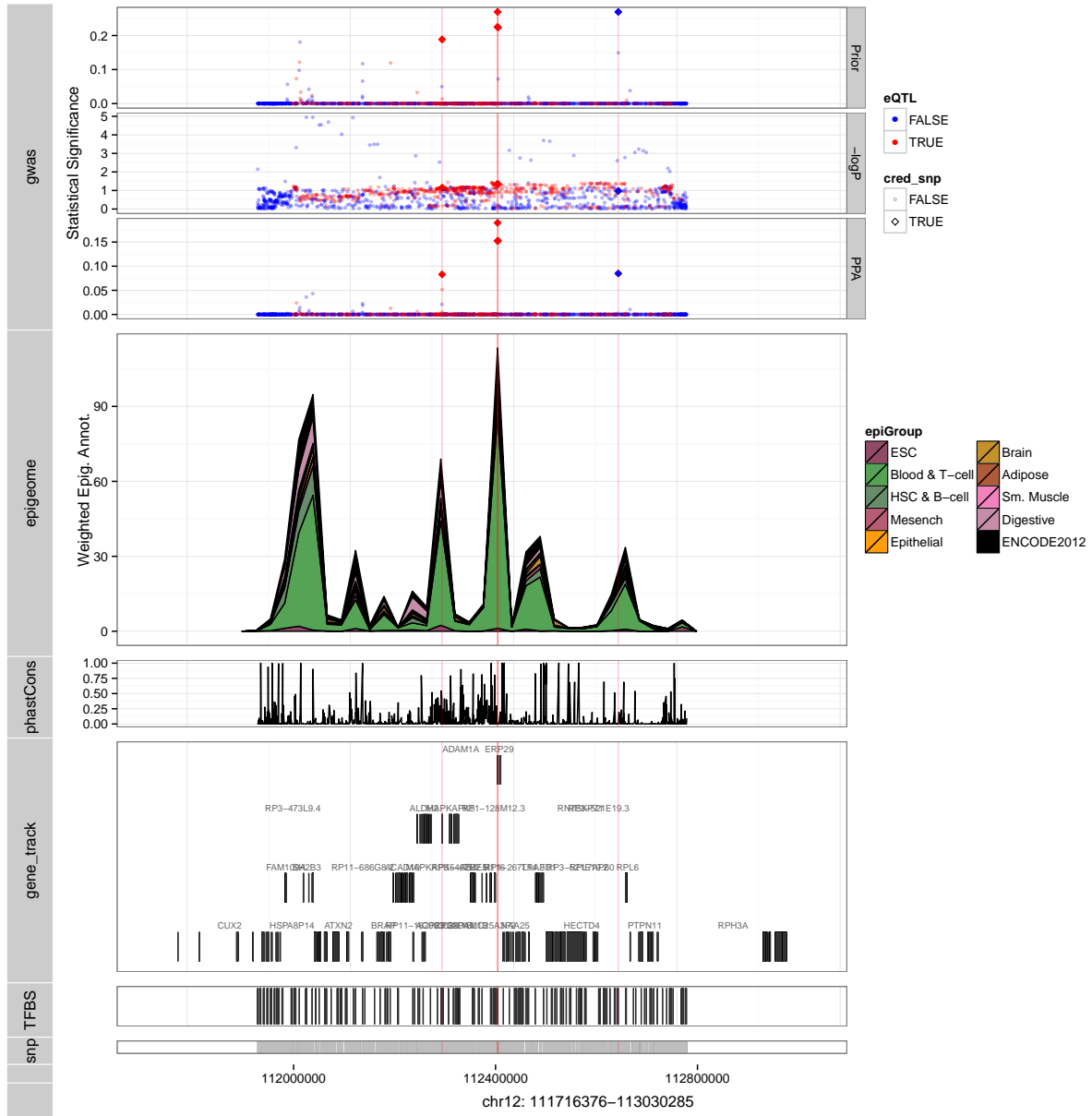
Juvenile Idiopathic Arthritis



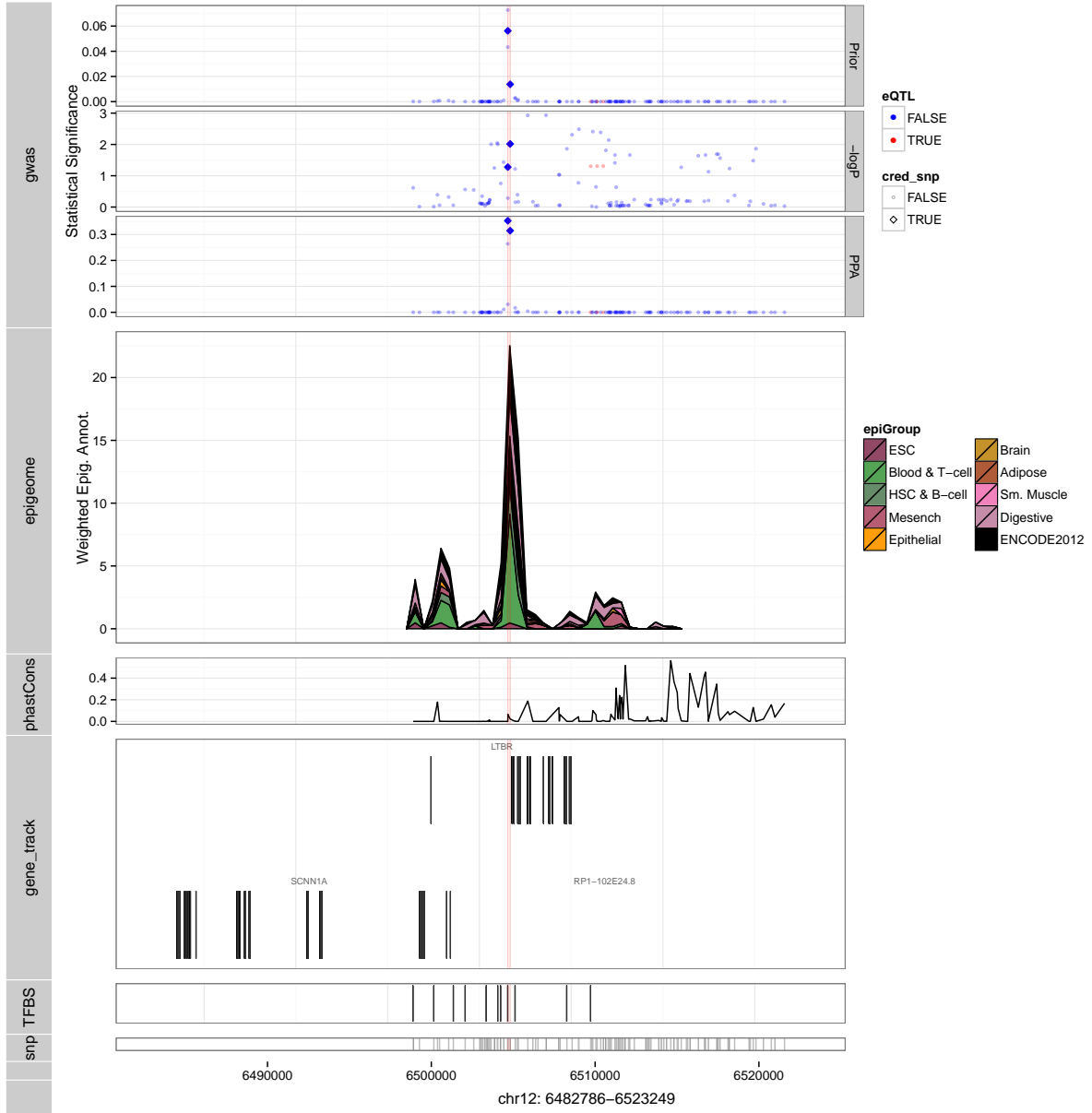
Juvenile Idiopathic Arthritis



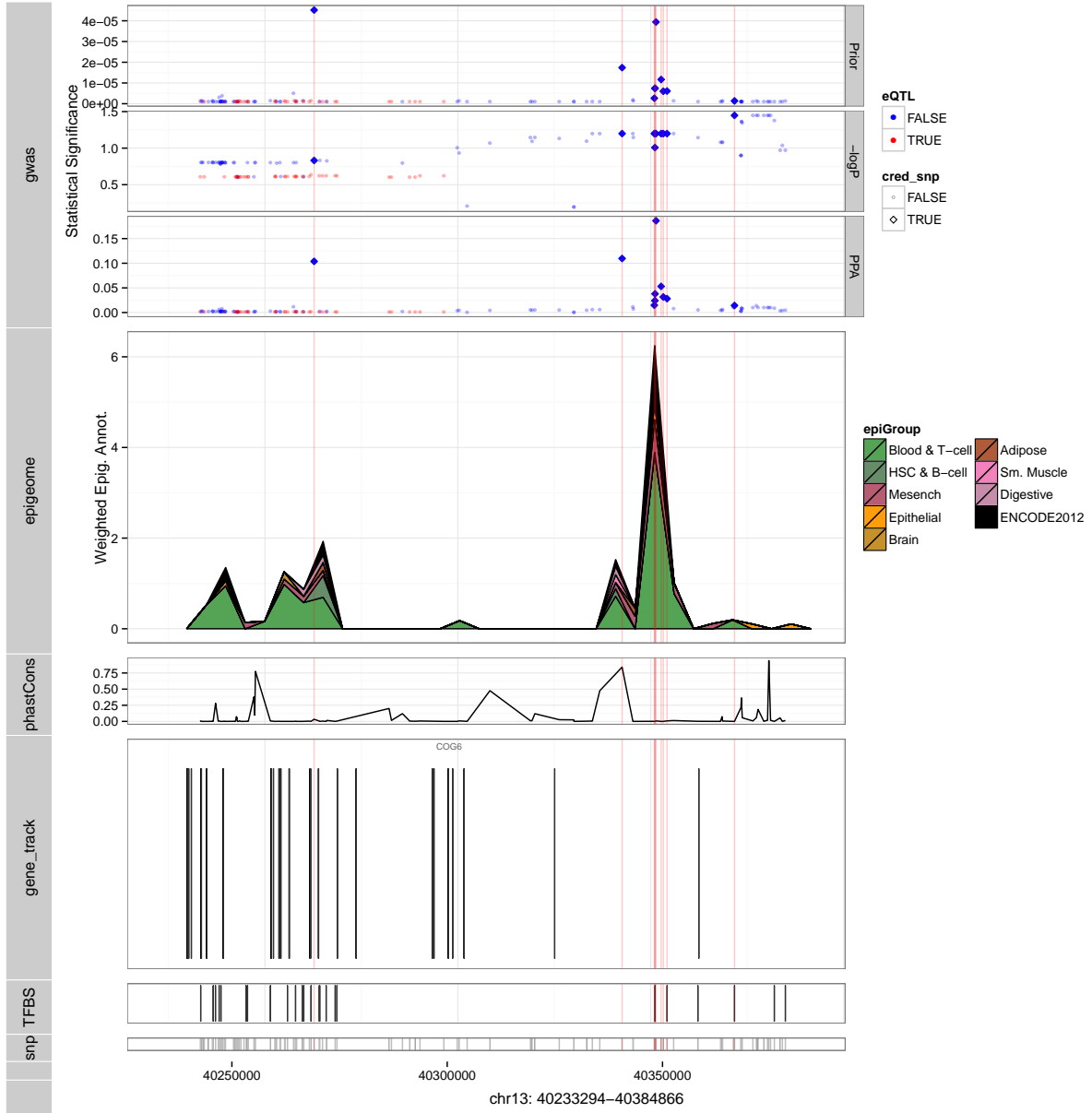
Juvenile Idiopathic Arthritis



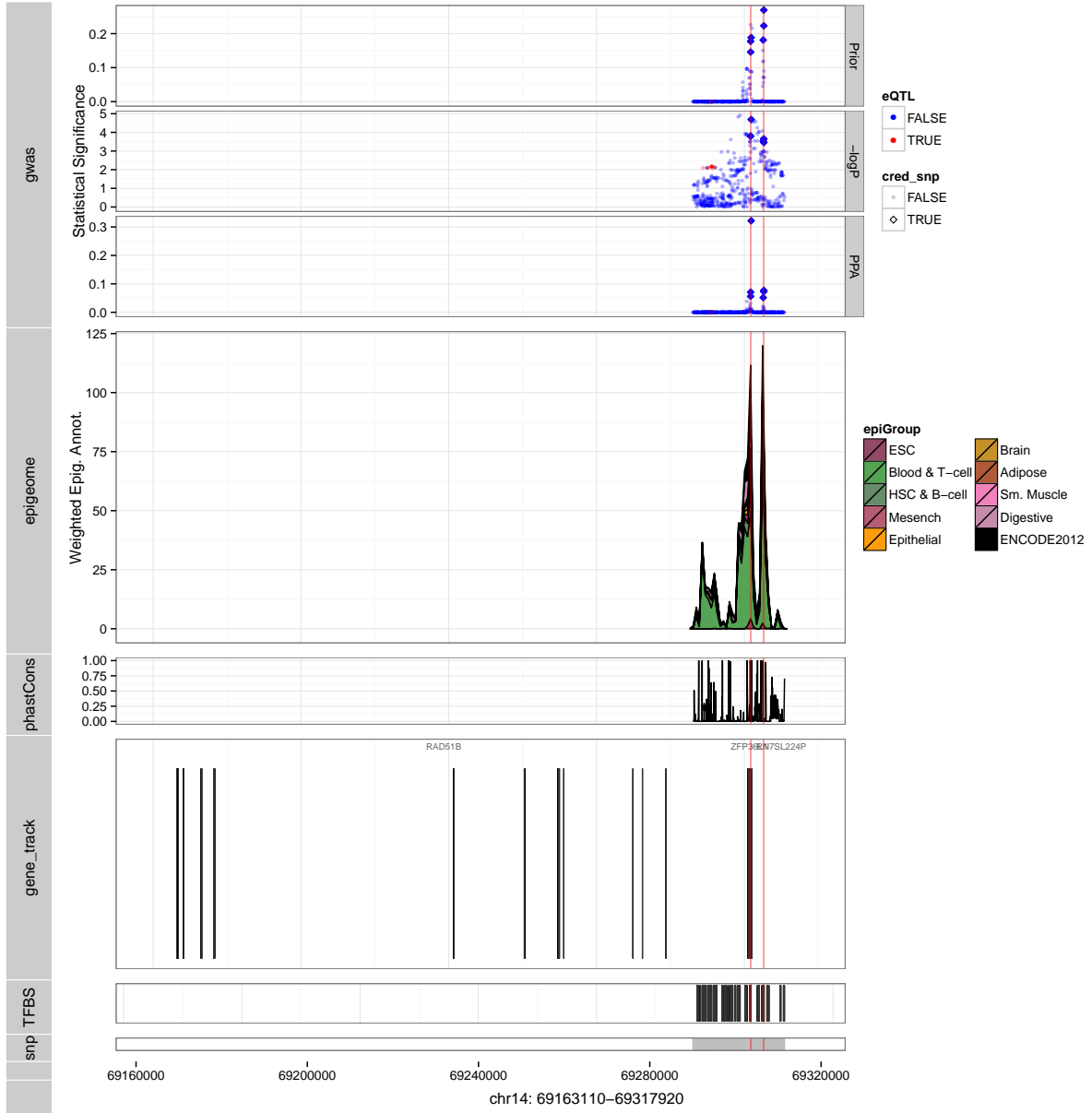
Juvenile Idiopathic Arthritis



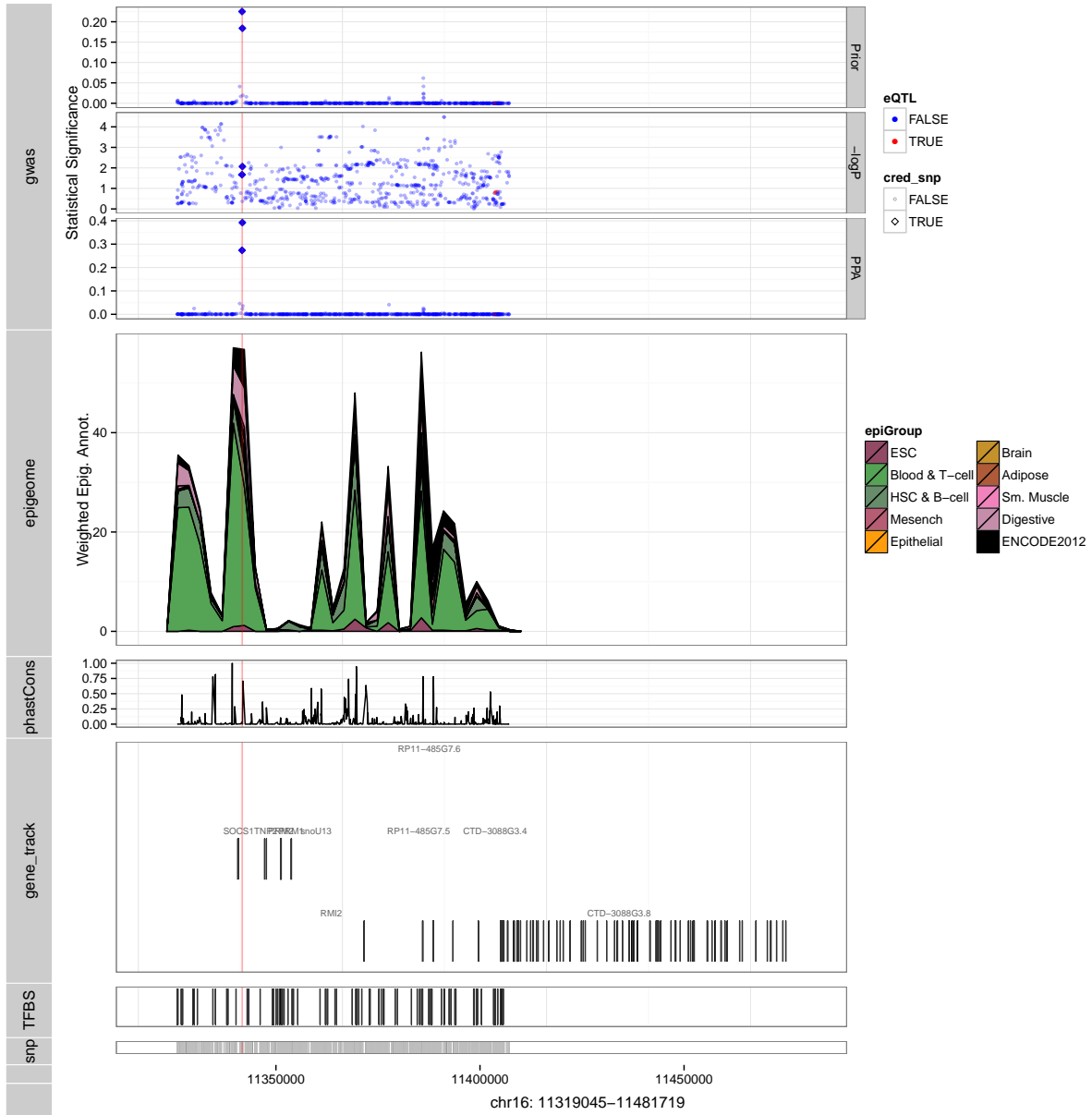
Juvenile Idiopathic Arthritis



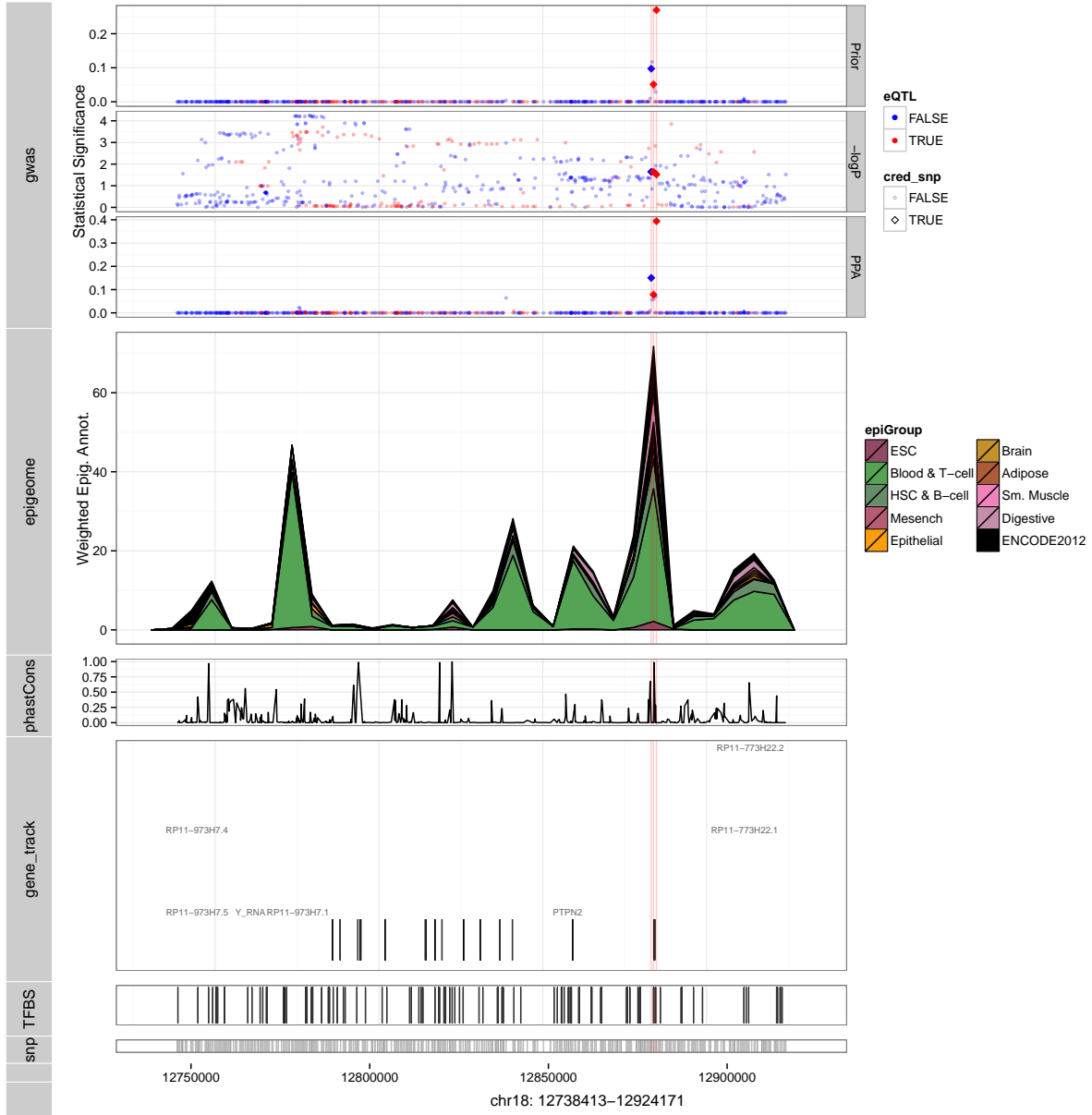
Juvenile Idiopathic Arthritis



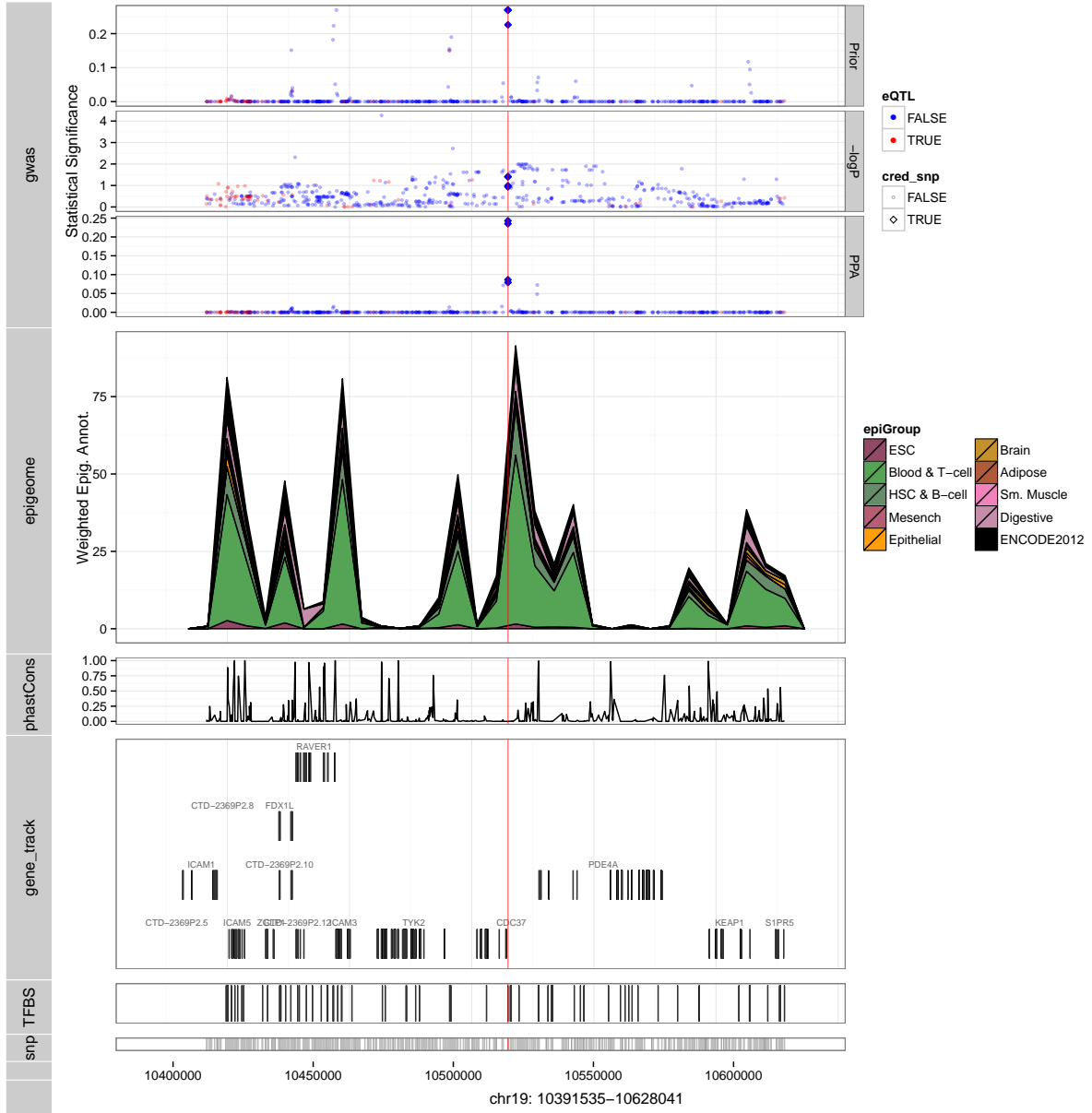
Juvenile Idiopathic Arthritis



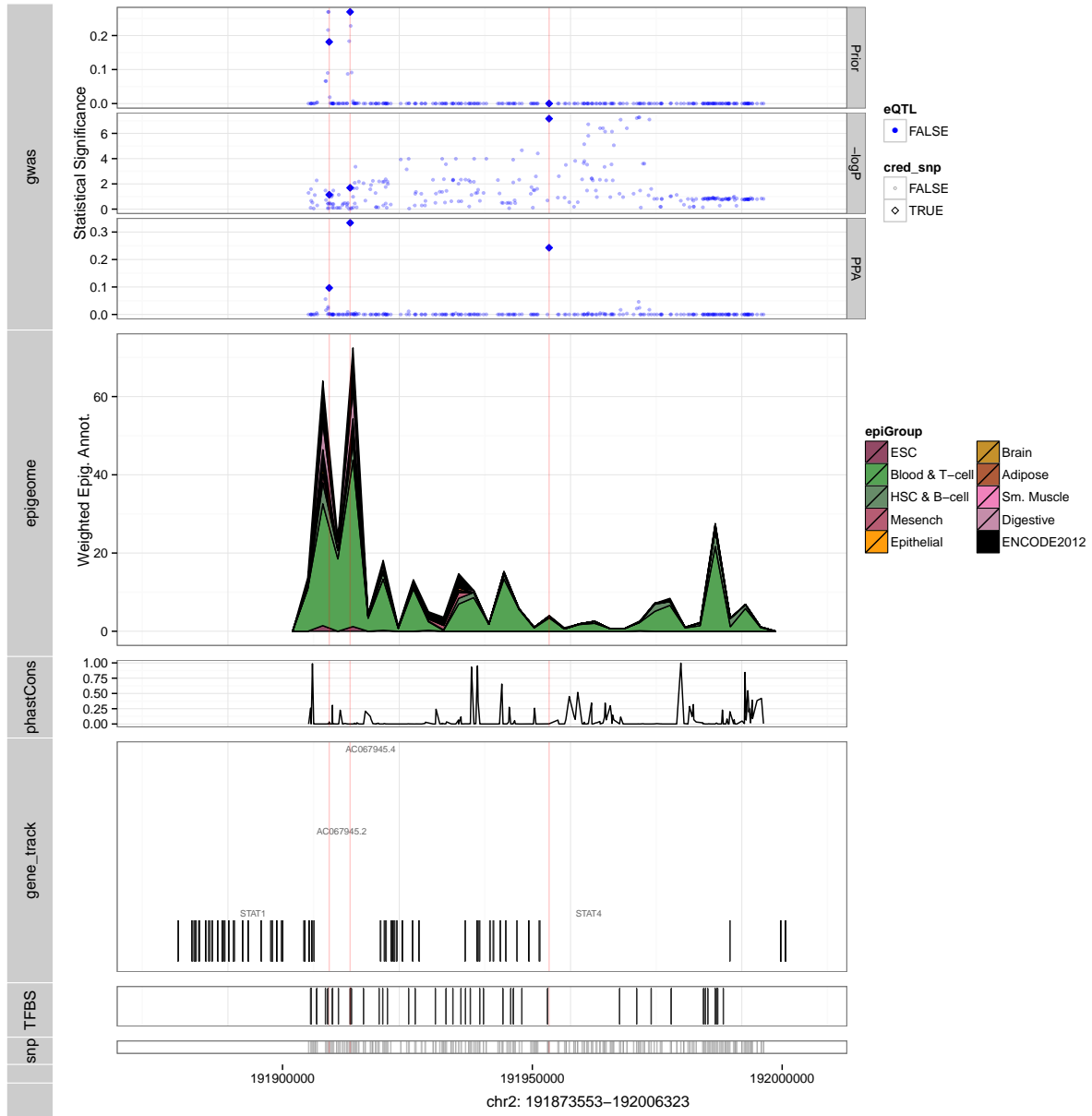
Juvenile Idiopathic Arthritis



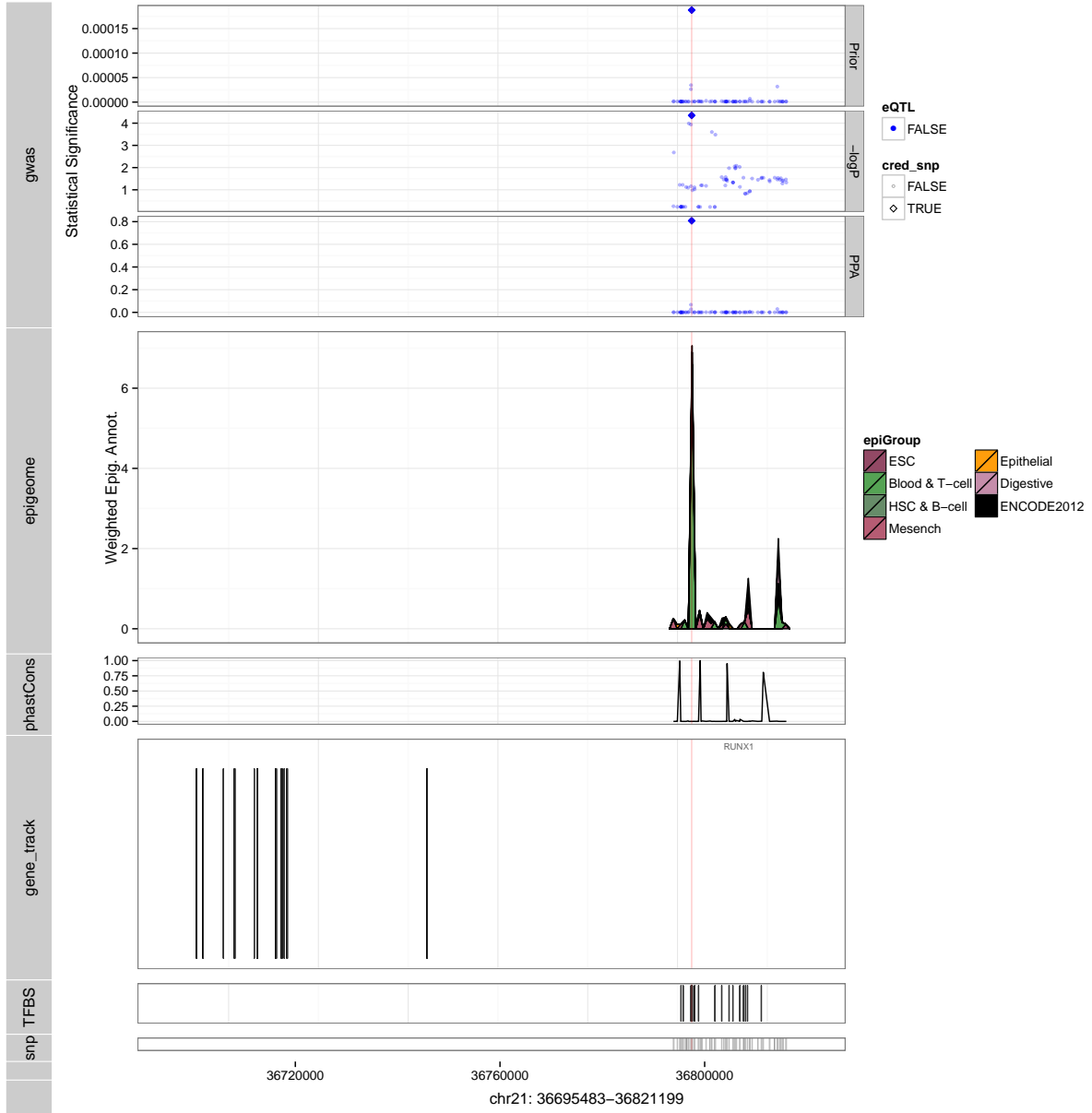
Juvenile Idiopathic Arthritis



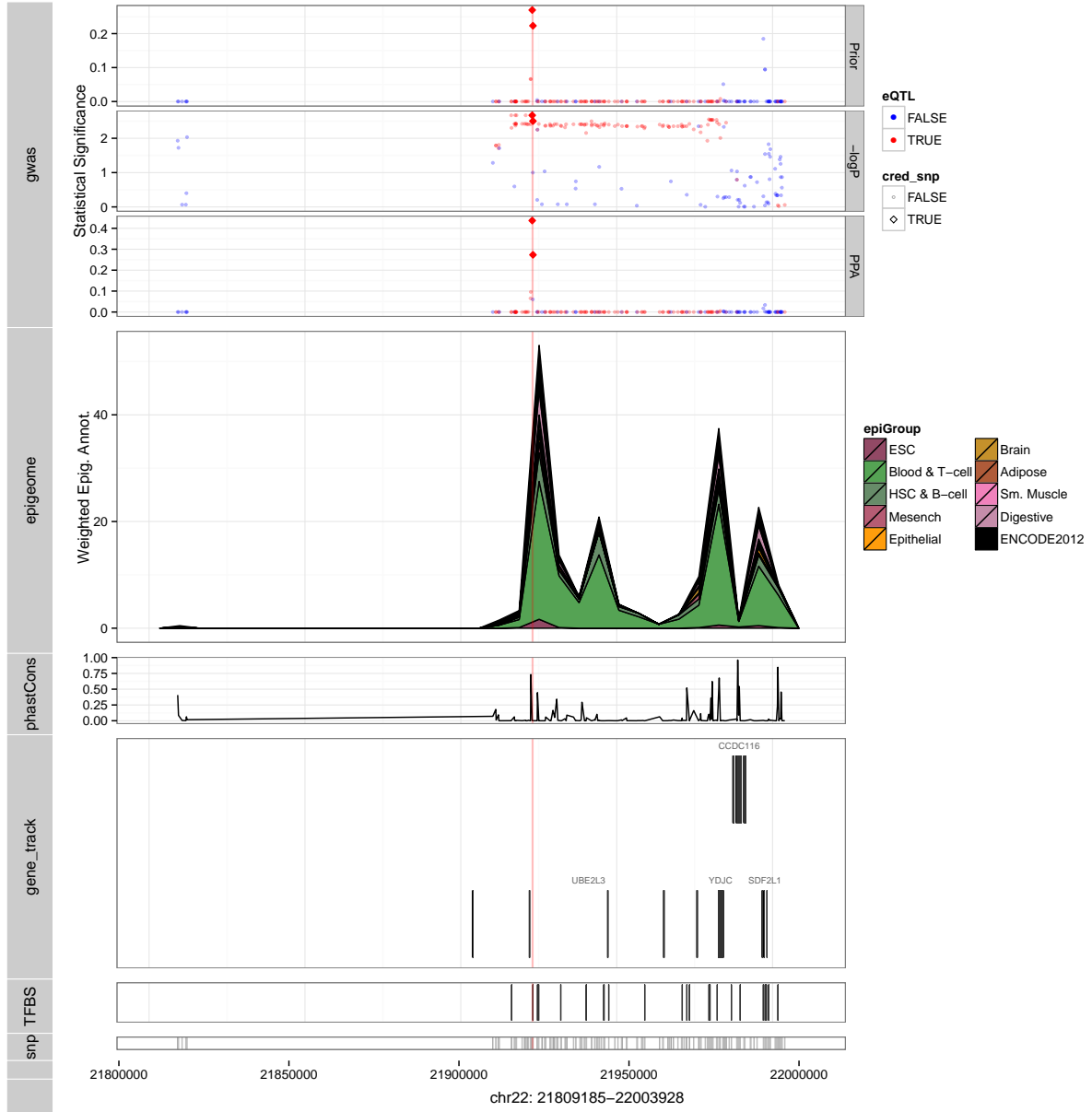
Juvenile Idiopathic Arthritis



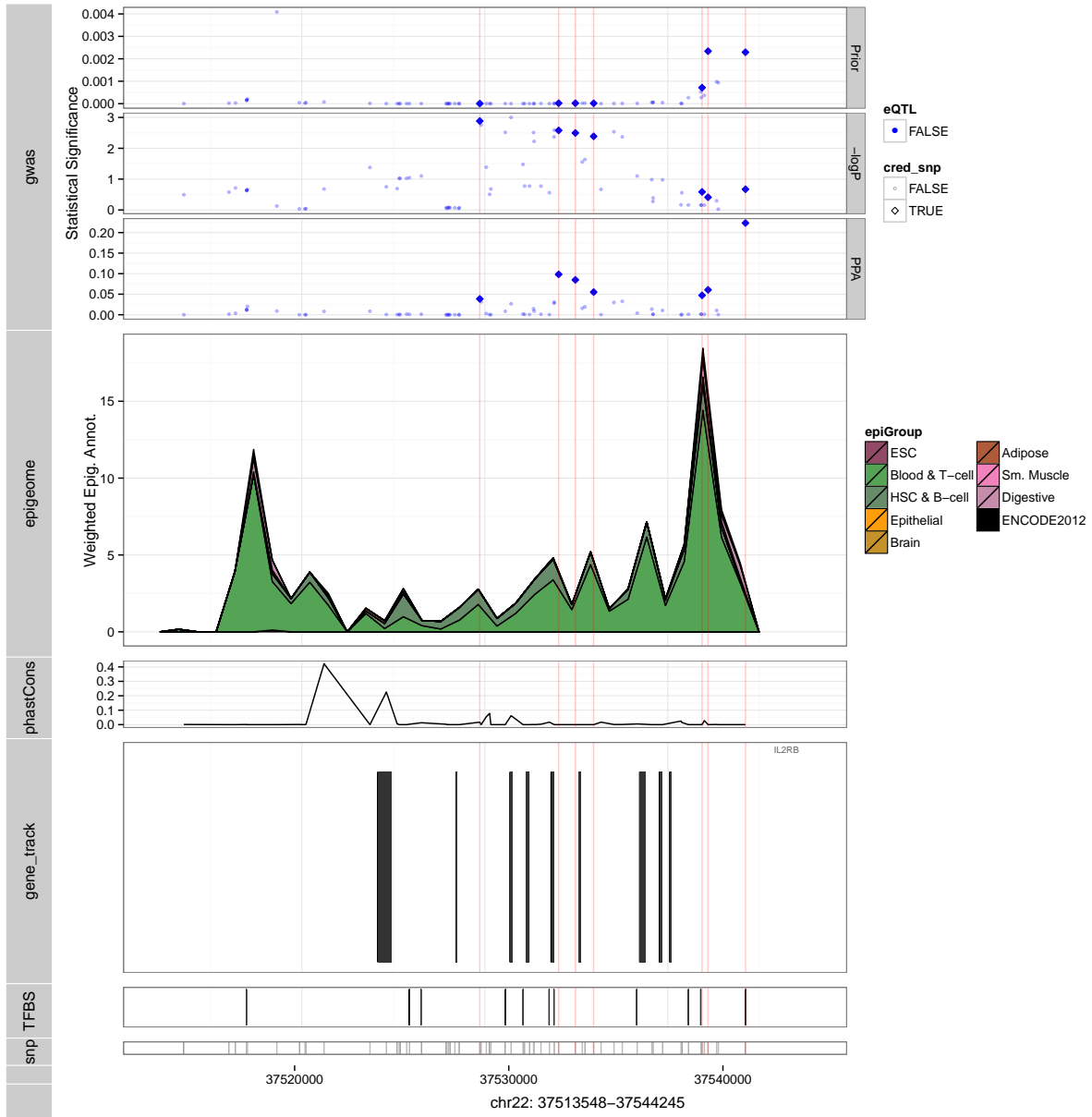
Juvenile Idiopathic Arthritis



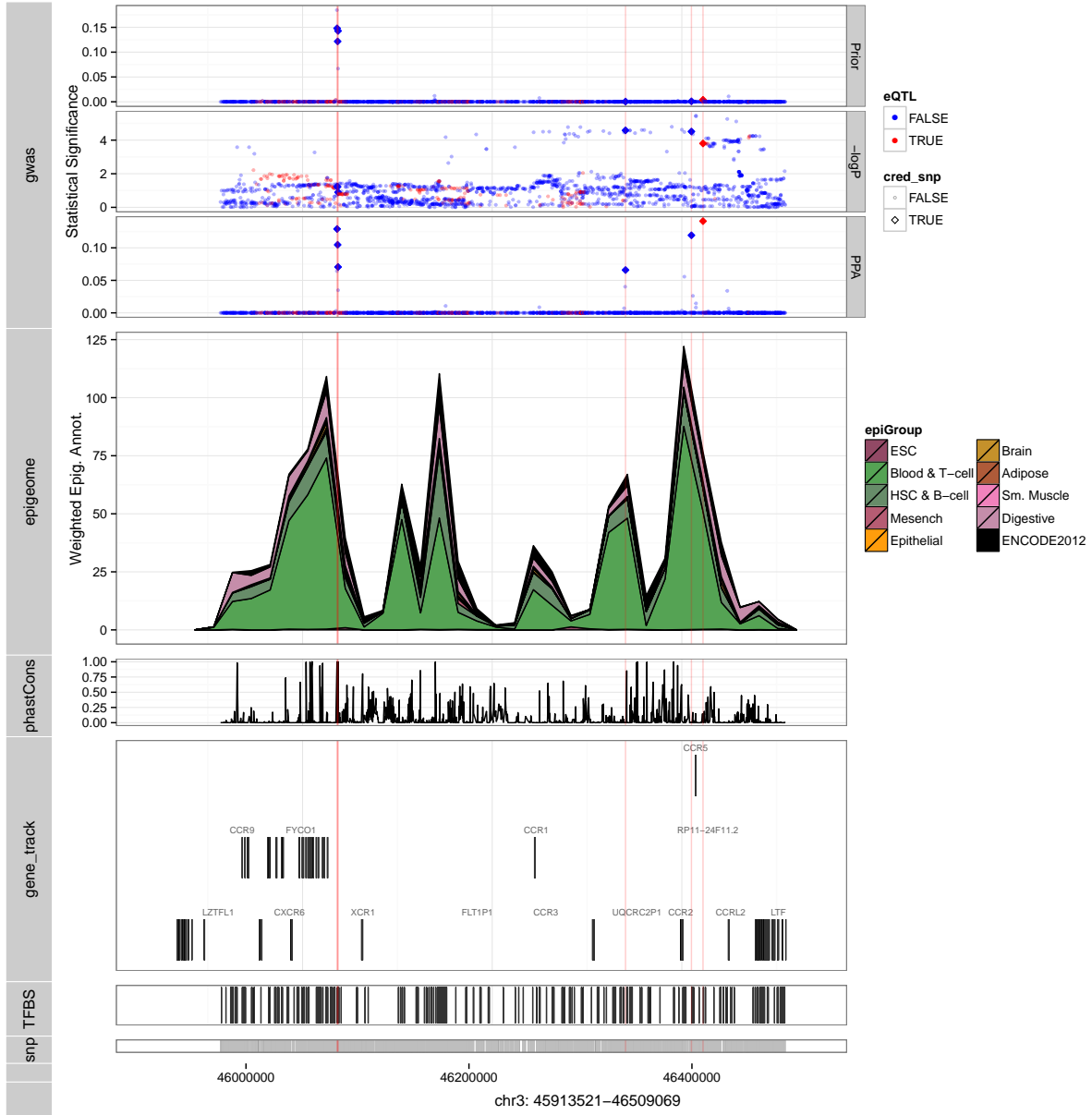
Juvenile Idiopathic Arthritis



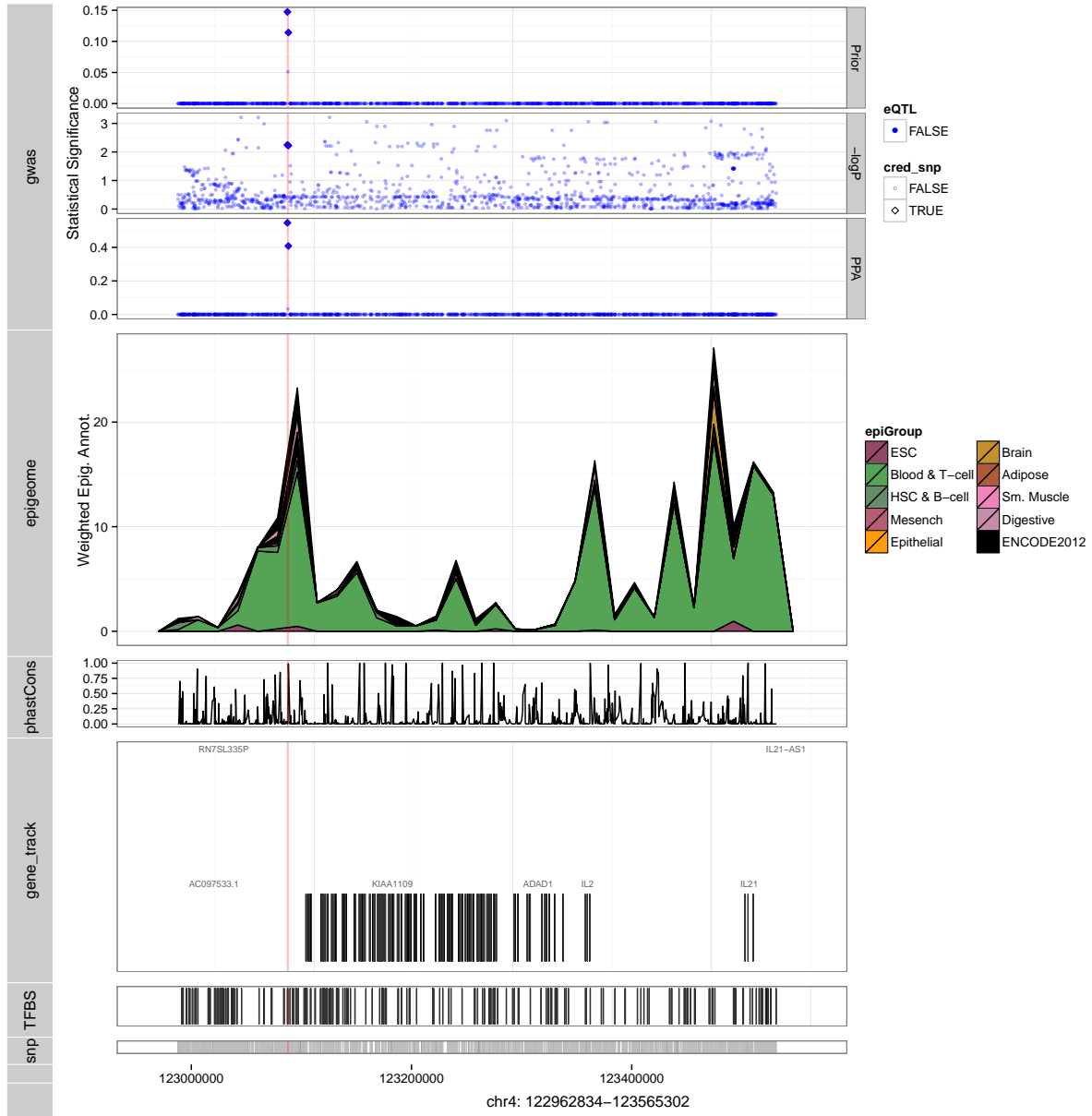
Juvenile Idiopathic Arthritis



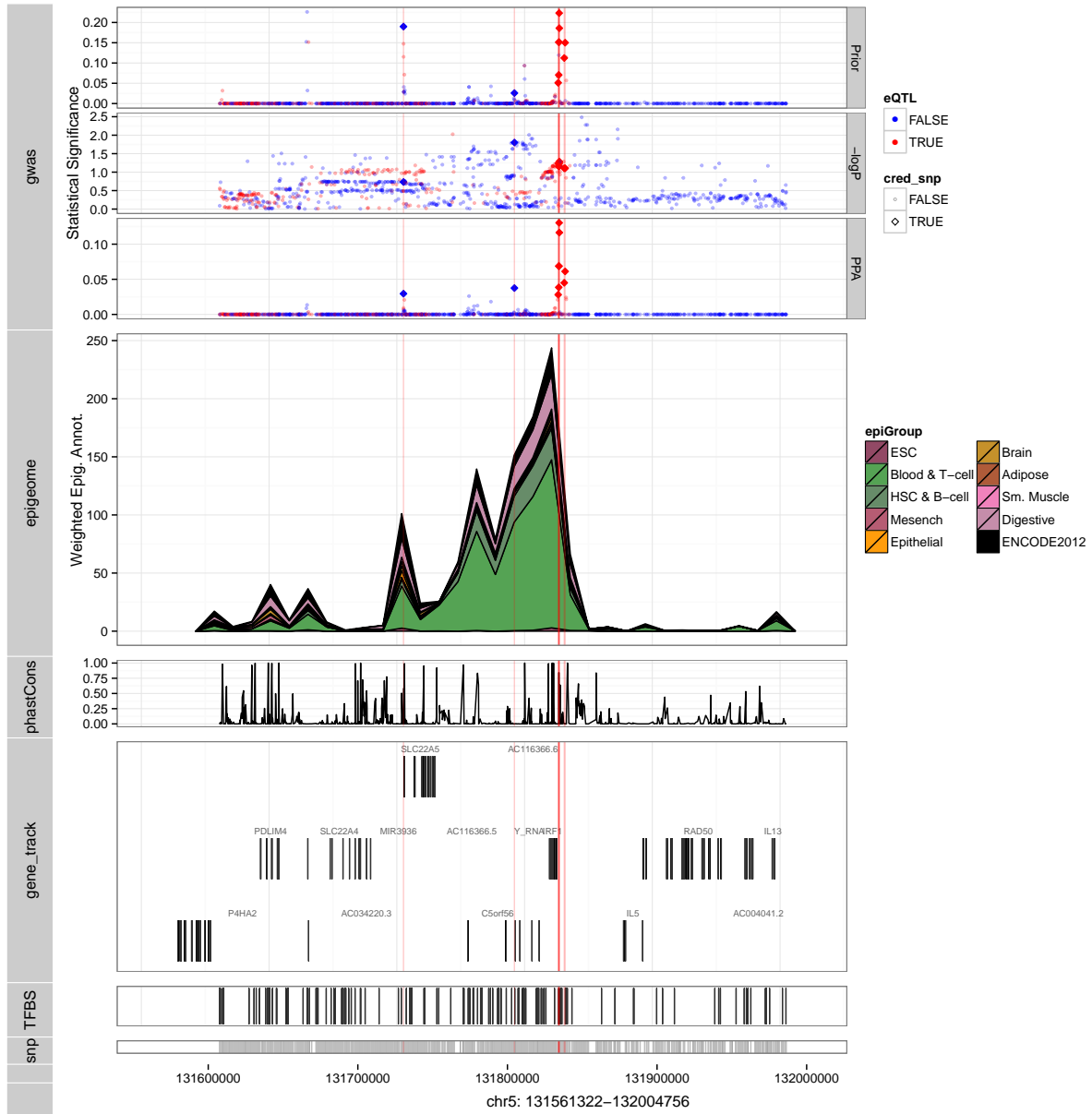
Juvenile Idiopathic Arthritis



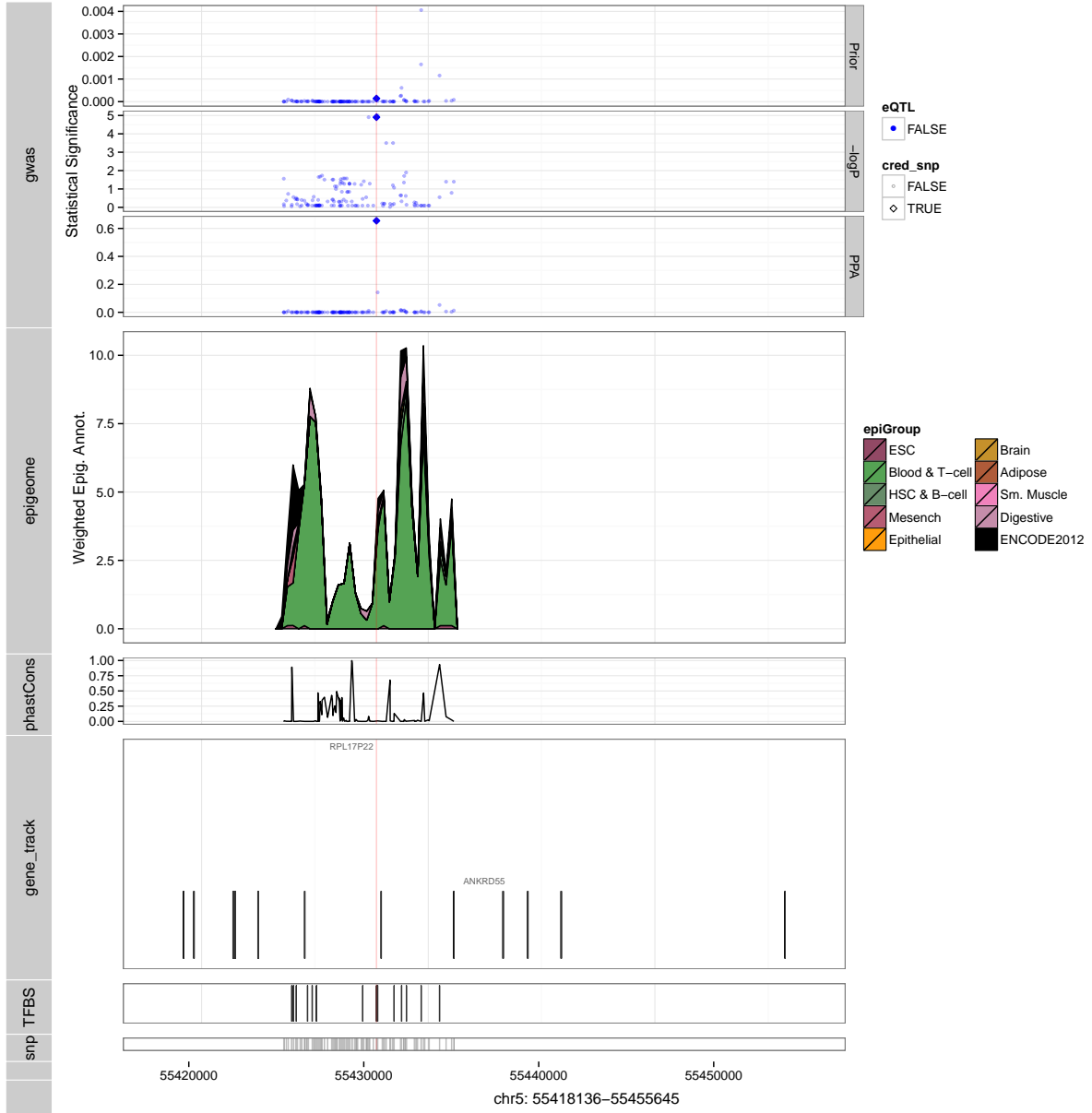
Juvenile Idiopathic Arthritis



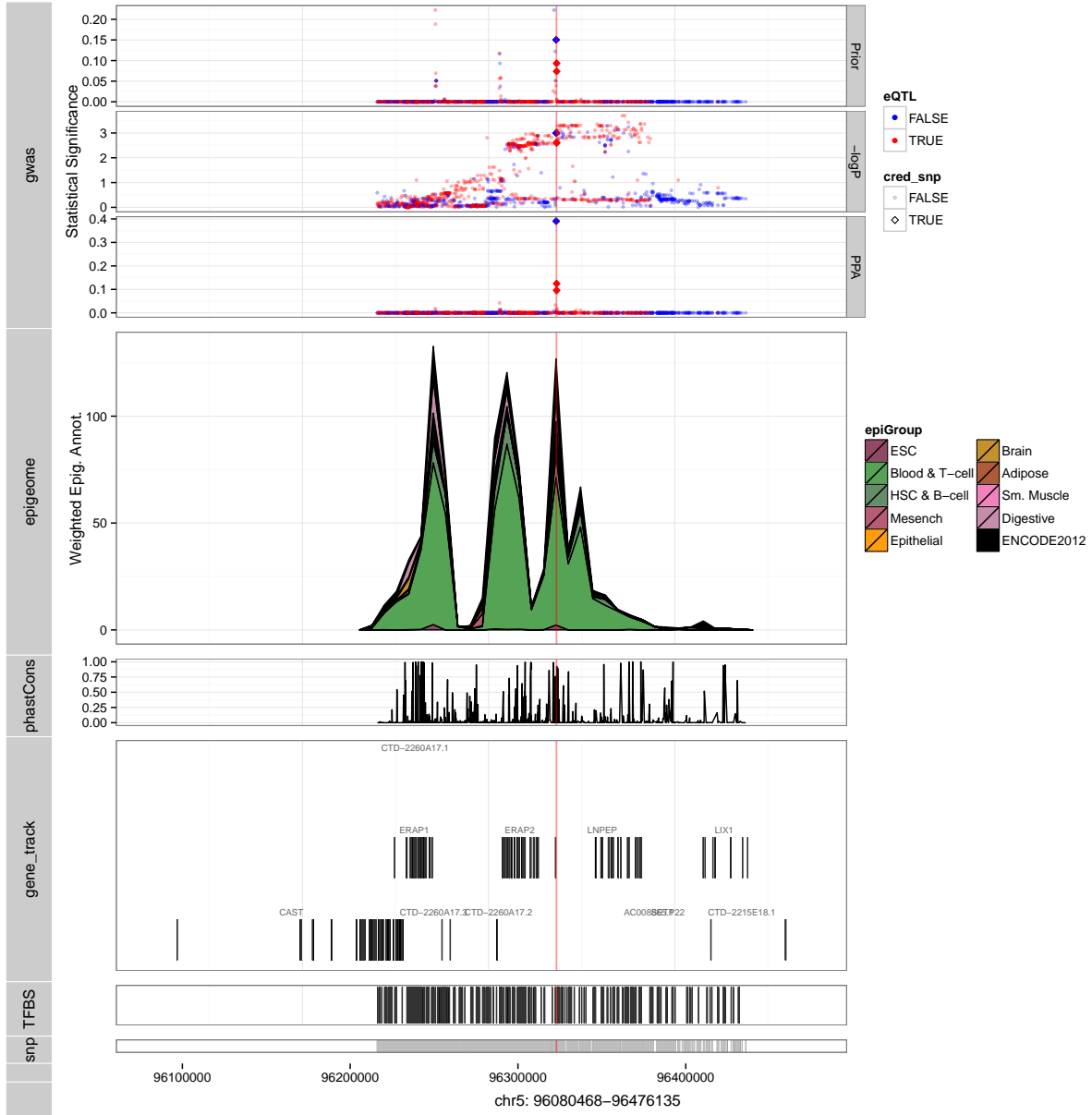
Juvenile Idiopathic Arthritis



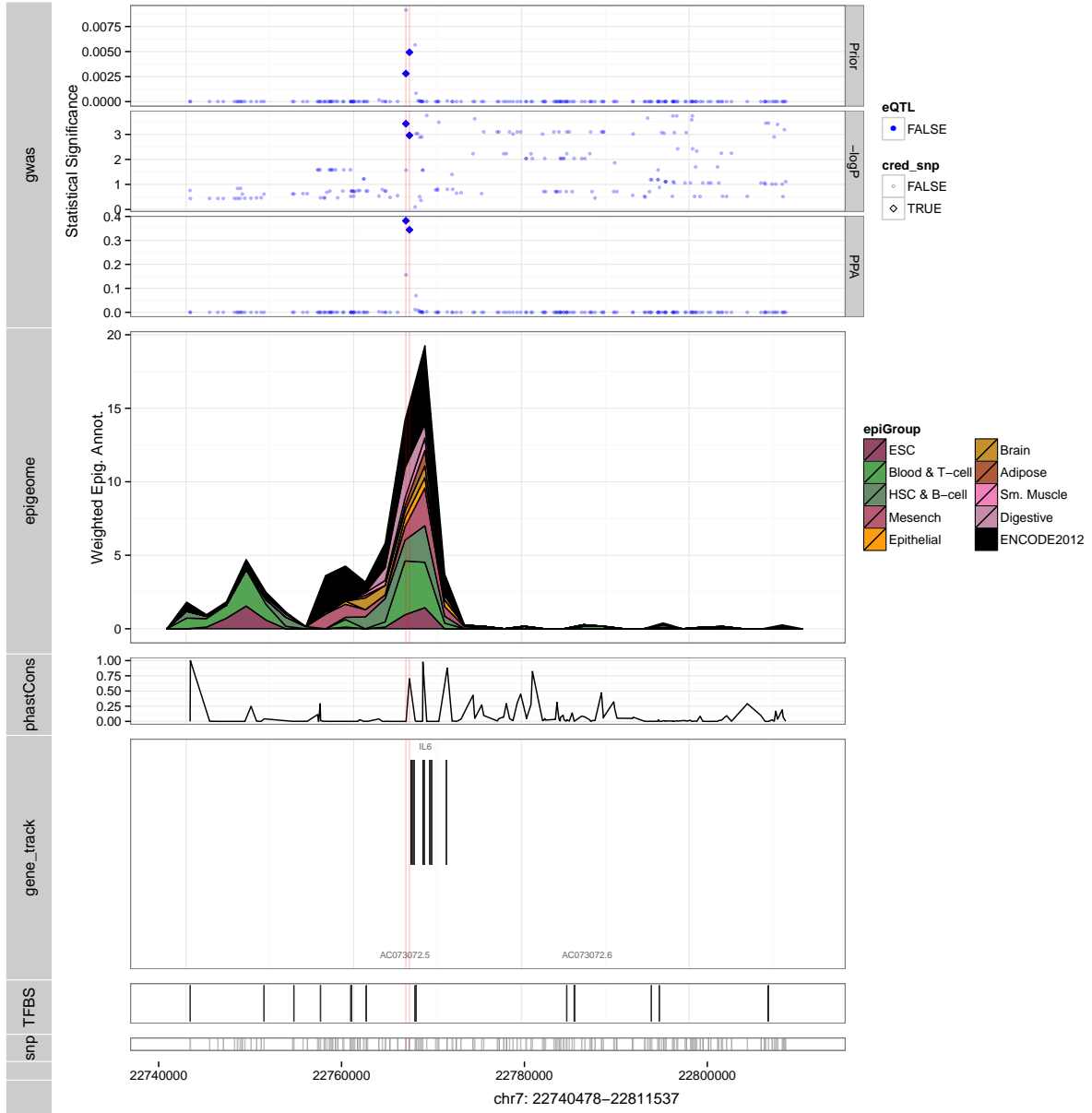
Juvenile Idiopathic Arthritis



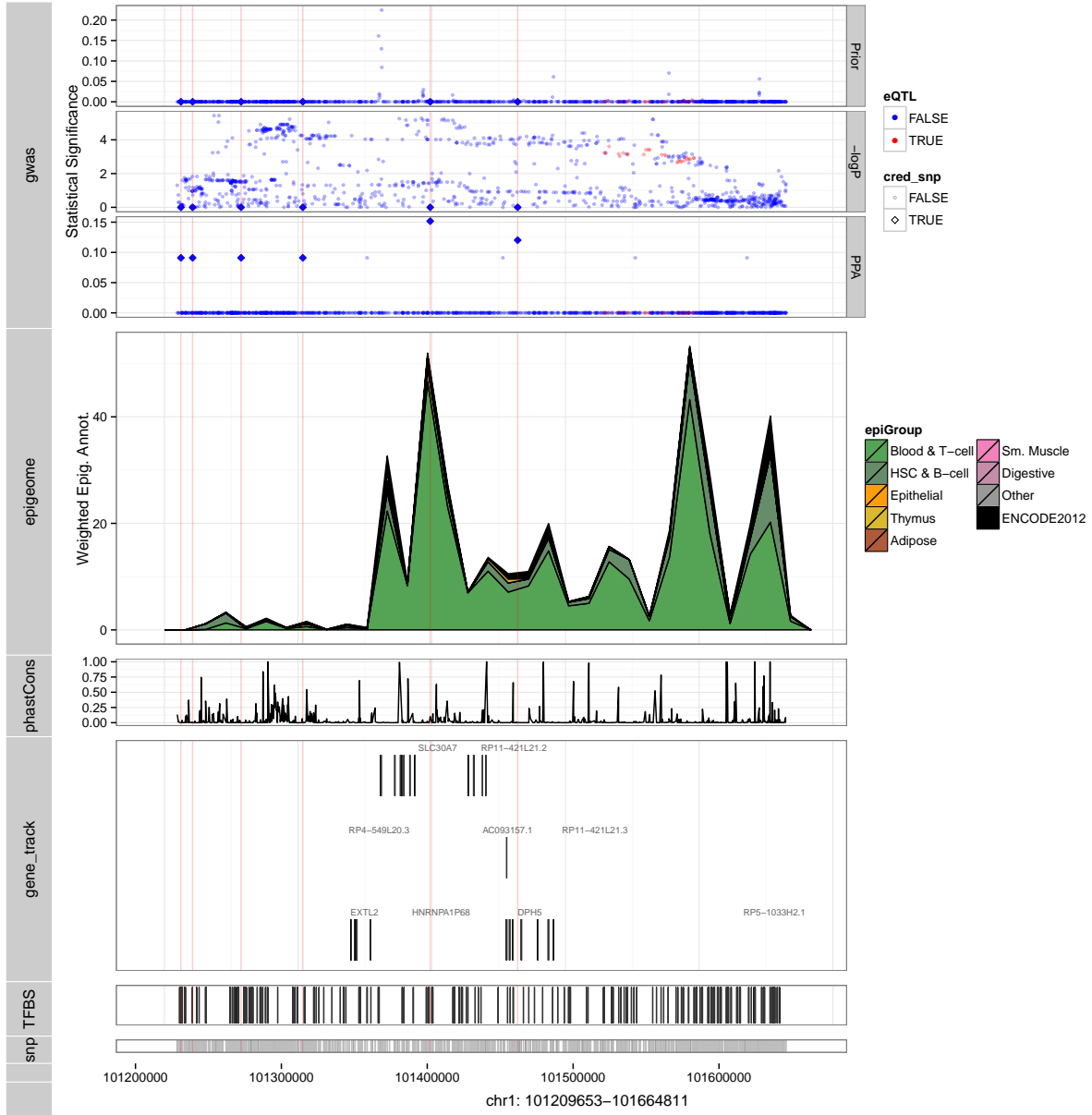
Juvenile Idiopathic Arthritis



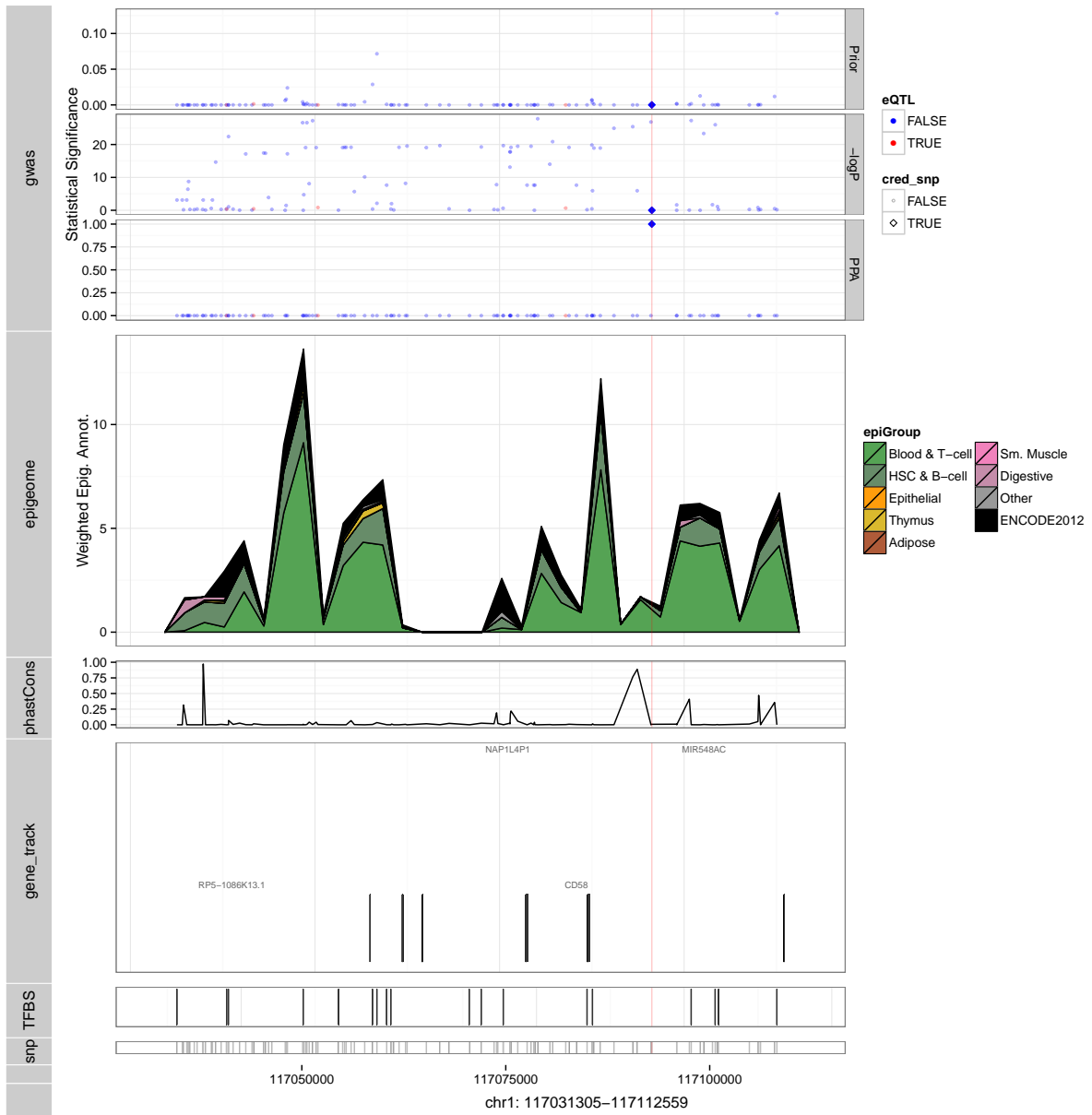
Juvenile Idiopathic Arthritis



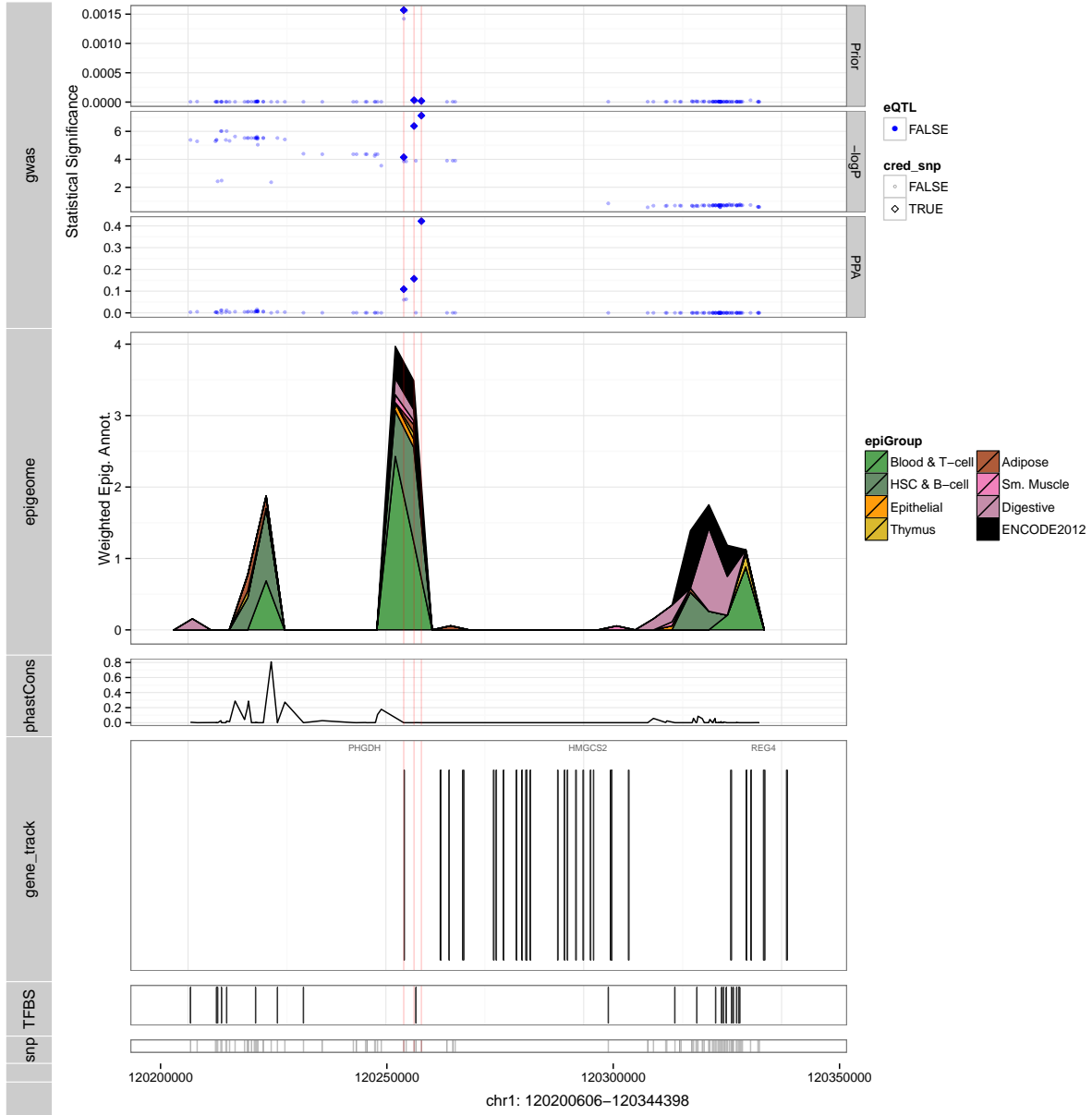
Multiple Sclerosis



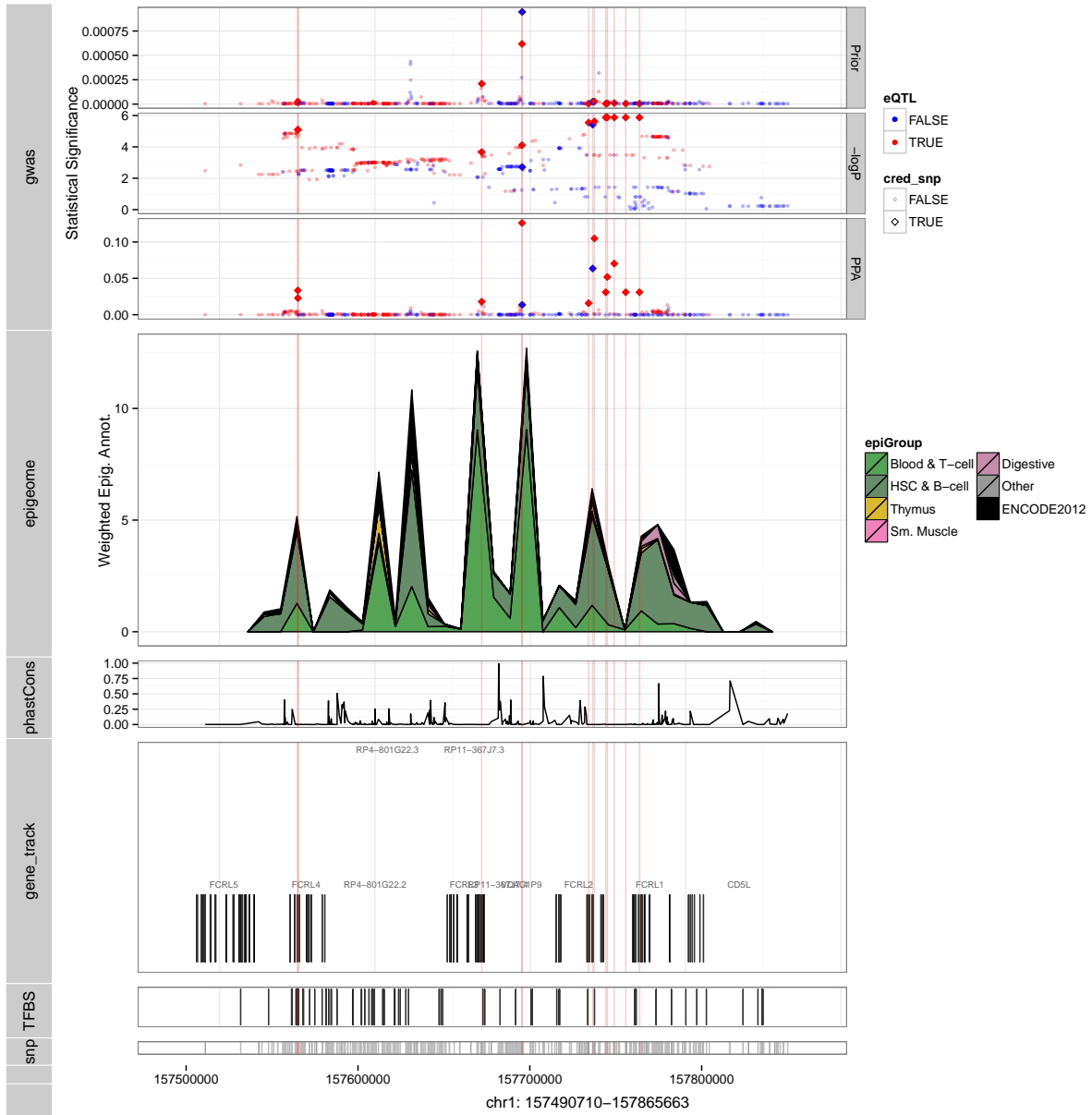
Multiple Sclerosis



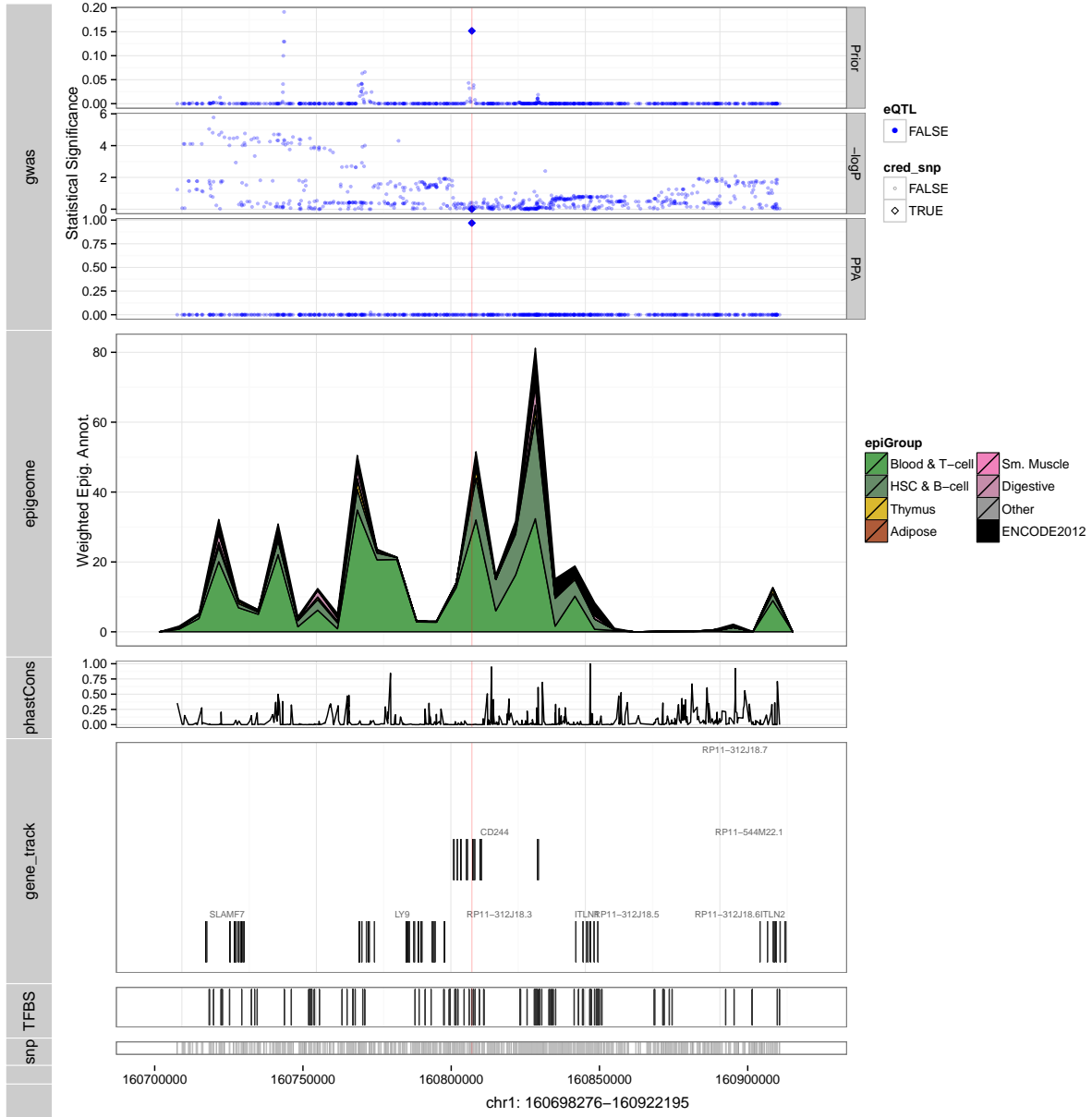
Multiple Sclerosis



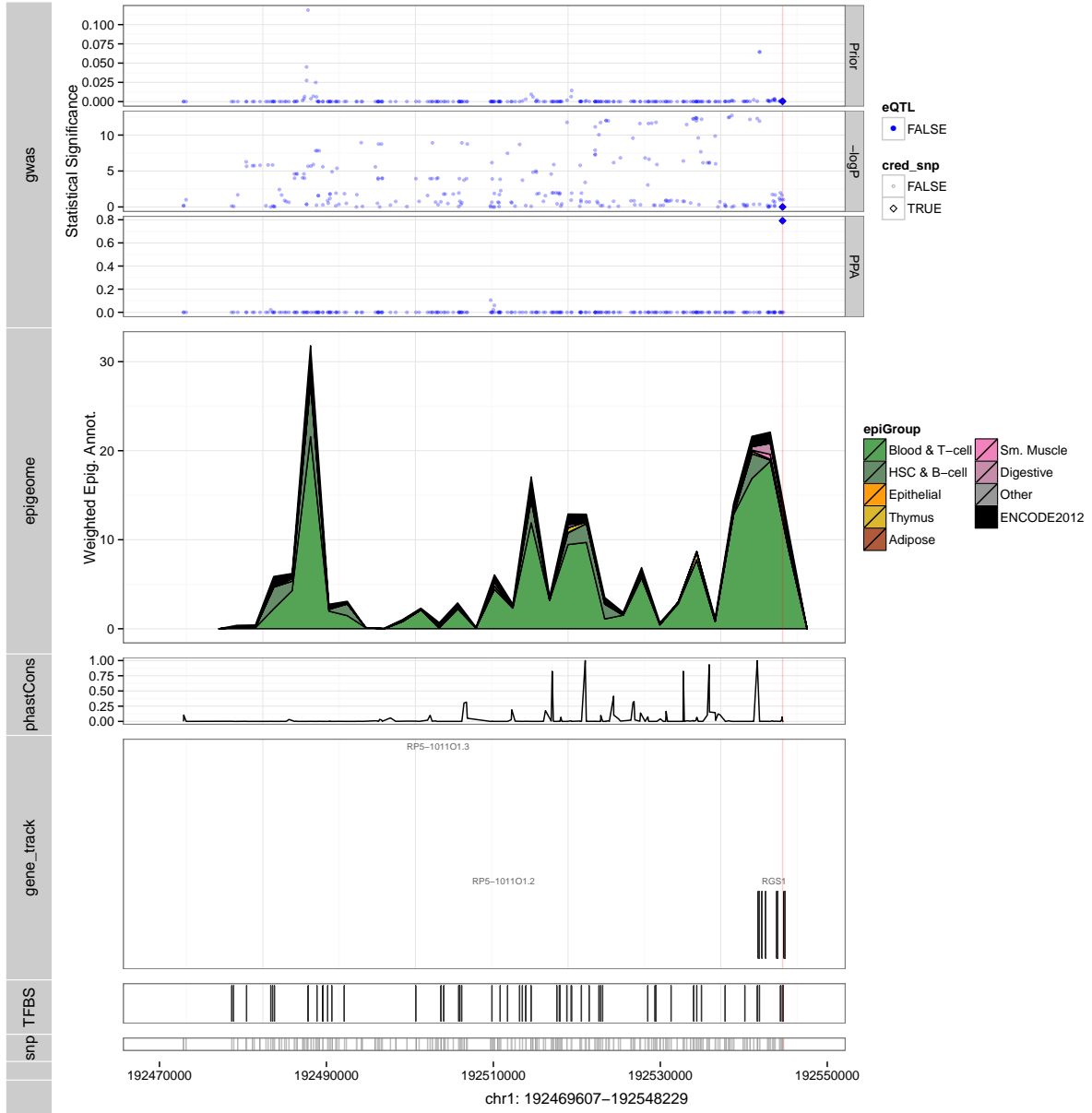
Multiple Sclerosis



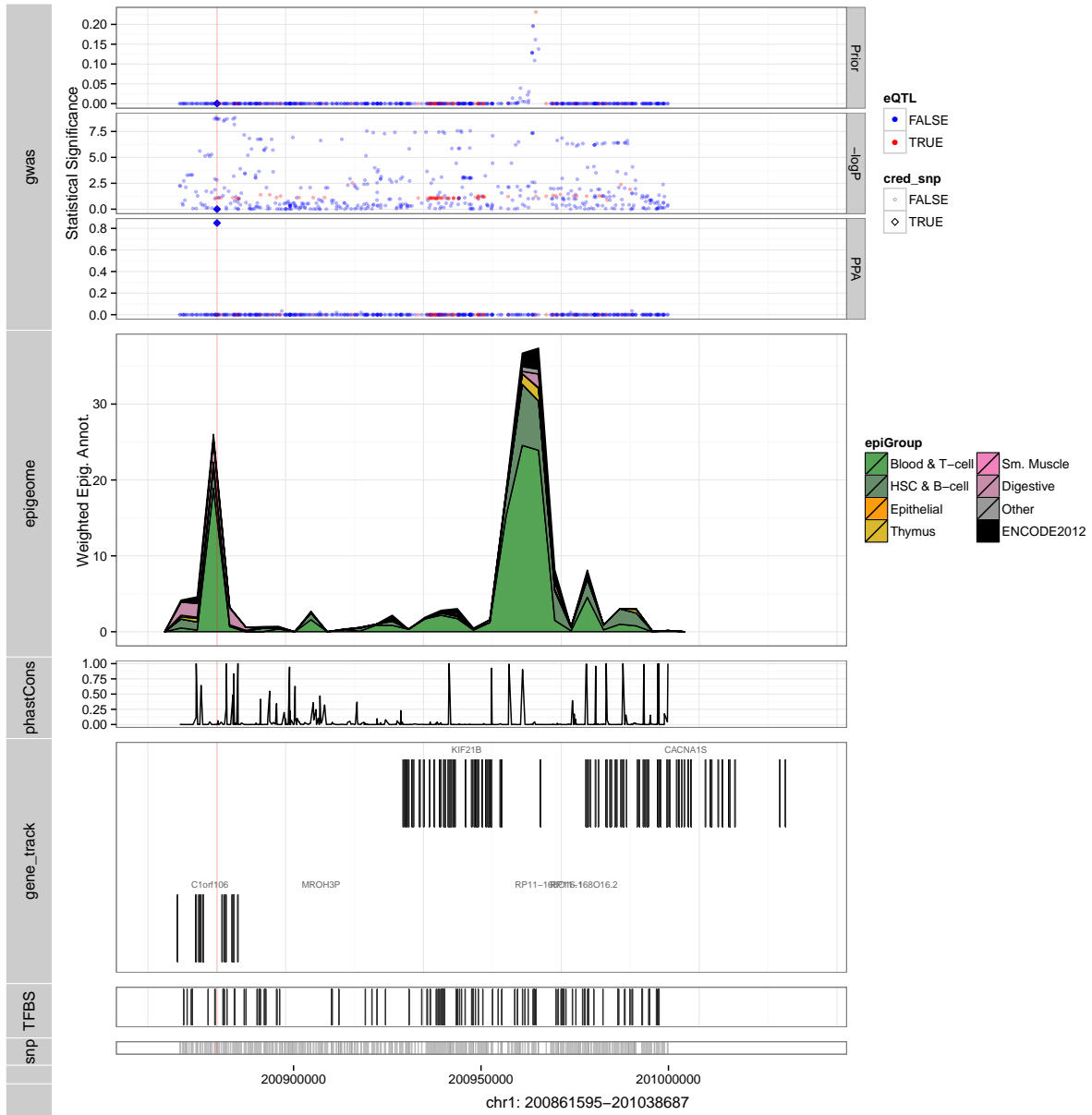
Multiple Sclerosis



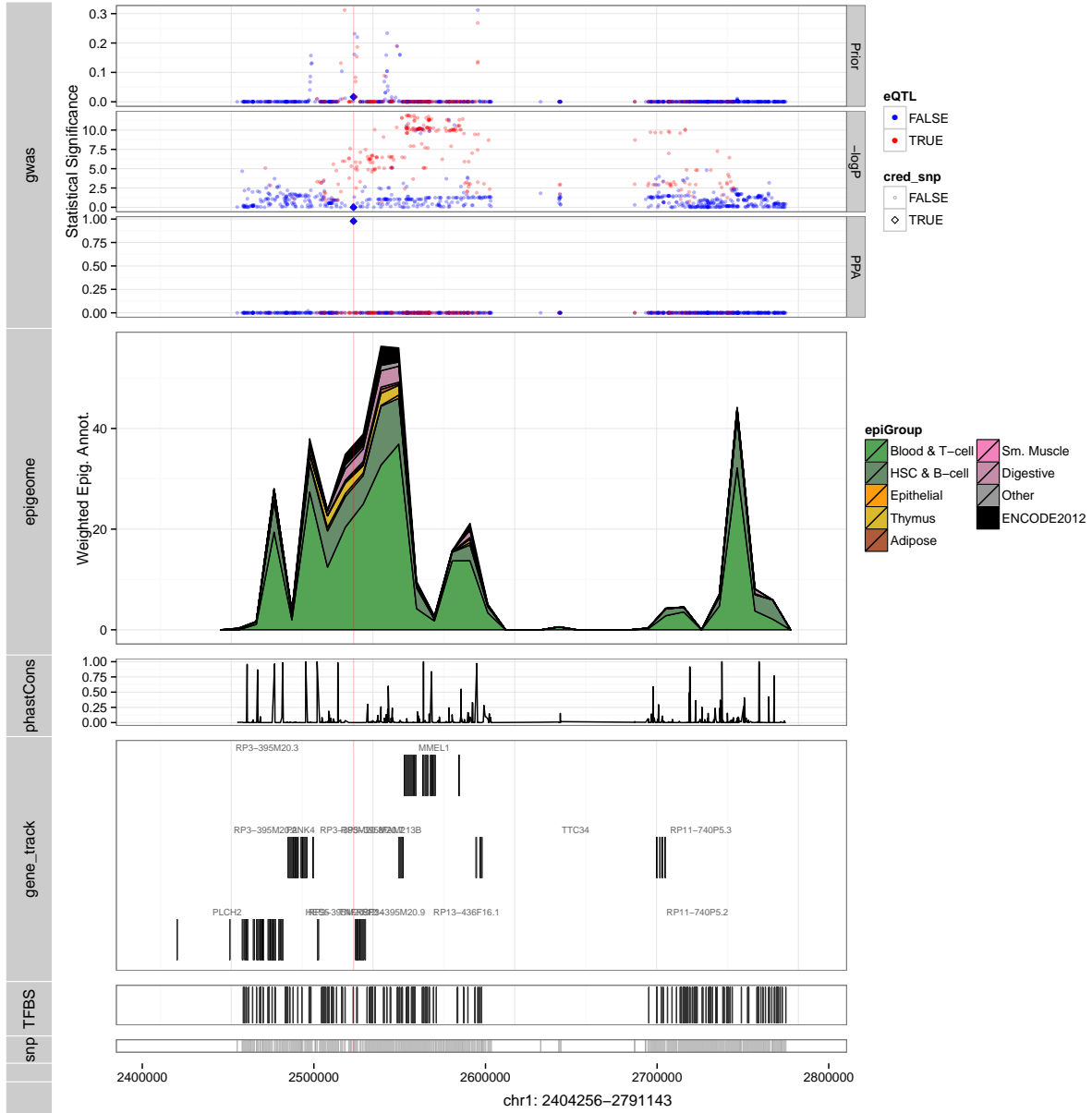
Multiple Sclerosis



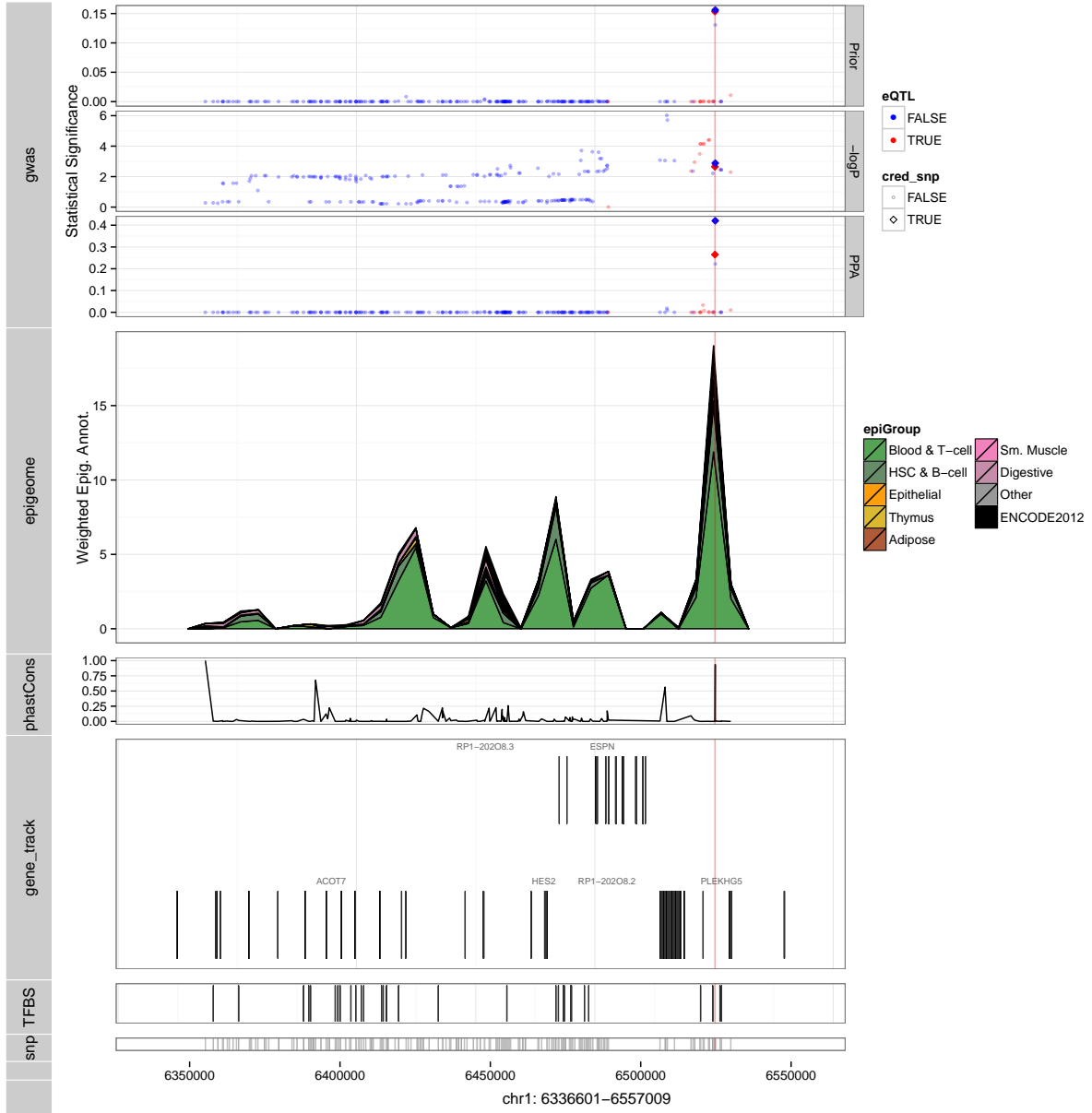
Multiple Sclerosis



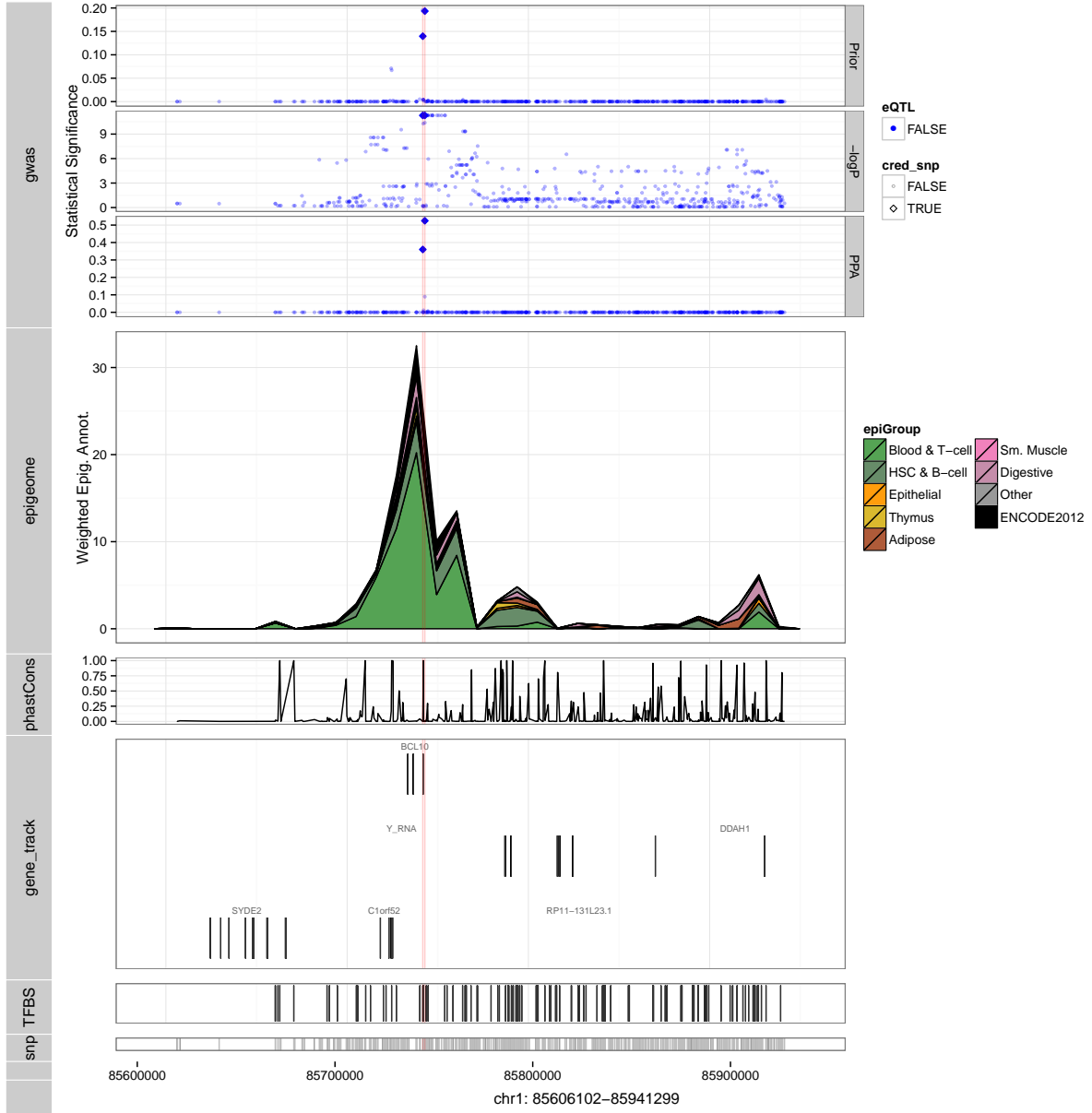
Multiple Sclerosis



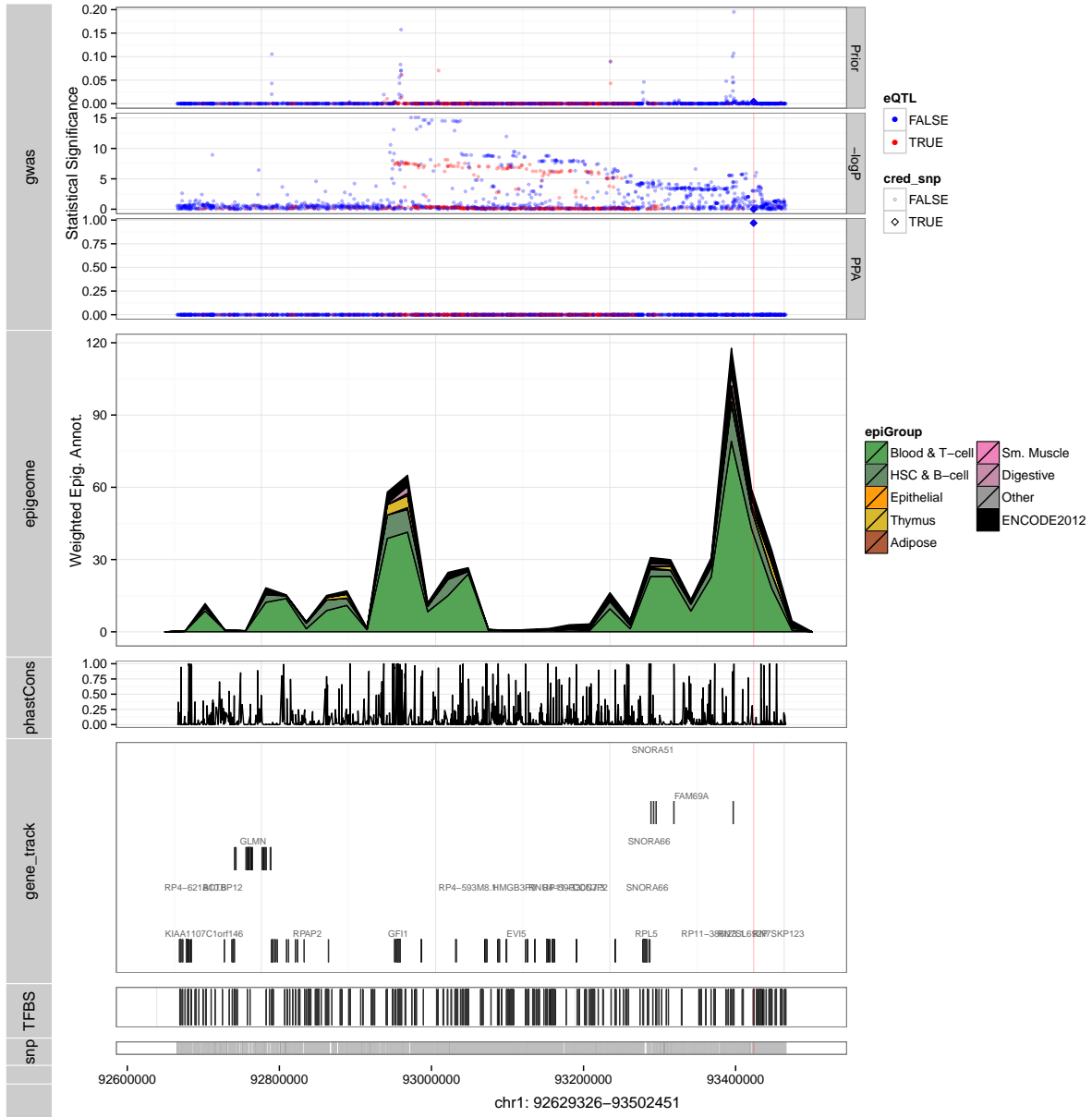
Multiple Sclerosis



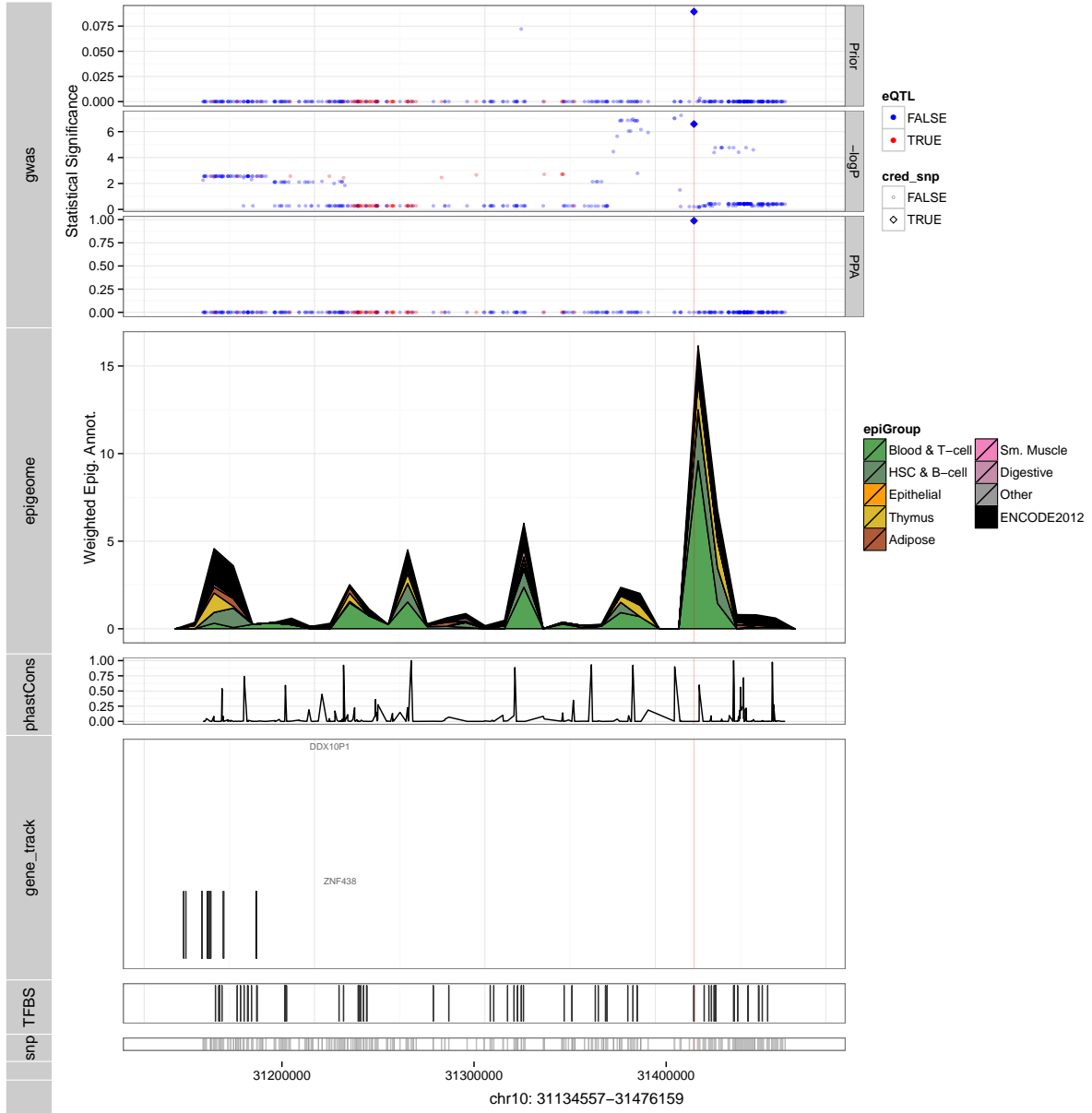
Multiple Sclerosis



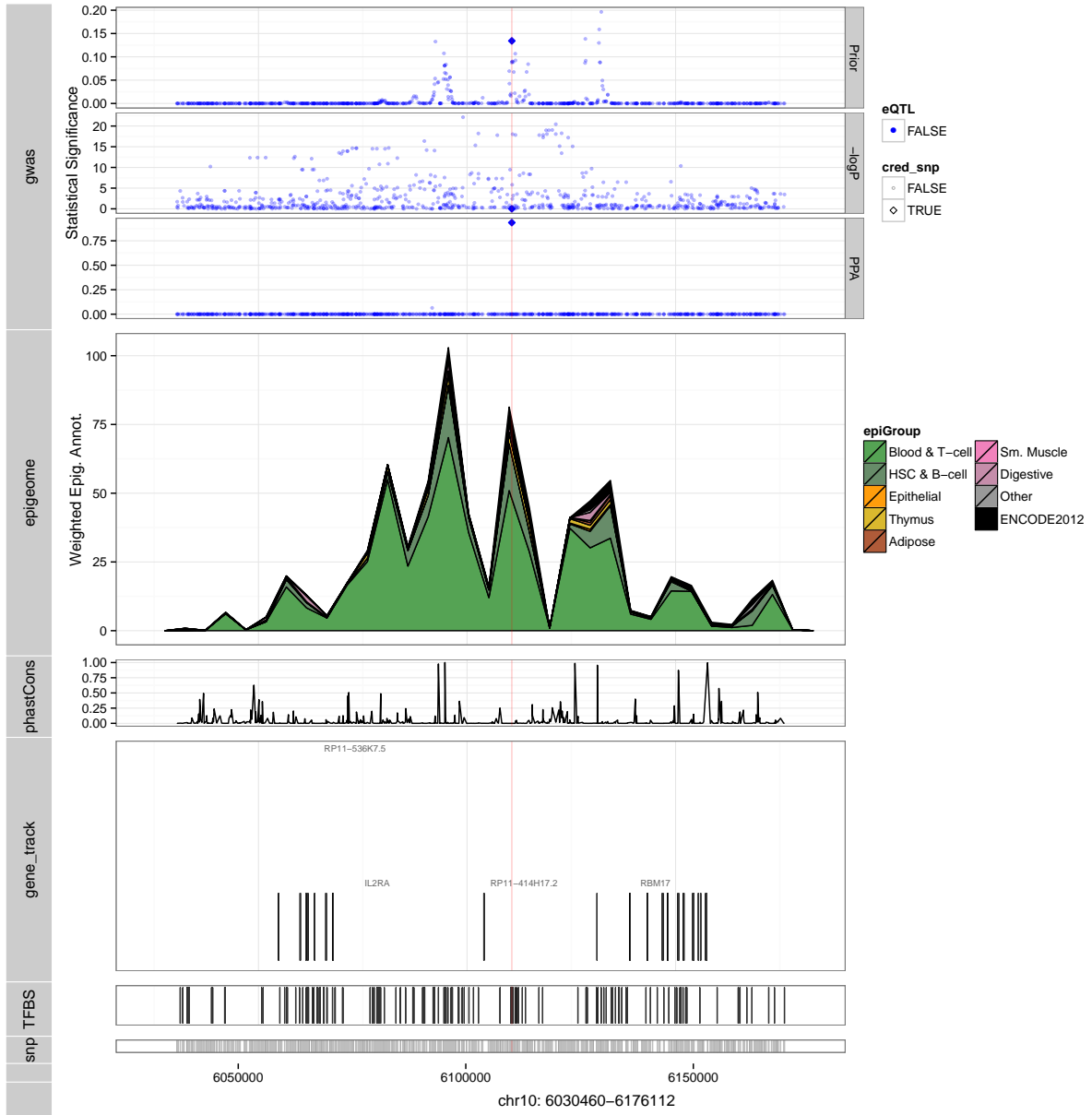
Multiple Sclerosis



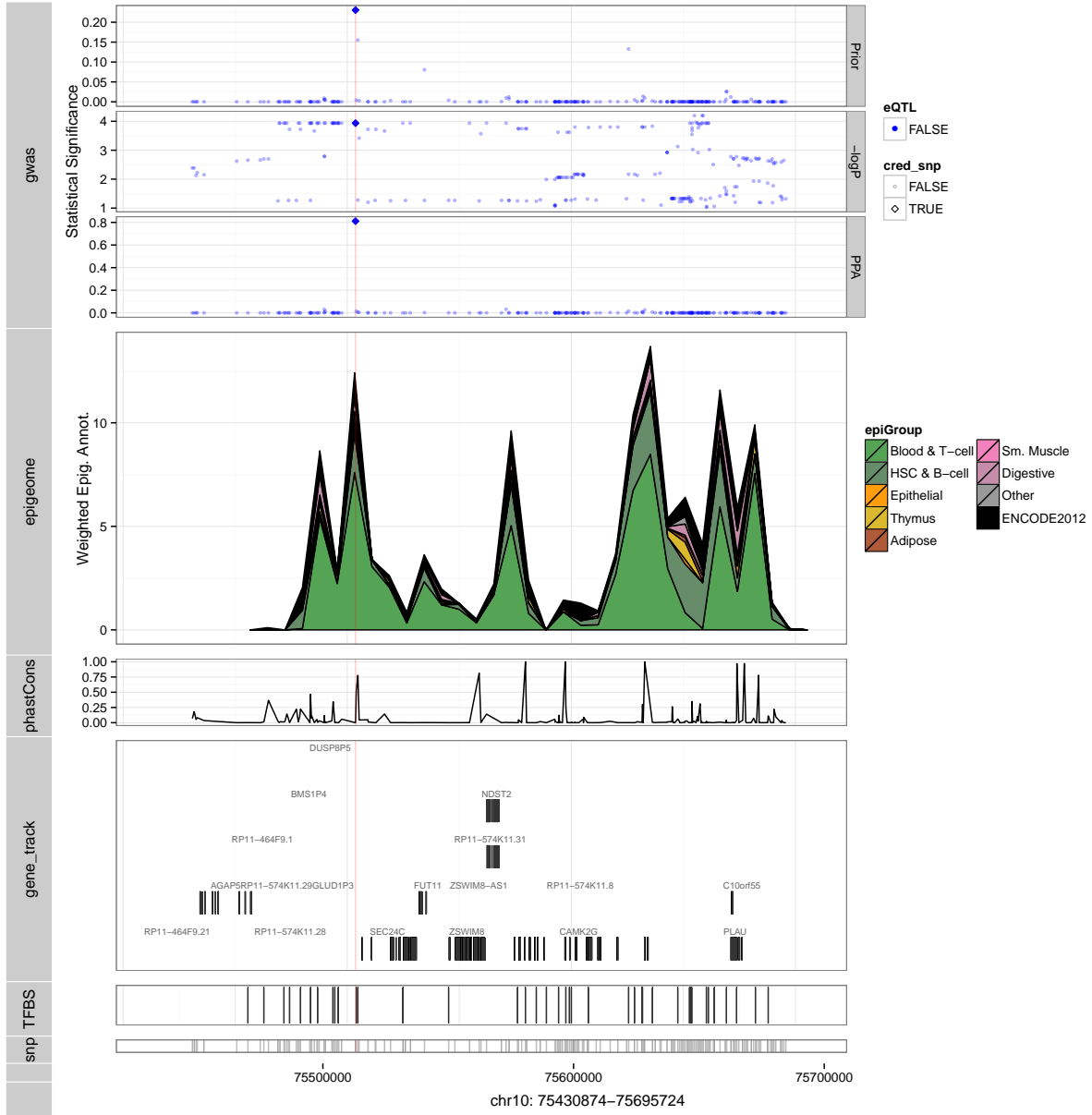
Multiple Sclerosis



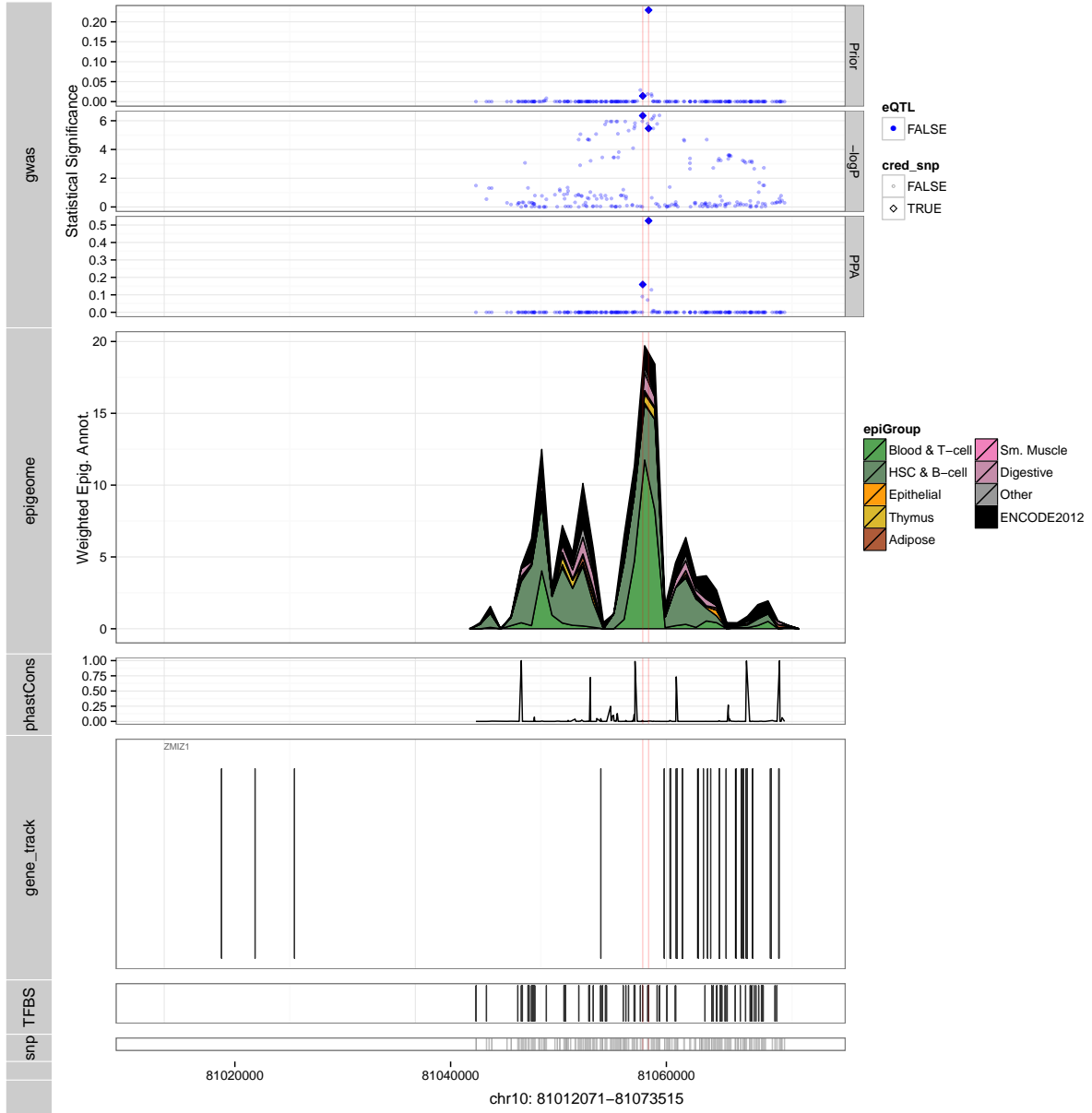
Multiple Sclerosis



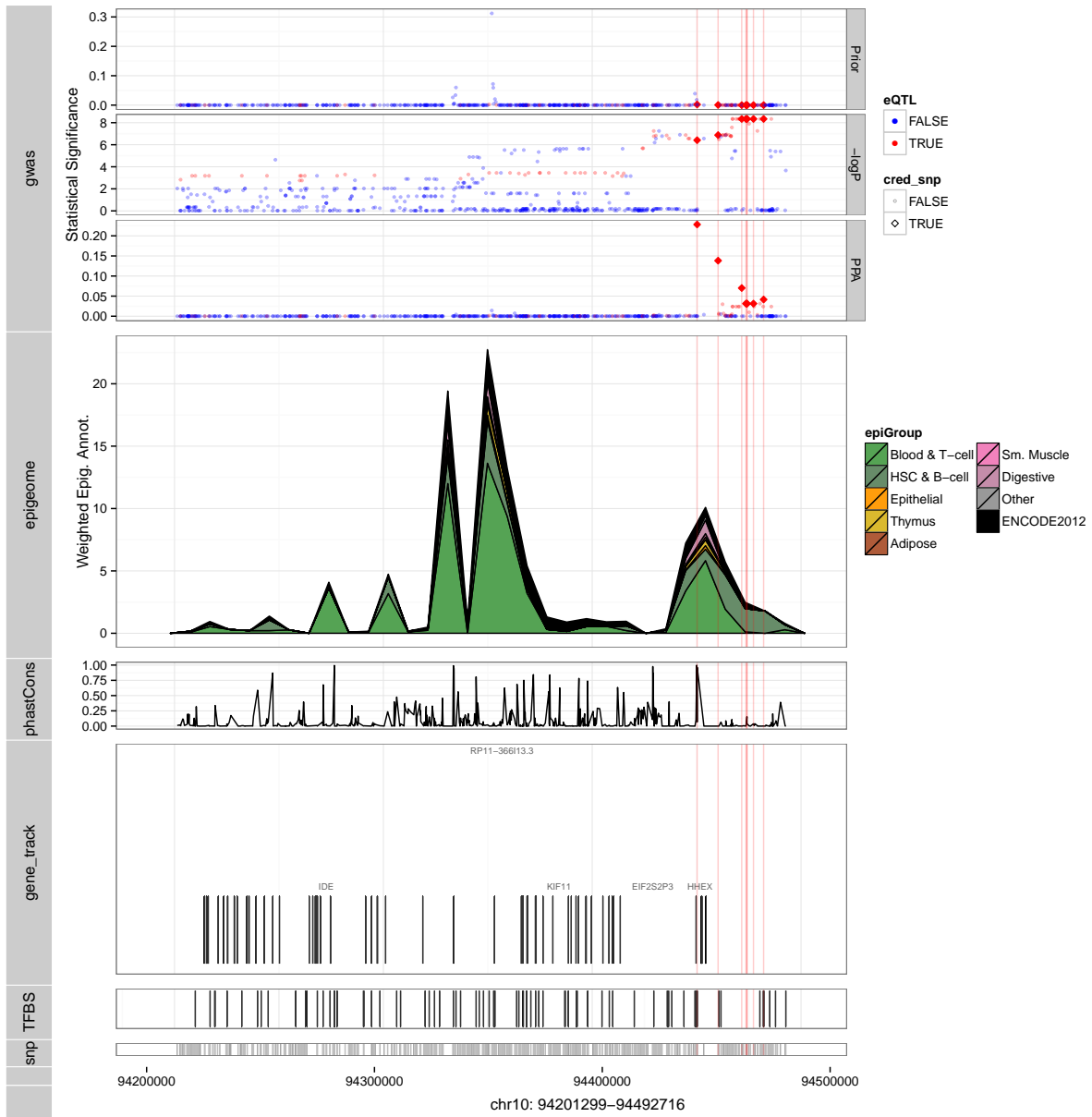
Multiple Sclerosis



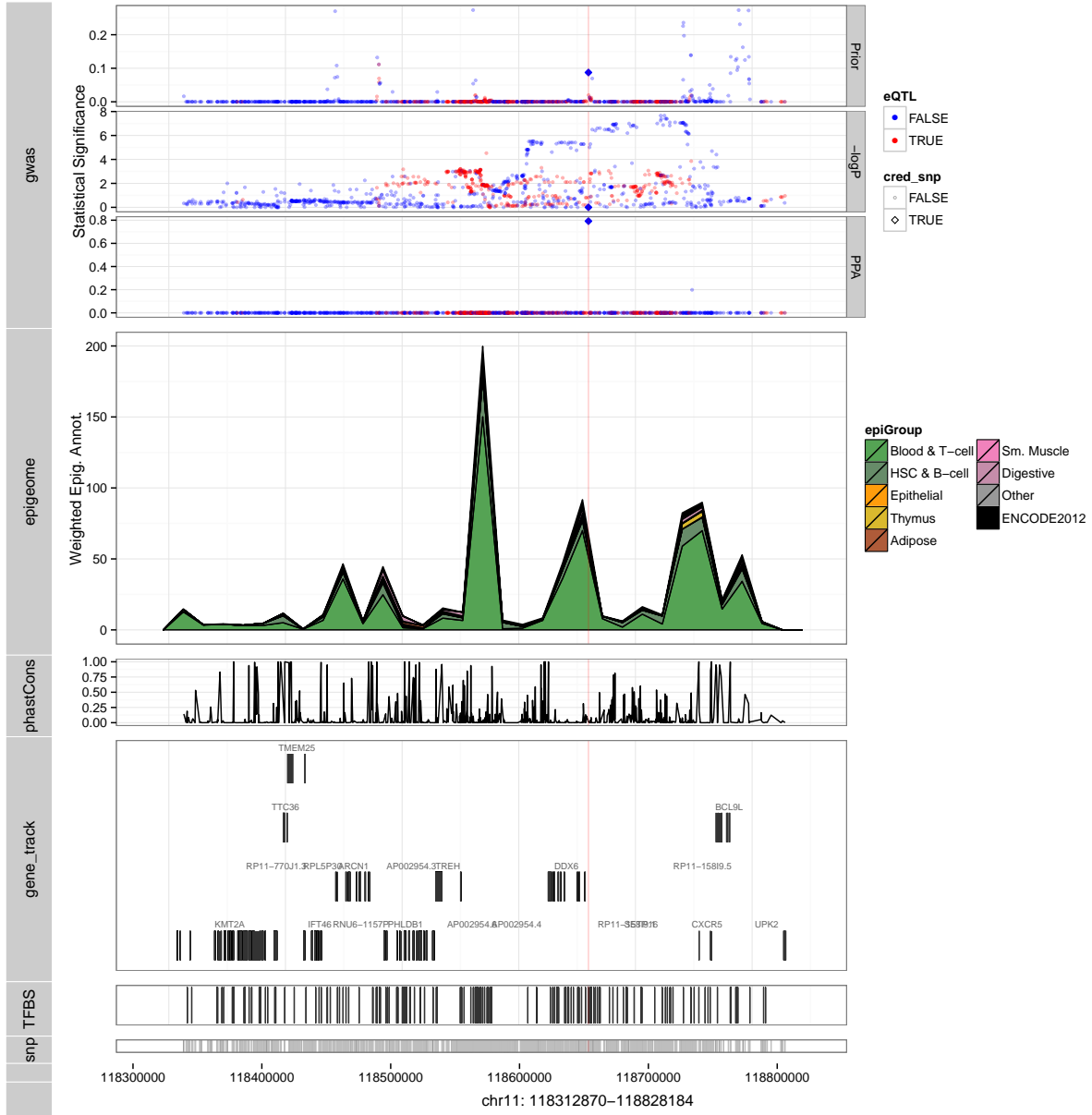
Multiple Sclerosis



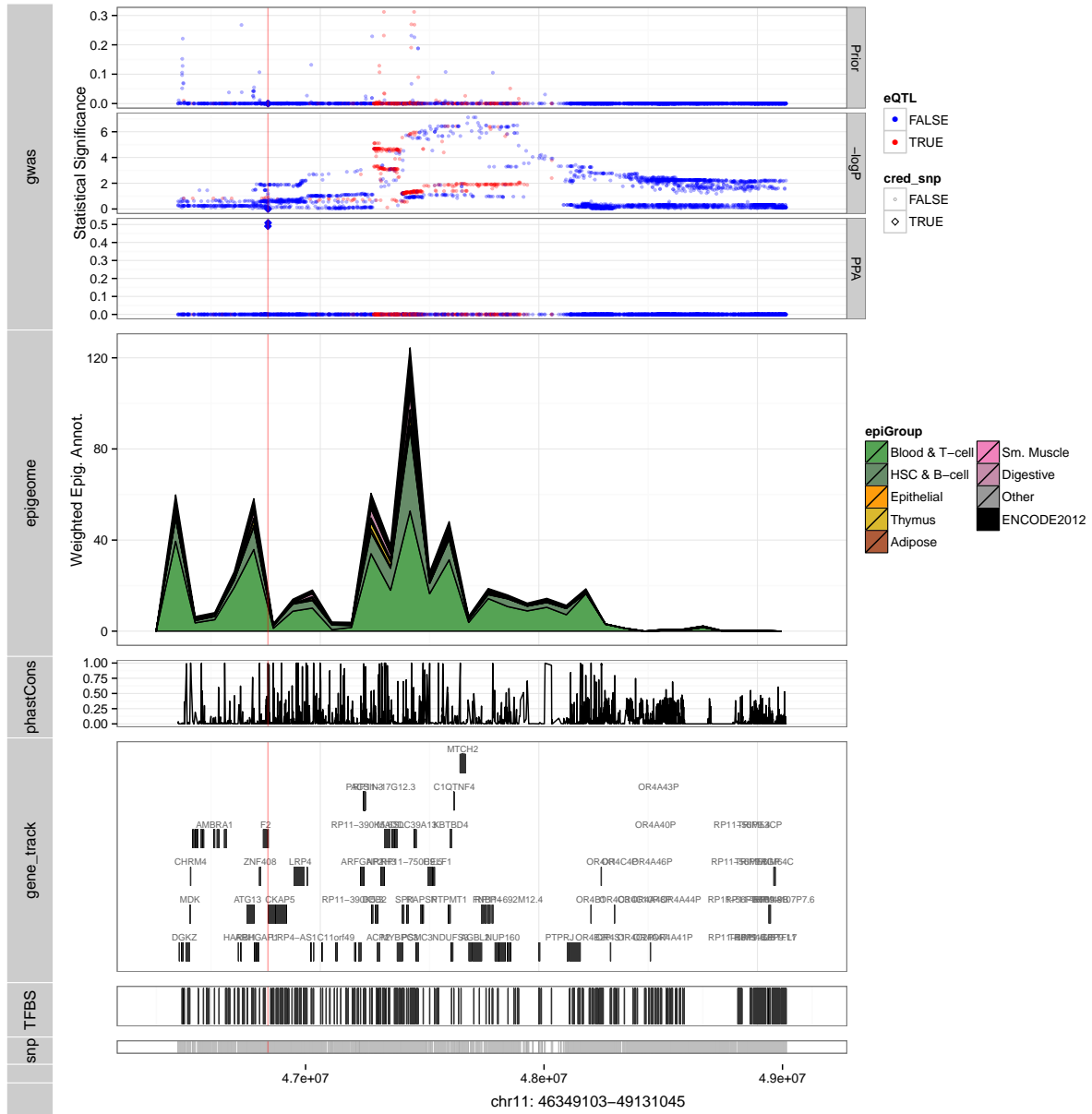
Multiple Sclerosis



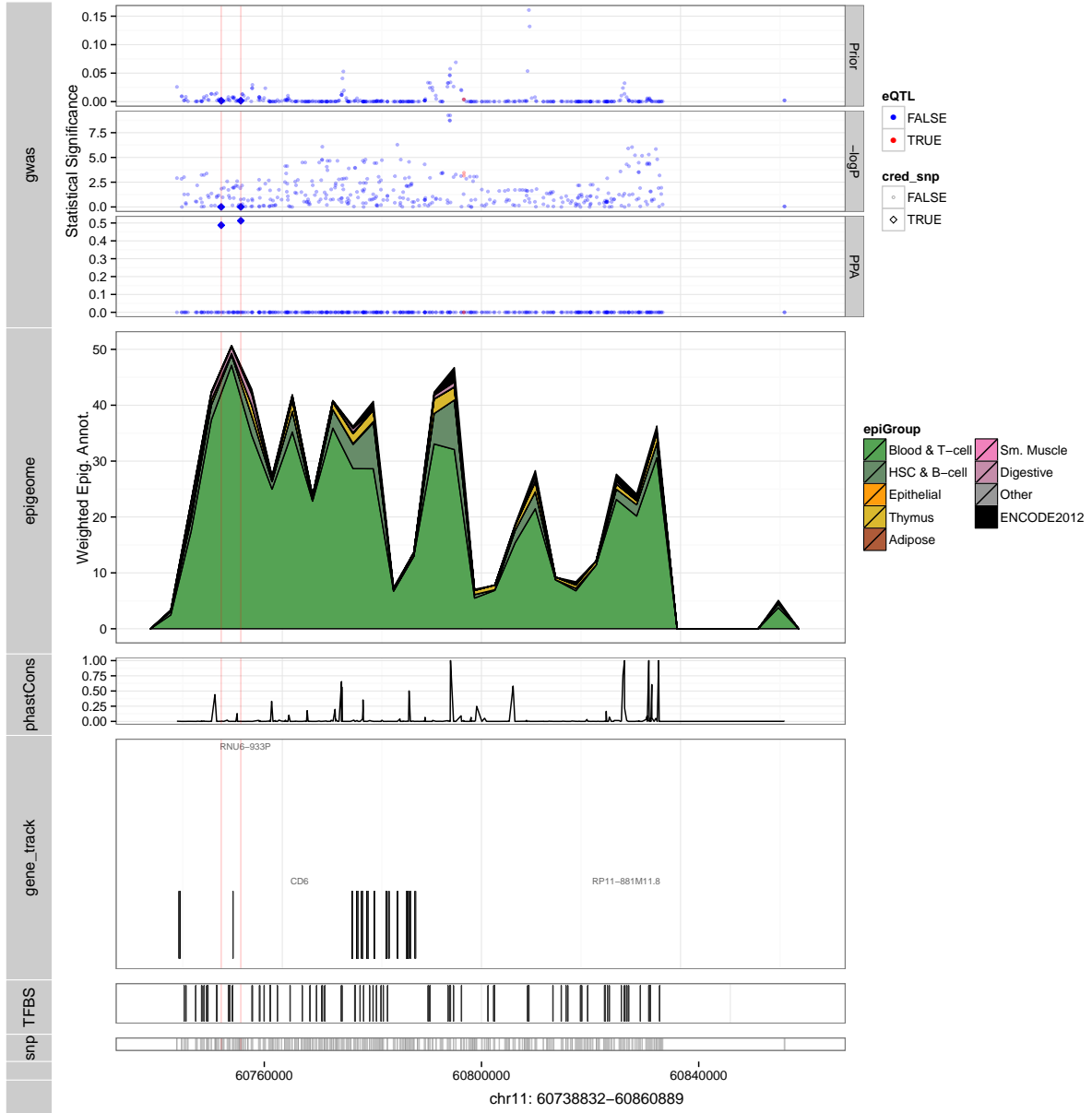
Multiple Sclerosis



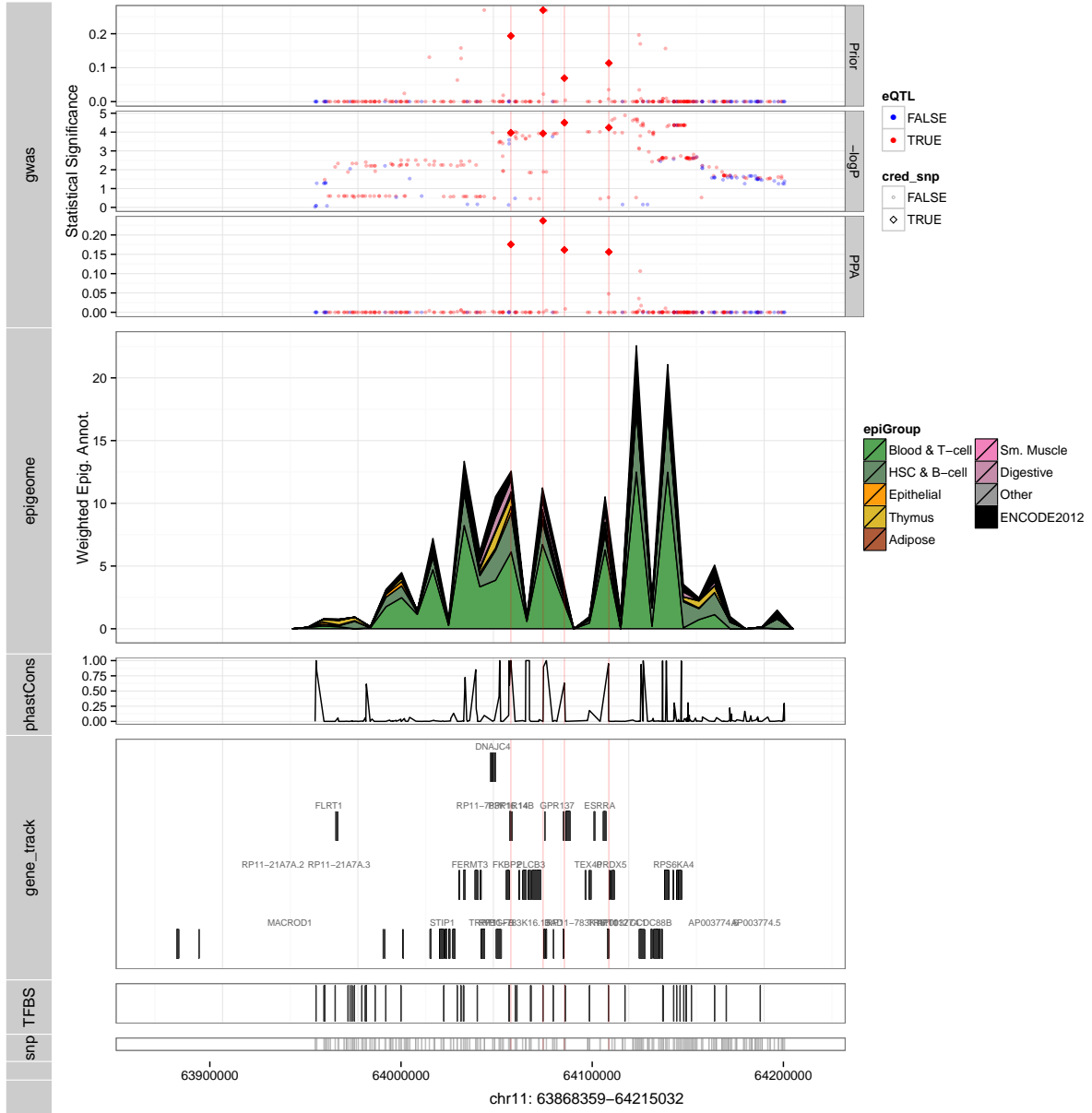
Multiple Sclerosis



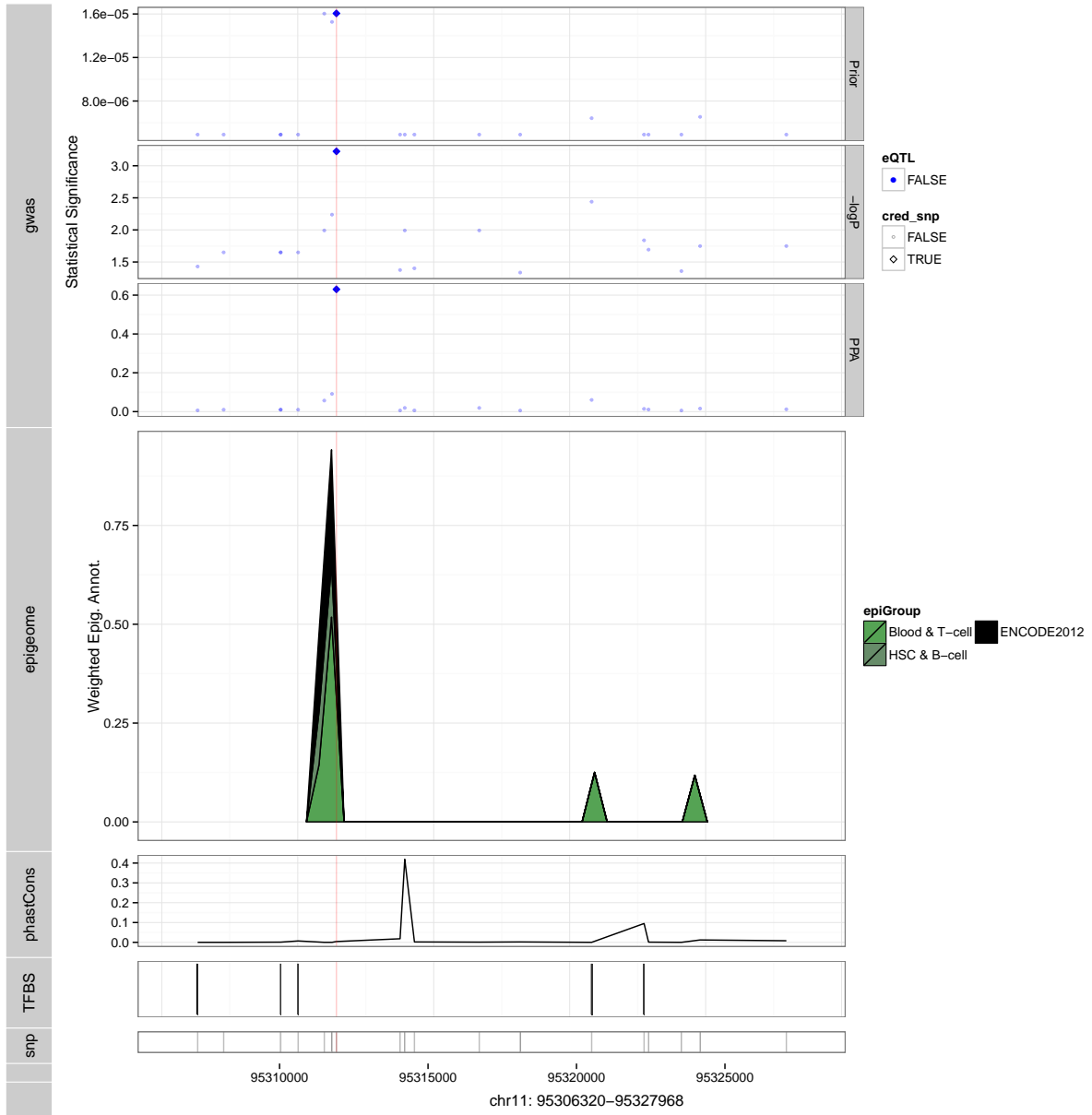
Multiple Sclerosis



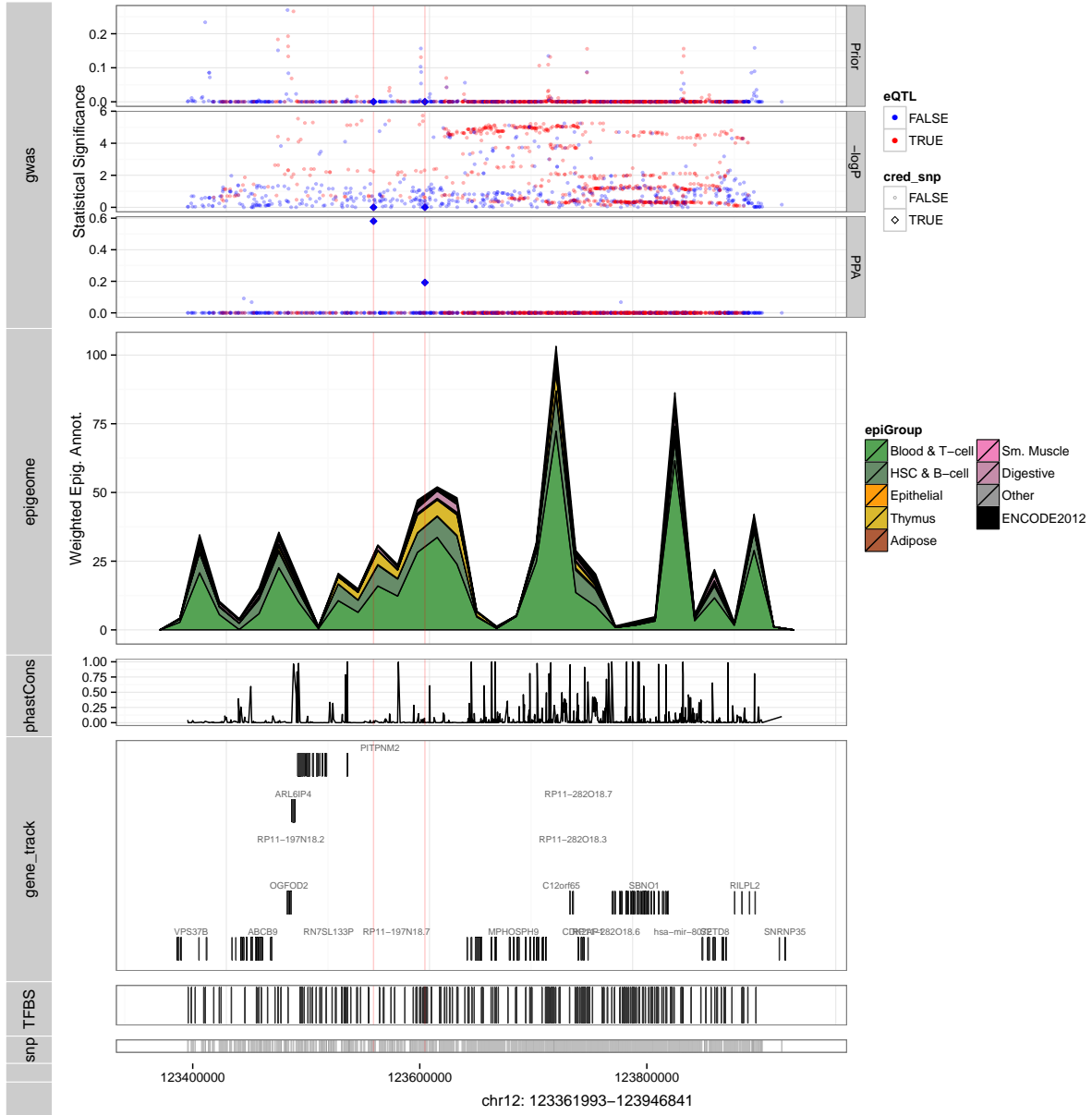
Multiple Sclerosis



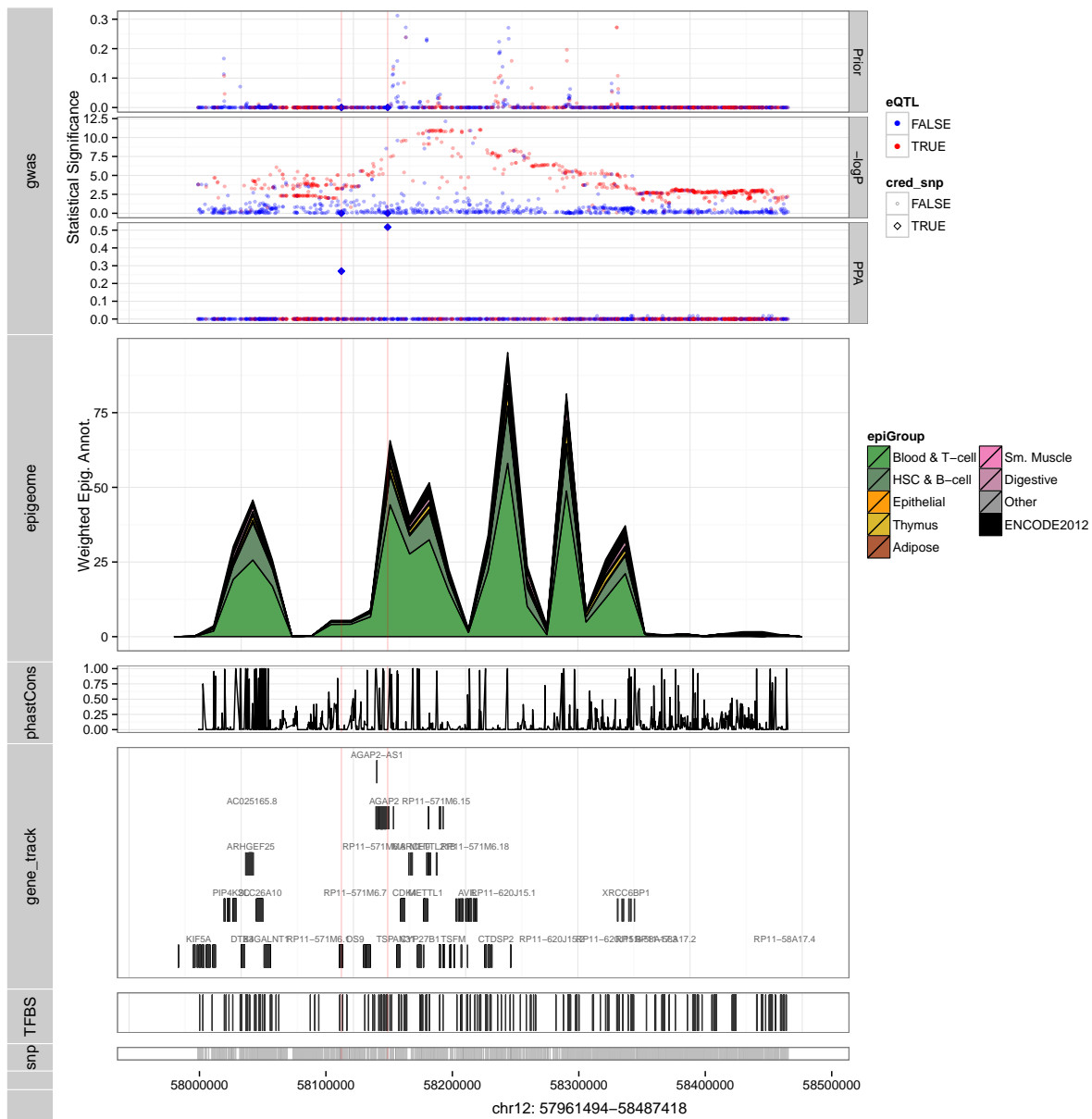
Multiple Sclerosis



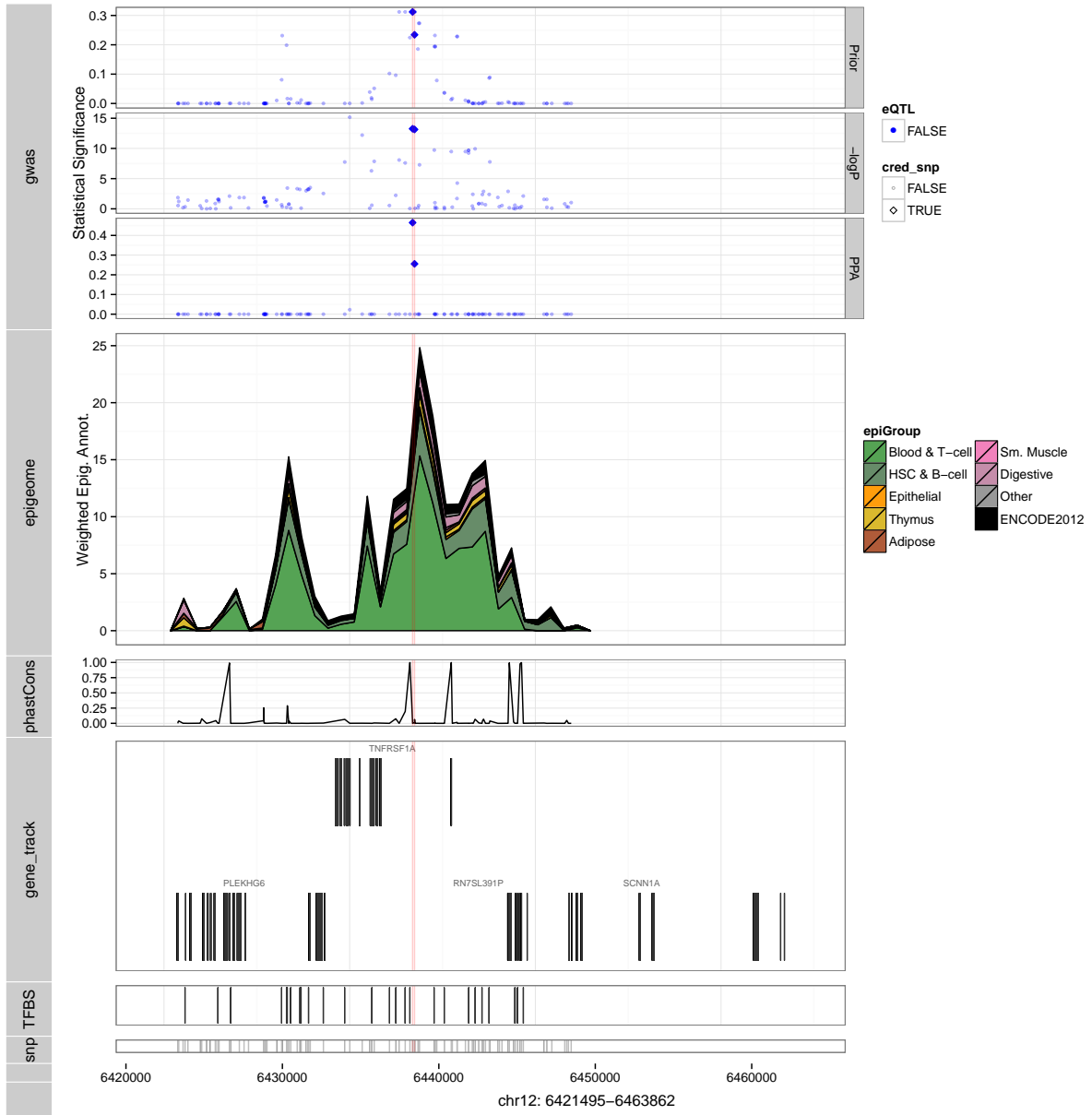
Multiple Sclerosis



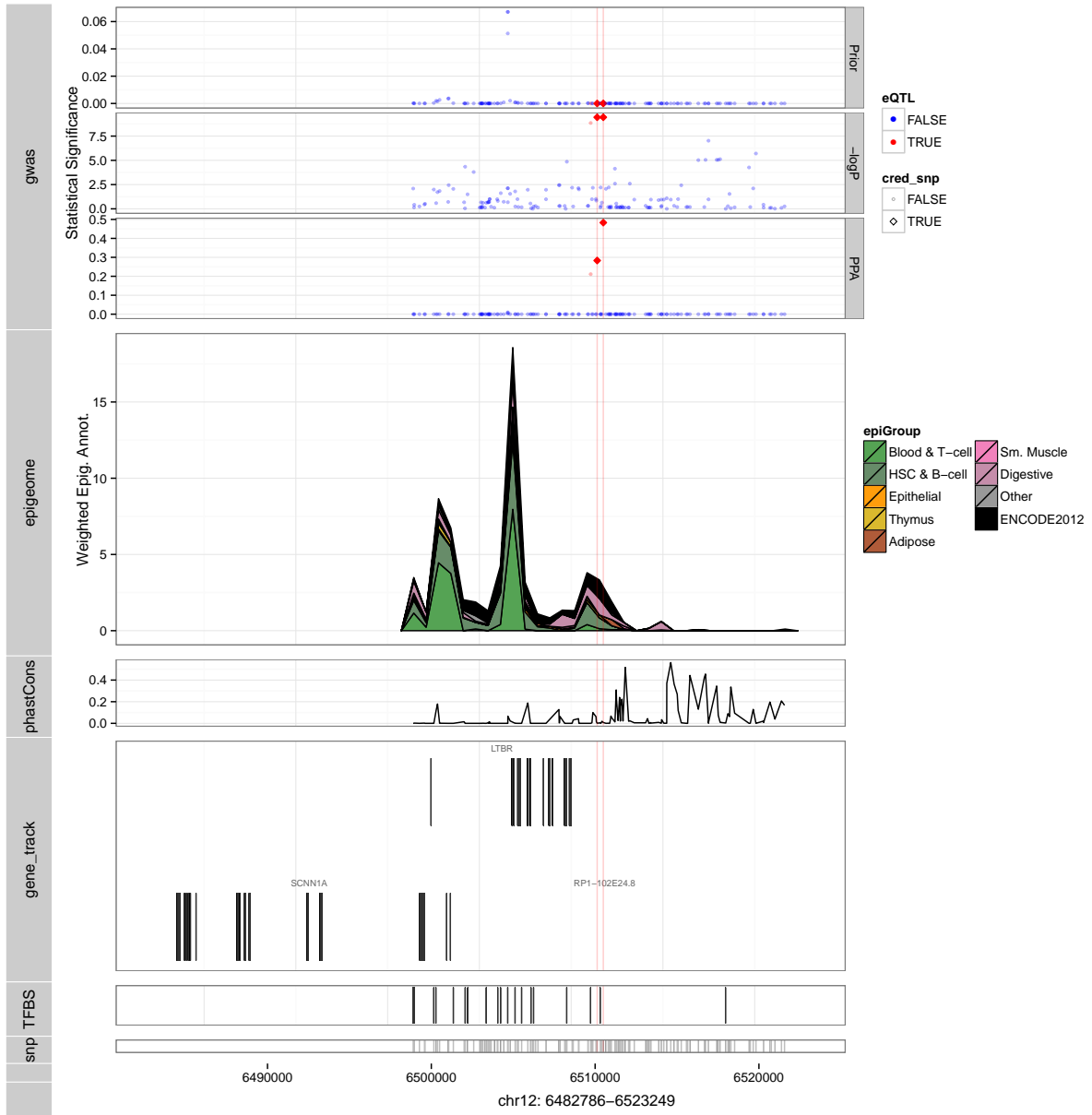
Multiple Sclerosis



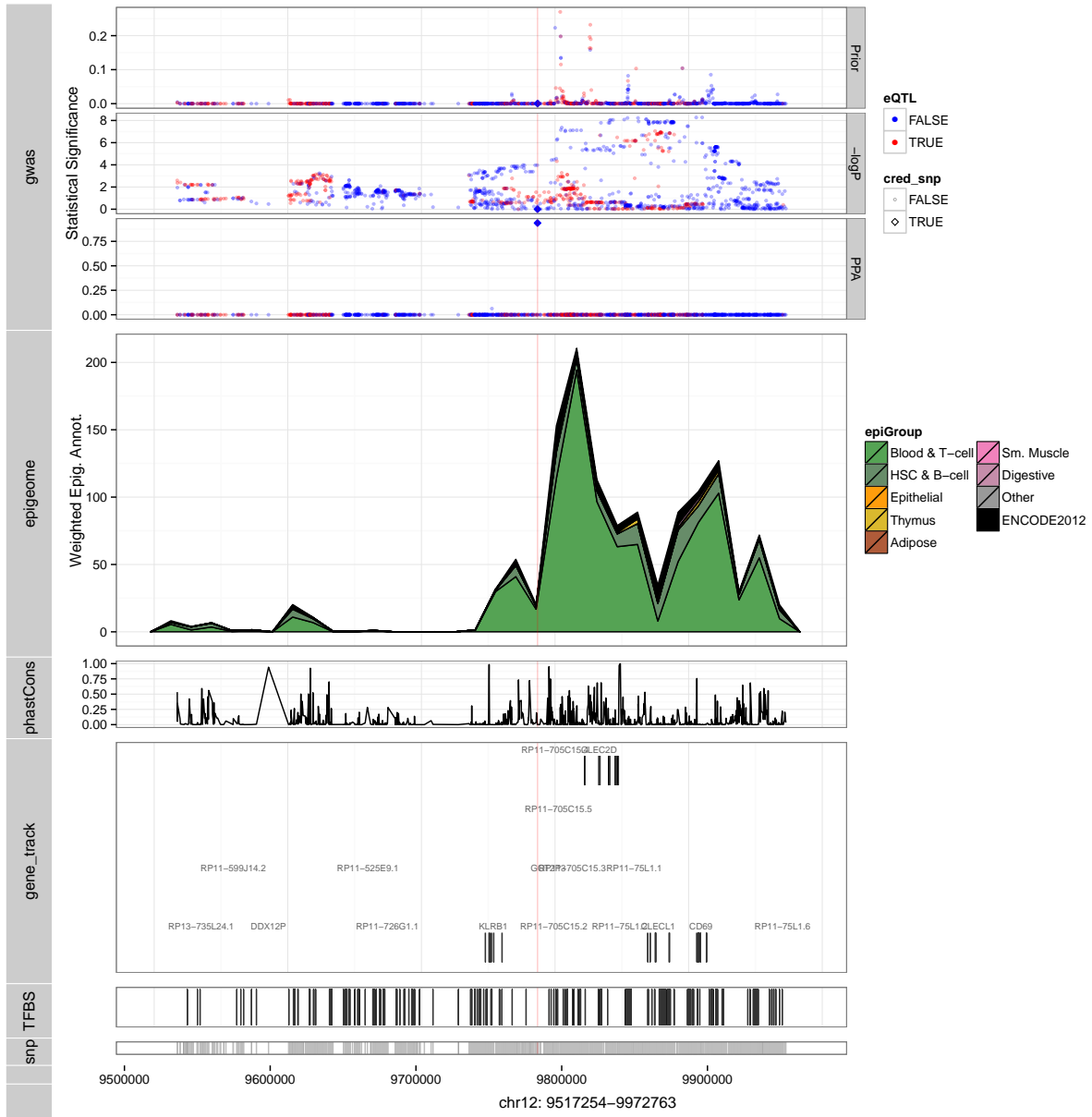
Multiple Sclerosis



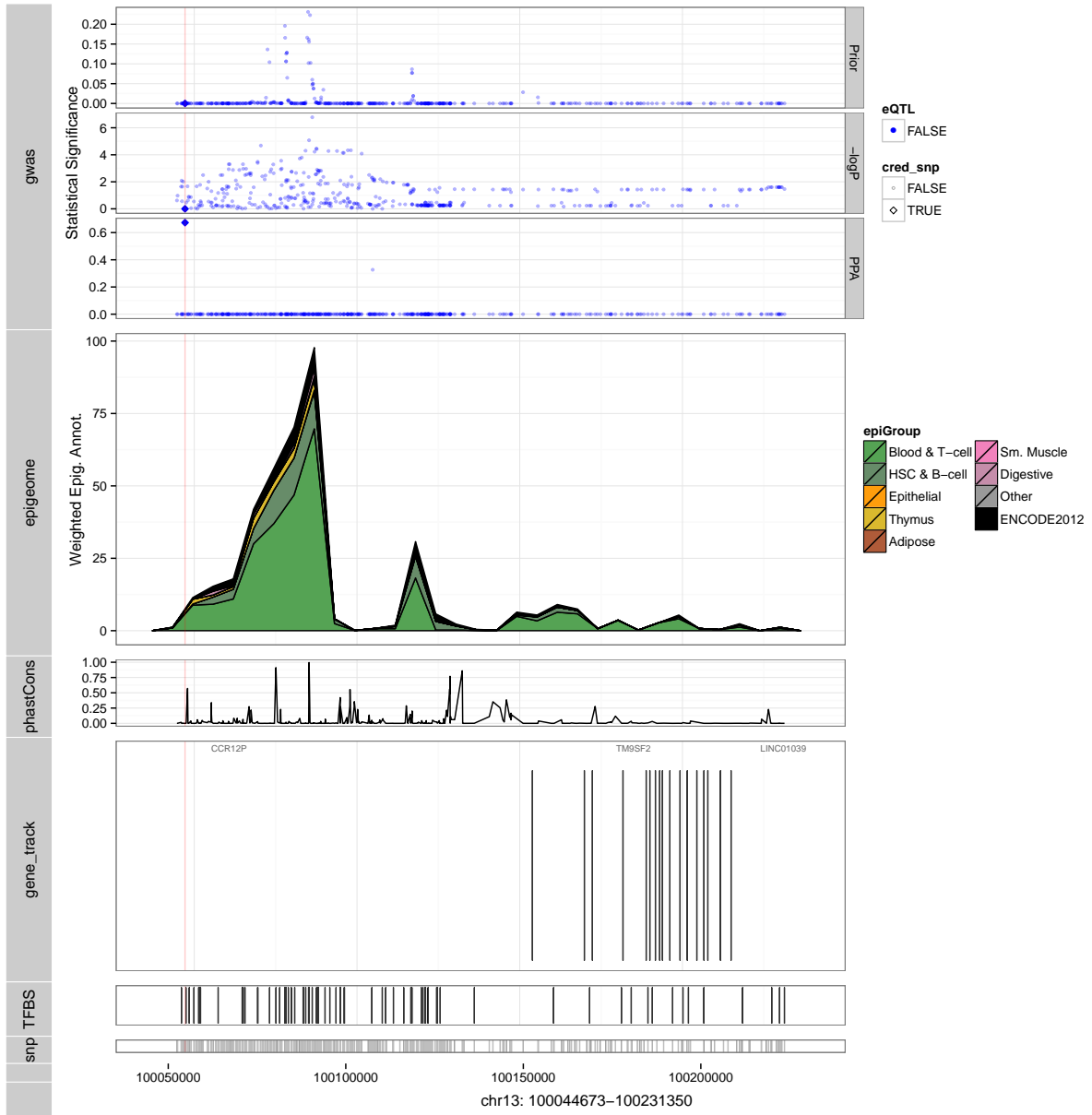
Multiple Sclerosis



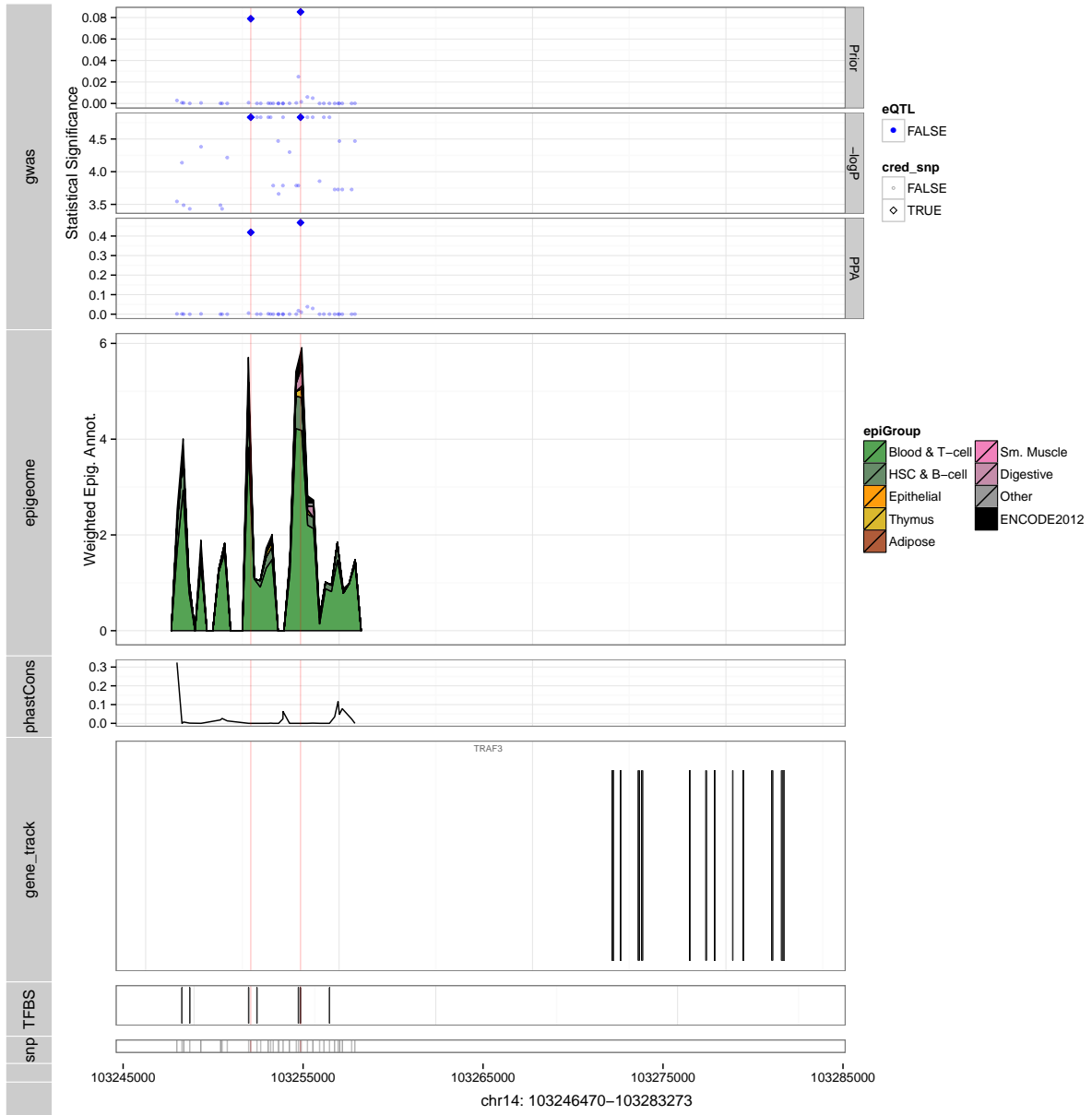
Multiple Sclerosis



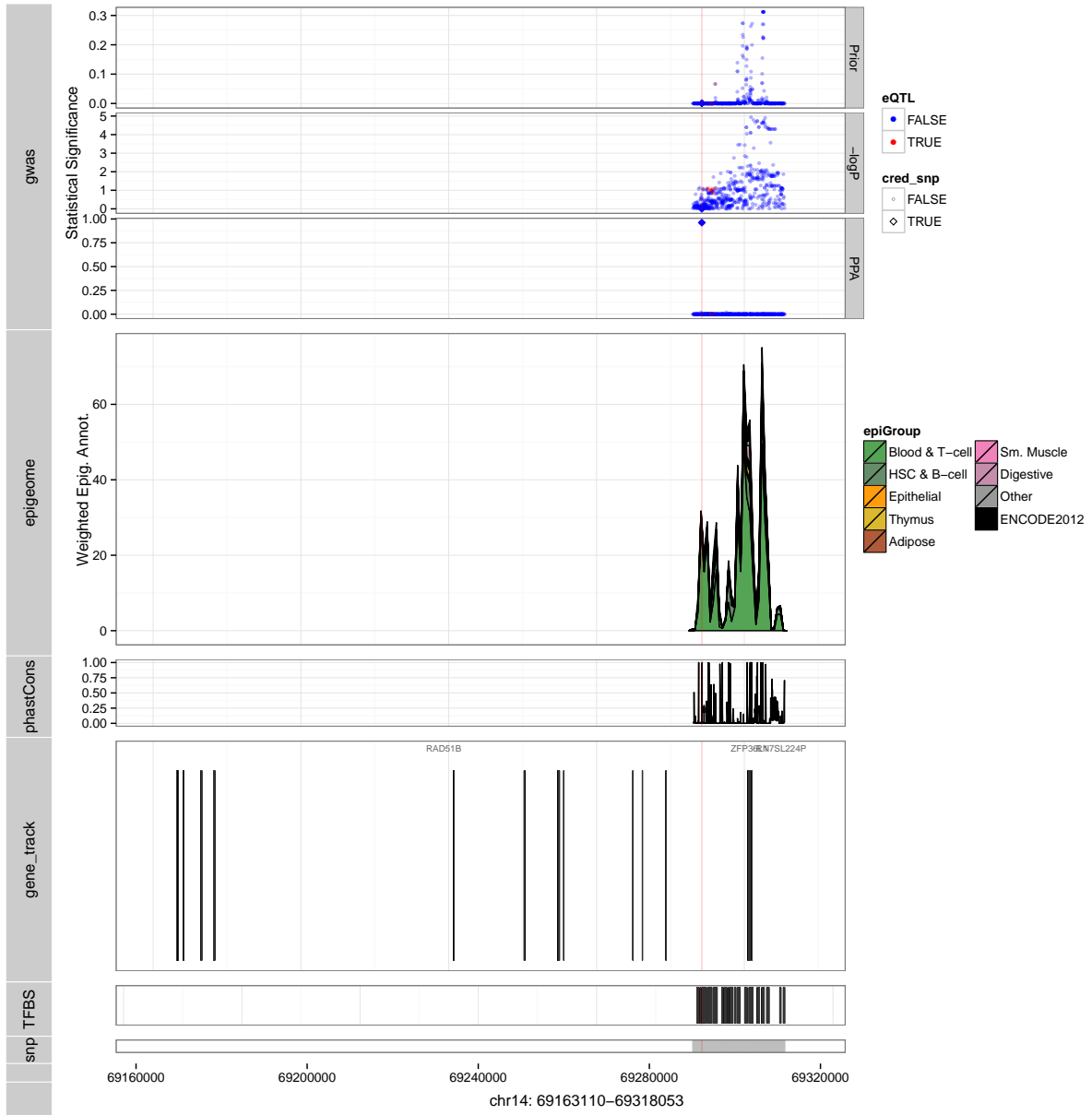
Multiple Sclerosis



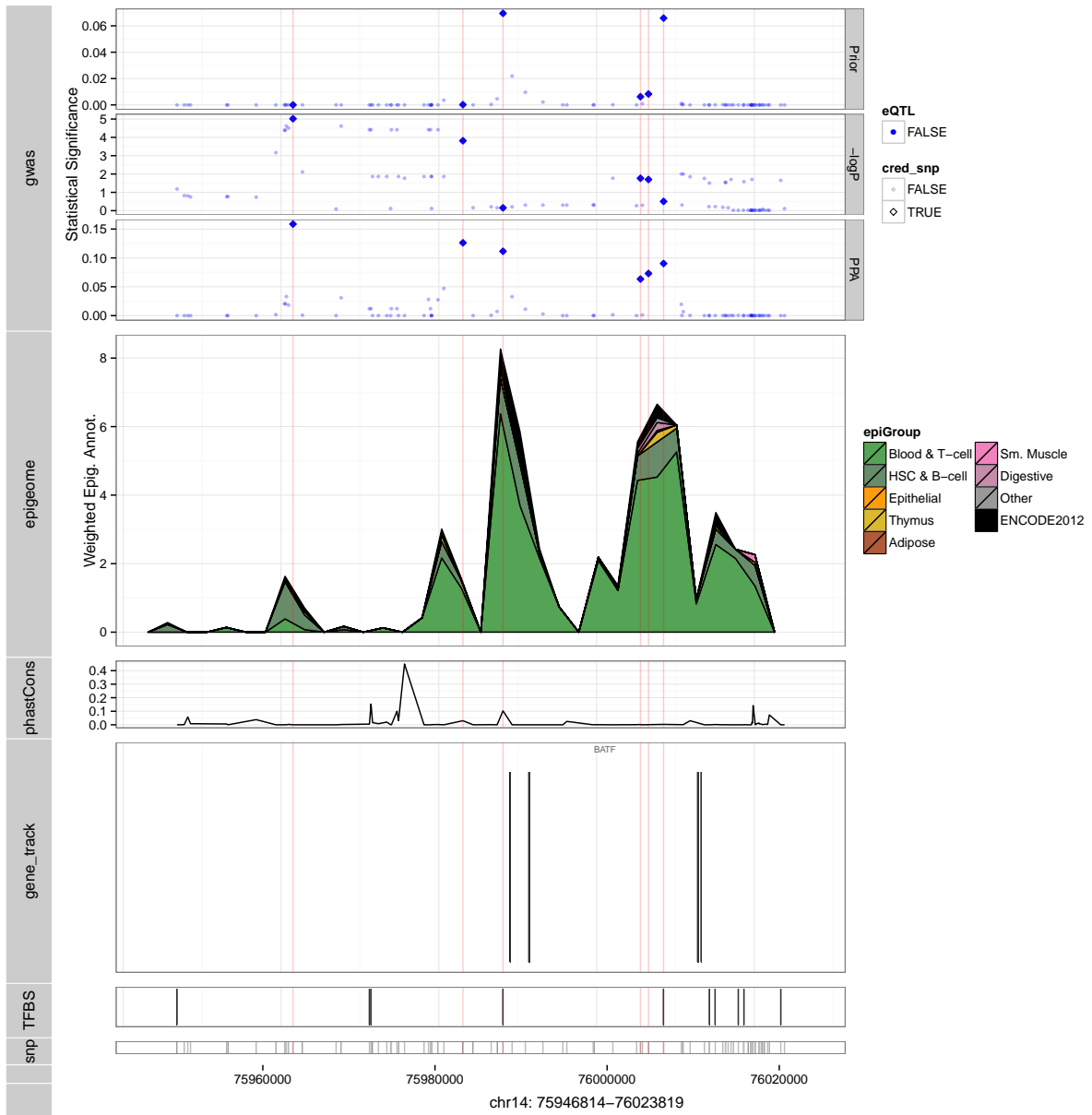
Multiple Sclerosis



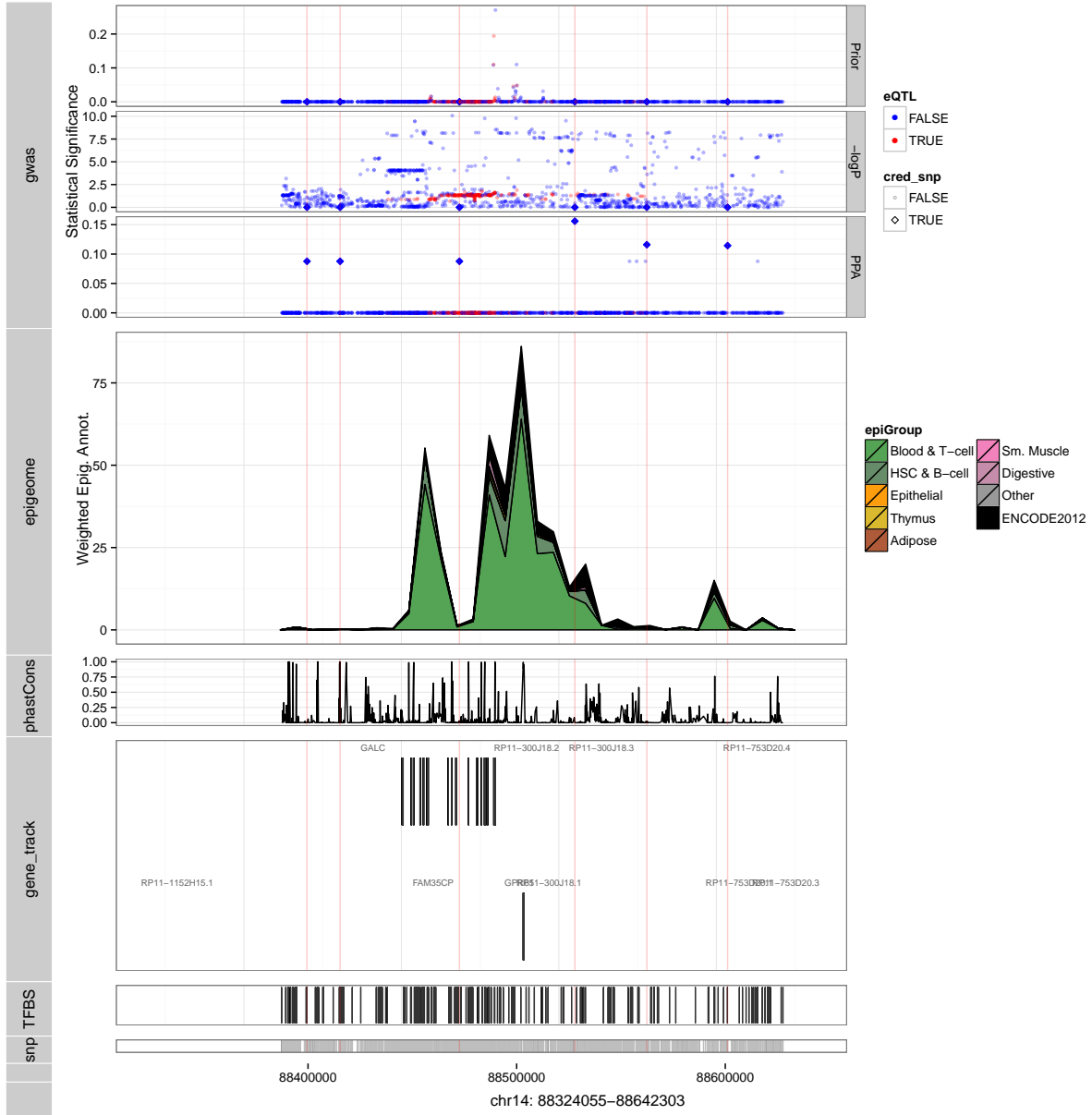
Multiple Sclerosis



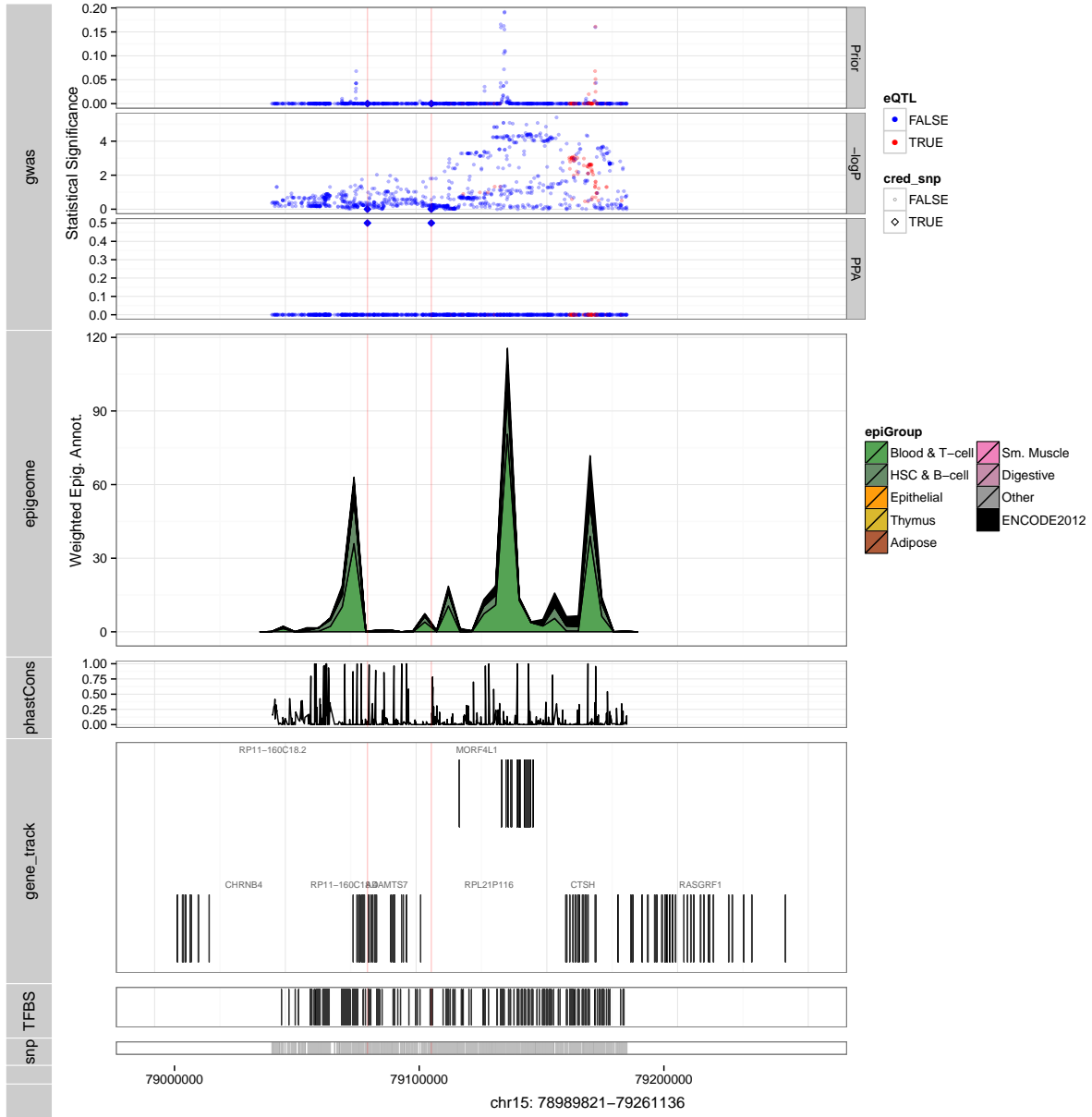
Multiple Sclerosis



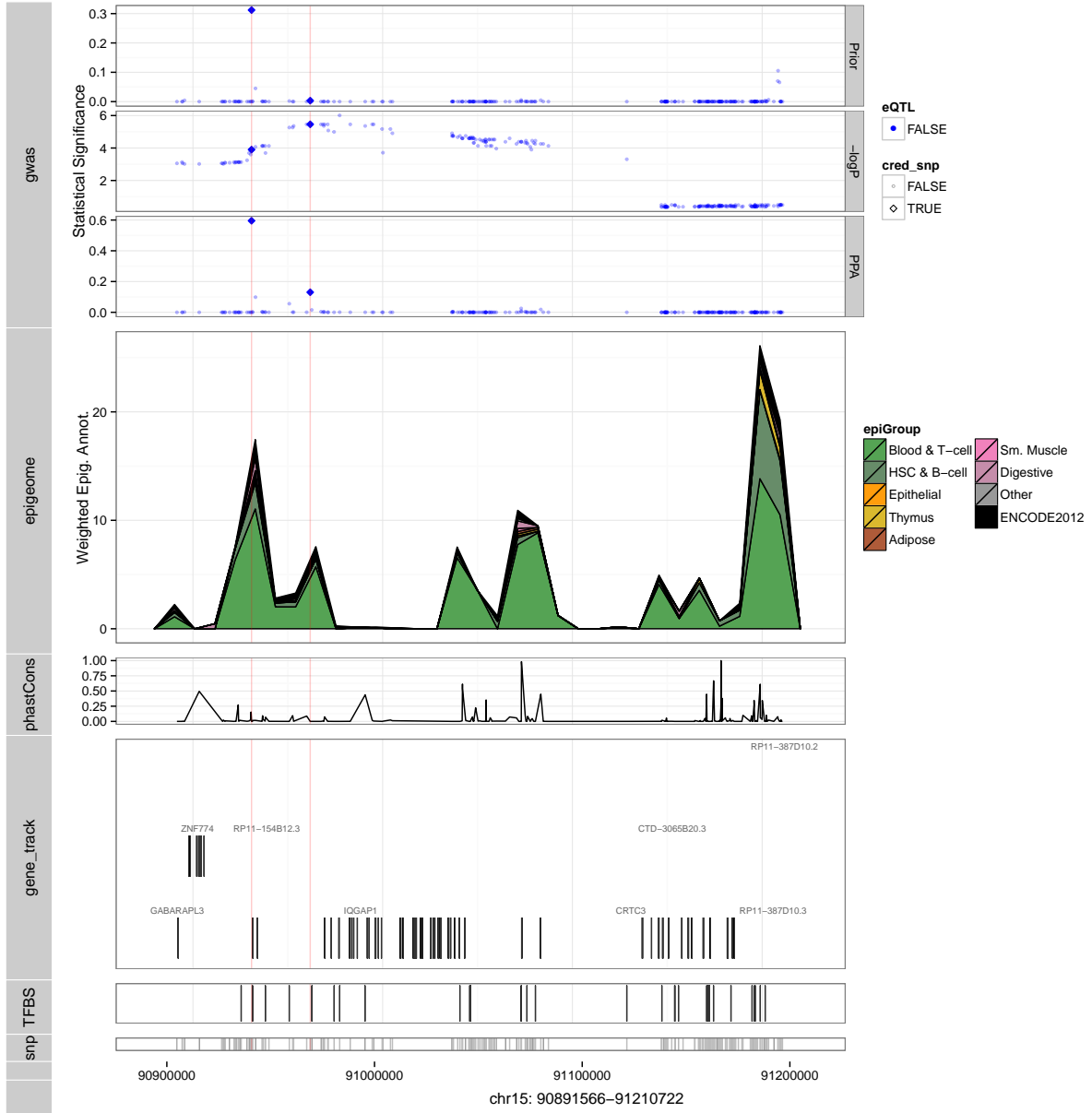
Multiple Sclerosis



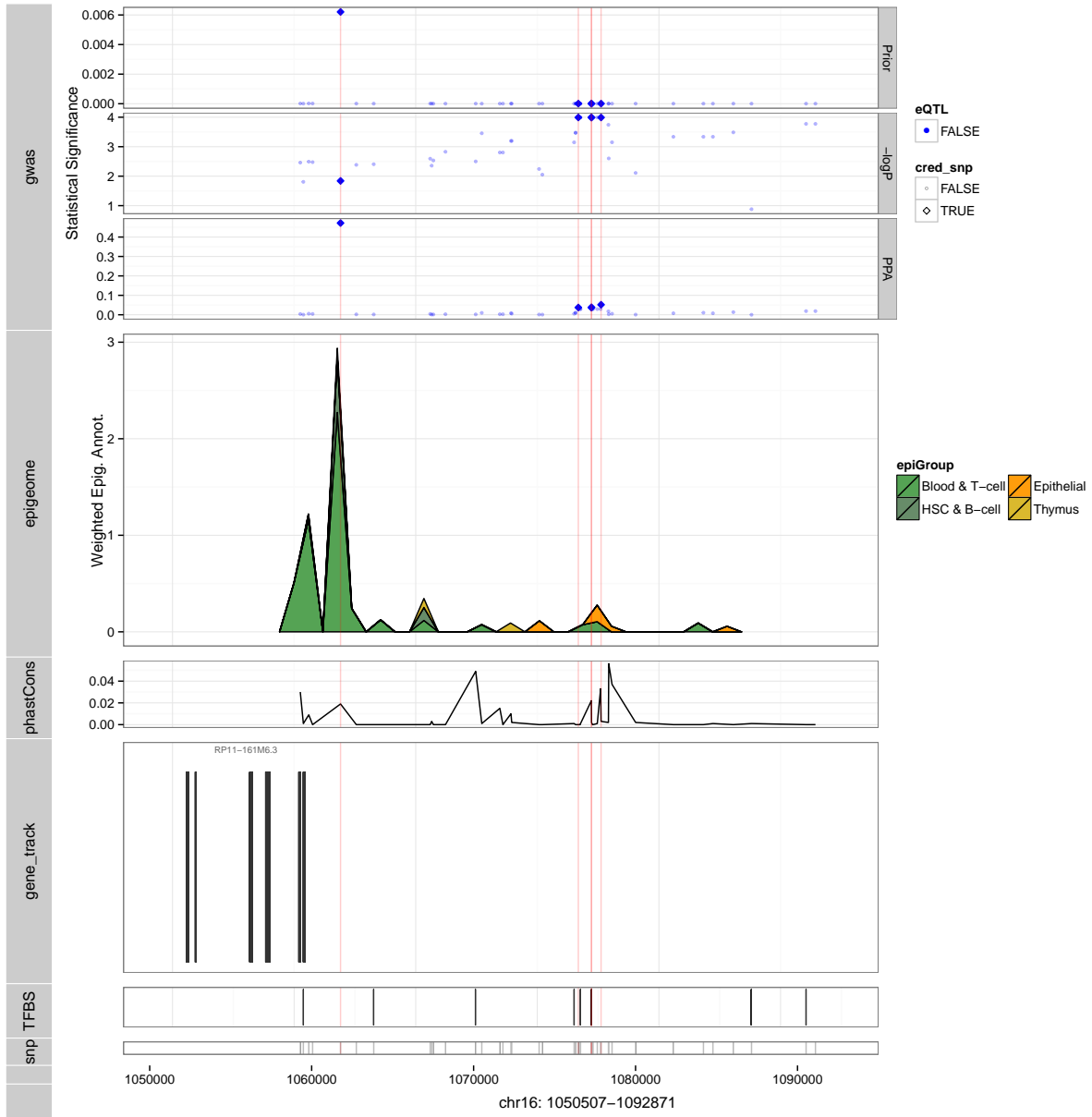
Multiple Sclerosis



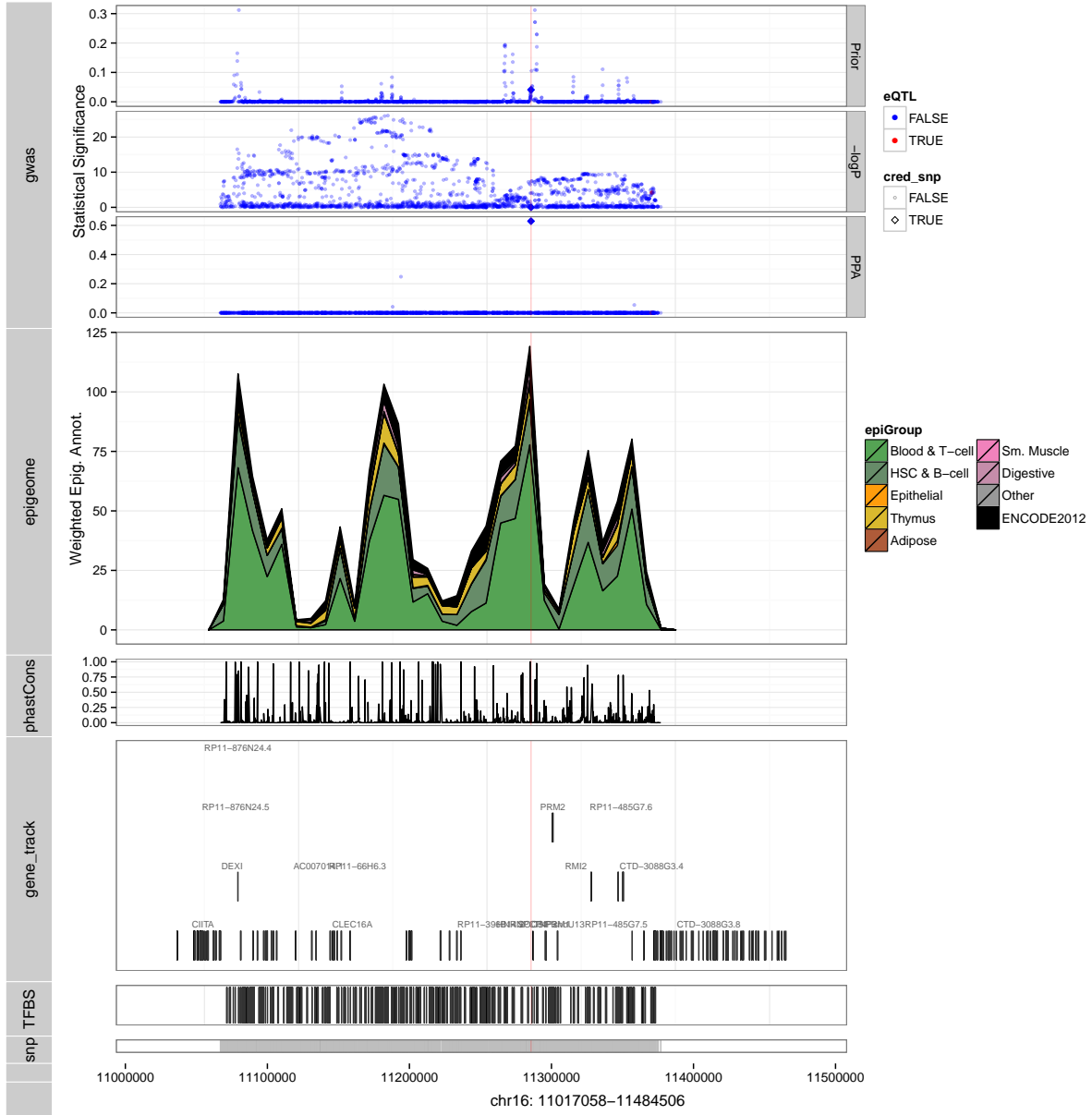
Multiple Sclerosis



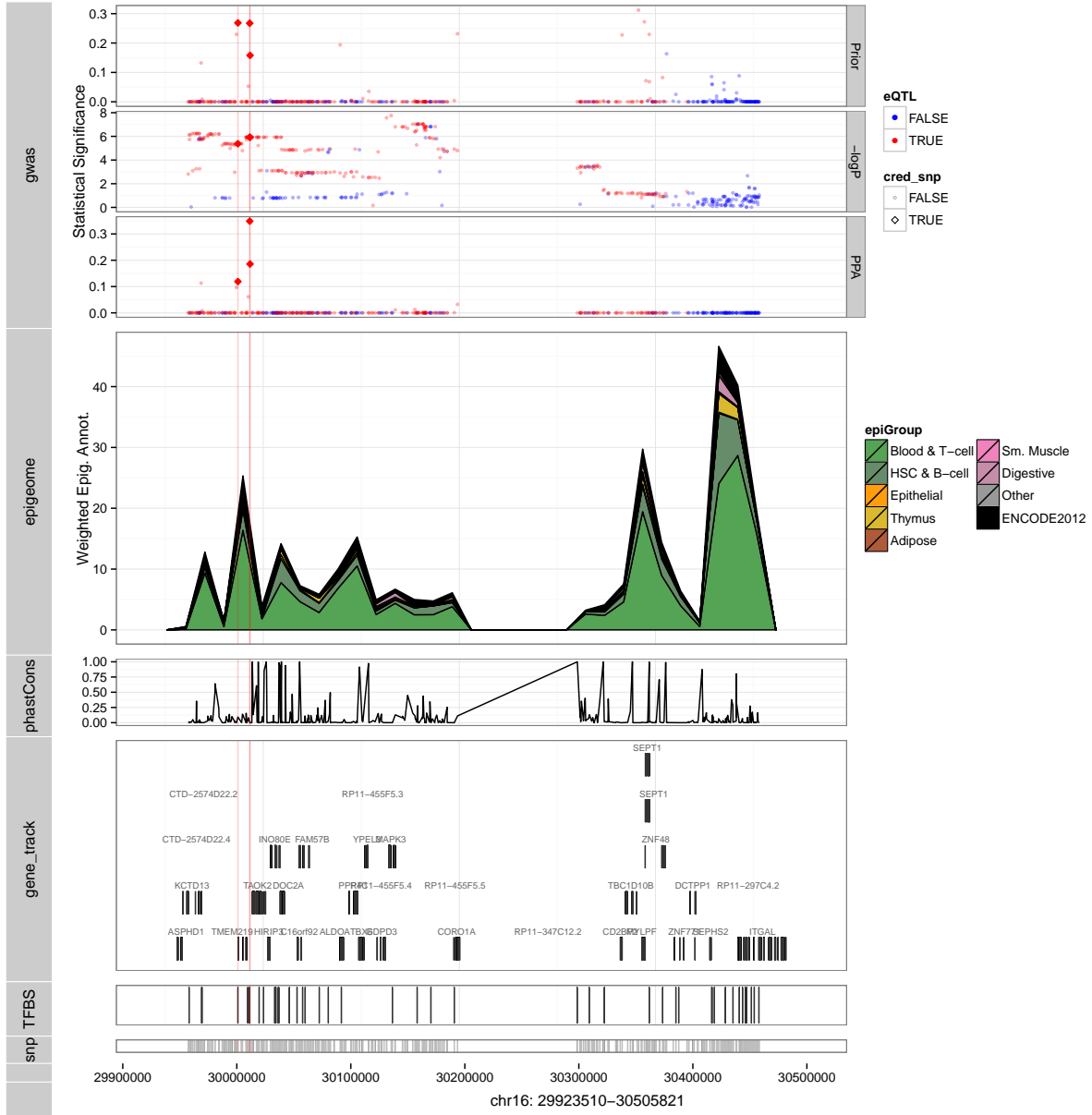
Multiple Sclerosis



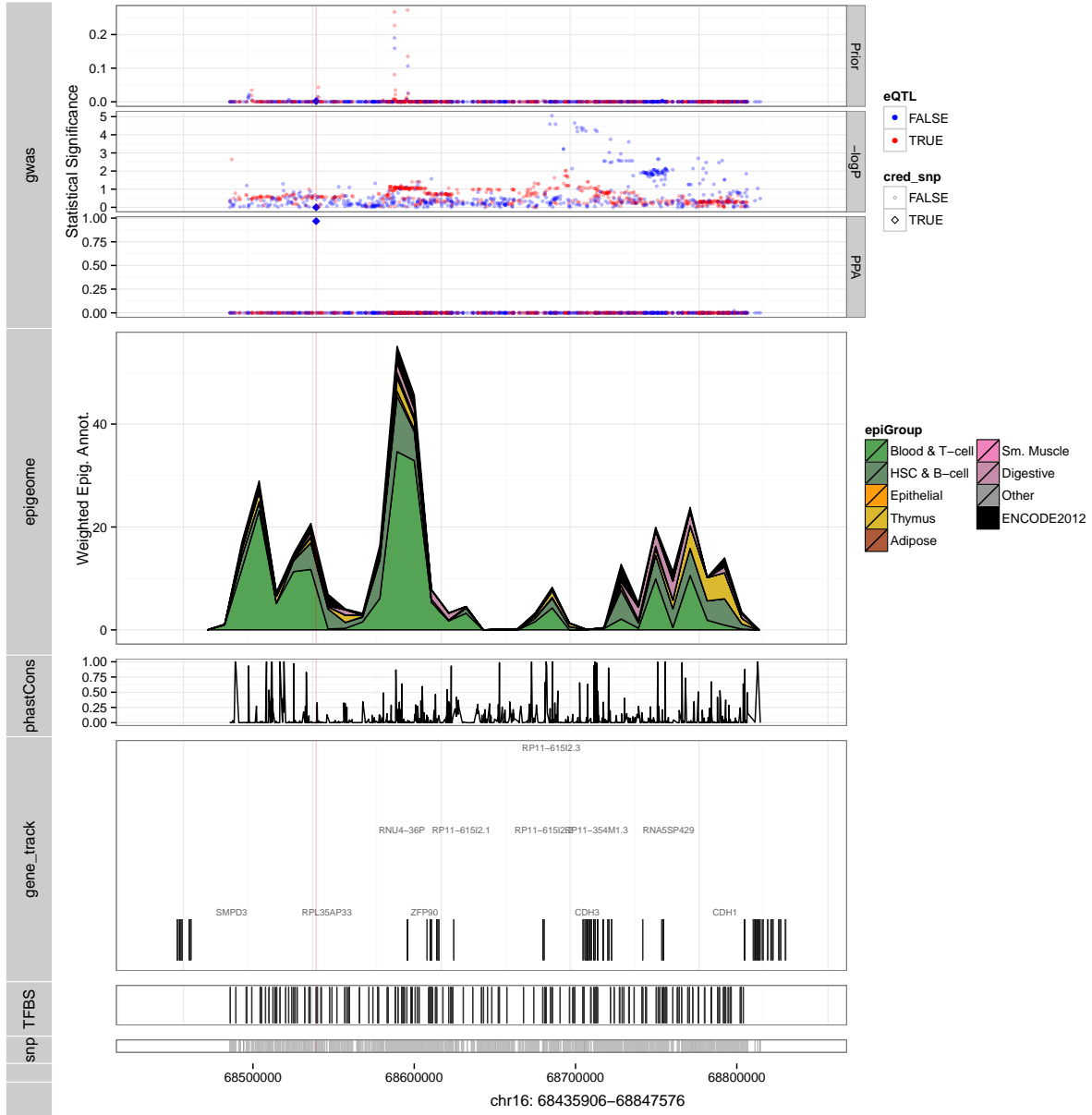
Multiple Sclerosis



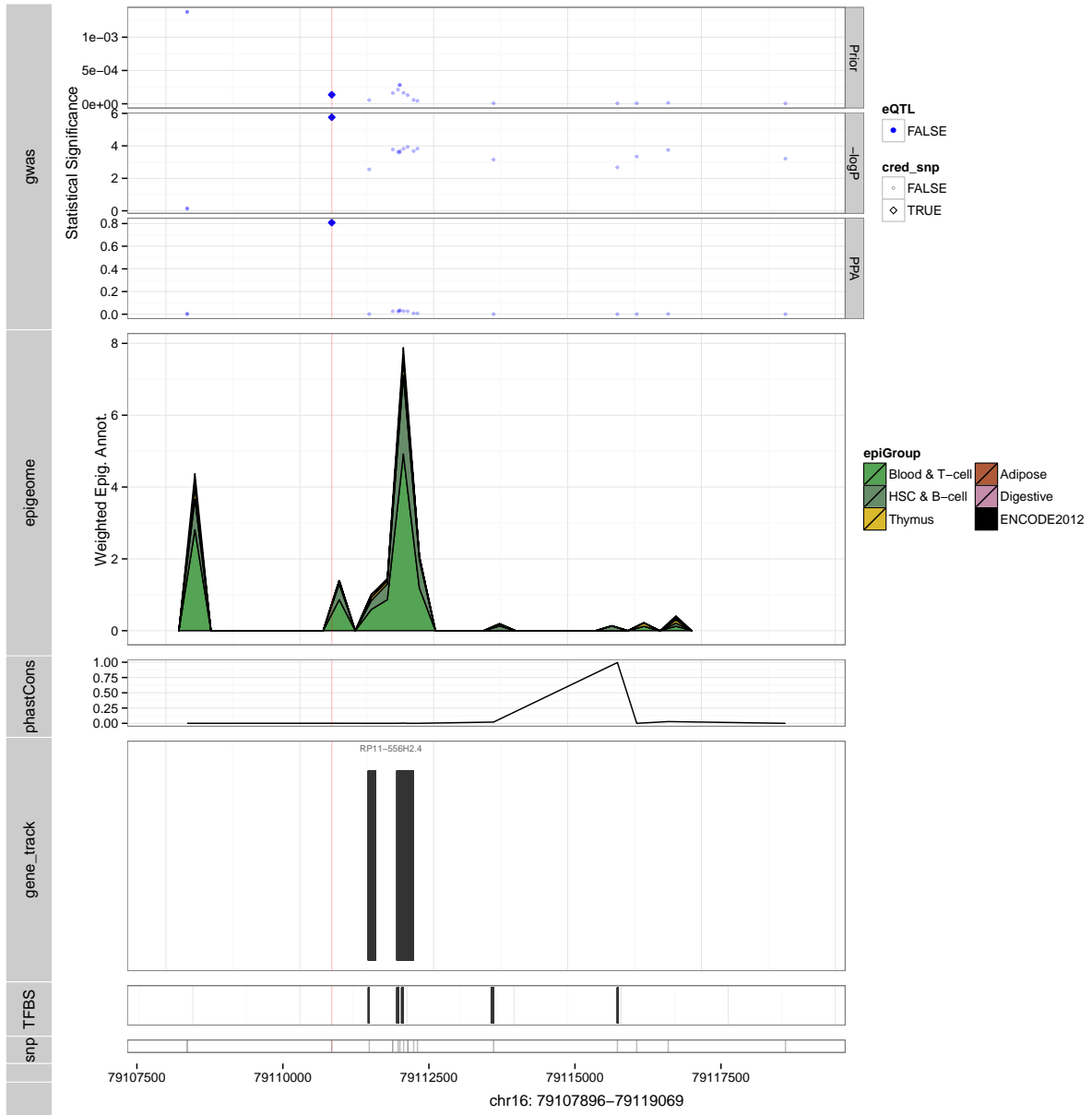
Multiple Sclerosis



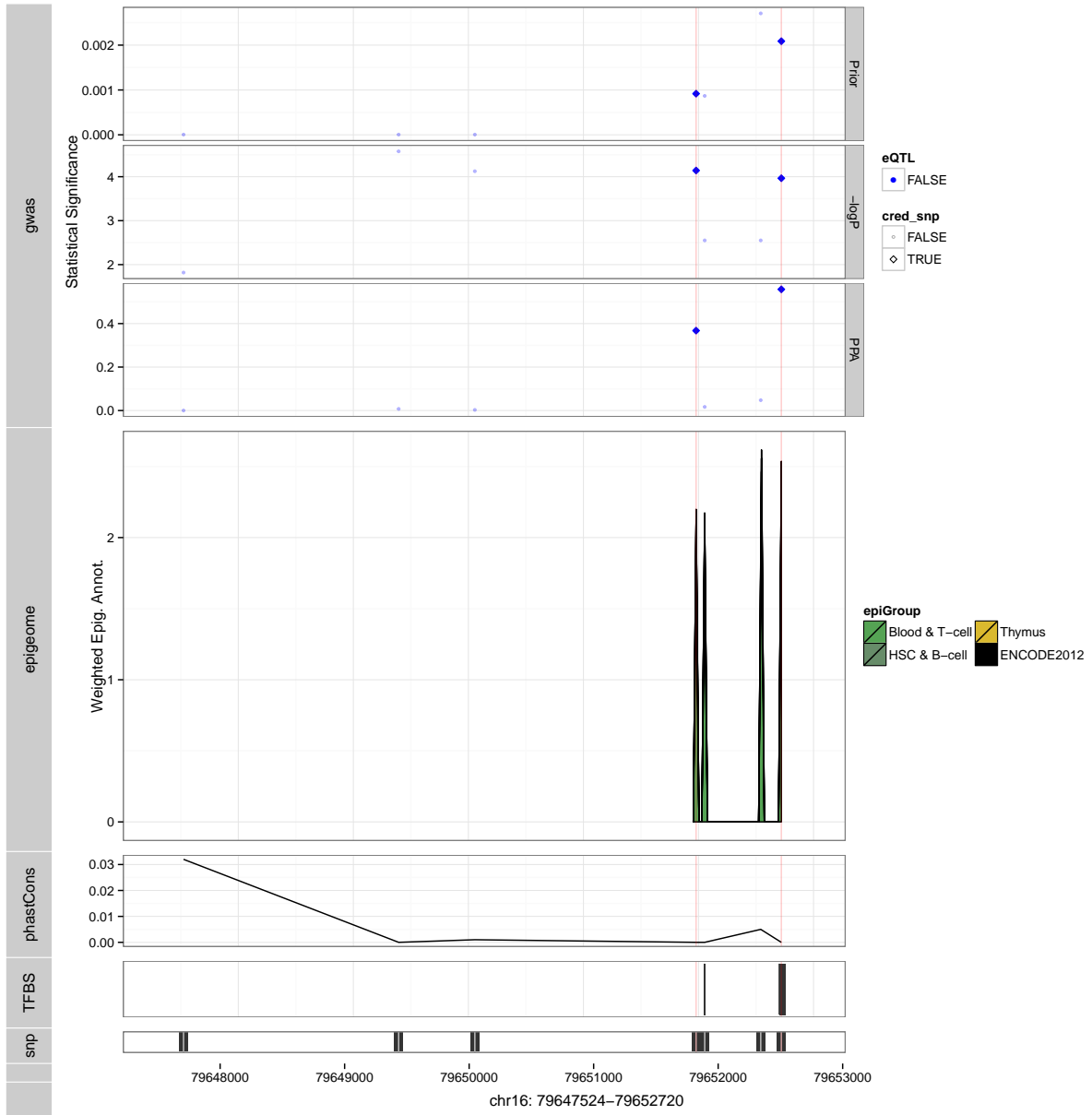
Multiple Sclerosis



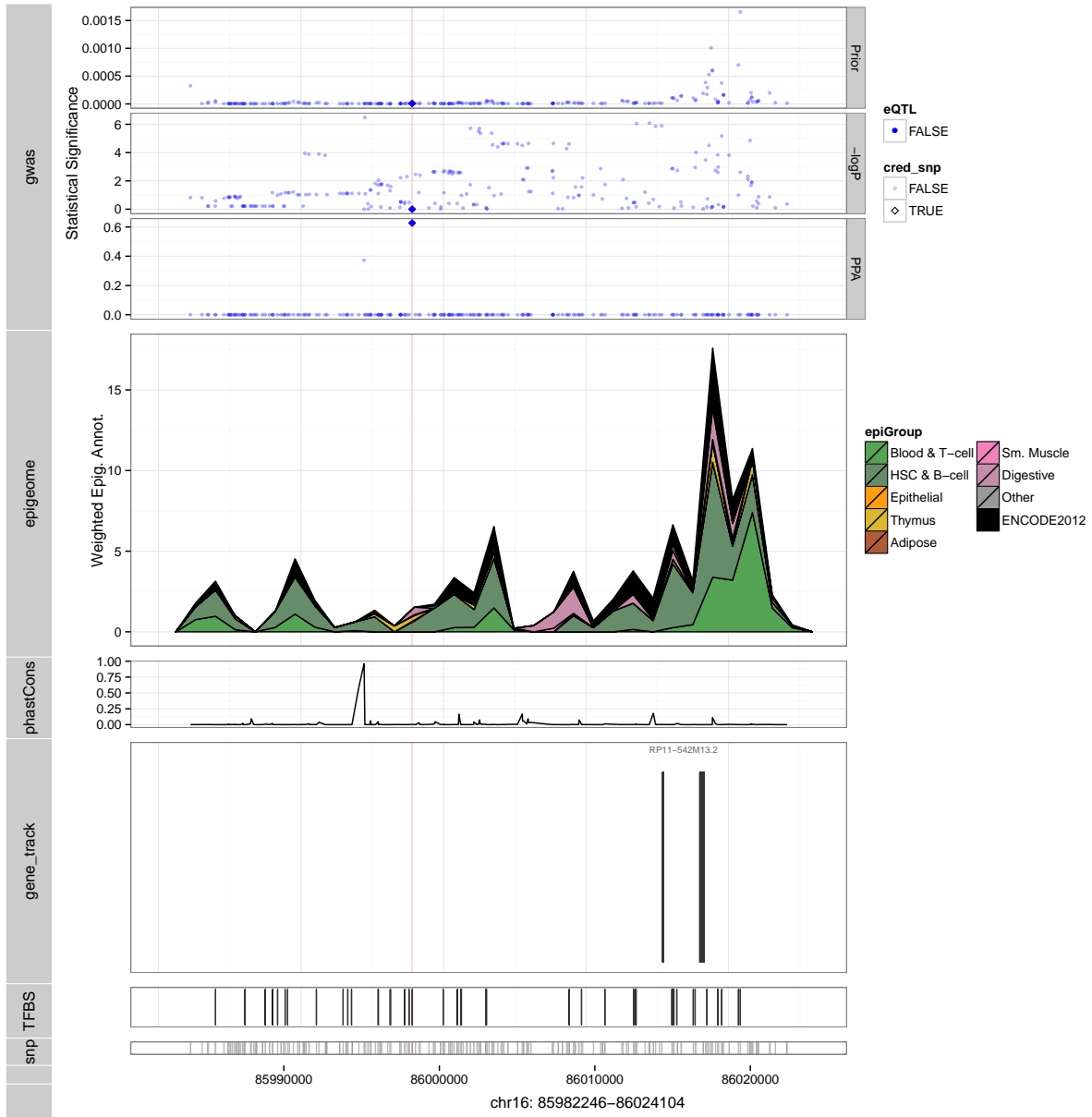
Multiple Sclerosis



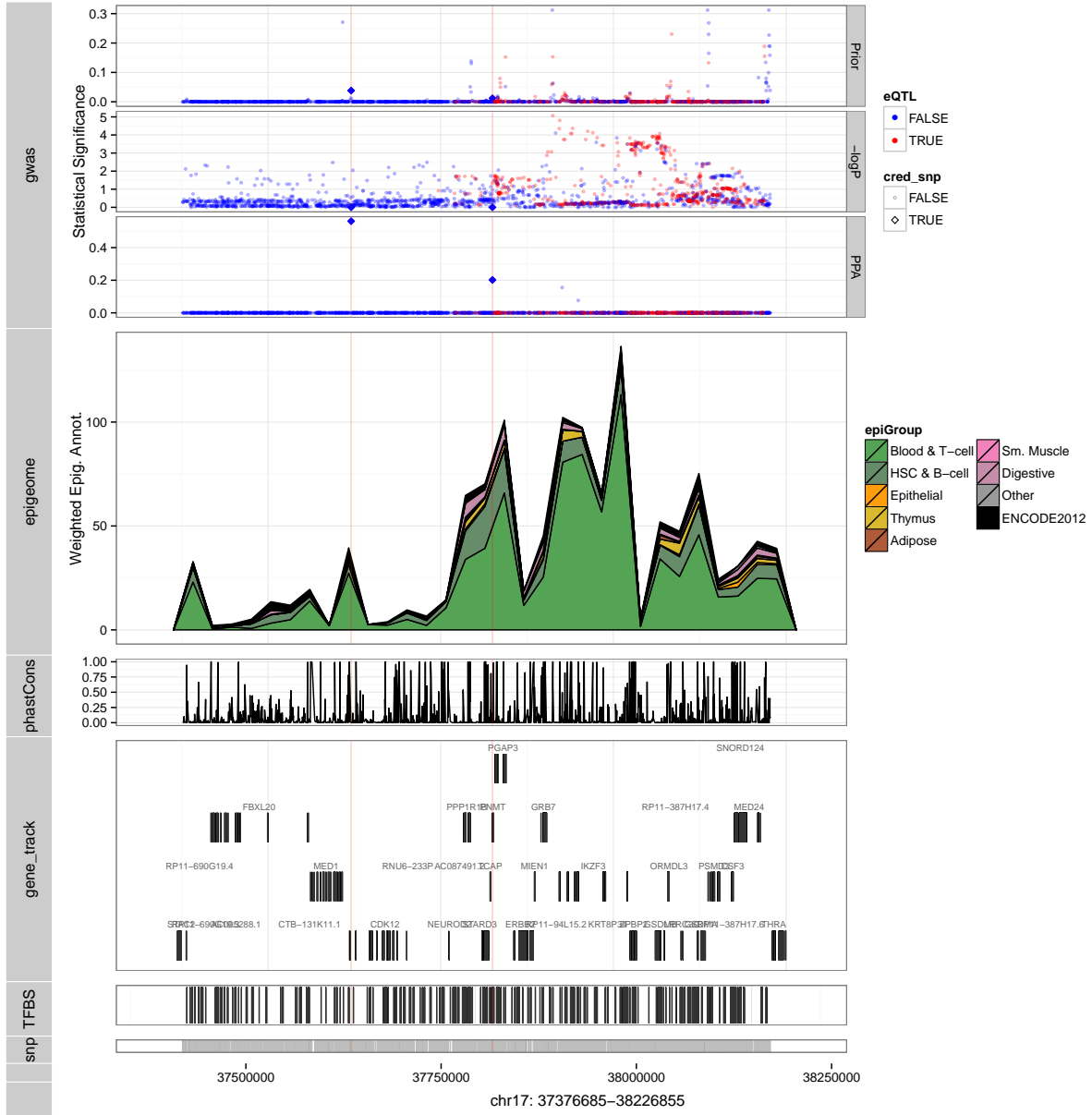
Multiple Sclerosis



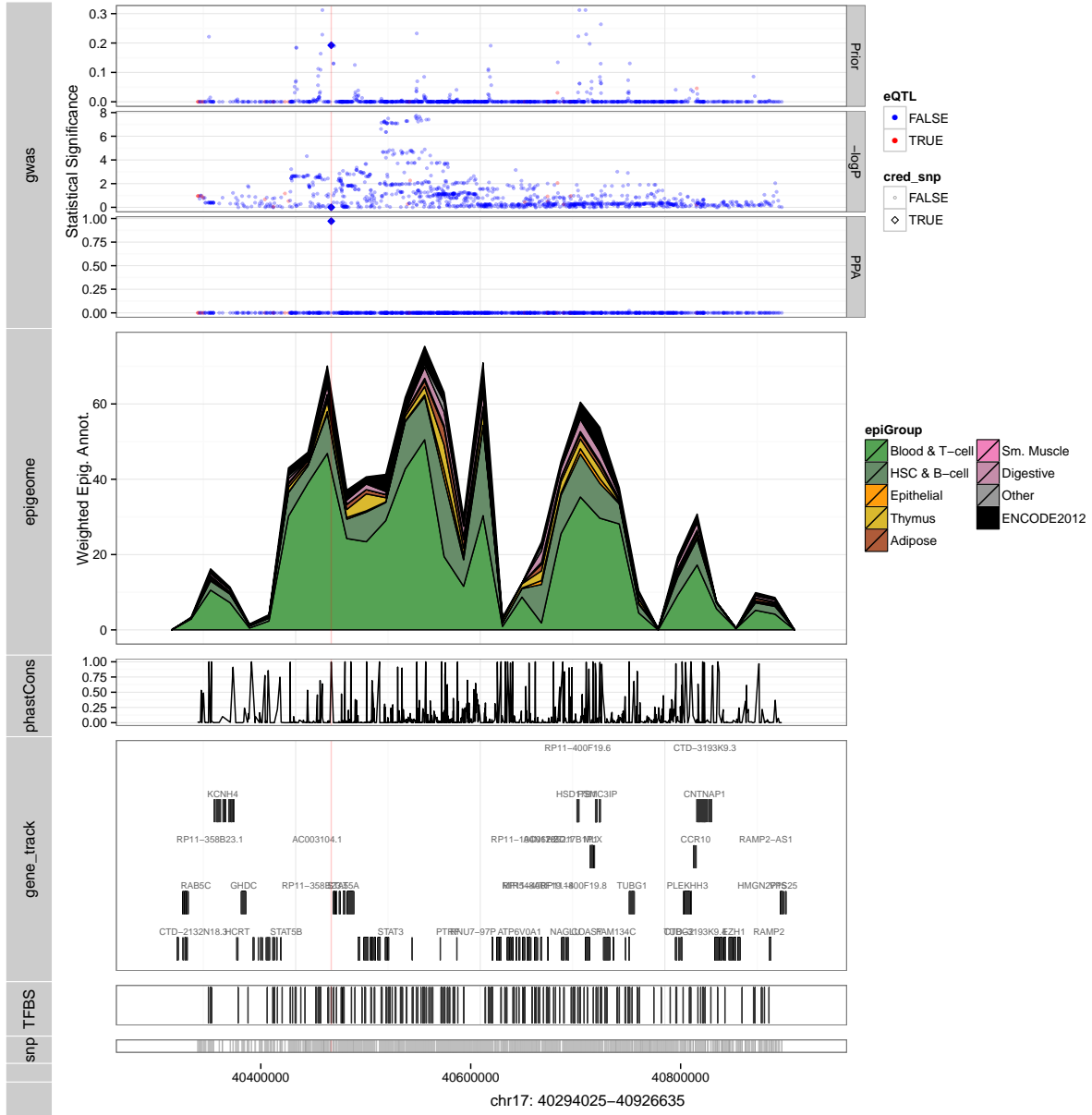
Multiple Sclerosis



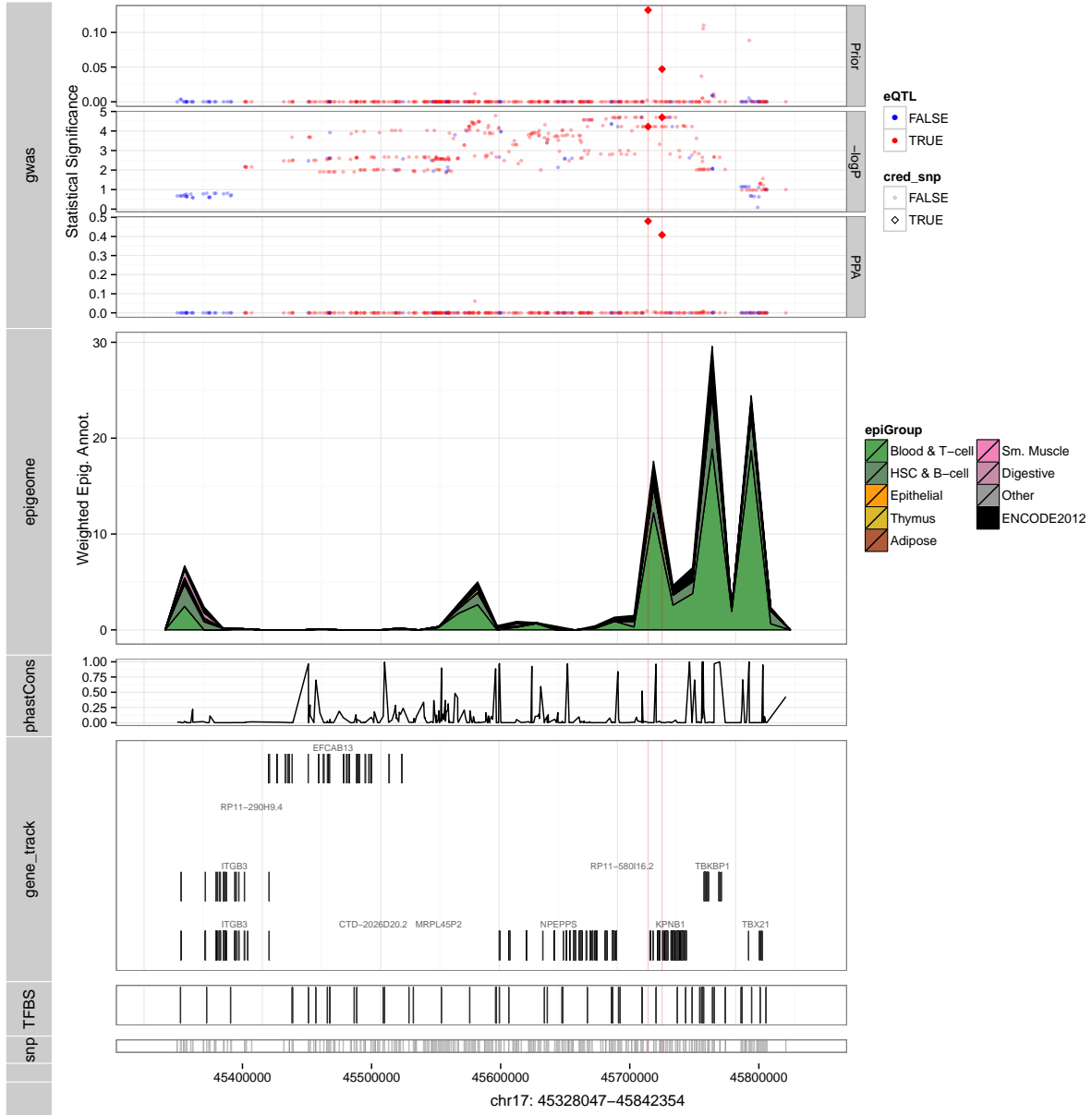
Multiple Sclerosis



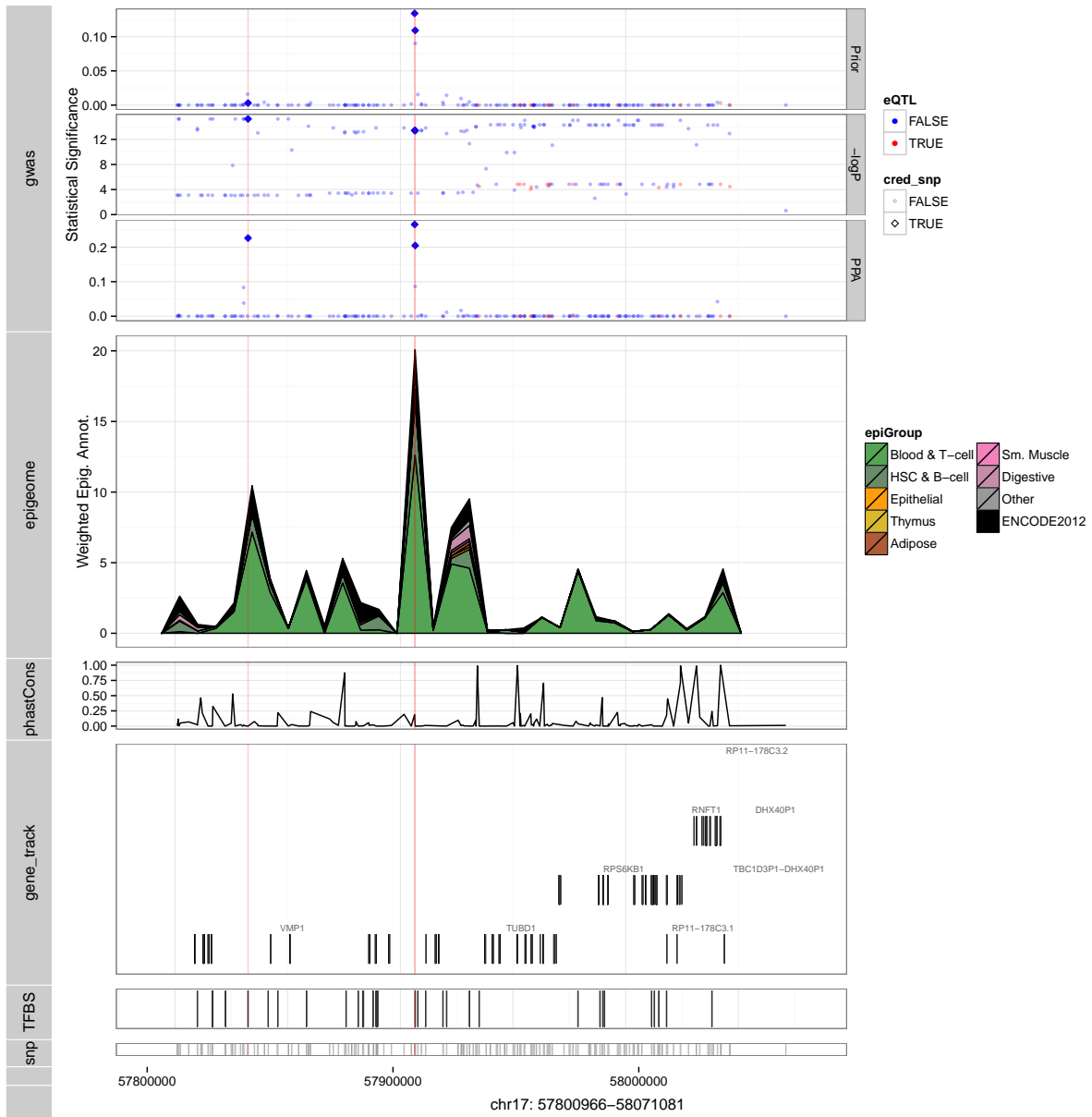
Multiple Sclerosis



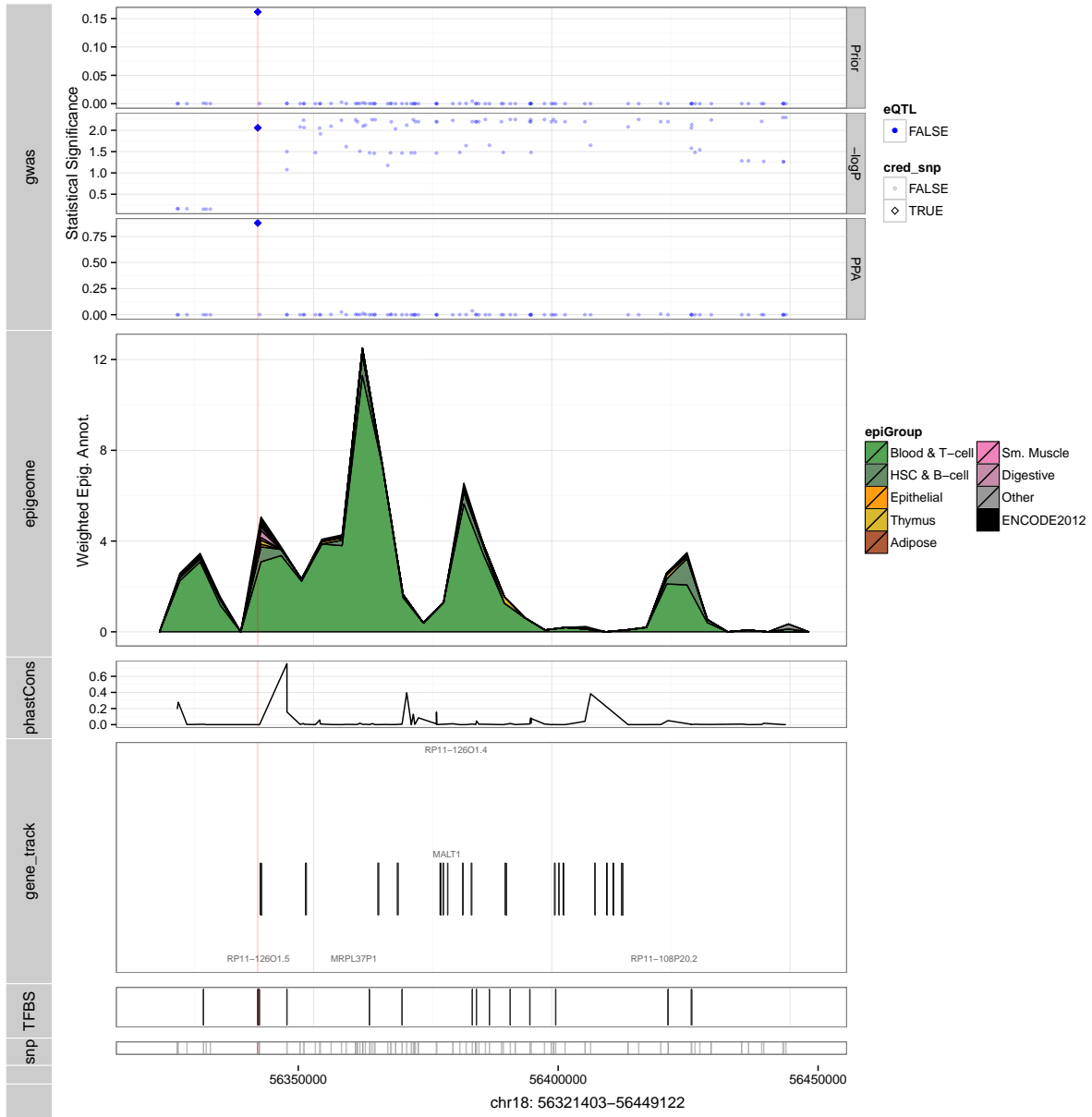
Multiple Sclerosis



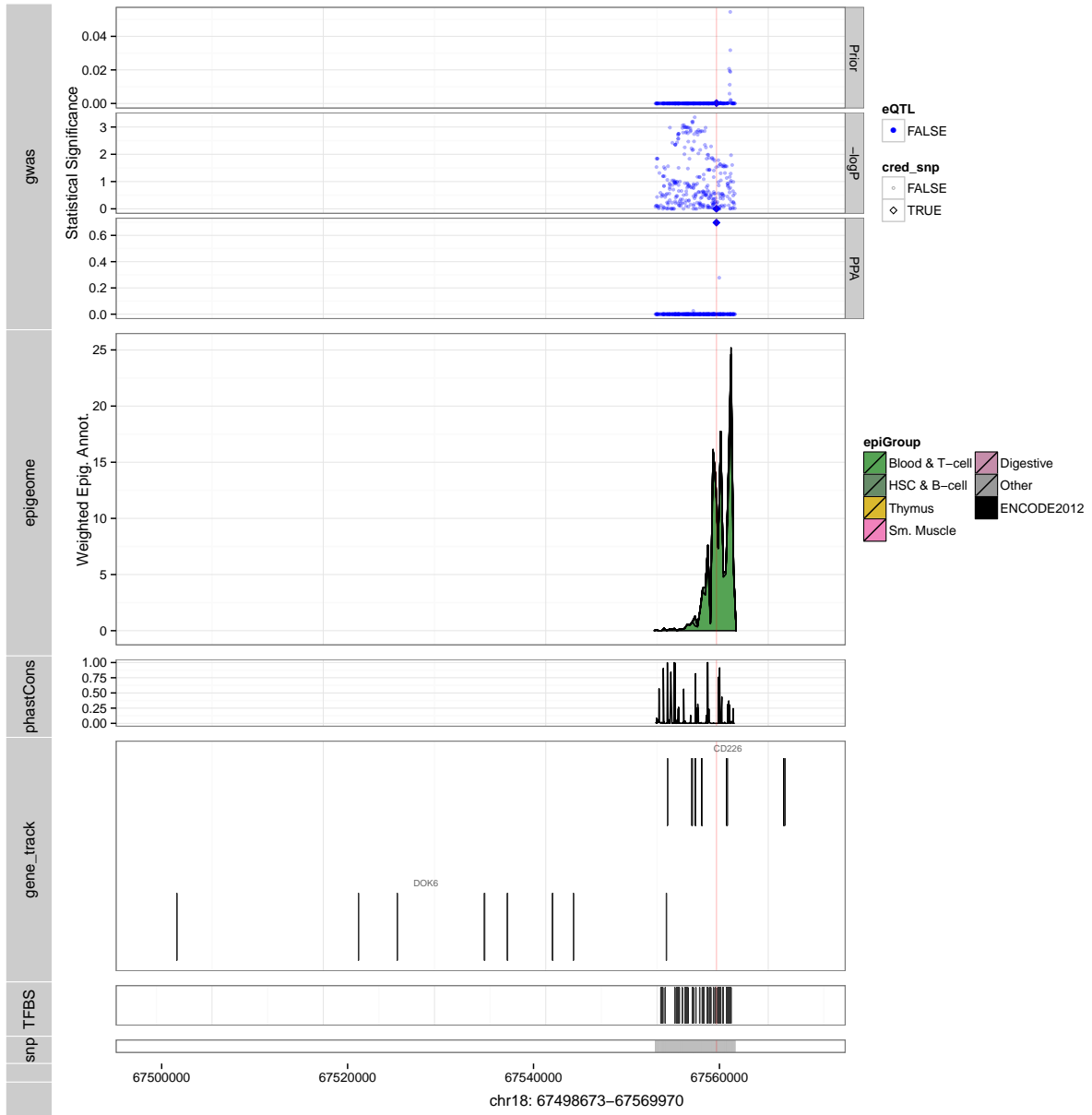
Multiple Sclerosis



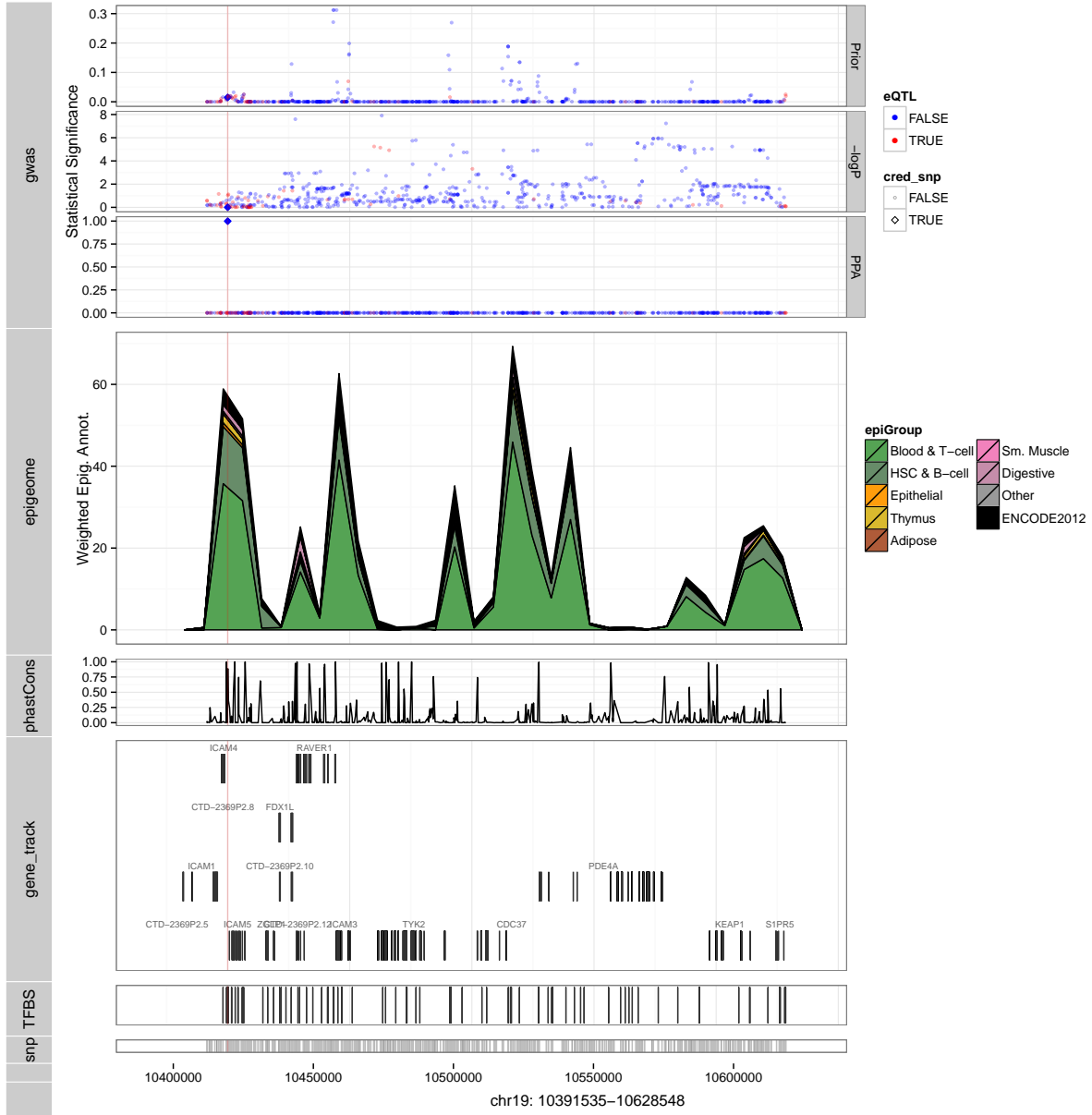
Multiple Sclerosis



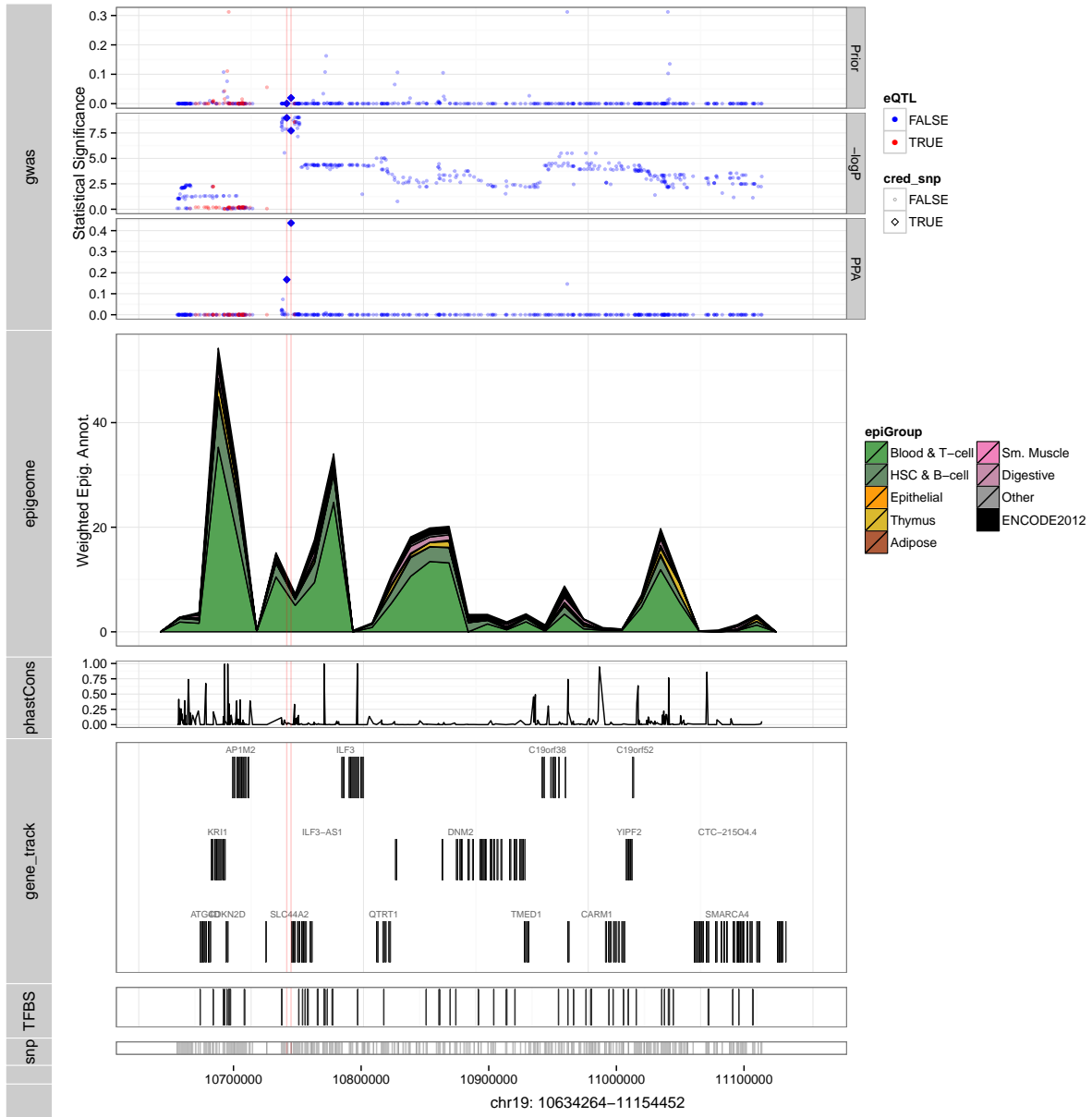
Multiple Sclerosis



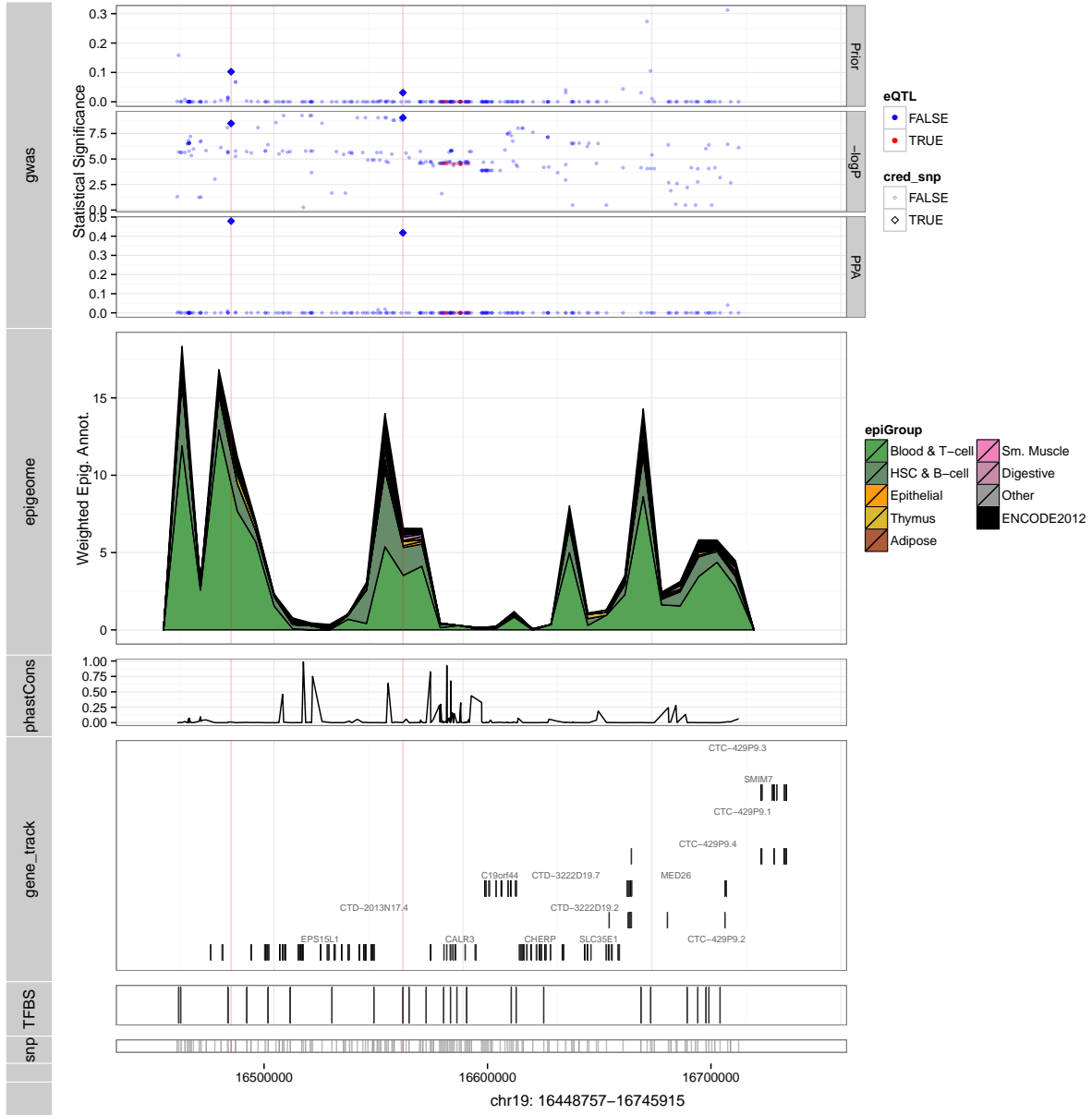
Multiple Sclerosis



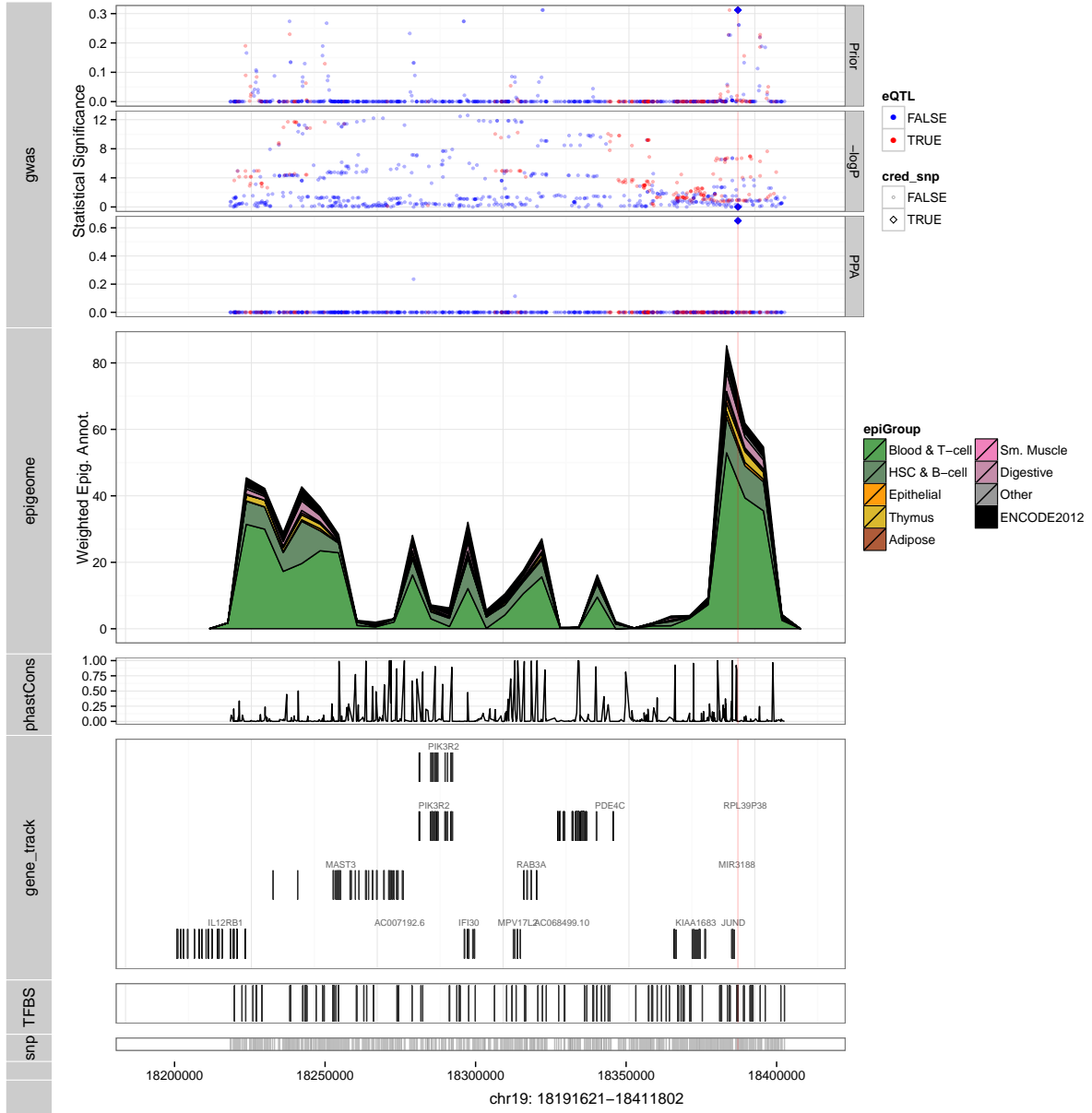
Multiple Sclerosis



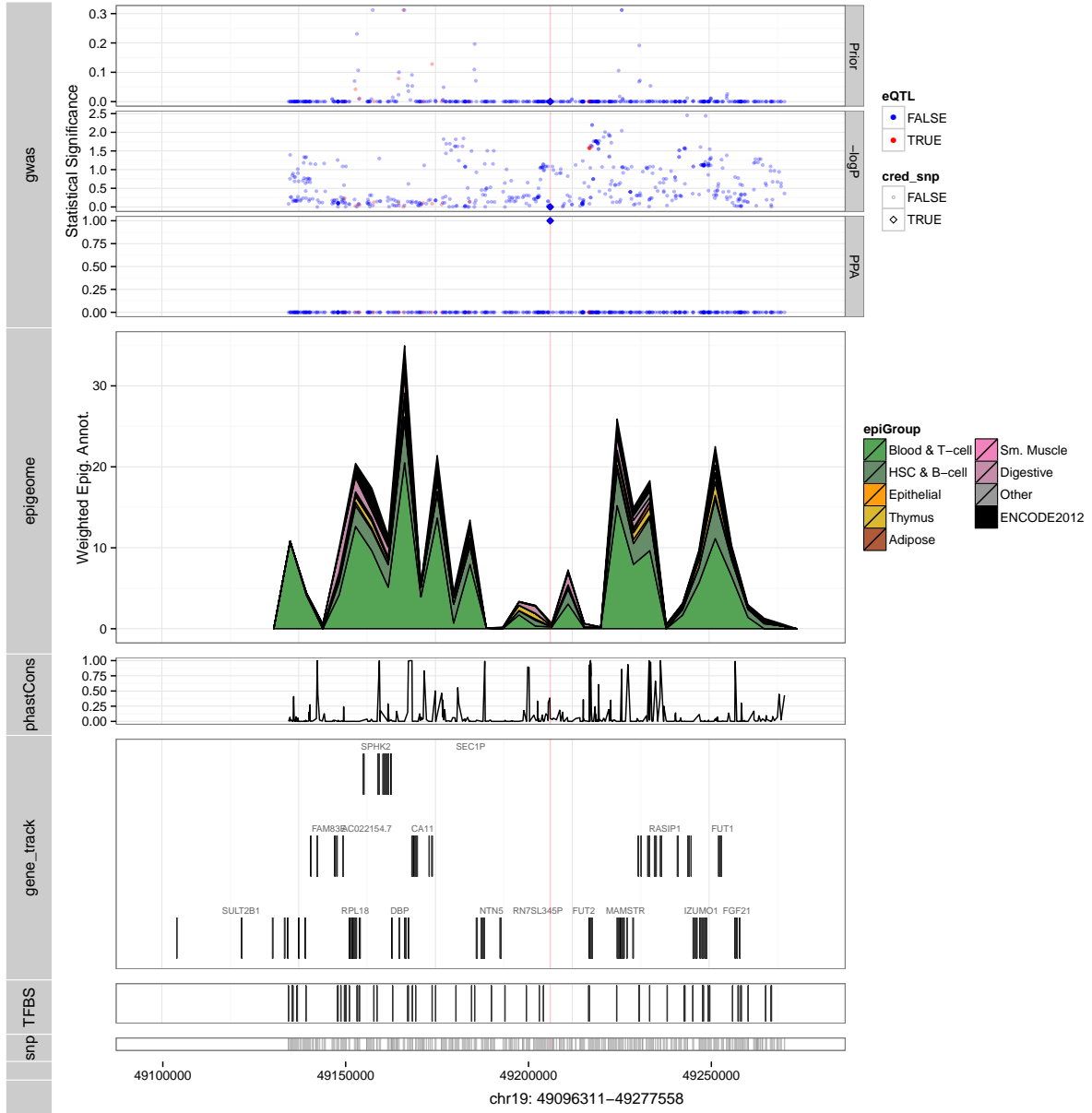
Multiple Sclerosis



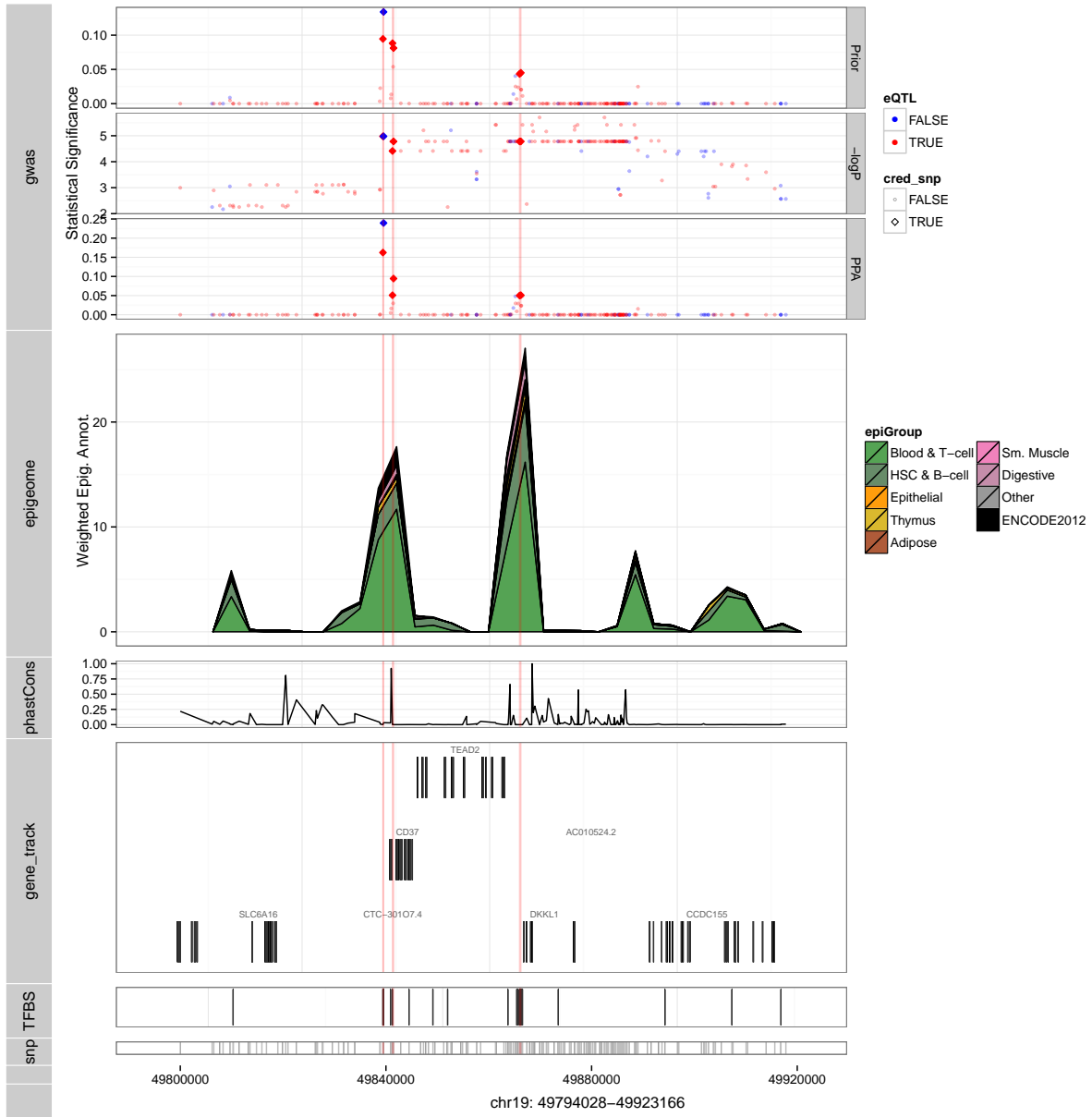
Multiple Sclerosis



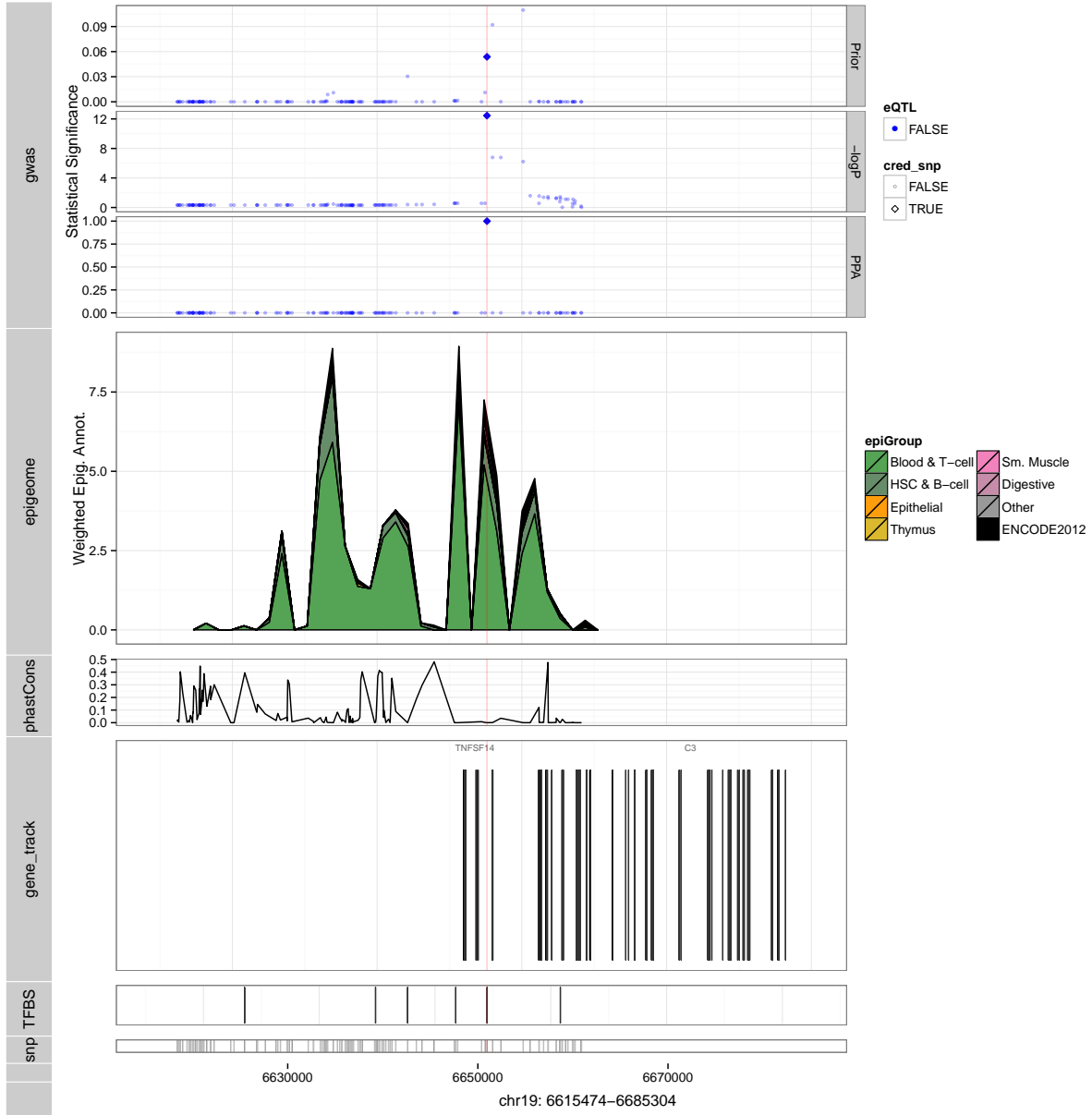
Multiple Sclerosis



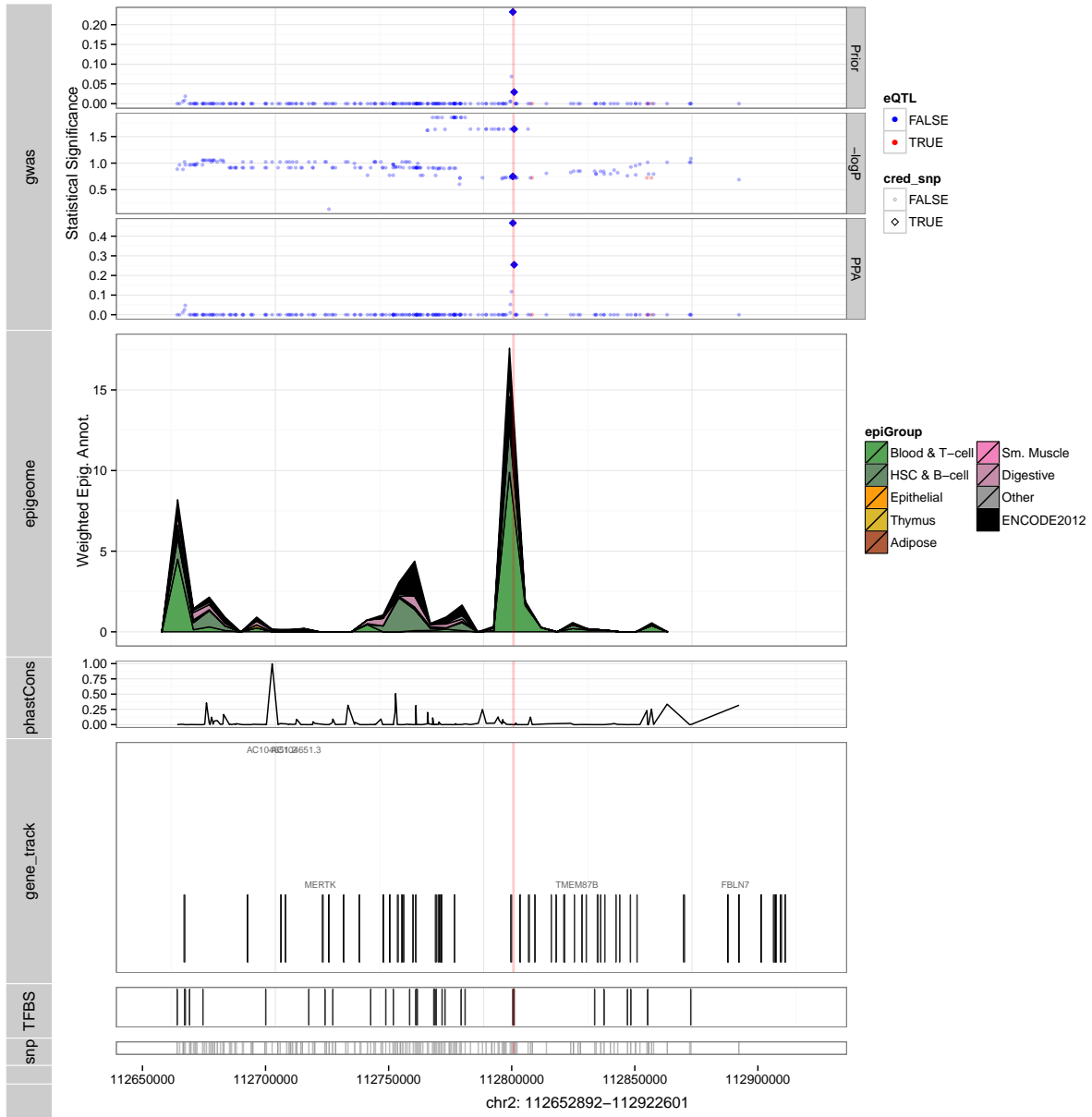
Multiple Sclerosis



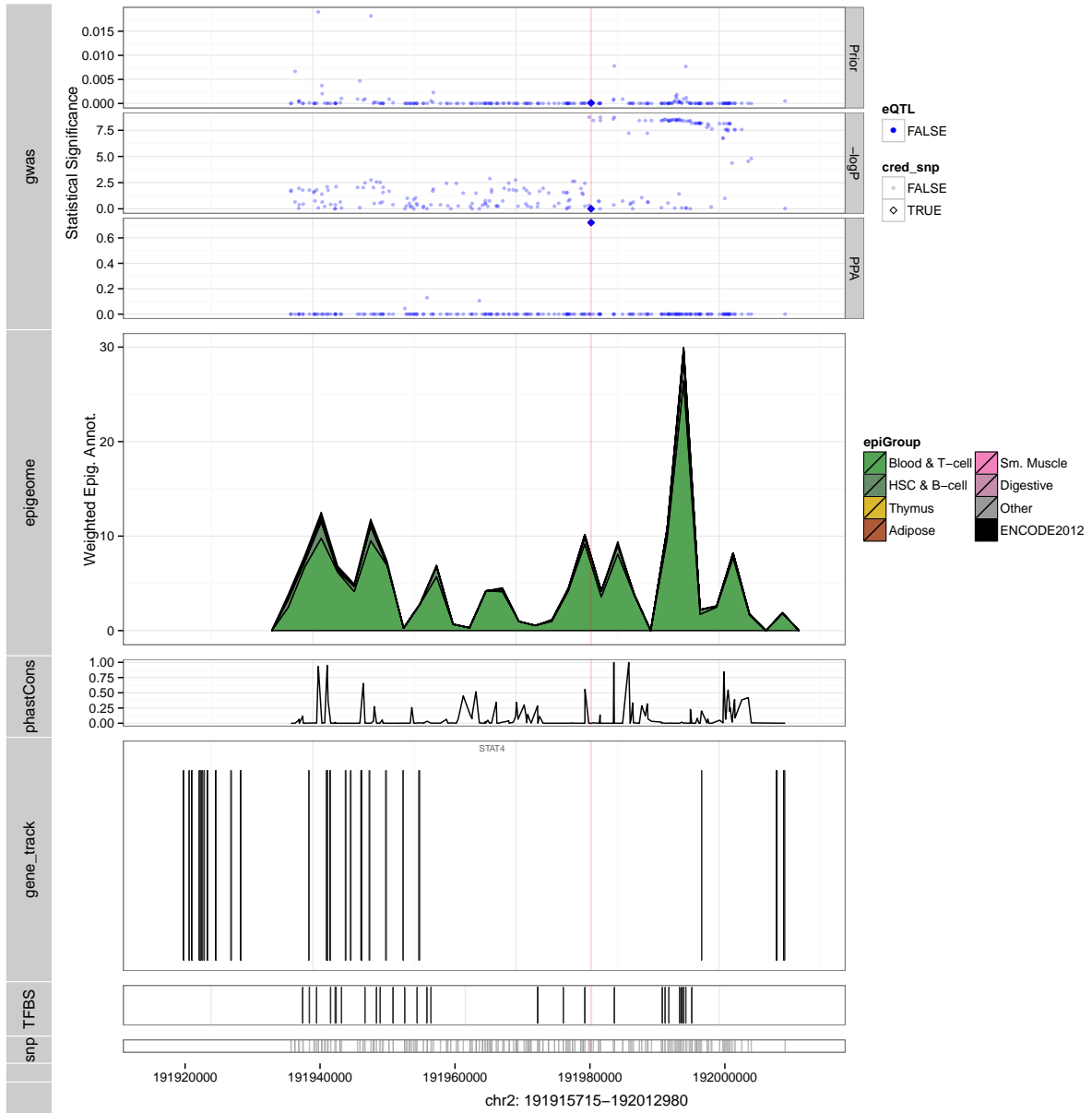
Multiple Sclerosis



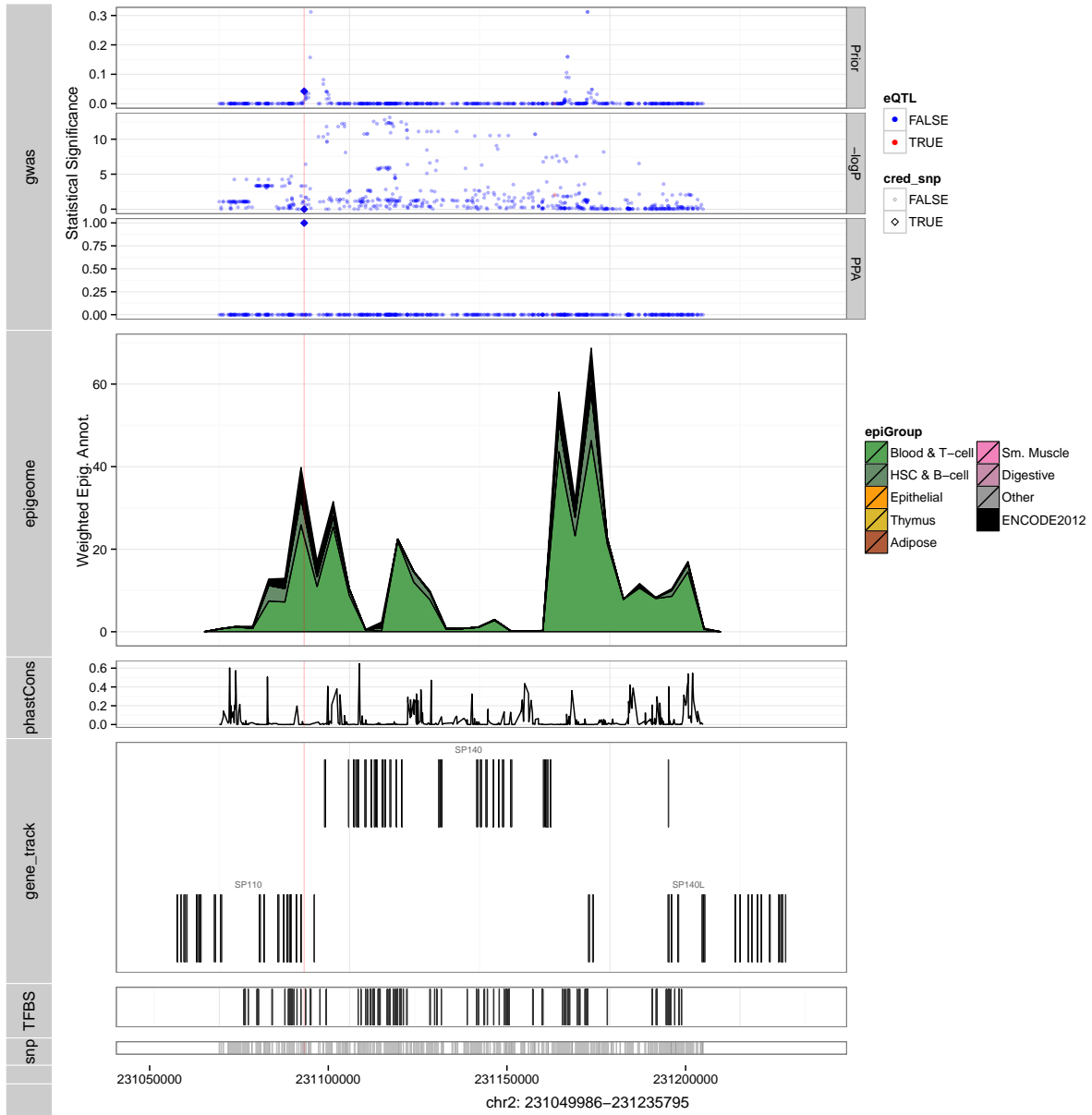
Multiple Sclerosis



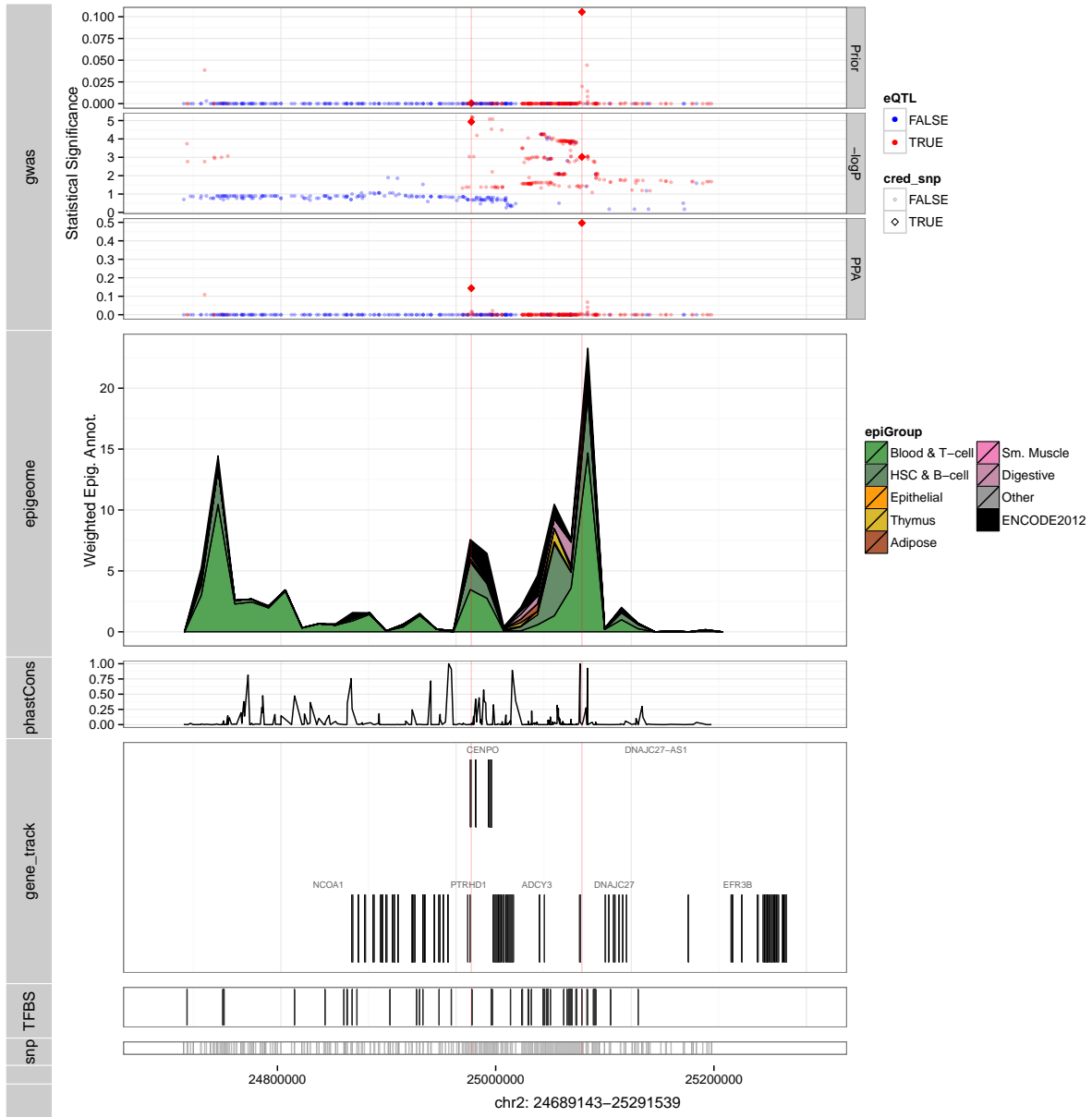
Multiple Sclerosis



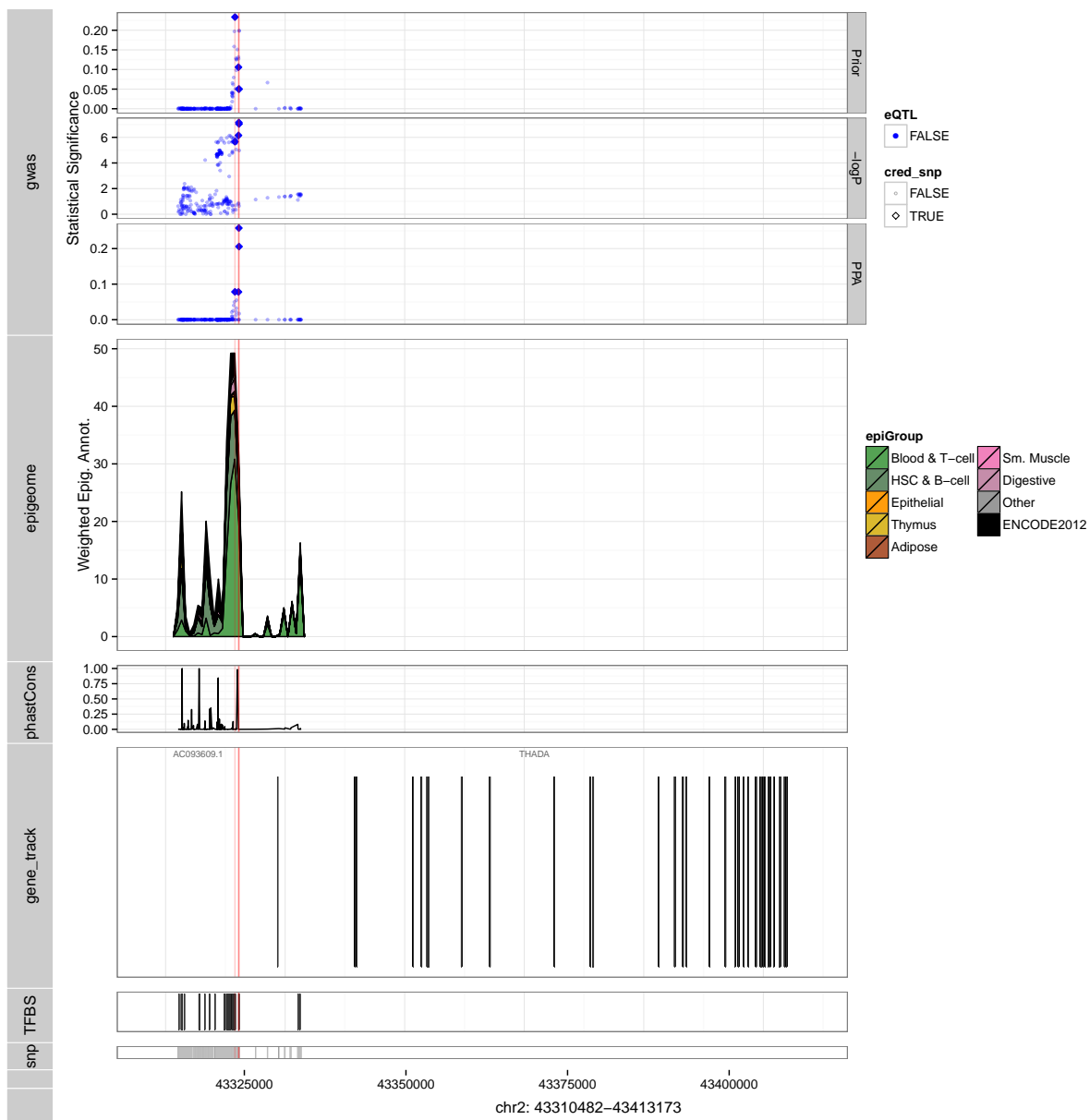
Multiple Sclerosis



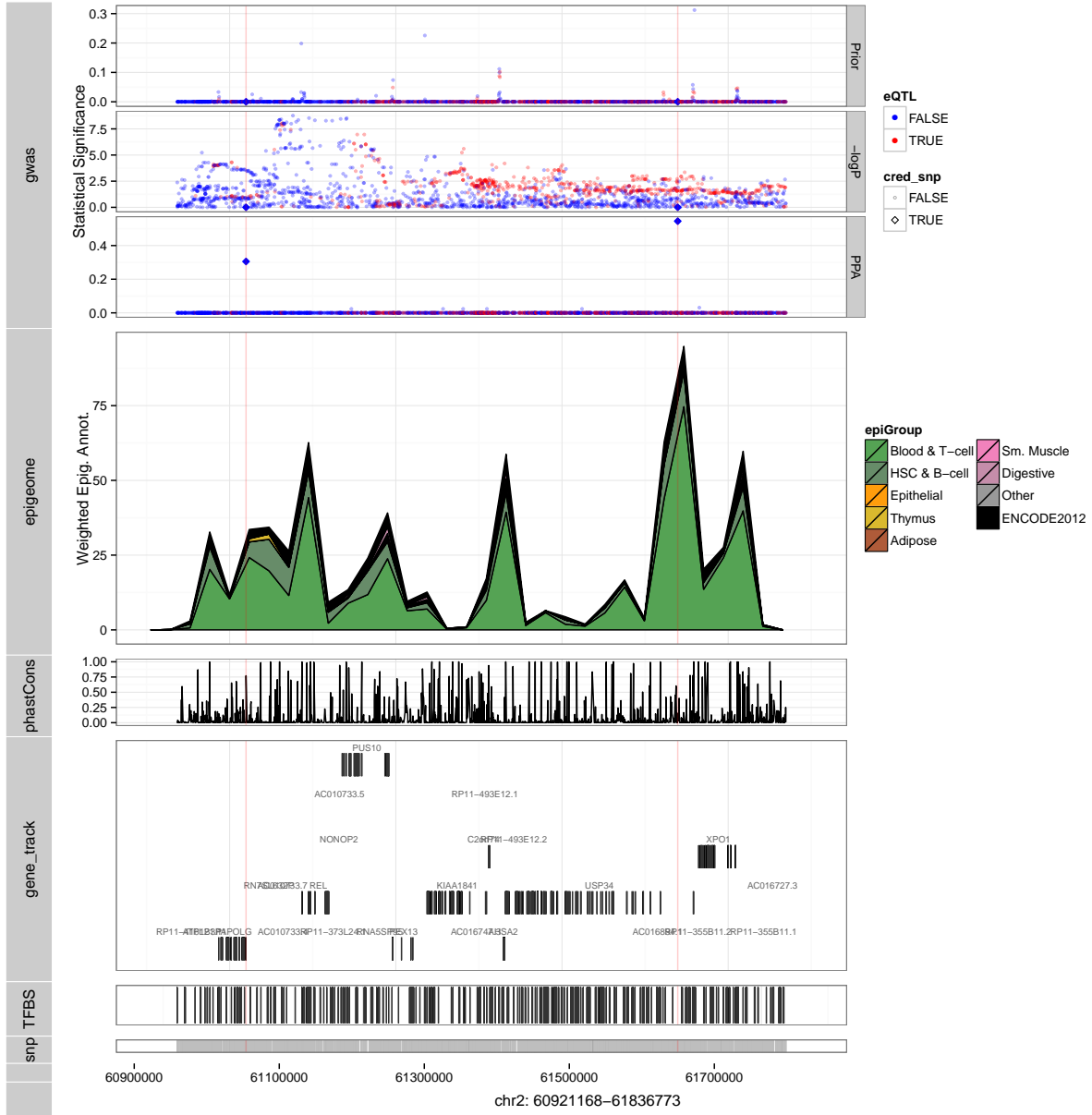
Multiple Sclerosis



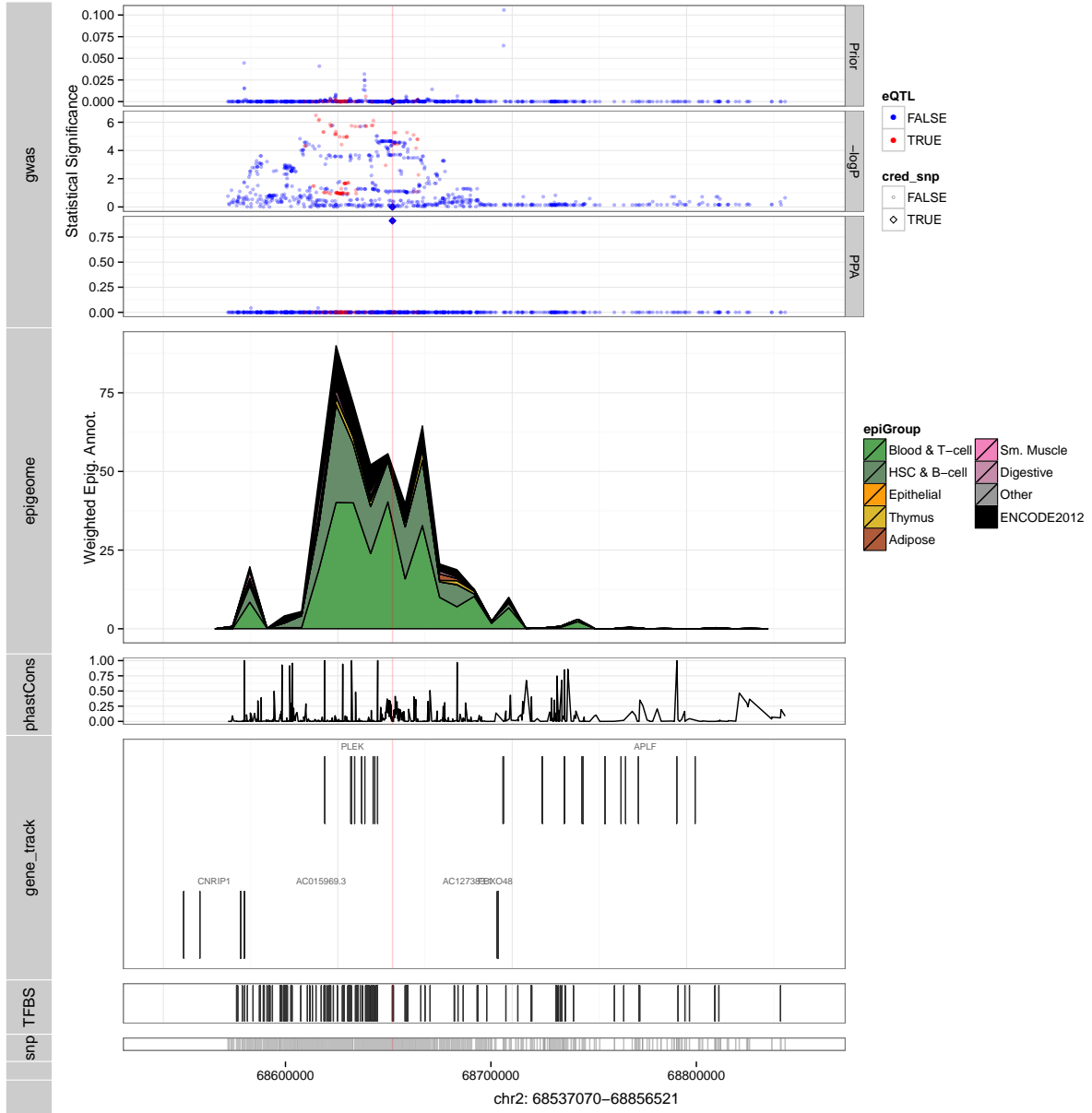
Multiple Sclerosis



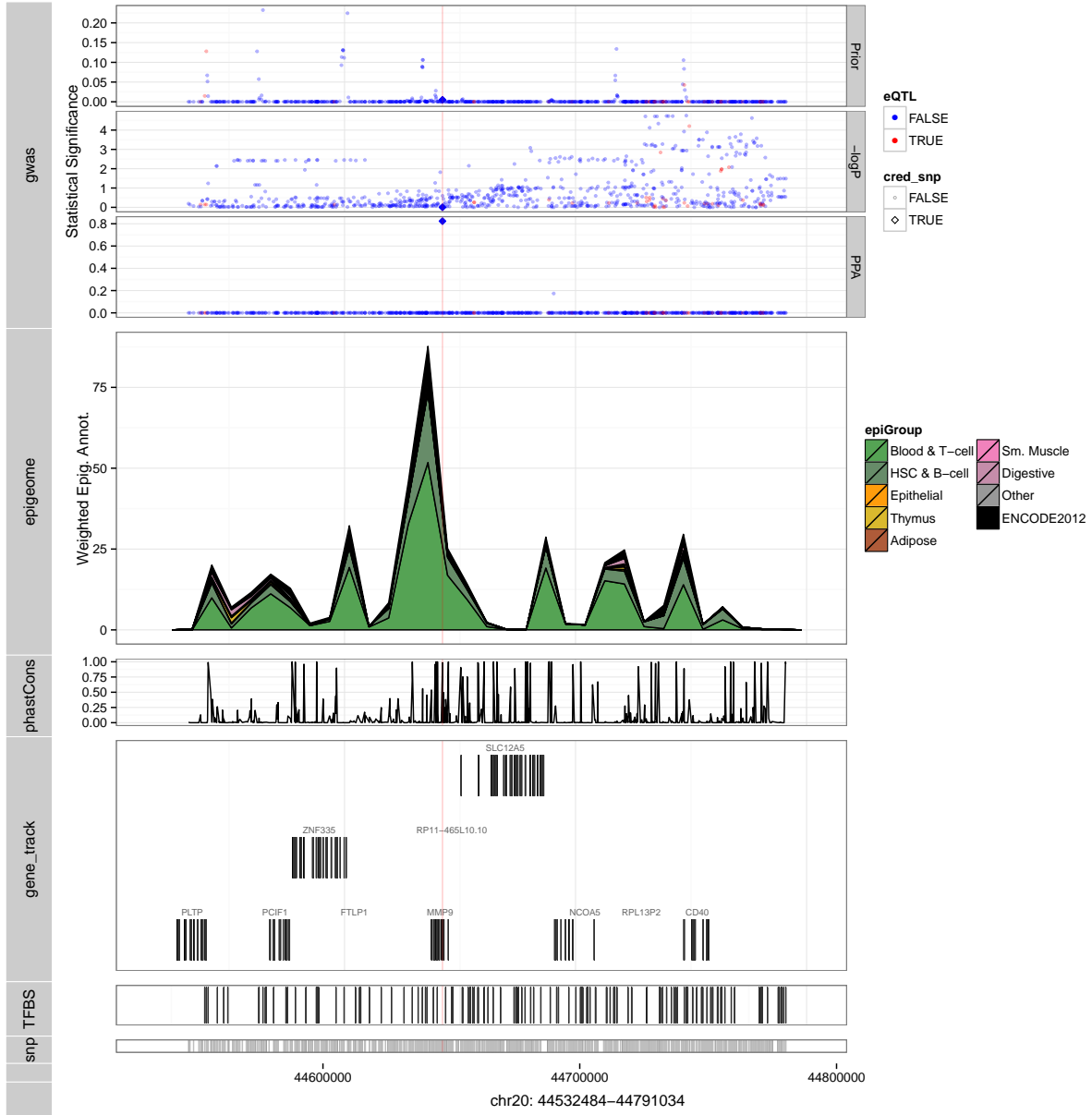
Multiple Sclerosis



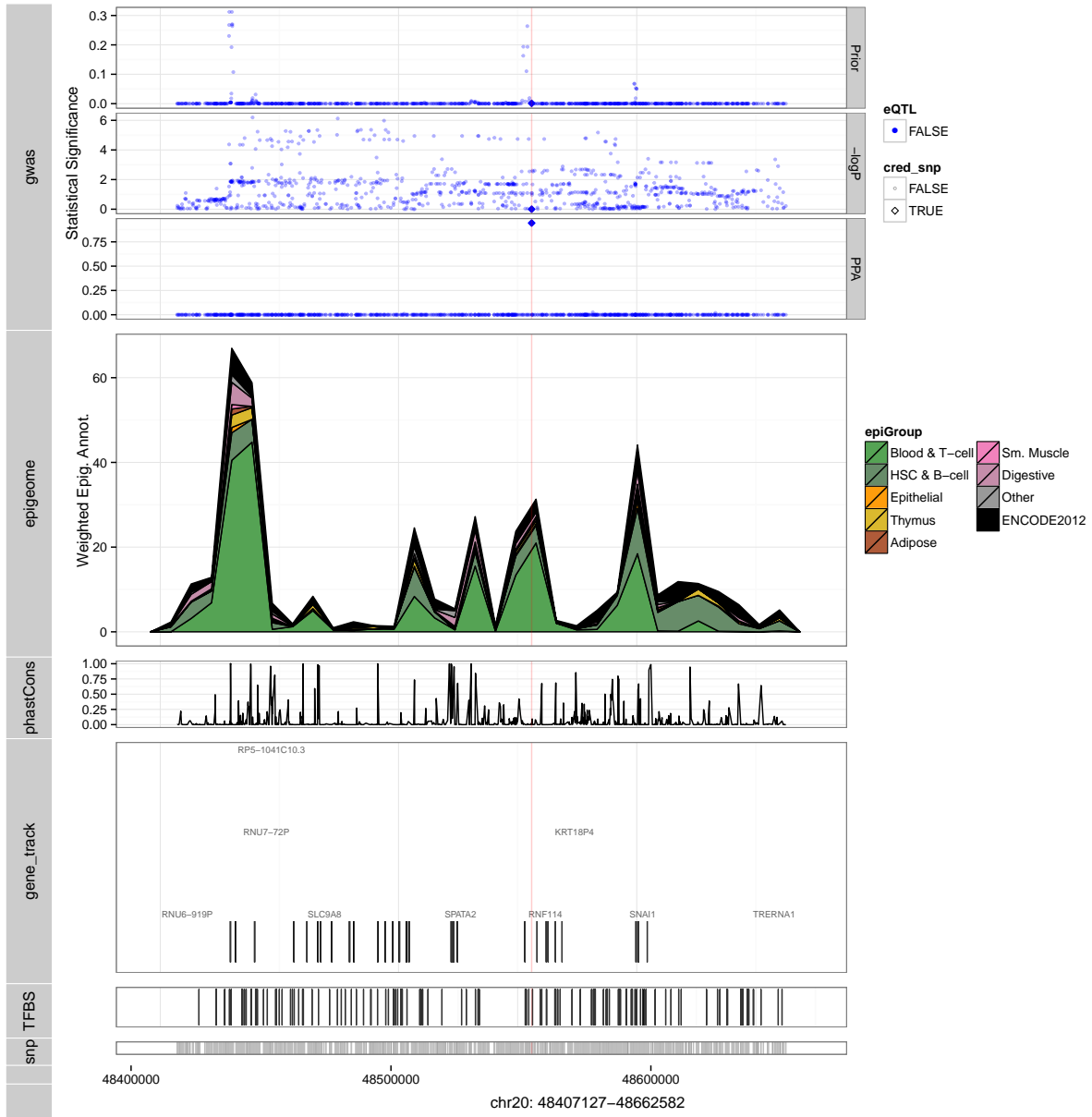
Multiple Sclerosis



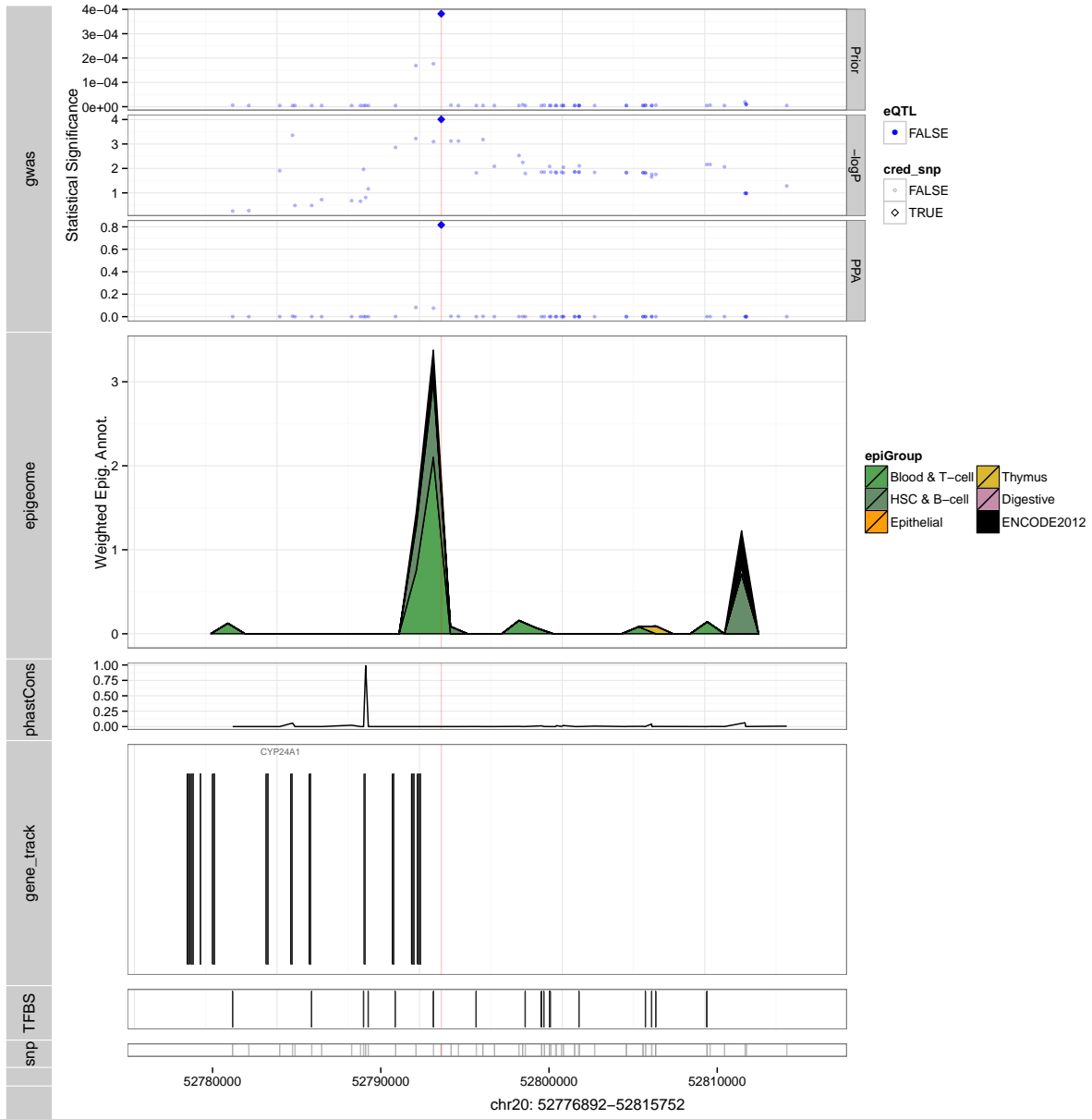
Multiple Sclerosis



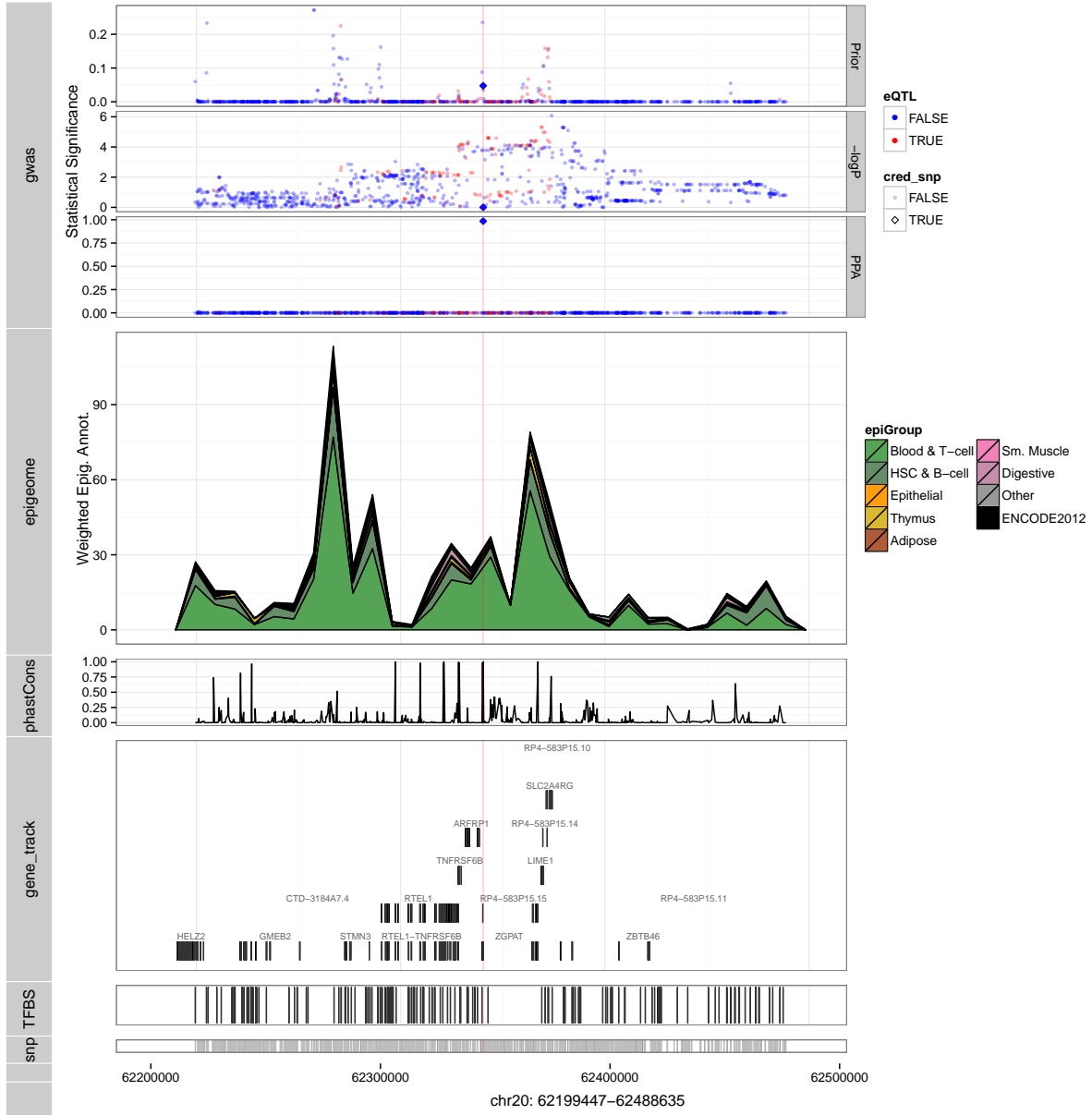
Multiple Sclerosis



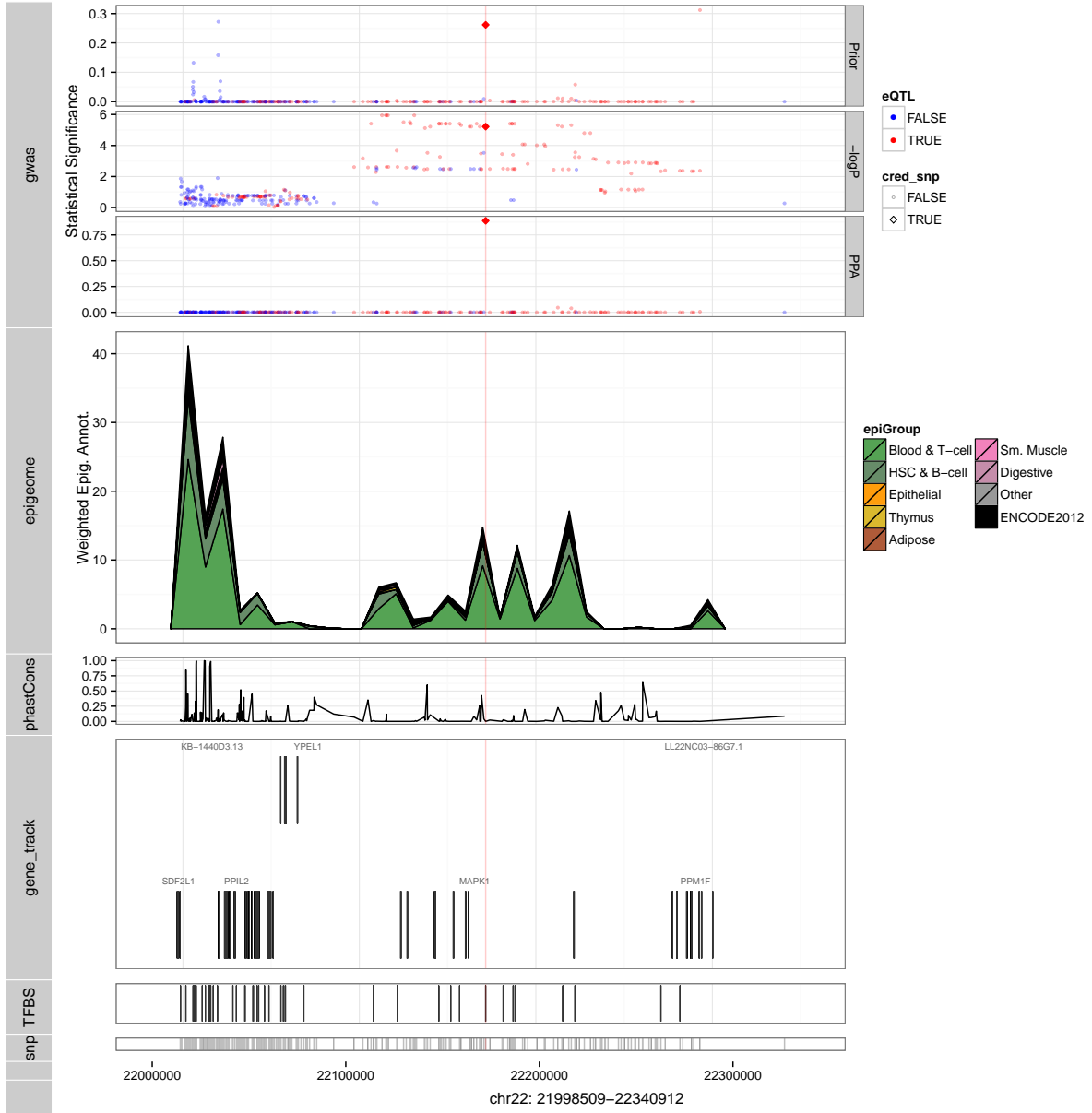
Multiple Sclerosis



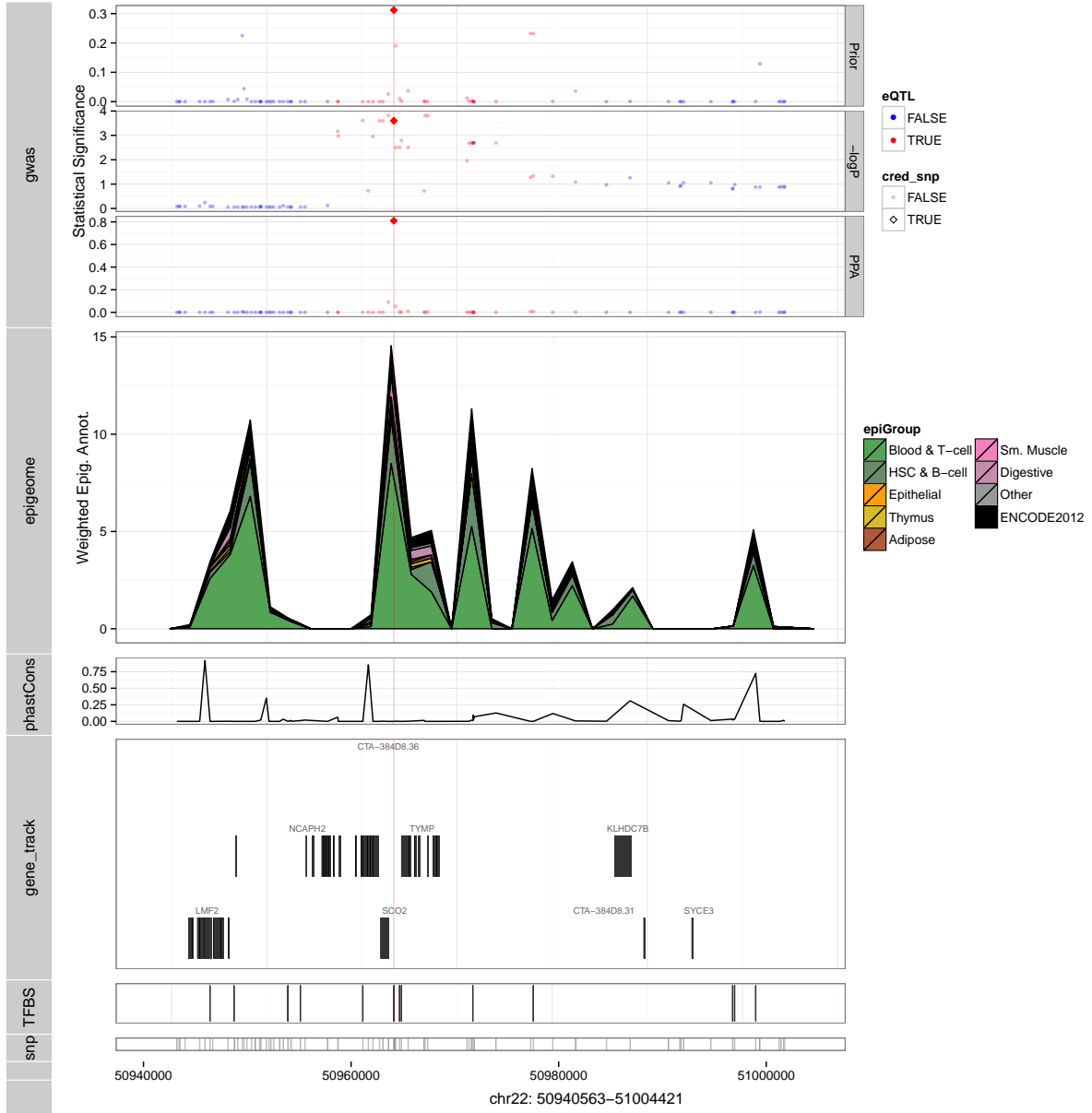
Multiple Sclerosis



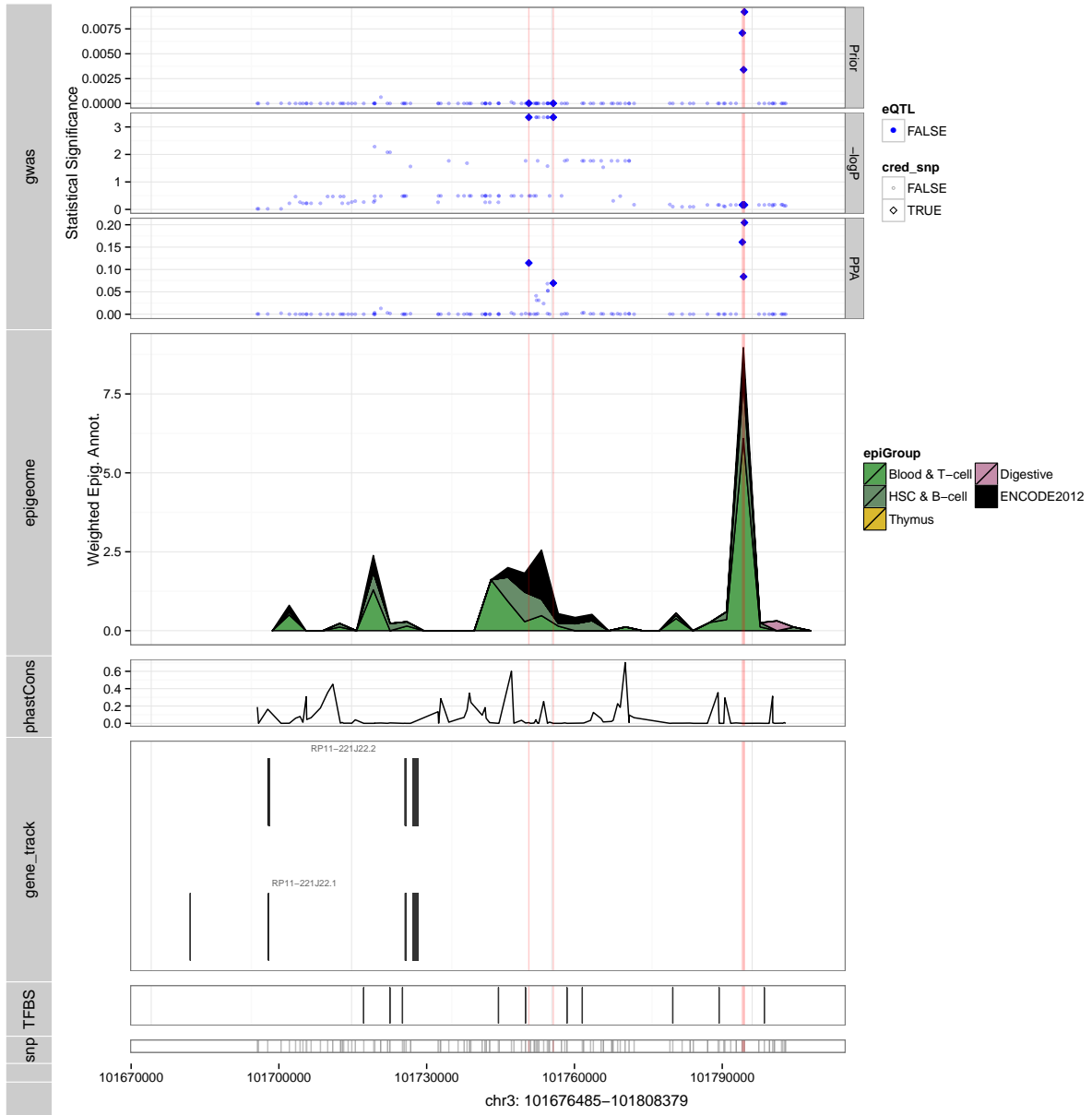
Multiple Sclerosis



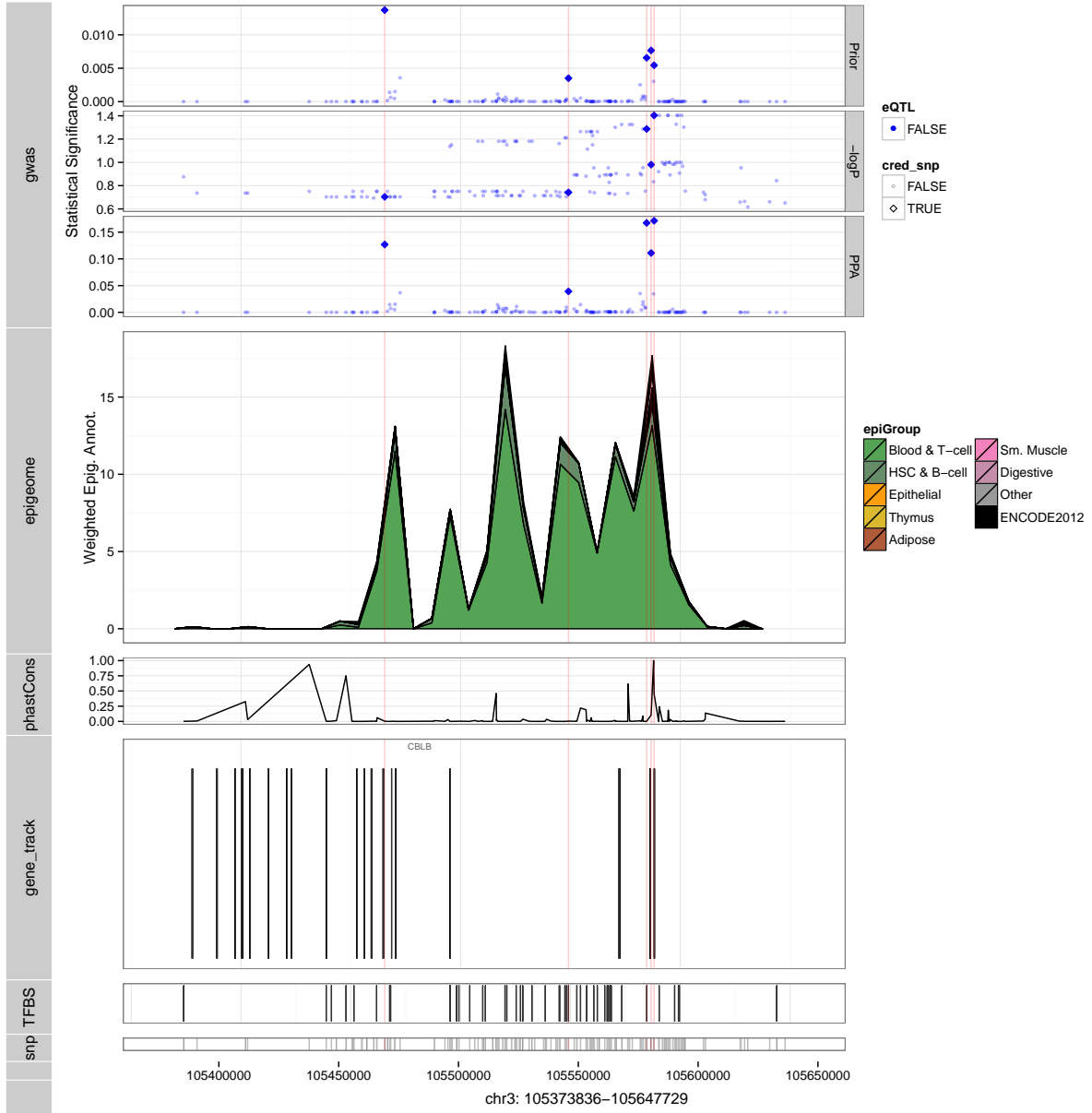
Multiple Sclerosis



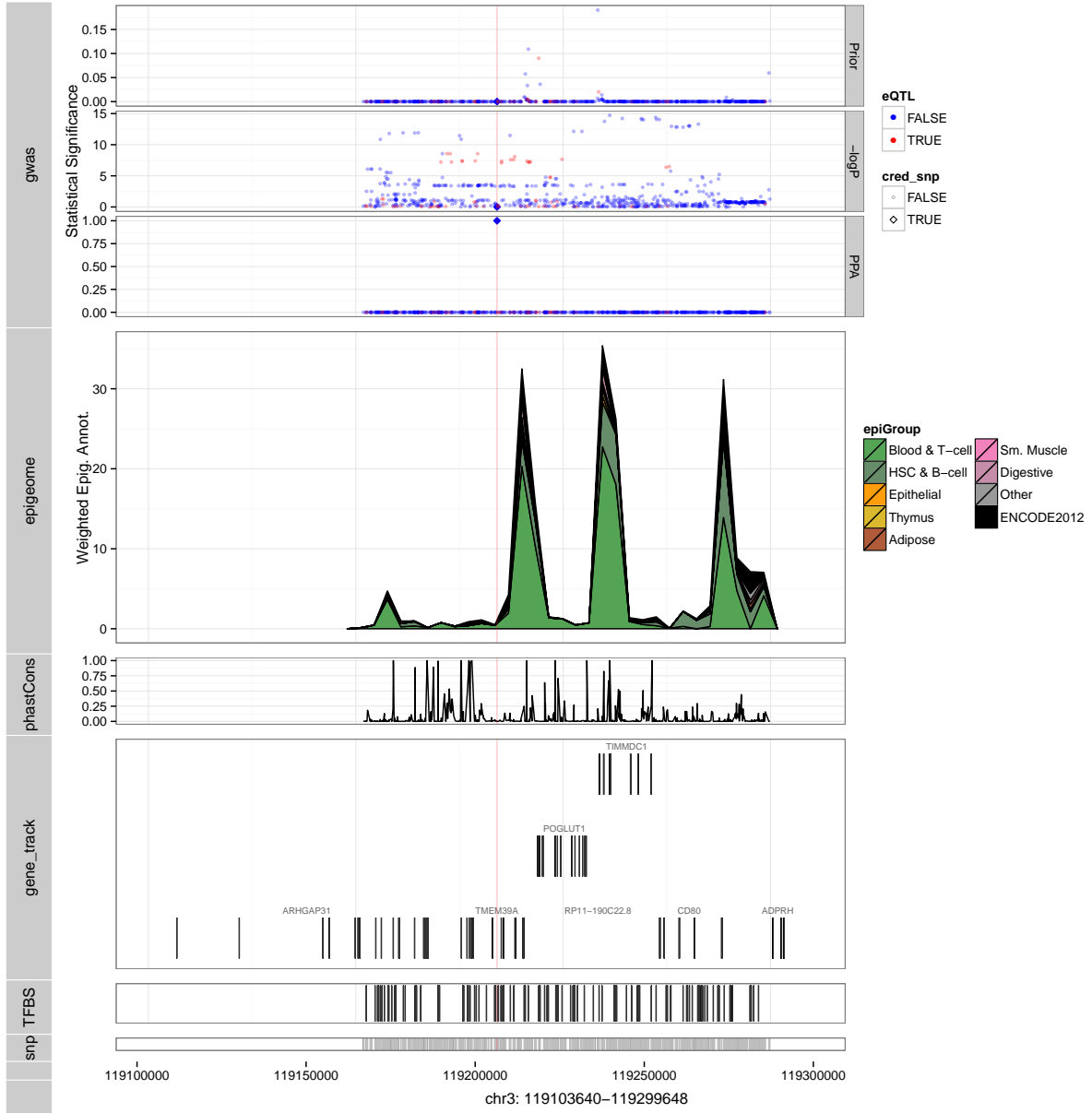
Multiple Sclerosis



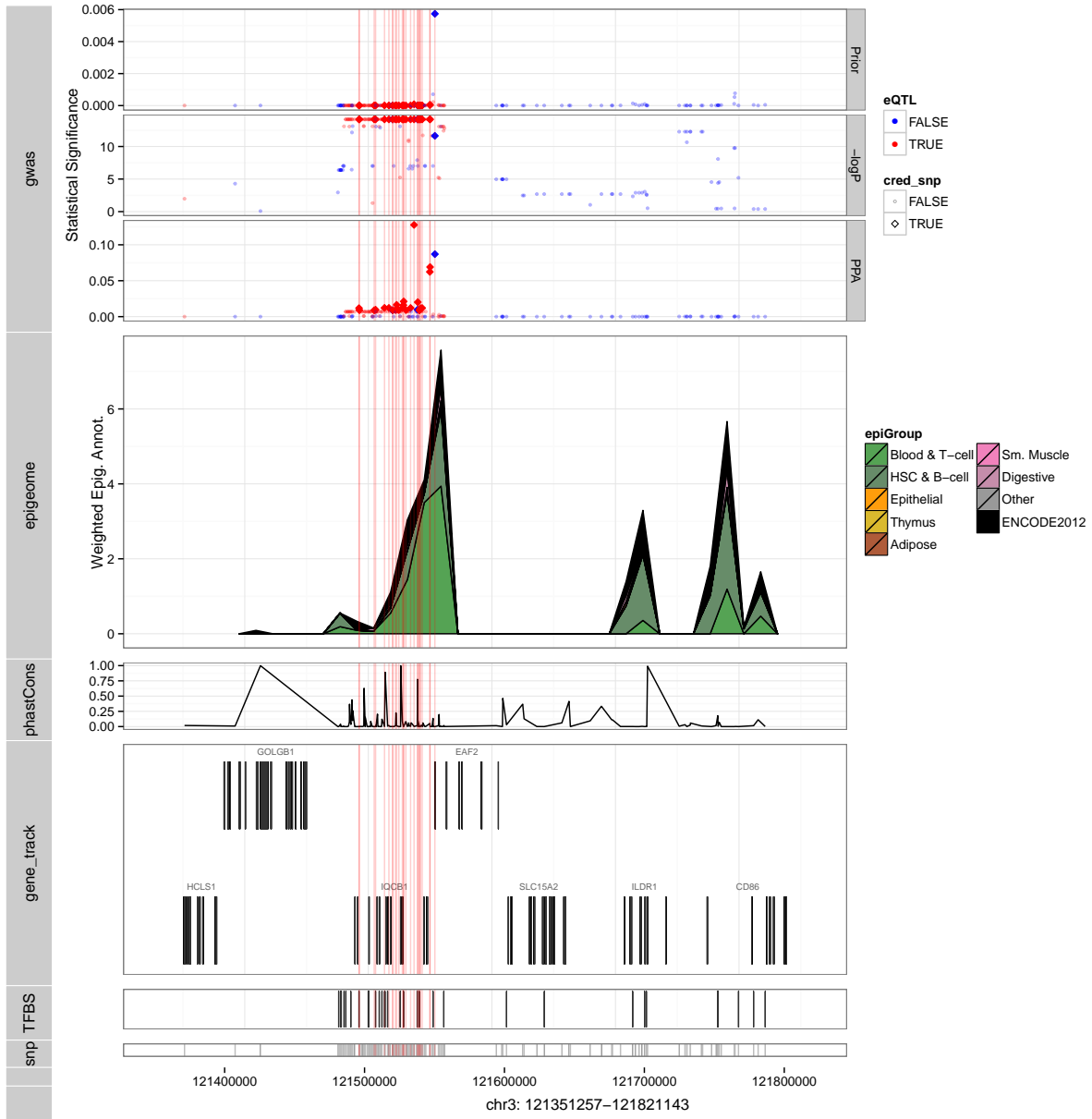
Multiple Sclerosis



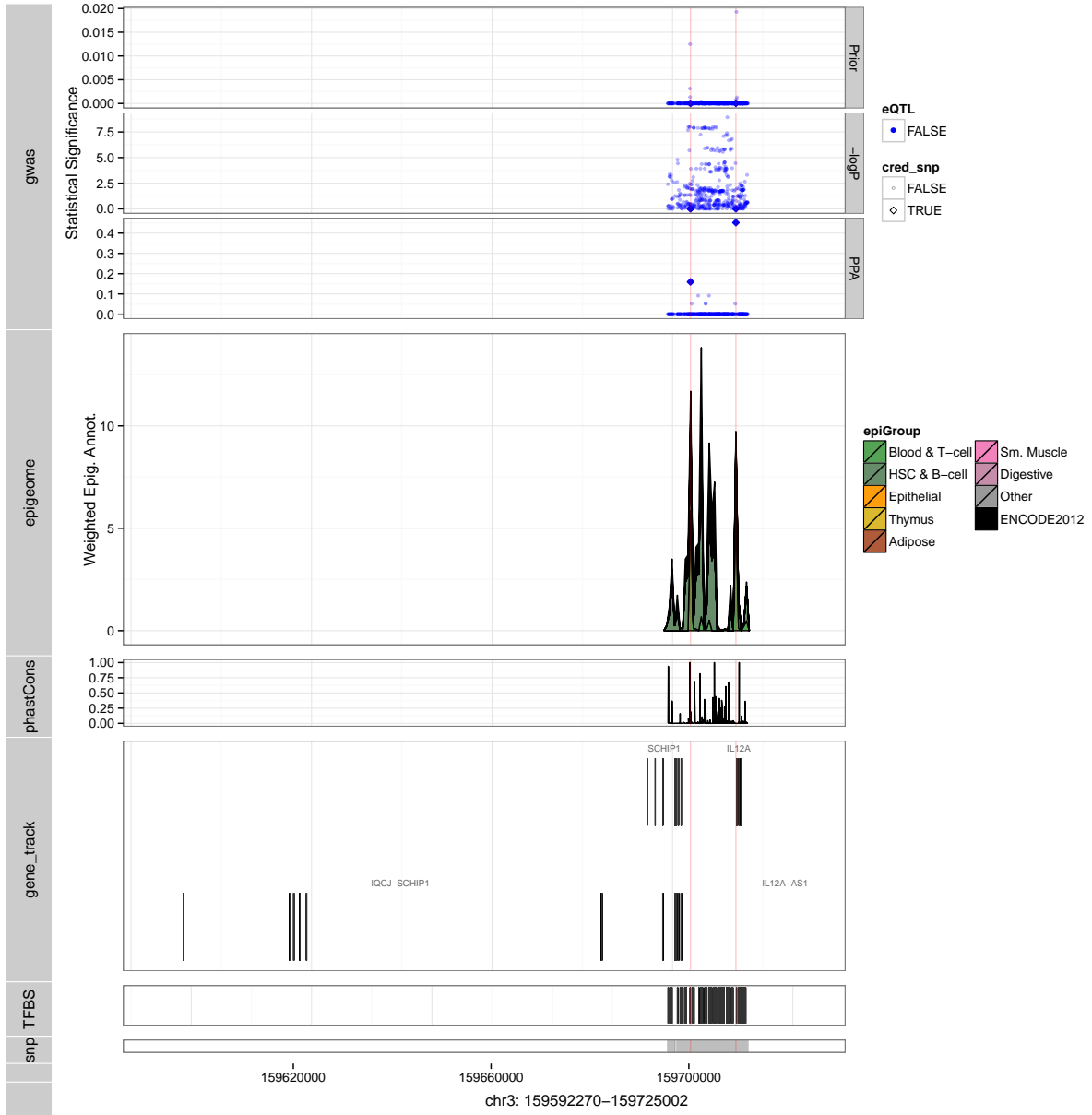
Multiple Sclerosis



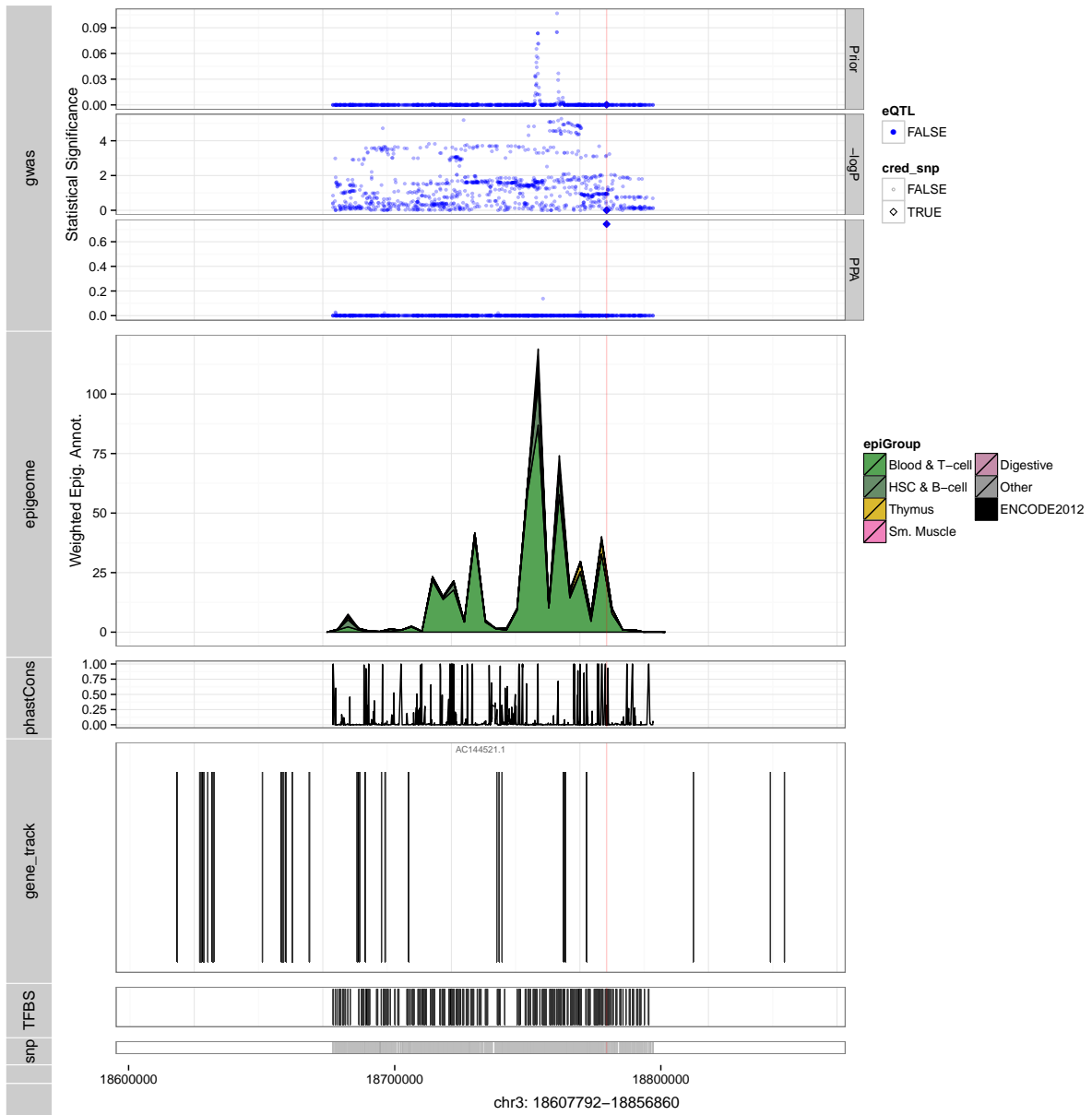
Multiple Sclerosis



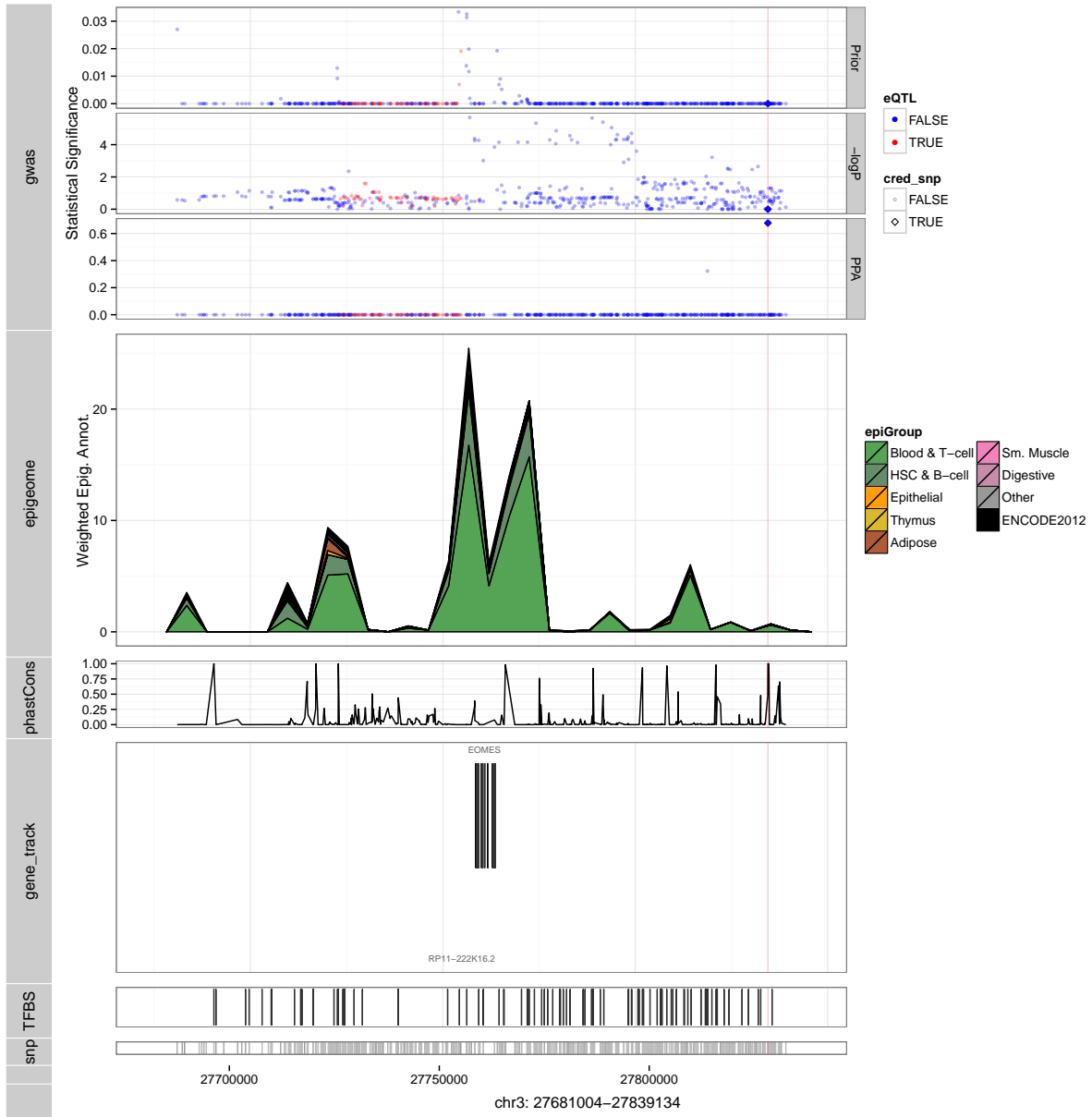
Multiple Sclerosis



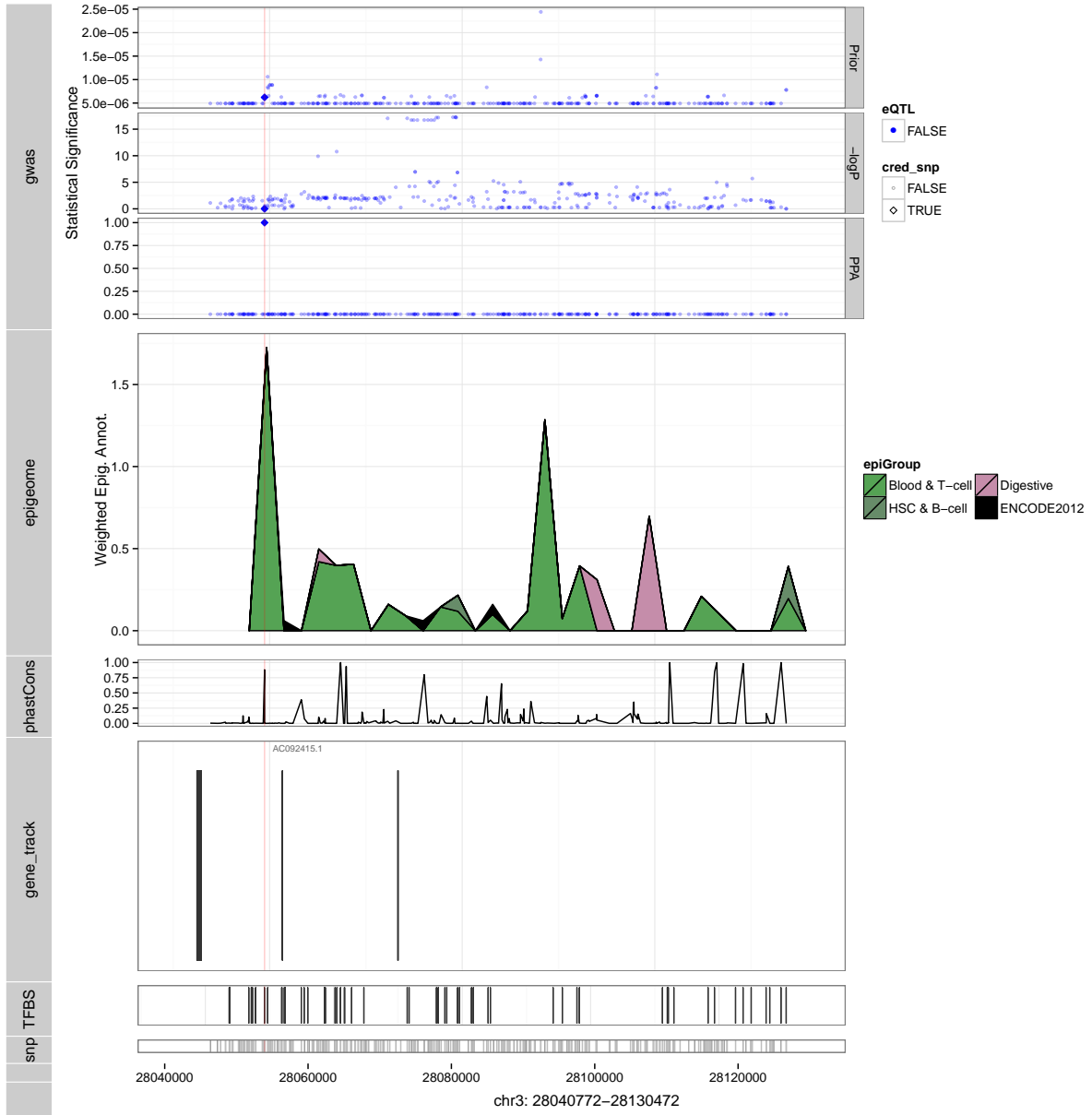
Multiple Sclerosis



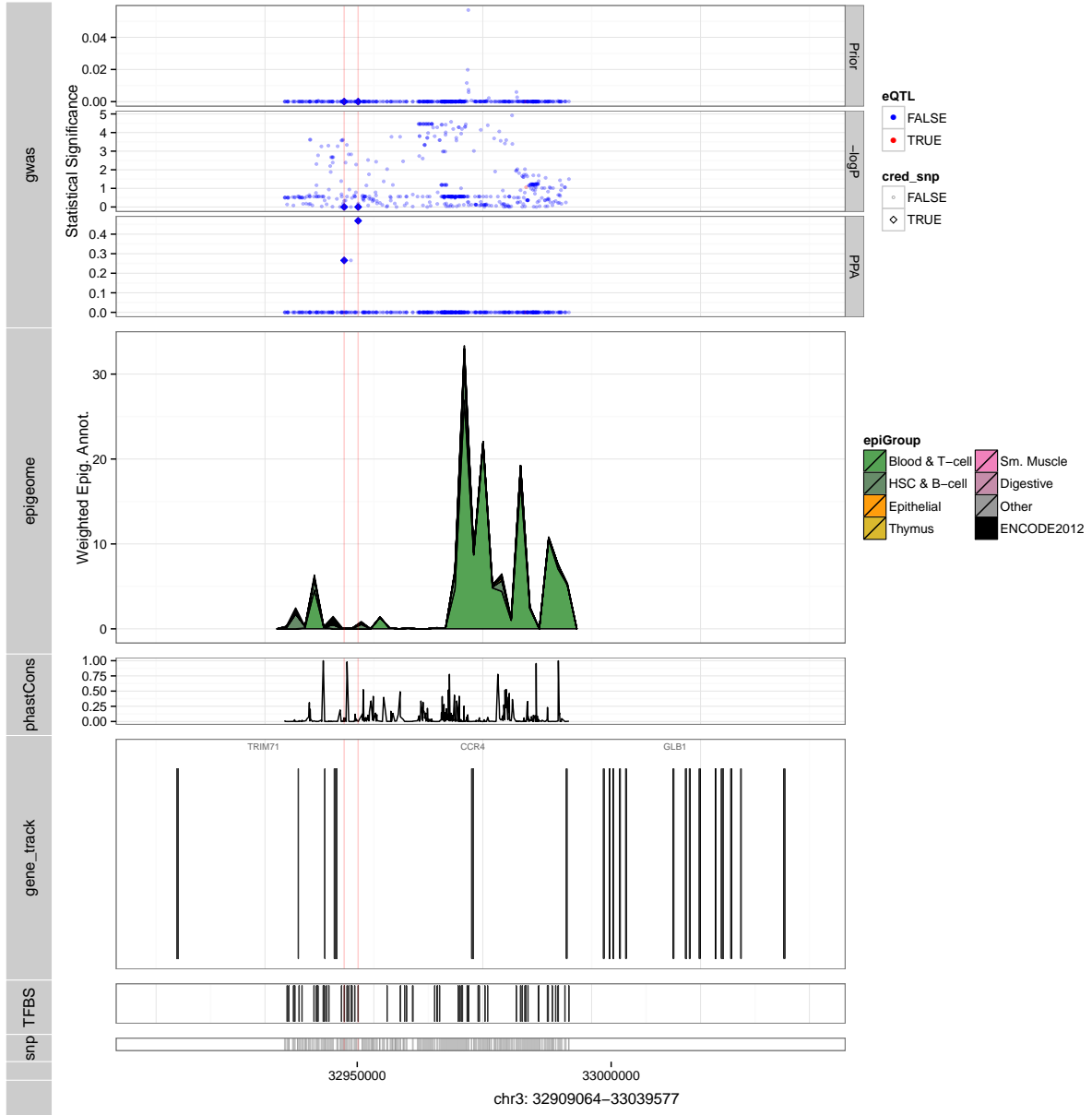
Multiple Sclerosis



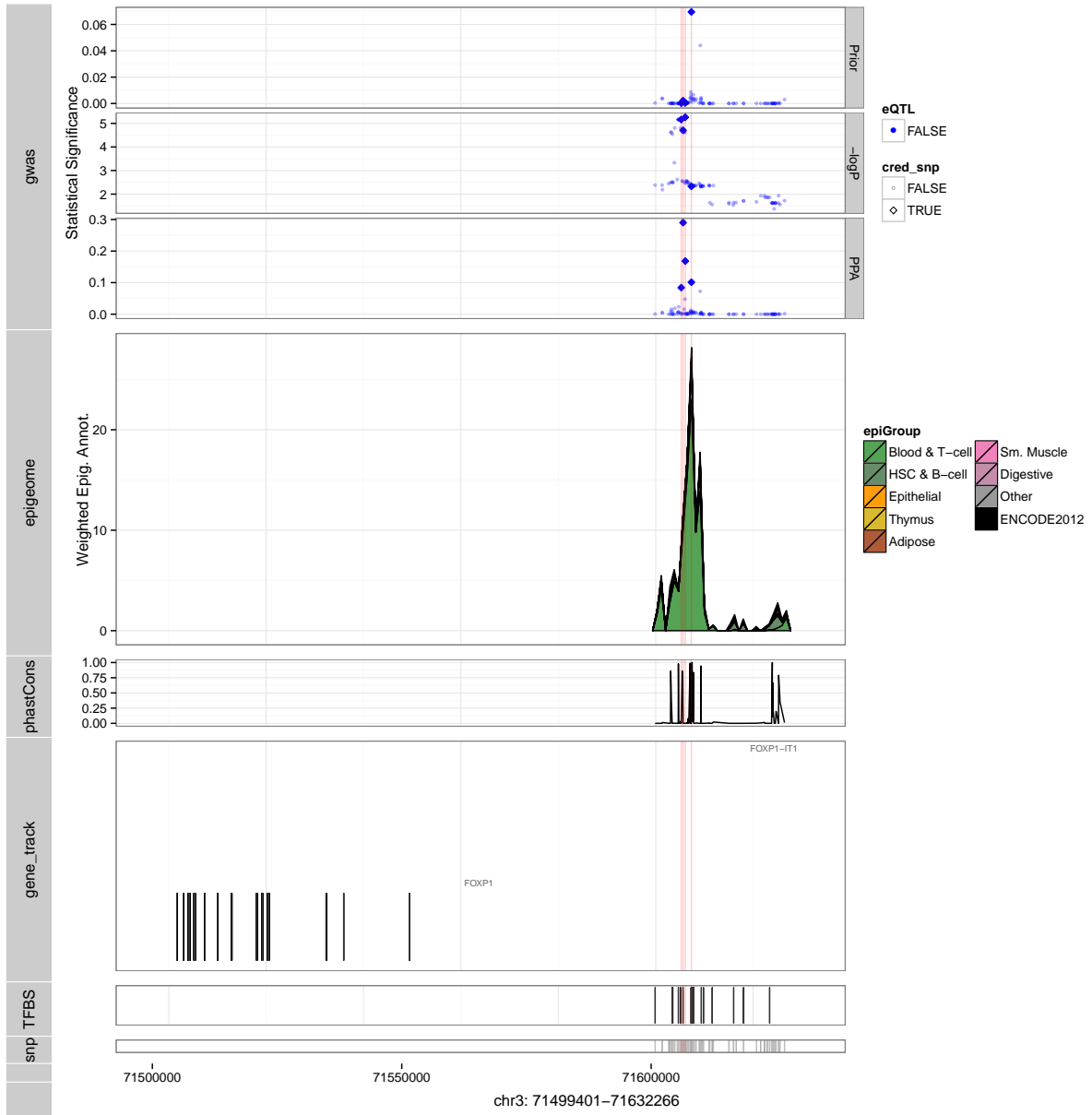
Multiple Sclerosis



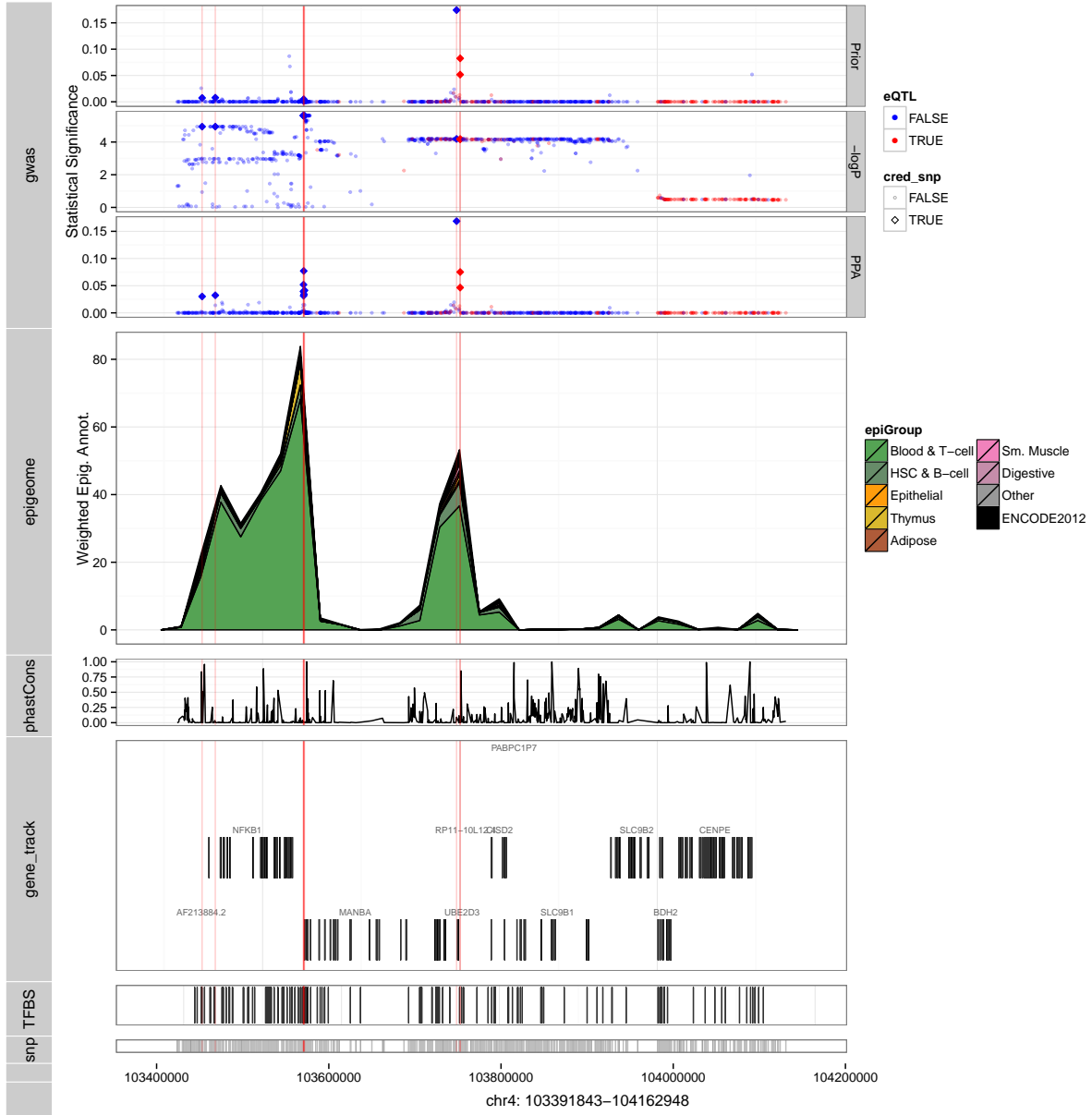
Multiple Sclerosis



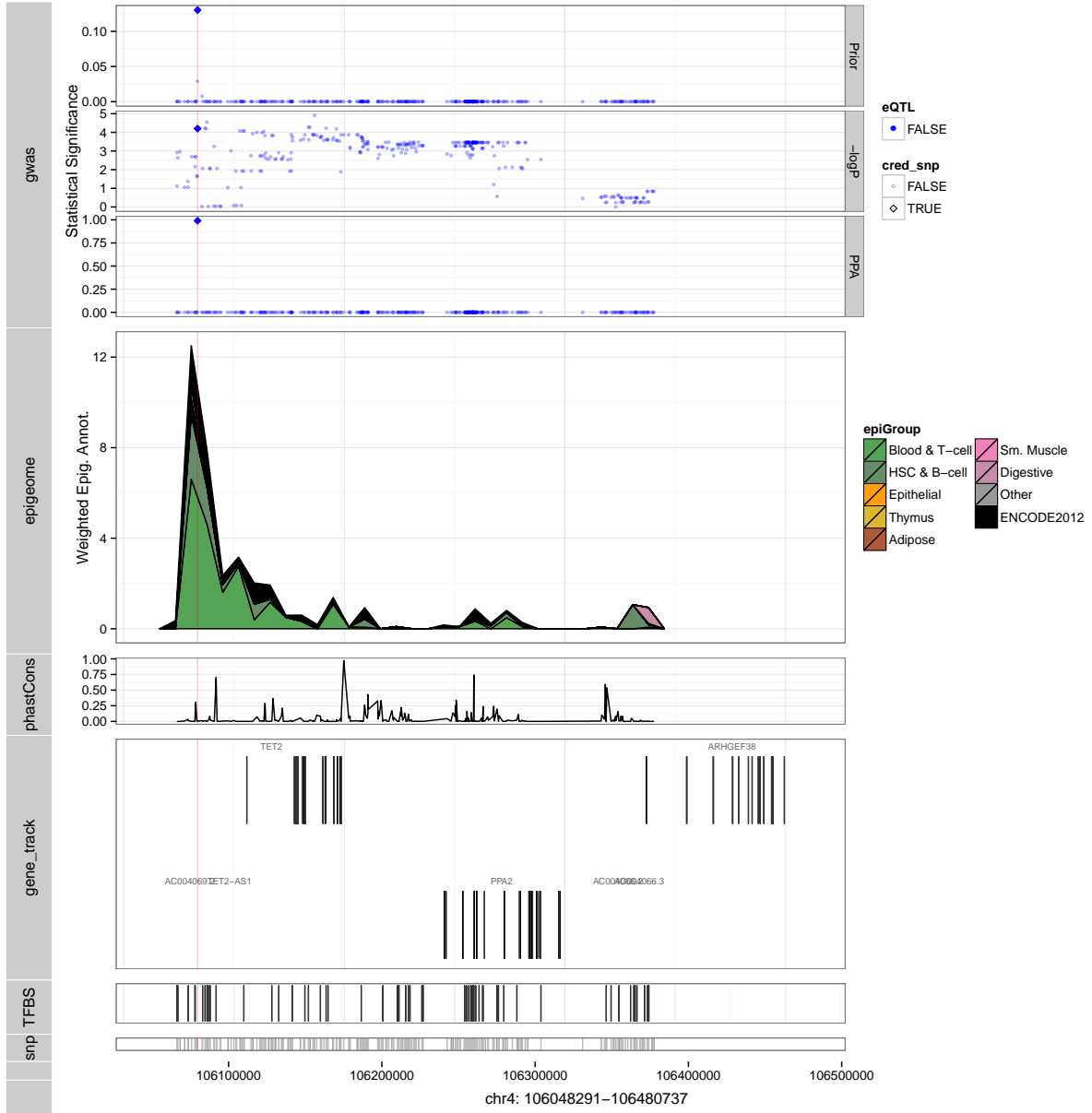
Multiple Sclerosis



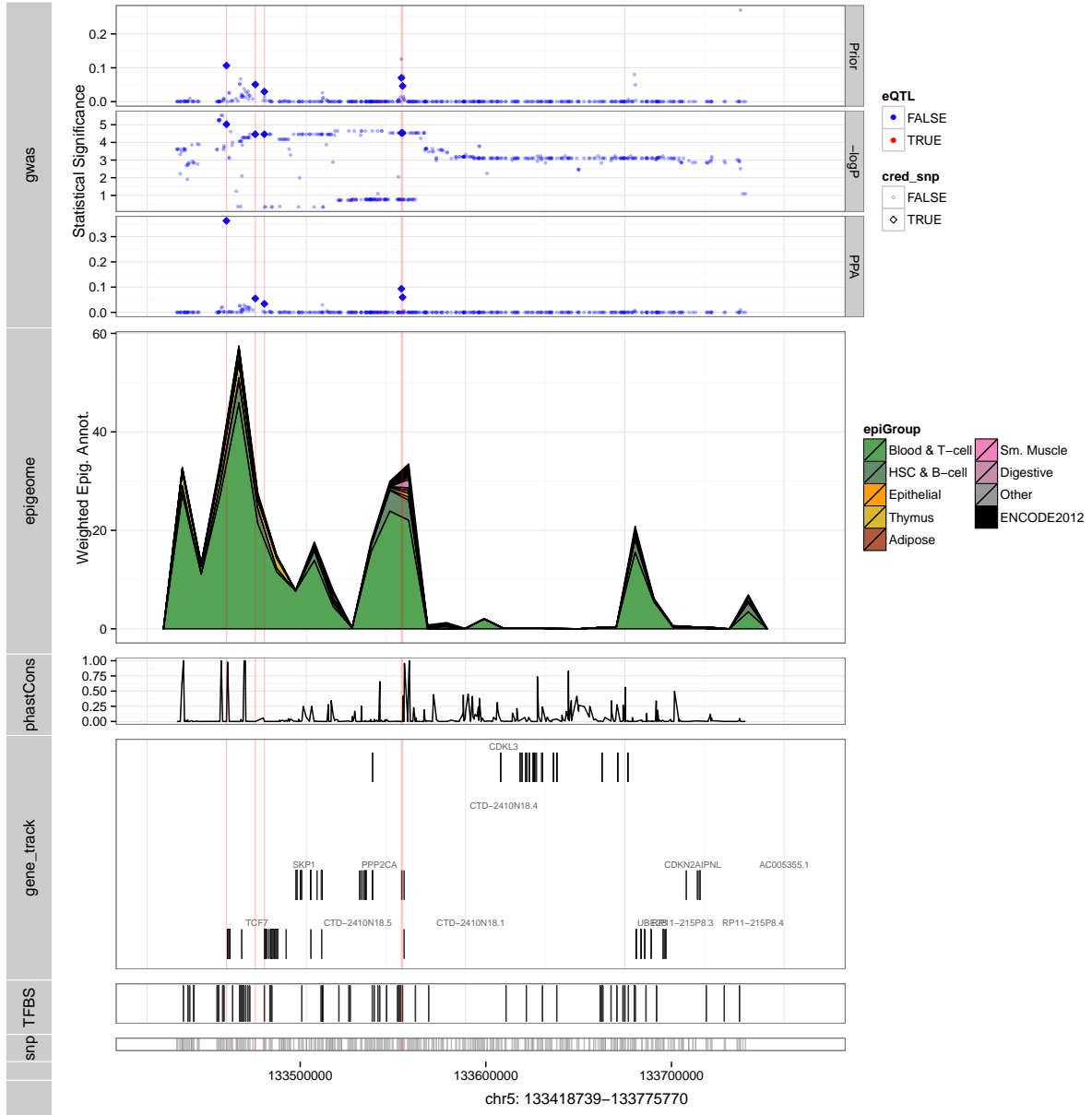
Multiple Sclerosis



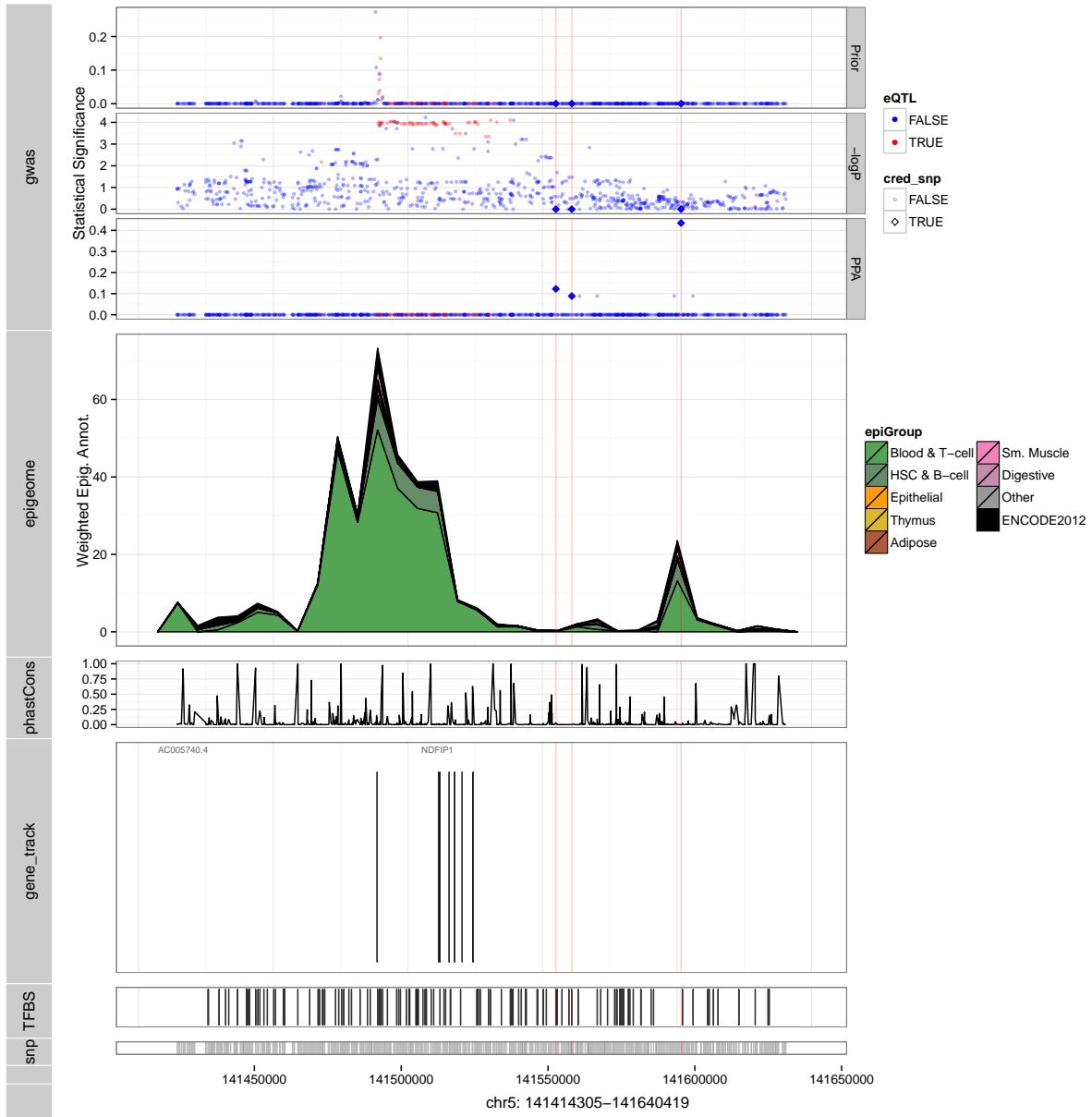
Multiple Sclerosis



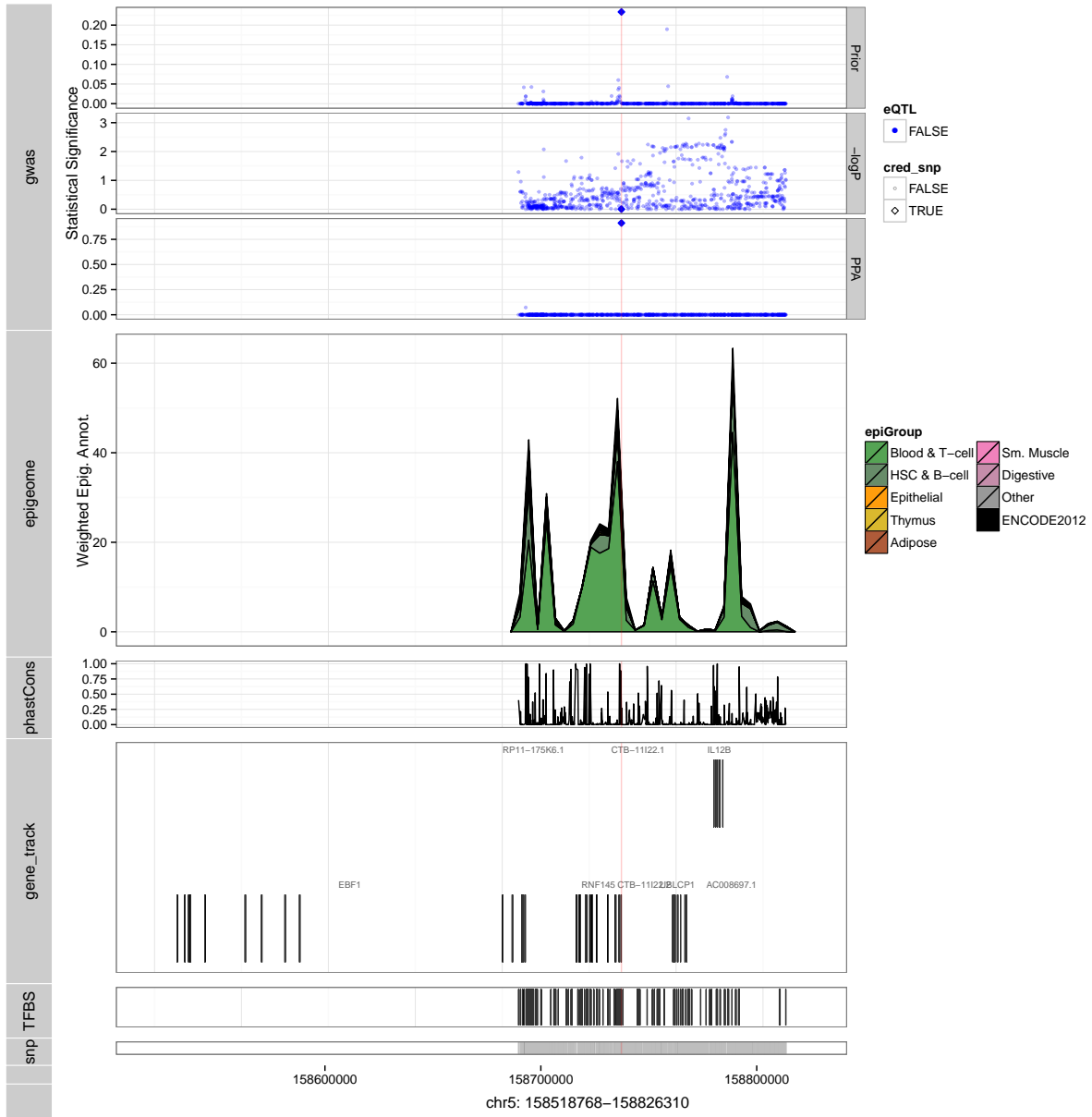
Multiple Sclerosis



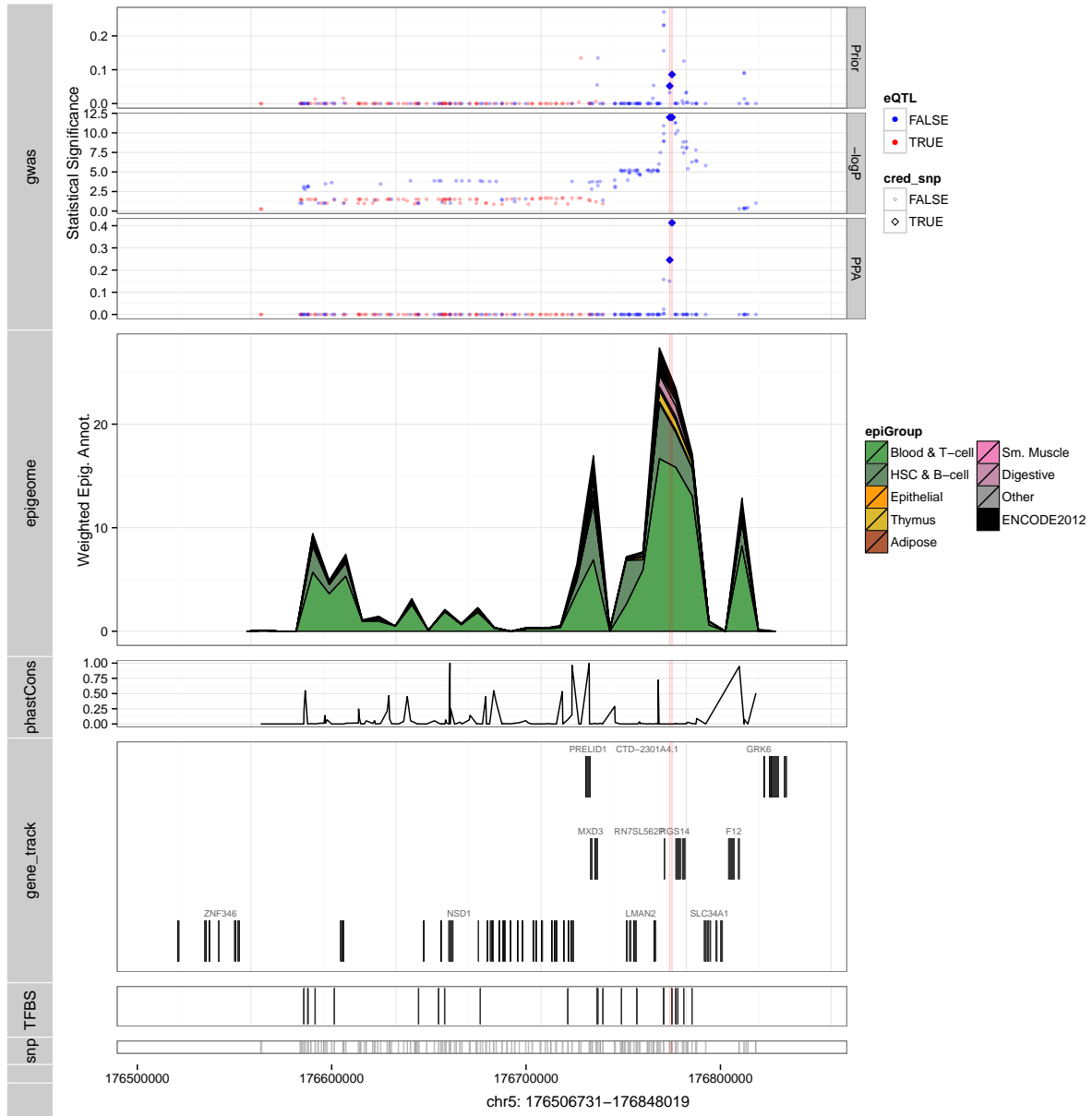
Multiple Sclerosis



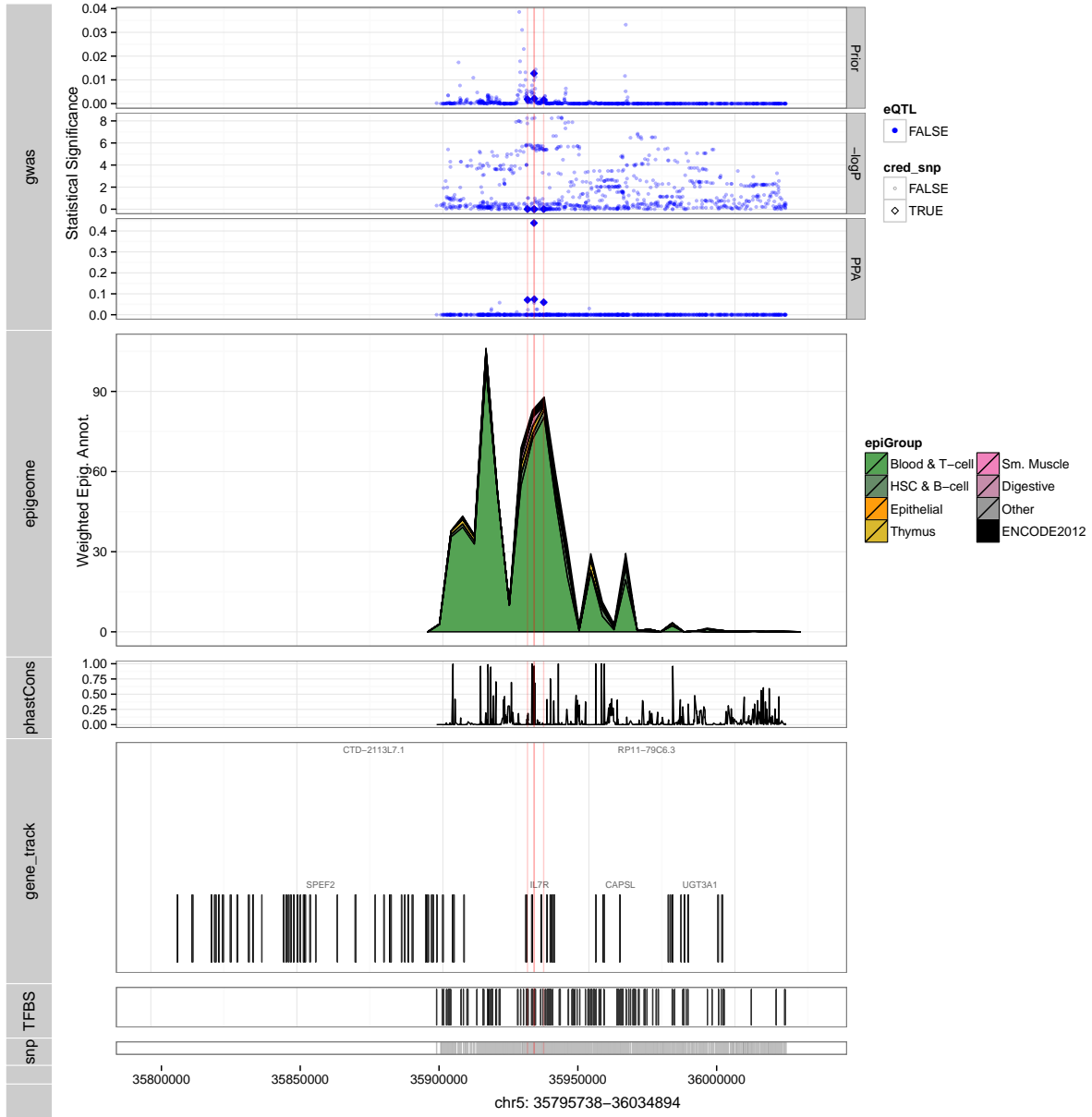
Multiple Sclerosis



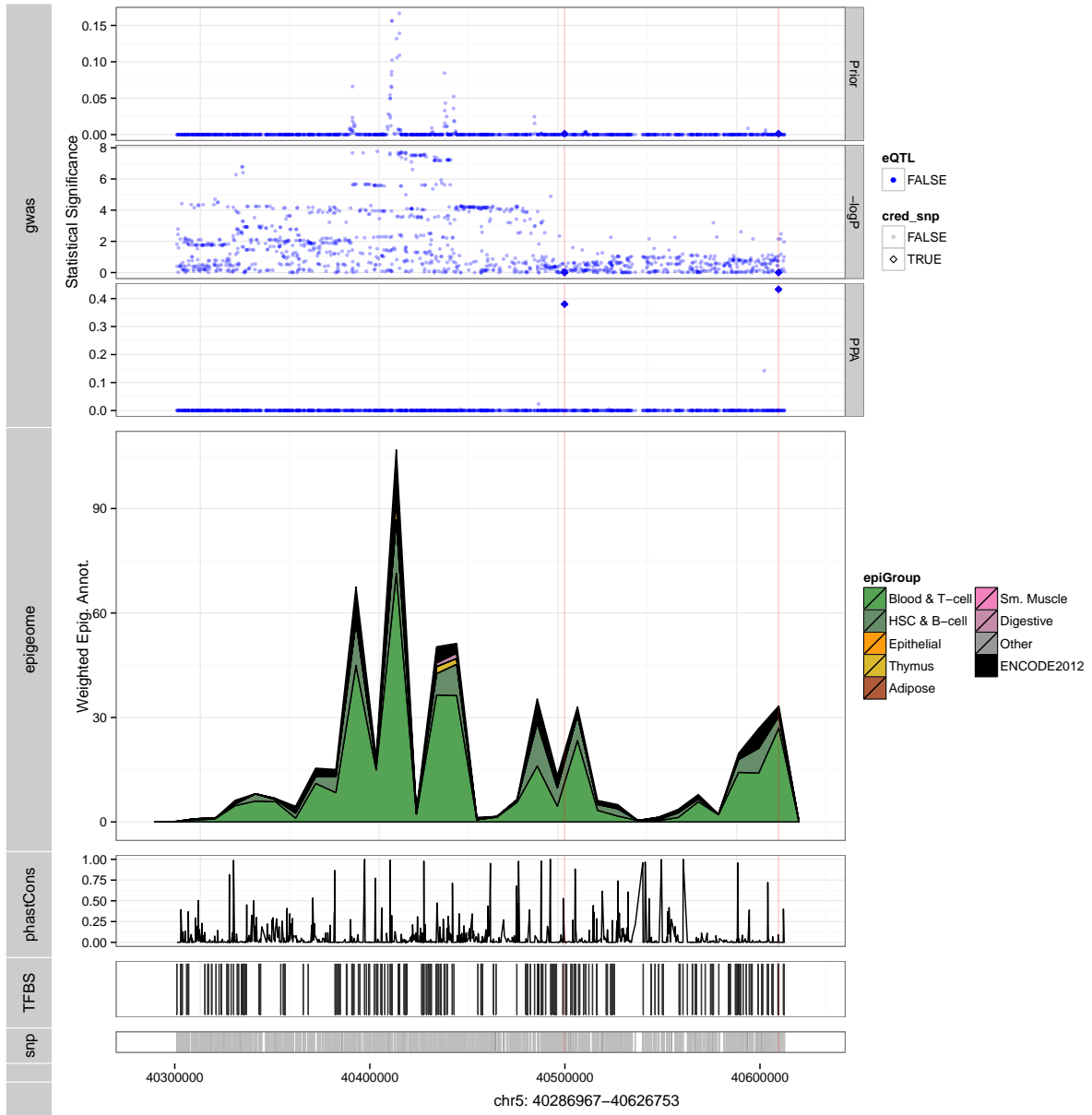
Multiple Sclerosis



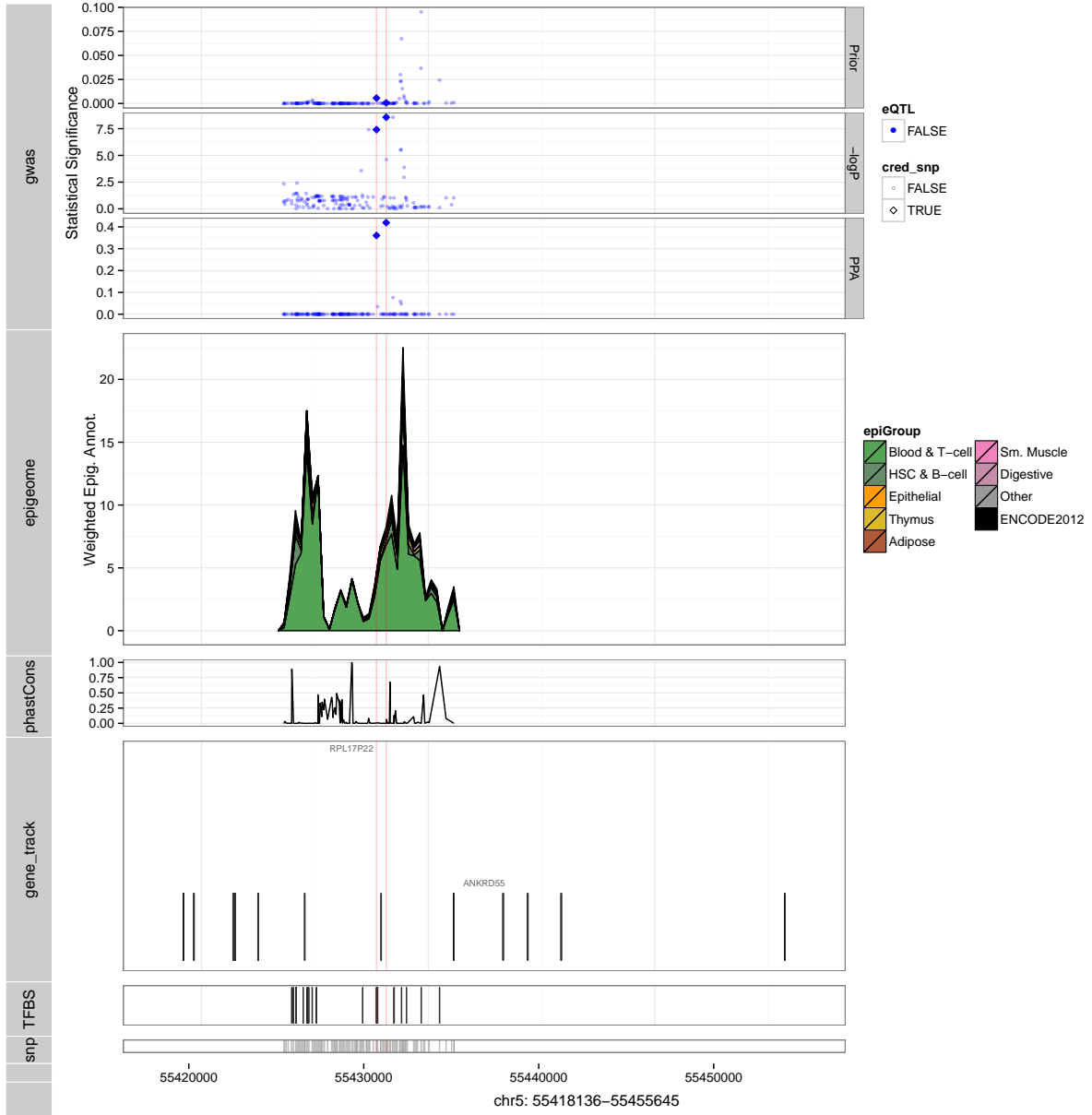
Multiple Sclerosis



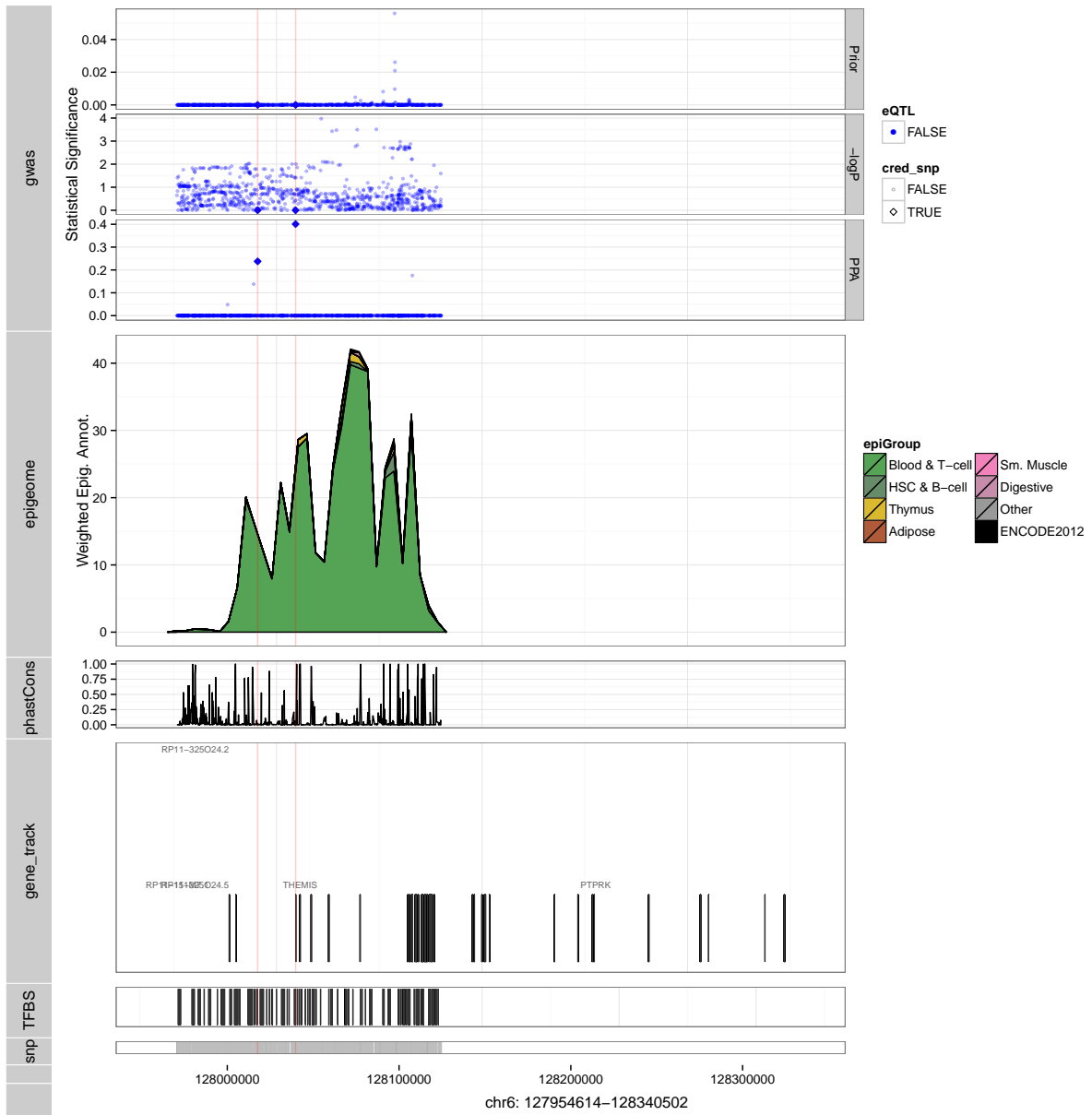
Multiple Sclerosis



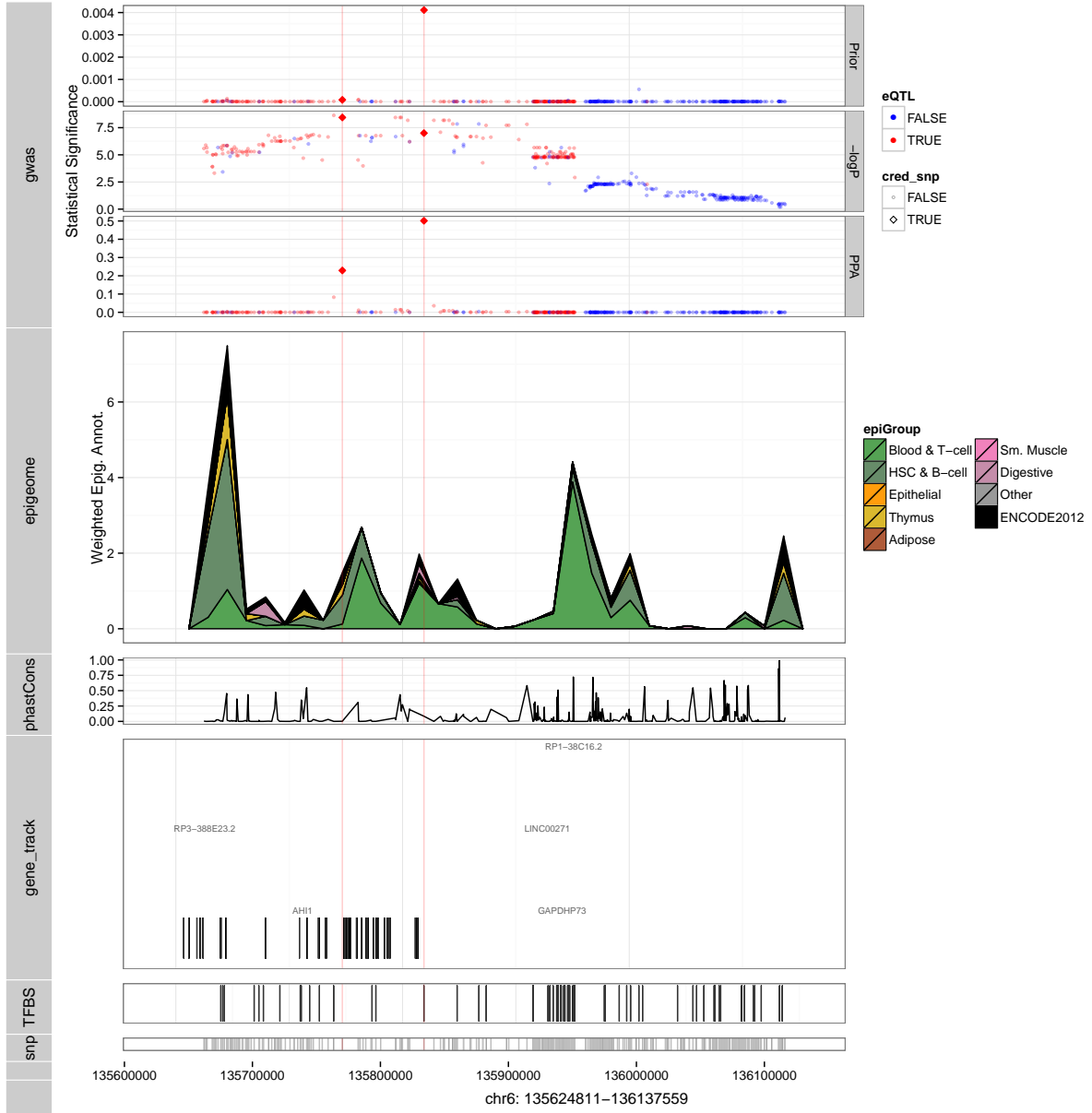
Multiple Sclerosis



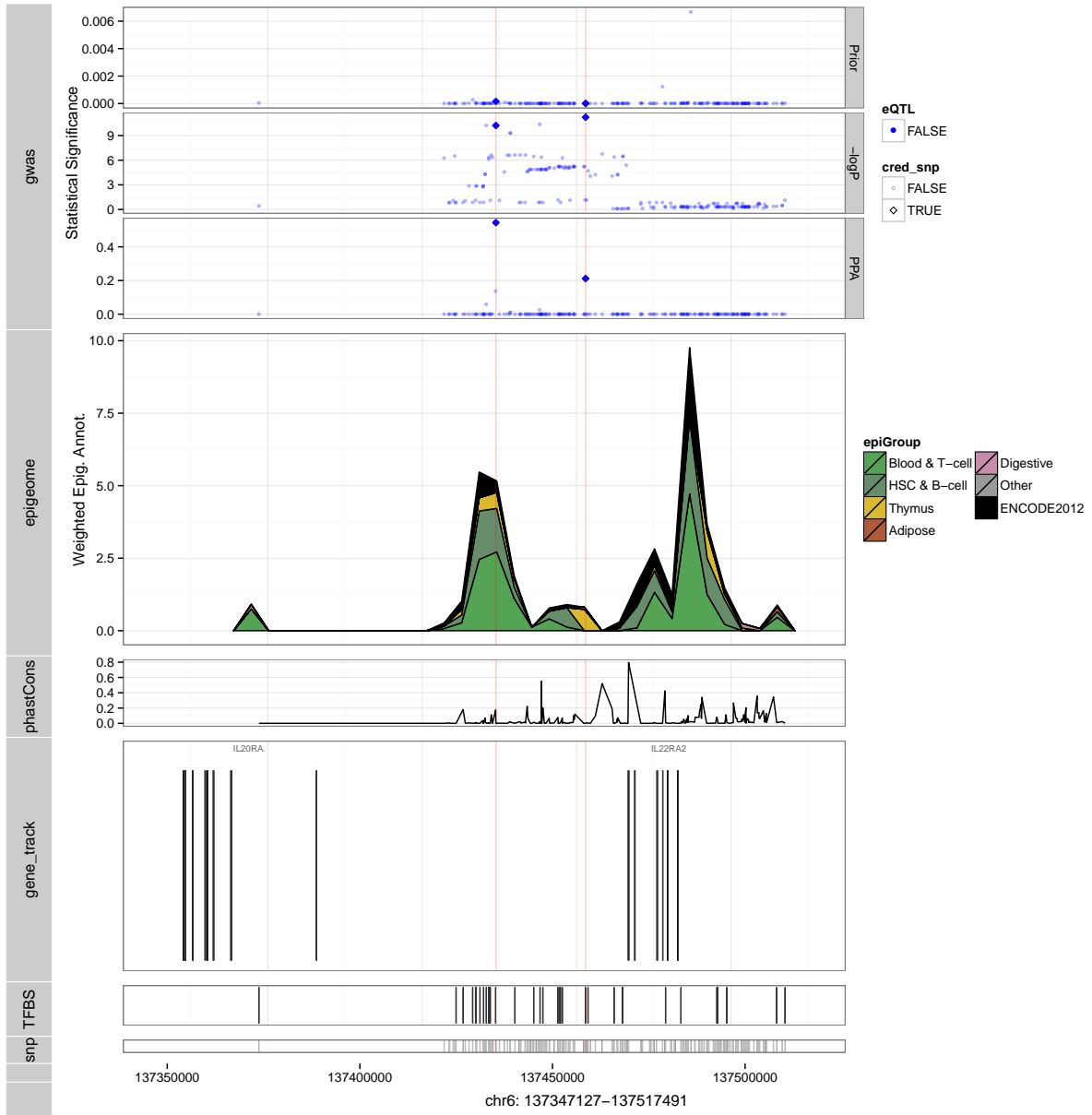
Multiple Sclerosis



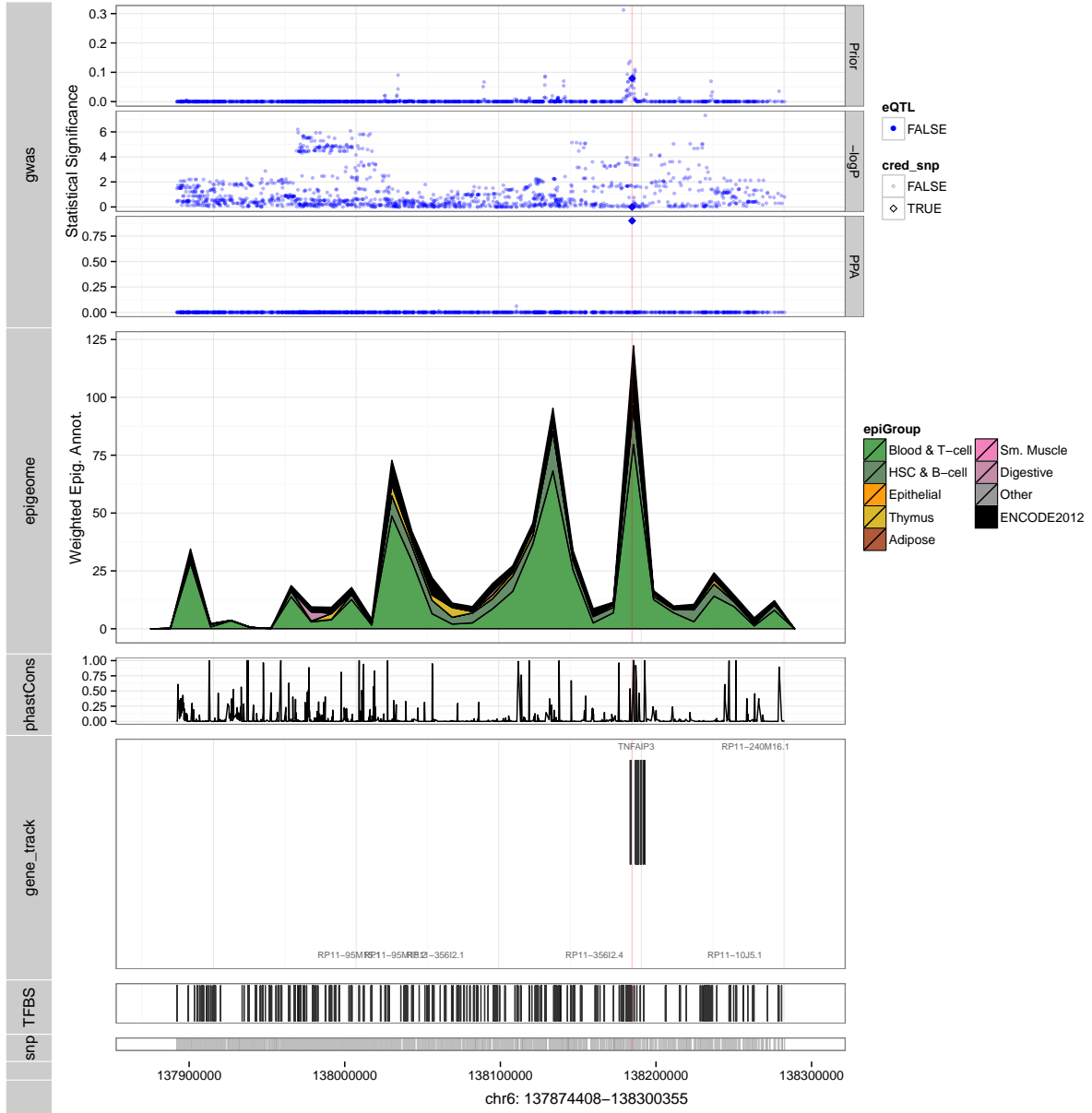
Multiple Sclerosis



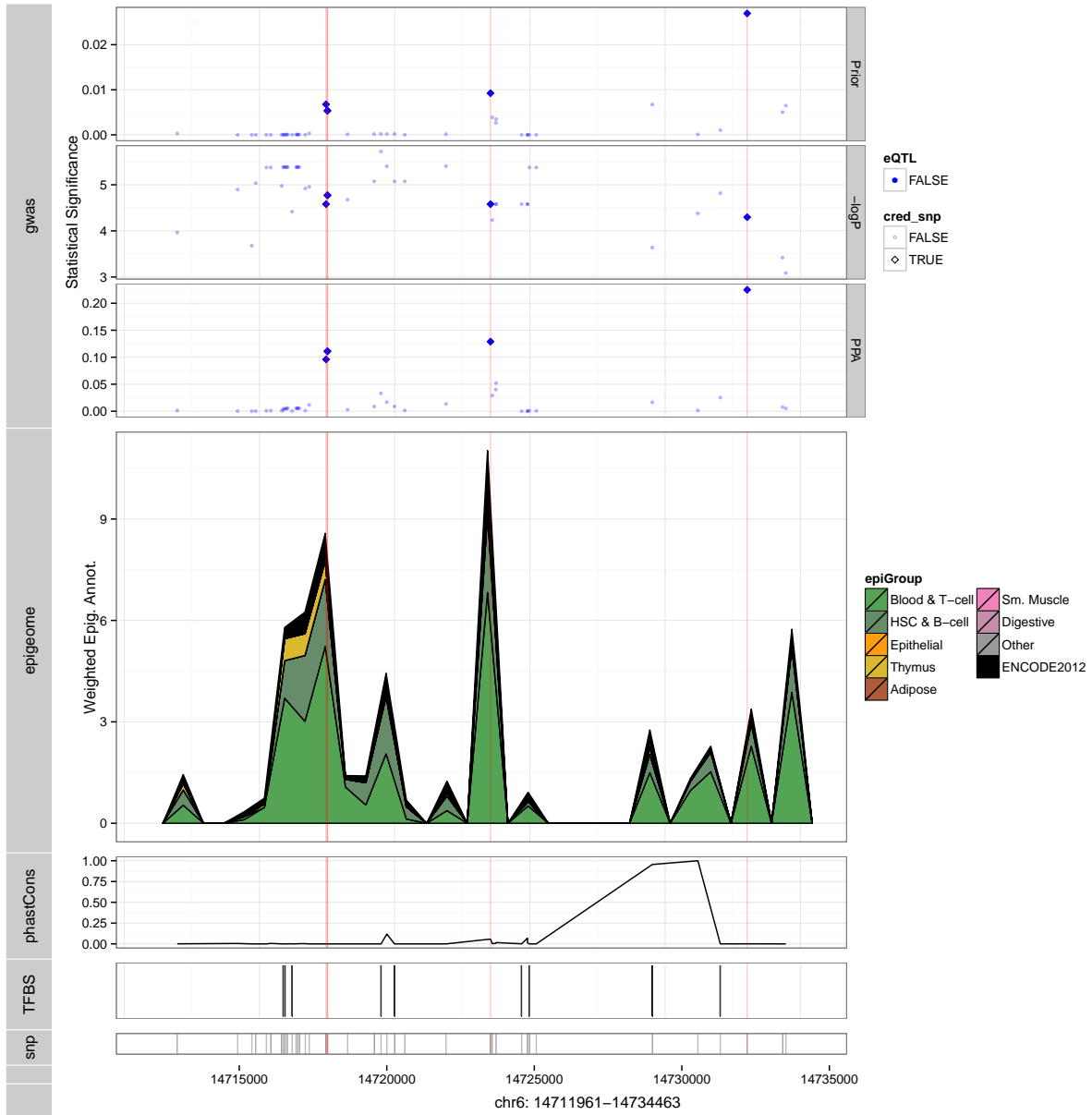
Multiple Sclerosis



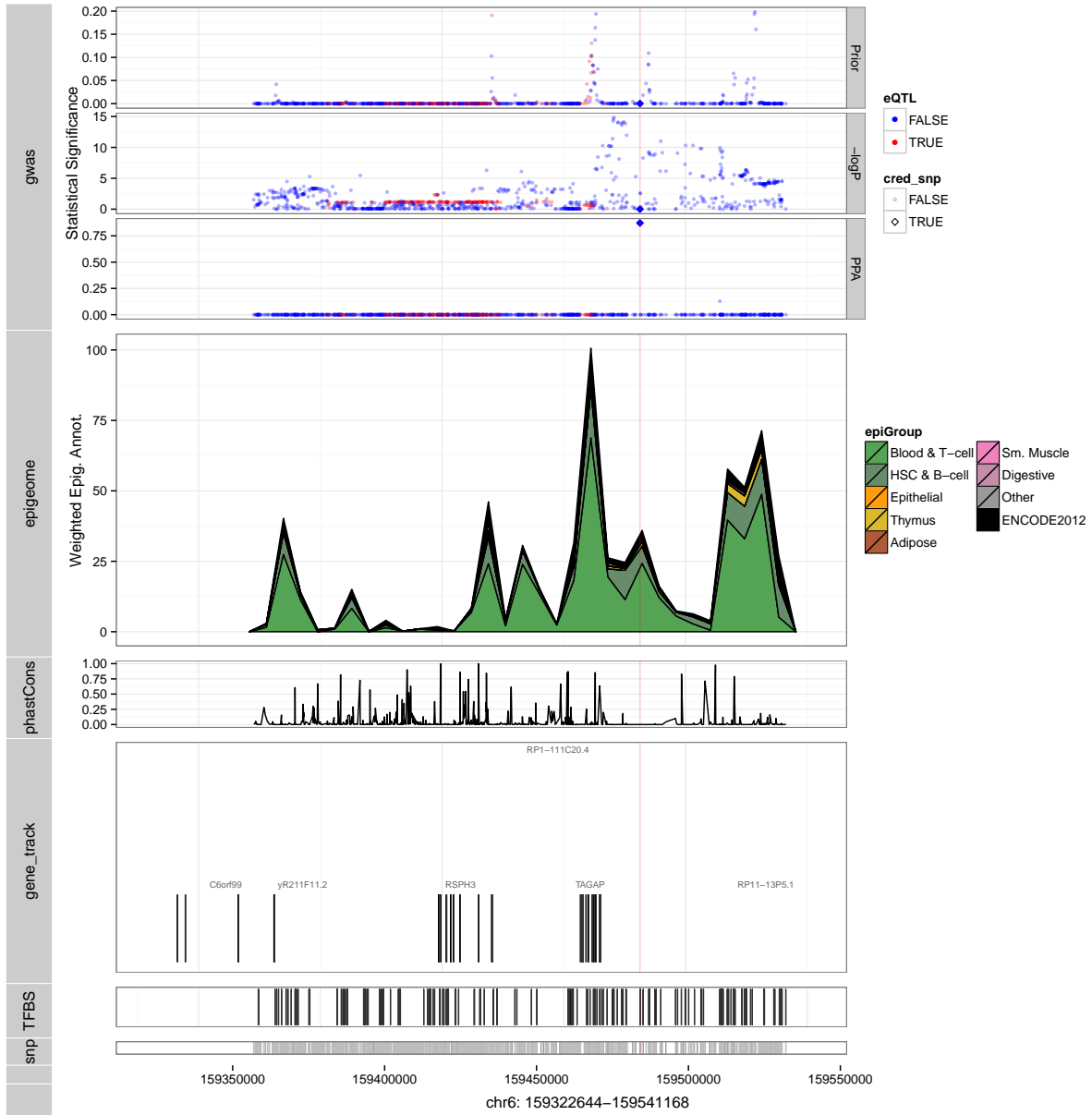
Multiple Sclerosis



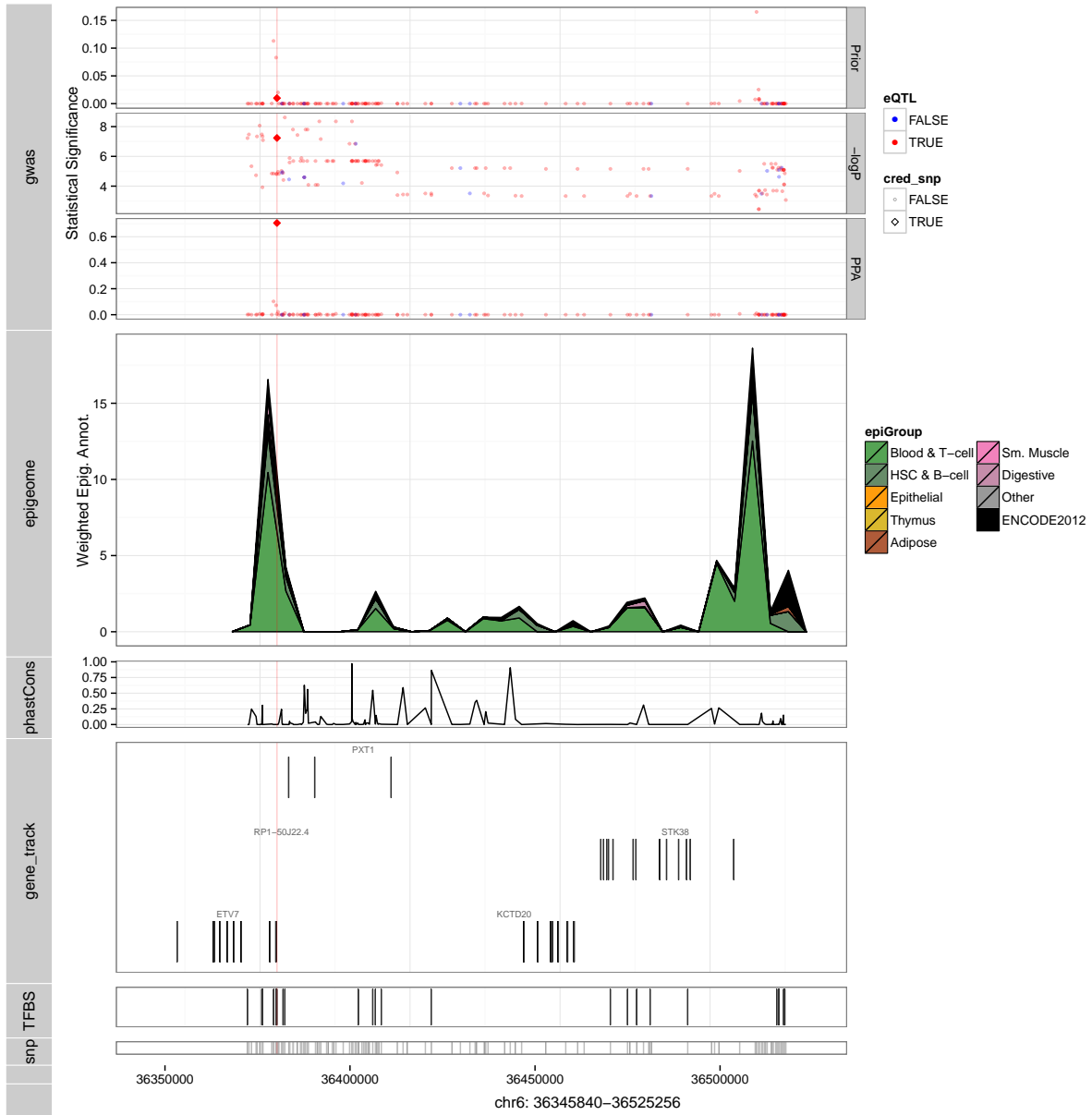
Multiple Sclerosis



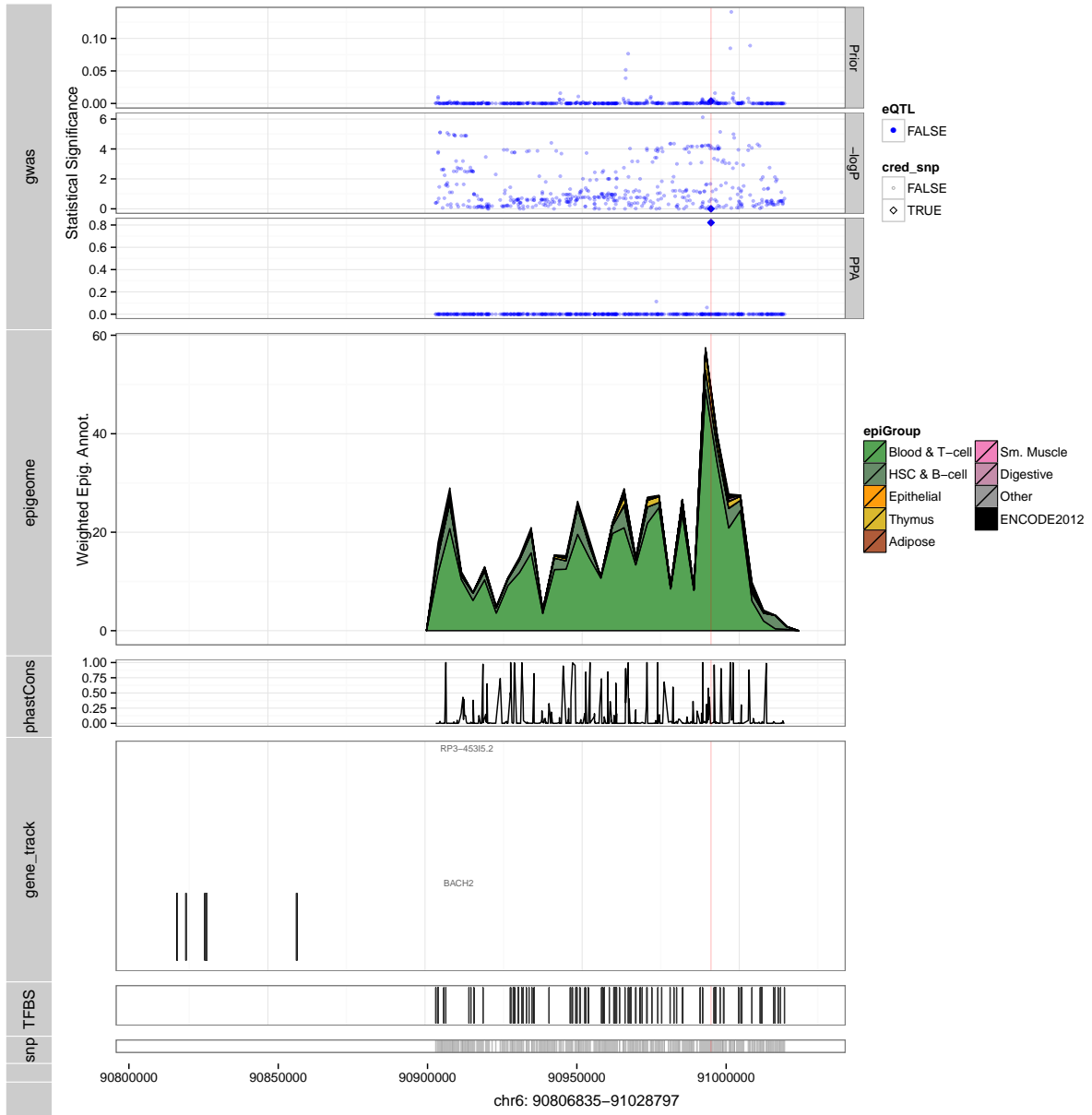
Multiple Sclerosis



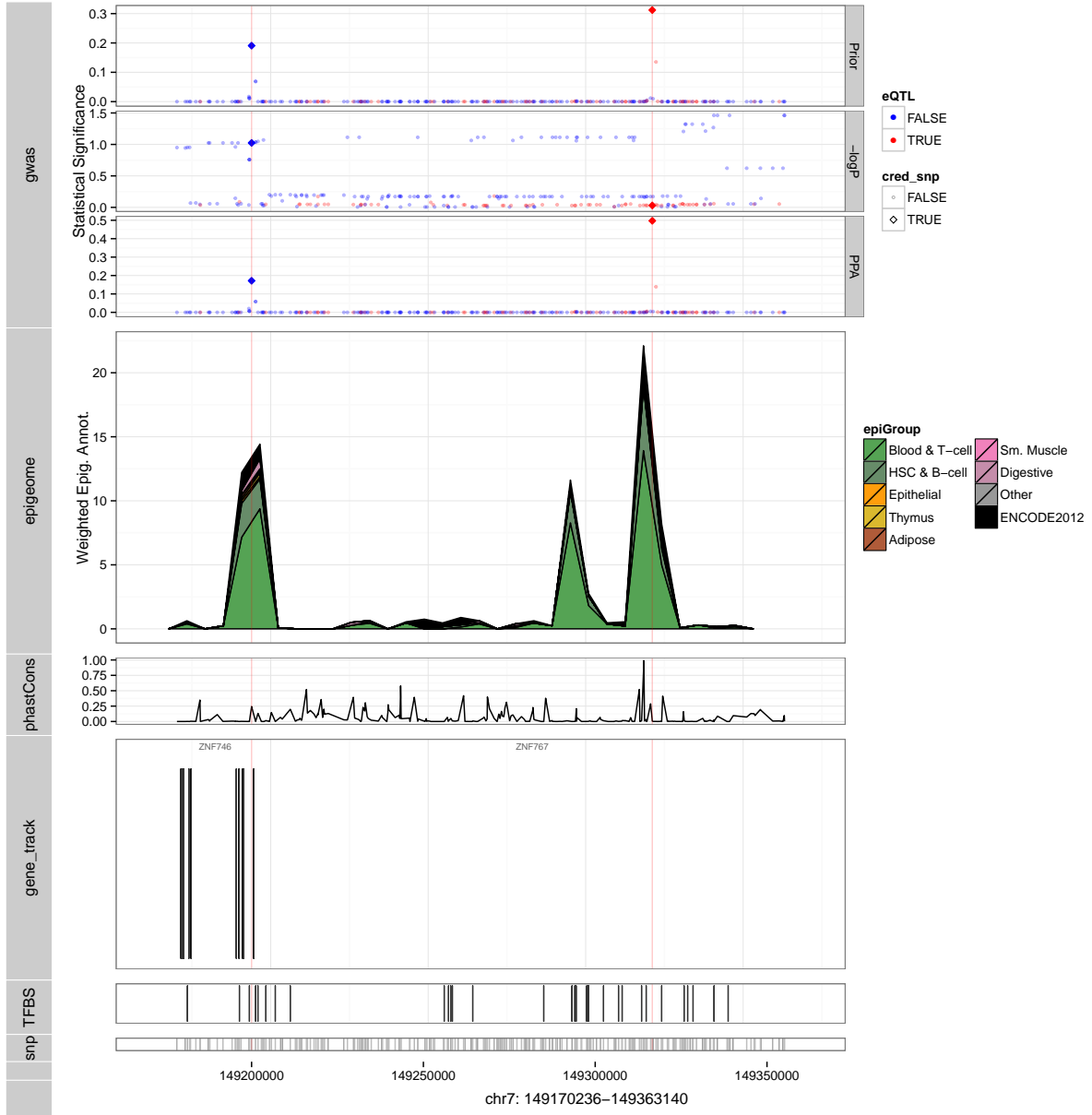
Multiple Sclerosis



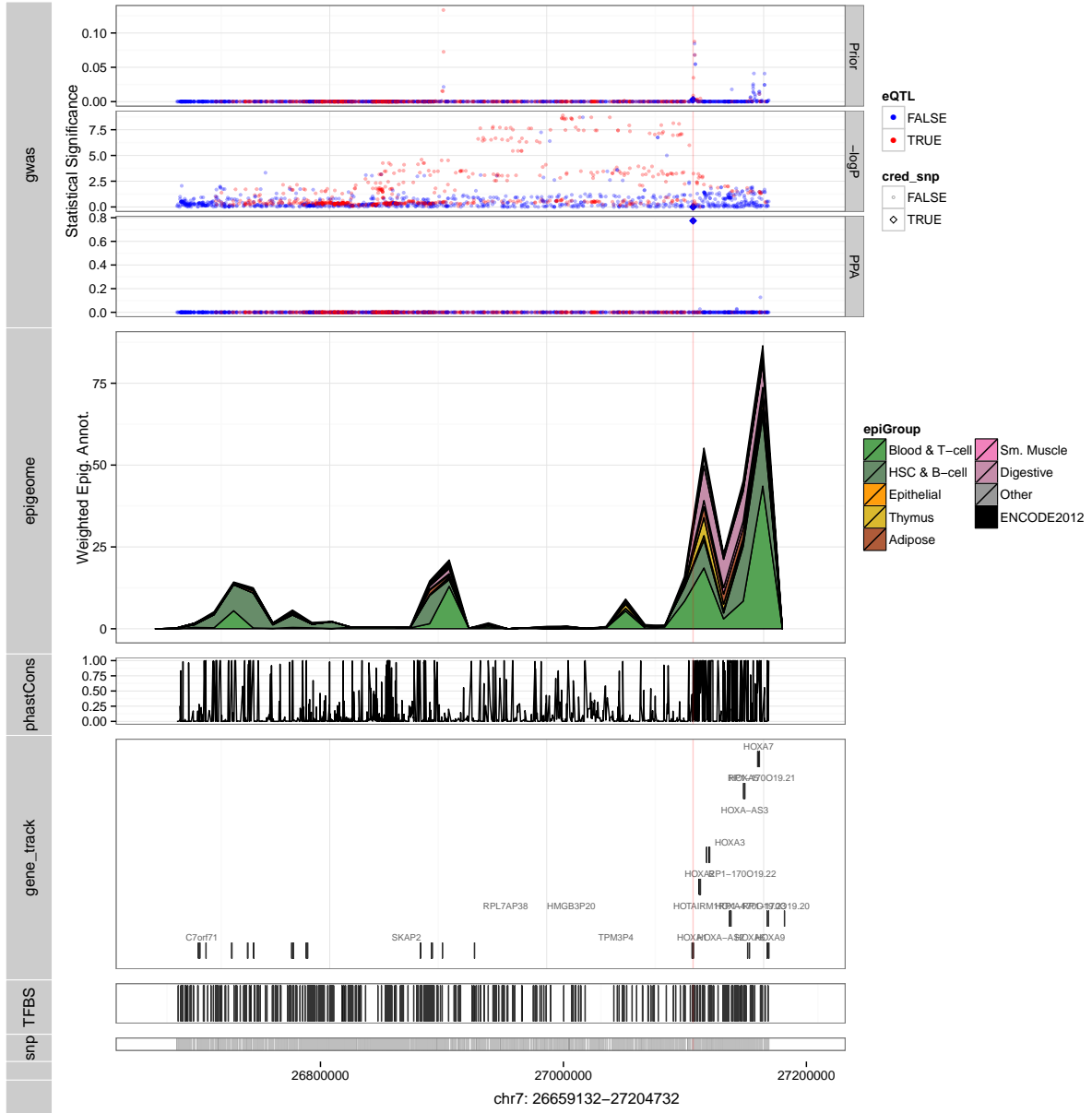
Multiple Sclerosis



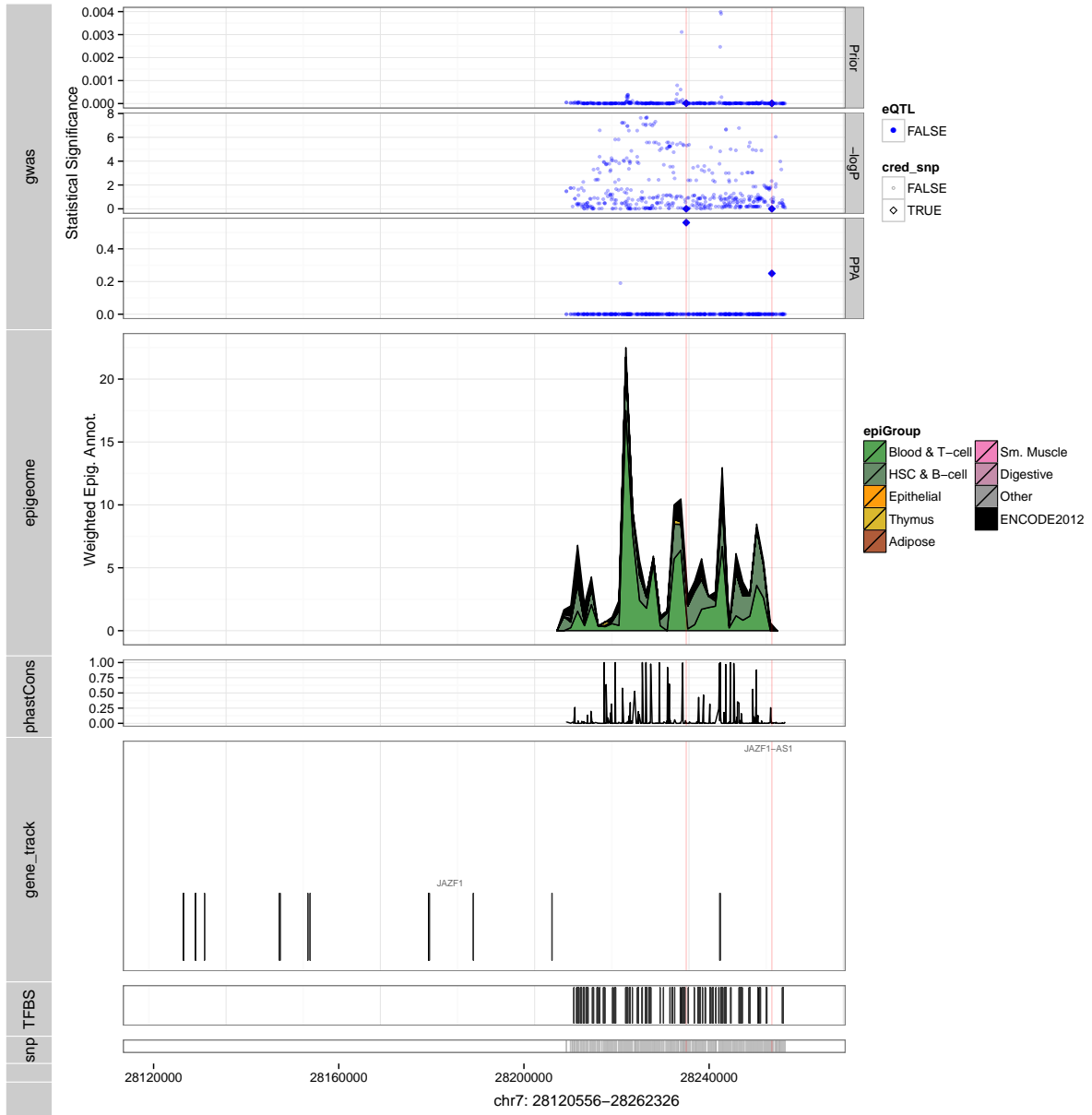
Multiple Sclerosis



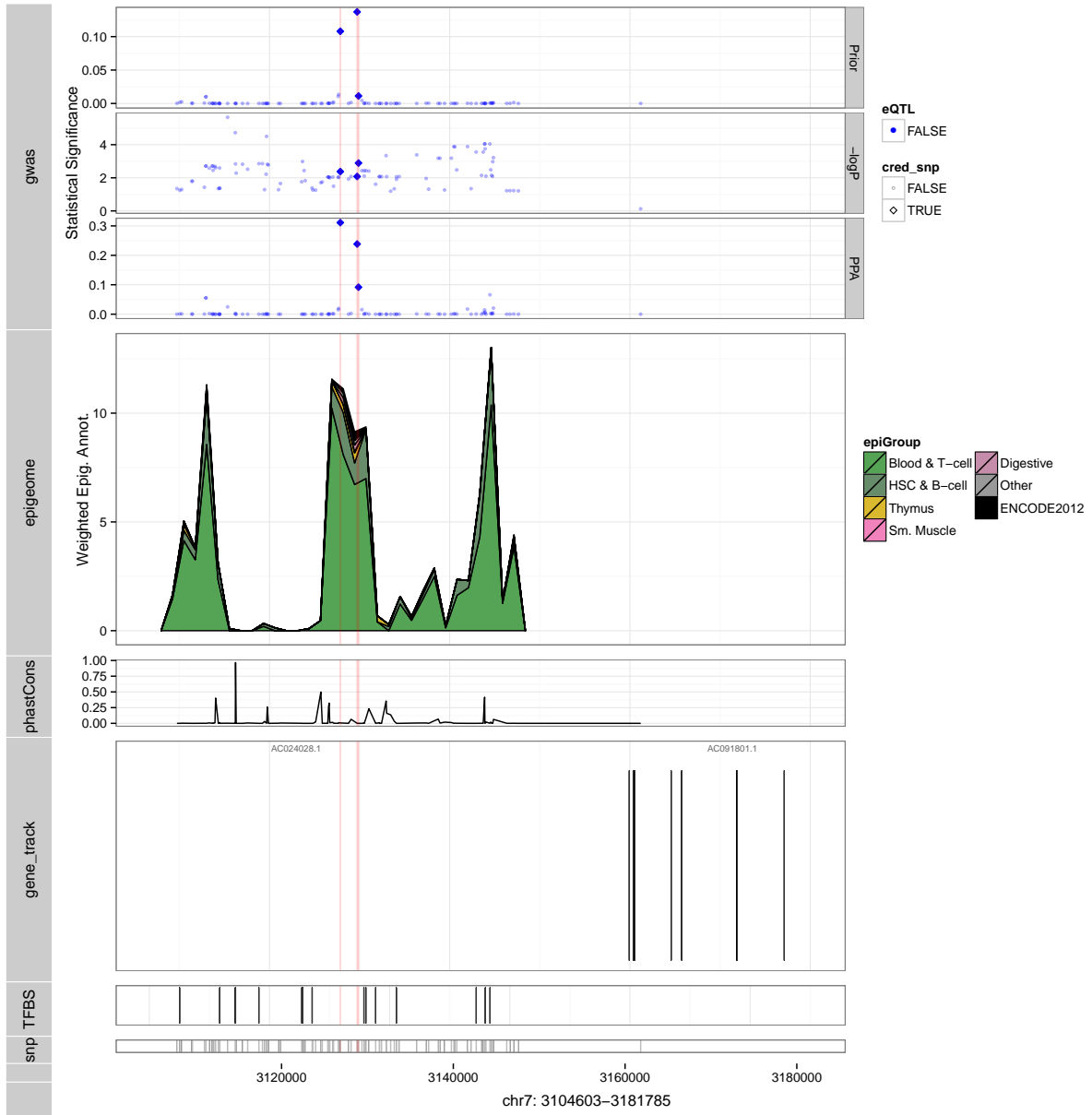
Multiple Sclerosis



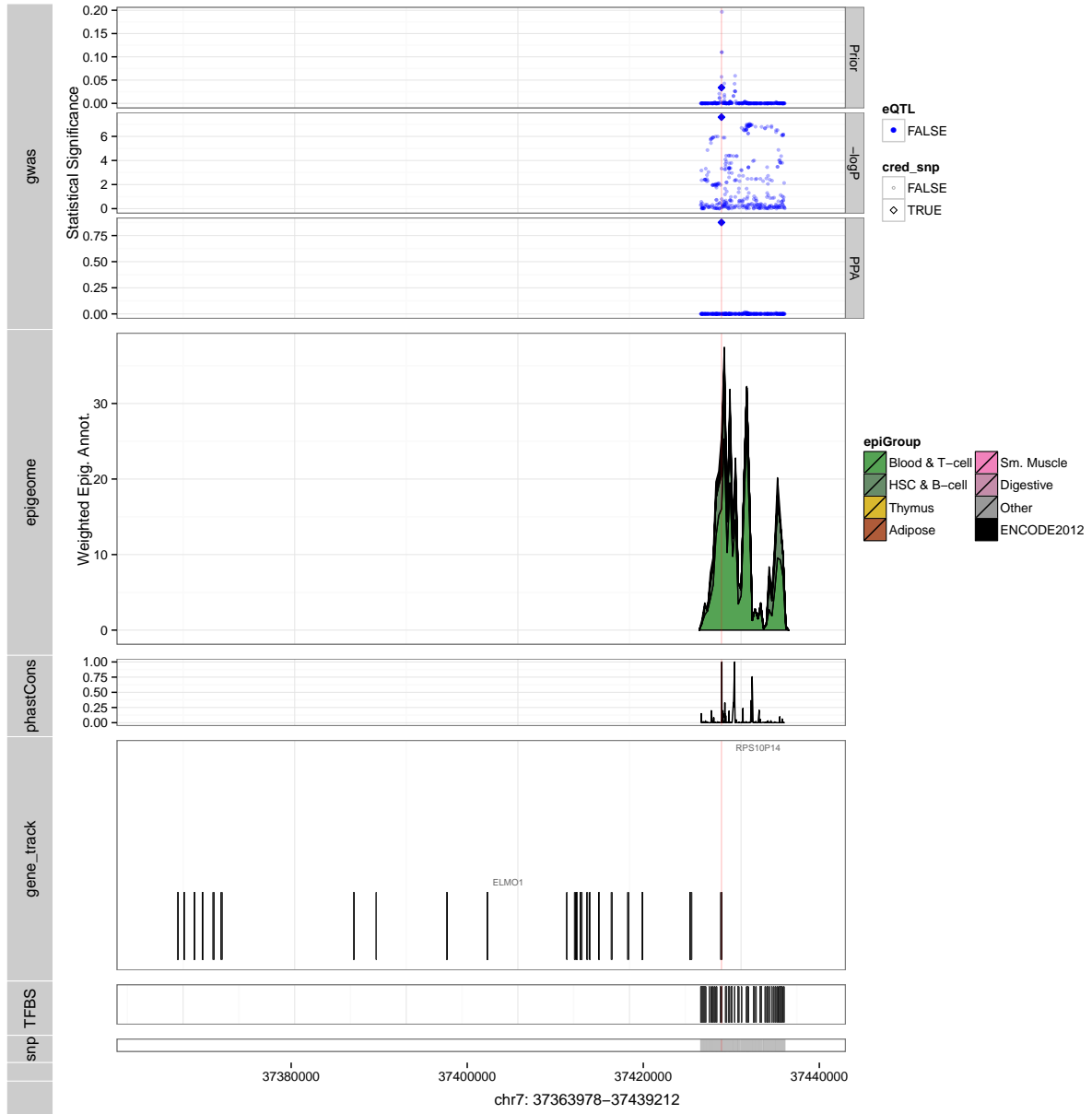
Multiple Sclerosis



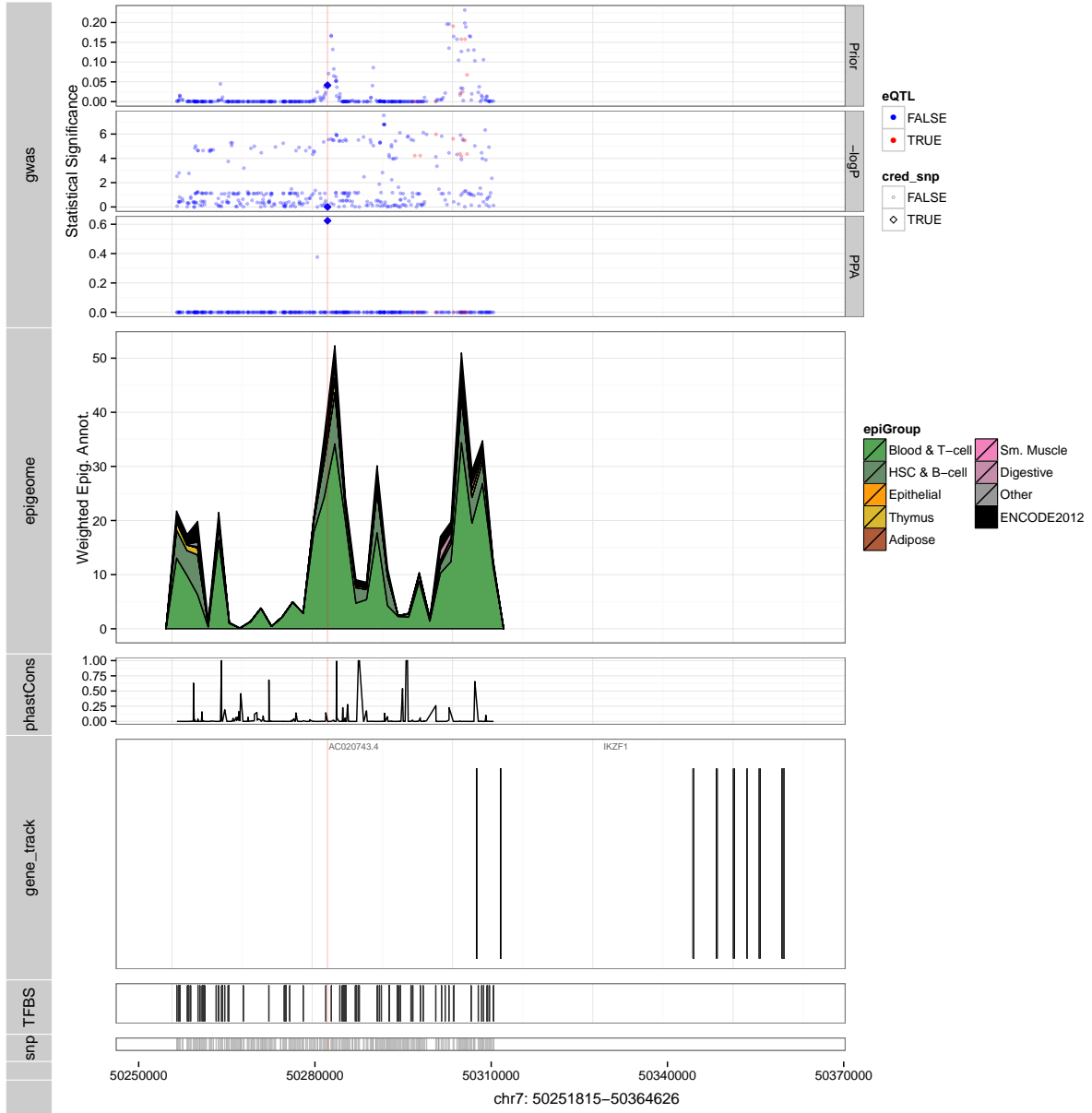
Multiple Sclerosis



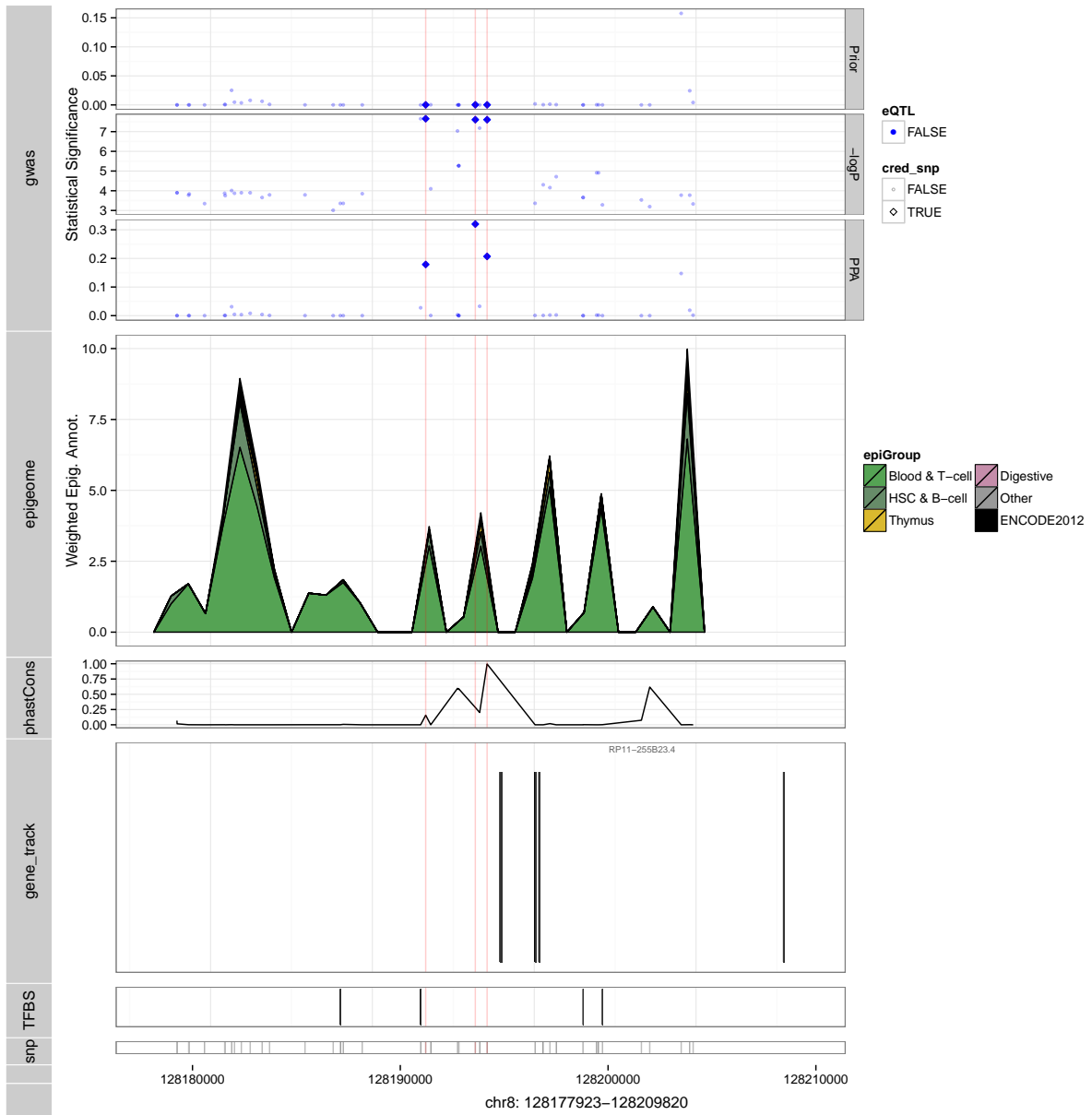
Multiple Sclerosis



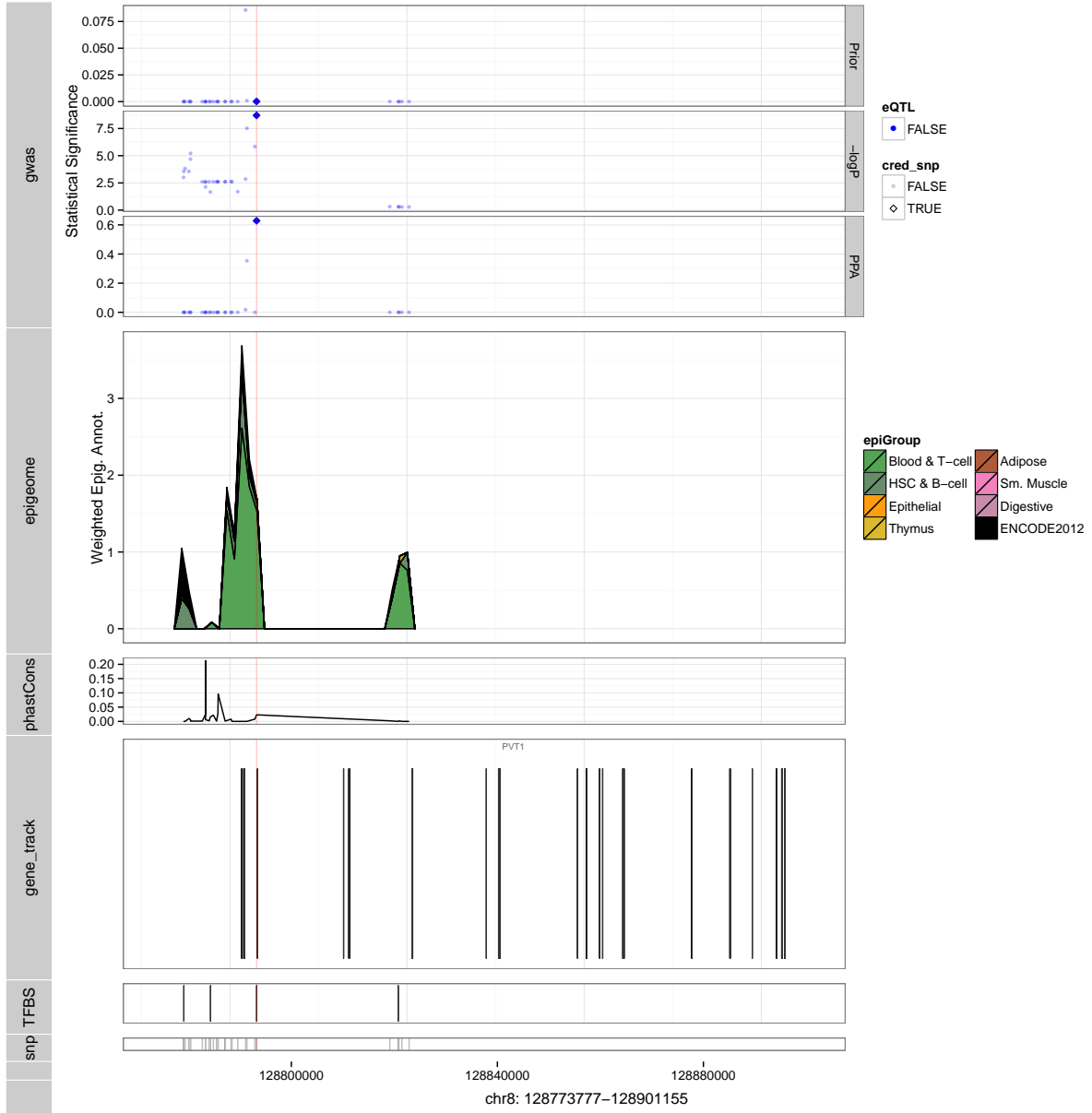
Multiple Sclerosis



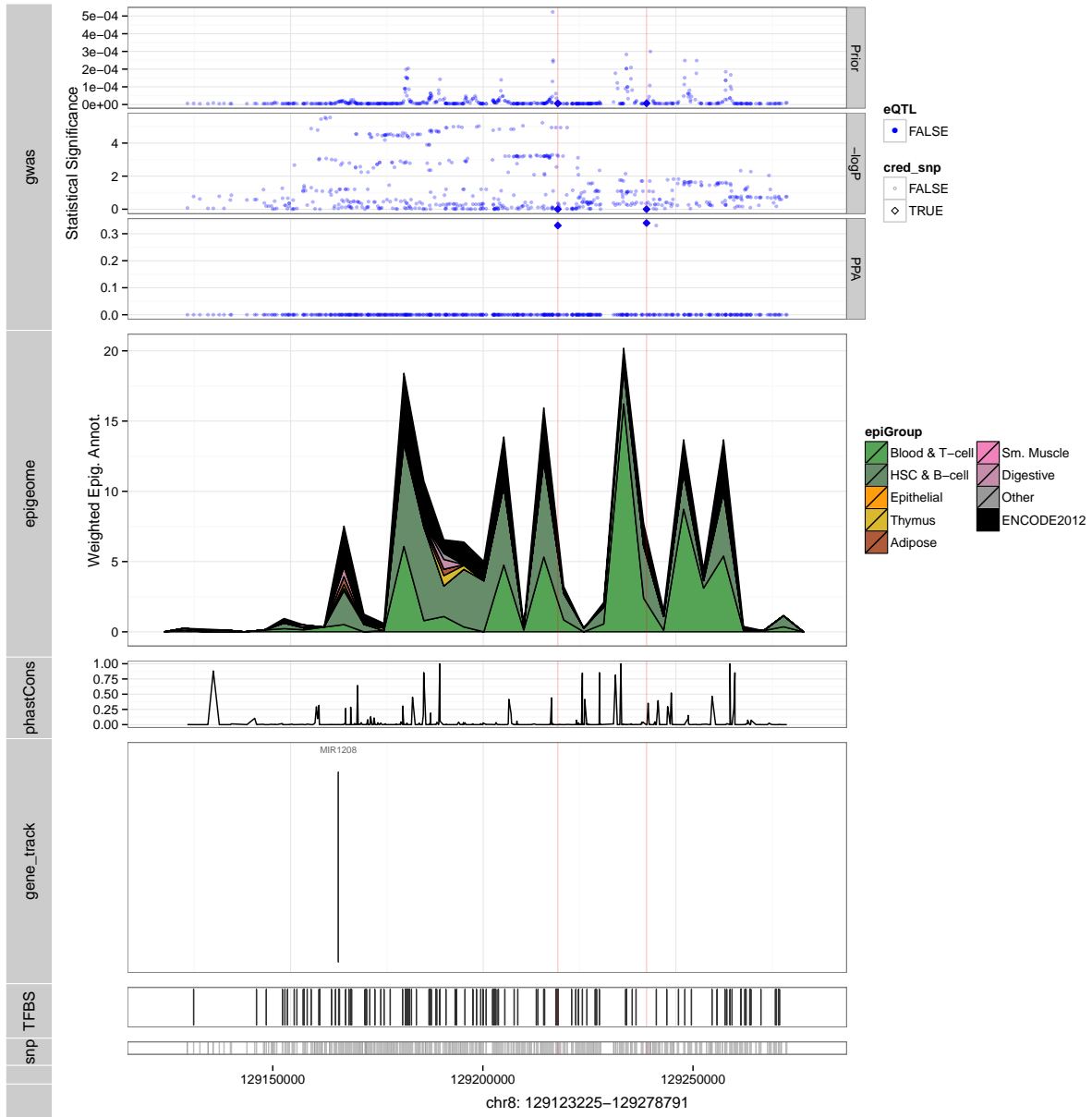
Multiple Sclerosis



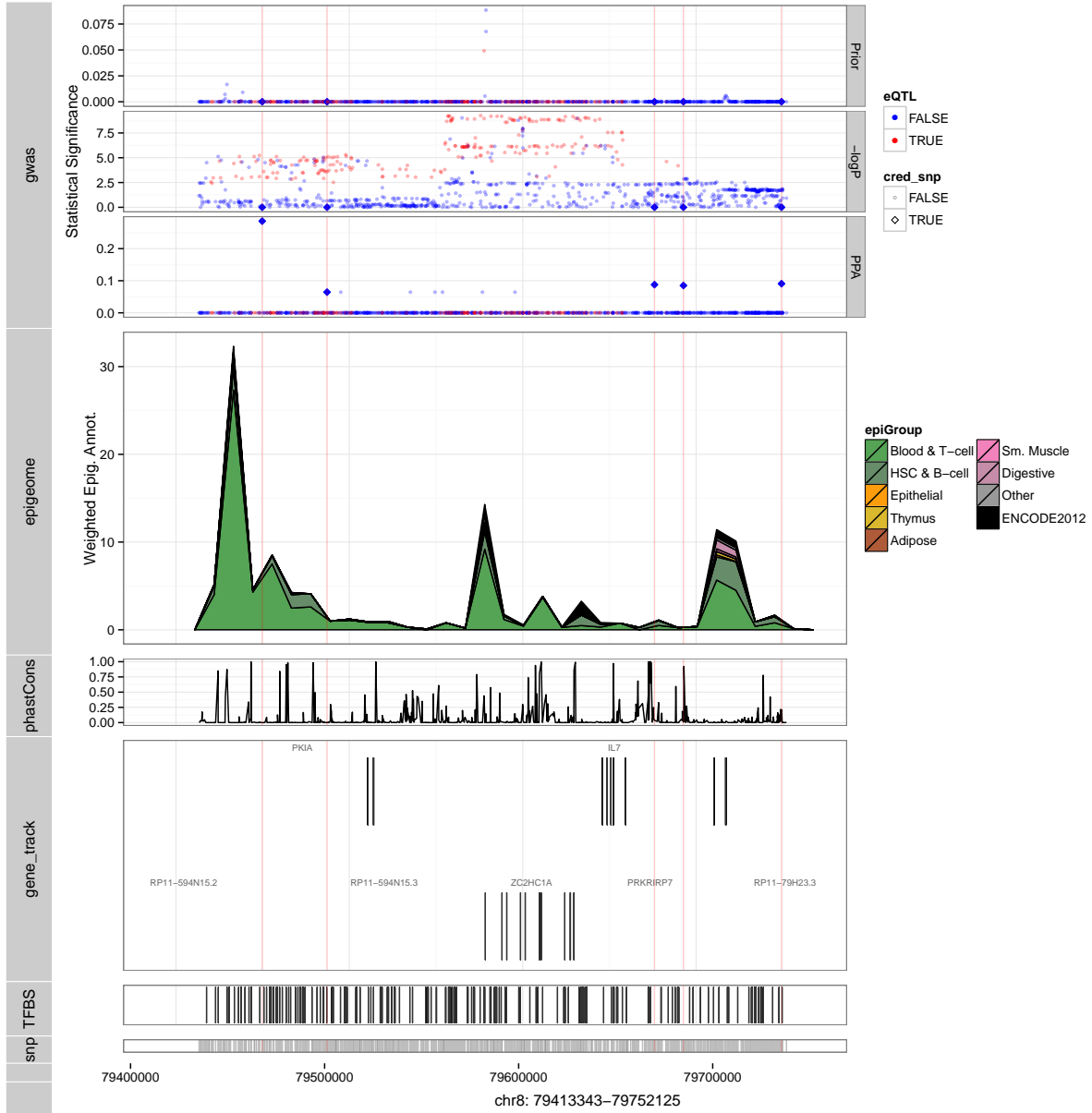
Multiple Sclerosis



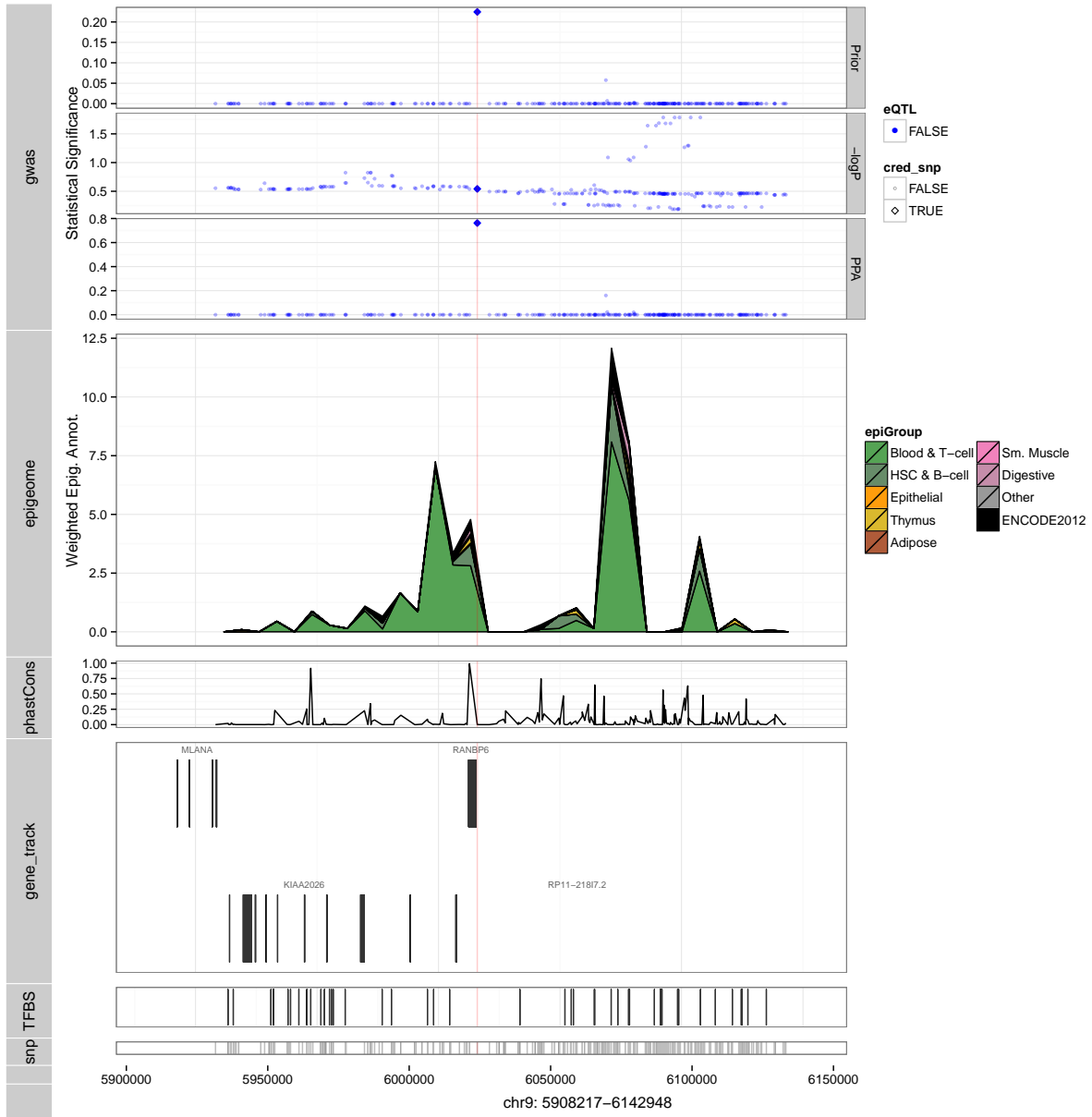
Multiple Sclerosis



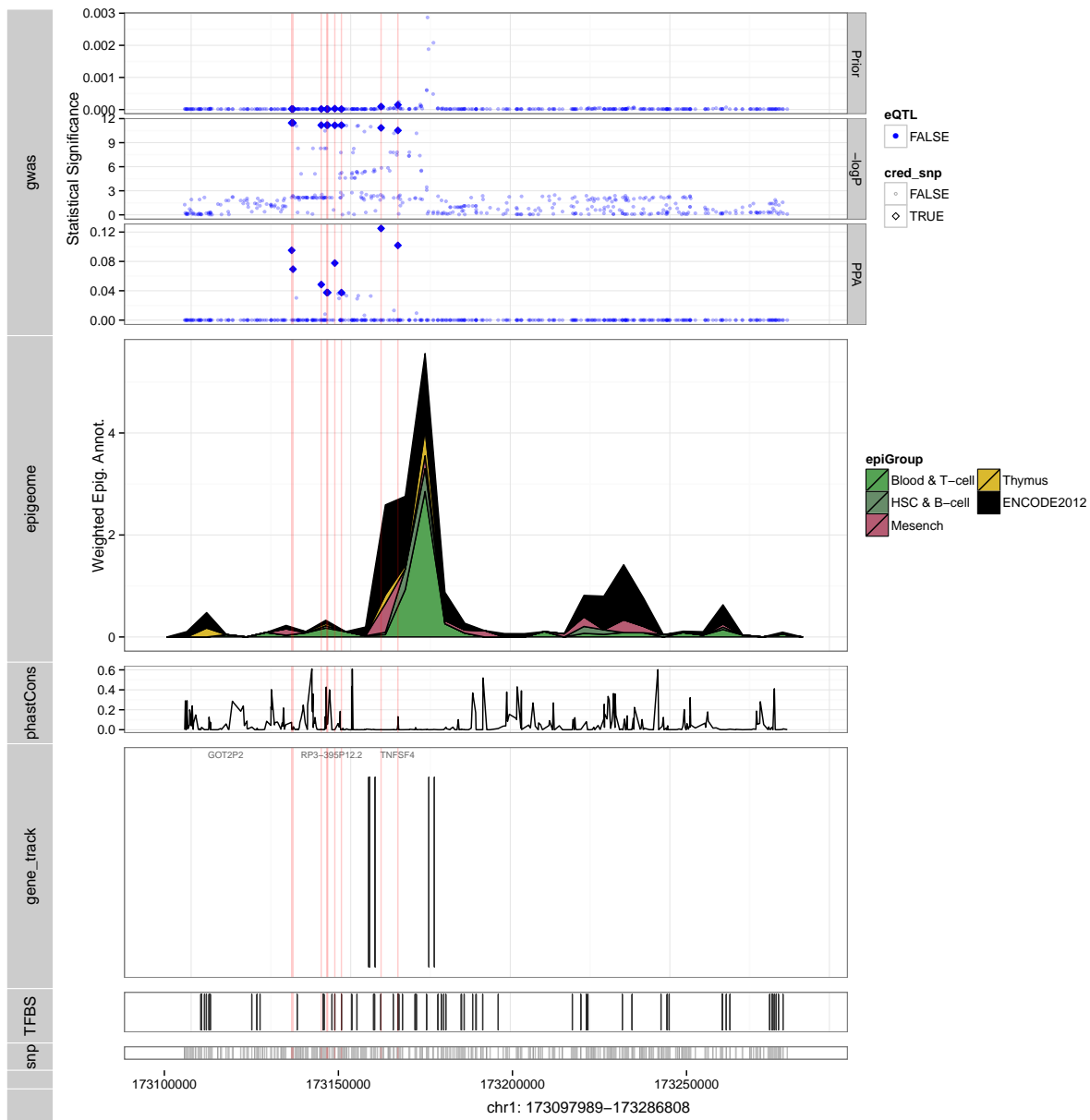
Multiple Sclerosis



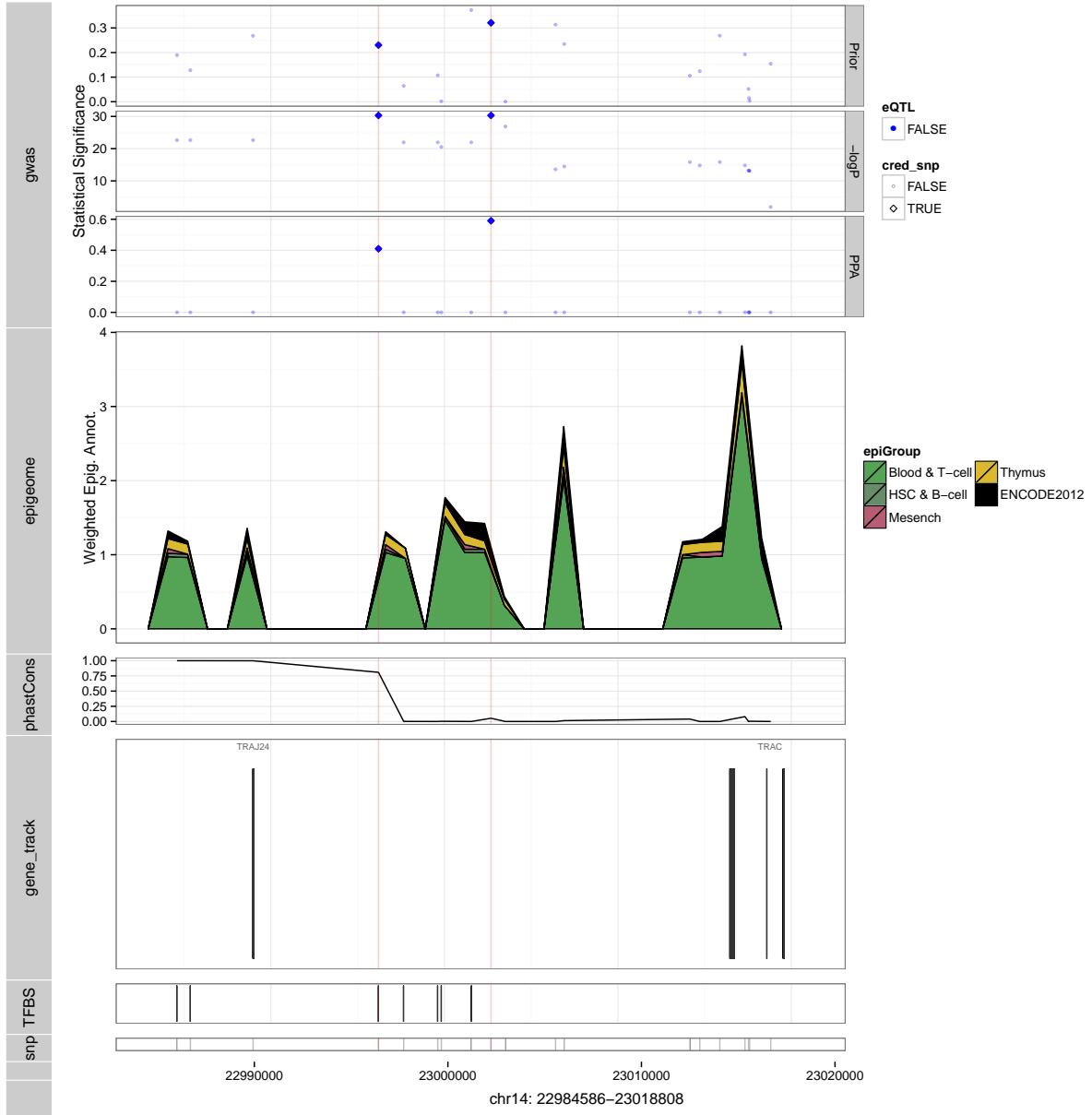
Multiple Sclerosis



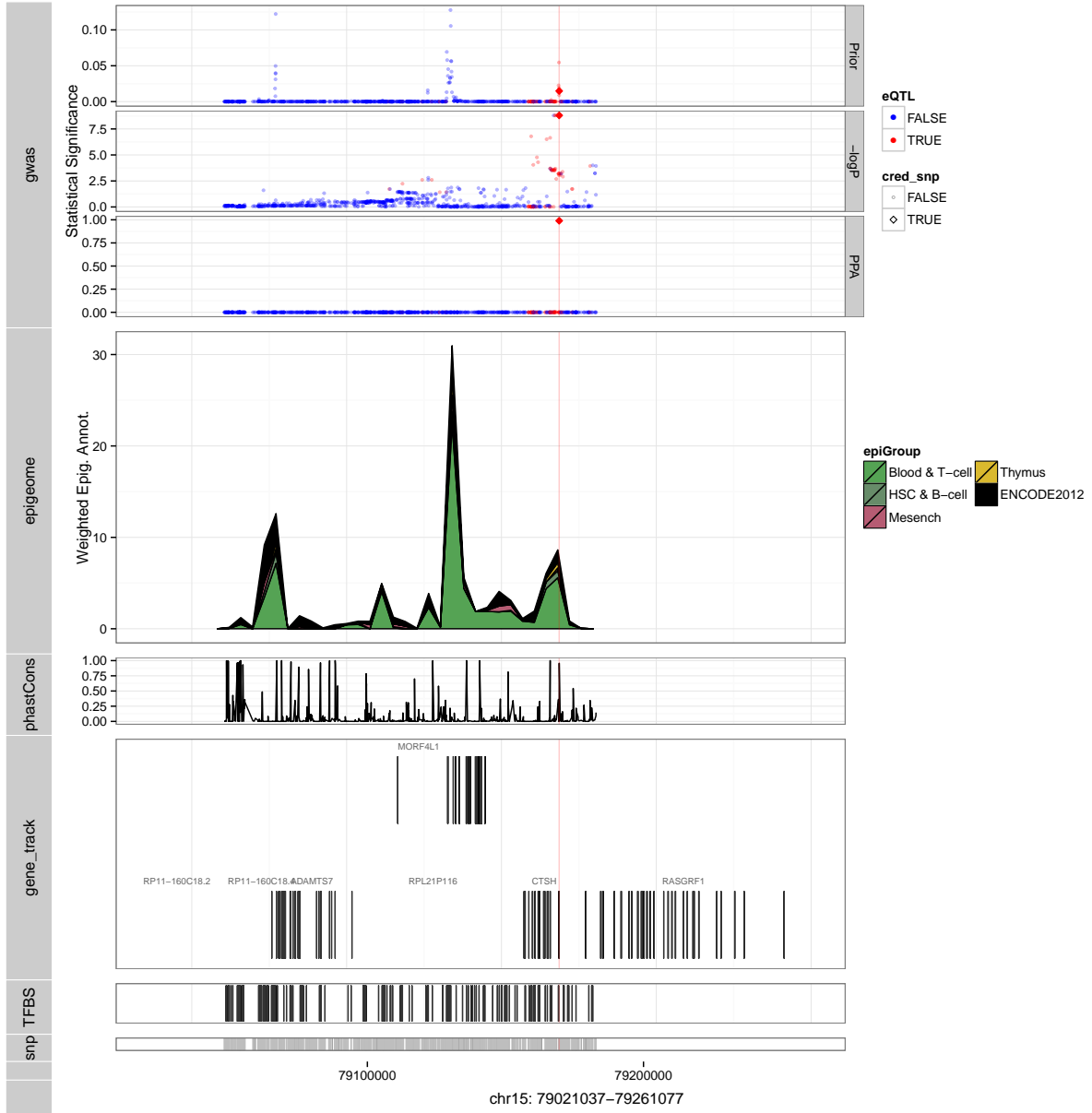
Narcolepsy



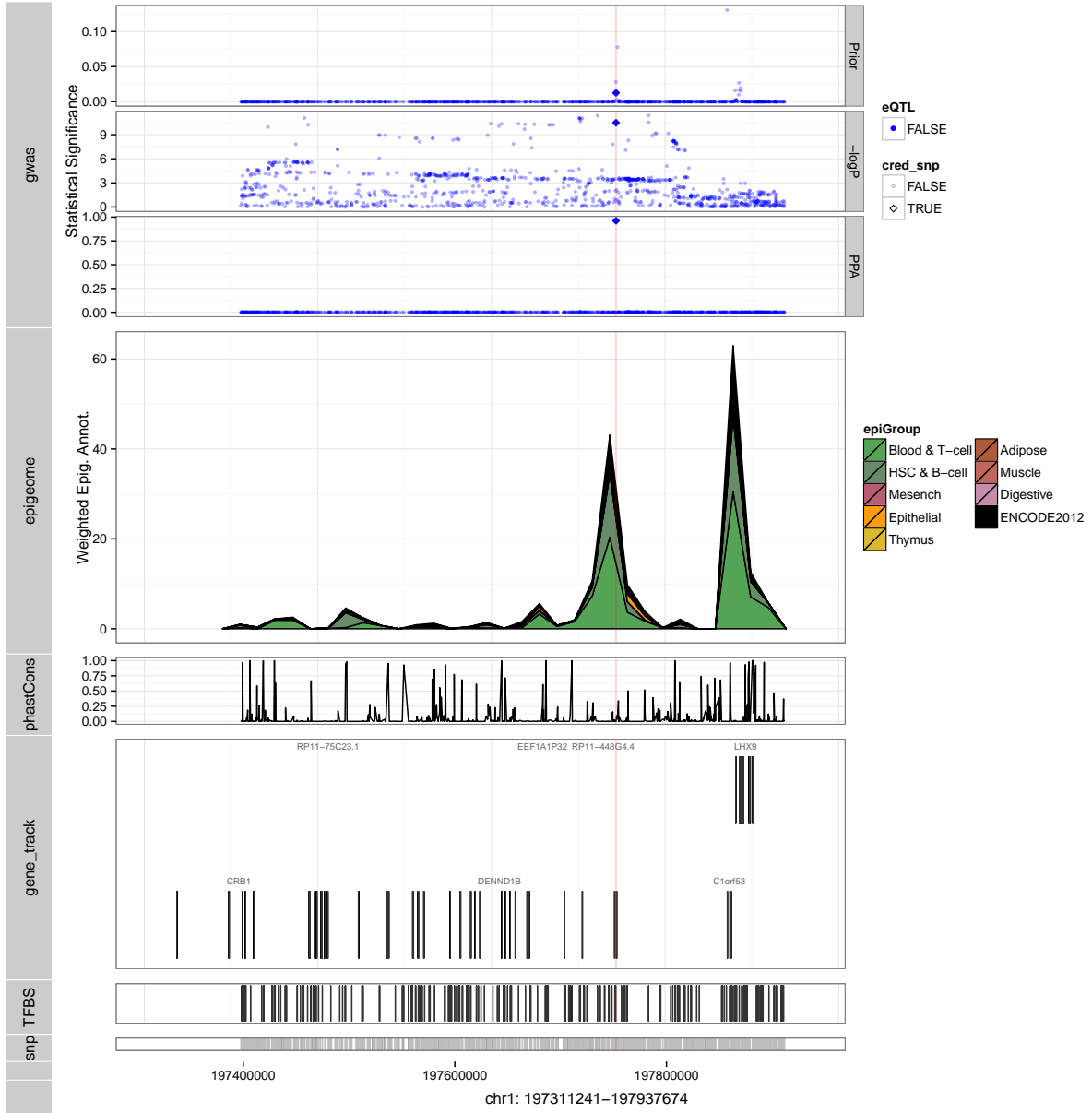
Narcolepsy



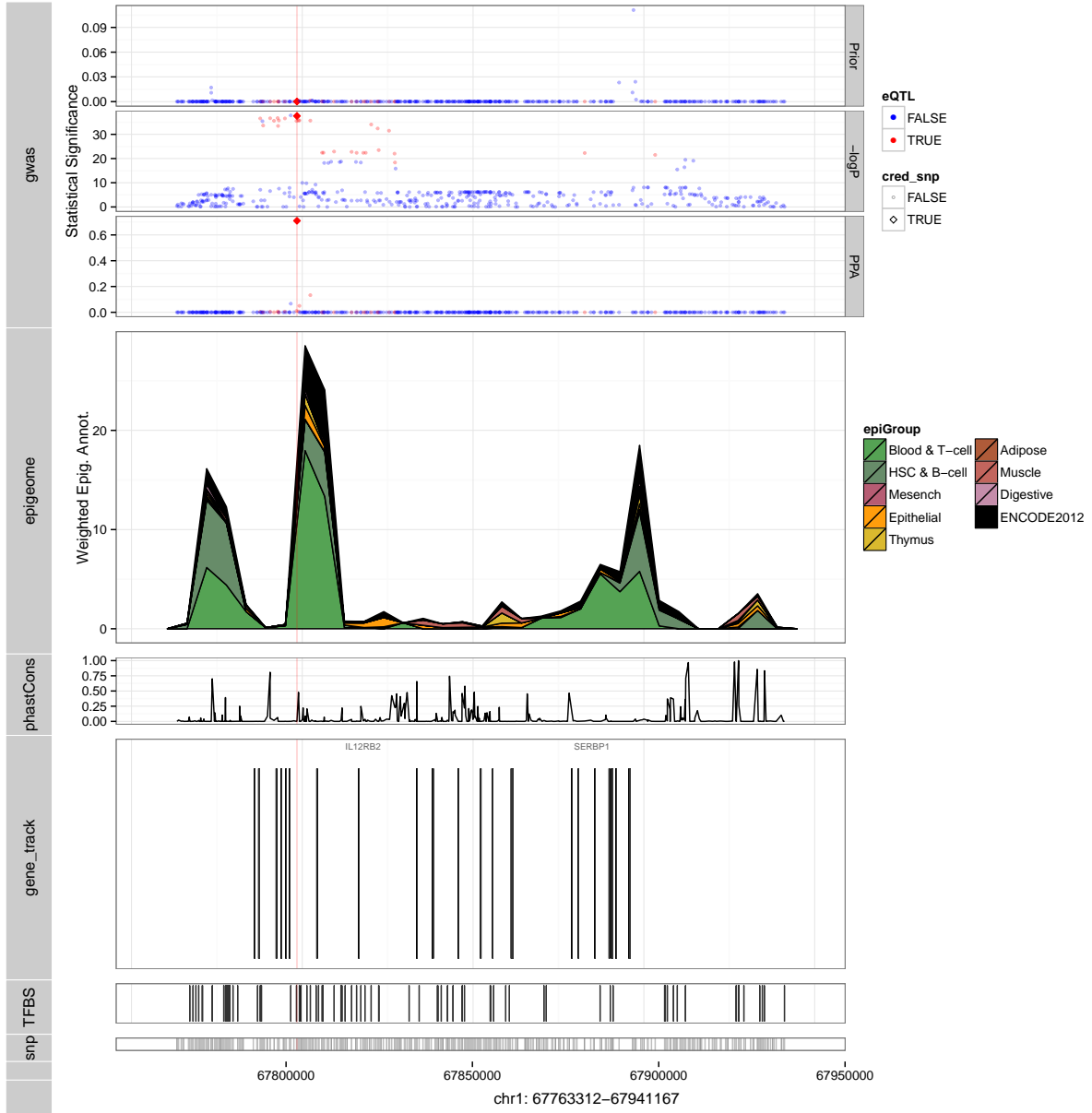
Narcolepsy



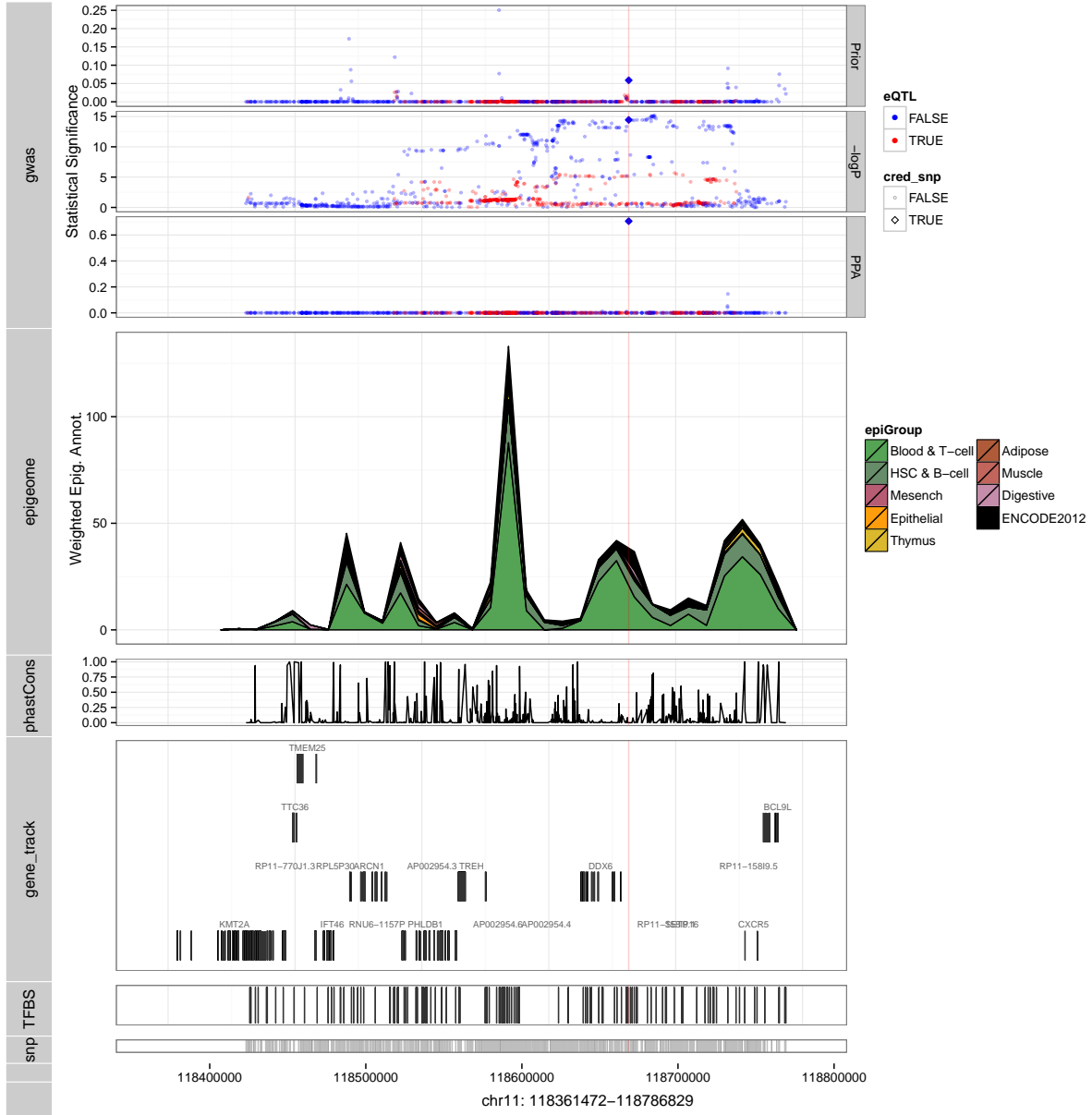
Primary Biliary Cirrhosis



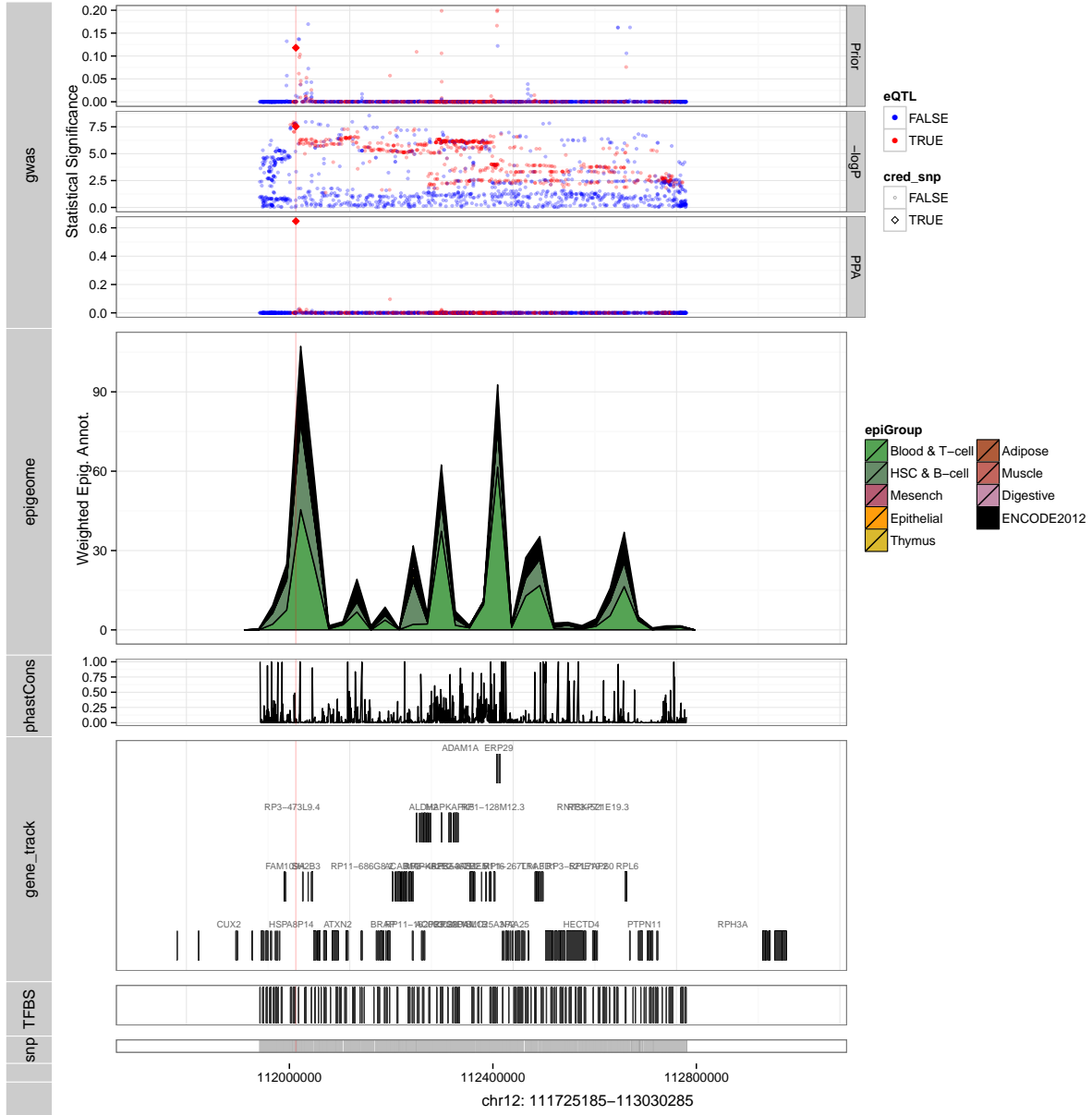
Primary Biliary Cirrhosis



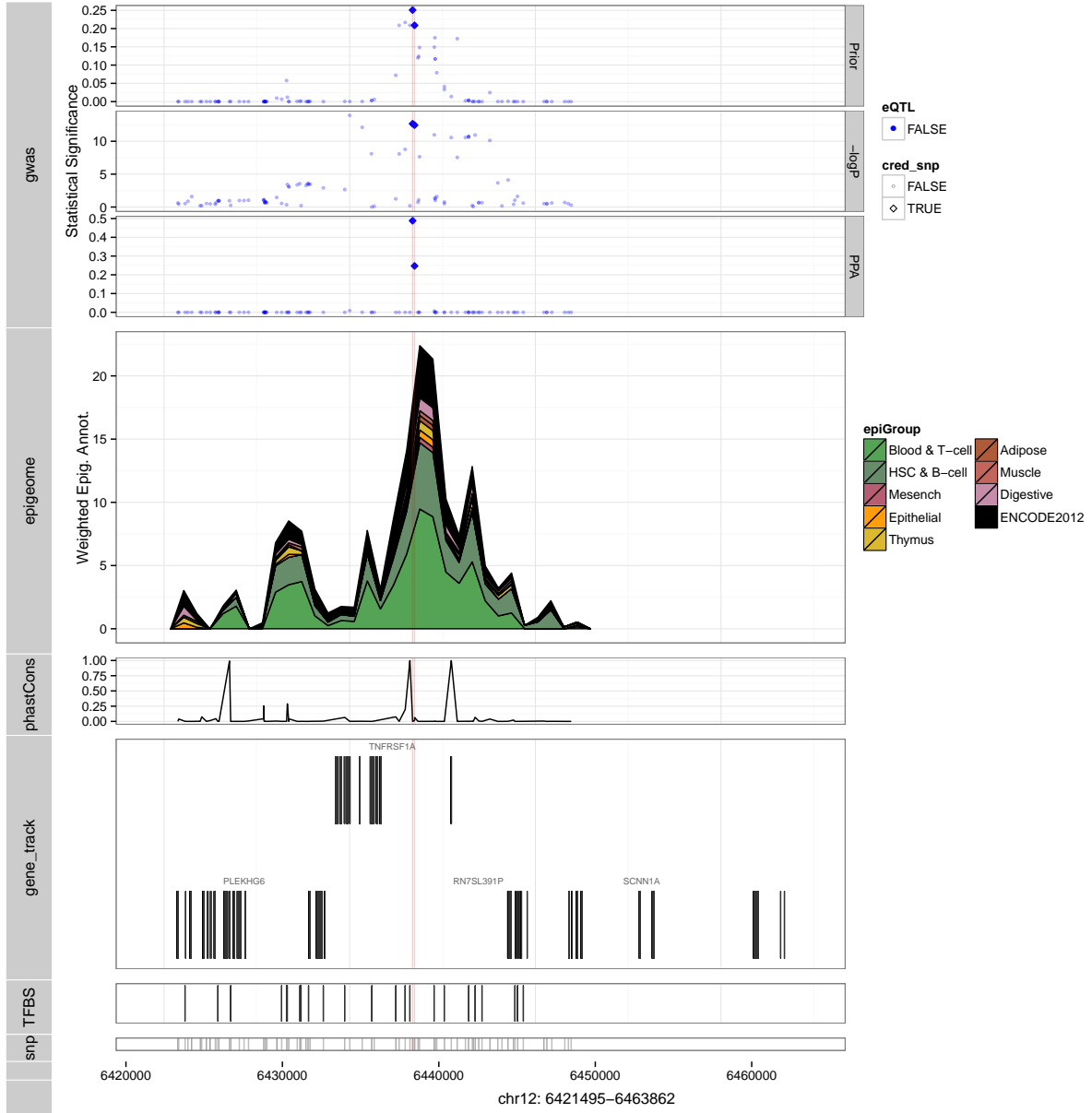
Primary Biliary Cirrhosis



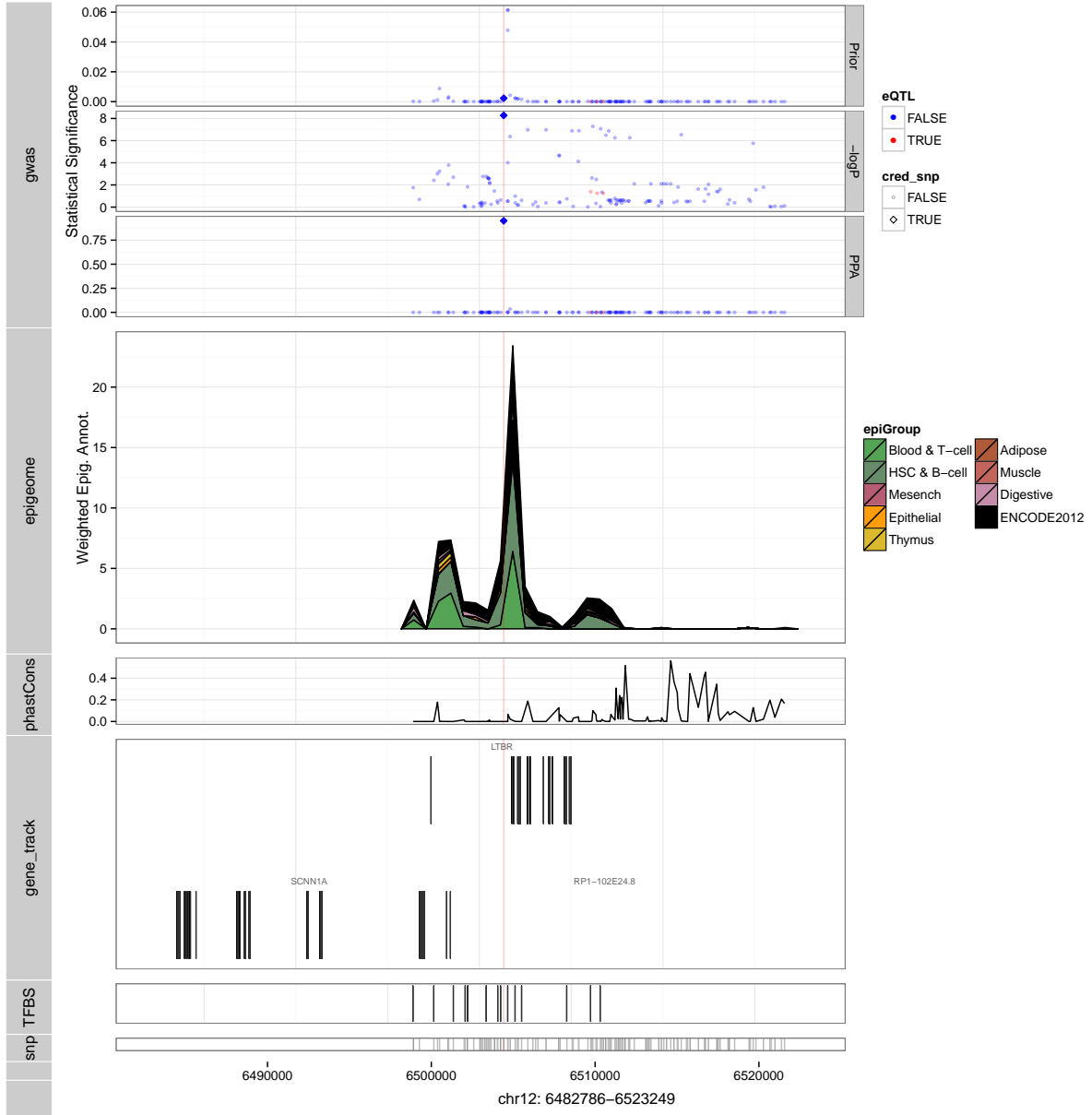
Primary Biliary Cirrhosis



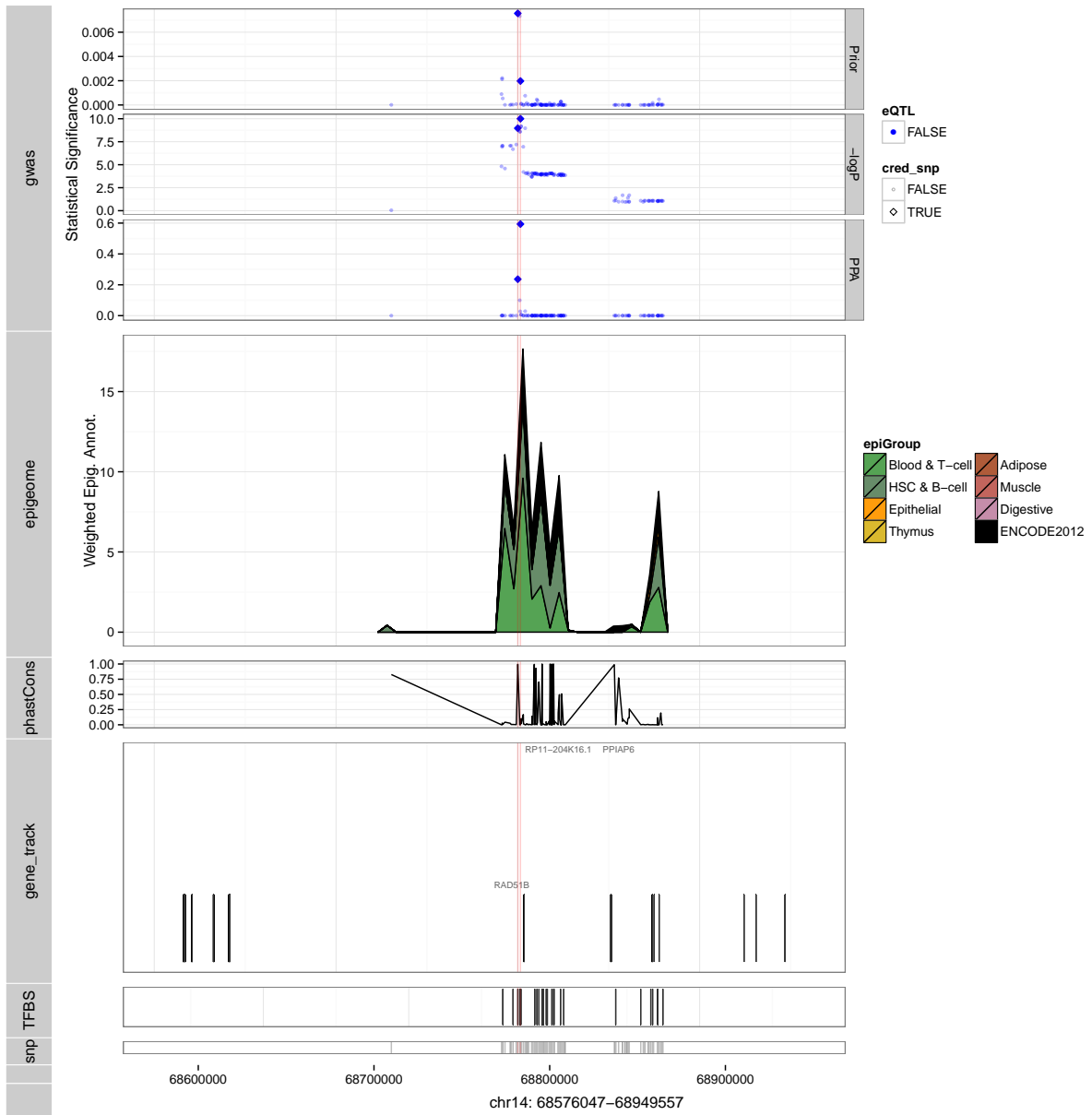
Primary Biliary Cirrhosis



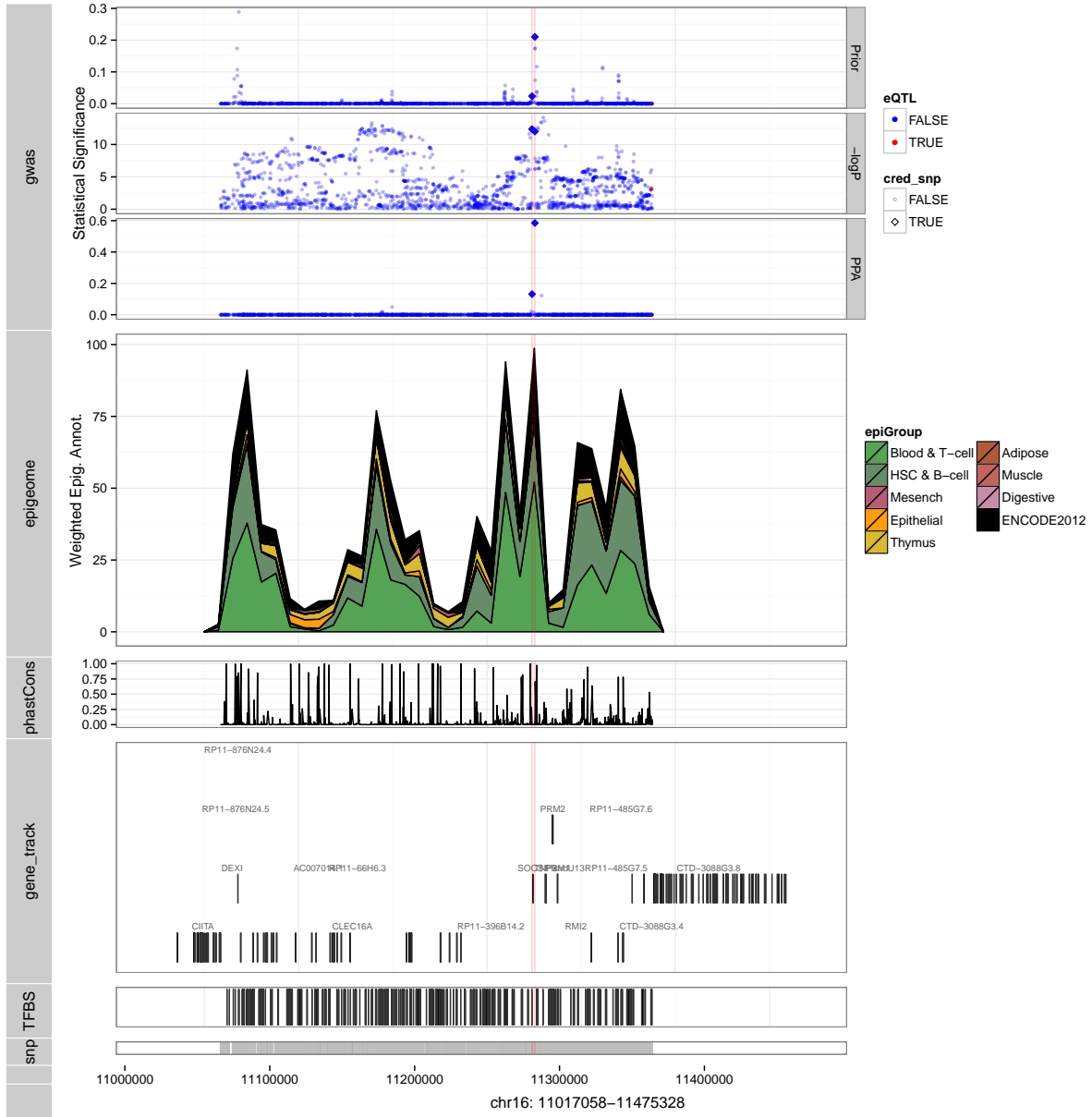
Primary Biliary Cirrhosis



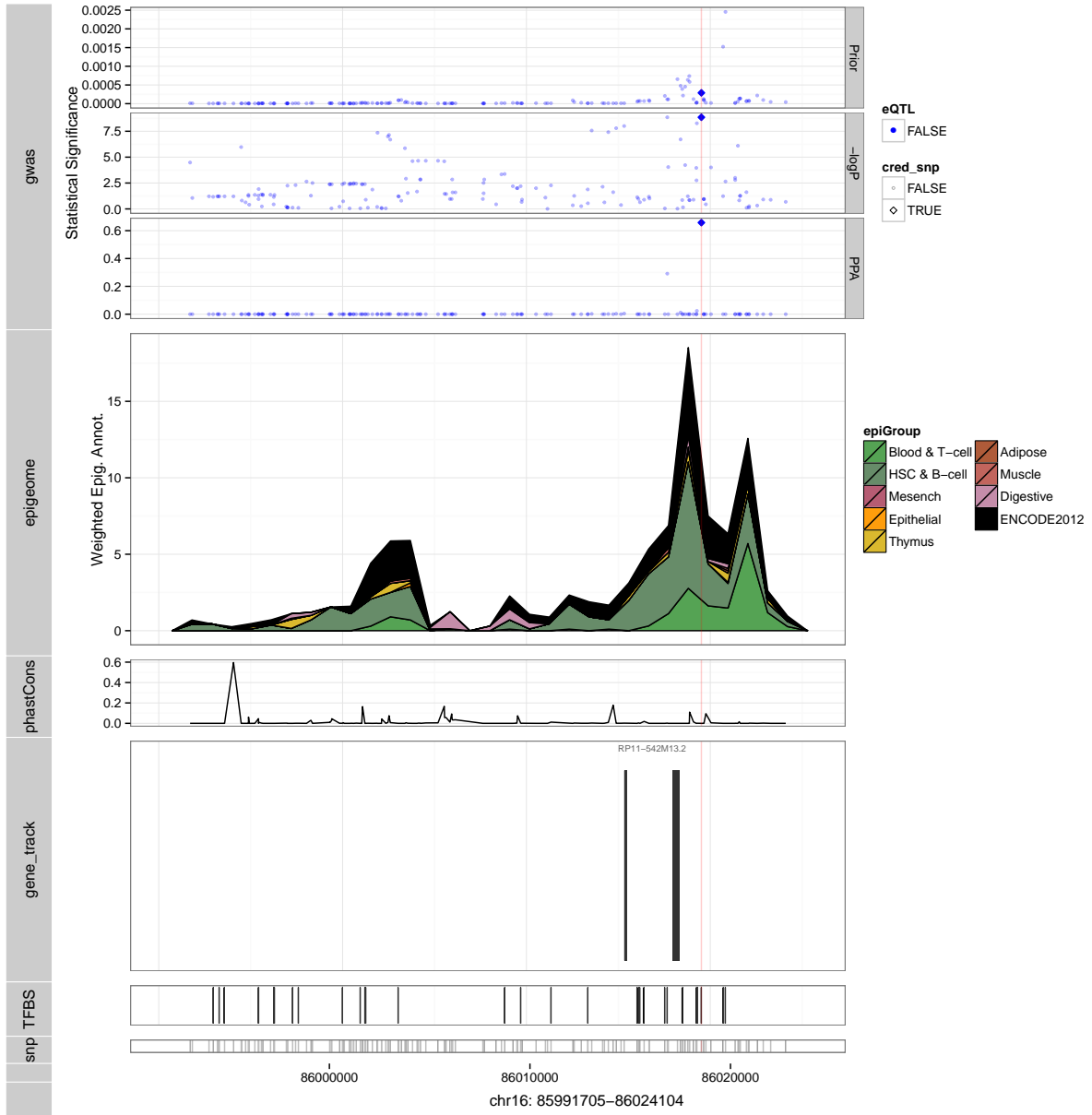
Primary Biliary Cirrhosis



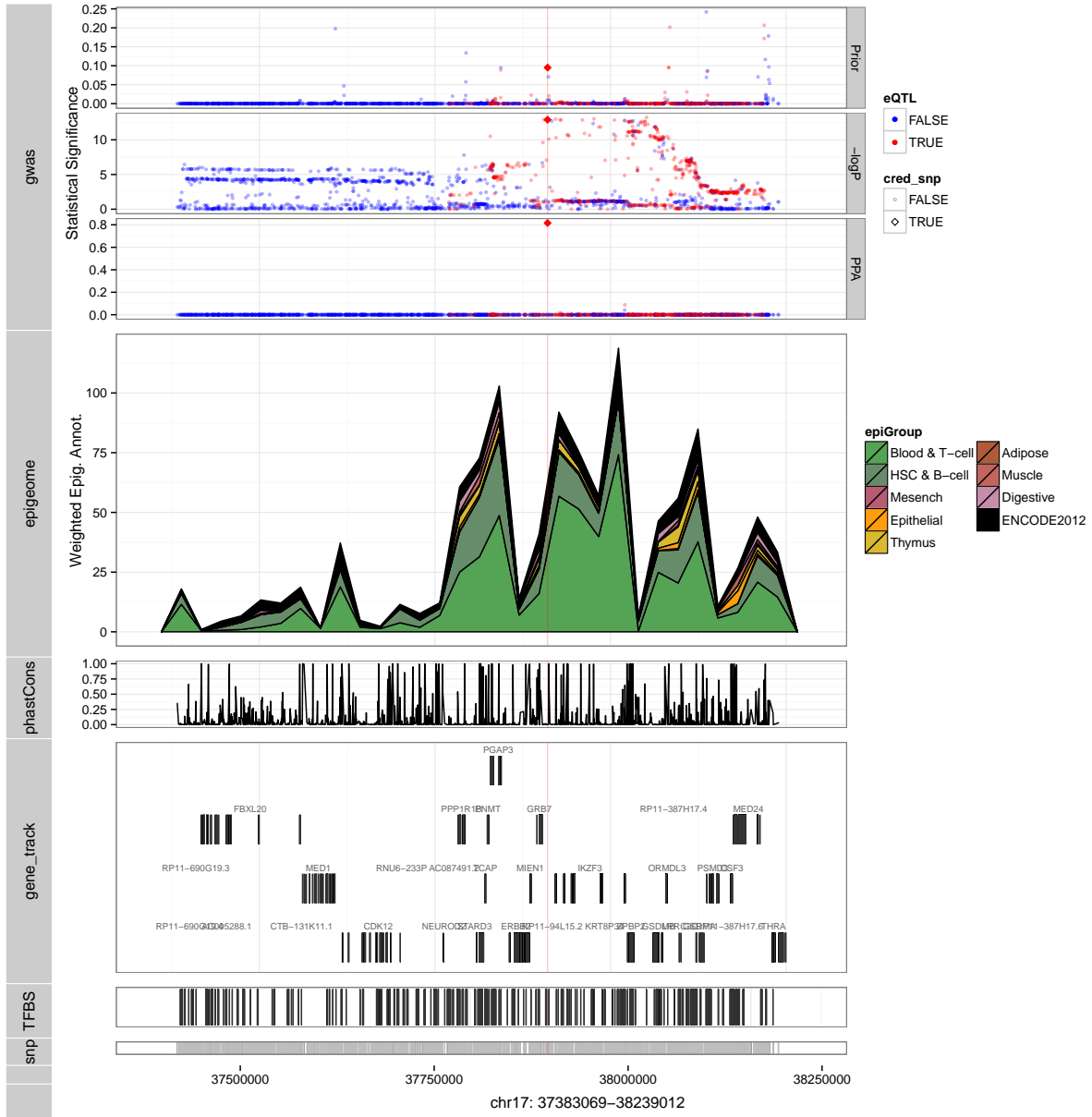
Primary Biliary Cirrhosis



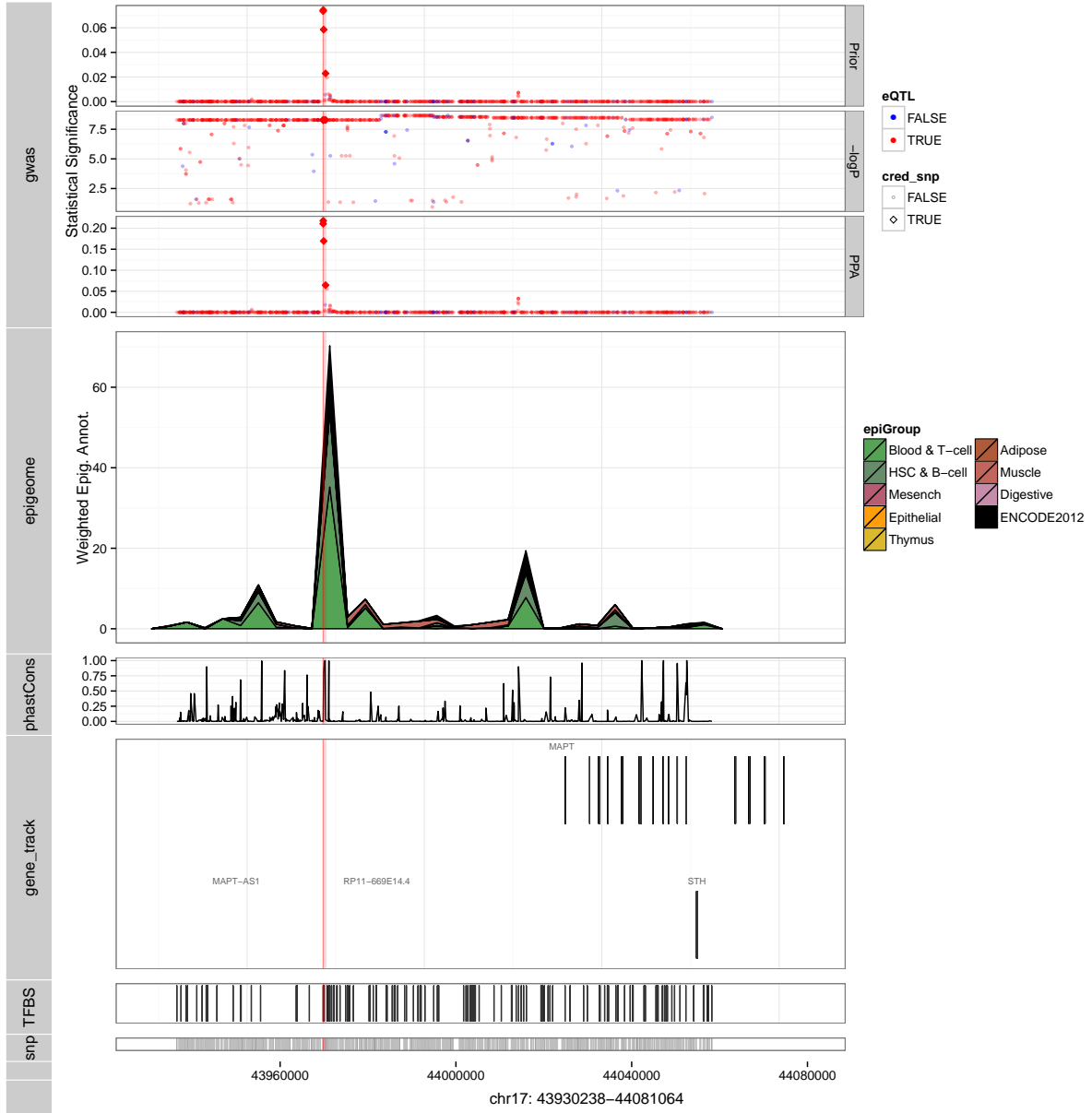
Primary Biliary Cirrhosis



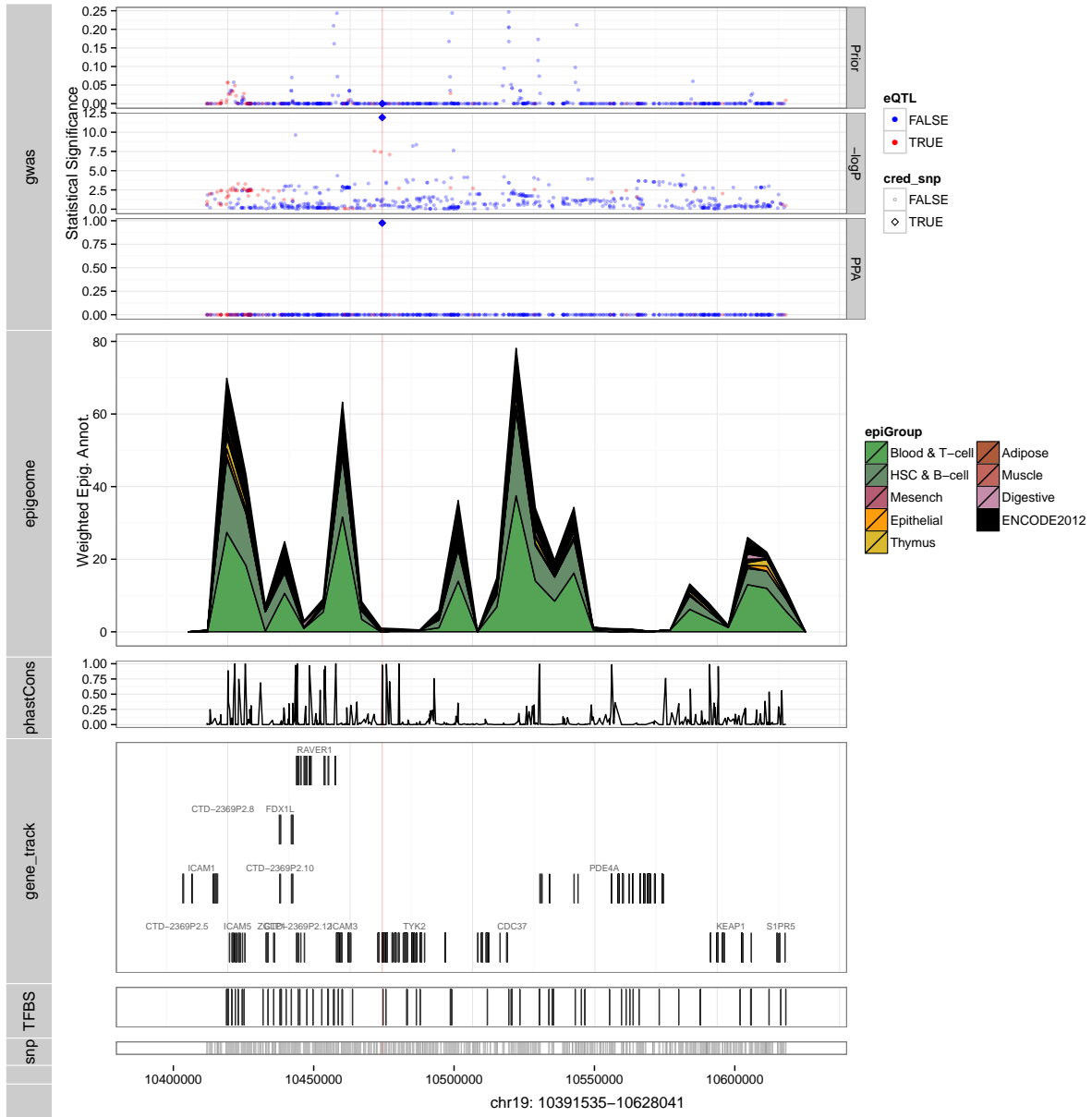
Primary Biliary Cirrhosis



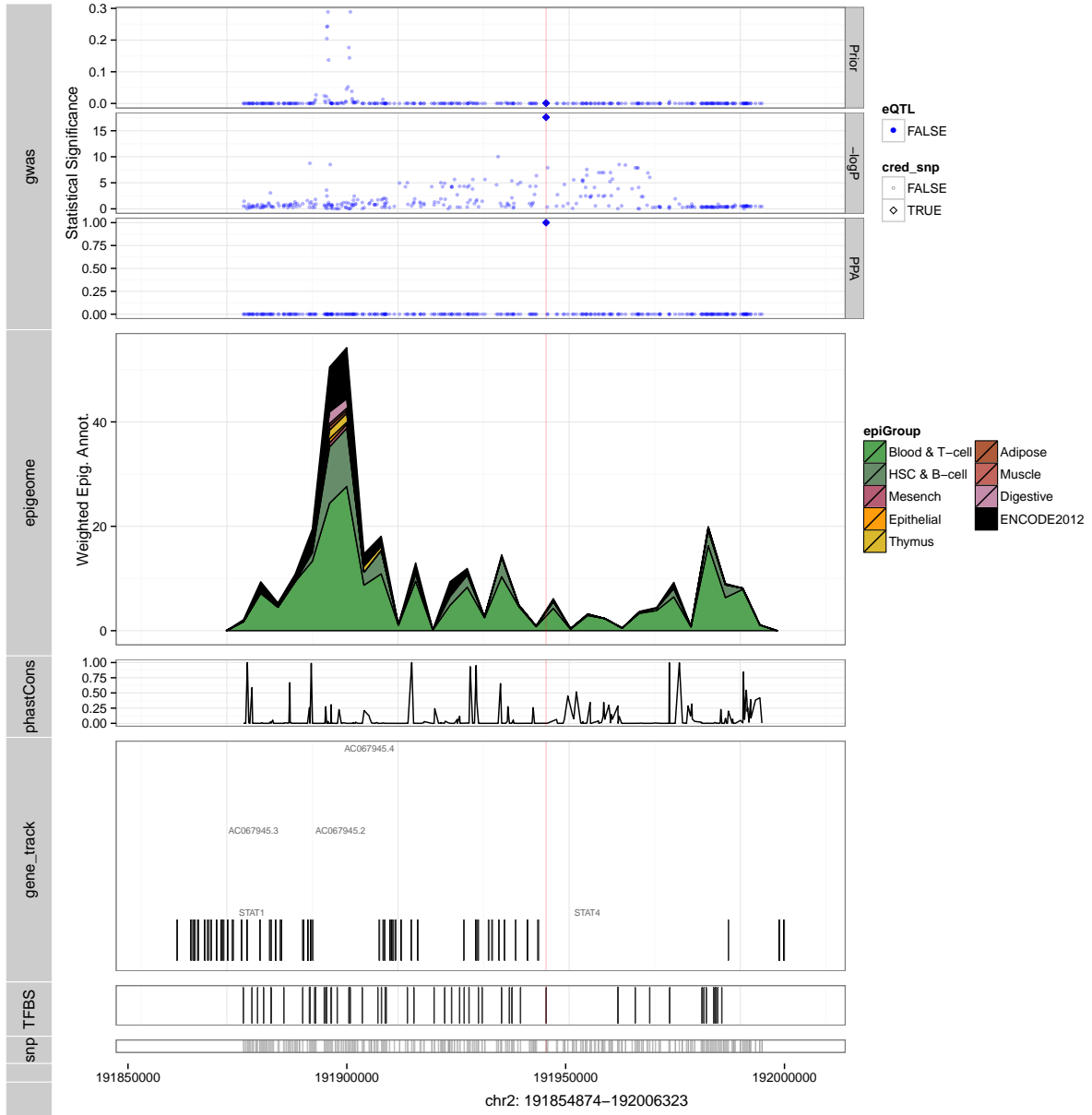
Primary Biliary Cirrhosis



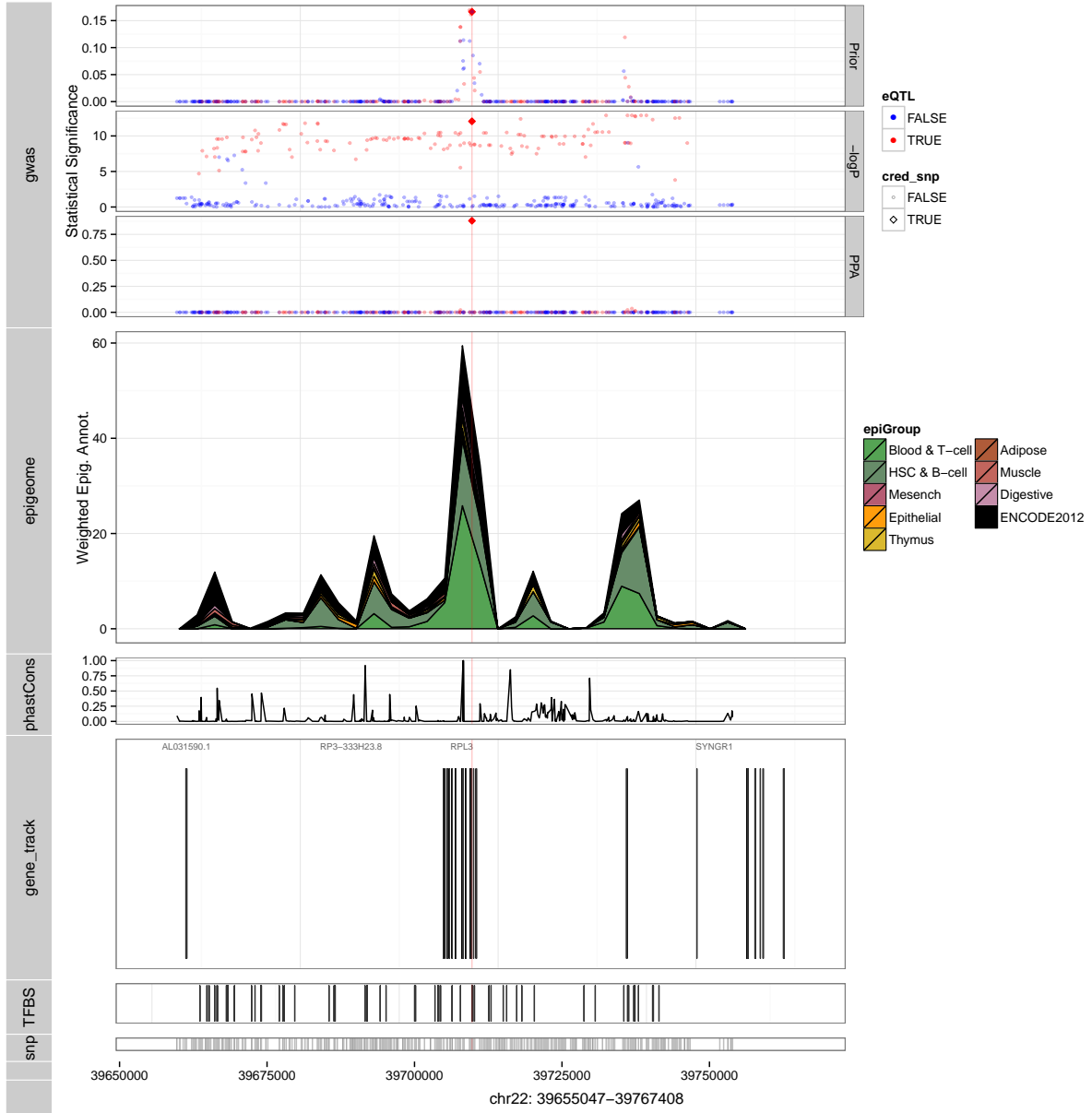
Primary Biliary Cirrhosis



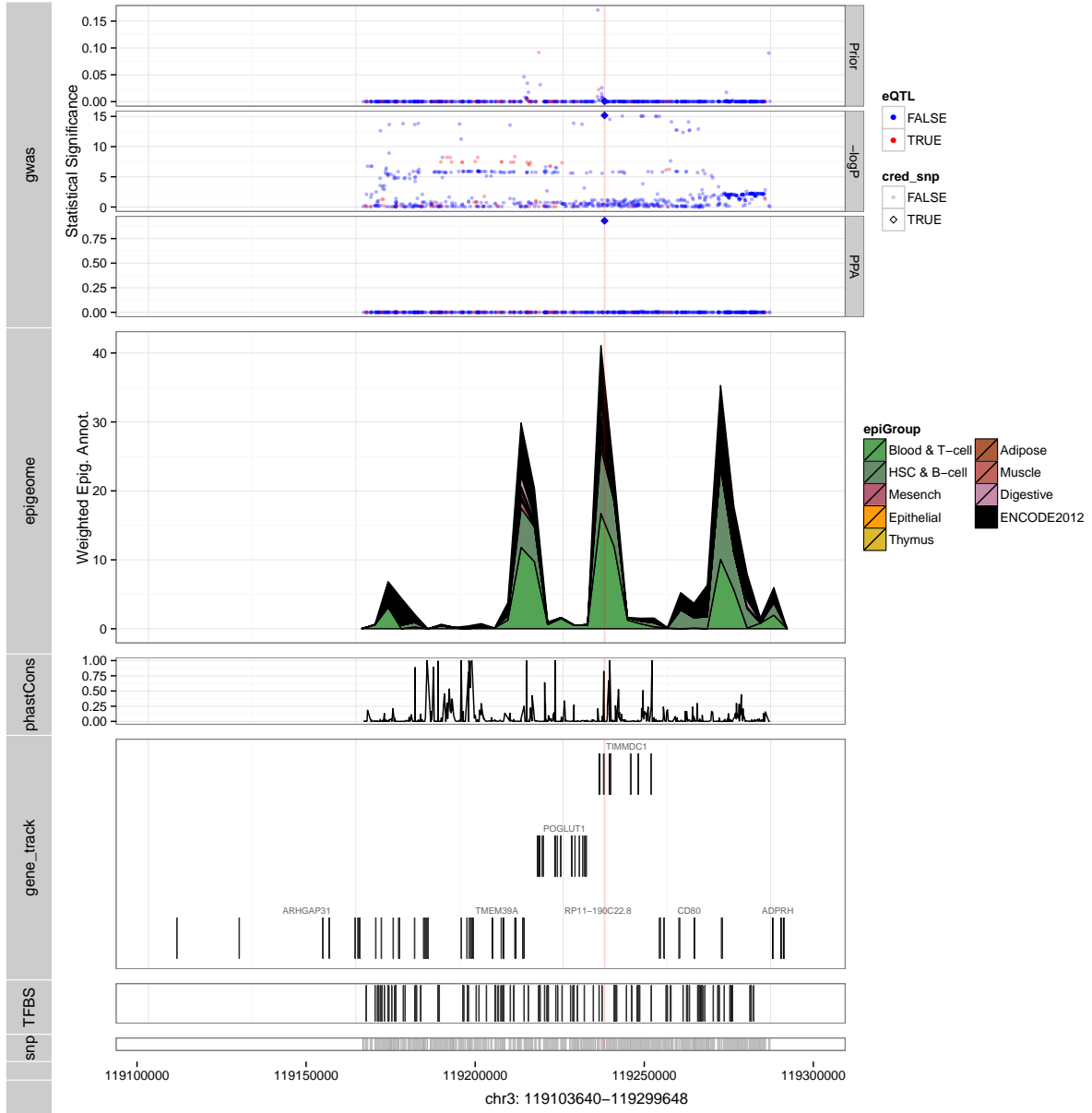
Primary Biliary Cirrhosis



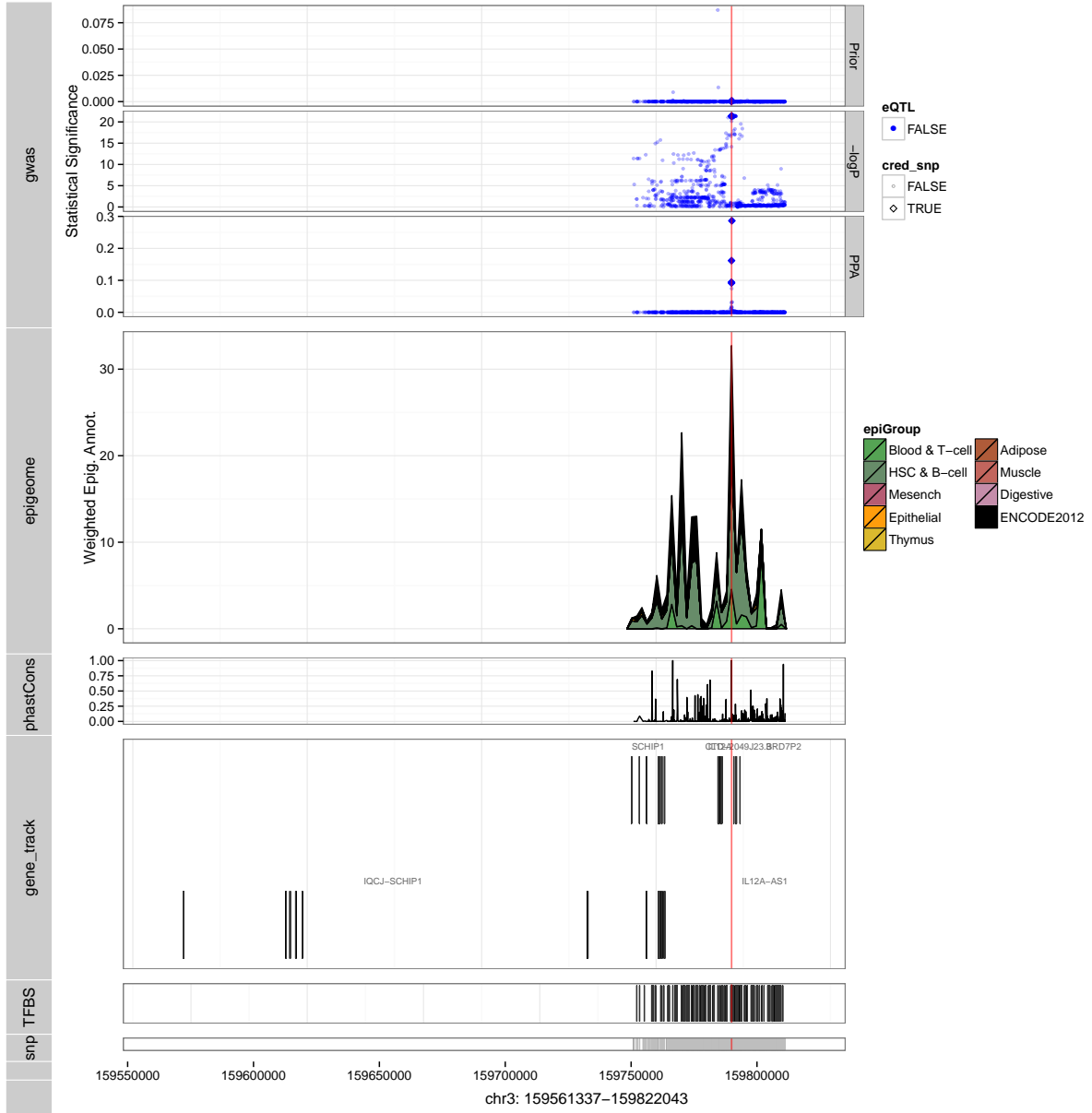
Primary Biliary Cirrhosis



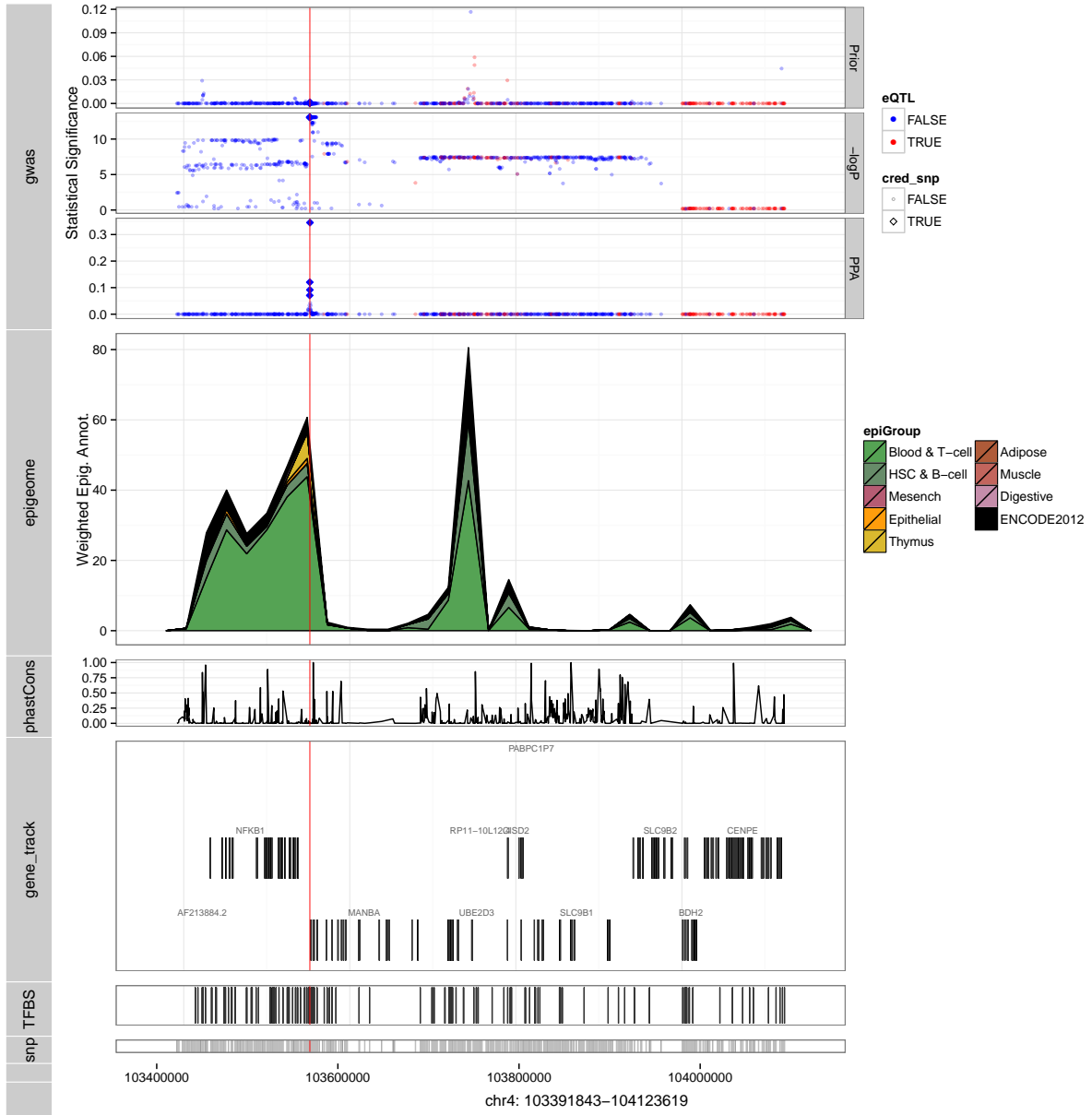
Primary Biliary Cirrhosis



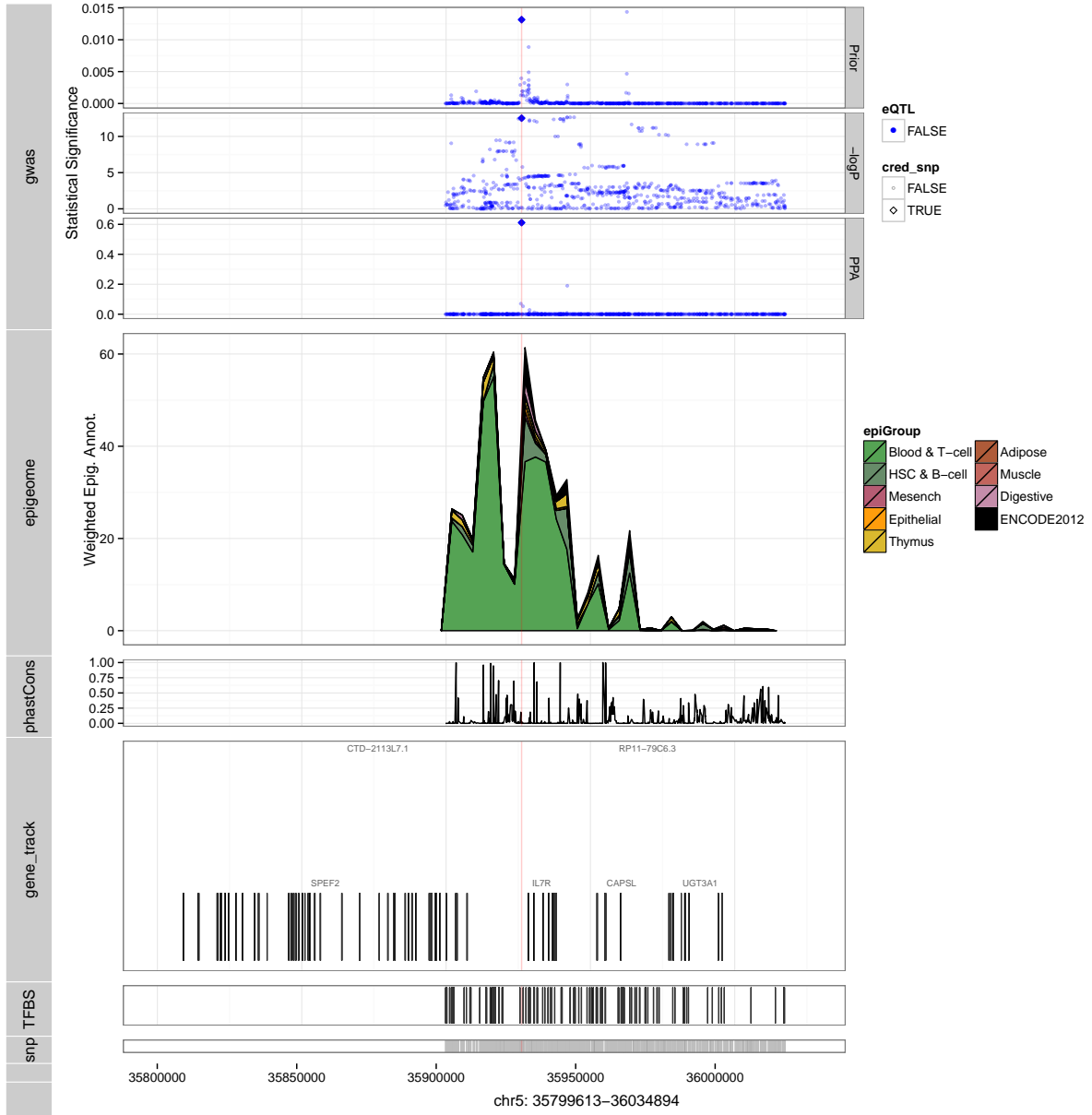
Primary Biliary Cirrhosis



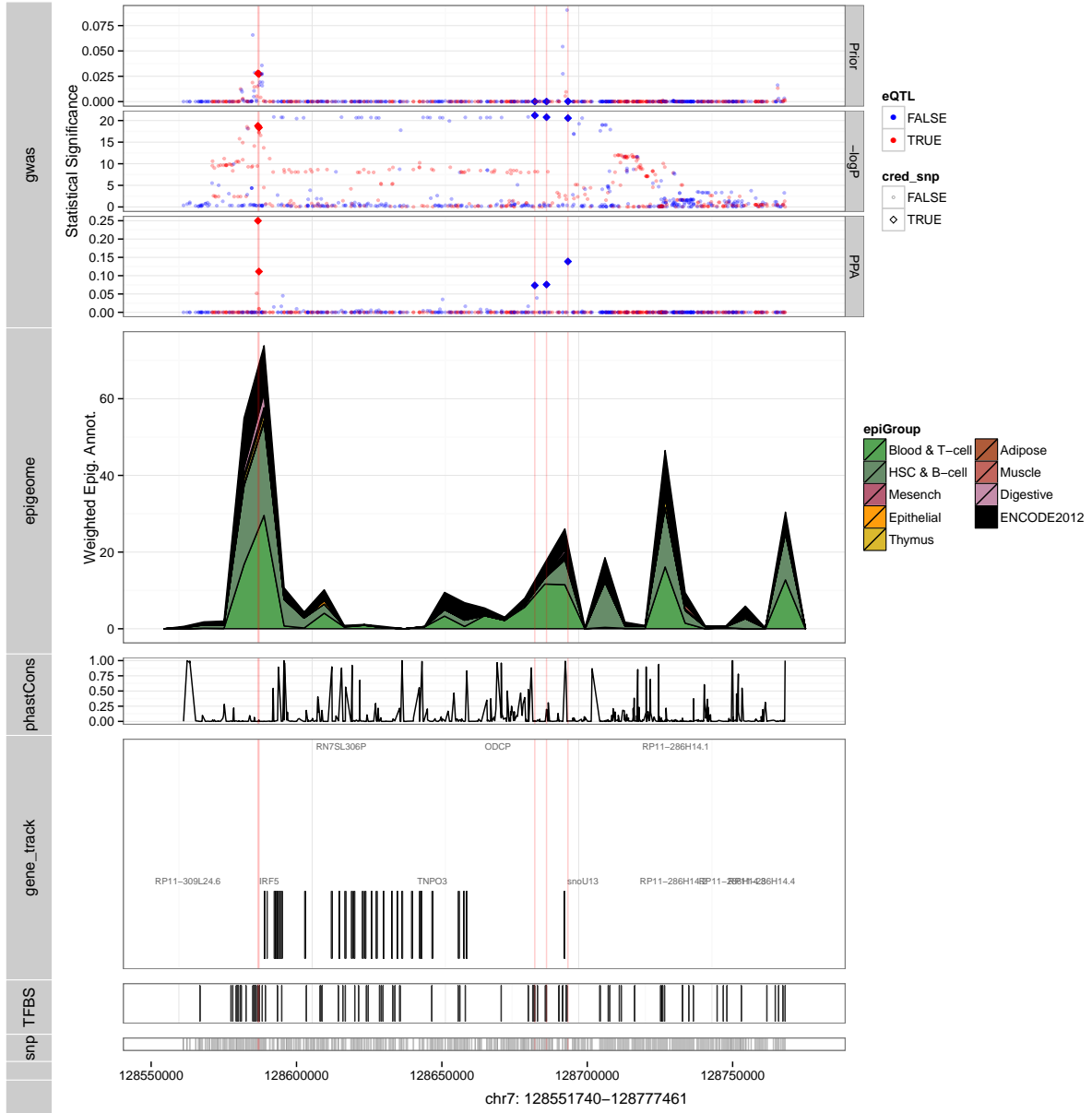
Primary Biliary Cirrhosis



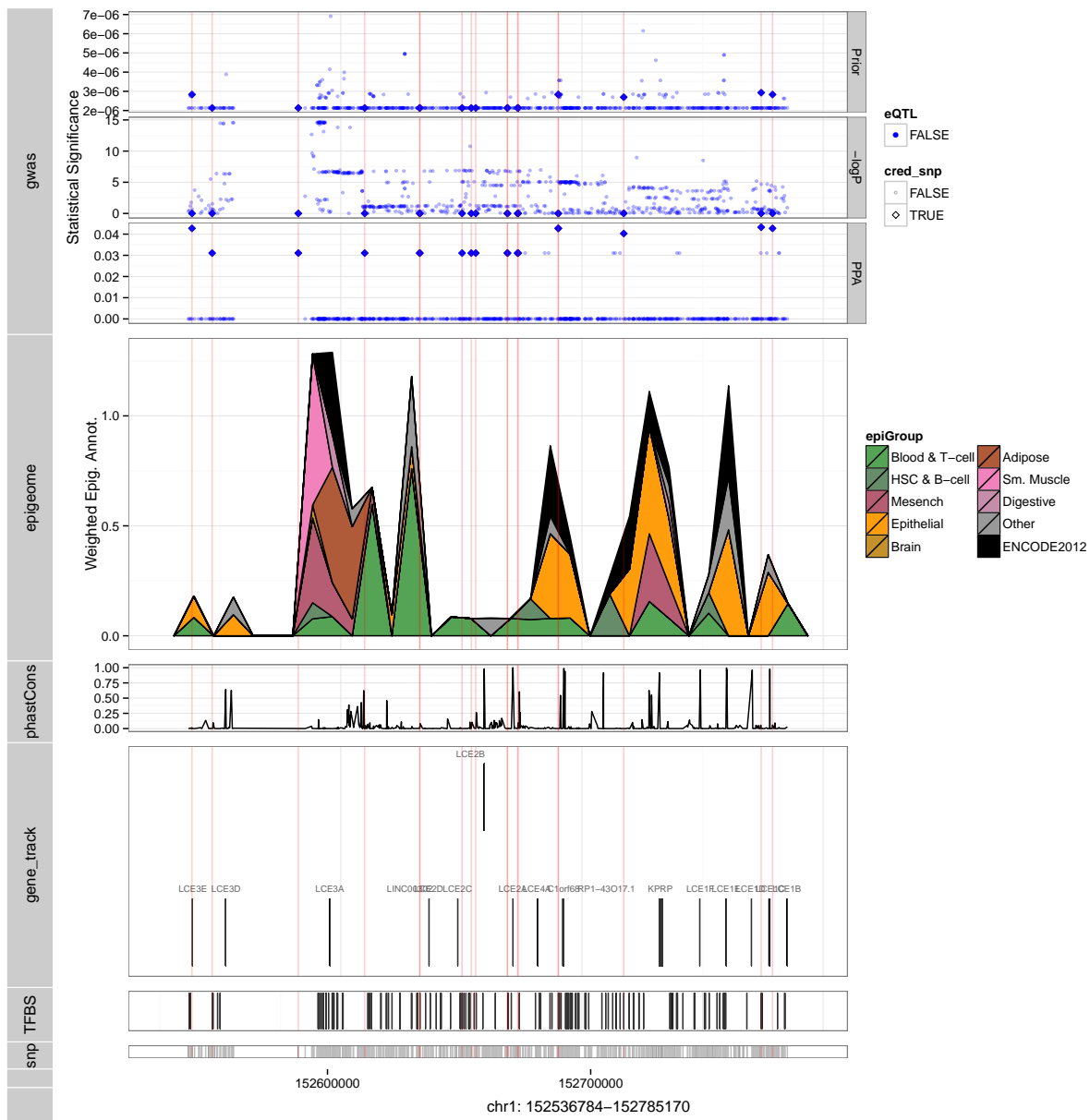
Primary Biliary Cirrhosis



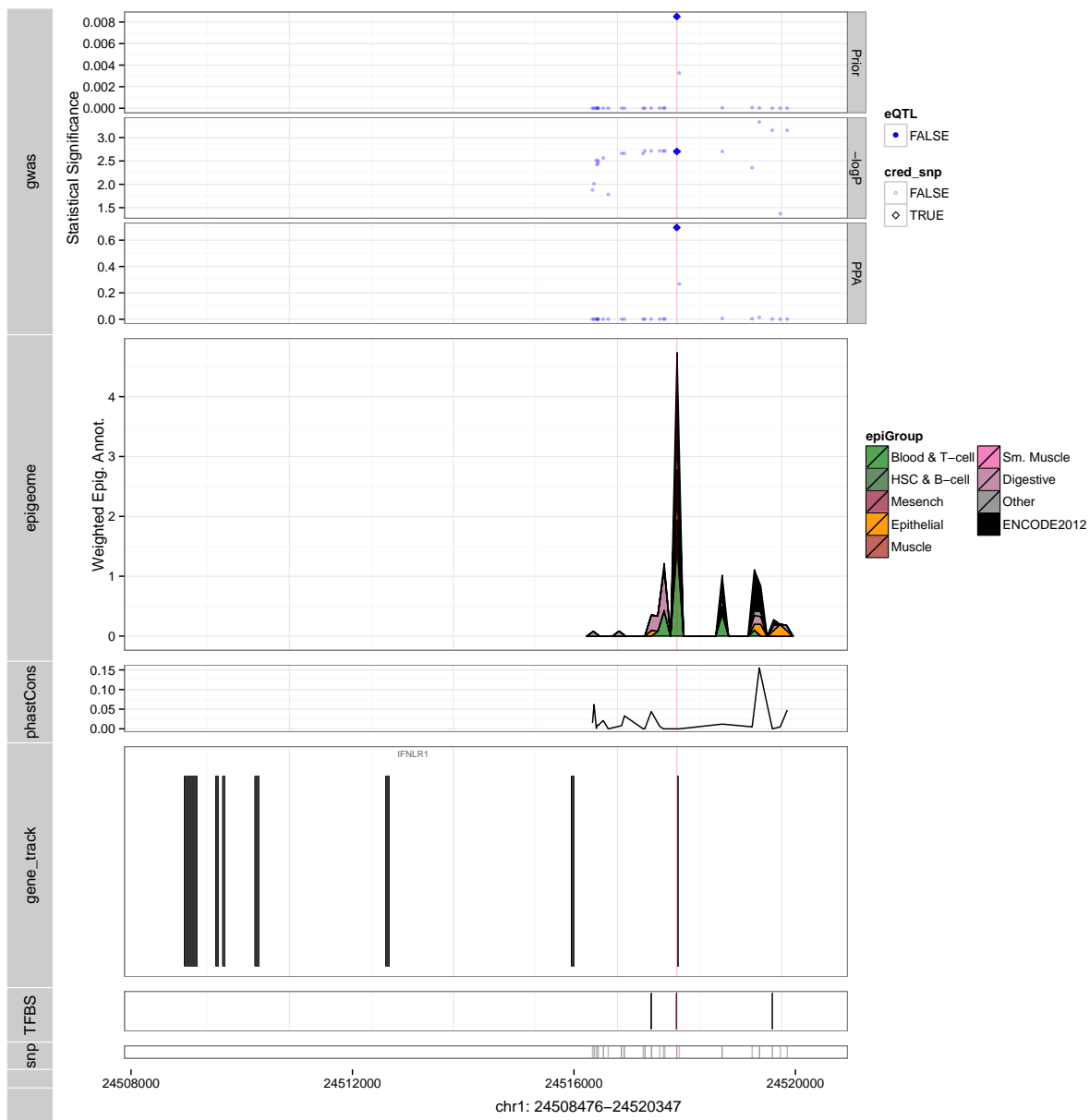
Primary Biliary Cirrhosis



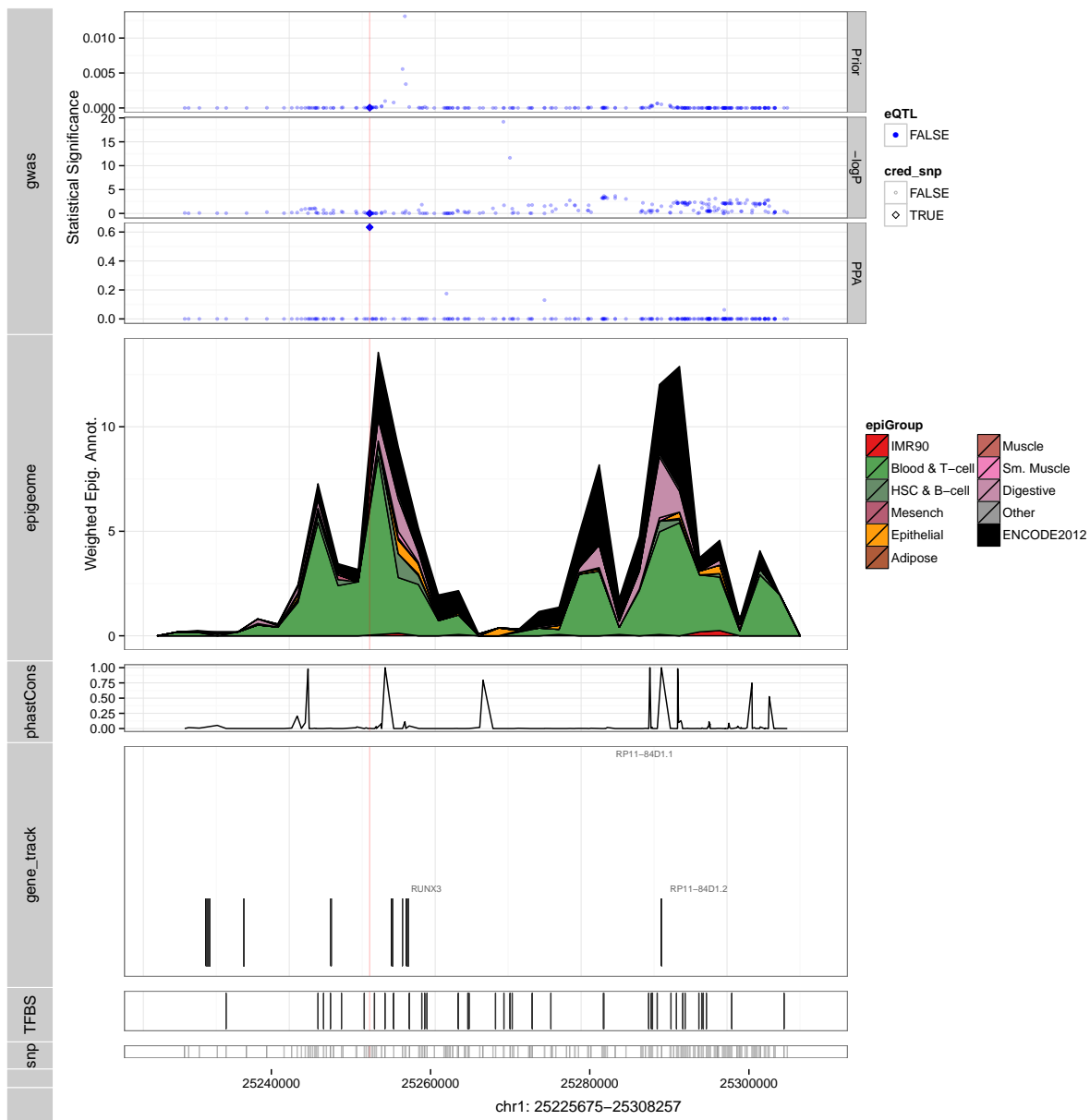
Psoriasis



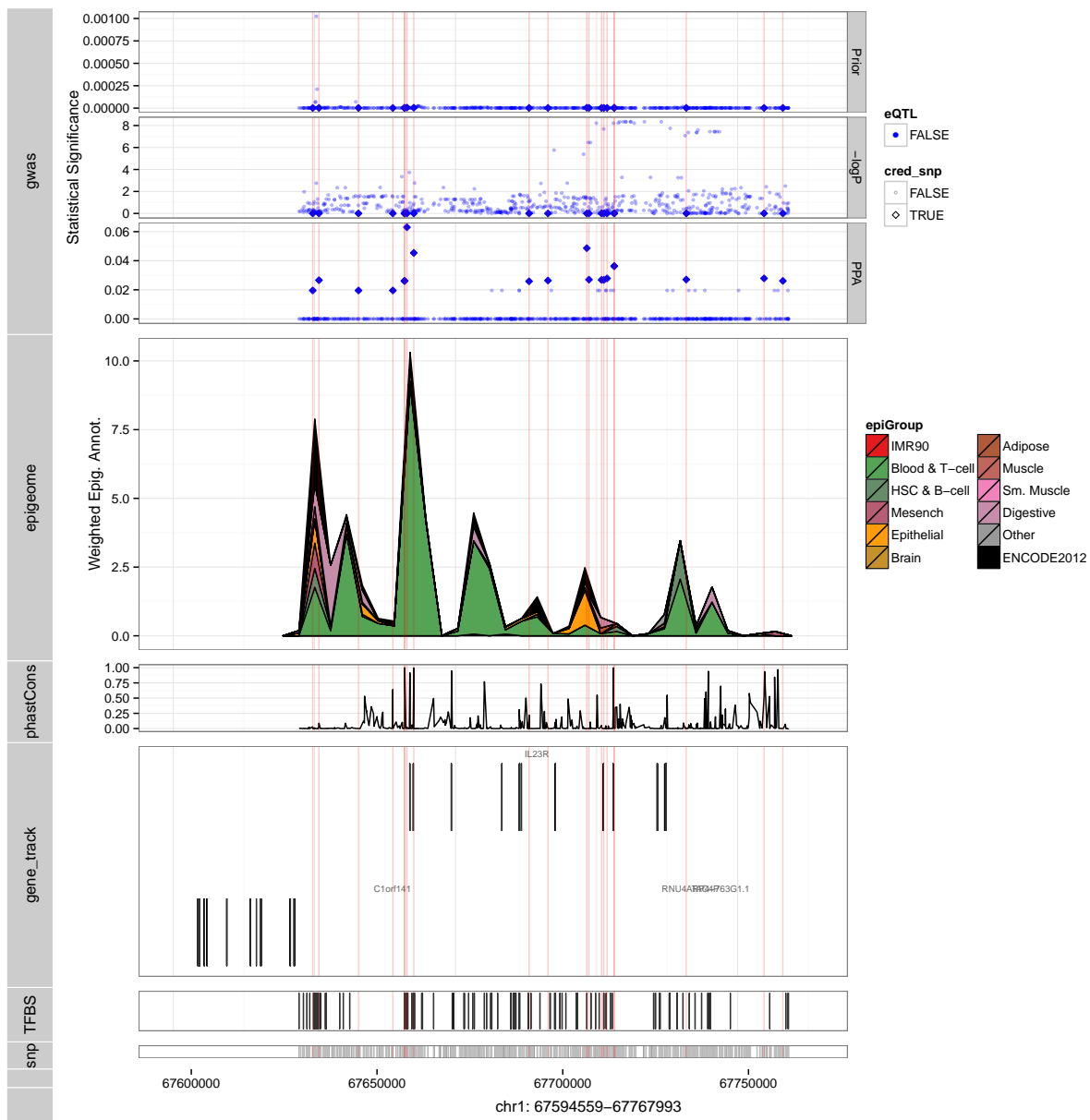
Psoriasis



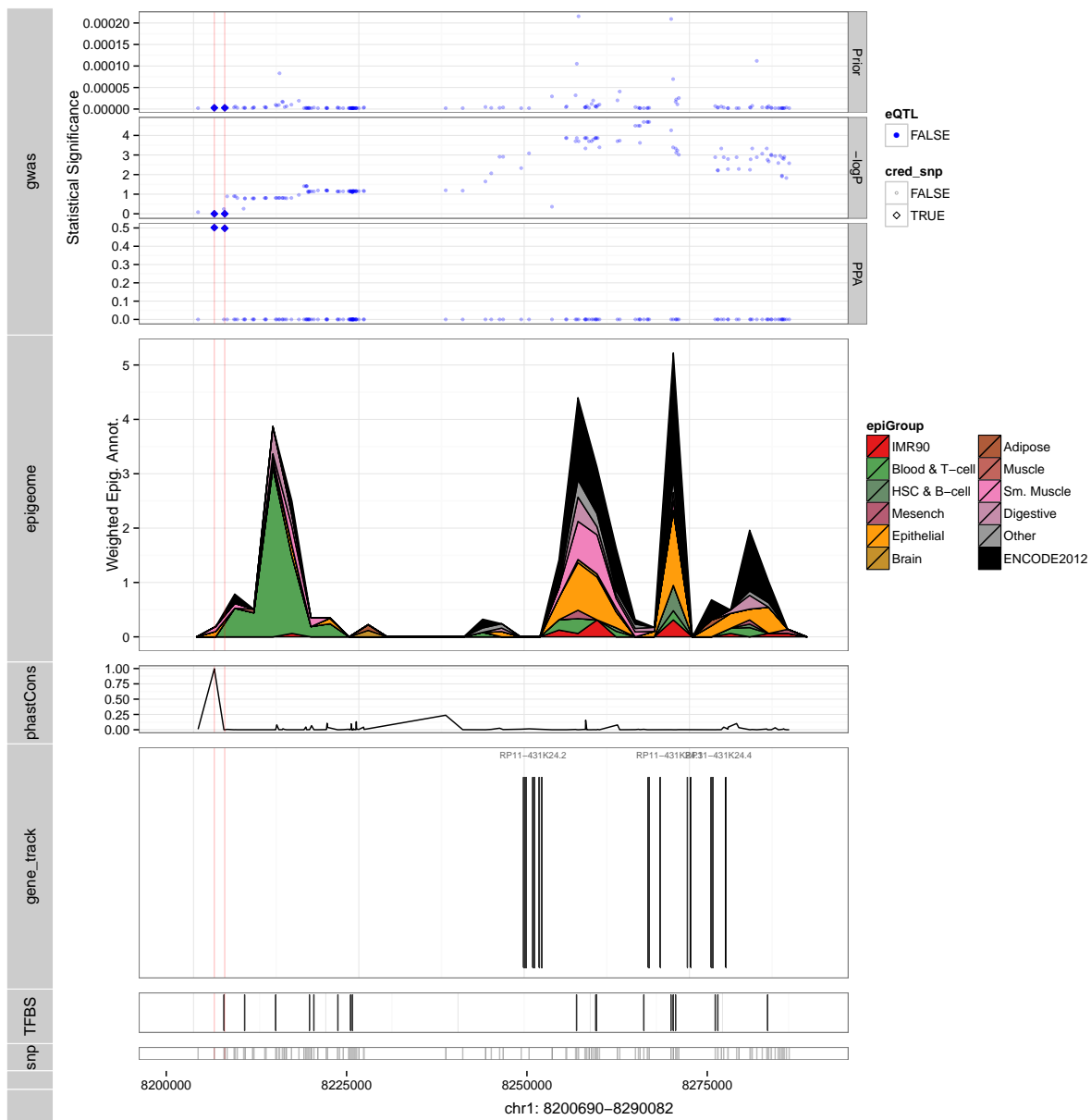
Psoriasis



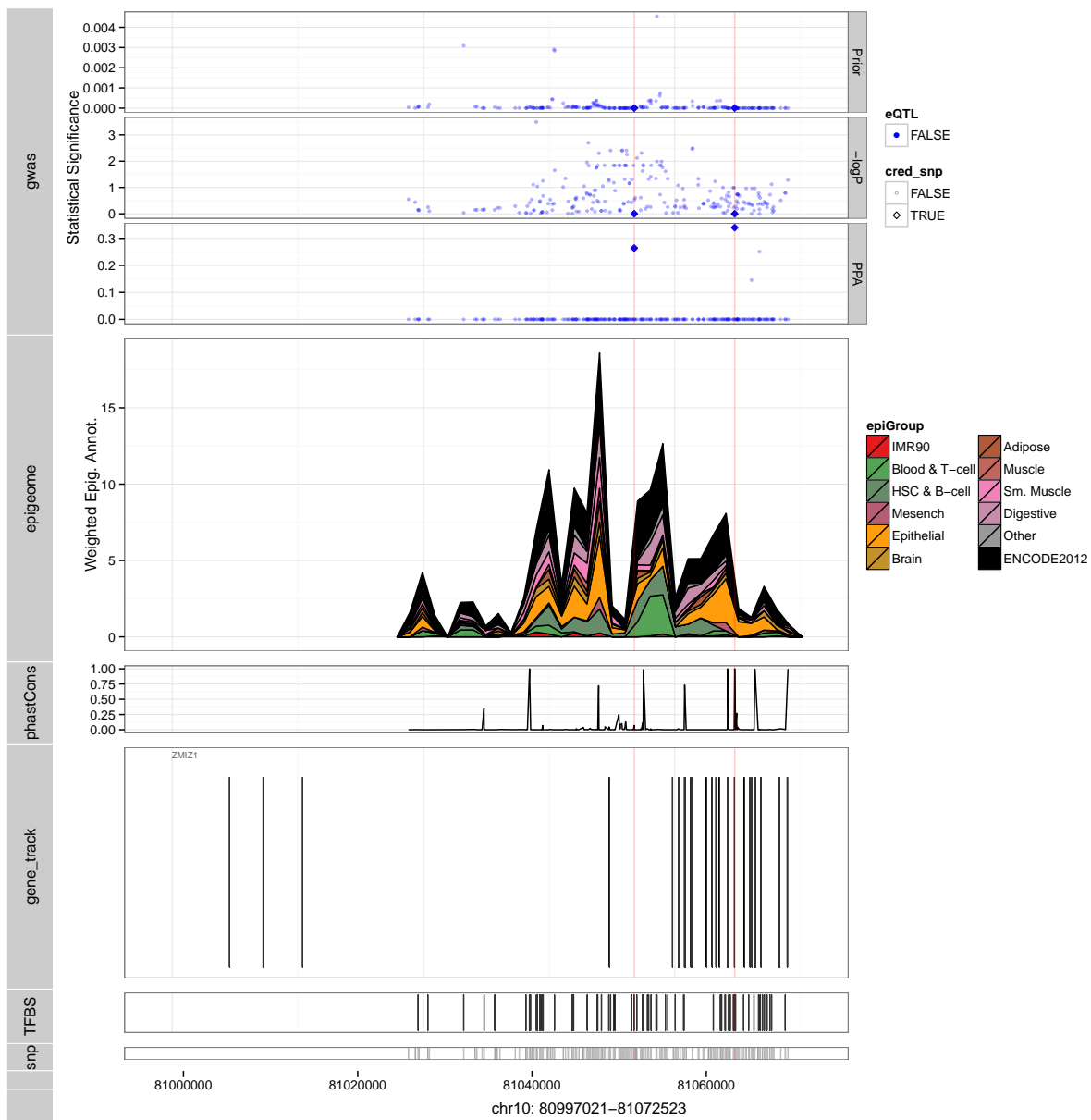
Psoriasis



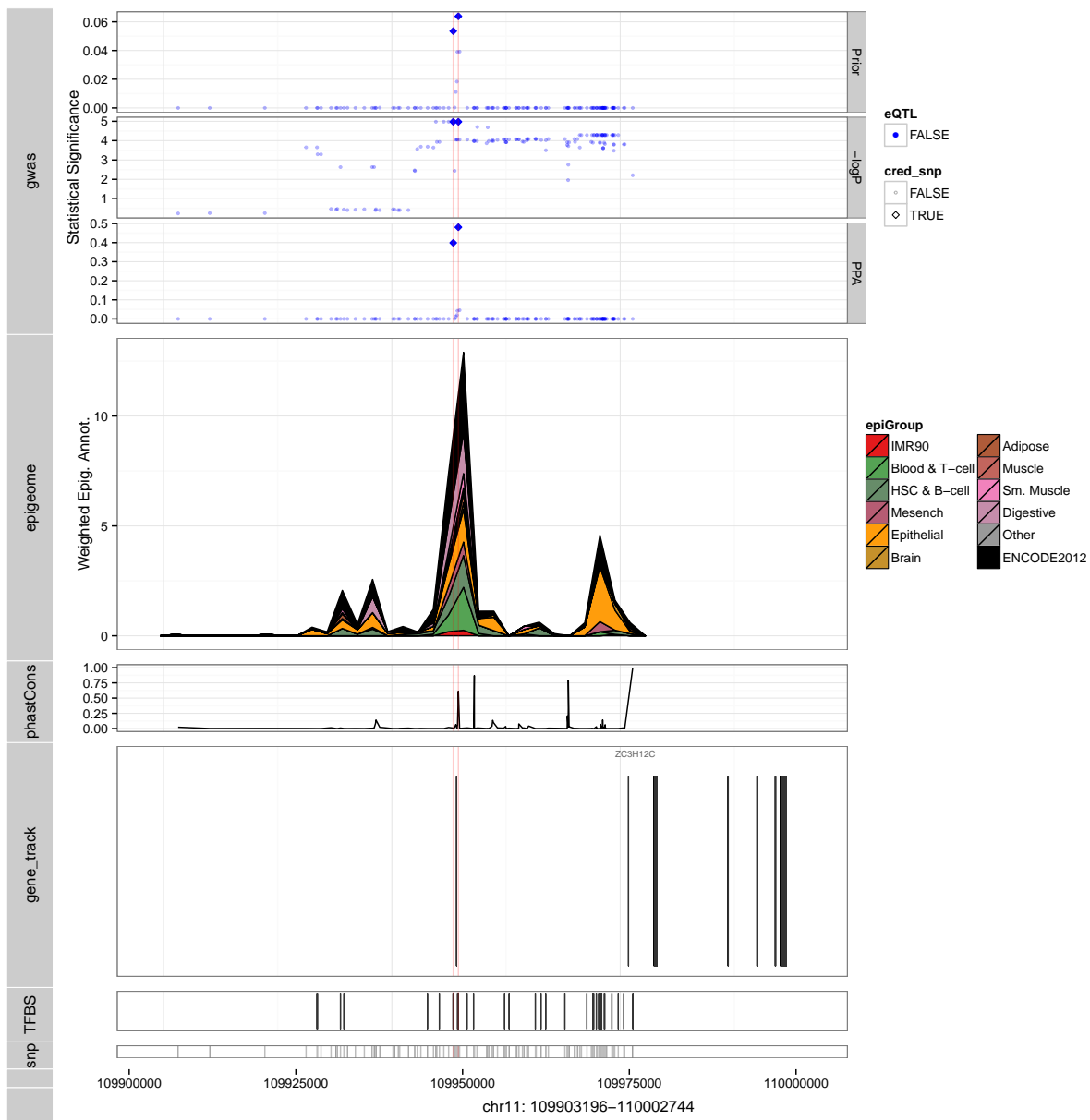
Psoriasis



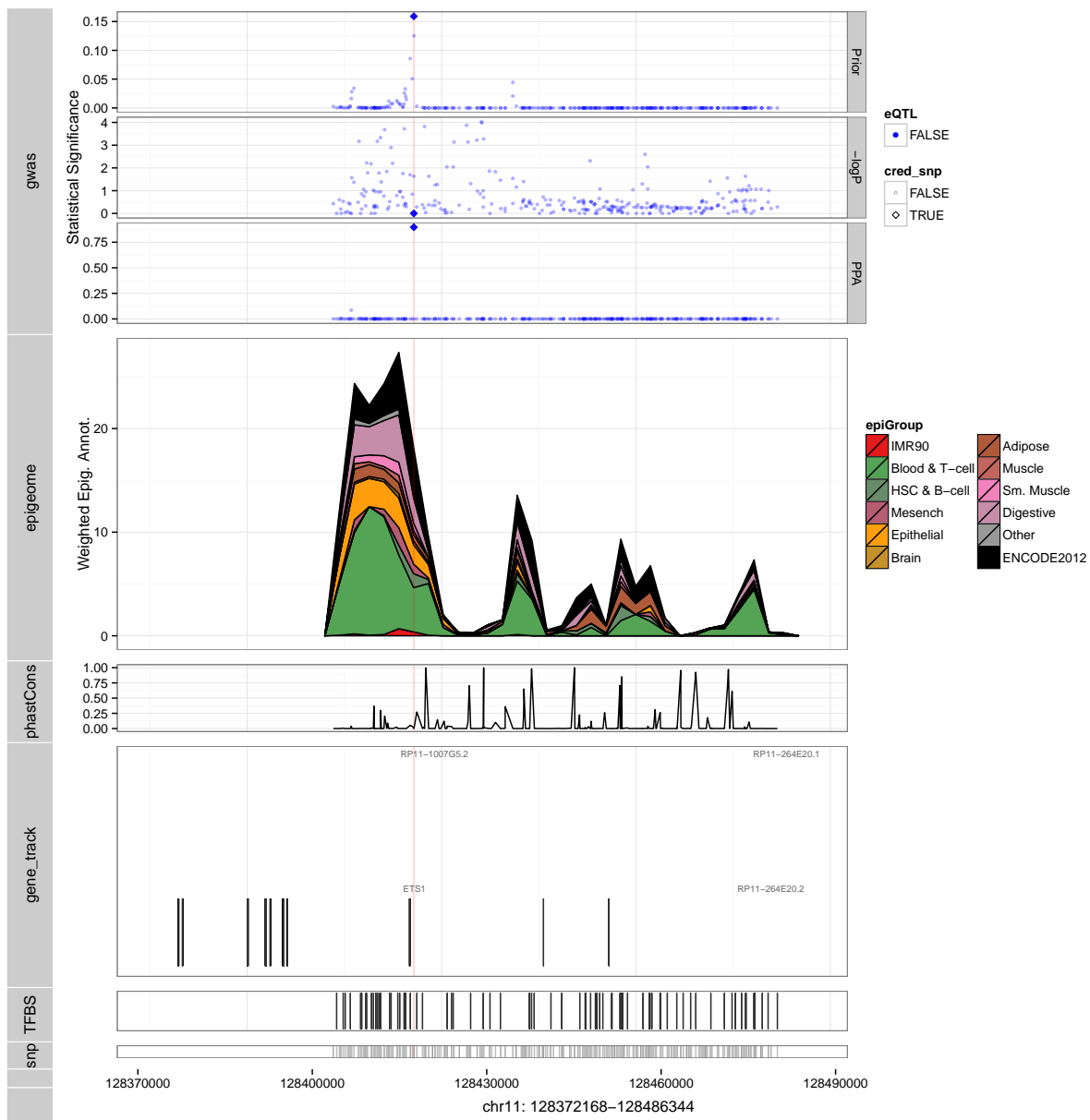
Psoriasis



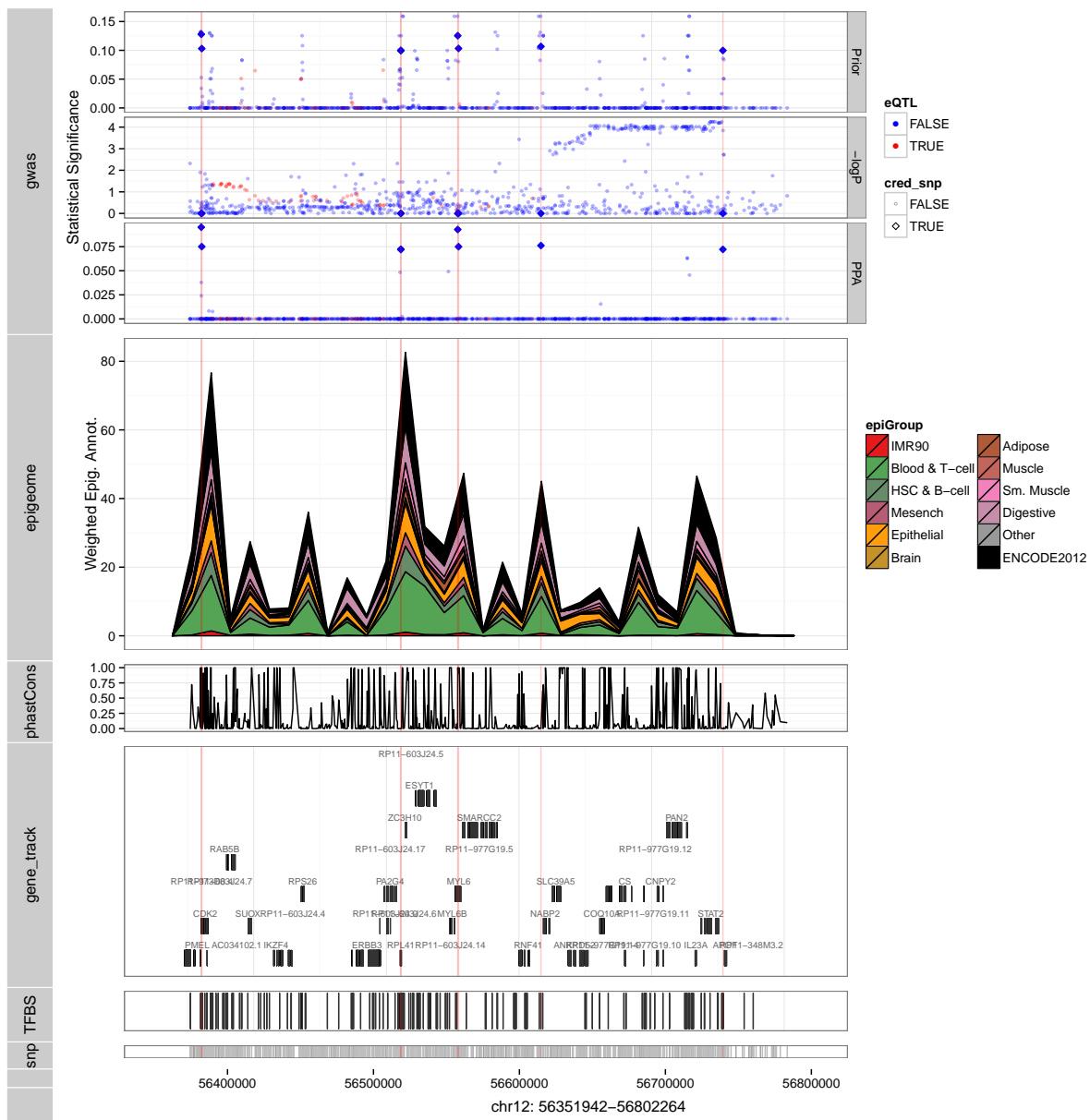
Psoriasis



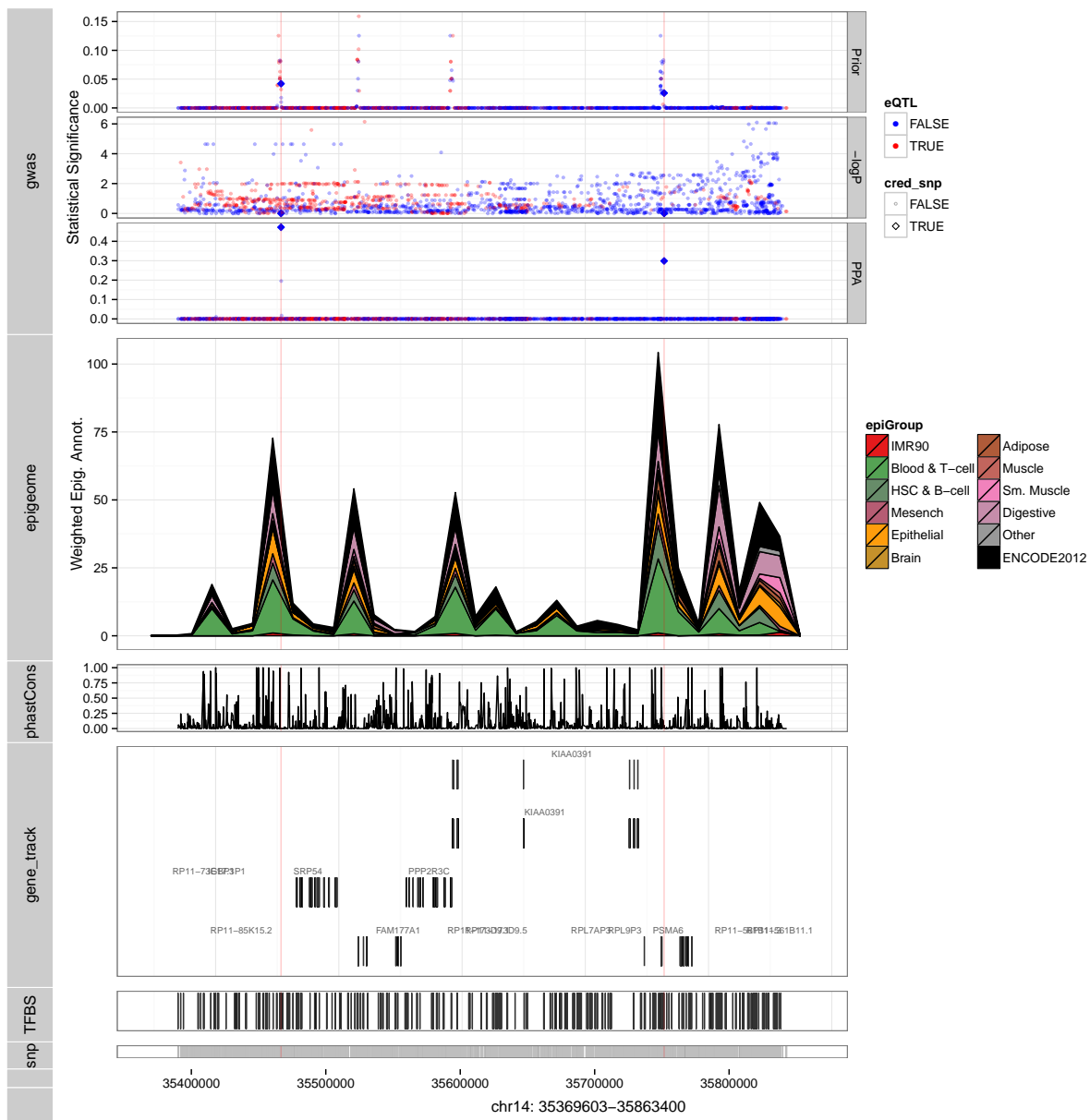
Psoriasis



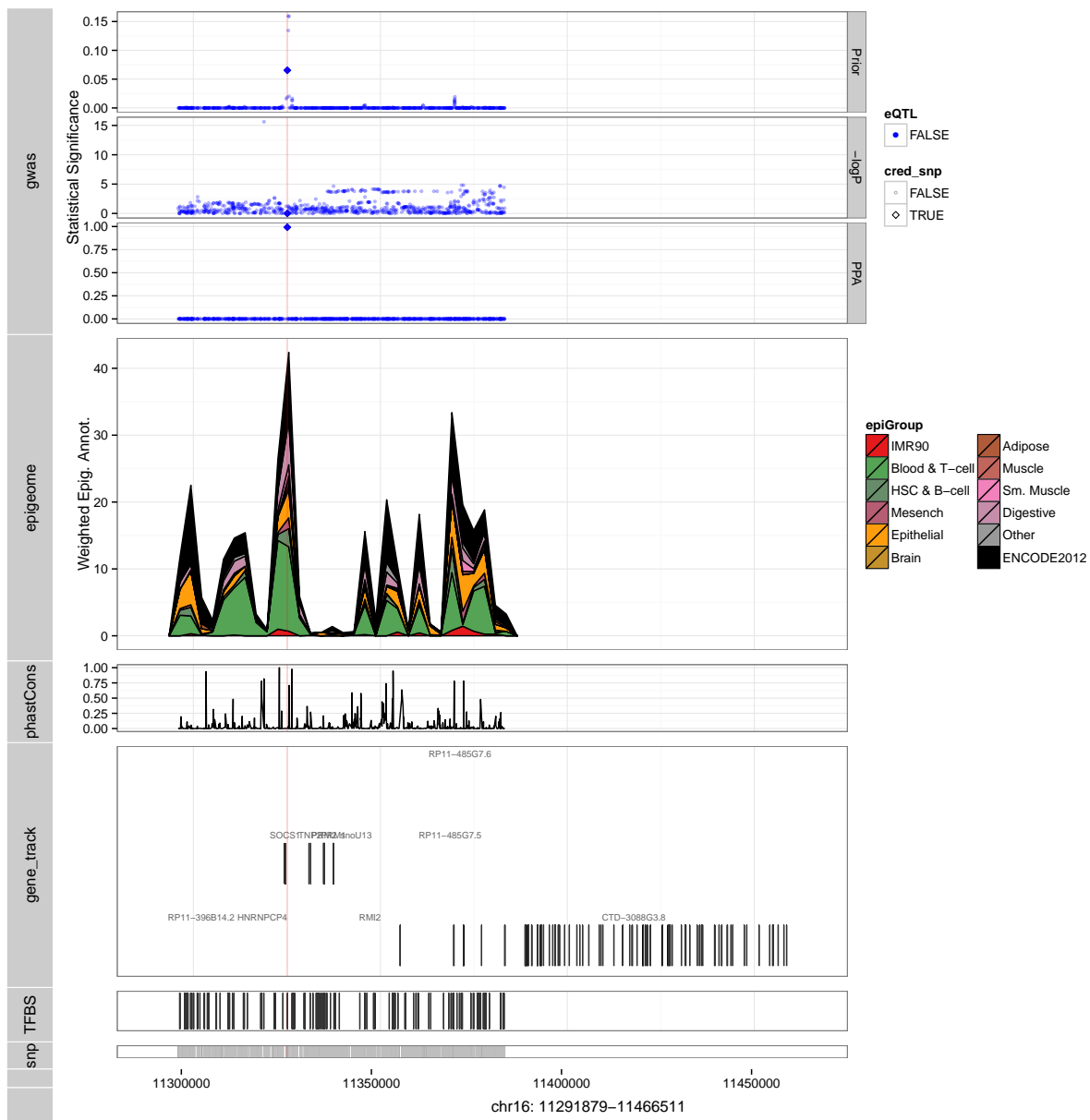
Psoriasis



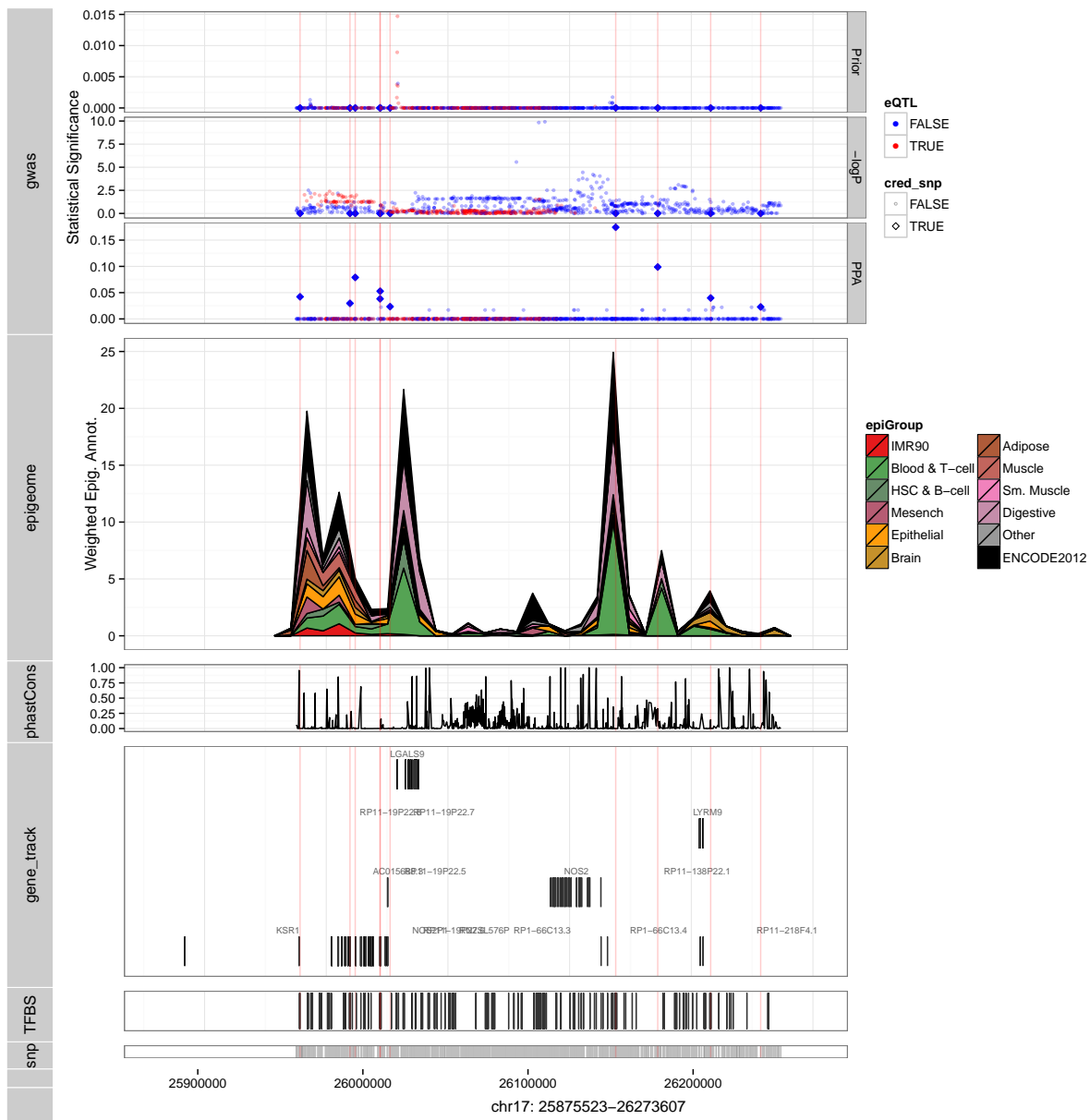
Psoriasis



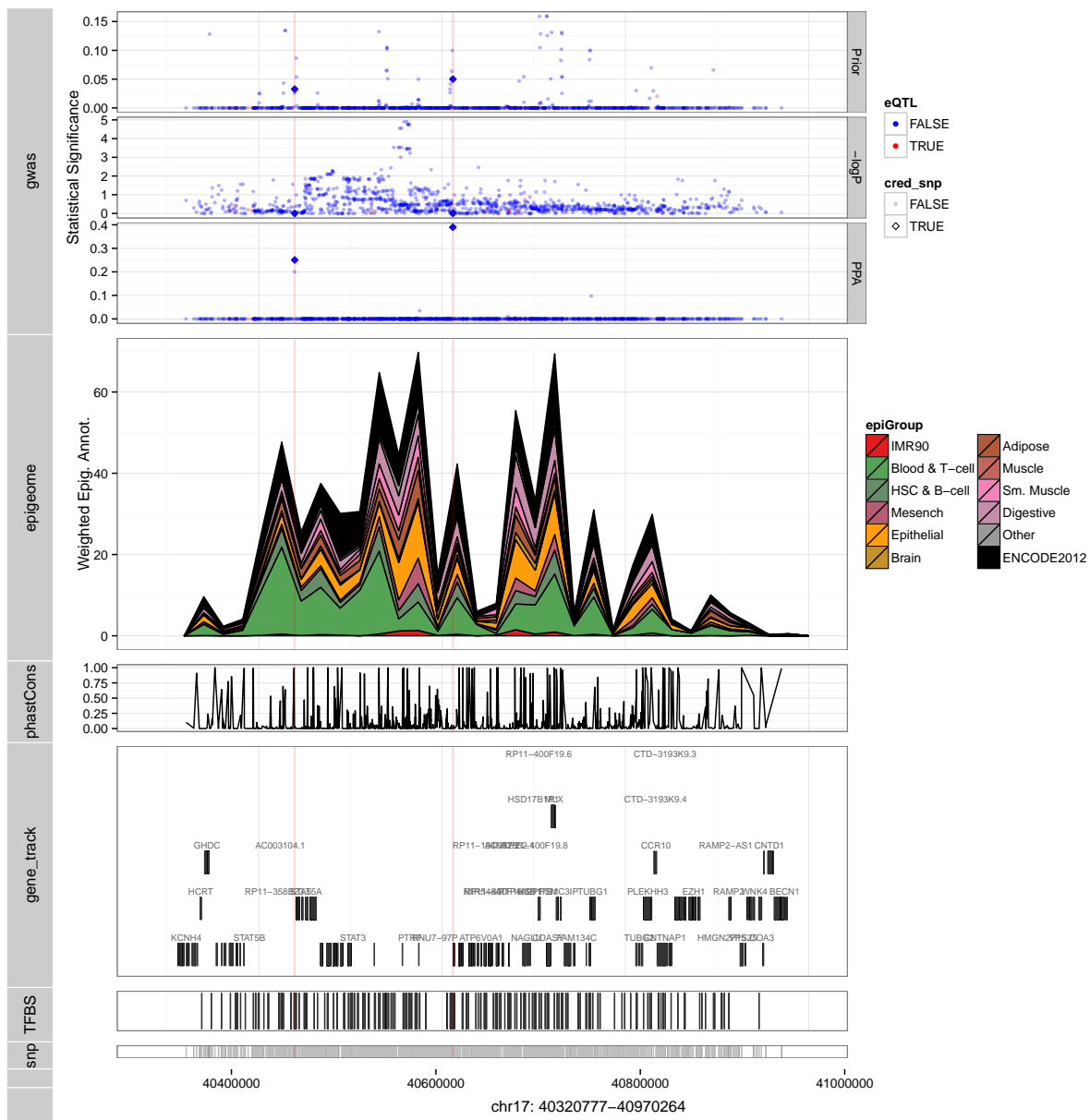
Psoriasis



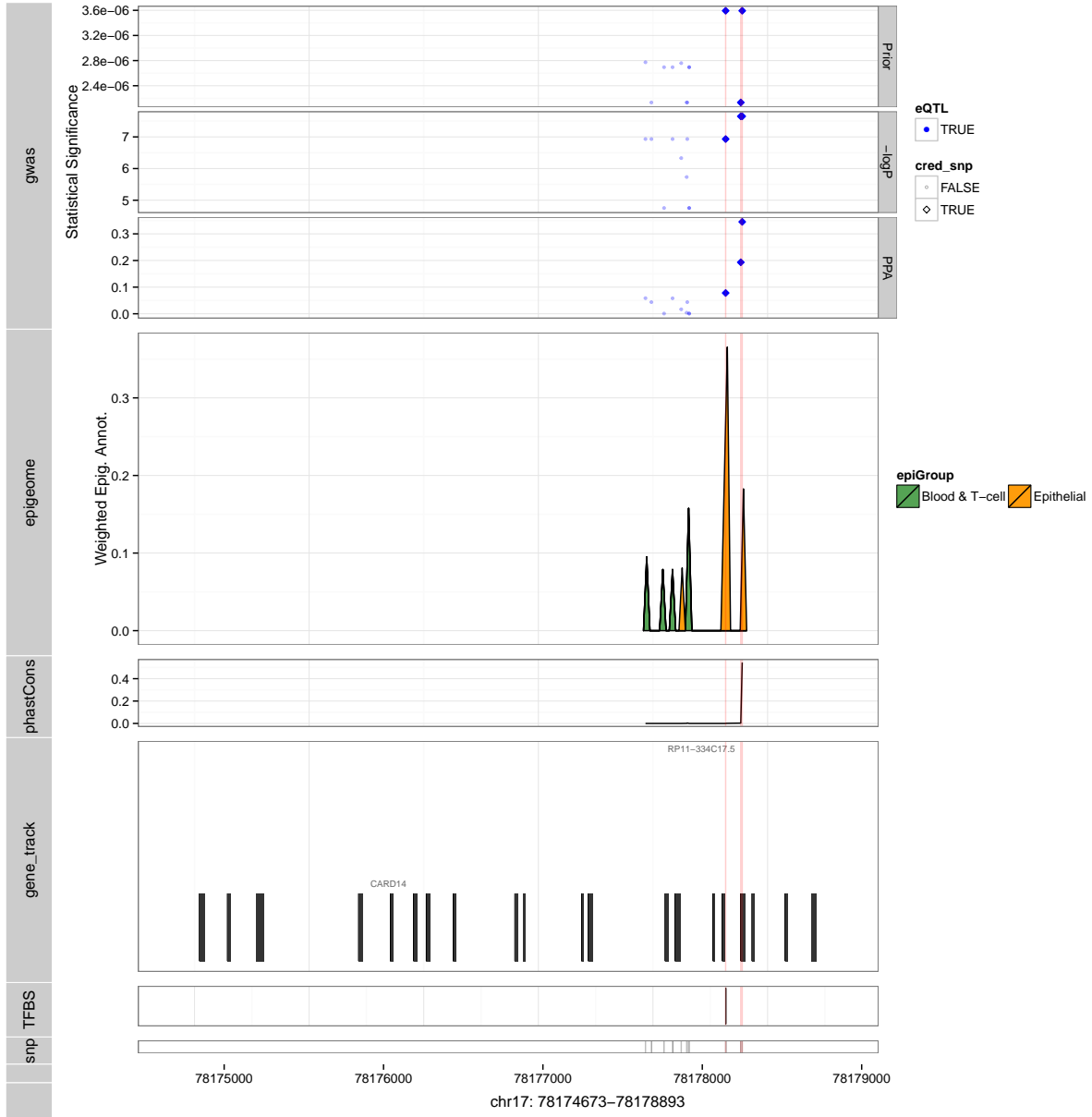
Psoriasis



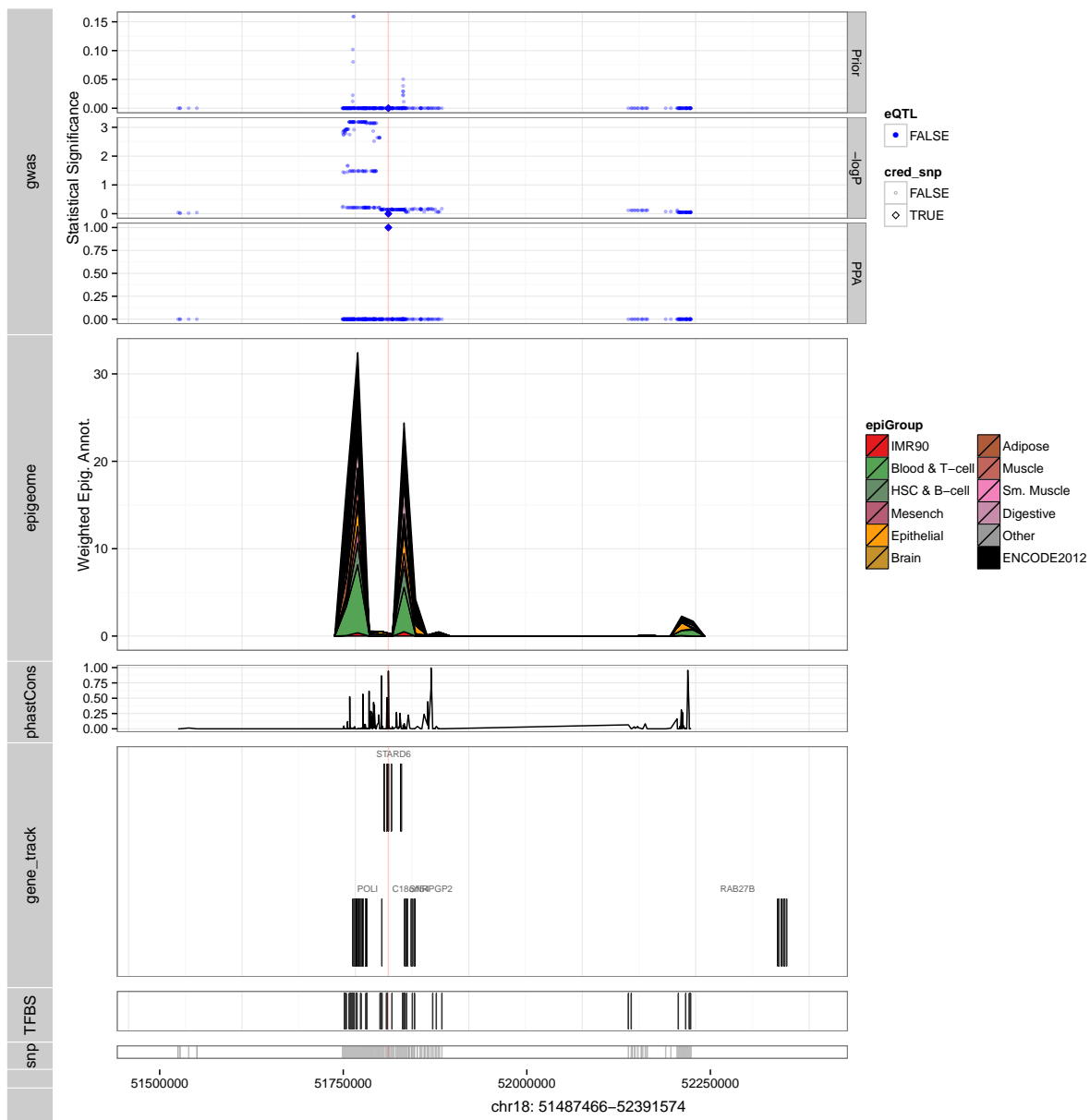
Psoriasis



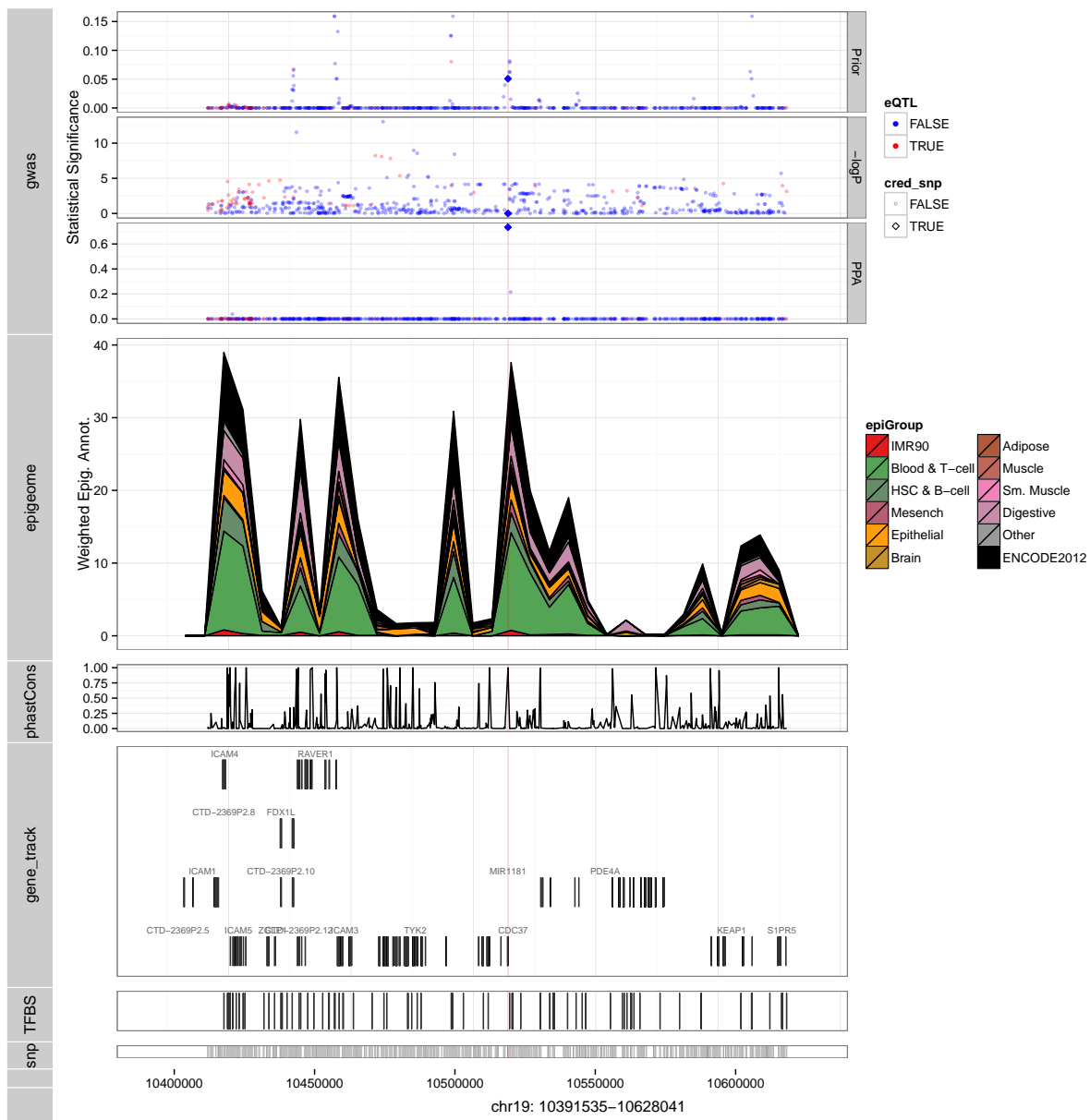
Psoriasis



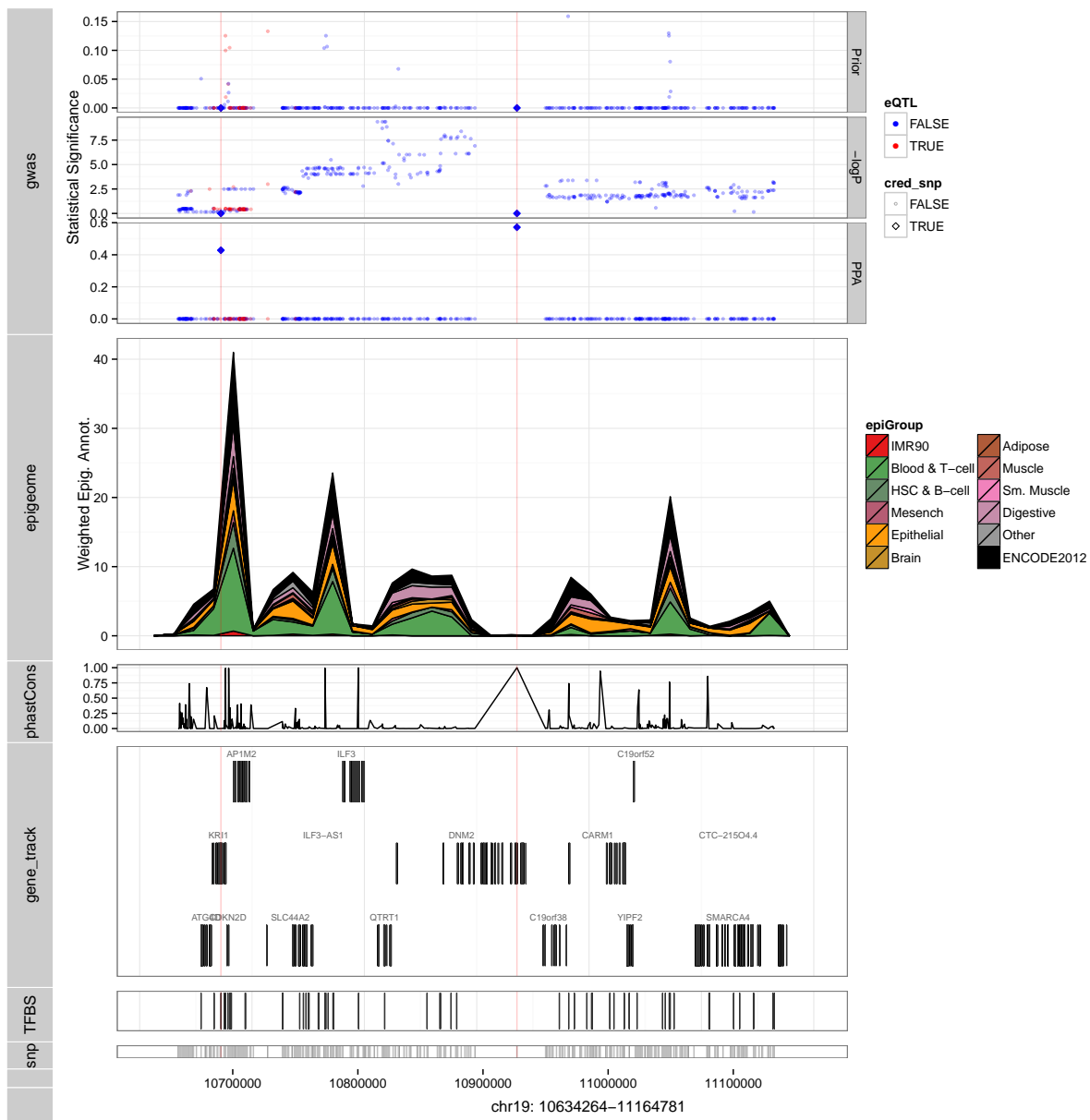
Psoriasis



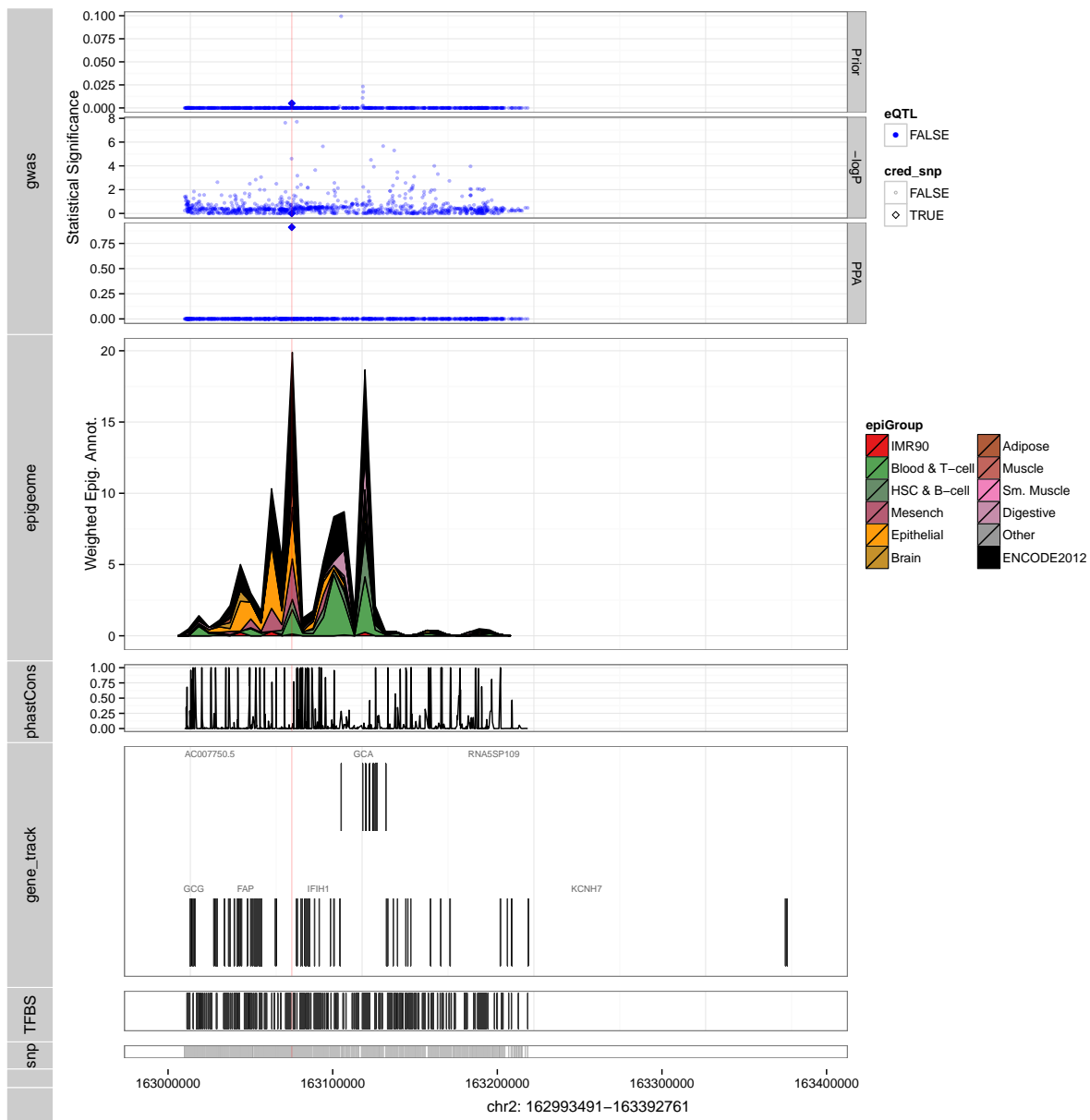
Psoriasis



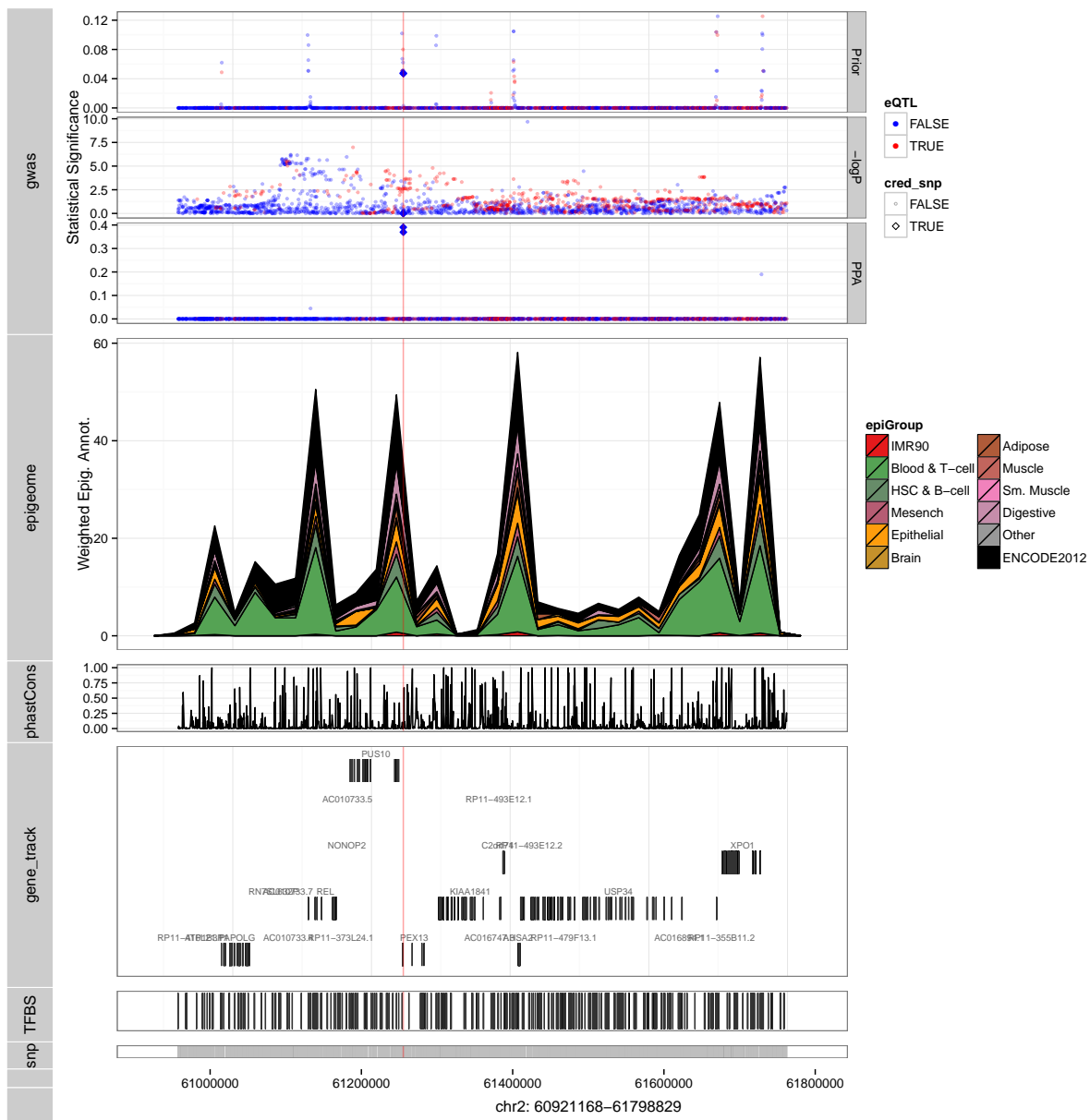
Psoriasis



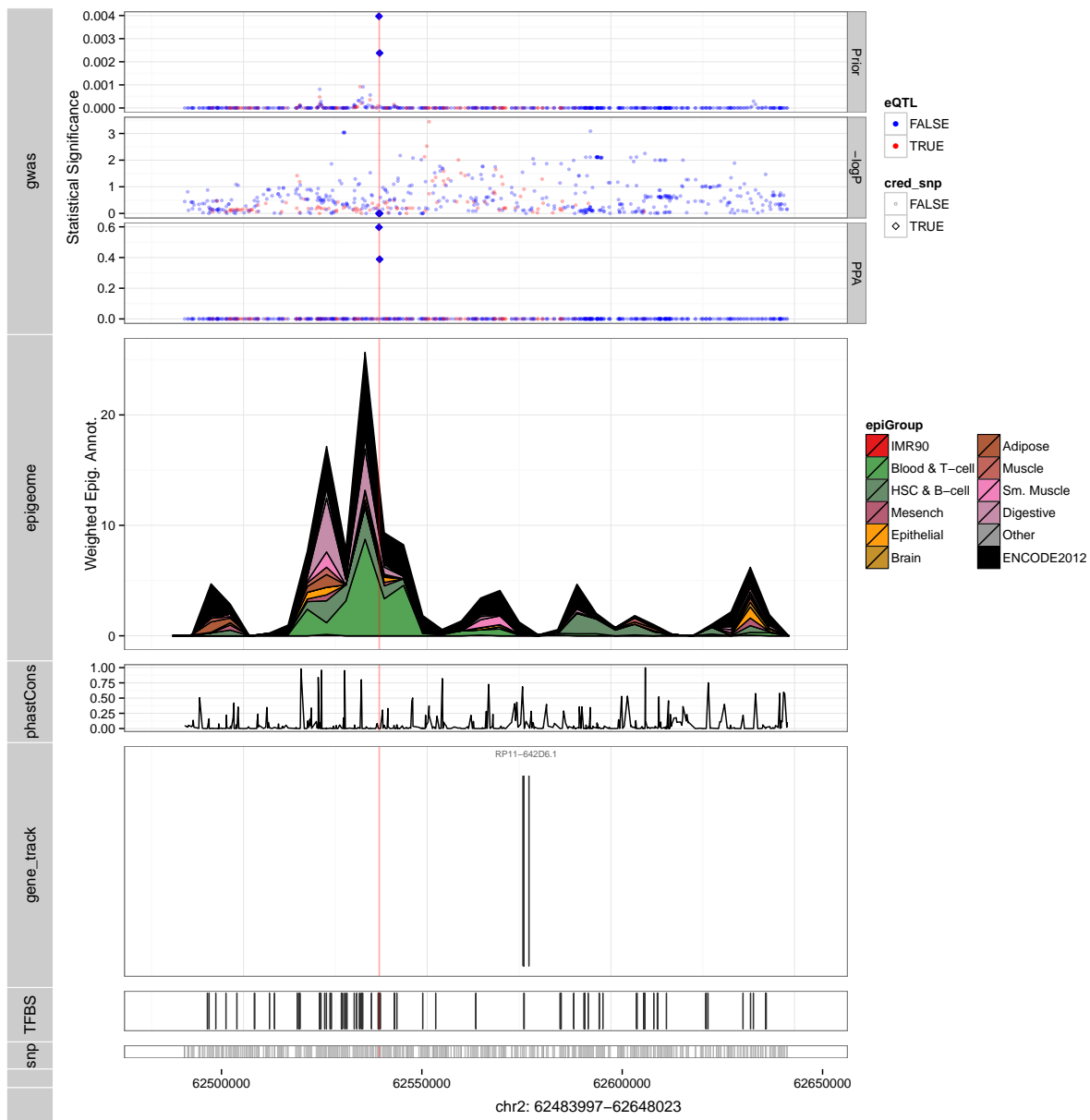
Psoriasis



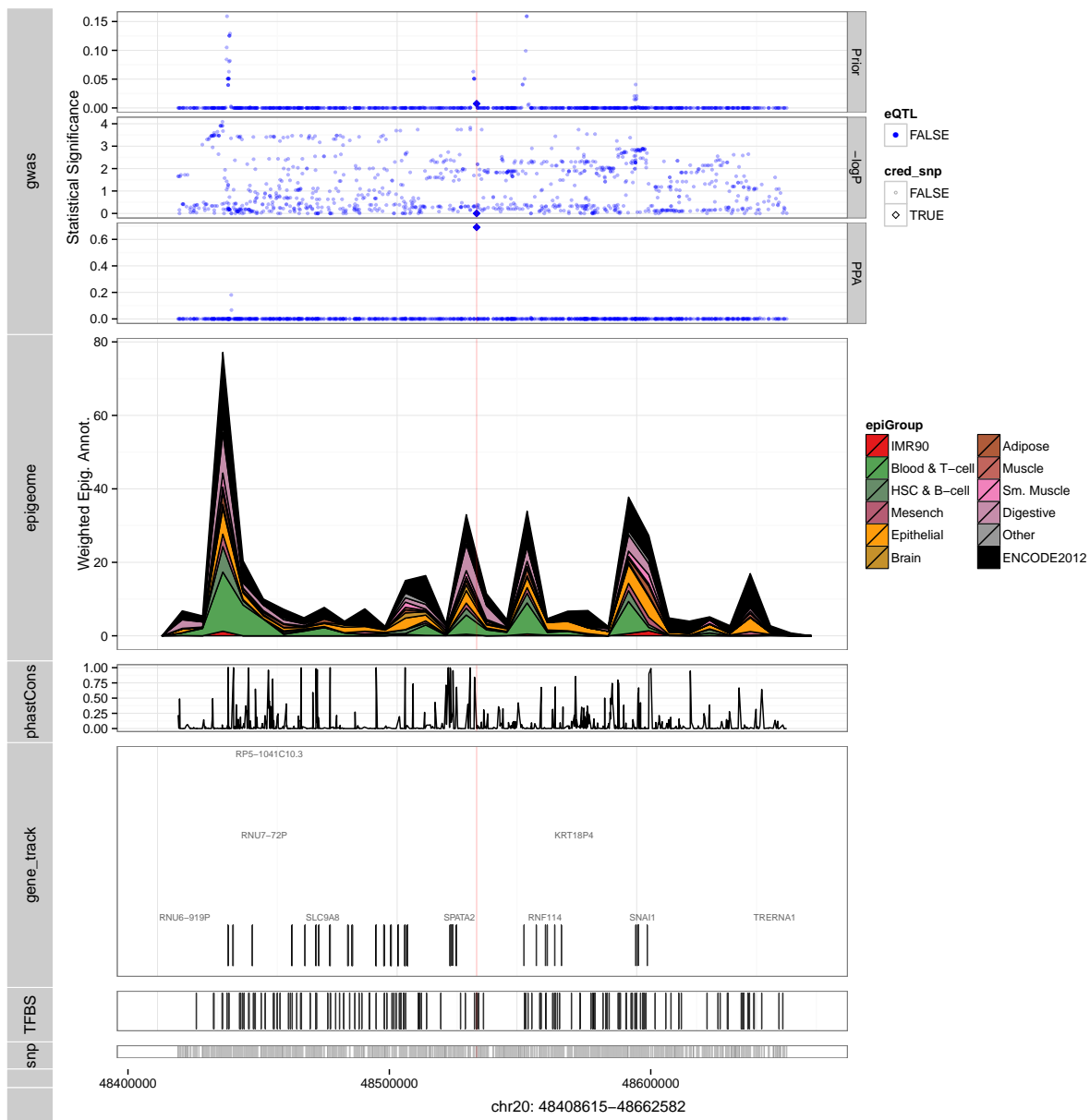
Psoriasis



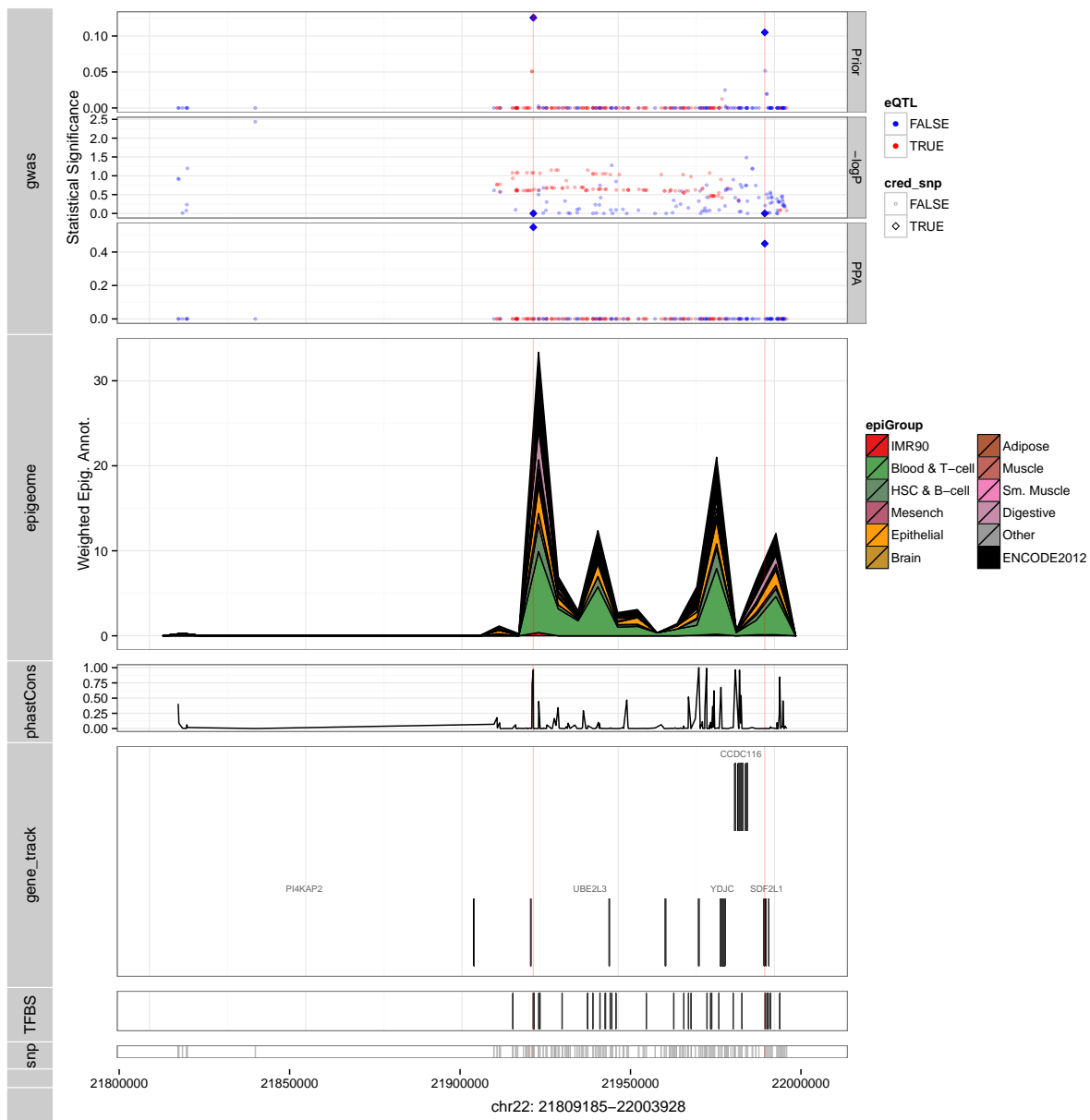
Psoriasis



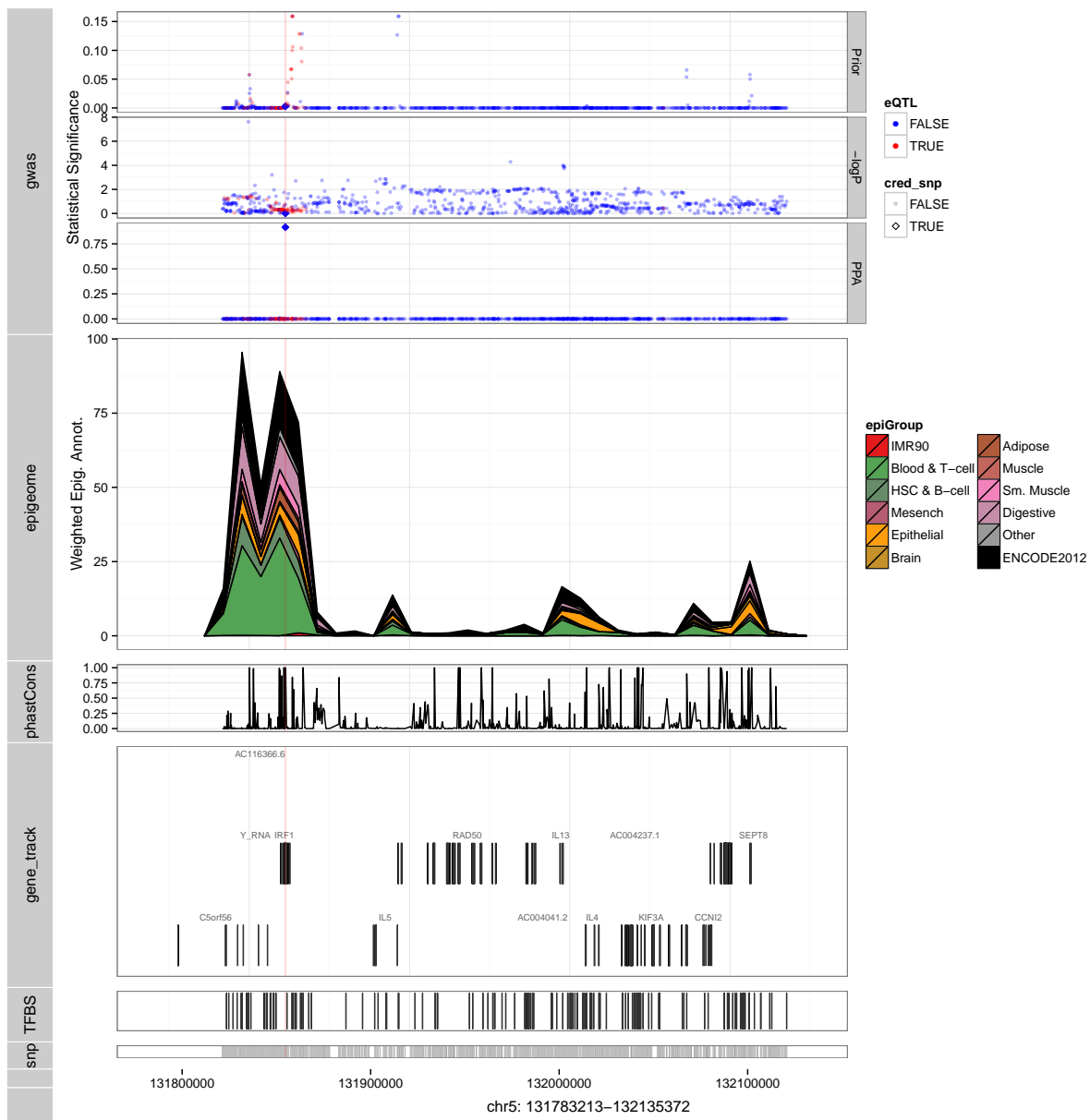
Psoriasis



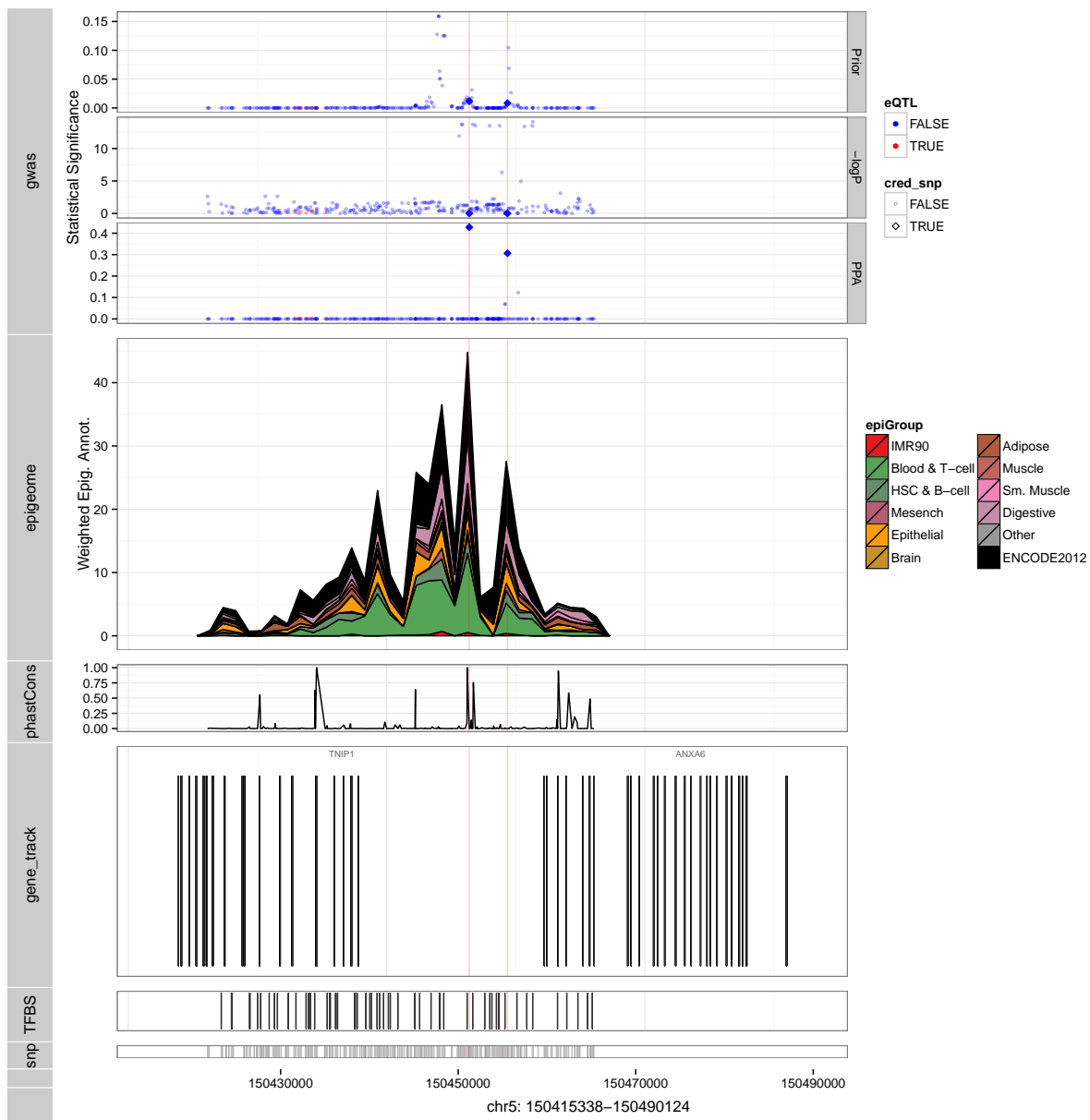
Psoriasis



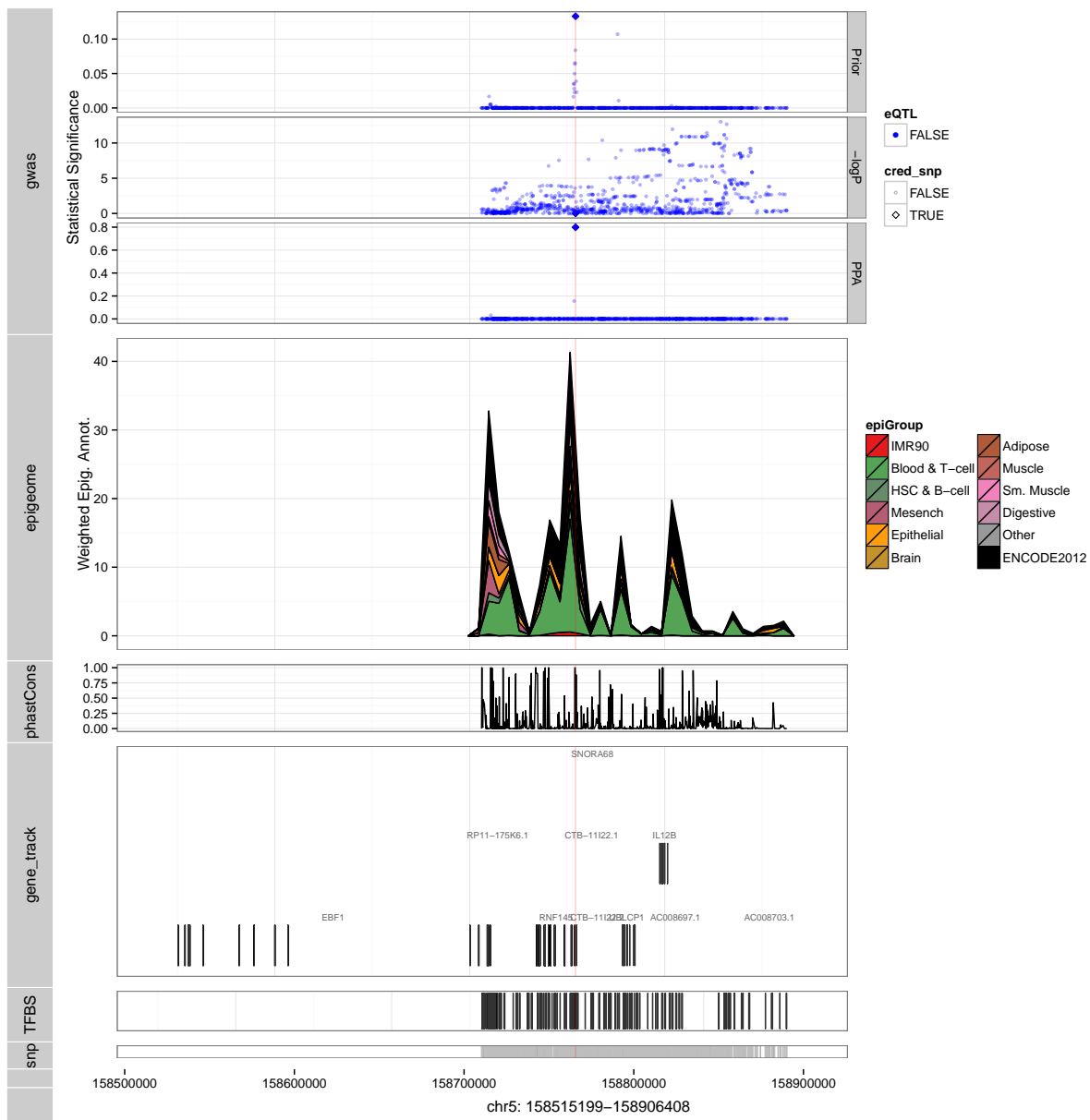
Psoriasis



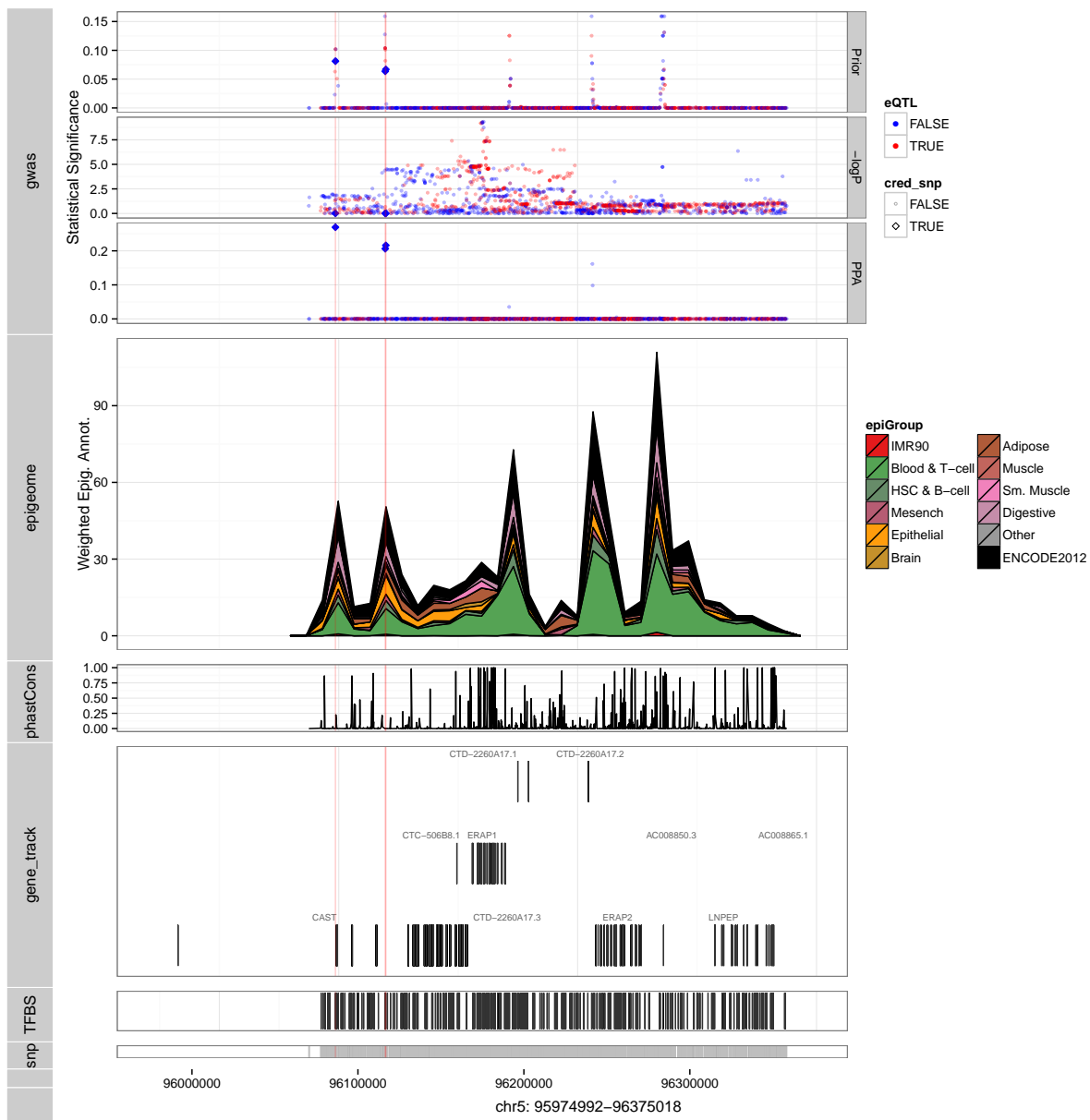
Psoriasis



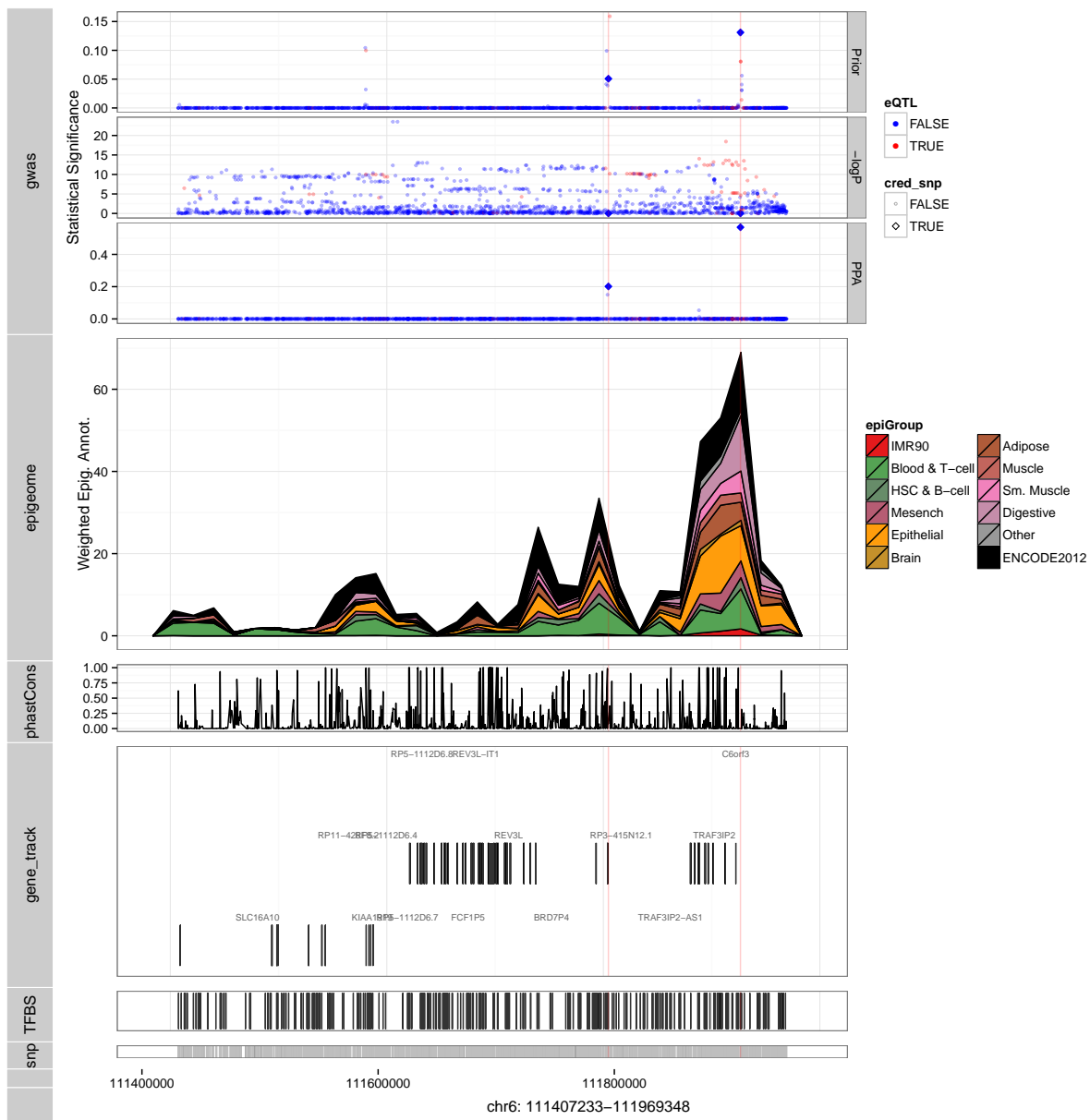
Psoriasis



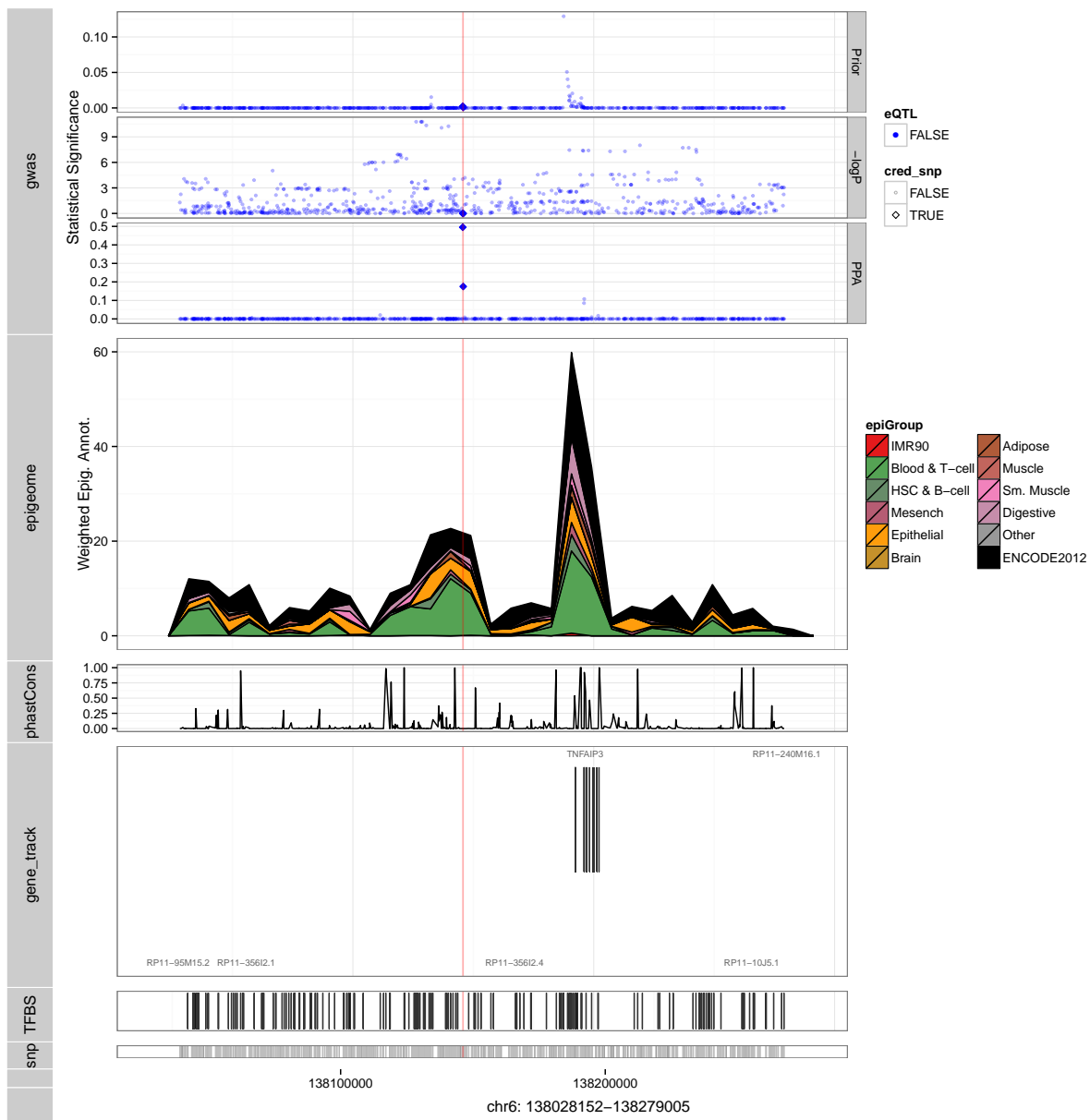
Psoriasis



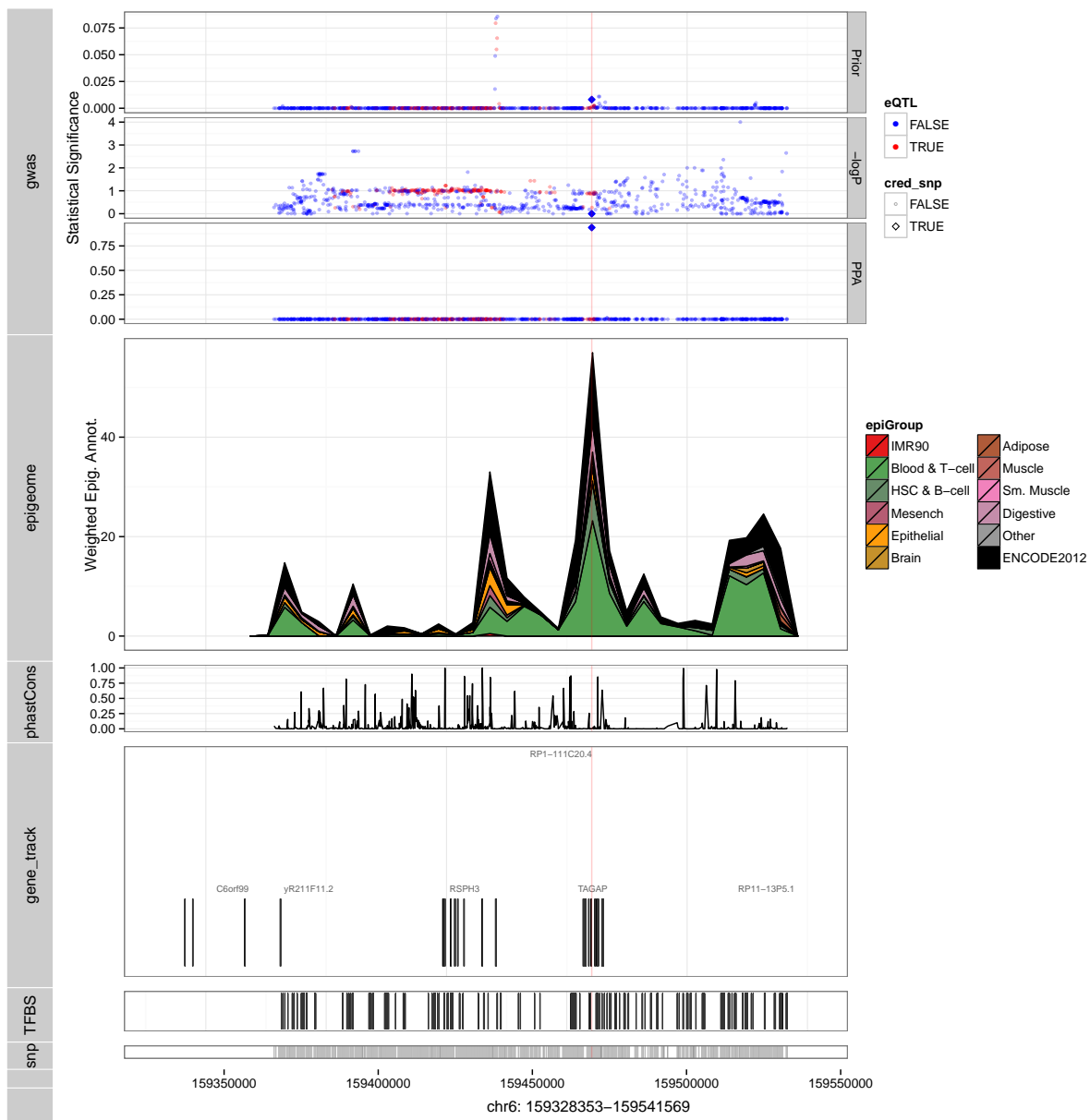
Psoriasis



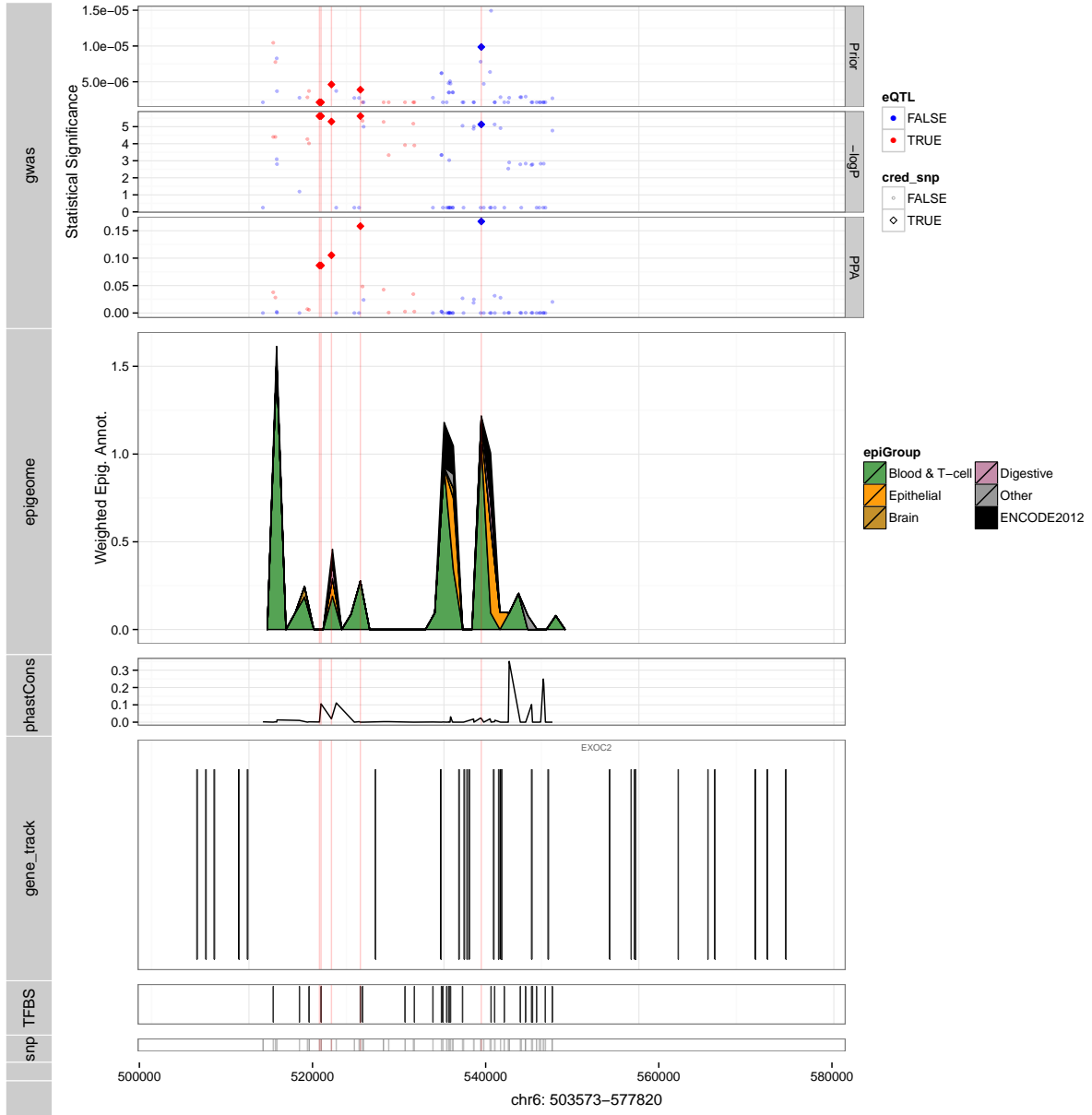
Psoriasis



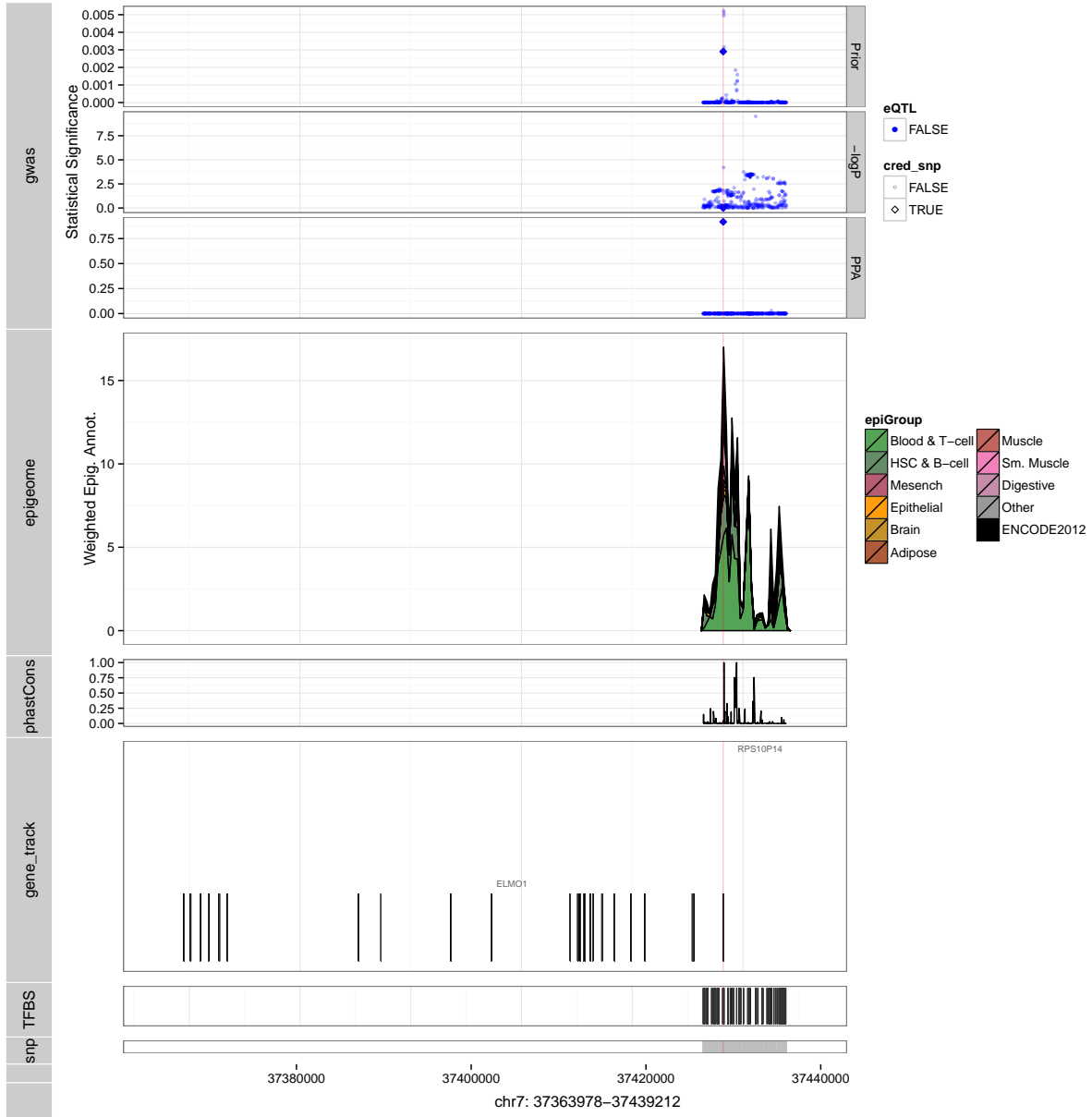
Psoriasis



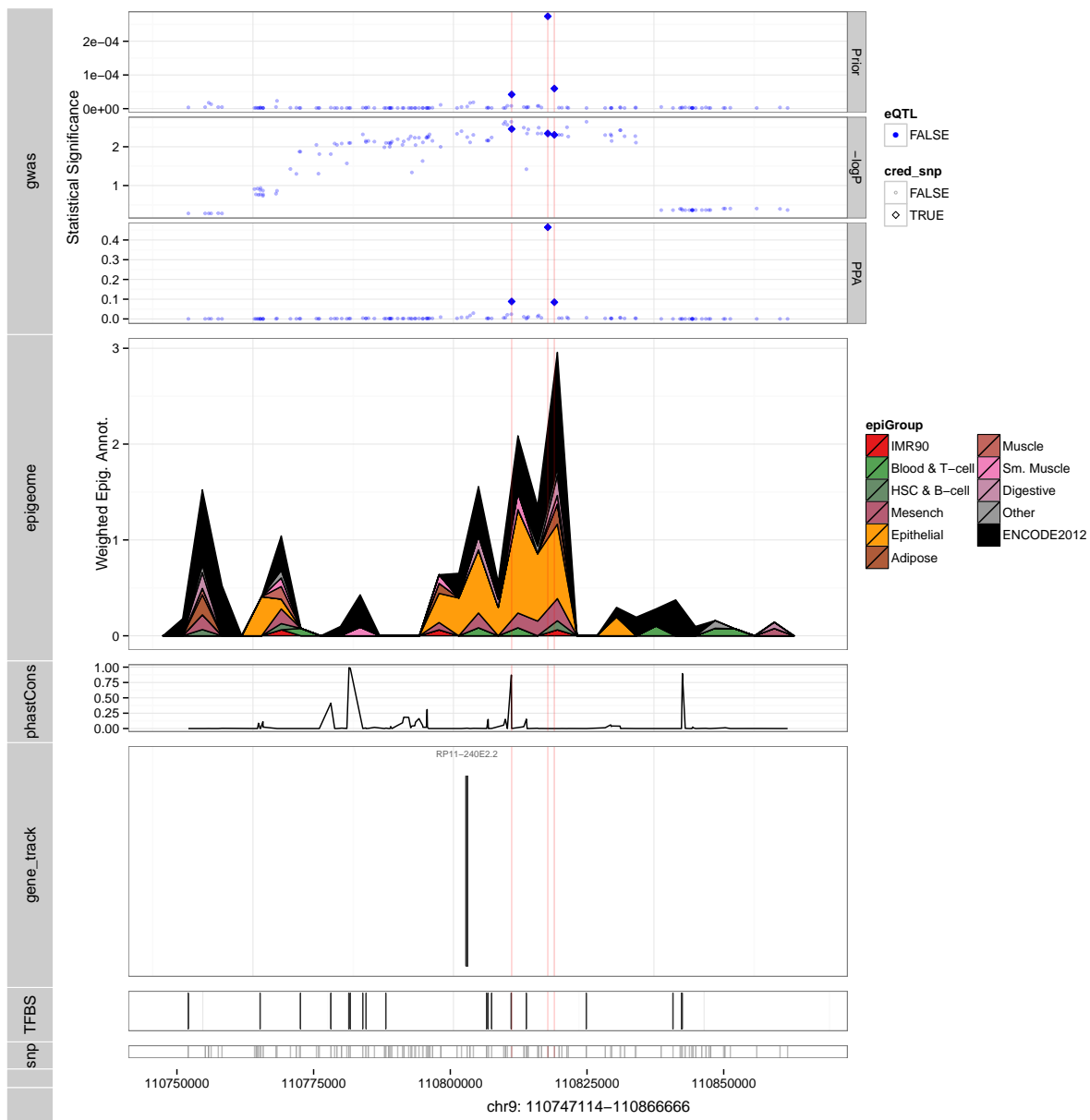
Psoriasis



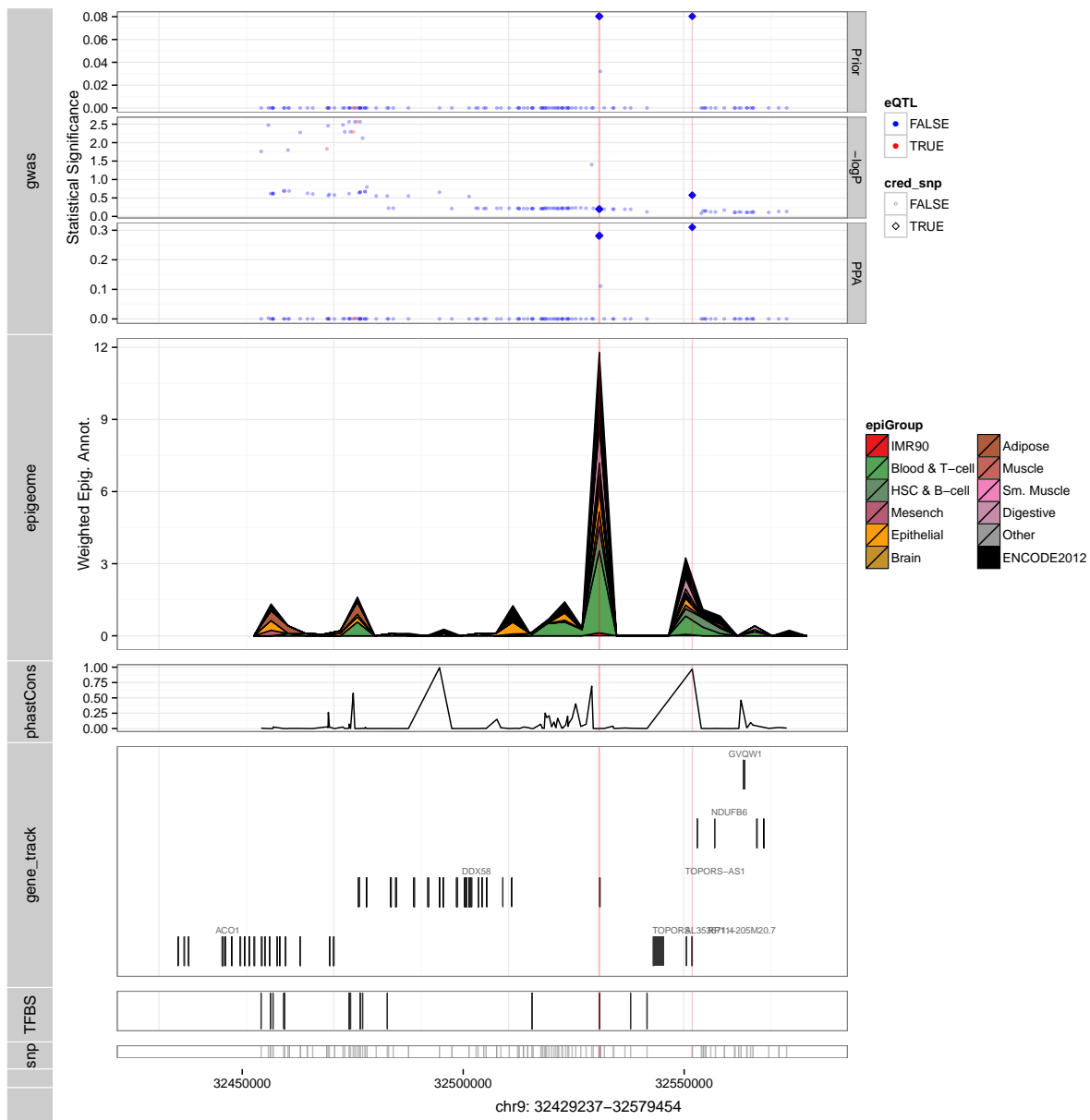
Psoriasis



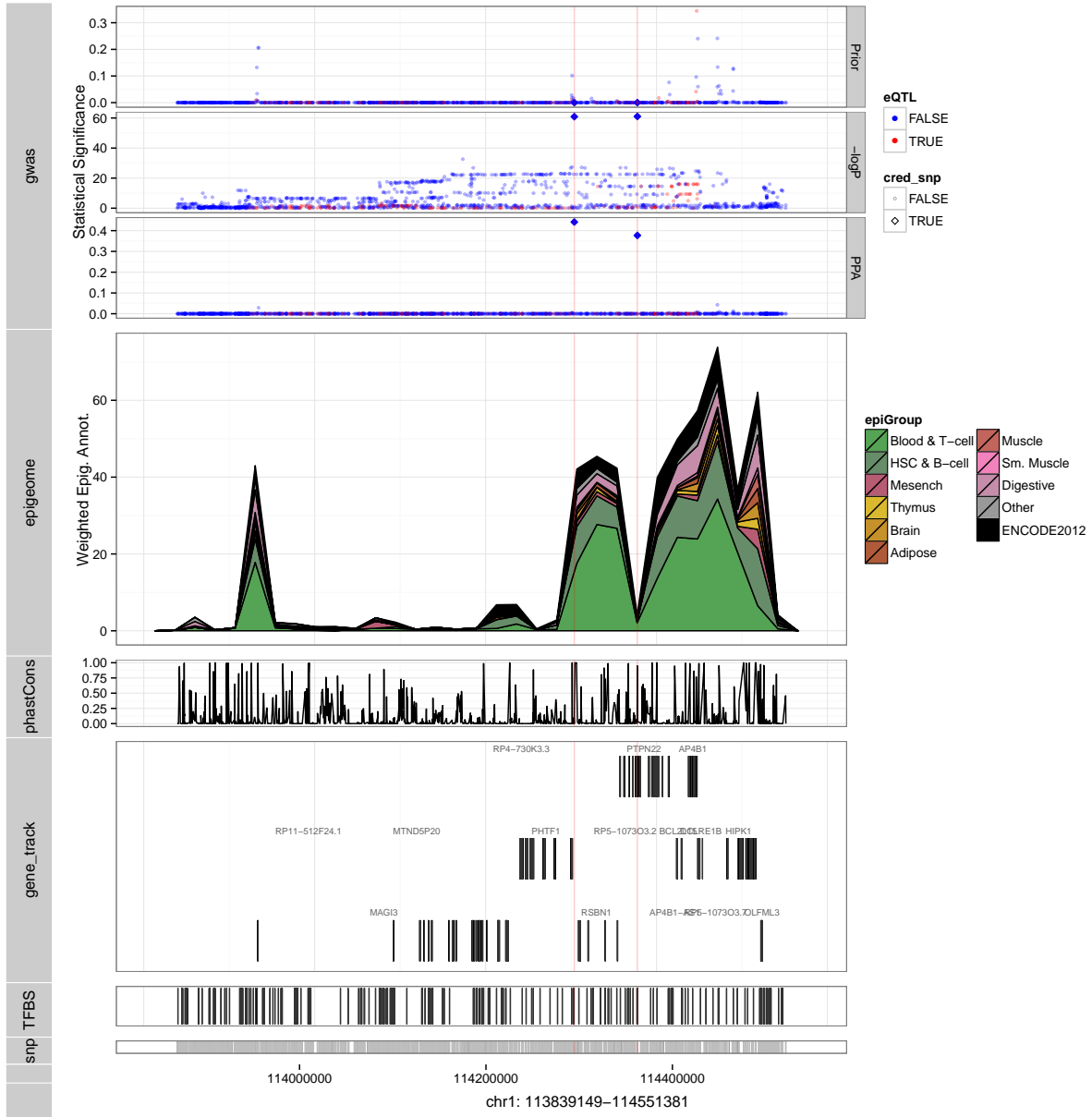
Psoriasis



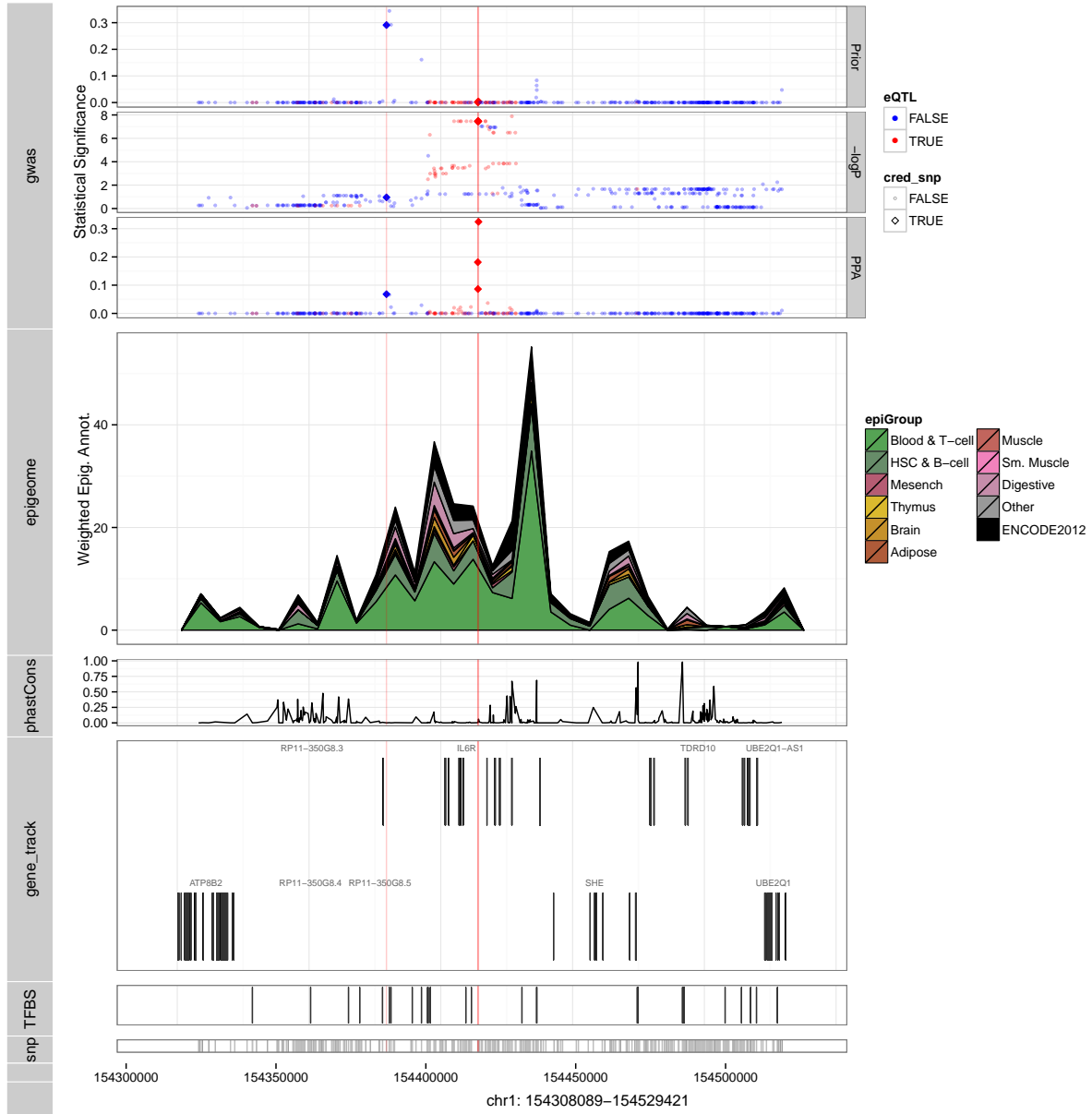
Psoriasis



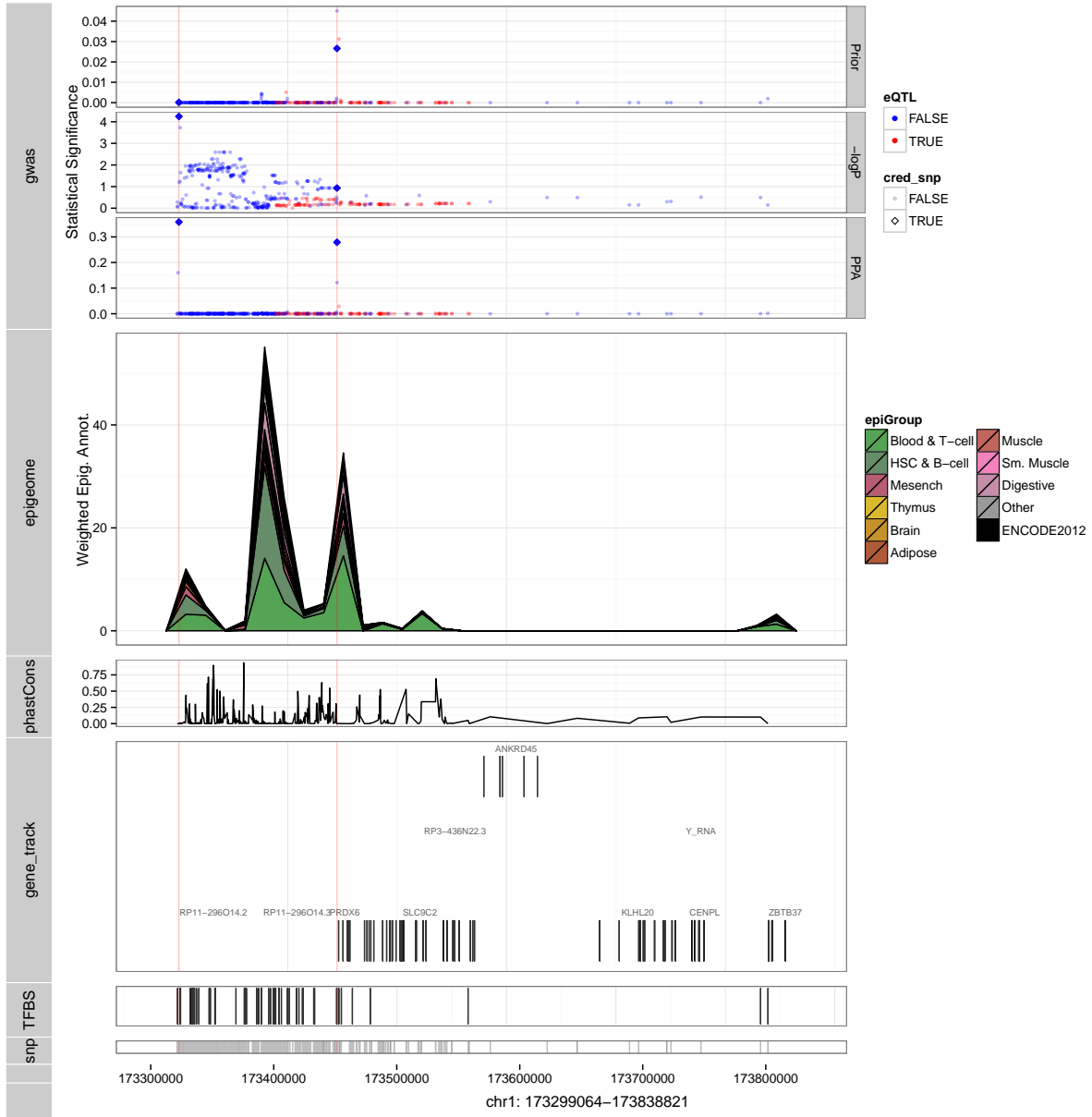
Rheumatoid Arthritis



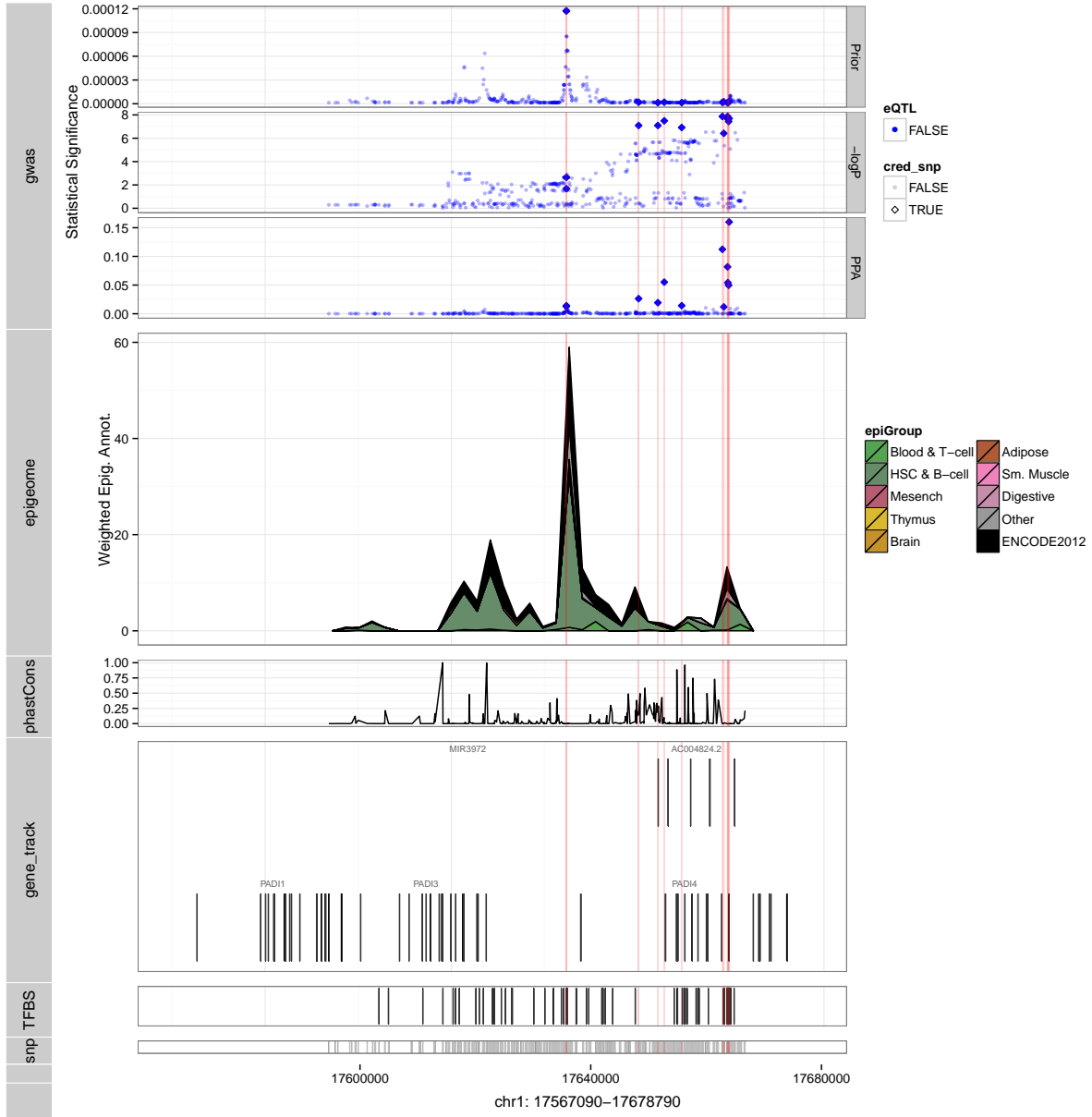
Rheumatoid Arthritis



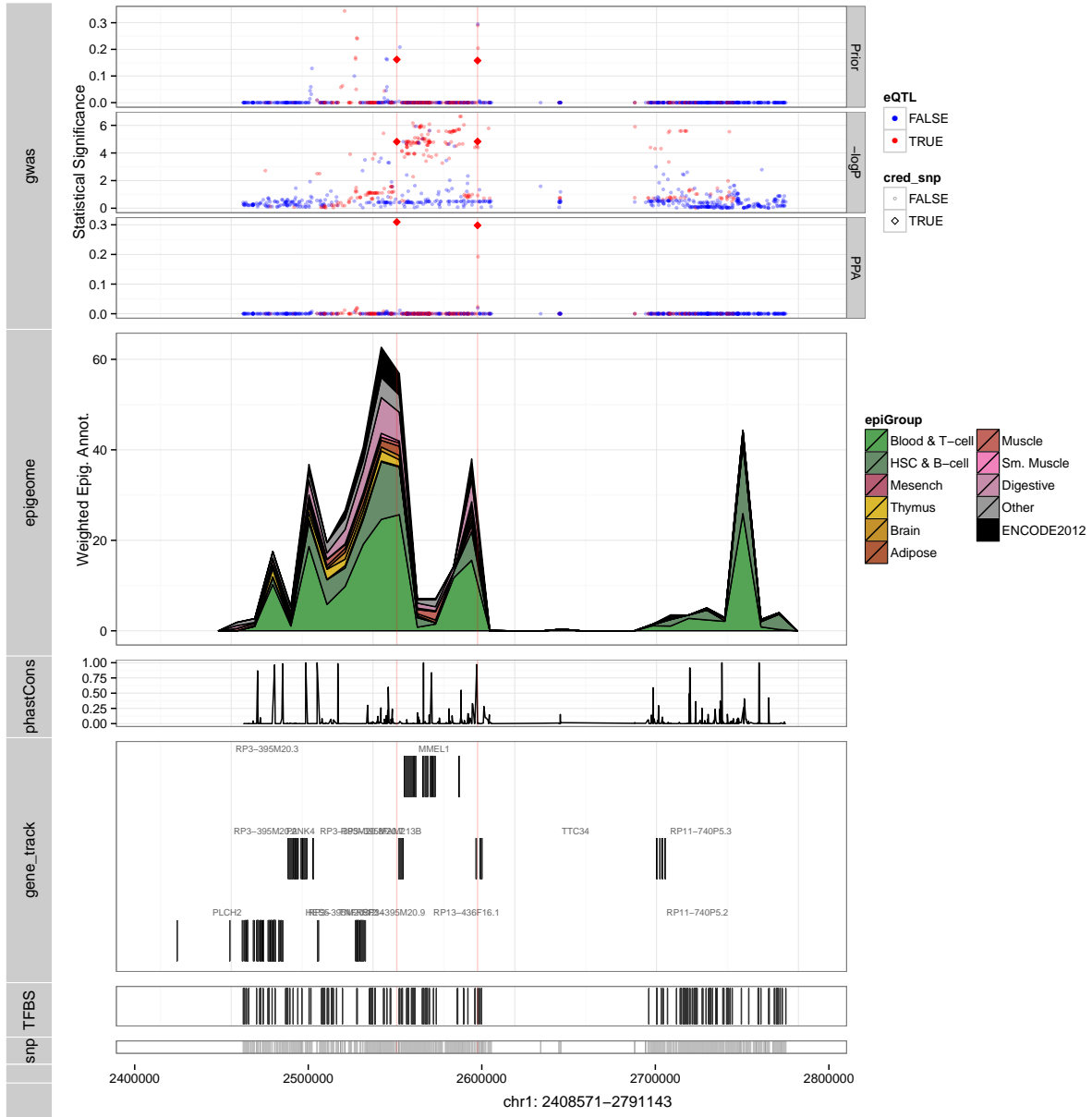
Rheumatoid Arthritis



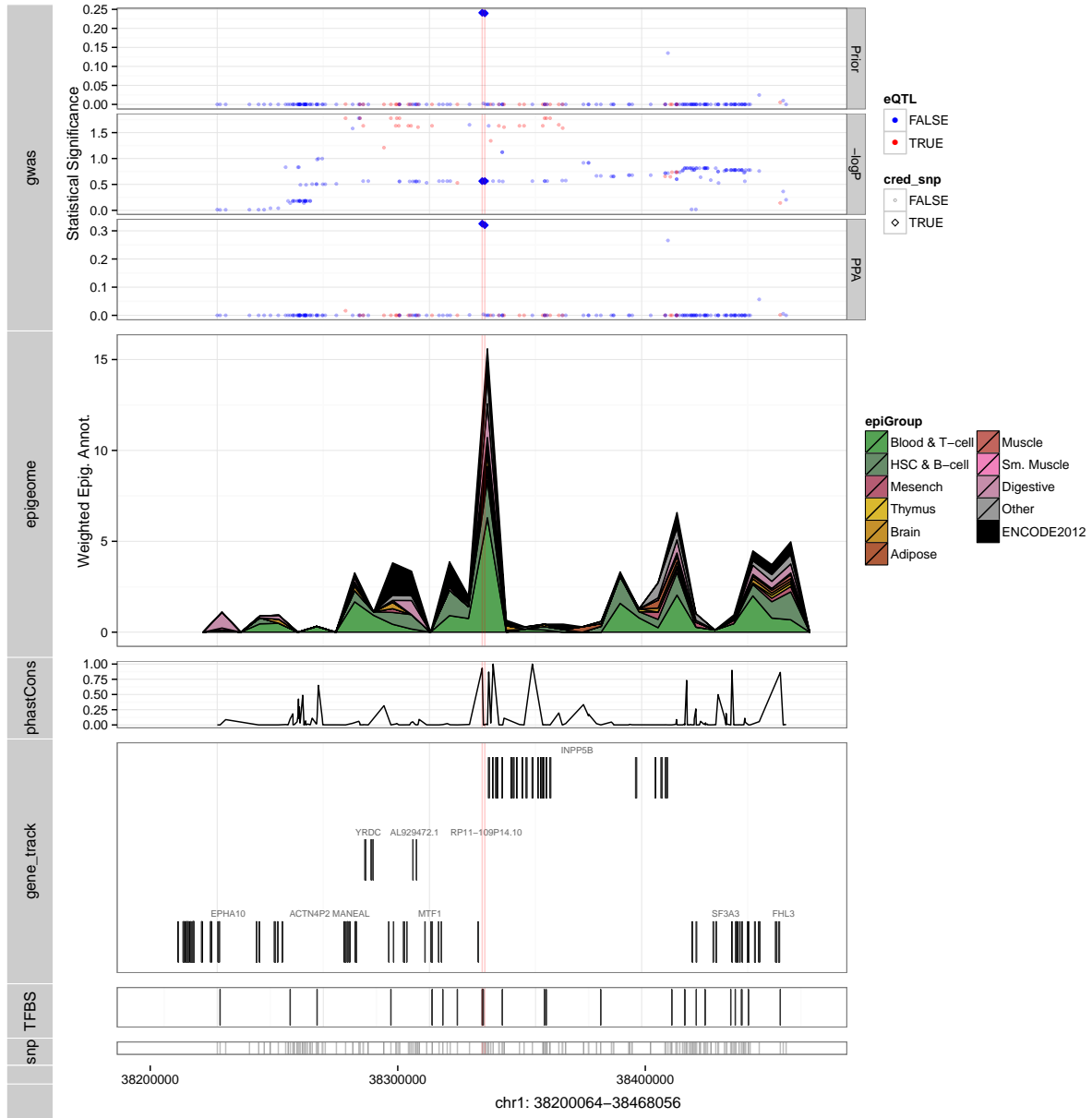
Rheumatoid Arthritis



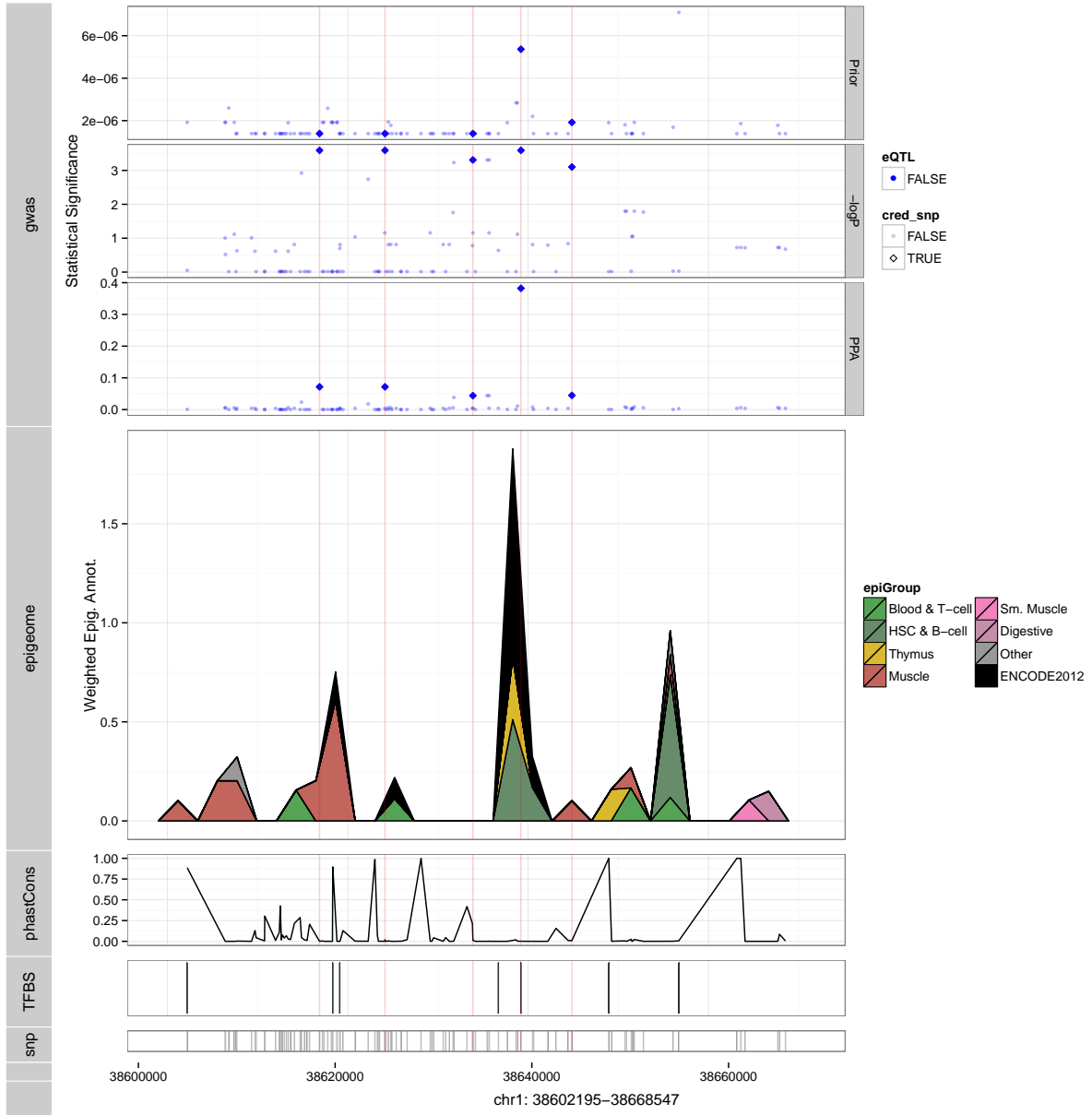
Rheumatoid Arthritis



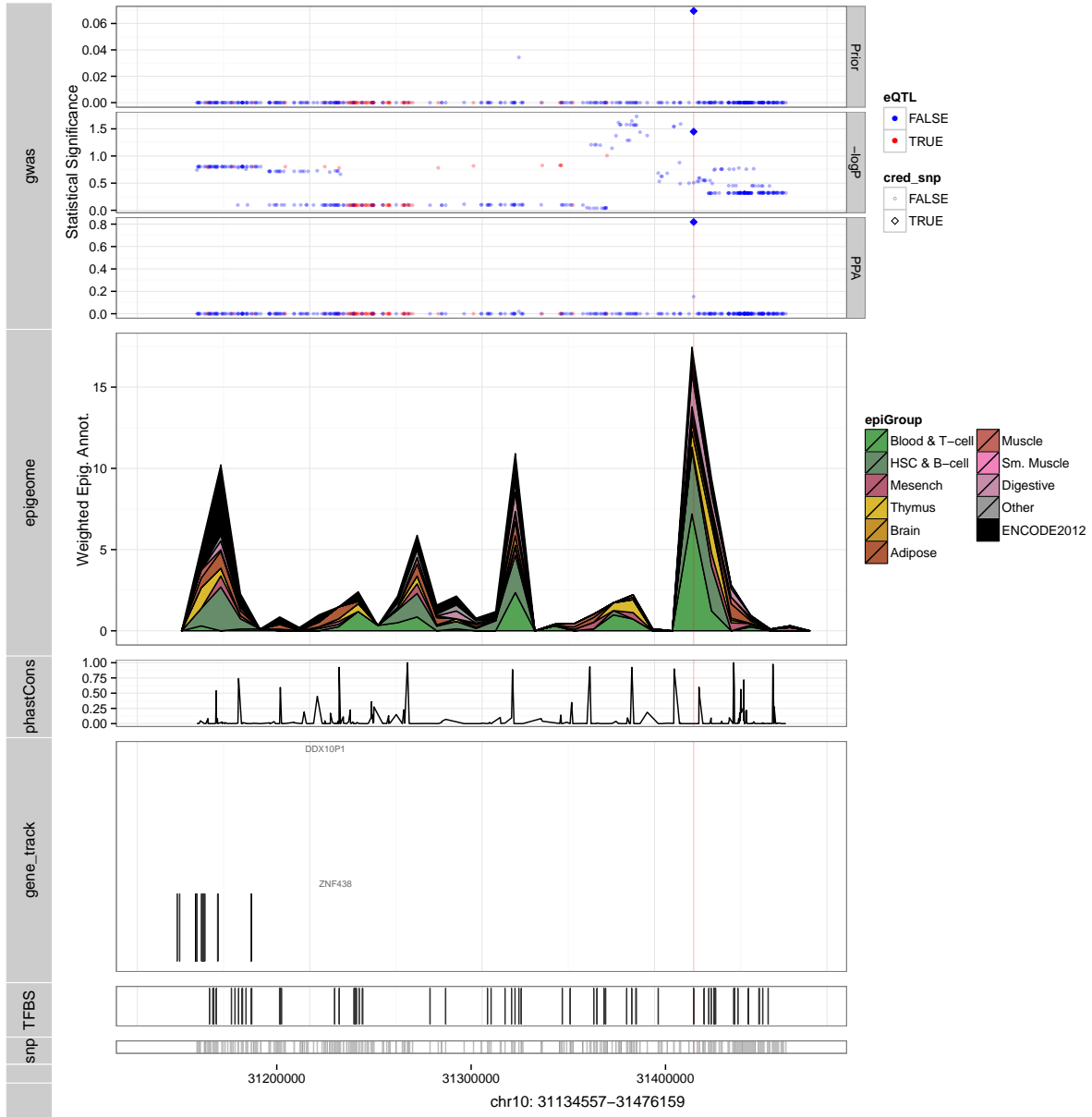
Rheumatoid Arthritis



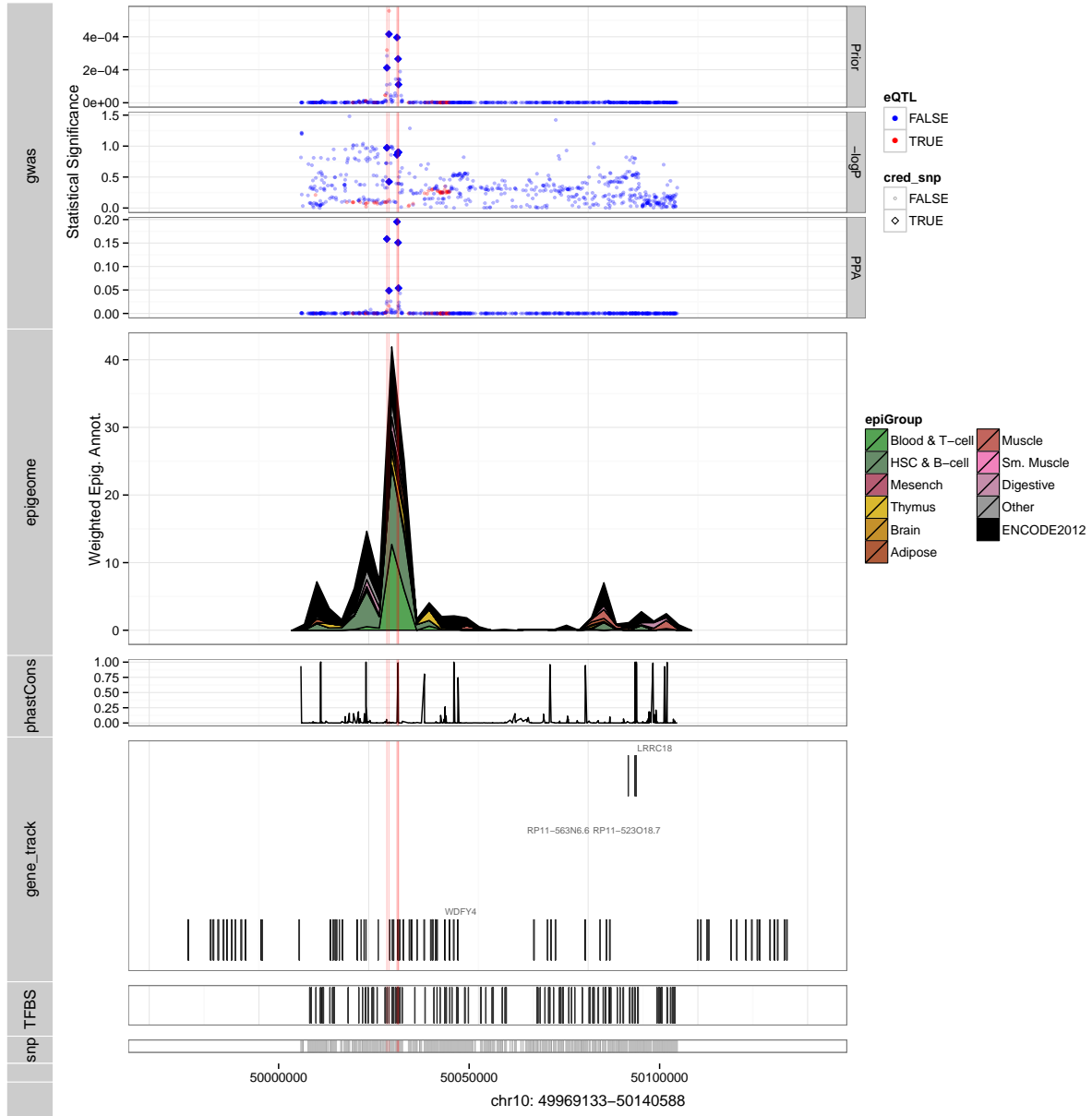
Rheumatoid Arthritis



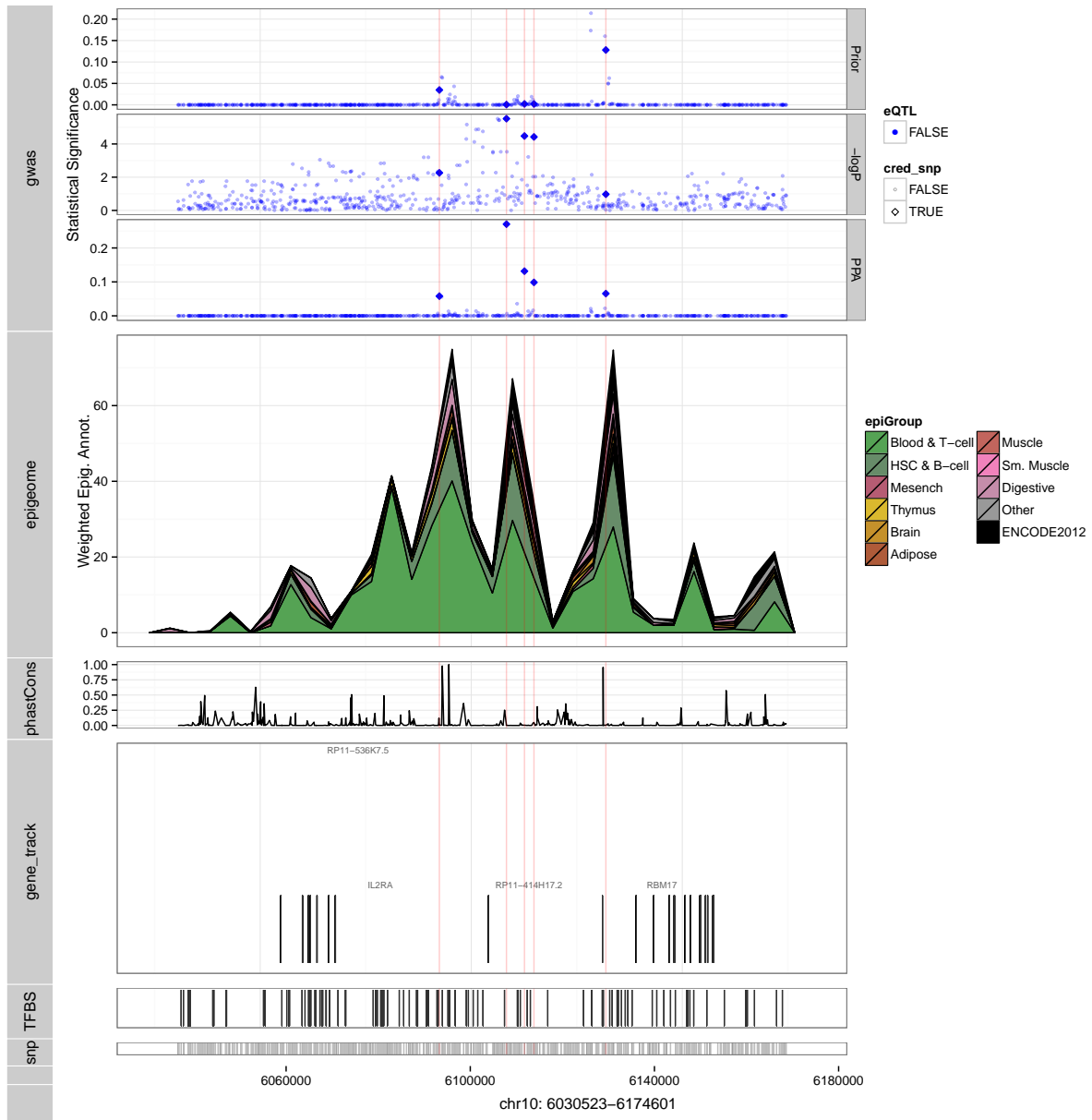
Rheumatoid Arthritis



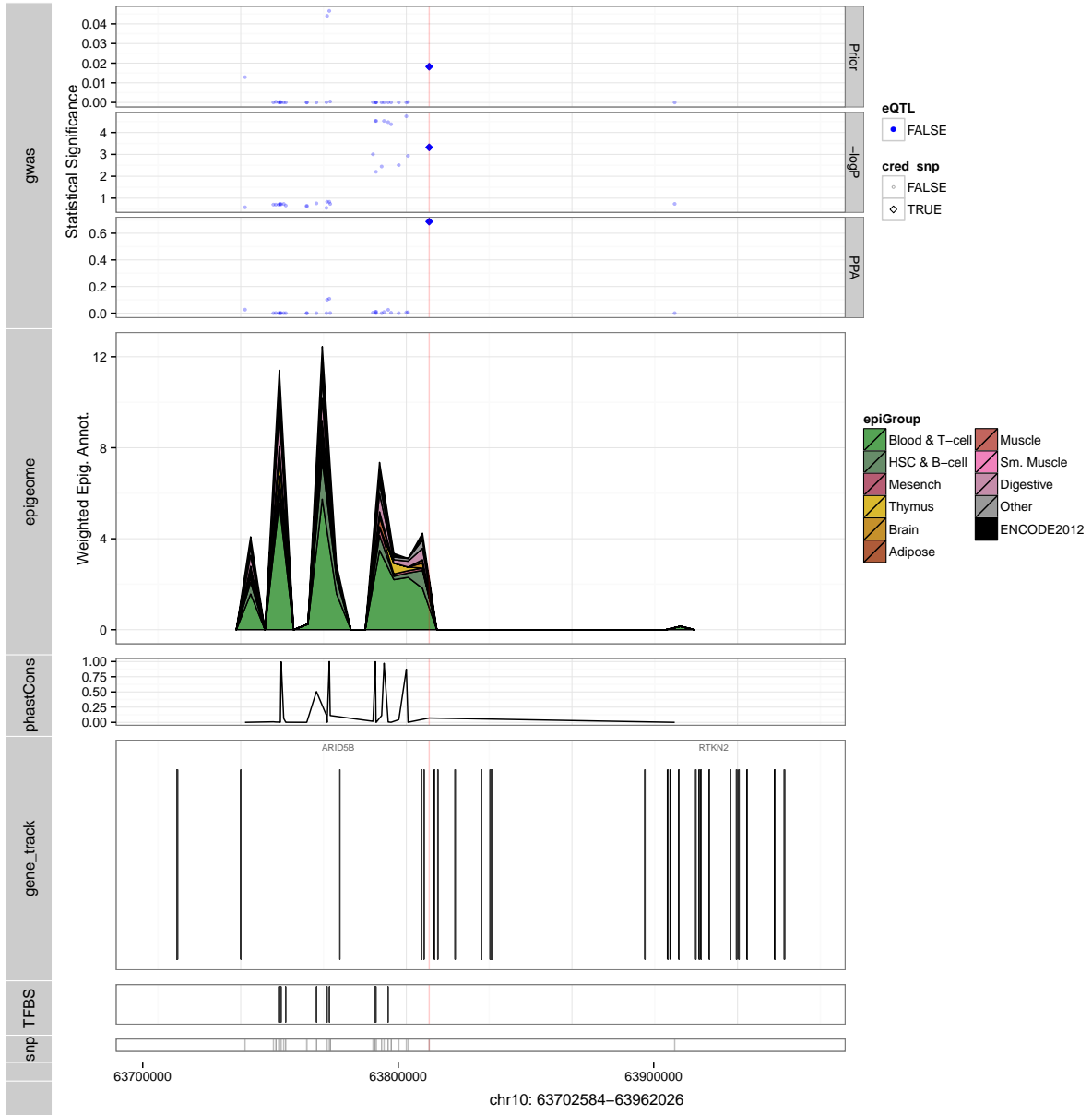
Rheumatoid Arthritis



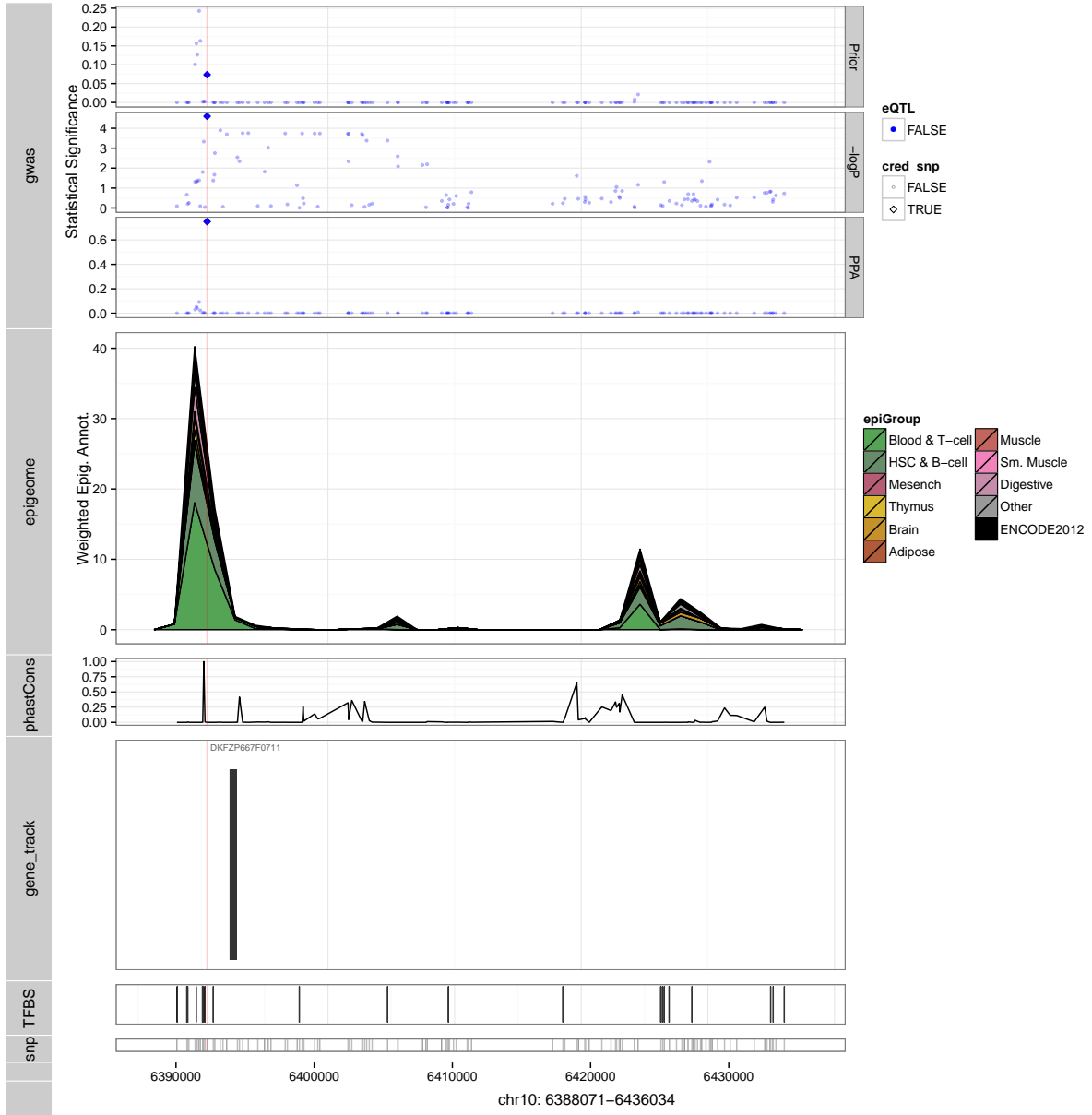
Rheumatoid Arthritis



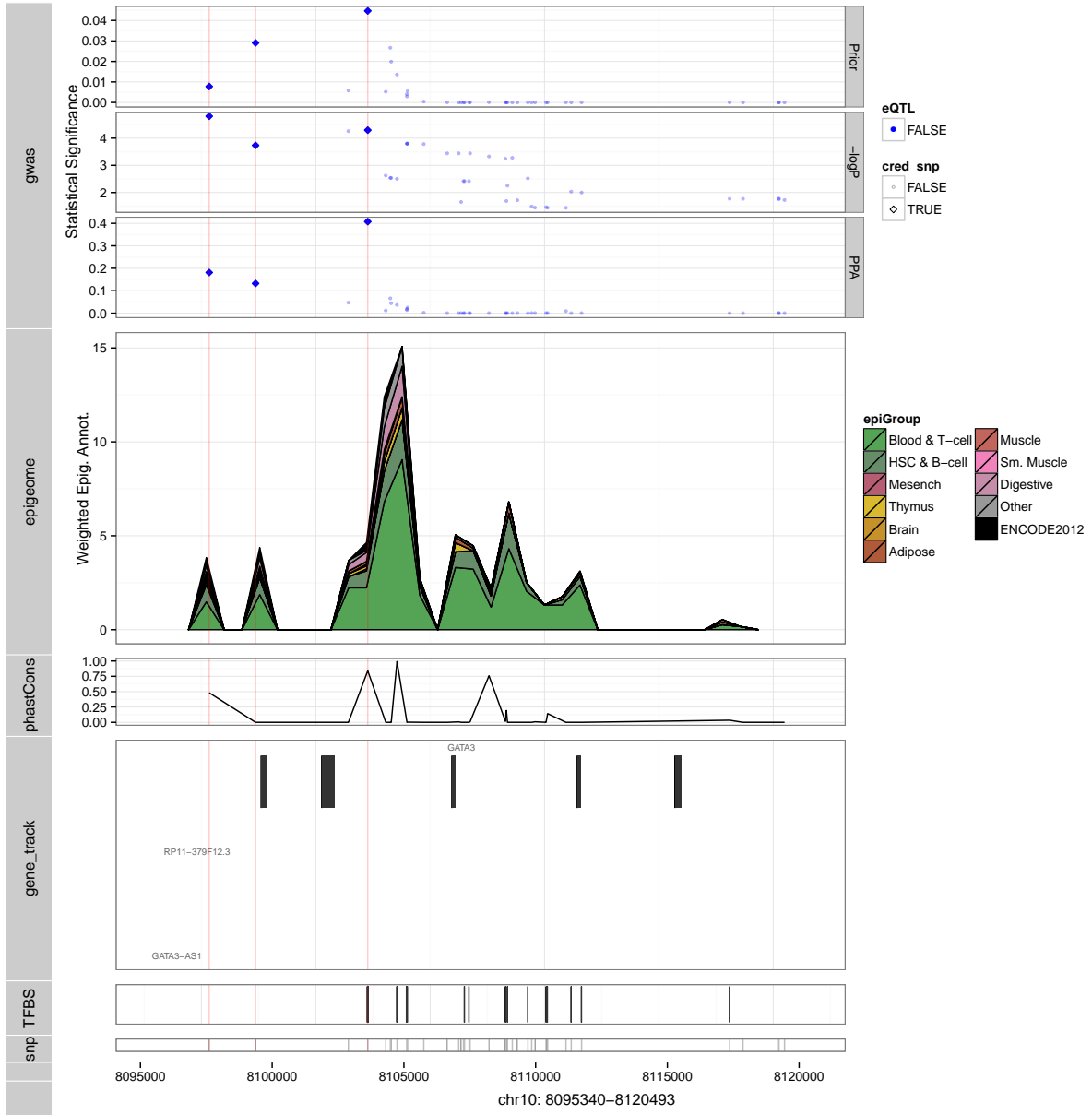
Rheumatoid Arthritis



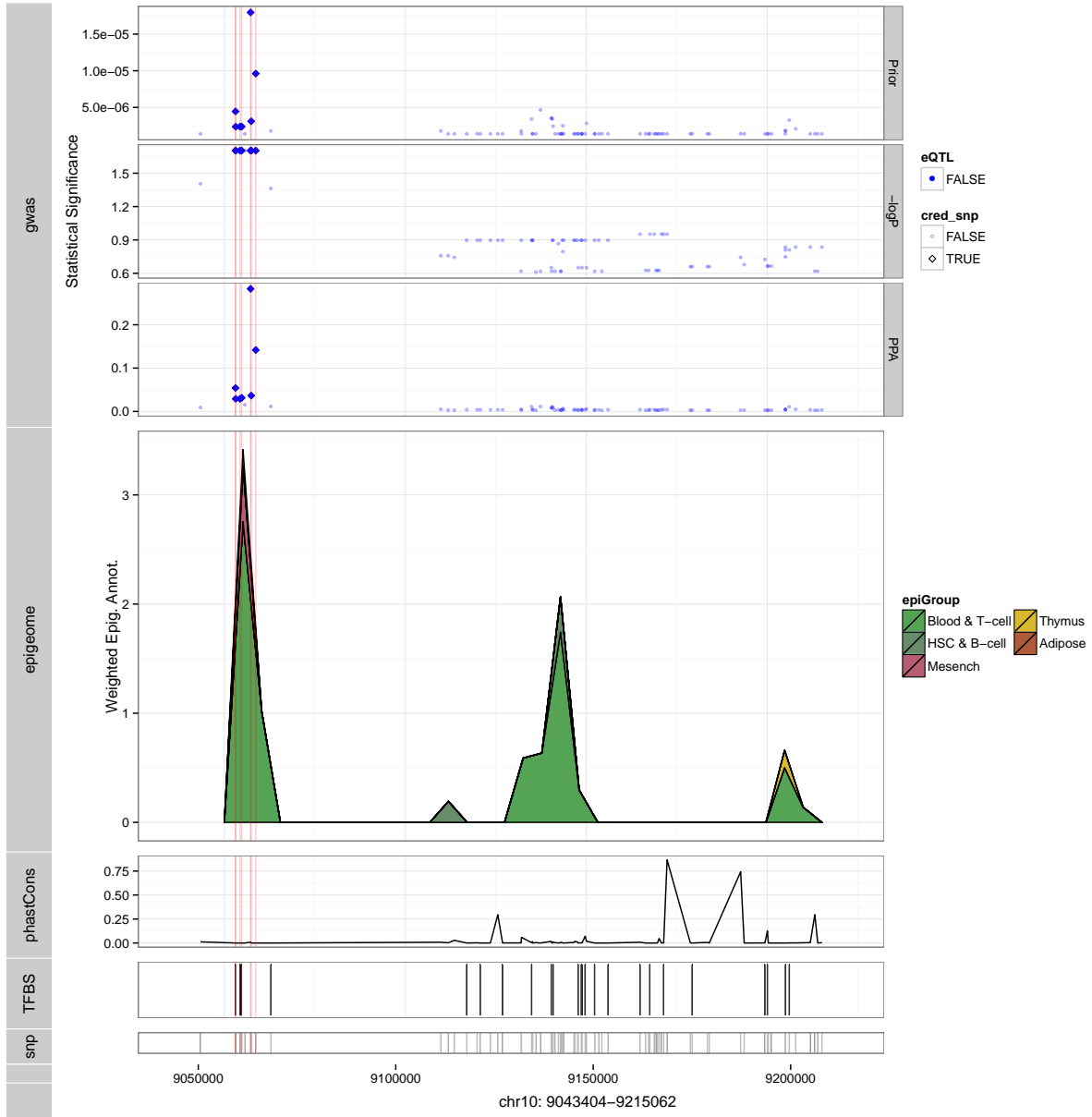
Rheumatoid Arthritis



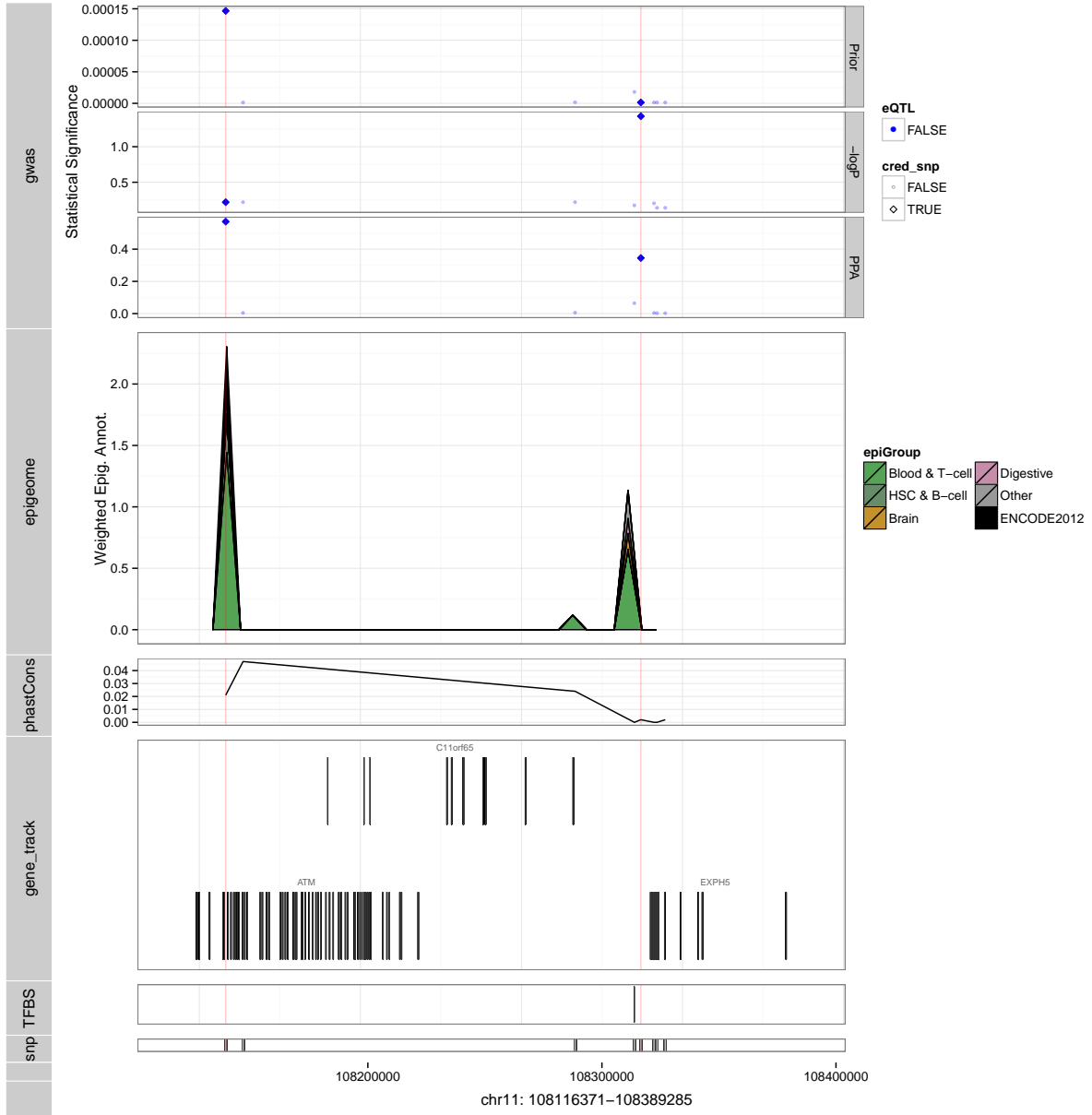
Rheumatoid Arthritis



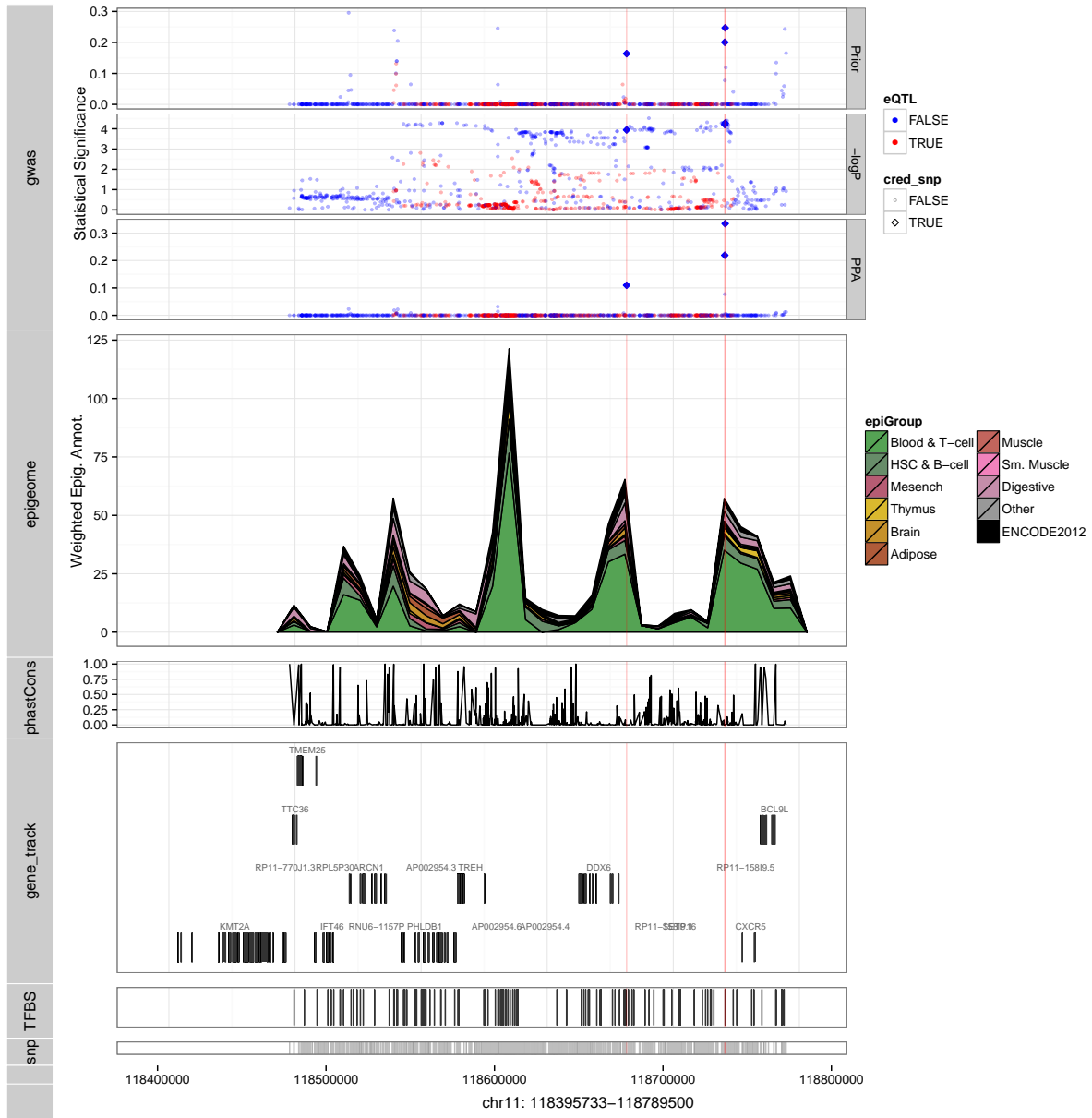
Rheumatoid Arthritis



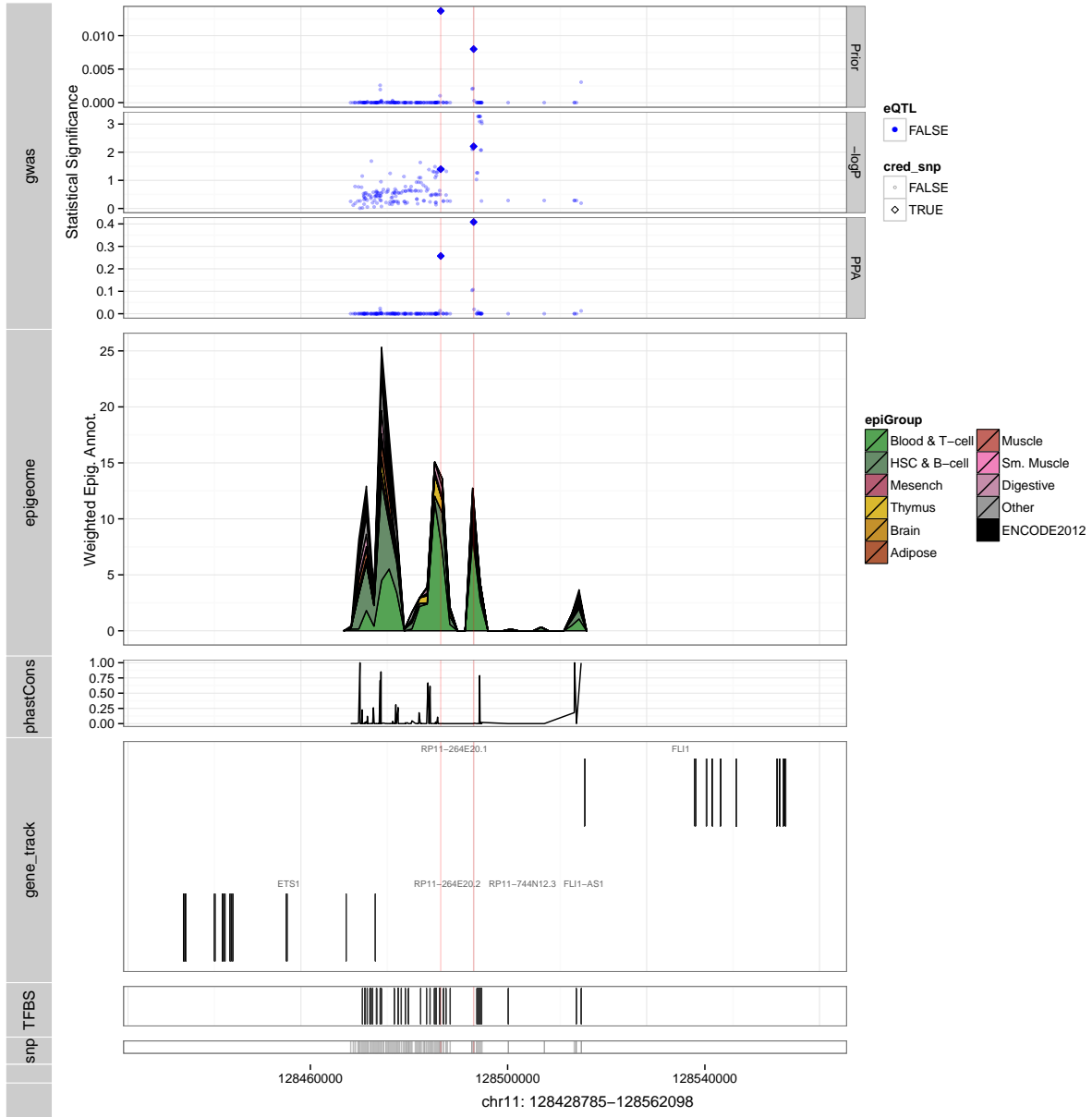
Rheumatoid Arthritis



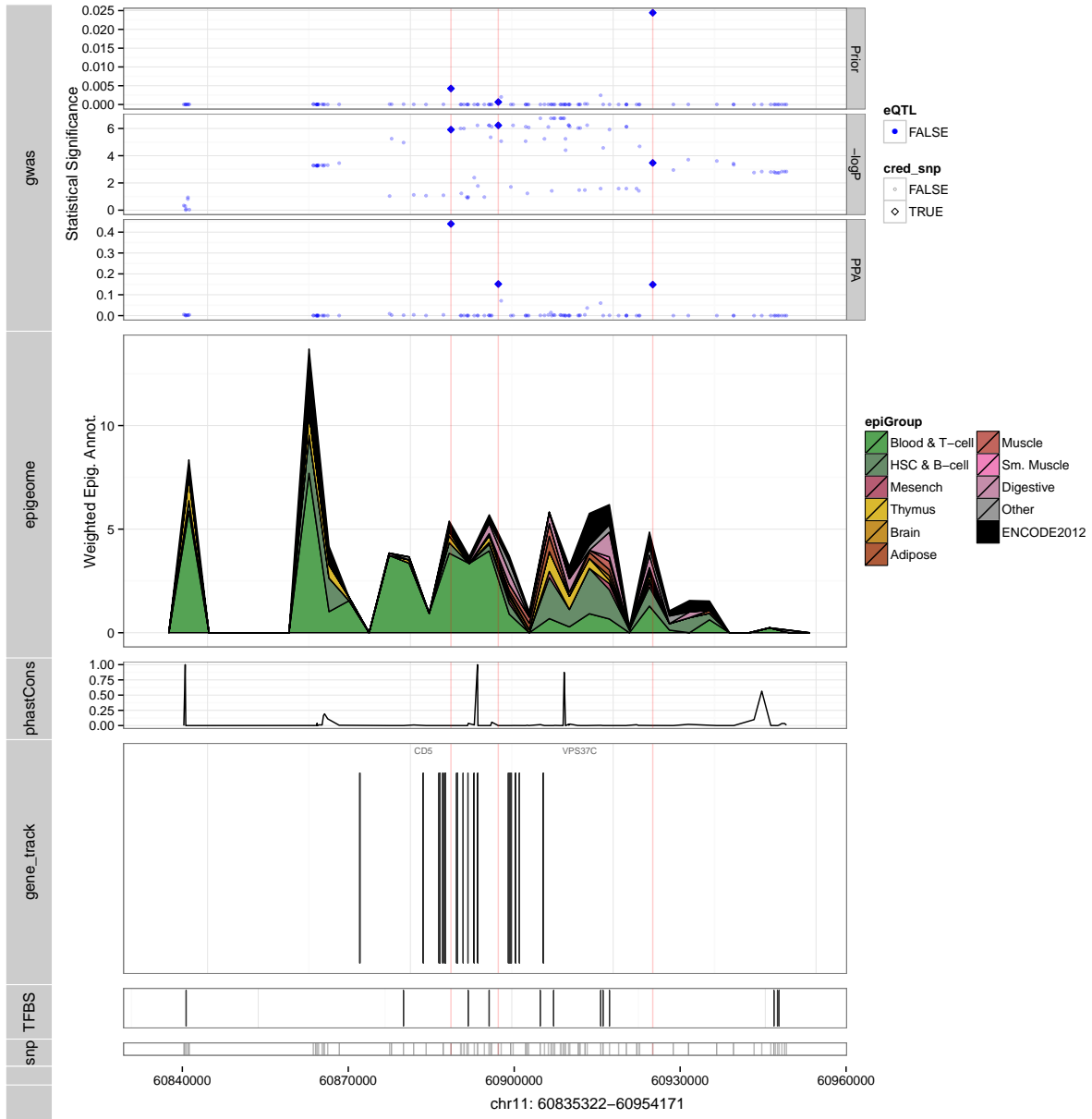
Rheumatoid Arthritis



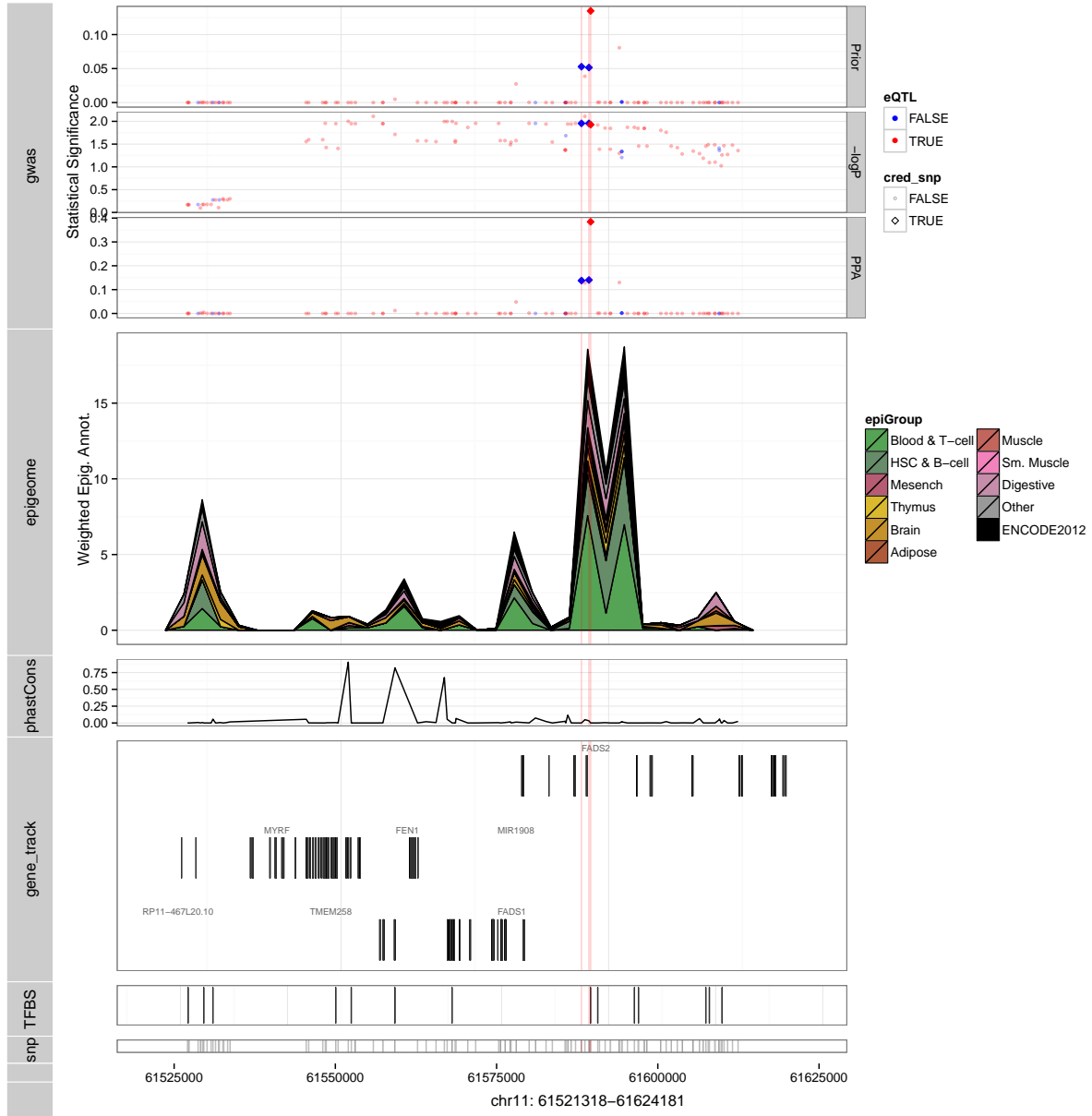
Rheumatoid Arthritis



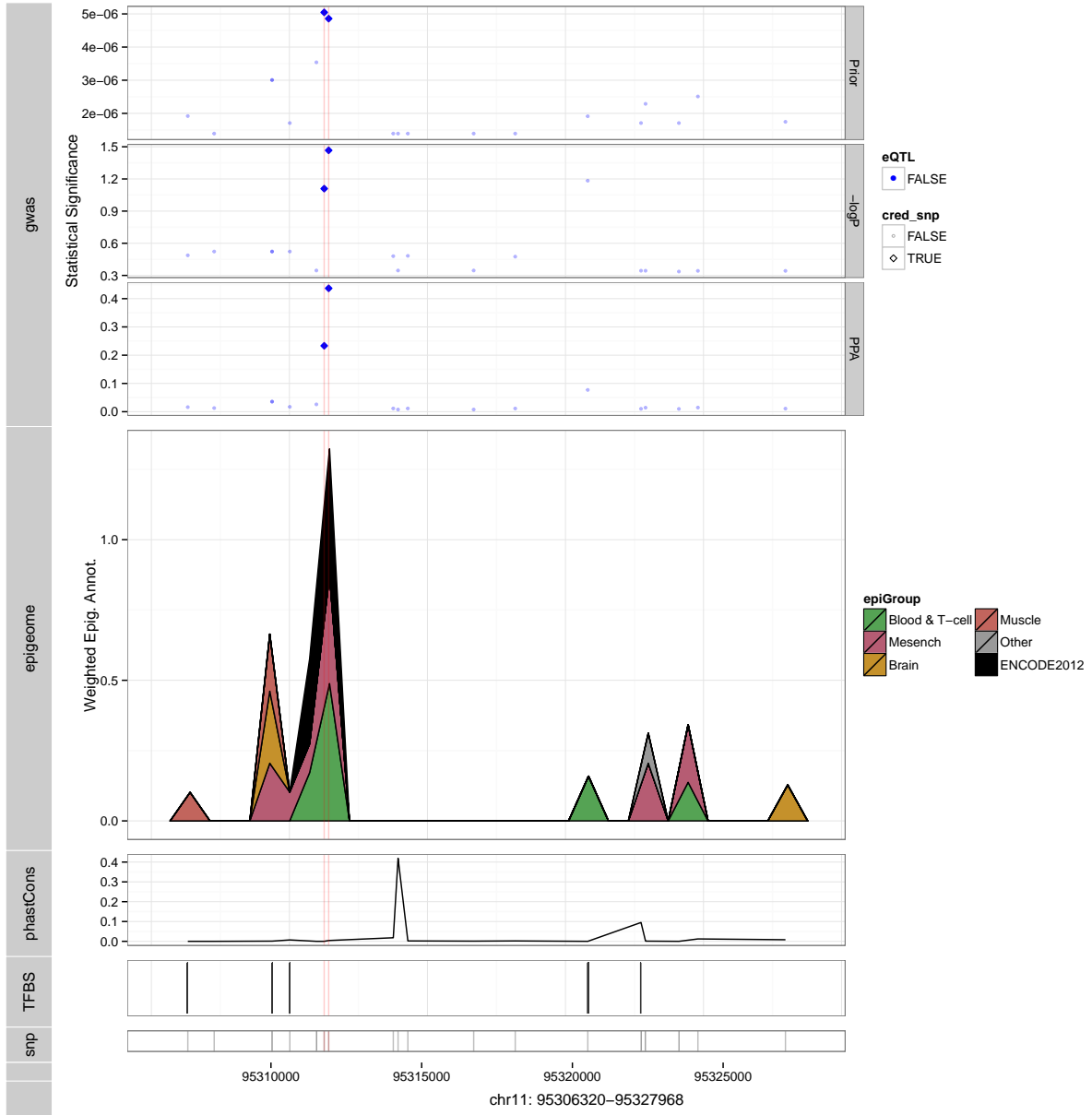
Rheumatoid Arthritis



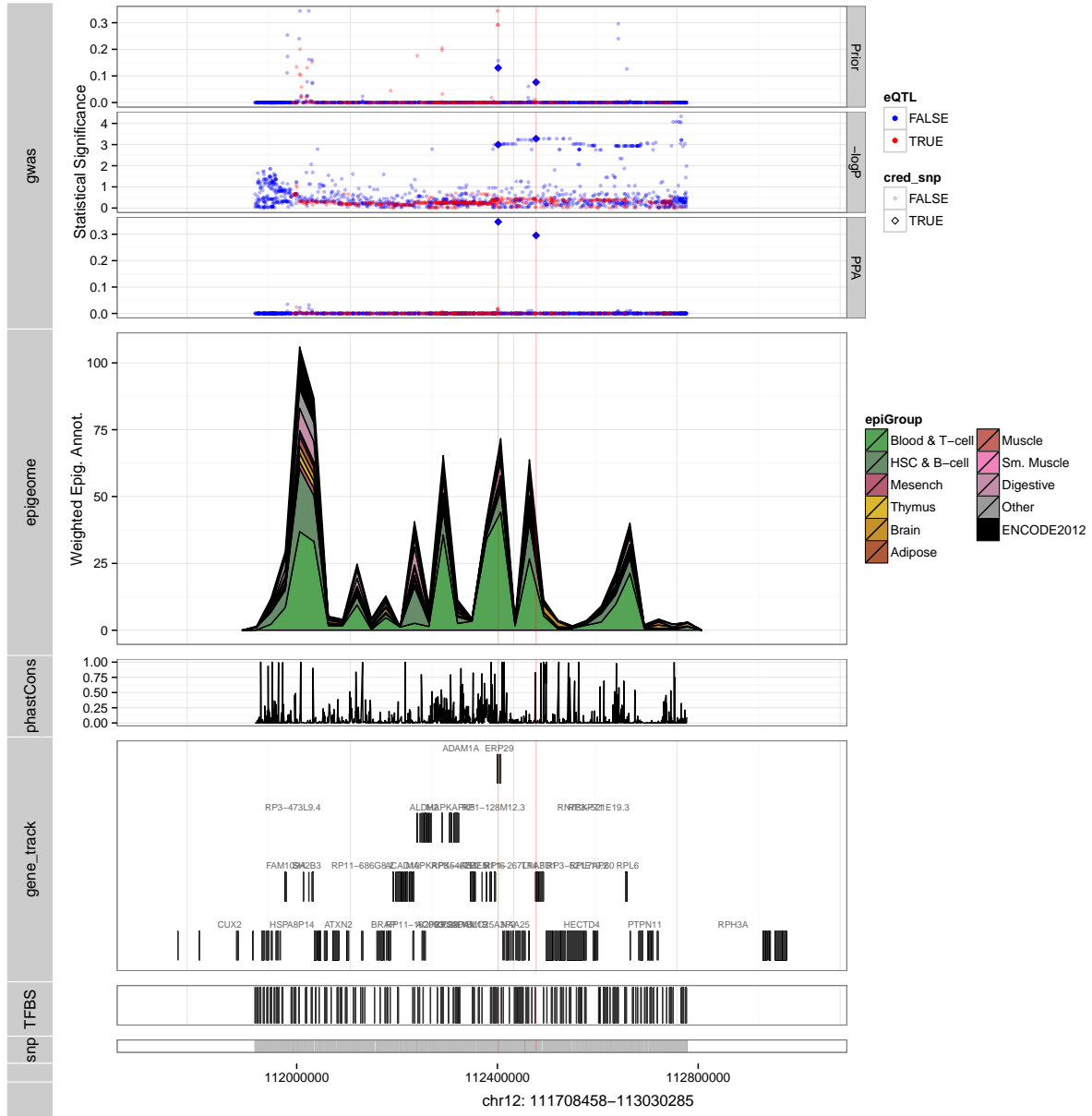
Rheumatoid Arthritis



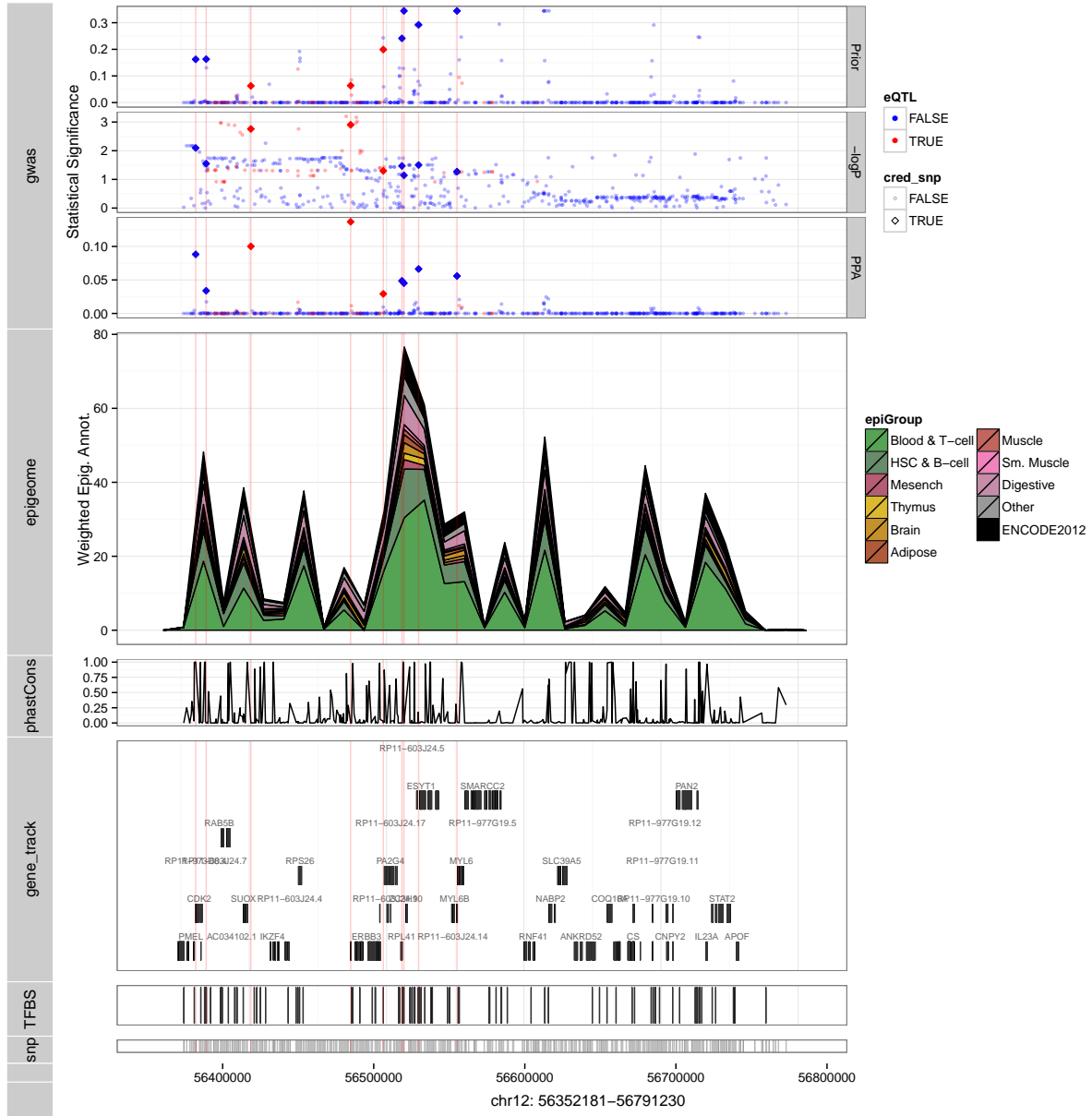
Rheumatoid Arthritis



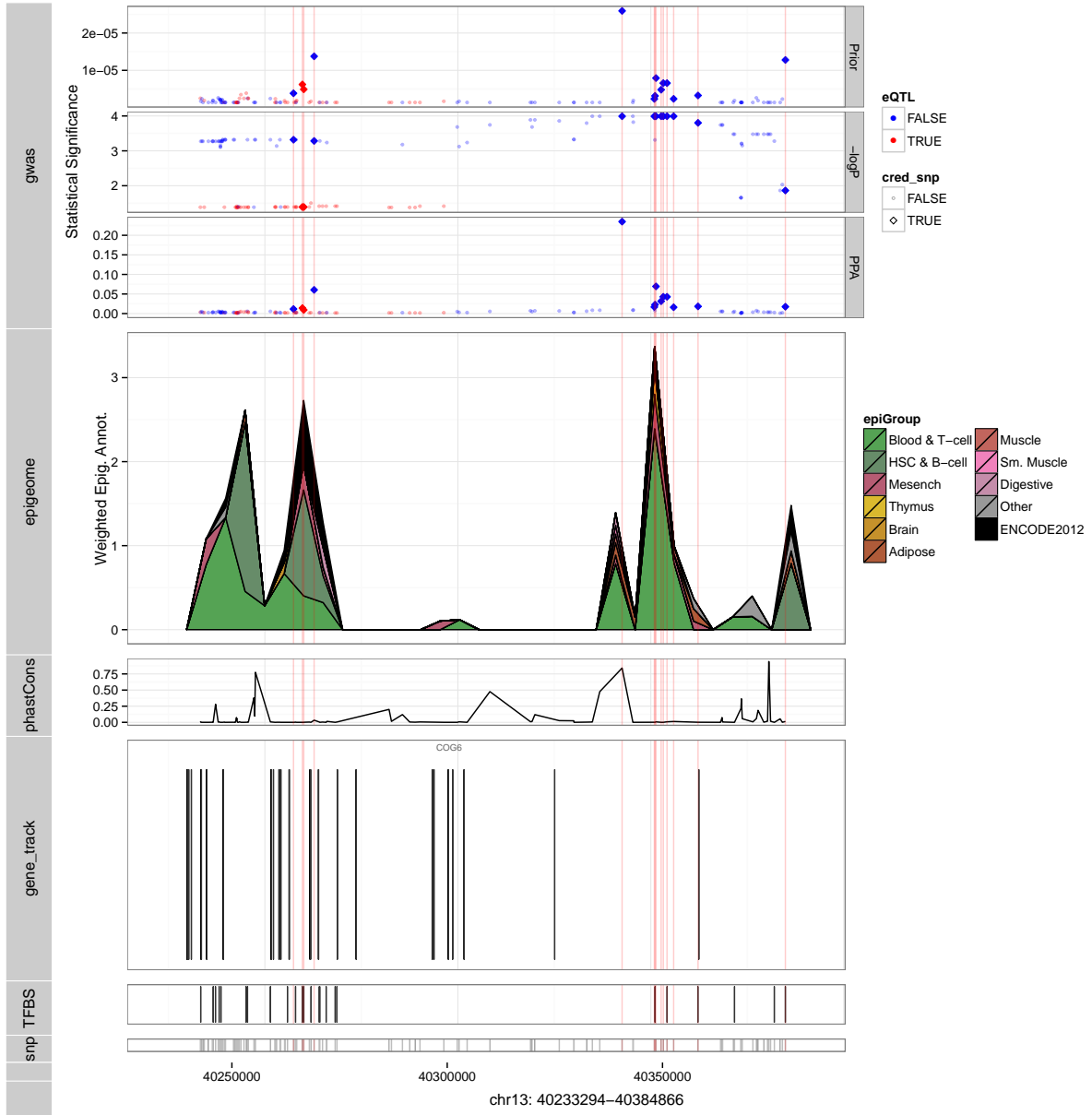
Rheumatoid Arthritis



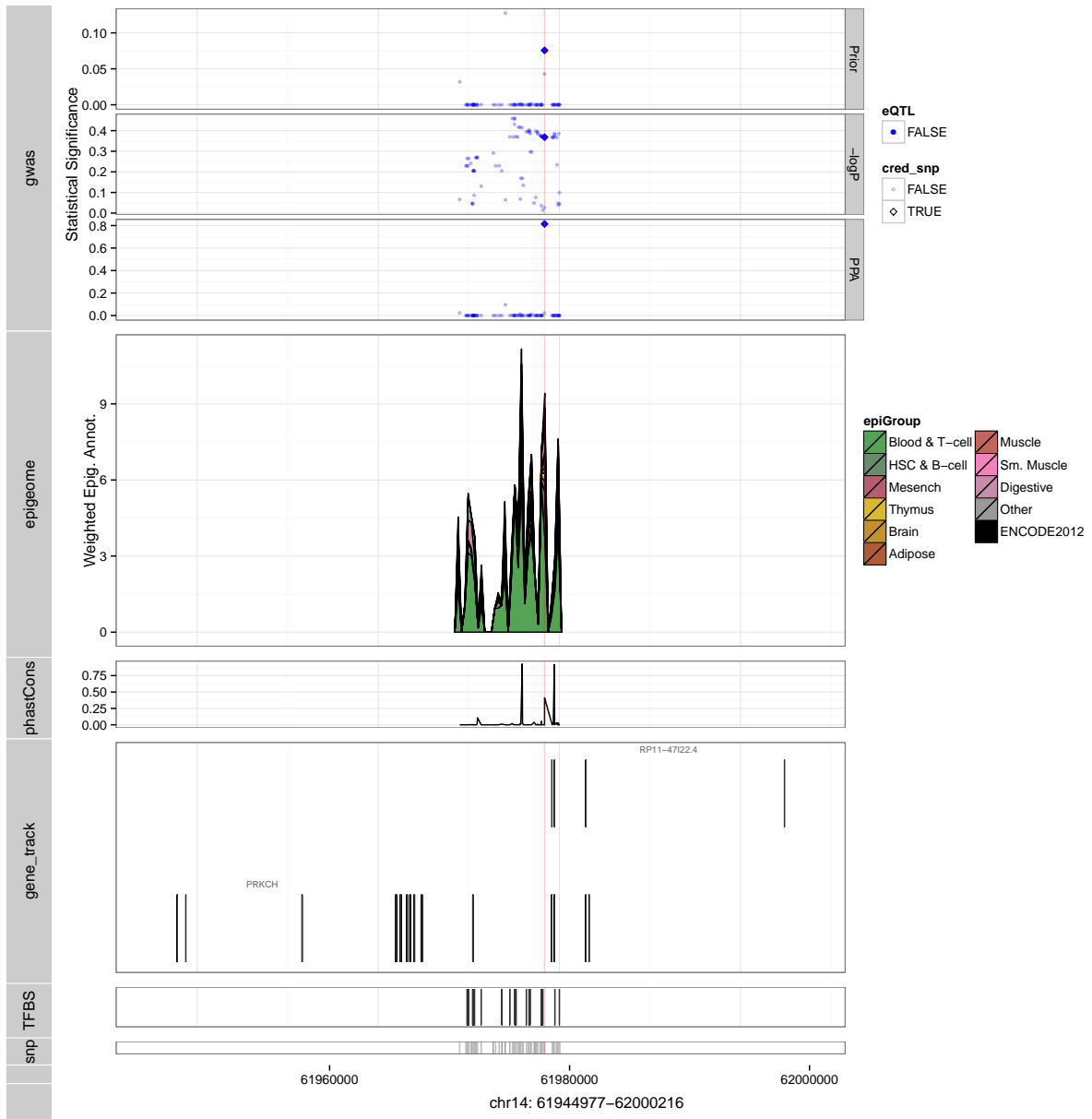
Rheumatoid Arthritis



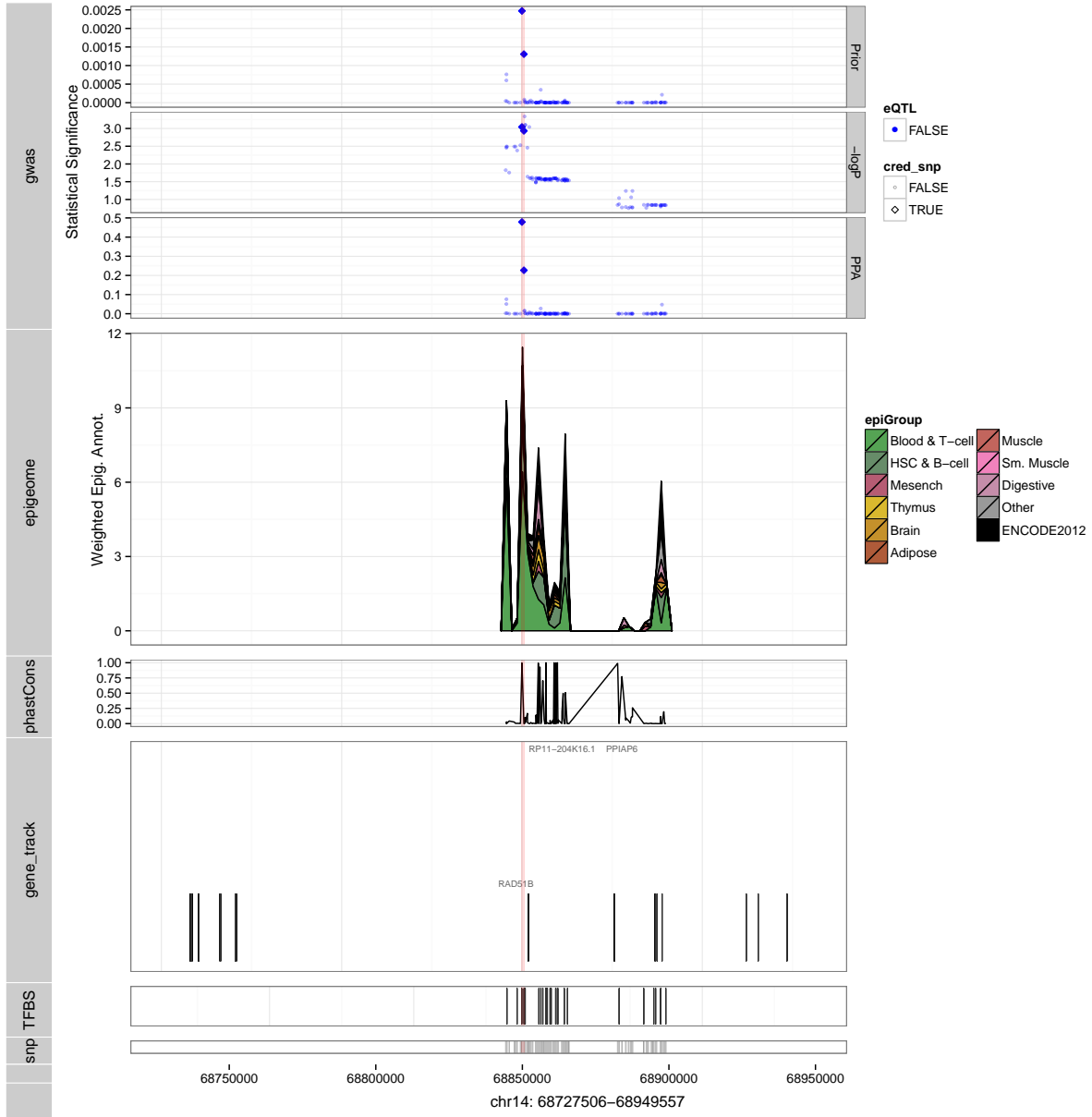
Rheumatoid Arthritis



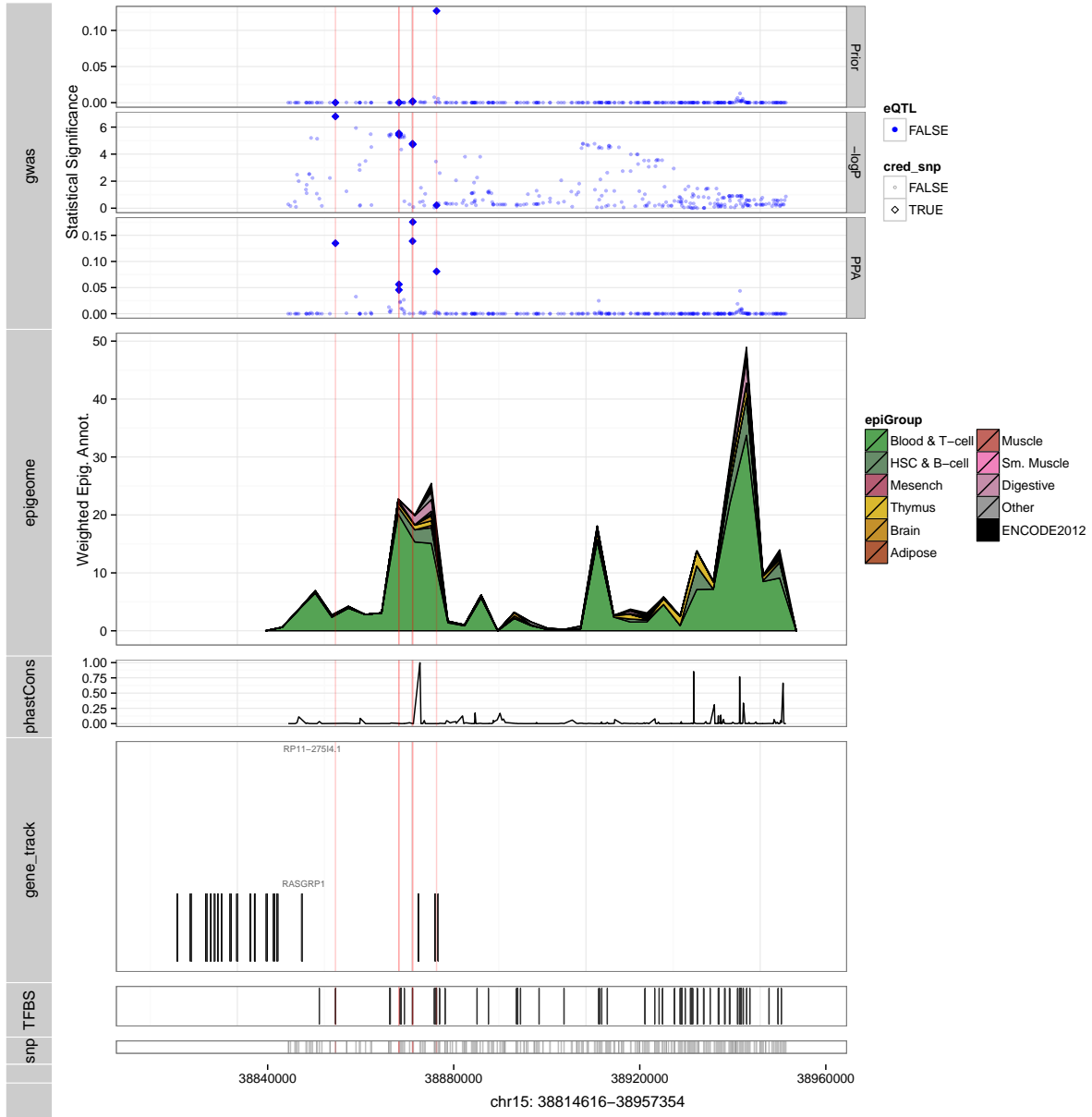
Rheumatoid Arthritis



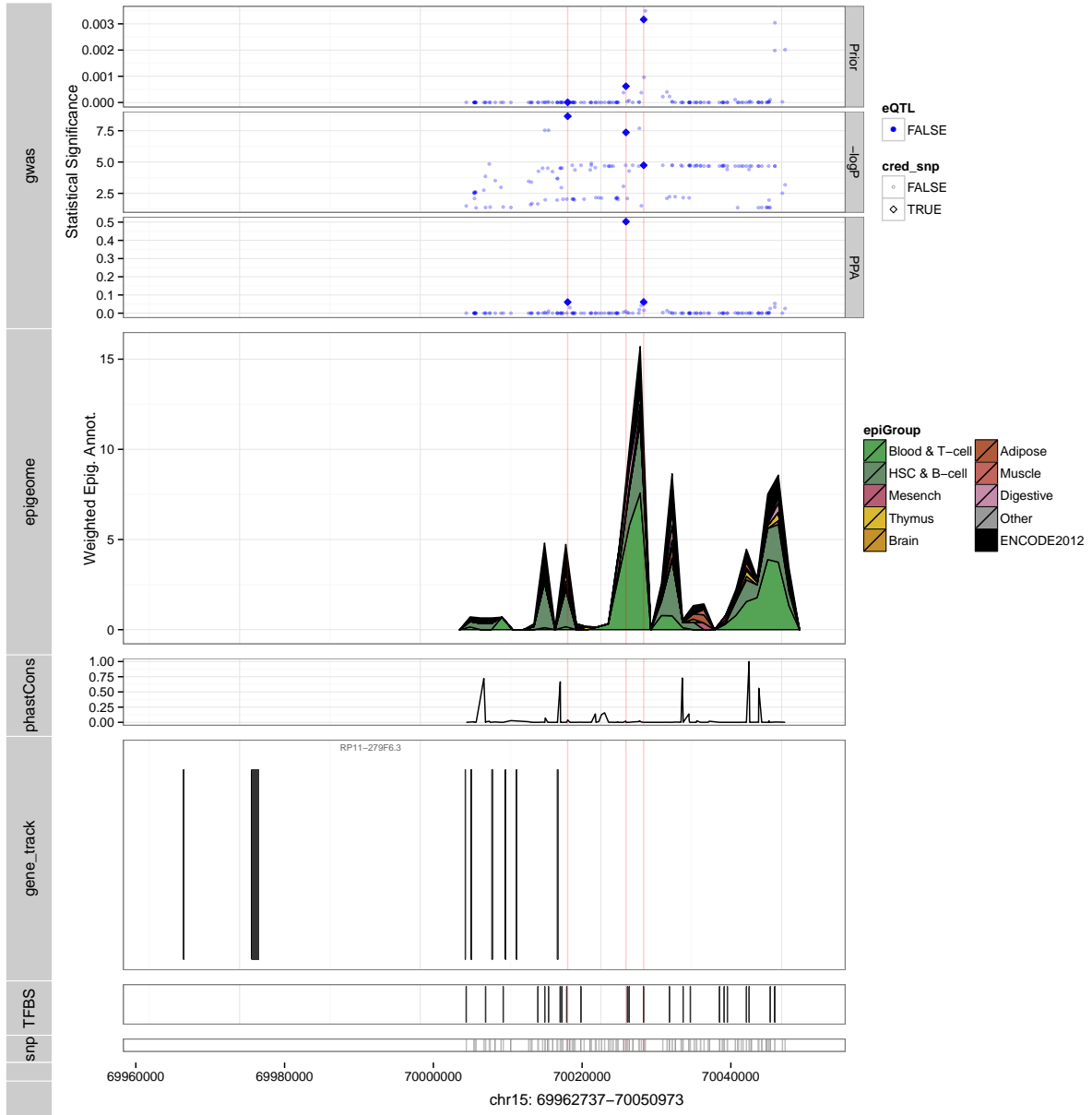
Rheumatoid Arthritis



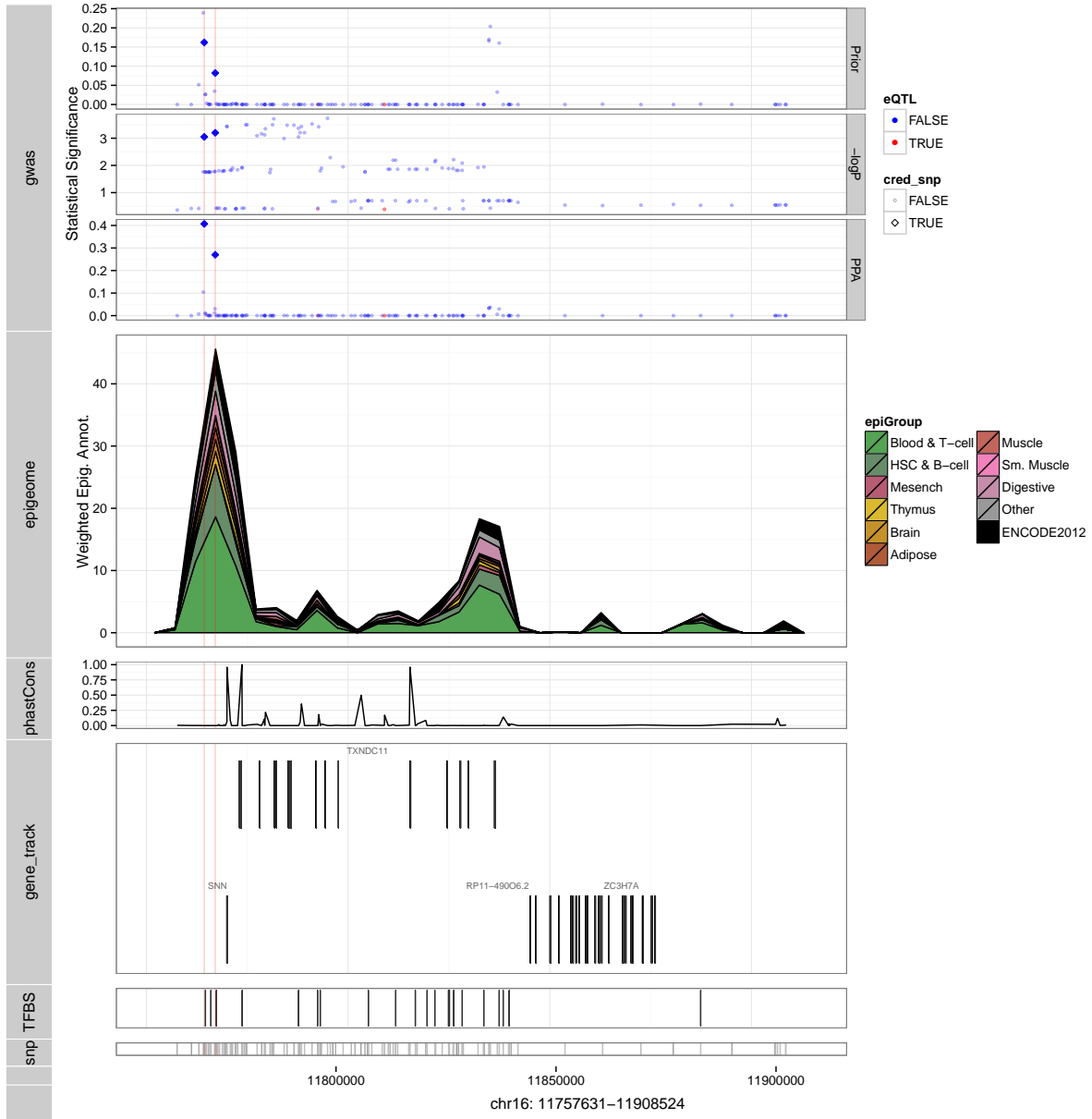
Rheumatoid Arthritis



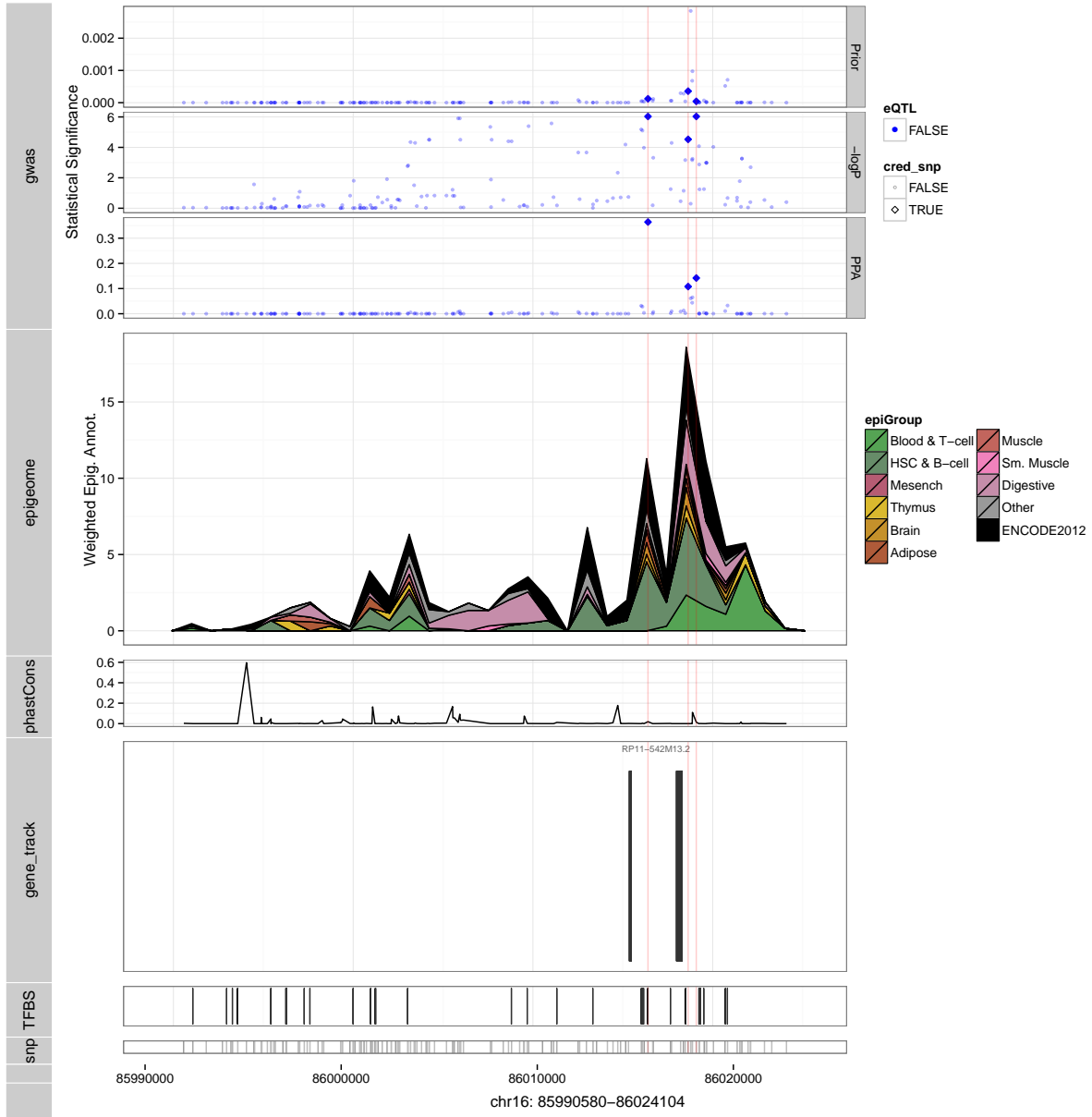
Rheumatoid Arthritis



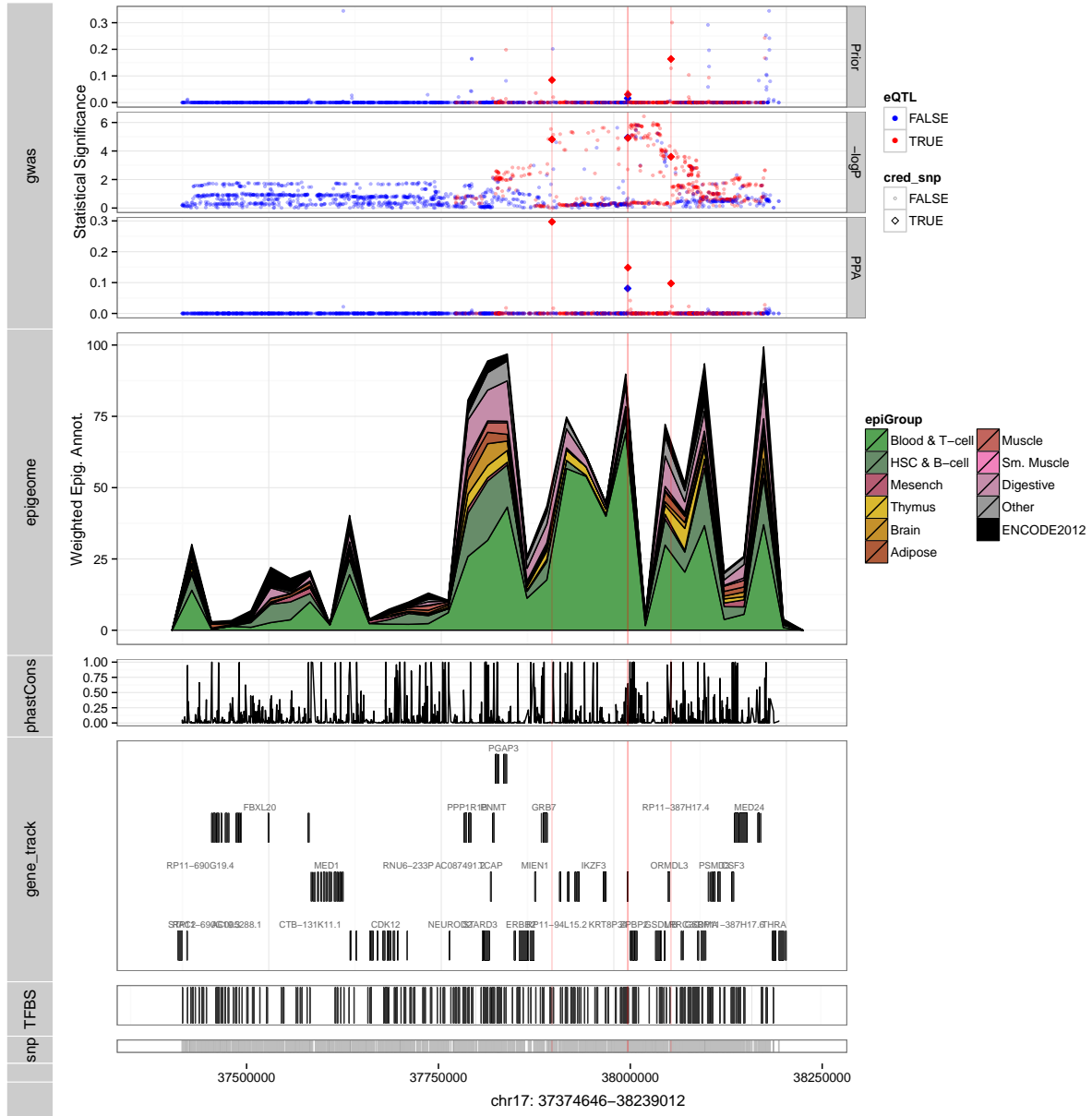
Rheumatoid Arthritis



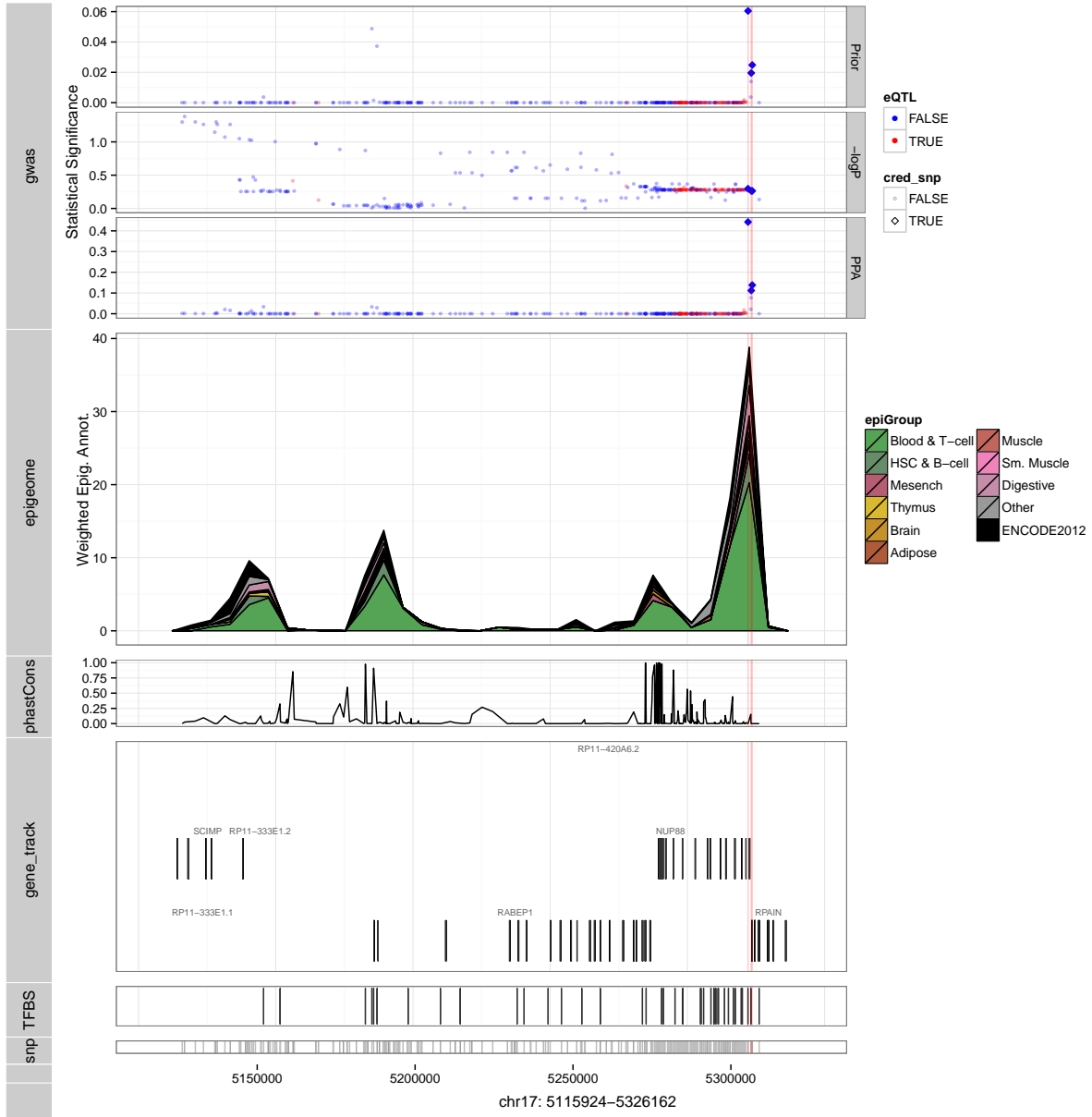
Rheumatoid Arthritis



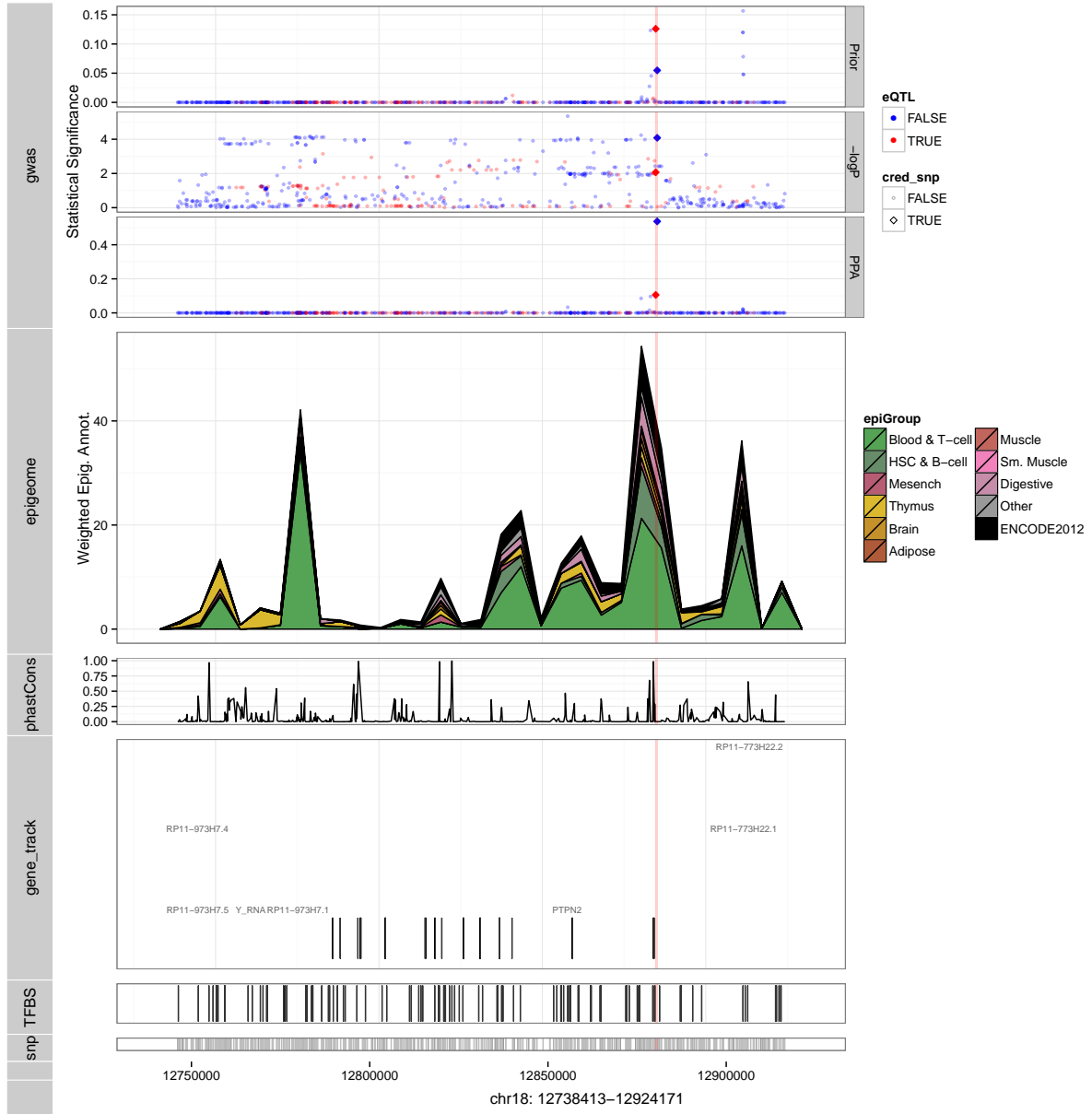
Rheumatoid Arthritis



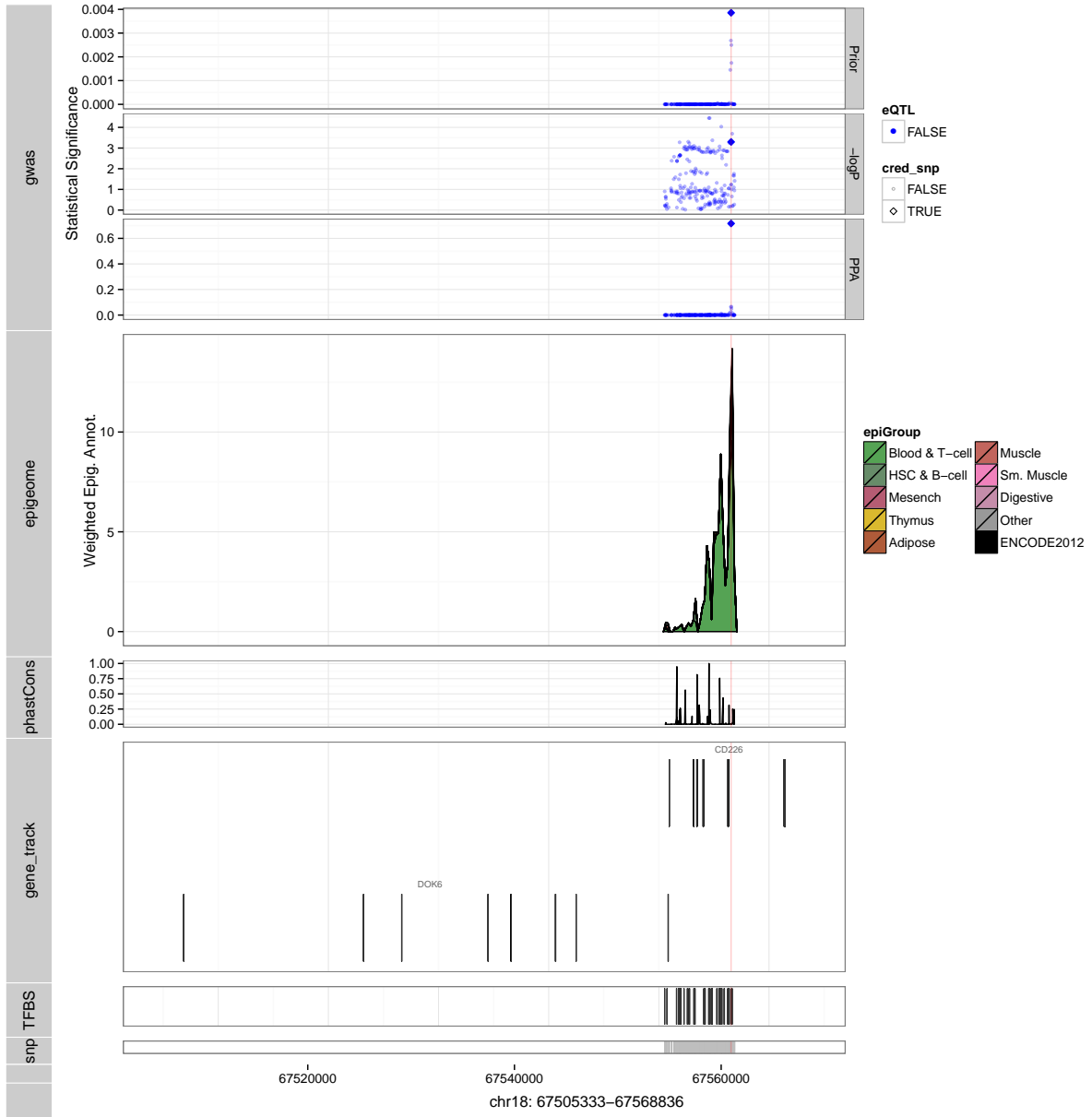
Rheumatoid Arthritis



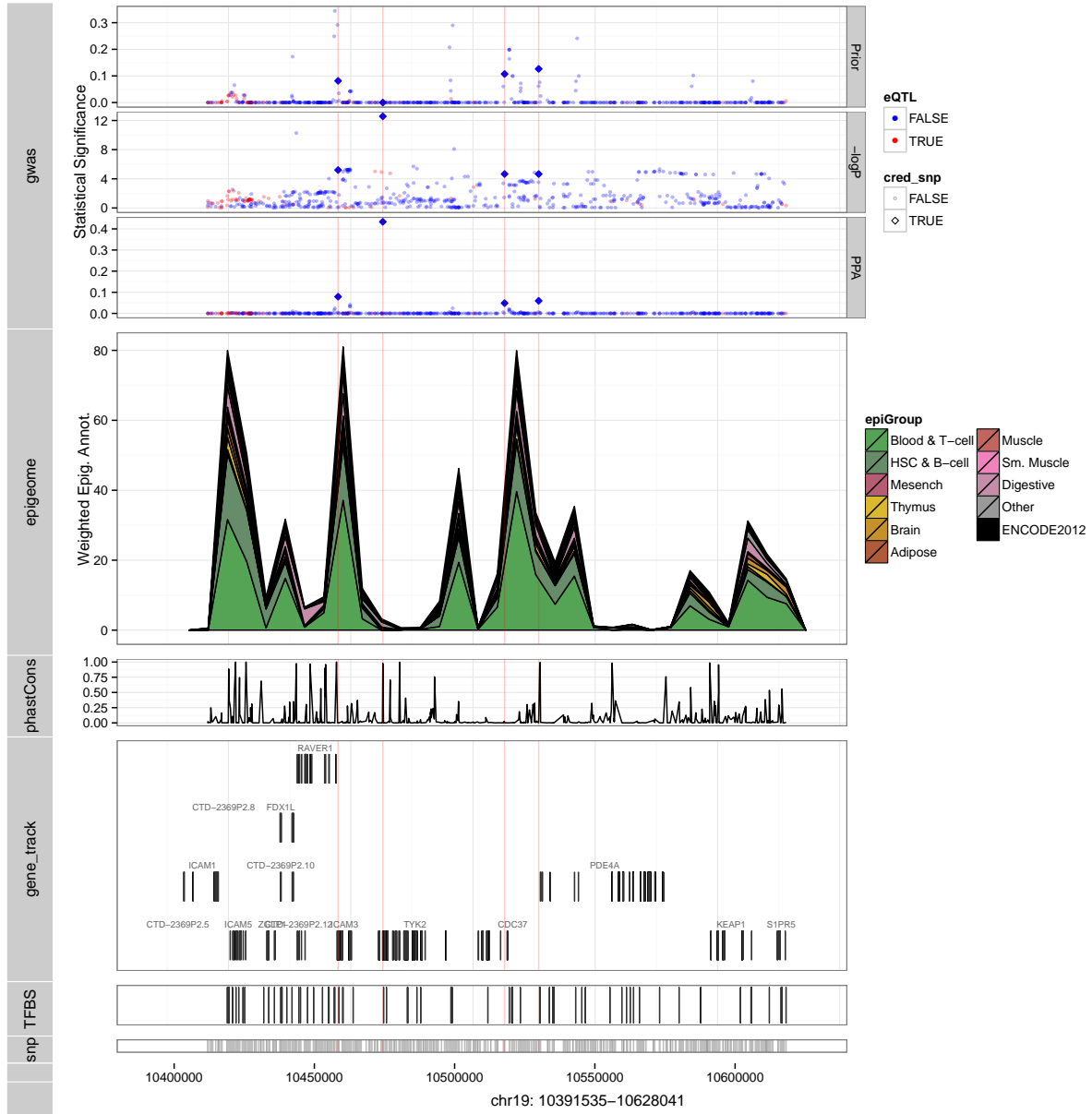
Rheumatoid Arthritis



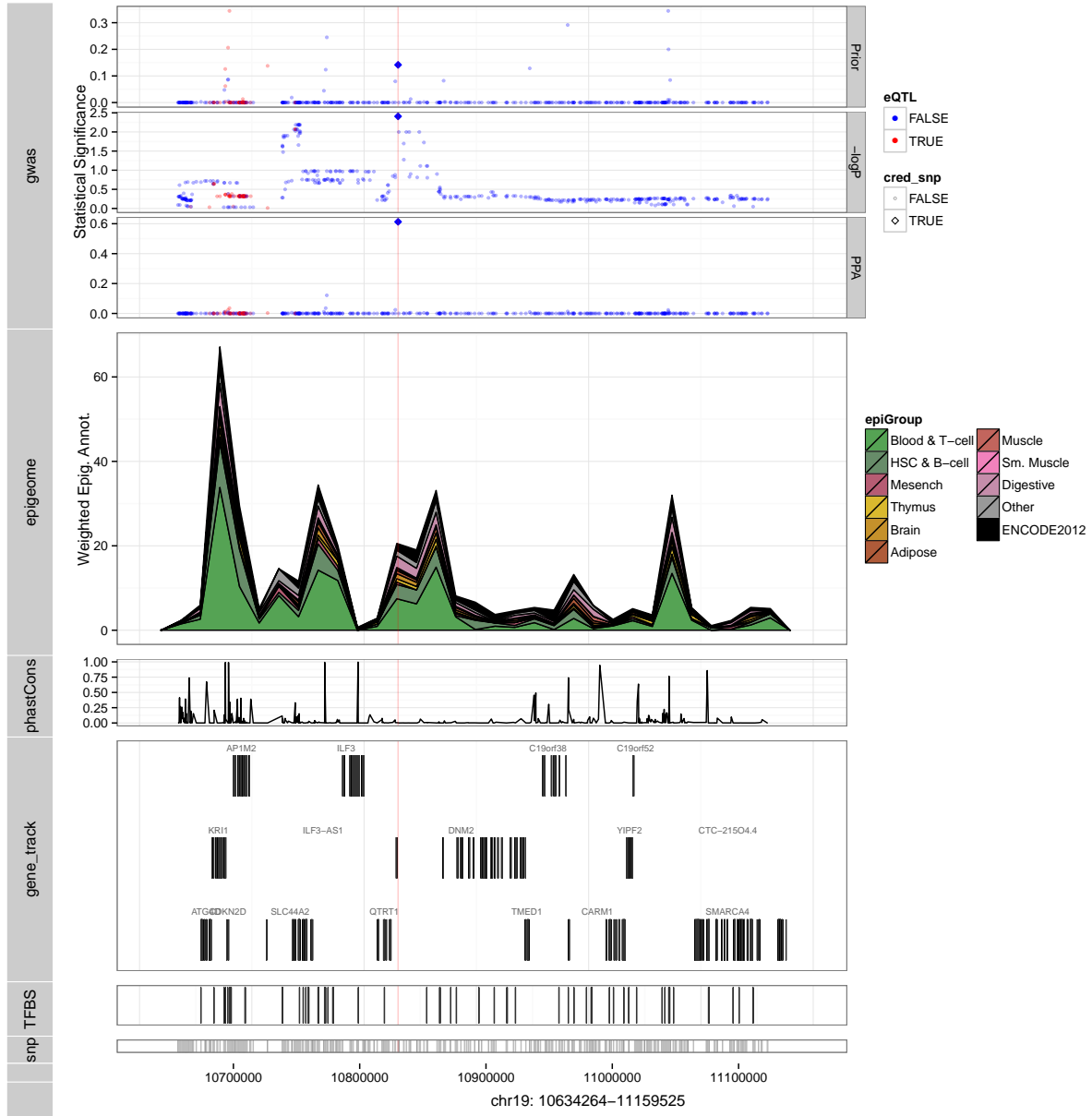
Rheumatoid Arthritis



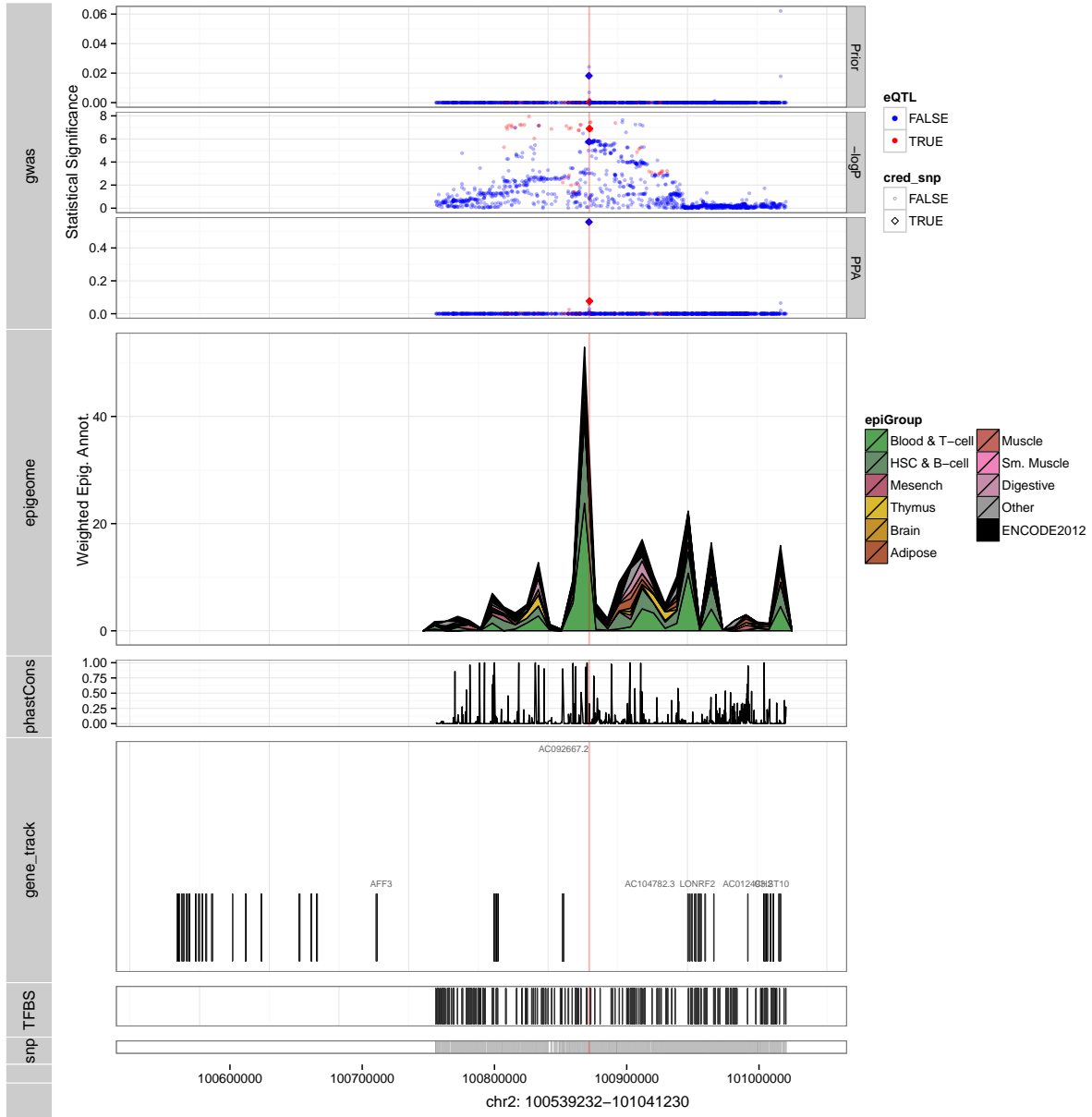
Rheumatoid Arthritis



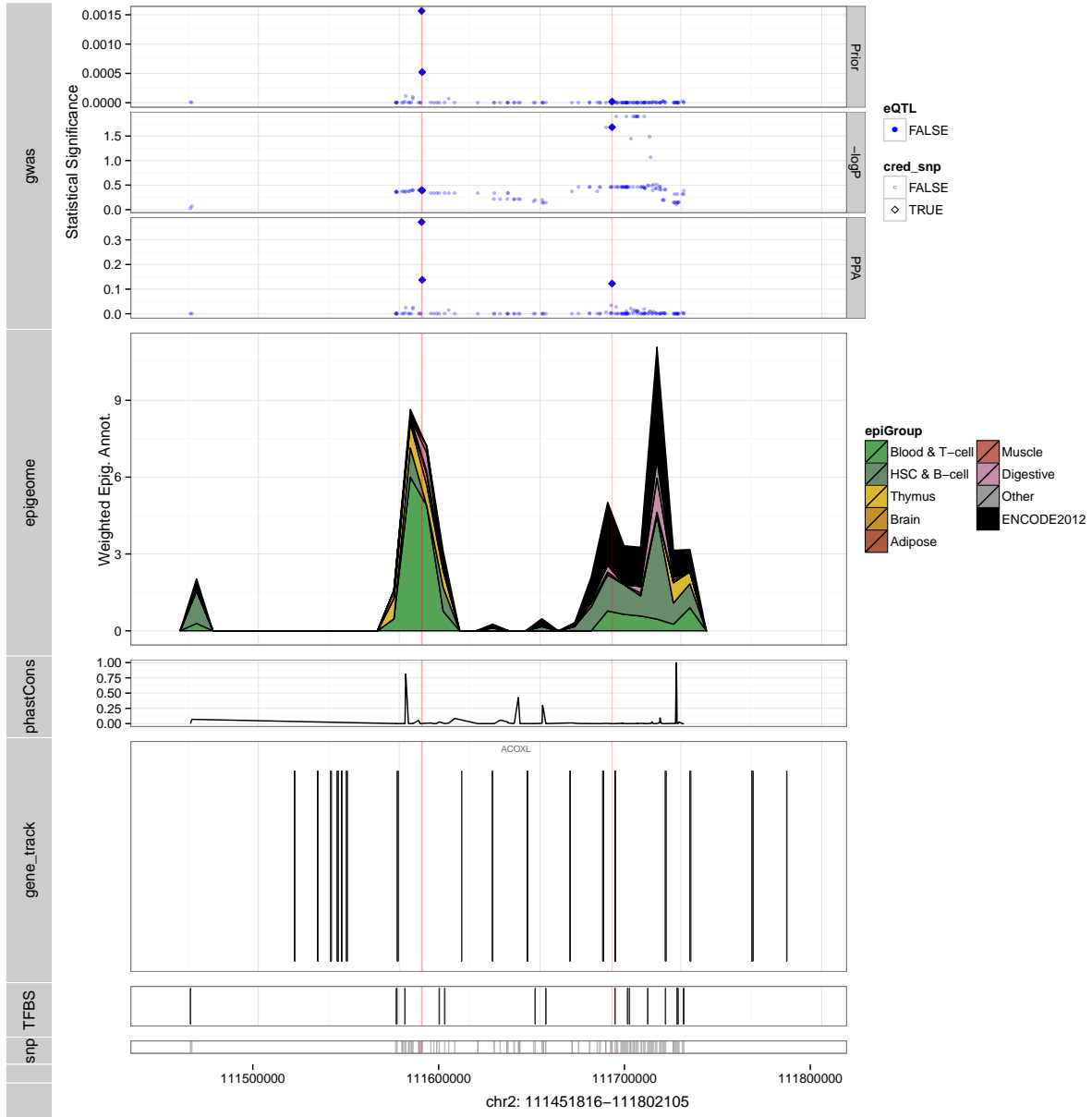
Rheumatoid Arthritis



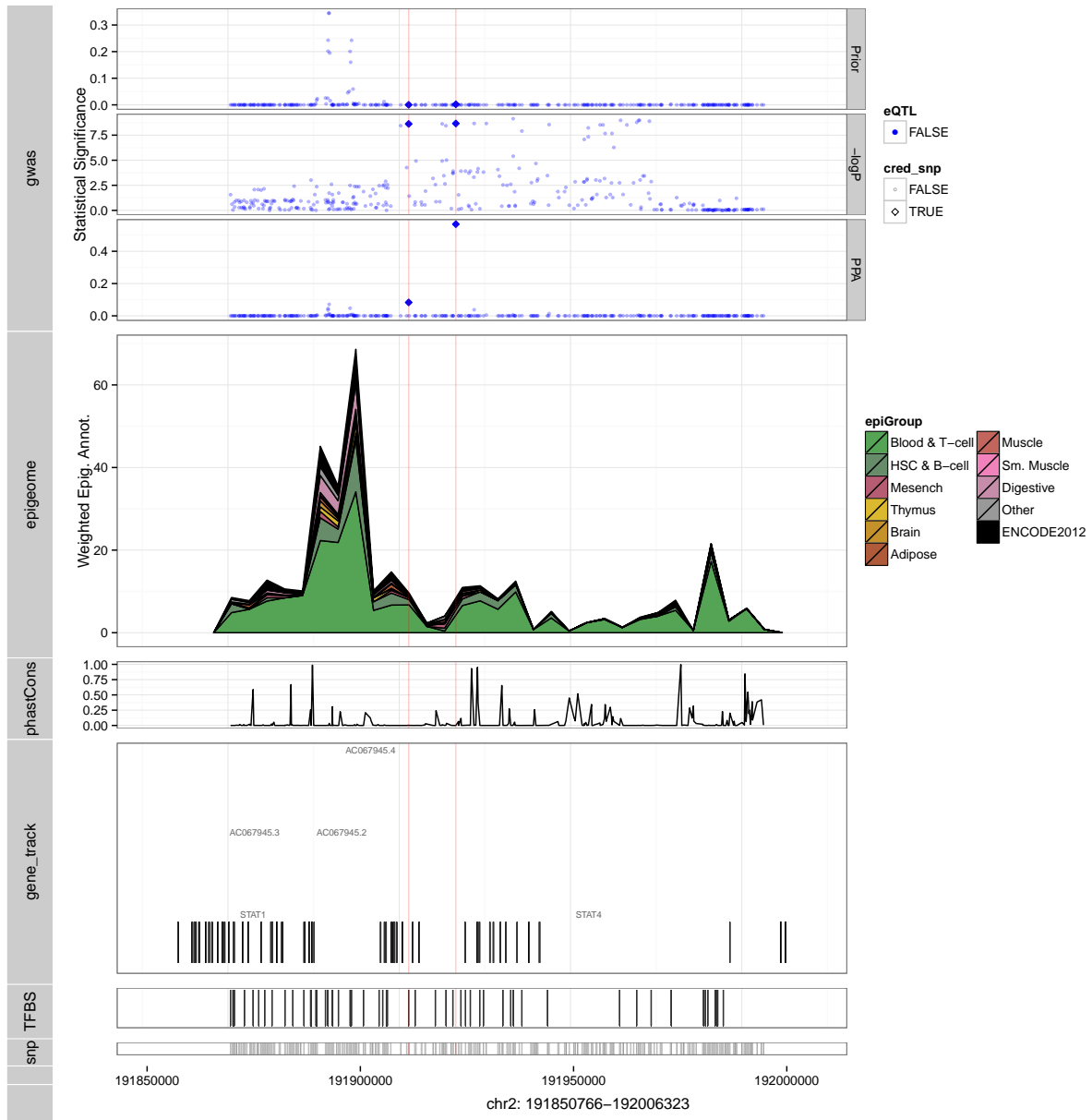
Rheumatoid Arthritis



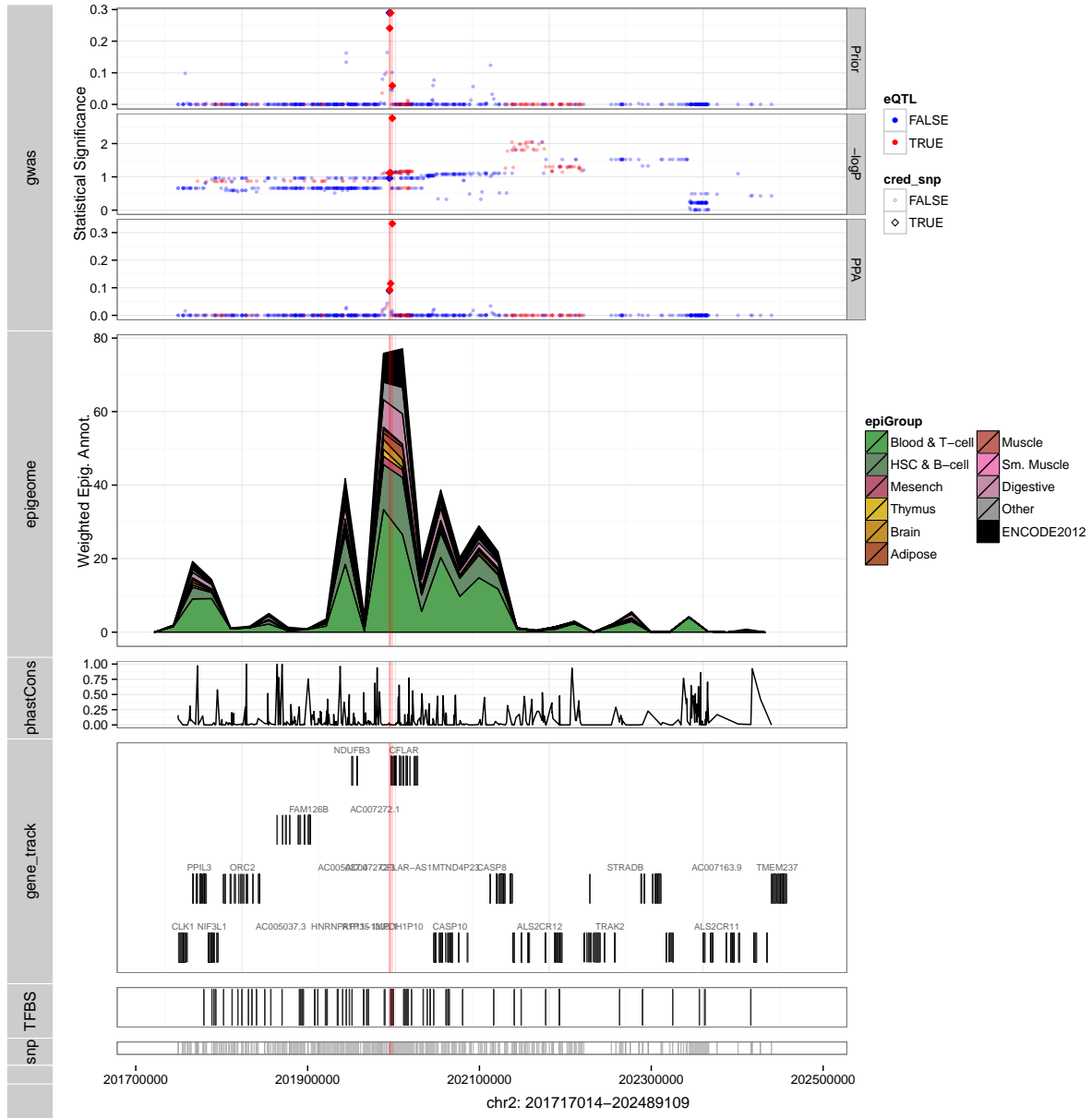
Rheumatoid Arthritis



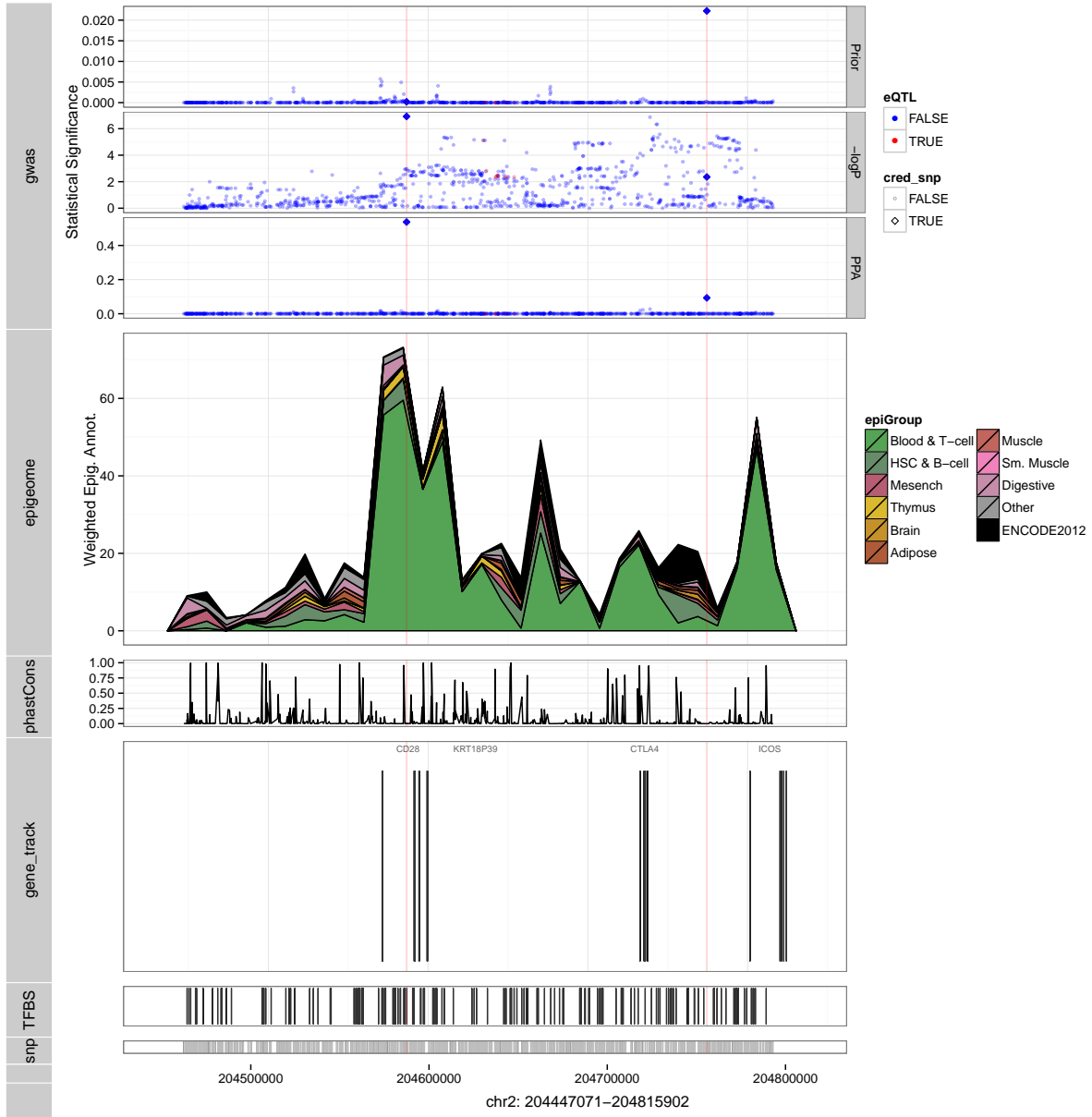
Rheumatoid Arthritis



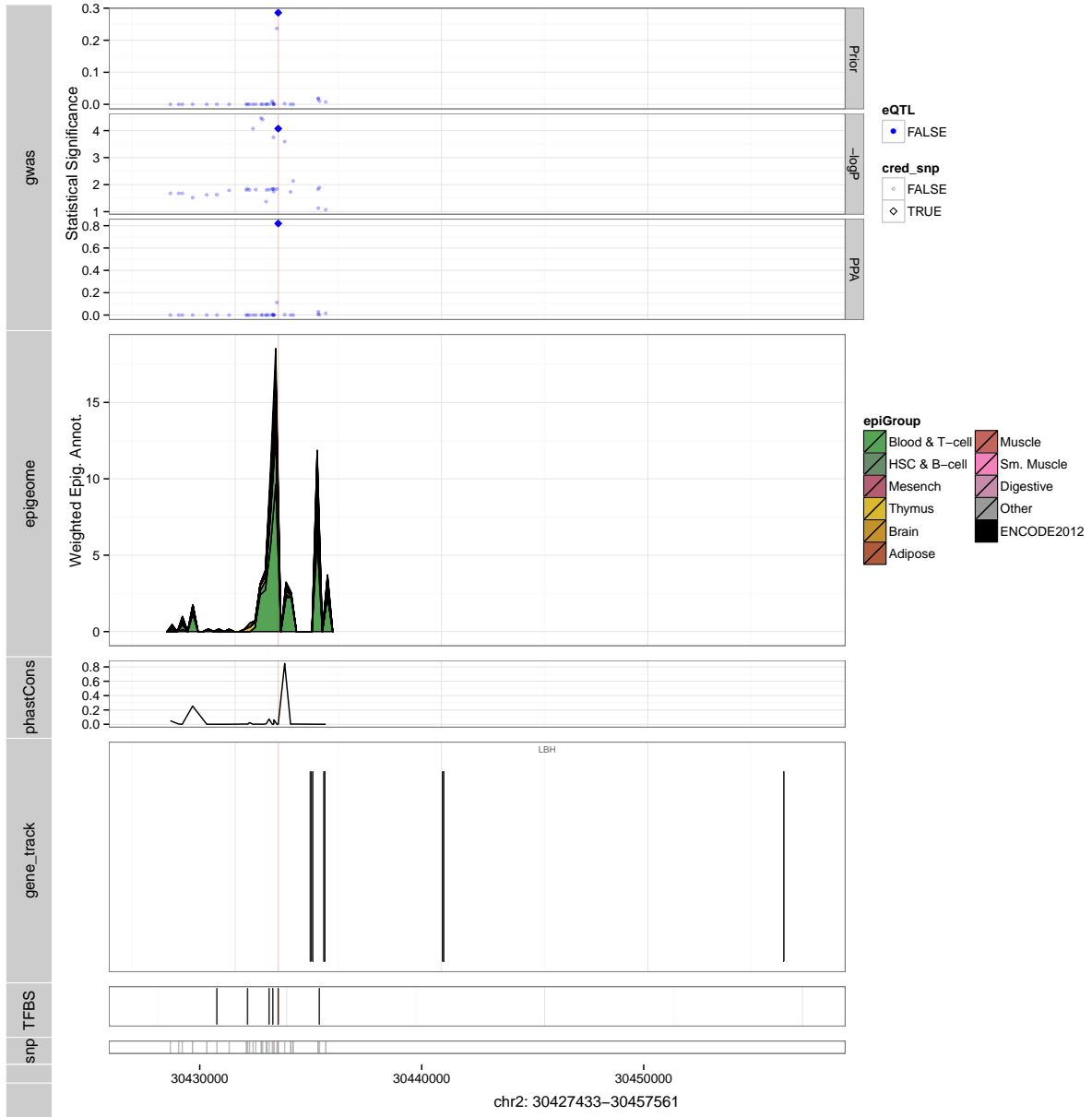
Rheumatoid Arthritis



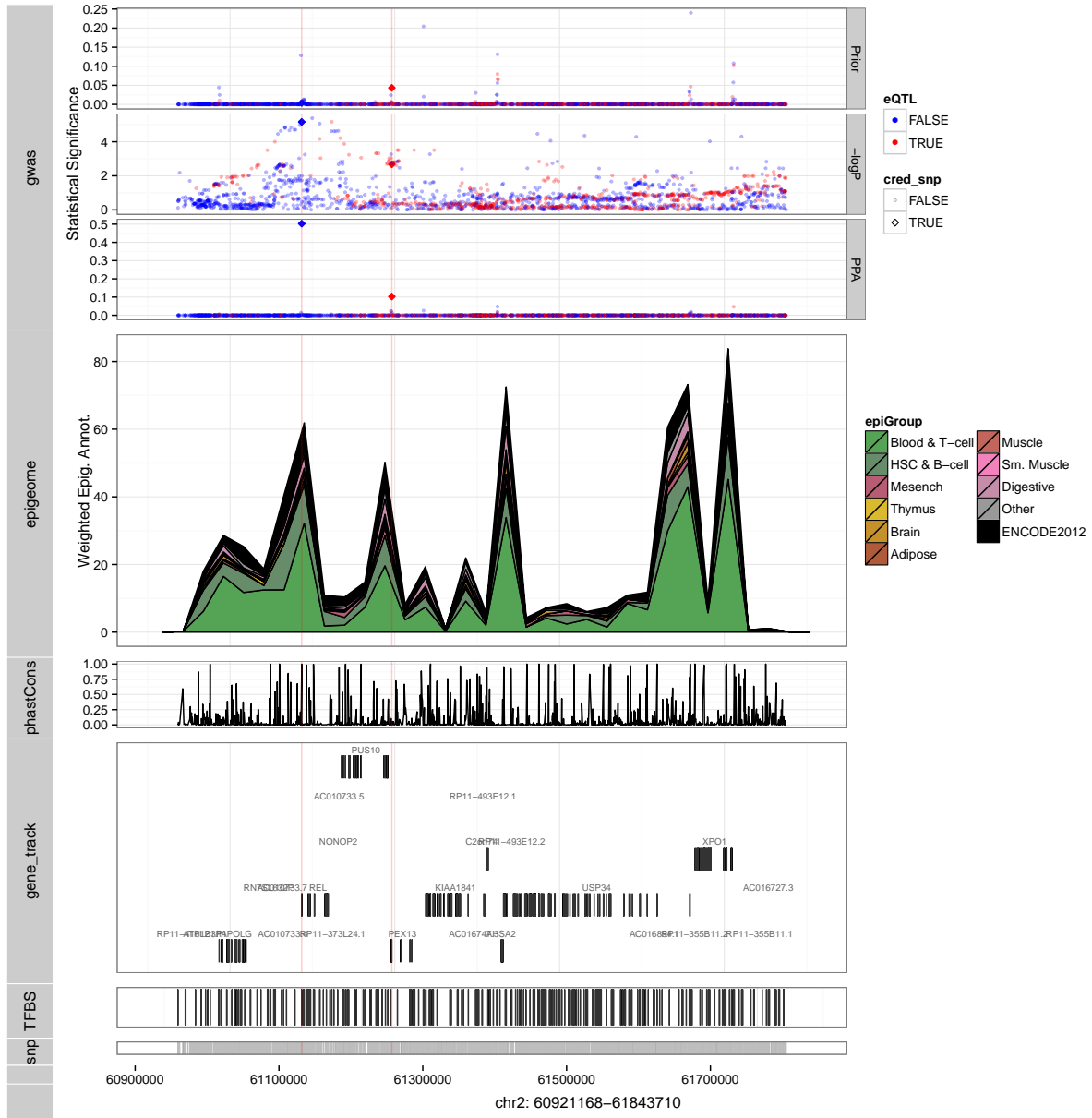
Rheumatoid Arthritis



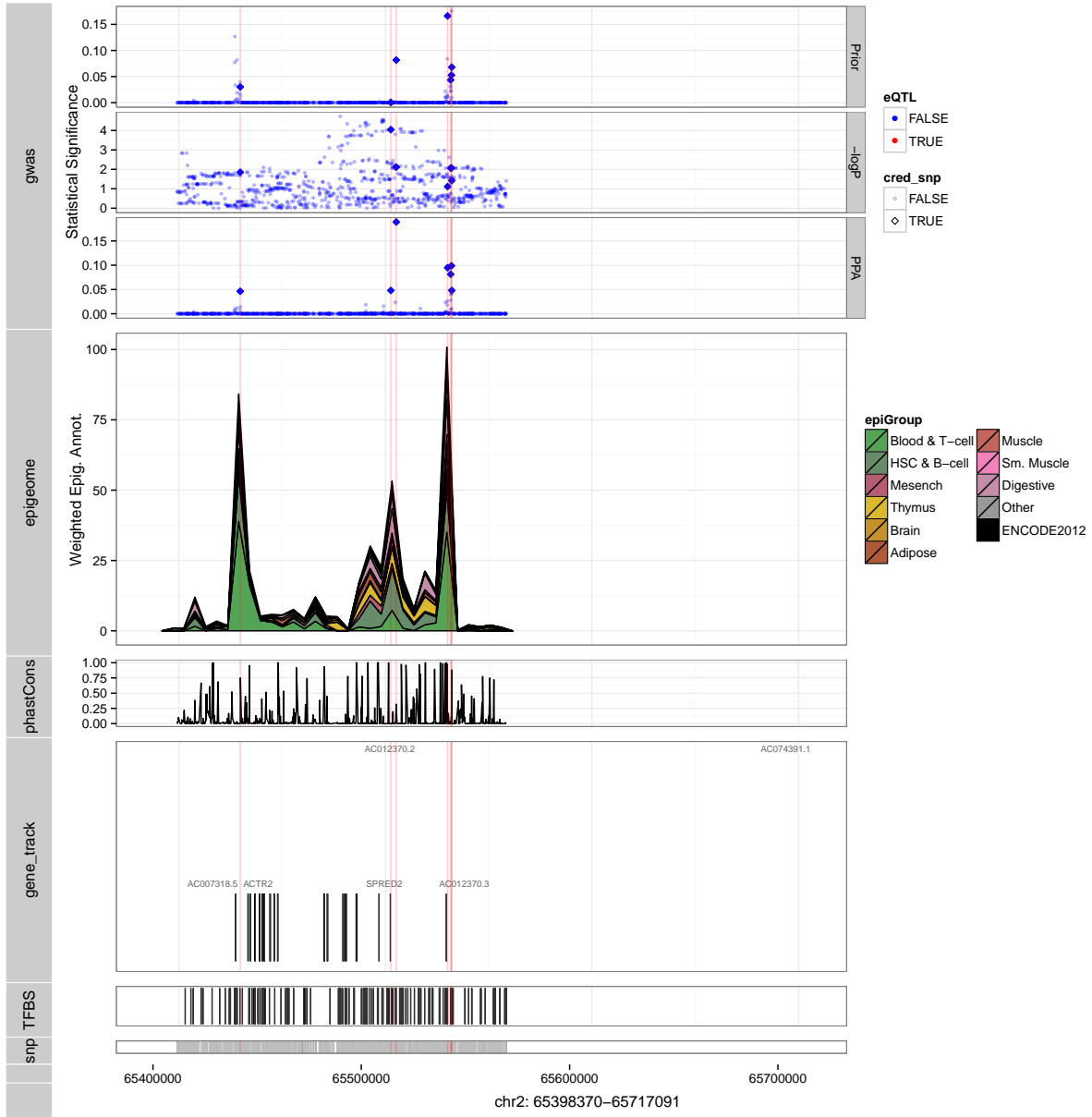
Rheumatoid Arthritis



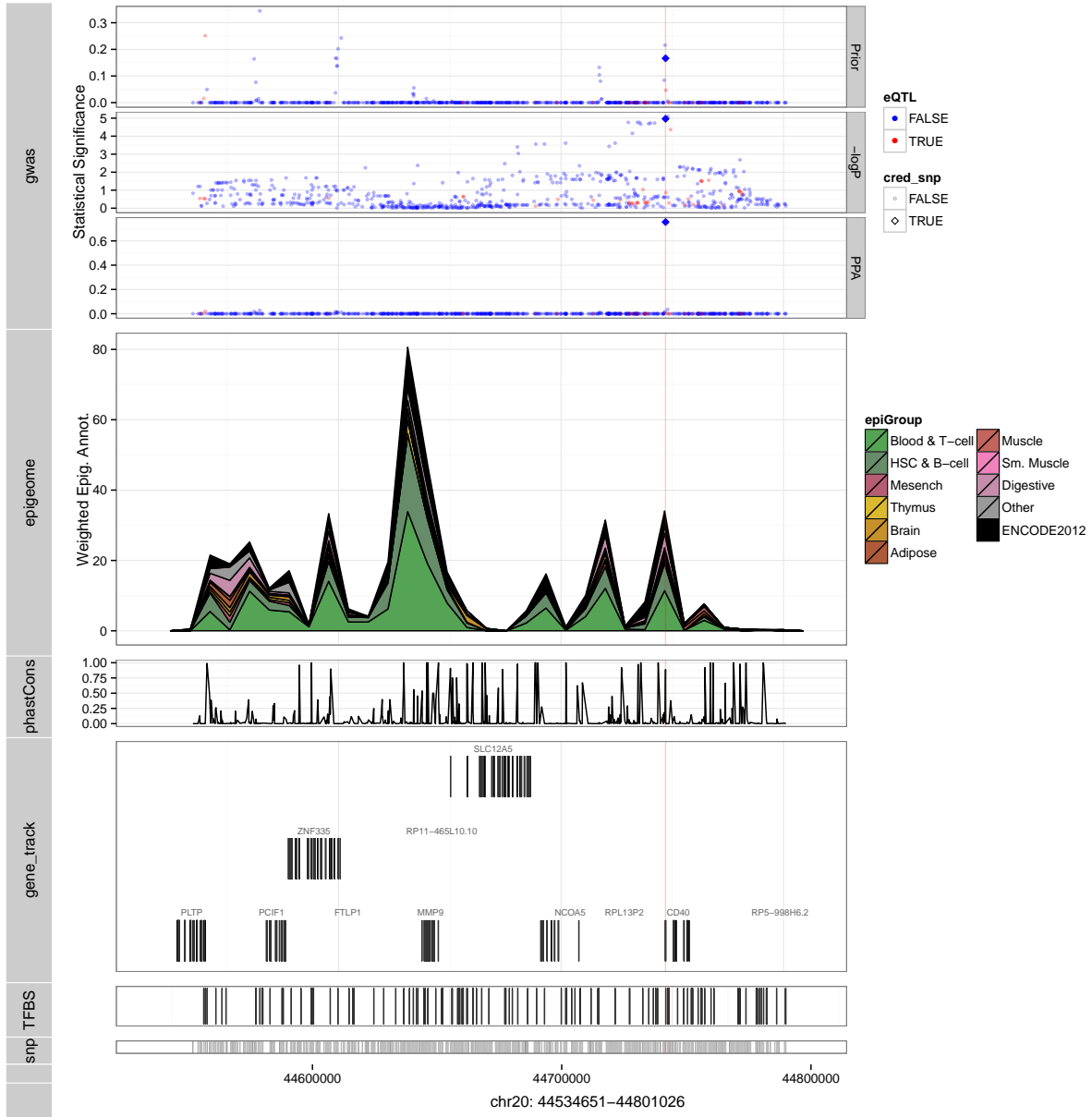
Rheumatoid Arthritis



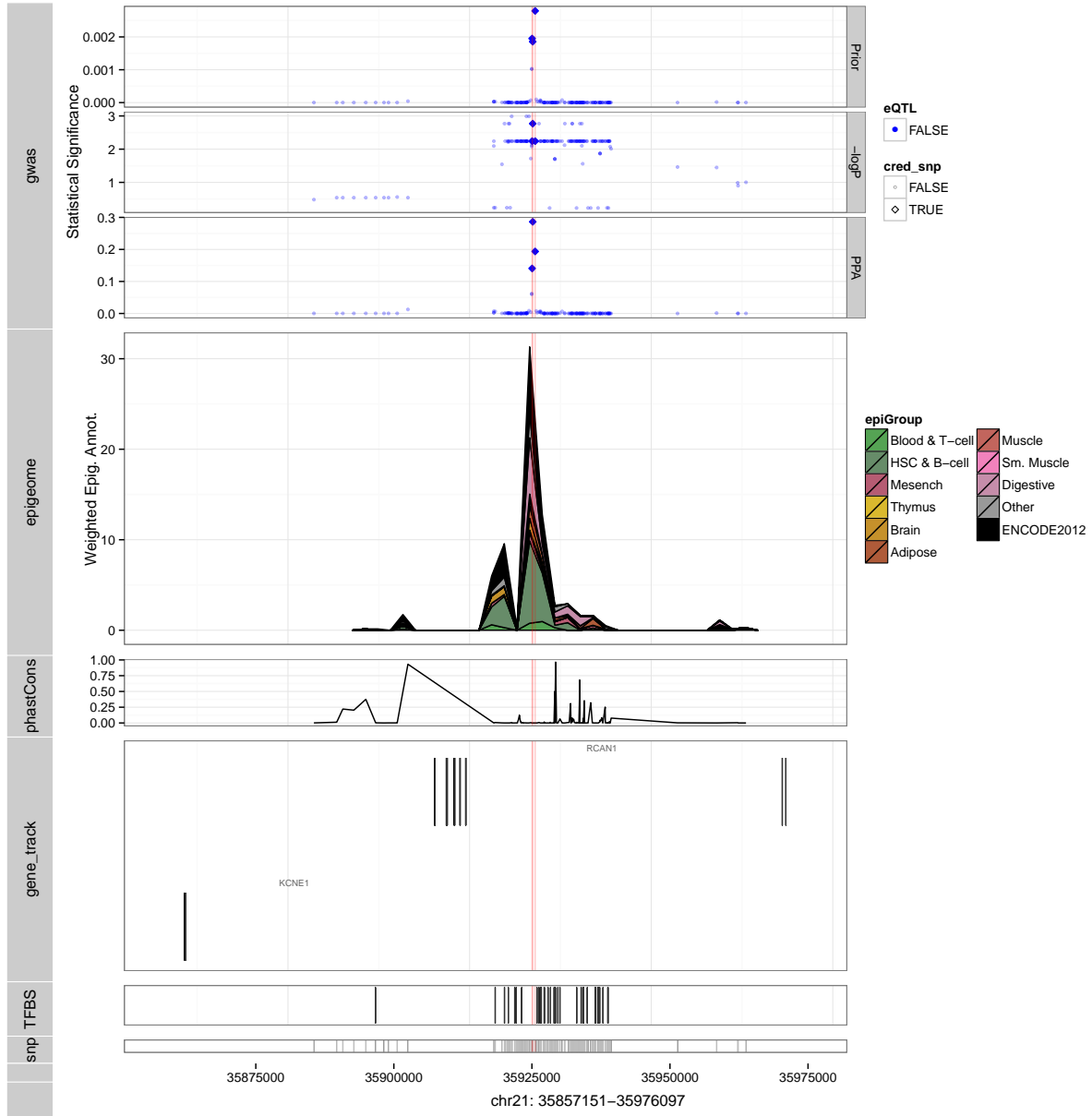
Rheumatoid Arthritis



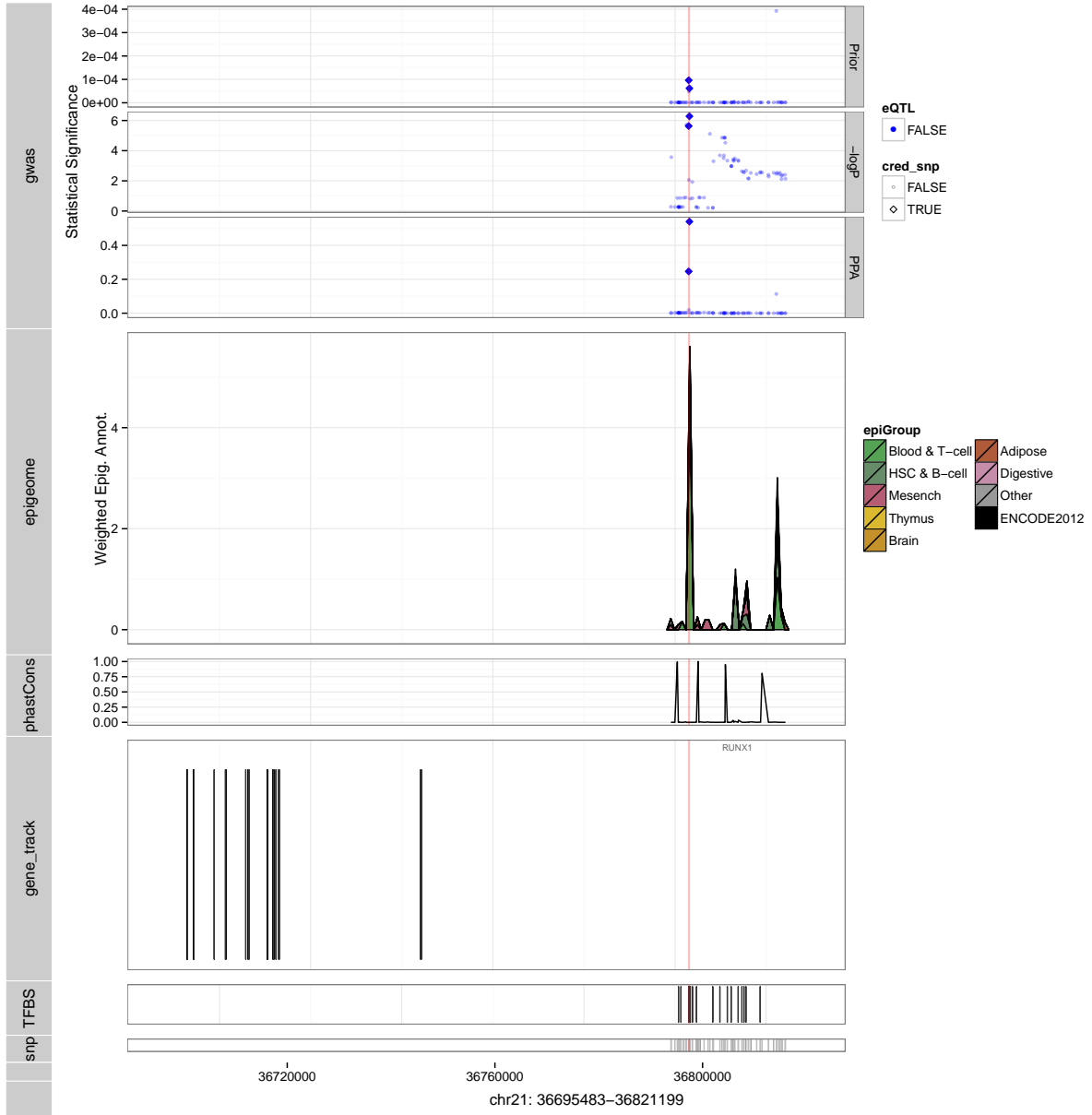
Rheumatoid Arthritis



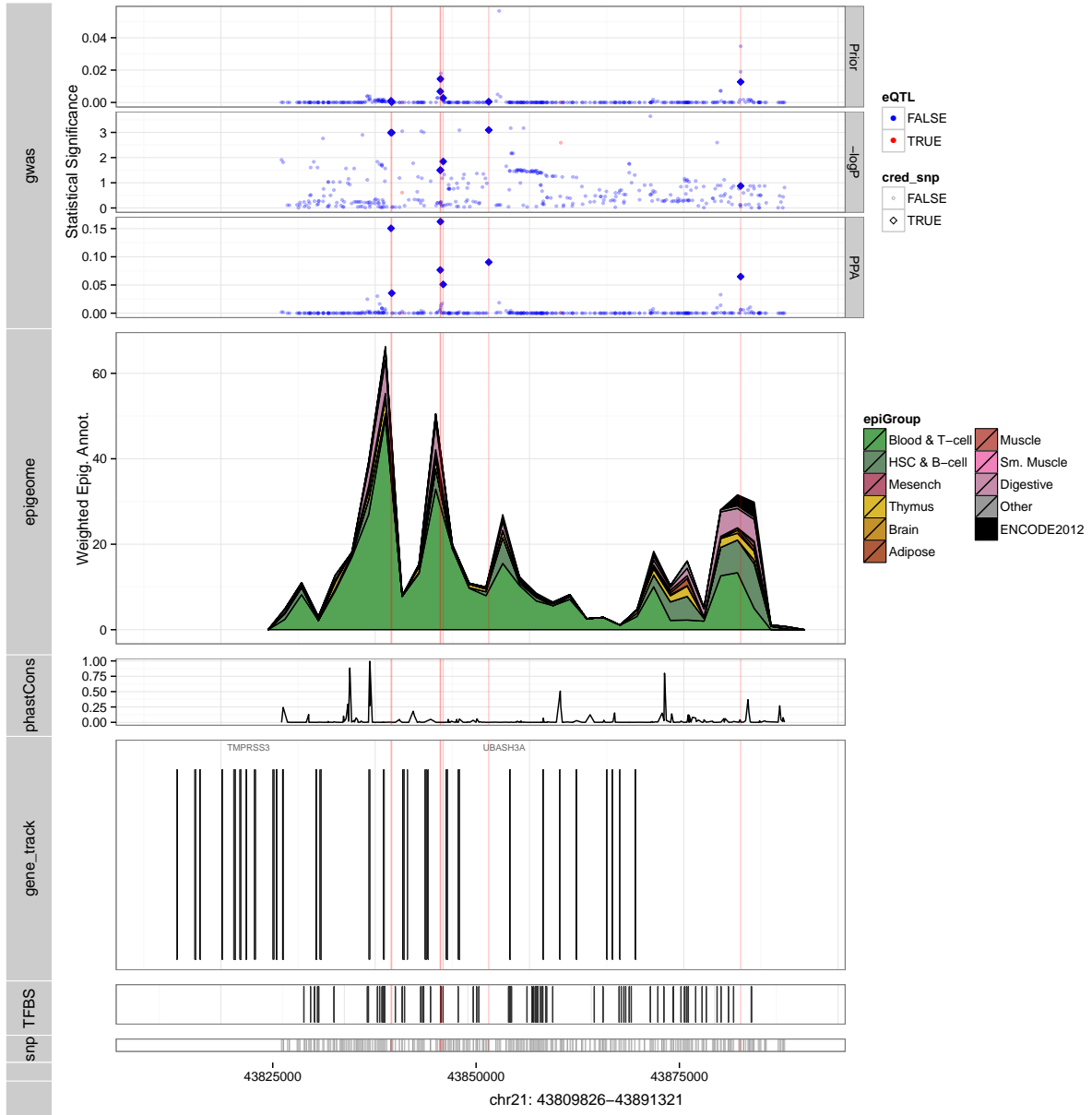
Rheumatoid Arthritis



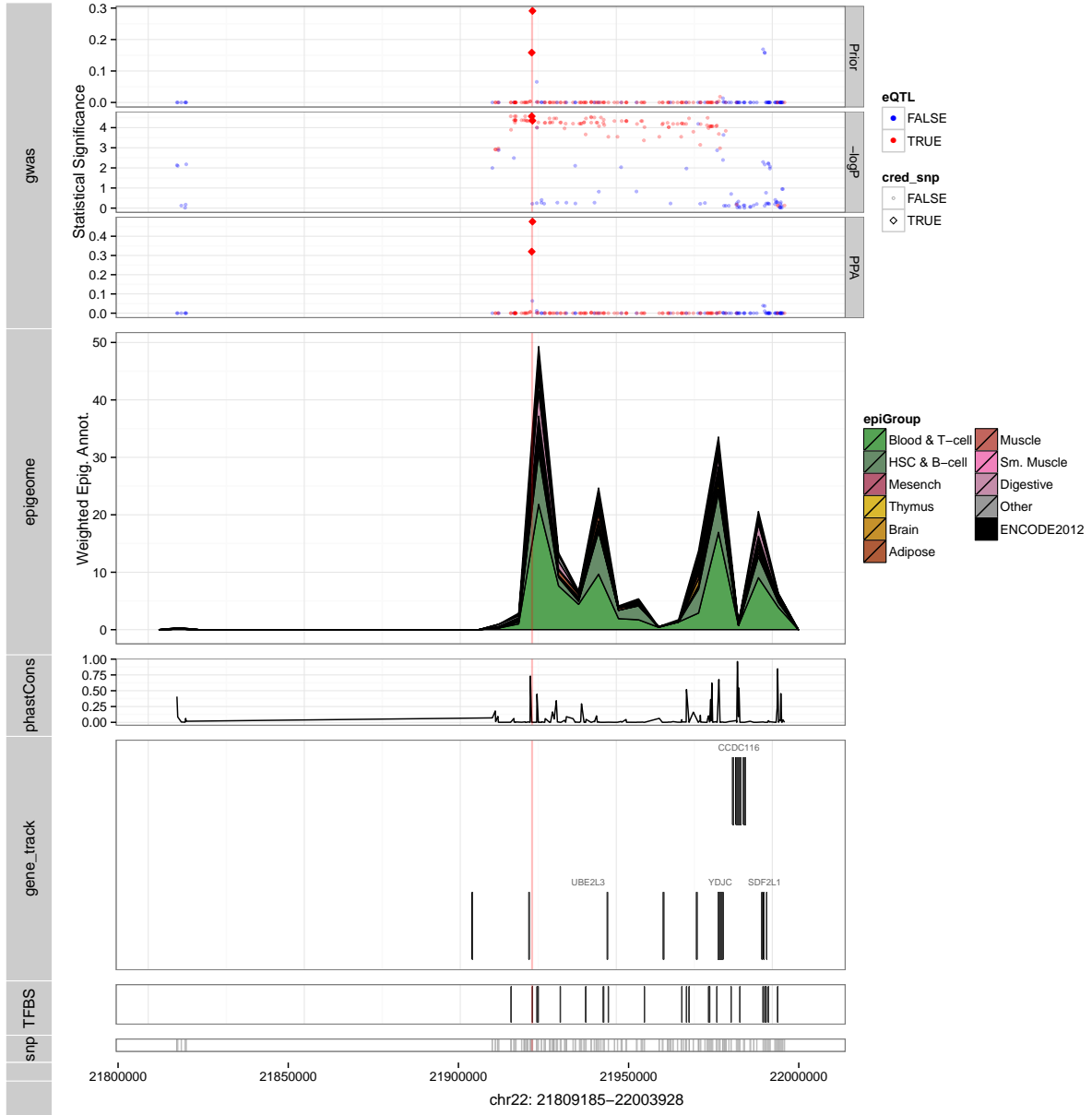
Rheumatoid Arthritis



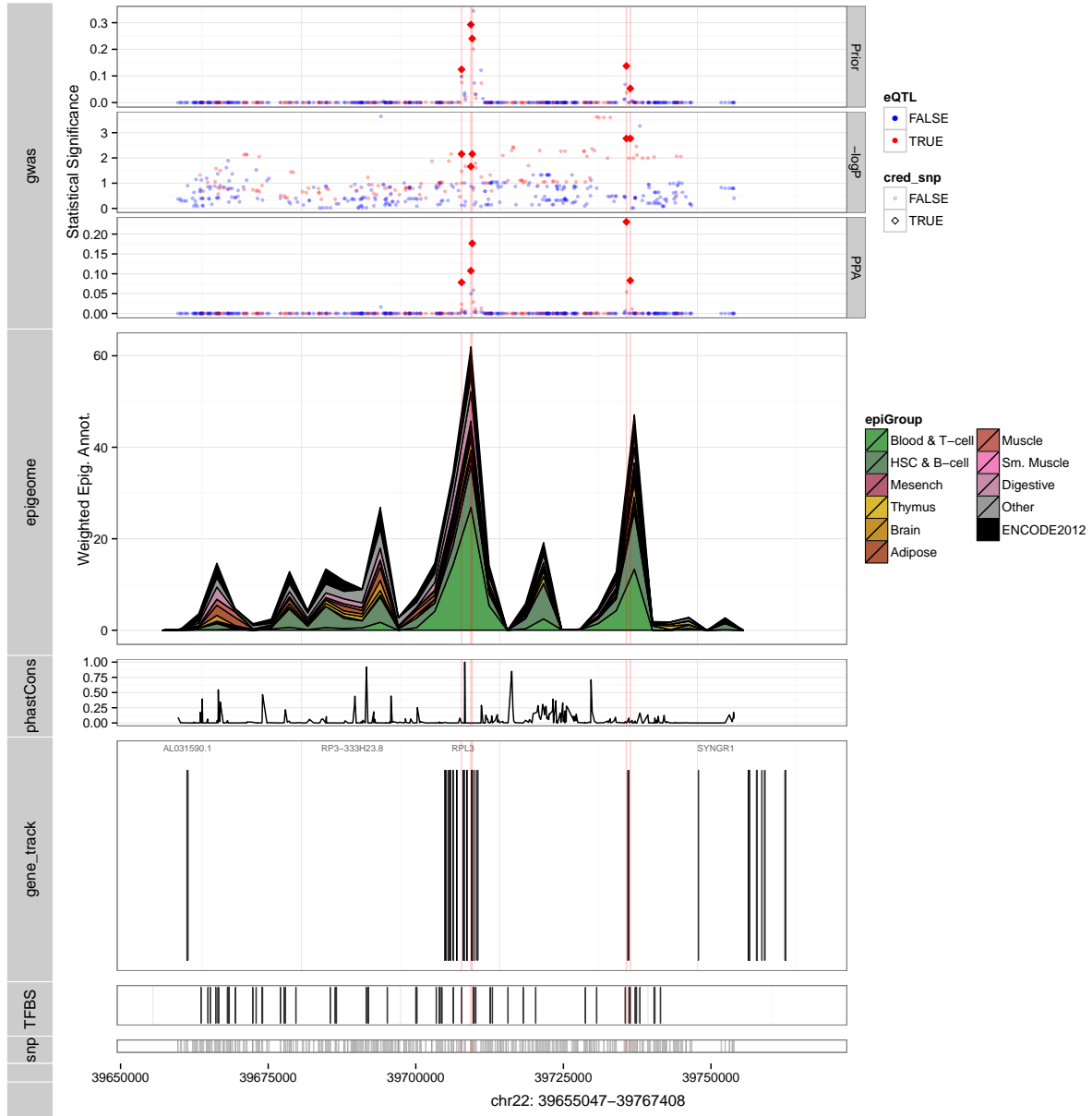
Rheumatoid Arthritis



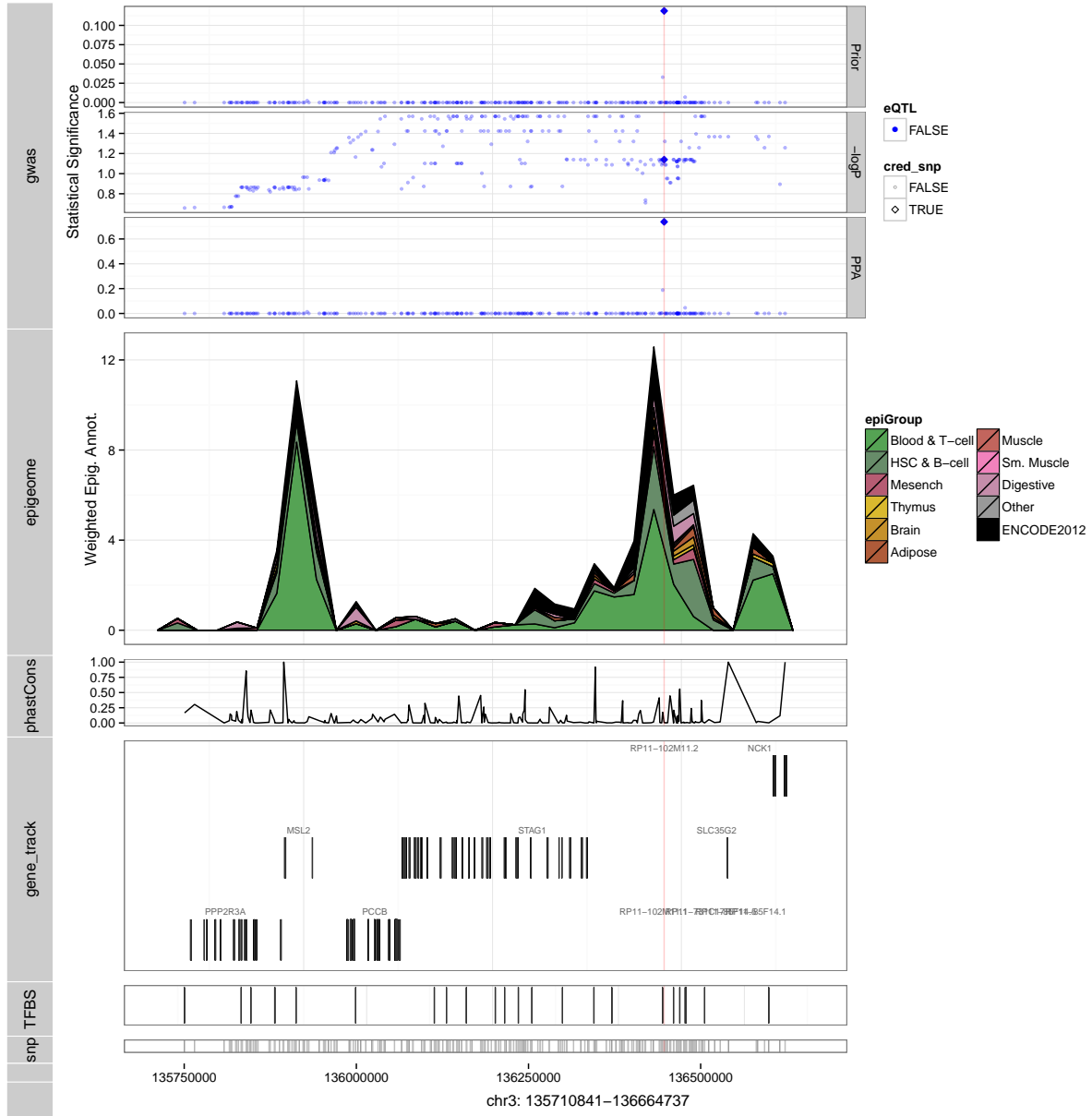
Rheumatoid Arthritis



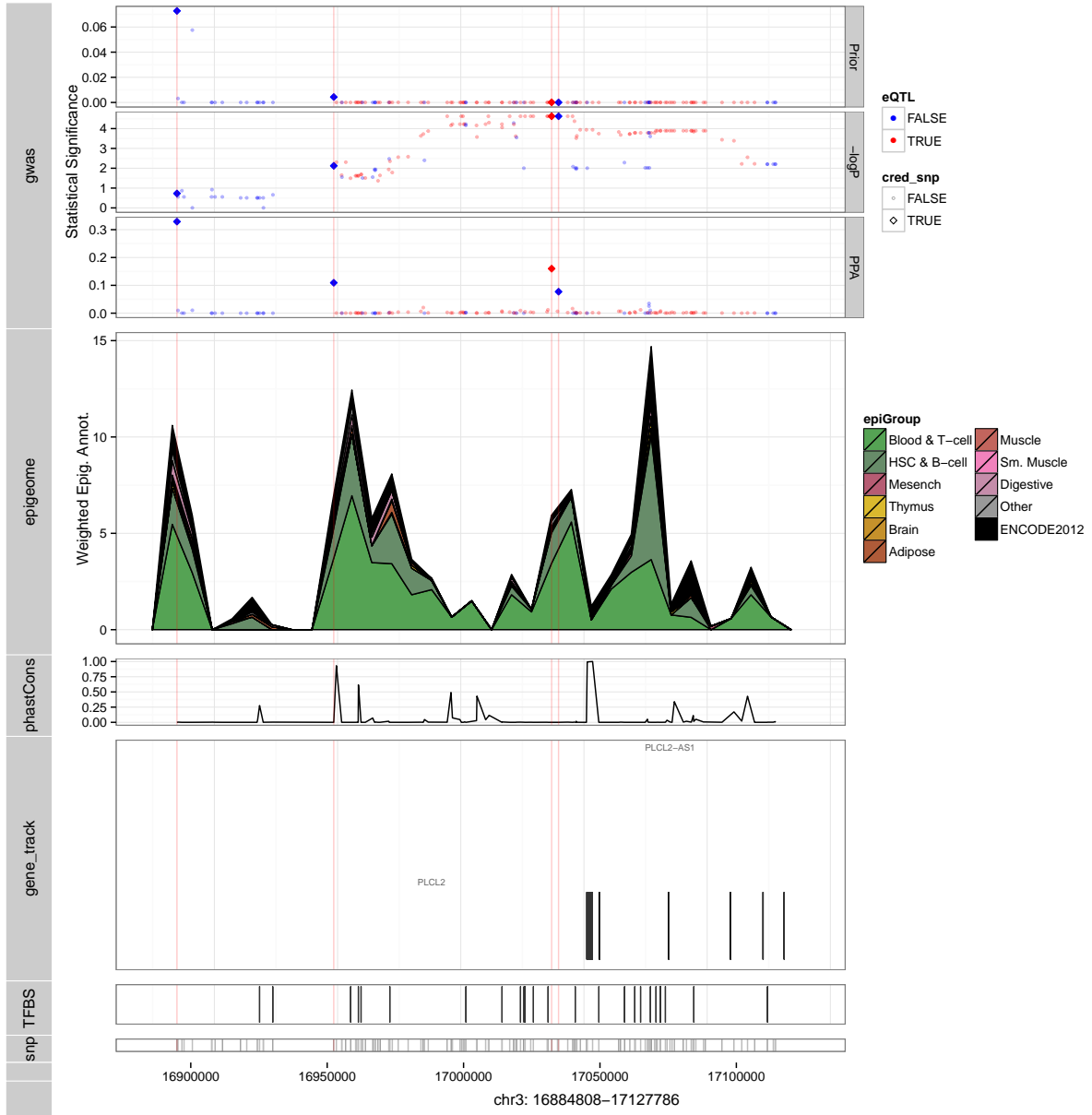
Rheumatoid Arthritis



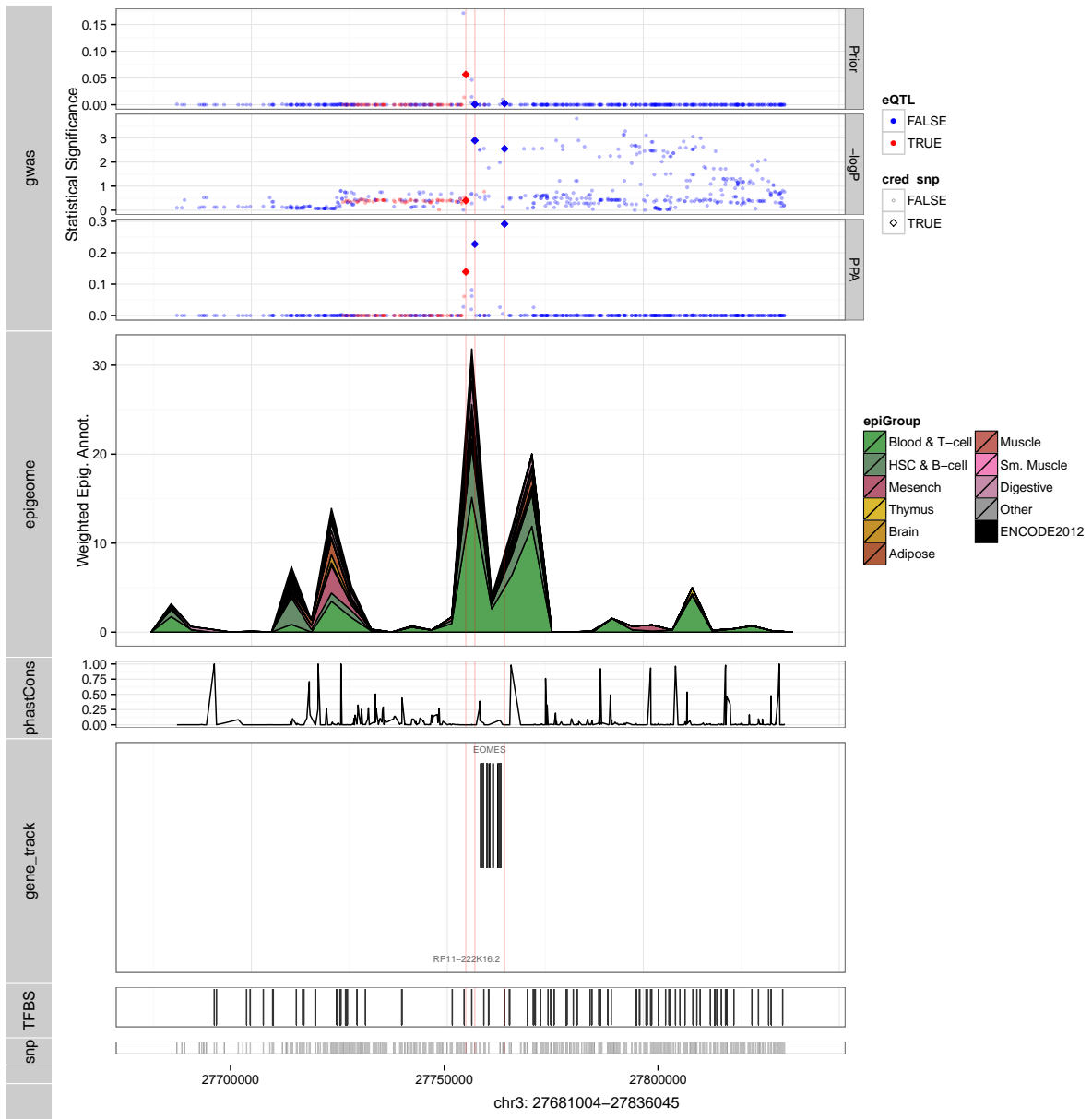
Rheumatoid Arthritis



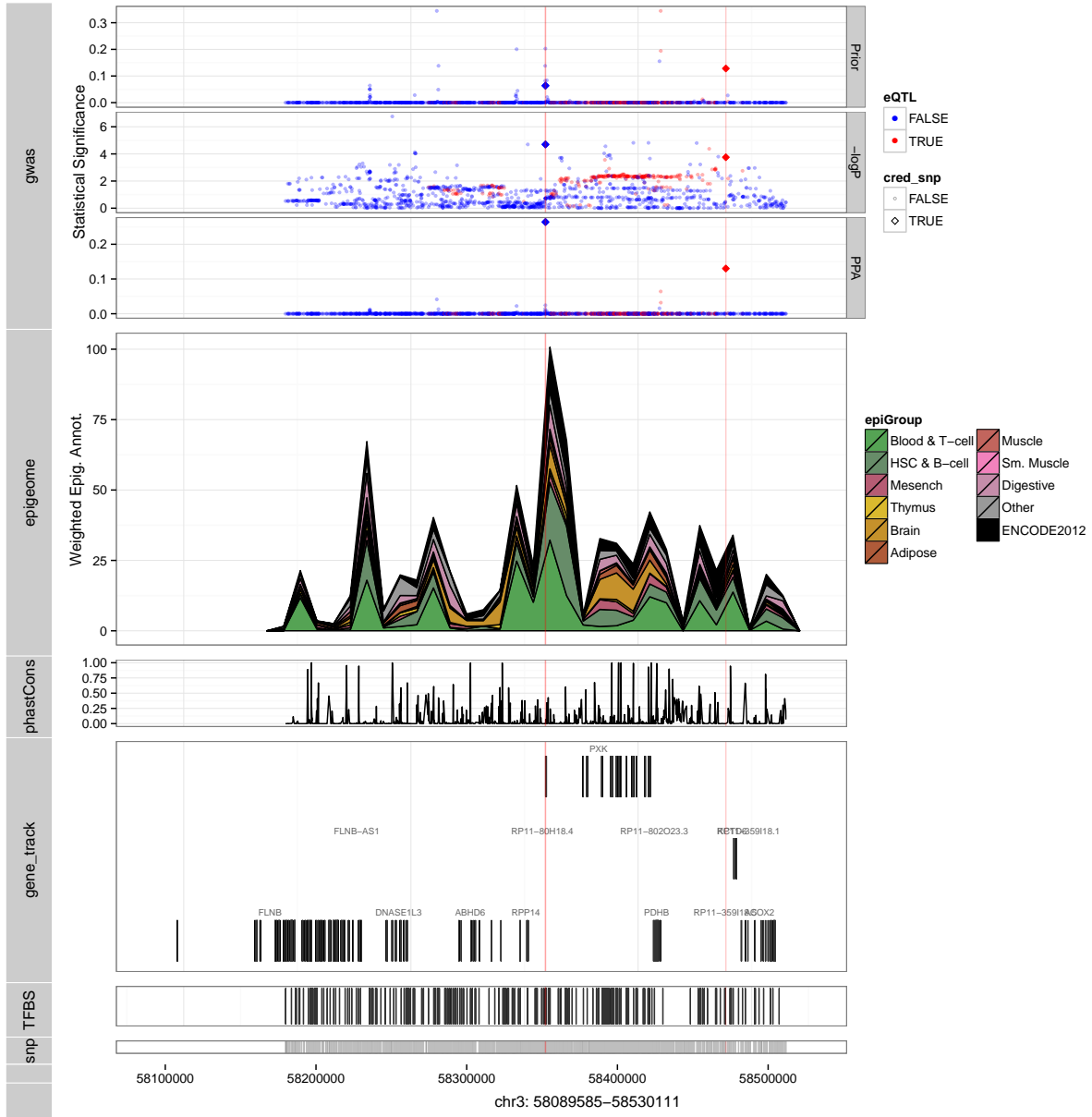
Rheumatoid Arthritis



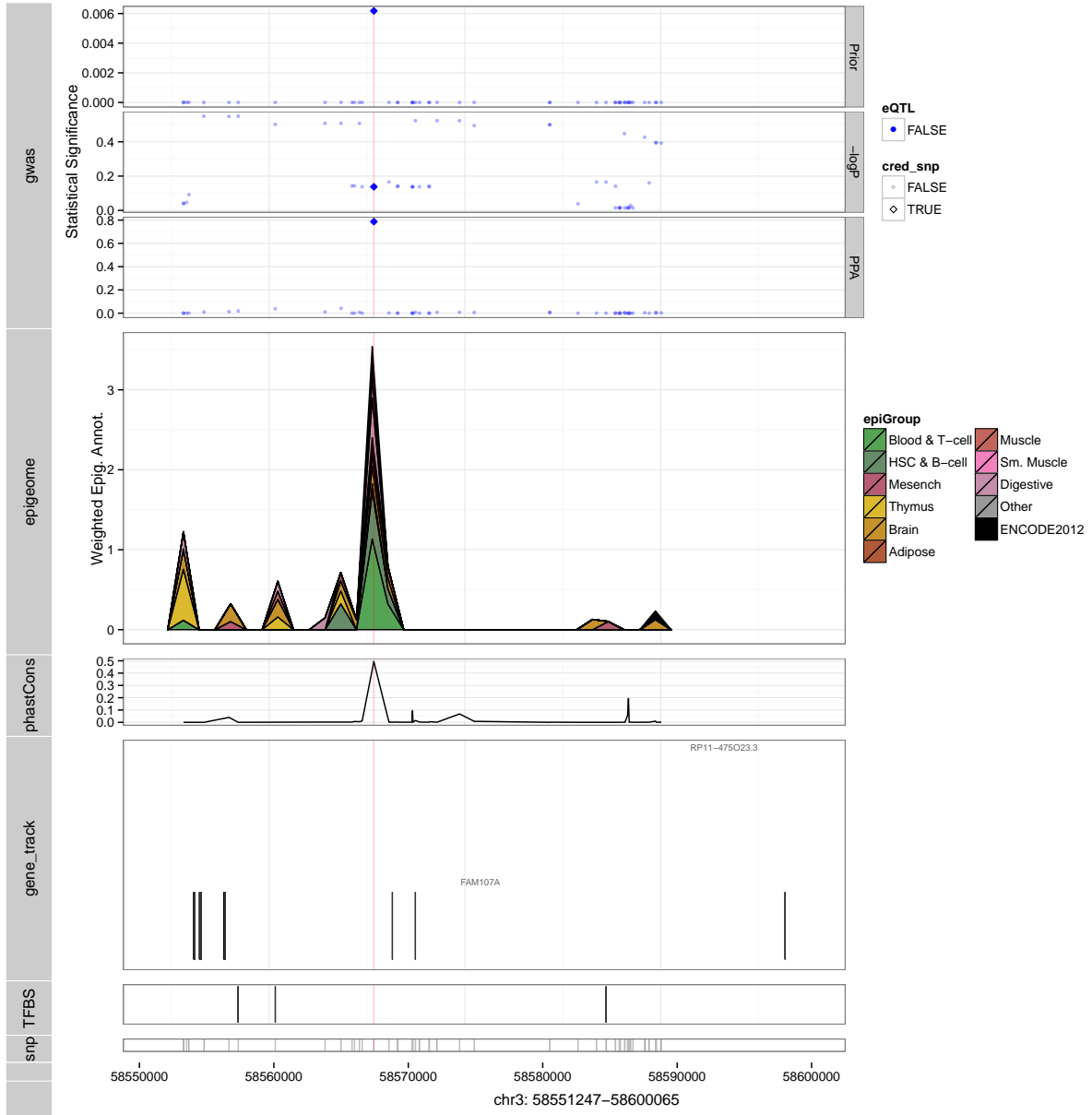
Rheumatoid Arthritis



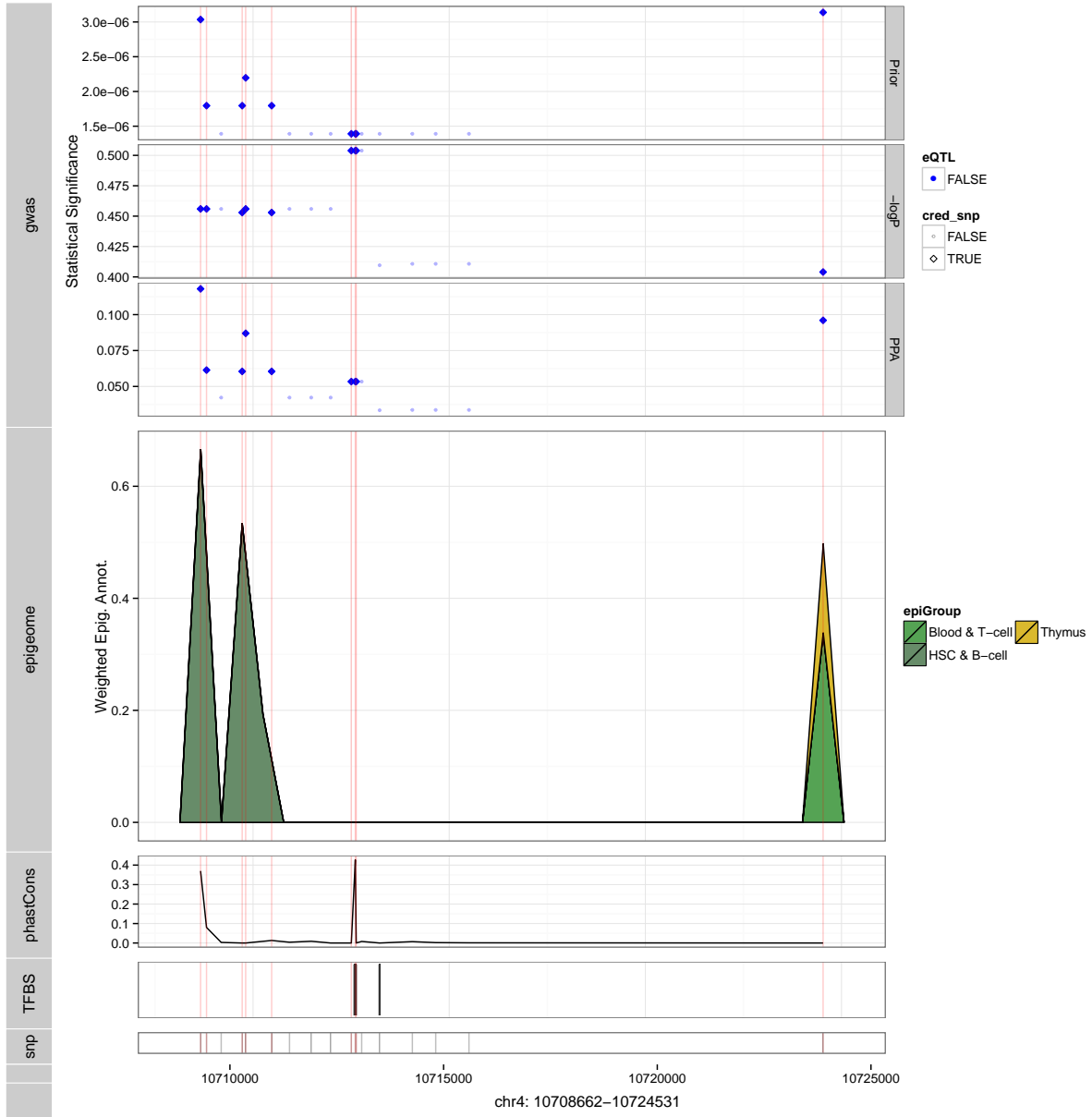
Rheumatoid Arthritis



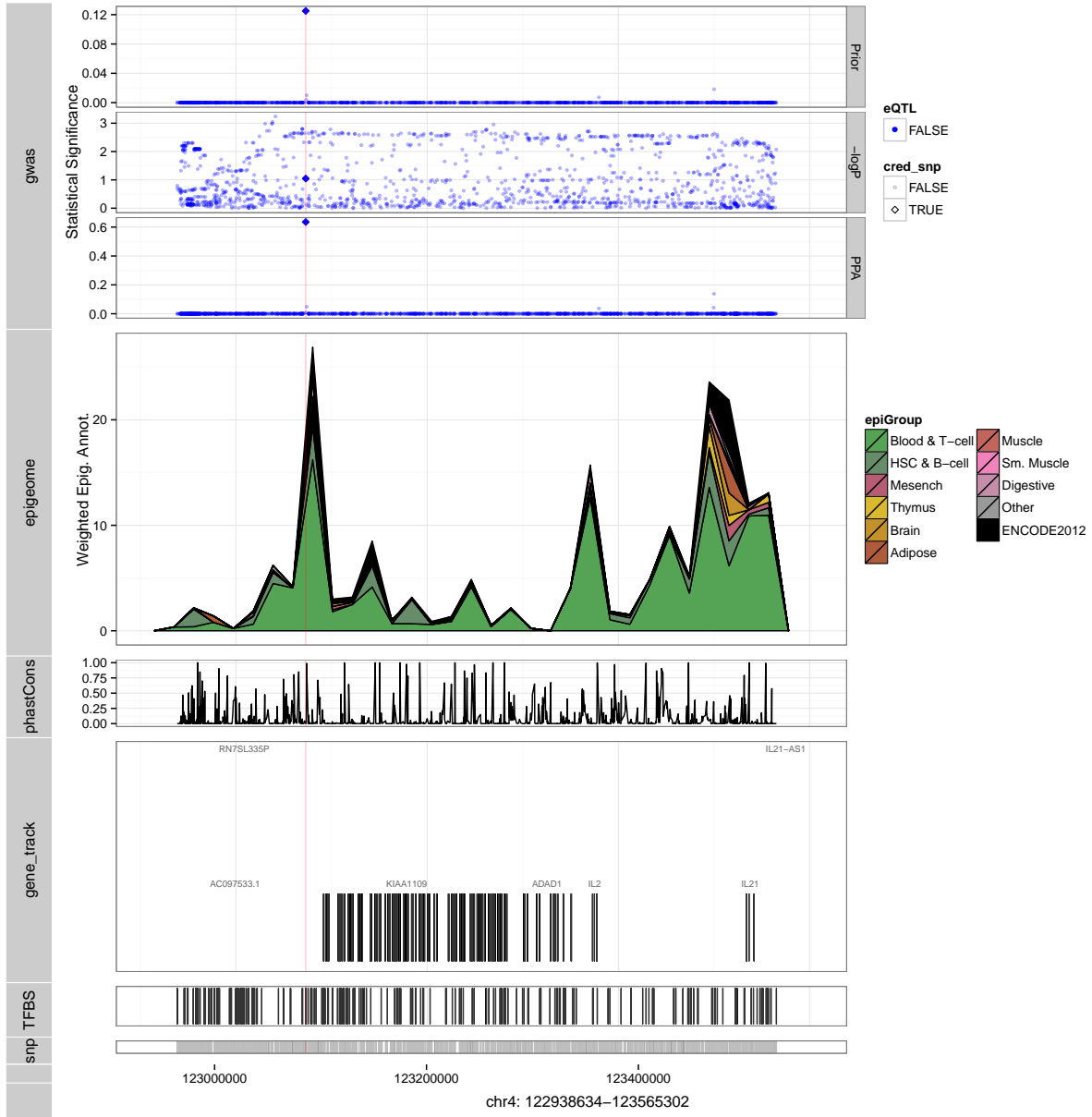
Rheumatoid Arthritis



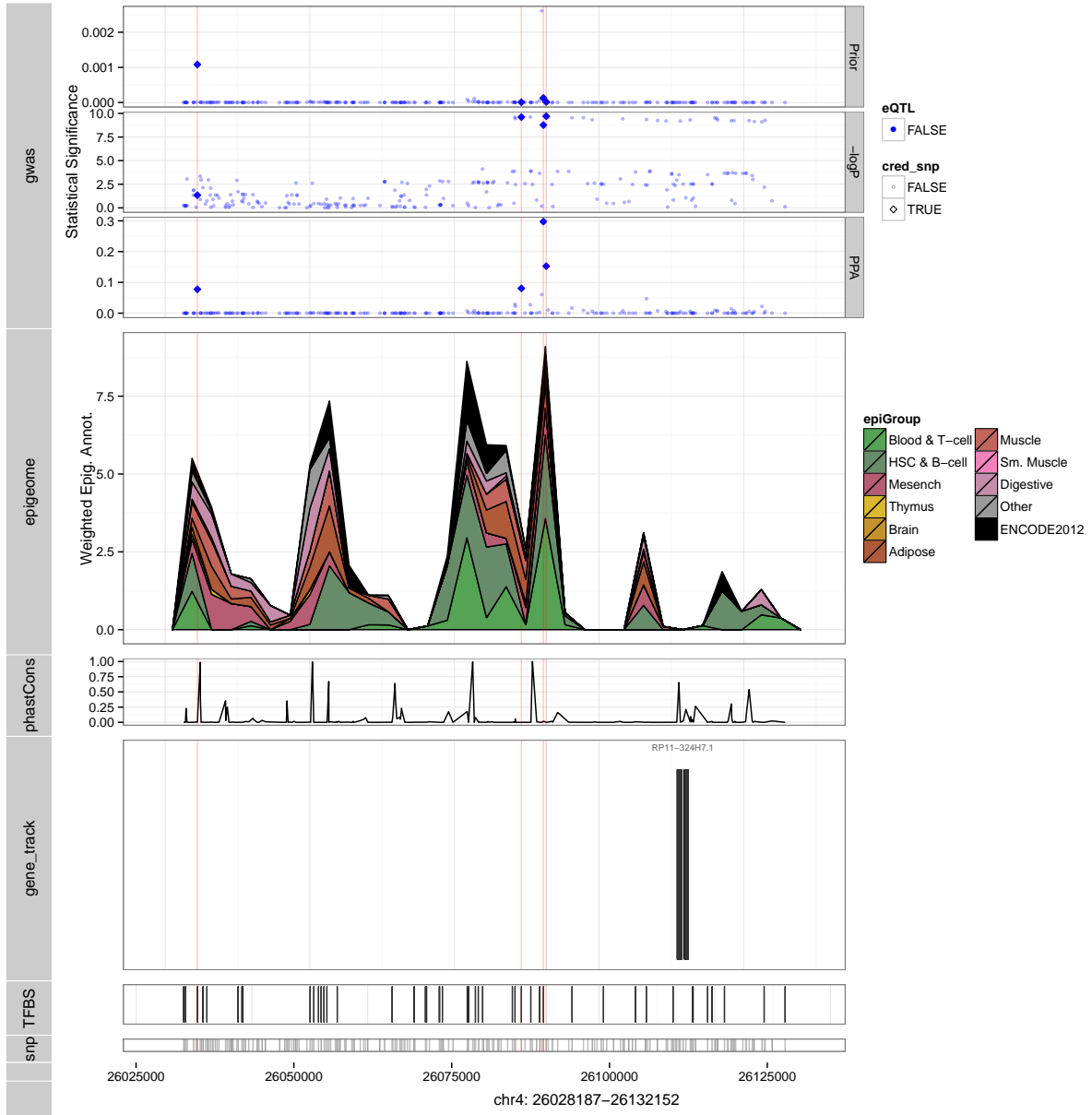
Rheumatoid Arthritis



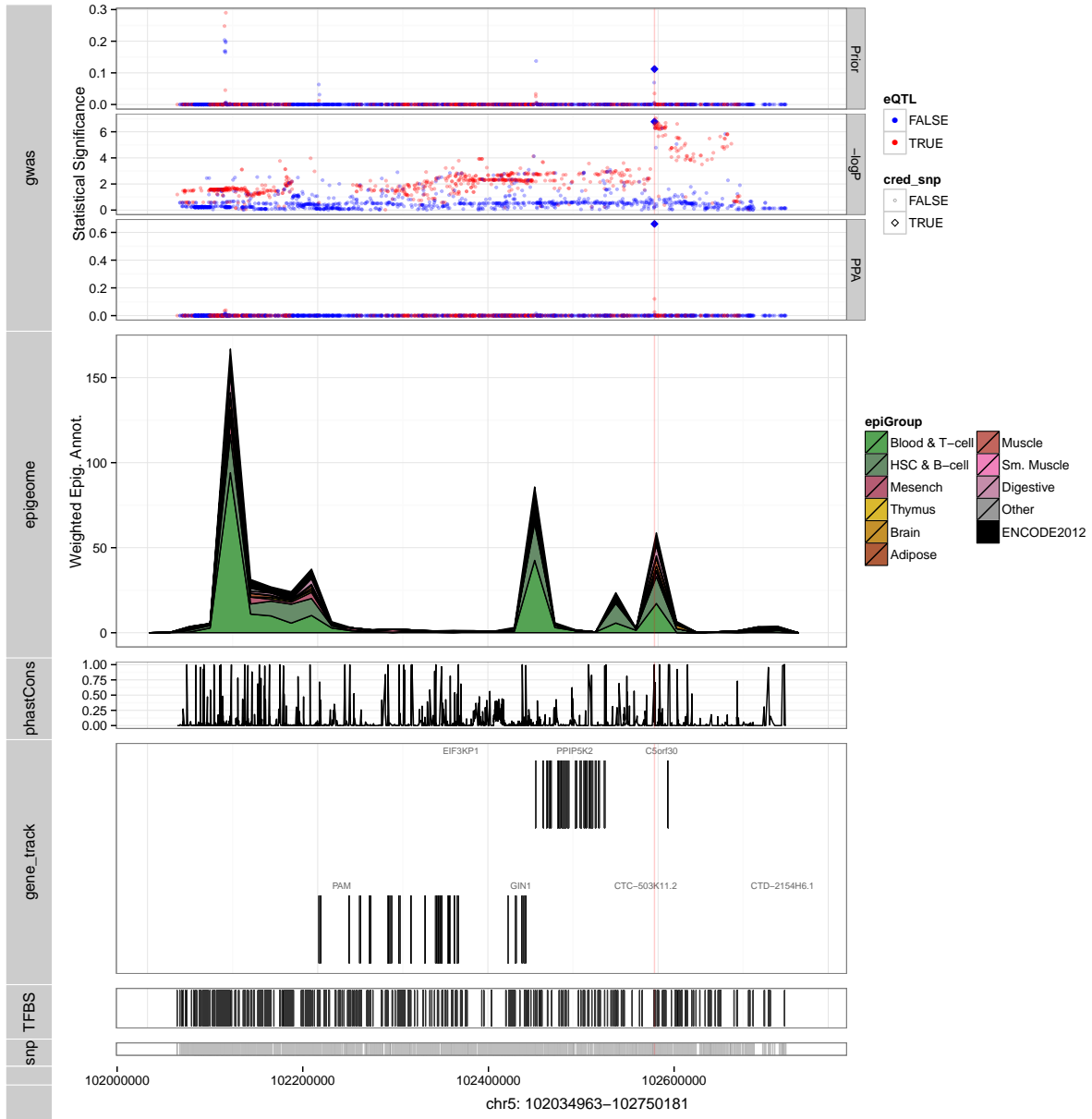
Rheumatoid Arthritis



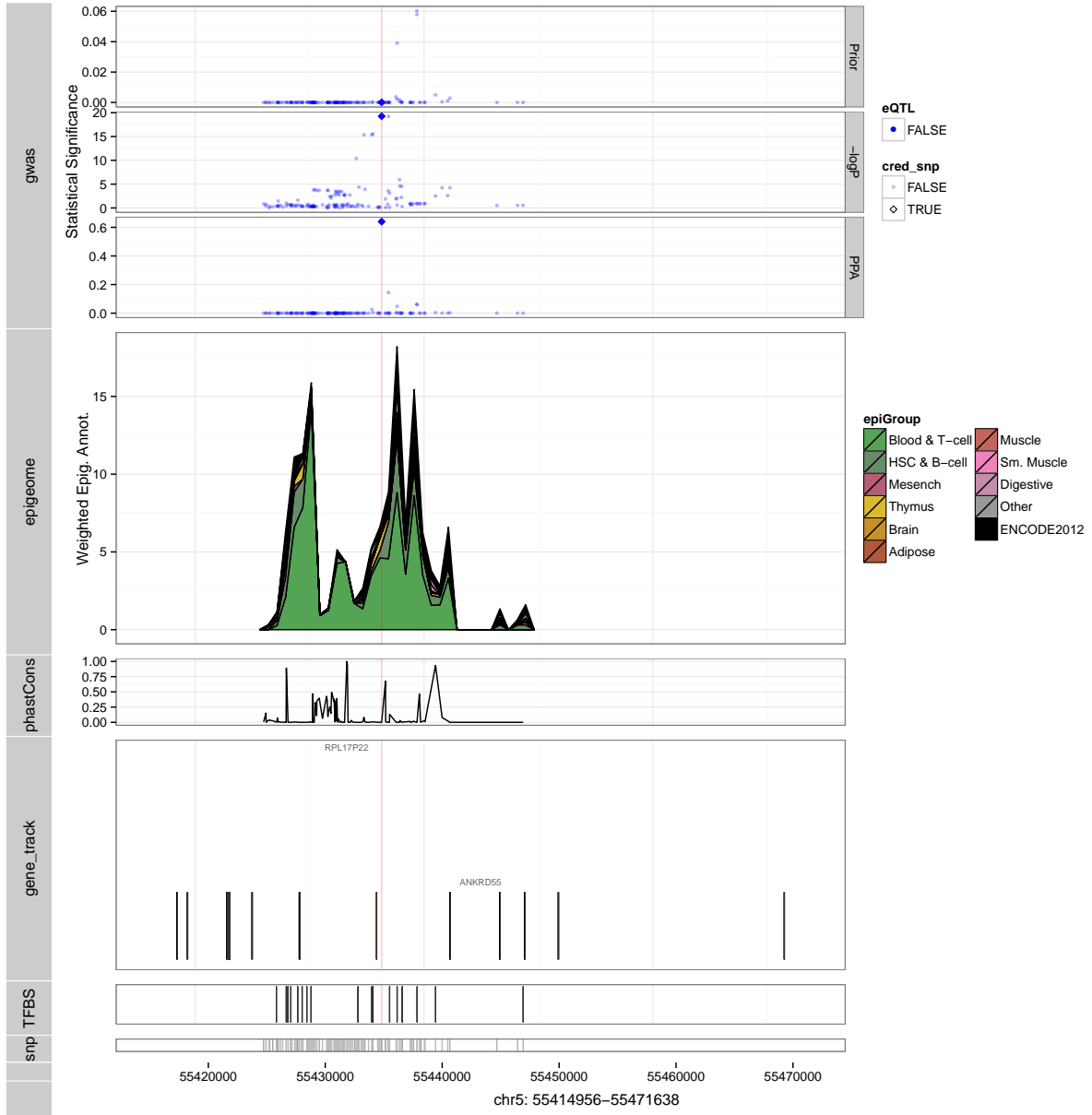
Rheumatoid Arthritis



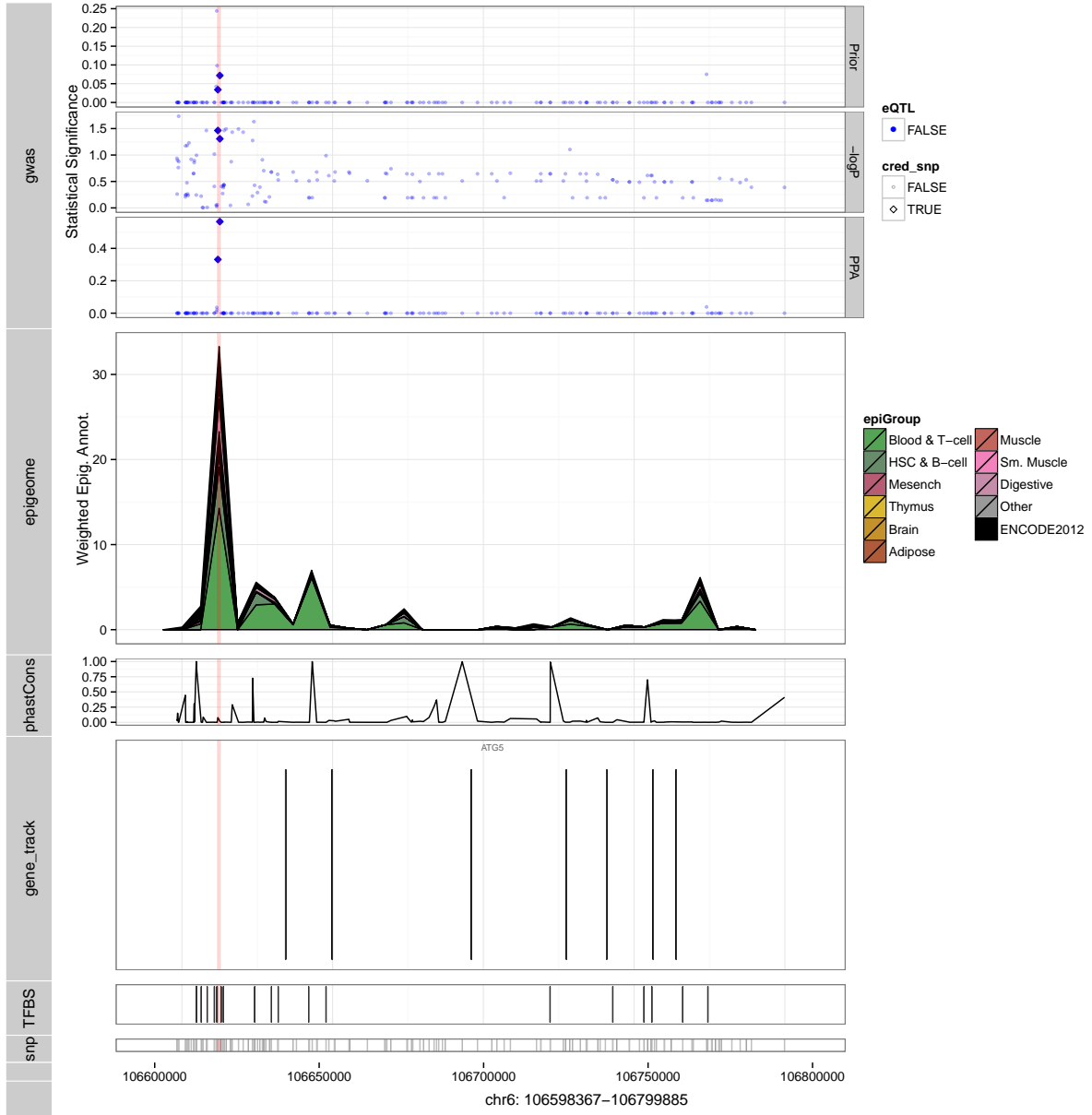
Rheumatoid Arthritis



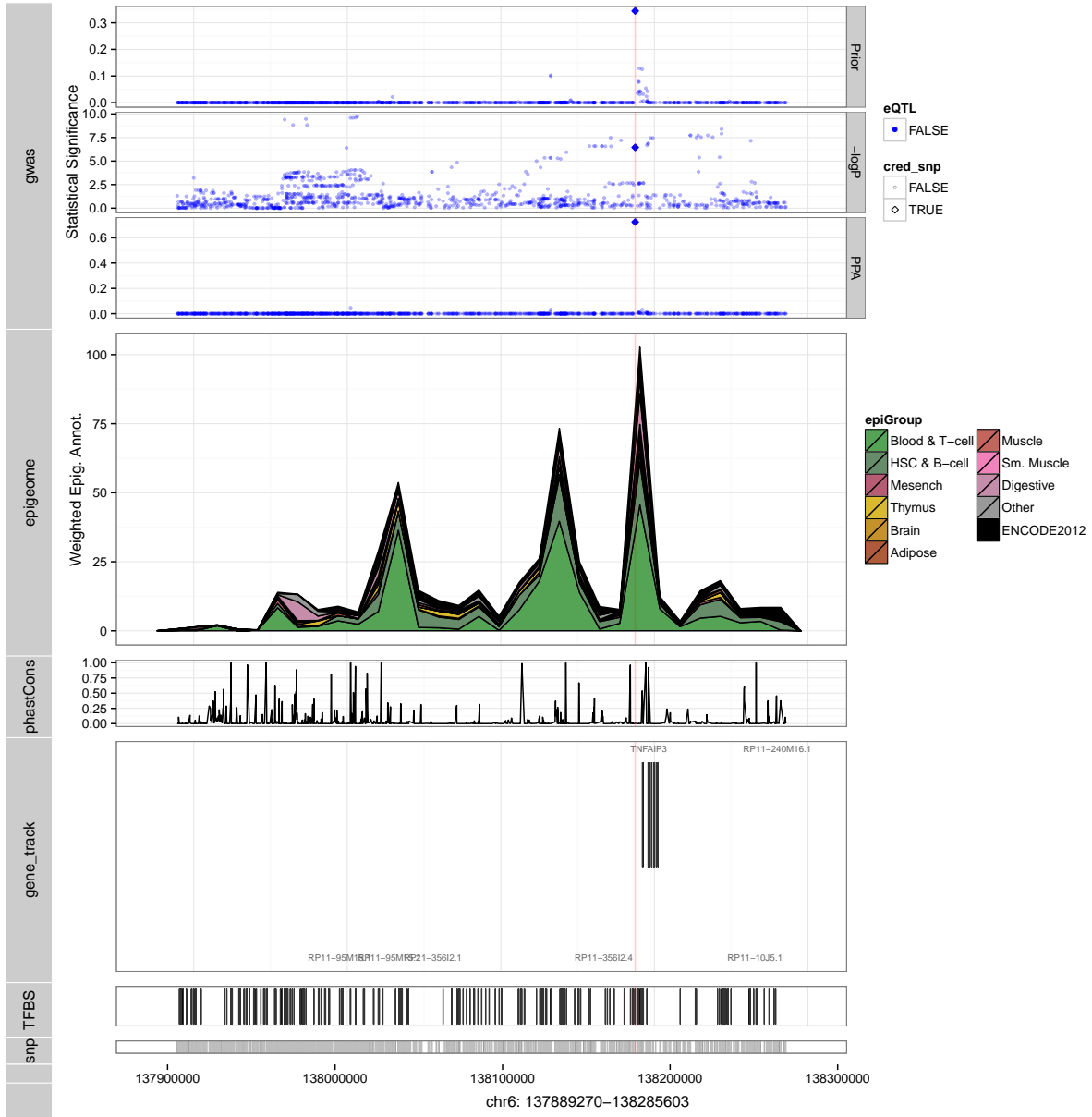
Rheumatoid Arthritis



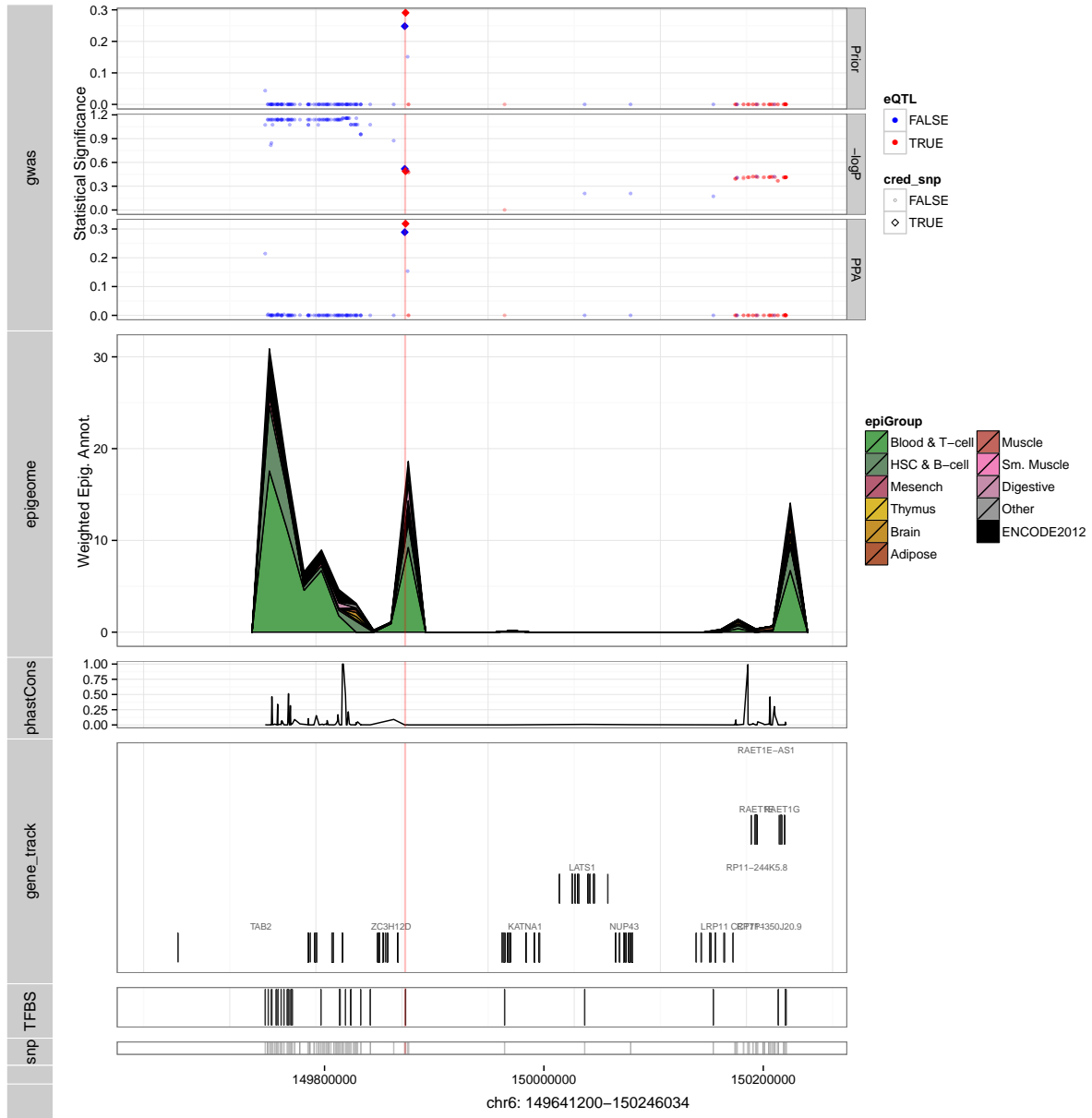
Rheumatoid Arthritis



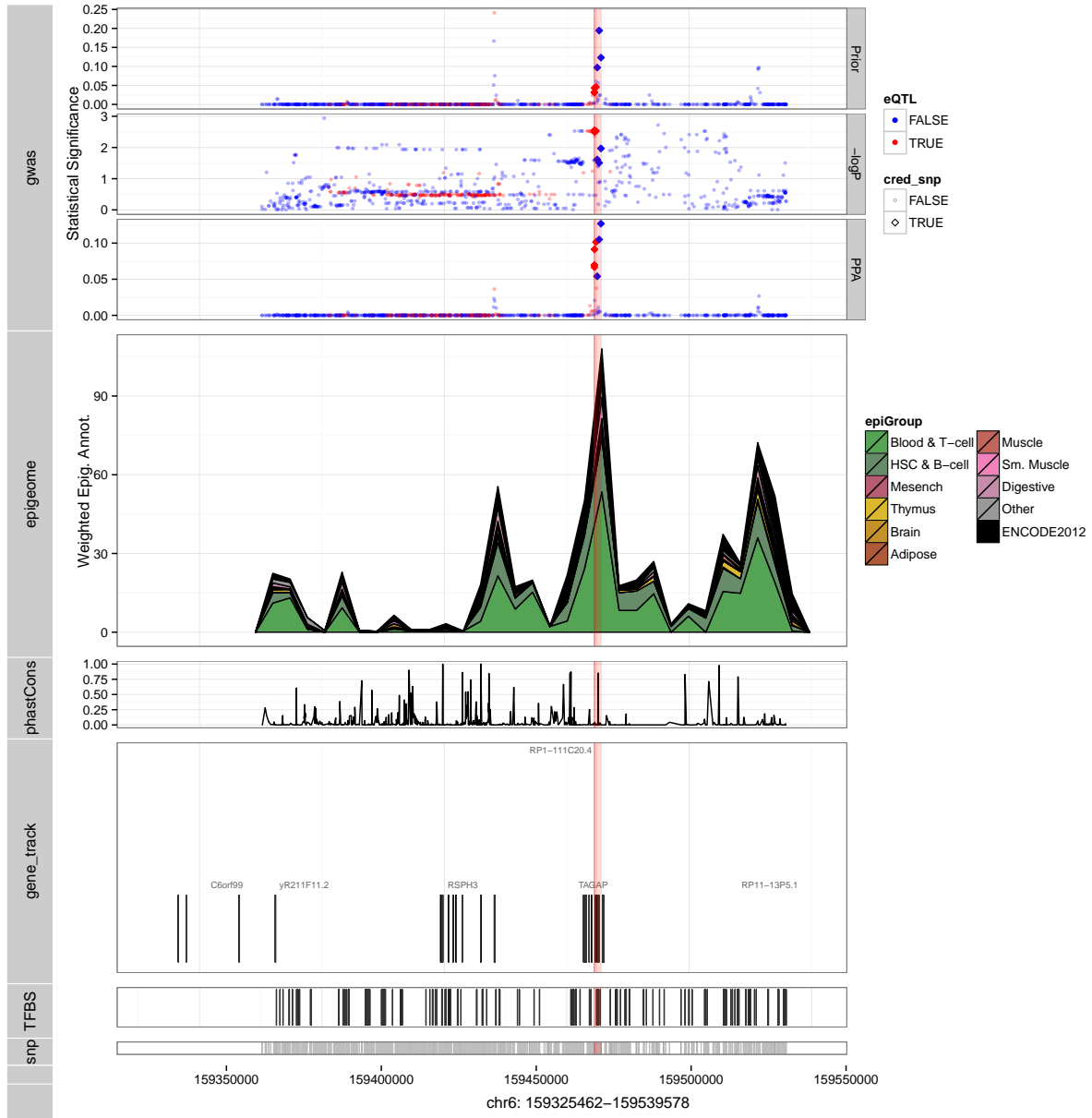
Rheumatoid Arthritis



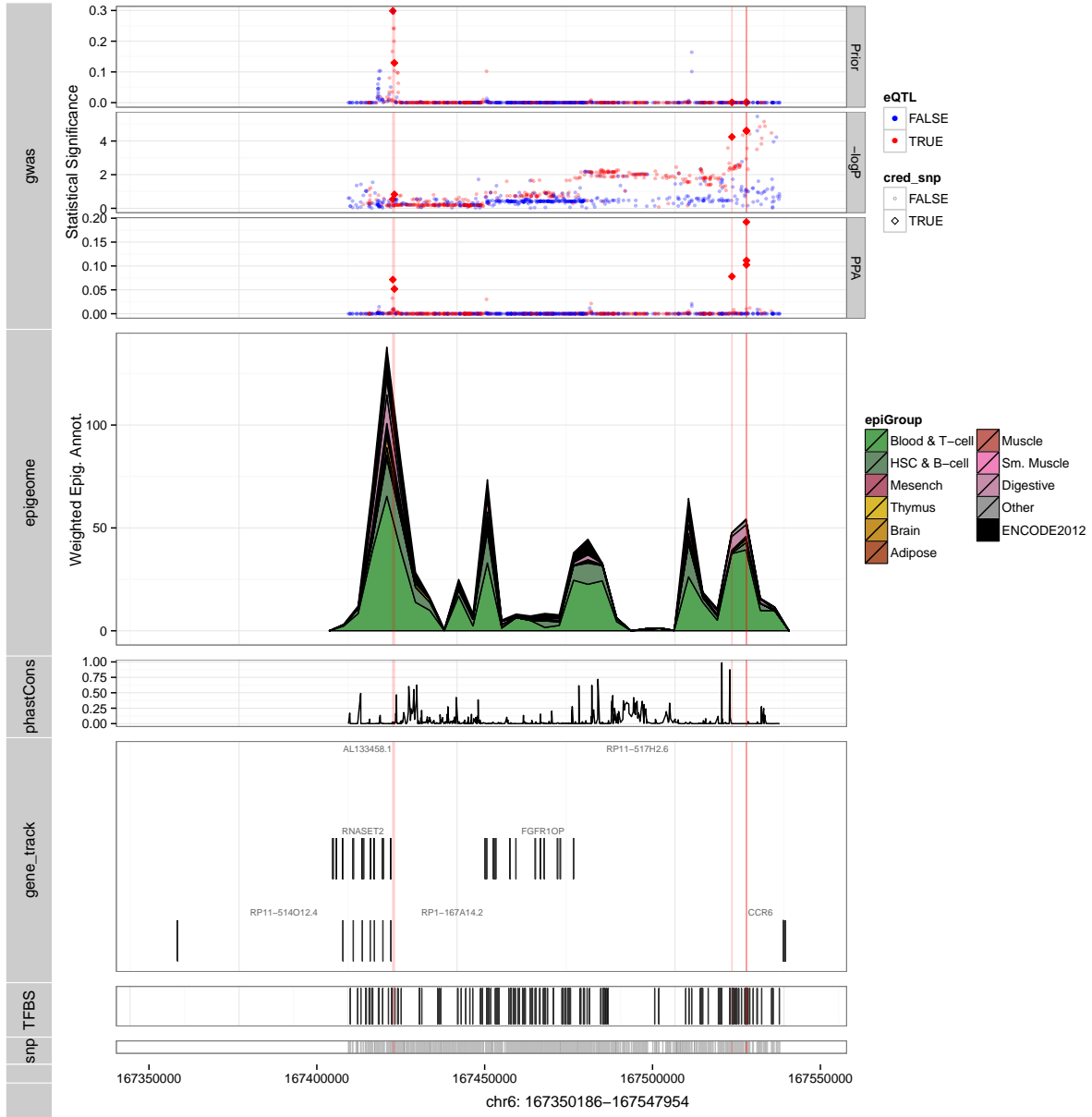
Rheumatoid Arthritis



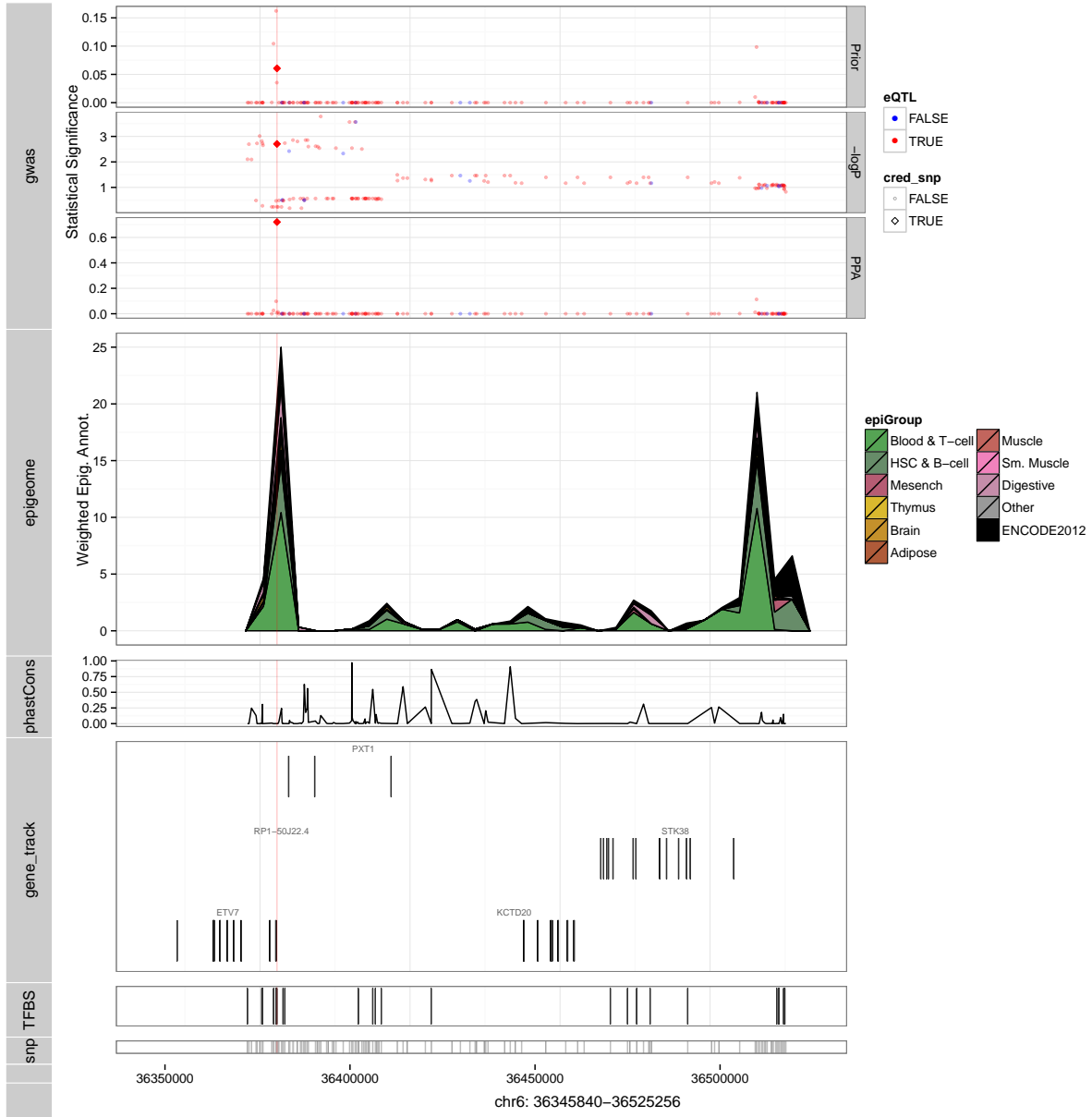
Rheumatoid Arthritis



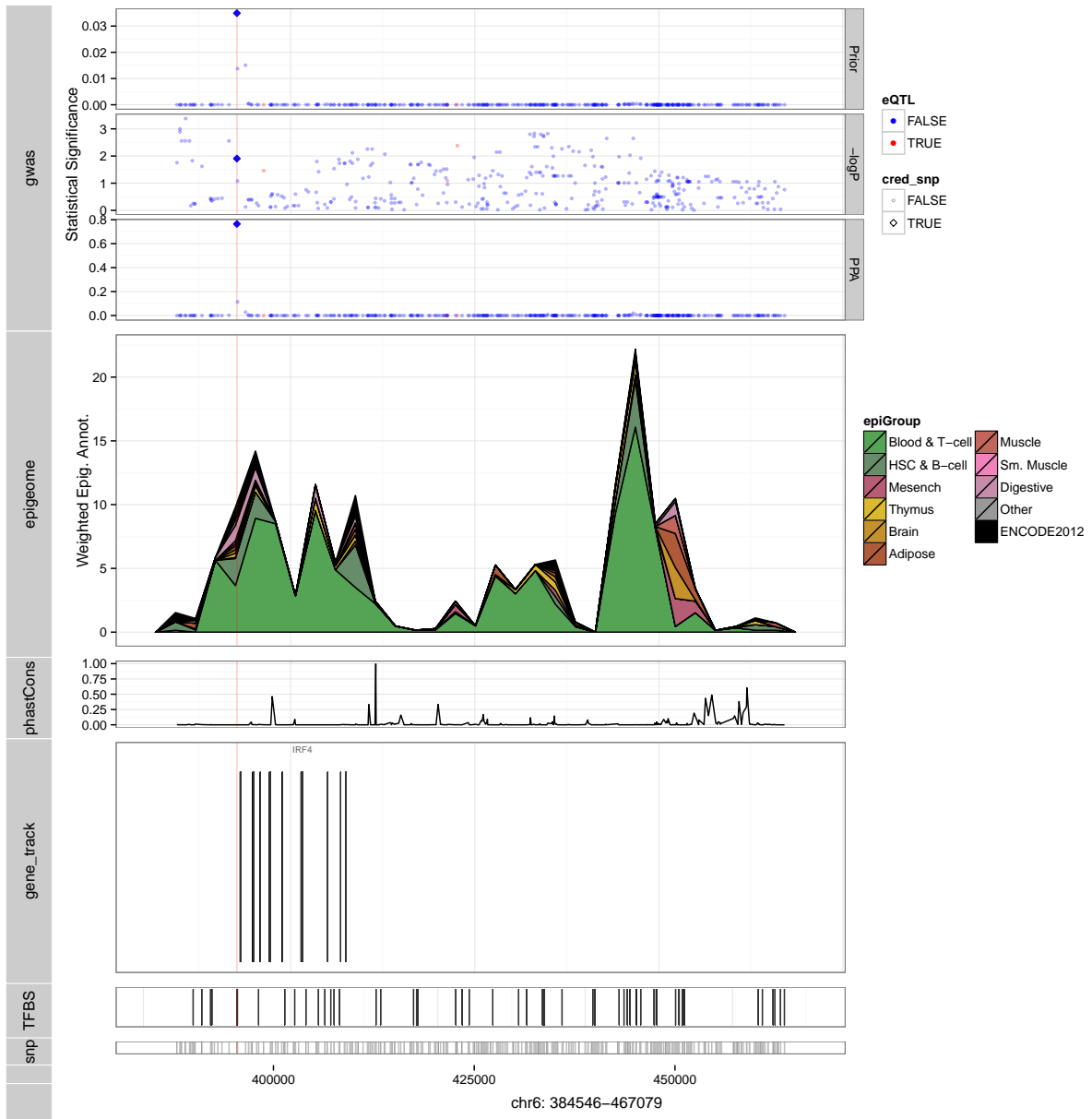
Rheumatoid Arthritis



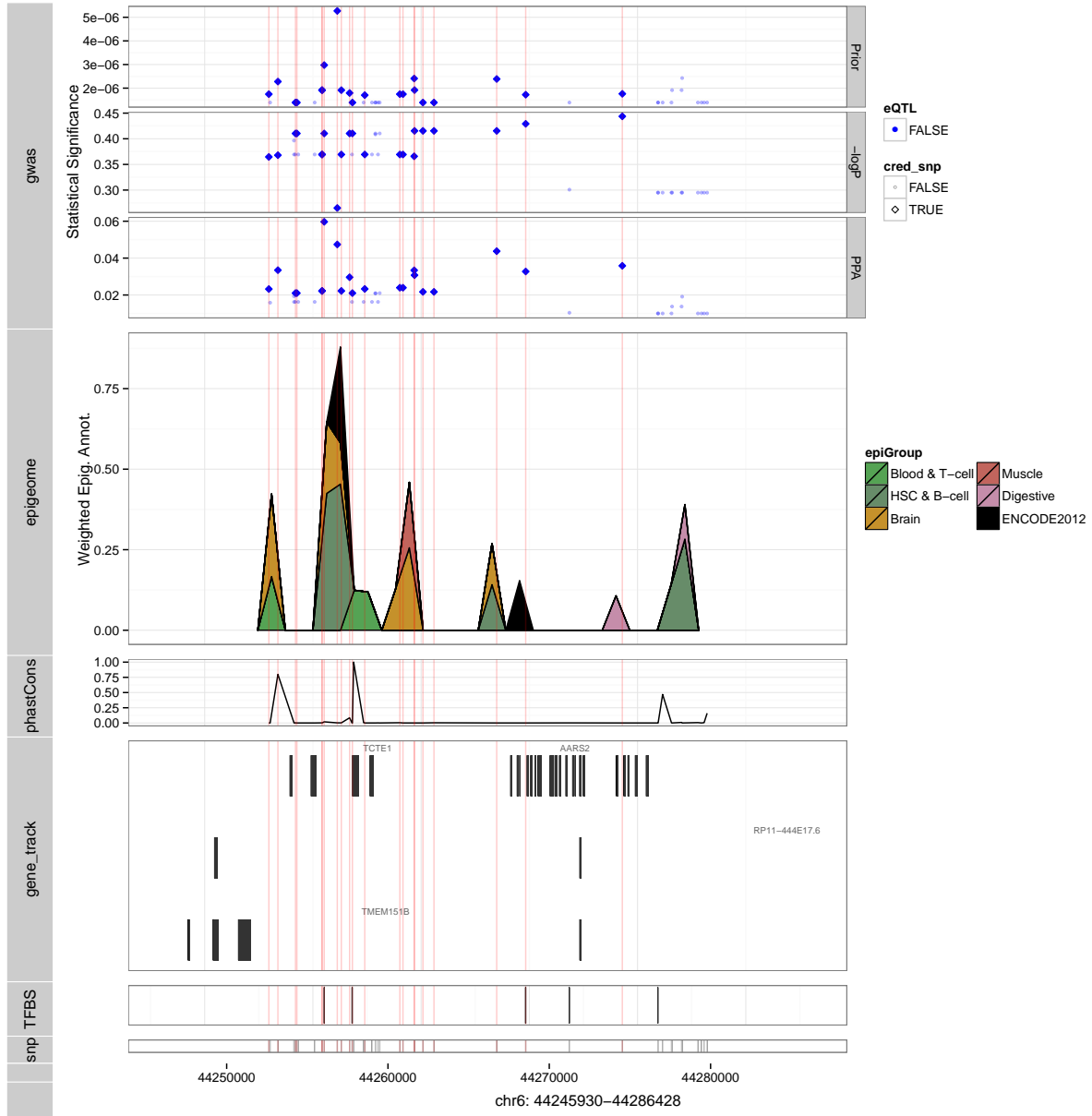
Rheumatoid Arthritis



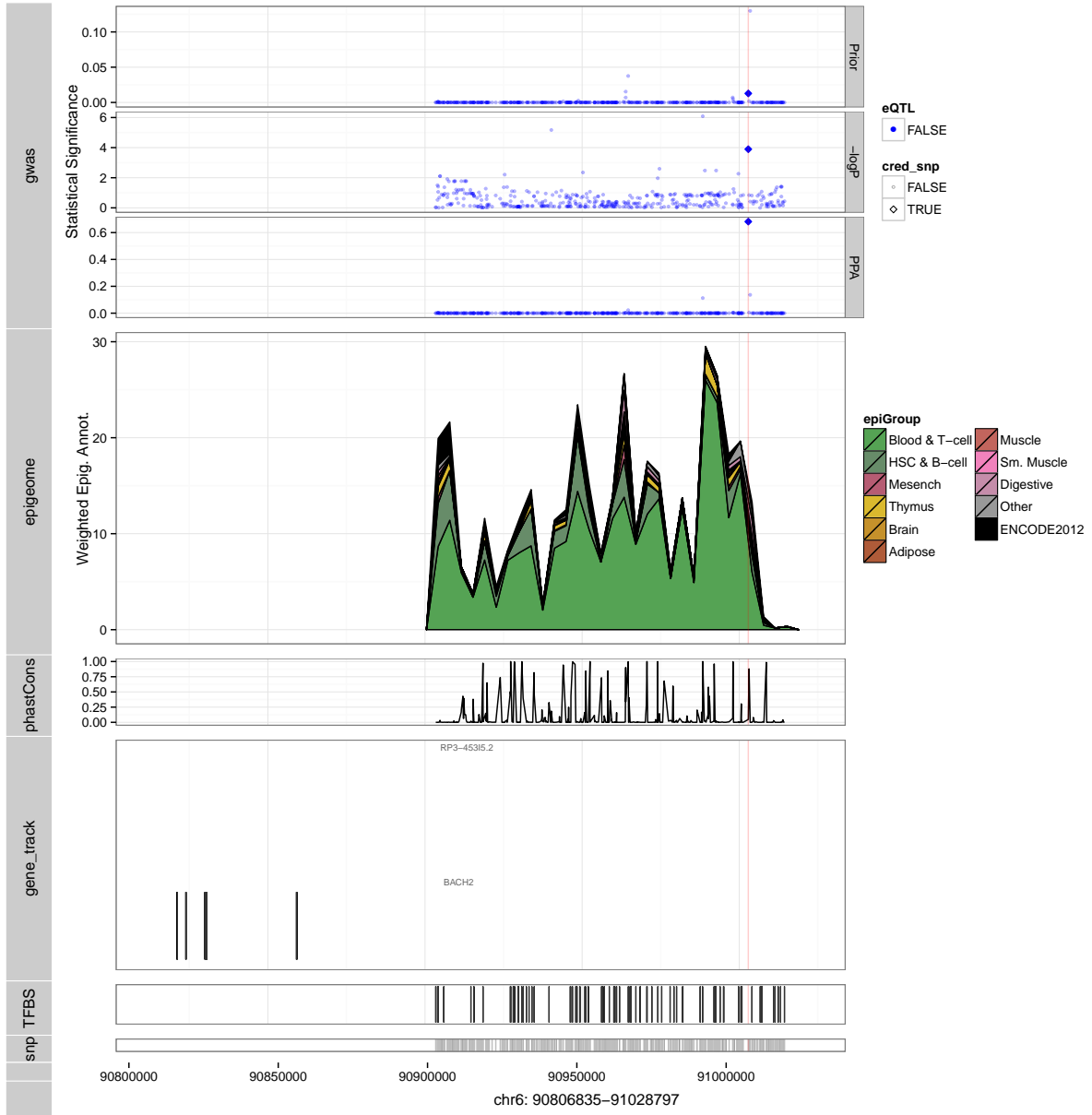
Rheumatoid Arthritis



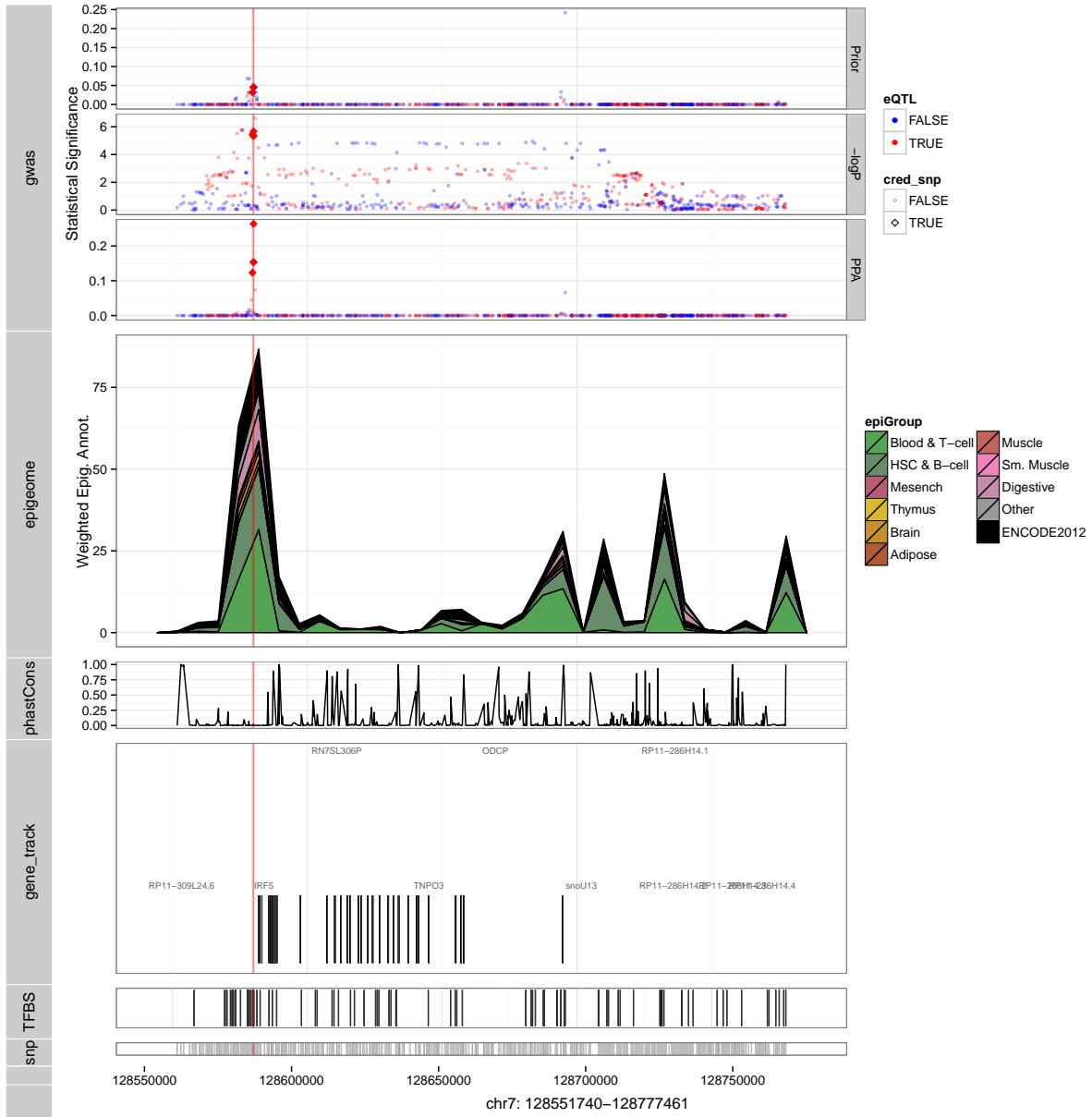
Rheumatoid Arthritis



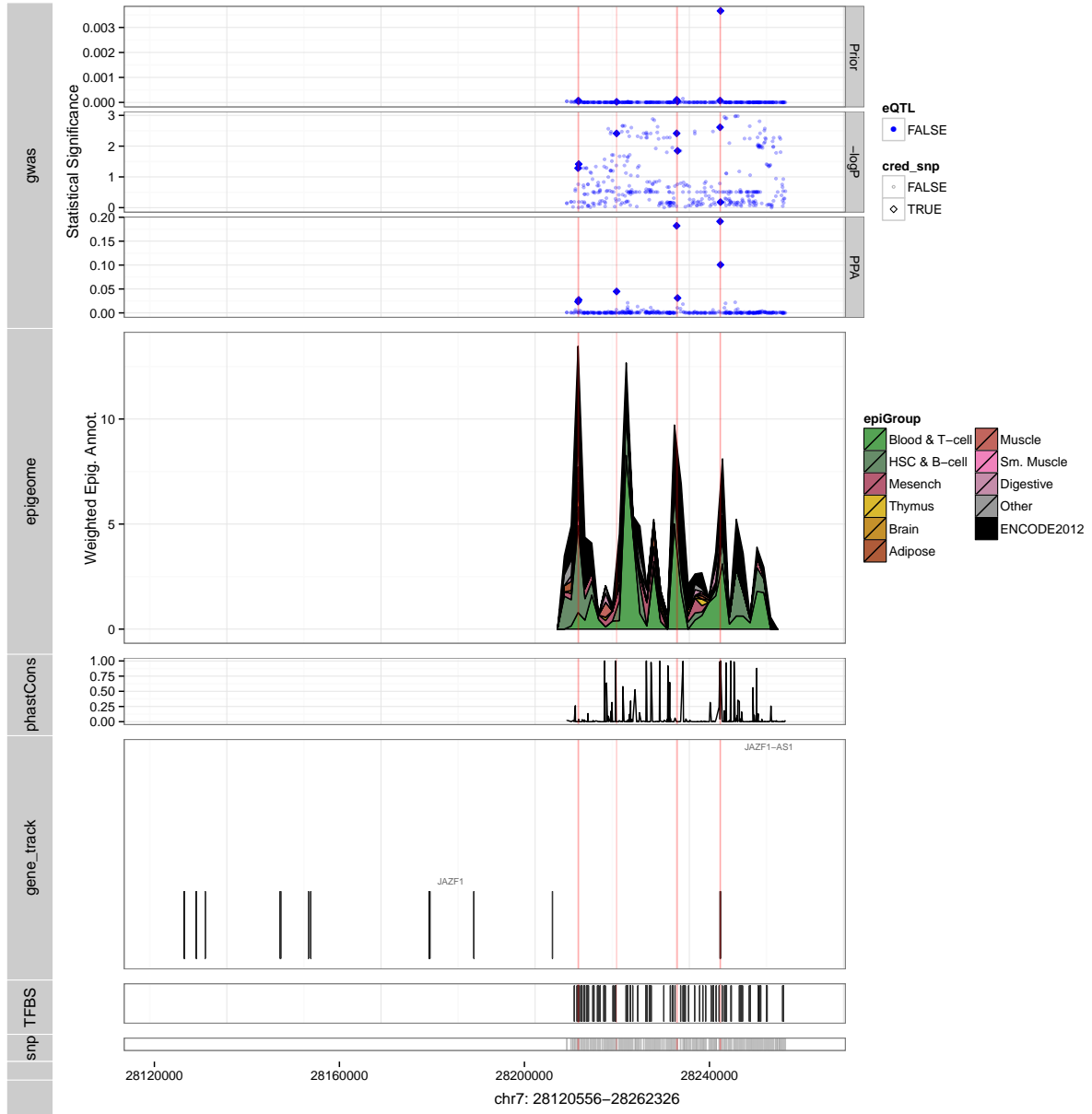
Rheumatoid Arthritis



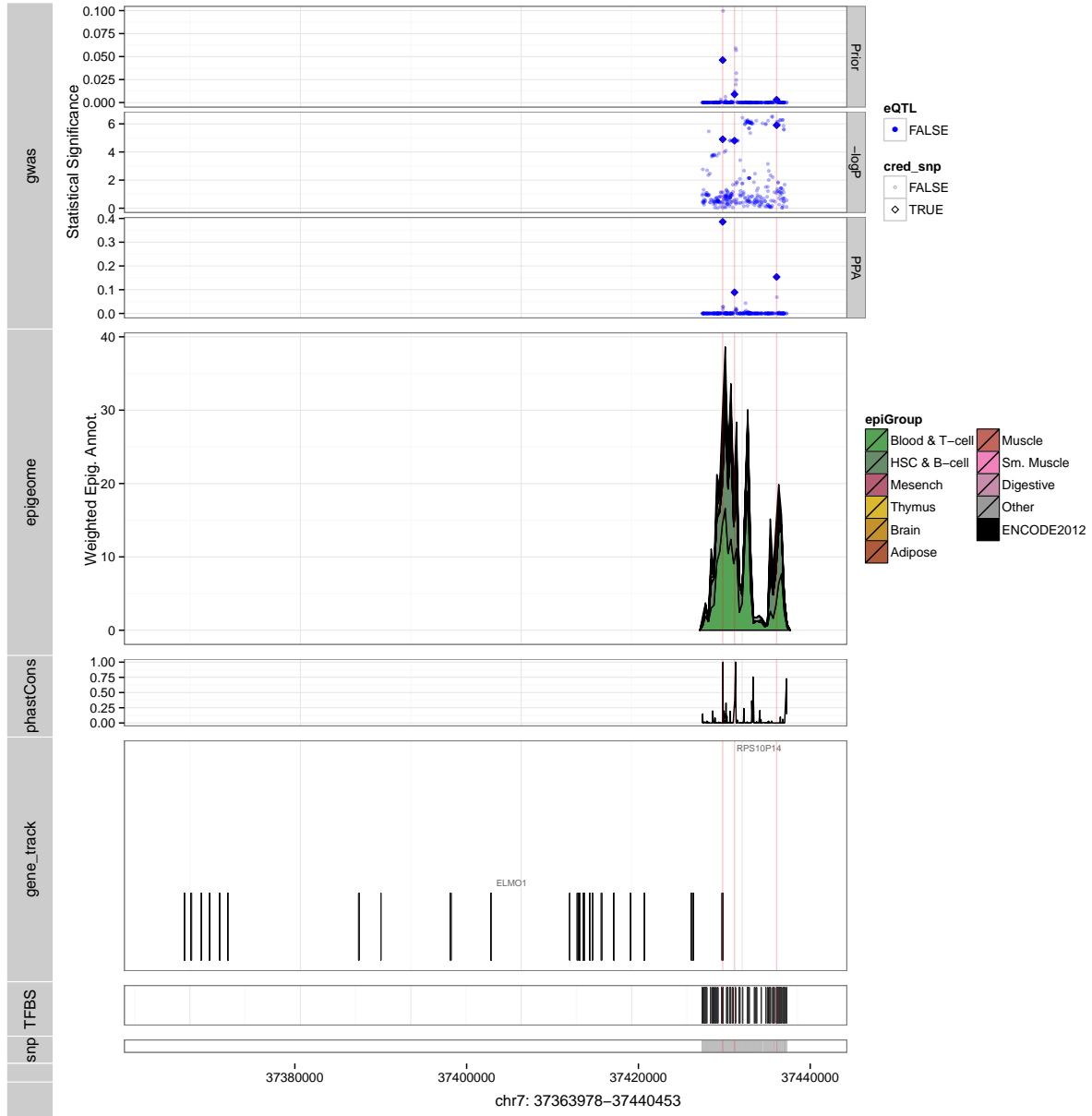
Rheumatoid Arthritis



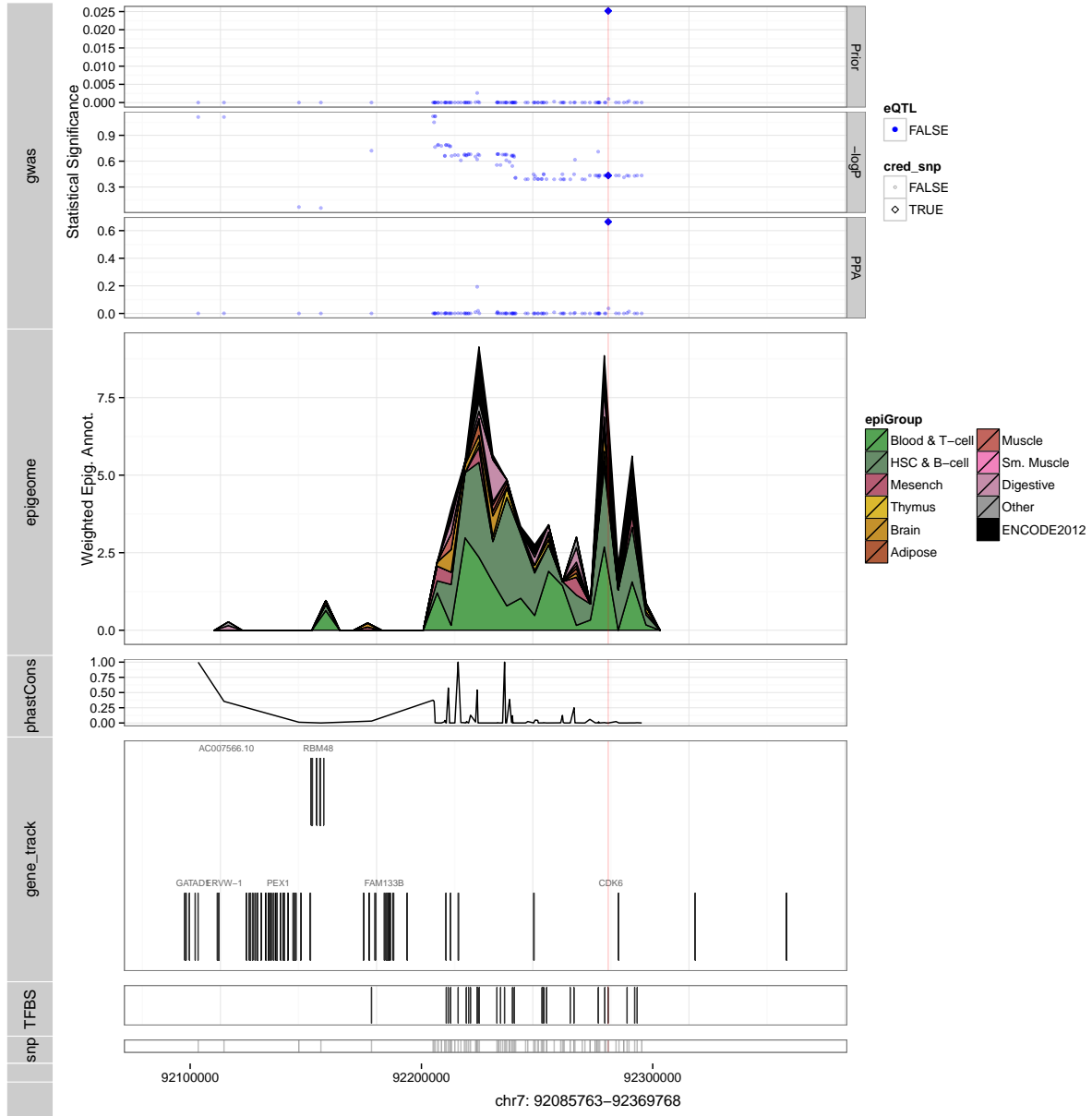
Rheumatoid Arthritis



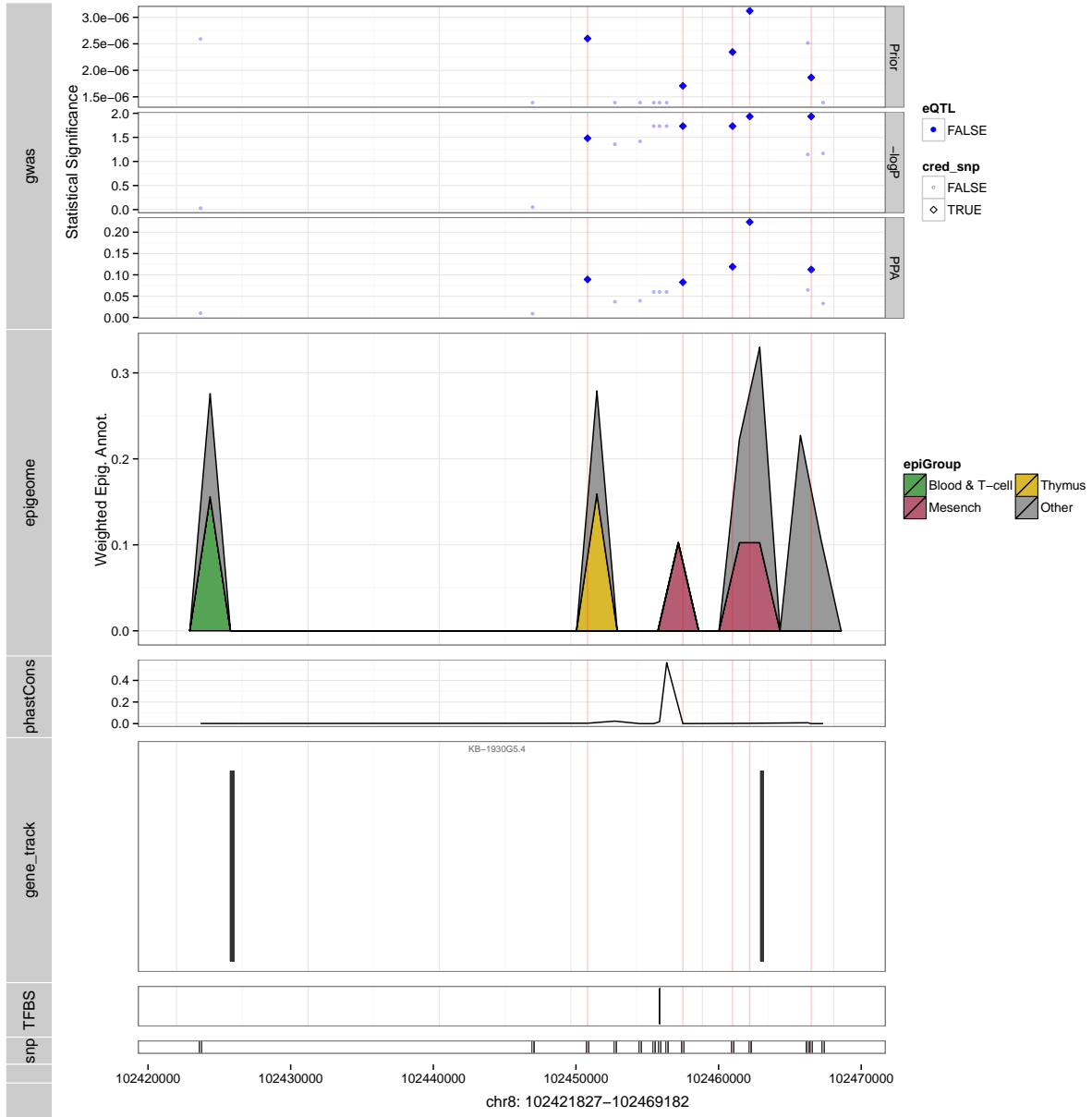
Rheumatoid Arthritis



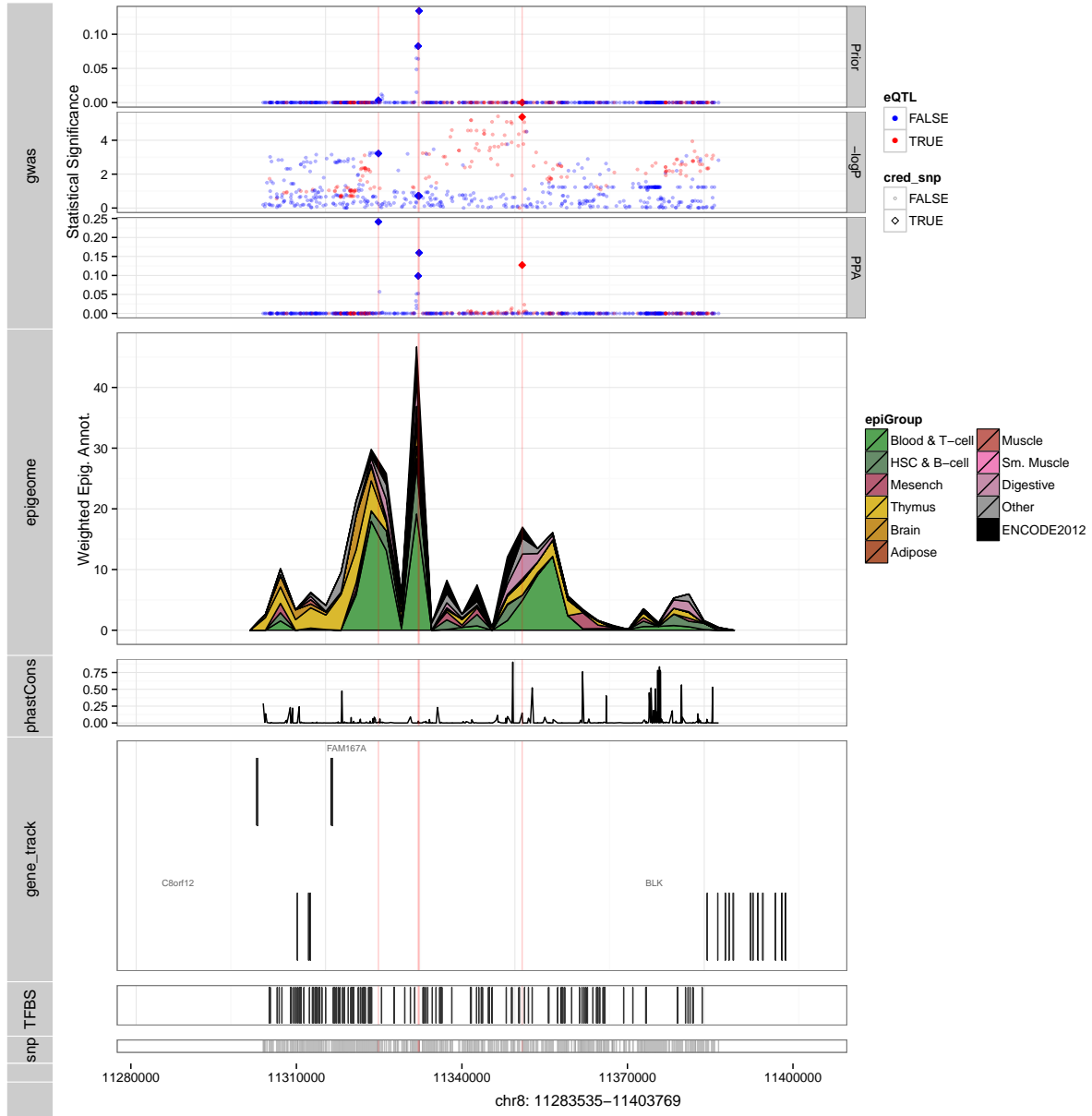
Rheumatoid Arthritis



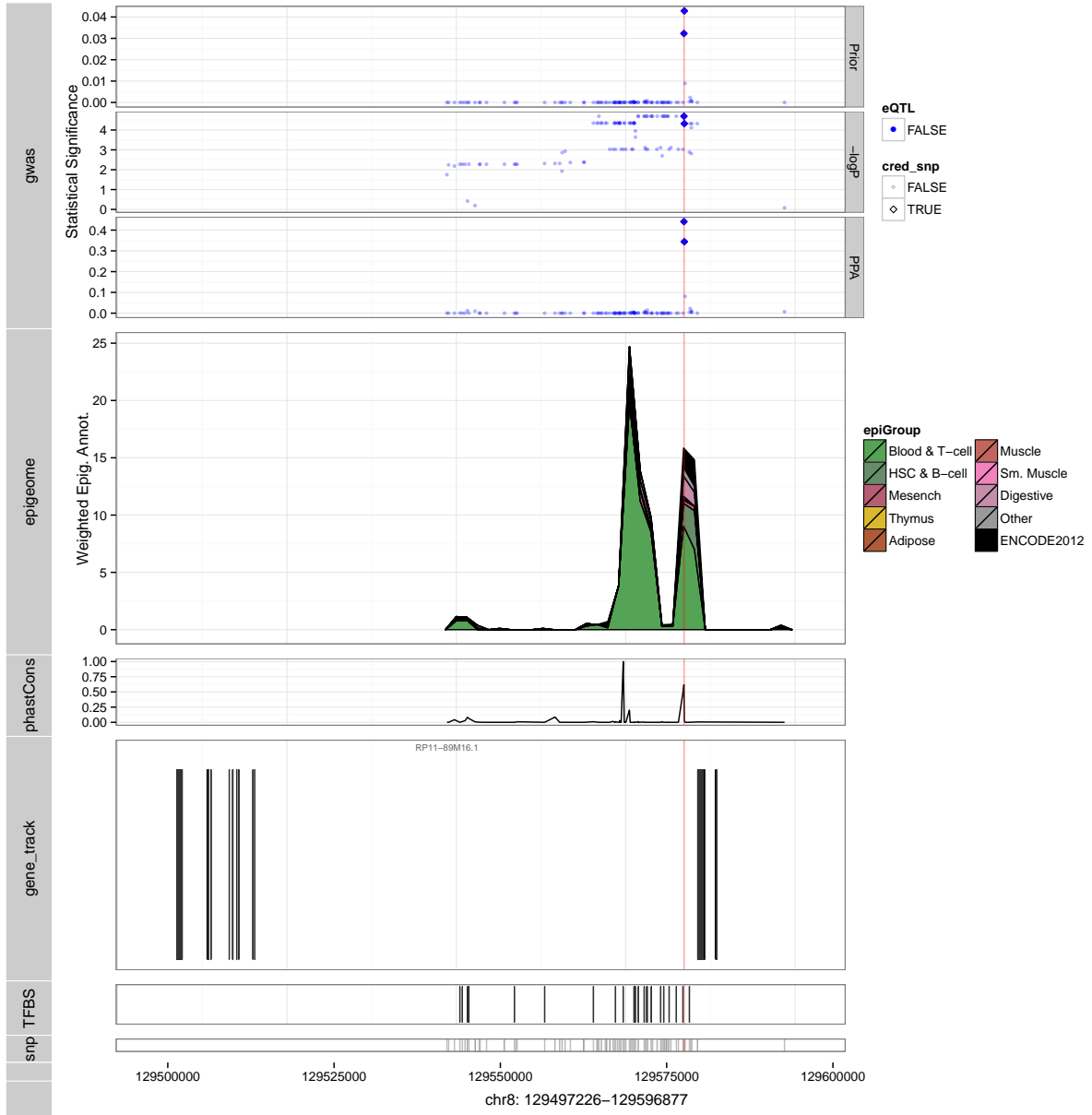
Rheumatoid Arthritis



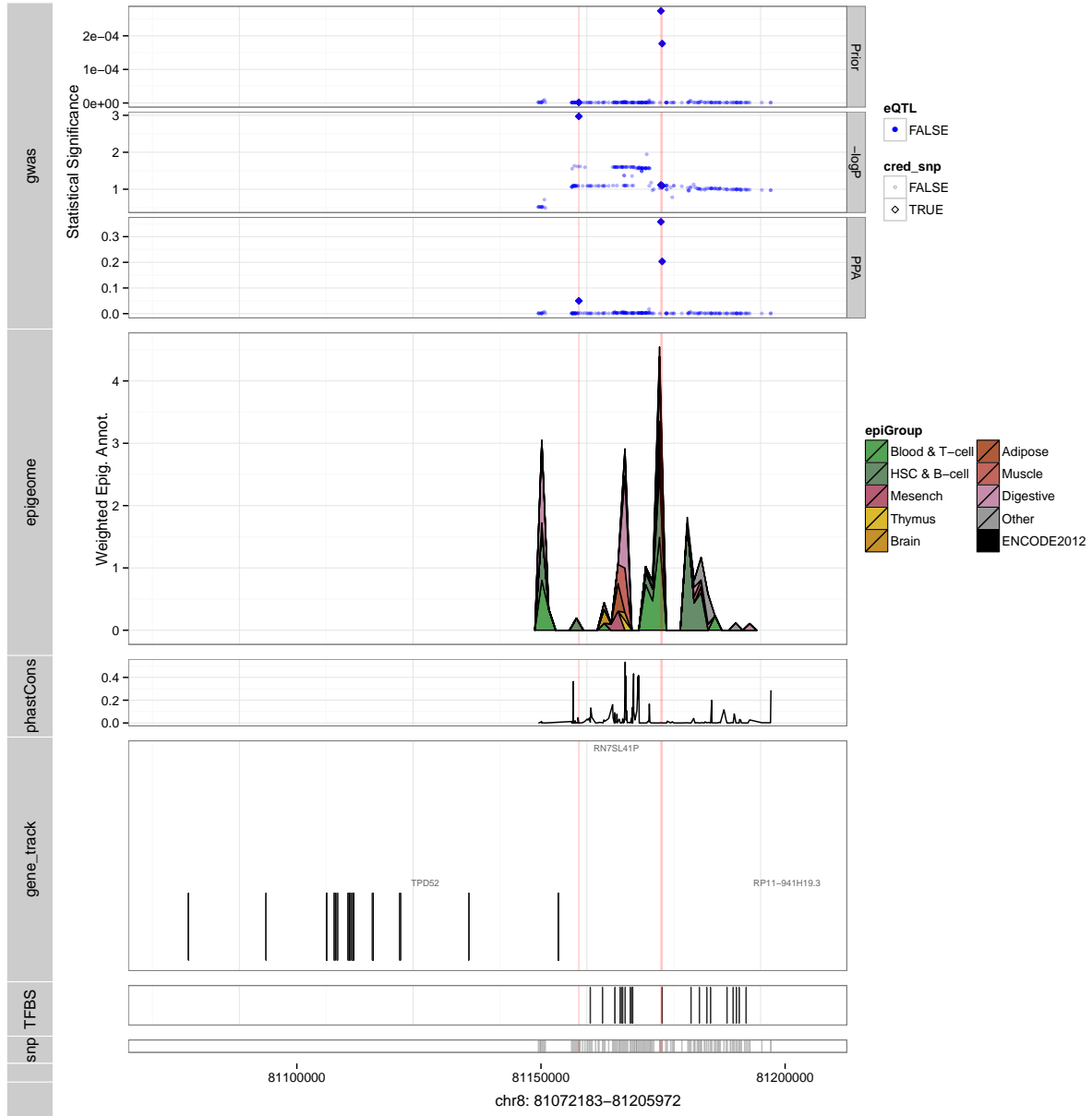
Rheumatoid Arthritis



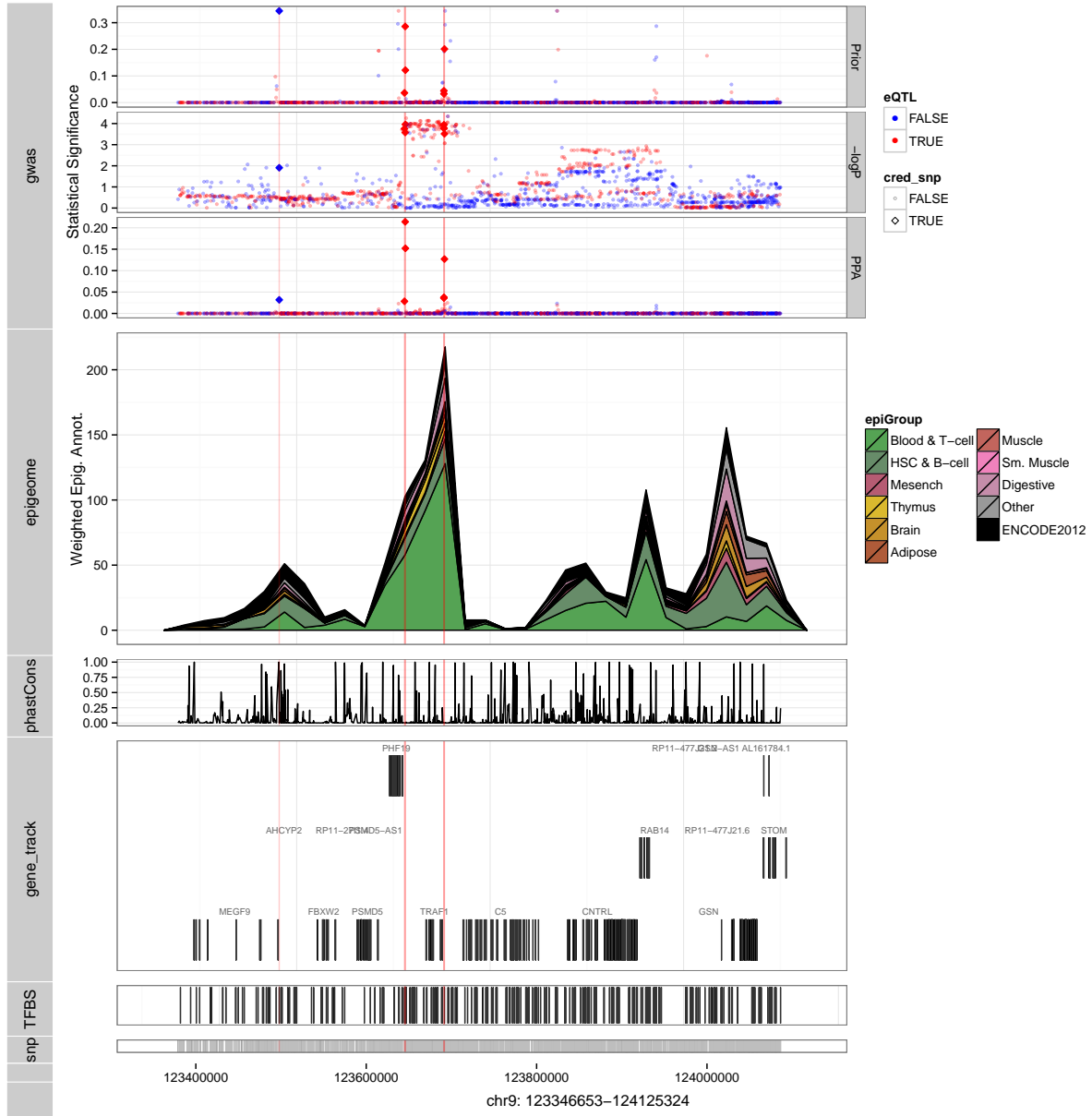
Rheumatoid Arthritis



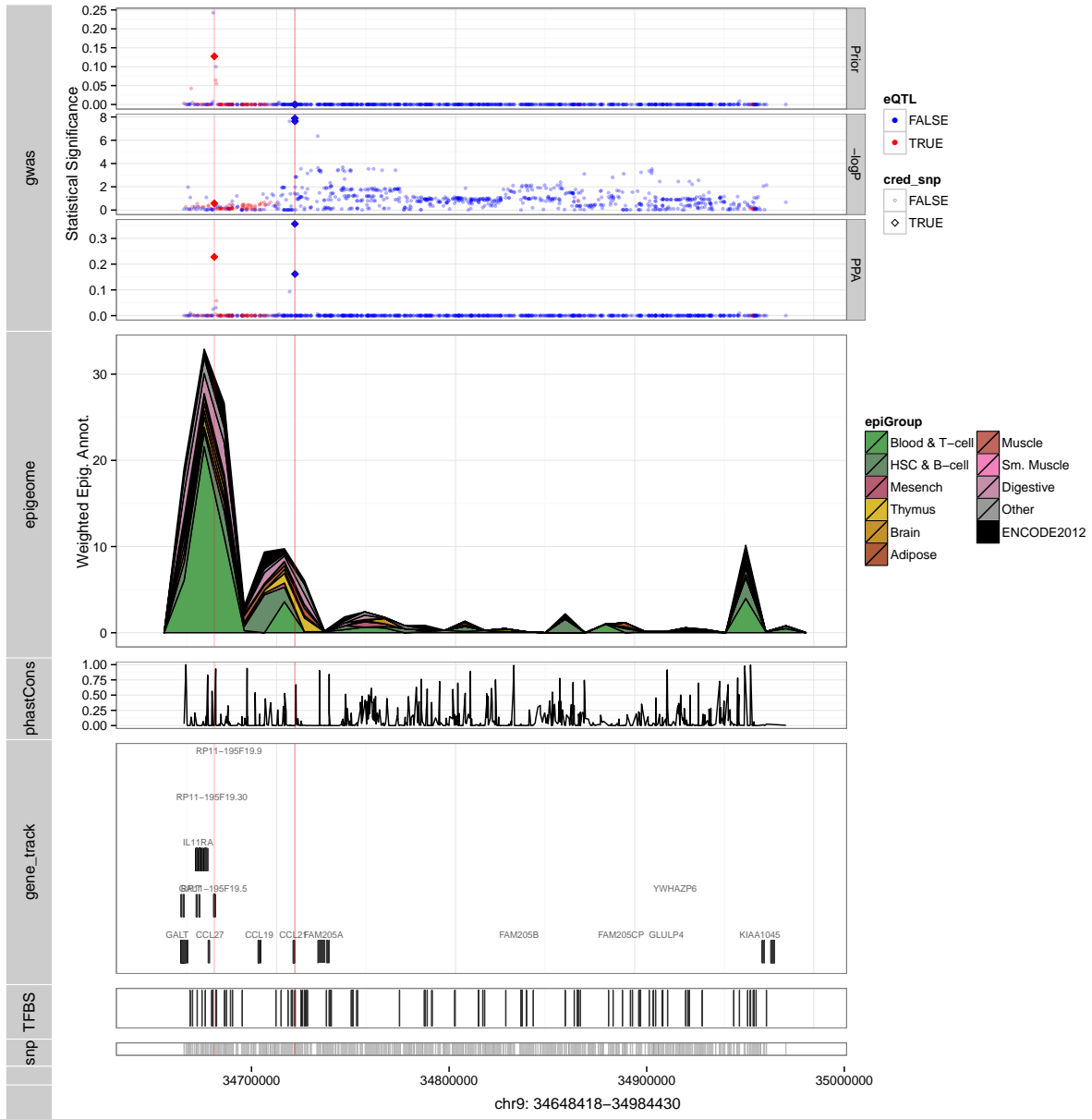
Rheumatoid Arthritis



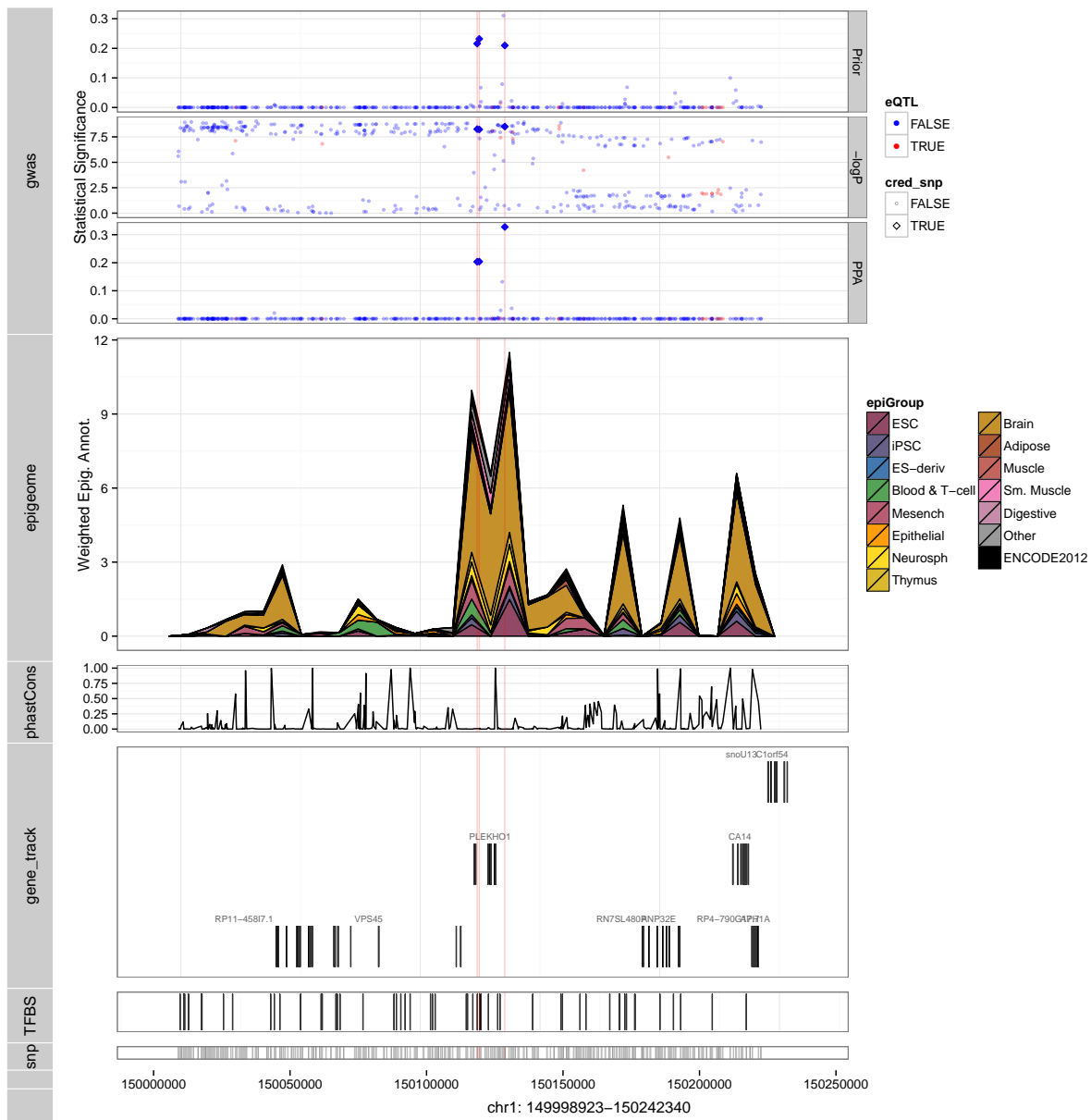
Rheumatoid Arthritis



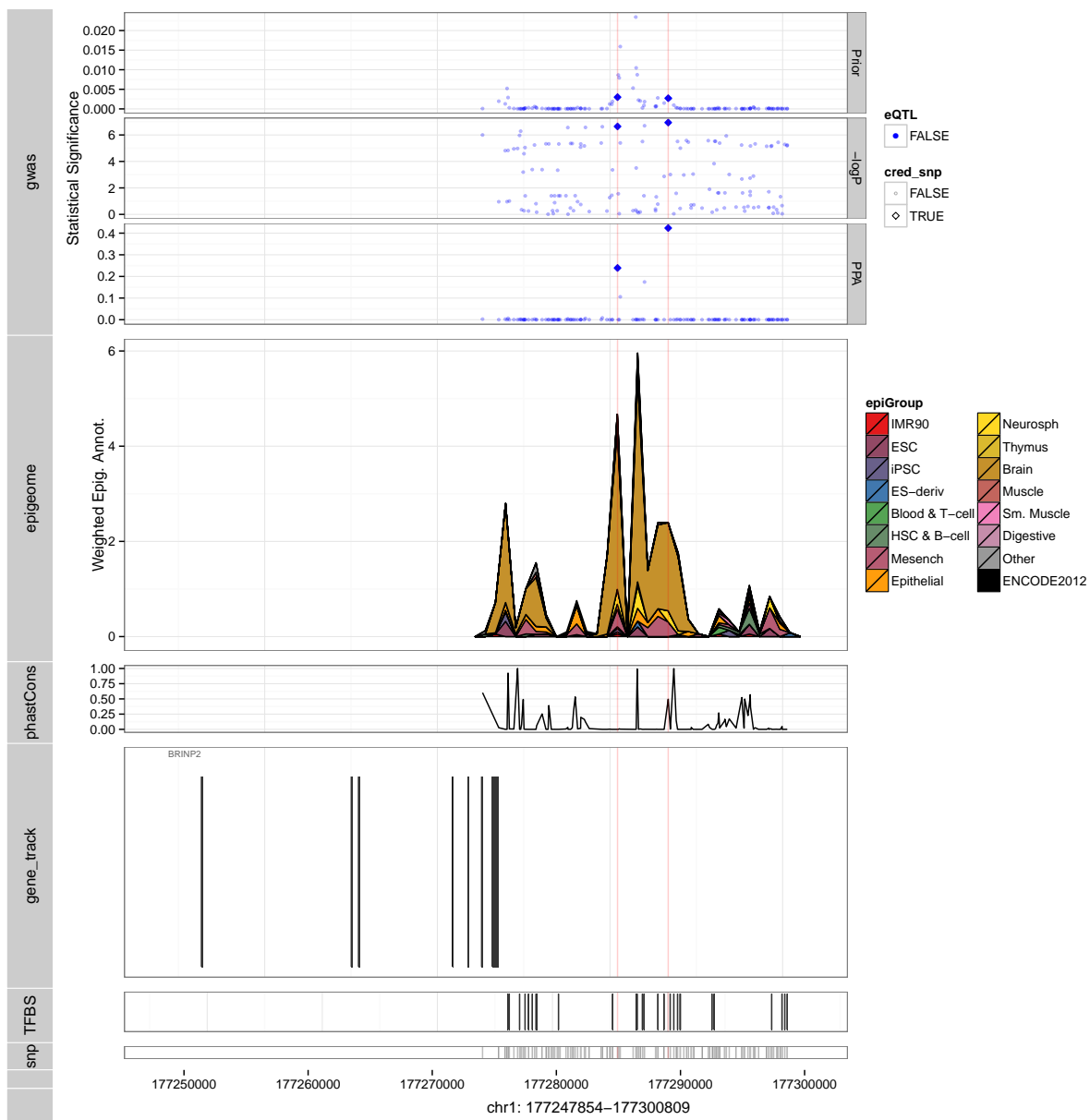
Rheumatoid Arthritis



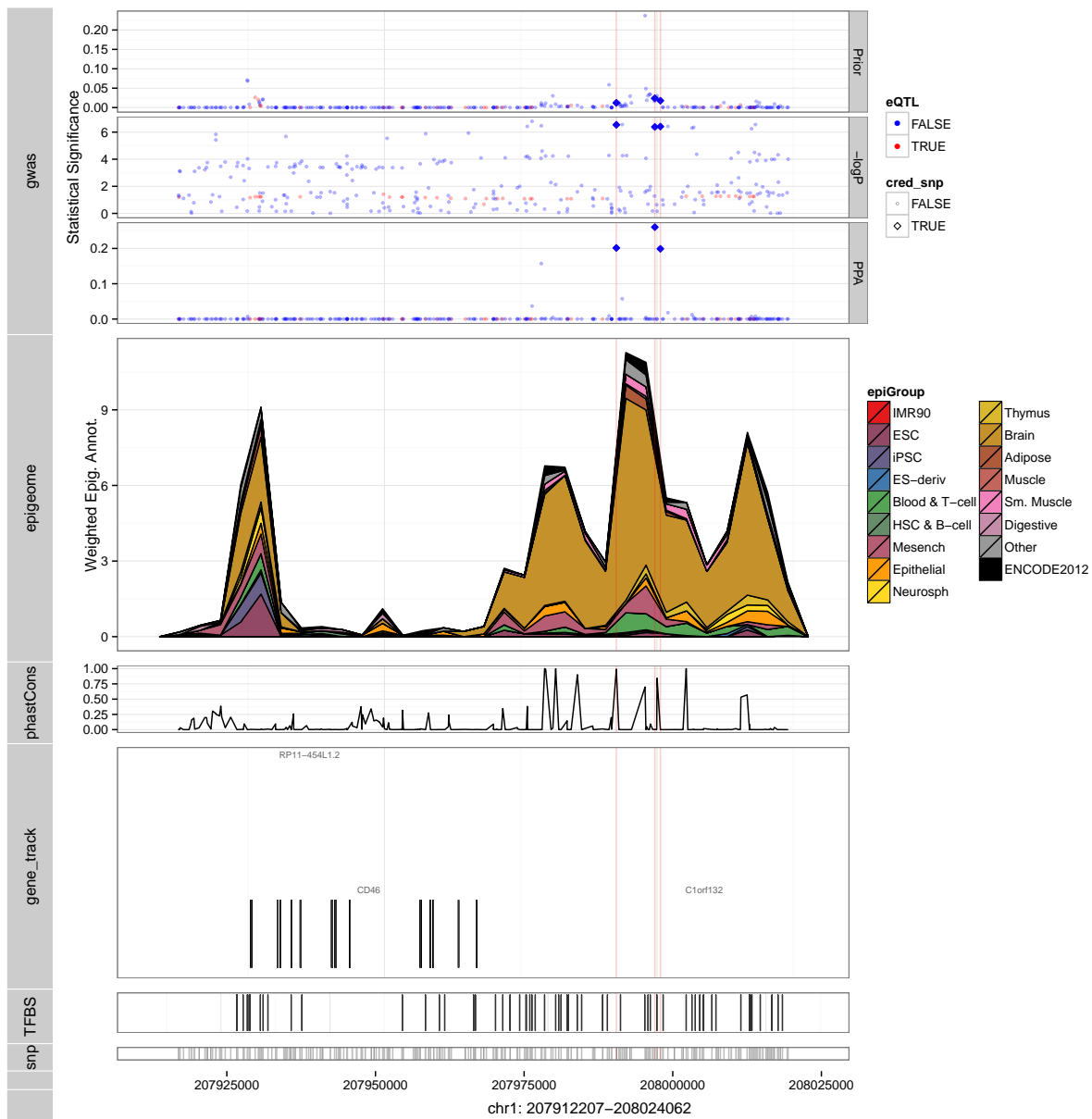
Schizophrenia



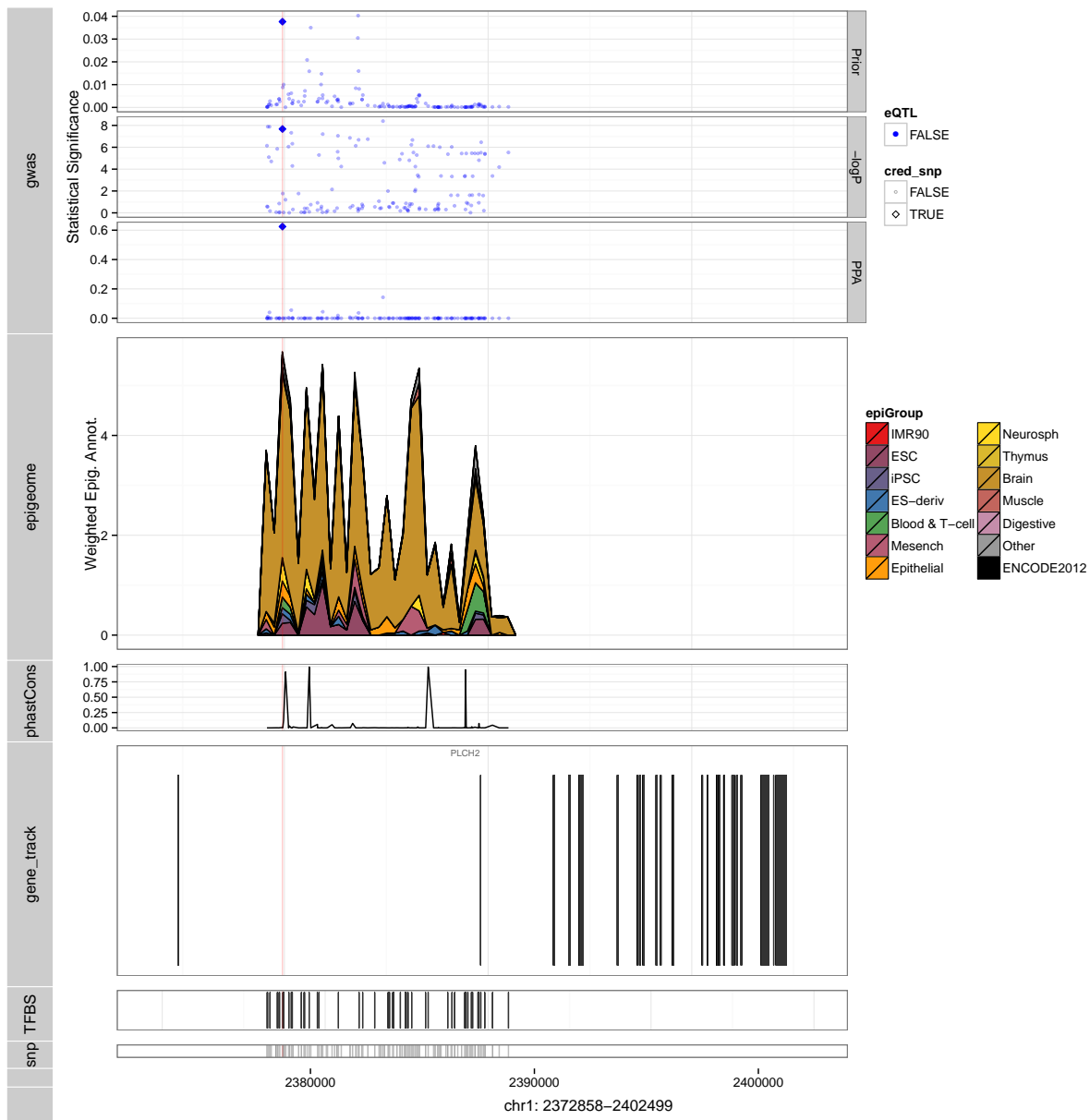
Schizophrenia



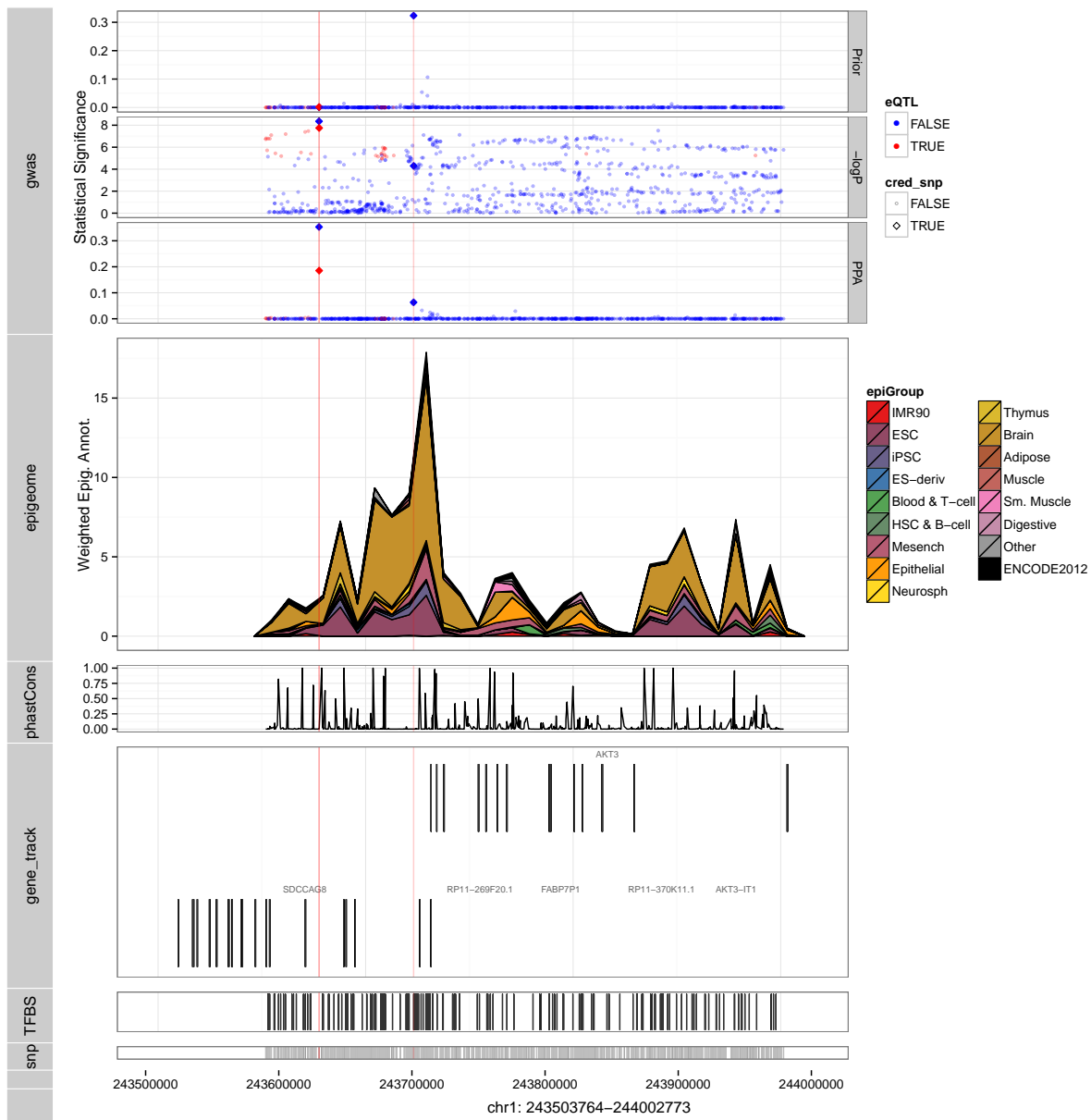
Schizophrenia



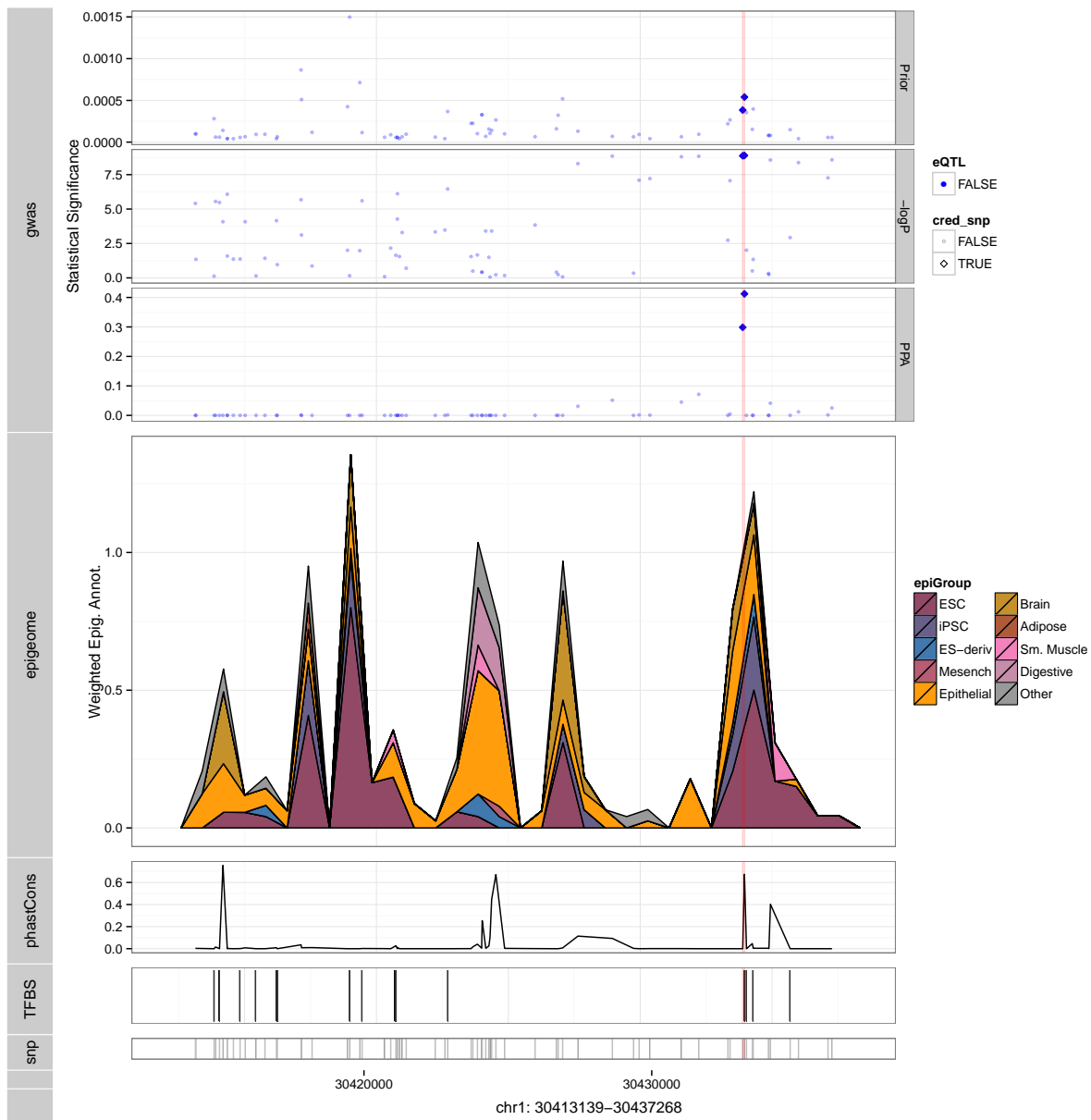
Schizophrenia



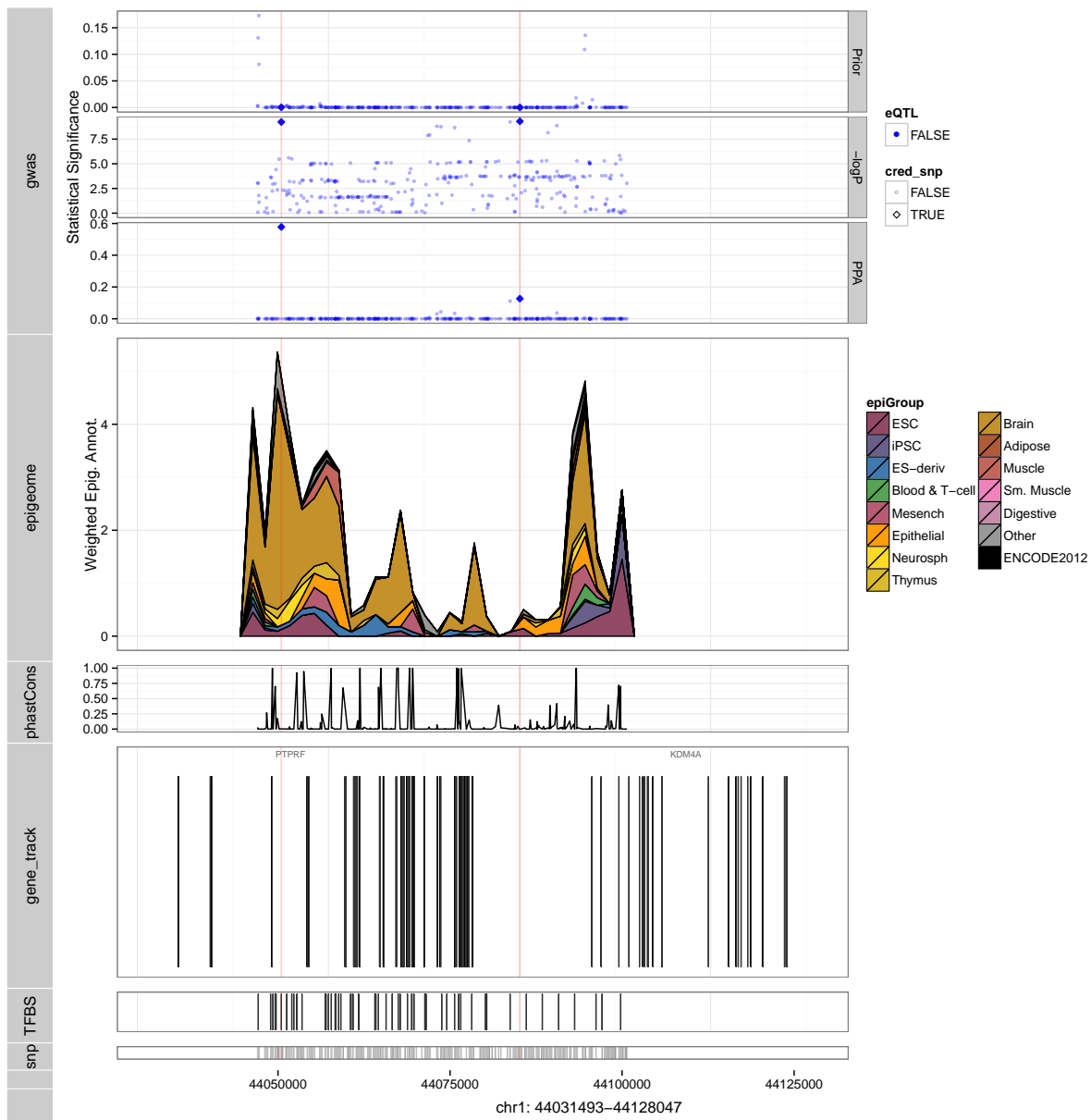
Schizophrenia



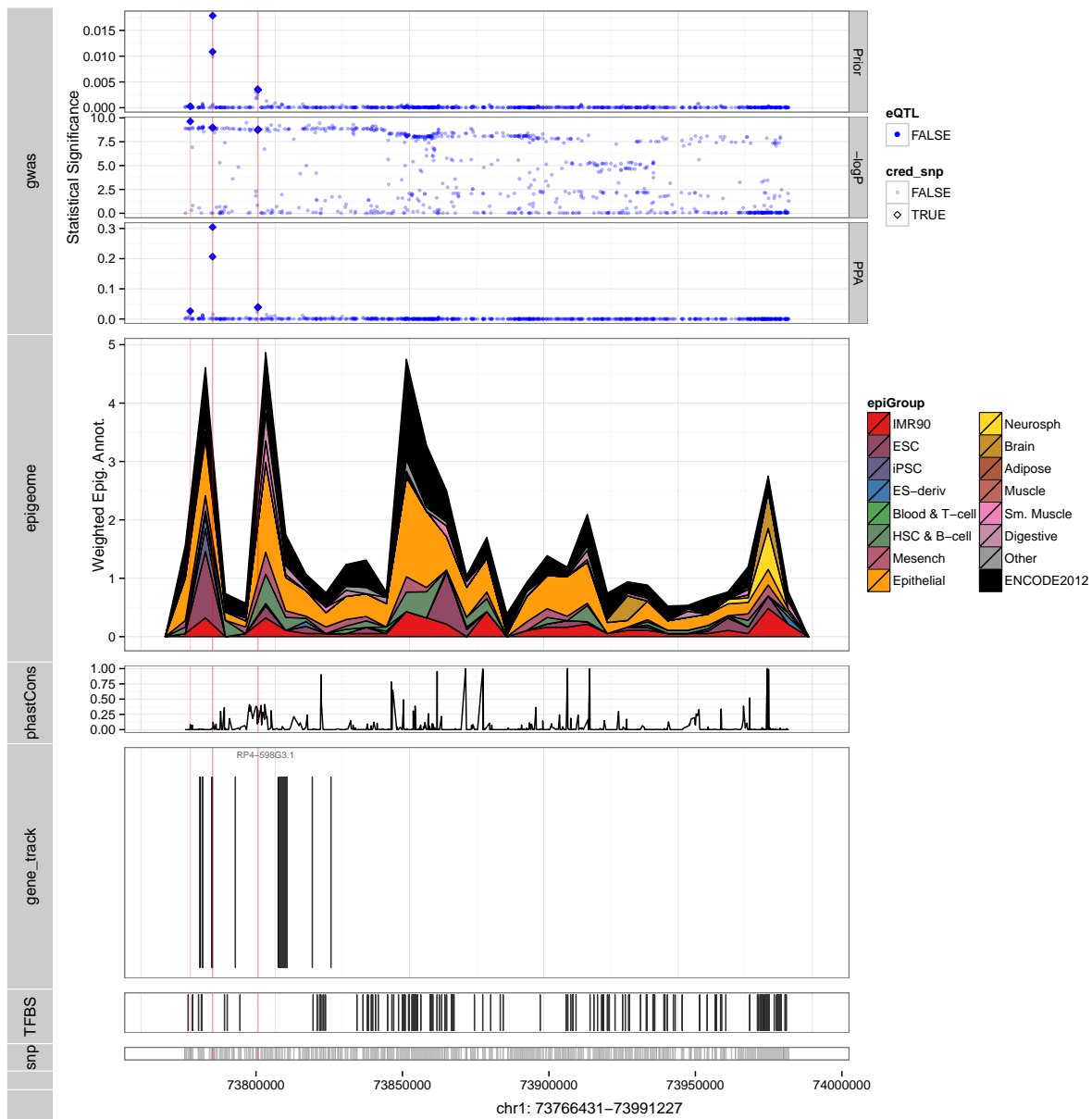
Schizophrenia



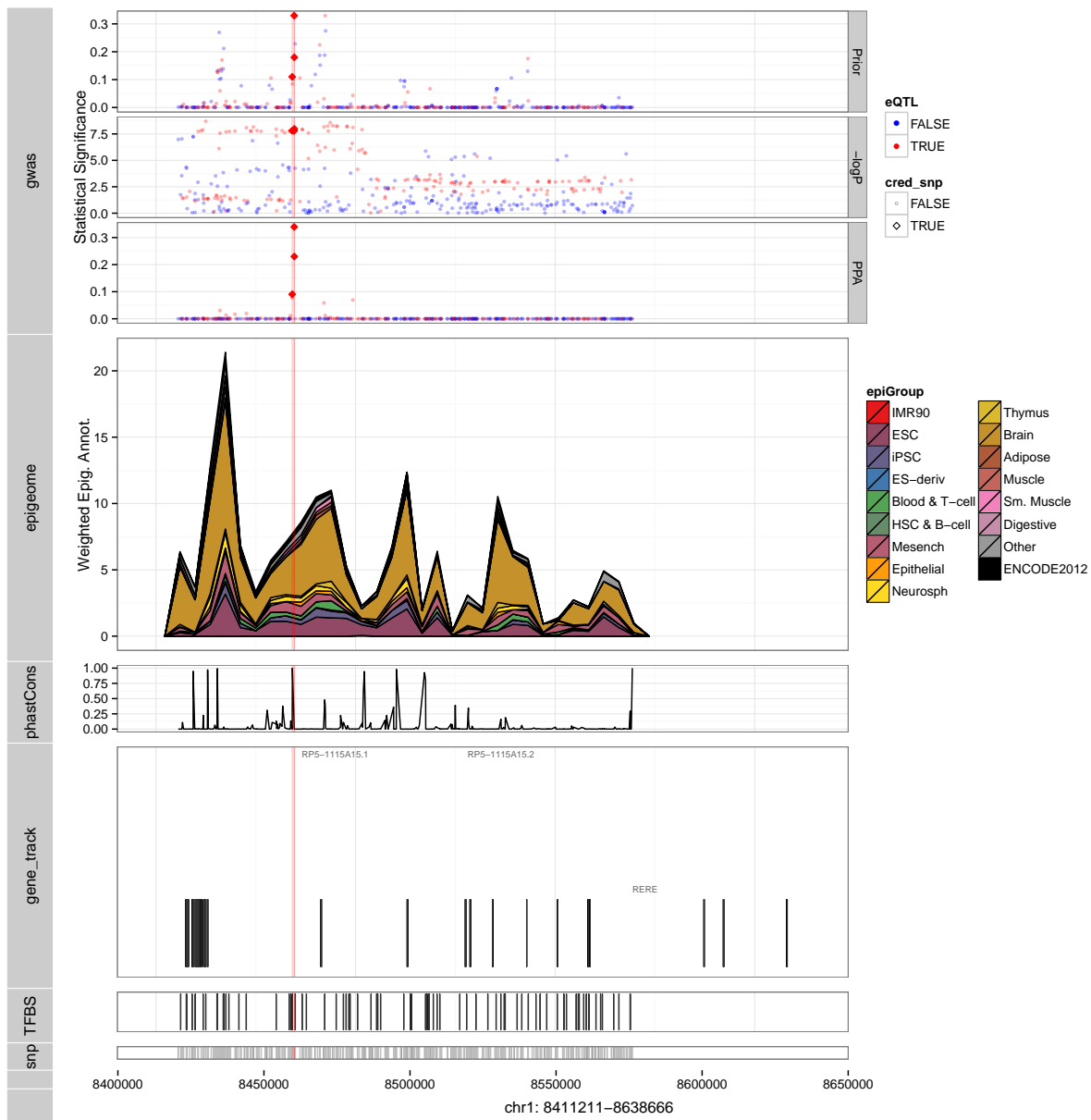
Schizophrenia



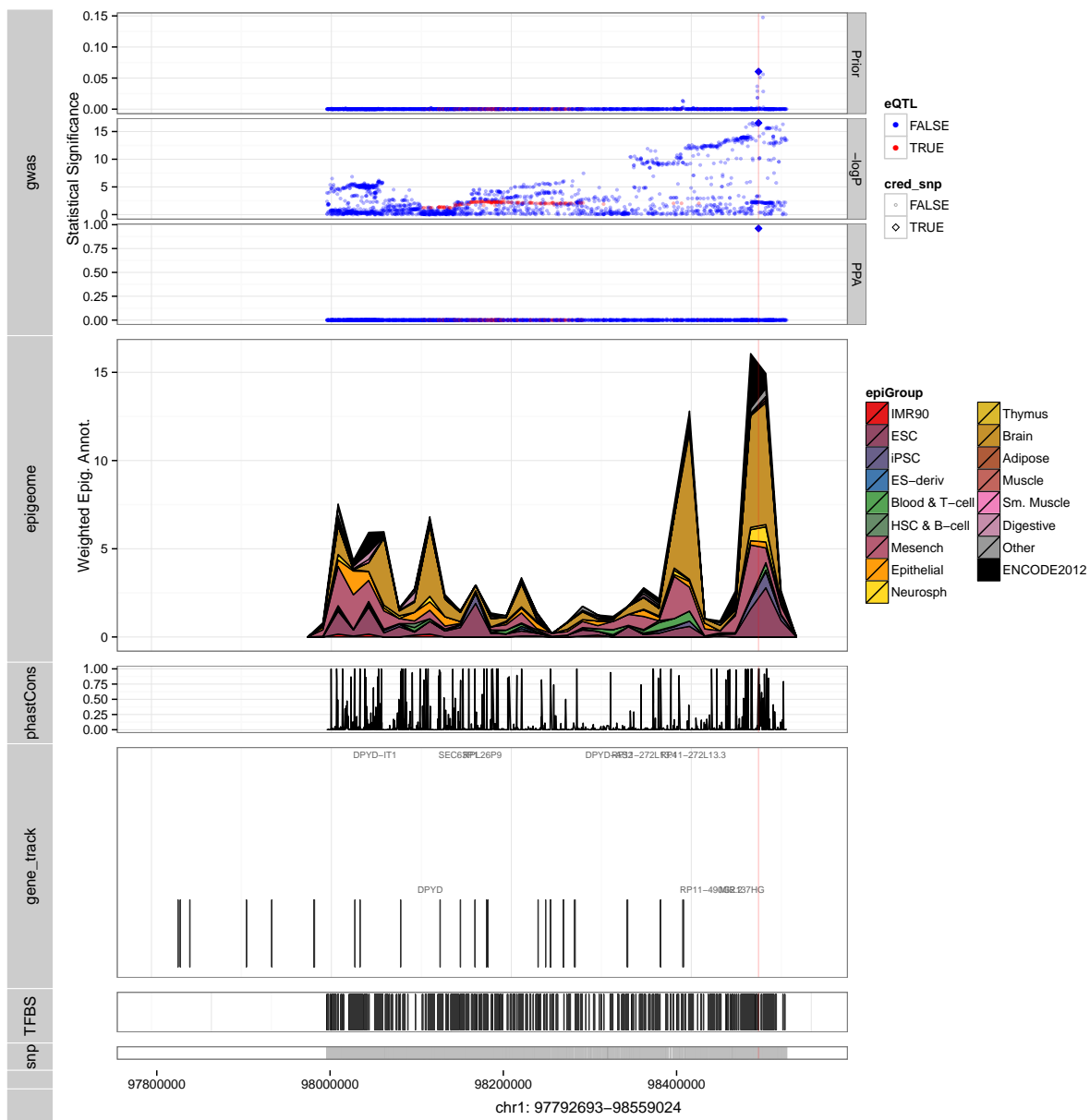
Schizophrenia



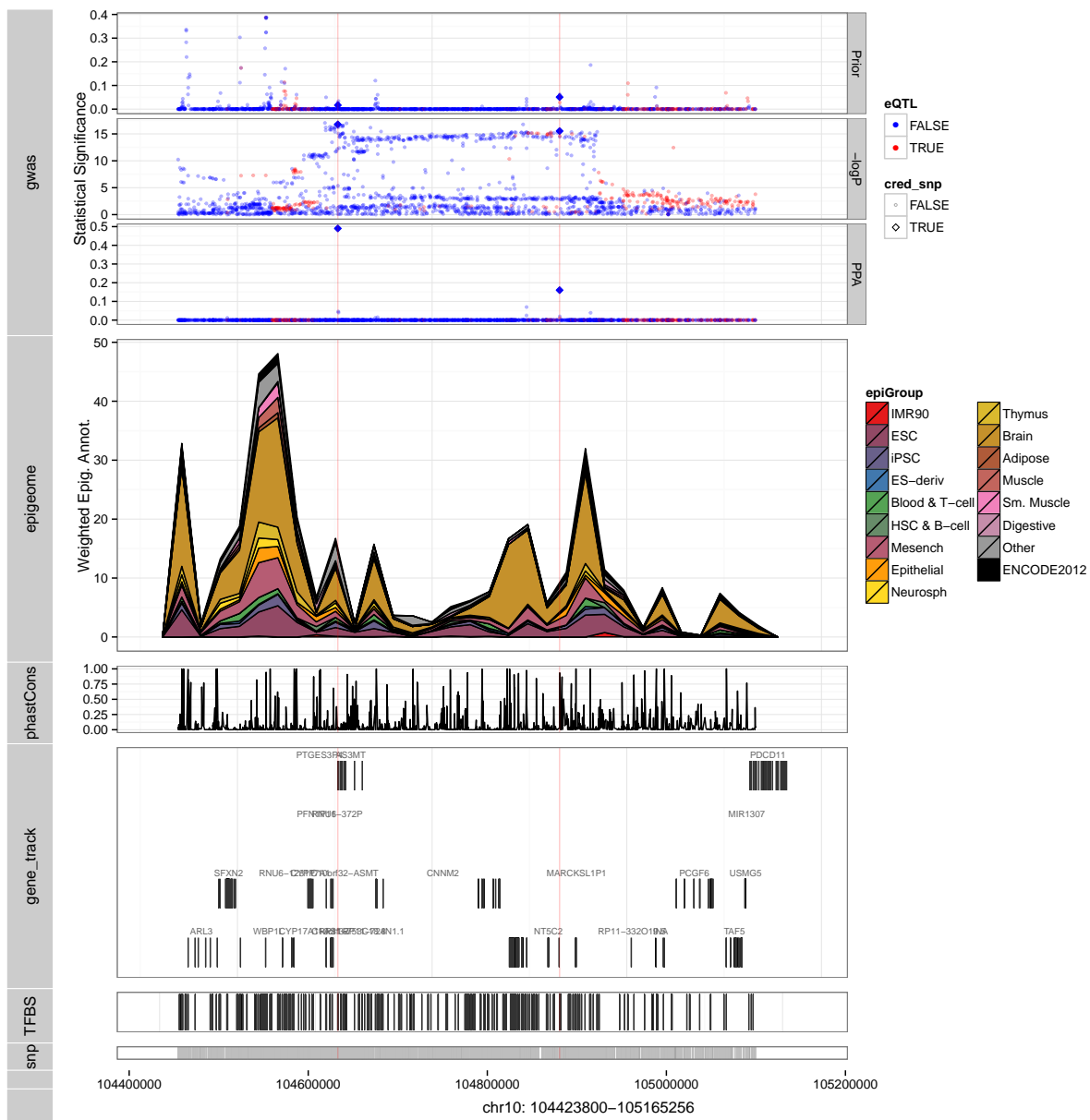
Schizophrenia



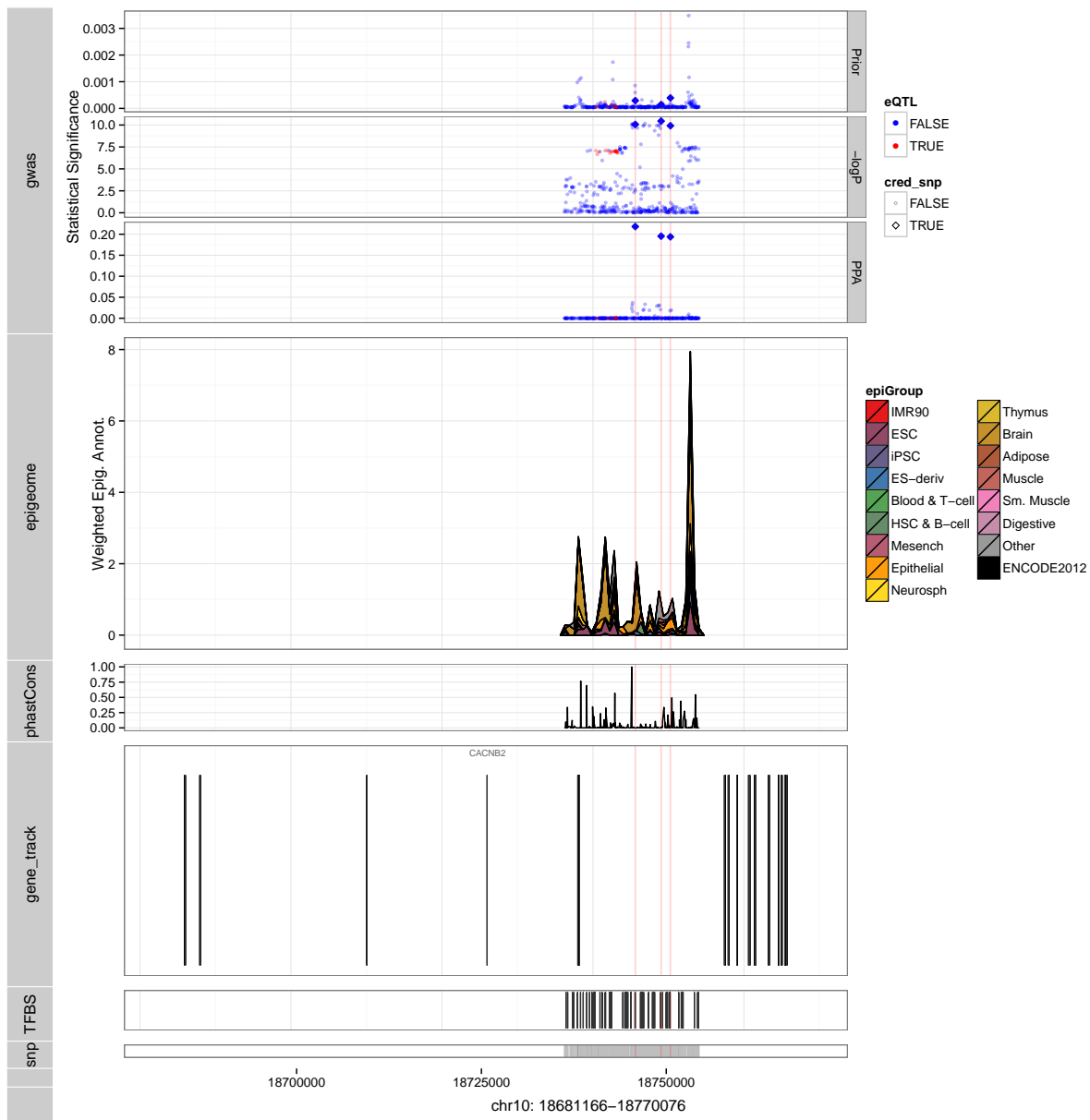
Schizophrenia



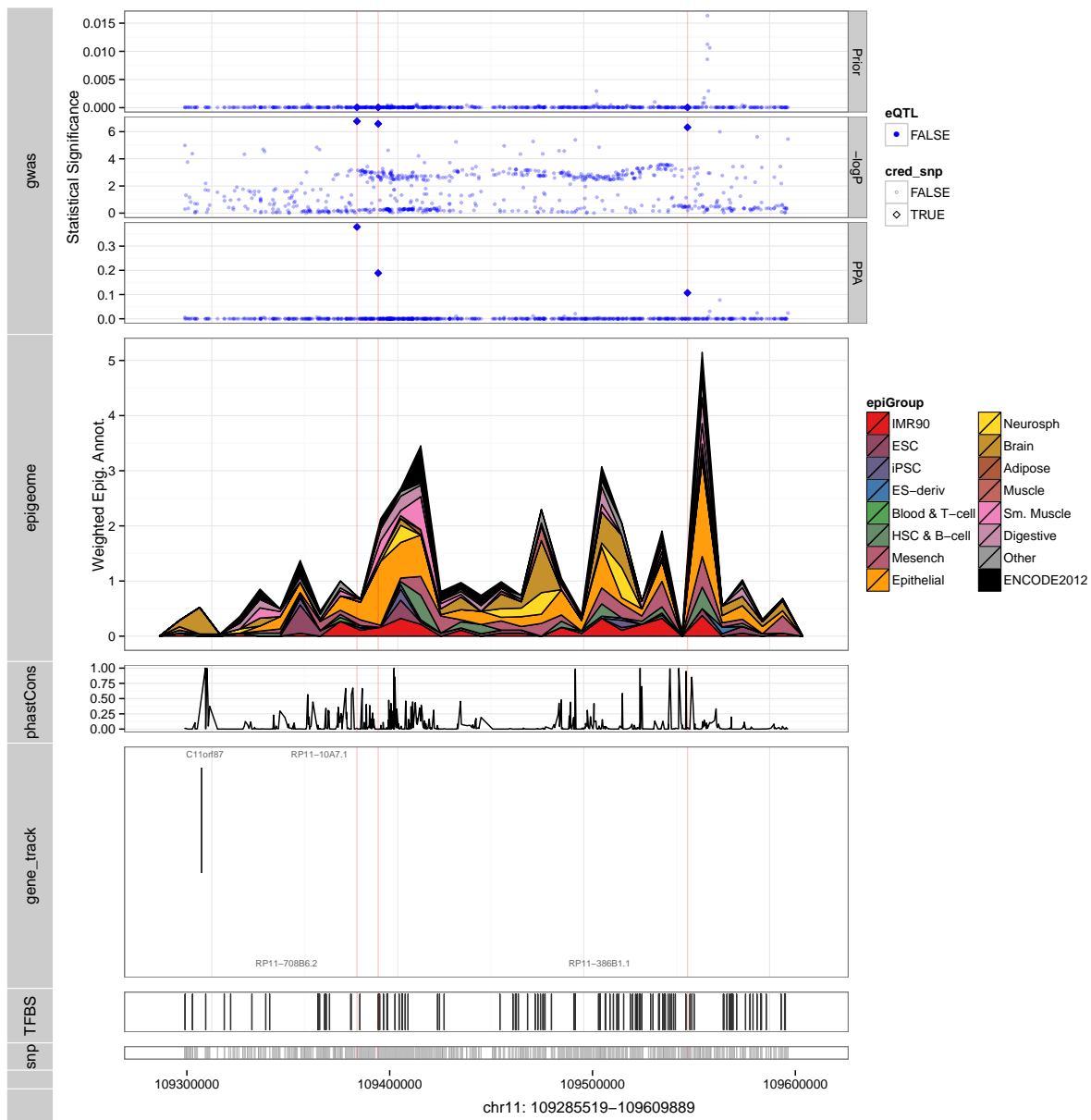
Schizophrenia



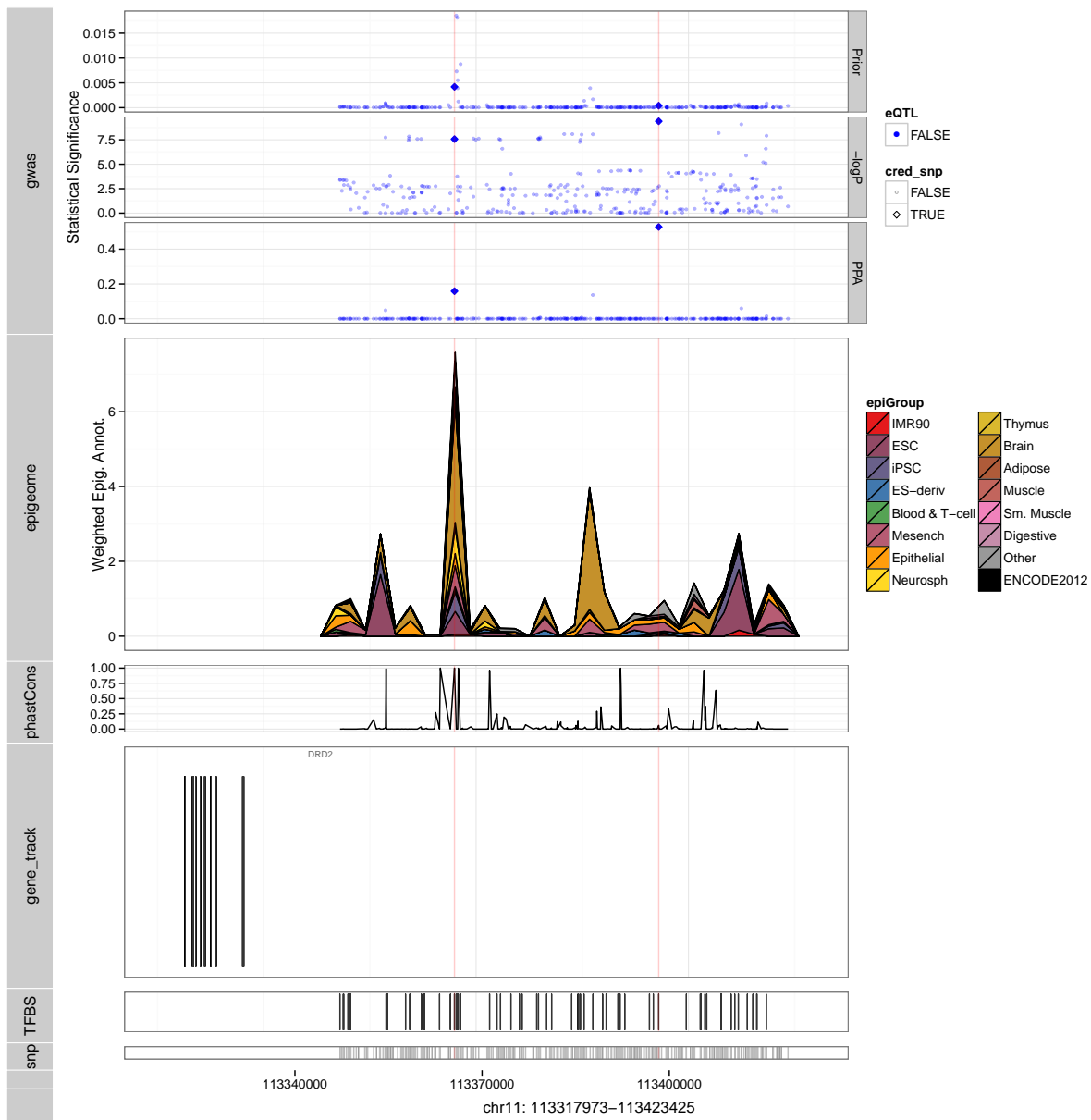
Schizophrenia



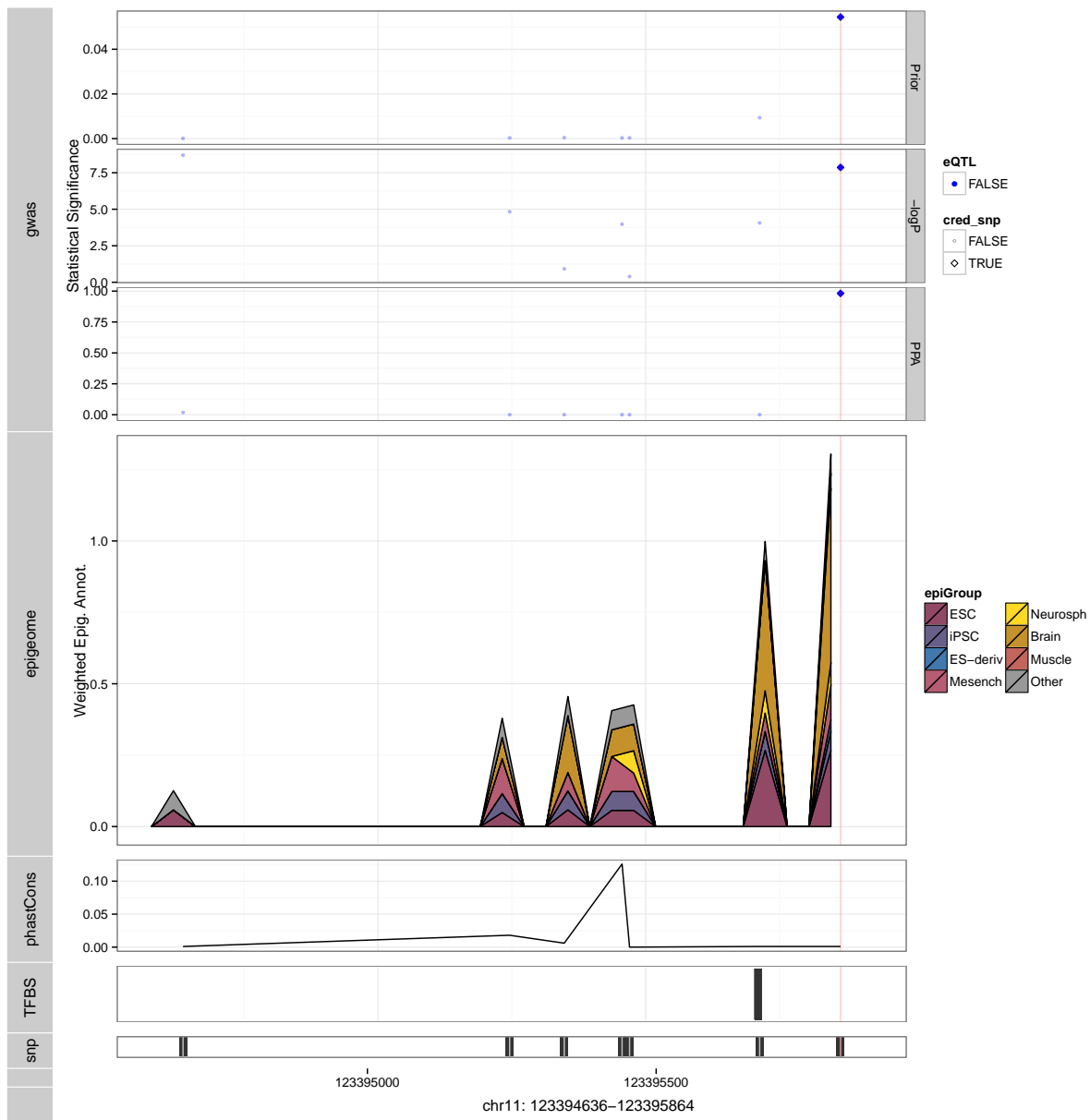
Schizophrenia



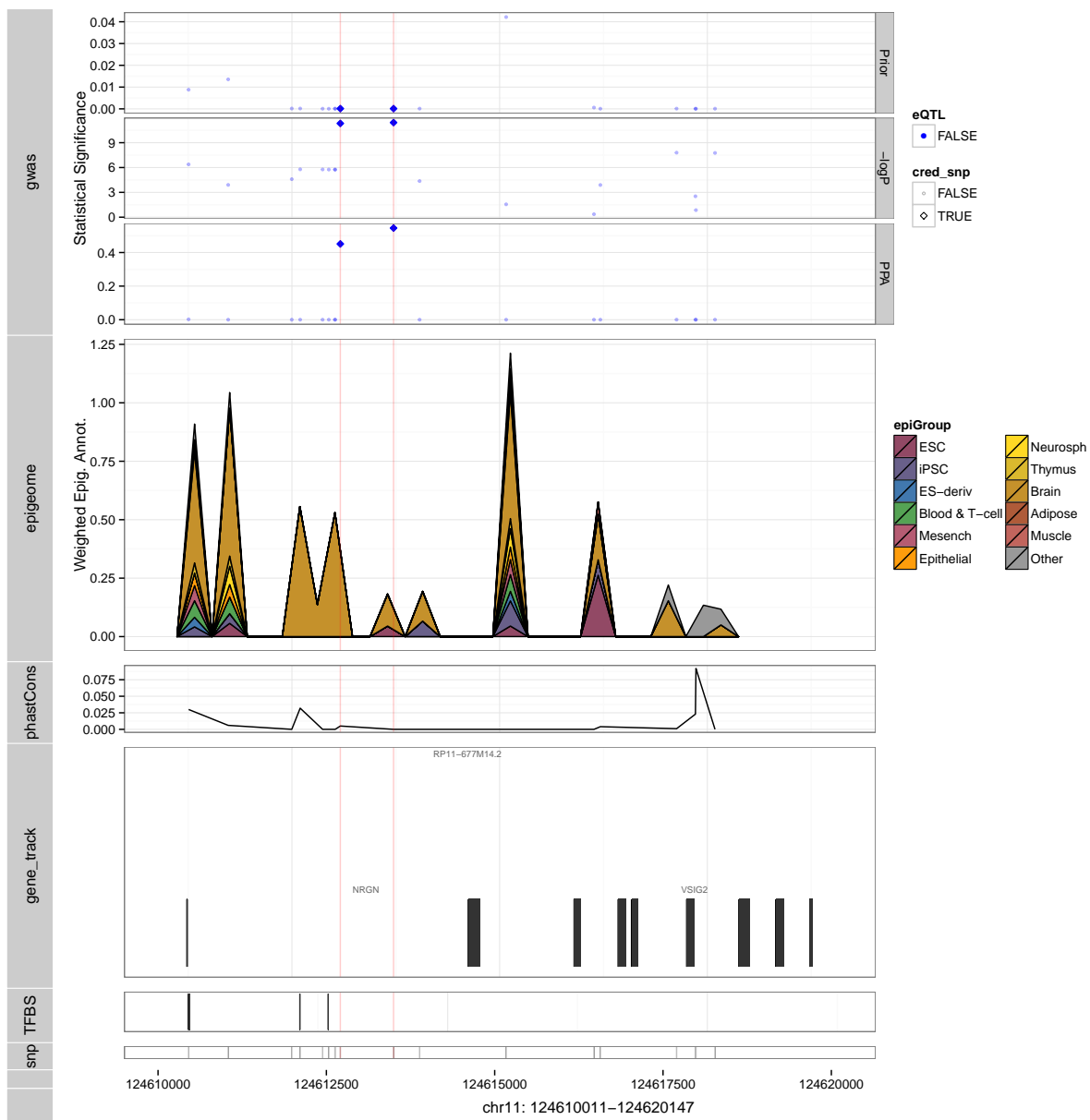
Schizophrenia



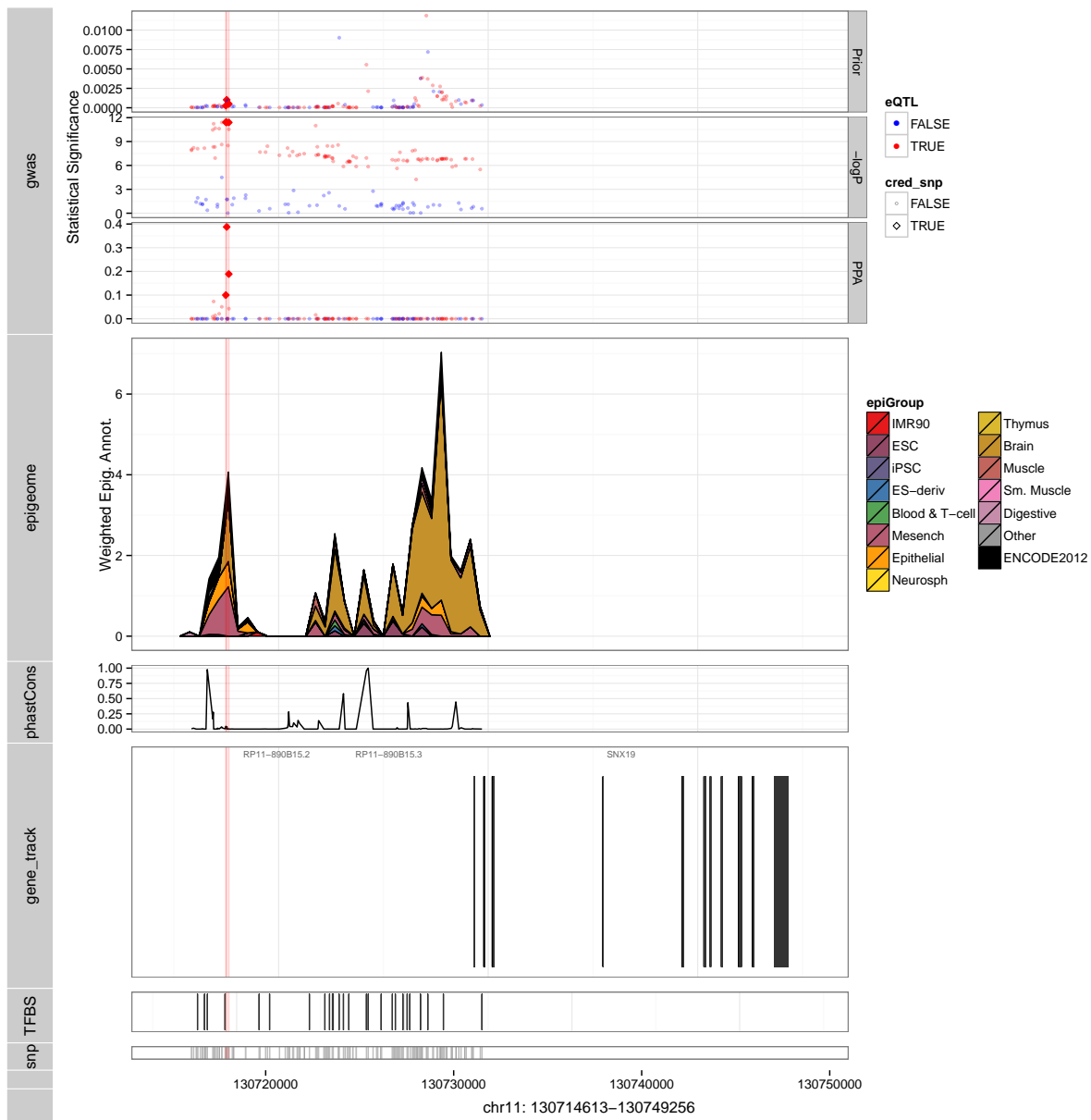
Schizophrenia



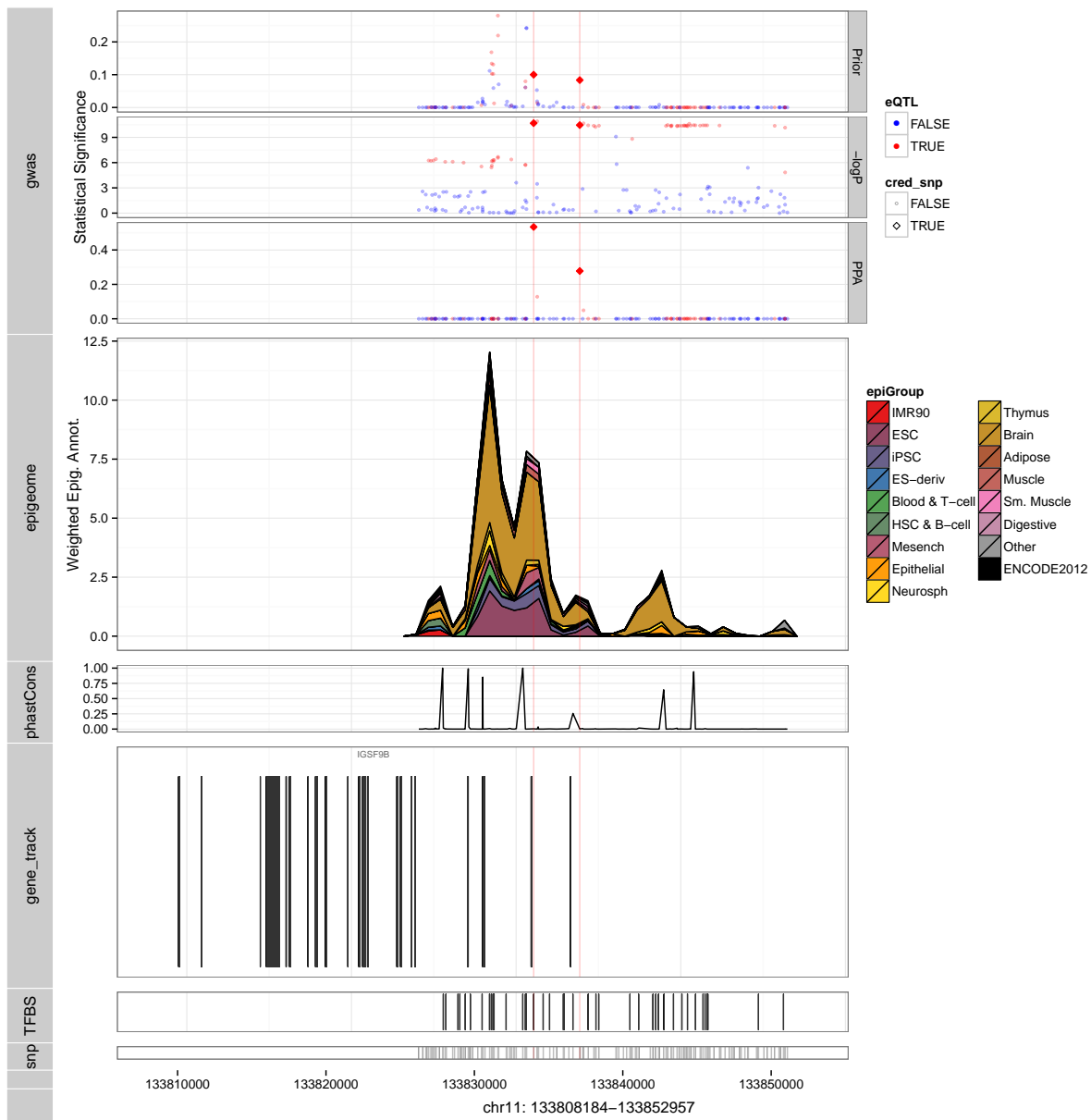
Schizophrenia



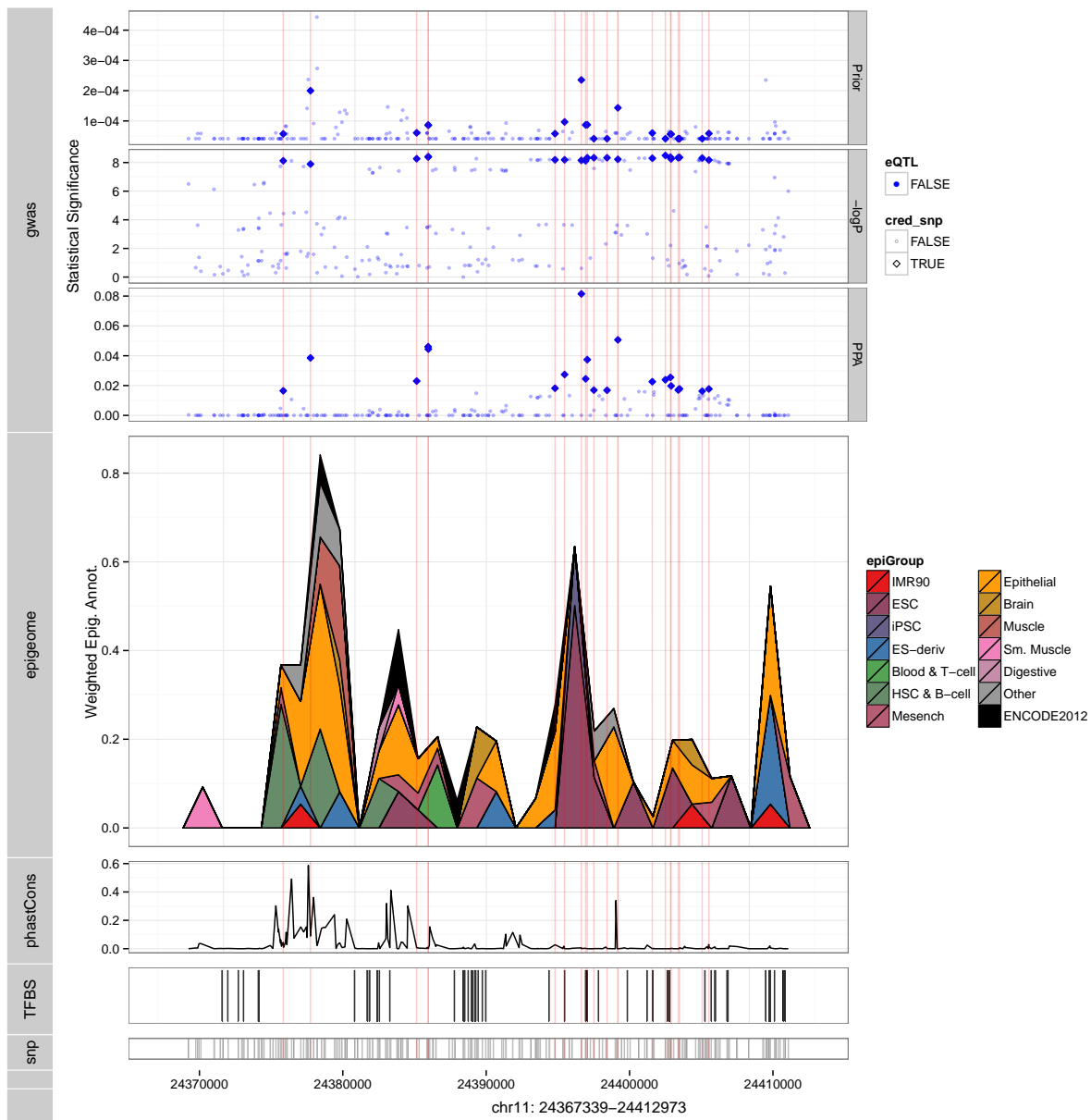
Schizophrenia



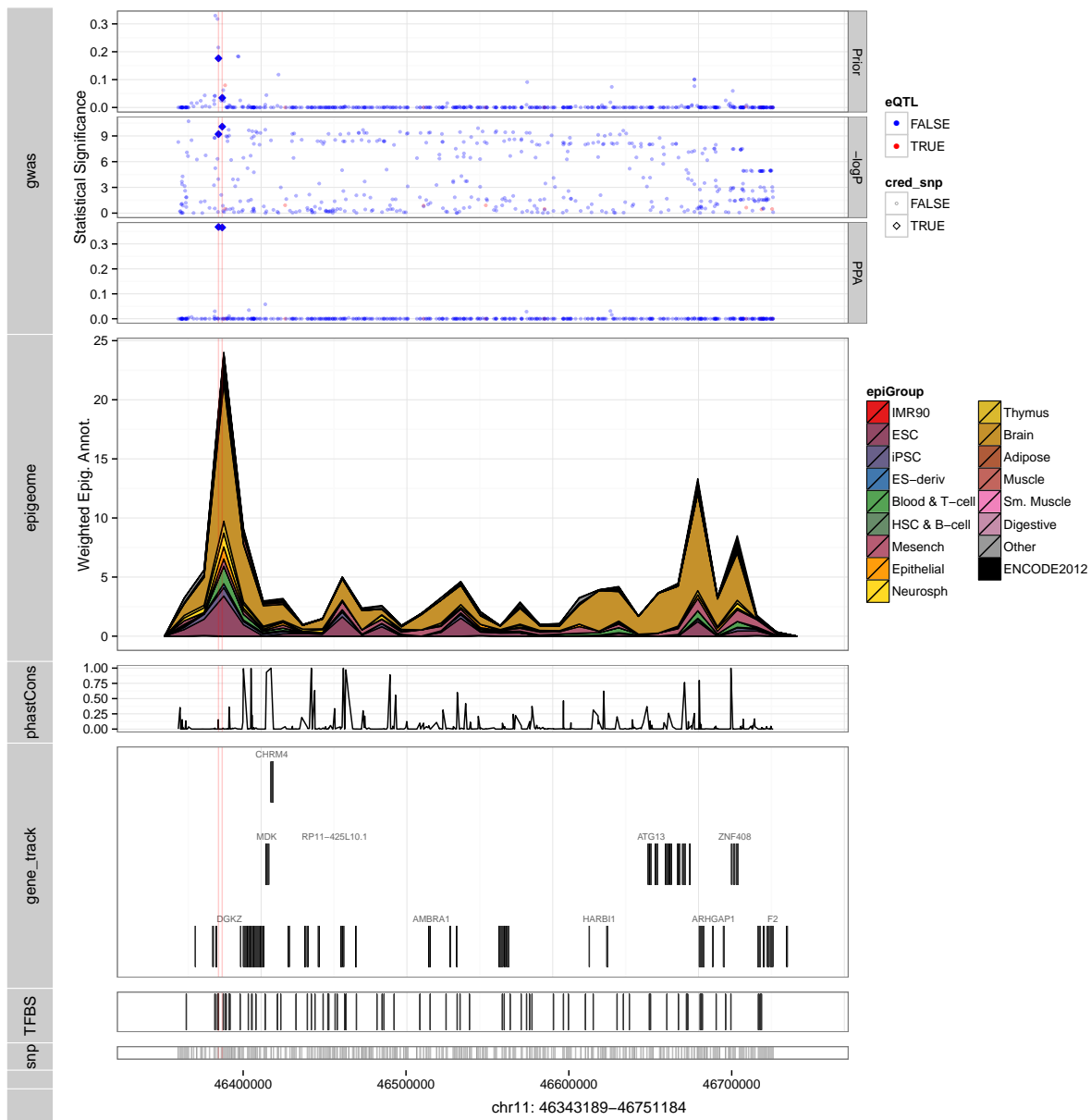
Schizophrenia



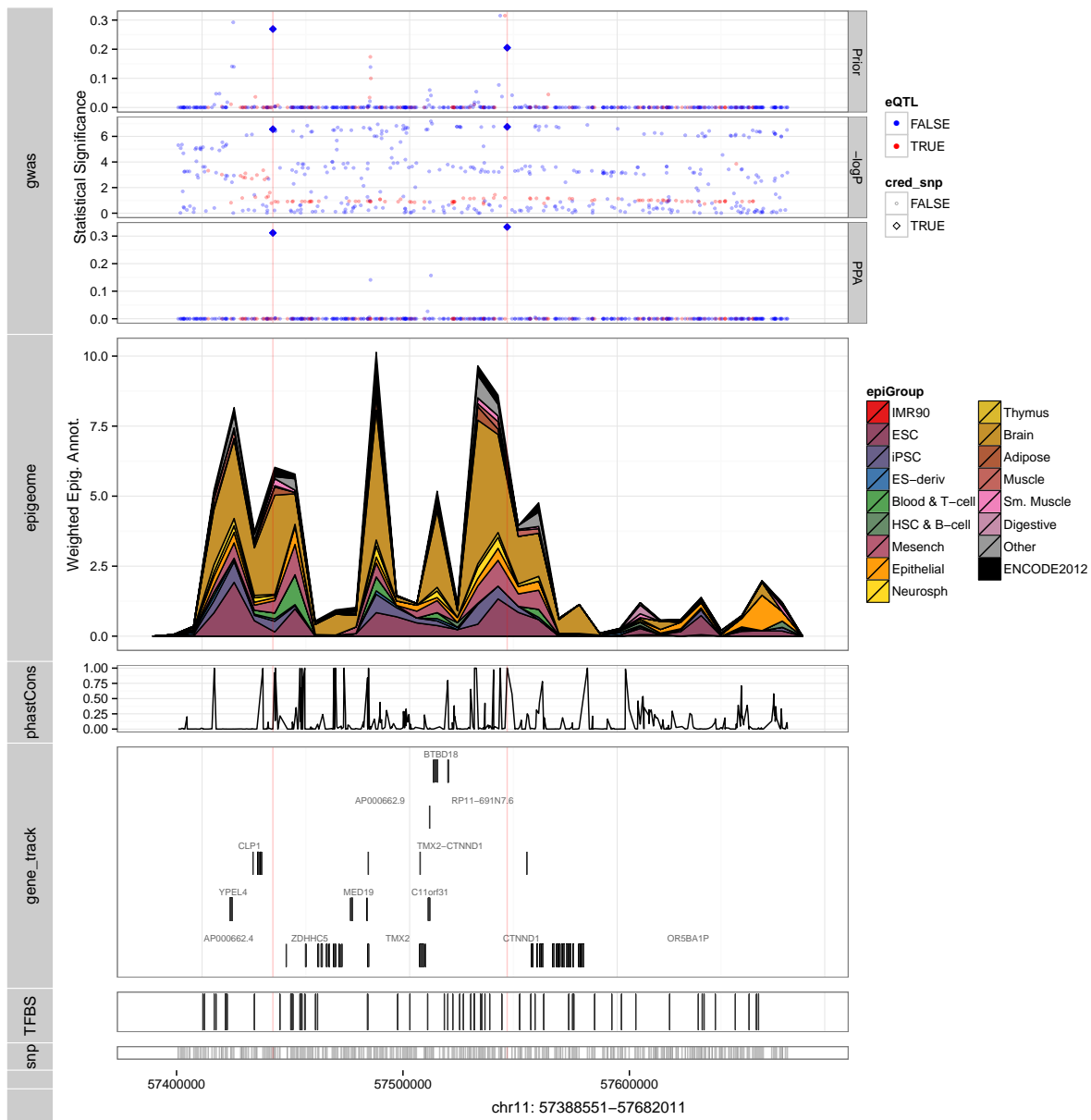
Schizophrenia



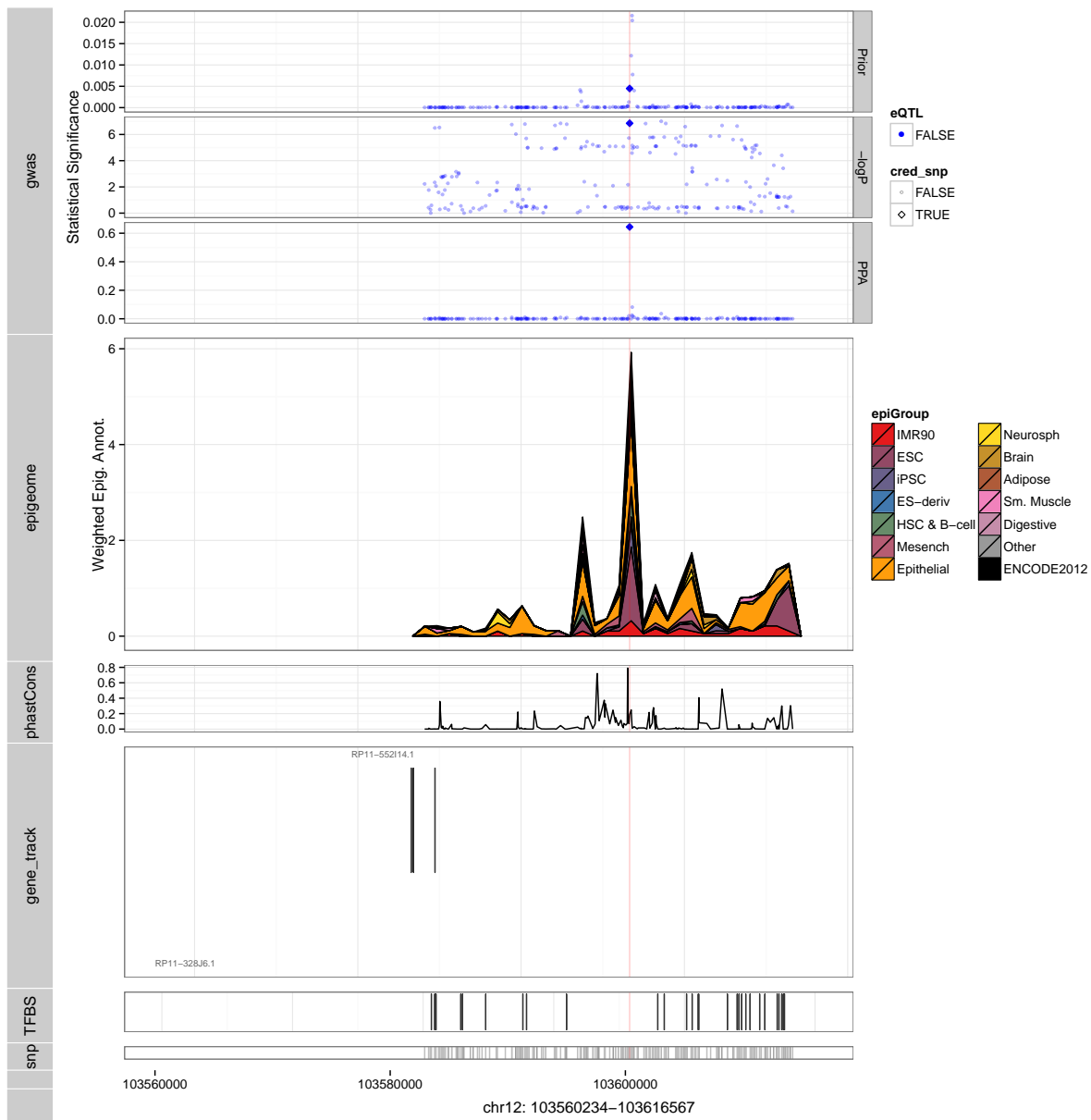
Schizophrenia



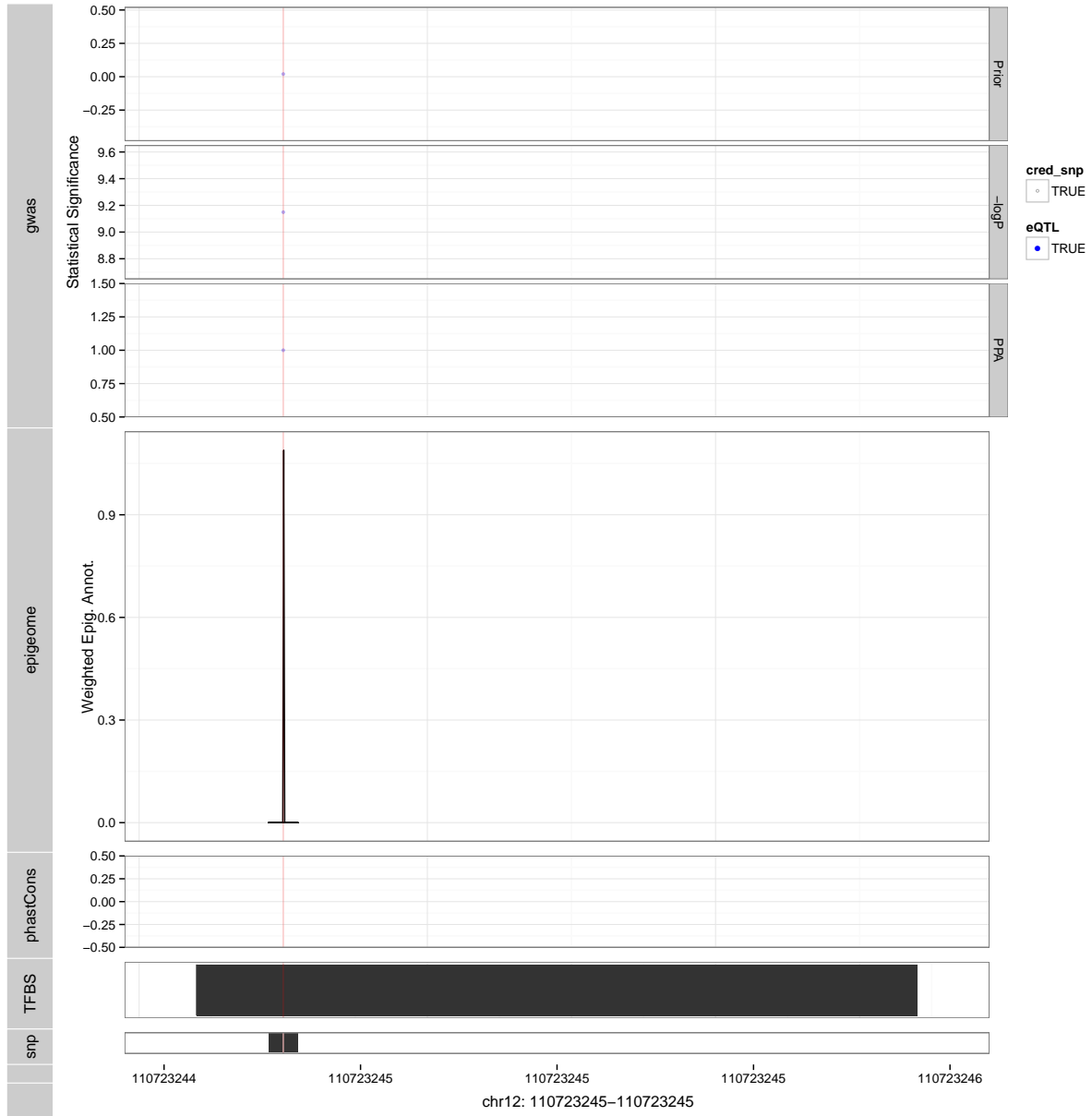
Schizophrenia



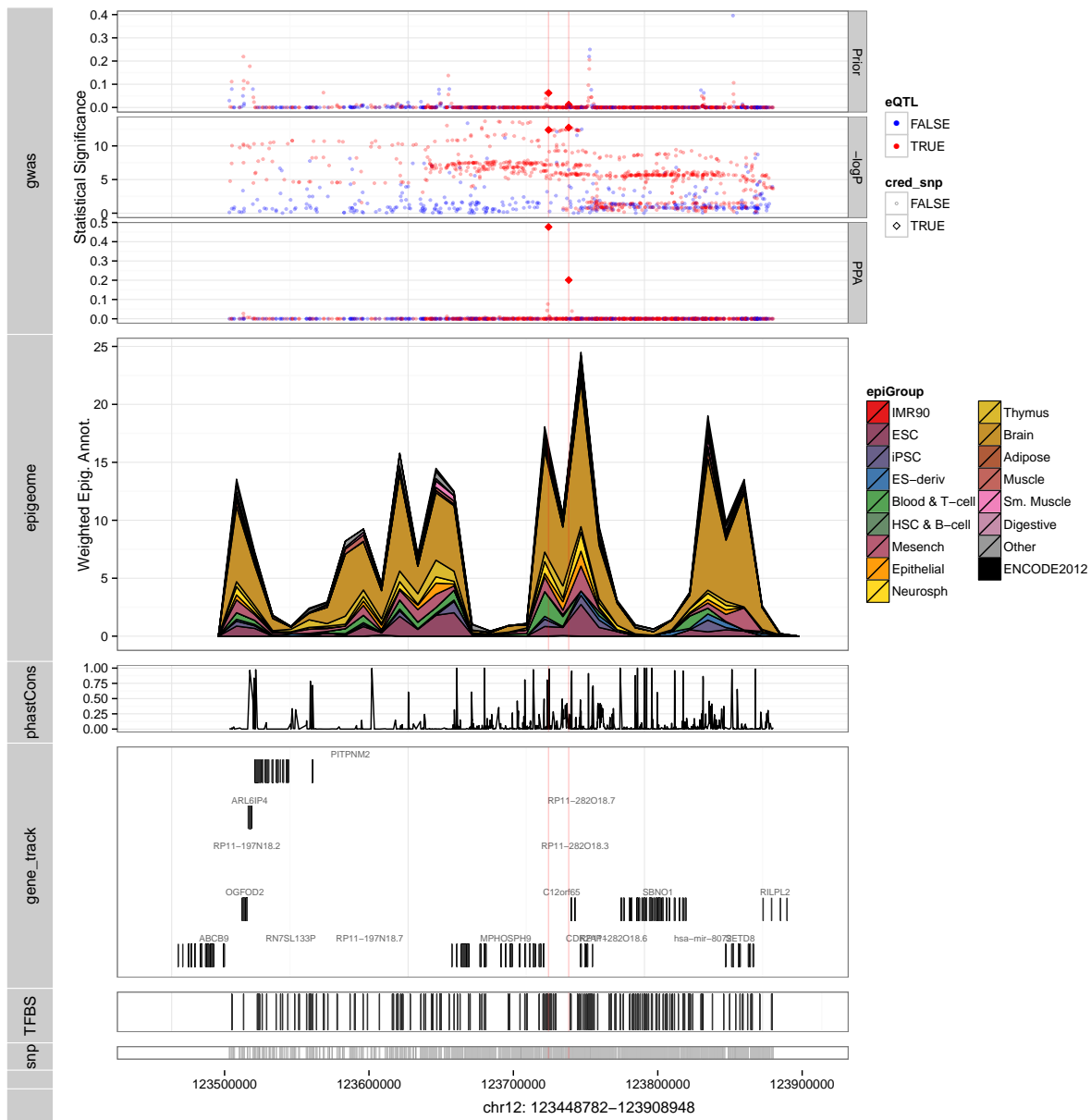
Schizophrenia



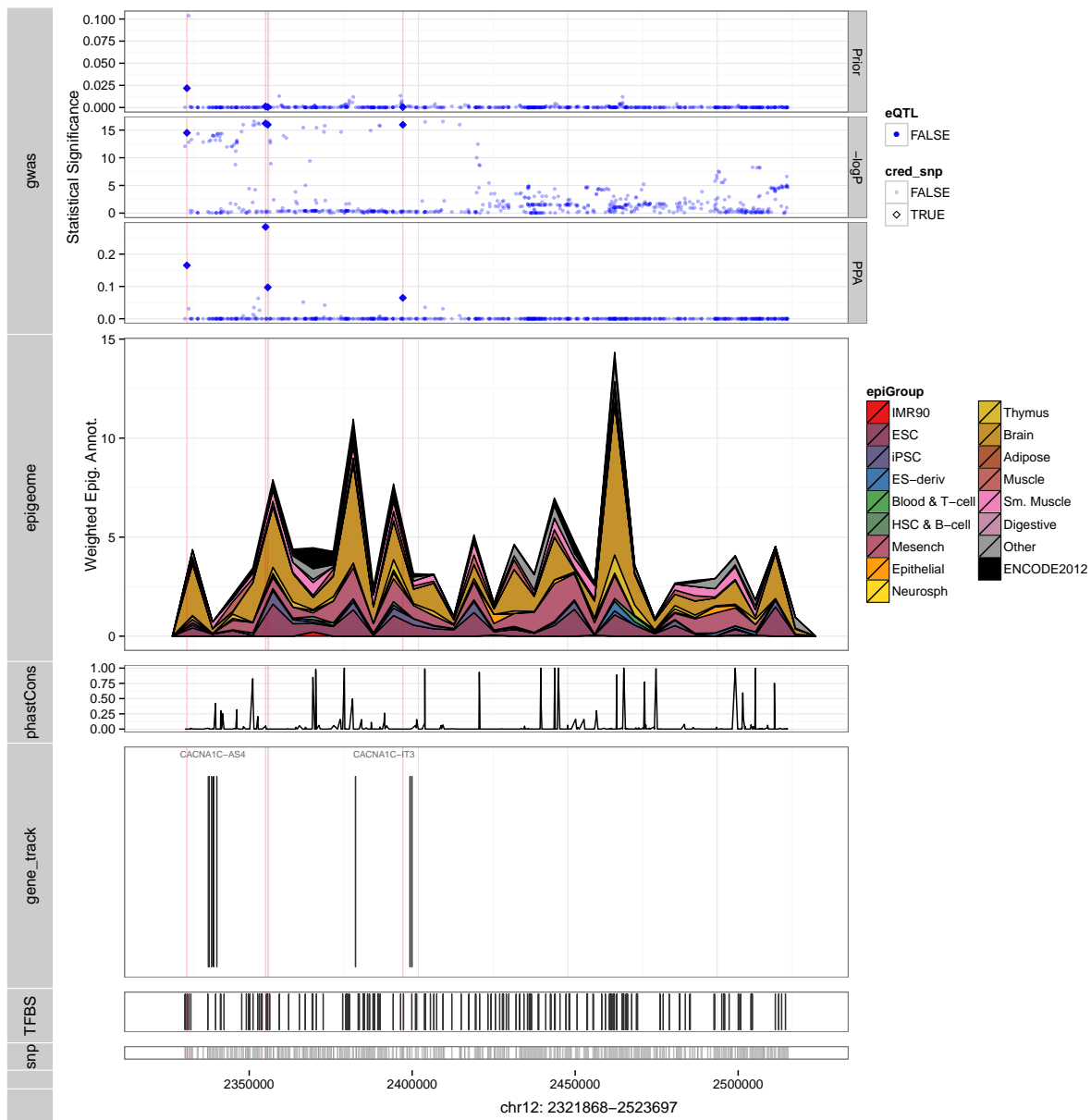
Schizophrenia



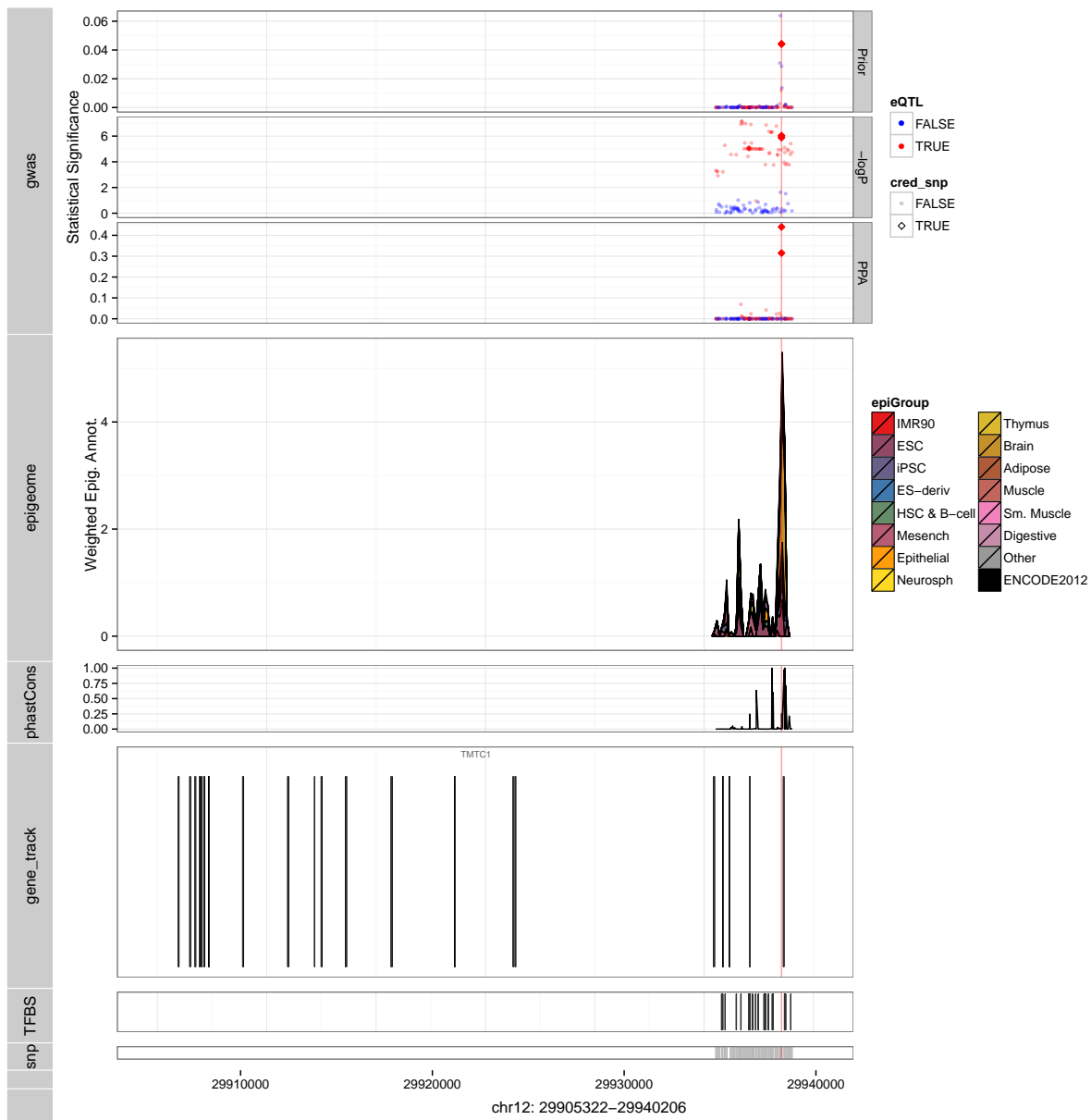
Schizophrenia



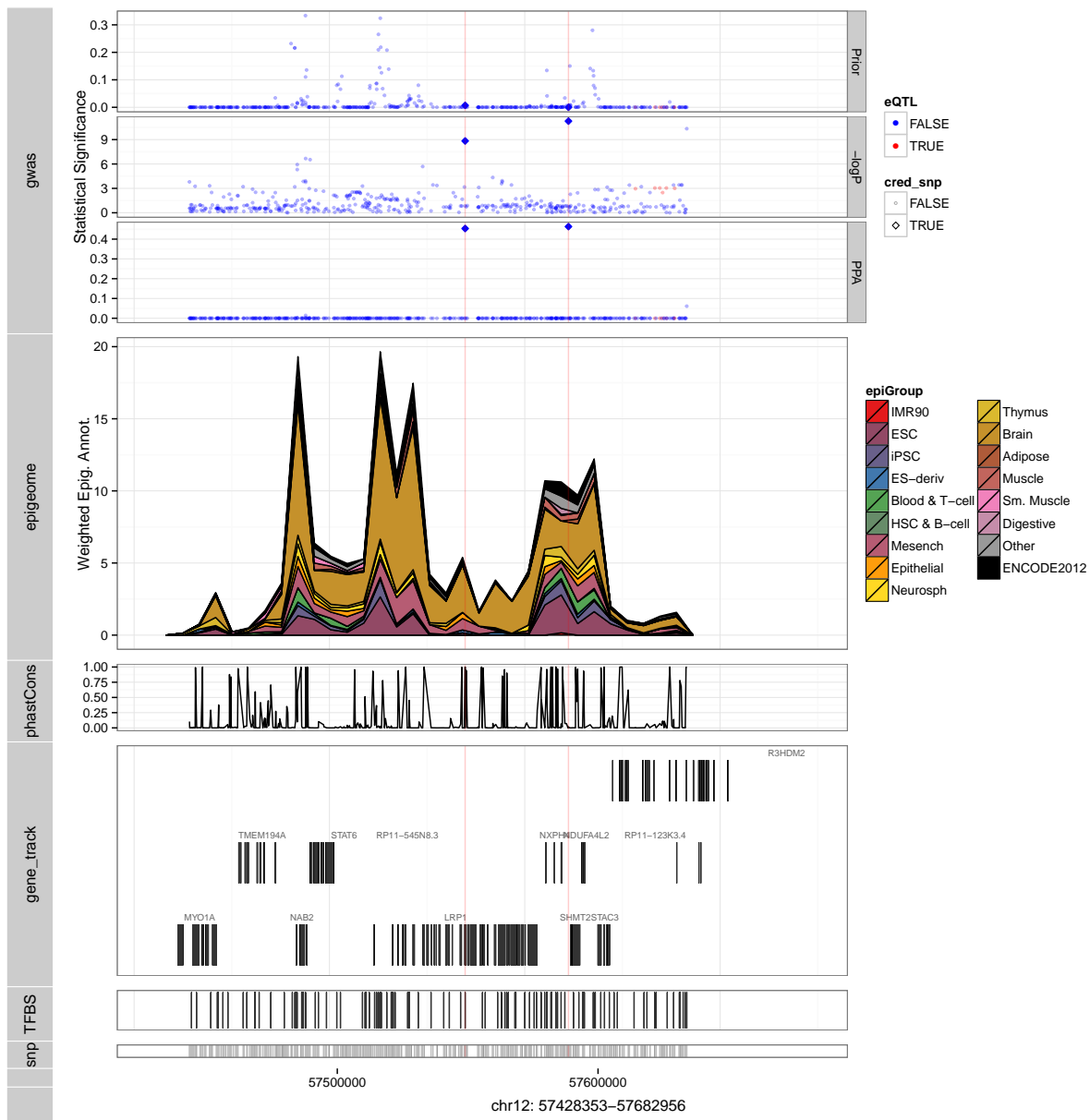
Schizophrenia



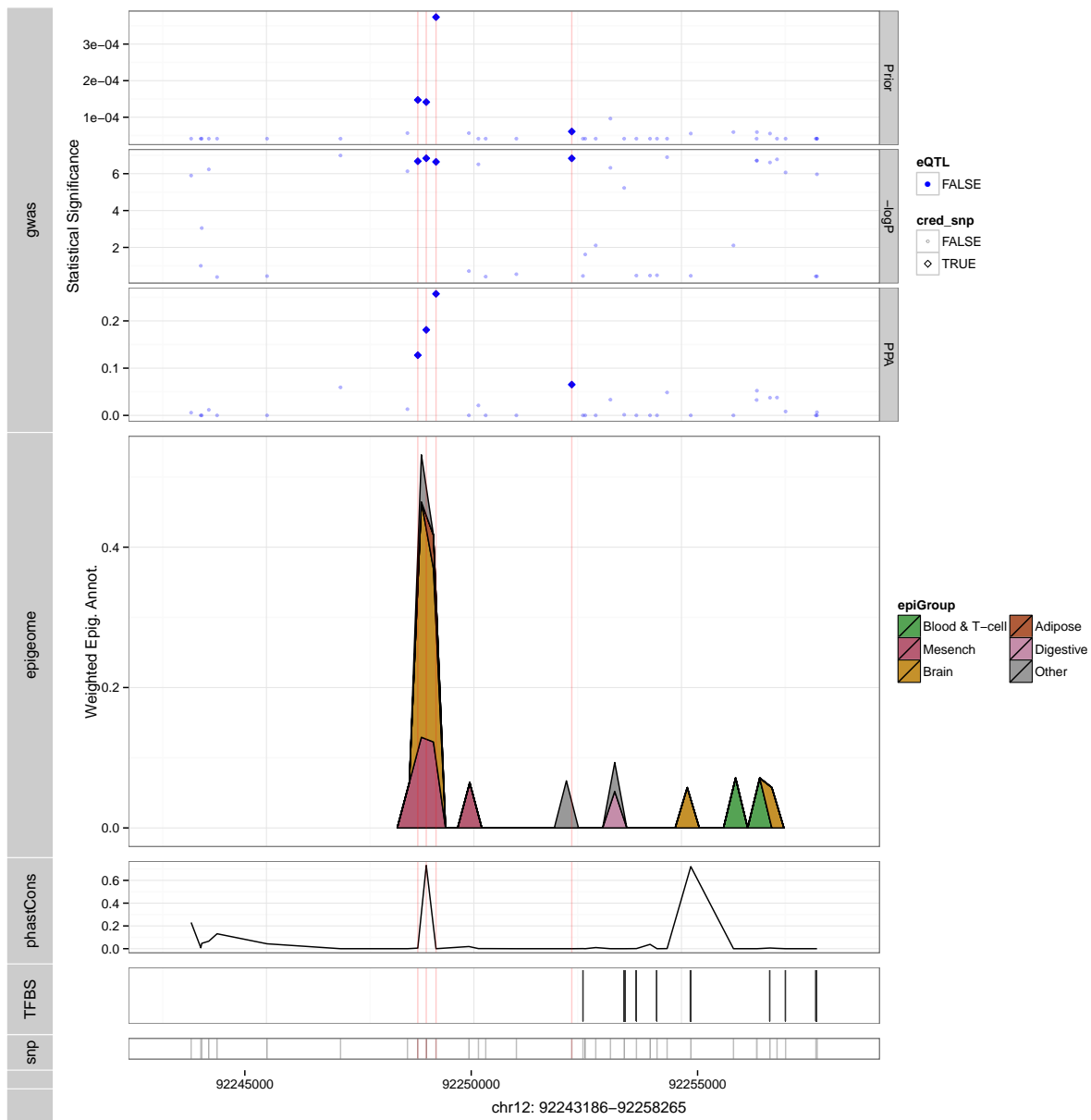
Schizophrenia



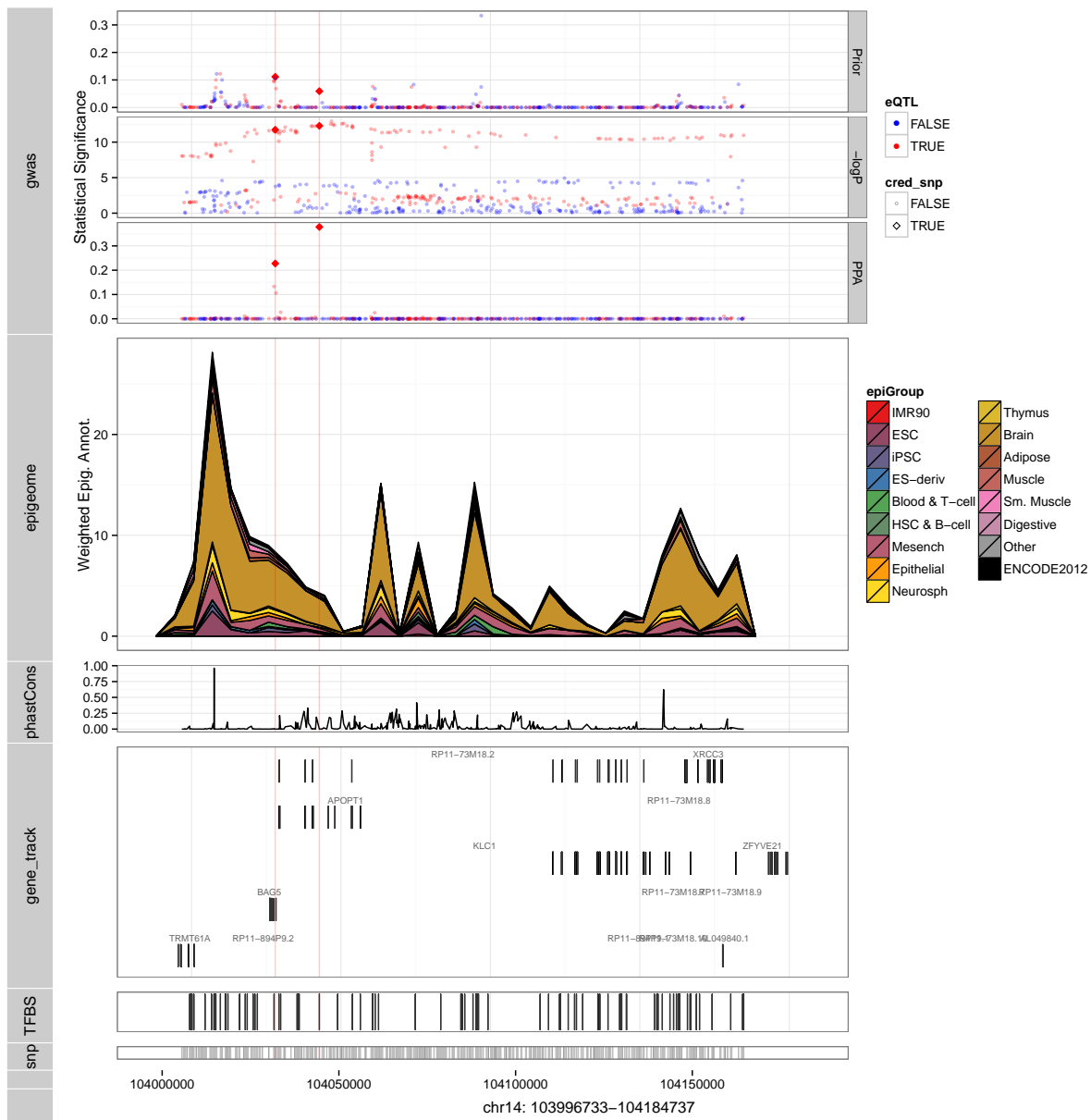
Schizophrenia



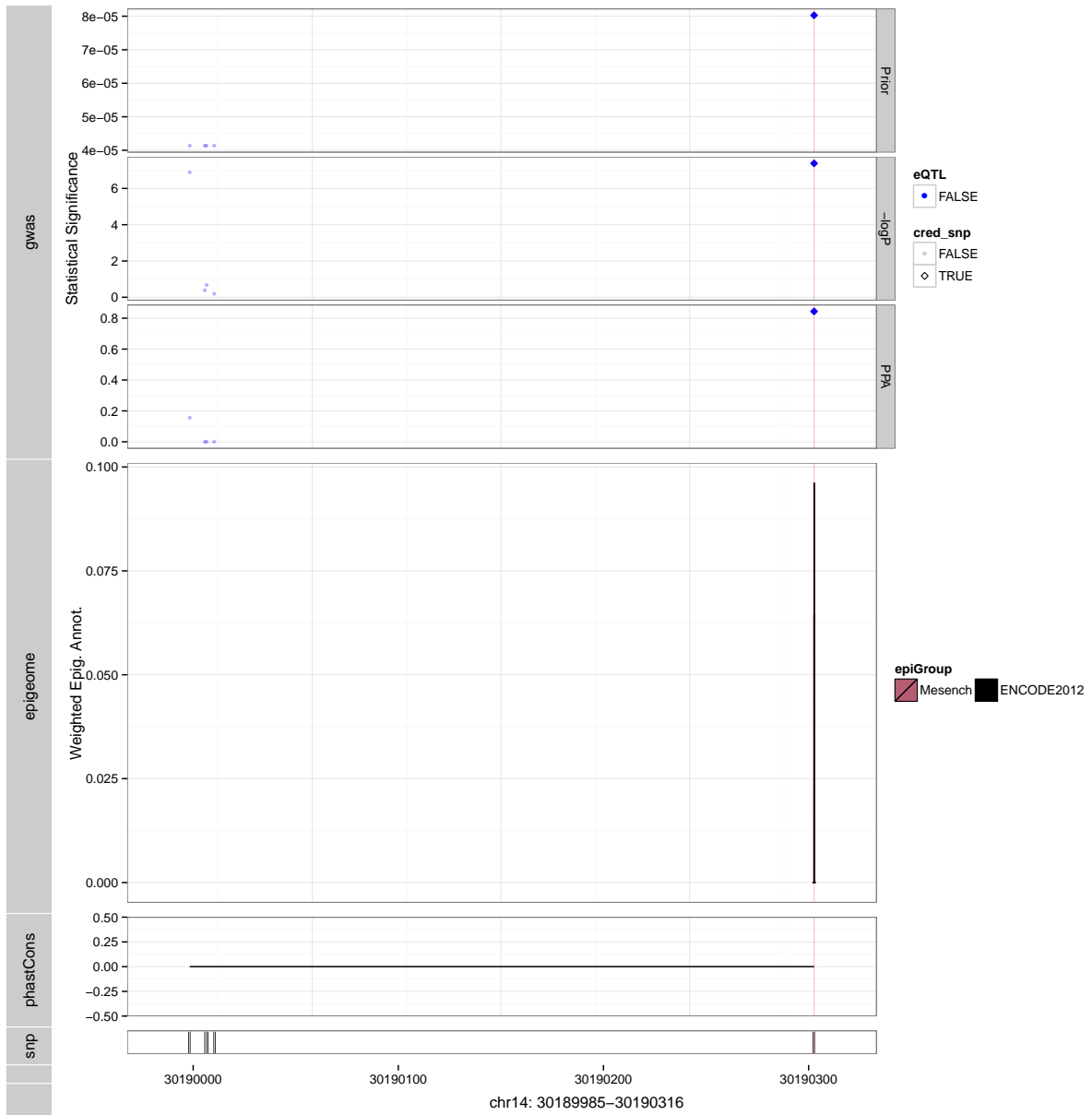
Schizophrenia



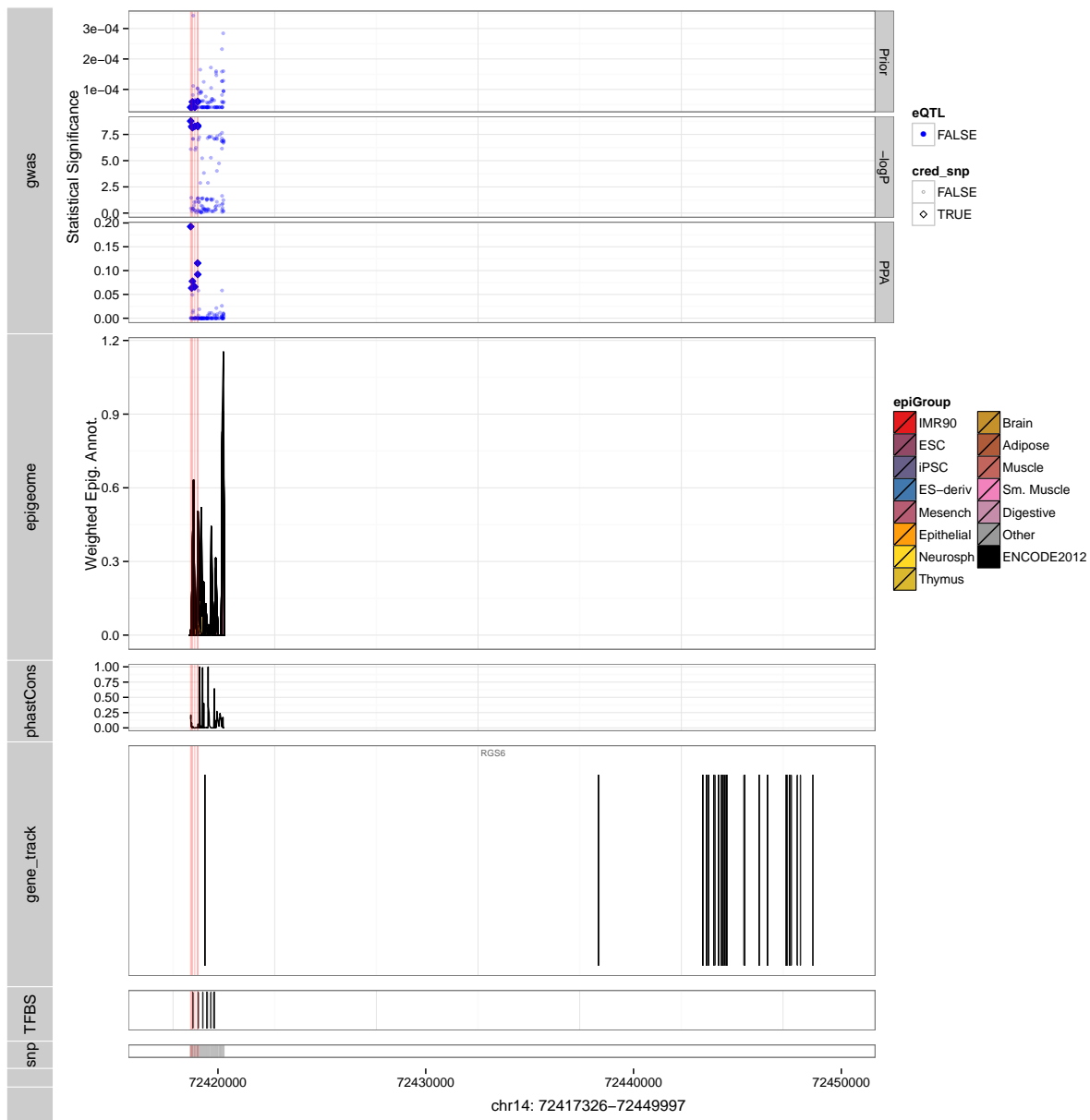
Schizophrenia



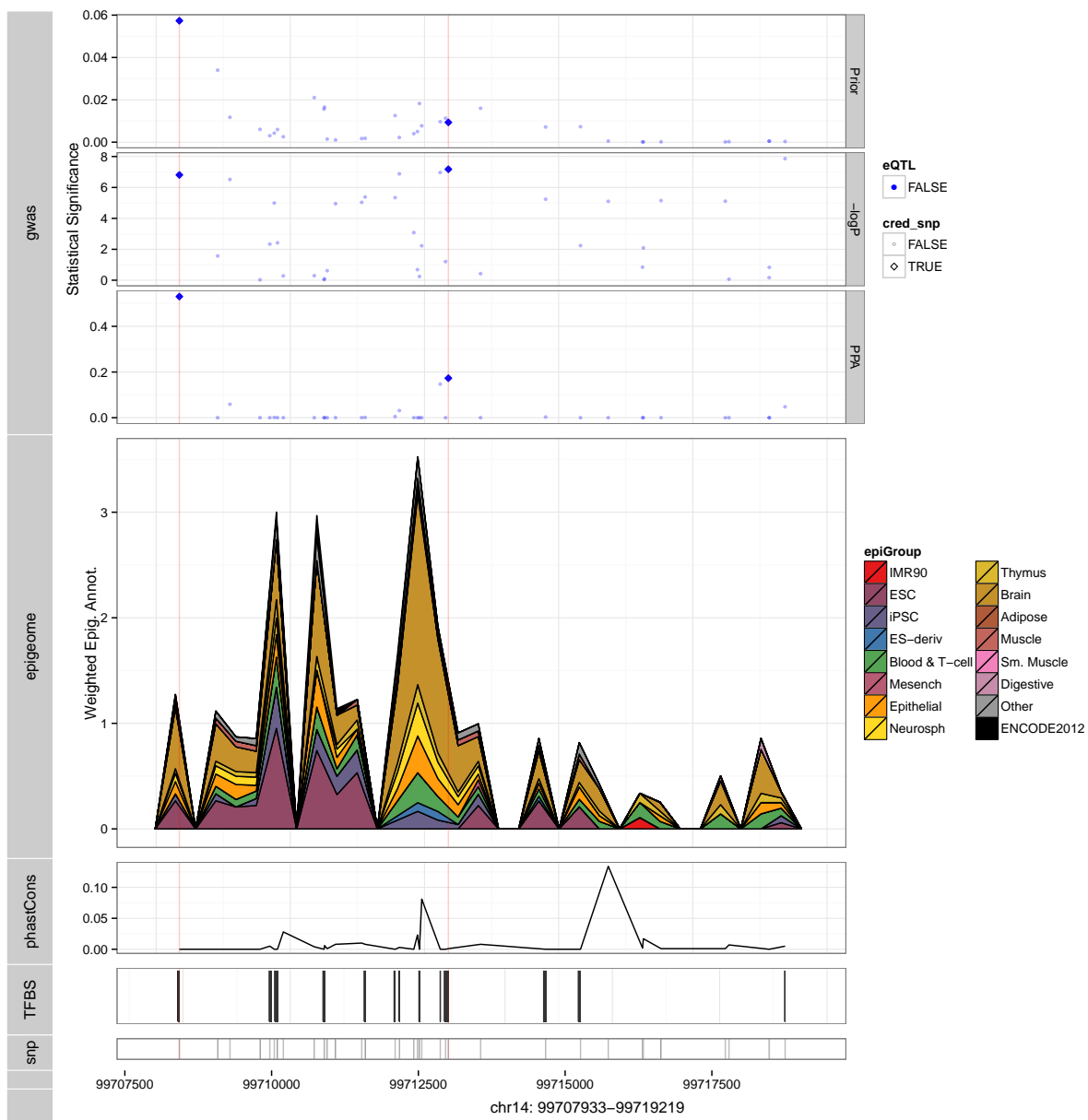
Schizophrenia



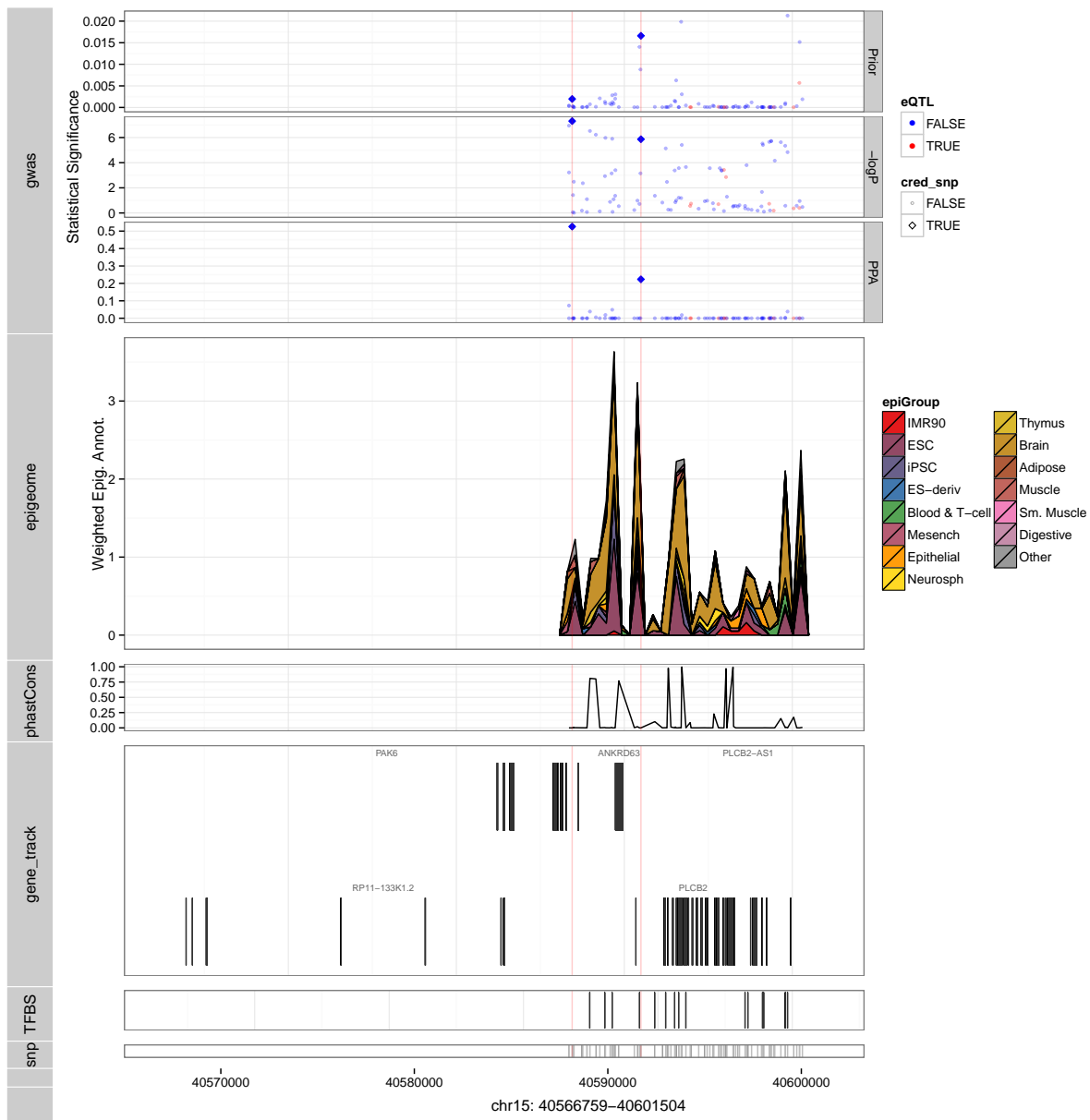
Schizophrenia



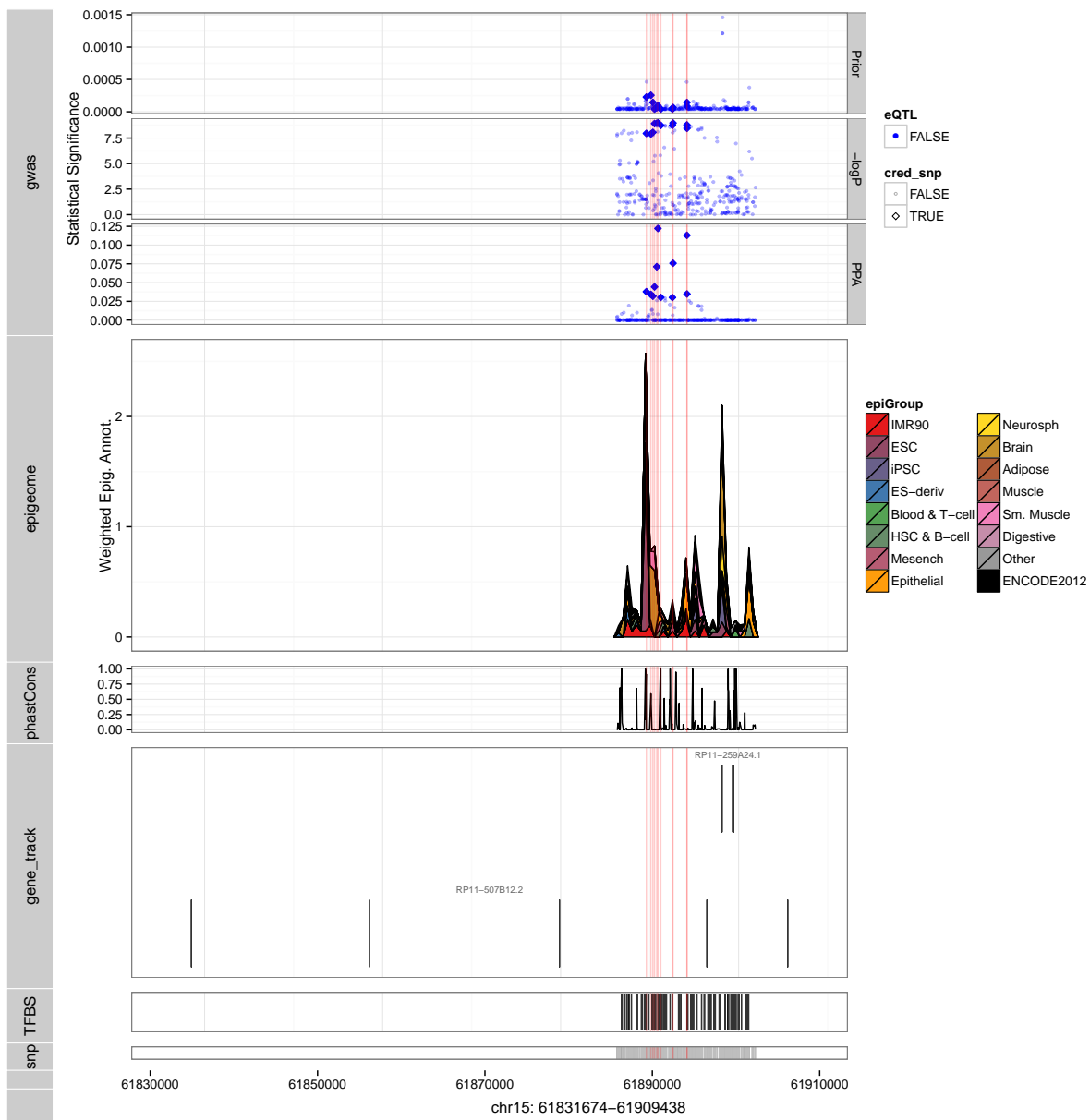
Schizophrenia



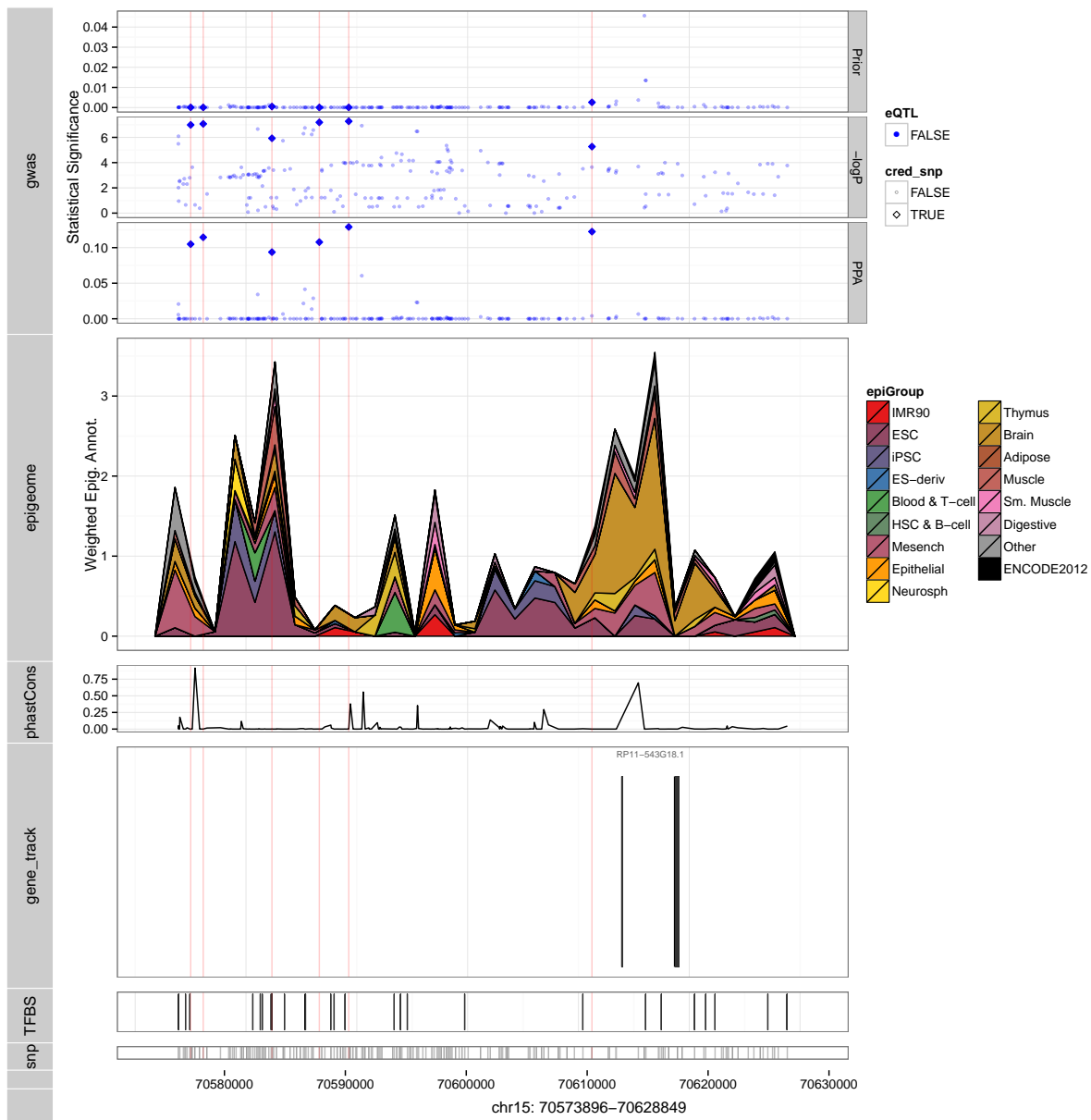
Schizophrenia



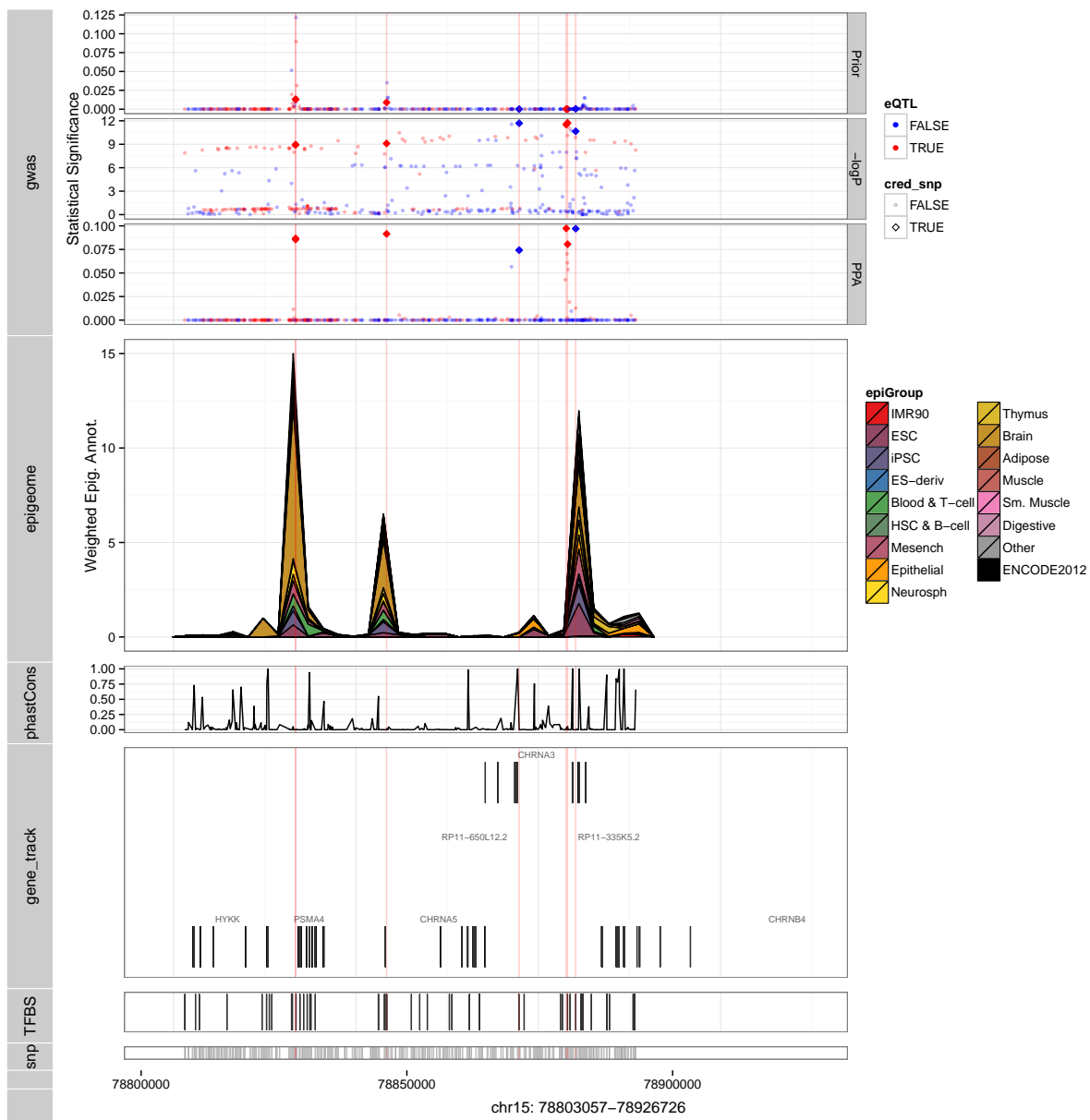
Schizophrenia



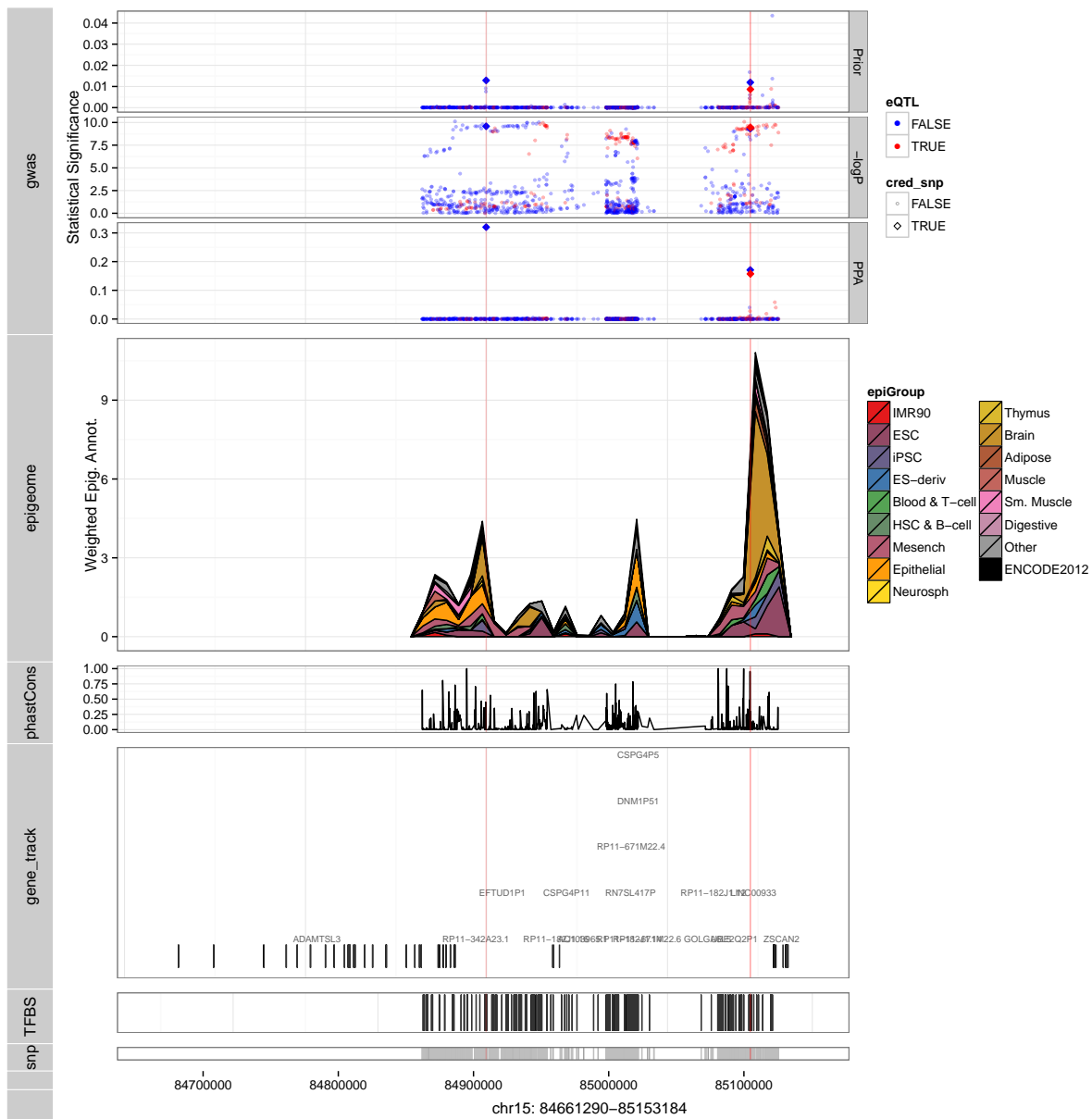
Schizophrenia



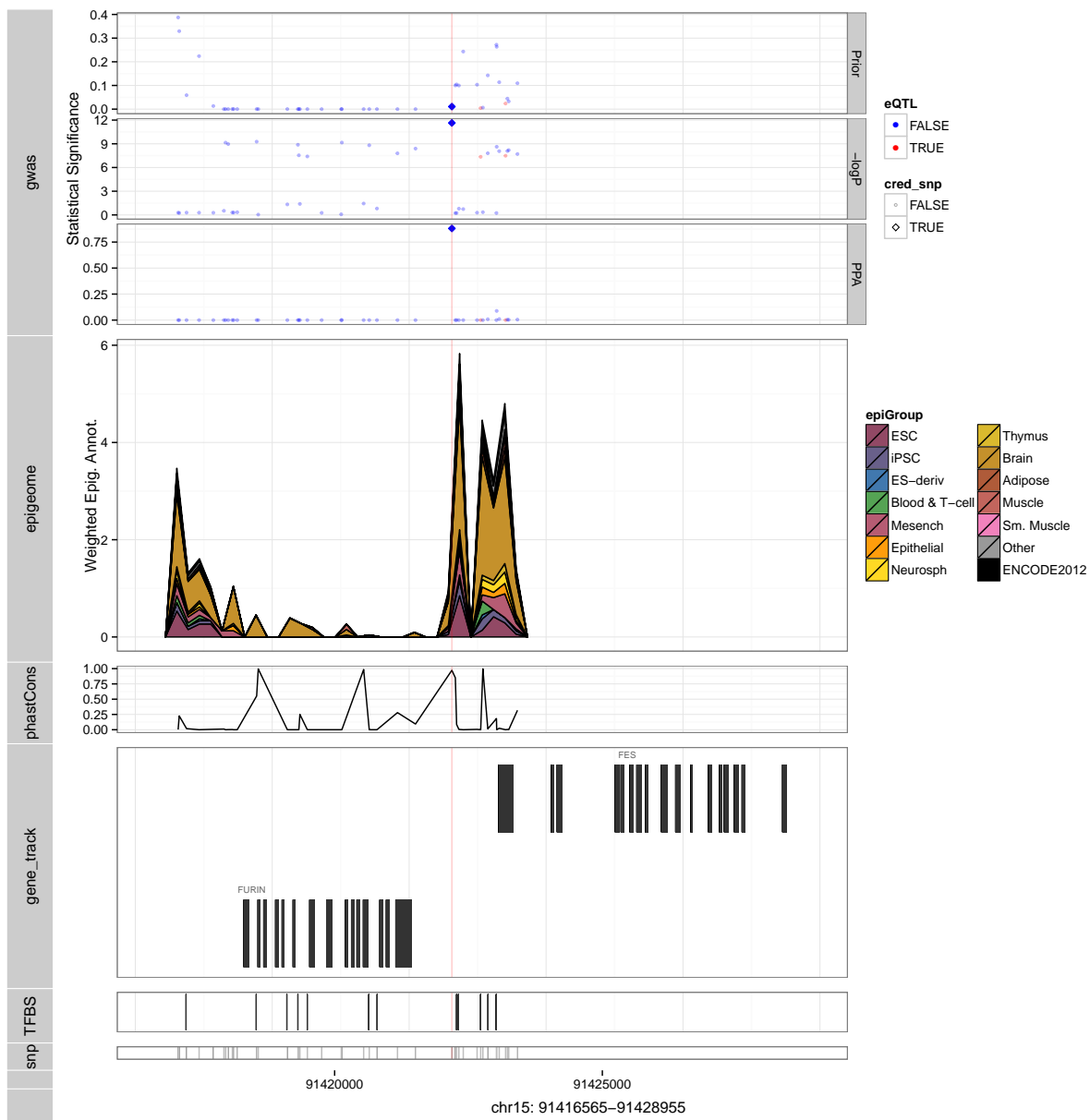
Schizophrenia



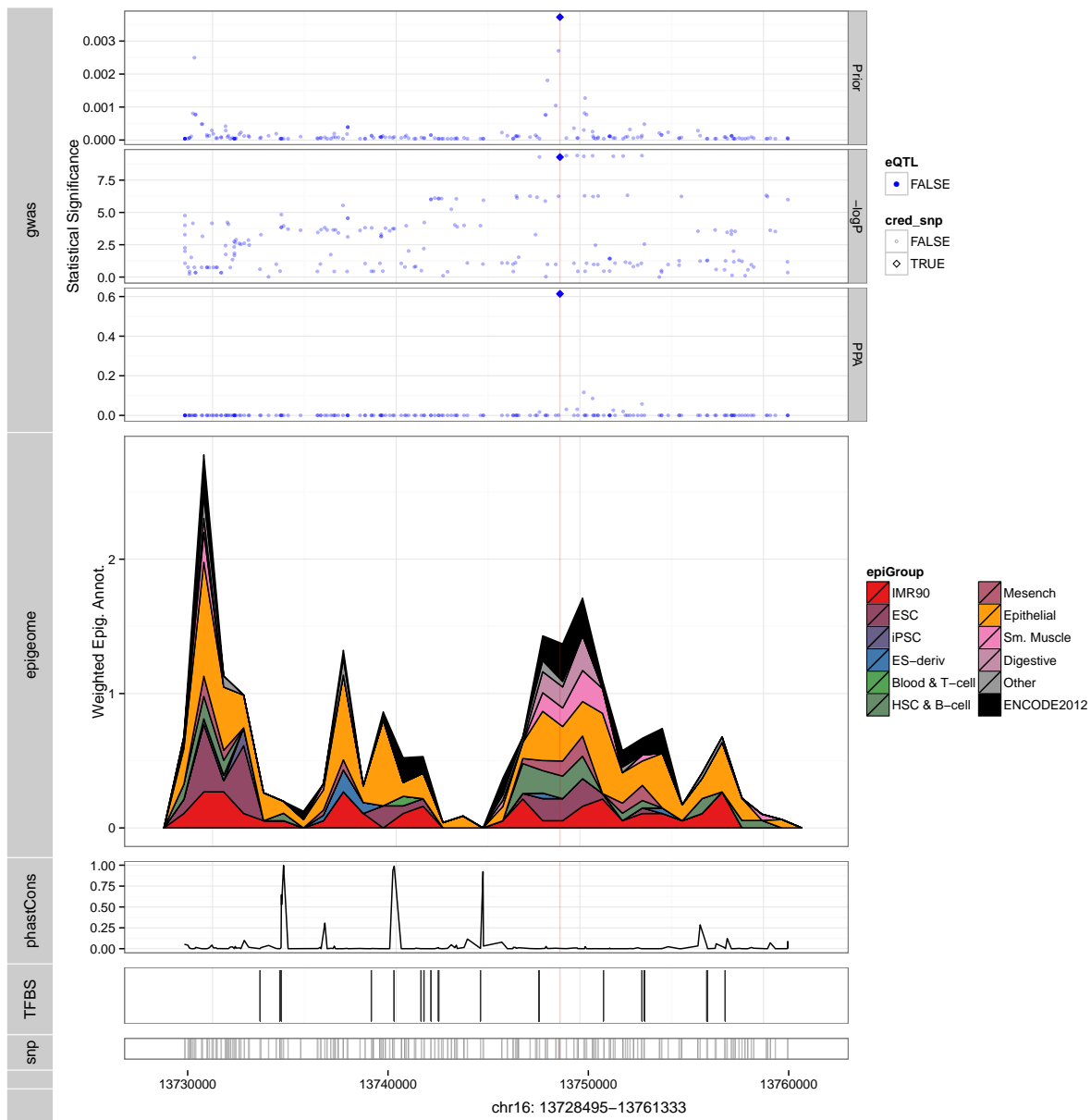
Schizophrenia



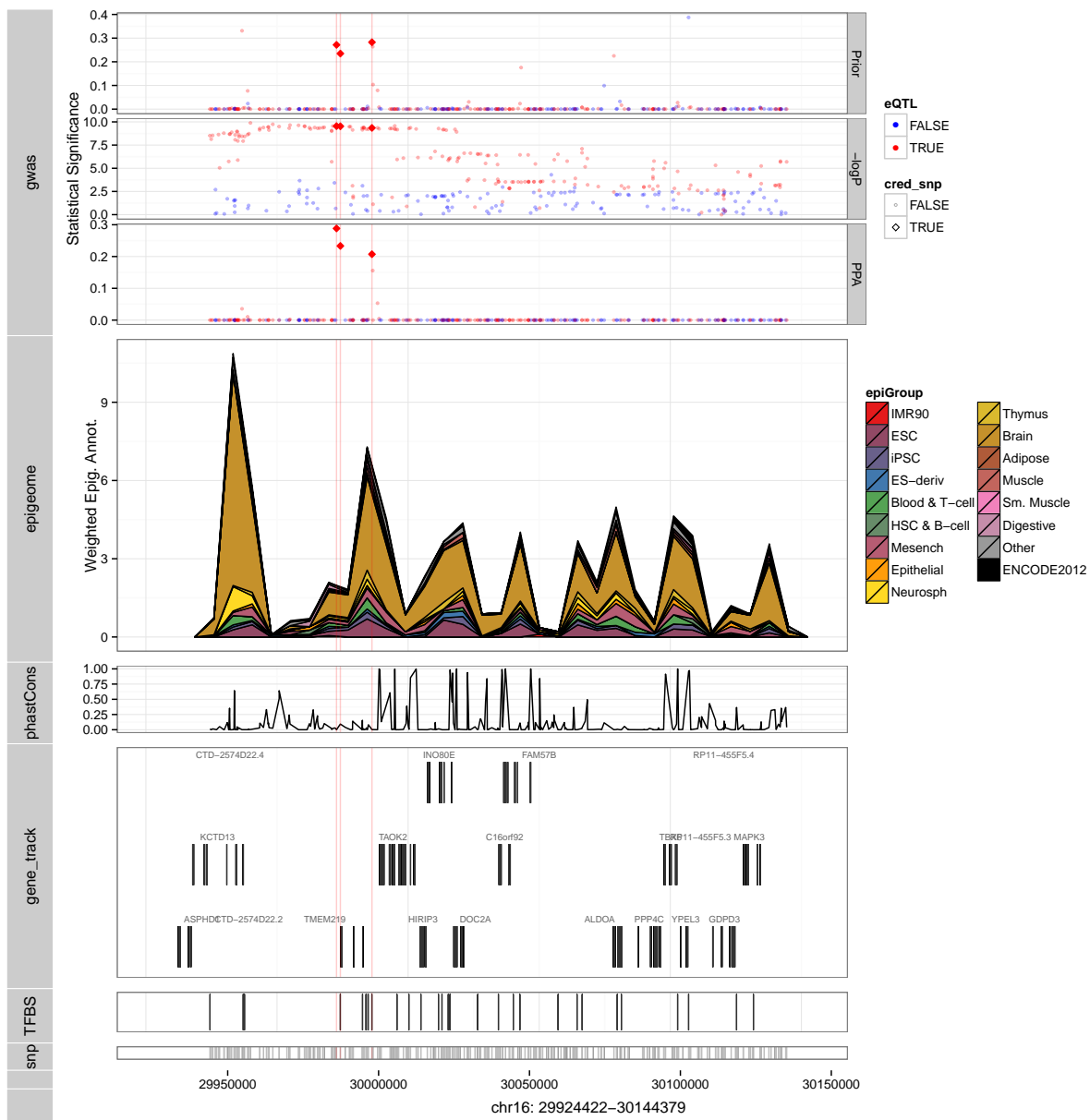
Schizophrenia



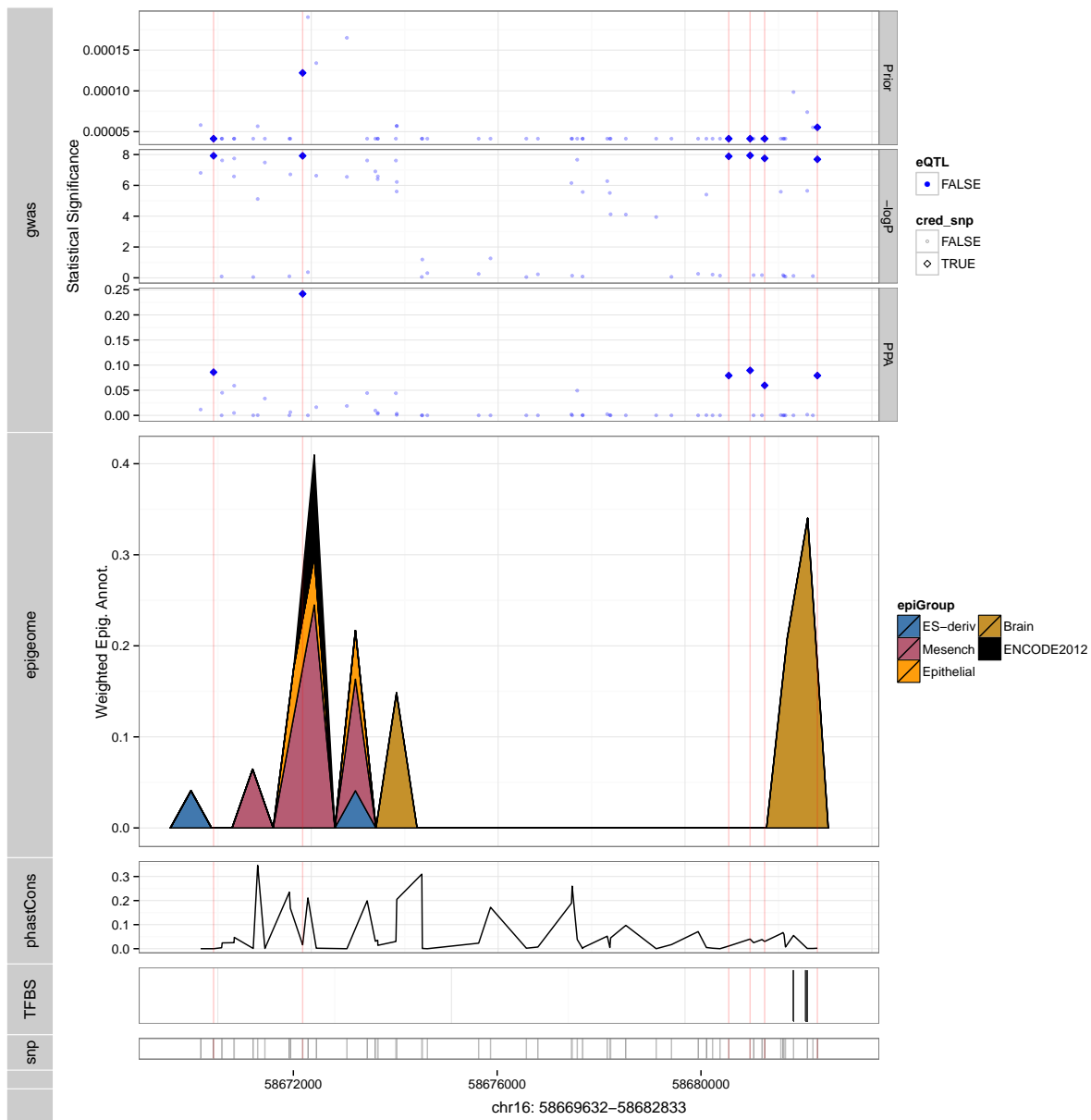
Schizophrenia



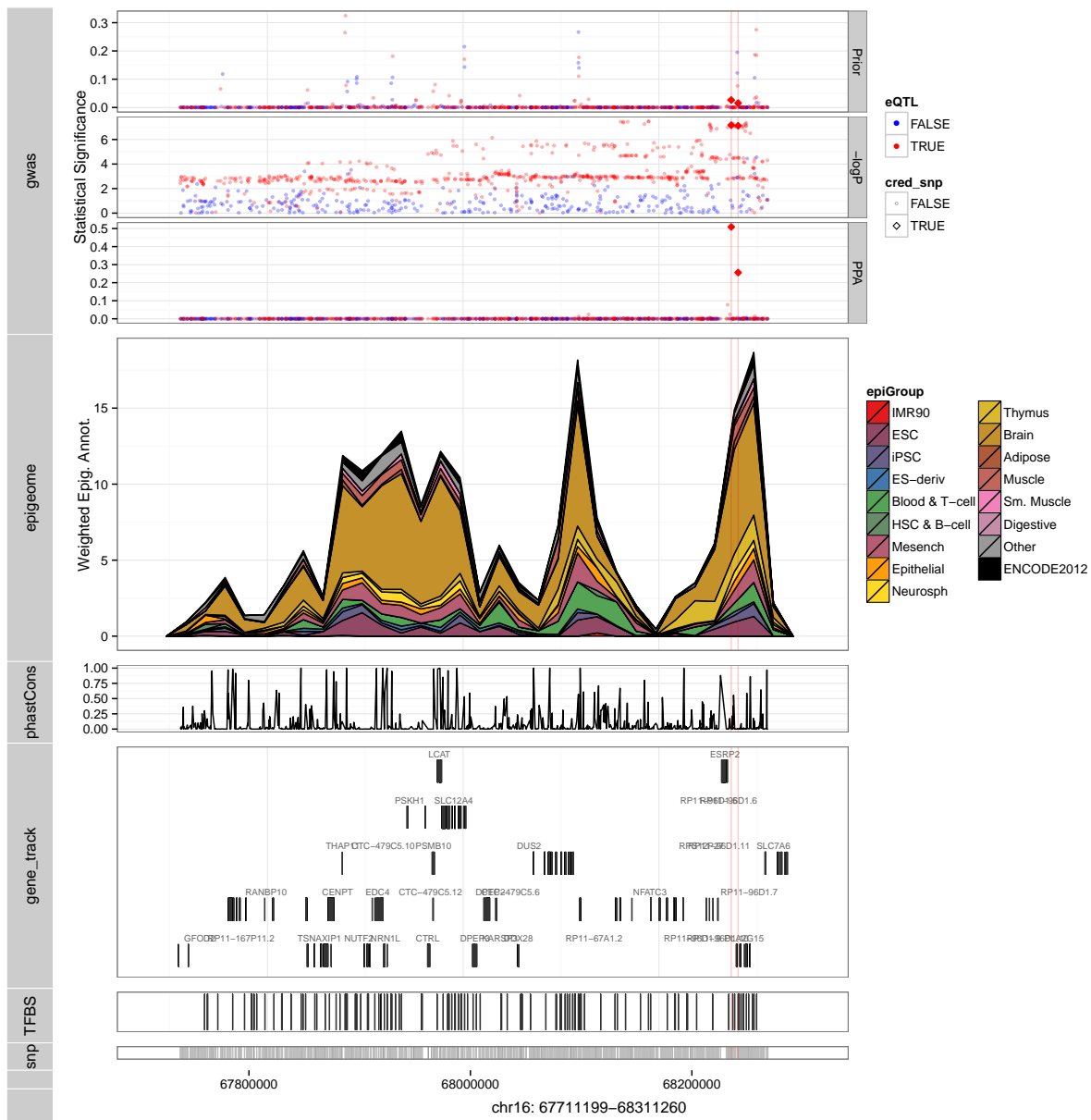
Schizophrenia



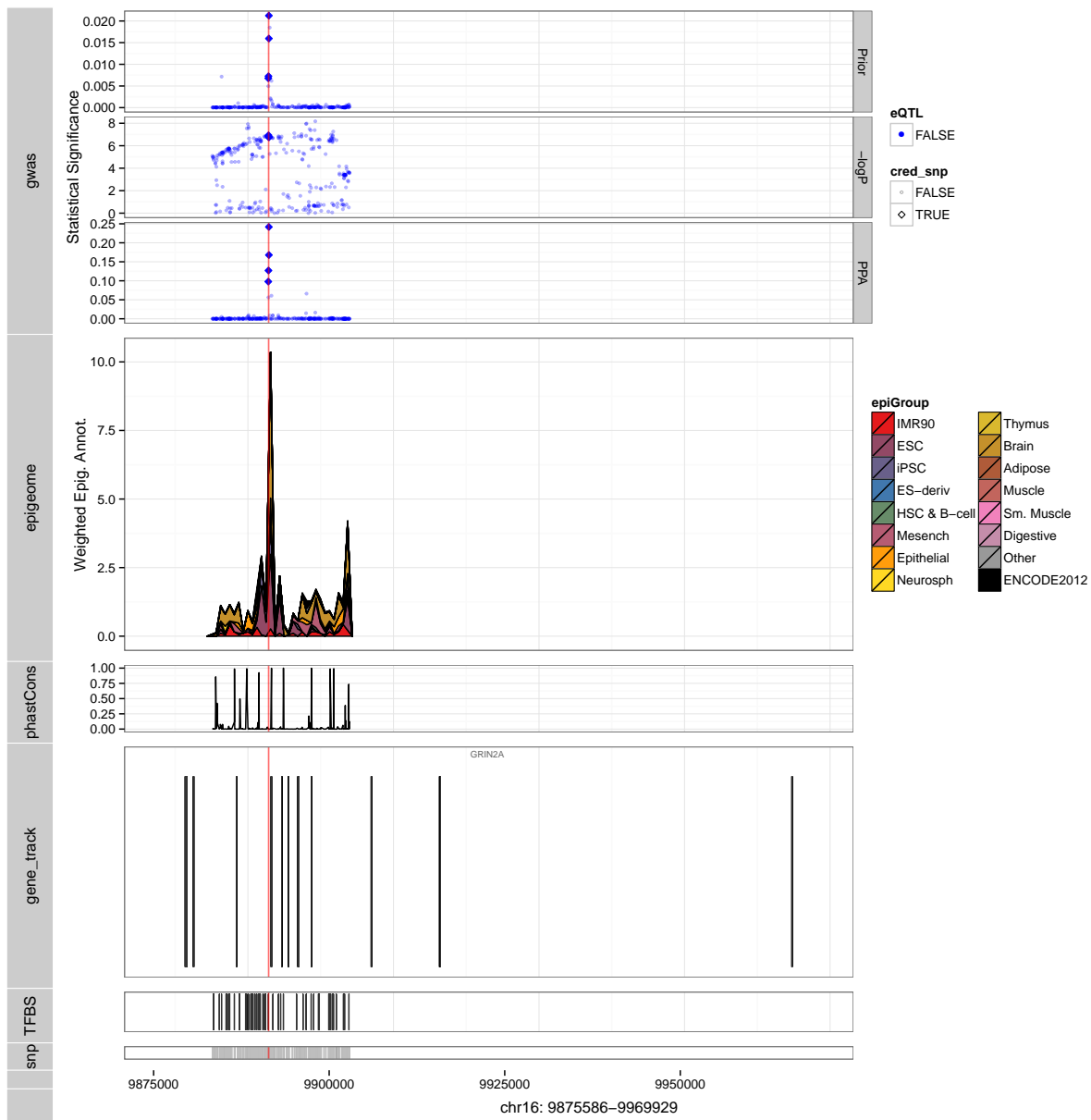
Schizophrenia



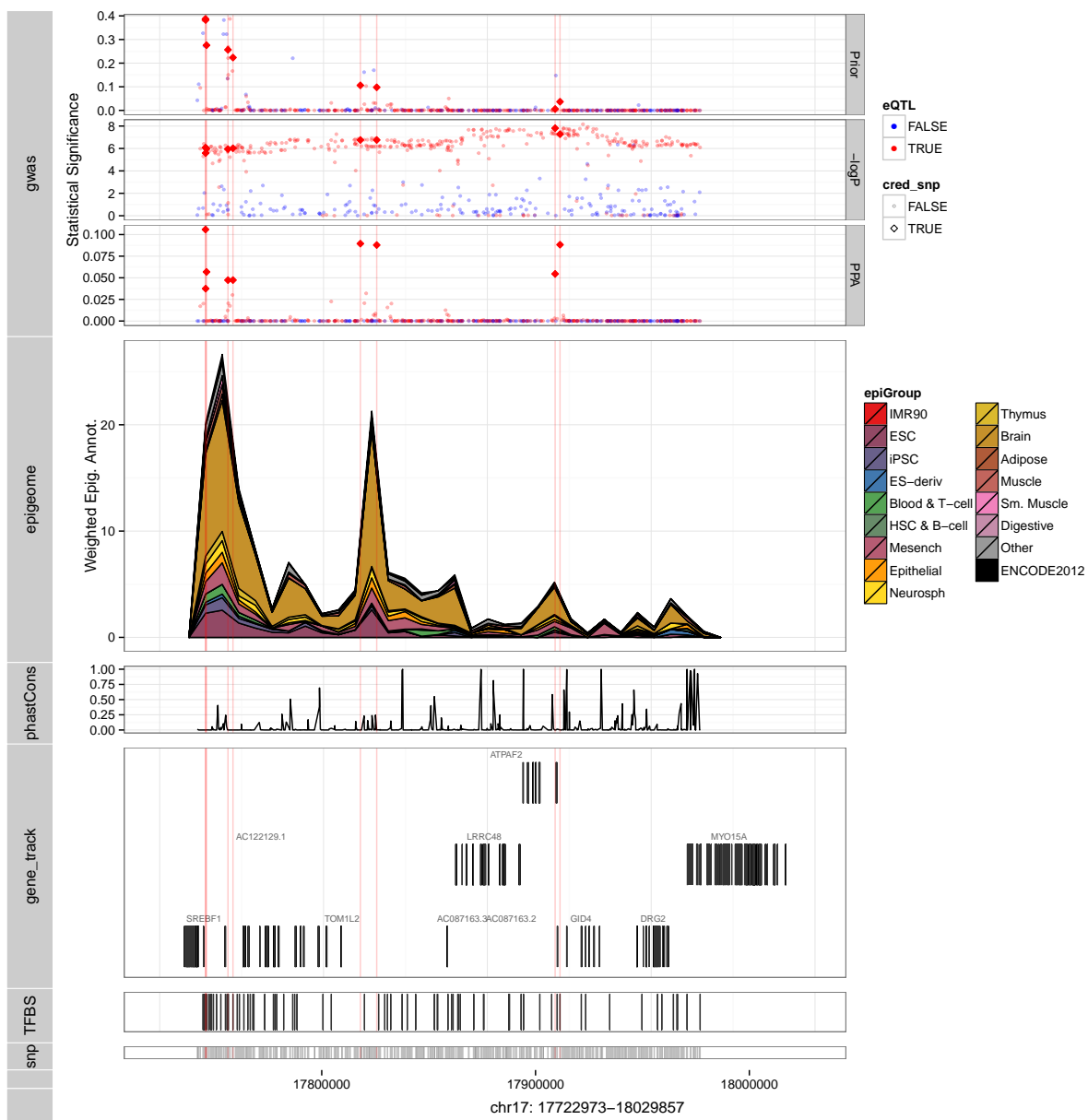
Schizophrenia



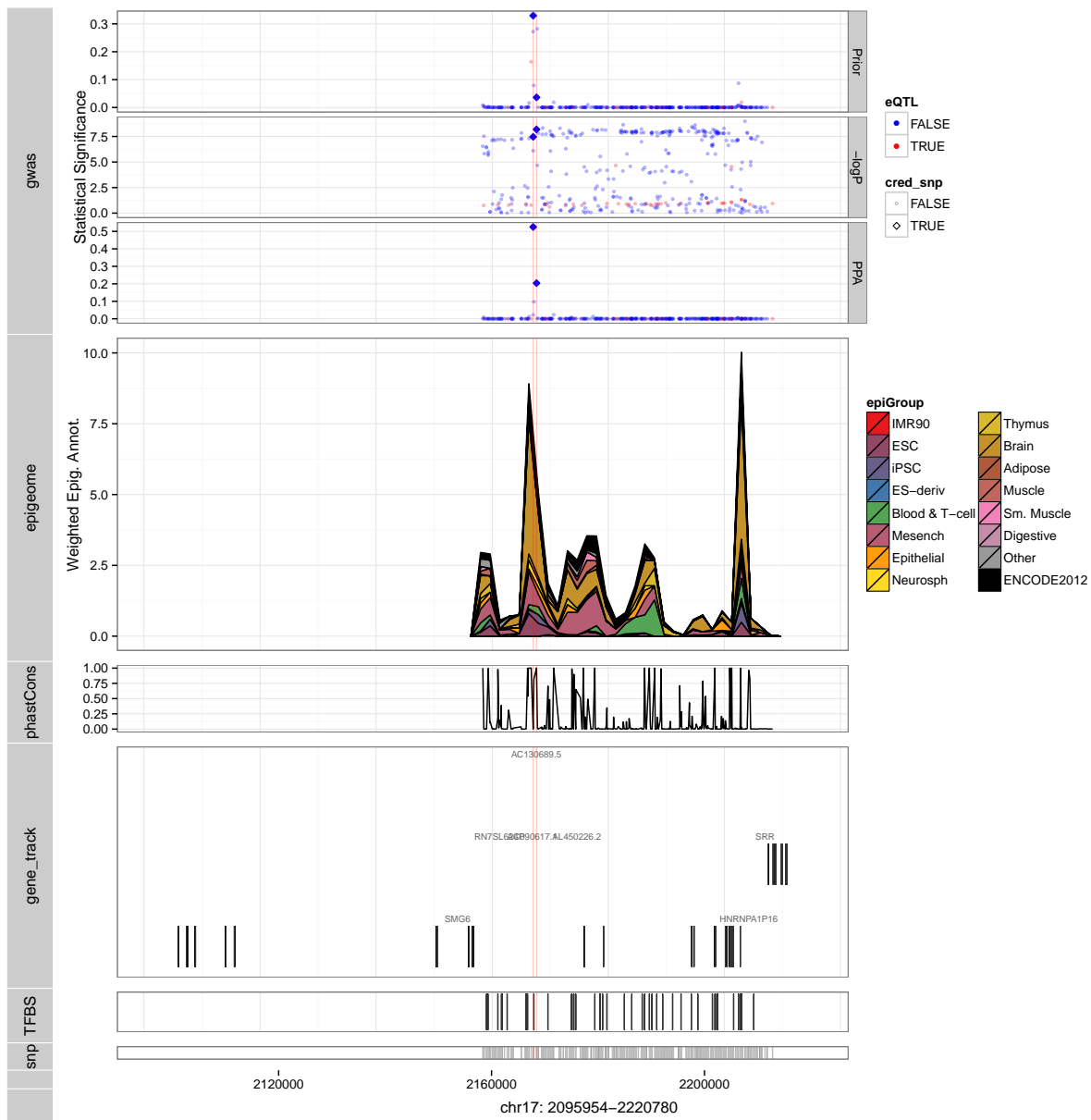
Schizophrenia



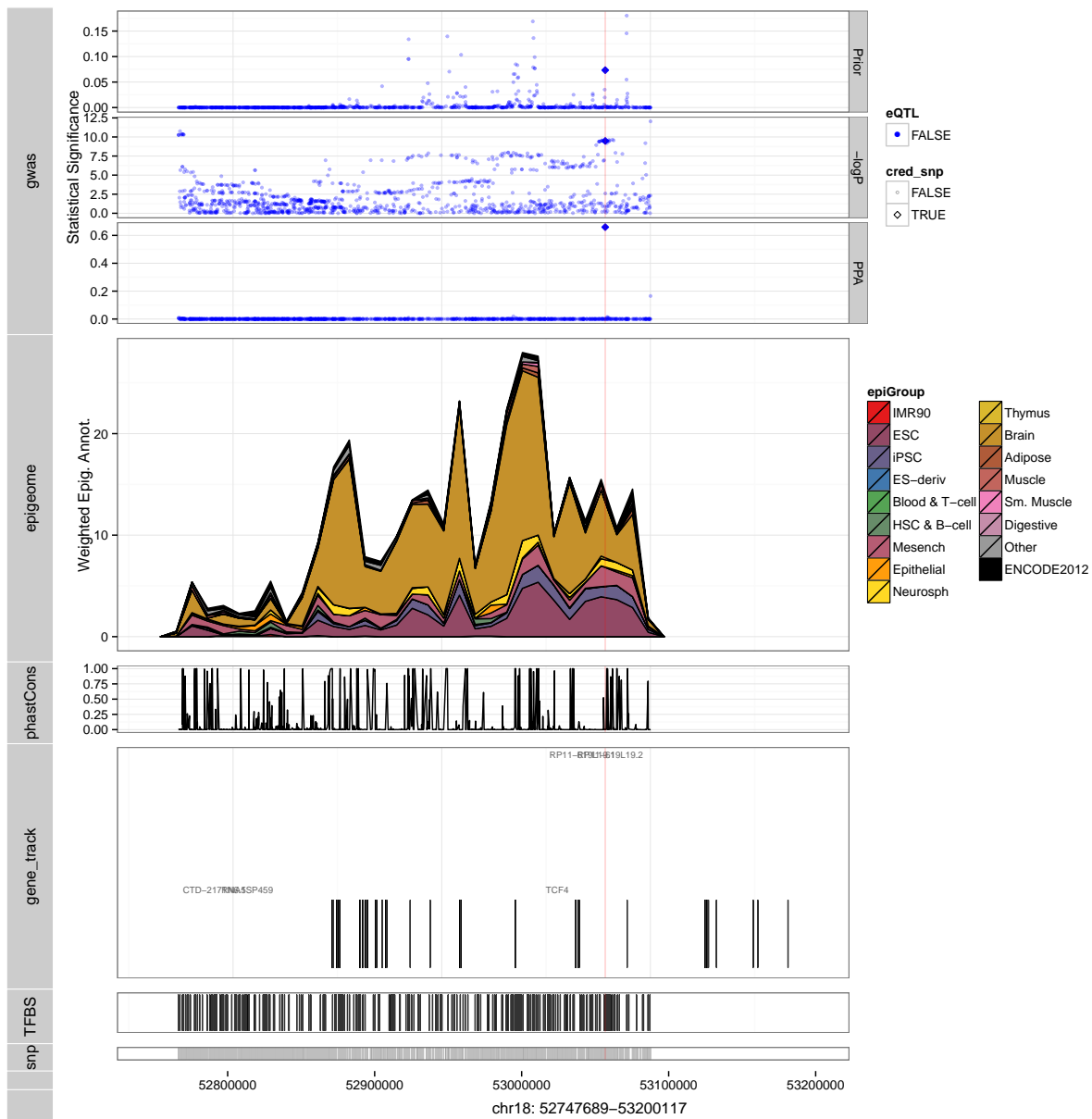
Schizophrenia



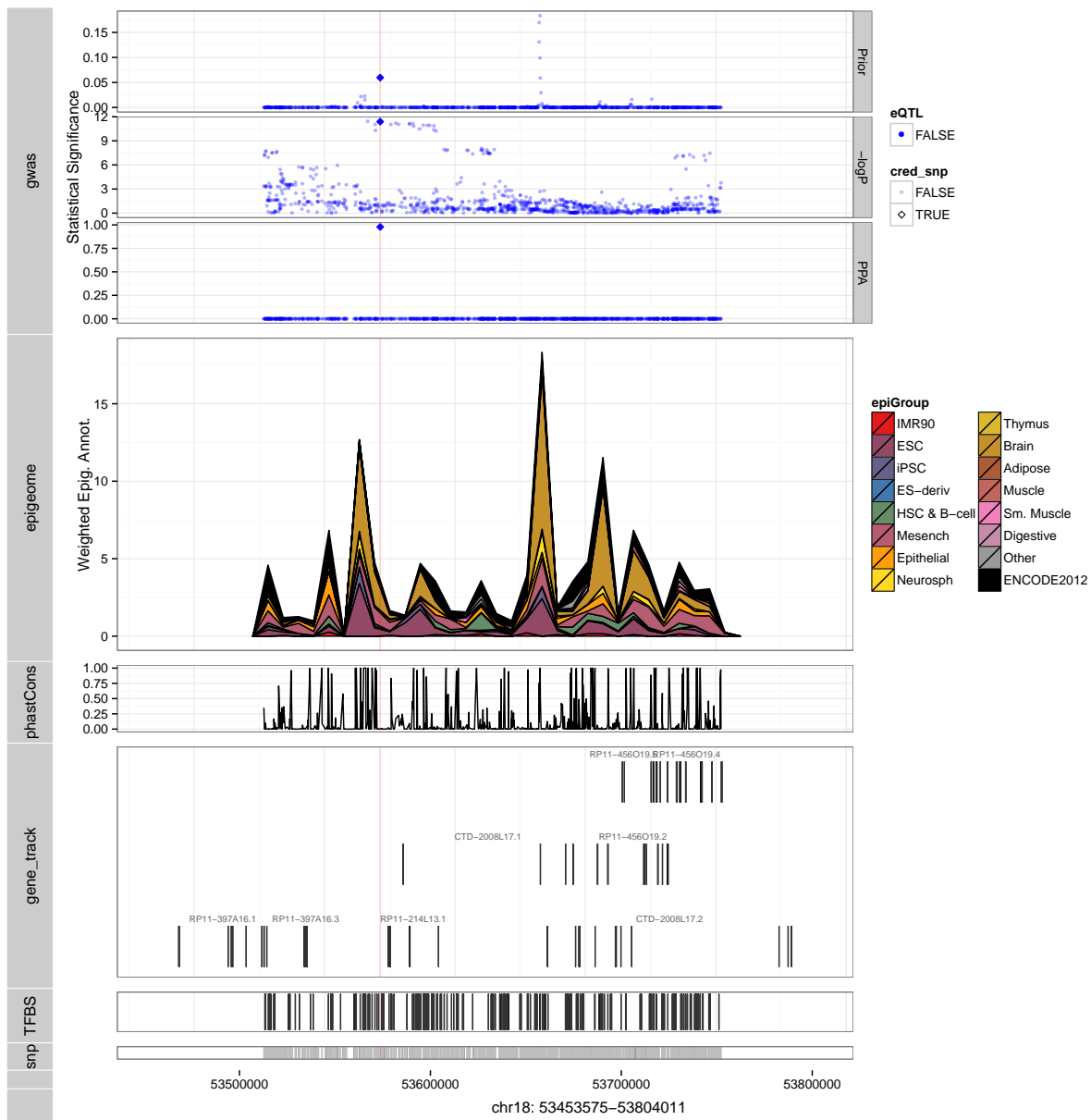
Schizophrenia



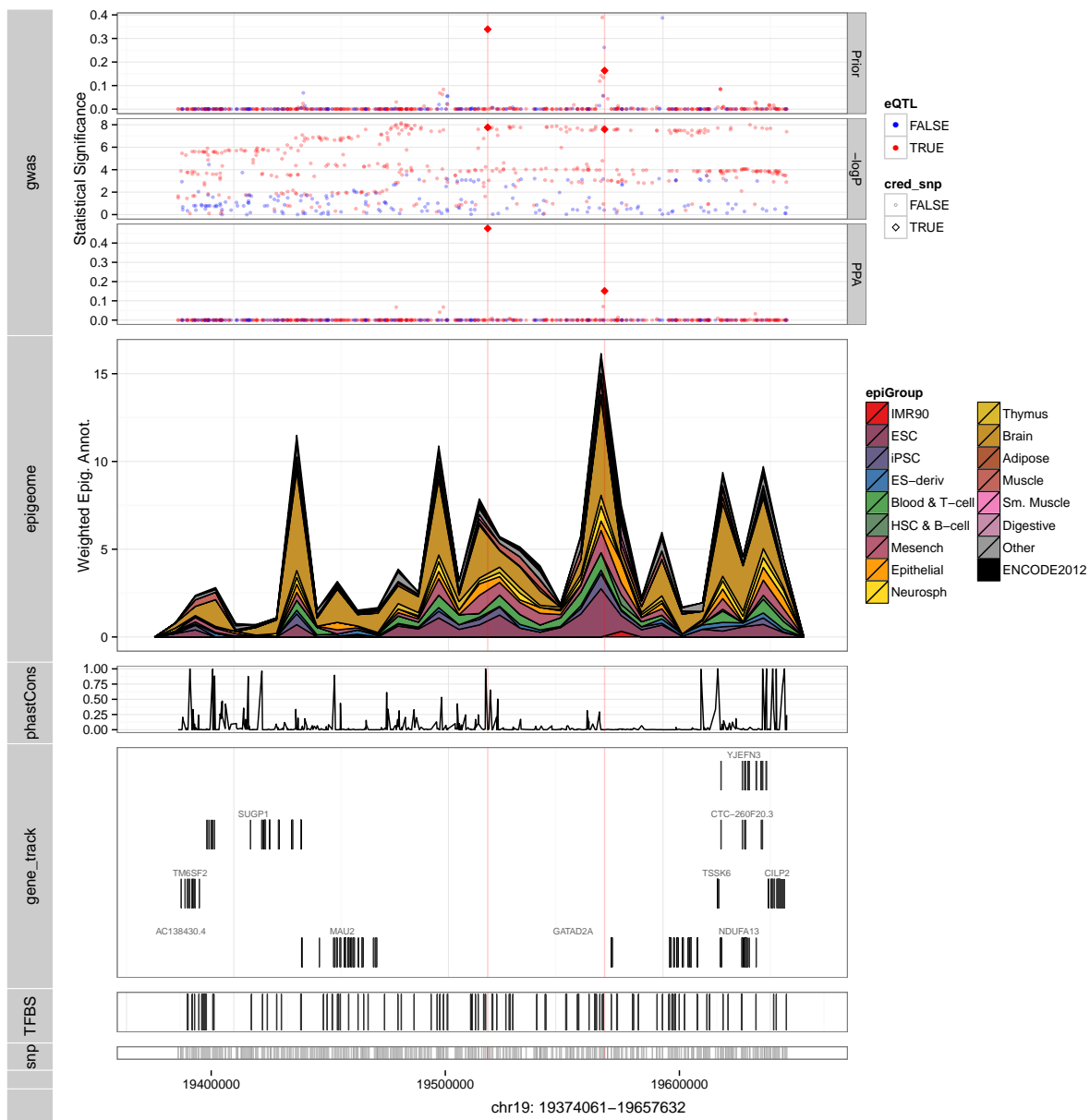
Schizophrenia



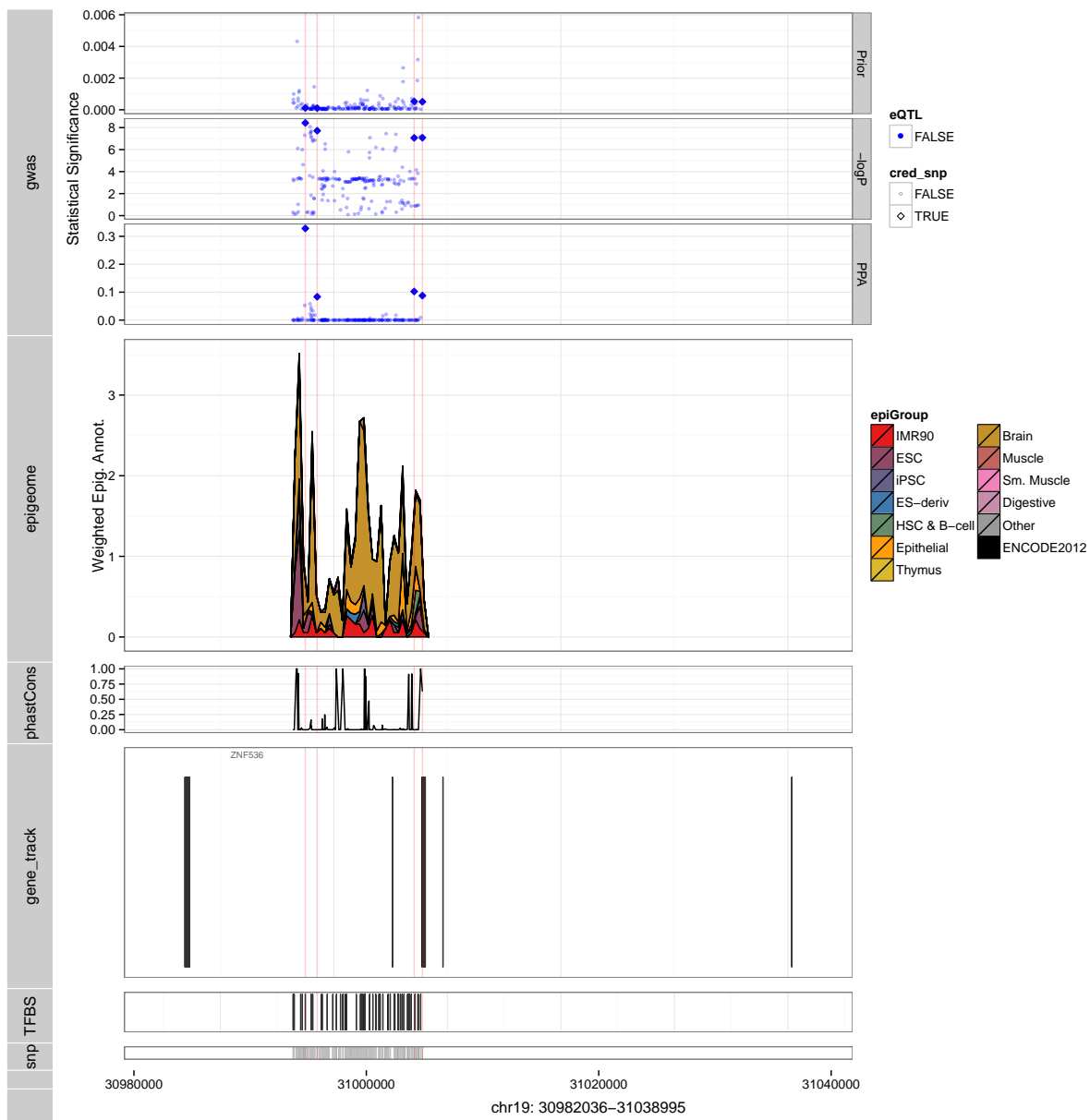
Schizophrenia



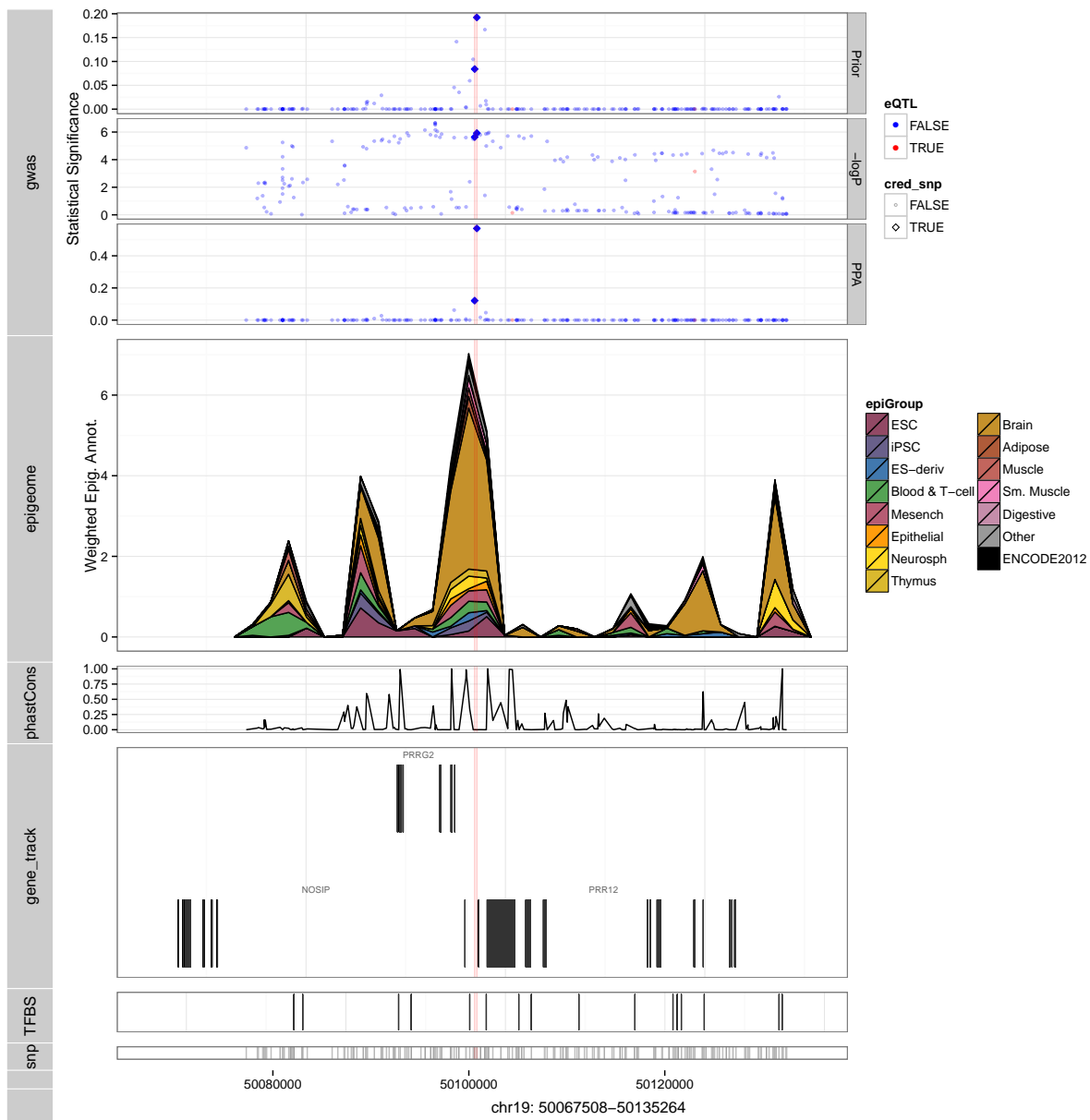
Schizophrenia



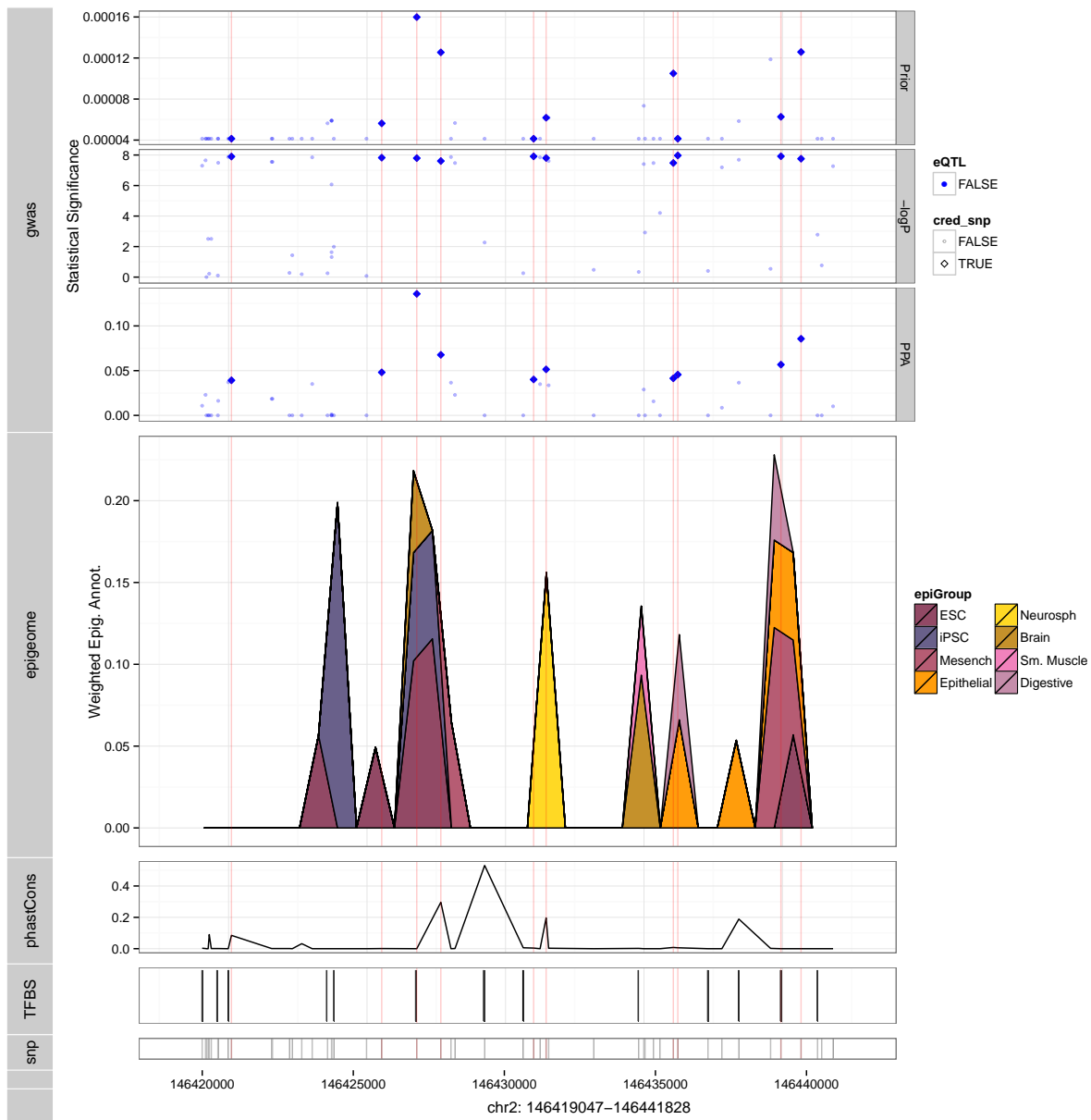
Schizophrenia



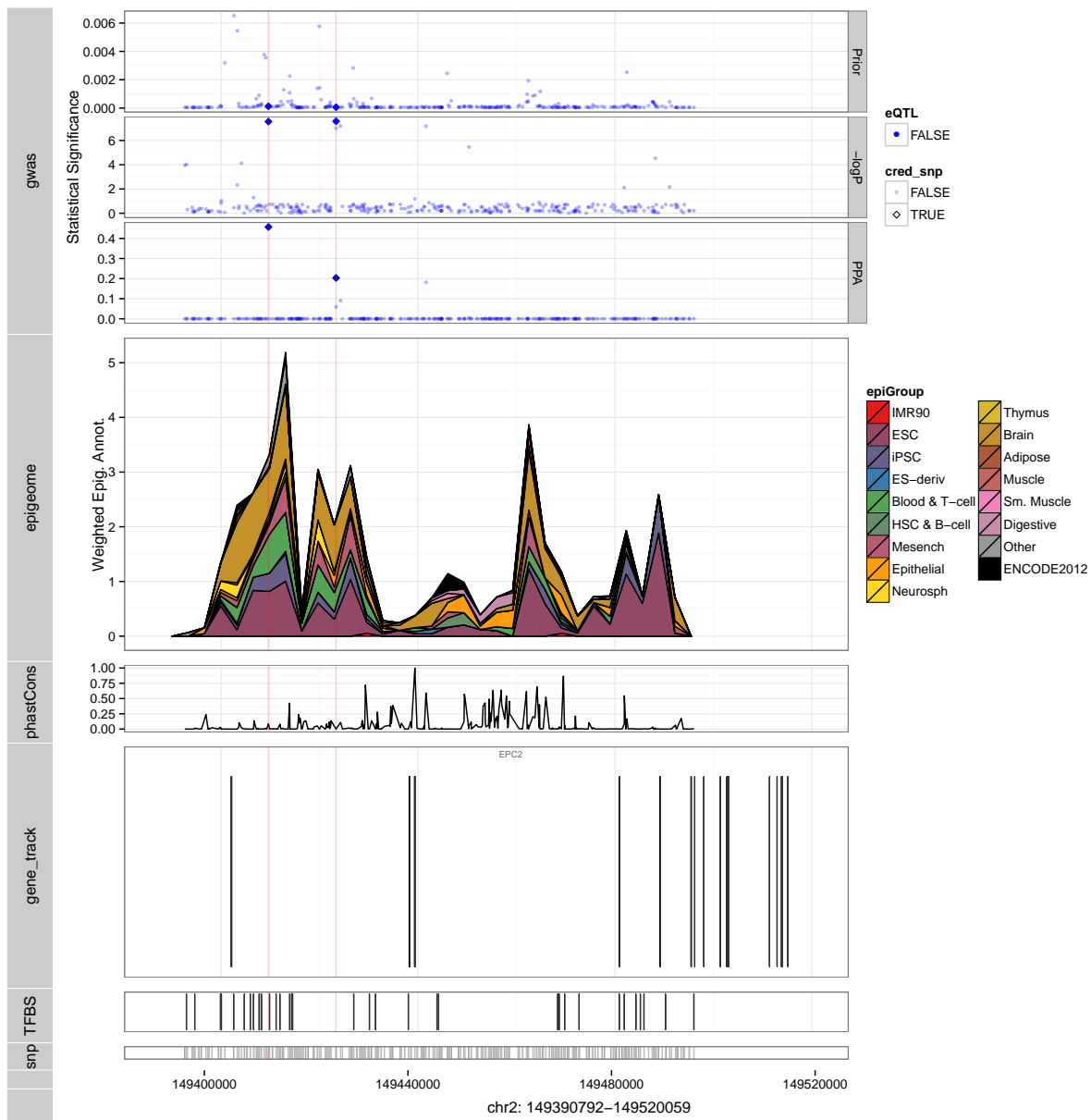
Schizophrenia



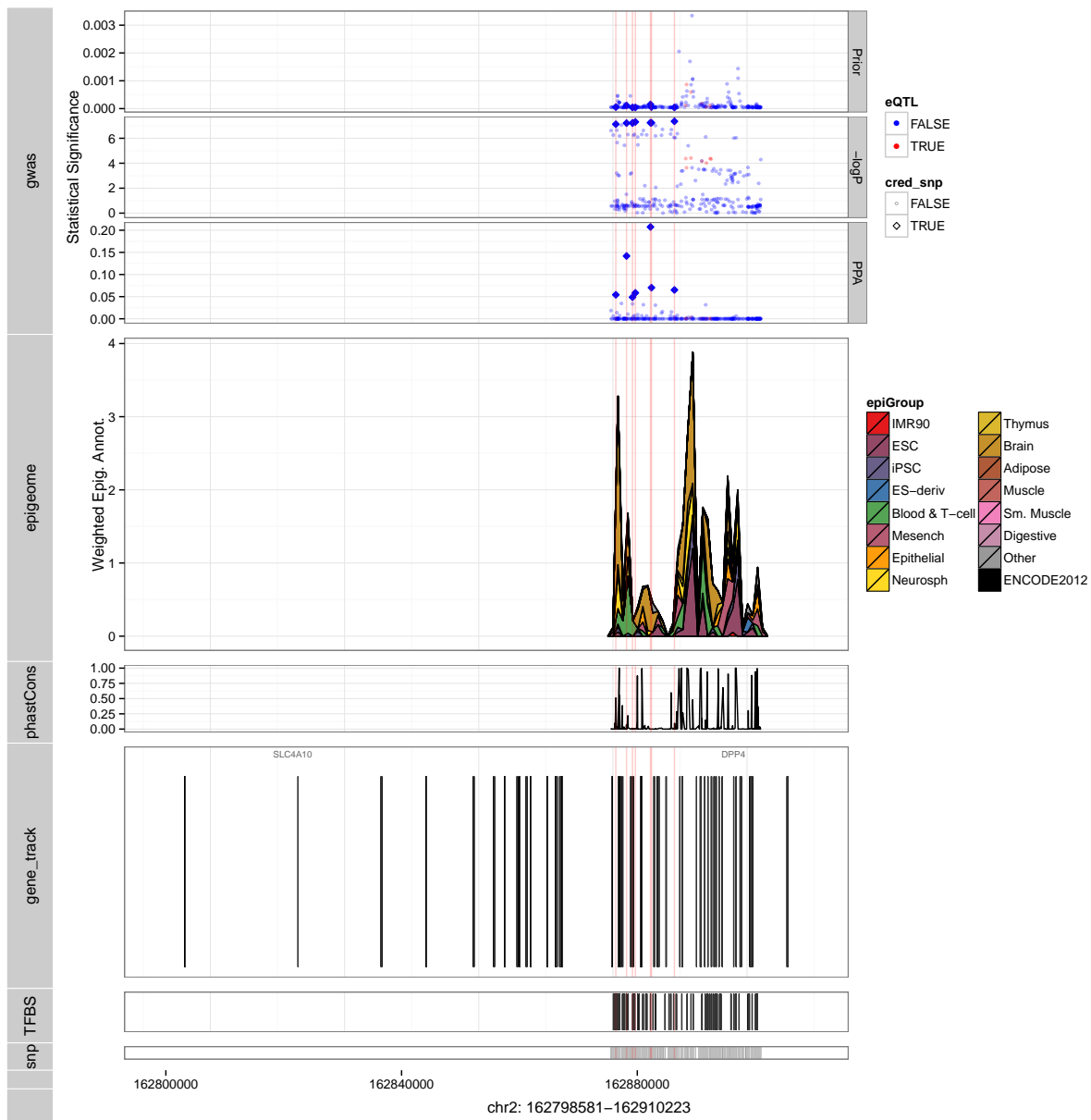
Schizophrenia



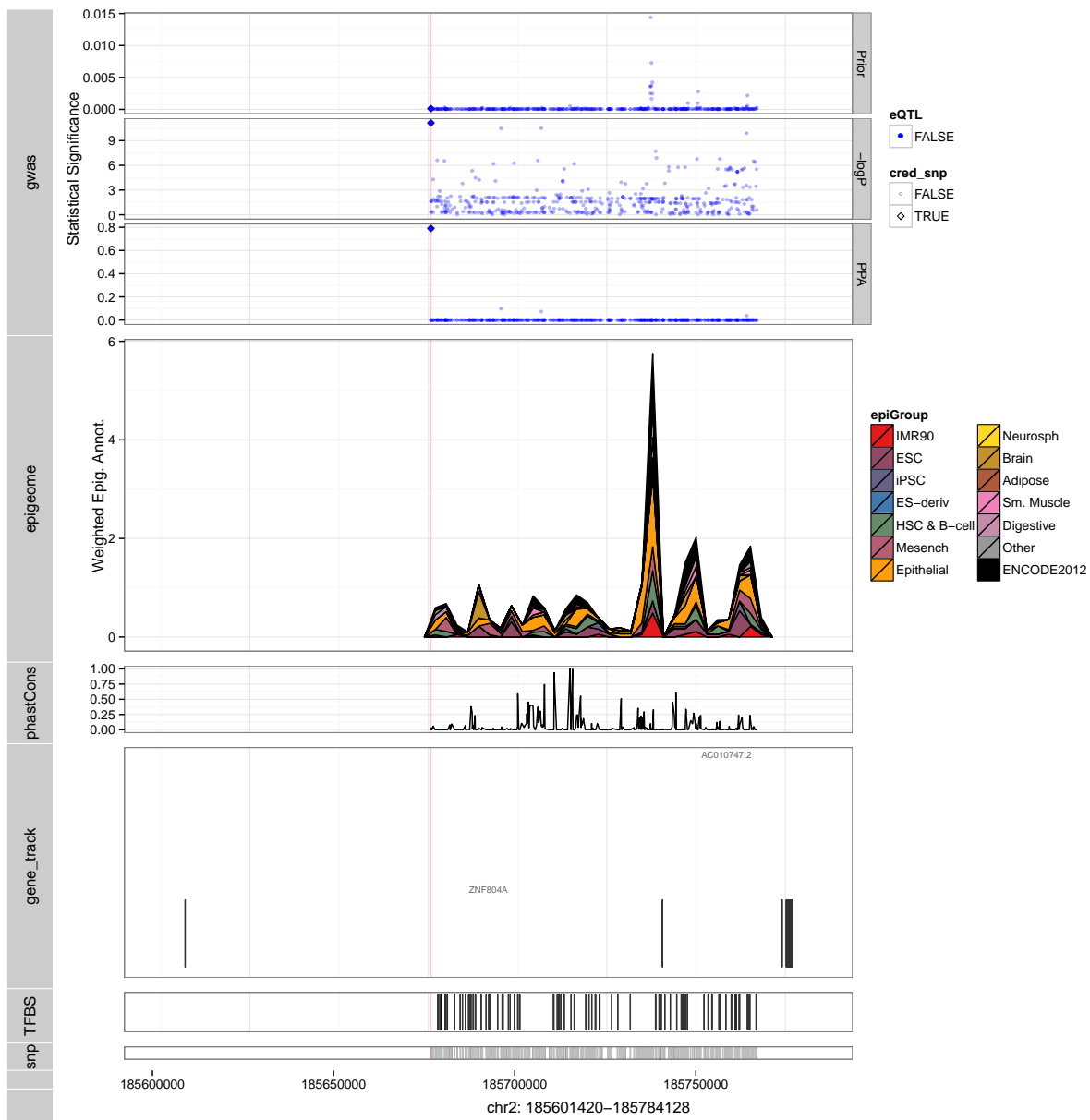
Schizophrenia



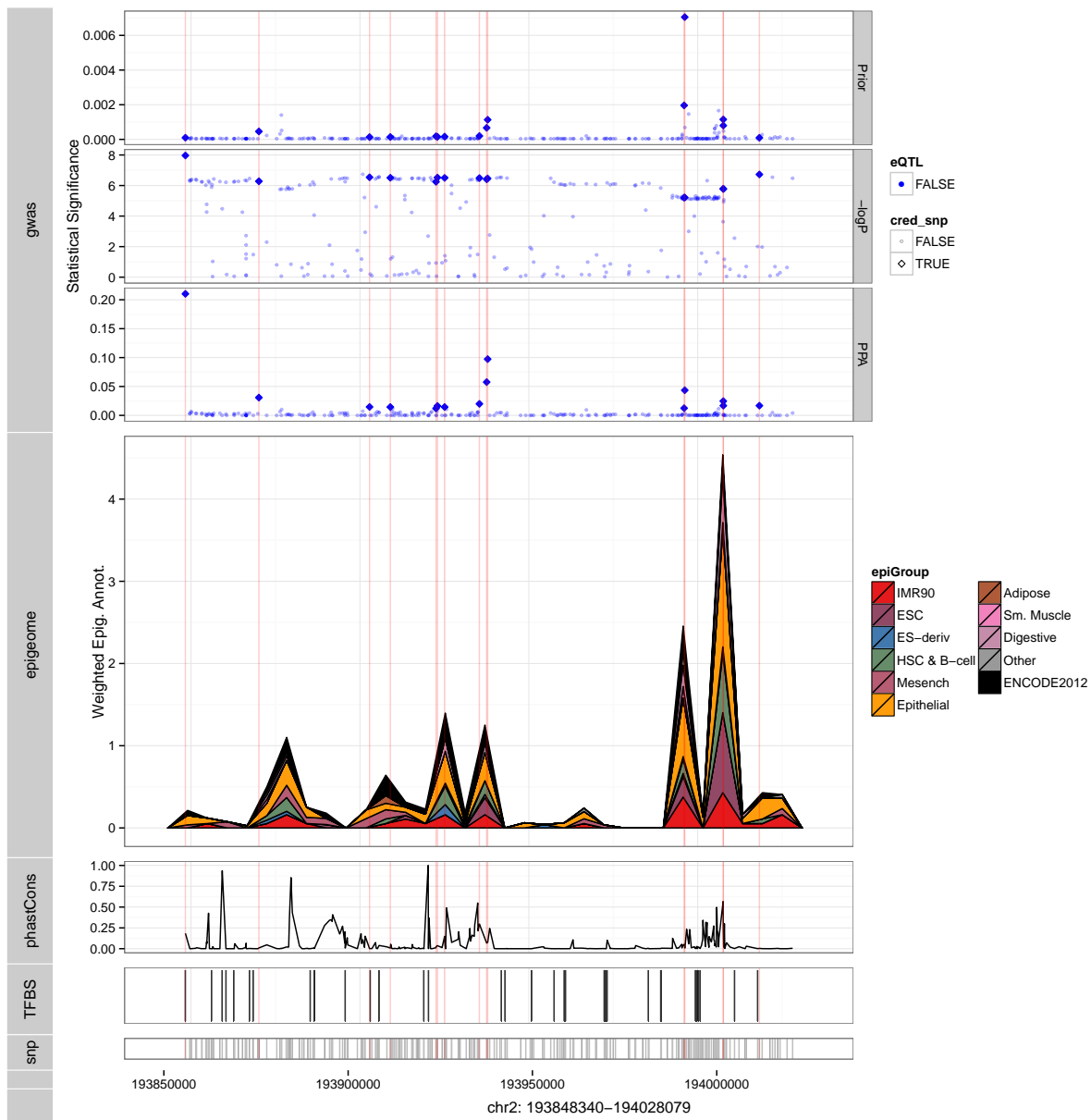
Schizophrenia



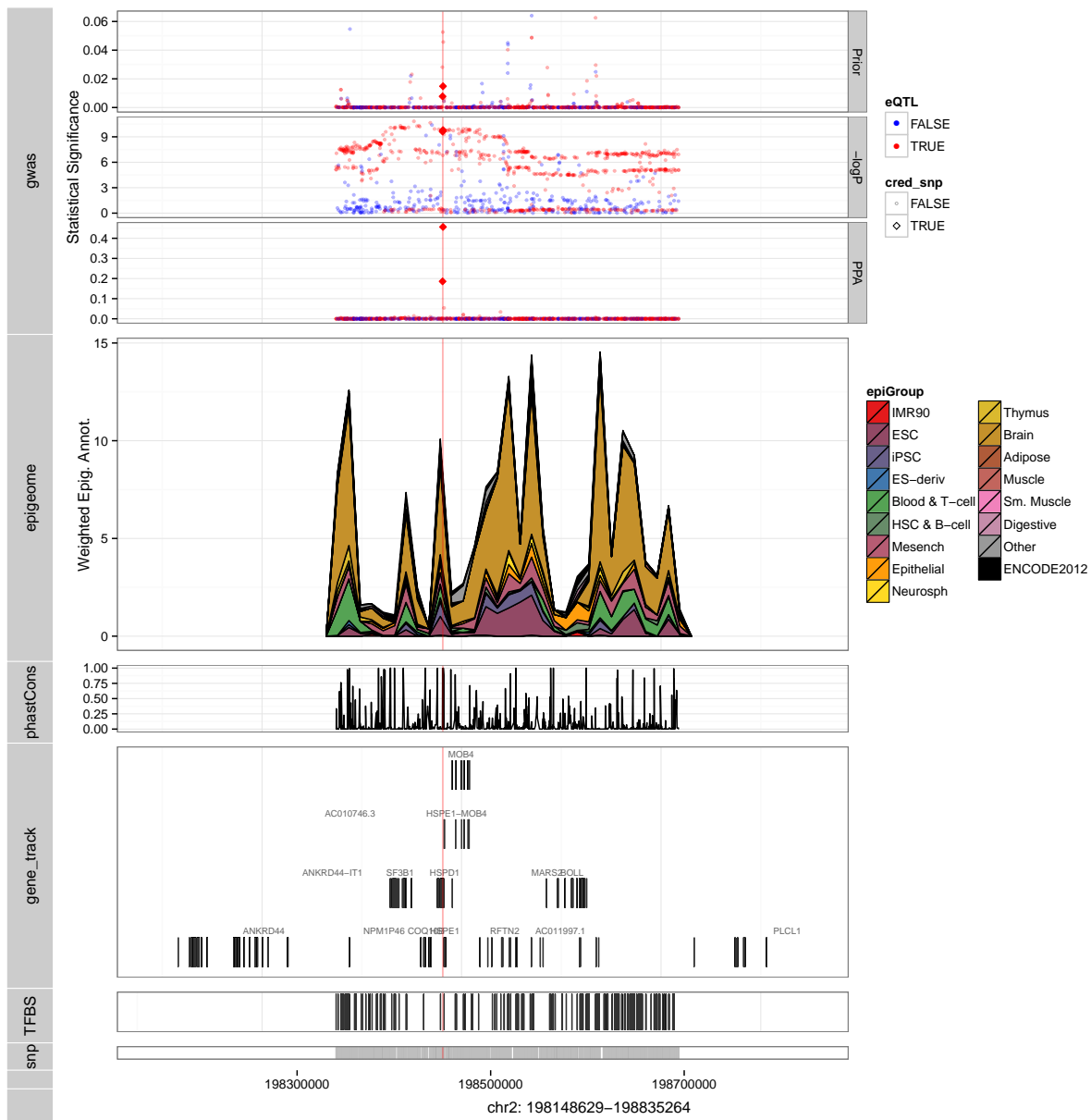
Schizophrenia



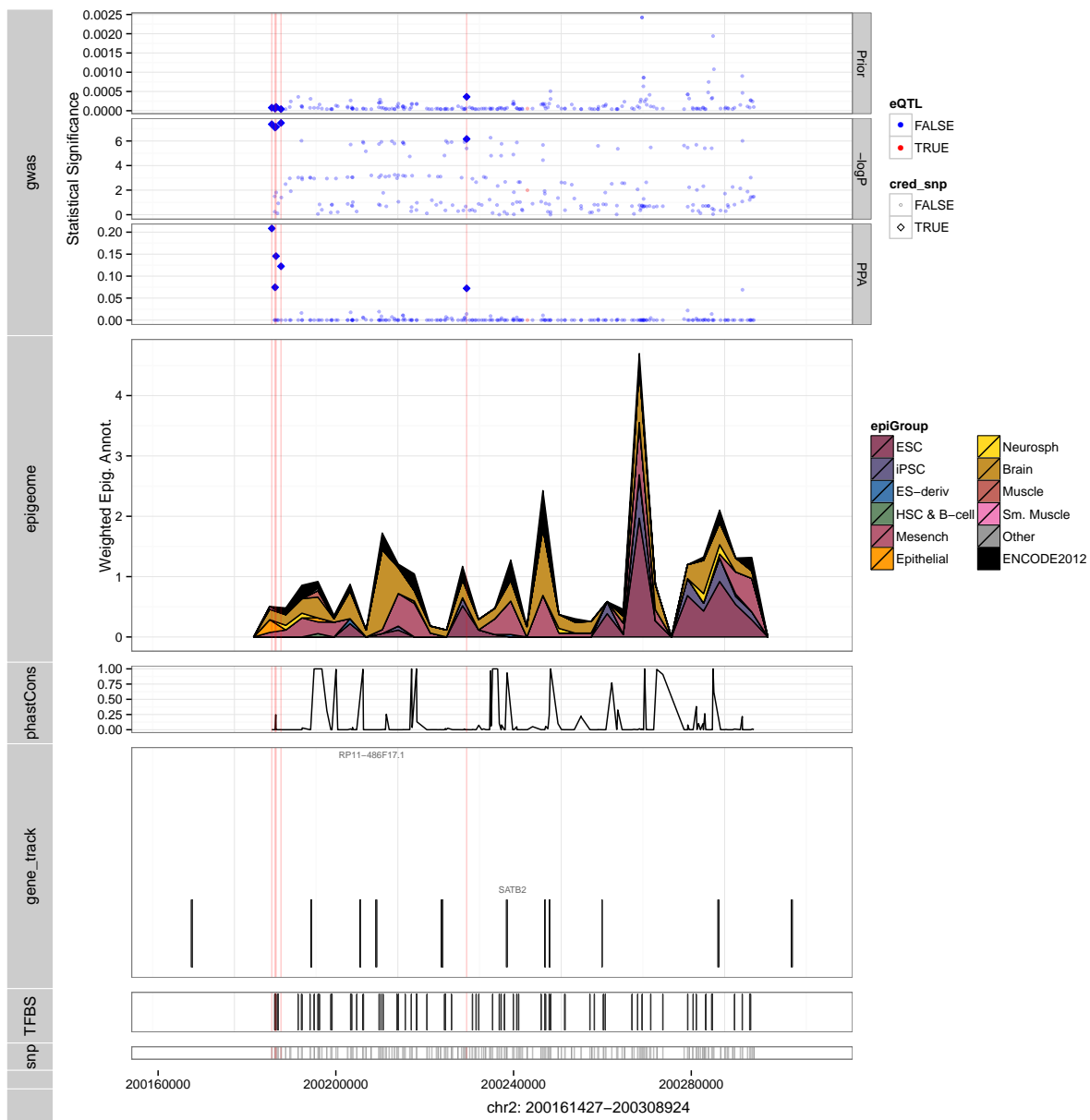
Schizophrenia



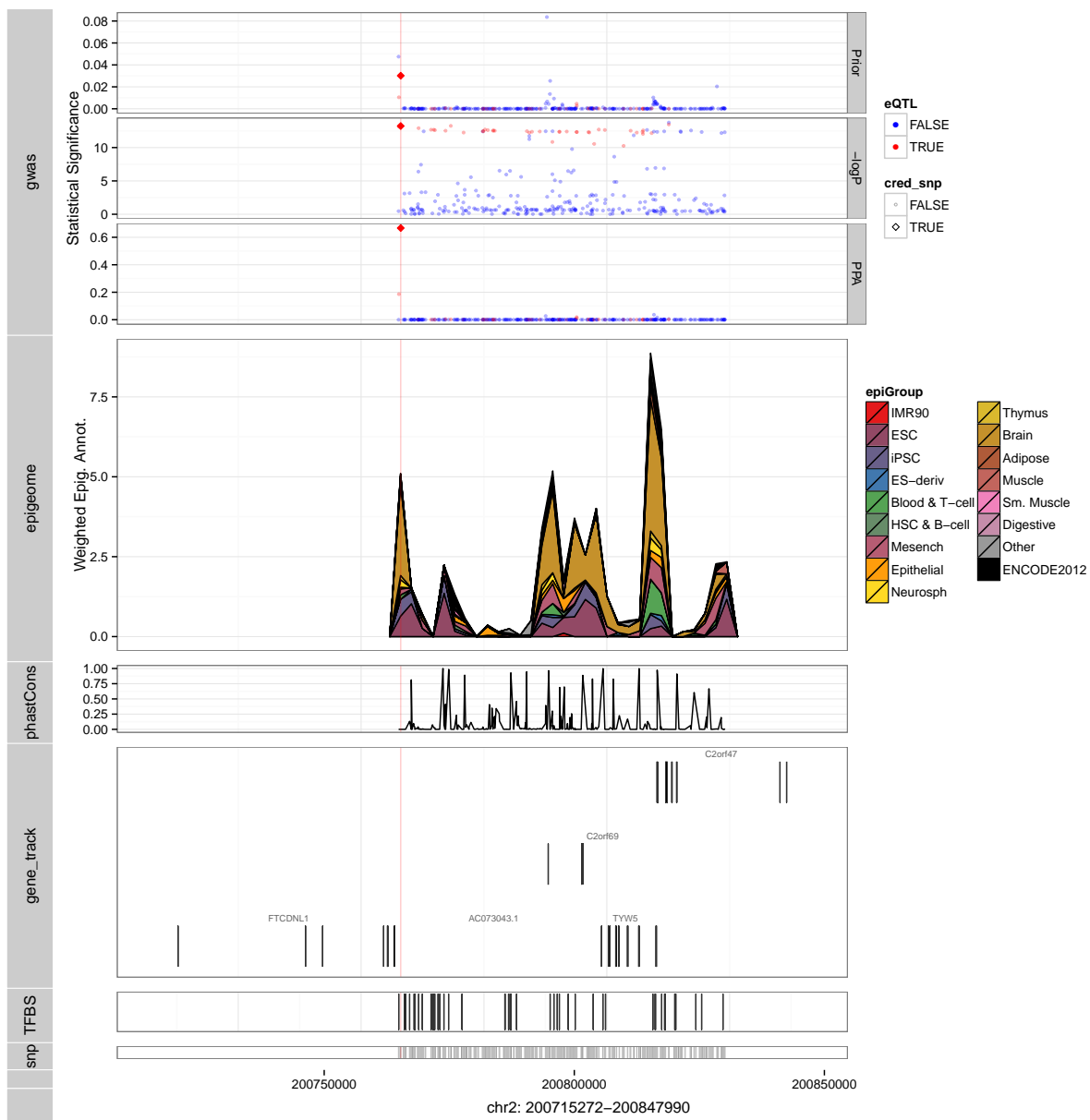
Schizophrenia



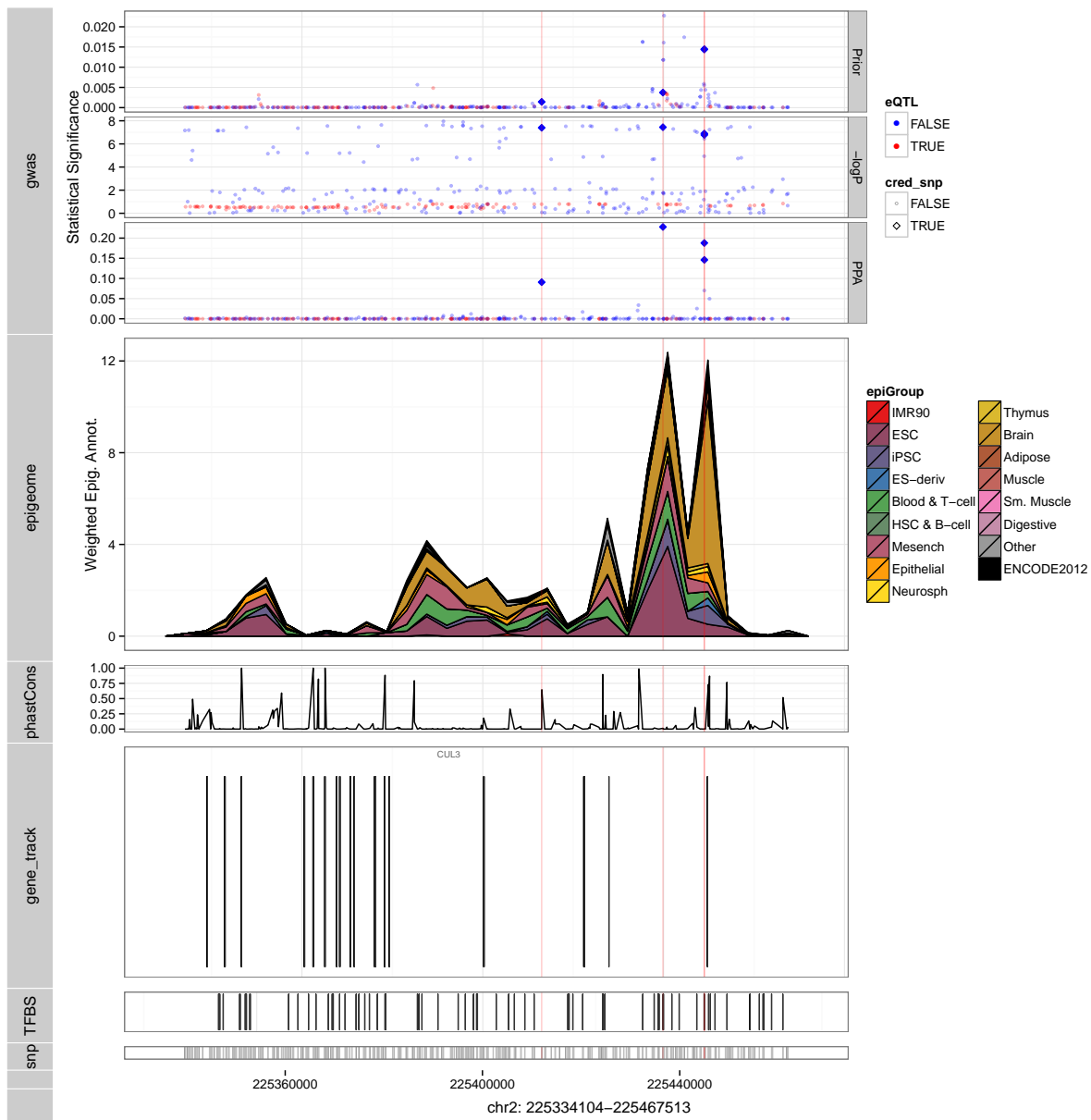
Schizophrenia



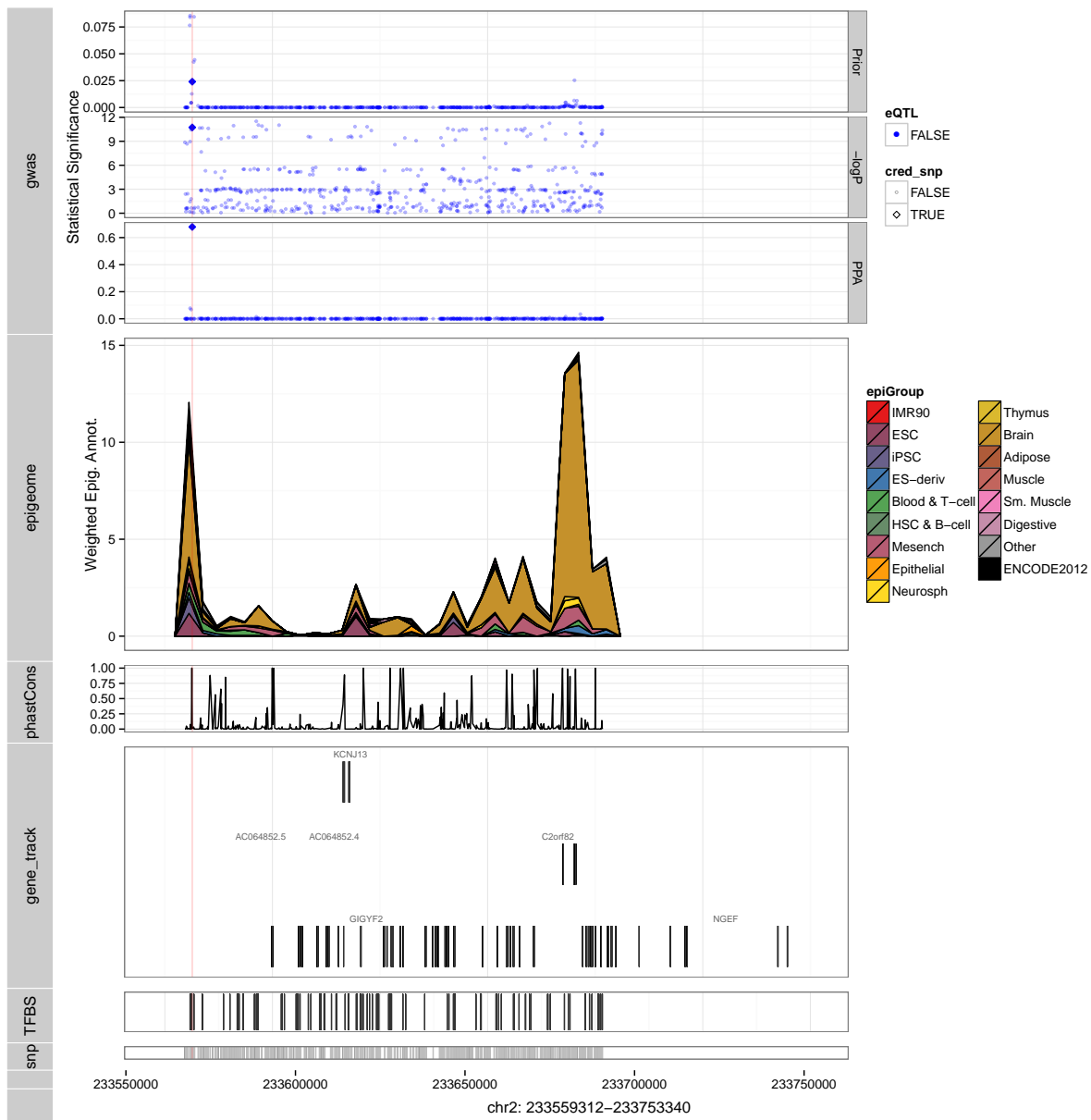
Schizophrenia



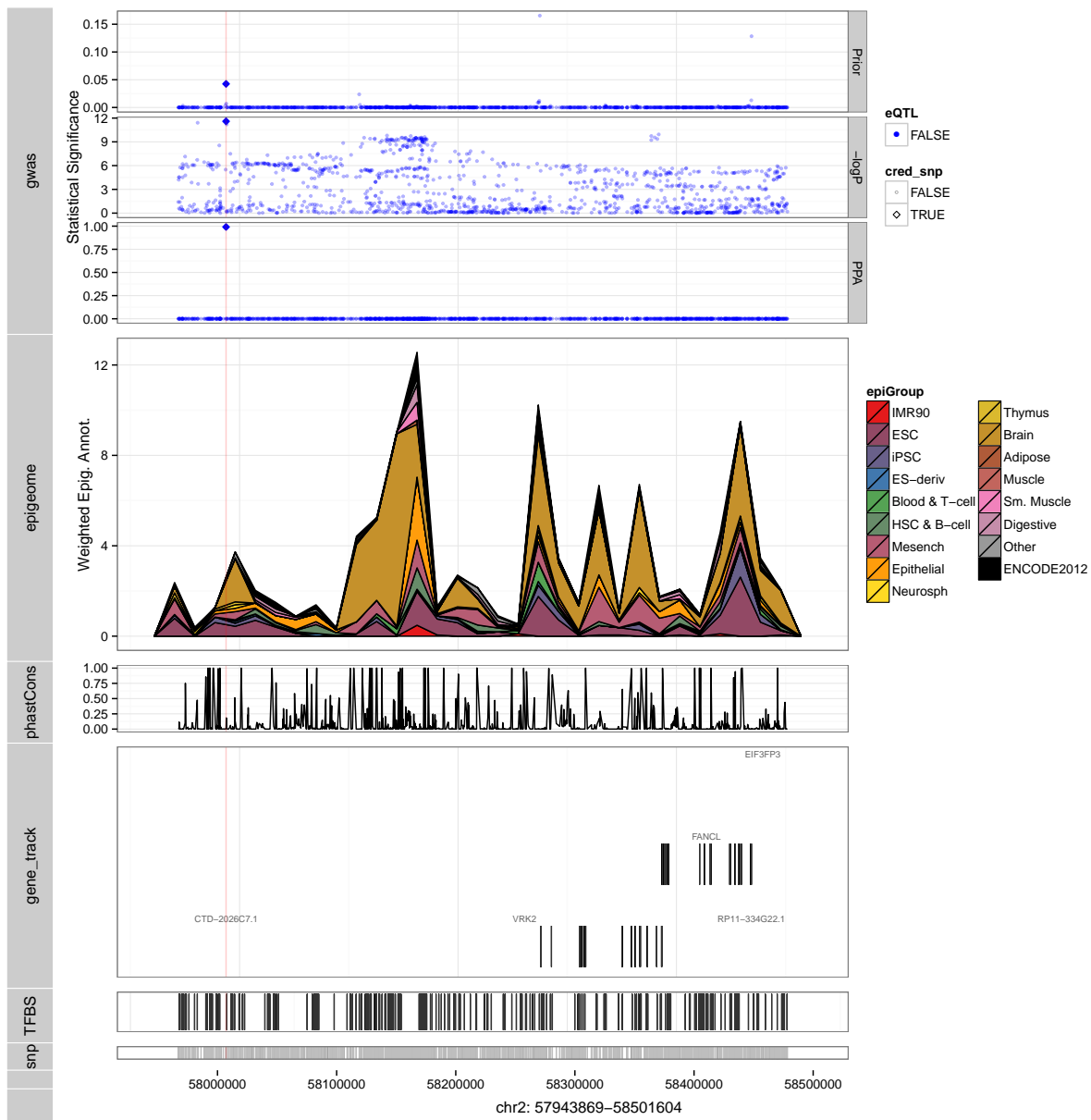
Schizophrenia



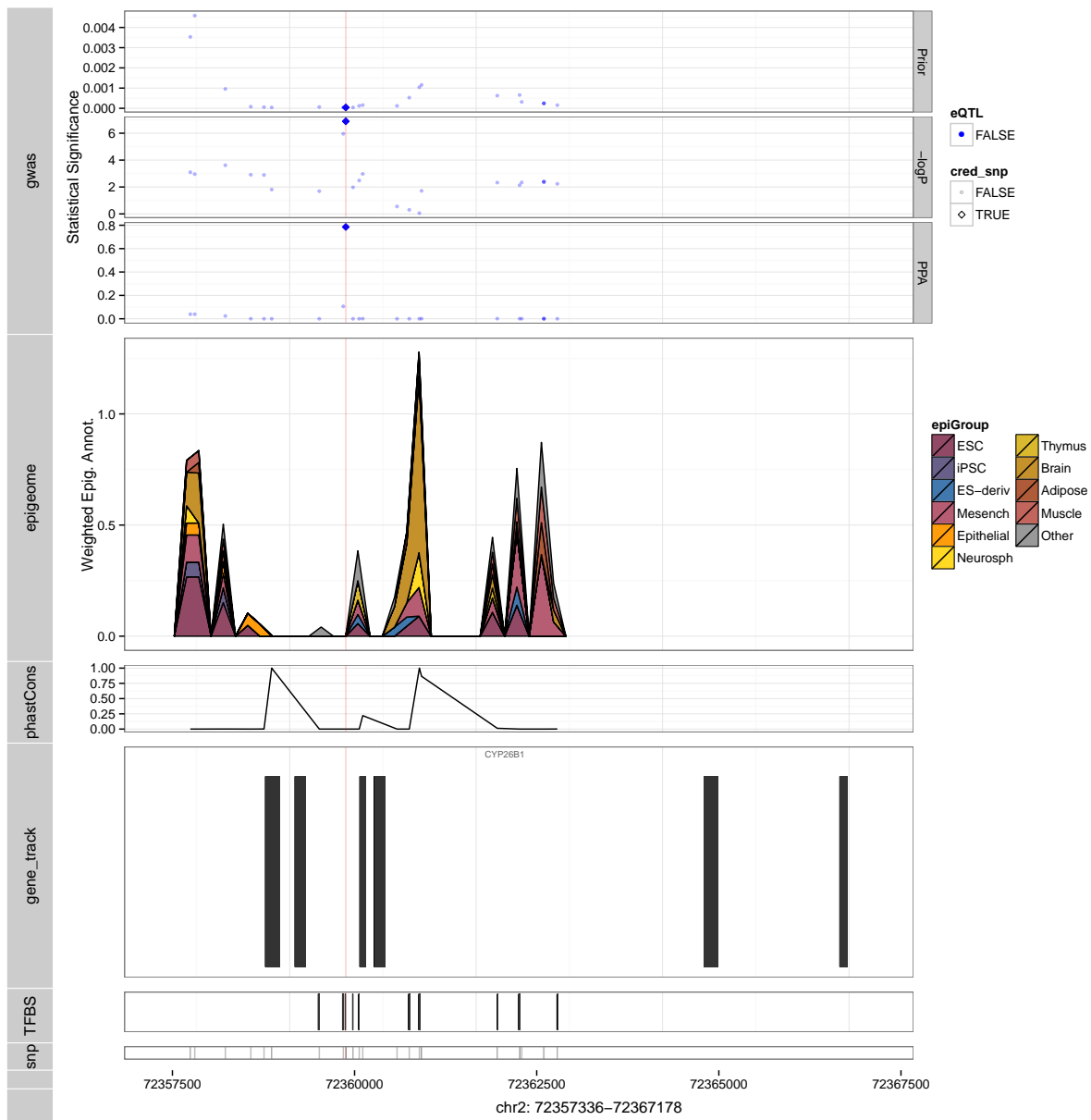
Schizophrenia



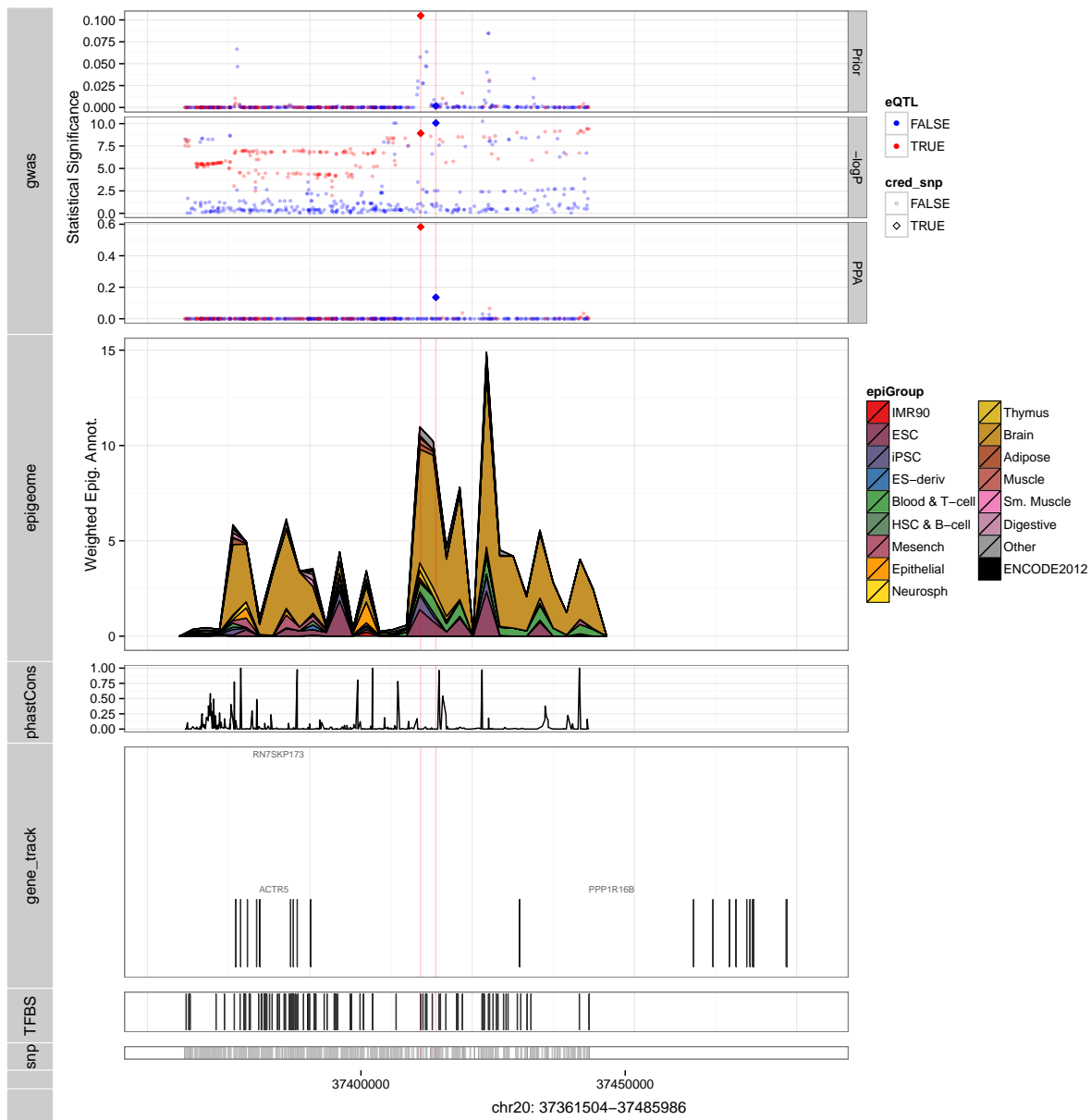
Schizophrenia



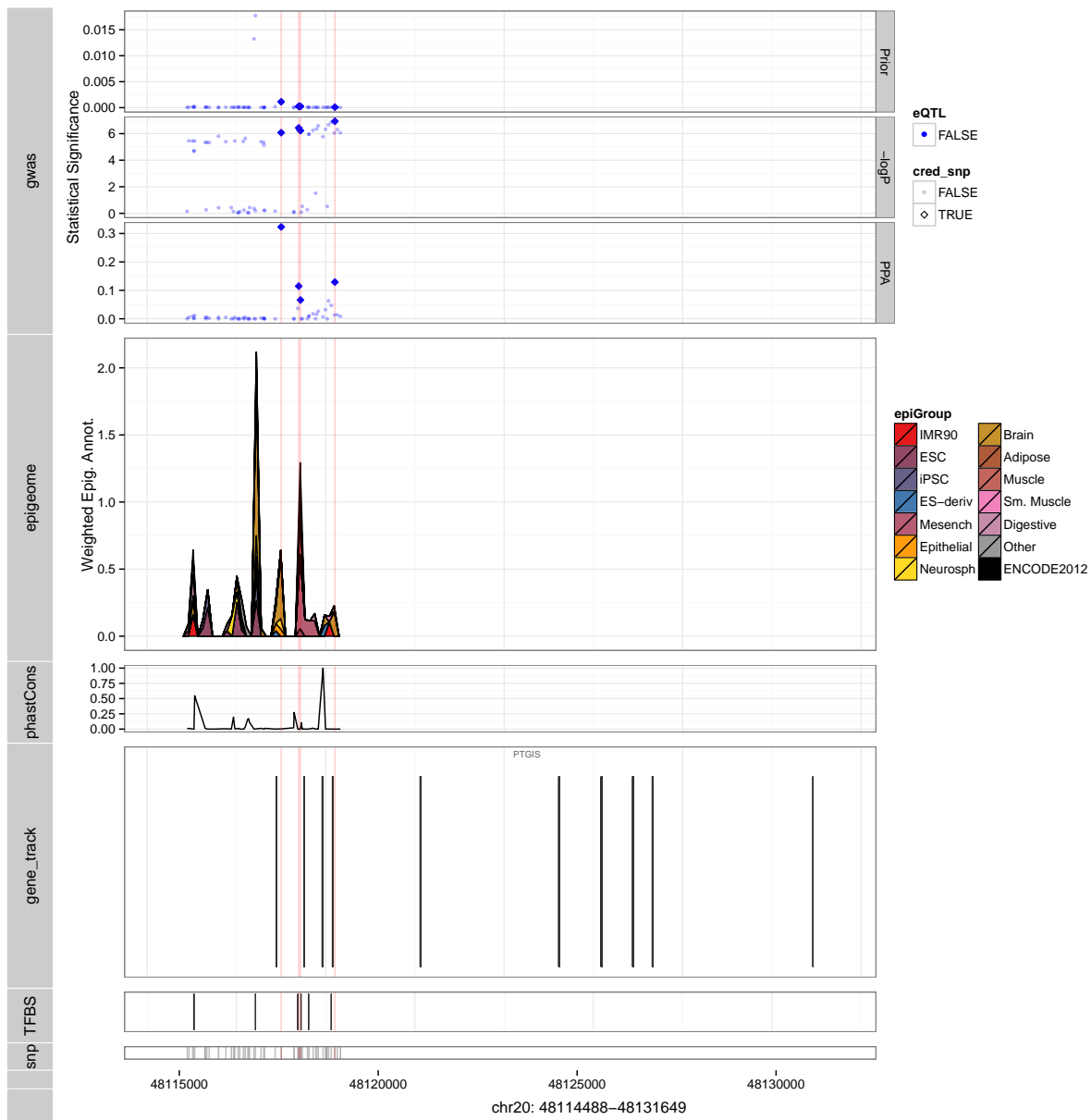
Schizophrenia



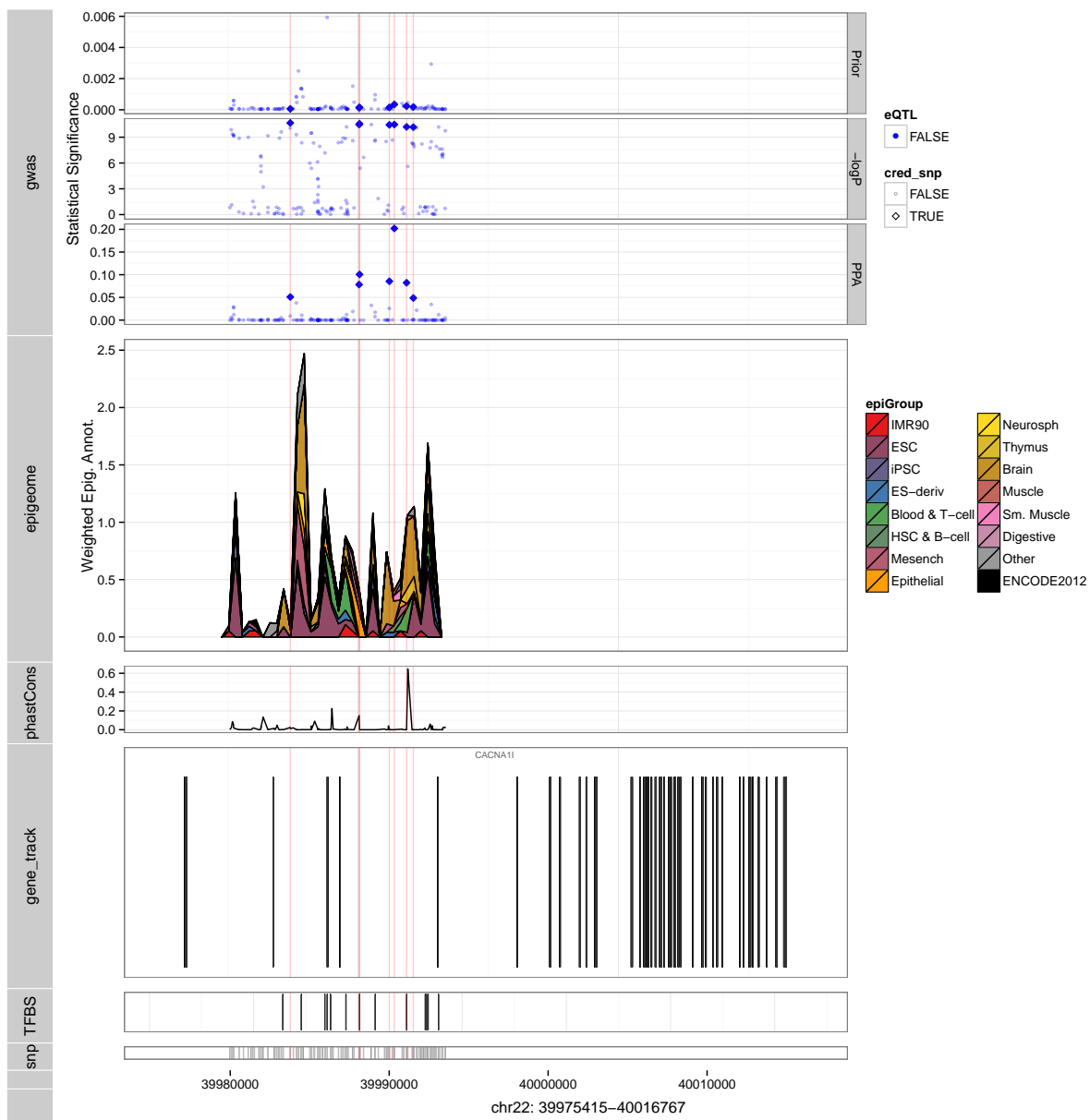
Schizophrenia



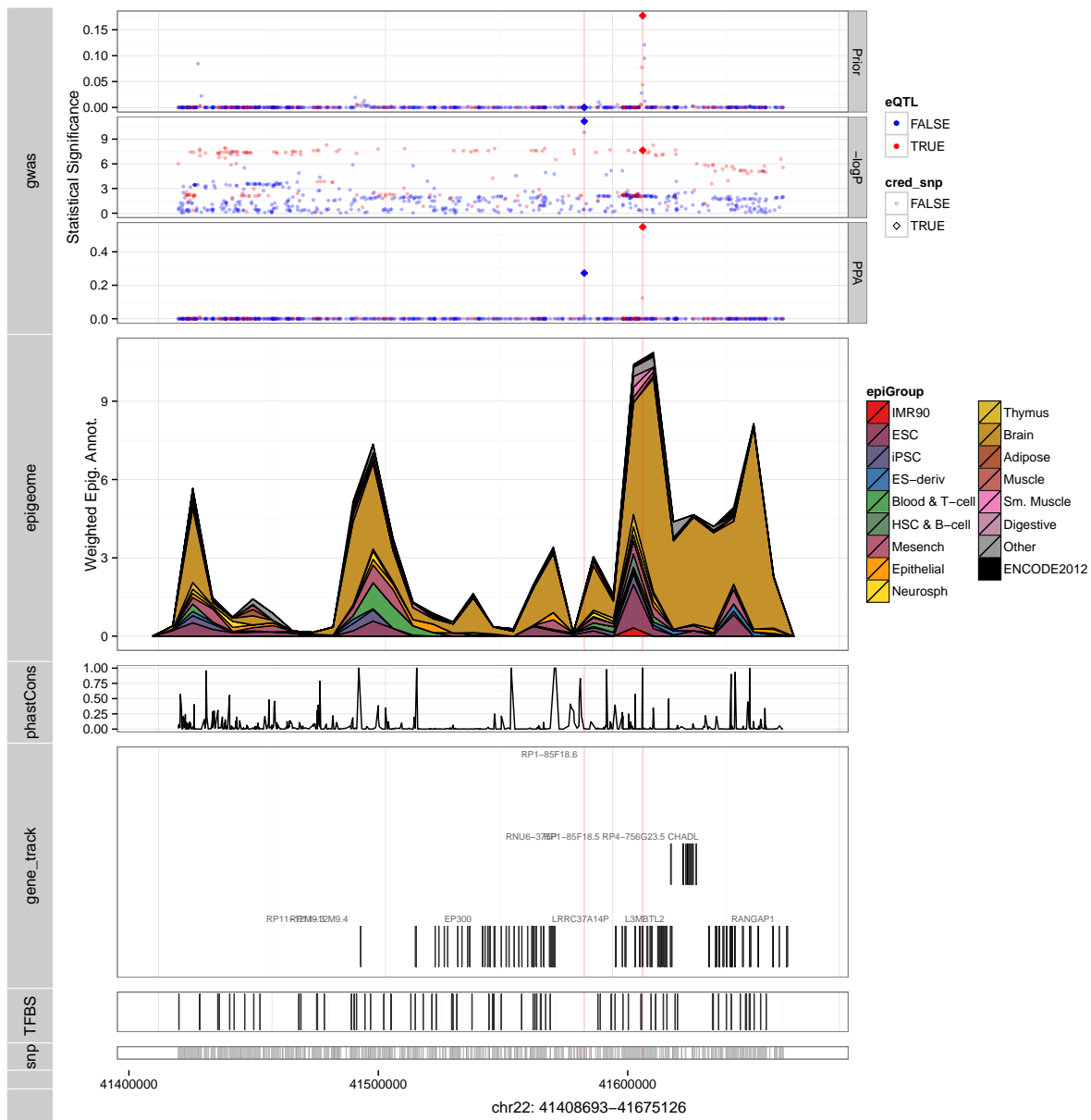
Schizophrenia



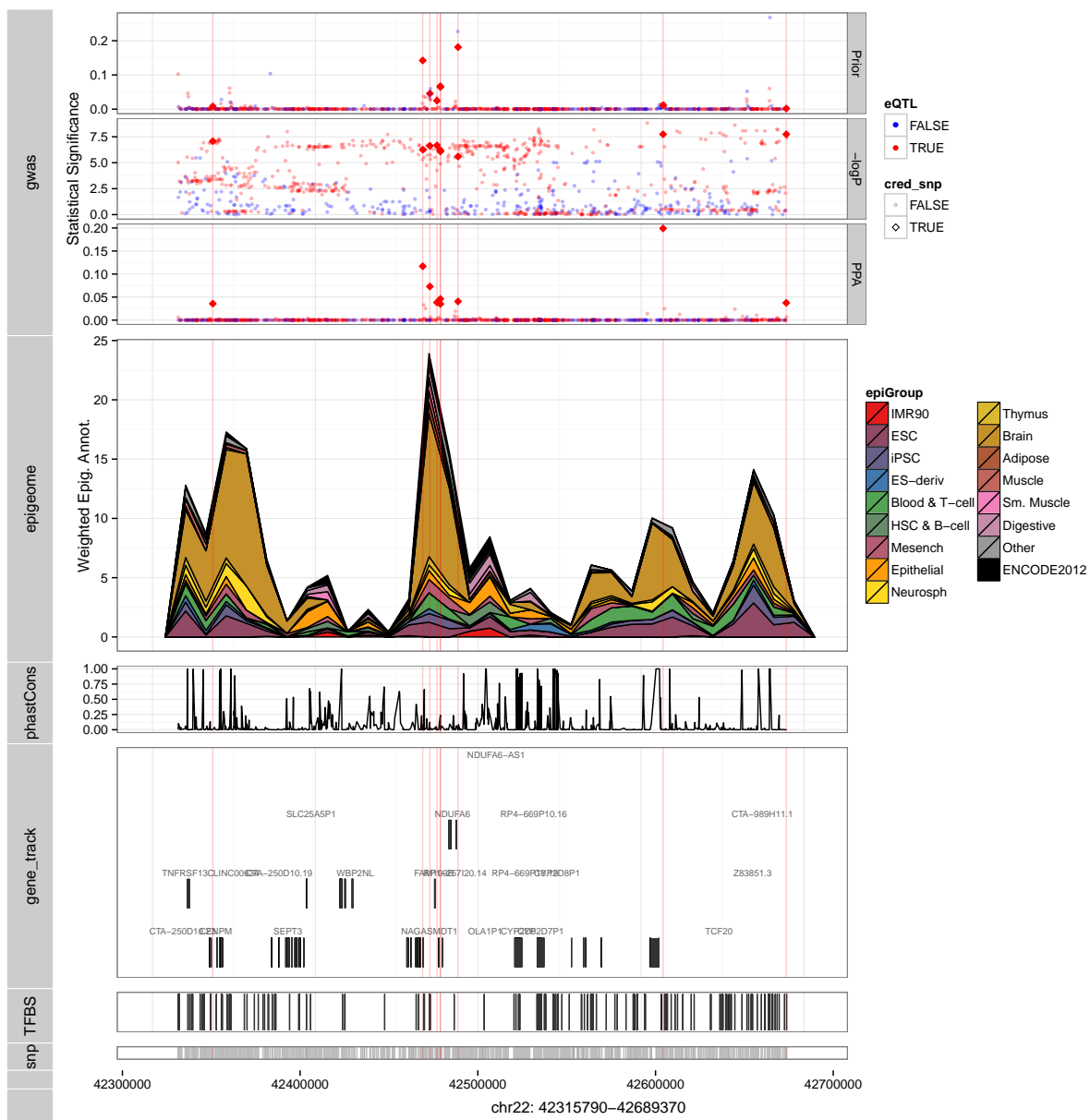
Schizophrenia



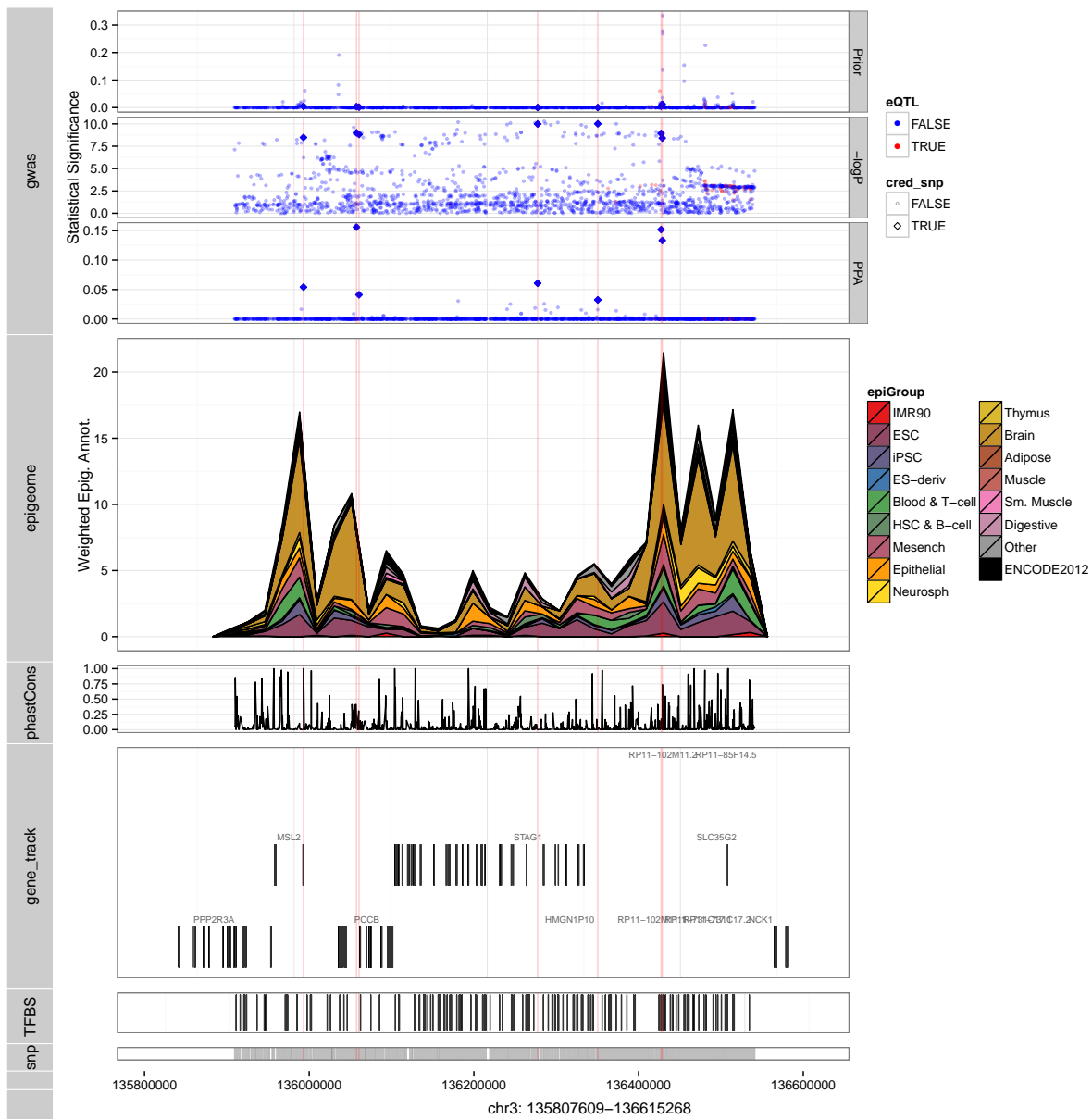
Schizophrenia



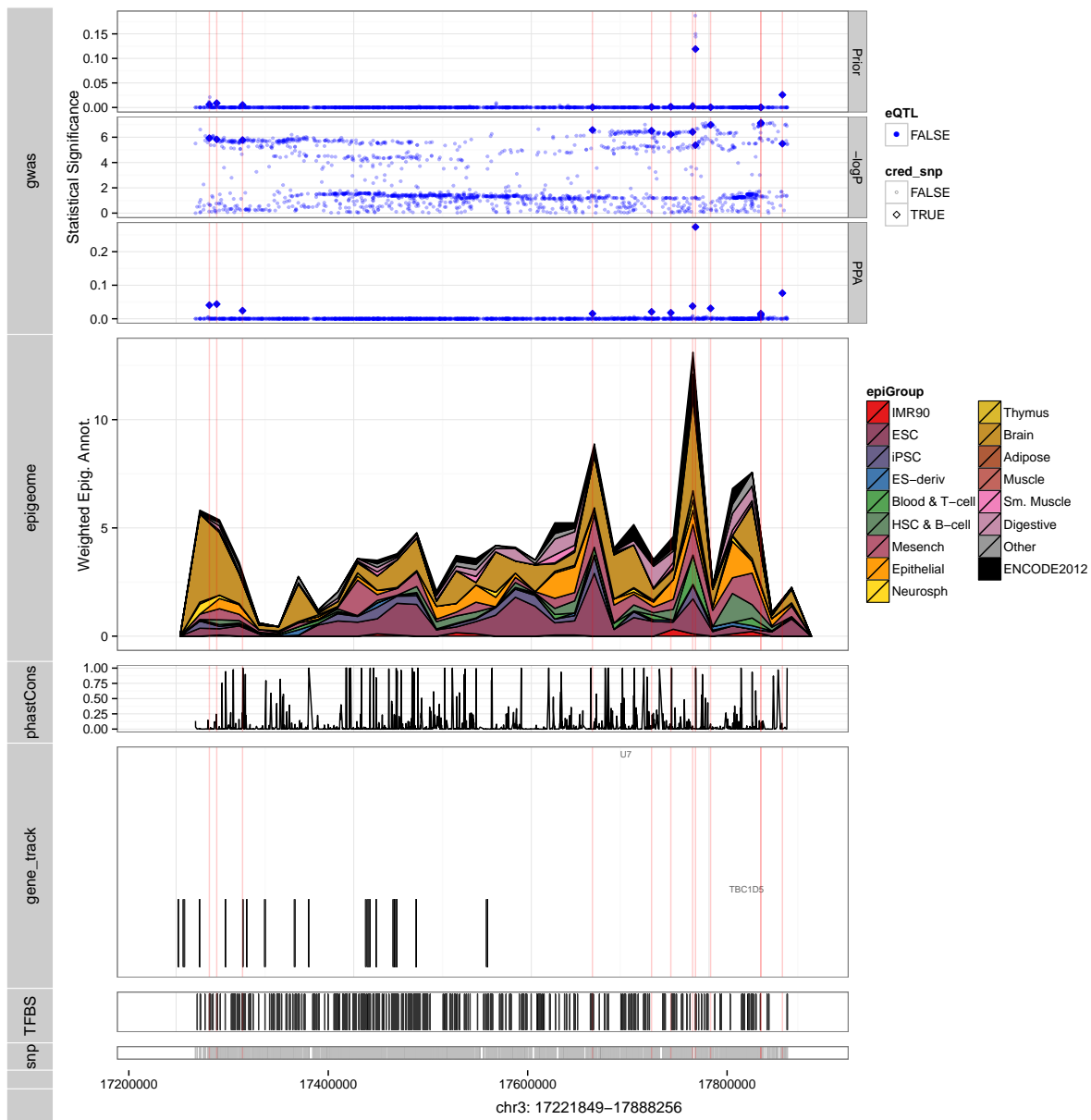
Schizophrenia



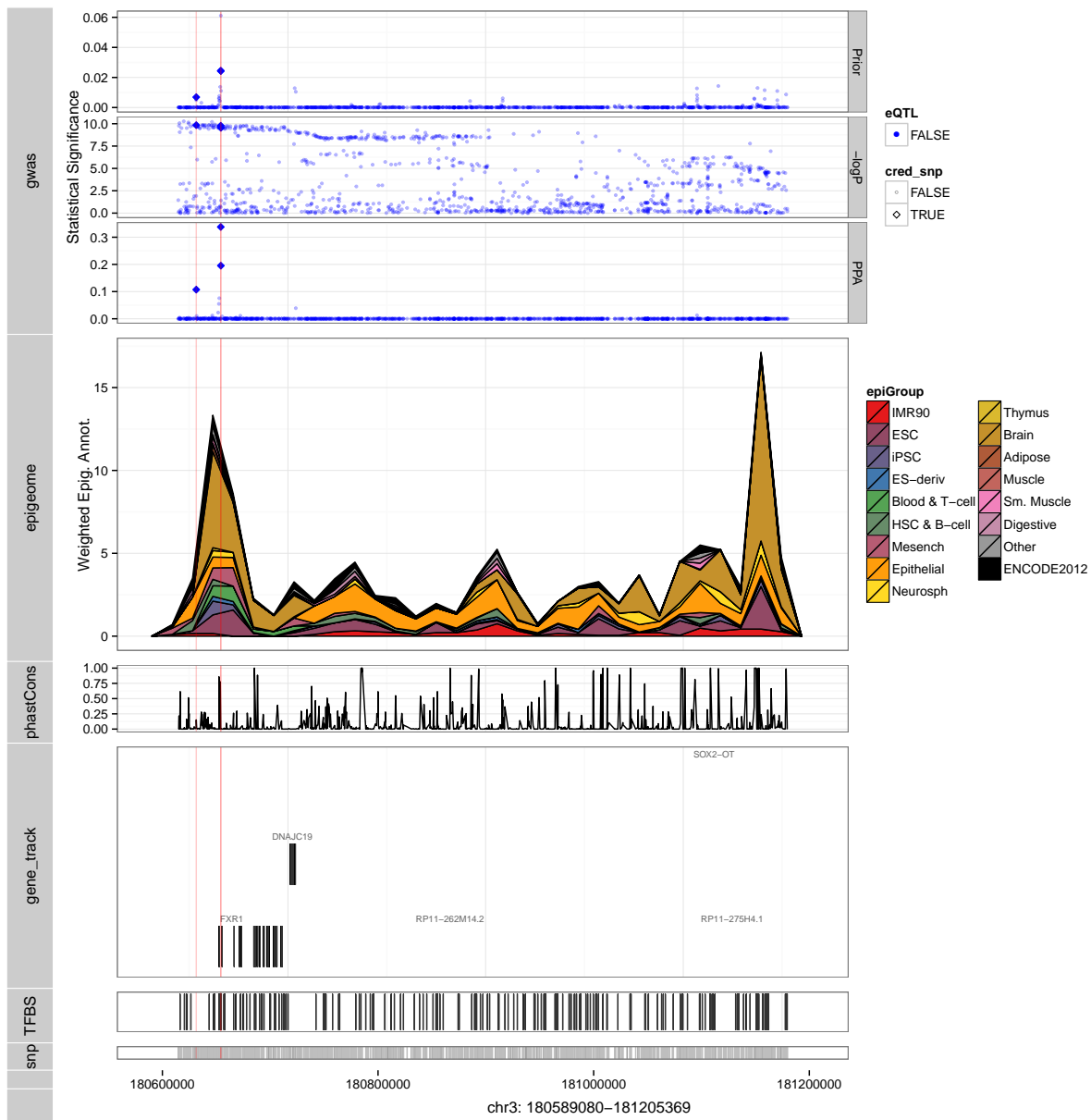
Schizophrenia



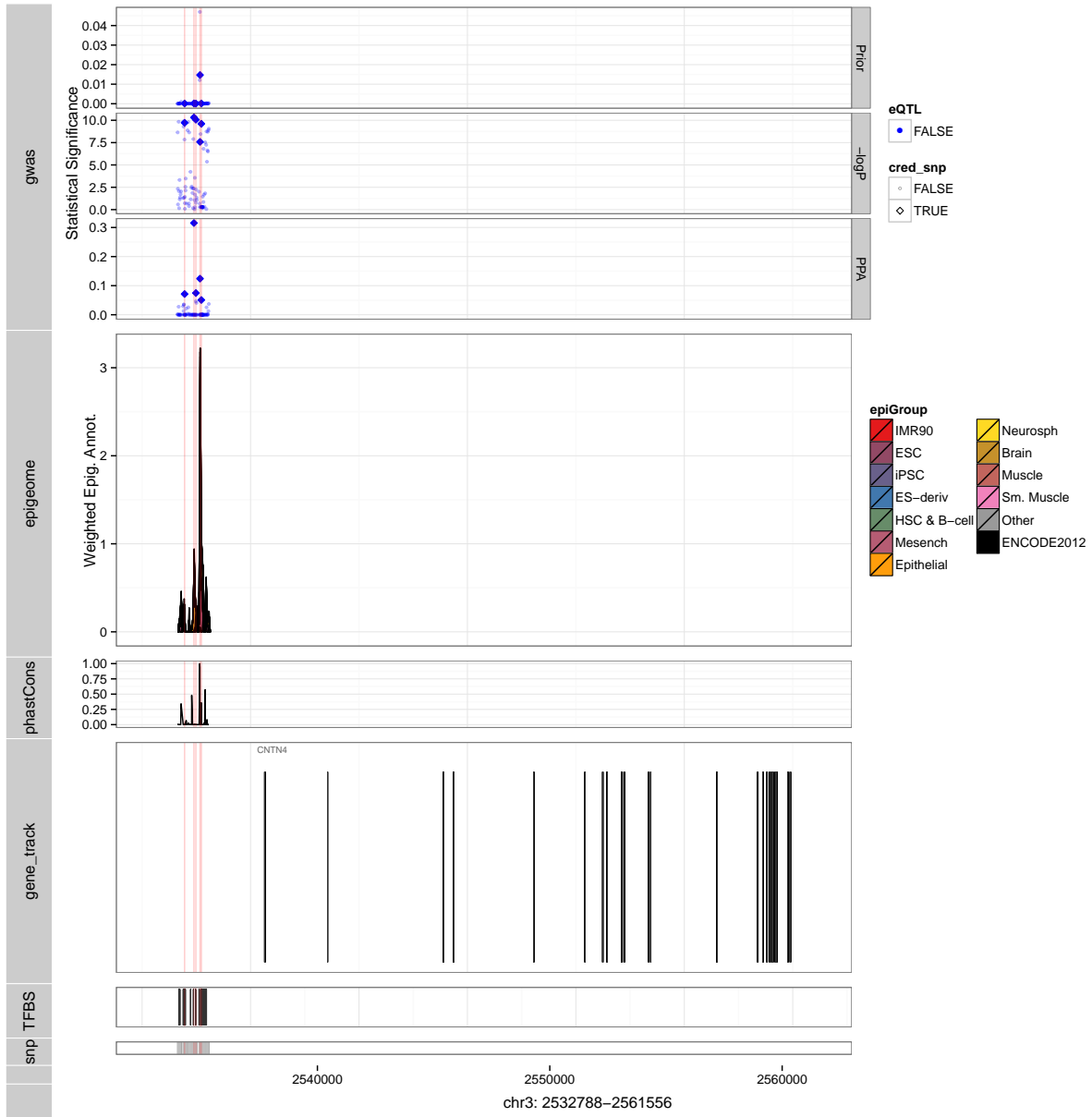
Schizophrenia



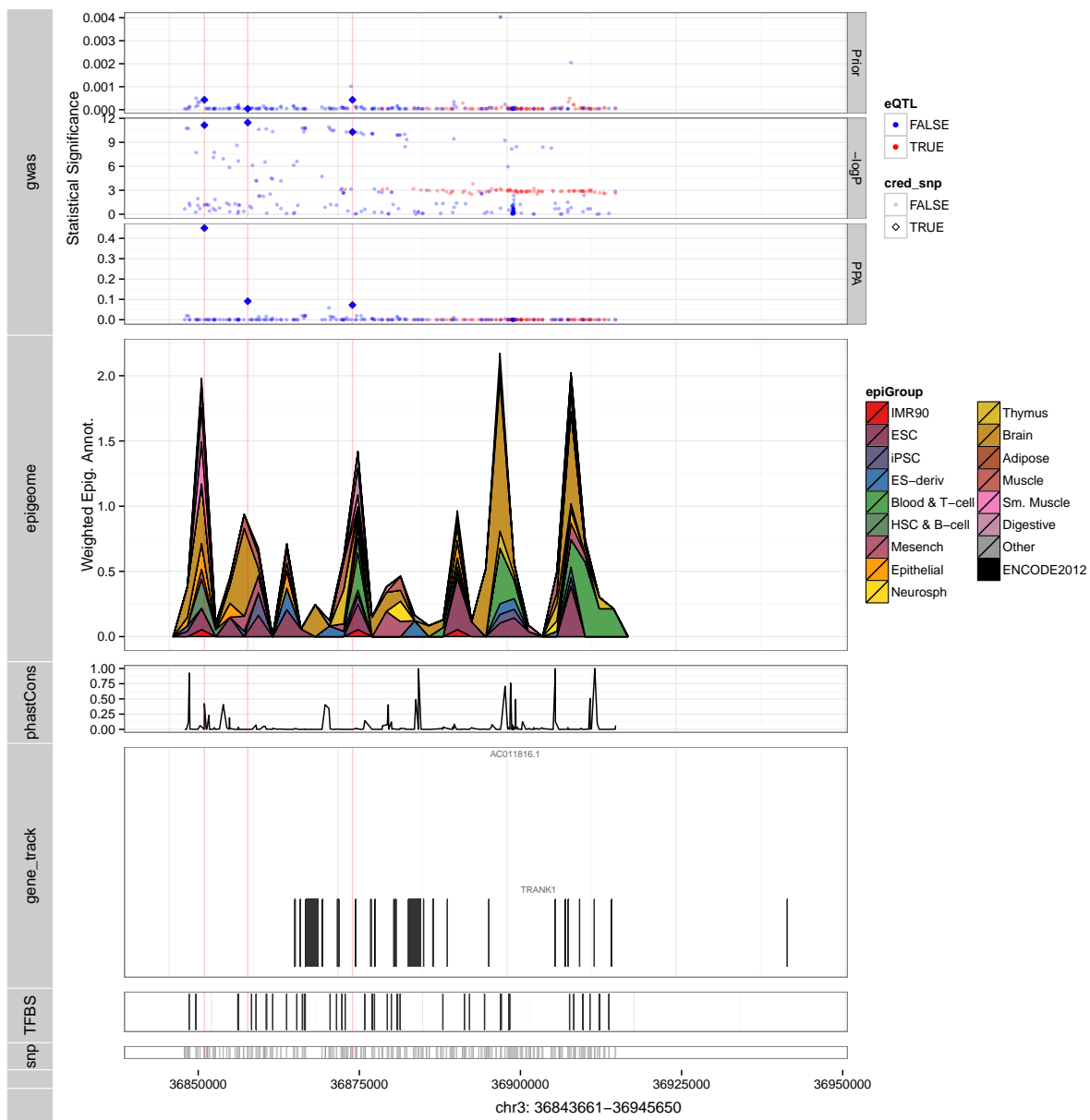
Schizophrenia



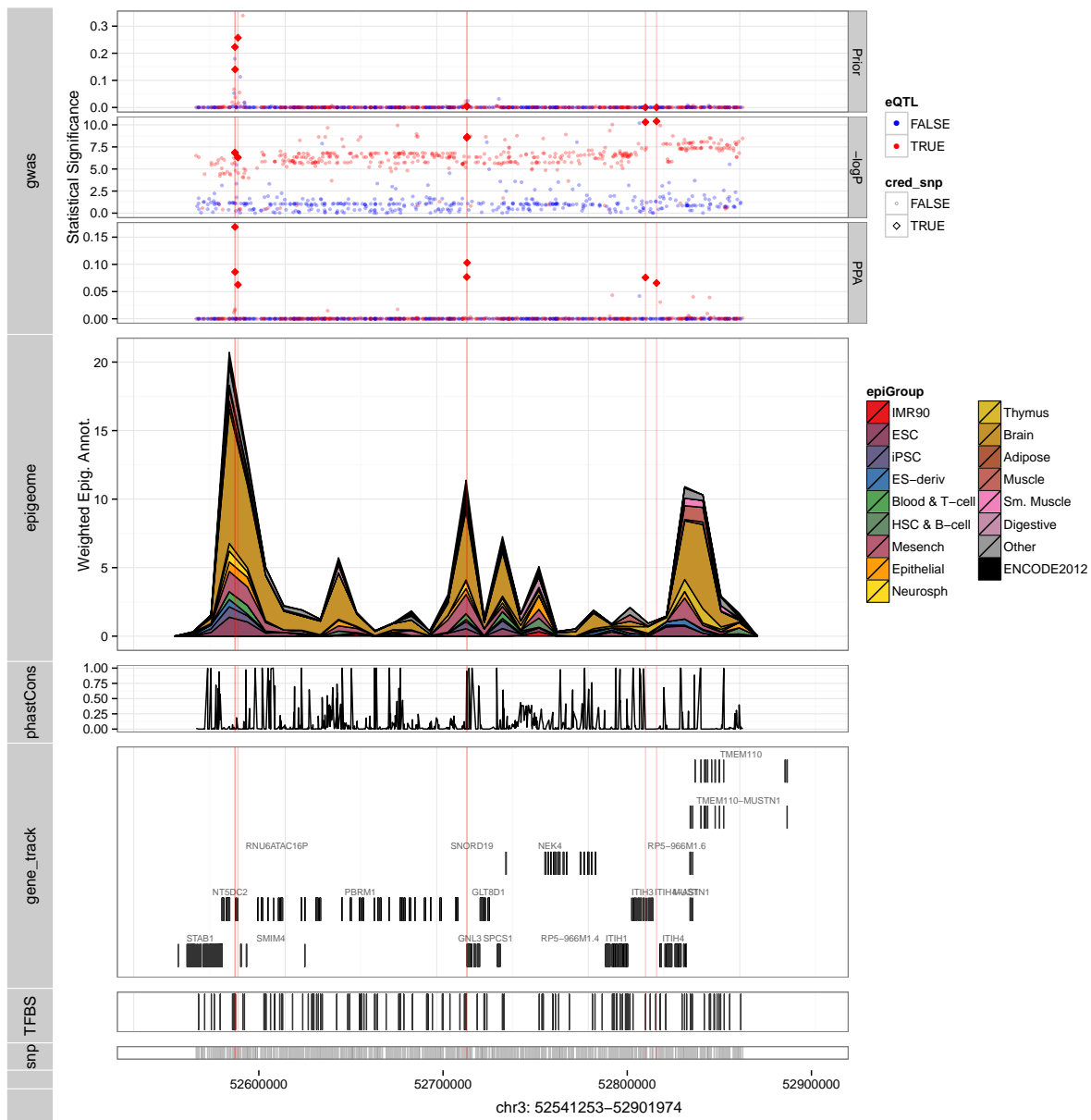
Schizophrenia



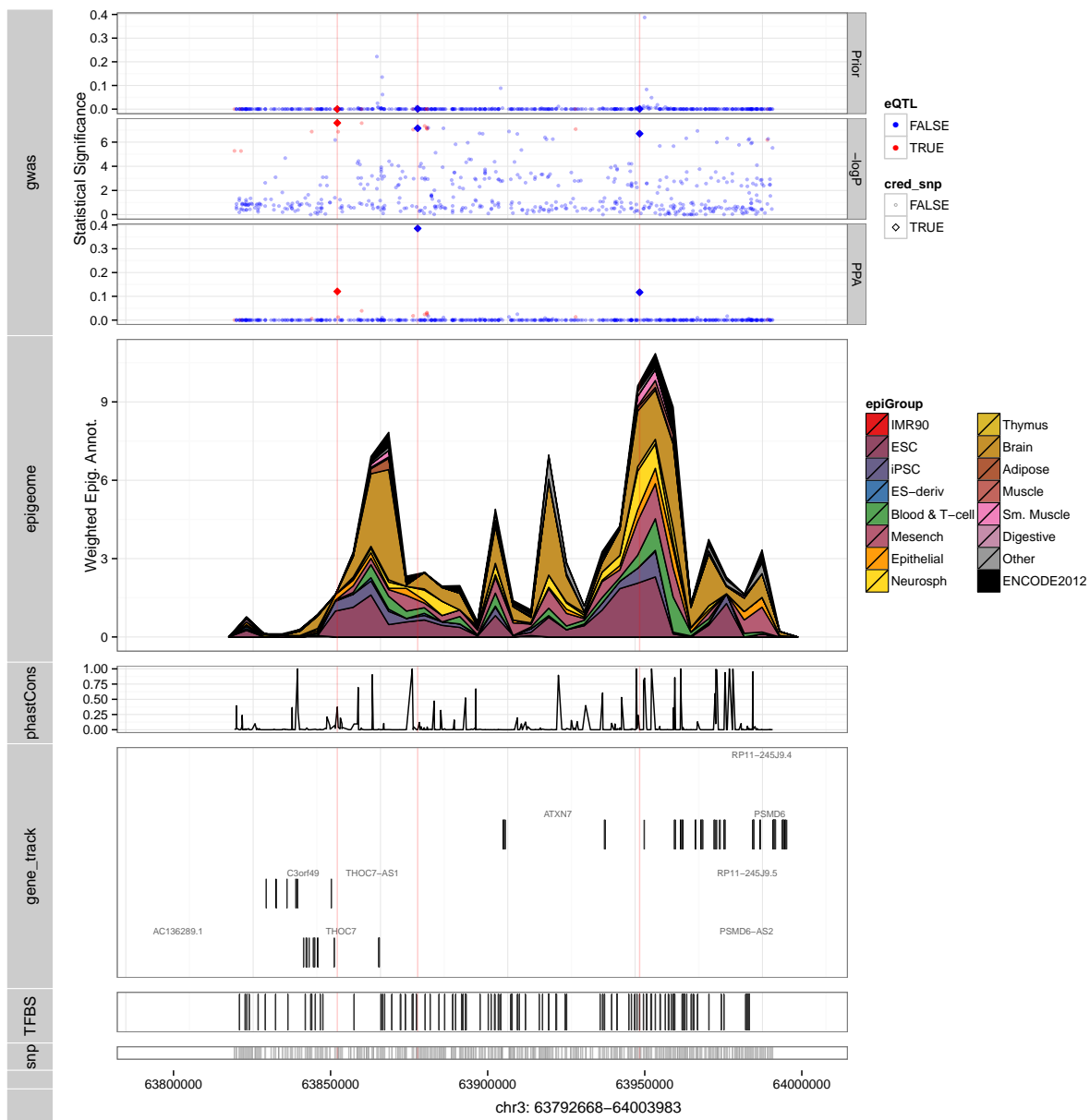
Schizophrenia



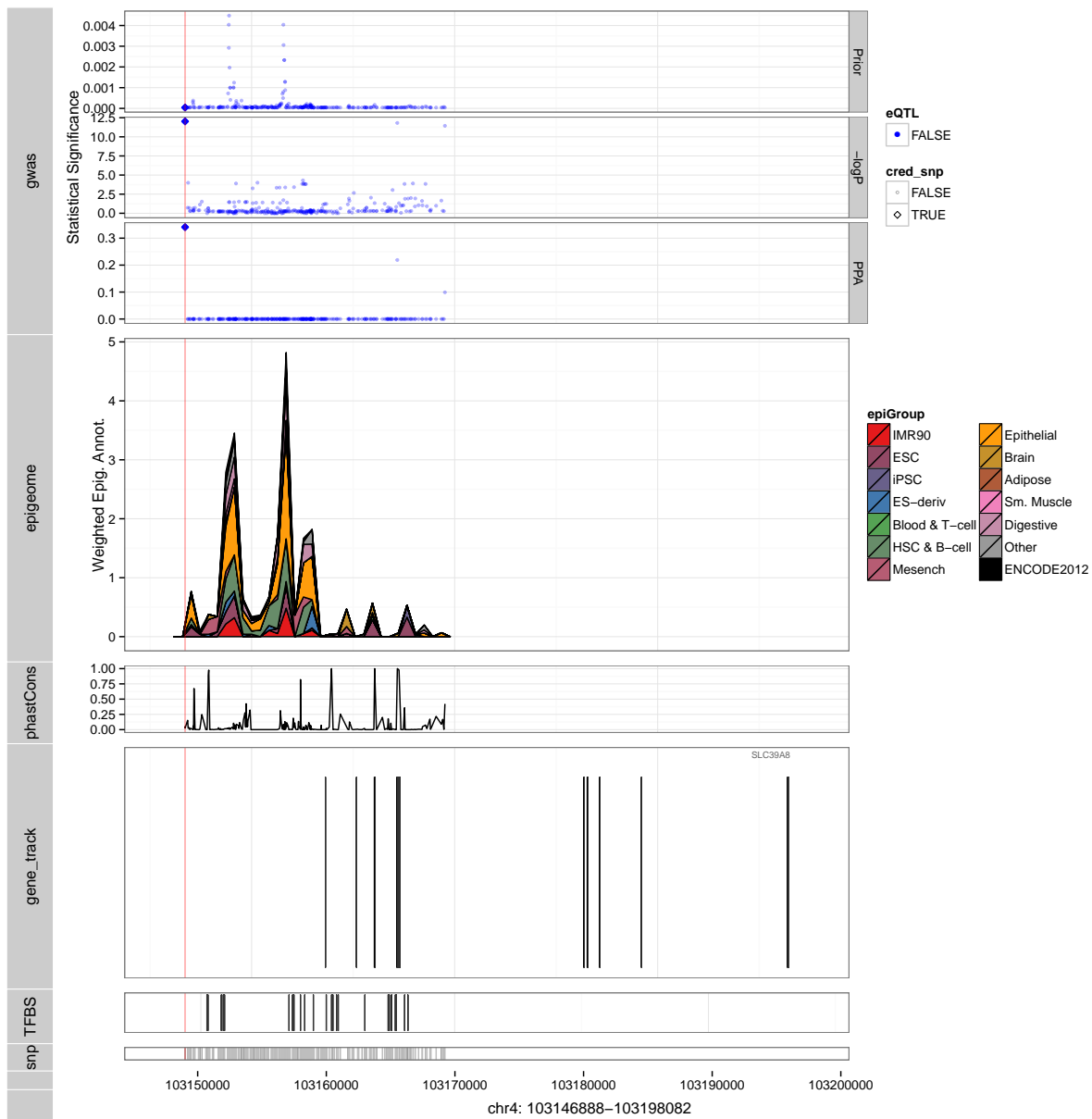
Schizophrenia



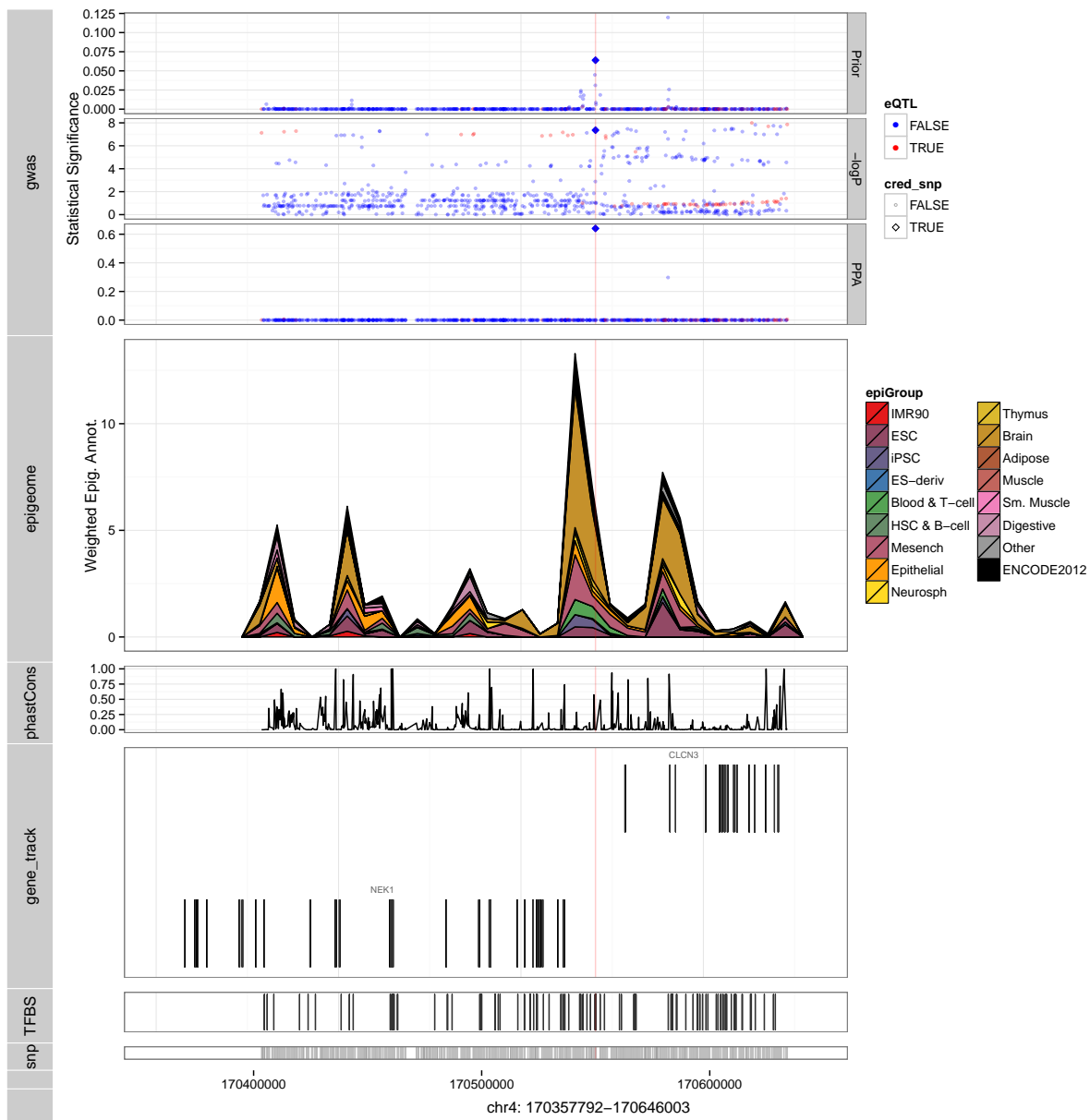
Schizophrenia



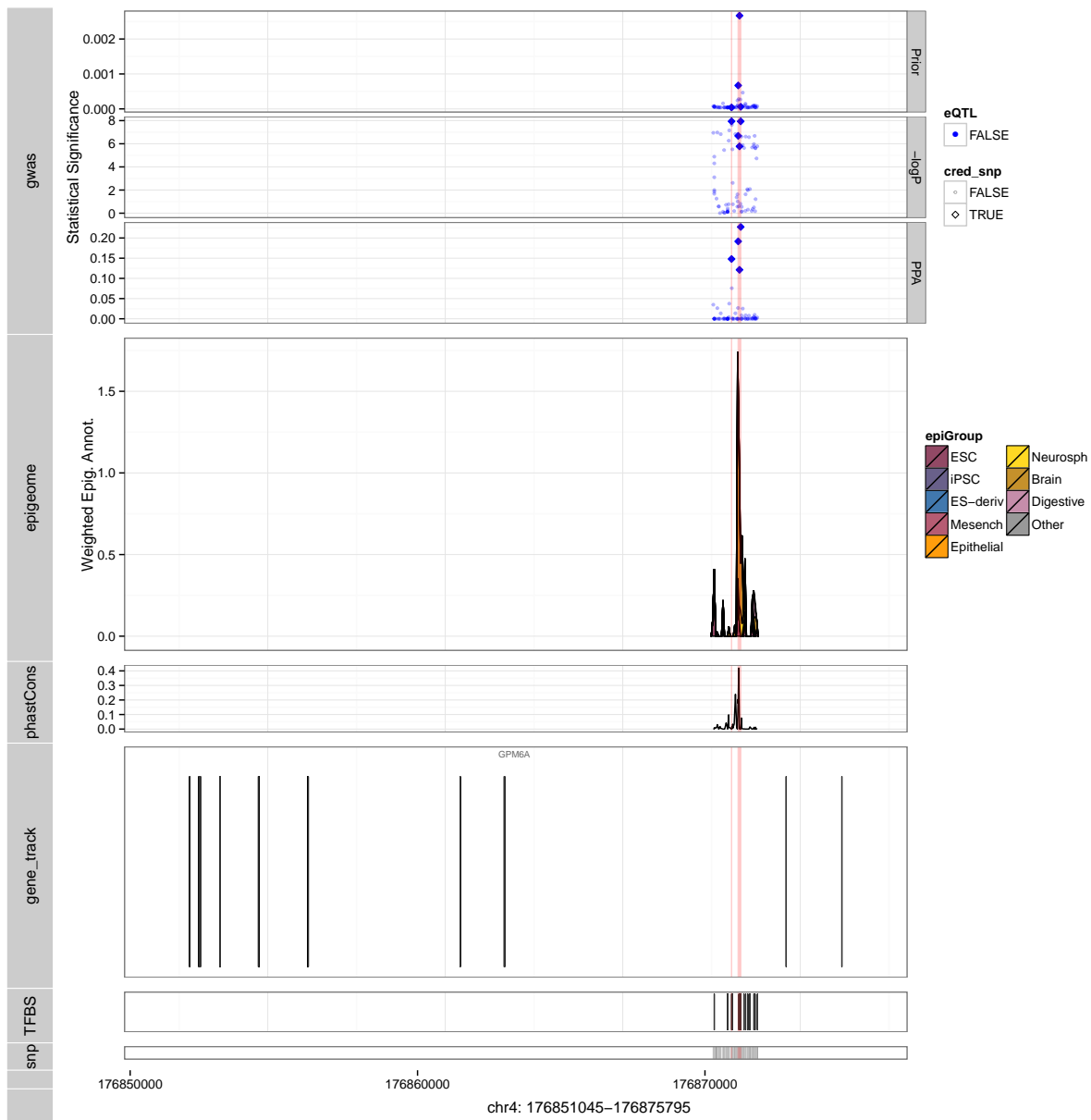
Schizophrenia



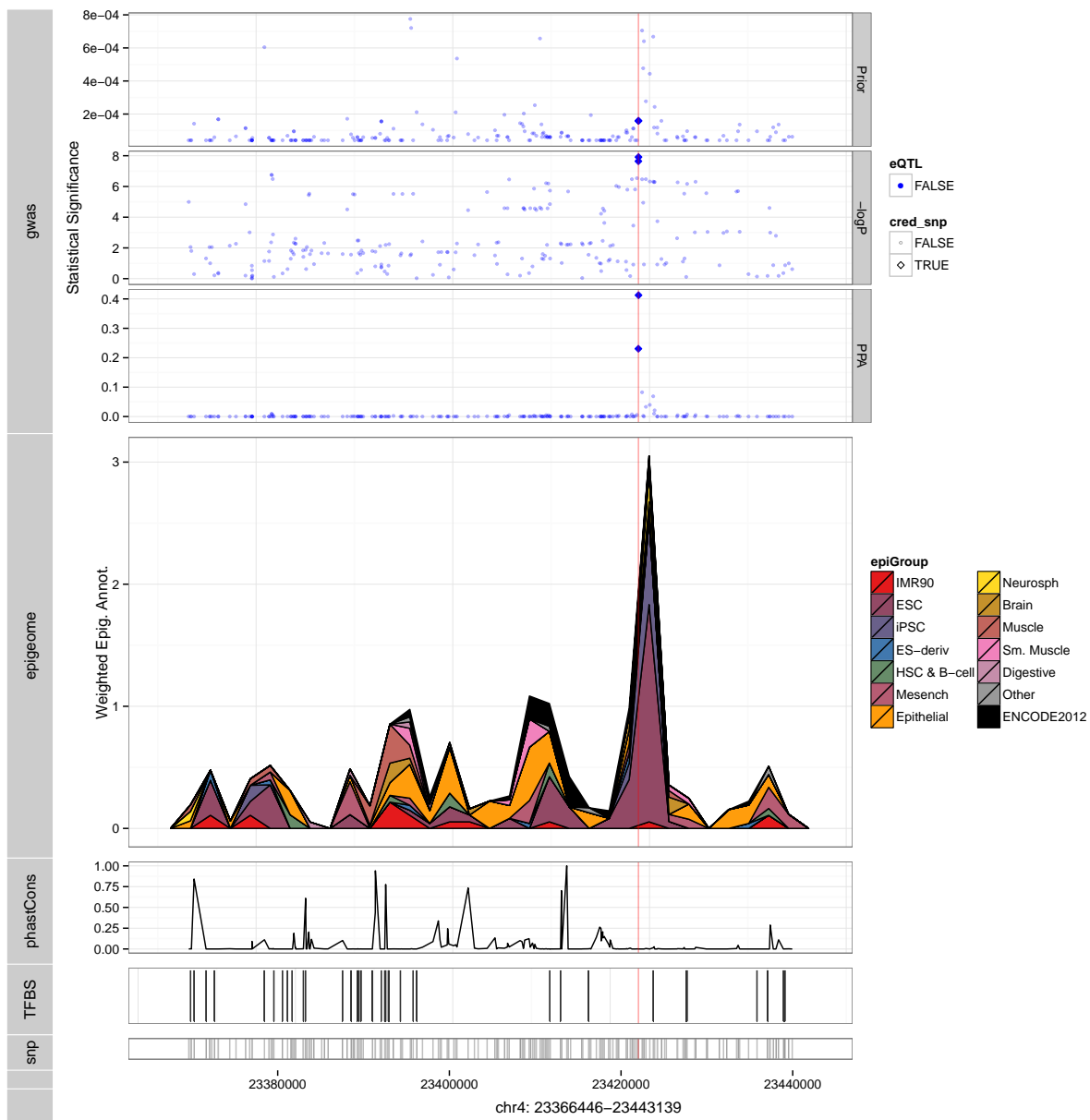
Schizophrenia



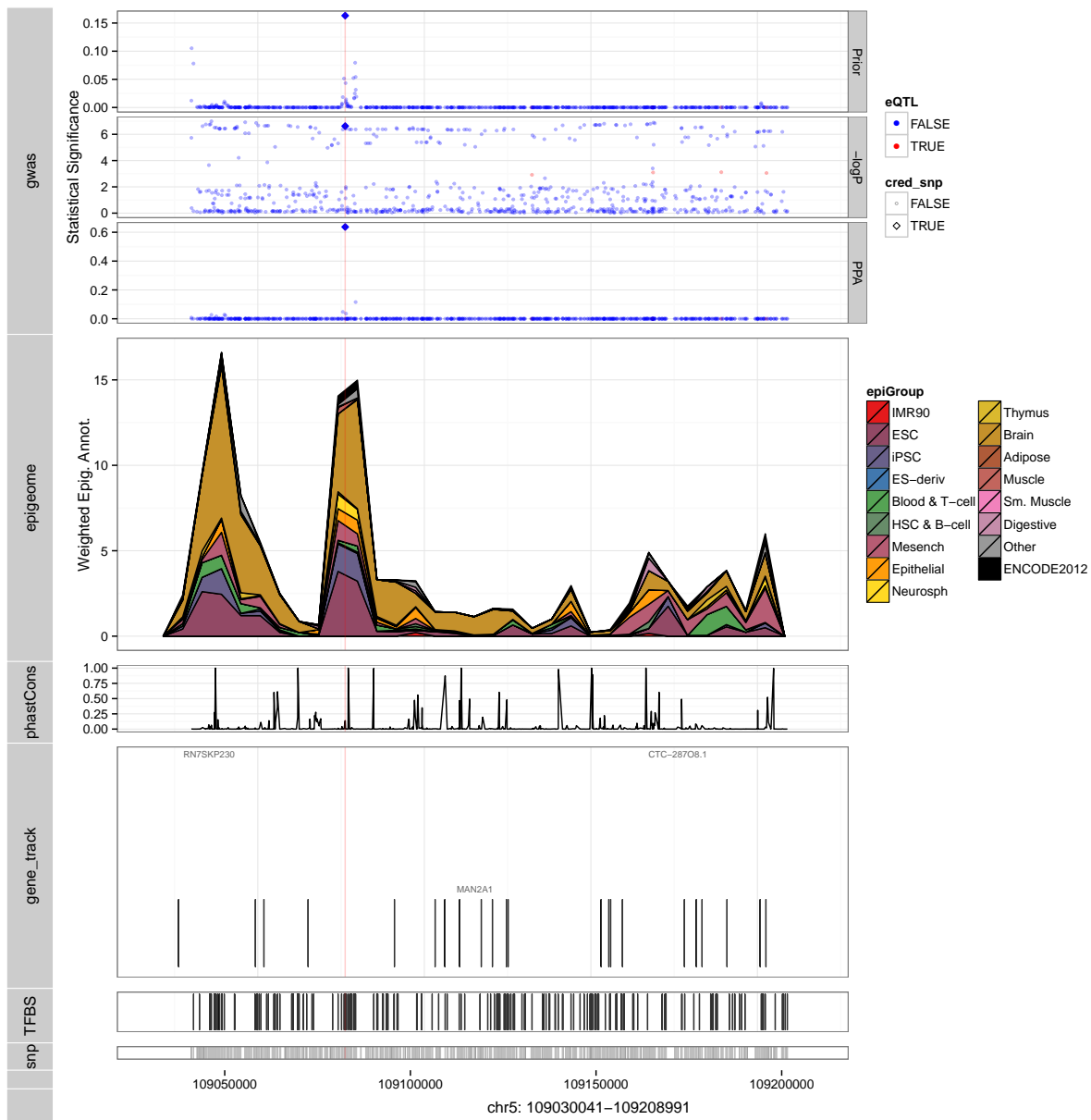
Schizophrenia



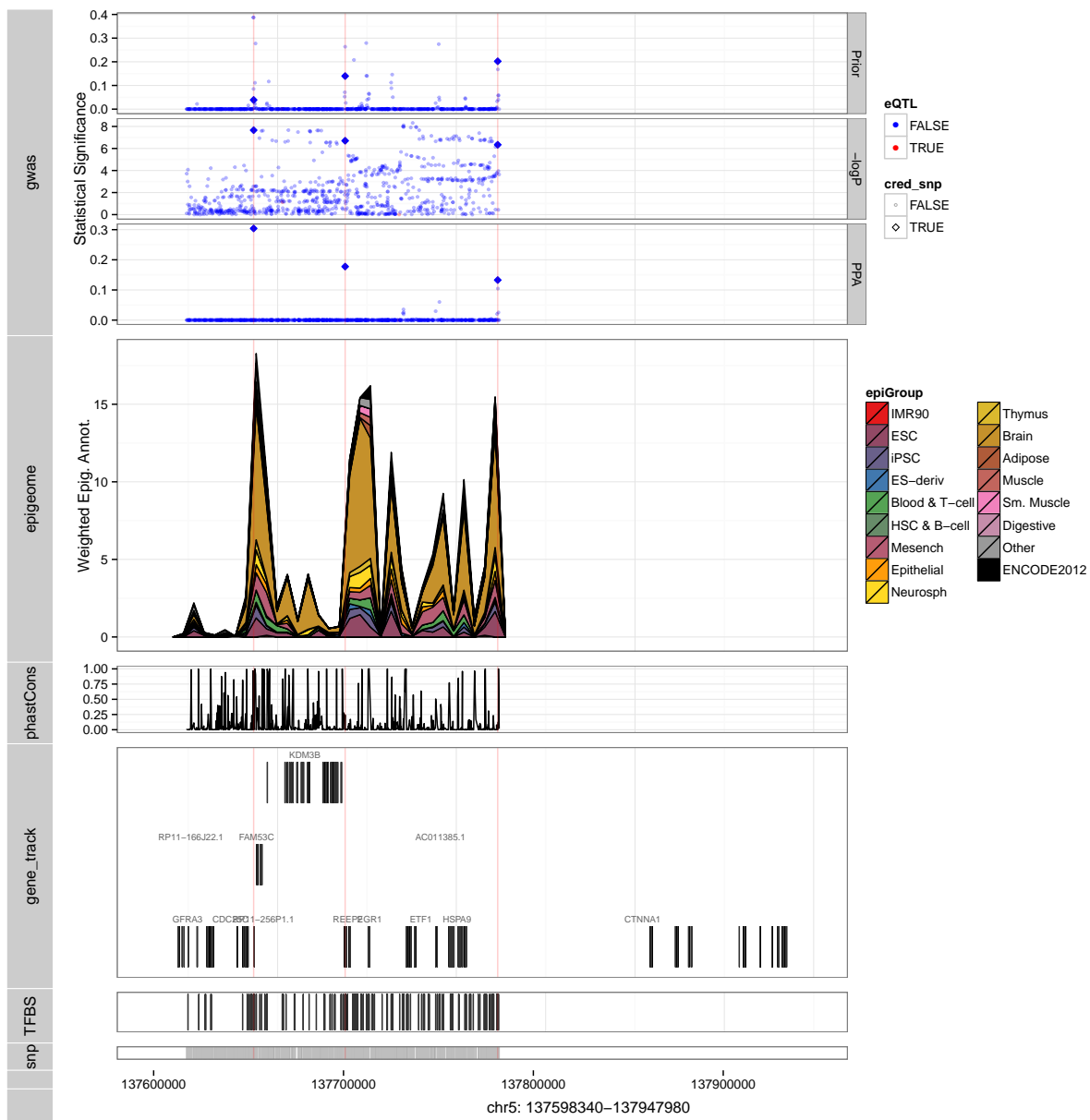
Schizophrenia



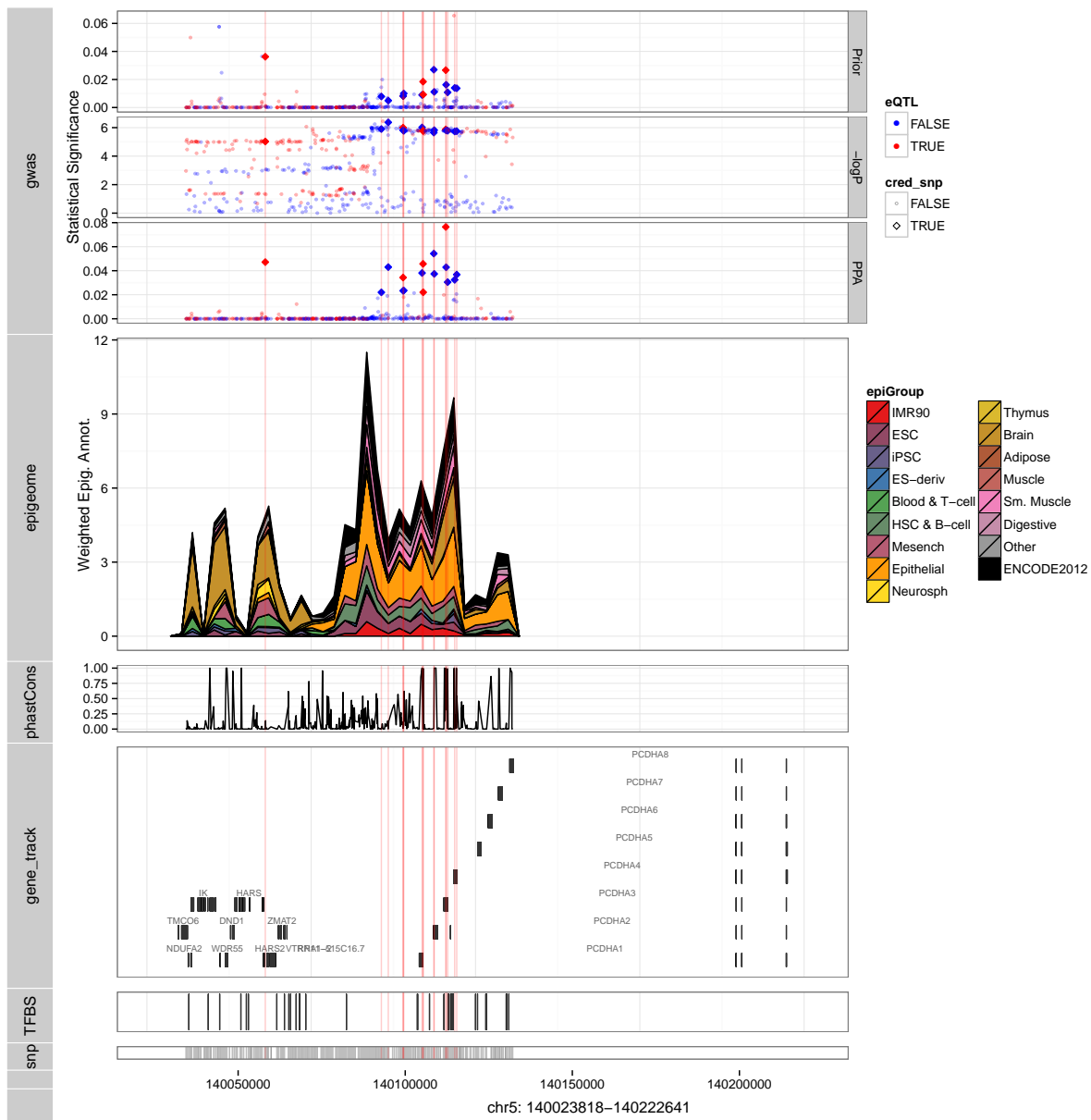
Schizophrenia



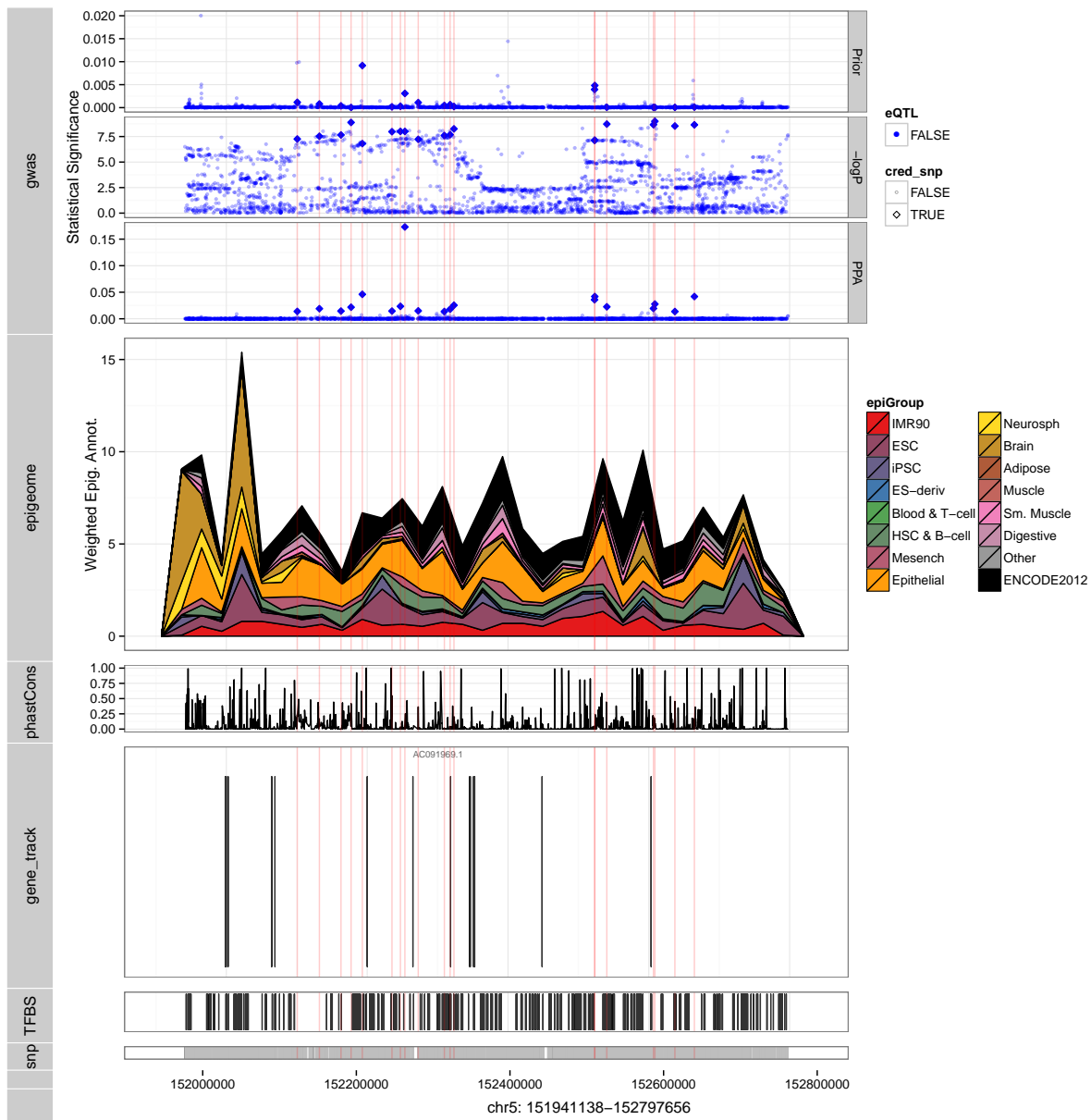
Schizophrenia



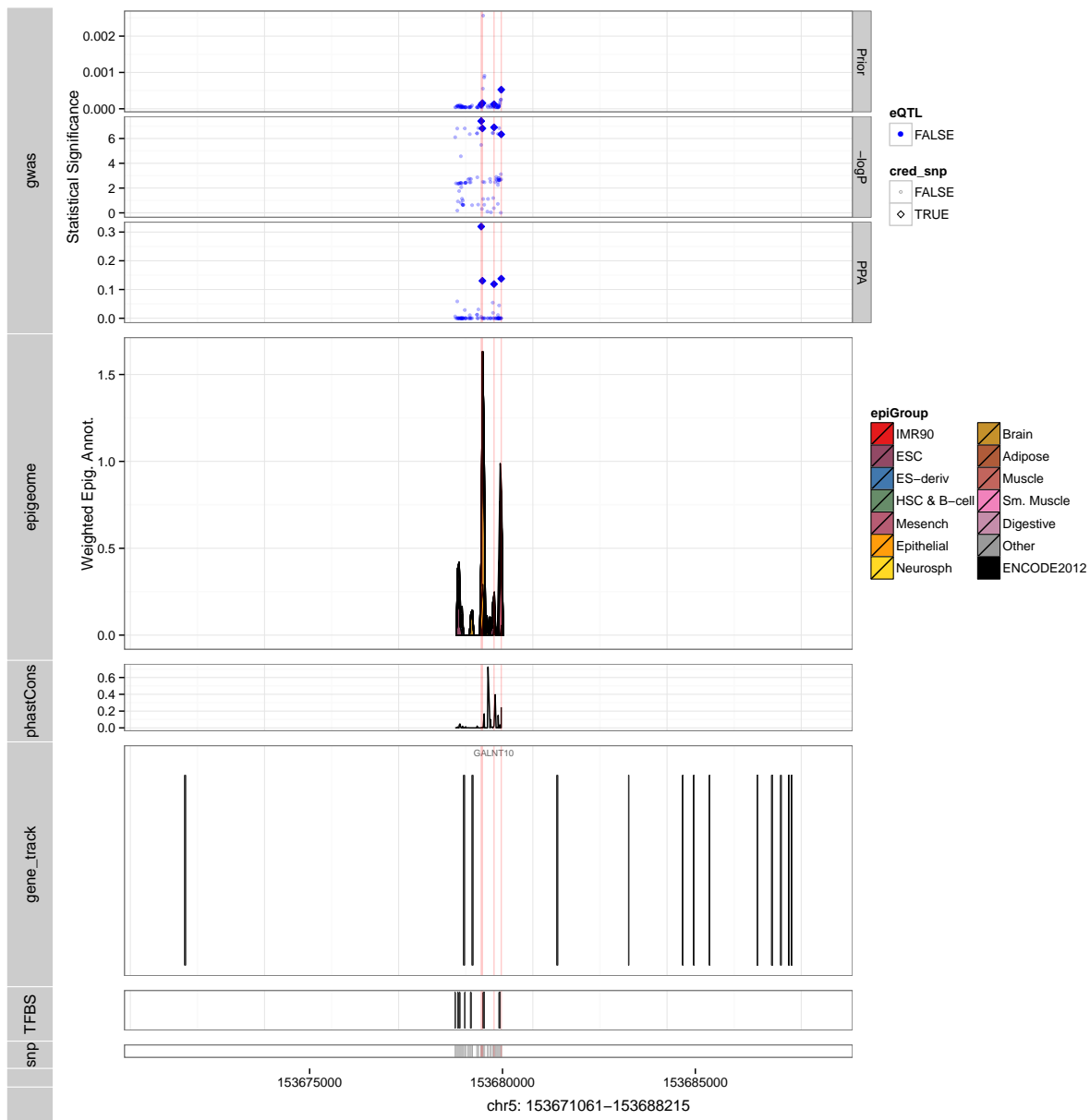
Schizophrenia



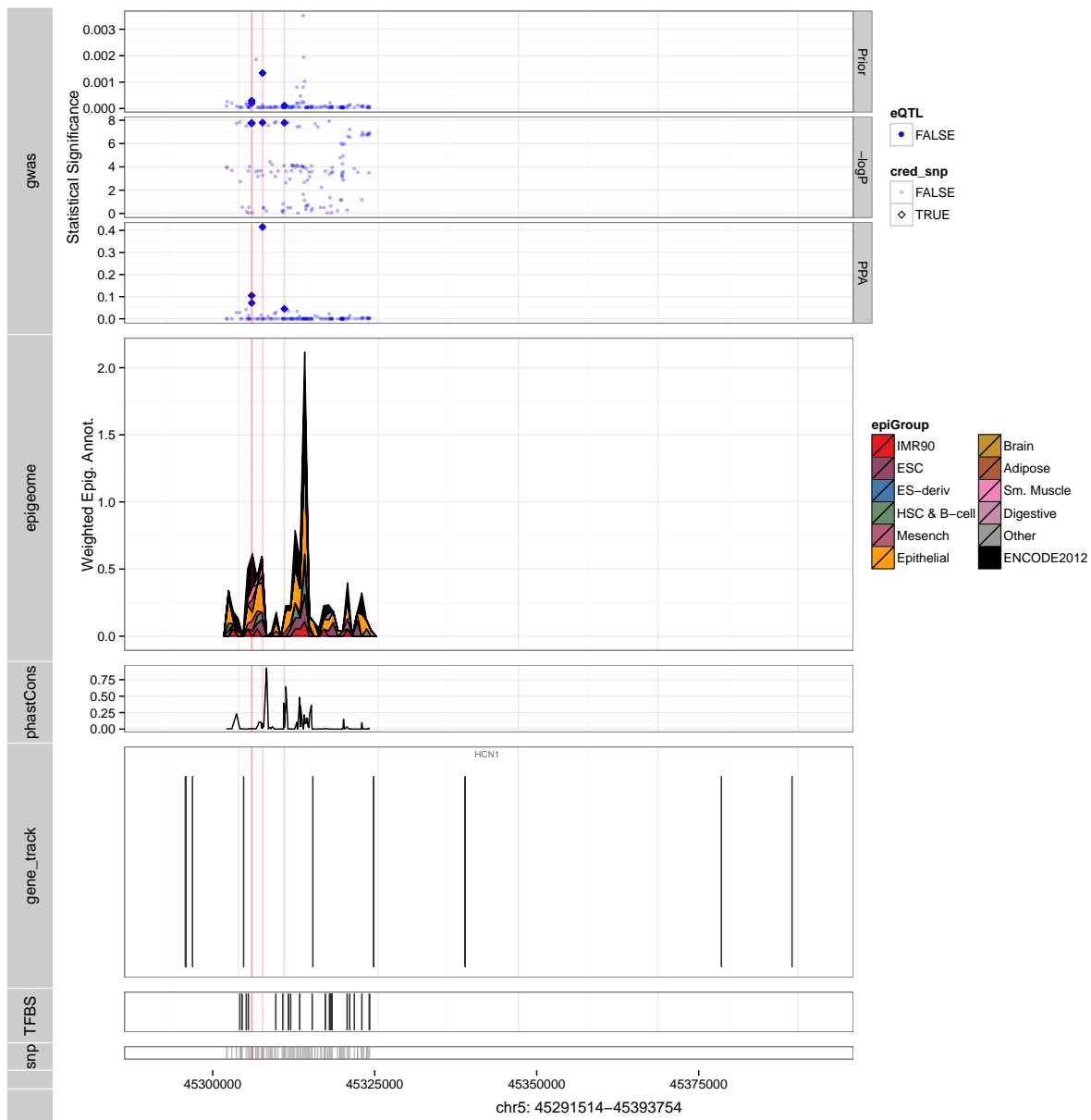
Schizophrenia



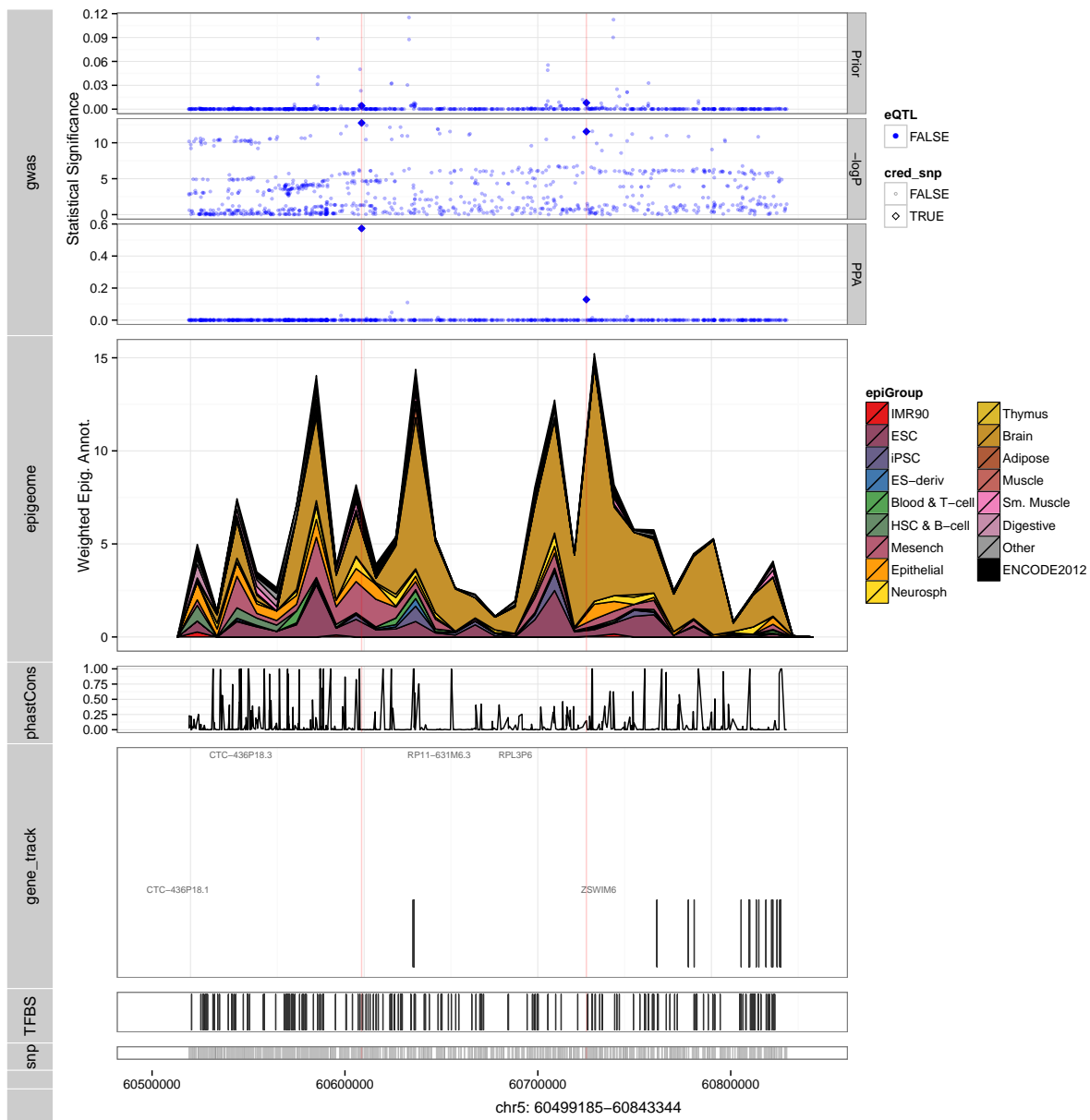
Schizophrenia



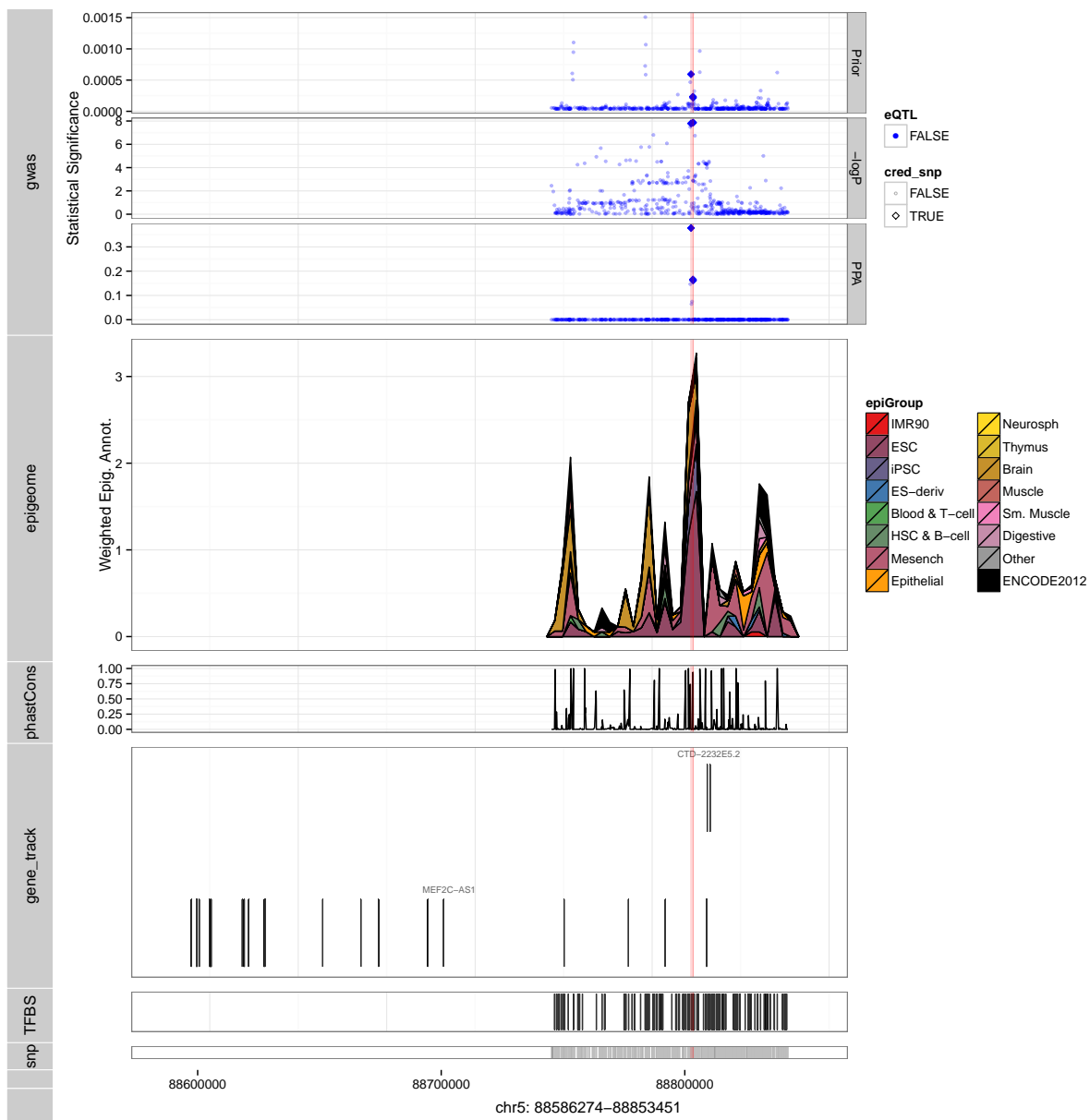
Schizophrenia



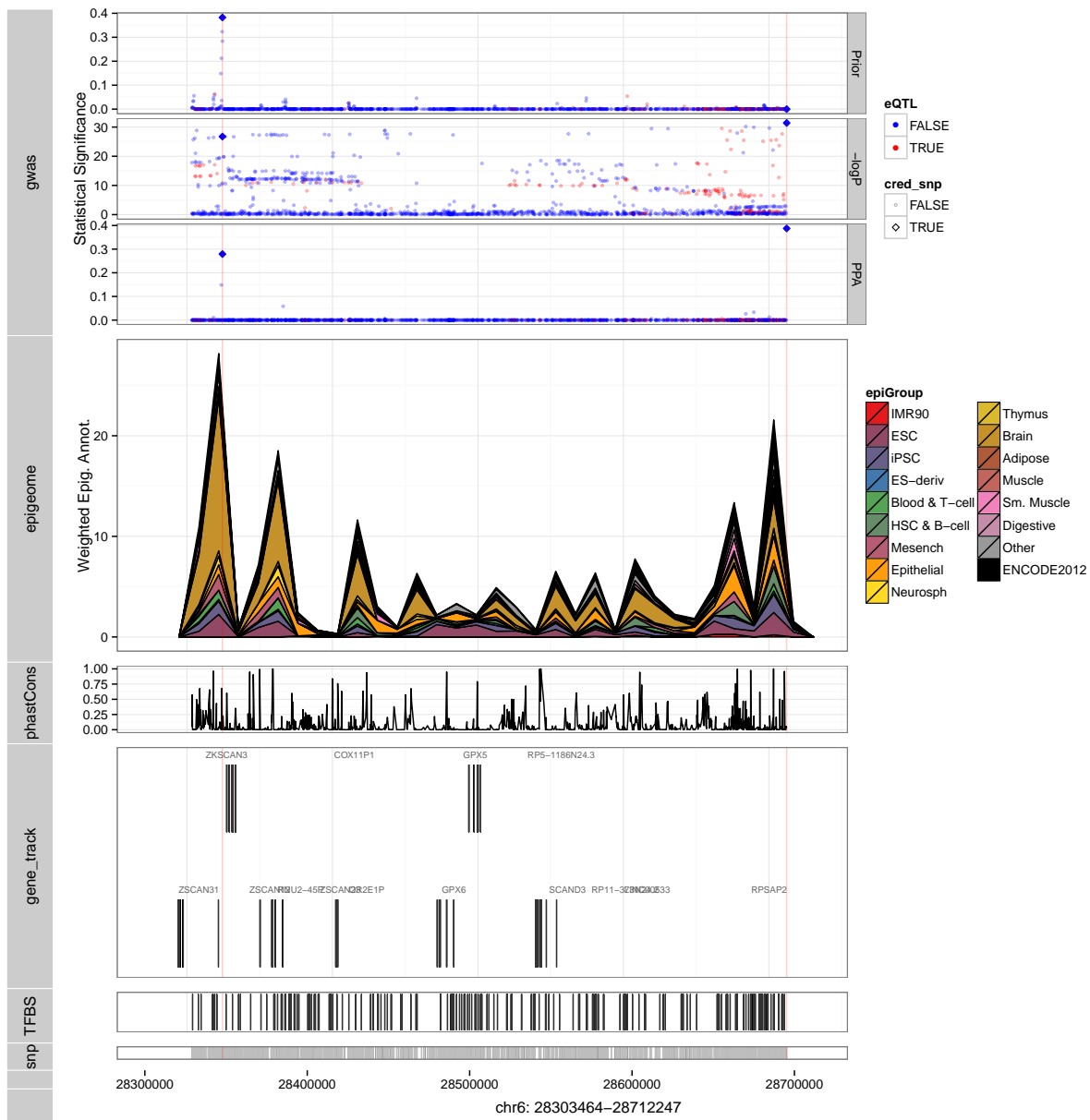
Schizophrenia



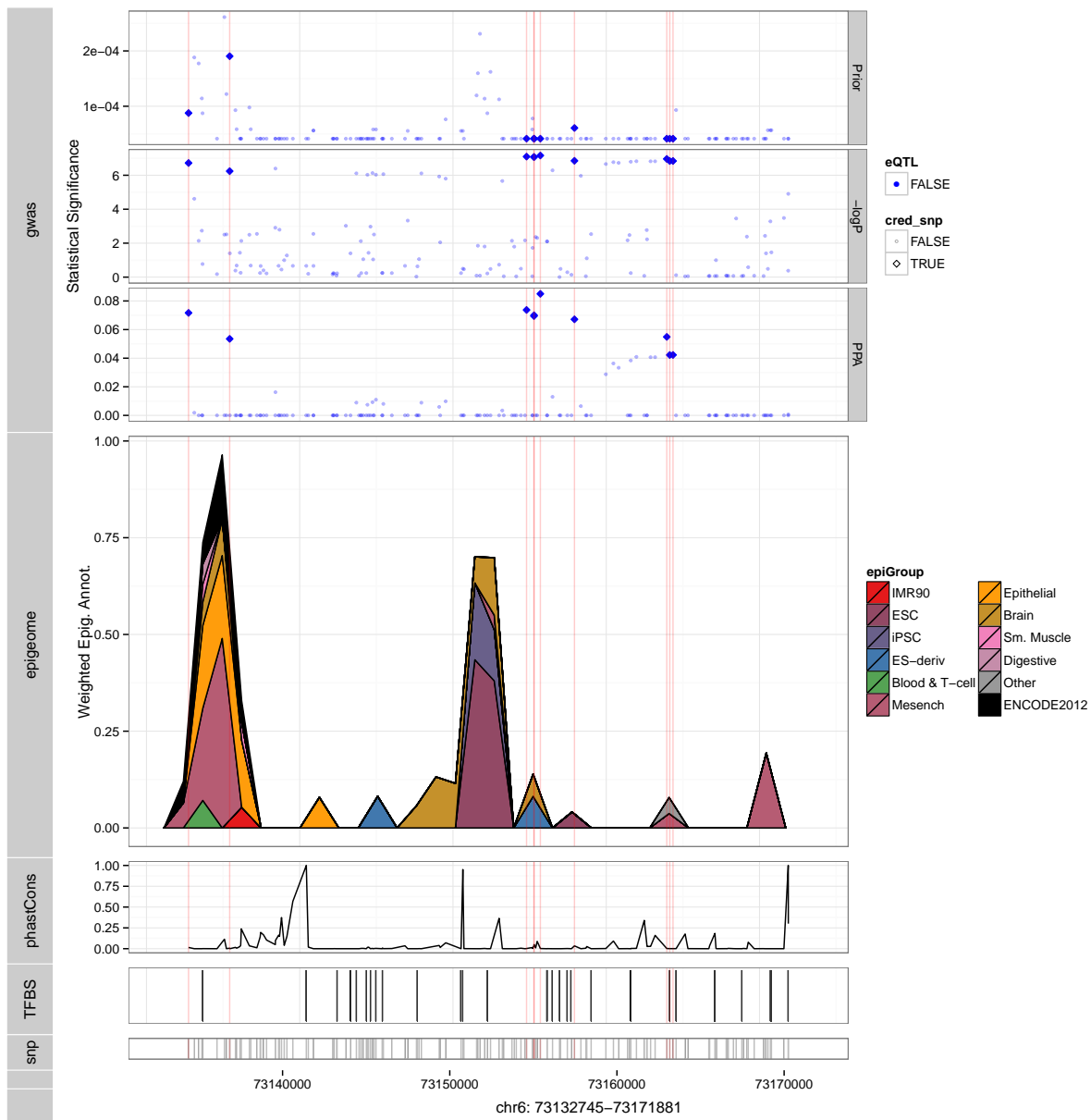
Schizophrenia



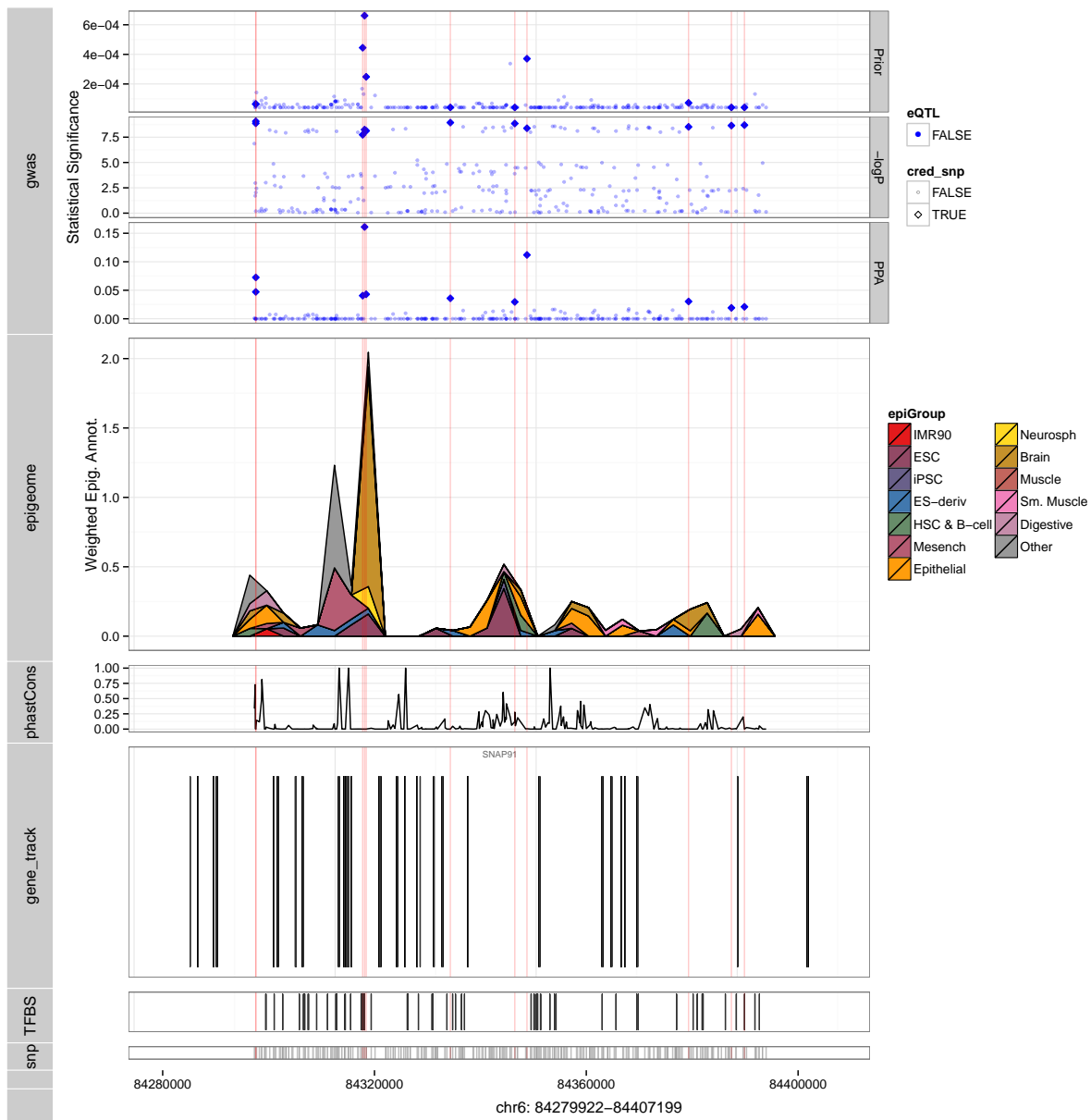
Schizophrenia



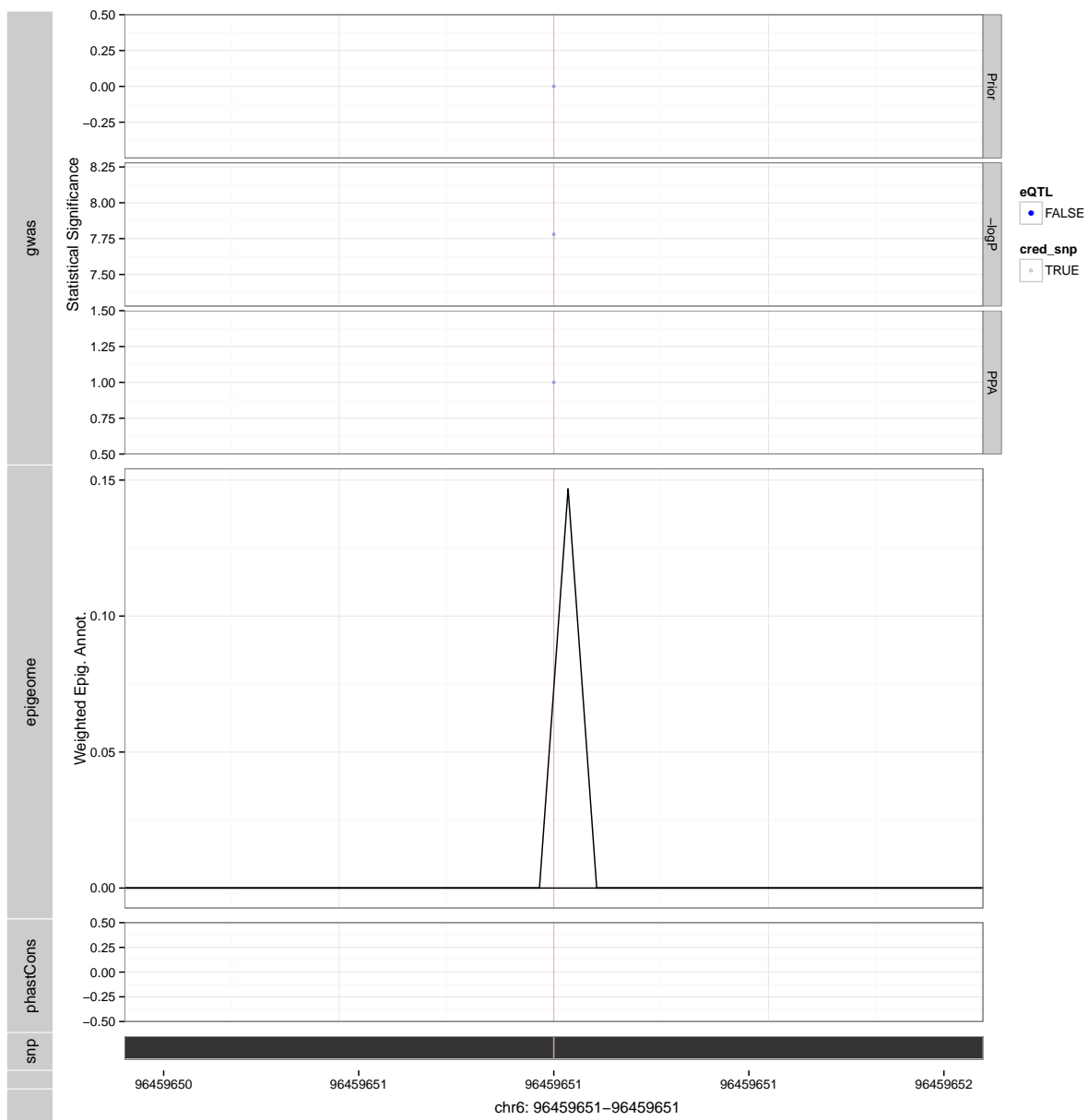
Schizophrenia



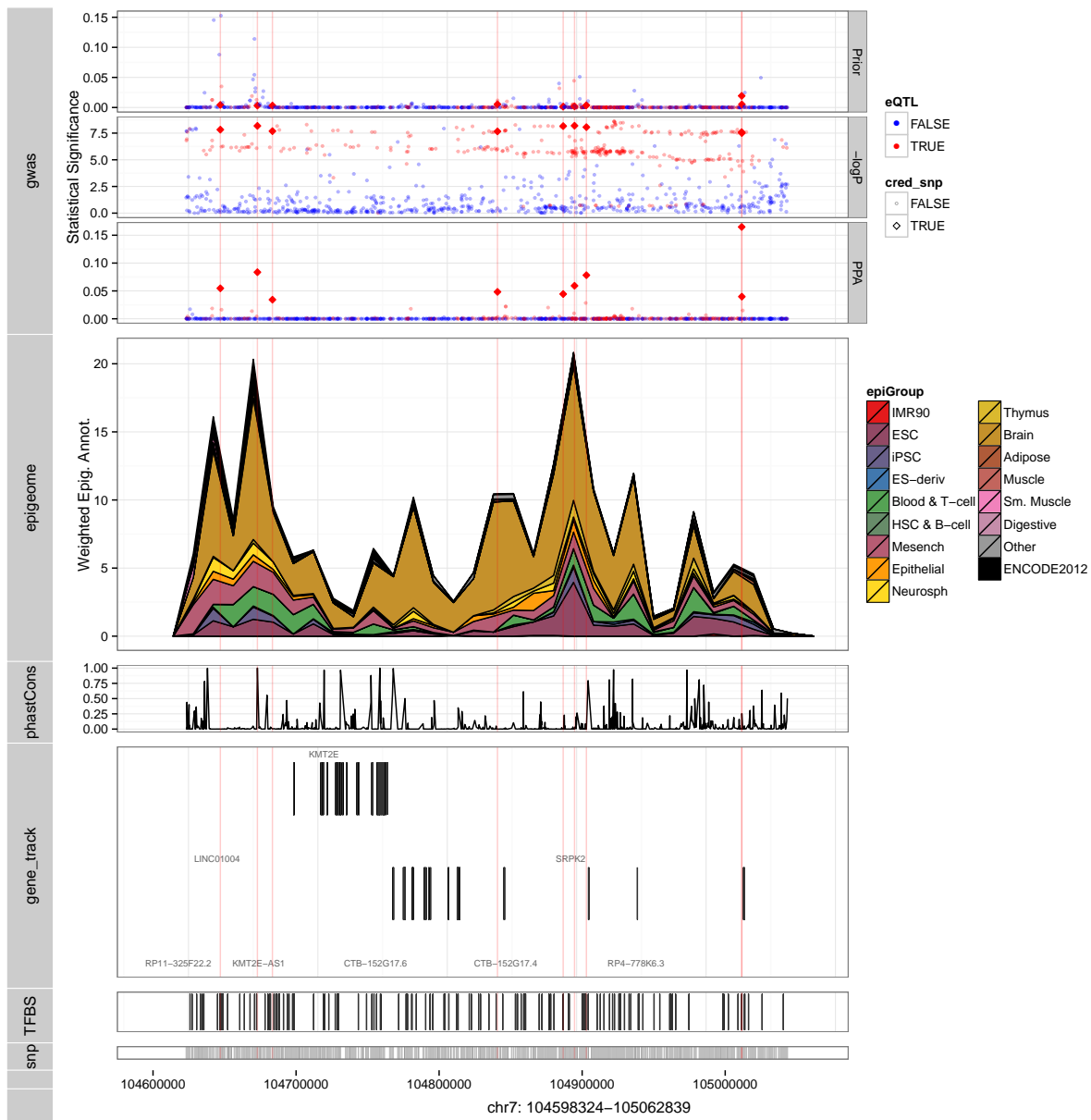
Schizophrenia



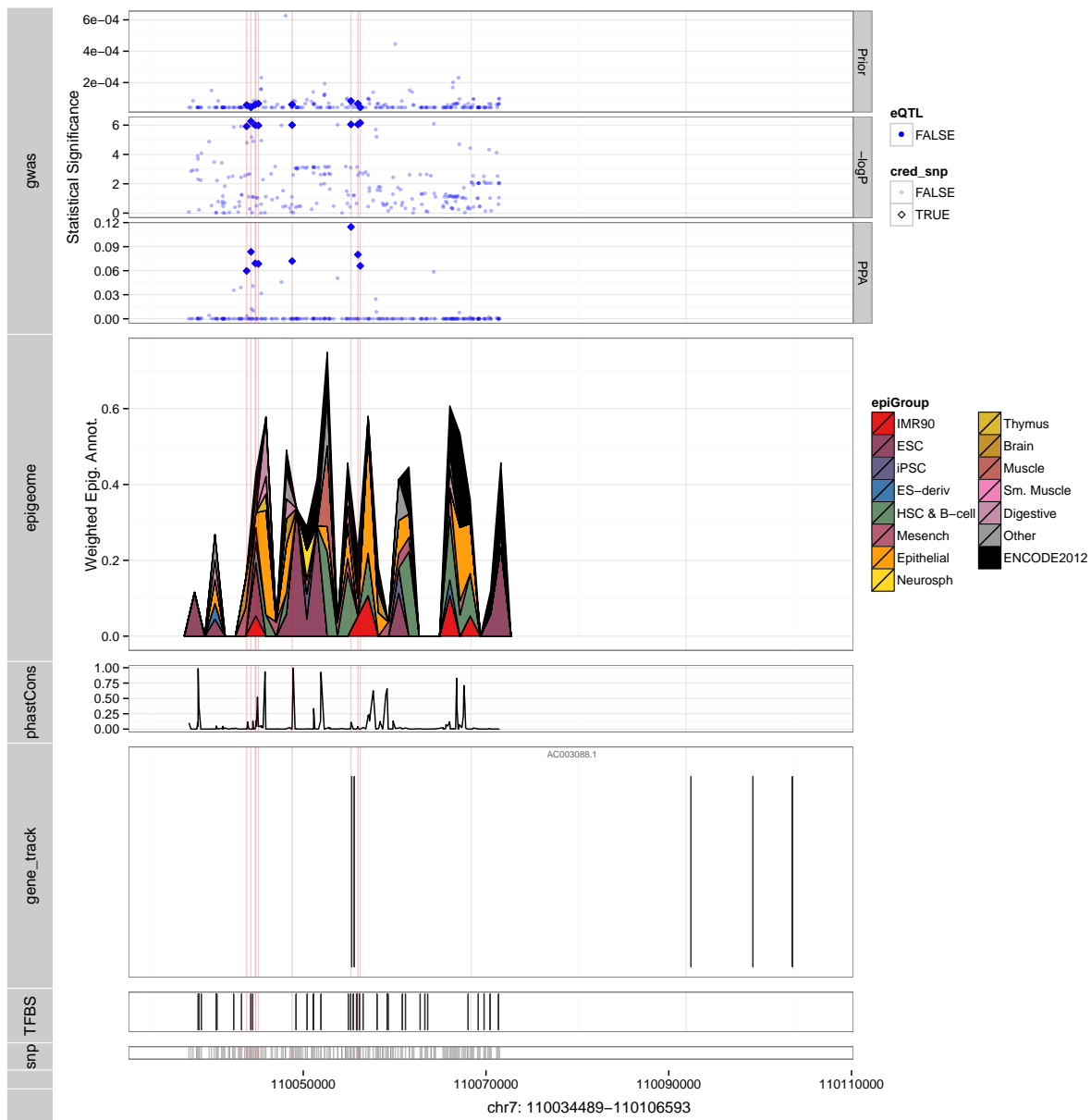
Schizophrenia



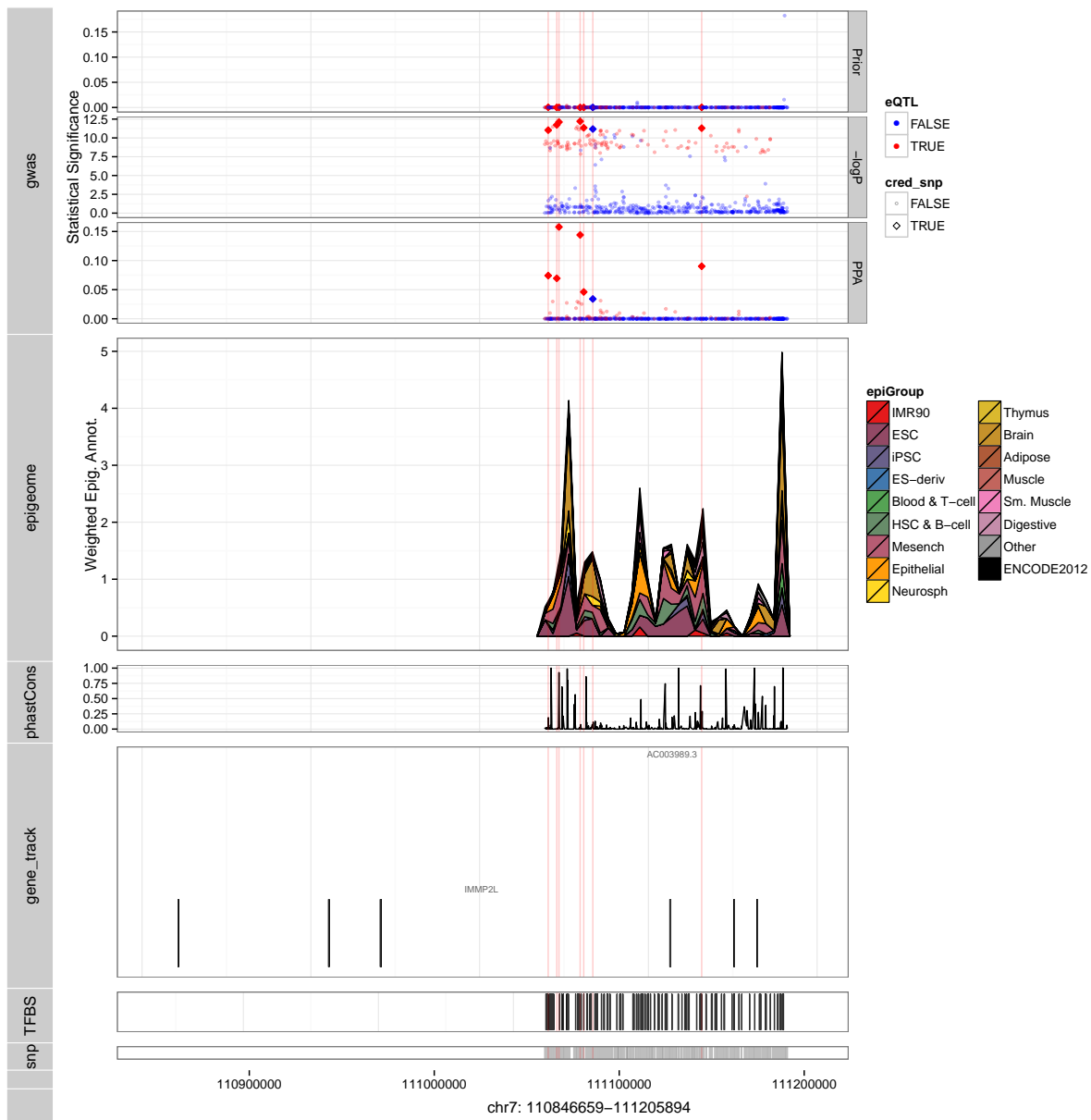
Schizophrenia



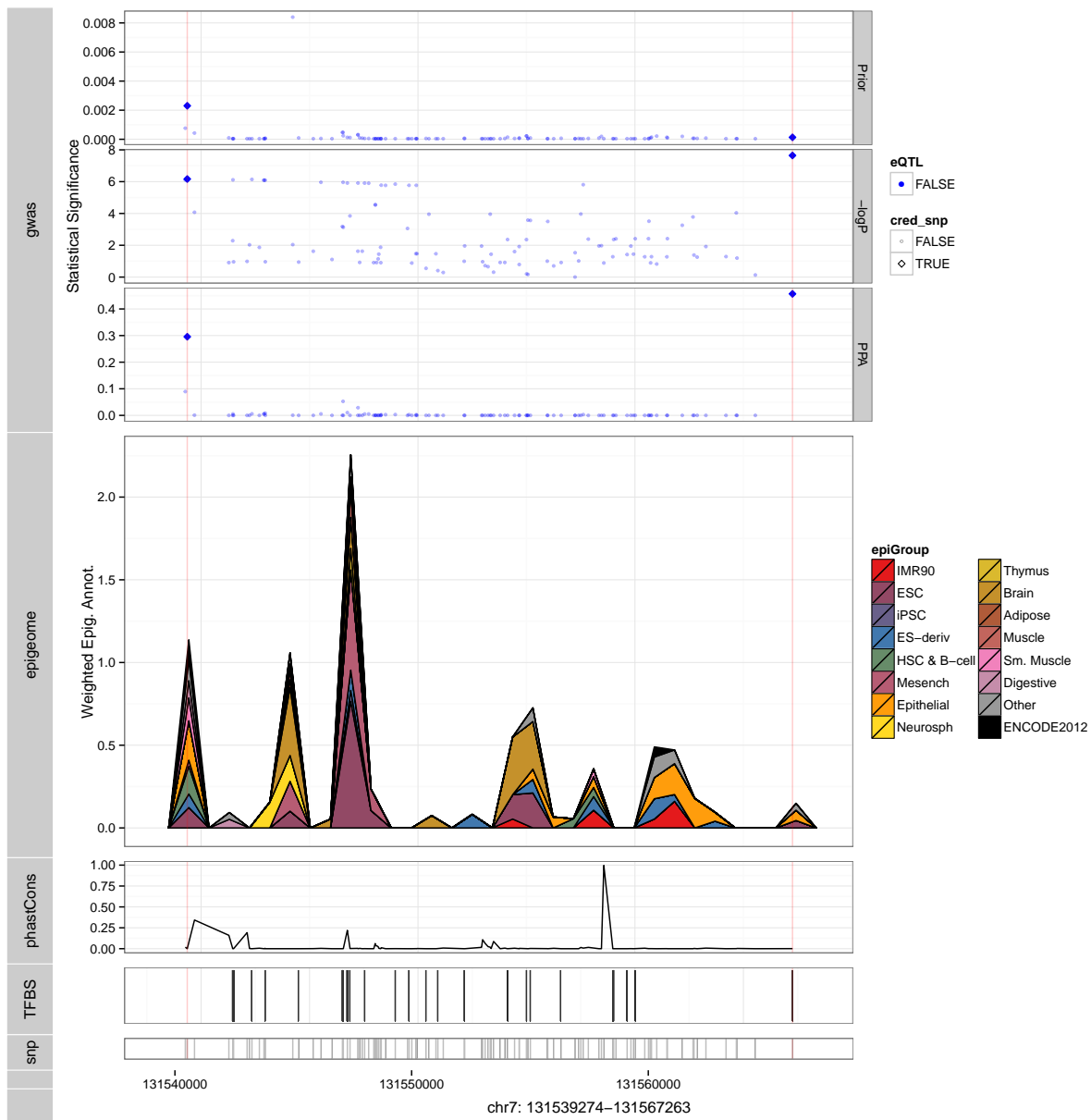
Schizophrenia



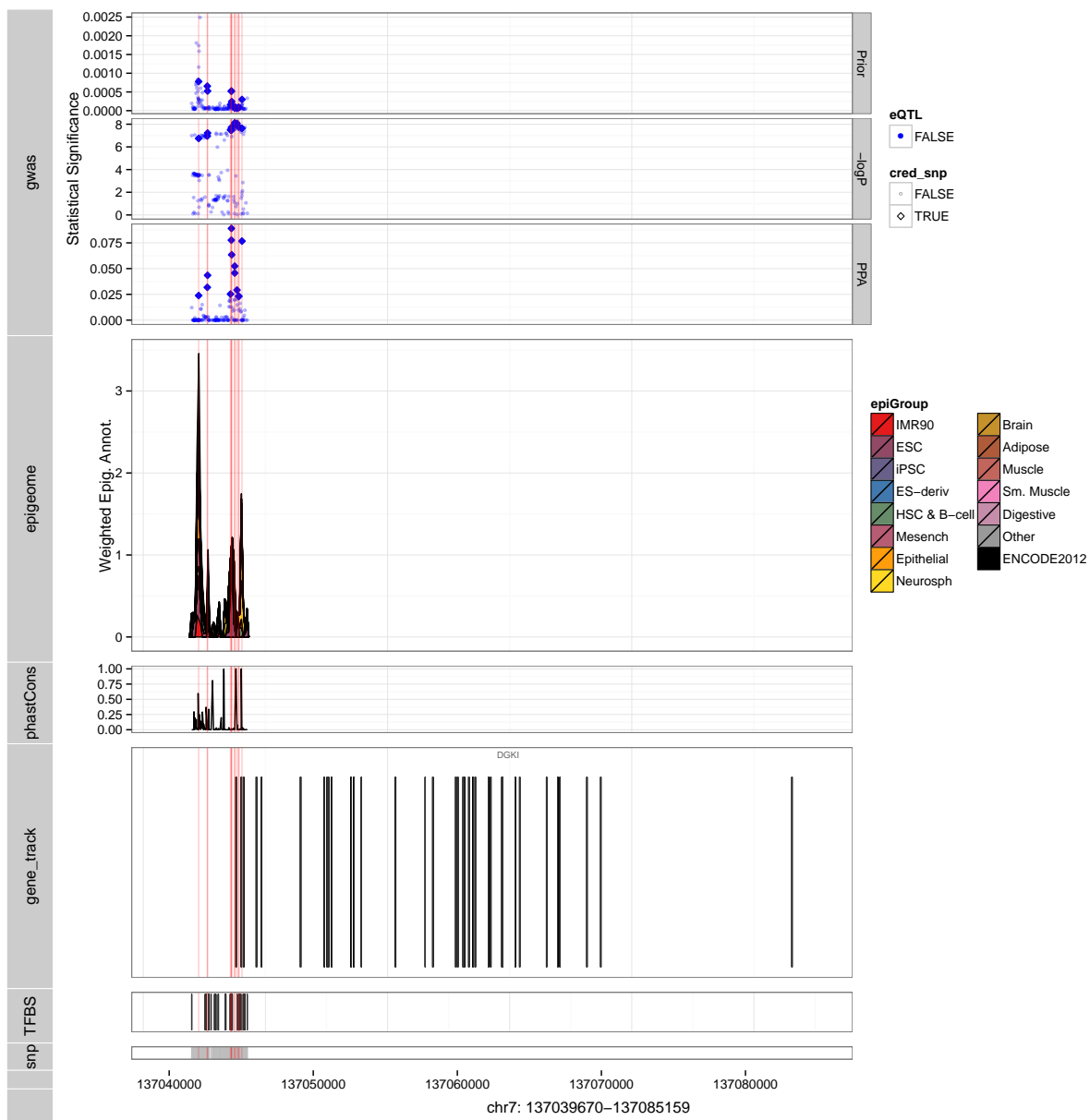
Schizophrenia



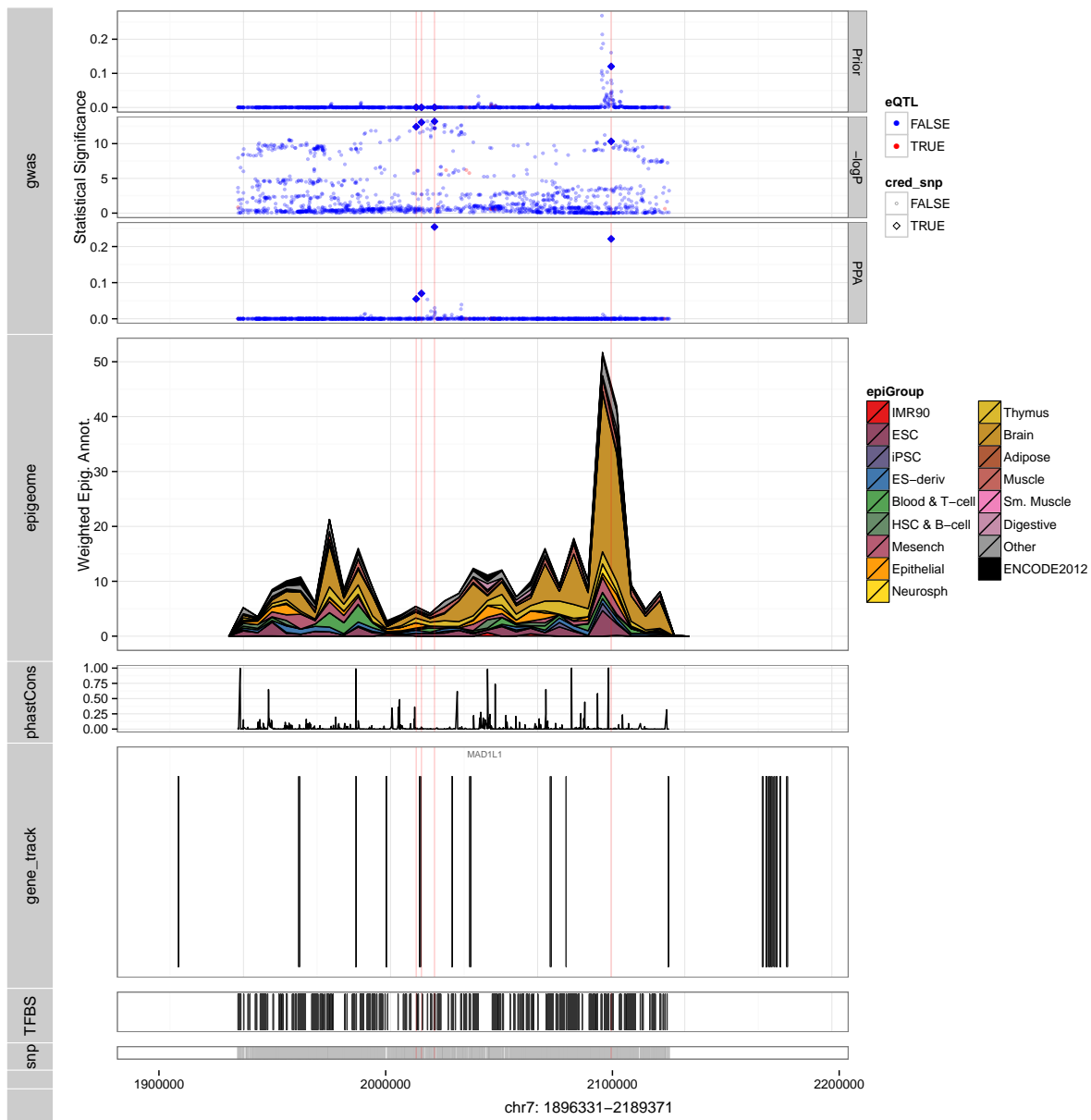
Schizophrenia



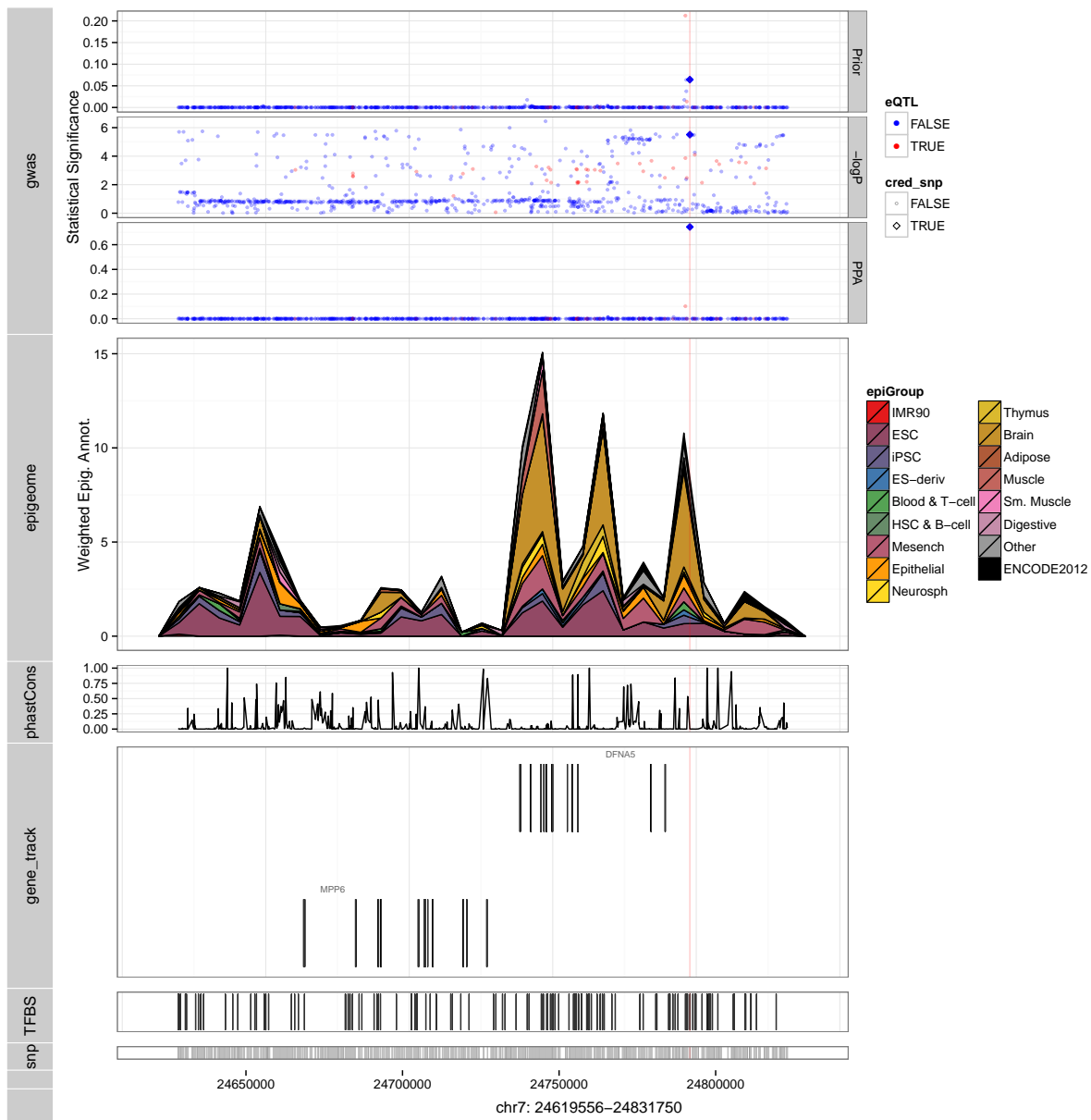
Schizophrenia



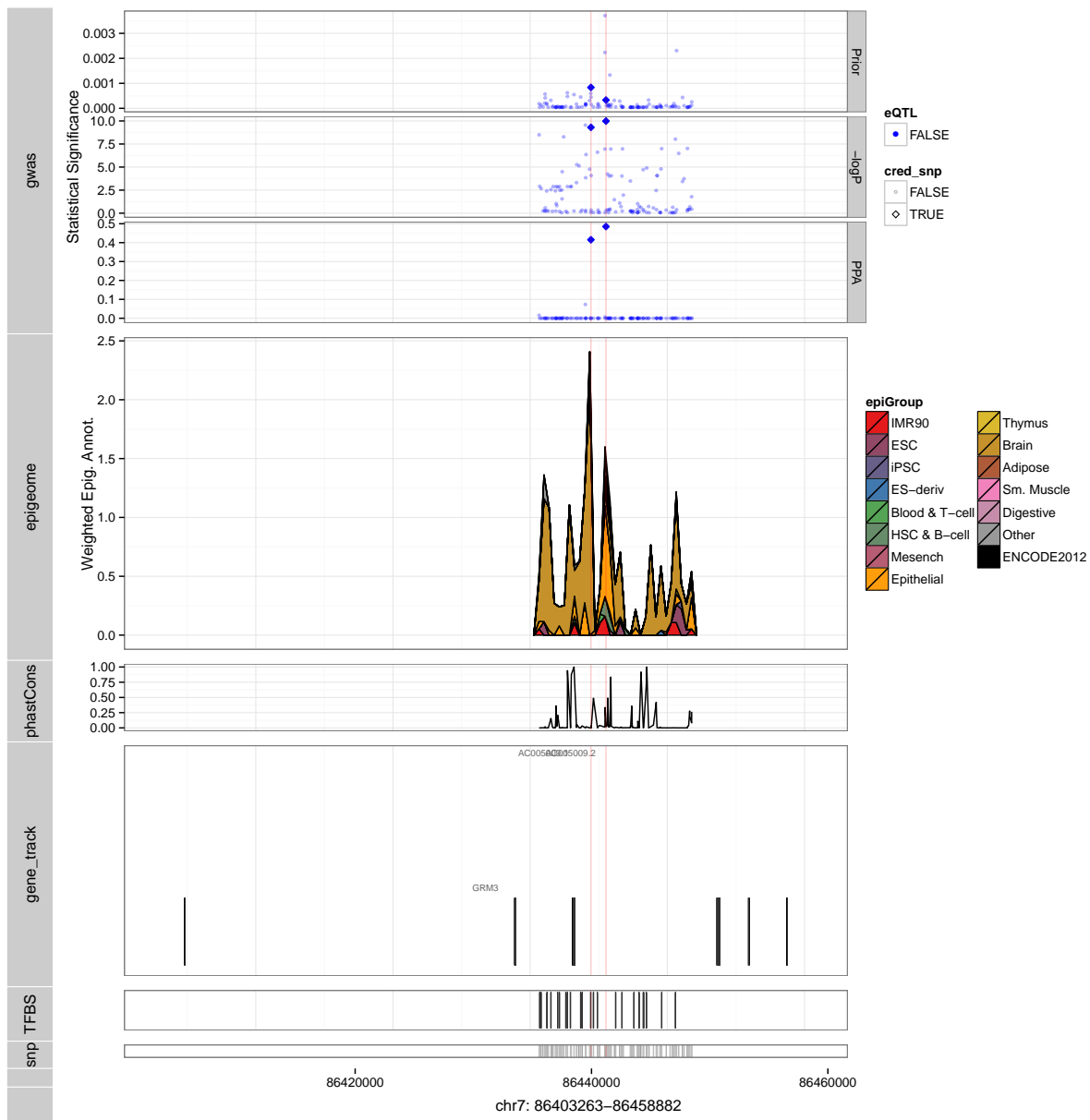
Schizophrenia



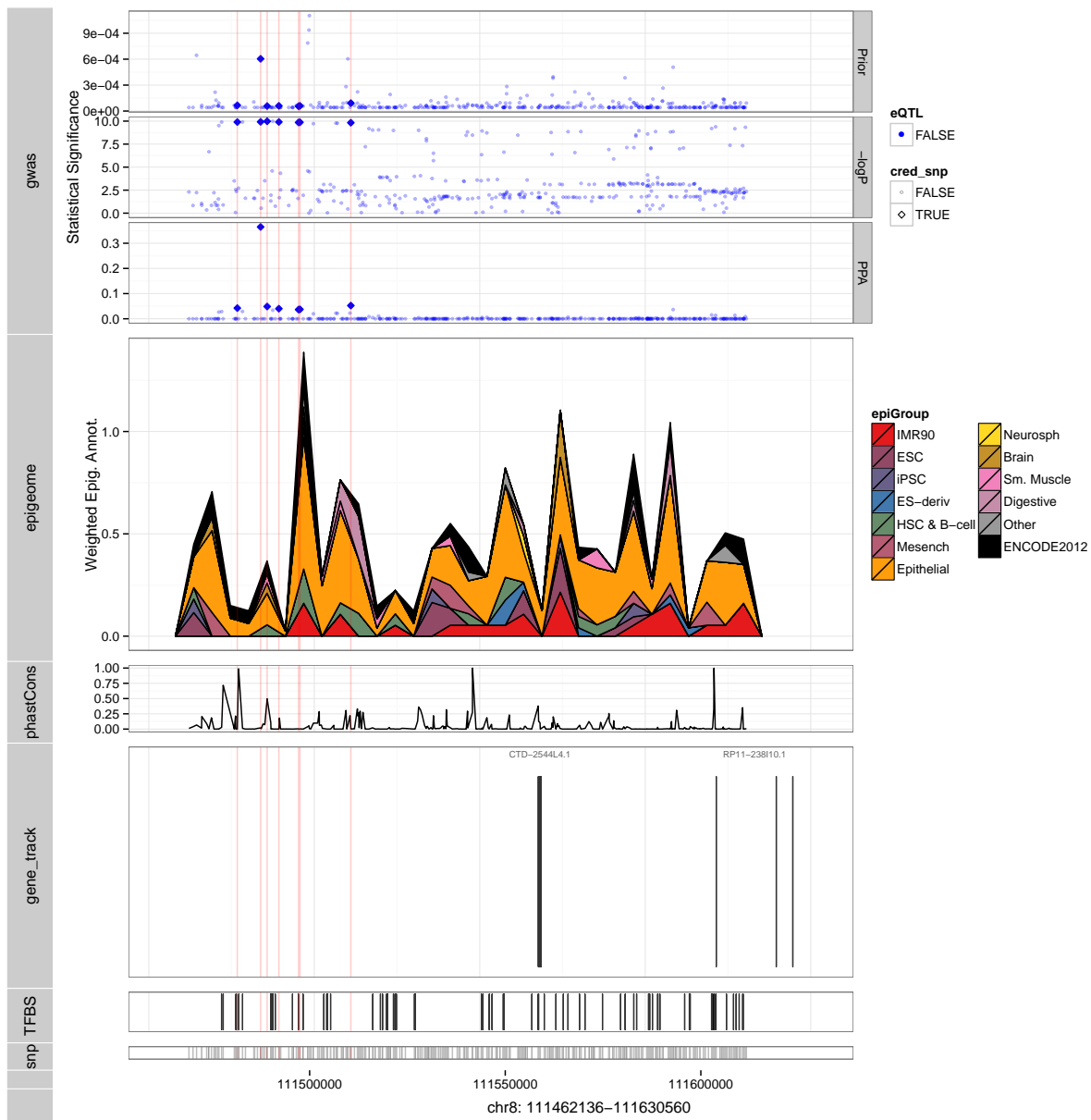
Schizophrenia



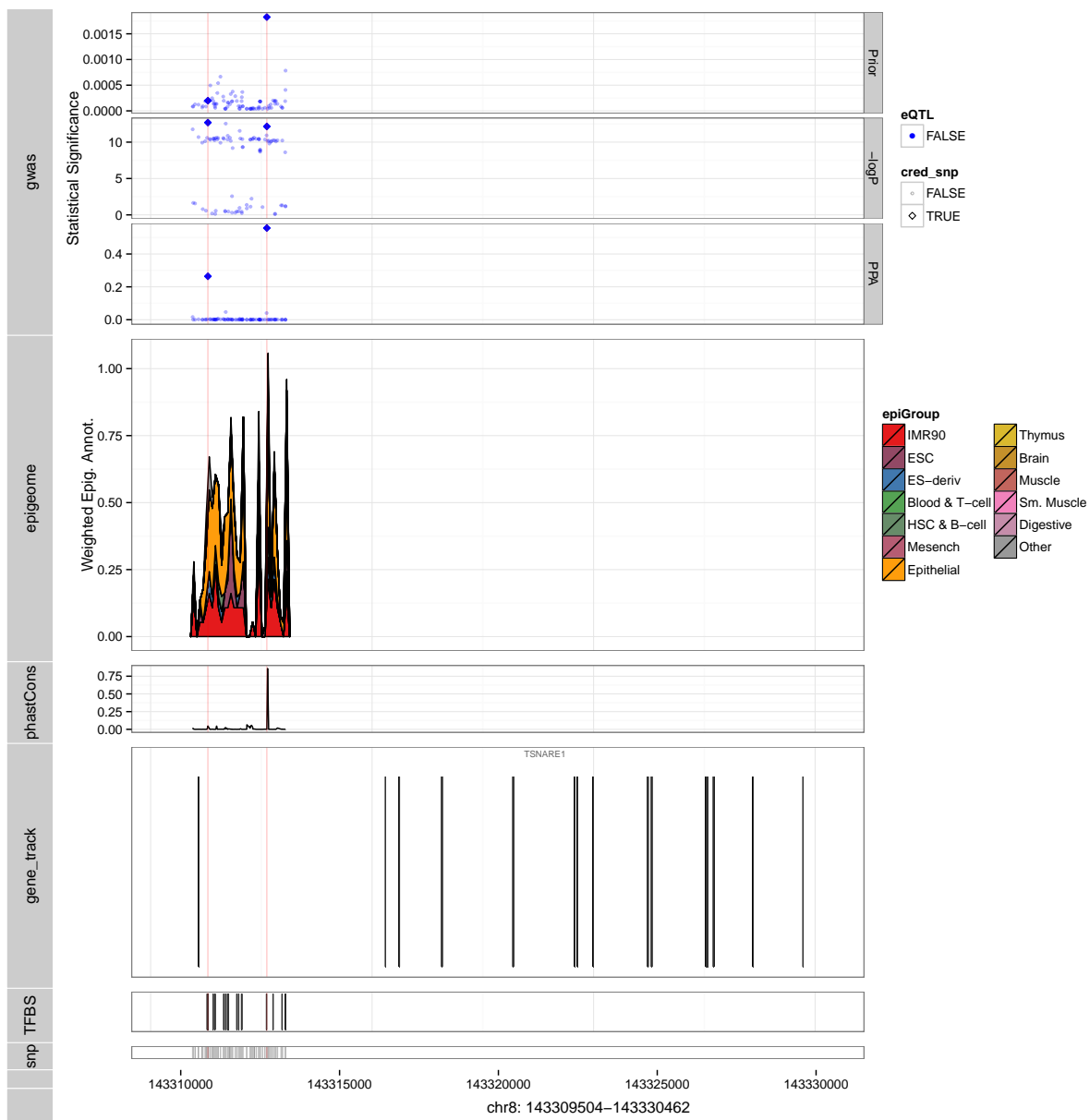
Schizophrenia



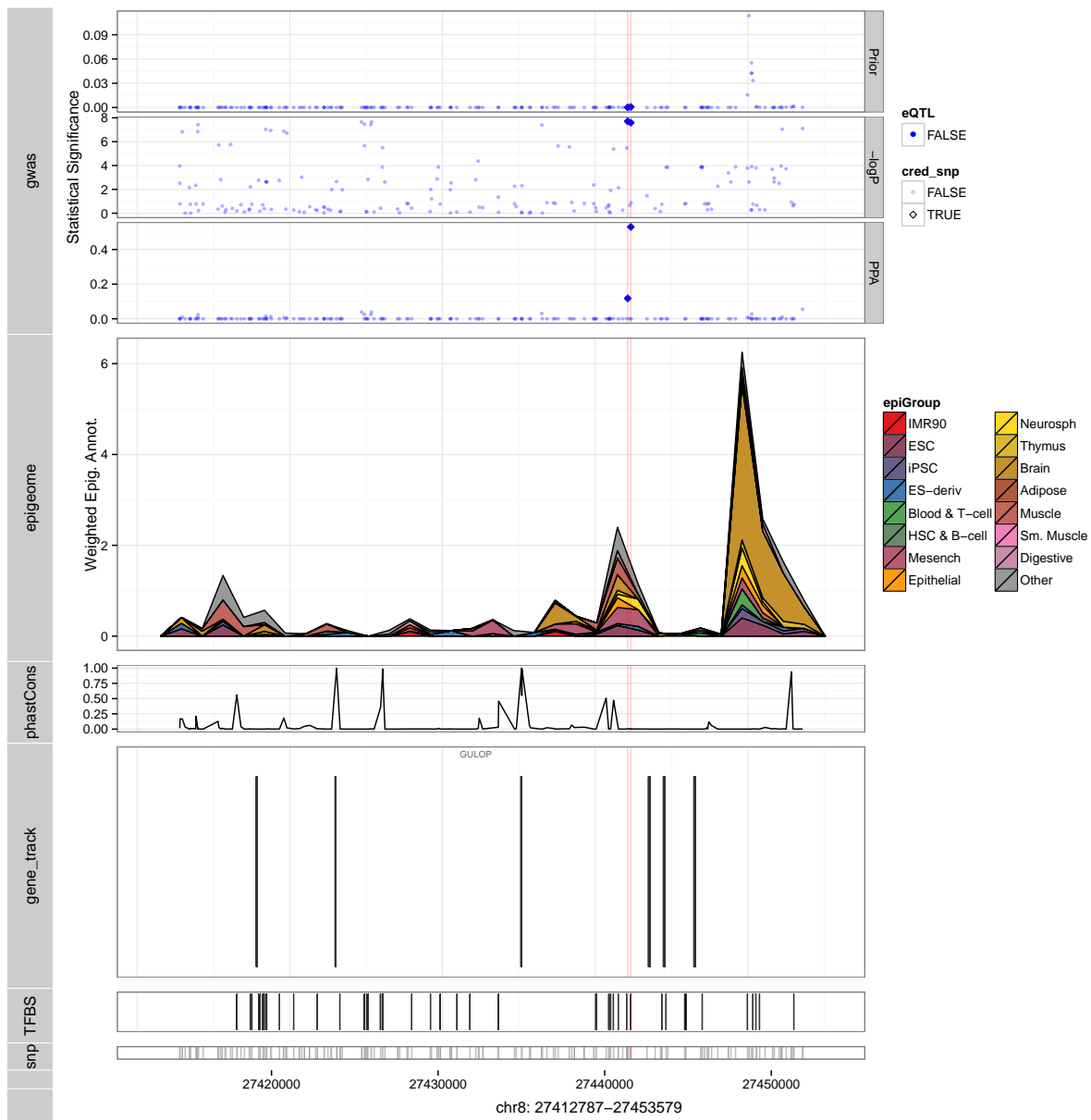
Schizophrenia



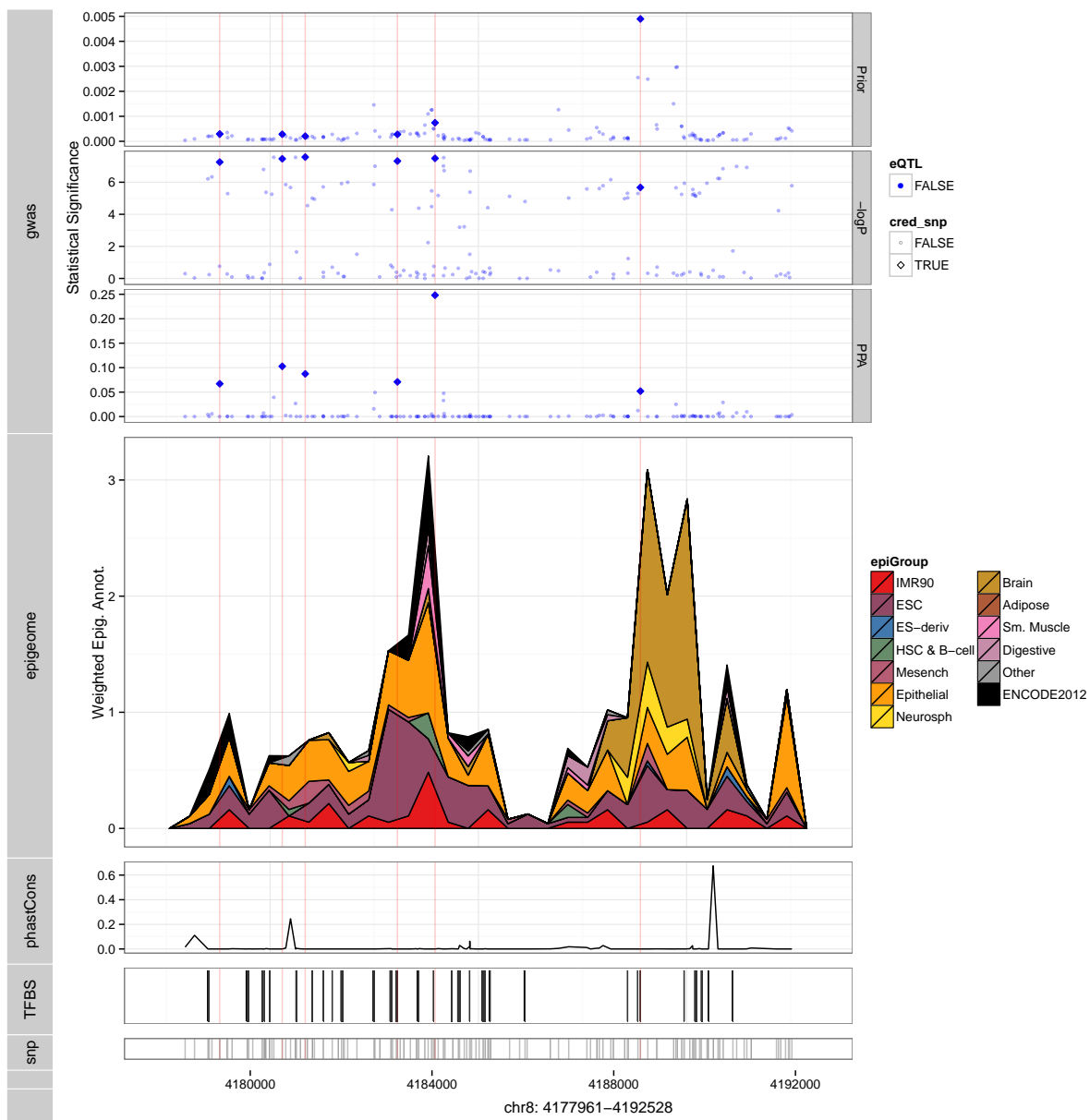
Schizophrenia



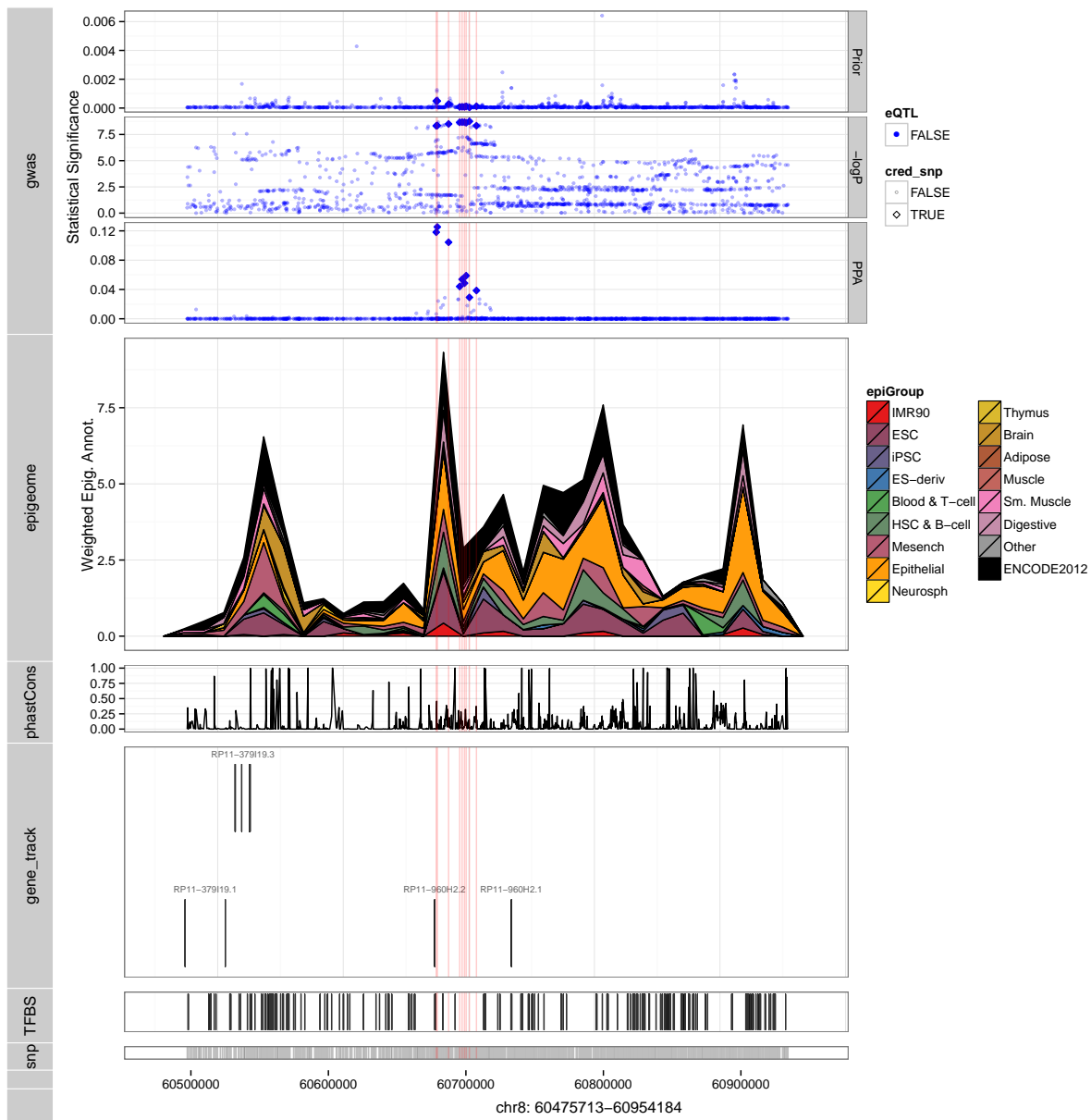
Schizophrenia



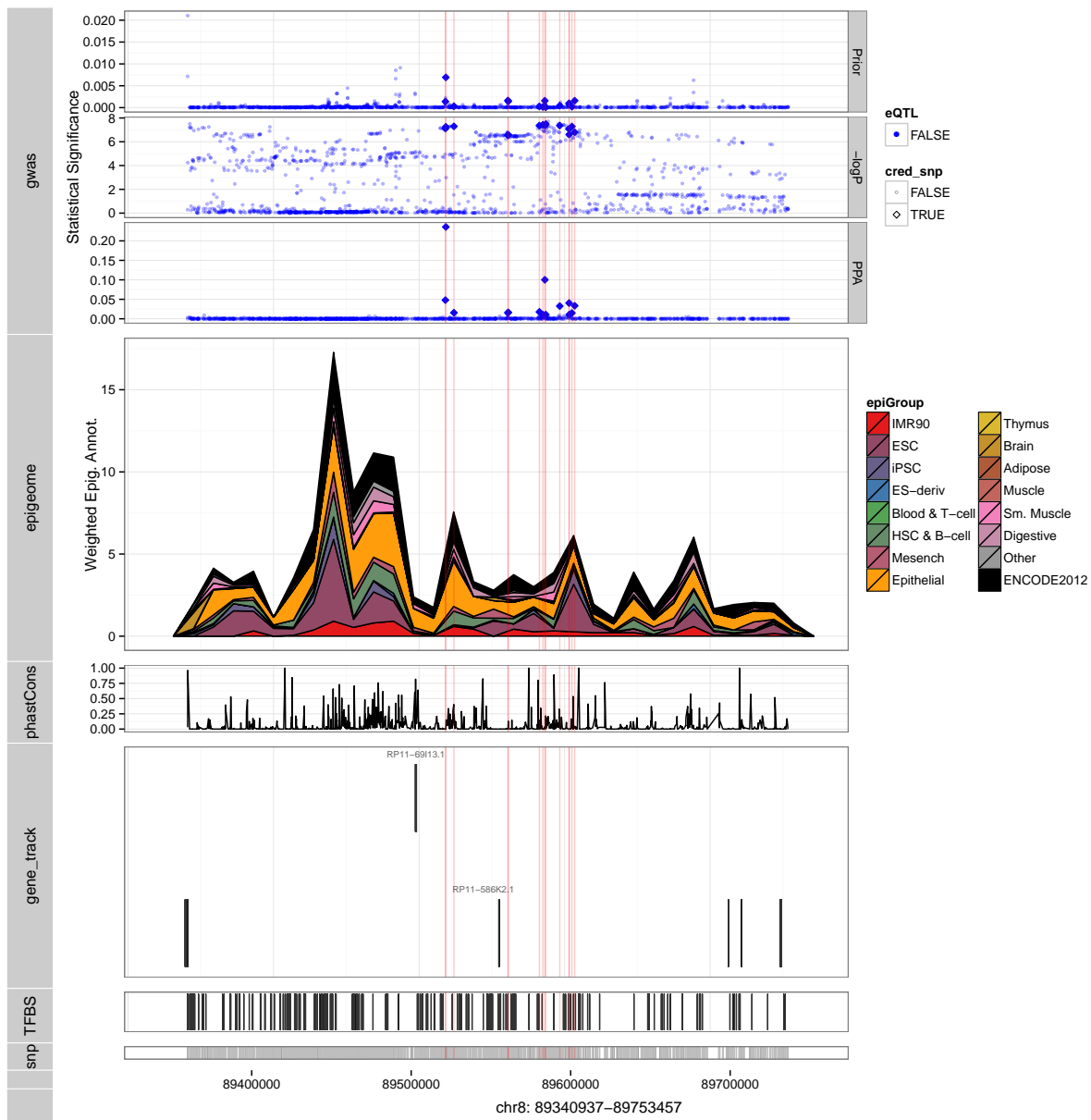
Schizophrenia



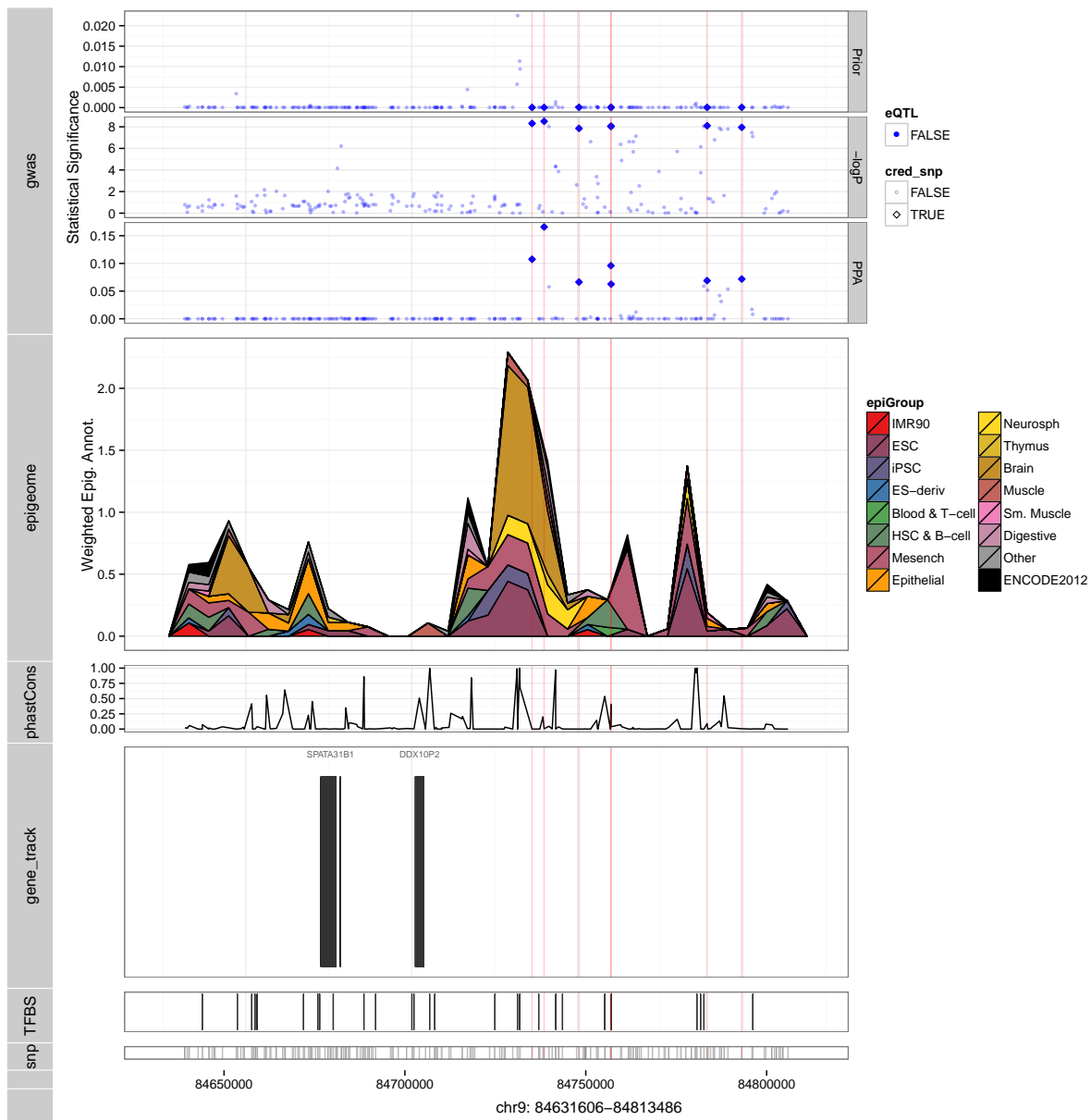
Schizophrenia



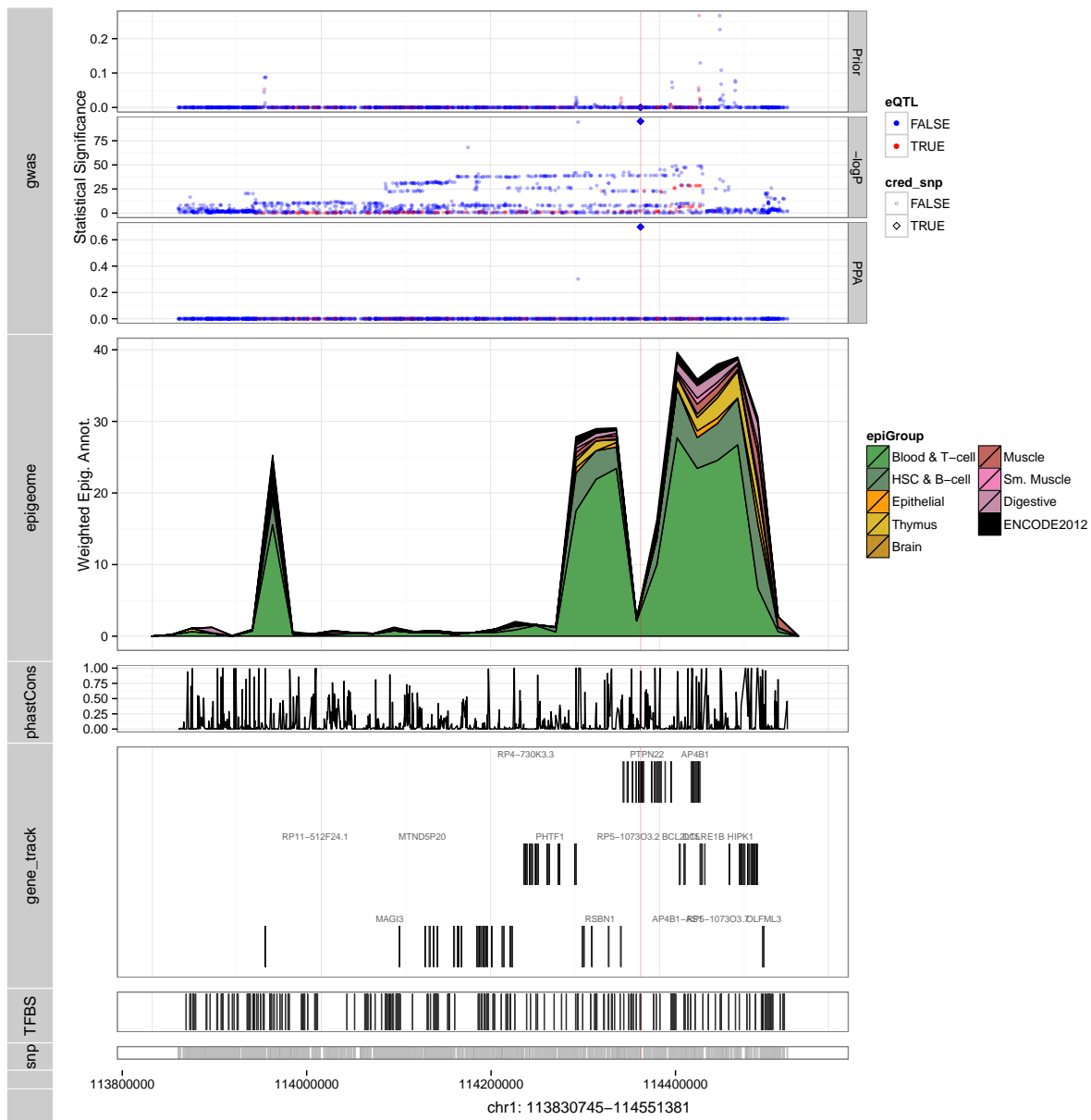
Schizophrenia



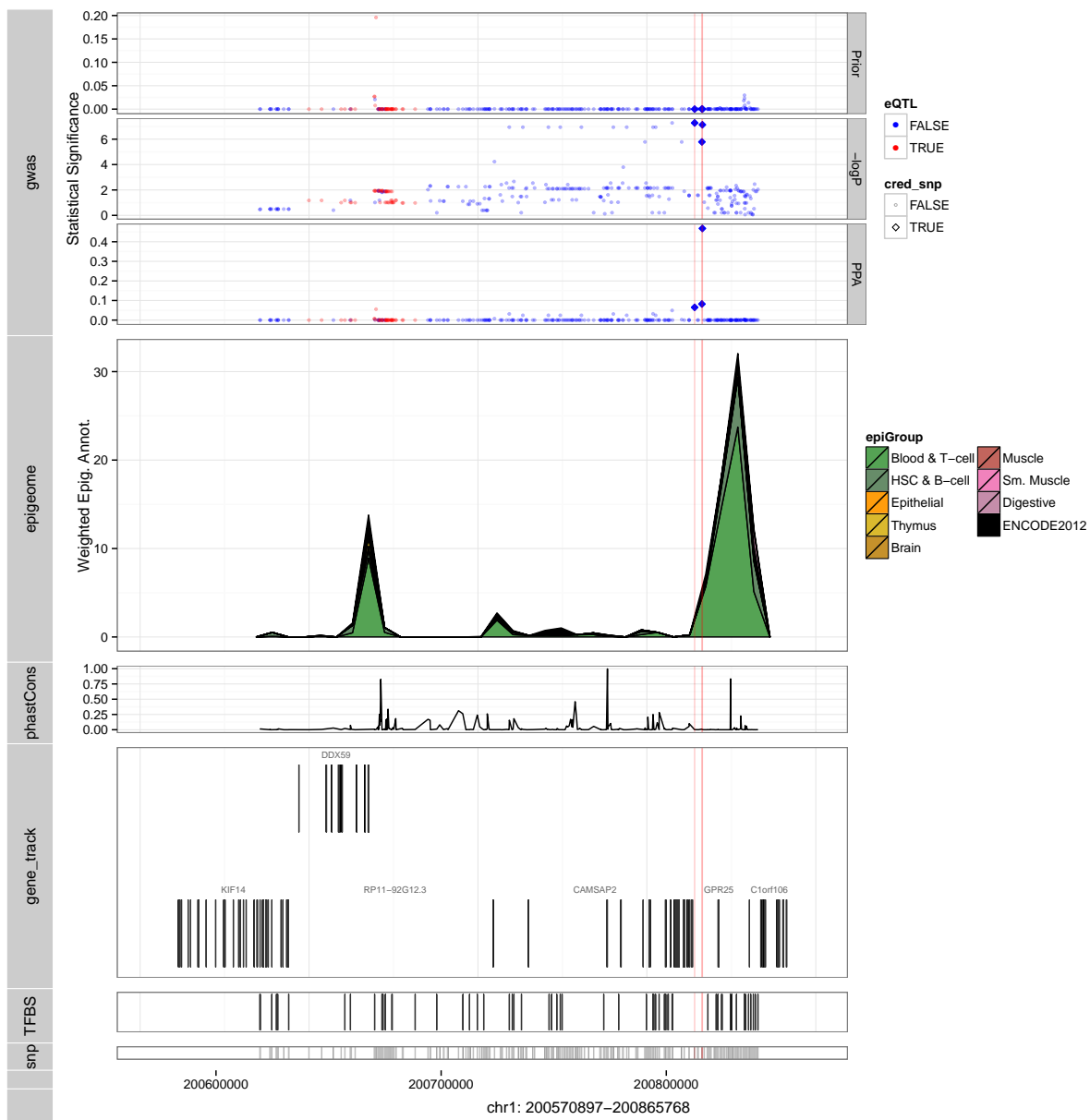
Schizophrenia



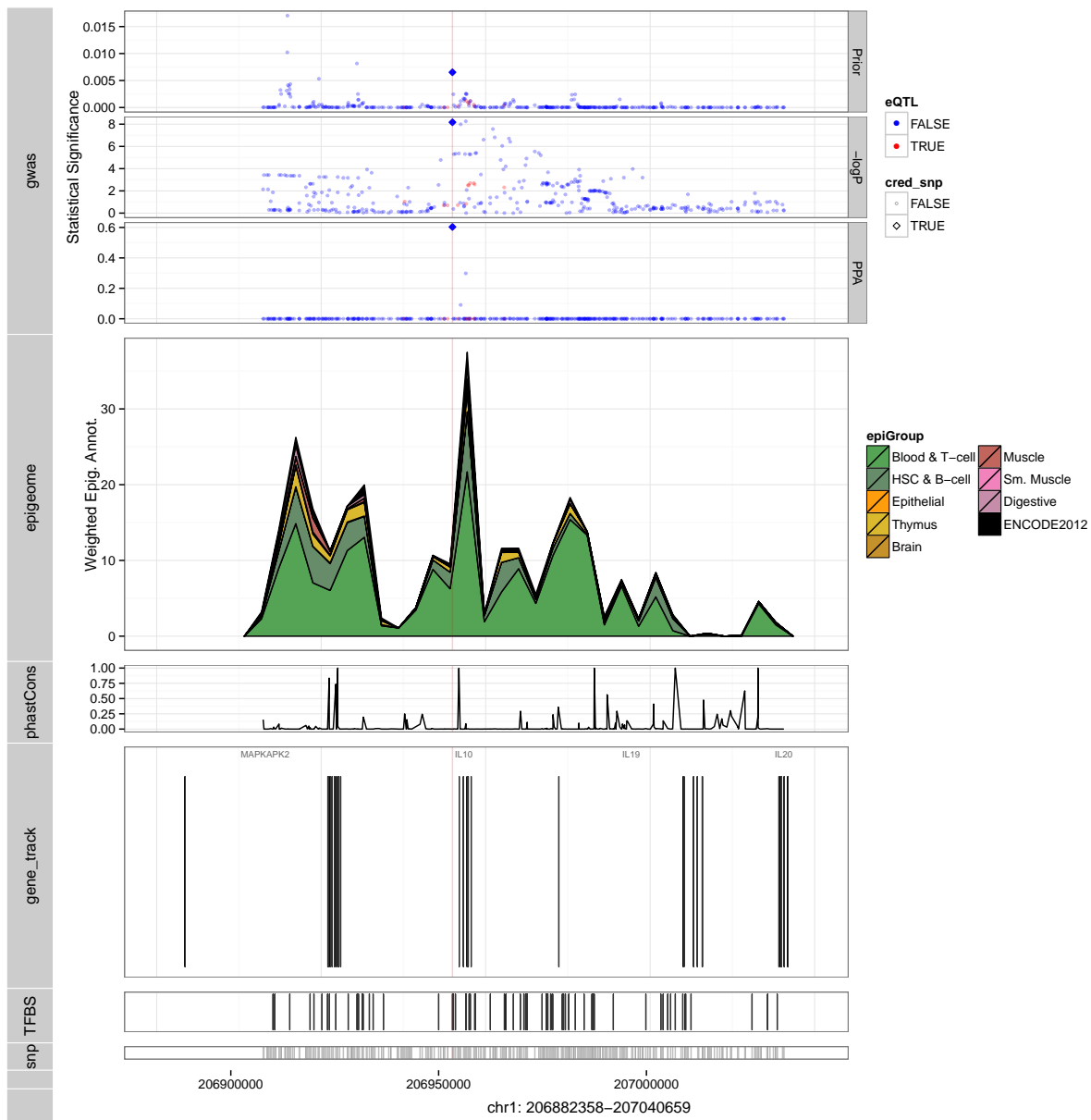
Type 1 Diabetes



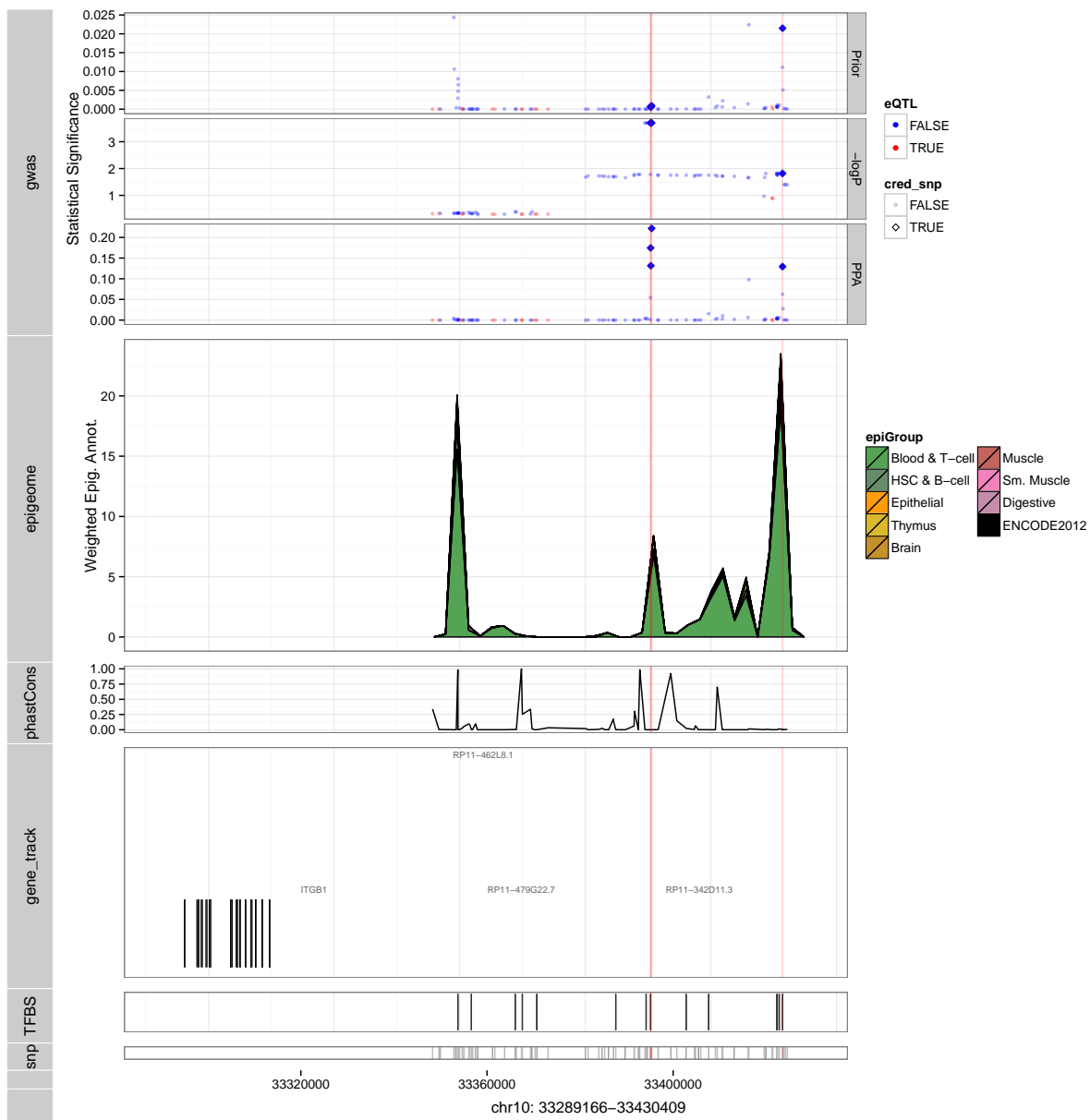
Type 1 Diabetes



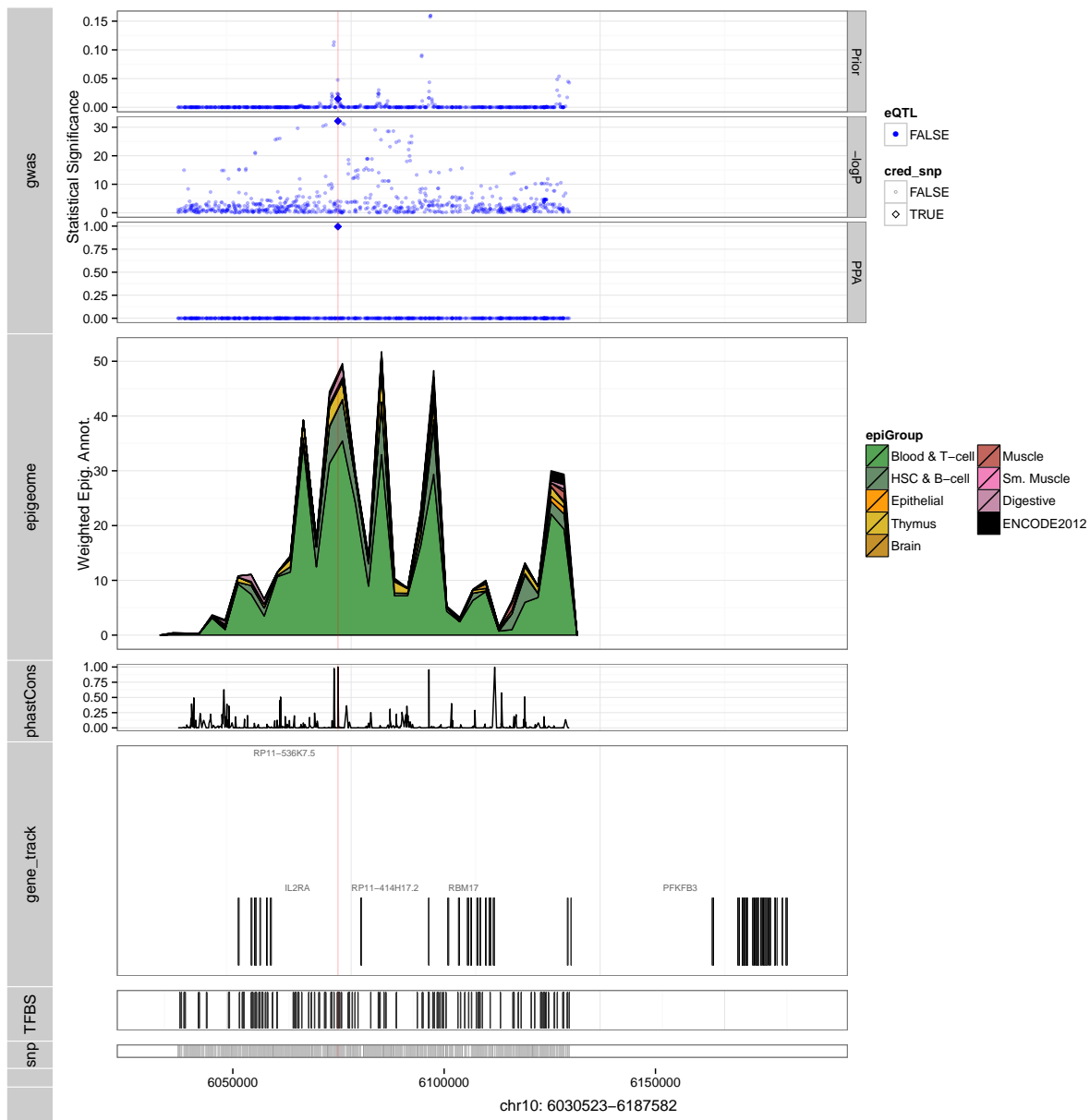
Type 1 Diabetes



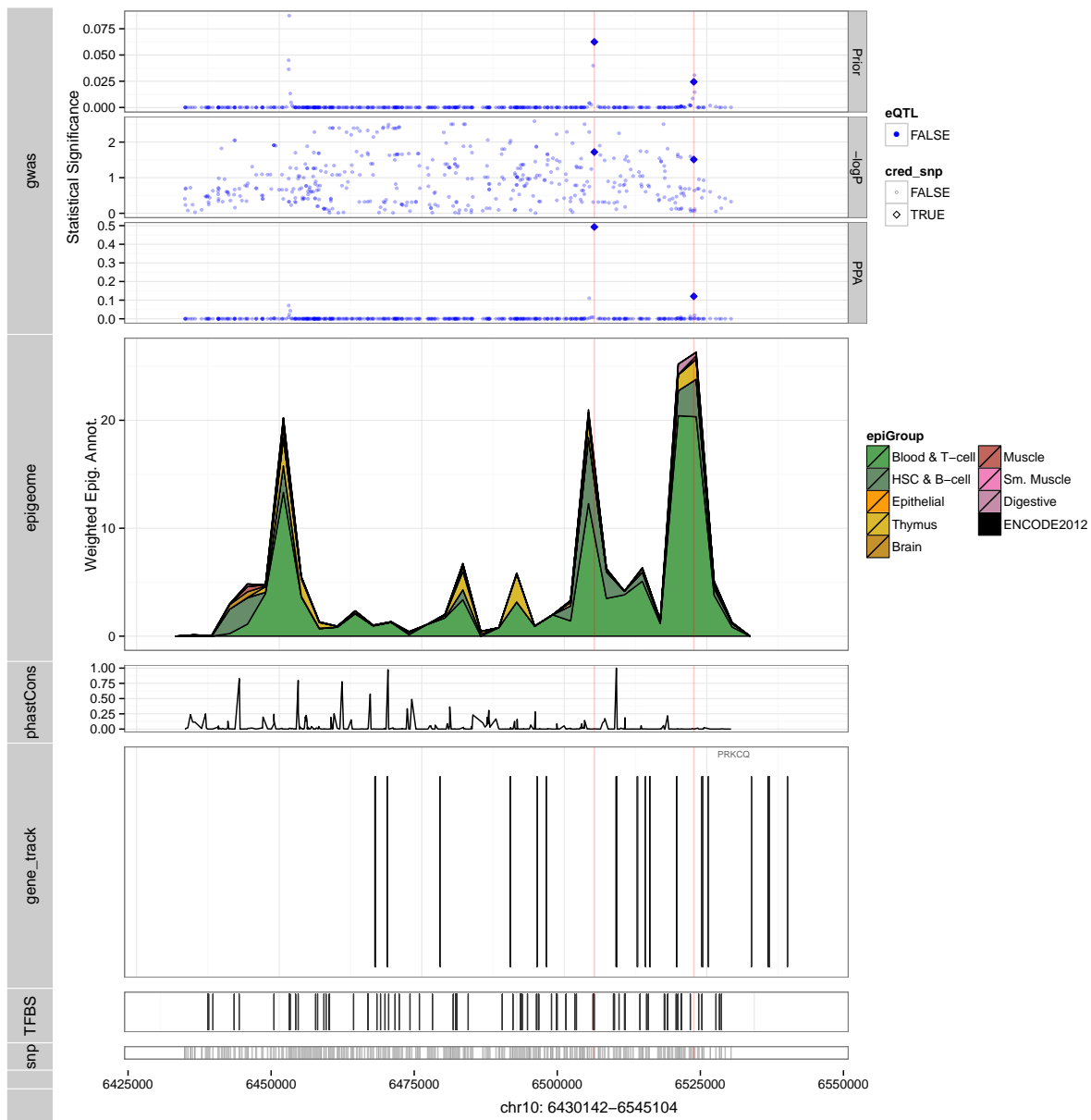
Type 1 Diabetes



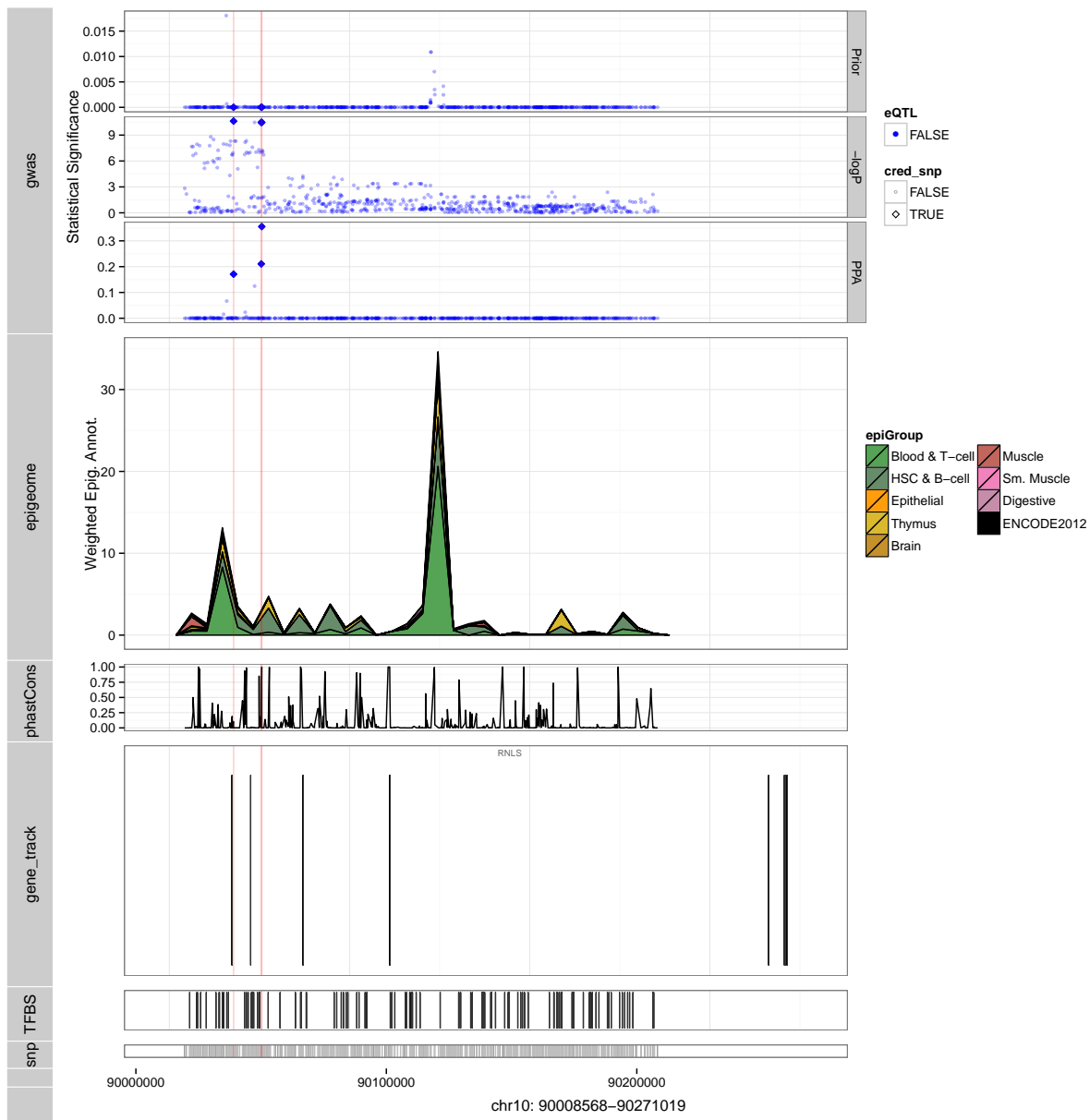
Type 1 Diabetes



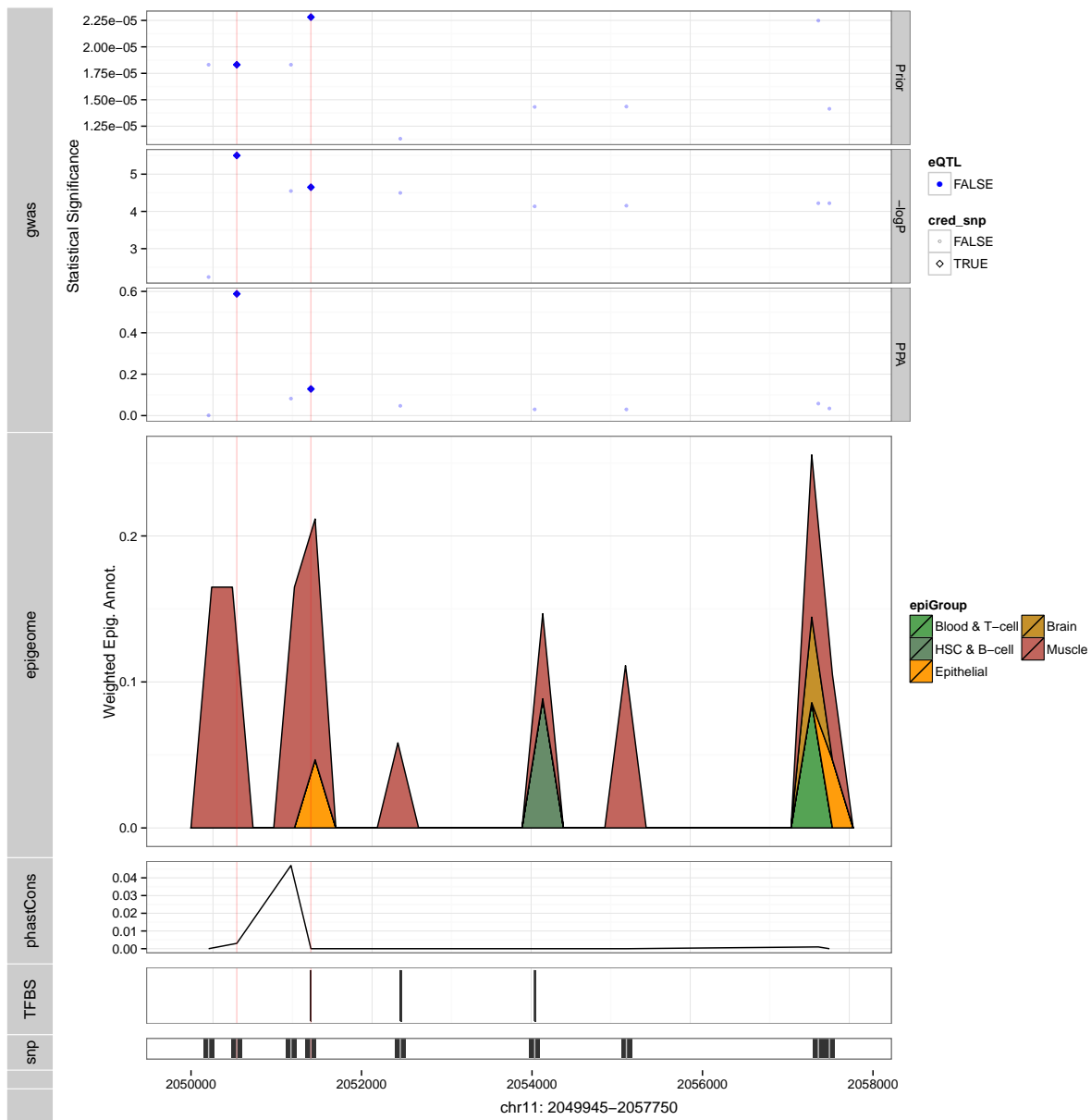
Type 1 Diabetes



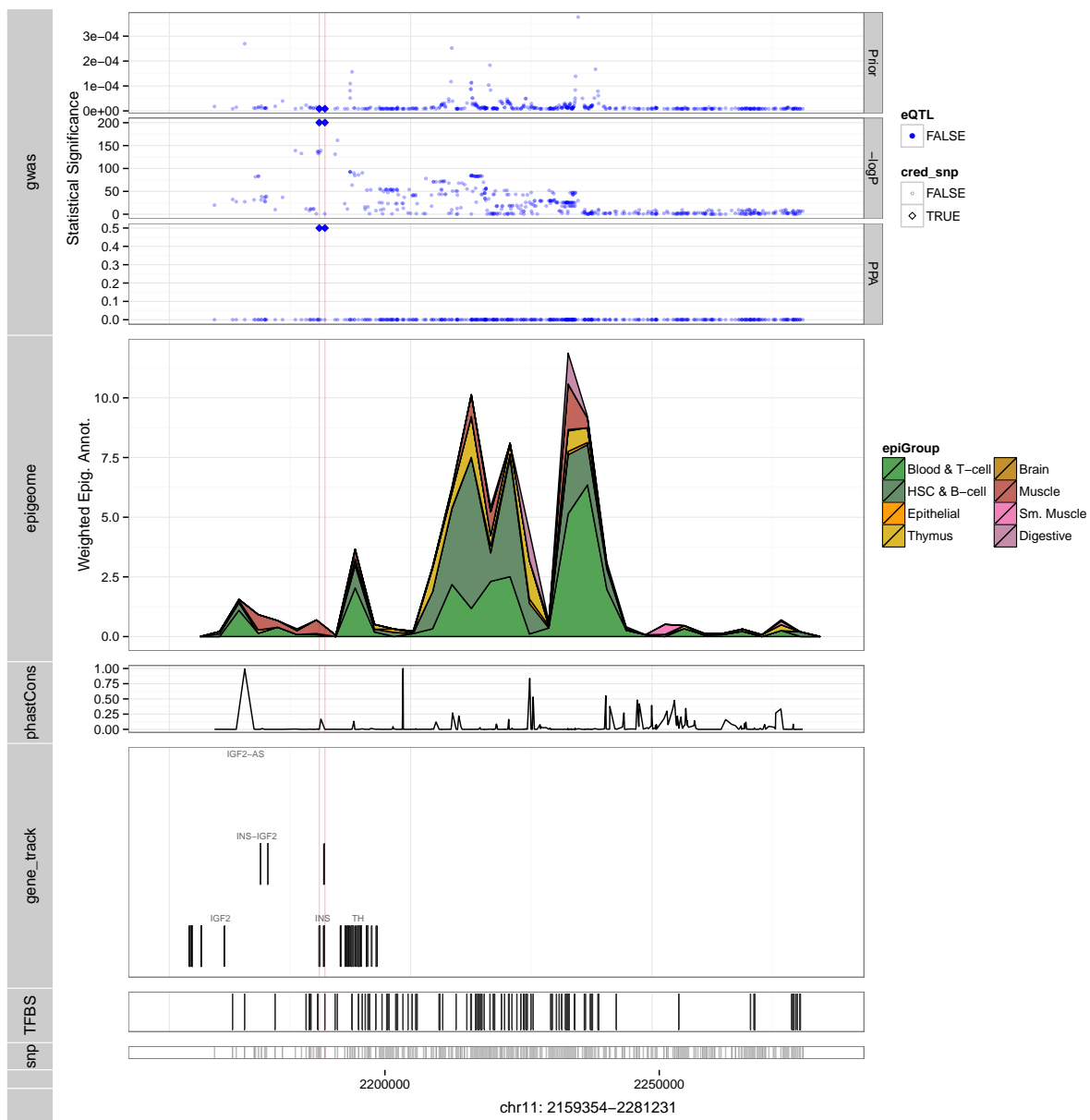
Type 1 Diabetes



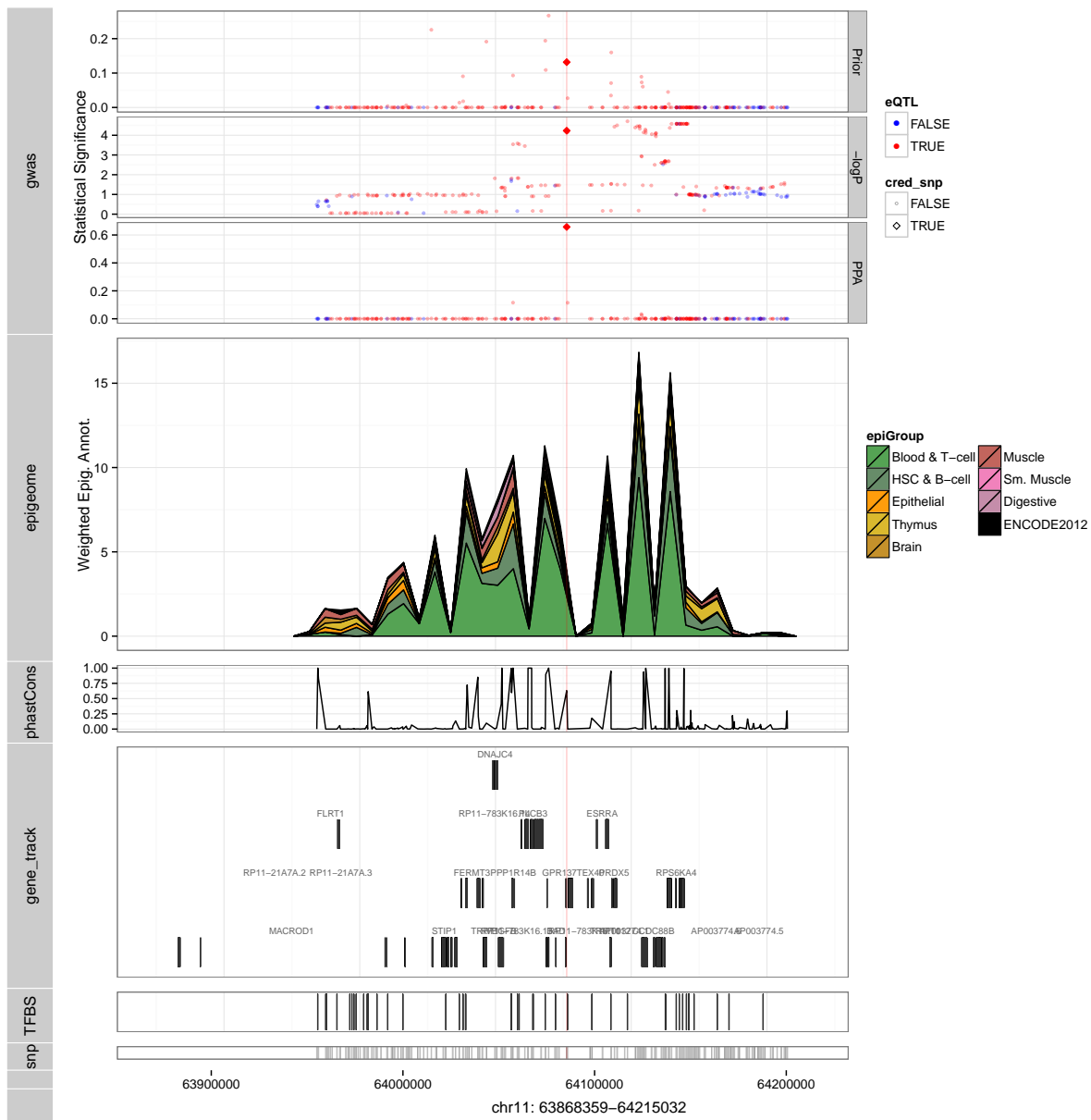
Type 1 Diabetes



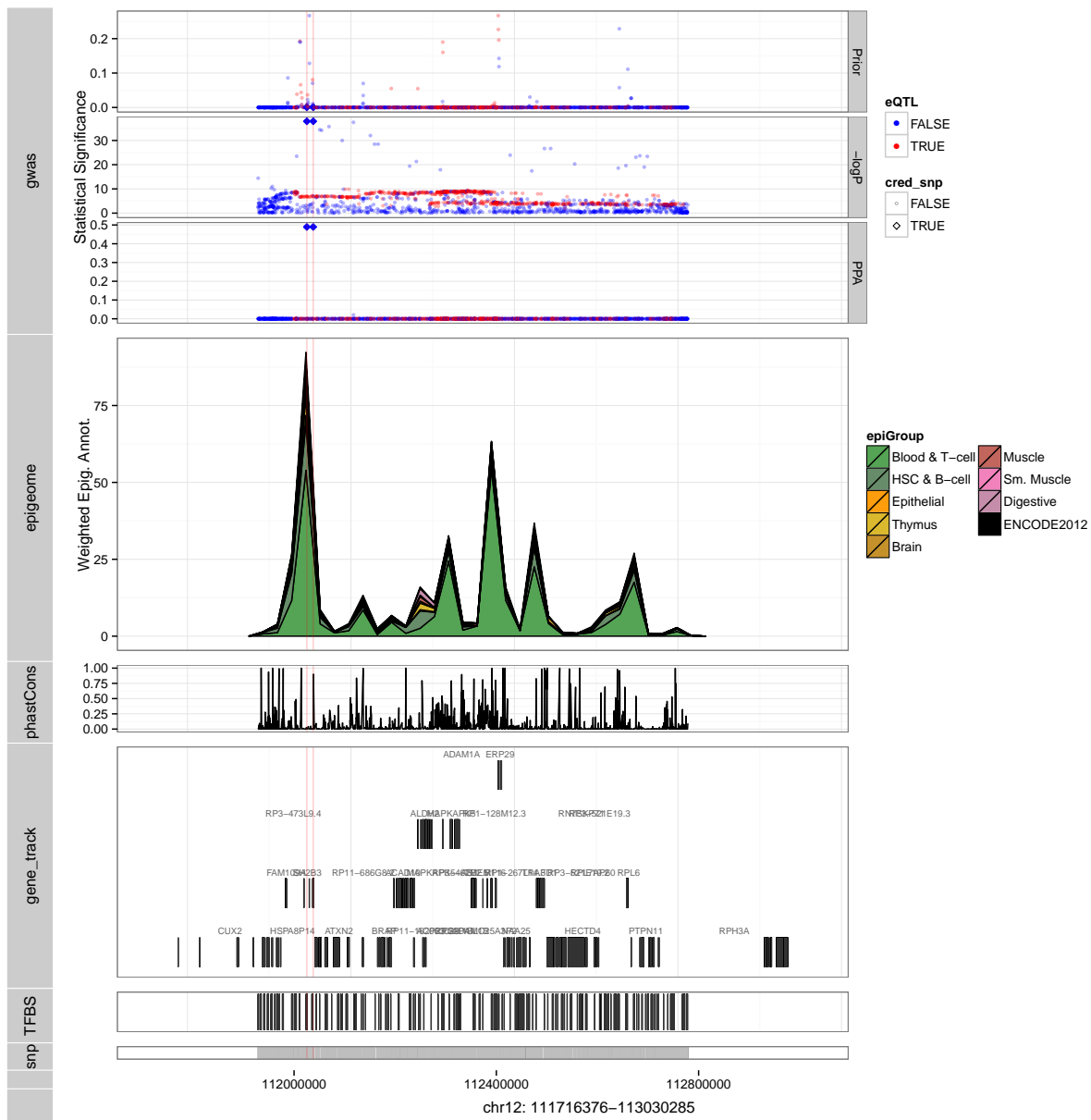
Type 1 Diabetes



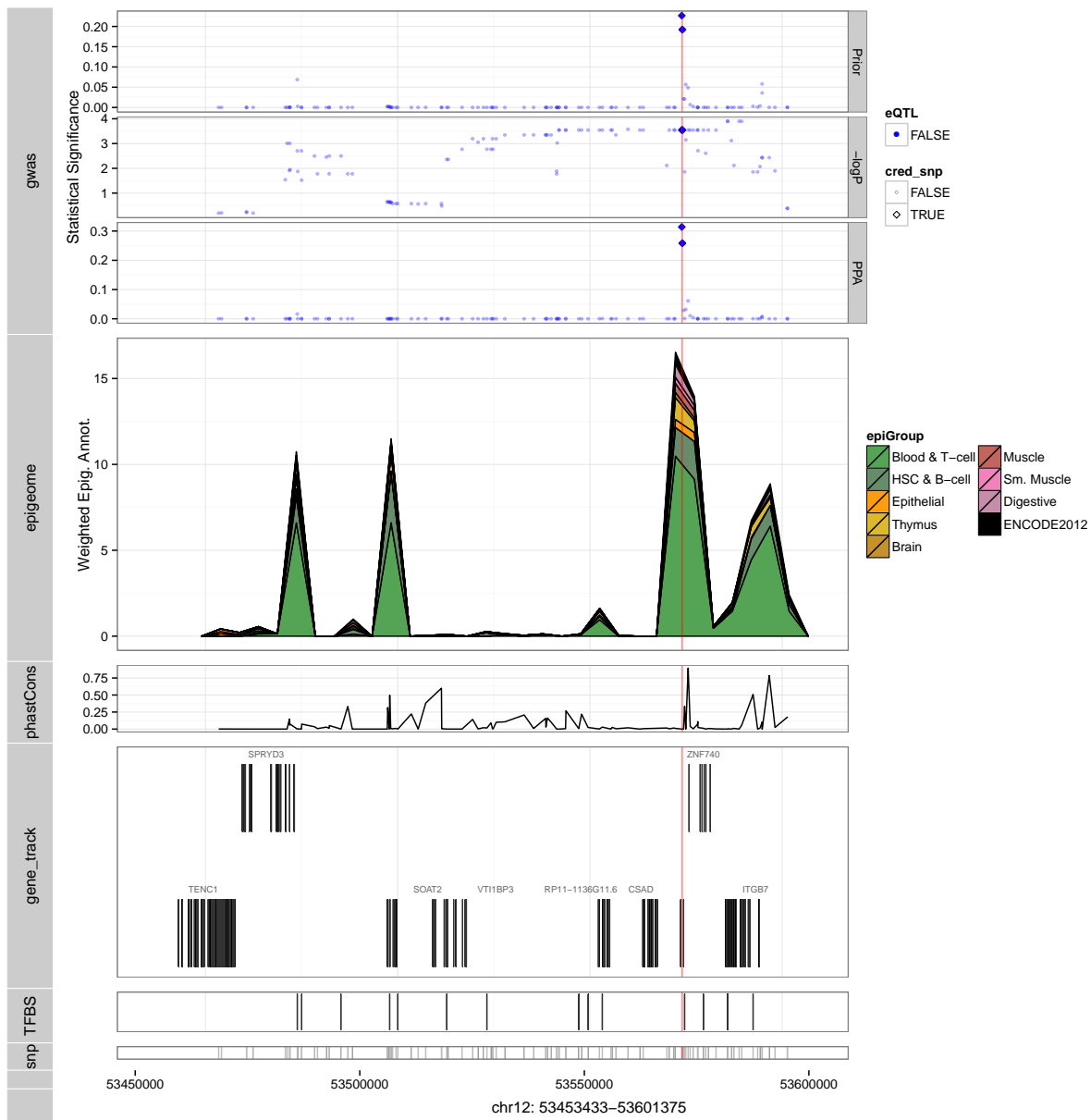
Type 1 Diabetes



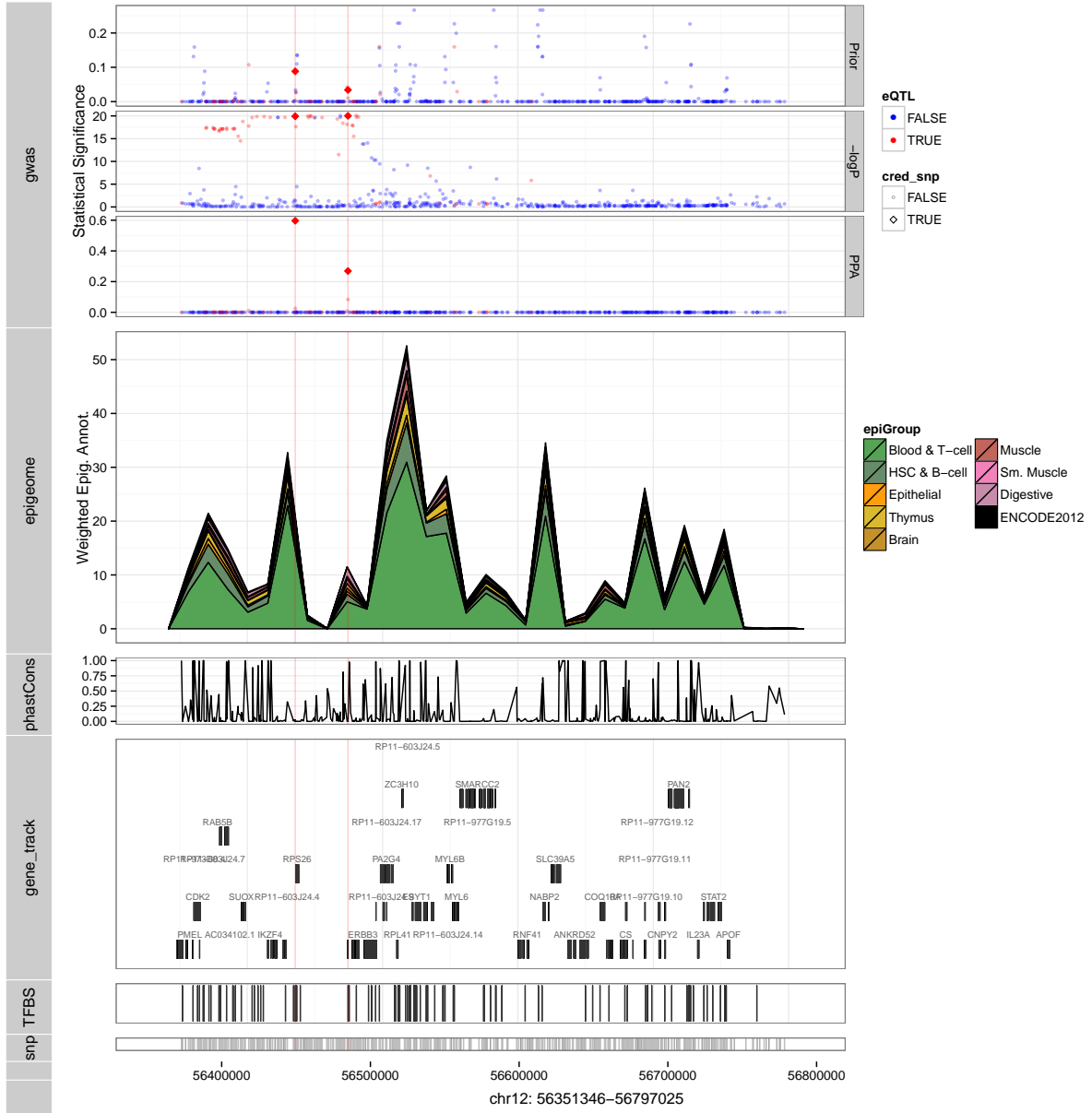
Type 1 Diabetes



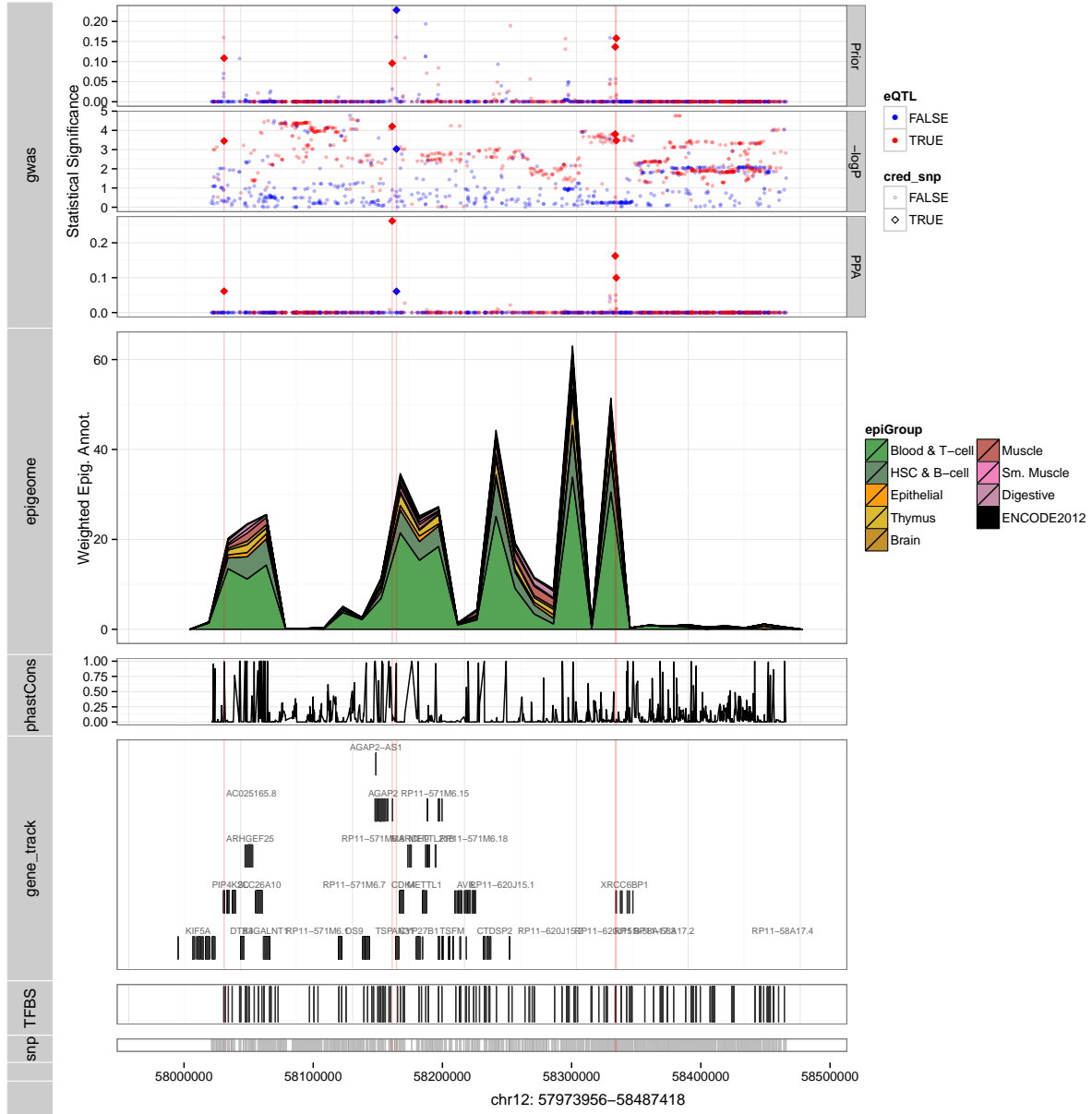
Type 1 Diabetes



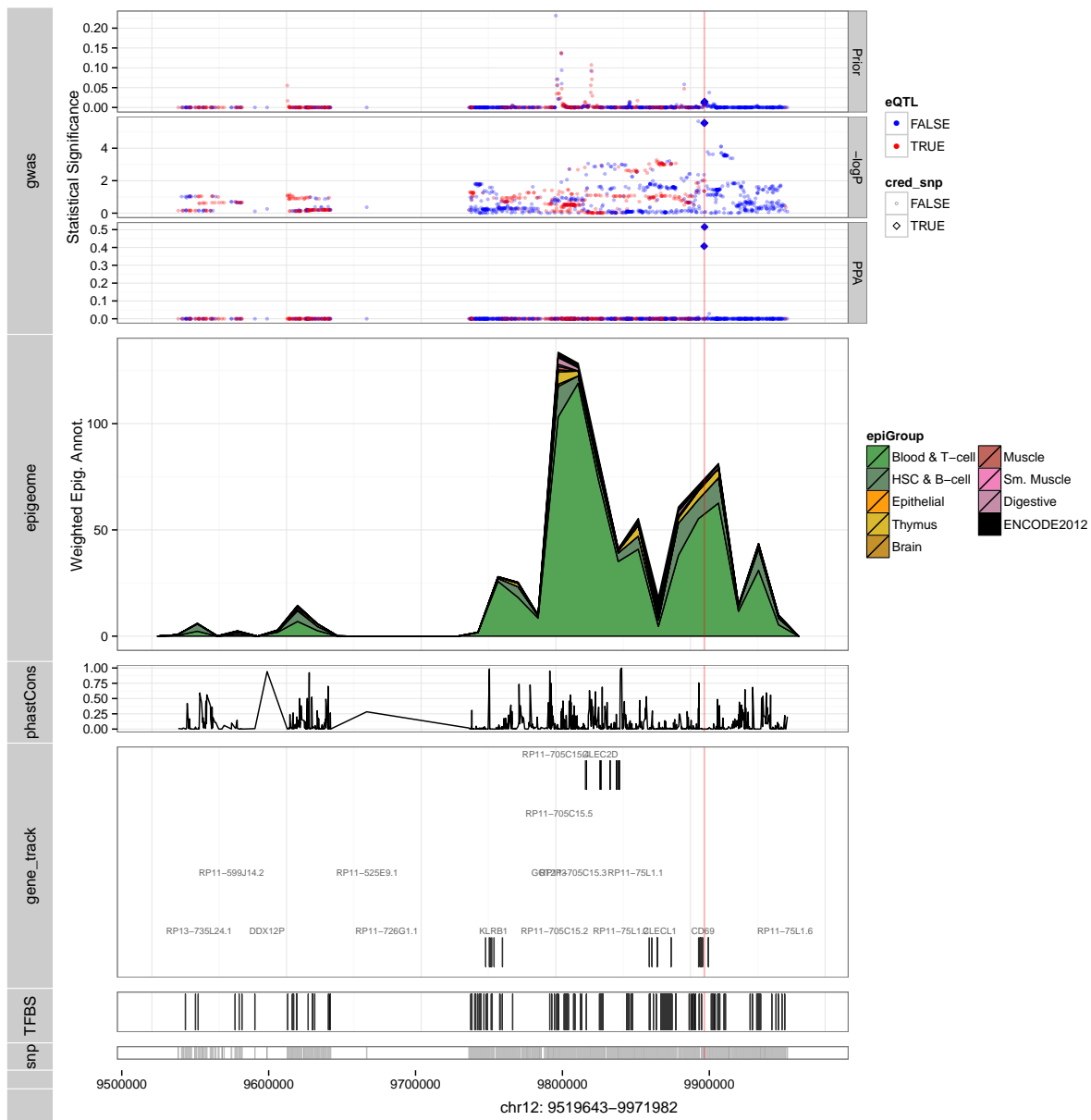
Type 1 Diabetes



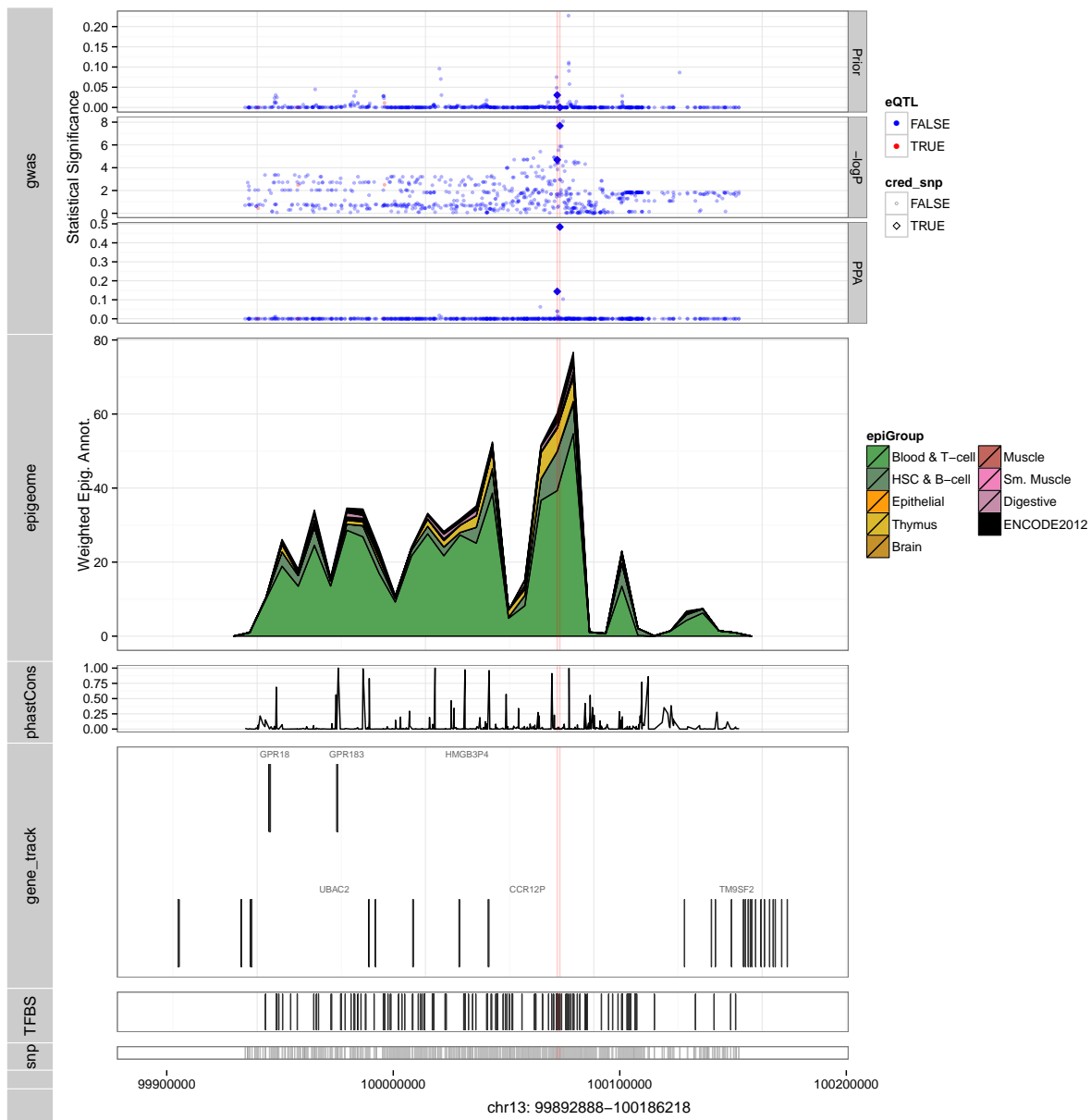
Type 1 Diabetes



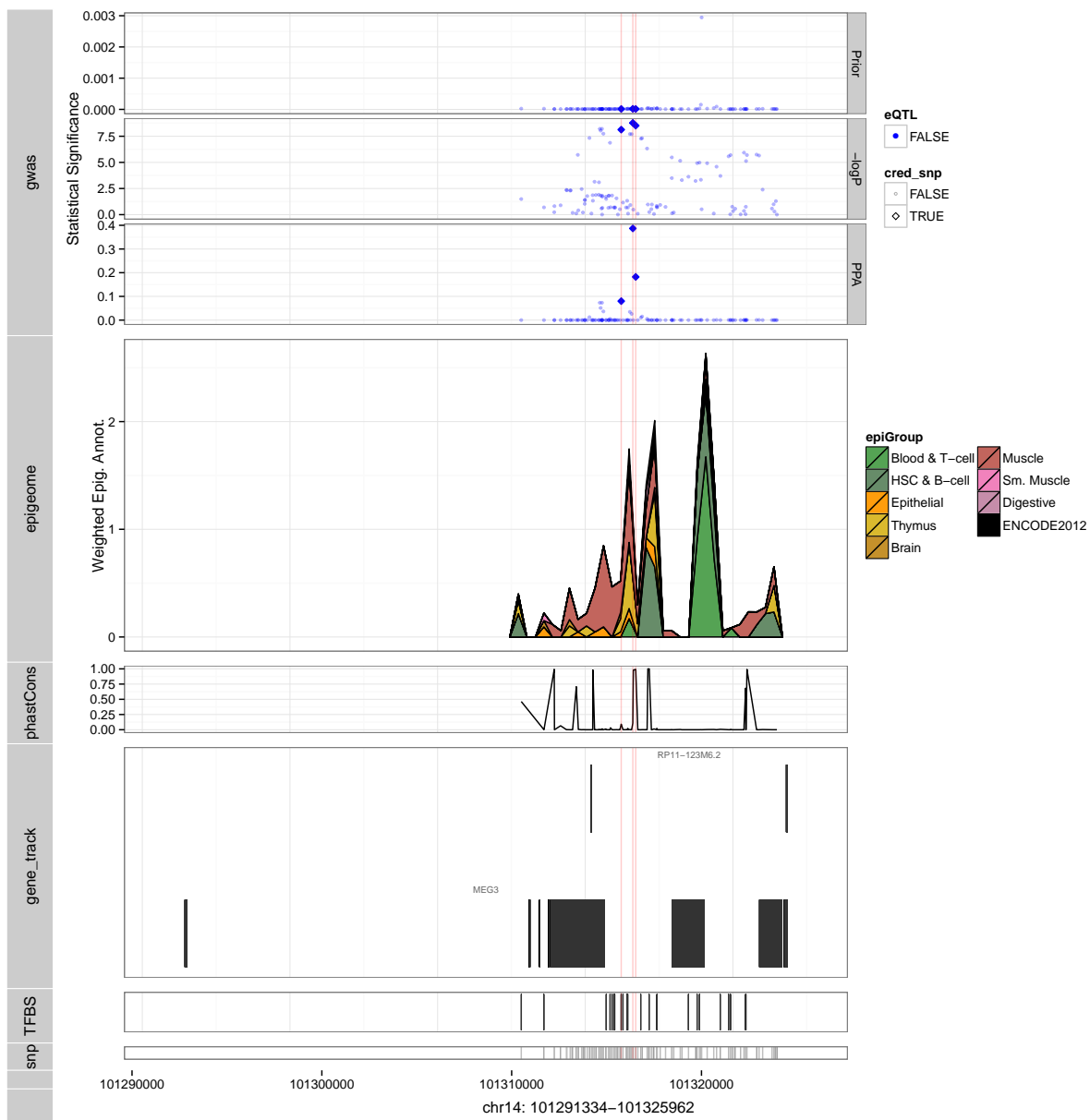
Type 1 Diabetes



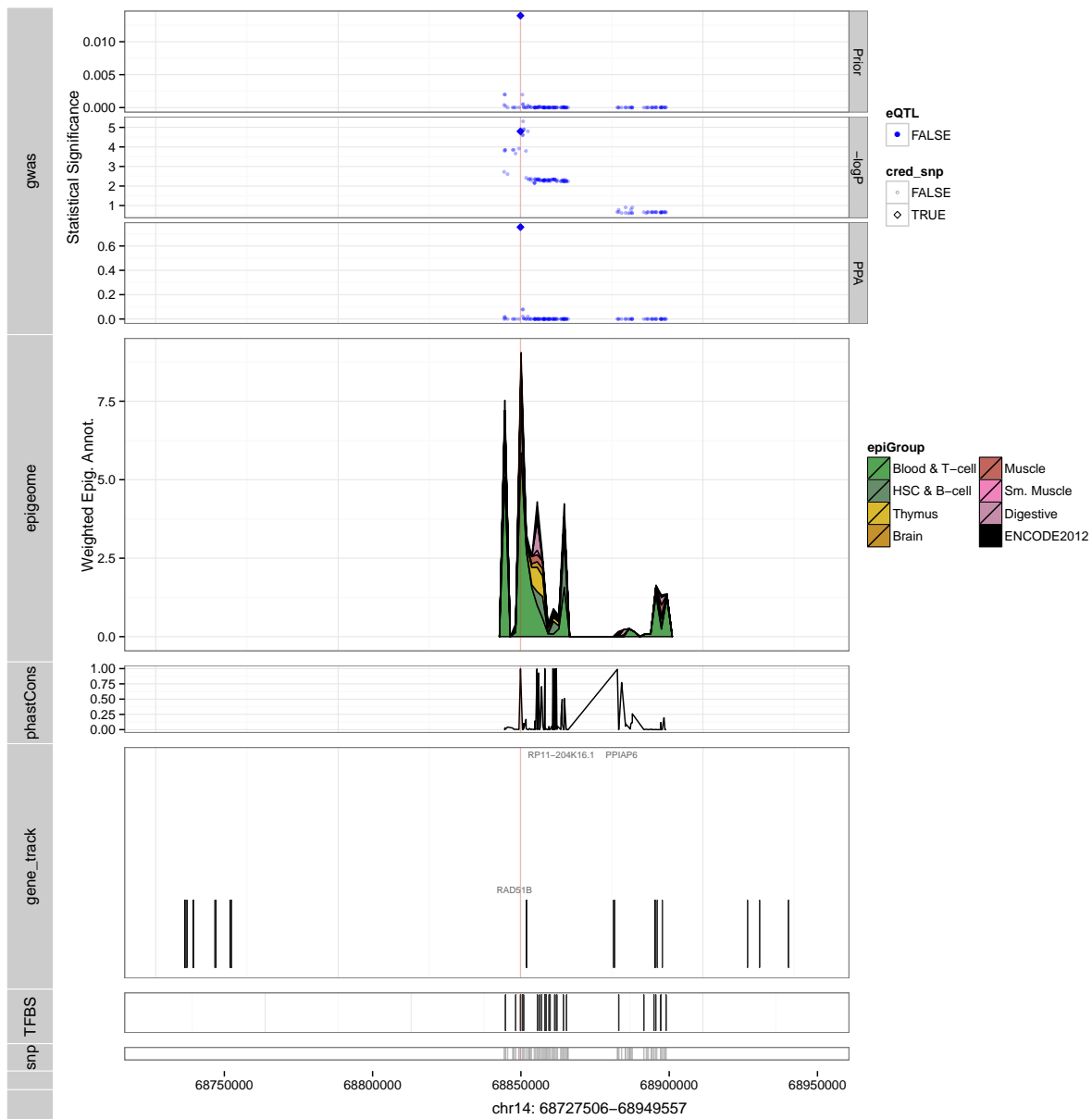
Type 1 Diabetes



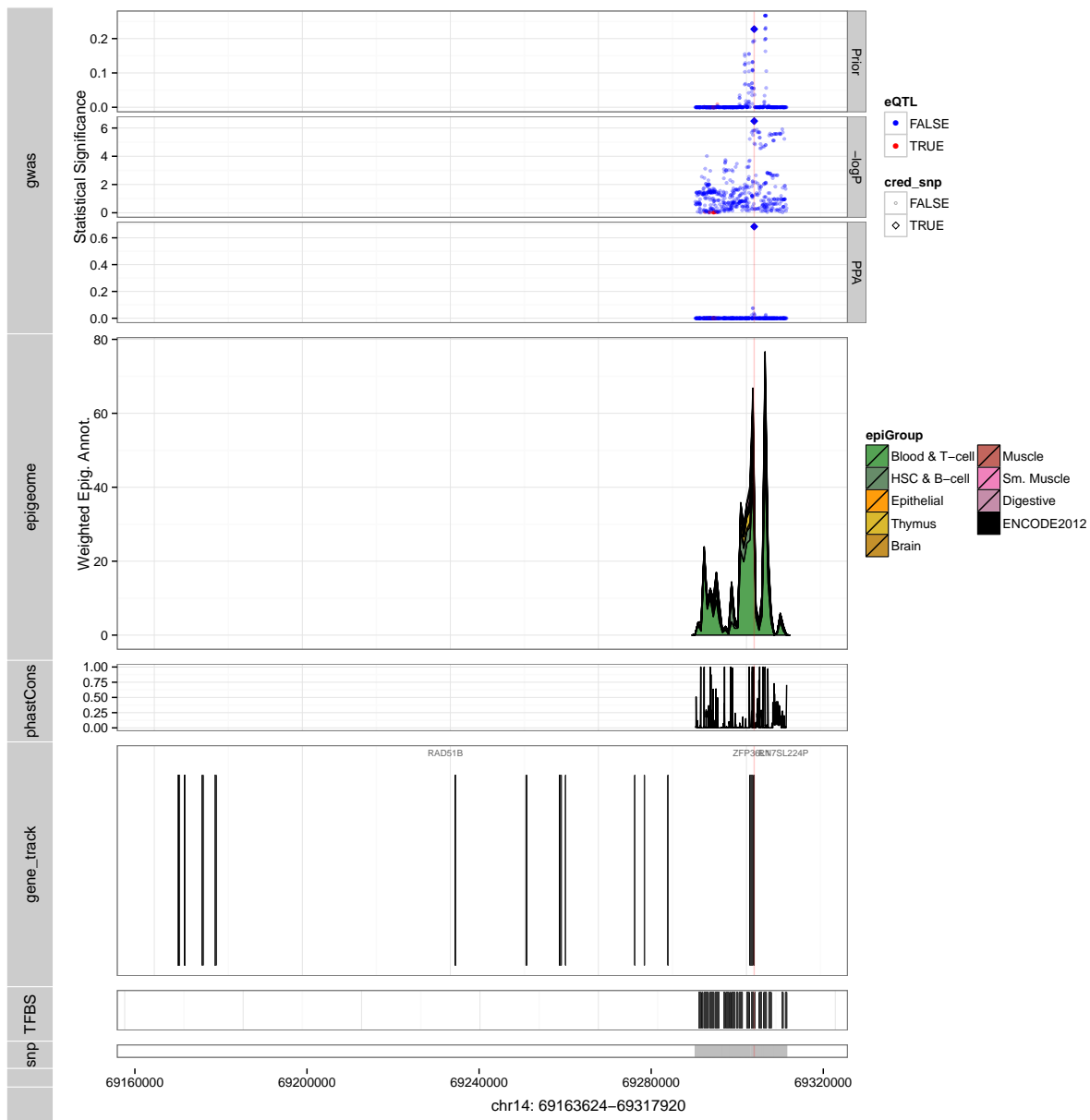
Type 1 Diabetes



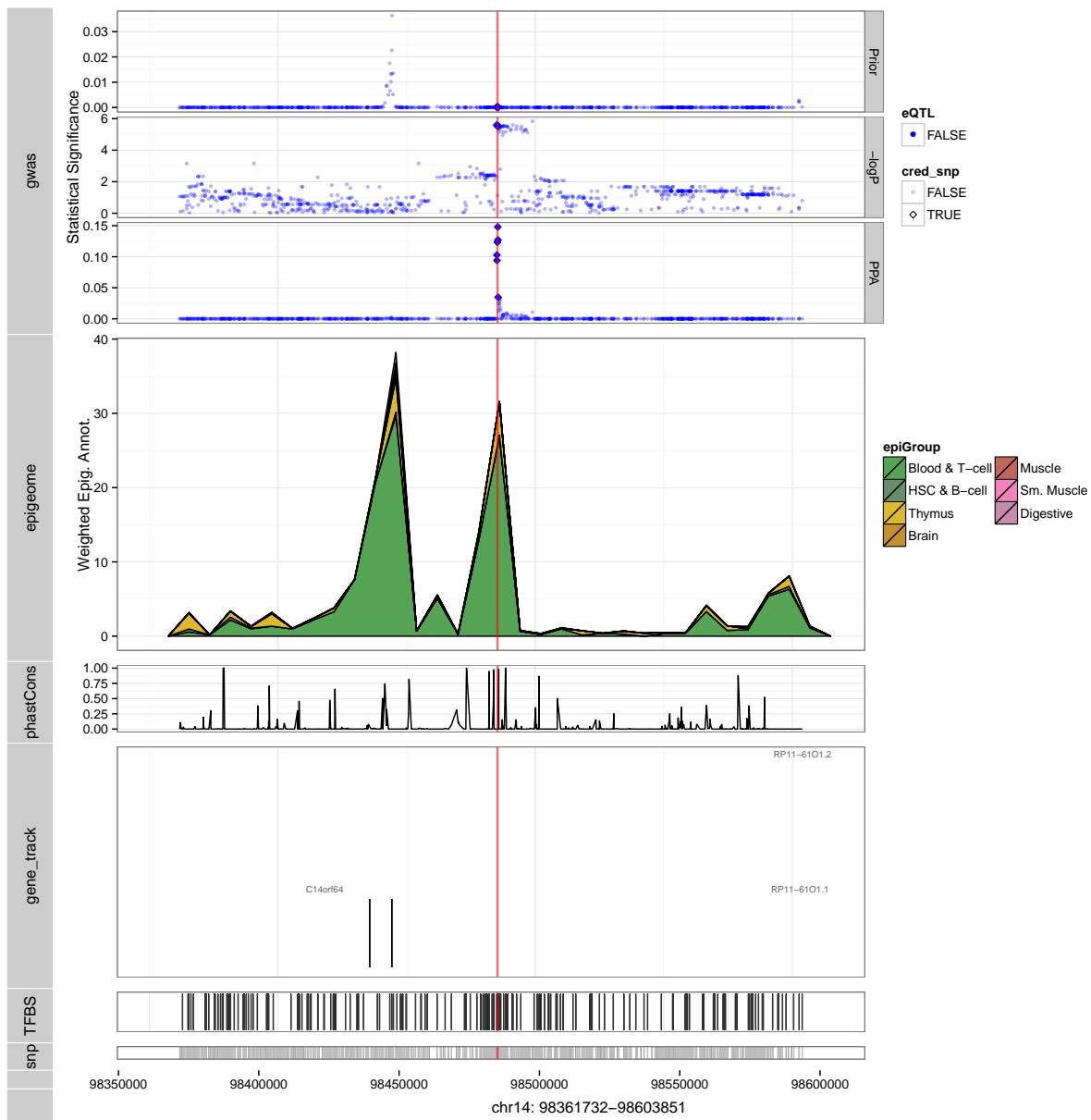
Type 1 Diabetes



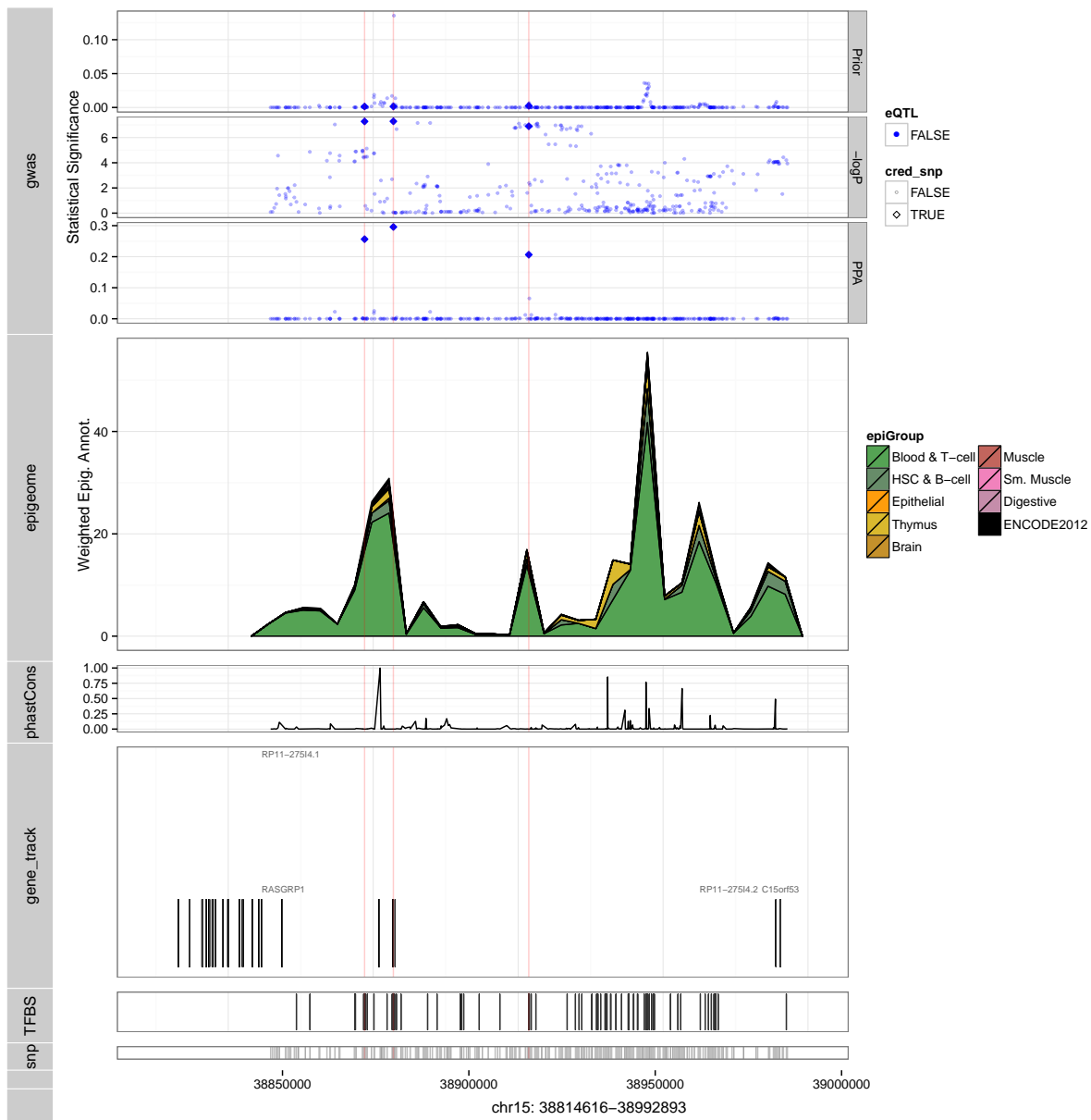
Type 1 Diabetes



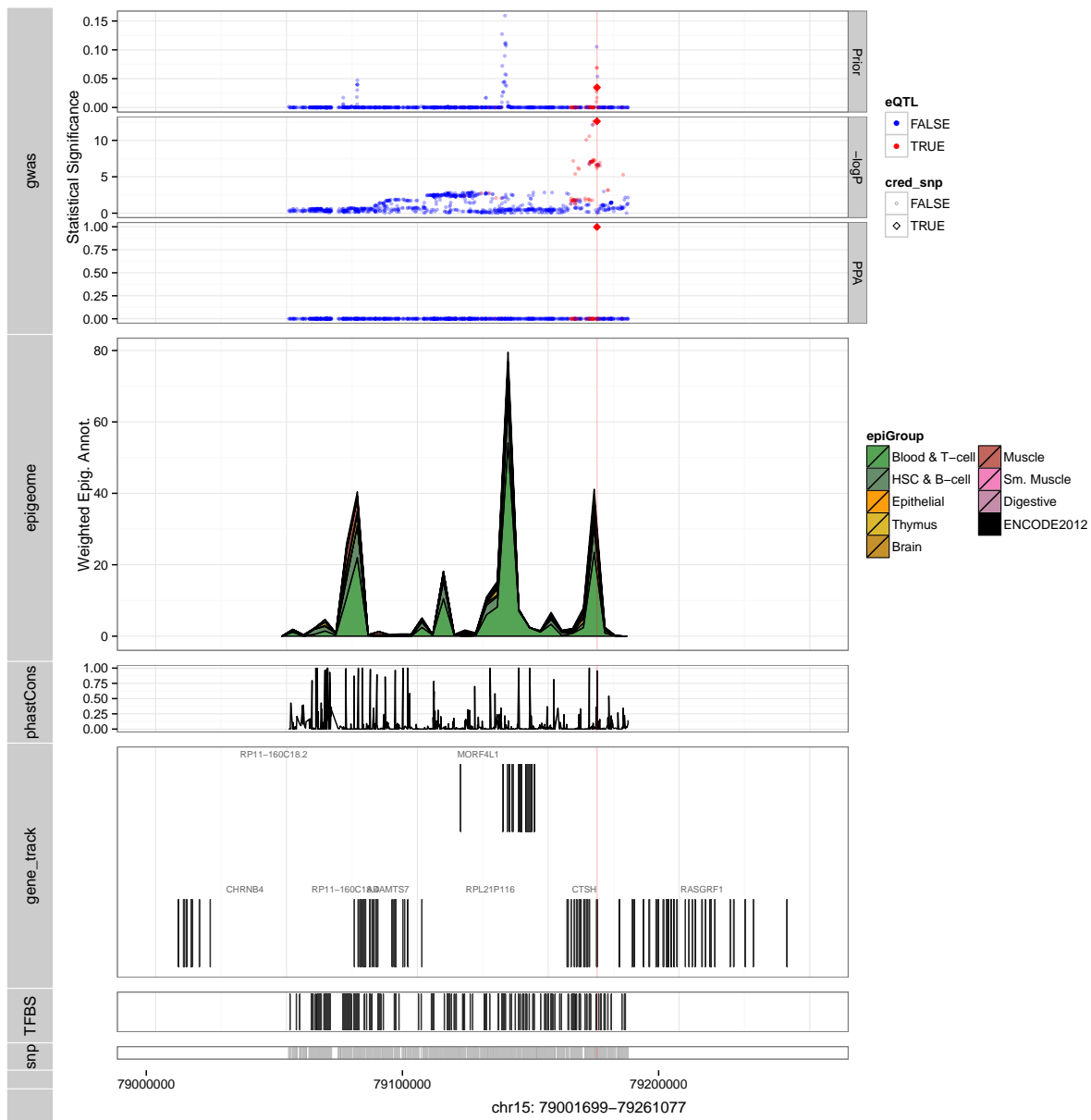
Type 1 Diabetes



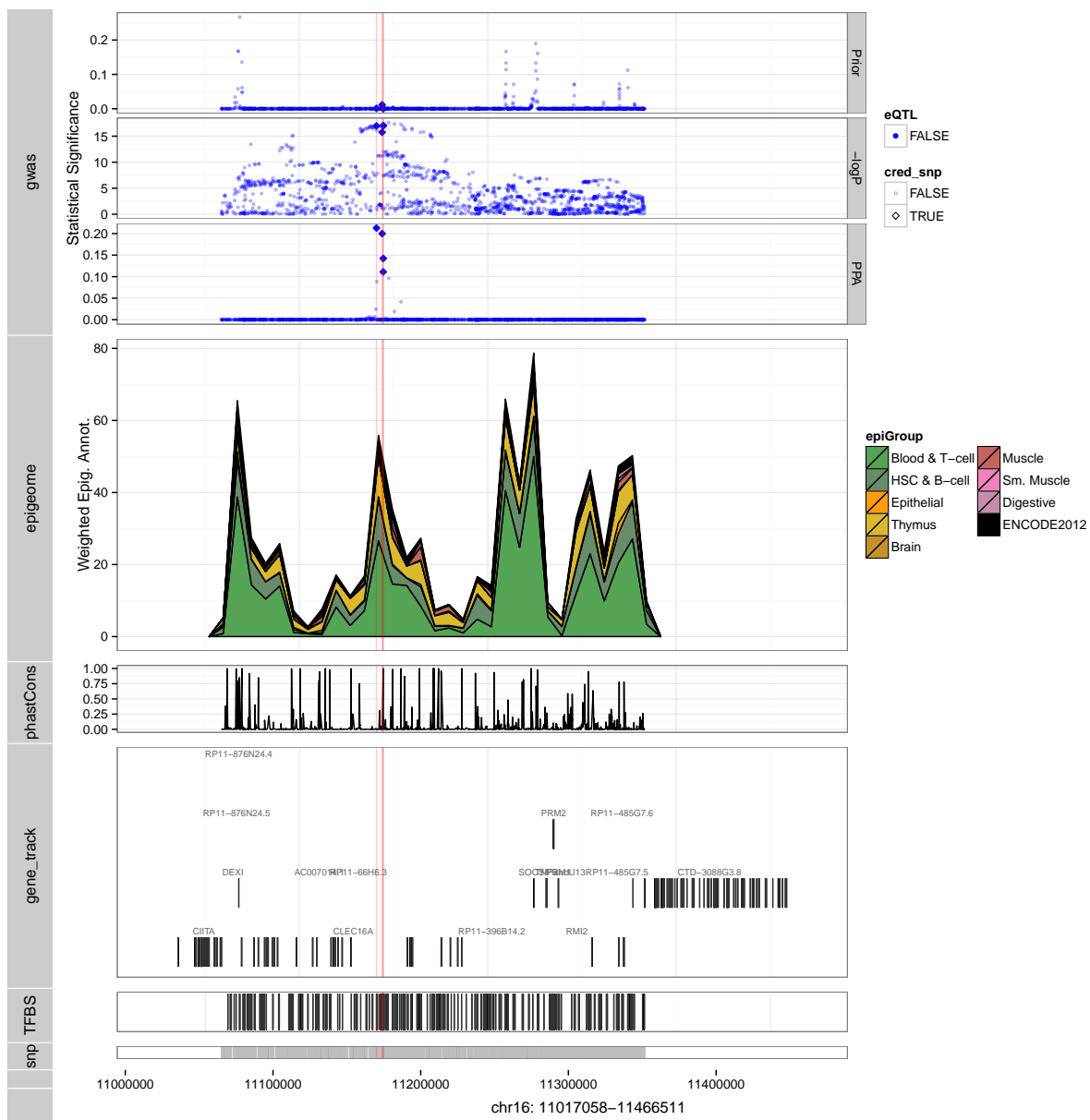
Type 1 Diabetes



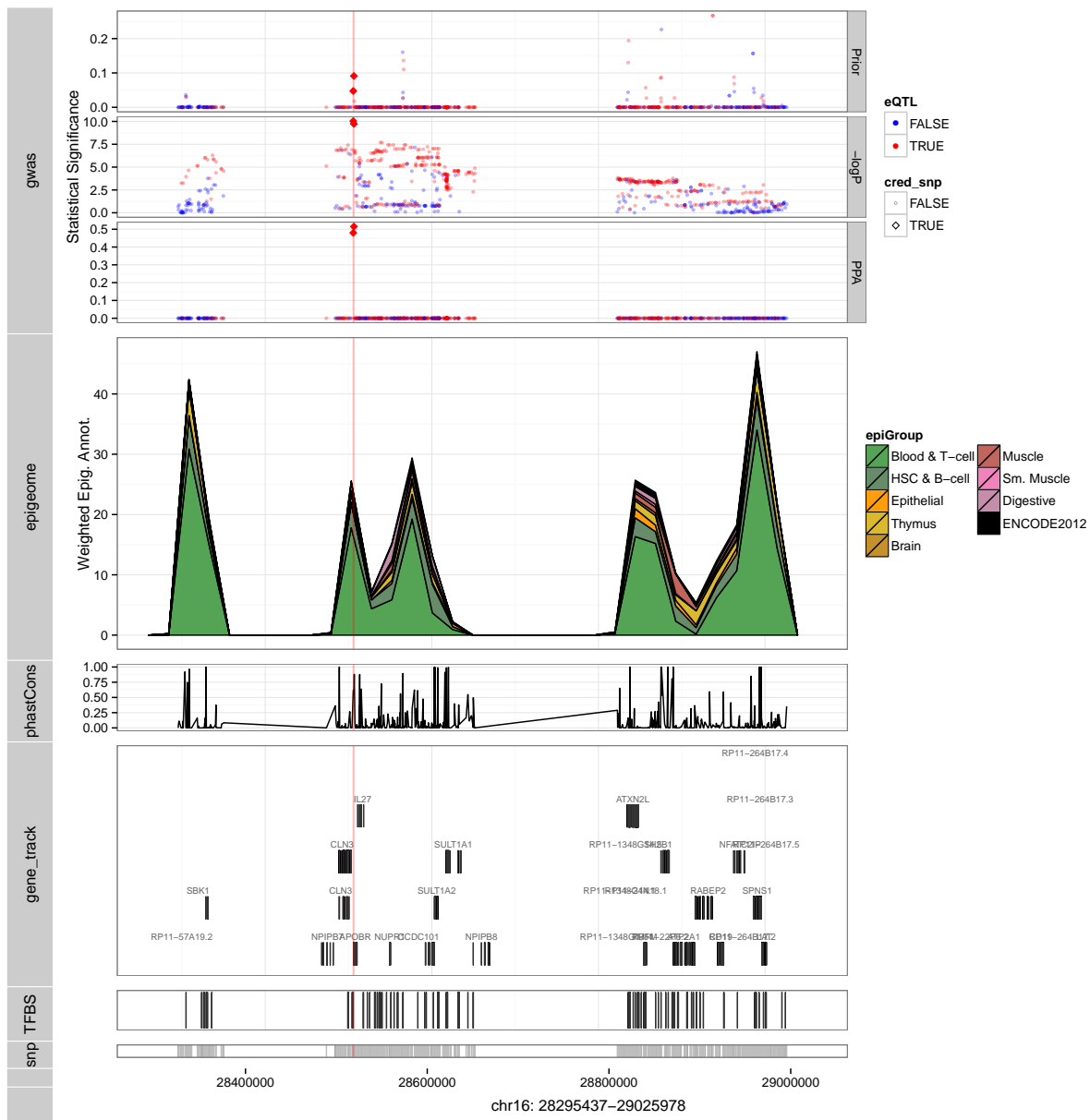
Type 1 Diabetes



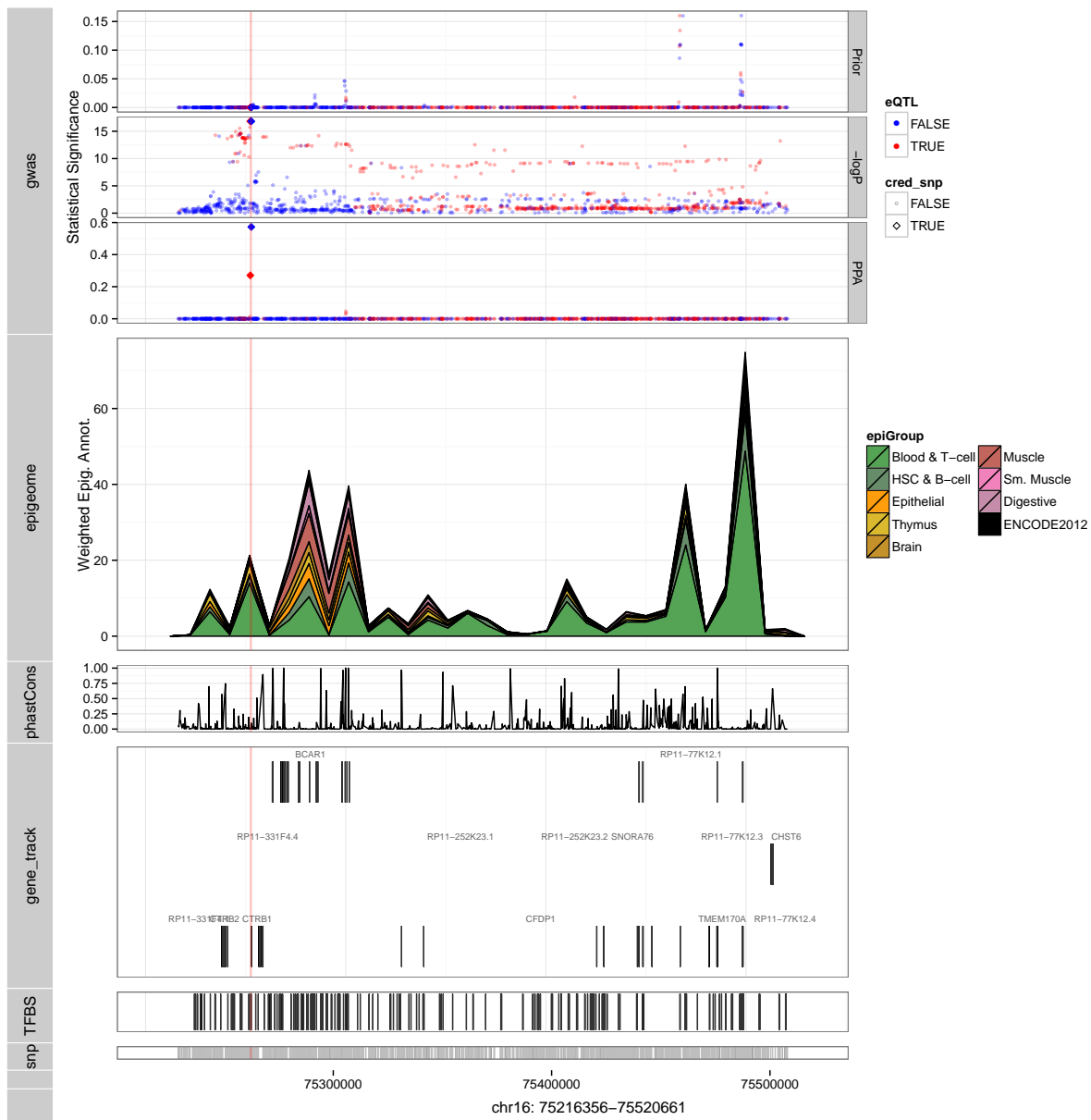
Type 1 Diabetes



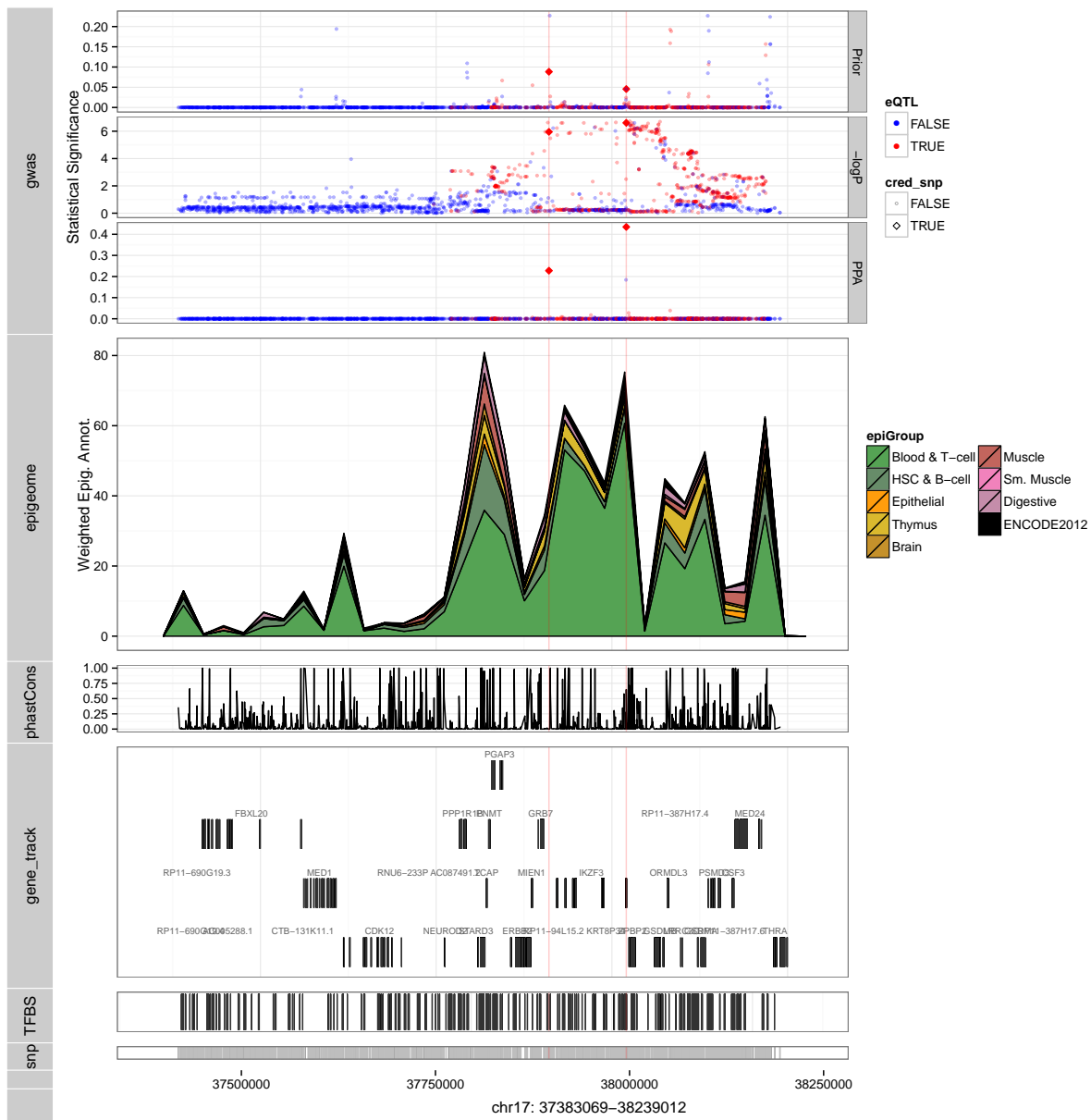
Type 1 Diabetes



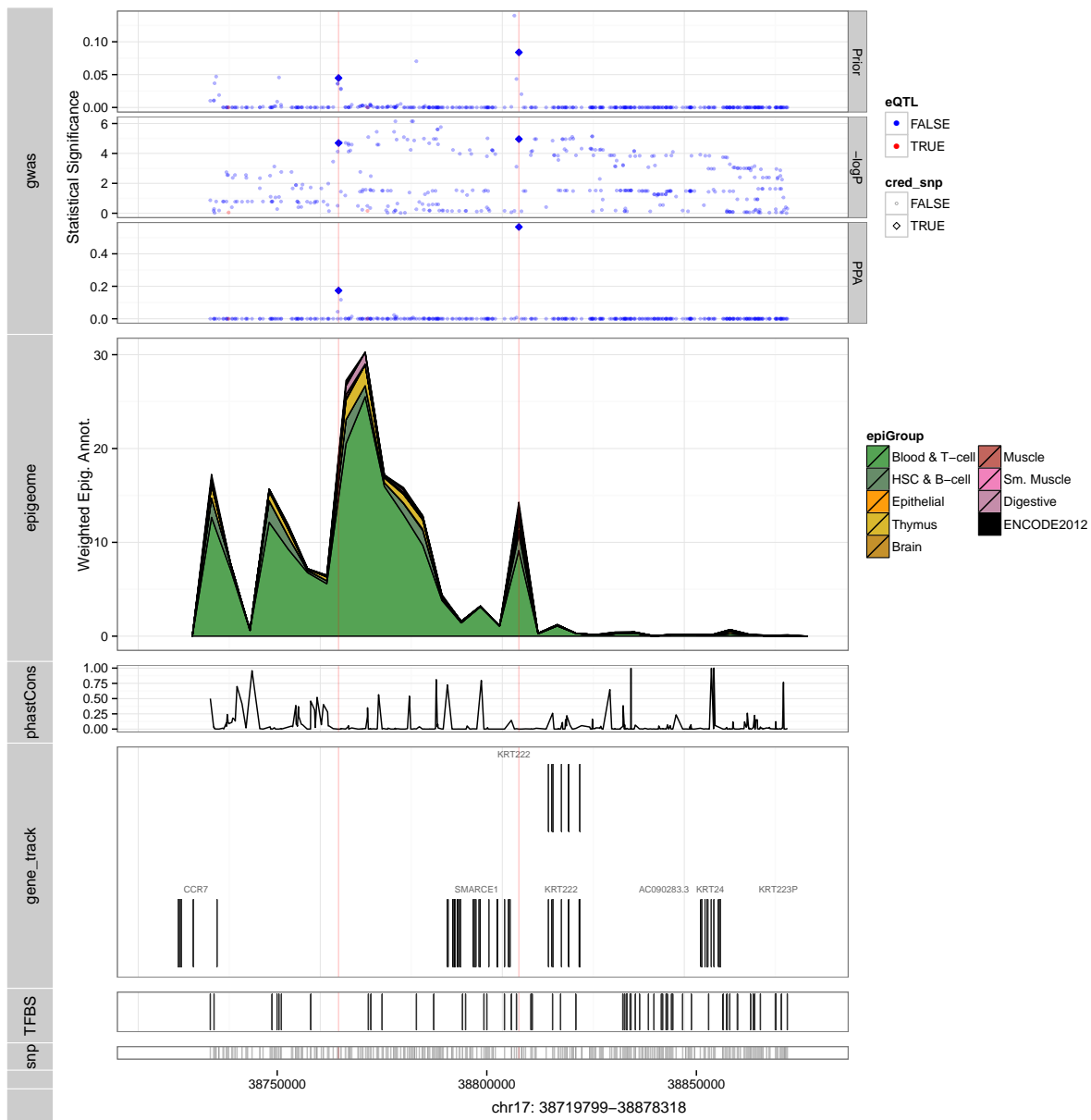
Type 1 Diabetes



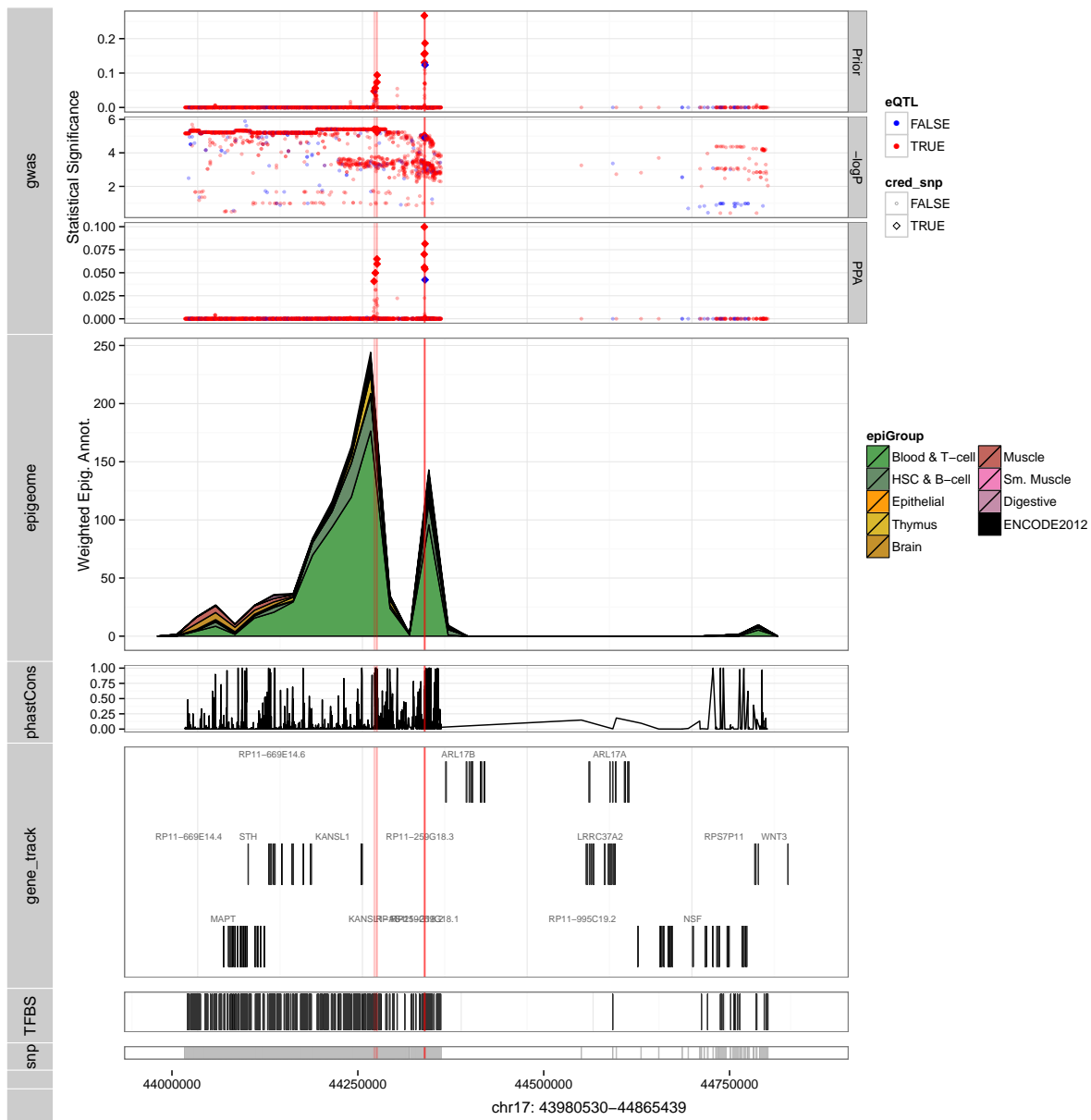
Type 1 Diabetes



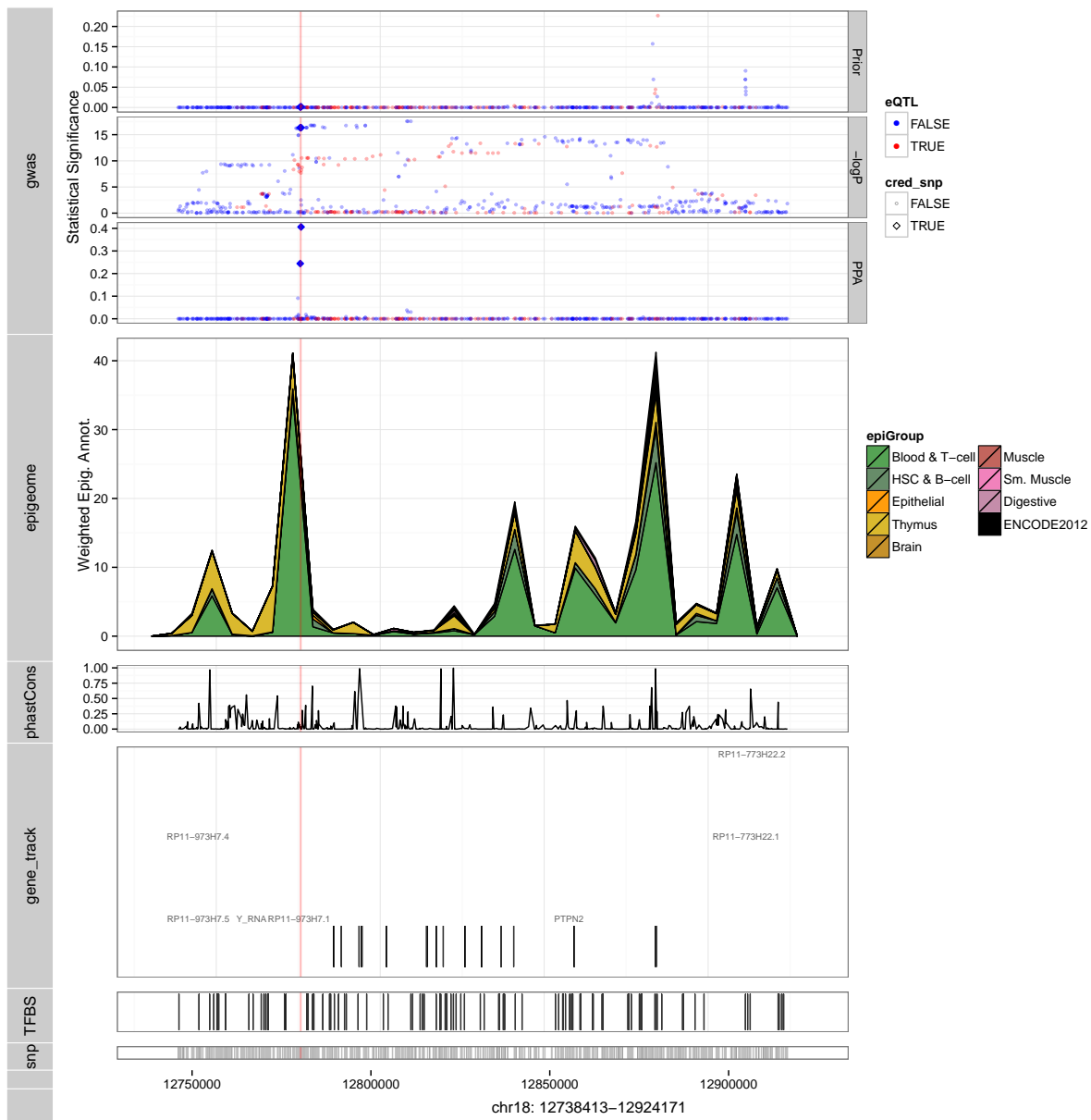
Type 1 Diabetes



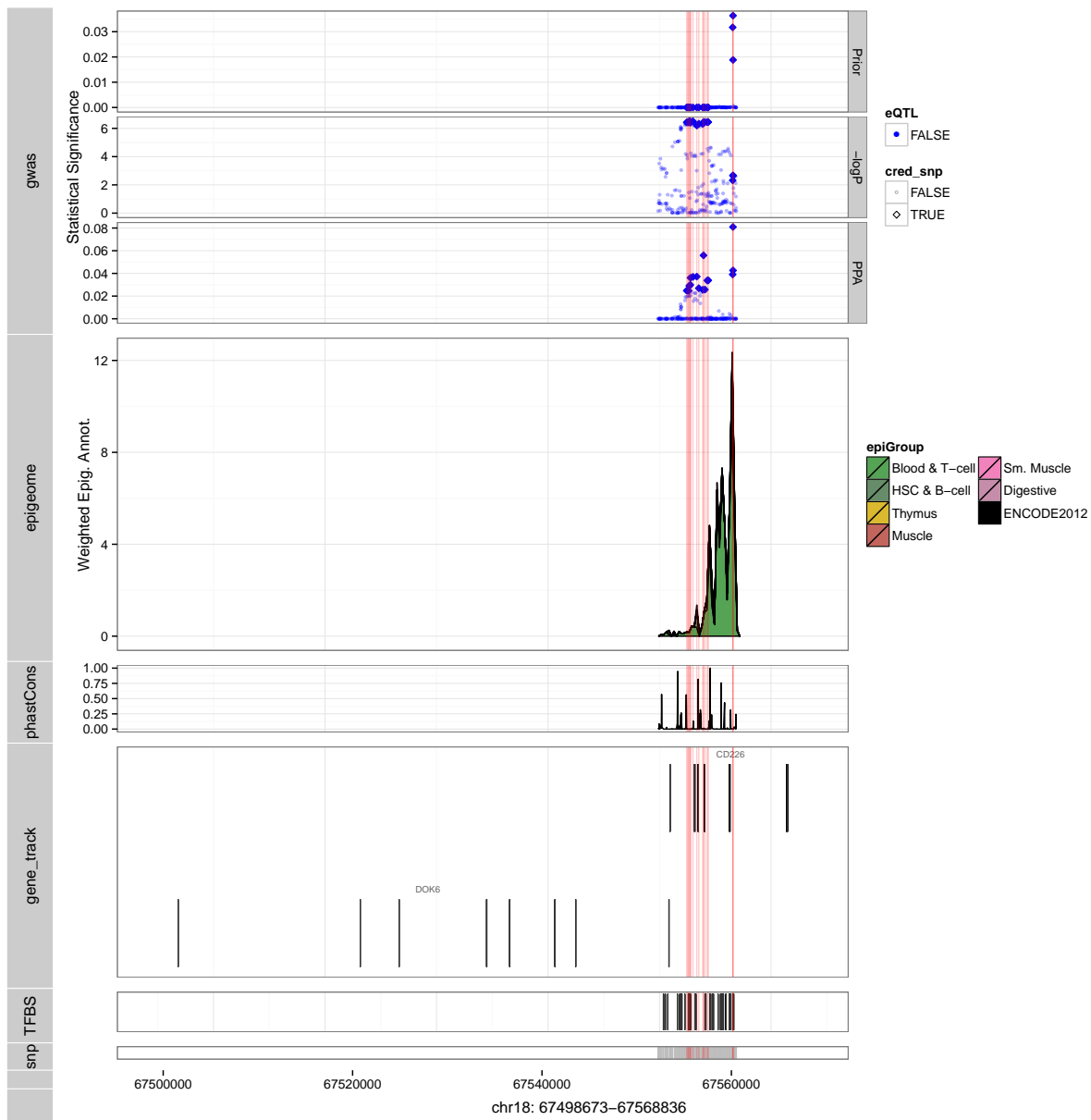
Type 1 Diabetes



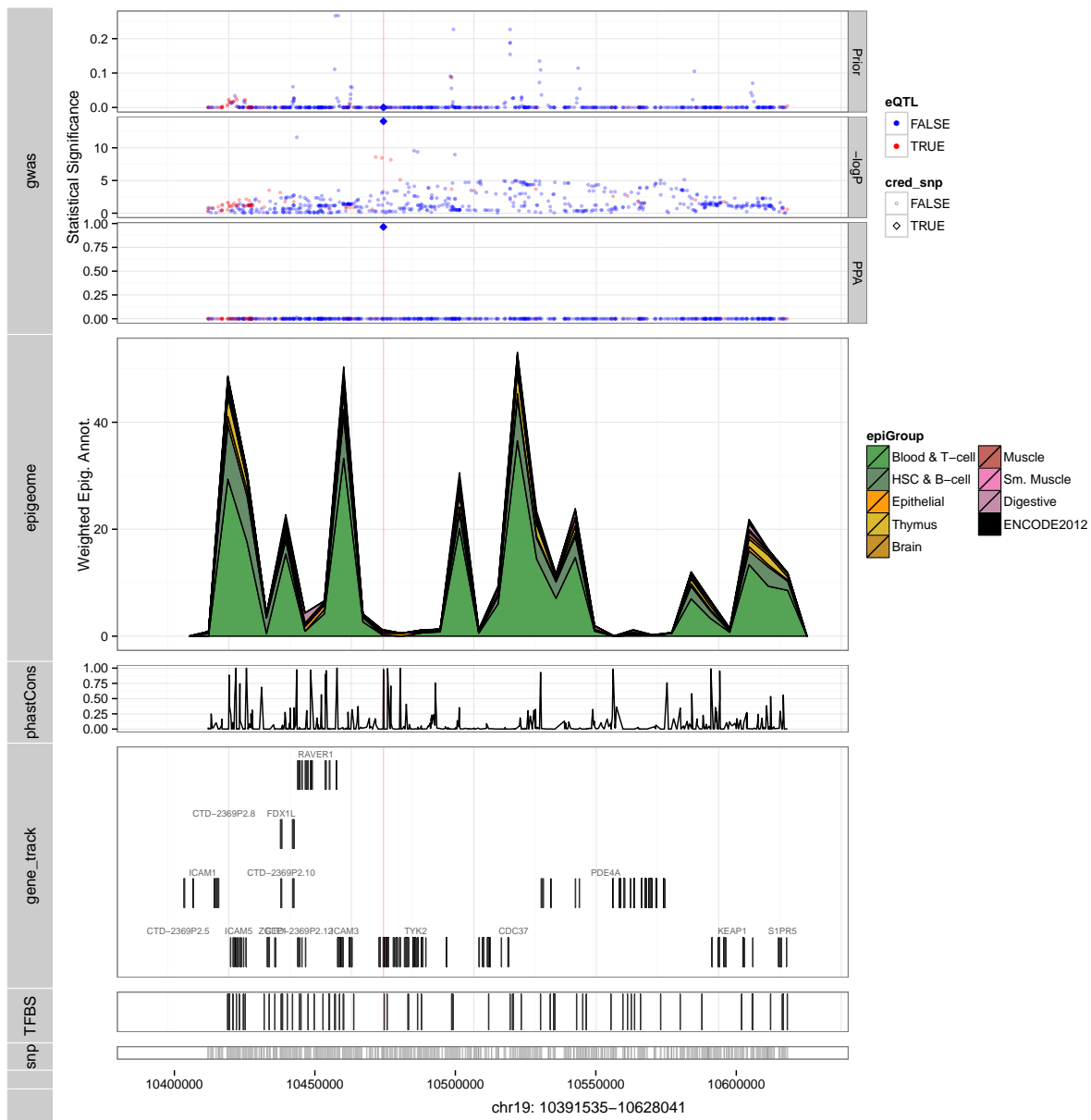
Type 1 Diabetes



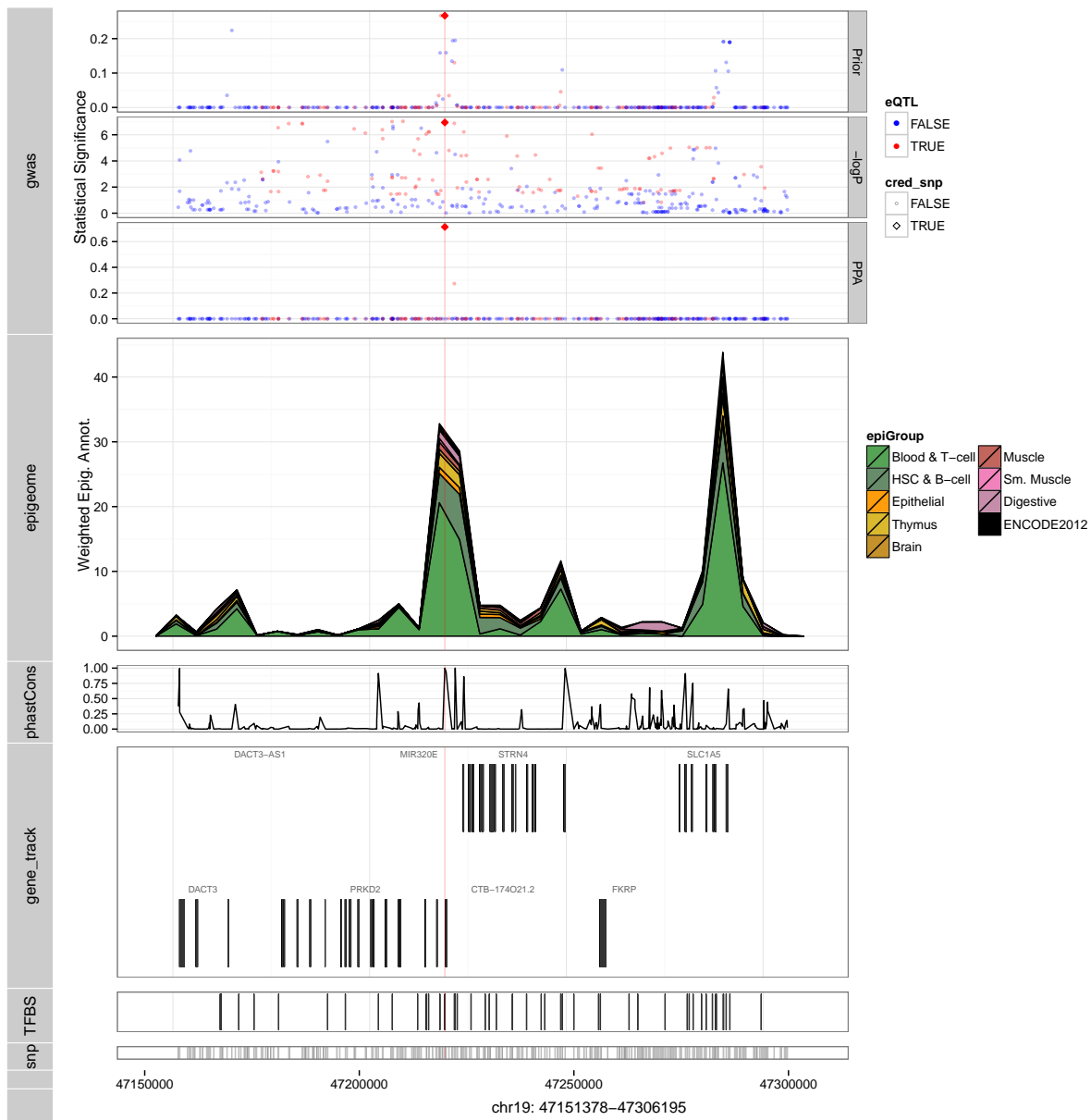
Type 1 Diabetes



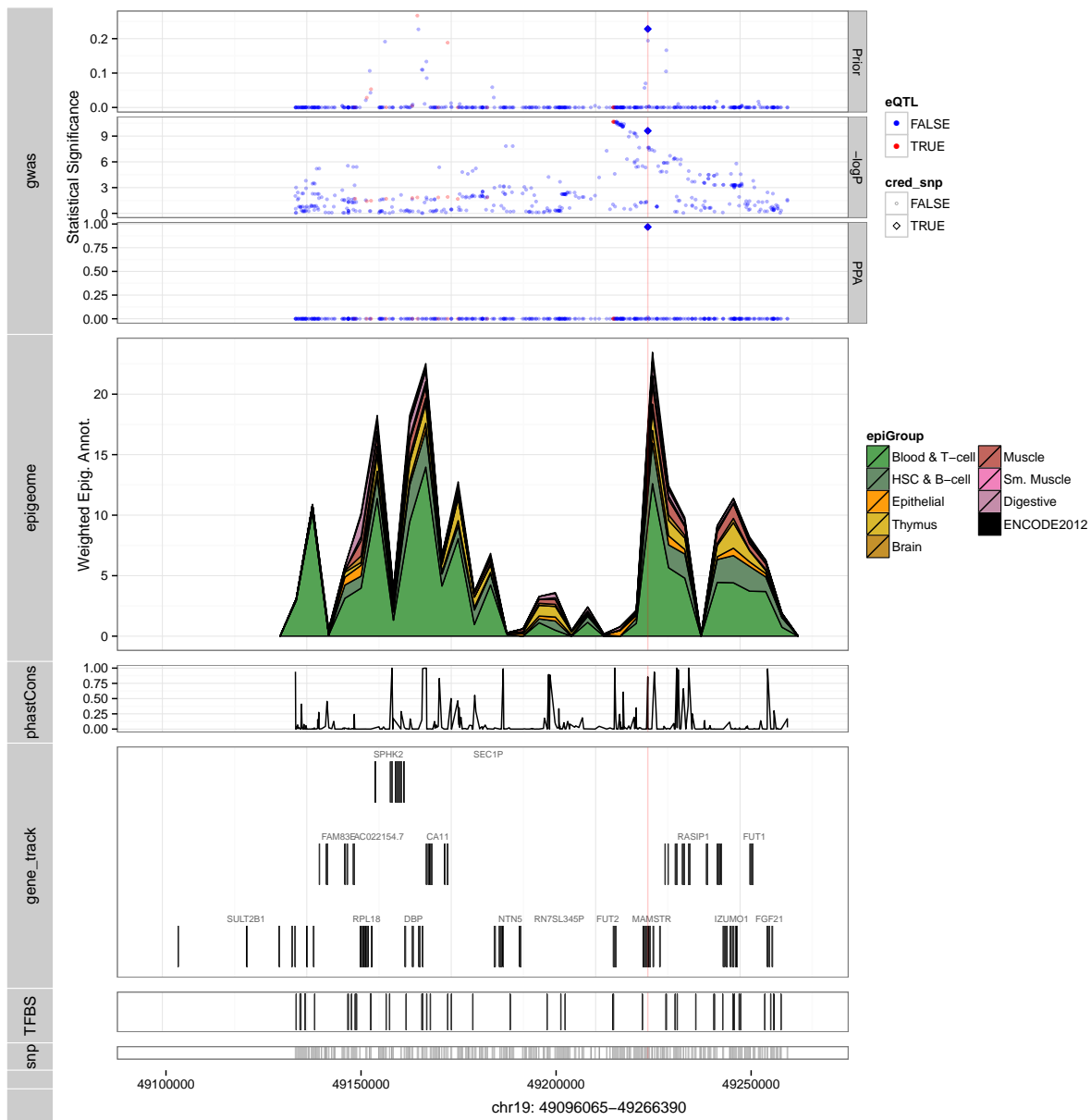
Type 1 Diabetes



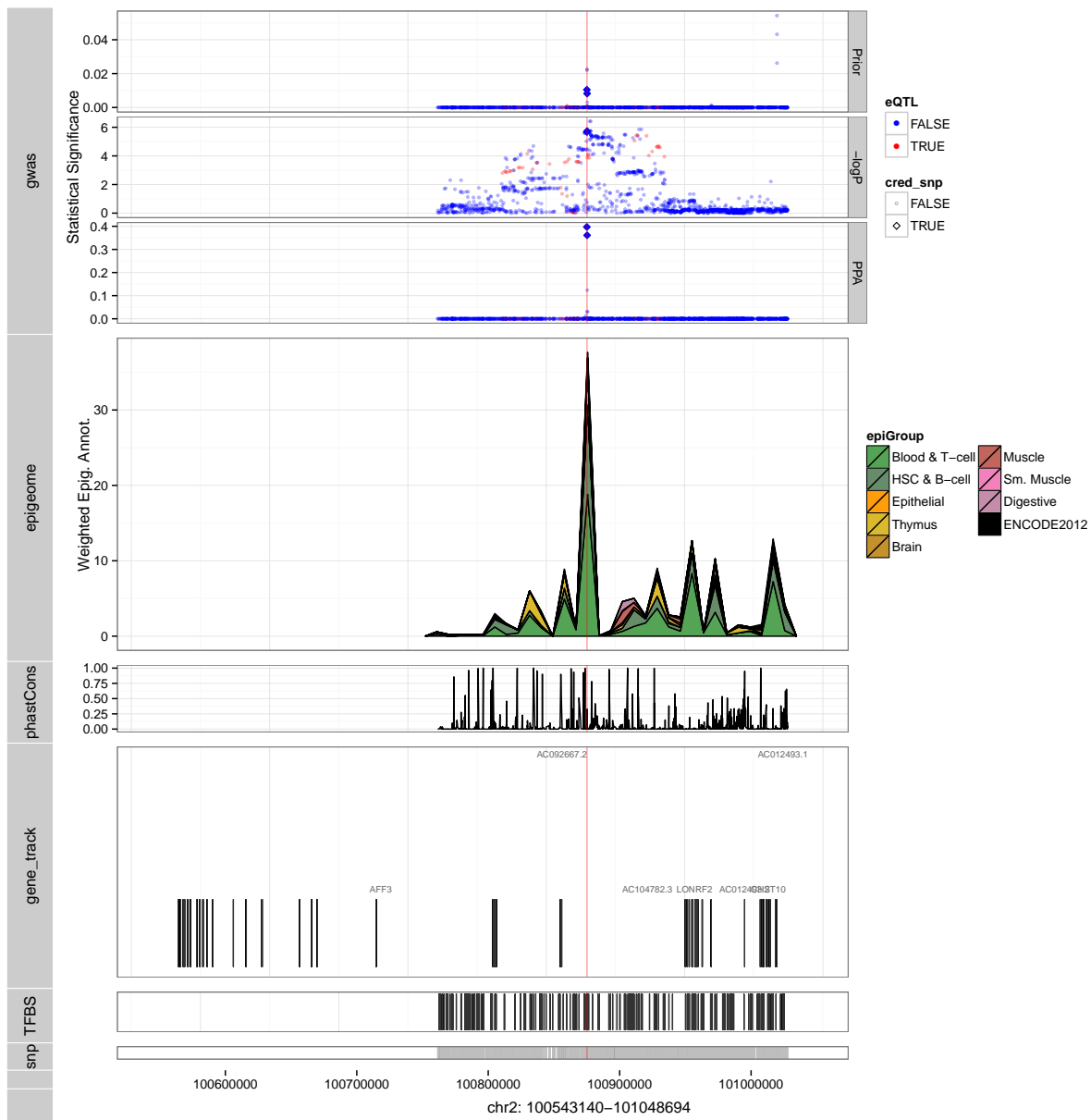
Type 1 Diabetes



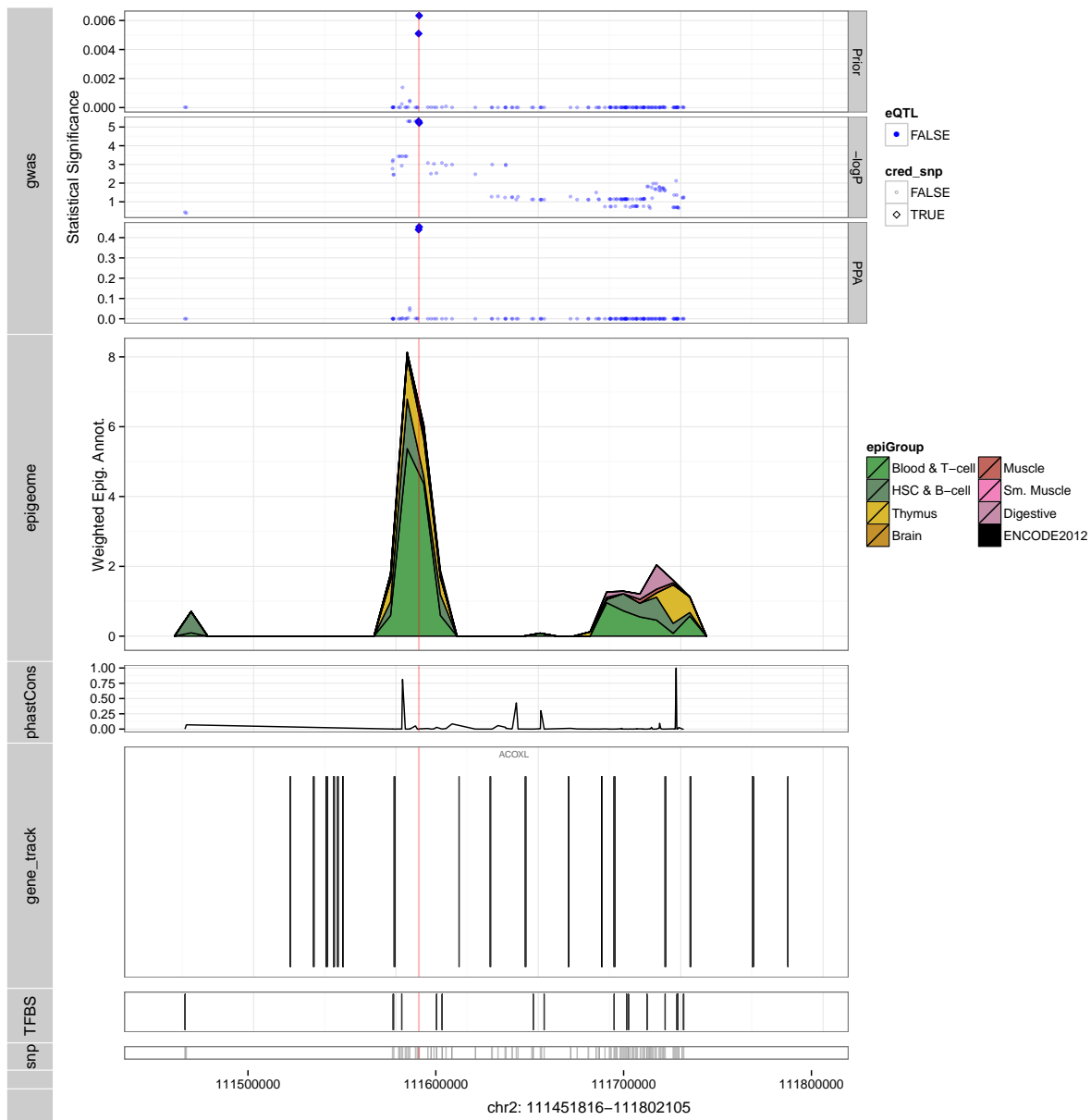
Type 1 Diabetes



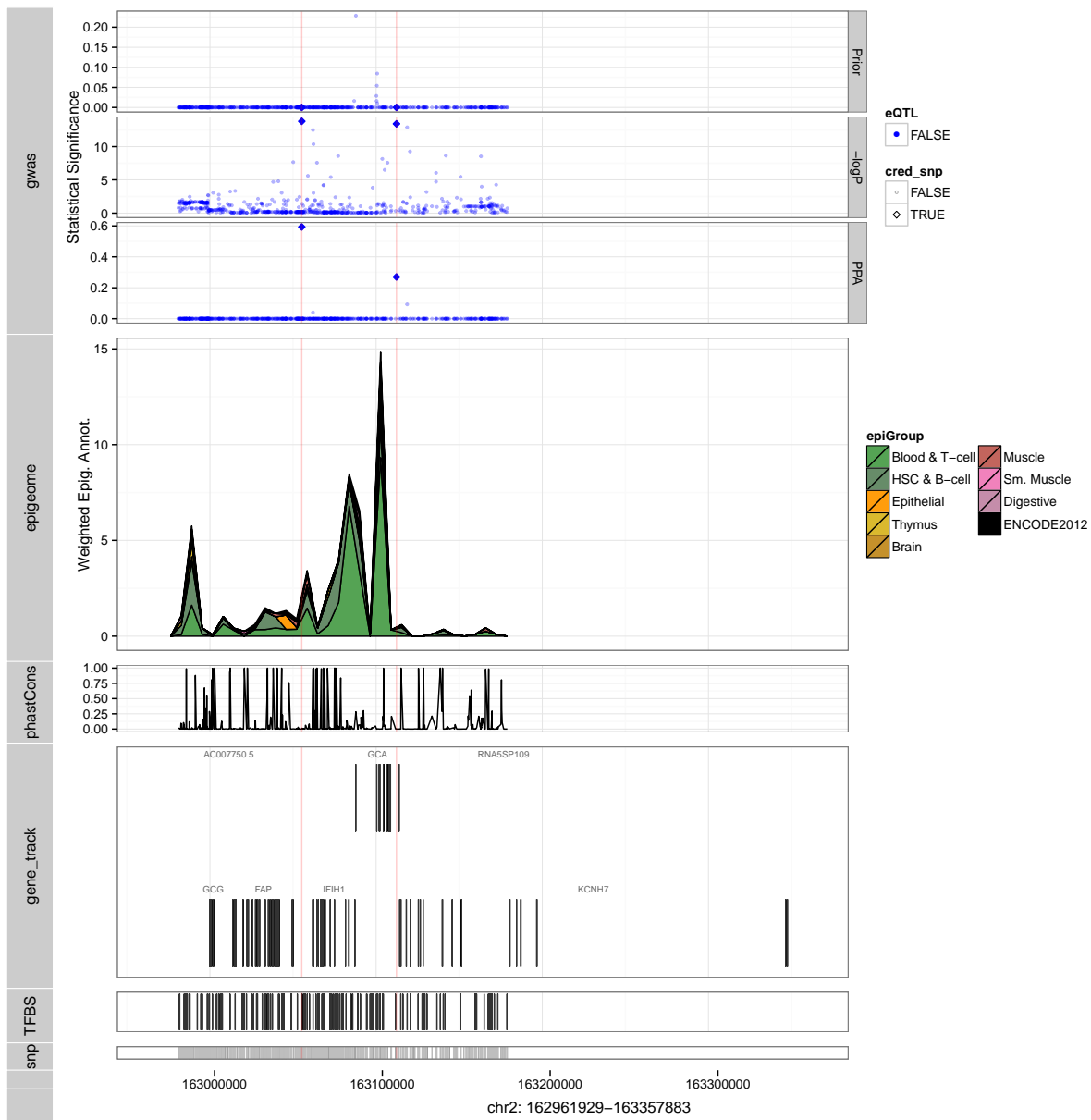
Type 1 Diabetes



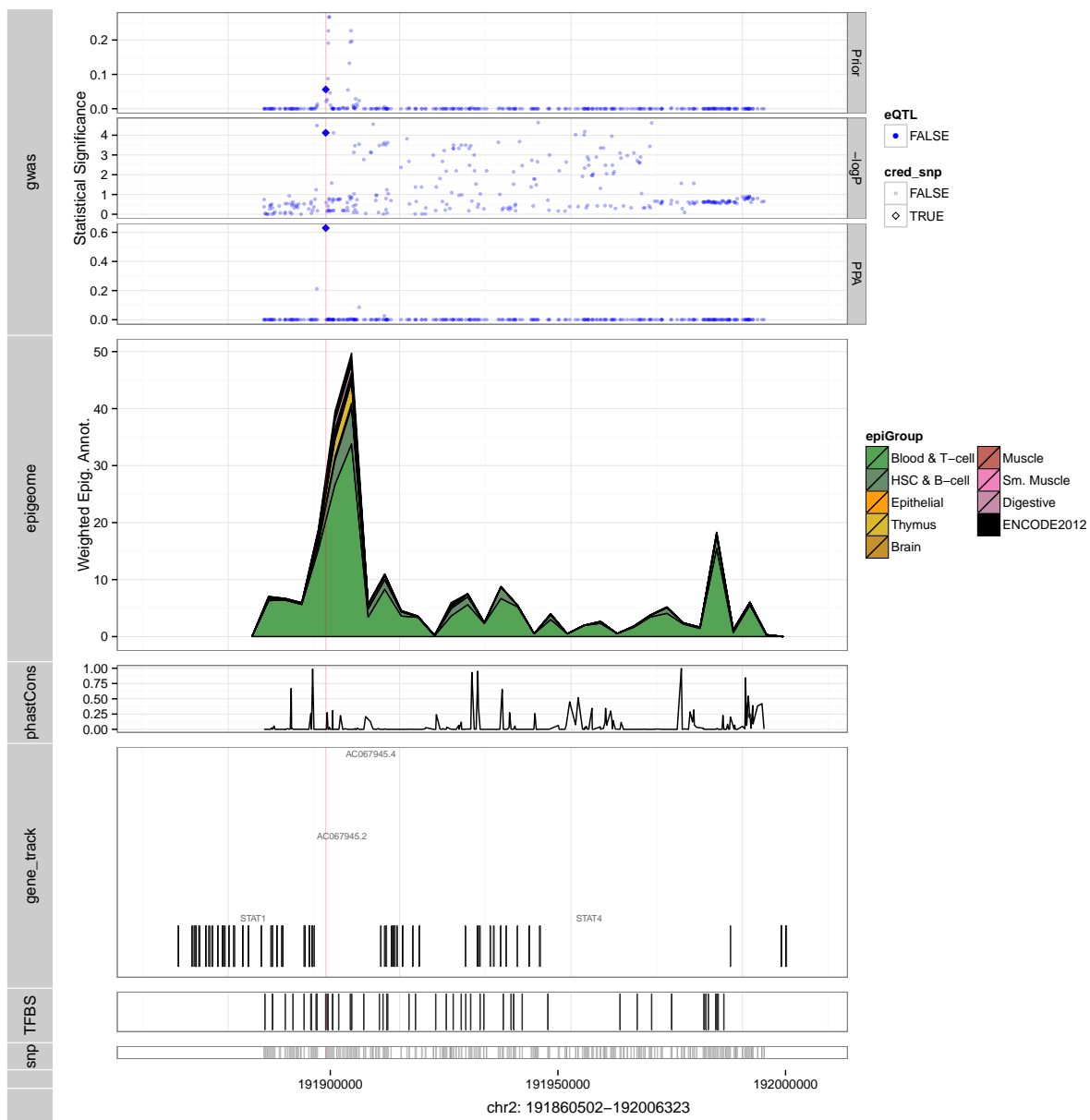
Type 1 Diabetes



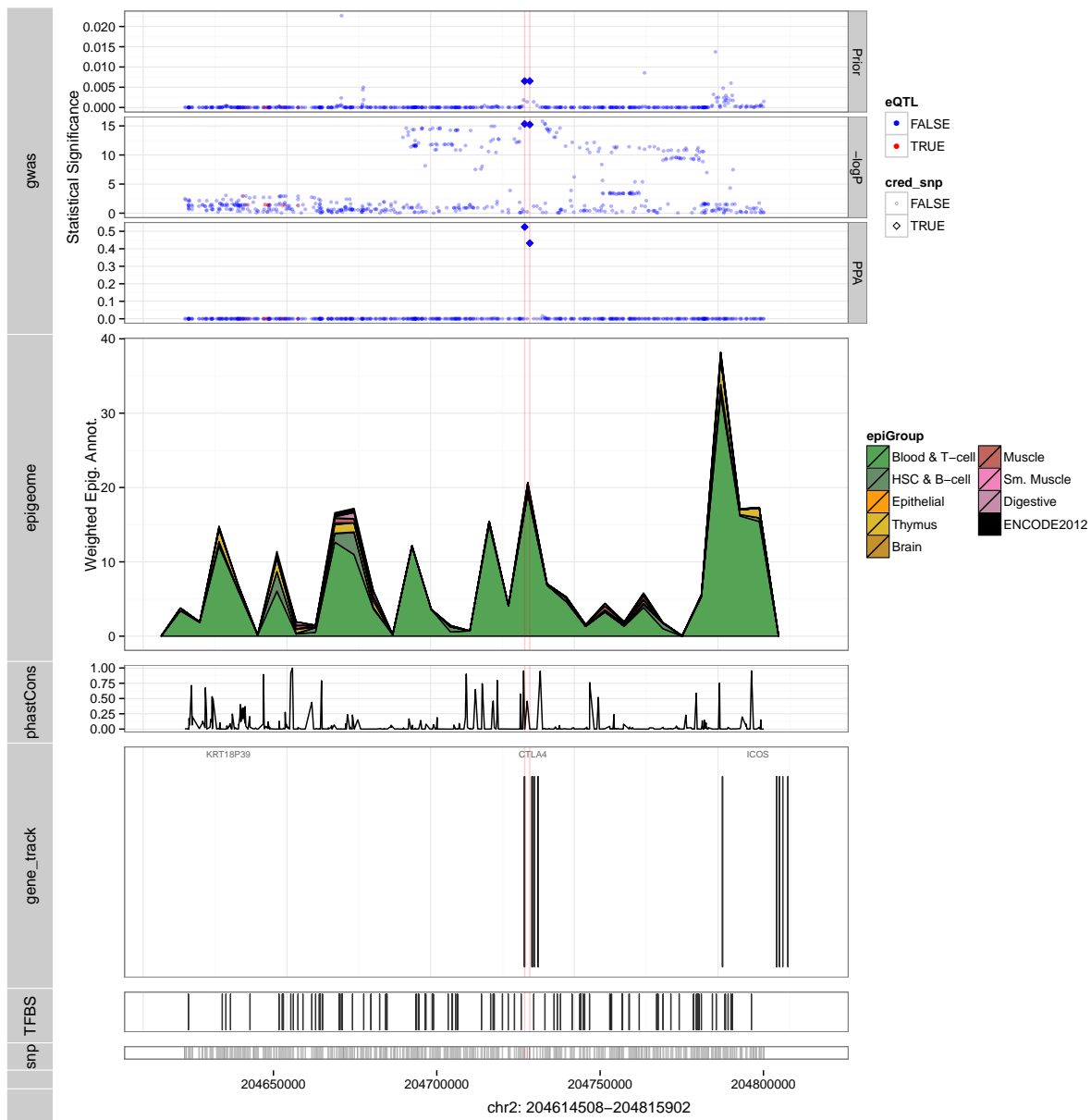
Type 1 Diabetes



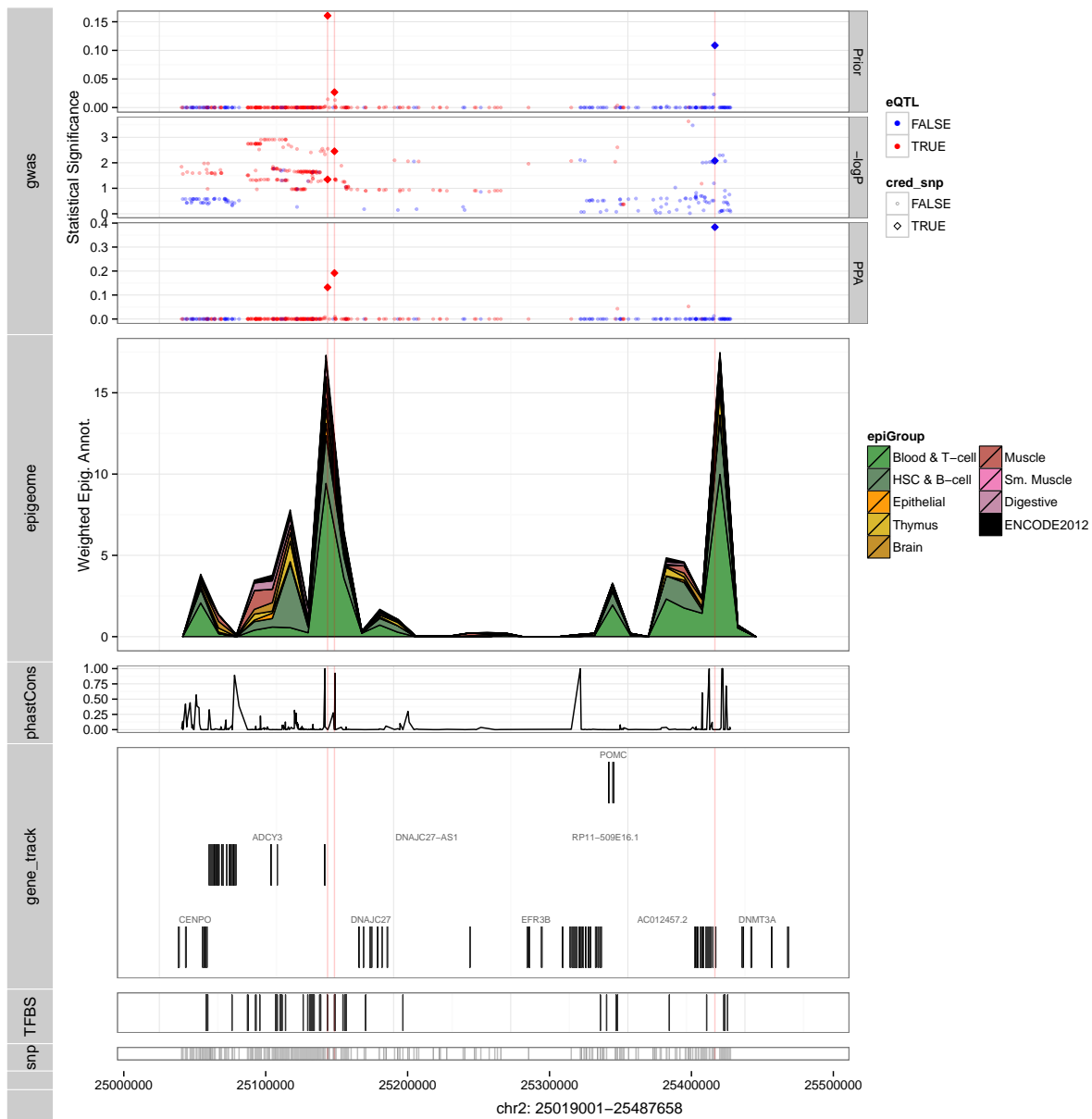
Type 1 Diabetes



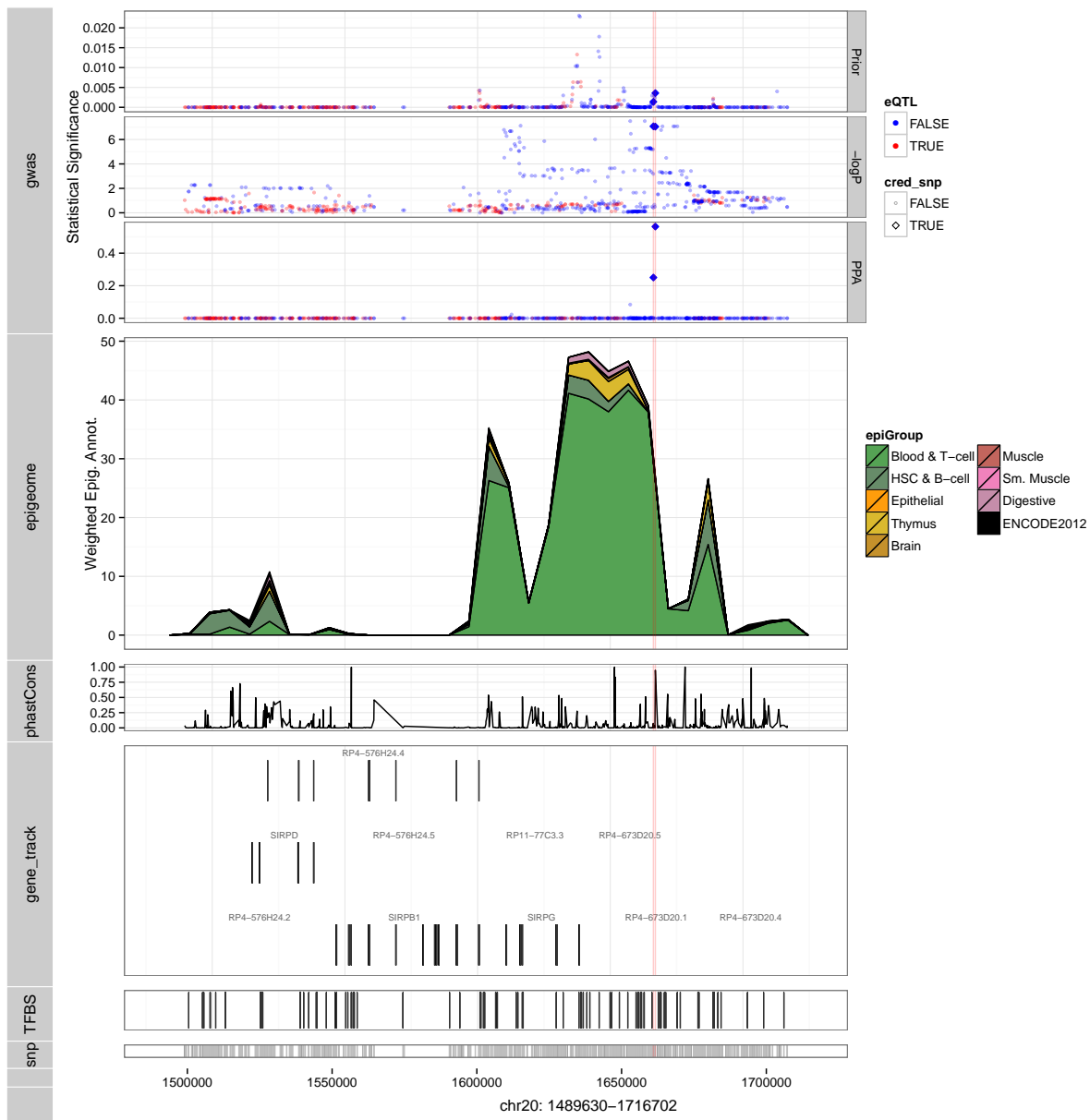
Type 1 Diabetes



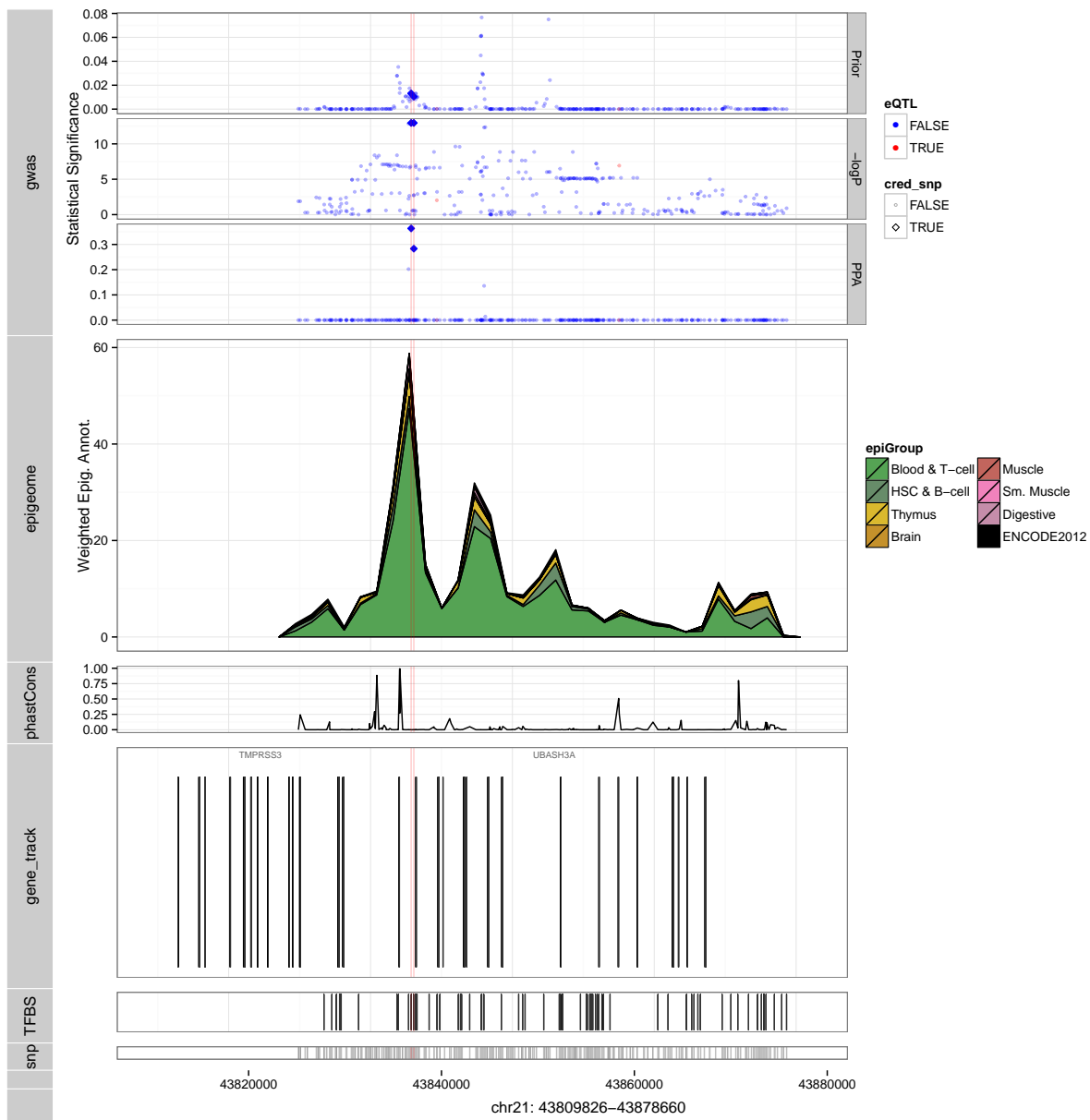
Type 1 Diabetes



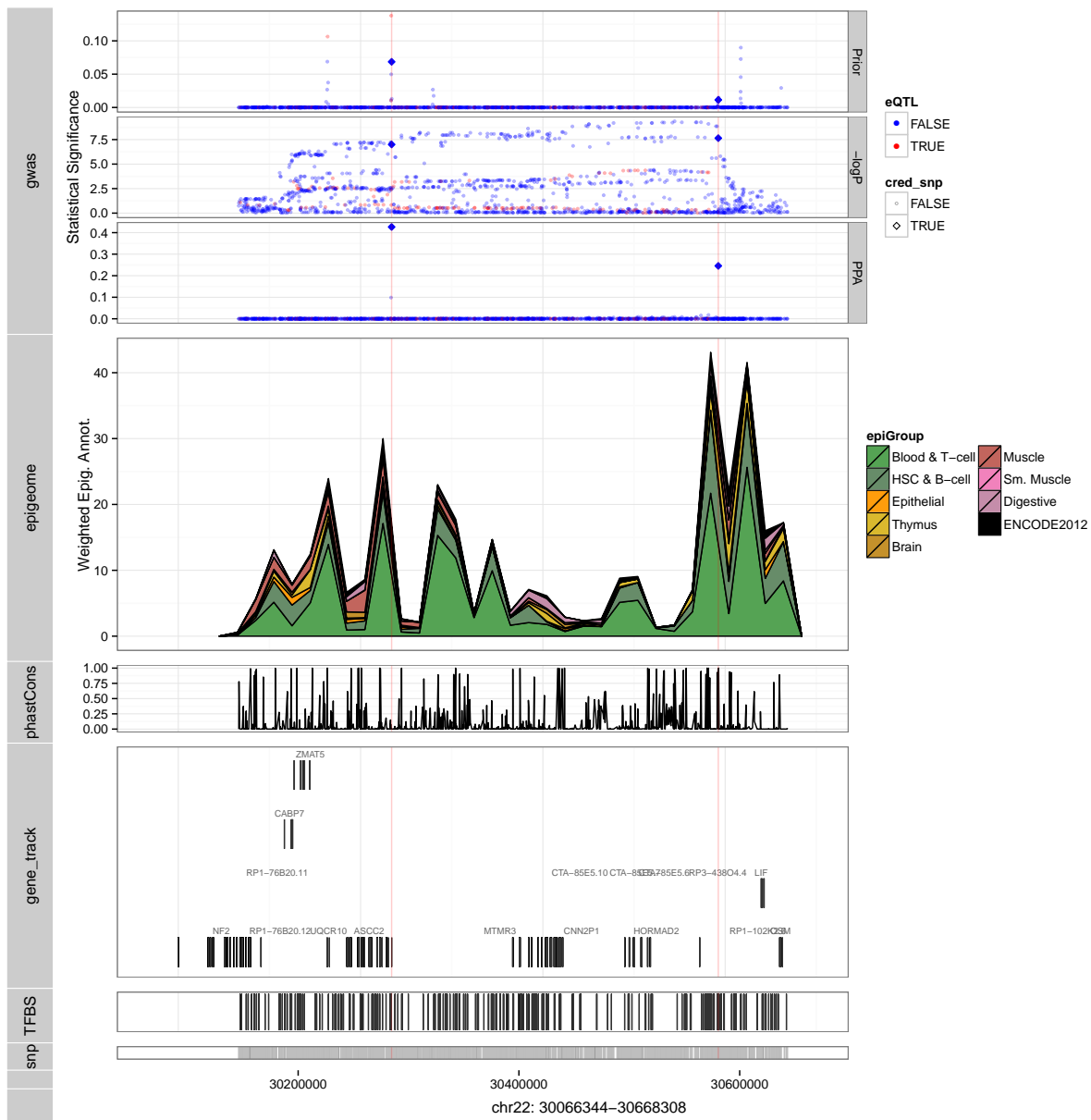
Type 1 Diabetes



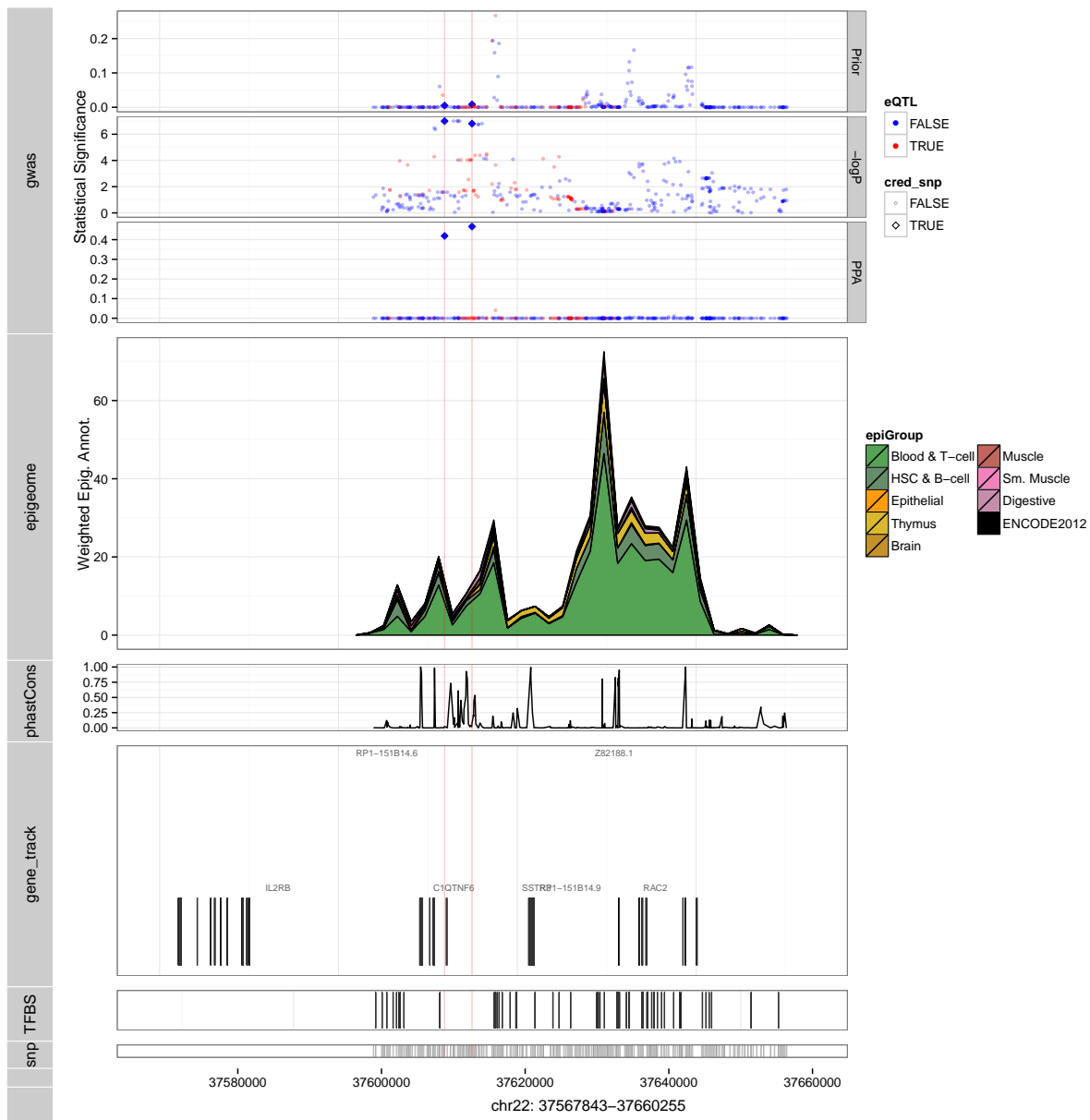
Type 1 Diabetes



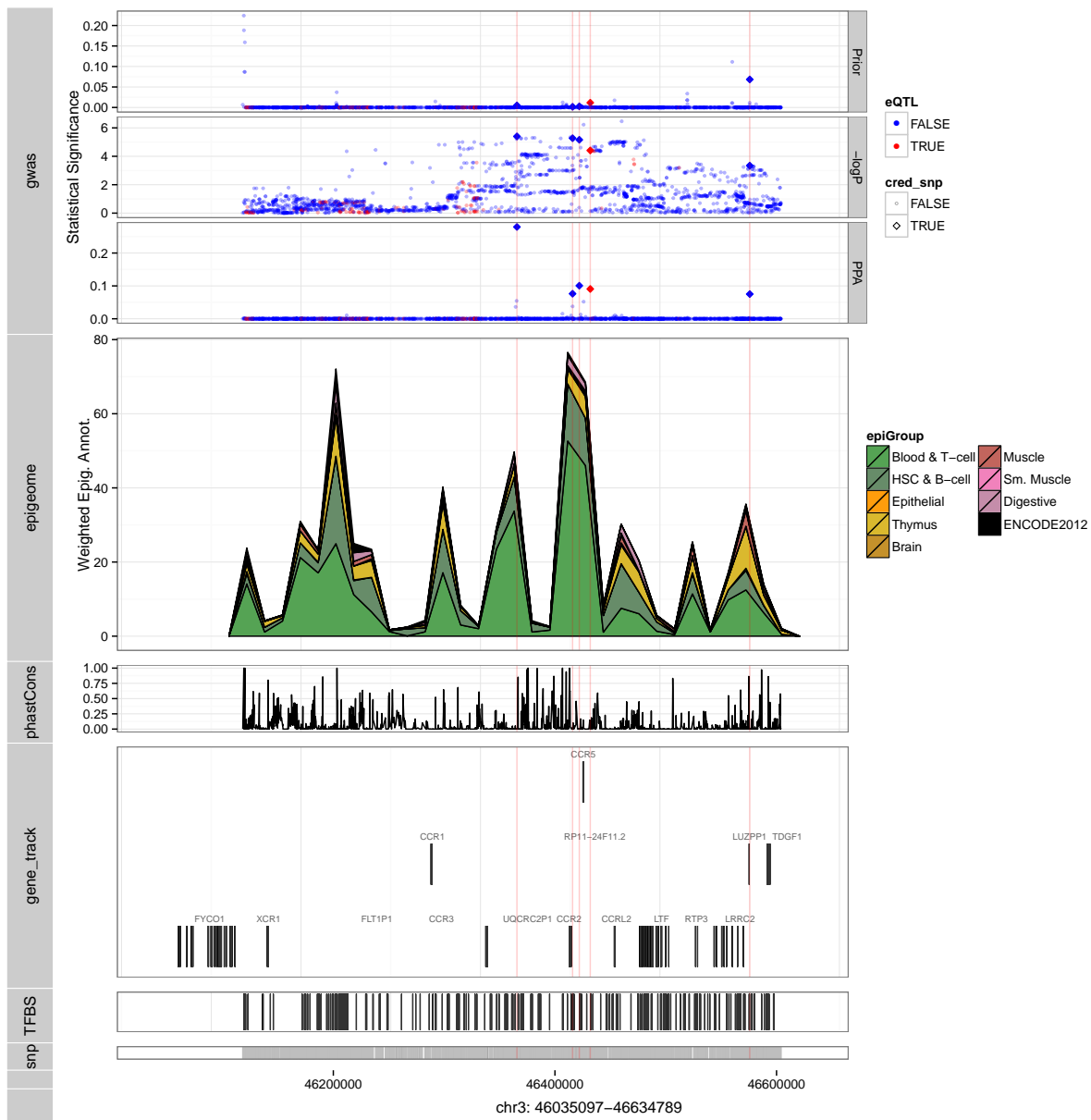
Type 1 Diabetes



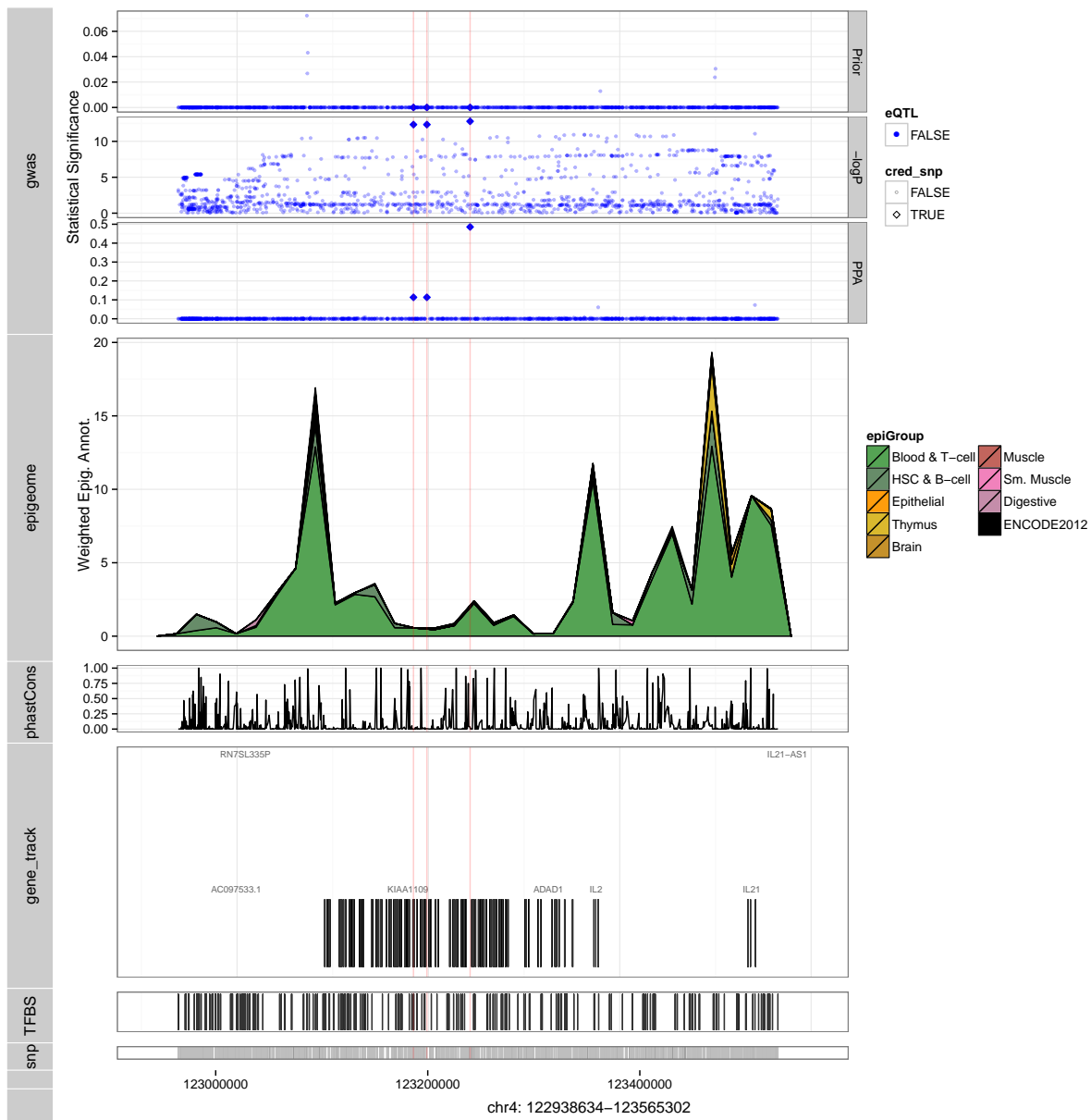
Type 1 Diabetes



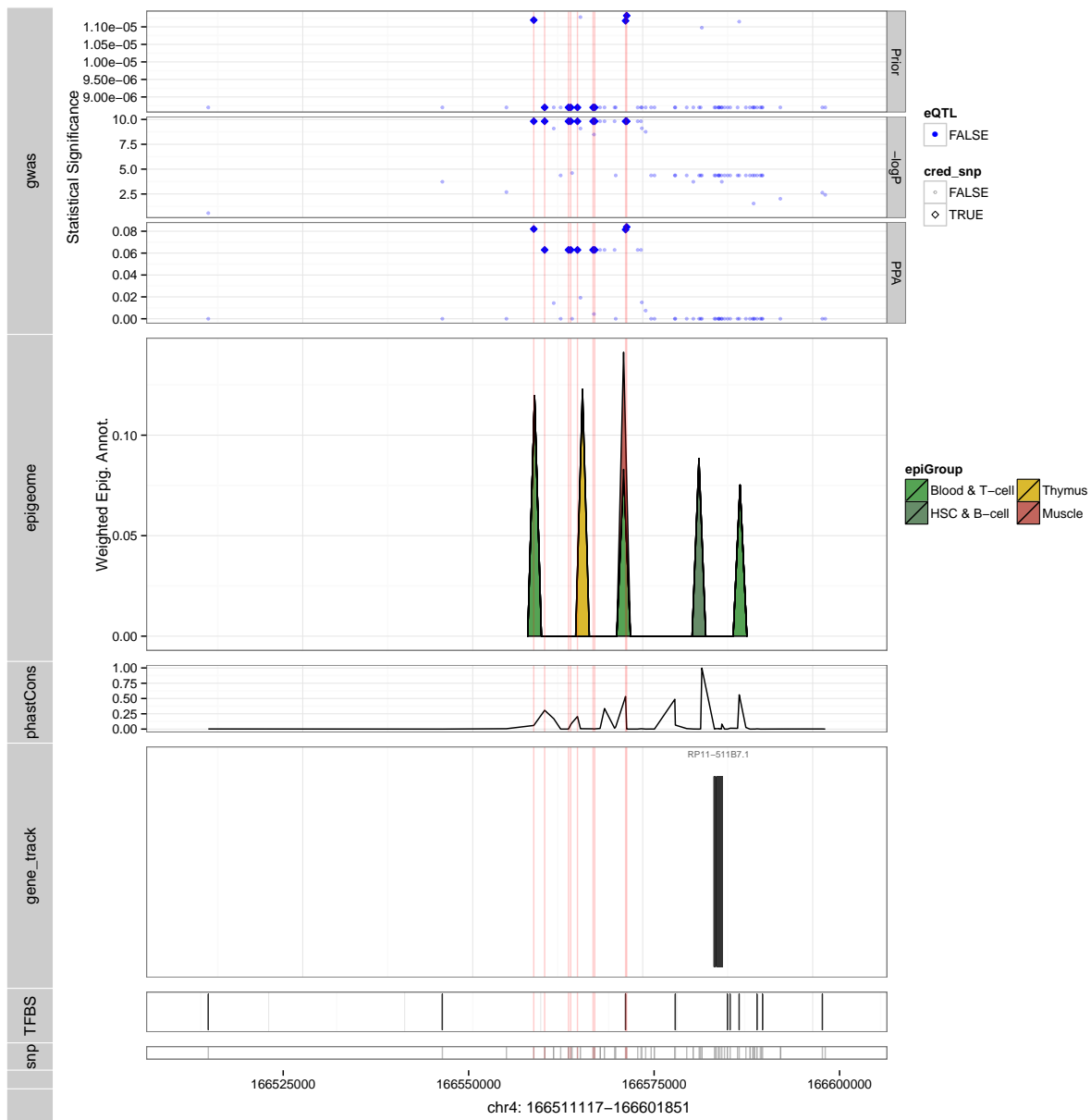
Type 1 Diabetes



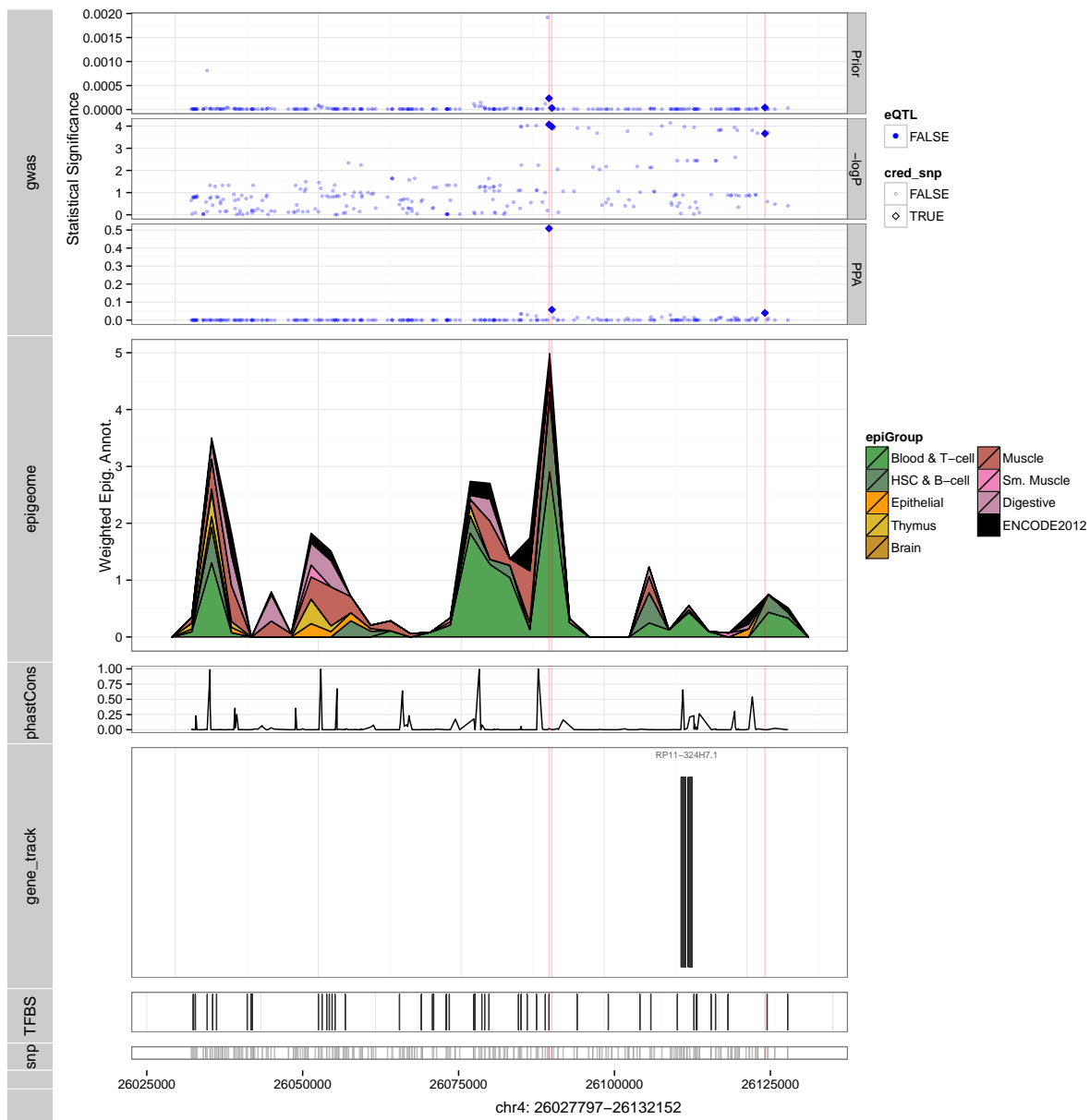
Type 1 Diabetes



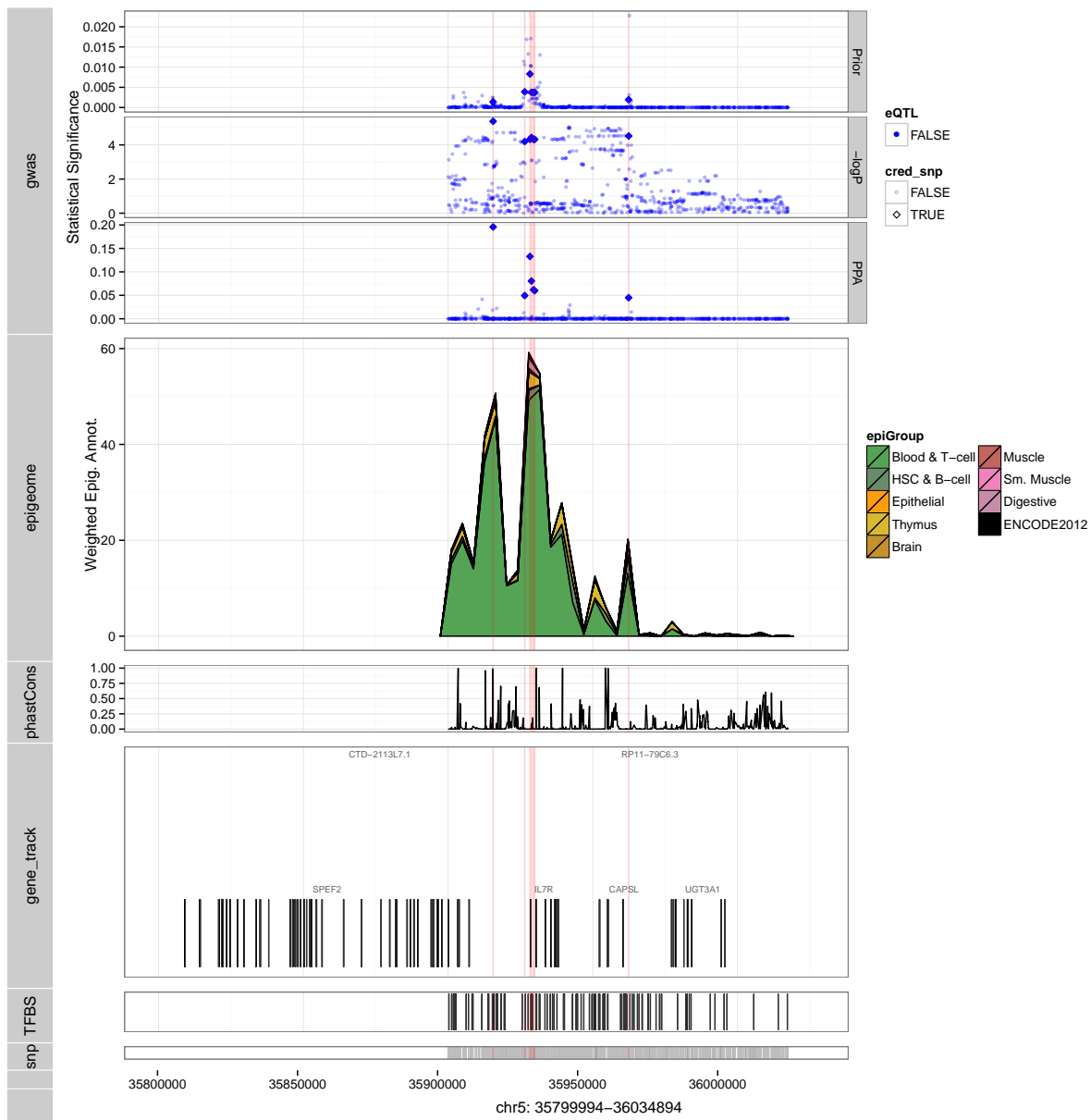
Type 1 Diabetes



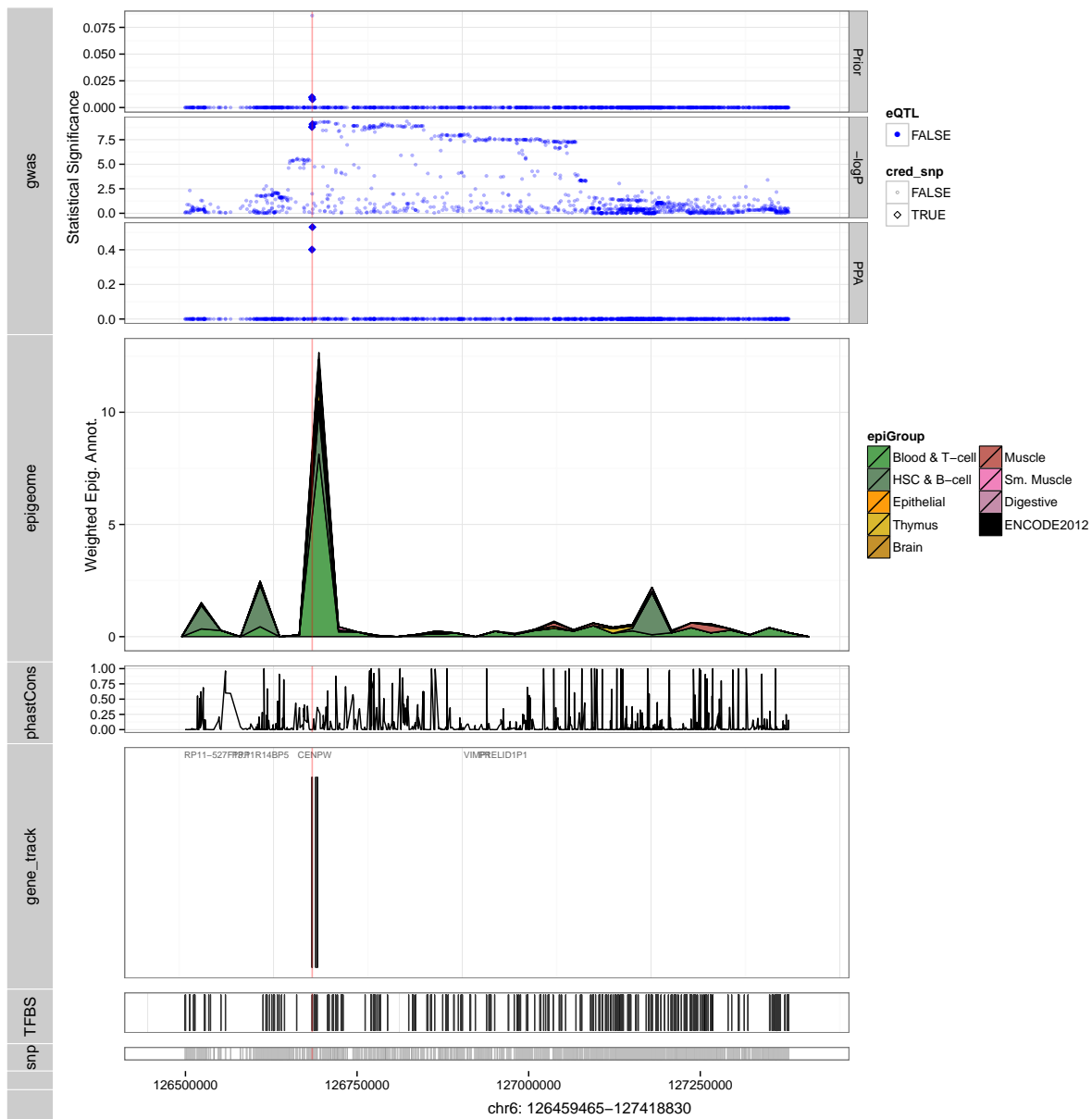
Type 1 Diabetes



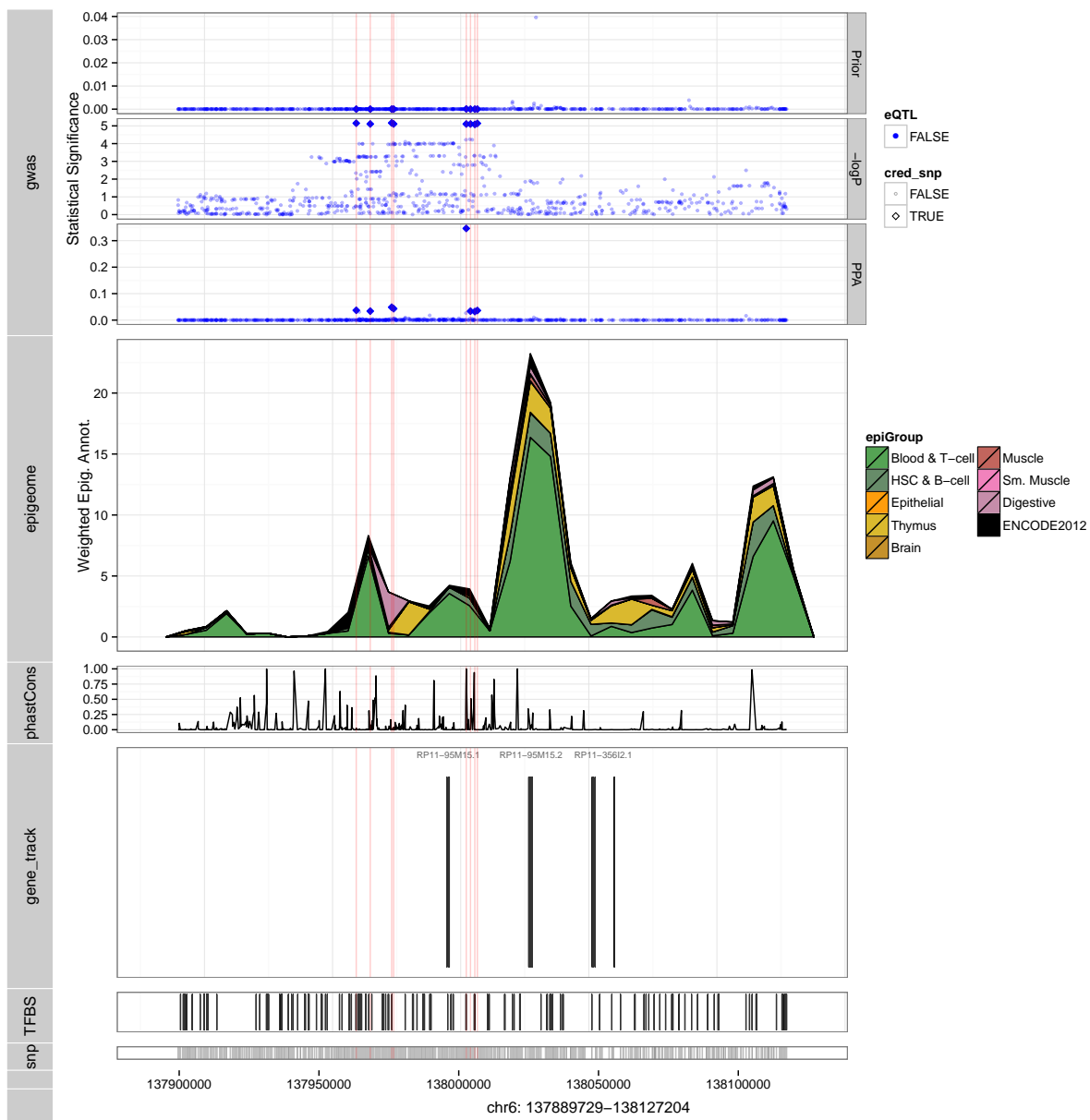
Type 1 Diabetes



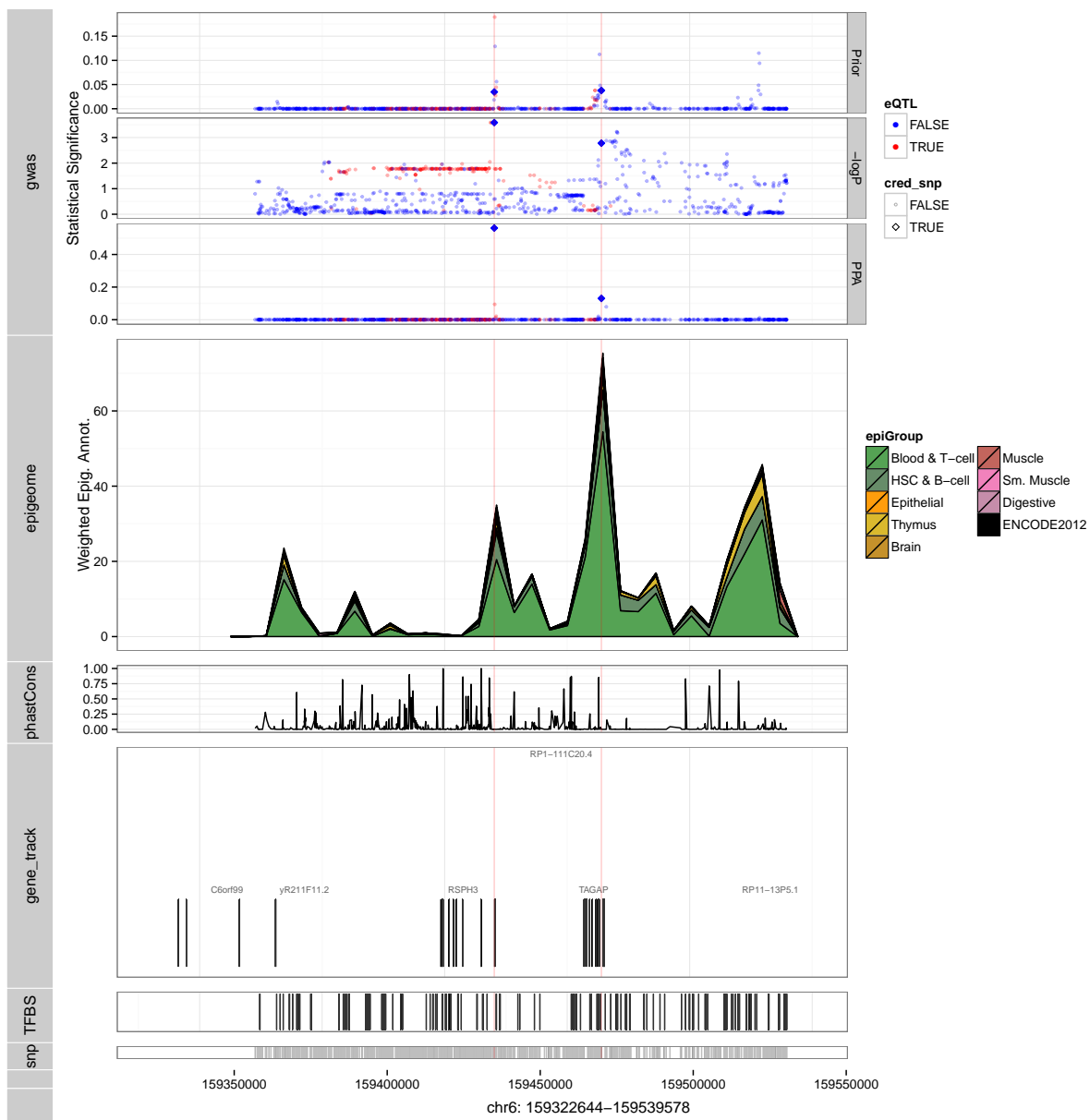
Type 1 Diabetes



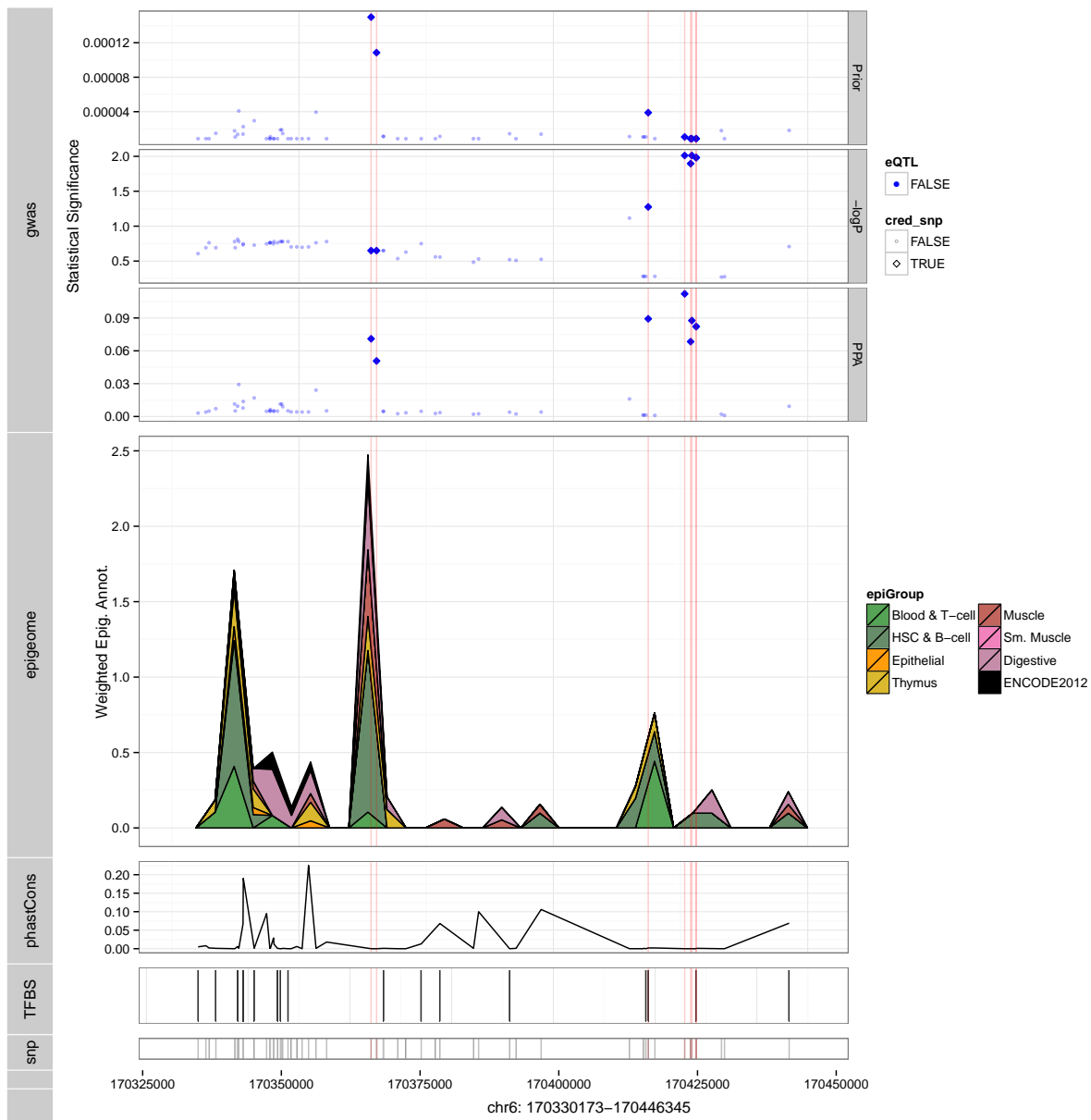
Type 1 Diabetes



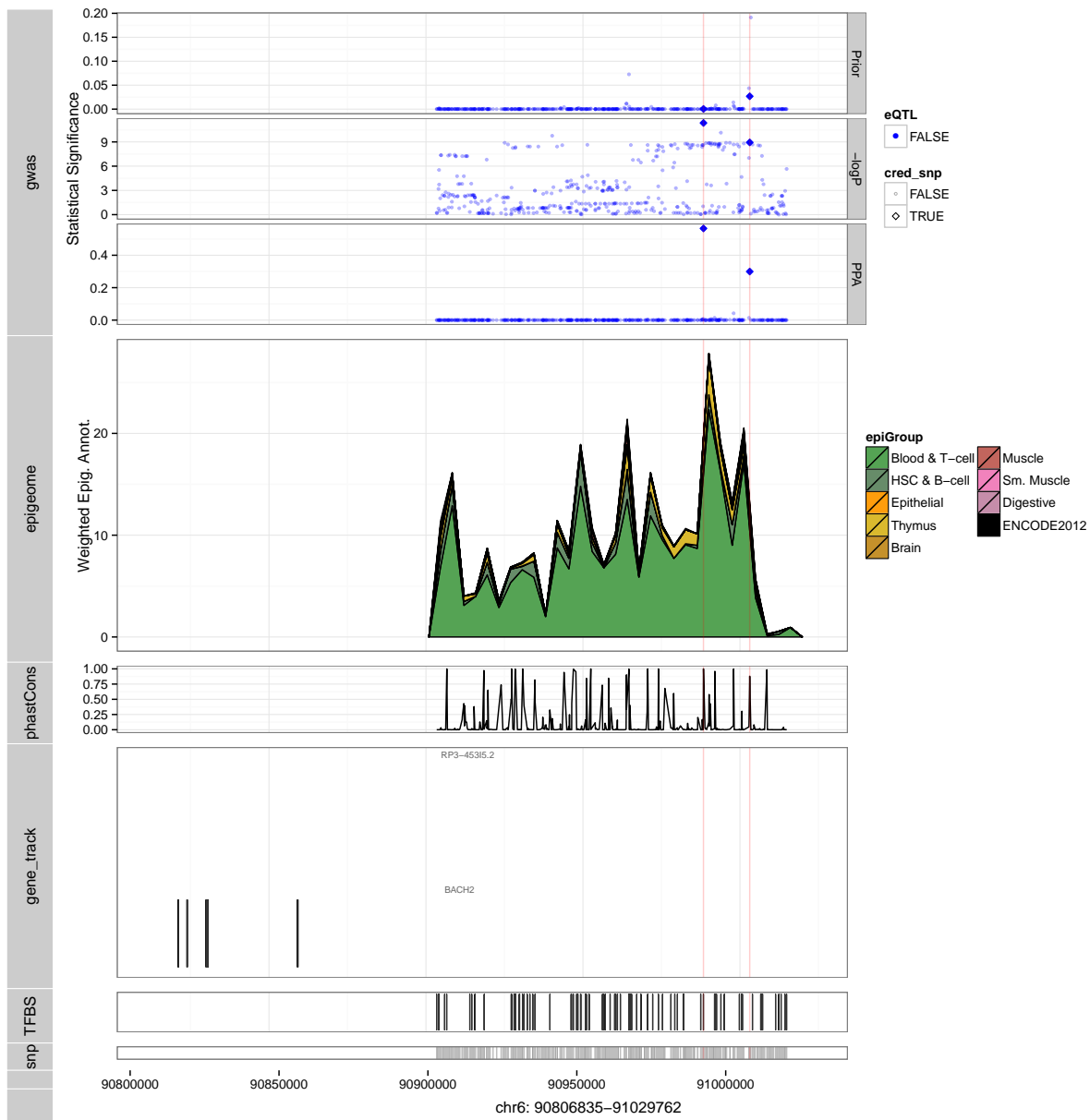
Type 1 Diabetes



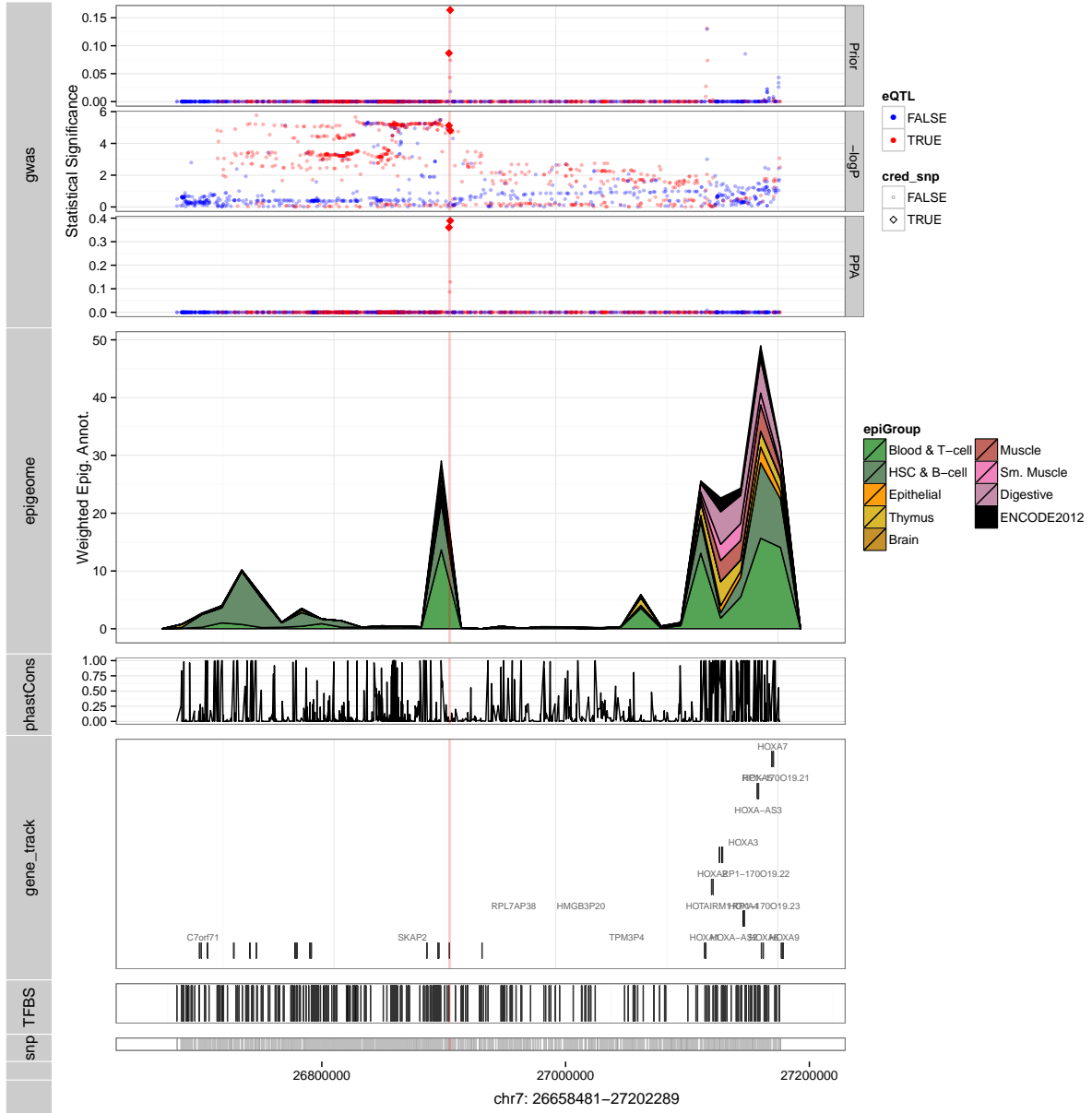
Type 1 Diabetes



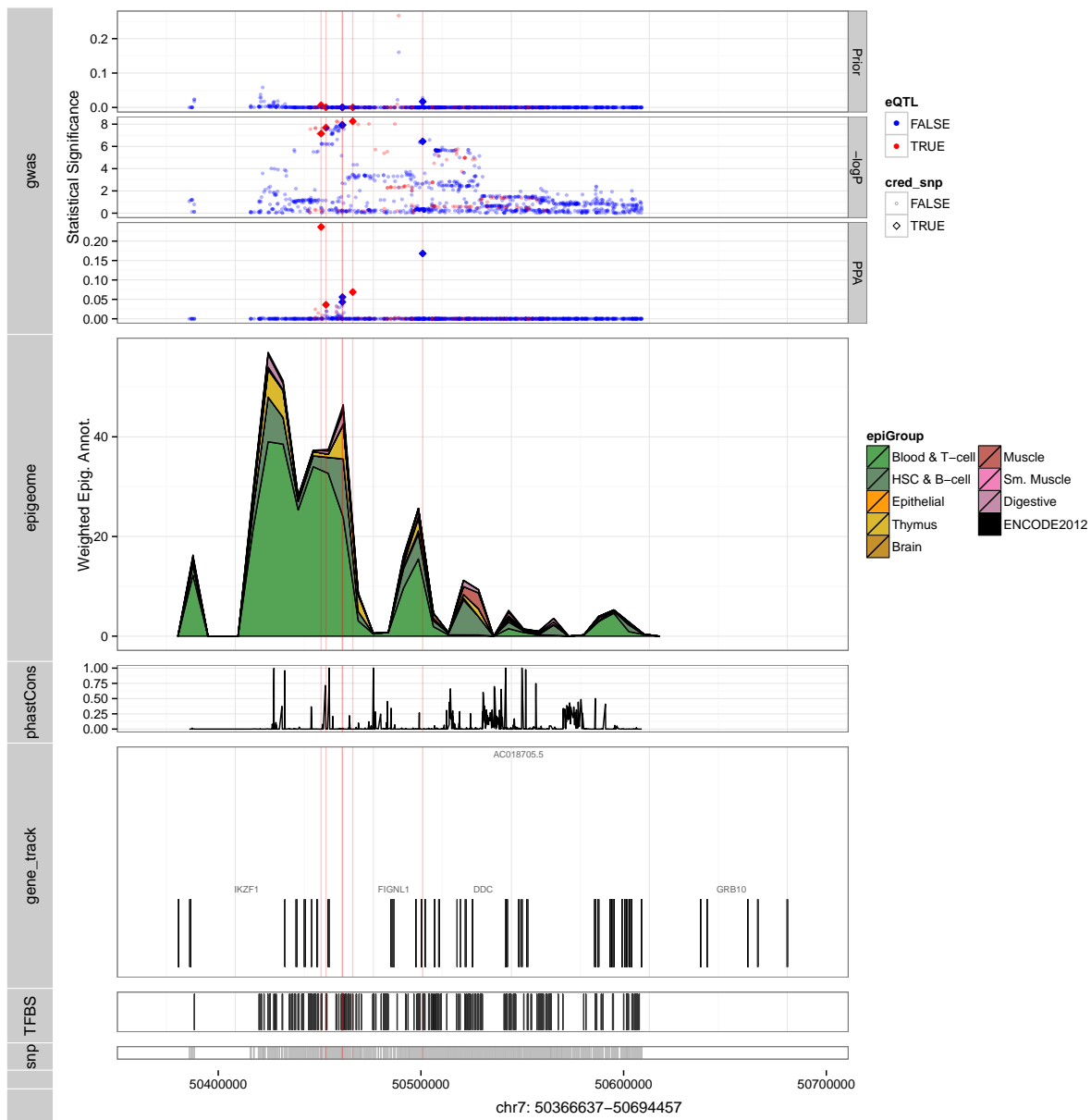
Type 1 Diabetes



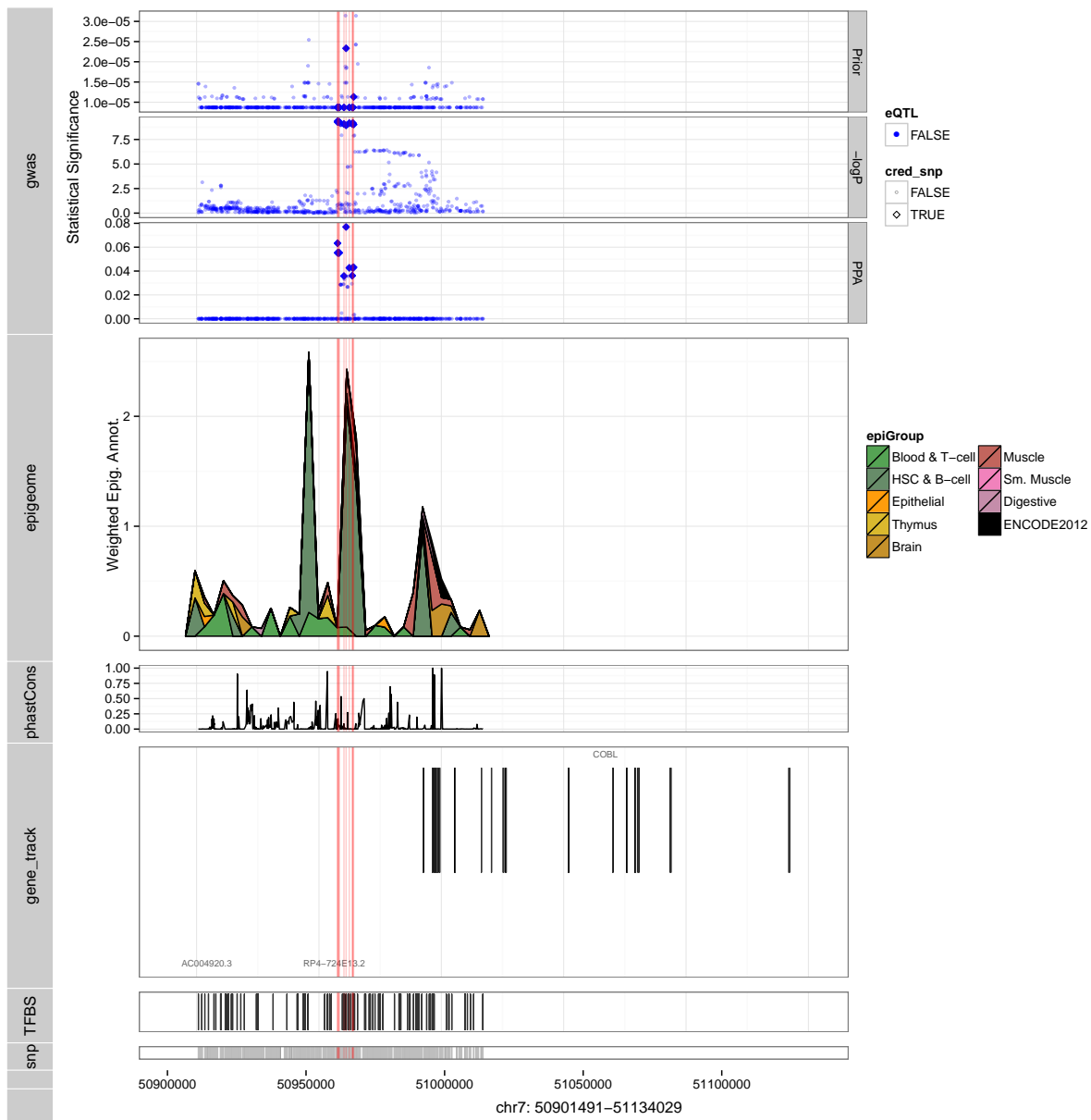
Type 1 Diabetes



Type 1 Diabetes



Type 1 Diabetes



Type 1 Diabetes

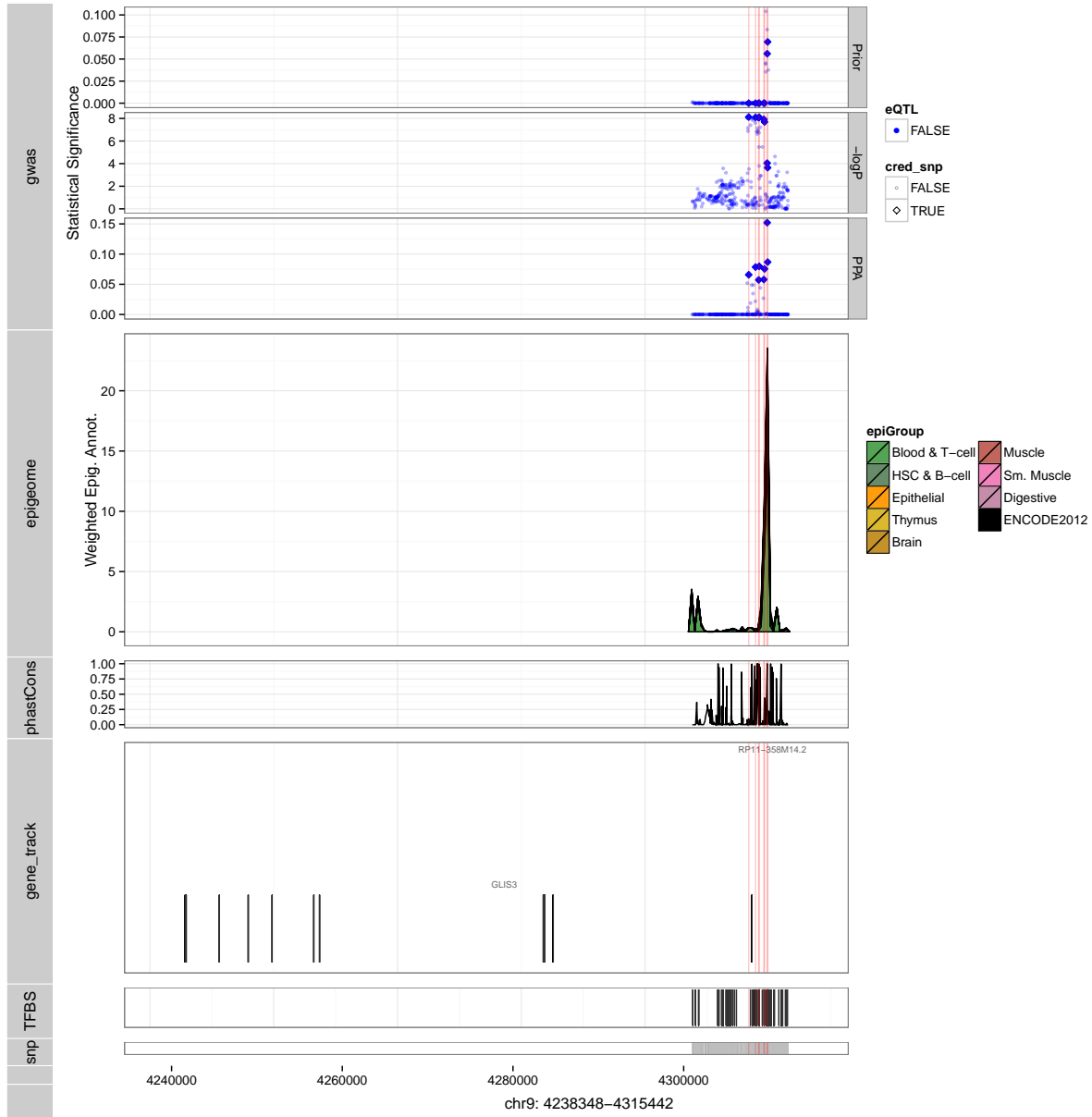


Fig. S5: Visualization of fine-mapping results on 469 risk loci across 10 traits. The upper panel displays the model prior, the genetic signals of GWAS $-\log_{10}$ p-values, and PPA; the middle panel illustrates the cumulative density of weighted epigenomic profiles colored based on the epigenomic group; the bottom tracks show the conservation, gene annotations (Gencode 19), transcription factor binding sites (TFBS), and SNP positions.

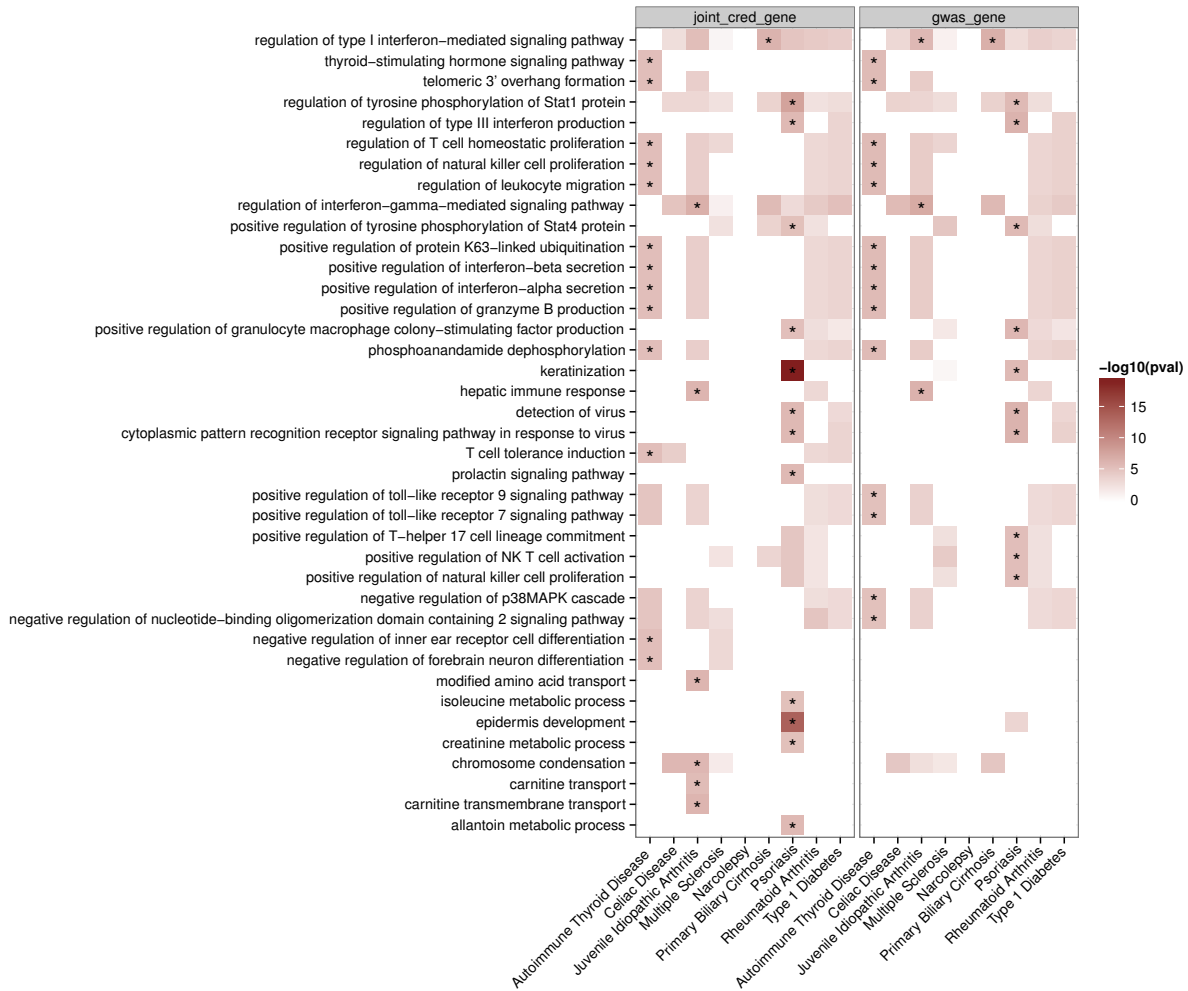


Fig. S6: Gene ontology enrichments across the 9 traits. Rows are the GO biological processes and columns are the 10 traits. Color intensities in each cell reflect the significance level in terms of $-\log_{10}$ p-value. Asterisks indicate q-values above significant cutoff after correcting for multiple testings ($FDR < 0.005$).

2 Supplementary Tables

Table S1: Full enrichment results for the 848 epigenomic annotations (Excel)

Table S2: Credible SNPs and related functional genomic information (Excel)

Table S3: Functional enrichments of credible SNPs (Excel)

Table S4: Gene ontology enrichment results using credible genes (Excel)

Table S5: Enrichments for eQTL of multi-trait model (Excel)

Table S6: Credible SNPs inferred from the multi-trait model on the 9 immune diseases and related functional genomic information (Excel)

Table S7: Gene ontology enrichment results using credible genes from cross-trait model (Excel)

3 Supplementary Text S1: HMC method details and RiVIERA algorithm outlines

3.1 Hamiltonian Monte Carlo (HMC) sampling for w_{kd} , w_{0d} , μ_d , ϕ_d

To sample epigenomic effects w_{kd} , causal mean μ_d , causal precision ϕ_d , we employ Hamiltonian Monte Carlo (also known as hybrid Monte Carlo) (HMC) [7,8]. HMC is one of the most powerful MCMC methods [7–9]. By extending the state space to include auxiliary momentum variables, and then using Hamiltonian dynamics to traverse long probability contours in the extended state space, HMC is able to move long distances in state space in a single update step and thus largely bypasses the slow exploration of the state space that occurs when Metropolis updates are done using a simple random-walk proposal distribution [9]. However, the essential elements for HMC are partial derivatives or gradients of the potential energy function $U = -\log p(\Theta|\mathcal{D})$ with respect to the variable of interests, which are not always tractable.

Sampling model parameters q by HMC can be intuitively visualized as a particle that slides over a frictionless surface [9]. When climbing on a rising slope, the particles momentum allows it to continue to explore the parameter space with decreasing kinetic energy and increasing potential energy (i.e., decreasing posterior), until the kinetic energy reaches zero, at which point it will slide back down with increasing kinetic energy and decreasing potential energy (i.e., increasing posterior). Thus, the momentum can be built up along the HMC trajectory to tolerate to some extent the deterioration of posterior probability upon hill climbing in order to seek for better parameter space. As a result, the HMC algorithm is able to explore much larger parameter space and much less prone to getting trapped within local suboptimal regions than simple Metropolis random walk.

In our case, solving HMC inference is feasible because $U = -\log p(\Theta|\mathcal{D})$ (i.e., joint posterior) is differentiable with respect to the model parameters $\mu_d, \phi_d, w_{kd}, w_{0d}$. With some simple linear algebra, we obtain the following gradients:

$$\frac{\partial U}{\partial \mu_d} = -\frac{\mu_0 \phi_0 - 1}{\mu_d} + \frac{(1 - \mu_0) \phi_0 - 1}{1 - \mu_d} - \sum_{v=1}^V c_{vd} \frac{\partial \log f(a_{vd}; \mu_d, \phi_d)}{\partial \mu_d} \quad (1)$$

$$\frac{\partial U}{\partial \phi_d} = -\sum_{v=1}^V c_{vd} \{[\mu(a_{vd}^* - \mu_d^*) + \log(1 - a_{vd}) - \psi((1 - \mu_d)\phi_d)] + \psi(\phi_d)\} \quad (2)$$

$$\frac{\partial U}{\partial w_{kd}} = \sum_{d'=1}^D w_{kd'} \lambda_{dd'} + \sum_{v=1}^V (\pi_{vd} - c_{vd}) e_{vk} \quad (3)$$

$$\frac{\partial U}{\partial w_{0d}} = \sum_{v=1}^V (\pi_{vd} - c_{vd}) + \lambda_{0d} (w_{0d} - \log \frac{\pi_0}{1 - \pi_0}) \quad (4)$$

where $\psi(\cdot)$ is the digamma function and

$$\frac{\partial \log f(a_{vd}; \mu_d, \phi_d)}{\partial \mu_d} = \phi_d \left[\log \frac{a_{vd}}{1 - a_{vd}} - \{\psi(\mu_d \phi_d) - \psi((1 - \mu_d)\phi_d)\} \right] \quad (5)$$

The gradient calculations were verified by comparing them individually to the changes in potential energy $\Delta U(q) = \frac{U(q+\xi) - U(q-\xi)}{2 \times \epsilon}$, where $\xi = 10^{-4}$ and $\frac{\partial U}{\partial q} \approx \Delta U(q)$ within a very small numerical discrepancy (e.g., 10^{-8}).

Given the gradients, we apply the standard HMC procedure [8,9] known as the “leapfrog” method [8,9]. In a nutshell, the Hamiltonian dynamics is defined as

$$H(q, p) = U(q) + K(p) \tag{6}$$

where the potential energy $U(q) = -\log p(\Theta|\mathcal{D})$ (i.e., negative log posterior defined as above) and q denotes the position variable in a fictitious physical system. In our case, the position variable $q \in \Theta = \{\mu_d, \phi_d, \mathbf{w}_d, w_{0d}\}$. $K(p)$ is the kinetic energy, where the auxiliary variable p is drawn independently from $\mathcal{N}(0, 1)$ to model the momentum for each position variable q .

As described in Algorithm 1, we simulate the Hamiltonian dynamics via the “leapfrog” method. The procedure starts with a half-step update of the momentum, followed by $L - 1$ full-step updates of both position and momentum variables, and ends with another half-step update of the momentum. During the leapfrog updates, we constrain $q \in \{\mu_d, \phi_d, \mathbf{w}_d\}$ to be positive by changing the sign of the momentum variable p and the position variable q once q becomes negative. This is equivalent to setting an infinite potential energy on the those values that violate the positive constraint, which will give the corresponding positions probability of zero. Intuitively, we can visualize it as reverting the trajectory of the particle as if it were to bounce off the wall given by the positive constraint [9].

At the end of this trajectory, we apply a Metropolis update to accept the proposed Hamiltonian state at the probability $\min(1, \exp[-\Delta H])$, where $\Delta H = H^* - H^{cur}$. Thus, we will always accept the proposed state if the Hamiltonian dynamics is lowered or unchanged in contrast to the current one. Because of the discrete-time procedure, we must use a small step size ϵ to compensate for the numerical imprecision introduced in simulating the Hamiltonian system. Automated procedure adapting the step size ϵ and step number L to the Metropolis acceptance rate is an active research field [9, 10]. A rule-of-thumb is to maintain the acceptance rate at around 65%. Here we set the step size ϵ to 0.001 and number of steps L to 100 based on some preliminary runs, where the acceptance rates are within the range of [50%, 90%] over 1000 MCMC samples.

3.2 RiVIERA inference algorithm

The pseudocode for RiVIERA is outlined in Algorithm 2.

Algorithm 1 HMC procedure to simultaneously sample $w_{kd}, w_{0d}, \mu_d, \phi_d$

- 1: Given ϵ, L , and q , where $q \in \{w_{kd}, w_{0d}, \mu_d, \phi_d\}$
- 2: Set $q^{cur} \leftarrow q^0 \leftarrow q$
- 3: Sample $p^{cur} \sim \mathcal{N}(0, 1)$
- 4: Set $p \leftarrow p^{cur} - (\epsilon/2) \frac{\partial U}{\partial q}$
- 5: **for** $i = 1 \dots L$ **do**
- 6: Set $q^i \leftarrow q^{i-1} + \epsilon p^{i-1}$
- 7: **if** $i \neq L$ **then**
- 8: Set $p^i \leftarrow p^{i-1} - \epsilon \frac{\partial U}{\partial q^i}$
- 9: **else**
- 10: Set $p^i \leftarrow p^{i-1} - (\epsilon/2) \frac{\partial U}{\partial q^i}$
- 11: **end if**
- 12: **if** $q \in \{\mathbf{w}, \mu, \phi\}$ AND $q^i < 0$ **then**
- 13: $q^i \leftarrow -q^i, p^i \leftarrow -p^i$
- 14: **end if**
- 15: **end for**
- 16: Set $H^* \leftarrow U(q^L) + \frac{1}{2} \sum_m (p_m^L)^2$
- 17: Set $H^{cur} \leftarrow U(q^{cur}) + \frac{1}{2} \sum_m (p_m^{cur})^2$
- 18: **if** $Unif(0, 1) < \exp(-\{H^* - H^{cur}\})$ **then**
- 19: Set $q \leftarrow q^L$
- 20: **else**
- 21: Set $q \leftarrow q^{cur}$
- 22: **end if**

Algorithm 2 RiVIERA algorithm

Input:

A: $V \times D$ GWAS summary statistics matrix as p-values for V variants across D diseases
E: $V \times K$ annotation matrix for V variants and K epigenomic annotations
L: $B \times 2$ matrix indicating start and end indices of the SNPs for each locus $b = 1, \dots, B$
 Θ_0 : $\pi_0, \mu_0, \phi_0, \nu_0, \lambda_0, \alpha_0, \beta_0, T, \epsilon, L$ (model settings or hyperparameters)

Output: :

$\hat{\pi}_v, \hat{c}_v, \hat{f}_k$: estimated expected values of priors, causal indicators, enrichments averaged across T' MCMC runs

- 1: Initialize model parameters $\mathbf{w} \sim \mathcal{N}(0, 1), (\mu, \phi) \leftarrow (\mu_0, \phi_0), w_0 \leftarrow \text{logit}(\pi_0)$
- 2: **for** epoch = 1 To T **do**
- 3: Gibbs sample $\Lambda_w | \mathbf{W} \sim \text{Wishart}((\Lambda_0^{-1} + \mathbf{S})^{-1}, \nu_0 + K)$
- 4: Gibbs sample $\lambda_0 | w_0 \sim \text{Gamma}(\alpha_0 + 0.5, (\beta_0 + \frac{(w_{0d} - \mu_{w_0})^2}{2})^{-1})$
- 5: Randomly sampled a locus b from $(1, \dots, B)$
- 6: Compute empirical prior $\pi_{vd} \forall v \in \mathcal{V}_b; d = 1, \dots, D$
- 7: Compute PPA $p(c_{vd} | a_{vd}, \pi_{vd}) \forall v \in \mathcal{V}_b; d = 1, \dots, D$
- 8: HMC sample $w_{kd}, w_{0d}, \mu_d, \phi_d \forall k = 1, \dots, K; d = 1, \dots, D$
- 9: **end for**
- 10: Estimate $\hat{c}_{vd} = \frac{1}{T'} \sum_{t'=1}^{T'} c_{vd}^{(t')}$ and $\hat{f}_{kd} = \frac{1}{T'} \sum_{t=1}^{T'} \log \frac{1}{|\mathcal{C}_d|} \sum_{v \in \mathcal{C}_d} \frac{p(c_{vd} | \mathbf{w}_d^{(t)})}{p(c_{vd} | \mathbf{w}_d^{(t)}, w_{kd}^{(t)} = 0)}$

4 Supplementary Text S2: GWAS simulation

4.1 Simulating genotypes

As the first step of the simulation, we generated 10000 genotypes (**Fig. ??**). In particular, we use HapGen2 [1] to simulate haplotypes by conditioning on the 1000 Genome CEU population haplotypes (phase 1 version 3) so that the simulated data has the same LD patterns as the reference panel. However, HapGen2 is computationally demanding and can only simulate several thousands of SNPs for the chosen cohort size. To remedy that, we obtained the approximately independent LD blocks estimated from LDetect [2] and simulated 10,000 genotypes using HapGen2 together for each LD block separately. We only did this once for all of the simulation runs.

For each simulation run, we randomly sampled 100 LD blocks. For each sampled LD block, we then sampled 500 consecutive SNPs or used the whole block if it contains less or equal to 500 SNPs, which resulted in on average ~ 38 kb per locus. Thus, the maximum number of SNPs generated per simulation run is 500,000 SNPs. The sampling step was done mainly for computational reason in order to run many simulation runs in parallel. We then filtered out SNPs with allele frequency lower than 1%.

4.2 Simulating epigenomic enrichments

We chose 20 representative cell types from the 19 primary groups defined by Epigenome Roadmap Consortium [3]. Whenever available, for each of the 20 chosen tissues or cell types, we obtained epigenomic profiles for DNase and six core histone marks namely H3K4me1, H3K4me3, H3K36me1, H3K27me3, H3K9me3, and H3K9ac (**Fig. S1**). In total, we obtained 100 epigenomic annotations in BigWig format. For each epigenomic annotation, we then thresholded their values to be 1 for p-values < 0.01 and 0 otherwise.

The fold-enrichment of annotation k is then:

$$f_k = \frac{m_k/m_c}{a_k/m} \quad (7)$$

where

- m_k : number of causal variants harbored in annotation k ;
- m_c : the number of causal variants, which we set to 100, giving on average 1 causal variant per locus for the 100 simulated loci per simulated dataset;
- a_k : total number of variants from the 100 loci harbored in annotation k ;
- m : total number of variants from the 100 loci;

The maximum fold-enrichment for annotation k is then:

$$f_{\max,k} = \begin{cases} m/a_k, & \text{if } a_k > m_c \\ m/m_c, & \text{if } a_k < m_c \end{cases} \quad (8)$$

We then sampled from uniform distribution the fold-enrichment for each annotation within the corresponding range defined by (8) and subsequently solved for m_k to sample causal variants from that annotation:

$$f_k \sim U(1, f_{max,k}) \quad (9)$$

$$m_k = \frac{f_k a_k m_c}{m} \quad (10)$$

Due to the previously observed enrichments [3, 11], we started sampling causal variants from annotations corresponding to DNase, H3K4me1, and H3K4me3 and then the remaining annotations. The sampling continued until we reached or exceed the defined number of causal variants (i.e., 100). We then randomly chose 100 causal variants from the candidate causal variants. Because of the overlapping between annotations and the above rounding, we recomputed the fold-enrichment for each annotation using Eq (7).

4.3 Simulating GWAS summary statistics

We then simulated the effect sizes for causal SNPs as a function of minor allele frequency (p_i):

$$\beta_i = \frac{1}{\sqrt{2p_i(1-p_i)}} \quad (11)$$

We then simulated the quantitative phenotype or liability as:

$$\mathbf{y} = \mathbf{X}\beta + \epsilon \quad (12)$$

$$\epsilon \sim \mathcal{N}(0, \sigma_e^2 I_n) \quad (13)$$

Here \mathbf{X} is the standardized genotype of SNPs across individuals, and $\sigma_e^2 = \frac{\sigma_g^2 - h_g^2 \sigma_g^2}{h_g^2}$ (fixed at 0.25), such that $h_g^2 = \frac{\sigma_g^2}{\sigma_e^2 + \sigma_g^2}$ and $\sigma_g^2 = \text{Var}(X\beta) = \beta' \Sigma_g \beta$ is the phenotypic variance explained by the genetics [11], where Σ_g is the genotypic correlation matrix (i.e., linkage disequilibrium) estimated as the Pearson correlation from the 10,000 simulated individuals. Finally, we simulated p-value and z-score (as t -statistics) by regressing phenotype \mathbf{y} on \mathbf{X} for each SNP i : ($\mathbf{y} \sim \mathbf{x}_i$). We repeatedly generated simulated datasets using the approach described above and evaluated each fine-mapping method on each of the simulated dataset.

References

1. Su, Z., Marchini, J. & Donnelly, P. HAPGEN2: simulation of multiple disease SNPs. *Bioinformatics (Oxford, England)* **27**, 2304–2305 (2011).
2. Berisa, T. & Pickrell, J. K. Approximately independent linkage disequilibrium blocks in human populations. *Bioinformatics (Oxford, England)* (2015).
3. Consortium, R. E. *et al.* Integrative analysis of 111 reference human epigenomes. *Nature* **518**, 317–330 (2015).

4. Pickrell, J. K. Joint Analysis of Functional Genomic Data and Genome-wide Association Studies of 18 Human Traits. *The American Journal of Human Genetics* **94**, 559–573 (2014).
5. Kichaev, G. *et al.* Integrating functional data to prioritize causal variants in statistical fine-mapping studies. *PLoS genetics* **10**, e1004722 (2014).
6. Chung, D., Yang, C., Li, C., Gelernter, J. & Zhao, H. GPA: A Statistical Approach to Prioritizing GWAS Results by Integrating Pleiotropy and Annotation. *PLoS Genetics* **10**, e1004787 (2014).
7. Duane, S., Kennedy, A. D., Pendleton, B. J. & Roweth, D. Hybrid monte carlo. *Physics letters B* **195**, 216–222 (1987).
8. Neal, R. M. *Probabilistic inference using Markov chain Monte Carlo methods*. Ph.D. thesis, University of Toronto (1993).
9. Neal, R. M. Mcmc using hamiltonian dynamics. *Handbook of Markov Chain Monte Carlo* **2** (2011).
10. Homan, M. D. & Gelman, A. The no-u-turn sampler: Adaptively setting path lengths in hamiltonian monte carlo. *The Journal of Machine Learning Research* **15**, 1593–1623 (2014).
11. Gusev, A. *et al.* Partitioning Heritability of Regulatory and Cell-Type-Specific Variants across 11 Common Diseases. *AJHG* **95**, 535–552 (2014).
12. Burton, P. R. *et al.* Genome-wide association study of 14,000 cases of seven common diseases and 3,000 shared controls. *Nature* **447**, 661–678 (2007).